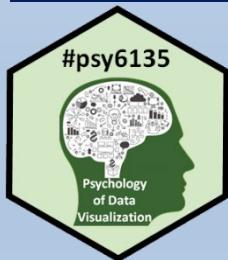
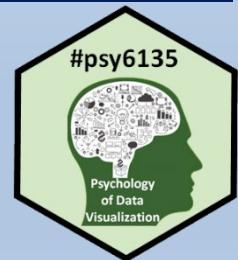


Visualizing Uncertainty



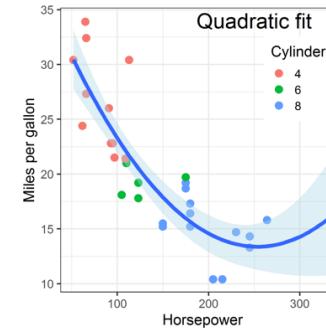
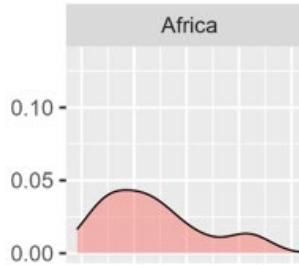
Michael Friendly
Psych 6135

<https://friendly.github.io/6135/>



Today's topics

- Uncertainty in statistics & visualization
- Visualizing distributions
- “Error bars”
- Bayesian uncertainty
- Uncertainty in fitted curves
- Hypothetical outcome plots
- Cartographic uncertainty

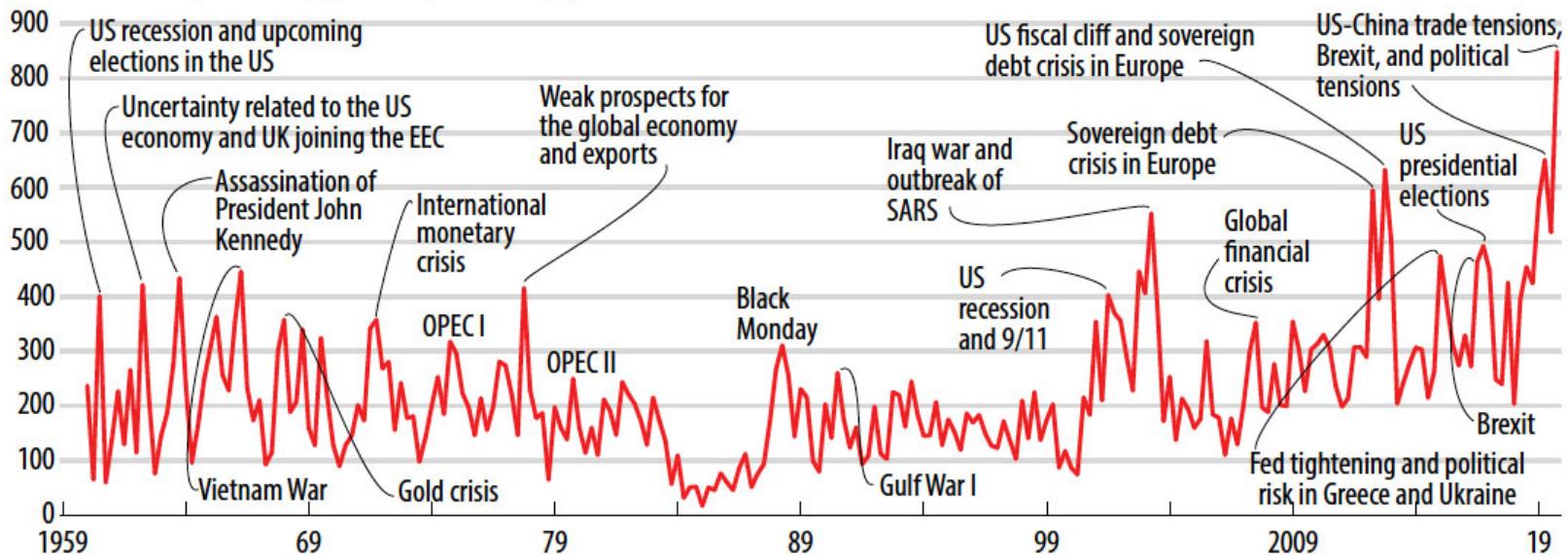


What is uncertainty?

Uncertain times

Global uncertainty has surged to a record high.

(WUI index: 1959 Q1 to 2019 Q4, GDP weighted average)

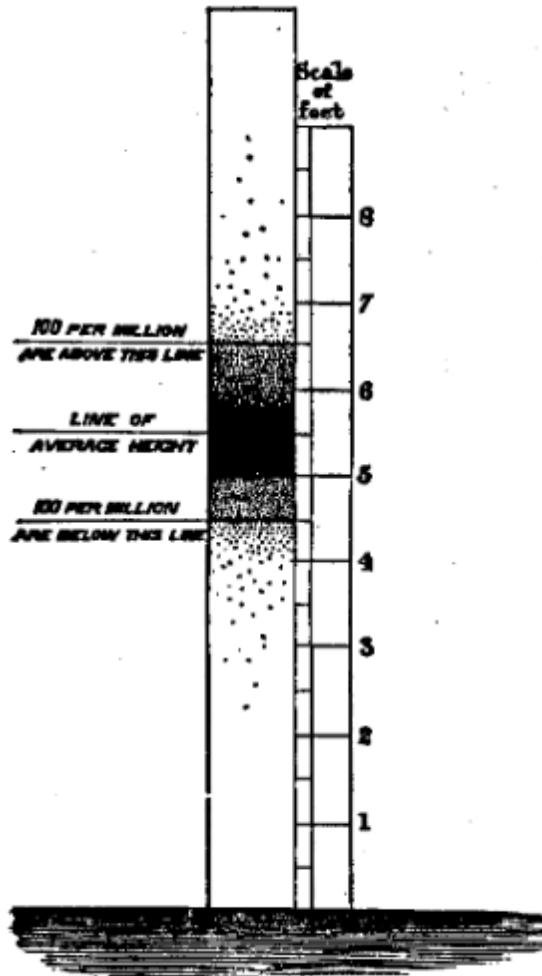


Sources: Ahir, H., N. Bloom and D. Furceri (2018), World Uncertainty Index (WUI), mimeo.

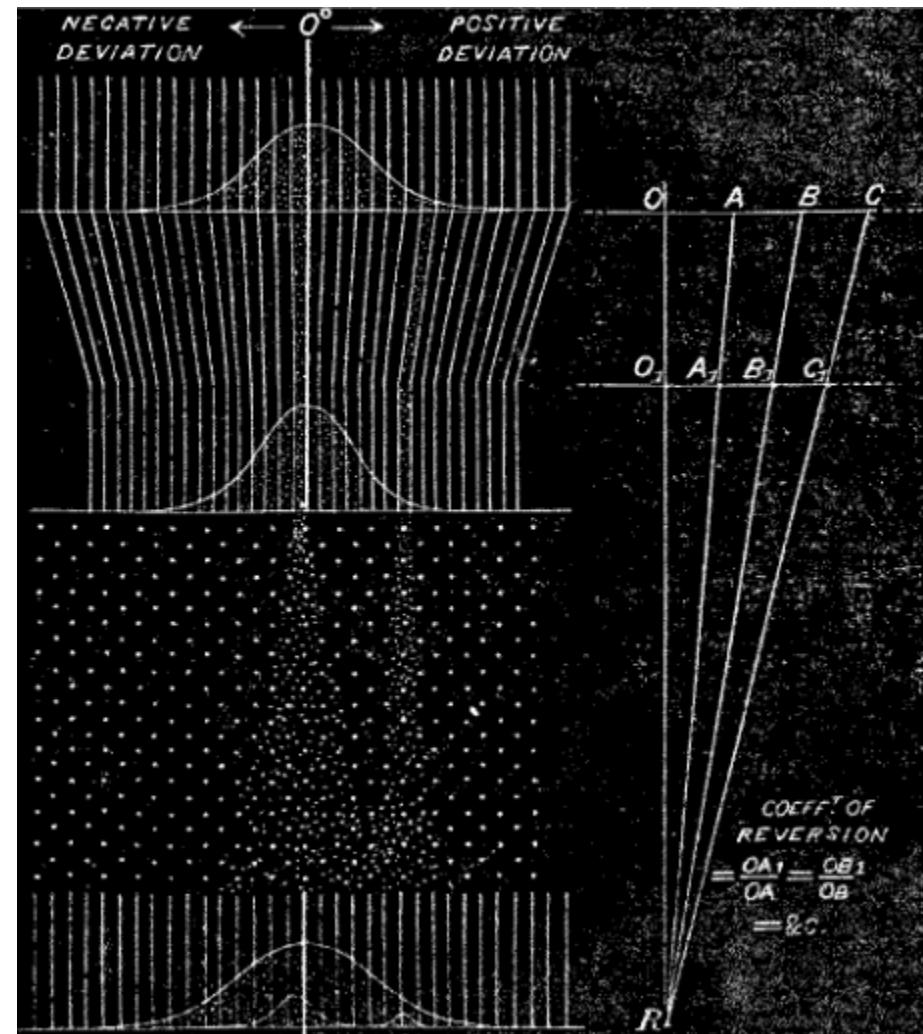
Note: The WUI is computed by counting the frequency of the word "uncertain" (or the variant) in Economist Intelligence Unit country reports. The WUI is then normalized by total number of words and rescaled by multiplying by 1,000. A higher number means higher uncertainty and vice versa. The aggregate and disaggregate data by country and regions are available at www.worlduncertaintyindex.com.

Galton: Variation & Uncertainty

Distribution of human height
(Hereditary Genius, 1867)



Quincunx: How many small effects → Normal

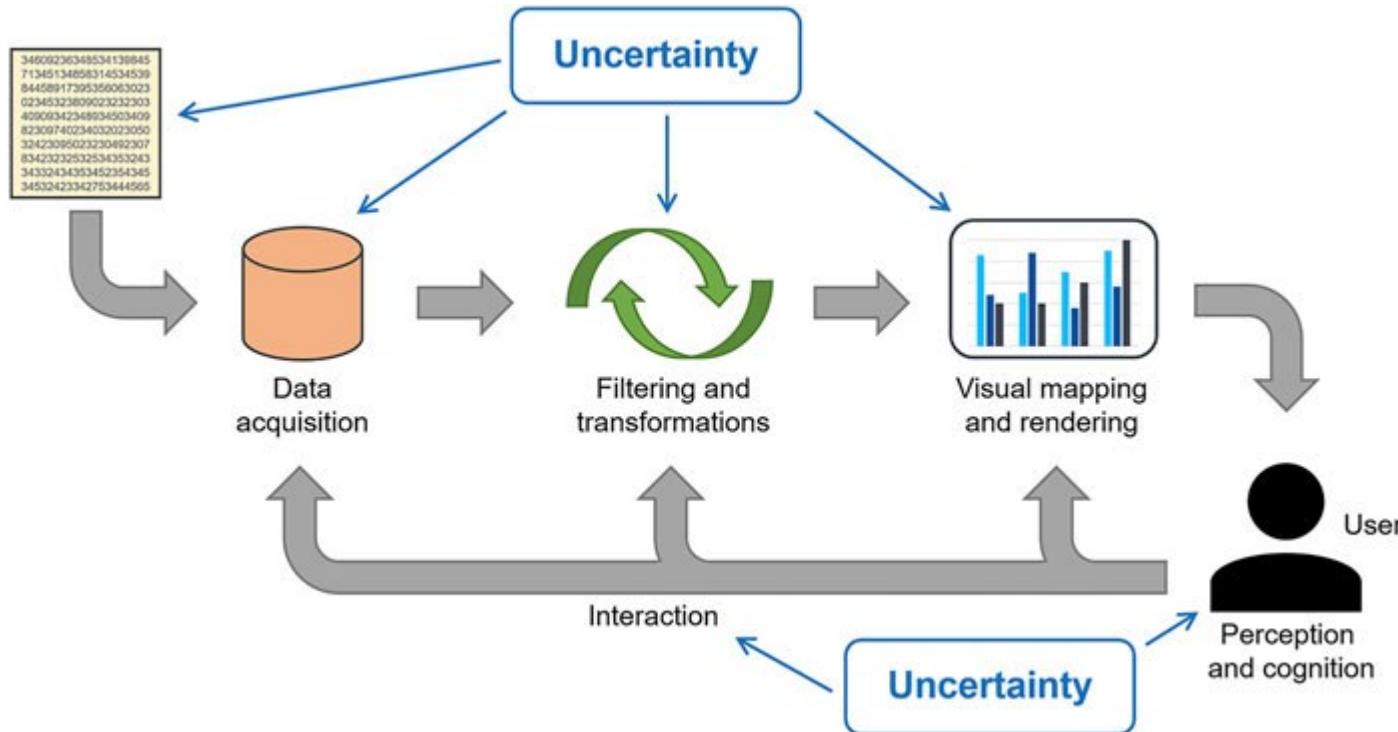


Sources of uncertainty

- Where does the uncertainty in statistics come from? There are four main sources:
 - **Data:** data can contain random error or have missing entries.
 - **Assumptions:** model assumptions asses plausible values from distributions.
 - **Models:** there is choice over the techniques and models we use.
 - Different analysts may choose different methods, yielding different estimates.
 - **Replications:** Estimates of effects can vary from study to study. How to synthesize these?

See: [Uncertainty Toolkit, Ch 3](#) for other terms to understand uncertainty

Where does uncertainty come from?



From: D. Weiskopf, <https://www.frontiersin.org/articles/10.3389/fbinf.2022.793819/full>

Problems: data, models, graphics

- Uncertainty is fundamental to data analysis & models
 - **data**: IQR, std dev., std error, ... (variation)
 - **assumptions**: we assume some distribution for errors, e.g., $\varepsilon \sim \mathcal{N}(0, \sigma^2)$, independent with constant variance
 - **models**:
 - classical: confidence intervals, p-values;
 - Bayesian: credible intervals, posterior distributions
- In data graphics,
 - Easy to show “fit” – means, regression estimates, ...
 - Harder to show the uncertainty in these numbers

P-values, significance & uncertainty

ASA President's Task Force on Statistical Significance

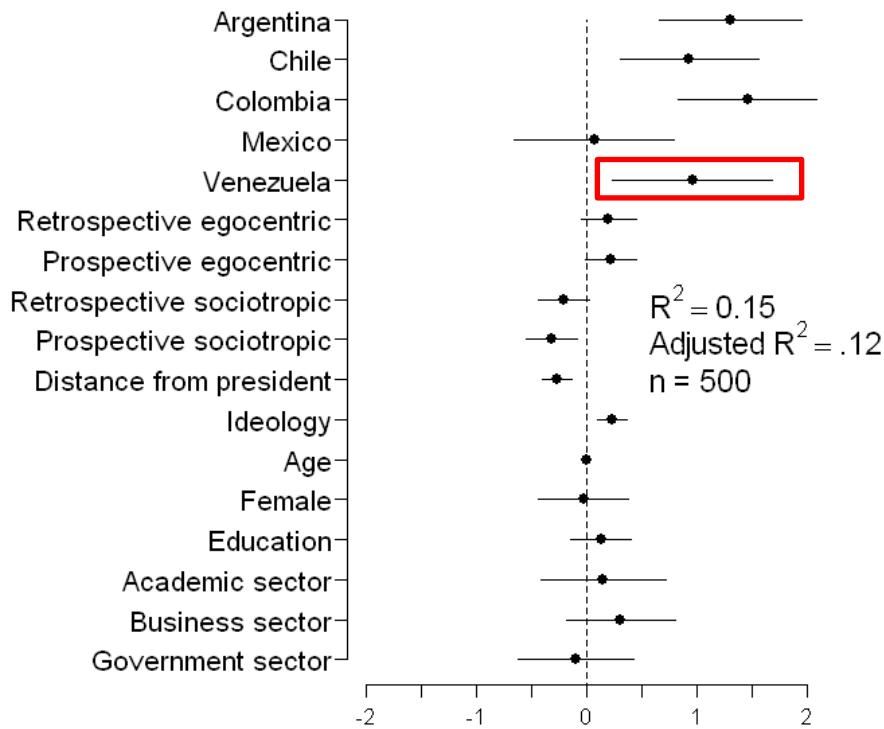
- “Much of the controversy surrounding **statistical significance** can be dispelled by better understanding of uncertainty, variability, multiplicity & replicability”
- “Different measures of uncertainty can **complement** each other; no single measure serves all purposes”
- “Controlling and accounting for uncertainty begins with the **design** of the study”
- “The **theoretical basis** of statistical science offers general strategies for dealing with uncertainty”
 - **Frequentist** approach: p-values, confidence intervals & prediction intervals
 - **Bayesian** approach: Bayes factors, posterior probability distributions, credible intervals

Model fits as uncertainties

Table 2 from Stevens (2006): Determinants of Authoritarian Aggression

Variable	Coefficient (Standard Error)
Constant	.41 (.93)
Countries	
Argentina	1.31 (.33)*** B,M
Chile	.93 (.32)*** B,M
Colombia	1.46 (.32) *** B,M
Mexico	.07 (.32) A,CH,CO,V
Venezuela	.96 (.37)## B,M
Threat	
Retrospective egocentric economic perceptions	.20 (.13)
Prospective egocentric economic perceptions	.22 (.12)*
Retrospective sociotropic economic perceptions	-.21 (.12)*
Prospective sociotropic economic perceptions	-.32 (.12)**
Ideological Distance from president	
Ideology	
Ideology	.23 (.07) ***
Individual Differences	
Age	.00 (.01)
Female	-.03 (.21)
Education	.13 (.14)
Academic Sector	.15 (.29)
Business Sector	.31 (.25)
Government Sector	-.10 (.27)
R ²	.15
Adjusted R ²	.12
n	500
### p < .01, ## p < .05, *p < .10 (two-tailed)	
A Coefficient is significantly different from Argentina's at p < .05;	
B Coefficient is significantly different from Brazil's at p < .05;	
CH Coefficient is significantly different from Chile's at p < .05;	
CO Coefficient is significantly different from Colombia's at p < .05;	
M Coefficient is significantly different from Mexico's at p < .05;	
V Coefficient is significantly different from Venezuela's at p < .05	

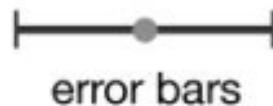
Coefficients** & std errors express uncertainty
Can we do better?



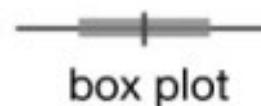
Source: tables2graphs.com

Graphical annotations for uncertainty

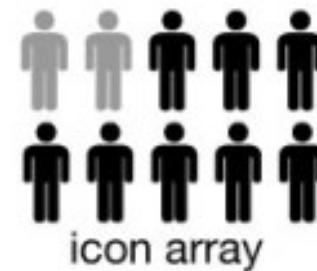
Intervals and Ratios



error bars



box plot



icon array

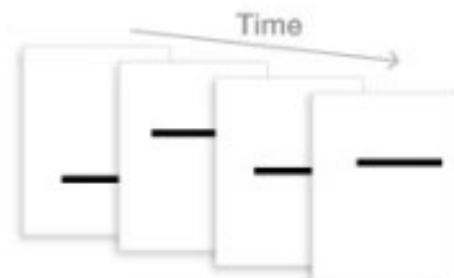
Distributions



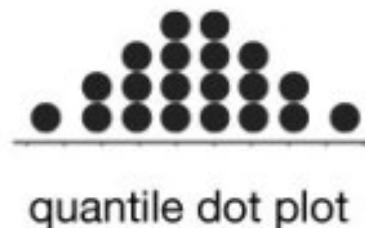
violin plot



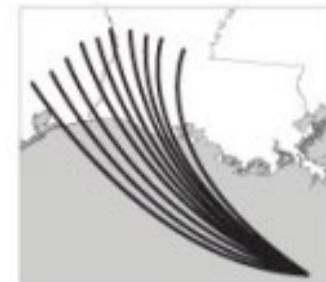
gradient plot



hypothetical outcome plot



quantile dot plot



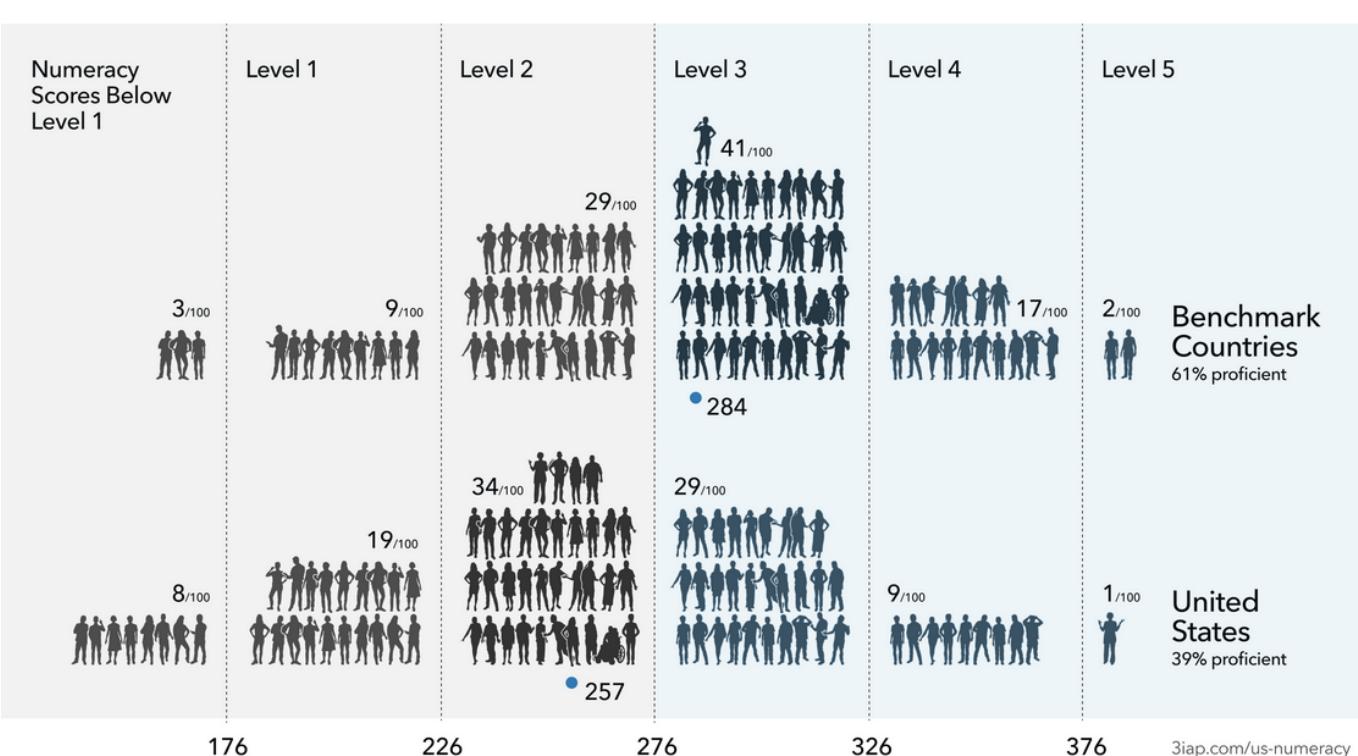
ensemble plot

Putting the people back into charts about them:

U.S. Numeracy Education Has Room for Improvement

Comparing PIAAC Numeracy Scores

- 为人 = 1% of test takers
- = average score
- 浅蓝色 = proficient range



From: <https://3iap.com/us-numeracy>

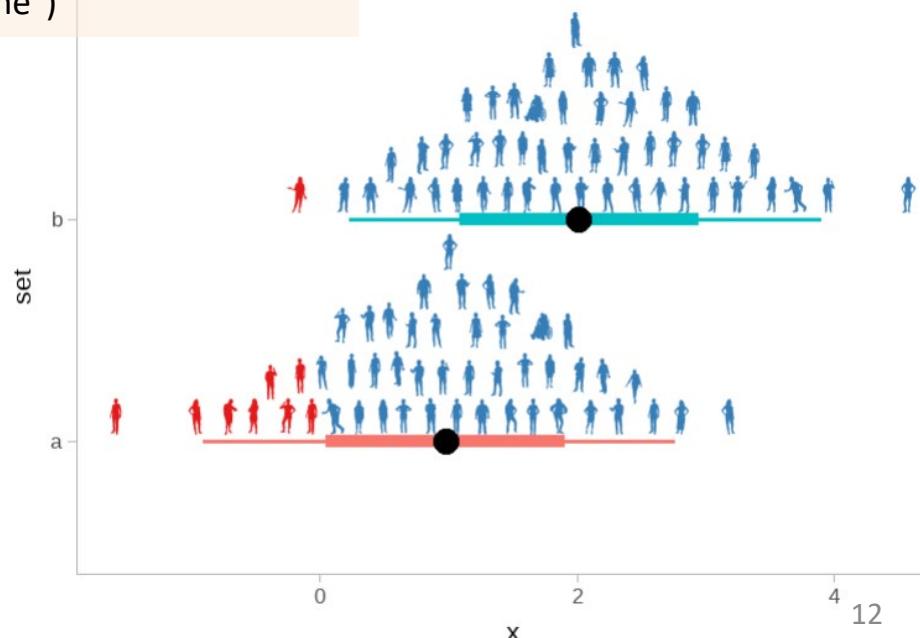
Weepeople font: <https://github.com/propublica/weepeople>

Using weepeople font in R graphics

See: https://github.com/mjskay/uncertainty-examples/blob/master/weepeople_dotplots.md

1. Download font from: <https://github.com/propublica/weepeople/>
2. Register font: `systemfonts::register_font(name = "weepeople")`

```
df = data.frame(x = qnorm(ppoints(100), 1:2),
  set = c("a", "b"), icon = factor(sample(52, 100, replace = TRUE)))
people = c(letters, toupper(letters))
df |> ggplot(aes(x = x, y = set, group = set, shape = icon, color = x > 0)) +
  geom_dots(family = "weepeople", dotsize = 2.4, layout = "swarm") +
  scale_shape_manual(values = people, guide = "none") +
  scale_color_brewer(palette = "Set1", guide = "none")
```



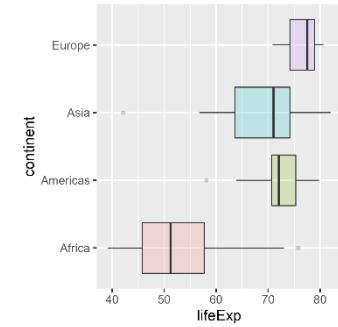
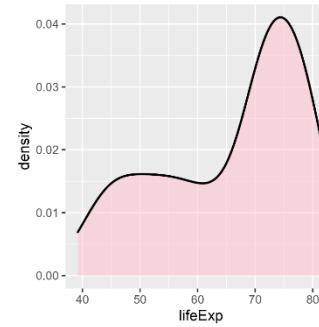
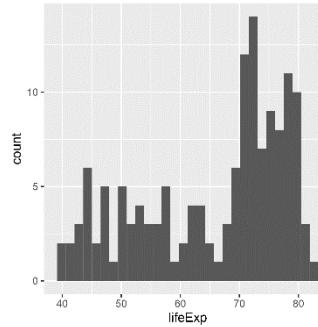
Code:

<https://github.com/friendly/6135/R/weepeople.R>

Visualizing distributions

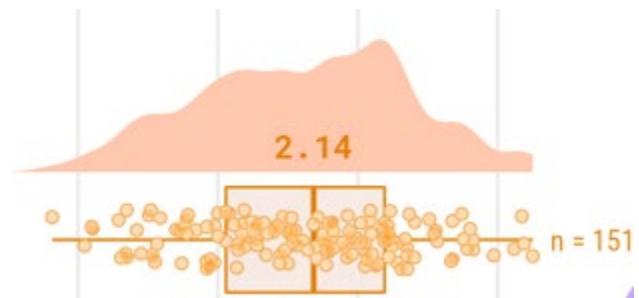
- The basics:

- Histograms
- Density plots
- Boxplots



- Doing better:

- violin plots
- rainclouds
- {ggdist}: data, distribution, interval



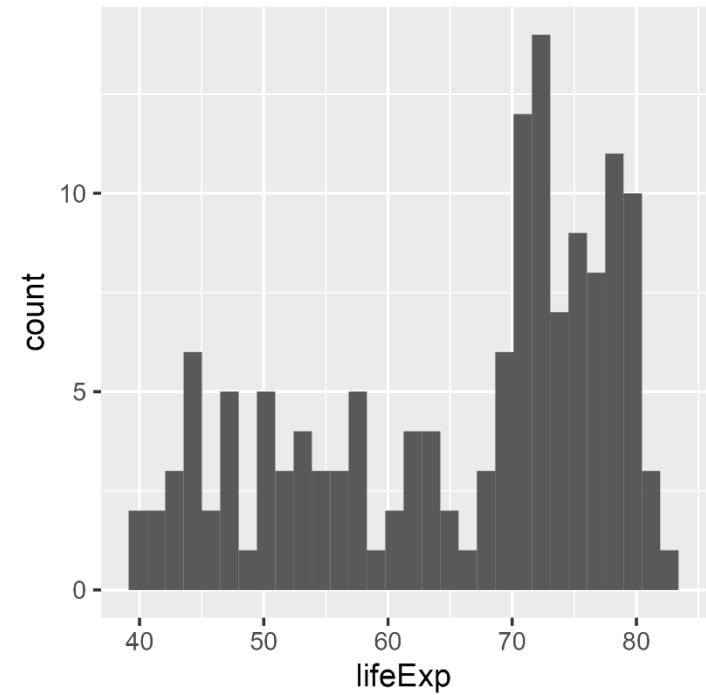
Histograms

- Perhaps the simplest display
 - divide the data into bins: [40-42), [42-44), ...
 - bar plot of the frequencies: length \sim frequency in bin

```
library(gapminder)
gapminder_2002 <- gapminder %>%
  filter(year == 2002)

ggplot(gapminder_2002,
       aes(x = lifeExp)) +
  geom_histogram()
```

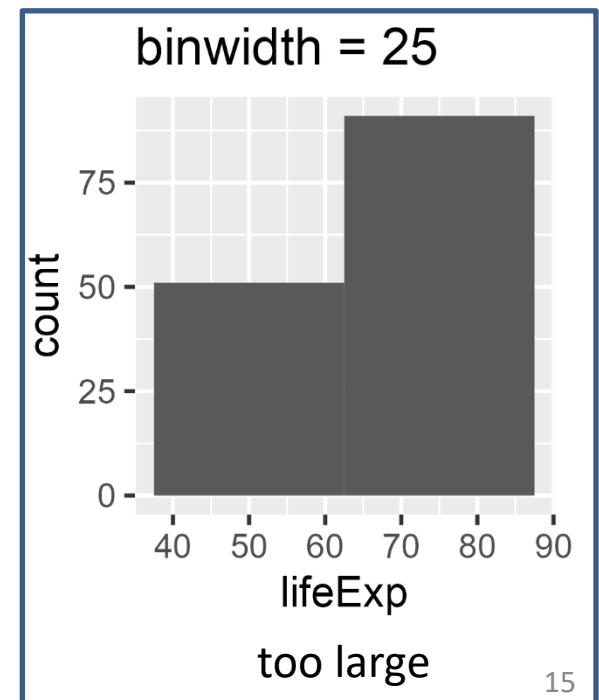
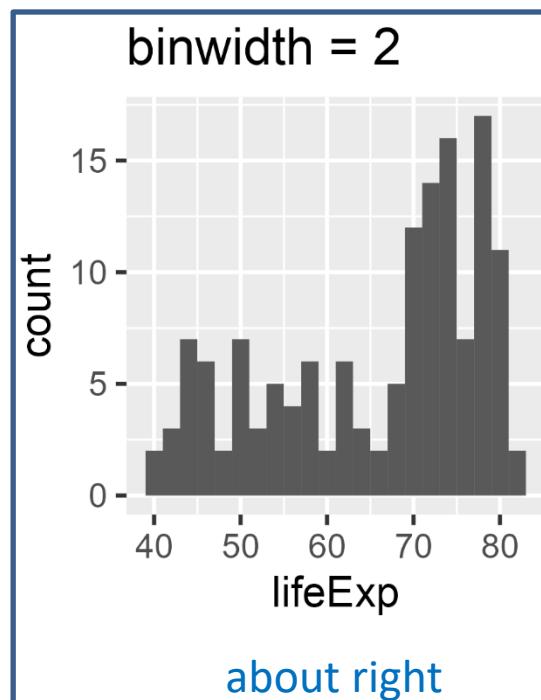
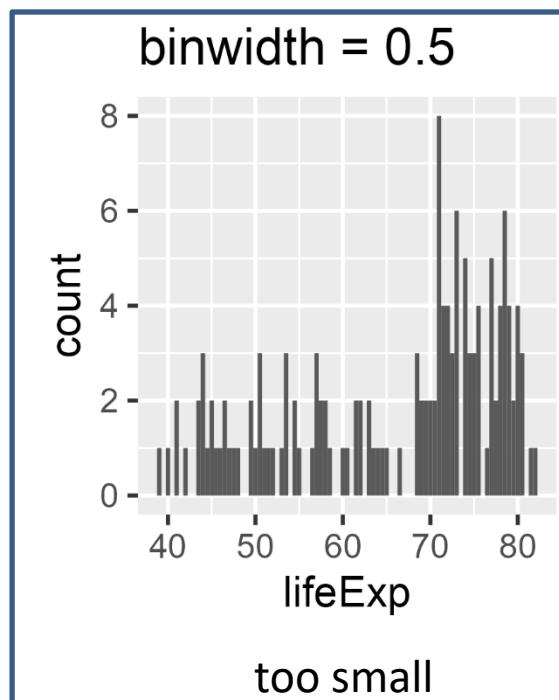
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.



