Information Visualization II

UM Big Data Summer Institute 2019

Matthew Kay
Assistant Professor
School of Information & Computer Science and Engineering
University of Michigan

Last time

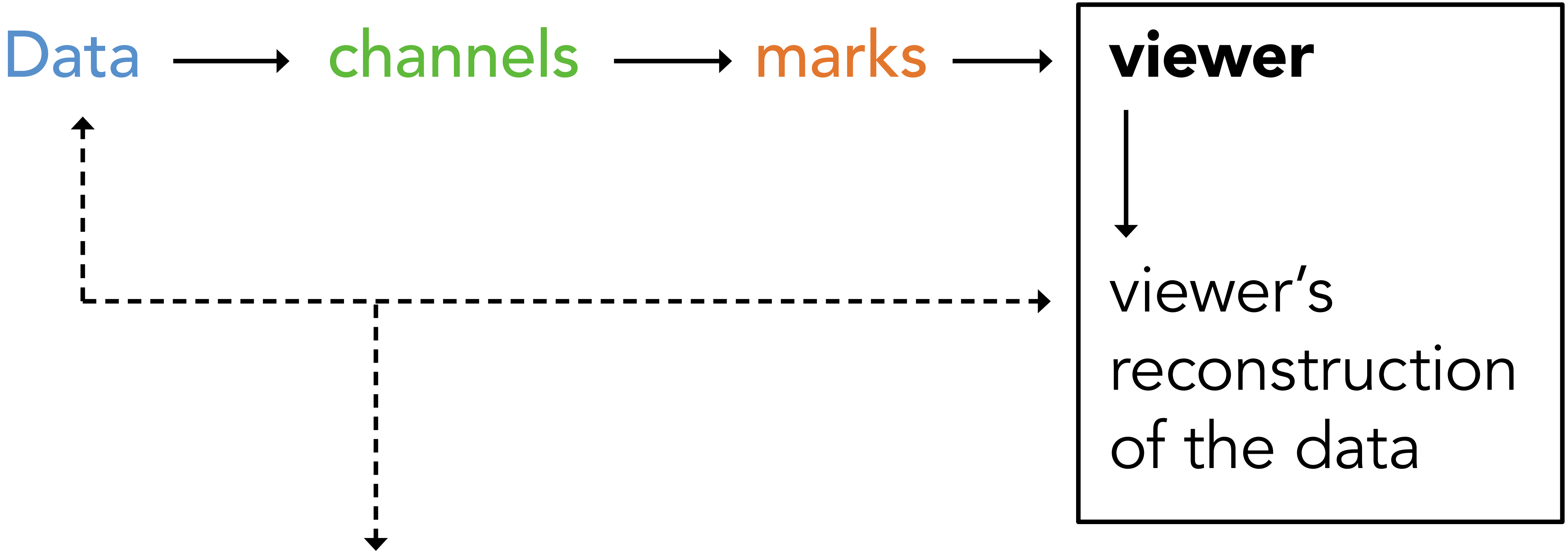
Last time

Understanding the effectiveness of different visual channels / encodings.

Understanding where your viewer will look and what they want to do (tasks).

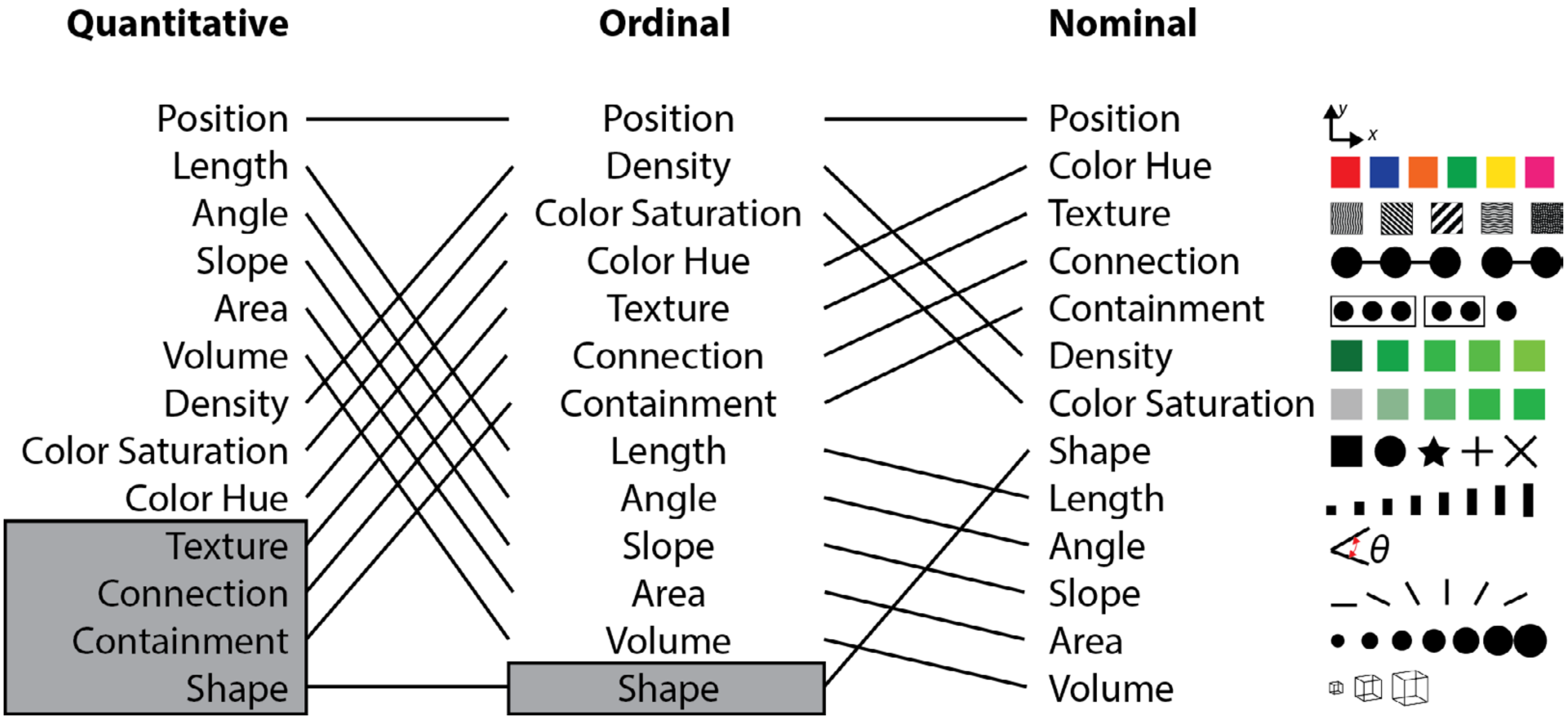
Visualizing as a reflex during analysis.

Systematic design via channel effectiveness



How well do these match, given the channel used?

Systematic design via channel effectiveness



Today

What I want to do today

Talk about:

Uncertainty visualization

Multivariate visualization (a bit)

Run through some examples (if time)

Uncertainty

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 qualifie[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]was not signi[illegible]nt, $F(2, 1276) = 0.06$, $p = .94$, $\eta_p^2 < .001$. All other main effect[illegible]nd interactions were n[illegible]significant and irrelevant to our hypotheses, all $F \leq 0.9$[illegible]$p \geq .39$, $\eta_p^2 \leq .001$.

Alternatives...

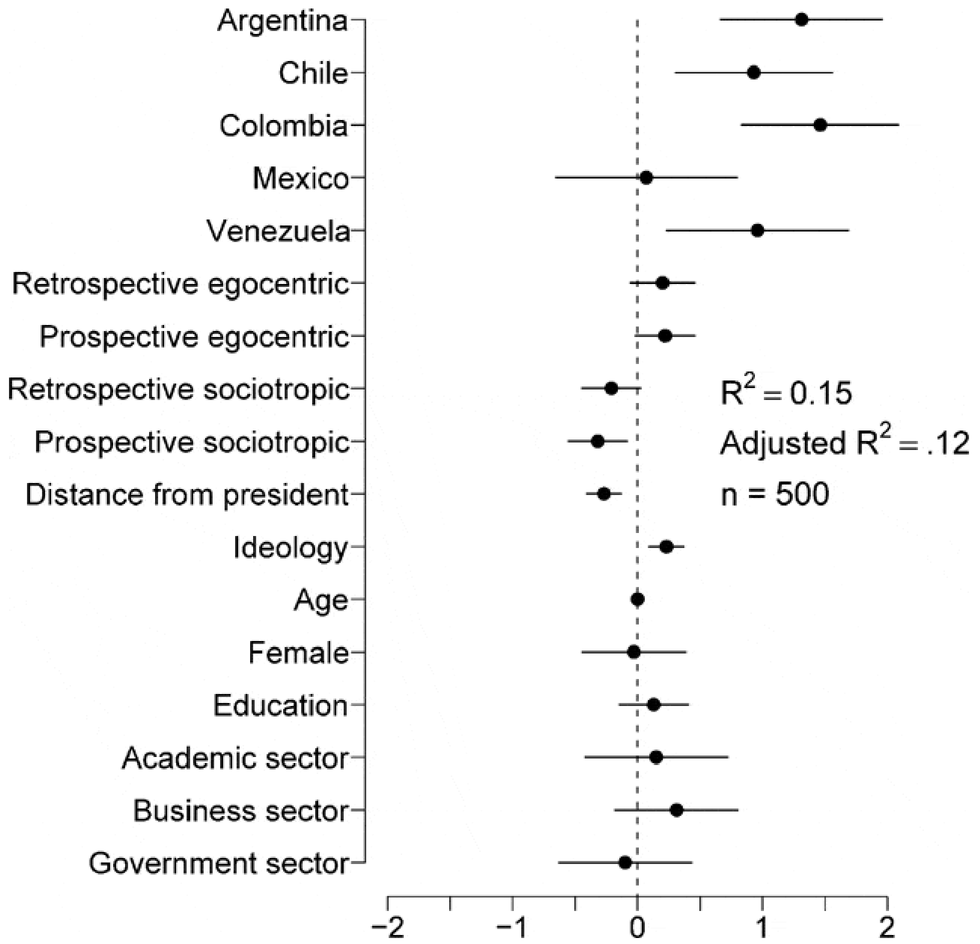
Variable	Coefficient (Standard Error)
Constant	.41 (.93)
Countries	
Argentina	1.31 (.33)**B,M
Chile	.93 (.32)**B,M
Colombia	1.46 (.32)**B,M
Mexico	.07 (.32)A,CH,CO,V
Venezuela	.96 (.37)**B,M
Threat	
Retrospective egocentric economic perceptions	.20 (.13)
Prospective egocentric economic perceptions	.22 (.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)

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)

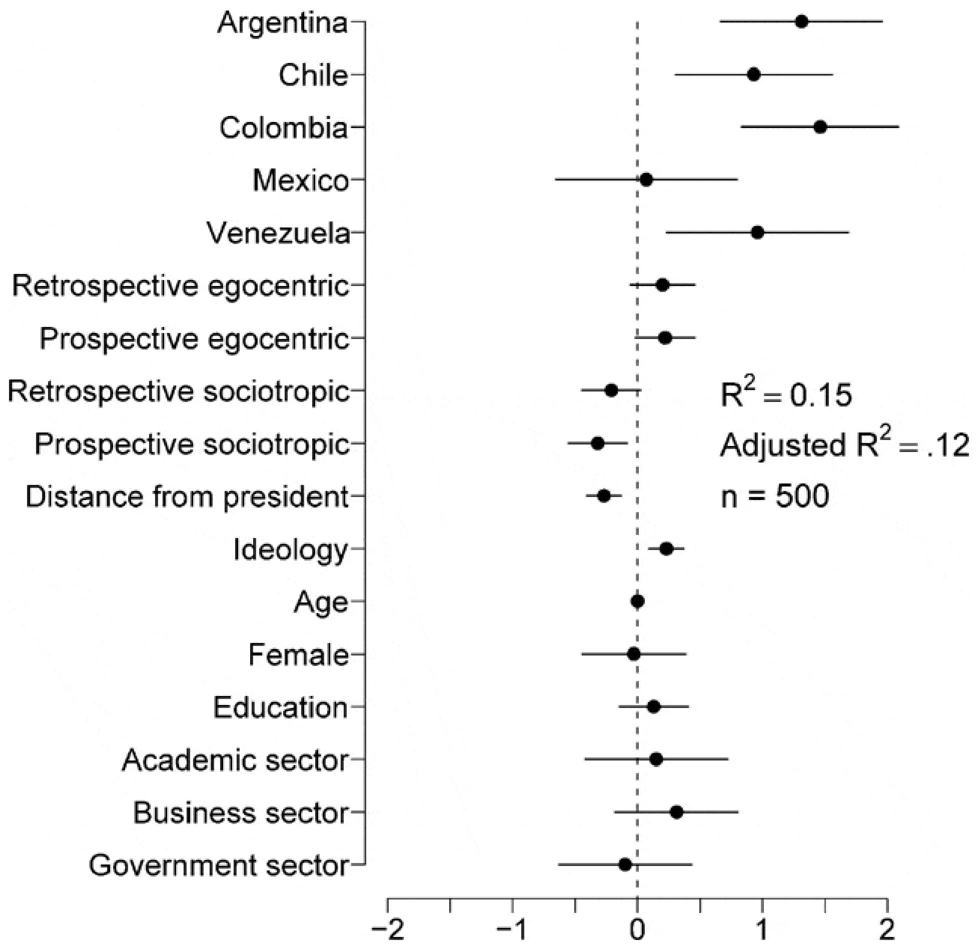


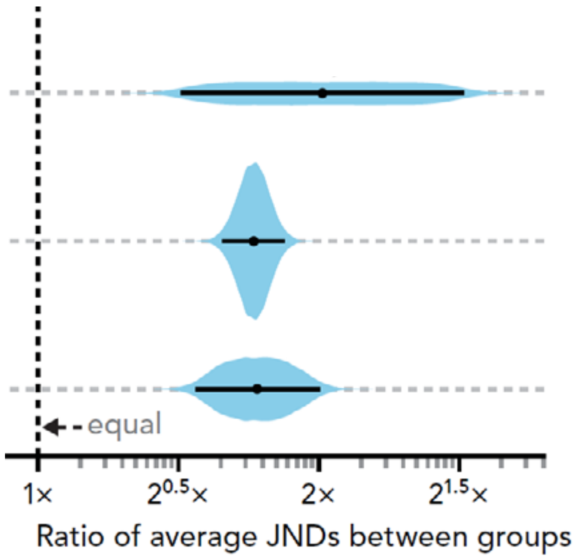
[Jonathan P Kastellec and Eduardo L Leoni. 2007. Using Graphs Instead of Tables in Political Science. Perspectives on politics 5, 4: 755–771]

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)

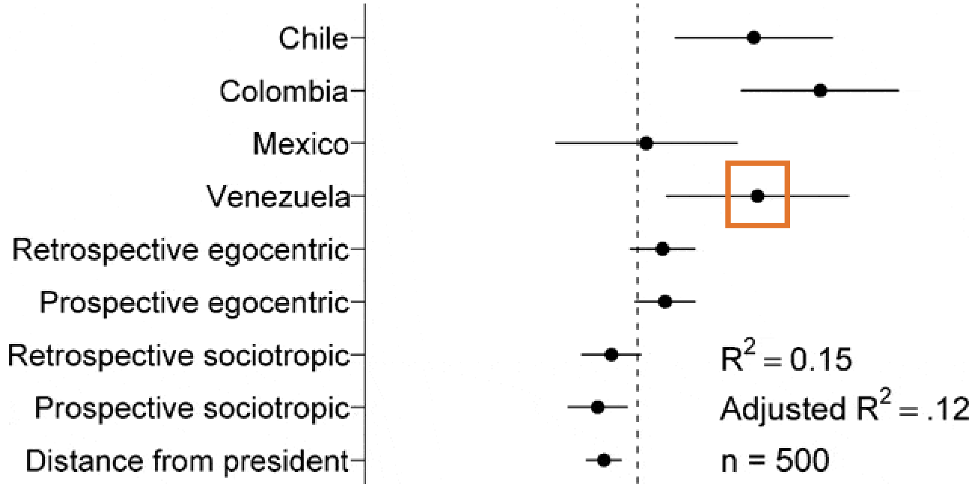


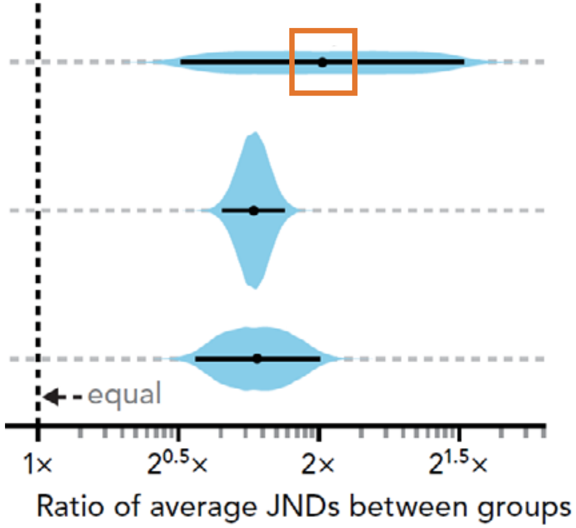


[Jonathan P Kastellec and Eduardo L Leoni. 2007. Using Graphs Instead of Tables in Political Science. Perspectives on politics 5, 4: 755–771]

How easy is it to ignore the uncertainty?

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)*





This contributes to dichotomania...

Dichotomania...

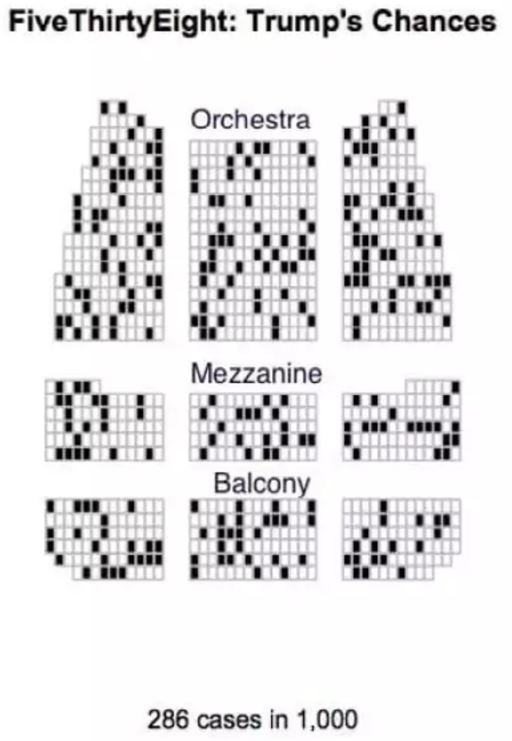
Predictions from last US presidential election

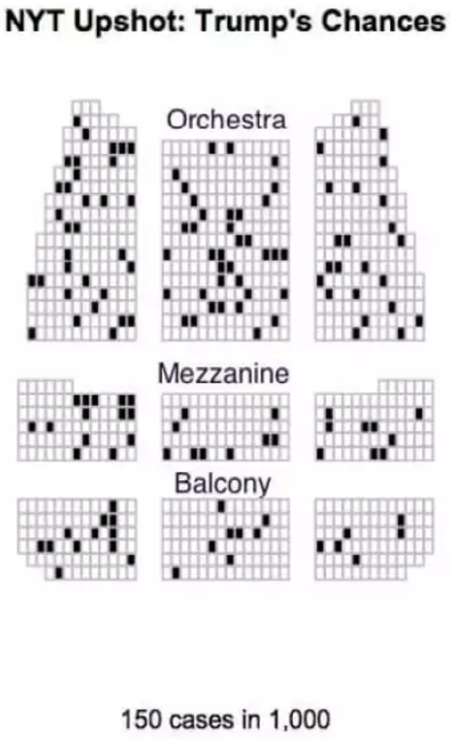
[http://wapo.st/2fCYvDW]

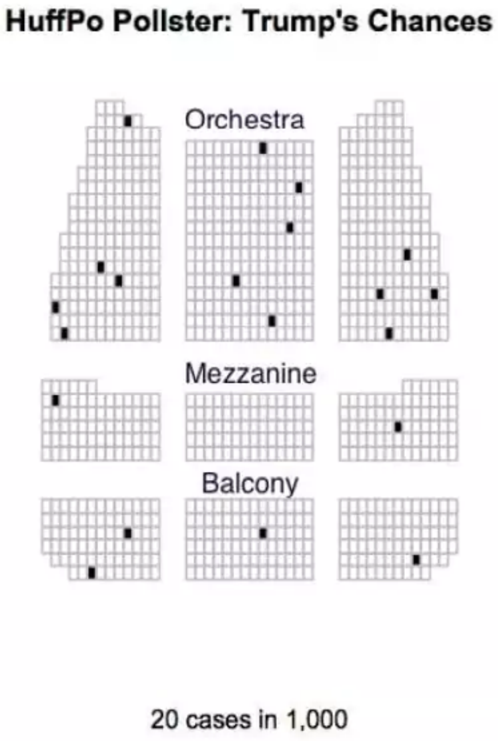
FiveThirtyEight: Trump's Chances	NYT Upshot: Trump's Chances	HuffPo Pollster: Trump's Chances
28%	15%	2%

Predictions from last presidential election

[http://wapo.st/2fCYvDW]







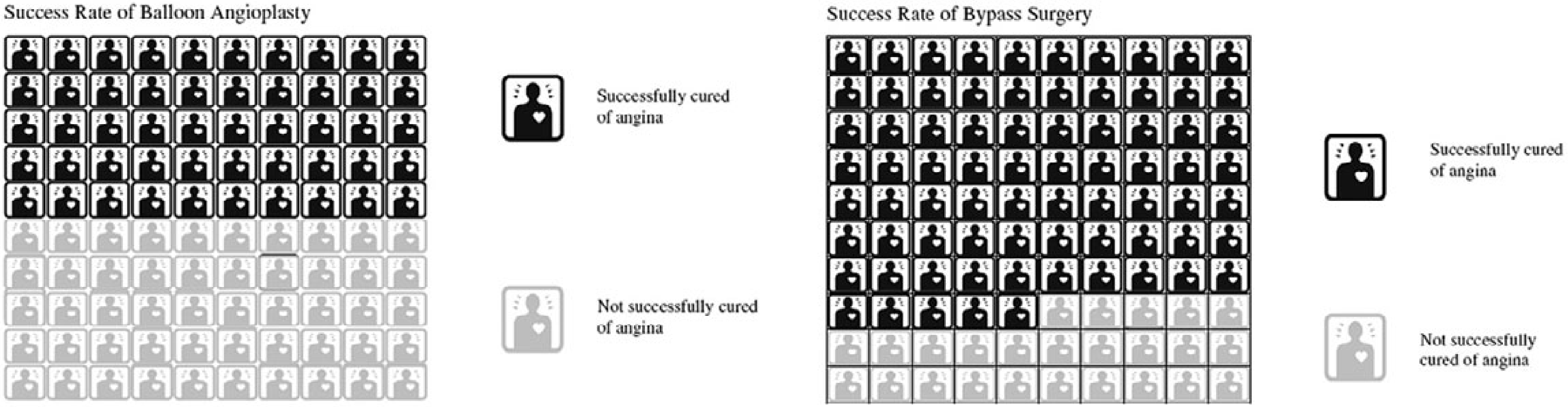
People are very good at ignoring uncertainty...

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

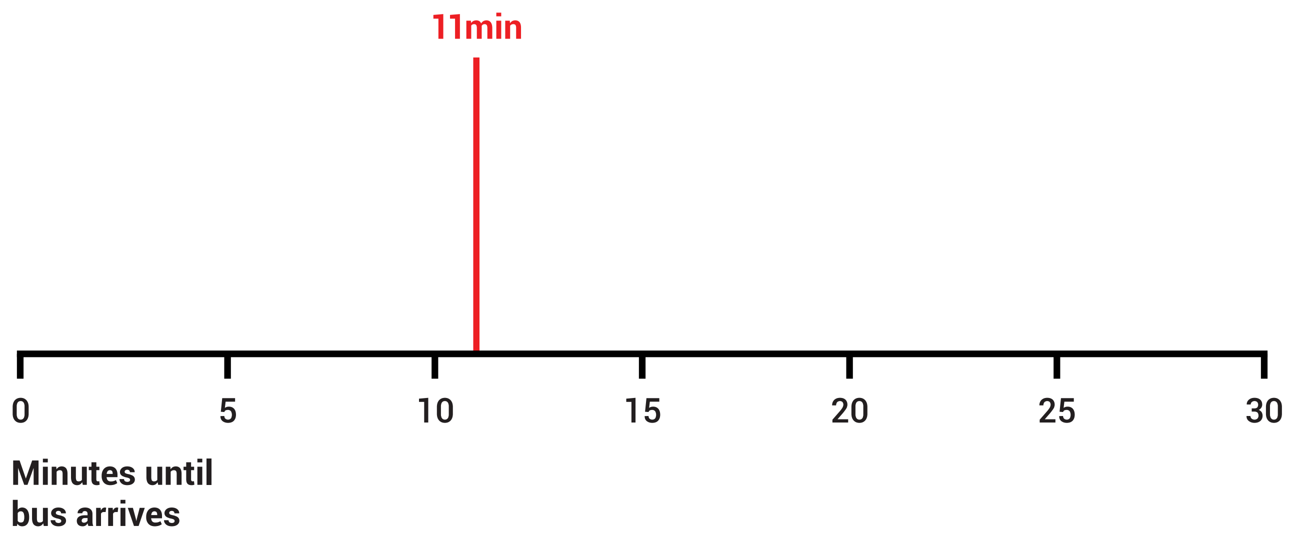
What is an icon array for a continuous distribution?

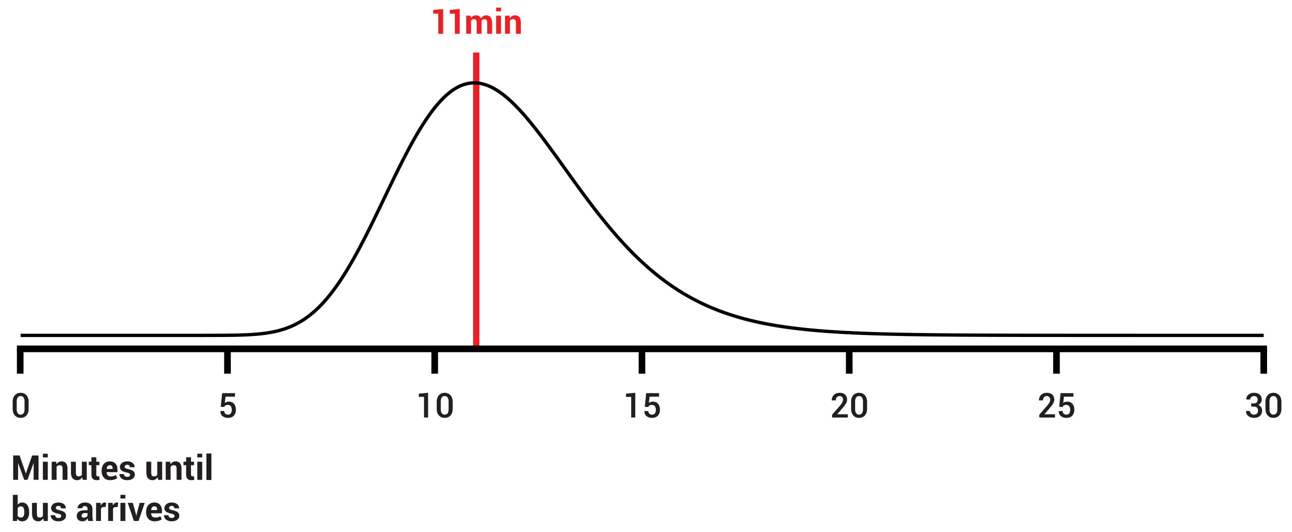
What is an icon array for a continuous distribution?

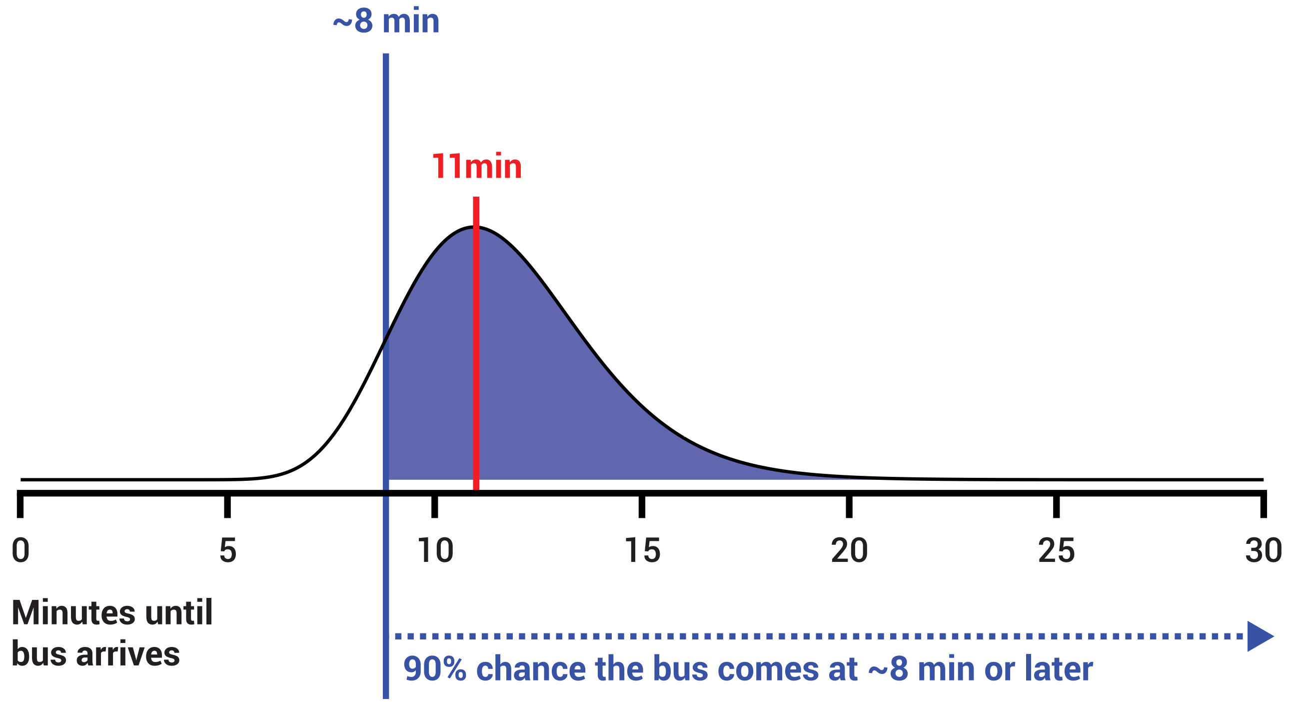
An example scenario...

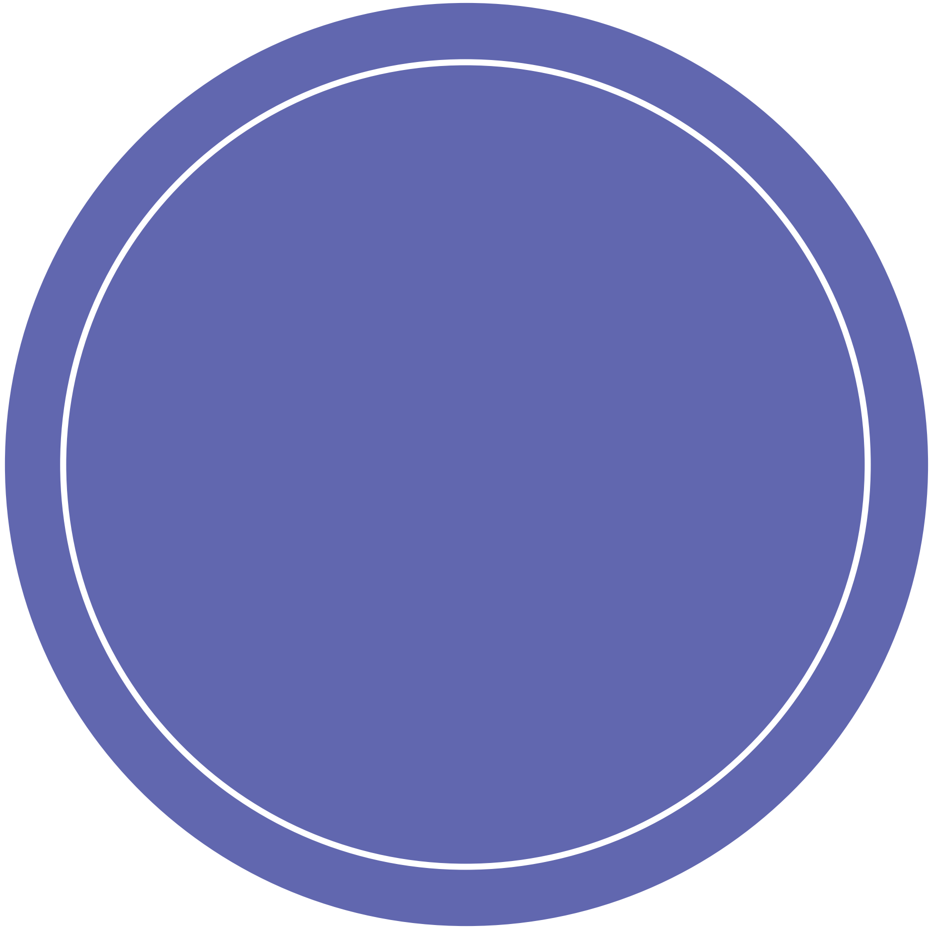
11:05 - 8 min delay
28
BROADVIEW
FREMONT
11:09 - on time
5
16
NORTHGATE
WALLINGFORD
11:10 - on time
6
358E
AURORA VILLAGE
VIA AURORA AVE N
8
120
DOWNTOWN
SEATTLE WHITE
CENTER
11:15 - 6 min delay
11
5
NORTHGATE
GREENWOOD
11:17 - 3 min delay
13
Be advised:
Bus arrival estimates are based on the best available information but actual times will vary.
Traffic and other conditions can affect the accuracy of this information.
SDOT
OneBusAway
King County
this bus stop.
transit.htm
SONY

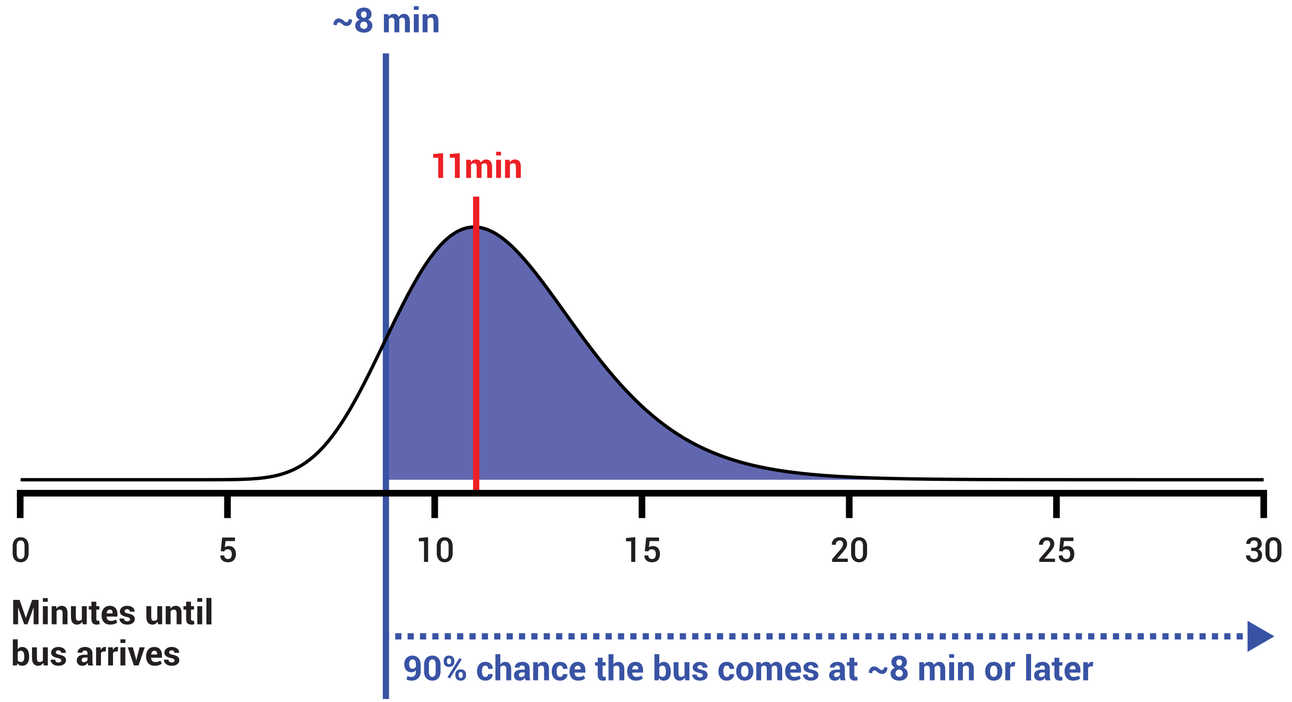
Do I have time to get a coffee?

