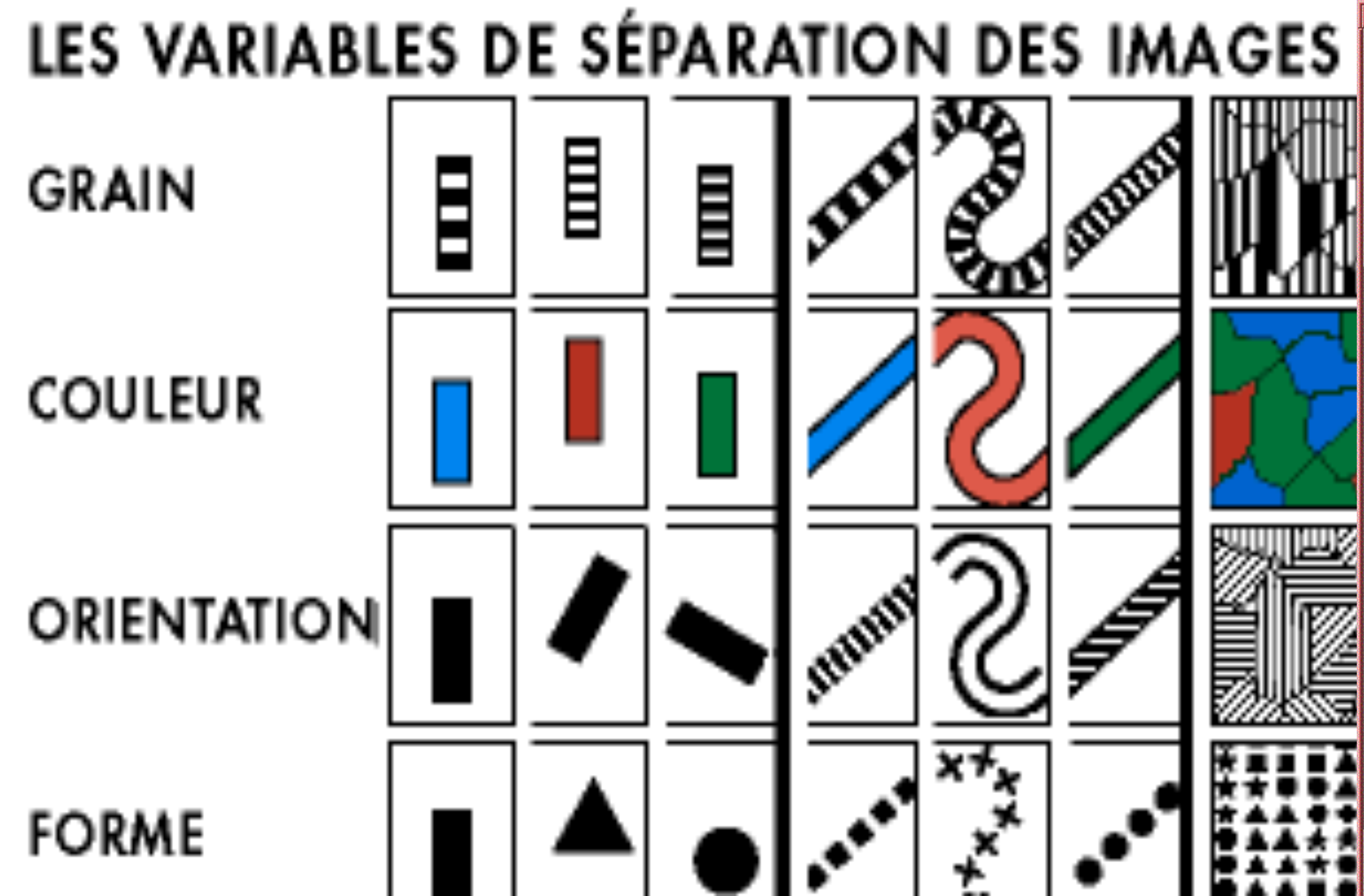
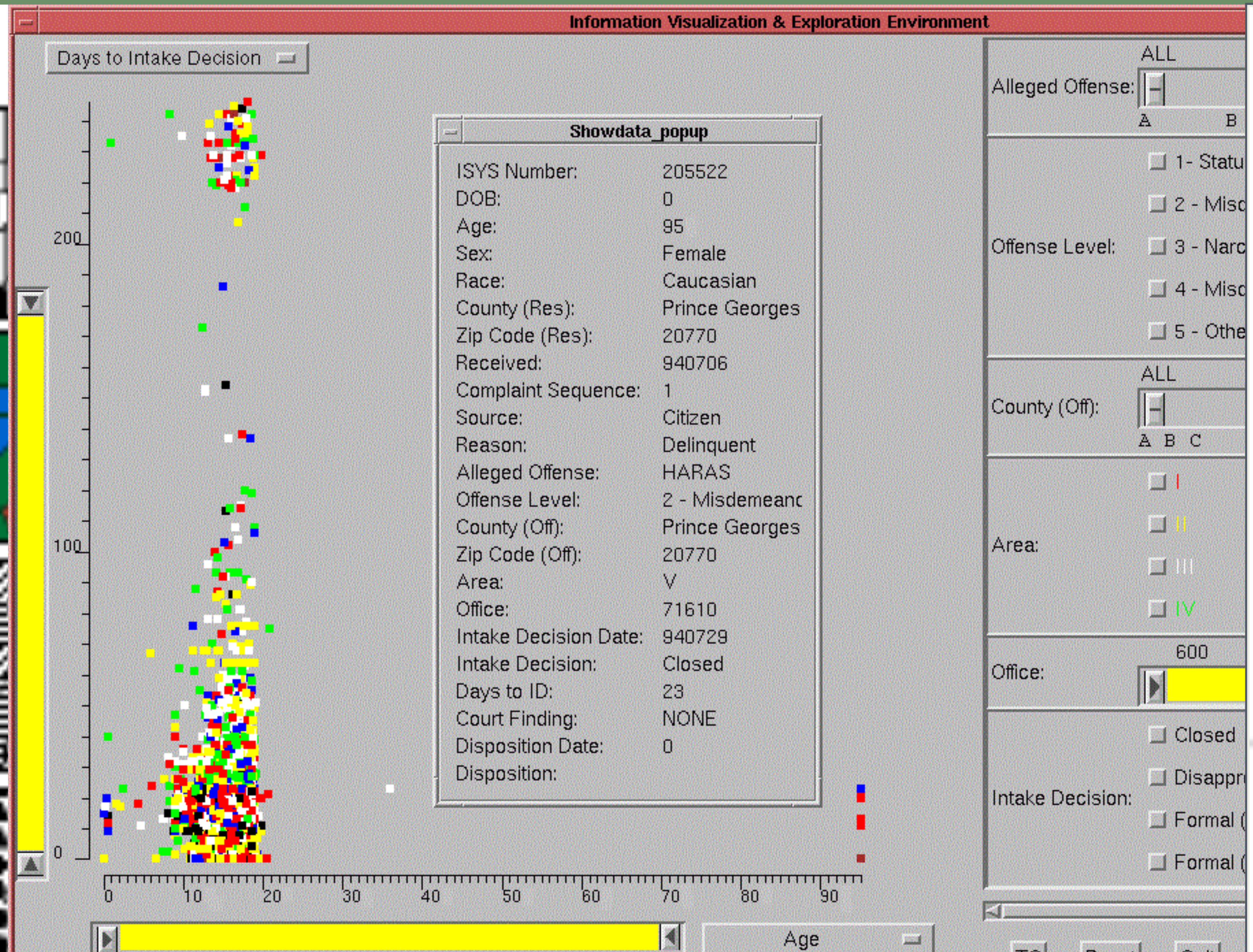
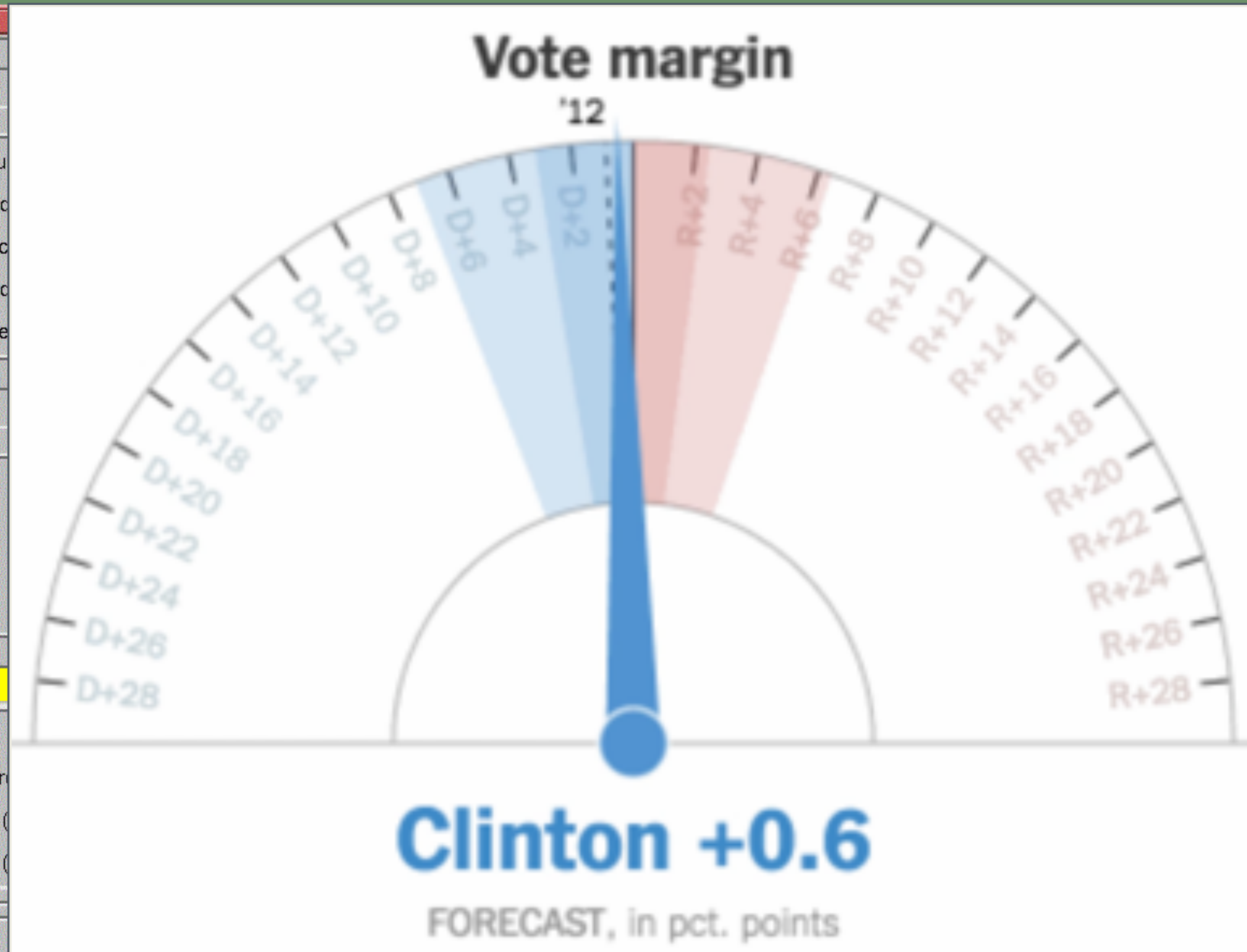
Visualization, EVA, & Uncertainty

A Crash Course

Arvind Satyanarayan



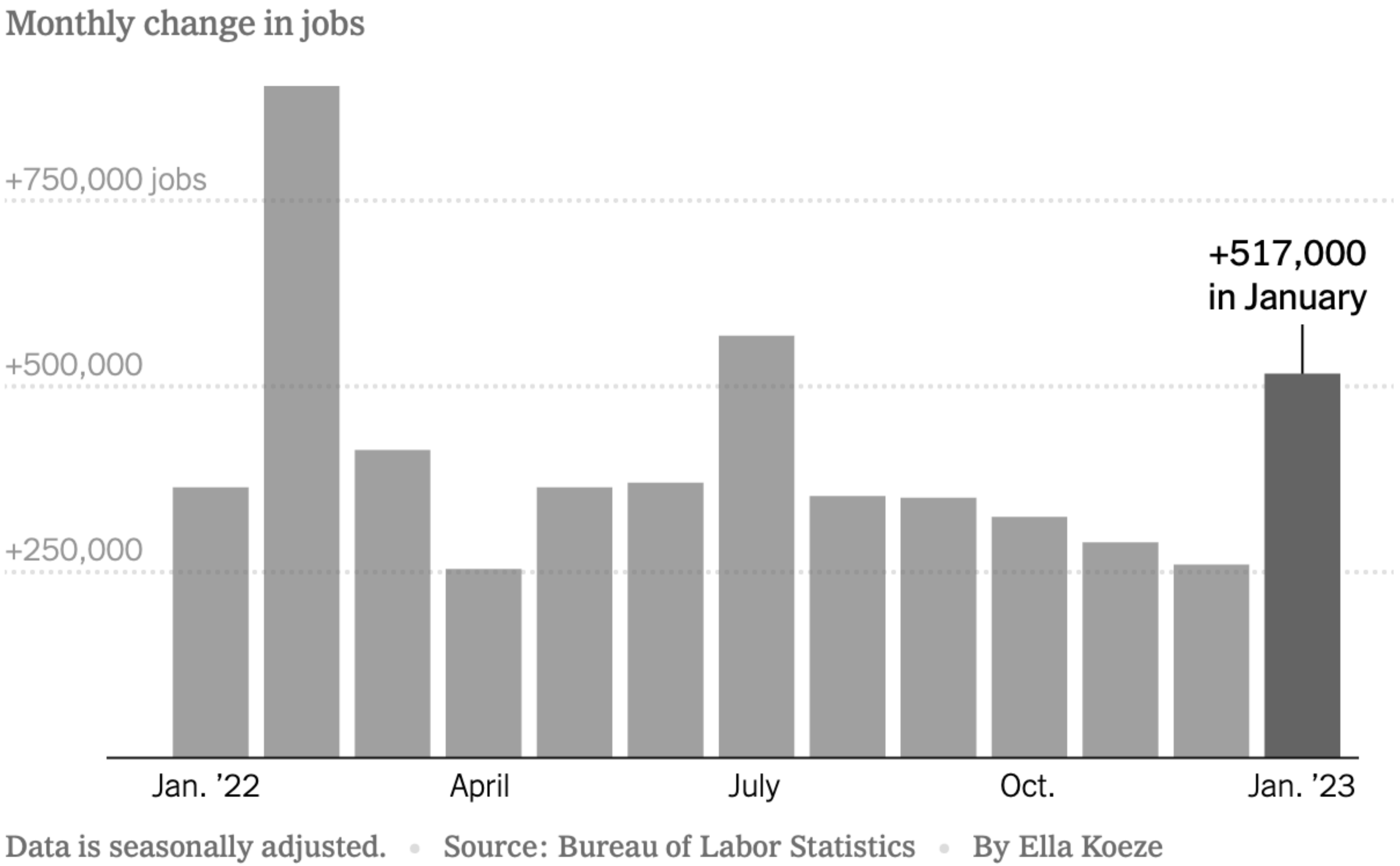


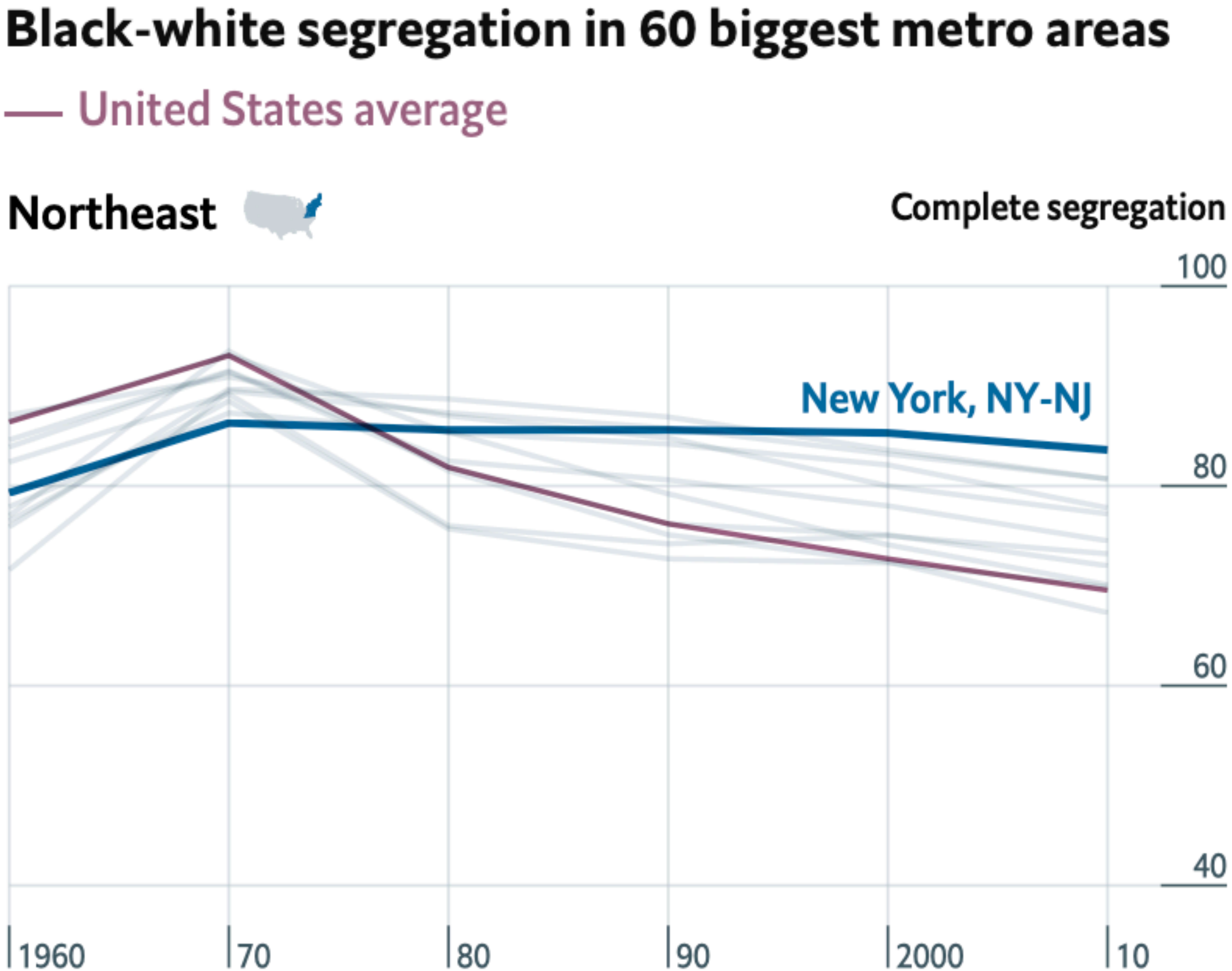


PART ONE

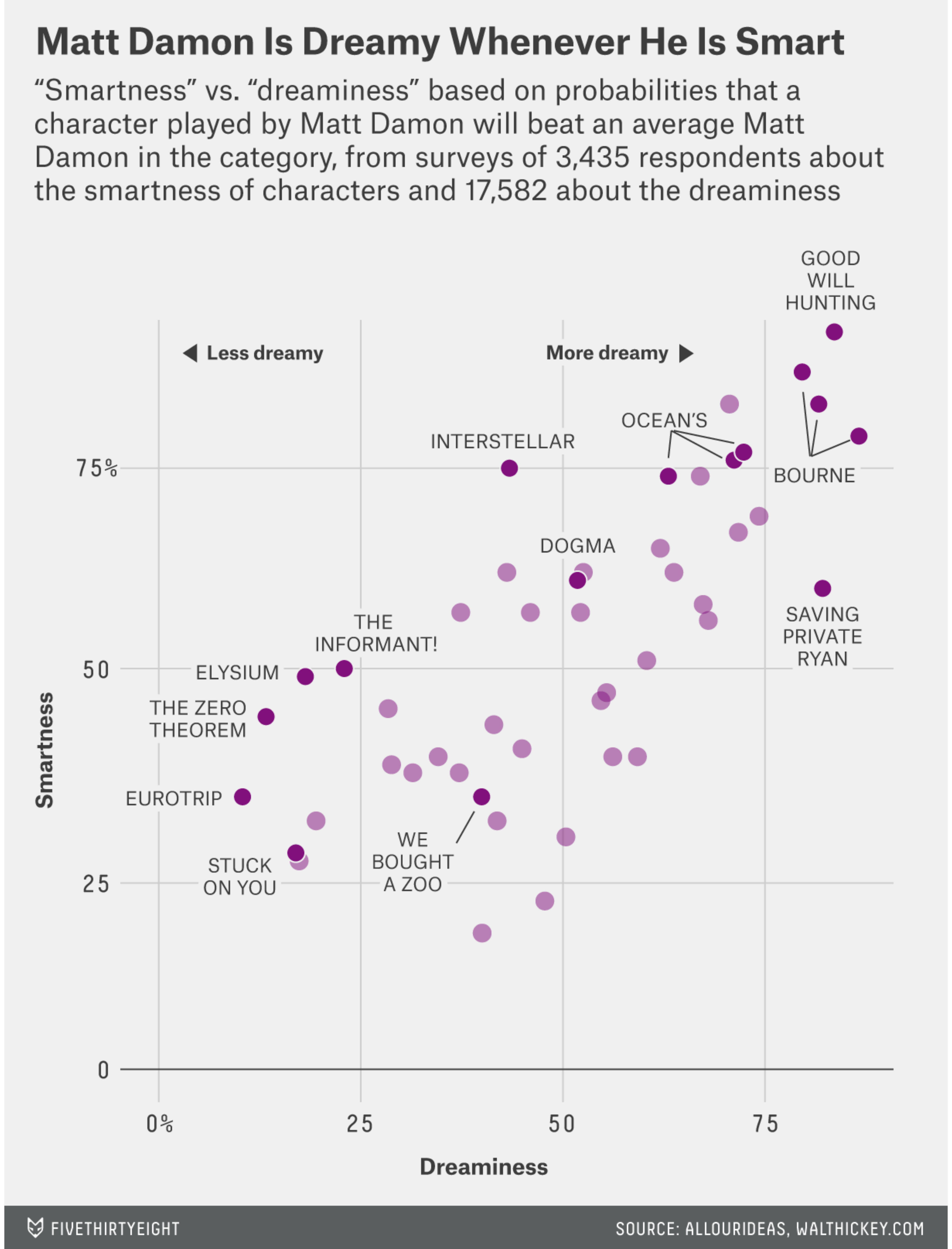
Data & Image Models

Name That Chart


Monthly change in jobs
+750,000 jobs
+500,000
+250,000
+517,000
in January
Jan. ’22
April
July
Oct.
Jan. ’23
Data is seasonally adjusted. • Source: Bureau of Labor Statistics • By Ella Koeze



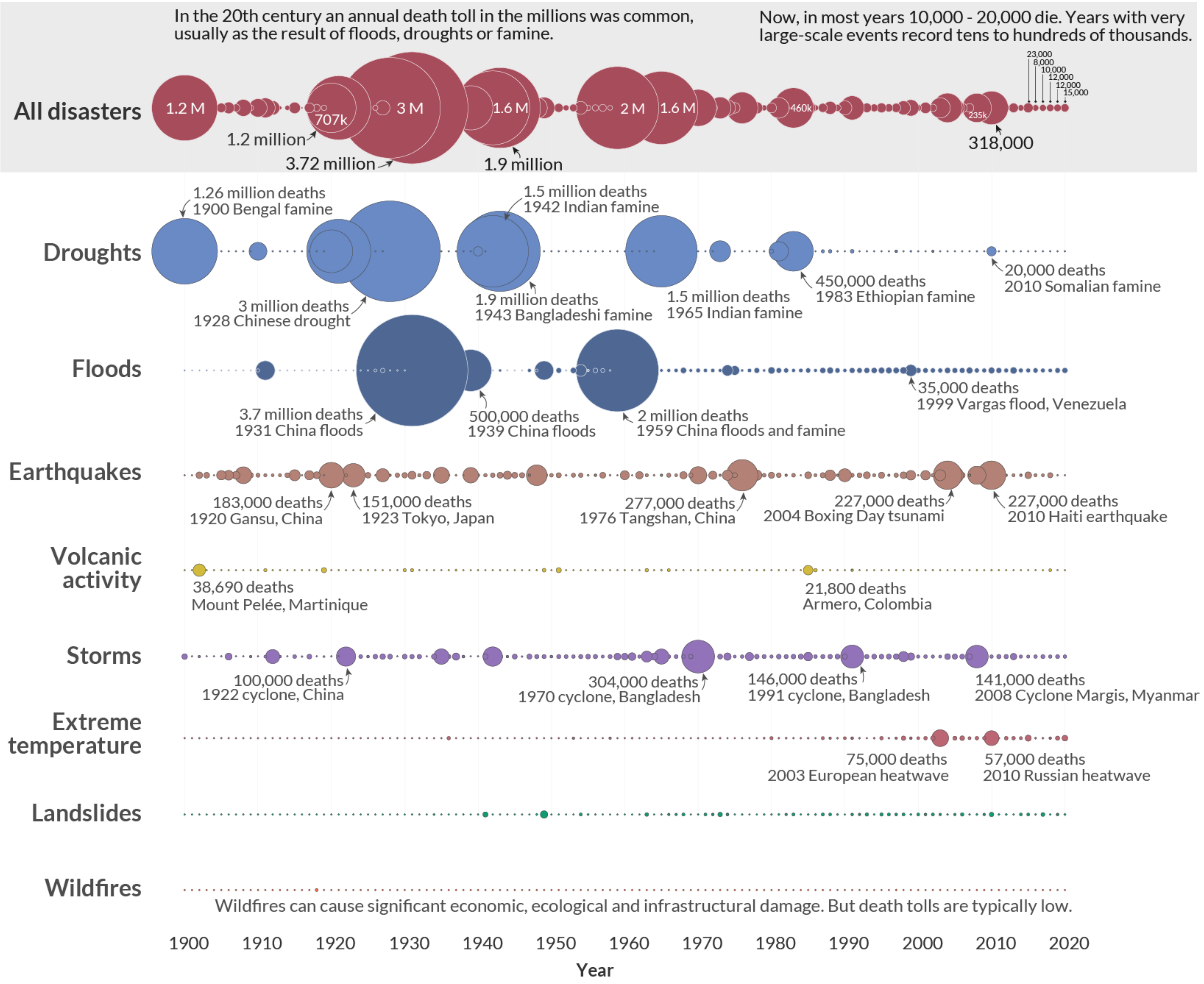
[The Economist, April 2018]