Histograms: bin width

- Explicitly selecting the binwidth shows:
 - the “Goldilocks” principle: **just about right**
 - the default is often OK, but optimal “best” is harder to define

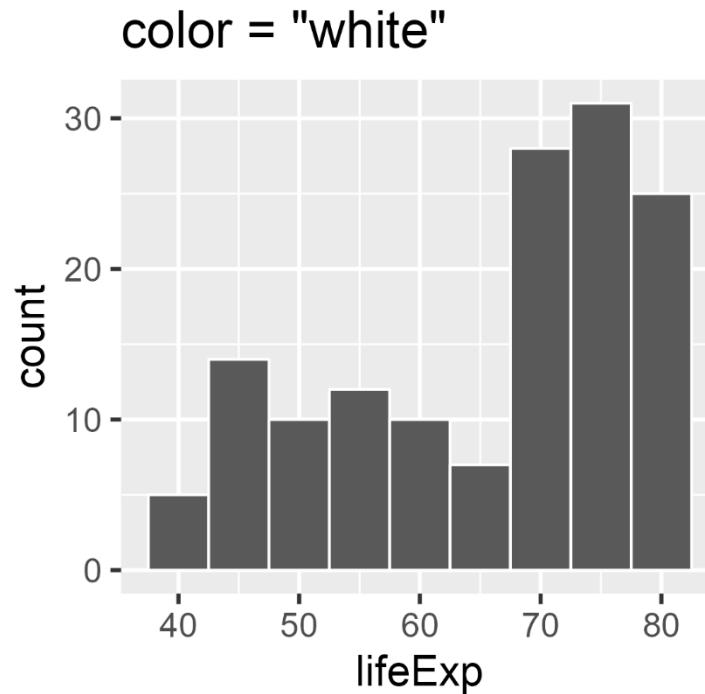
```
ggplot(gapminder_2002, aes(x = lifeExp)) + geom_histogram(binwidth = )
```



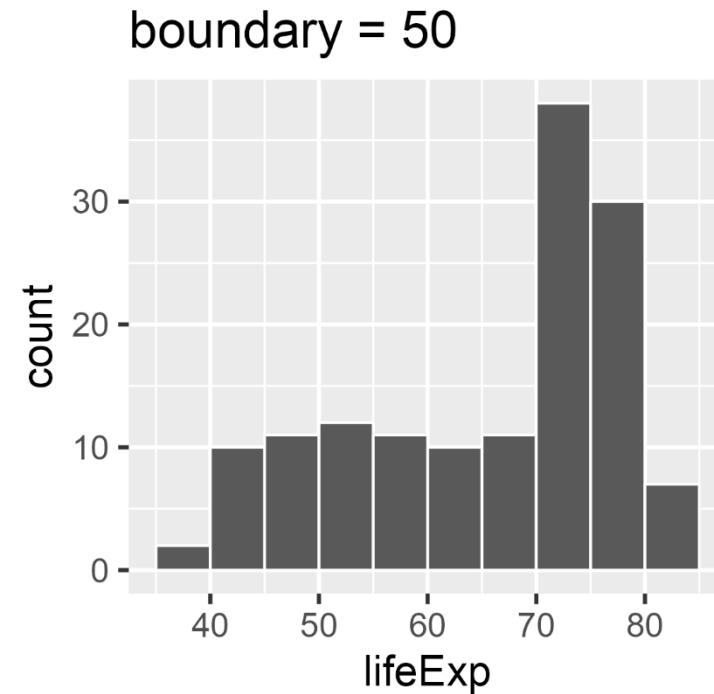
Histograms: other properties

- Pay attention to graphic details
 - border color to make bars distinct
 - set bar boundaries: to edges? – it can make a difference

`geom_histogram(..., color = "white")`

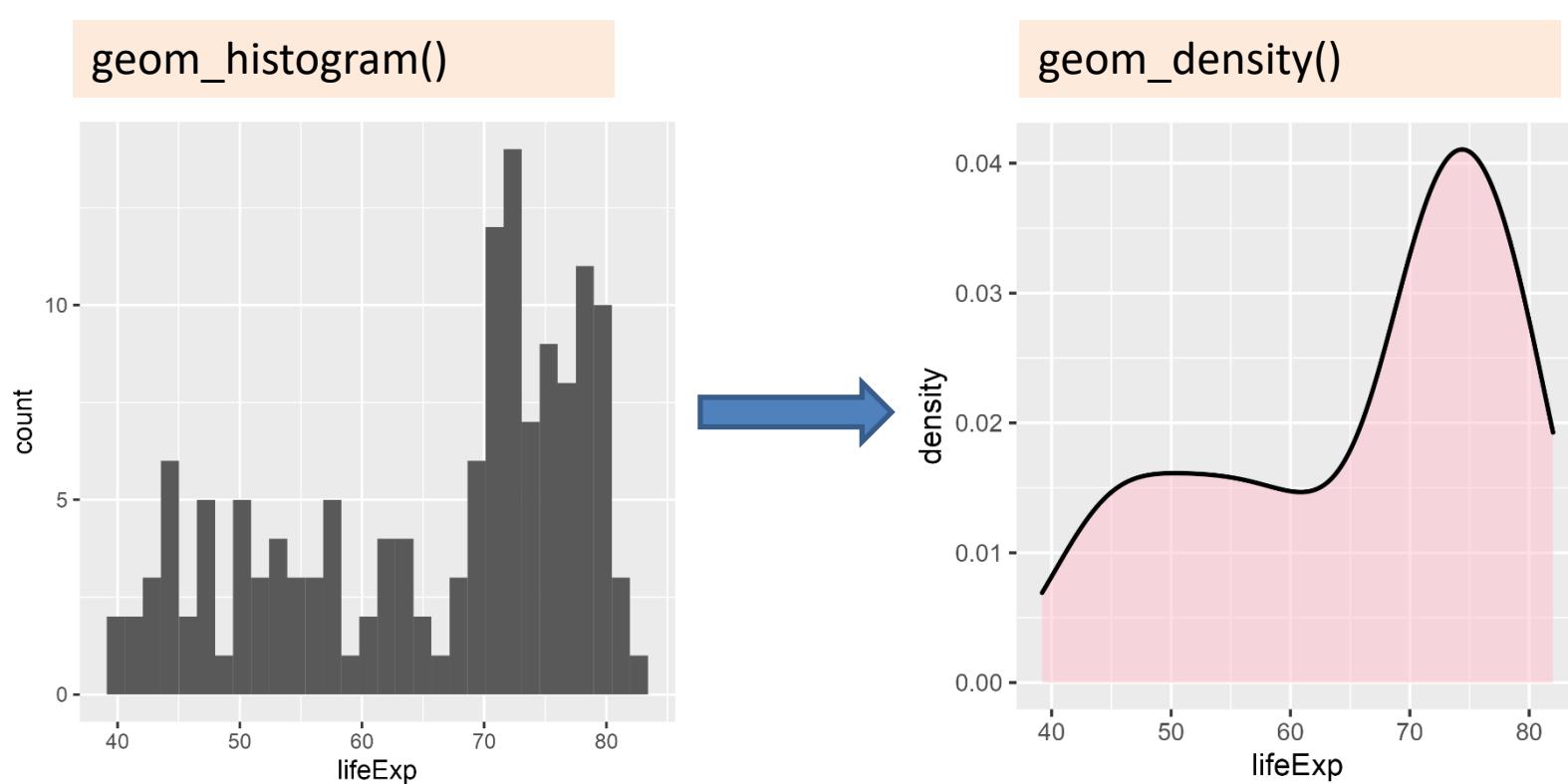


`geom_histogram(..., boundary=50)`



Density plots

- Basic idea: Smooth the distribution to avoid artifacts of discrete bins and bin centers
 - Uses a “kernel”, e.g, gaussian, averaged over a moving window



Kernel density estimation

Imagine a distribution of potential density centered at each X_i , w/ sd = h (bandwidth)

$$x \sim \mathcal{N}(\mu=X_i, \sigma=h)$$

Five observations, each with a distribution

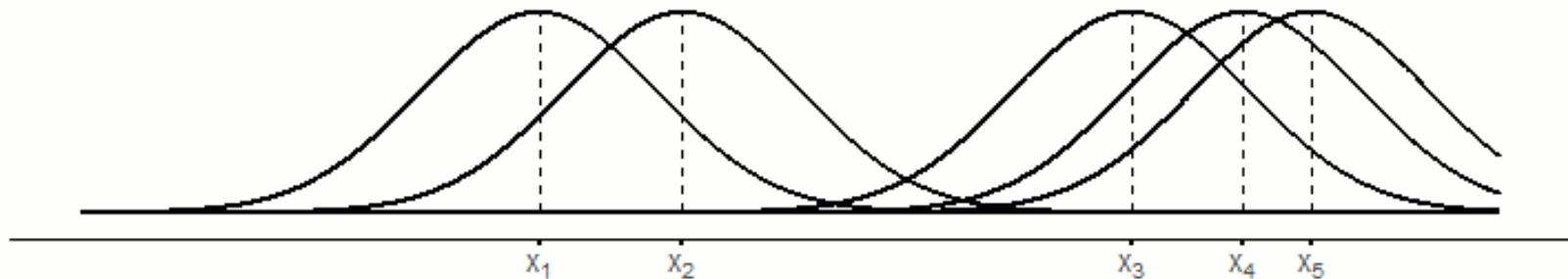
A moving window sweeps across, averaging the density for all observations

Kernel function

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{x^2}{2}\right]$$

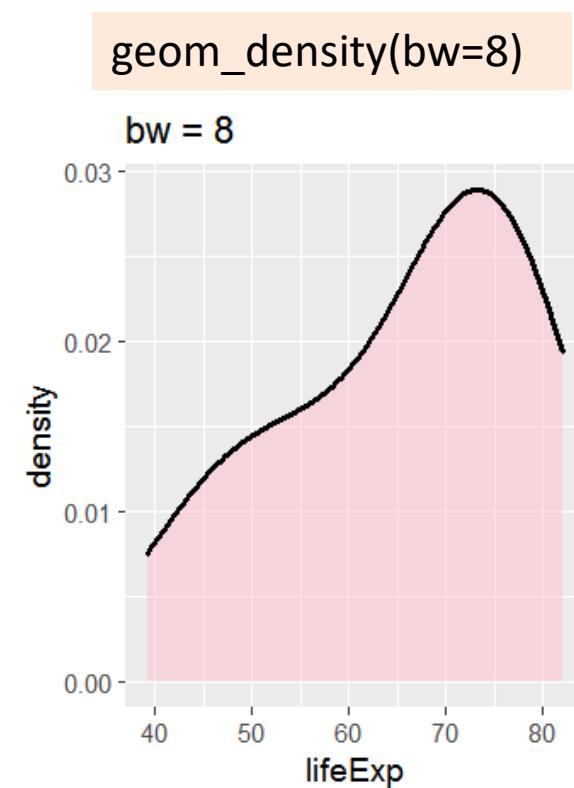
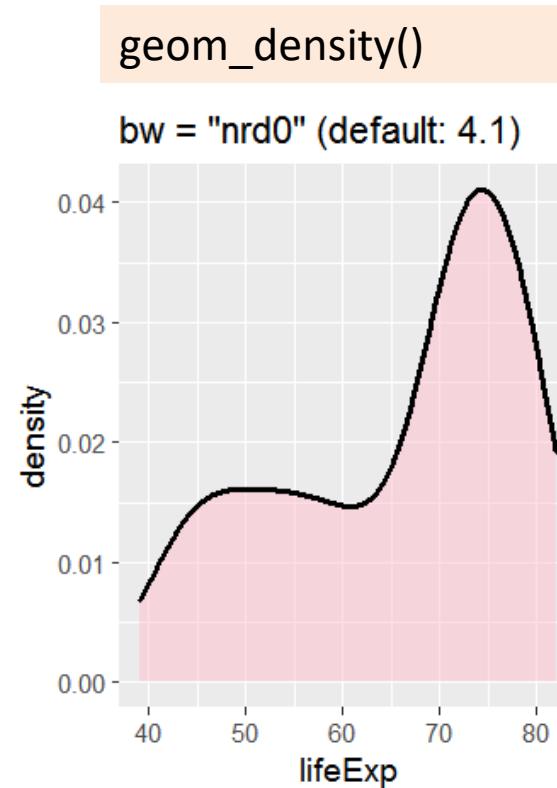
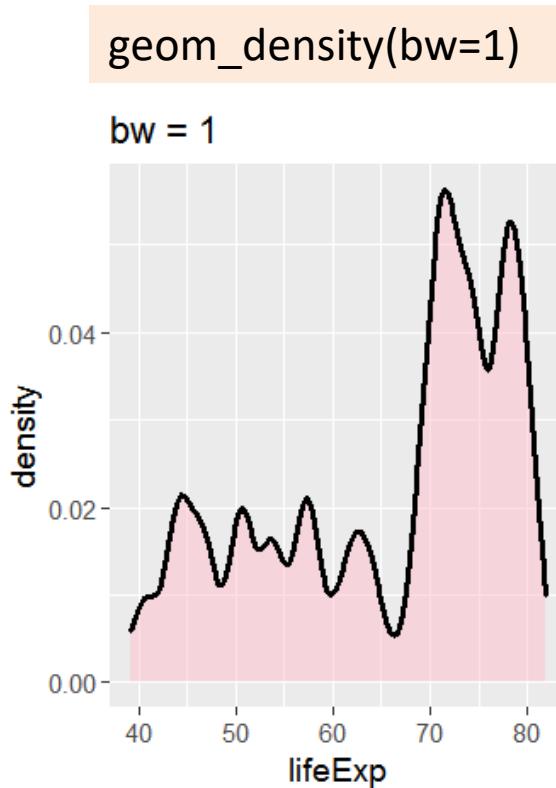
The Kernel Density Estimator is:

$$f(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x - x_i}{h}\right)$$



Density plots: bandwidth

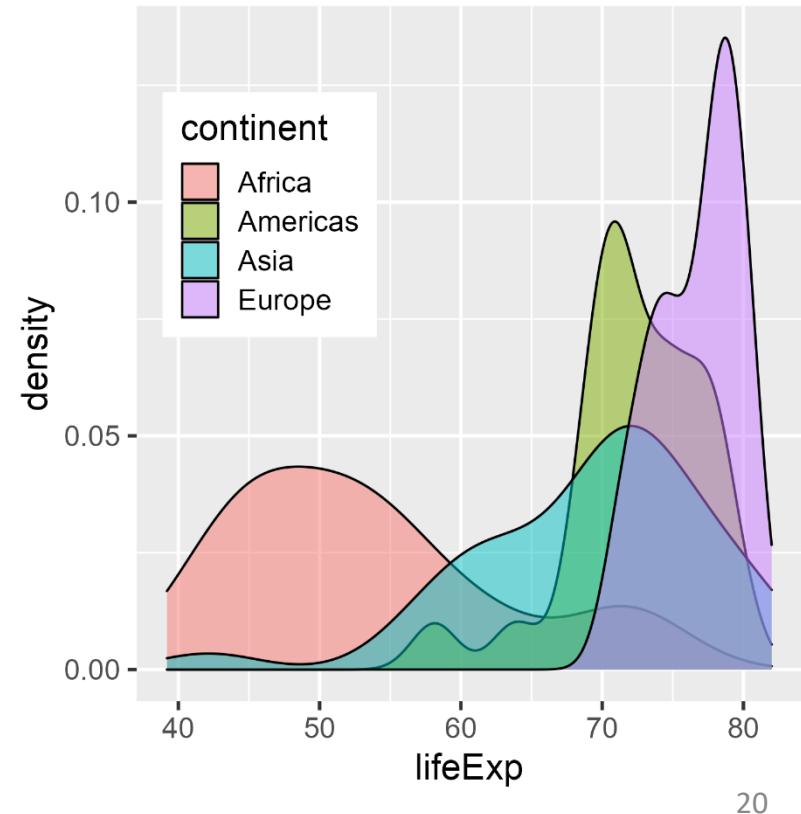
- The result depends on the width of the moving window – **bandwidth**
 - The default calculation is usually reasonable, but beware of weird data



Comparing groups

For multiple groups, using the fill aesthetic → overlaid curves -- is a decent start
But even with transparency it may be hard to see the separate curves

```
gap_2002c <-  
  gapminder_2002 %>%  
  filter(continent != "Oceania")  
  
ggplot(gap_2002c,  
       aes(x = lifeExp,  
            fill = continent)) +  
  geom_density(alpha = 0.5) +  
  theme(legend.position = c(.2, .7))
```

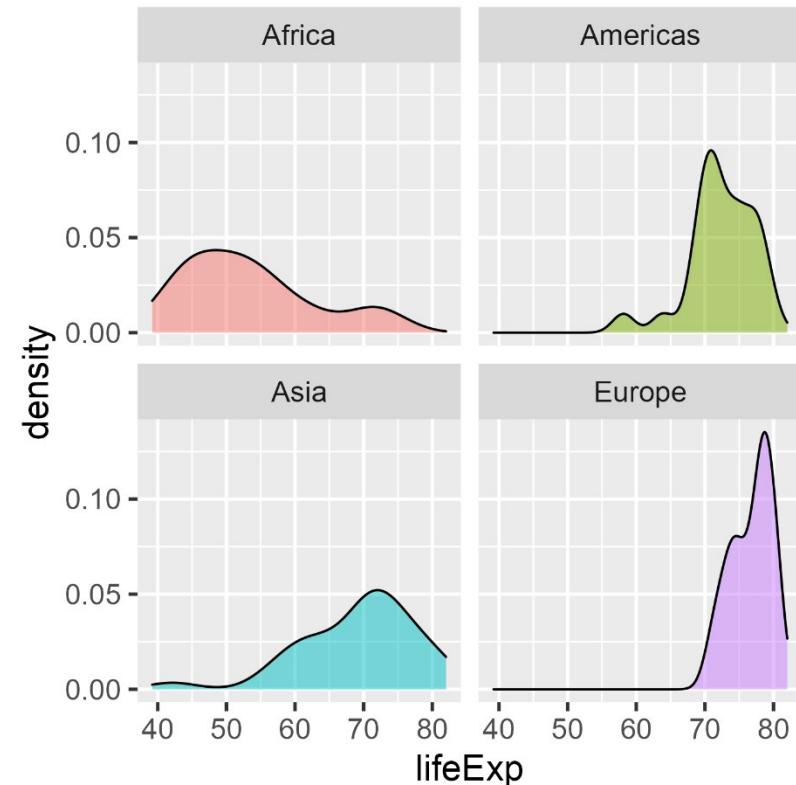


NB: ggplot picks a **joint** bandwidth, here: 2.52

Comparing groups: Facets

Faceting solves the overlap problem, but the eye has to move from panel to panel to make comparisons.

```
ggplot(gap_2002c,  
       aes(x = lifeExp,  
            fill = continent)) +  
  geom_density(alpha = 0.5) +  
  facet_wrap(~ continent) +  
  theme(legend.position = "none")
```

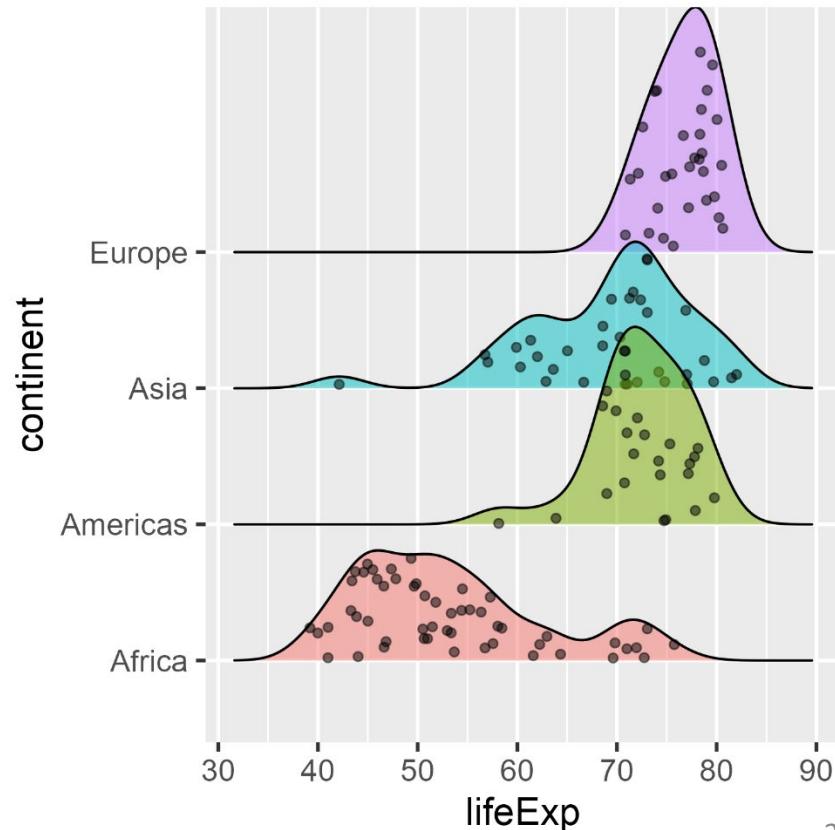


{ggridges}: Ridgeline plots

Ridgeline plots are partially overlapping density plots, suggesting a mountain range.

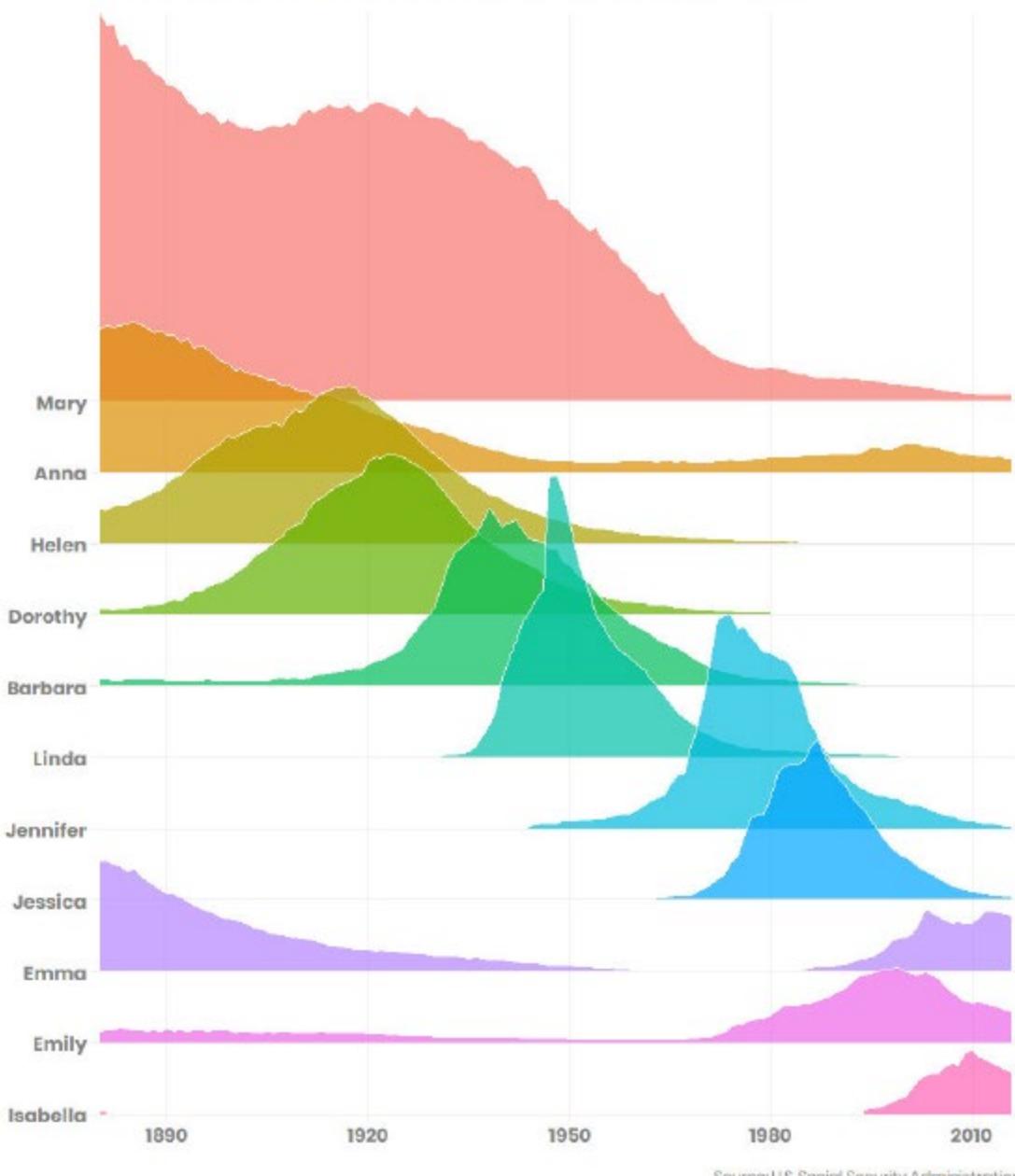
- Useful for comparing distributions over time or circumstances
- Adding jittered points helps to show where the data are

```
library(ggridges)
ggplot(gap_2002c,
       aes(x=lifeExp,
           y=continent,
           fill=continent)) +
  geom_density_ridges(
    alpha = 0.5,
    jittered_points=TRUE) +
  theme(legend.position = "none")
```



Most popular girl names in the U.S.

Top 2 names with the highest mean and/or maximum per quarter are shown.



Baby names

Ridgeline plots are particularly effective with more than a few categories, and when the distributions differ in **shape** as well as **central location**

Which names stand out from the rest?

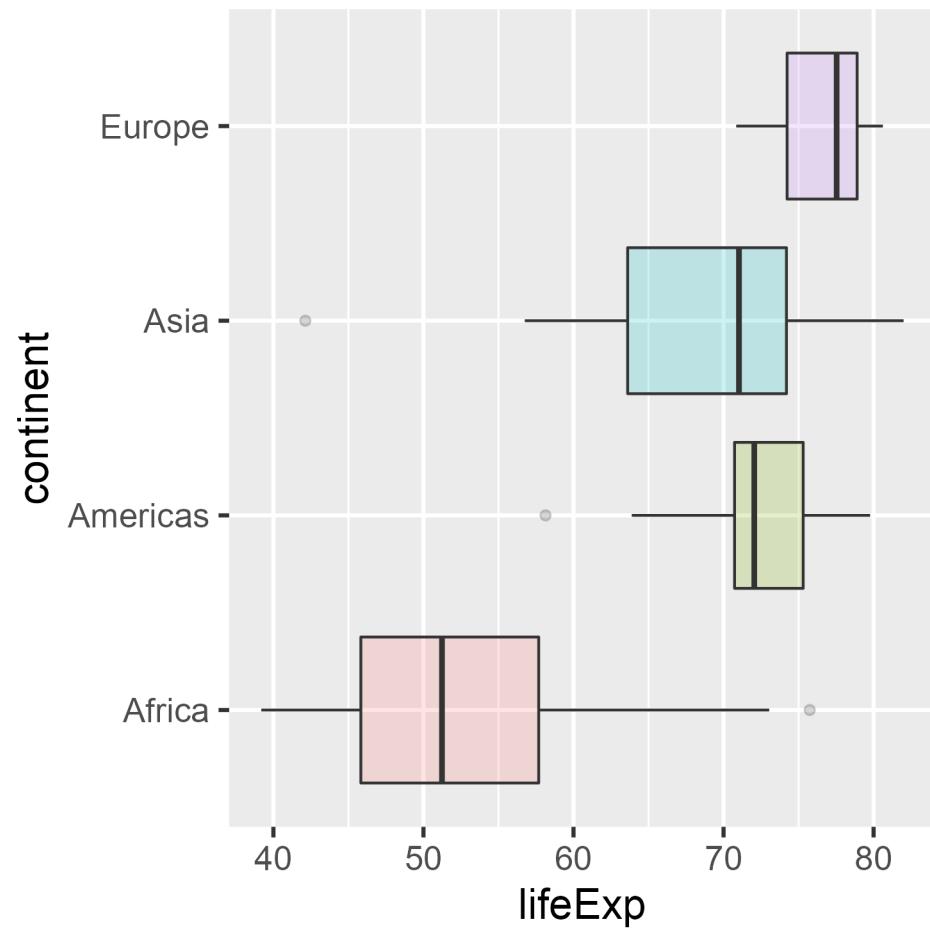
What is the role of color here?