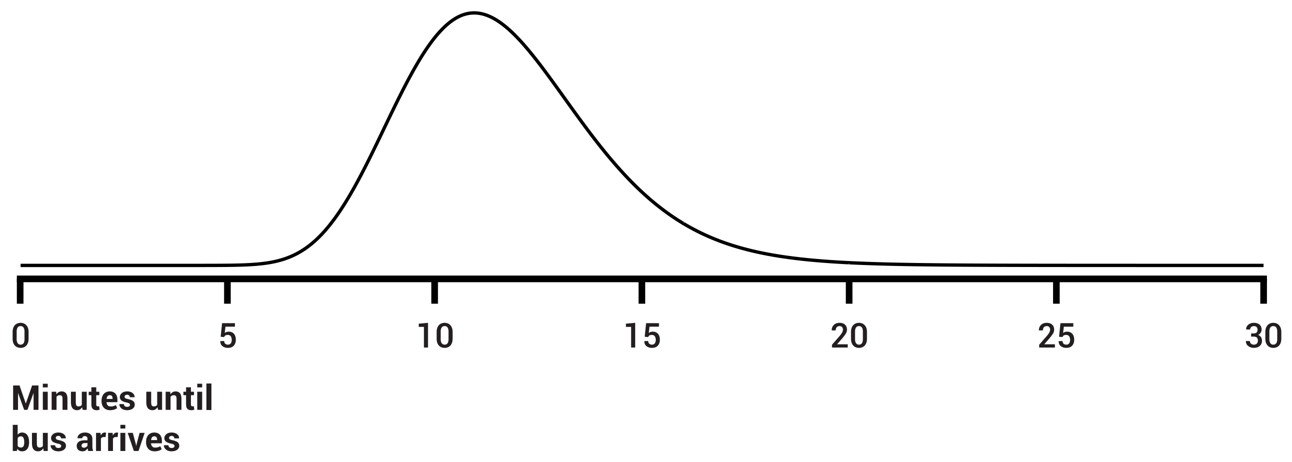

11min
0
5
10
15
20
25
30
Minutes until
bus arrives

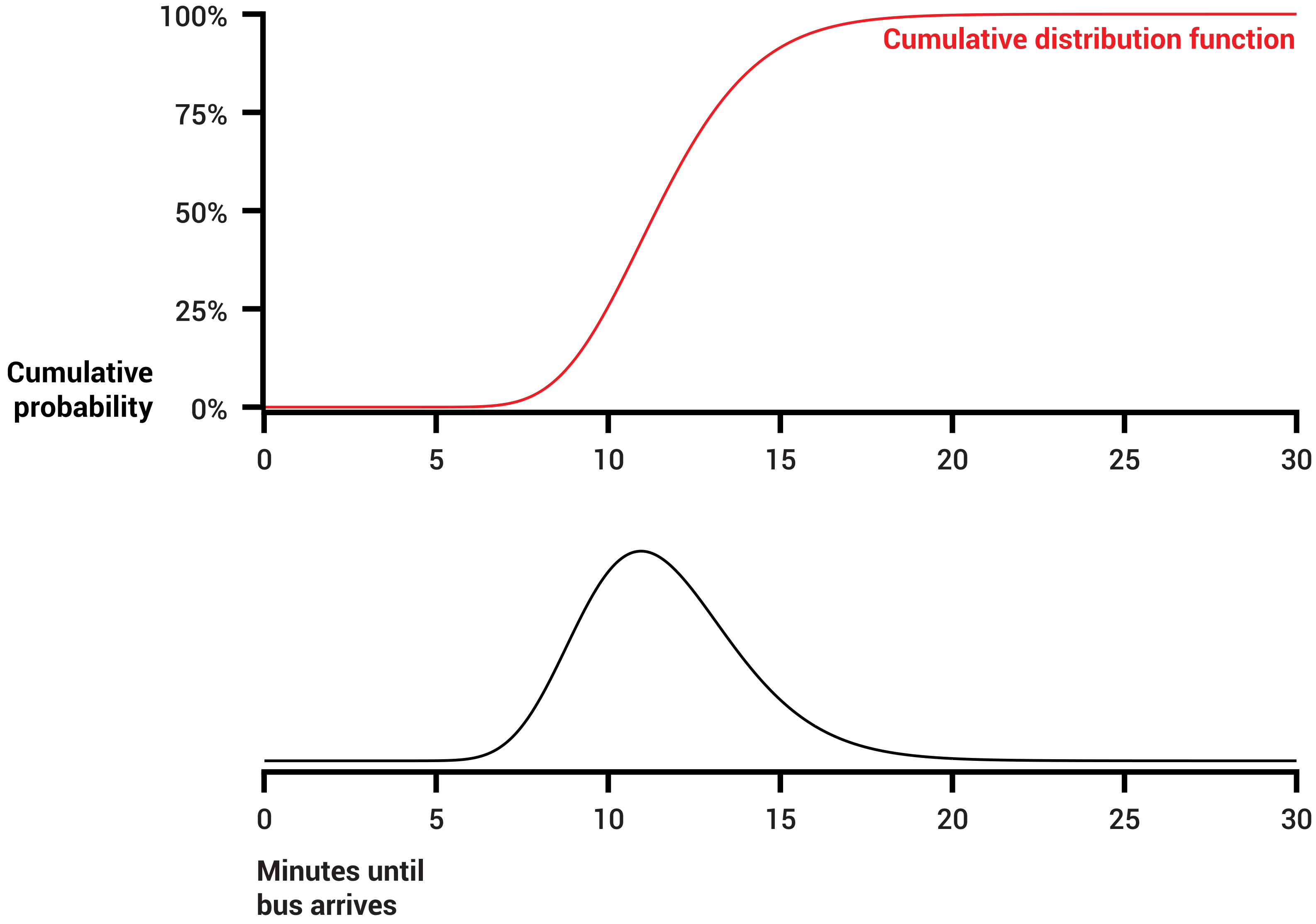

11min
0
5
10
15
20
25
30
Minutes until
bus arrives


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

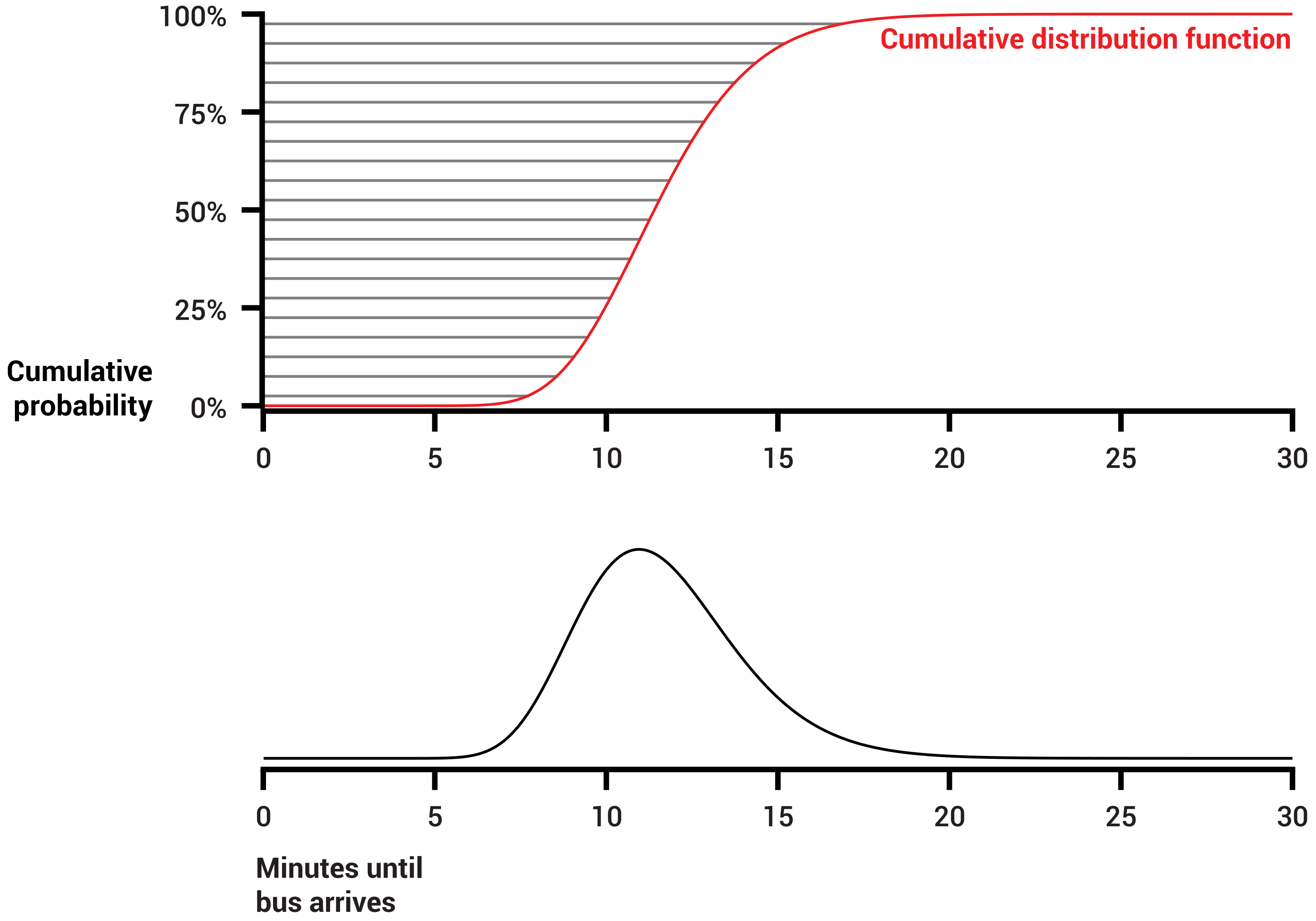


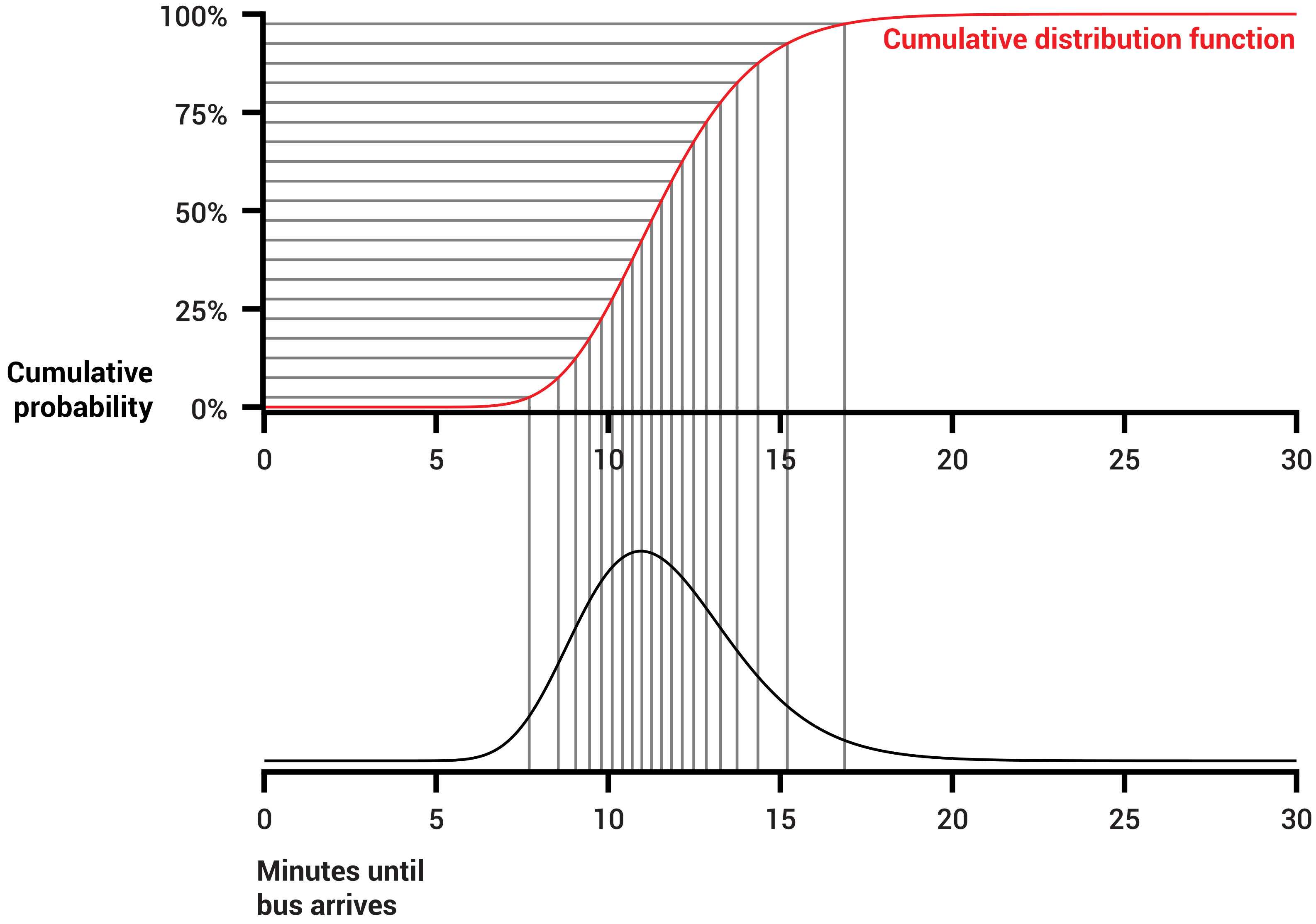

~8 min
11min
0
5
10
15
20
25
30
Minutes until
bus arrives
90% chance the bus comes at ~8 min or later

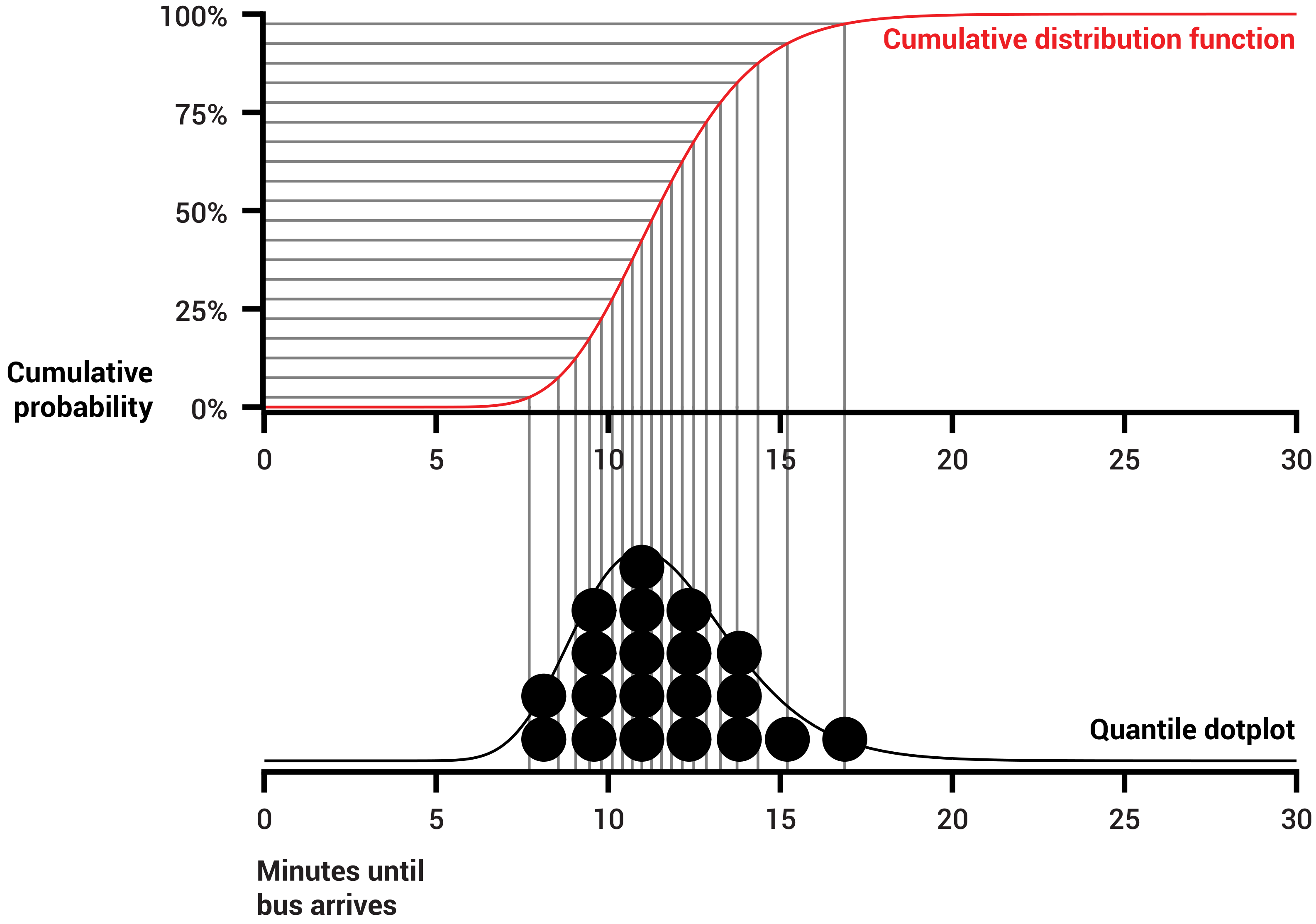

0
5
10
15
20
25
30
Minutes until
bus arrives

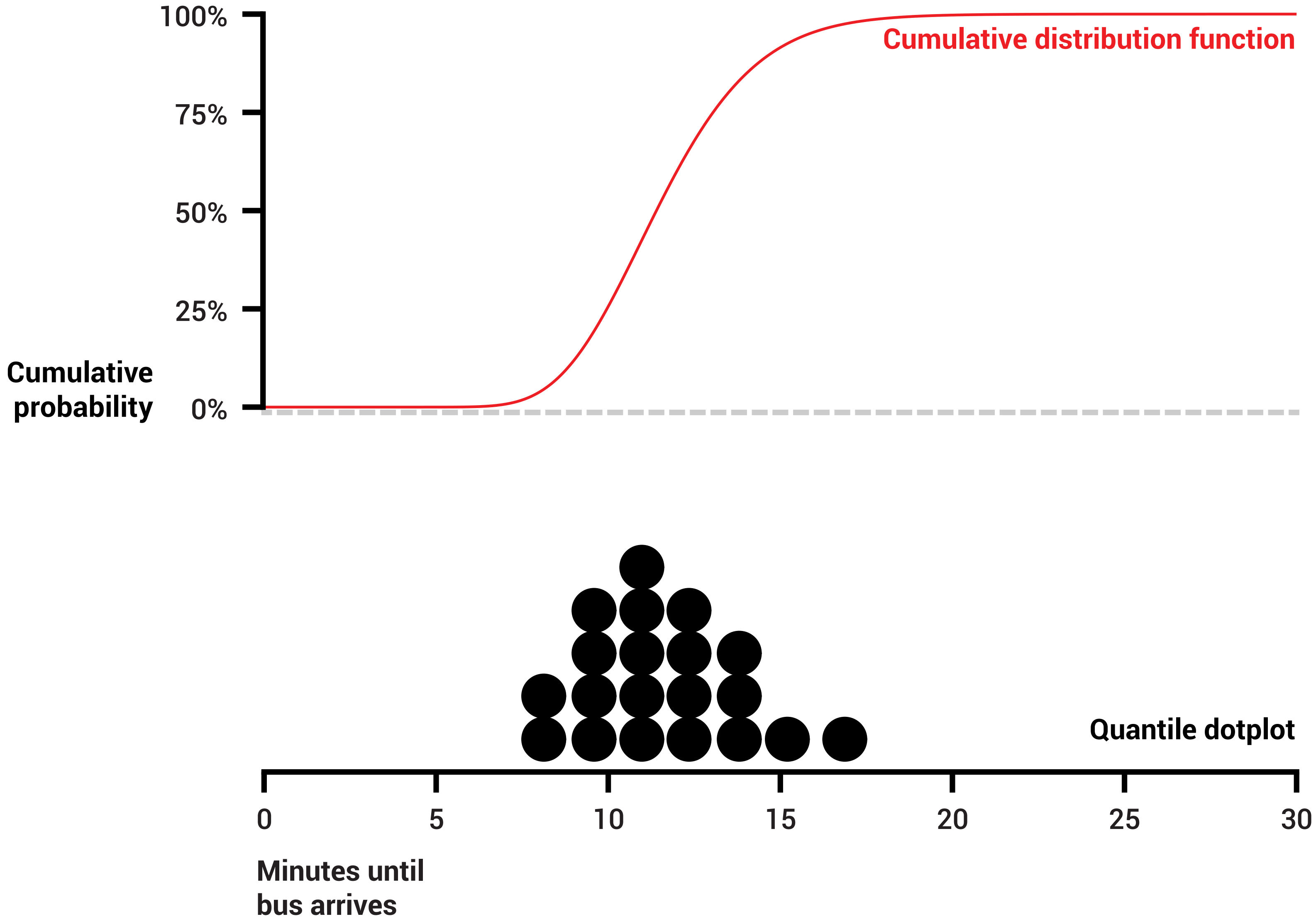


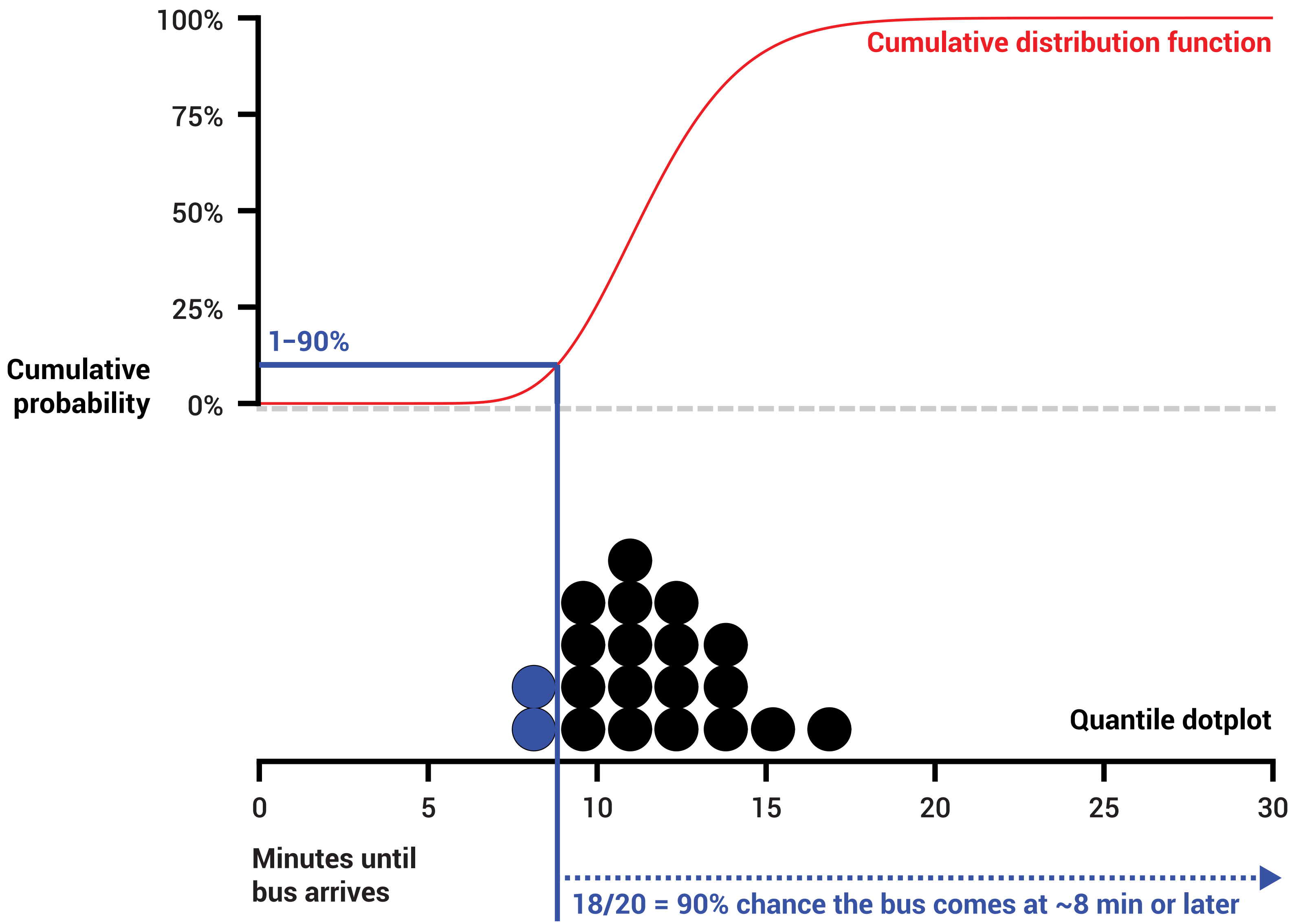
100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
Minutes until bus arrives

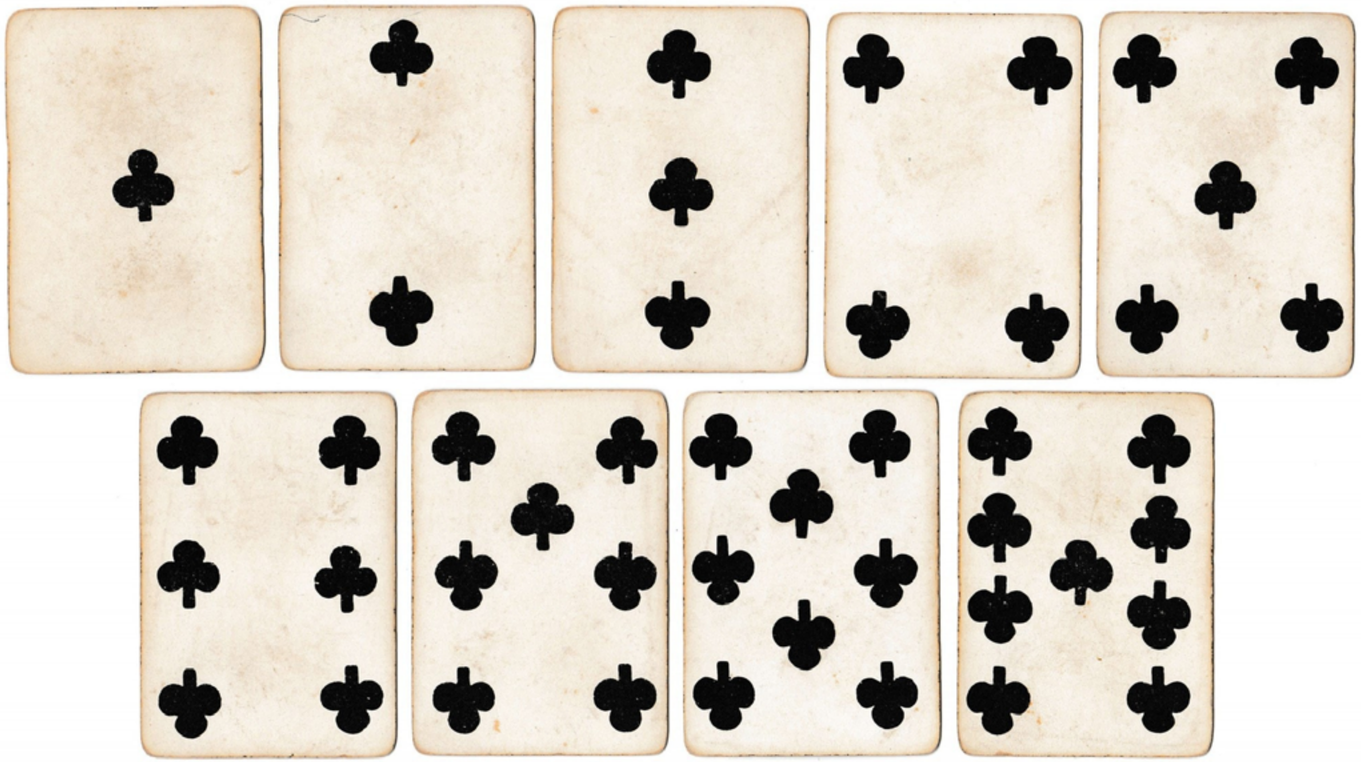

100%
75%
50%
25%
0%
Cumulative
probability
Cumulative distribution function
0
5
10
15
20
25
30
0
5
10
15
20
25
30
Minutes until
bus arrives

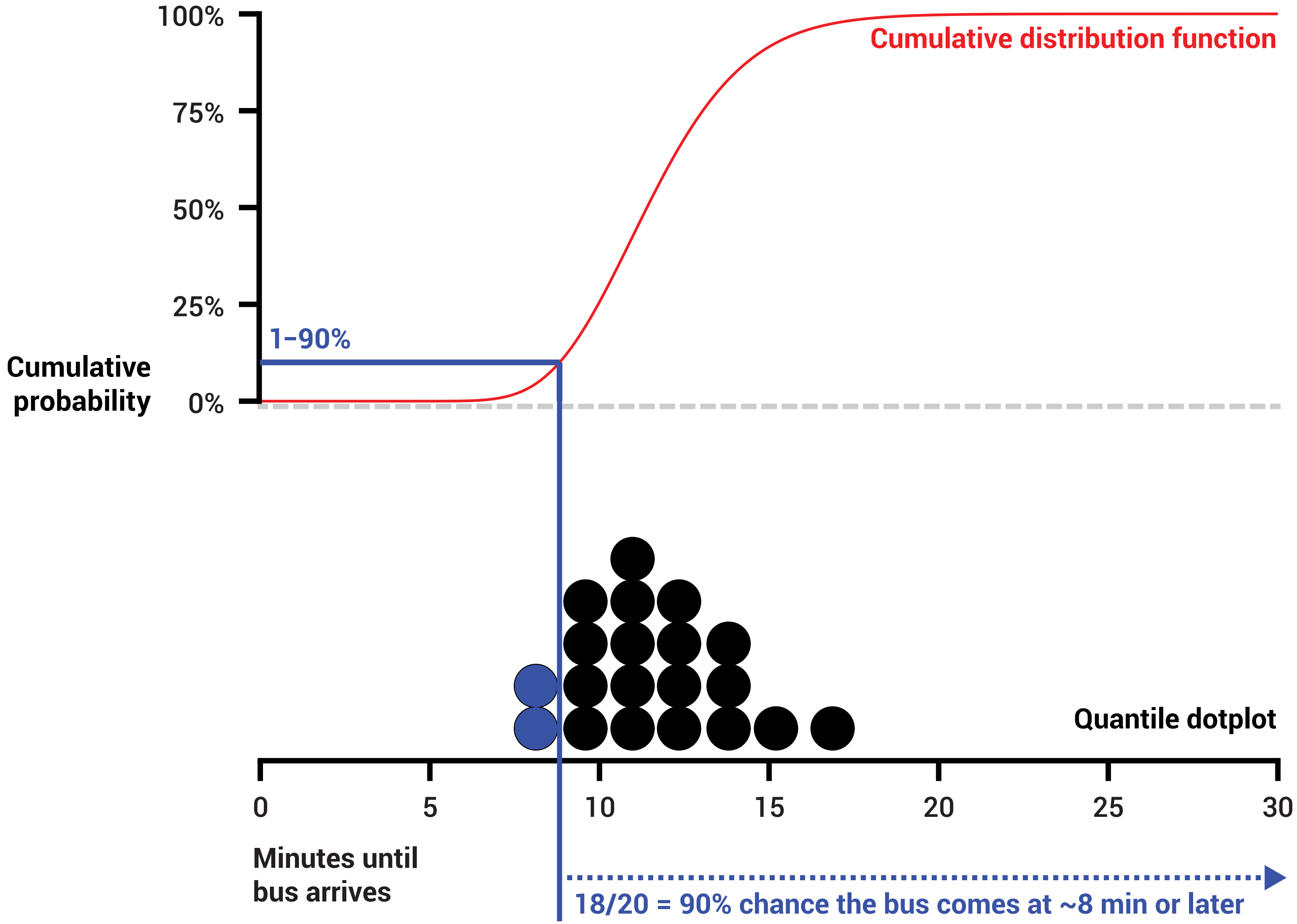

100%
75%
50%
25%
0%
Cumulative probability
Cumulative distribution function
0
5
10
15
20
25
30
Minutes until bus arrives


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

Quantile dotplots

[Kay et al 2016, Fernandes et al 2018]

Better estimates, decisions with time

Variance decreases:
Even worst performers improve

Good uncertainty displays are possible!

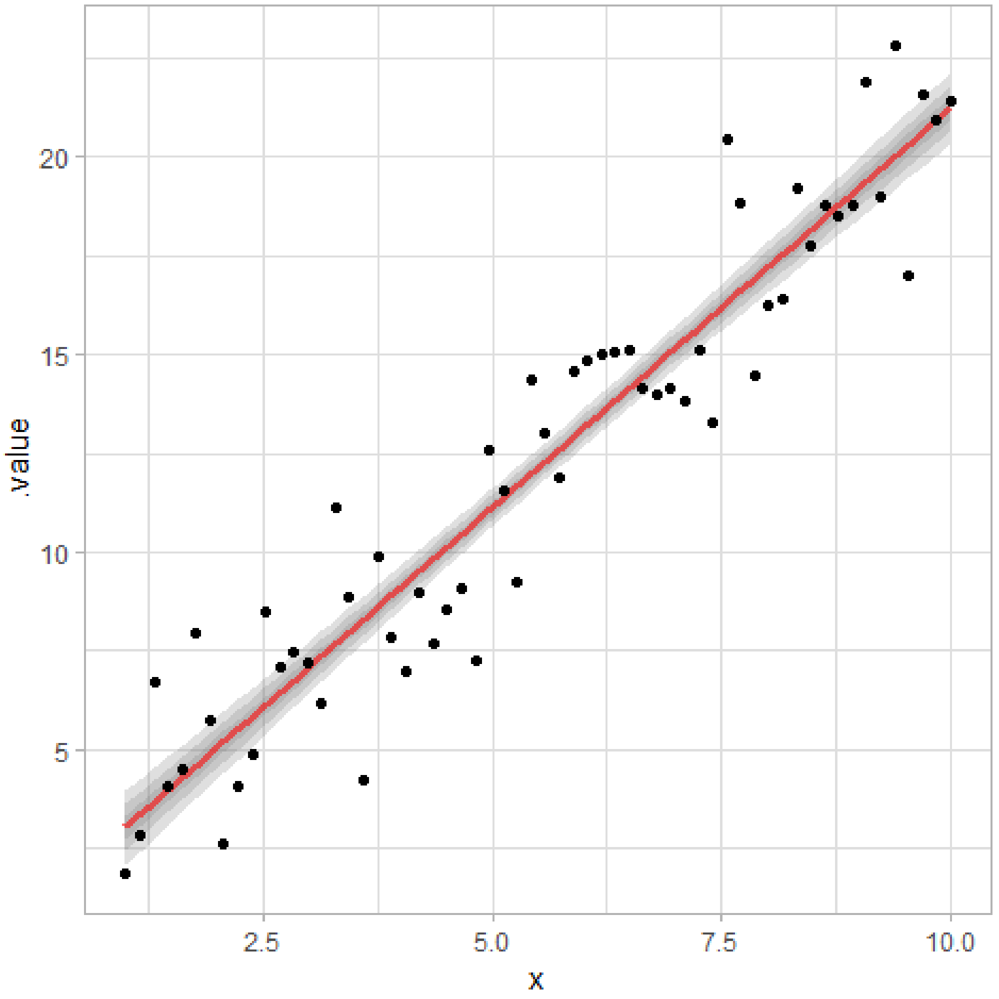
(Sidebar —
Uncertainty: what am I talking about?)

For the purposes of the first half of this talk…

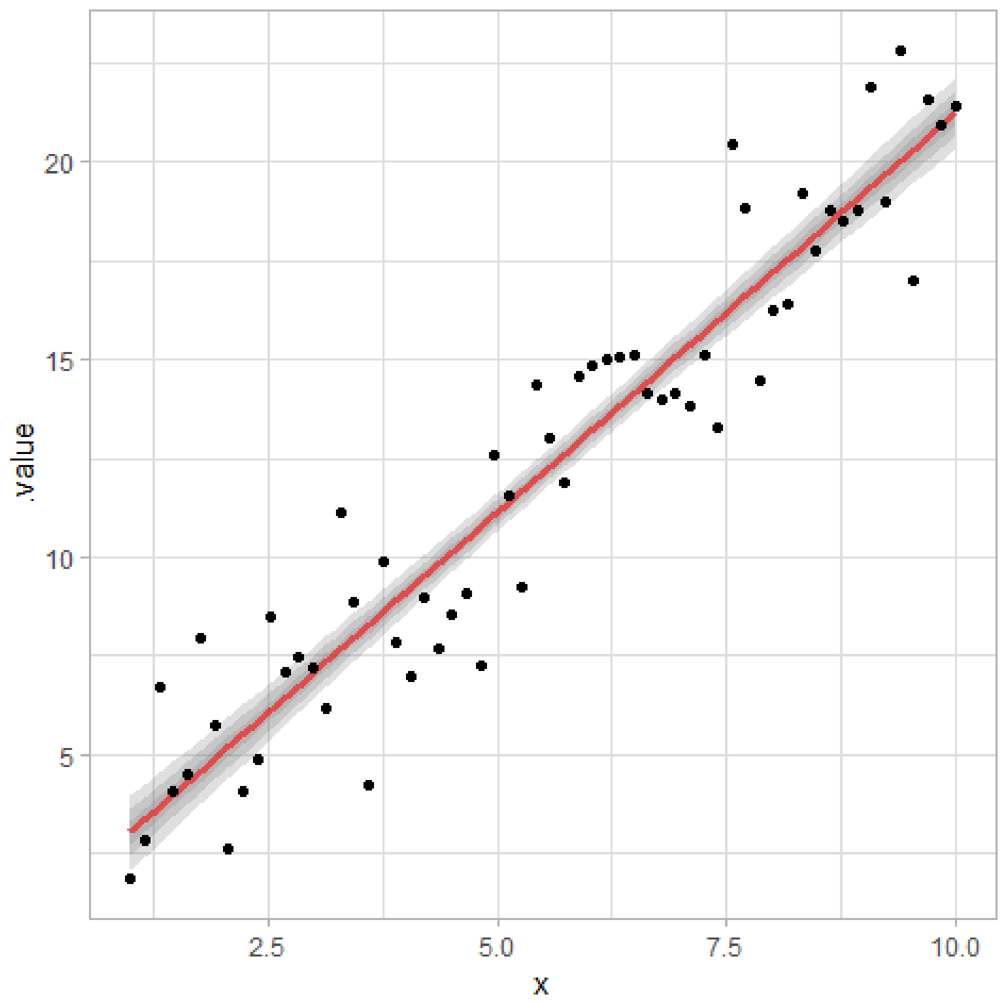
I am largely adopting a Bayesian view of uncertainty

Put another way: uncertainty is probability

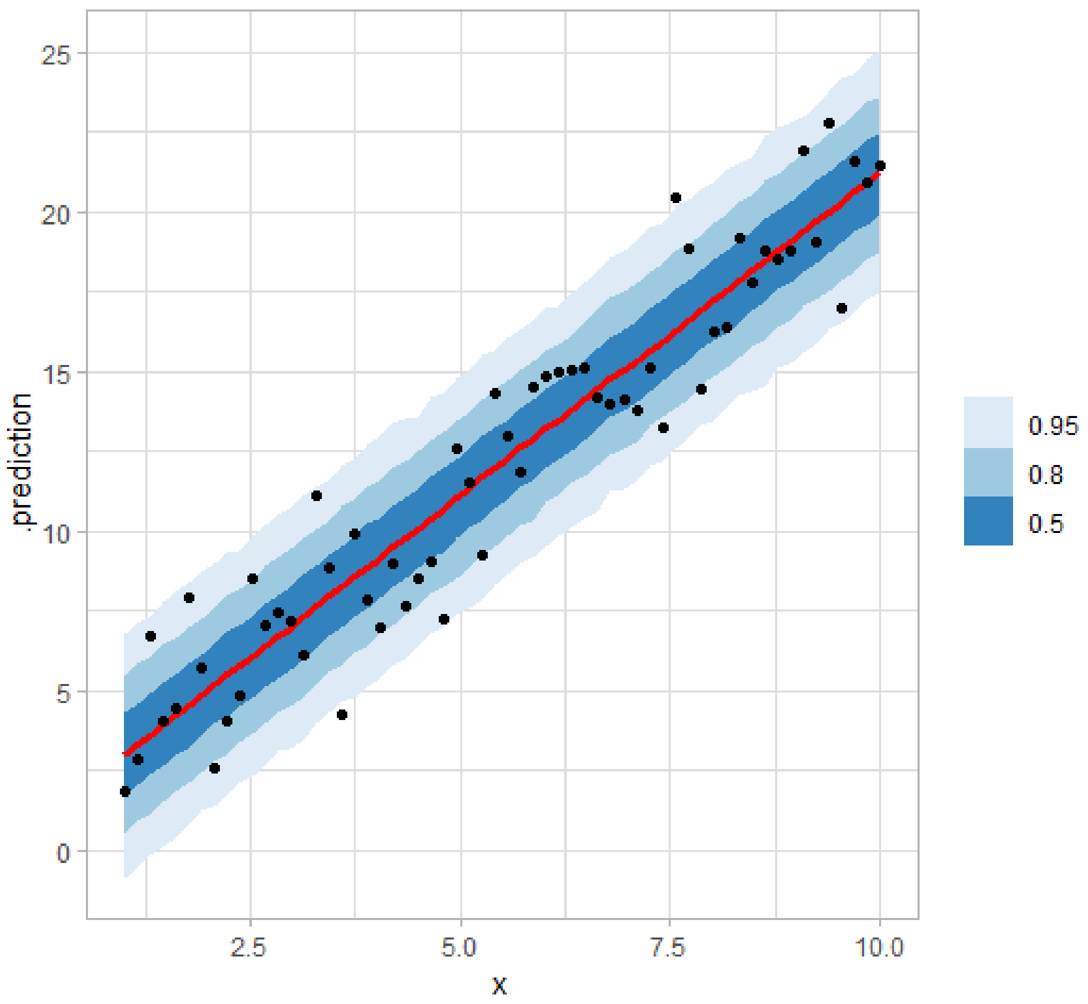
Epistemic uncertainty



Epistemic uncertainty



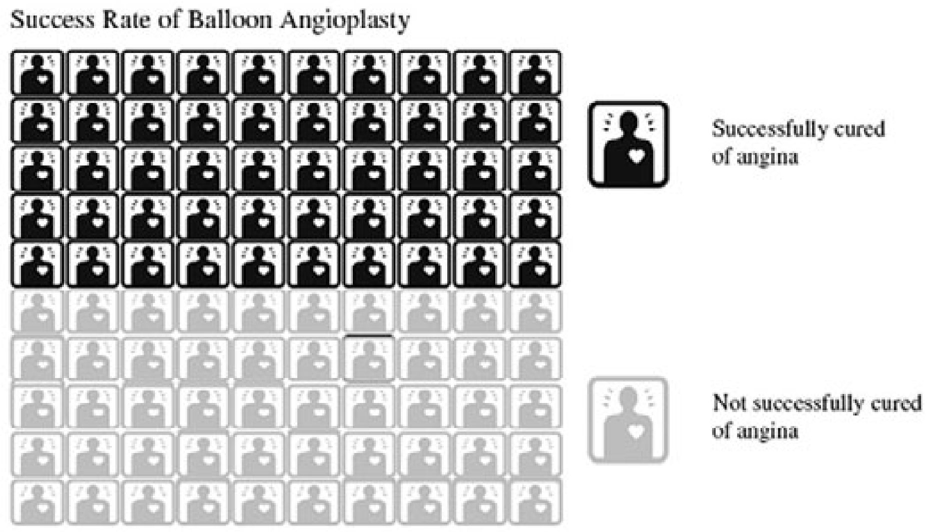
Aleatory uncertainty

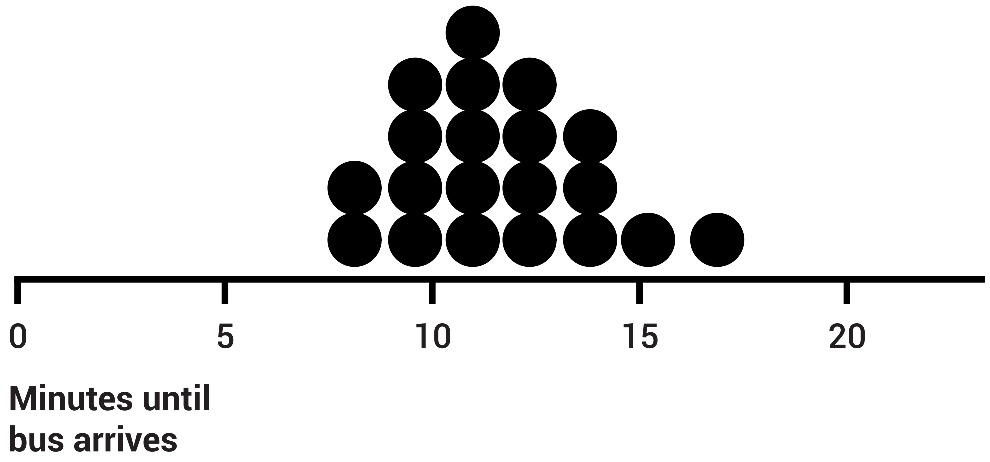


(End sidebar —
Back to uncertainty vis)

Other discrete outcome uncertainty visualizations...

