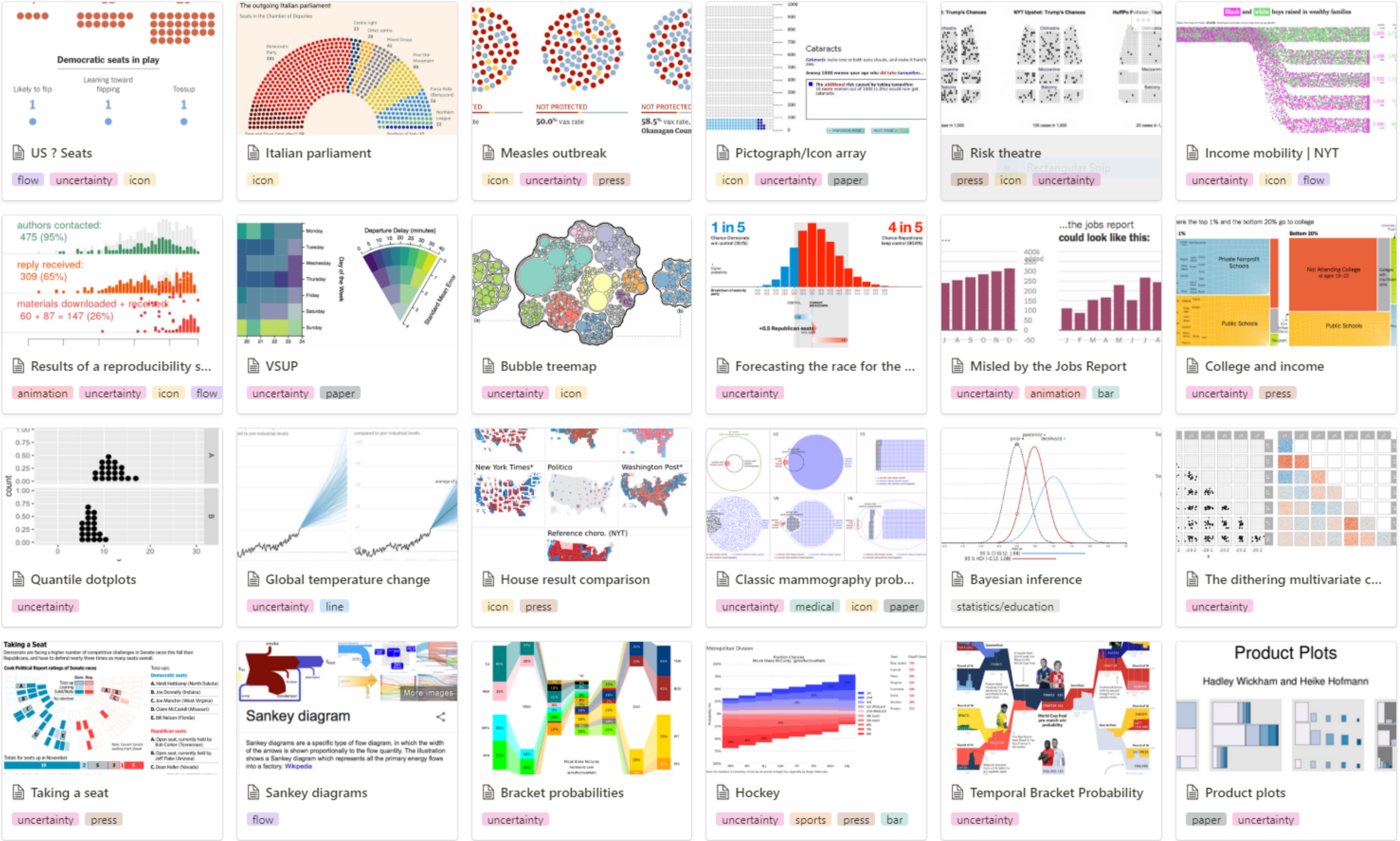
A biased tour of the uncertainty visualization zoo

Matthew Kay
Assistant Professor
School of Information
University of Michigan



[courtesy Xiaoying Pu, Puhe Liang]

What happens when we ignore uncertainty?

A mixed-design ANOVA with sex of face (male, female) as a within-subjects factor and self-rated attractiveness (low, average, high) and oral contraceptive use (true, false) as between-subjects factors revealed a main effect of sex of face, $F(1, 1276) = 1372$, $p < .001$, $\eta_p^2 = .52$. This was qualified by interactions between sex of face and SRA, $F(2, 1276) = 6.90$, $p = .001$, $\eta_p^2 = .011$, and between sex of face and oral contraceptive use, $F(1, 1276) = 5.02$, $p = .025$, $\eta_p^2 = .004$. The predicted interaction among sex of face, SRA and oral contraceptive use was not significant, $F(2, 1276) = 0.06$, $p = .94$, $\eta_p^2 < .001$. All other main effects and interactions were non-significant and irrelevant to our hypotheses, all $F \leq 0.94$, $p \geq .39$, $\eta_p^2 \leq .001$.

A mixed-design ANOVA with sex of face (male, female) as a within-subjects factor and self-rated attractiveness (low, average, high) and oral contraceptive use (true, false) as between-subjects factors revealed a main effect of sex of face, $F(1, 1276) = 1372$, $p < .001$, $\eta_p^2 = .52$. This was qualified by interactions between sex of face and SRA, $F(2, 1276) = 6.90$, $p = .001$, $\eta_p^2 = .011$, and between sex of face and oral contraceptive use, $F(1, 1276) = 5.02$, $p = .025$, $\eta_p^2 =$ [illegible]. The predicted interaction among sex of face, SRA and oral contraceptive use was not significant, $F(2, 1276) = 0.06$, $p = .94$, $\eta_p^2 < .001$. All other main effects and interactions were not significant and irrelevant to our hypotheses, all $F \leq$ [illegible], $p \geq .39$, $\eta_p^2 \leq .001$.

Alternatives…

Table 7
Stevens et al. 2006, table 2: 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	−.27 (.07)**
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

**$p < .01$, *$p < .05$, #$p < .10$ (twotailed)

[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 $p < .05$;

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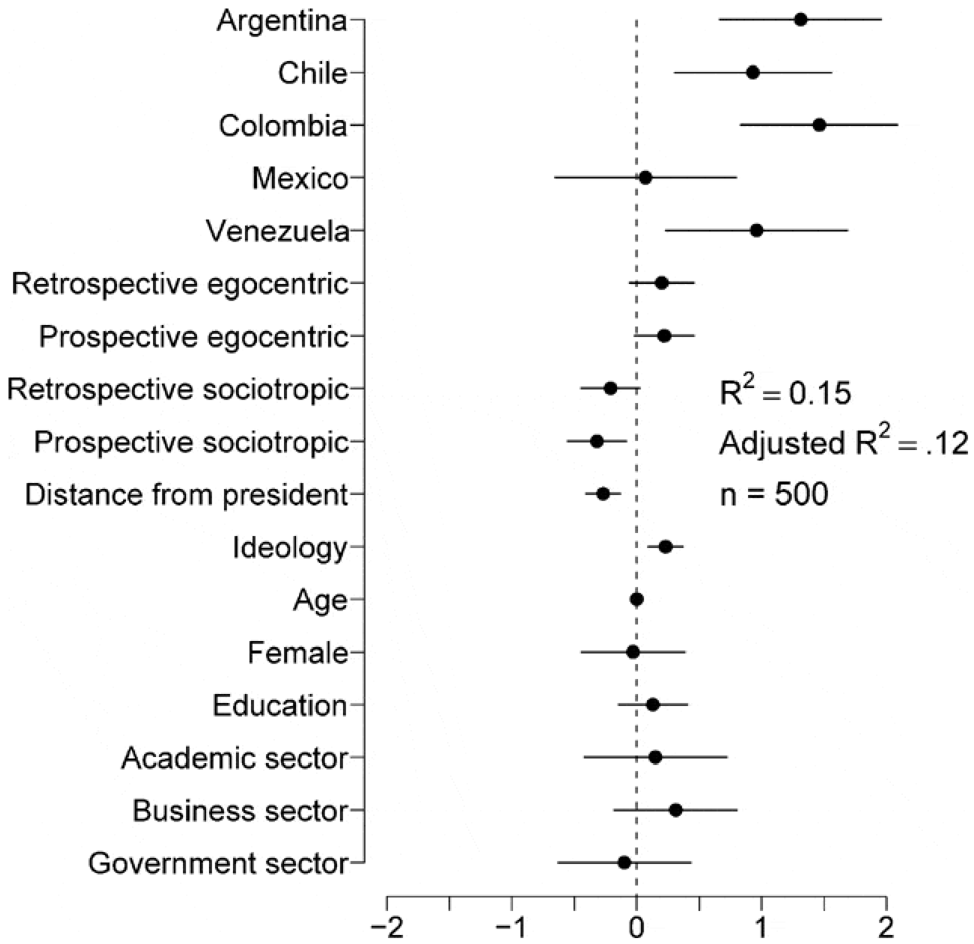

[Jonathan P Kastellec and Eduardo L Leoni. 2007. Using Graphs Instead of Tables in Political Science. Perspectives on politics 5, 4: 755–771]

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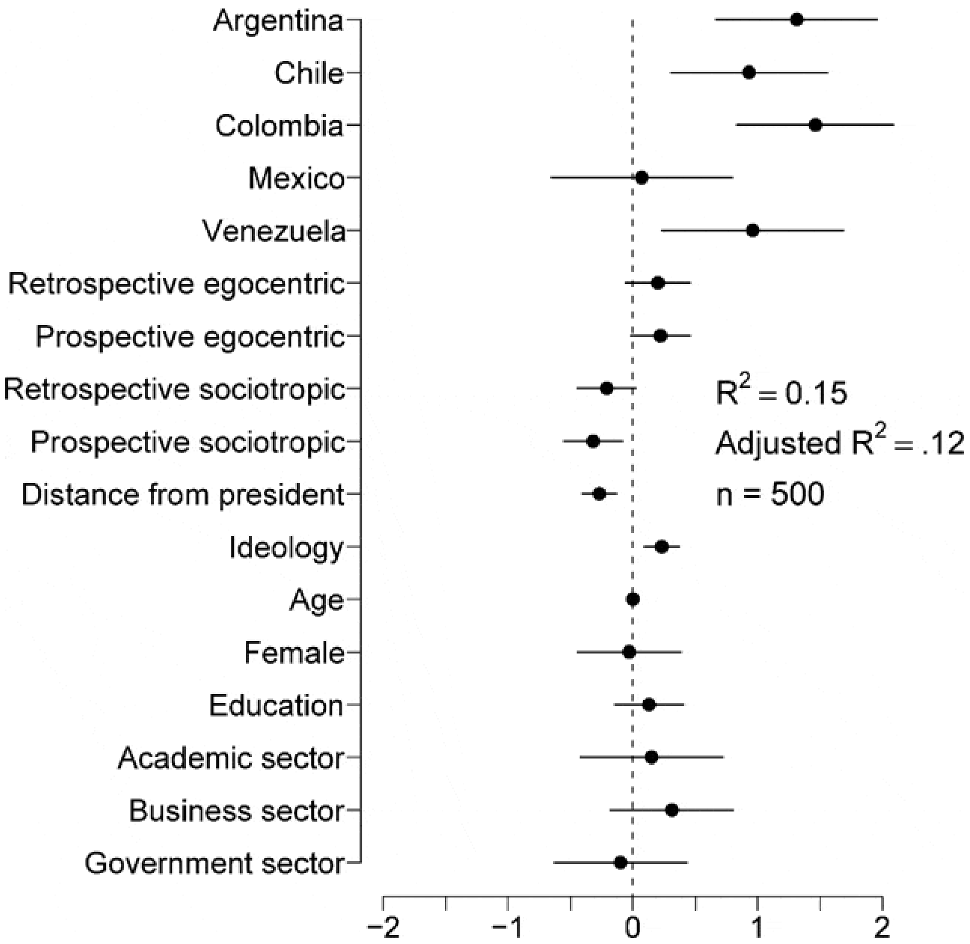
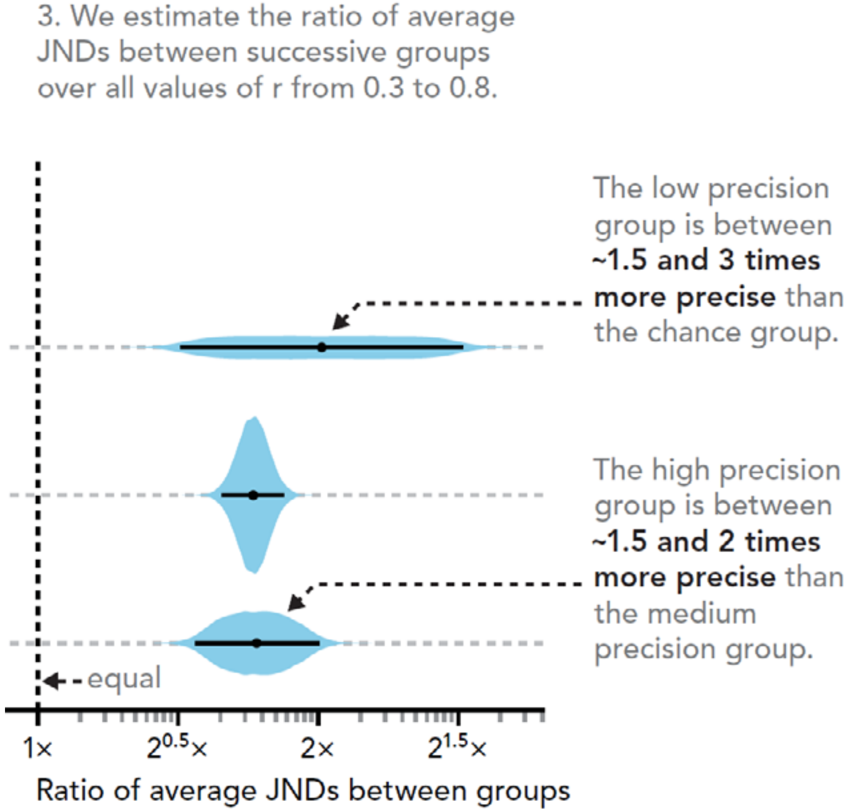
Adjusted R^2	.12
N	500

**p < .01, *p < .05, #p < .10 (twotailed)
ACoefficient is significantly different from Argentina's at p < .05;
BCoefficient is significantly different from Brazil's at p < .05;
CHCoefficient is significantly different from Chile's at p < .05;
COCoefficient is significantly different from Colombia's at p < .05;
MCoefficient is significantly different from Mexico's at p < .05;
VCoefficient is significantly different from Venezuela's at p < .05.





[Jonathan P Kastellec and Eduardo L Leoni. 2007. Using Graphs Instead of Tables in Political Science. Perspectives on politics 5, 4: 755–771]

How easy is it to ignore the uncertainty?

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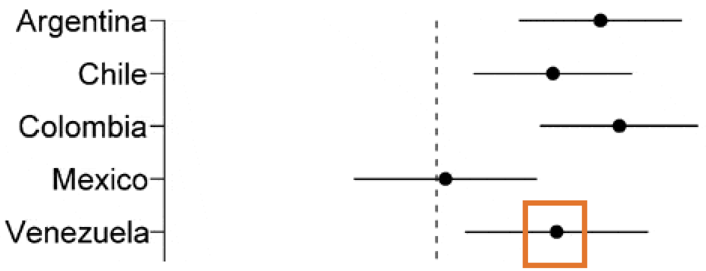

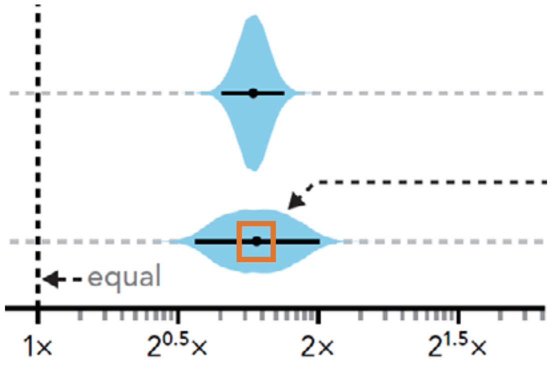

This contributes to dichotomania

Dichotomania...

Predictions from 2016 presidential election

[Justin H. Gross, Washington Post, http://wapo.st/2fCYvDW]

FiveThirtyEight	NYT Upshot	HuffPo Pollster
28%	15%	2%

Predictions from 2016 presidential election

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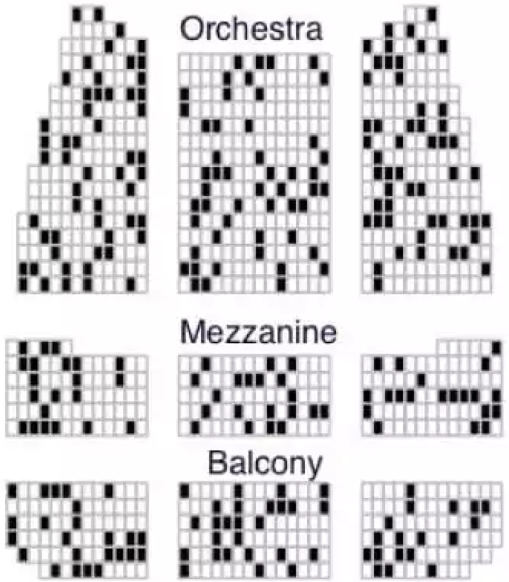
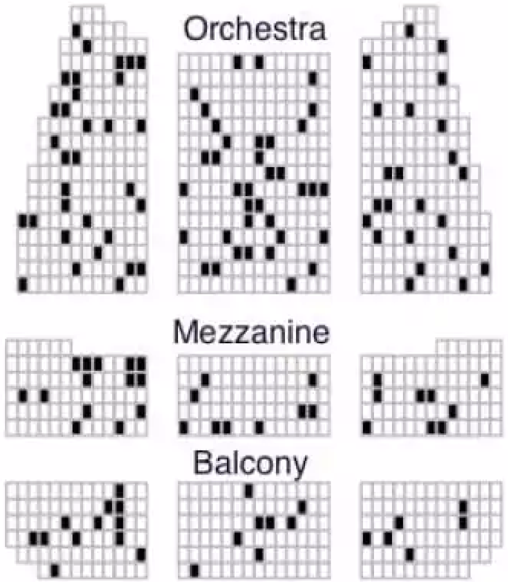
FiveThirtyEight



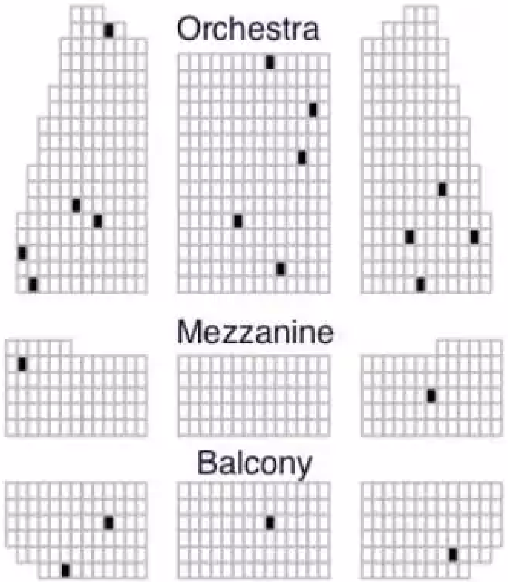
286 cases in 1,000

NYT Upshot



150 cases in 1,000

HuffPo Pollster



20 cases in 1,000

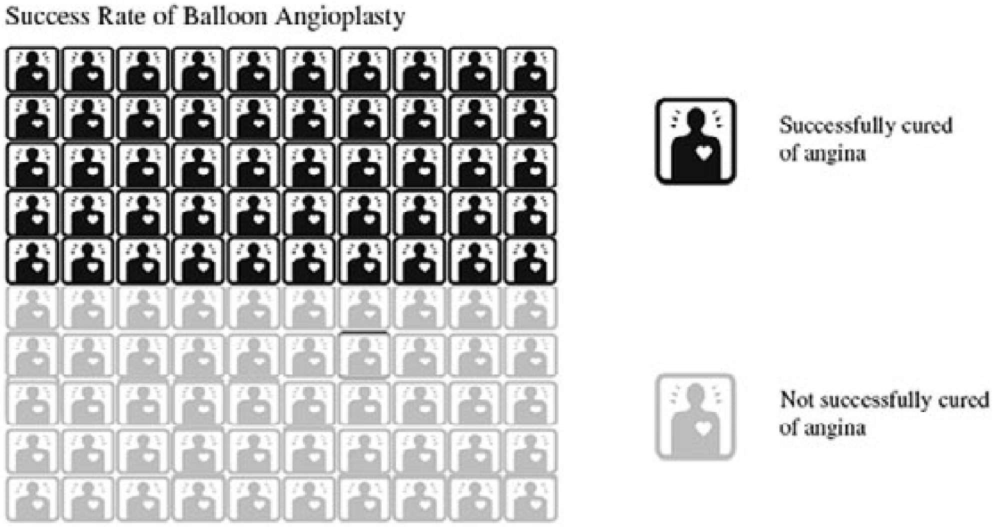
People are very good at ignoring uncertainty...

People are very good at ignoring uncertainty...

Especially when we provide bad uncertainty representations

Icon arrays in medical risk communication

[Figure from Fagerlin, Wang, Ubel. Reducing the influence of anecdotal reasoning on people's health care decisions: Is a picture worth a thousand statistics? Medical Decision Making 2005; 25:398–405]

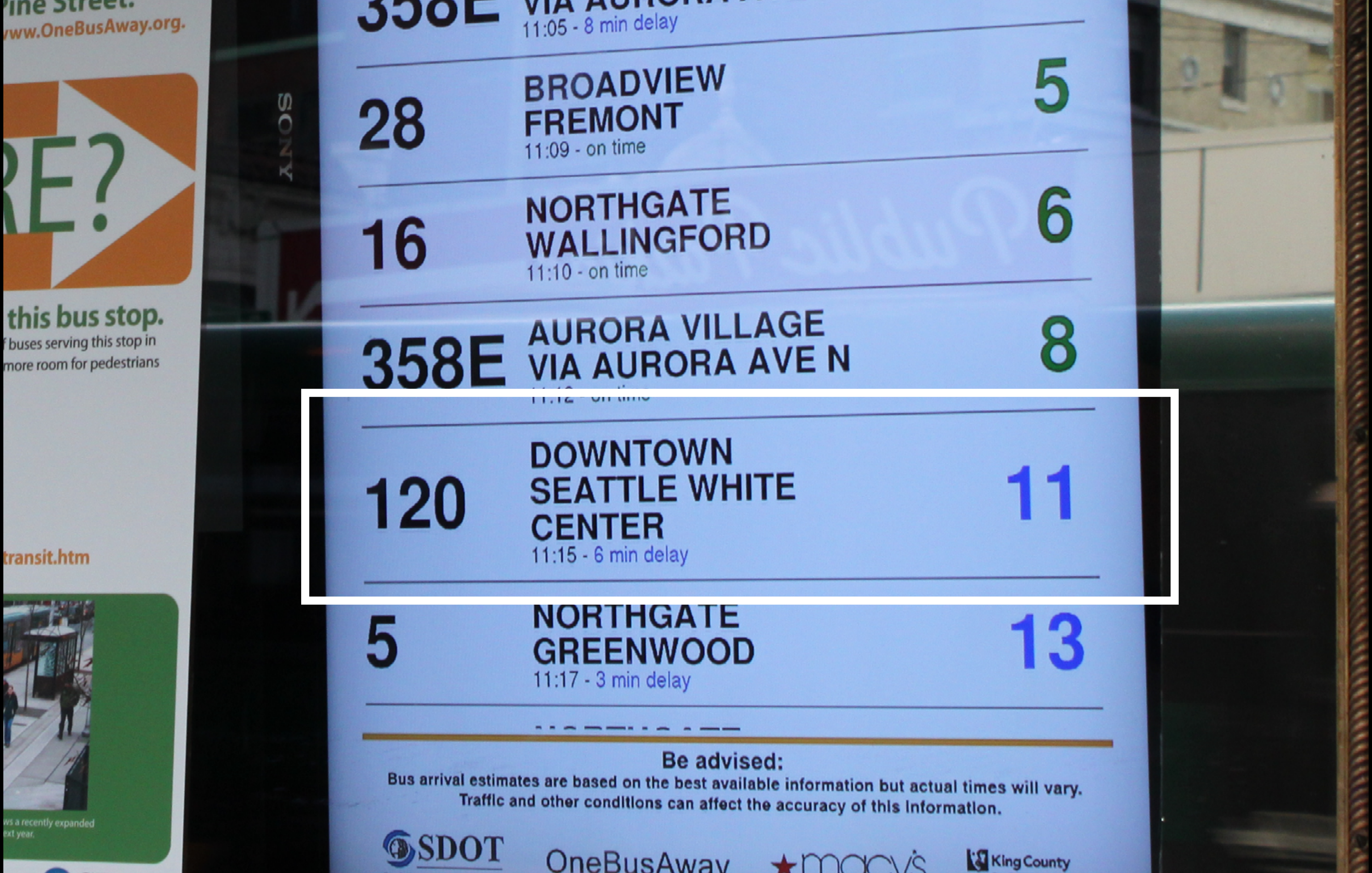


Frequency framing or discrete outcome visualization

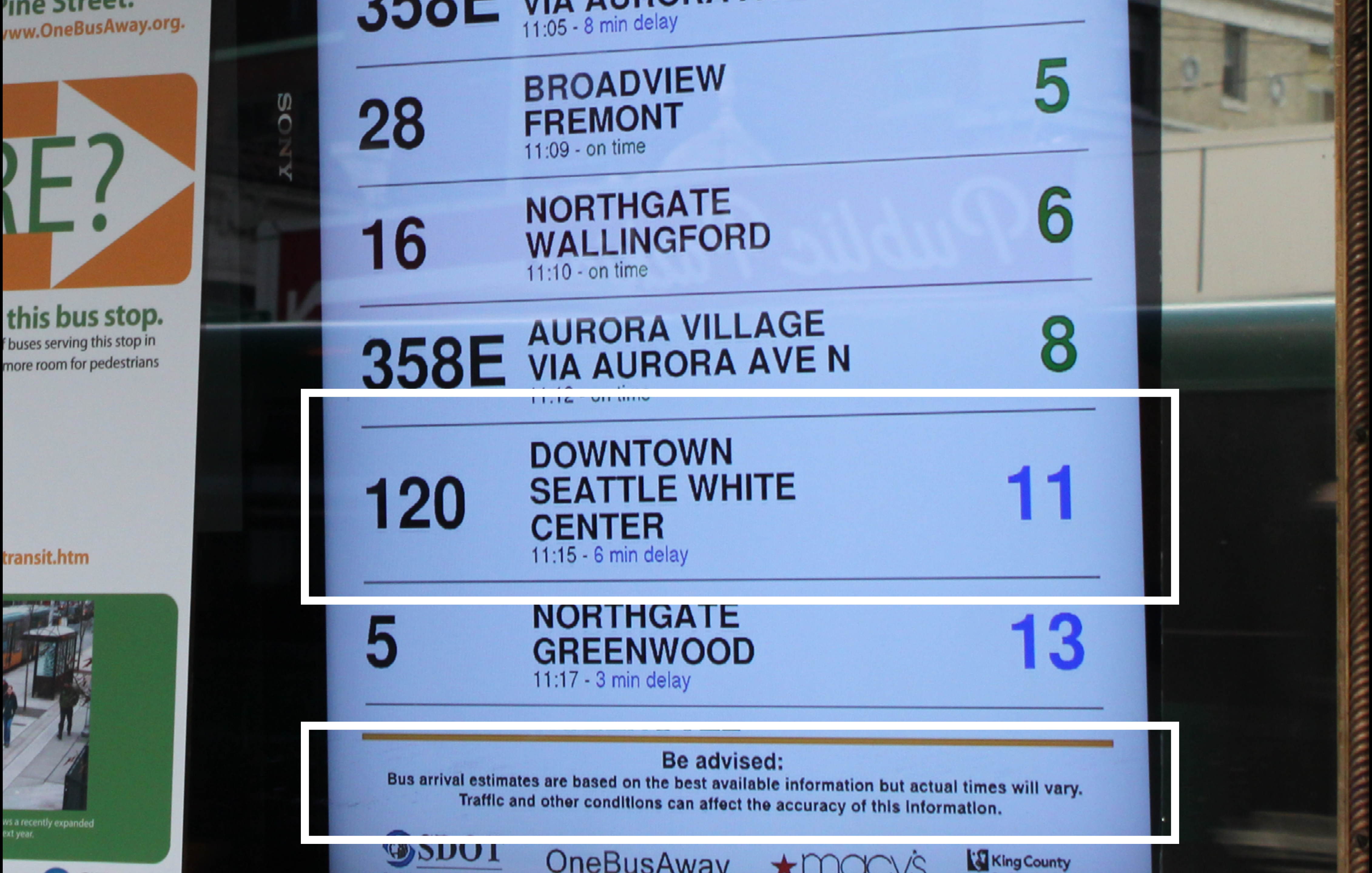
What is an icon array for a continuous distribution?

What is an icon array for a continuous distribution?

An example scenario...



www.OneBusAway.org.
RE?
this bus stop.
f buses serving this stop in
more room for pedestrians
transit.htm
ws a recently expanded
ext year.
SONY
11:05 - 8 min delay
28
BROADVIEW
FREMONT
11:09 - on time
5
16
NORTHGATE
WALLINGFORD
11:10 - on time
6
358E
AURORA VILLAGE
VIA AURORA AVE N
8
120
DOWNTOWN
SEATTLE WHITE
CENTER
11:15 - 6 min delay
11
5
NORTHGATE
GREENWOOD
11:17 - 3 min delay
13
Be advised:
Bus arrival estimates are based on the best available information but actual times will vary.
Traffic and other conditions can affect the accuracy of this information.
SDOT
OneBusAway
macy's
King County



Pine Street.
www.OneBusAway.org.
RE?
this bus stop.
f buses serving this stop in
more room for pedestrians
transit.htm
ws a recently expanded
ext year.
SONY
11:05 - 8 min delay
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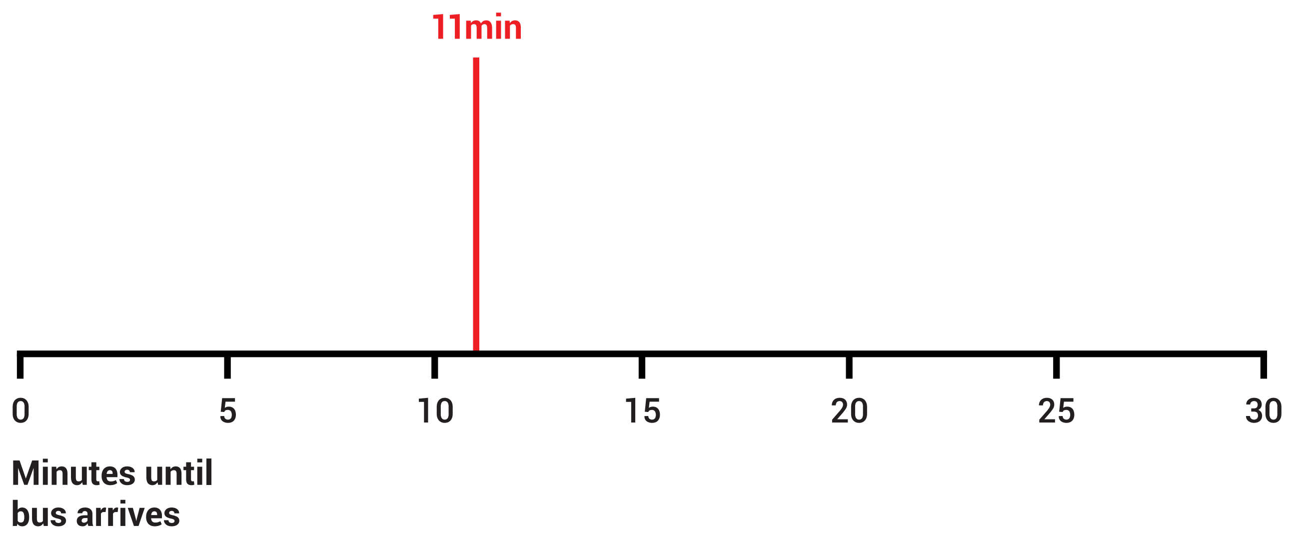
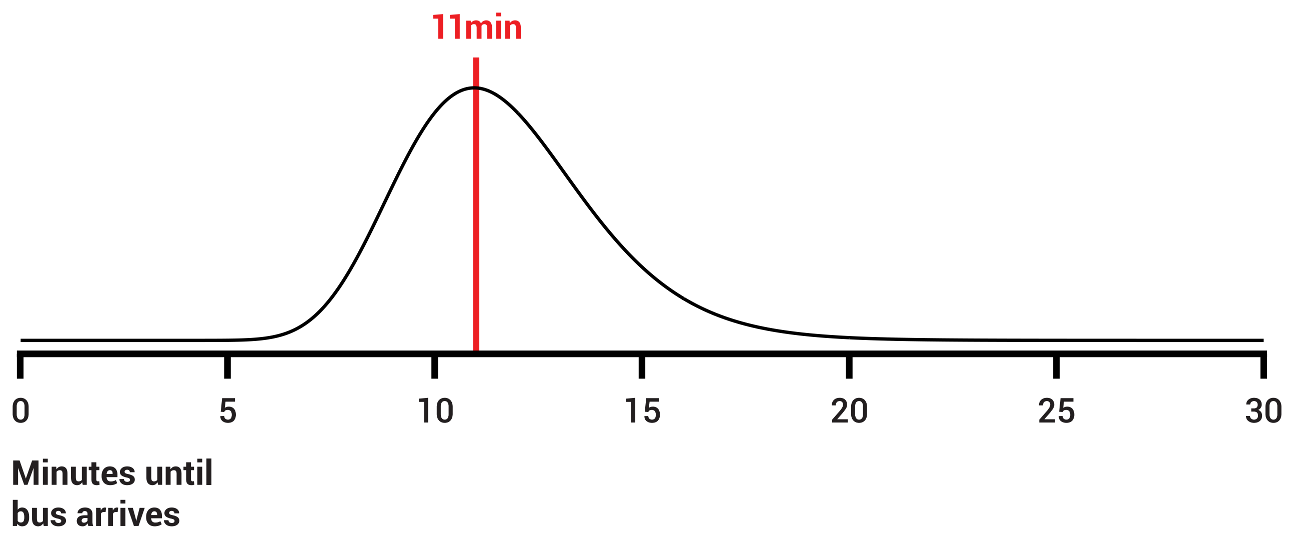
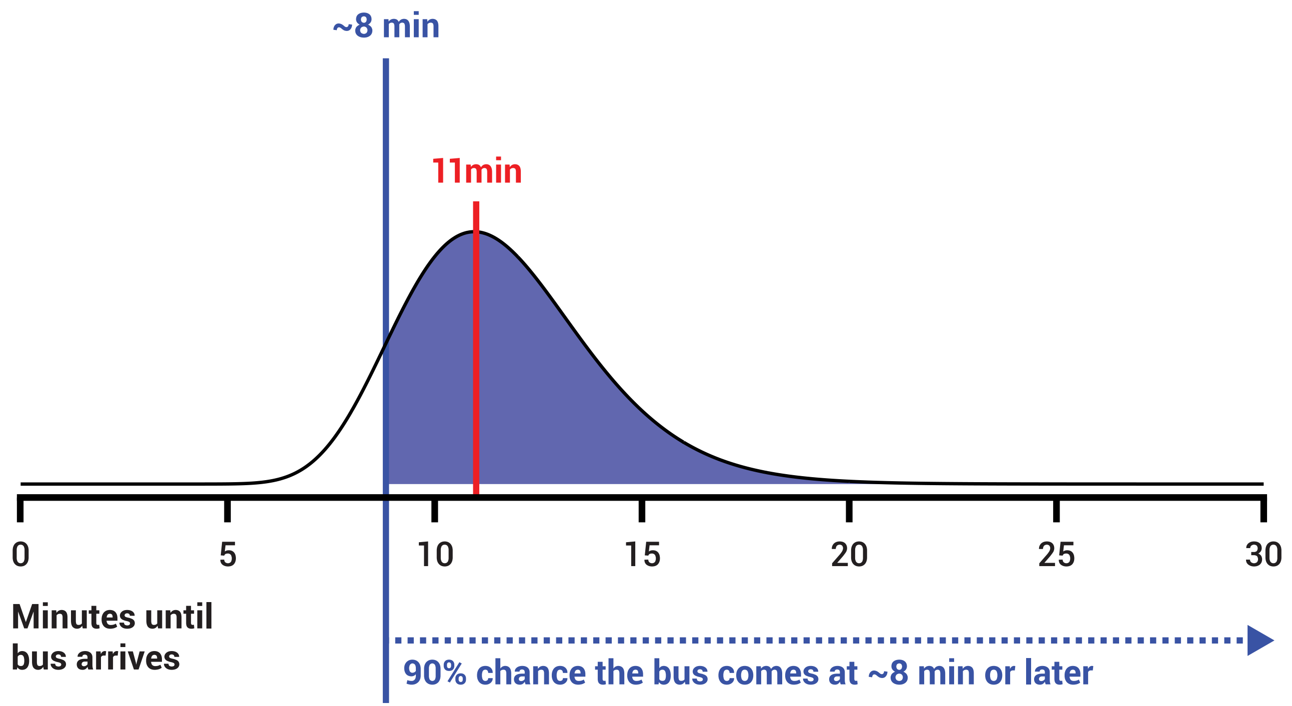
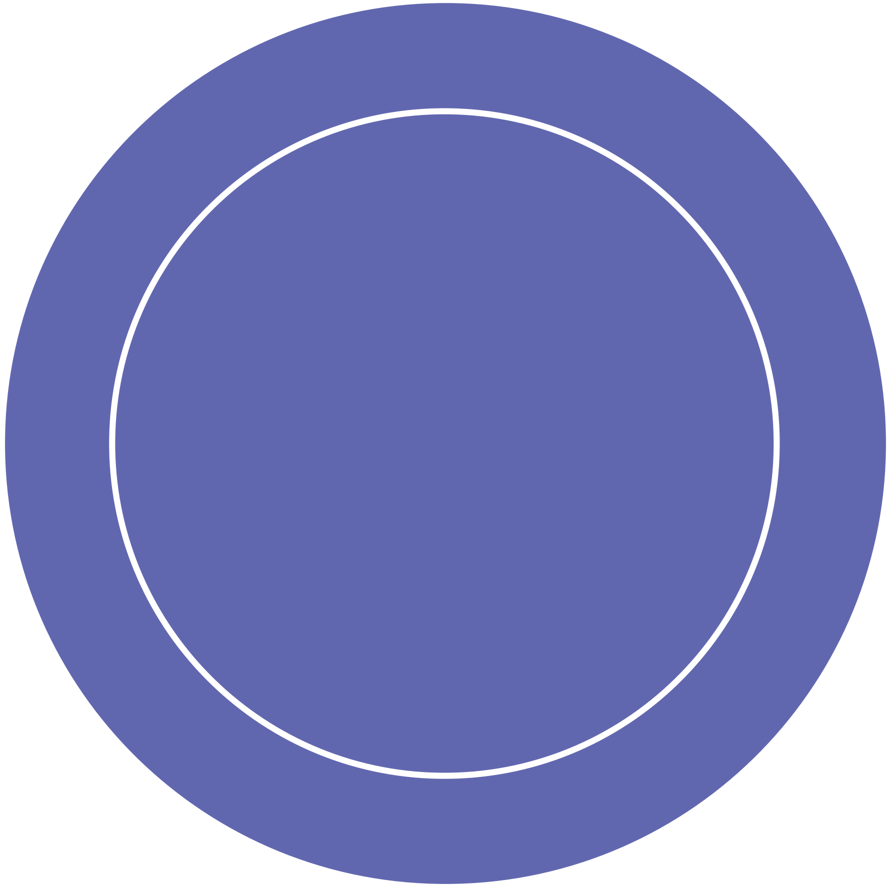
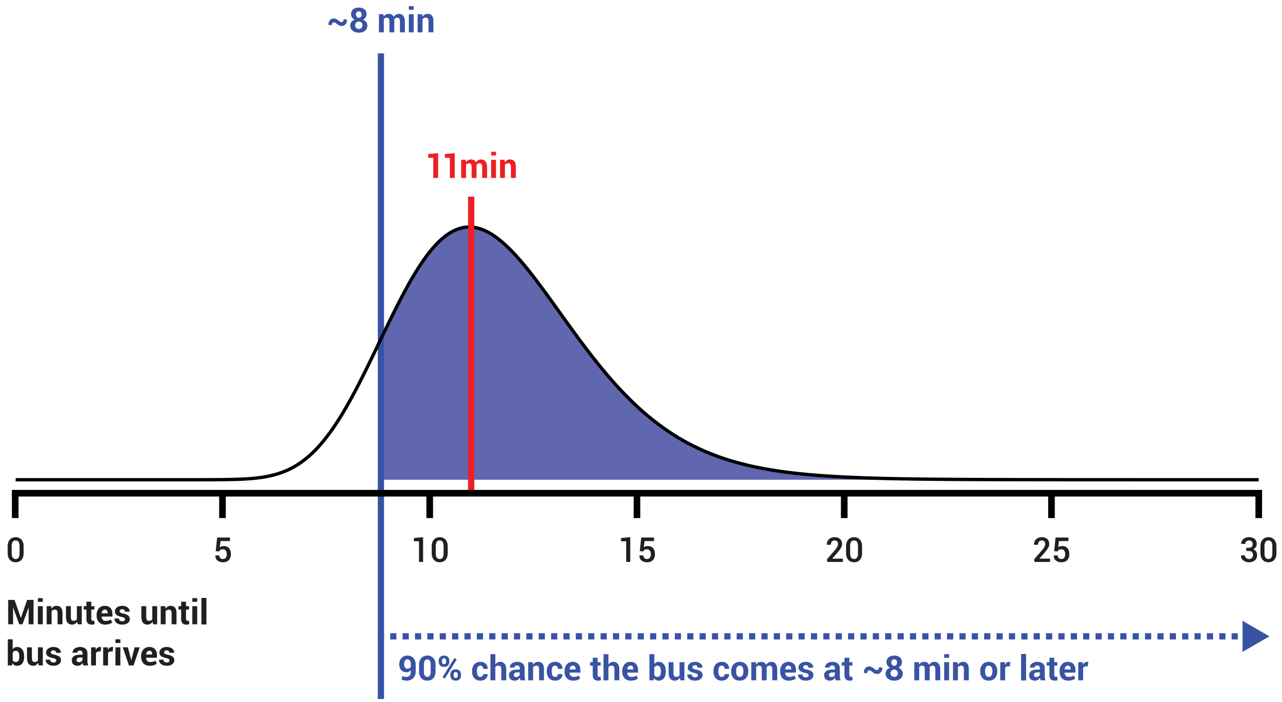
Do I have time to get a coffee?

