Uncertainty visualization

SI 649 W20: Information visualization

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& Computer Science and Engineering
University of Michigan

Uncertainty visualization

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 ANOV[illegible]ith sex of face (male, female) as a wit[illegible]subjects factor and self-rated attractiveness (lo[illegible]verage, high) and oral contr[illegible]ptive use (true, false) as between-subjects factors reveal[illegible] main effect of se[illegible]ace, $F(1, 1276) = 1372$, $p < .001$, $\eta_p^2 = .52$. This was qualified [illegible] interacti[illegible] between sex of face and SRA, $F(2, 1276) = 6.90$, $p = .001$, $\eta_p^2 = .011$, a[illegible]een sex of face and oral contraceptive use, $F(1, 1276) = 5.02$, $p = .025$, $\eta_p^2 =$ [illegible]redicted interaction among sex of face, SRA and oral contraceptive u[illegible]as not signi[illegible]nt, $F(2, 1276) = 0.06$, $p = .94$, $\eta_p^2 < .001$. All other main effect[illegible]nd interactions were [illegible] significant and irrelevant to our hypotheses, all $F \leq 0.9$[illegible]$\geq .39$, $\eta_p^2 \leq .001$.

Alternatives…

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)

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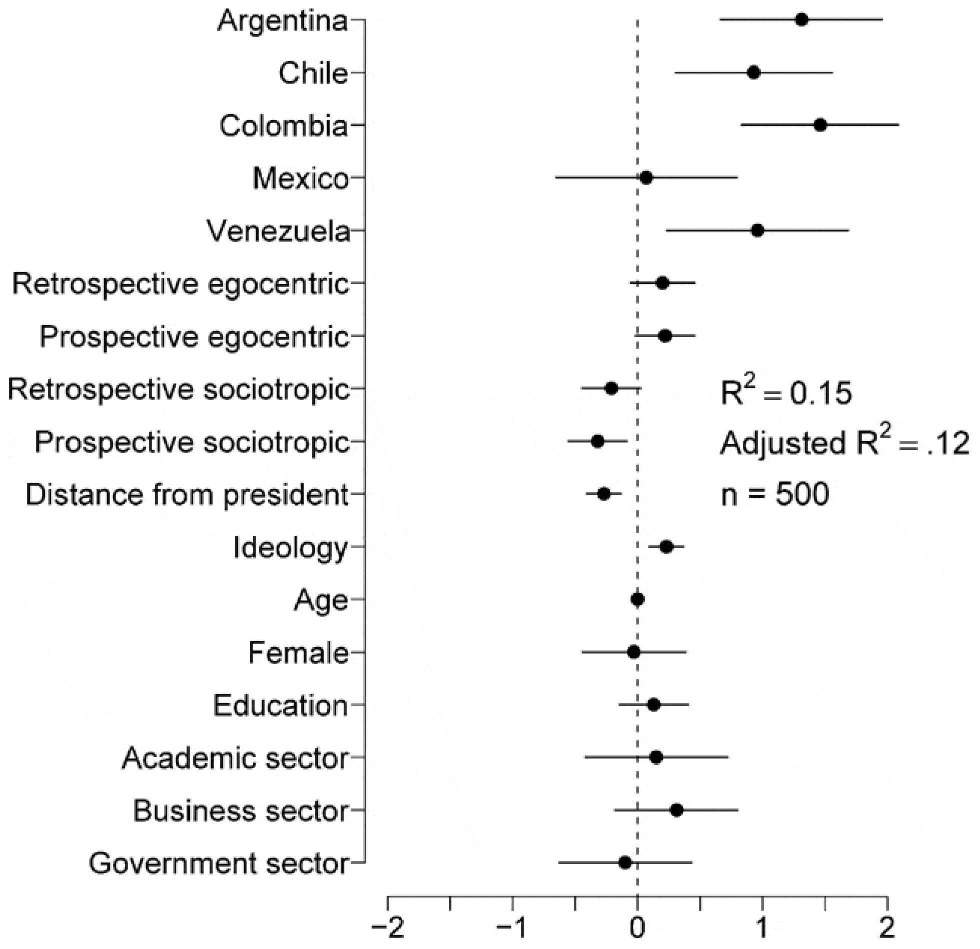

[Jonathan P Kastellec and Eduardo L Leoni. 2007. Using Graphs Instead of Tables in Political Science. Perspectives on politics 5, 4: 755–771]

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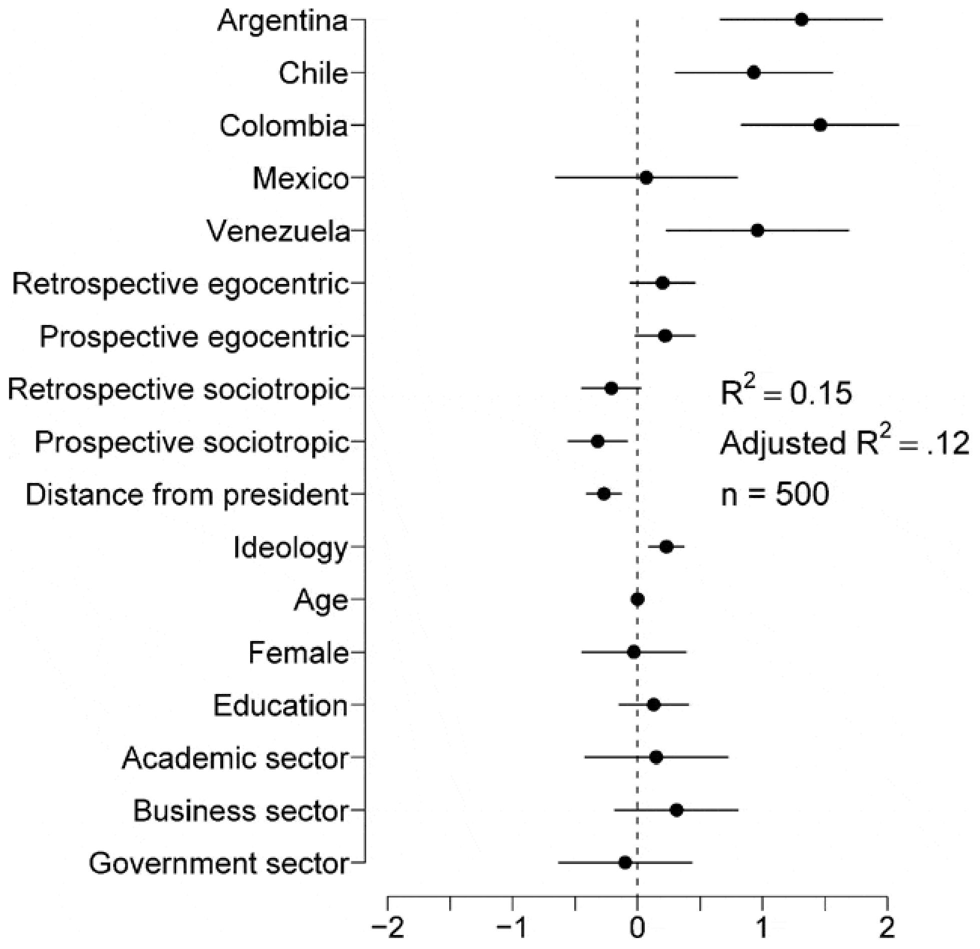

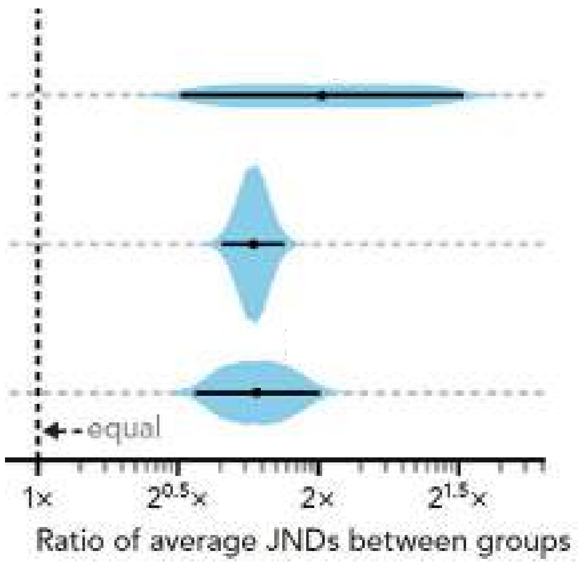

[Jonathan P Kastellec and Eduardo L Leoni. 2007. Using Graphs Instead of Tables in Political Science. Perspectives on politics 5, 4: 755–771]

How easy is it to ignore the uncertainty?

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Countries	
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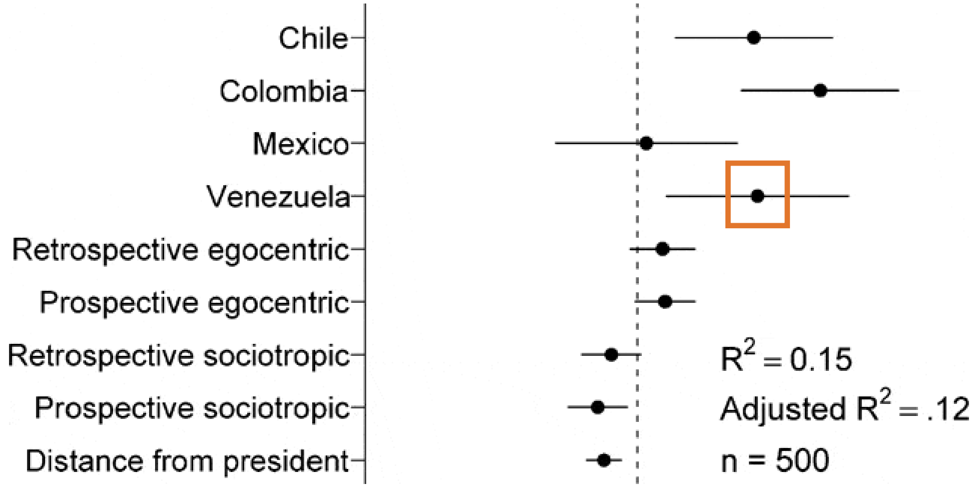
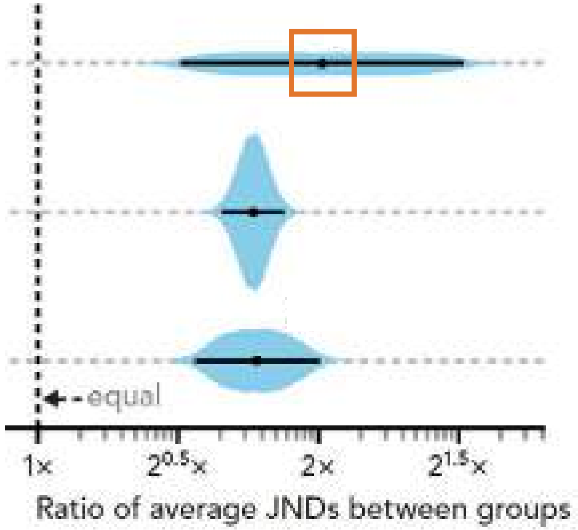




This contributes to dichotomania

Dichotomania...

Predictions from 2016 presidential election

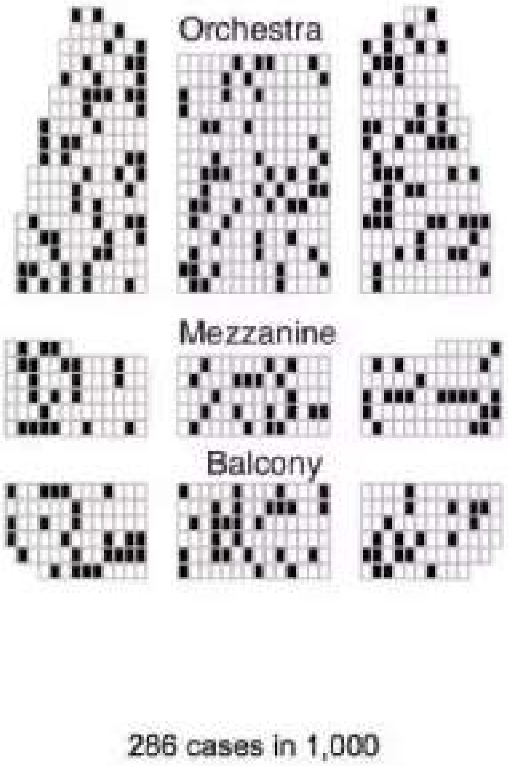
[Justin H. Gross, Washington Post, http://wapo.st/2fCYvDW]

FiveThirtyEight	NYT Upshot	HuffPo Pollster
28%	15%	2%

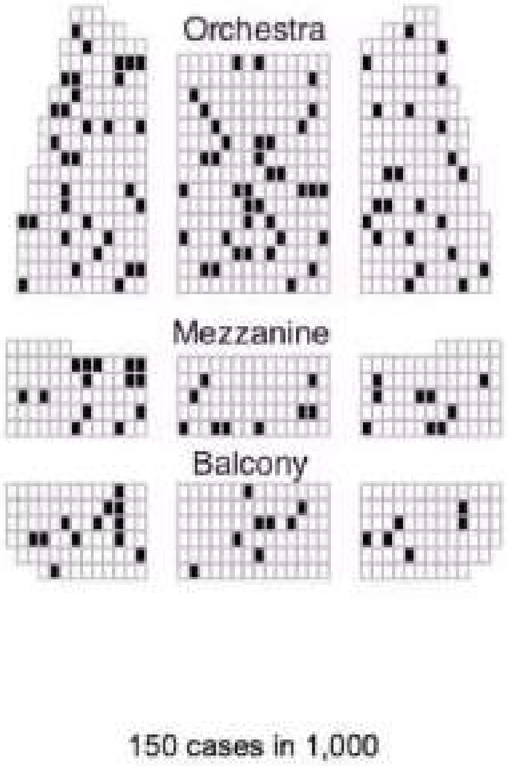
Predictions from 2016 presidential election

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

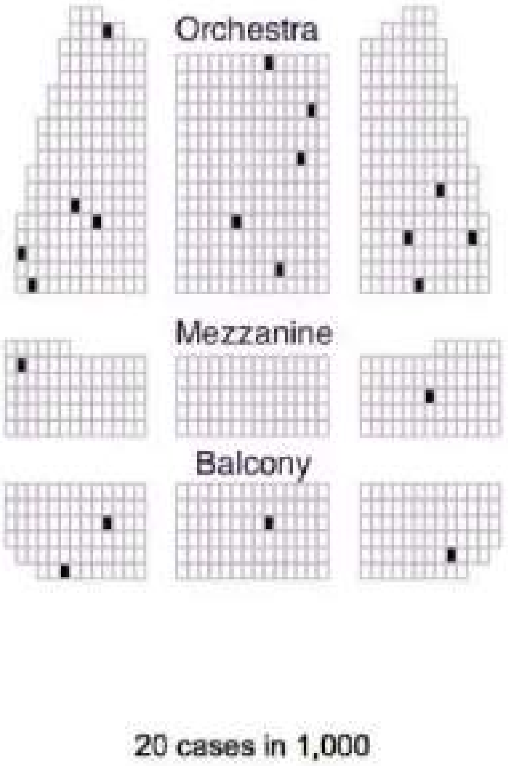
FiveThirtyEight



NYT Upshot



HuffPo Pollster



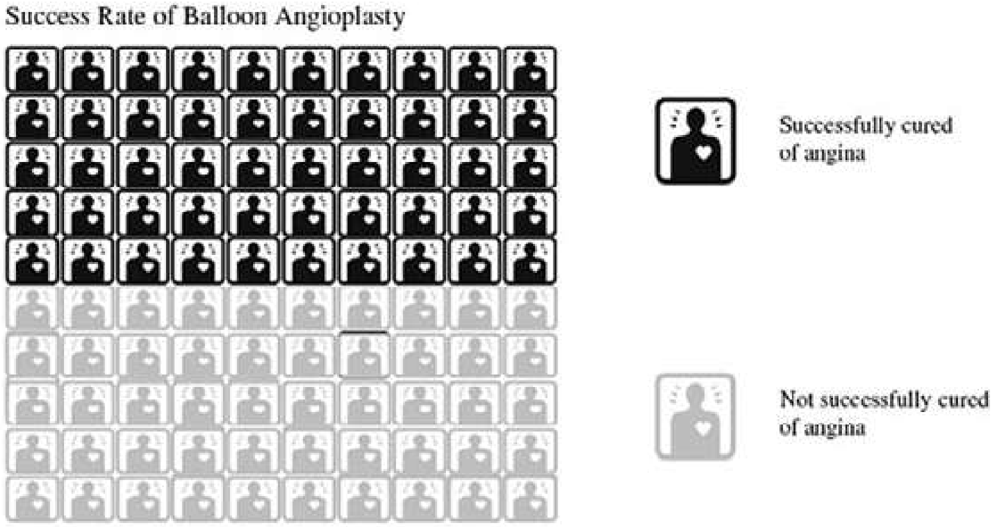
People are very good at ignoring uncertainty…

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]

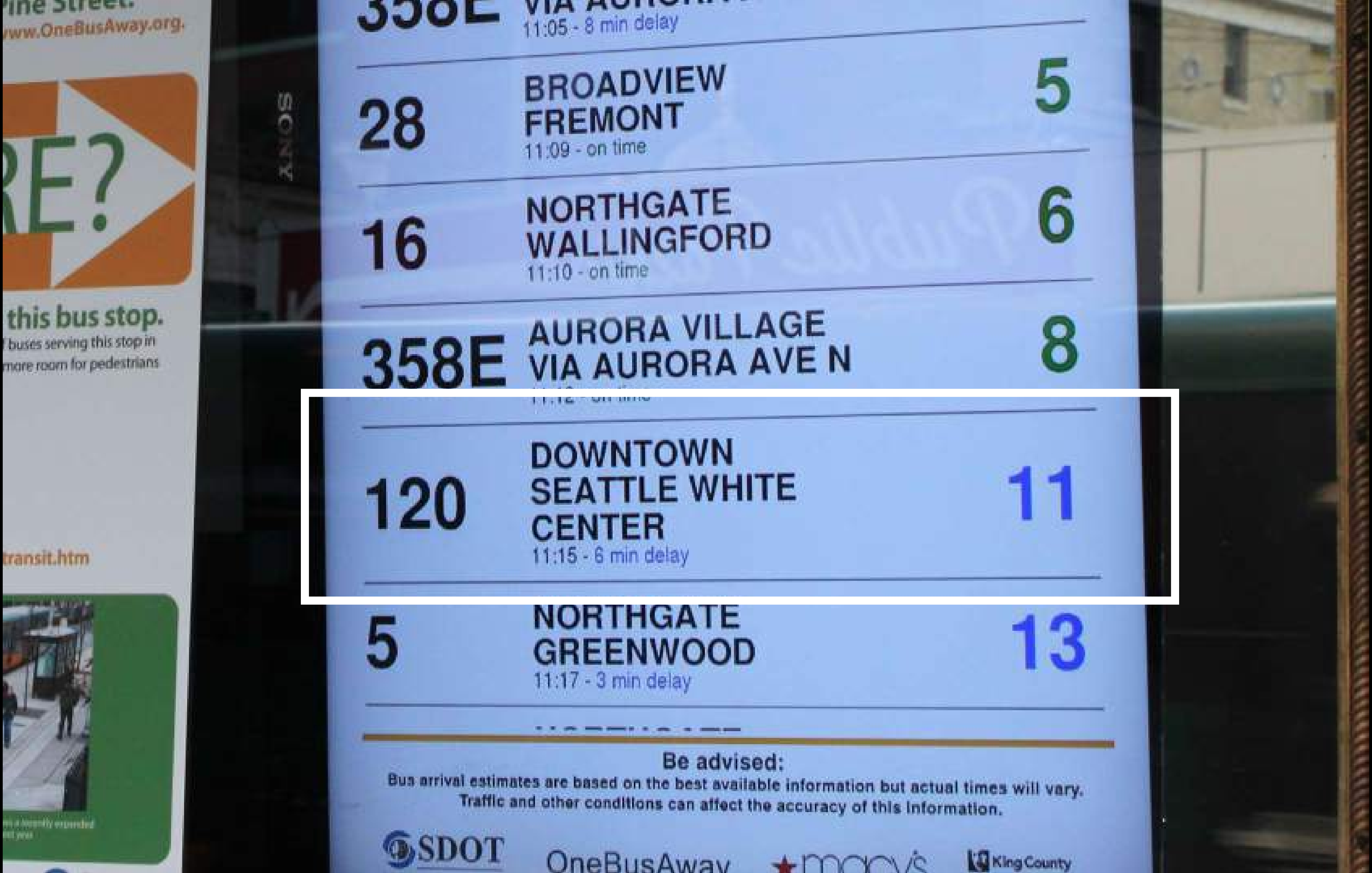


Frequency framing or discrete outcome visualization

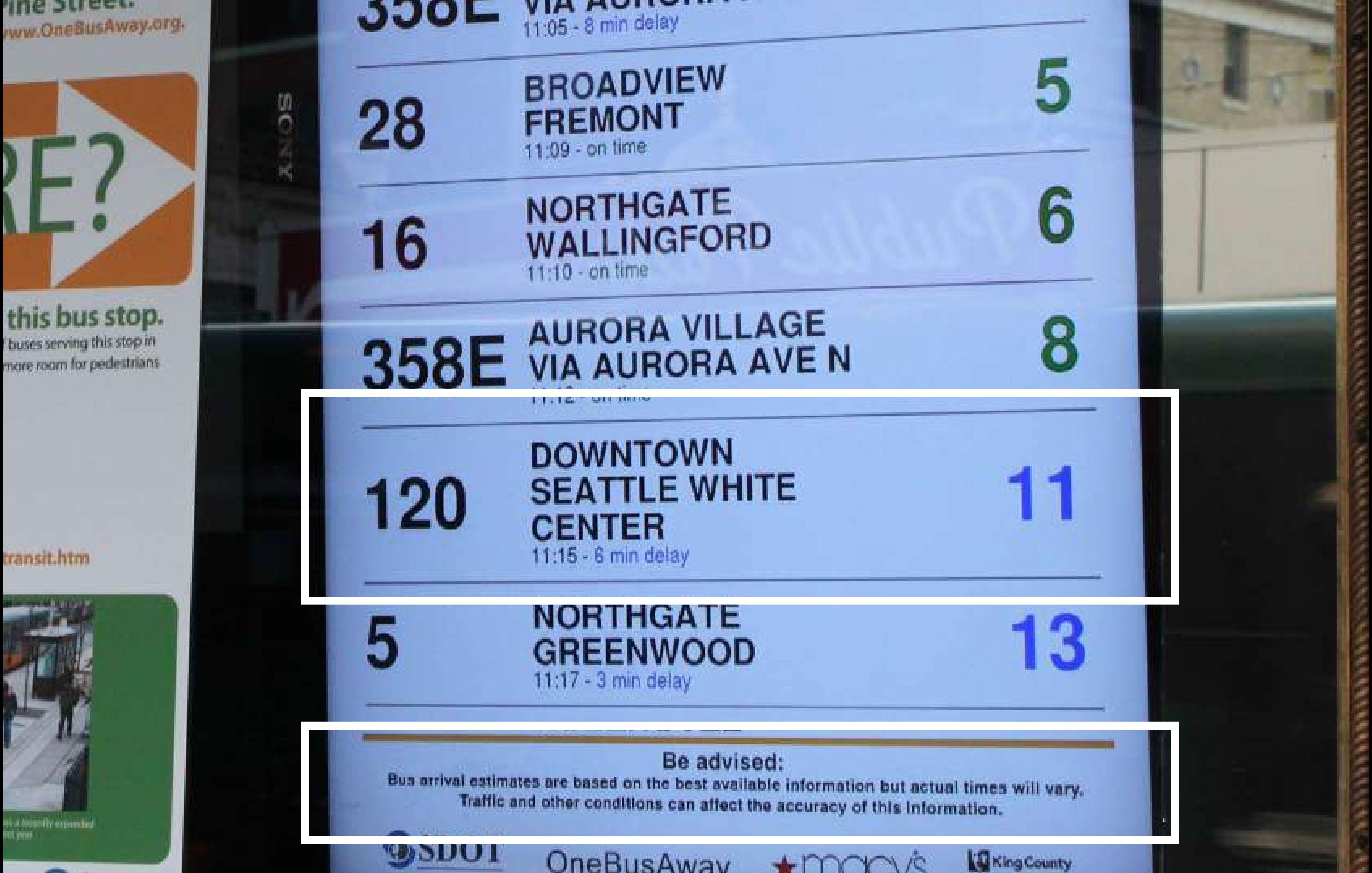
What is an icon array for a continuous distribution?

What is an icon array for a continuous distribution?

An example scenario...



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
King County
SONY
www.OneBusAway.org.
this bus stop.
transit.htm


11:05 - 8 min delay
28
BROADVIEW
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SDOT
OneBusAway
King County
SONY
www.OneBusAway.org.
this bus stop.
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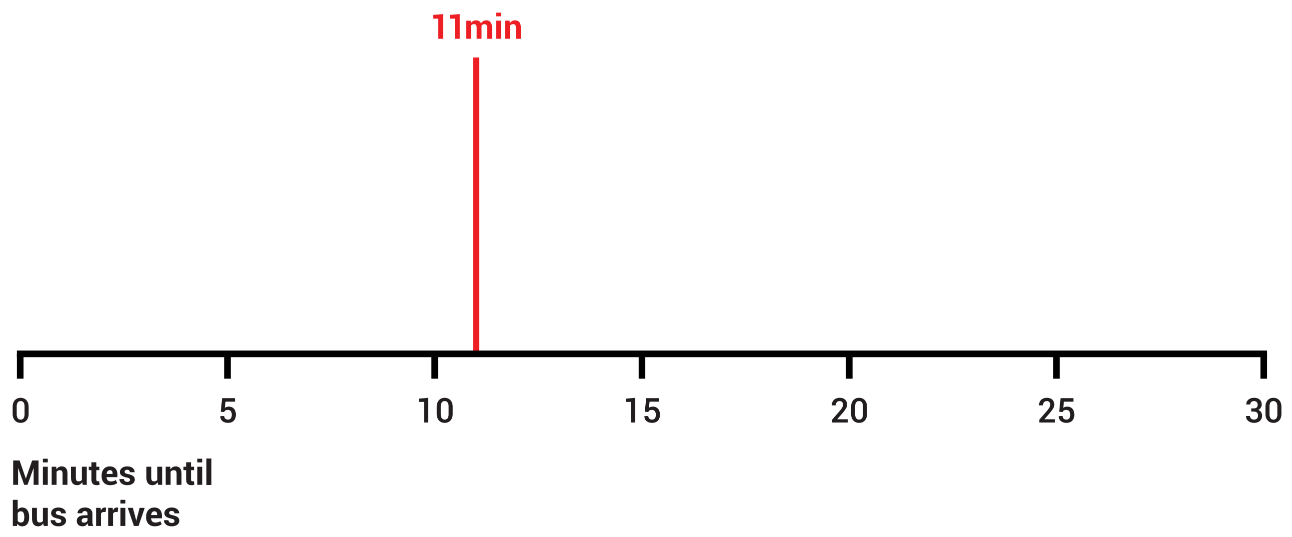
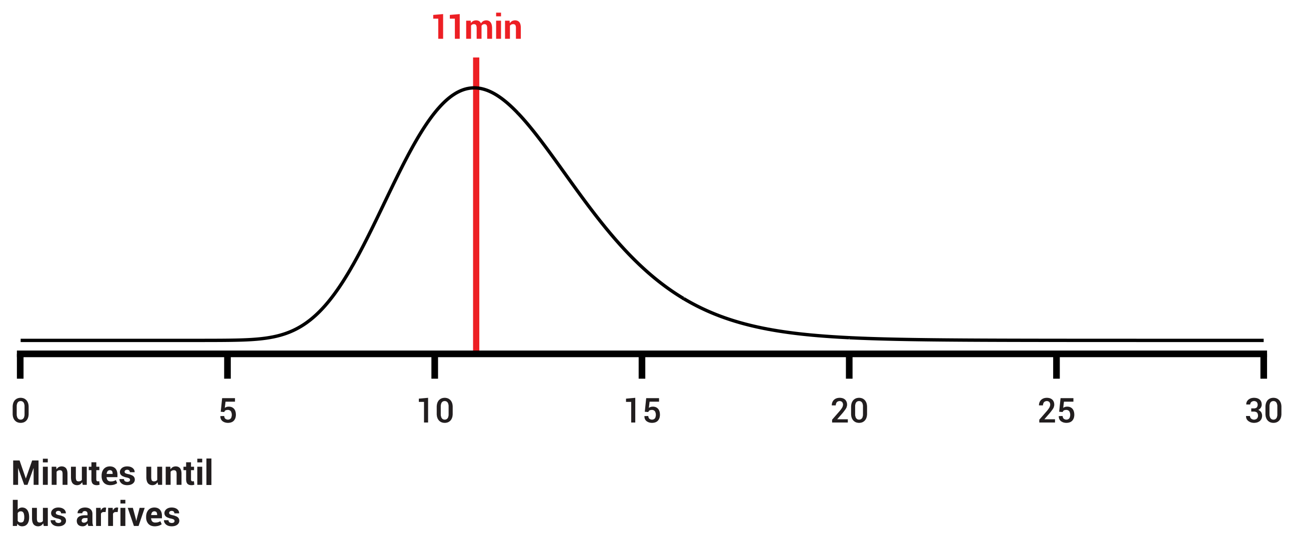
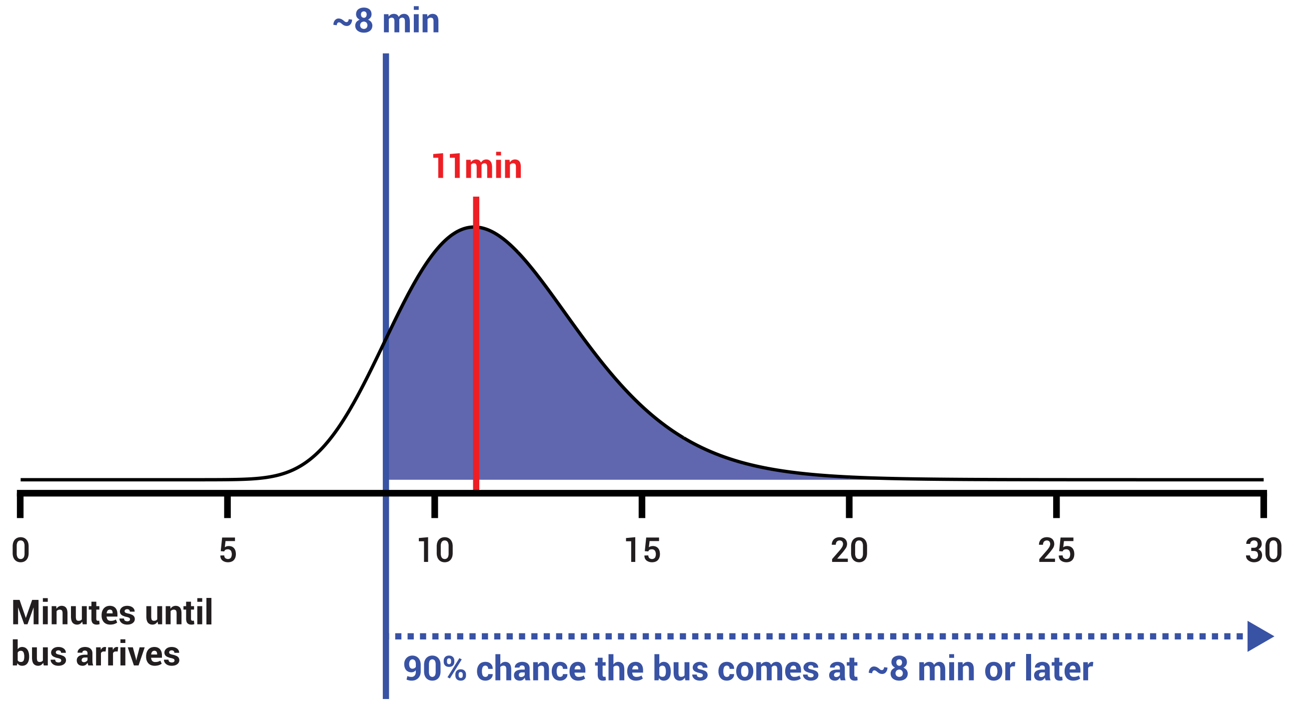
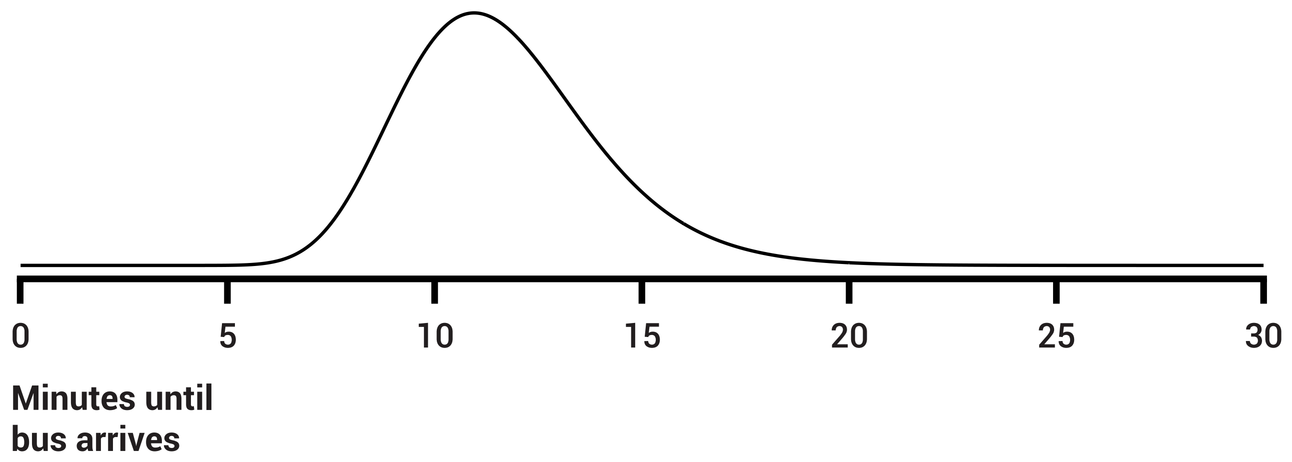
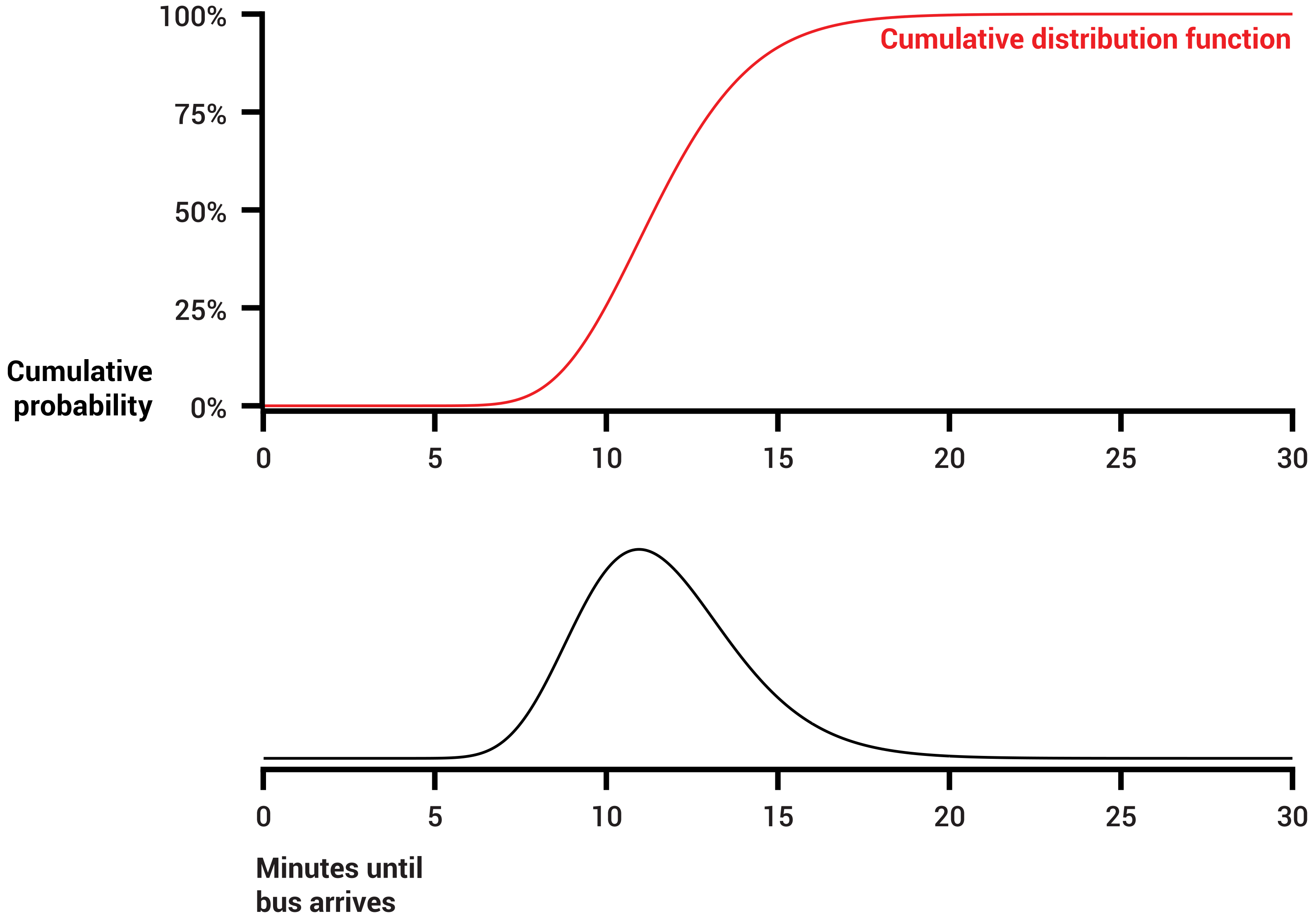
Do I have time to get a coffee?

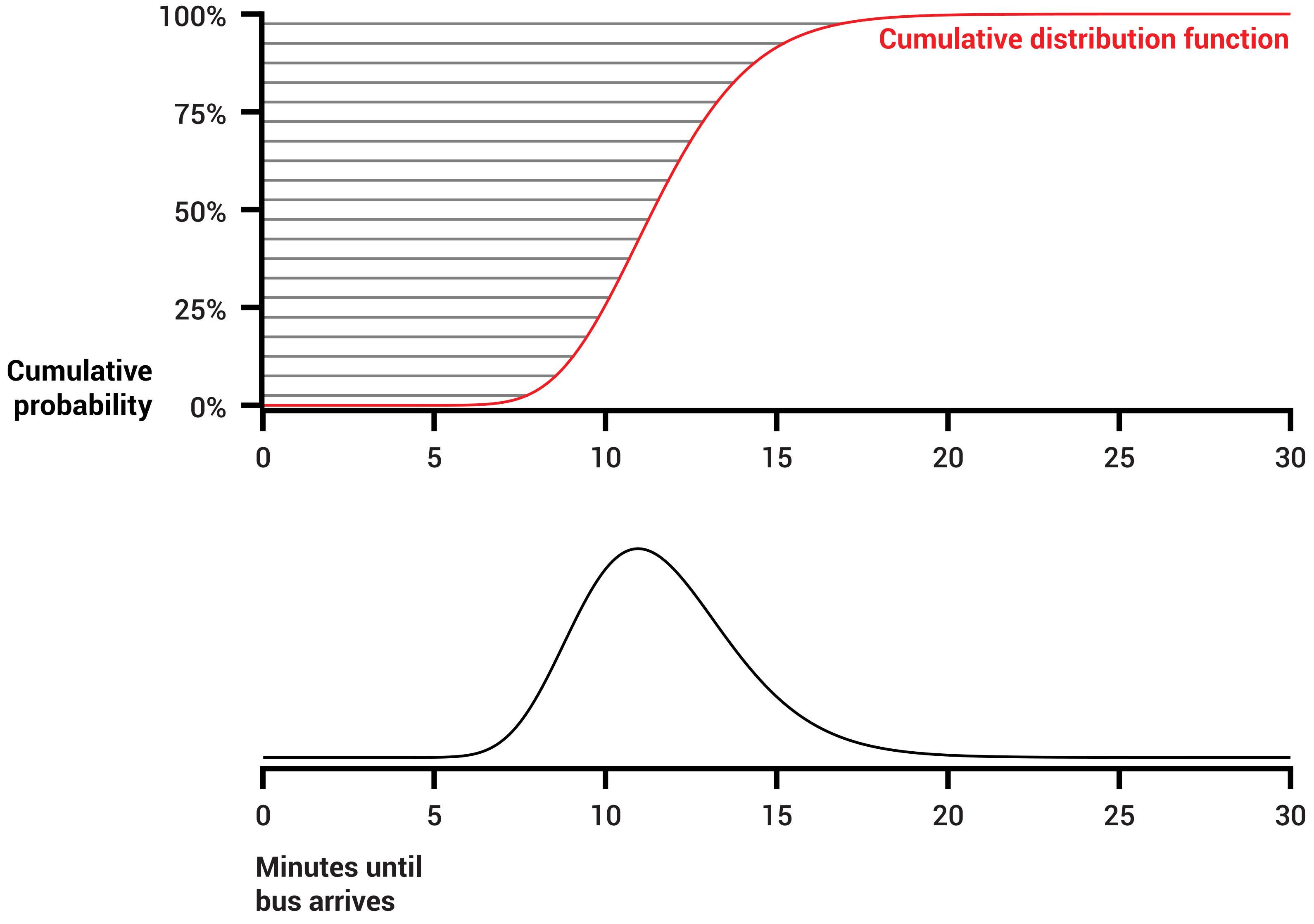

11min
0
5
10
15
20
25
30
Minutes until
bus arrives


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


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%
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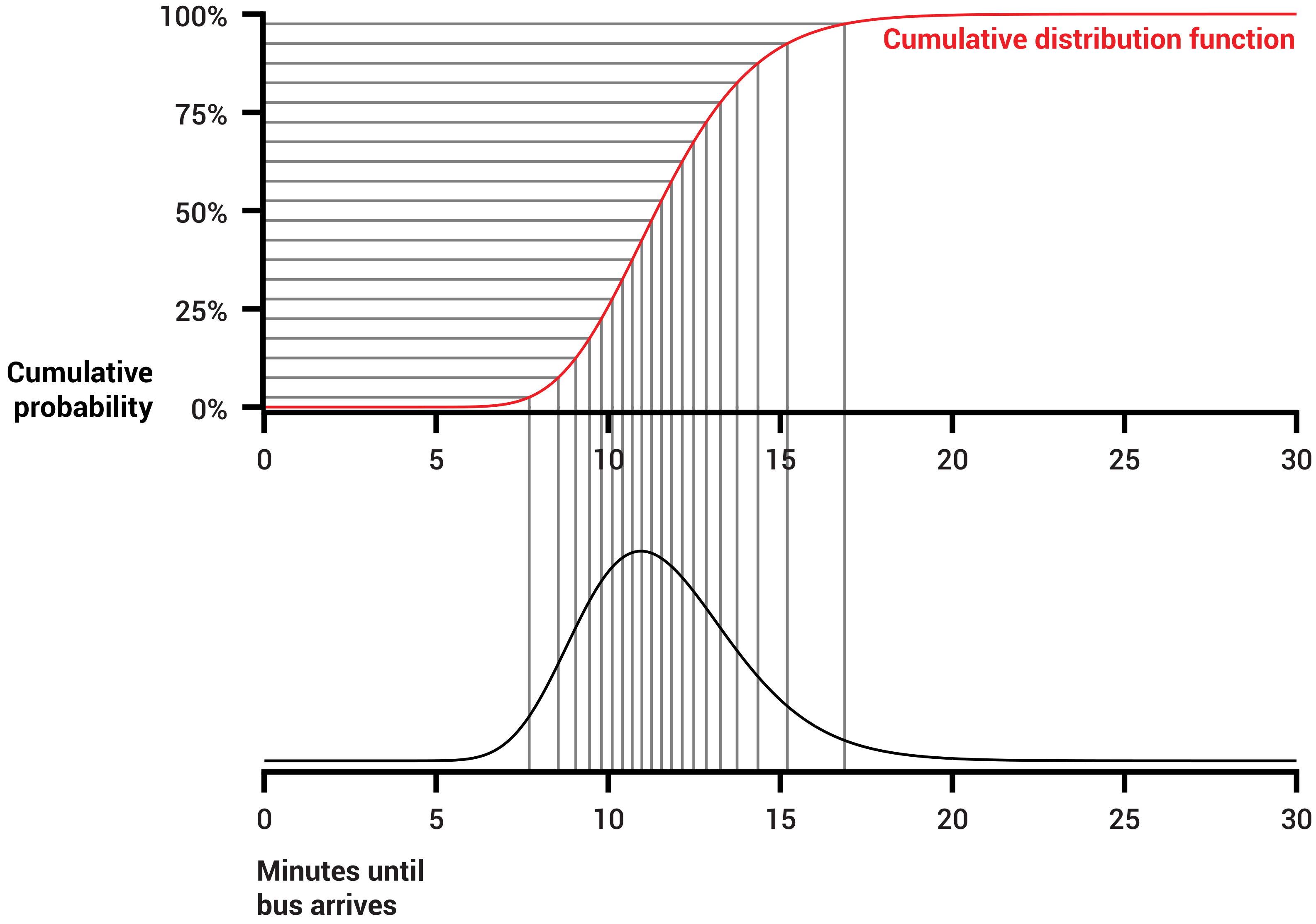