Note the subtle use of white to outline each distribution

Boxplots

Boxplots give a more schematic summary of a dataset—
median, quartiles, whiskers & outliers

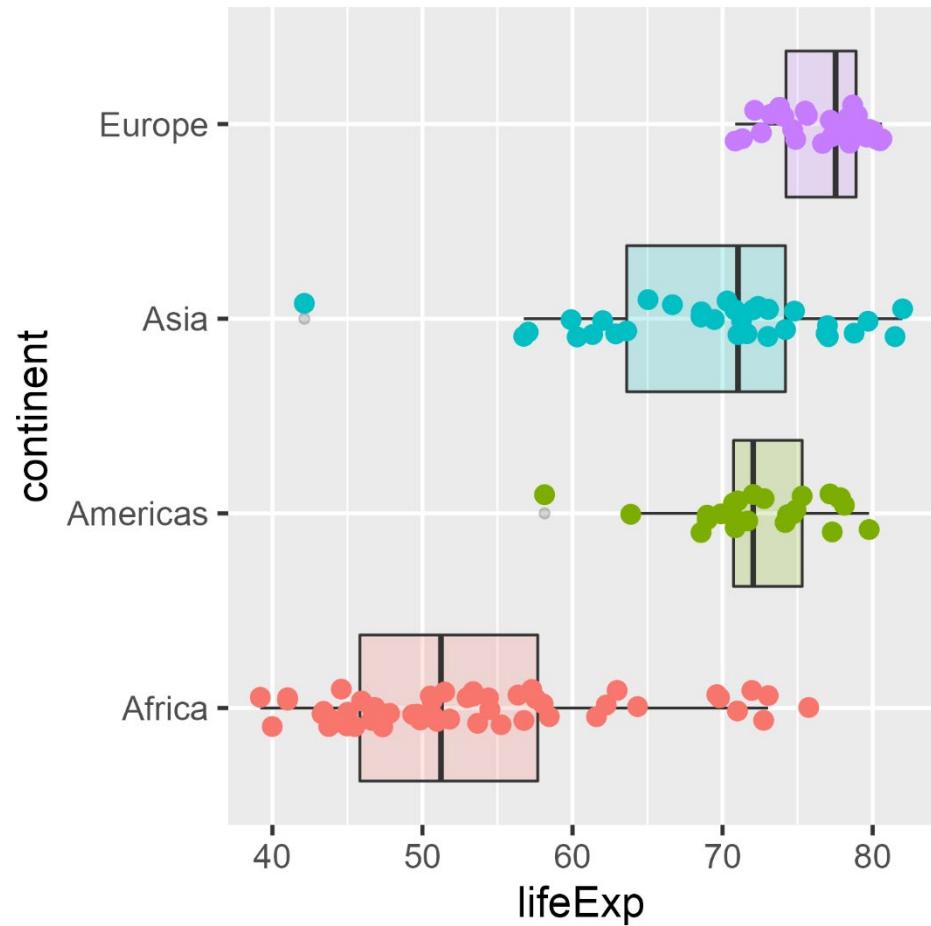
```
ggplot(gap_2002c,  
       aes(x=lifeExp,  
            y=continent,  
            fill=continent)) +  
  geom_boxplot(alpha = 0.2) +  
  theme(legend.position = "none")
```



Boxplots

But perhaps too schematic— it sometimes helps to see the data as jittered points

```
ggplot(gap_2002c,  
       aes(x=lifeExp,  
            y=continent,  
            fill=continent)) +  
  geom_boxplot(alpha = 0.2) +  
  geom_point(aes(color = continent),  
             position =  
               position_jitter(height=0.1)) +  
  theme(legend.position = "none")
```

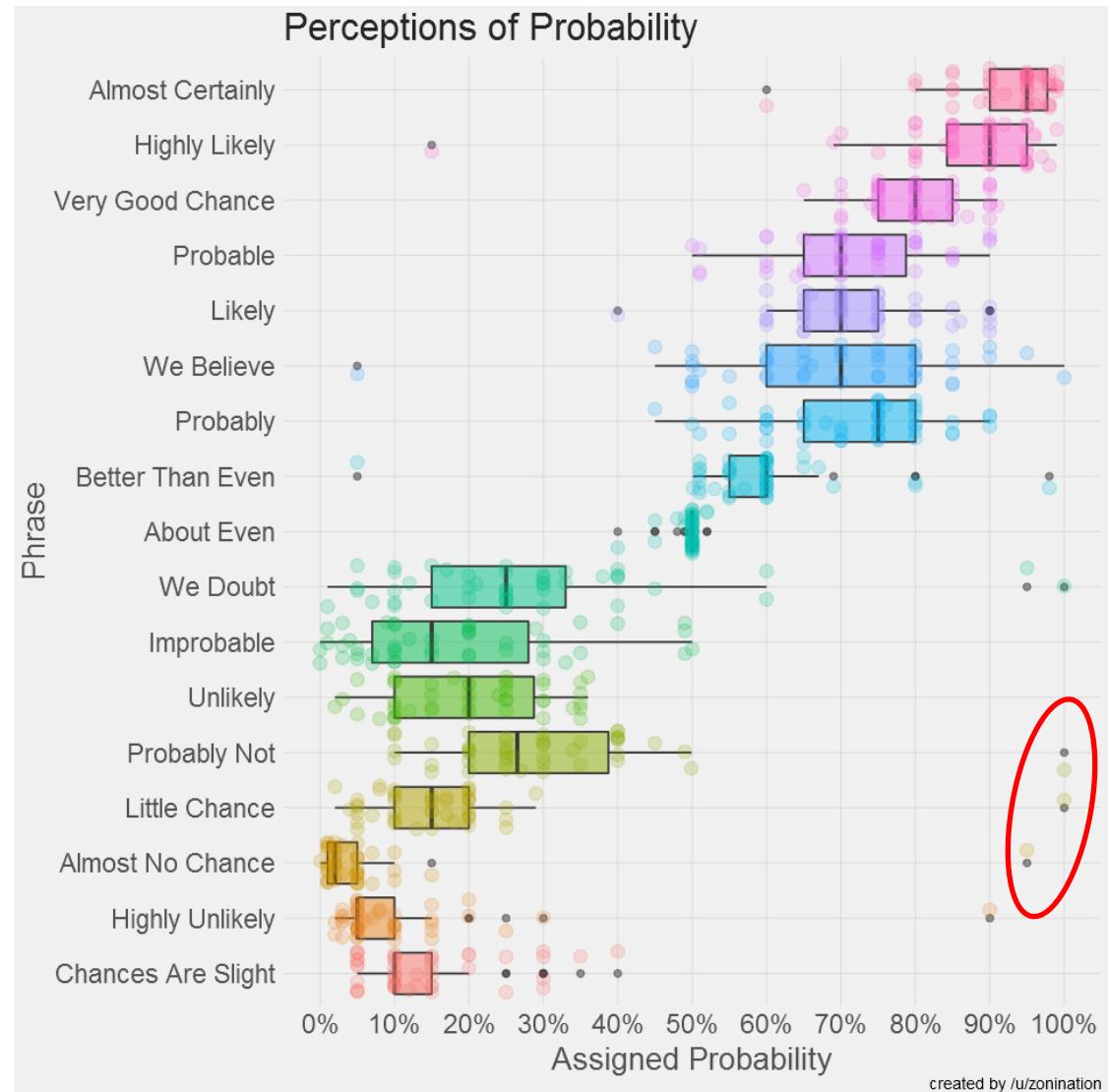


How people view “probability”

What makes this graph successful?

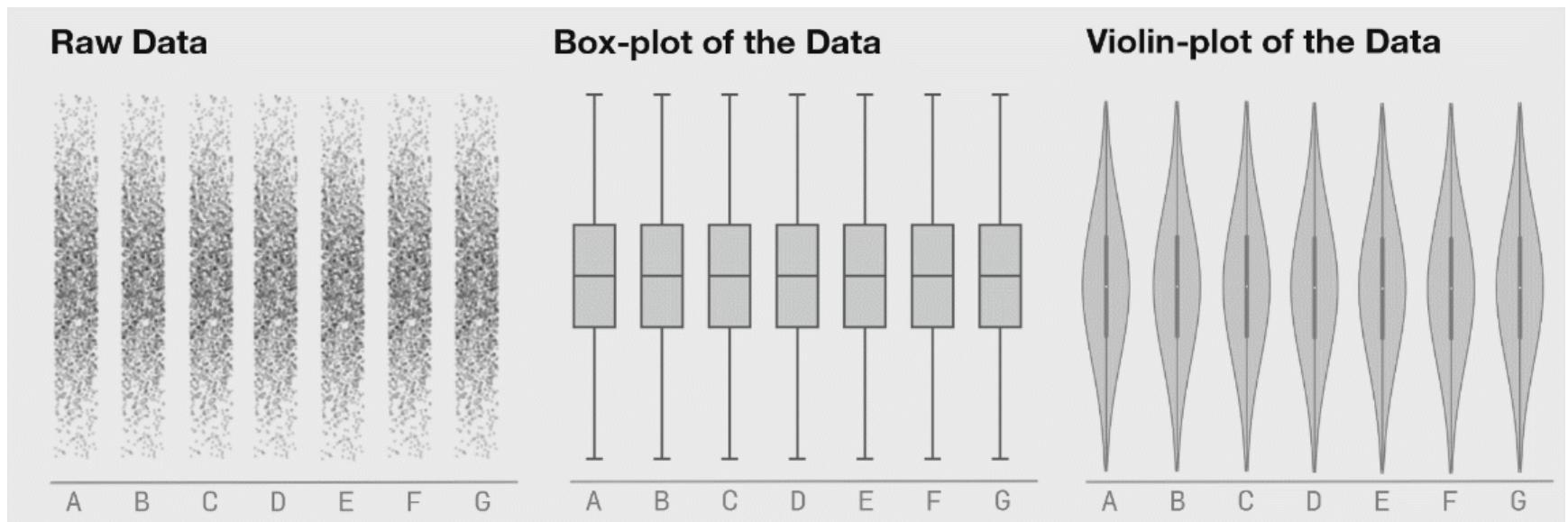
Note the wide range of variability (uncertainty) in the estimates:
“about even” vs. “we believe”

Outliers: individuals who misunderstood instructions?



Problems with boxplots revealed

Boxplots are fine for unimodal distributions – well summarized by Q1, Median, Q3
They are insensitive to **multi-modal** data

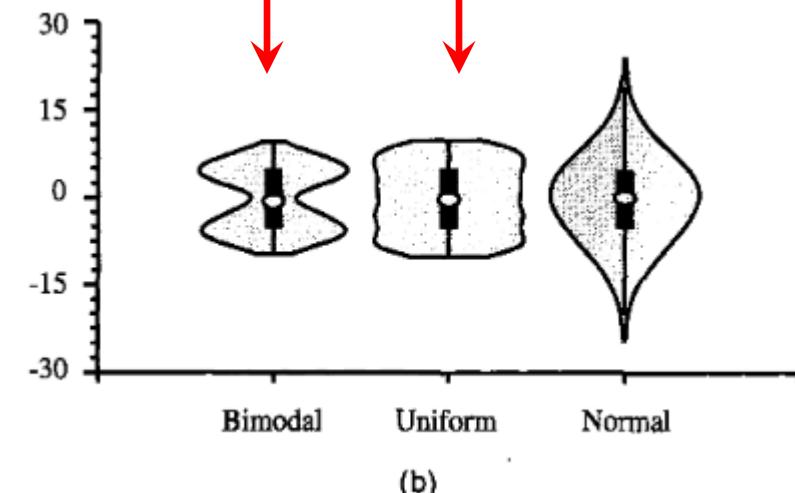
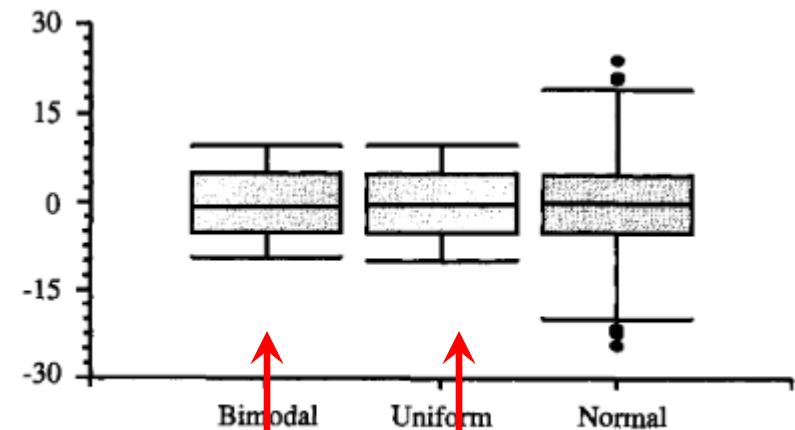
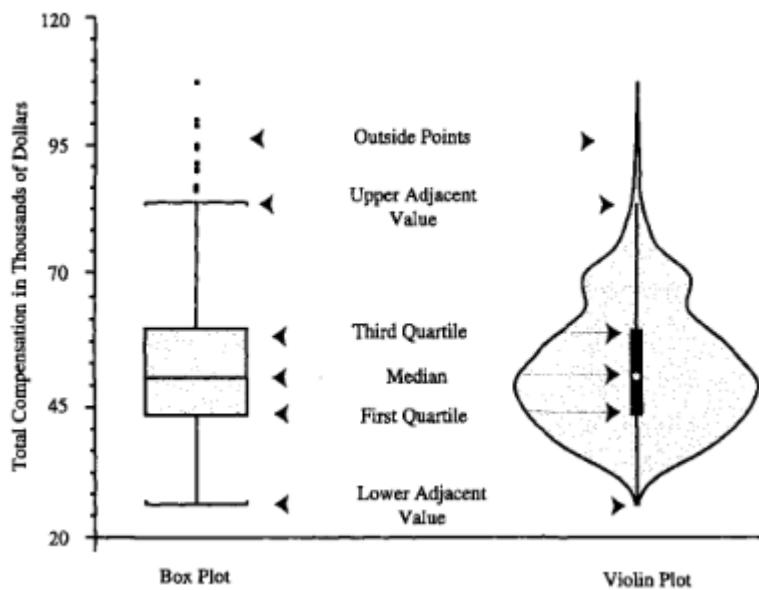


Violin plots

Boxplots are great for \sim normal data

- Shows center, spread, outliers

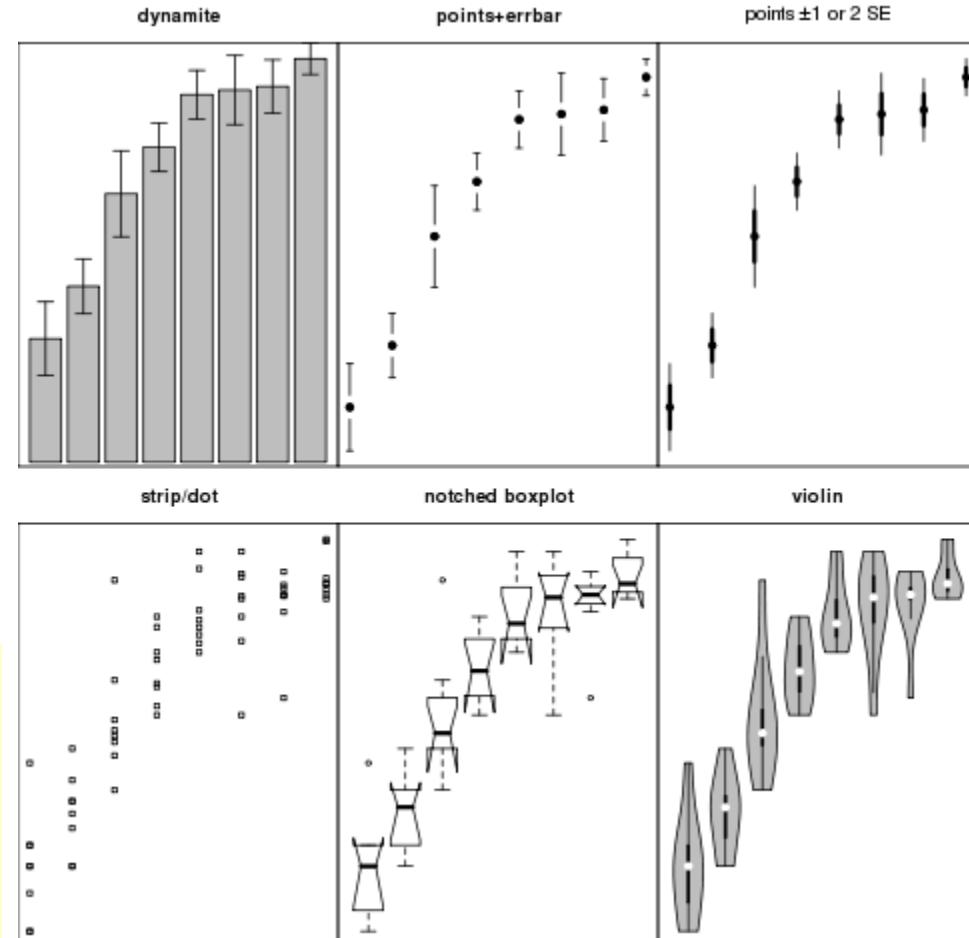
Violin plots add a (reflected) density curve to show the **shape** of the distribution



Comparing groups: Summary + Uncertainty

Six different graphs for comparing groups in a one-way design

- which group means differ?
- equal variability?
- distribution shape?
- what do error bars mean?
- unusual observations?

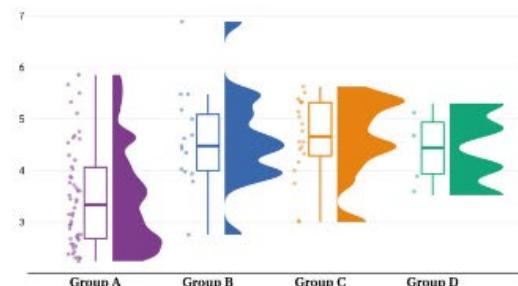
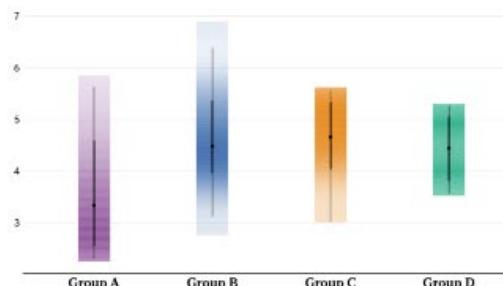
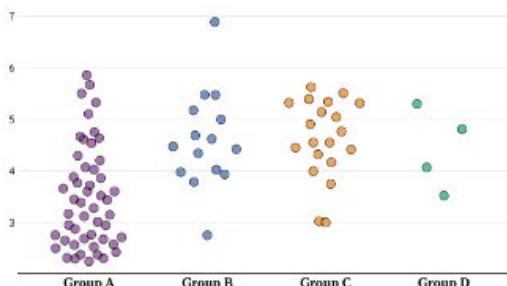
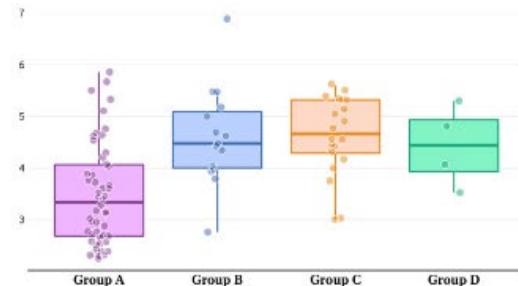
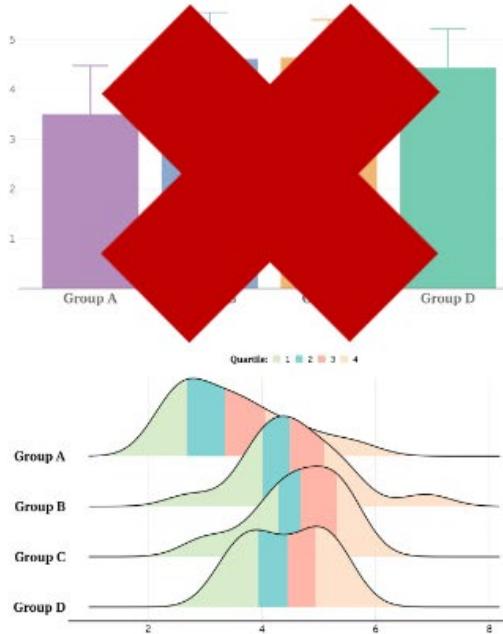
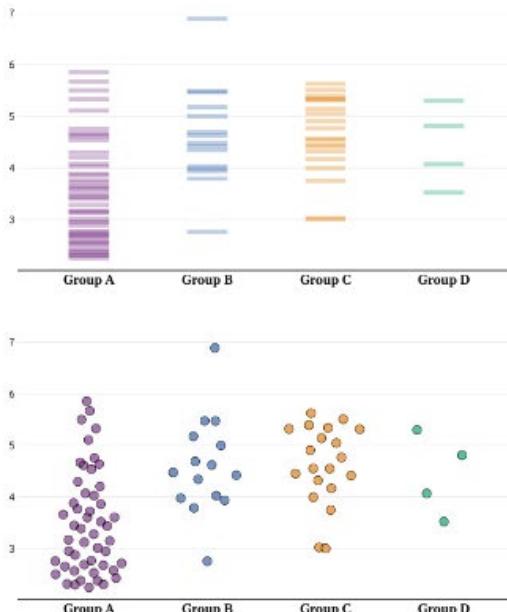


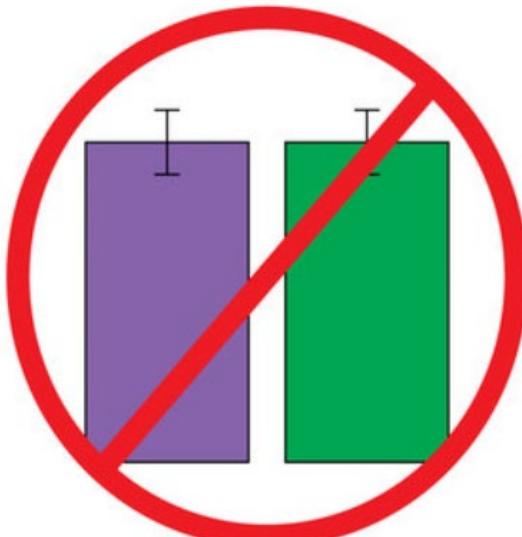
Never use dynamite plots

Always explain what error bars mean

Consider tradeoff between summarization & exposure

Alternatives to dynamite plots





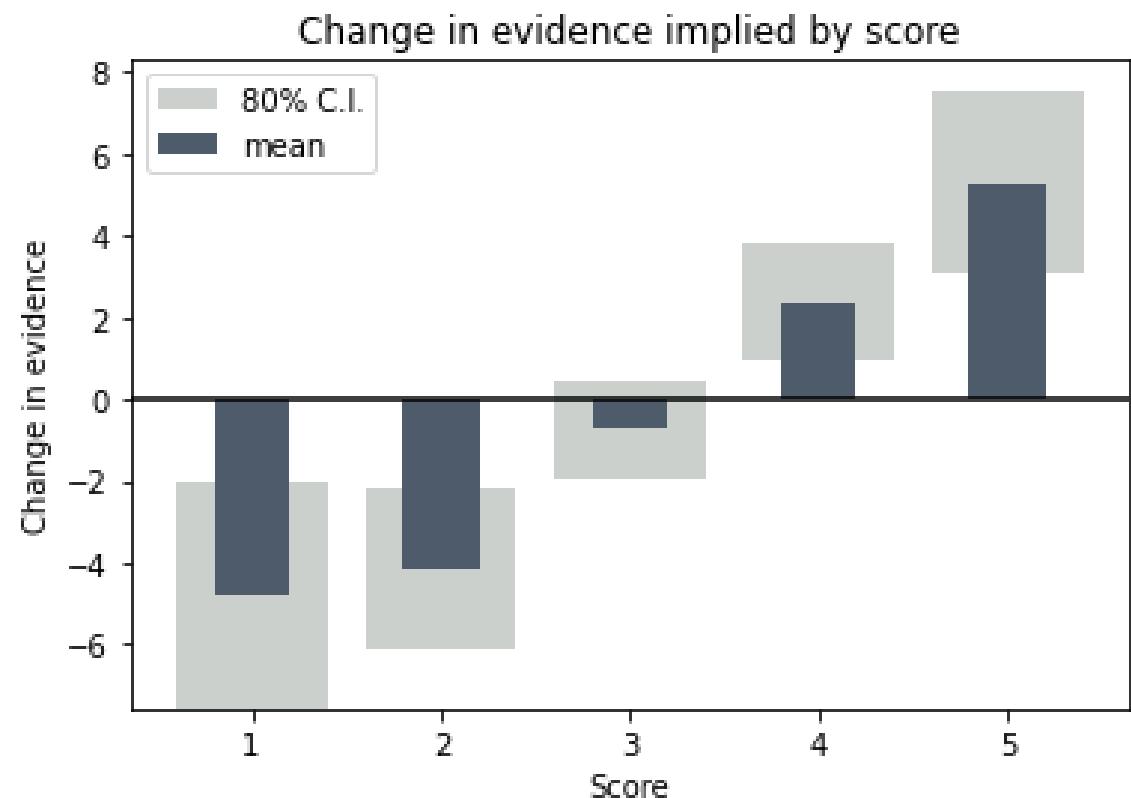
#barbarplots

“Friends don’t let friends
make barplots” (video)

<https://barbarplots.github.io/>

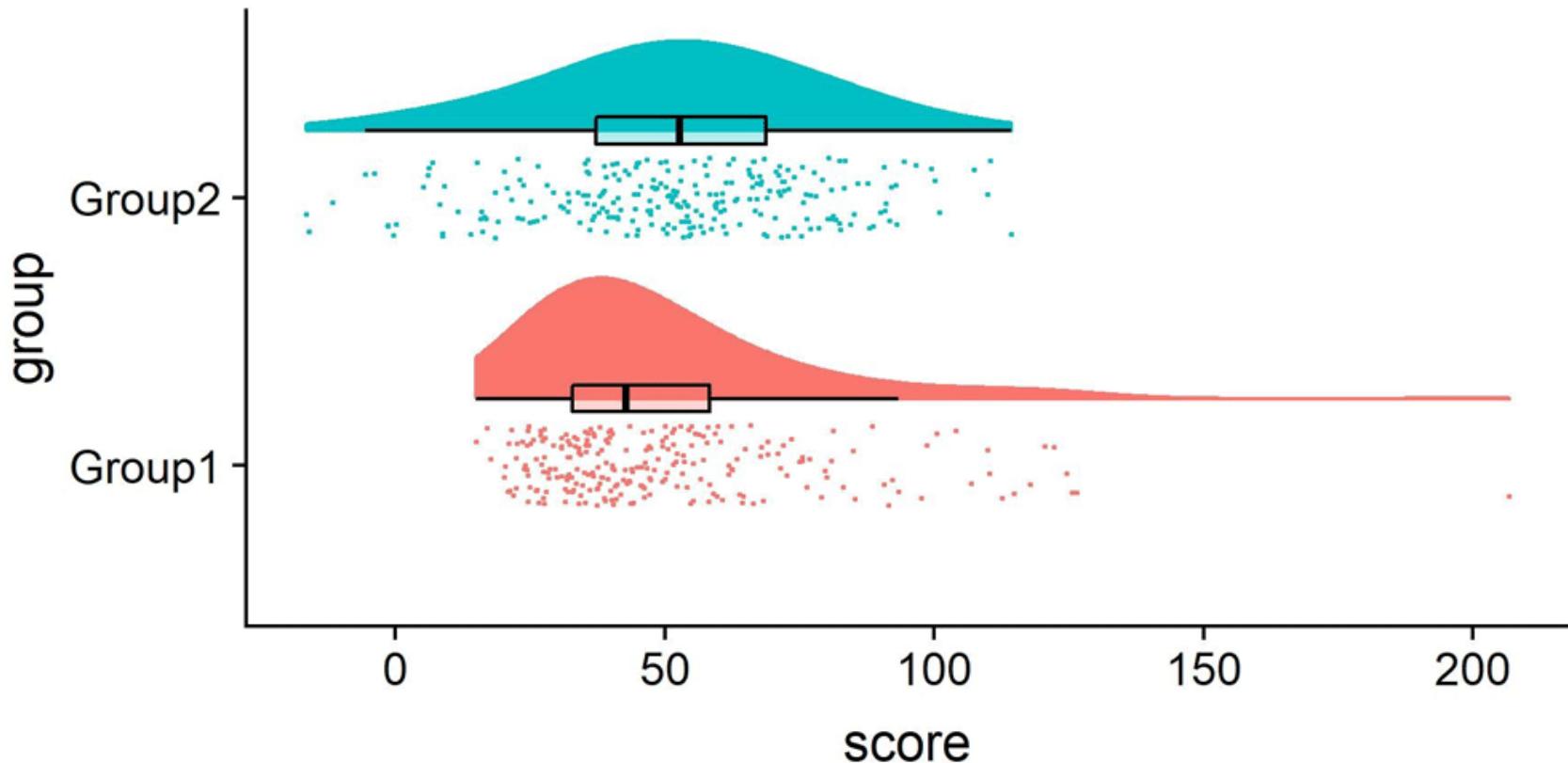
De-fusing the barplot

If you insist on bars, use a better visual representation of uncertainty or CI



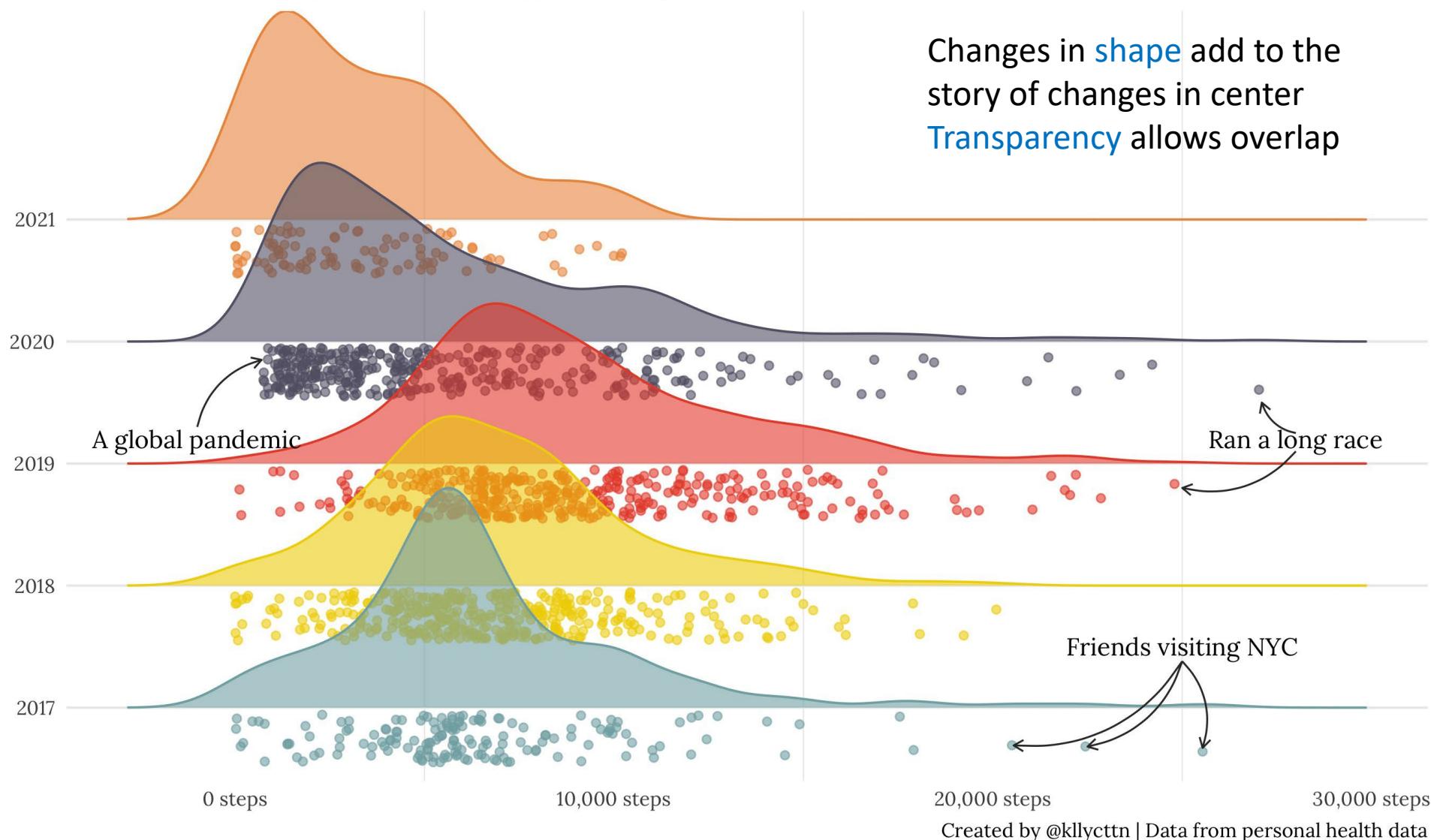
Raincloud plots

Raincloud plots combine **density** curve & **boxplot**, but also show the observations as jittered **points**