Discrete outcome uncertainty visualization





Predictions from 2016 presidential election

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

FiveThirtyEight	NYT Upshot	HuffPo Pollster
28%	15%	2%

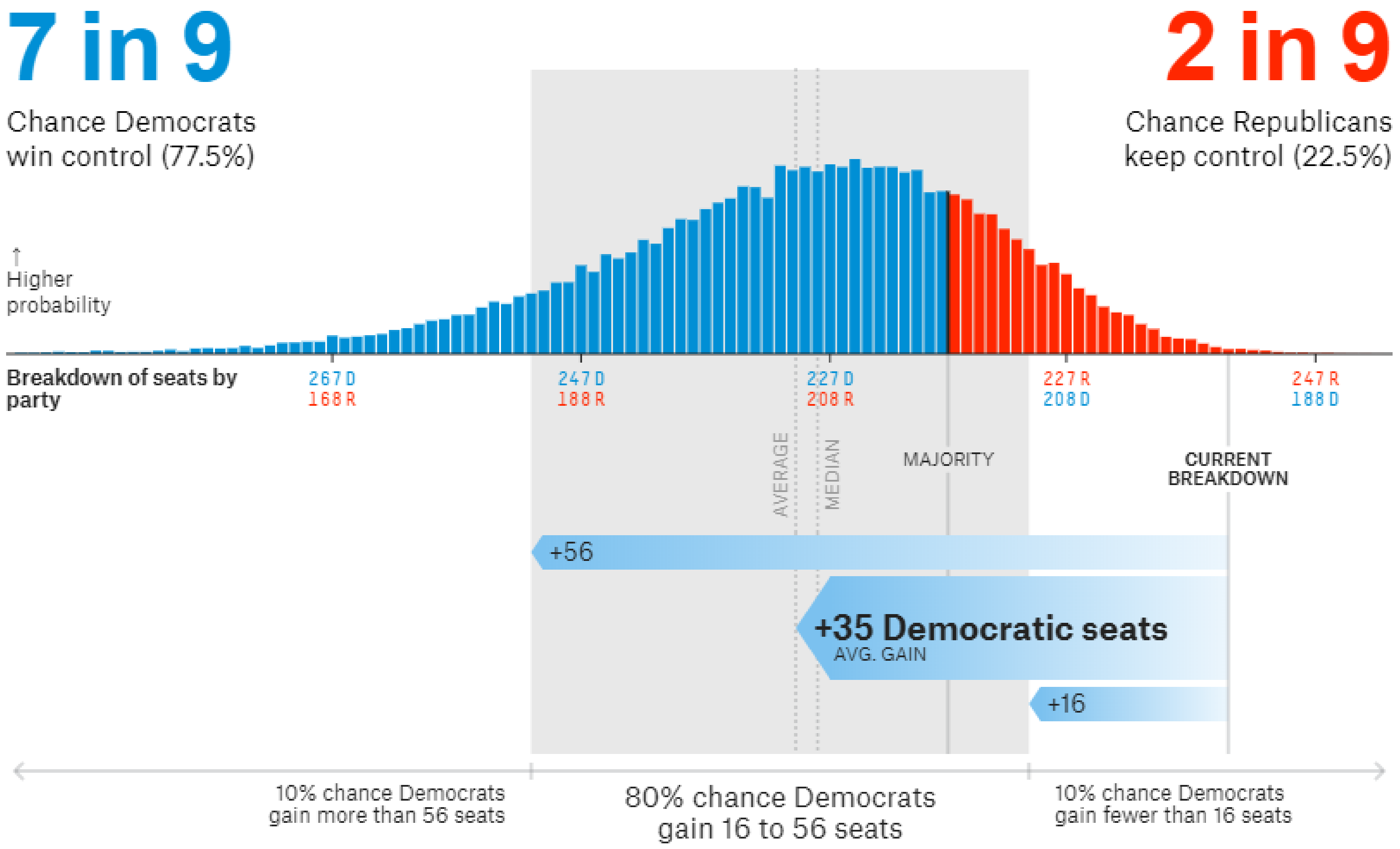
Predictions from 2016 presidential election

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

FiveThirtyEight	NYT Upshot	HuffPo Pollster
28%	15%	2%

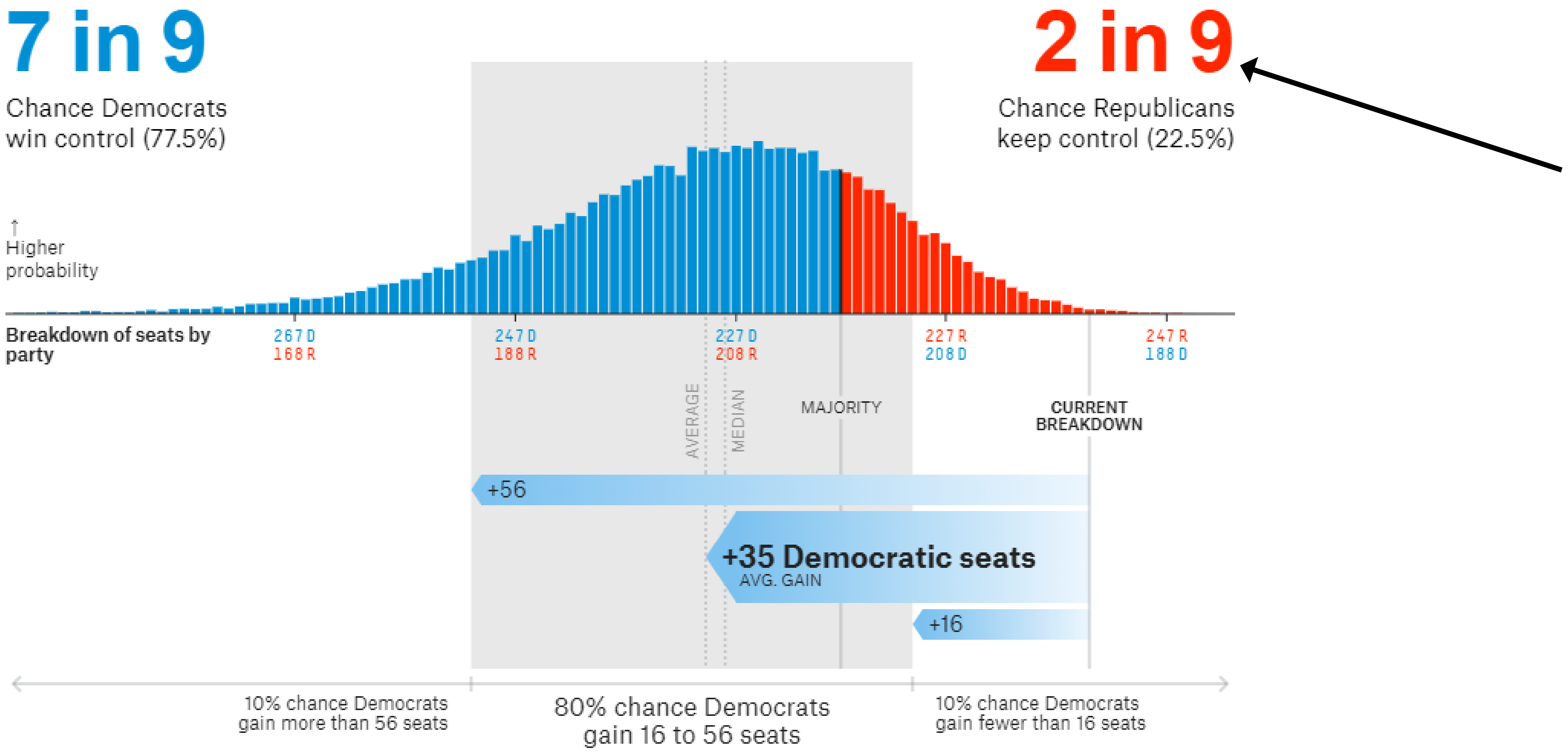
FiveThirtyEight’s 2018 House forecast

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



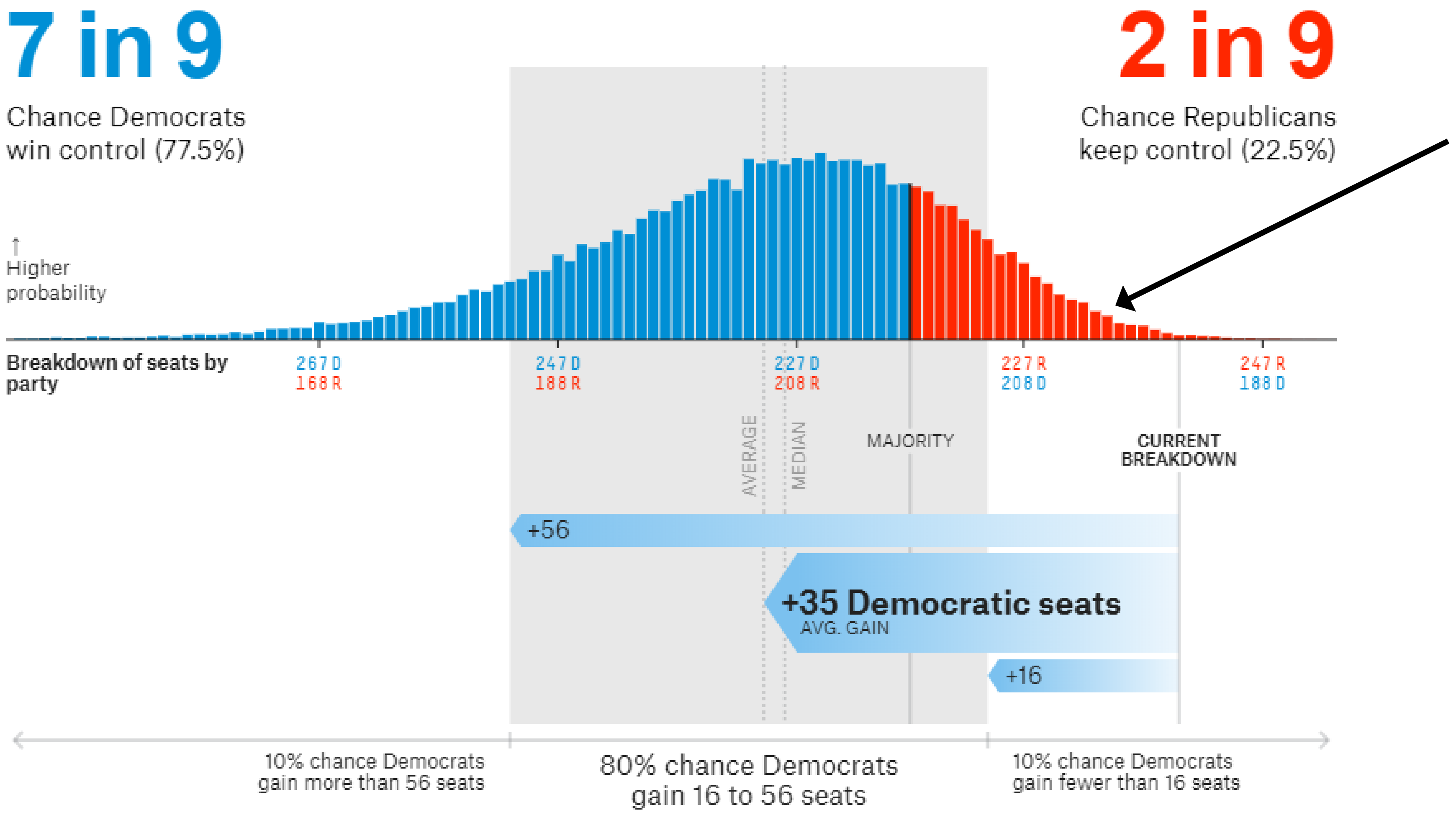
FiveThirtyEight's 2018 House forecast

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



FiveThirtyEight's 2018 House forecast

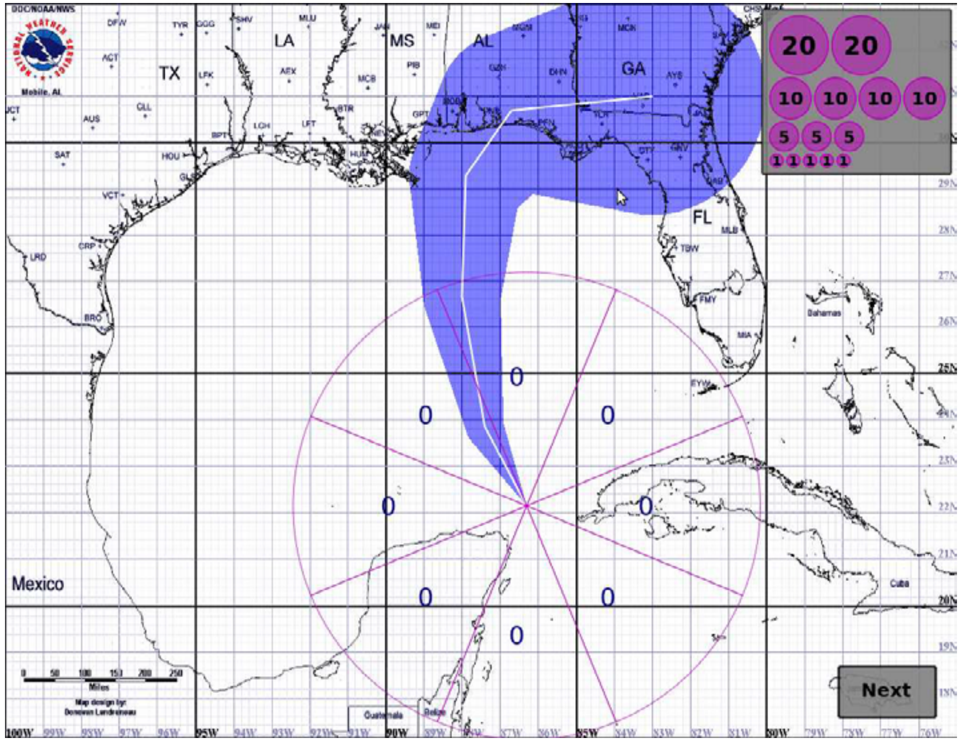
[https://projects.fivethirtyeight.com/2018-midterm-election-forecast/house/]



Other discrete outcome uncertainty visualizations...

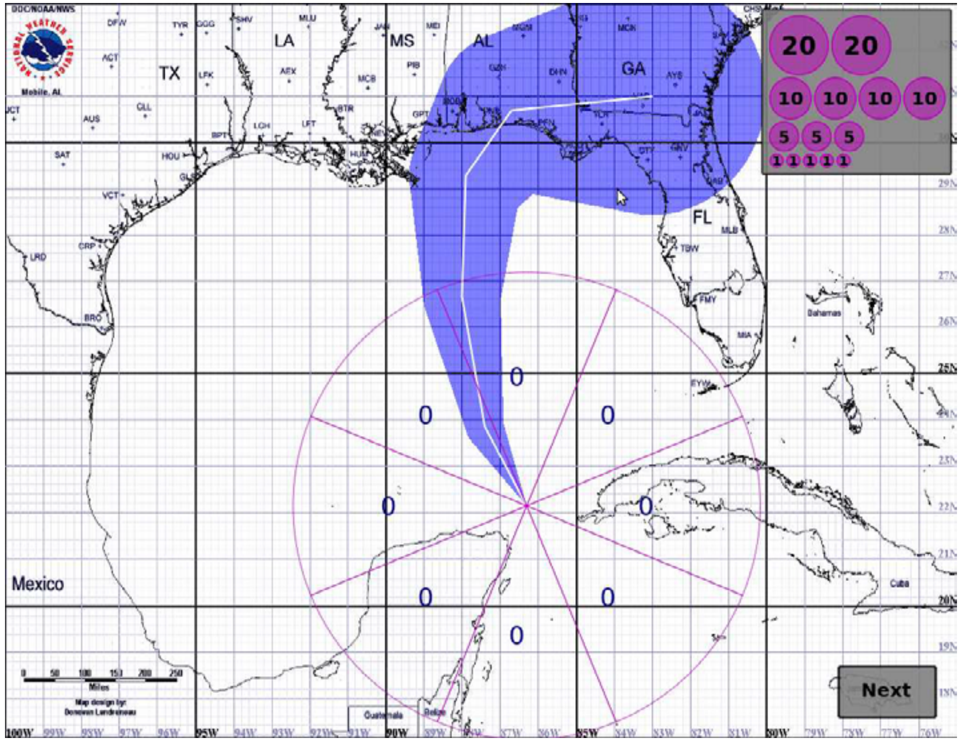
Hurricane error cones

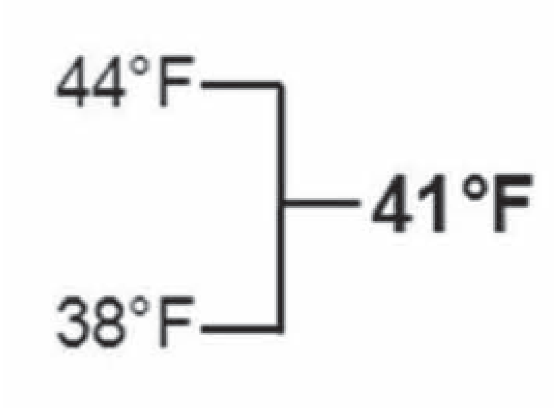
[Cox, House, Lindell. Visualizing Uncertainty in Predicted Hurricane Tracks. International Journal for Uncertainty Quantification, 3(2), 143–156, 2013]



Deterministic construal errors

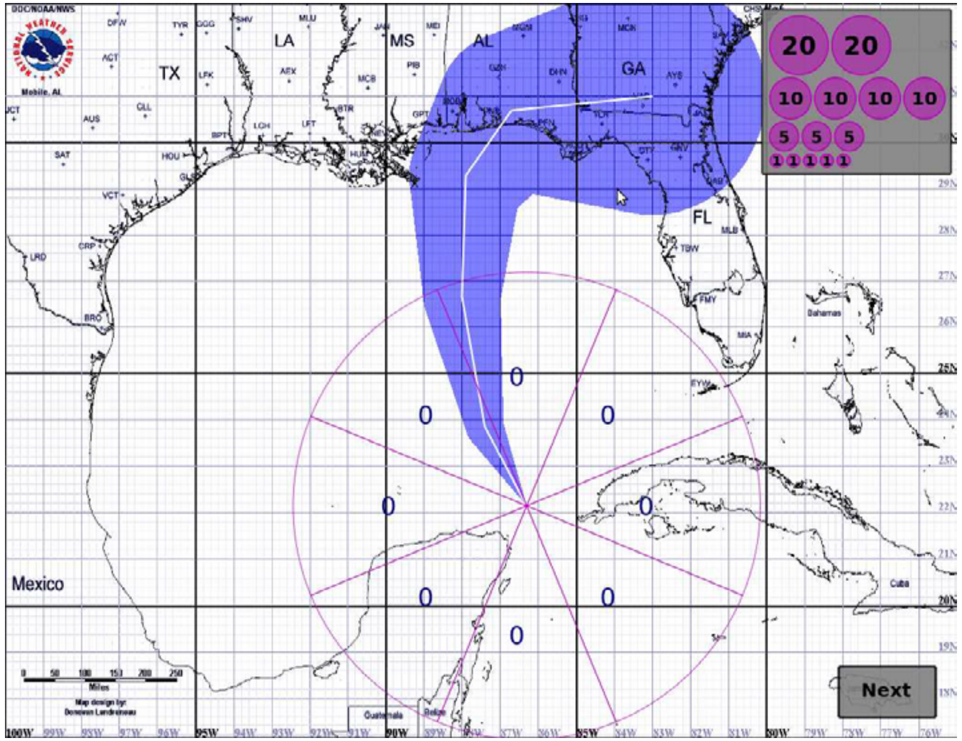
[Joslyn & LeClerc. Decisions With Uncertainty: The Glass Half Full. Current Directions in Psych. Science, 22(4), 2013]

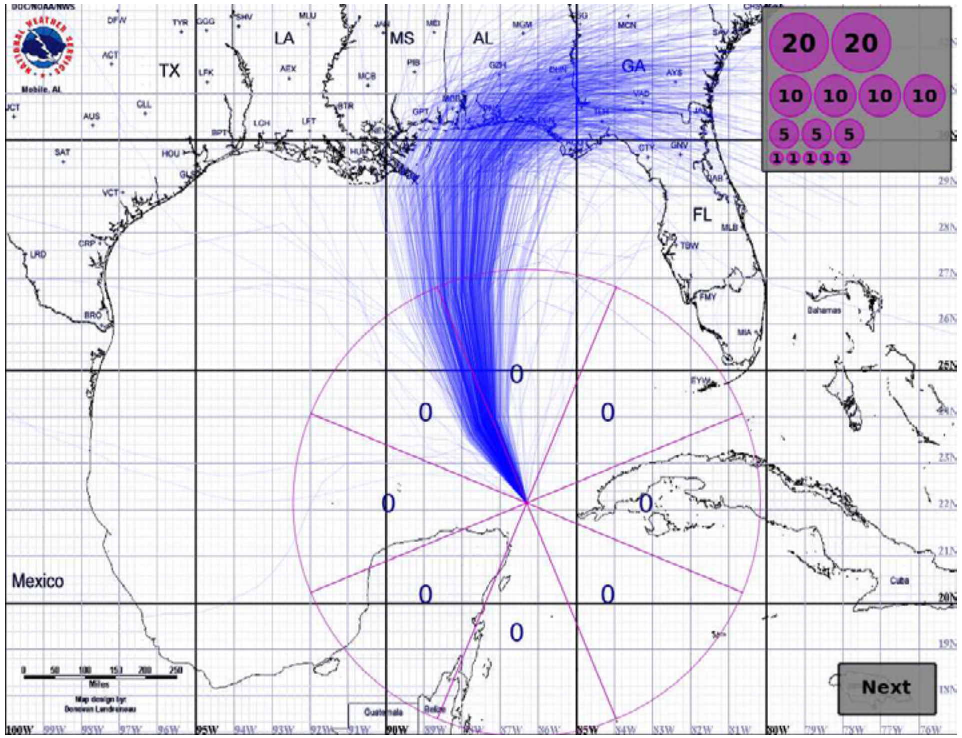




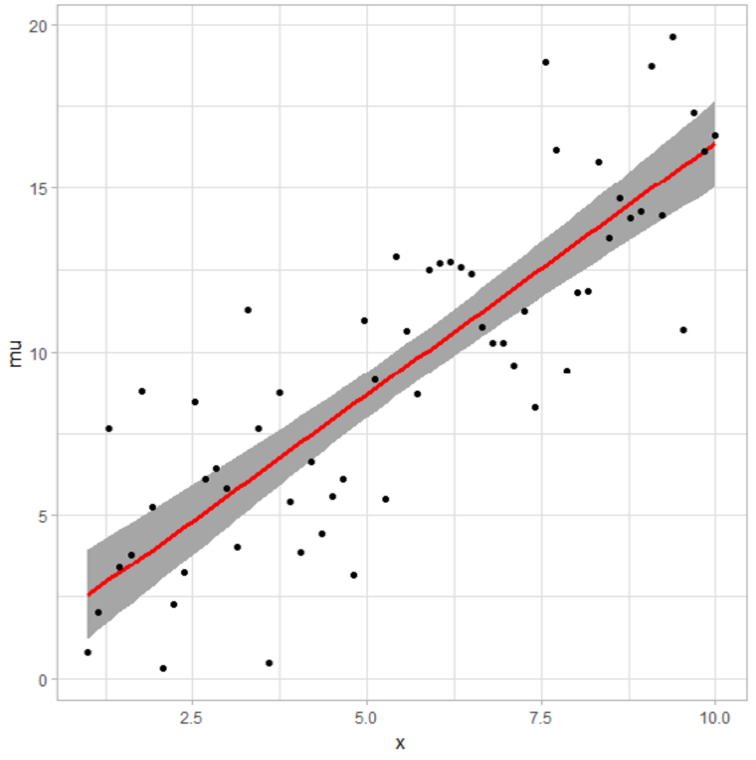
Hurricane error cones

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

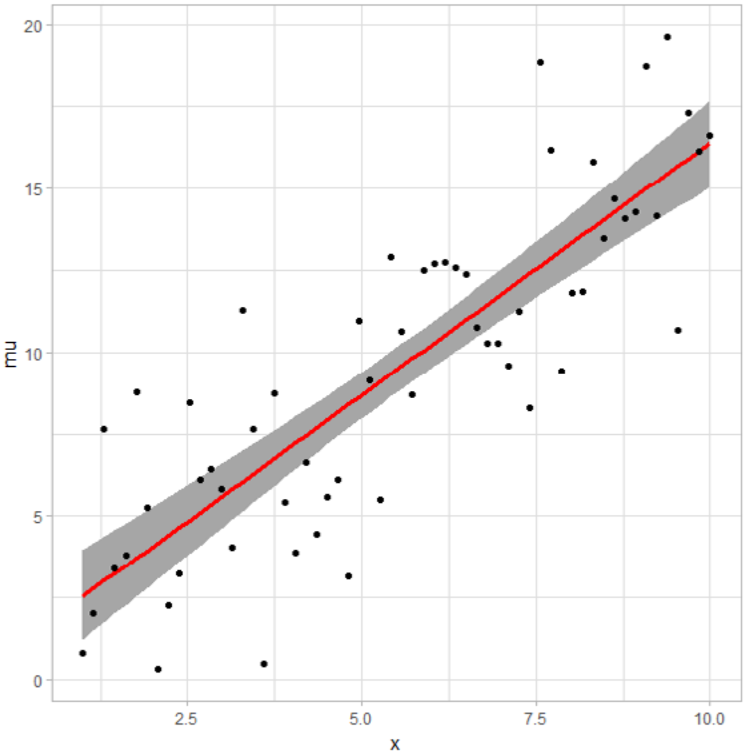


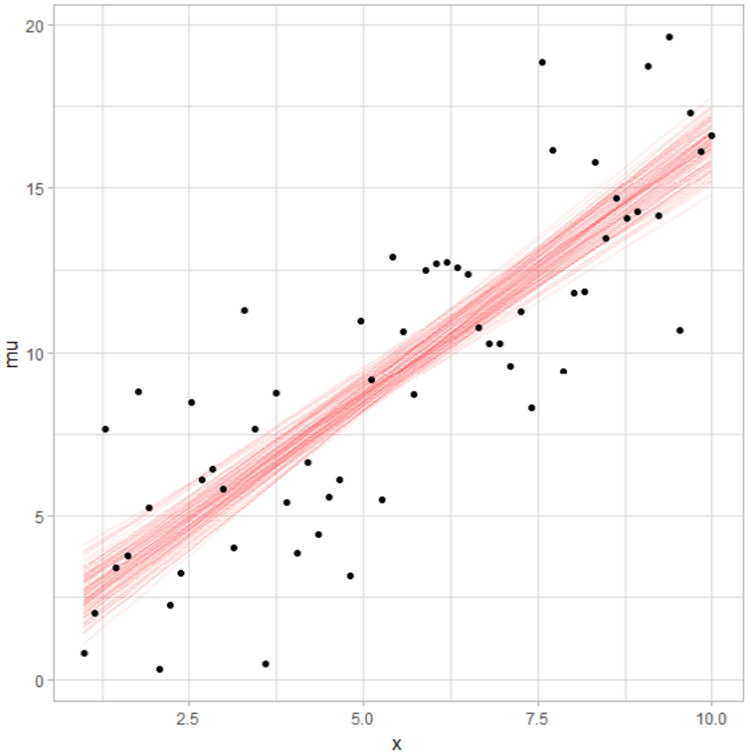


Fit line uncertainty



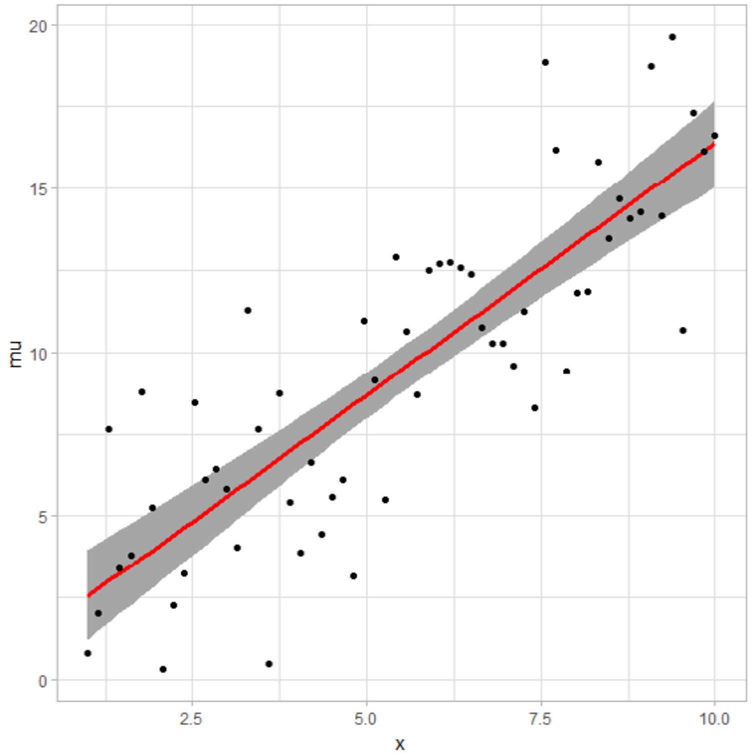
Fit line uncertainty

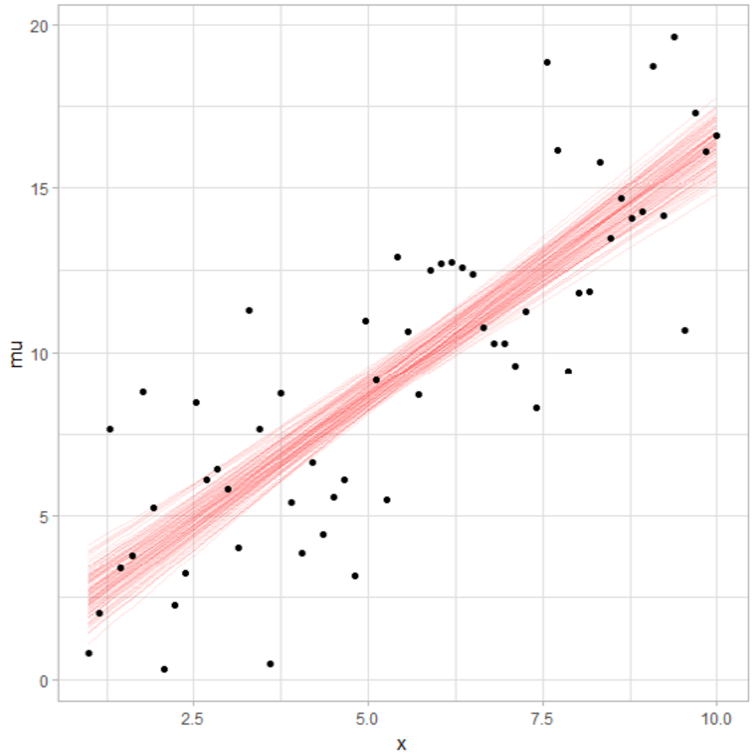


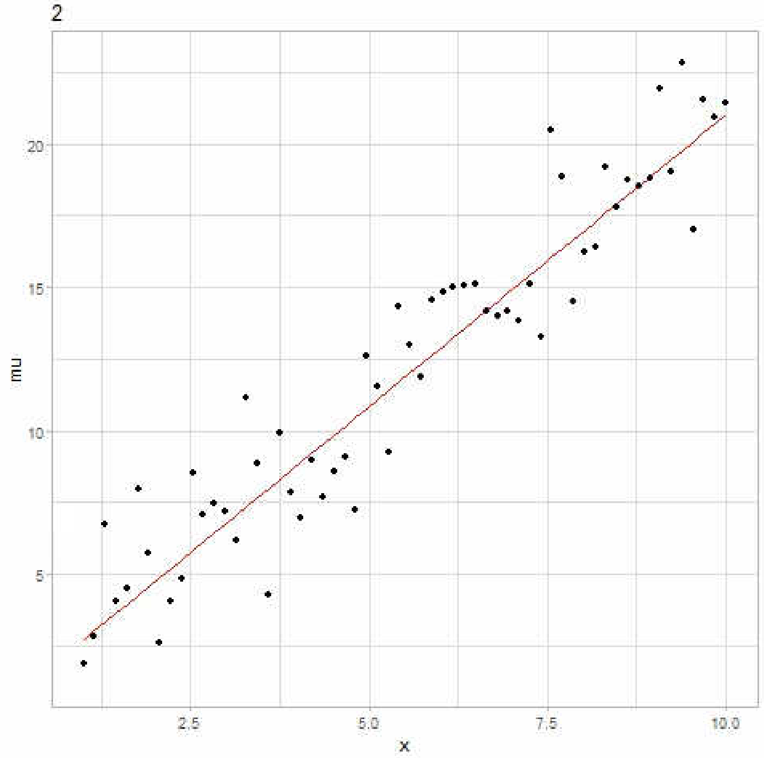


Fit line uncertainty

Hypothetical outcome plots (HOPs)



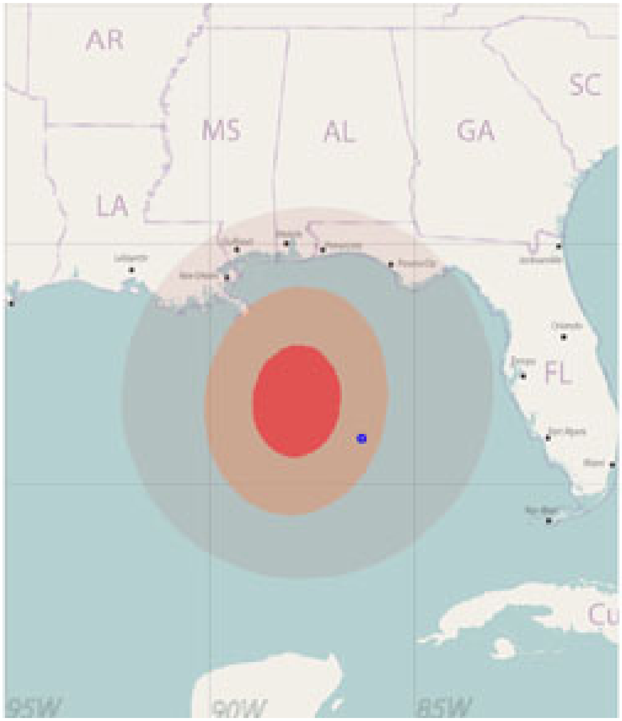




[Hullman, Resnick, Adar. Hypothetical Outcome Plots Outperform Error Bars and Violin Plots for Inferences about Reliability of Variable Ordering. PloS One, 10(11). 2015]

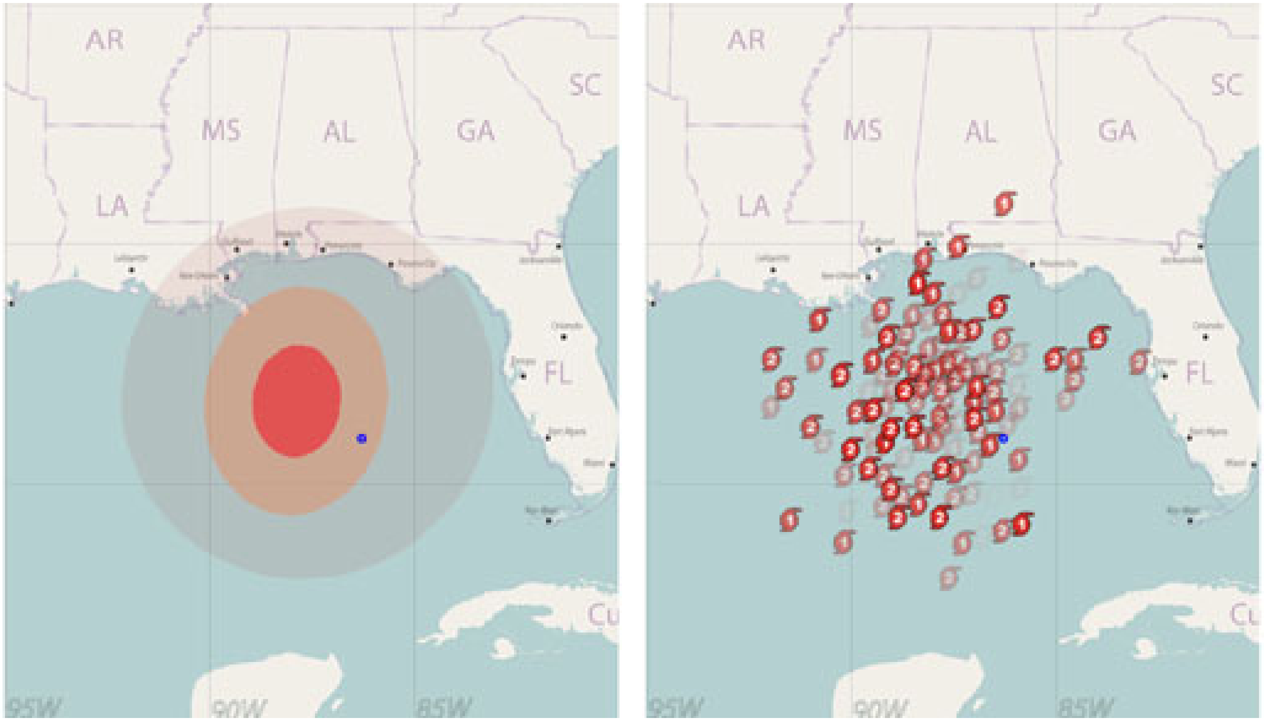
Hurricane location

[Liu et al, Uncertainty Visualization by Representative Sampling..., 2016]



Hurricane location

[Liu et al, Uncertainty Visualization by Representative Sampling..., 2016]

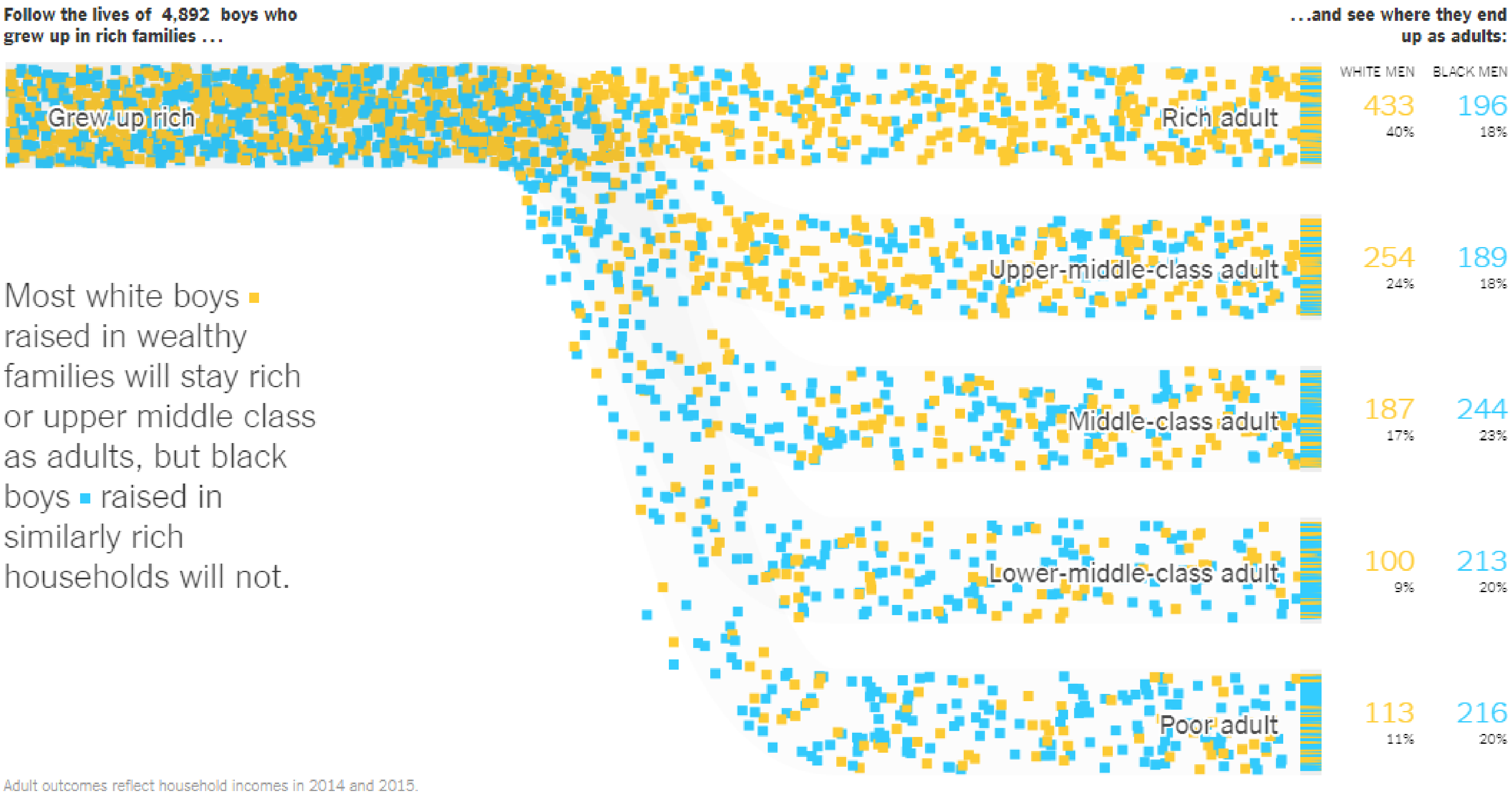


Animation helps people experience uncertainty

This can be very powerful...

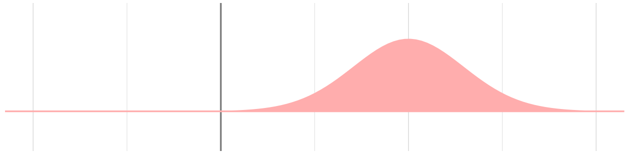
Income of black boys from wealthy families

[https://nyti.ms/2GGpFZw]



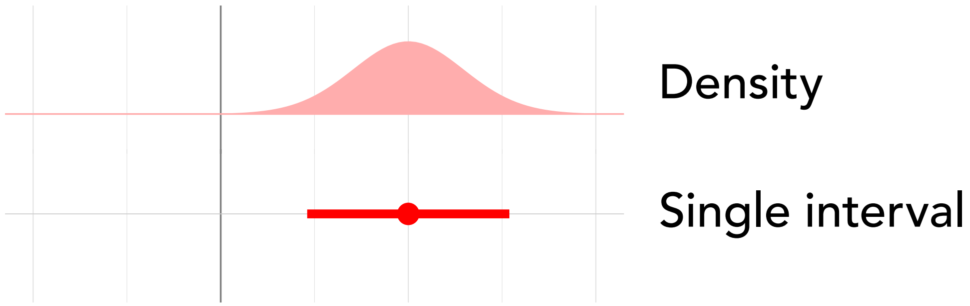
Plenty of options just for point estimates…

Uncertainty in point estimates...

