Uncertainty visualization with tidybayes and ggdist

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Collective

TIDYBAYES

GGDIST

Strategies for effective uncertainty visualization

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Examples with tidybayes and ggdist (and posterior...?)

Ignoring uncertainty is easy...

Predictions from 2016 presidential election

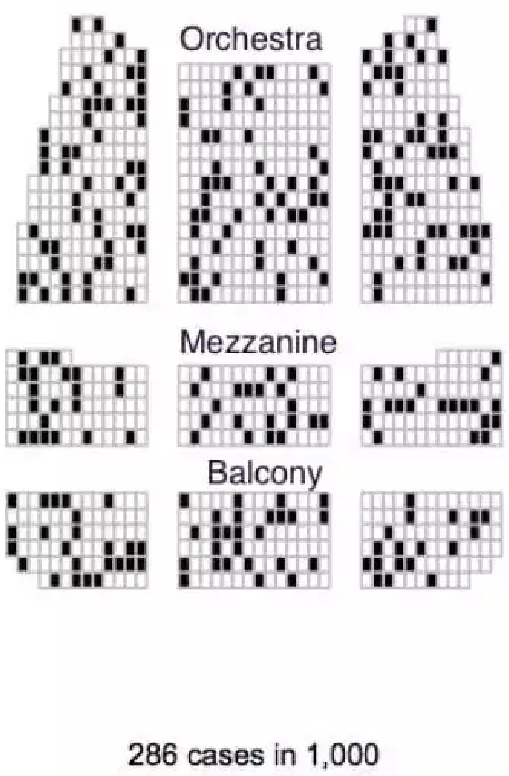
[Justin H. Gross, Washington Post, http://wapo.st/2fCYvDW]

FiveThirtyEight	NYT Upshot	HuffPo Pollster
28%	15%	2%

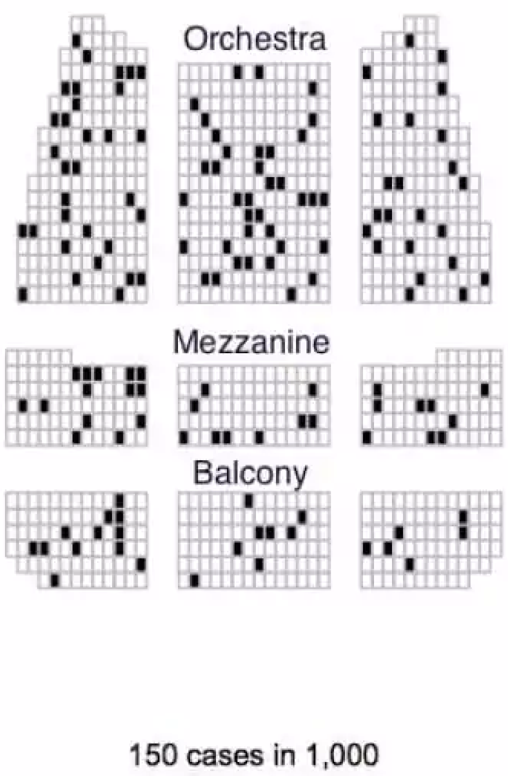
Predictions from 2016 presidential election

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

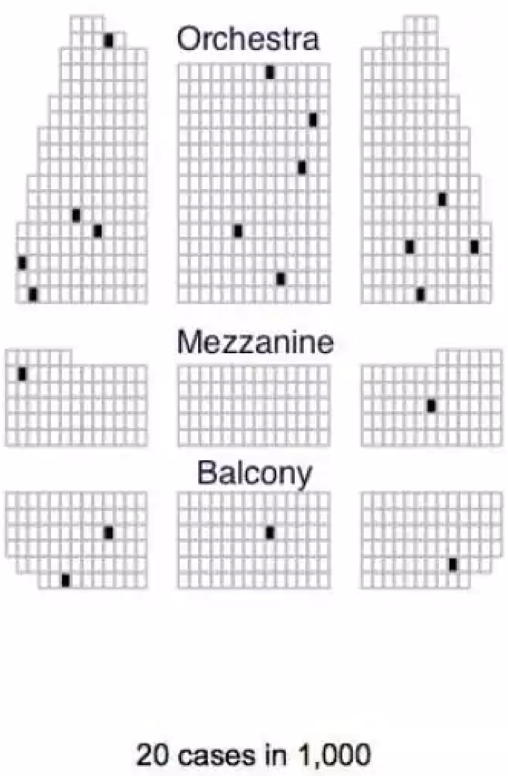
FiveThirtyEight



NYT Upshot



HuffPo Pollster



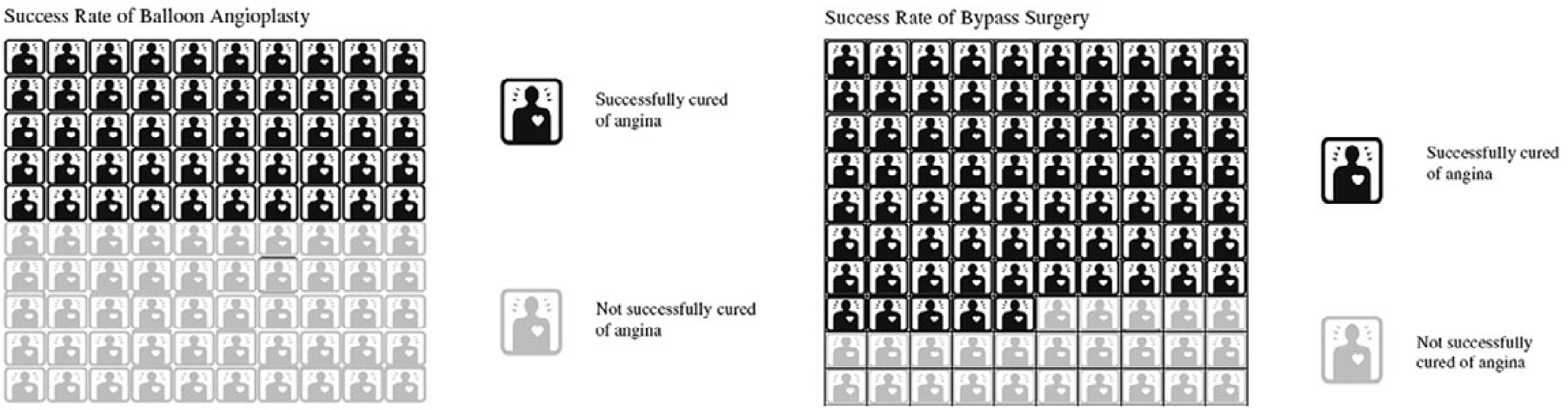
People are very good at ignoring uncertainty…

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]



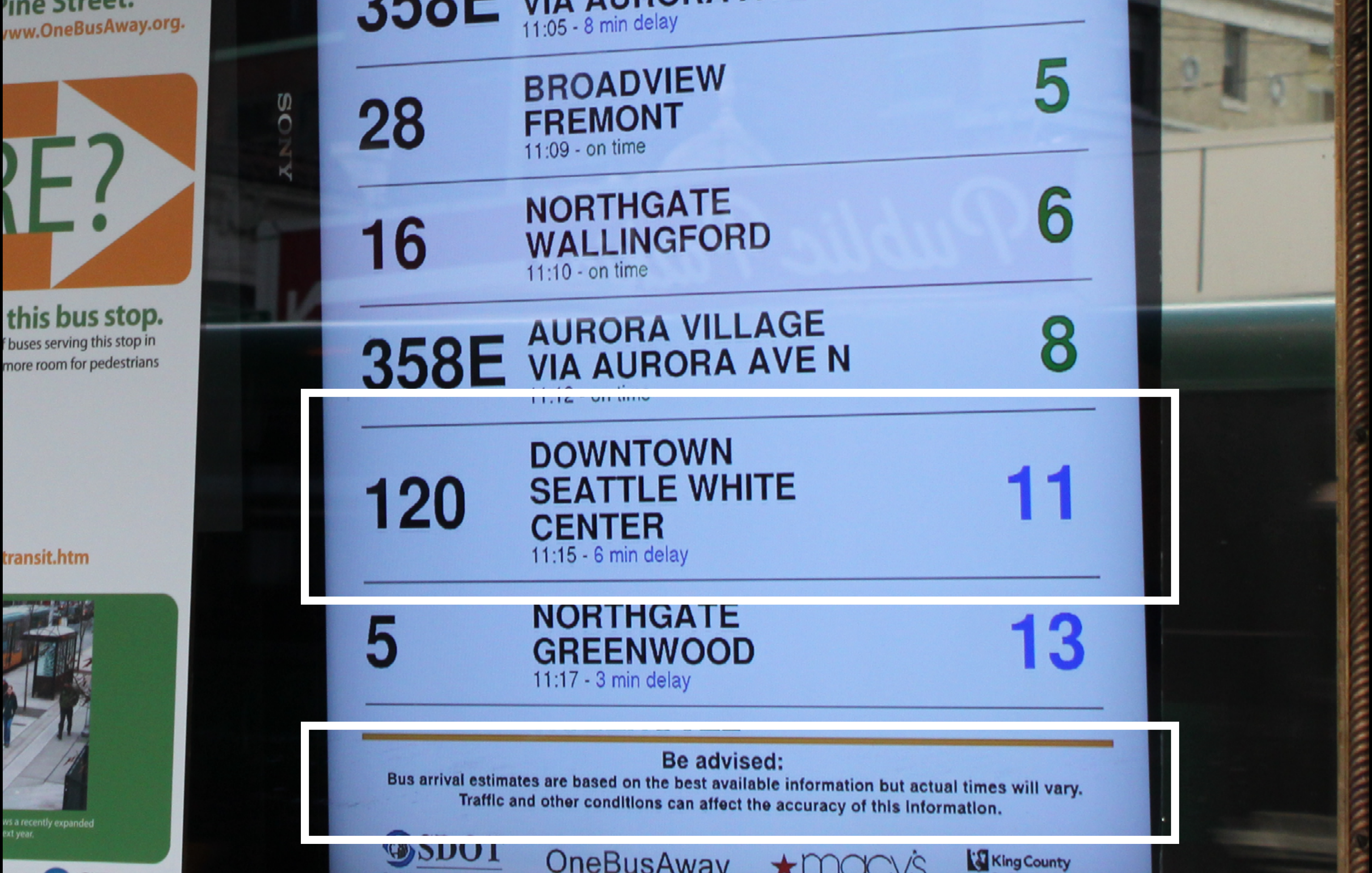
Frequency framing or discrete outcome visualization

What is an icon array for a continuous distribution?

What is an icon array for a continuous distribution?

An example scenario...

www.OneBusAway.org.
RE?
this bus stop.
buses serving this stop in
more room for pedestrians
transit.htm
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
King County



11:05 - 8 min delay
28
BROADVIEW
FREMONT
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5
16
NORTHGATE
WALLINGFORD
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Be advised:
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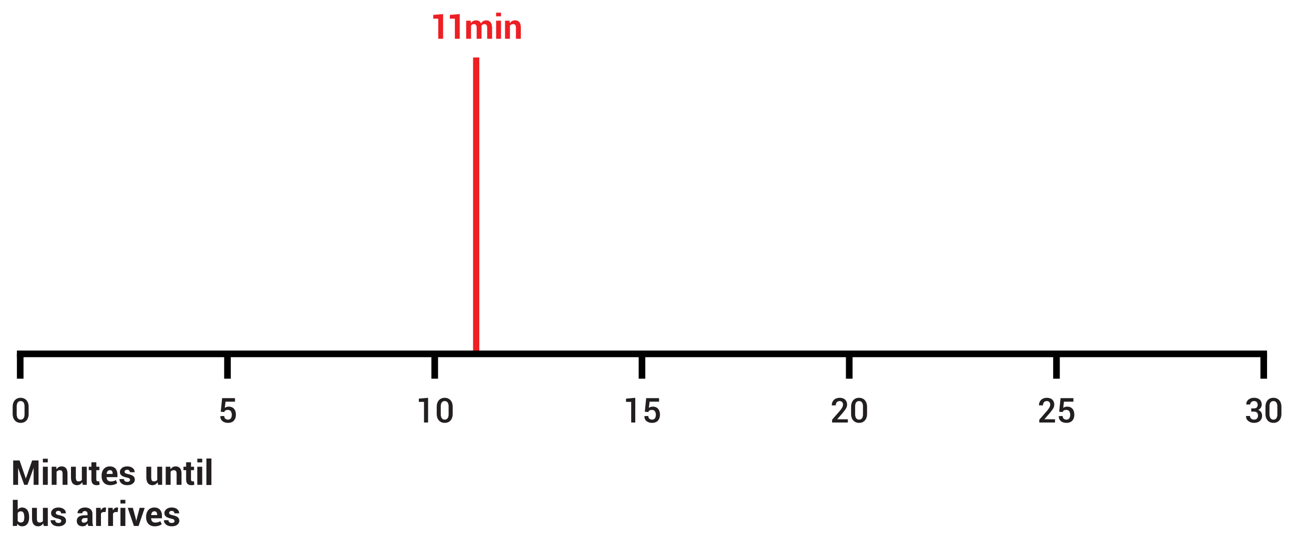
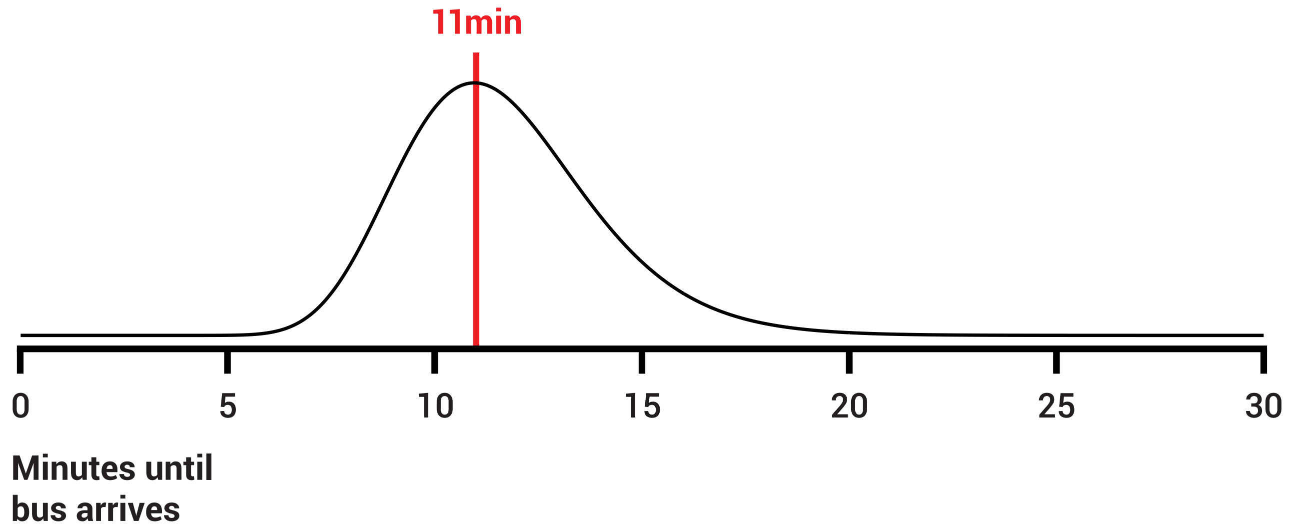
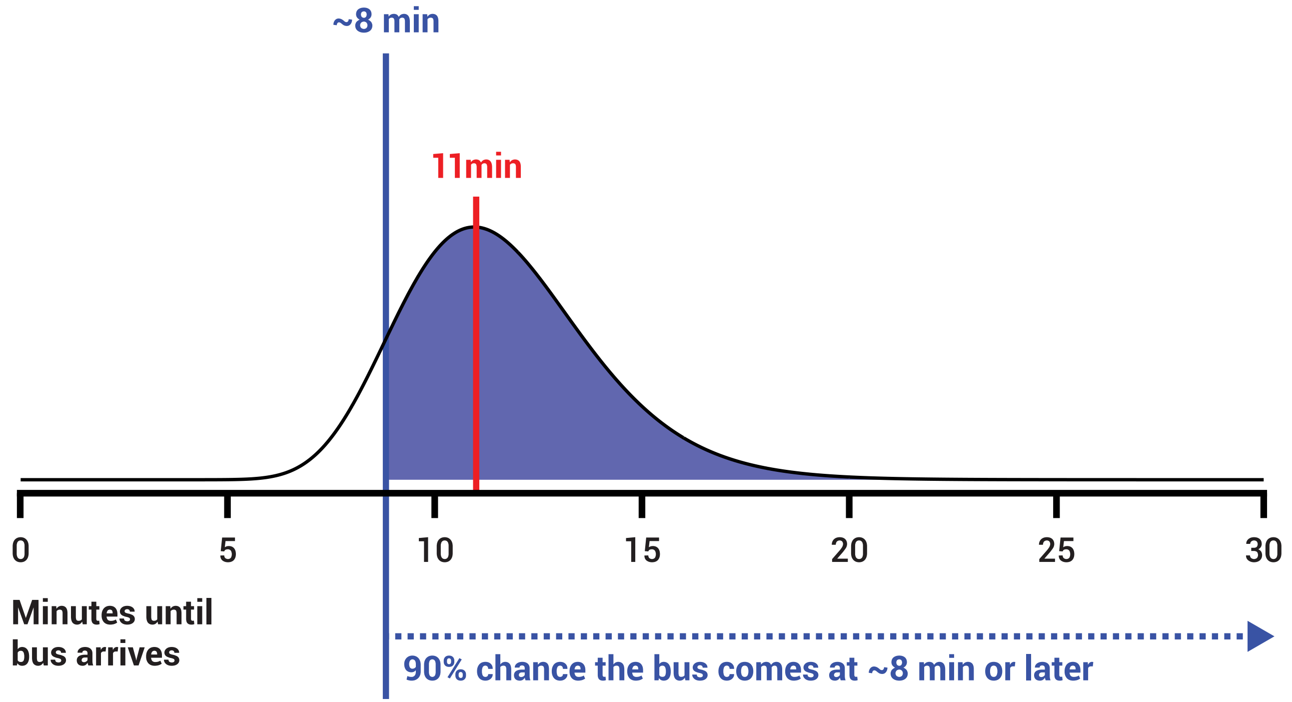
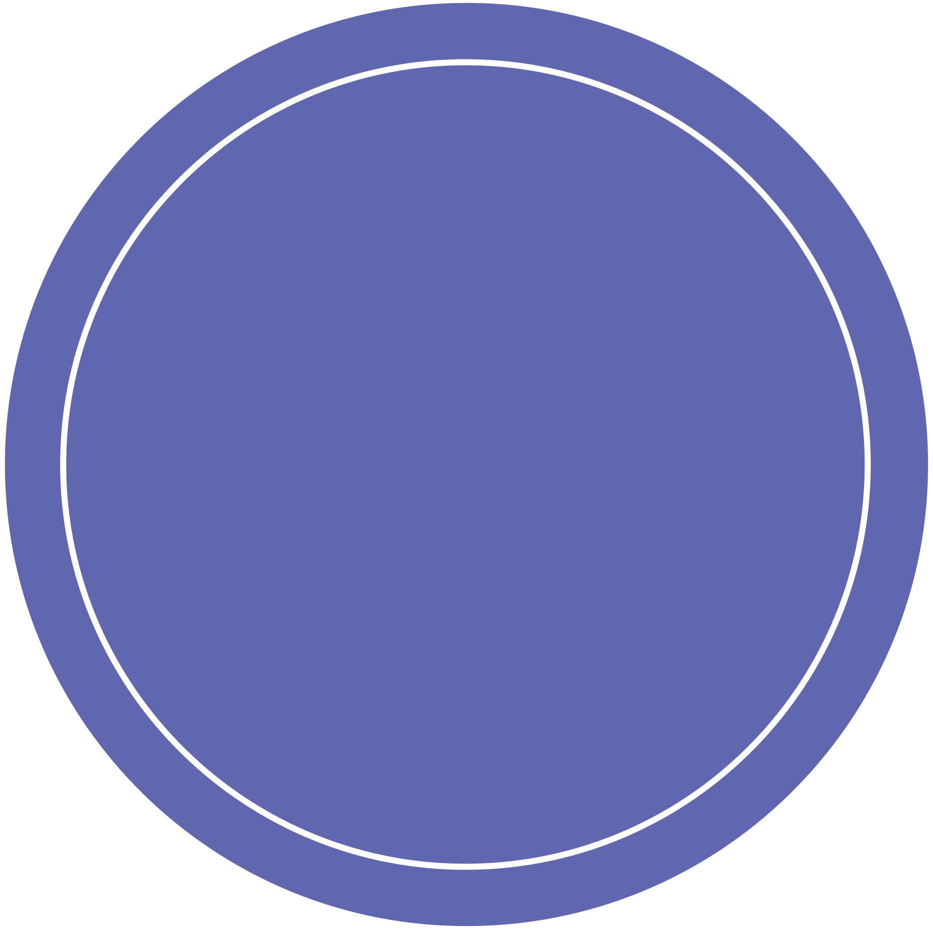
SDOT
OneBusAway
macy's
King County
www.OneBusAway.org.
this bus stop.
transit.htm
SONY

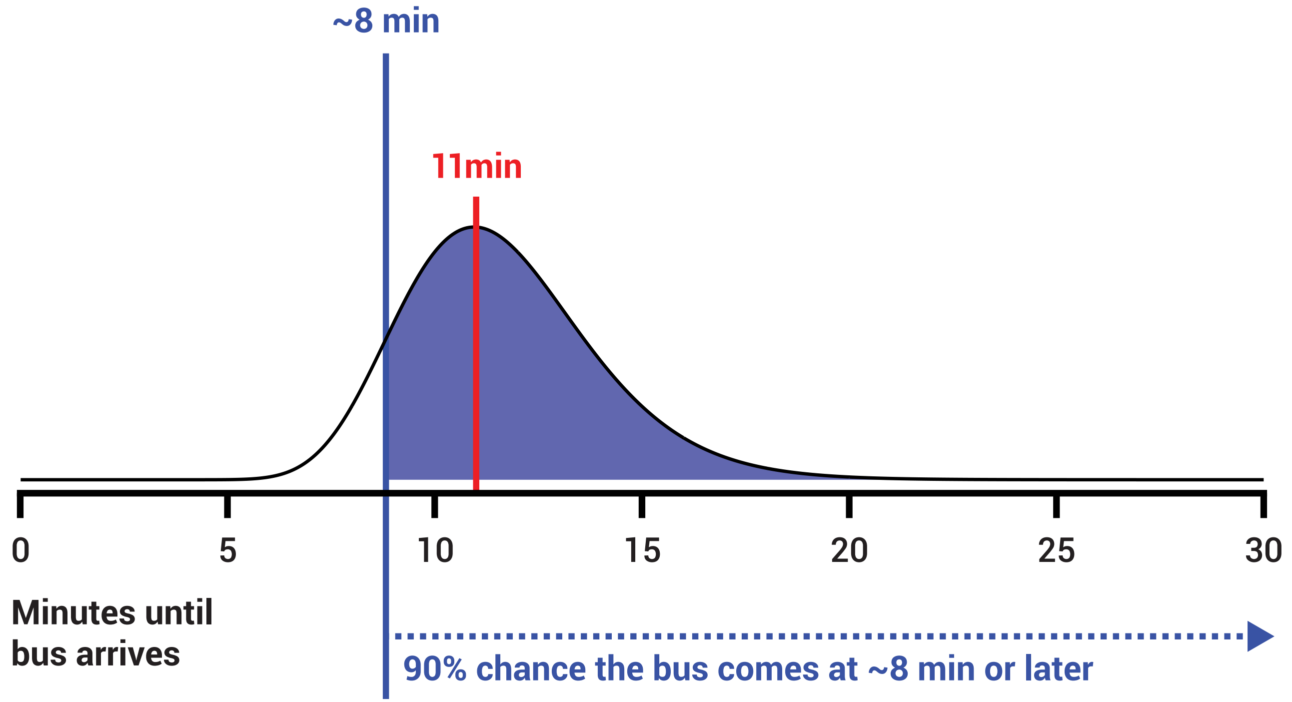
Do I have time to get a coffee?


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
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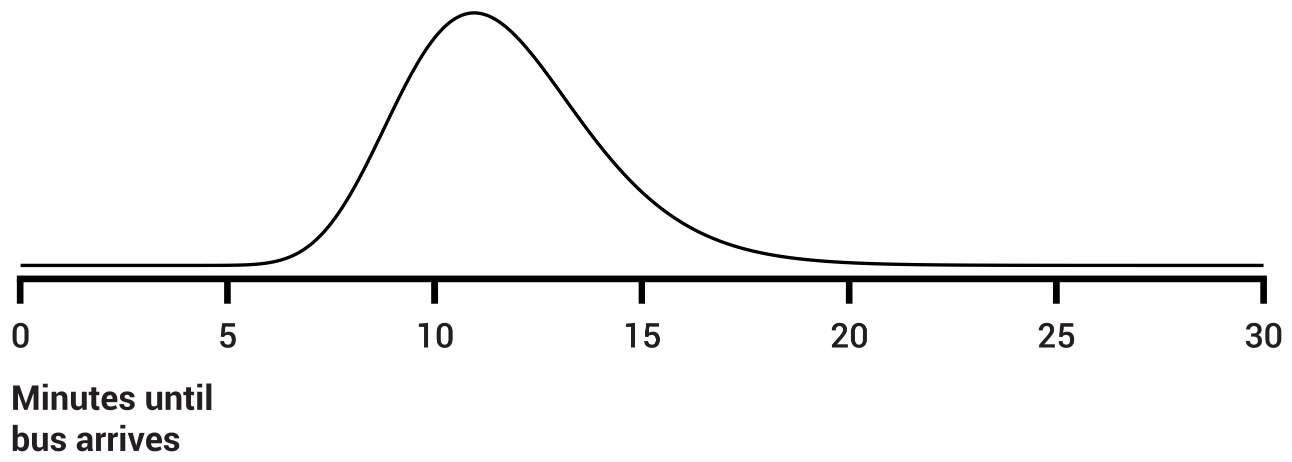
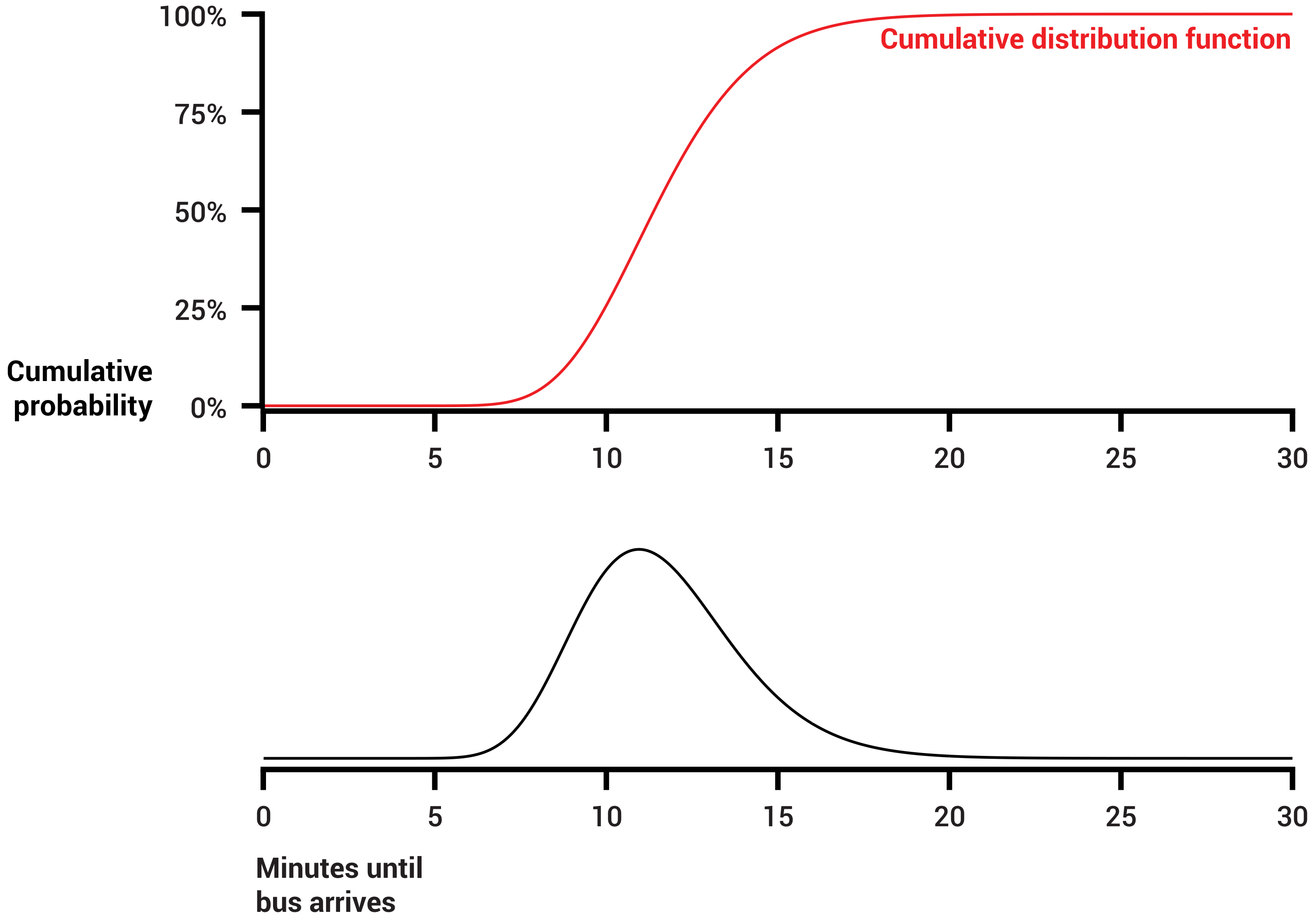
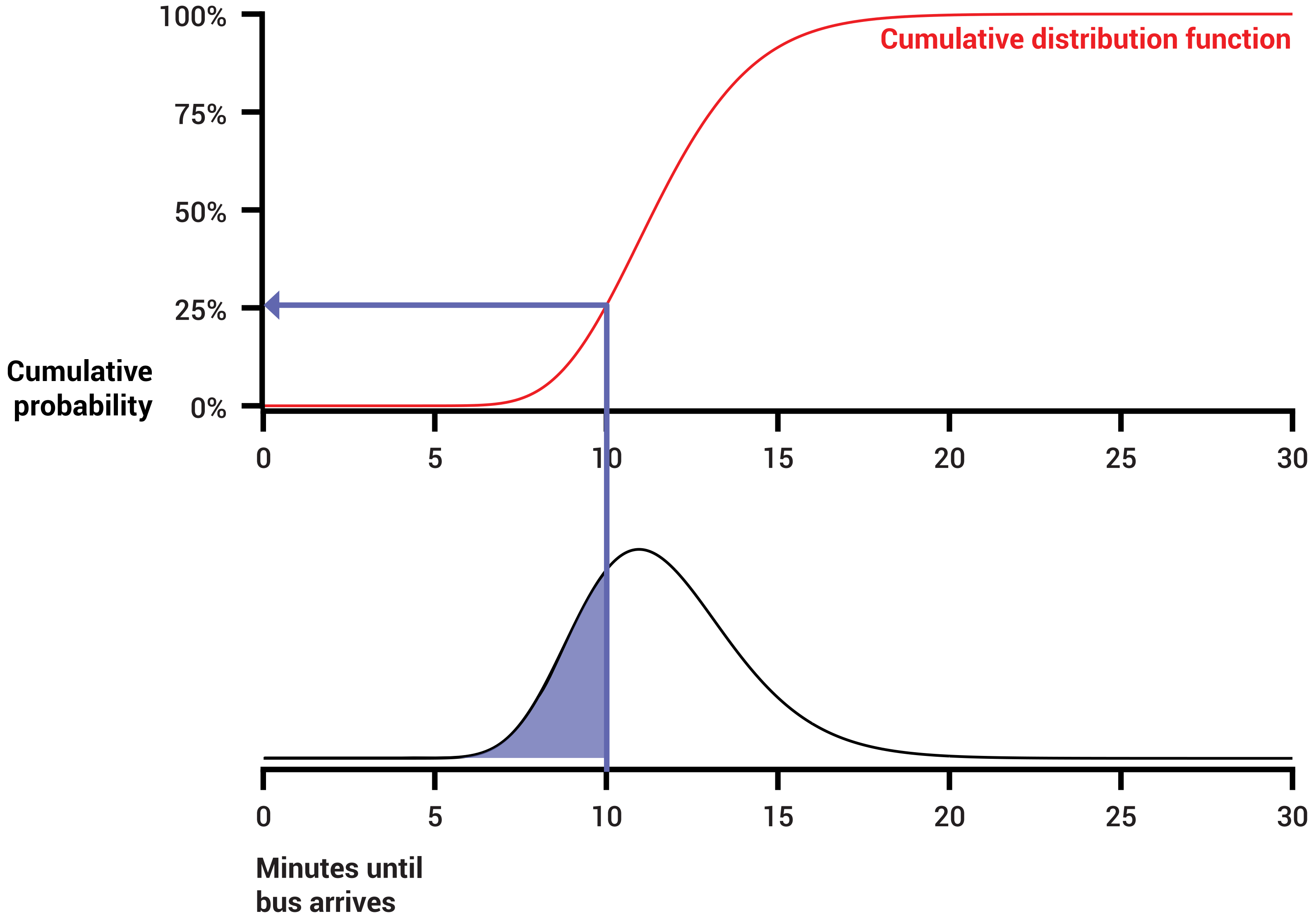
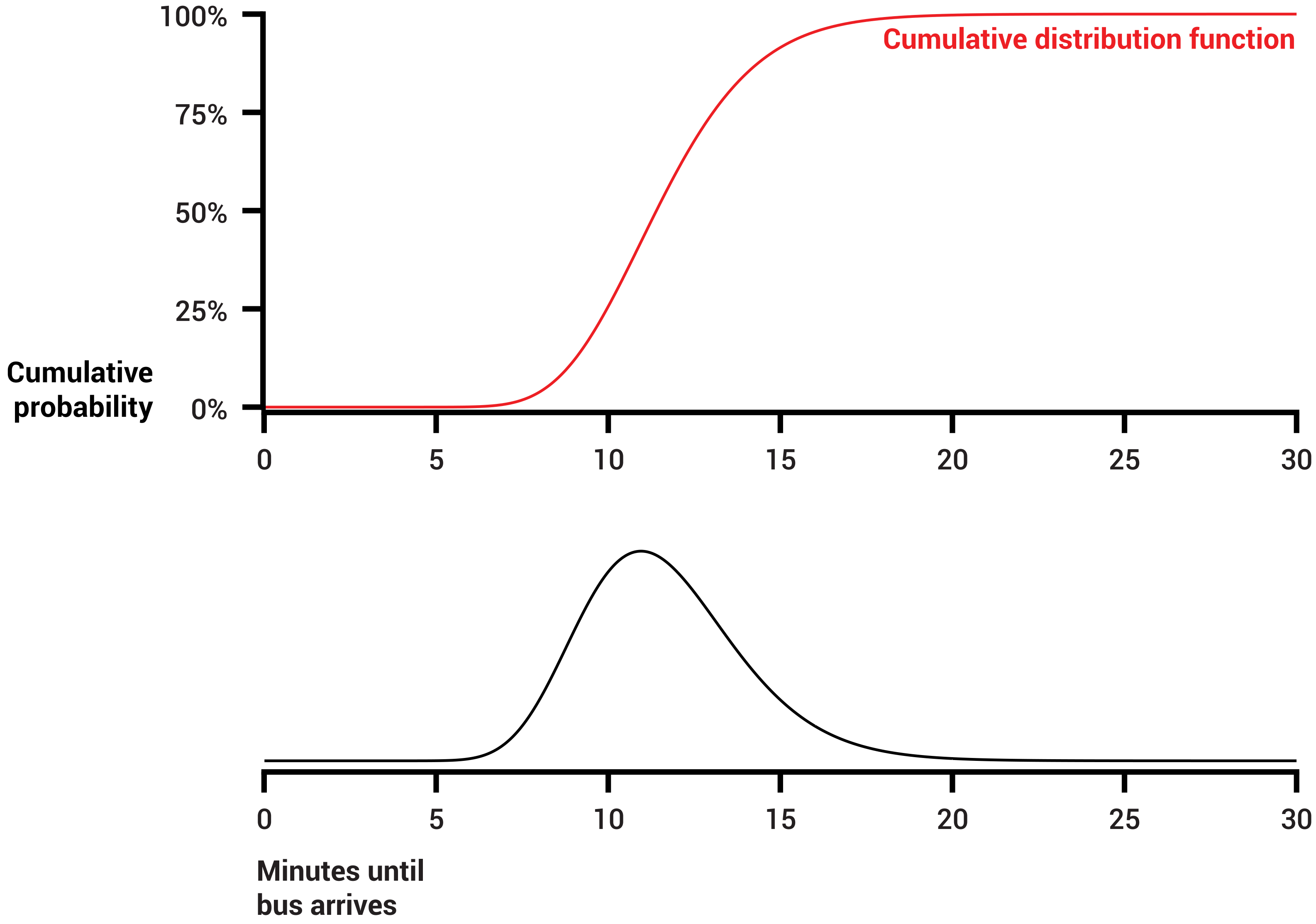
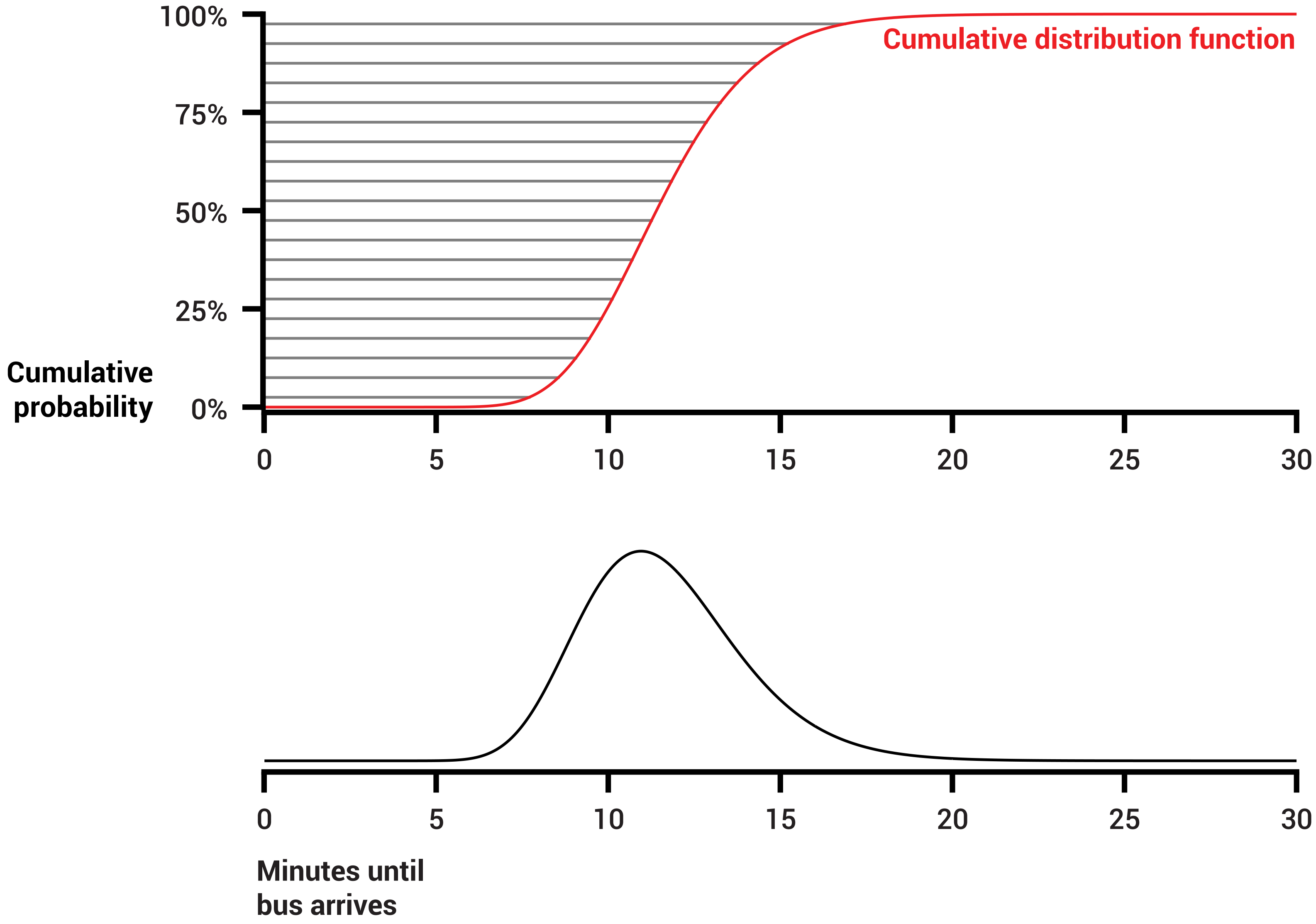
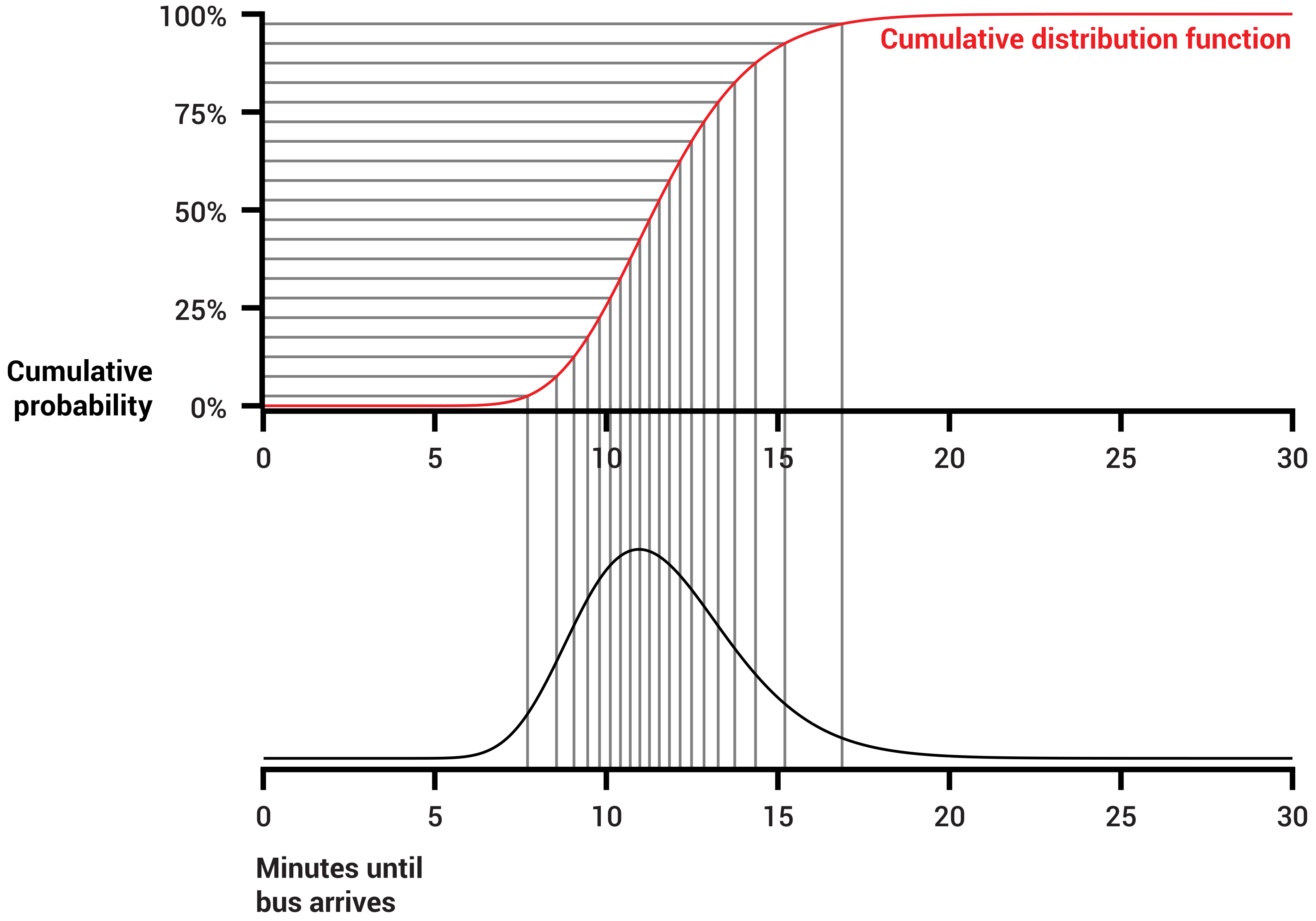

0
5
10
15
20
25
30
Minutes until
bus arrives


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

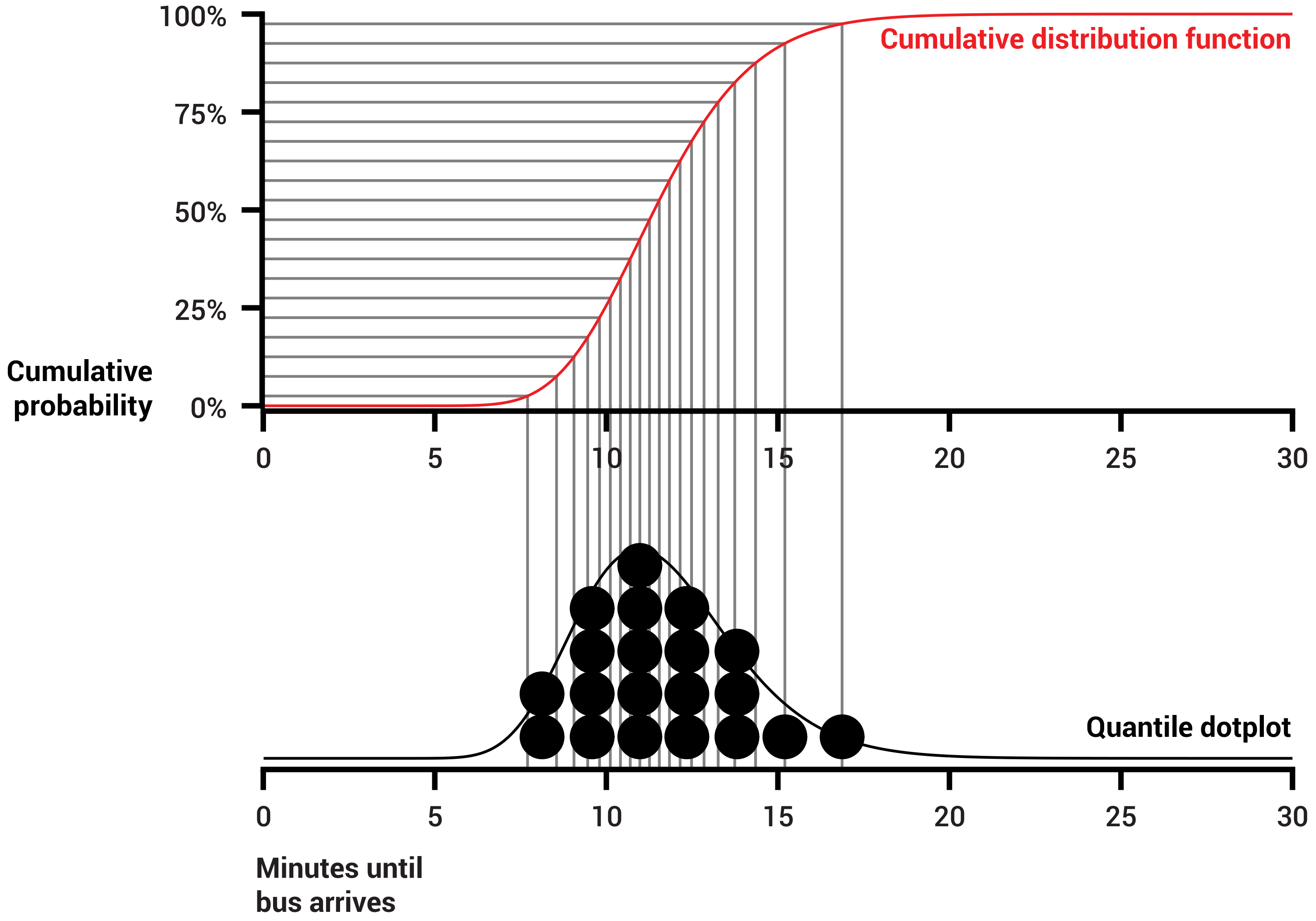

100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
Minutes until bus arrives

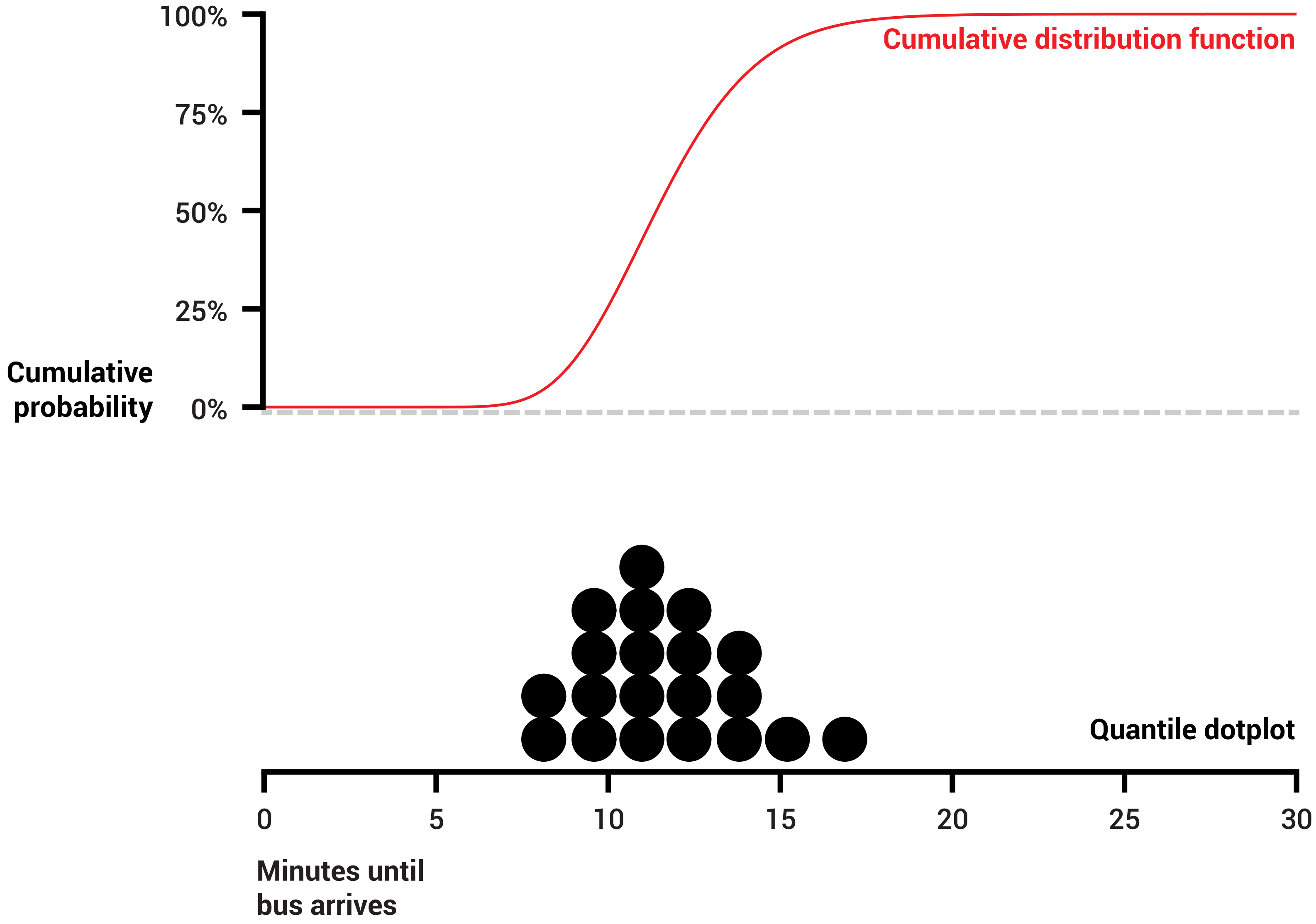

100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
0
5
10
15
20
25
30
Minutes until bus arrives

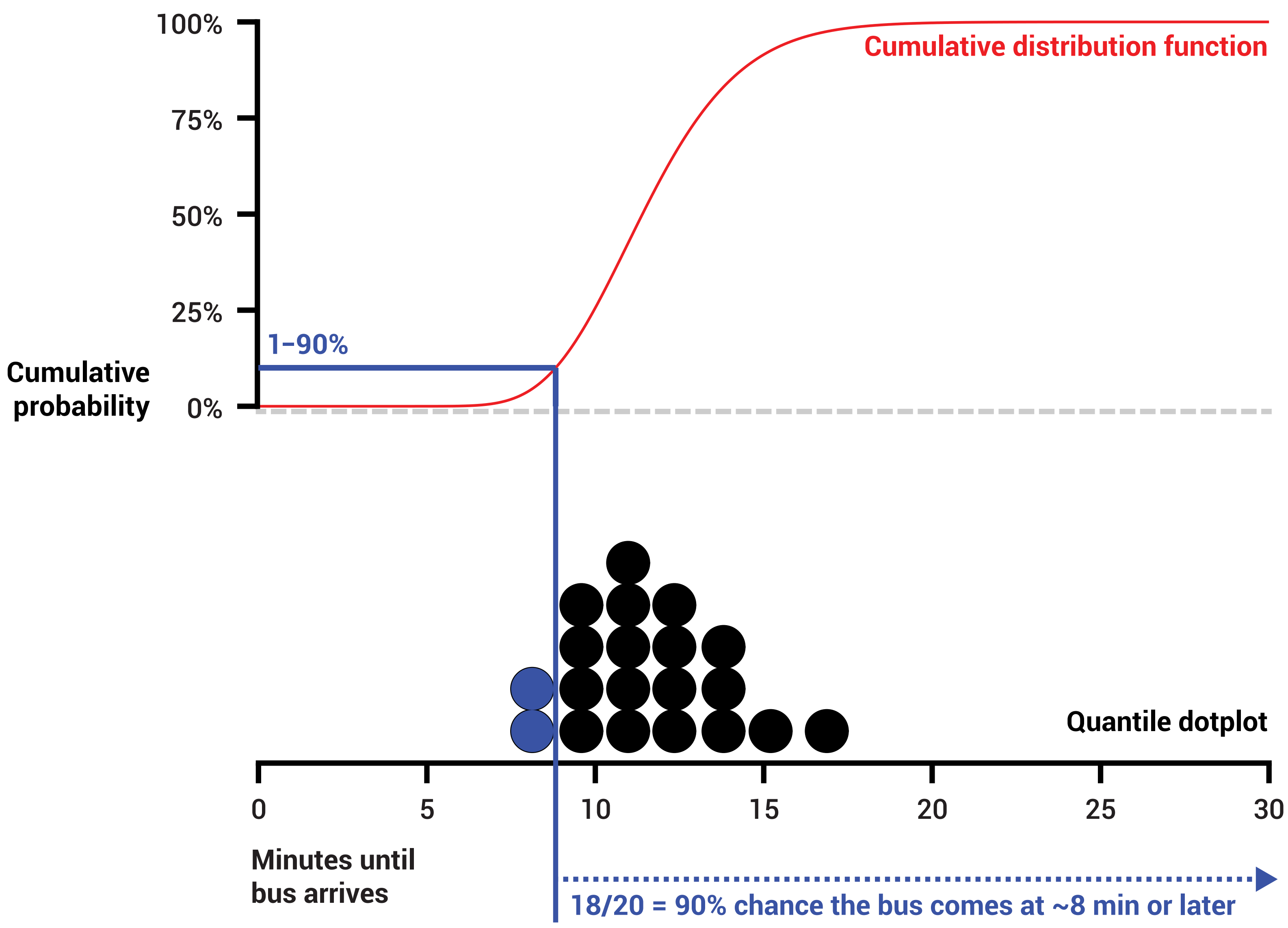

100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
0
5
10
15
20
25
30
Minutes until bus arrives



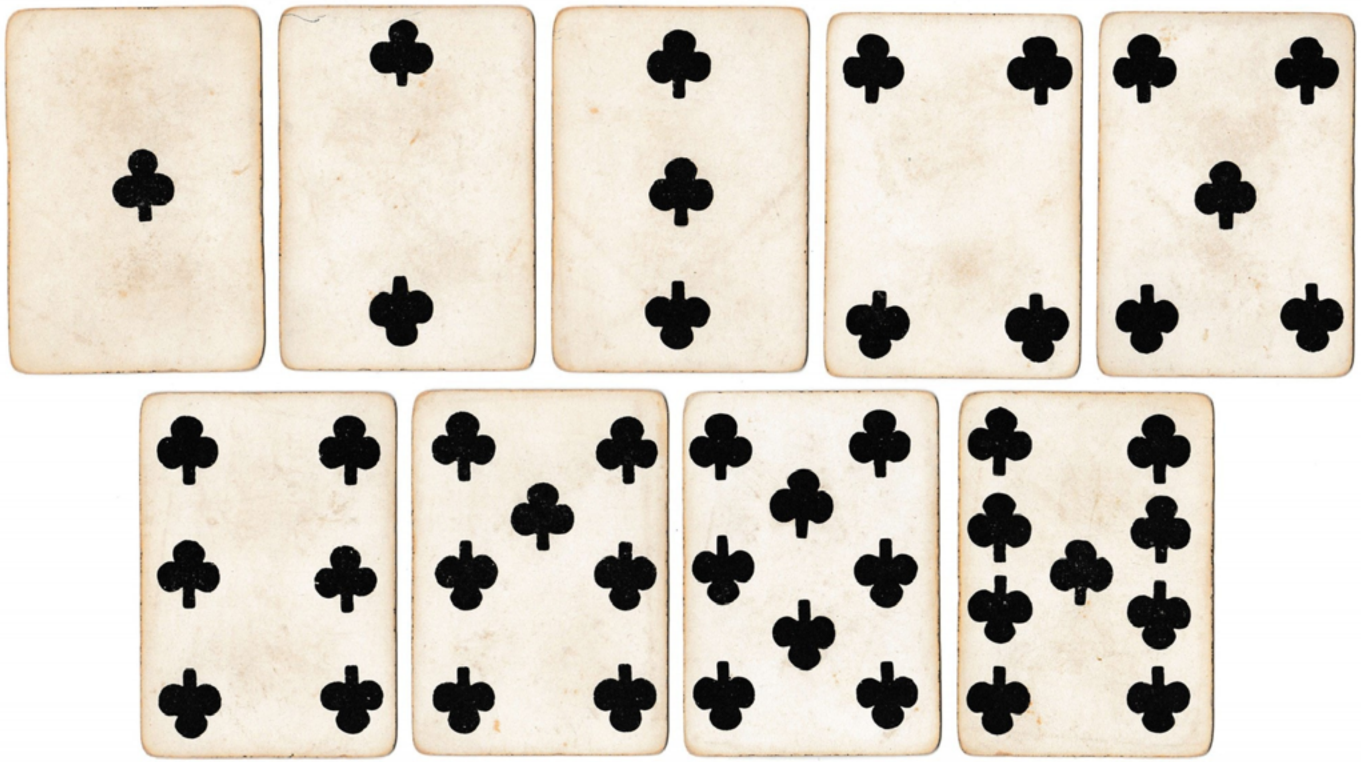
100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
Minutes until bus arrives

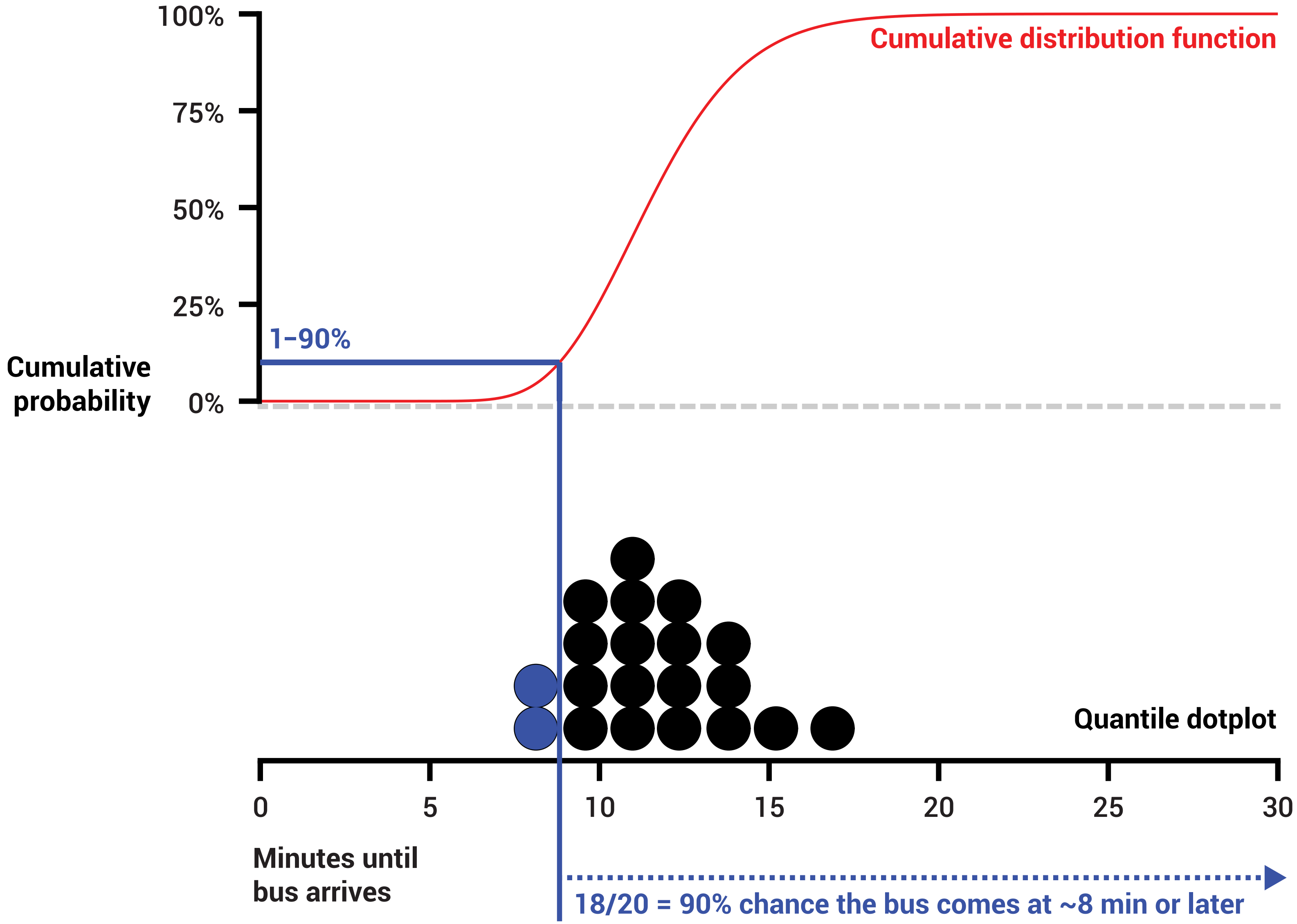

100%
75%
50%
25%
0%
Cumulative
probability
Cumulative distribution function
0
5
10
15
20
25
30
Quantile dotplot
0
5
10
15
20
25
30
Minutes until
bus arrives


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





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

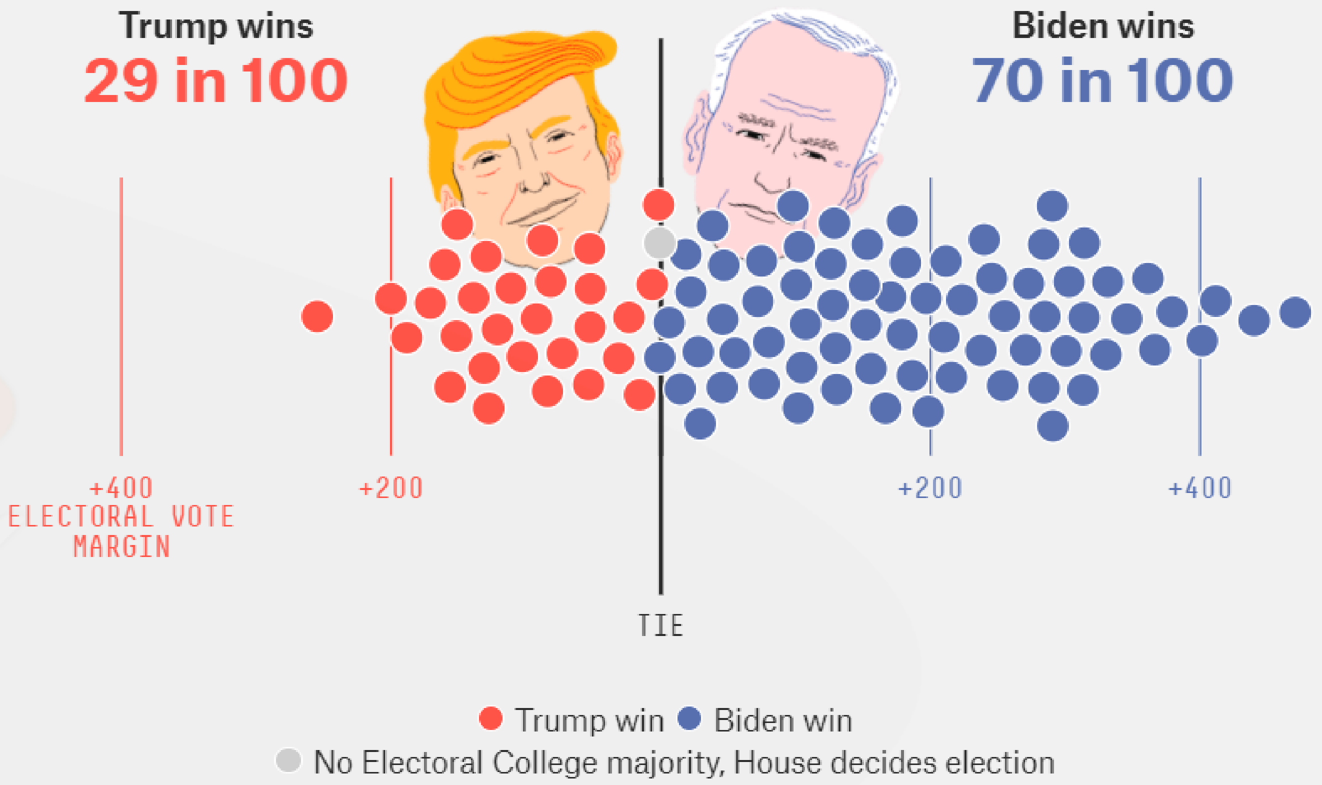
task requirements
visualization perception
uncertainty cognition

task requirements
visualization perception
uncertainty cognition

effective uncertainty visualization design

Biden is *favored* to win the election

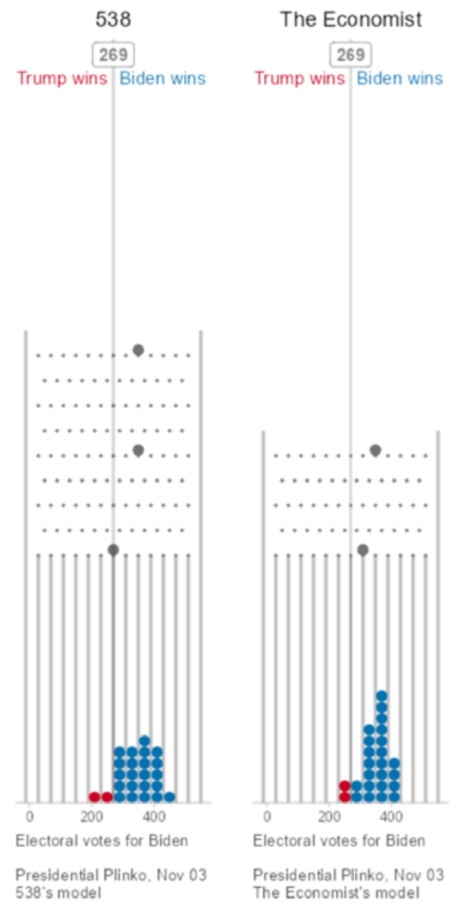
We simulate the election 40,000 times to see who wins most often. The sample of 100 outcomes below gives you a good idea of the range of scenarios our model thinks is possible.