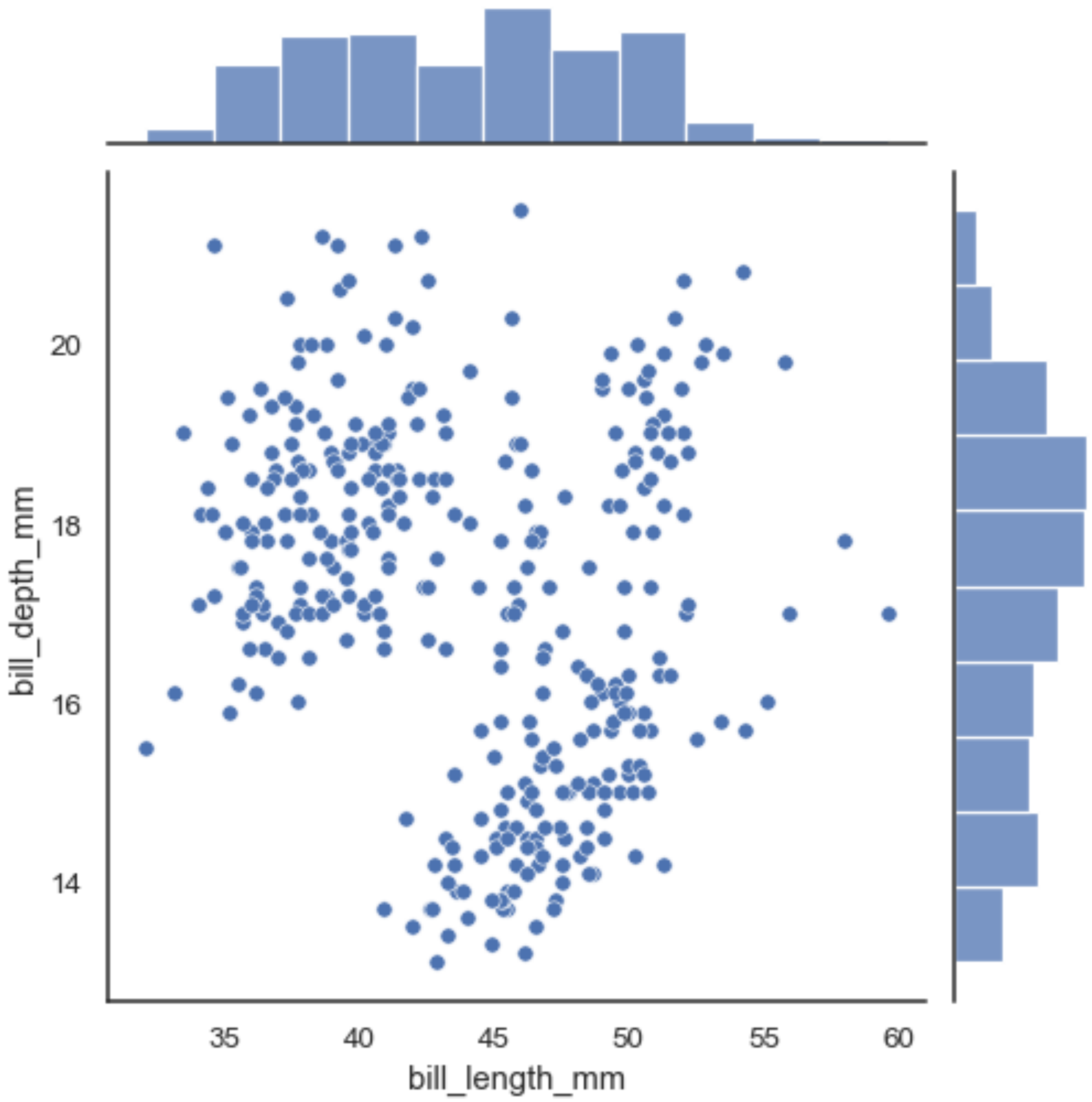
Matt Damon Is Dreamy Whenever He Is Smart
"Smartness" vs. "dreaminess" based on probabilities that a character played by Matt Damon will beat an average Matt Damon in the category, from surveys of 3,435 respondents about the smartness of characters and 17,582 about the dreaminess
GOOD WILL HUNTING
Less dreamy
More dreamy
OCEAN'S
INTERSTELLAR
BOURNE
75%
DOGMA
THE INFORMANT!
SAVING PRIVATE RYAN
50
ELYSIUM
THE ZERO THEOREM
Smartness
EUROTRIP
WE BOUGHT A ZOO
STUCK ON YOU
25
0
0%
25
50
75
Dreaminess
FIVETHIRTYEIGHT
SOURCE: ALLOURIDEAS, WALTHICKEY.COM

Global deaths from disasters over more than a century

The size of the bubble represents the estimated annual death toll. The largest years are labeled with this total figure, alongside large-scale events that contributed to the majority – although usually not all – of these deaths.



Data source: EM-DAT, CRED / UCLouvain, Brussels, Belgium – www.emdat.be (D. Guha-Sapir).
OurWorldinData.org – Research and data to make progress against the world's largest problems.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16
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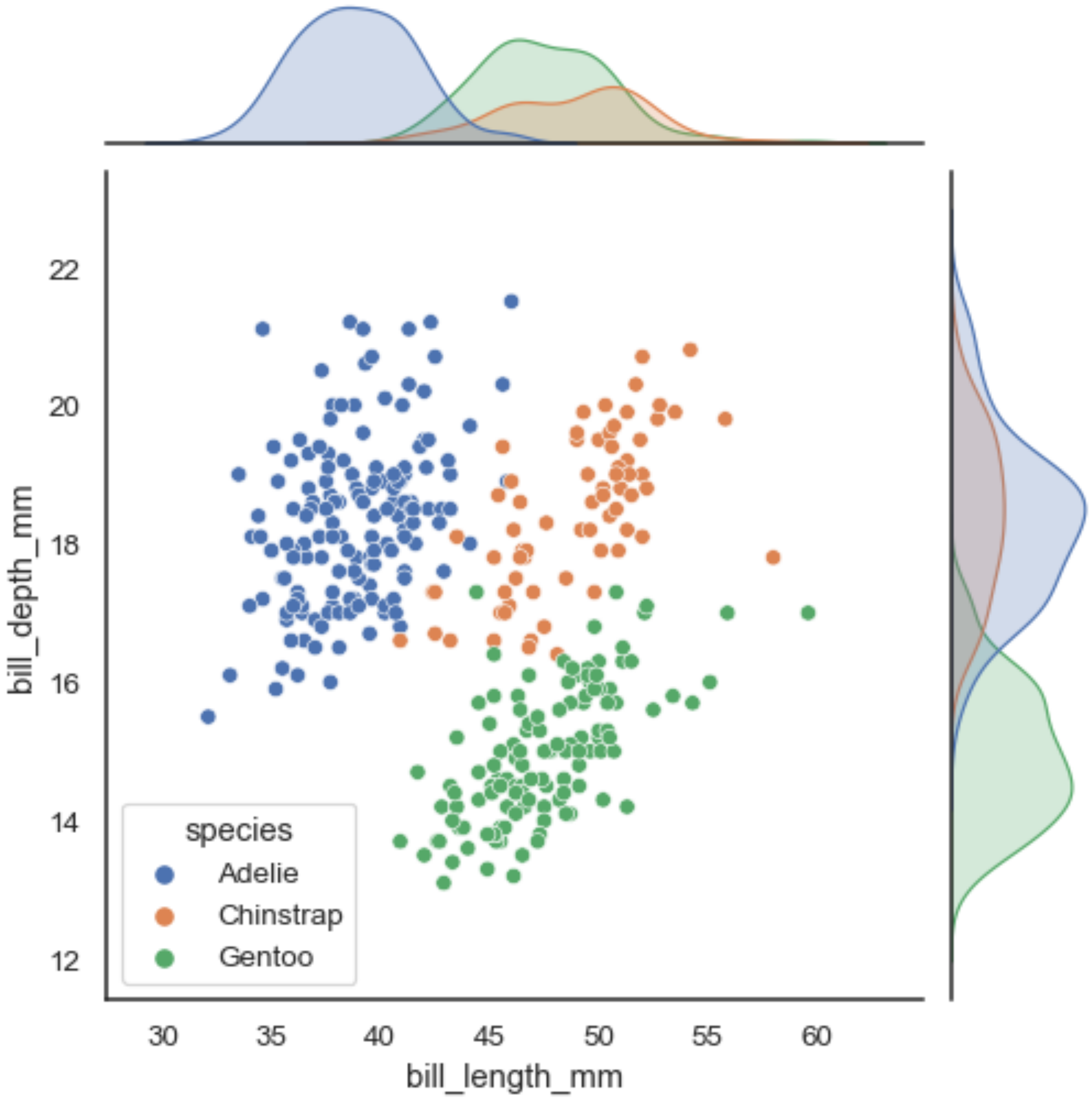
35
40
45
50
55
60
bill_length_mm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12
bill_depth_mm
species
Adelie
Chinstrap
Gentoo
30
35
40
45
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55
60
bill_length_mm

METRICS

HANNAH FAIRFIELD

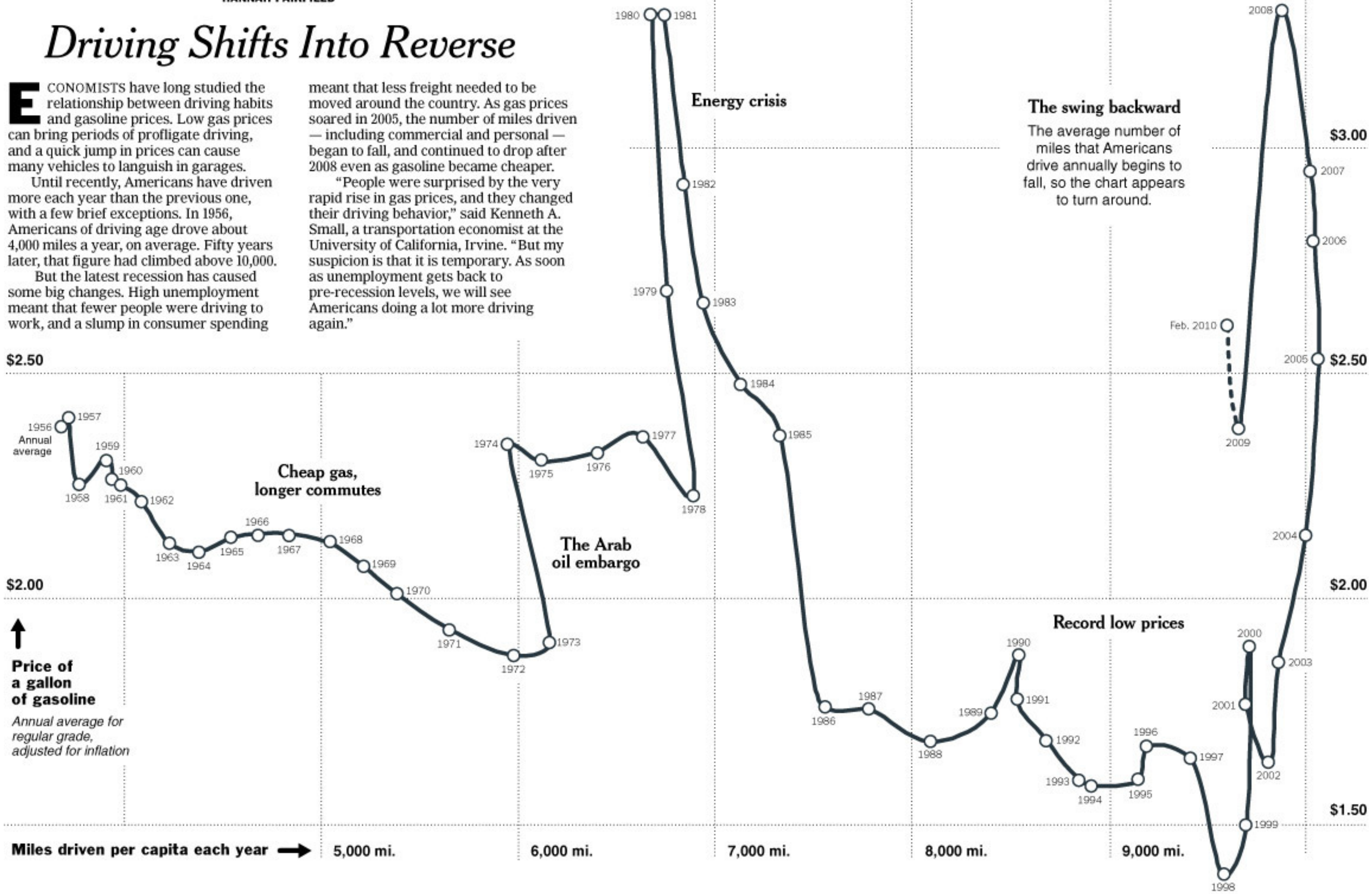
Driving Shifts Into Reverse

ECONOMISTS have long studied the relationship between driving habits and gasoline prices. Low gas prices can bring periods of profligate driving, and a quick jump in prices can cause many vehicles to languish in garages.

Until recently, Americans have driven more each year than the previous one, with a few brief exceptions. In 1956, Americans of driving age drove about 4,000 miles a year, on average. Fifty years later, that figure had climbed above 10,000.

But the latest recession has caused some big changes. High unemployment meant that fewer people were driving to work, and a slump in consumer spending meant that less freight needed to be moved around the country. As gas prices soared in 2005, the number of miles driven — including commercial and personal — began to fall, and continued to drop after 2008 even as gasoline became cheaper.

"People were surprised by the very rapid rise in gas prices, and they changed their driving behavior," said Kenneth A. Small, a transportation economist at the University of California, Irvine. "But my suspicion is that it is temporary. As soon as unemployment gets back to pre-recession levels, we will see Americans doing a lot more driving again."



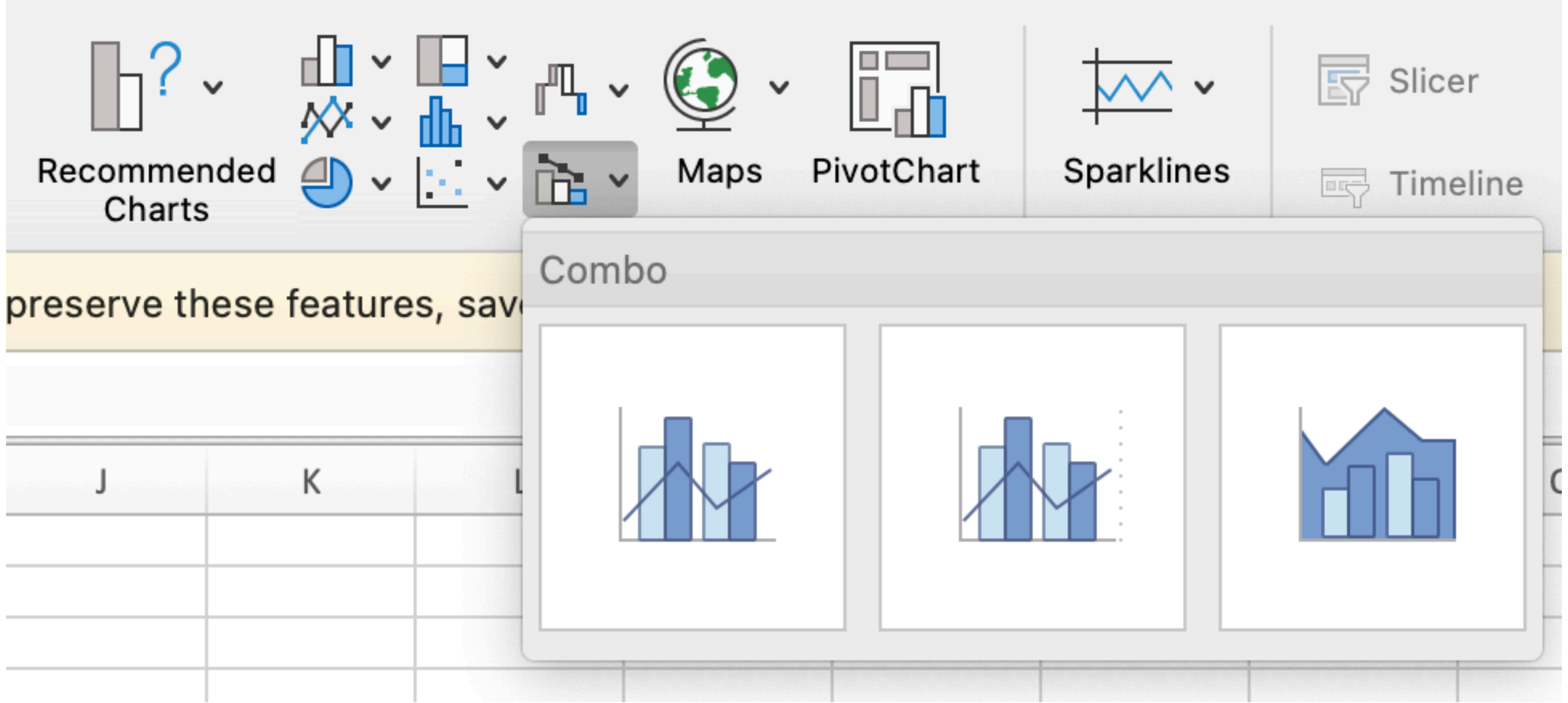

Recommended Charts
Maps
PivotChart
Sparklines
Slicer
Timeline
Combo
preserve these features, sav
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Chart editor
Setup
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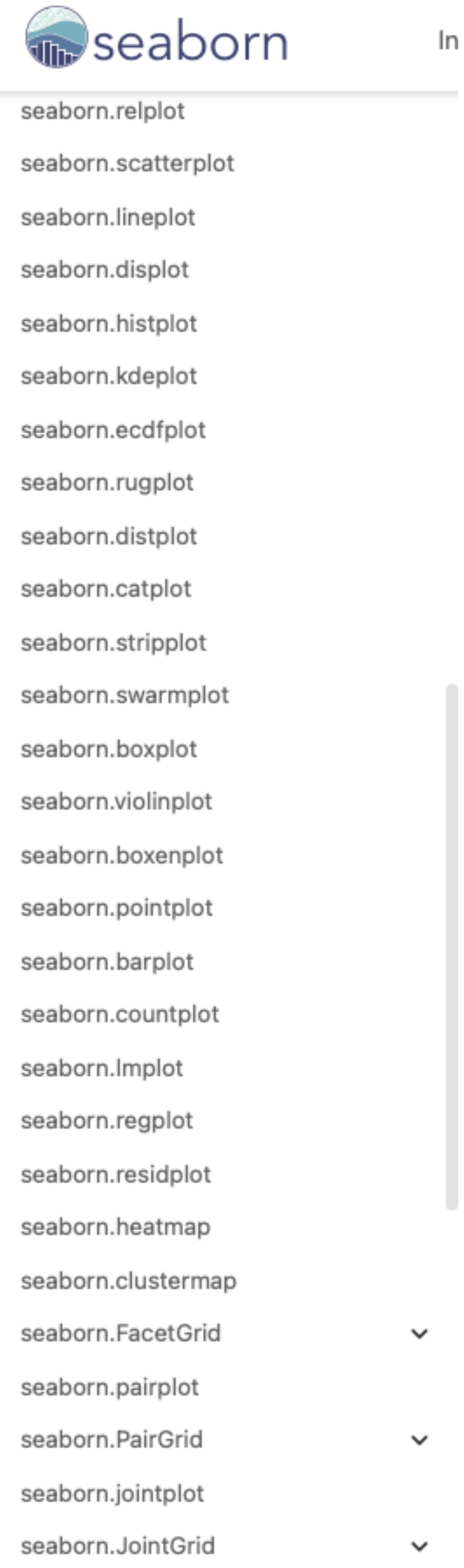
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seaborn.violinplot
seaborn.boxenplot
seaborn.pointplot
seaborn.barplot
seaborn.countplot
seaborn.lmplot
seaborn.regplot
seaborn.residplot
seaborn.heatmap
seaborn.clustermap
seaborn.FacetGrid
seaborn.pairplot
seaborn.PairGrid
seaborn.jointplot
seaborn.JointGrid

Data Visualization

Mapping or Visual Encoding

Data → **Visual**

Attribute Types

Attribute Types

Nominal

Labels or categories.

E.g., Fruits: apples, bananas, cantaloupes, …

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Labels or categories.

E.g., Fruits: apples, bananas, cantaloupes, …

Ordinal

Ordered.

E.g., Quality of meat: Grade A, AA, AAA

Attribute Types

Nominal

Labels or categories.

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Ordered.

E.g., Quality of meat: Grade A, AA, AAA

Quantitative (Interval)

Interval (zero can be arbitrarily located).

E.g., Dates: Jan 19, 2018; Location: (Lat 42.36, -71.09)
Only differences can be calculated (e.g., distances or spans).

Quantitative (Ratio)

Attribute Types

Nominal Labels or categories.
E.g., Fruits: apples, bananas, cantaloupes, ...

Ordinal Ordered.
E.g., Quality of meat: Grade A, AA, AAA

Quantitative (Interval) Interval (zero can be arbitrarily located).
E.g., Dates: Jan 19, 2018; Location: (Lat 42.36, -71.09)
Only differences can be calculated (e.g., distances or spans).

Quantitative (Ratio) Ratio (fixed zero / meaningful baseline).
E.g., Physical measurement: length, mass, temperature
Counts and amounts. Can measure ratios or proportions.

Attribute Types

Nominal
$=, \neq$

Labels or categories.
E.g., Fruits: apples, bananas, cantaloupes, …

Ordinal
$=, \neq, <, >$

Ordered.
E.g., Quality of meat: Grade A, AA, AAA

Quantitative (Interval)
$=, \neq, <, >, -$

Interval (zero can be arbitrarily located).
E.g., Dates: Jan 19, 2018; Location: (Lat 42.36, -71.09)
Only differences can be calculated (e.g., distances or spans).

Quantitative (Ratio)
$=, \neq, <, >, -, \%$

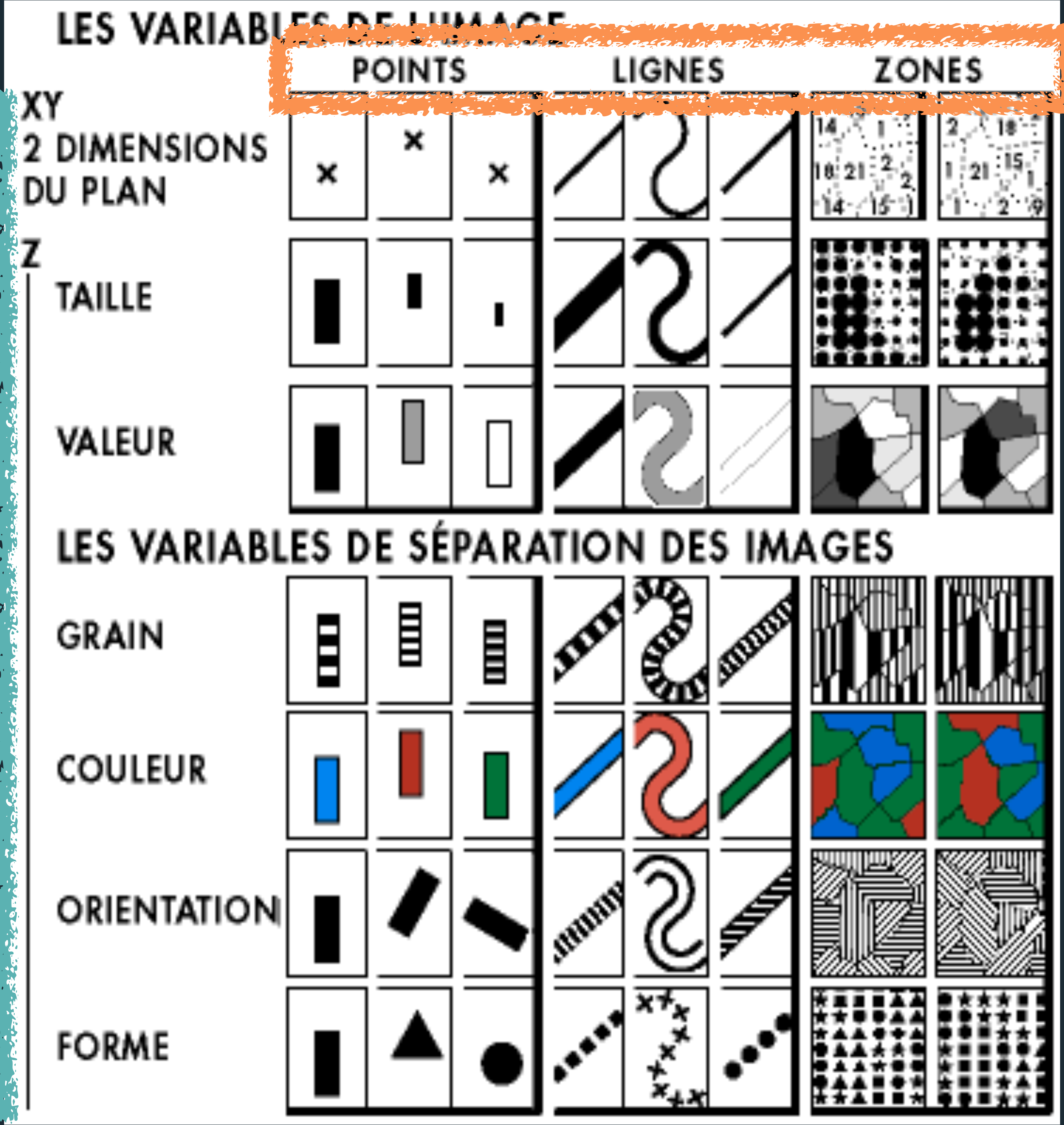
Ratio (fixed zero / meaningful baseline).
E.g., Physical measurement: length, mass, temperature
Counts and amounts. Can measure ratios or proportions.

Visual Variables

Also called visual *channels*.

Used to encode data values as characteristics of marks.

** From 1967, so Bertin only accounted for visualizations that were printable, white paper.*



Marks

Basic graphical elements that represent data items.