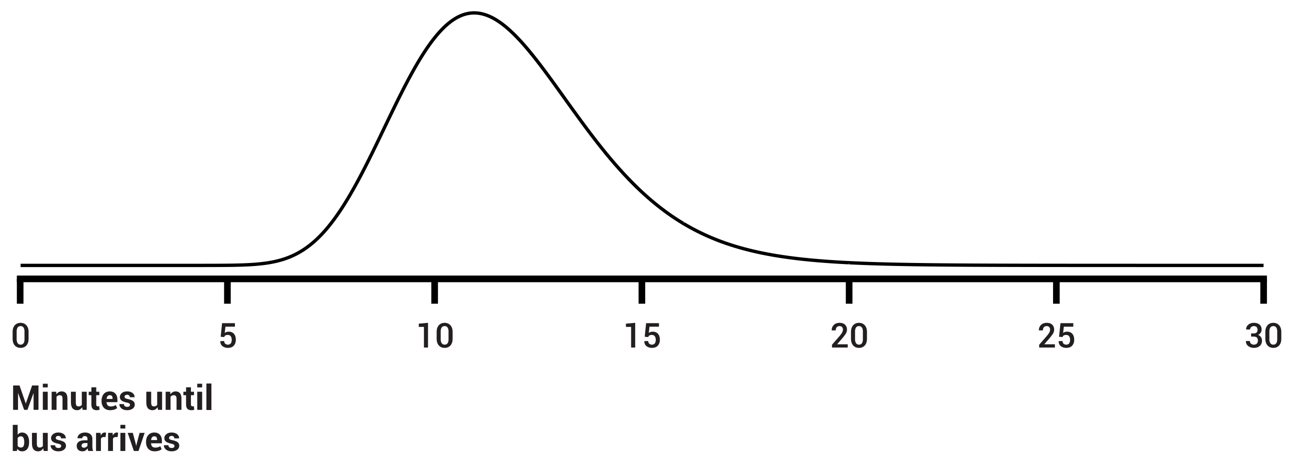

11min
0
5
10
15
20
25
30
Minutes until
bus arrives

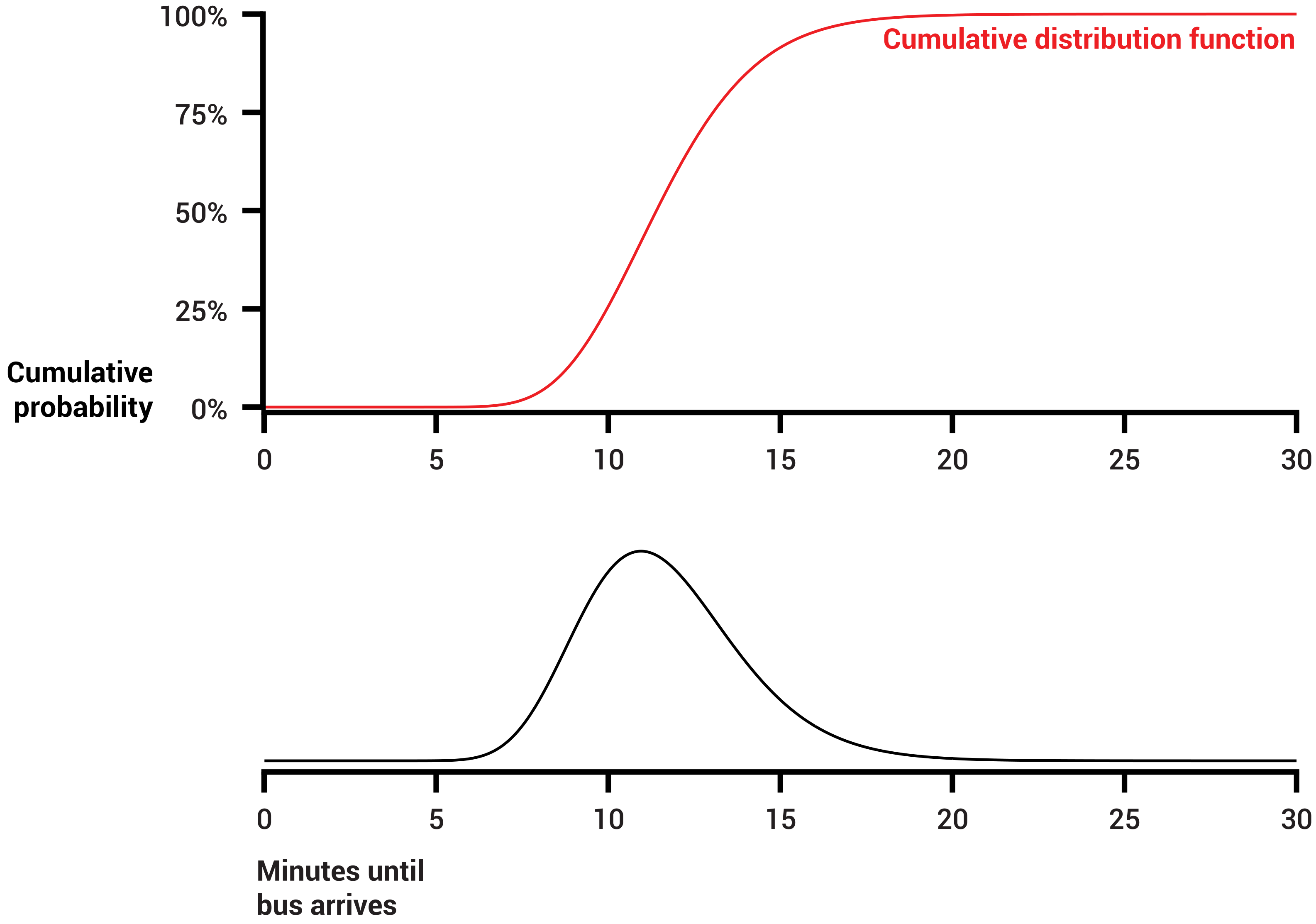

11min
0
5
10
15
20
25
30
Minutes until
bus arrives

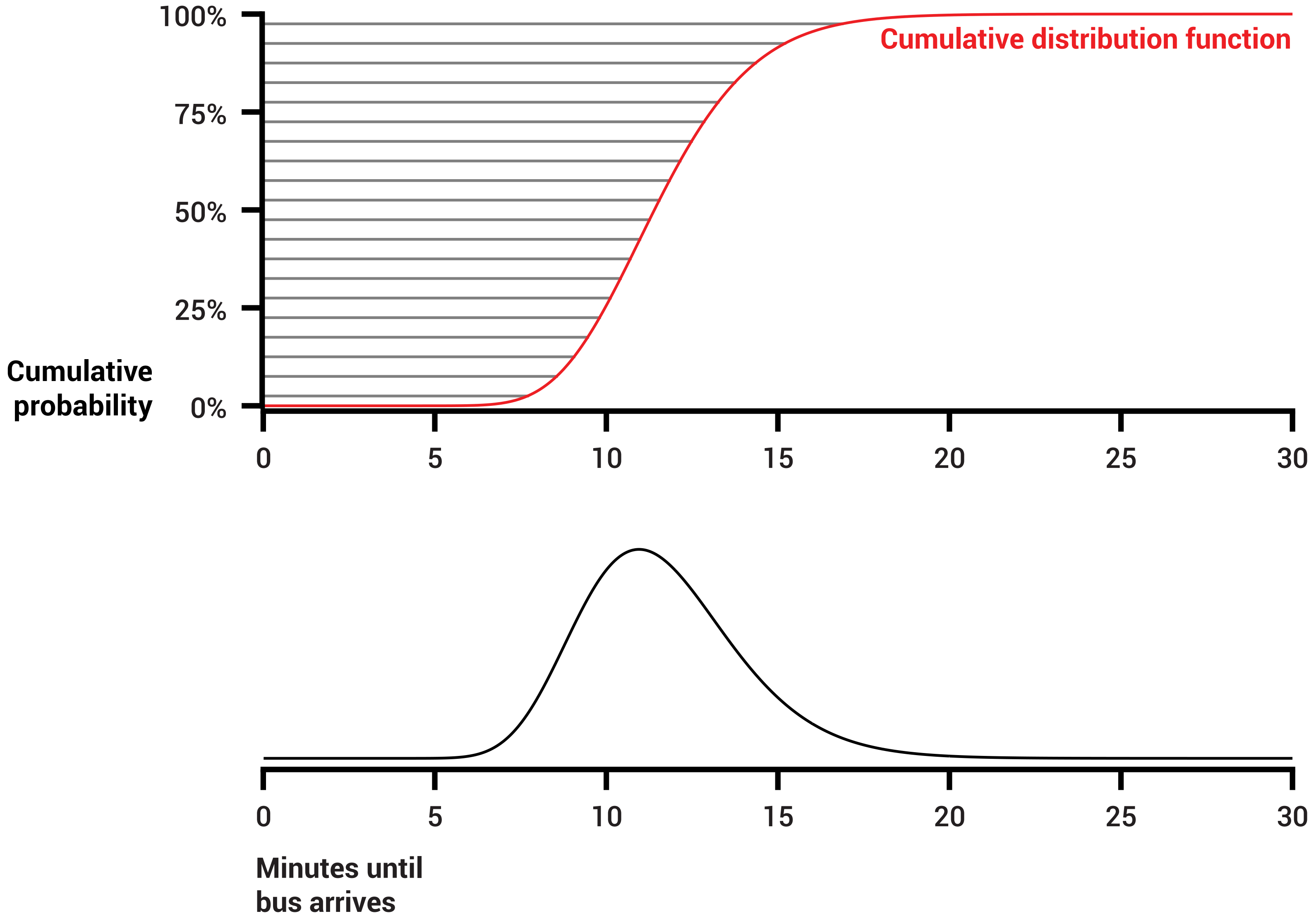

~8 min
11min
0
5
10
15
20
25
30
Minutes until
bus arrives
90% chance the bus comes at ~8 min or later



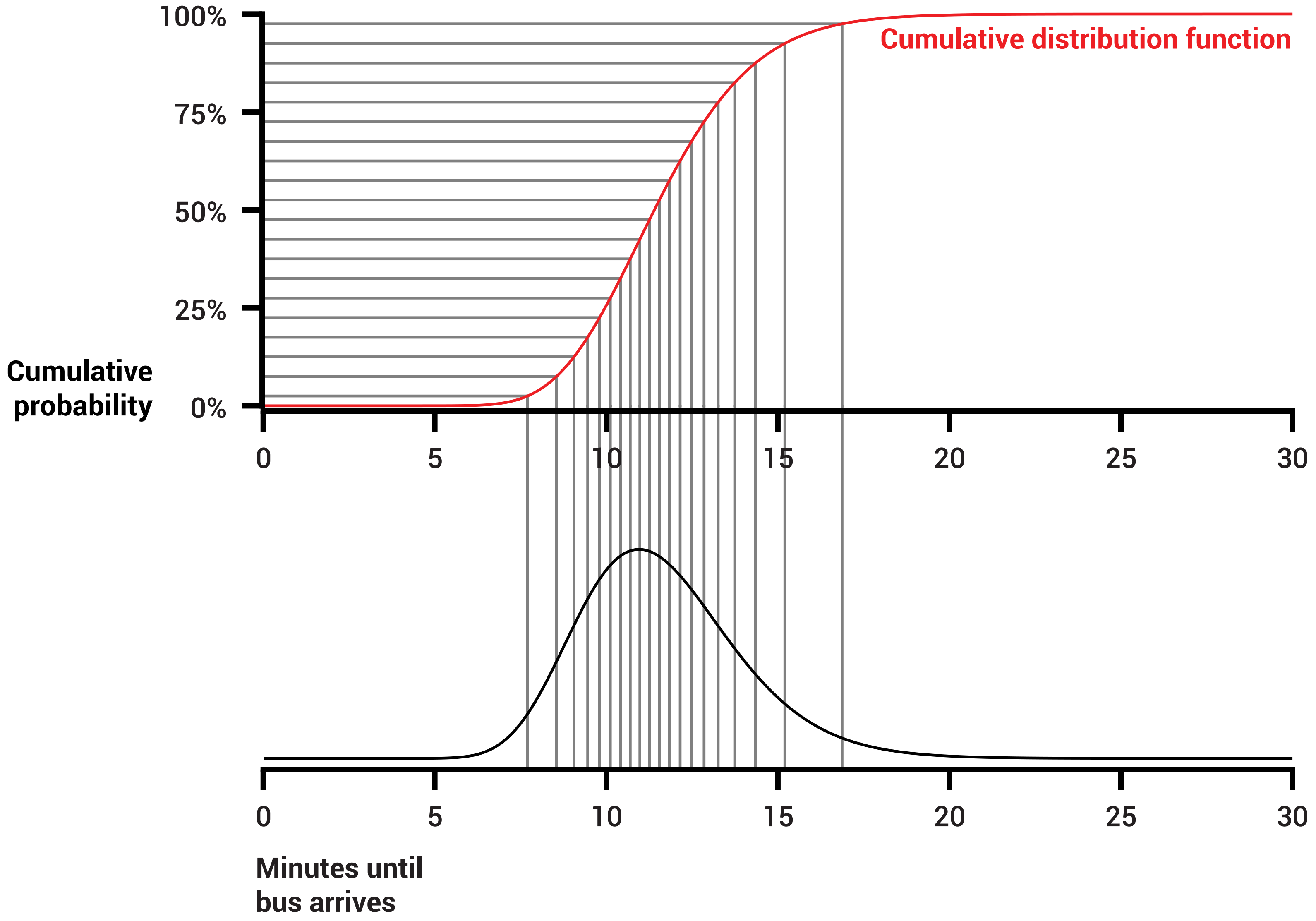

~8 min
11min
0
5
10
15
20
25
30
Minutes until bus arrives
90% chance the bus comes at ~8 min or later

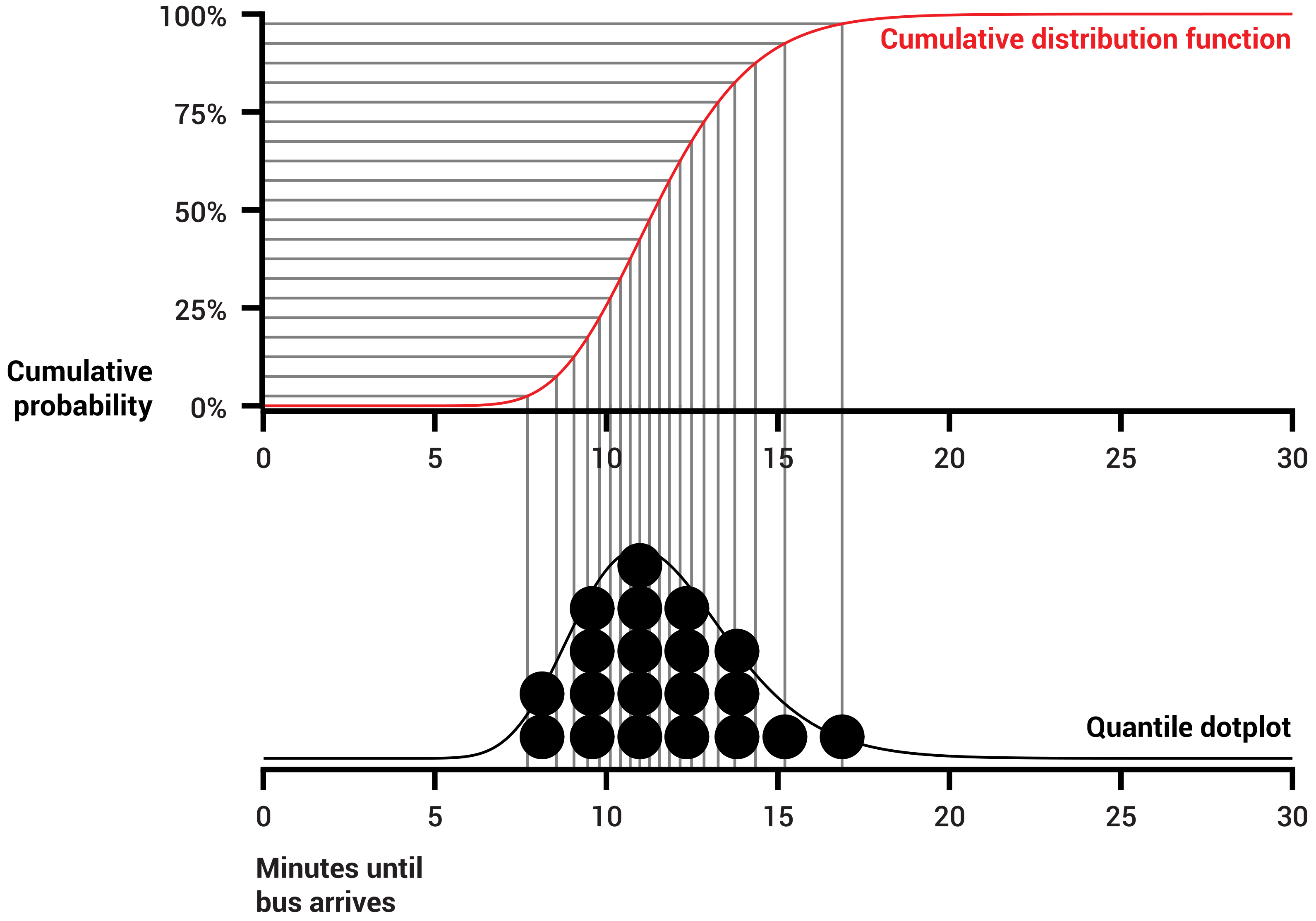

0
5
10
15
20
25
30
Minutes until bus arrives

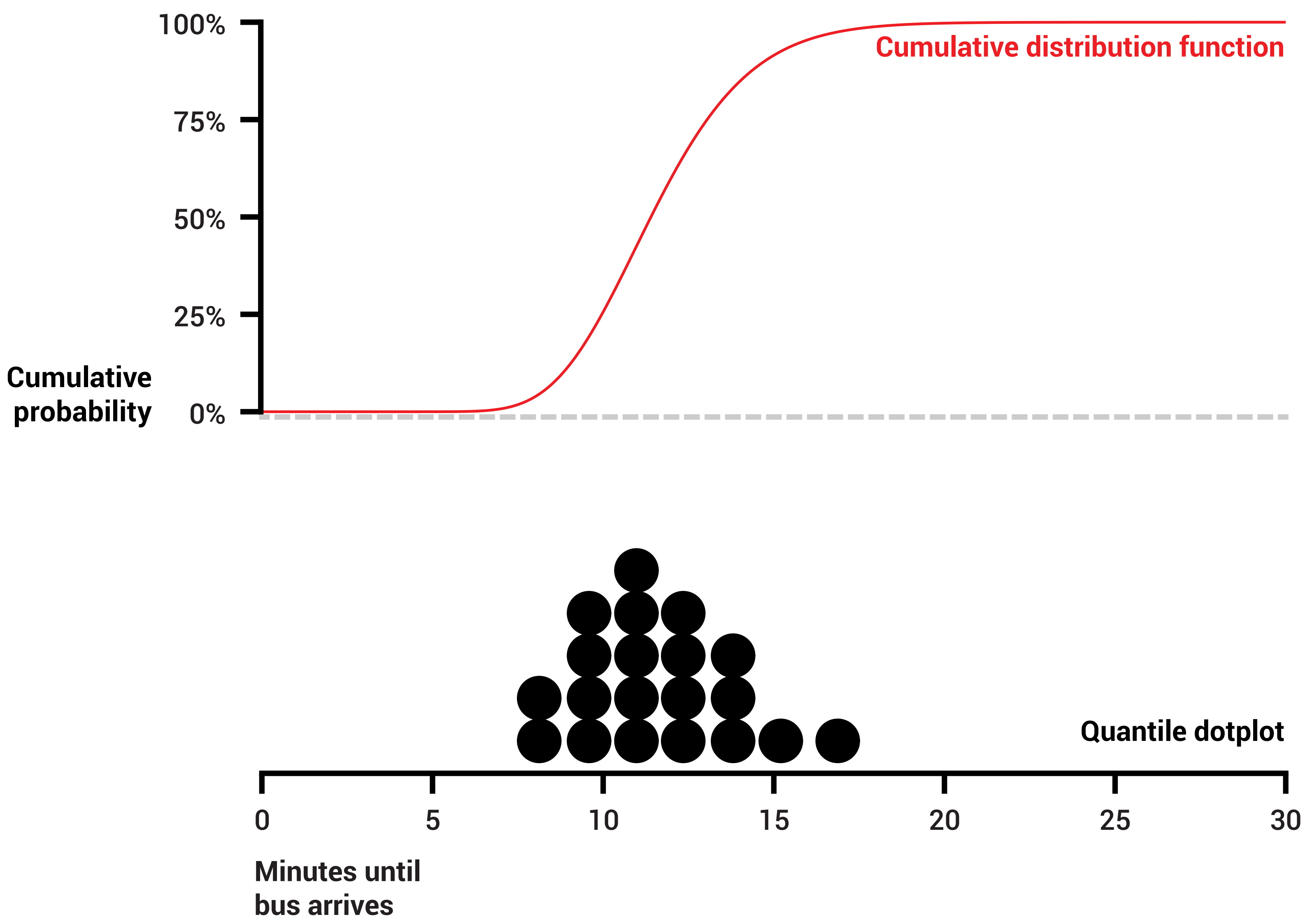

100%
75%
50%
25%
0%
Cumulative
probability
Cumulative distribution function
0
5
10
15
20
25
30
0
5
10
15
20
25
30
Minutes until
bus arrives

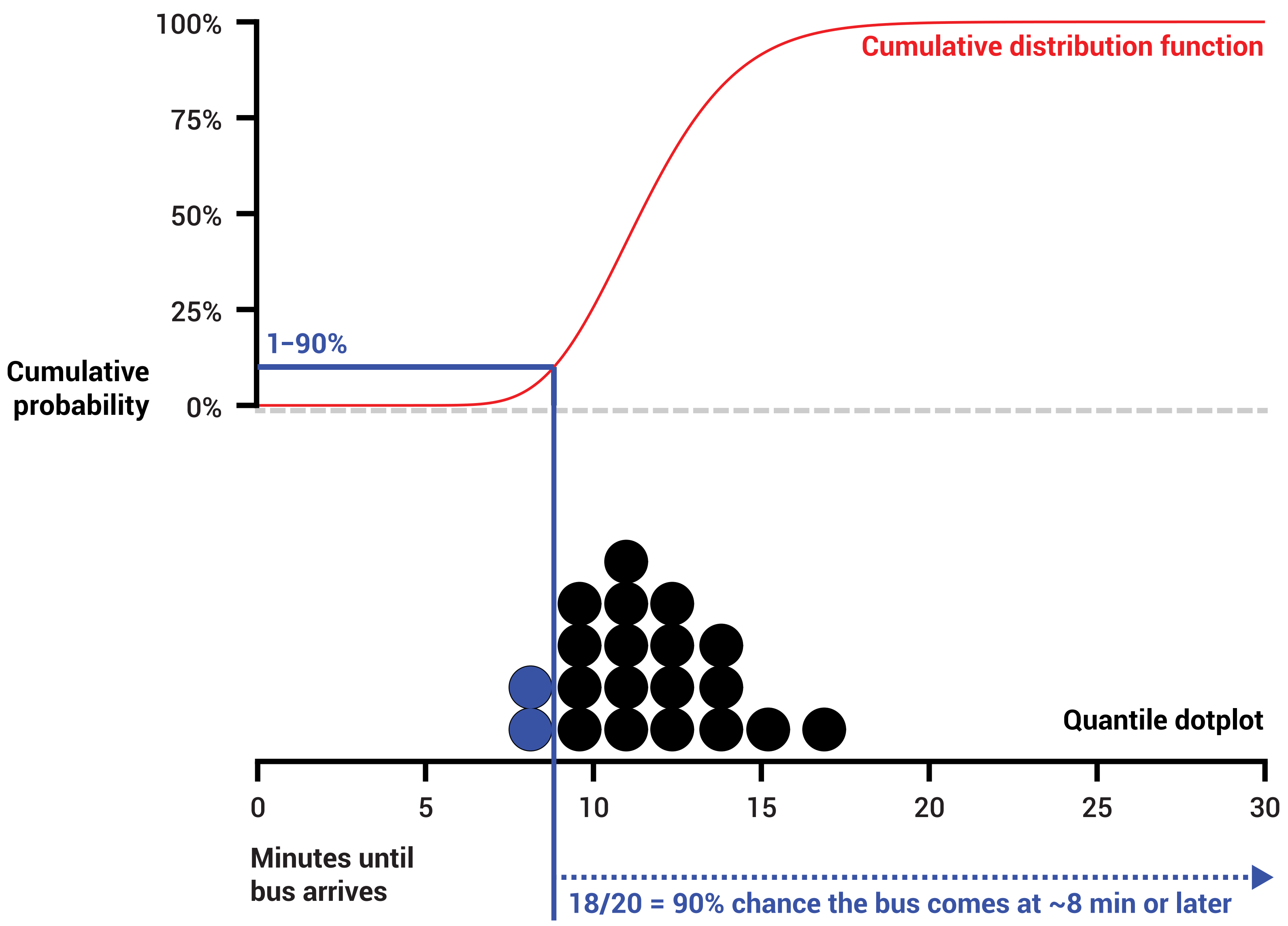


100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
Minutes until bus arrives


100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
Minutes until bus arrives


100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
Quantile dotplot
0
5
10
15
20
25
30
Minutes until bus arrives

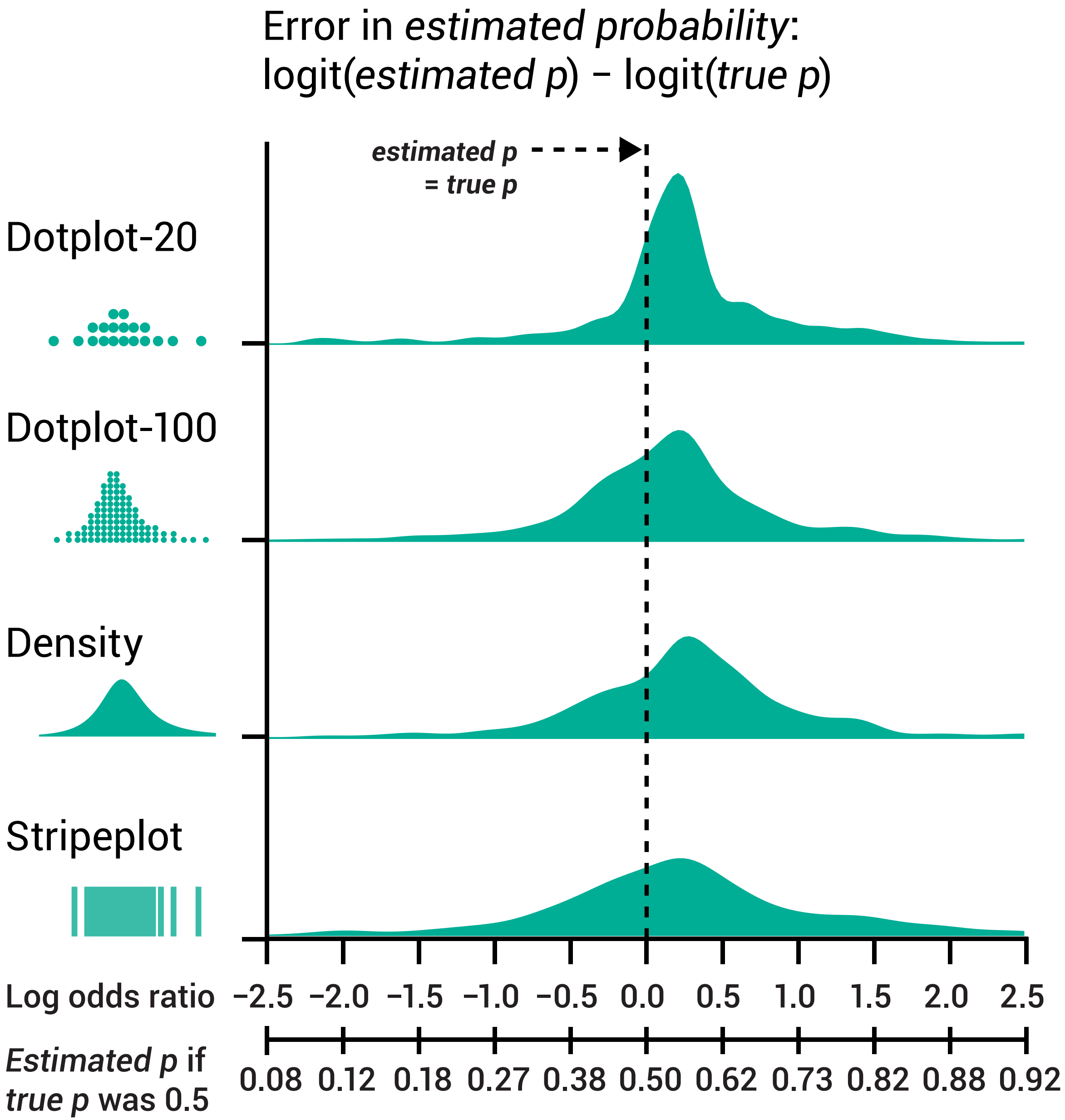

100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
Quantile dotplot
0
5
10
15
20
25
30
Minutes until bus arrives


100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
1−90%
Quantile dotplot
0
5
10
15
20
25
30
Minutes until bus arrives
18/20 = 90% chance the bus comes at ~8 min or later

Quantile dotplots

[**Kay**, Kola, Hullman, Munson. When (ish) is My Bus? User-centered Visualizations of Uncertainty in Everyday, Mobile Predictive Systems. CHI 2016]

Better estimates (perceptually)



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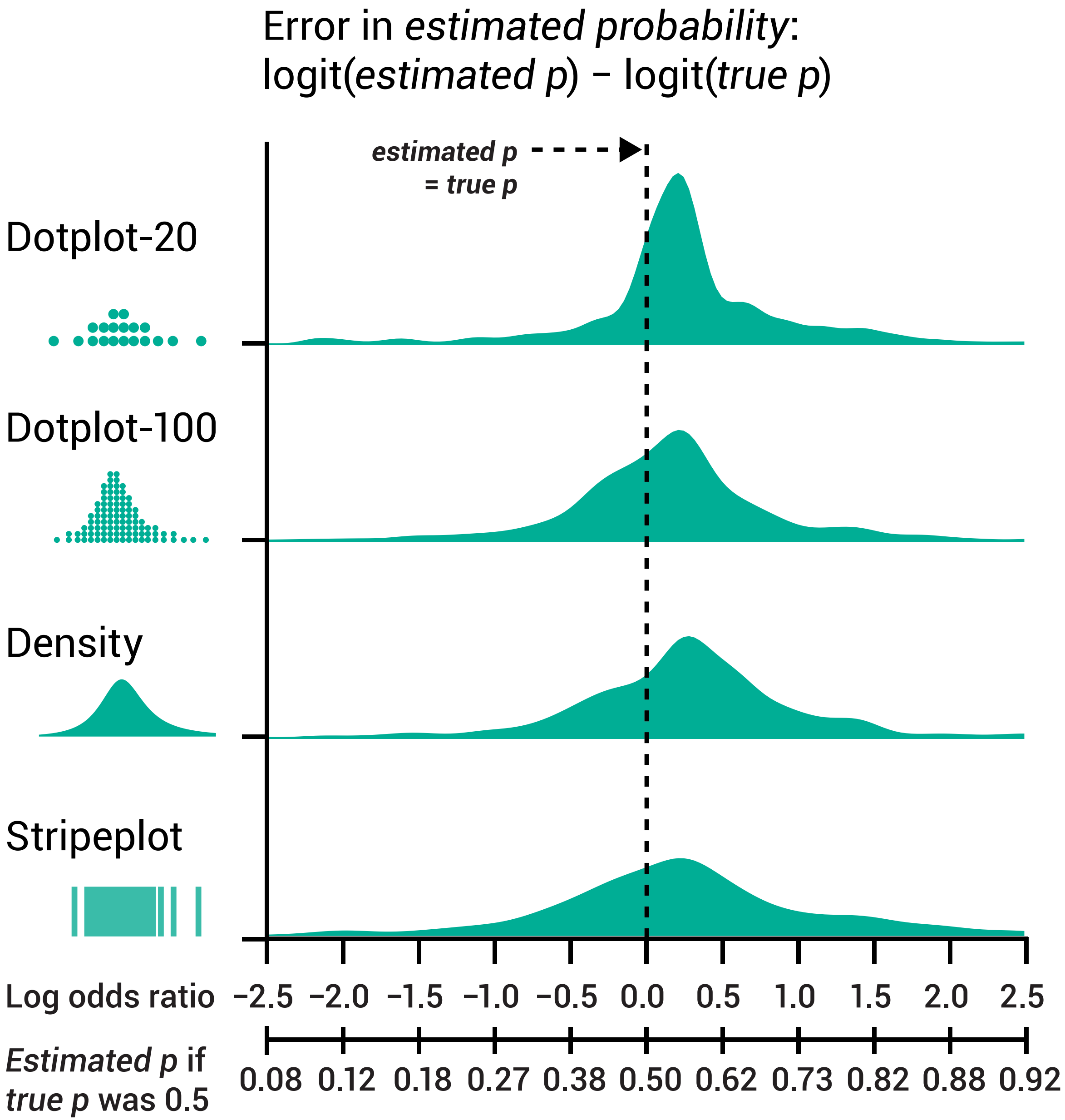
Better estimates (perceptually)

↓?