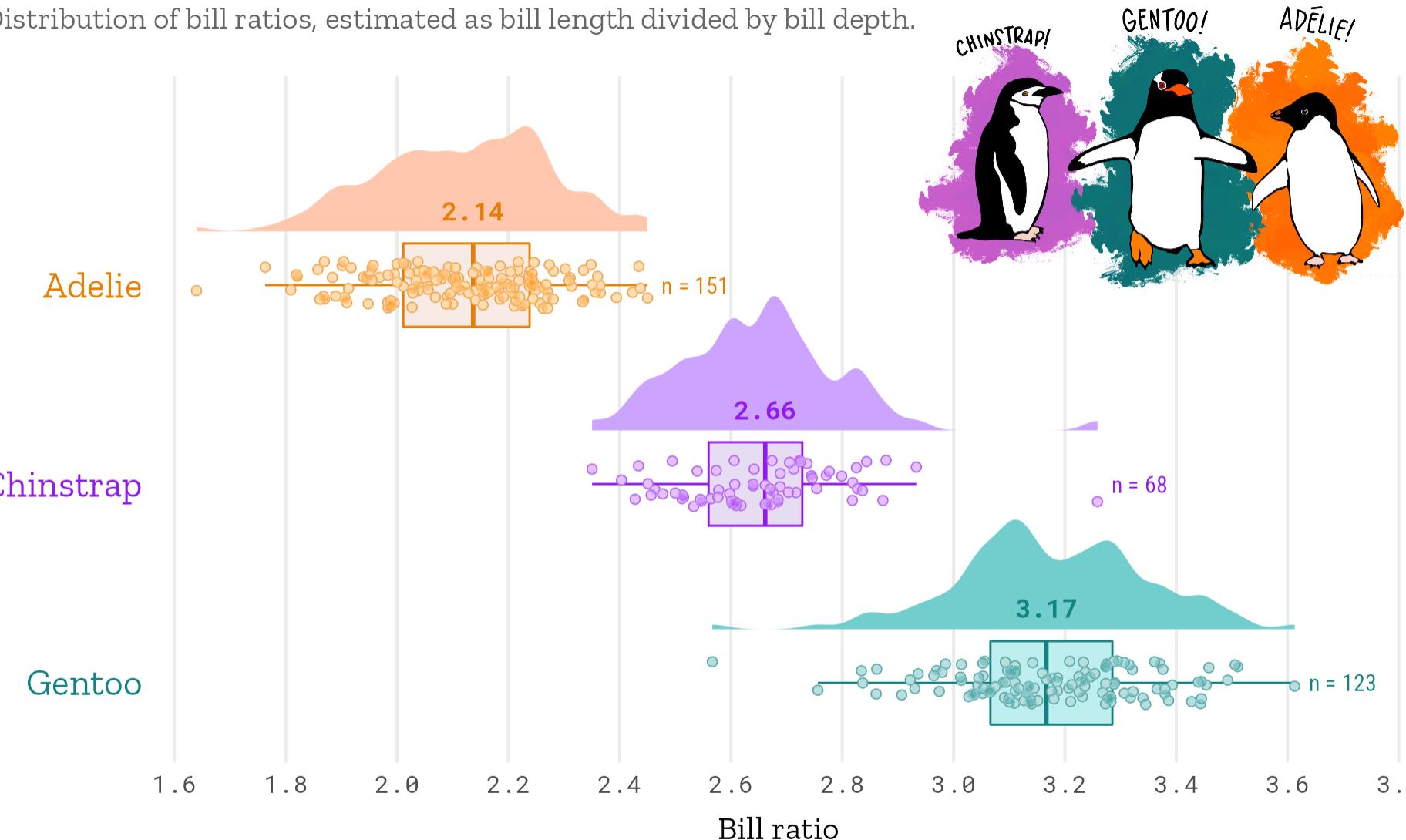
How many steps have I taken since 2017?

Since July 2017, I have tracked the number of steps I've taken (almost) every day. In a little over 4 years, I have taken **9,232,798** steps. This includes days spent walking around New York with visiting friends, running a half-marathon, and a pandemic that dropped my step count to nearly 0.



Bill Ratios of Brush-Tailed Penguins (*Pygoscelis* spec.)

Distribution of bill ratios, estimated as bill length divided by bill depth.



Graphical excellence!

Gorman, Williams & Fraser (2014) PLoS ONE DOI: [10.1371/journal.pone.0090081](https://doi.org/10.1371/journal.pone.0090081)
Visualization: Cédric Scherer • Illustration: Allison Horst

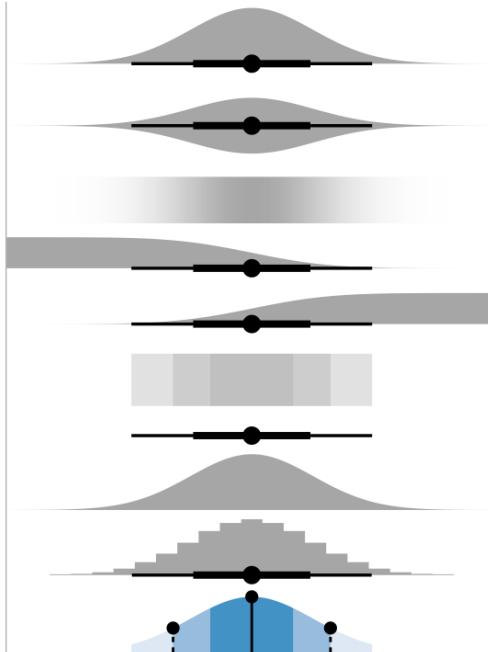
{ggdist} package



The {ggdist} package provides three families of geoms for visualizing uncertainty

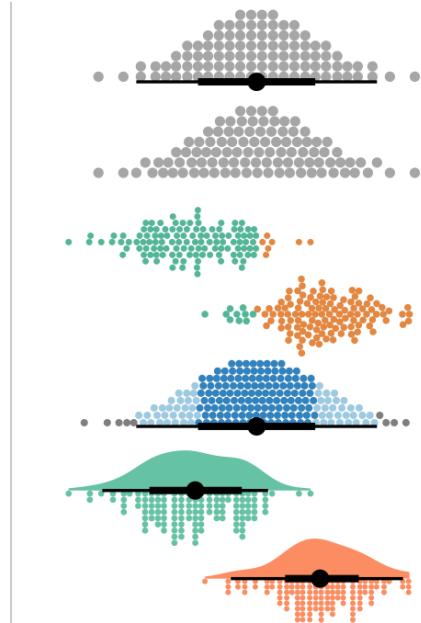
Point estimates + intervals

slabinterval



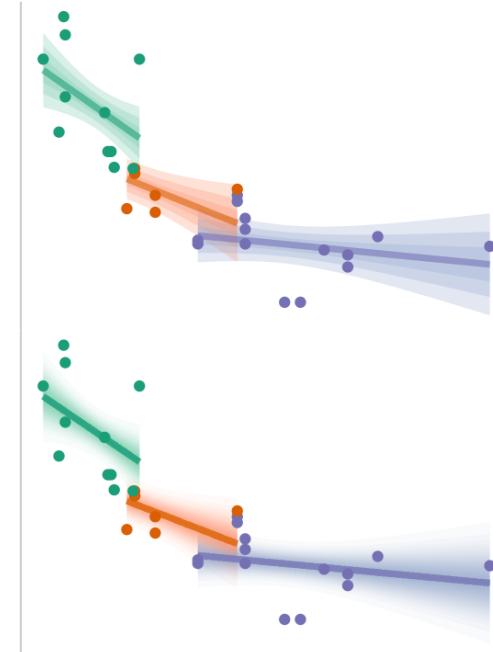
Dots + intervals

dotsinterval



Fitted lines + uncertainty bands

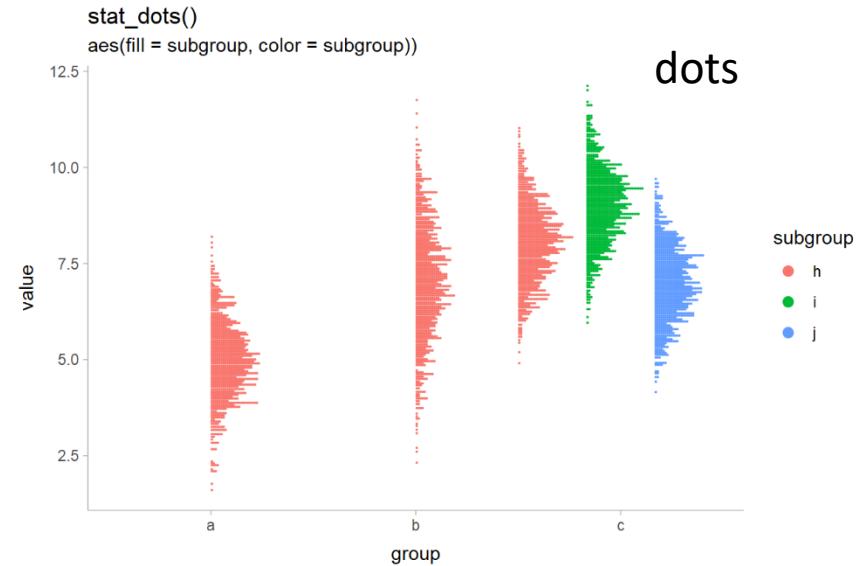
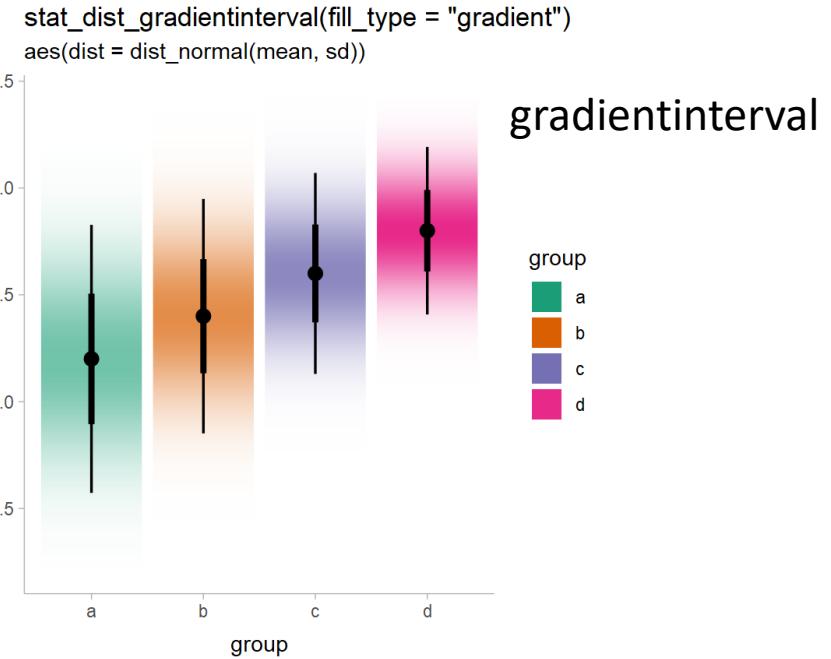
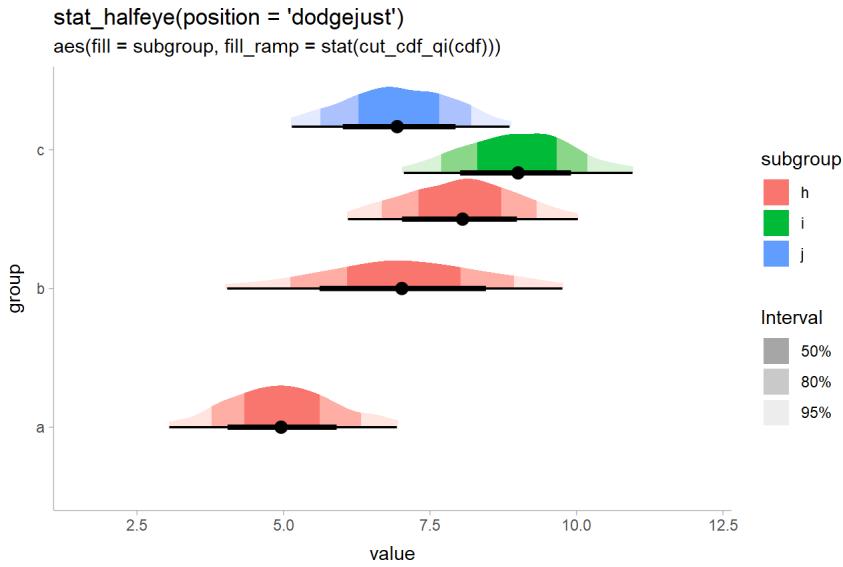
lineribbon



Some examples from the three main families of ggdist geometries

Design of {ggdist} makes it easy to combine two or more graphical representations –
data + distribution + interval

halfeye, varying fill



One-way ANOVA example

```
set.seed(5)
n <- 10; ngrps <- 5
ABC <- tibble(
  grp = rep(c("A", "B", "C", "D", "E"), n),
  response = rnorm(n * ngrps, c(0, 1, 2, 1, -1), 0.5)
)
```

```
ABC.mod = lm(response ~ grp, data = ABC)
broom::tidy(ABC.mod)
```

```
# A tibble: 5 × 5
  term      estimate std.error statistic    p.value
  <chr>        <dbl>     <dbl>     <dbl>      <dbl>
1 (Intercept)  0.182     0.173     1.05  0.300
2 grpB         0.833     0.245     3.40  0.00143
3 grpC         1.69      0.245     6.91  0.0000000138
4 grpD         0.846     0.245     3.45  0.00122
5 grpE        -1.12      0.245    -4.56  0.0000394
```

Frequentist theory

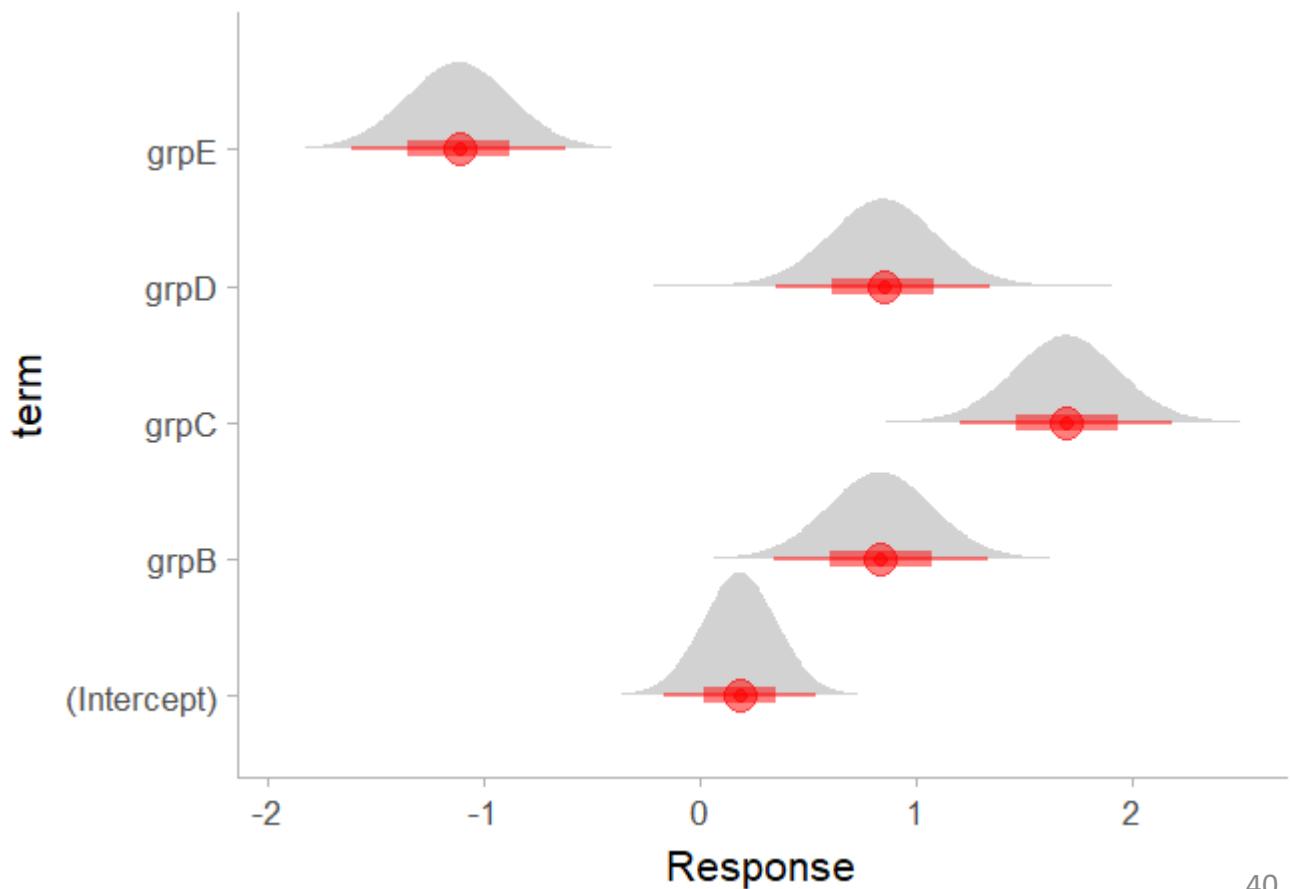
$$\tilde{\beta}_i \sim \text{student_t}(\nu, \hat{\beta}_i, \sigma_{\hat{\beta}_i})$$

v: df.residual(mod)

β_i : estimate

$\sigma(\beta_i)$: std.error

```
ABC.mod |>
  tidy() |>
  ggplot(aes(y = term)) +
  stat_halfeye(
    aes(xdist = dist_student_t(df = df.residual(ABC.mod),
                                mu = estimate, sigma = std.error)),
    alpha = 0.5, interval_size_range = c(1, 3), color = "red") +
  xlab("Response")
```



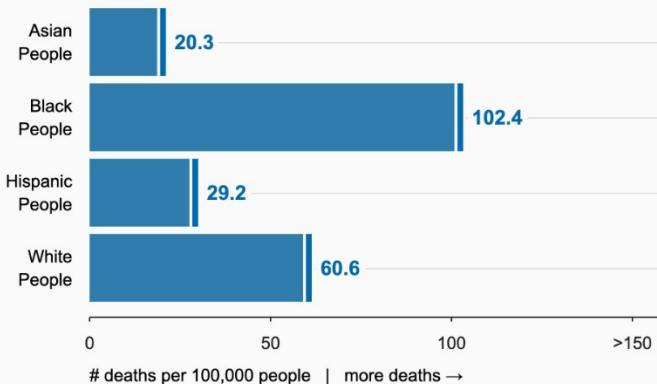
What works?

Holder & Padilla (2024): Compare different graph forms for visualizing risk disparities between racial and other social groups

Early deaths from heart disease

How many younger adults died each year from heart disease? Crude mortality rates for U.S. adults, ages 15-64

= National Average



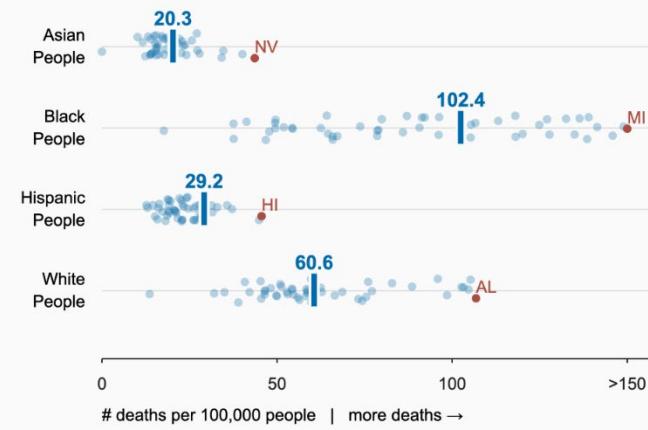
Each bar shows the average mortality rate for each group, across all 50 states. Mortality data is from the CDC's WONDER database, from 2018-2021, for diseases of heart (I00-I09,I11,I13,I20-I51).

Health outcomes vary widely by geography.

Michigan and **Alabama** have the most deaths from heart disease for younger Black and White adults.

How many younger adults died each year from heart disease? Crude mortality rates for U.S. adults, ages 15-64

= National Average



Each dot is 1 U.S. state. Dots are positioned horizontally based on the state's mortality rate for the corresponding group. Dots are randomly positioned vertically within each row for visual separation. The vertical lines show the overall group average across all 50 states. Mortality data is from the CDC's WONDER database, from 2018-2021, for diseases of heart (I00-I09,I11,I13,I20-I51).

Attribution Measures

Higher values indicate stronger beliefs.

Environment



Insurance



Health Habits

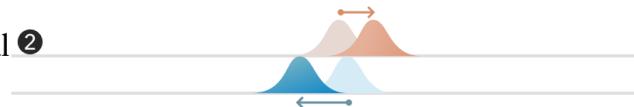


Genetics ①



External vs Personal ②

ext. = 0, per. = 100



Conventional Measures ③

Higher values indicate stronger beliefs, intent, or support.

Perceived Vulnerability



Behavioral Intent



Policy Support



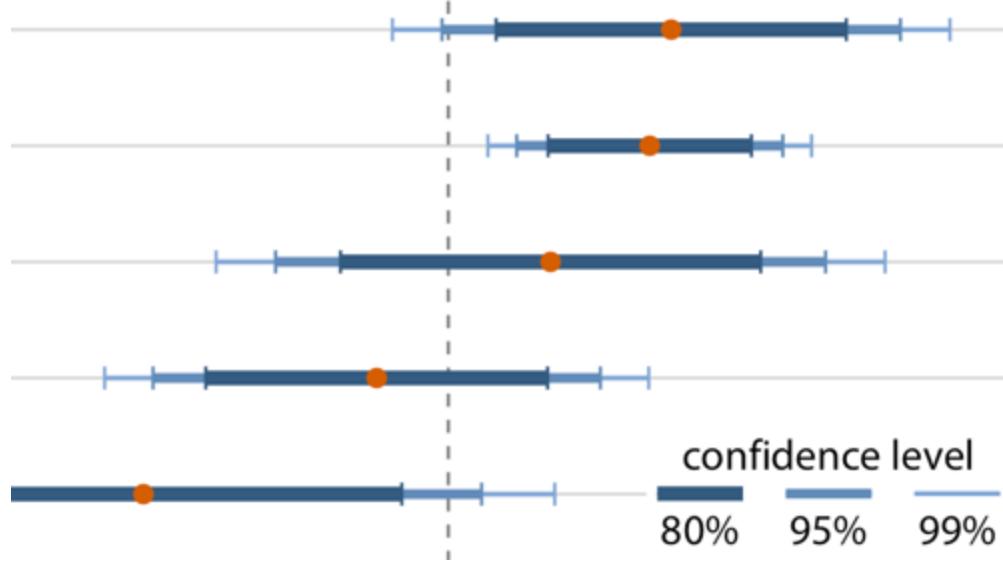
40 50 60 70 80

before ↘ after

bars ↗

geo-emph ↛

significant ↞



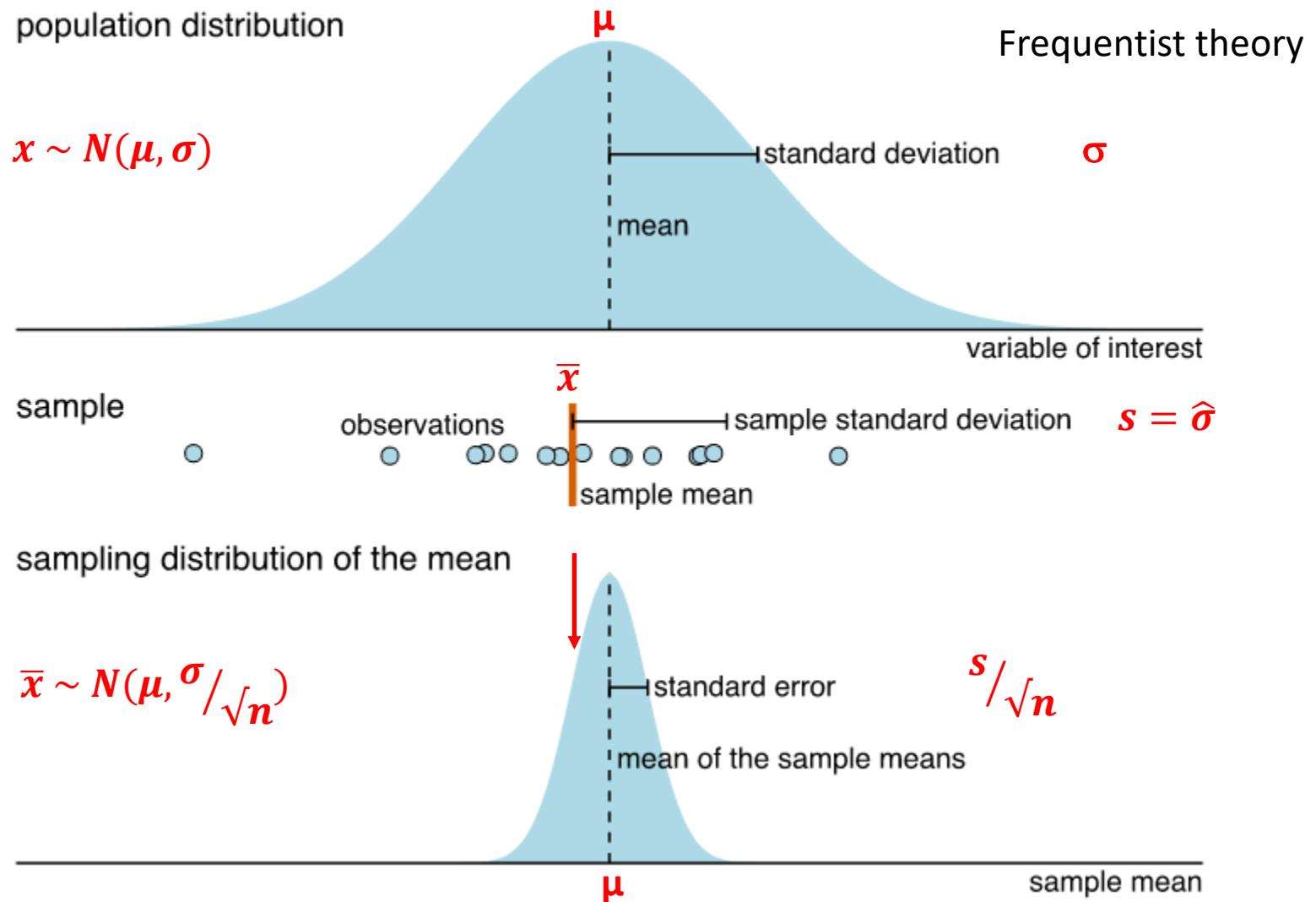
Standard deviation vs. standard error

What is a “confidence interval”

Frequentist vs. Bayesian

Error bars

Key ideas of statistical sampling



What's a “confidence interval”?



Steve Haroz @steveharoz.com · 2h

A 95% confidence interval could be

- a) $1.96 * \text{the standard error}$
- b) $1.96 * \text{the standard error of means}$
- c) 95% inner quantile of bootstrapped means
- d) 95% inner quantile of bootstrapped subject means
- e) $1.96 * \text{the standard deviation}$
- f) 95% inner quantile of values
- g) 95% of damn near anything

#stats



3



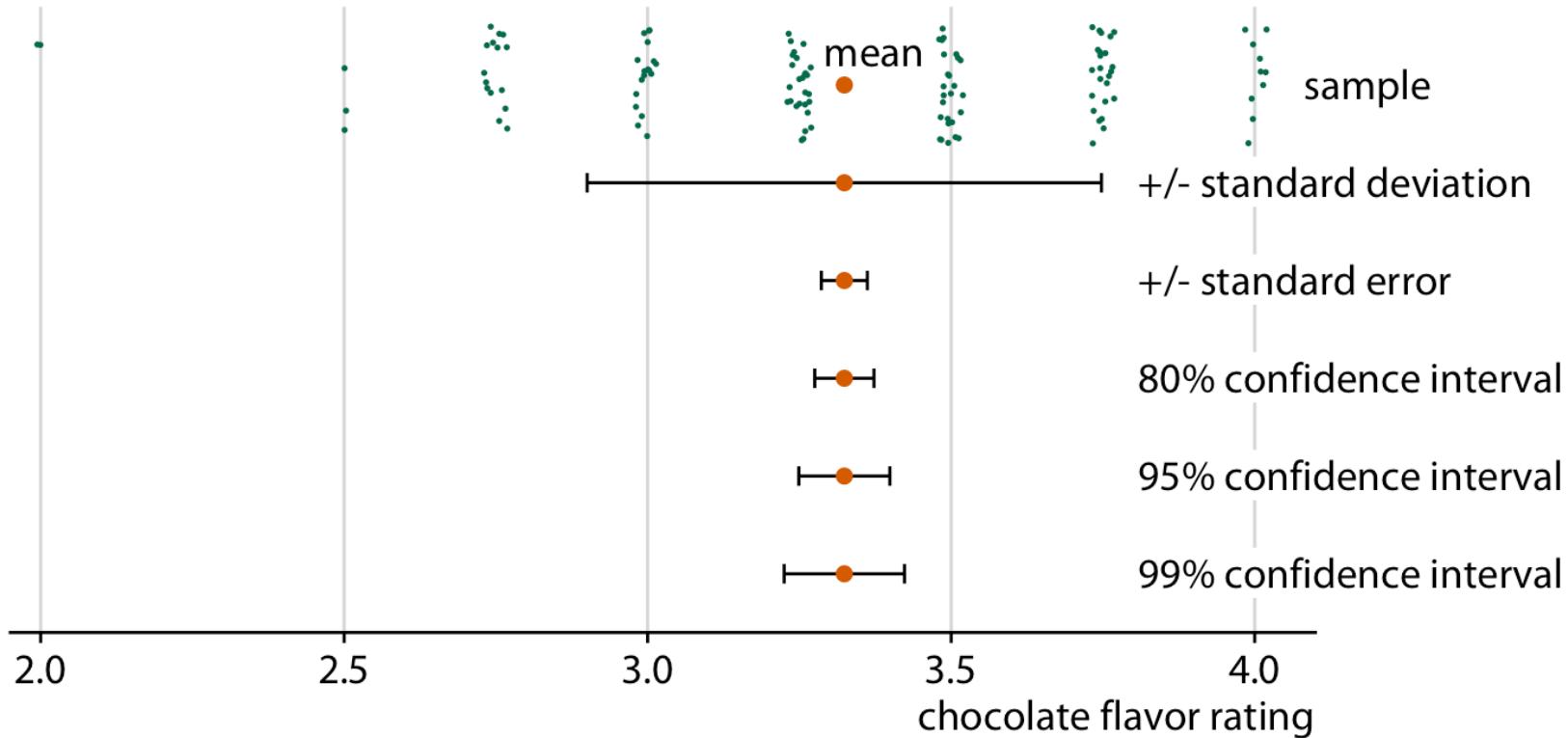
6

...