Presidential Plinko

[http://presidential-plinko.com/]

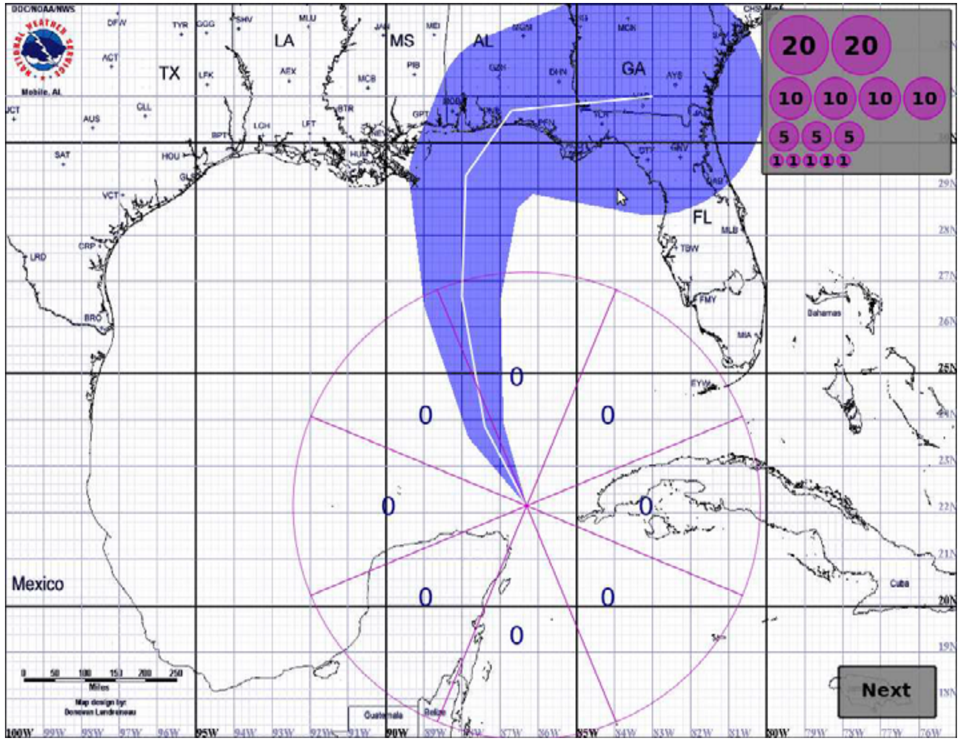
Pre-election day predictions



More examples (and pitfalls...)

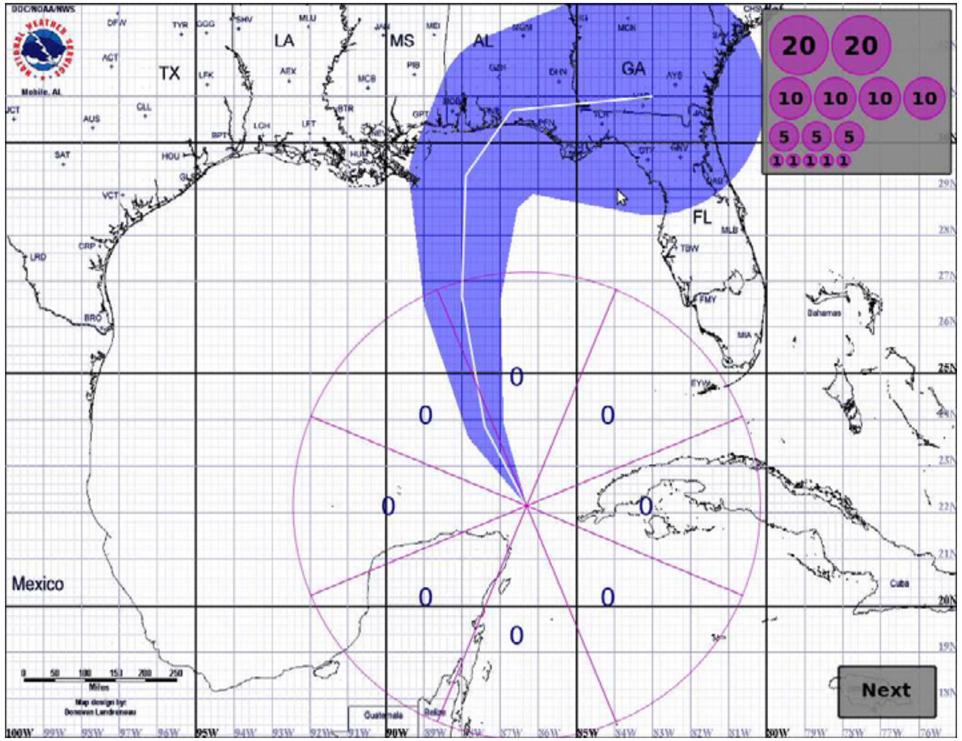
Hurricane error cones

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



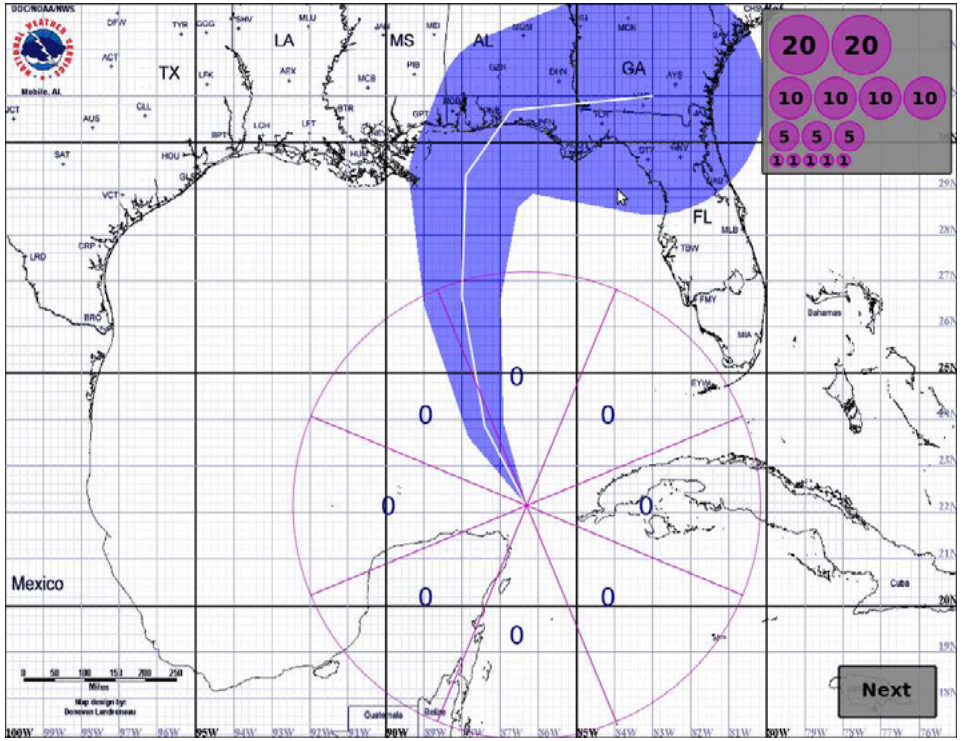
Deterministic construal errors

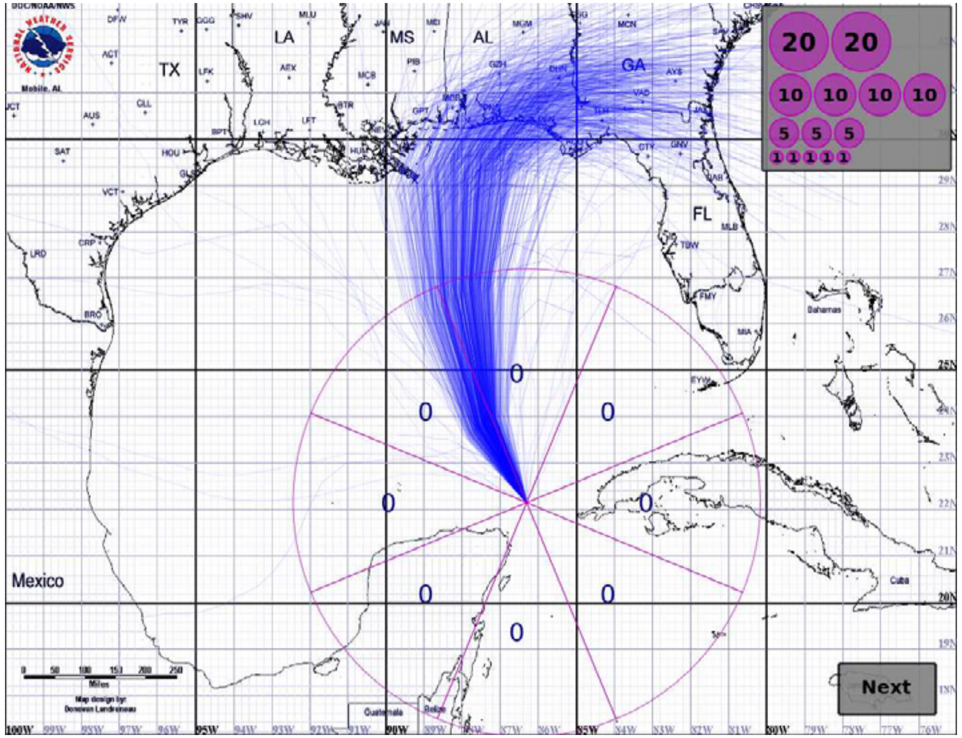
[Joslyn & LeClerc. Decisions With Uncertainty: The Glass Half Full. Current Directions in Psych. Science, 22(4), 2013]



Spaghetti plots for hurricane predictions

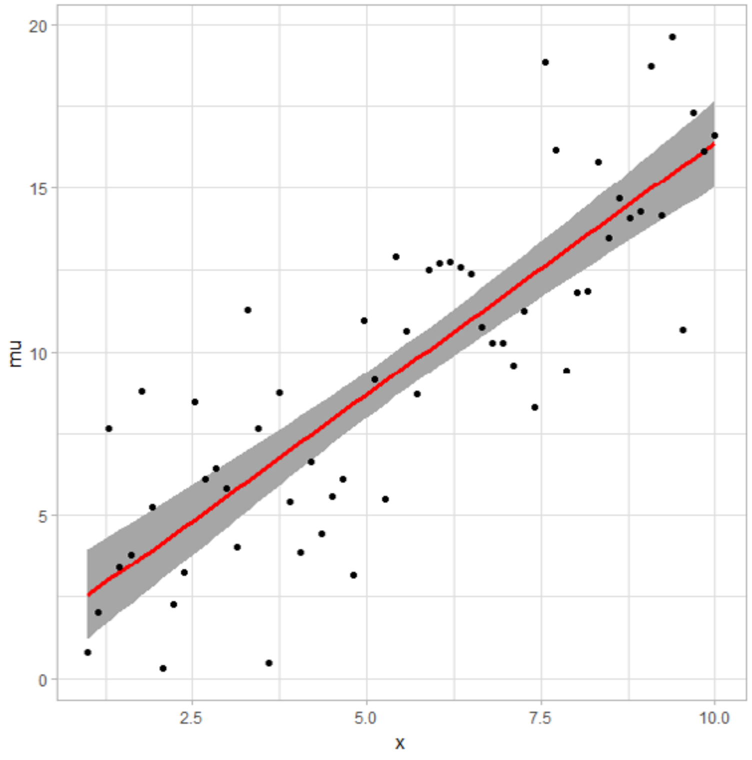
[Cox, House, Lindell. Visualizing Uncertainty in Predicted Hurricane Tracks. International Journal for Uncertainty Quantification, 3(2), 143–156, 2013]





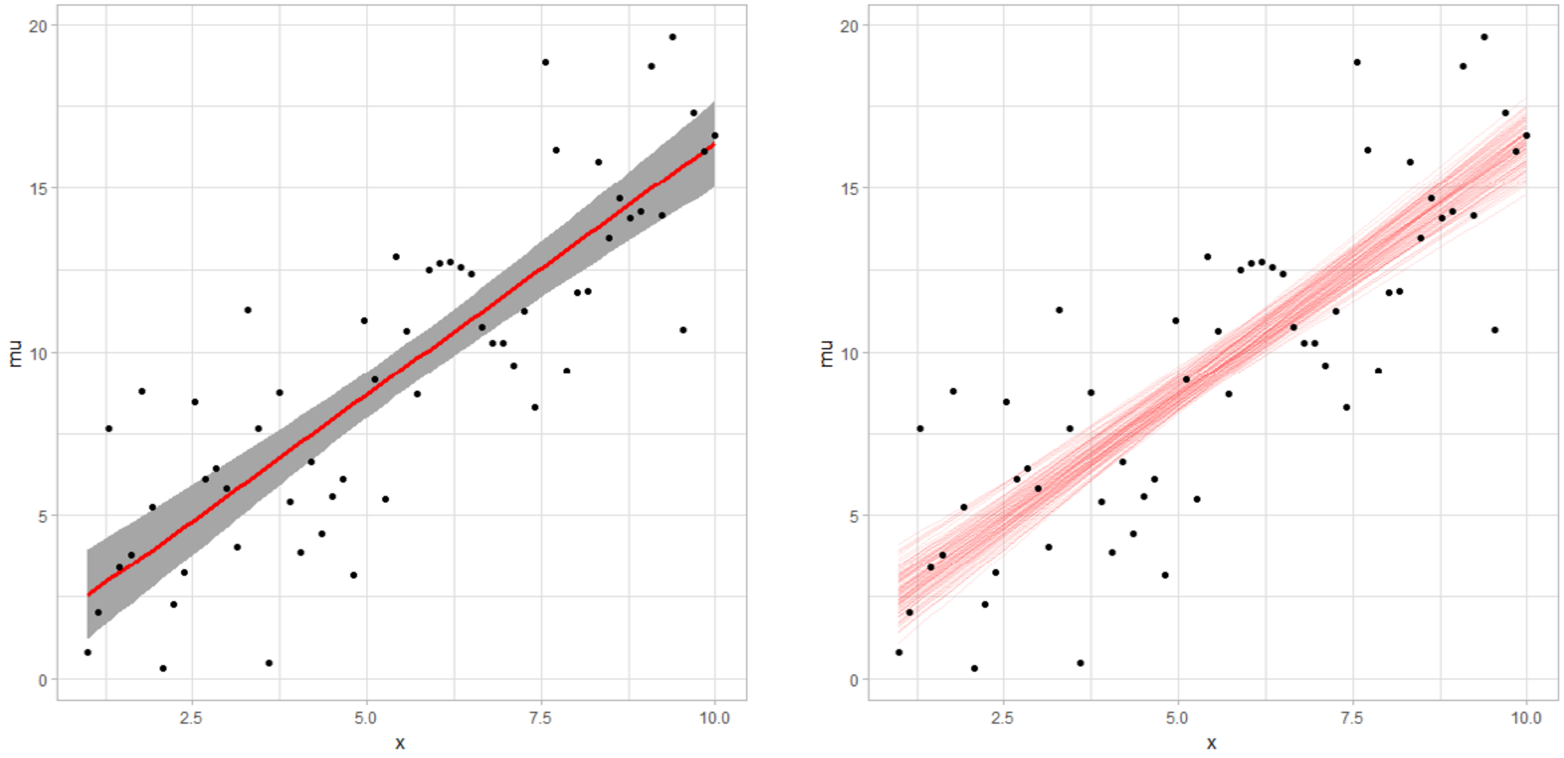
Fit line uncertainty

[https://github.com/mjskay/uncertainty-examples/blob/master/linear-regression.md]



Fit line uncertainty

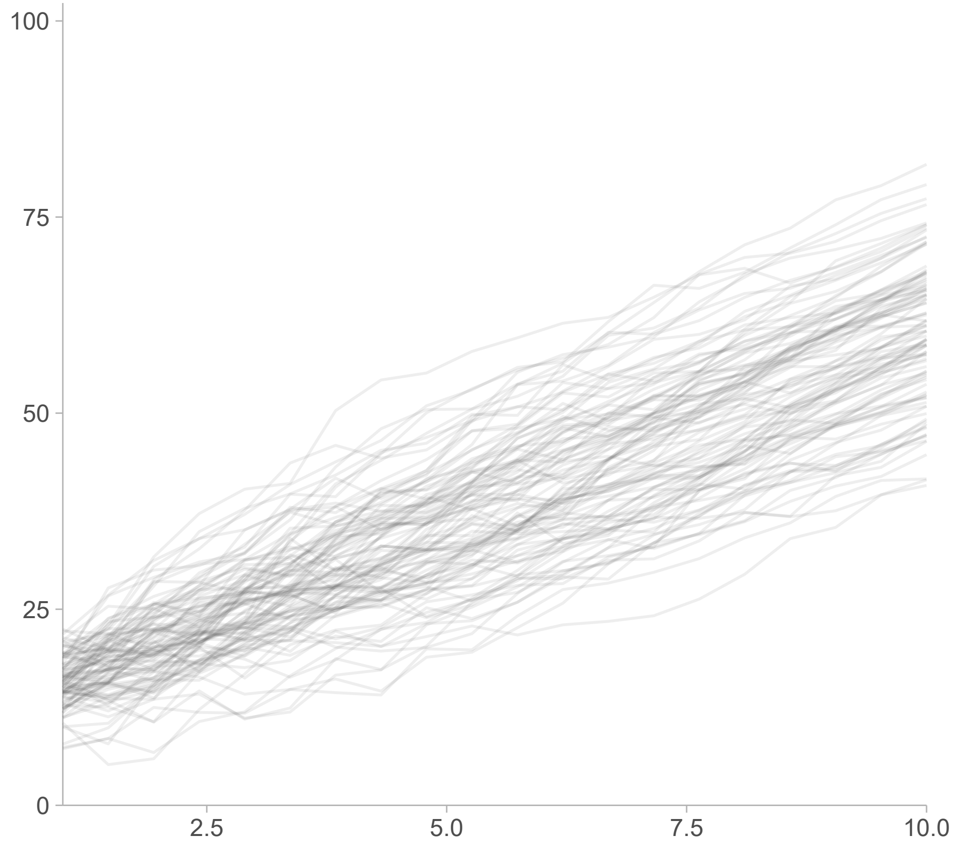
[https://github.com/mjskay/uncertainty-examples/blob/master/linear-regression.md]



Spaghettis help when you have correlated distributions…

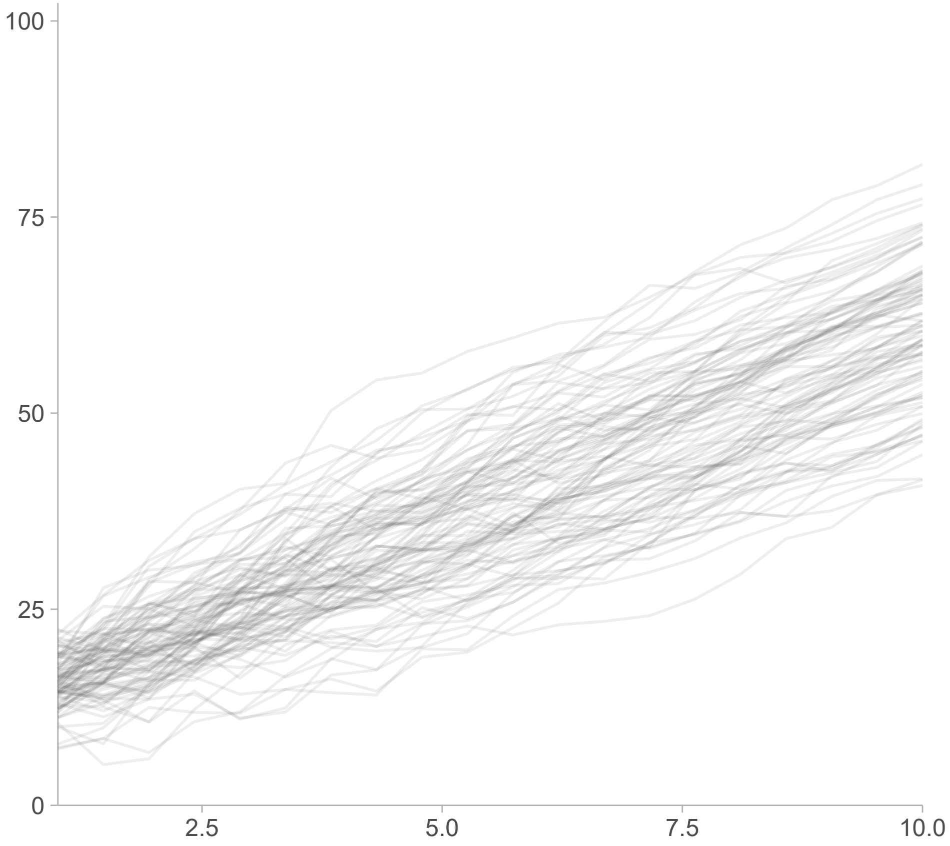
Intervals obscure correlation

High correlation

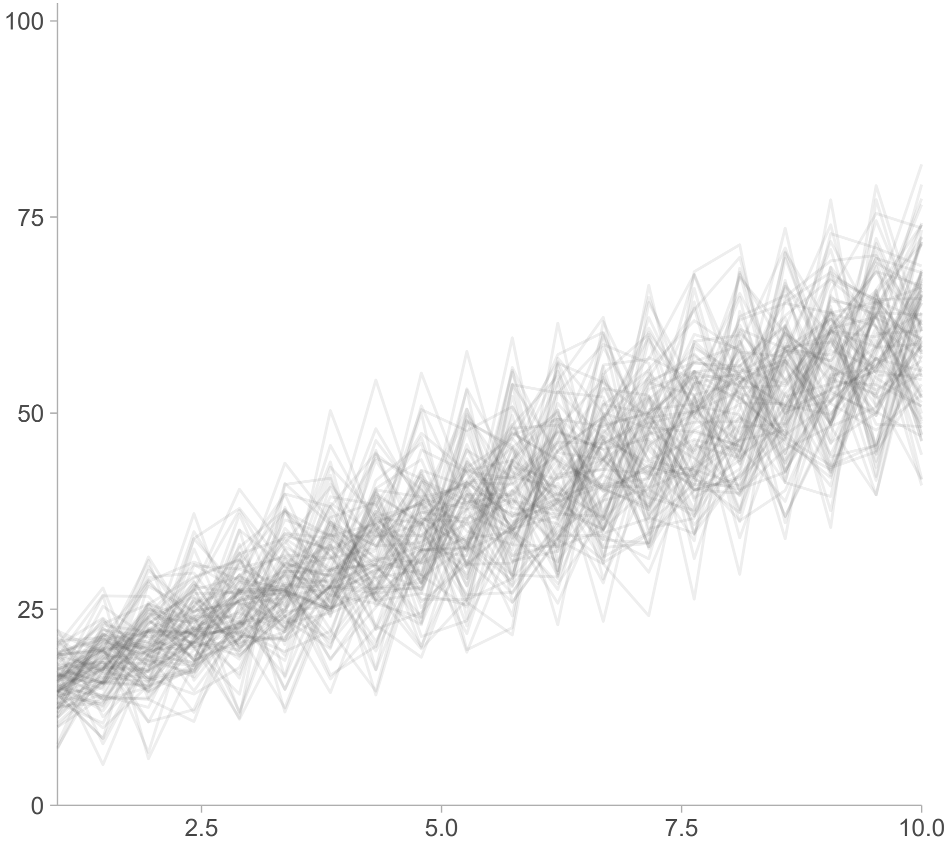


Intervals obscure correlation

High correlation

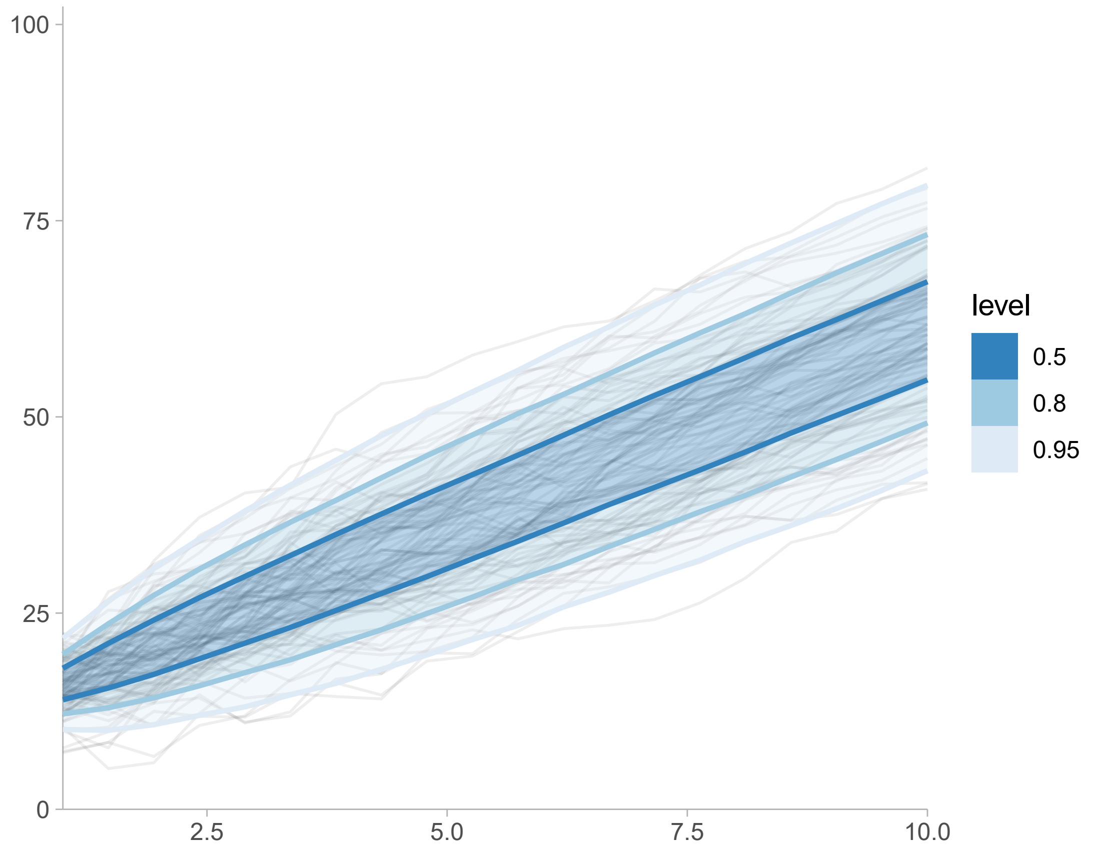


No correlation

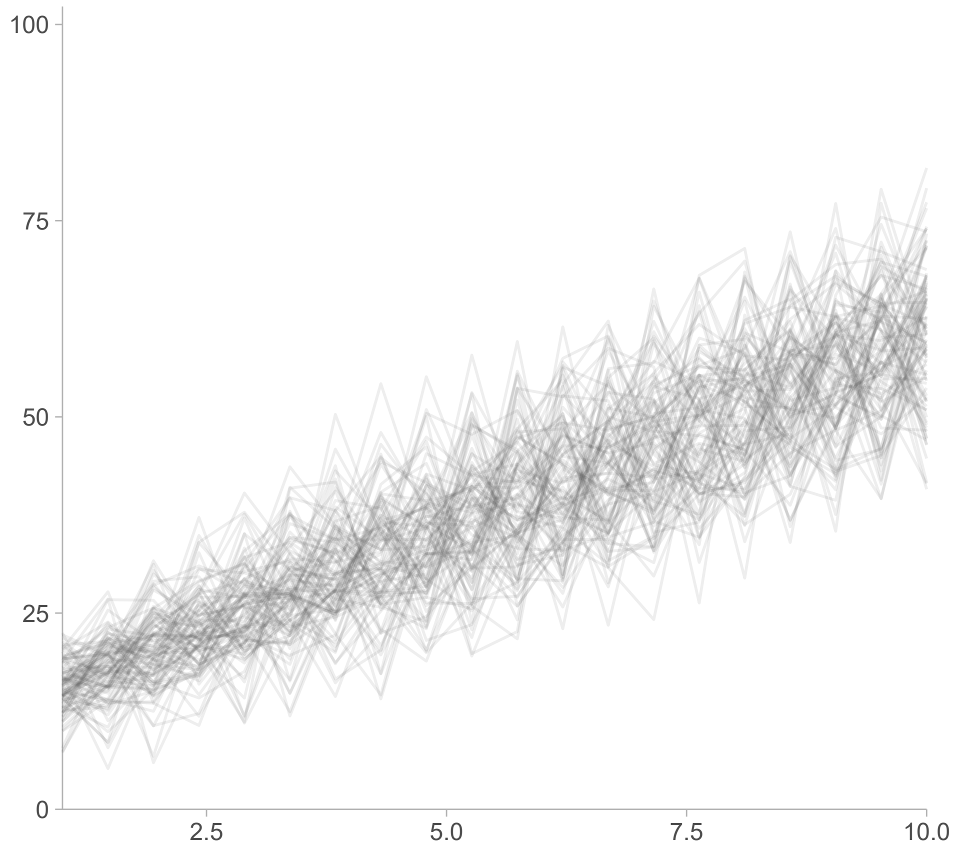


Intervals obscure correlation

High correlation

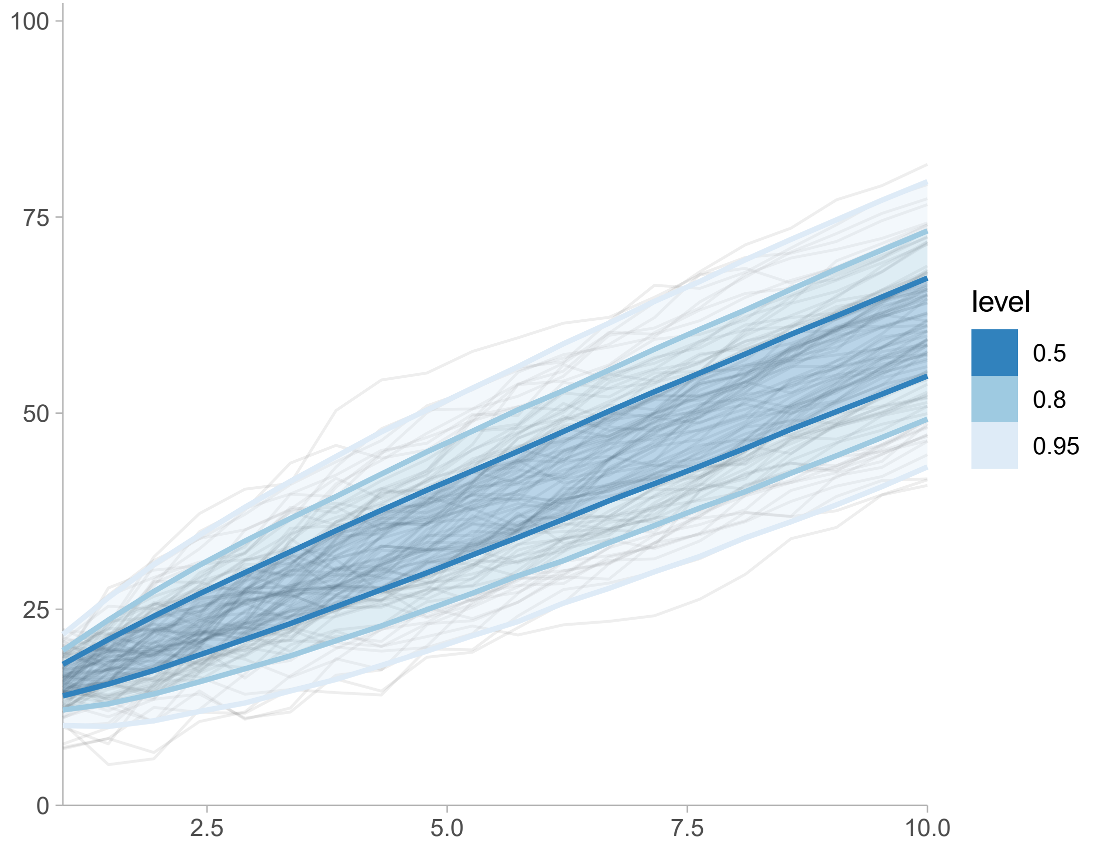


No correlation

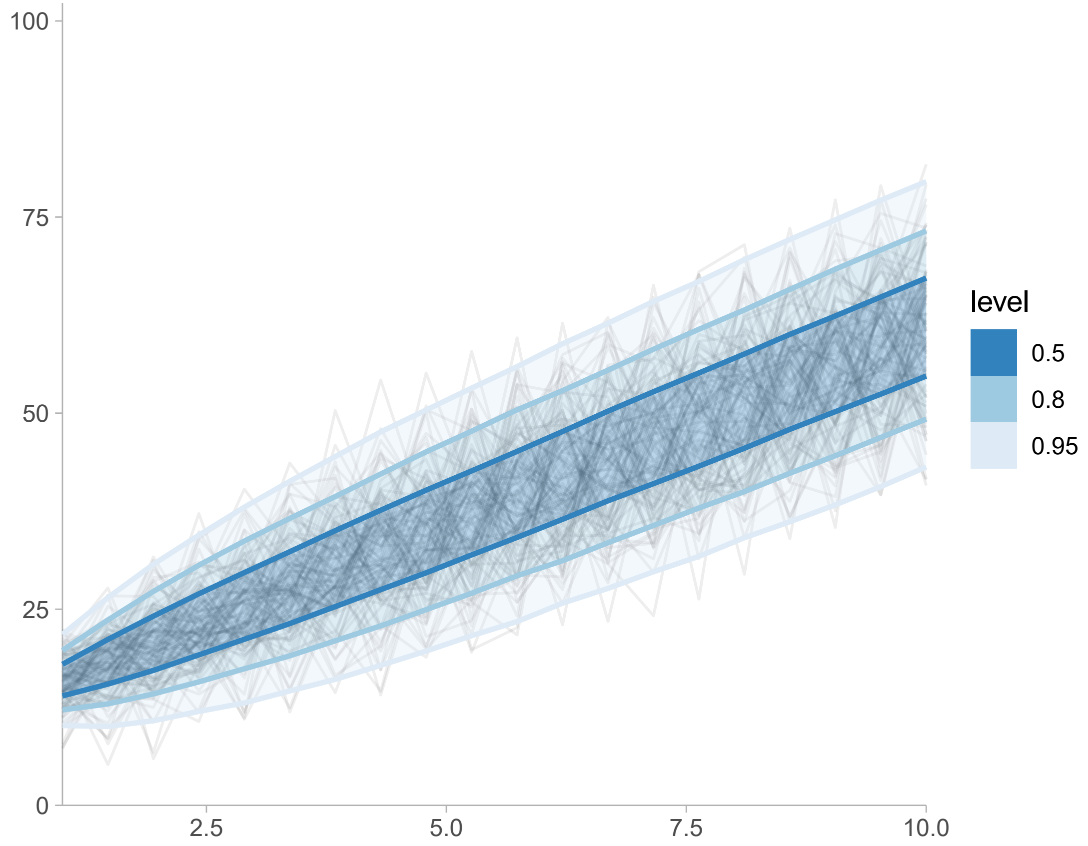


Intervals obscure correlation

High correlation

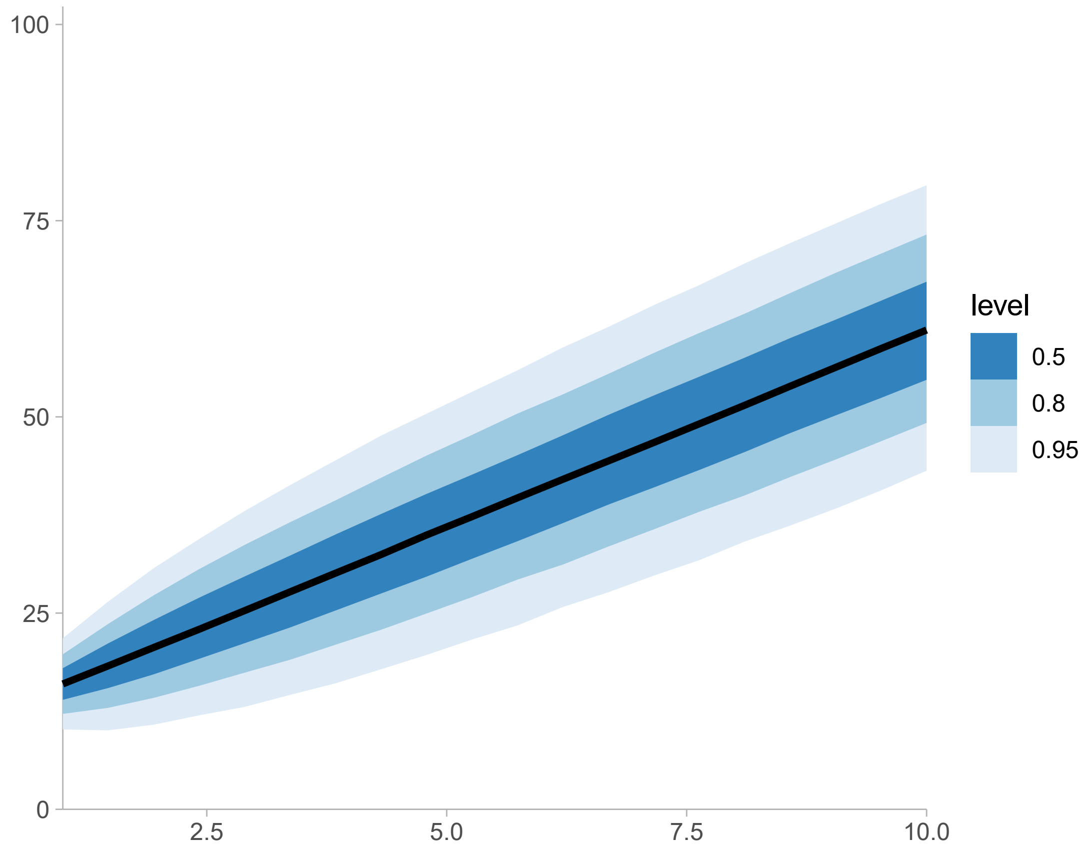


No correlation

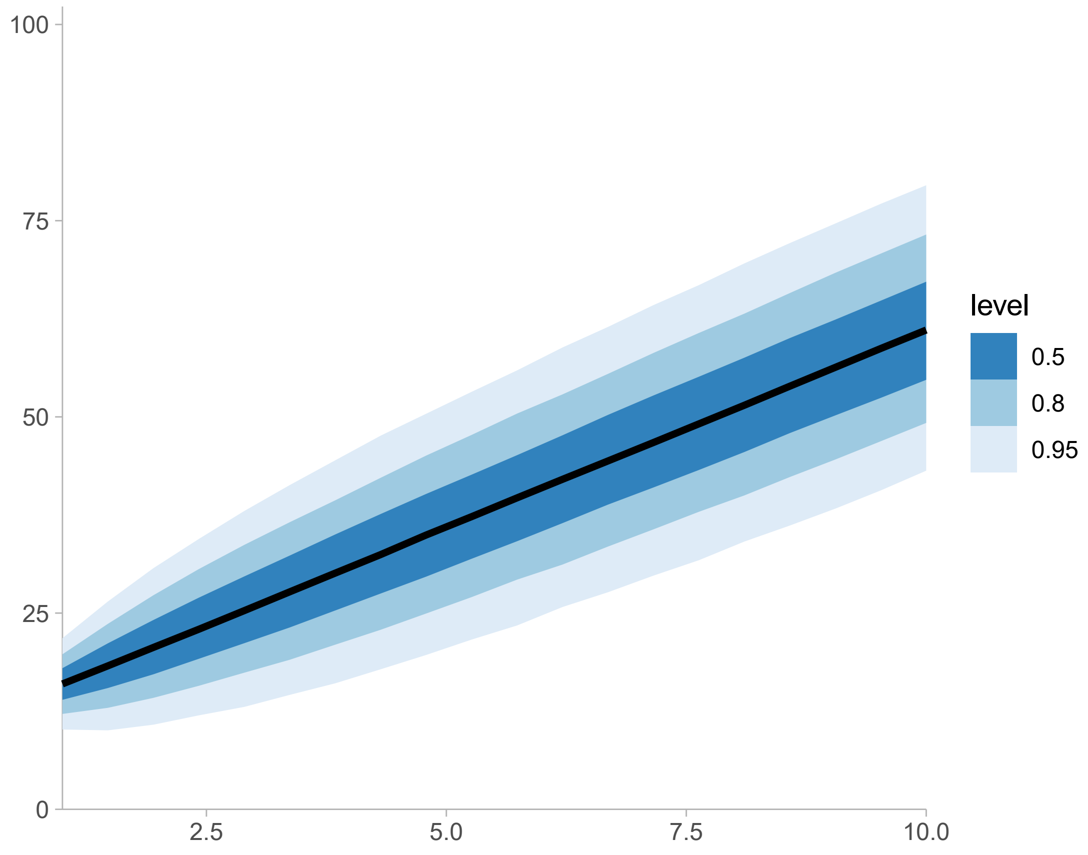


Intervals obscure correlation

High correlation

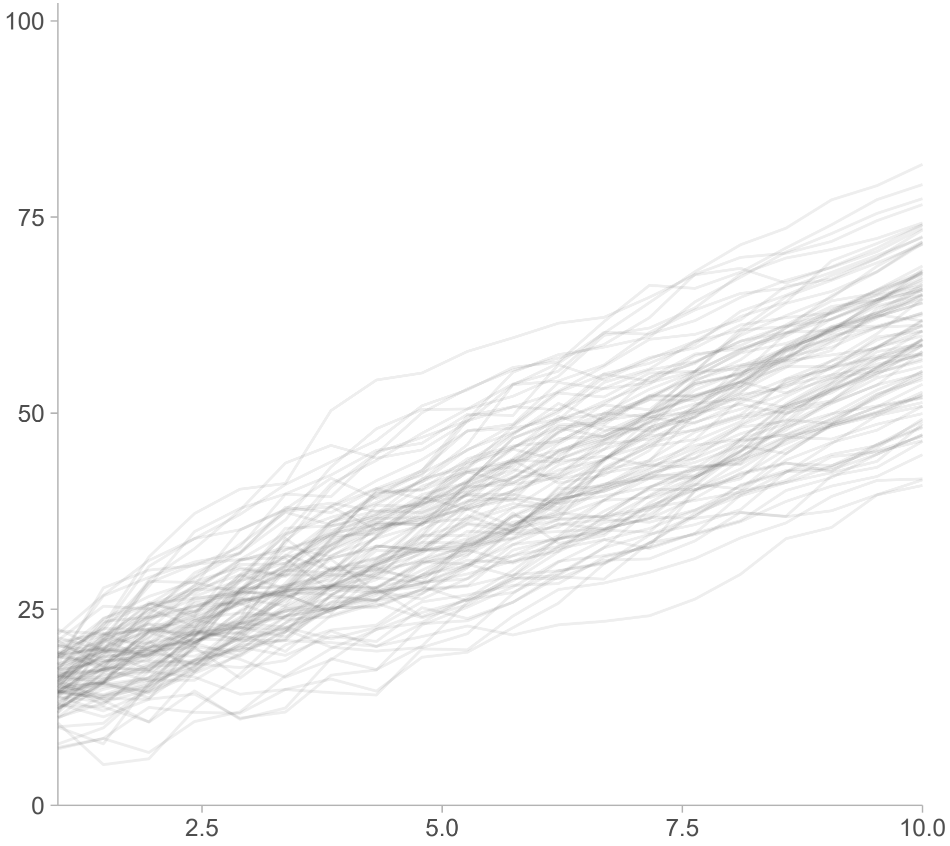


No correlation

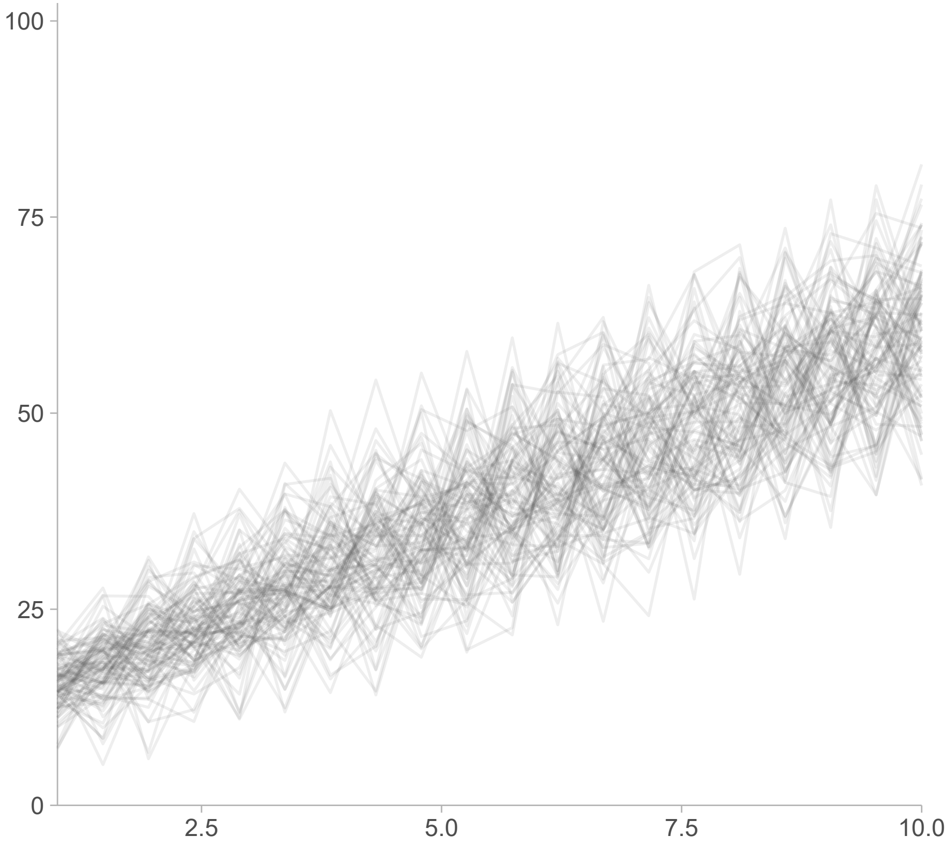


Intervals obscure correlation

High correlation



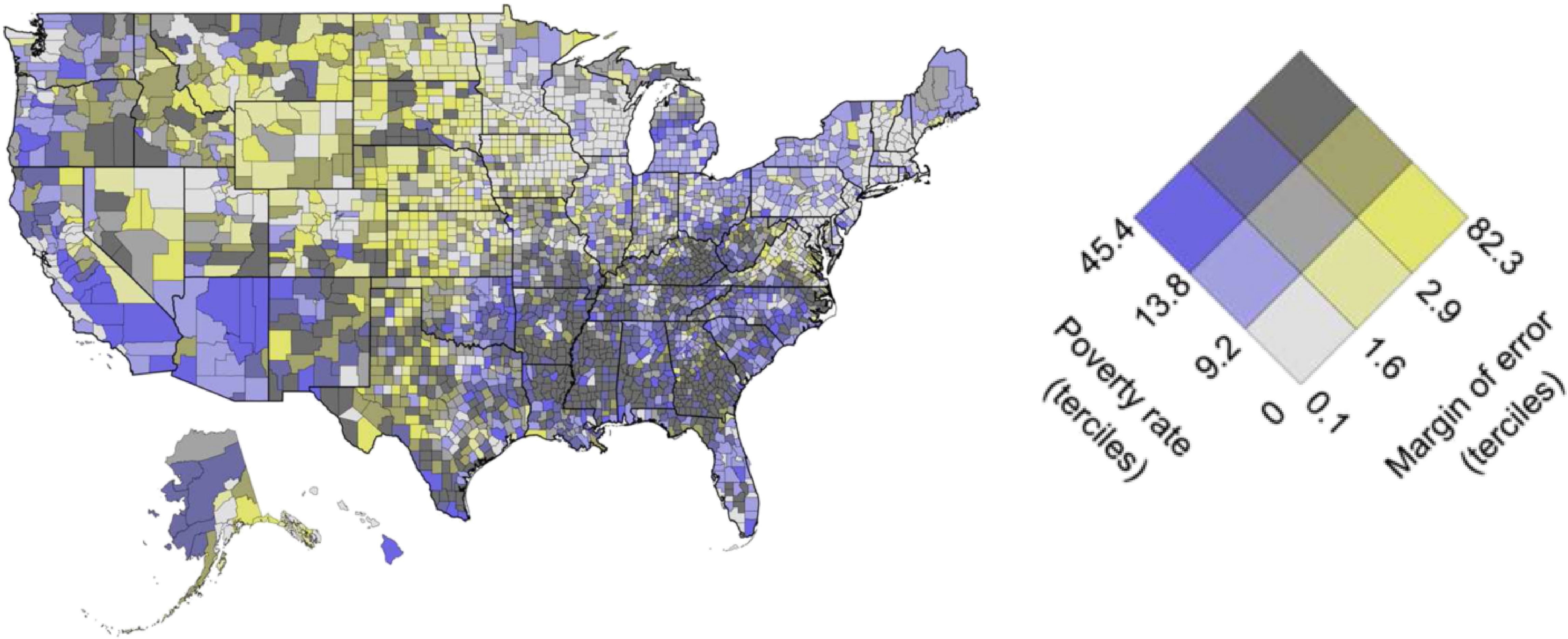
No correlation



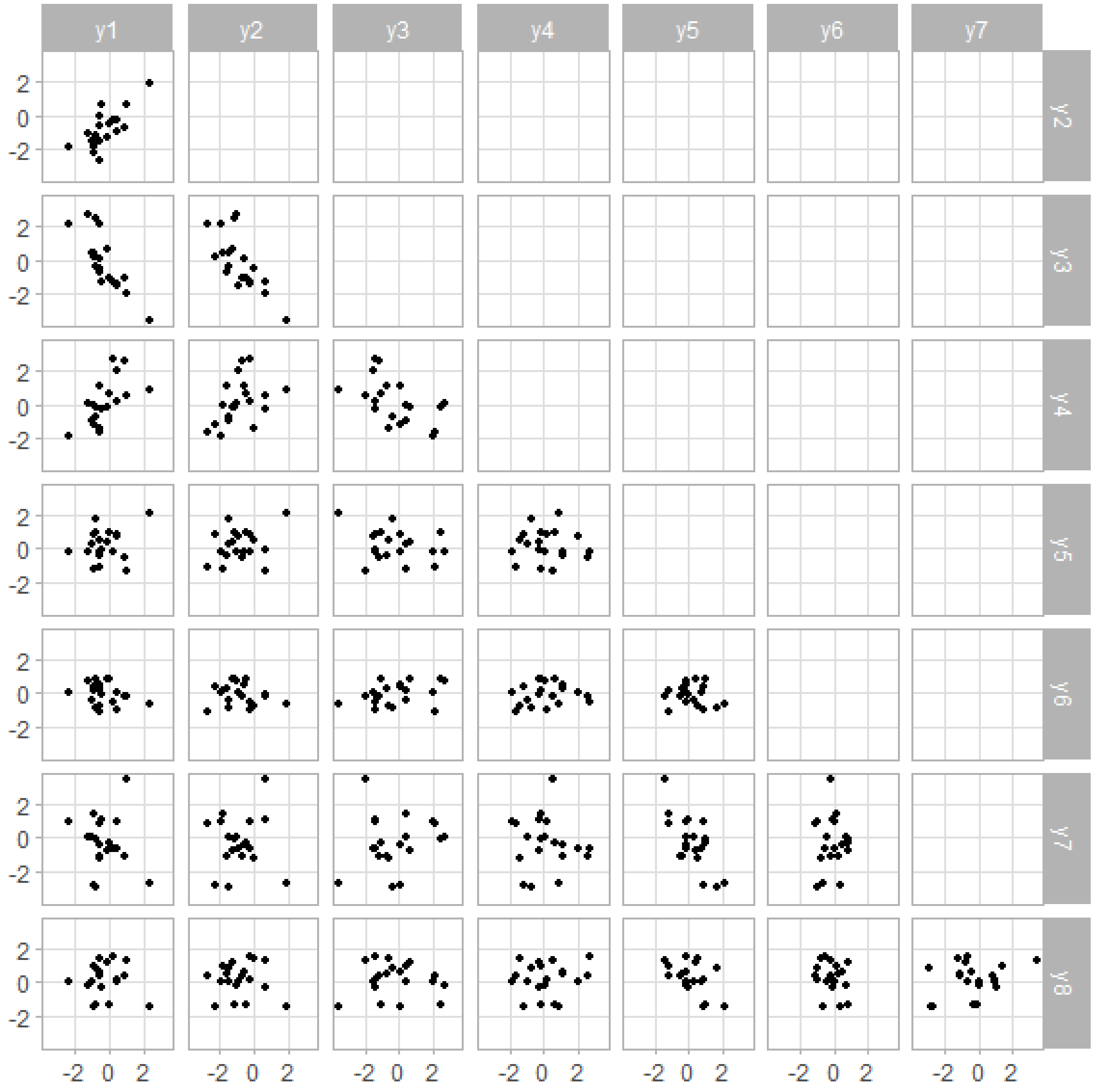
Cartographic uncertainty

Can we do something more “intuitive”?

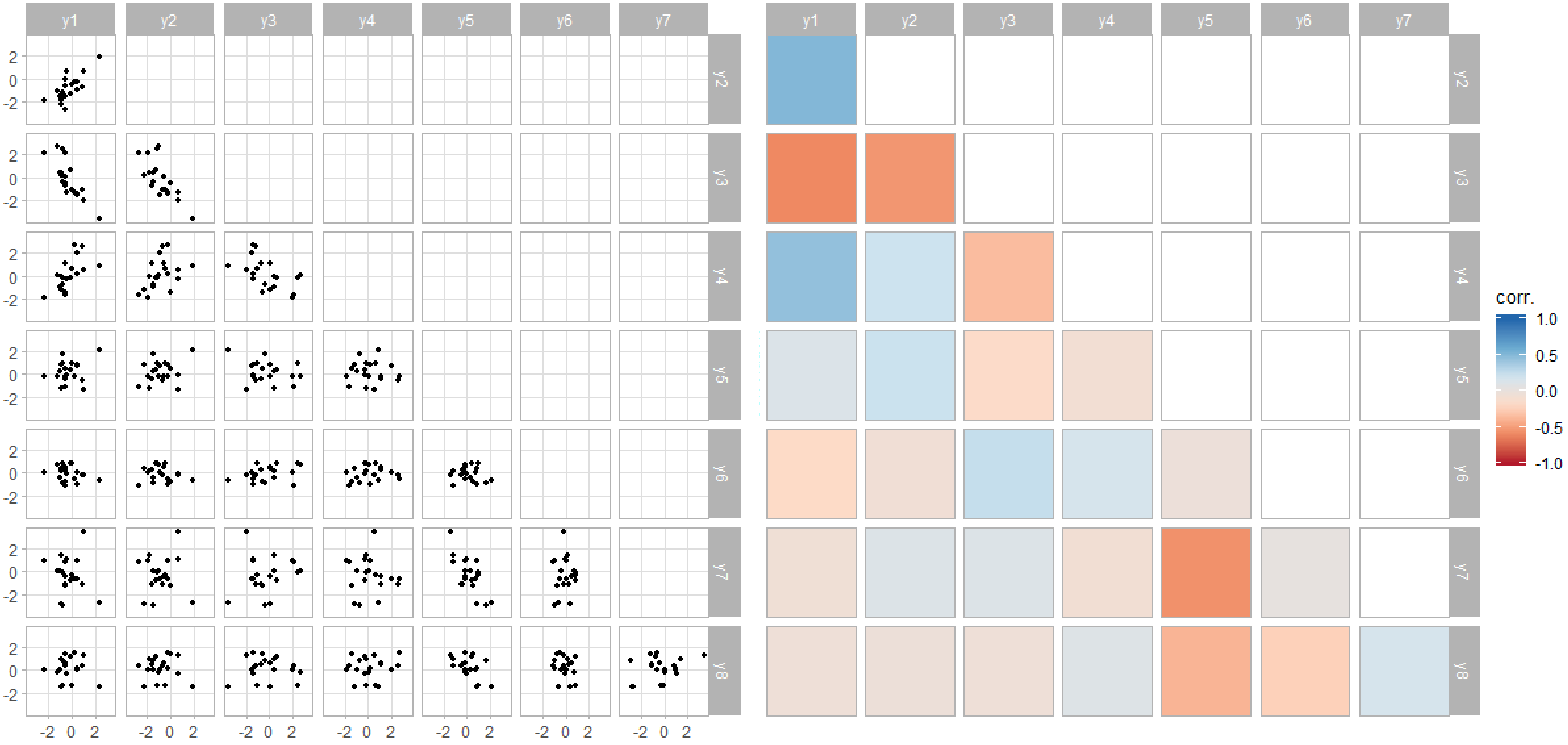
[Lucchesi & Wikle. Visualizing uncertainty in areal data with bivariate choropleth maps, map pixelation and glyph rotation. Stat, 292–302, 2017]



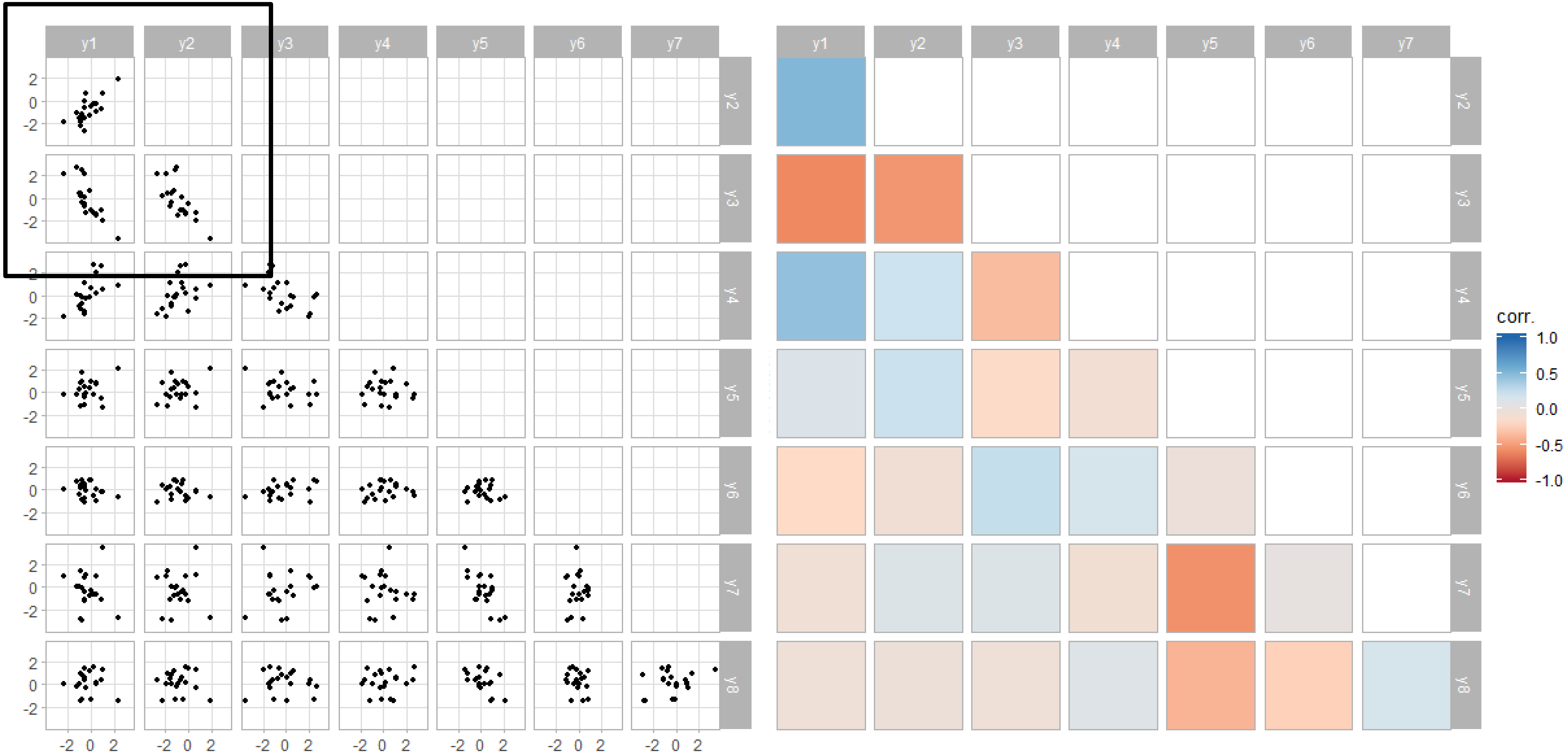
I'm not a map vis person...