better decisions



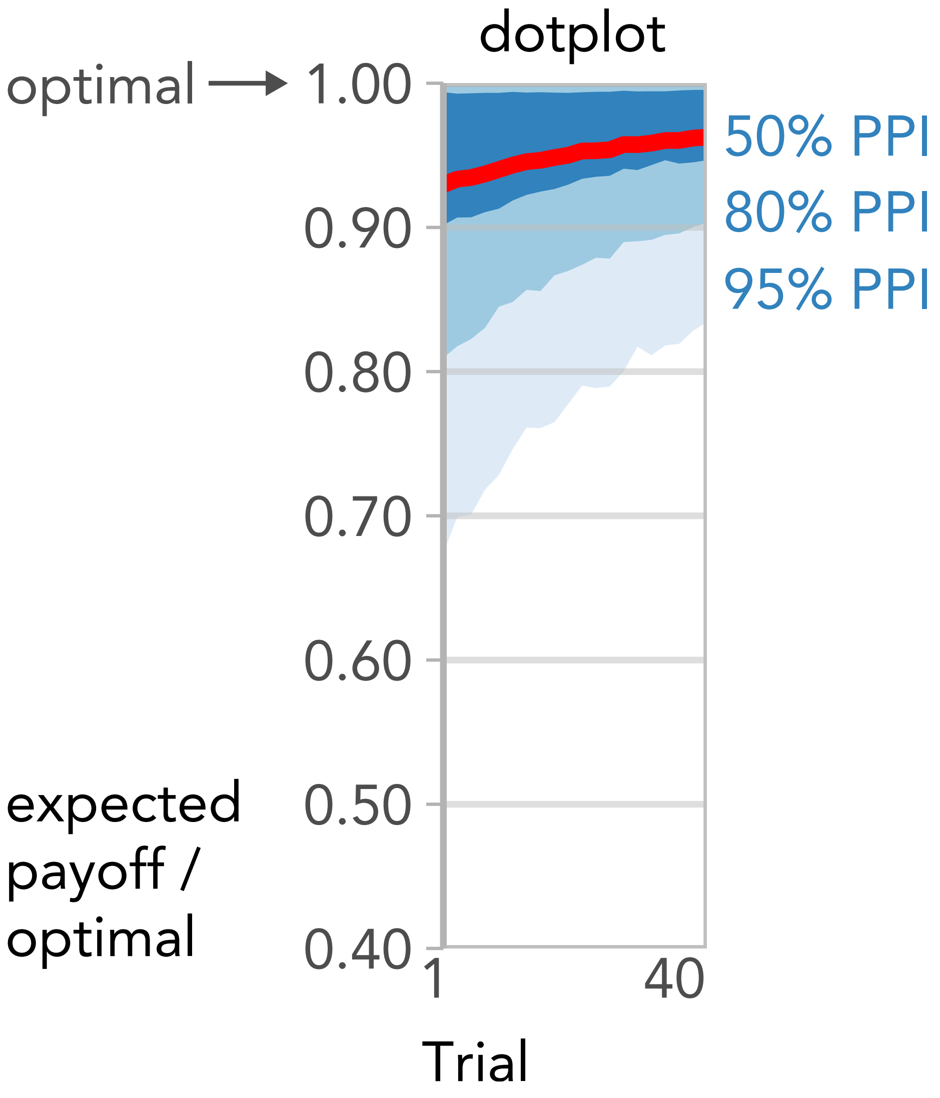
Quantile dotplots

[Fernandes, Munson, Hullman, **Kay**. Uncertainty Displays Using Quantile Dotplots or CDFs Improve Transit Decision-Making. CHI 2018]

Better estimates
(perceptually)

↓

better decisions
(in this case)



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[Fernandes, Munson, Hullman, **Kay**. Uncertainty Displays Using Quantile Dotplots or CDFs Improve Transit Decision-Making. CHI 2018]

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↓

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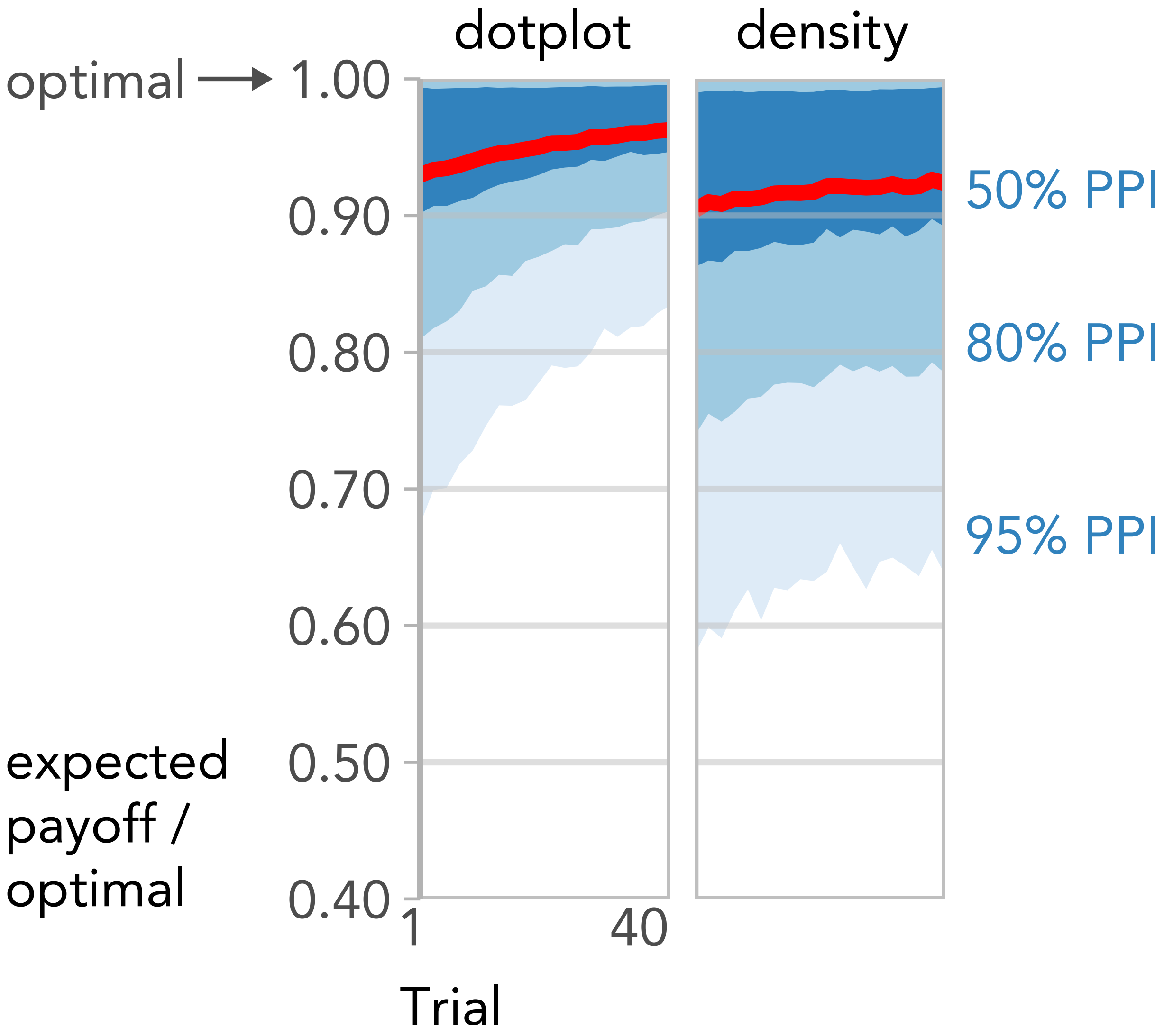
(in this case)

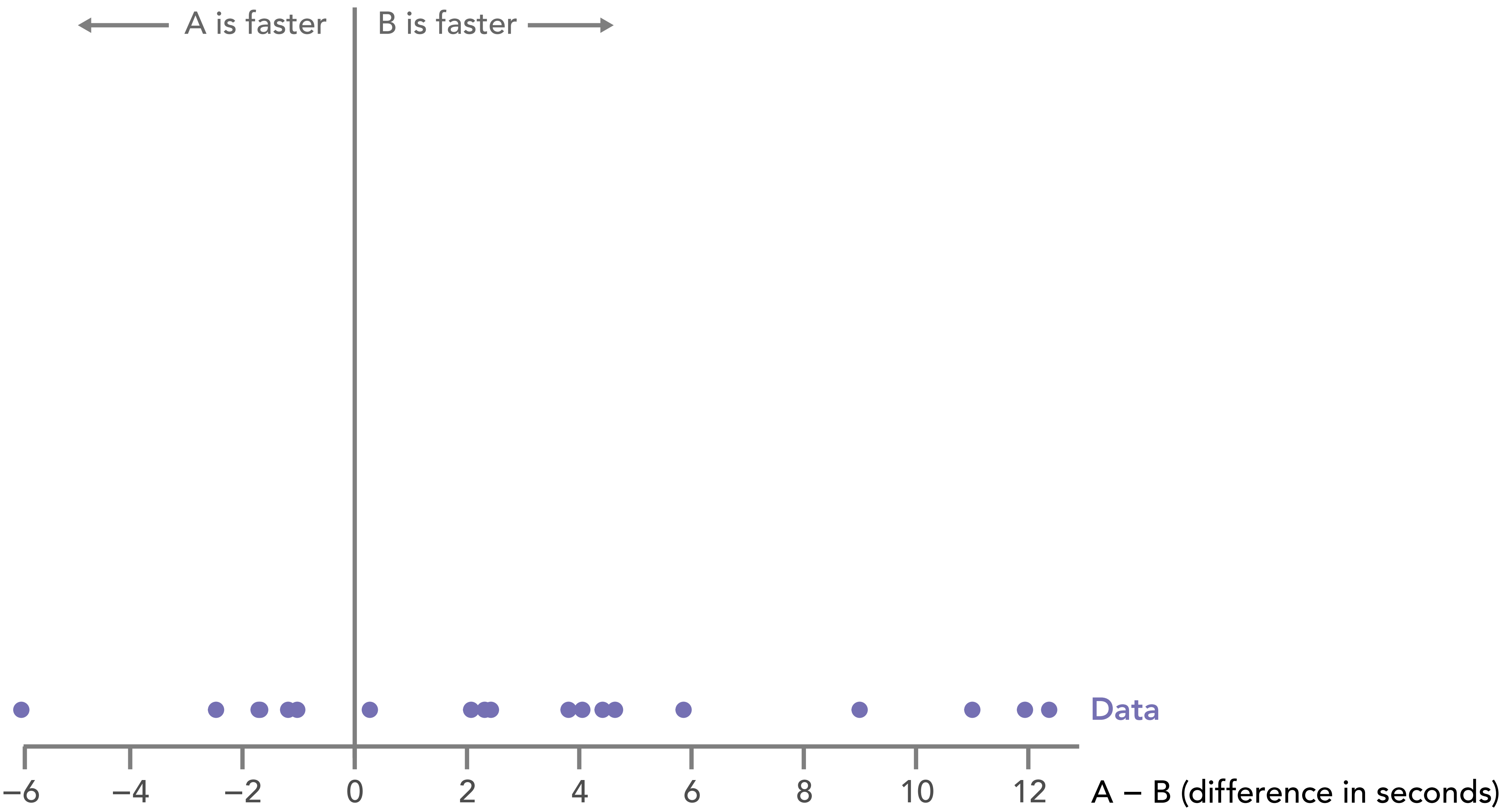


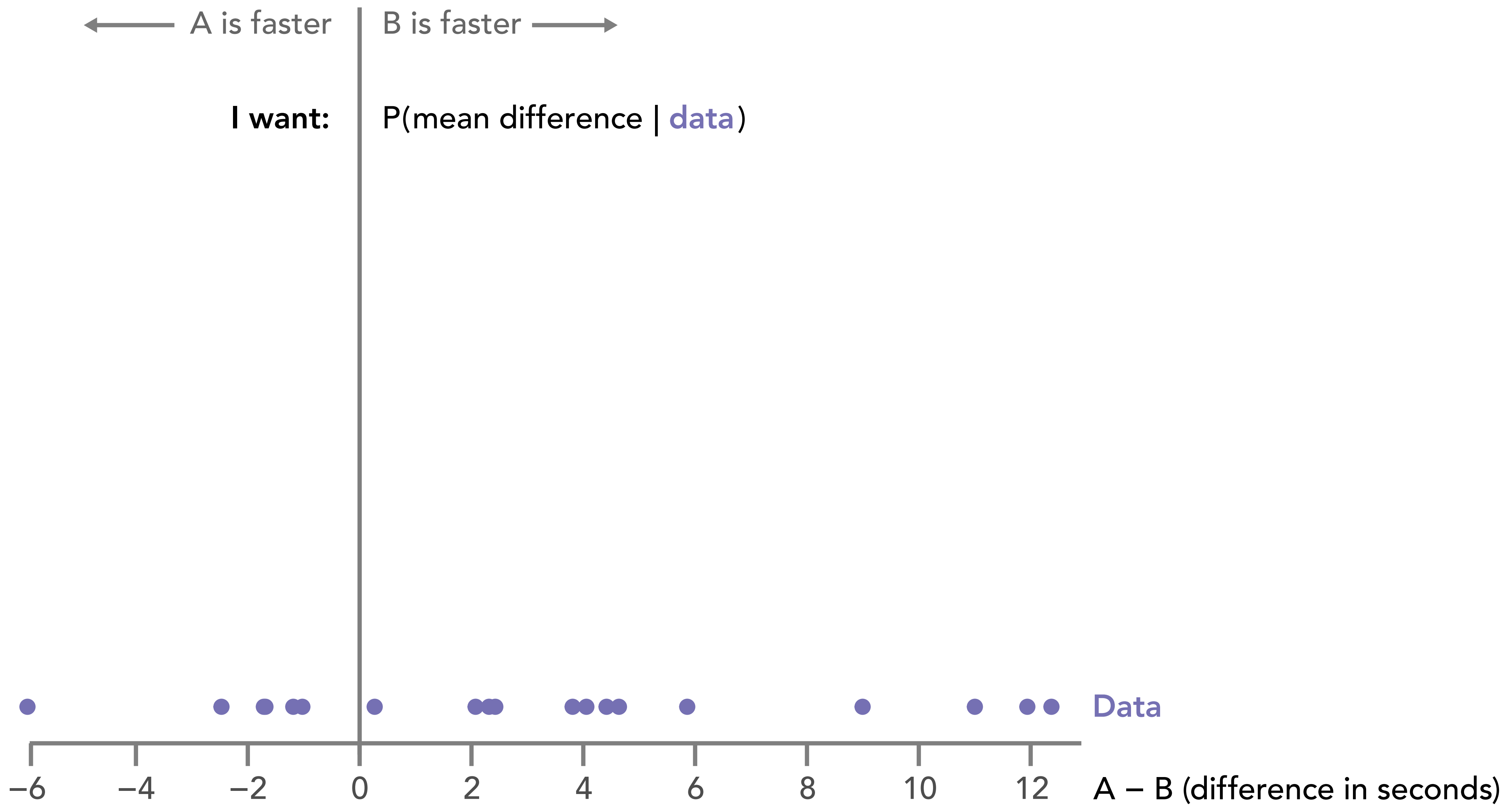
(Sidebar —
Uncertainty: what am I talking about?)

For the purposes of this talk...

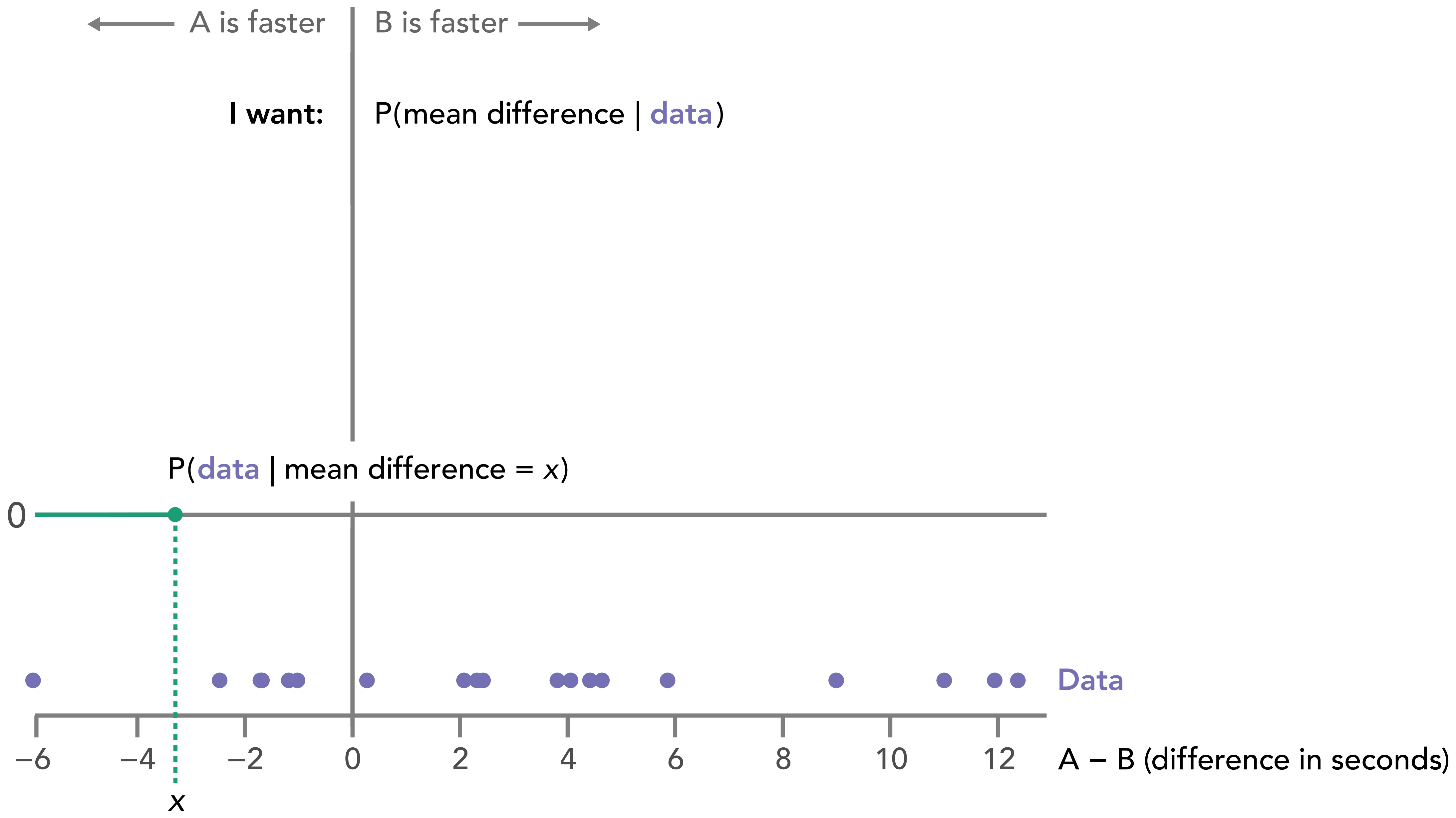
I am largely adopting a Bayesian view of uncertainty

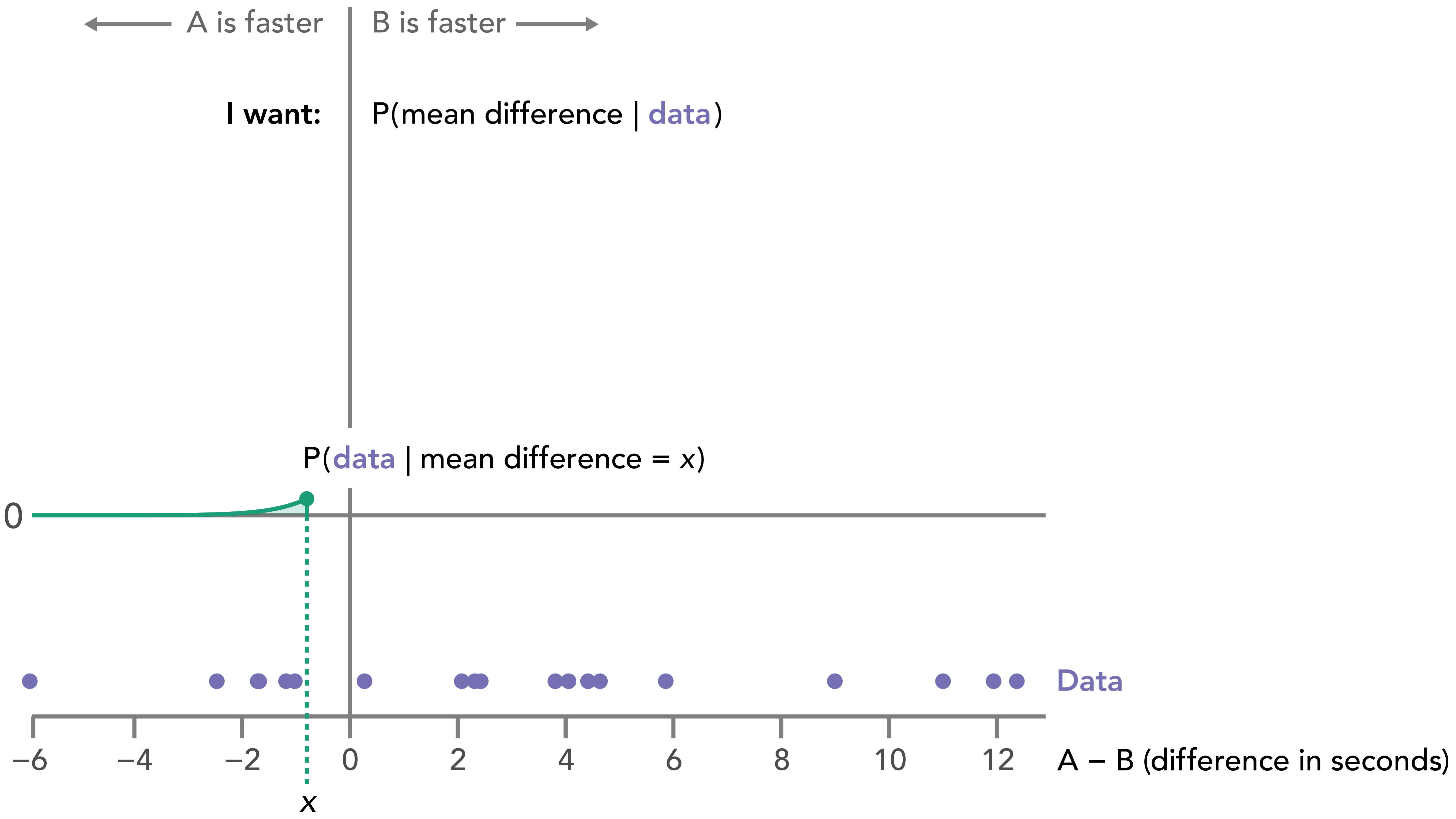
Put another way: uncertainty is probability


A is faster
B is faster
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)

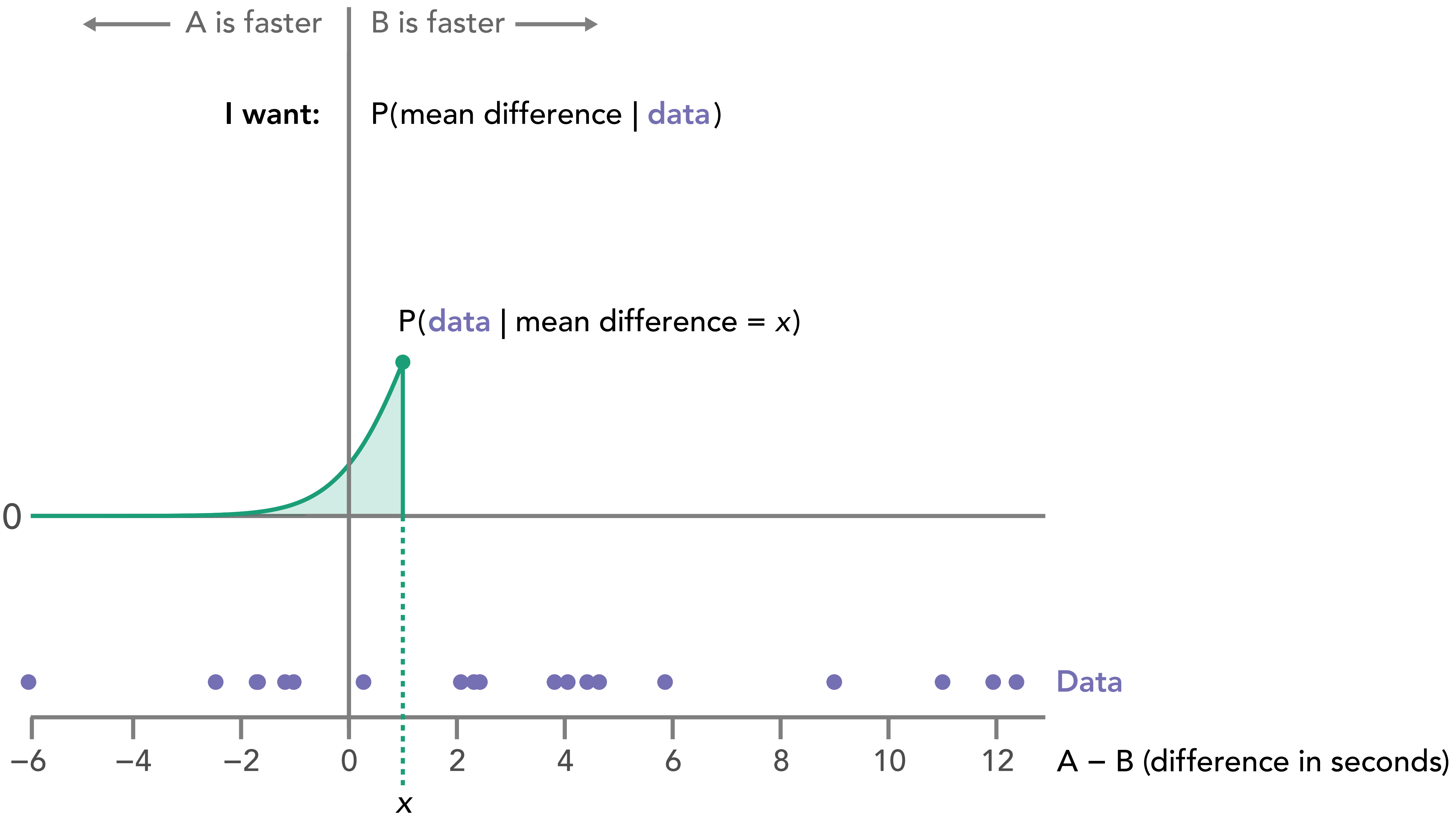


A is faster
B is faster
I want:
P(mean difference | data)
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)


A is faster
B is faster
I want:
P(mean difference | data)
P(data | mean difference = x)
0
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)
x



A is faster
B is faster
I want:
P(mean difference | data)
P(data | mean difference = x)
0
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)
x



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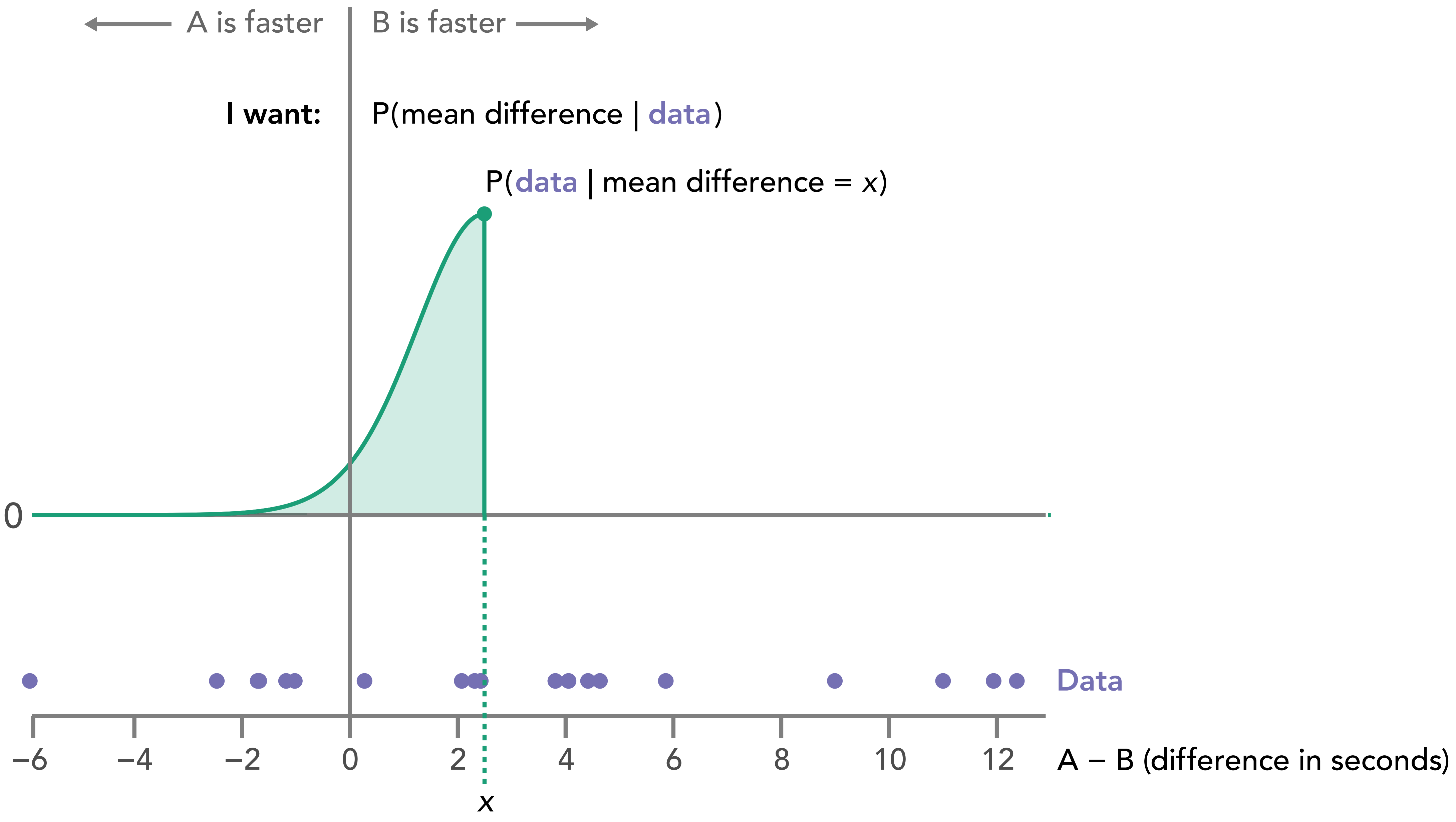
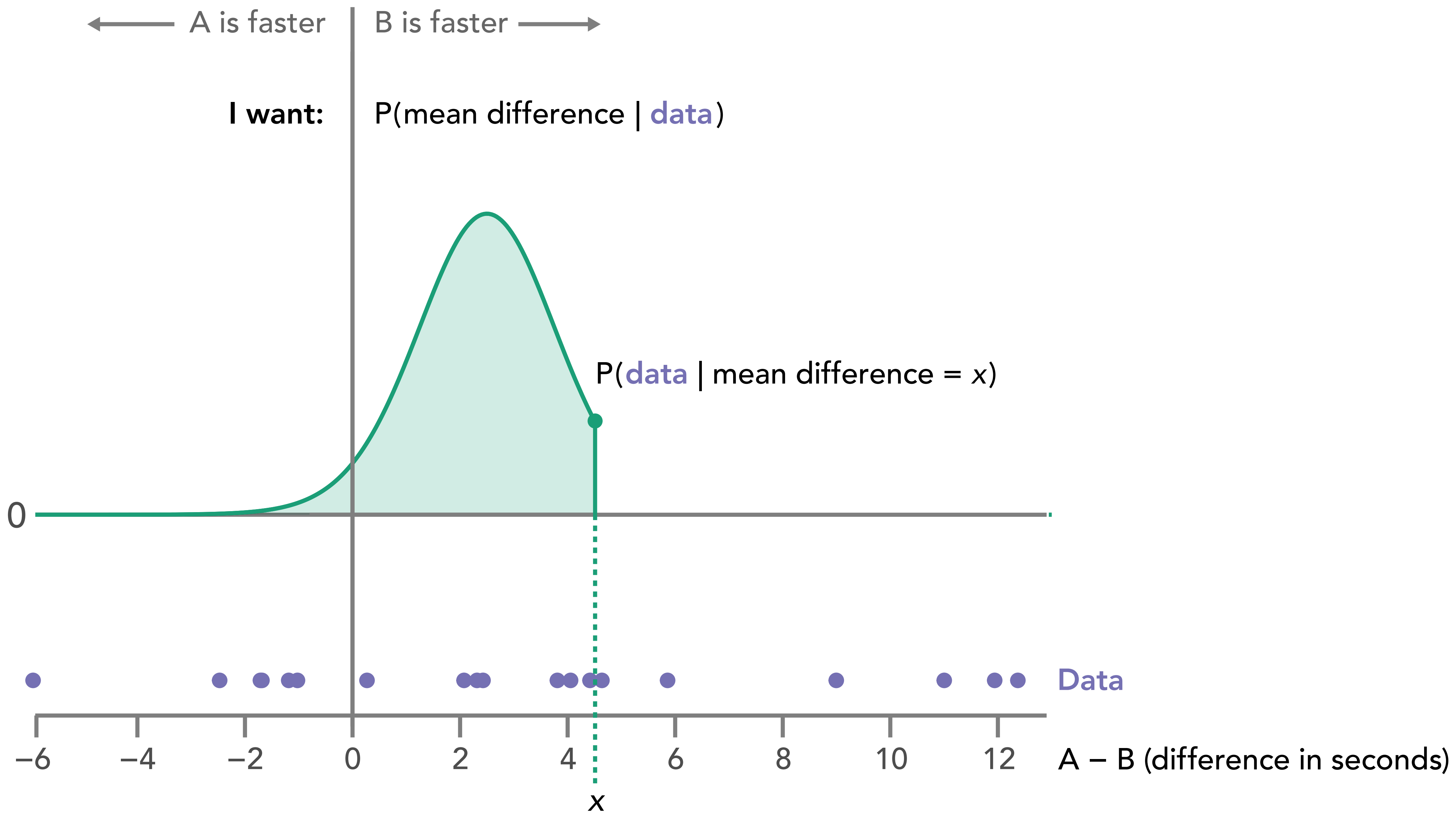
B is faster
I want:
P(mean difference | data)
P(data | mean difference = x)
0
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)
x