Channels: Expressiveness Types and Effectiveness Ranks

➔ Magnitude Channels

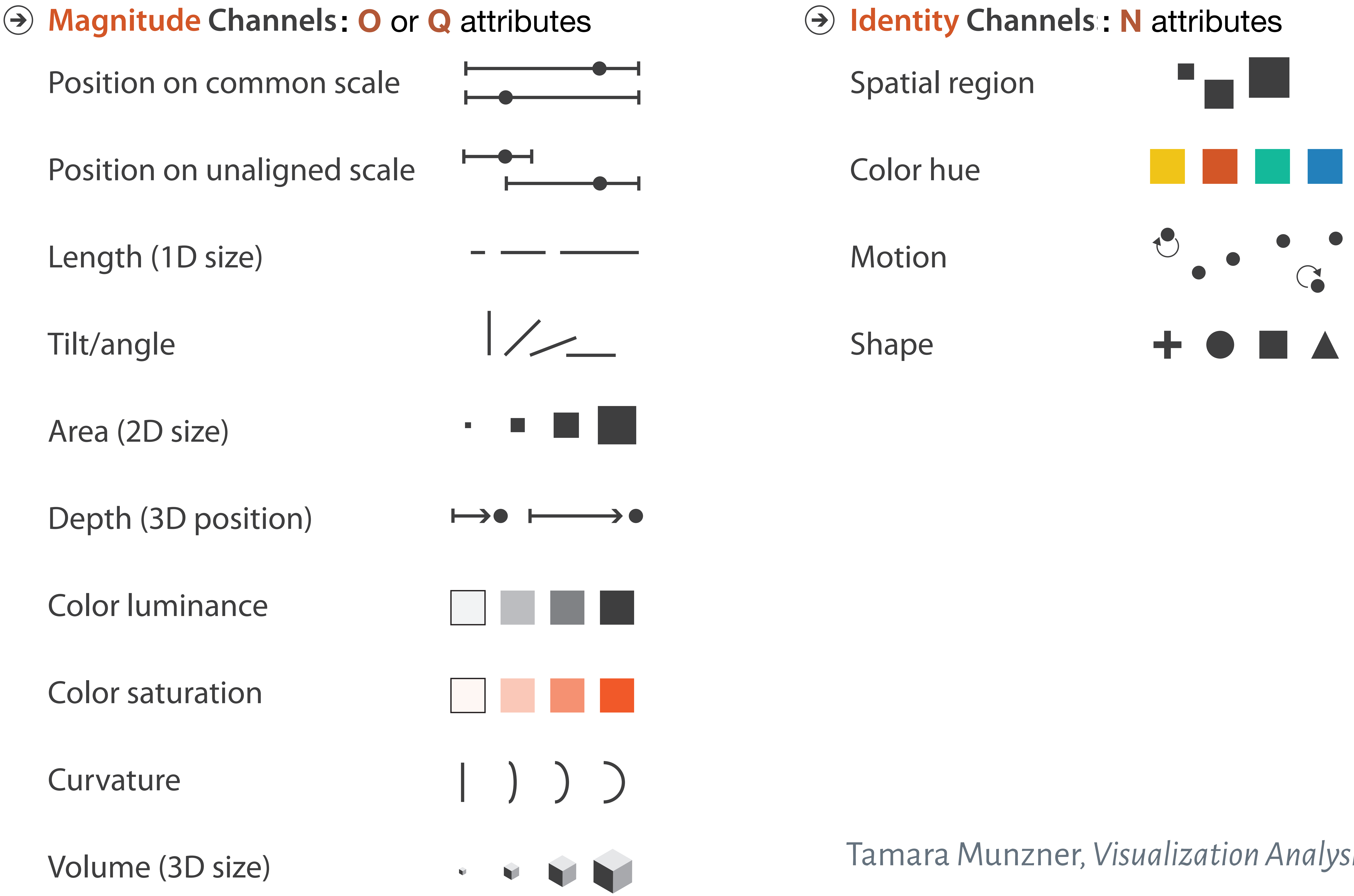
- Position on common scale
- Position on unaligned scale
- Length (1D size)
- Tilt/angle
- Area (2D size)
- Depth (3D position)
- Color luminance
- Color saturation
- Curvature
- Volume (3D size)

➔ Identity Channels:

- Spatial region
- Color hue
- Motion
- Shape

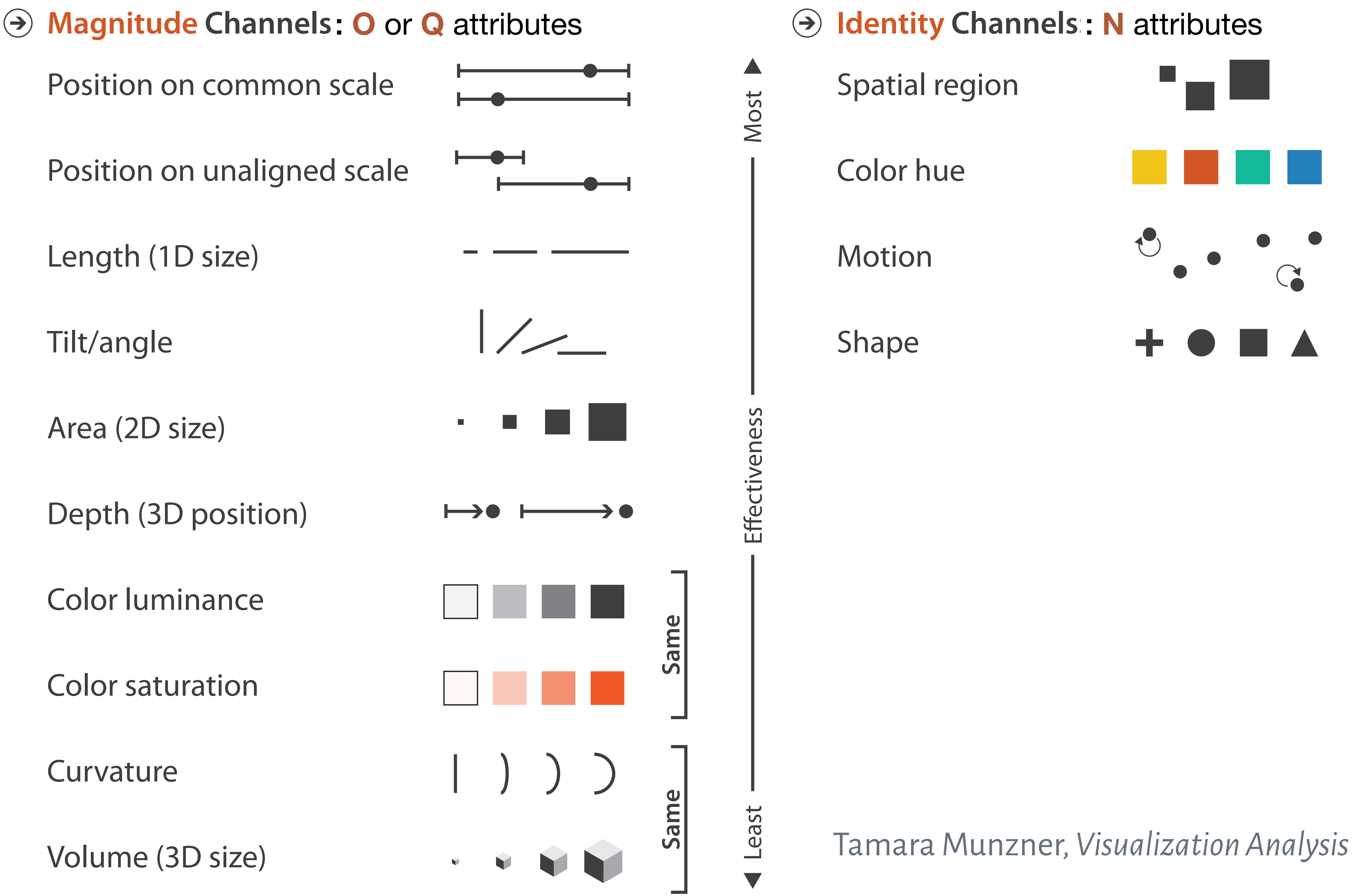
Tamara Munzner, *Visualization Analysis and Design* (2014).

Channels: Expressiveness Types and Effectiveness Ranks



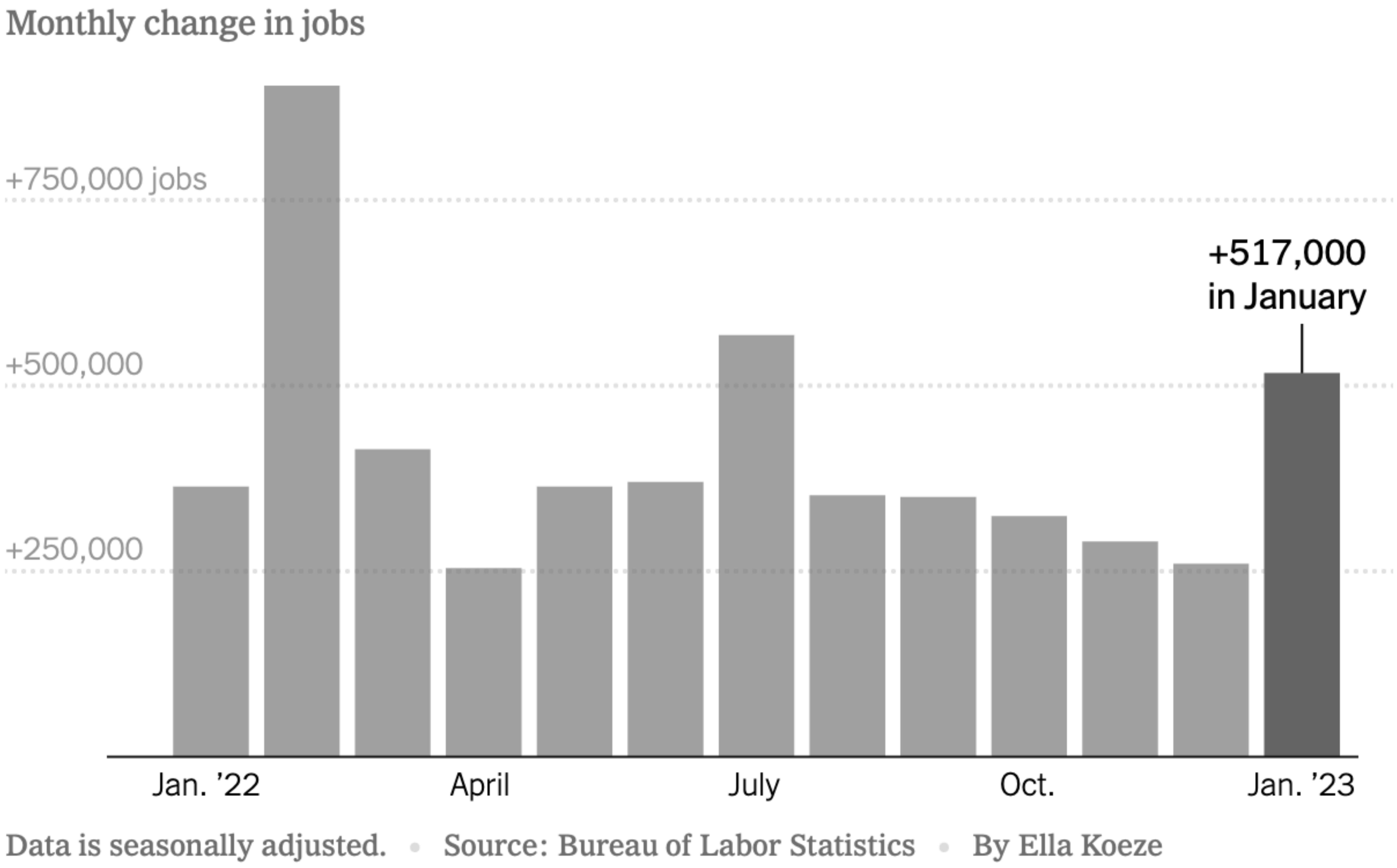
Tamara Munzner, *Visualization Analysis and Design* (2014).

Channels: Expressiveness Types and Effectiveness Ranks



Tamara Munzner, *Visualization Analysis and Design* (2014).

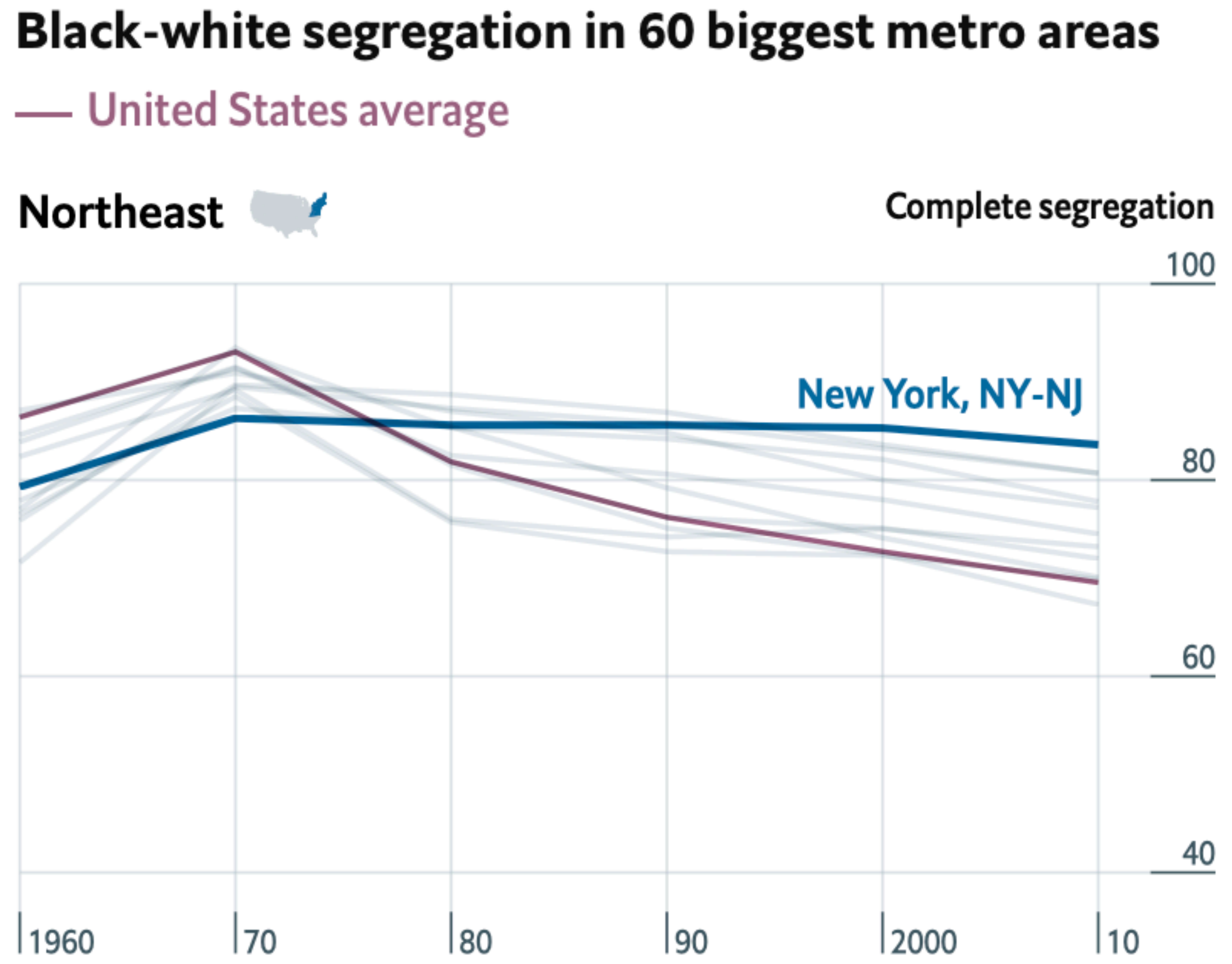
Name That ~~Chart~~ Visual Encoding



Mark: `bar`

X-Axis: `month` (O)

Y-Axis: `jobs` (Q-Ratio)

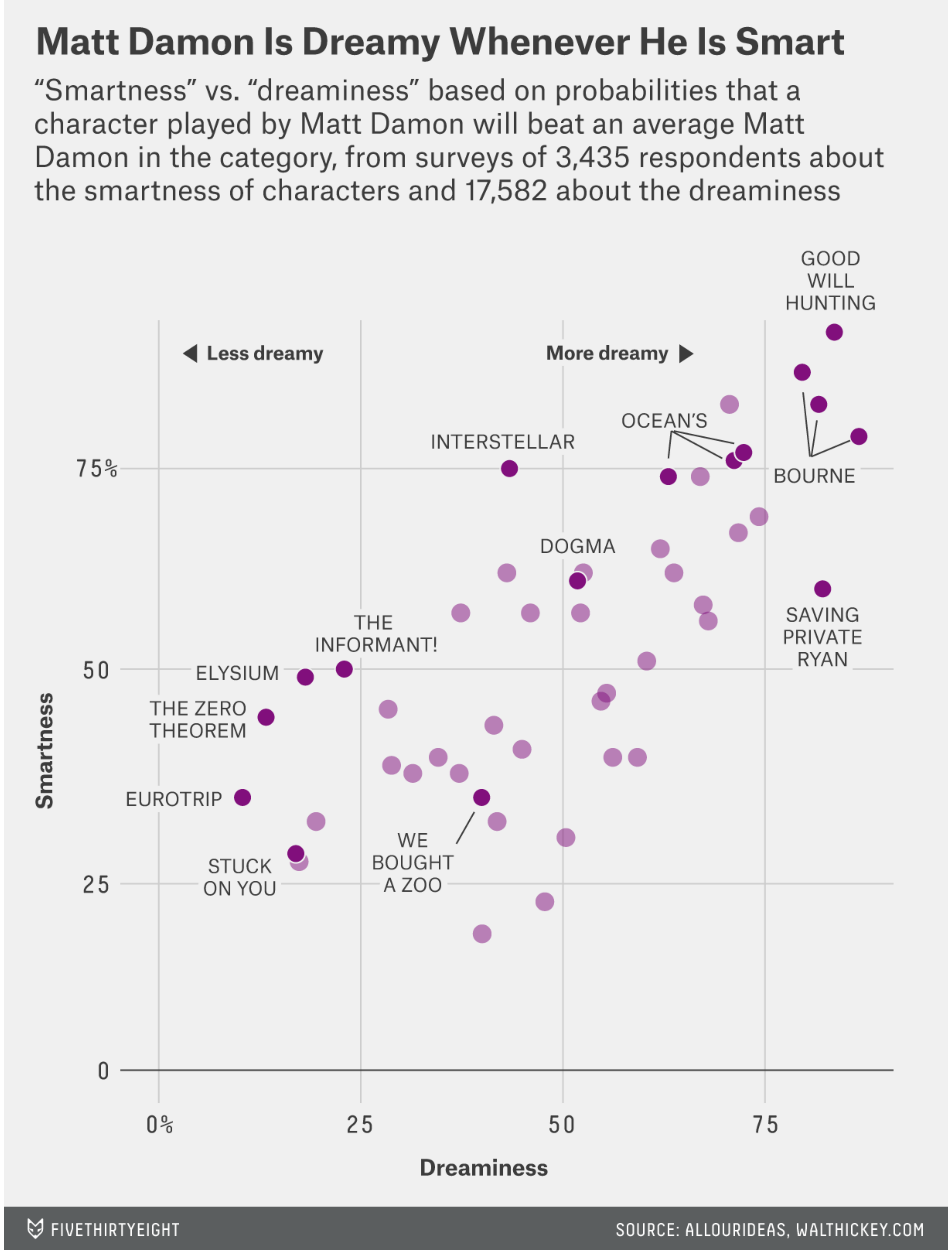


Mark: `line`

X-Axis: `year` (Q-Interval)

Y-Axis: `segregation index` (Q-Ratio)

[The Economist, April 2018]

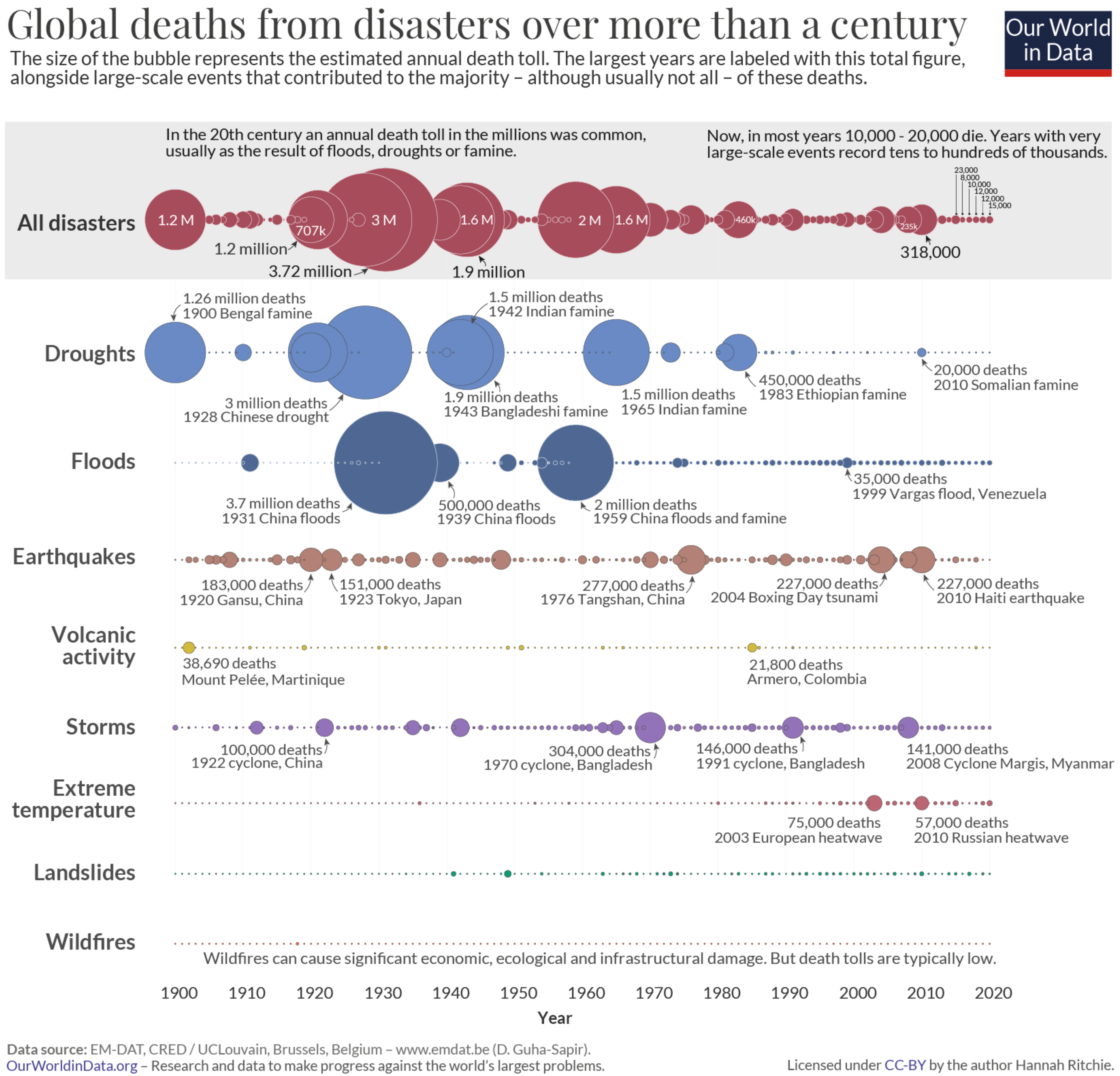


Mark: `circle`

X-Axis: `dreaminess` (Q-Ratio)

Y-Axis: `smartness` (Q-Ratio)

Color: ?? (*annotation purposes only*)



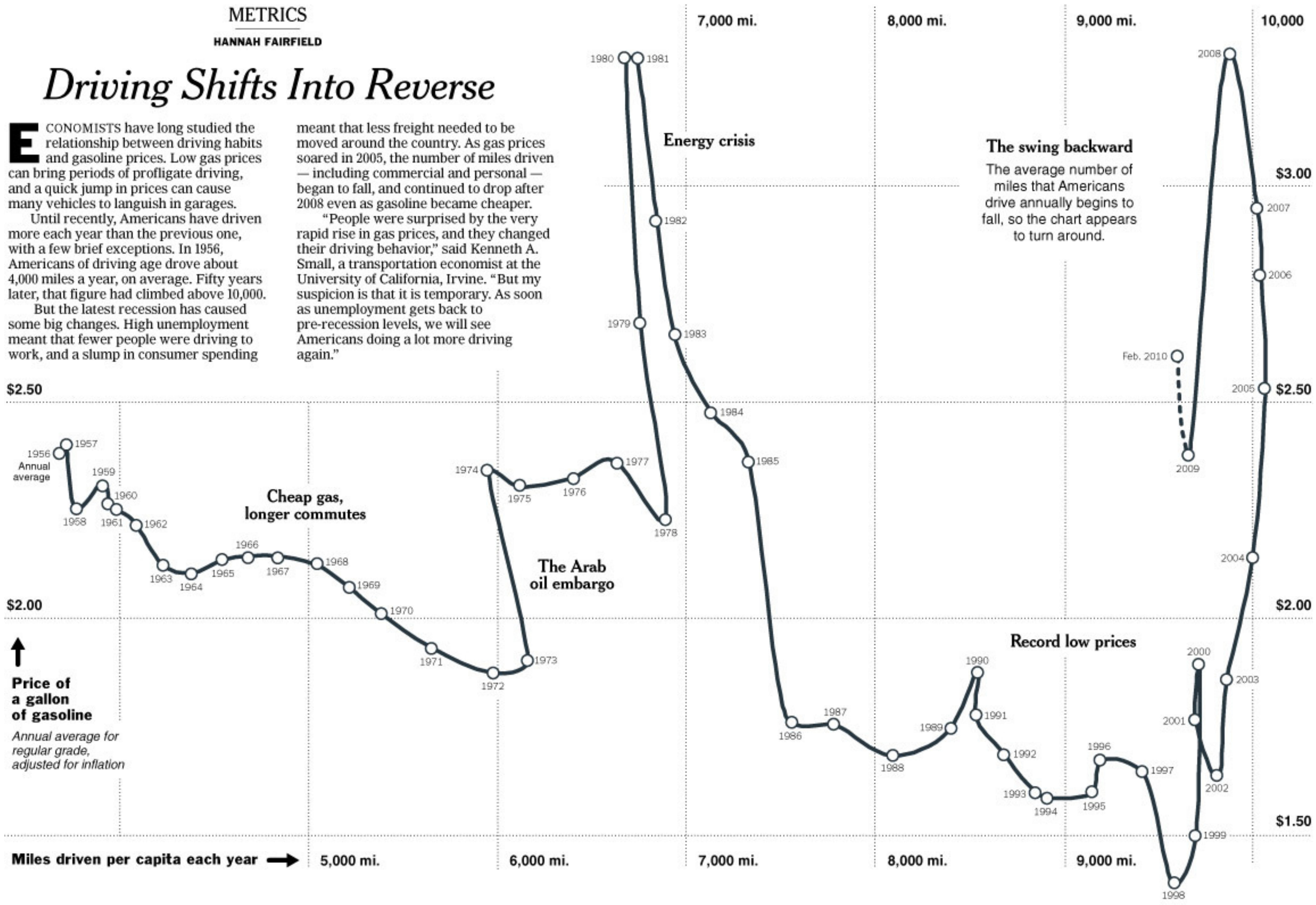
Mark: `circle`

X-Axis: `year` (Ordinal)