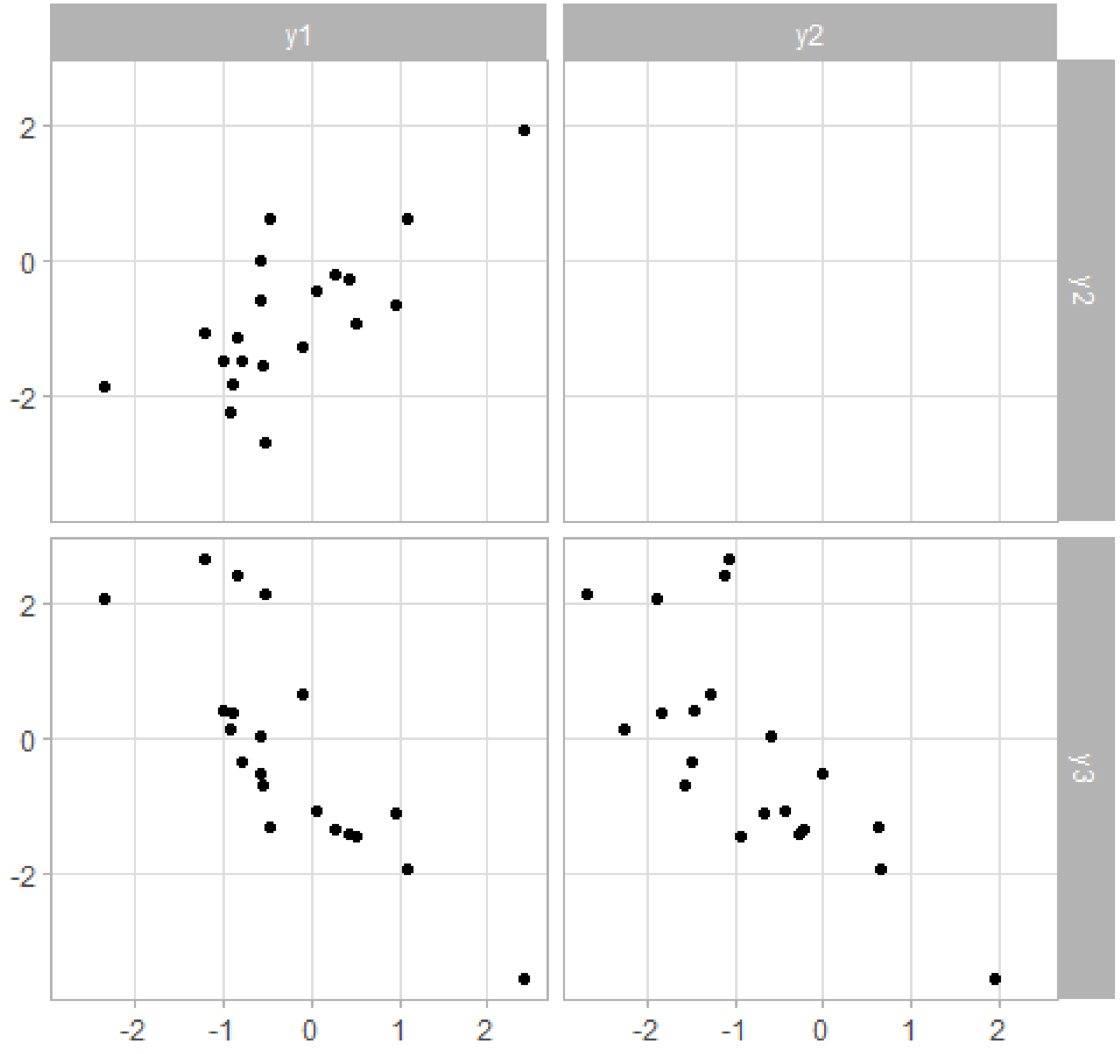


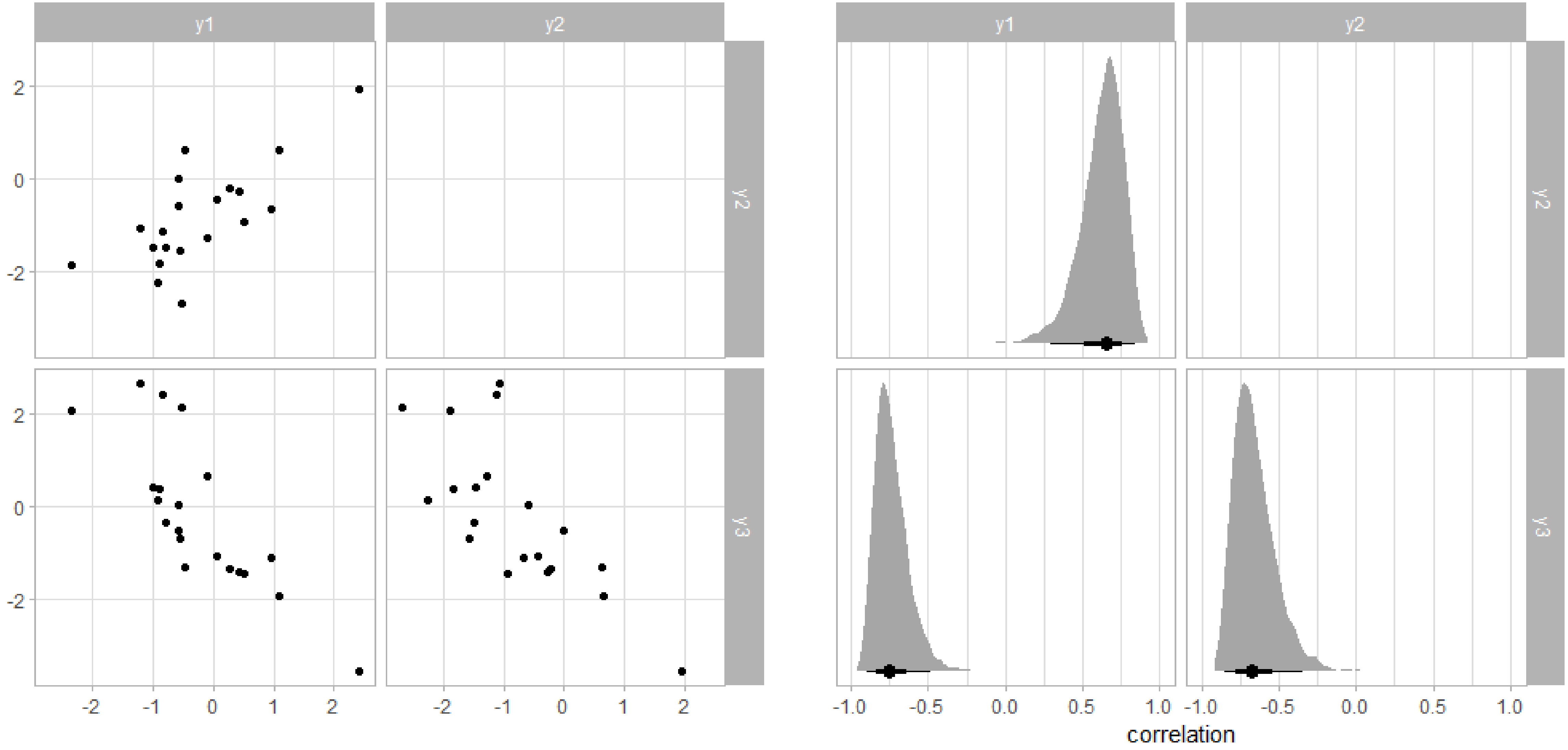
y1
y2
y3
y4
y5
y6
y7
y2
y3
y4
y5
y6
y7
y8
2
0
-2
-2 0 2

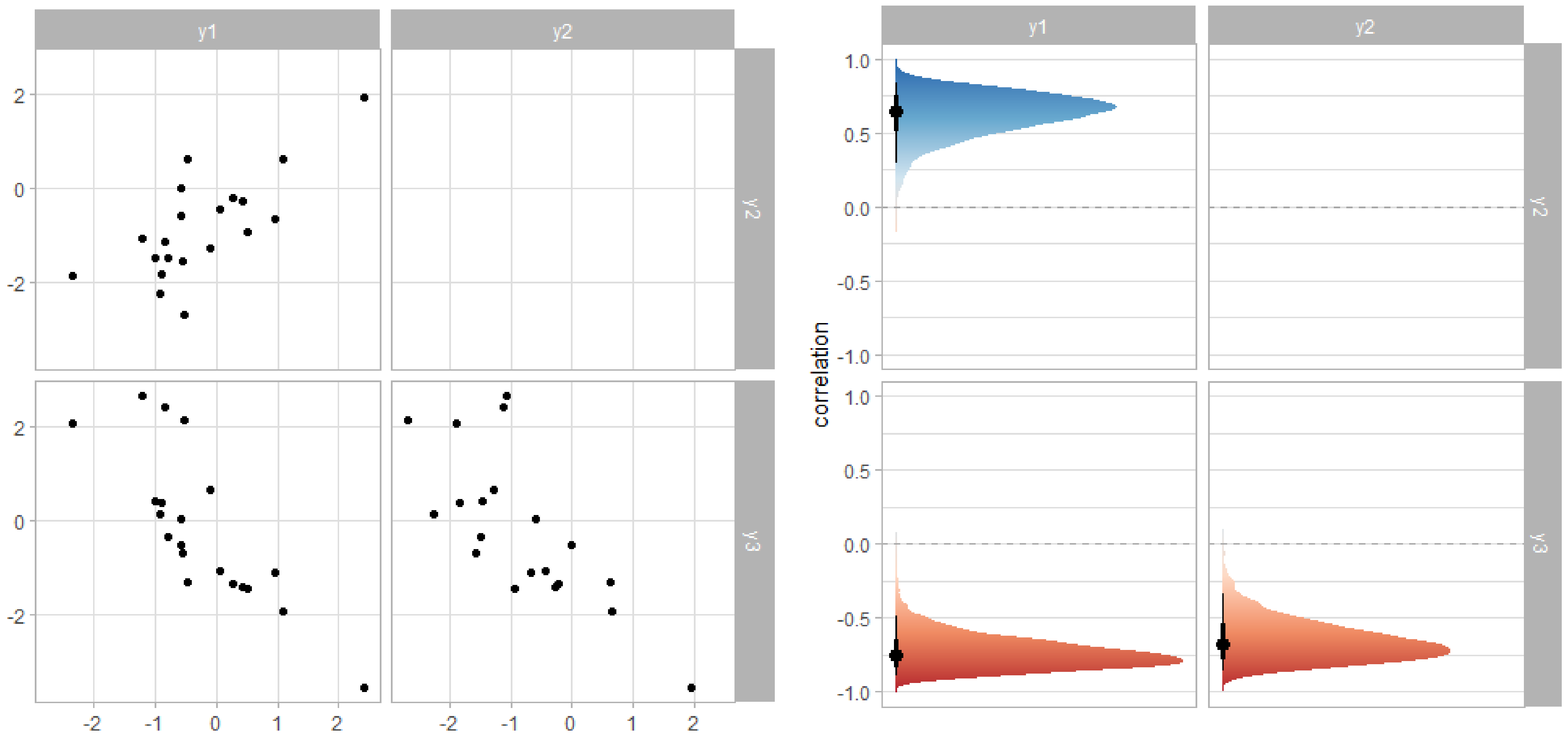


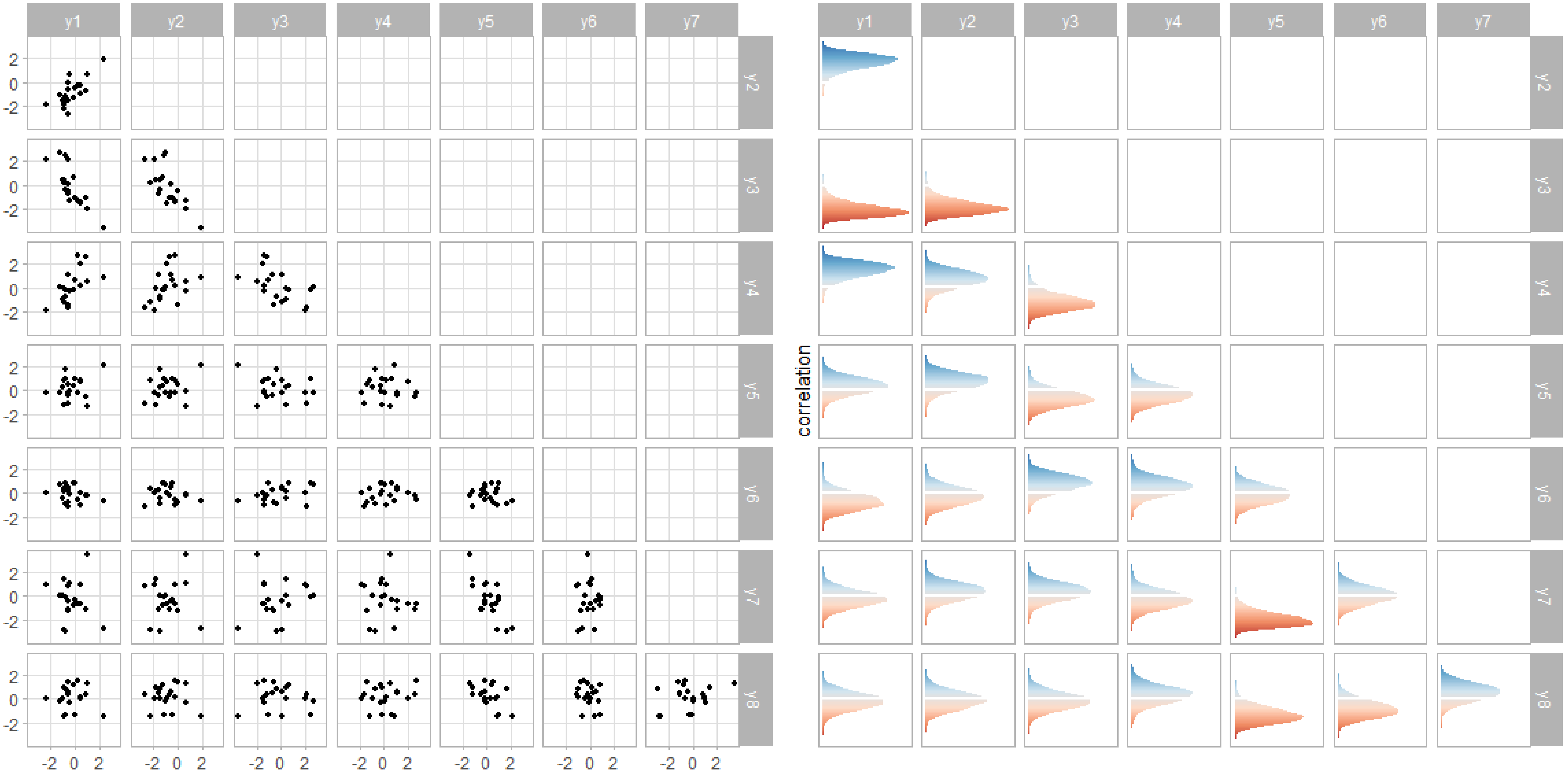
y1
y2
y3
y4
y5
y6
y7
y8
corr.
1.0
0.5
0.0
-0.5
-1.0
-2
0
2


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

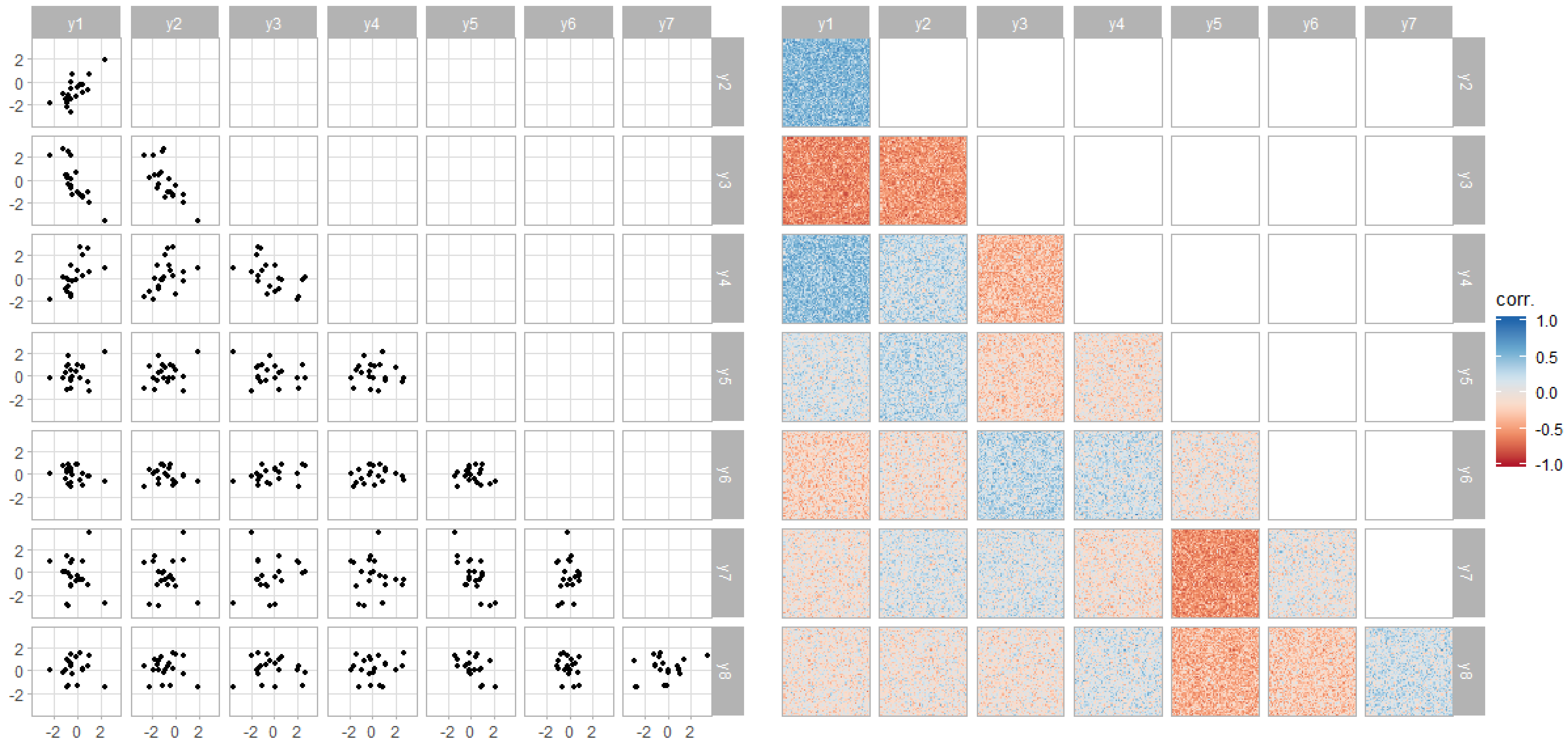

y1
y2
y2
y3
2
0
-2
2
0
-2
-2
-1
0
1
2
-2
-1
0
1
2

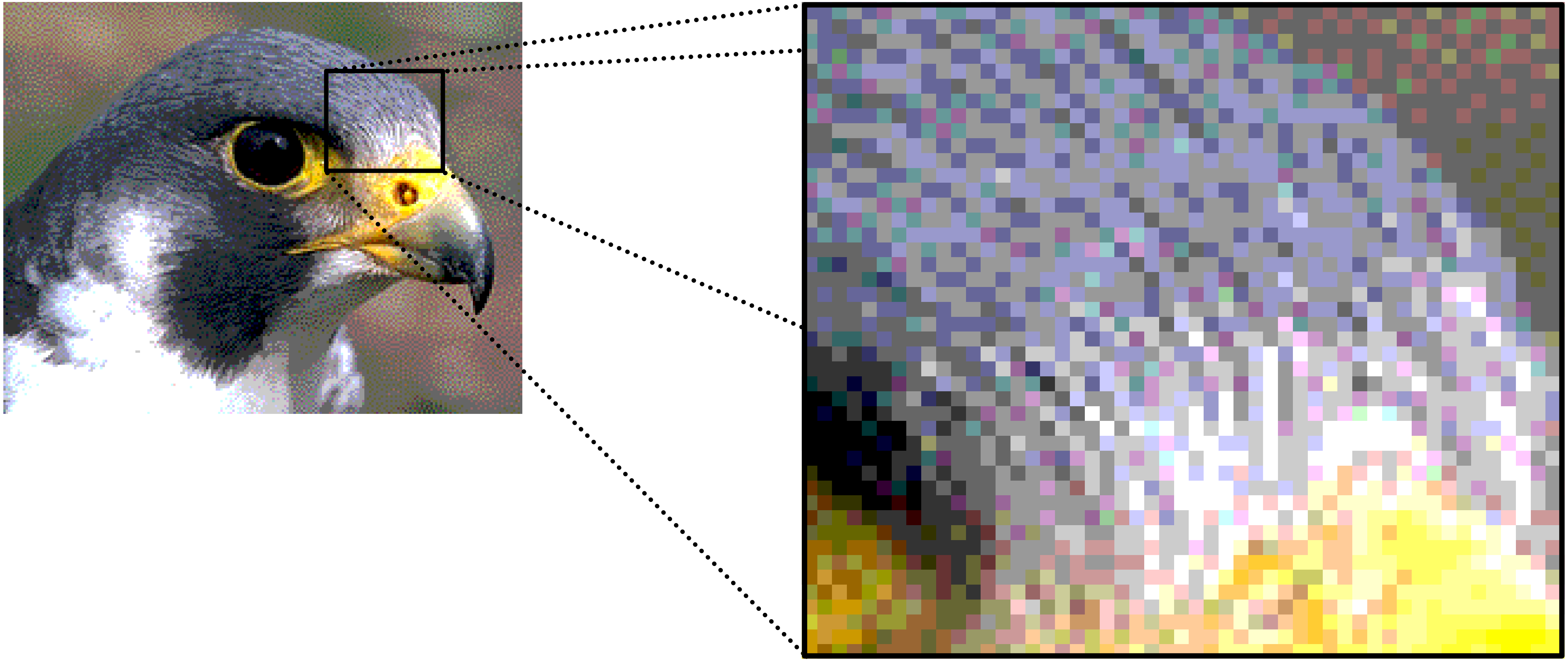

y1
y2
y2
y3
2
0
-2
-2
-1
0
1
2
-1.0
-0.5
0.0
0.5
1.0
correlation

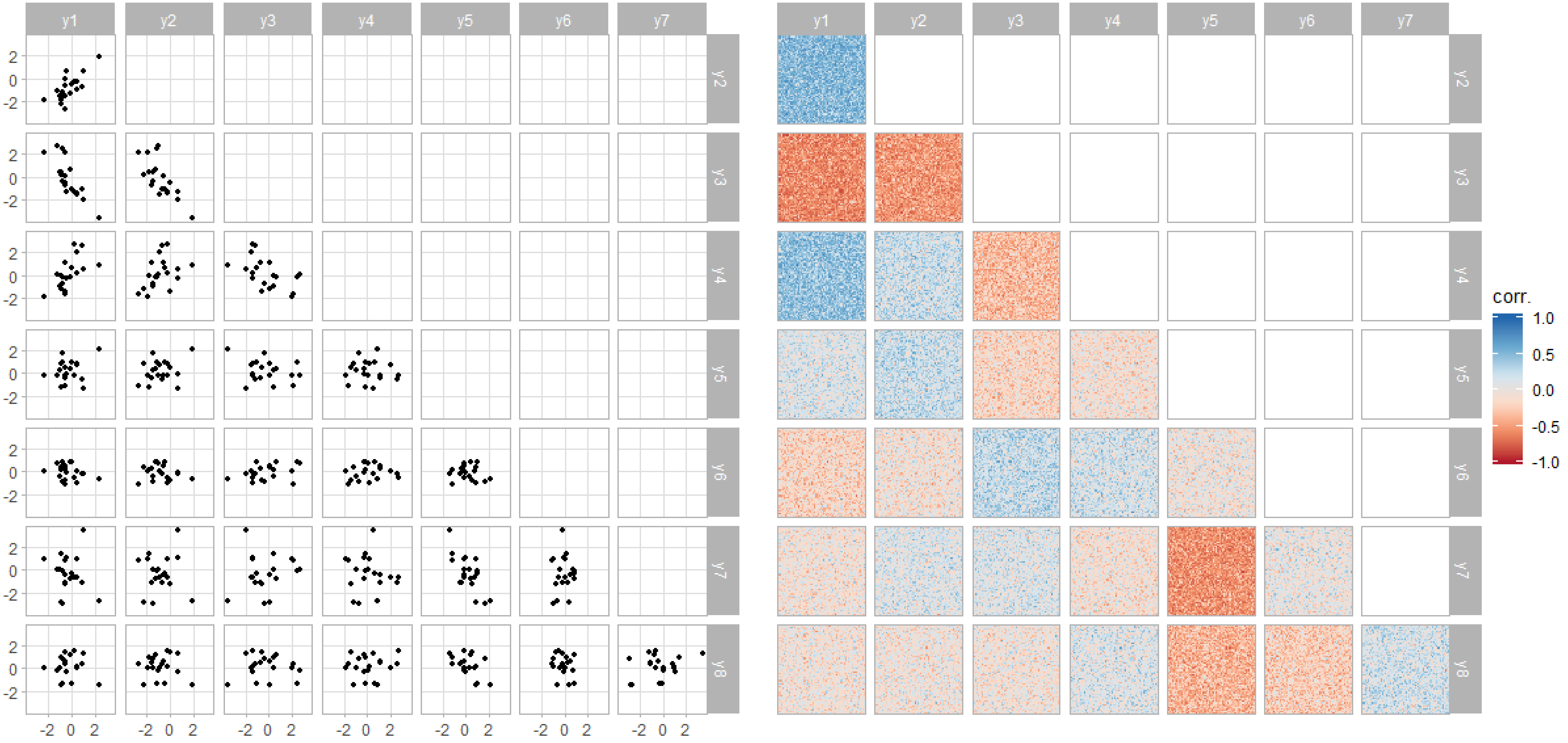

y1
y2
y2
y3
correlation
y1
y2
y2
y3



y1
y2
y3
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
-2
0
2

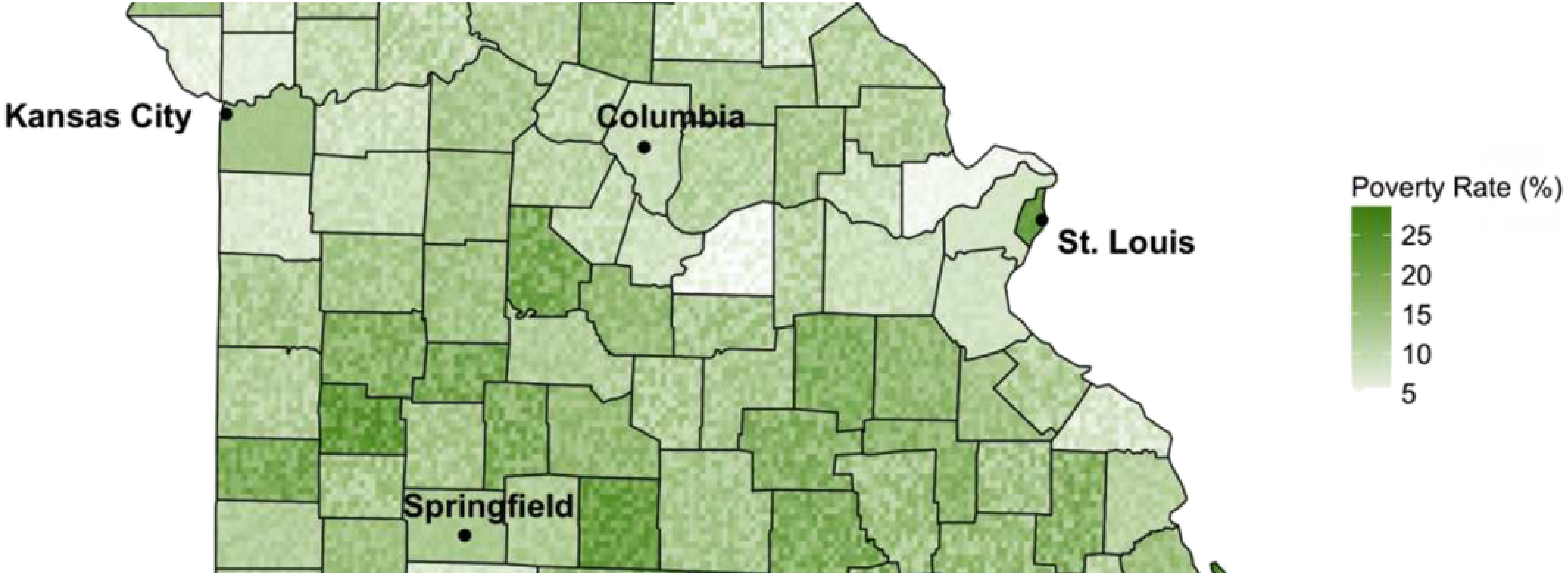



y1
y2
y3
y4
y5
y6
y7
y8
2
0
-2
-2 0 2
corr.
1.0
0.5
0.0
-0.5
-1.0

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]



Uncertainty -> ~dither (samples from dist)

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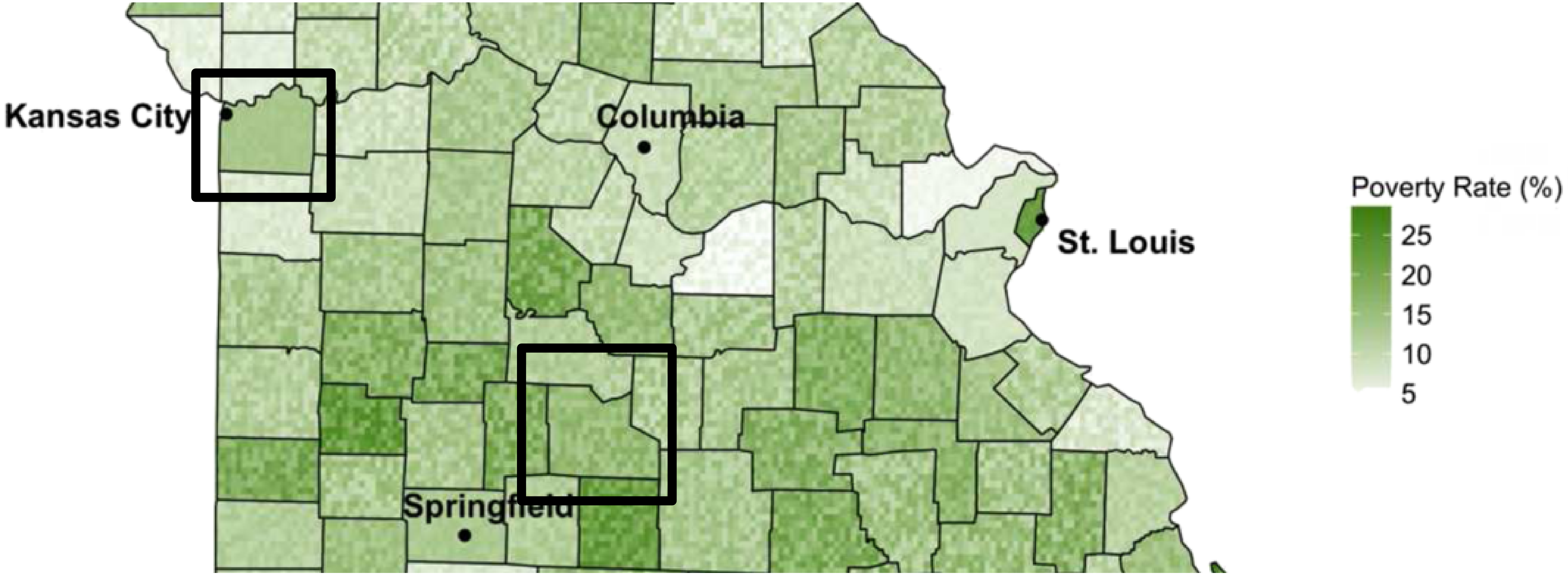


Uncertainty -> ~dither (samples from dist)

[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

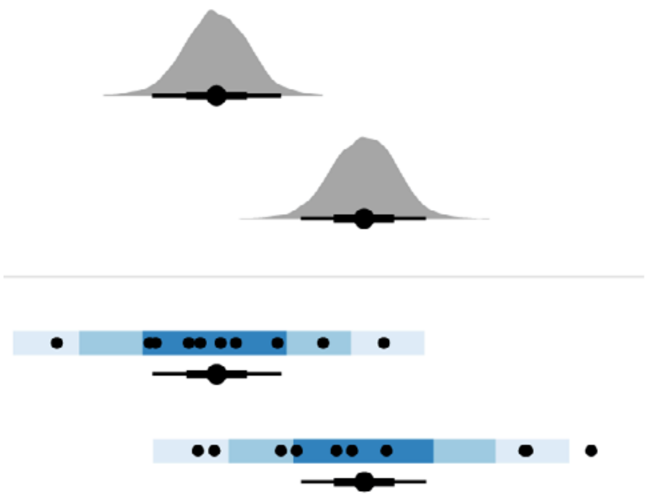
Building effective, complex, correct uncertainty visualizations is **hard**

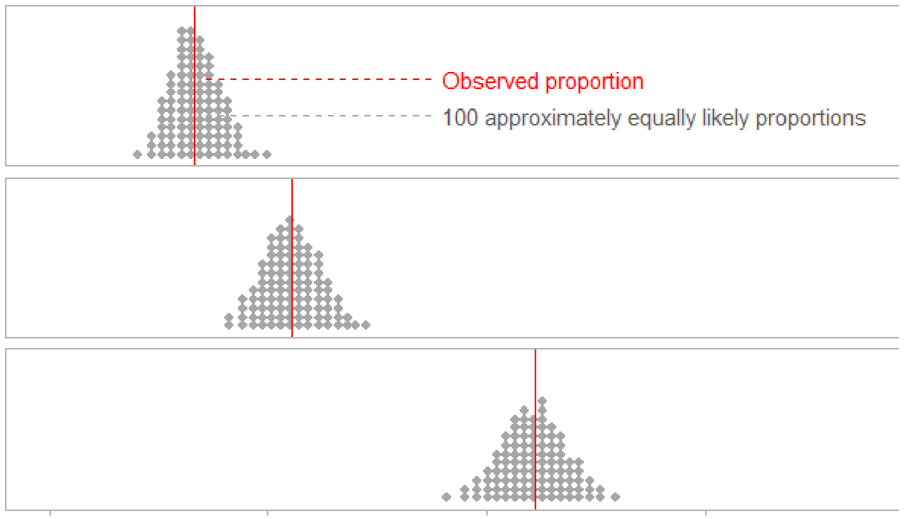
Building effective, complex, correct uncertainty visualization is hard

Prototyping takes time, is brittle

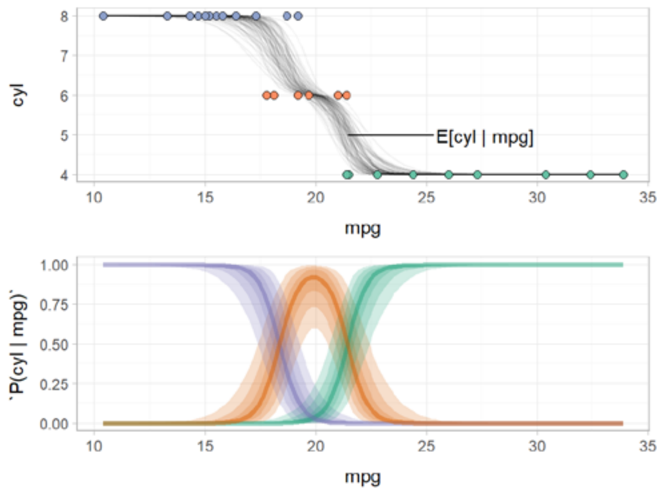
Have to munge posterior draws (a pain!)

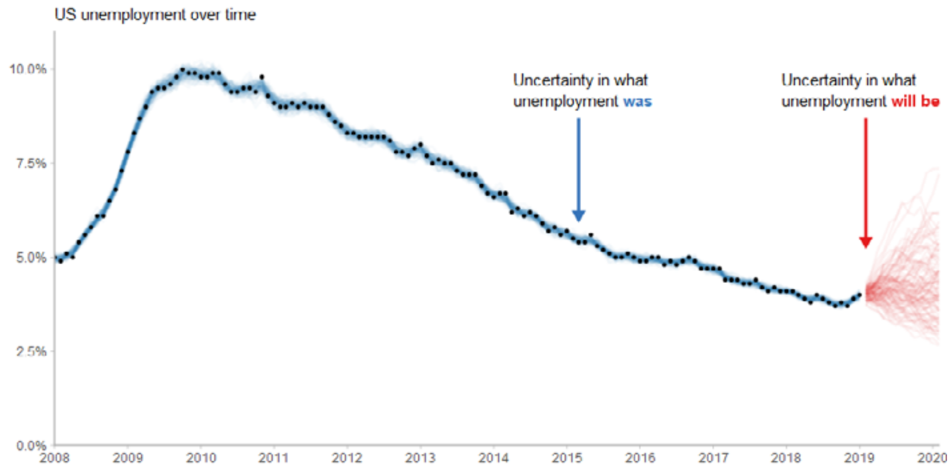
Need to be able to navigate the design space

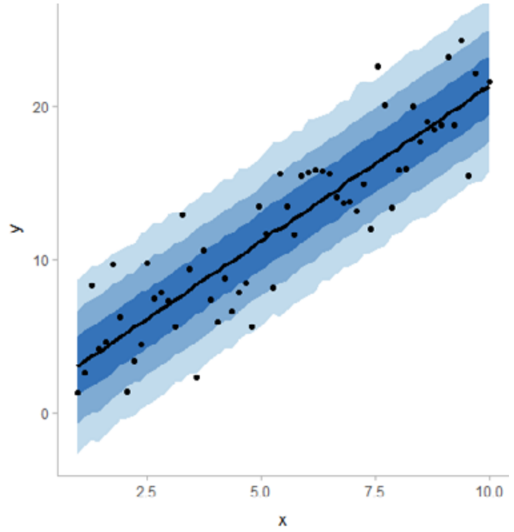




TIDYBAYES







http://mjskay.github.io/tidybayes/

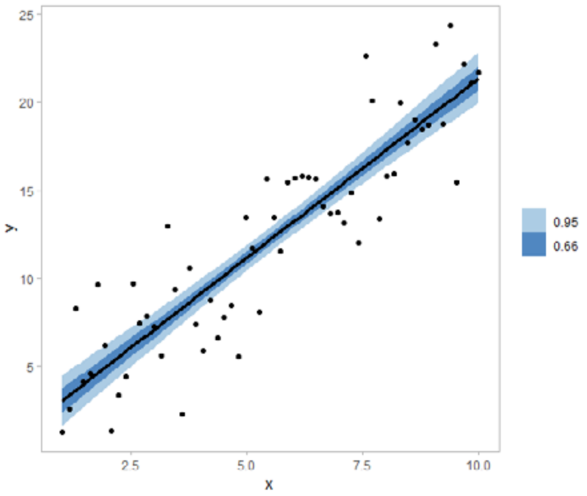
https://github.com/mjskay/uncertainty-examples

1. GRID
2. CONDITION

(2b. MUNGE)

3. PLOT

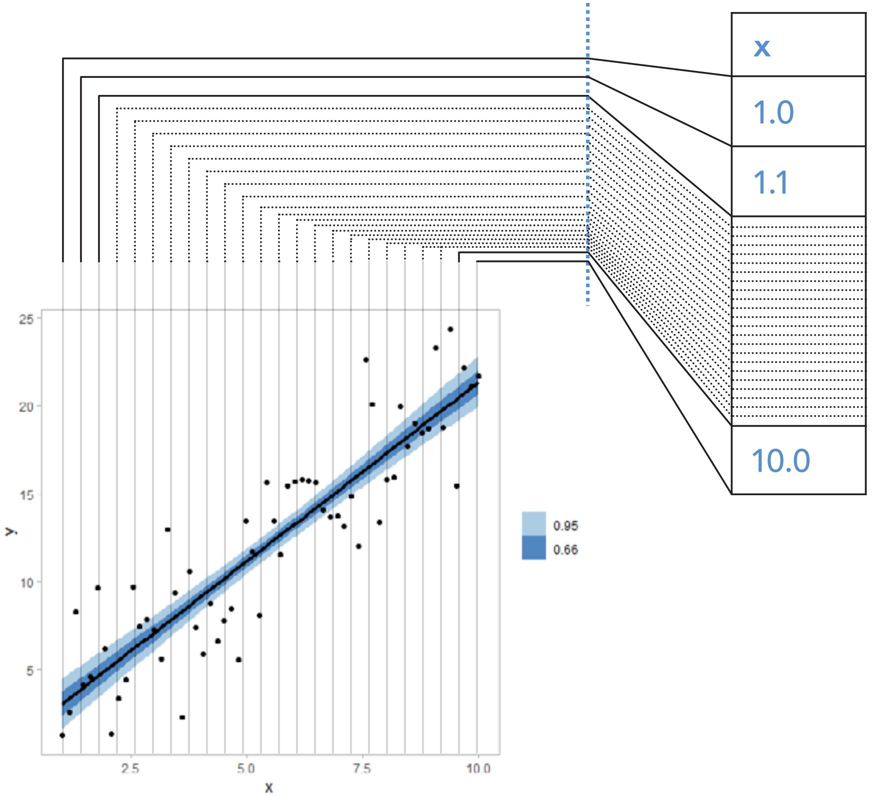
```
m = brm(y ~ x, data = df)
```

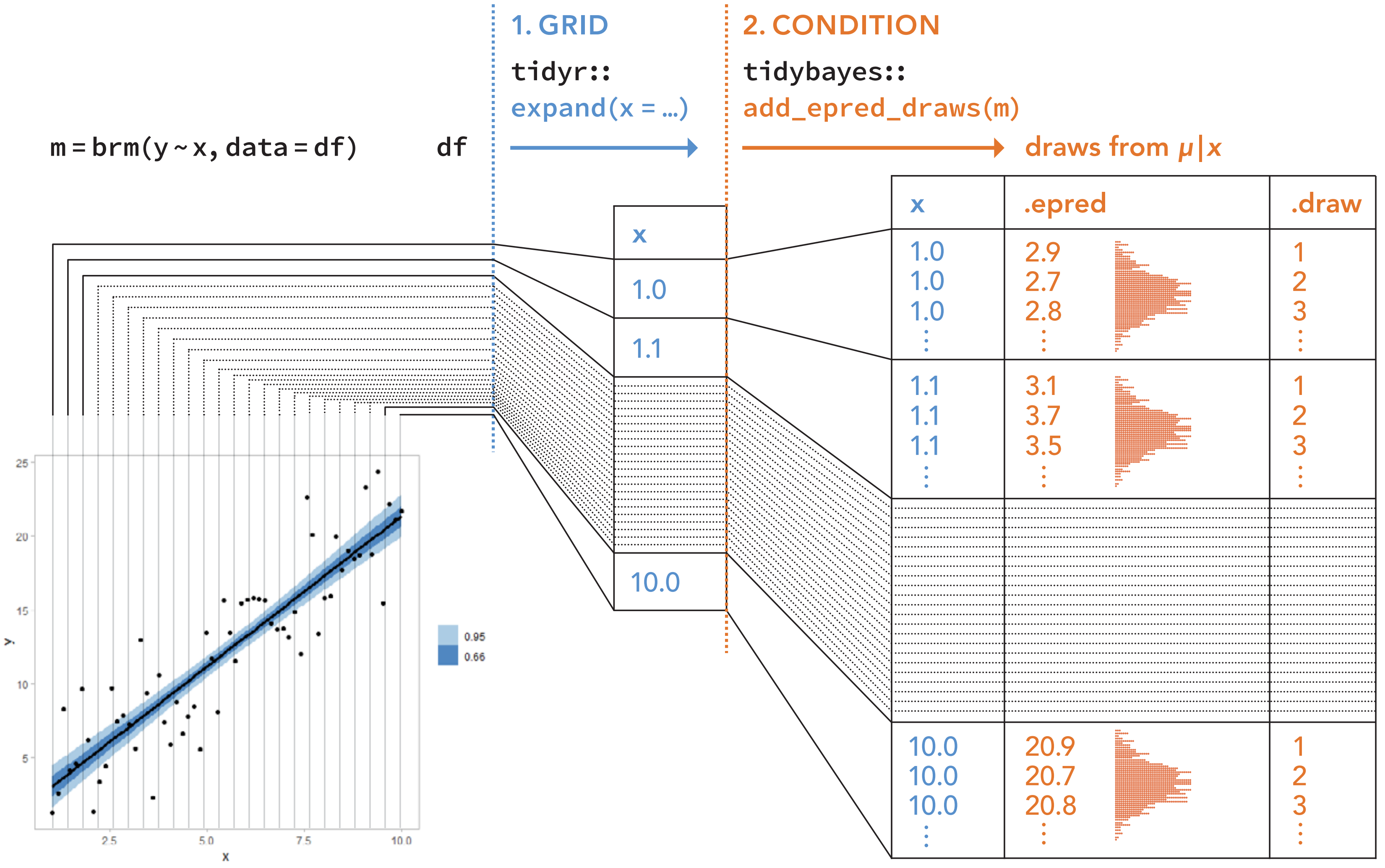


1. GRID

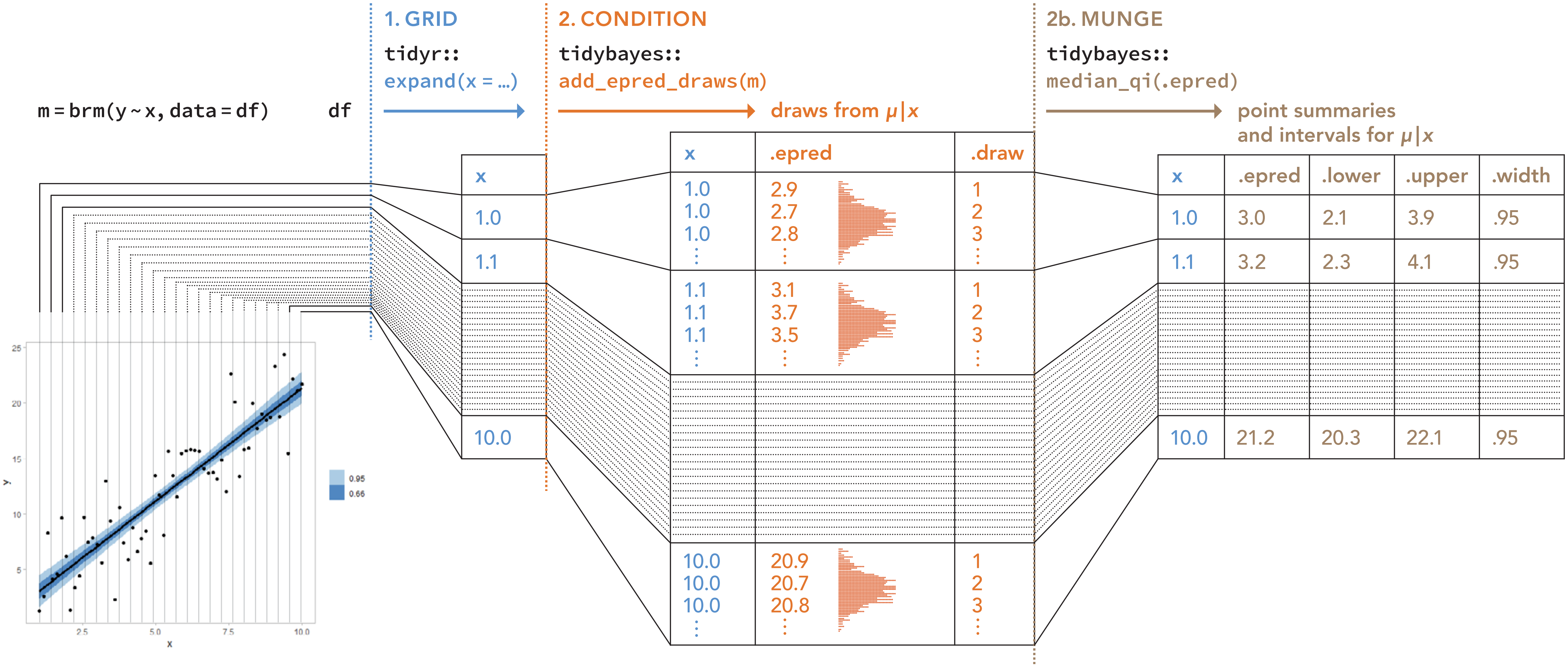
```
tidyr::
expand(x = seq_range(x, n = 25))
```

```
m = brm(y ~ x, data = df)      df
```

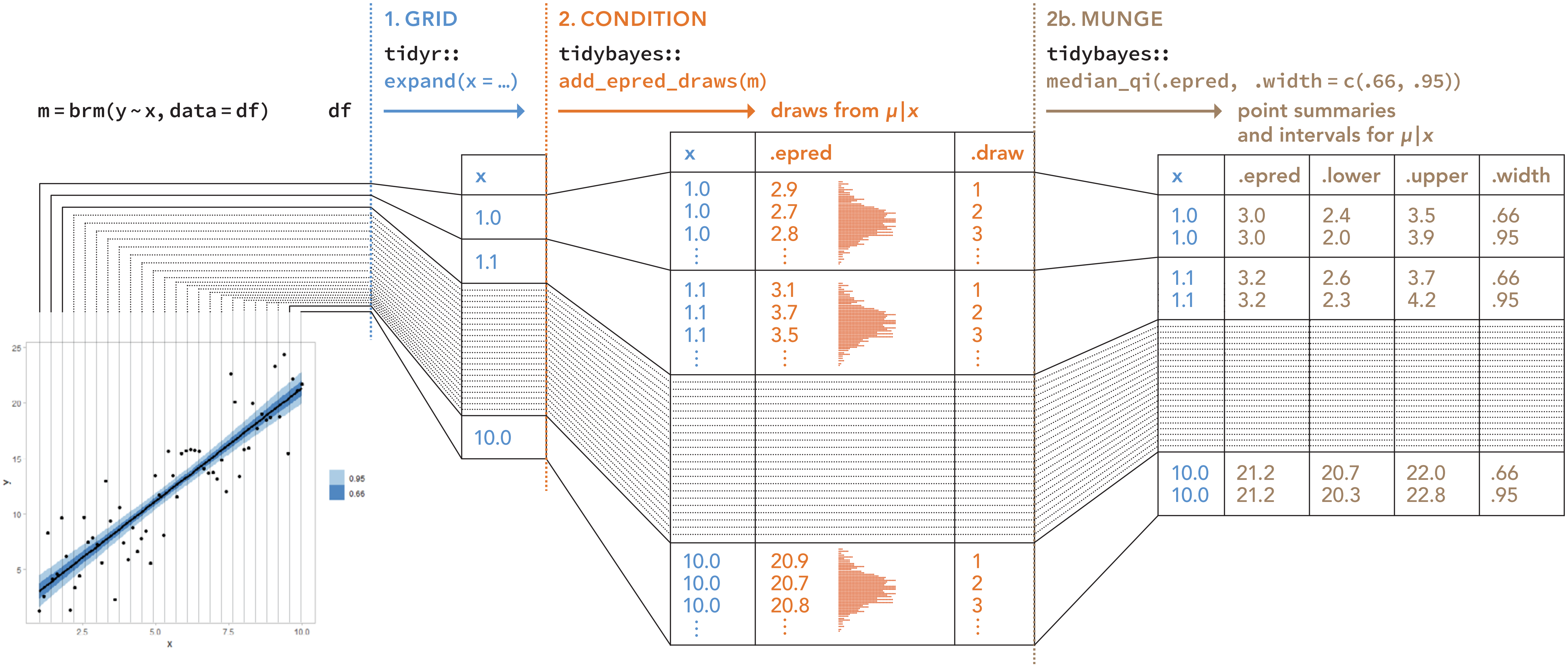




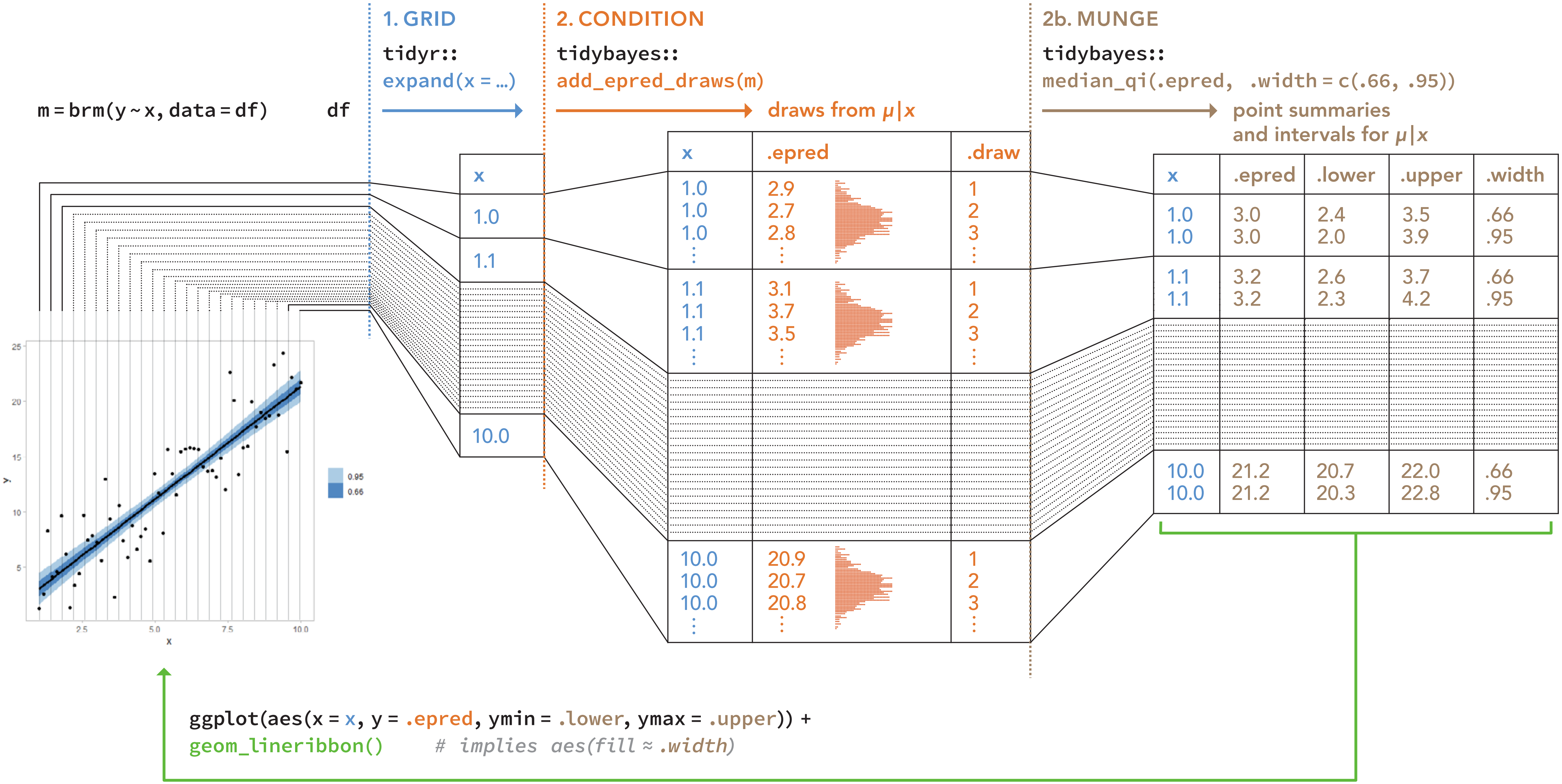
1. GRID
tidyr::
expand(x = ...)
2. CONDITION
tidybayes::
add_epred_draws(m)
m = brm(y ~ x, data = df)
df
draws from μ|x
x
1.0
1.1
10.0
x
.epred
.draw
1.0 1.0 1.0
2.9 2.7 2.8
1 2 3
1.1 1.1 1.1
3.1 3.7 3.5
1 2 3
10.0 10.0 10.0
20.9 20.7 20.8
1 2 3
0.95
0.66

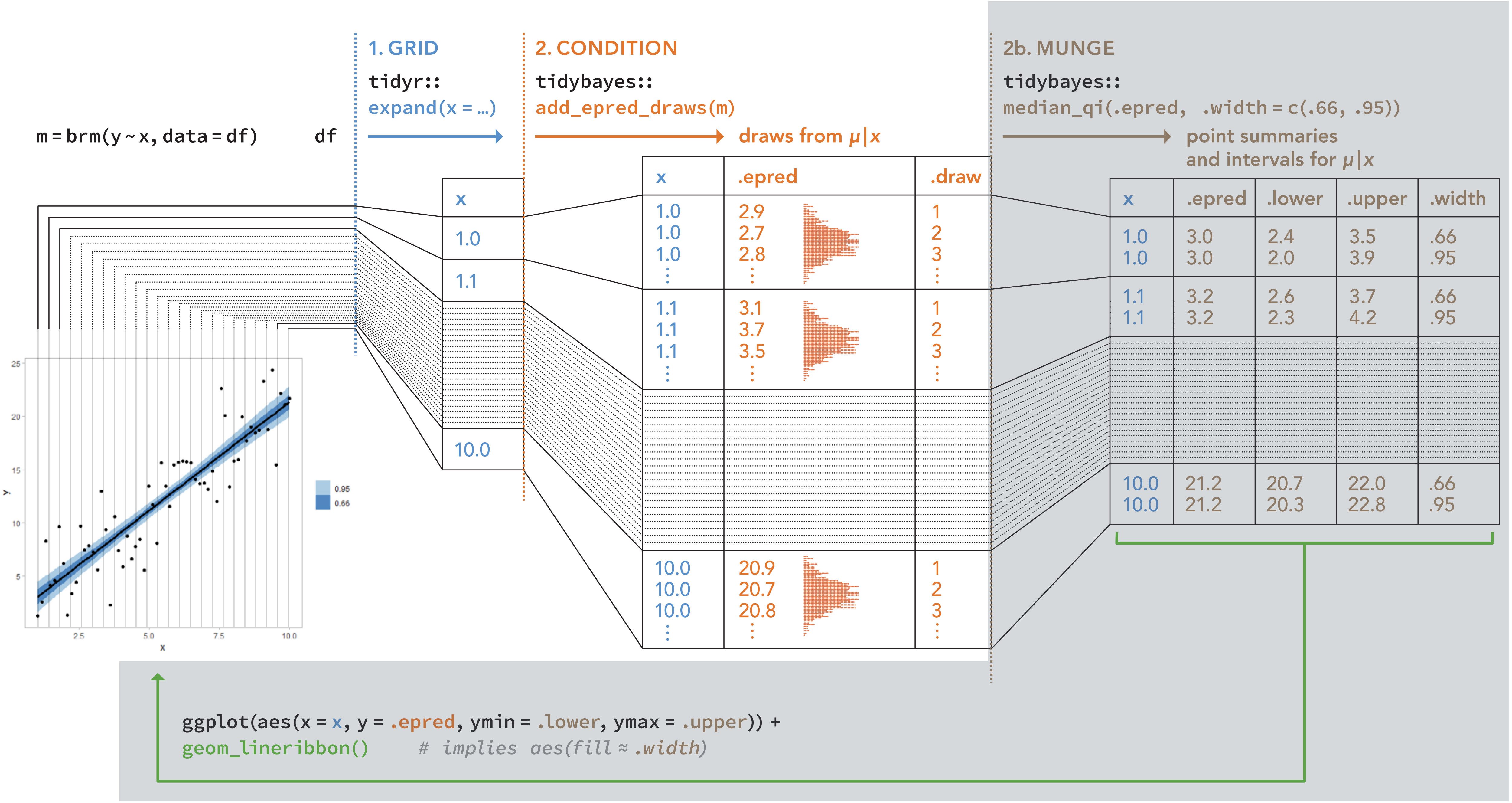


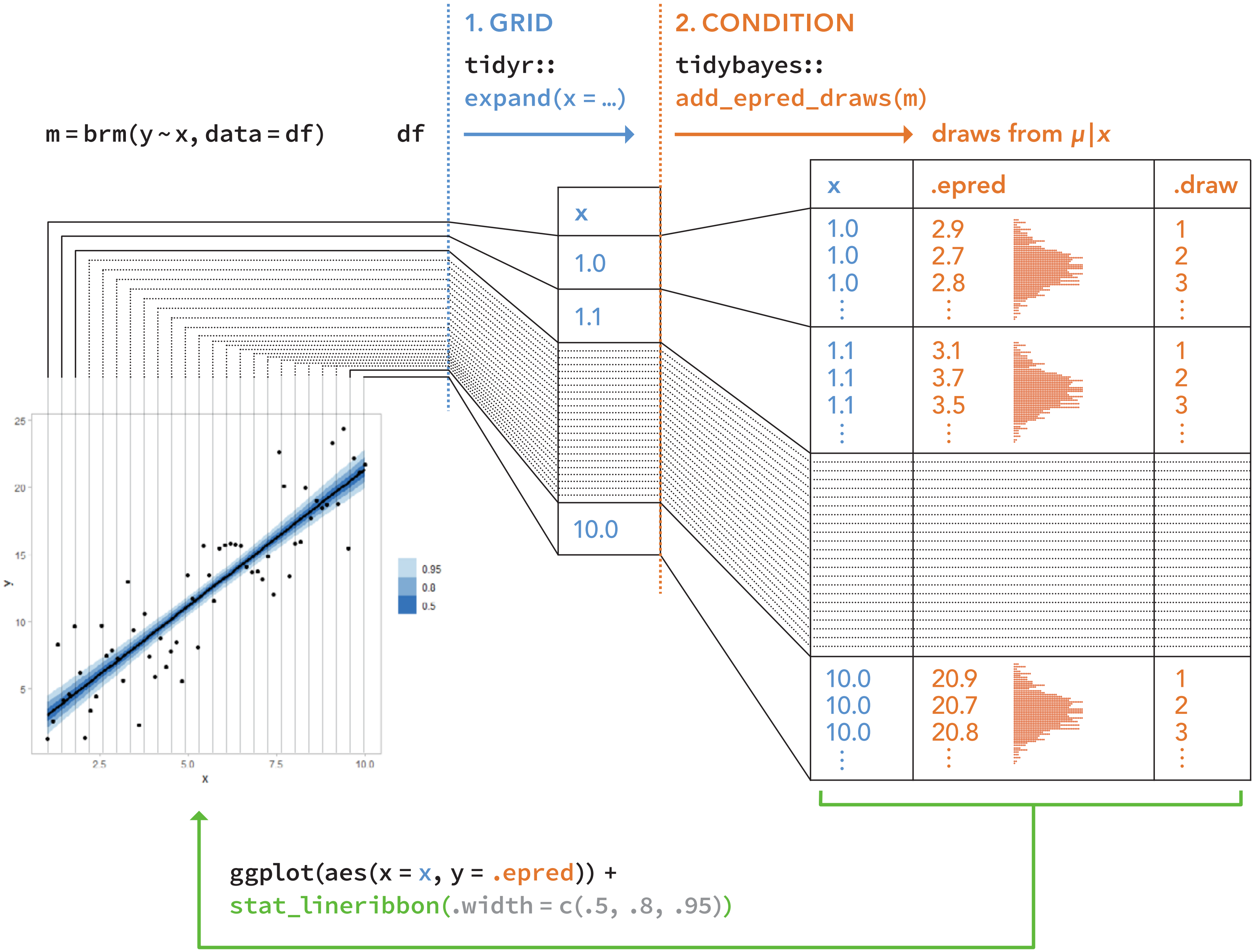
m = brm(y ~ x, data = df)
df
1. GRID
tidyr::
expand(x = ...)
2. CONDITION
tidybayes::
add_epred_draws(m)
draws from μ|x
2b. MUNGE
tidybayes::
median_qi(.epred)
point summaries
and intervals for μ|x
x
1.0
1.1
10.0
x
.epred
.draw
1.0 2.9 1
1.0 2.7 2
1.0 2.8 3
1.1 3.1 1
1.1 3.7 2
1.1 3.5 3
10.0 20.9 1
10.0 20.7 2
10.0 20.8 3
x .epred .lower .upper .width
1.0 3.0 2.1 3.9 .95
1.1 3.2 2.3 4.1 .95
10.0 21.2 20.3 22.1 .95
0.95
0.66