A is faster
B is faster
I want:
P(mean difference | data)
P(data | mean difference = x)
0
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)
x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−6
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4
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8
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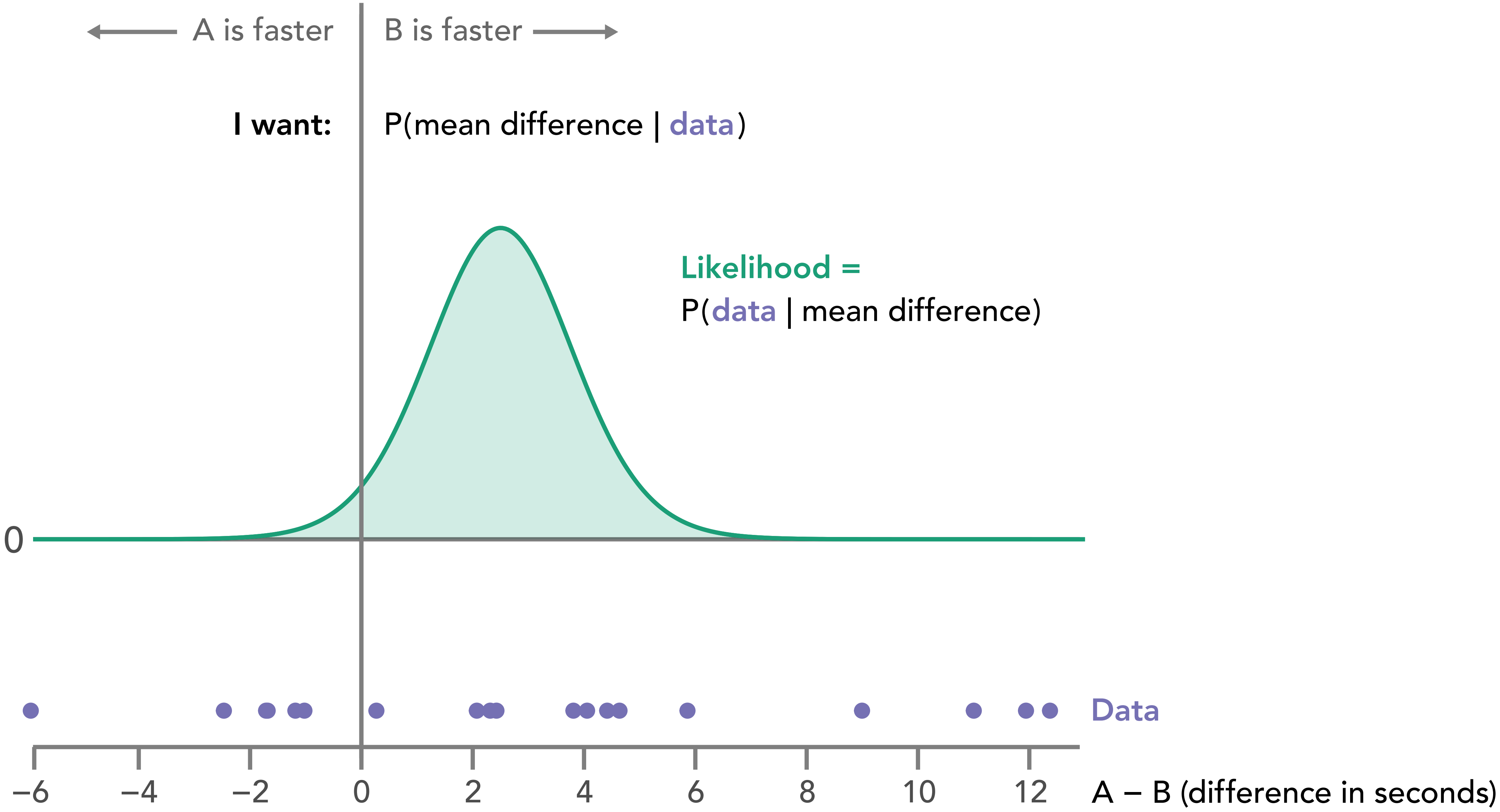
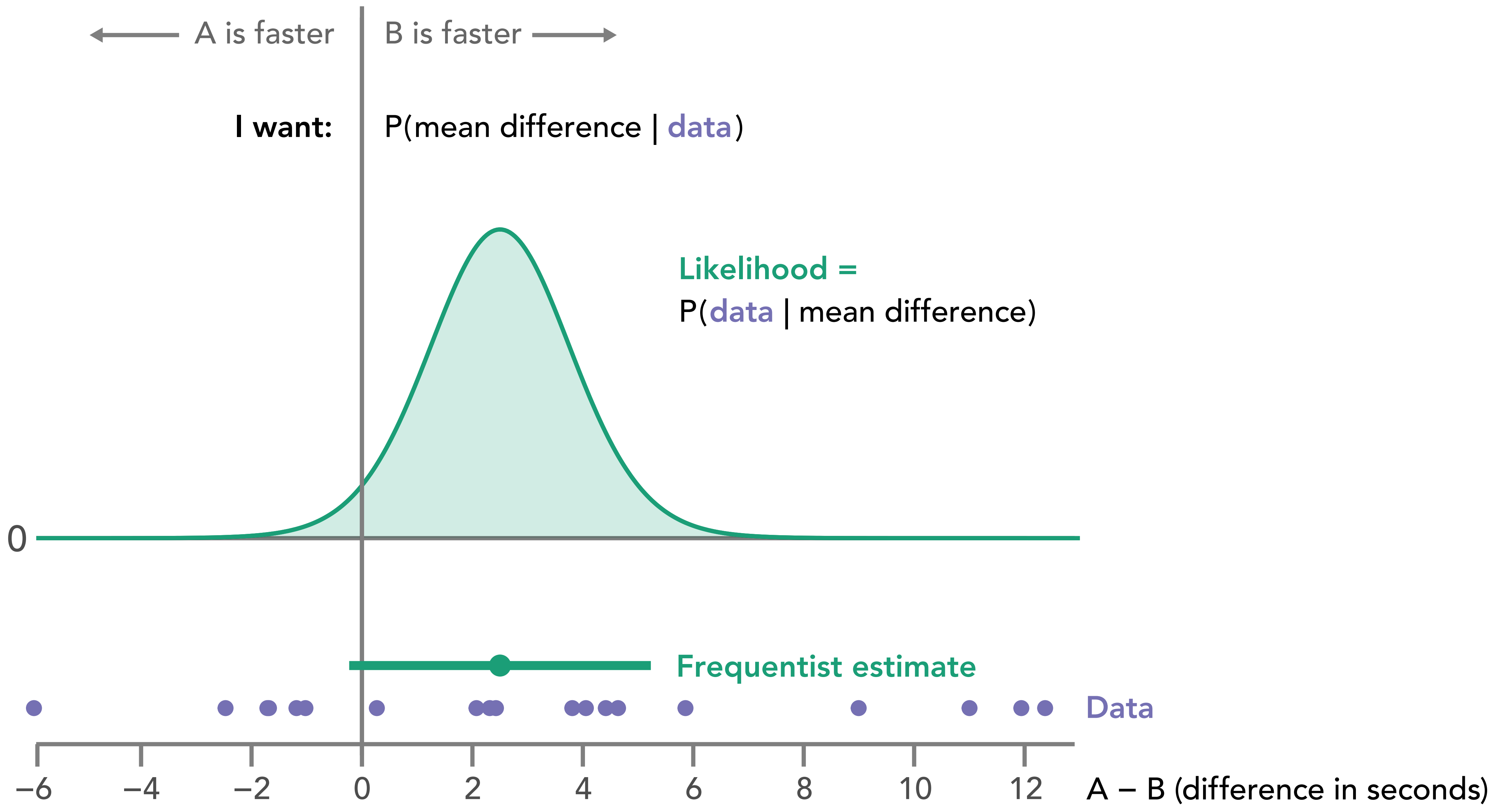
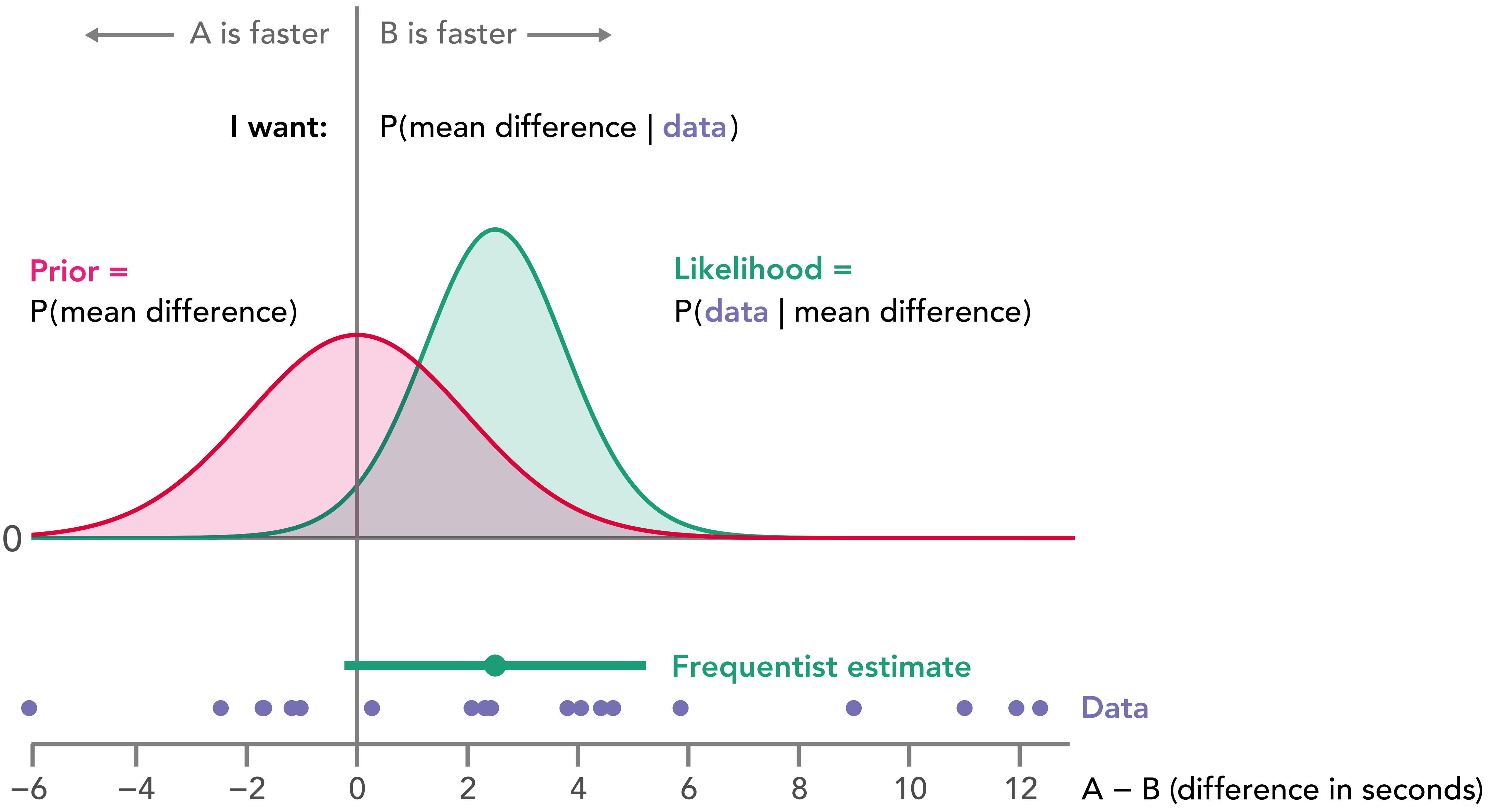
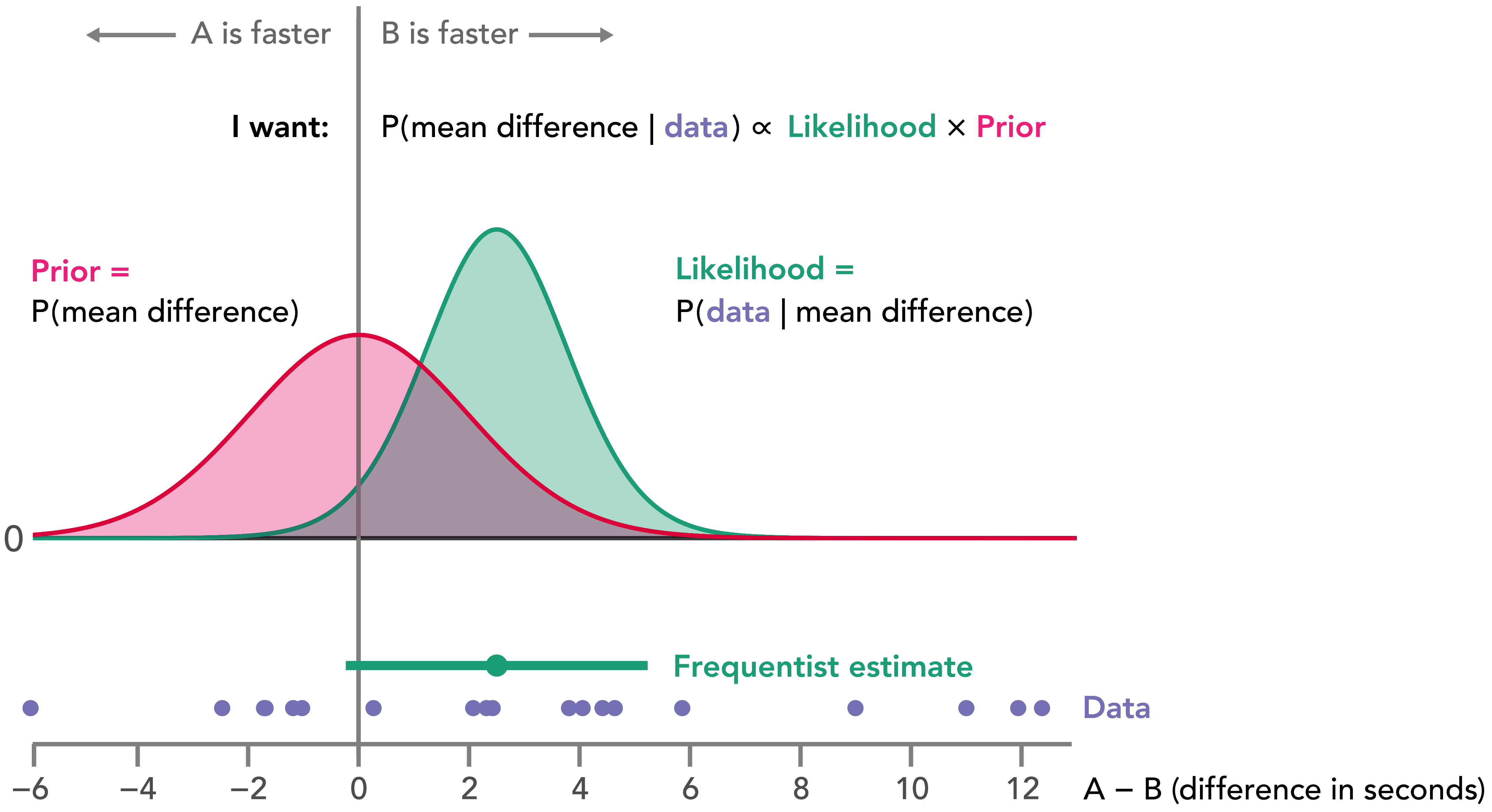
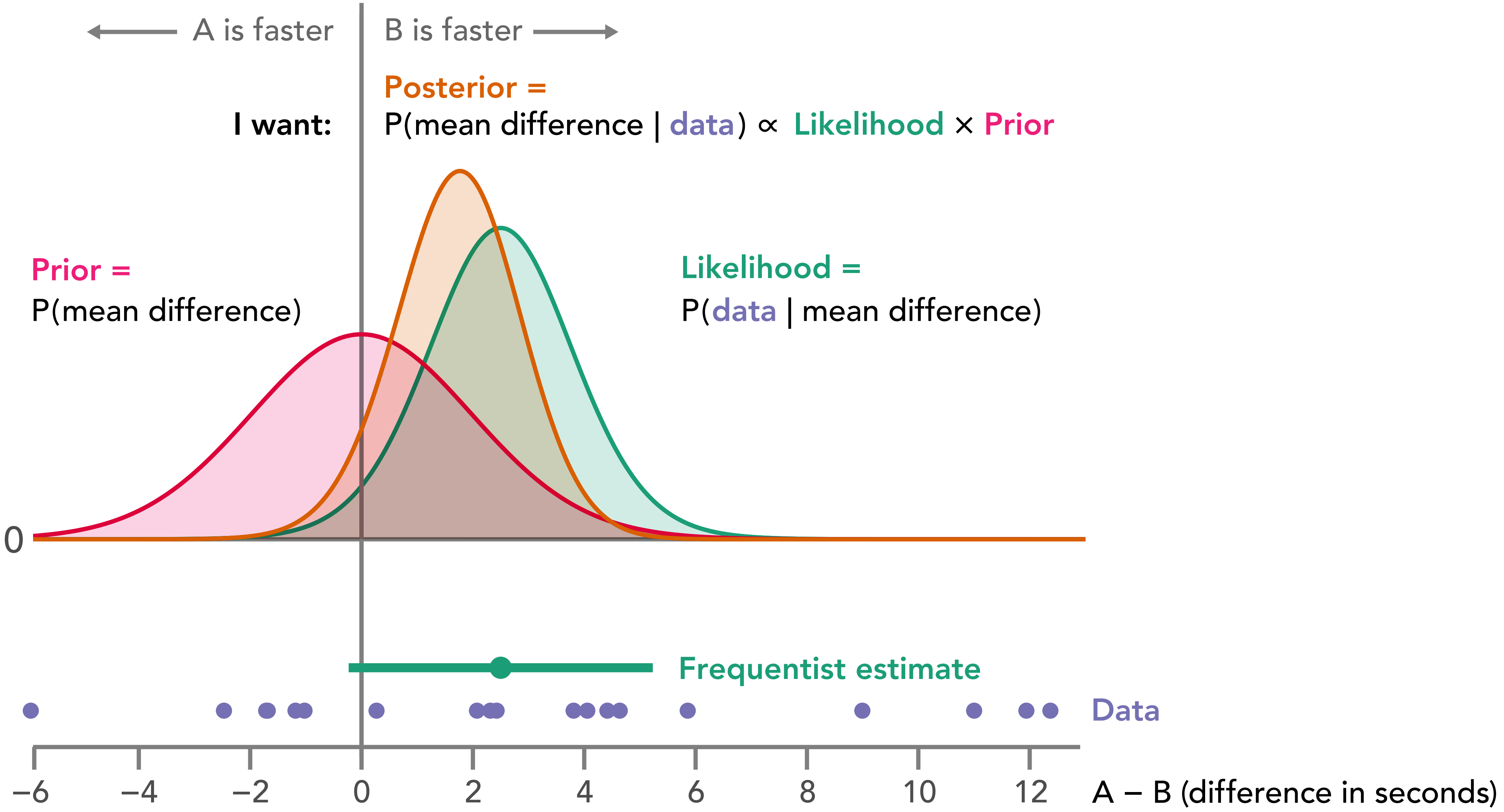
A − B (difference in seconds)
x

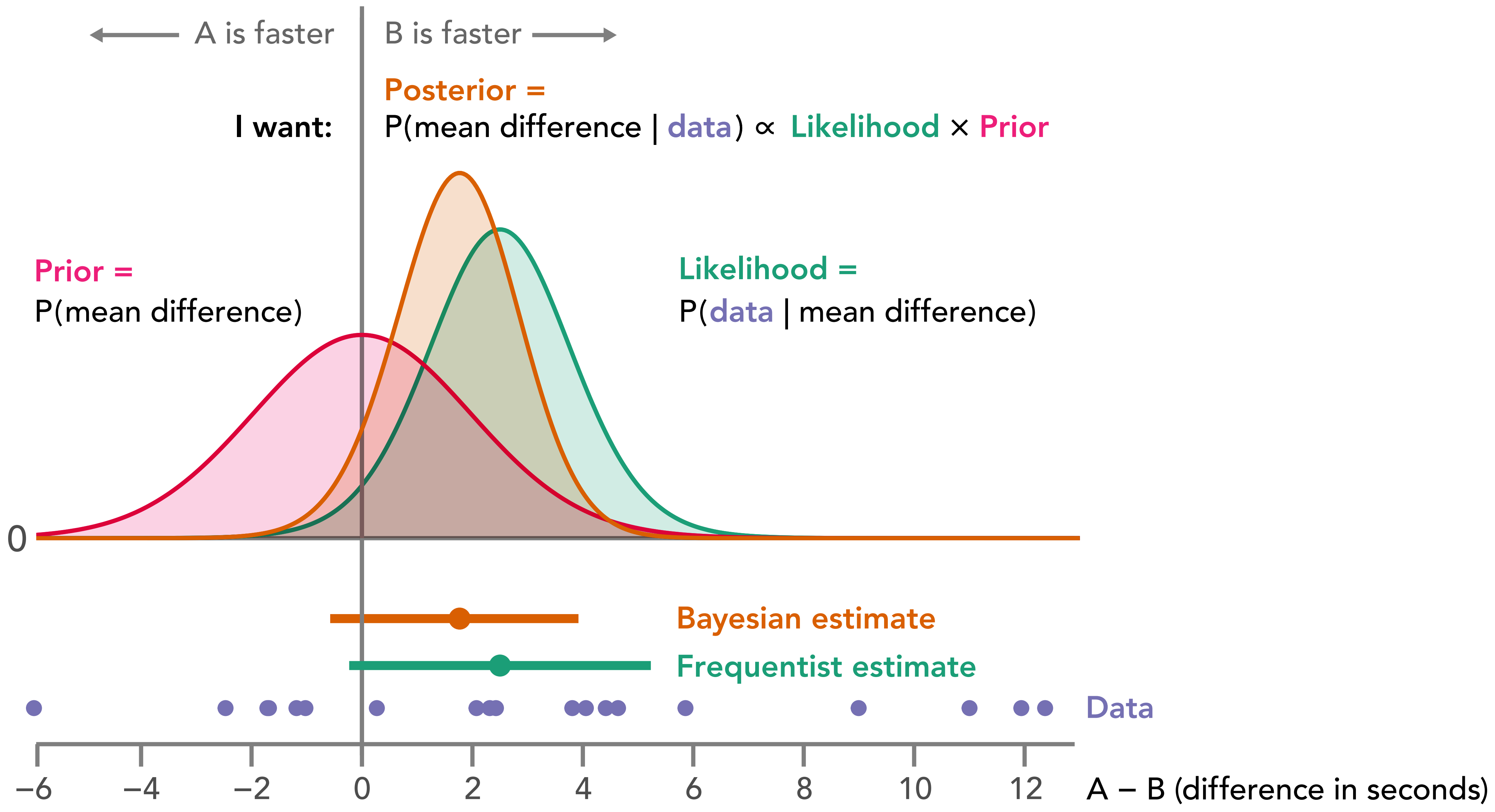

A is faster
B is faster
I want:
P(mean difference | data)
Likelihood =
P(data | mean difference)
0
Data
−6
−4
−2
0
2
4
6
8
10
12
A – B (difference in seconds)


A is faster
B is faster
I want:
P(mean difference | data)
Likelihood =
P(data | mean difference)
0
Frequentist estimate
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)

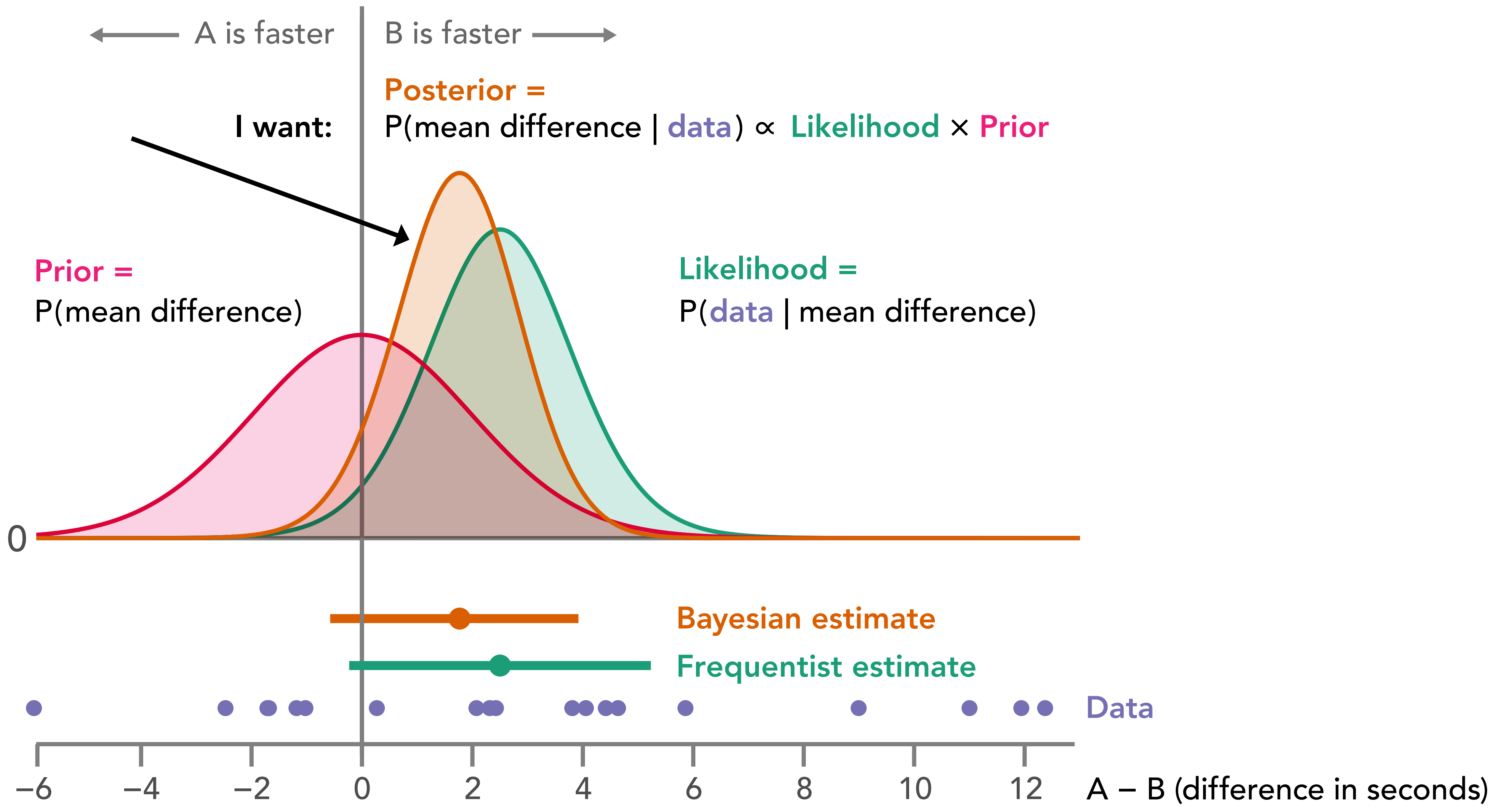

A is faster
B is faster
I want:
P(mean difference | data)
Prior =
P(mean difference)
Likelihood =
P(data | mean difference)
0
Frequentist estimate
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)


A is faster
B is faster
I want:
P(mean difference | data) ∝ Likelihood × Prior
Prior =
P(mean difference)
Likelihood =
P(data | mean difference)
0
Frequentist estimate
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)

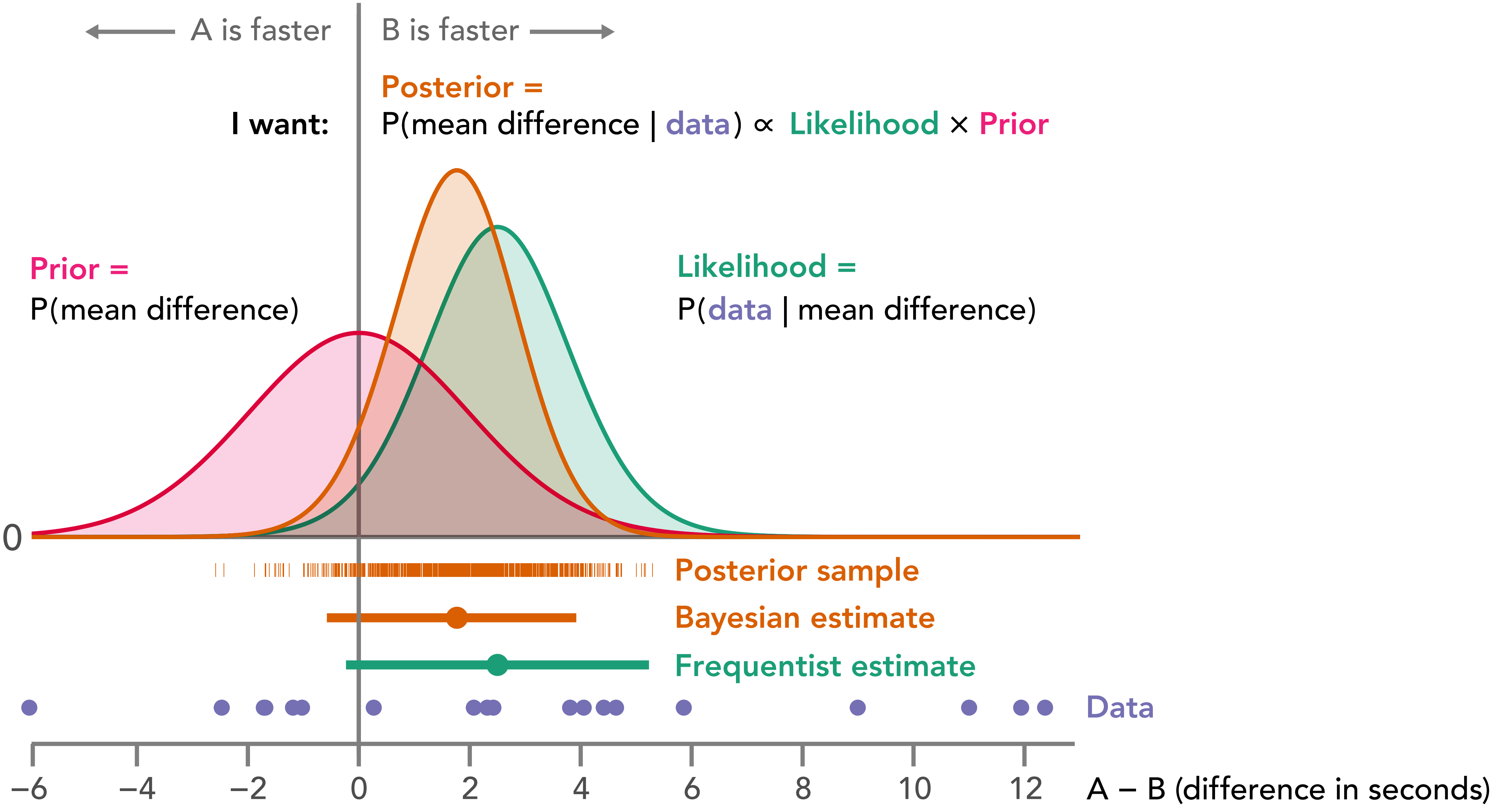

A is faster
B is faster
Posterior =
I want:
P(mean difference | data) ∝ Likelihood × Prior
Prior =
P(mean difference)
Likelihood =
P(data | mean difference)
0
Frequentist estimate
Data
−6
−4
−2
0
2
4
6
8
10
12
A – B (difference in seconds)

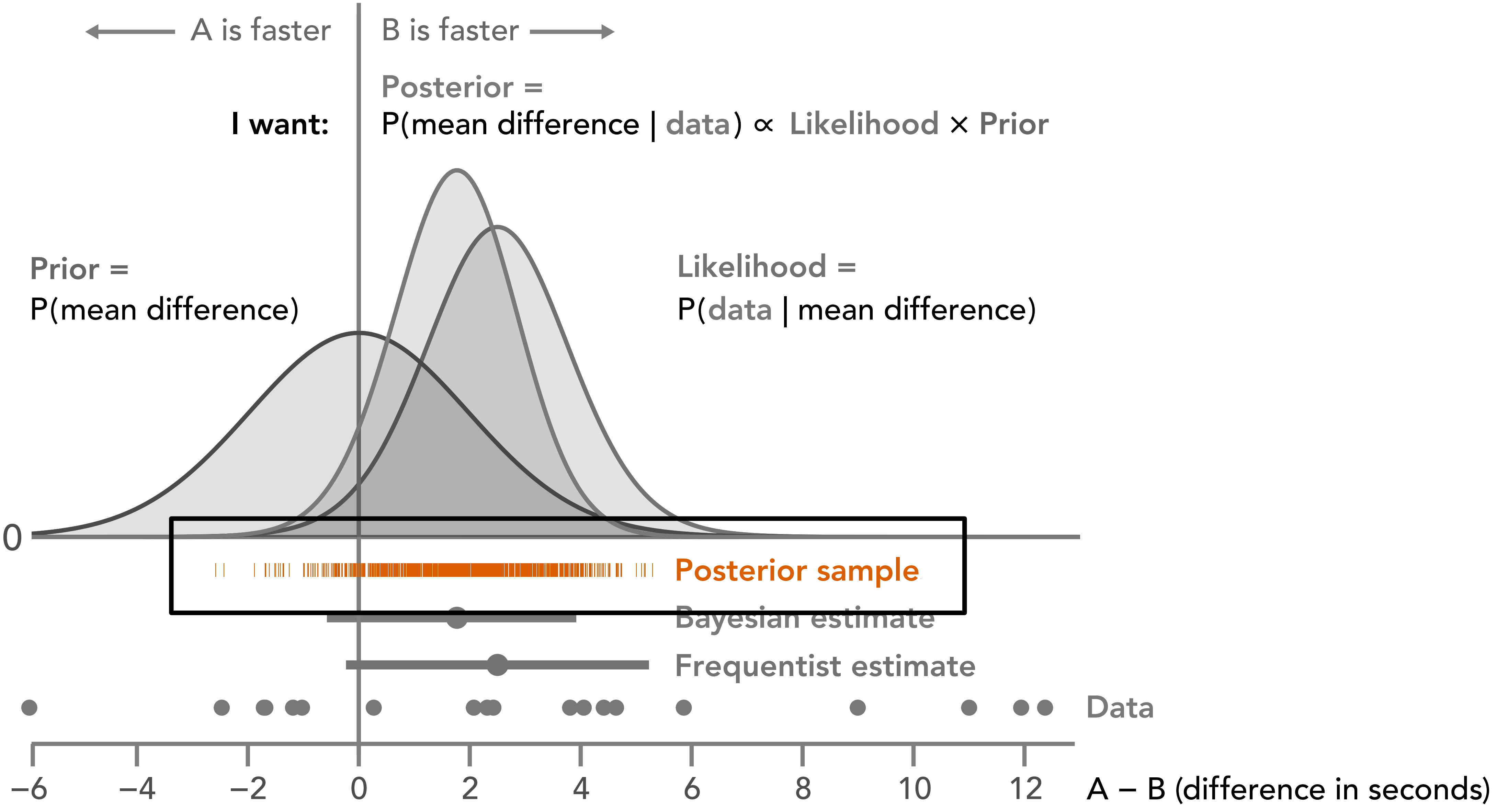


A is faster
B is faster
Posterior =
I want:
P(mean difference | data) ∝ Likelihood × Prior
Prior =
P(mean difference)
Likelihood =
P(data | mean difference)
0
Bayesian estimate
Frequentist estimate
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)



A is faster
B is faster
Posterior =
I want:
P(mean difference | data) ∝ Likelihood × Prior
Prior =
P(mean difference)
Likelihood =
P(data | mean difference)
0
Bayesian estimate
Frequentist estimate
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)


A is faster
B is faster
Posterior =
I want:
P(mean difference | data) ∝ Likelihood × Prior
Prior =
P(mean difference)
Likelihood =
P(data | mean difference)
0
Posterior sample
Bayesian estimate
Frequentist estimate
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)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Posterior sample
Bayesian estimate
Frequentist estimate
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−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)

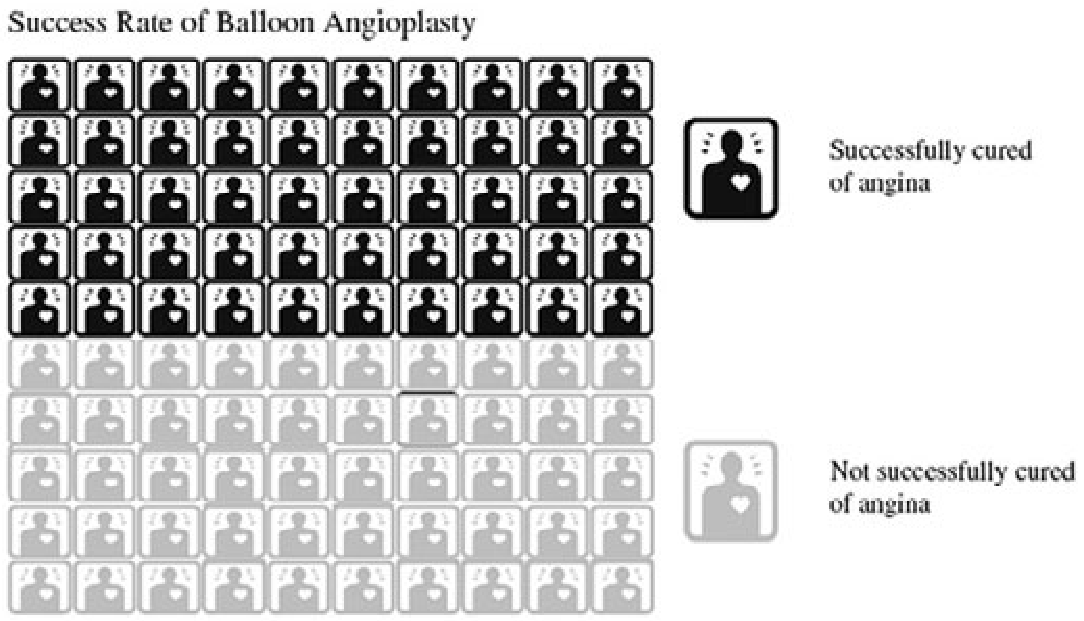
For the purposes of this talk…

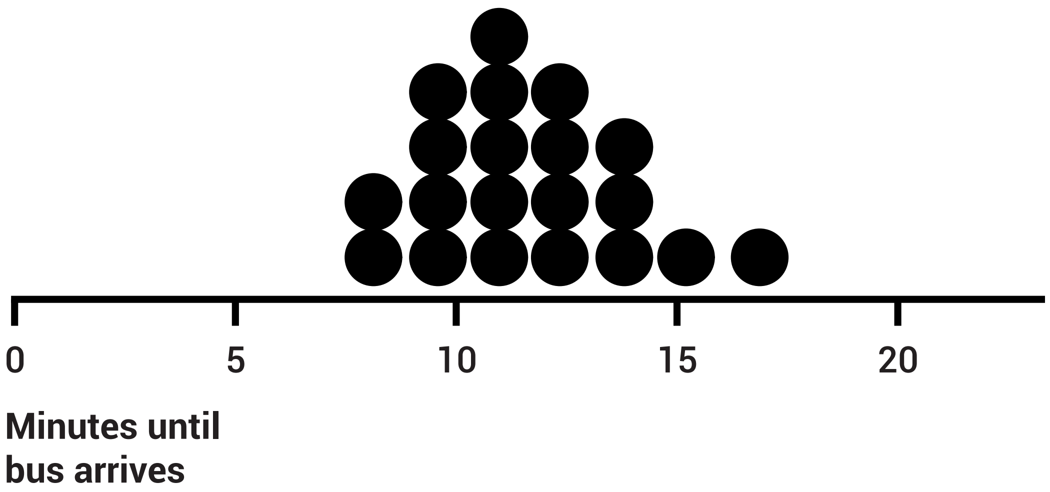
I am largely adopting a Bayesian view of uncertainty

Put another way: uncertainty is probability

(End sidebar —
Back to uncertainty vis)

Discrete outcome / frequency framing





Predictions from 2016 presidential election

[Justin H. Gross, Washington Post, http://wapo.st/2fCYvDW]

FiveThirtyEight	NYT Upshot	HuffPo Pollster
28%	15%	2%

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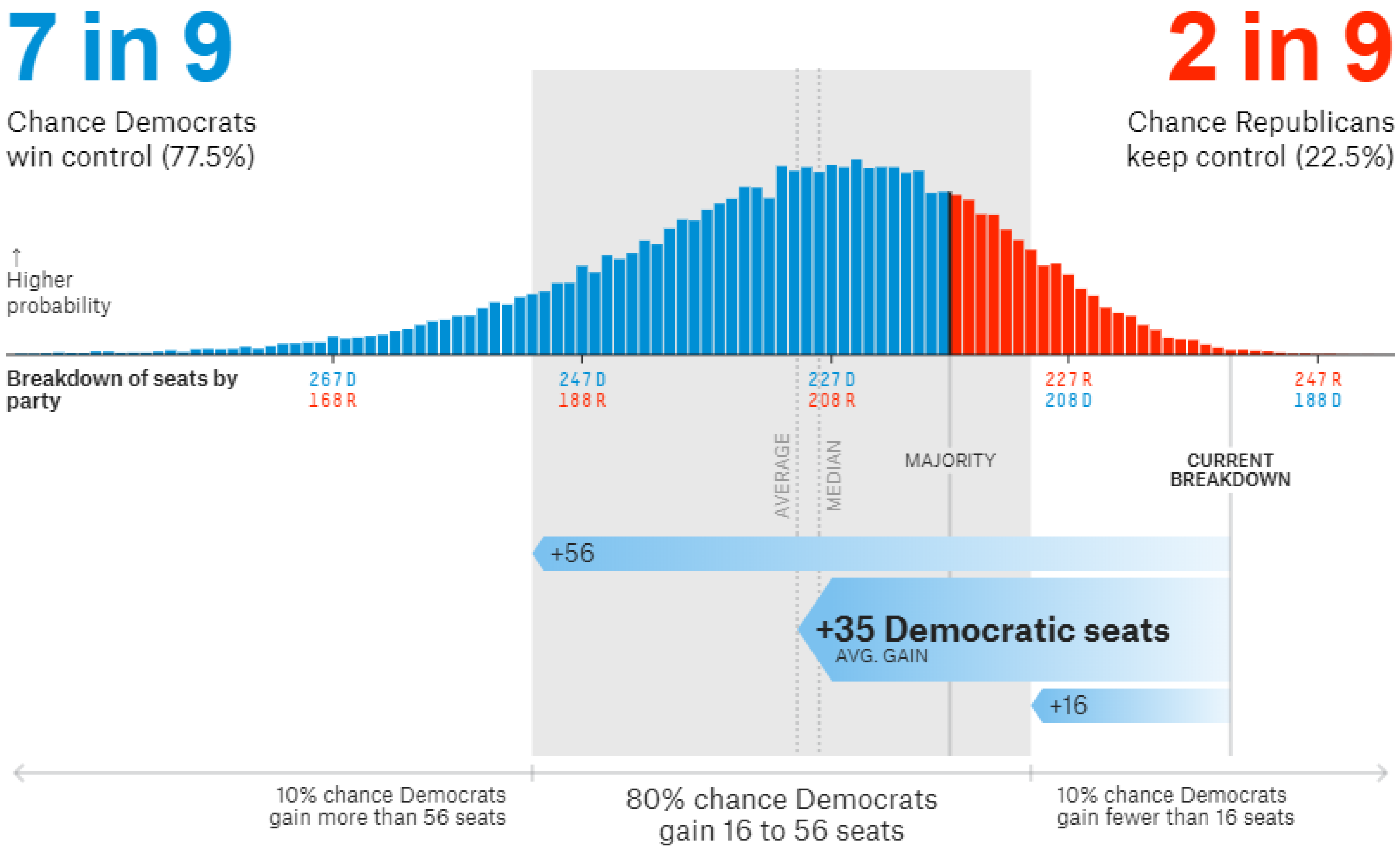
FiveThirtyEight's new House forecast