Y-Axis: `category` (Nominal)

Color: `category` (Nominal)

Size: `deaths` (Q-Ratio)



Mark: `circle`

X-Axis: `miles` (Q-Ratio)
Y-Axis: `price` (Q-Ratio)

+

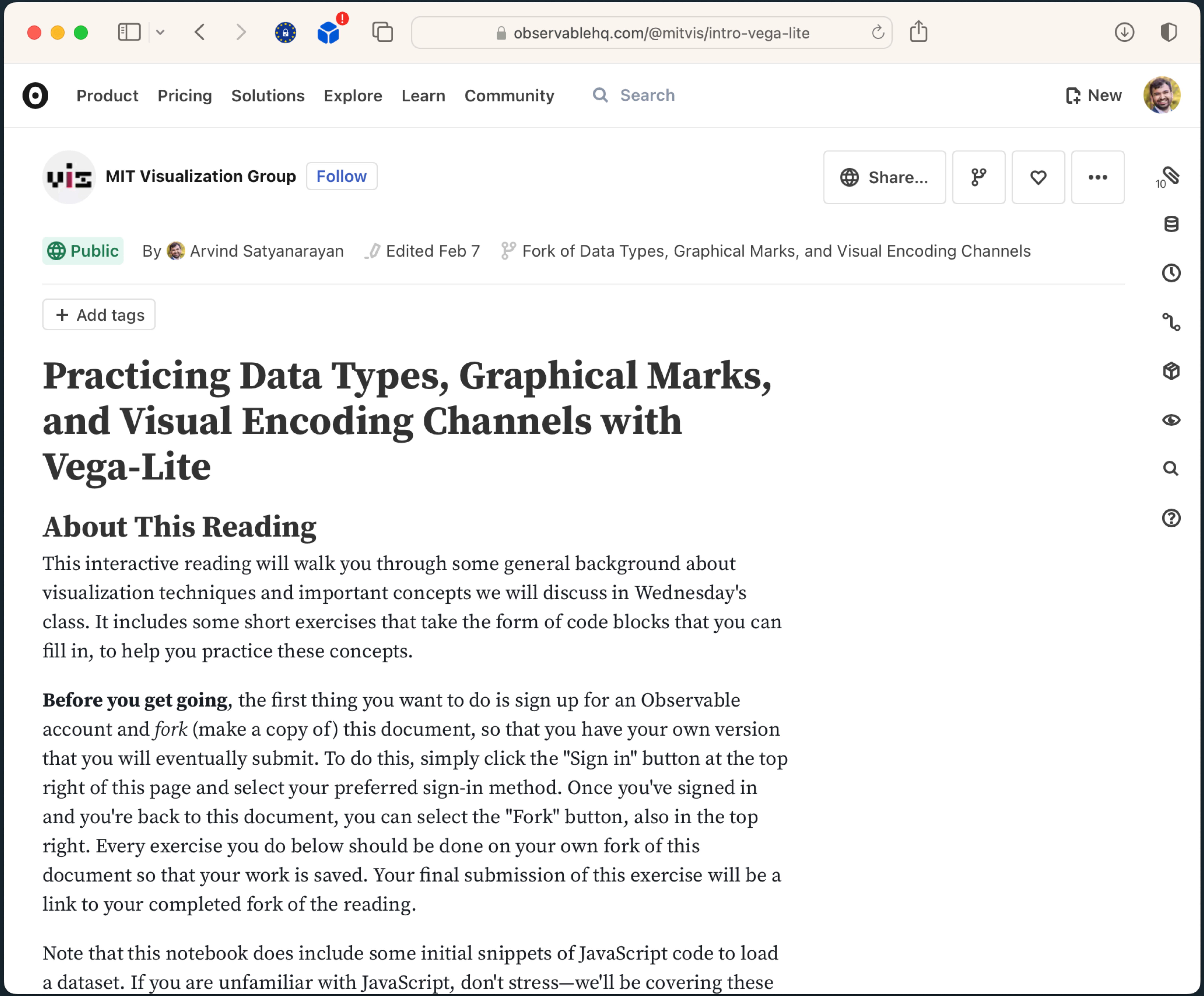
Mark: `text`

X-Axis: `miles` (Q-Ratio)
Y-Axis: `price` (Q-Ratio)
Label: `year` (Nominal)

+

Mark: `line`

X-Axis: `miles` (Q-Ratio)
Y-Axis: `price` (Q-Ratio)
Order: `year` (Ordinal)



Practicing Data Types, Graphical Marks, and Visual Encoding Channels with Vega-Lite

About This Reading

This interactive reading will walk you through some general background about visualization techniques and important concepts we will discuss in Wednesday's class. It includes some short exercises that take the form of code blocks that you can fill in, to help you practice these concepts.

Before you get going, the first thing you want to do is sign up for an Observable account and *fork* (make a copy of) this document, so that you have your own version that you will eventually submit. To do this, simply click the "Sign in" button at the top right of this page and select your preferred sign-in method. Once you've signed in and you're back to this document, you can select the "Fork" button, also in the top right. Every exercise you do below should be done on your own fork of this document so that your work is saved. Your final submission of this exercise will be a link to your completed fork of the reading.

Note that this notebook does include some initial snippets of JavaScript code to load a dataset. If you are unfamiliar with JavaScript, don't stress—we'll be covering these

Interactive workbook

https://observablehq.com/@mitvis/intro-vega-lite

PART ONE

Data & Image Models

PART TWO

Exploratory Visual Analysis

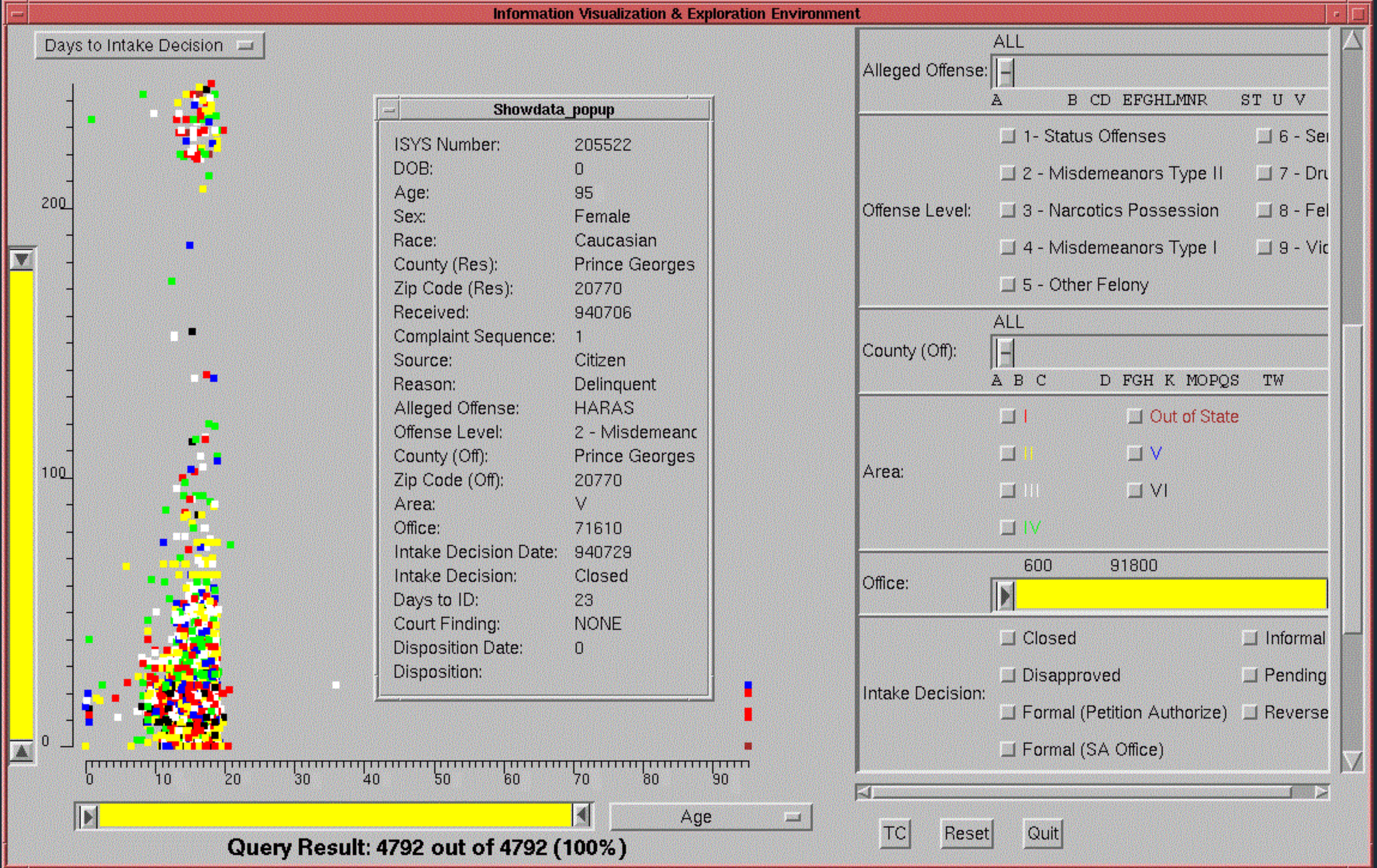
“The first sign that a visualization is good is that **it shows you a problem in your data**. Every successful visualization that I've been involved with has had this stage where you realize, ***"Oh my God, this data is not what I thought it would be!"*** So already, you've discovered something.”

– **Martin Wattenberg**

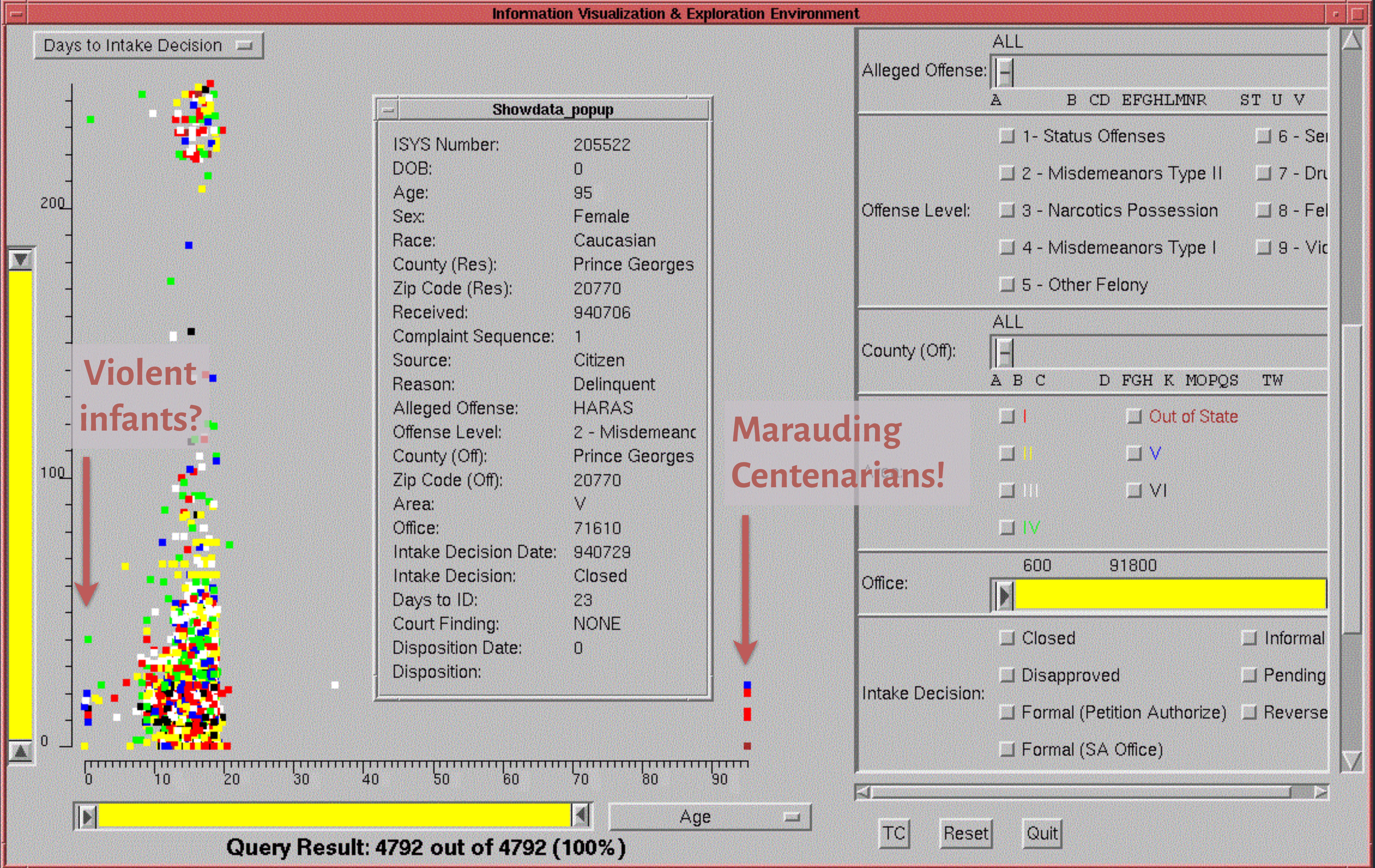
Co-lead of Google's People + AI Initiative

ACM Queue, Mar 2010

Ch15: Visualization Data Mining Models. Thearling et al., *Information Visualization in Data Mining & Knowledge Discovery* 2002.



Ch 15: Visualization Data Mining Models. Thearling et al.,
Information Visualization in Data Mining & Knowledge Discovery 2002.



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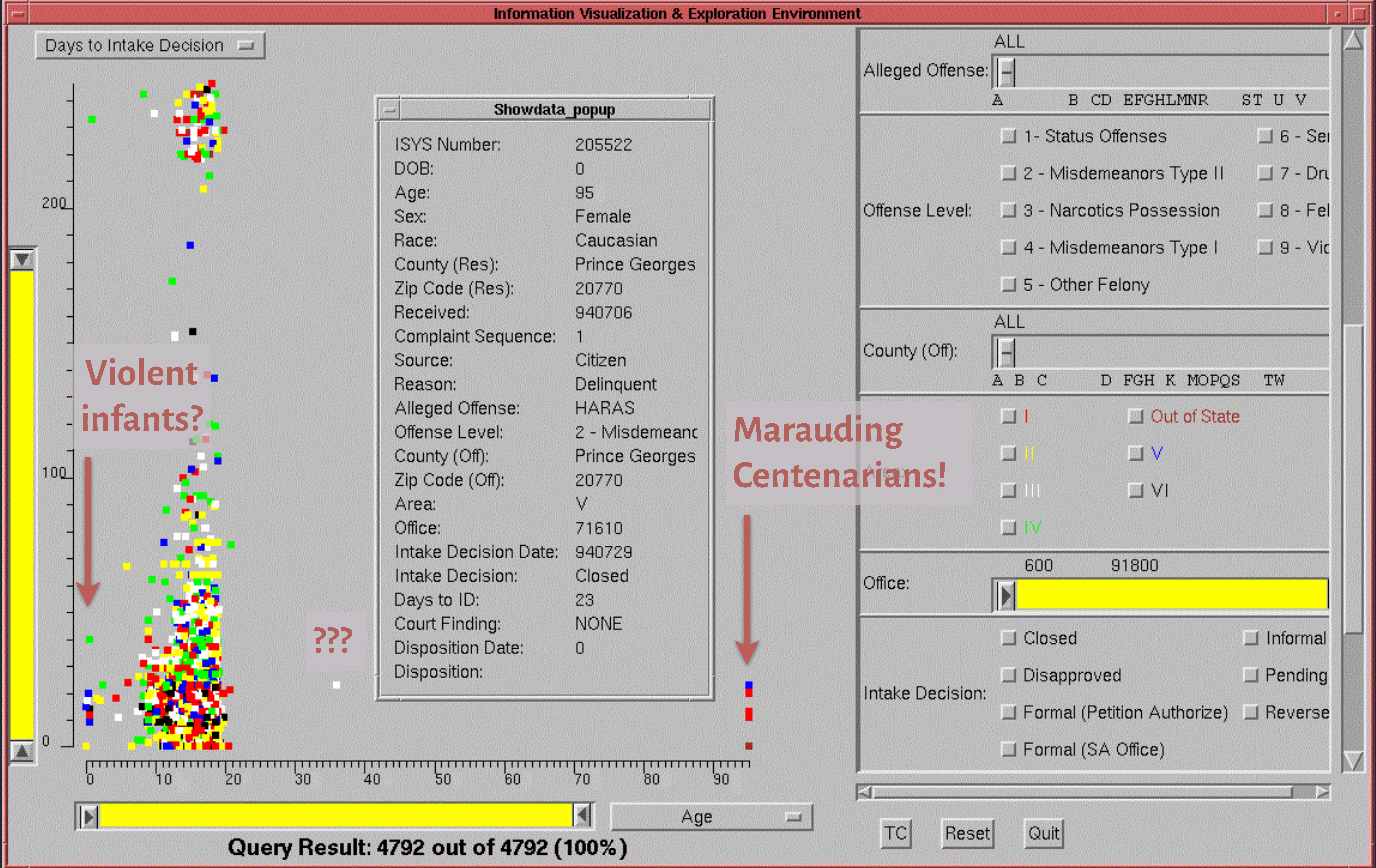
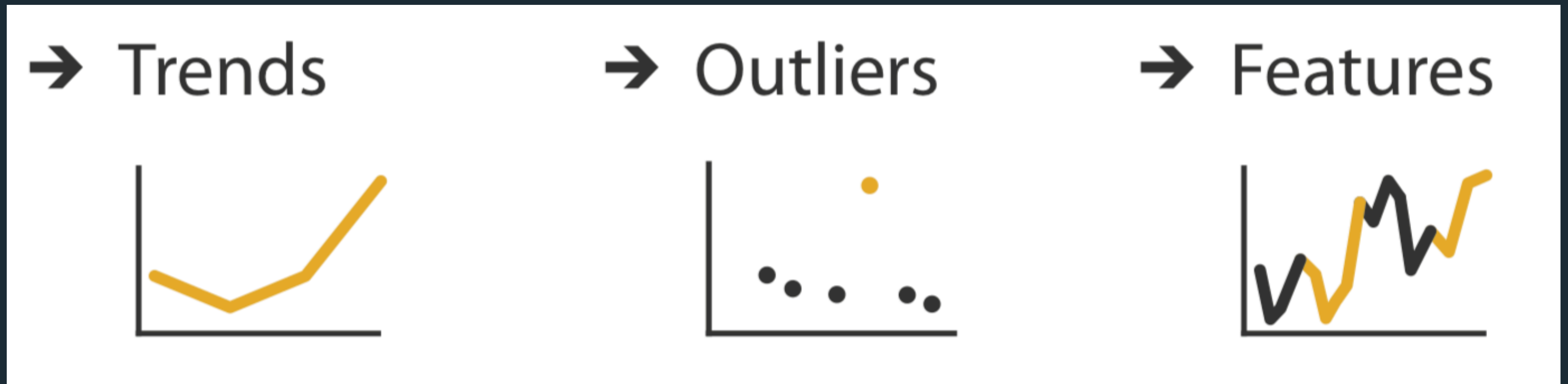


Exploratory Visual Analysis



Process

1. Construct graphics to address questions.
2. Inspect "answer" and ask new questions.
3. Iterate…

Tamara Munzner, *Visualization Analysis and Design* (2014).

Exploratory Visual Analysis

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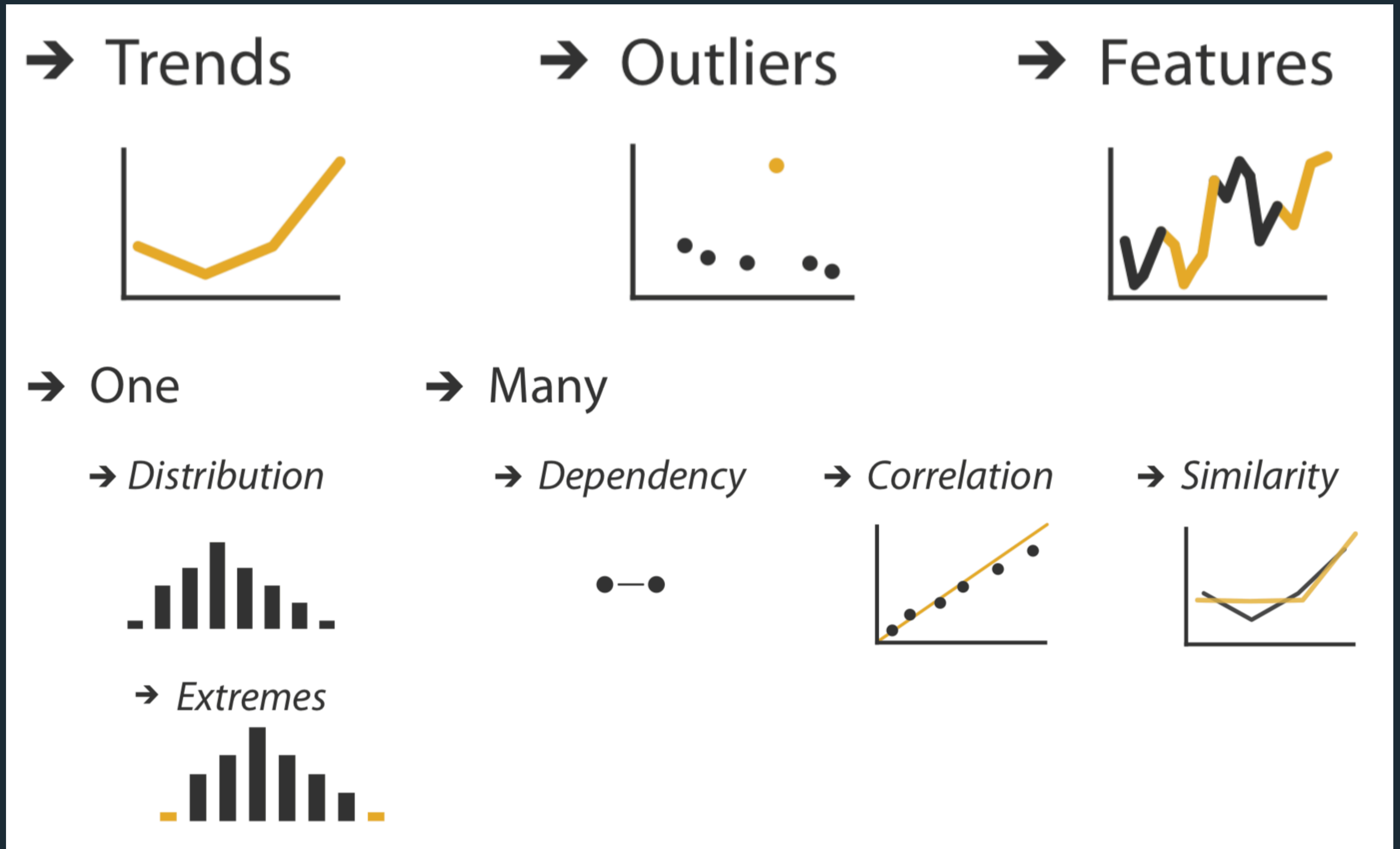

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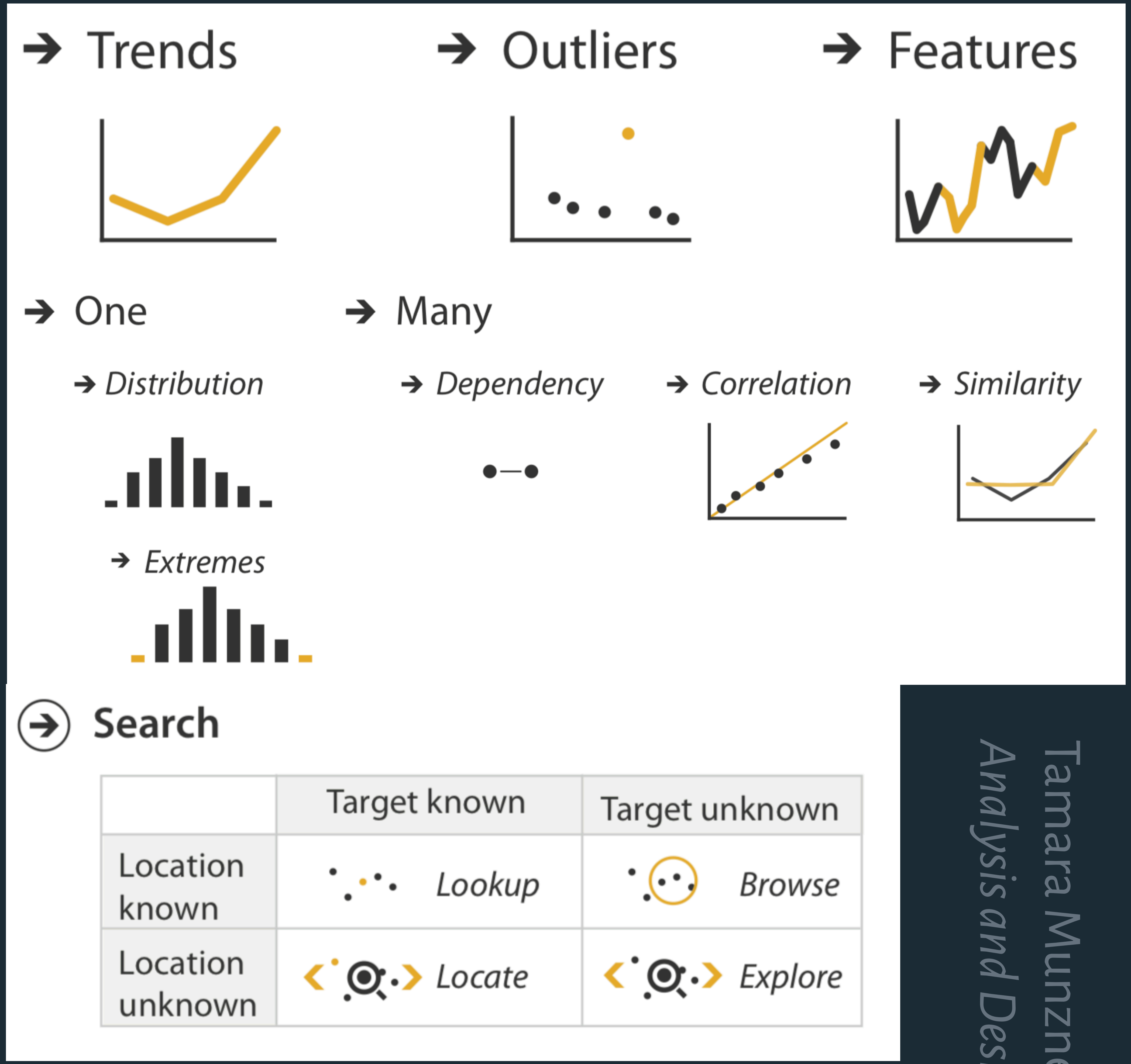