100%
75%
50%
25%
0%
Cumulative
probability
Cumulative distribution function
0
5
10
15
20
25
30
0
5
10
15
20
25
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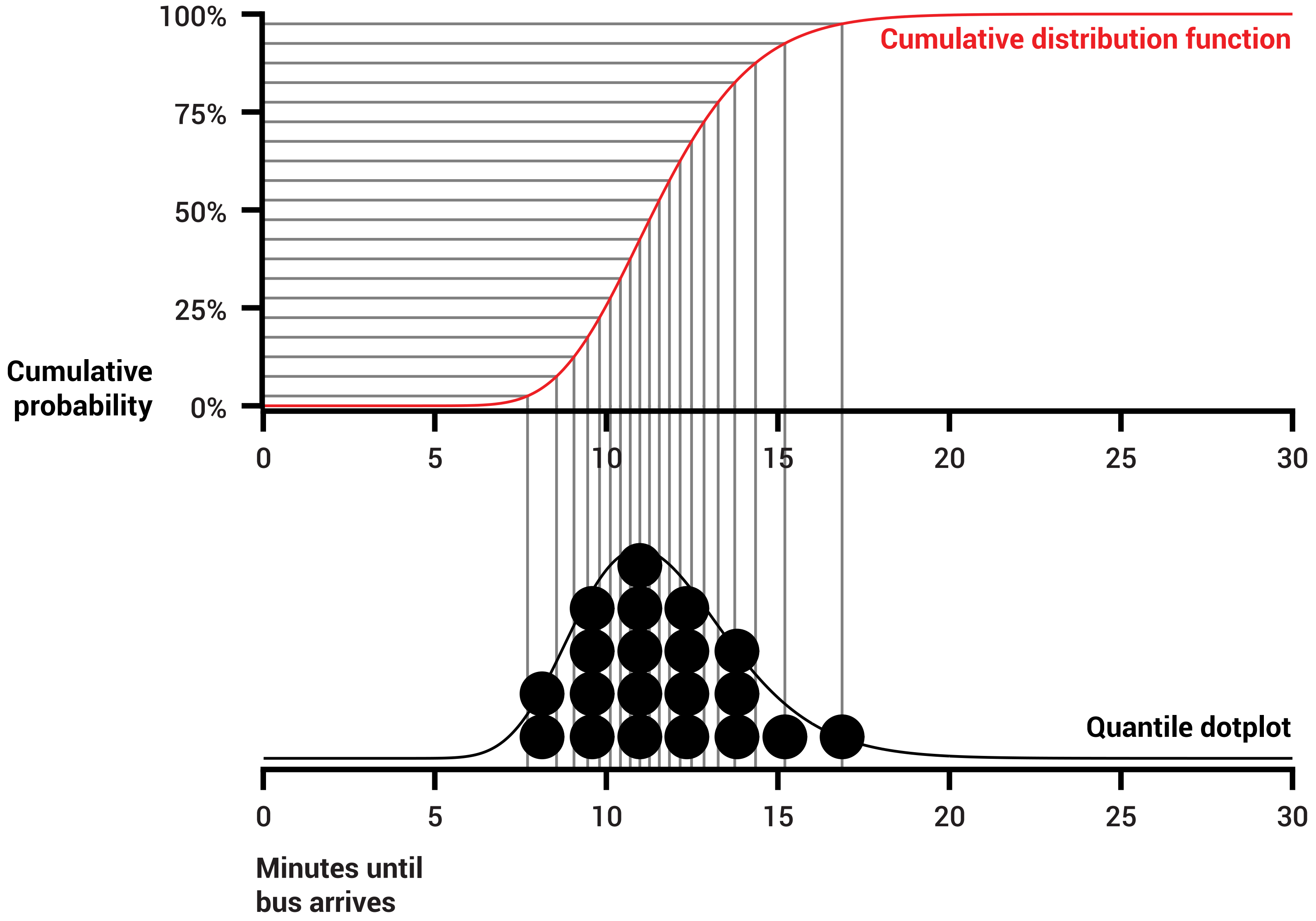
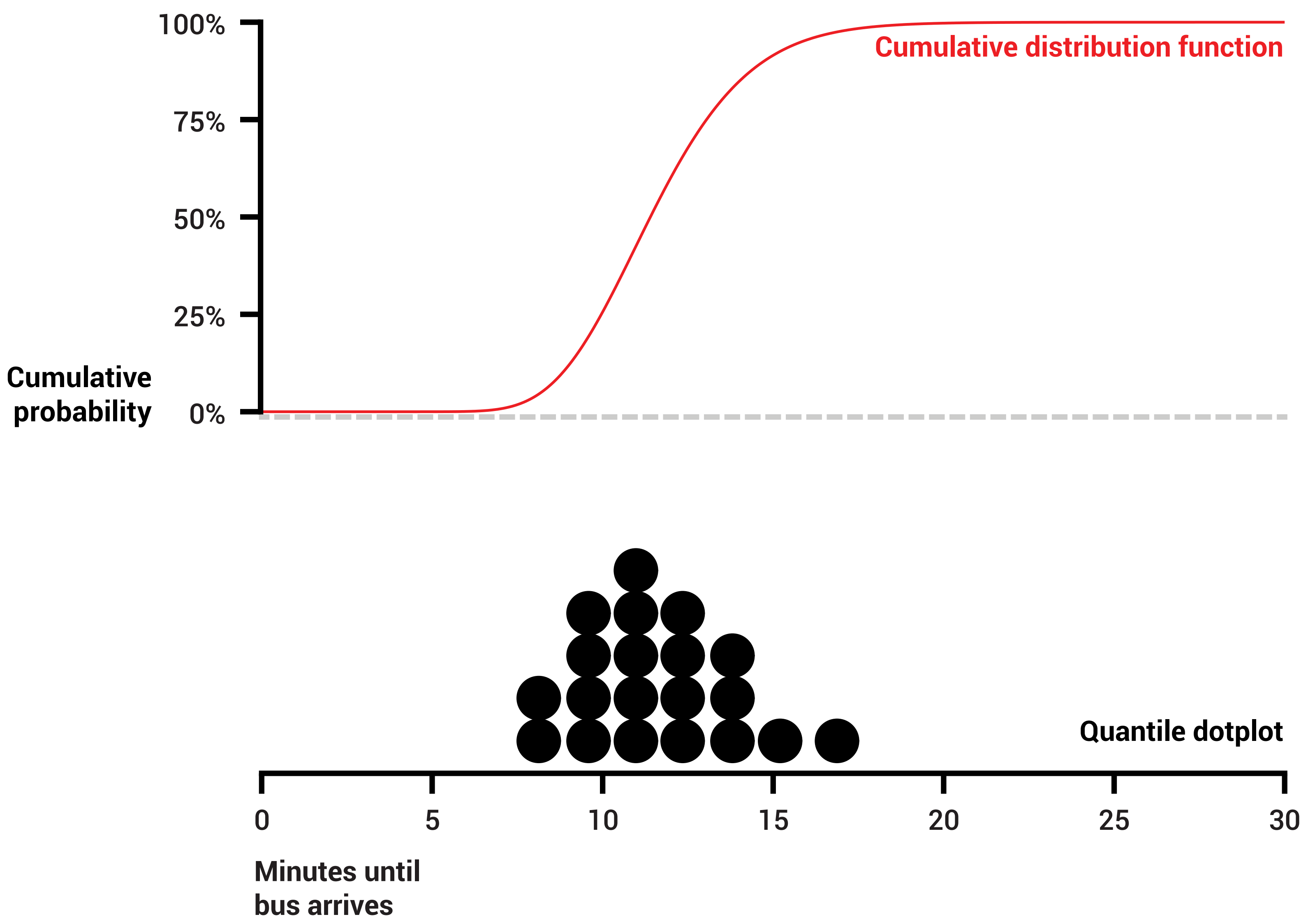
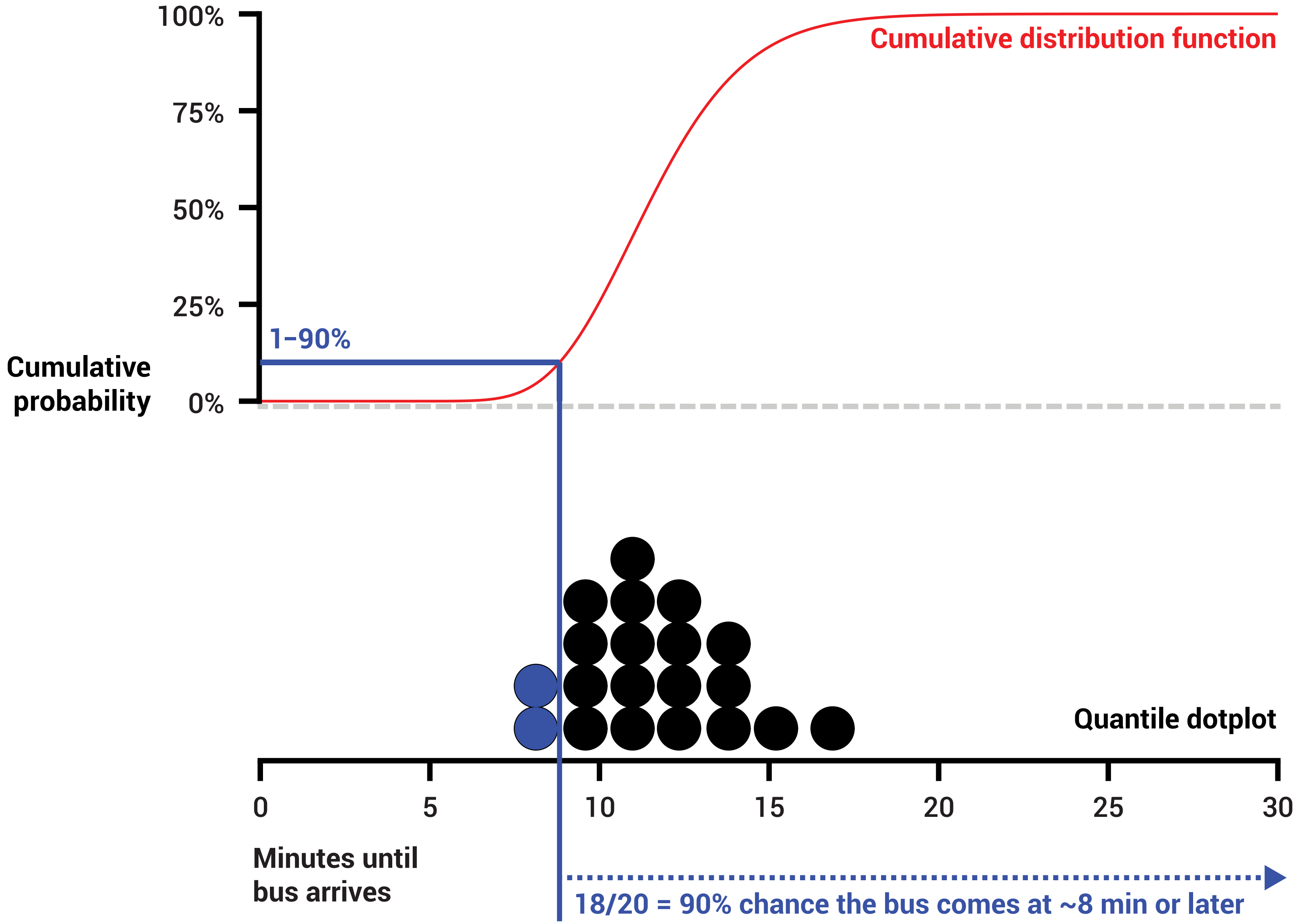
Minutes until
bus arrives



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

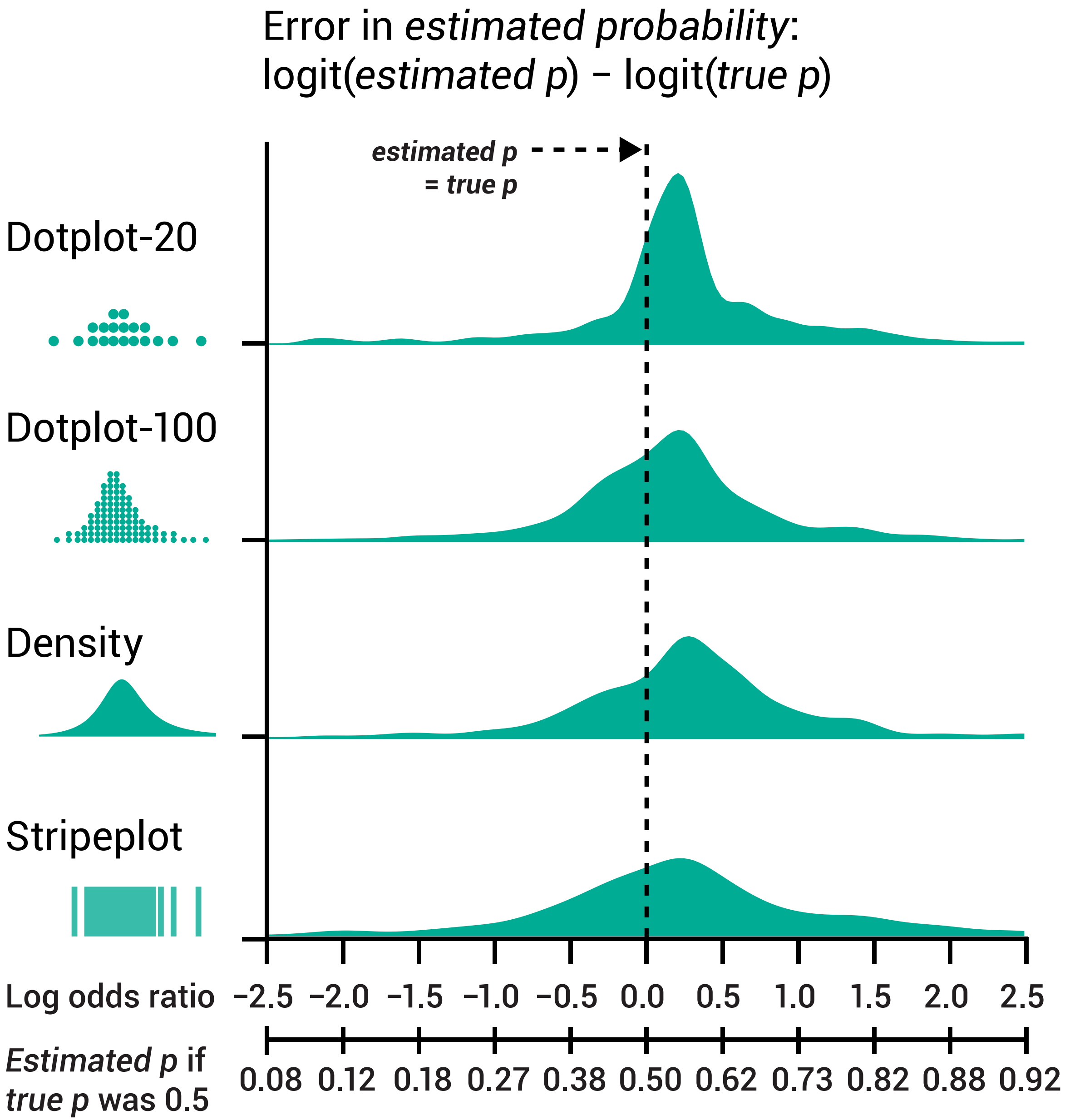


100%
75%
50%
25%
Cumulative probability
0%
1−90%
Cumulative distribution function
Quantile dotplot
0
5
10
15
20
25
30
Minutes until bus arrives
18/20 = 90% chance the bus comes at ~8 min or later

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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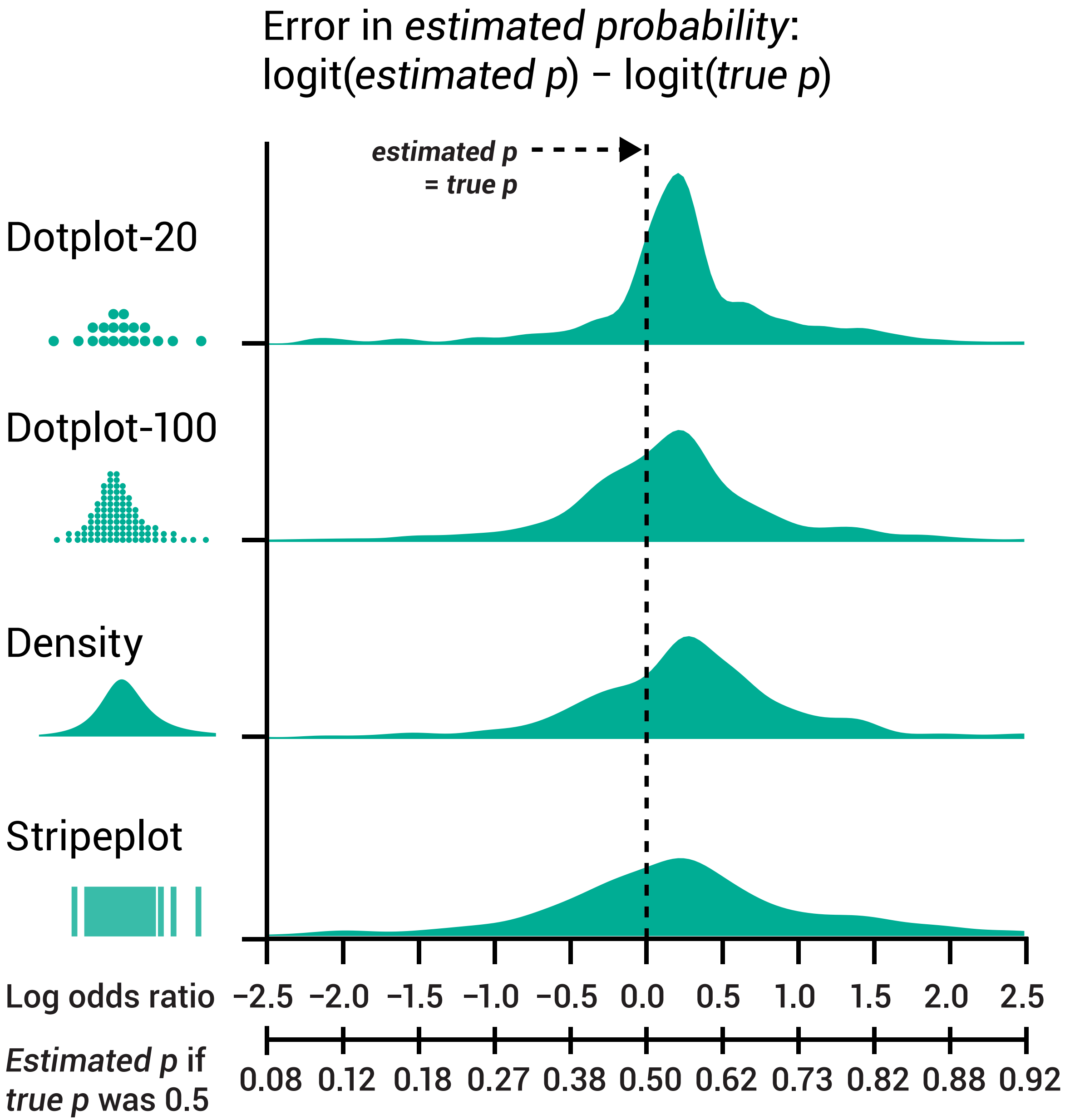
Better estimates (perceptually)

↓?

better decisions



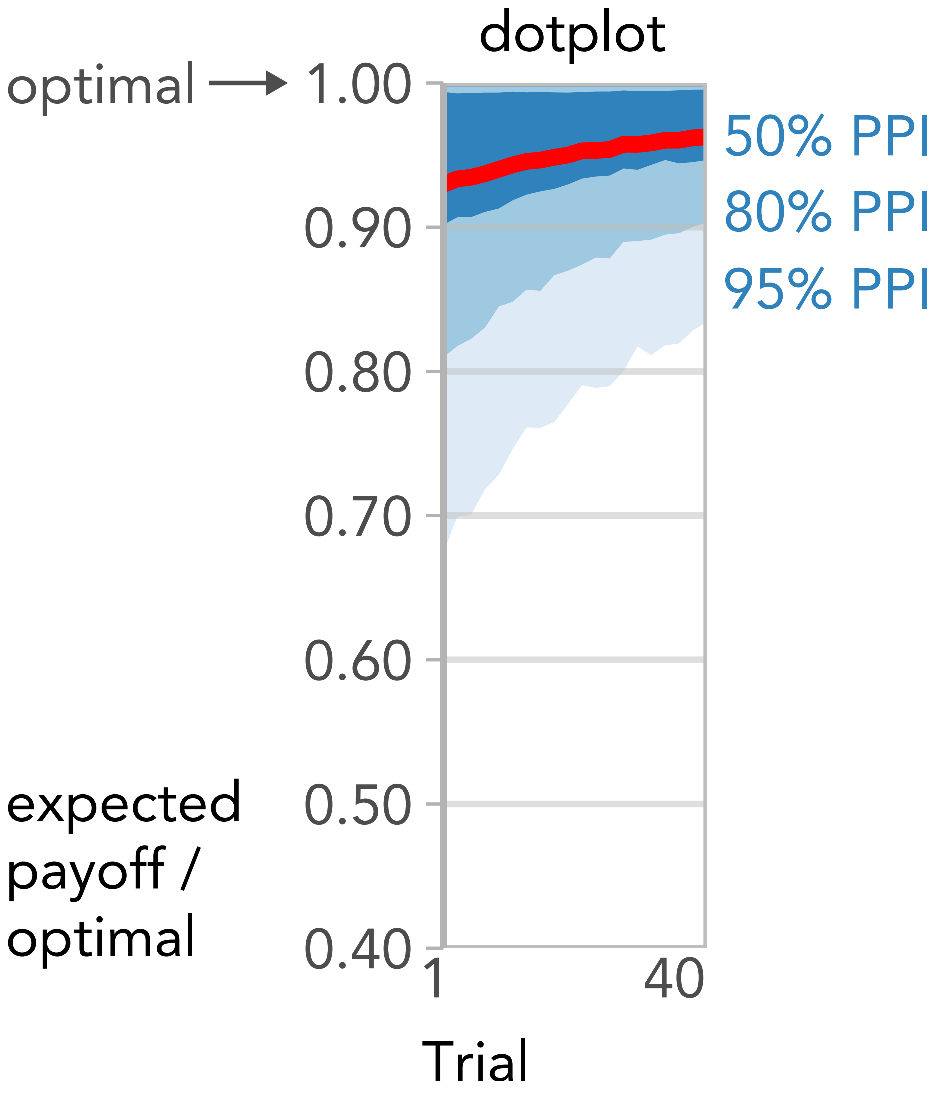
Quantile dotplots

[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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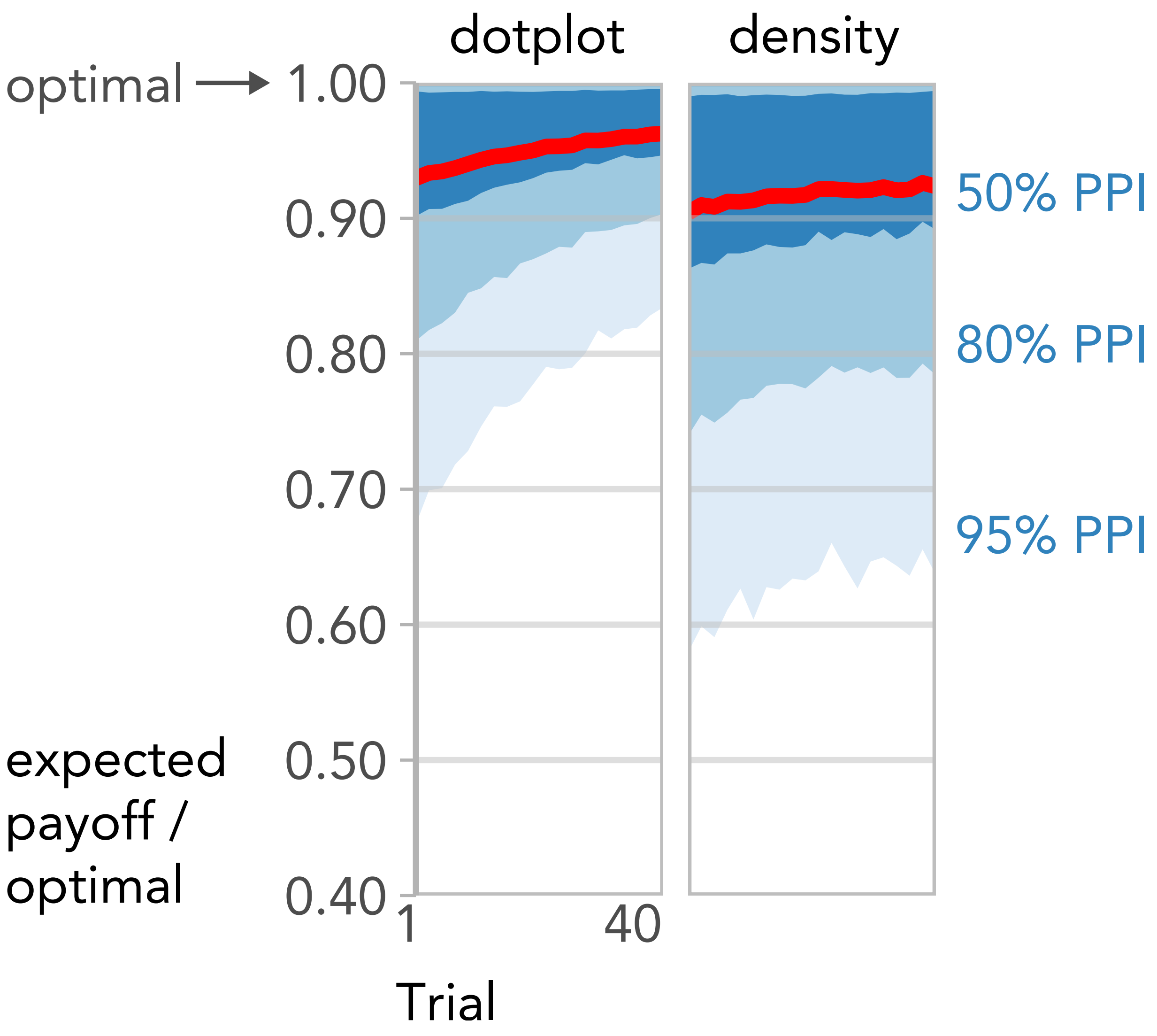
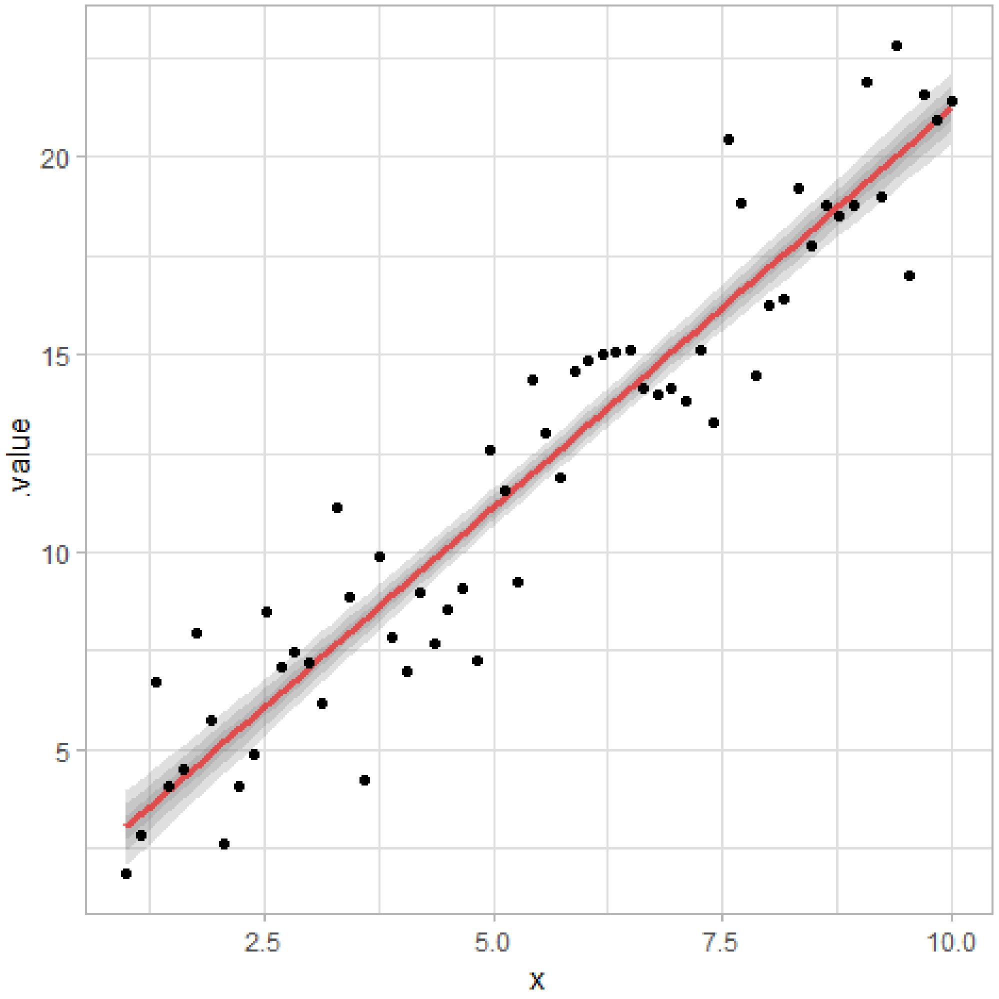


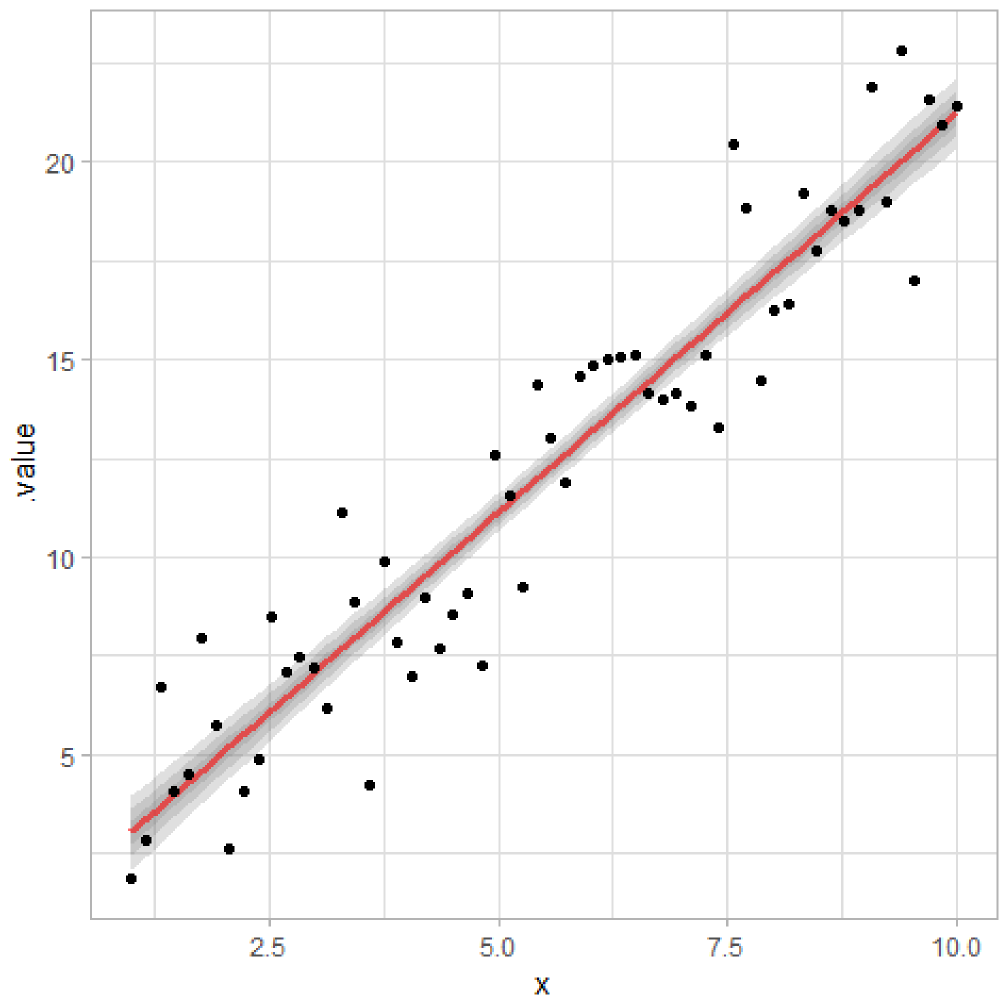
(Sidebar —

Uncertainty: what am I talking about?)

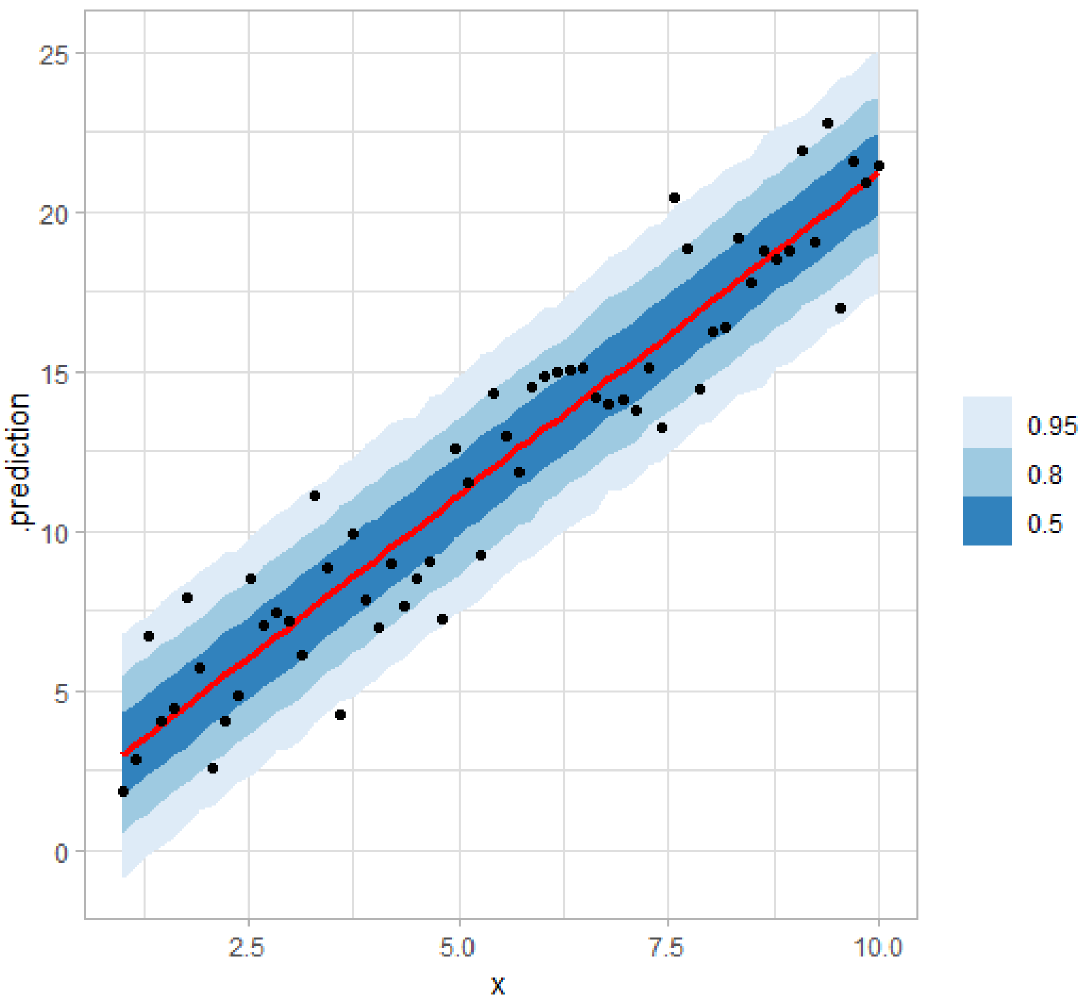
Parameter uncertainty



Parameter uncertainty

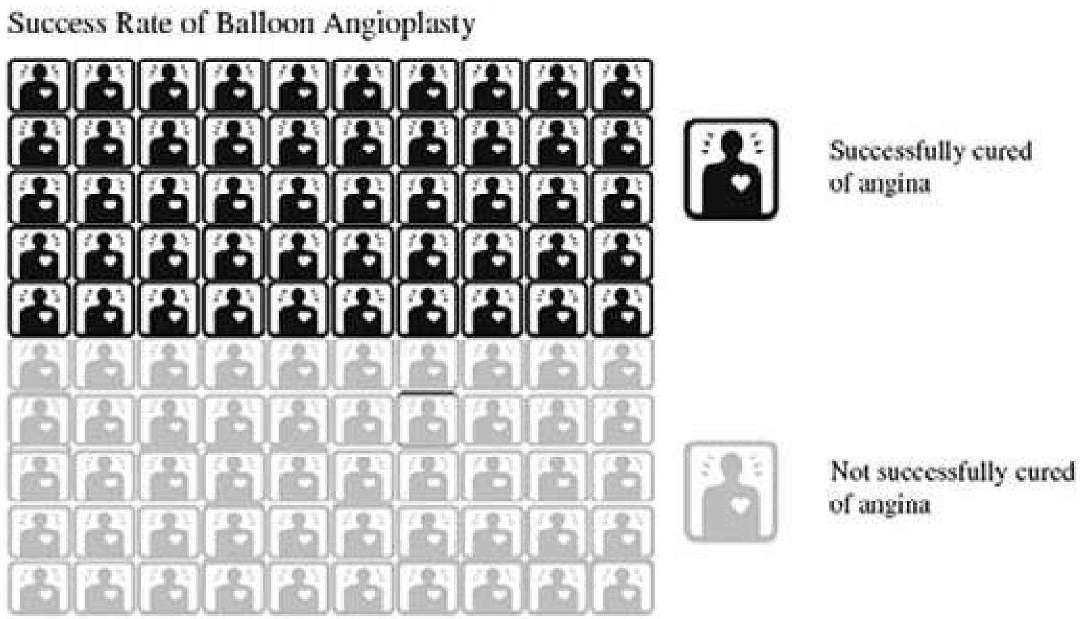


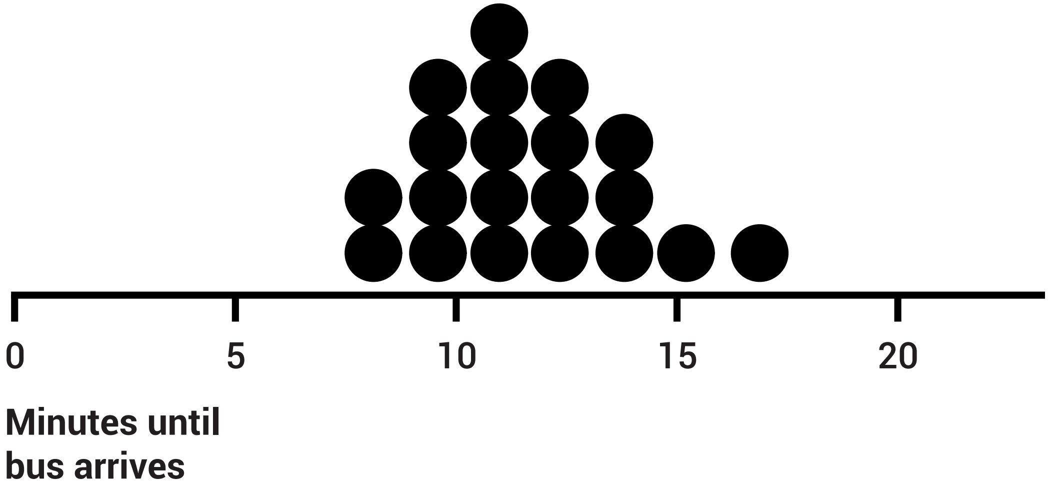
Predictive uncertainty



(End sidebar —
Back to uncertainty vis)

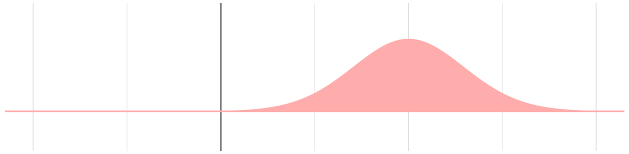
Discrete outcome / frequency framing



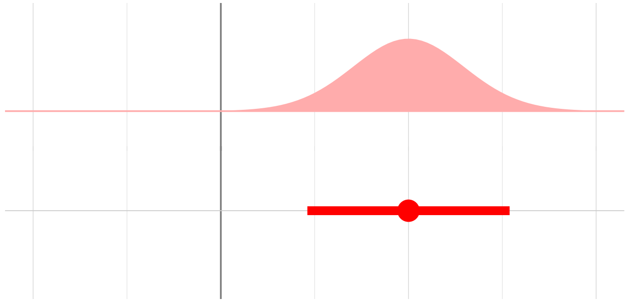


Let’s step back to the “simplest” case…

Uncertainty in point estimates…

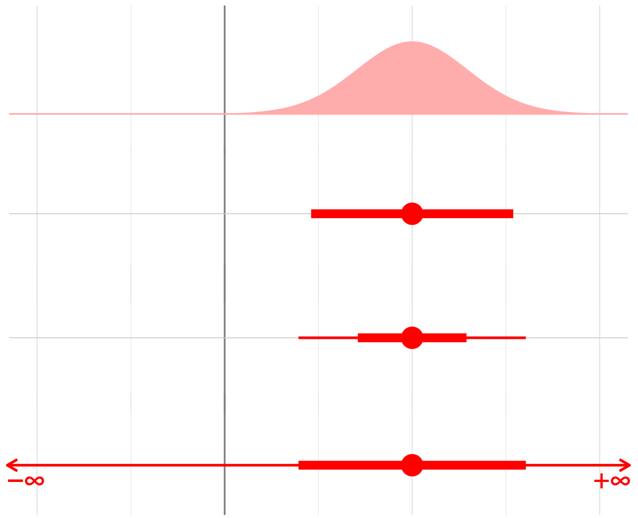


Uncertainty in point estimates…



Single interval

Uncertainty in point estimates…

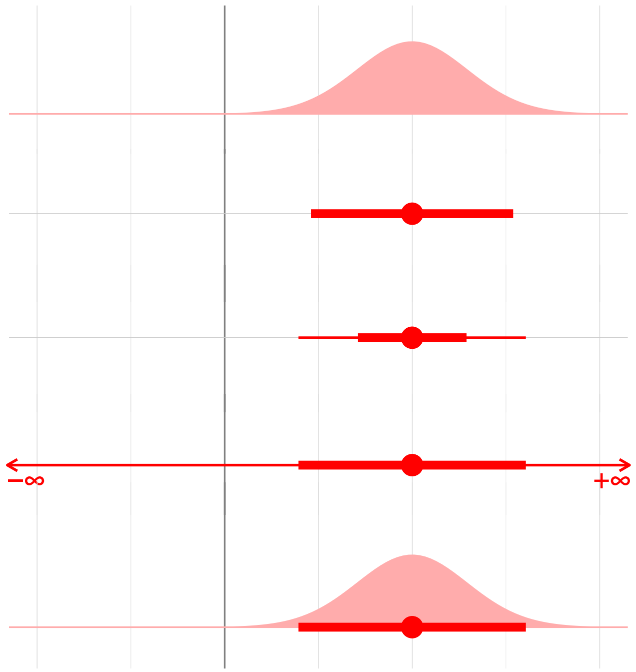


Single interval

Double inteval

Interval + 100% interval

Uncertainty in point estimates…



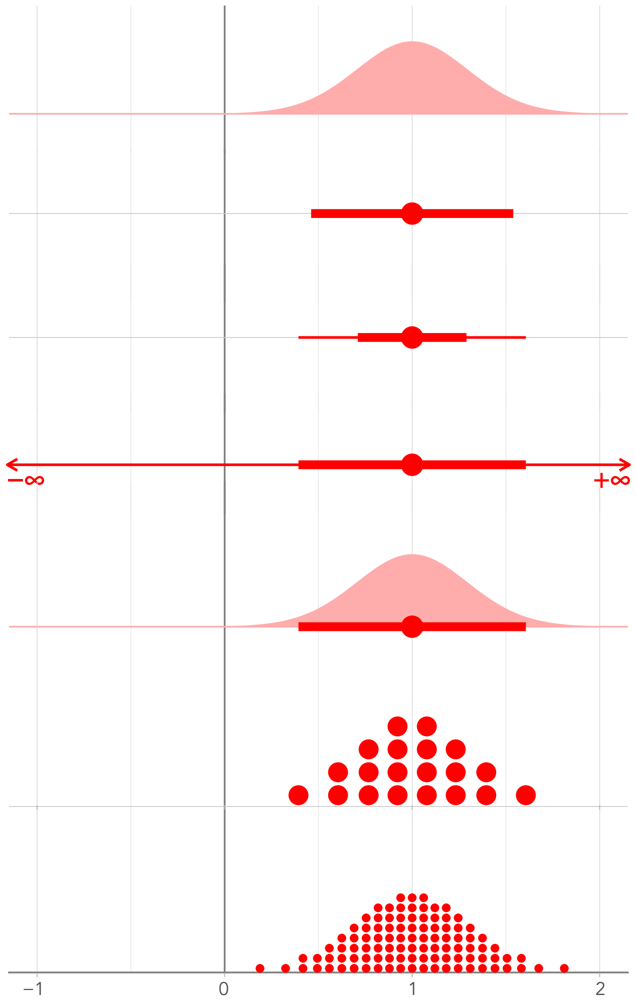
Single interval

Double inteval

Interval + 100% interval

Density + interval

Uncertainty in point estimates...