[https://projects.fivethirtyeight.com/2018-midterm-election-forecast/house/]



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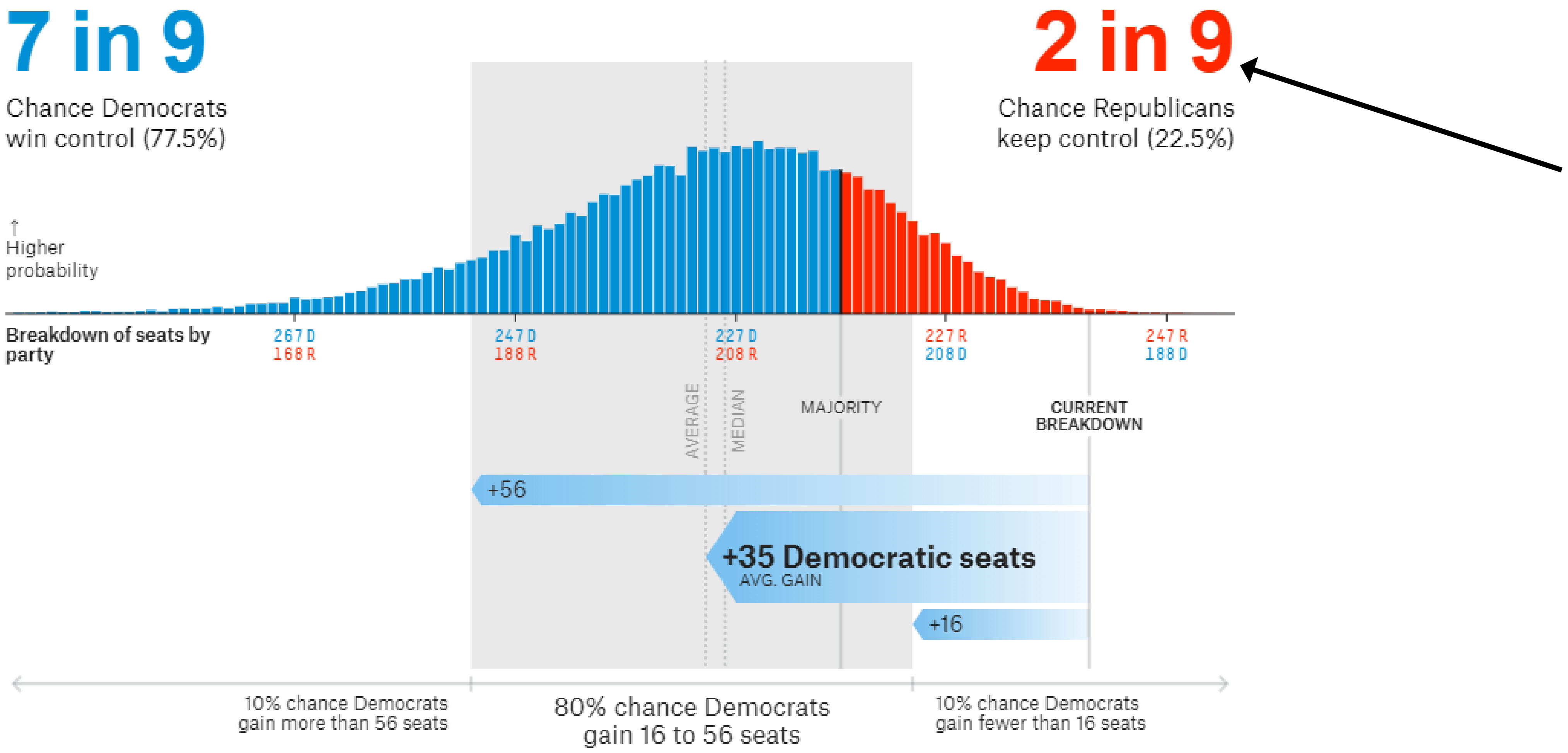

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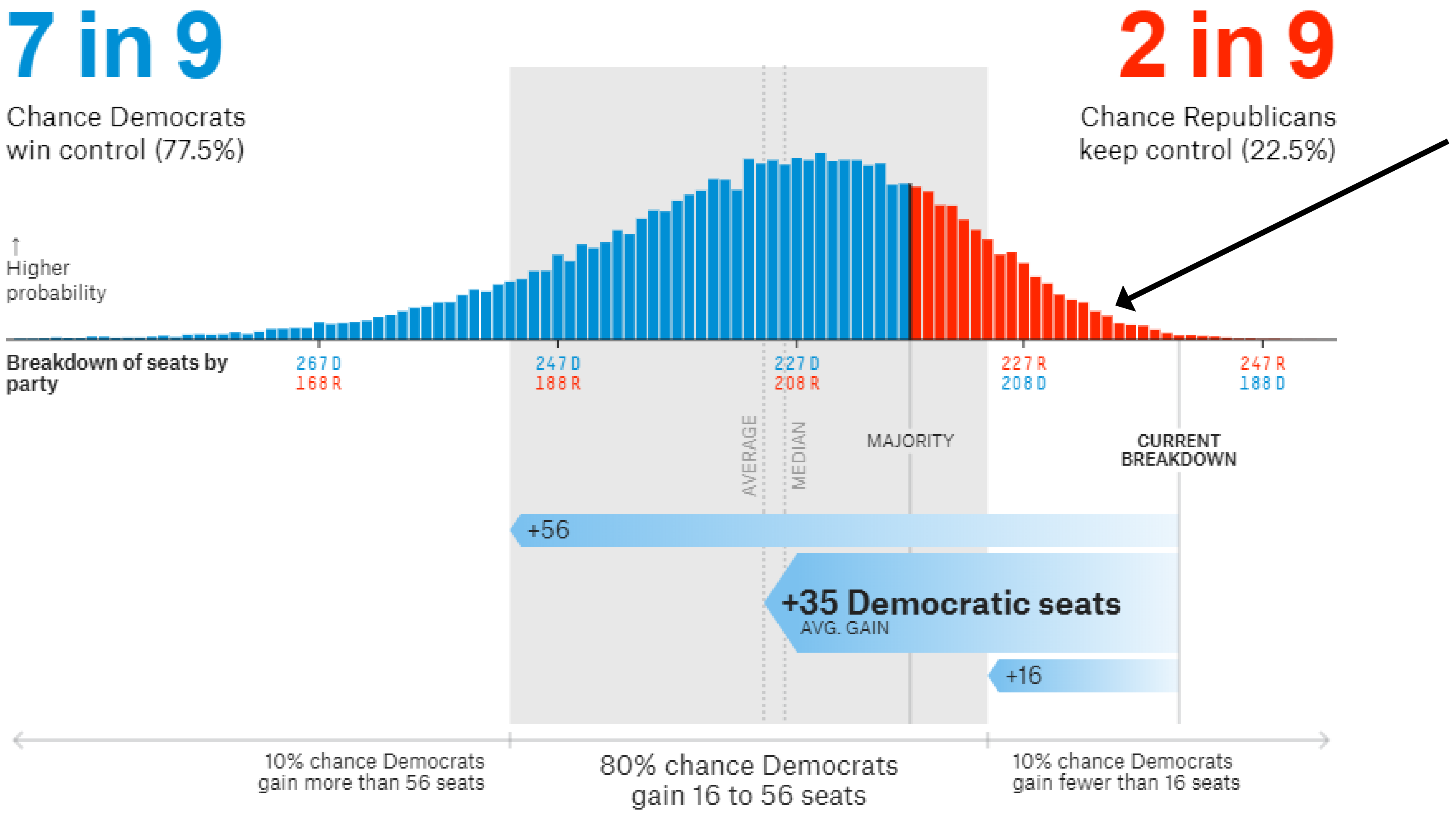
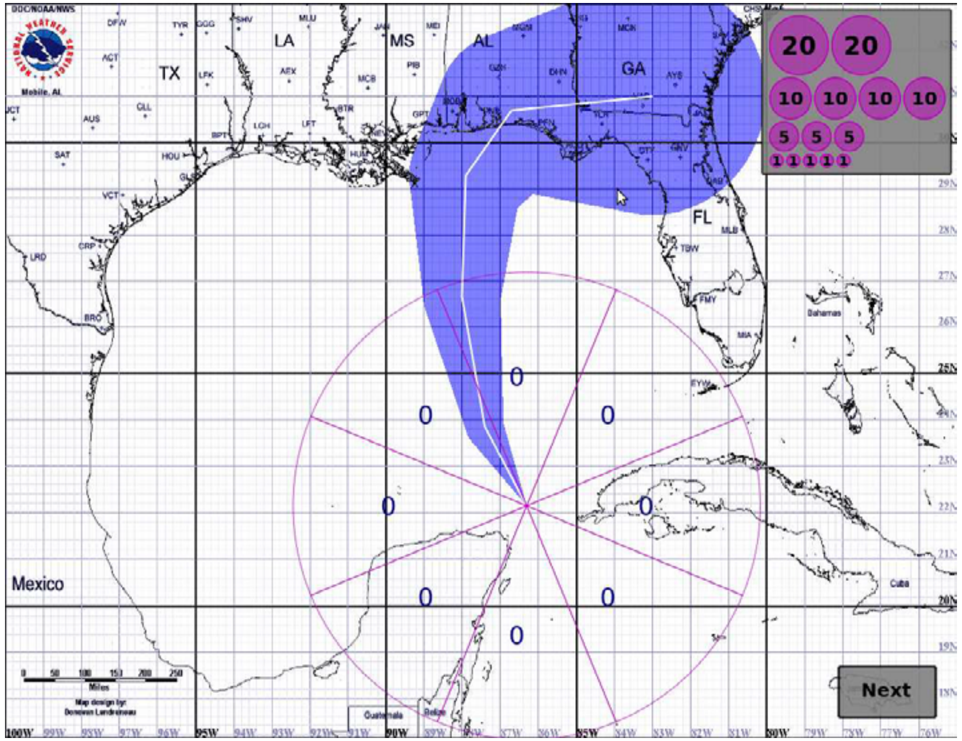


Other discrete outcome uncertainty visualizations…

Hurricane error cones

[Cox, House, Lindell. Visualizing Uncertainty in Predicted Hurricane Tracks. International Journal for Uncertainty Quantification, 3(2), 143–156, 2013]



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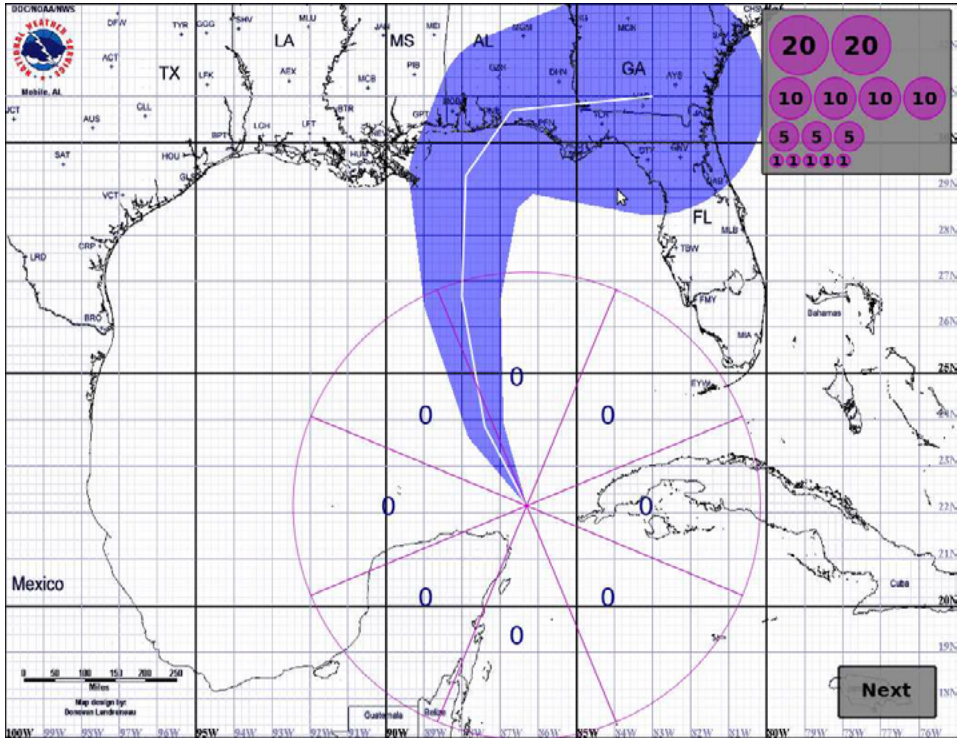
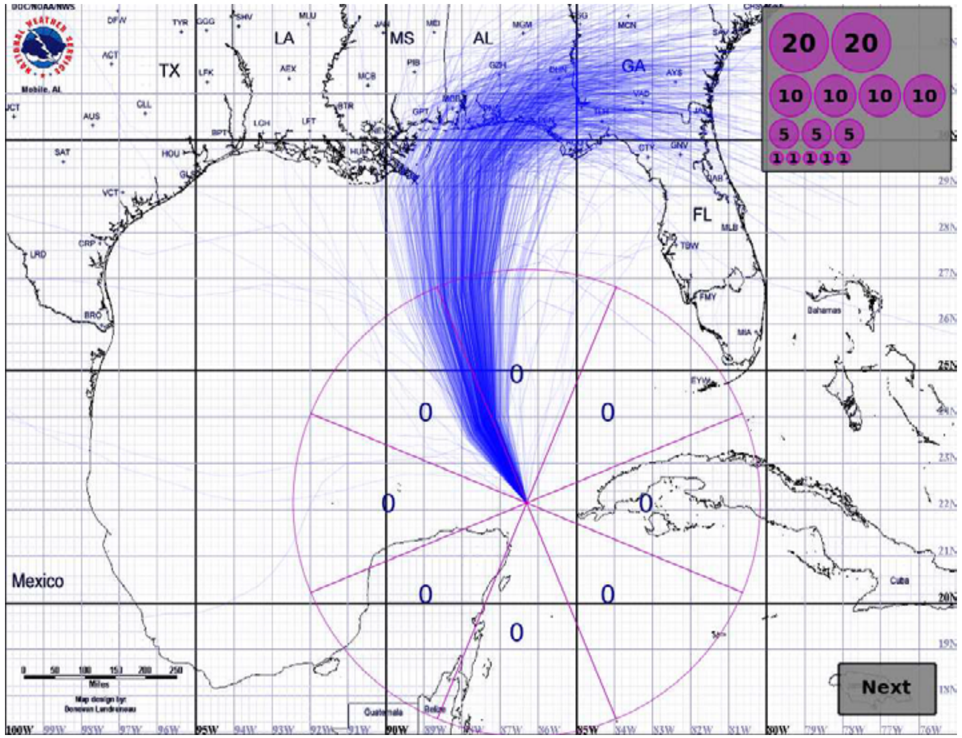
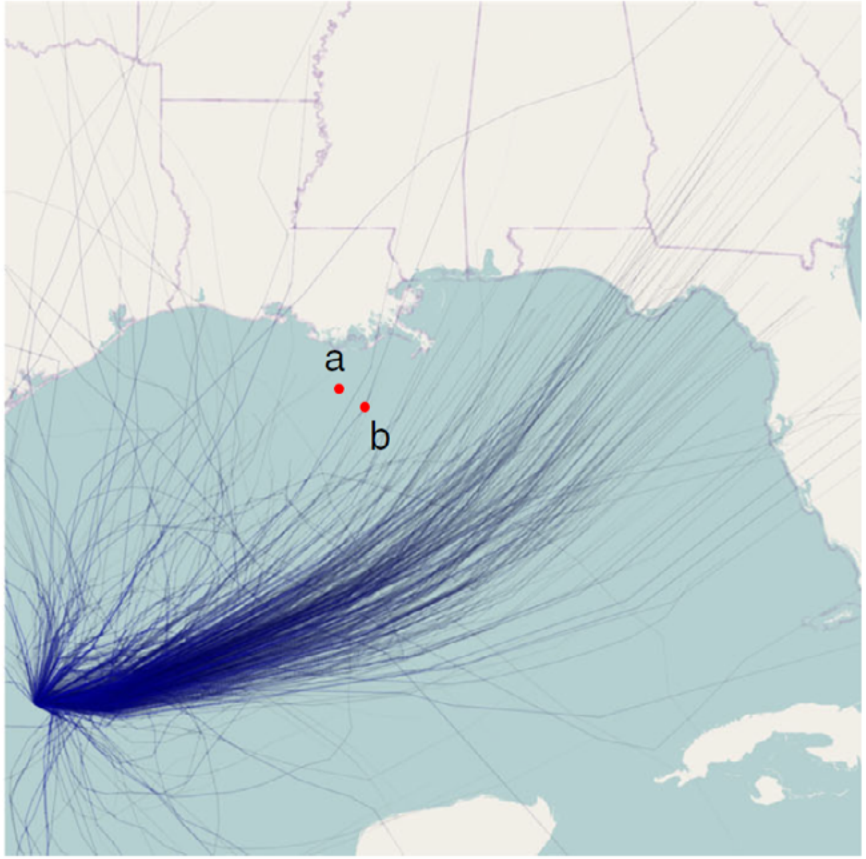




(but problems with ensembles...)

[Padilla, Ruginski, Creem-Regehr. Effects of ensemble and summary displays on interpretations of geospatial uncertainty data. Cognitive Research: Principles and Implications, 2(1), 40, 2017]



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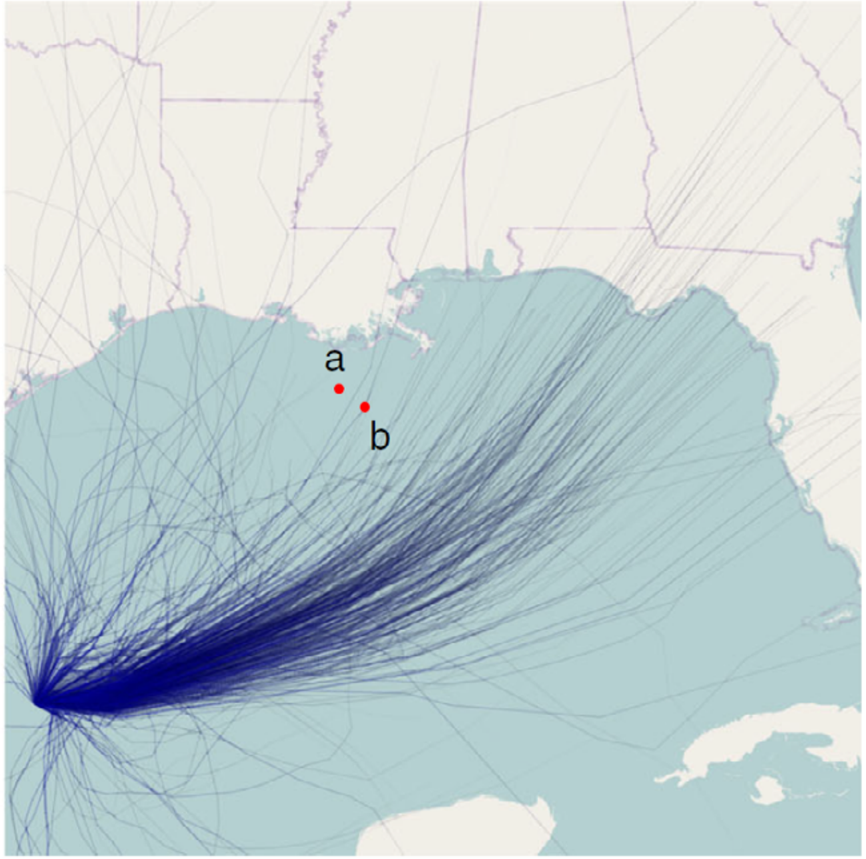
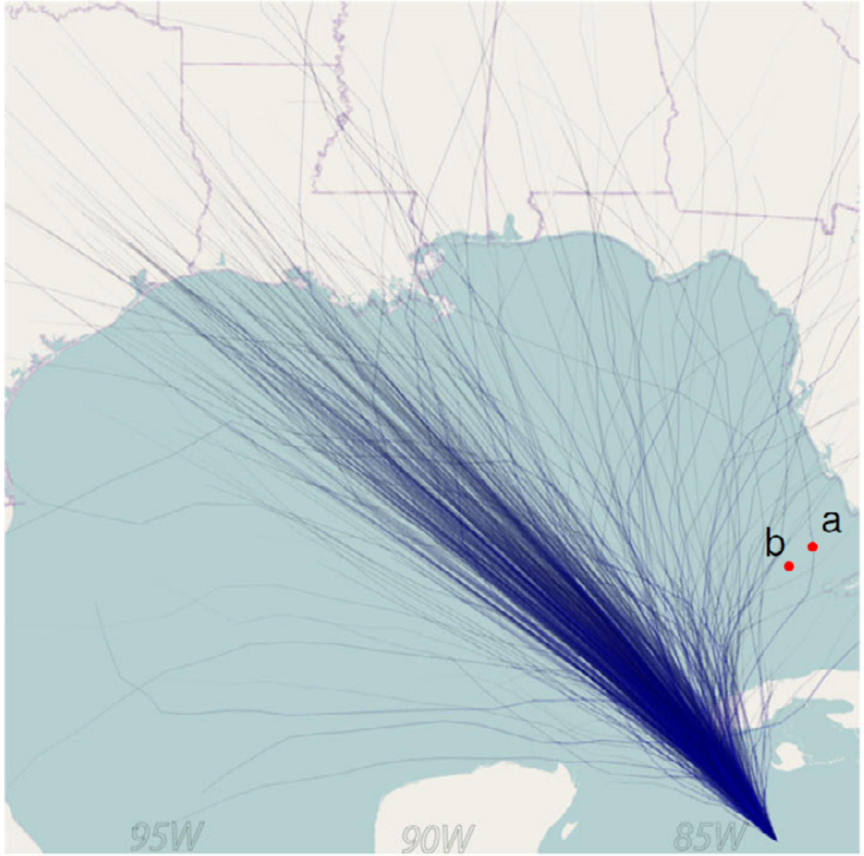
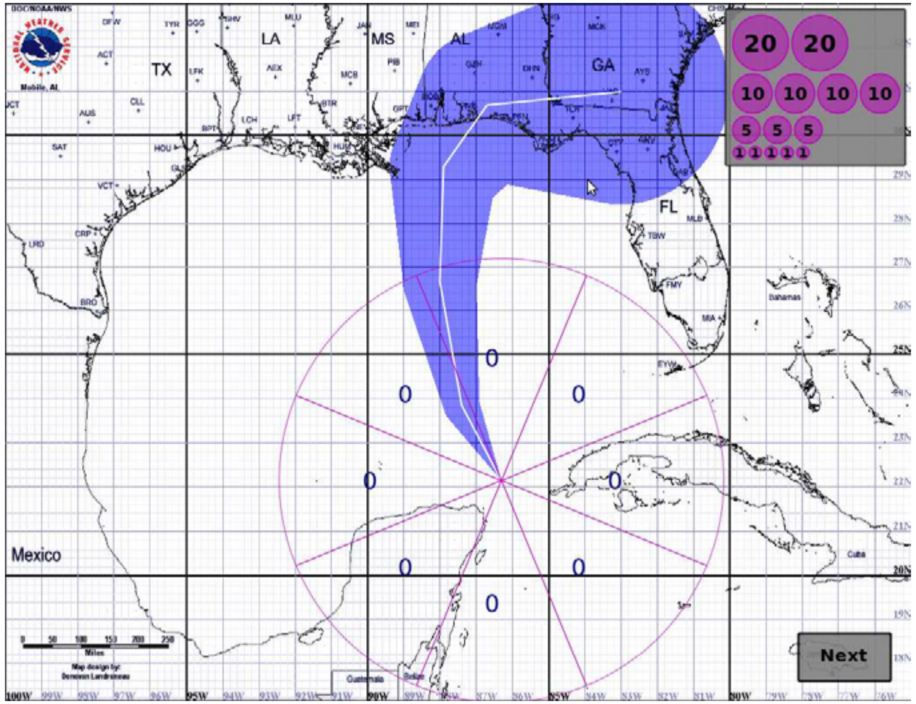




Deterministic construal errors

[Joslyn & LeClerc. Decisions With Uncertainty: The Glass Half Full. Current Directions in Psych. Science, 22(4), 2013]



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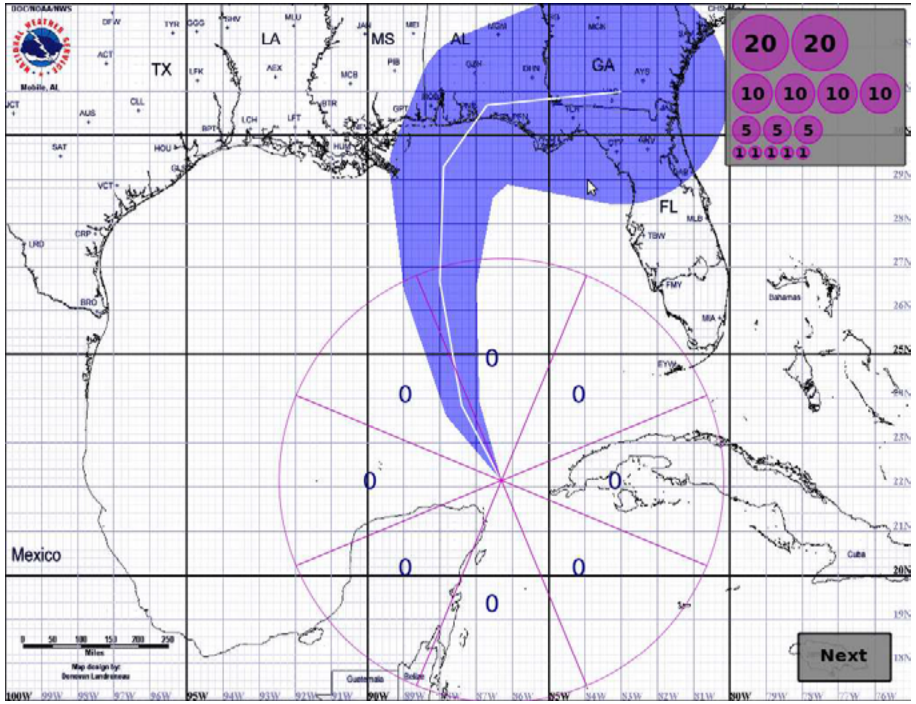

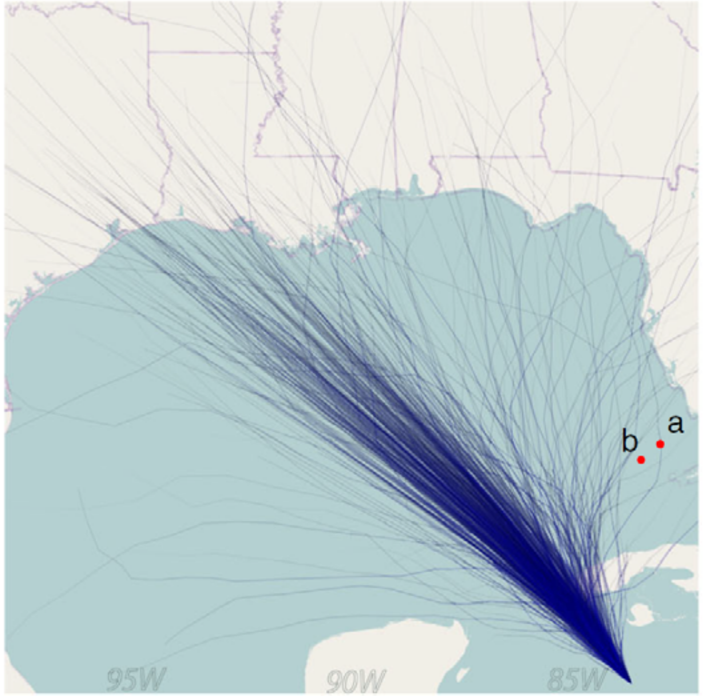

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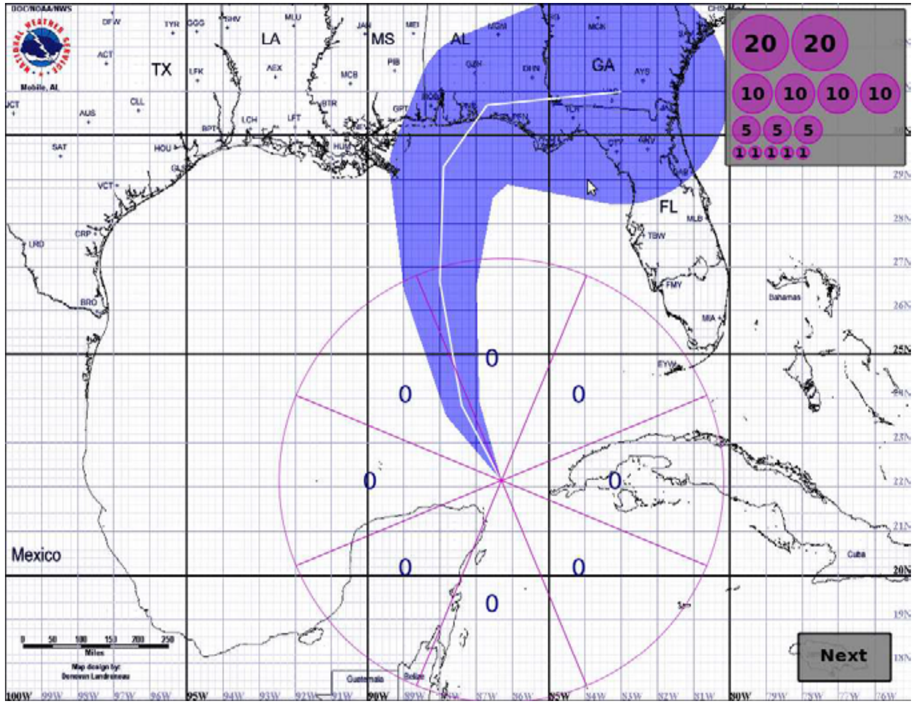
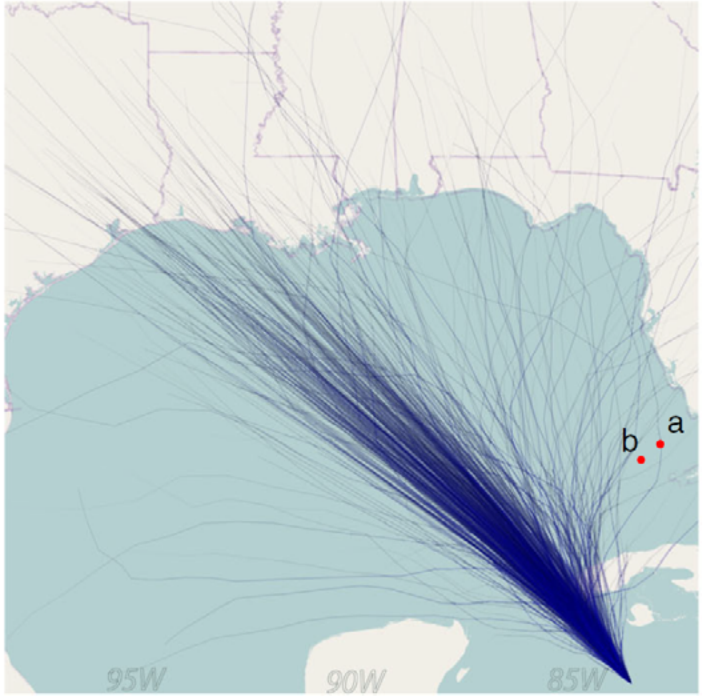
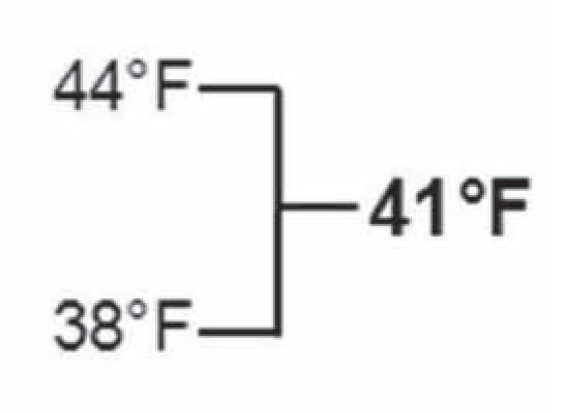
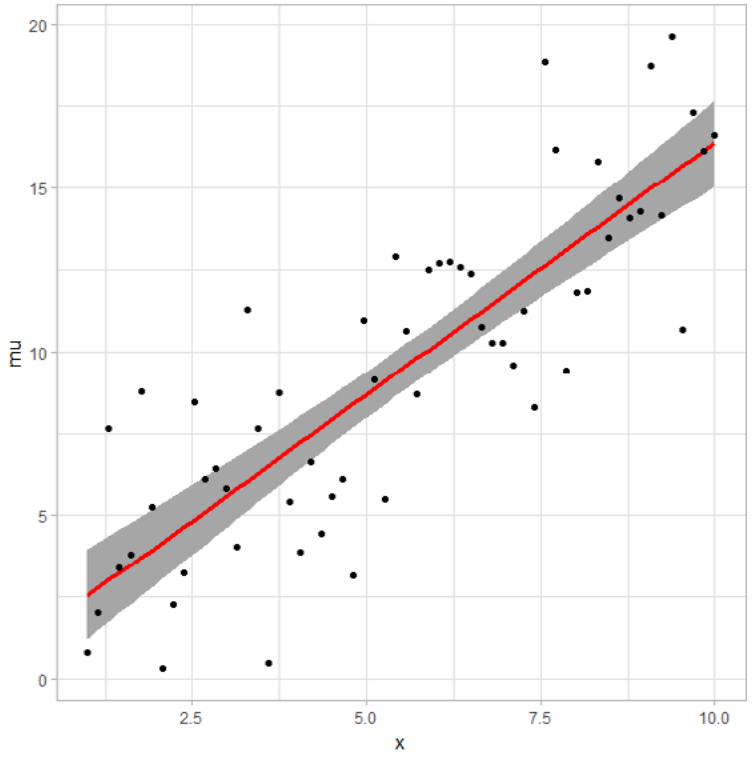