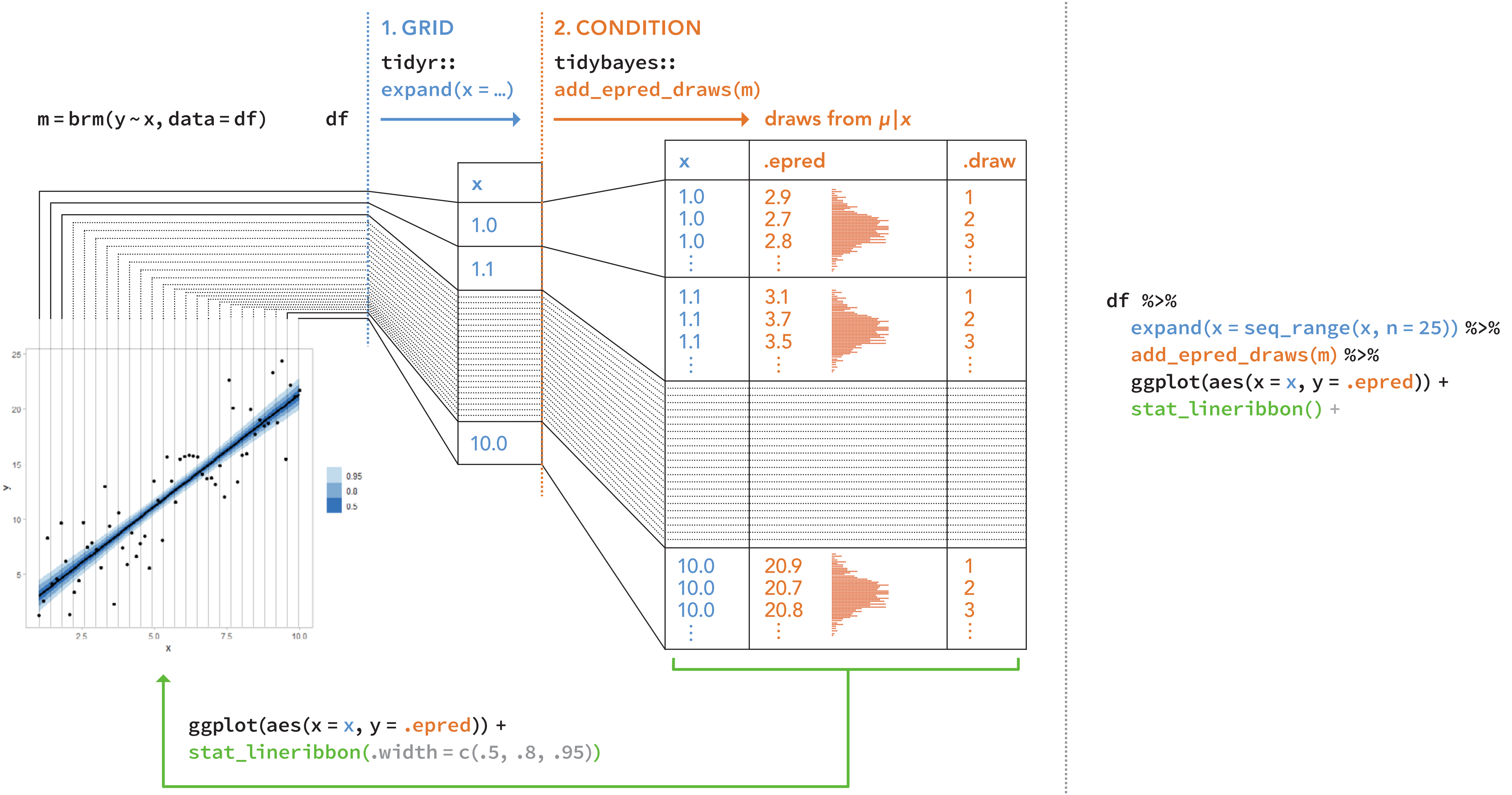
m = brm(y ~ x, data = df)
df
1. GRID
tidyr::
expand(x = ...)
2. CONDITION
tidybayes::
add_epred_draws(m)
draws from μ|x
2b. MUNGE
tidybayes::
median_qi(.epred, .width = c(.66, .95))
point summaries
and intervals for μ|x
x
1.0
1.1
10.0
x
.epred
.draw
1.0 1.0 1.0
2.9 2.7 2.8
1 2 3
1.1 1.1 1.1
3.1 3.7 3.5
1 2 3
10.0 10.0 10.0
20.9 20.7 20.8
1 2 3
x
.epred
.lower
.upper
.width
1.0 1.0
3.0 3.0
2.4 2.0
3.5 3.9
.66 .95
1.1 1.1
3.2 3.2
2.6 2.3
3.7 4.2
.66 .95
10.0 10.0
21.2 21.2
20.7 20.3
22.0 22.8
.66 .95
0.95
0.66
y
x


m = brm(y ~ x, data = df)
df
1. GRID
tidyr::
expand(x = ...)
2. CONDITION
tidybayes::
add_epred_draws(m)
draws from μ|x
2b. MUNGE
tidybayes::
median_qi(.epred, .width = c(.66, .95))
point summaries
and intervals for μ|x
x
1.0
1.1
10.0
x
.epred
.draw
1.0
1.0
1.0
2.9
2.7
2.8
1
2
3
1.1
1.1
1.1
3.1
3.7
3.5
1
2
3
10.0
10.0
10.0
20.9
20.7
20.8
1
2
3
x
.epred
.lower
.upper
.width
1.0
1.0
3.0
3.0
2.4
2.0
3.5
3.9
.66
.95
1.1
1.1
3.2
3.2
2.6
2.3
3.7
4.2
.66
.95
10.0
10.0
21.2
21.2
20.7
20.3
22.0
22.8
.66
.95
0.95
0.66
ggplot(aes(x = x, y = .epred, ymin = .lower, ymax = .upper)) +
geom_lineribbon()   # implies aes(fill ≈ .width)

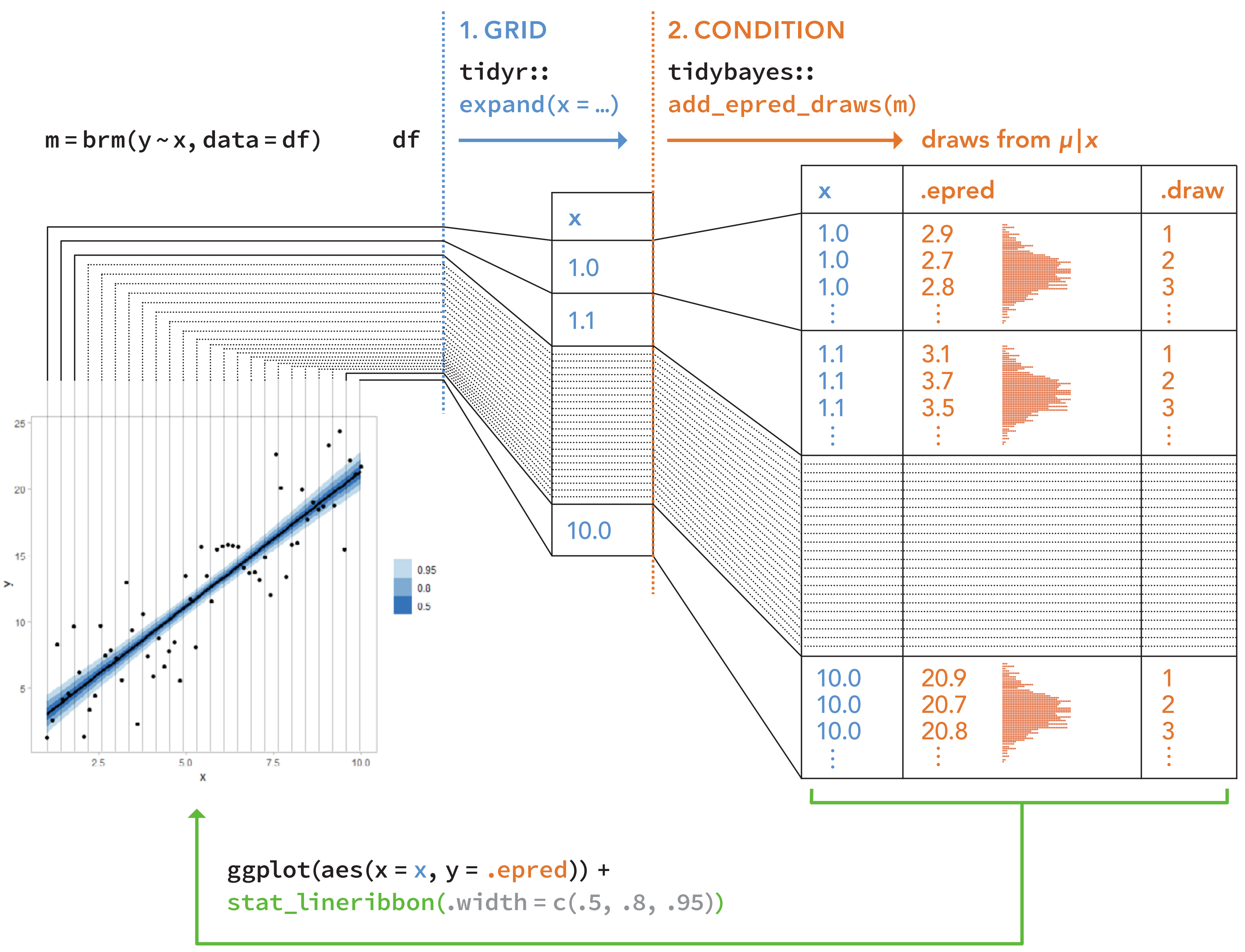

m = brm(y ~ x, data = df)
df
1. GRID
tidyr::
expand(x = …)
x
1.0
1.1
10.0
2. CONDITION
tidybayes::
add_epred_draws(m)
draws from μ|x
x
.epred
.draw
1.0 1.0 1.0
2.9 2.7 2.8
1 2 3
1.1 1.1 1.1
3.1 3.7 3.5
1 2 3
10.0 10.0 10.0
20.9 20.7 20.8
1 2 3
2b. MUNGE
tidybayes::
median_qi(.epred, .width = c(.66, .95))
point summaries
and intervals for μ|x
x
.epred
.lower
.upper
.width
1.0 1.0
3.0 3.0
2.4 2.0
3.5 3.9
.66 .95
1.1 1.1
3.2 3.2
2.6 2.3
3.7 4.2
.66 .95
10.0 10.0
21.2 21.2
20.7 20.3
22.0 22.8
.66 .95
25
20
15
10
5
y
2.5
5.0
7.5
10.0
x
0.95
0.66
ggplot(aes(x = x, y = .epred, ymin = .lower, ymax = .upper)) +
geom_lineribbon()   # implies aes(fill ≈ .width)



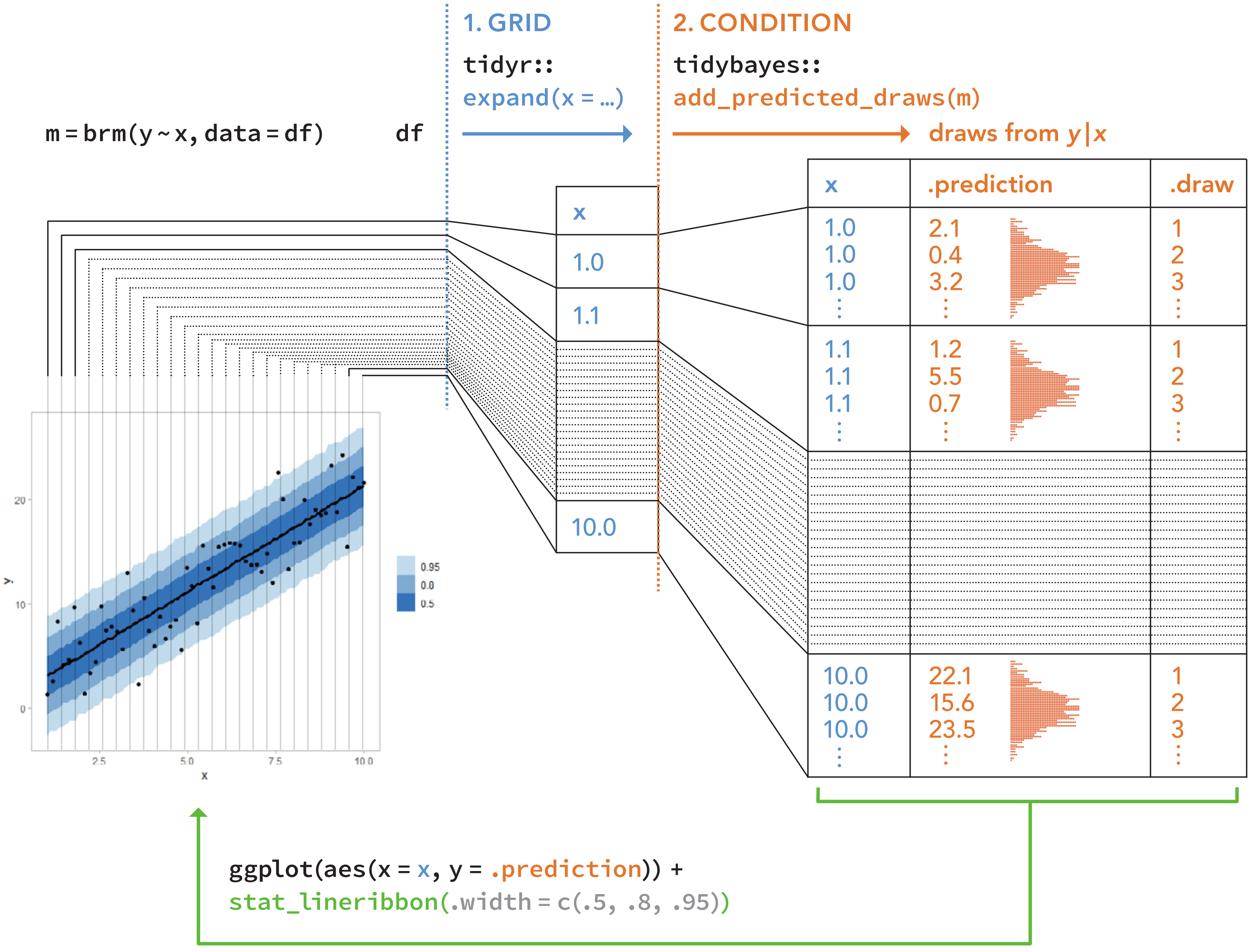
m = brm(y ~ x, data = df)
df
1. GRID
tidyr::
expand(x = ...)
2. CONDITION
tidybayes::
add_epred_draws(m)
draws from μ|x
x
1.0
1.1
10.0
x
.epred
.draw
1.0 1.0 1.0
2.9 2.7 2.8
1 2 3
1.1 1.1 1.1
3.1 3.7 3.5
1 2 3
10.0 10.0 10.0
20.9 20.7 20.8
1 2 3
25
20
15
10
5
y
2.5
5.0
7.5
10.0
x
0.95
0.8
0.5
ggplot(aes(x = x, y = .epred)) +
stat_lineribbon(.width = c(.5, .8, .95))



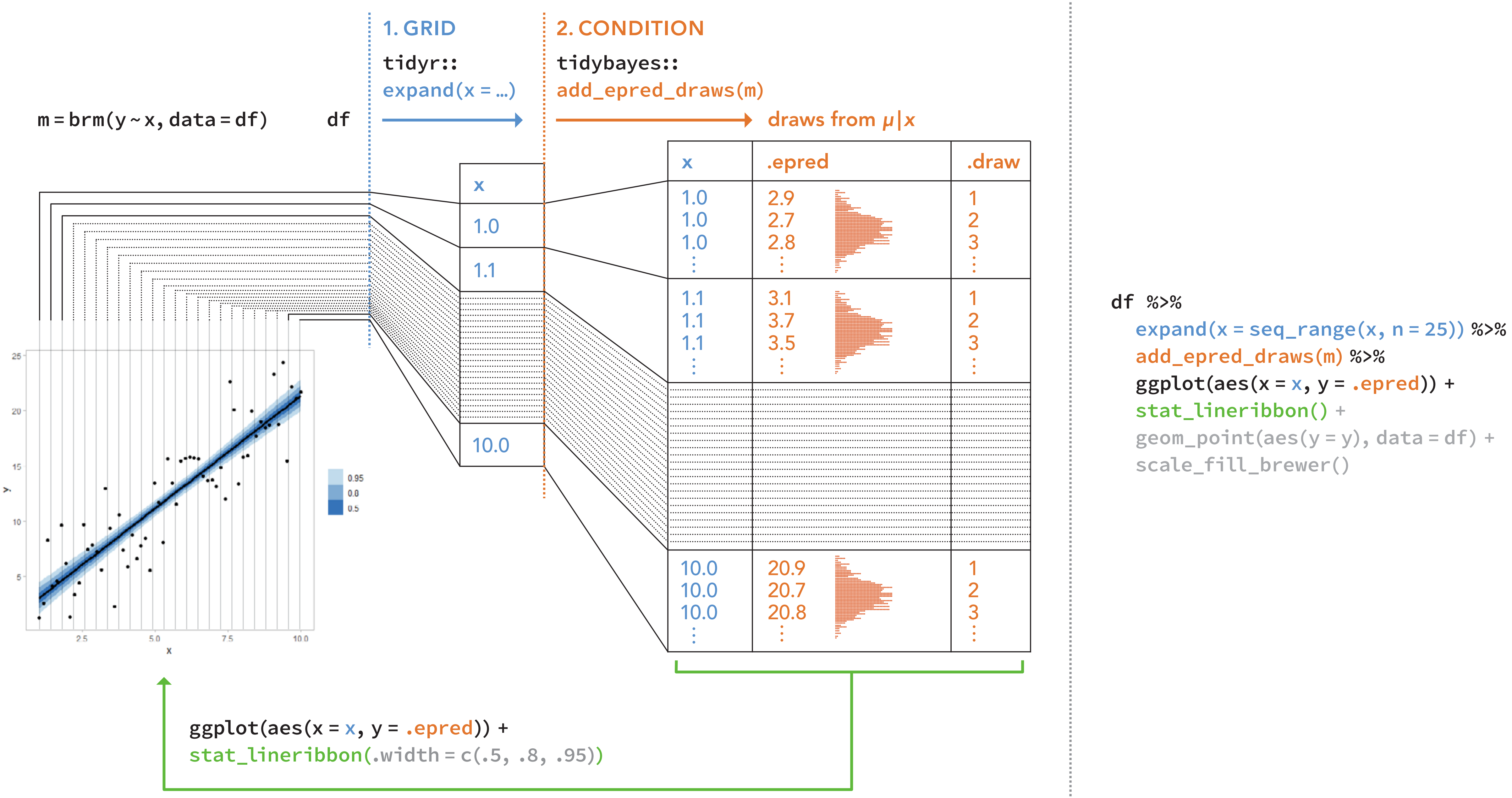
1. GRID
tidyr::
expand(x = …)
2. CONDITION
tidybayes::
add_epred_draws(m)
m = brm(y ~ x, data = df)
df
draws from μ|x
x
1.0
1.1
10.0
x
.epred
.draw
1.0
1.0
1.0
2.9
2.7
2.8
1
2
3
1.1
1.1
1.1
3.1
3.7
3.5
1
2
3
10.0
10.0
10.0
20.9
20.7
20.8
1
2
3
25
20
15
10
5
y
2.5
5.0
7.5
10.0
x
0.95
0.8
0.5
ggplot(aes(x = x, y = .epred)) +
stat_lineribbon(.width = c(.5, .8, .95))
df %>%
expand(x = seq_range(x, n = 25)) %>%
add_epred_draws(m) %>%
ggplot(aes(x = x, y = .epred)) +
stat_lineribbon() +

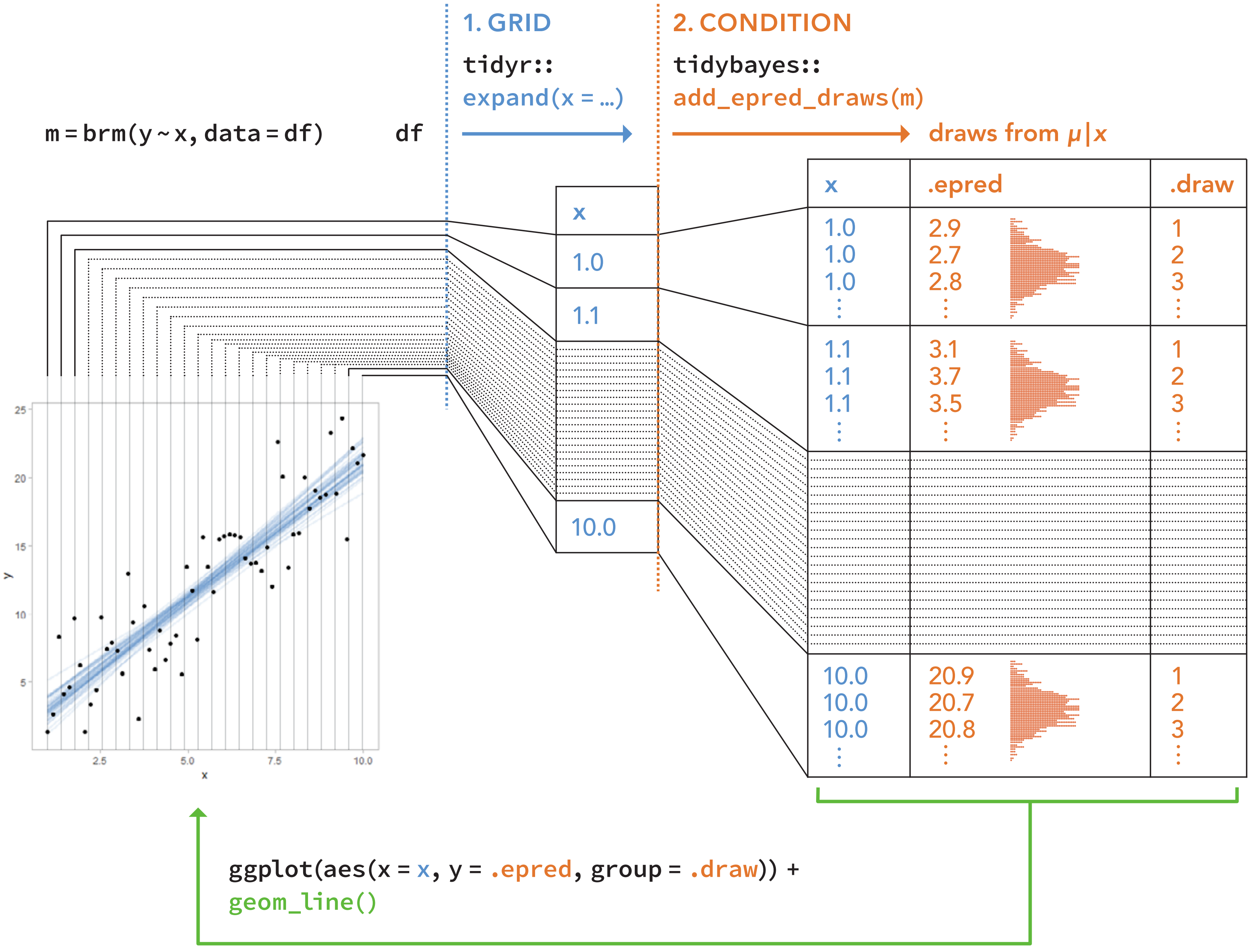



```
df %>%
  expand(x = seq_range(x, n = 25)) %>%
  add_epred_draws(m) %>%
  ggplot(aes(x = x, y = .epred)) +
  stat_lineribbon() +
  geom_point(aes(y = y), data = df) +
  scale_fill_brewer()
```



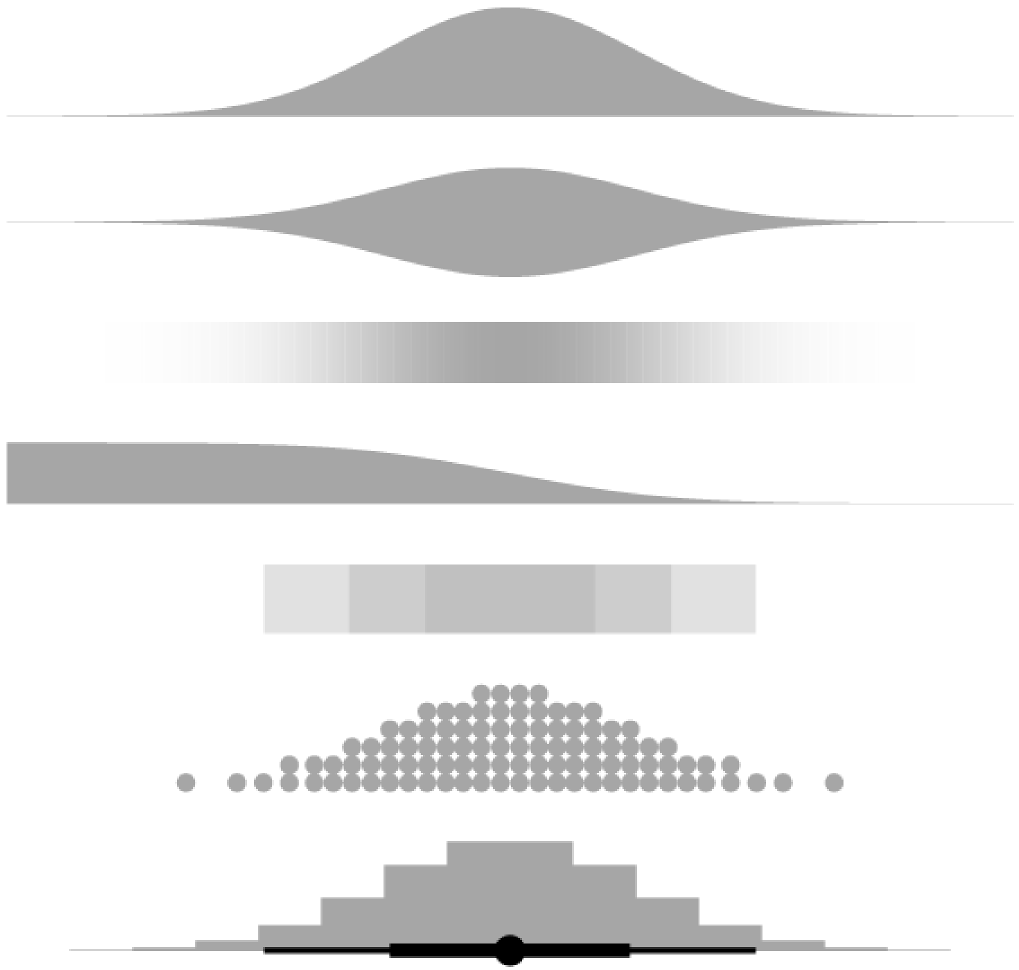

```
df %>%
  expand(x = seq_range(x, n = 25)) %>%
  add_predicted_draws(m) %>%
  ggplot(aes(x = x, y = .prediction)) +
  stat_lineribbon() +
  geom_point(aes(y = y), data = df) +
  scale_fill_brewer()
```

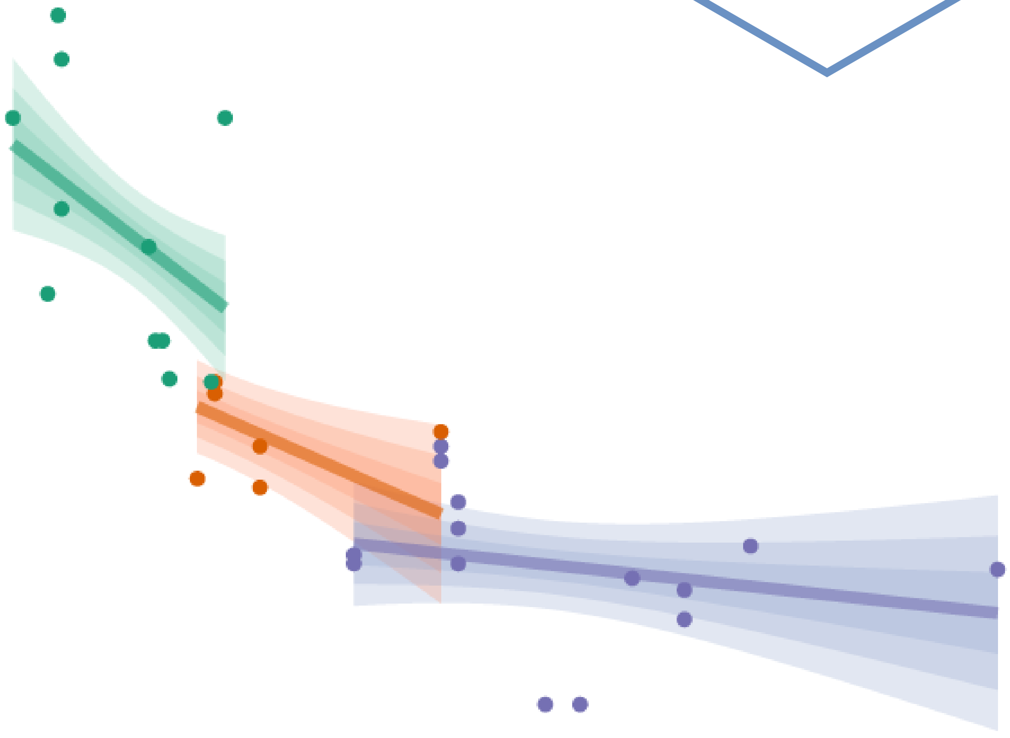

1. GRID
tidyr::
expand(x = …)
2. CONDITION
tidybayes::
add_epred_draws(m)
m = brm(y ~ x, data = df)
df
draws from μ|x
x
1.0
1.1
10.0
x
.epred
.draw
1.0 1.0 1.0
2.9 2.7 2.8
1 2 3
1.1 1.1 1.1
3.1 3.7 3.5
1 2 3
10.0 10.0 10.0
20.9 20.7 20.8
1 2 3
0.95
0.8
0.5
ggplot(aes(x = x, y = .epred)) +
stat_lineribbon(.width = c(.5, .8, .95))
df %>%
expand(x = seq_range(x, n = 25)) %>%
add_epred_draws(m) %>%
ggplot(aes(x = x, y = .epred)) +
stat_lineribbon() +
geom_point(aes(y = y), data = df) +
scale_fill_brewer()




```
df %>%
  expand(x = seq_range(x, n = 25)) %>%
  add_epred_draws(m, n = 100) %>%
  ggplot(aes(x, .epred, group = .draw)) +
  geom_line() +
  geom_point(aes(y = y), data = df) +
  scale_fill_brewer()
```

1. GRID
2. CONDITION
(2b. MUNGE)
3. PLOT





GGDIST

http://mjskay.github.io/ggdist/

Uncertainty in the grammar of graphics

1. **Derive a distribution** describing your uncertainty: a posterior distribution, a posterior predictive, etc.

Uncertainty in the grammar of graphics

1. **Derive a distribution** describing your uncertainty: a posterior distribution, a posterior predictive, etc.

2. **Map properties of the distribution** (location, scale, quantiles, density) onto visual channels (aka aesthetics)

Uncertainty in what US unemployment will be in May 2019: Continuous encodings

Density plot

$f_{unemp}(x) \rightarrow y$

Uncertainty in what US unemployment will be in May 2019: Continuous encodings

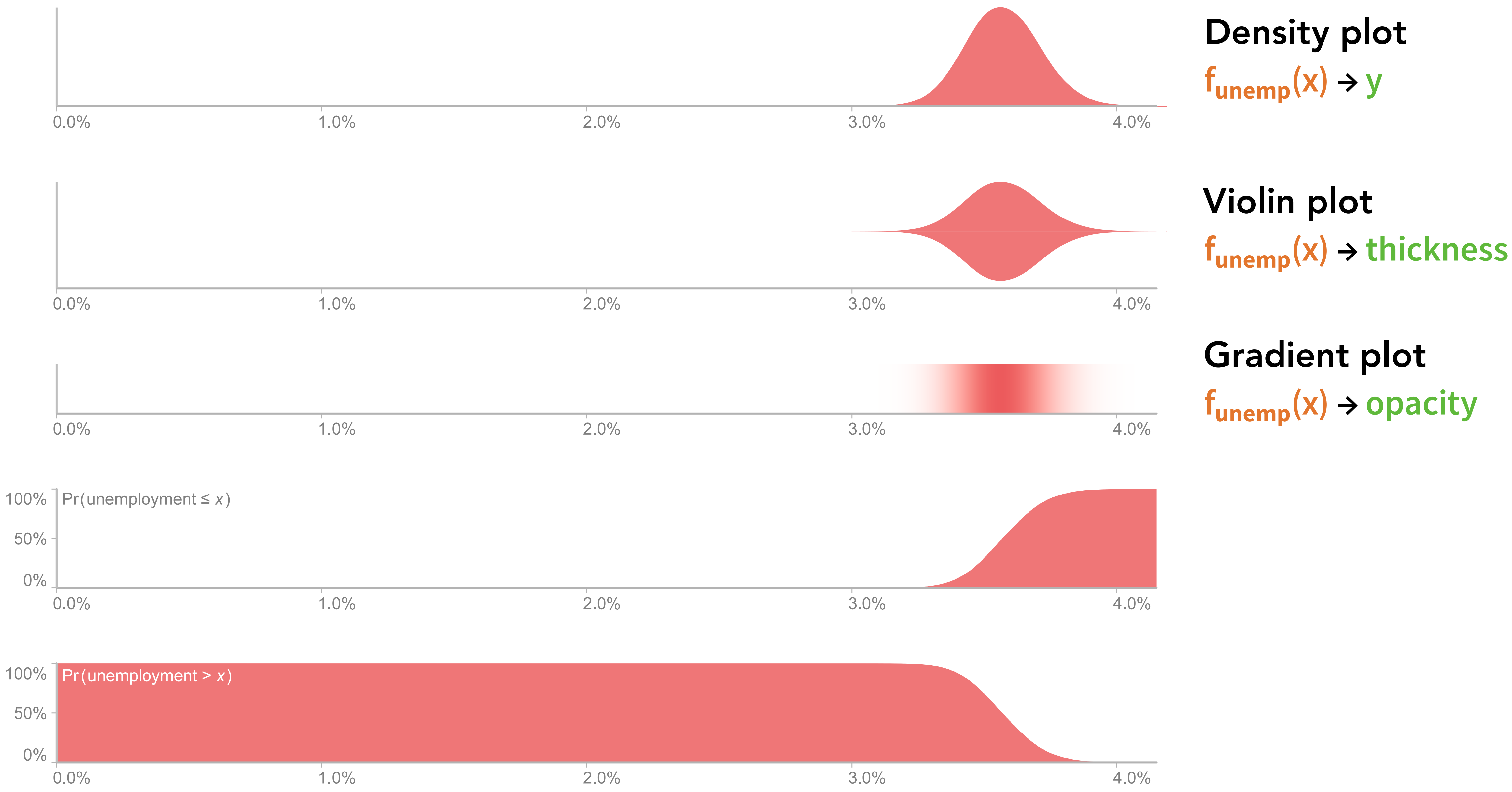
Density plot

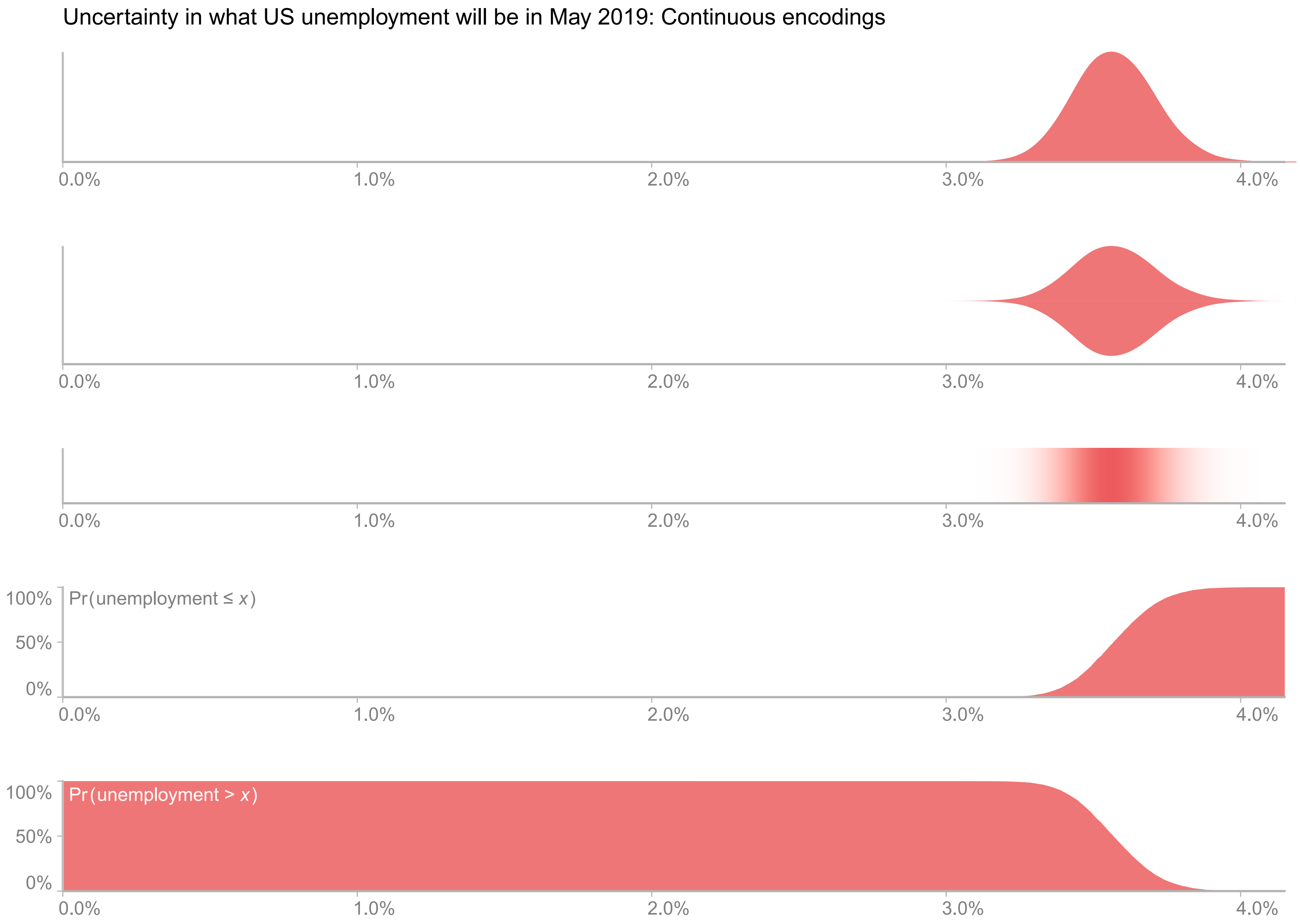
$f_{unemp}(x) \rightarrow y$

Violin plot

$f_{unemp}(x) \rightarrow \text{thickness}$

Uncertainty in what US unemployment will be in May 2019: Continuous encodings





Density plot

$f_{unemp}(x) \rightarrow y$

Violin plot

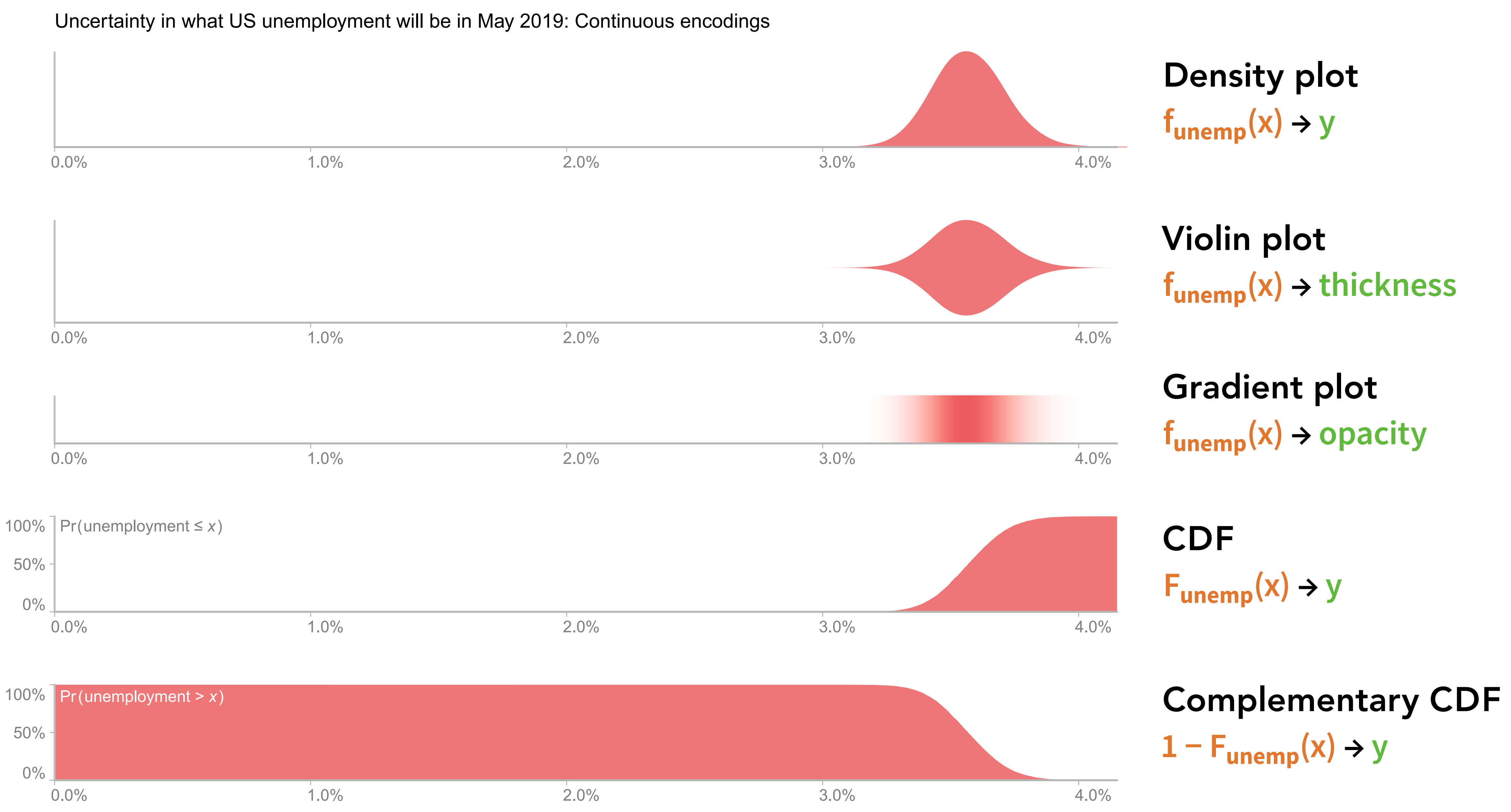
$f_{unemp}(x) \rightarrow$ thickness

Gradient plot

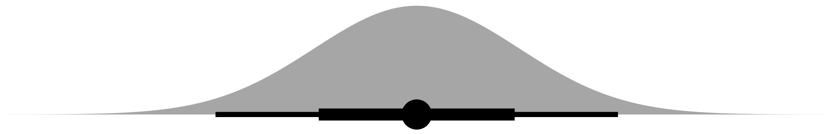
$f_{unemp}(x) \rightarrow$ opacity

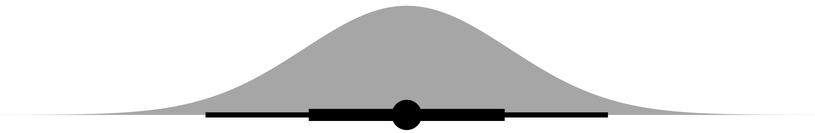
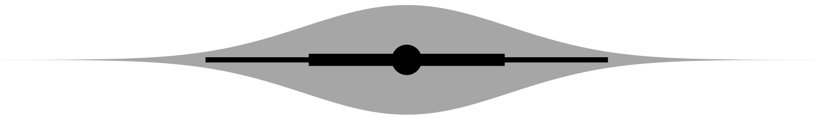
CDF

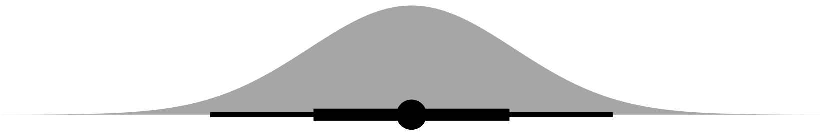
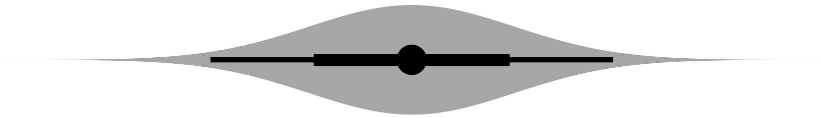
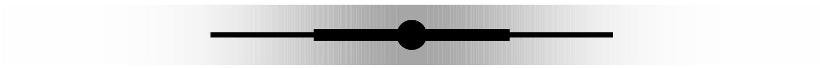
$F_{unemp}(x) \rightarrow y$

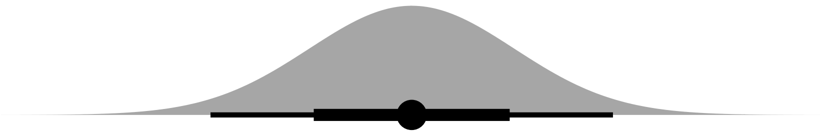
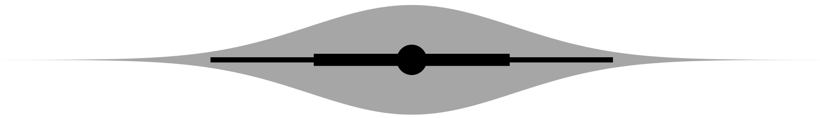
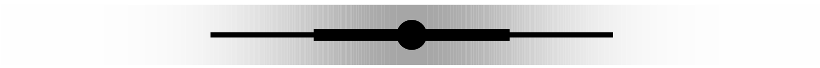


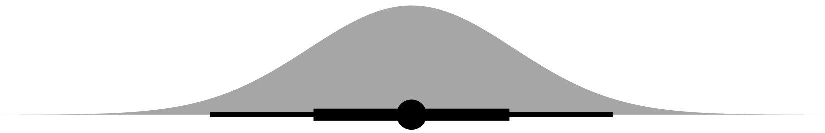
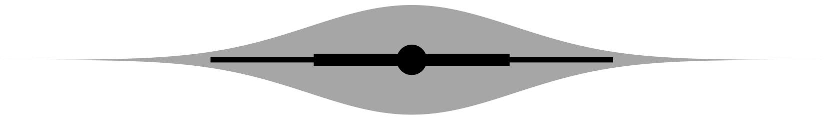
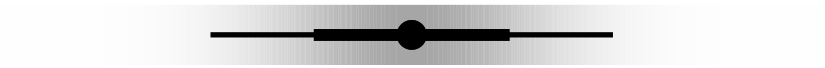
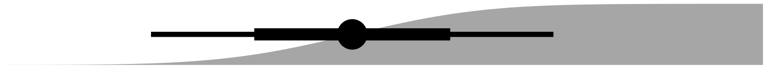
Uncertainty in what US unemployment will be in May 2019: Continuous encodings
0.0%
1.0%
2.0%
3.0%
4.0%
Density plot
$f_{unemp}(x) \rightarrow y$
Violin plot
$f_{unemp}(x) \rightarrow$ thickness
Gradient plot
$f_{unemp}(x) \rightarrow$ opacity
100%
50%
0%
Pr(unemployment ≤ x)
CDF
$F_{unemp}(x) \rightarrow y$
Pr(unemployment > x)
Complementary CDF
$1 - F_{unemp}(x) \rightarrow y$

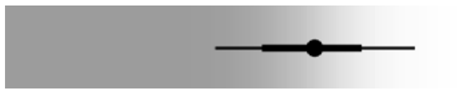
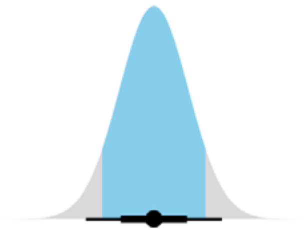
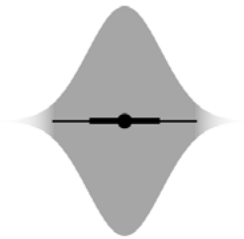
This geometry ...	... uses these defaults: mapping =	slab_type =	side =	
	aesthetic mapping	*function assigned to the computed aesthetic* **f**	*side to draw the slab on*	
stat_sample_slabinterval() stat_dist_slabinterval()	aes(thickness = f)	**"pdf"**	"topright"	
stat_halfeye() stat_dist_halfeye()	aes(thickness = f)	"pdf"	"topright"	

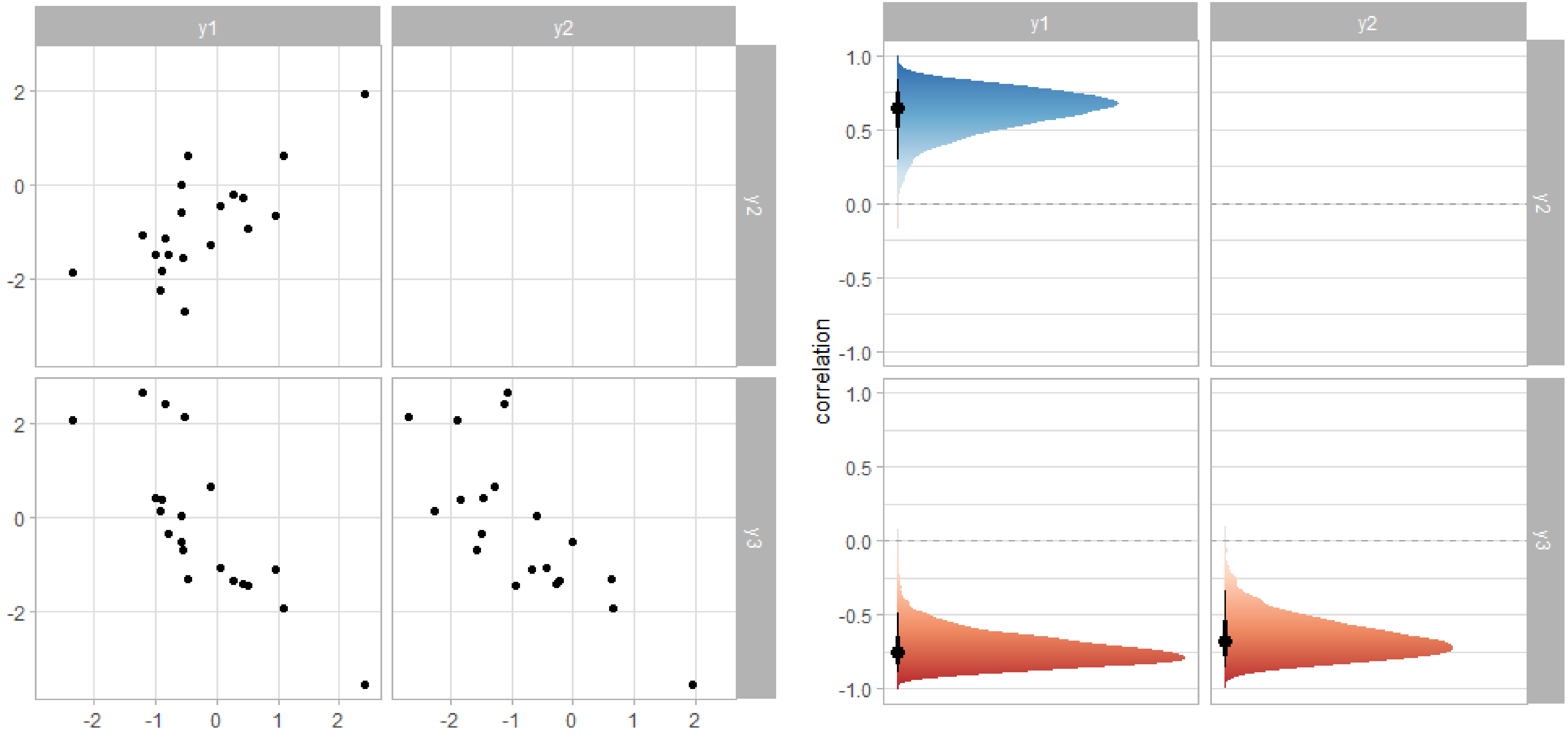
This geometry ...	... uses these defaults: mapping = *aesthetic mapping*	**slab_type =** *function assigned to the computed aesthetic* **f**	side = *side to draw the slab on*	
stat_sample_slabinterval() stat_dist_slabinterval()	aes(thickness = **f**)	**"pdf"**	"topright"	
stat_halfeye() stat_dist_halfeye()	aes(thickness = f)	"pdf"	"topright"	
stat_eye() stat_dist_eye()	aes(thickness = f)	"pdf"	"both"	

This geometry ...	... uses these defaults: mapping = *aesthetic mapping*	slab_type = *function assigned to the computed aesthetic* **f**	side = *side to draw the slab on*	
stat_sample_slabinterval() stat_dist_slabinterval()	aes(thickness = f)	"pdf"	"topright"	
stat_halfeye() stat_dist_halfeye()	aes(thickness = f)	"pdf"	"topright"	
stat_eye() stat_dist_eye()	aes(thickness = f)	"pdf"	"both"	
stat_gradientinterval() stat_dist_gradientinterval()	aes(slab_alpha = f)	"pdf"	"topright"	

This geometry ...	... uses these defaults:			
	mapping = *aesthetic mapping*	slab_type = *function assigned to the computed aesthetic* **f**	side = *side to draw the slab on*	
stat_sample_slabinterval() stat_dist_slabinterval()	aes(thickness = f)	**"pdf"**	"topright"	
stat_halfeye() stat_dist_halfeye()	aes(thickness = f)	"pdf"	"topright"	
stat_eye() stat_dist_eye()	aes(thickness = f)	"pdf"	"both"	
stat_gradientinterval() stat_dist_gradientinterval()	aes(slab_alpha = f)	"pdf"	"topright"	
stat_histinterval()	aes(thickness = f)	**"histogram"**	"topright"	

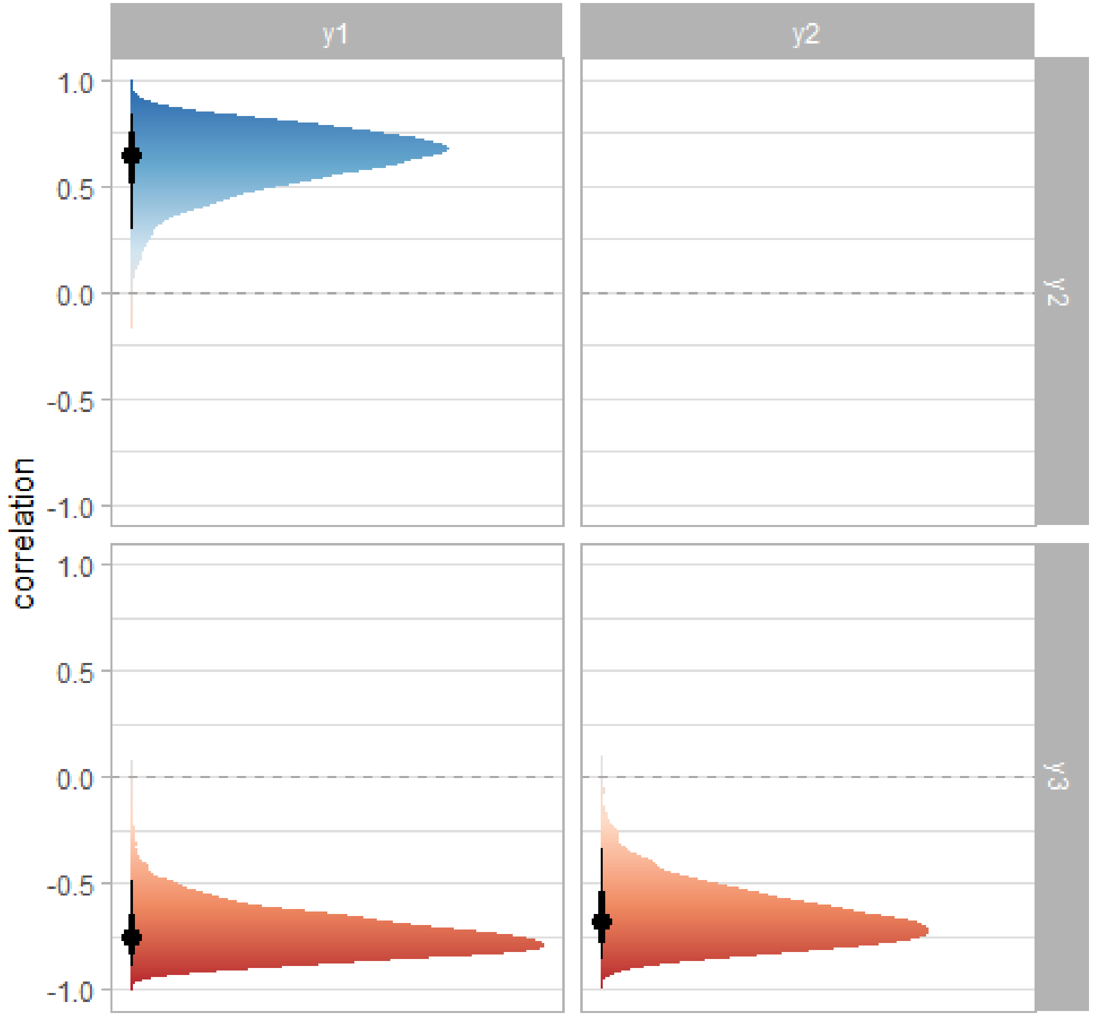
This geometry ...	... uses these defaults: mapping = *aesthetic mapping*	slab_type = *function assigned to the computed aesthetic* **f**	side = *side to draw the slab on*	
stat_sample_slabinterval() stat_dist_slabinterval()	aes(thickness = f)	"pdf"	"topright"	
stat_halfeye() stat_dist_halfeye()	aes(thickness = f)	"pdf"	"topright"	
stat_eye() stat_dist_eye()	aes(thickness = f)	"pdf"	"both"	
stat_gradientinterval() stat_dist_gradientinterval()	aes(slab_alpha = f)	"pdf"	"topright"	
stat_histinterval()	aes(thickness = f)	"histogram"	"topright"	
stat_cdfinterval() stat_dist_cdfinterval()	aes(thickness = f)	"cdf"	"topleft"	

This geometry ...	... combined with this mapping ...	... does this:
stat_gradientinterval() stat_dist_gradientinterval()	aes(slab_alpha = stat(cdf))	
stat_halfeye() stat_dist_halfeye()	aes(fill = stat(abs(x) < 1.5))	
stat_gradientinterval() stat_dist_gradientinterval()	aes(slab_alpha = stat(−pmax(abs(1 − 2*cdf), .95)))	
stat_eye() stat_dist_eye()	aes(slab_alpha = stat(−pmax(abs(1 − 2*cdf), .95)))	
stat_halfeye() stat_dist_halfeye()	aes(fill = stat(cut_cdf_qi(cdf, .width = c(.66, .95, 1))))	

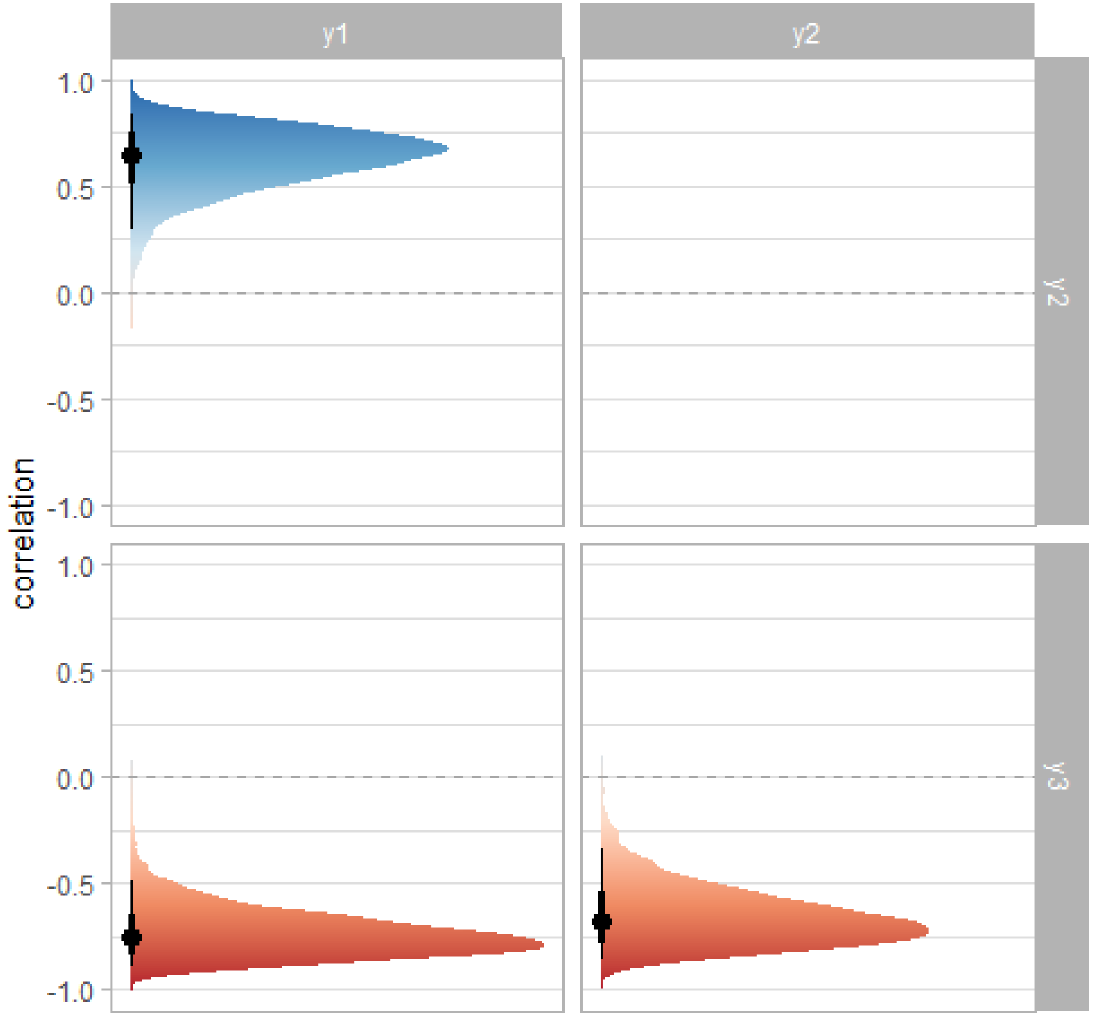


y1
y2
y2
y3
correlation
1.0
0.5
0.0
-0.5
-1.0
-2
-1
0
1
2

```
rescor_plot_heat = m %>%
  gather_draws(`rescor.*`, regex = TRUE) %>%
  separate(.variable,
    c(".rescor", ".col", ".row"), sep = "__"
  ) %>%
  ggplot(aes(y = .value, x = 0)) +
  stat_halfeye(
    aes(fill = stat(y)),
  ) +
  facet_grid(.row ~ .col)
```



```
rescor_plot_heat = m %>%
  gather_draws(`rescor.*`, regex = TRUE) %>%
  separate(.variable,
    c(".rescor", ".col", ".row"), sep = "__"
  ) %>%
  ggplot(aes(y = .value, x = 0)) +
  stat_halfeye(
    aes(fill = stat(y)),
    fill_type = "gradient" # R 4.1!!!
  ) +
  facet_grid(.row ~ .col)
```

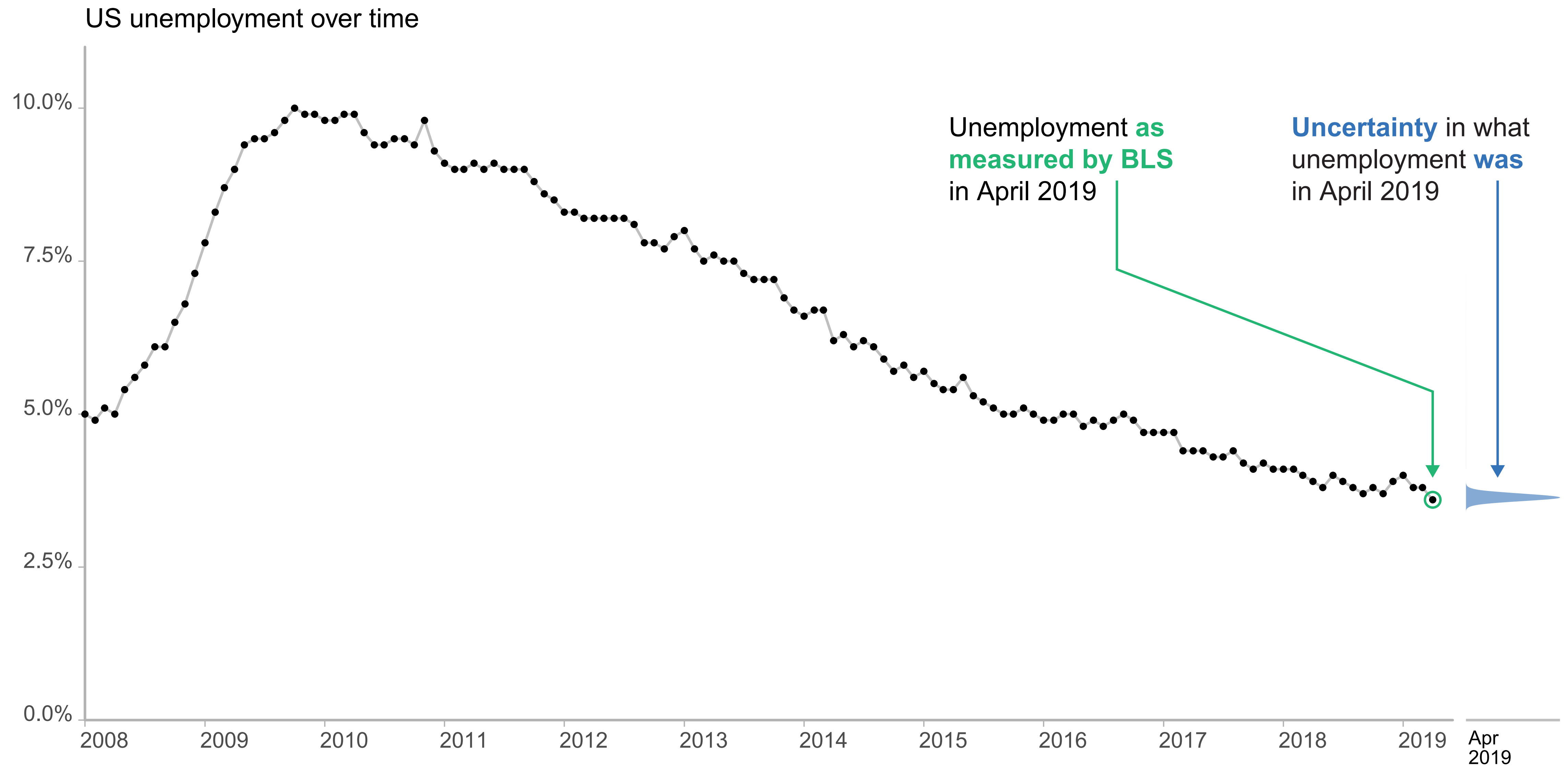


This approach allows us to...