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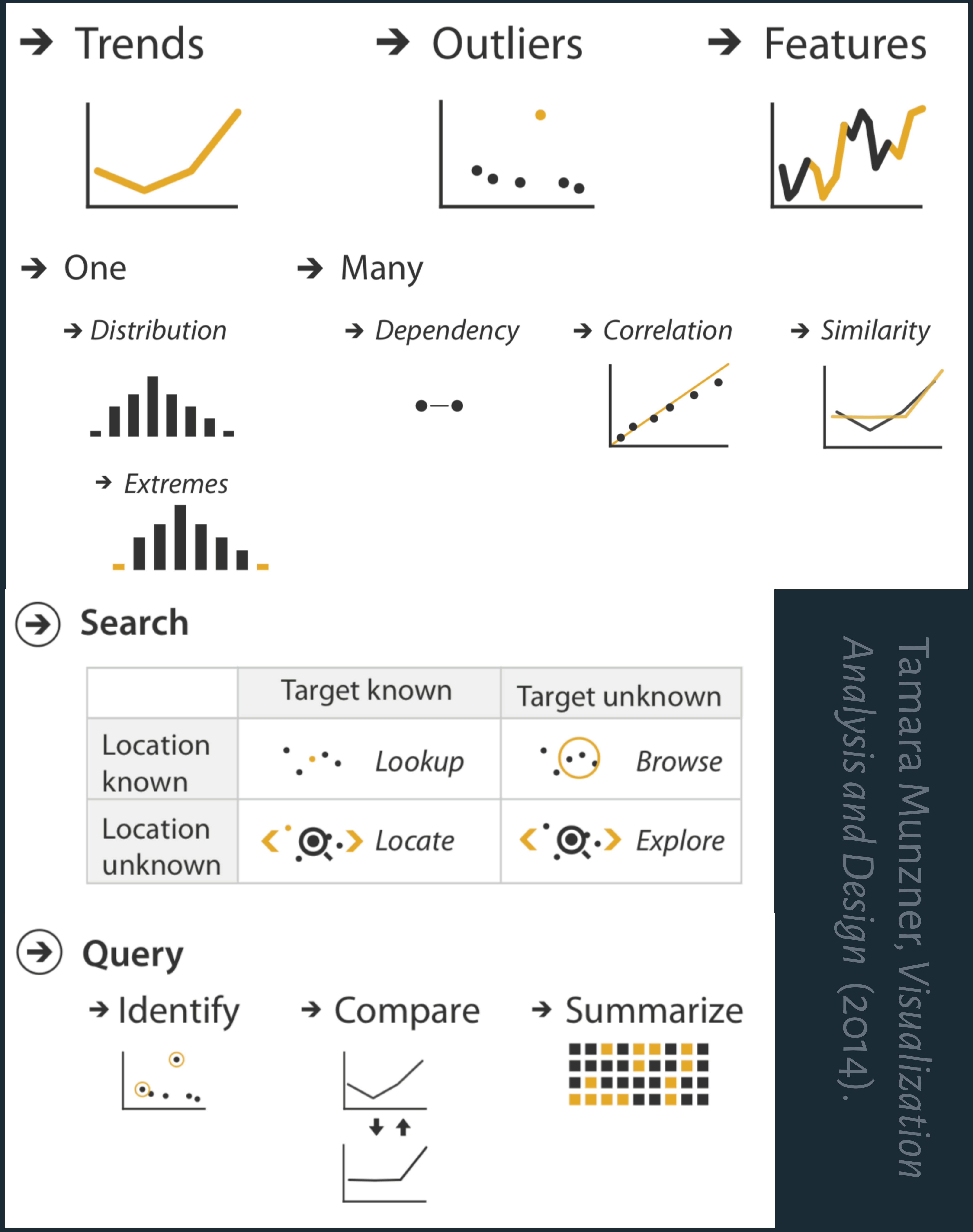

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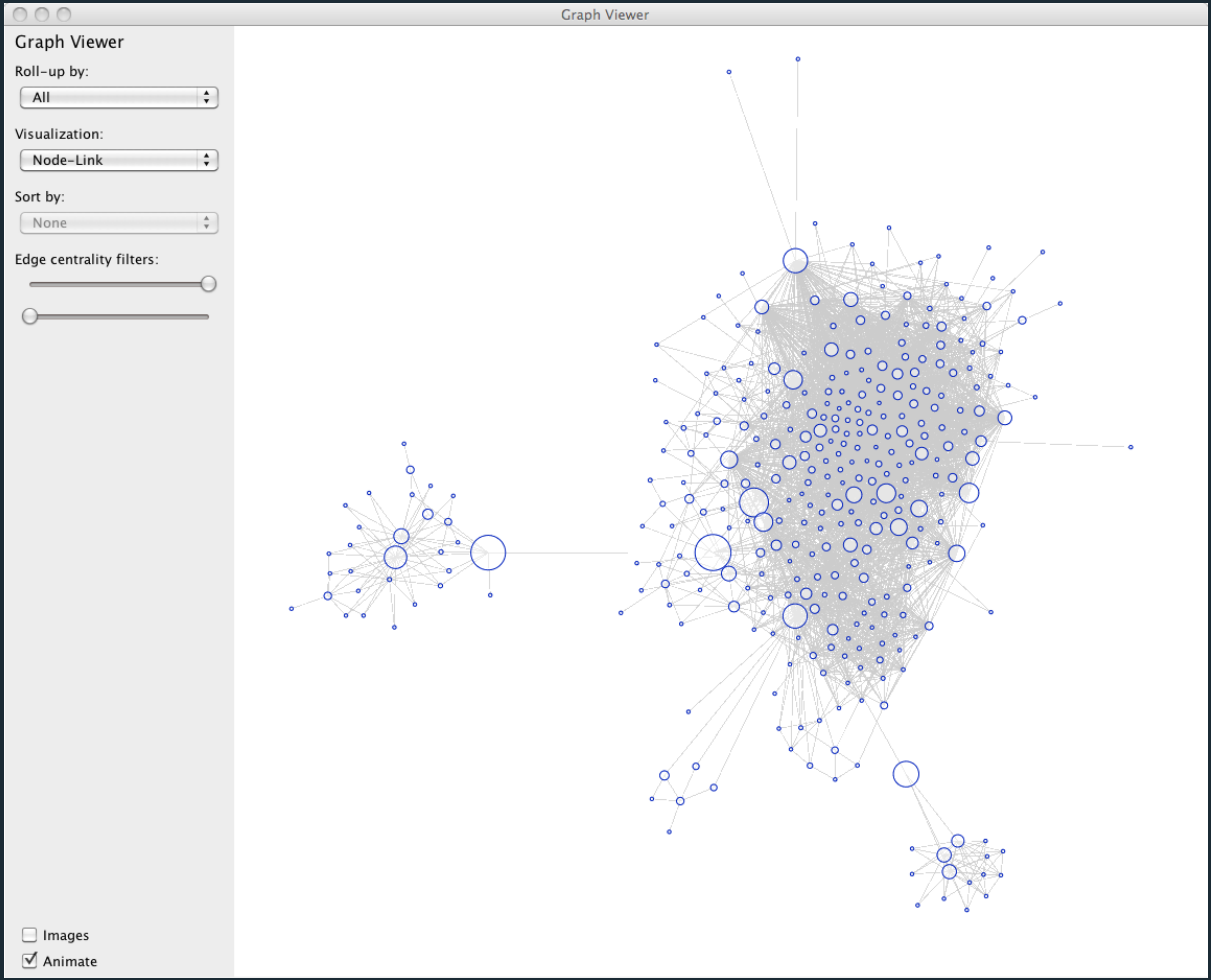
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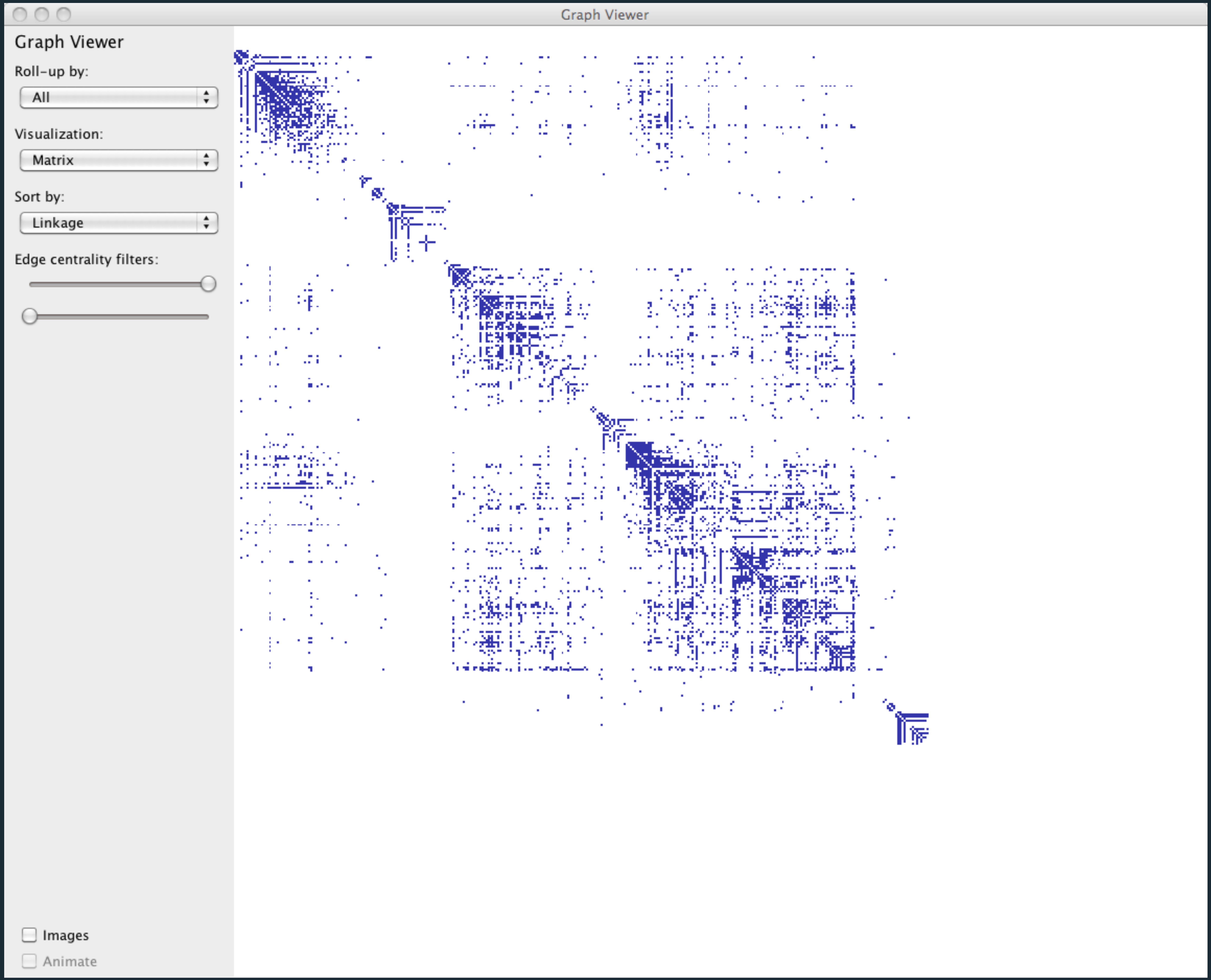
Graph Viewer
Roll-up by:
All
Visualization:
Node-Link
Sort by:
None
Edge centrality filters:
Images
Animate


Graph Viewer
Graph Viewer
Roll-up by:
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Visualization:
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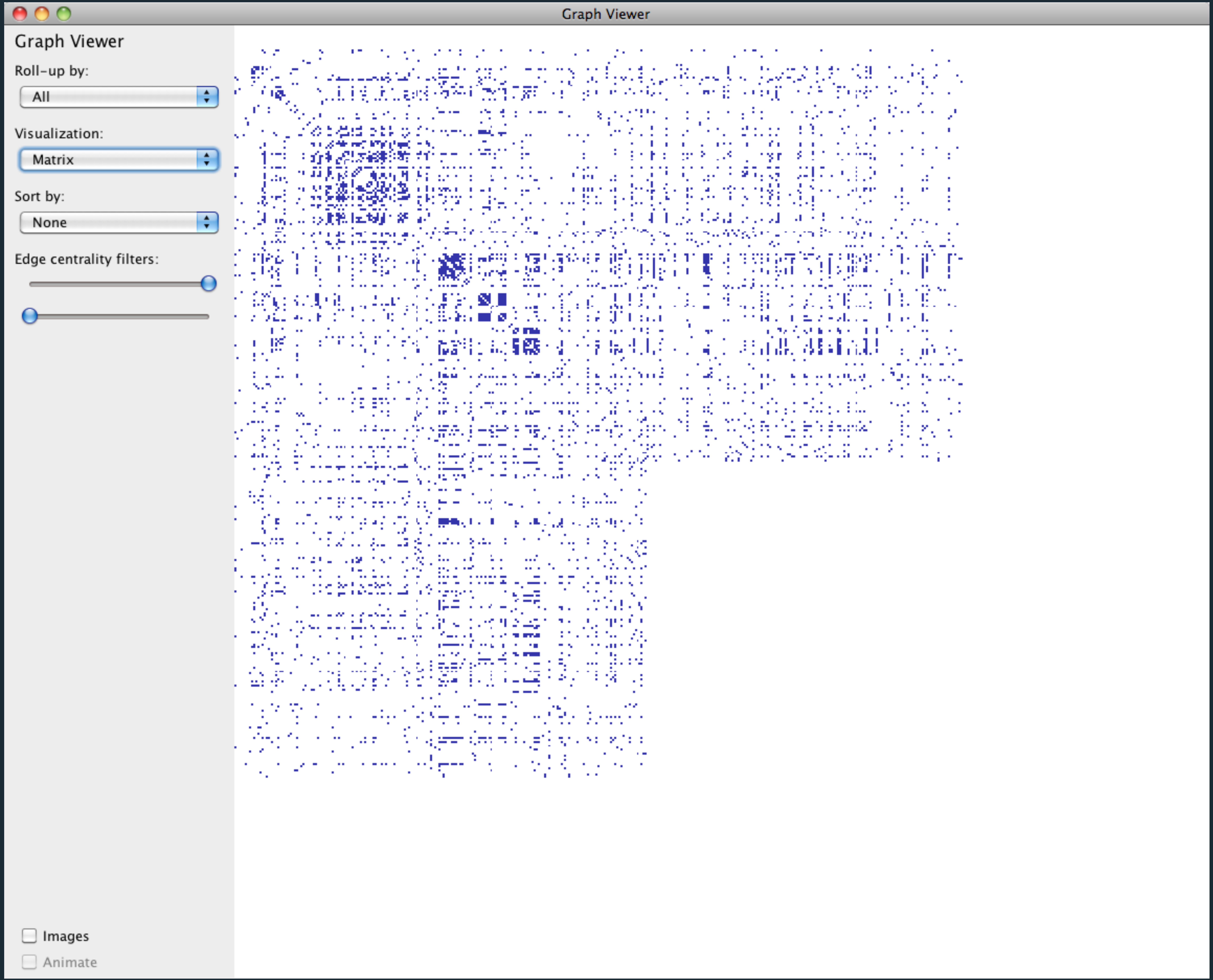
Edge centrality filters:
Images
Animate

Missing Values



Berkeley |||||||||||||||||||||||||||||||

Cornell ||||

Harvard |||||||||

Harvard University |||||||

Stanford ||||||||||||||||||||

Stanford University ||||||||||

UC Berkeley |||||||||||||||||||||

UC Davis ||||||||||

University of California at Berkeley |||||||||||||||

University of California, Berkeley ||||||||||||||||||

University of California, Davis |||

Exploratory Visual Analysis

Process

1. Construct graphics to address questions.
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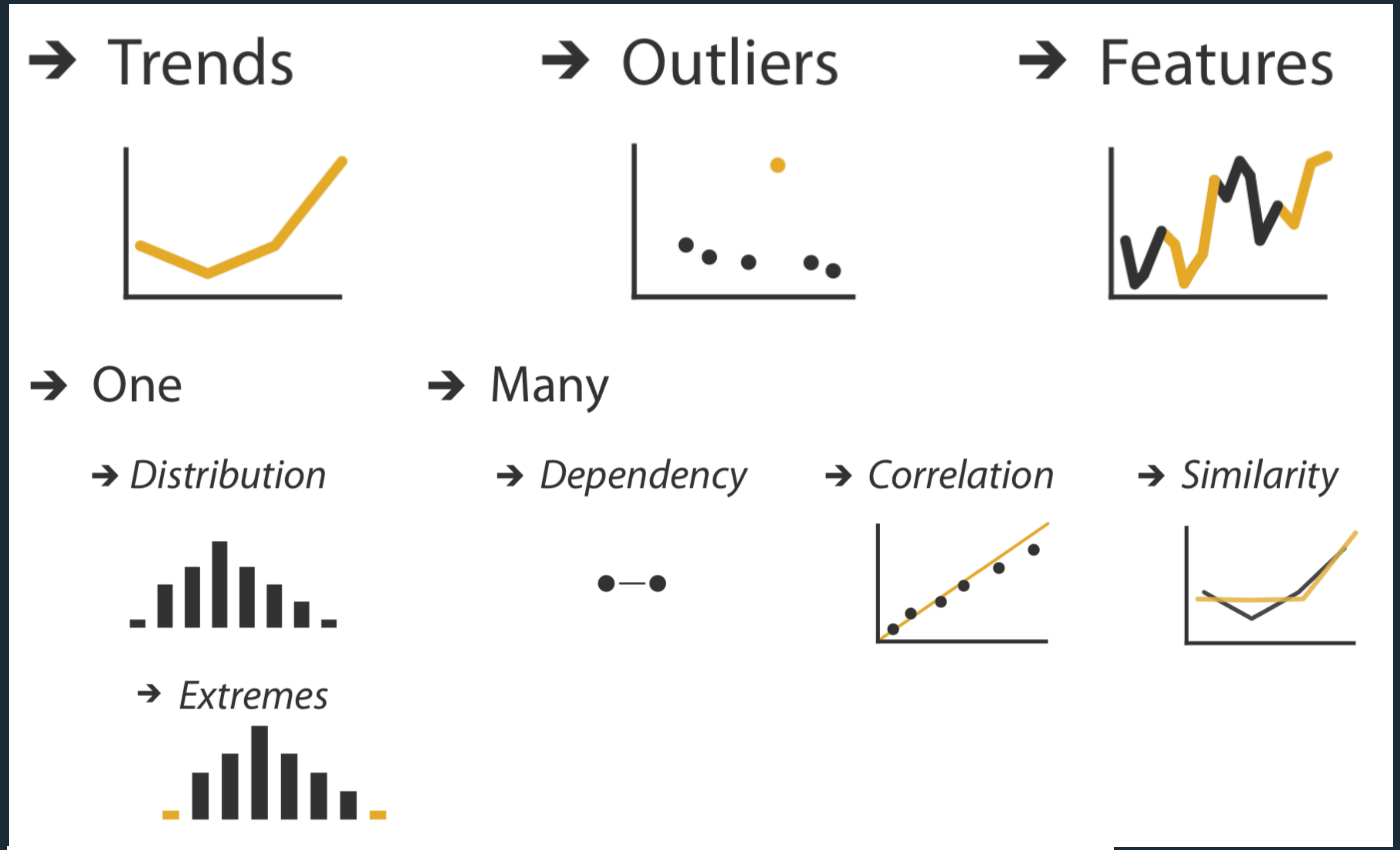
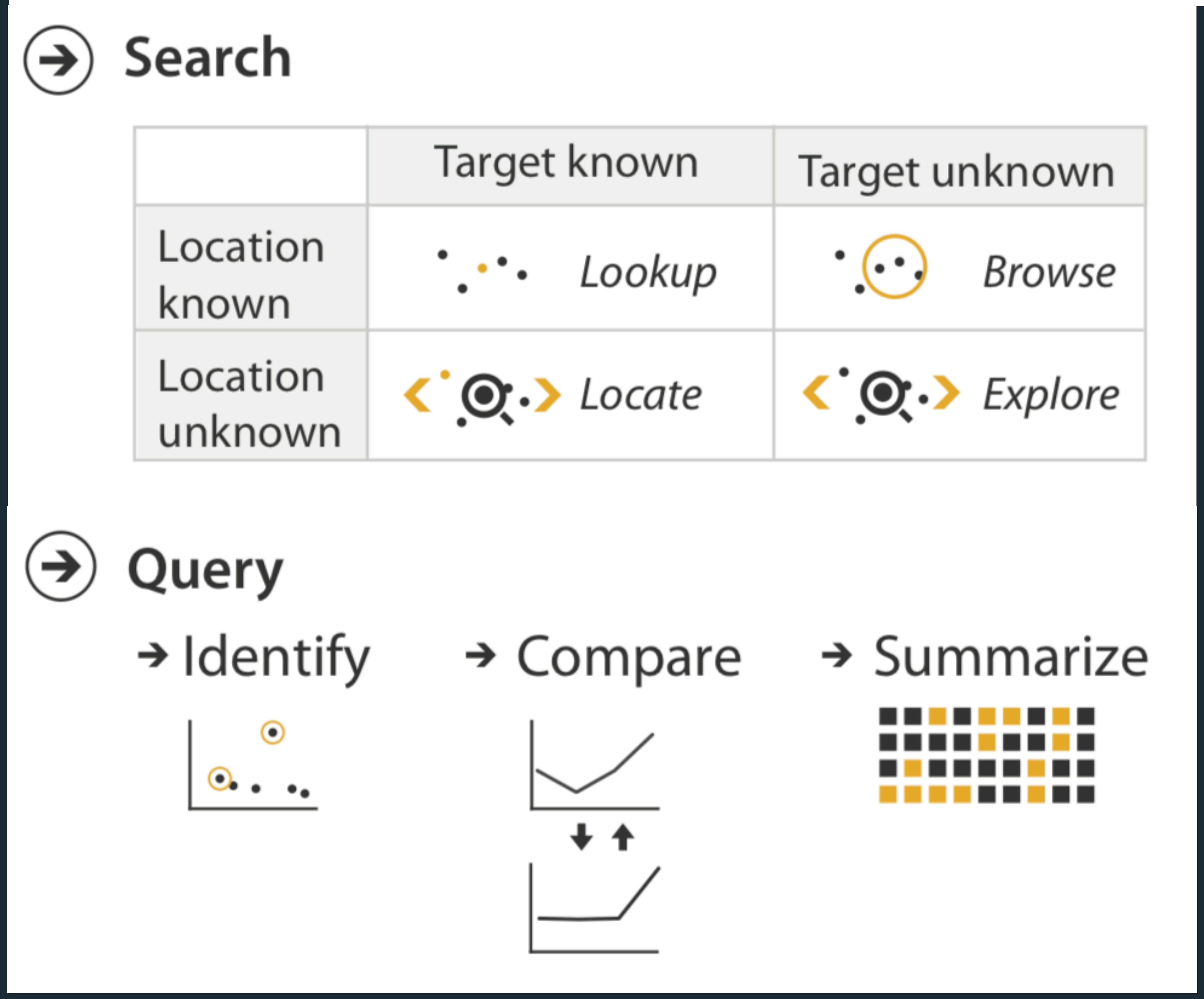
Lessons

✓ Check **data quality** and your **assumptions**.

✓ Start with **univariate summaries**, then consider **relationships between variables**.





Tamara Munzner, *Visualization Analysis and Design* (2014).

Analysis Example: Antibiotic Effectiveness

Analysis Example: Antibiotic Effectiveness

Collected prior to 1951

Genus of Bacteria	String (N)
Species of Bacteria	String (N)
Antibiotic Applied	String (N)
Gram-Staining?	Pos / Neg (N)
Min. Inhibitory Con. (g)	Number (Q)

Analysis Example: Antibiotic Effectiveness

Collected prior to 1951	
Genus of Bacteria	String (N)
Species of Bacteria	String (N)
Antibiotic Applied	String (N)
Gram-Staining?	Pos / Neg (N)
Min. Inhibitory Con. (g)	Number (Q)

Table 1—Burtin's Data

	Antibiotic			
Bacteria	**Penicillin**	**Streptomycin**	**Neomycin**	**Gram Staining**
Aerobacter aerogenes	870	1	1.6	negative
Brucella abortus	1	2	0.02	negative
Brucella anthracis	0.001	0.01	0.007	positive
Diplococcus pneumoniae	0.005	11	10	positive
Escherichia coli	100	0.4	0.1	negative
Klebsiella pneumoniae	850	1.2	1	negative
Mycobacterium tuberculosis	800	5	2	negative
Proteus vulgaris	3	0.1	0.1	negative
Pseudomonas aeruginosa	850	2	0.4	negative
Salmonella (Eberthella) typhosa	1	0.4	0.008	negative
Salmonella schottmuelleri	10	0.8	0.09	negative
Staphylococcus albus	0.007	0.1	0.001	positive
Staphylococcus aureus	0.03	0.03	0.001	positive
Streptococcus fecalis	1	1	0.1	positive
Streptococcus hemolyticus	0.001	14	10	positive
Streptococcus viridans	0.005	10	40	positive

What questions might we ask?