Single interval

Double inteval

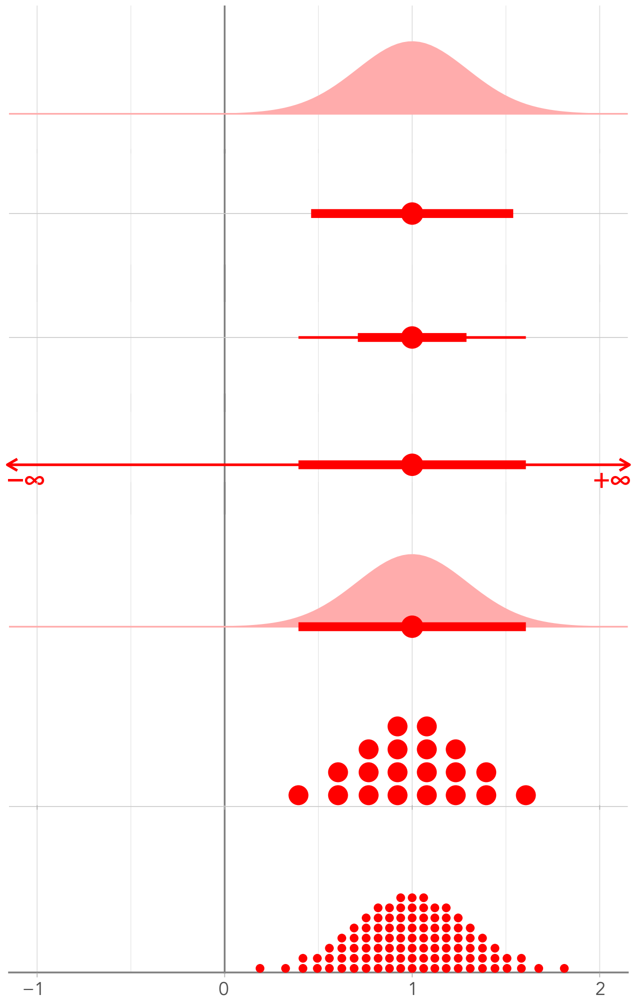
Interval + 100% interval

Density + interval

Quantile dotplot (20)

Quantile dotplot (100)

Uncertainty in point estimates...



Single interval

Double inteval

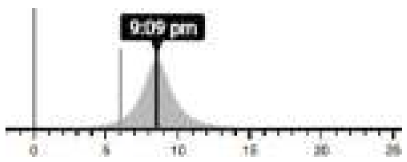
Interval + 100% interval

Density + interval

Quantile dotplot (20)

Quantile dotplot (100)

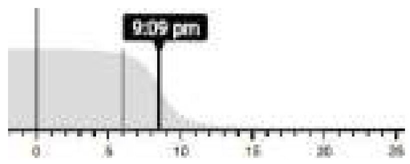
Probability Density Plots



Interval Plot

Probability Density and Interval Plot

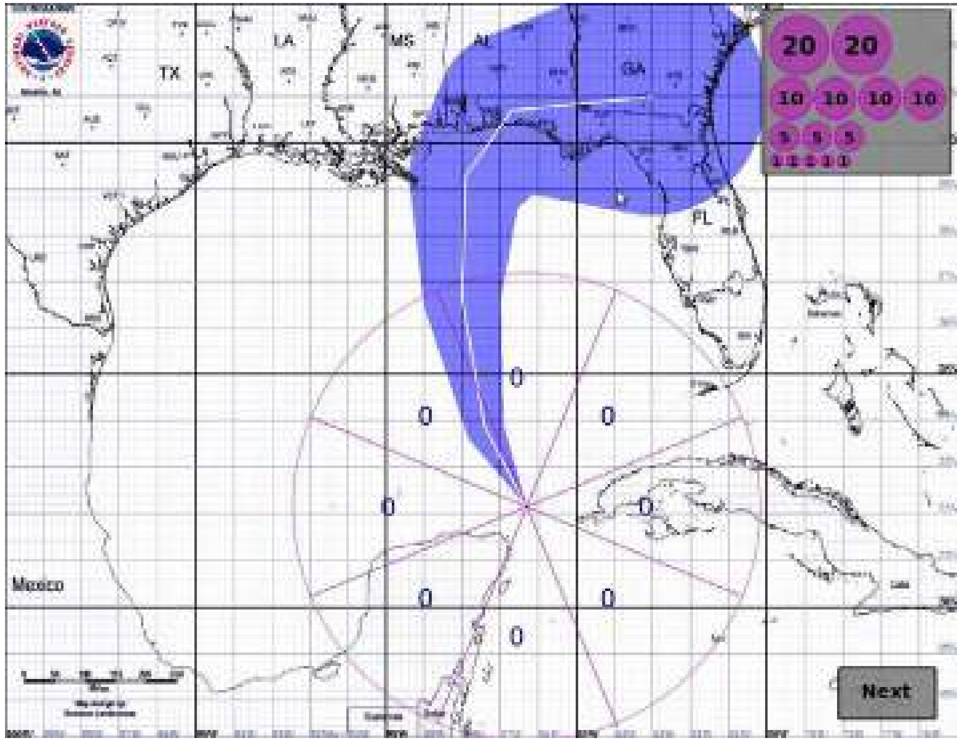
Complementary Cumulative Distribution Plot



Other discrete outcome uncertainty visualizations…

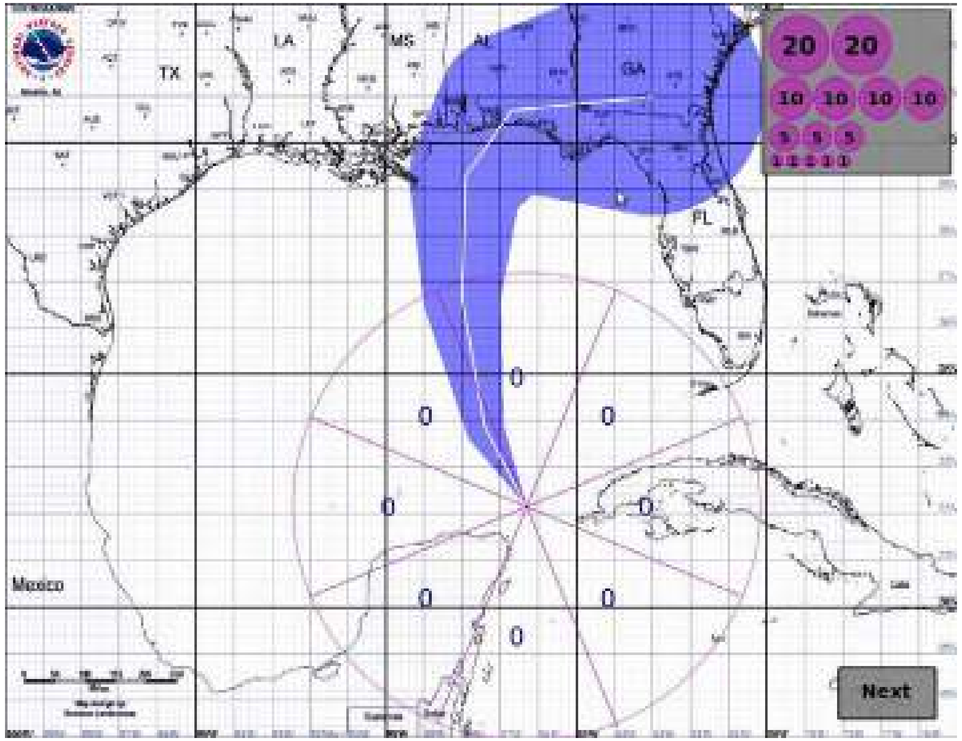
Hurricane error cones

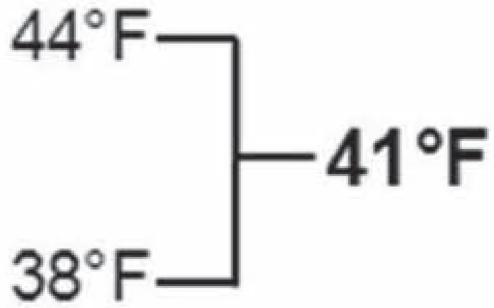
[Cox, House, Lindell. Visualizing Uncertainty in Predicted Hurricane Tracks. International Journal for Uncertainty Quantification, 3(2), 143–156, 2013]



Deterministic construal errors

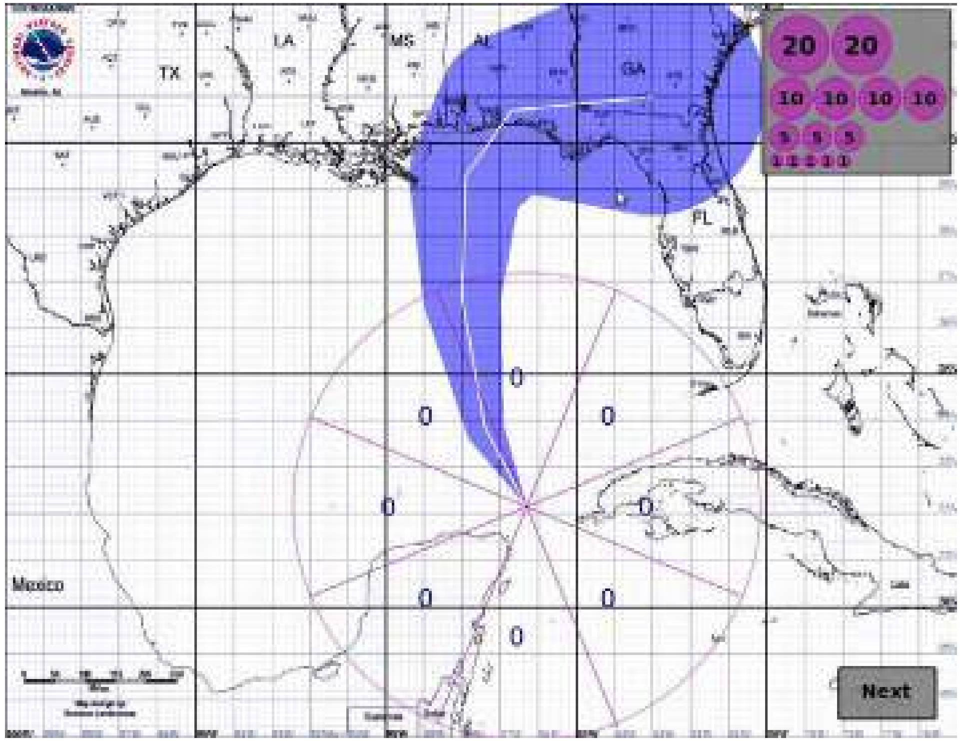
[Joslyn & LeClerc. Decisions With Uncertainty: The Glass Half Full. Current Directions in Psych. Science, 22(4), 2013]

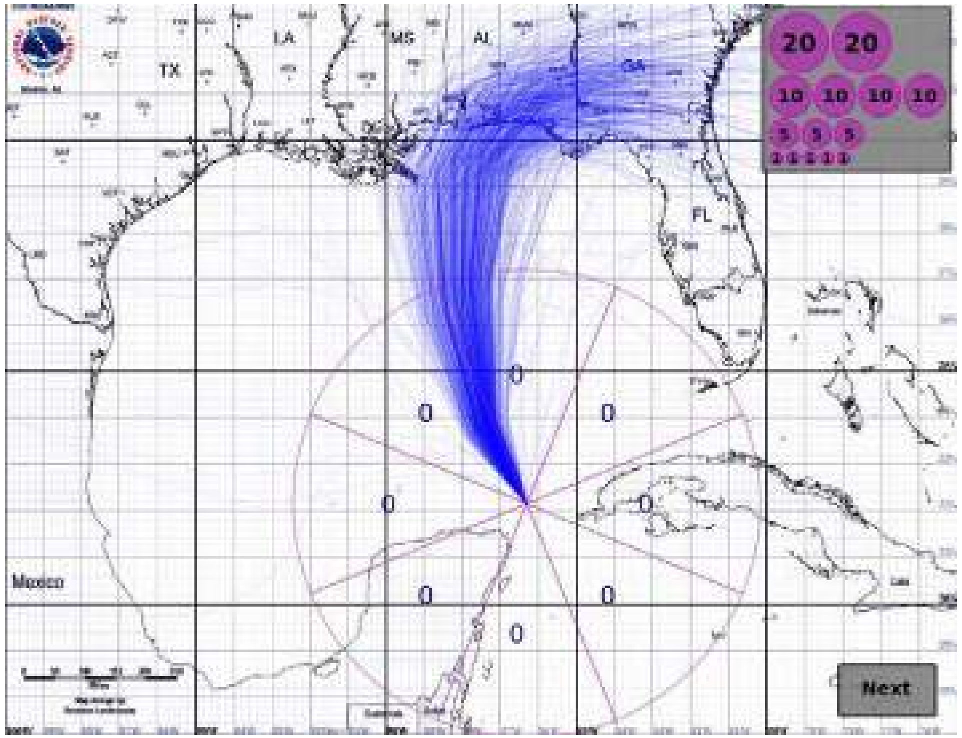




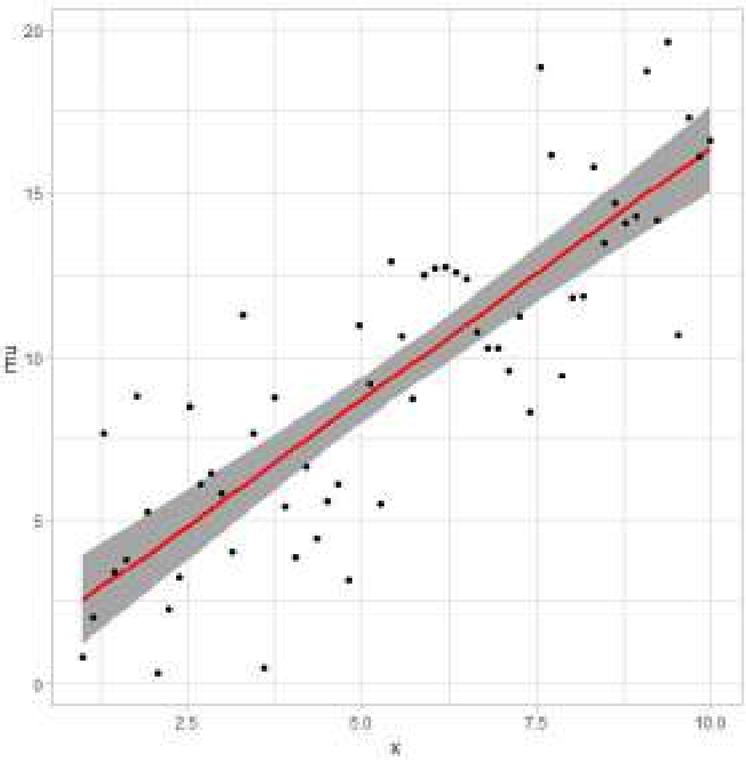
Hurricane error cones

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

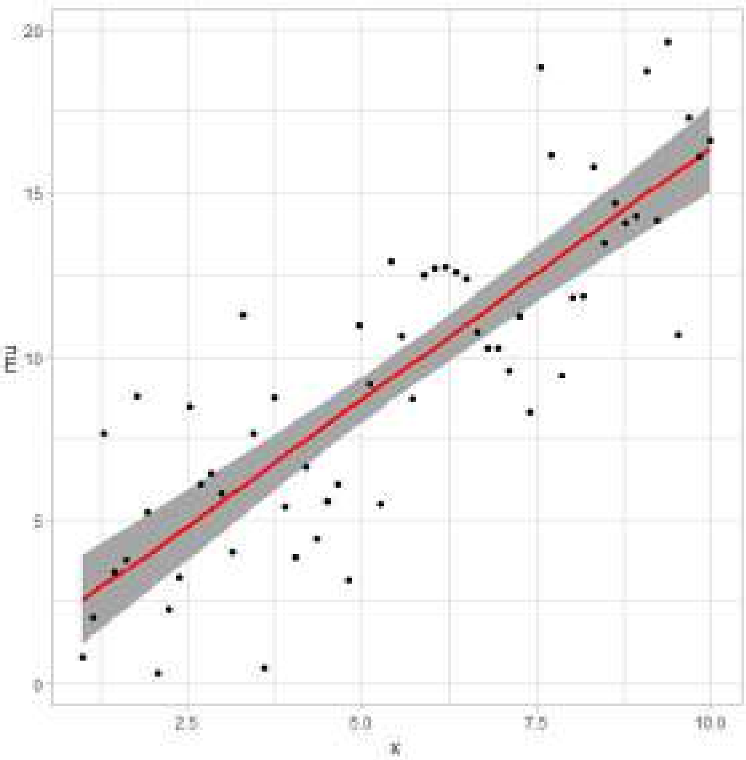


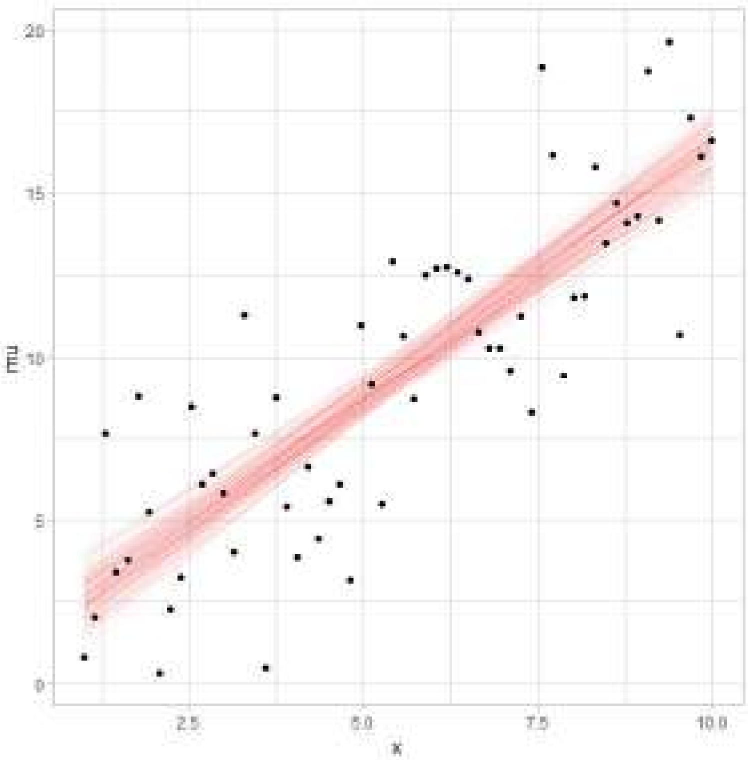


Fit line uncertainty

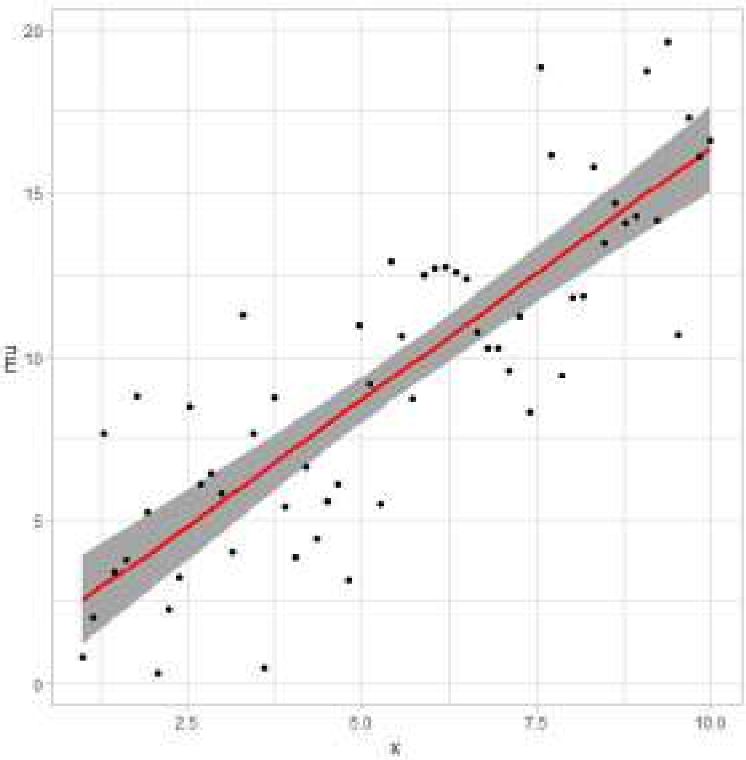


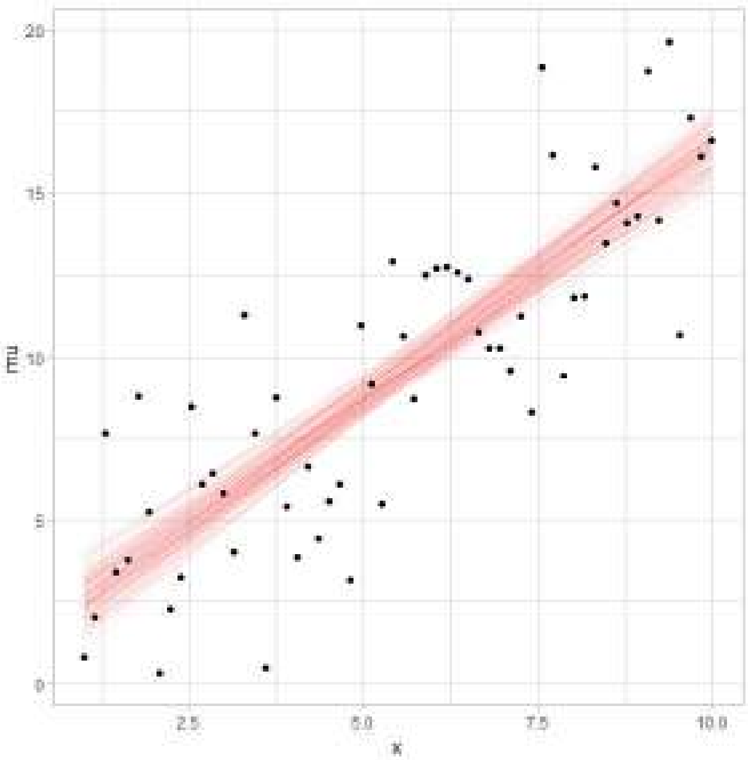
Fit line uncertainty



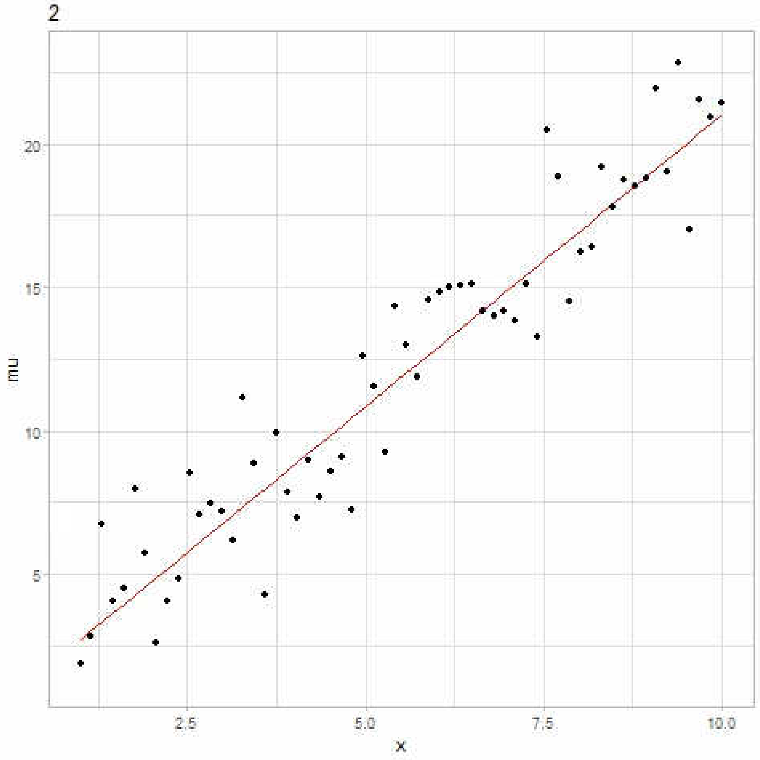


Fit line uncertainty





Hypothetical outcome plots (HOPs)



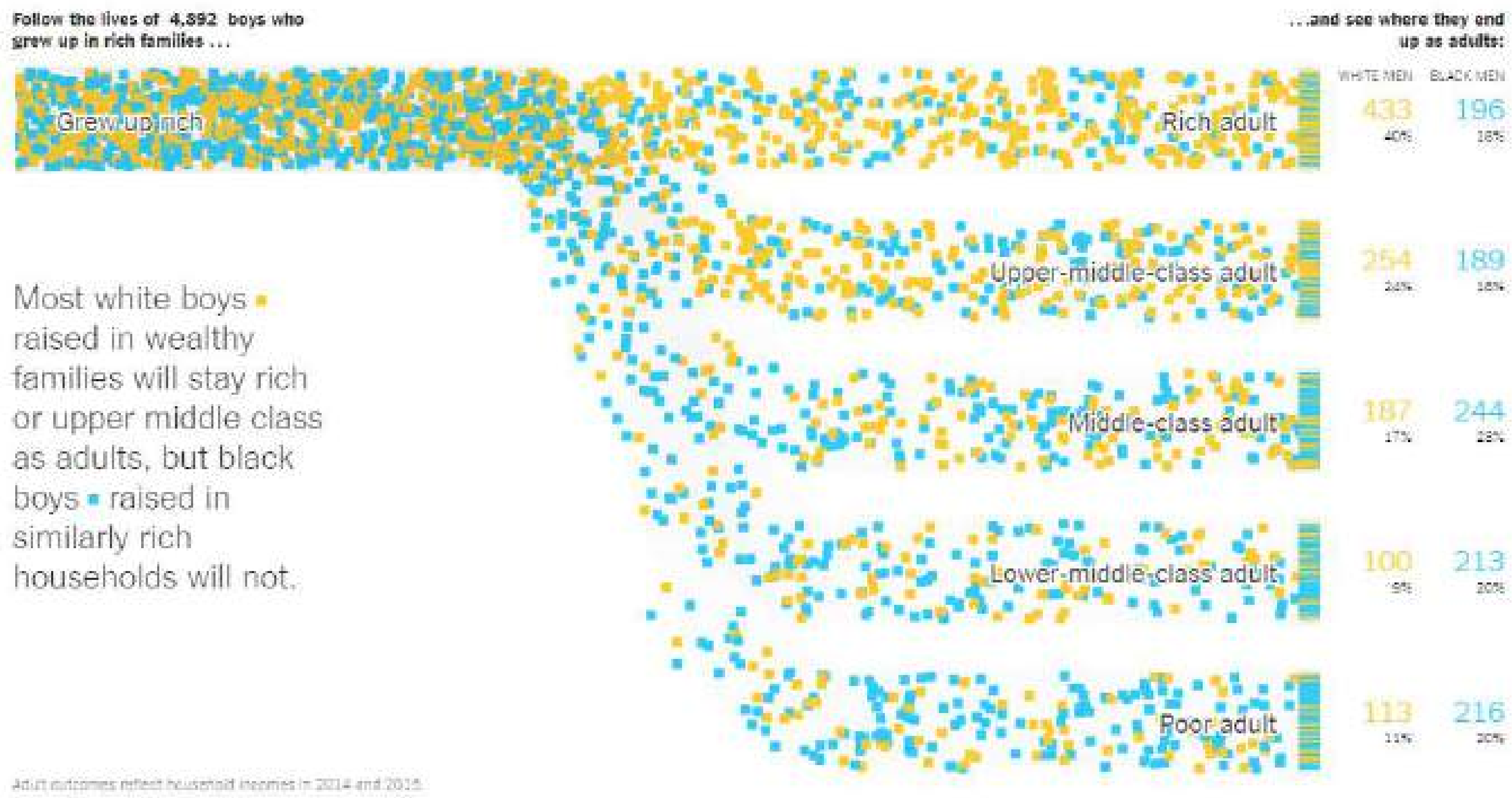
[Hullman, Resnick, Adar. Hypothetical Outcome Plots Outperform Error Bars and Violin Plots for Inferences about Reliability of Variable Ordering. PloS One, 10(11). 2015]

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]



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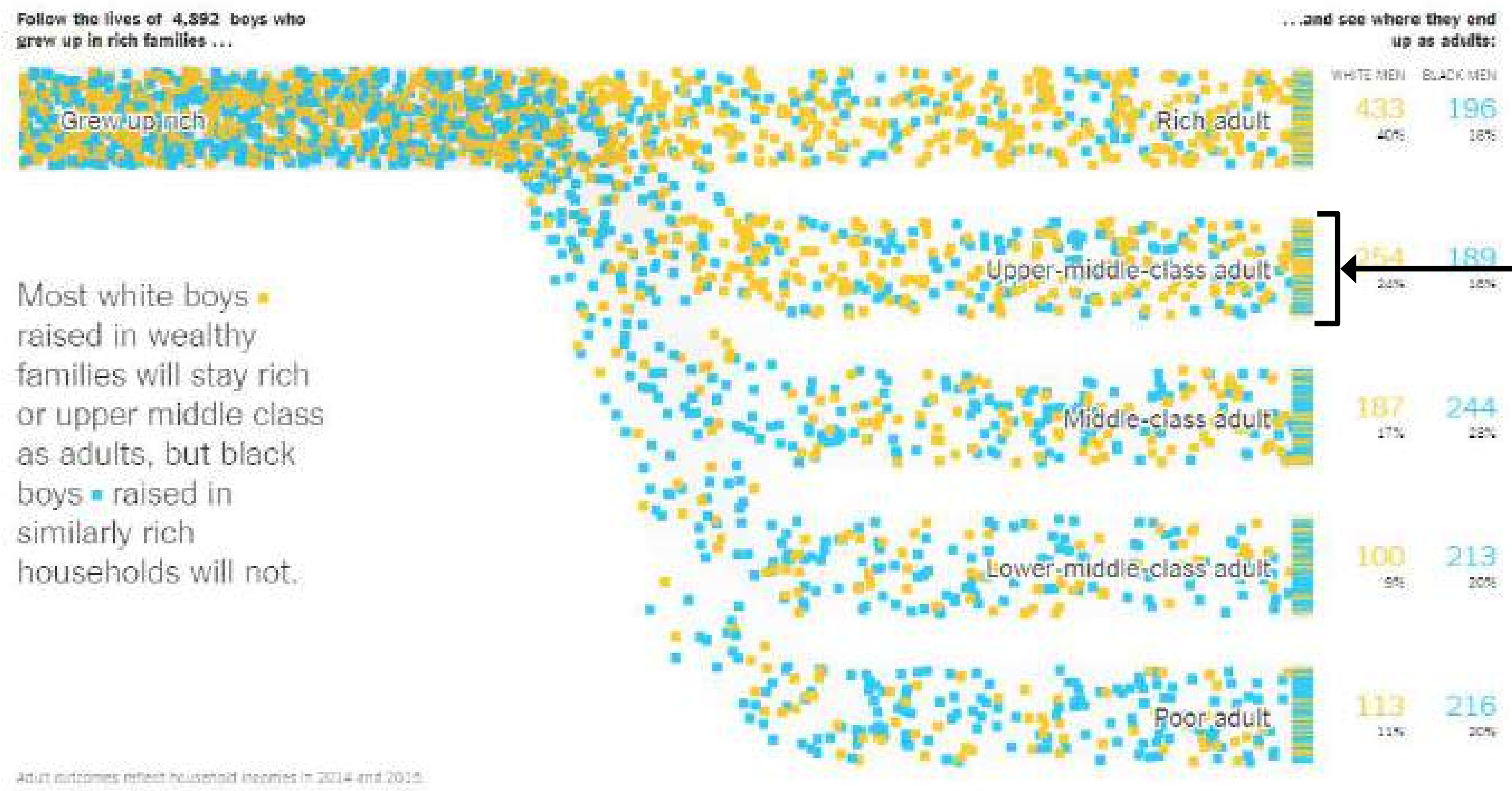
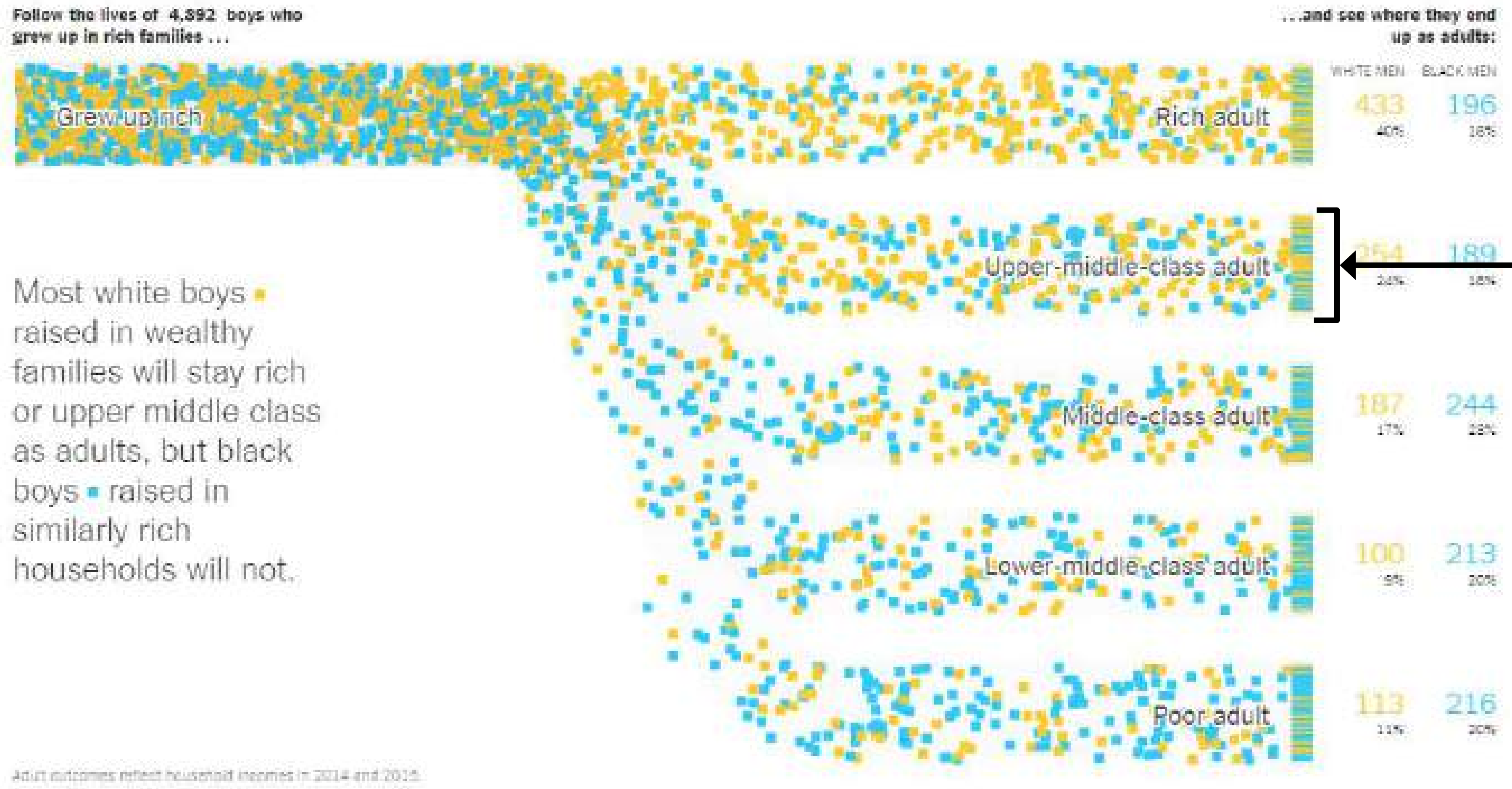


P(race | adult income)

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]



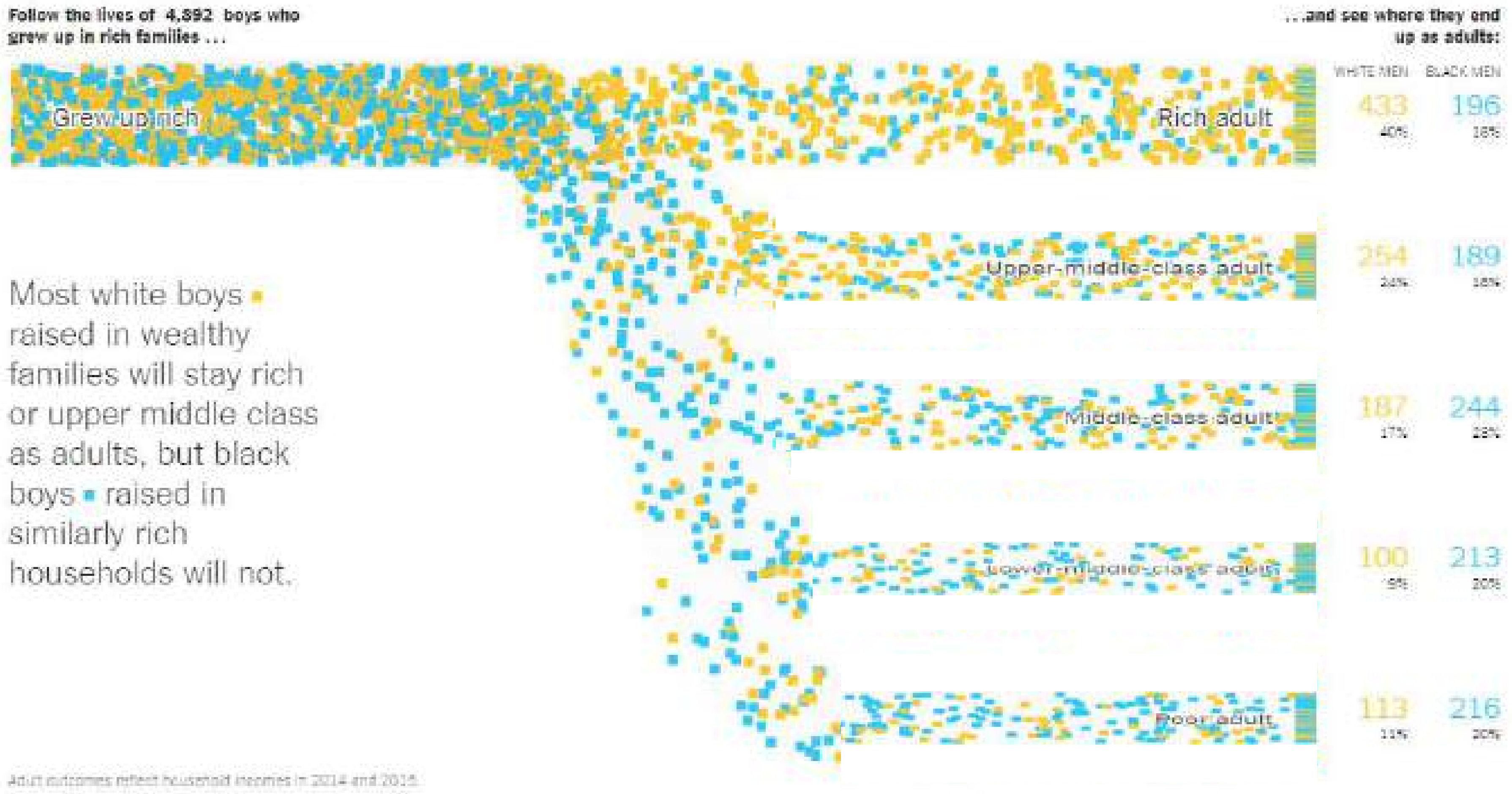
I want:

P(adult income | race)

P(race | adult income)

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]



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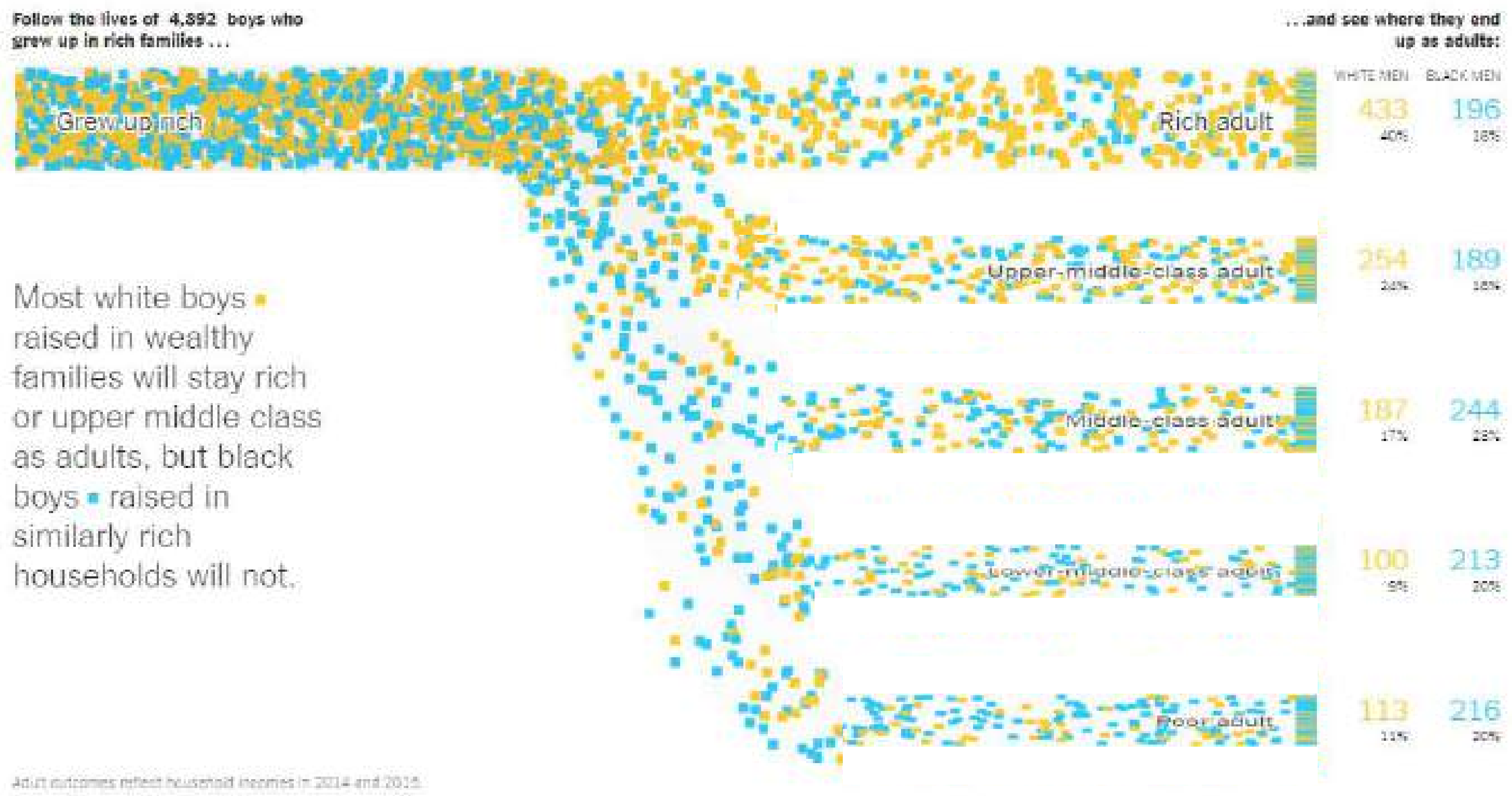

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P(adult income | race)

Income of black boys from wealthy families

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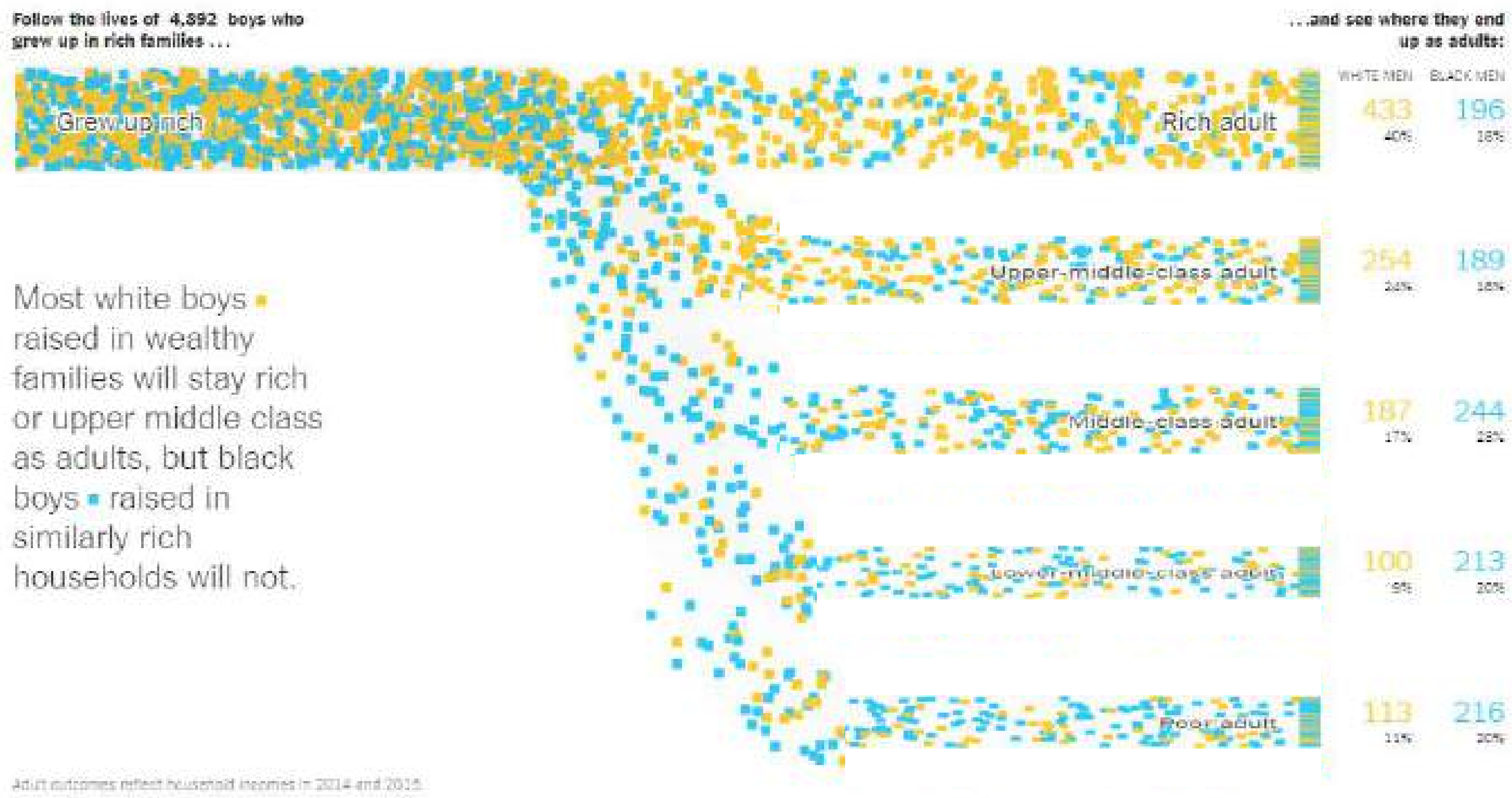
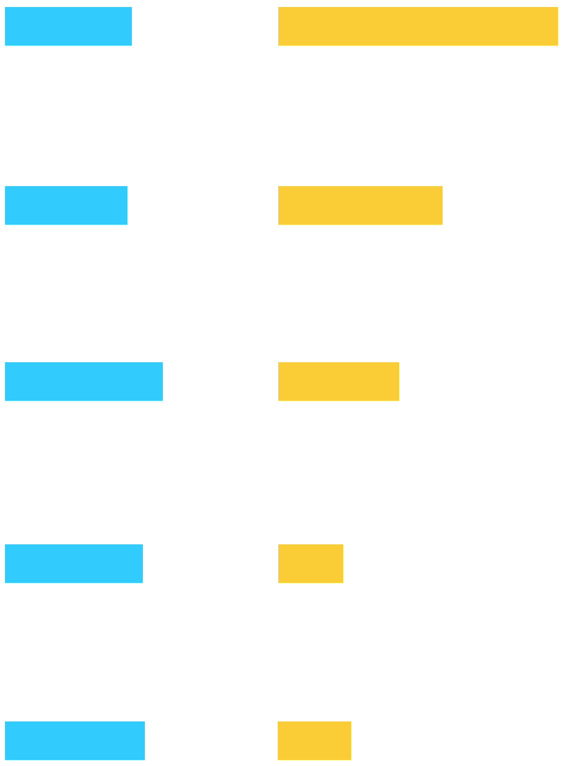


I want:

P(adult income | race)



Animation can aid understanding, but…

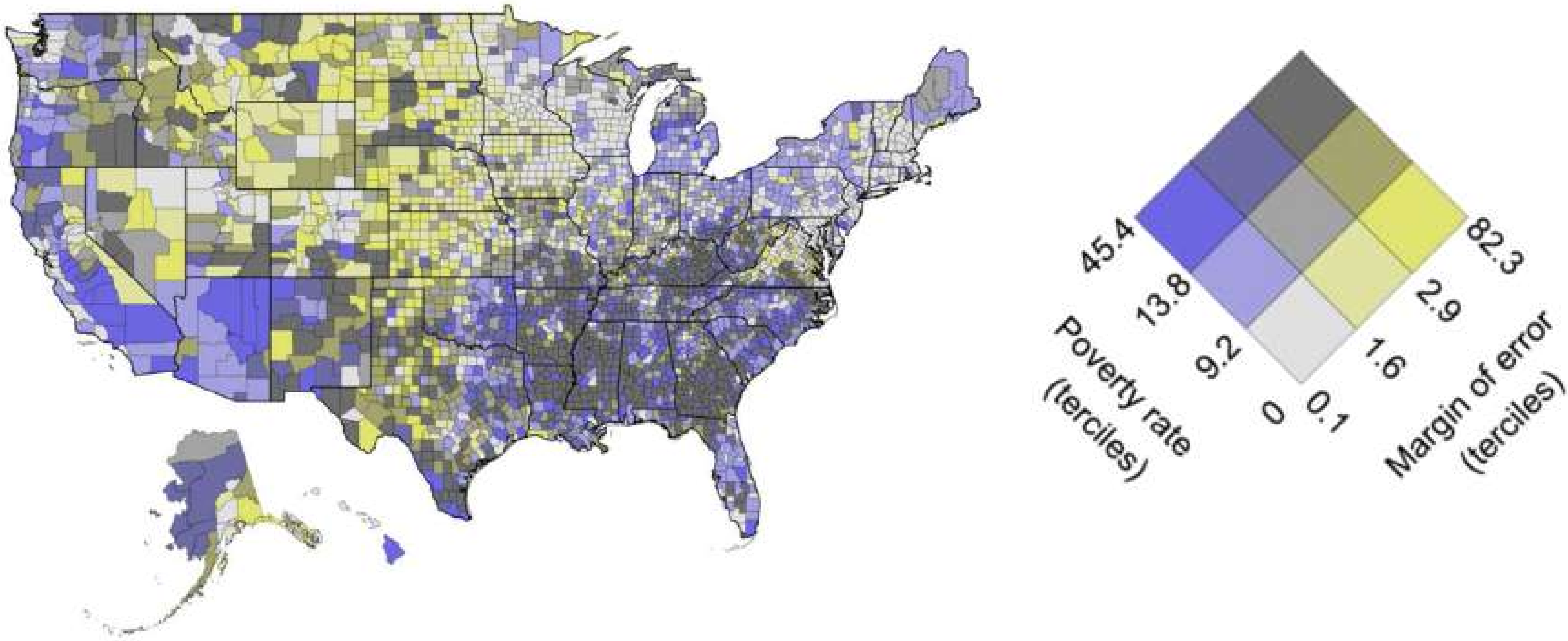
Animation can aid understanding, but...