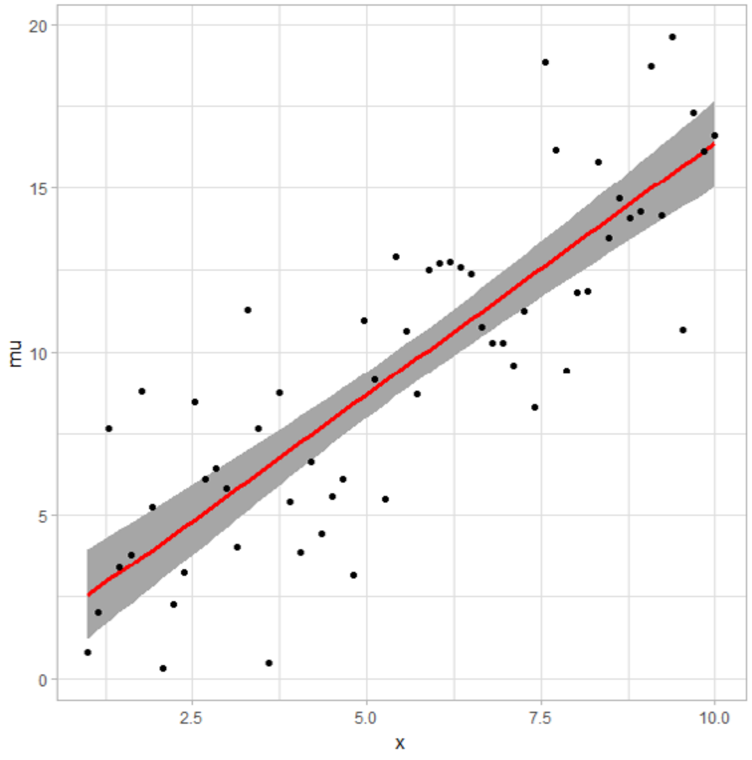


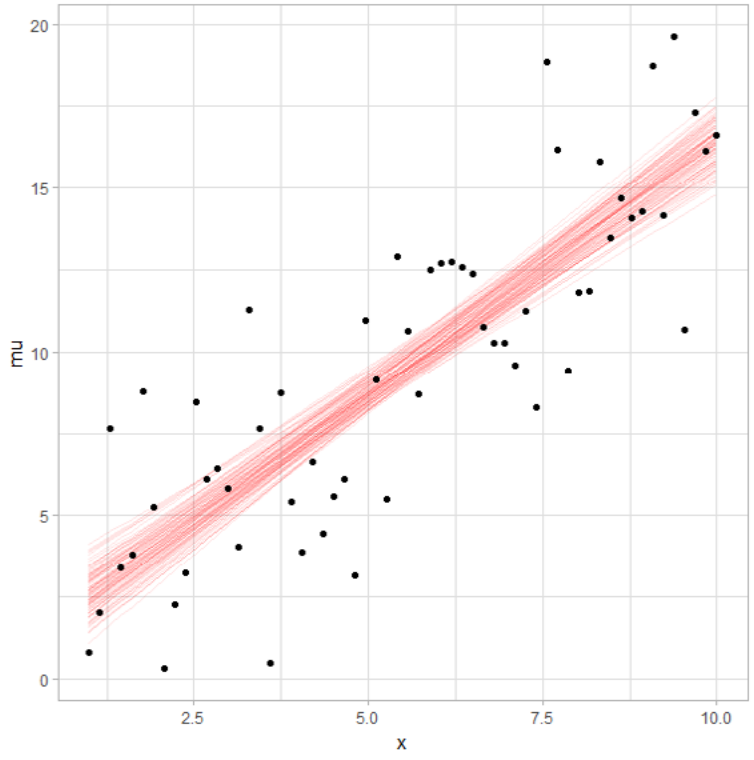


Fit line uncertainty

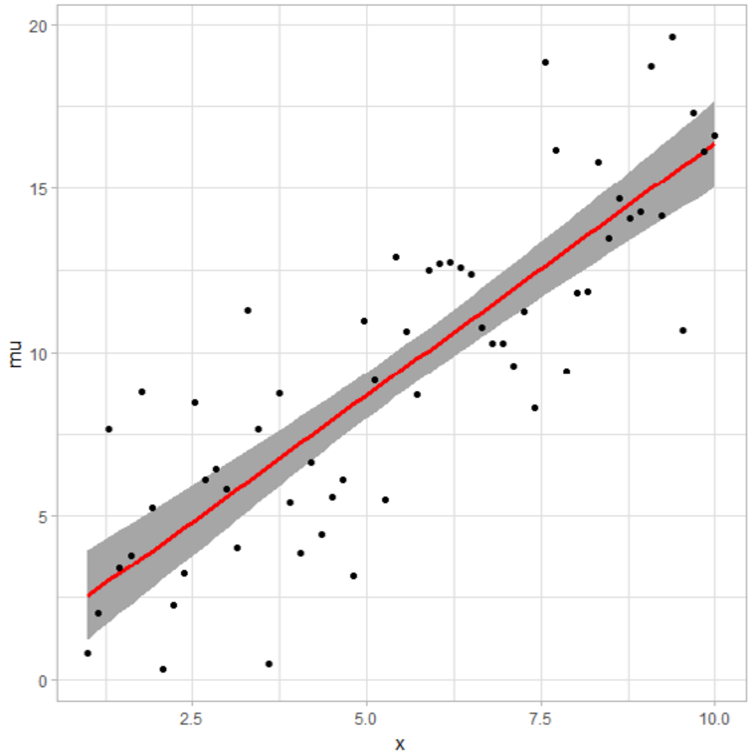


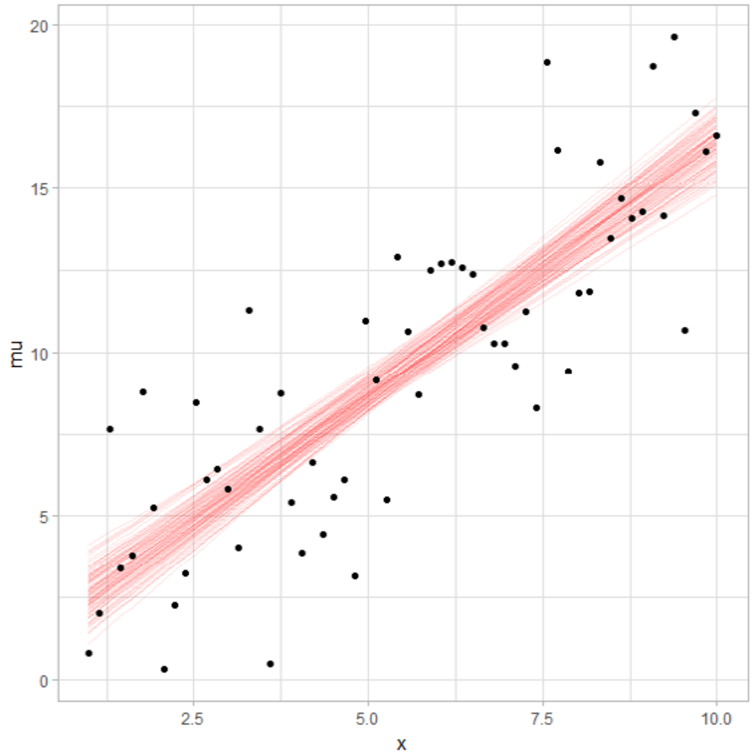
Fit line uncertainty



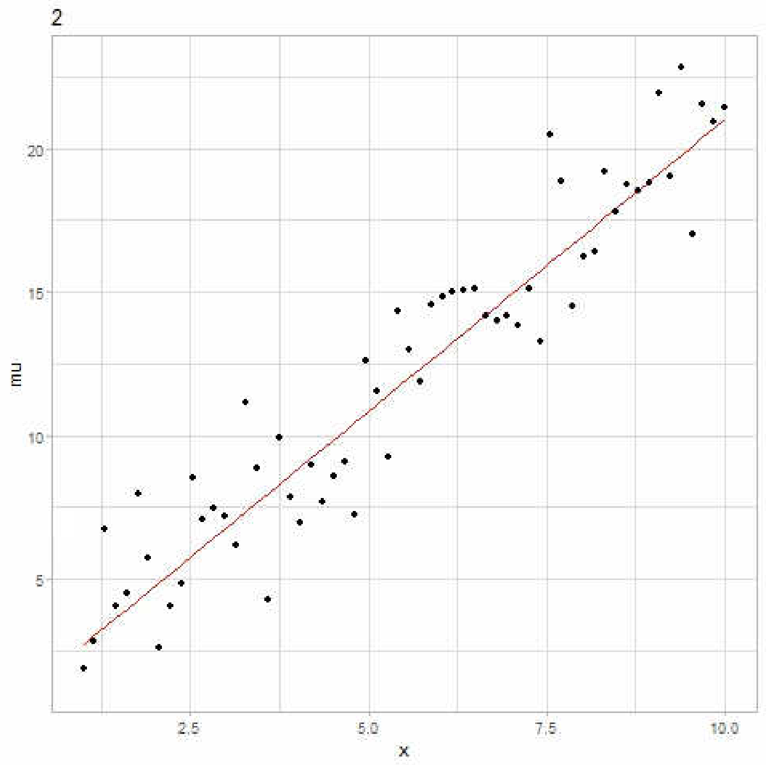


Fit line uncertainty



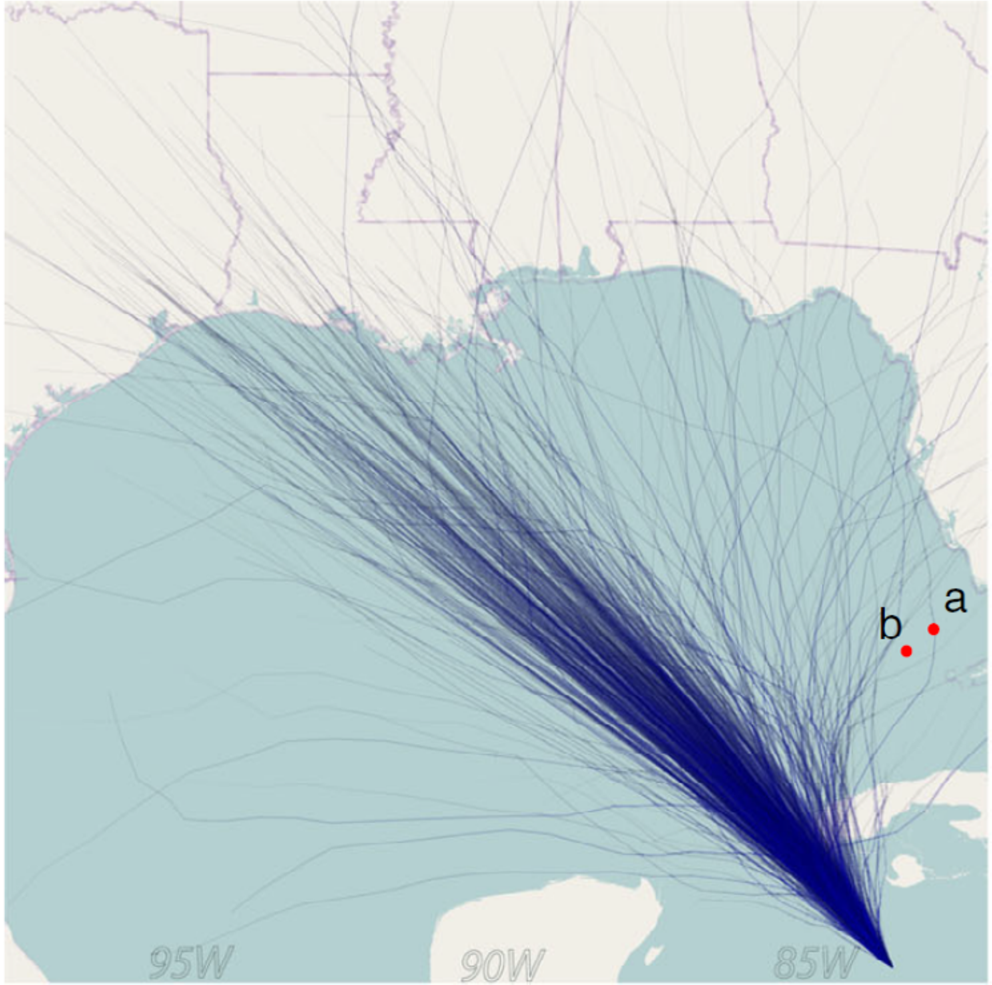


Hypothetical outcome plots (HOPs)

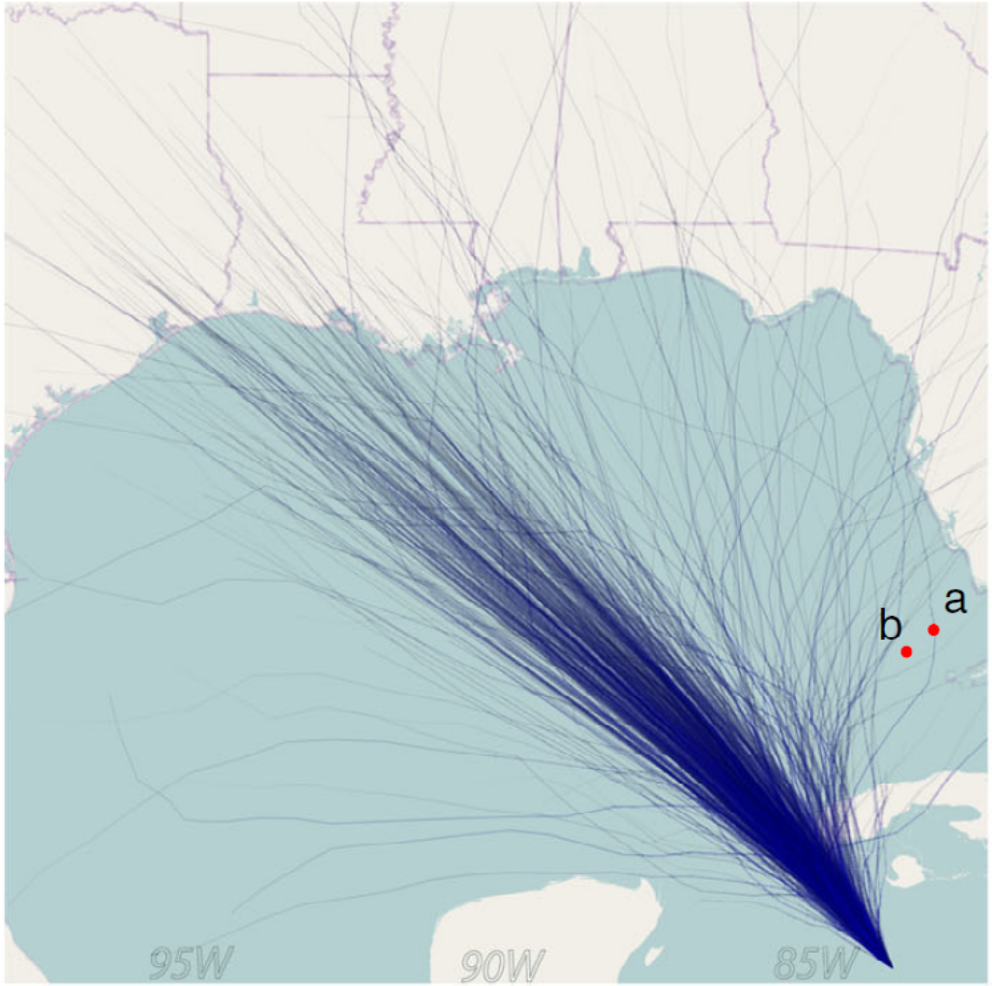


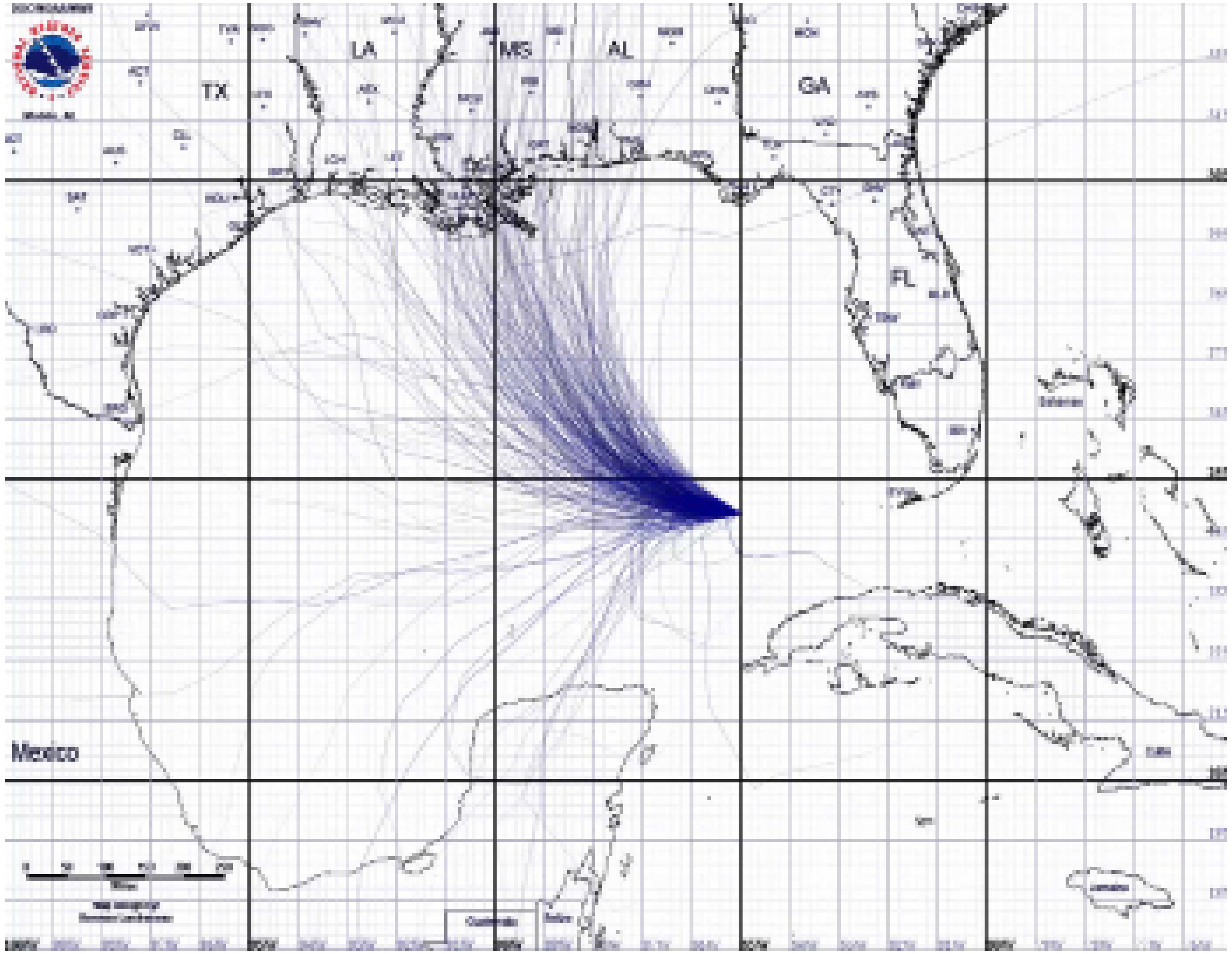
[Hullman, Resnick, Adar. Hypothetical Outcome Plots Outperform Error Bars and Violin Plots for Inferences about Reliability of Variable Ordering. PloS One, 10(11). 2015]

HOPs might aid deterministic construal errors



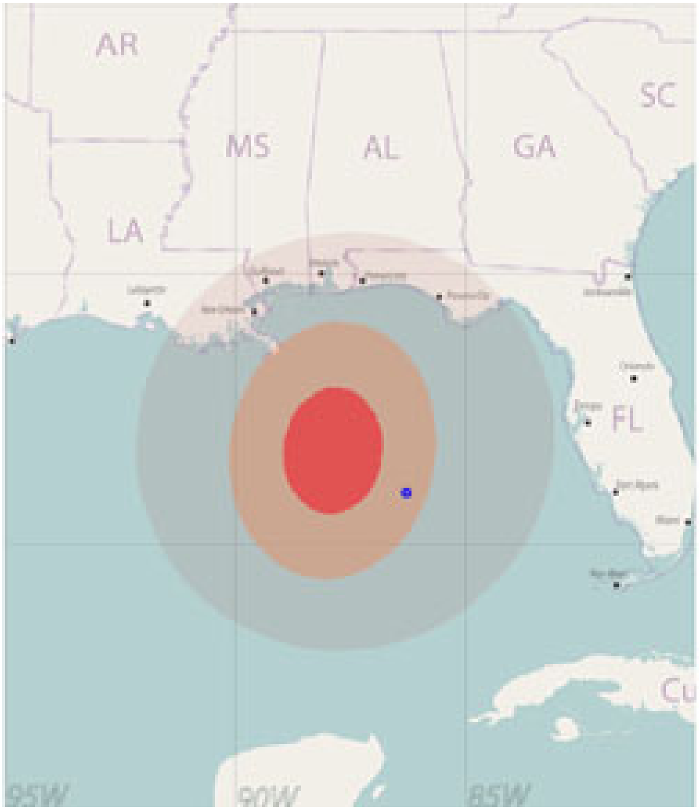
HOPs might aid deterministic construal errors





Hurricane location at a time slice…

[Liu, Boone, Ruginski, Padilla, Hegarty, Creem-Regehr, … House. Uncertainty Visualization by Representative Sampling from Prediction Ensembles. IEEE Transactions on Visualization and Computer Graphics, PP(99), 2016]



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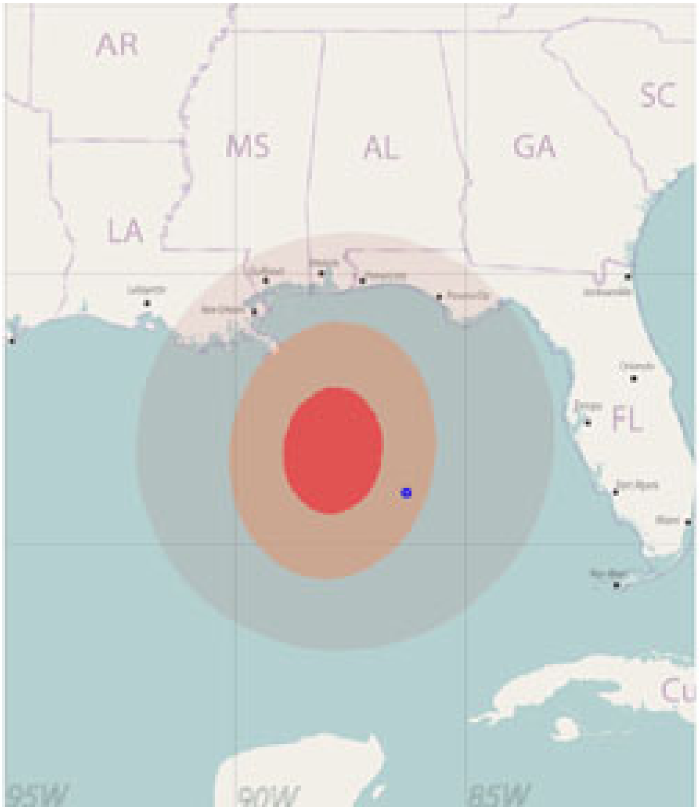
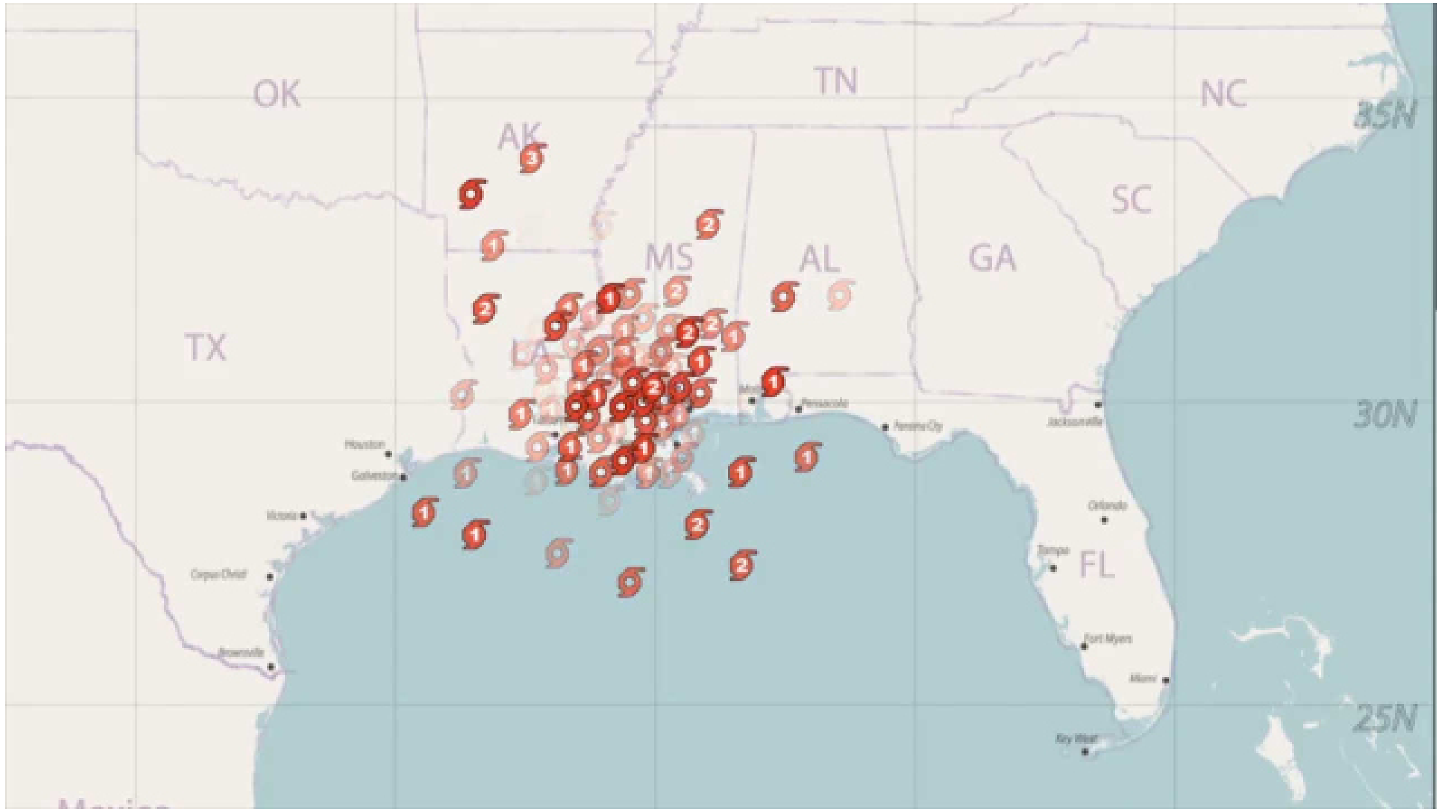


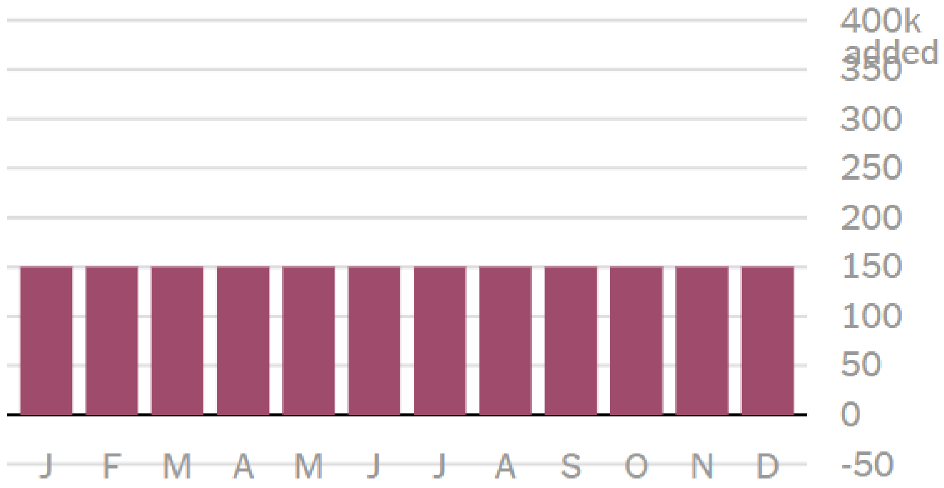


Animated uncertainty is showing up in the media...

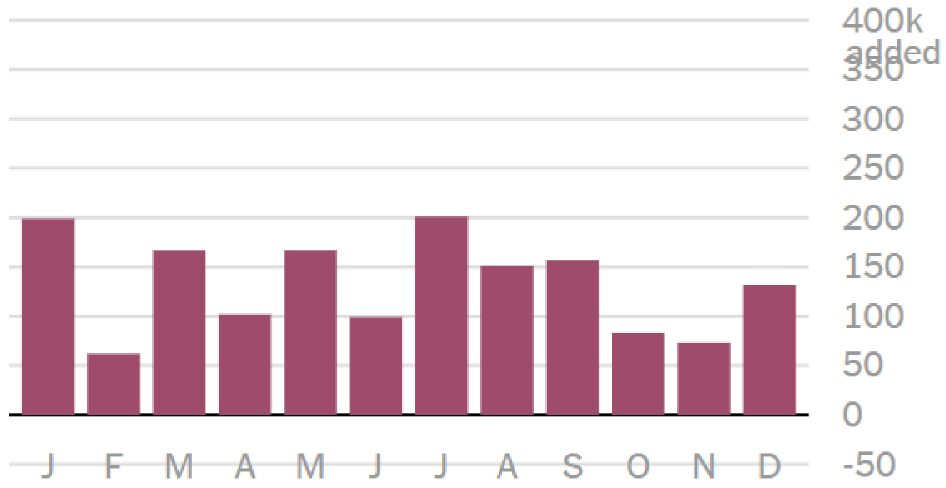
Jobs report (NYT)

[Irwin & Quealy, How Not to Be Misled by the Jobs Report, NYT The Upshot, 2014, https://nyti.ms/RyZB8a]

If job growth **were actually steady** over the last 12 months...



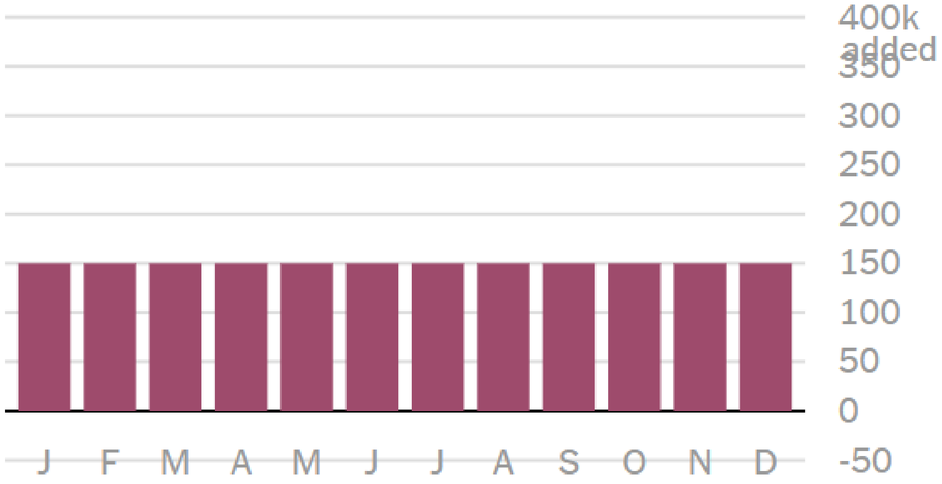
...the jobs report **could look like this**:



Turn out this actually works!

[Kale, Nguyen, **Kay**, Hullman. Hypothetical Outcome Plots Help Untrained Observers Judge Trends in Ambiguous Data. IEEE TVCG (Proc. InfoVis), 2018]

If job growth **were actually steady** over the last 12 months...



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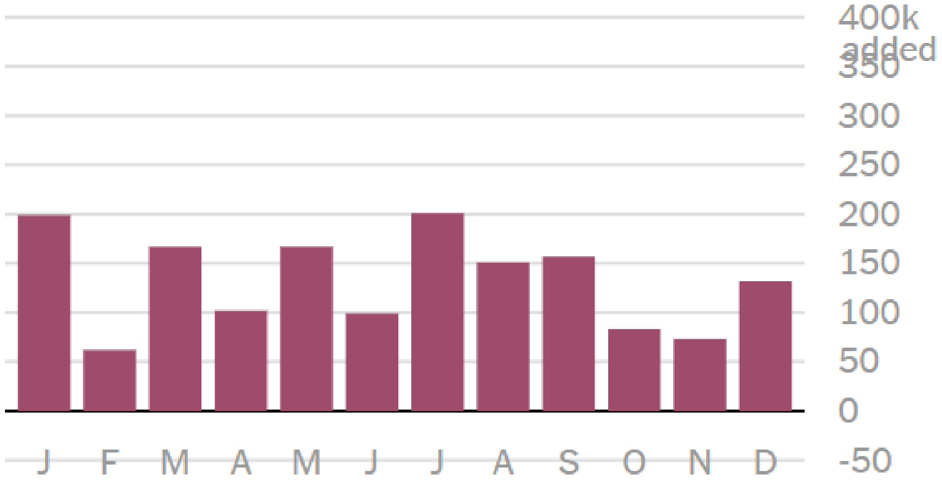
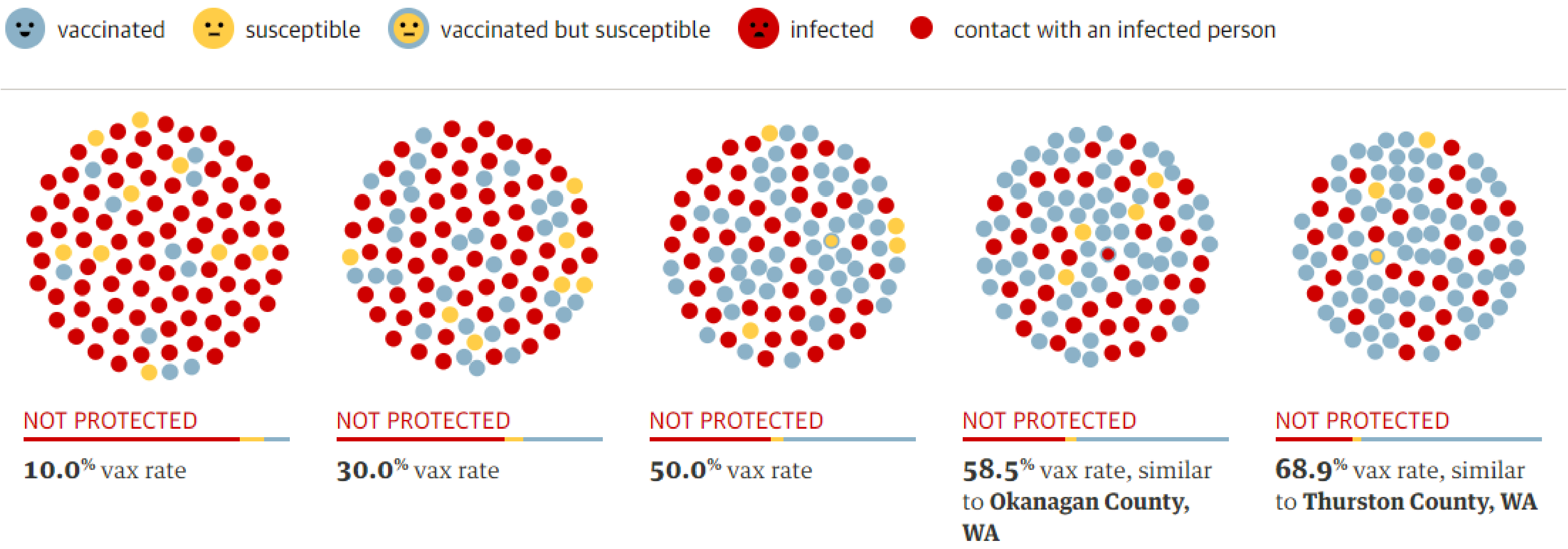


Measles vaccination

[Harris, Popovich, Powell, Watch how the measles outbreak spreads when kids get vaccinated – and when they don't, The Guardian, 2015, https://www.theguardian.com/society/ng-interactive/2015/feb/05/-sp-watch-how-measles-outbreak-spreads-when-kids-get-vaccinated]

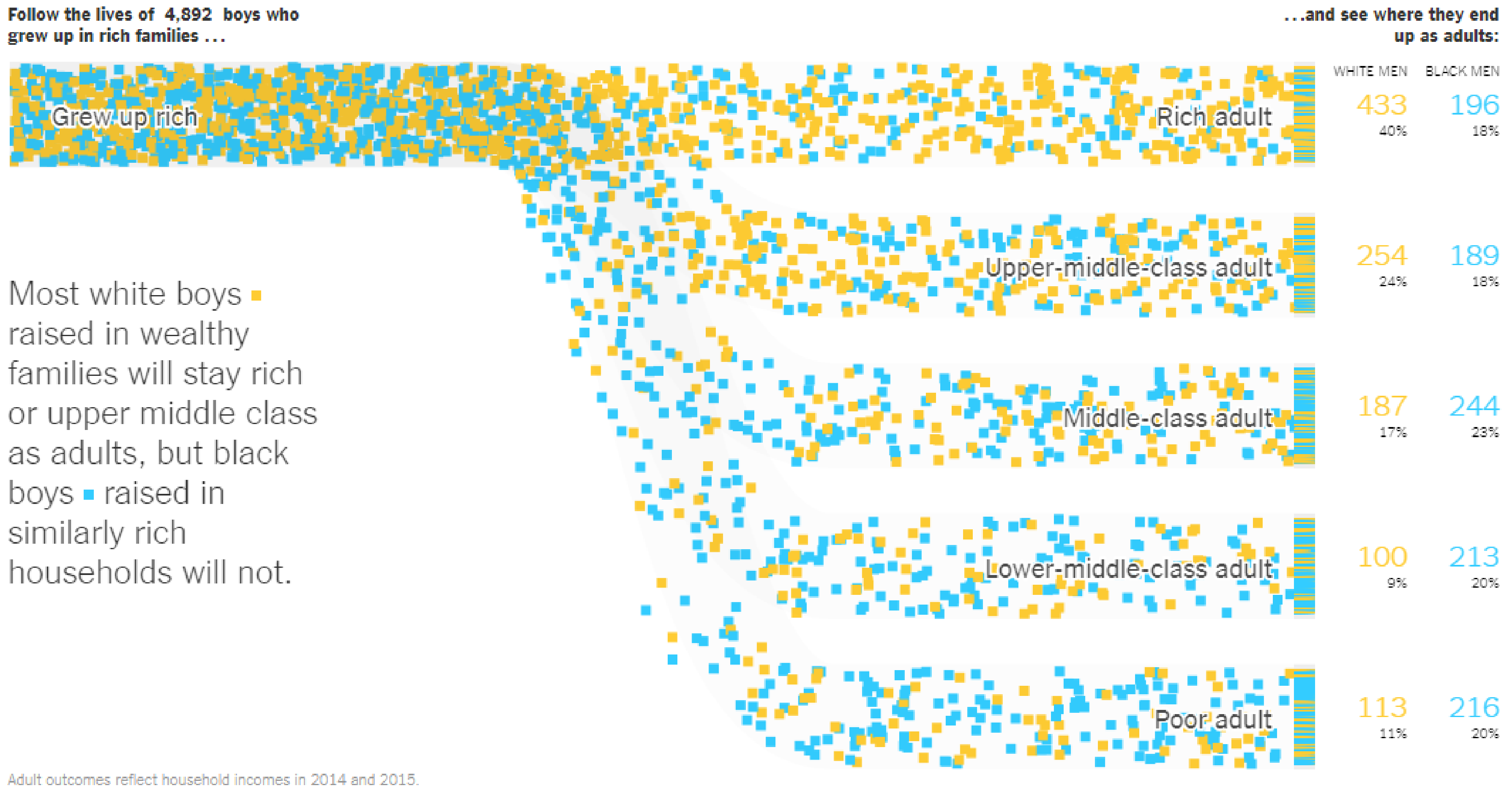


Animation helps people experience uncertainty

This can be very powerful...