<https://bsky.app/profile/steveharoz.com/post/3ko5xd7waa42m>

Visualizing distributions: Error bars

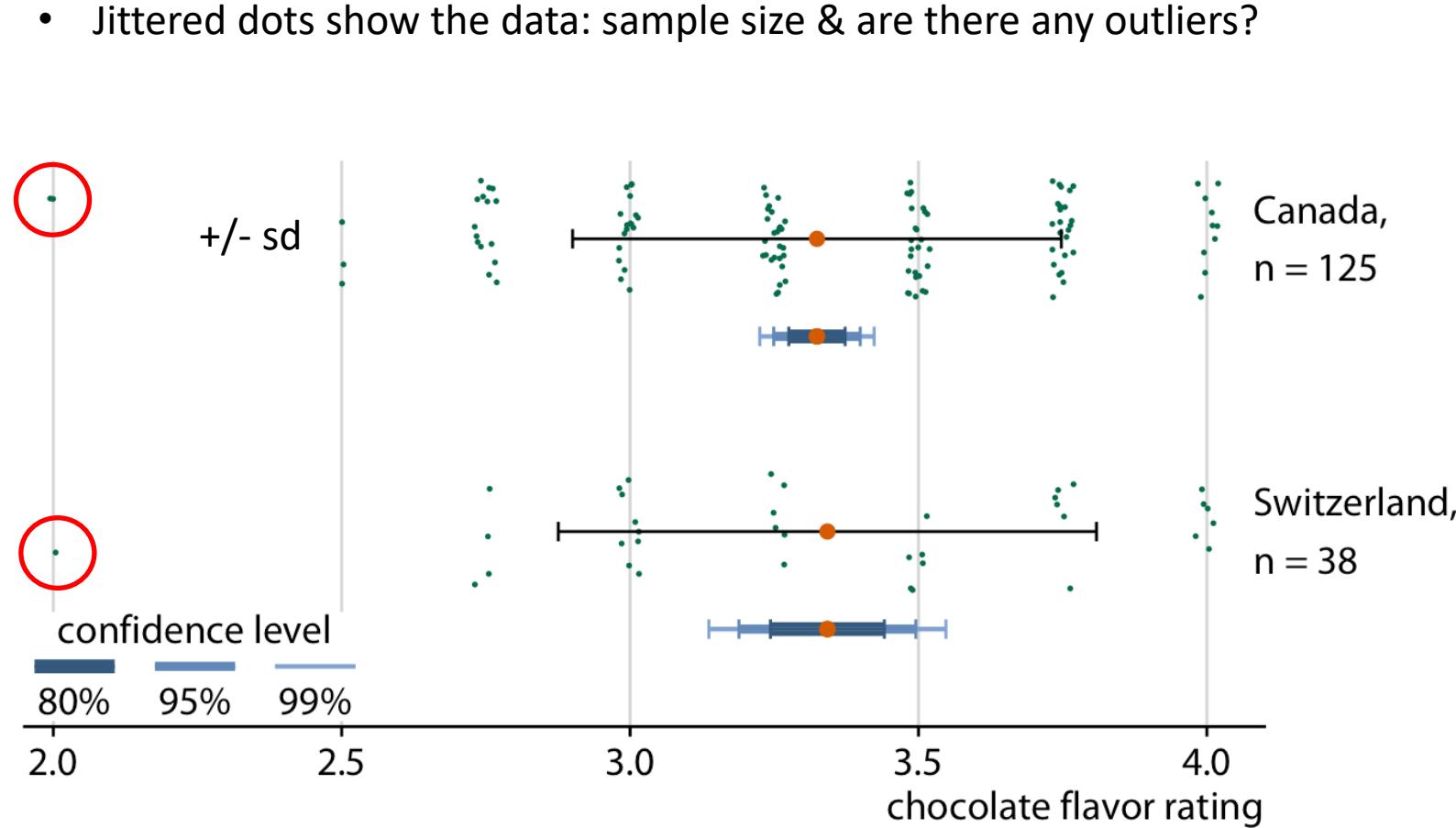
There are many ways to show variability in a single sample



Expert ratings of 125 chocolate bars manufactured in Canada

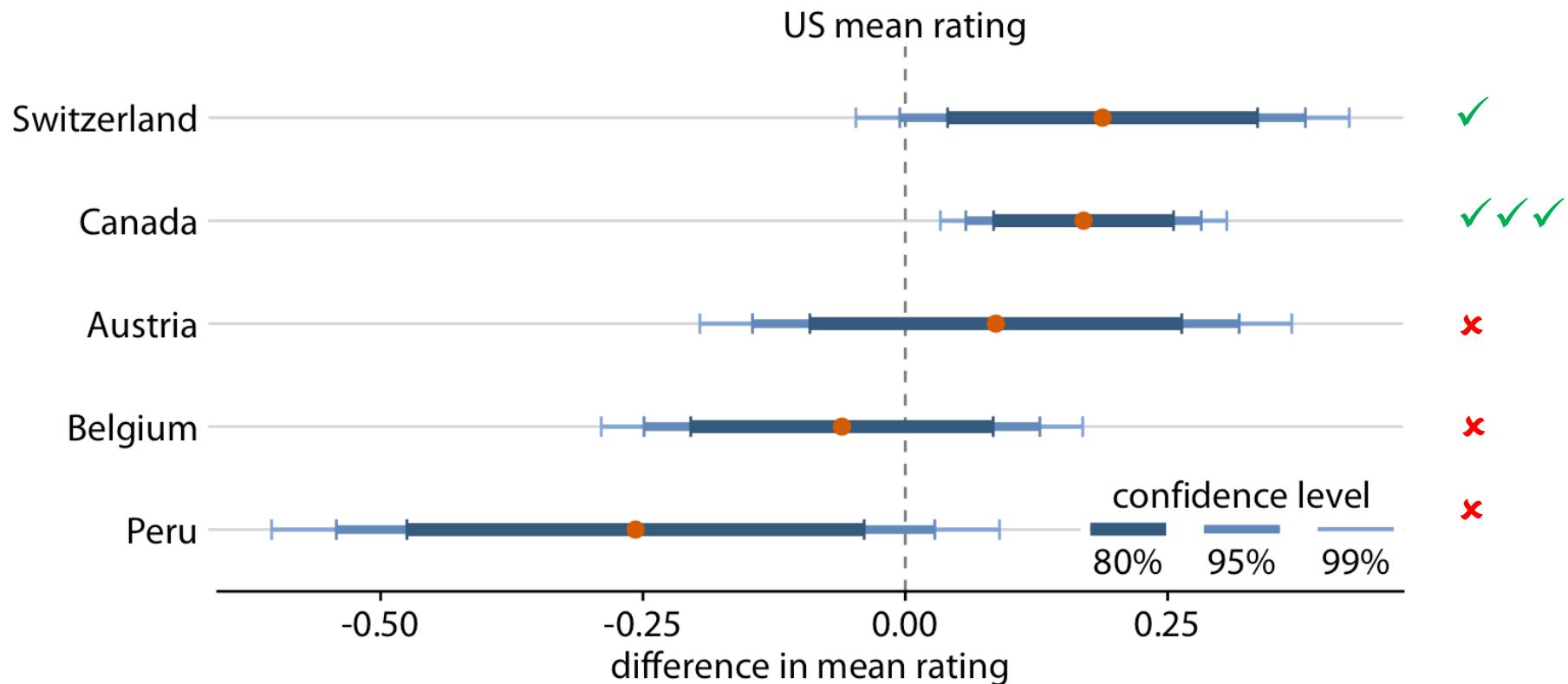
Comparing distributions: Sample size

- means and standard deviations are similar for Canada & Switzerland
- confidence interval widths $\sim 1/\sqrt{n}$
- can show different sized confidence bands together
- Jittered dots show the data: sample size & are there any outliers?



Comparing distributions: Contrasts

- For comparison of one group to all others, plot the **difference** directly
- Easy to see which differences exclude 0, at what confidence level



Intervals: Direct vs. Differences

The standard error for the **difference** between two means is always **larger than the standard error of either mean**

$$SE(\bar{x}) = \sqrt{s^2 / n}$$

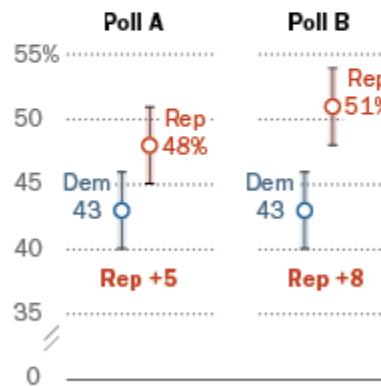
$$SE(\bar{x}_1 - \bar{x}_2) = \sqrt{s_1^2 / n_1 + s_2^2 / n_2}$$

When separate intervals are shown, the visual inference is that groups **differ** significantly if intervals do not **overlap**.

For election polls, different measures of the race have different margins of error

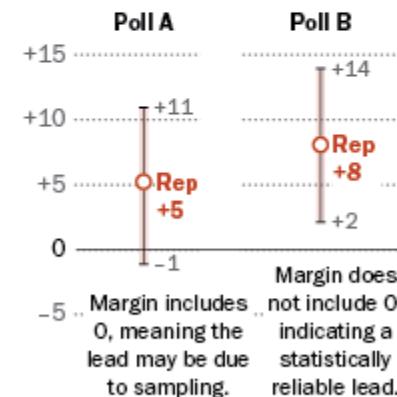
The margin of error reported for most polls applies to support for individual candidates ...

Margin of error for single candidate support
(MOE \pm 3 pct. points)



... while the margin of error for a candidate's lead is nearly twice as large.

Margin of error for difference between two candidates' level of support (%Rep – %Dem)
(MOE \pm 6 pct. points)



Source: Hypothetical polling results from a fictitious election.

PEW RESEARCH CENTER

What kind of intervals?



Frequentist

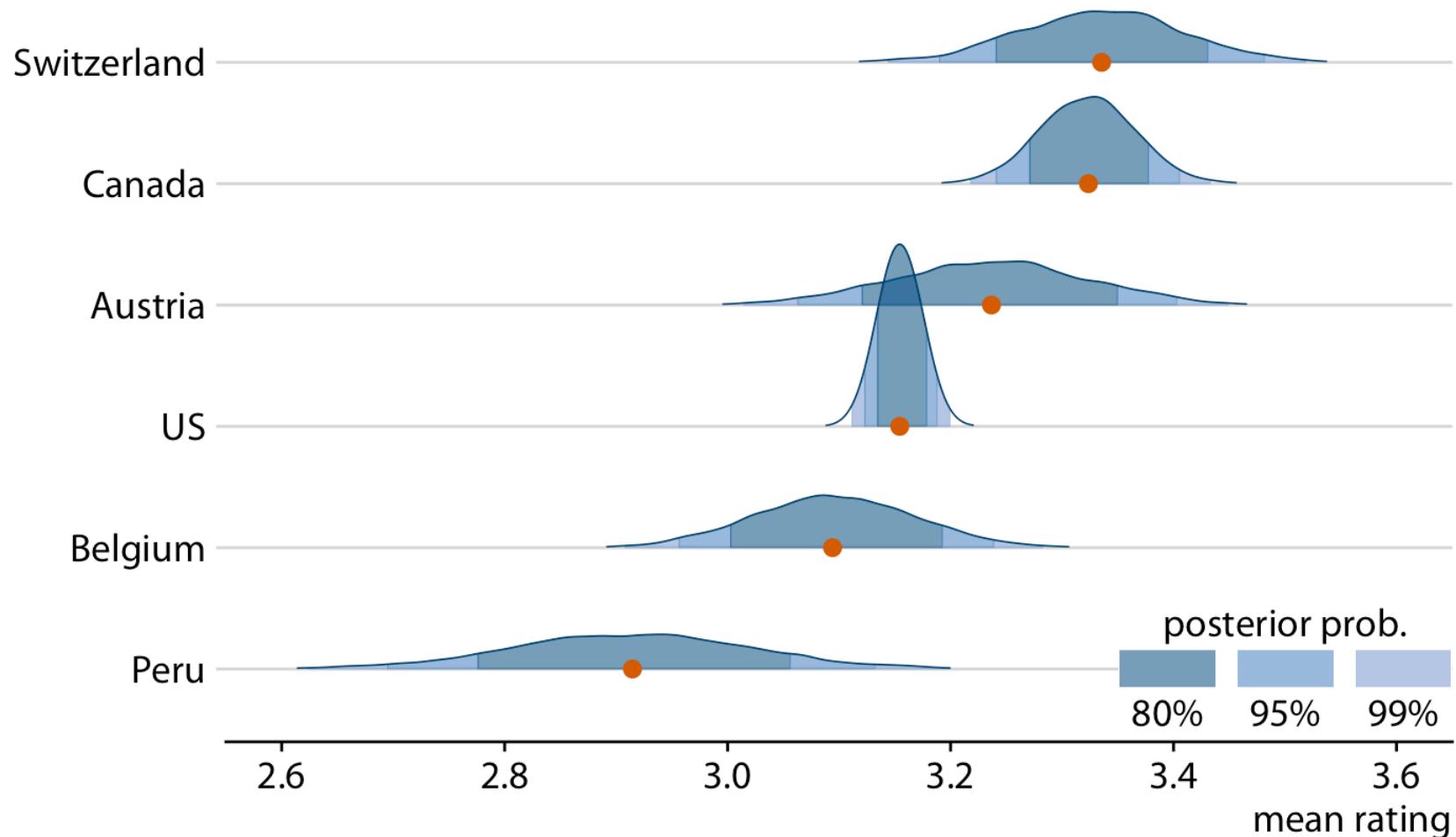
- Confidence interval
- Scope: repeated (hypothetical) samples
- Center: parameter estimate
 - $\mu \rightarrow \bar{x}$; $\beta \rightarrow \hat{\beta}$
- Width: \sim std. error = $\hat{\sigma}/\sqrt{n}$
- Interpretation: true parameter w/in this interval $1-\alpha$ % (in repeated samples)

Bayesian

- Credibility interval
- Scope: repeated draws from the posterior distribution
- Center: median of posterior distribution
- Width: MAD sd of posterior
- Interpretation: Given prior, expect parameter w/in this interval $1-\alpha$ % of draws

Bayesian intervals

Distribution of repeated draws from posterior distribution



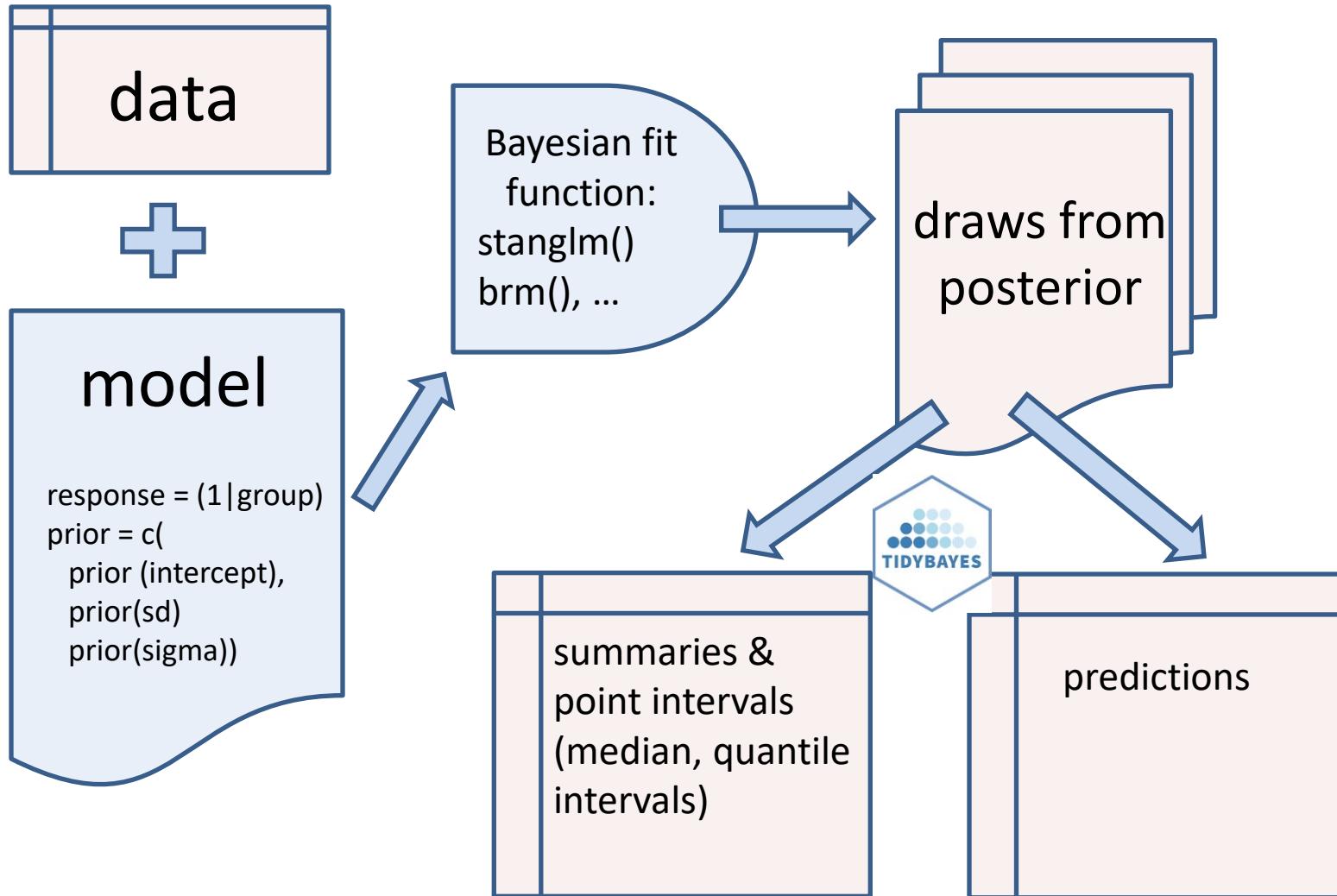
tidybayes: Bayesian analysis + tidy data + geoms

- The {tidybayes} package makes it easier to combine Bayesian analysis with insightful ggplot visualization
 - Bayesian packages: JAGS, Stan (rstanarm), brms
 - Inputs: data, model specifications aren't tidy
 - Need to translate data into forms these packages expect
 - Outputs: Posterior draws, distributions aren't tidy
 - Need to translate these into form suitable for summaries & plotting
 - → Extract tidy fits and predictions from models
 - → Summarize posterior distributions
 - → Visualize priors and posteriors



Docs: <http://mjskay.github.io/tidybayes/>

The Bayesian process



Posterior = Prior × Likelihood

We have: Data, some model, some parameter(s) of interest, θ

Can calculate likelihood, $p(Data|\theta)$

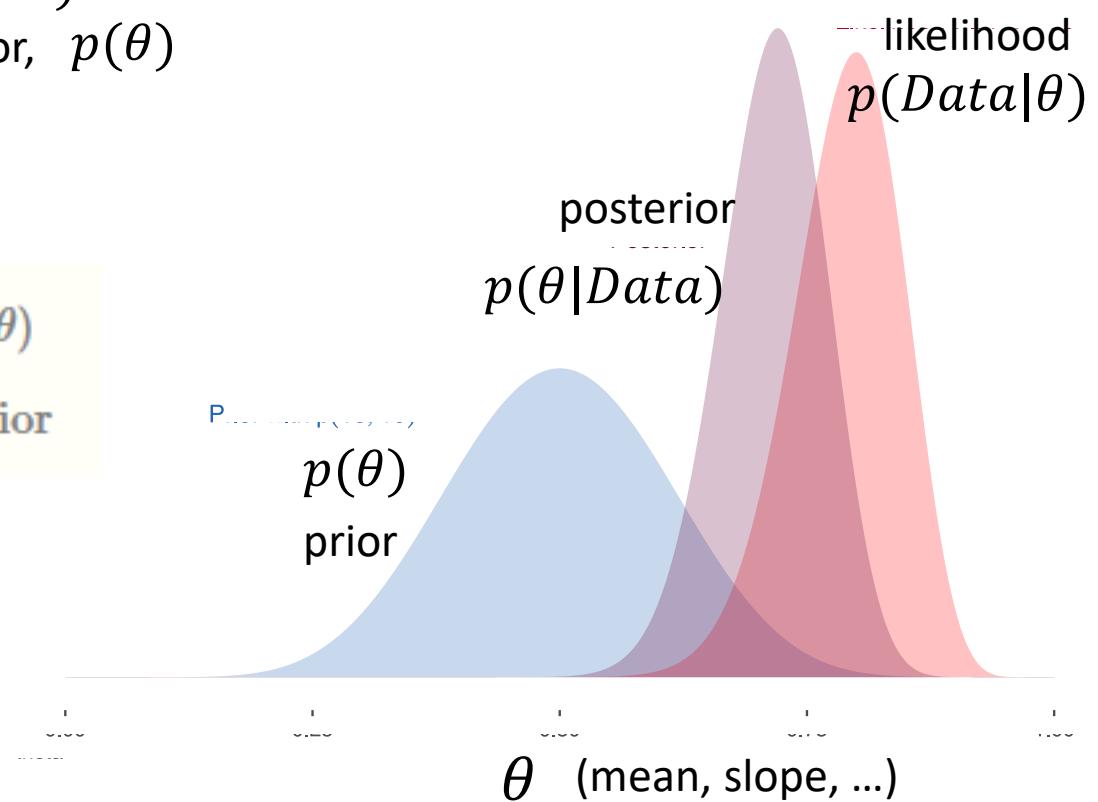
Want: posterior: $p(\theta|Data)$

Previous research: some prior, $p(\theta)$

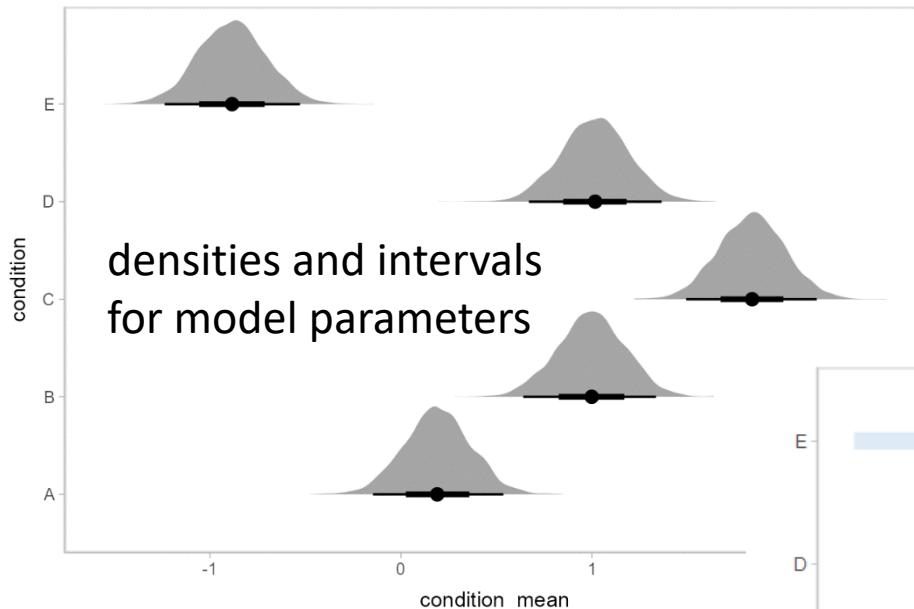
Bayes theorem:

$$p(\theta|Data) \propto p(Data|\theta) \cdot p(\theta)$$

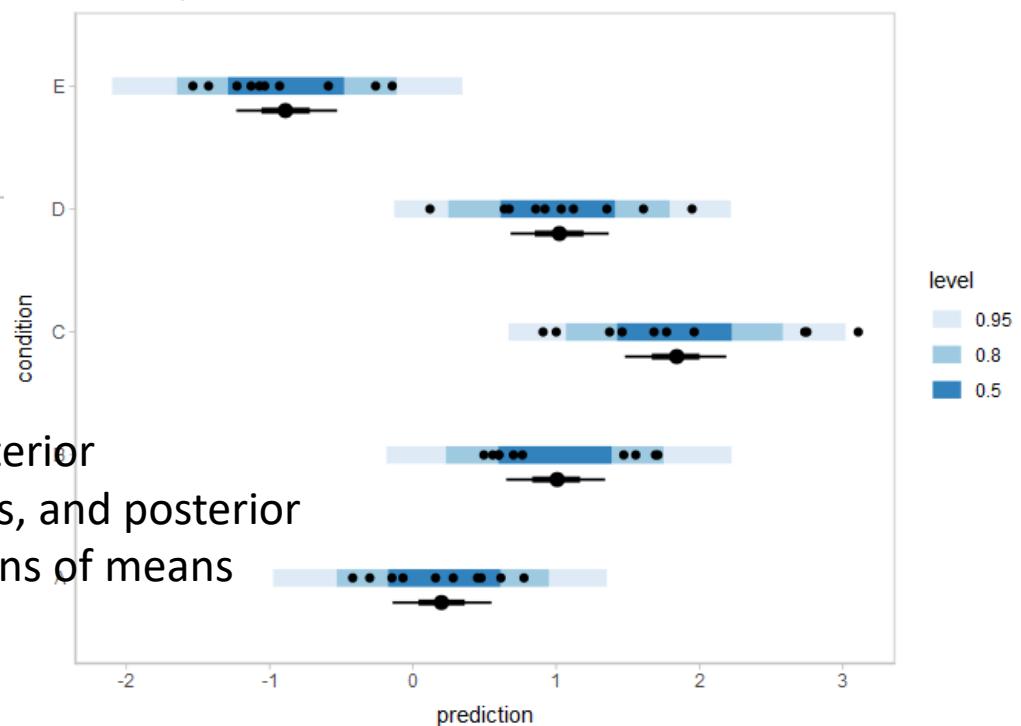
$$\text{posterior} \propto \text{likelihood} \cdot \text{prior}$$

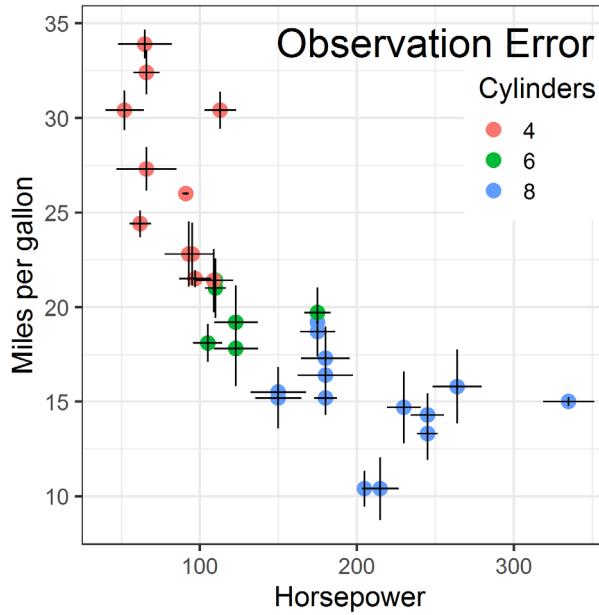
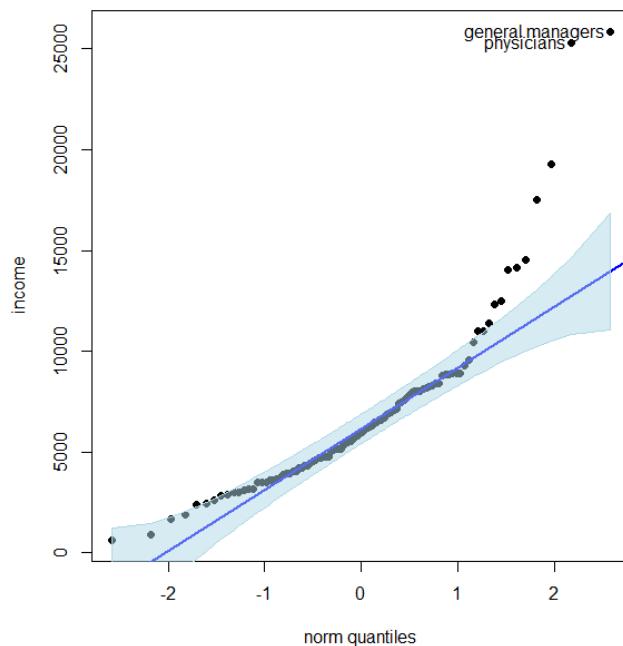


tidybayes plots



Everything we can do for data with
{ggdist} we can do for Bayesian
models with {tidybayes}





- QQplots
- Model fit plots

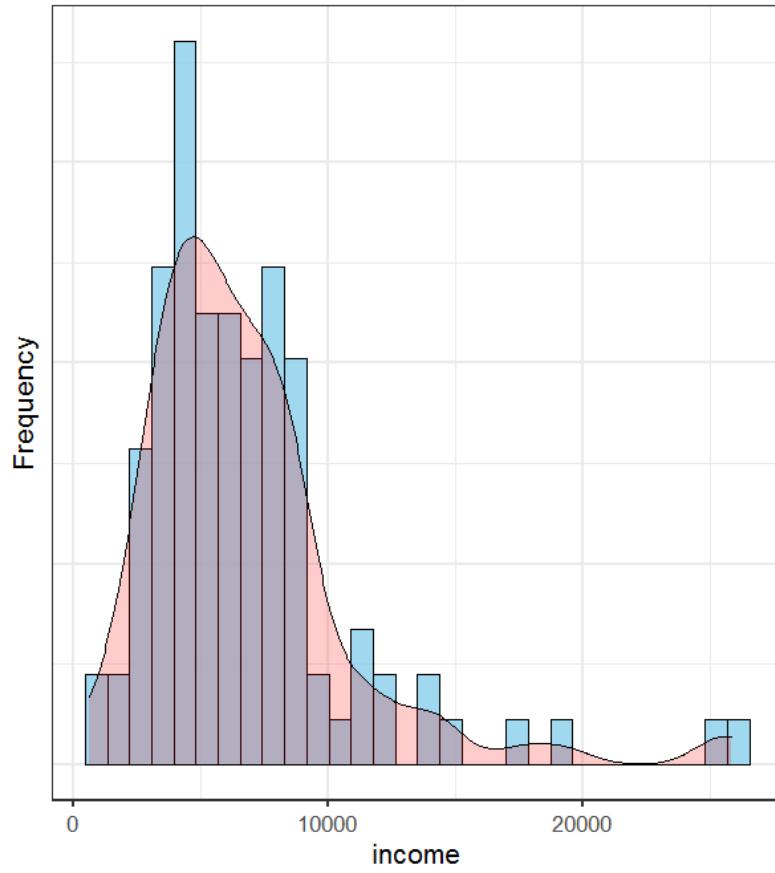
Uncertainty in fits & curves

QQ plots

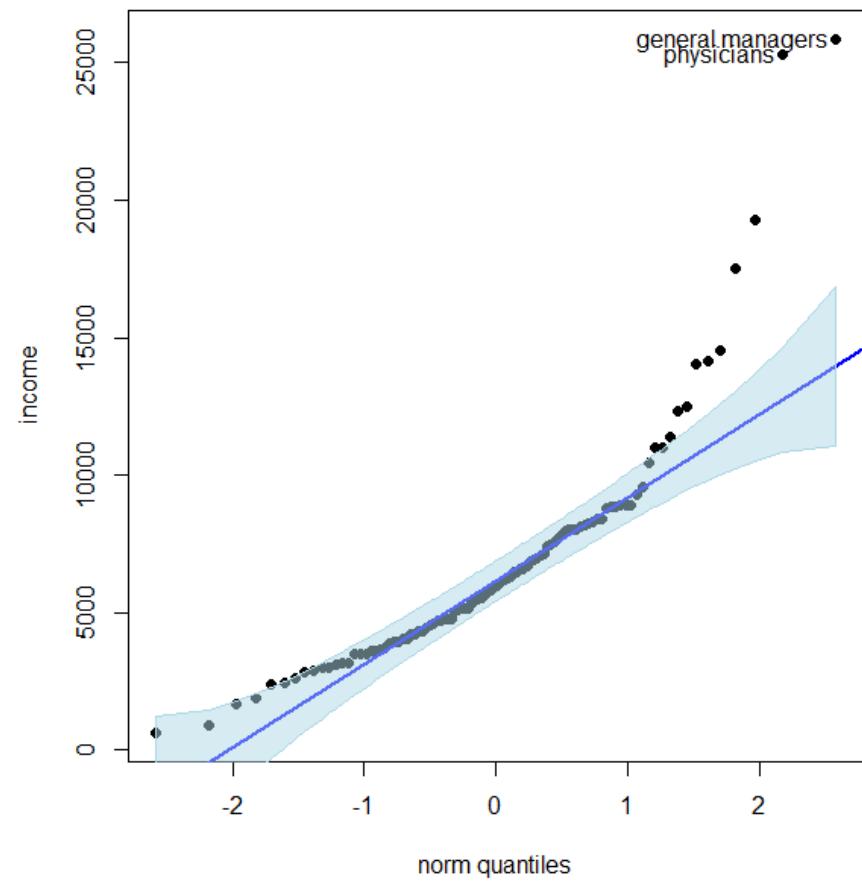
- How close is my data to a {Normal | exponential | χ^2 } distribution?
- There are lots of statistical tests, but these don't tell **why** or **where** a distribution is rejected.
- These tests are also overly sensitive to small departures
- Plot observed Quantiles vs. theoretical Quantiles
 - If observed \sim theoretical with **slope = 1**, OK
 - **Confidence bands** help to identify deviation from model & outliers
- Use cases:
 - Is a single variable reasonably normally distributed?
 - Are the residuals from my linear model Normal?
 - Outliers in multivariate data? $D^2 \sim \chi^2 \rightarrow$ chisq QQ plot

Prestige data: income

Income is clearly **positively** skewed.
(But normality is not required for predictors.)