Building effective, complex, correct uncertainty visualizations is **hard**

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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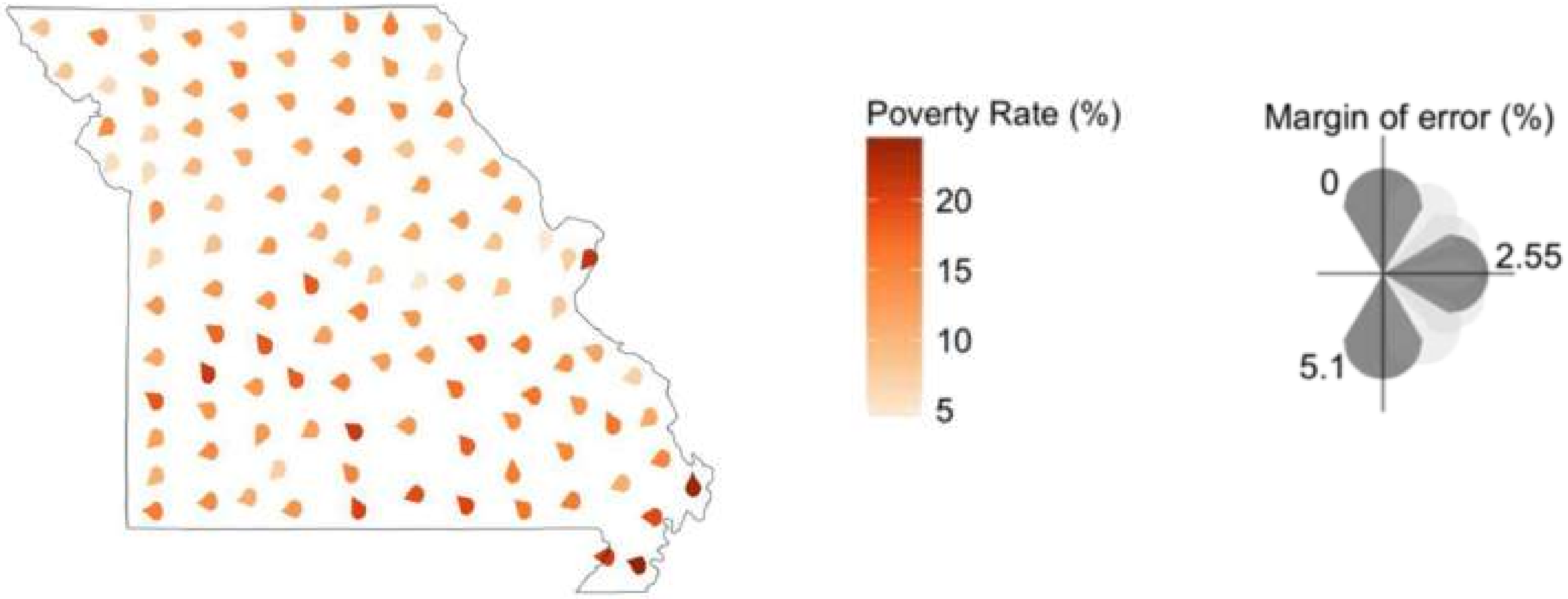

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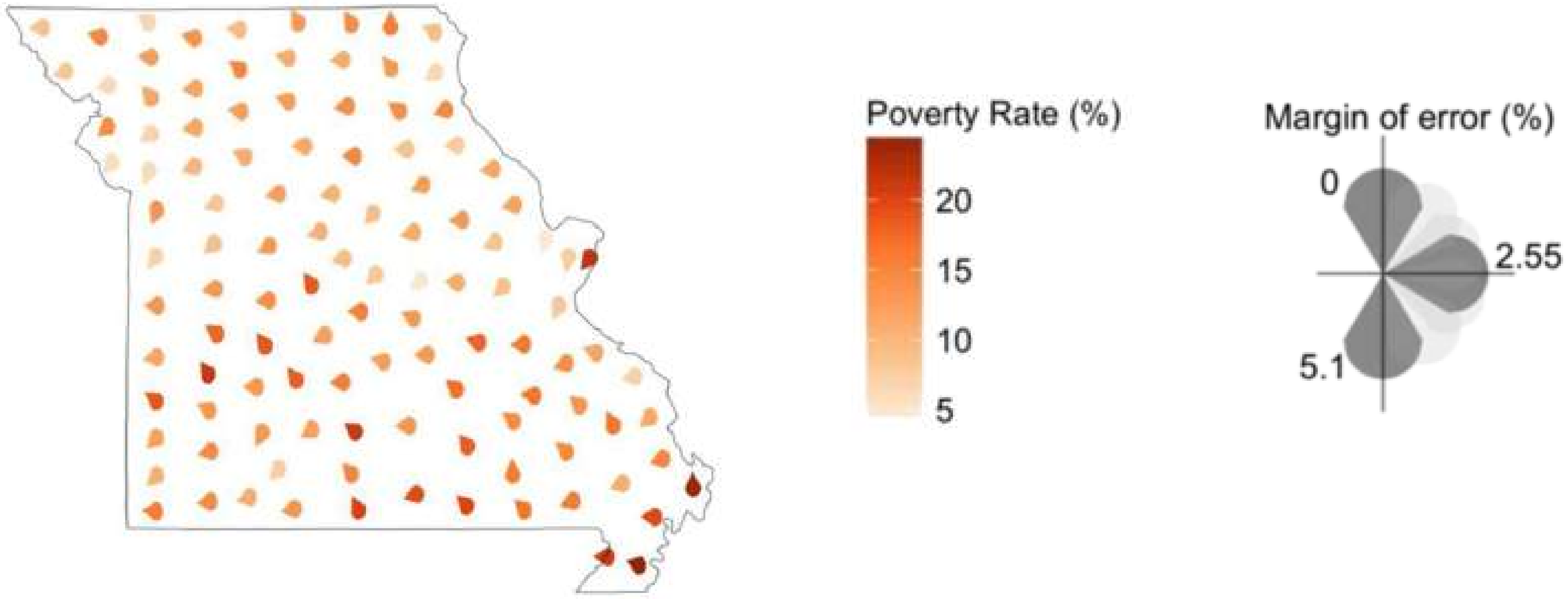
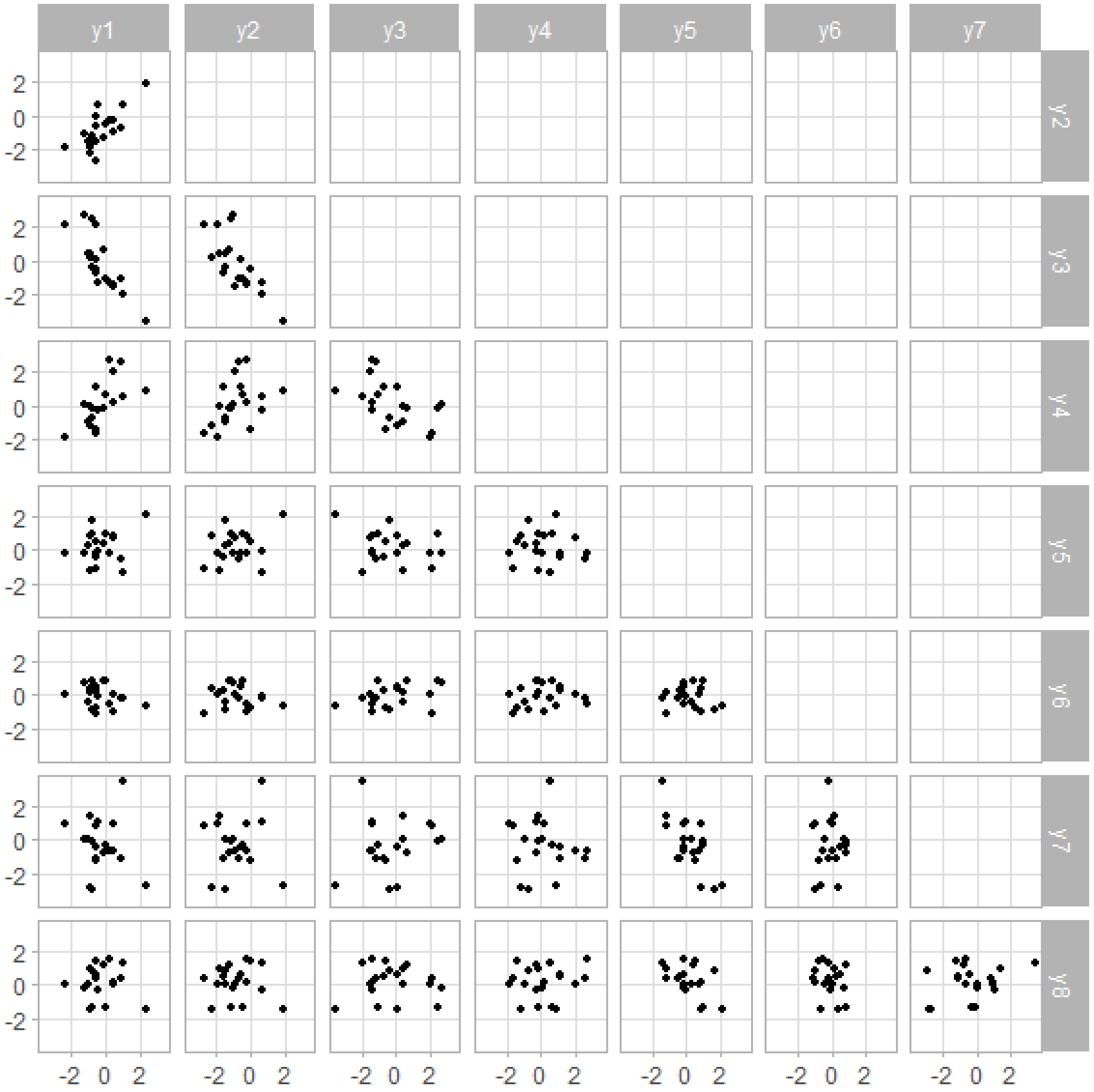
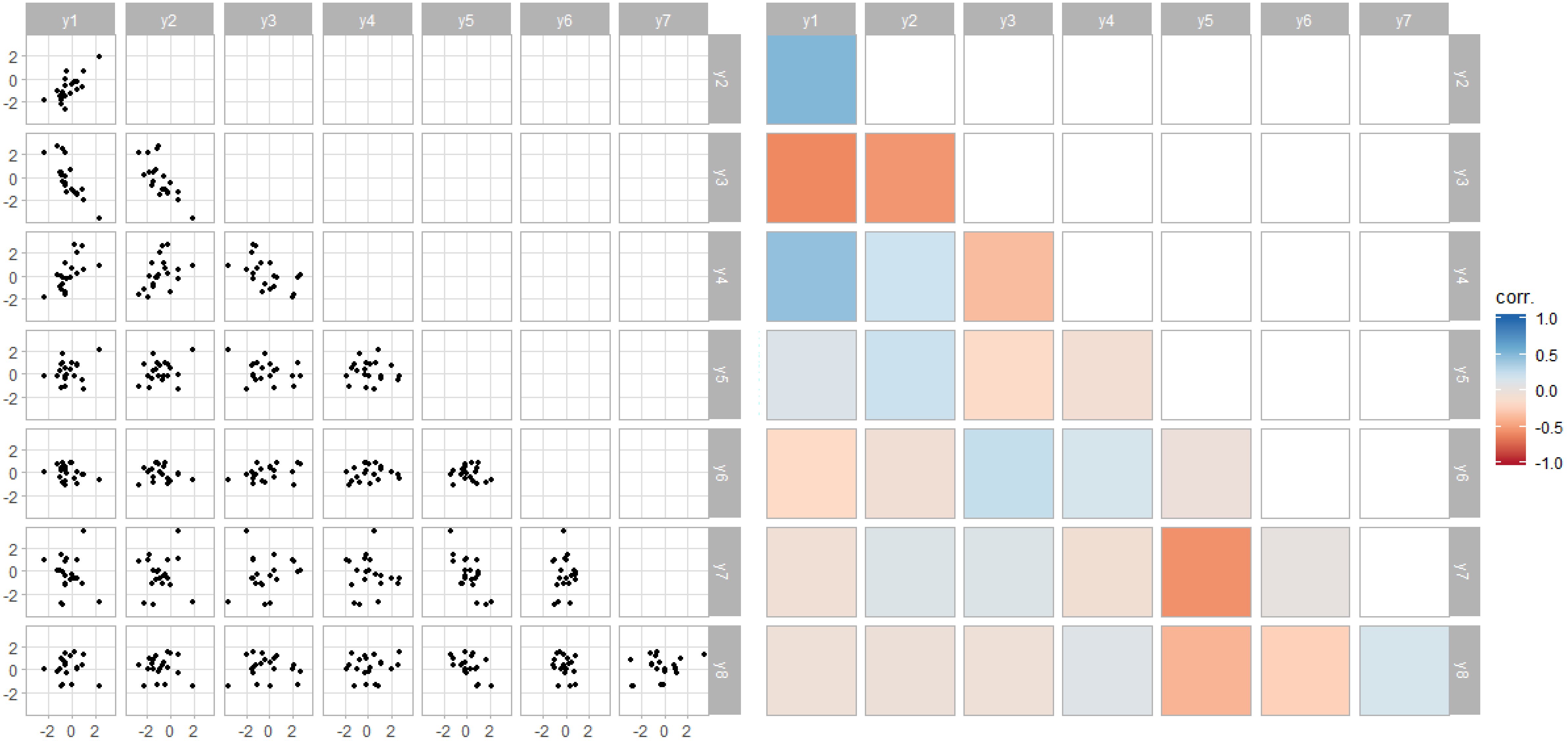


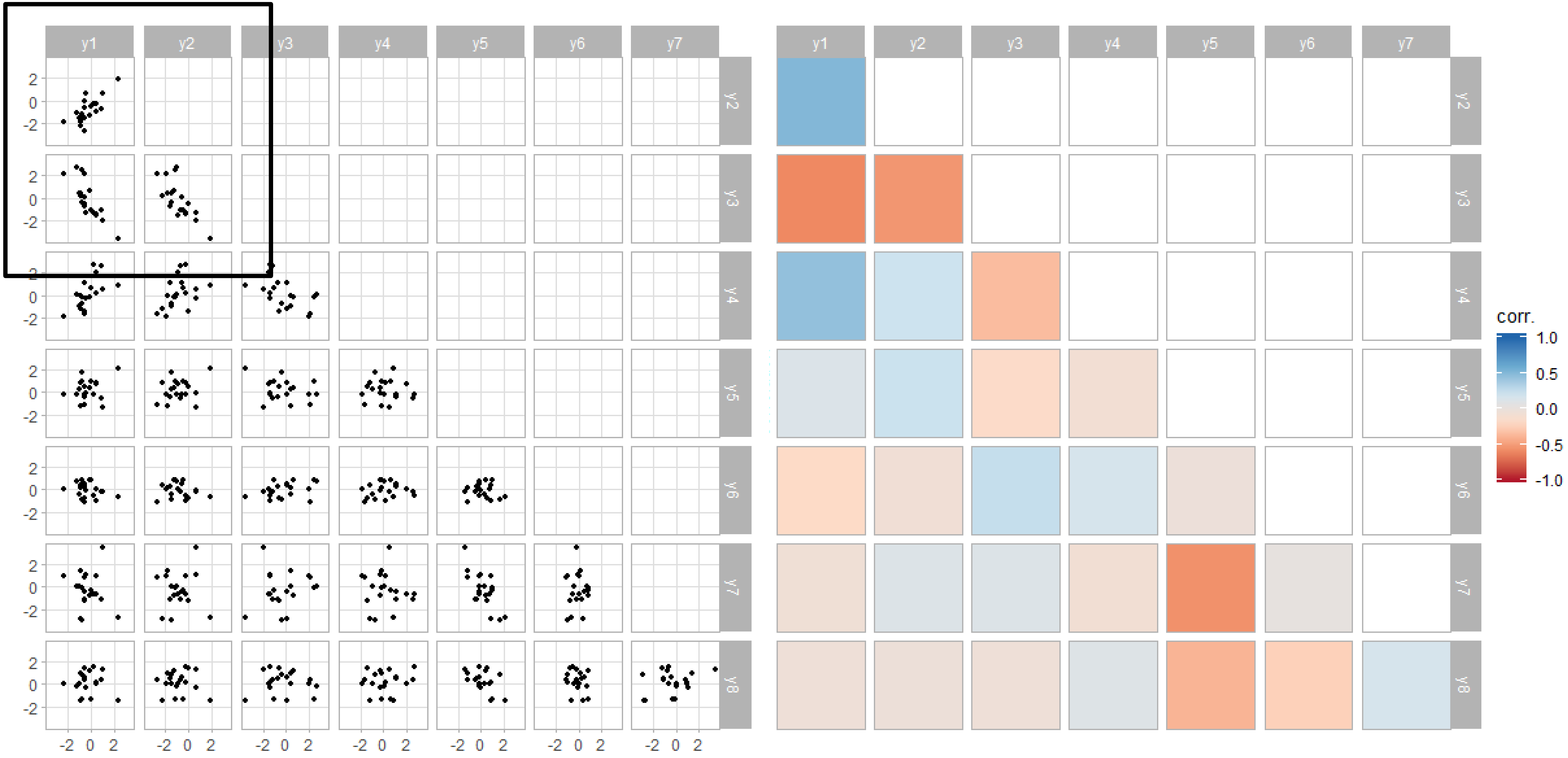
Very abstract…

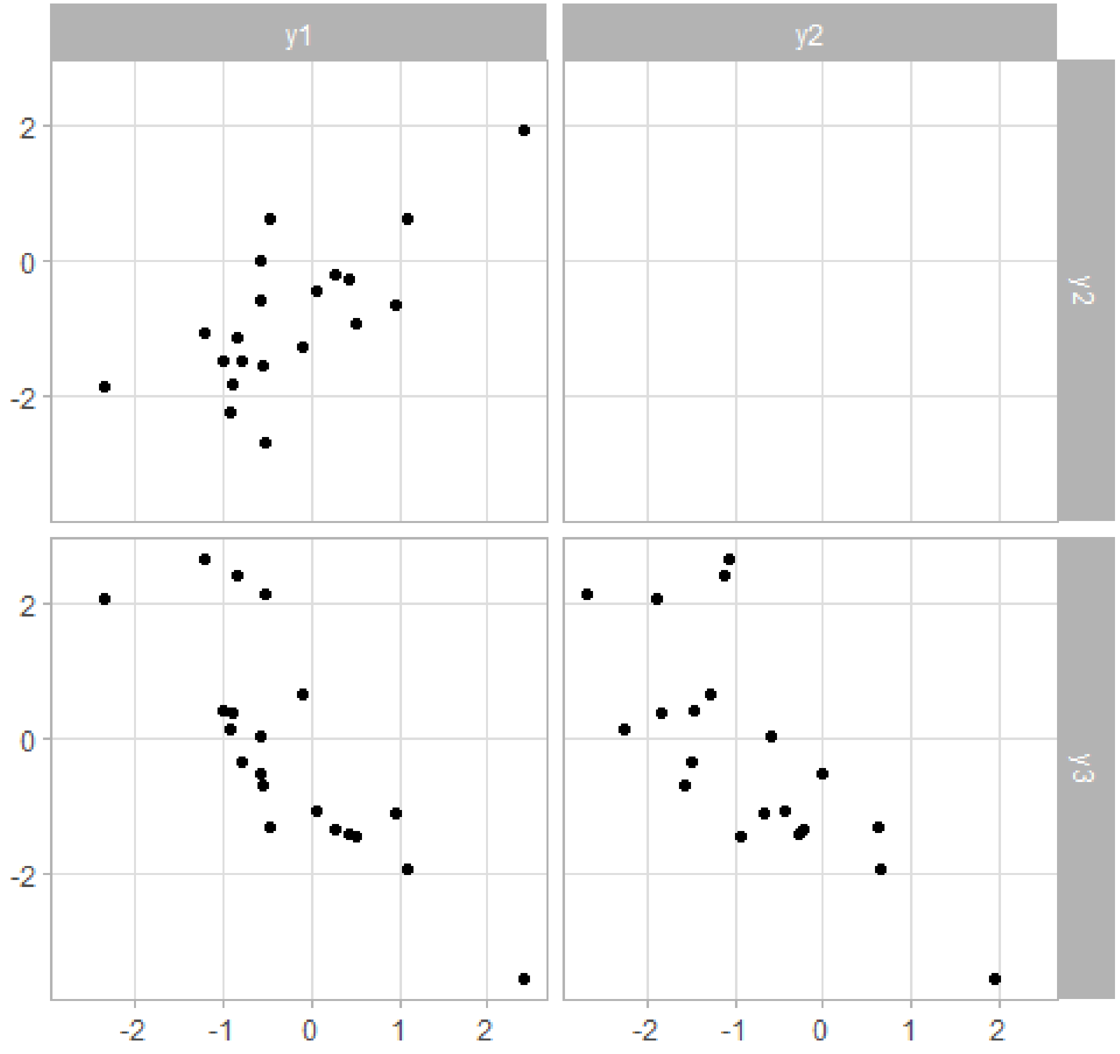
Let’s take a detour…


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

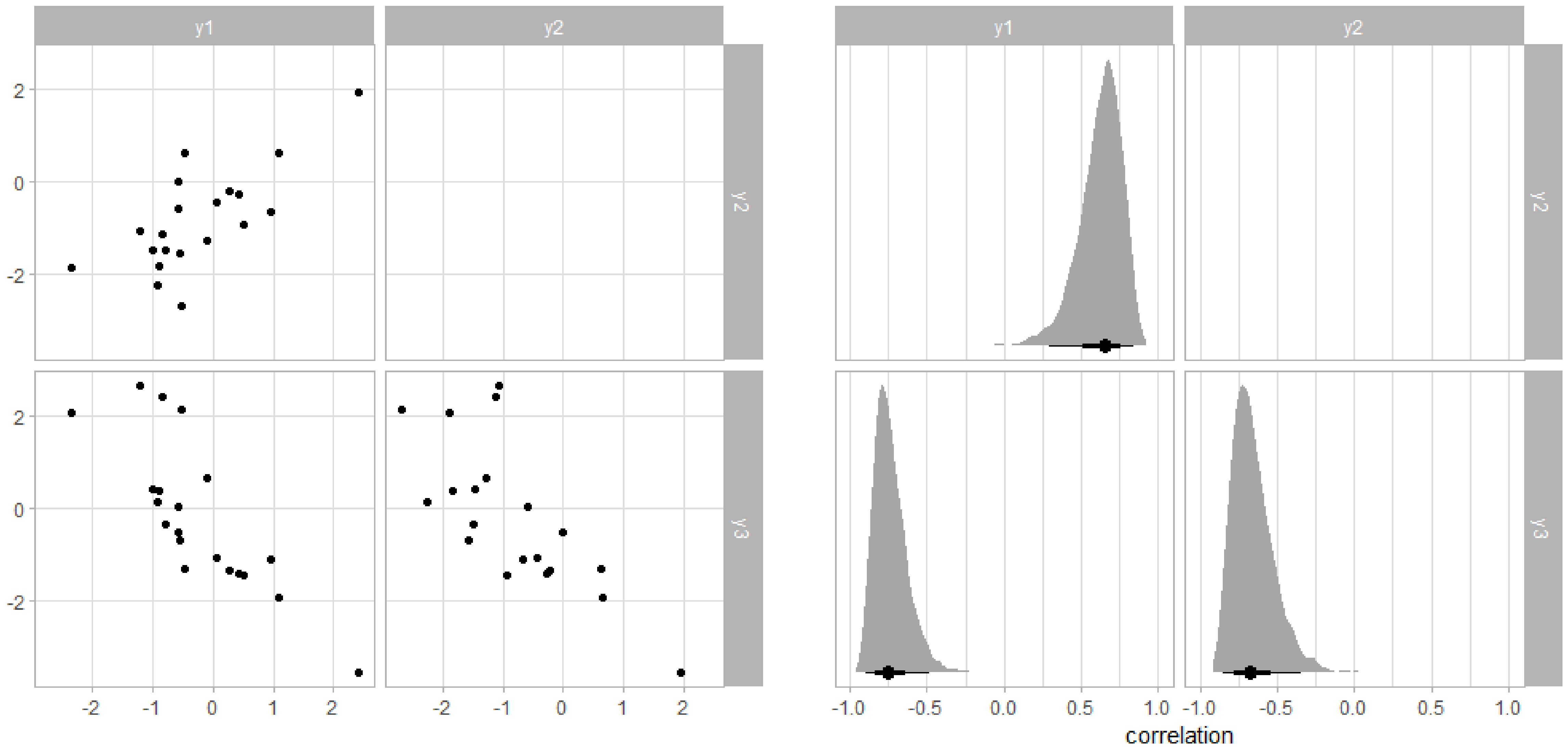


y1
y2
y3
y4
y5
y6
y7
y8
2
0
-2
corr.
1.0
0.5
0.0
-0.5
-1.0


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



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


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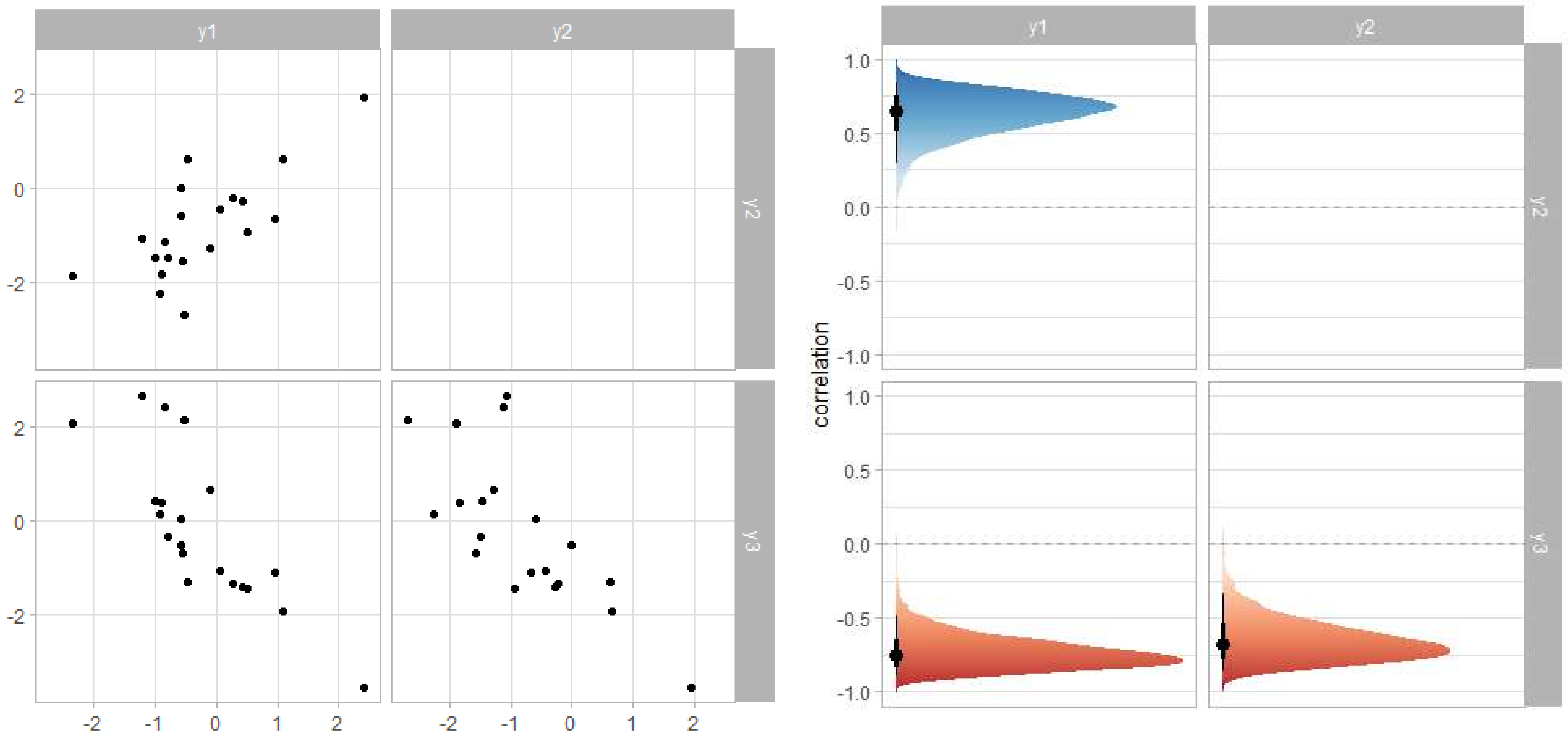
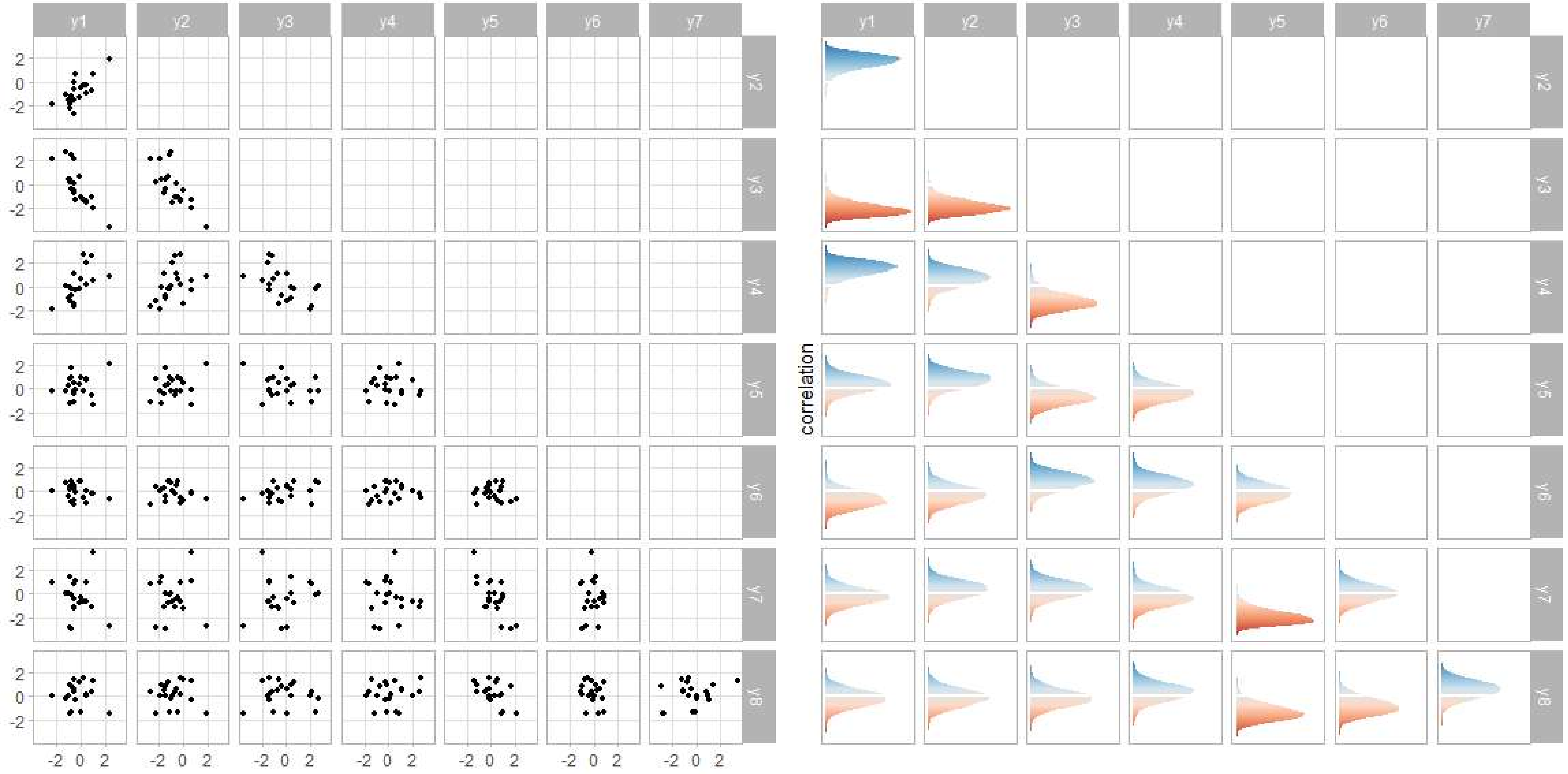
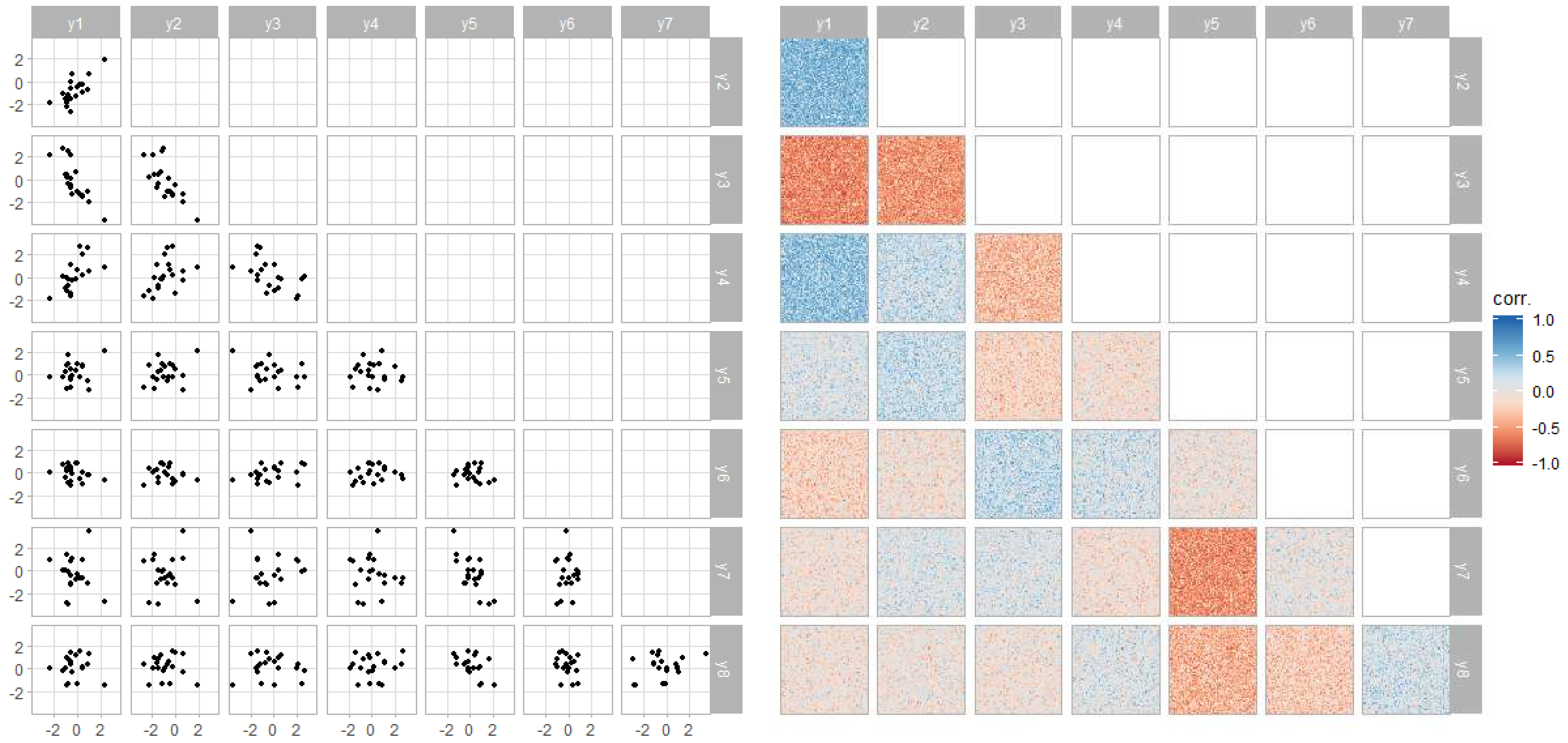
0
-2
2
0
-2
-2
-1
0
1
2
-2
-1
0
1
2
-1.0
-0.5
0.0
0.5
1.0
-1.0
-0.5
0.0
0.5
1.0
correlation



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


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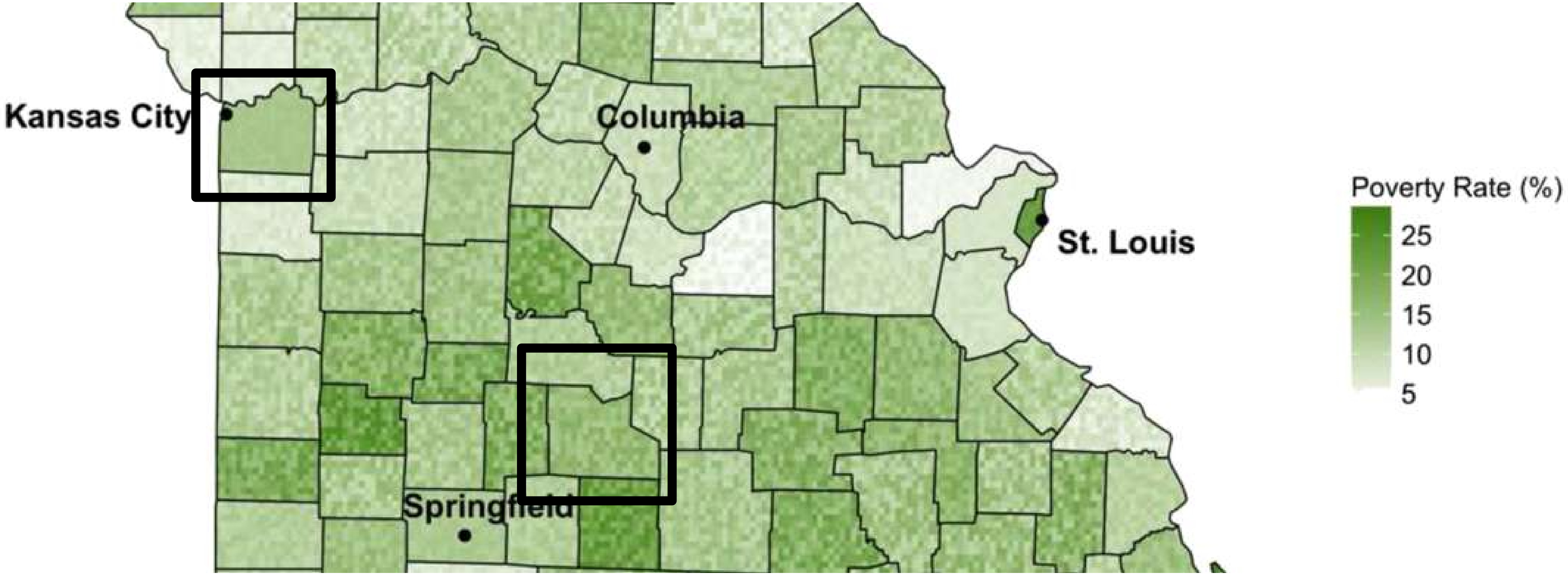


Uncertainty -> ~dither (samples from dist)

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

Discrete outcomes

Maybe more intuitive, maybe less?