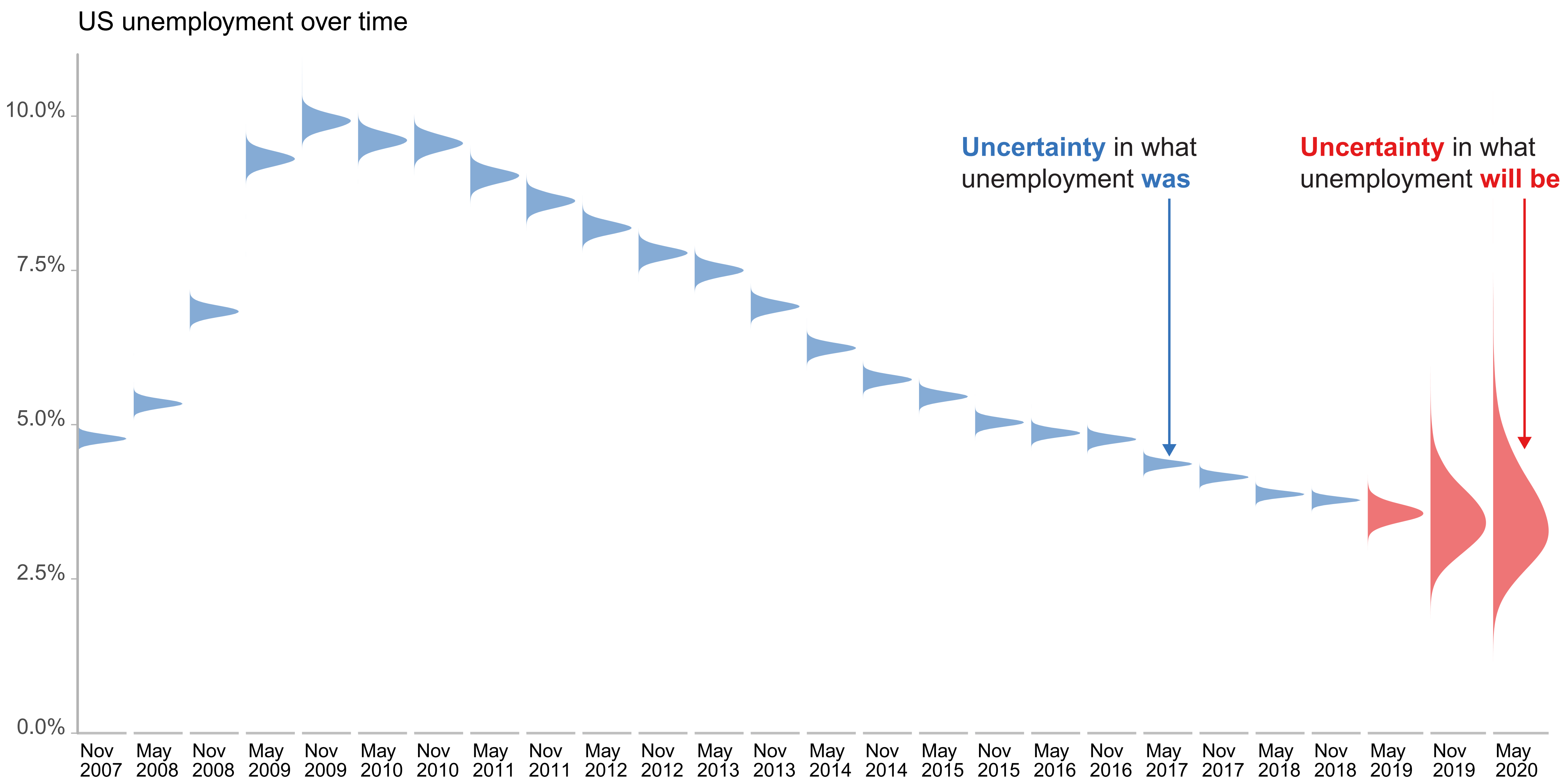
1. **Quickly prototype** a variety of designs without learning a bunch of "chart type" functions

2. **Reason about visualization effectiveness** using the grammar of graphics and visual perception

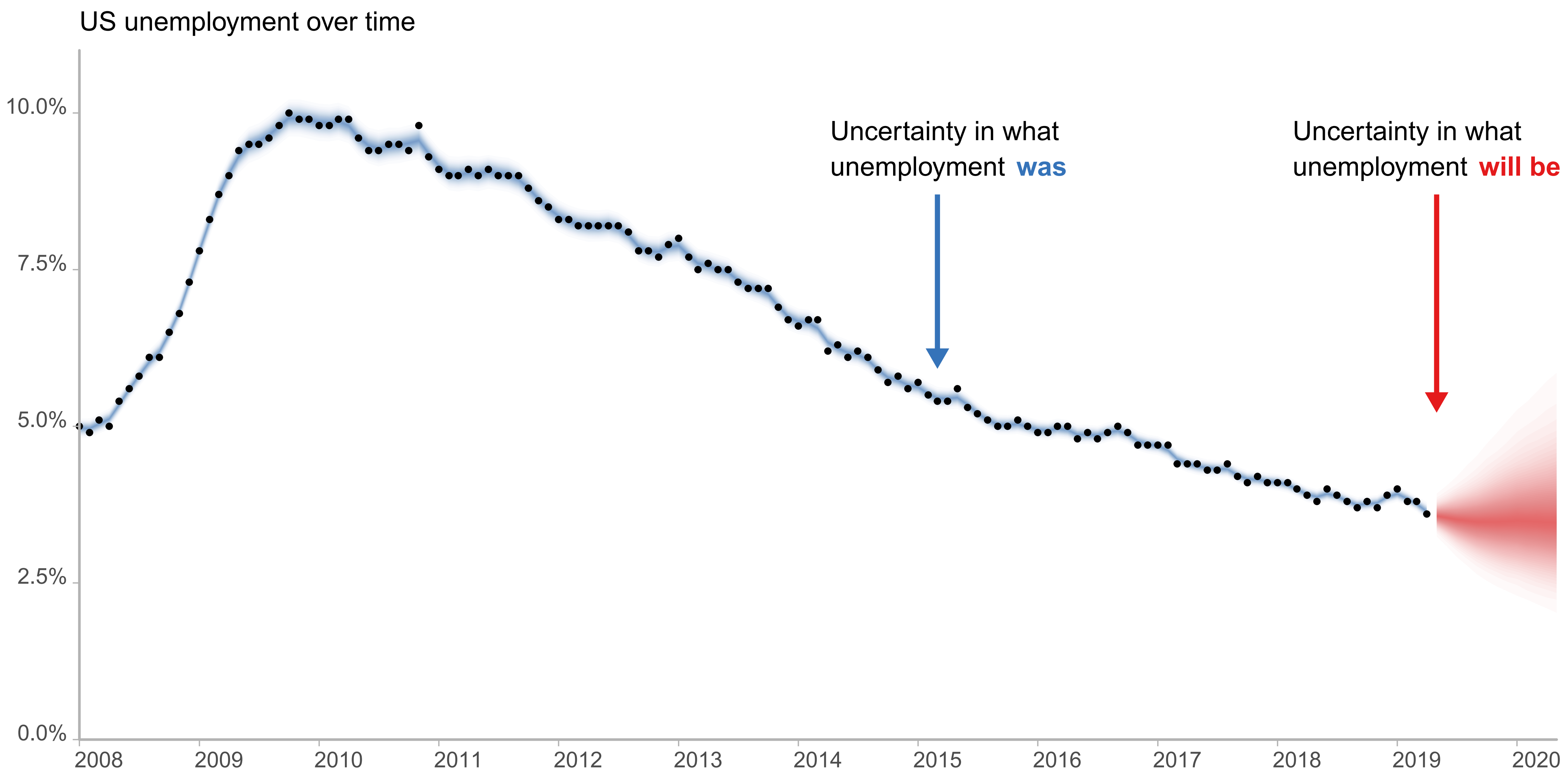
Reasoning about effectiveness…



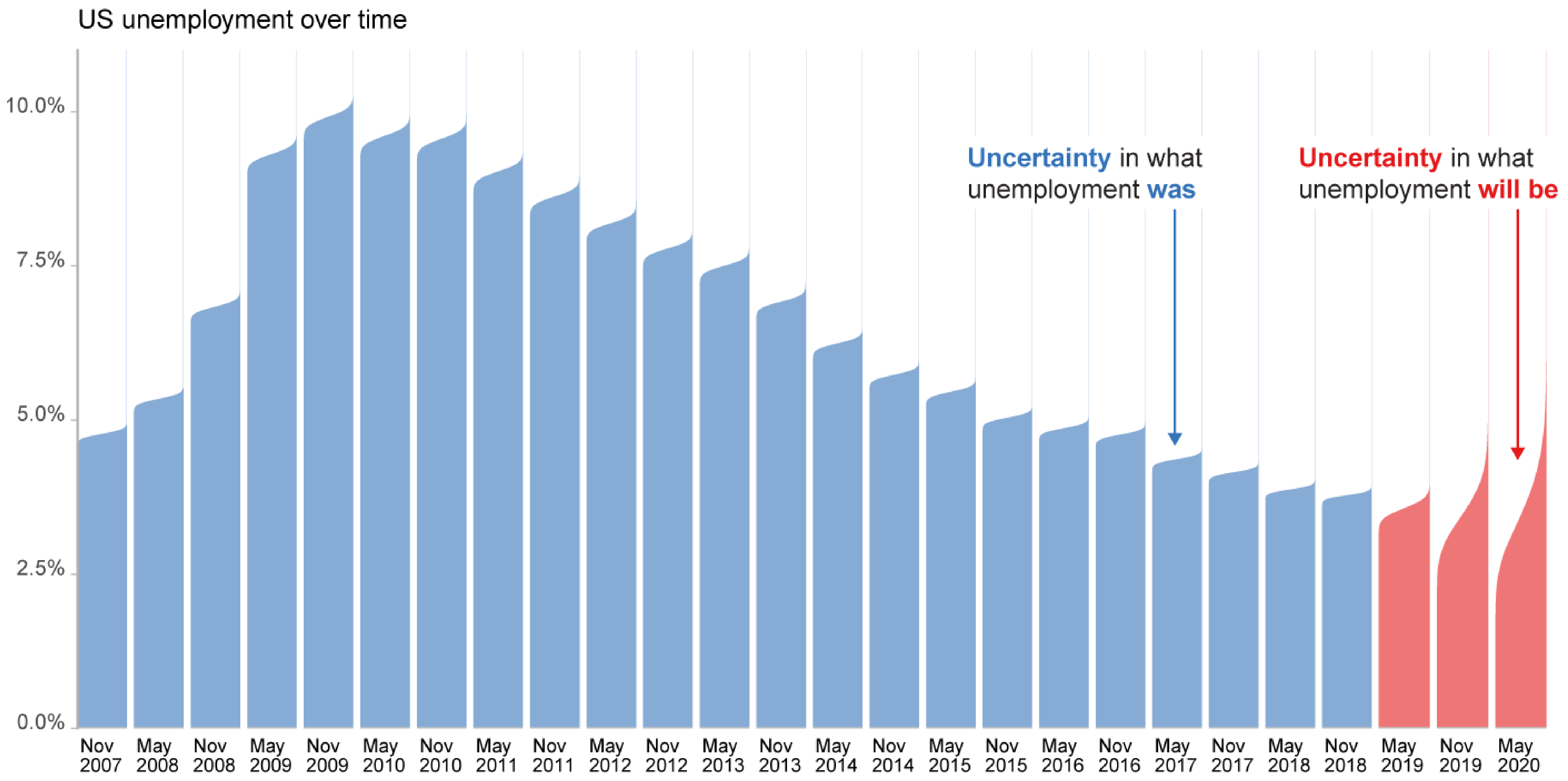
[https://github.com/mjskay/uncertainty-examples/blob/master/us-unemployment.Rmd]



[https://github.com/mjskay/uncertainty-examples/blob/master/us-unemployment.Rmd]



[https://github.com/mjskay/uncertainty-examples/blob/master/us-unemployment.Rmd]



[https://github.com/mjskay/uncertainty-examples/blob/master/us-unemployment.Rmd]

Reasoning about effectiveness means…

Thinking about visual channel accuracy

Tradeoffs in resolution

Audience tasks and metaphor

(demos)

The ultimate goal: a flexible language for specifying and reasoning about uncertainty visualizations

Thanks!

Students: Xiaoying Pu, Brian Hall, Abhraneel Sarma, Puhe Liange, Tara Kola, Michael Fernandes, Logan Walls

Collaborators: Jessica Hullman, Sean Munson, Julie Kientz, Shwetak Patel, Alex Kale, Gregory Nelson, Eric Hekler, Jeff Heer, Steve Haroz, Pierre Dragicevic, Yvonne Jansen, Fanny Chevalier

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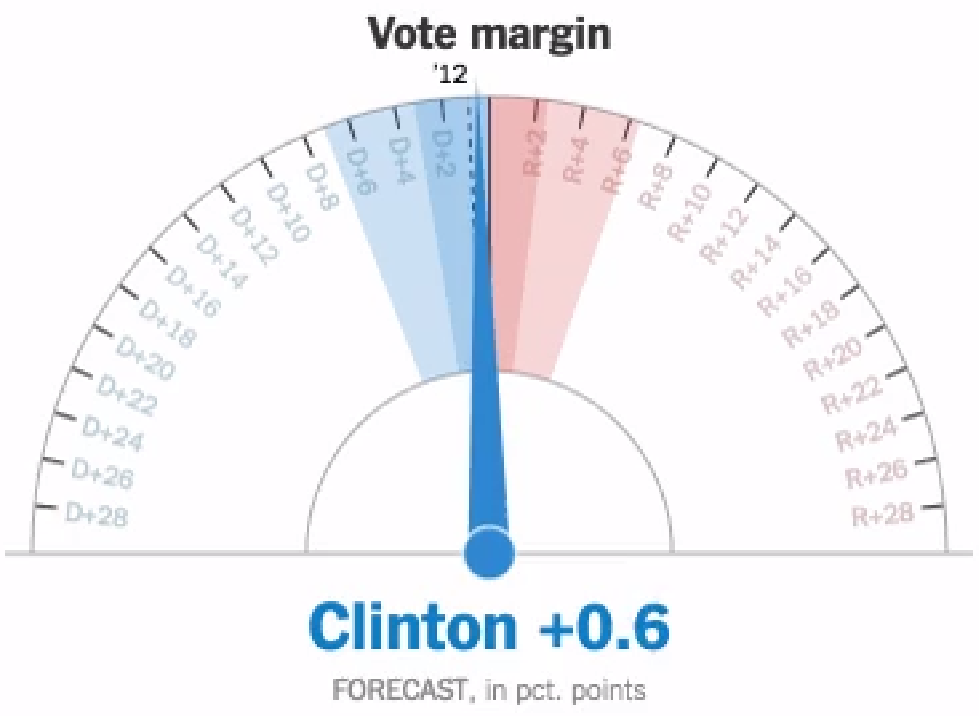
Collective

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**

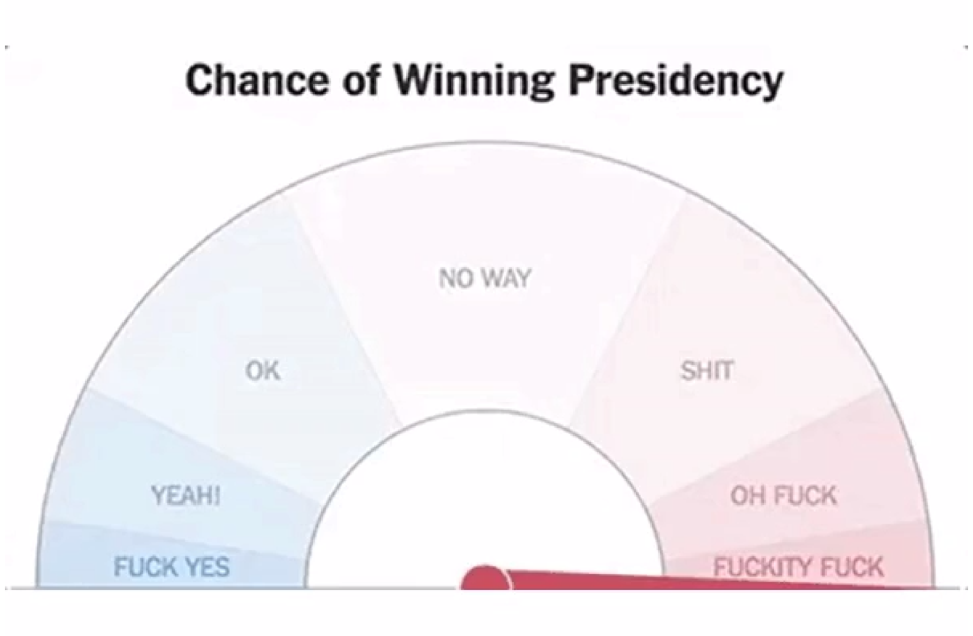


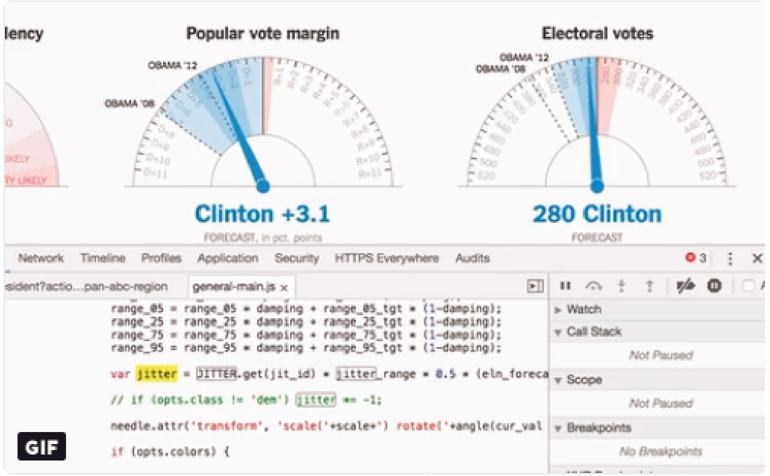
Photo: rhyselsmore/Twitter

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…

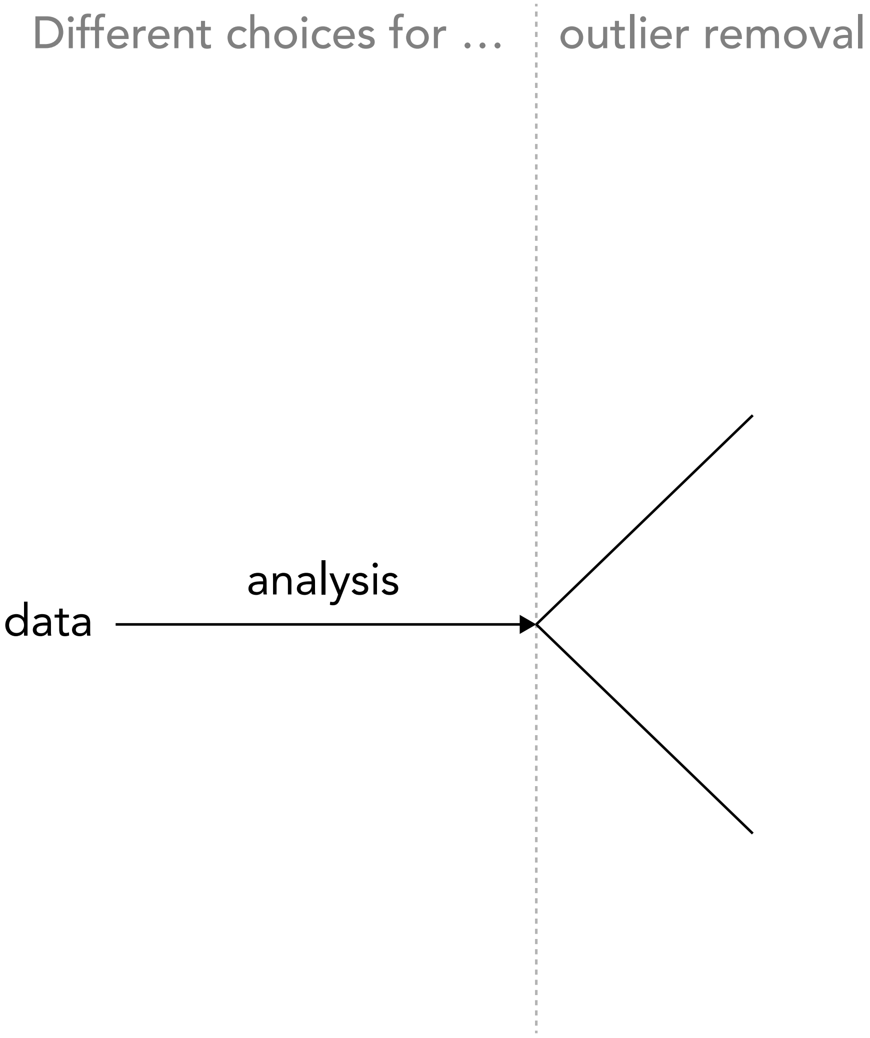
present well-calibrated uncertainty
that cannot be ignored
in ways people can actually understand

Let’s step back from
strictly probabilistic uncertainty

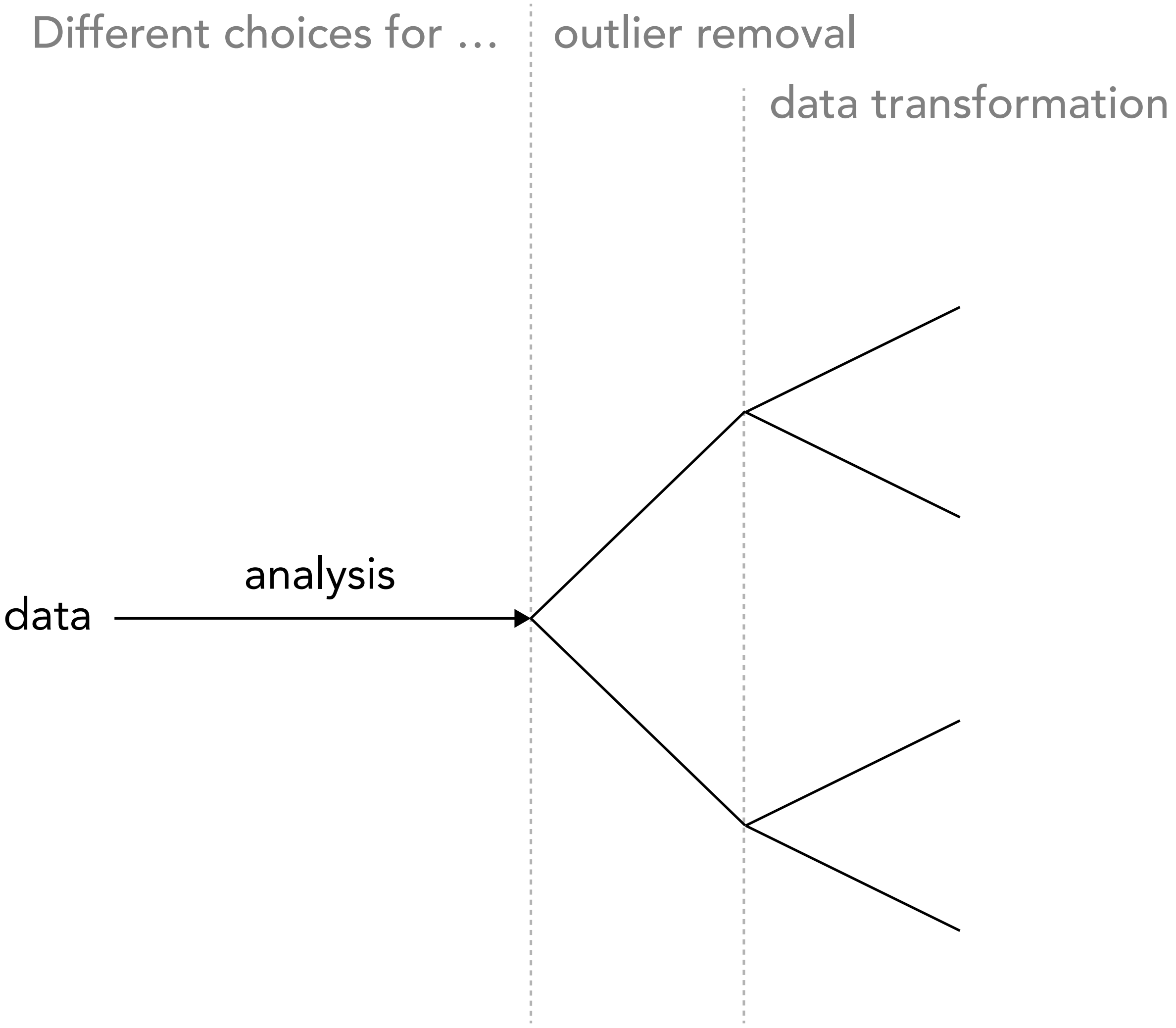
$$\text{data} \xrightarrow{\text{analysis}} p < 0.05$$

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

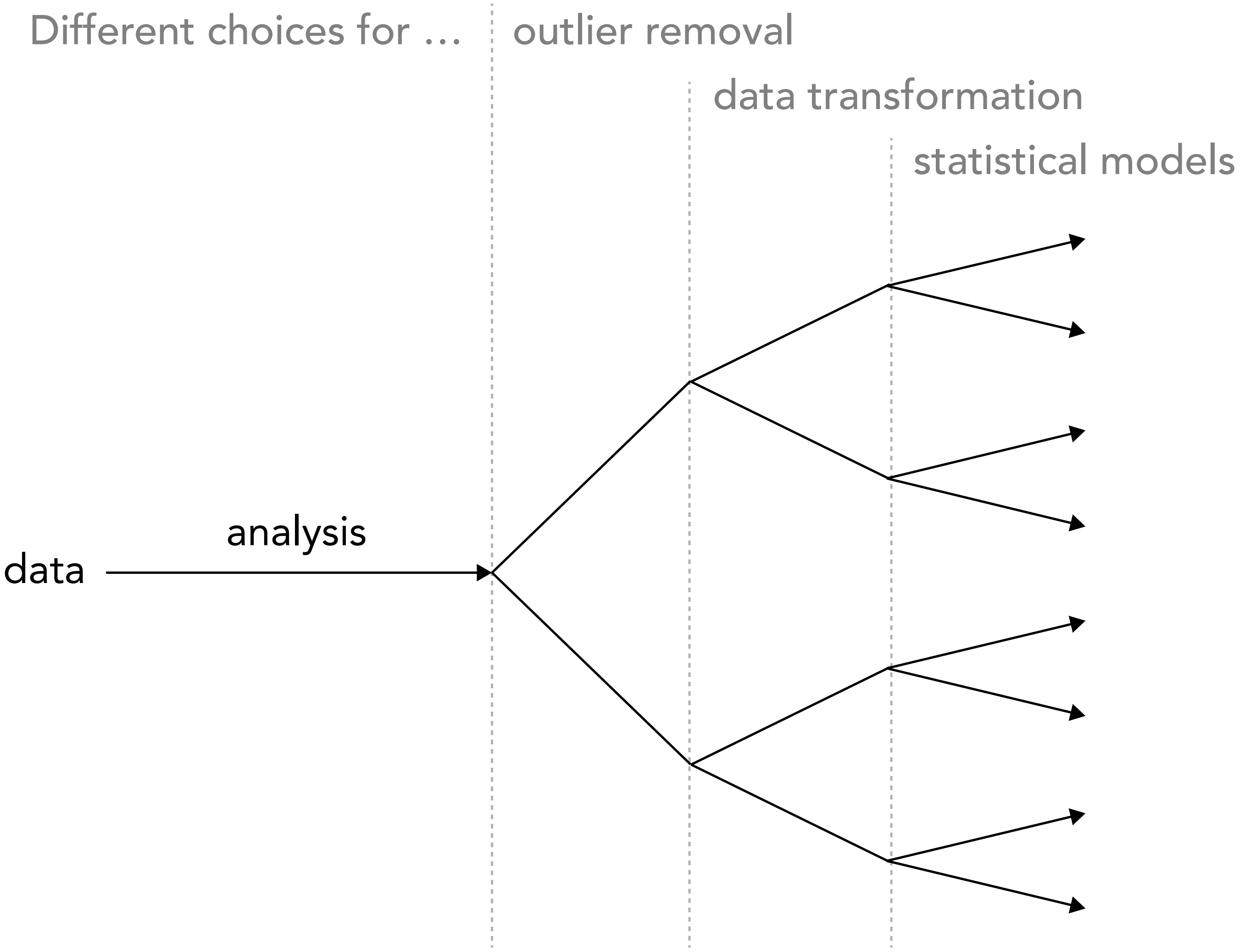
Garden of forking paths [Gelman and Loken 2014]



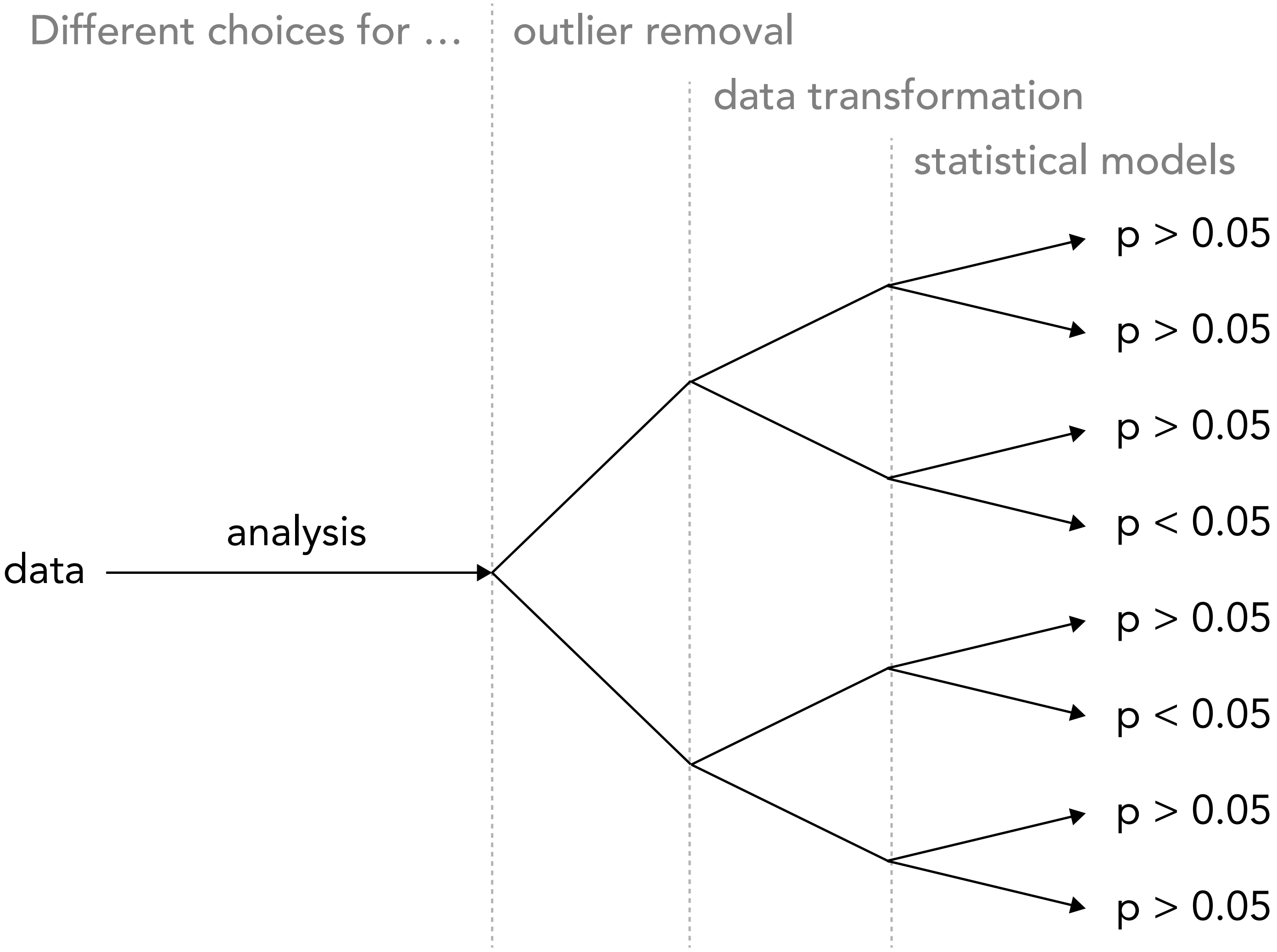
Garden of forking paths [Gelman and Loken 2014]



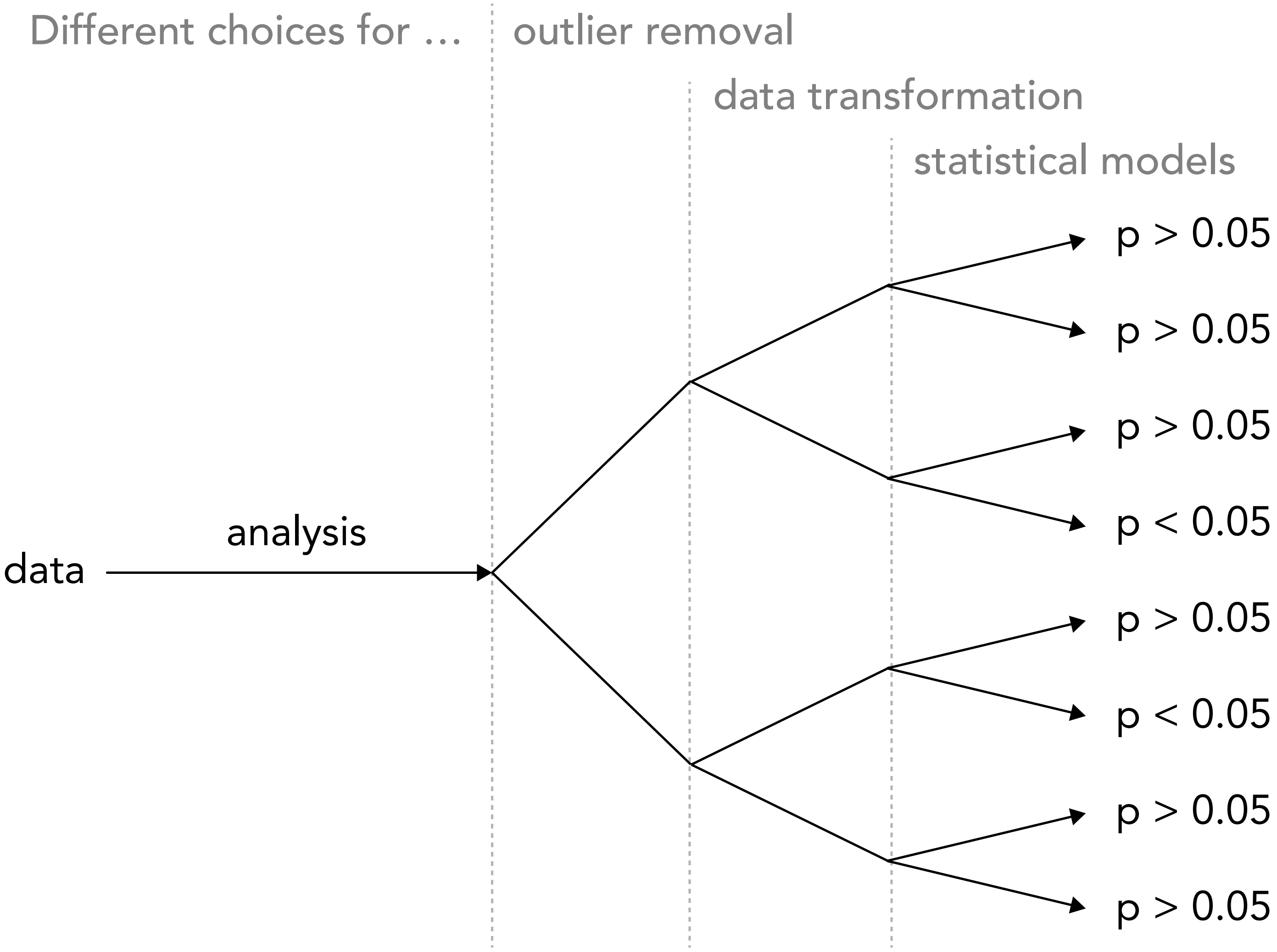
Garden of forking paths [Gelman and Loken 2014]



Garden of forking paths [Gelman and Loken 2014]

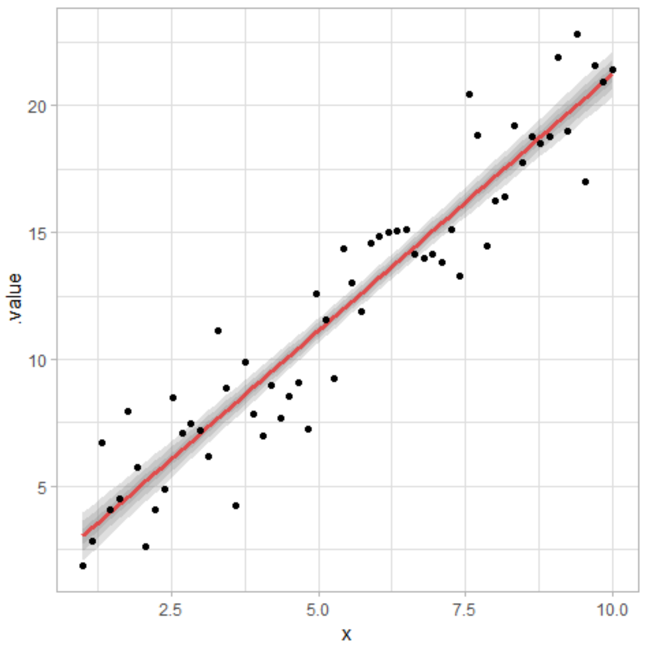


Garden of forking paths [Gelman and Loken 2014]

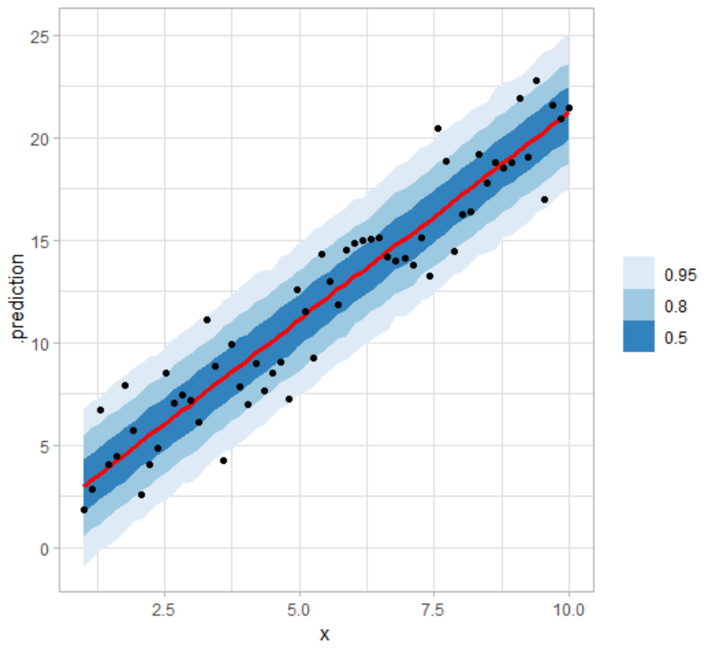


This is **specification uncertainty**

Parameter uncertainty



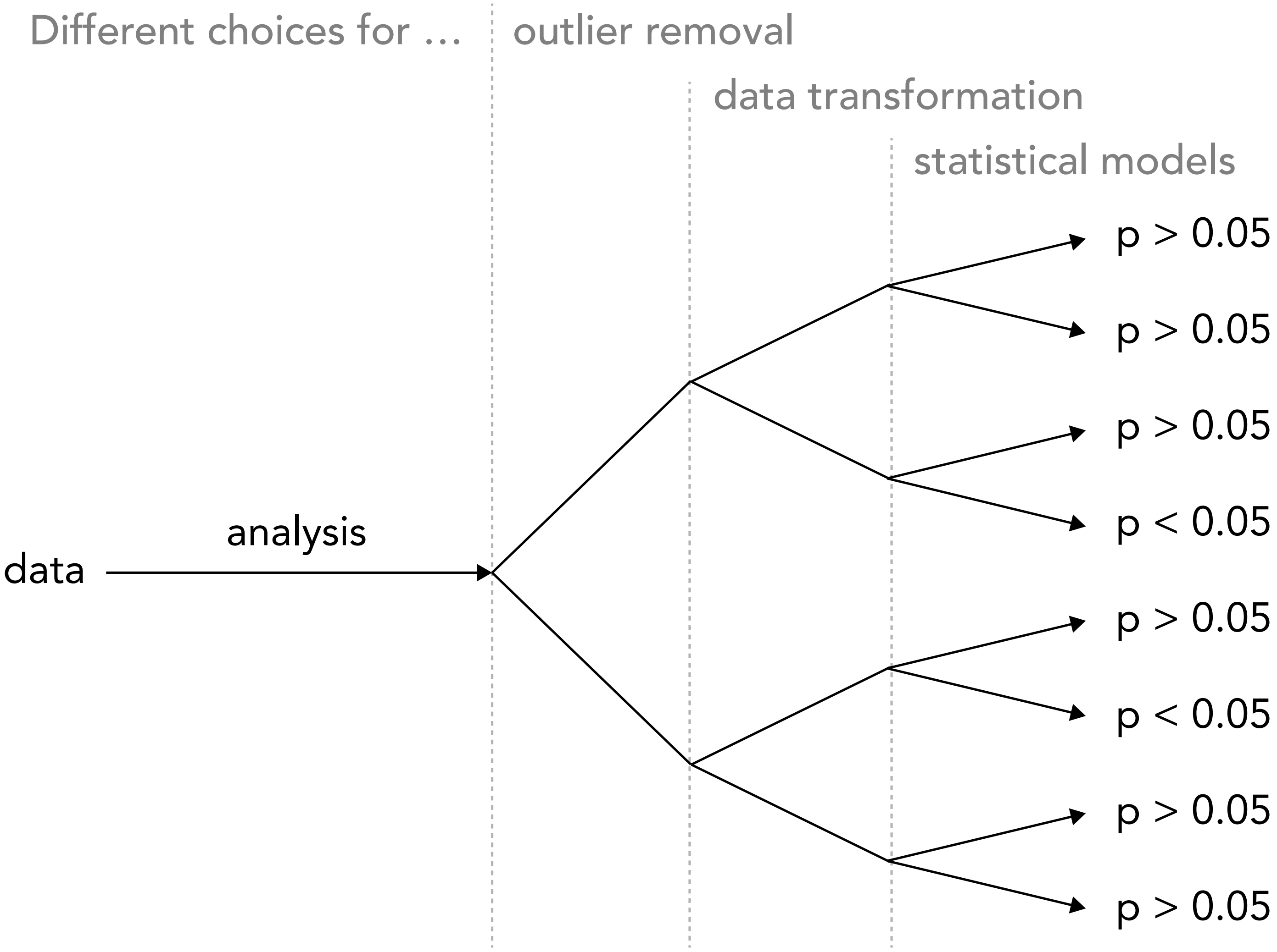
Predictive uncertainty



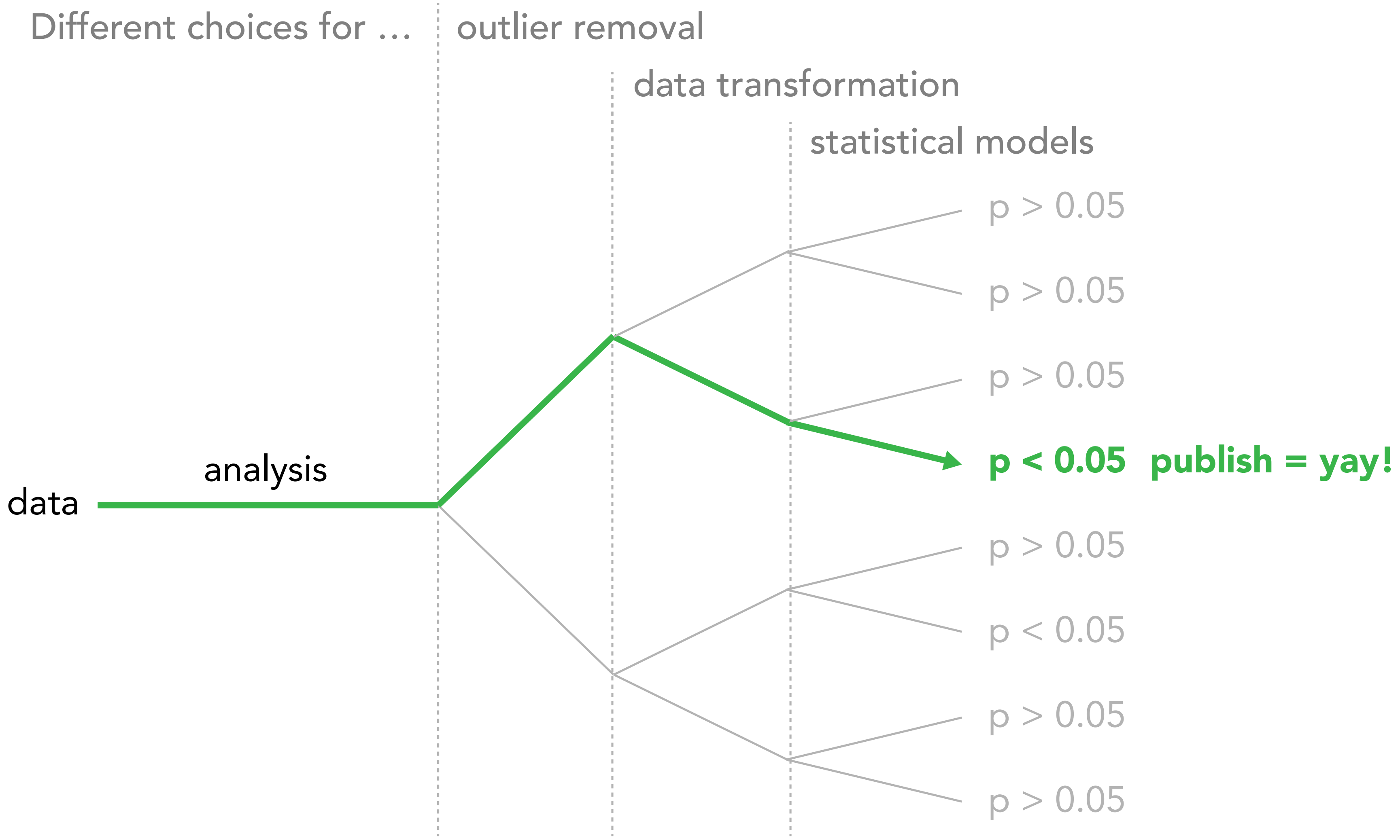
Specification uncertainty

How well does this describe reality?

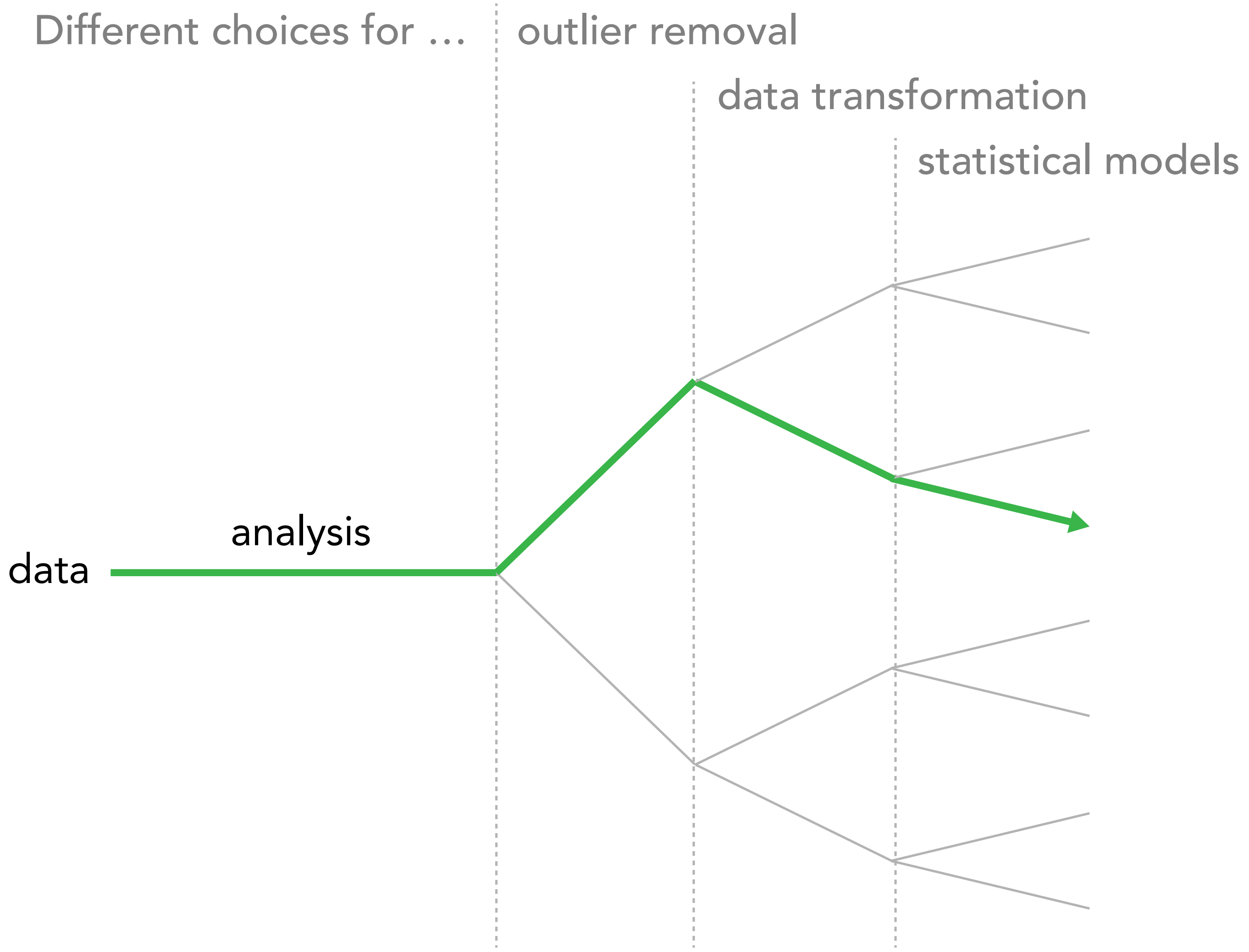
Garden of forking paths [Gelman and Loken 2014]



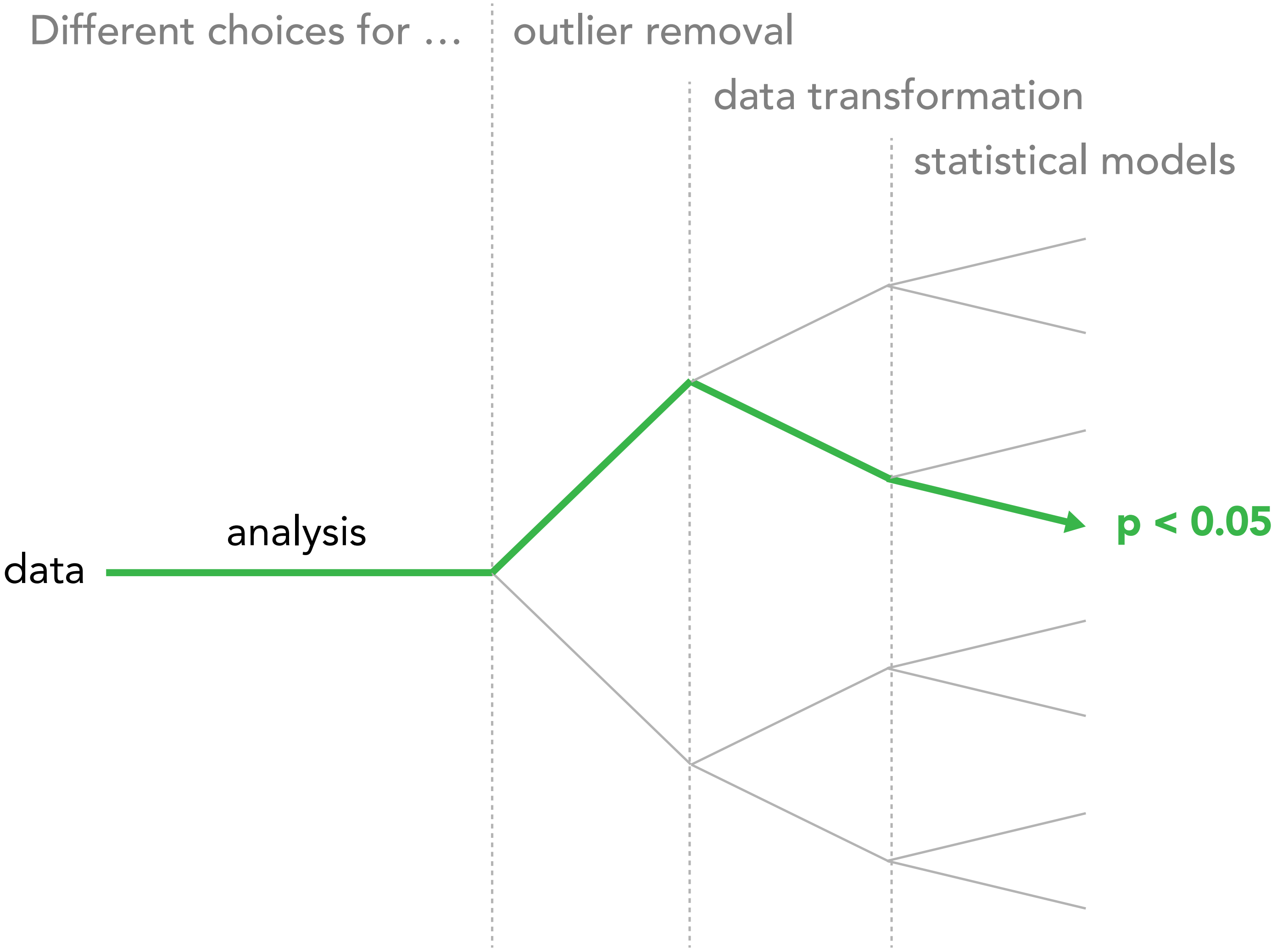
Garden of forking paths [Gelman and Loken 2014]



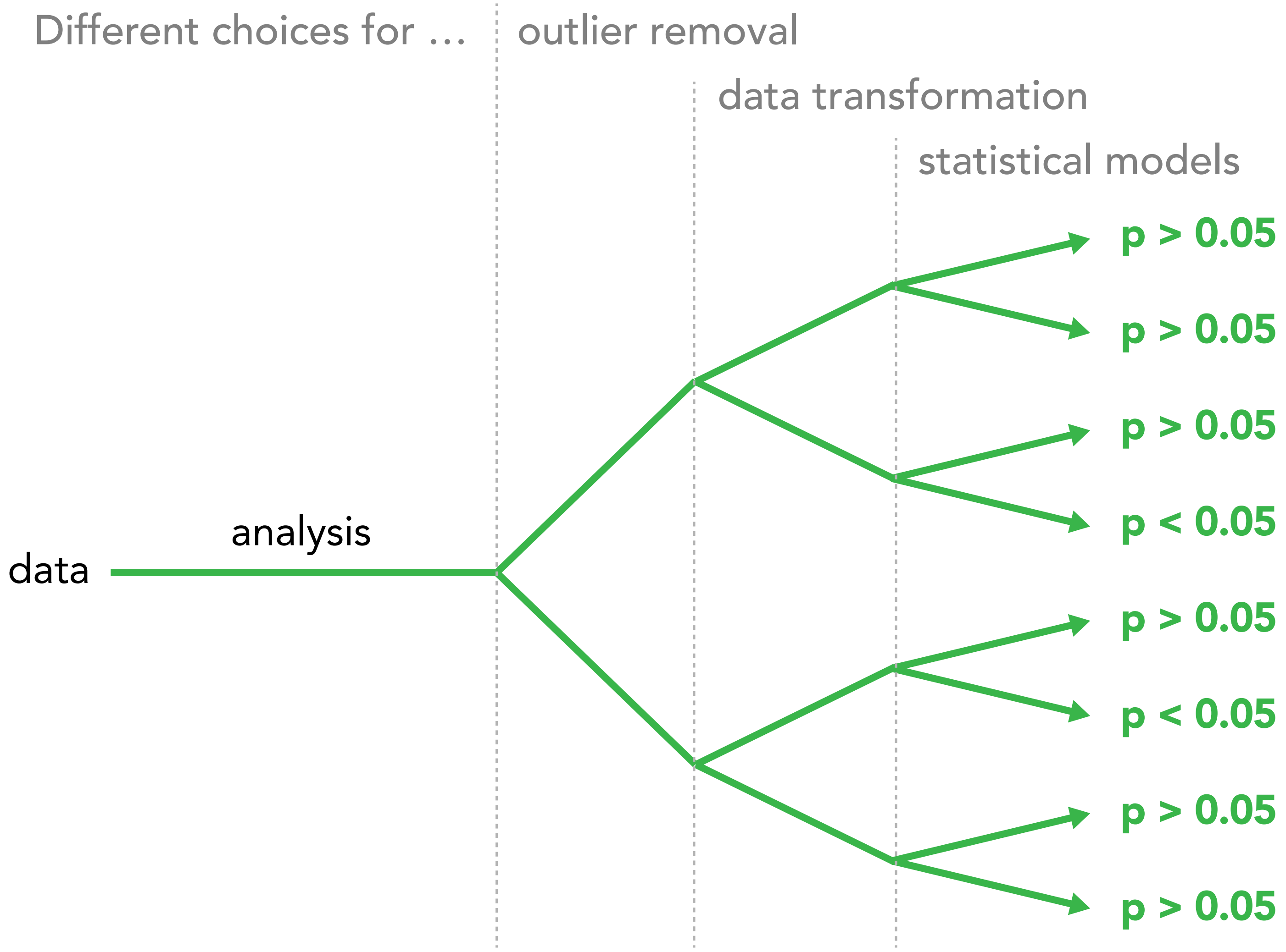
(pre-registration / hold-out)



(pre-registration / hold-out)



(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

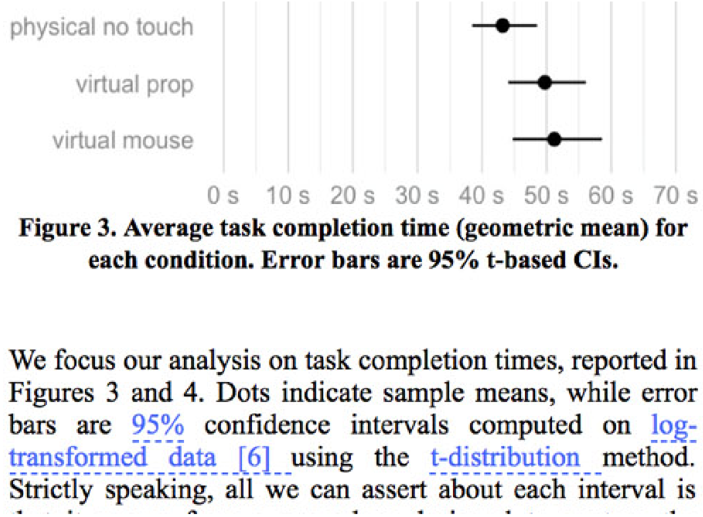
Donation preferences

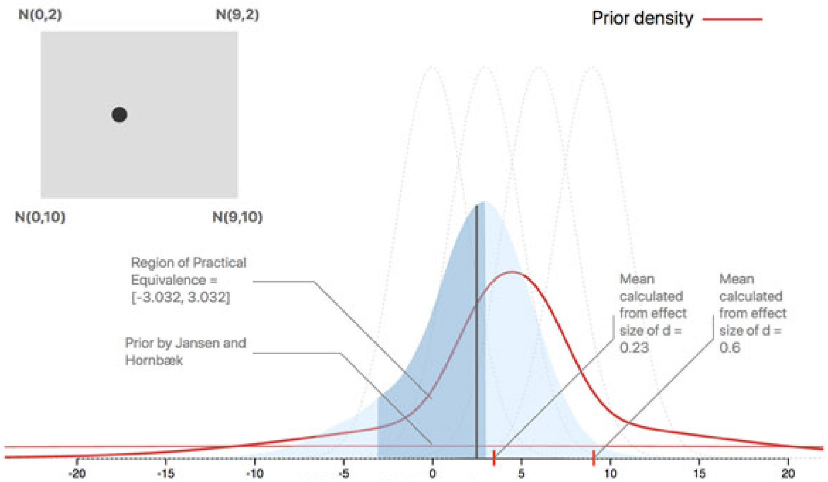
			R1					R2					R3				
			F1	F2	F3	F4	F5	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
NMO1	ECL1	EC 1	0	0	0	0	0	0.03	0.04	0.01	0.04	0.01	0.01	0.01	0	0.01	0
		EC 2	0.07	0.1	0.01	0.06	0	0.19	0.33	0.09	0.35	0.14	0.1	0.18	0.03	0.17	0.04
	ECL2	EC 1	0.01	0.01	0	0 .01	0	0.03	0.04	0.01	0.05	0.01	0.01	0.01	0	0.02	0
		EC 2	0.08	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

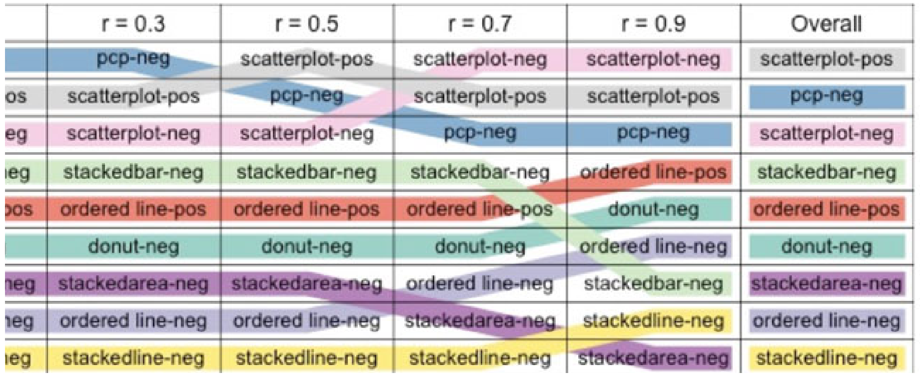
[Steegen, Tuerlinckz, Gelman, Vanpaemel. Increasing Transparency Through a Multiverse Analysis. Perspectives on Psychological Science, 2016]

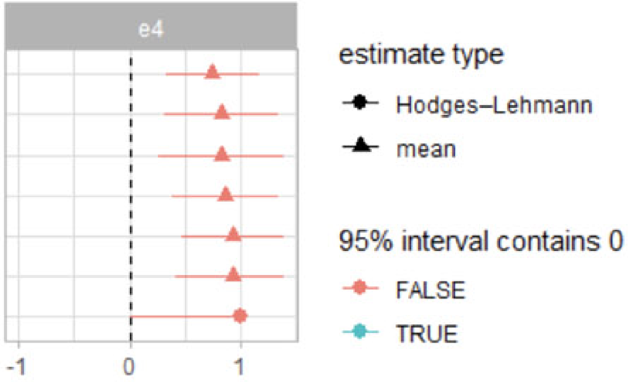
Explorable Multiverse Analysis Reports

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









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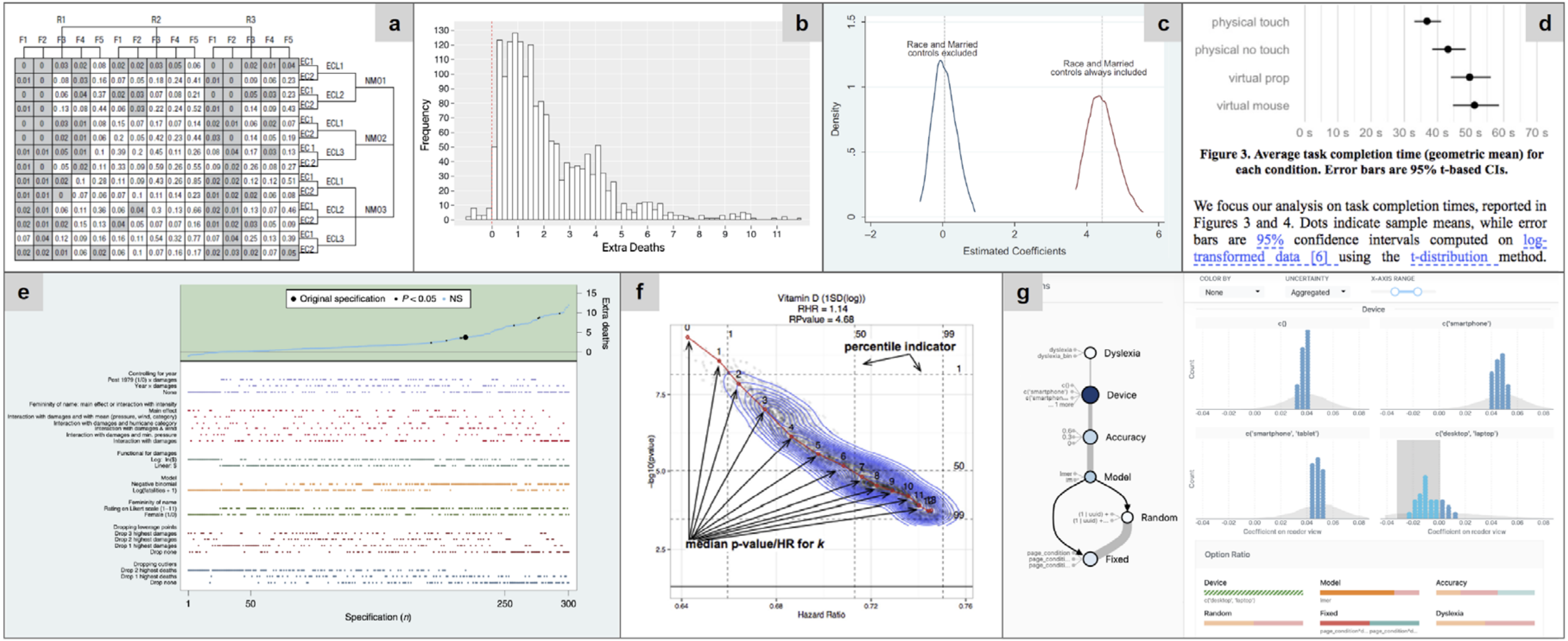
We need better ways to acknowledge specification uncertainty and have a conversation about it through the literature