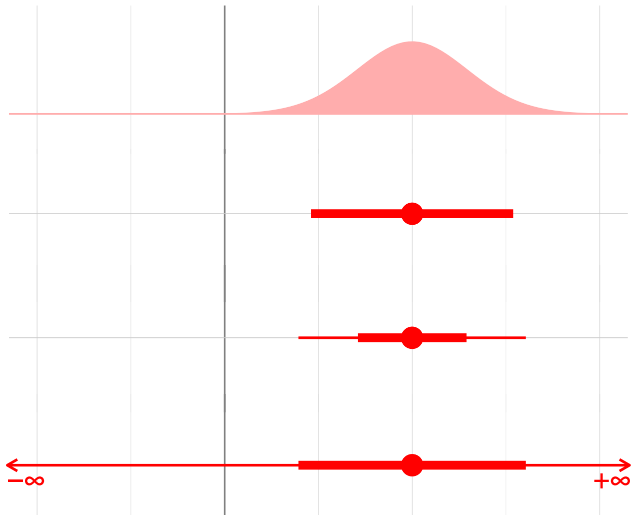


Density

Uncertainty in point estimates…



Uncertainty in point estimates…



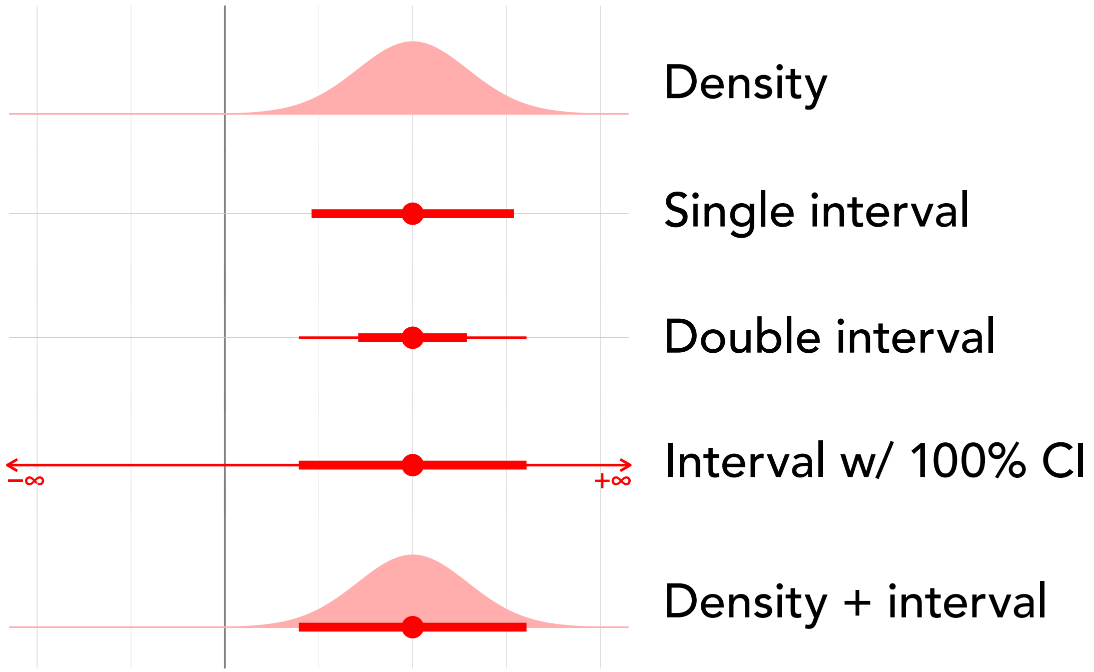
Density

Single interval

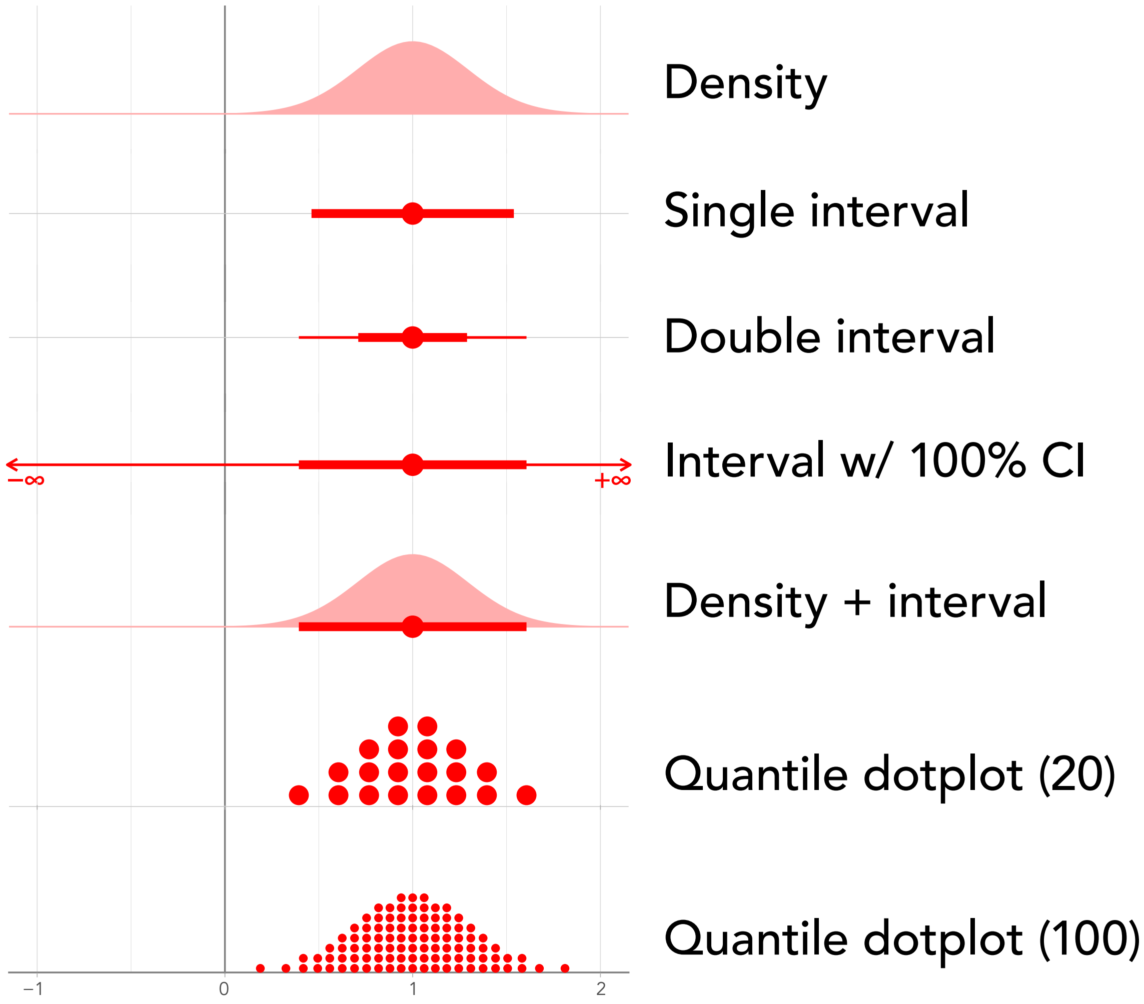
Double interval

Interval w/ 100% CI

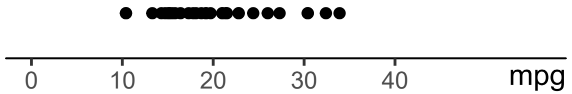
Uncertainty in point estimates…



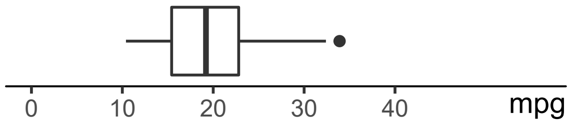
Uncertainty in point estimates…



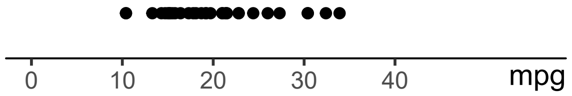
[Sidebar: distribution visualizations]



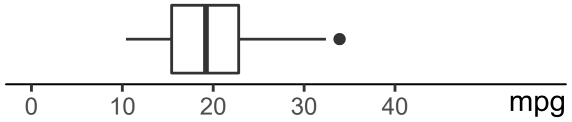
Raw data



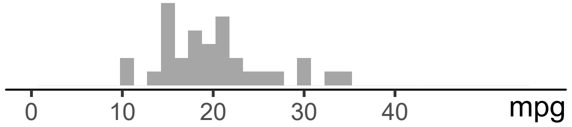
Boxplot



Raw data

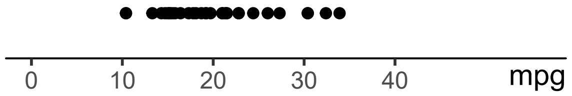


Boxplot

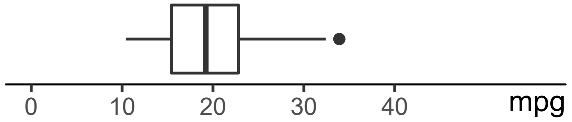


Histogram

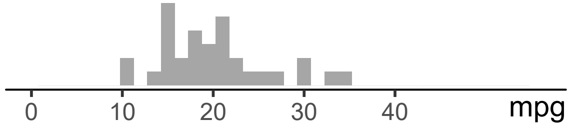
Raw data



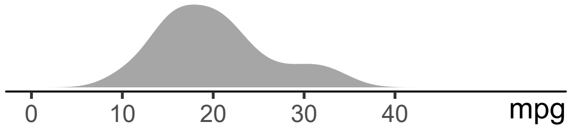
Boxplot

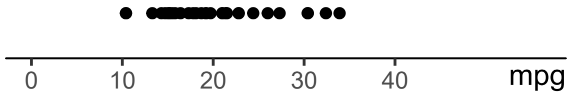


Histogram

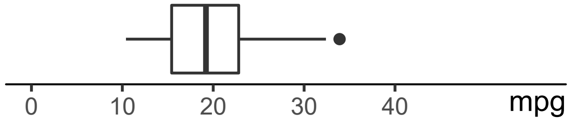


Density plot

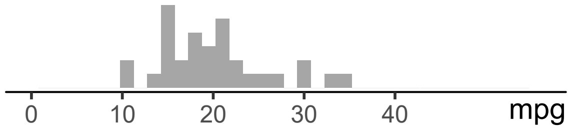




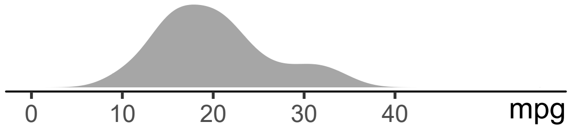
Raw data



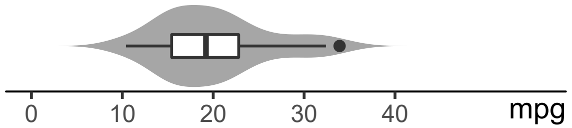
Boxplot



Histogram

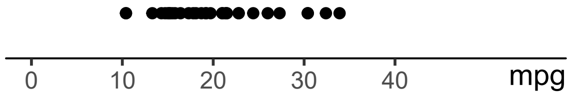


Density plot

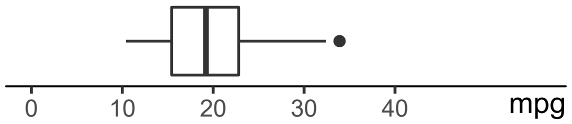


Violin plot

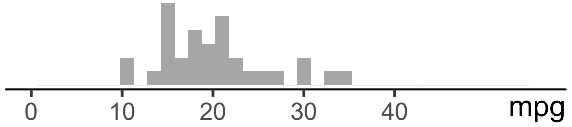
(or similar: “bean plot”)



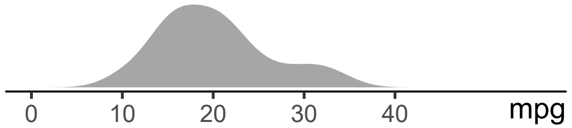
Raw data



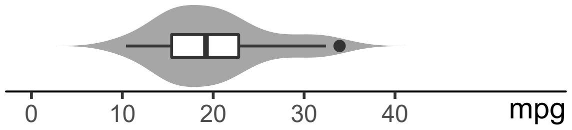
Boxplot



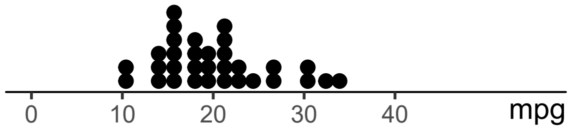
Histogram



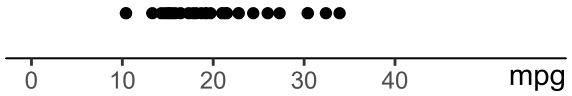
Density plot



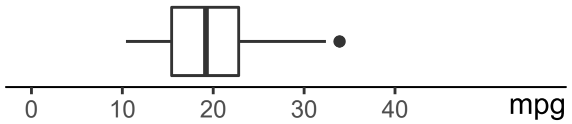
Violin plot (or similar: “bean plot”)



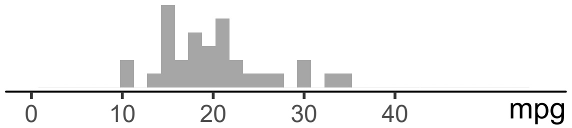
(Wilkinson) dotplot (or similar: “beeswarm”)



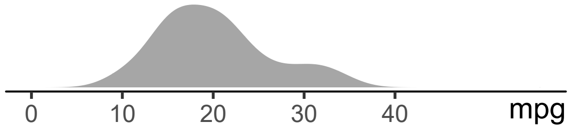
Raw data



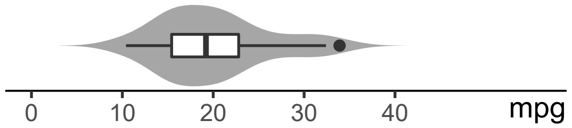
Boxplot



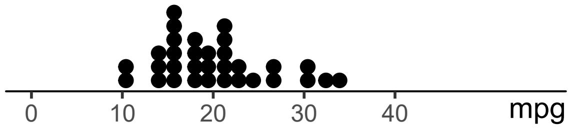
Histogram



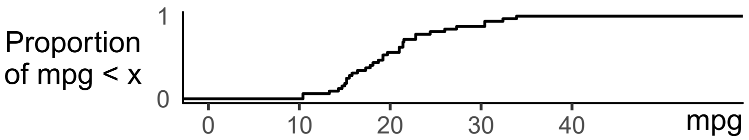
Density plot



Violin plot (or similar: “bean plot”)



(Wilkinson) dotplot (or similar: “beeswarm”)

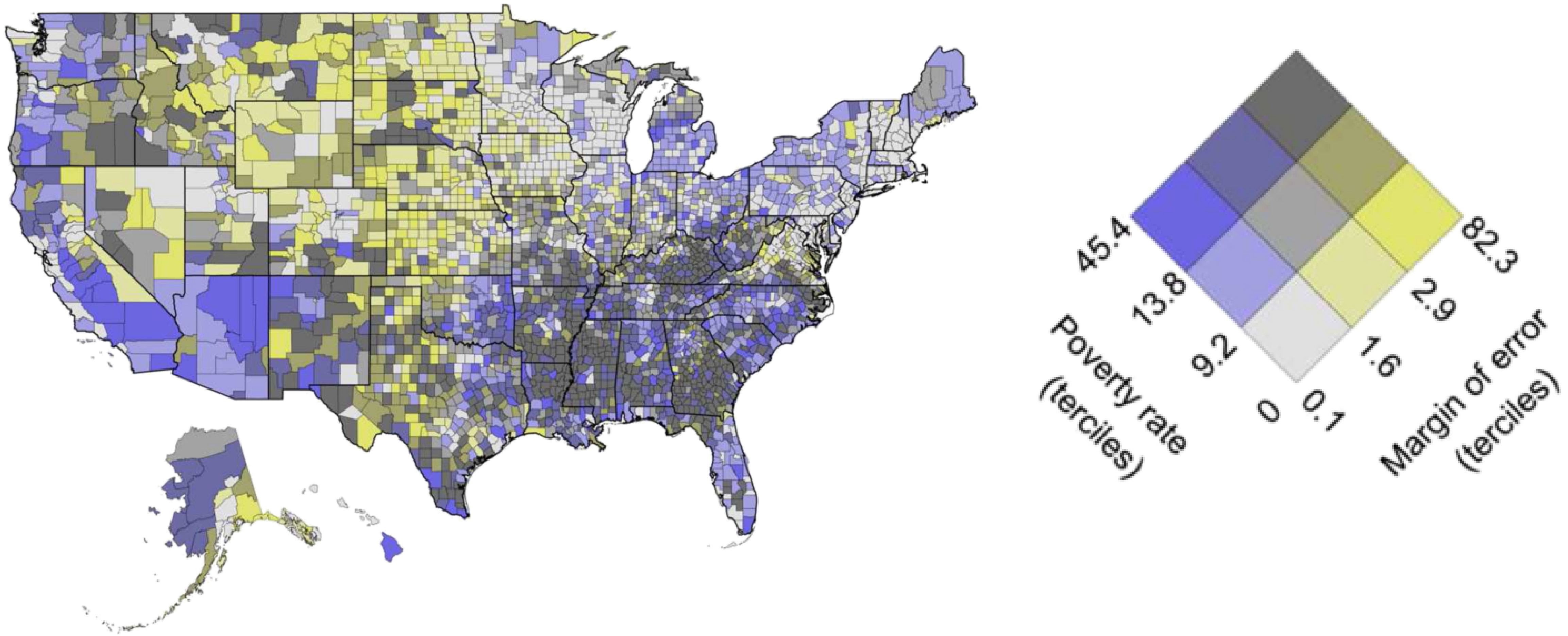


Cumulative distribution function (CDF)

Cartographic uncertainty

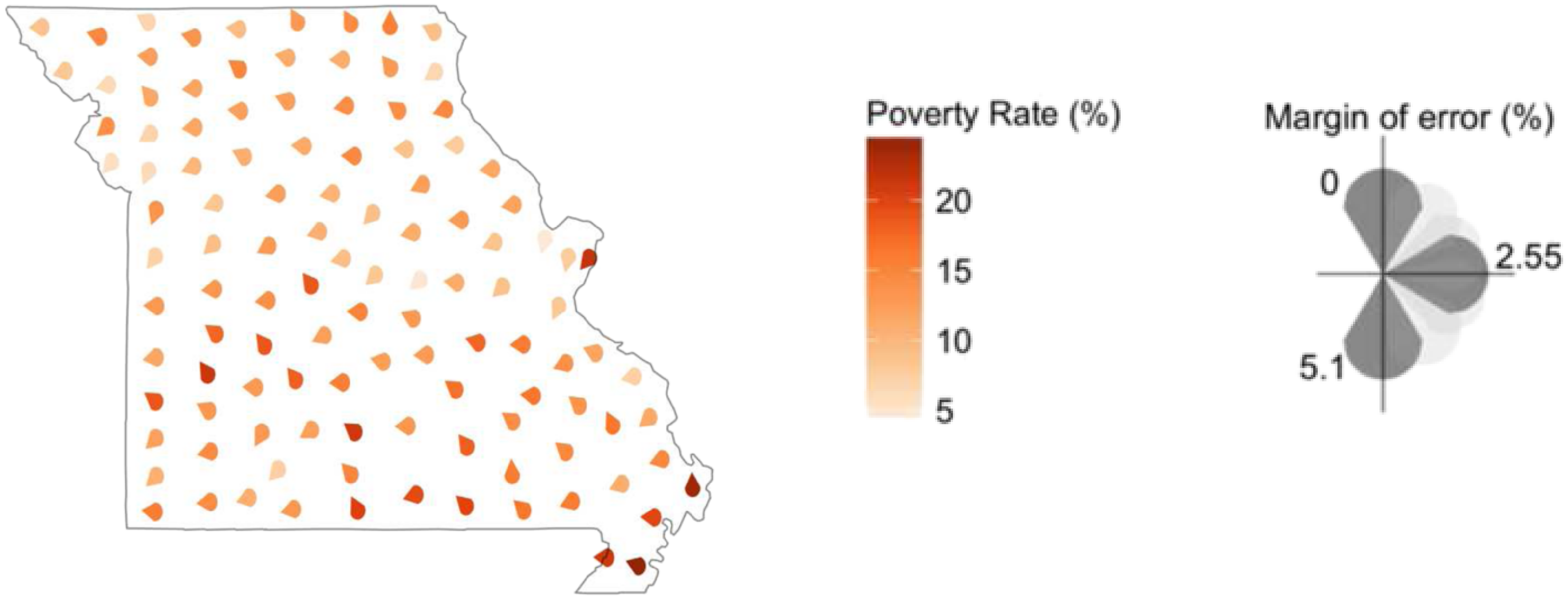
Just map to another visual channel, right?

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



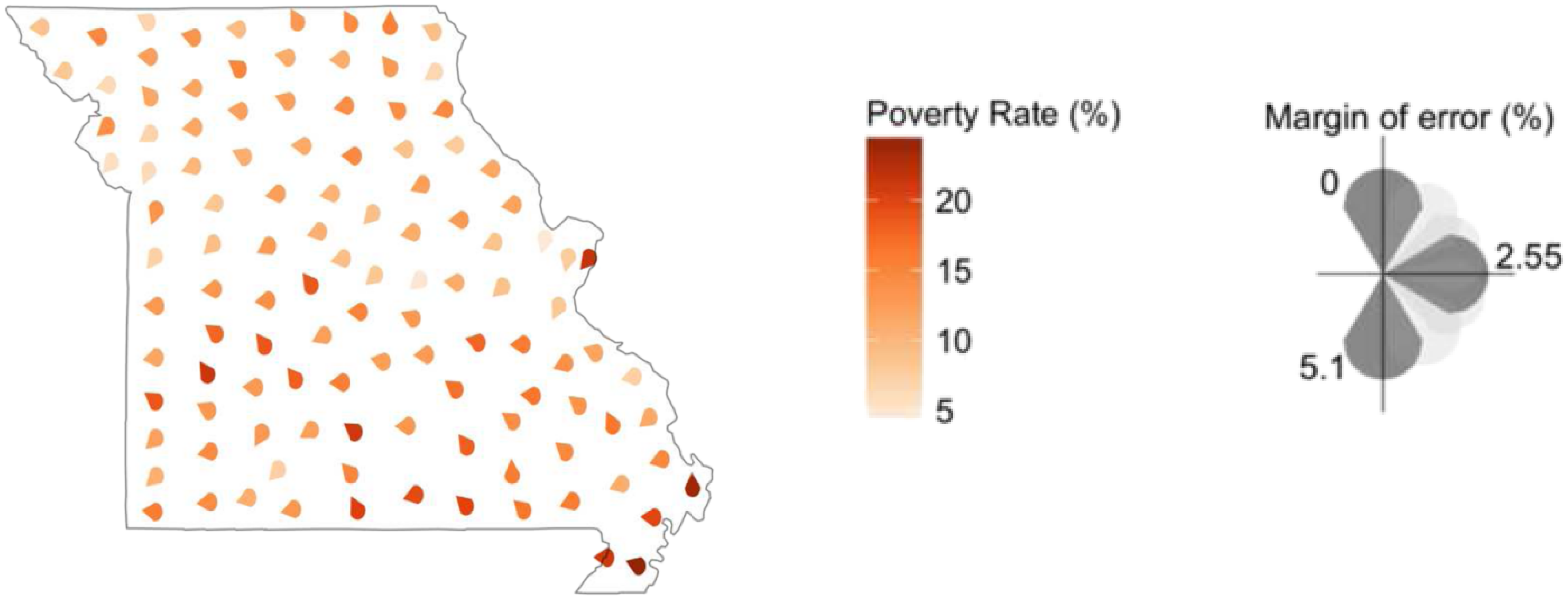
Just map to another visual channel, right?

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



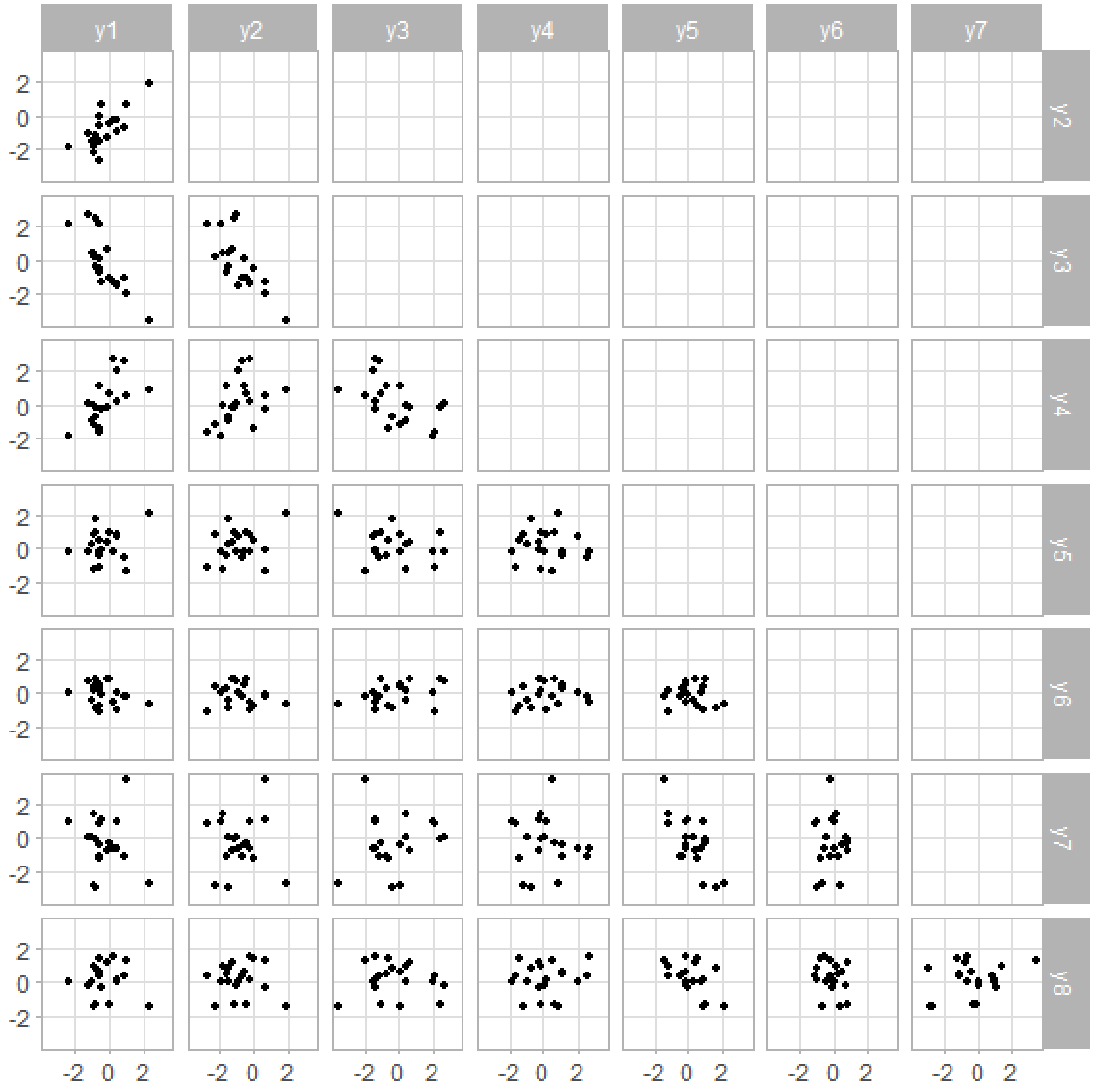
Just map to another visual channel, right?

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

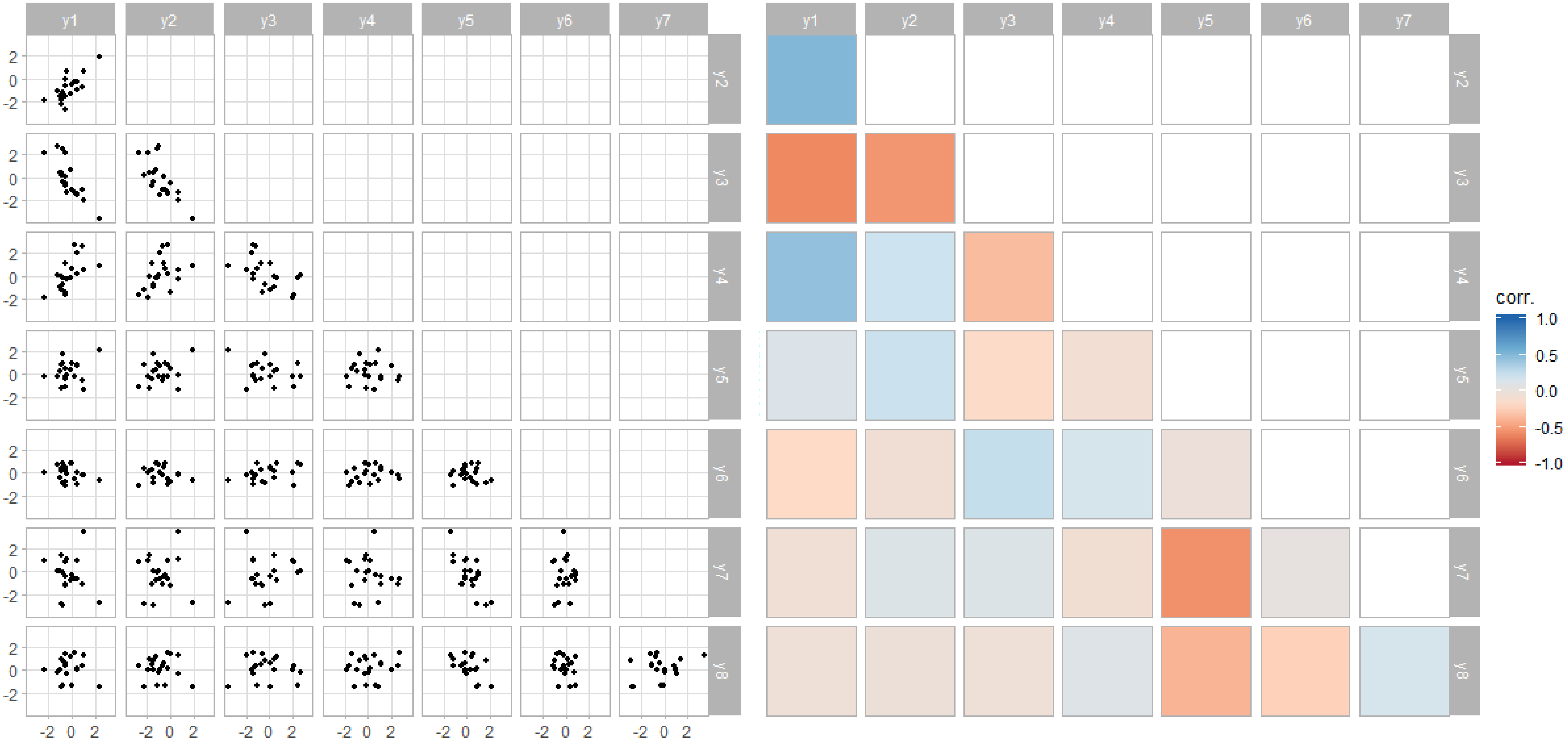


Very abstract…

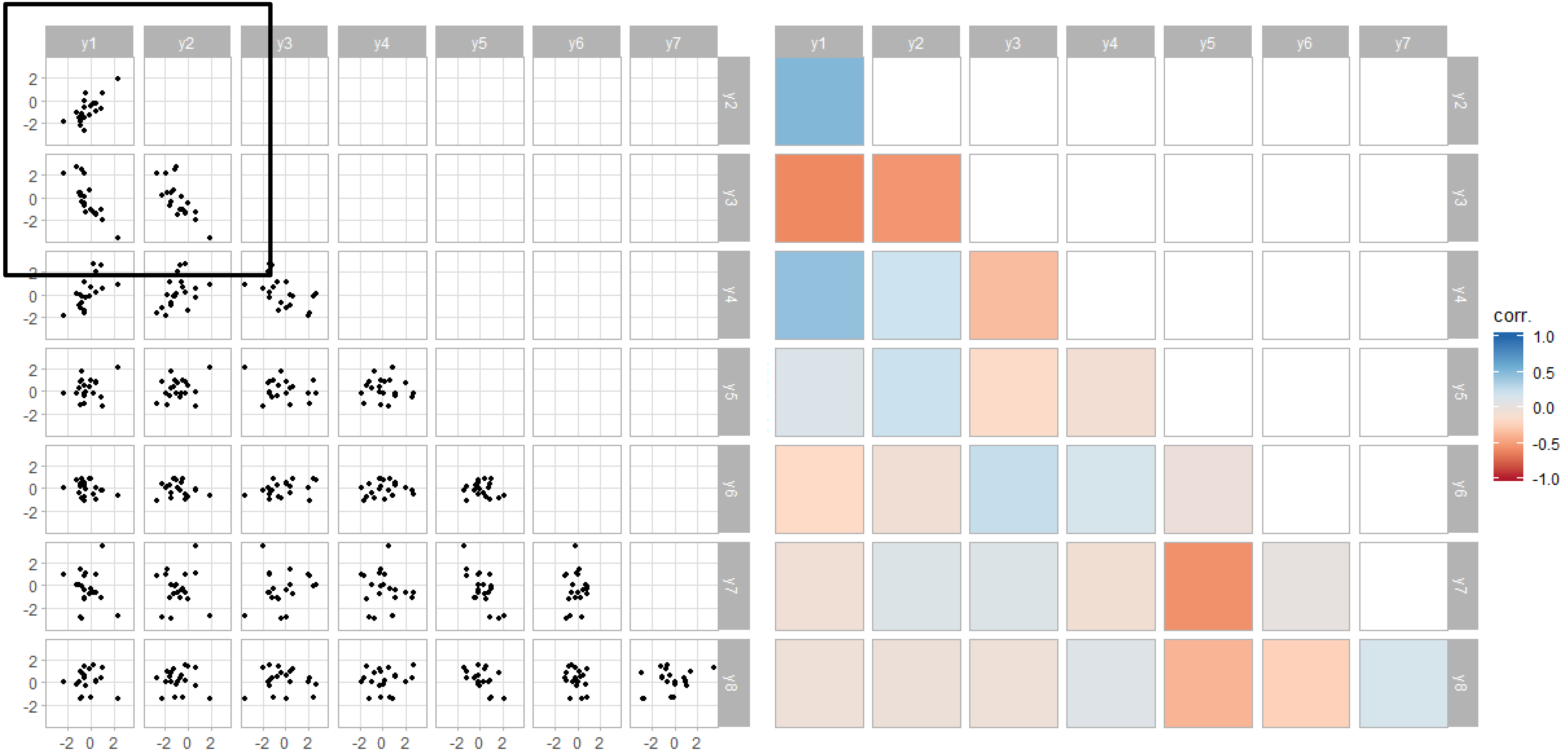
I'm not a map vis person...



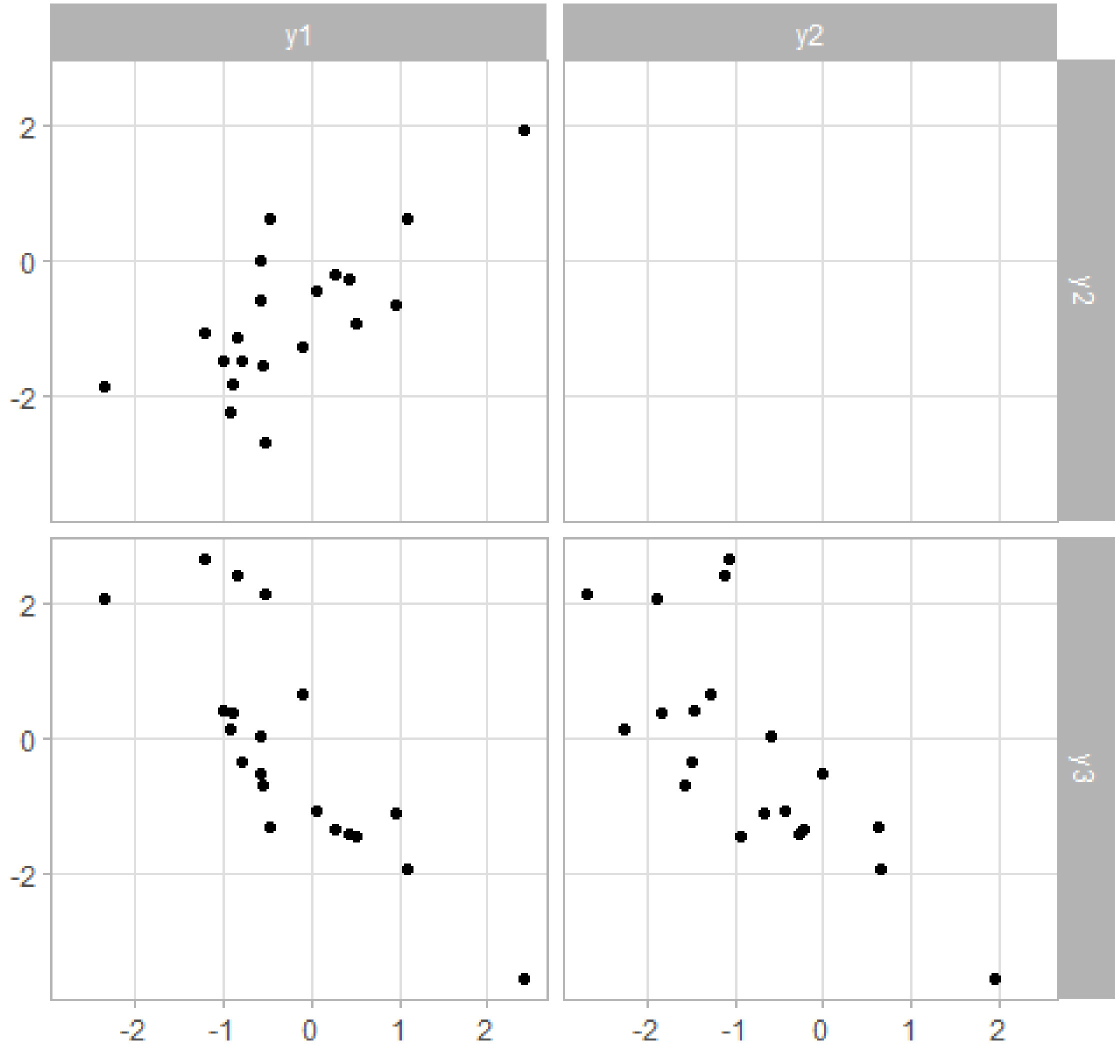
y1
y2
y3
y4
y5
y6
y7
y2
y3
y4
y5
y6
y7
y8
2
0
-2
-2 0 2