Possible deterministic construal errors

Let's step back from
strictly probabilistic uncertainty

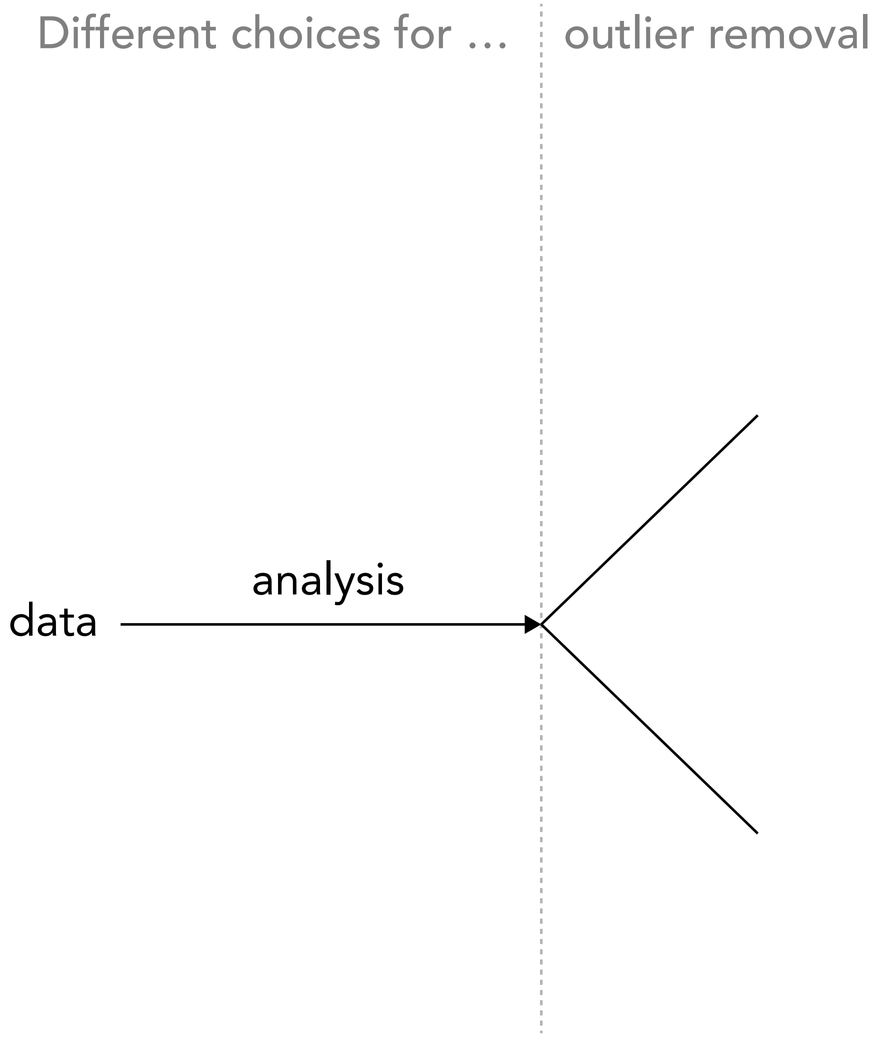
Garden of forking paths [Gelman and Loken 2014]

data $\xrightarrow{\text{analysis}}$ $p < 0.05$

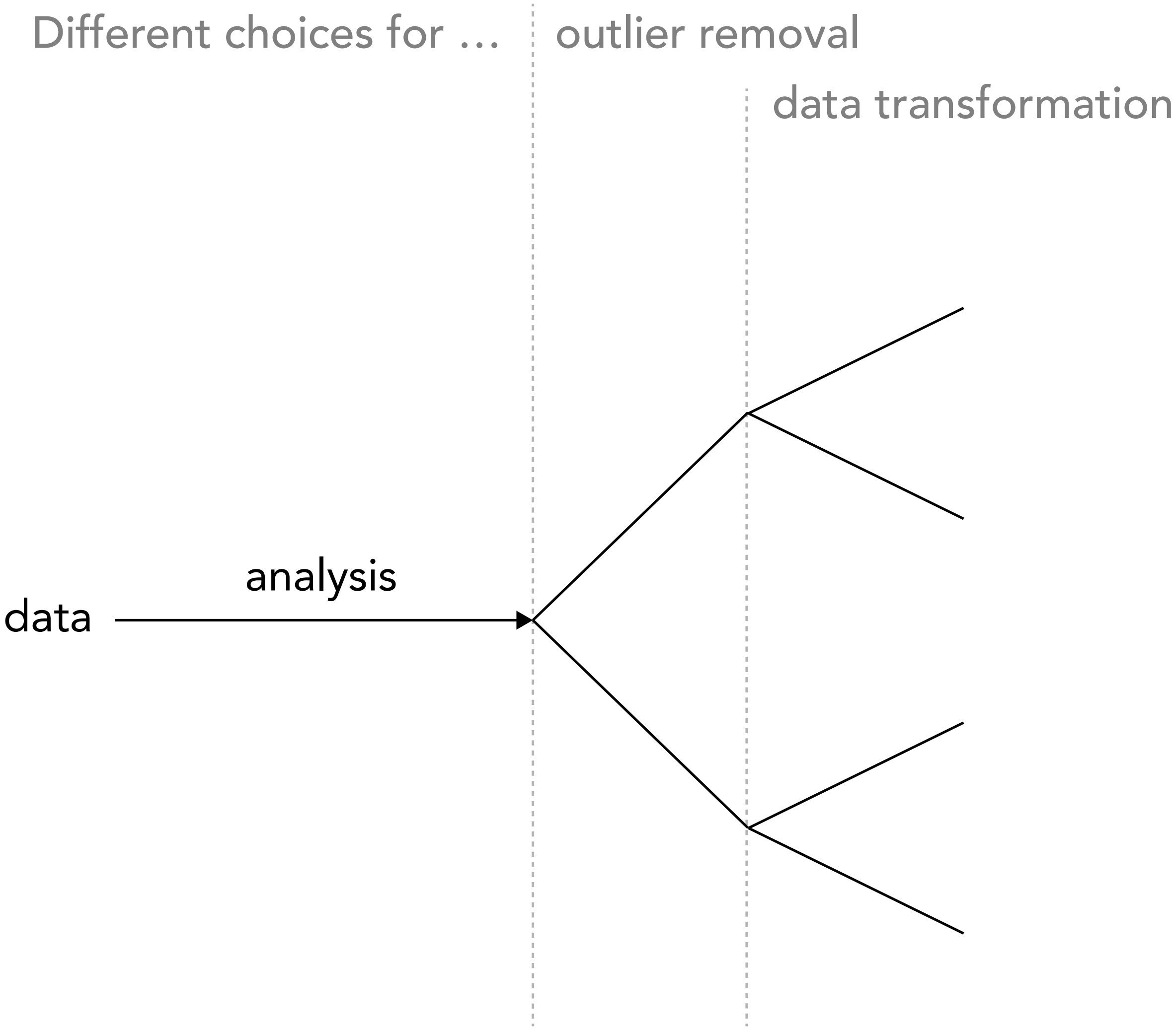
Garden of forking paths [Gelman and Loken 2014]

$\text{data} \xrightarrow{\text{analysis}}$

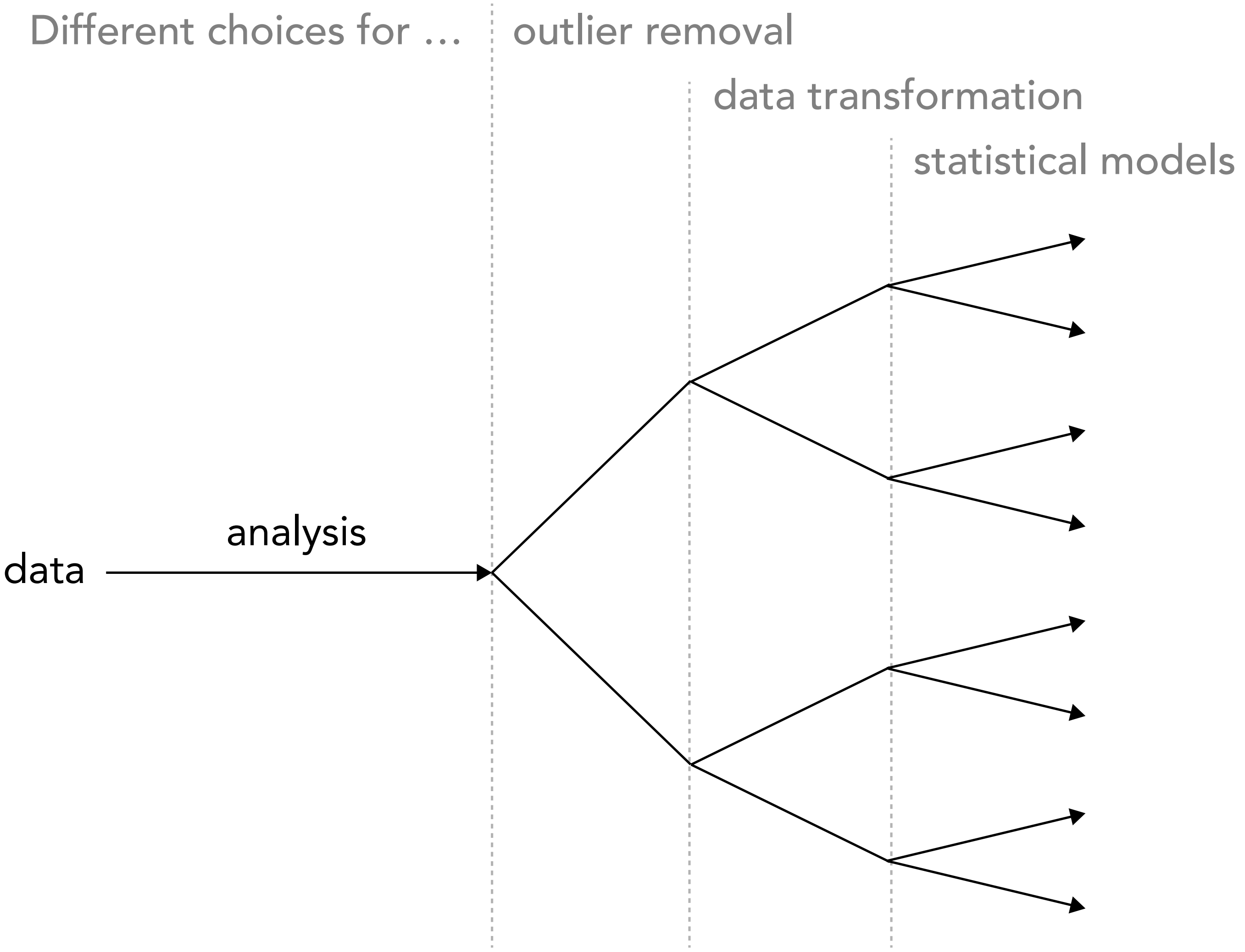
Garden of forking paths [Gelman and Loken 2014]



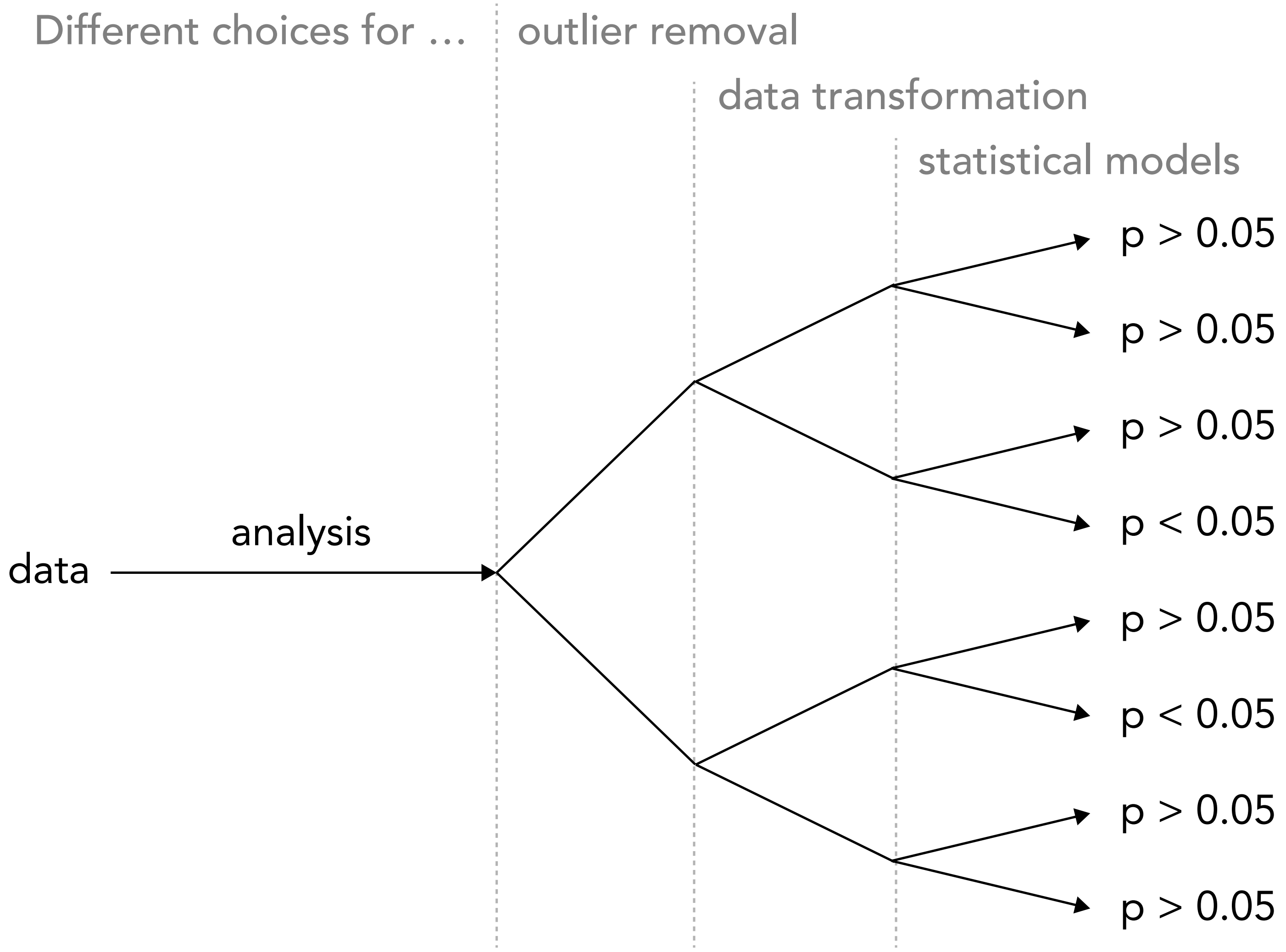
Garden of forking paths [Gelman and Loken 2014]



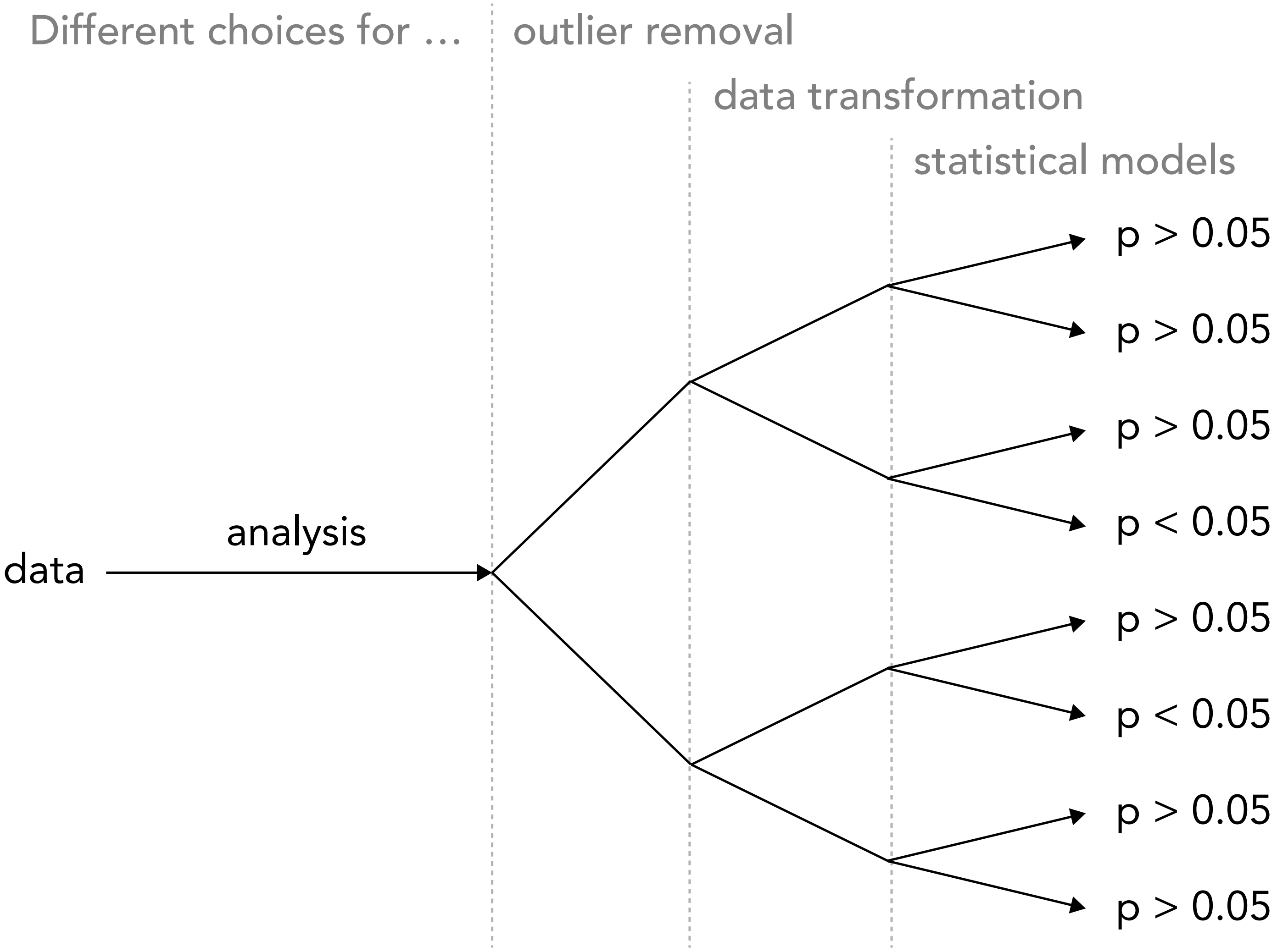
Garden of forking paths [Gelman and Loken 2014]



Garden of forking paths [Gelman and Loken 2014]

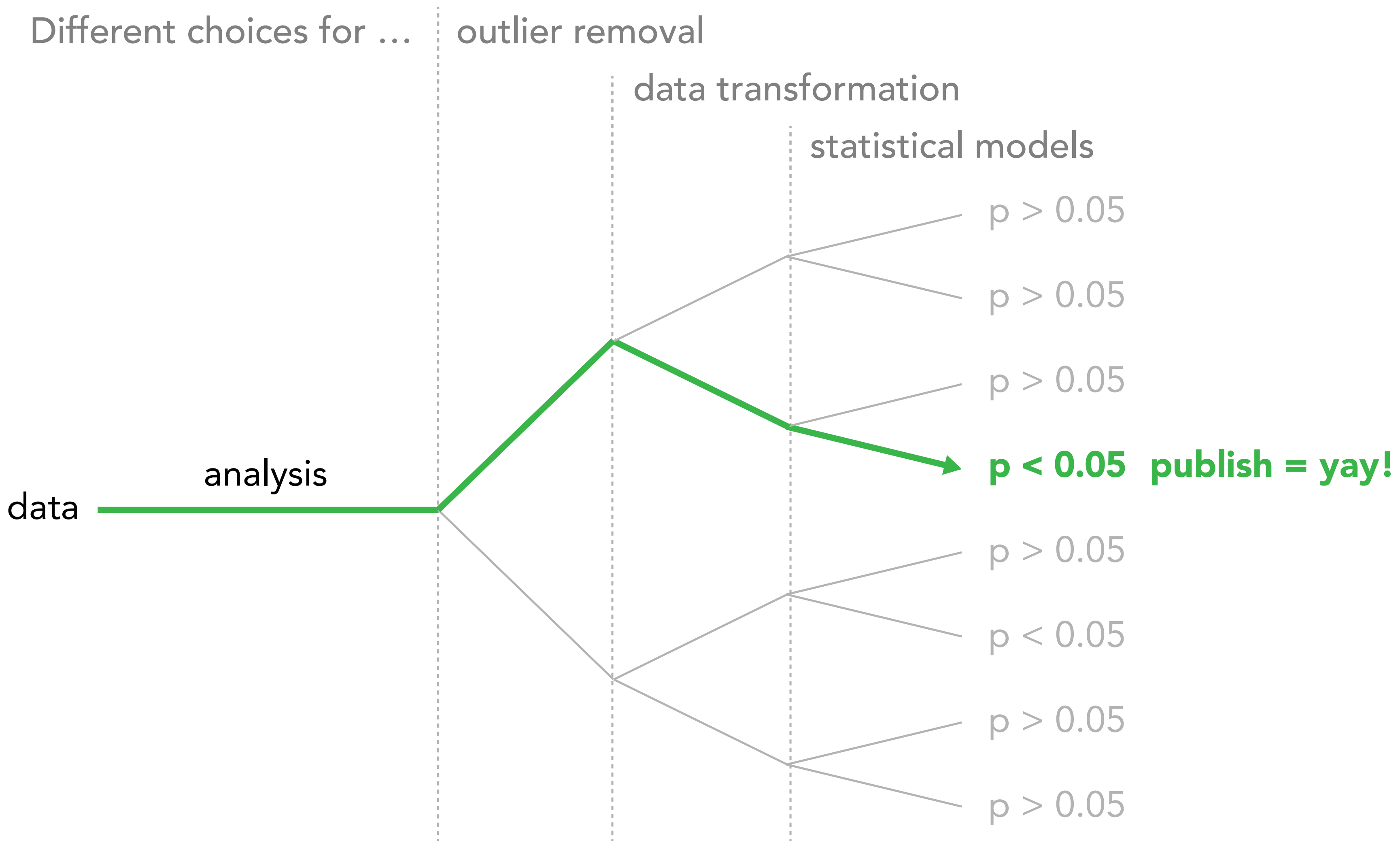


Garden of forking paths [Gelman and Loken 2014]

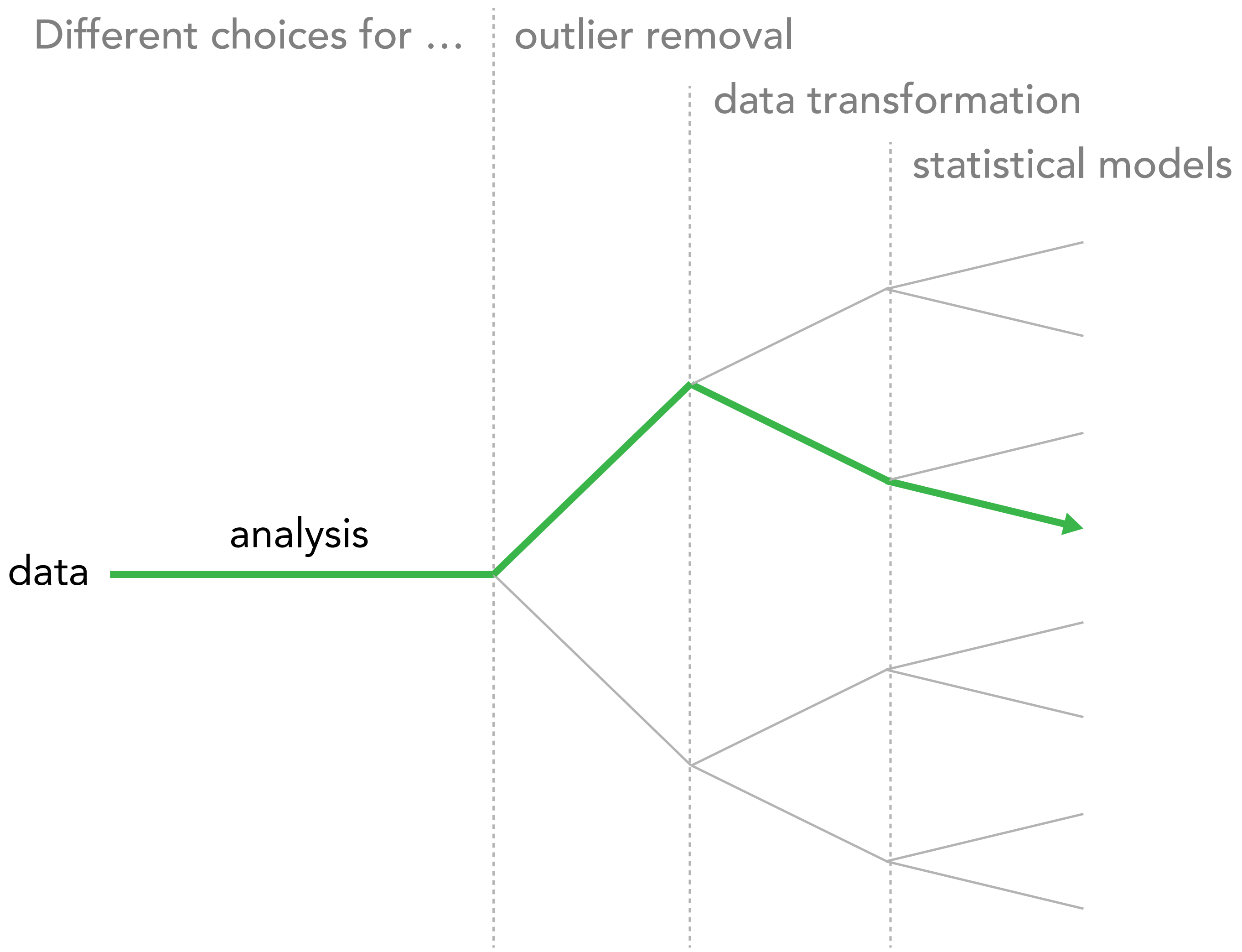


This is model/ specification uncertainty

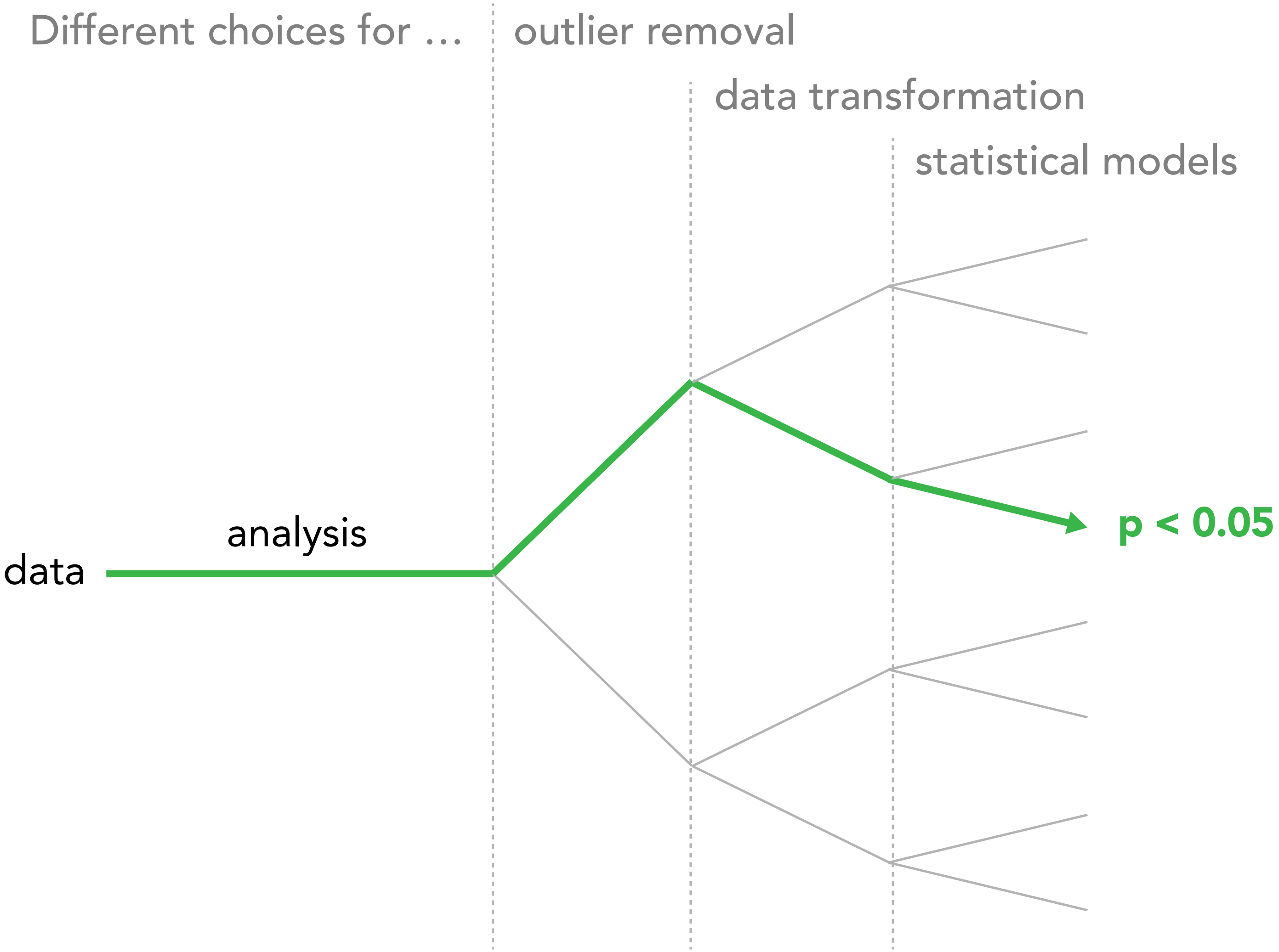
Garden of forking paths [Gelman and Loken 2014]



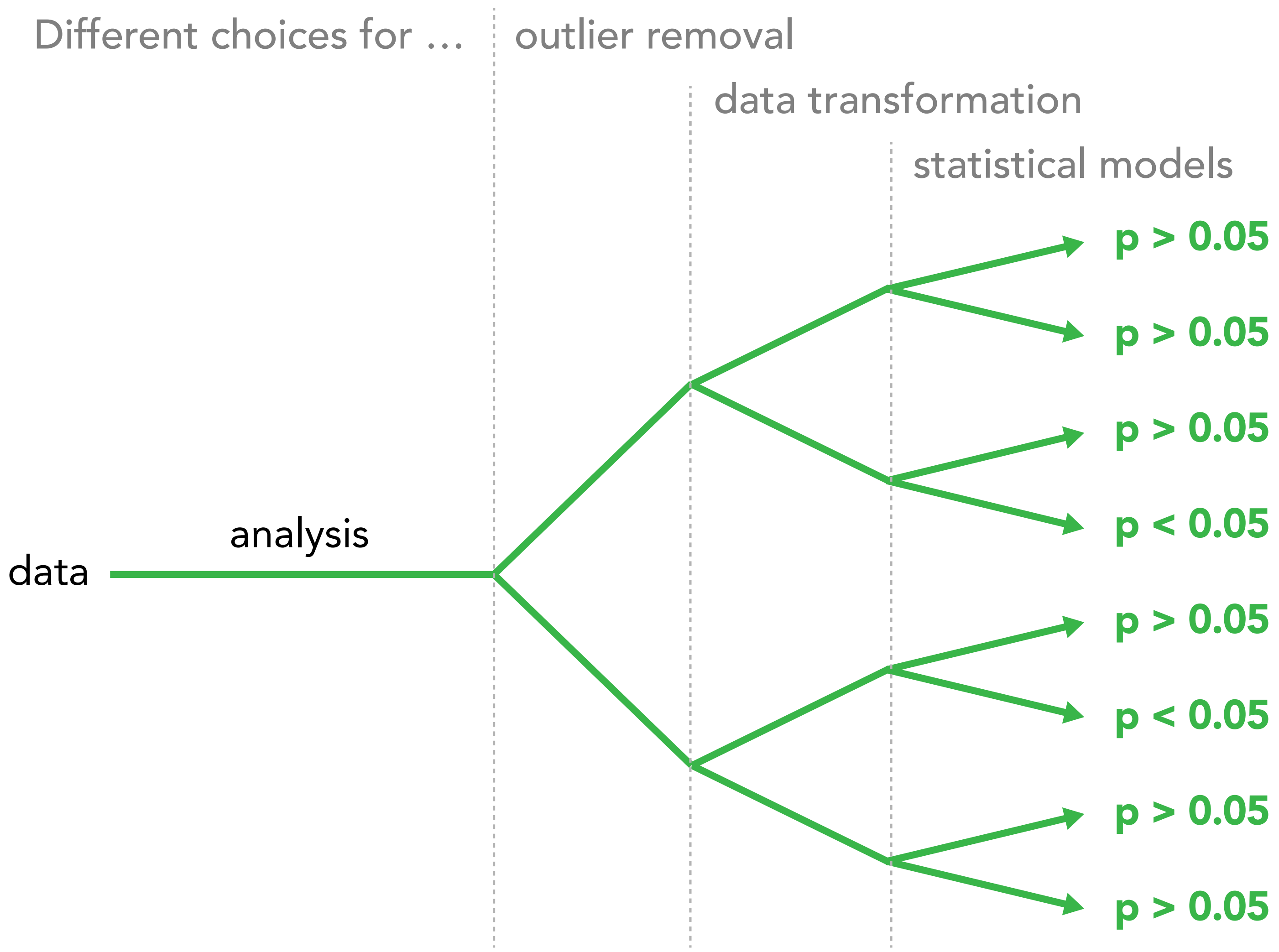
Garden of forking paths [Gelman and Loken 2014]



(pre-registration)



(multiverse analysis) [Steegen, Tuerlinckz, Gelman, Vanpaemel 2014]



Religiosity (Study 2)

			R1					R2					R3				
			F1	F2	F3	F4	F5	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
NMO1	ECL1	EC1	0	0	0.03	0.02	0.08	0.02	0.02	0.03	0.05	0.06	0	0	0.02	0.01	0.04
		EC2	0.01	0	0 .08	0.03	0.16	0.07	0.05	0.18	0.24	0.41	0.01	0	0.09	0.06	0.23
	ECL2	EC1	0	0	0.06	0.04	0.37	0.02	0.03	0.07	0.08	0.21	0	0	0.05	0.03	0.23
		EC2	0.01	0	0 .13	0.08	0.44	0.06	0.03	0.22	0.24	0.52	0.01	0	0.14	0.09	0.43
NMO2	ECL1	EC1	0	0	0.03	0.01	0.08	0.15	0.07	0.17	0.07	0.14	0.02	0.01	0.06	0.02	0.07
		EC2	0	0	0.02	0.01	0.06	0.2	0.05	0.42	0.23	0.44	0.03	0	0.14	0.05	0.19
	ECL3	EC 1	0.01	0.01	0.05	0.01	0.1	0.39	0.2	0.45	0.11	0.26	0.08	0.04	0.17	0.03	0.13
		EC 2	0.01	0	0 .05	0.02	0.11	0.33	0.09	0.59	0.26	0.55	0.09	0.02	0.26	0.08	0.27
NMO3	ECL1	EC1	0.01	0.01	0.02	0.1	0.28	0.11	0.09	0.43	0.26	0.85	0.02	0.02	0.12	0.12	0.51
		EC2	0.01	0.01	0	0 .07	0.06	0.07	0.1	0.11	0.14	0.23	0.01	0.02	0.02	0.06	0.08
	ECL2	EC1	0.02	0.01	0.06	0.11	0.36	0.06	0.04	0.3	0.13	0.66	0.02	0.01	0.13	0.07	0.46
		EC2	0.02	0.01	0.02	0.15	0.13	0.04	0.05	0.07	0.07	0.16	0.01	0.02	0.03	0.05	0.09
	ECL3	EC1	0.07	0.04	0.12	0.09	0.16	0.16	0.11	0.54	0.32	0.77	0.07	0.04	0.25	0.13	0.39
		EC2	0.02	0.02	0.01	0.06	0.02	0.06	0.1	0.07	0.16	0.17	0.02	0.03	0.02	0.07	0.05

Social political attitudes

			R1					R2					R3				
			F1	F2	F3	F4	F5	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
NMO1	ECL1	EC 1	0	0	0	0	0	0.18	0.19	0.3	0.07	0.21	0.01	0.01	0.04	0	0 .03
		EC 2	0.01	0.01	0.02	0	0 .02	0.93	0.76	0.99	0.52	0.78	0.24	0.15	0.37	0.06	0.23
	ECL2	EC 1	0	0	0	0	0	0.17	0.26	0.3	0.13	0.27	0.02	0.02	0.06	0.01	0.05
		EC 2	0.02	0.01	0.04	0	0 .01	0.89	0.86	0.98	0.47	0.66	0.24	0.2	0.42	0.05	0.19
NMO2	ECL1	EC 1	0.01	0.01	0.01	0	0	0.47	0.45	0.21	0.06	0.07	0.09	0.11	0.04	0.01	0.01
		EC 2	0.06	0.05	0.02	0.01	0	0.94	0.93	0.4	0.24	0.13	0.4	0.41	0.13	0.06	0.02
	ECL3	EC 1	0.01	0.01	0	0	0	0.49	0.45	0.22	0.08	0.1	0.1	0.11	0.04	0.01	0.02
		EC 2	0.1	0.11	0.02	0.02	0	0.87	0.91	0.32	0.27	0.18	0.42	0.48	0.12	0.09	0.04
NMO3	ECL1	EC 1	0	0	0.01	0	0 .02	0.19	0.22	0.1	0.07	0.29	0.02	0.03	0.02	0.01	0.07
		EC 2	0.01	0	0 .01	0	0 .01	0.46	0.62	0.08	0.08	0.1	0.1	0.14	0.02	0.01	0.02
	ECL2	EC 1	0.01	0	0 .01	0	0 .01	0.37	0.27	0.18	0.09	0.23	0.07	0.05	0.03	0.01	0.04
		EC 2	0.03	0.02	0.01	0.02	0.01	0.76	0.84	0.13	0.16	0.1	0.24	0.29	0.04	0.04	0.02
	ECL3	EC 1	0.01	0.01	0.02	0	0	0.37	0.35	0.18	0.09	0.24	0.08	0.08	0.05	0.01	0.04
		EC 2	0.05	0.04	0.03	0.01	0	0 .9	0.97	0.22	0.18	0.16	0.36	0.45	0.09	0.04	0.02

Voting preferences

			R1					R2					R3				
			F1	F2	F3	F4	F5	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
NMO1	ECL1	EC 1	0	0	0	0.01	0	0 .04	0 .04	0 .02	0.07	0 .02	0 .01	0 .01	0	0.03	0.01
		EC 2	0.11	0.14	0.01	0.08	0	0 .38	0 .6	0.19	0.38	0.16	0.22	0.37	0.07	0.2	0 .05
	ECL2	EC 1	0.01	0.02	0	0 .03	0	0.03	0.05	0.01	0.08	0.03	0.01	0.02	0	0 .04	0.01
		EC 2	0.13	0.15	0.01	0.07	0	0 .27	0 .36	0 .14	0 .27	0 .14	0.16	0 .22	0.05	0 .13	0 .04
NMO2	ECL1	EC 1	0.01	0.01	0	0	0.01	0.04	0.06	0.03	0.04	0.06	0.01	0.02	0.01	0.02	0.02
		EC 2	0.05	0.03	0.01	0	0	0.19	0.22	0.08	0.09	0.12	0.08	0.09	0.03	0.03	0.03
	ECL3	EC 1	0.01	0.01	0	0	0.01	0.05	0.07	0.02	0.05	0.08	0.01	0.02	0.01	0.02	0.03
		EC 2	0.08	0.04	0.01	0	0	0.22	0.25	0.06	0.14	0.15	0.11	0.11	0.02	0.04	0.04
NMO3	ECL1	EC 1	0.11	0.13	0.03	0.08	0.02	0.05	0.09	0.05	0.07	0.08	0.04	0.06	0.02	0.05	0.03
		EC 2	0.42	0.32	0.04	0.18	0	0 .59	0 .68	0 .23	0 .4	0.23	0.45	0.5	0.09	0 .28	0.06
	ECL2	EC 1	0.07	0.09	0.01	0.07	0.01	0.08	0.12	0.08	0.08	0.11	0.04	0.07	0.02	0.05	0.03
		EC 2	0.28	0.28	0.02	0.18	0	0 .47	0 .54	0 .16	0 .37	0 .19	0.31	0.38	0.05	0.25	0.04
	ECL3	EC 1	0.08	0.1	0 .02	0 .04	0 .01	0 .11	0 .14	0 .08	0 .14	0 .19	0 .06	0 .09	0.03	0 .07	0 .06
		EC 2	0.28	0.27	0.04	0.09	0	0 .54	0 .66	0 .22	0 .44	0 .31	0 .37	0 .47	0.09	0 .25	0.07

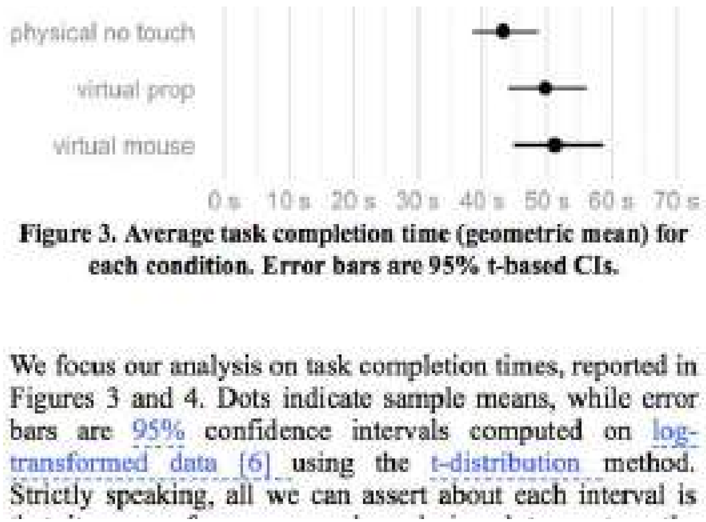
Donation preferences

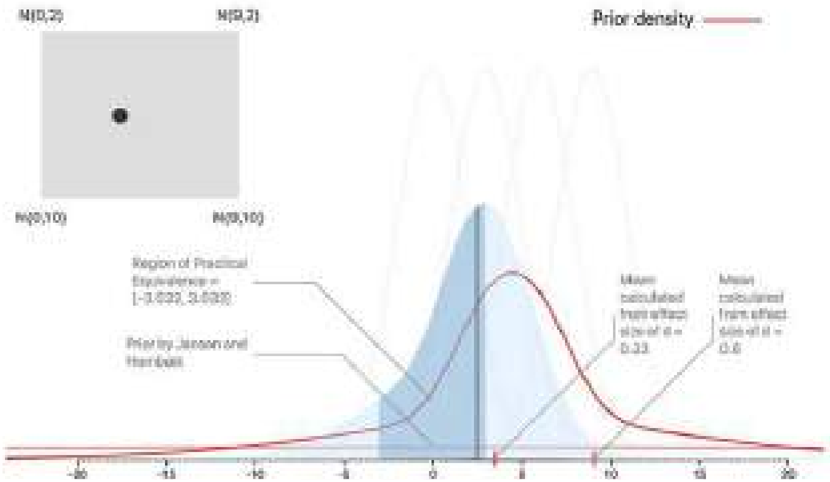
			R1					R2					R3				
			F1	F2	F3	F4	F5	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
NMO1	ECL1	EC 1	0	0	0	0	0	0.03	0.04	0.01	0.04	0.01	0.01	0.01	0	0.01	0
		EC 2	0.07	0.1	0 .01	0 .06	0	0.19	0.33	0.09	0.35	0.14	0.1	0 .18	0 .03	0 .17	0 .04
	ECL2	EC 1	0.01	0.01	0	0 .01	0	0.03	0.04	0.01	0.05	0.01	0.01	0.01	0	0 .02	0
		EC 2	0.08	0.11	0.01	0.06	0	0 .12	0 .16	0 .06	0 .25	0 .11	0 .07	0 .09	0.02	0 .11	0 .03
NMO2	ECL1	EC 1	0.01	0.01	0	0	0.01	0.03	0.05	0.02	0.03	0.05	0.01	0.02	0	0 .01	0 .02
		EC 2	0.03	0.02	0	0	0	0.07	0.09	0.03	0.05	0.06	0.03	0.04	0.01	0.02	0.01
	ECL3	EC 1	0.01	0.01	0	0	0.01	0.06	0.09	0.02	0.06	0.09	0.02	0.03	0.01	0.02	0.03
		EC 2	0.08	0.05	0.02	0	0	0.16	0.19	0.04	0.1	0 .1	0.08	0.08	0.02	0.03	0.03
NMO3	ECL1	EC 1	0.08	0.17	0.02	0.06	0.01	0.03	0.08	0.02	0.04	0.04	0.02	0.07	0.01	0.03	0.01
		EC 2	0.42	0.4	0 .04	0 .24	0 .01	0 .37	0 .41	0 .11	0 .32	0 .16	0 .31	0 .35	0 .05	0 .26	0 .05
	ECL2	EC 1	0.05	0.12	0.01	0.05	0.01	0.04	0.09	0.03	0.05	0.05	0.02	0.06	0.01	0.03	0.01
		EC 2	0.28	0.37	0.02	0.24	0.01	0.27	0.3	0 .07	0 .3	0.12	0.2	0 .25	0.02	0 .22	0 .03
	ECL3	EC 1	0.08	0.18	0.02	0.03	0.01	0.08	0.18	0.06	0.09	0.12	0.04	0.13	0.02	0.04	0.04
		EC 2	0.37	0.44	0.07	0.14	0.01	0.48	0.56	0.19	0.41	0.27	0.37	0.47	0.09	0.26	0.08

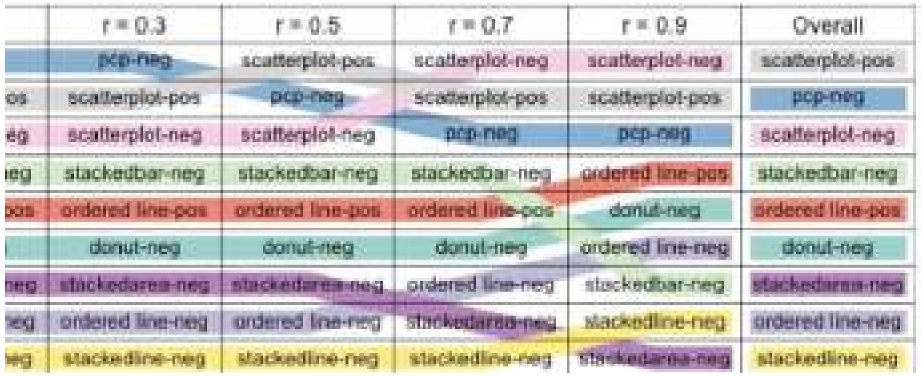
[Steegen, Tuerlinckz, Gelman, Vanpaemel. Increasing Transparency Through a Multiverse Analysis. Perspectives on Psychological Science, 2016]

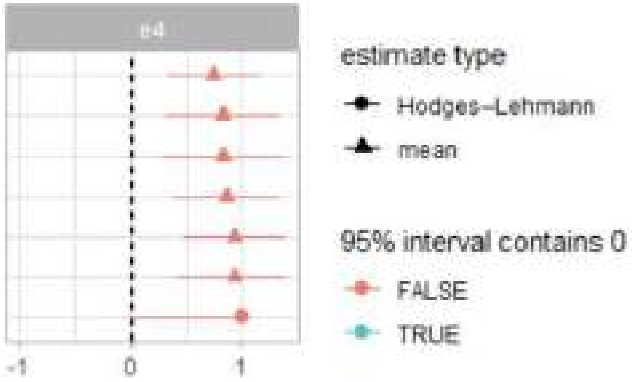
Explorable Multiverse Analysis Reports

[Dragicevic, Jansen, Sarma, **Kay**, and Chevalier. Increasing the Transparency of Research Papers with Explorable Multiverse Analyses. CHI 2019: https://explorablemultiverse.github.io/]









Explorable Multiverse Analysis Reports

[Dragicevic, Jansen, Sarma, **Kay**, and Chevalier. Increasing the Transparency of Research Papers with Explorable Multiverse Analyses. CHI 2019: https://explorablemultiverse.github.io/]

We need better ways to acknowledge specification uncertainty and have a conversation about it through the literature.