Explorable Multiverse Analysis Reports

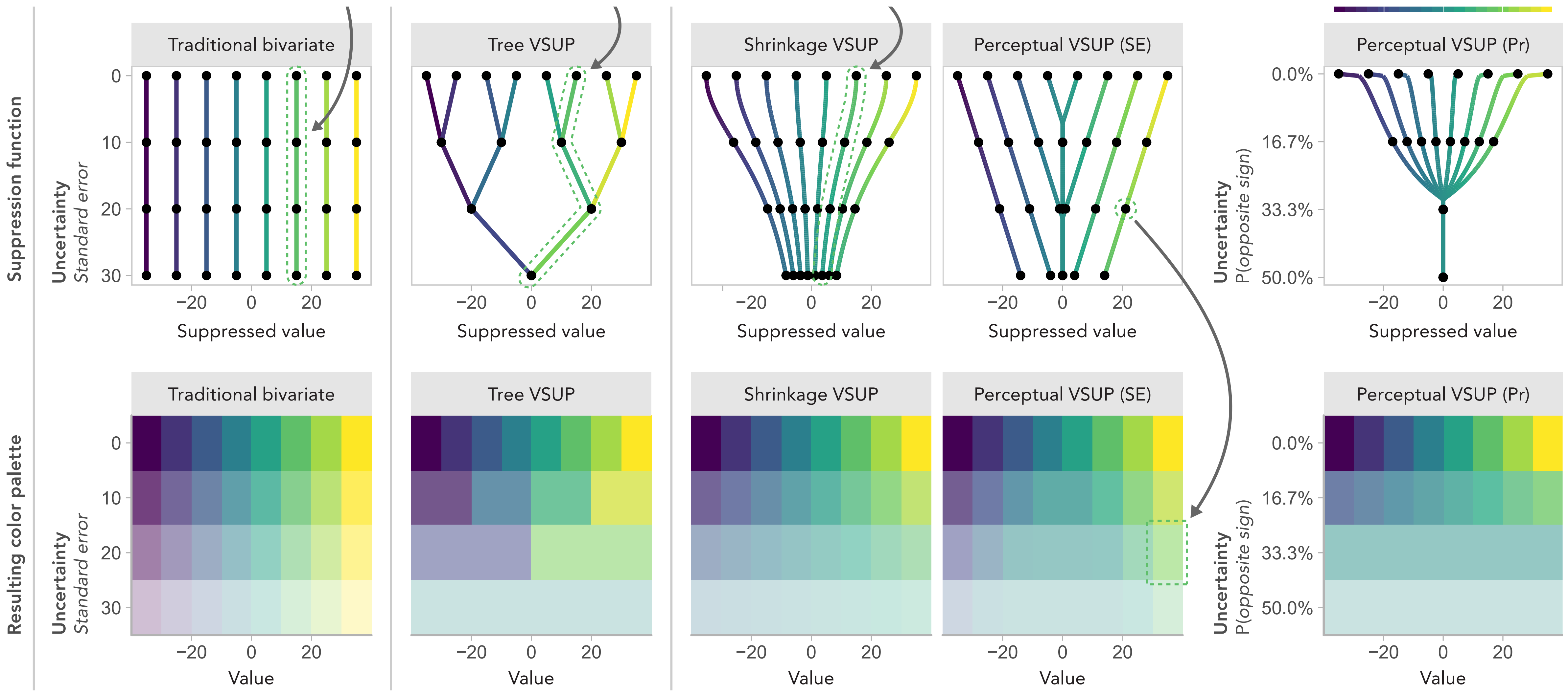
[Dragicevic, Jansen, Sarma, **Kay**, and Chevalier. Increasing the Transparency of Research Papers with Explorable Multiverse Analyses. CHI 2019: https://explorablemultiverse.github.io/. **Best Paper**]

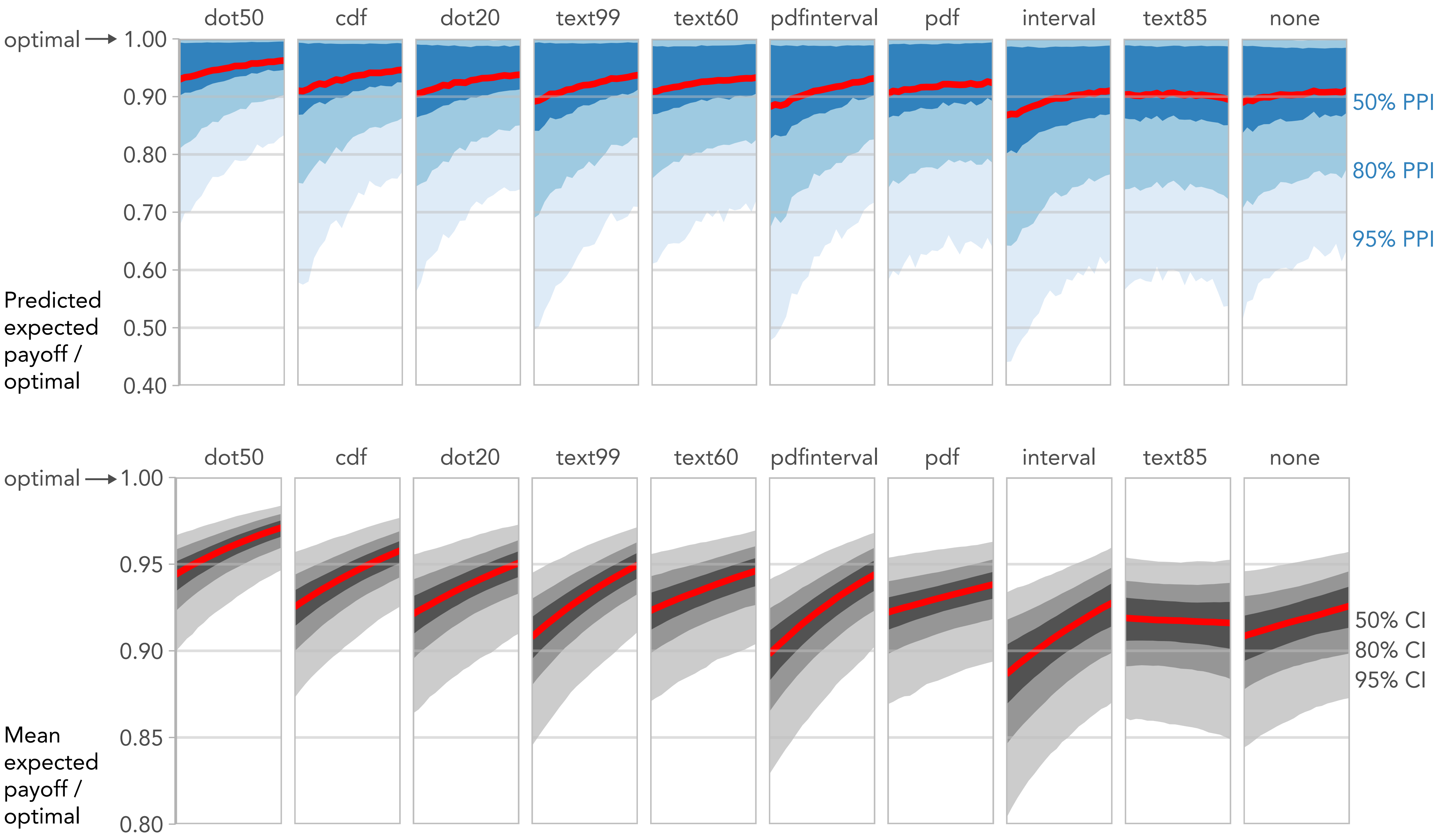
We need better ways to acknowledge specification uncertainty and have a conversation about it through the literature

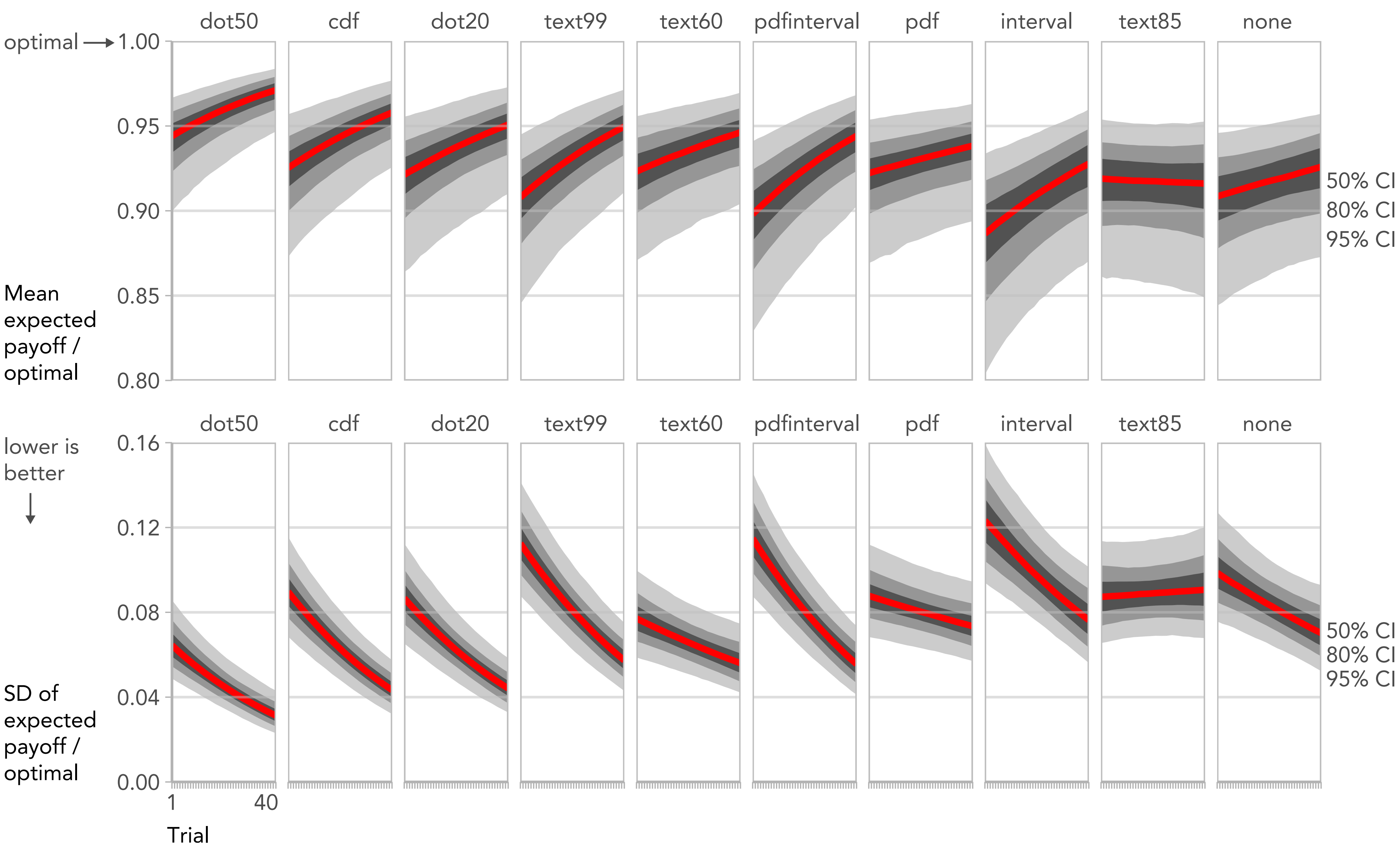
Currently building an R package [Abhraneel Sarma] and a visualization design space [Brian Hall]


a
R1
R2
R3
F1
F2
F3
F4
F5
ECL1
ECL2
ECL3
NM01
NM02
NM03
b
Frequency
Extra Deaths
c
Race and Married controls excluded
Race and Married controls always included
Density
Estimated Coefficients
d
physical touch
physical no touch
virtual prop
virtual mouse
0 s
10 s
20 s
30 s
40 s
50 s
60 s
70 s
Figure 3. Average task completion time (geometric mean) for each condition. Error bars are 95% t-based CIs.
We focus our analysis on task completion times, reported in Figures 3 and 4. Dots indicate sample means, while error bars are 95% confidence intervals computed on log-transformed data [6] using the t-distribution method.
e
Original specification
P < 0.05
NS
Extra deaths
Specification (n)
f
Vitamin D (1SD(log))
RHR = 1.14
RPvalue = 4.68
percentile indicator
median p-value/HR for k
-log10(pvalue)
Hazard Ratio
g
Dyslexia
Device
Accuracy
Model
Random
Fixed
COLOR BY
UNCERTAINTY
X-AXIS RANGE
None
Aggregated
Device
Count
Coefficient on reader view
Option Ratio
Model
Accuracy
Random
Fixed
Dyslexia

[Kay. How Much Value Should an Uncertainty Palette Suppress? https://osf.io/6xcnw/]



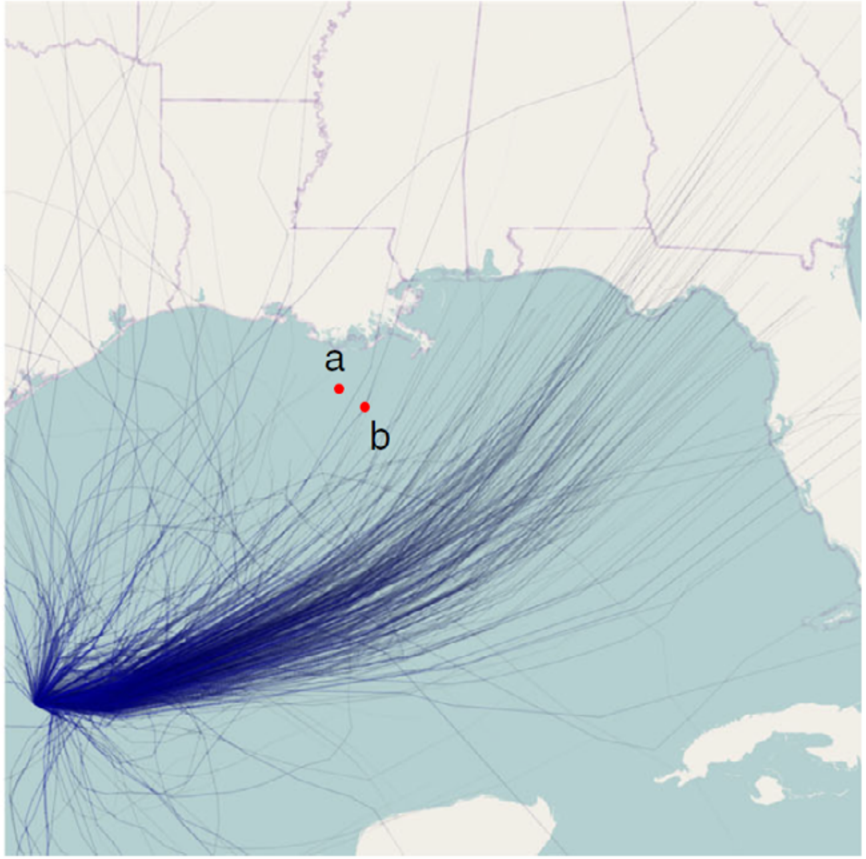

dot50
cdf
dot20
text99
text60
pdfinterval
pdf
interval
text85
none
optimal
1.00
0.90
0.80
0.70
0.60
0.50
0.40
Predicted expected payoff / optimal
50% PPI
80% PPI
95% PPI
dot50
cdf
dot20
text99
text60
pdfinterval
pdf
interval
text85
none
optimal
1.00
0.95
0.90
0.85
0.80
Mean expected payoff / optimal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

(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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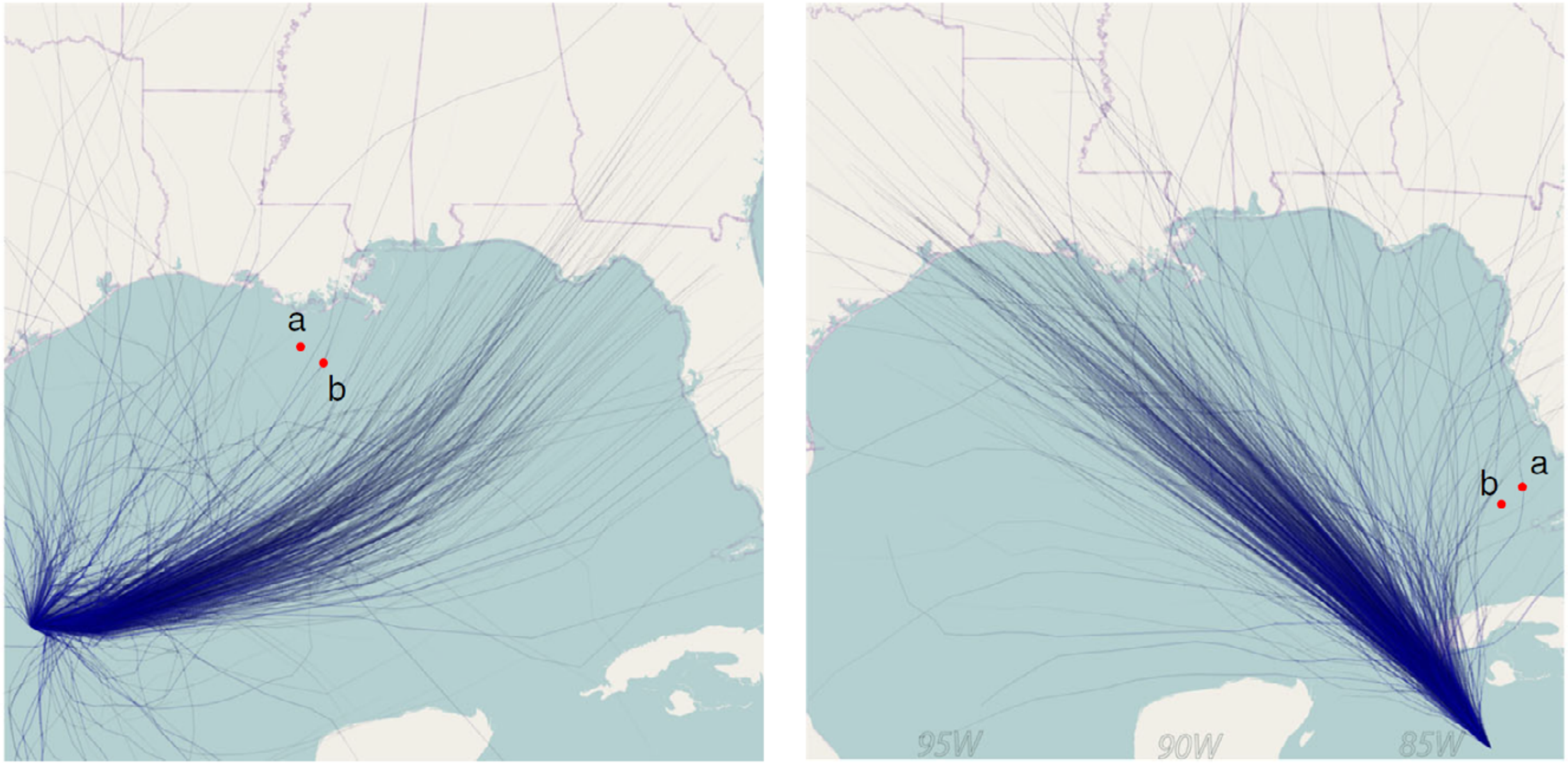
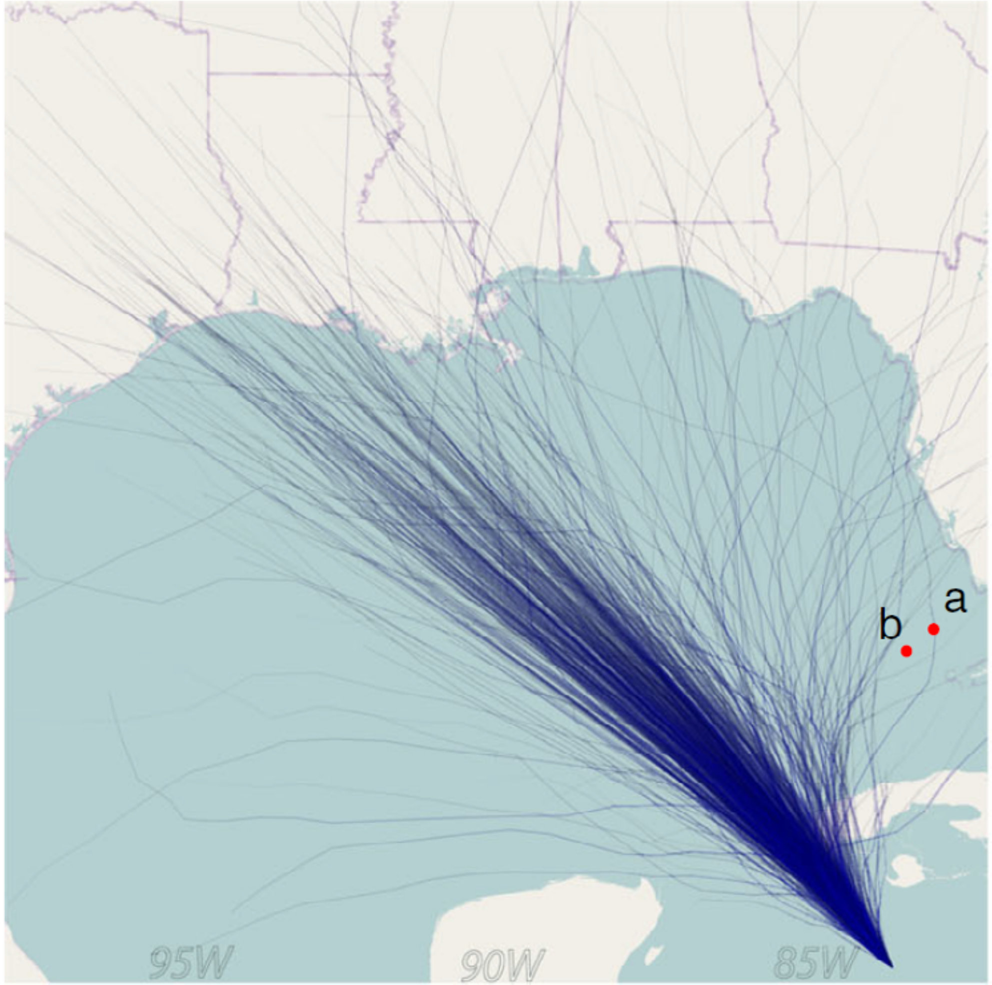


HOPs might aid deterministic construal errors



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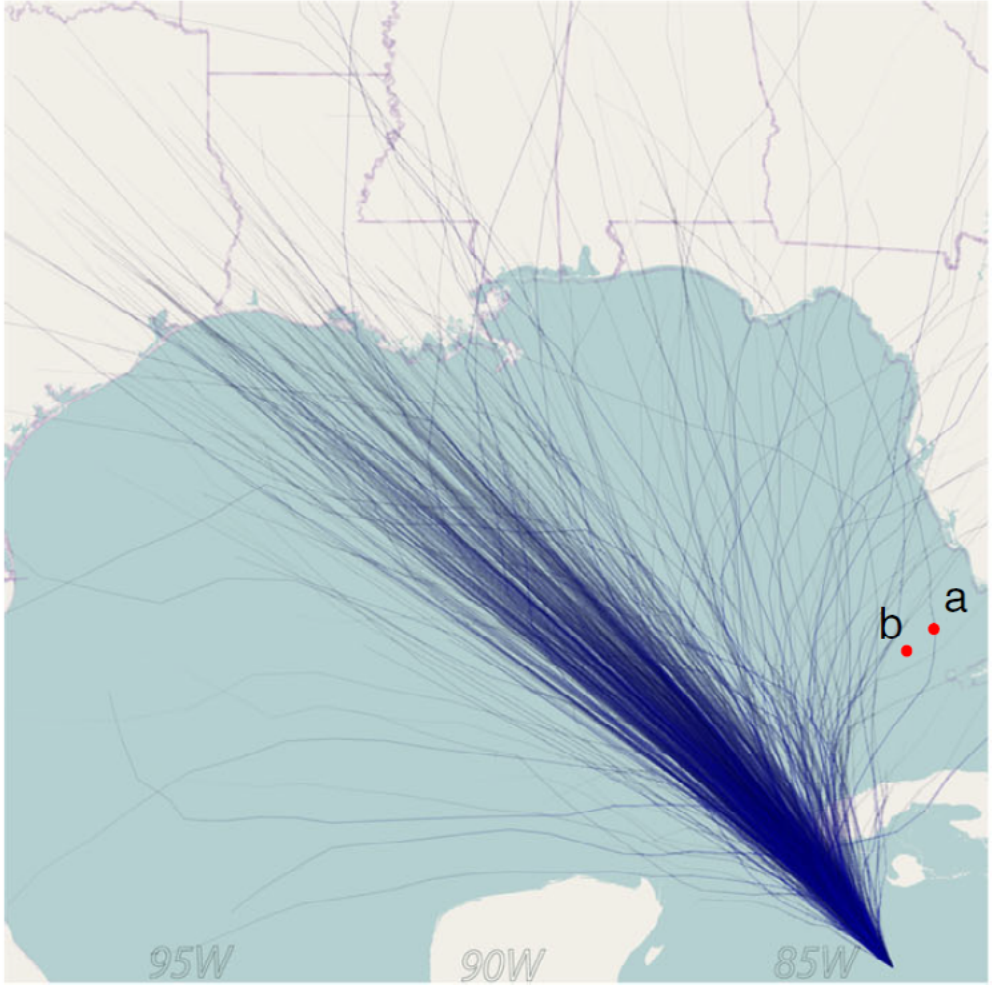
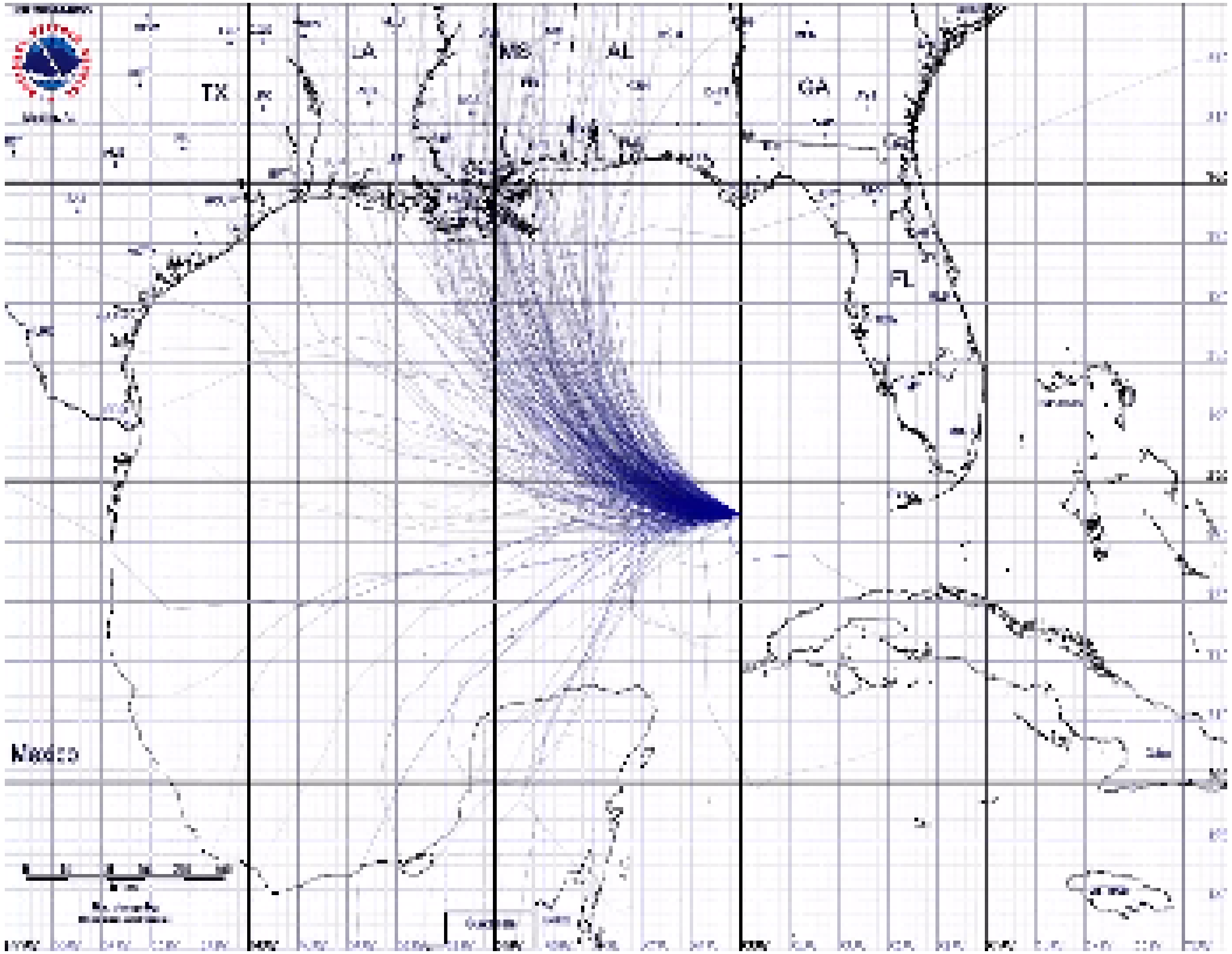
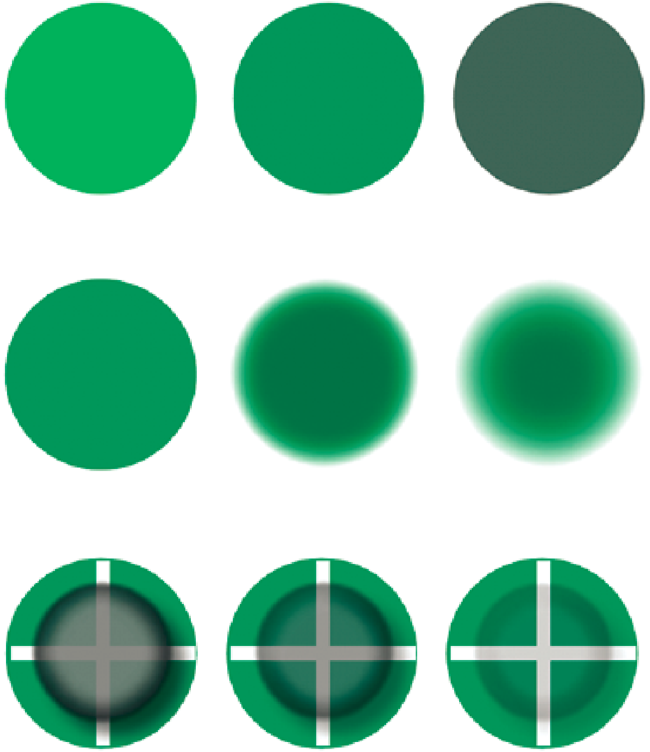




Glyph-based uncertainty

[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

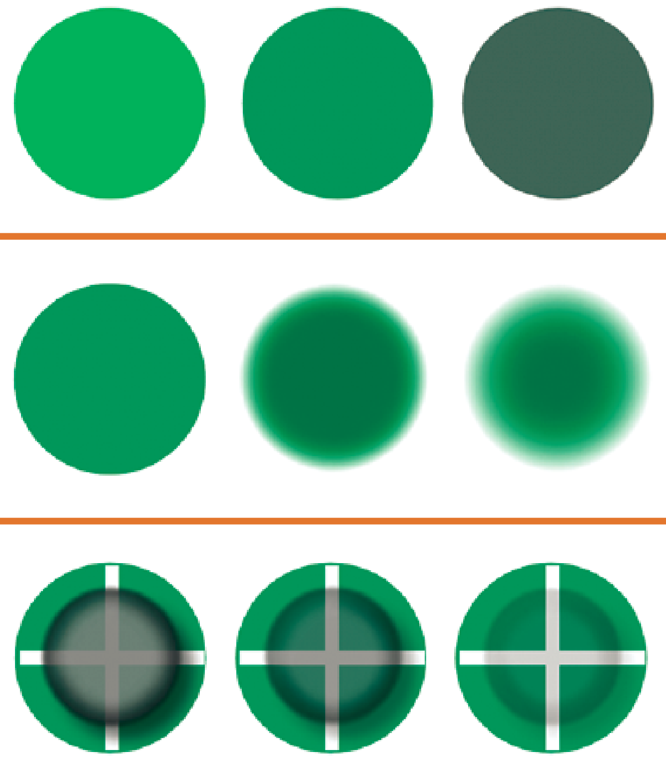
Blur

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

More intuitive?

But how accurate?

Blur

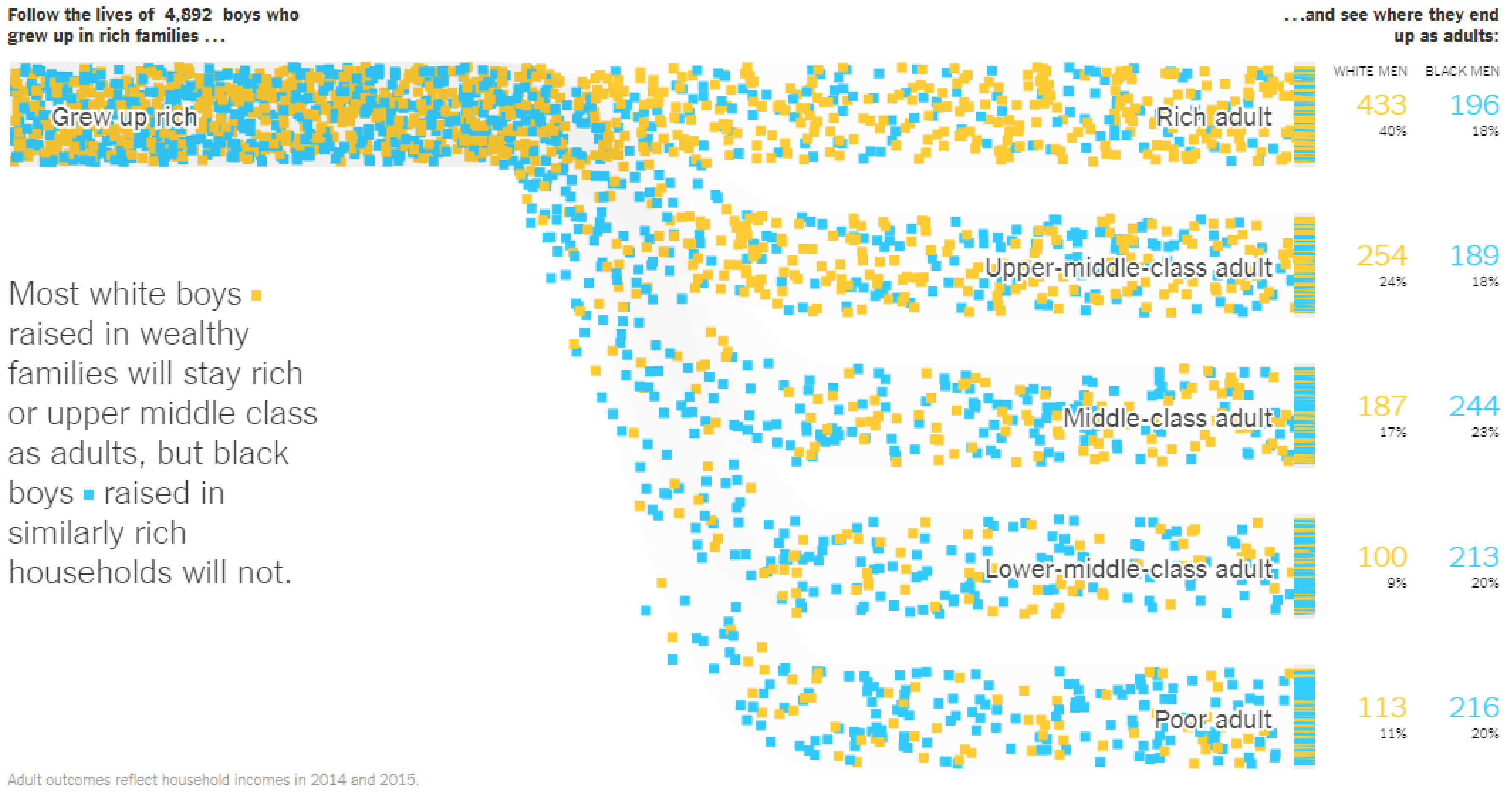
More uncertainty →

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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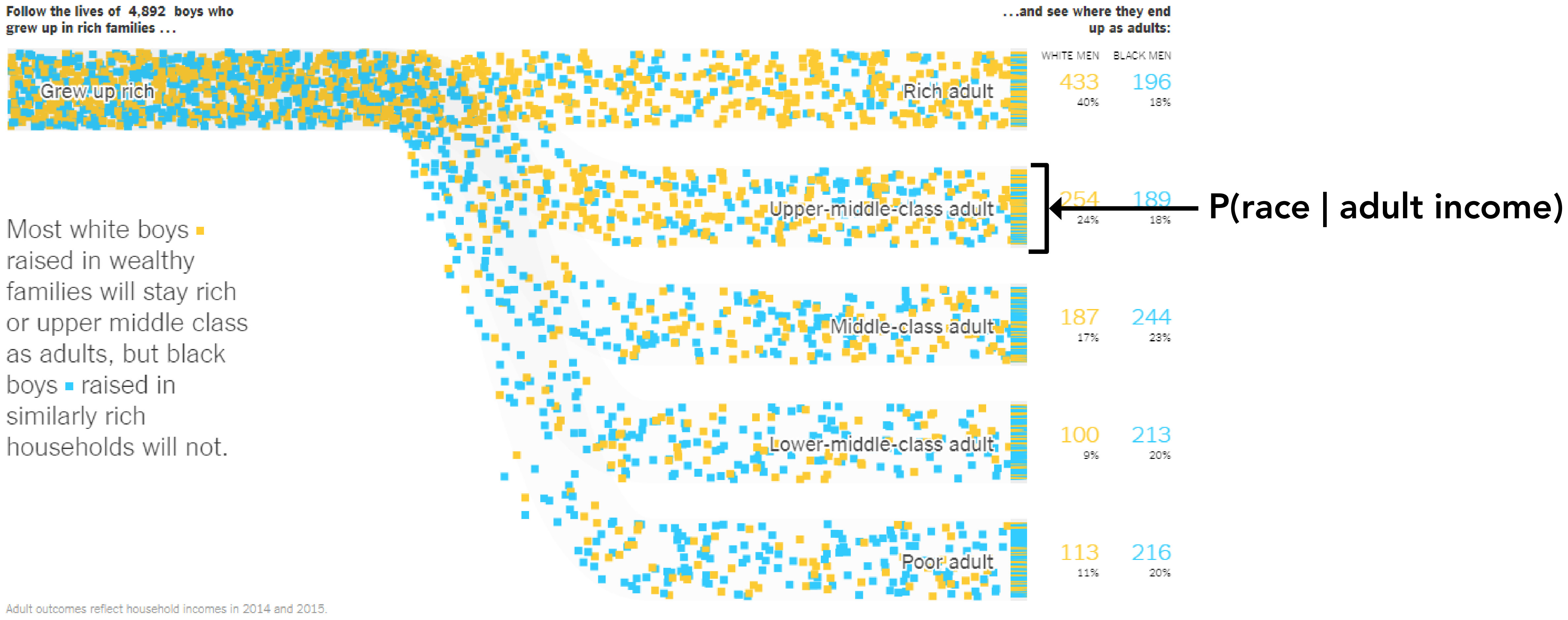

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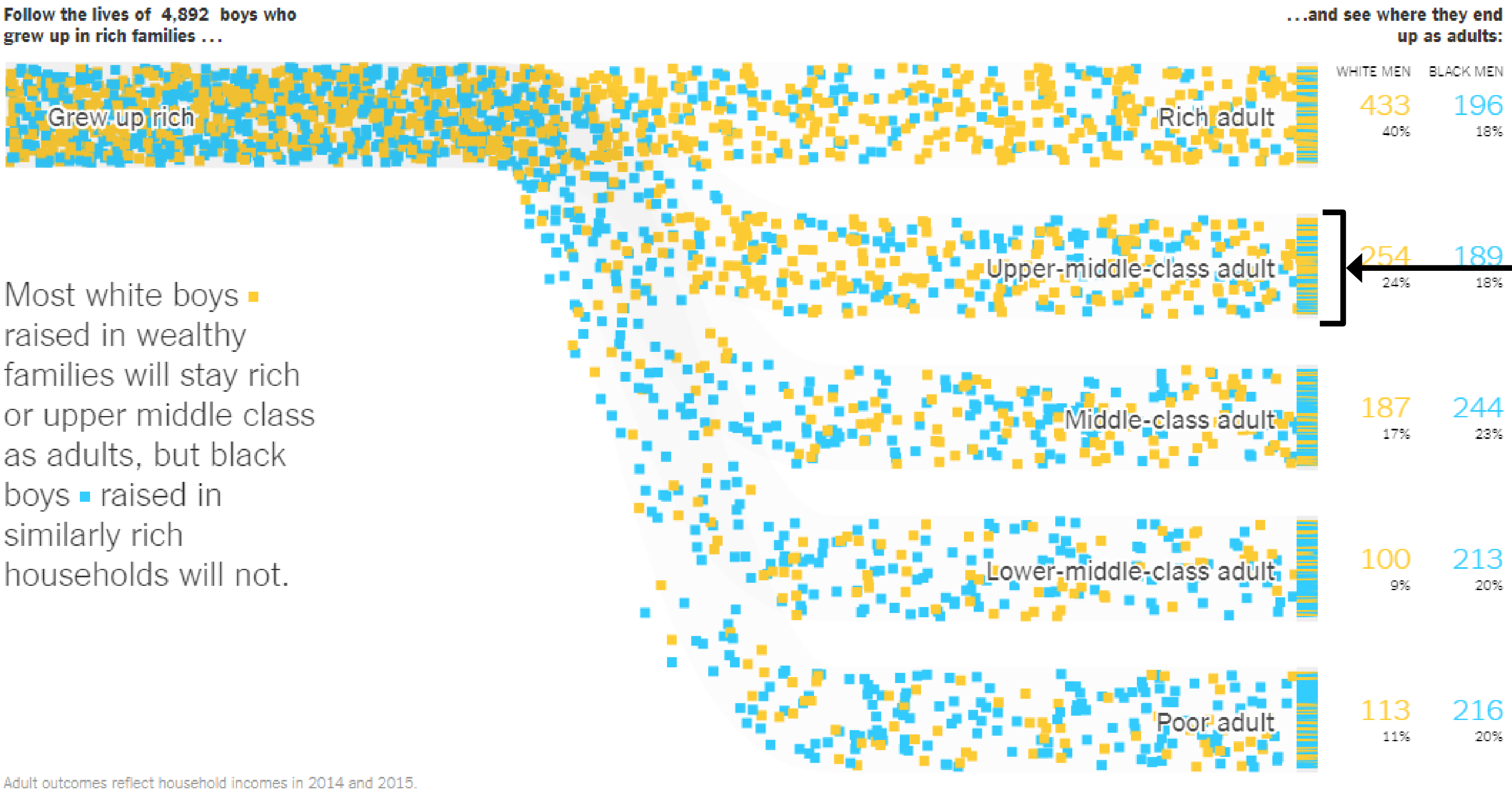

I want:

P(adult income | race)

P(race | adult income)

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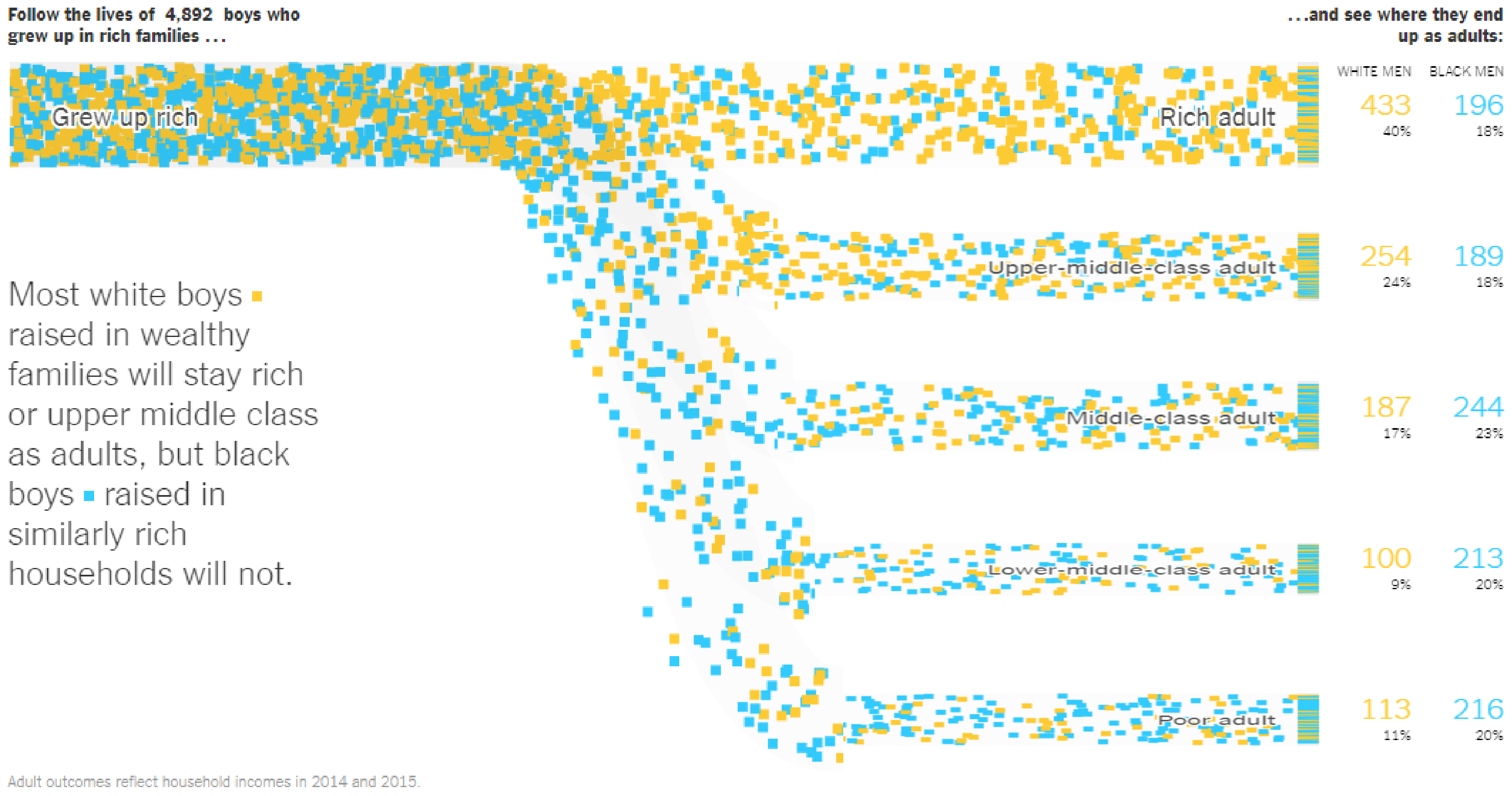

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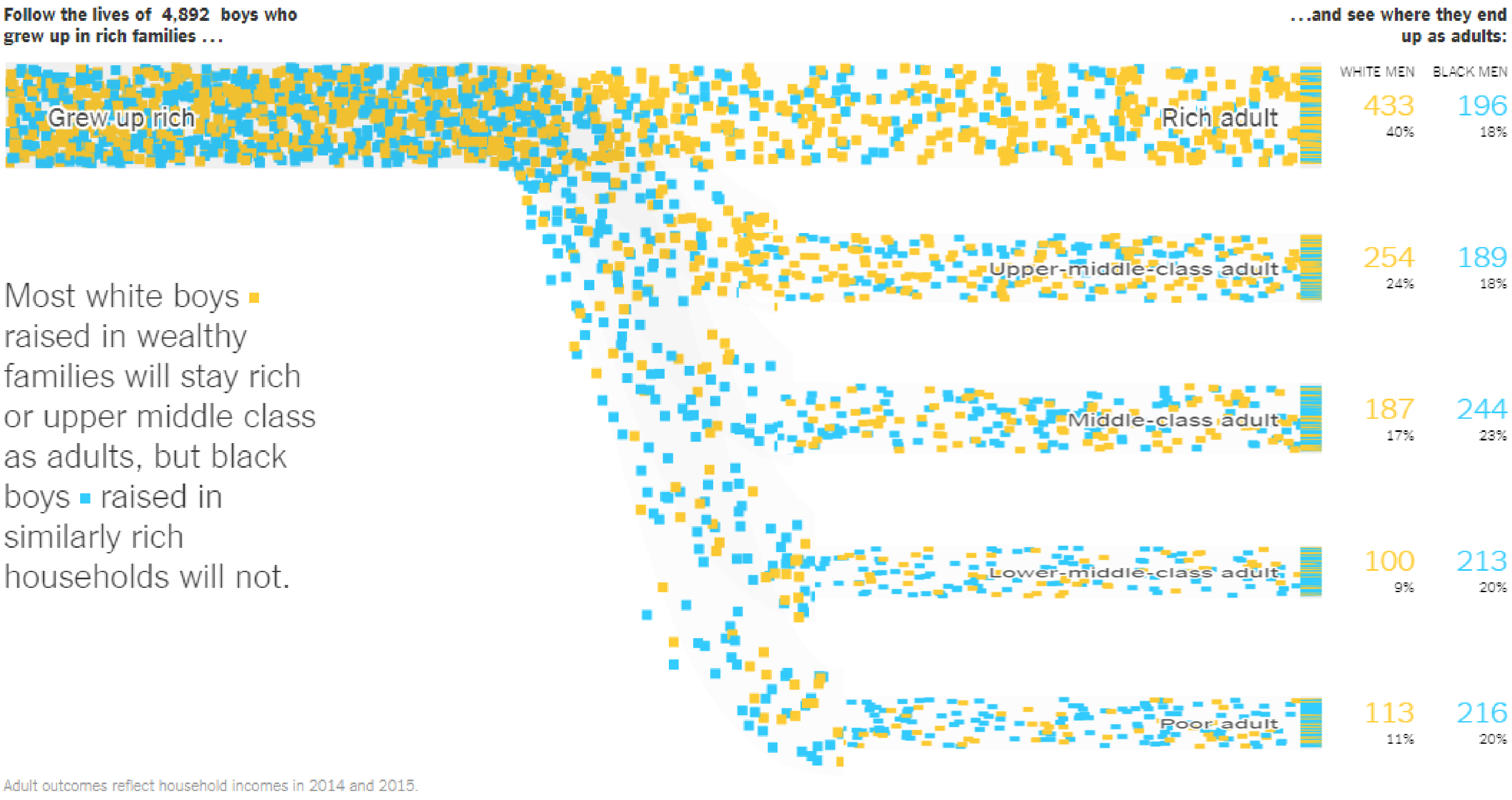

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P(adult income | race)

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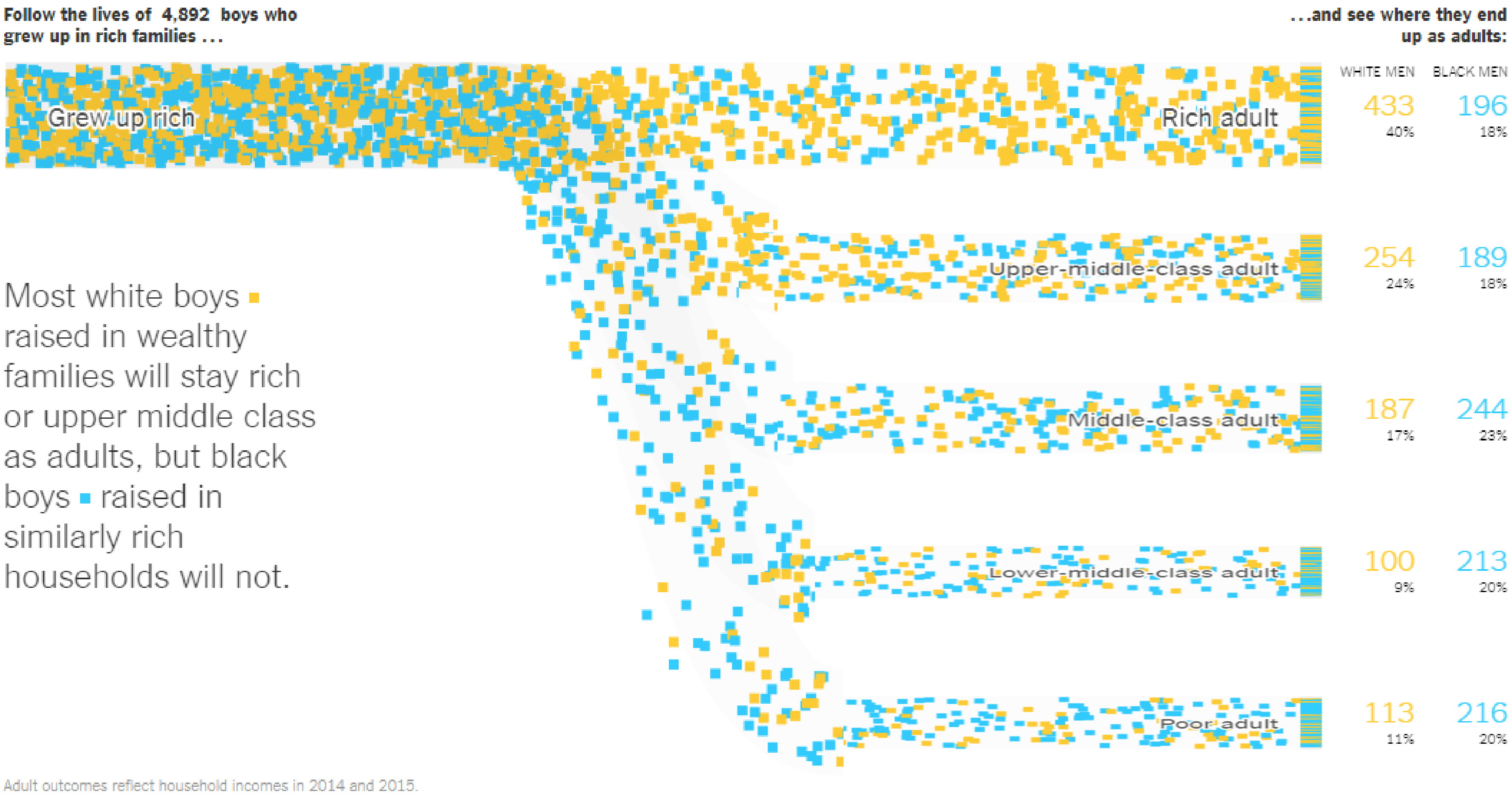

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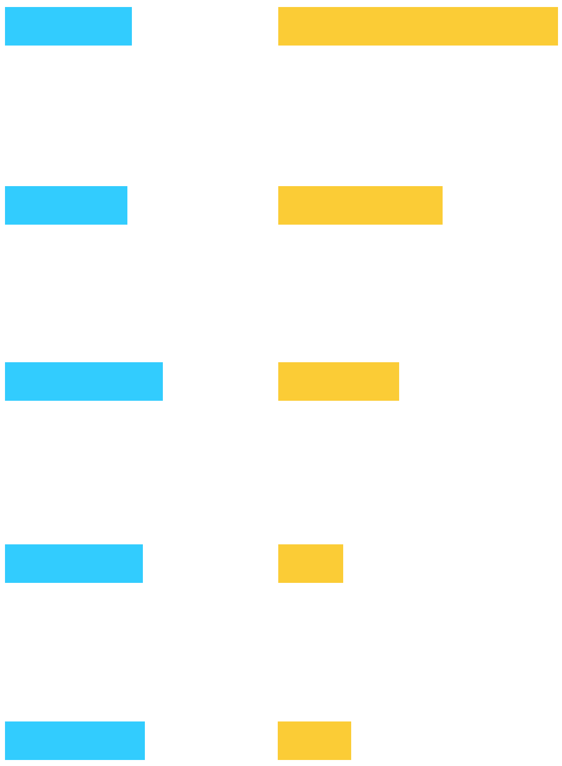
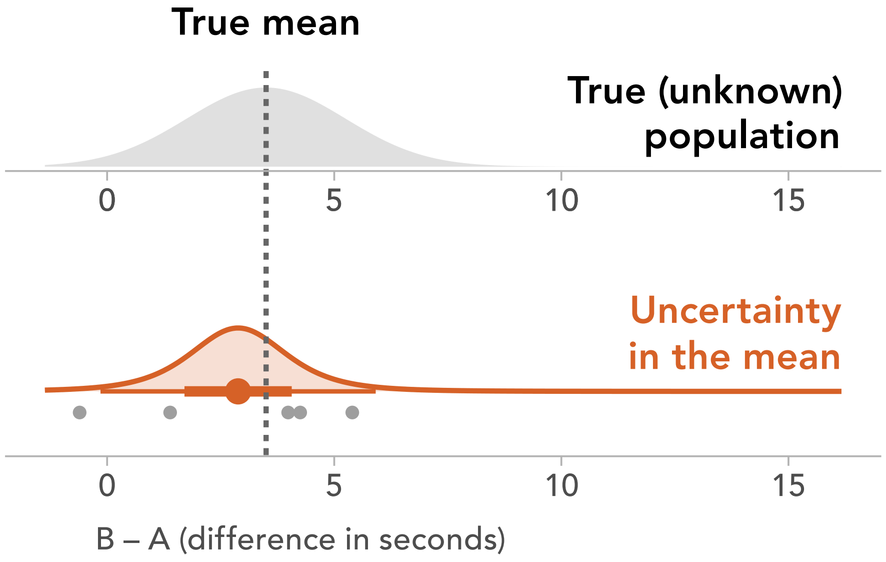
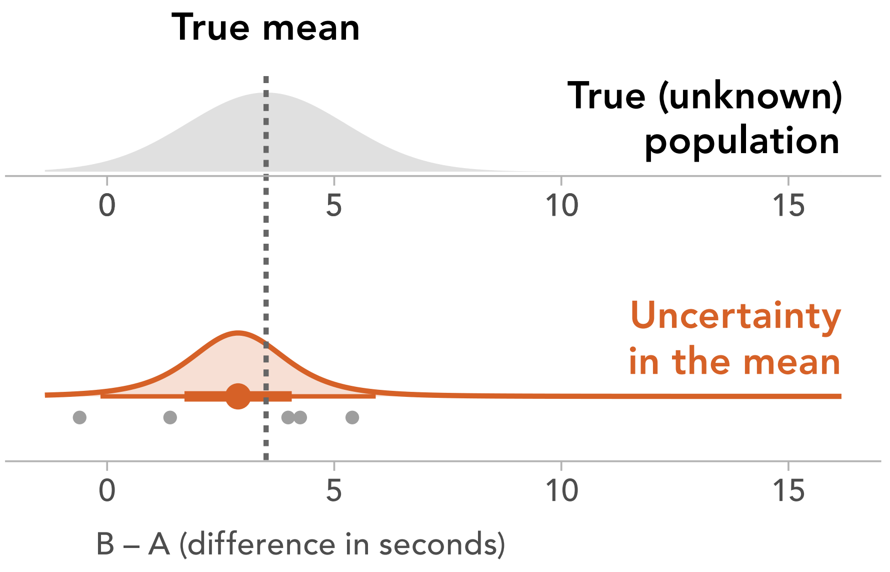


Parameter uncertainty



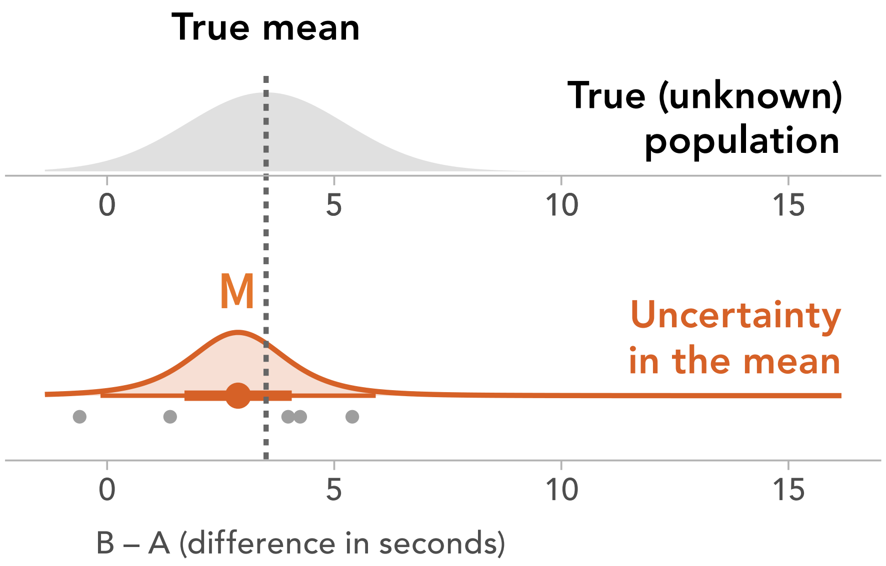
Parameter uncertainty



1. Derive a confidence distribution

2. Map distribution properties onto visual channels

Parameter uncertainty

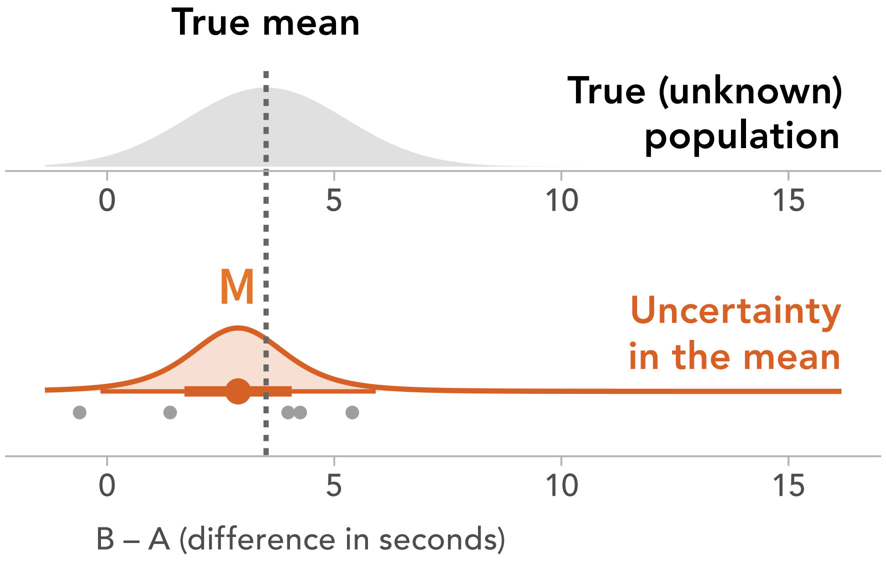


1. Derive a confidence distribution

   M ~ t(*df*, $\bar{x}$, *se*)   *scaled/shifted Student's t*

2. Map distribution properties onto visual channels

Parameter uncertainty



1. Derive a confidence distribution

$M \sim t(df, \bar{x}, se)$ — *scaled/shifted Student's t*

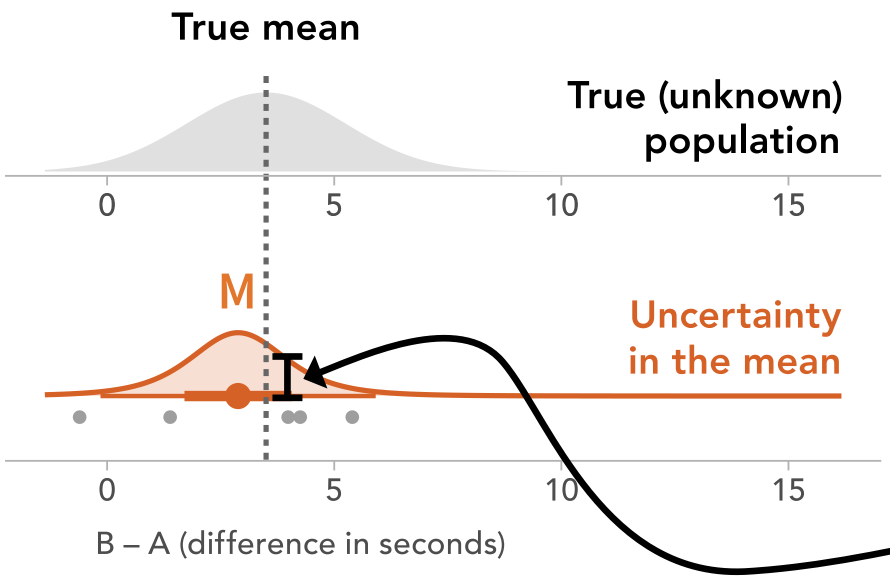
$f_M(m) = f_t(m \mid df, \bar{x}, se)$ — *density*