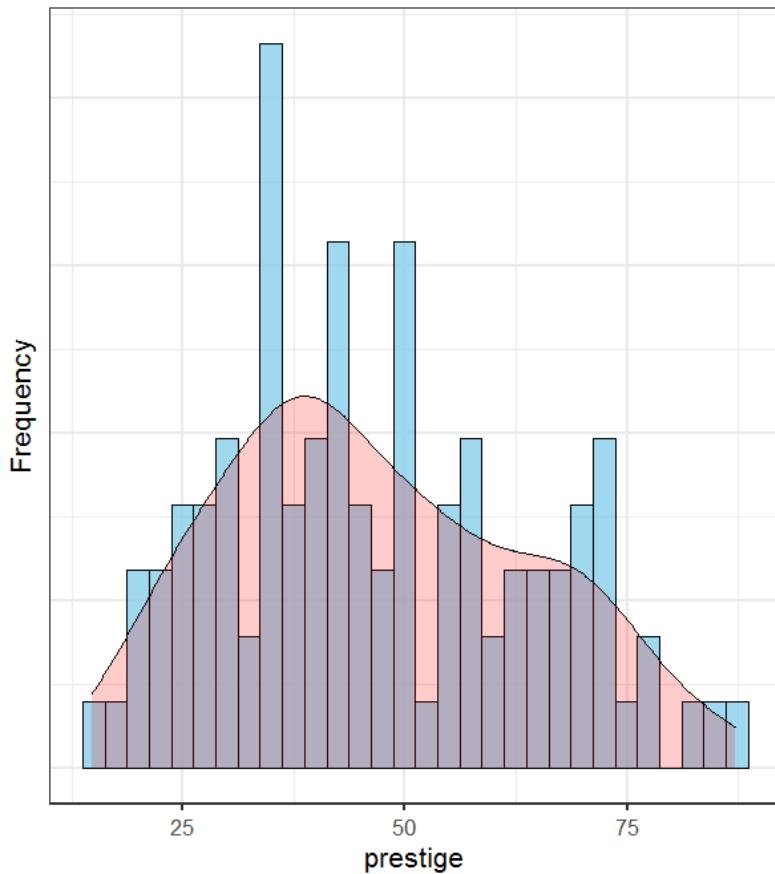


This shows up as a **U-shaped** pattern
The 95 % confidence band shows greatest departure in the upper tail

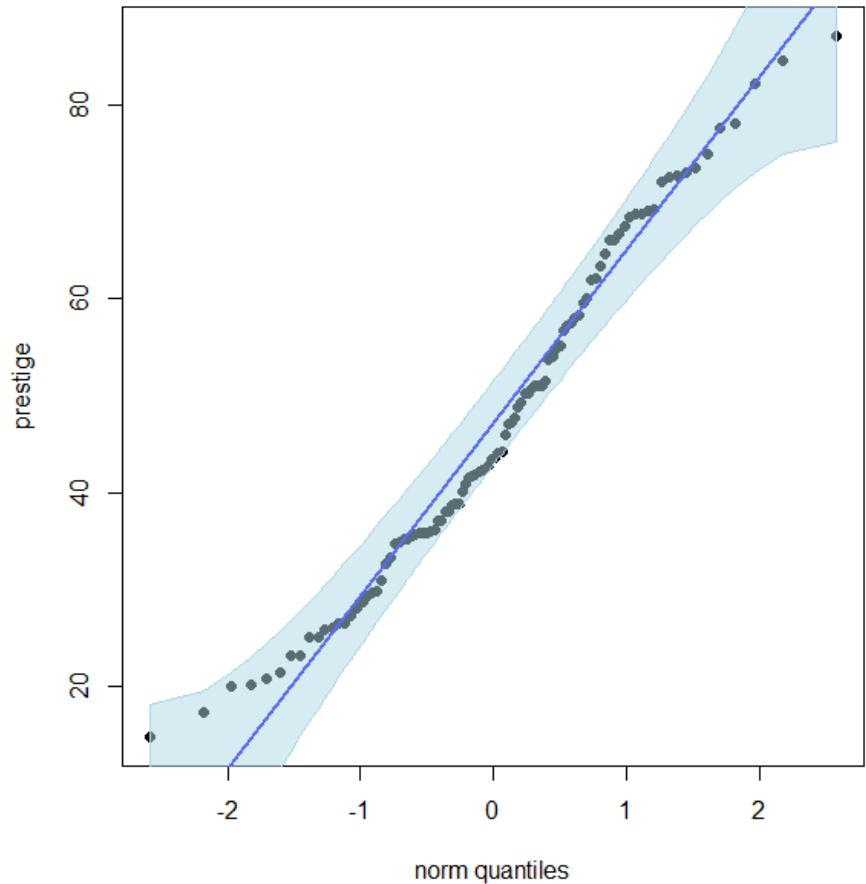


Prestige data: prestige

Occupational prestige doesn't look precisely normal, but not that bad.



The 95% confidence band includes all the observations



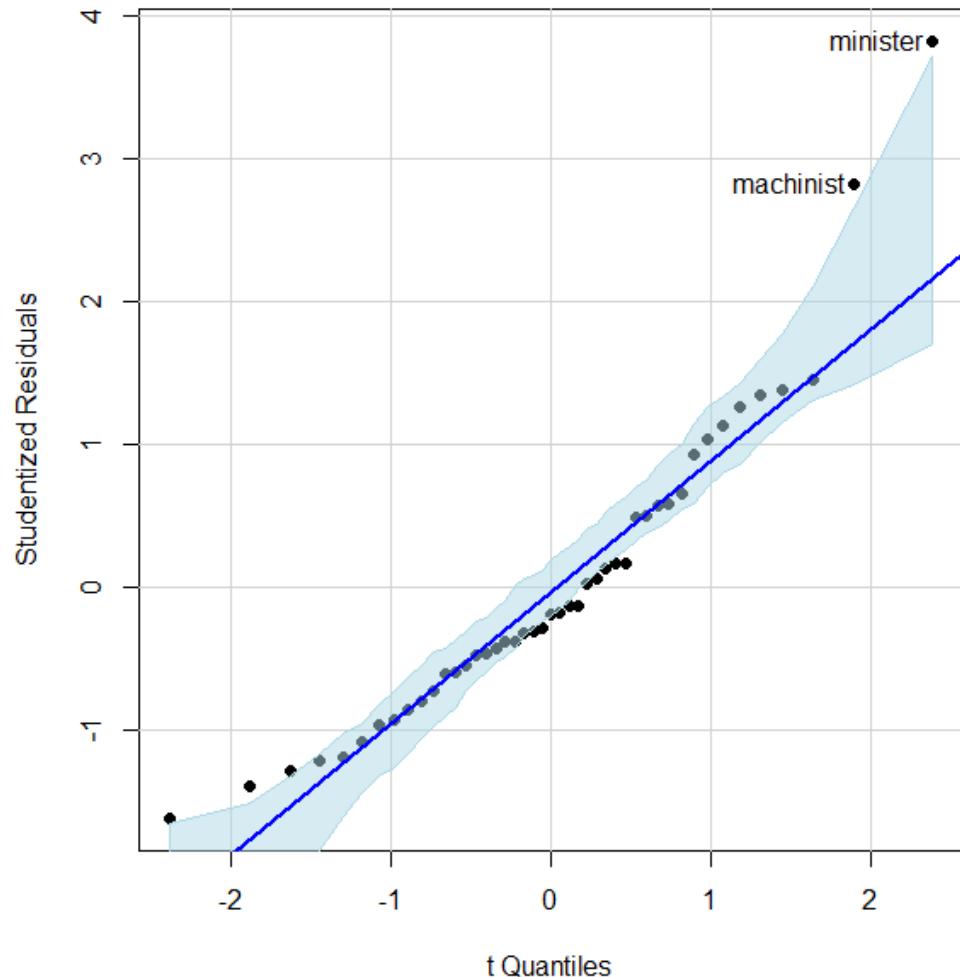
Prestige data: residuals

Normality of **residuals** is more important for linear models

Some small evidence of + skew

Confidence bands help to identify potential outliers – badly fitted pts

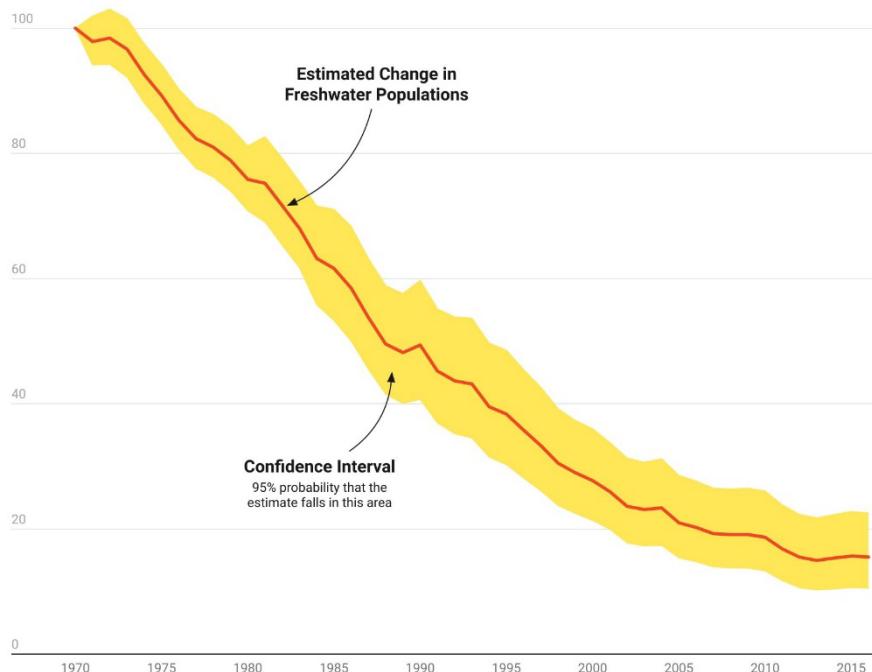
```
qqPlot(lm(prestige ~ income +  
education + type, data=Duncan))
```



Curves + Uncertainty

Humanity has wiped out 60% of animal populations since 1970 – and freshwater habitats are the worst hit with populations having collapsed by more than 80%

The Living Planet Index, produced for WWF by the Zoological Society of London, uses data on 16,704 populations of mammals, birds, fish, reptiles and amphibians to track the decline of wildlife. It underlines how the vast and growing consumption of food and resources by the global population is destroying the web of life upon which human society ultimately depends on.



Cédric Scherer used this graphic to argue about the decline of animal & freshwater populations.

Details aside, the confidence band gives visual evidence that the decline is systematic.

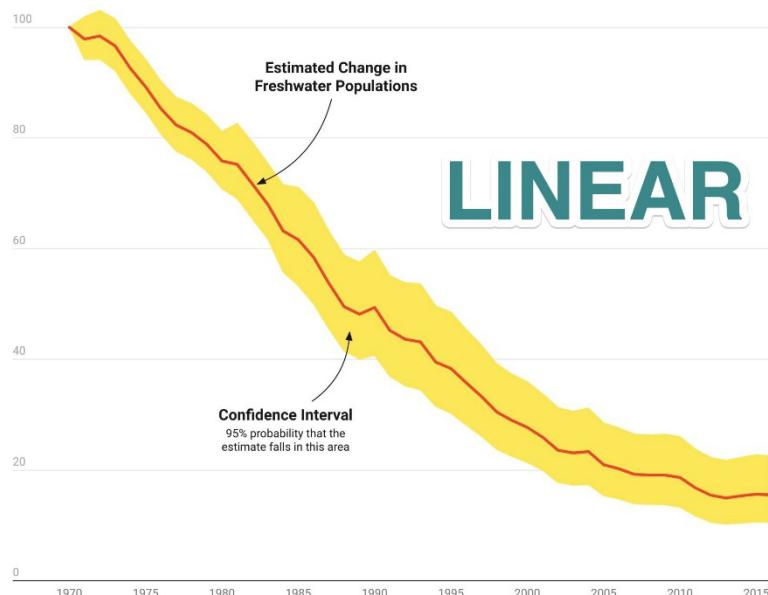
From: <https://twitter.com/CedScherer/status/1380211291466399744>

Curves + Uncertainty: Scale

Arguably, **percent** reduction in animal population should be viewed on a **log scale**. Transformed uncertainty intervals are here the logs of the Upper/Lower levels

Humanity has wiped out 60% of animal populations since 1970 — and freshwater habitats are the worst hit with populations having collapsed by more than 80%

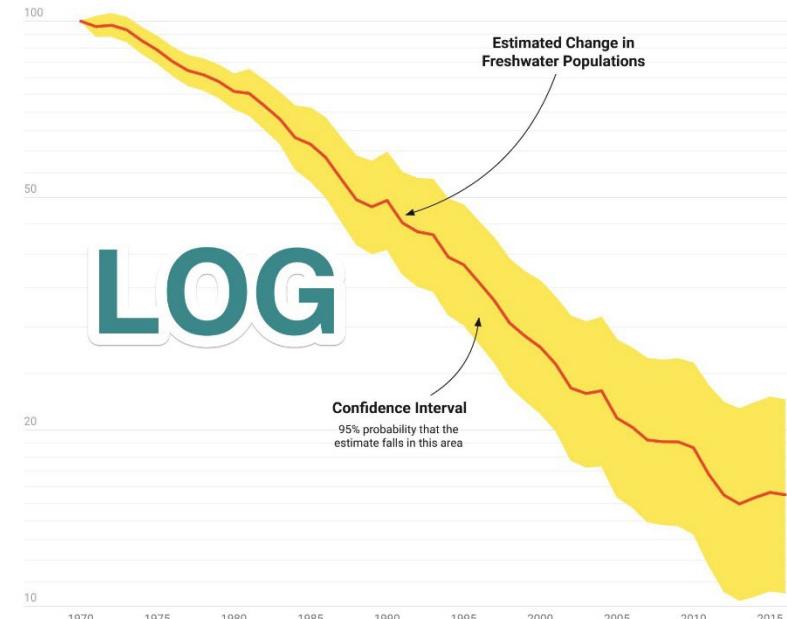
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#30DayChartChallenge 2021 | Day 8: Animals
Chart: Cédric Scherer • Source: World Wildlife Fund (WWF) and Zoological Society of London • Created with Datawrapper

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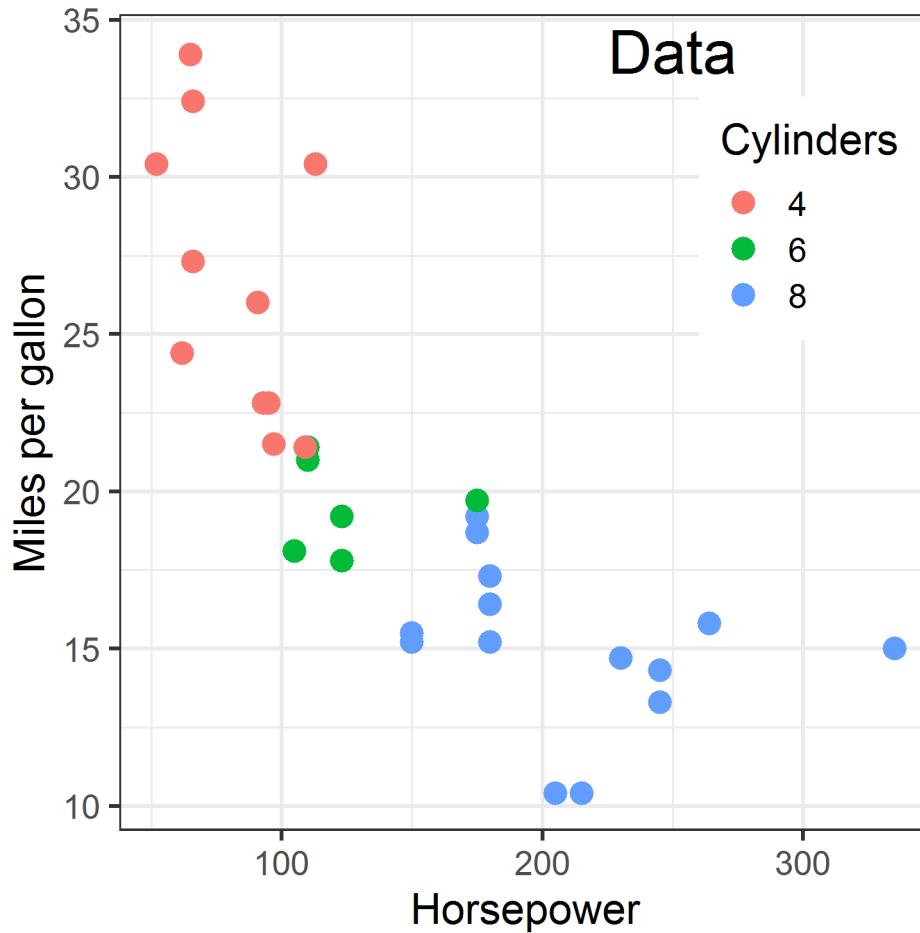
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#30DayChartChallenge 2021 | Day 8: Animals
Chart: Cédric Scherer • Source: World Wildlife Fund (WWF) and Zoological Society of London • Created with Datawrapper

Fitted curves

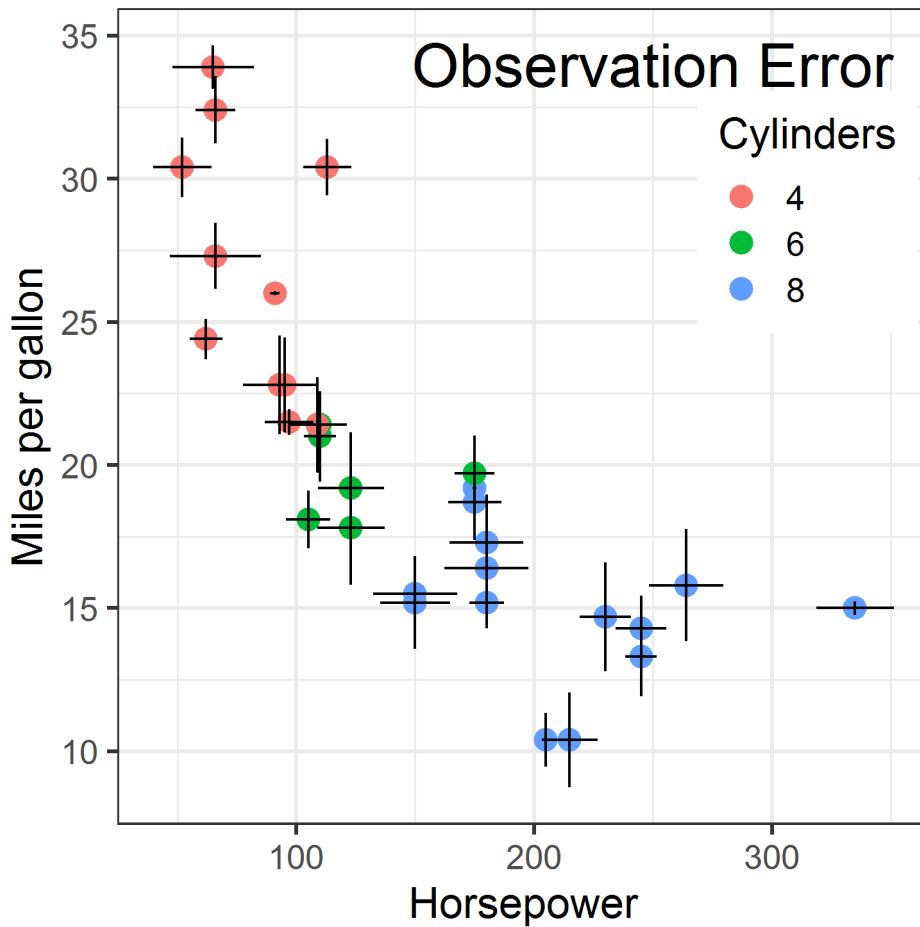
Data on gas mileage of *Motor Trend* 1974 cars



Sources of uncertainty:

- Observations: **measurement error** in MPG and/or HP?
- **Model form**: Linear? Quadratic?
Interaction with cylinders
- **Model fit uncertainty**: normal theory CIs? Bootstrap?
Bayesian?

Measurement uncertainty



Sometimes, we can quantify the uncertainty ("error") in values of x and or y .
e.g., each point is the average of $n > 1$ cars.

Fitted models allow for errors in y :
 $y = f(x) + \text{error}$
and find estimates to minimize error

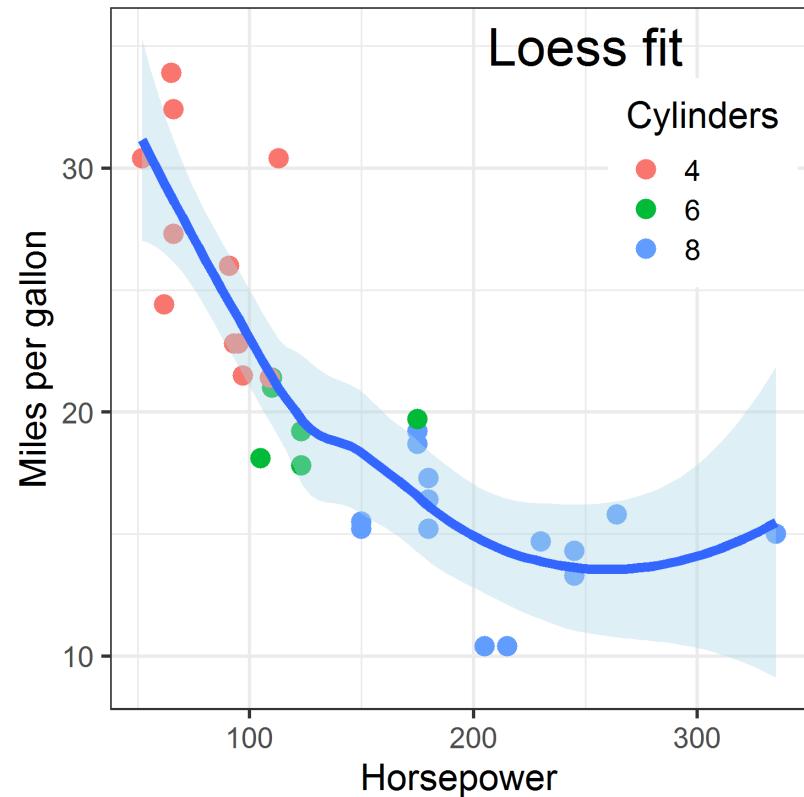
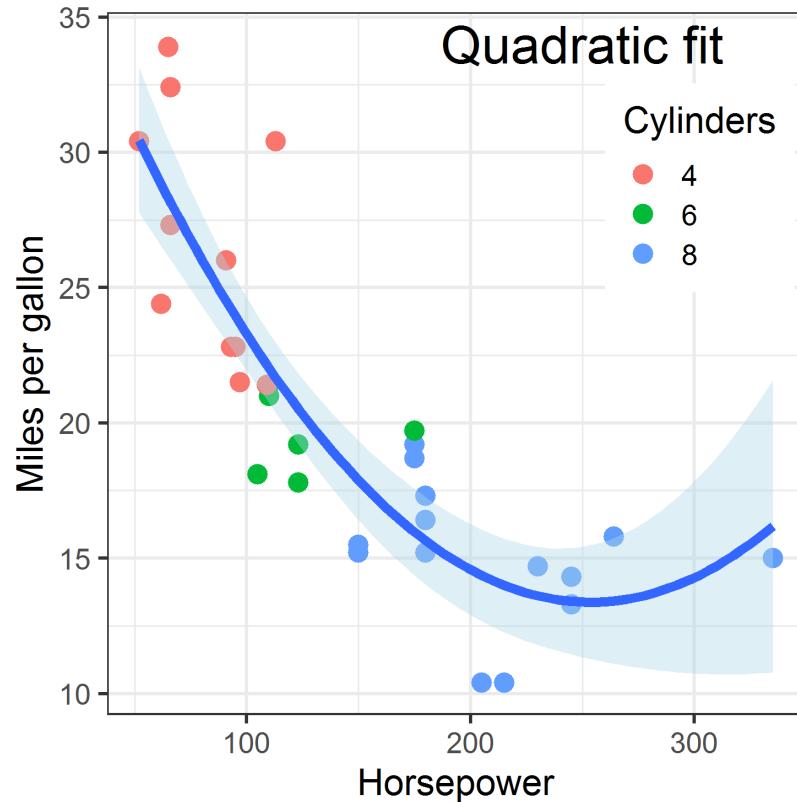
Most fitted models assume x is measured w/o error.

Big problem if $\text{error} \sim f(x, \text{other } xs)$

Model forms: nonlinear fits

When a relation is clearly non-linear, we can fit alternative models.