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

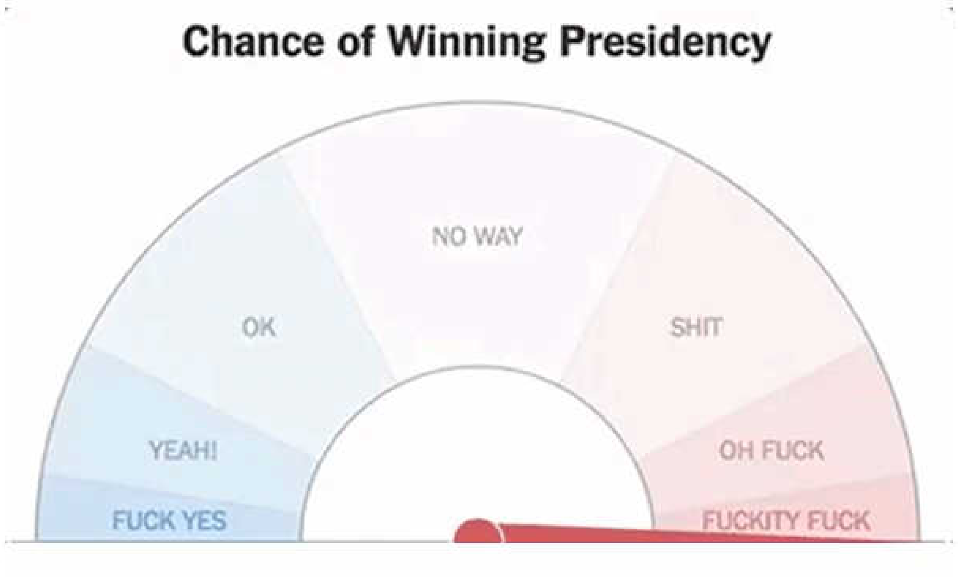


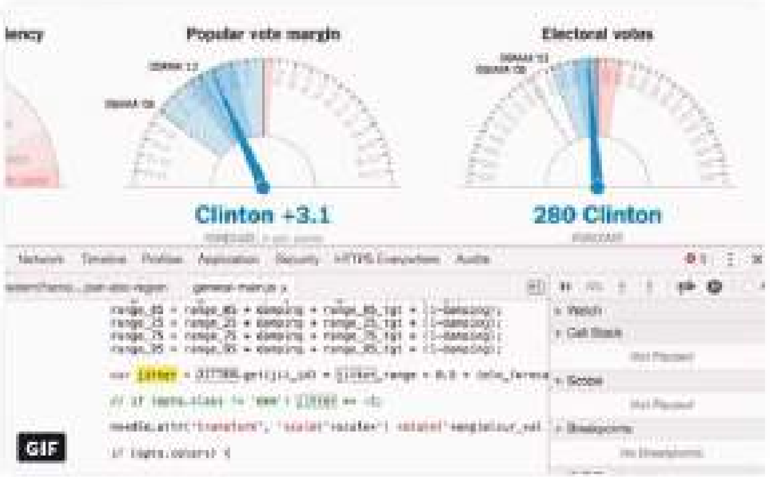
Photo: rhysetsmore/Twitter

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

Standard tools: intervals, densities, ...

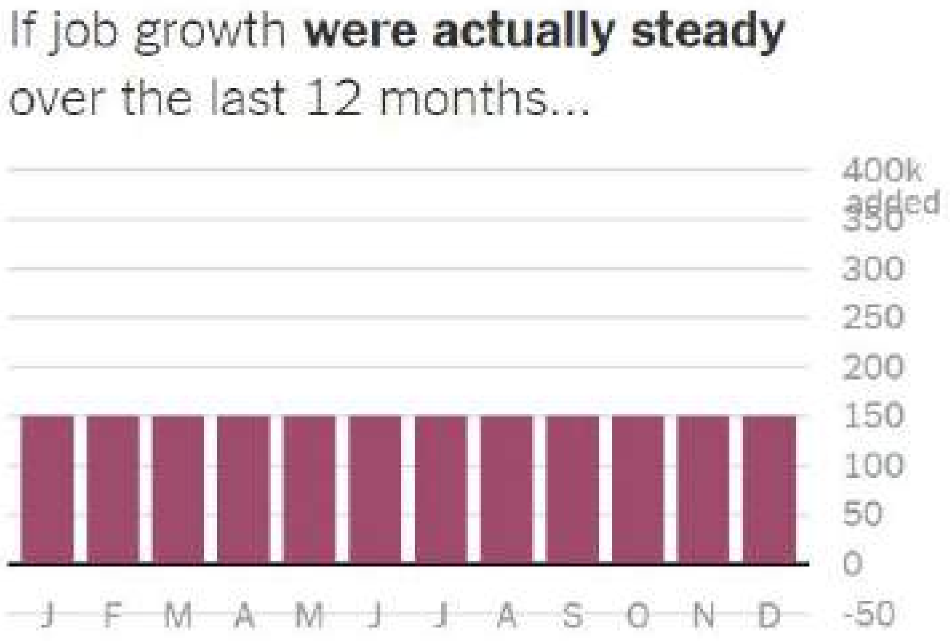
But discrete outcomes can improve understanding

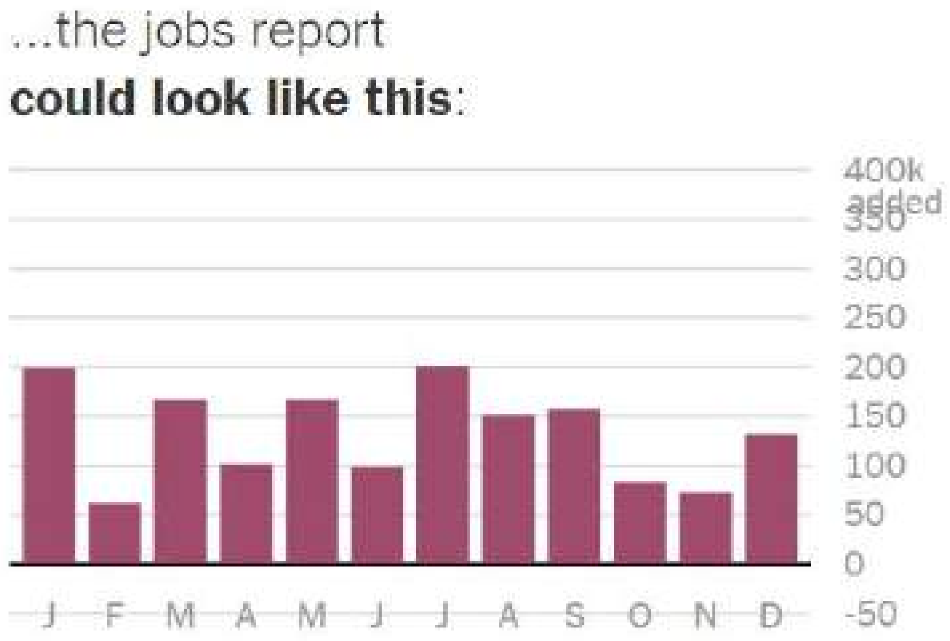
Beware deterministic construal errors

Jobs report (NYT)

[Irwin & Quealy, How Not to Be Misled by the Jobs Report, NYT The Upshot, 2014]

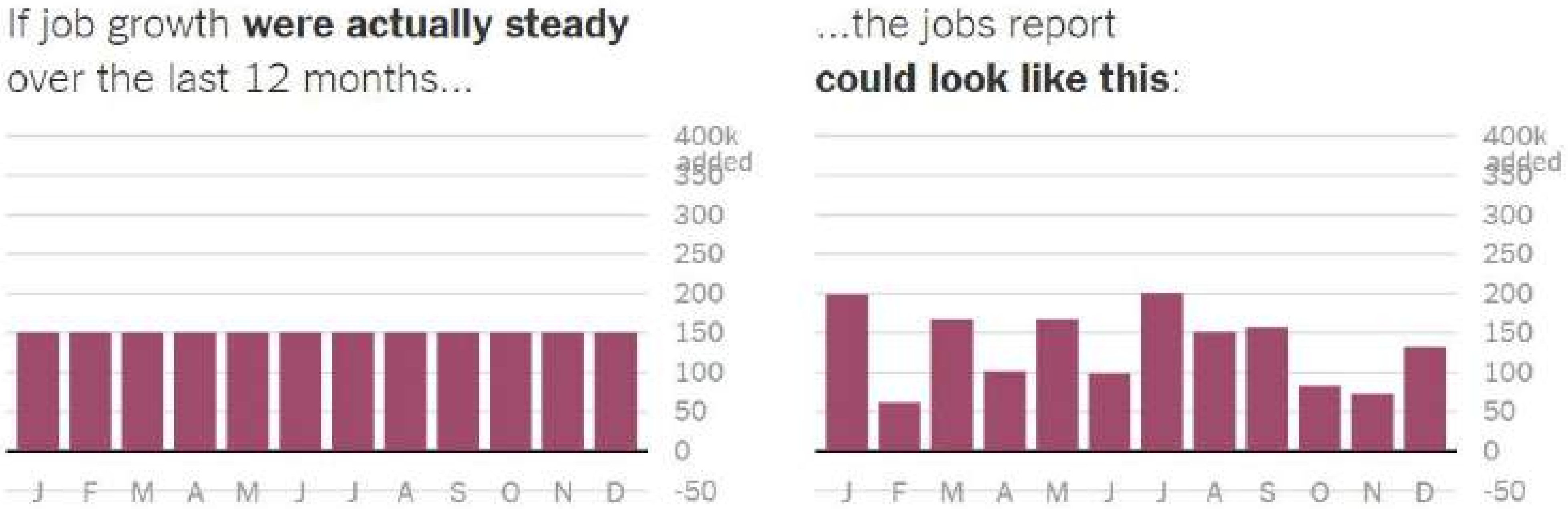
https://nyti.ms/RyZB8a





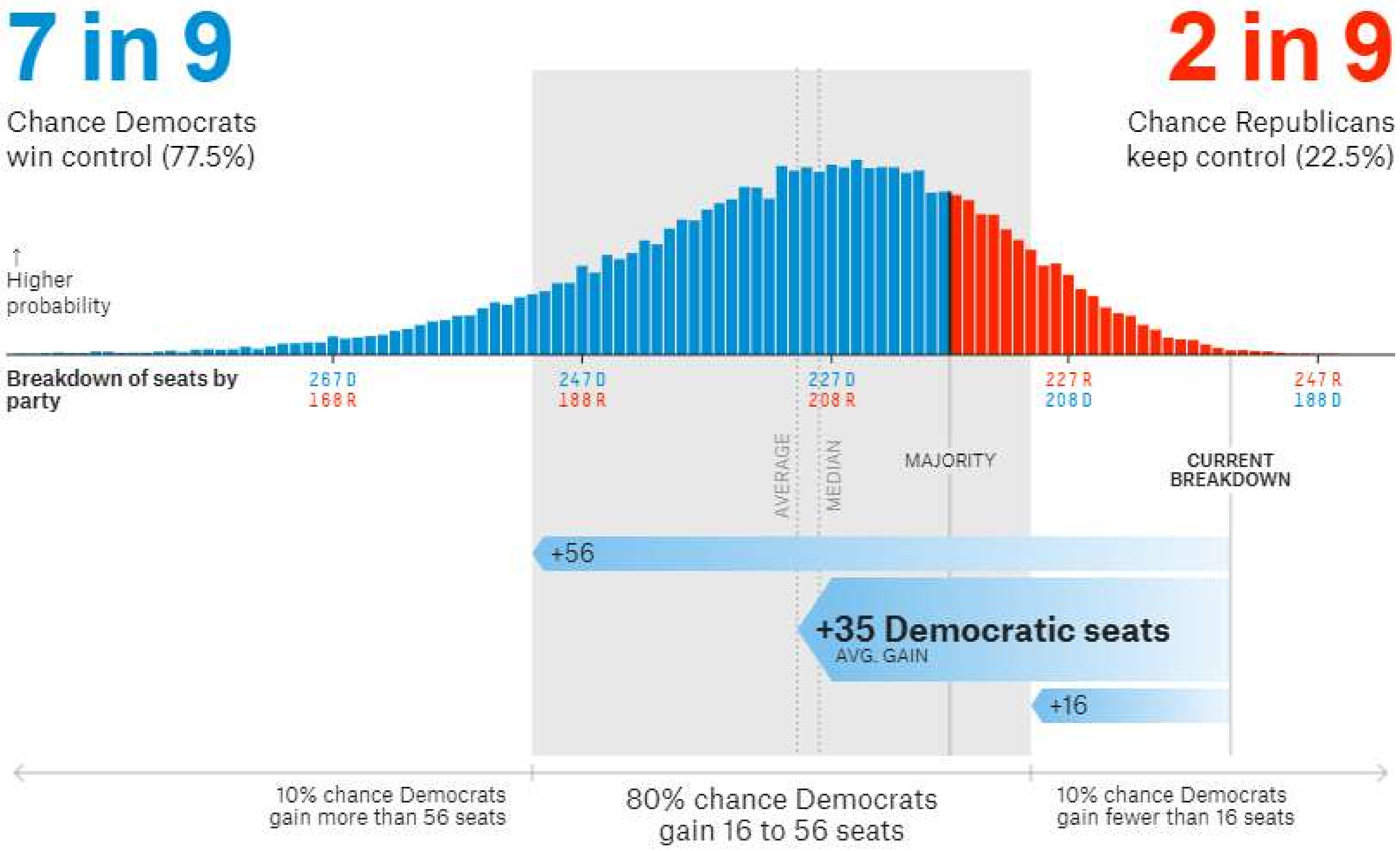
Animation can aid likelihood judgements

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



FiveThirtyEight's 2018 House forecast

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



FiveThirtyEight's 2018 House forecast

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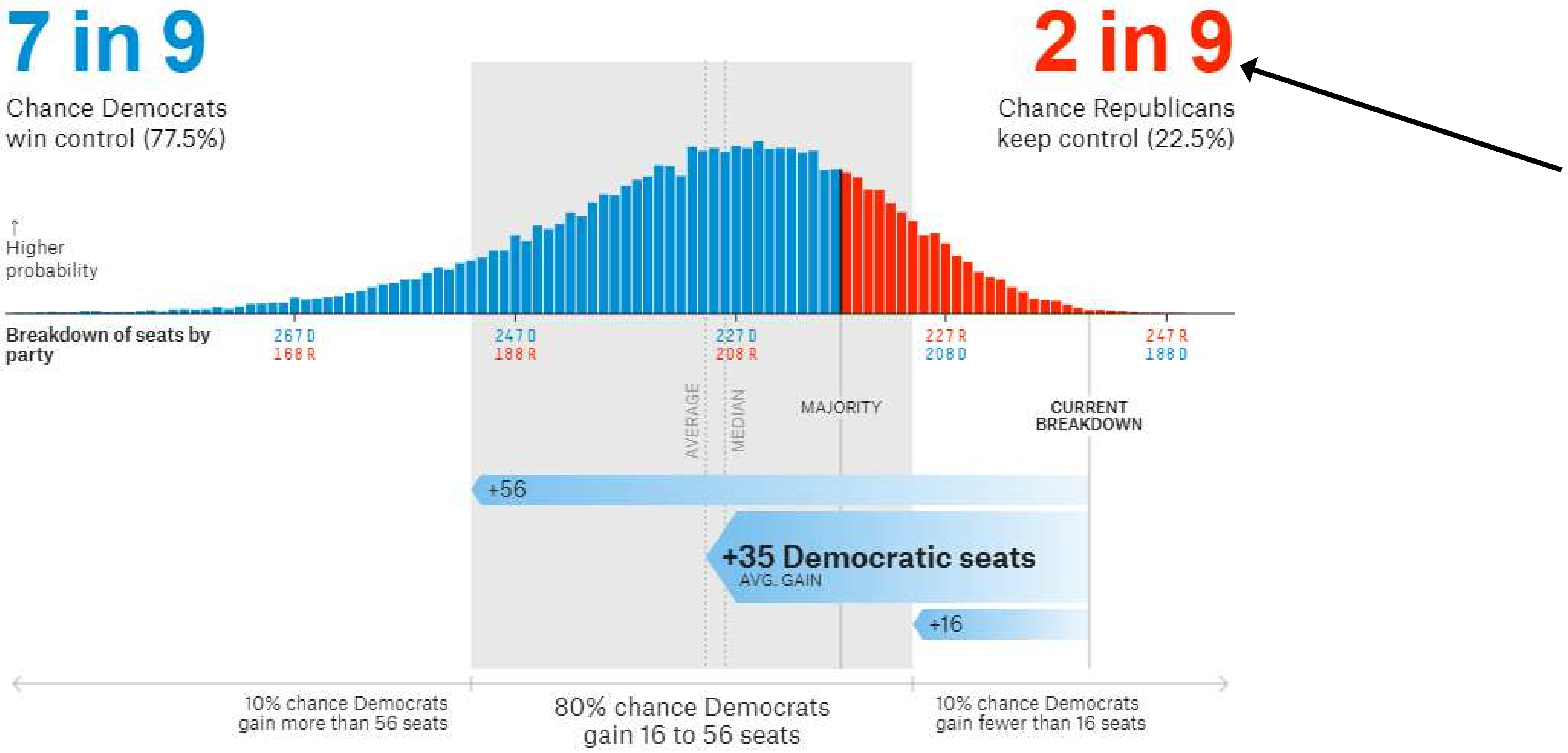

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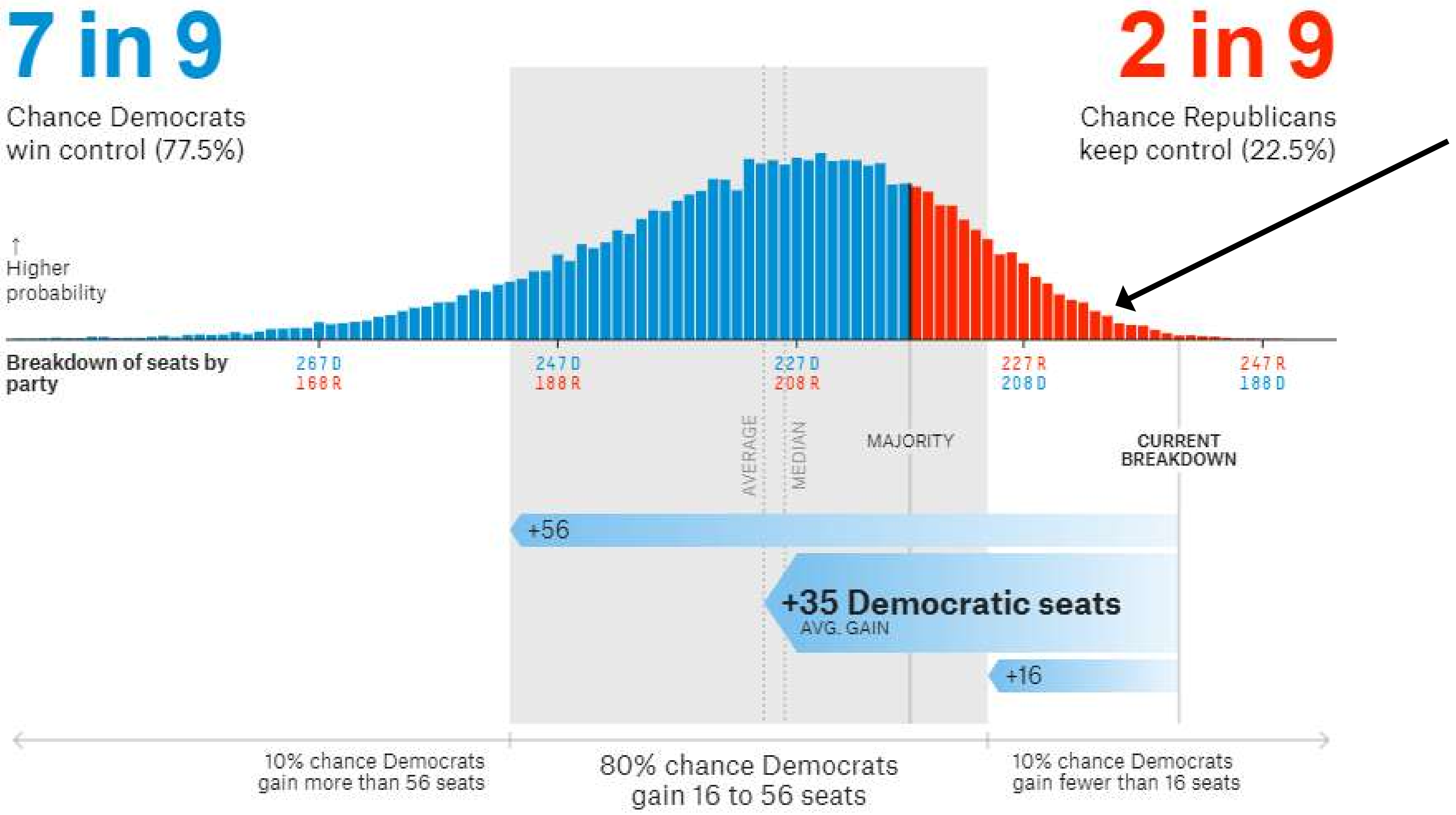
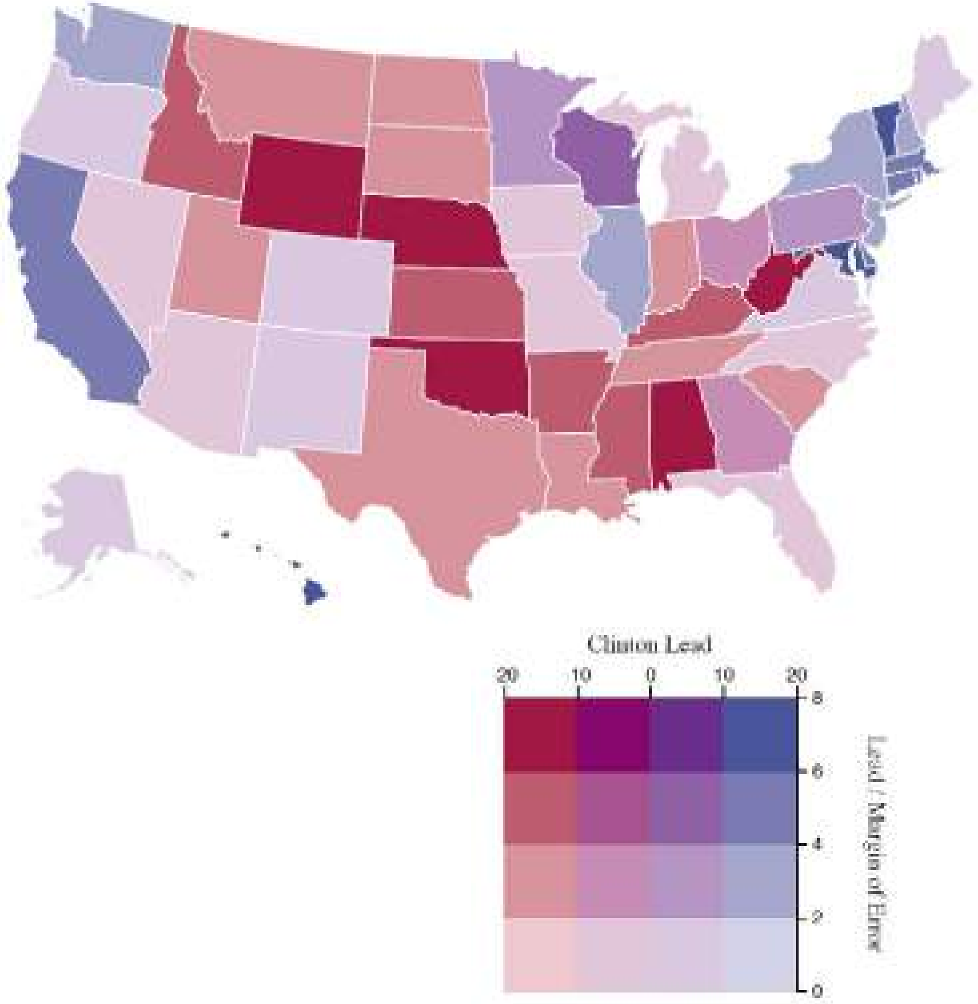
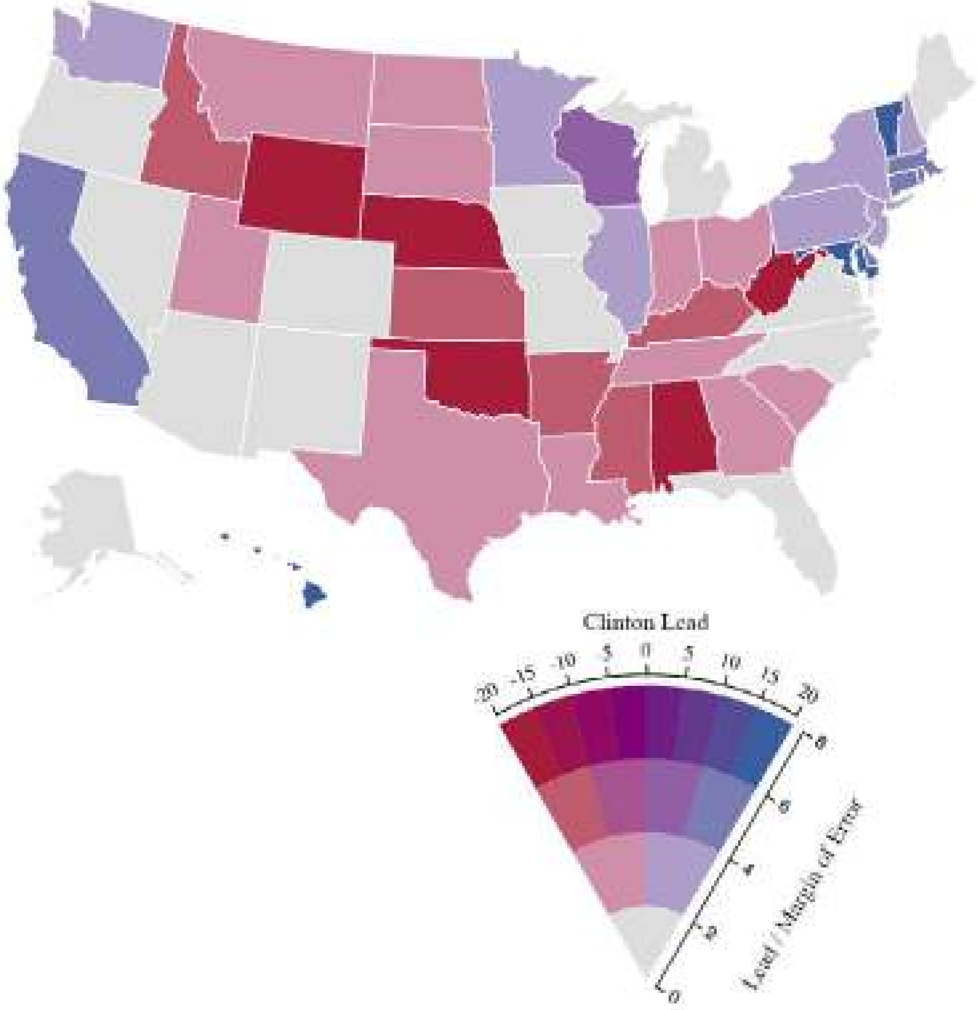


Addressing bias in perception of probability...

Value-suppressing uncertainty palettes

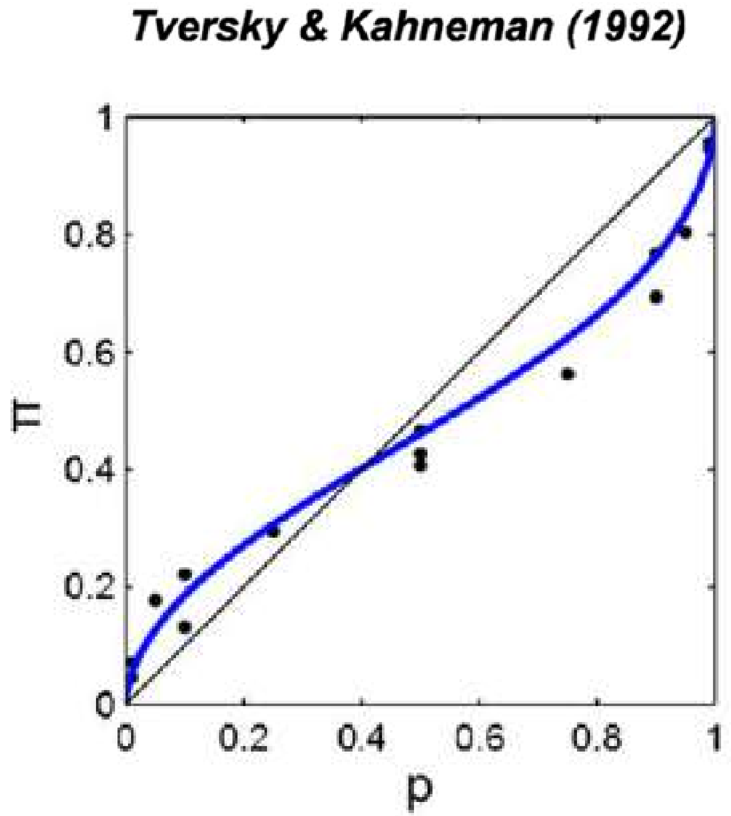
[Correll, Moritz, Heer. Value-Suppressing Uncertainty Palettes. CHI 2018]





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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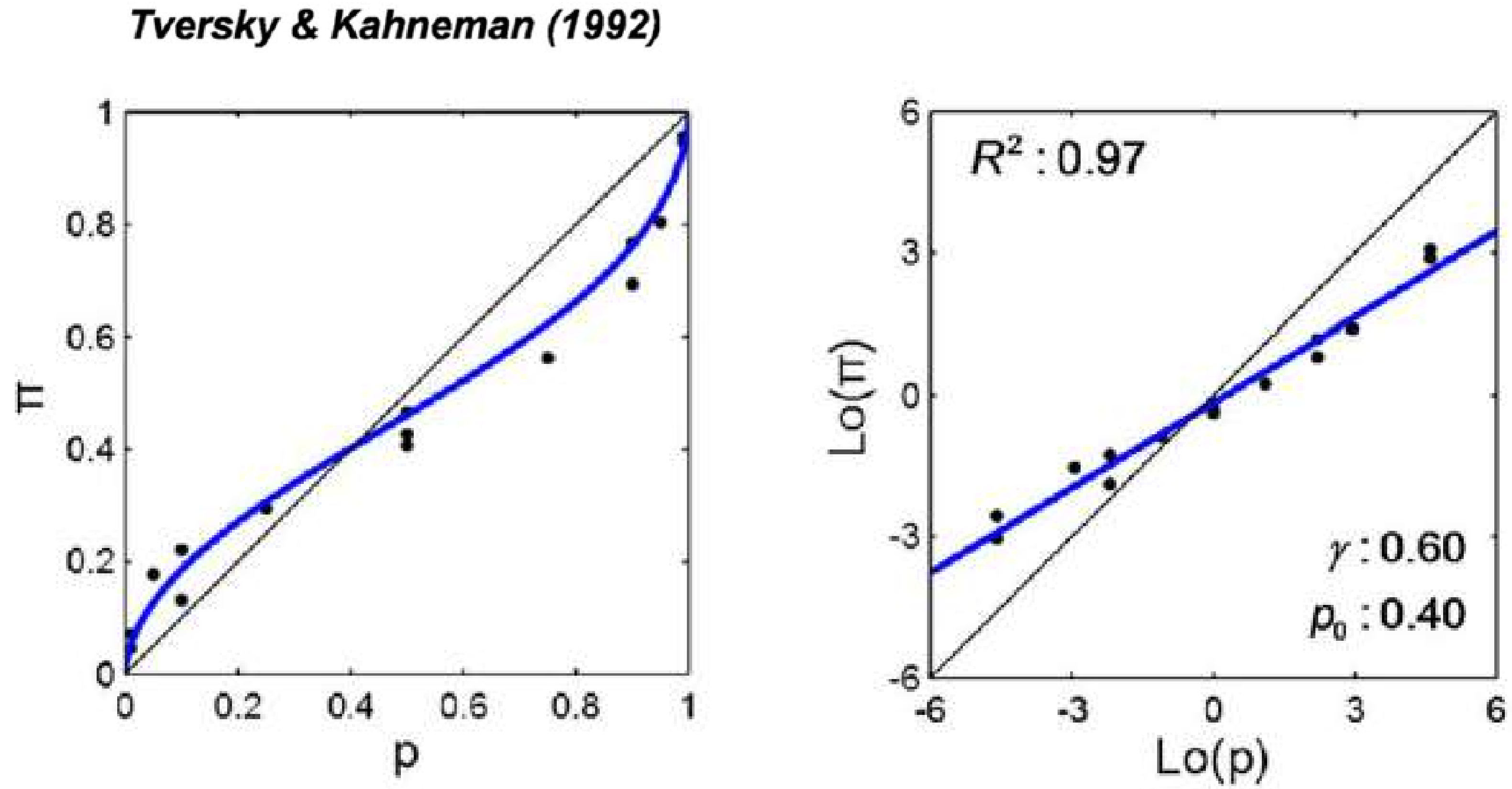

Linear-in-log-odds perception of proportions

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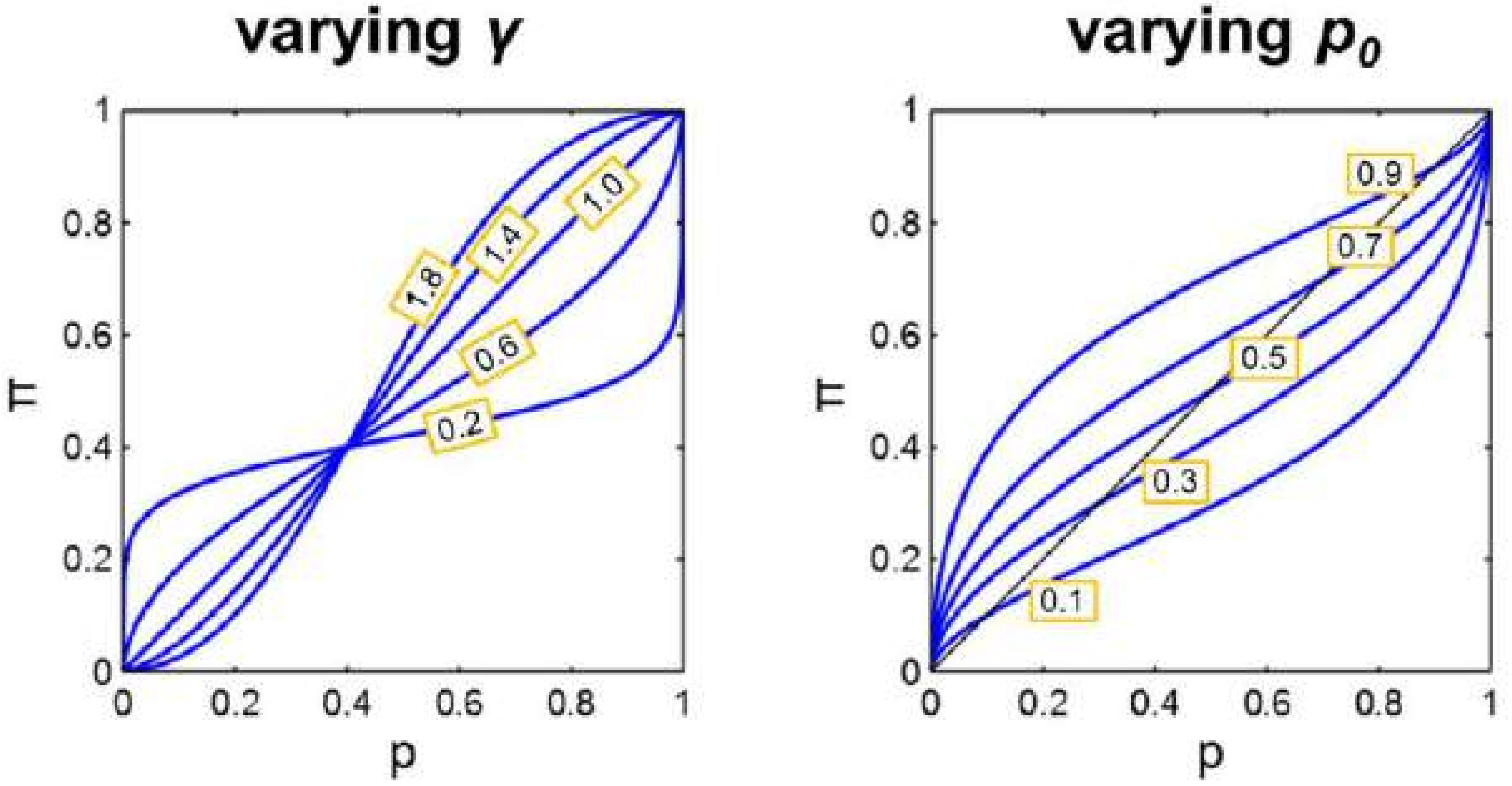

Hurricane location at a time slice…

[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]

Hurricane location at a time slice…

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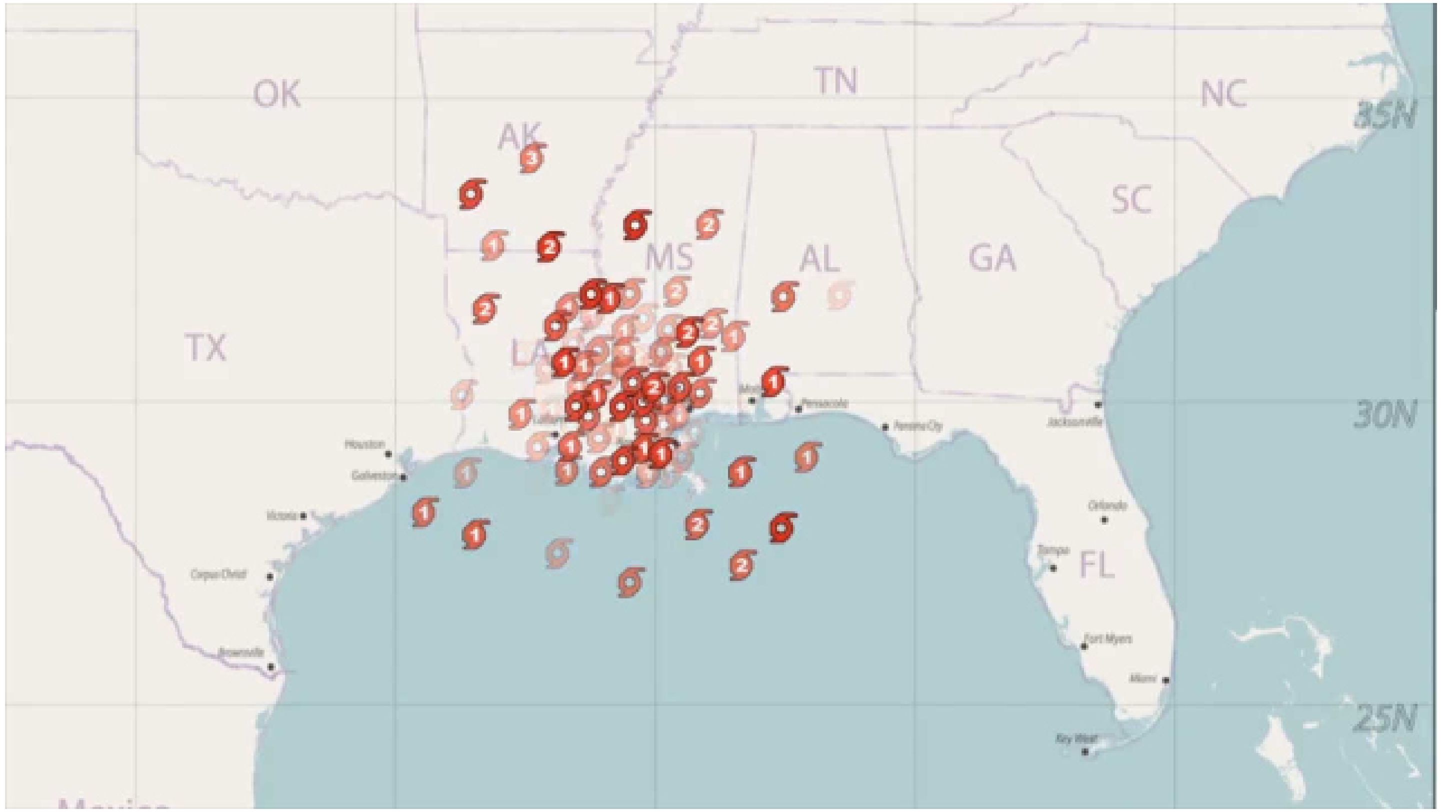
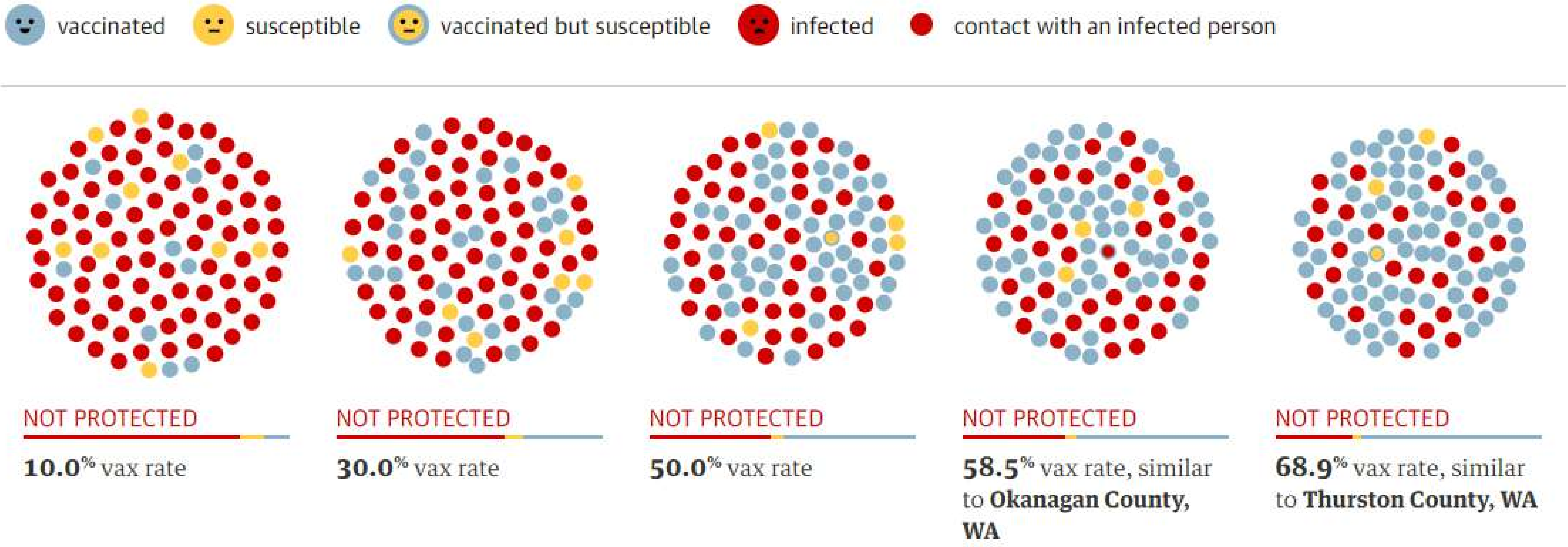


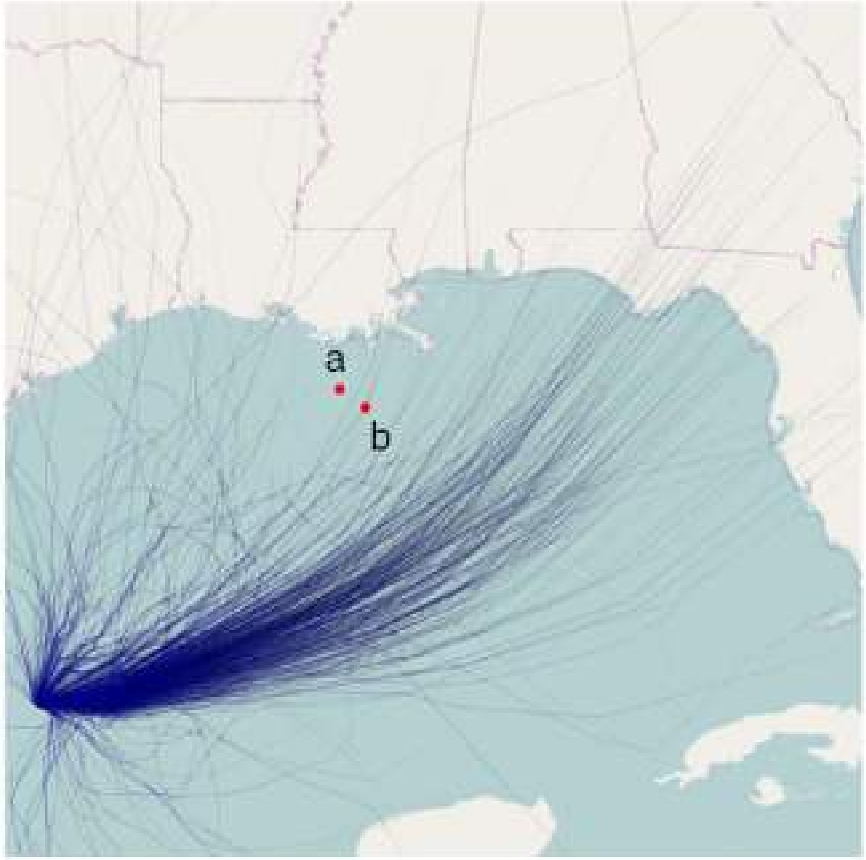
Measles vaccination

[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]