$F_M(m) = F_t(m \mid df, \bar{x}, se)$ — *CDF*

$F_M^{-1}(p) = F_t^{-1}(p \mid df, \bar{x}, se)$ — *quantile function*

2. Map distribution properties onto visual channels

Parameter uncertainty



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   $f_M(m) = f_t(m \mid df, \bar{x}, se)$ — *density*

   $F_M(m) = F_t(m \mid df, \bar{x}, se)$ — *CDF*

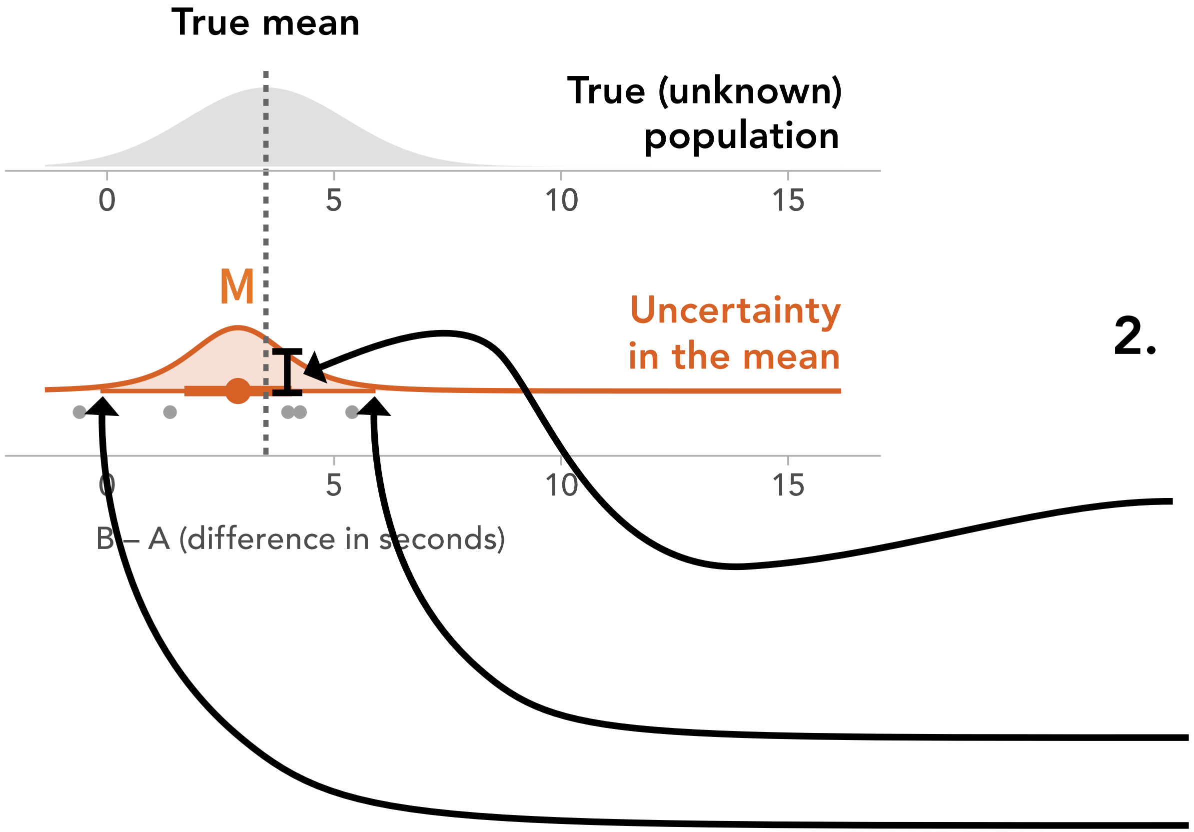
   $F_M^{-1}(p) = F_t^{-1}(p \mid df, \bar{x}, se)$ — *quantile function*

2. Map distribution properties onto visual channels

   f_M(x position) → y position

   mark: area

Parameter uncertainty



1. Derive a confidence distribution

$M \sim \mathrm{t}(df, \bar{x}, se)$	*scaled/shifted Student's t*
$f_M(m) = f_t(m \mid df, \bar{x}, se)$	*density*
$F_M(m) = F_t(m \mid df, \bar{x}, se)$	*CDF*
$F_M^{-1}(p) = F_t^{-1}(p \mid df, \bar{x}, se)$	*quantile function*

2. Map distribution properties onto visual channels

$f_M(\text{x position}) \rightarrow$ y position

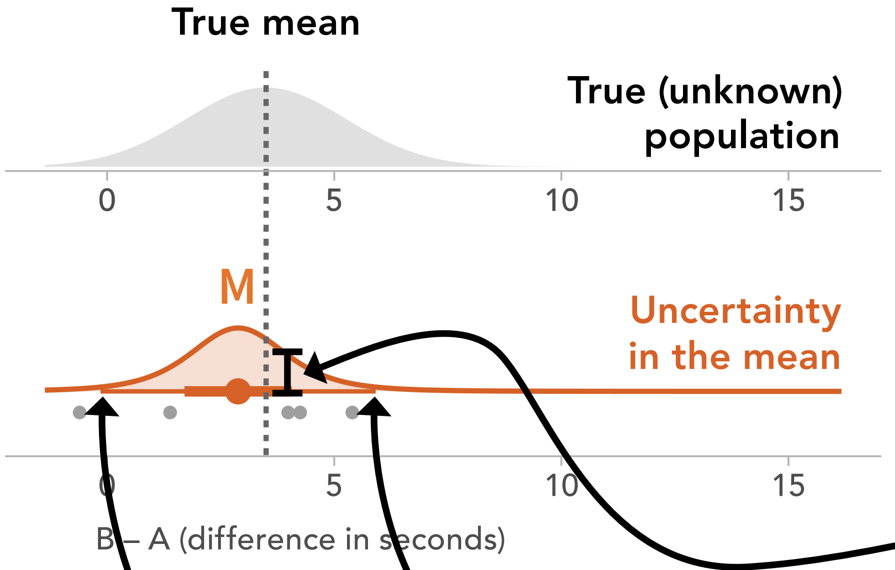
mark: area

$F_M^{-1}(0.975) \rightarrow x_1$ position

$F_M^{-1}(0.025) \rightarrow x_2$ position

mark: error bar

Parameter uncertainty



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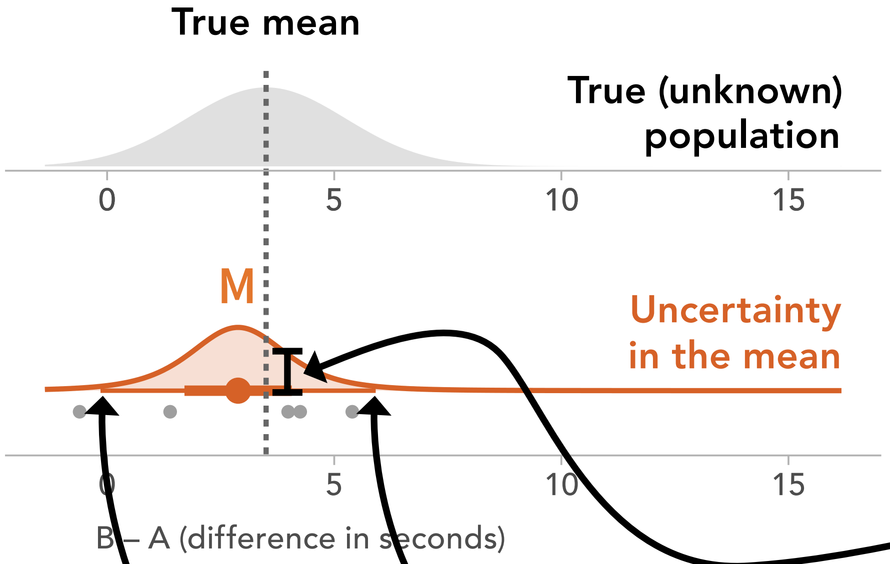


1. Derive a bootstrap sampling distribution

   Let $m^{(1)}, \ldots, m^{(k)}$ be bootstrap samples of the mean

   $f_M(m)$ = *kernel density estimator* of all $m^{(k)}$

   $F_M(m)$ = *empirical CDF* of all $m^{(k)}$

   $F_M^{-1}(p)$ = *empirical quantile function* of all $m^{(k)}$

2. Map distribution properties onto visual channels

   f_M(x position) → y position

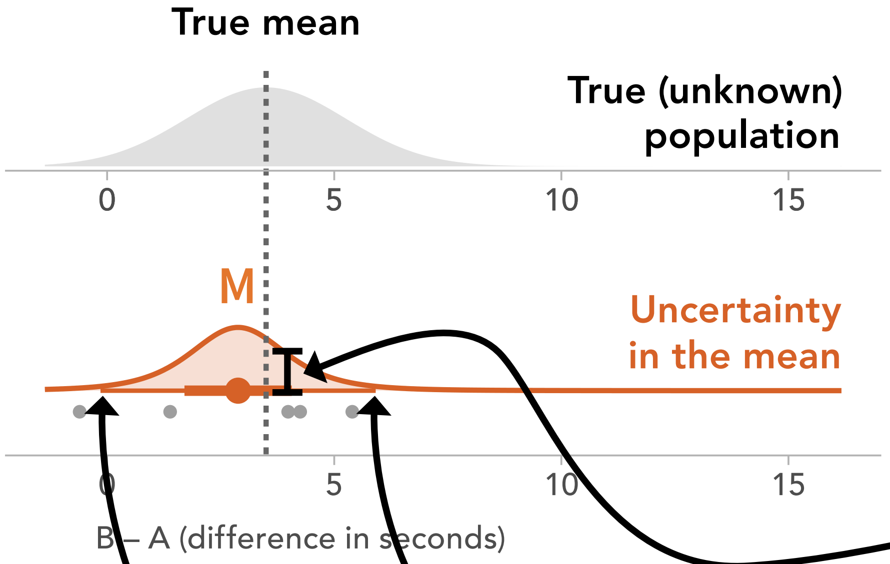
   mark: area

   $F_M^{-1}(0.975)$ → x_1 position

   $F_M^{-1}(0.025)$ → x_2 position

   mark: error bar

Parameter uncertainty



1. Derive a posterior distribution, $p(m \mid data)$

   Let $m^{(1)}, \ldots, m^{(k)}$ be samples from $p(m \mid data)$

   $f_M(m)$ = *kernel density estimator* of all $m^{(k)}$

   $F_M(m)$ = *empirical CDF* of all $m^{(k)}$

   $F_M^{-1}(p)$ = *empirical quantile function* of all $m^{(k)}$

2. Map distribution properties onto visual channels

   $f_M(\text{x position}) \rightarrow$ y position

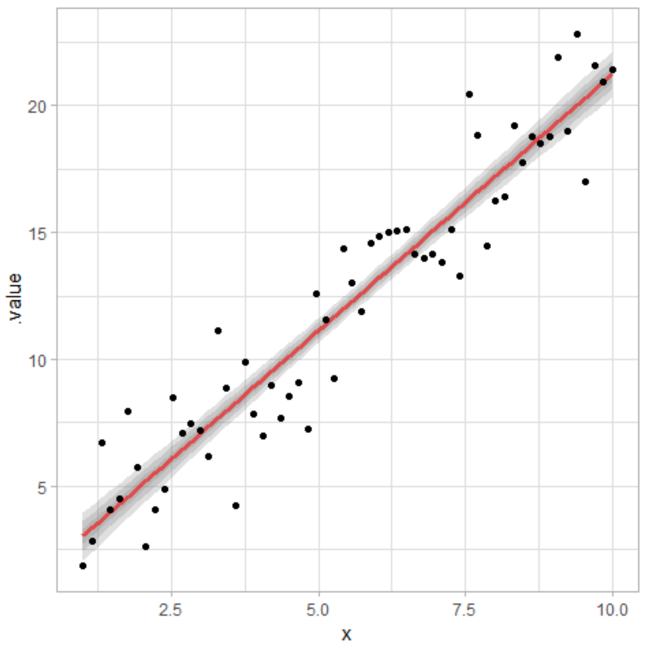
   mark: area

   $F_M^{-1}(0.975) \rightarrow x_1$ position

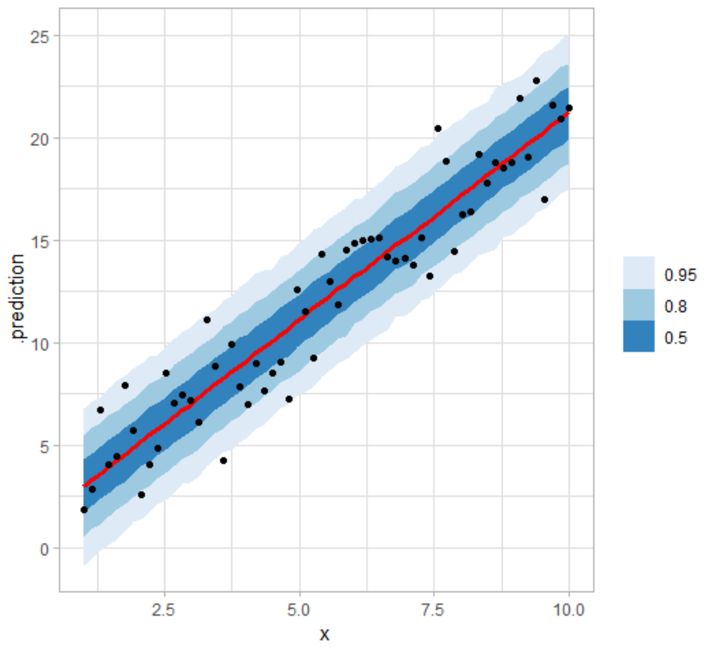
   $F_M^{-1}(0.025) \rightarrow x_2$ position

   mark: error bar

Parameter uncertainty



Predictive uncertainty



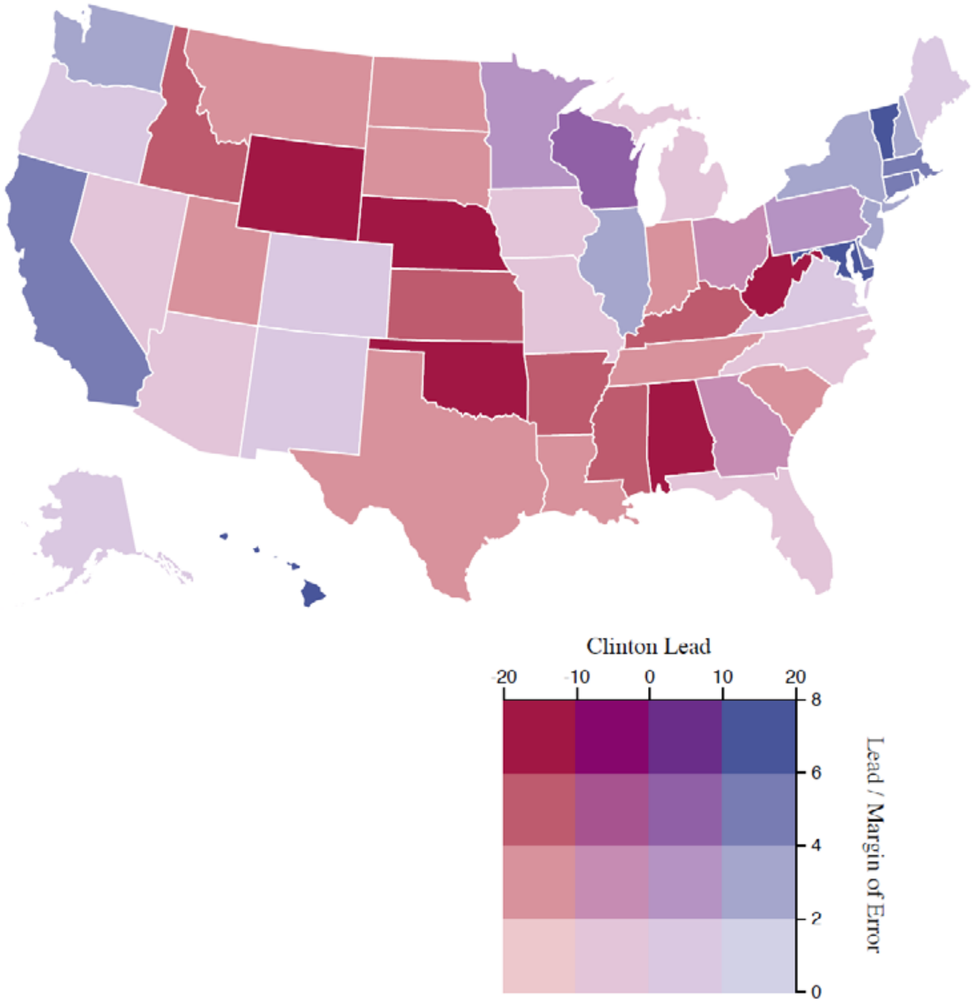
Specification uncertainty

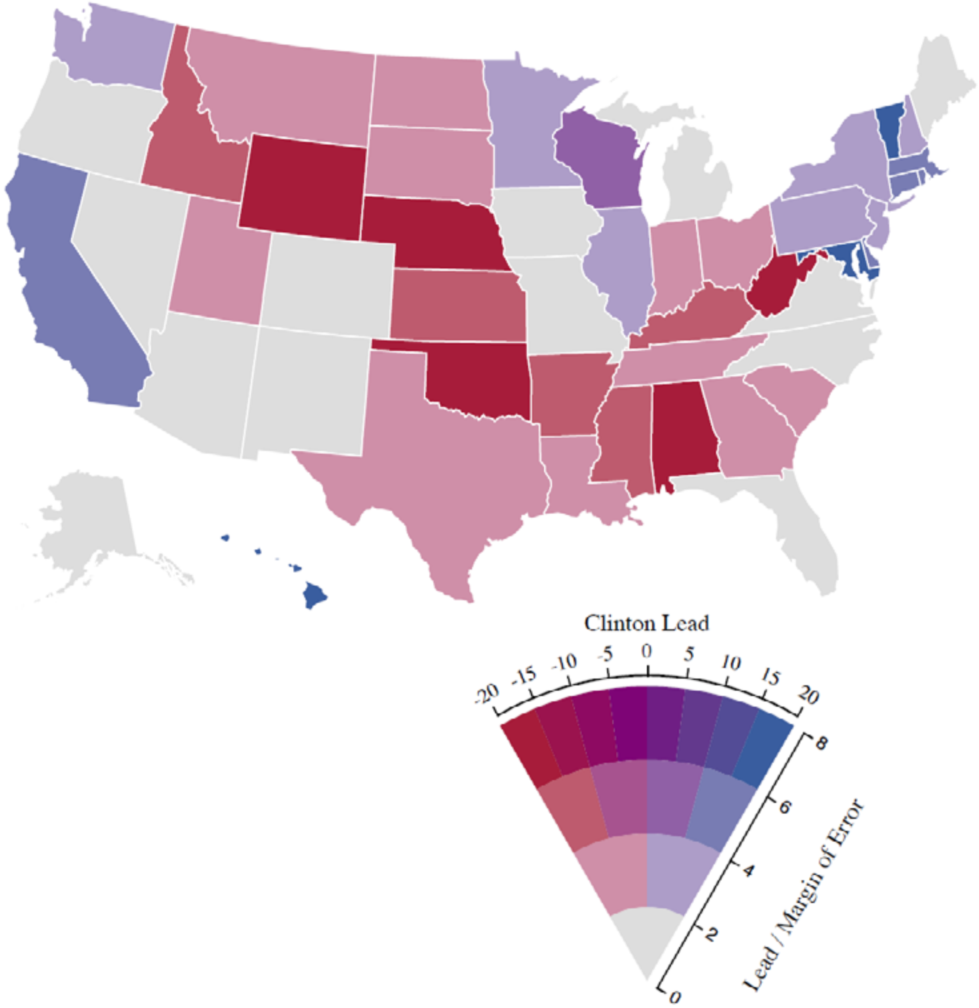
How well does this describe reality?

Addressing bias in perception of probability…

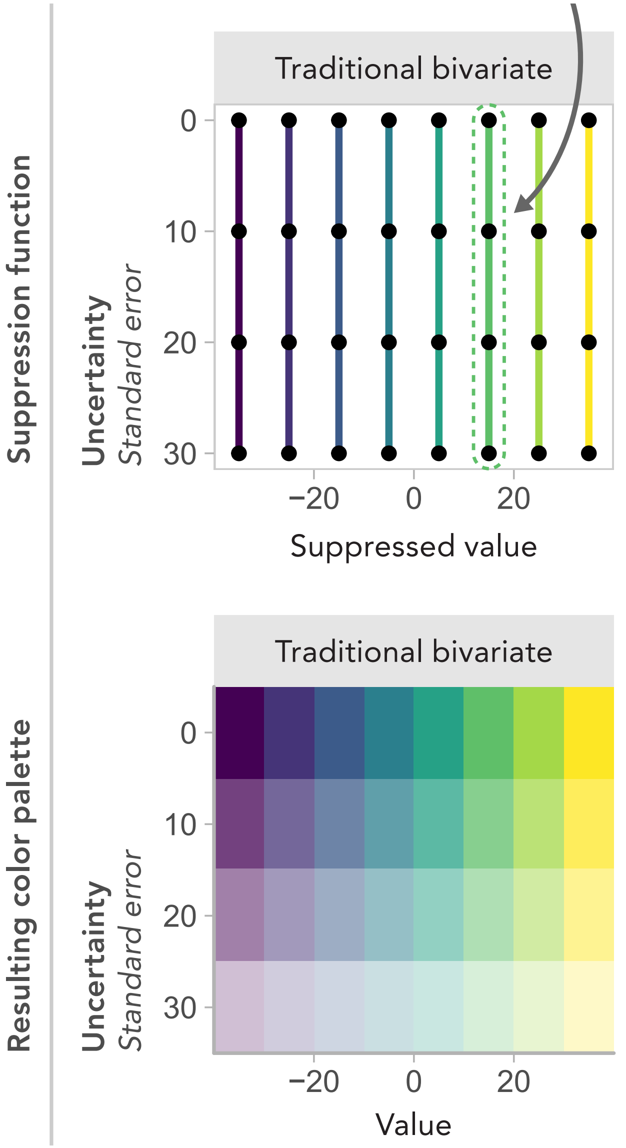
Value-suppressing uncertainty palettes

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





[Kay. How Much Value Should an Uncertainty Palette Suppress? https://osf.io/6xcnw/]



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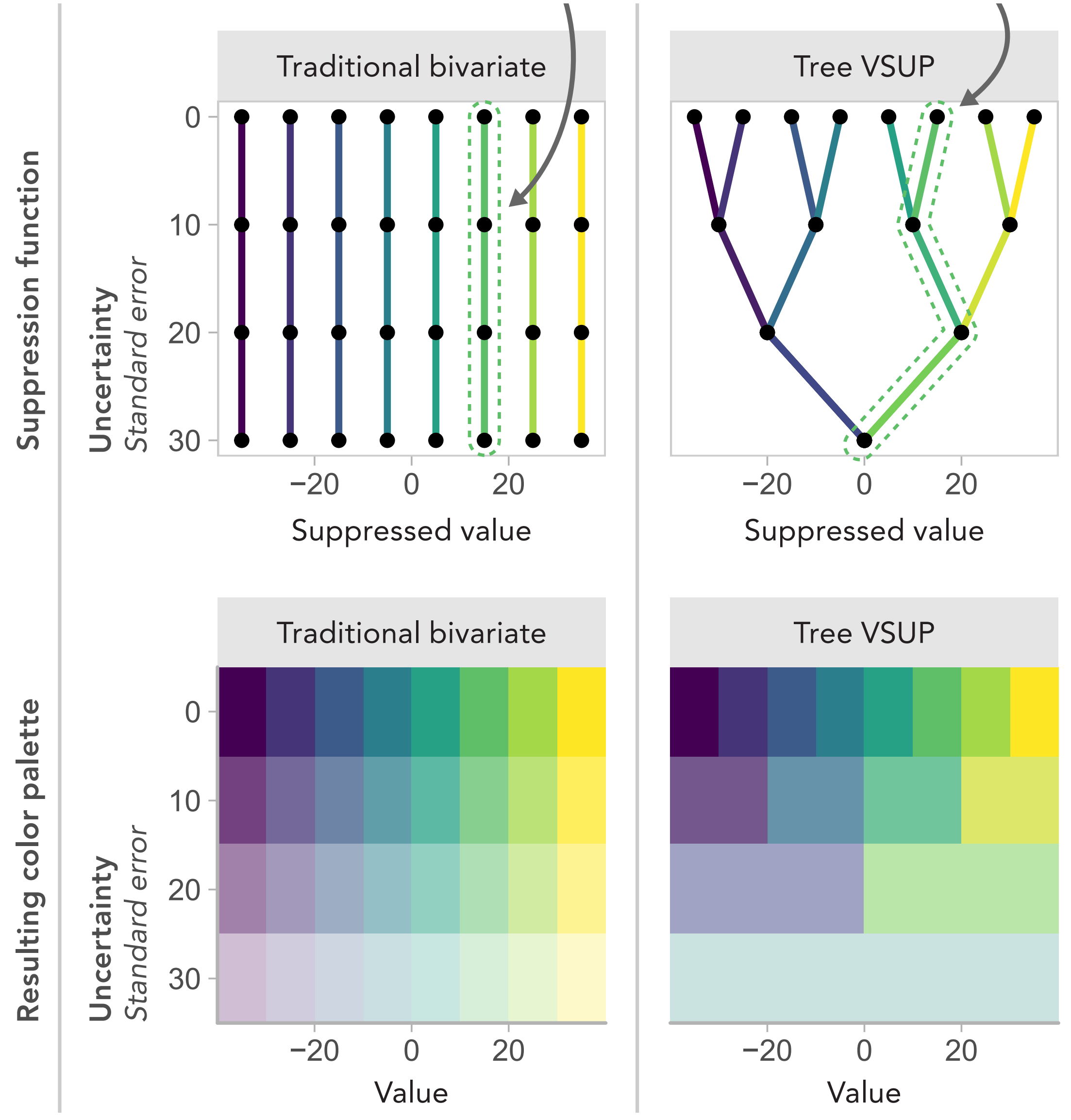

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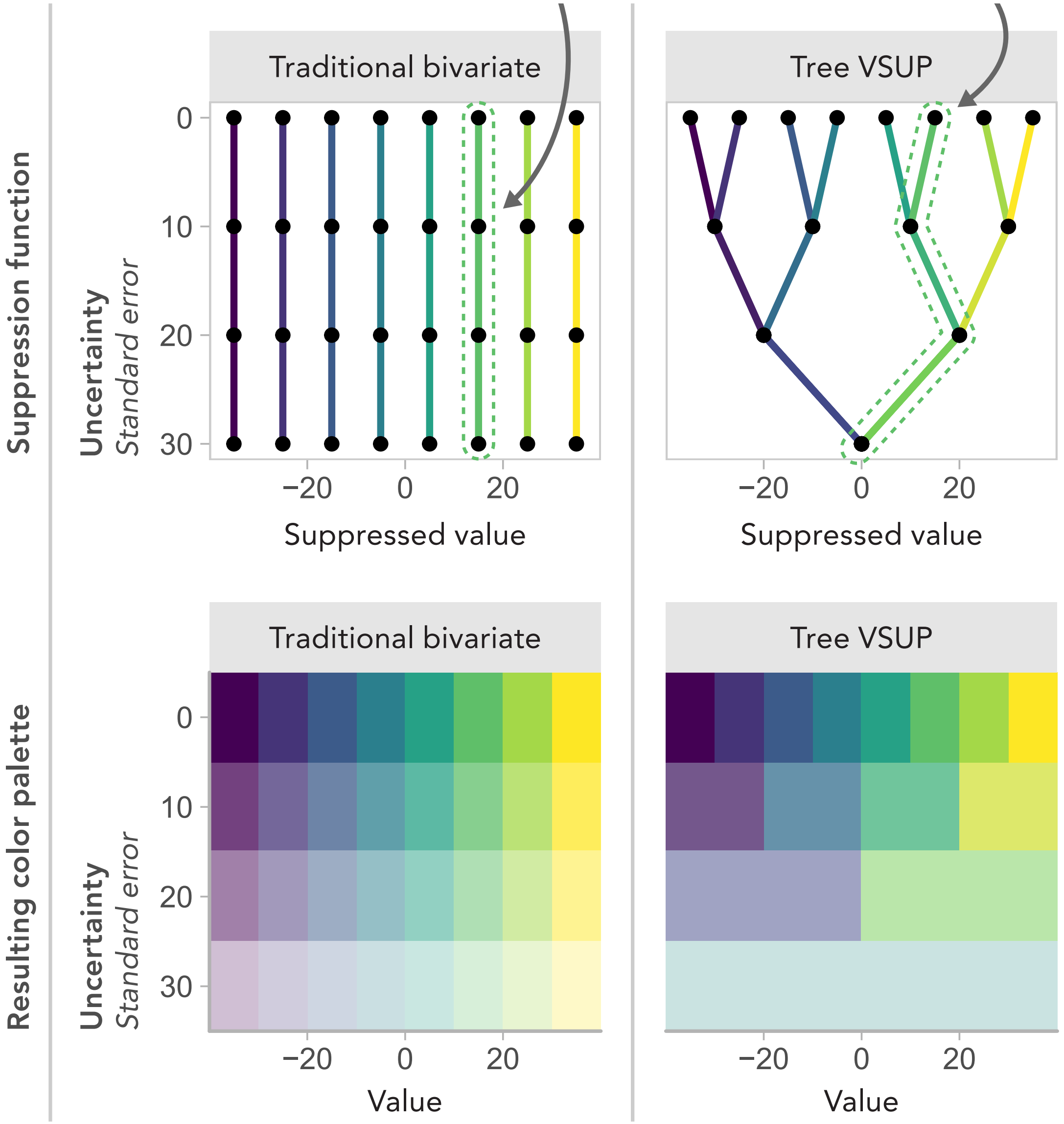

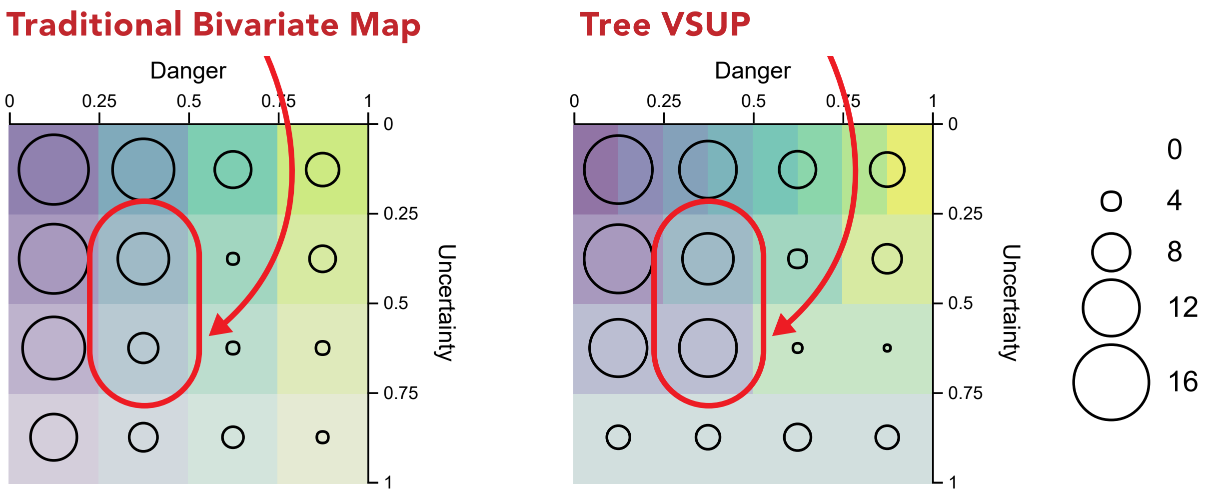

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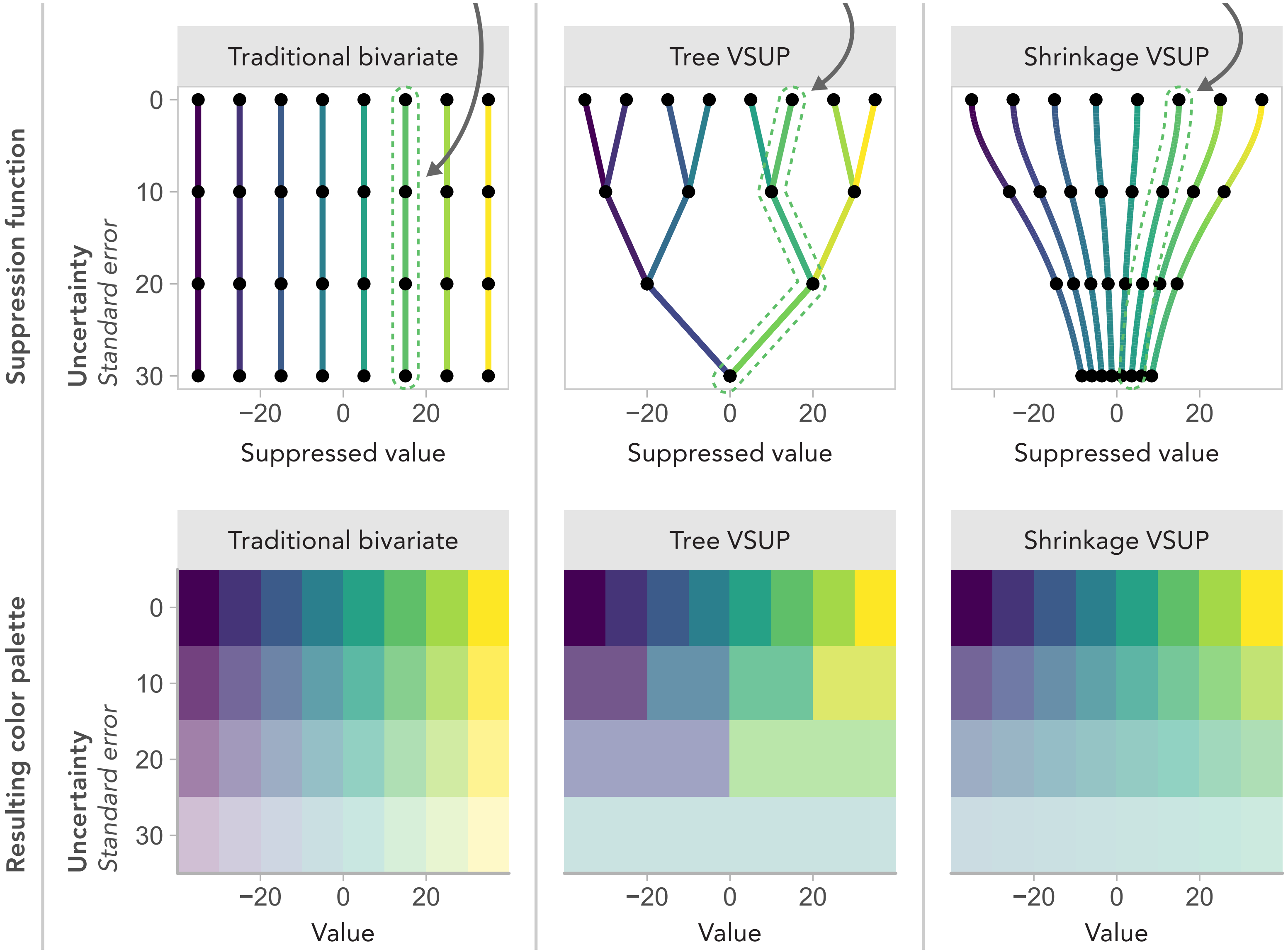
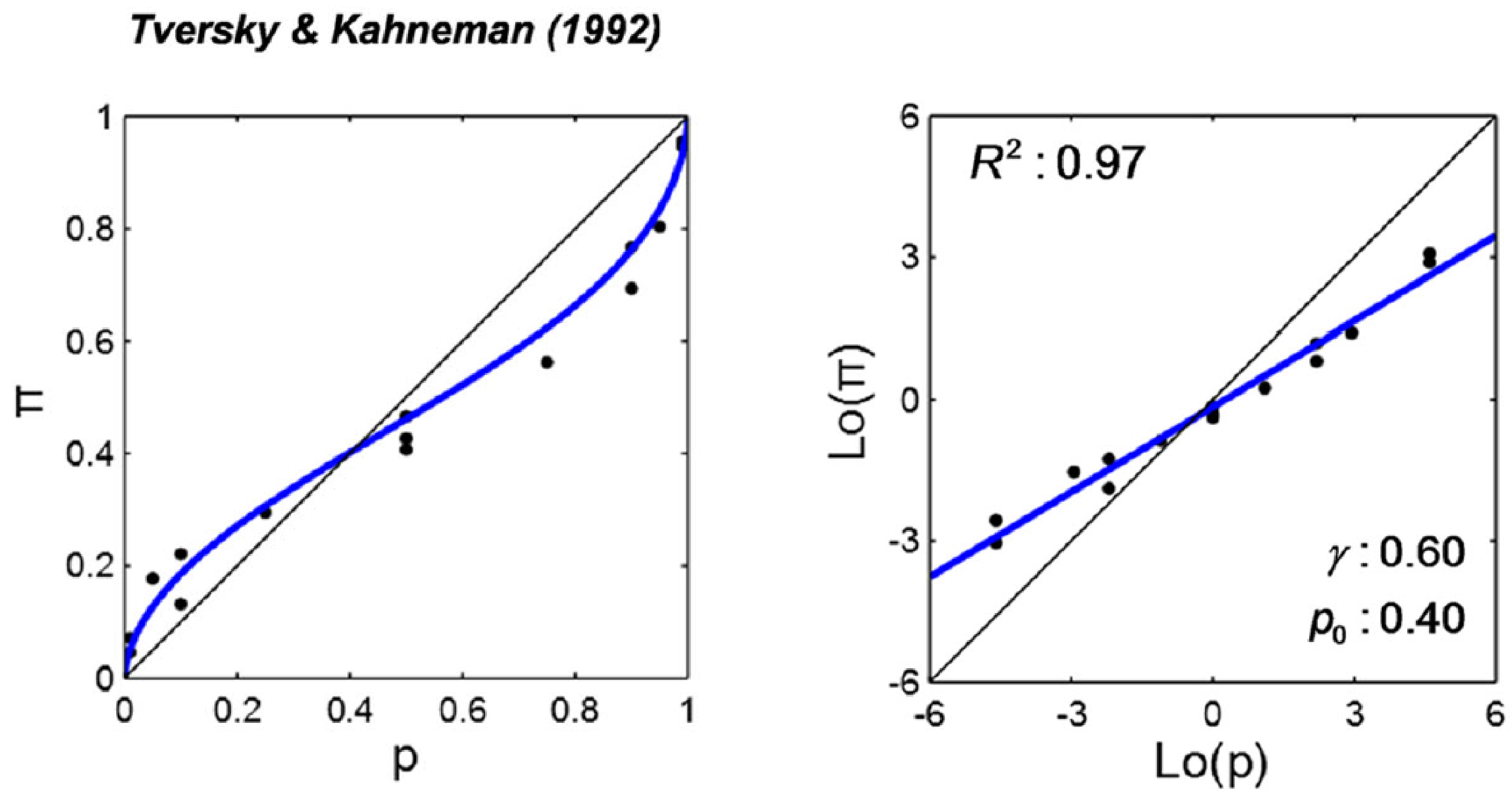


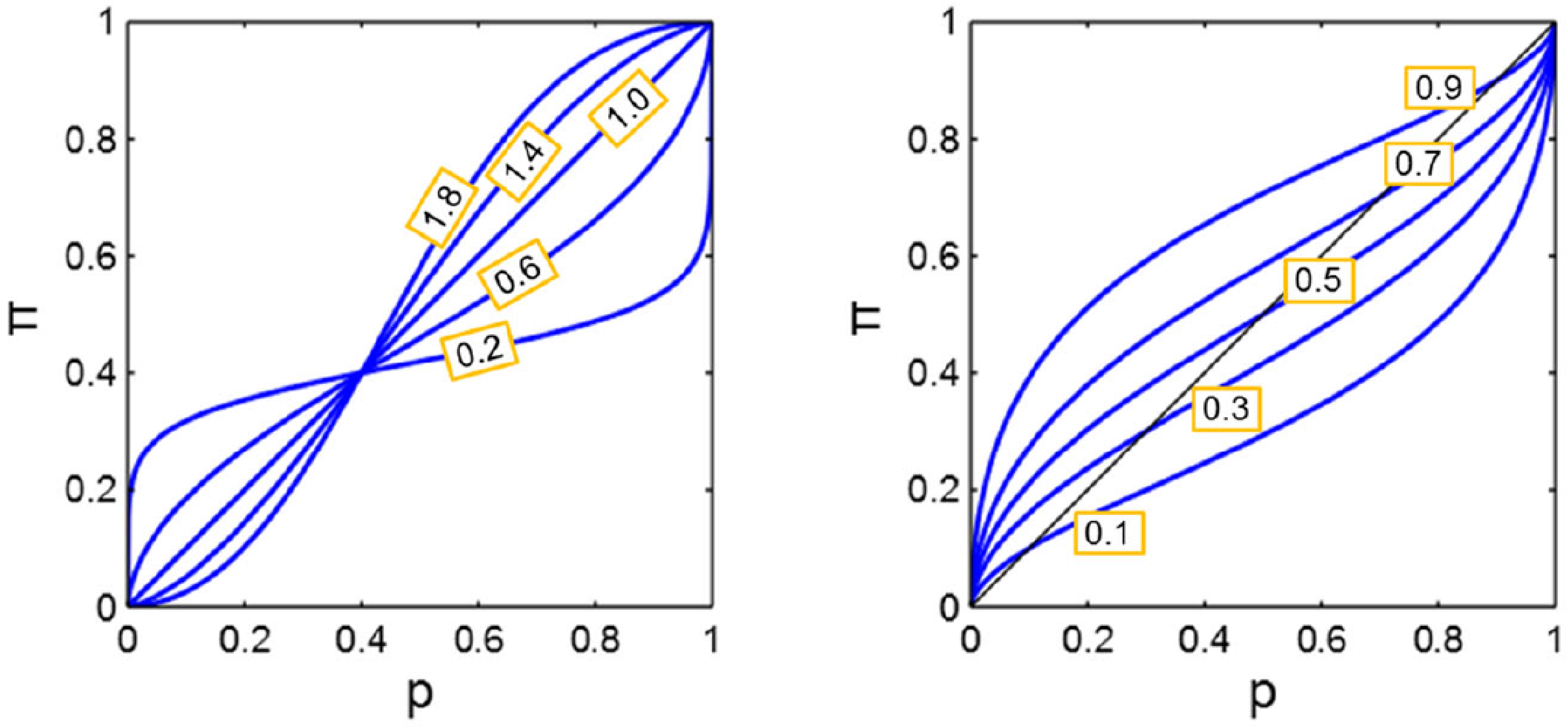
Linear-in-log-odds perception of proportions

[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]



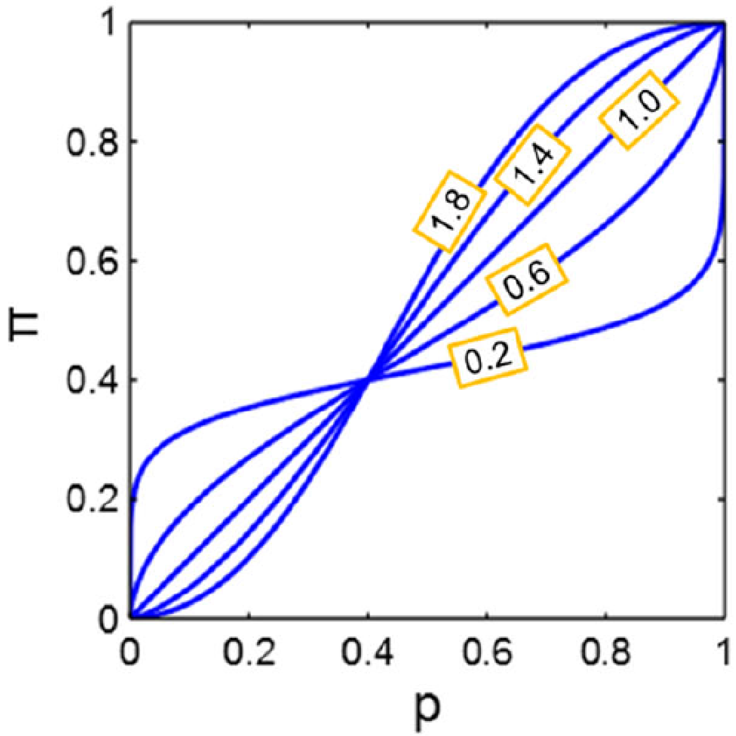
Linear-in-log-odds perception of proportions

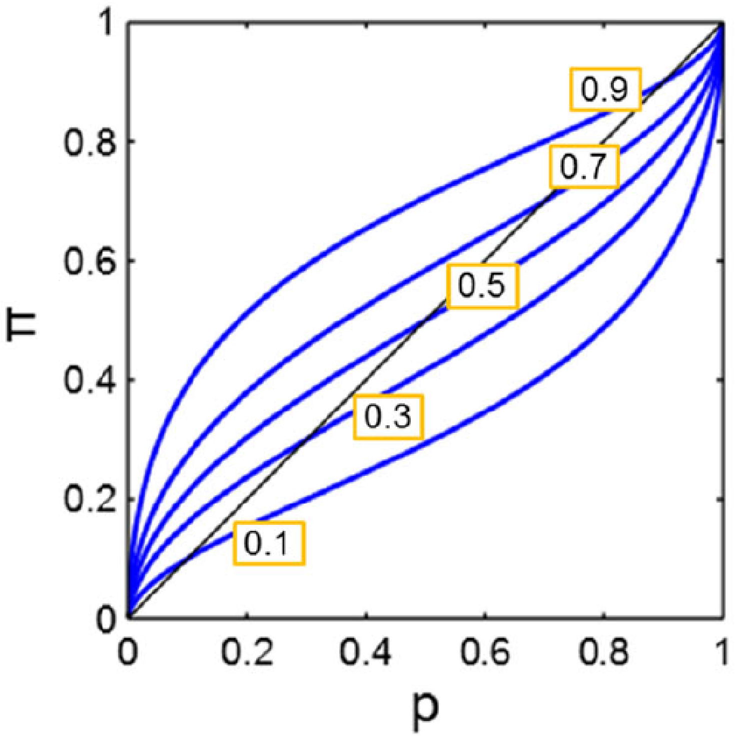
[Zhang & Maloney. Ubiquitous log odds: A common representation of probability and frequency distortion in perception, action, and cognition. Frontiers in Neuroscience, 6(JAN), 1–14, 2012]



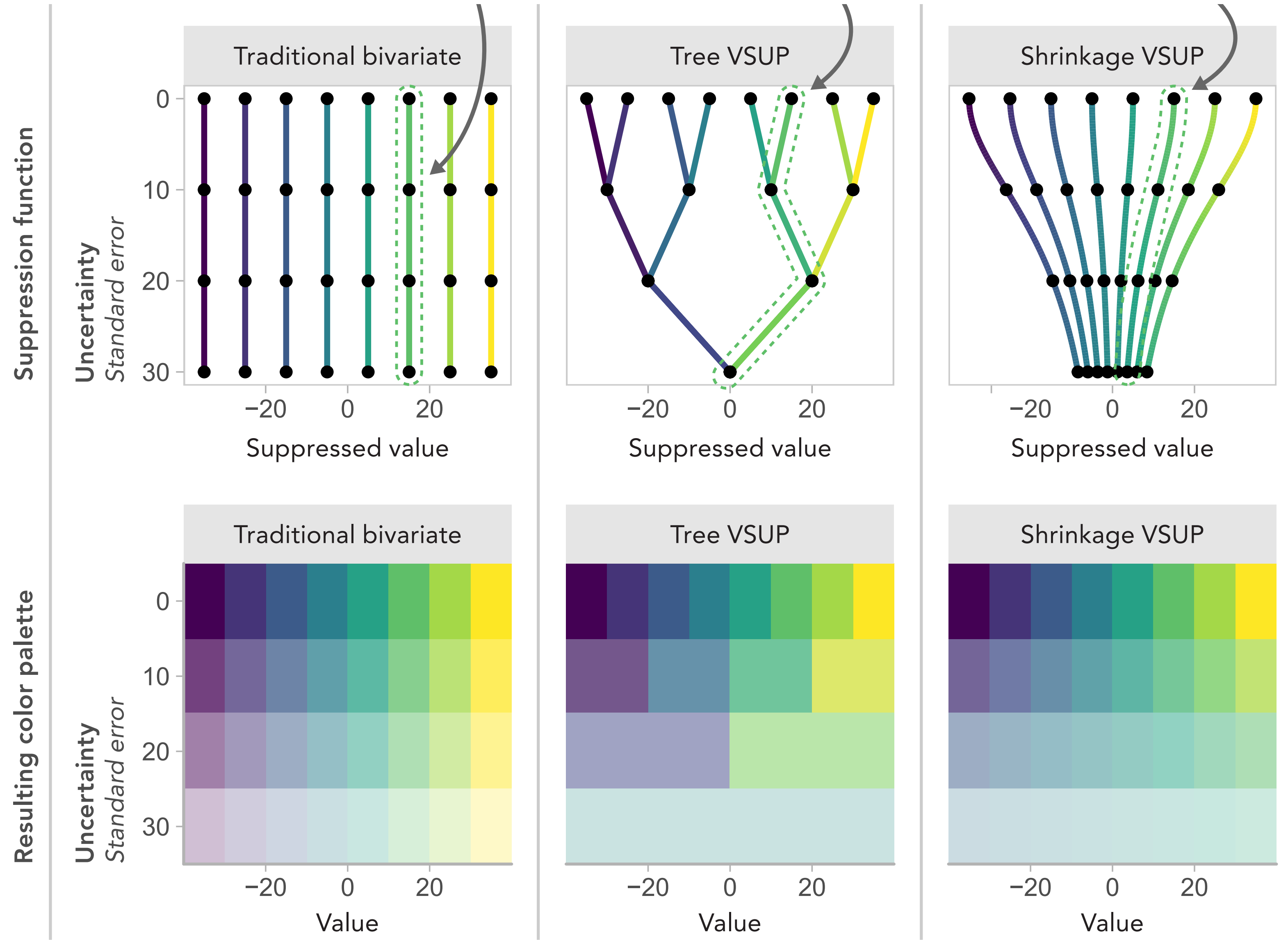
Linear-in-probit perception of proportions

[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]





[Kay. How Much Value Should an Uncertainty Palette Suppress? https://osf.io/6xcnw/]



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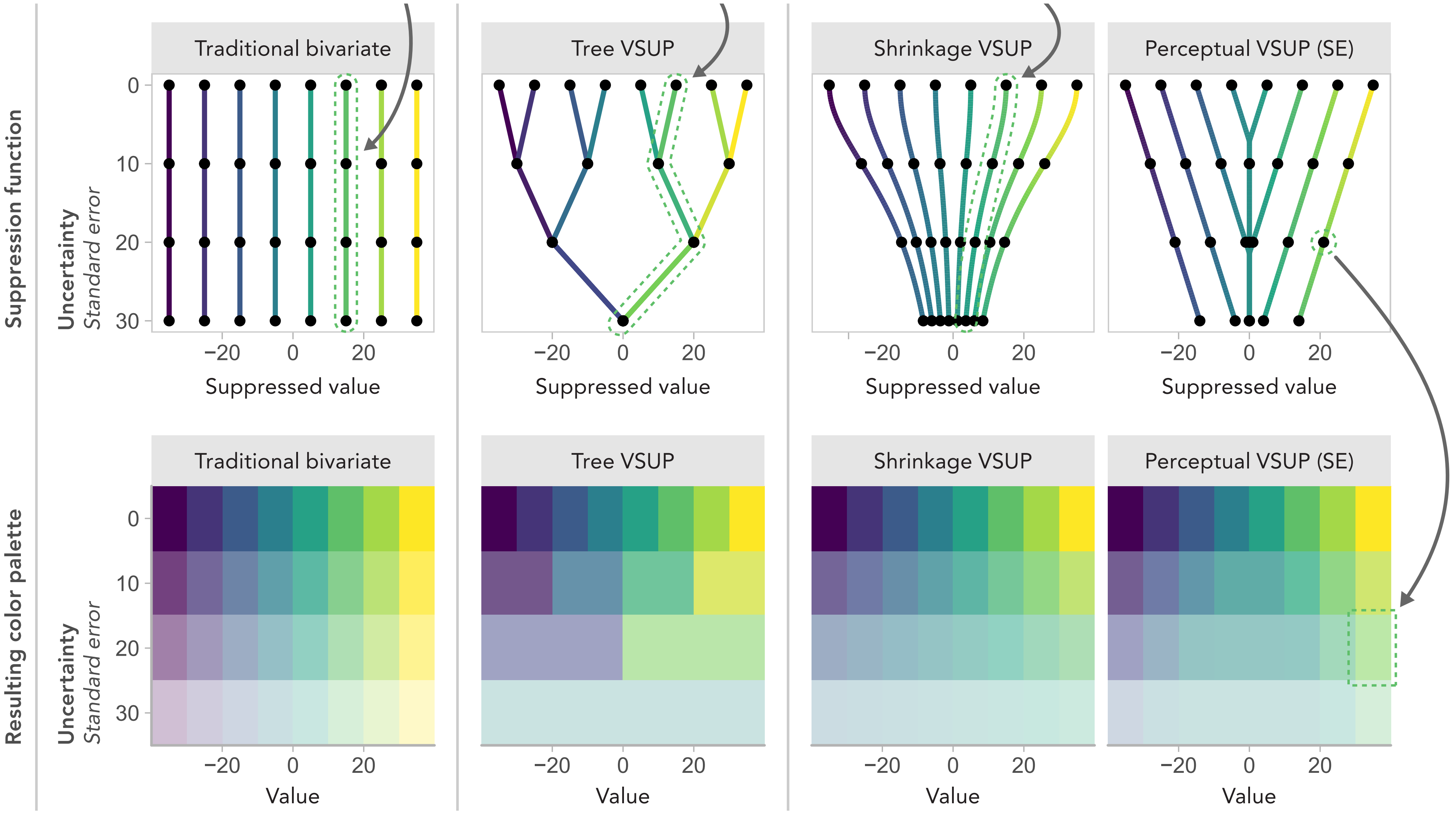
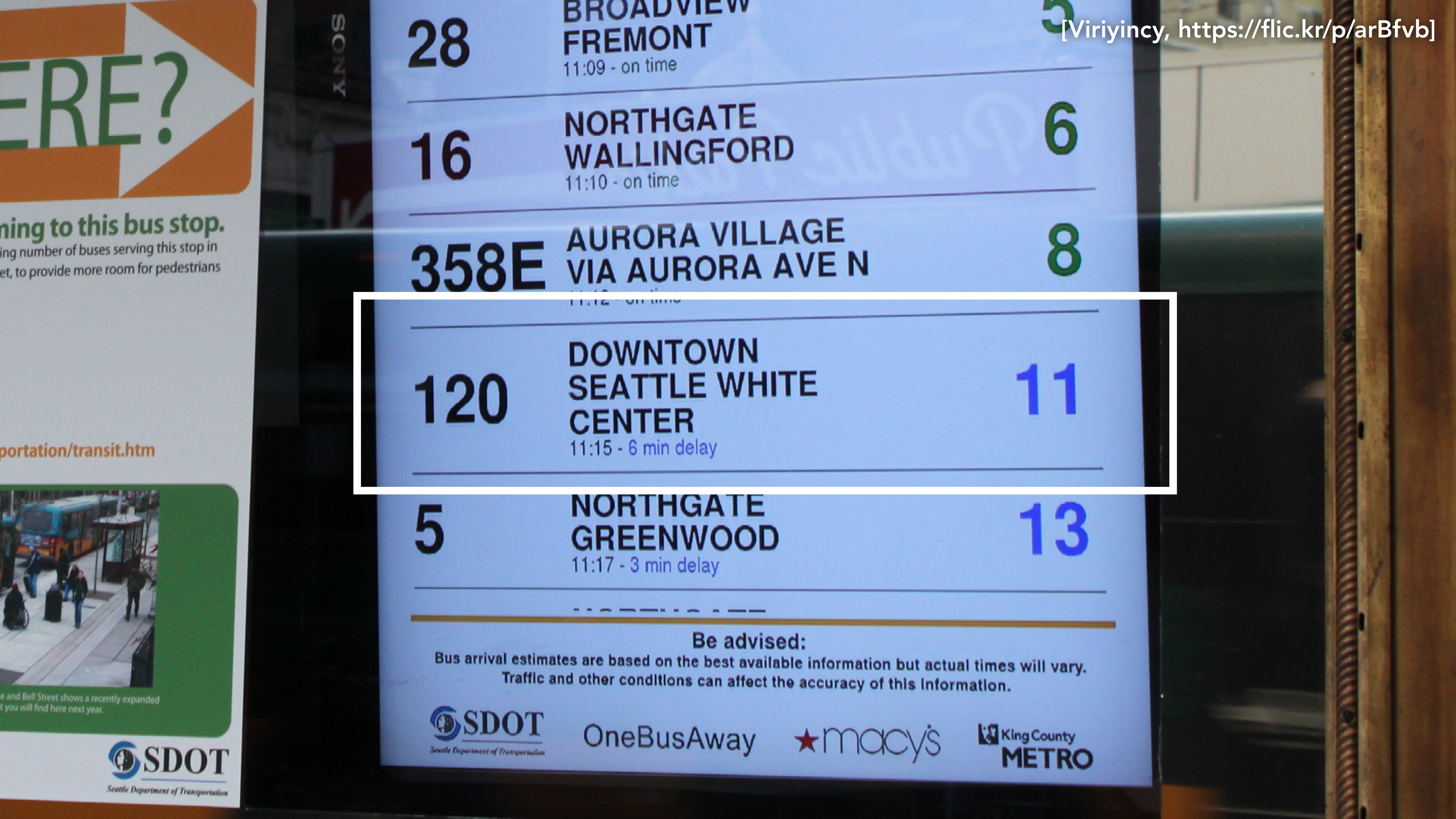
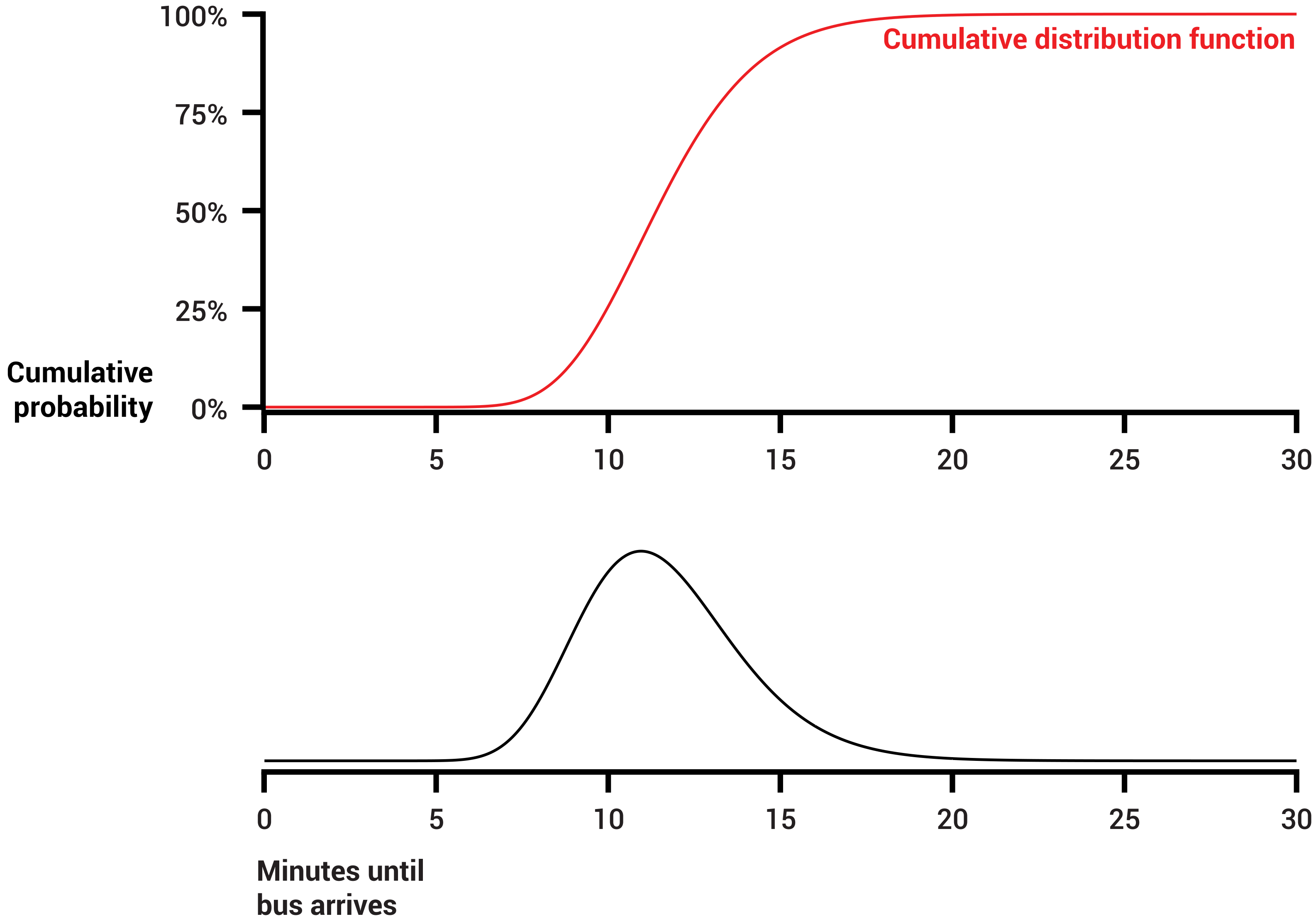
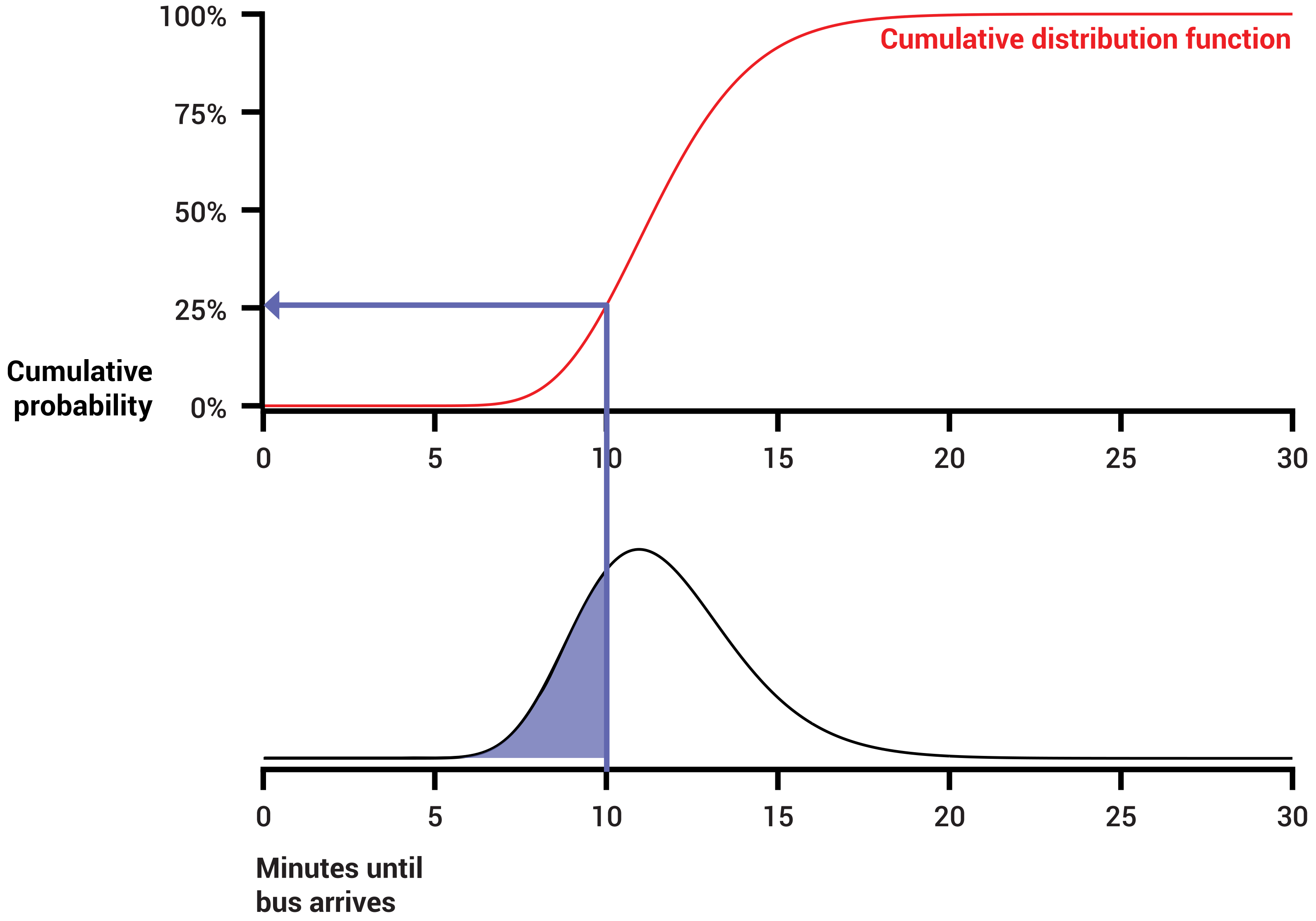
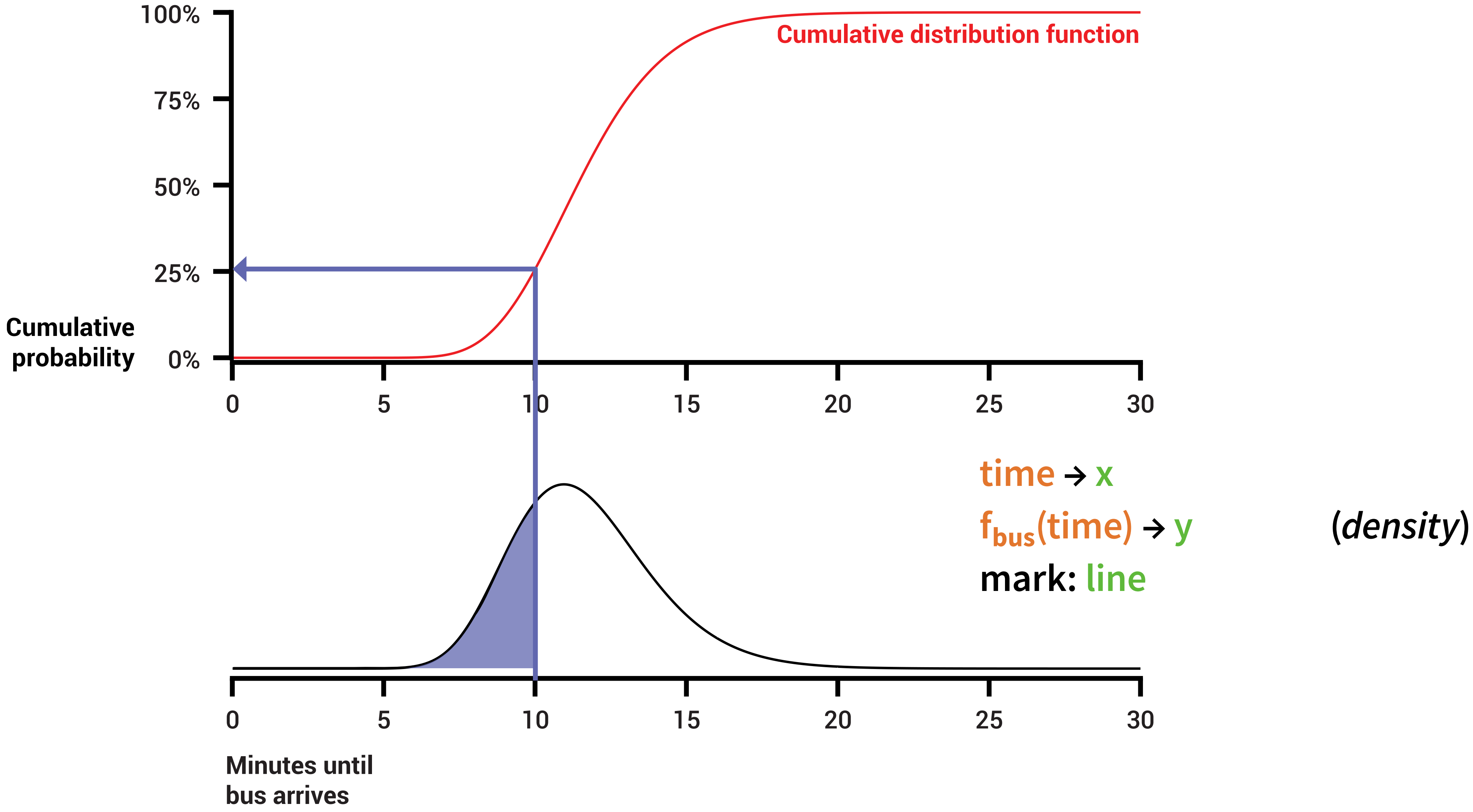