Collected prior to 1951

Genus of Bacteria	String (N)
Species of Bacteria	String (N)
Antibiotic Applied	String (N)
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Min. Inhibitory Con. (g)	Number (Q)

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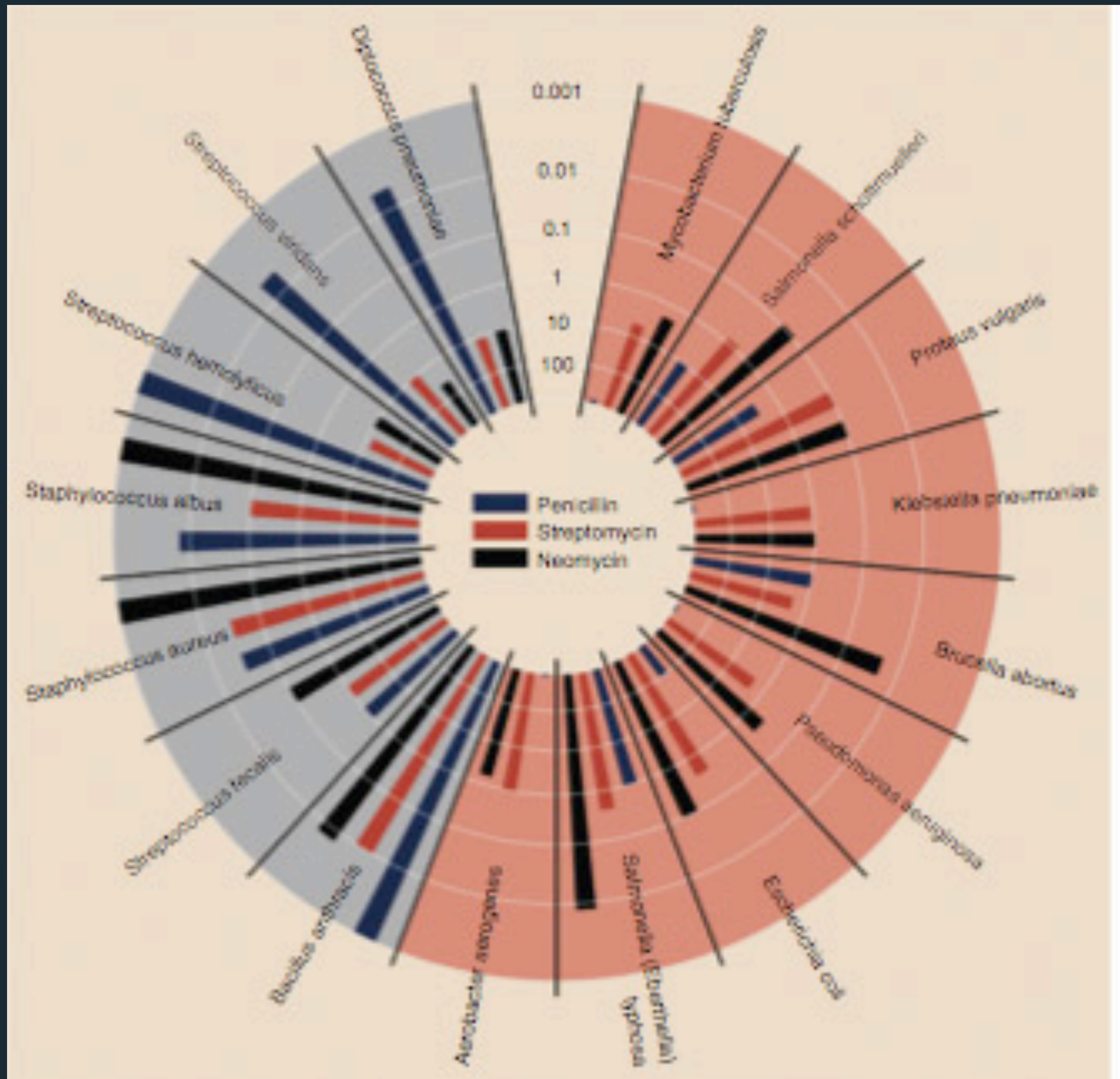
Diplococcus pneumoniae	0.005	11	10	positive
Escherichia coli	100	0.4	0.1	negative
Klebsiella pneumoniae	850	1.2	1	negative
Mycobacterium tuberculosis	800	5	2	negative
Proteus vulgaris	3	0.1	0.1	negative
Pseudomonas aeruginosa	850	2	0.4	negative
Salmonella (Eberthella) typhosa	1	0.4	0.008	negative
Salmonella schottmuelleri	10	0.8	0.09	negative
Staphylococcus albus	0.007	0.1	0.001	positive
Staphylococcus aureus	0.03	0.03	0.001	positive
Streptococcus fecalis	1	1	0.1	positive
Streptococcus hemolyticus	0.001	14	10	positive
Streptococcus viridans	0.005	10	40	positive

How do the drugs compare?



Bacteria	Penicillin	Antibiotic Streptomycin	Neomycin	Gram stain
Aerobacter aerogenes	870	1	1.6	–
Brucella abortus	1	2	0.02	–
Bacillus anthracis	0.001	0.01	0.007	+
Diplococcus pneumoniae	0.005	11	10	+
Escherichia coli	100	0.4	0.1	–
Klebsiella pneumoniae	850	1.2	1	–
Mycobacterium tuberculosis	800	5	2	–
Proteus vulgaris	3	0.1	0.1	–
Pseudomonas aeruginosa	850	2	0.4	–
Salmonella (Eberthella) typhosa	1	0.4	0.008	–
Salmonella schottmuelleri	10	0.8	0.09	–
Staphylococcus albus	0.007	0.1	0.001	+
Staphylococcus aureus	0.03	0.03	0.001	+
Streptococcus fecalis	1	1	0.1	+
Streptococcus hemolyticus	0.001	14	10	+
Streptococcus viridans	0.005	10	40	+

Original graphic by Will Burtin, 1951.

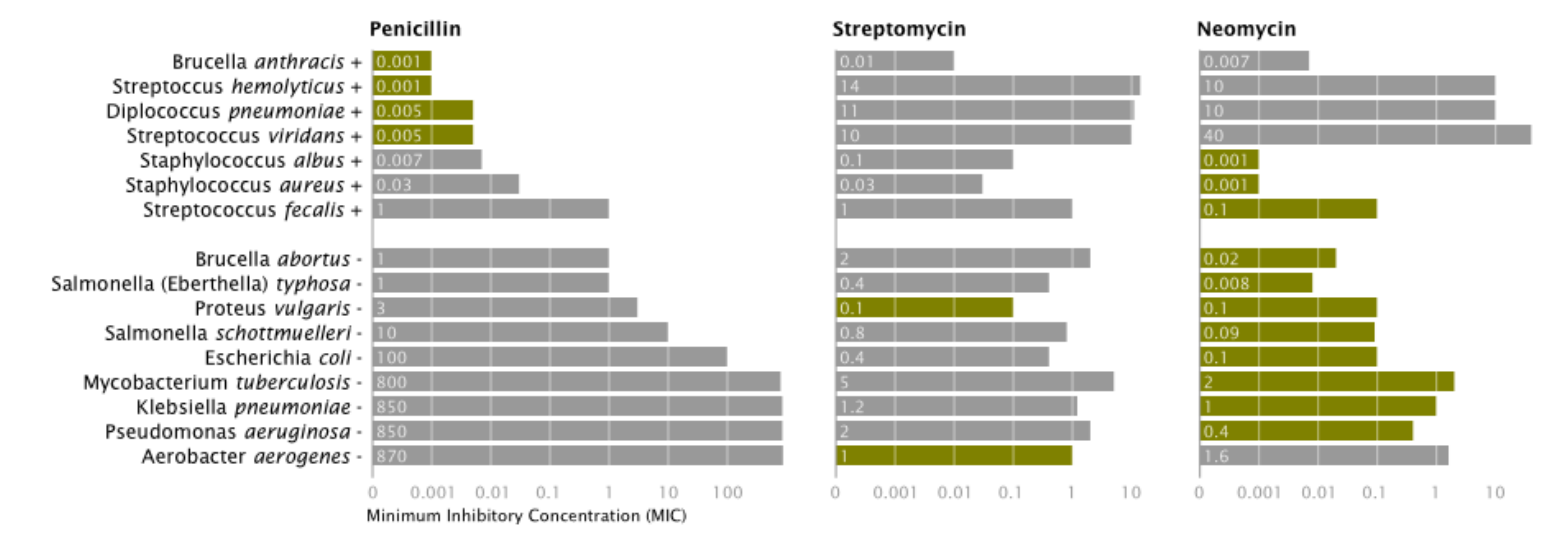
Encodings

Radius: 1 / log(MIC)

Bar Color: Antibiotic

Background Color: Gram Staining

How do the drugs compare?



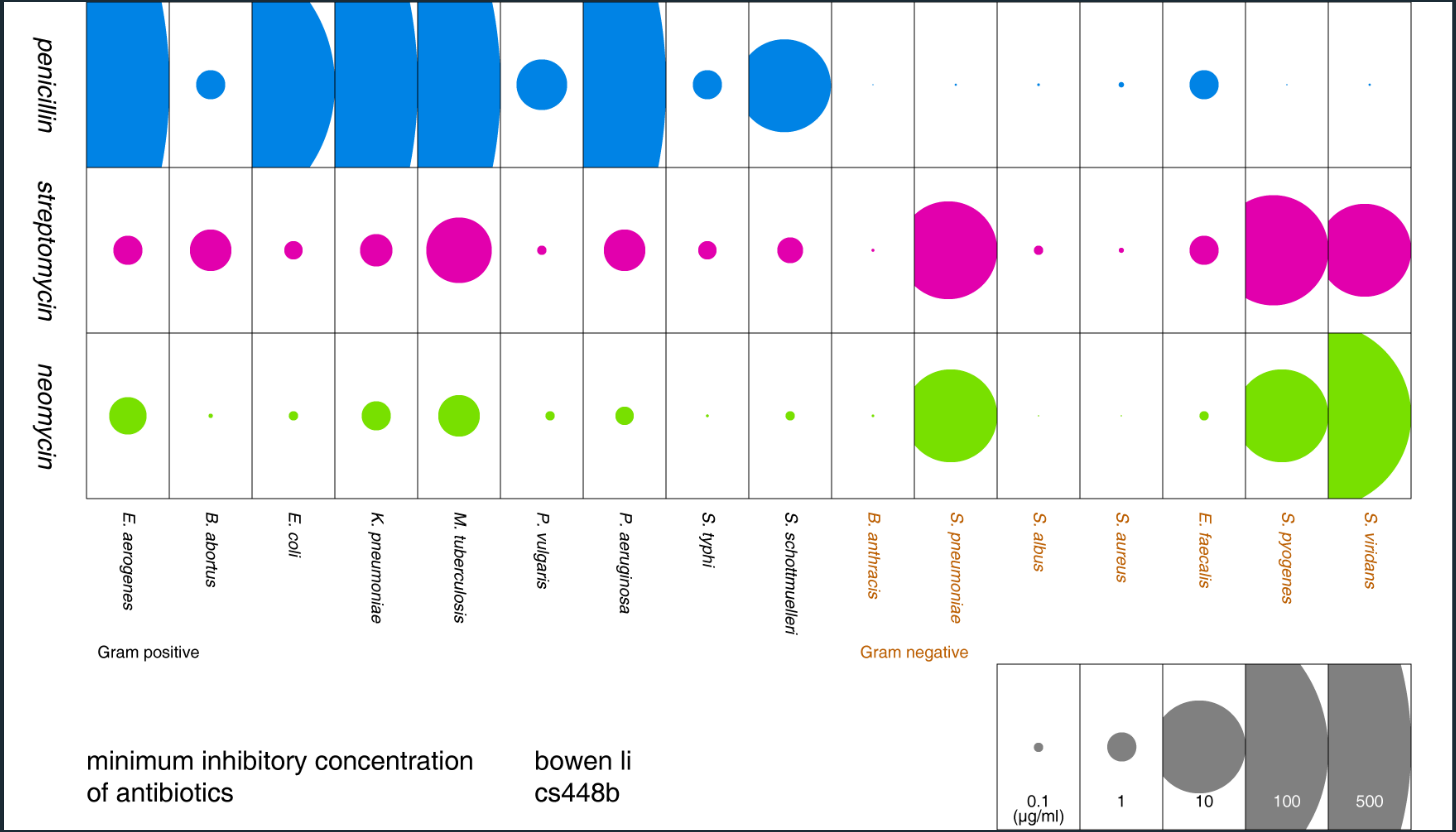
Mike Bostock, *Stanford CS448b* (Winter 2009).

X-Axis: Antibiotic | log(MIC)

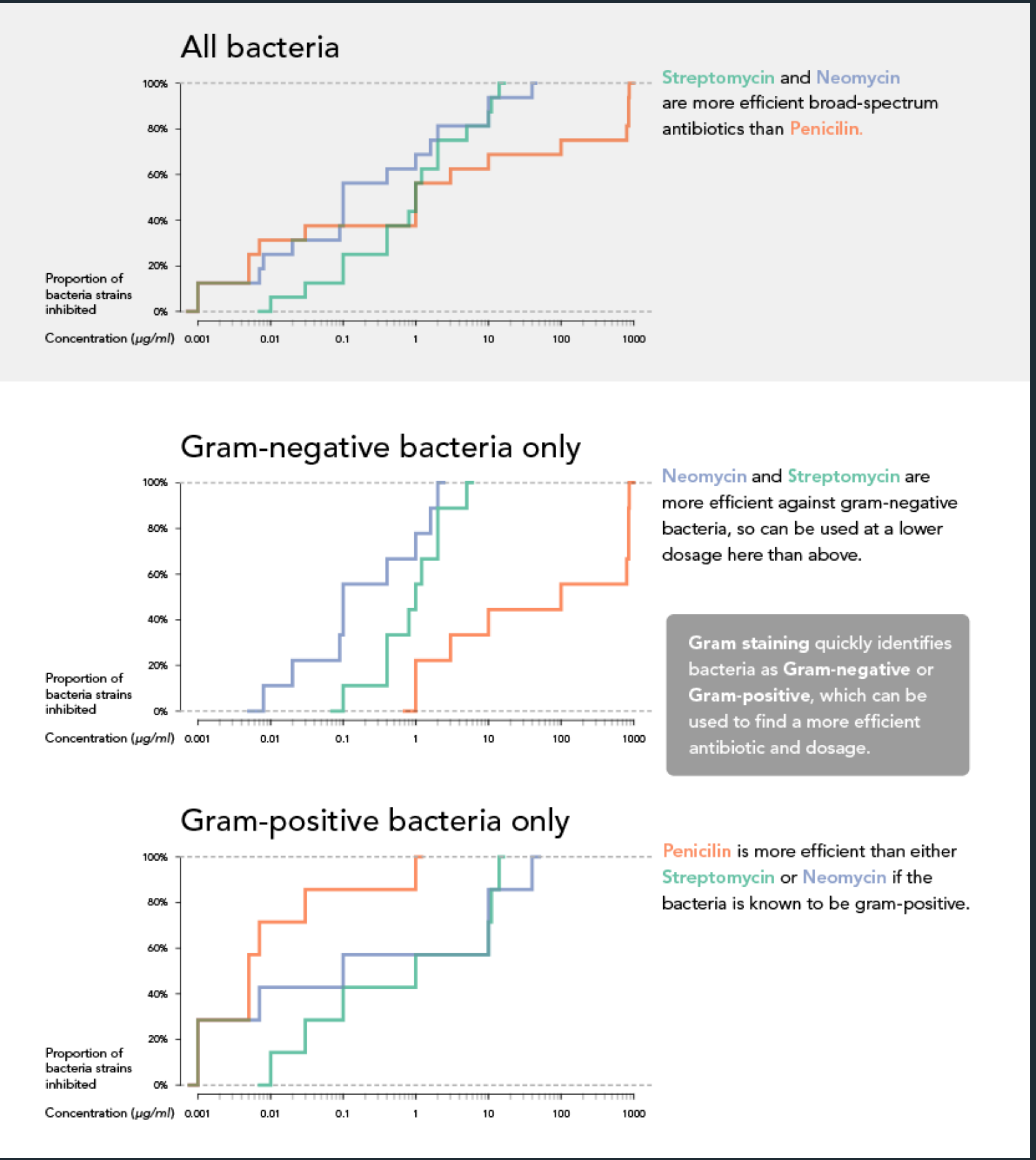
Y-Axis: Gram-Staining | Species

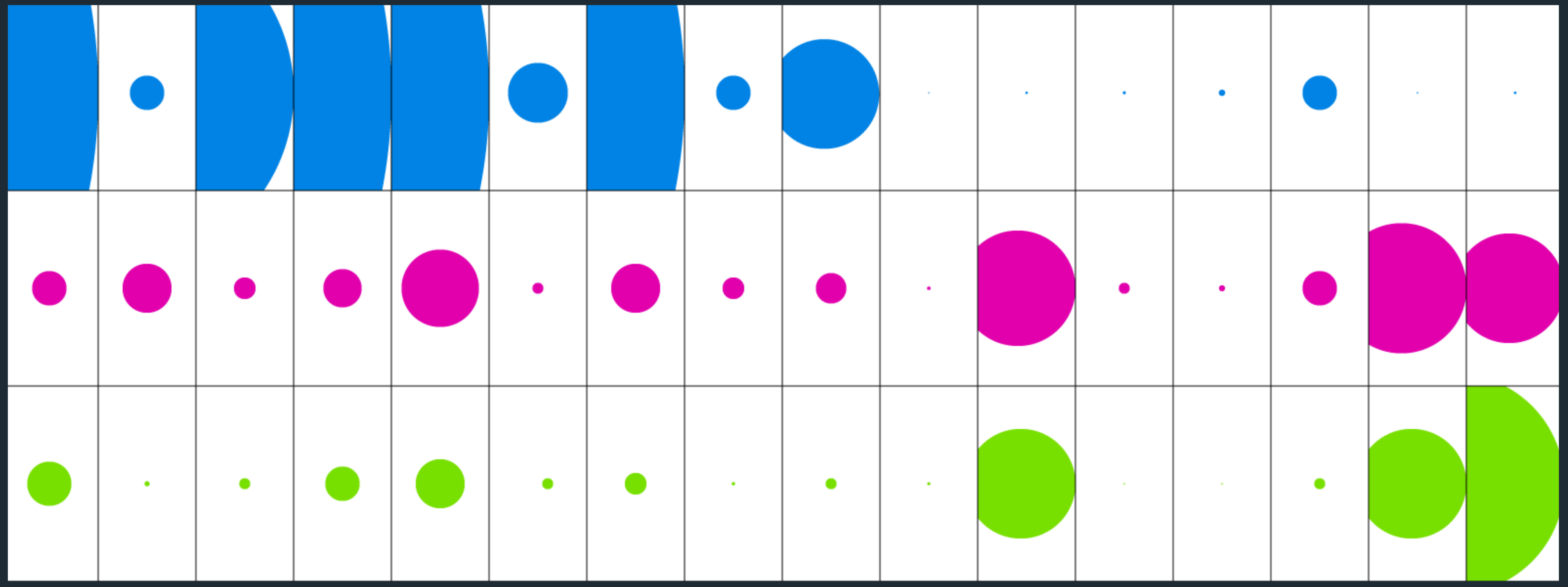
Color: Most Effective?

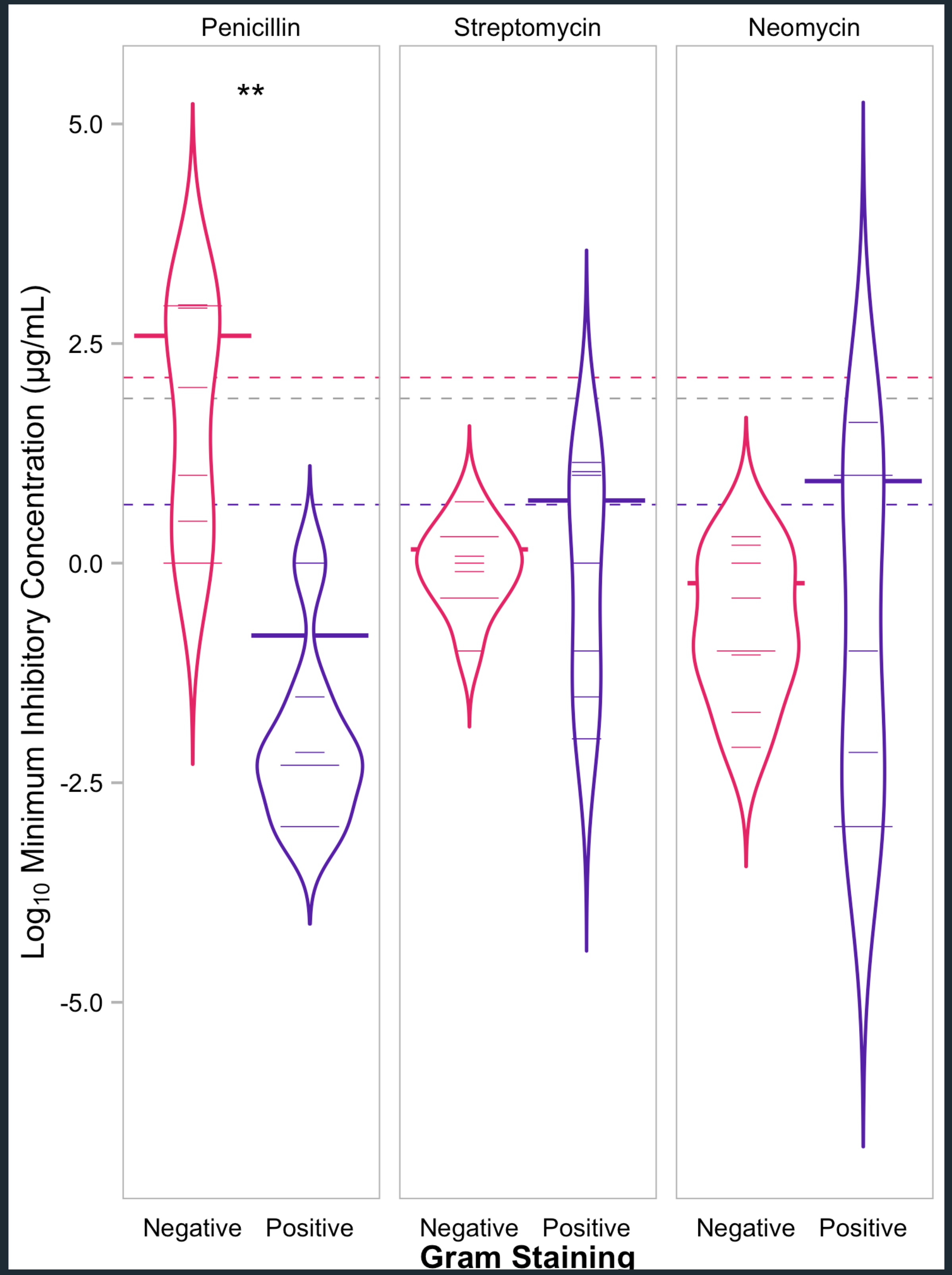
How do the drugs compare?

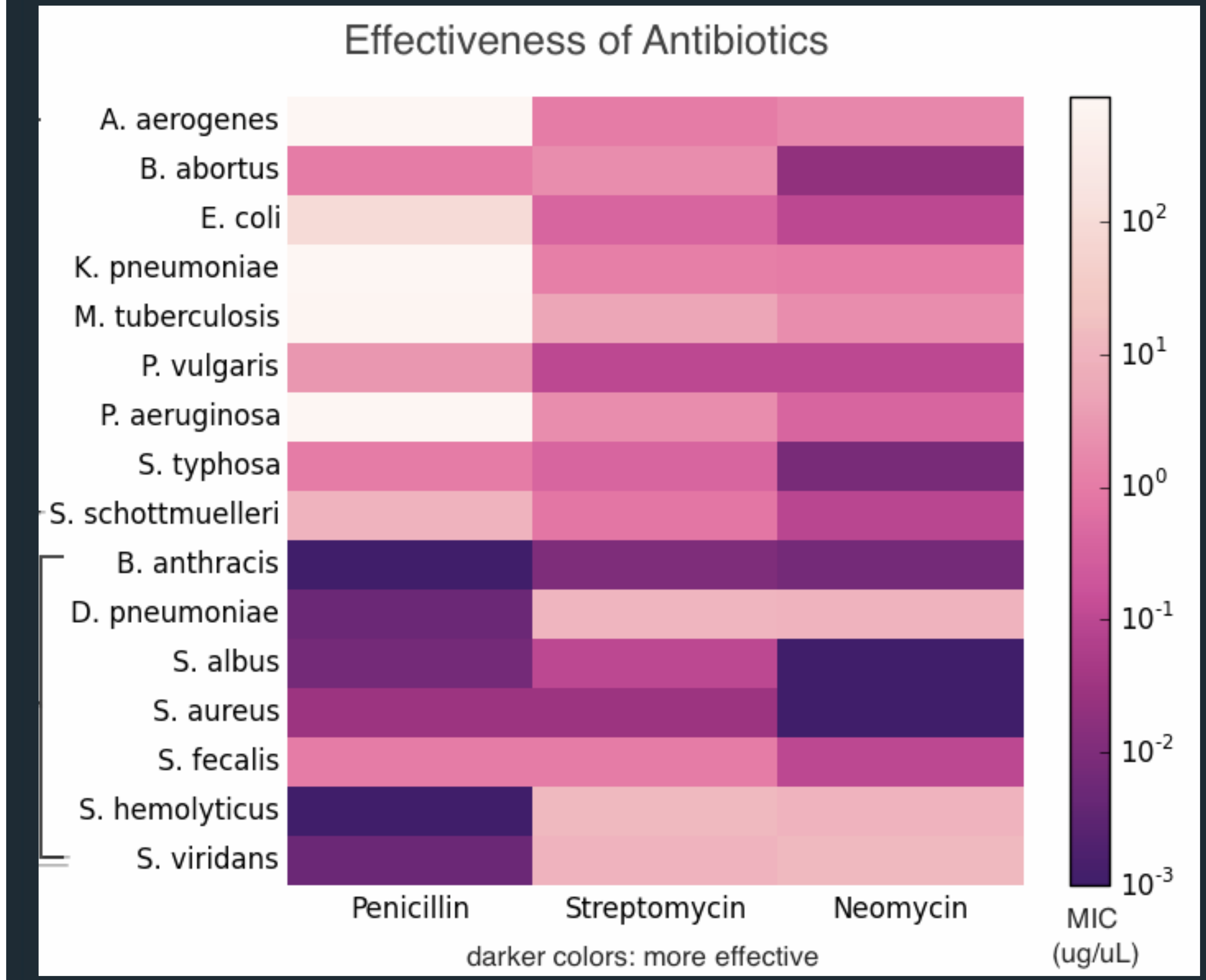


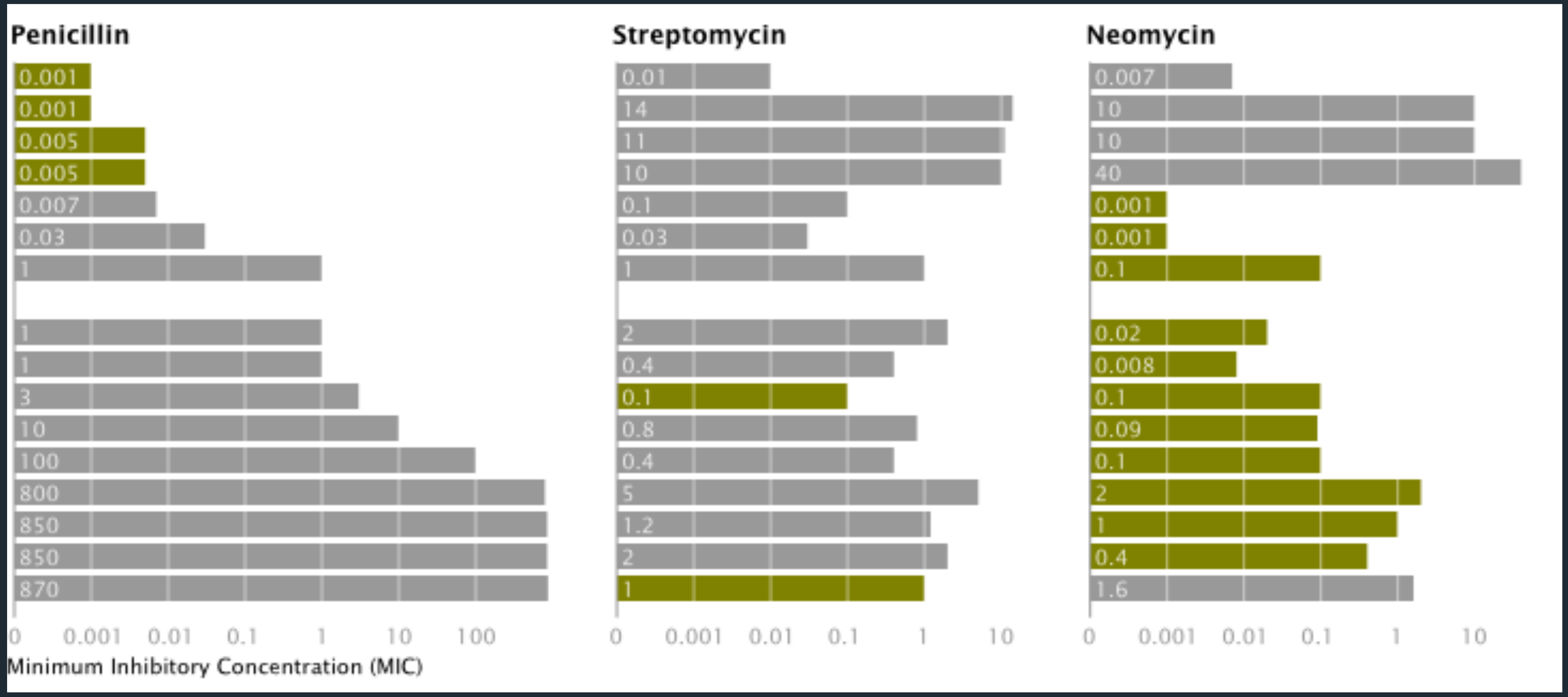
Bowen Li, *Stanford CS448b* (Fall 2009).