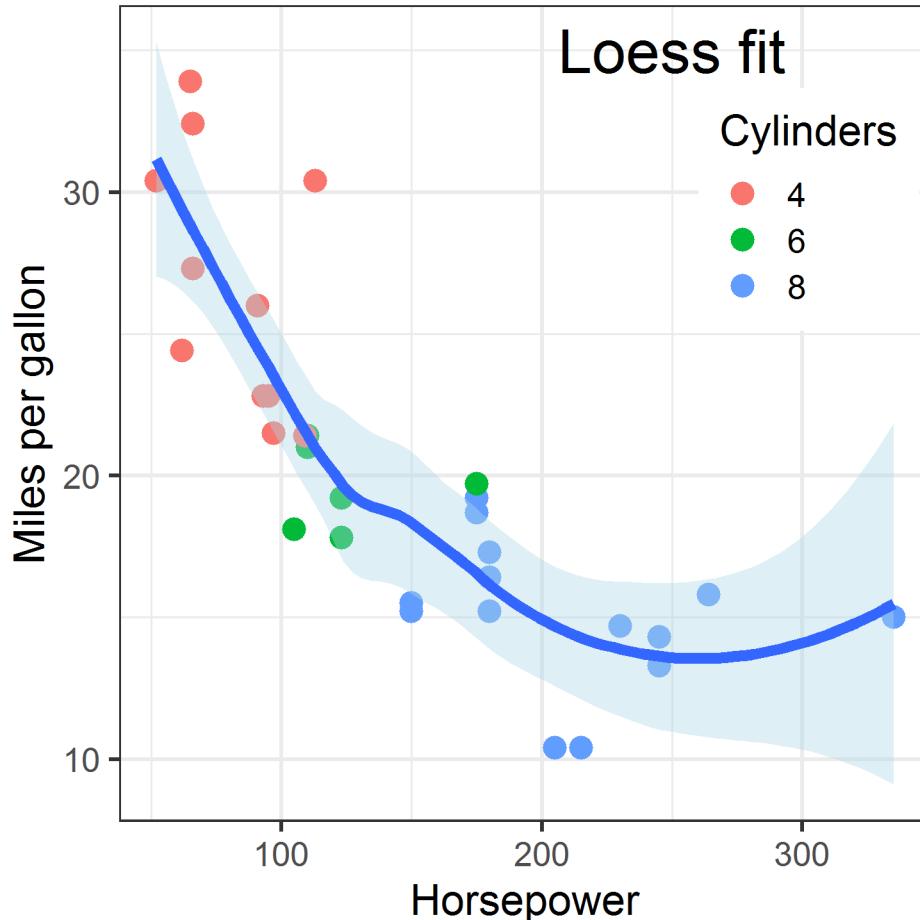
The CI bands tell us where the data is too thin to rely on the predicted value.



```
p1 + geom_smooth(method = lm, formula = y~poly(x,2), ...)
```

```
p1 + geom_smooth(method = loess, formula = y~x, ...)
```

Fitted curves: smoothers

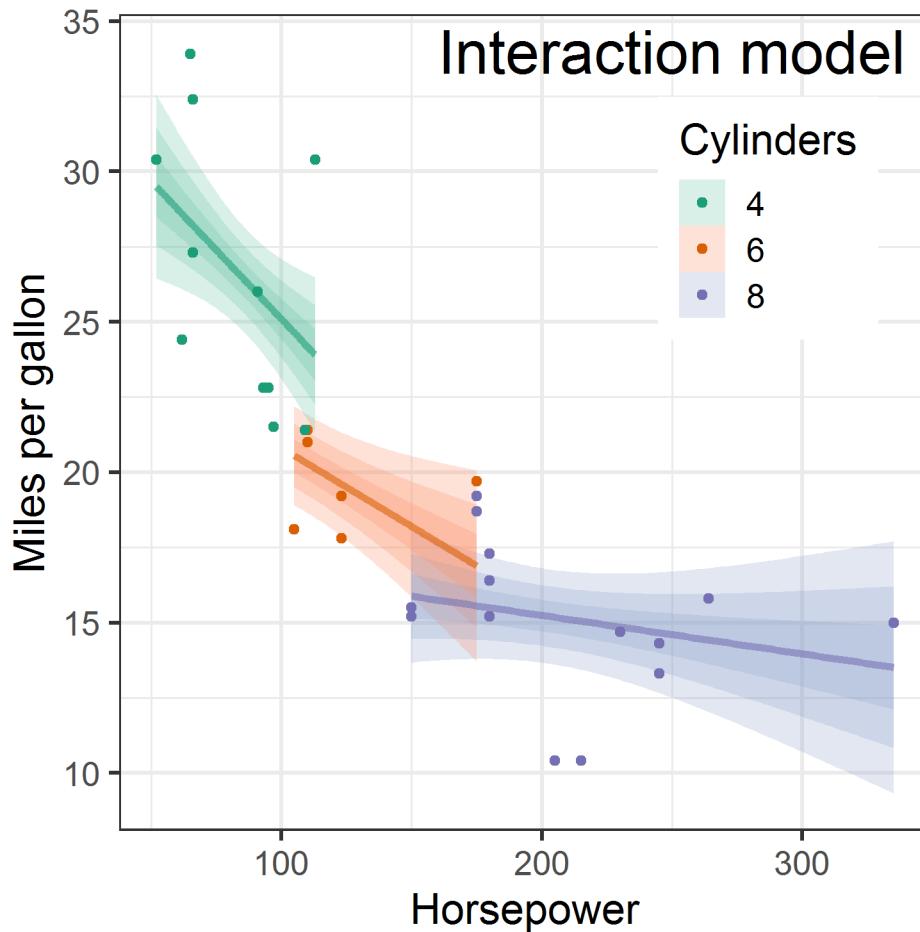


In each case, the confidence band gives visual evidence for uncertainty of the predicted values.

But, uncertainty may be expressed differently.

- a formula for std. error based on normal/large sample theory
- envelope of (normal) simulations
- Bayesian predictive distribution

Interaction models

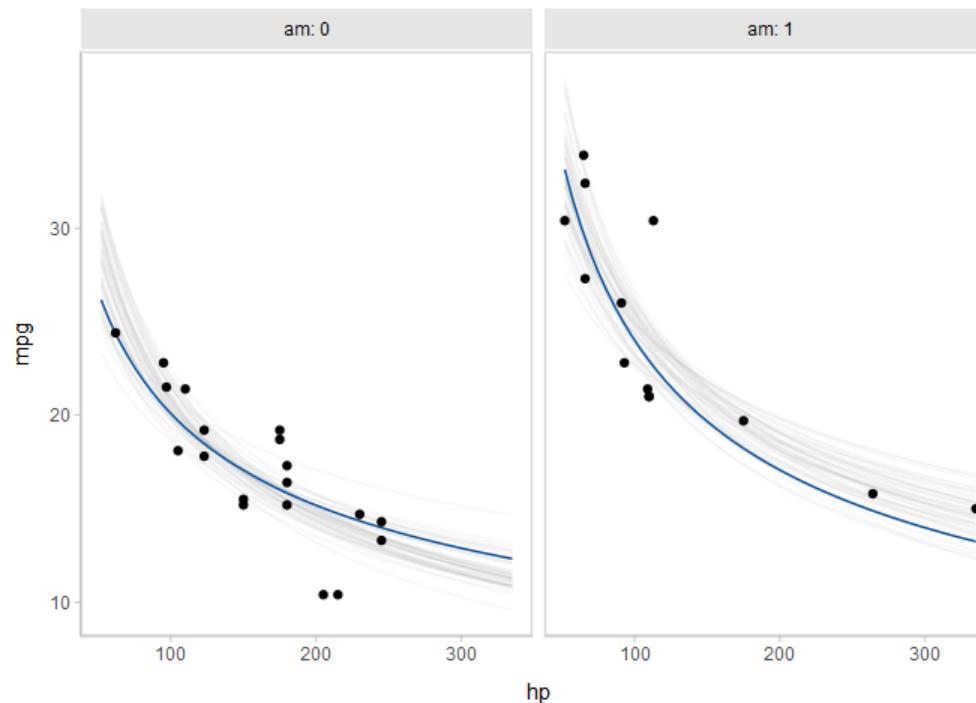


The non-linear relation between hp & mpg can (arguably) be better explained by a model that allows different slopes for 4, 6, 8 cylinders.

The graph shows normal theory CIs at 95%, 90%, and 80% for each cylinder level

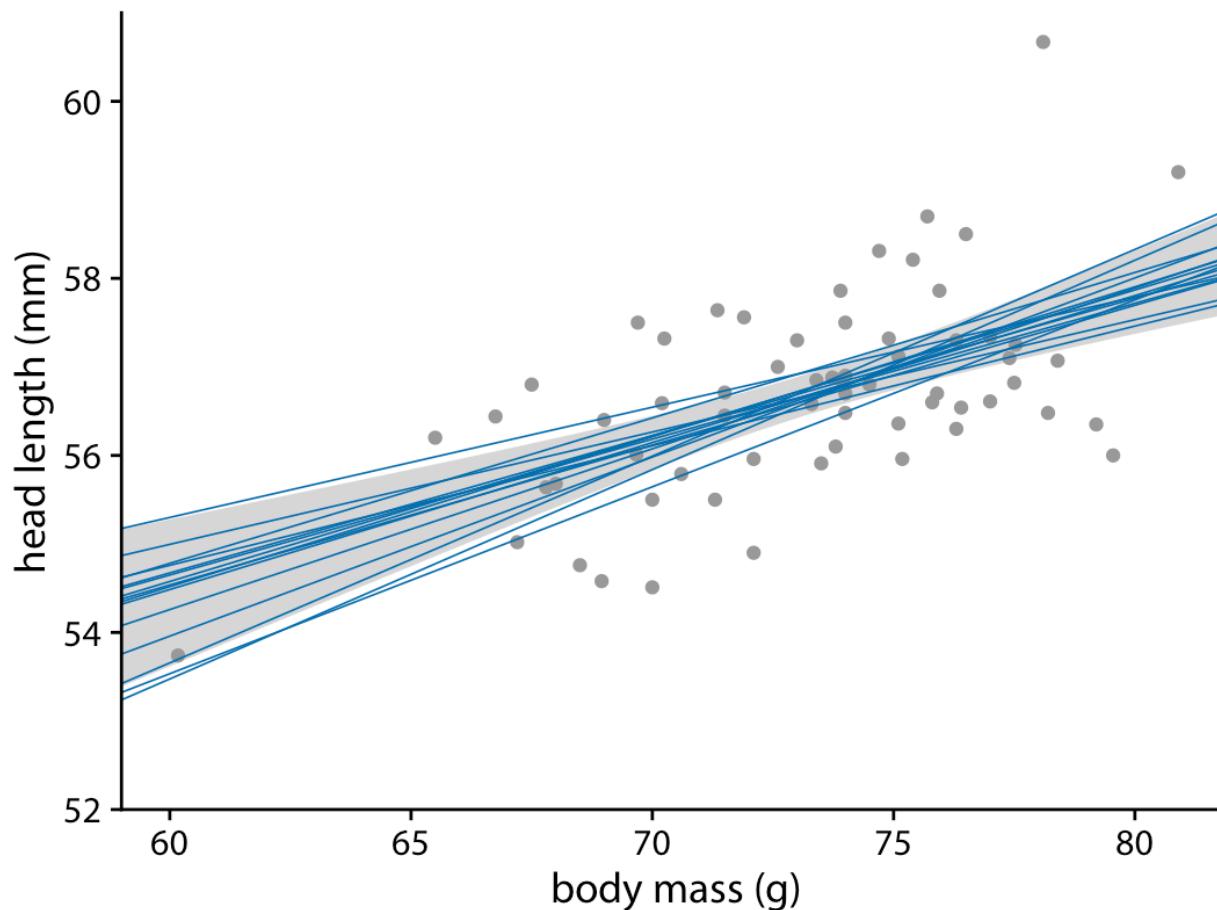
Hypothetical Outcome Plots

- Rather than showing a complete distribution or point estimate and error bars, Hypothetical Outcome Plots (HOPs) visualize a set of **draws** from a distribution
 - each draw is shown as a new plot in either a small multiples or animated form.



Simulations to convey uncertainty

Simulating fits from the data (e.g., bootstrap, Bayesian estimation) shows the variability. Doesn't rely on classical, normal theory.

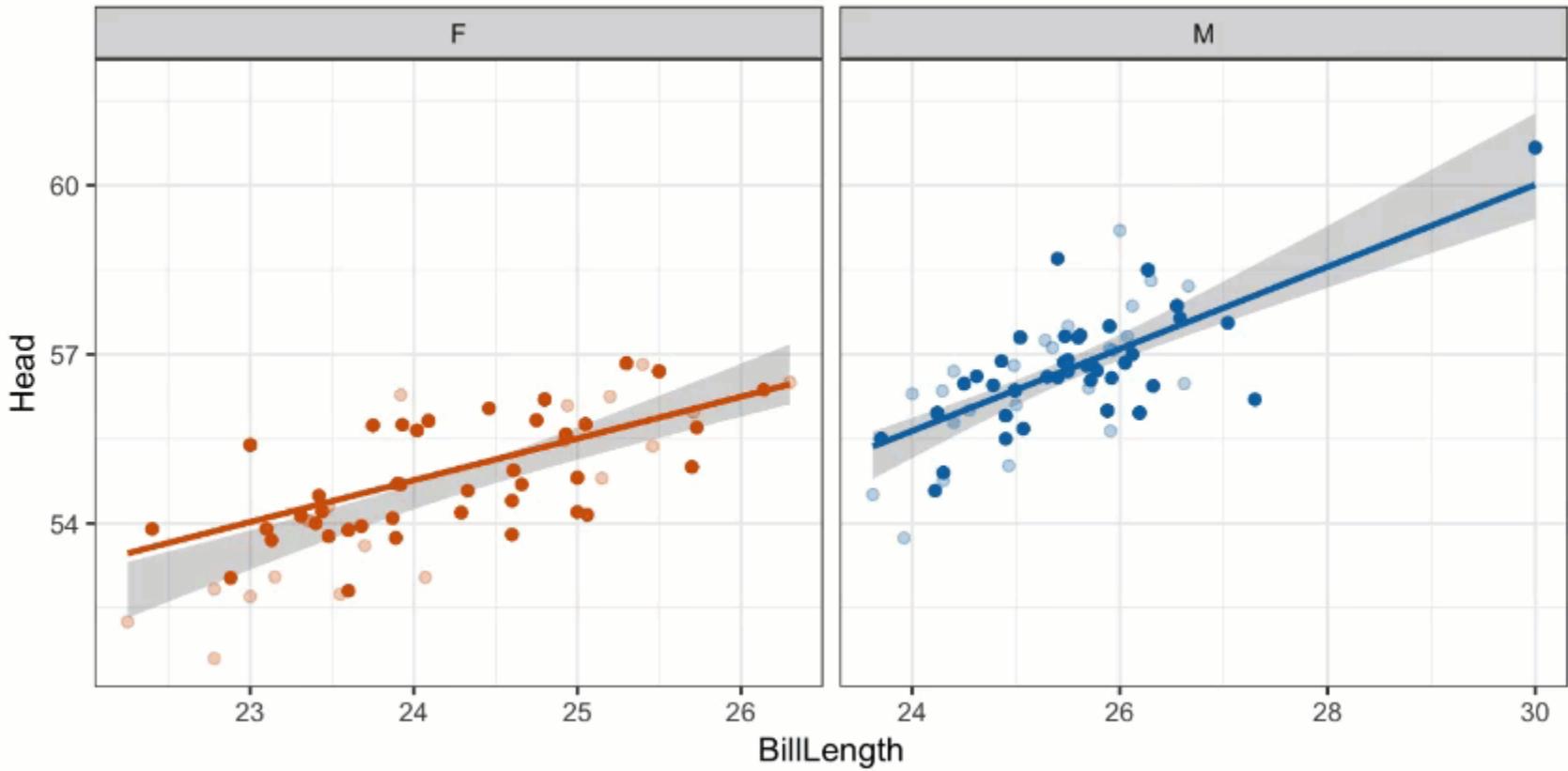


Animation to understand uncertainty

All assessments of uncertainty rely on a comparison: data vs. what could have been

- Sampling distributions, simulations, Bayesian posterior distributions, ...

Sometimes useful to appreciate the variability with animated graphics

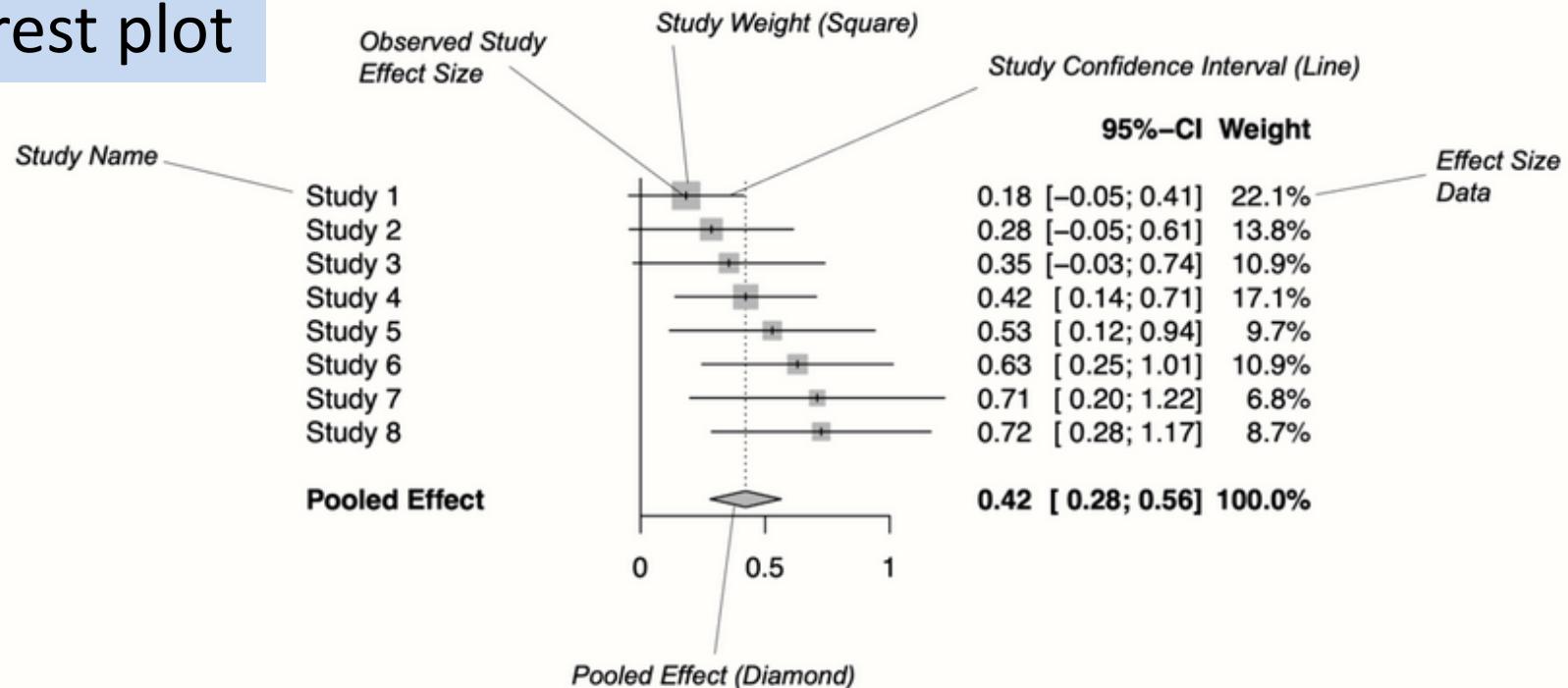


Replication uncertainty: Meta analysis

In meta analysis, we have multiple studies reporting the same effect.

- How to visualize/compare effect sizes?
- How to calculate a **pooled**, overall effect?
- How to assess **heterogeneity** of effects?

Forrest plot



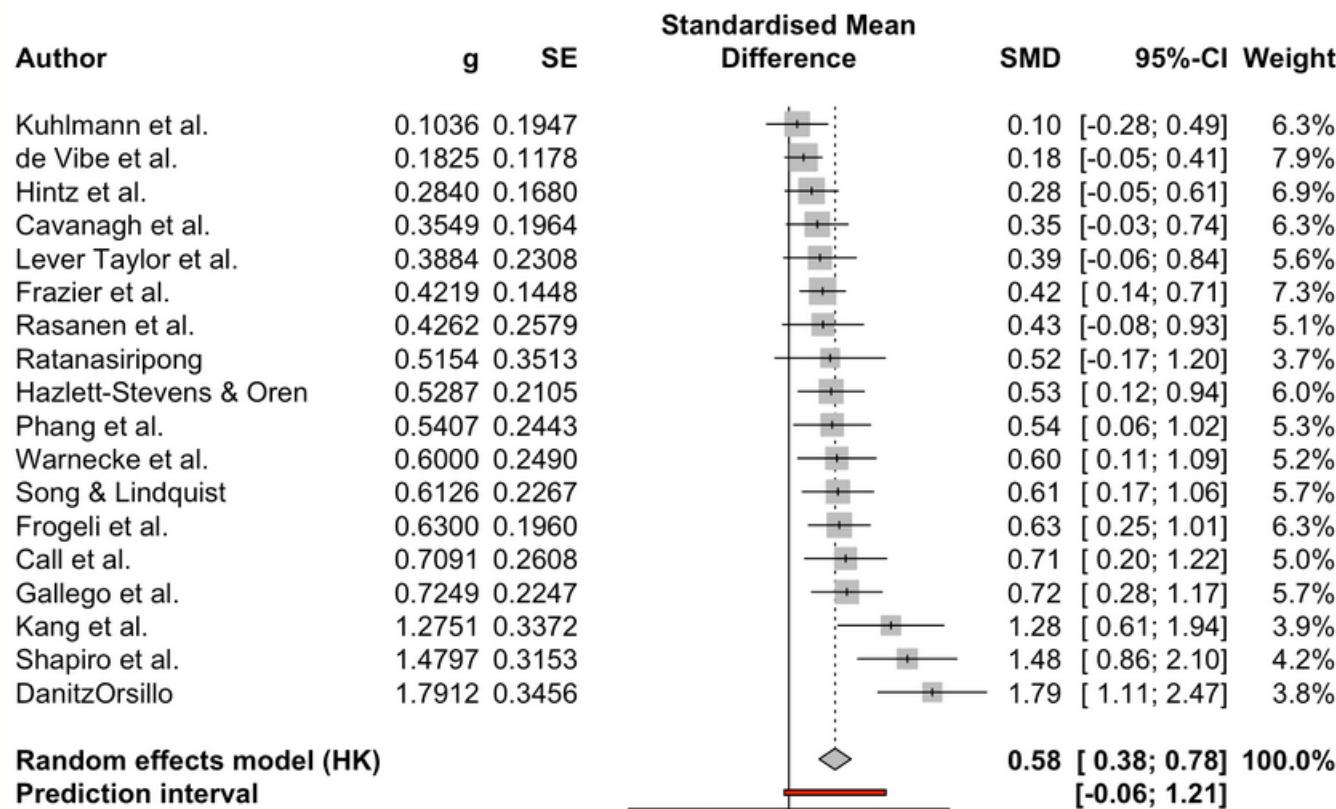
Forrest plots

Effect size: std. measure of size of effect (g)

Study weight: $\sim 1 / \text{SE}^2$

Pooled effect: weighted average of effect sizes

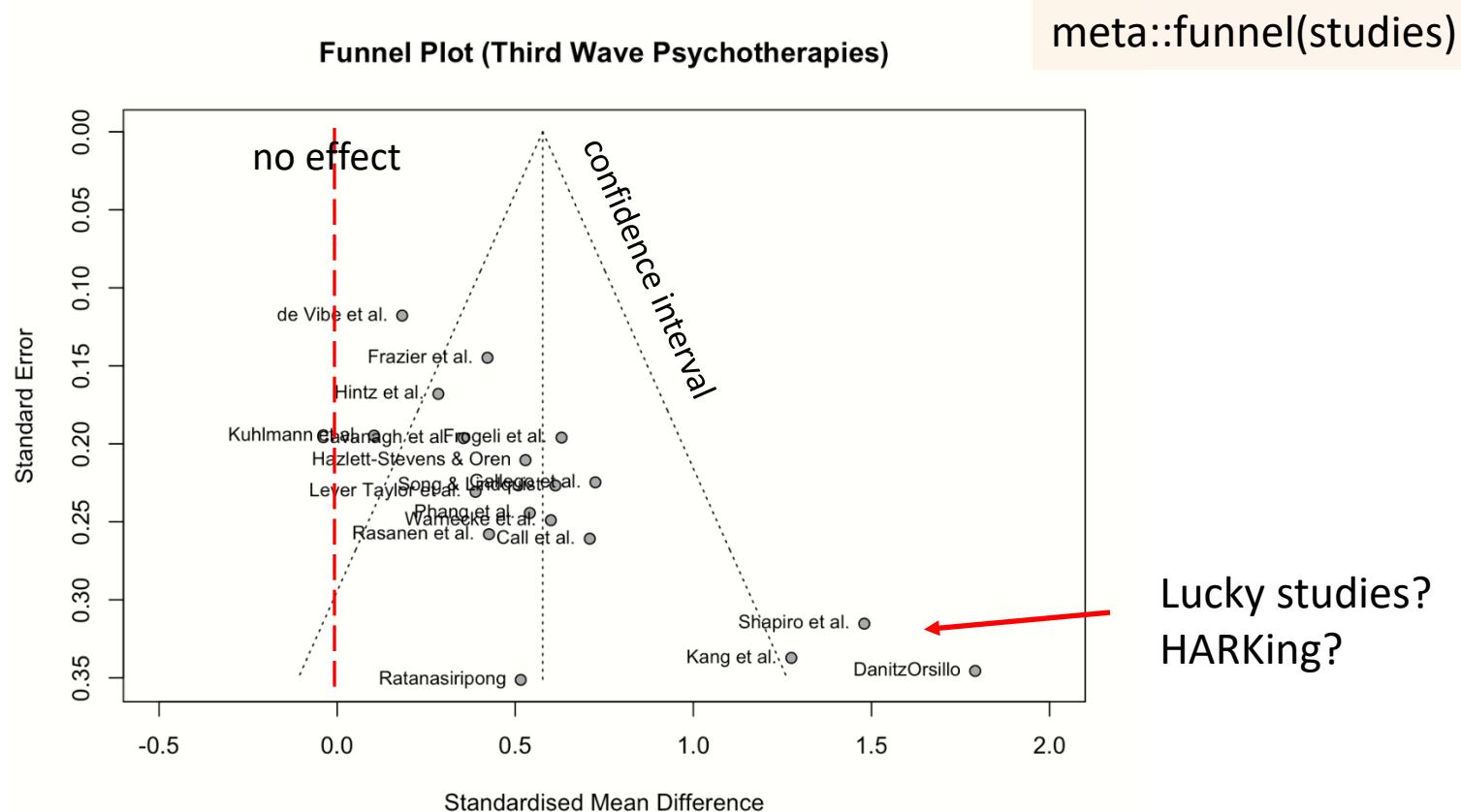
meta::forrest()



Heterogeneity: $I^2 = 63\%, p < 0.01$

Publication bias: Funnel plots

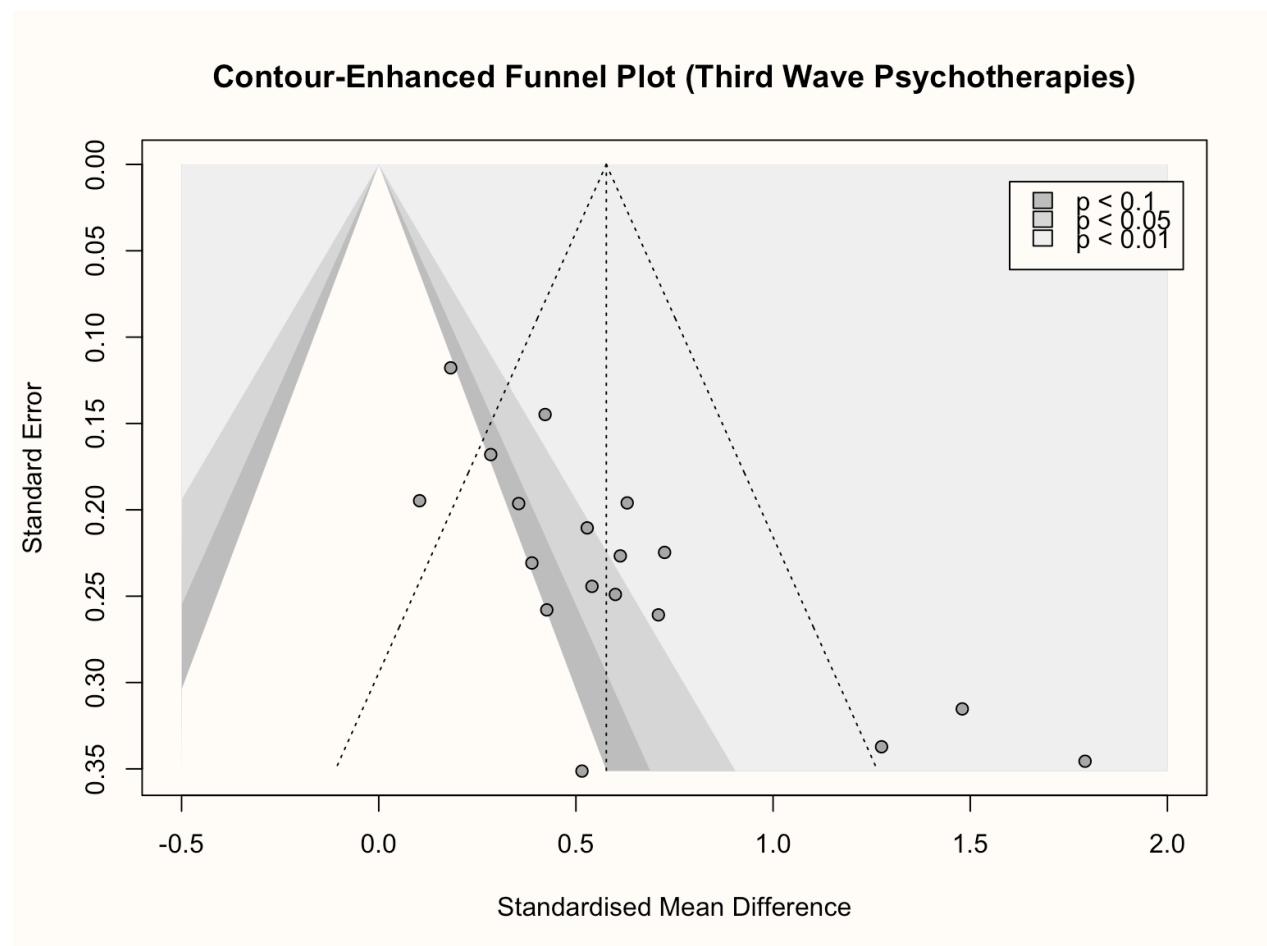
Publication bias: NS studies less likely to be published → effect overestimated
Funnel plot: Plot std. error vs. observed effect size
Should be symmetric when no publication bias