(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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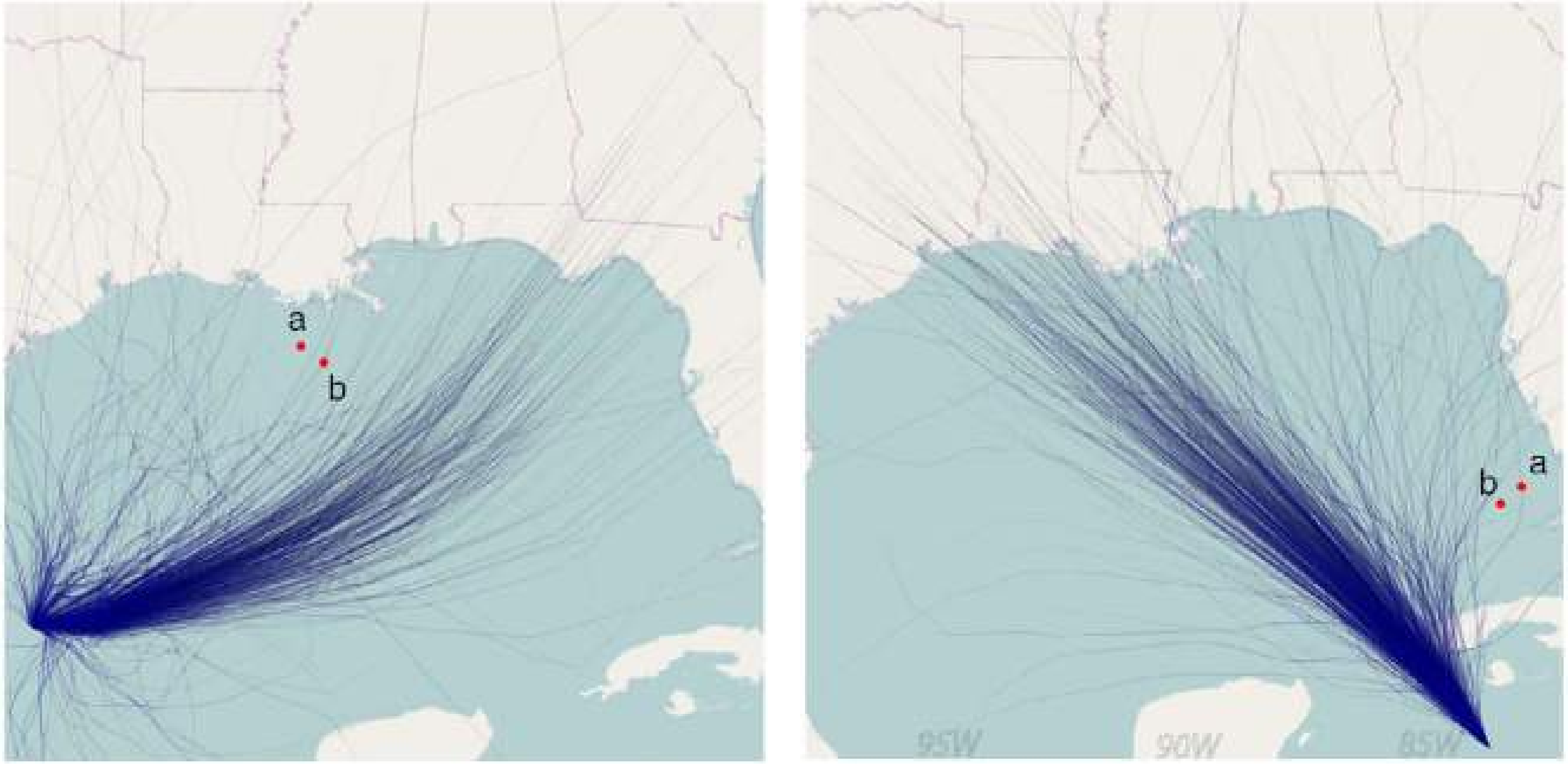
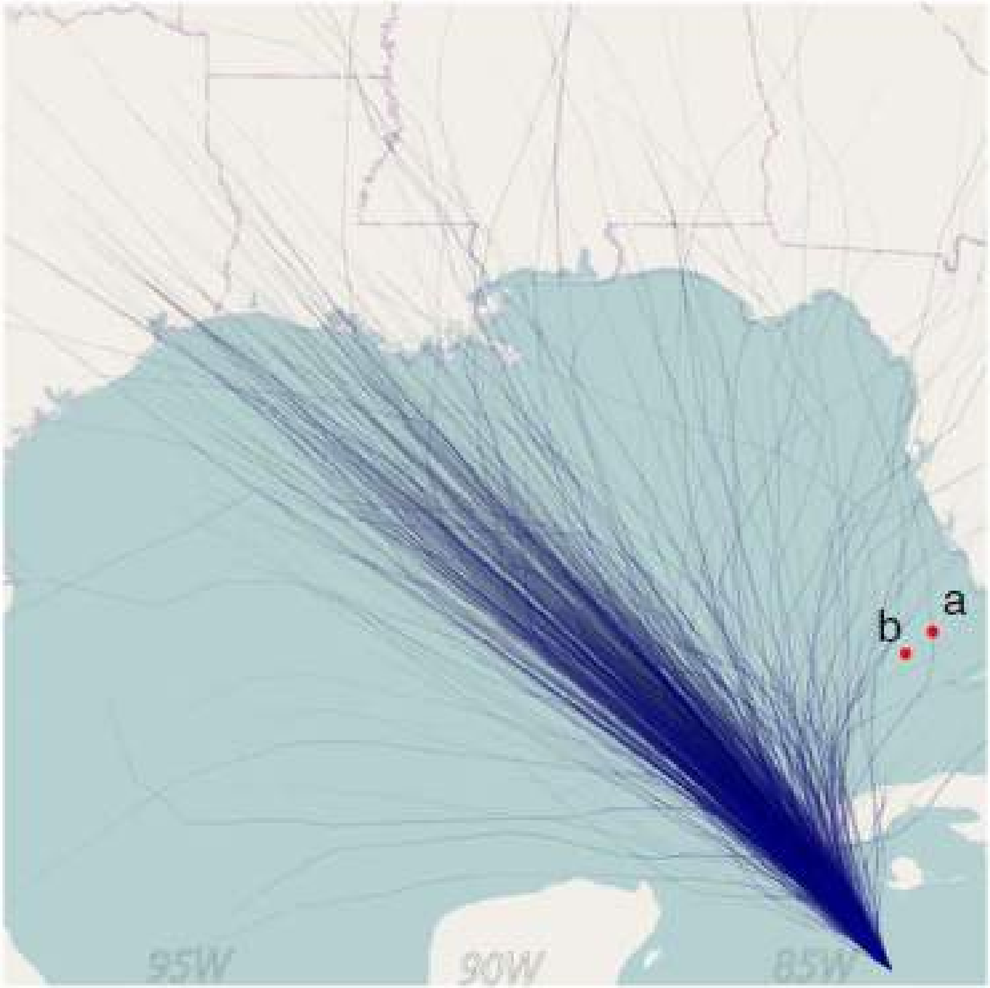
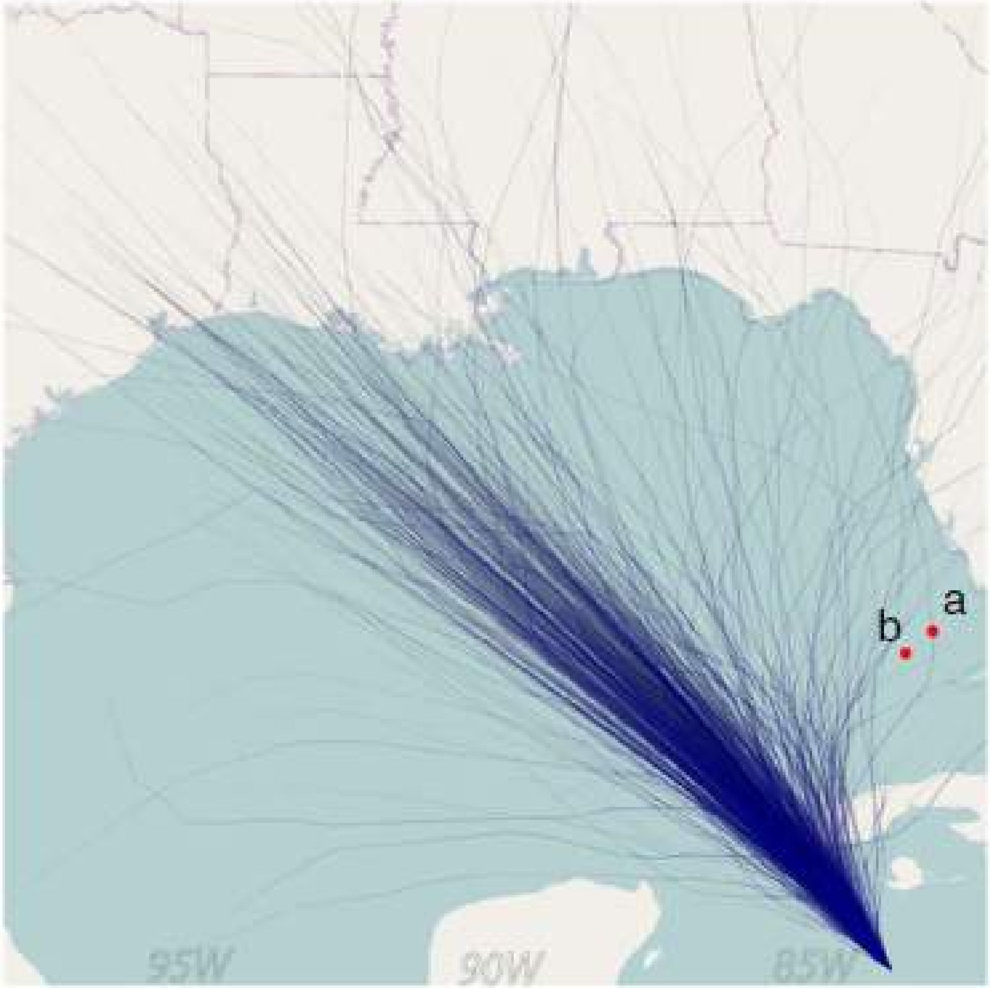
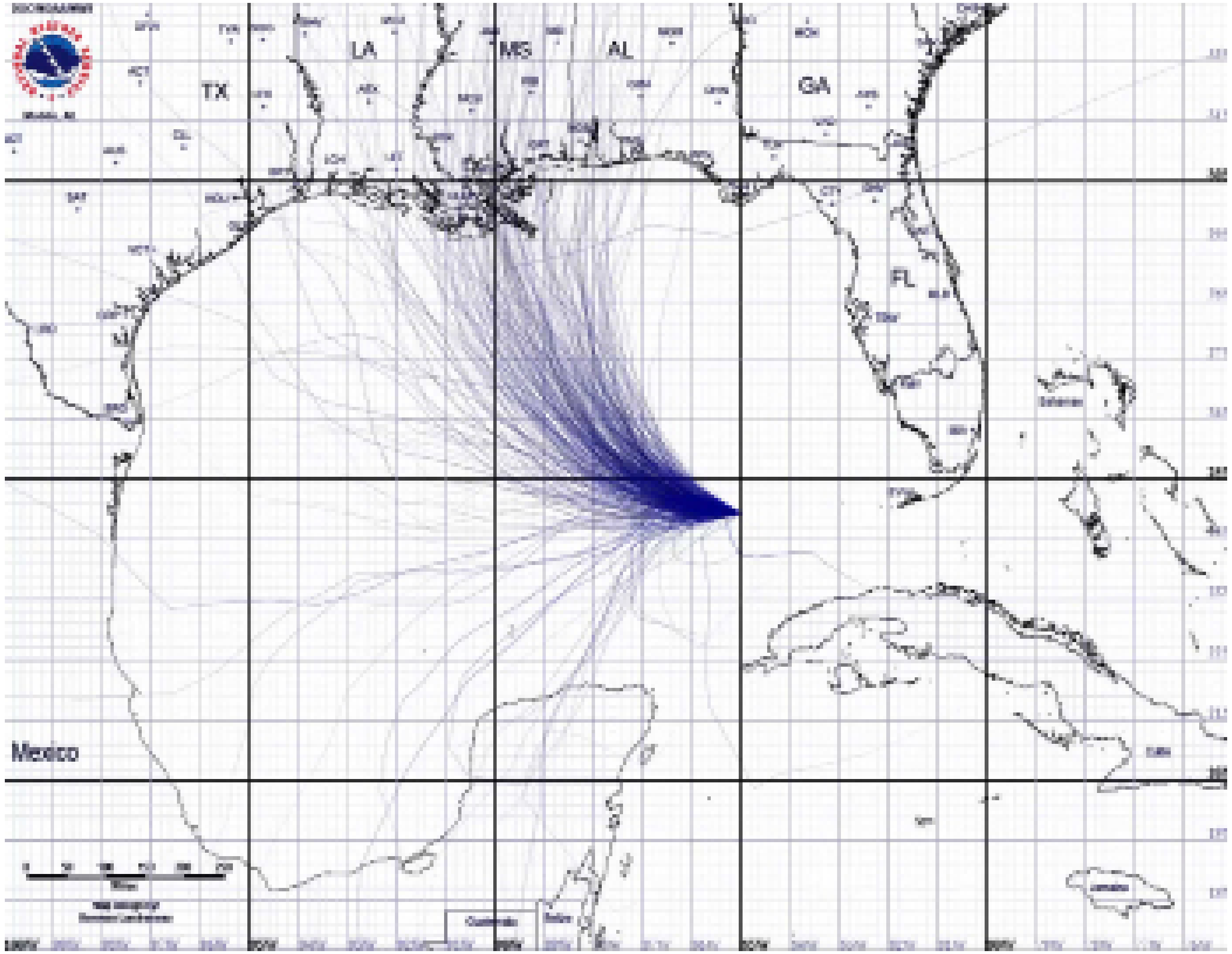


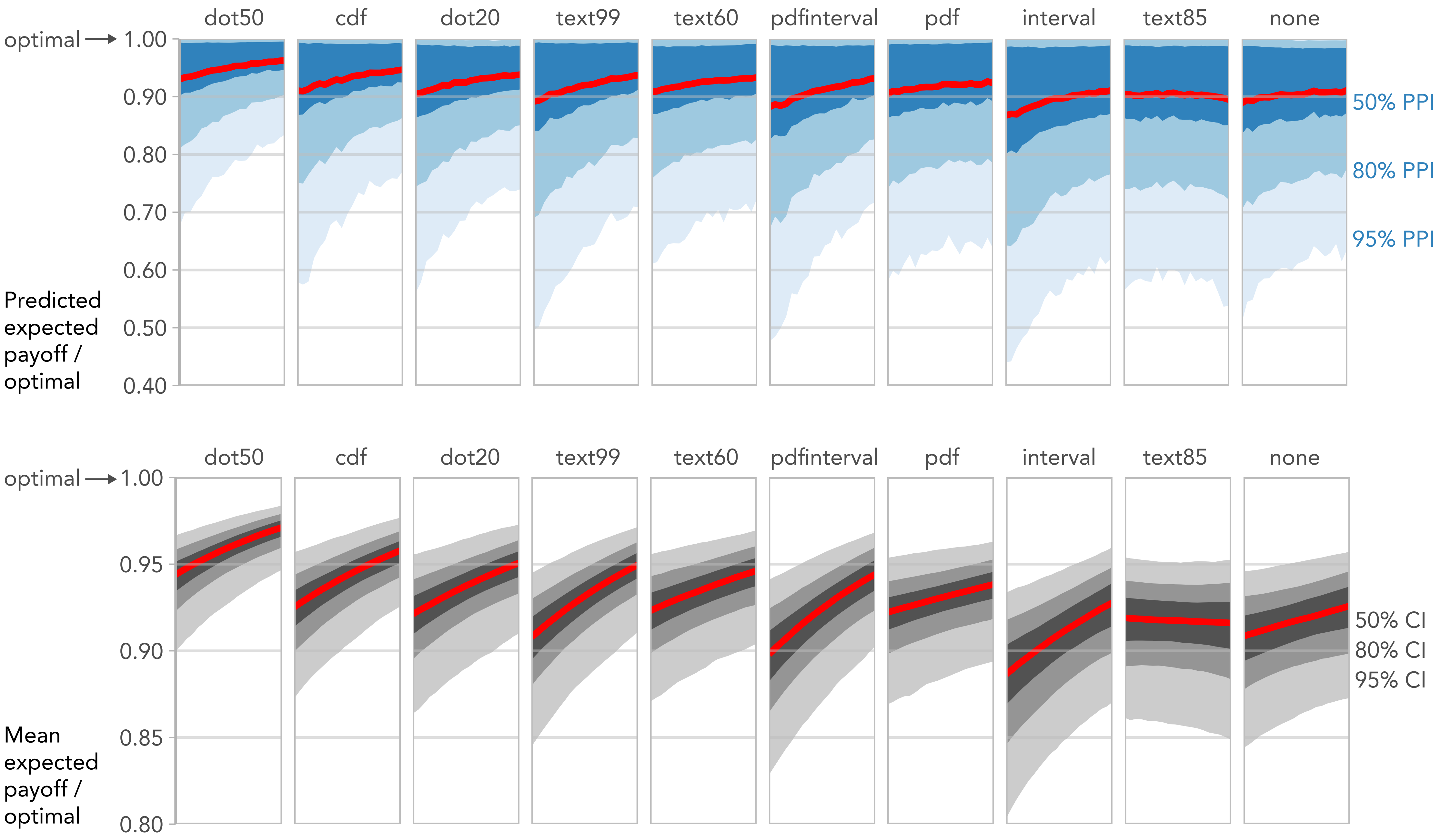
HOPs might aid deterministic construal errors

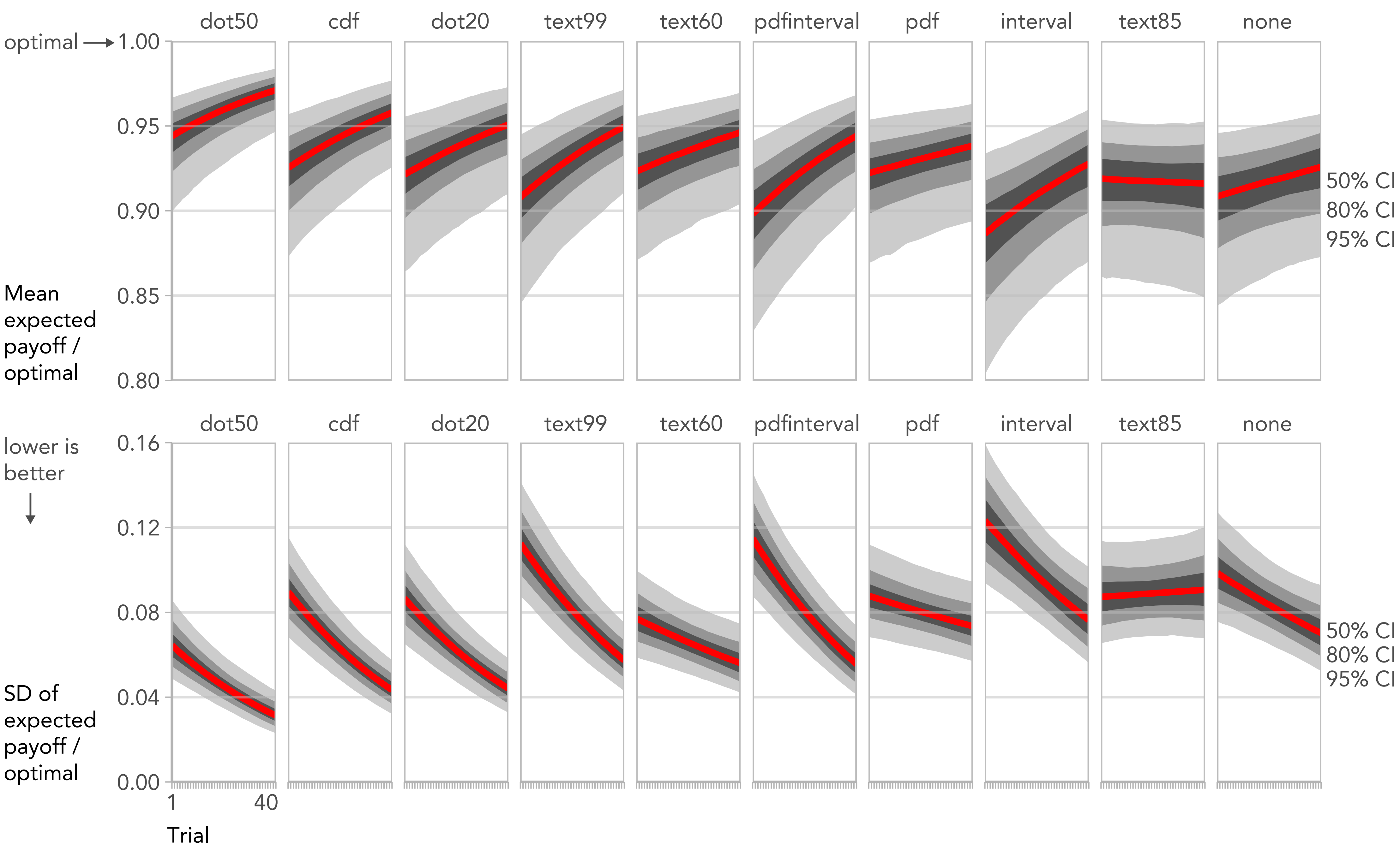


HOPs might aid deterministic construal errors





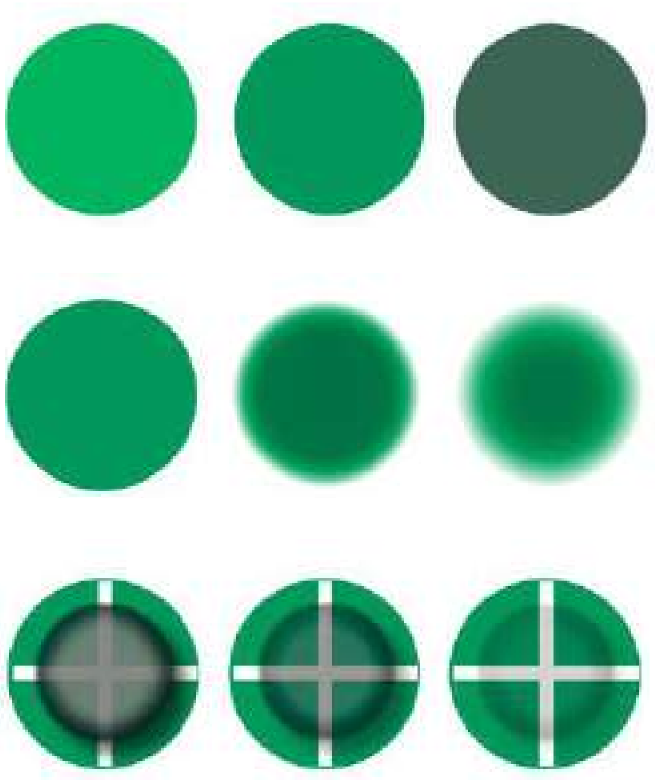

dot50
cdf
dot20
text99
text60
pdfinterval
pdf
interval
text85
none
optimal
1.00
0.90
0.80
0.70
0.60
0.50
0.40
Predicted expected payoff / optimal
50% PPI
80% PPI
95% PPI
dot50
cdf
dot20
text99
text60
pdfinterval
pdf
interval
text85
none
optimal
1.00
0.95
0.90
0.85
0.80
Mean expected payoff / optimal
50% CI
80% CI
95% CI



dot50
cdf
dot20
text99
text60
pdfinterval
pdf
interval
text85
none
optimal
1.00
0.95
0.90
0.85
0.80
Mean expected payoff / optimal
50% CI
80% CI
95% CI
lower is better
0.16
0.12
0.08
0.04
0.00
SD of expected payoff / optimal
1
40
Trial

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]



Color saturation

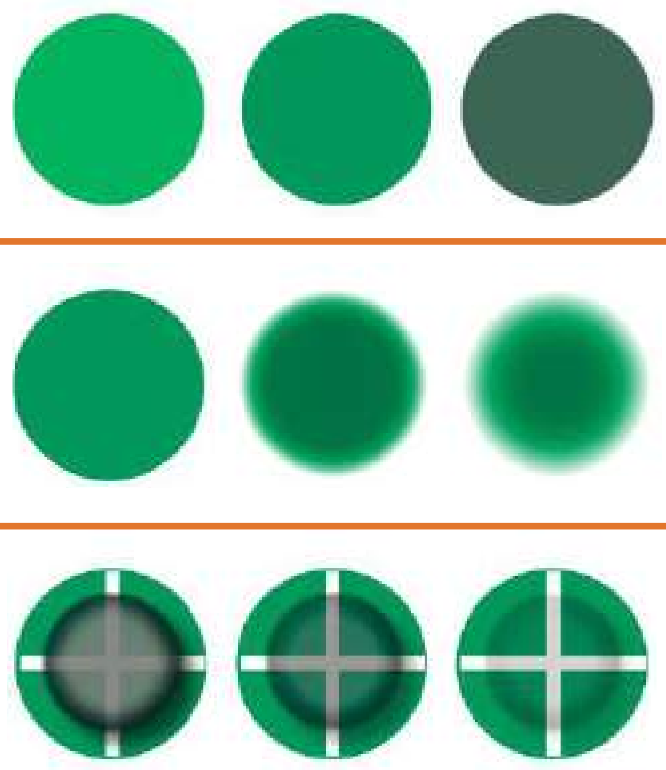
Blur

Blur

More uncertainty →

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]



Color saturation

Blur

Blur

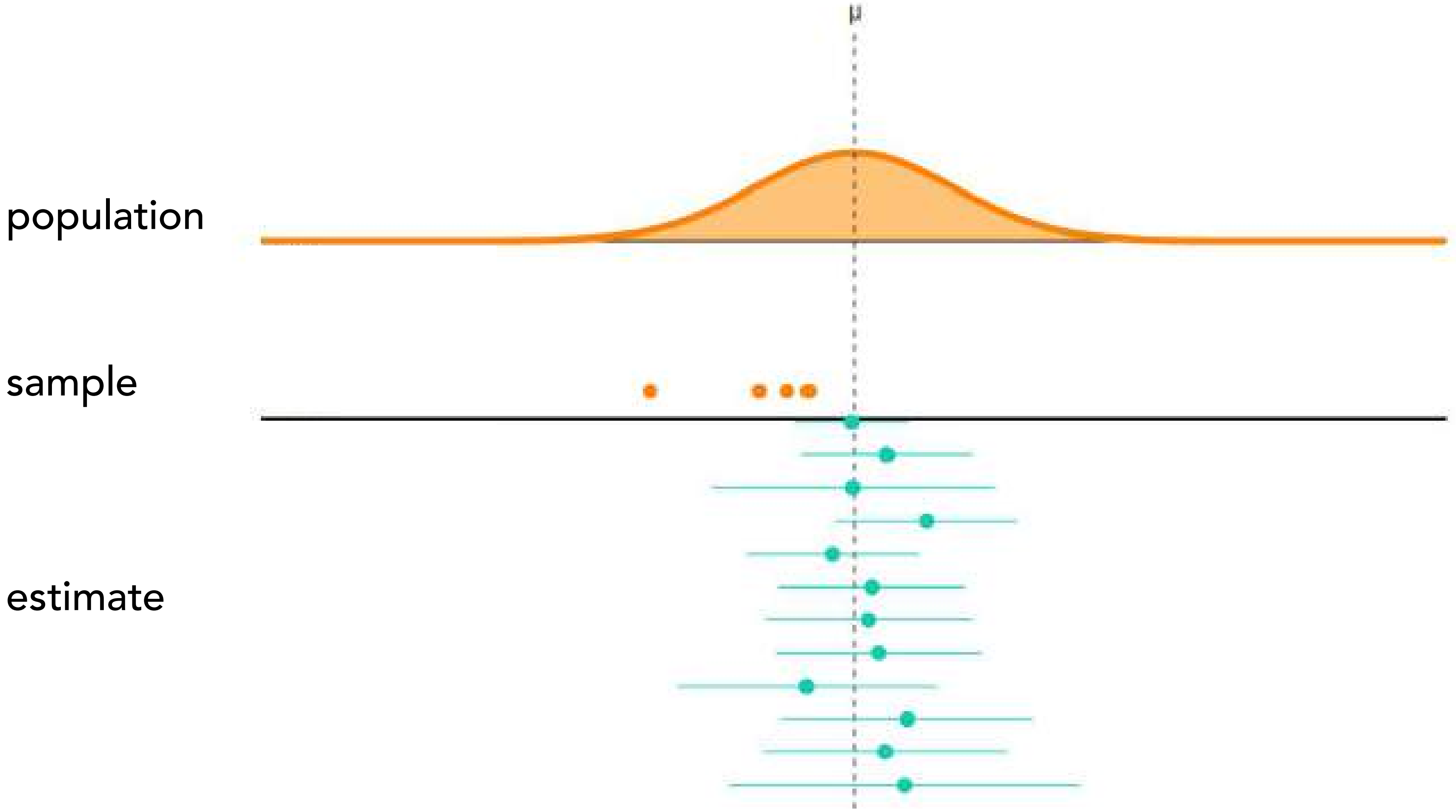
More intuitive?

But how accurate?

More uncertainty →

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

Frequentist view of uncertainty

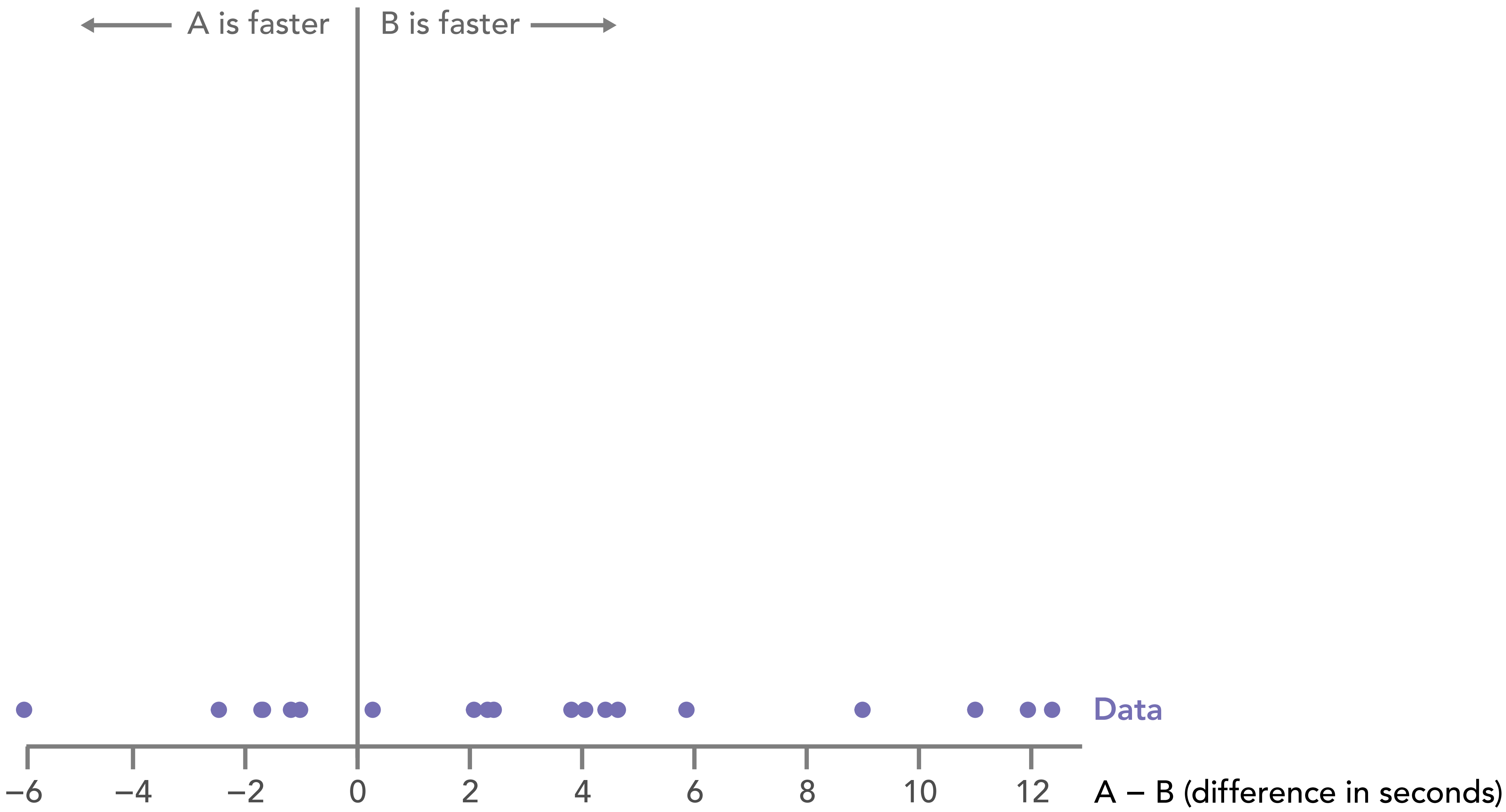


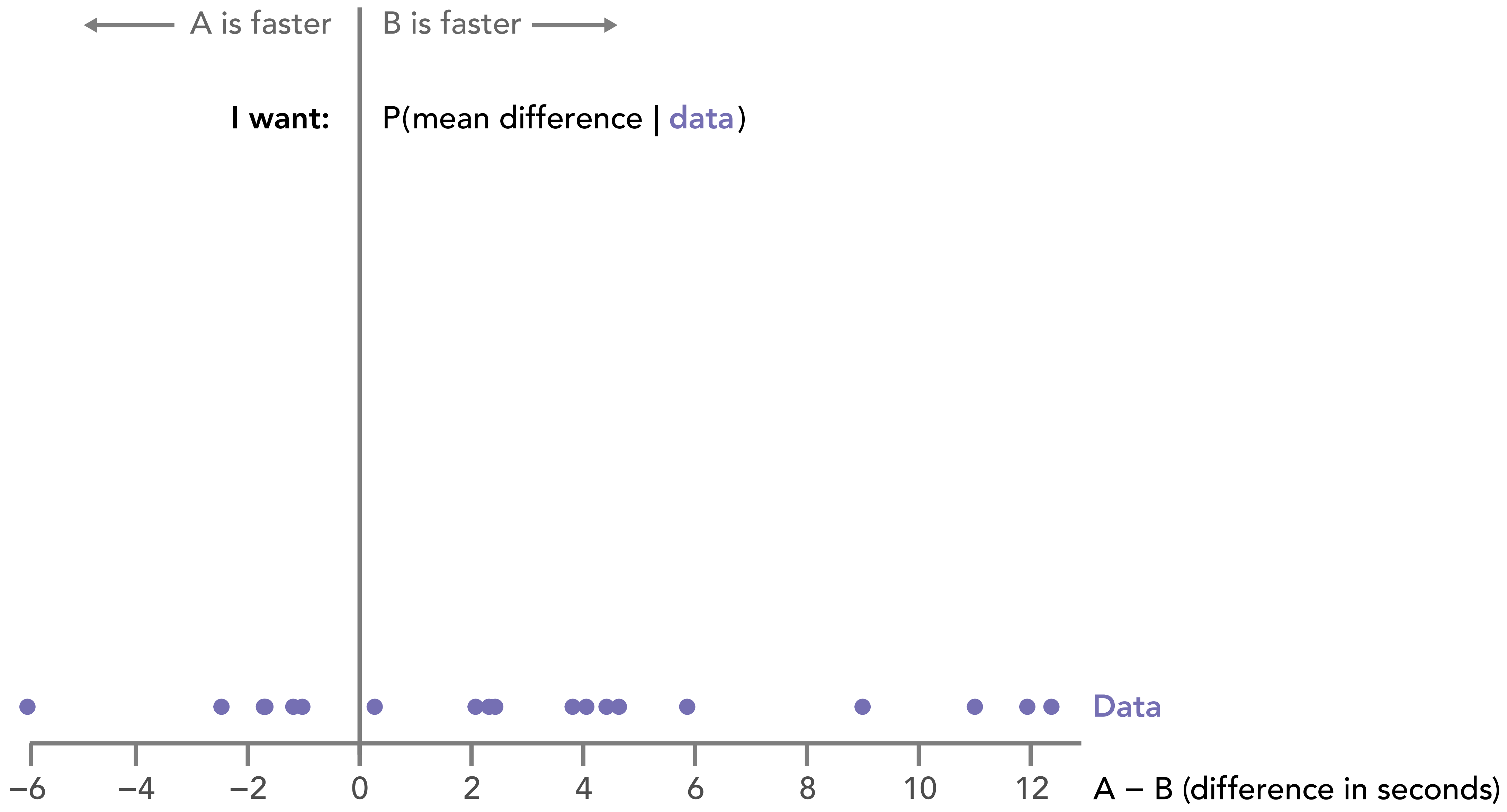
https://students.brown.edu/seeing-theory/frequentist-inference

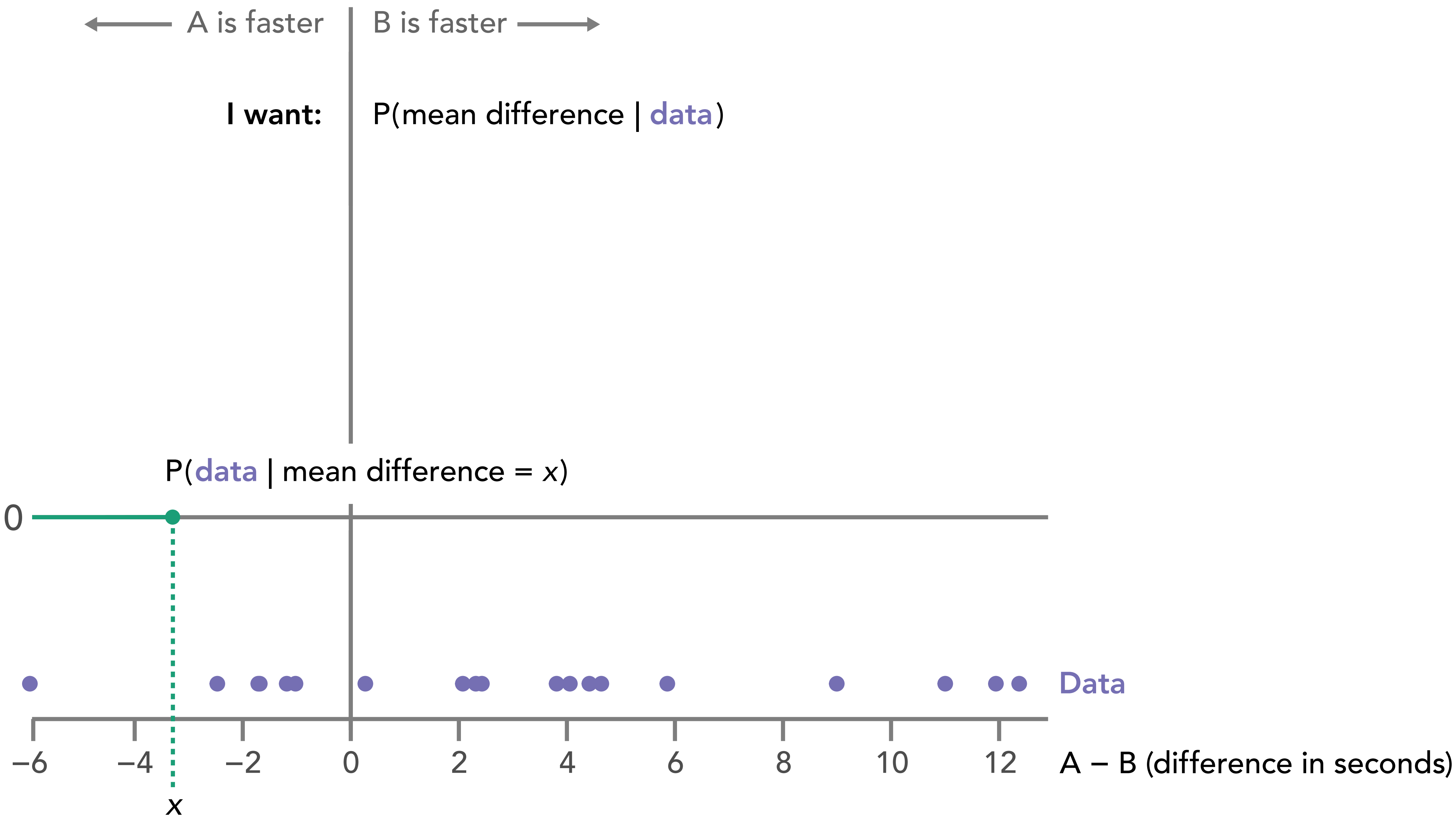
For the purposes of half of this lecture...