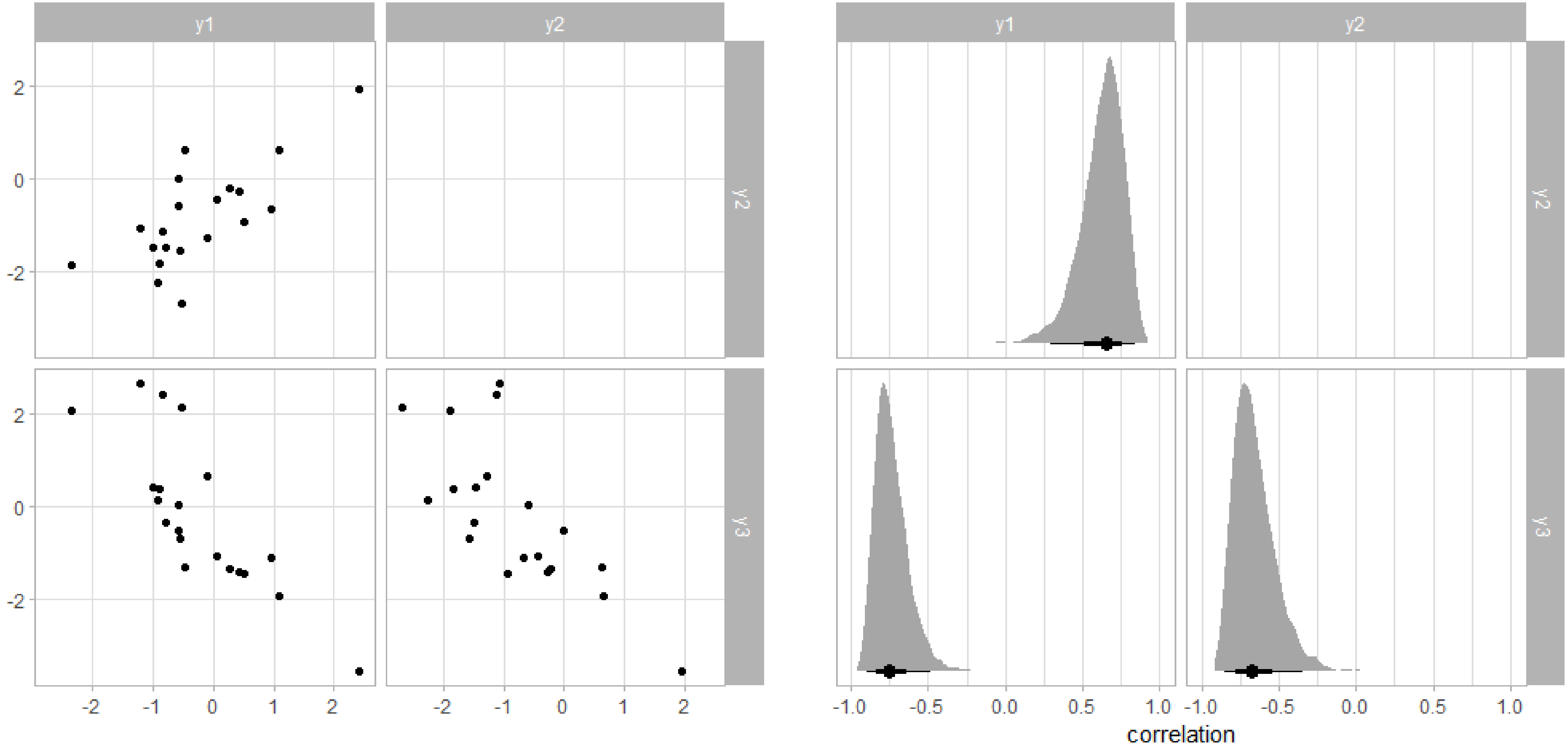


y1
y2
y3
y4
y5
y6
y7
y8
corr.
1.0
0.5
0.0
-0.5
-1.0
-2
0
2

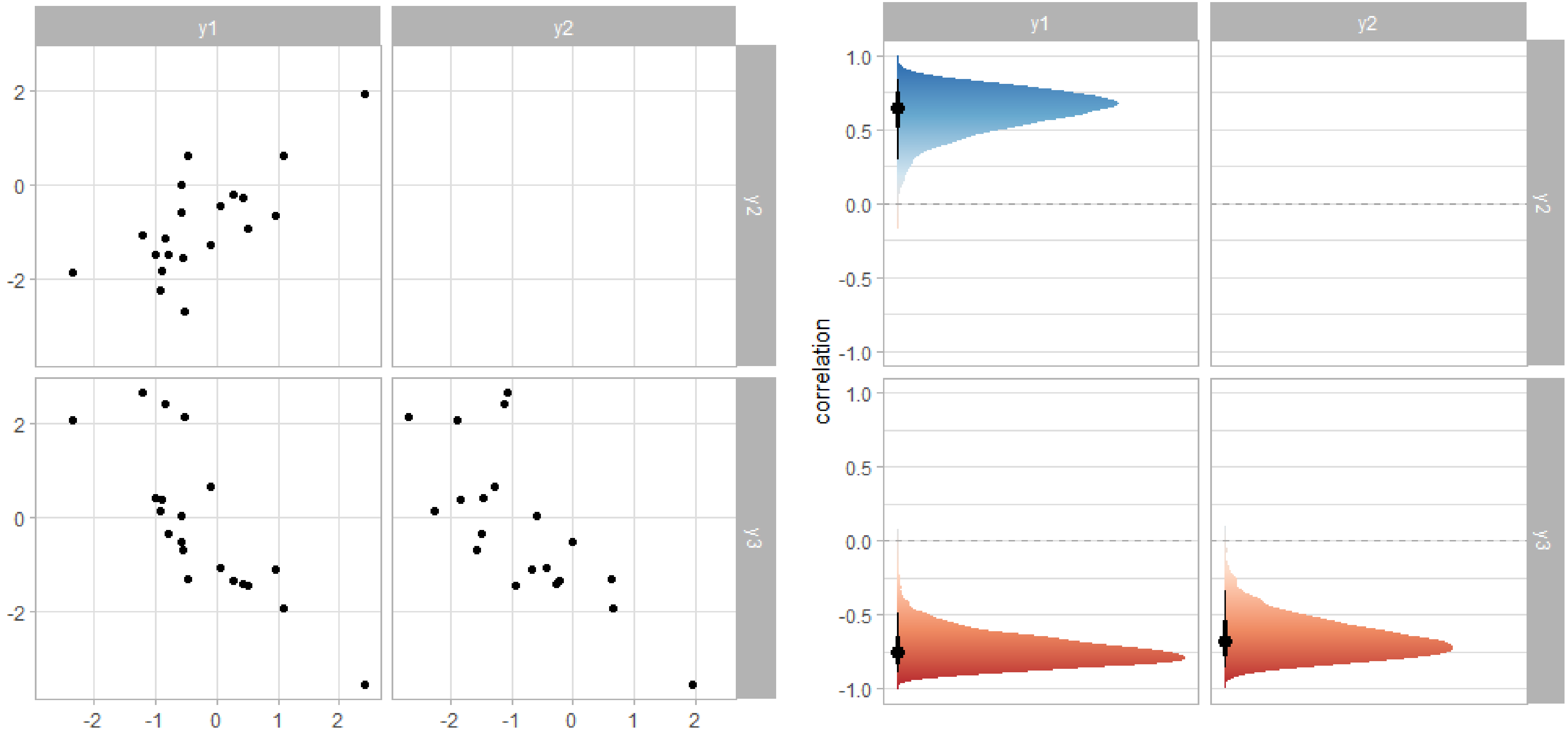


y1
y2
y3
y4
y5
y6
y7
y8
corr.
1.0
0.5
0.0
-0.5
-1.0

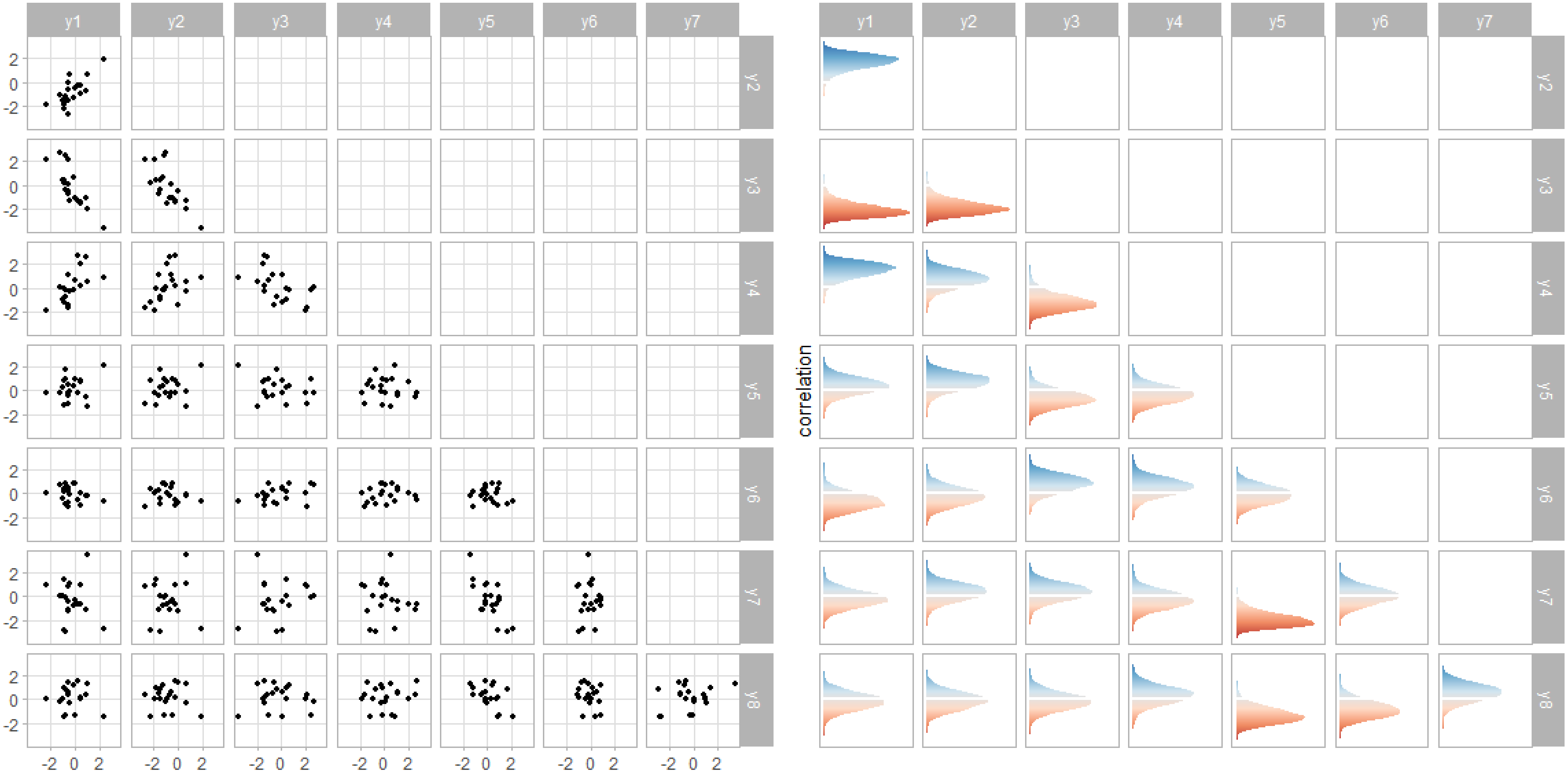

y1
y2
y2
y3
2
0
-2
2
0
-2
-2
-1
0
1
2
-2
-1
0
1
2

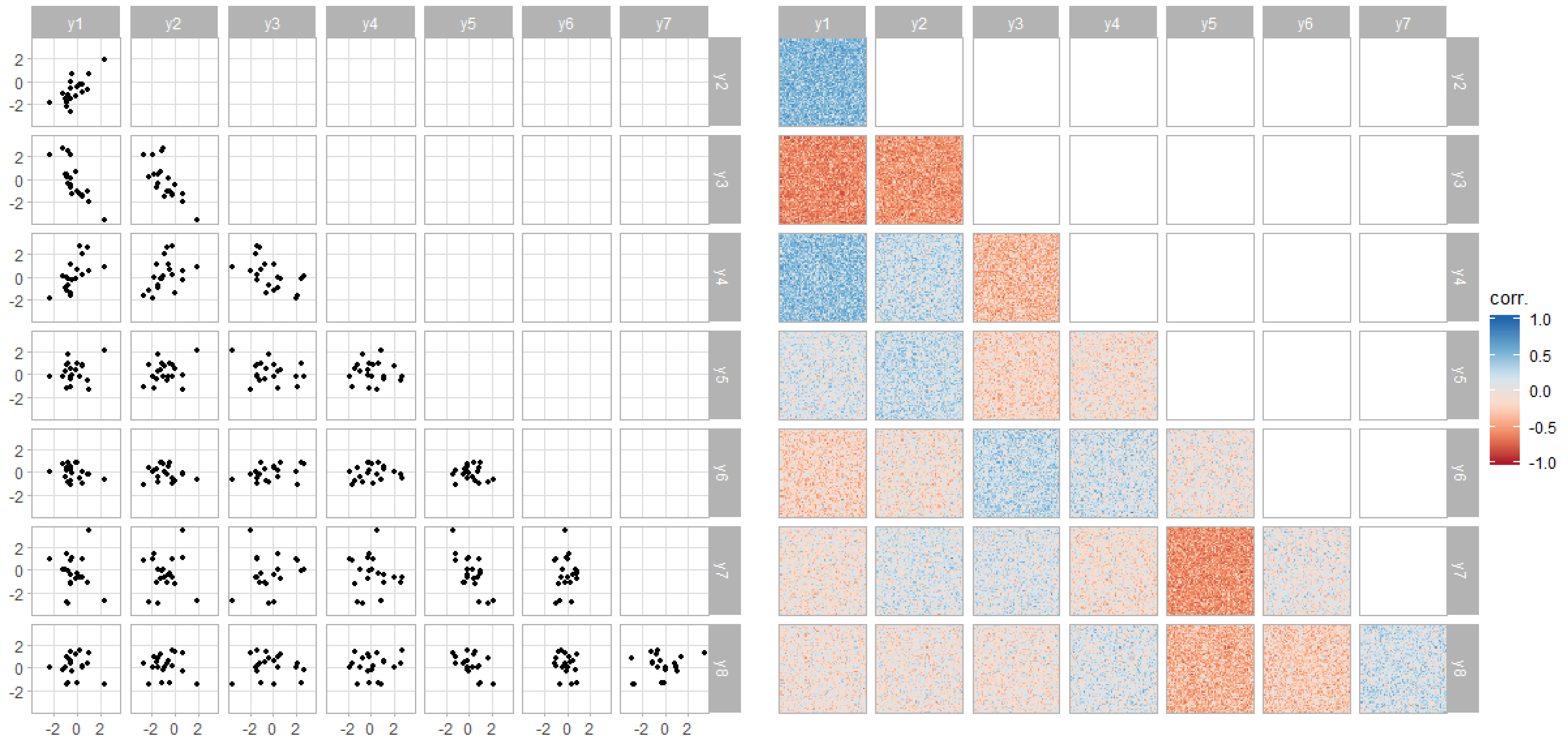


y1
y2
y2
y3
y1
y2
y2
y3
correlation

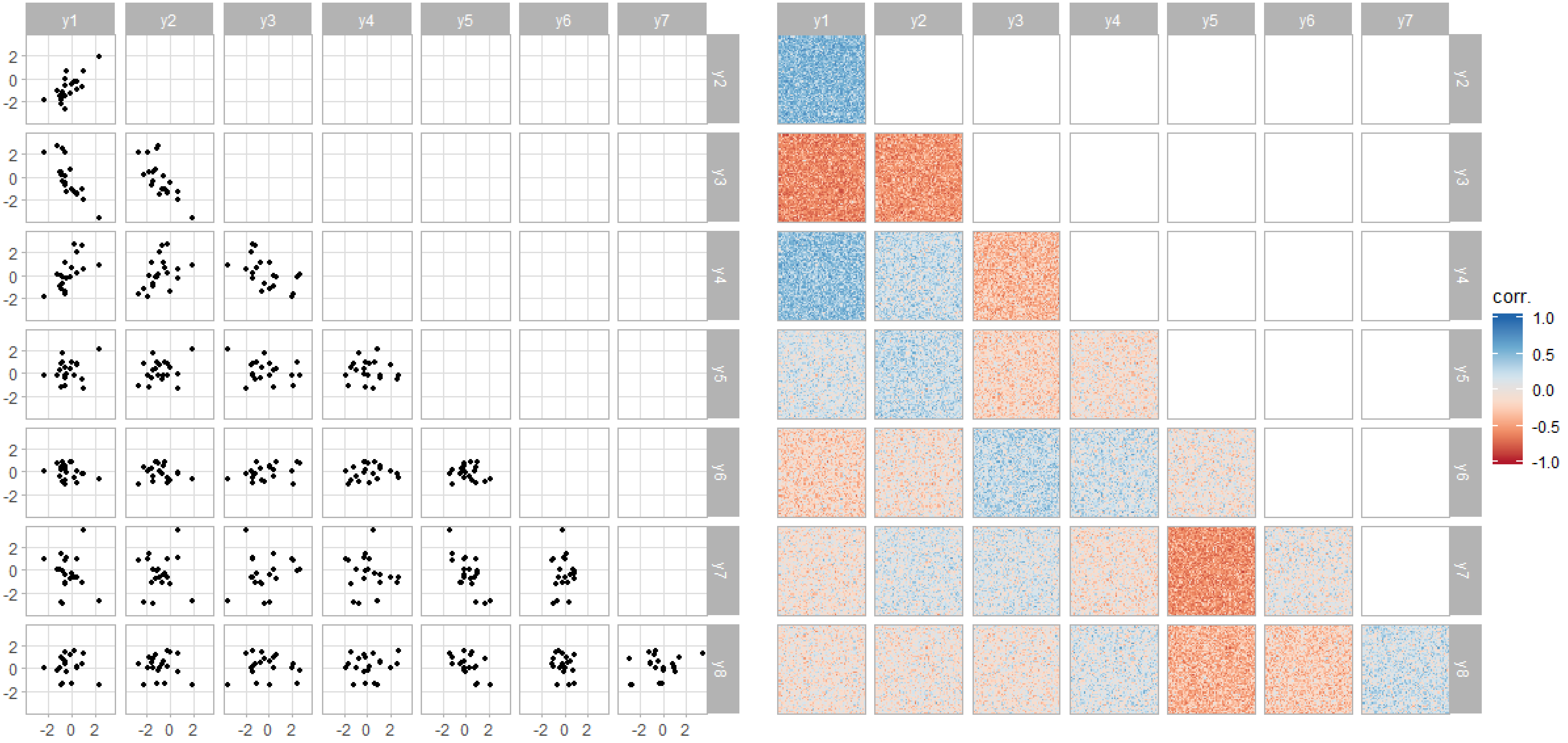


y1
y2
y2
y3
correlation


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

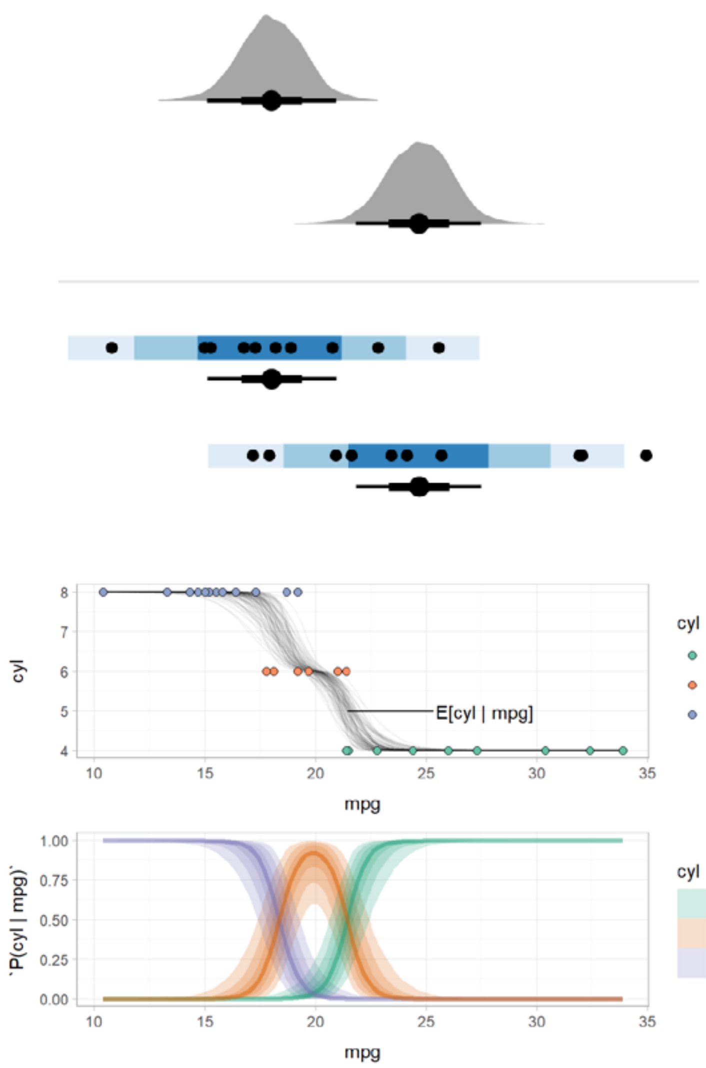


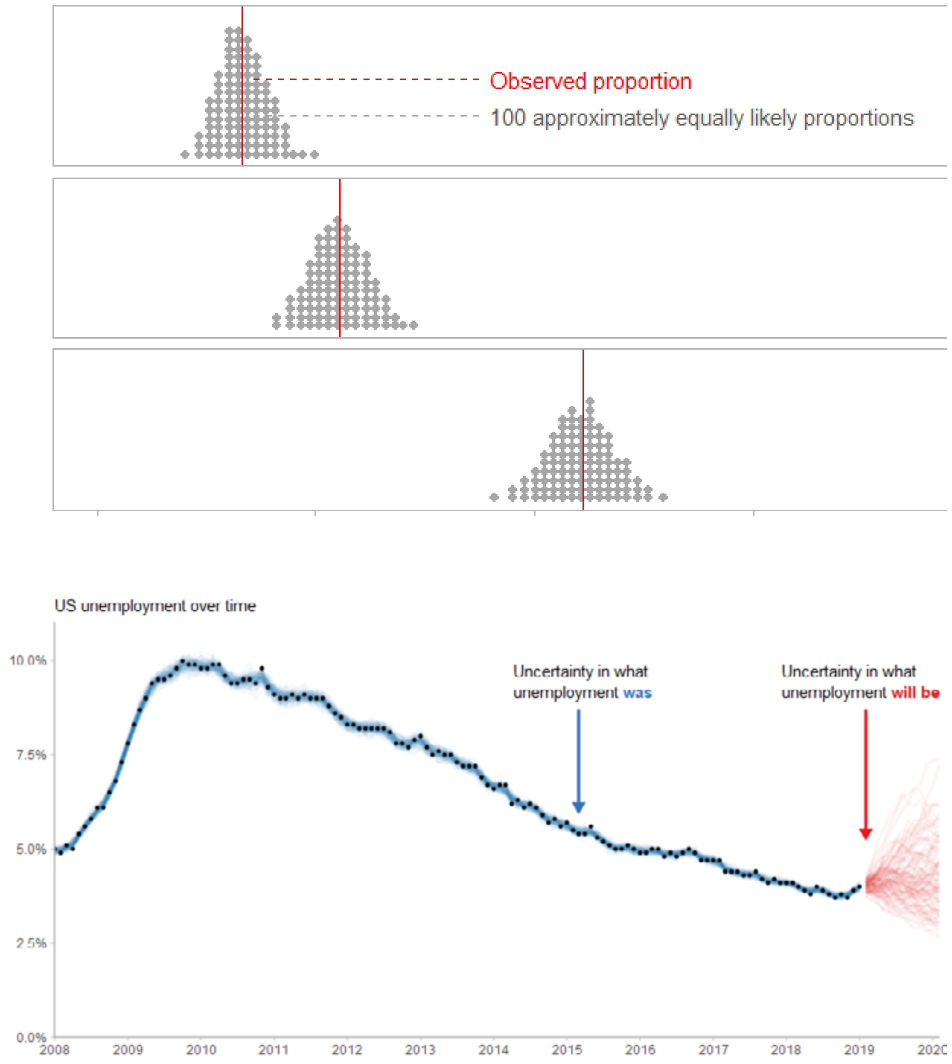
y1
y2
y3
y4
y5
y6
y7
y8
corr.
1.0
0.5
0.0
-0.5
-1.0

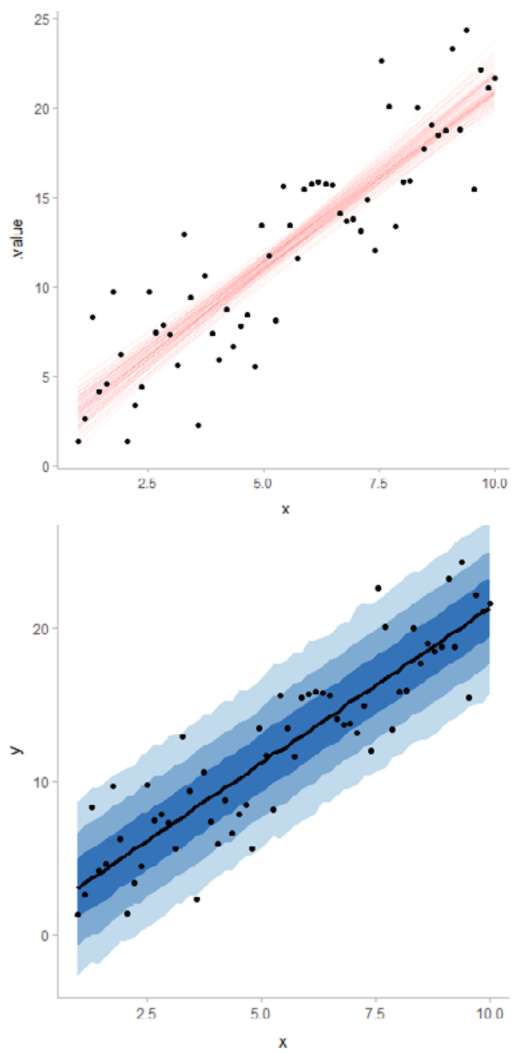



y1
y2
y3
y4
y5
y6
y7
y8
corr.
1.0
0.5
0.0
-0.5
-1.0

More examples...







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

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

Let’s step back from
strictly probabilistic uncertainty

Garden of forking paths [Gelman and Loken 2014]

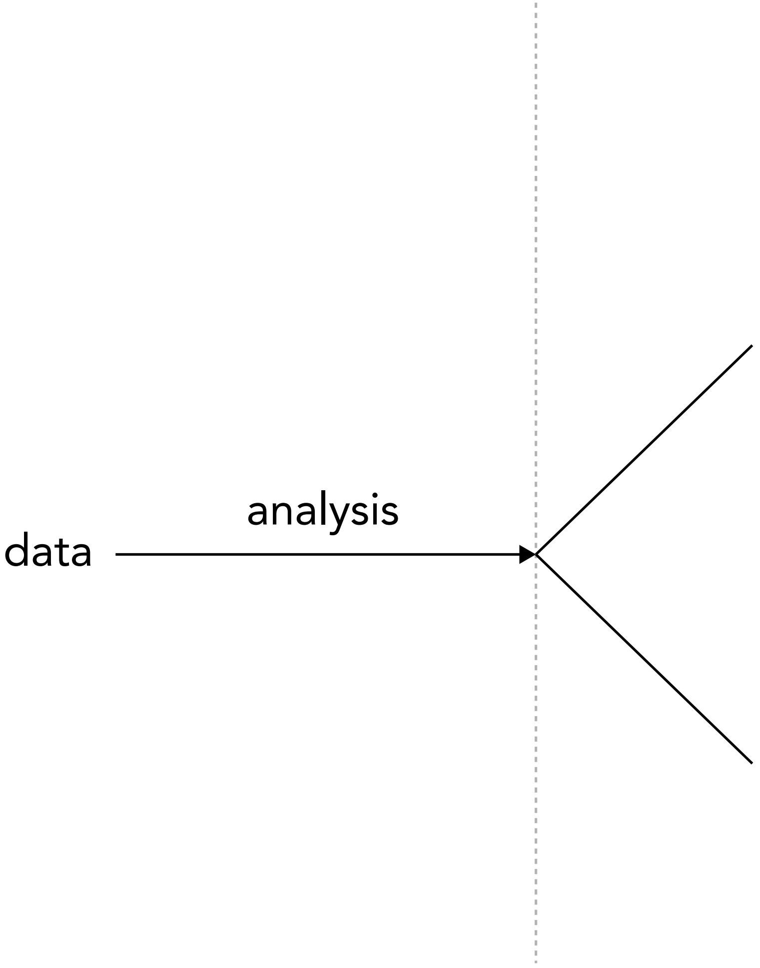
$\text{data} \xrightarrow{\text{analysis}} p < 0.05$

Garden of forking paths [Gelman and Loken 2014]

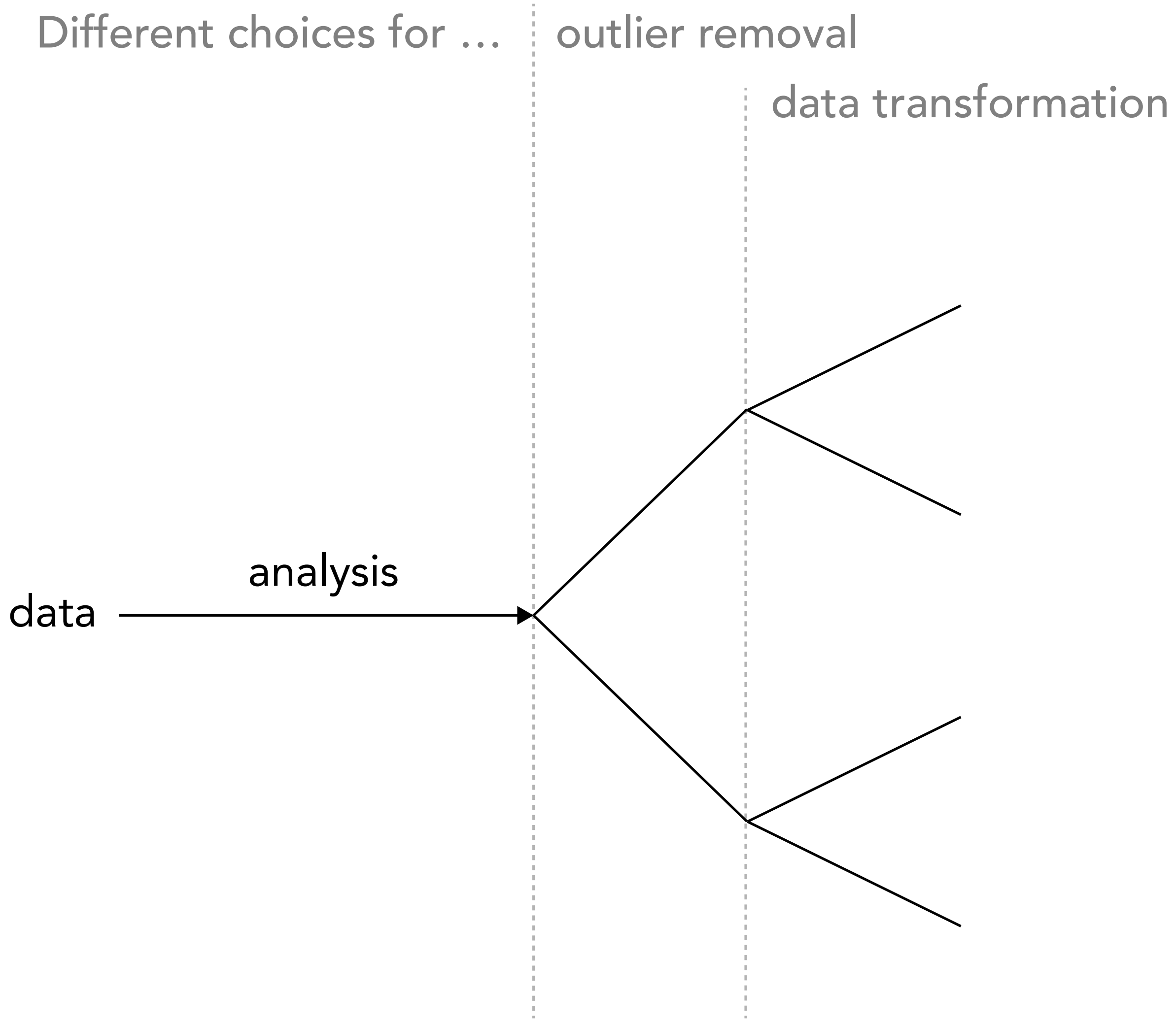
data $\xrightarrow{\text{analysis}}$

Garden of forking paths [Gelman and Loken 2014]

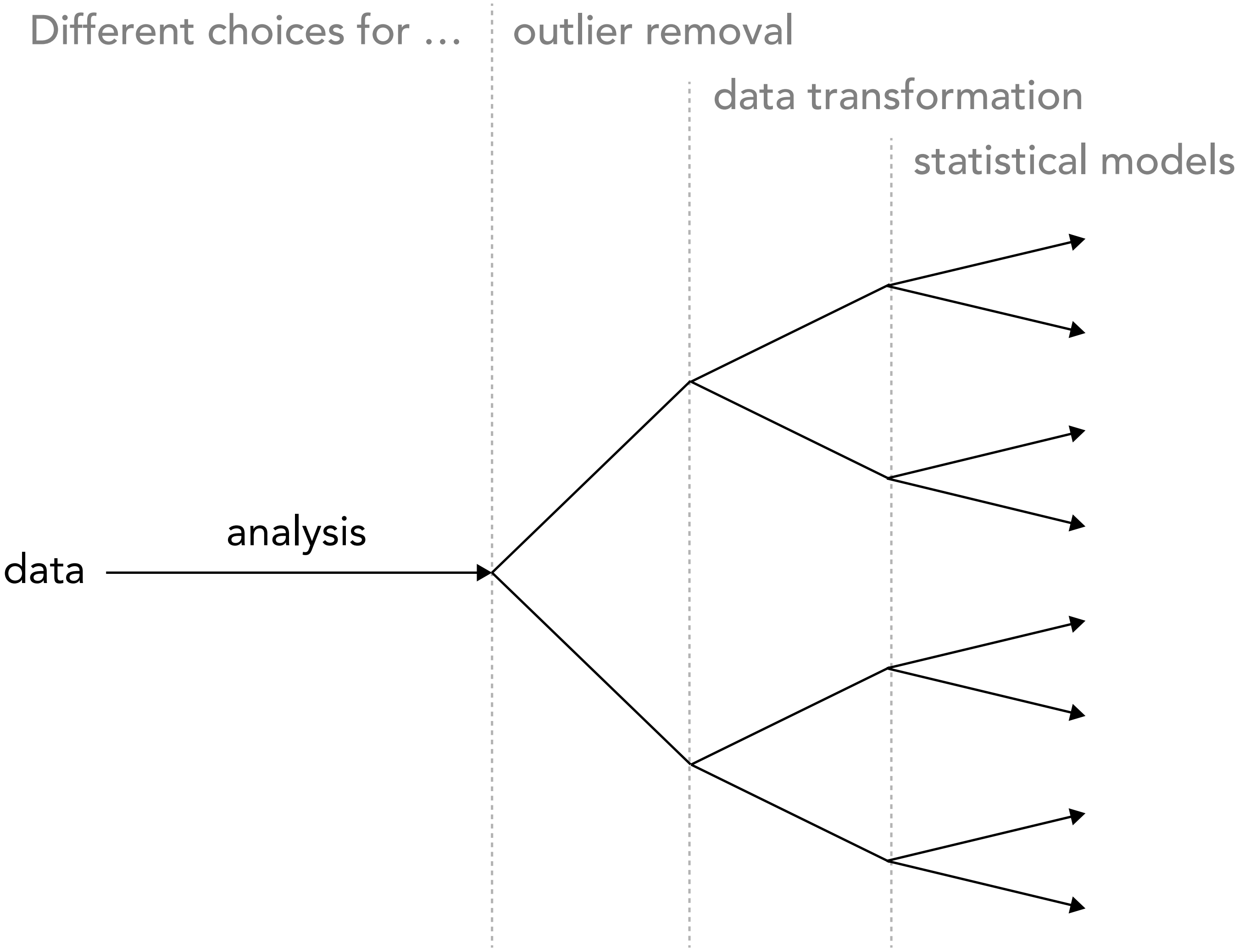
Different choices for … | outlier removal



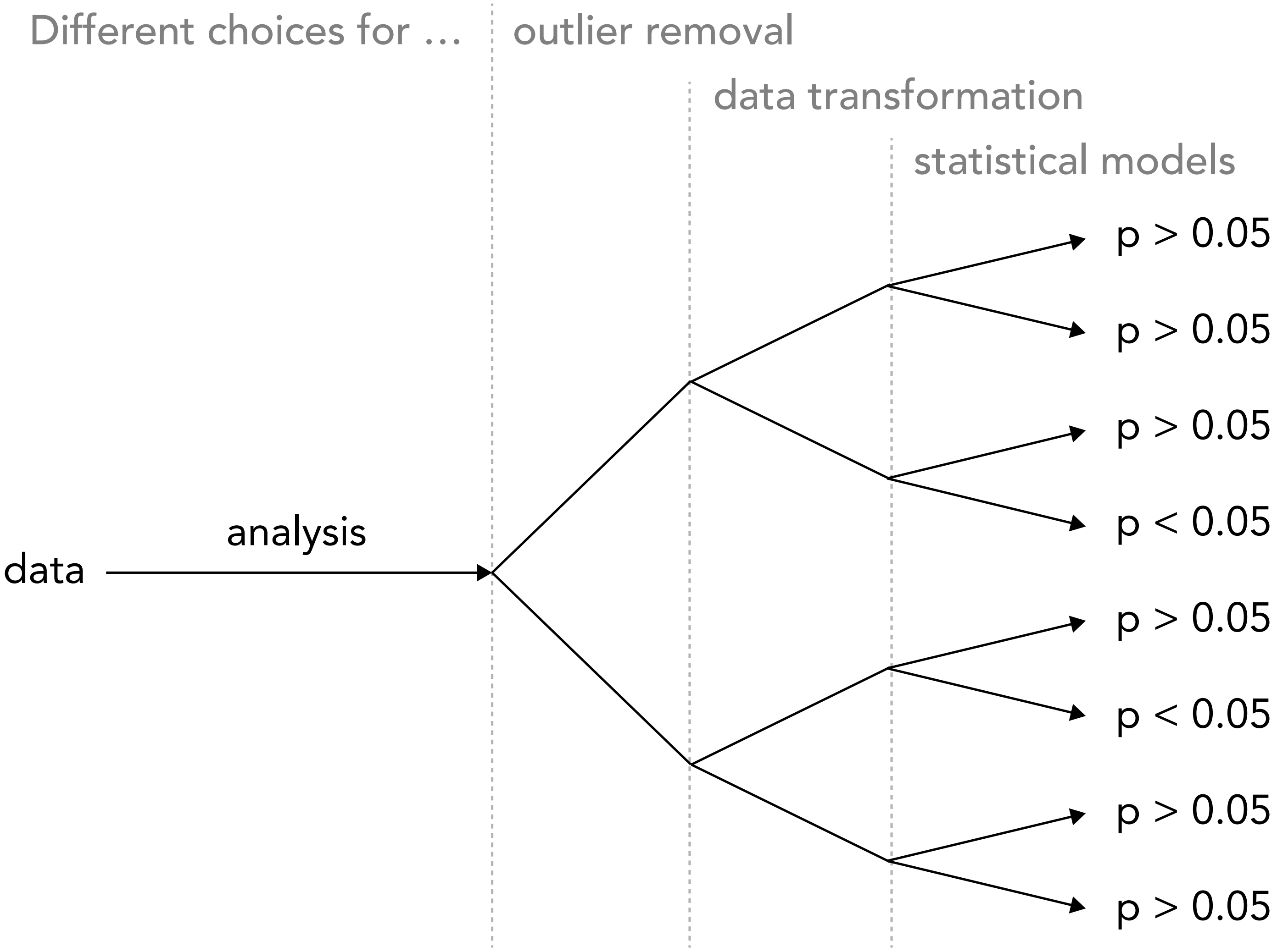
Garden of forking paths [Gelman and Loken 2014]



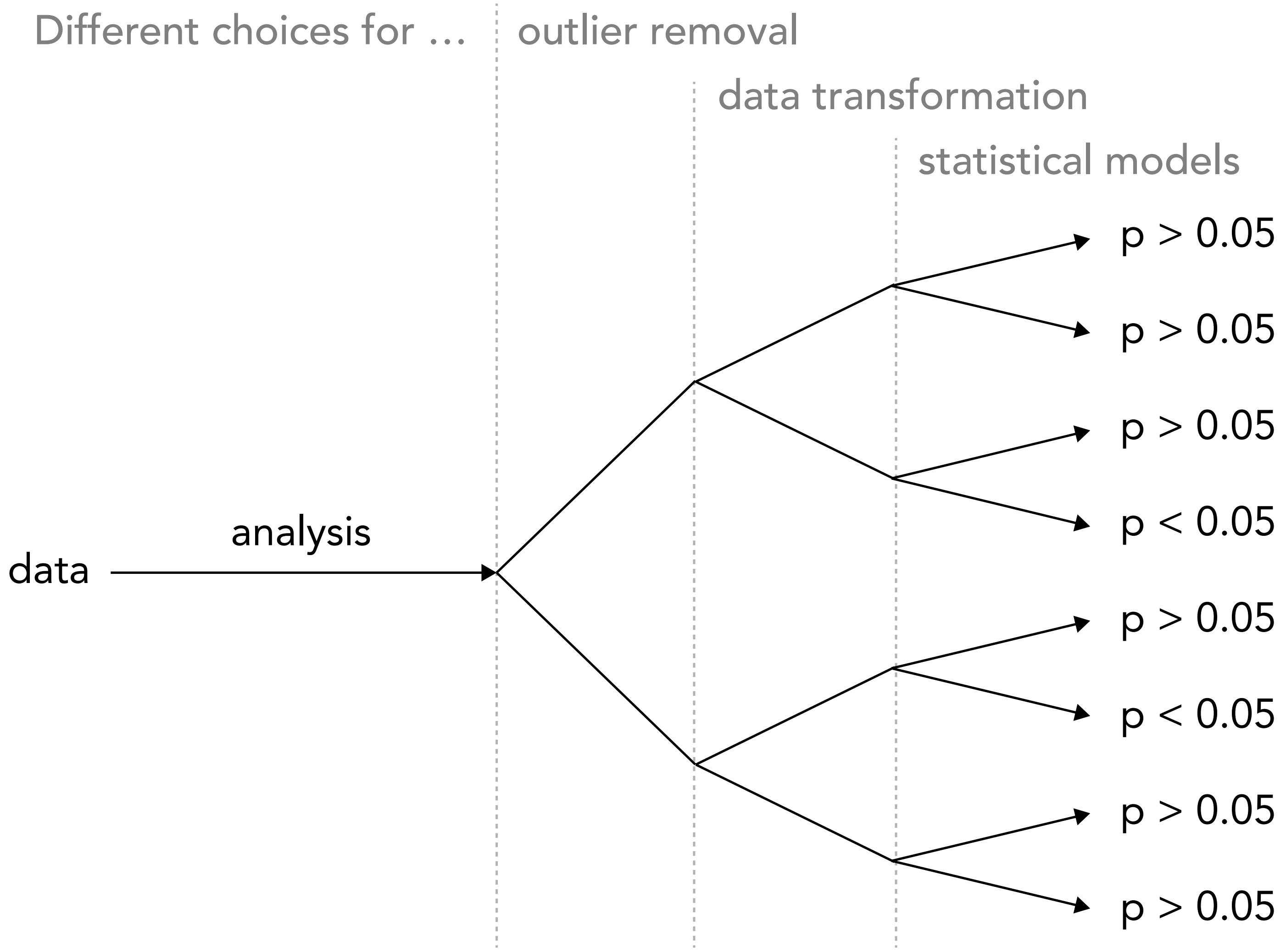
Garden of forking paths [Gelman and Loken 2014]



Garden of forking paths [Gelman and Loken 2014]

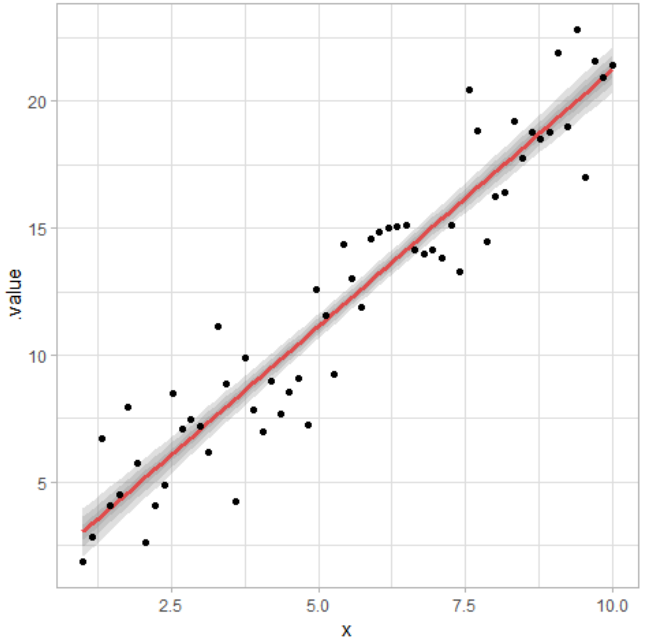


Garden of forking paths [Gelman and Loken 2014]