Income of black boys from wealthy families

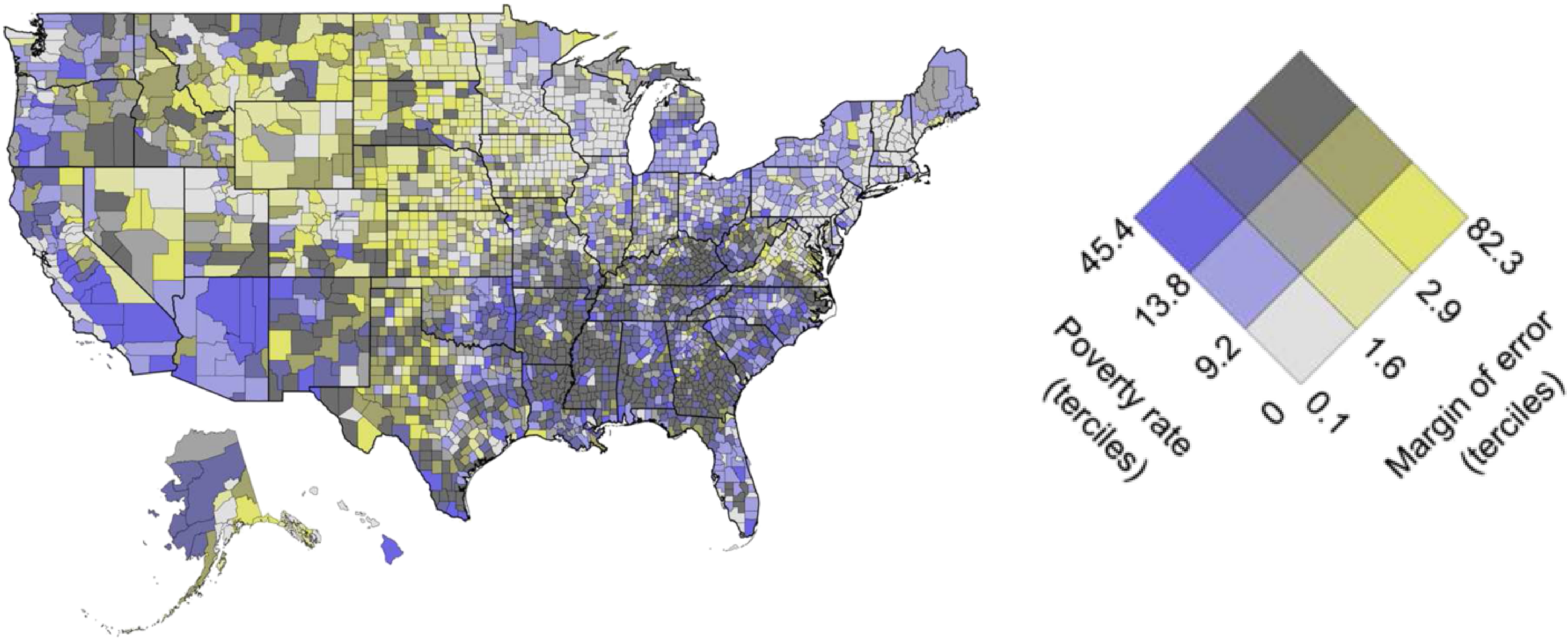
[Badger, Miller, Pearce, Quealy. Extensive Data Shows Punishing Reach of Racism for Black Boys, NYT Upshot, 2018, https://nyti.ms/2GGpFZw]



Cartographic uncertainty

Just map to another visual channel, right?

[Lucchesi & Wikle. Visualizing uncertainty in areal data with bivariate choropleth maps, map pixelation and glyph rotation. Stat, 292–302, 2017]



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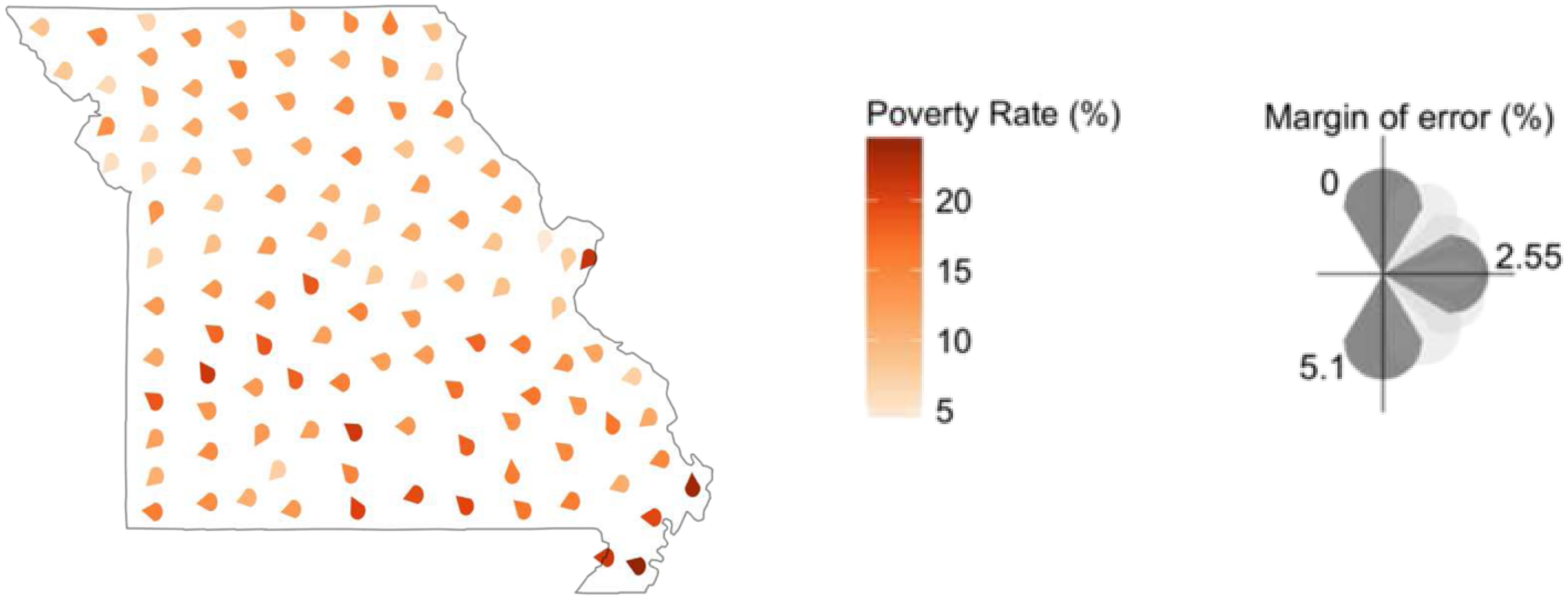

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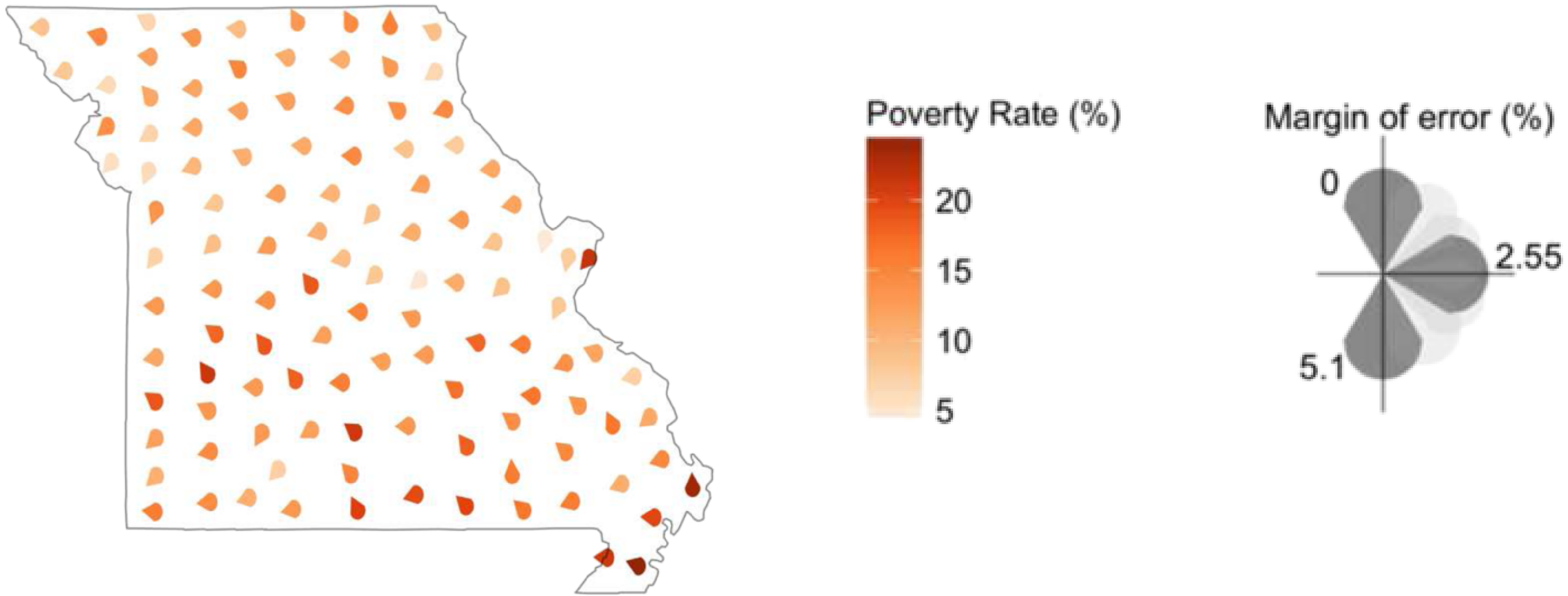
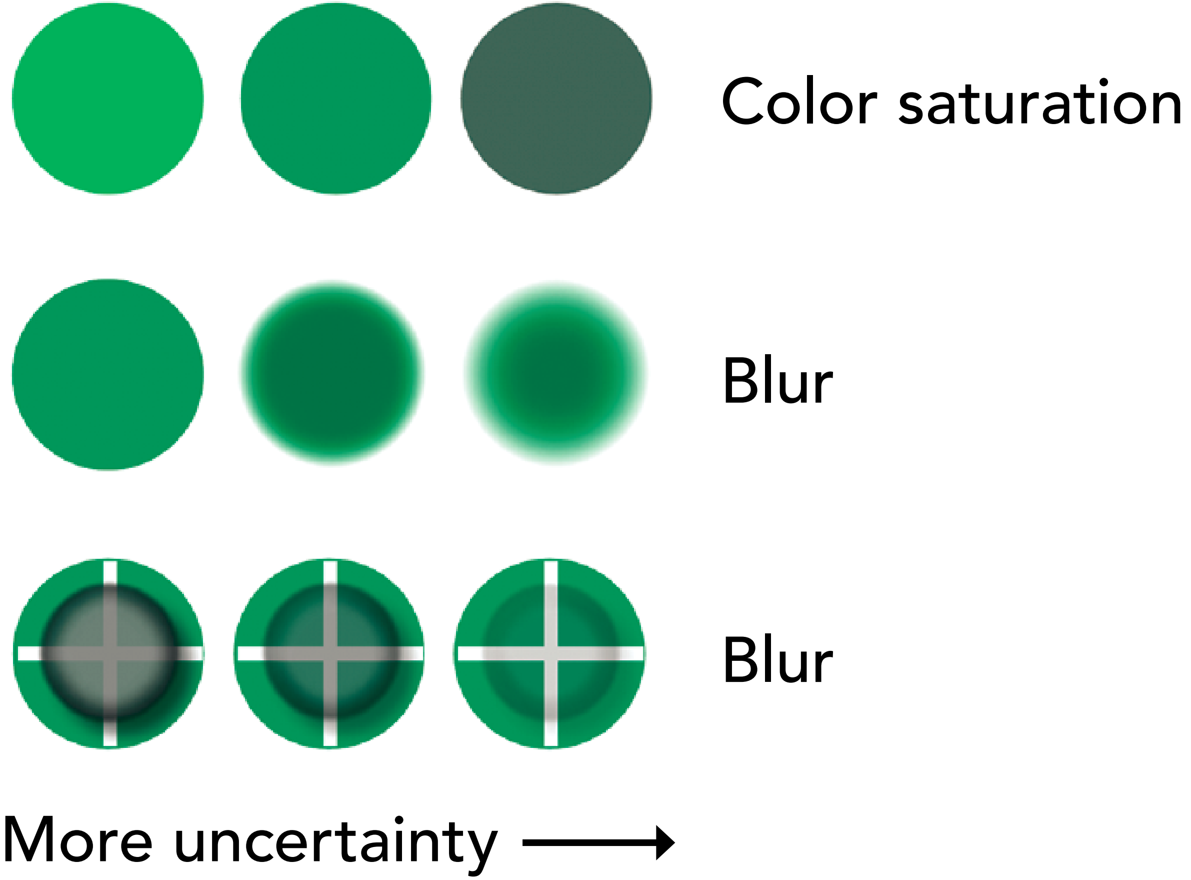


Very abstract…

Glyph-based uncertainty

[MacEachren, Robinson, Hopper, Gardner, Murray, Gahegan, Hetzler. Visualizing geospatial information uncertainty: What we know and what we need to know. Cartography and Geographic Information Science, 32(3), 139-160, 2005]



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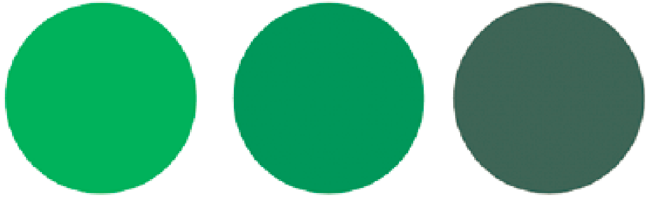
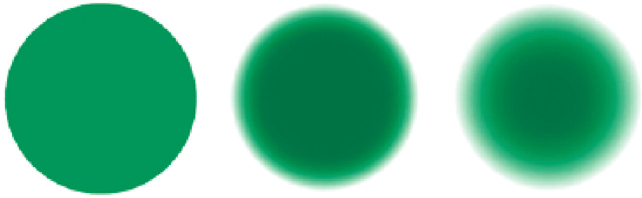


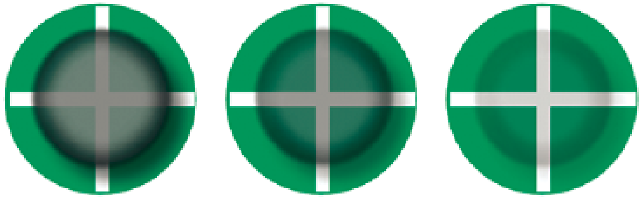
Color saturation



Blur

More intuitive?

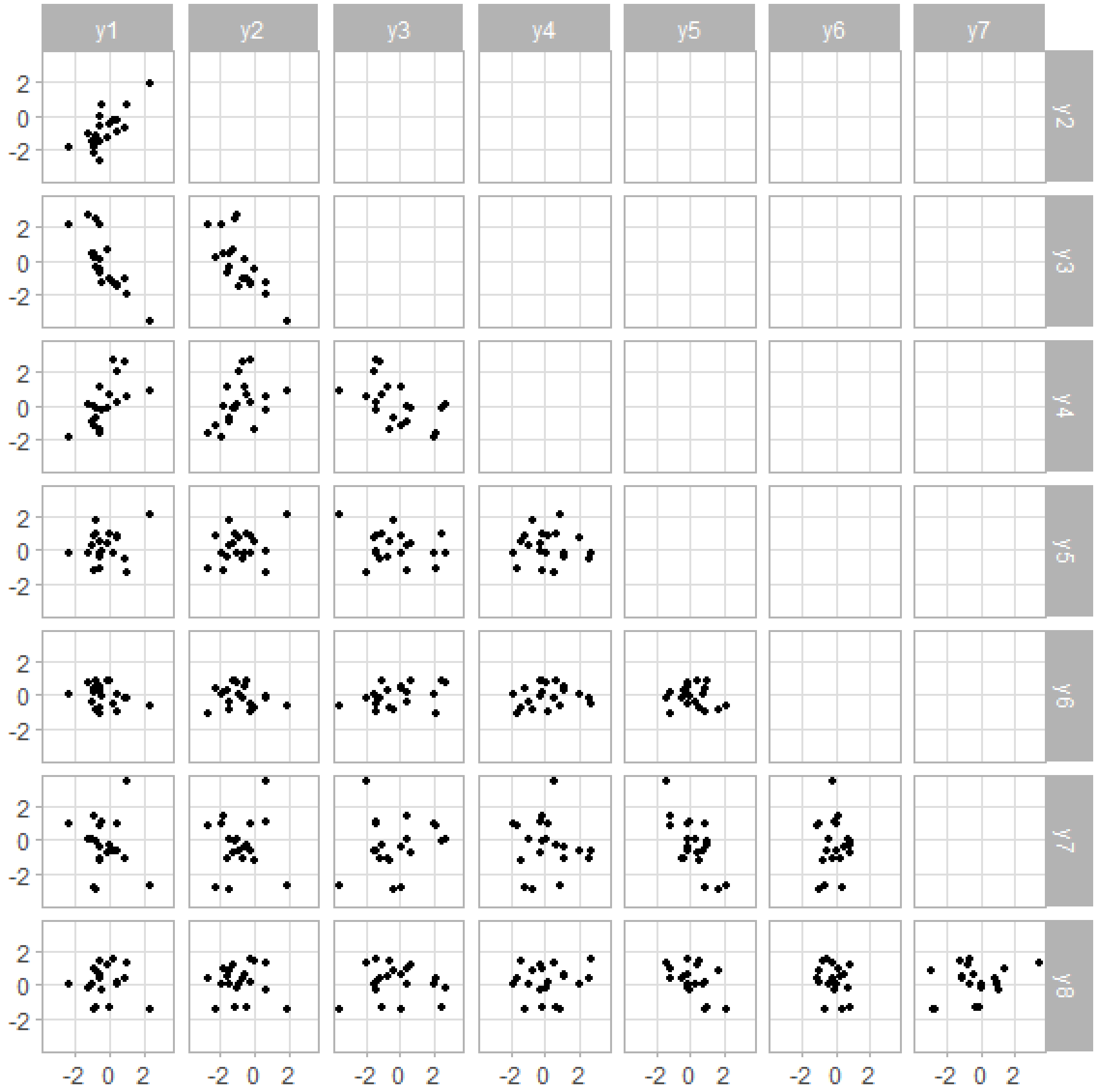
But how accurate?

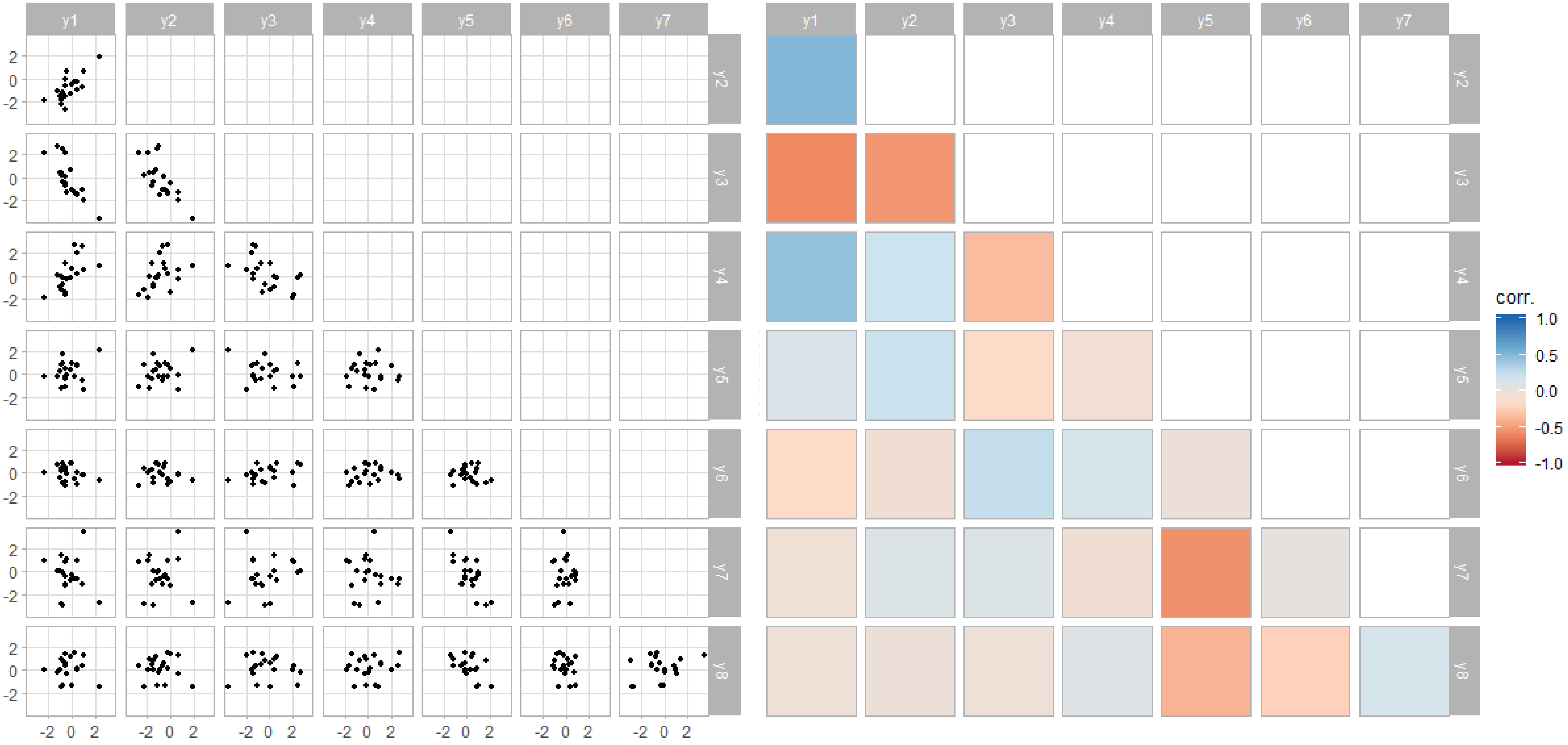


Blur

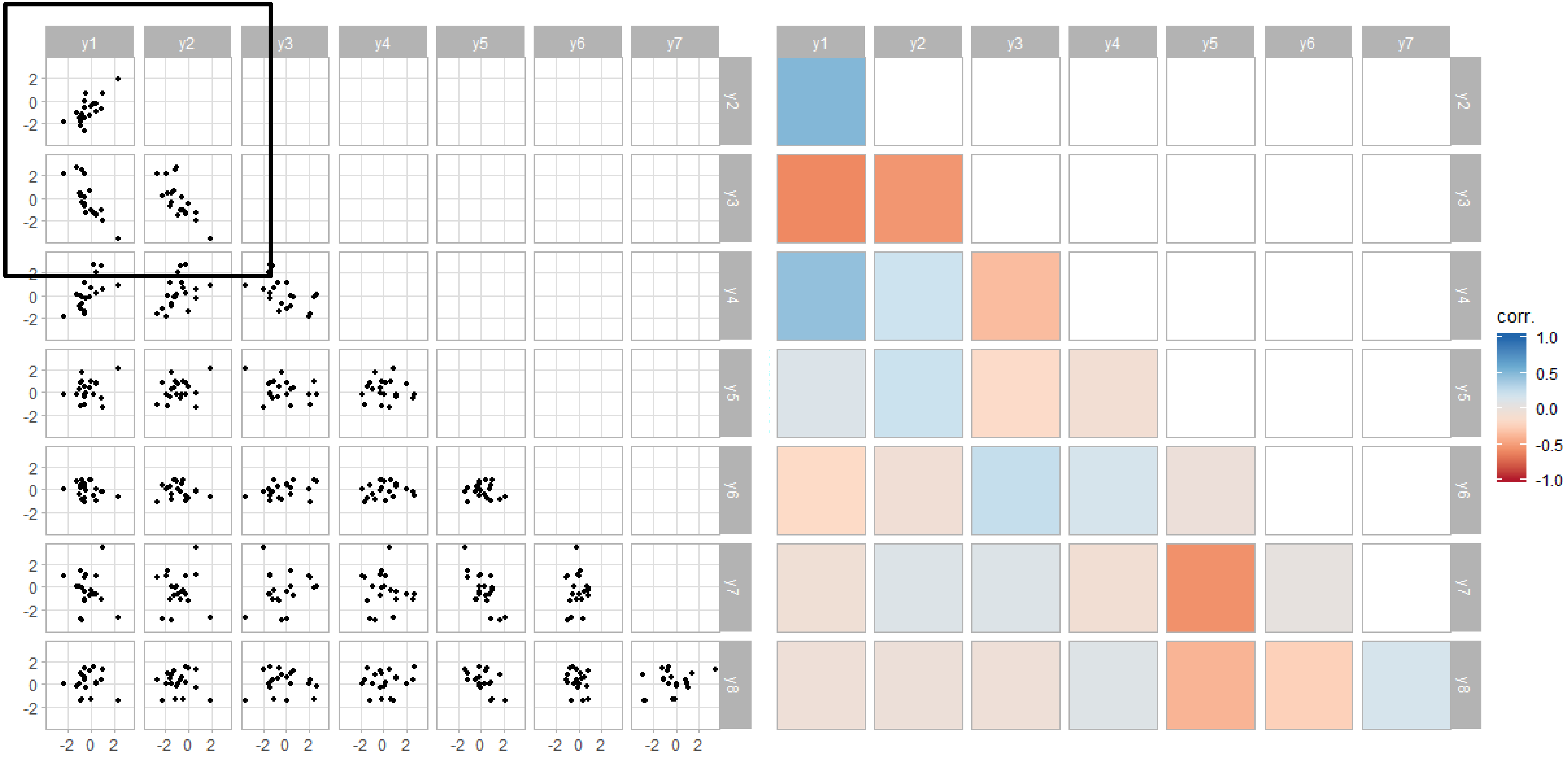
More uncertainty →

I'm not a GIS person, so let’s take a little detour

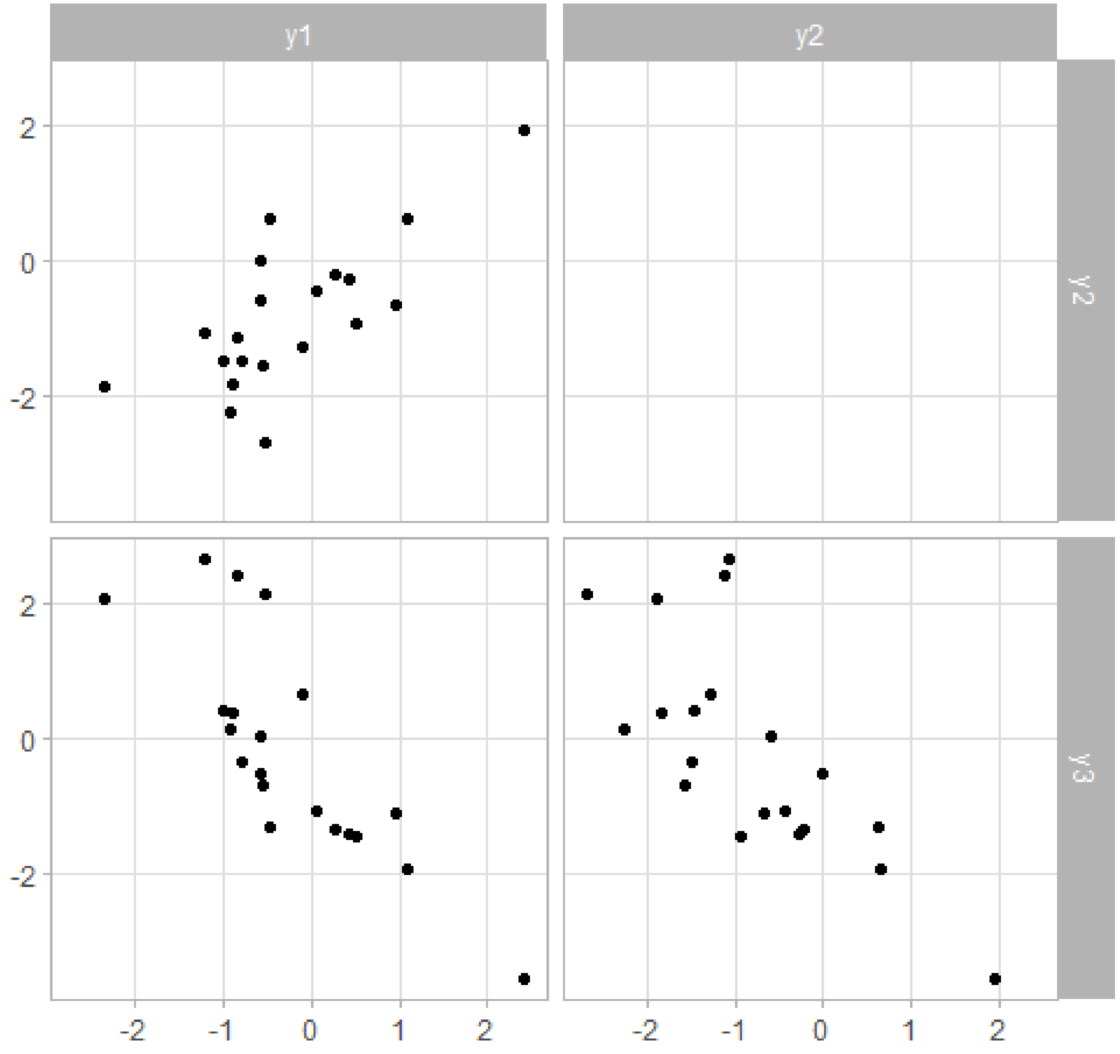

y1
y2
y3
y4
y5
y6
y7
y2
y3
y4
y5
y6
y7
y8
2
0
-2
-2 0 2



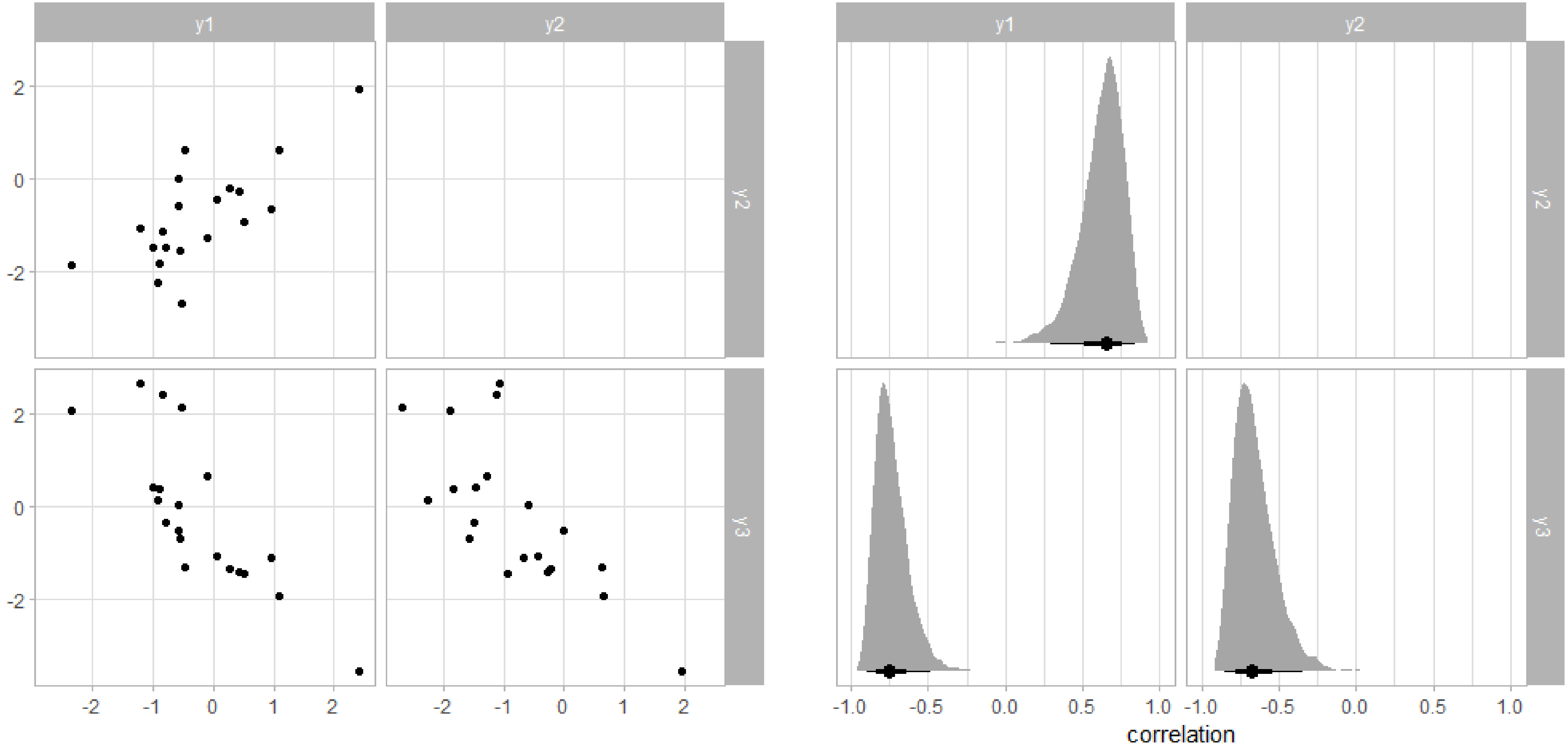
y1
y2
y3
y4
y5
y6
y7
y8
2
0
-2
corr.
1.0
0.5
0.0
-0.5
-1.0



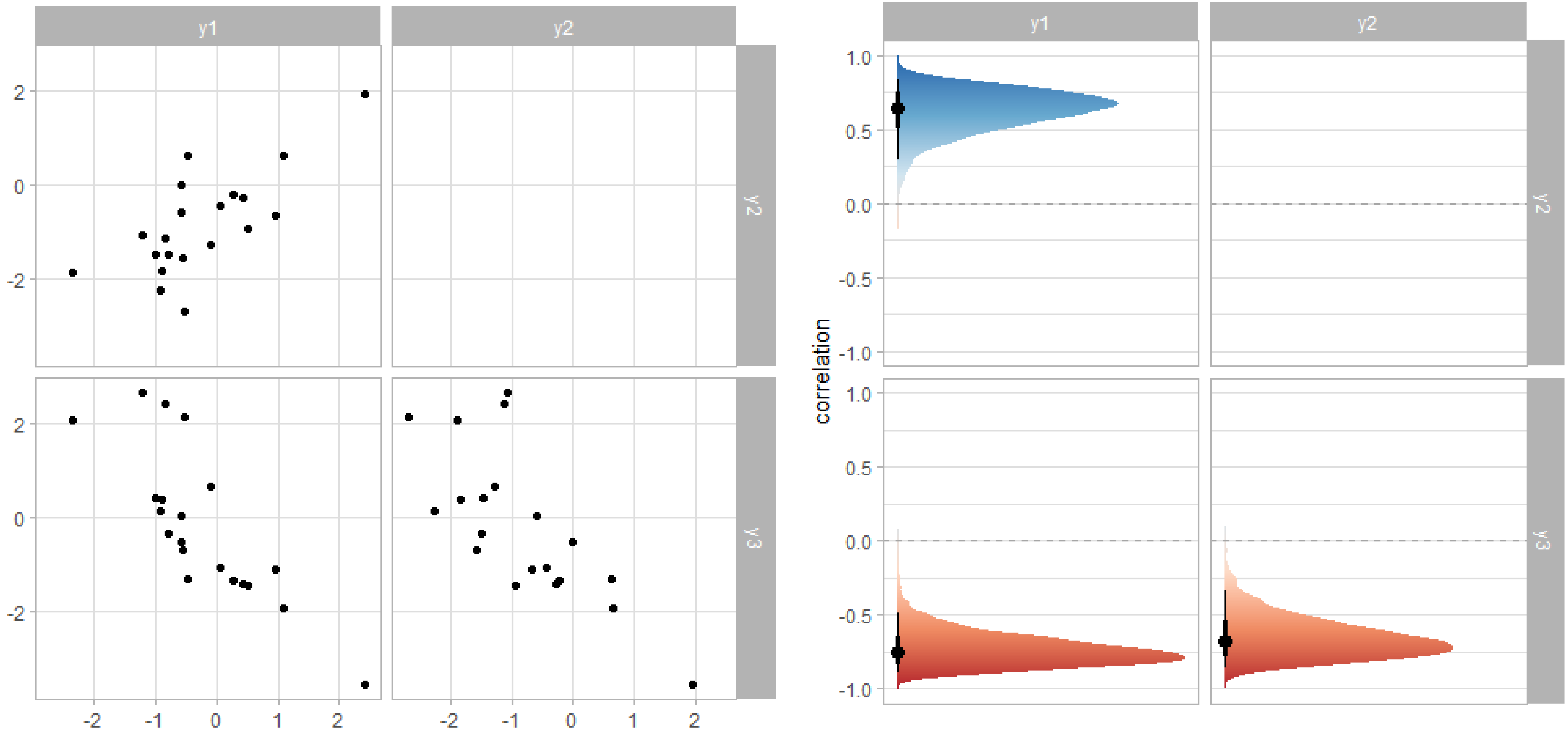
y1
y2
y3
y4
y5
y6
y7
y8
corr.
1.0
0.5
0.0
-0.5
-1.0