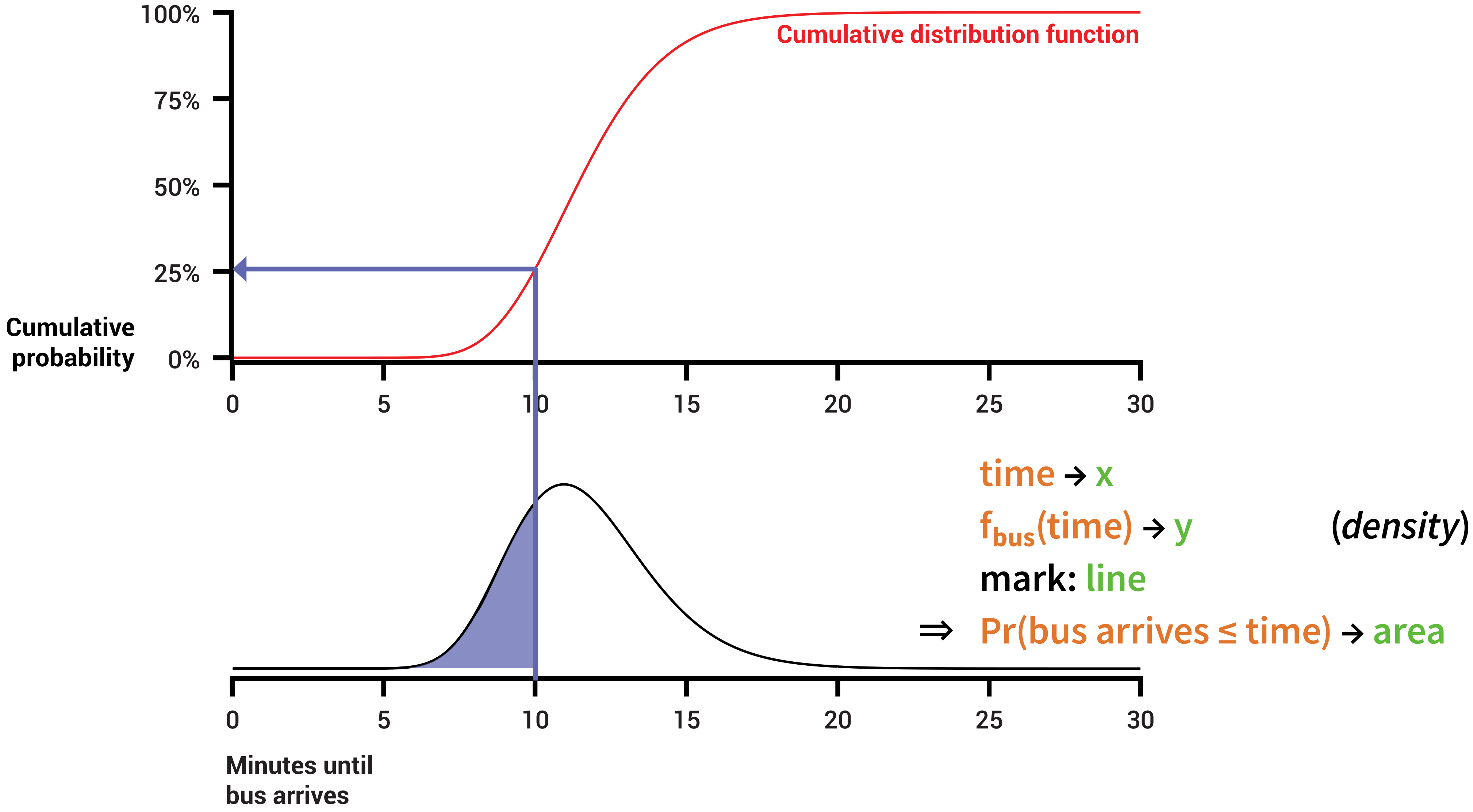
[Viriyincy, https://flic.kr/p/arBfvb]


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

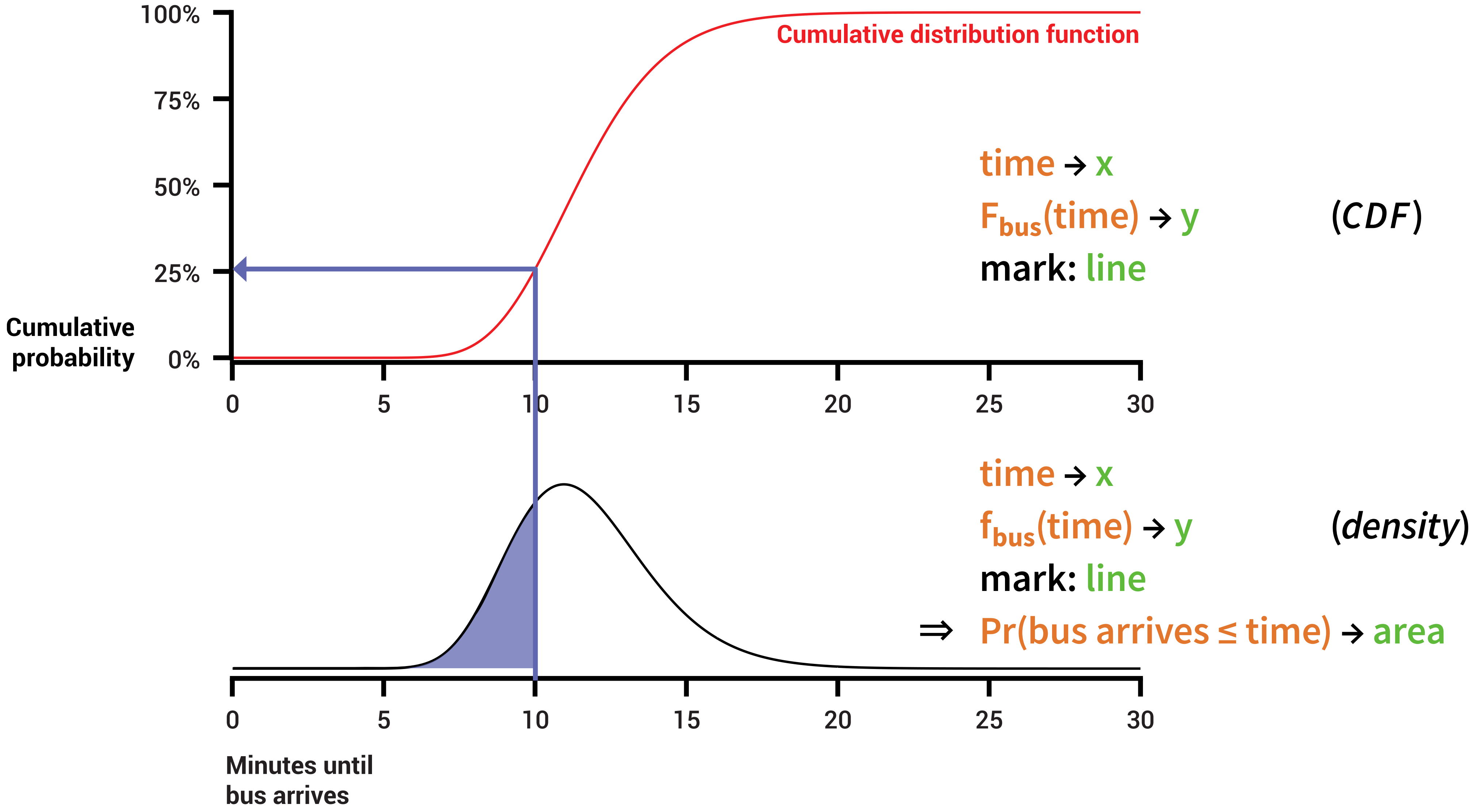

100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
0
5
10
15
20
25
30
Minutes until bus arrives



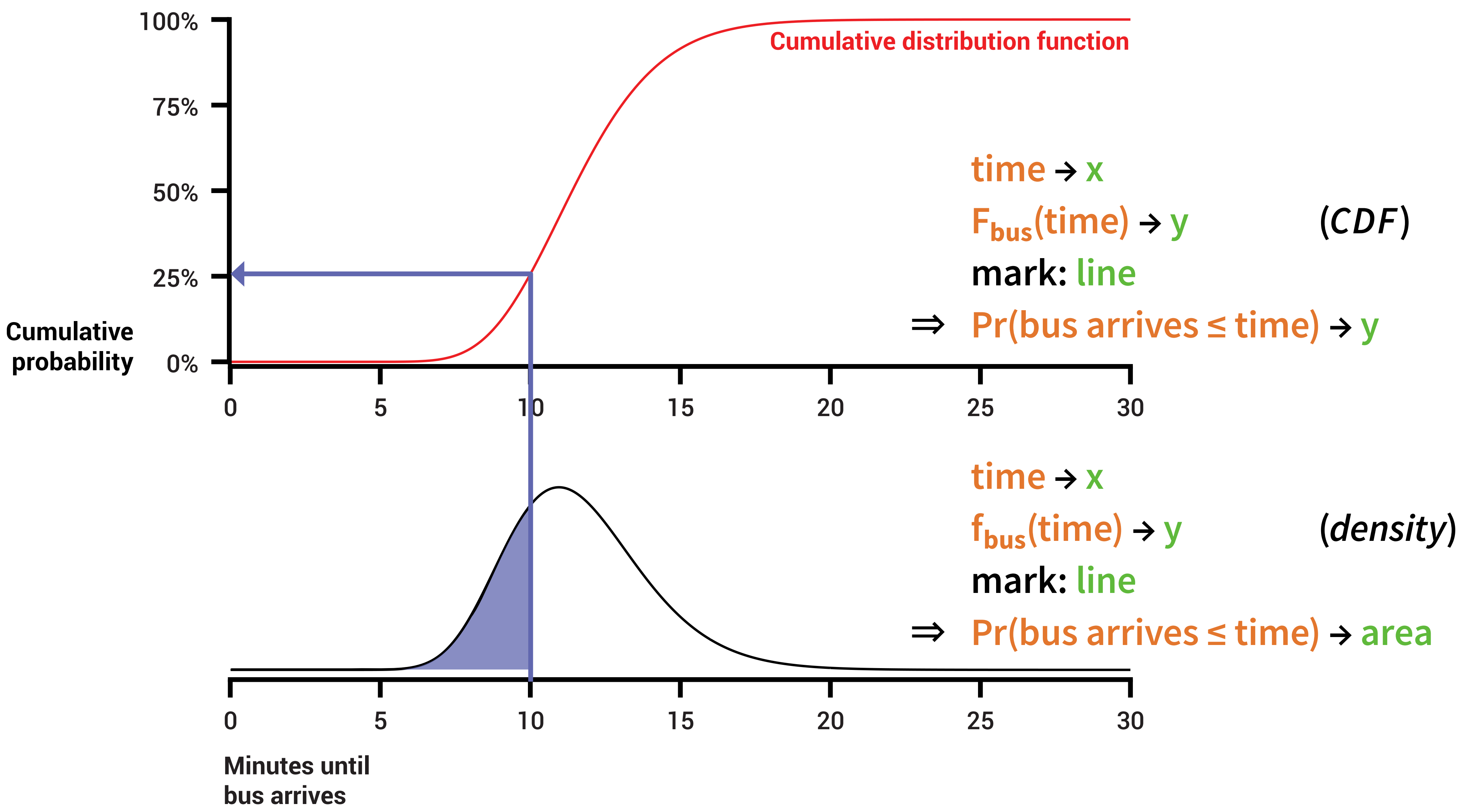
100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
time → x
f_bus(time) → y
(density)
mark: line
0
5
10
15
20
25
30
Minutes until bus arrives

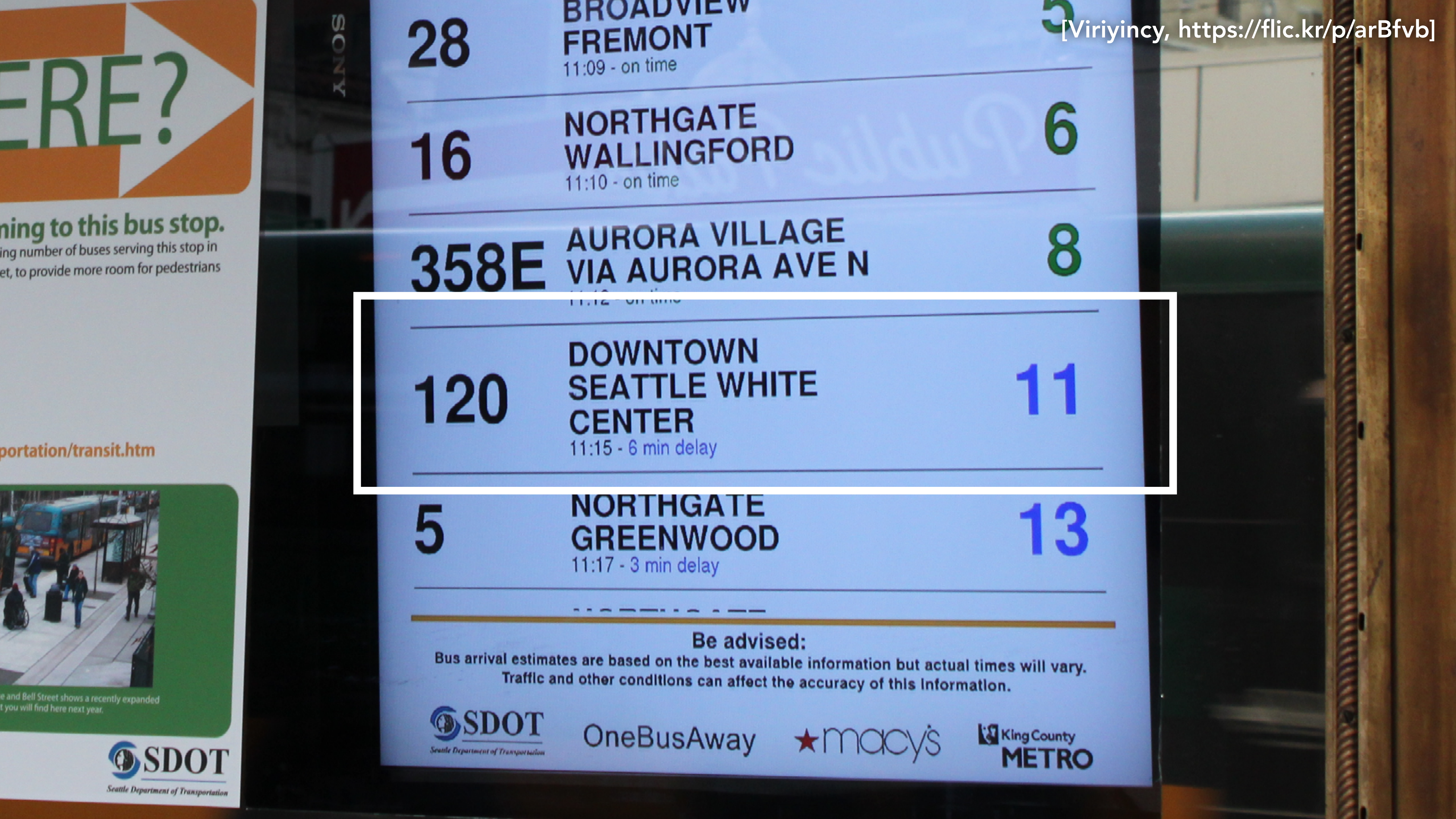


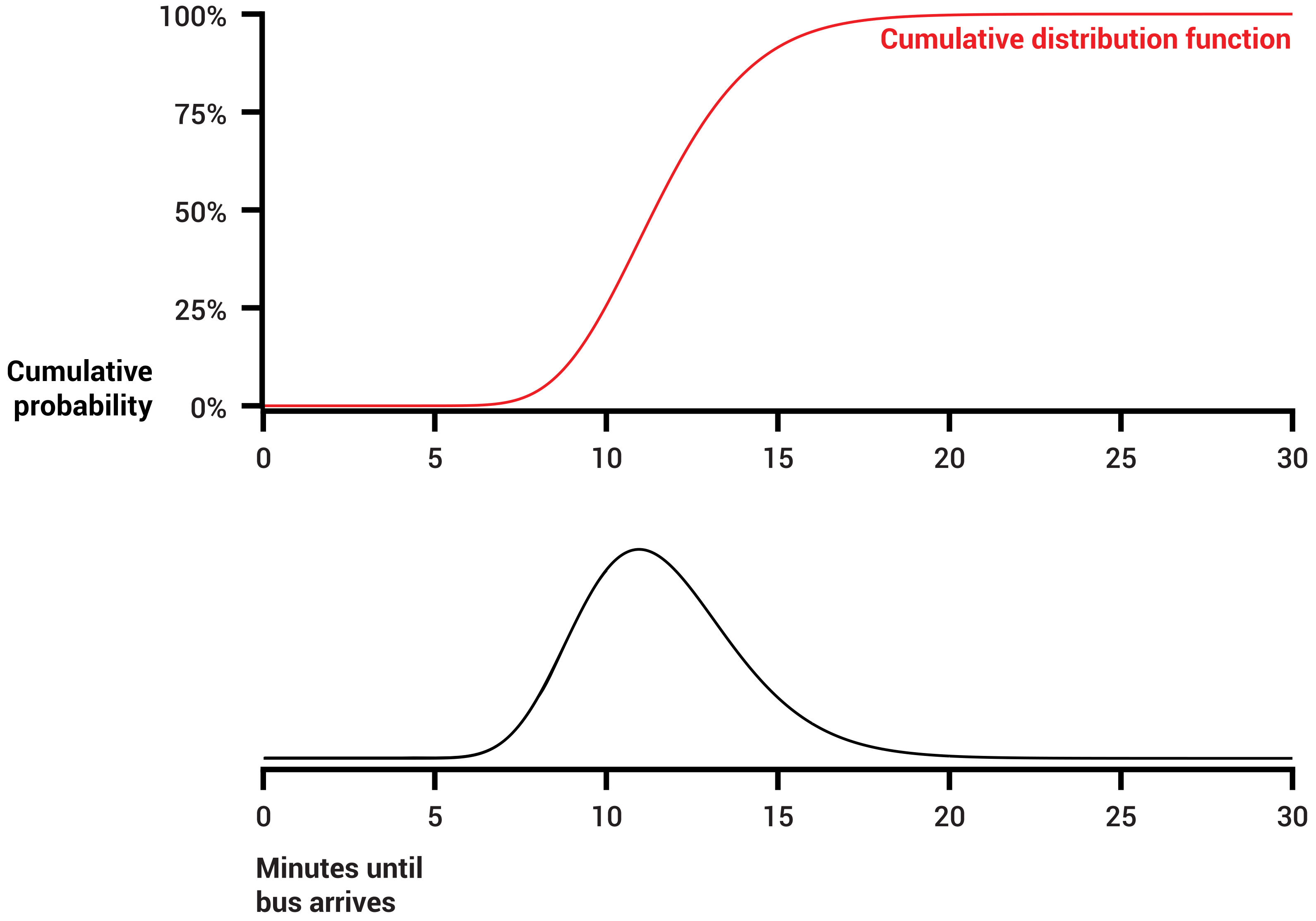
100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0 5 10 15 20 25 30
time → x
f_bus(time) → y
(density)
mark: line
⇒ Pr(bus arrives ≤ time) → area
0 5 10 15 20 25 30
Minutes until bus arrives

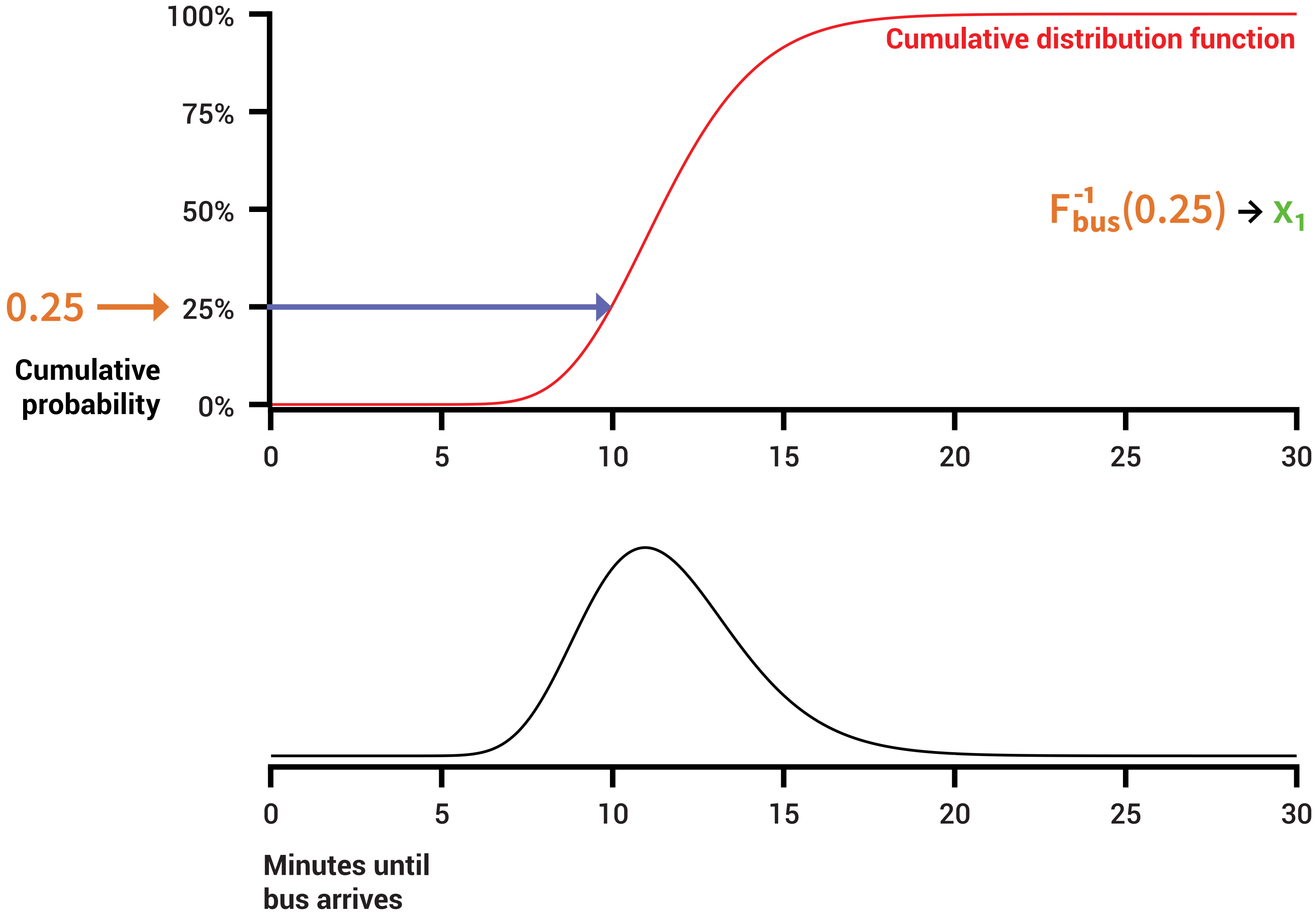


100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
time → x
F_bus(time) → y
(CDF)
mark: line
time → x
f_bus(time) → y
(density)
mark: line
⇒ Pr(bus arrives ≤ time) → area
0
5
10
15
20
25
30
Minutes until bus arrives

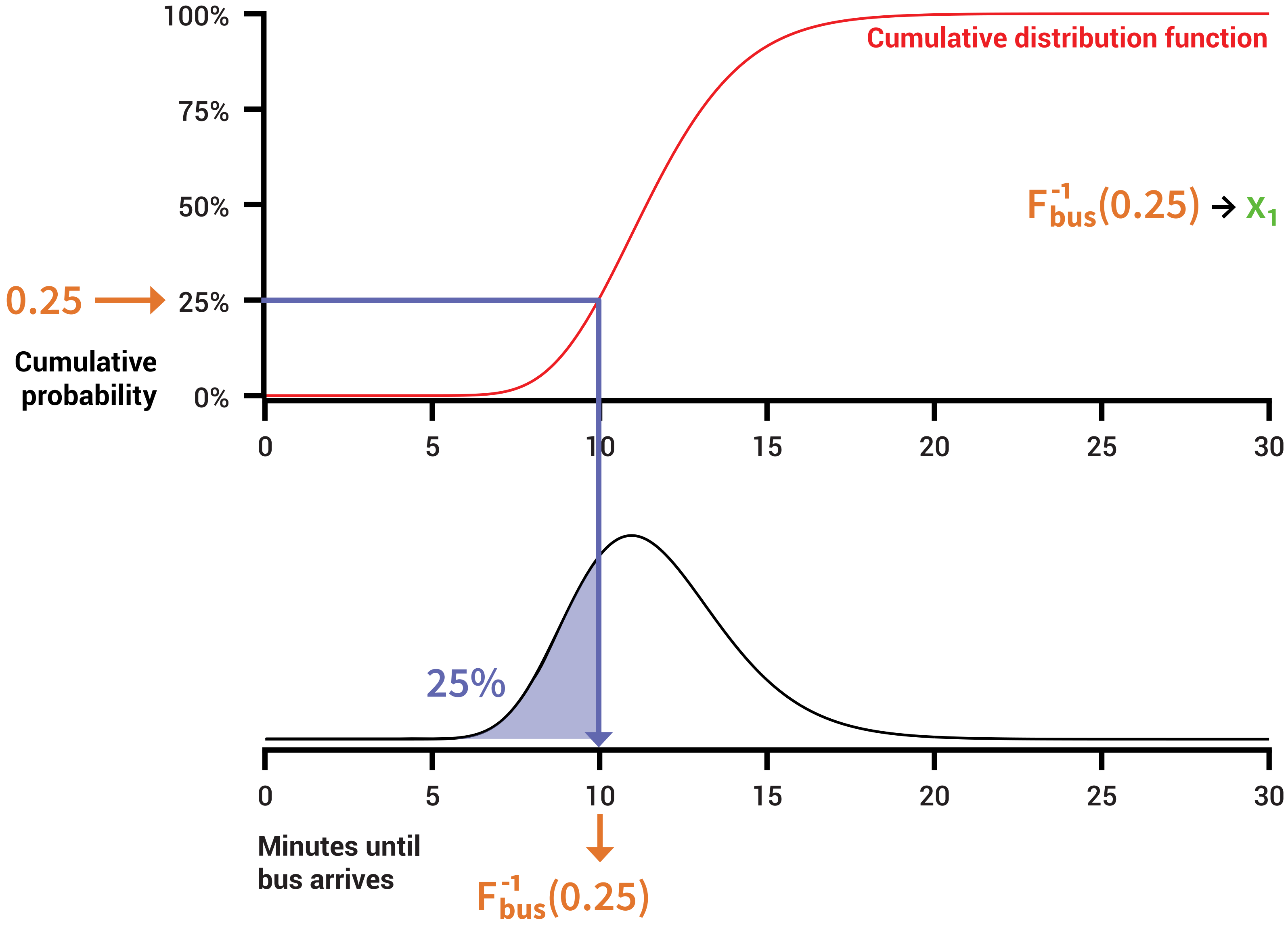

100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
time → x
F_{bus}(time) → y
(CDF)
mark: line
⇒ Pr(bus arrives ≤ time) → y
time → x
f_{bus}(time) → y
(density)
mark: line
⇒ Pr(bus arrives ≤ time) → area
Minutes until bus arrives


[Viriyincy, https://flic.kr/p/arBfvb]
28
FREMONT
11:09 - on time
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
METRO
ERE?
ning to this bus stop.
portation/transit.htm
SDOT
Seattle Department of Transportation

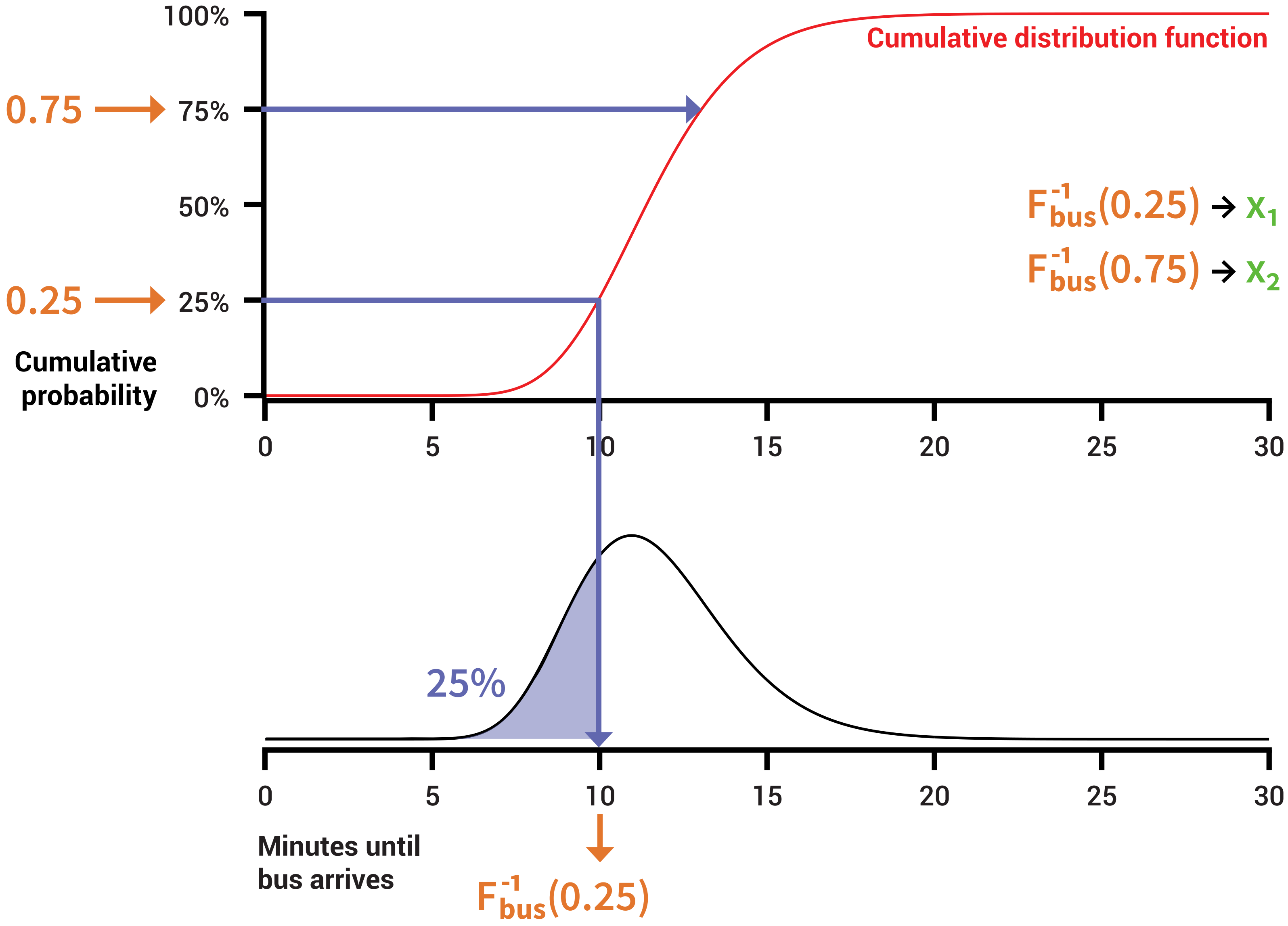

100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
0
5
10
15
20
25
30
Minutes until bus arrives



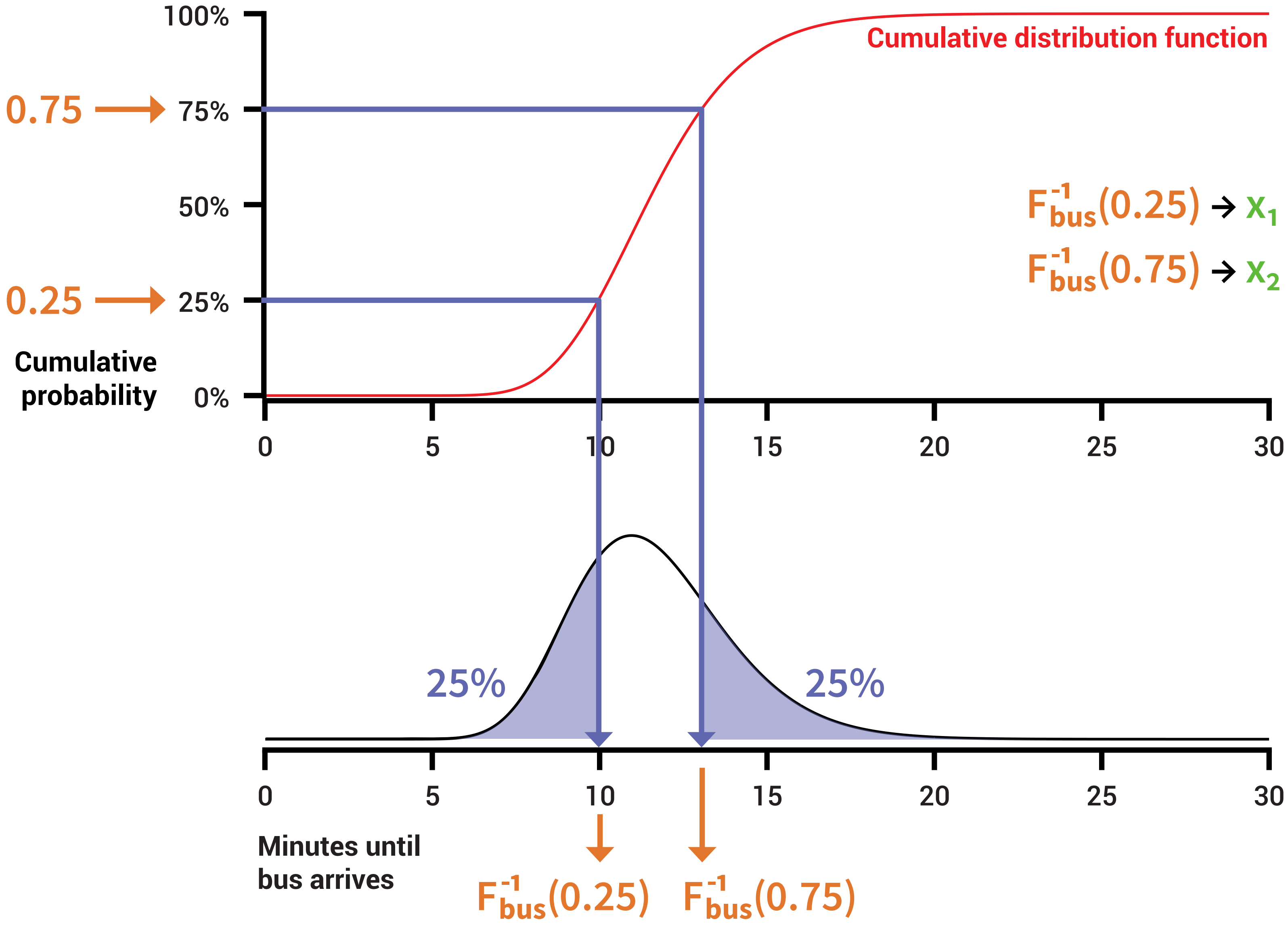
100%
75%
50%
25%
0%
0.25
Cumulative probability
Cumulative distribution function
$F^{-1}_{bus}(0.25) \rightarrow x_1$
0
5
10
15
20
25
30
Minutes until bus arrives



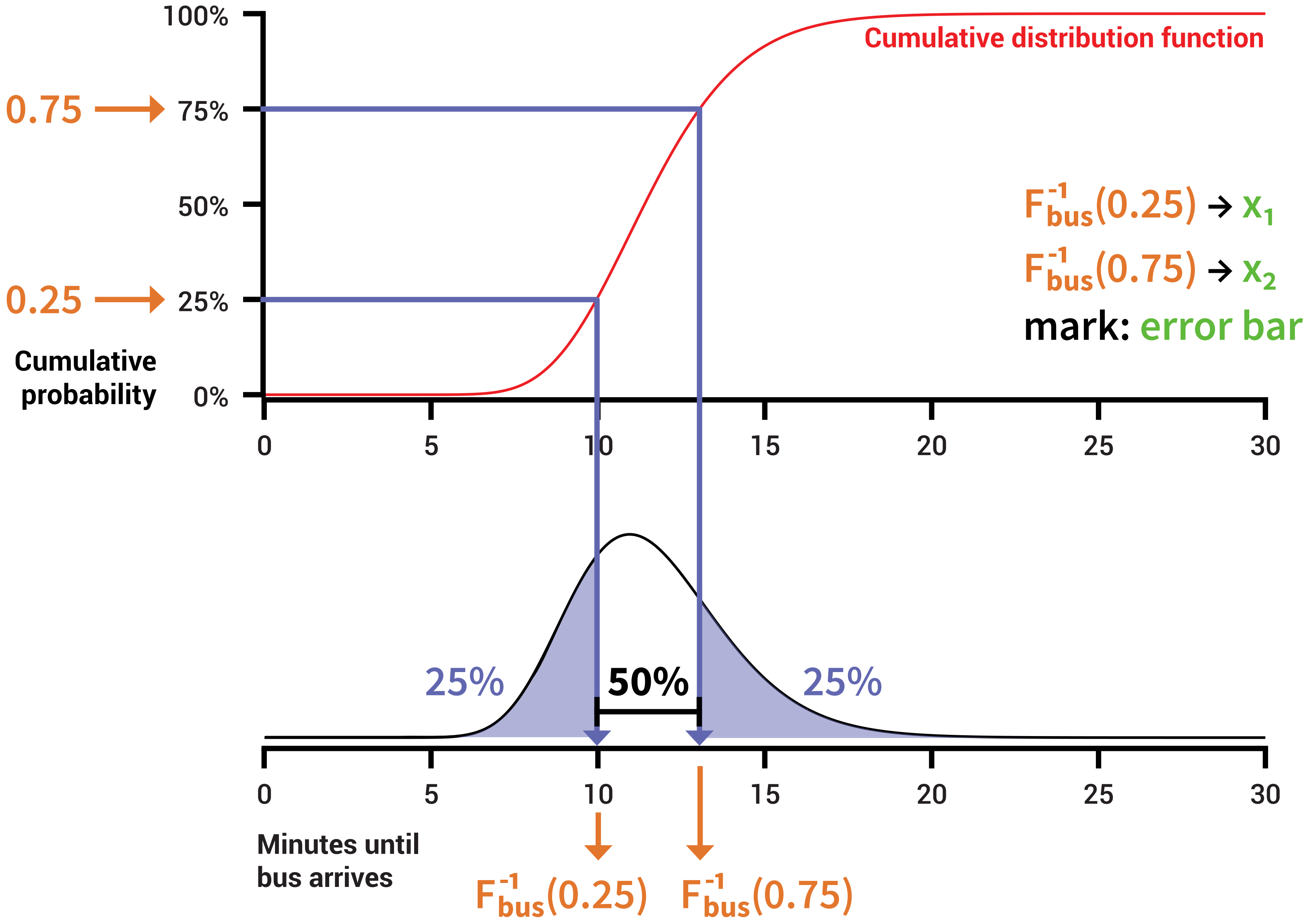
100%
75%
50%
25%
0%
0.25
Cumulative probability
Cumulative distribution function
$F^{-1}_{bus}(0.25) \rightarrow x_1$
0
5
10
15
20
25
30
25%
Minutes until bus arrives
$F^{-1}_{bus}(0.25)$



100%
Cumulative distribution function
0.75
75%
50%
$F^{-1}_{bus}(0.25) \rightarrow x_1$
$F^{-1}_{bus}(0.75) \rightarrow x_2$
0.25
25%
Cumulative probability
0%
0
5
10
15
20
25
30
25%
0
5
10
15
20
25
30
Minutes until bus arrives
$F^{-1}_{bus}(0.25)$



0.75
0.25
100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
$F^{-1}_{bus}(0.25) \rightarrow x_1$
$F^{-1}_{bus}(0.75) \rightarrow x_2$
0 5 10 15 20 25 30
25%
25%
0 5 10 15 20 25 30
Minutes until bus arrives
$F^{-1}_{bus}(0.25)$
$F^{-1}_{bus}(0.75)$

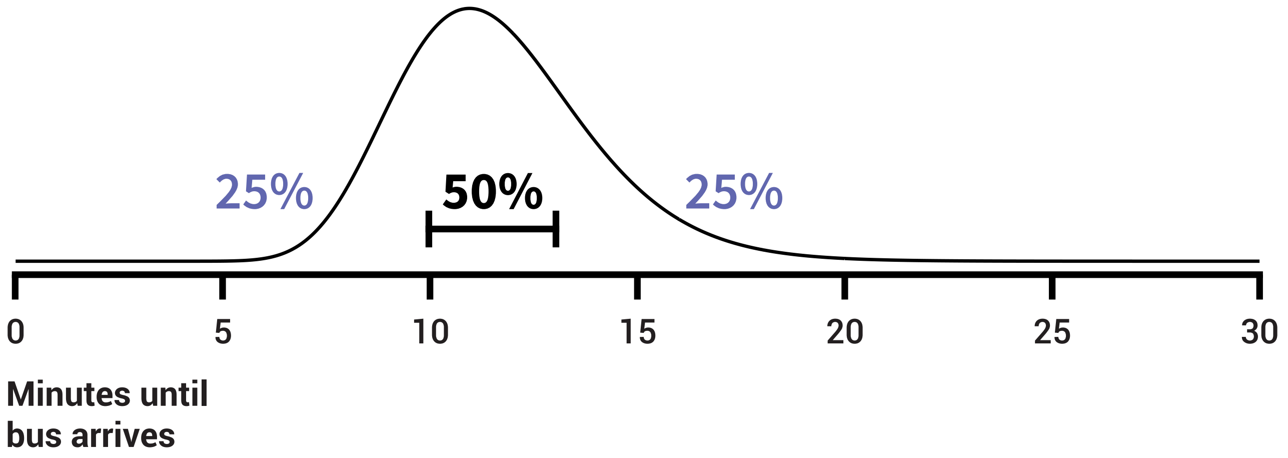


100%
75%
50%
25%
0%
0.75
0.25
Cumulative
probability
Cumulative distribution function
$F^{-1}_{bus}(0.25) \rightarrow x_1$
$F^{-1}_{bus}(0.75) \rightarrow x_2$
mark: error bar
0
5
10
15
20
25
30
25%
50%
25%
Minutes until
bus arrives
$F^{-1}_{bus}(0.25)$
$F^{-1}_{bus}(0.75)$

$F^{-1}_{bus}(0.25) \rightarrow x_1$

$F^{-1}_{bus}(0.75) \rightarrow x_2$

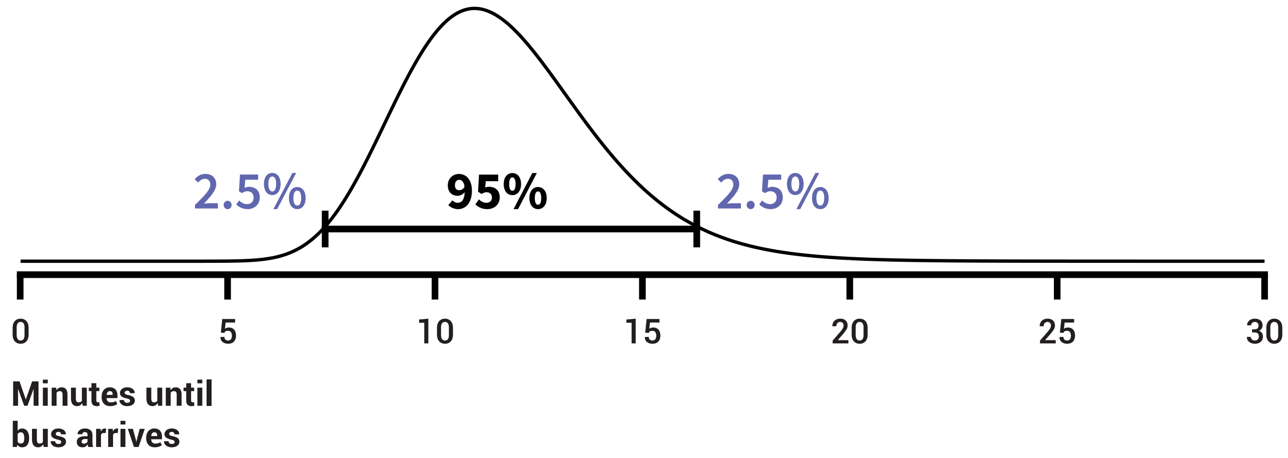
mark: error bar



$F^{-1}_{bus}(0.025) \rightarrow x_1$

$F^{-1}_{bus}(0.975) \rightarrow x_2$

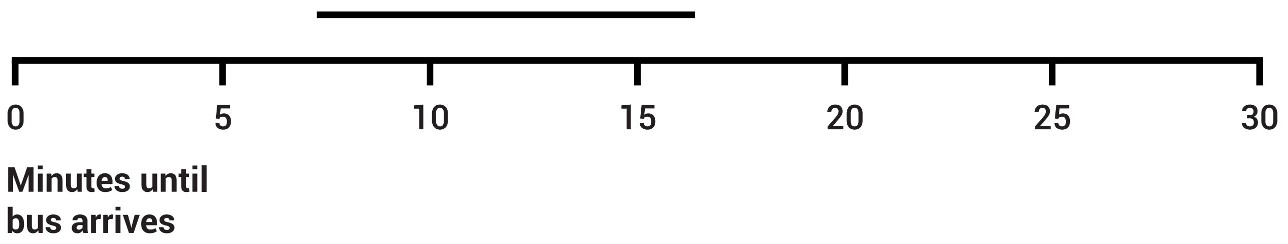
mark: error bar



$F^{-1}_{bus}(0.025) \rightarrow x_1$

$F^{-1}_{bus}(0.975) \rightarrow x_2$

mark: error bar



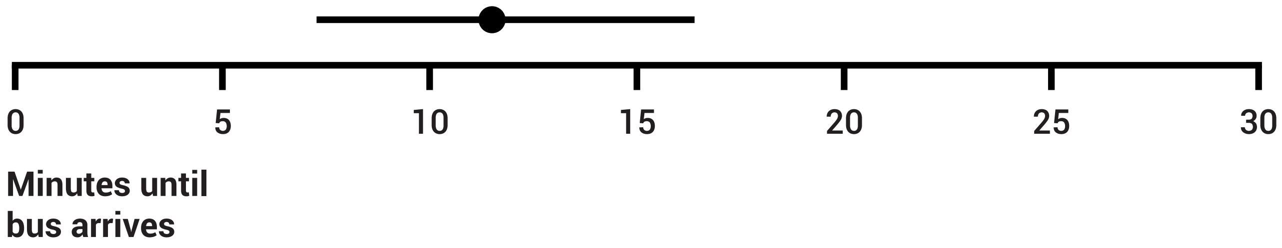
$F^{-1}_{bus}(0.025) \rightarrow x_1$

$F^{-1}_{bus}(0.975) \rightarrow x_2$

mark: error bar

$F^{-1}_{bus}(0.50) \rightarrow x$

mark: point



$F^{-1}_{bus}(0.025) \rightarrow x_1$

$F^{-1}_{bus}(0.975) \rightarrow x_2$

mark: error bar

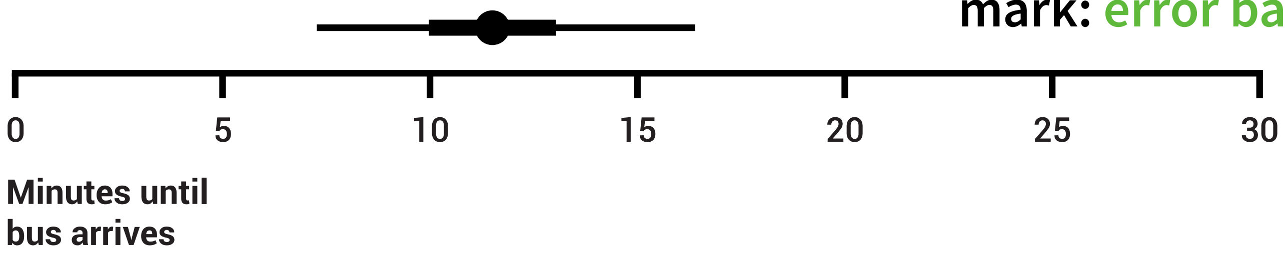
$F^{-1}_{bus}(0.50) \rightarrow x$

mark: point

$F^{-1}_{bus}(0.25) \rightarrow x_1$

$F^{-1}_{bus}(0.75) \rightarrow x_2$

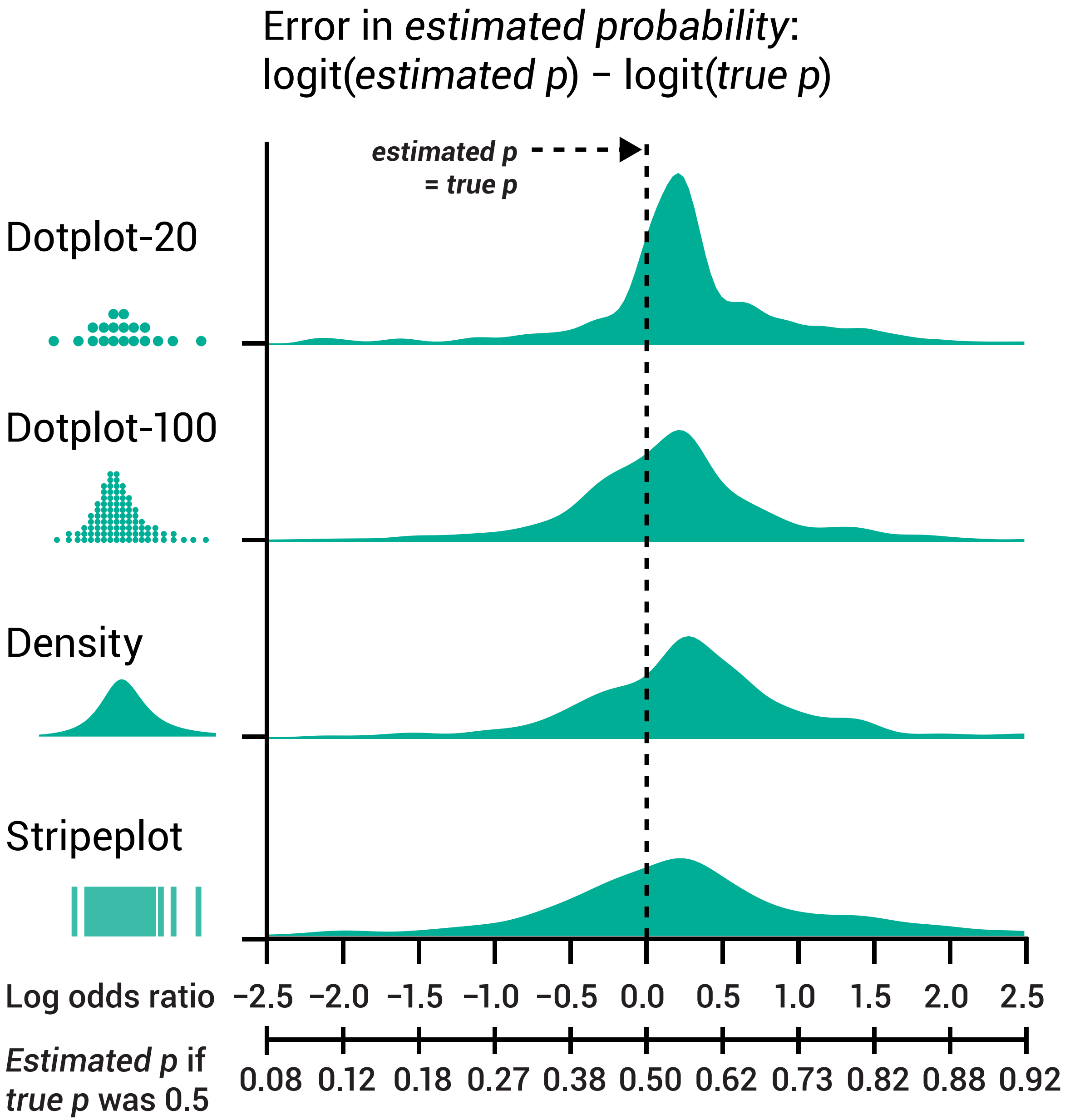
mark: error bar



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)



Quantile dotplots

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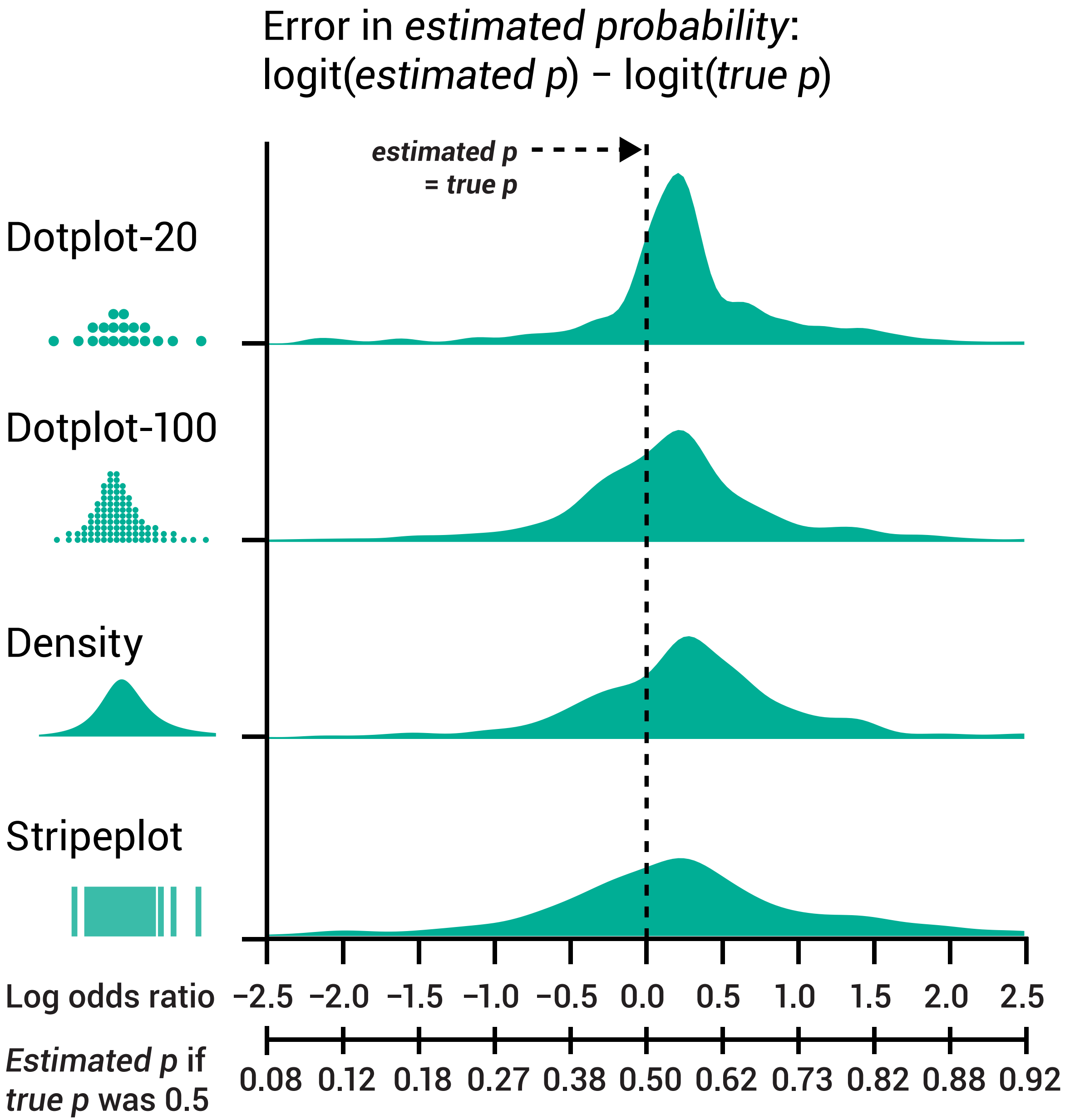
Better estimates (perceptually)

↓?

better decisions



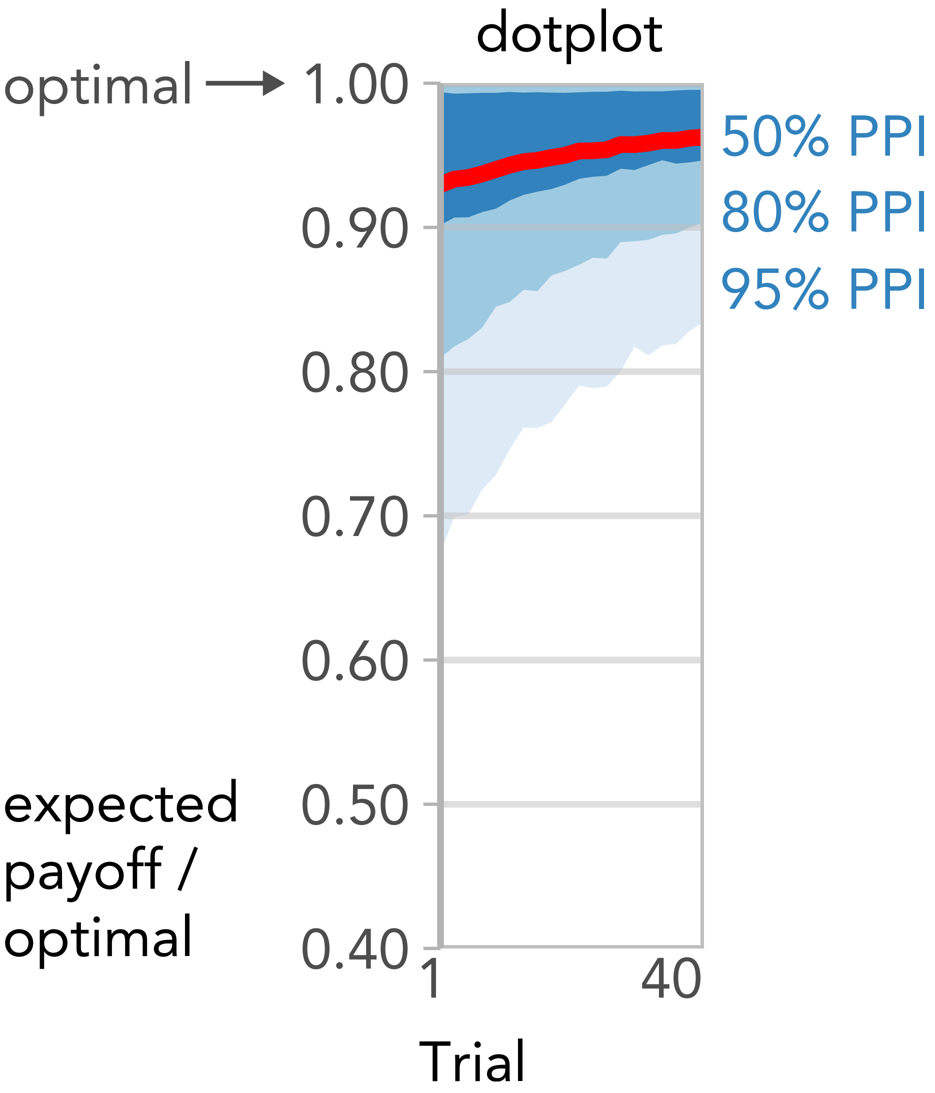
Quantile dotplots

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

Better estimates
(perceptually)

↓

better decisions
(in this case)



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Better estimates (perceptually)

↓

better decisions (in this case)