Contour-enhanced funnel plots

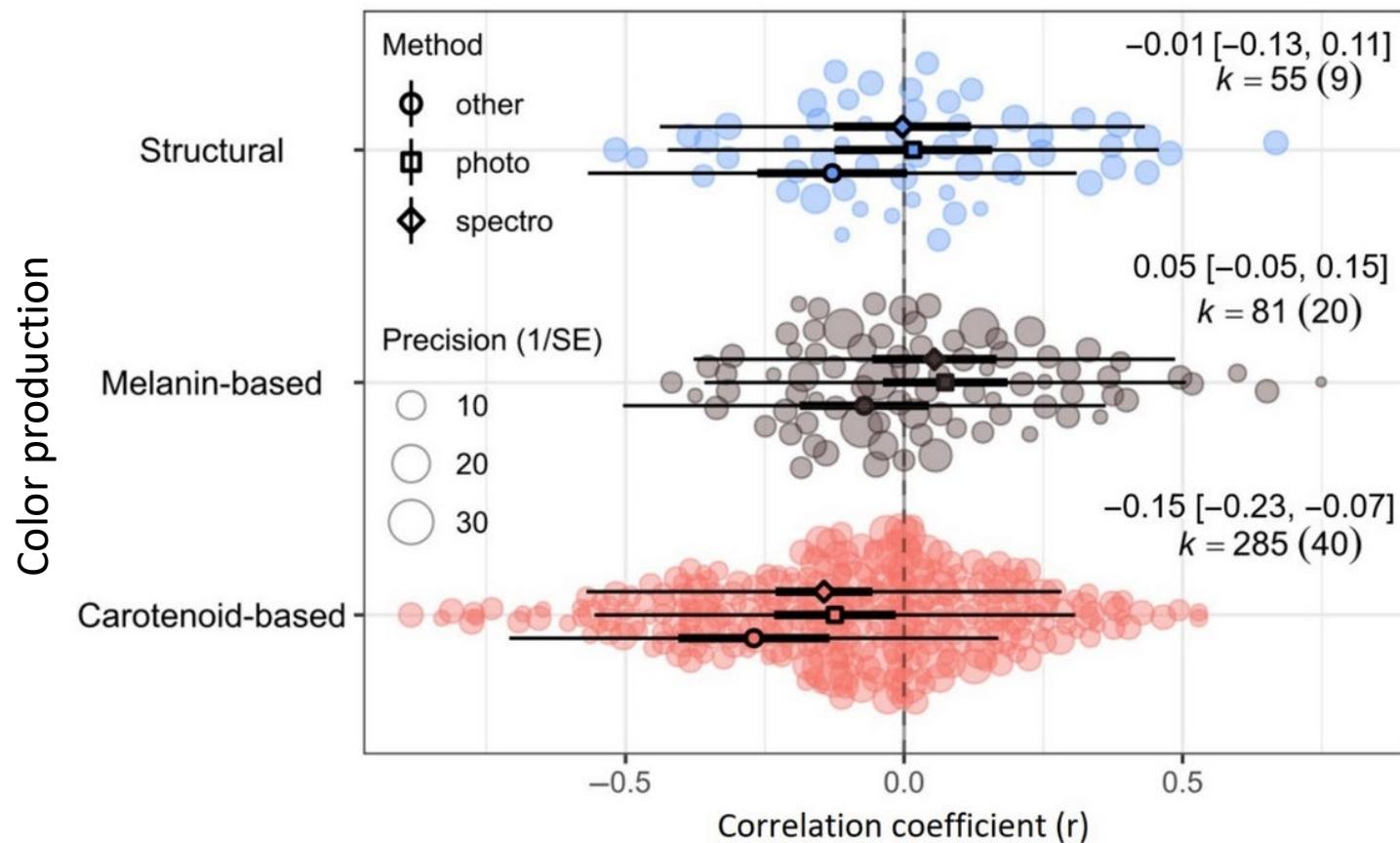
Funnel plots can be enhanced by showing contours of p-values

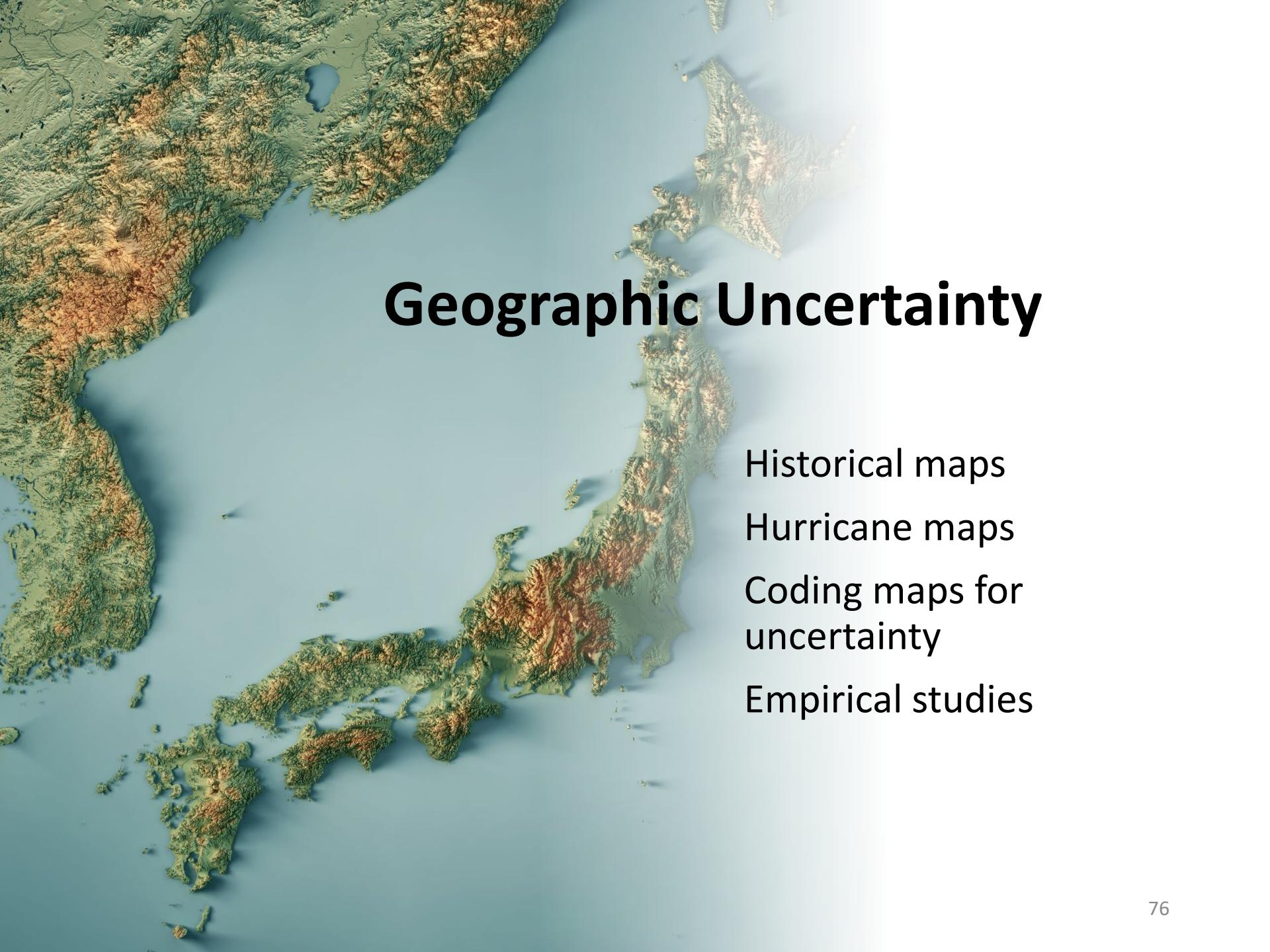
```
meta::funnel(studies, contour = c(0.9, 0.95, 0.99))
```



Orchard plots

Plot for interaction (moderator) effects between mechanism of colour production and pollutant type





Geographic Uncertainty

- Historical maps
- Hurricane maps
- Coding maps for uncertainty
- Empirical studies

Uncertainty in historical maps

Abraham Ortelius, *Theatrum Orbis Terrarum*, 1570

Monsters and other imagined creatures used to mark or mask unexplored areas



Here Be
Dragons!

Uncertainty in historical maps

Abraham Ortelius, *Geographia Sacra*, 1603



Source of the Nile?

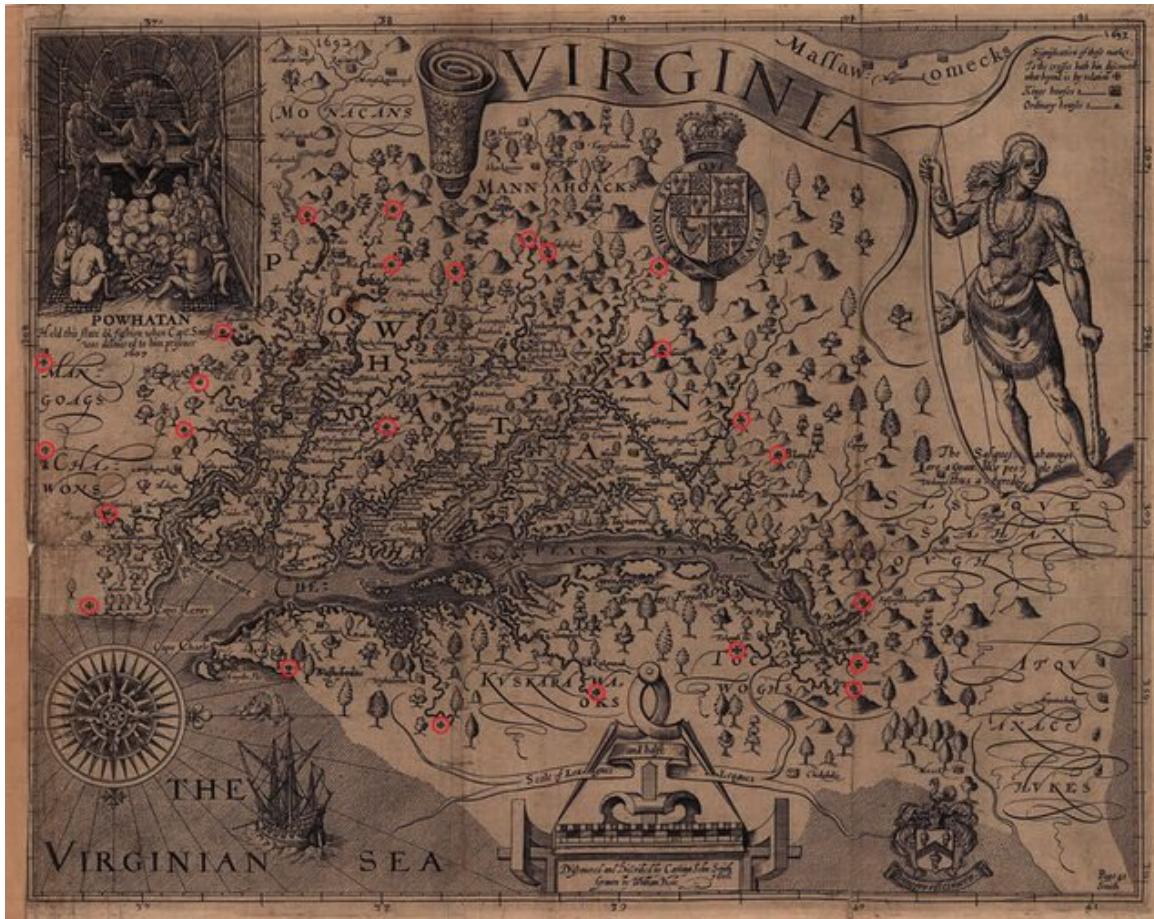
- Don't know!
- Hide in a cartouche

Location of Ophir
(mentioned in Bible)

- text describes 4 possible locations

Uncertainty in historical maps

John Smith's map, *Virginia*, 1612

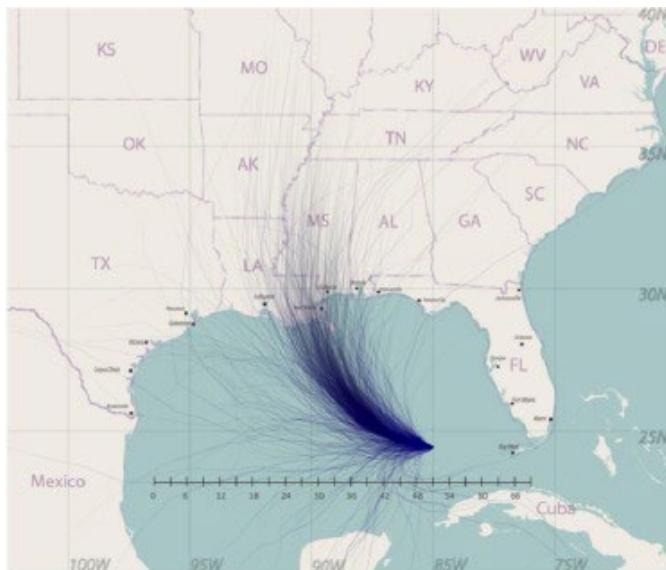


Uses ● markers to distinguish places he has visited, vs. those he just heard about

Geographic uncertainty

Predicting the path of hurricanes:

- Given what we can measure today (location, wind speed, direction, ...) where is **this** hurricane likely to be in 1 day, 3 days, 5 days?
- Most forecasts are based on an **ensemble of predictions**, representing the uncertainty in initial conditions, model physics, ...
- Often this is represented as a “cone of uncertainty”



(a) Storm path ensemble

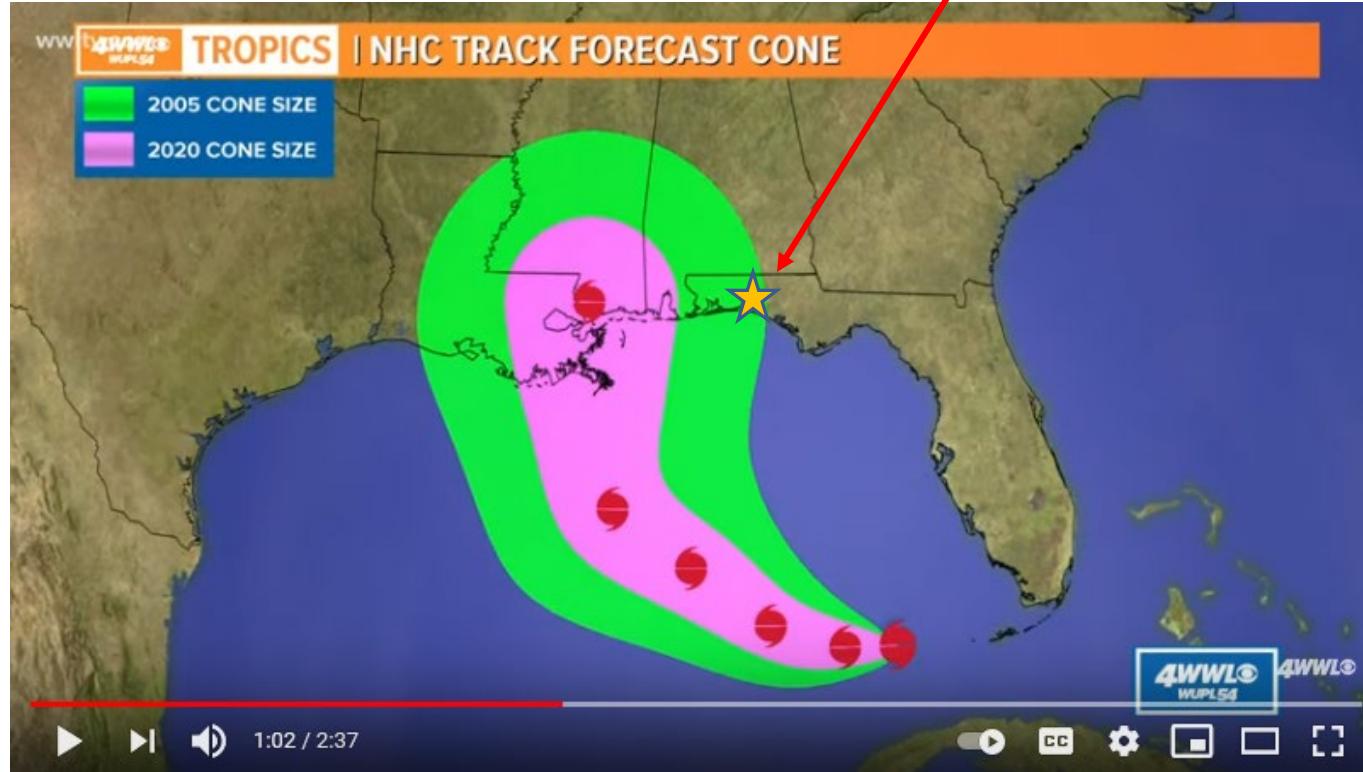


(b) Uncertainty cone.

What is the Cone of Uncertainty?

As seen on TV:

- The center is meant to track the average prediction, either over models or history
- The cone size generally represents some “2/3 confidence interval”
- Does this mean I am safe if I lived in Tallahassee FL in 2005? 2020?

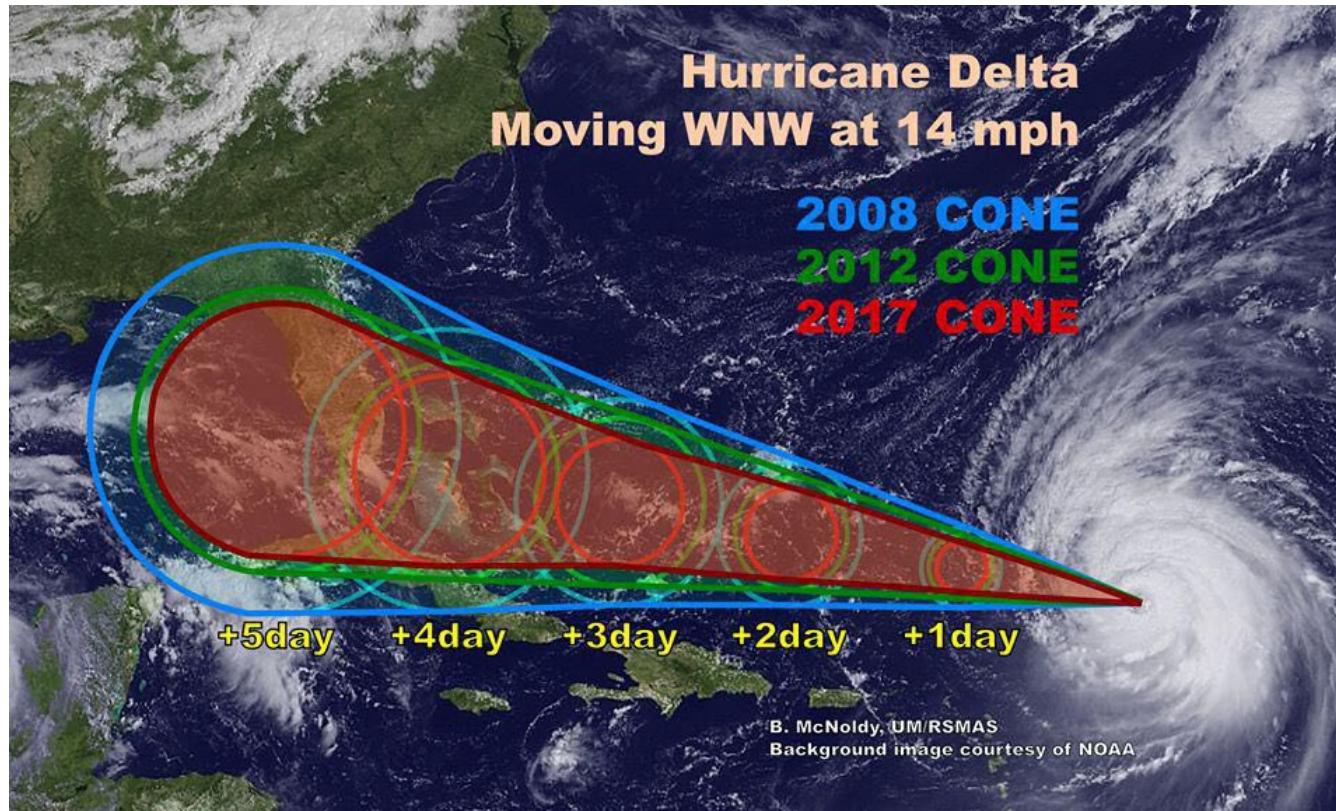


From: <https://www.youtube.com/watch?v=nE6XaHtpm04>

The Incredible Shrinking Cone

Changes in presumed accuracy are often shown as below

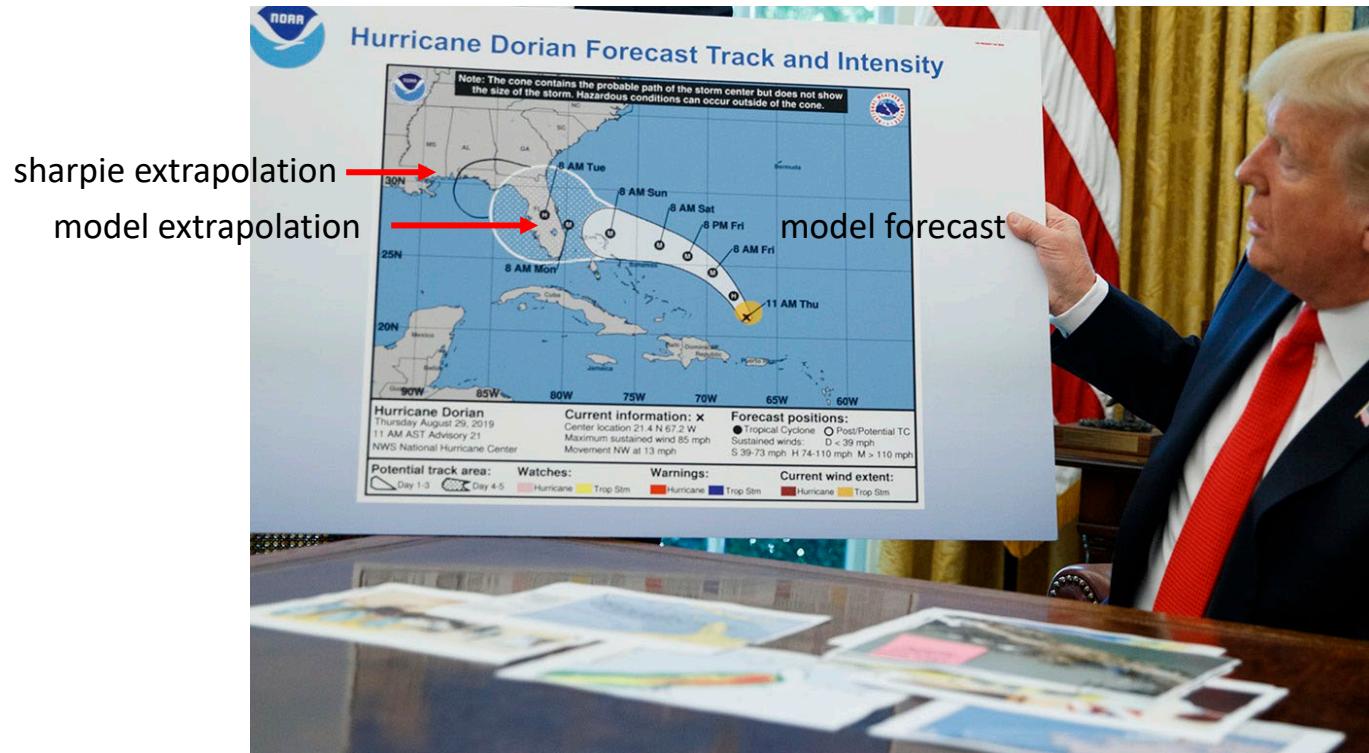
- The cone represents the probable track of the center of a tropical cyclone, formed by enclosing the area swept out by a set of circles along the forecast track (at 12, 24, 36 hours, etc).
- The size of each circle is set so that two-thirds of historical official forecast errors over a 5-year sample fall within the circle.



Sharpiegate

In Sept. 2019, Donald Trump went live with “extrapolated” predictions of the path of Hurricane Dorian.

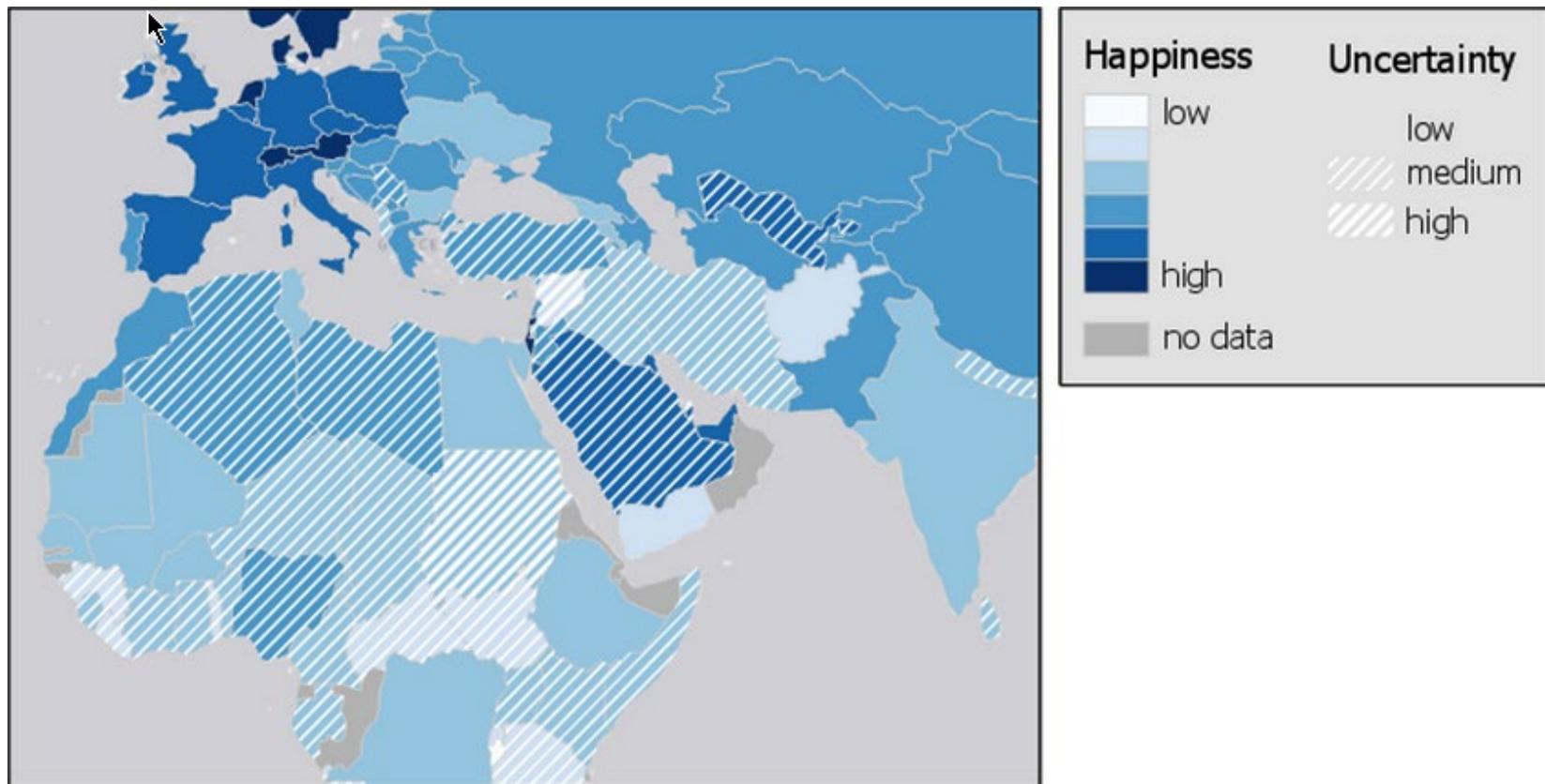
- He had earlier predicted it would hit Alabama & Georgia.
- Let it be said, let it be written (with a sharpie)



From: <https://www.theguardian.com/us-news/2019/sep/05/trump-hurricane-dorian-alabama-map-sharpiegate>

Coding maps for uncertainty

In choropleth maps we can show uncertainty with another visual attribute



From: <https://www.e-education.psu.edu/geog486/node/693>

Studies

Cheong et al. (2016)

- Participants presented with a house location ("X")
- Asked if they would stay or leave based on one of the wildfire hazard communication techniques shown here

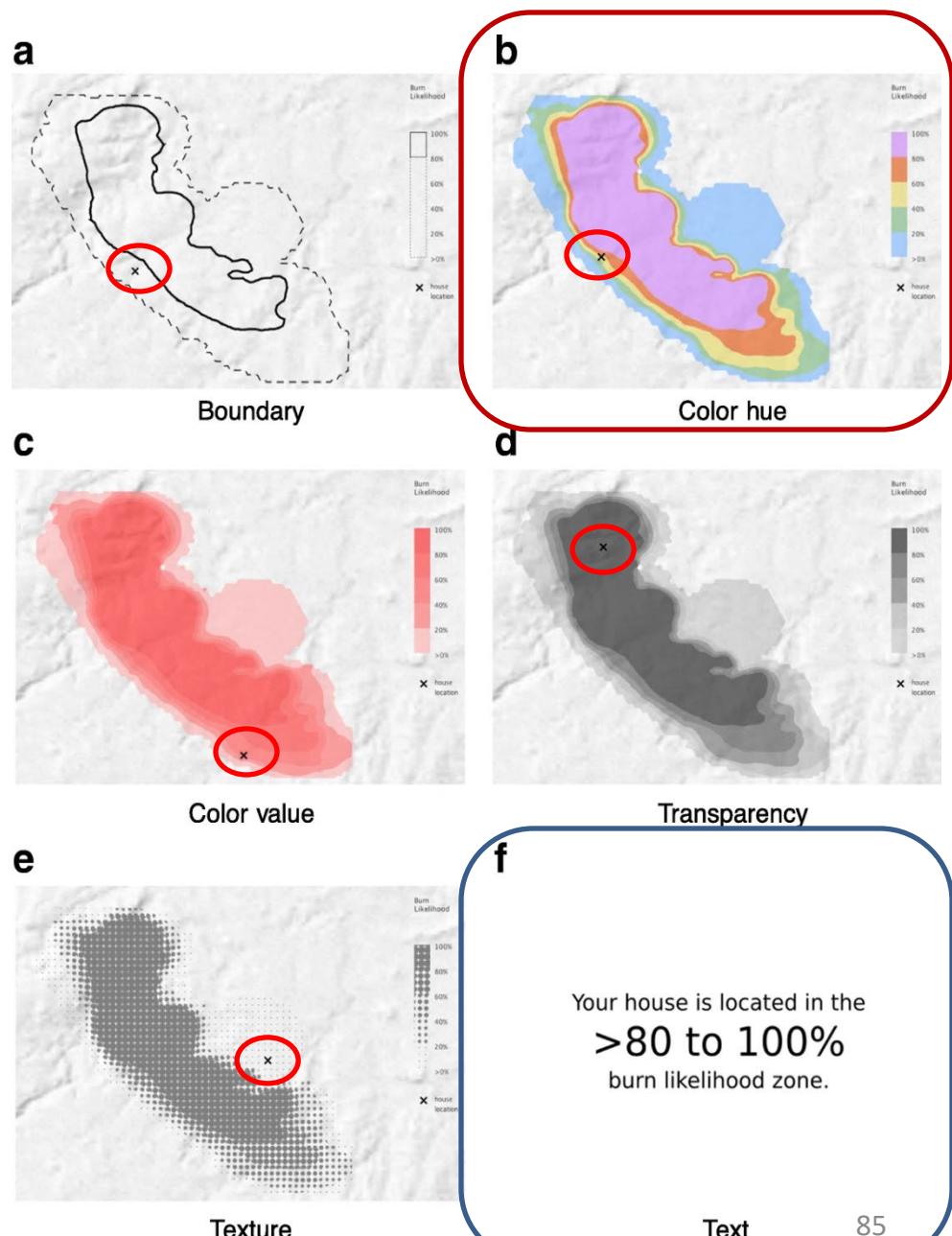
Results:

Display type mattered little when given 30 sec. to decide

With time pressure (5 sec.):

- color hue was best
- Text & simple boundary worst

Cheong, et al. (2016). Evaluating the impact of visualization of wildfire hazard upon decision making under uncertainty. *International Journal of Geographical Information Science*, 30(7), 1377–1404.



Summary

- Uncertainty is fundamental to data analysis & models
- Showing variation in distributions a basic problem
 - histograms, density plots, boxplots
 - Better: violin, raincloud, ...
 - `{ggdist}` offers many alternatives
- Error bars: many flavors; can show **multiple** intervals
- Bayesian methods, bootstrap, simulation
 - Different methods, but similar ways to show uncertainty
- Geographic data: need to be careful about interpretations