I am largely adopting a Bayesian view of uncertainty

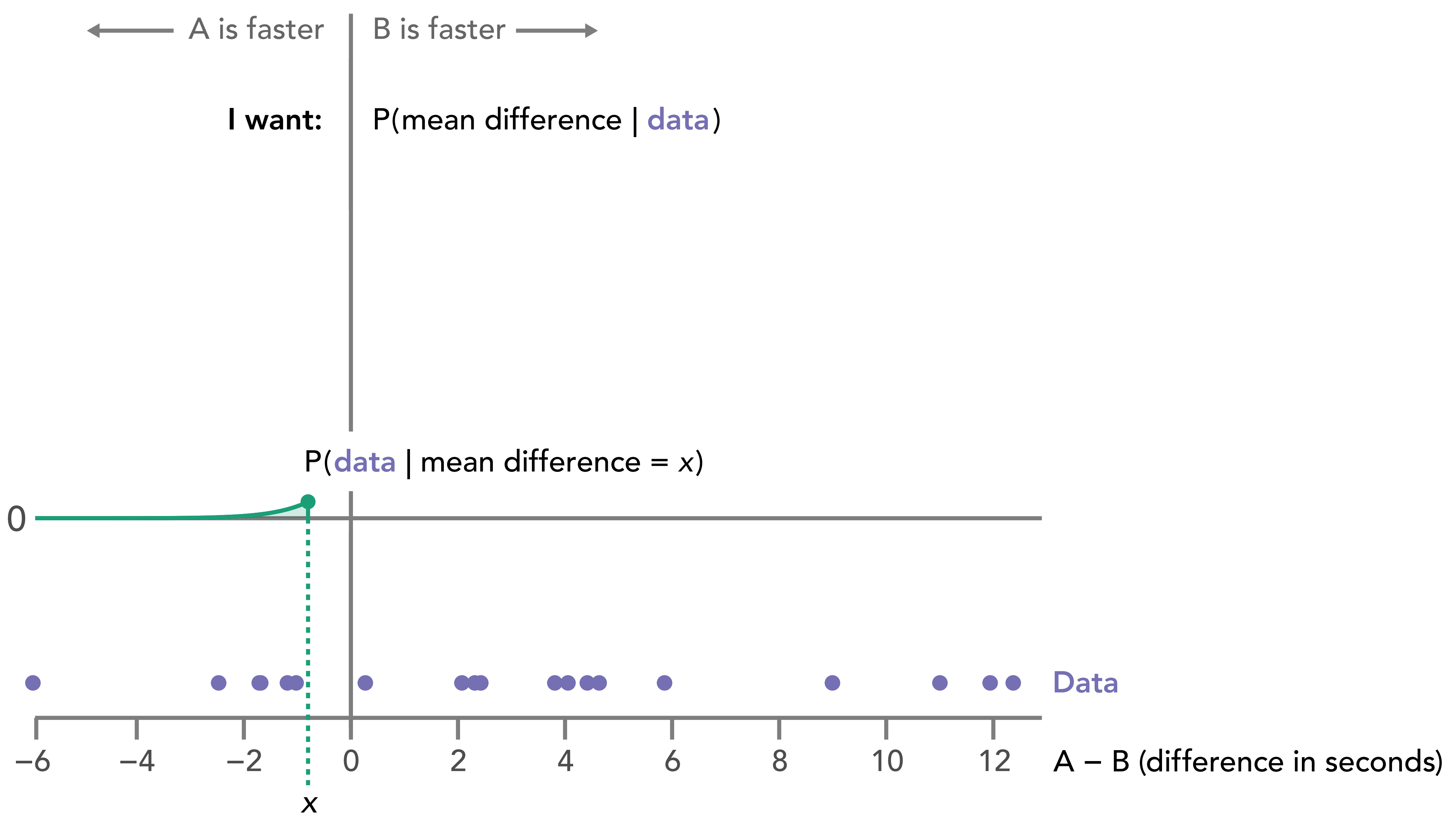
Put another way: uncertainty is probability


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

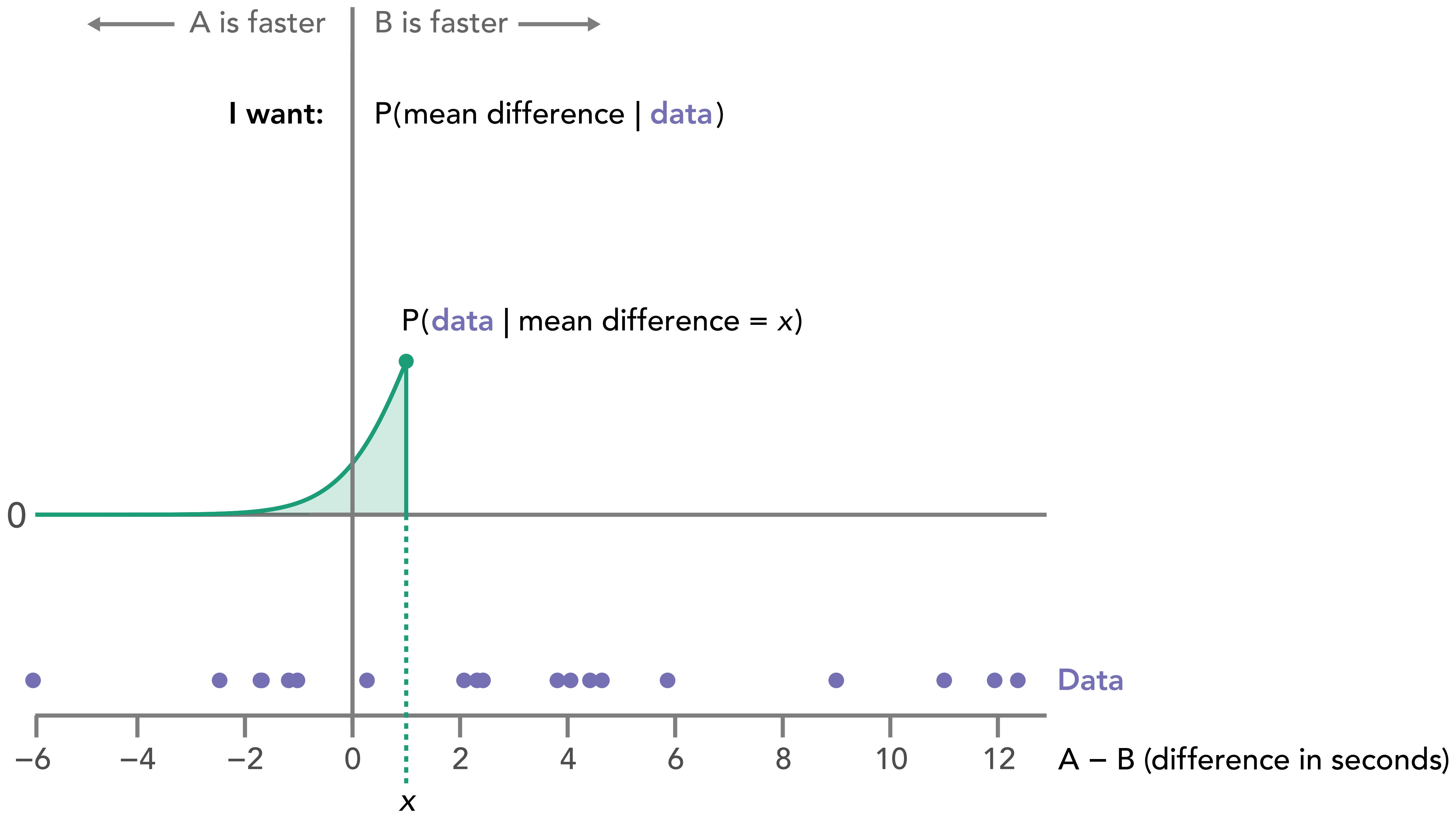

A is faster
B is faster
I want:
P(mean difference | data)
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)



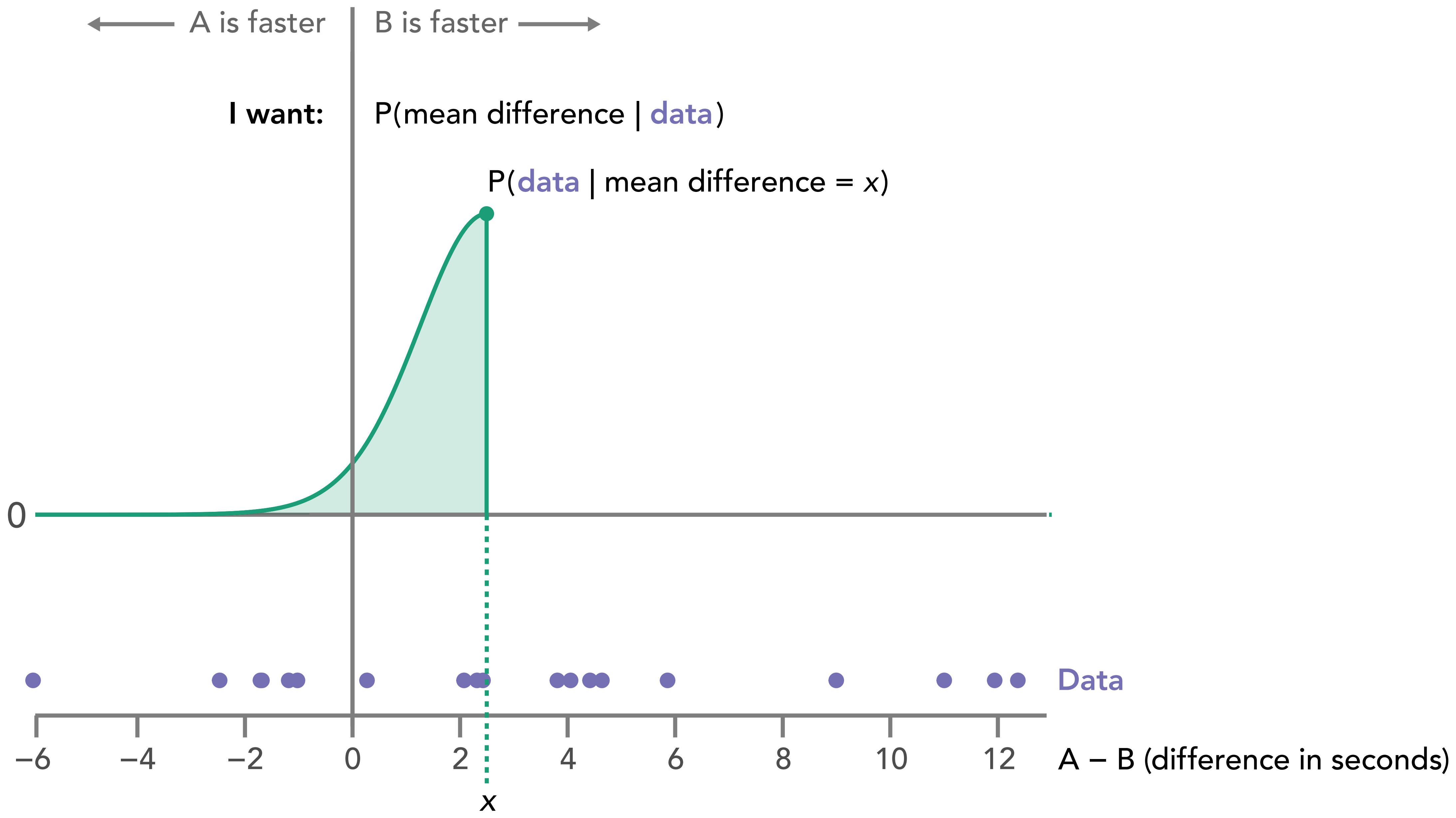
A is faster
B is faster
I want:
P(mean difference | data)
P(data | mean difference = x)
0
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)
x

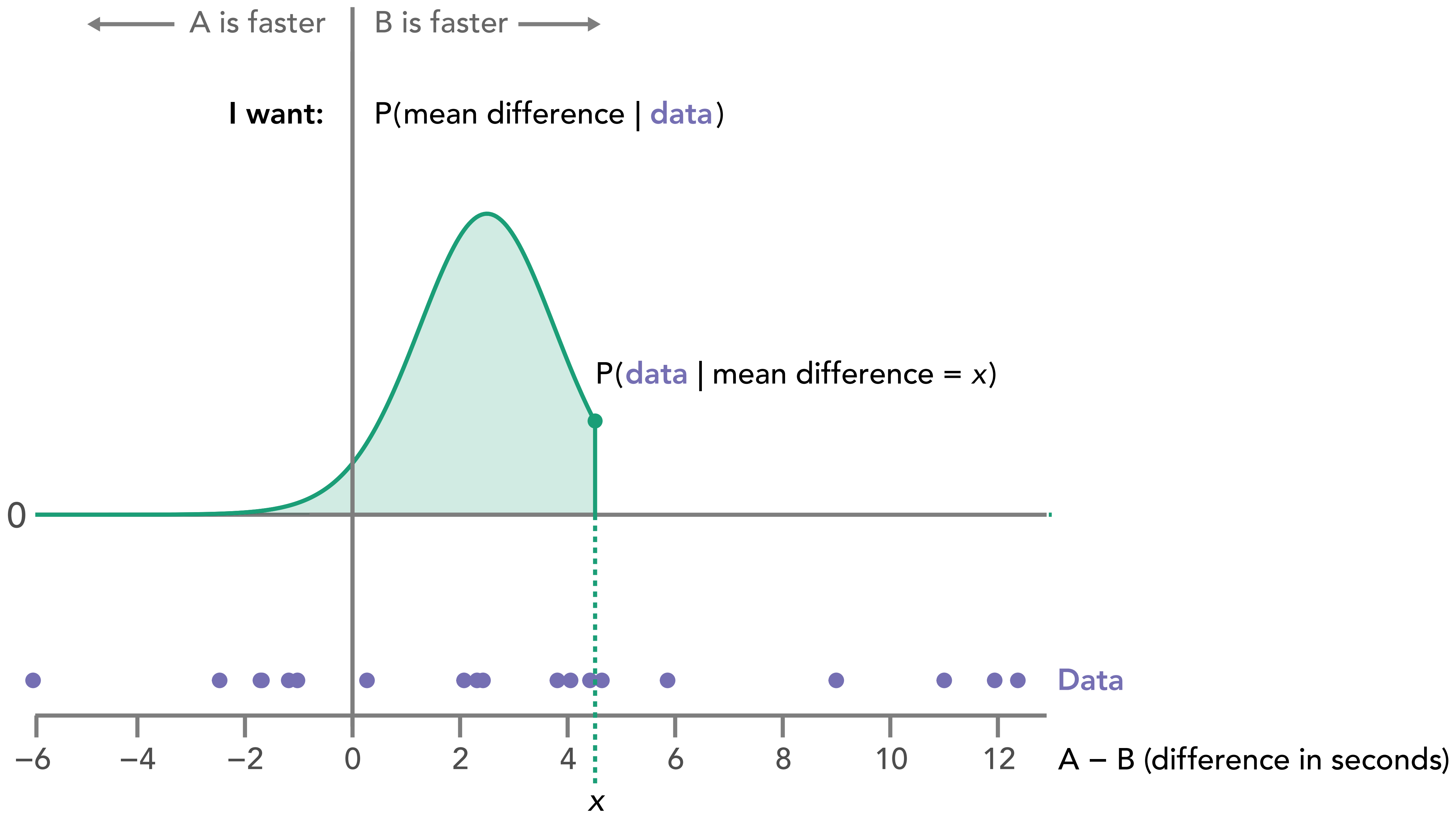


A is faster
B is faster
I want:
P(mean difference | data)
P(data | mean difference = x)
0
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)
x

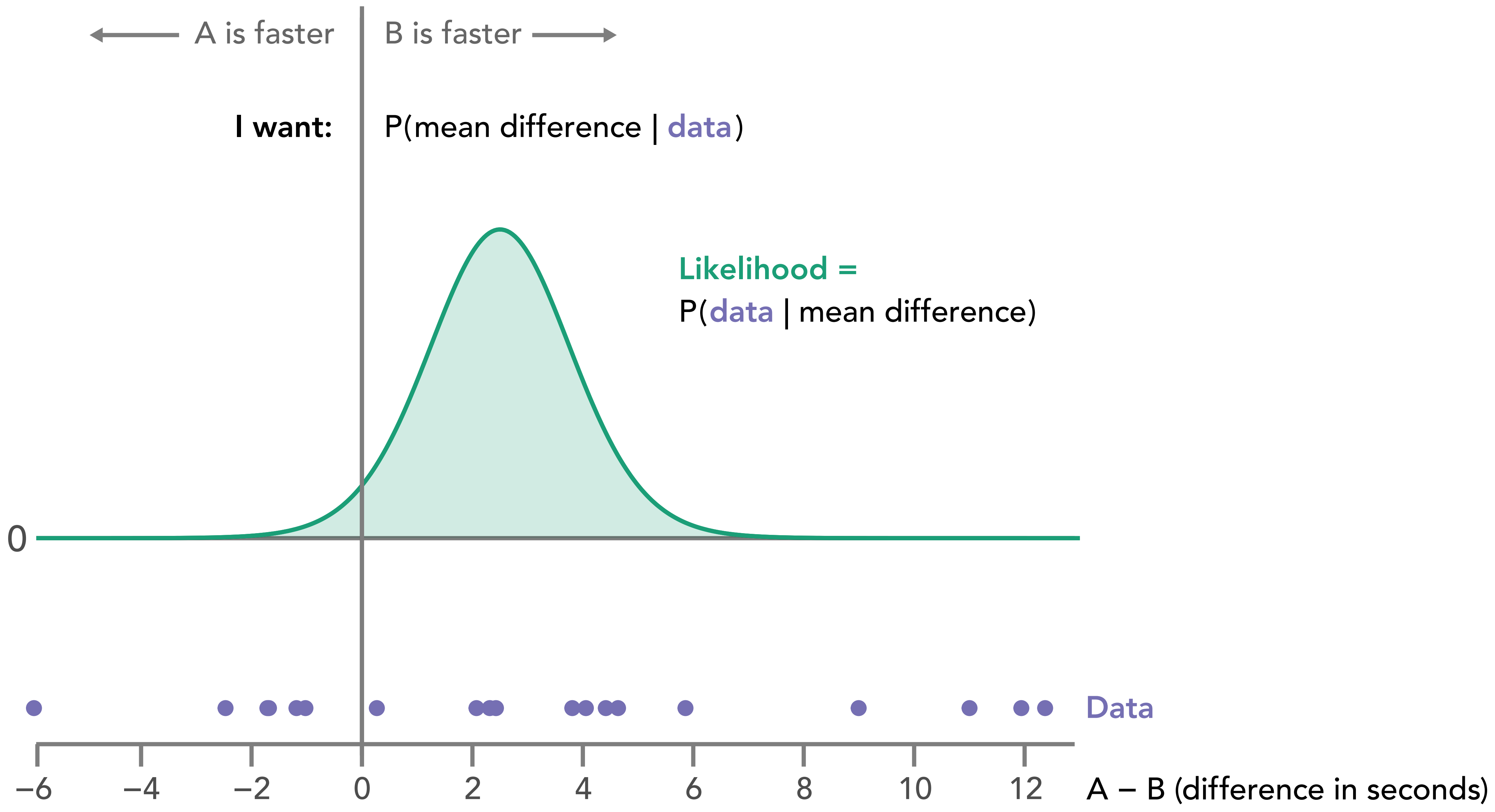


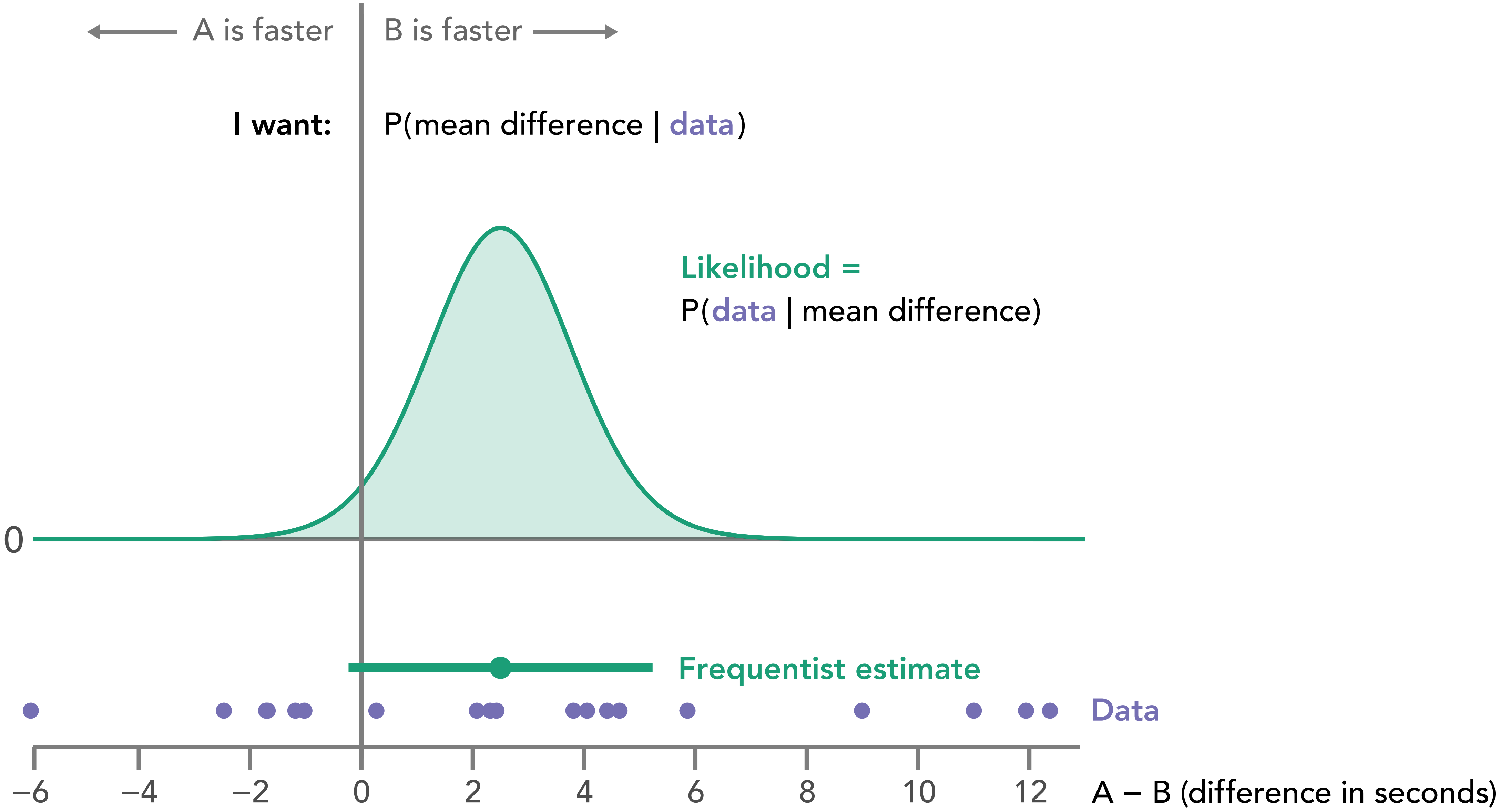
A is faster
B is faster
I want:
P(mean difference | data)
P(data | mean difference = x)
0
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)
x

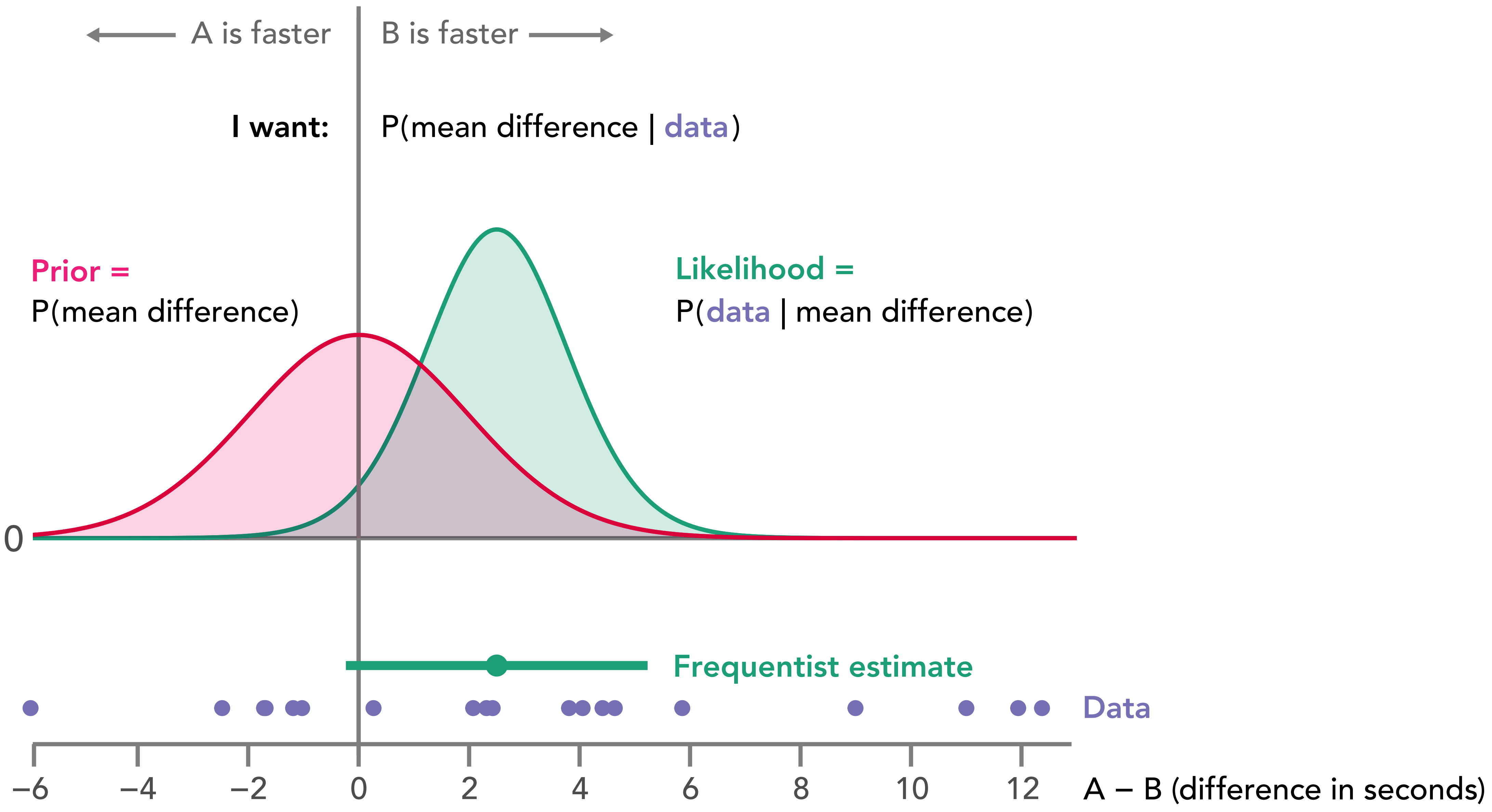

A is faster
B is faster
I want:
P(mean difference | data)
P(data | mean difference = x)
0
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)
x



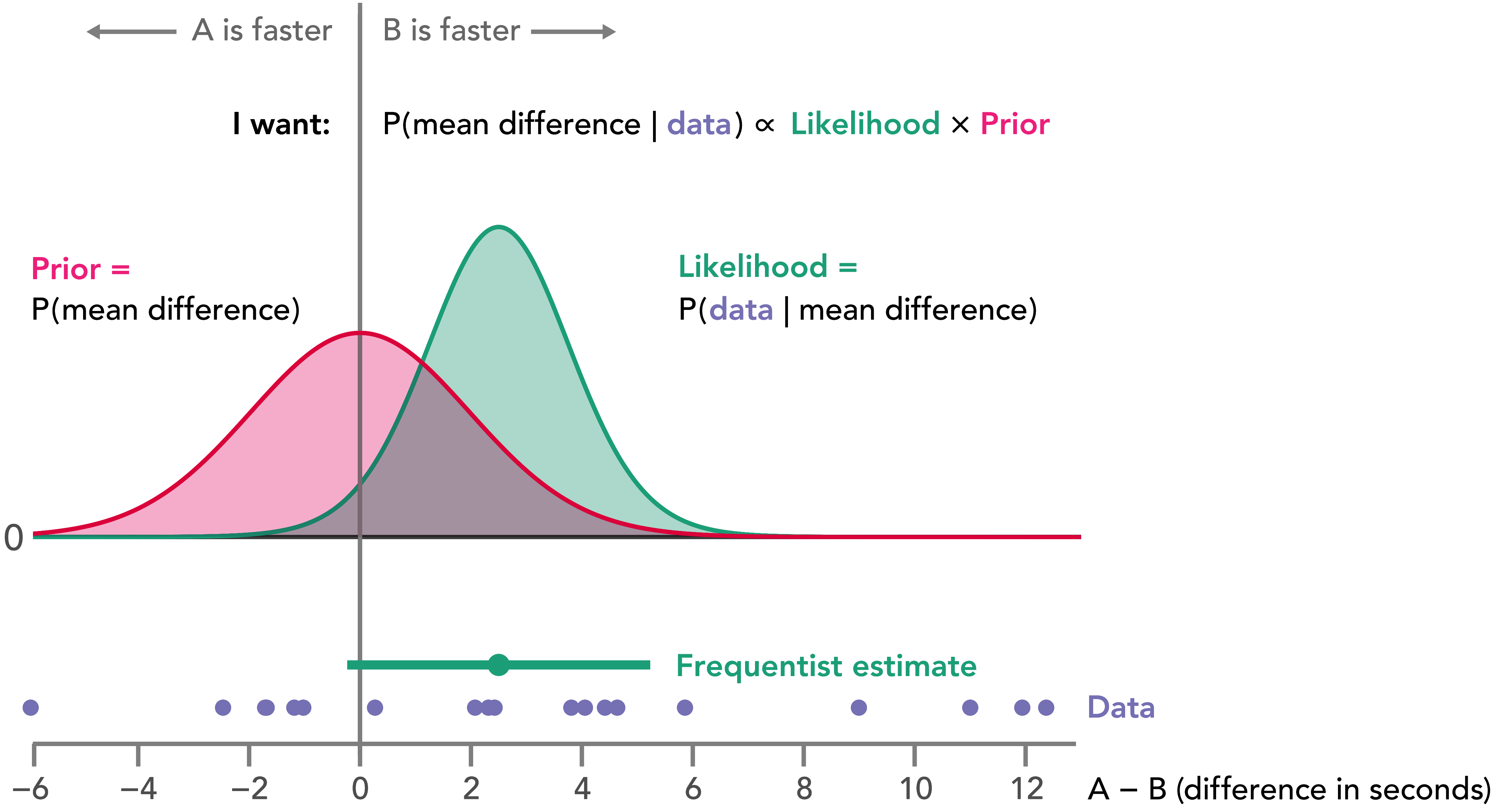
A is faster
B is faster
I want:
P(mean difference | data)
P(data | mean difference = x)
0
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)
x


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

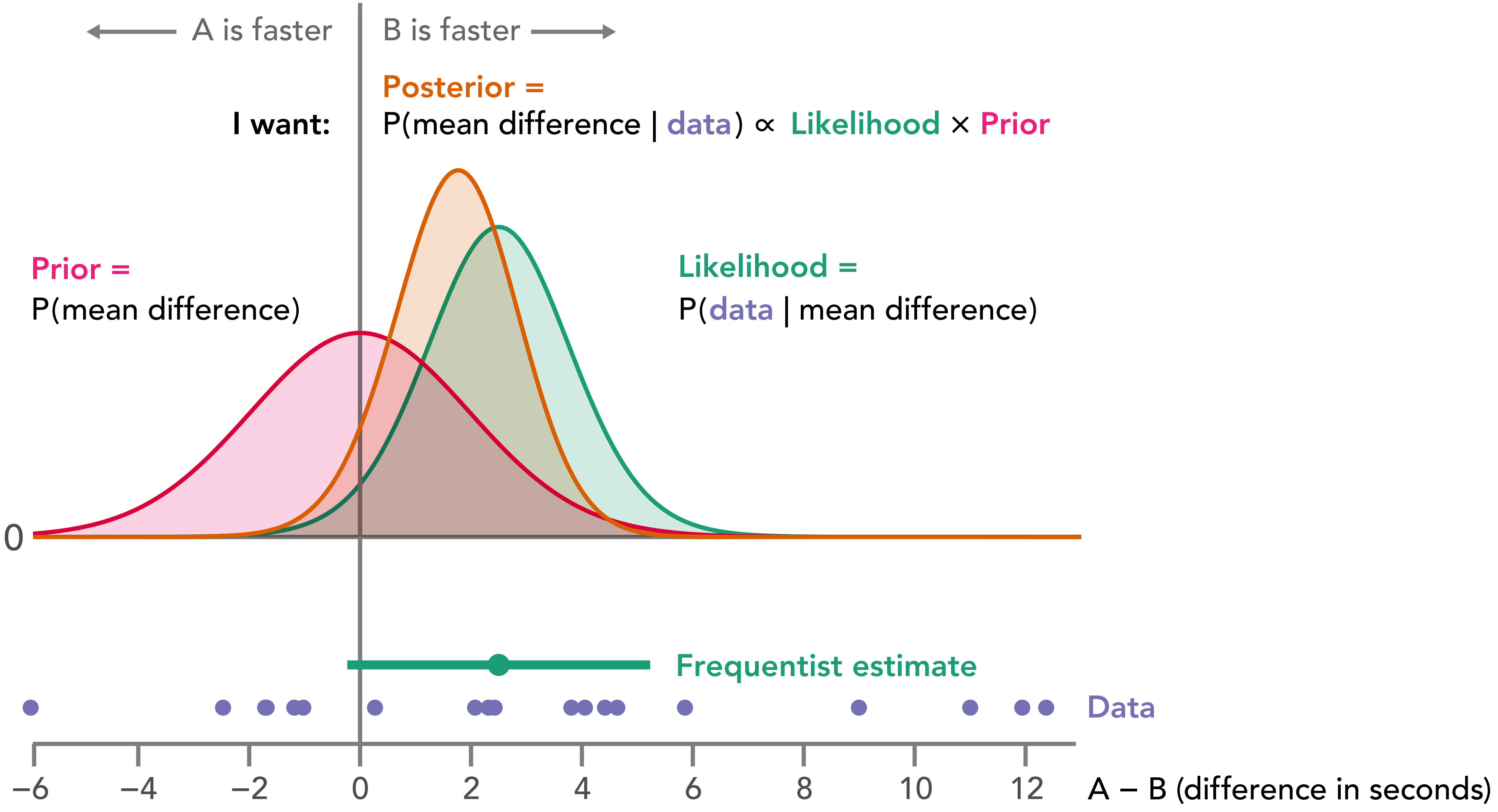

A is faster
B is faster
I want:
P(mean difference | data)
Likelihood =
P(data | mean difference)
0
Frequentist estimate
Data
−6
−4
−2
0
2
4
6
8
10
12
A − B (difference in seconds)



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)



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B is faster
Posterior =
I want:
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P(mean difference)
Likelihood =
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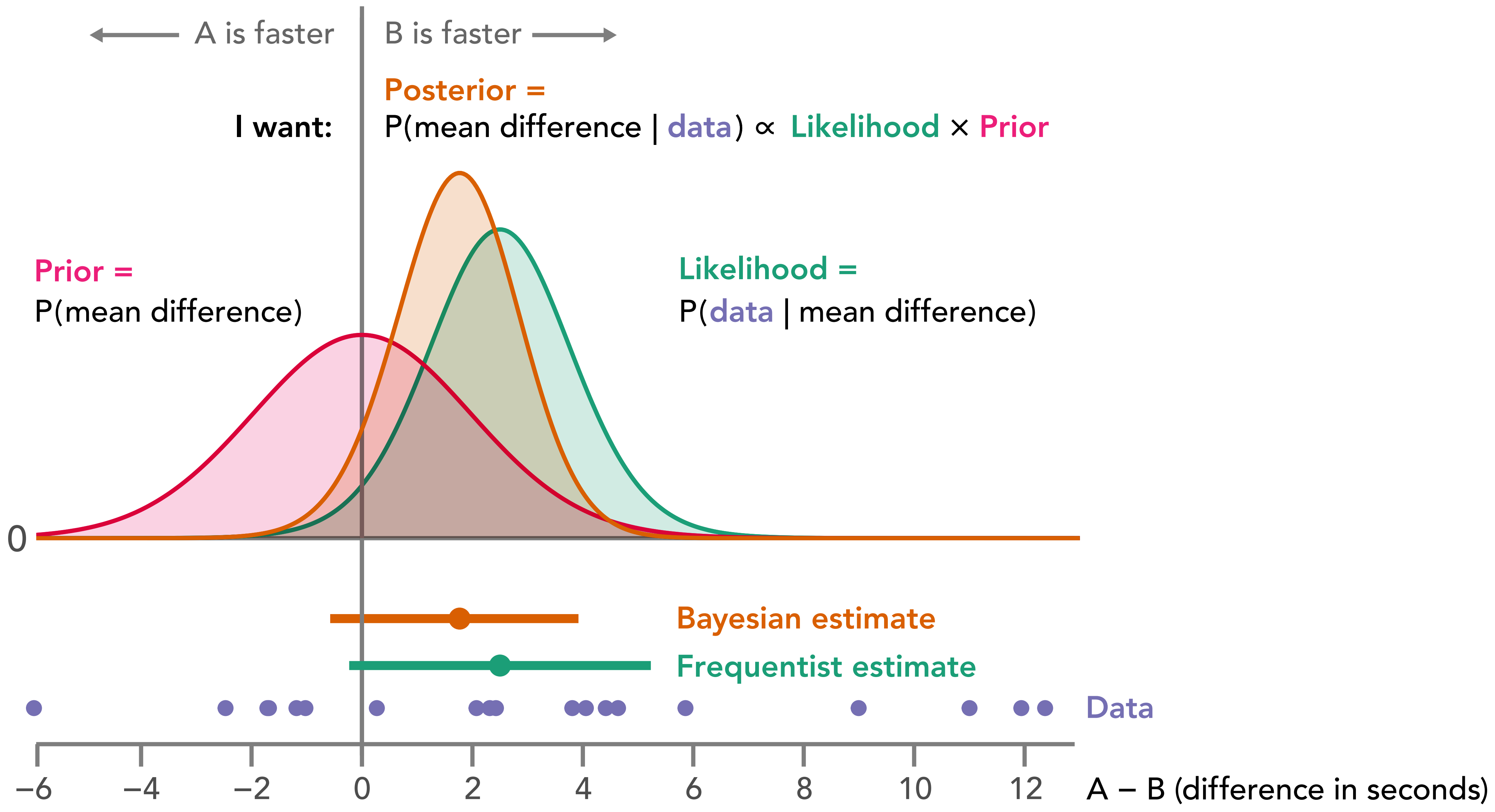
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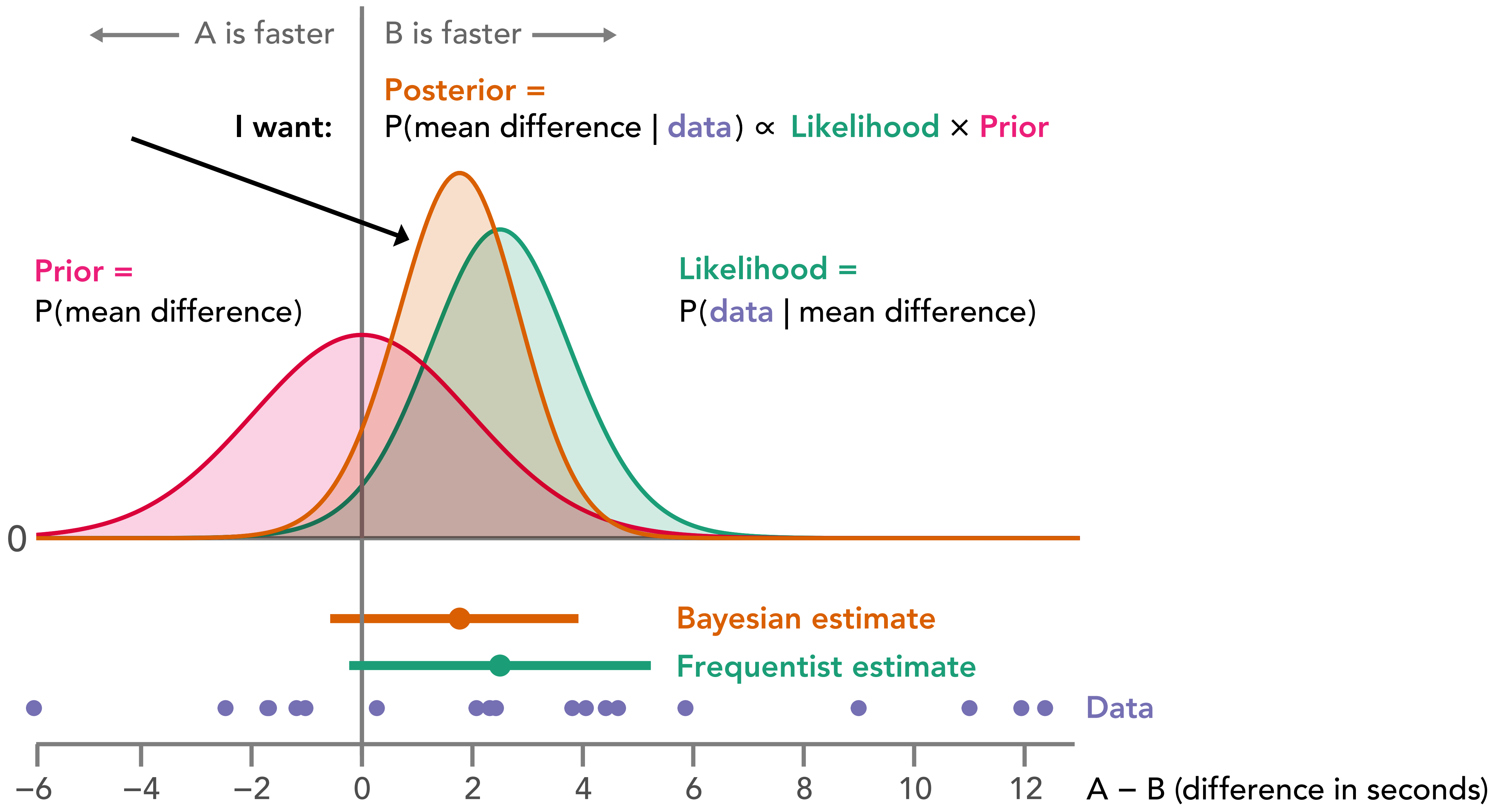

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Posterior =
I want:
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Bayesian estimate
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Data
−6
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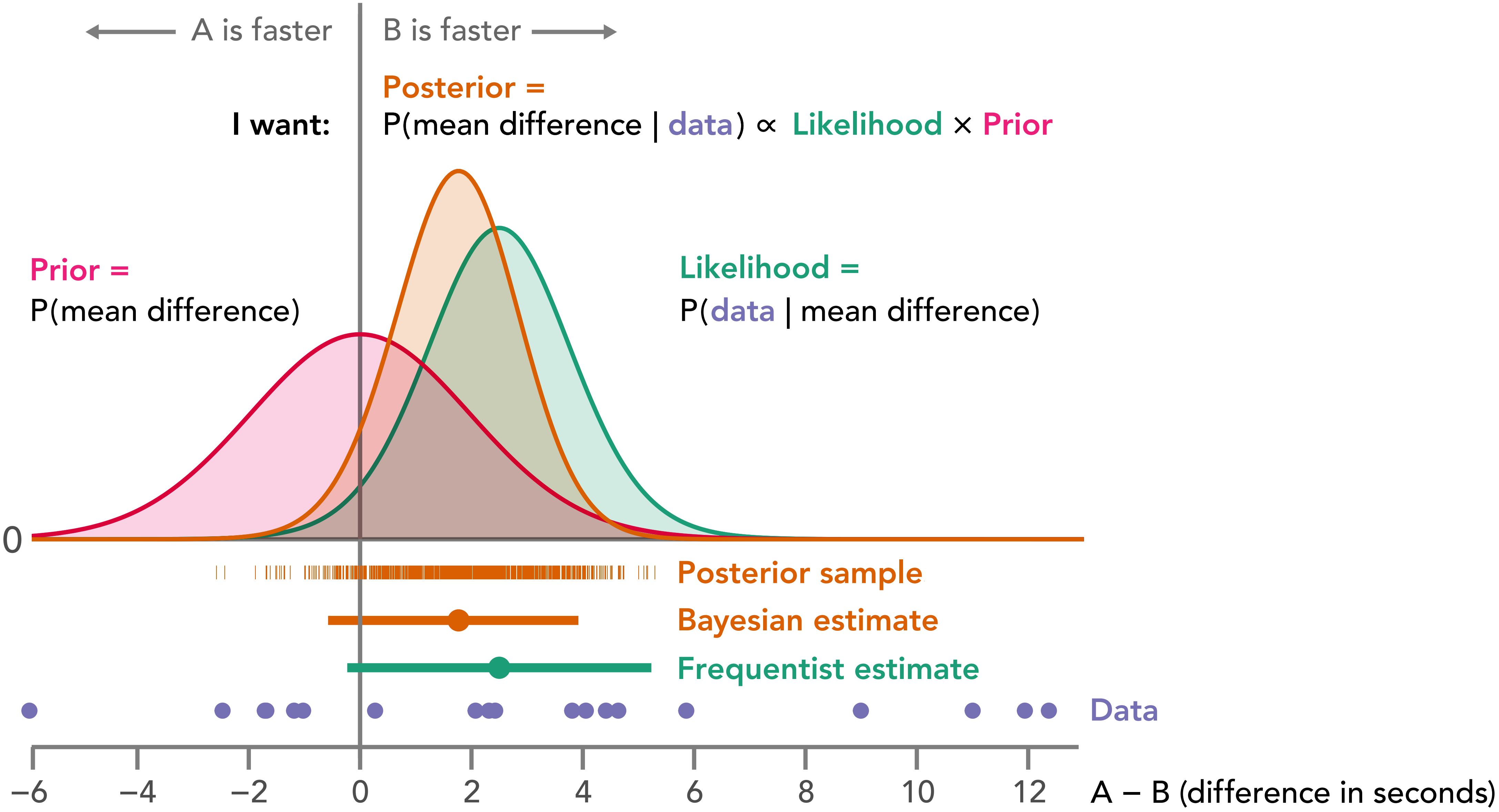
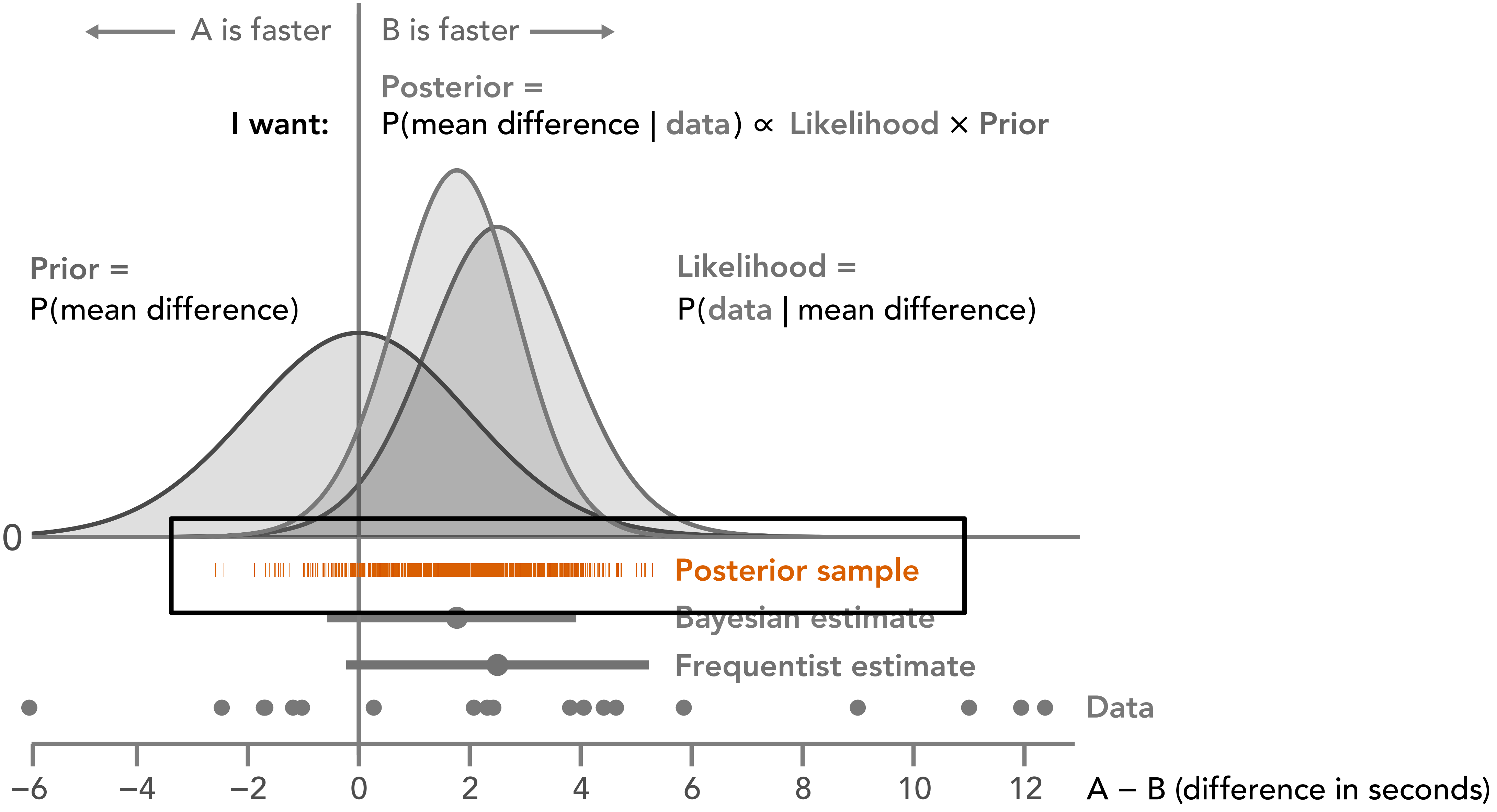
A − B (difference in seconds)


A is faster
B is faster
I want:
Posterior =
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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Prior =
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Posterior sample
Bayesian estimate
Frequentist estimate
Data
−6
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6
8
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A − B (difference in seconds)

For the purposes of the first half of this talk…

I am largely adopting a Bayesian view of uncertainty

Put another way: uncertainty is probability

Two other distinctions worth knowing

Uncertainty in parameters / estimates – epistemic

Uncertainty in what we know

Two other distinctions worth knowing

Uncertainty in parameters / estimates – epistemic

Uncertainty in what we know

Uncertainty in new observations – aleatory

Uncertainty in what we predict to happen