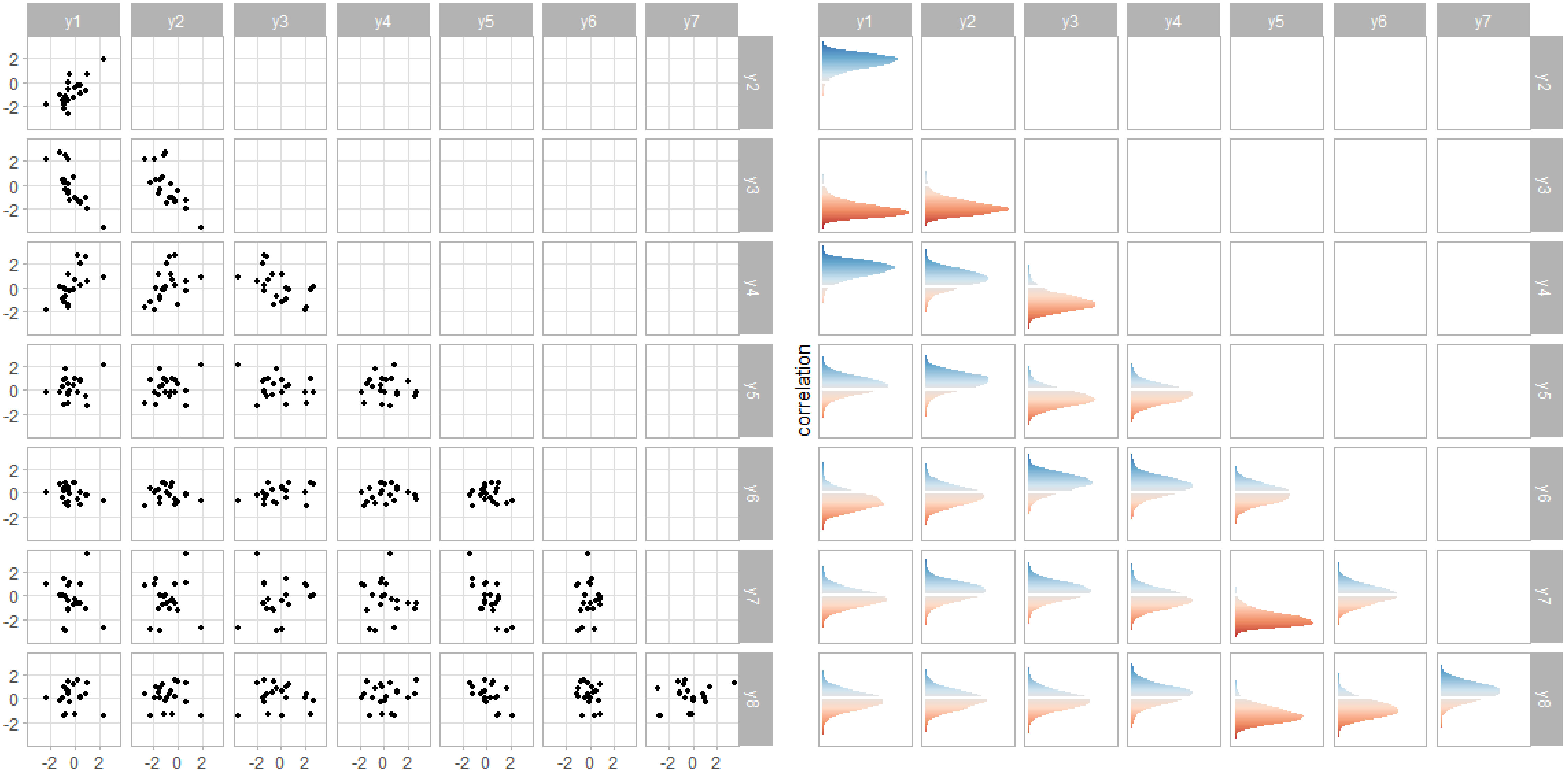
y1
y2
y2
y3
2
0
-2
2
0
-2
-2
-1
0
1
2
-2
-1
0
1
2



y1
y2
y1
y2
y2
y3
y2
y3
2
0
-2
-2
-1
0
1
2
-1.0
-0.5
0.0
0.5
1.0
correlation



y1
y2
y2
y3
correlation
1.0
0.5
0.0
-0.5
-1.0


y1
y2
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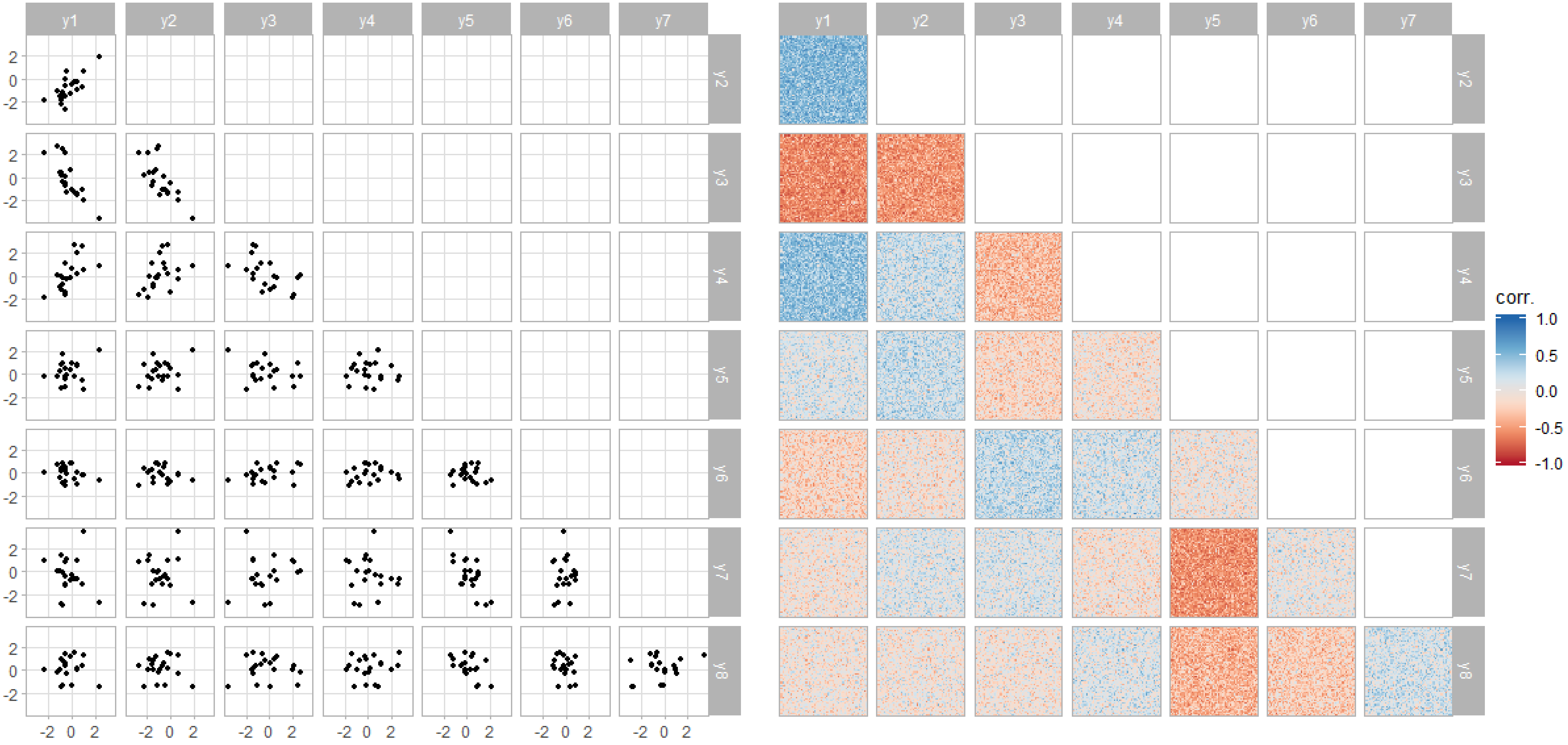
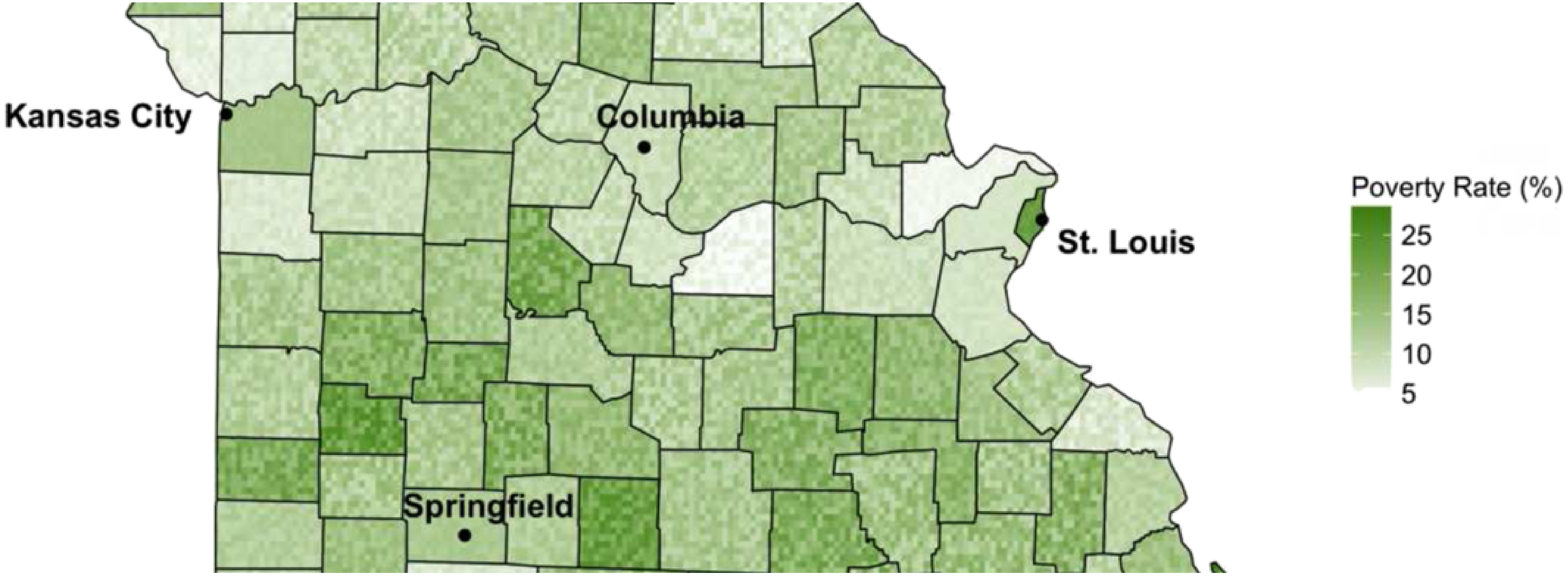
y4
y5
y6
y7
y8
correlation


y1
y2
y3
y4
y5
y6
y7
y8
corr.
1.0
0.5
0.0
-0.5
-1.0

...and back to map-land

Uncertainty -> ~dither (samples from dist)

[Lucchesi & Wikle. Visualizing uncertainty in areal data with bivariate choropleth maps, map pixelation and glyph rotation. Stat, 292–302, 2017]



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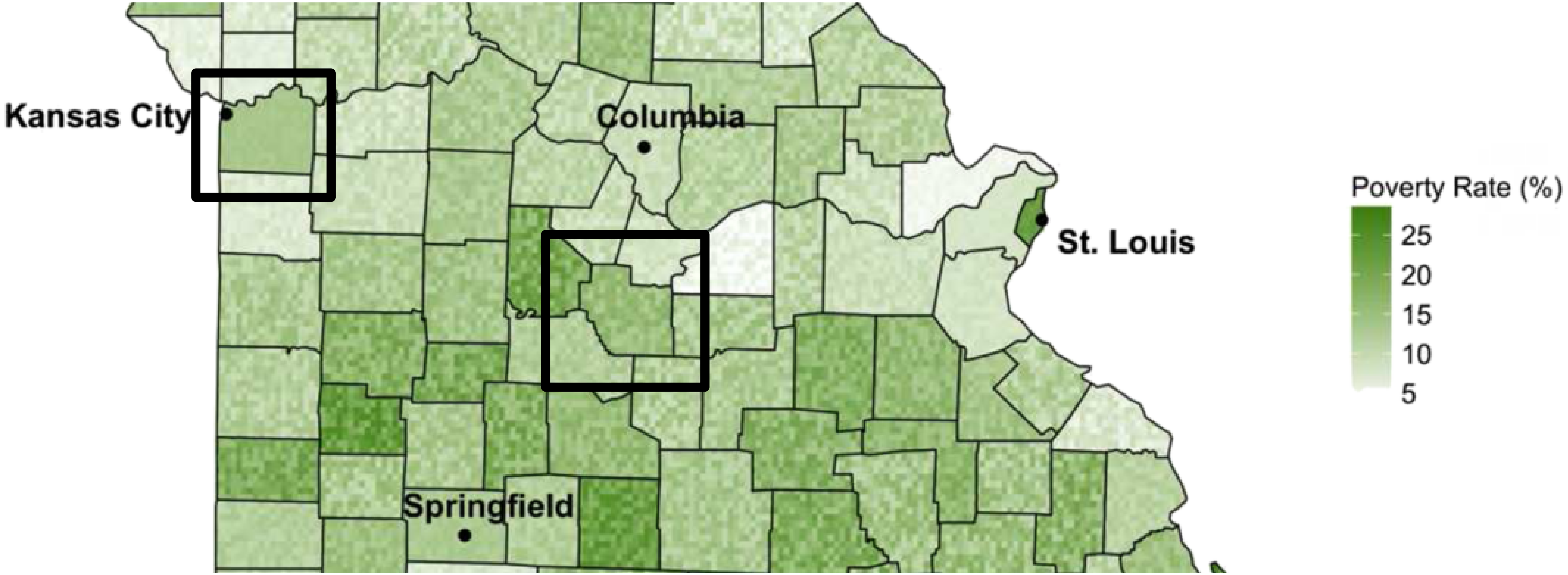

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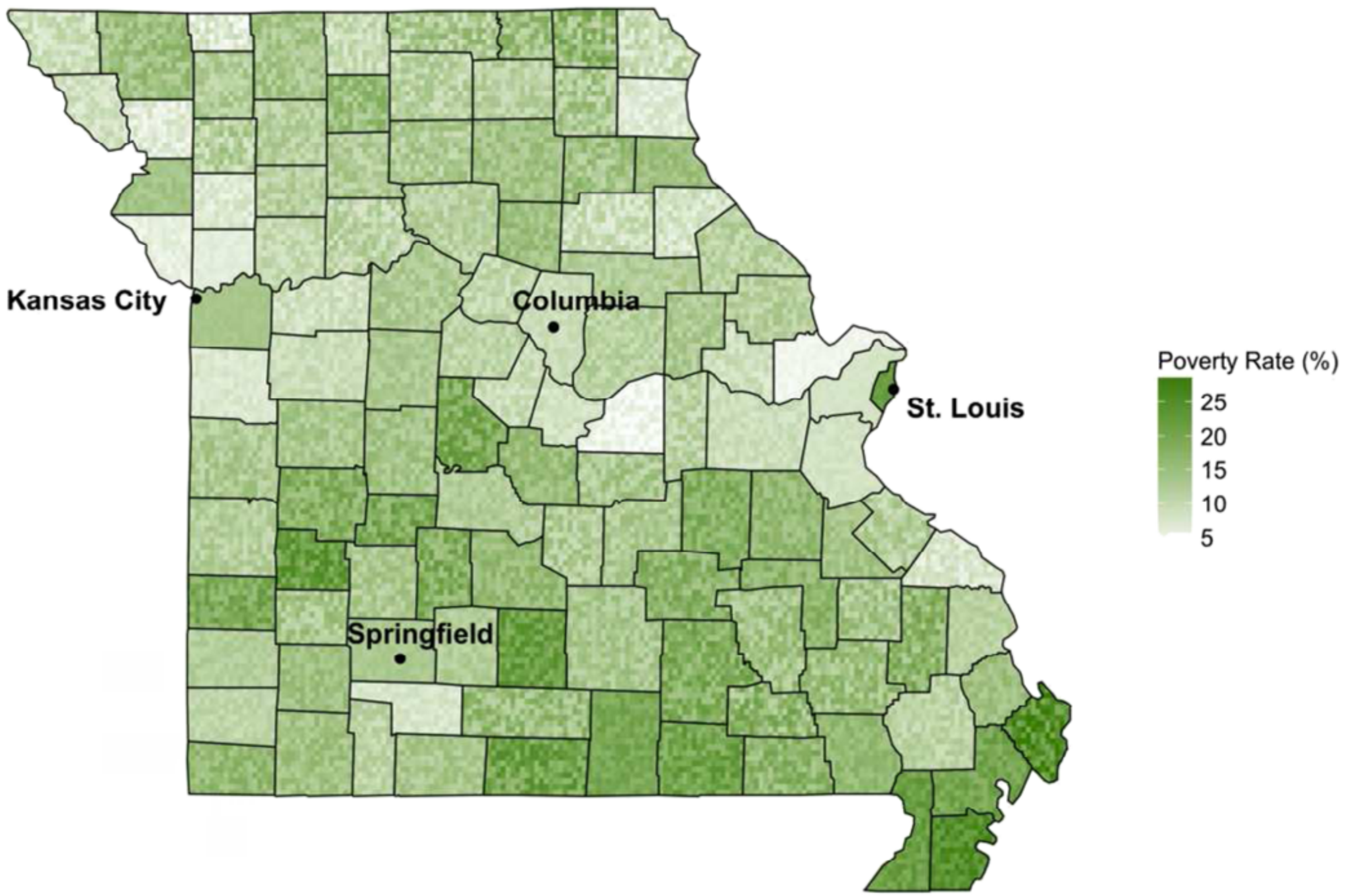


Discrete outcomes

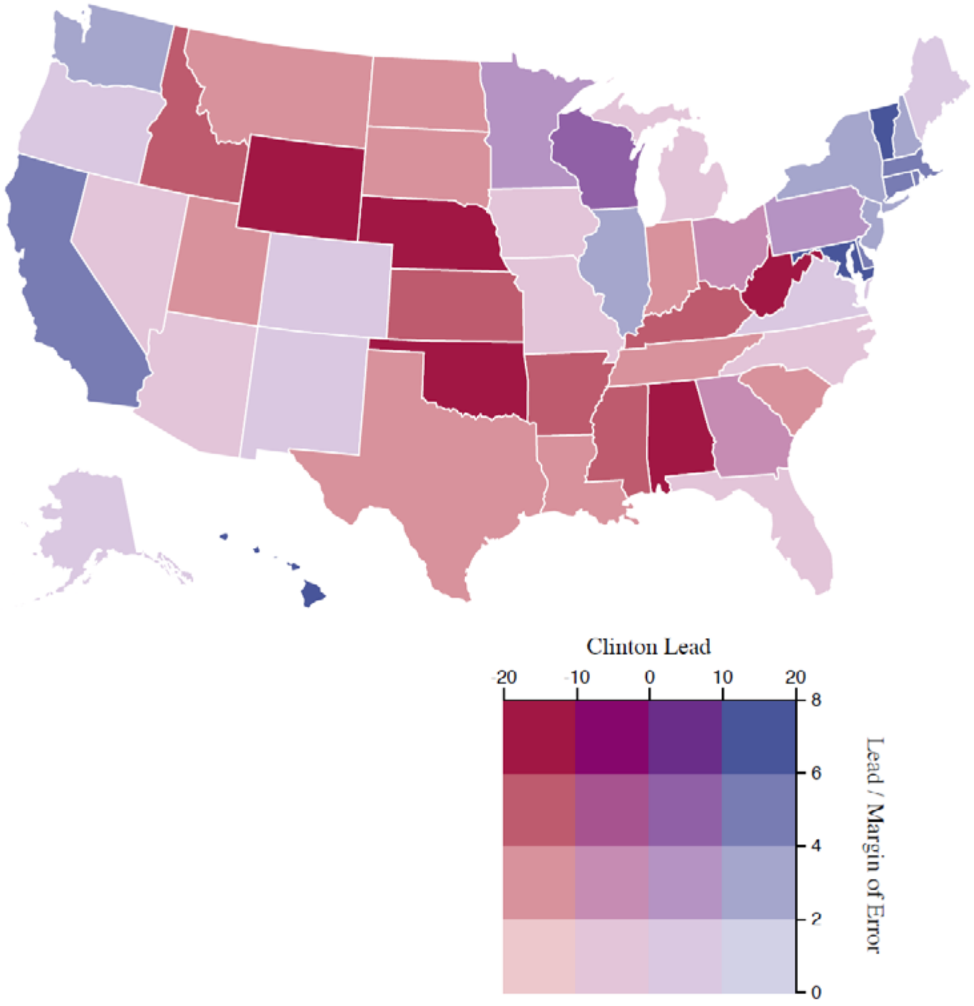
Maybe more intuitive, maybe less?

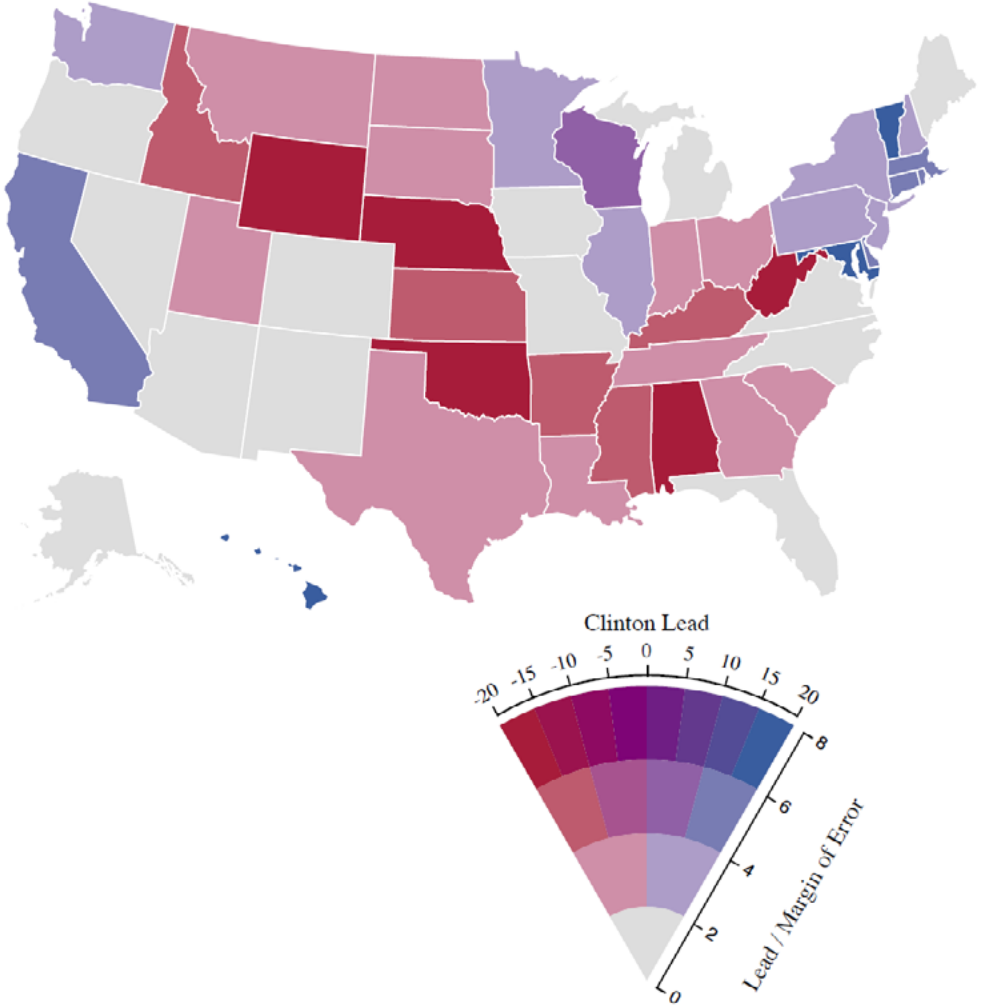
Possible deterministic construal errors

Addressing bias in perception of probability...

Value-suppressing uncertainty palettes

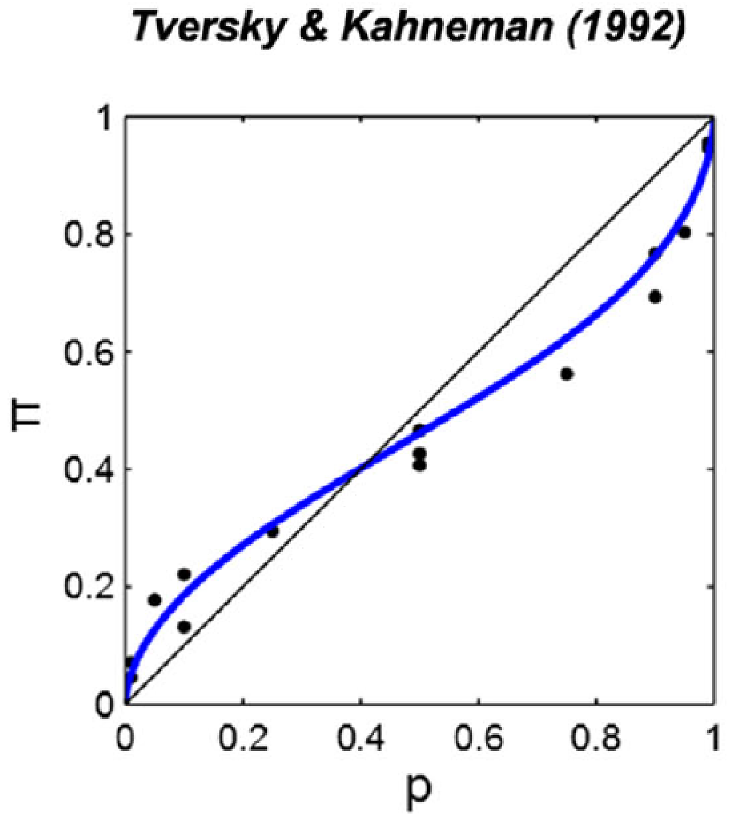
[Correll, Moritz, Heer. Value-Suppressing Uncertainty Palettes. CHI 2018]





Linear-in-log-odds perception of proportions

[Zhang & Maloney. Ubiquitous log odds: A common representation of probability and frequency distortion in perception, action, and cognition. Frontiers in Neuroscience, 6(JAN), 1–14, 2012]



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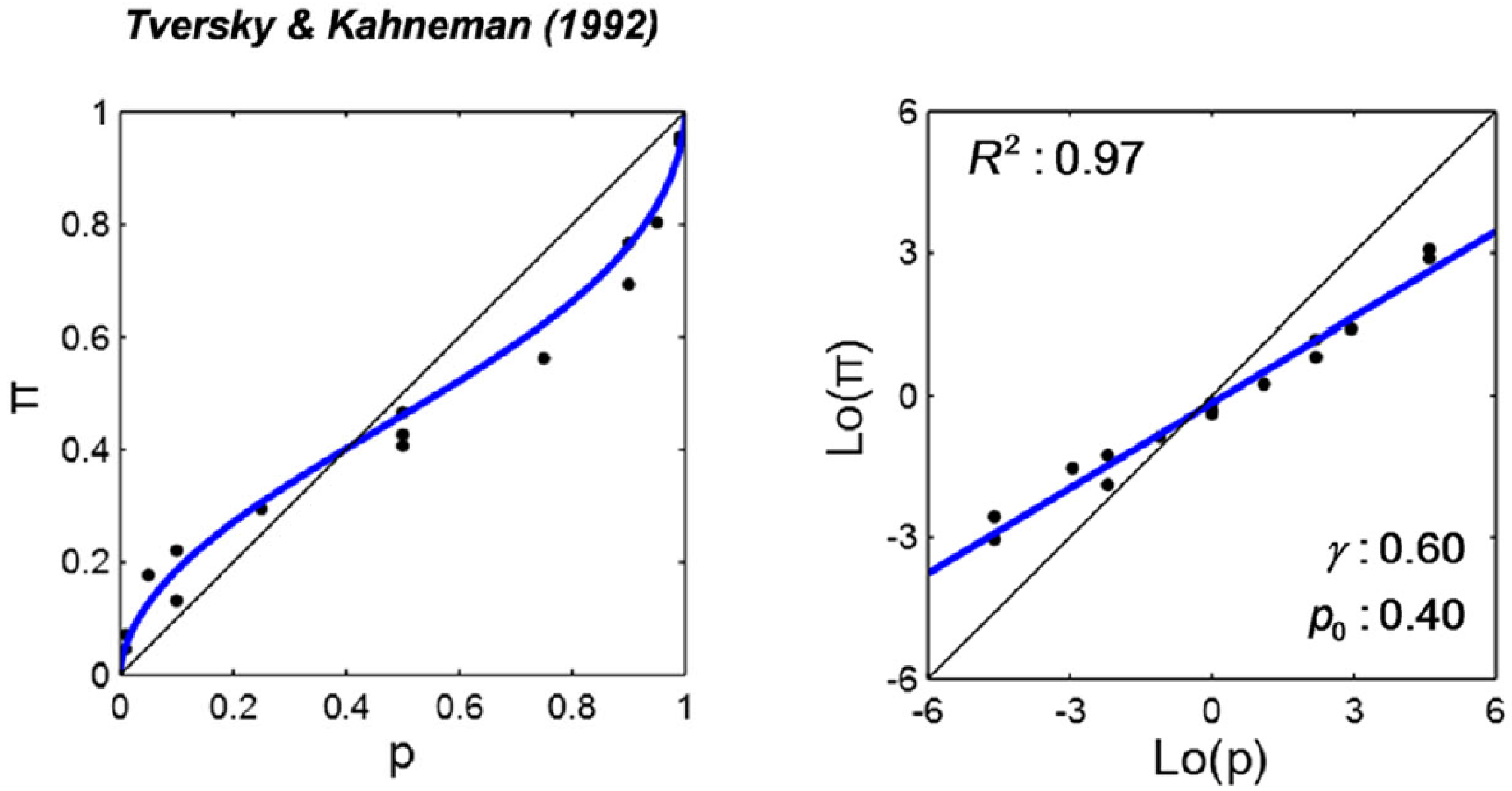

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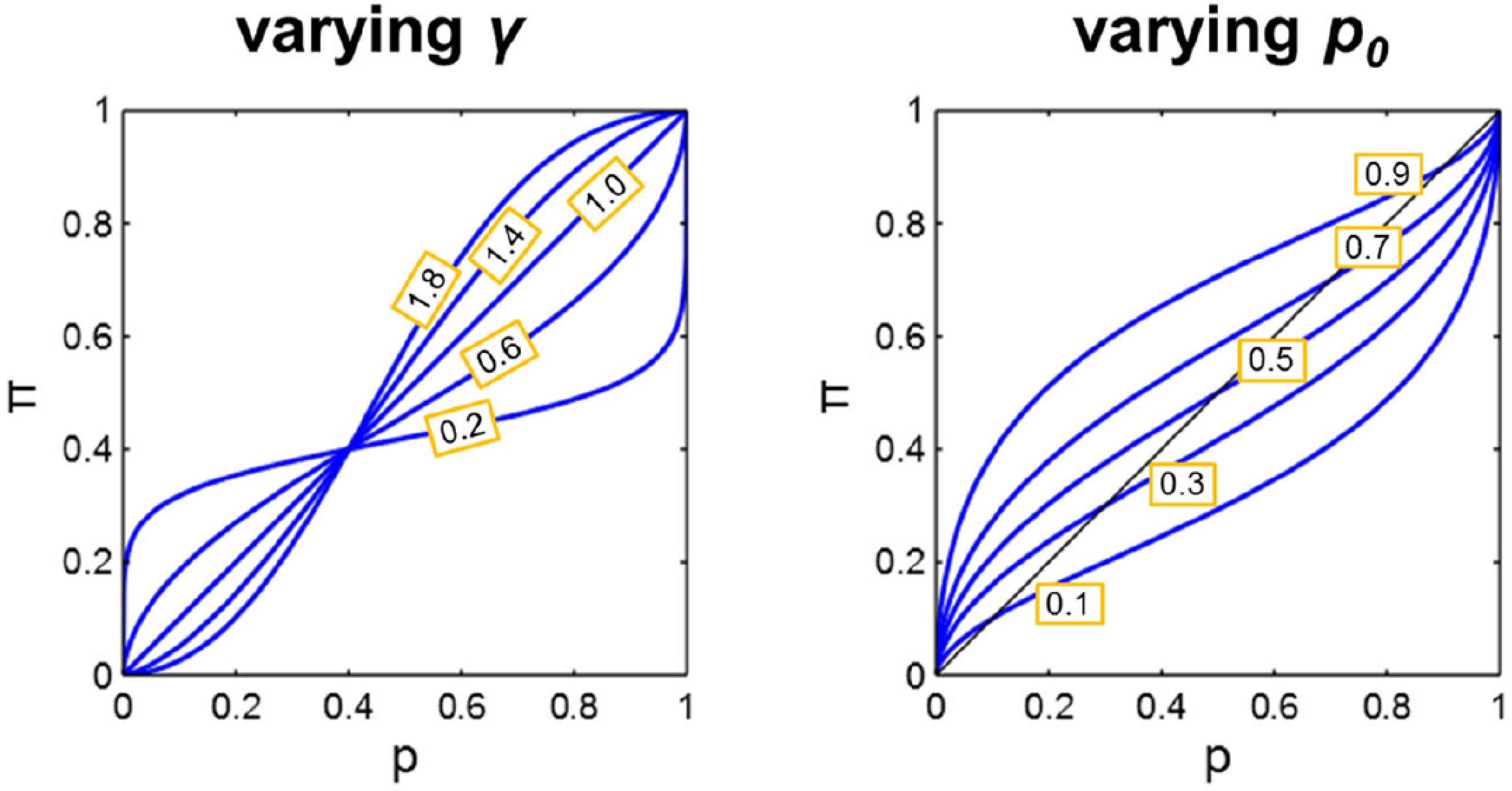


Going back to election data…

New York Times Election Needle

[https://www.nytimes.com/interactive/2016/11/08/us/elections/trump-clinton-election-night-live.html]

The Fake Twitchy Hell Dials of the New York *Times*’ Forecast Only Made Last Night Worse

By **Jake Swearingen**

Photo: rhyselsmore/Twitter

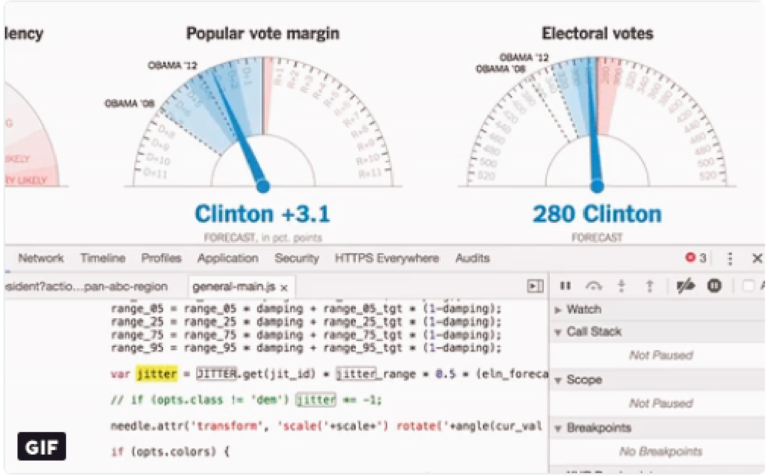
Around 9:30 last night, this tweet popped up on my timeline:

> stop tweeting the fucking hell dial
>
> — **erictoral vote (@ericlimer)** November 9, 2016

Alp Toker @atoker

Follow

Looking for trends in @nytimes's presidential forecast needle? Don't look too hard - the bounce is random jitter from your PC, not live data



Richard Porczak @tsiro

Follow

straight up: the NYT needle jitter is irresponsible design at best and unethical design at worst and you should stop looking at it

9:58 PM - 8 Nov 2016

509 Retweets **882** Likes

17 509 882

But shouldn't anxiety be proportional to uncertainty?

Uncertainty visualization as a moral imperative

We should…

present well-calibrated uncertainty
that cannot be ignored
in ways people can actually understand

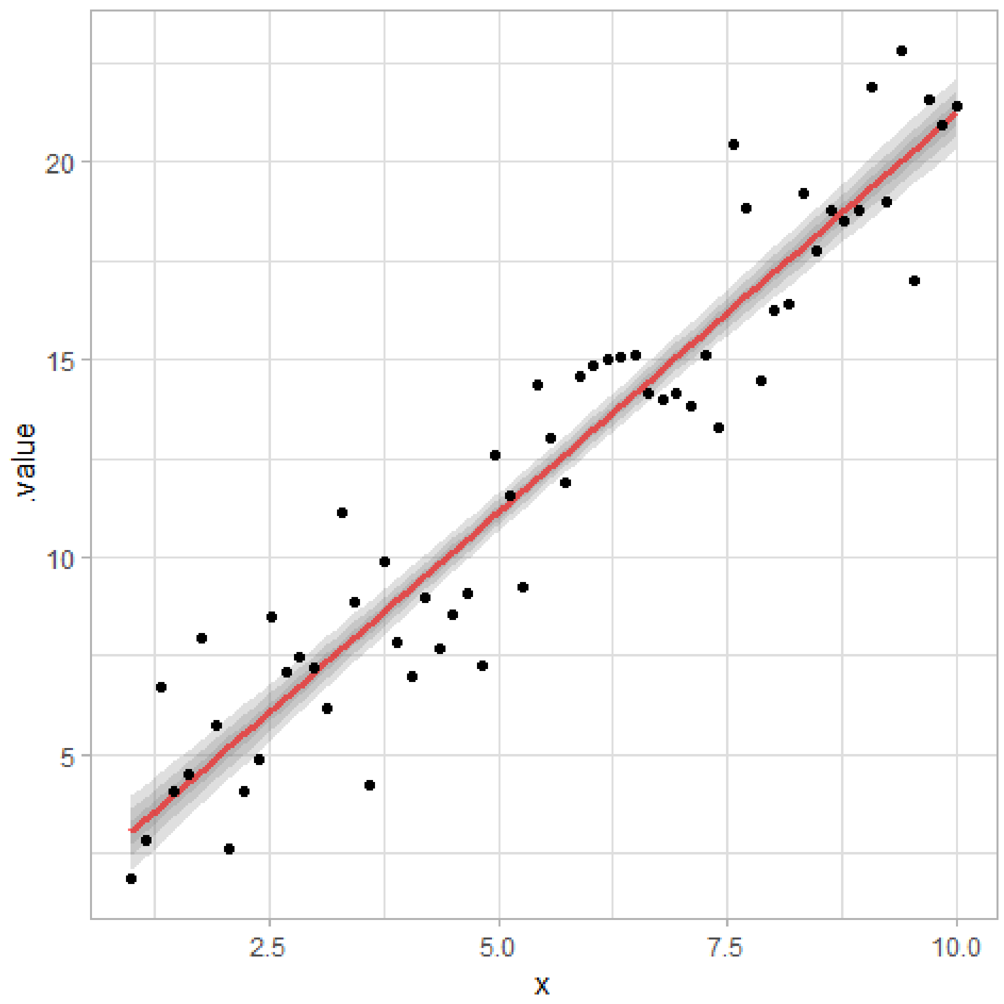
Thanks!

And thanks to: Jessica Hullman, Sean Munson, Julie Kientz, Shwetak Patel, Abhraneel Sarma, Xiaoying Pu, Tara Kola, Michael Fernandes, Logan Walls, Yea-Seul Kim, Samana Shrestha, Gregory Nelson, Eric Hekler, Dan Morris, mc schraefel, Michael Correll, Jeff Heer, Steve Haroz, Pierre Dragicevic

http://mjskay.github.io/tidybayes/
http://github.com/mjskay/uncertainty-examples

Matthew Kay
University of Michigan School of Information
mjskay@umich.edu

Epistemic uncertainty



Aleatory uncertainty