All bacteria
Streptomycin and Neomycin are more efficient broad-spectrum antibiotics than Penicilin.
Proportion of bacteria strains inhibited
Concentration (μg/ml)
Gram-negative bacteria only
Neomycin and Streptomycin are more efficient against gram-negative bacteria, so can be used at a lower dosage here than above.
Gram staining quickly identifies bacteria as Gram-negative or Gram-positive, which can be used to find a more efficient antibiotic and dosage.
Gram-positive bacteria only
Penicilin is more efficient than either Streptomycin or Neomycin if the bacteria is known to be gram-positive.

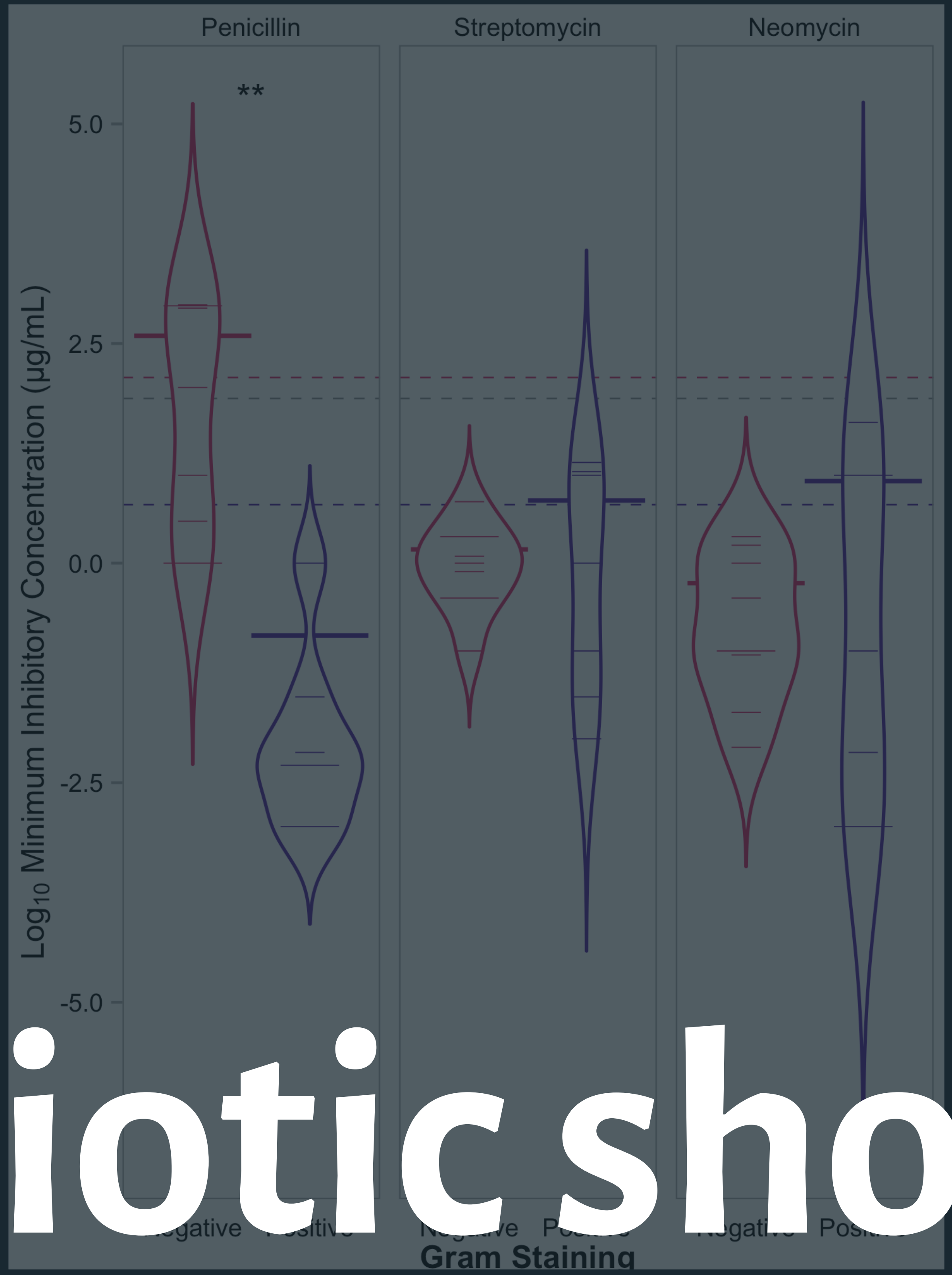


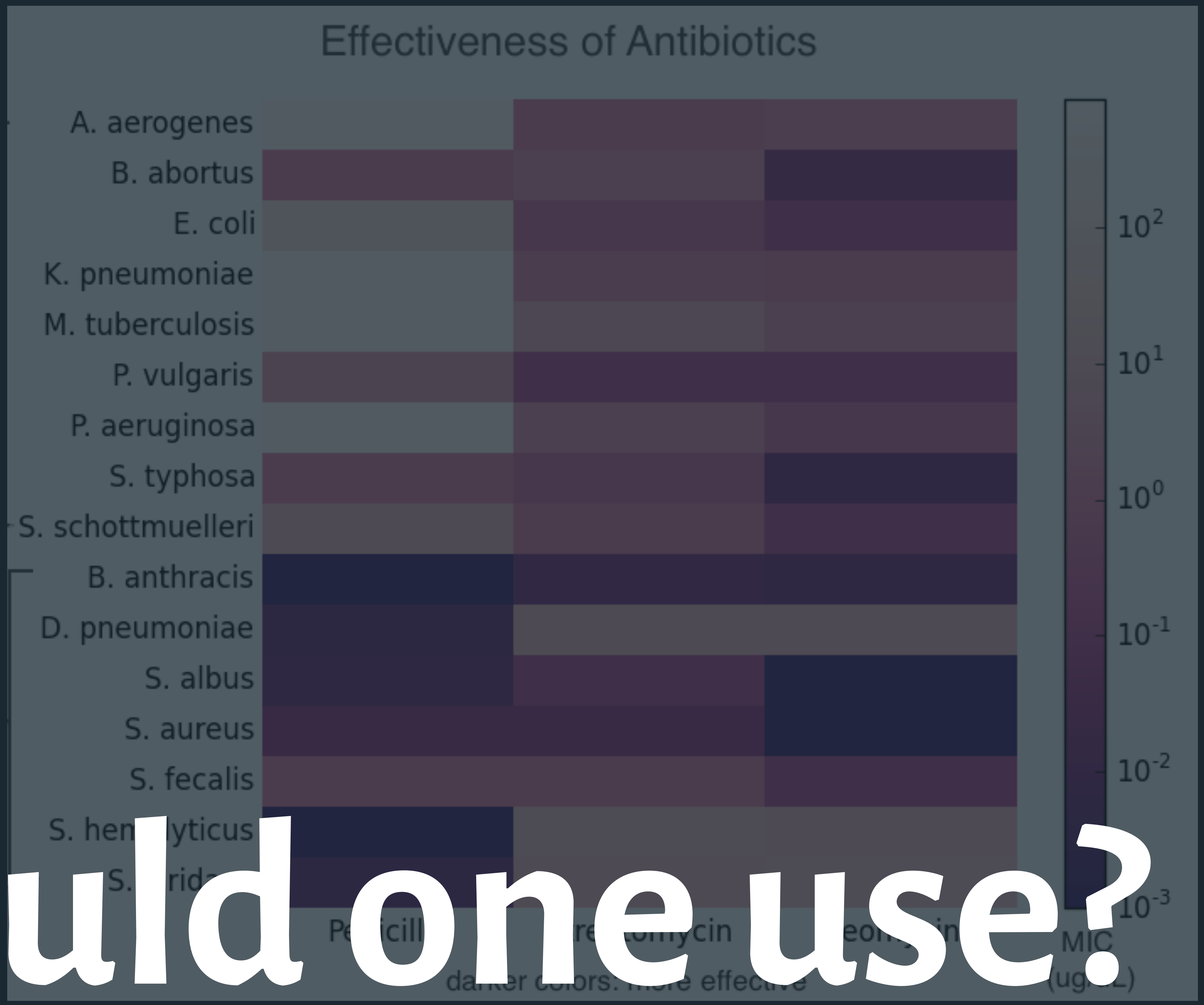

Penicillin
Streptomycin
Neomycin
Log10 Minimum Inhibitory Concentration (μg/mL)
Negative
Positive
Gram Staining

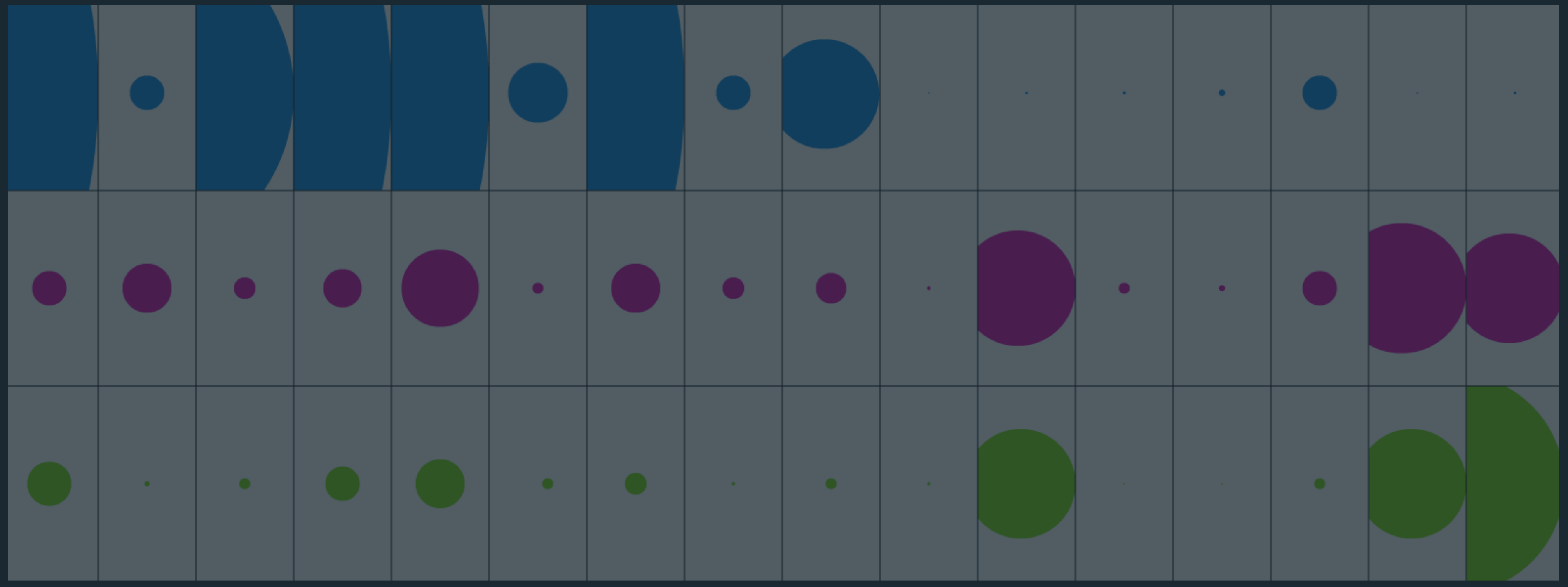

Effectiveness of Antibiotics
A. aerogenes
B. abortus
E. coli
K. pneumoniae
M. tuberculosis
P. vulgaris
P. aeruginosa
S. typhosa
S. schottmuelleri
B. anthracis
D. pneumoniae
S. albus
S. aureus
S. fecalis
S. hemolyticus
S. viridans
Penicillin
Streptomycin
Neomycin
darker colors: more effective
MIC (ug/uL)

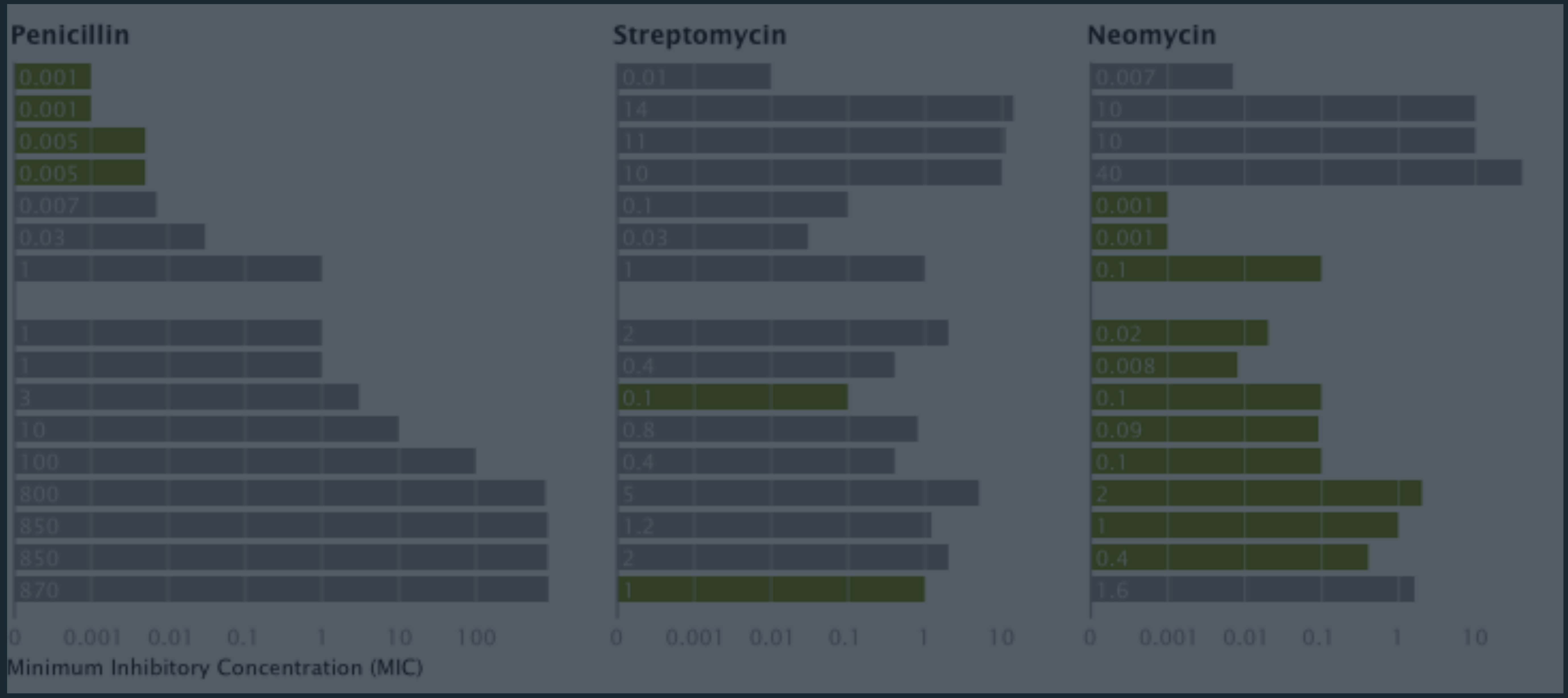

Penicillin
Streptomycin
Neomycin
Minimum Inhibitory Concentration (MIC)

Which antibiotic should one use?

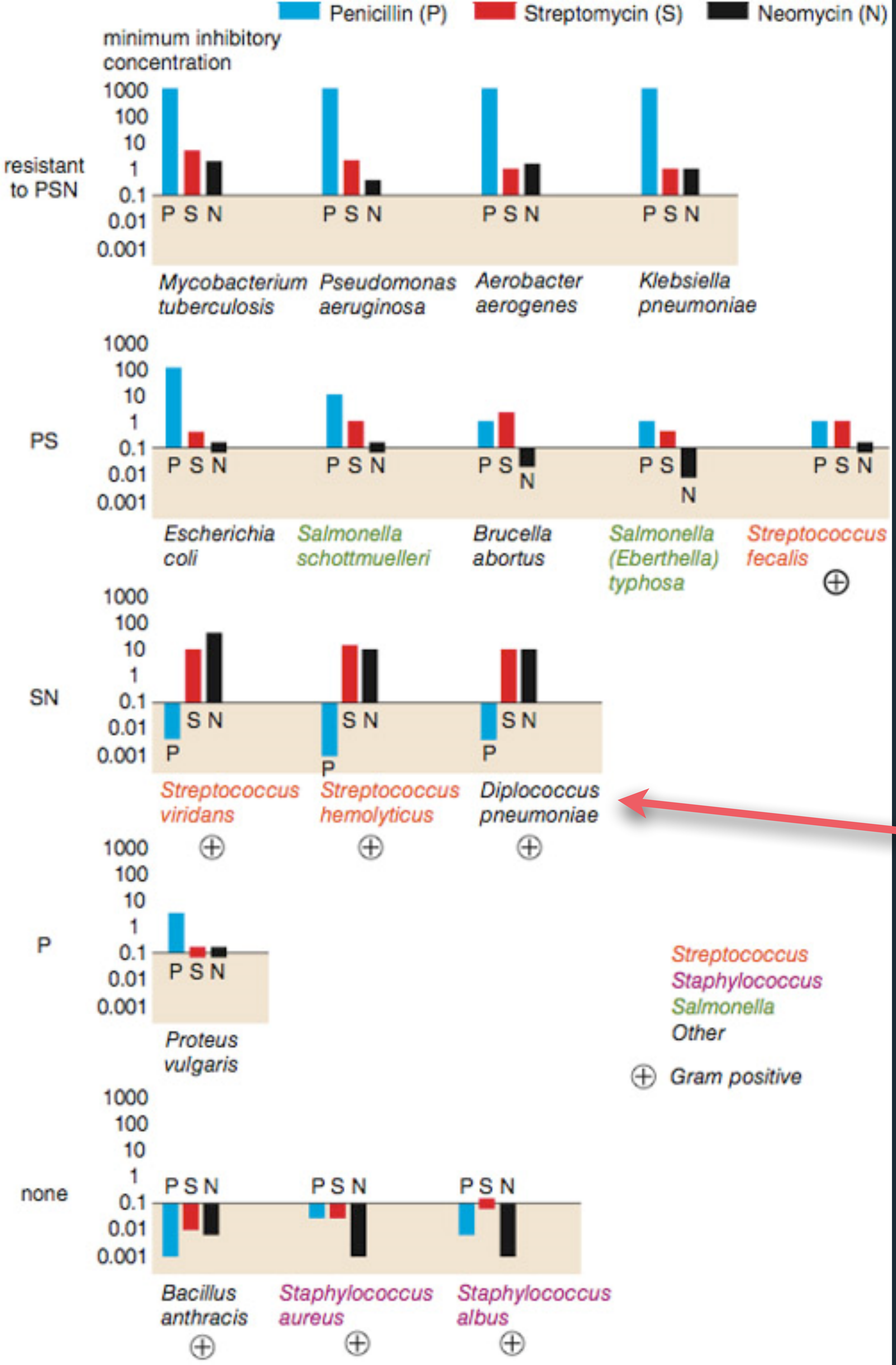








Do the bacteria group by antibiotic resistance?



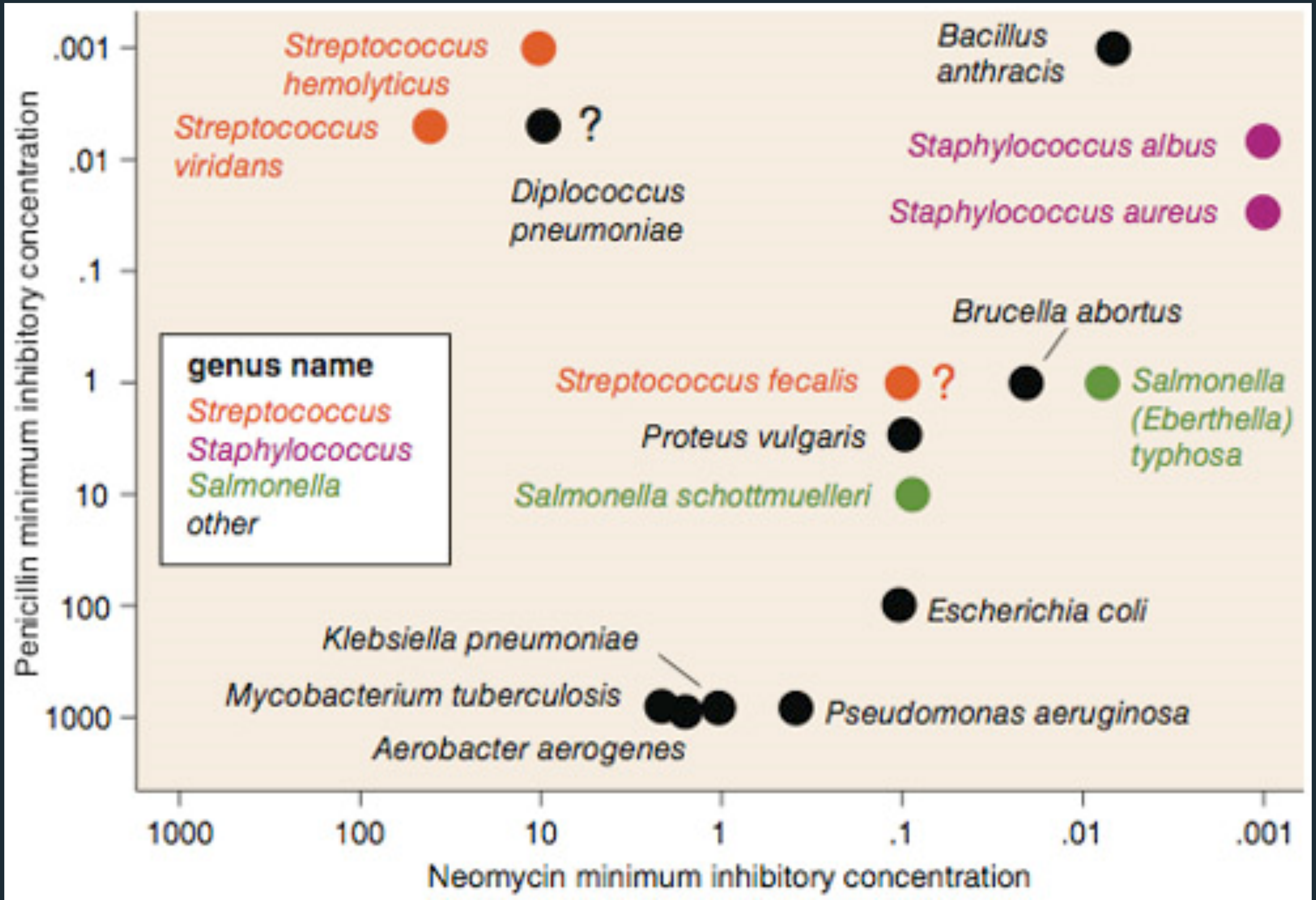
Wainer & Lysen. *American Scientist*, 2009

Not a streptococcus!
(realized ~30 yrs later)

Really a streptococcus!
(realized ~20 yrs later)

Do the bacteria group by resistance?
Do different drugs correlate?