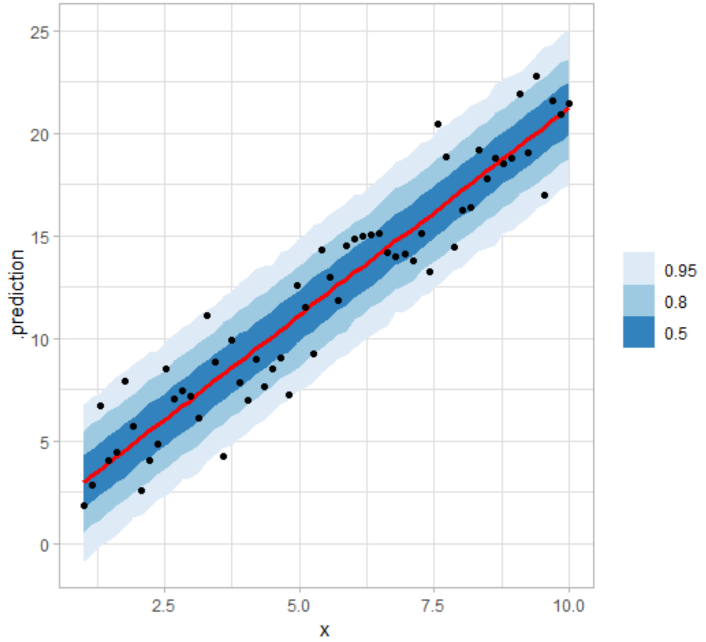


This is model/ specification uncertainty

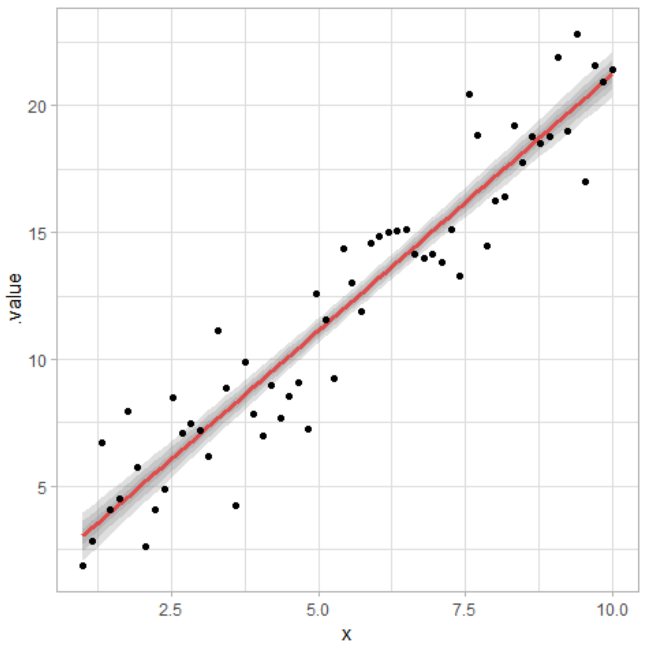
Epistemic uncertainty



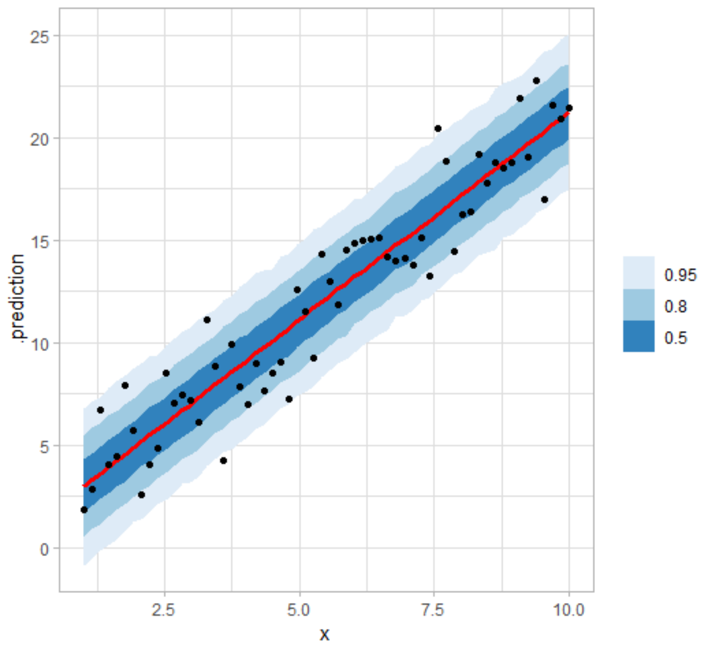
Aleatory uncertainty



Epistemic uncertainty



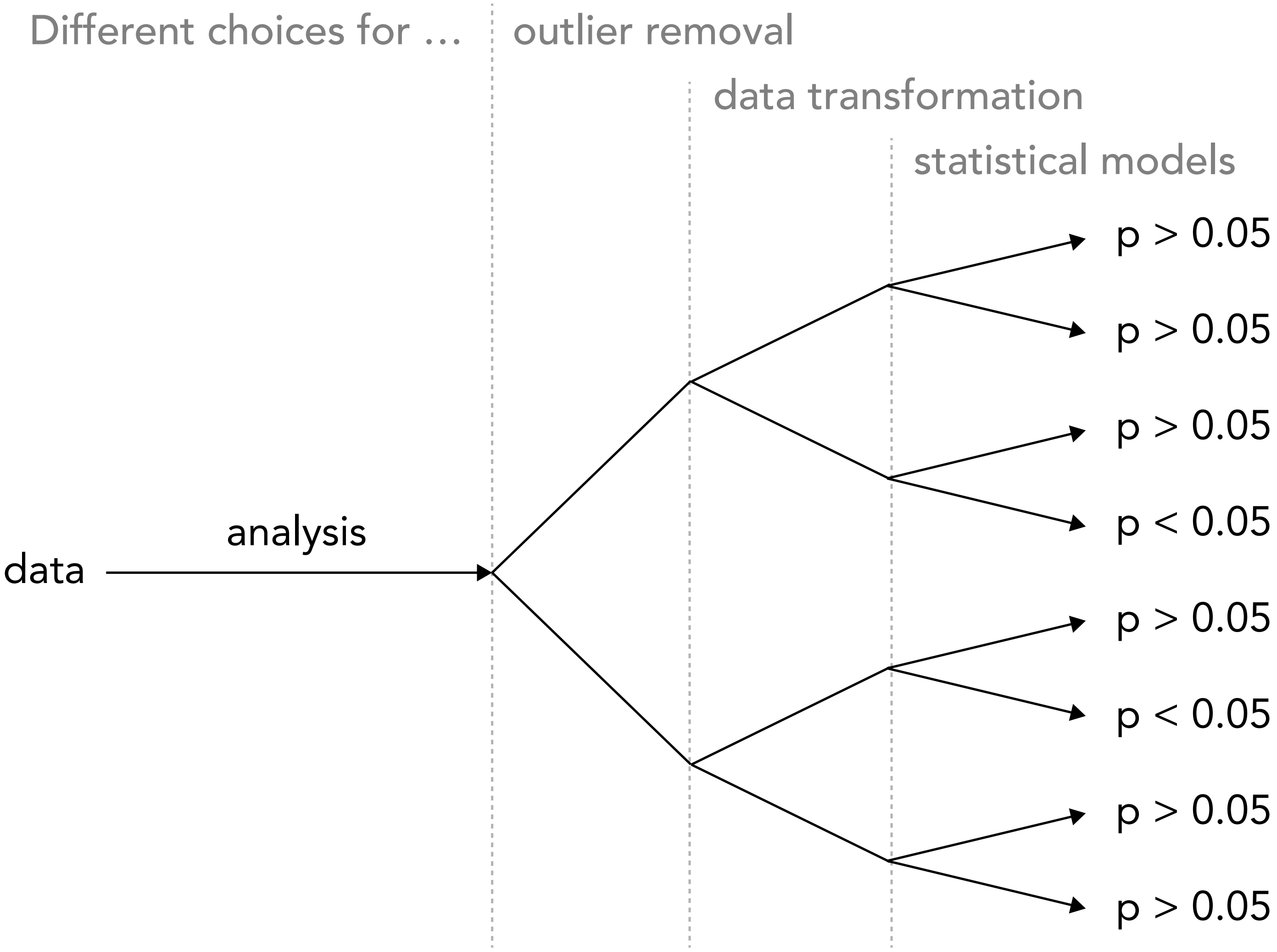
Aleatory uncertainty



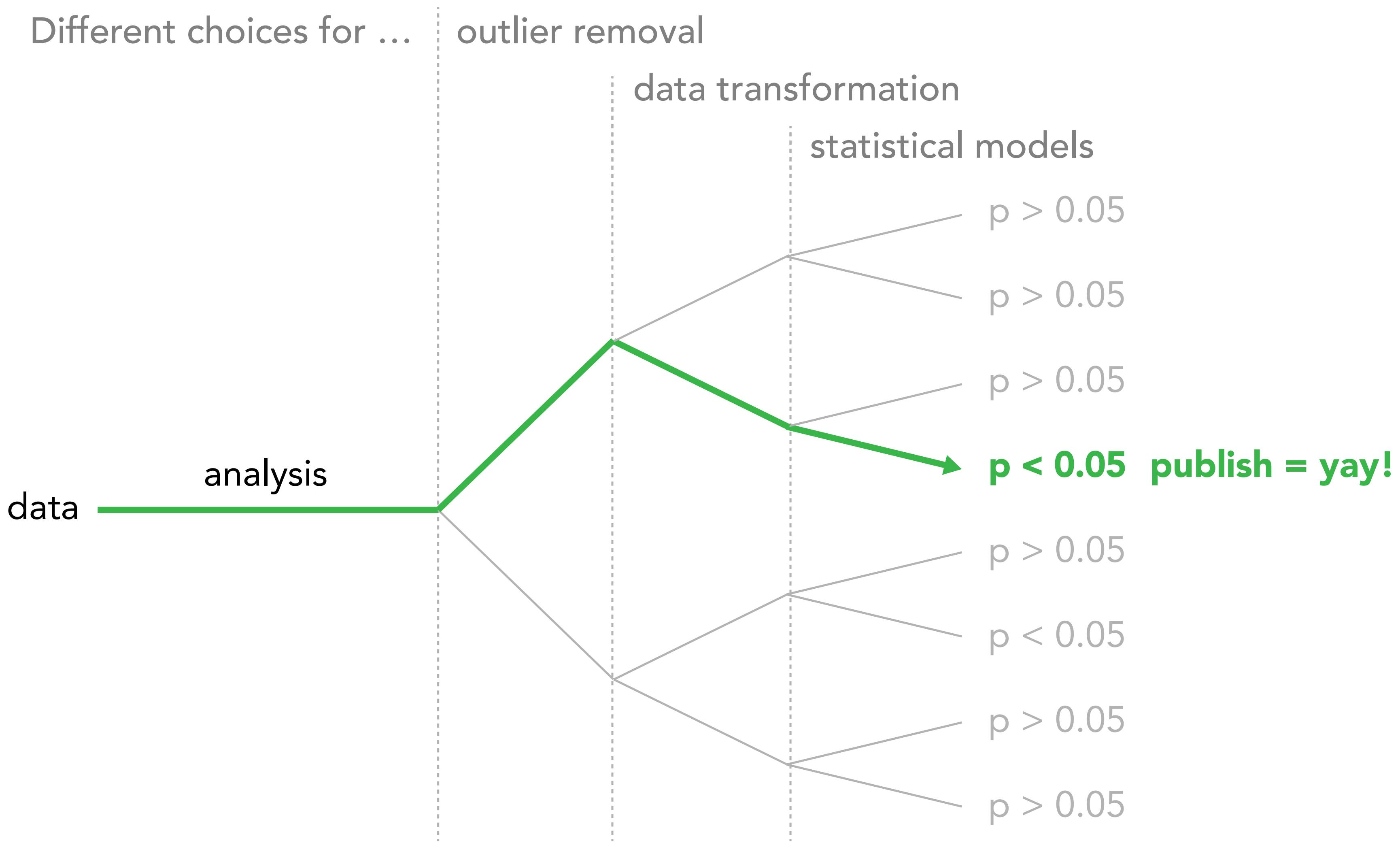
Ontological uncertainty

How well does this describe **reality**?

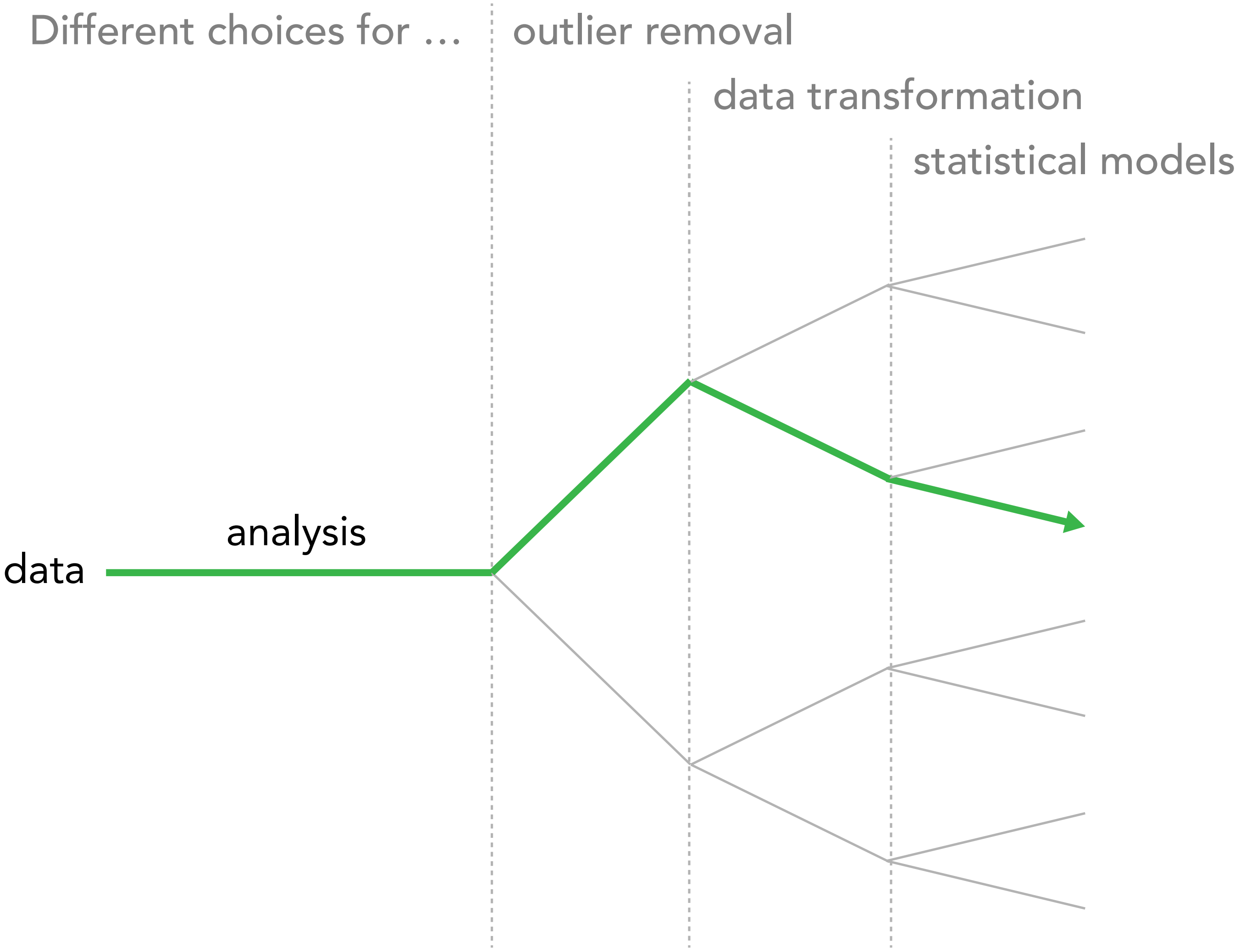
Garden of forking paths [Gelman and Loken 2014]



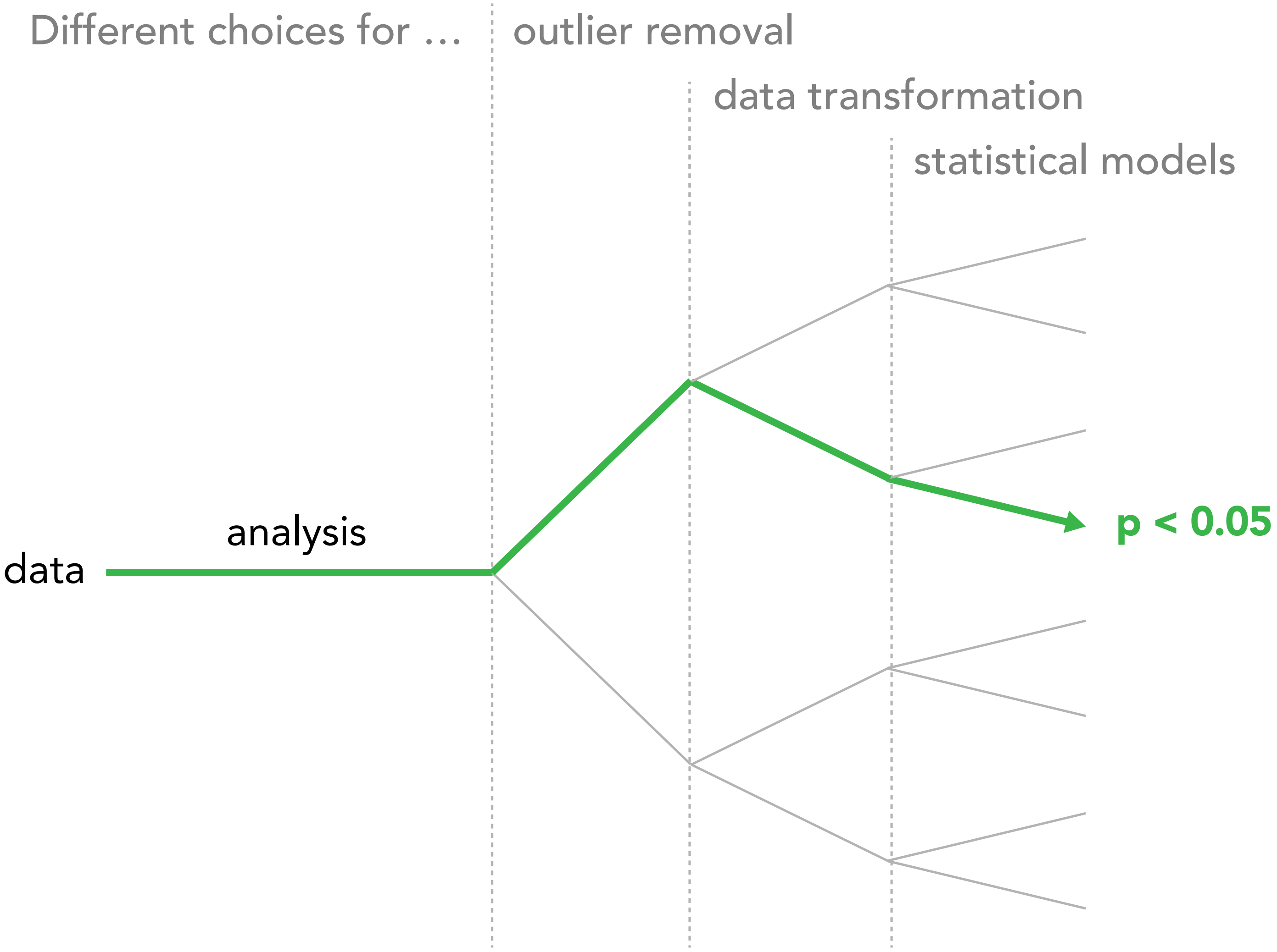
Garden of forking paths [Gelman and Loken 2014]



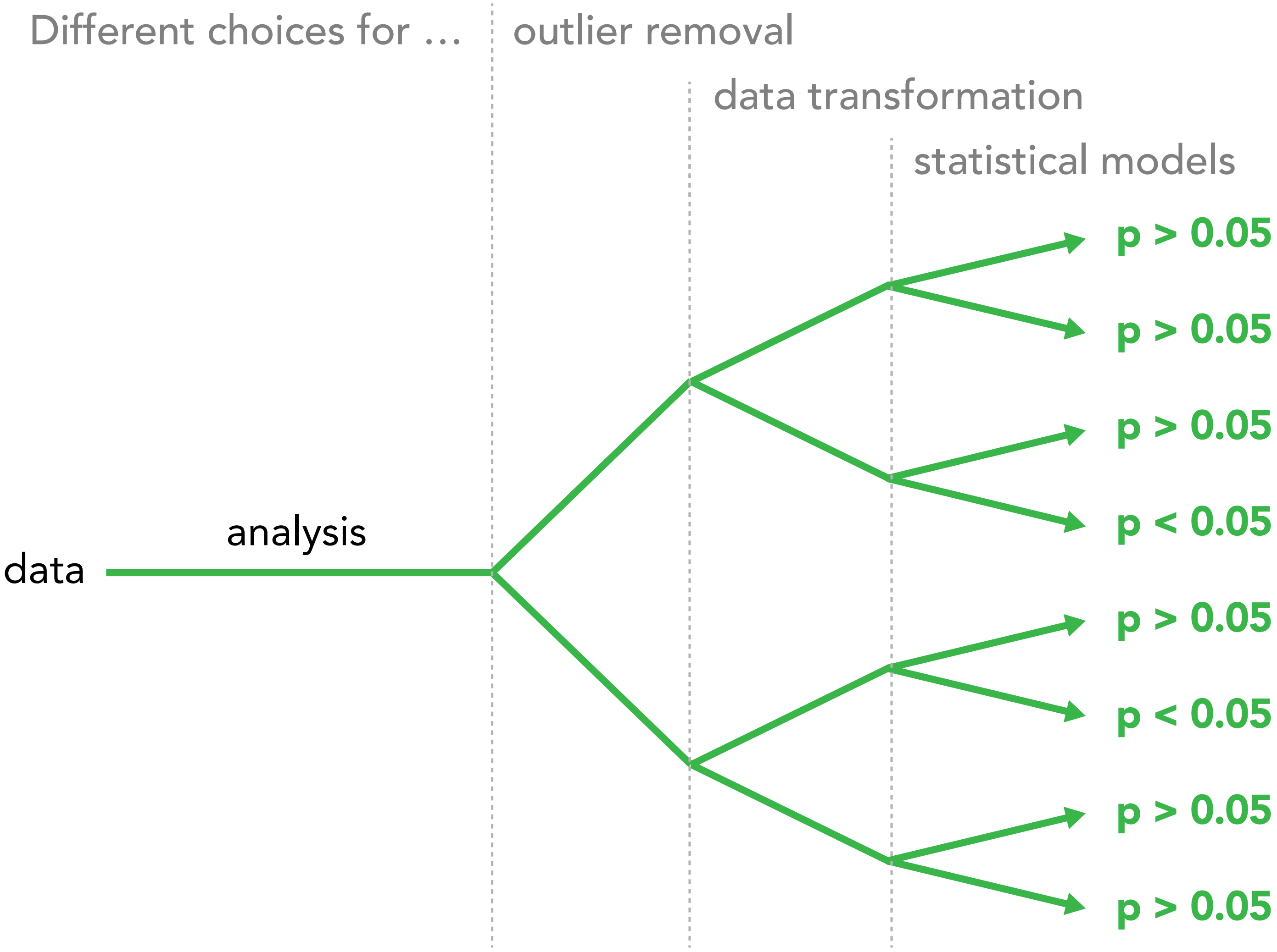
Garden of forking paths [Gelman and Loken 2014]

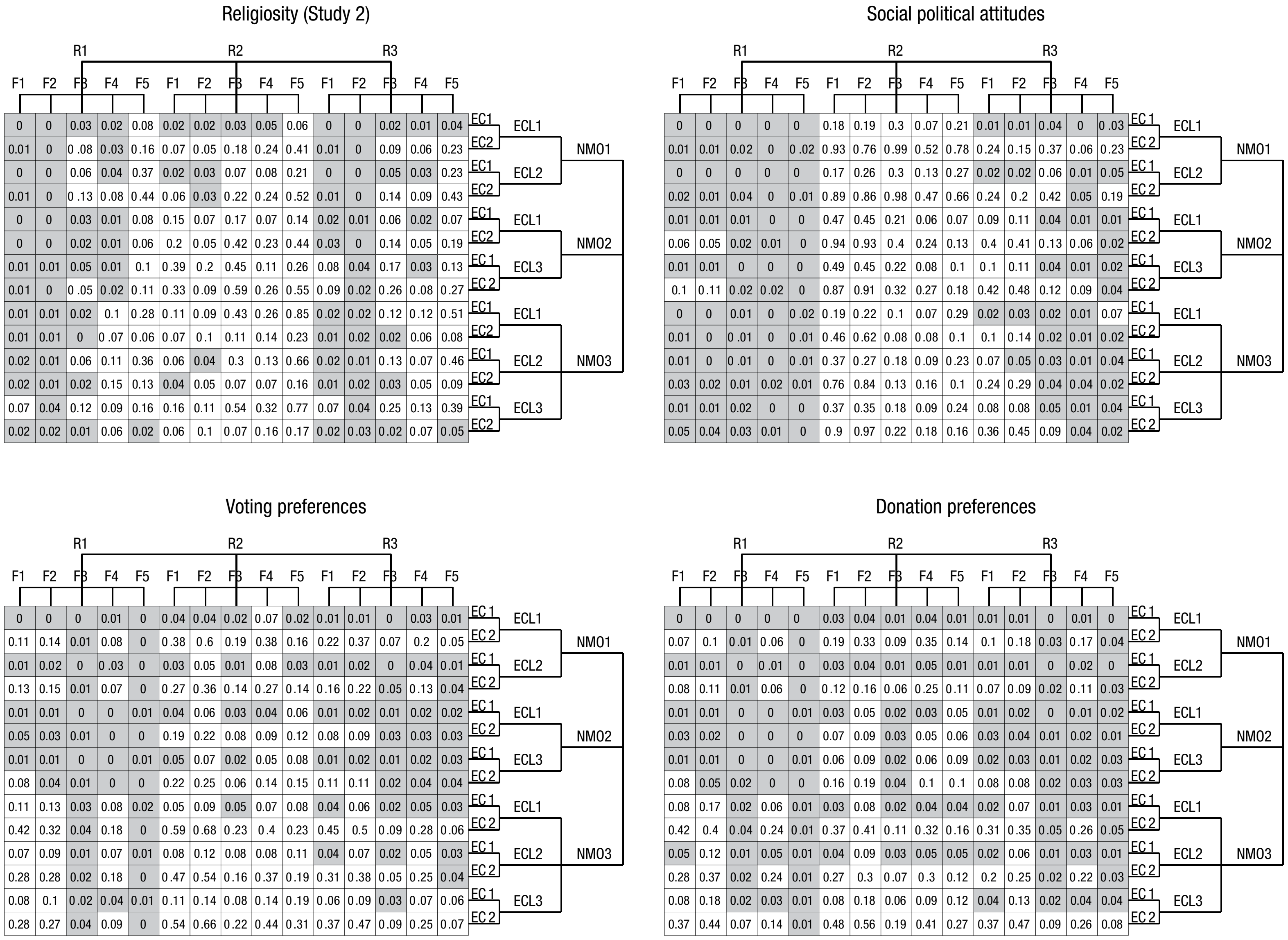


(pre-registration)



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





[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/]

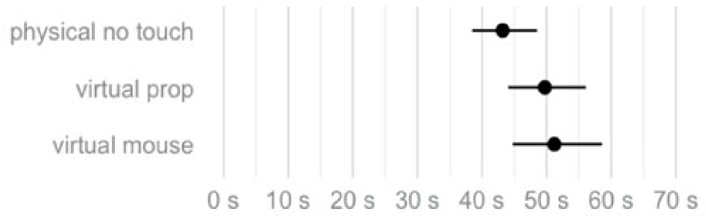
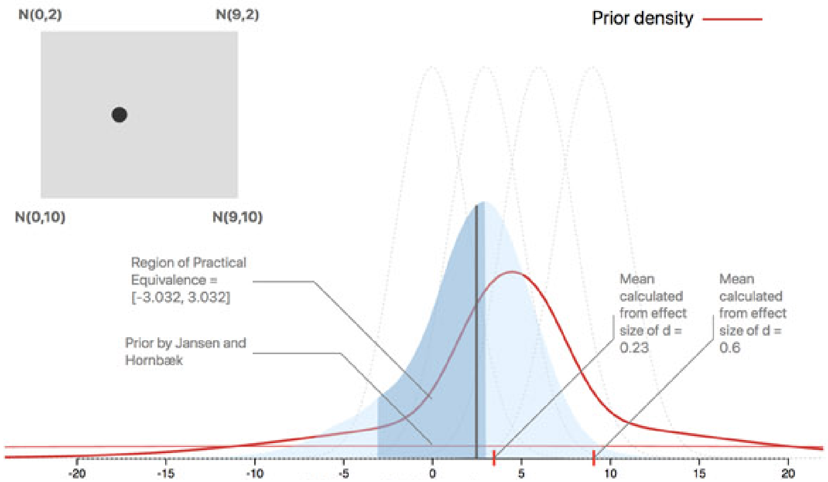
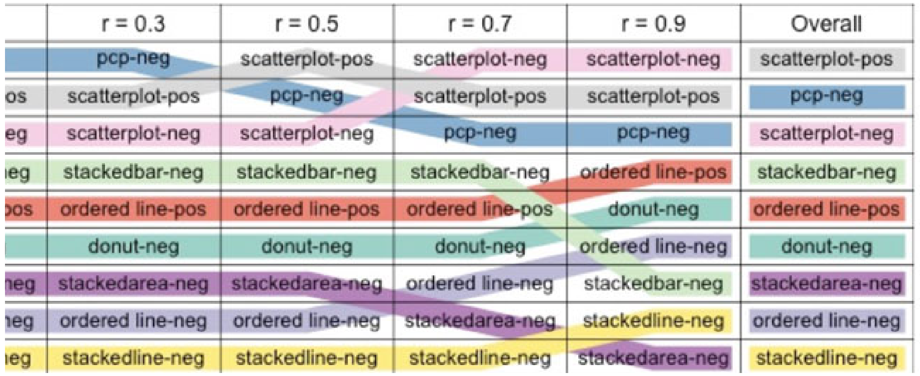
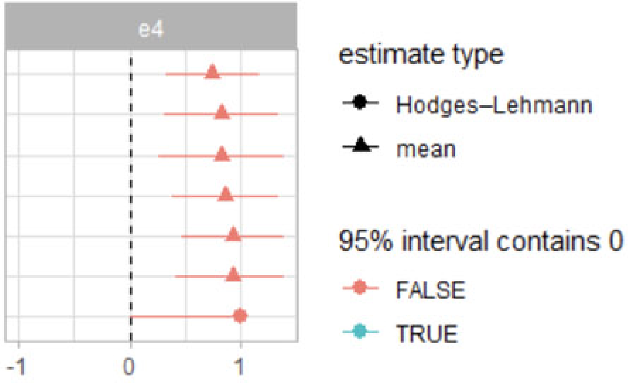


Figure 3. Average task completion time (geometric mean) for each condition. Error bars are 95% t-based CIs.

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. Strictly speaking, all we can assert about each interval is







Explorable Multiverse Analysis Reports

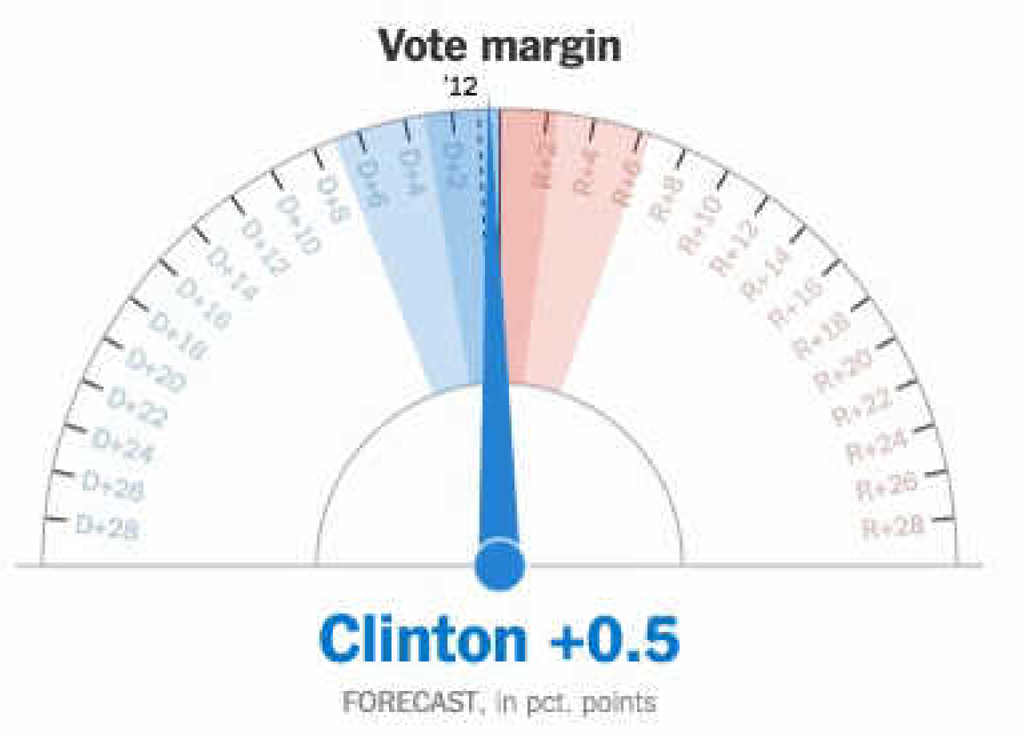
[Dragicevic, Jansen, Sarma, **Kay**, and Chevalier. Increasing the Transparency of Research Papers with Explorable Multiverse Analyses. CHI 2019: https://explorablemultiverse.github.io/]

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

Okay, but back to elections...

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**

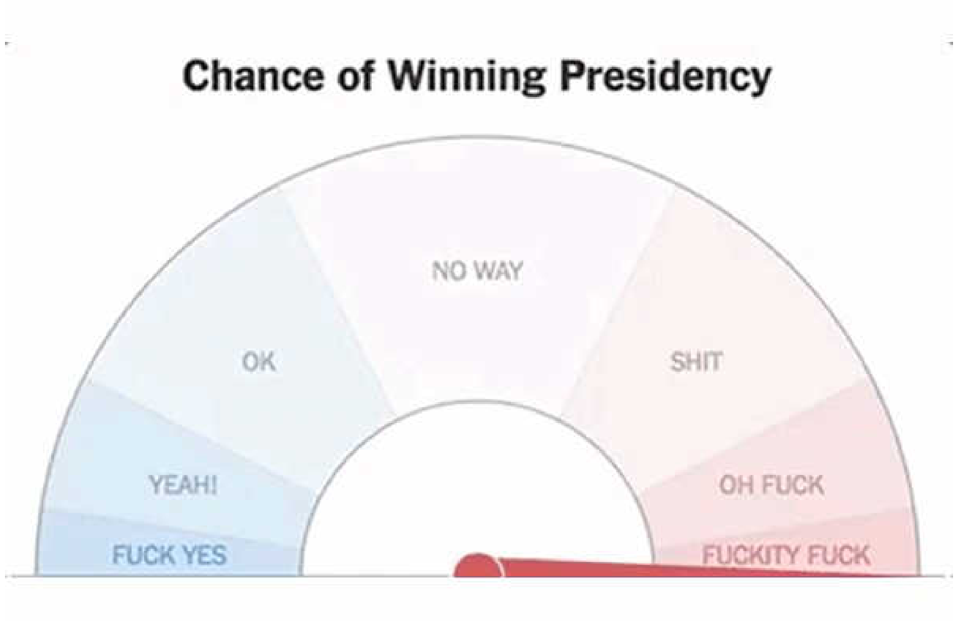


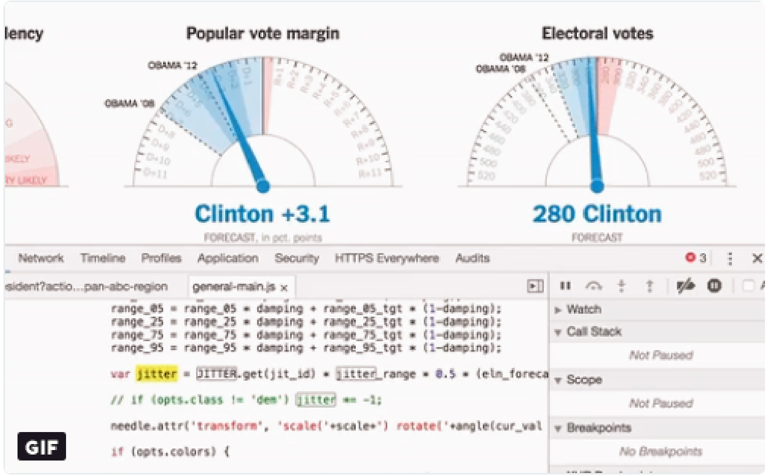
Photo: rhyselsmore/Twitter

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

Multivariate visualization

Multivariate data

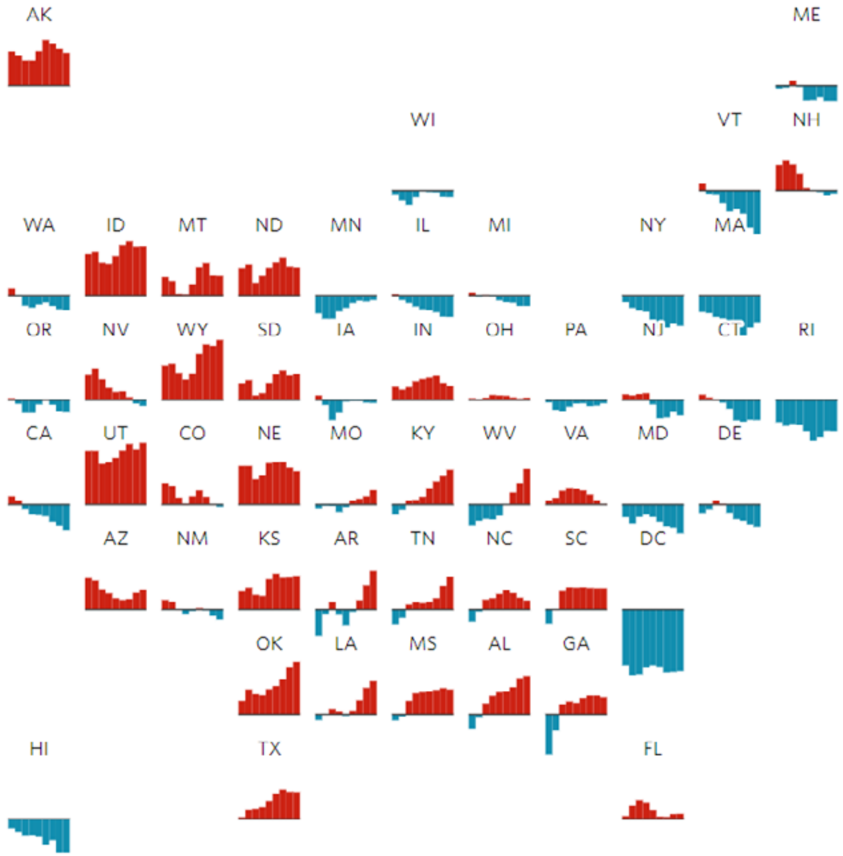
Examples of useful techniques for multivariate data:

1. Small multiples

2. Scatterplot matrices

3. Parallel coordinates

Small multiples



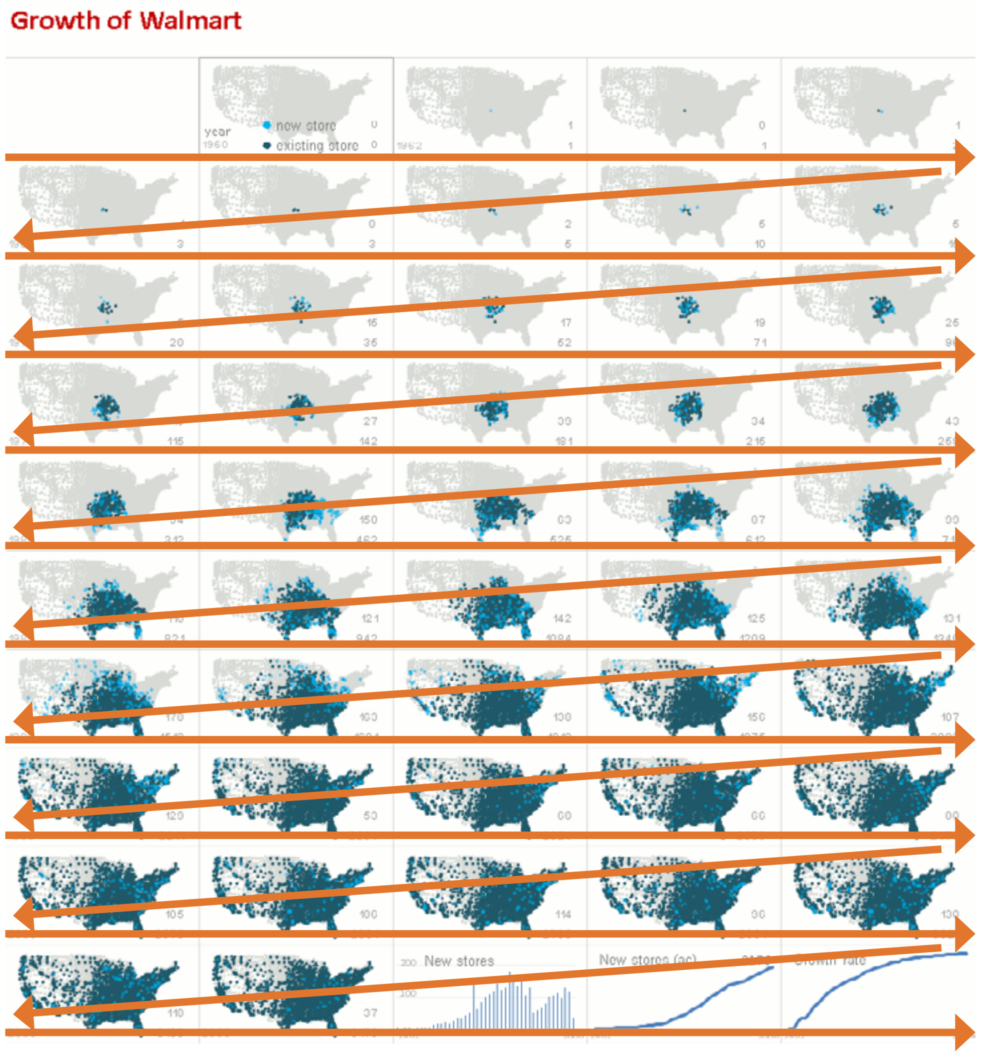
Value of small multiples

Reader-driven comparison

Micro-macro readings, layering

High-level properties through ensemble coding

Double use of position channel

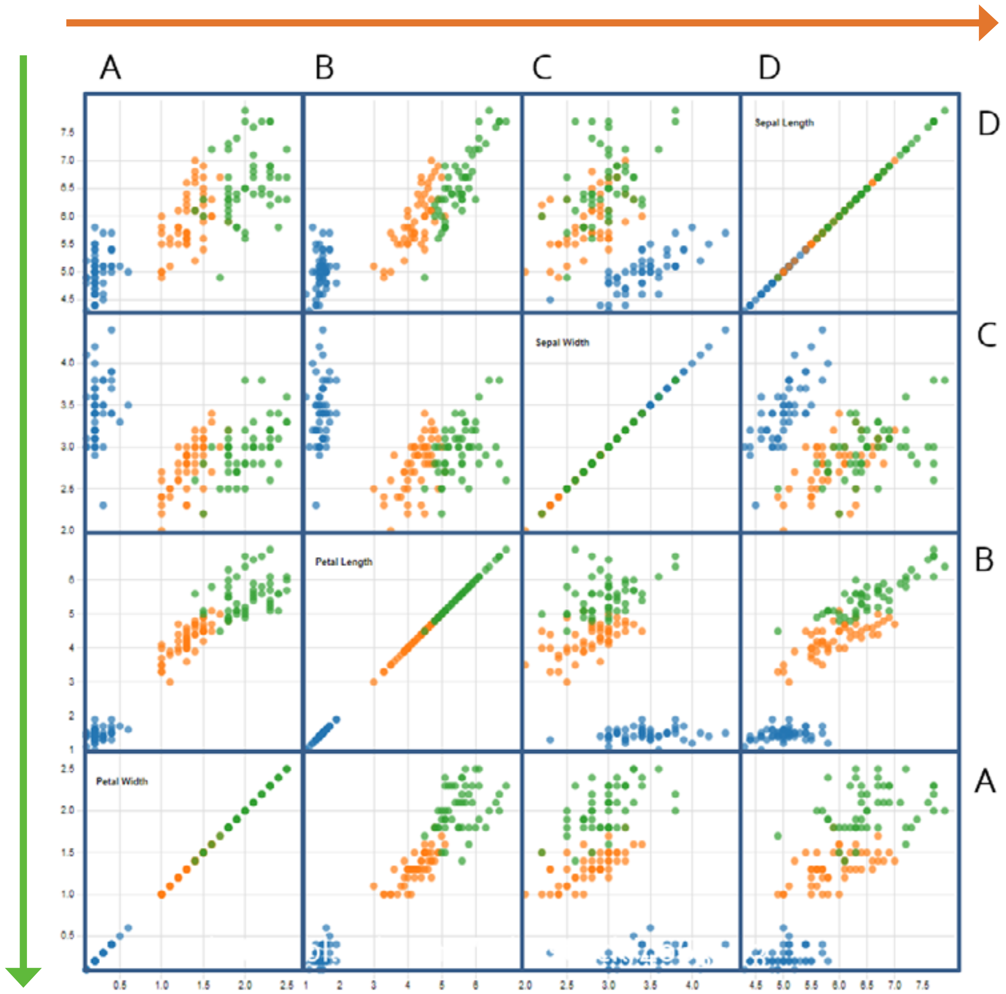


SPLOM: Scatterplot matrix

[https://bl.ocks.org/mbostock/4063663]

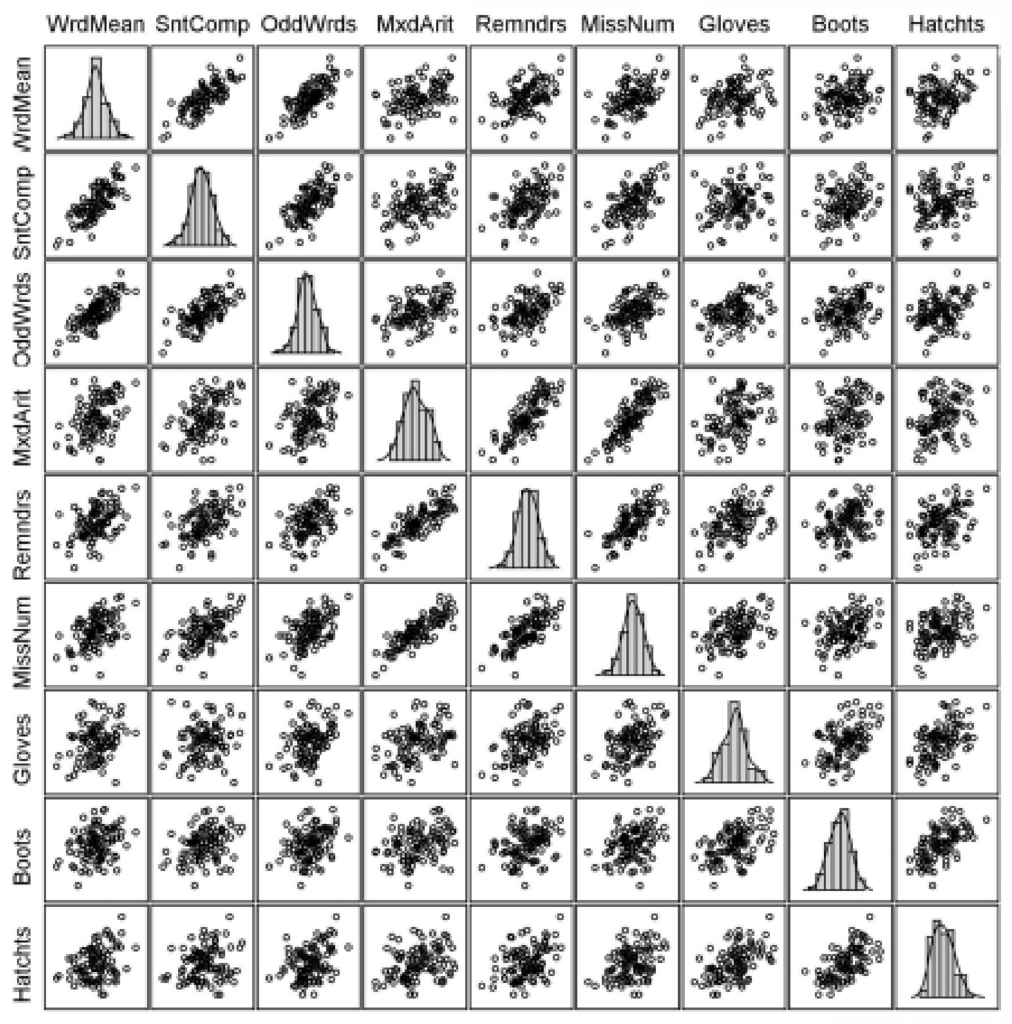
Special case of small multiples
variable -> column (x position)
variable -> row (y position)

Each panel:
column variable -> x position
row variable -> y position



SPLOMs don't scale well with many variables

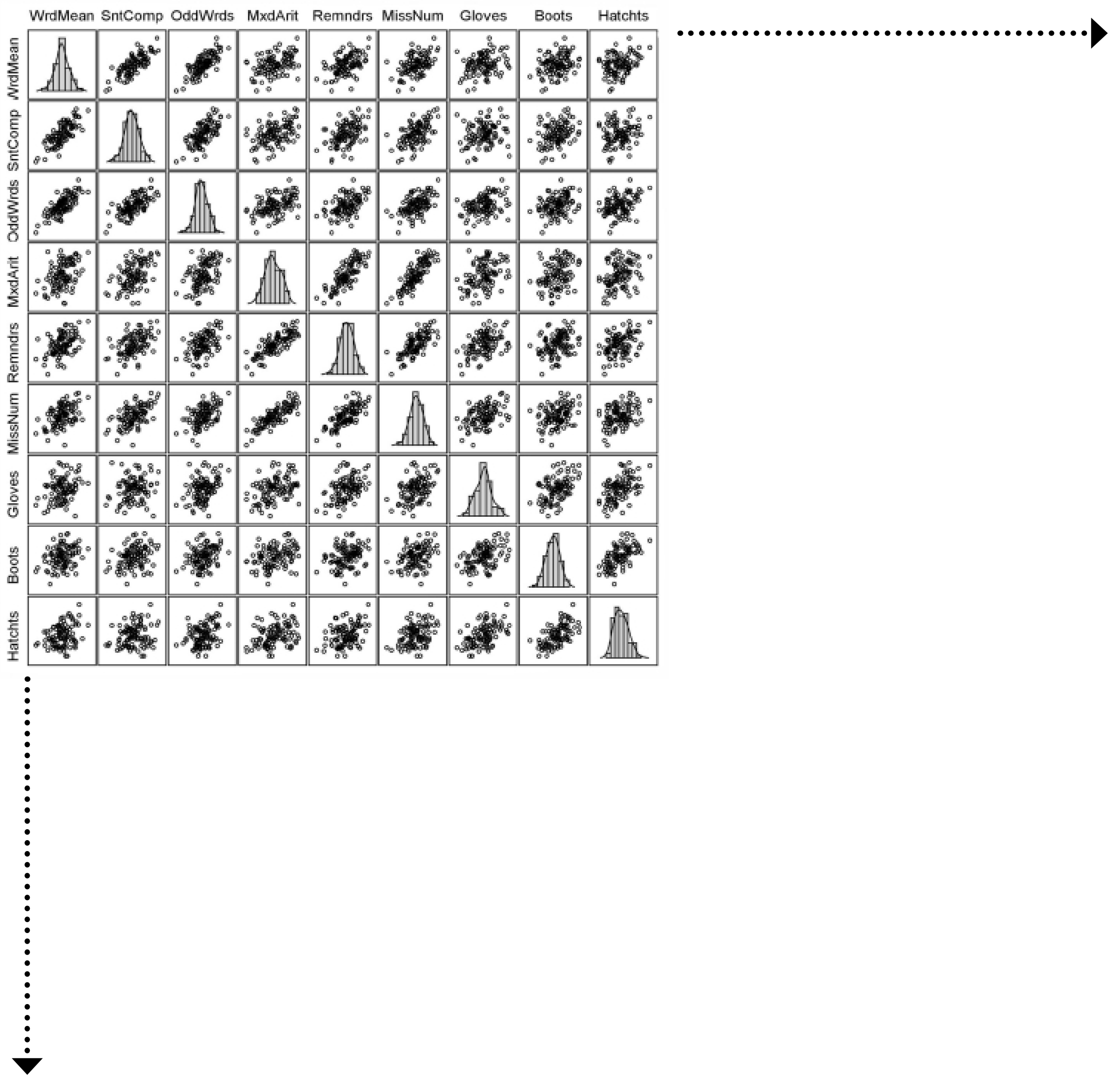
Scatterplot is best representation for correlation...



SPLOMs don't scale well with many variables

Scatterplot is best representation for correlation...

But SPLOMs don't always scale



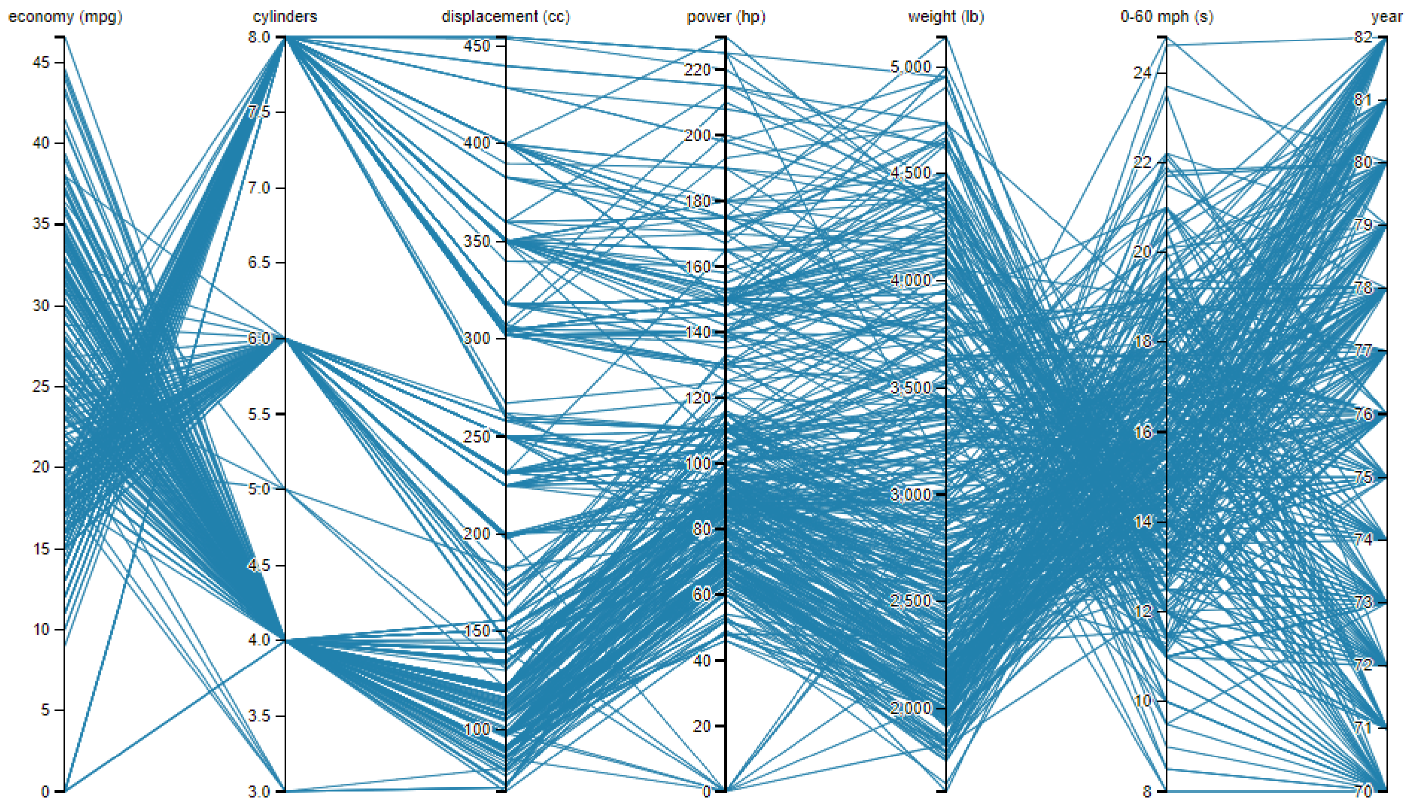
SPLOM alternative: parallel coordinates

[https://bl.ocks.org/jasondavies/1341281]

Scales better

But not best representation

Usually needs interactivity



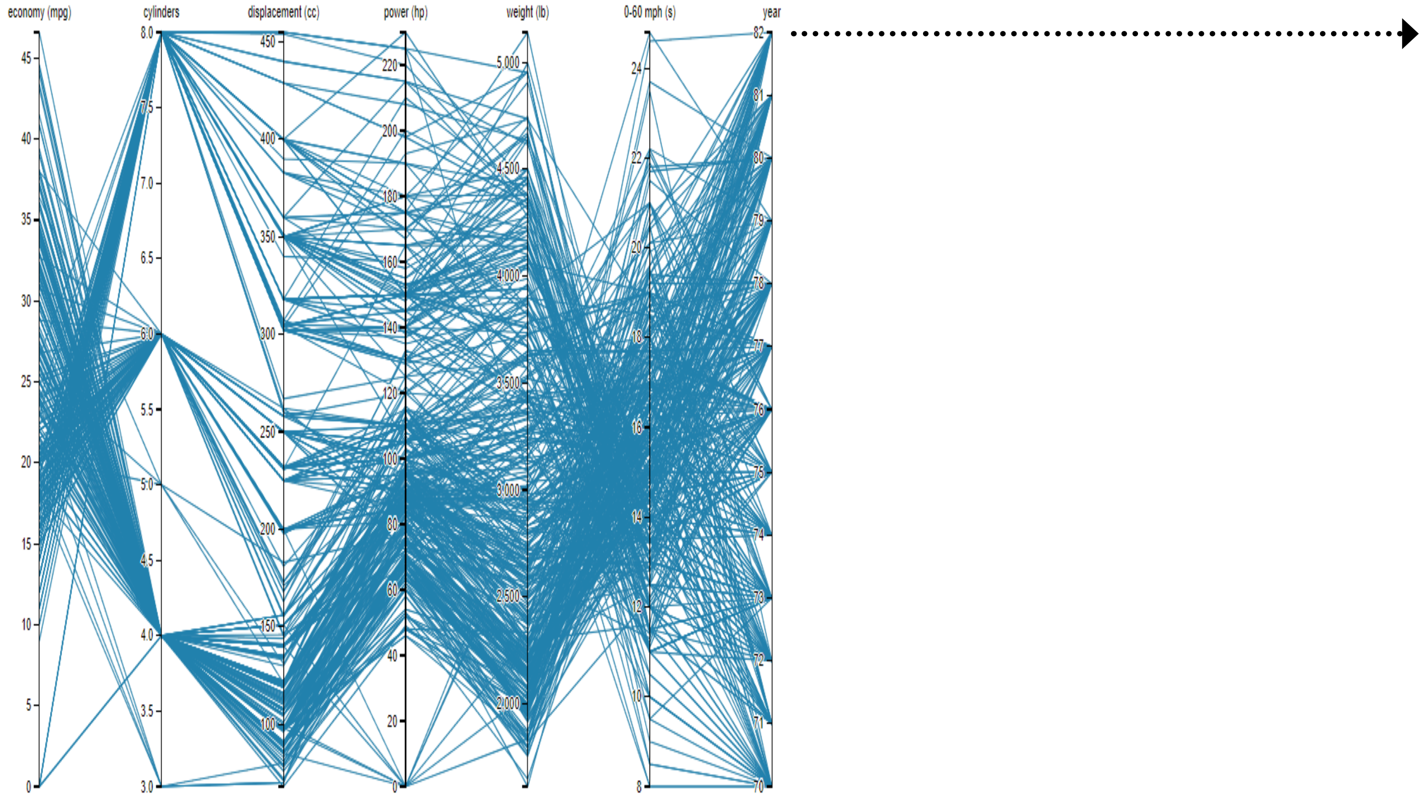
SPLOM alternative: parallel coordinates

[https://bl.ocks.org/jasondavies/1341281]

Scales better

But not best representation

Usually needs interactivity



Multivariate visualization

Small multiples help a lot (double position encoding!)

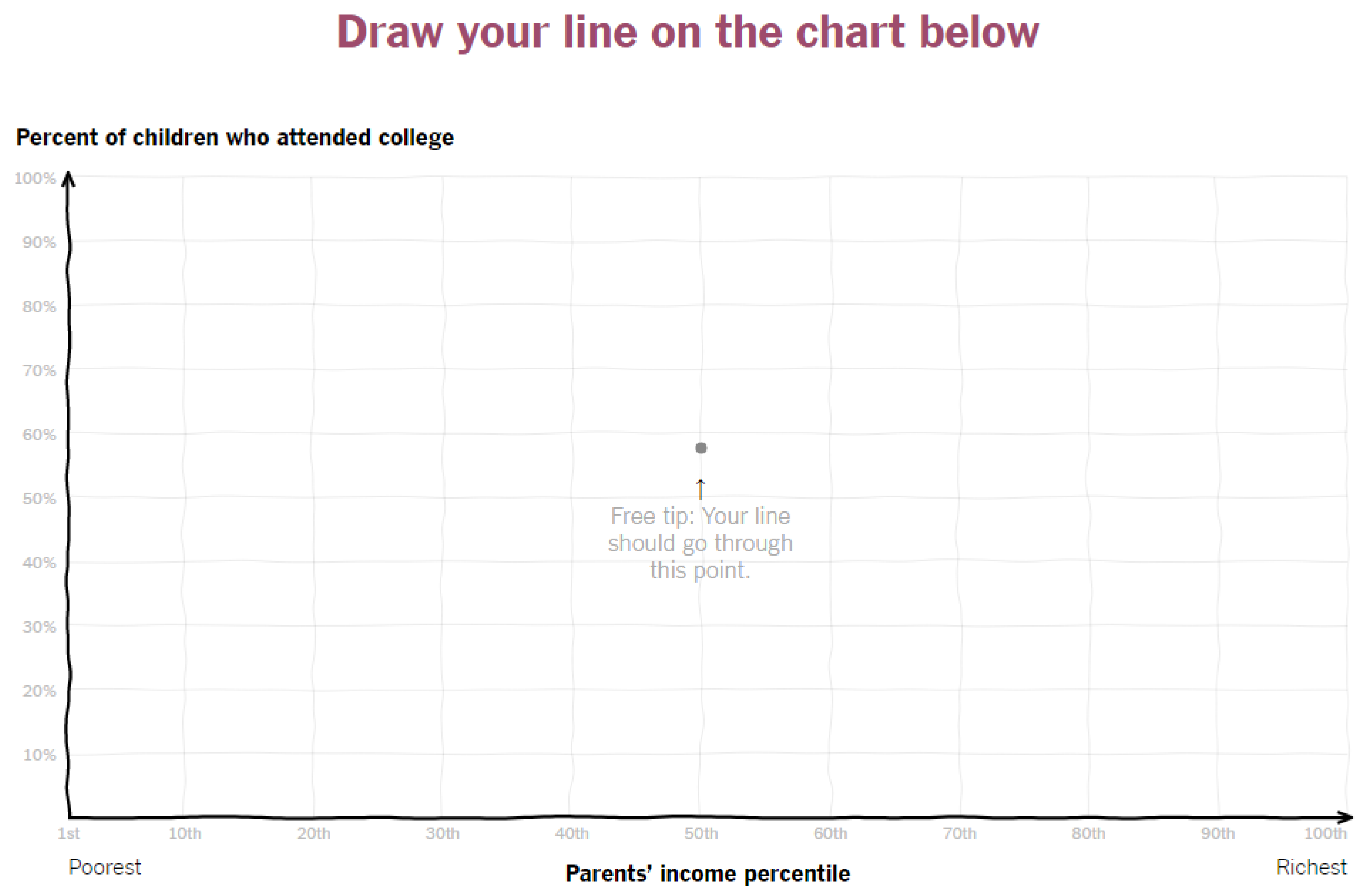
SPLOMs great for correlation

Parallel coordinates: trade effectiveness for scale

Other approaches: dimensionality reduction, then vis

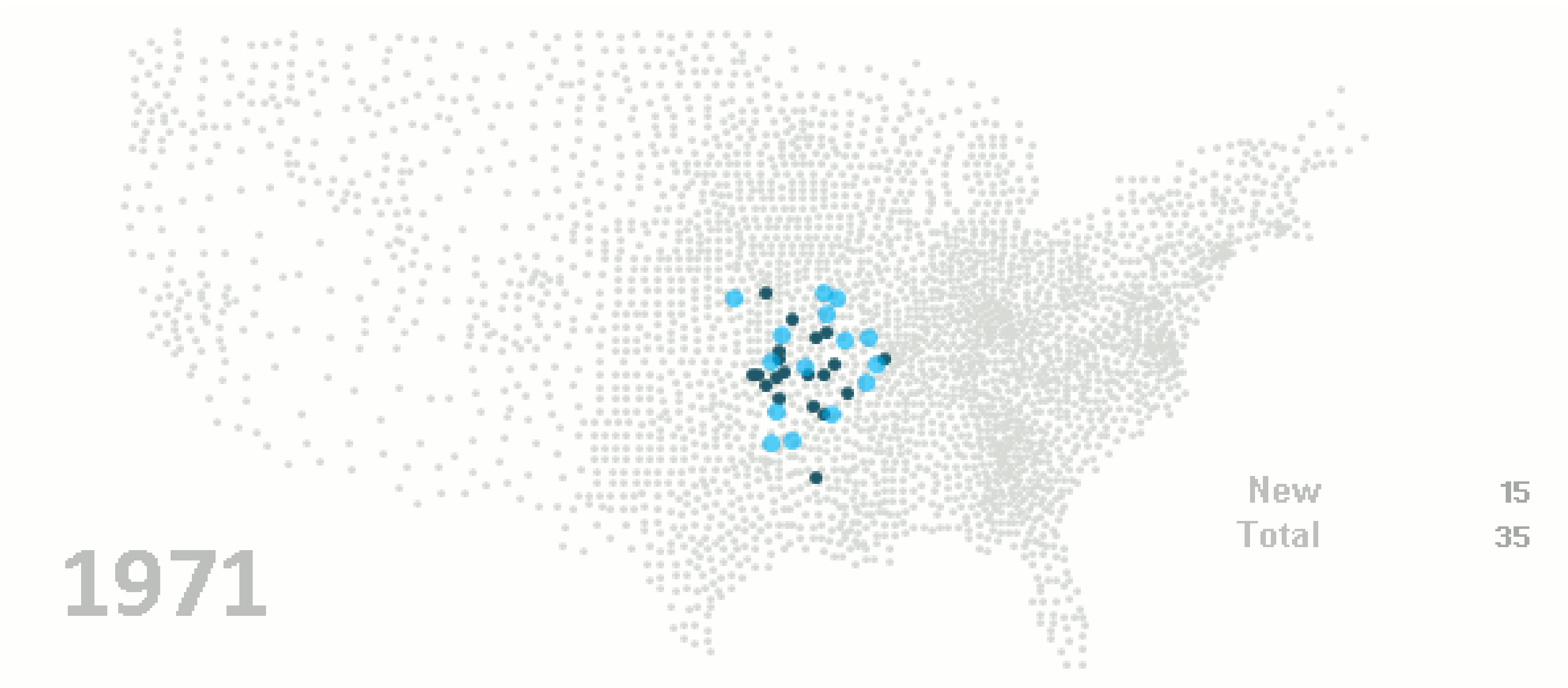
Examples / exercises

Prediction and memory



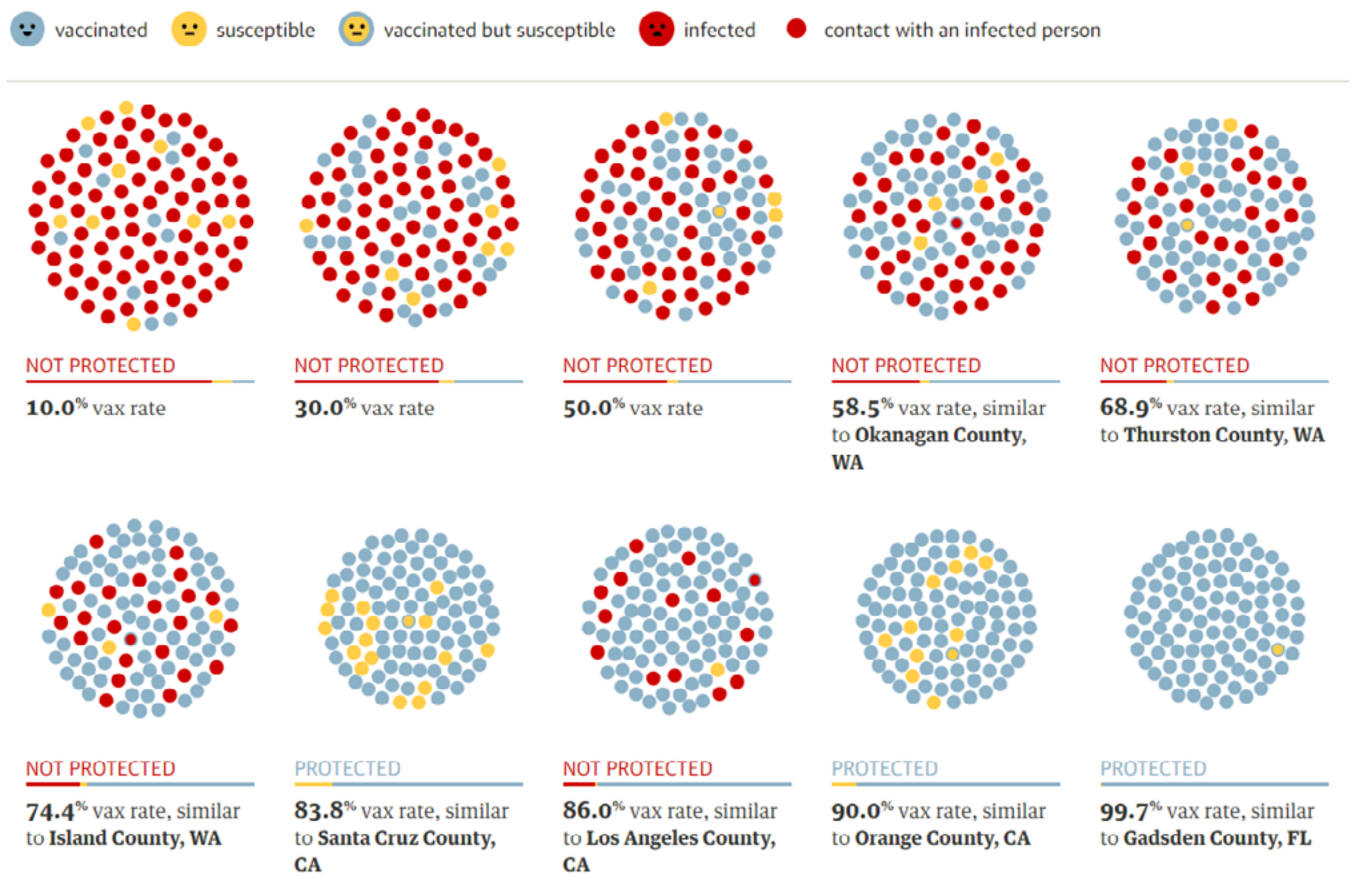
[https://nyti.ms/2jX8zue]

Small multiples versus animation



[https://excelcharts.com/animation-small-multiples-growth-walmart-excel-edition/]

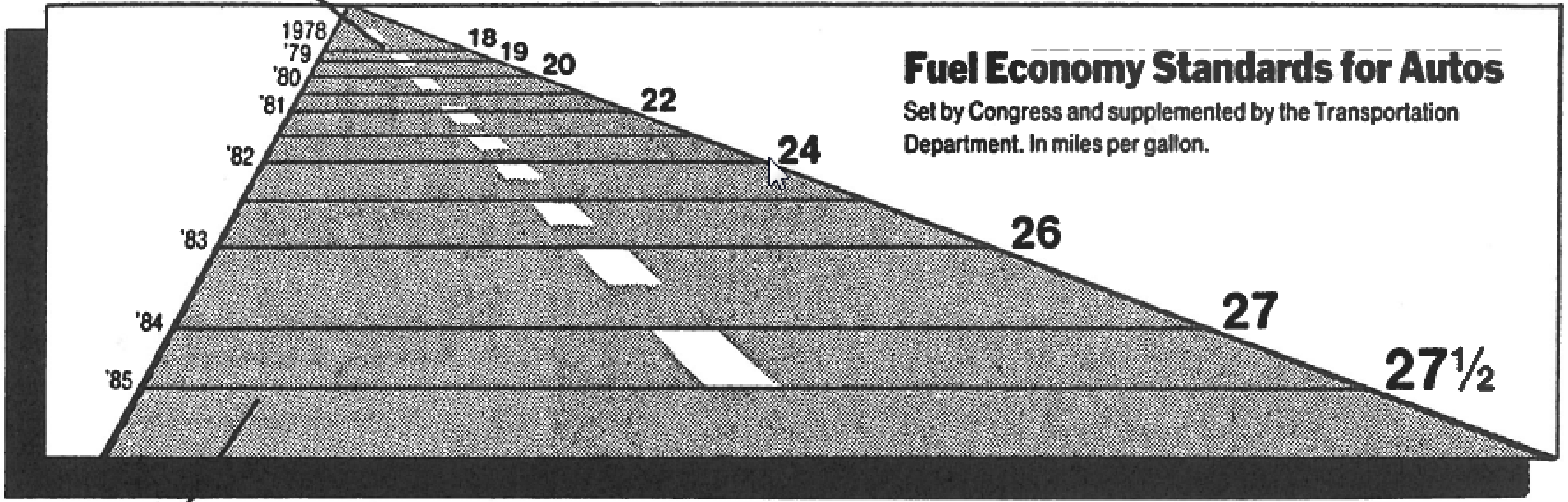
Measles vaccination



https://tinyurl.com/mjd5sv9

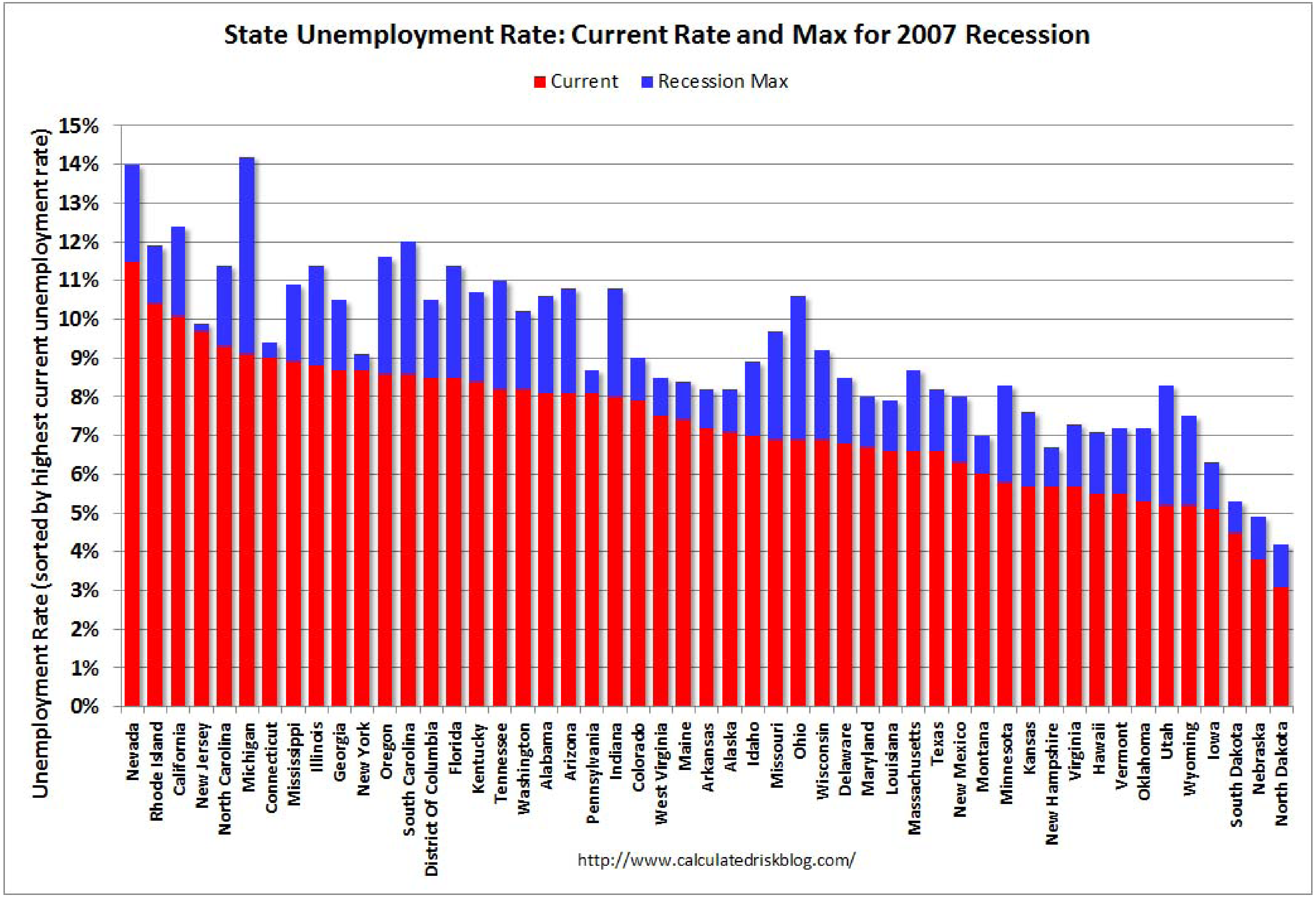
What’s wrong here?

This line, representing 18 miles per gallon in 1978, is 0.6 inches long.



This line, representing 27.5 miles per gallon in 1985, is 5.3 inches long.

New York Times, August 9, 1978, p. D-2.



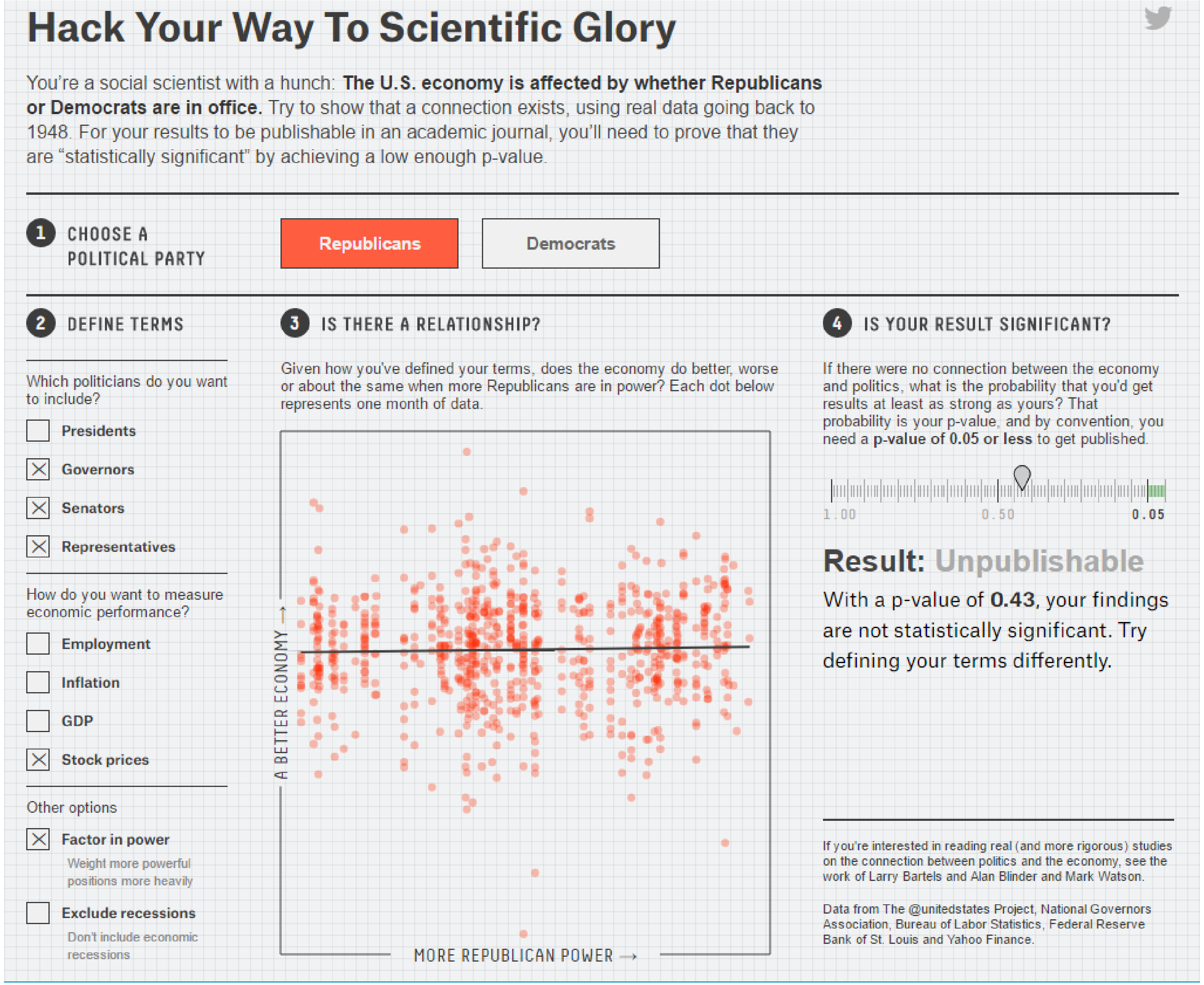
Group activity

What are the variables / types?

Channels / encodings?

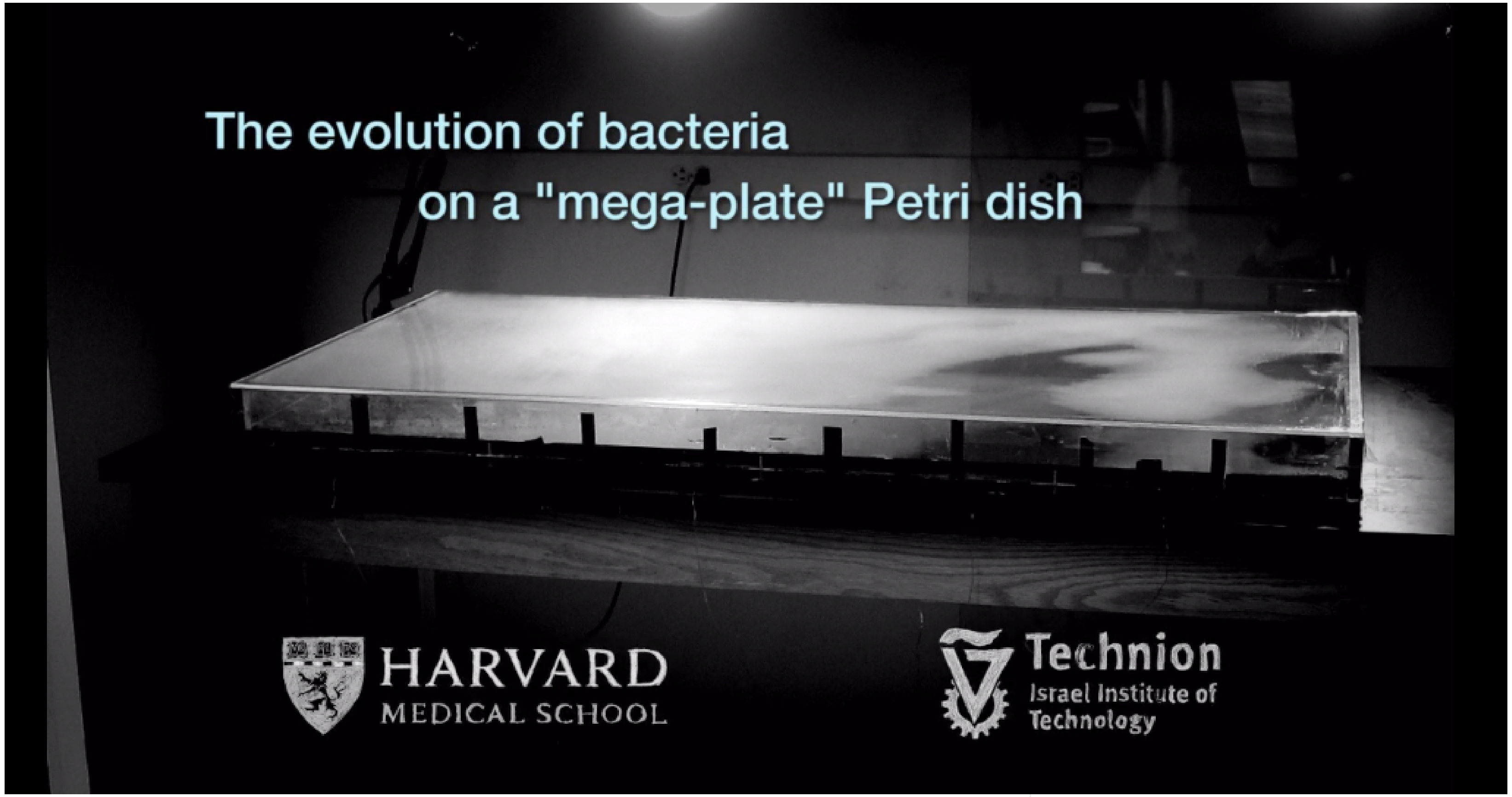
Marks?

Is this effective?



[https://fivethirtyeight.com/features/science-isnt-broken/]

Evolution of bacteria

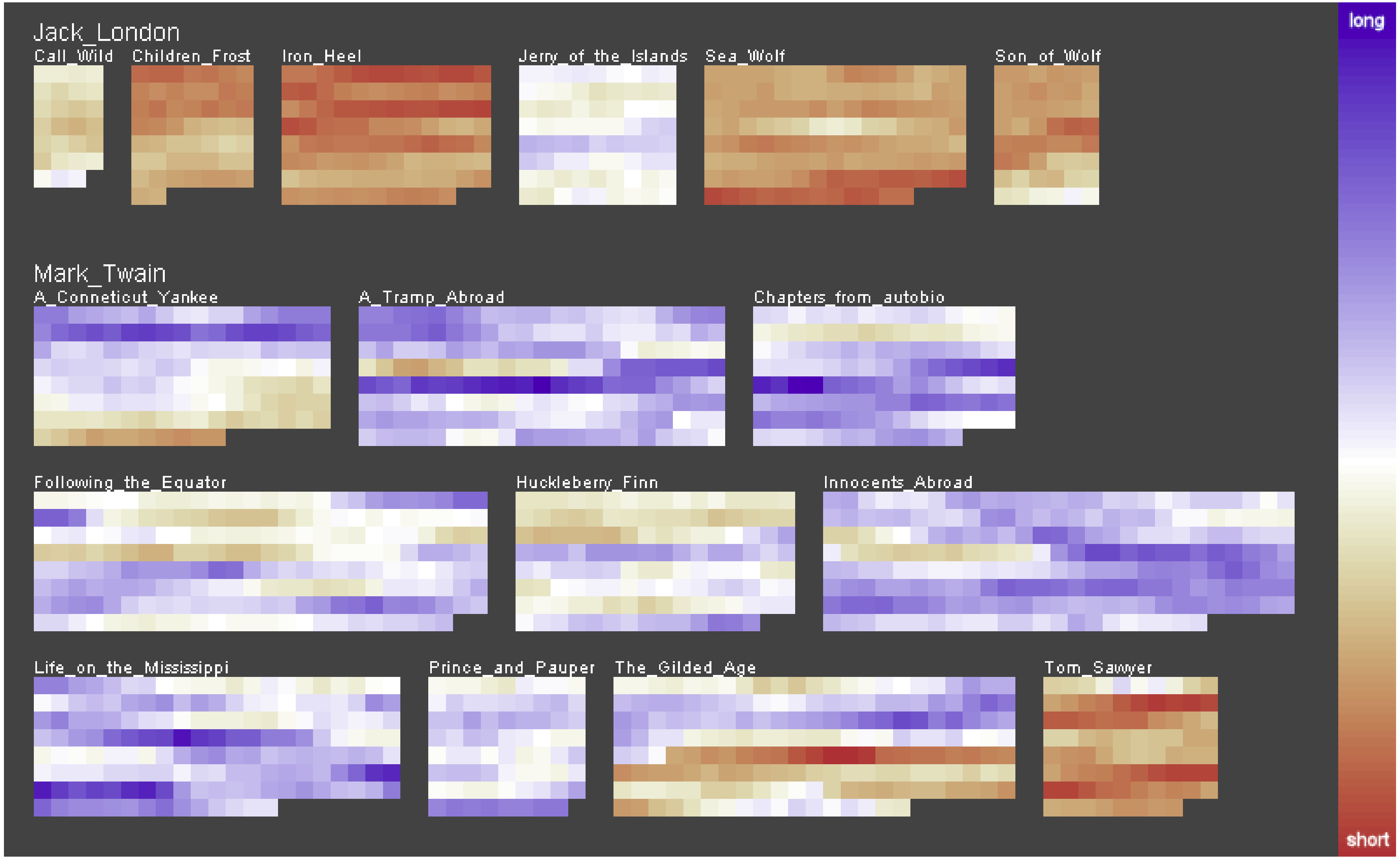


https://vimeo.com/180908160

Hyberbolic trees

[https://youtu.be/fhbQy_NCwWI]

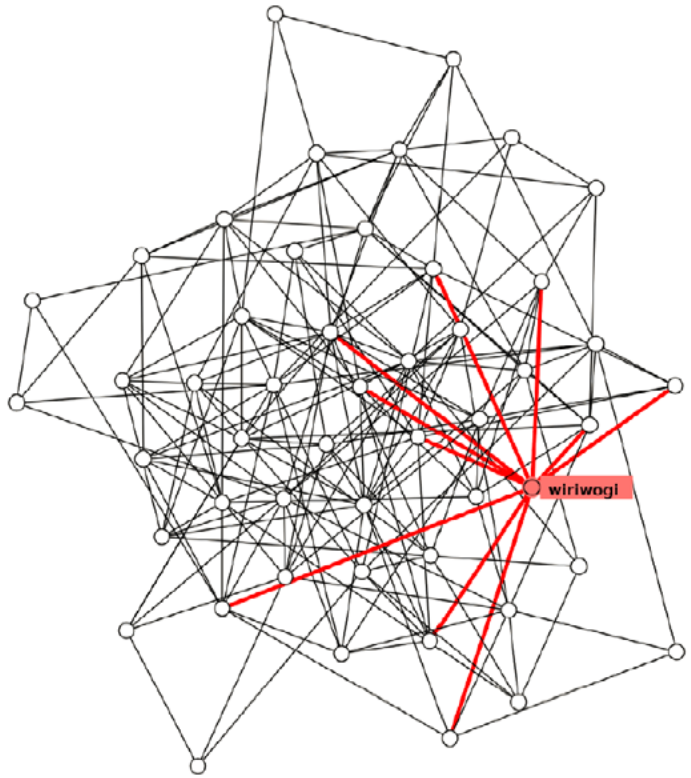
Document visualization: sentence length



[Keim & Oelke '07]

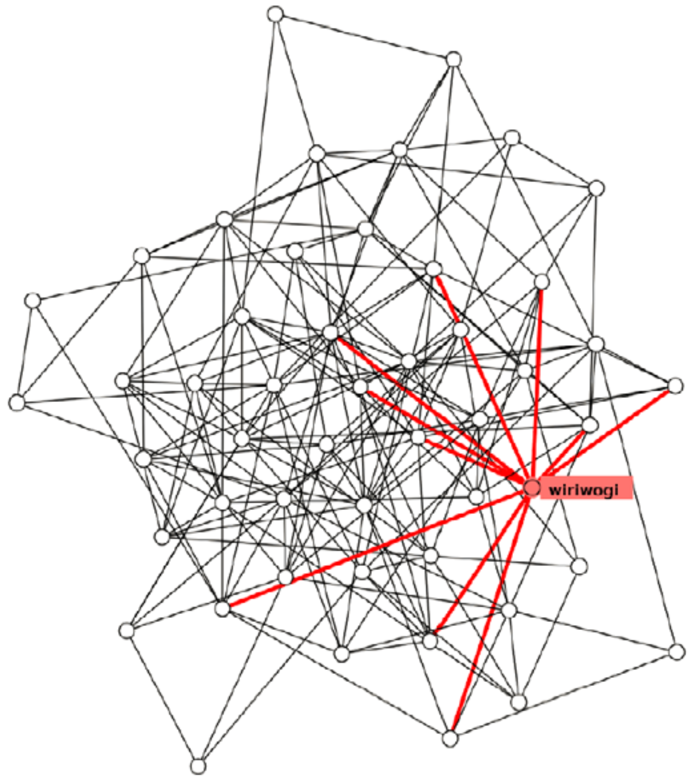
Node linearization

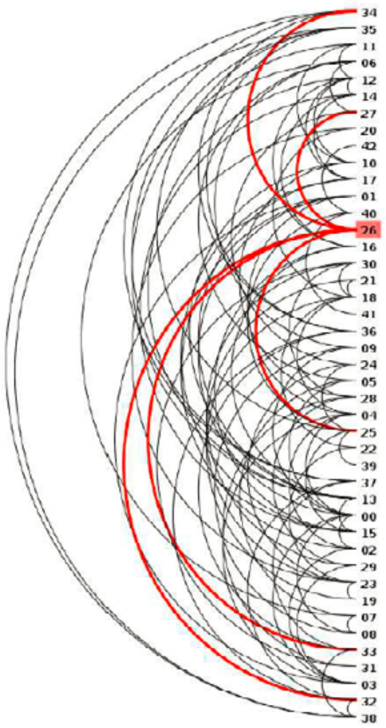
[McGuffin, Simple Algorithms for Network Visualization: A Tutorial, 2012]



Node linearization

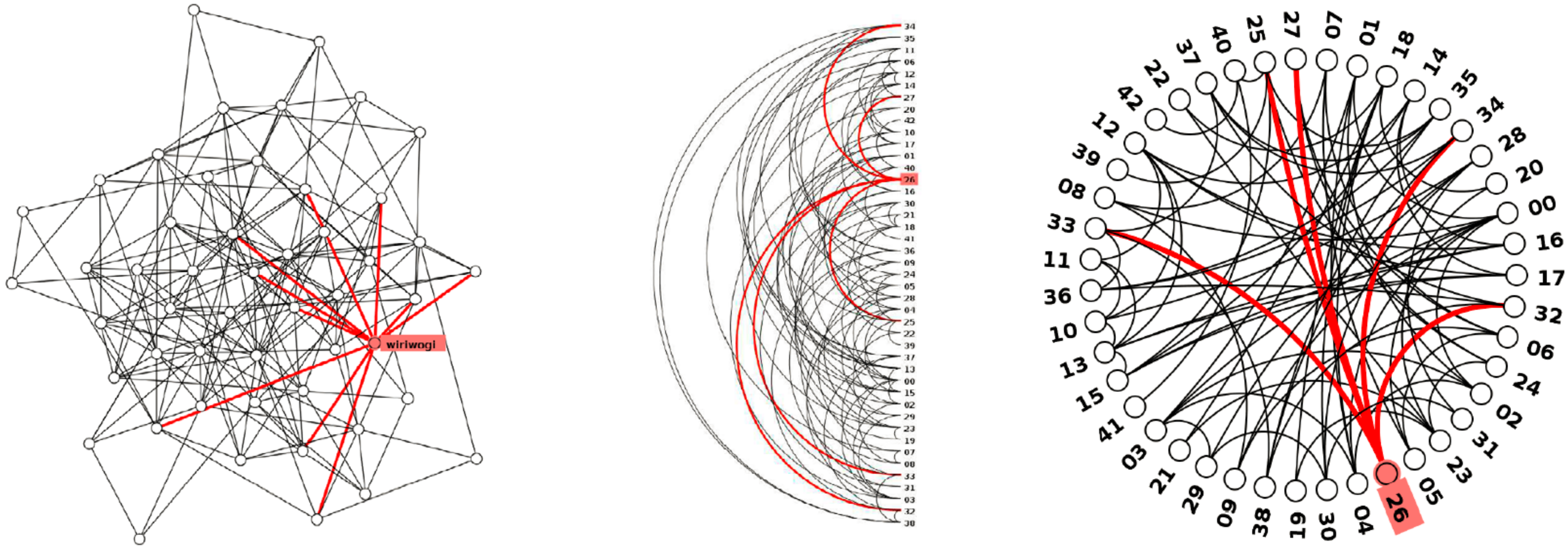
[McGuffin, Simple Algorithms for Network Visualization: A Tutorial, 2012]





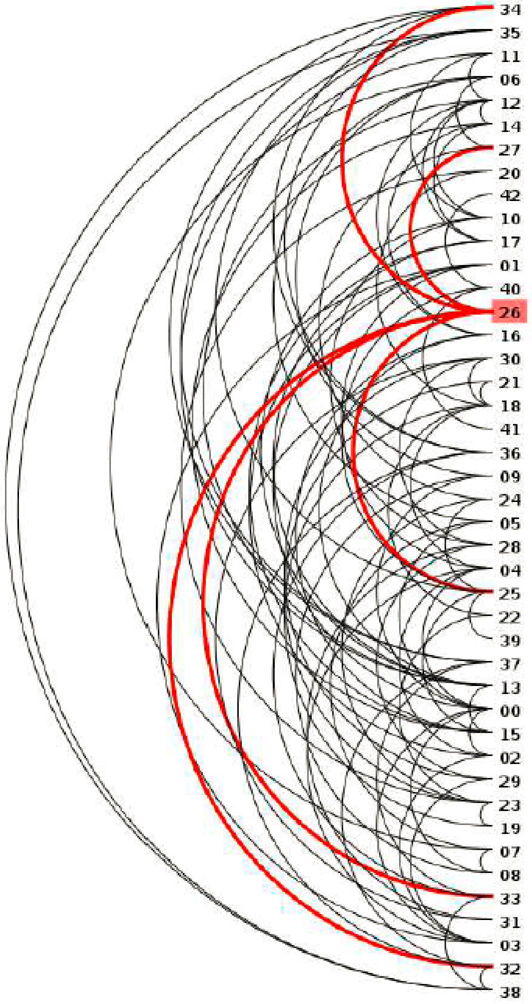
Node linearization

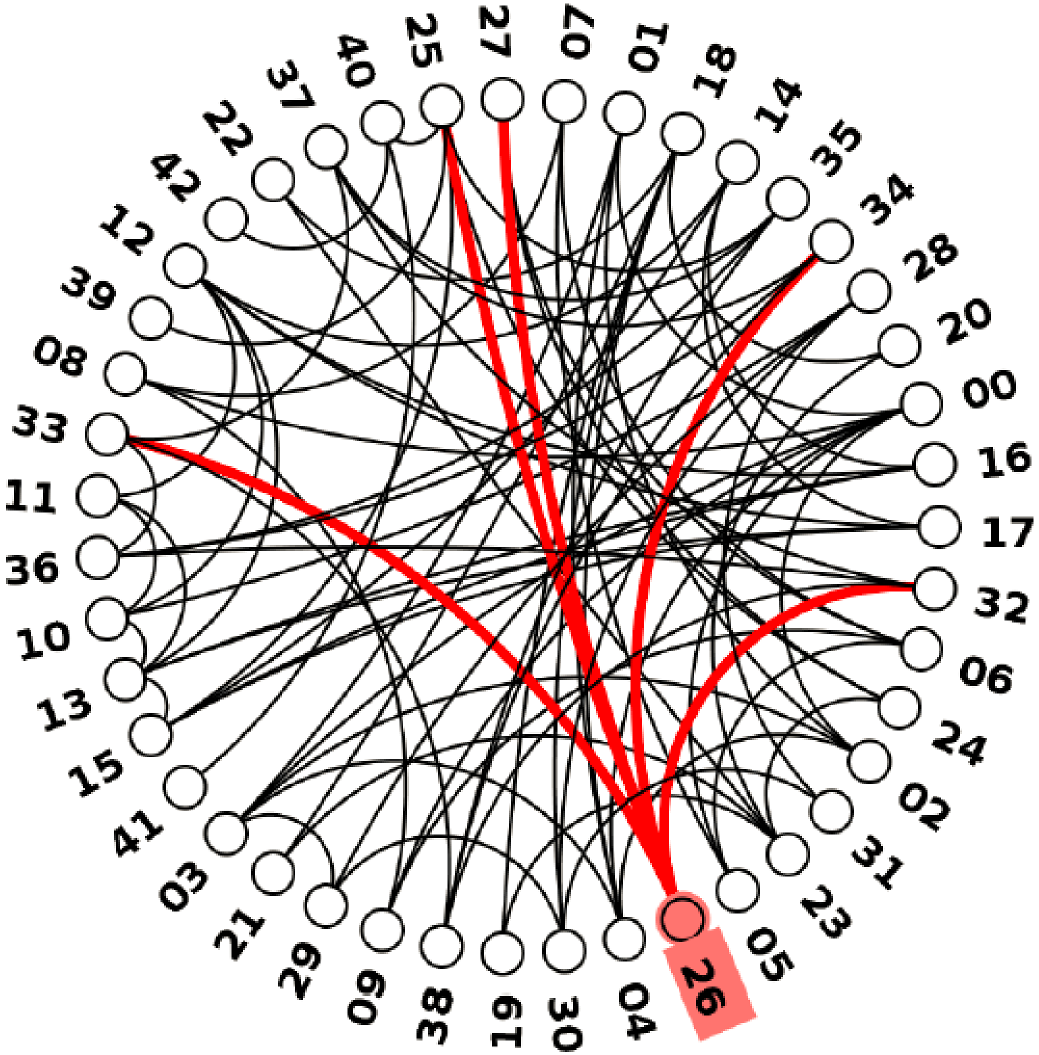
[McGuffin, Simple Algorithms for Network Visualization: A Tutorial, 2012]



Node linearization

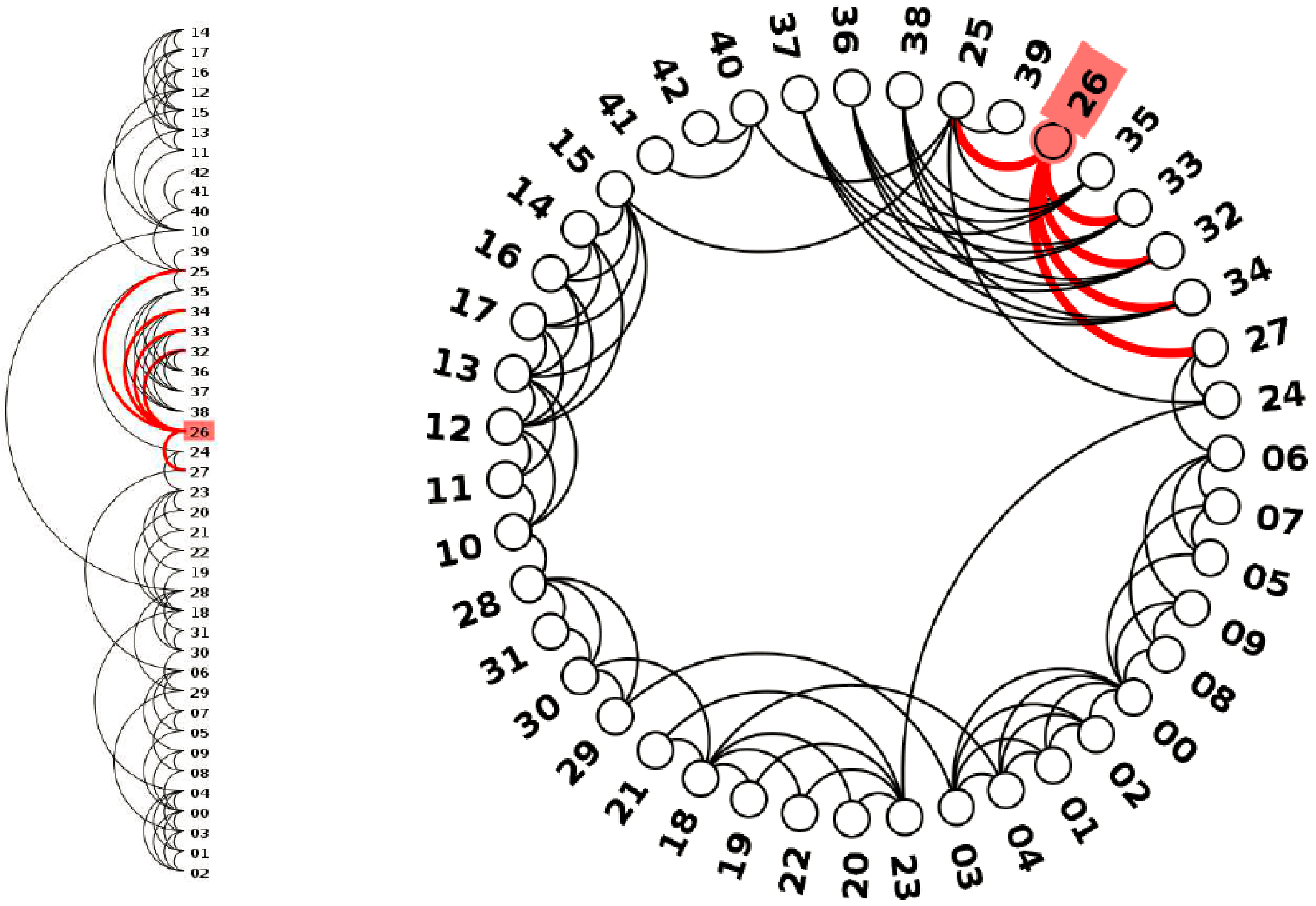
[McGuffin]





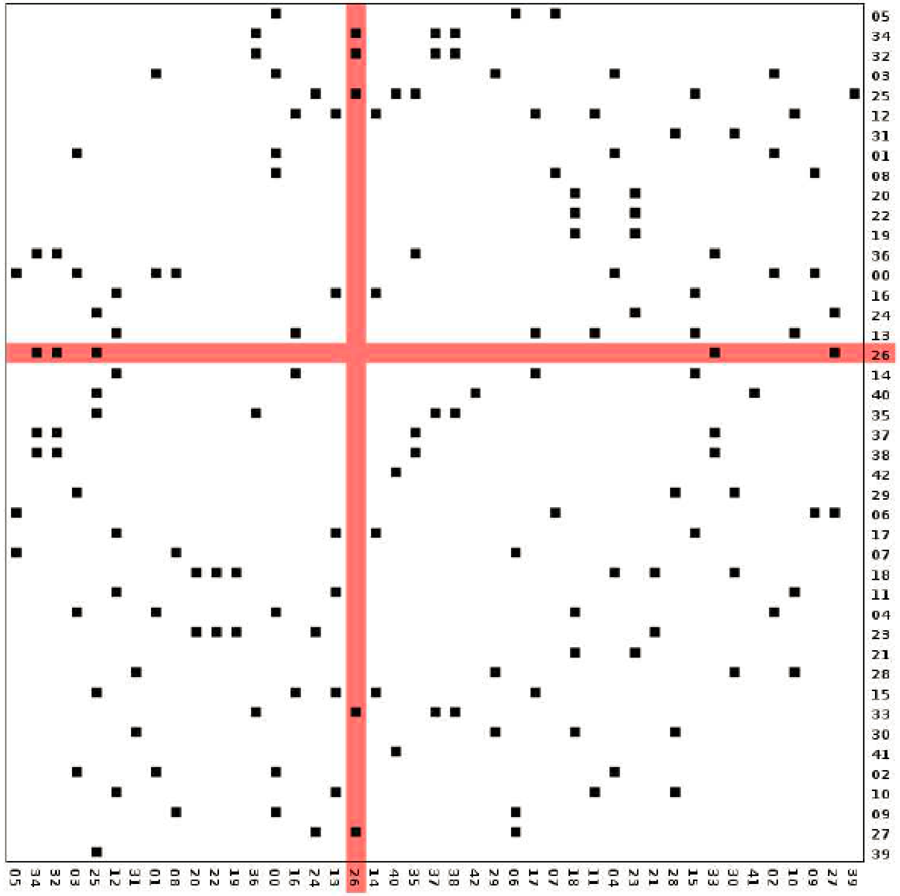
Node linearization: Barycentric order

[McGuffin]



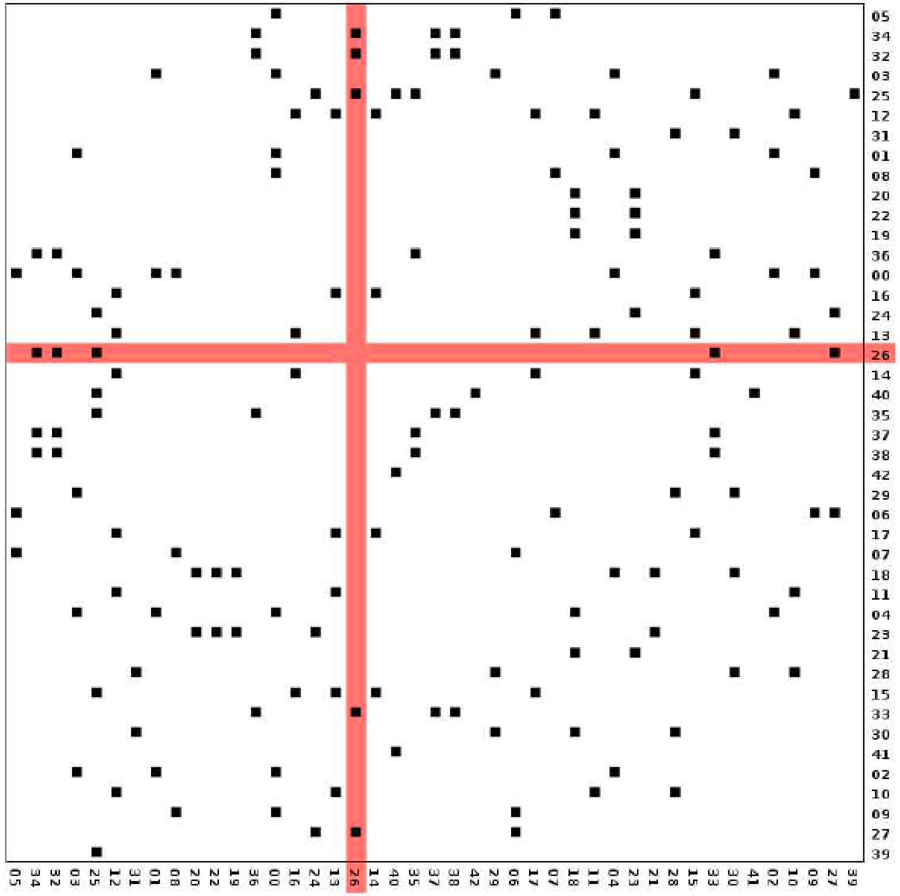
Node linearization: Barycentric order

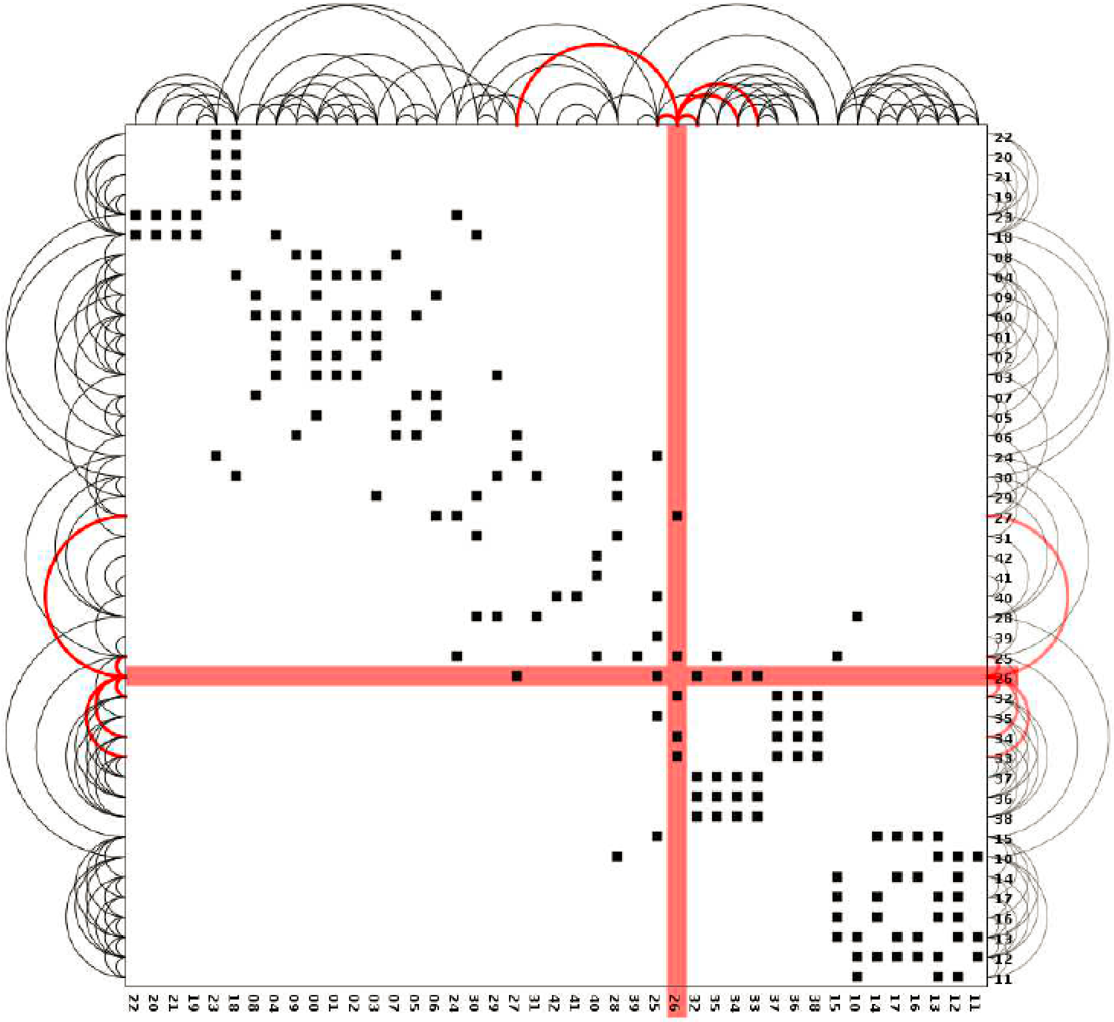
[McGuffin]



Node linearization: Barycentric order

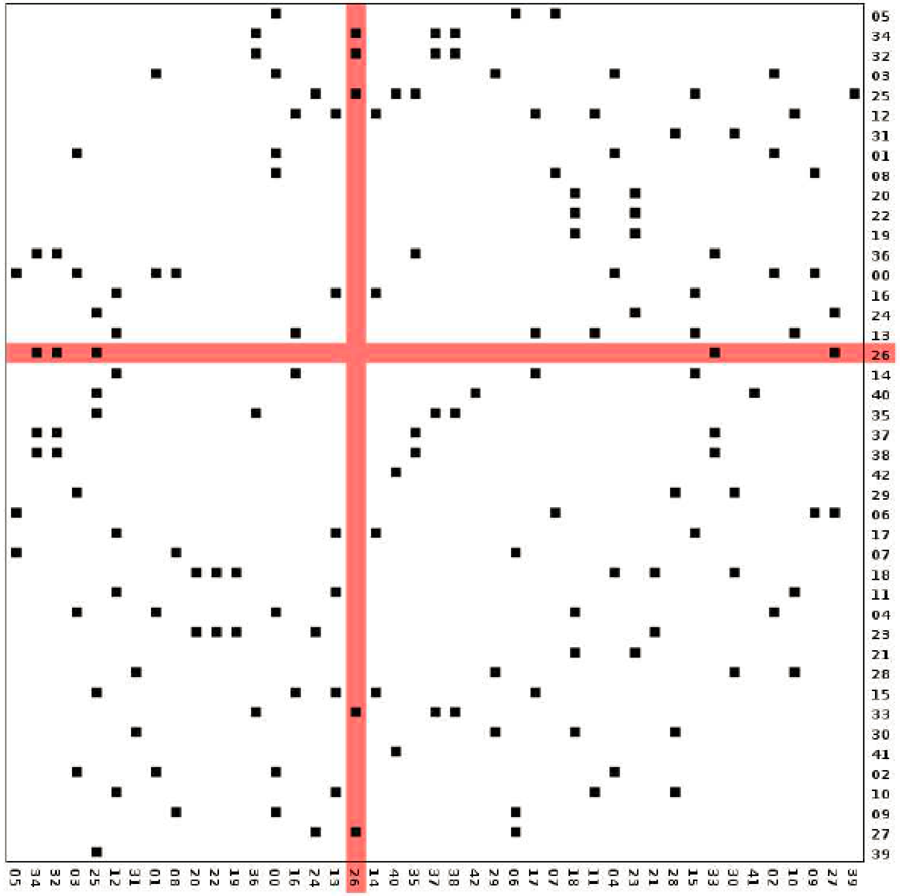
[McGuffin]

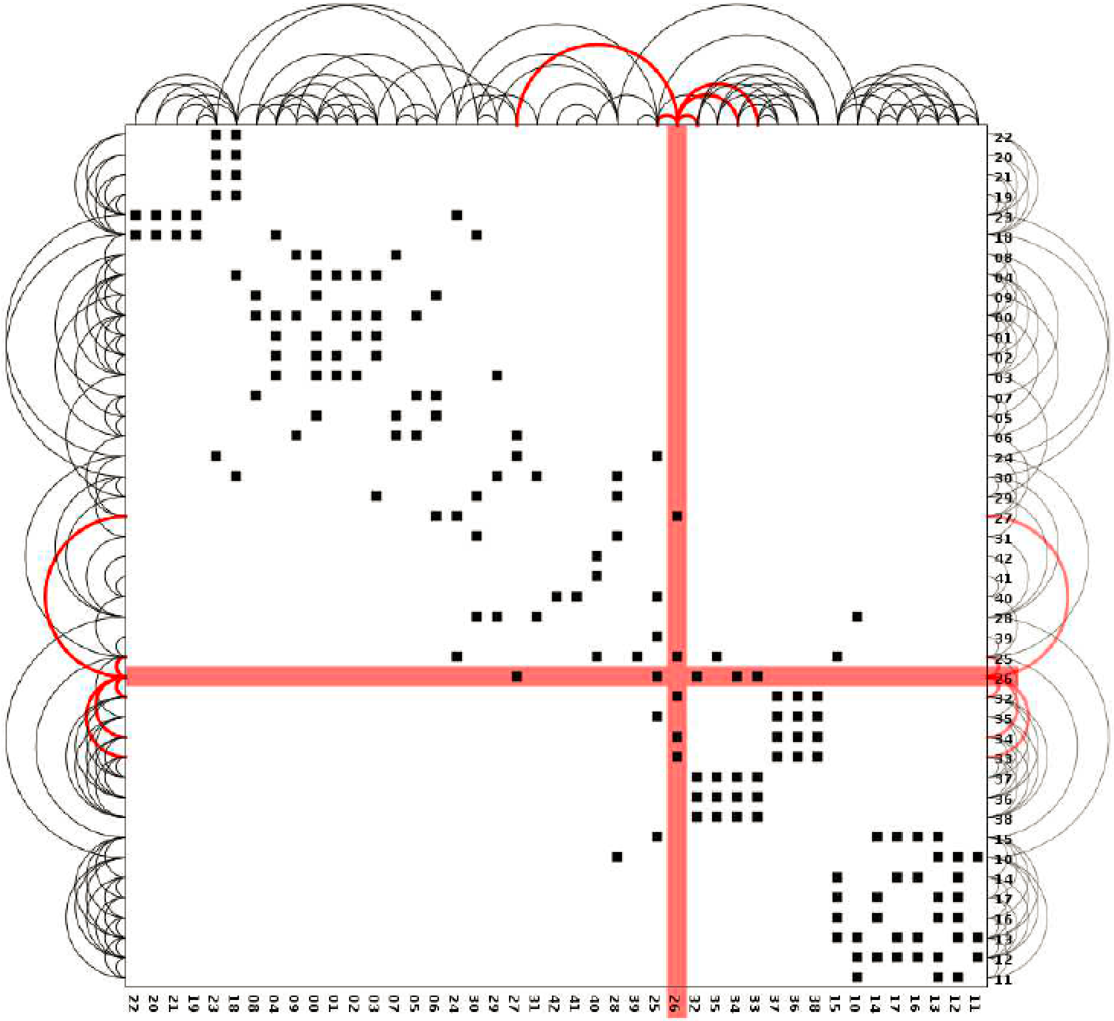




(also node-link + matrix example: MatLink)

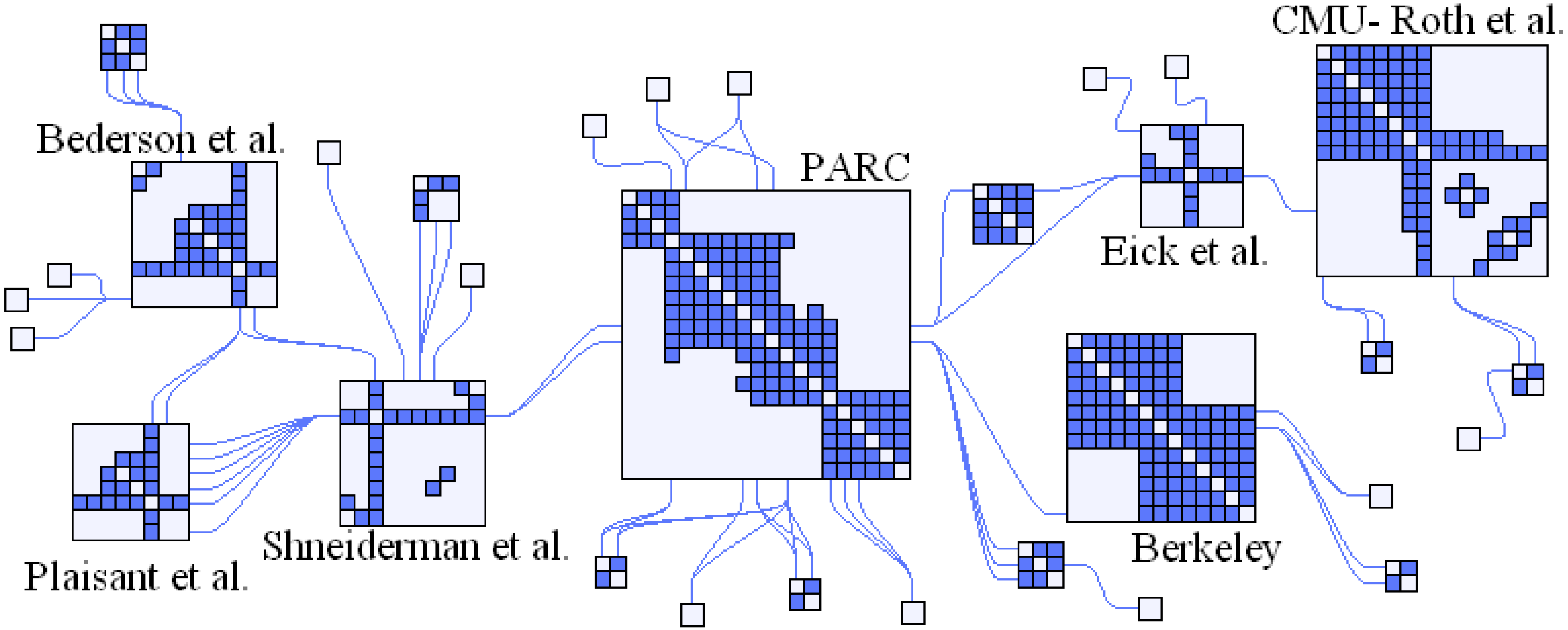
[McGuffin]





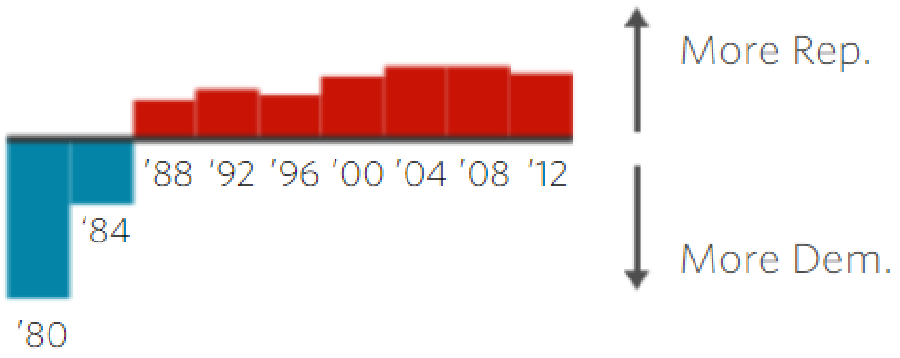
NodeTrix: the other way around

Riche et al, http://www.aviz.fr/Research/Nodetrix, https://www.youtube.com/watch?v=7G3MxyOcHKQ



Small multiples

PVI Score: State presidential vote relative to nationwide vote



[http://graphics.wsj.com/elections/2016/field-guide-red-blue-america/]