Wainer & Lysen. *American Scientist*, 2009



Exploratory Visual Analysis

Process

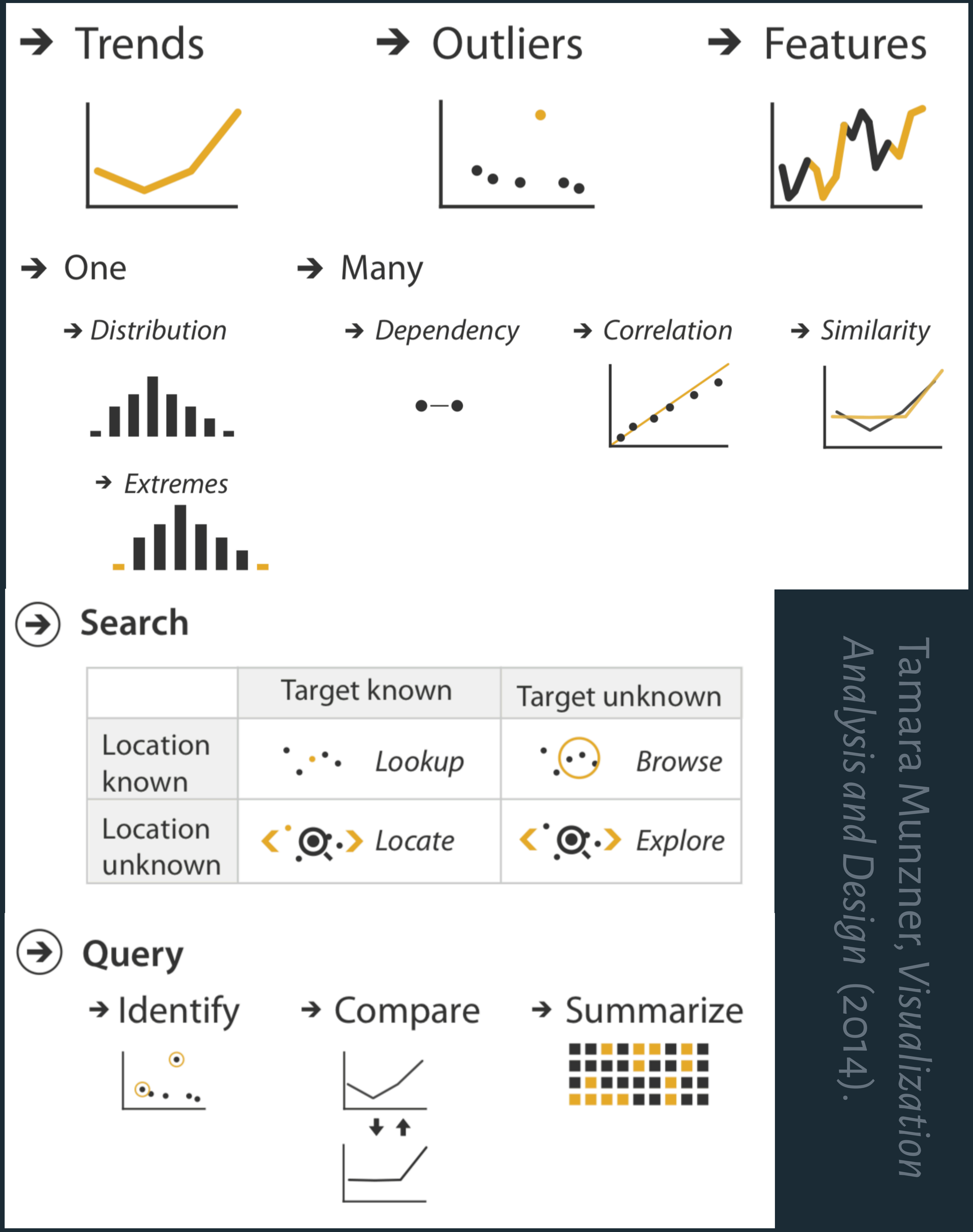
1. Construct graphics to address questions.
2. Inspect "answer" and ask new questions.
3. Iterate…

Lessons

✓ Check **data quality** and your **assumptions**.

✓ Start with **univariate summaries**, then consider **relationships between variables**.

✓ Avoid **premature fixation:** balance **data variation** and **design variation**.



Tamara Munzner, *Visualization Analysis and Design* (2014).

PART TWO

Exploratory Visual Analysis

PART THREE

Visualizing Uncertainty

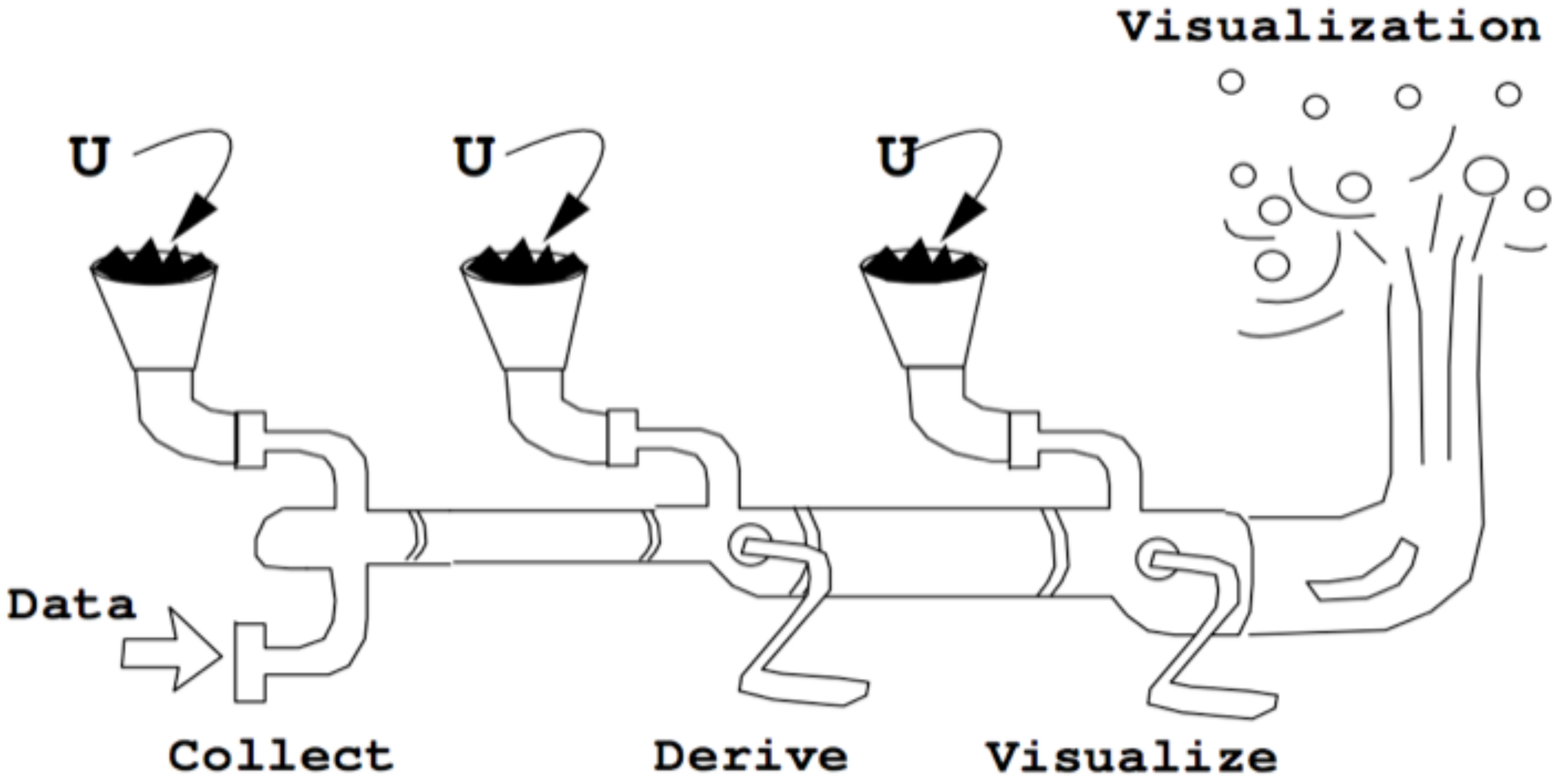
The possibility of many/other outcomes.

PART THREE

Visualizing Uncertainty

Sources & Types of Uncertainty

The possibility of many/other outcomes.

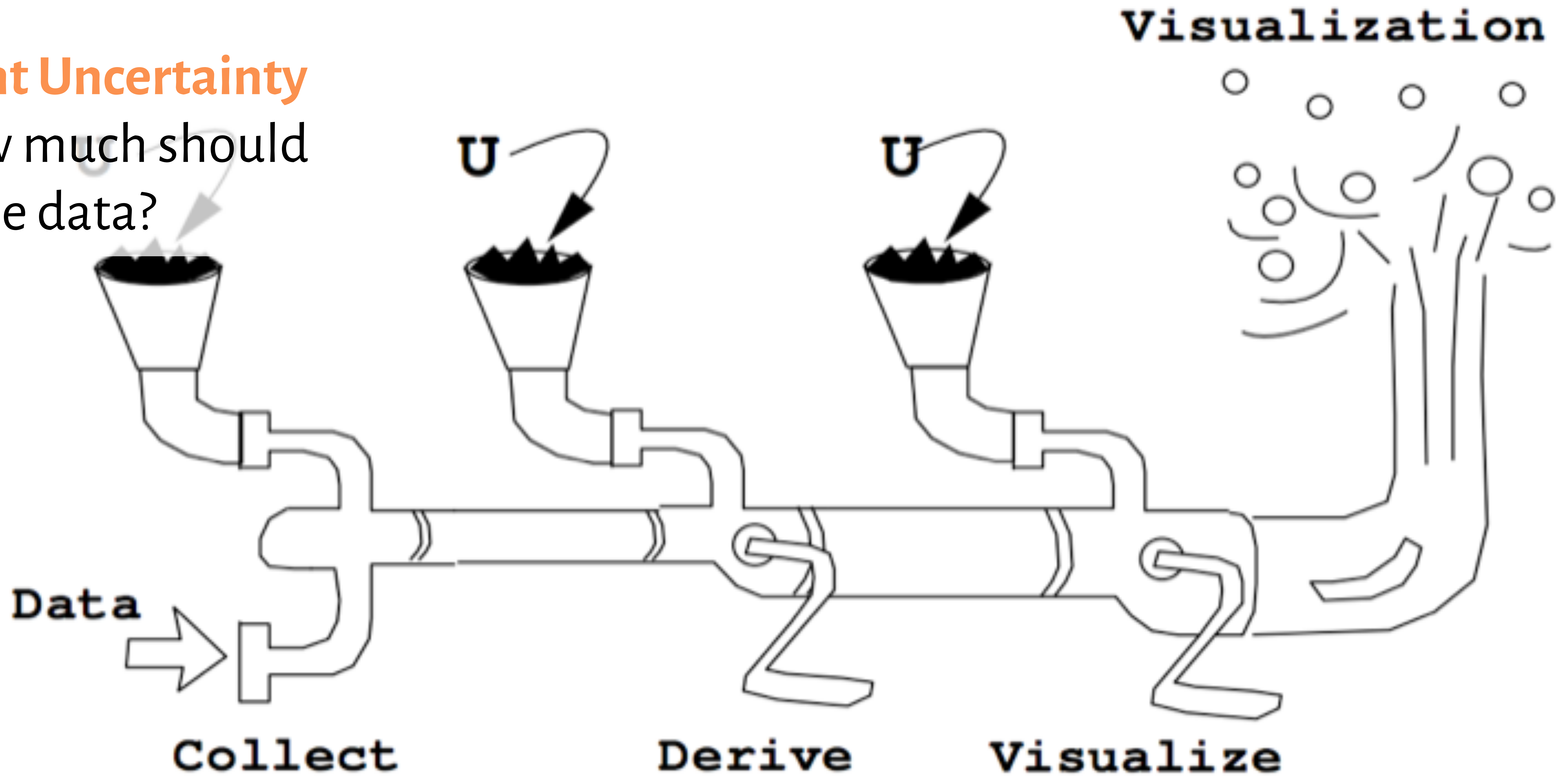


[Pang, Wittenbrink, Lodha. Approaches to Uncertainty Visualization.]

Sources & Types of *Uncertainty*

The possibility of many/other outcomes.

Measurement Uncertainty
How and how much should we sample the data?



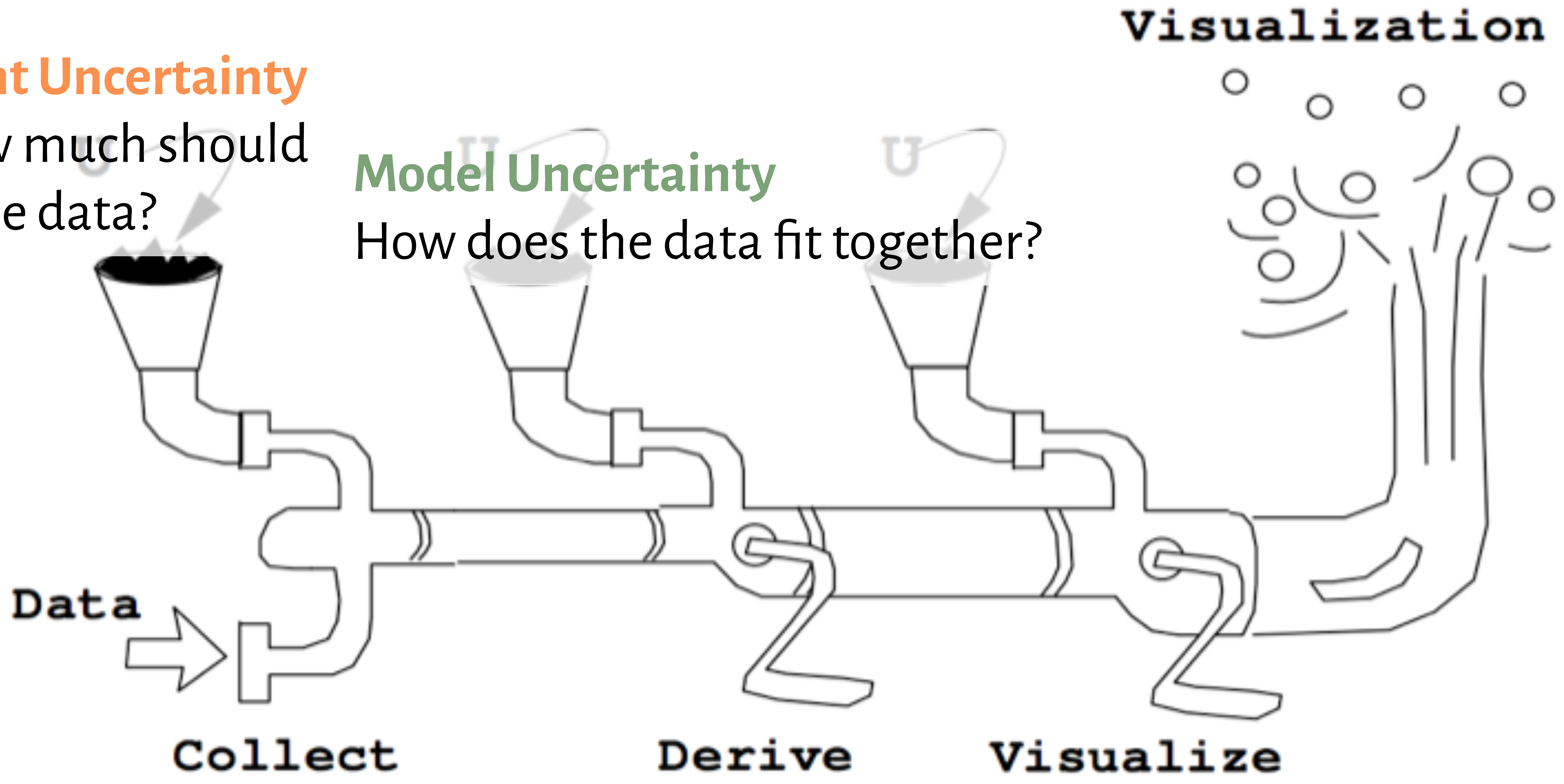
[Pang, Wittenbrink, Lodha. Approaches to Uncertainty Visualization.]

Sources & Types of *Uncertainty*

The possibility of many/other outcomes.

Measurement Uncertainty
How and how much should we sample the data?

Model Uncertainty
How does the data fit together?



[Pang, Wittenbrink, Lodha. Approaches to Uncertainty Visualization.]

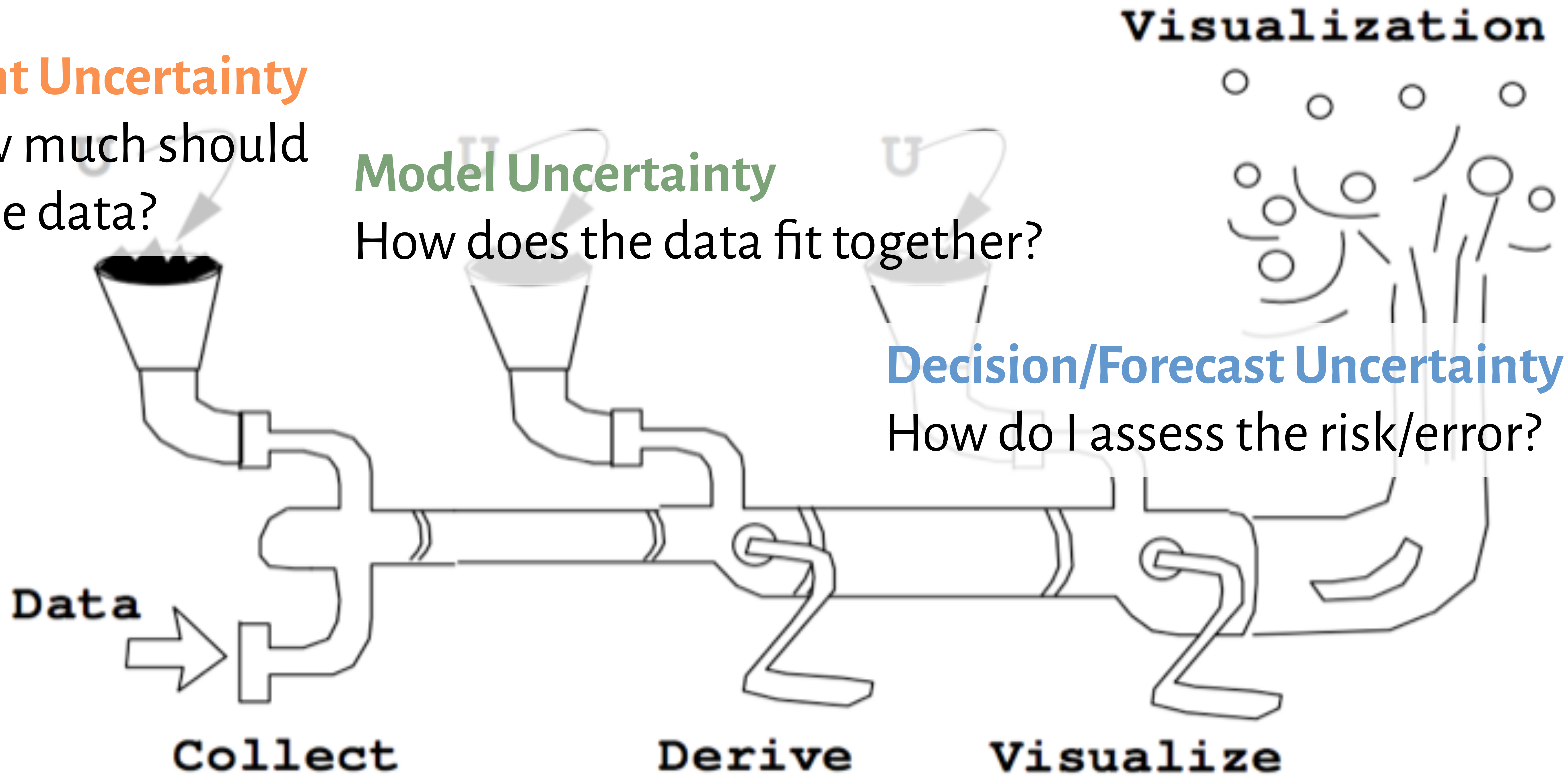
Sources & Types of *Uncertainty*

The possibility of many/other outcomes.

Measurement Uncertainty
How and how much should we sample the data?

Model Uncertainty
How does the data fit together?

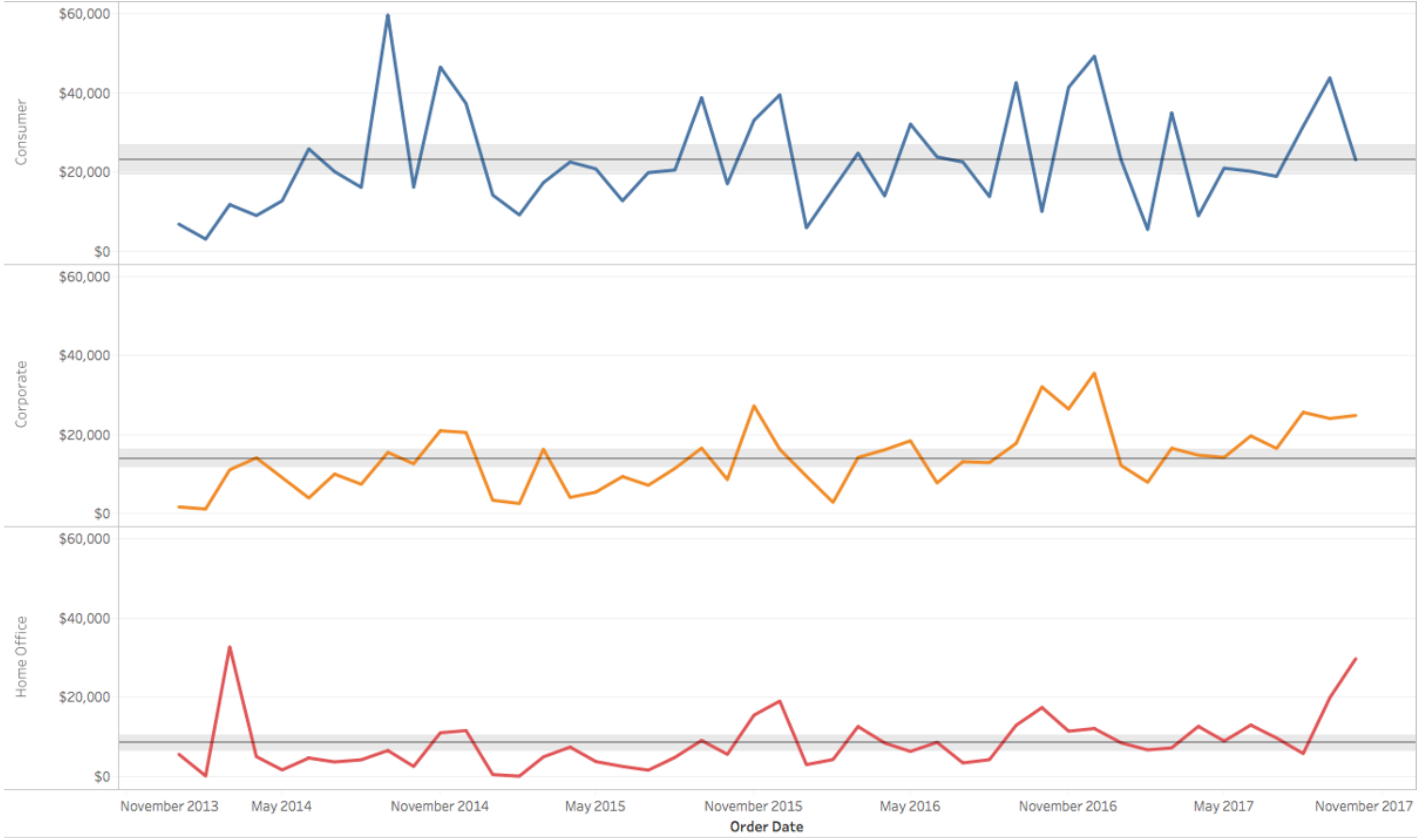
Decision/Forecast Uncertainty
How do I assess the risk/error?



[Pang, Wittenbrink, Lodha. Approaches to Uncertainty Visualization.]

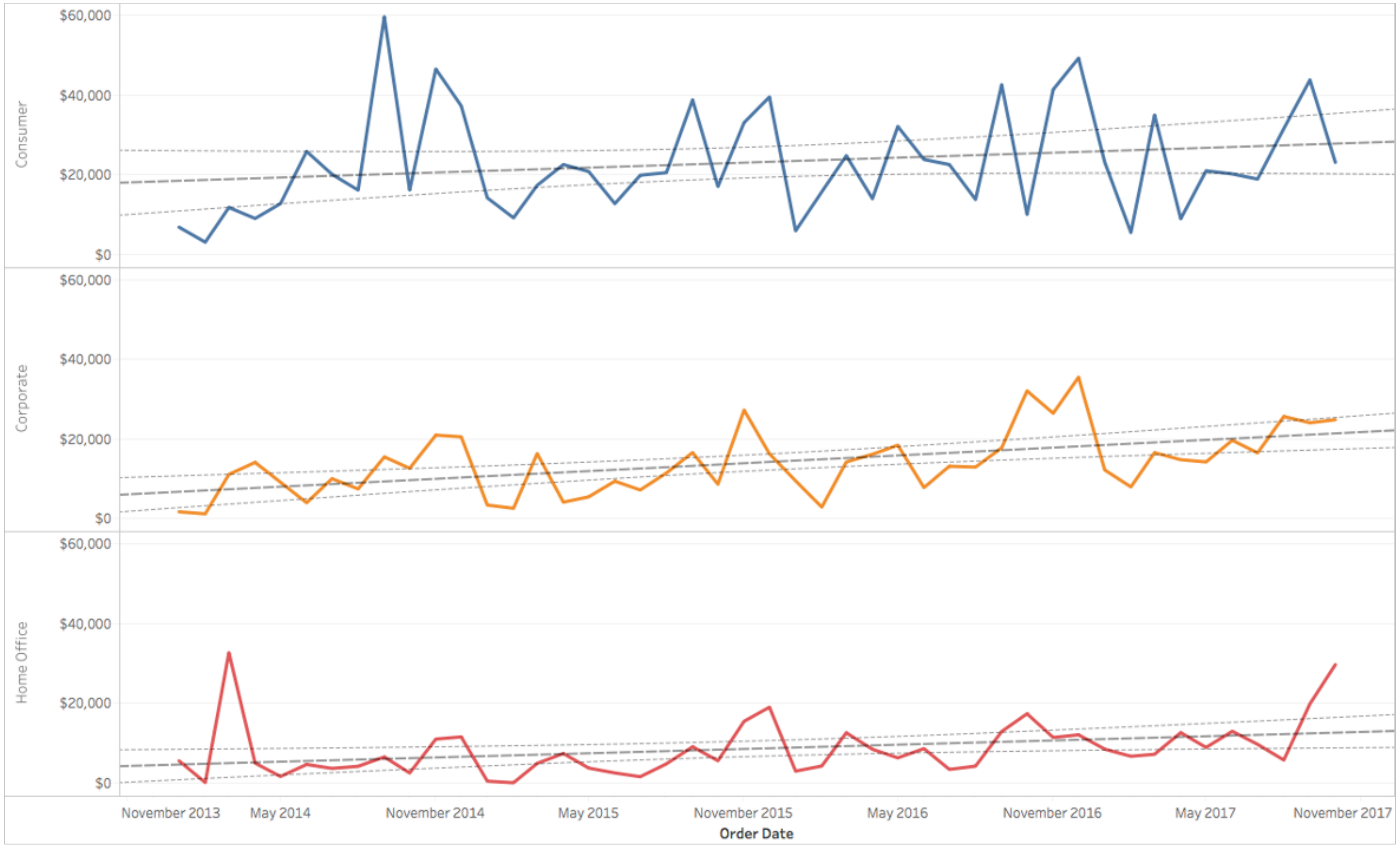
Visualizing Uncertainty

Measurement uncertainty in Tableau



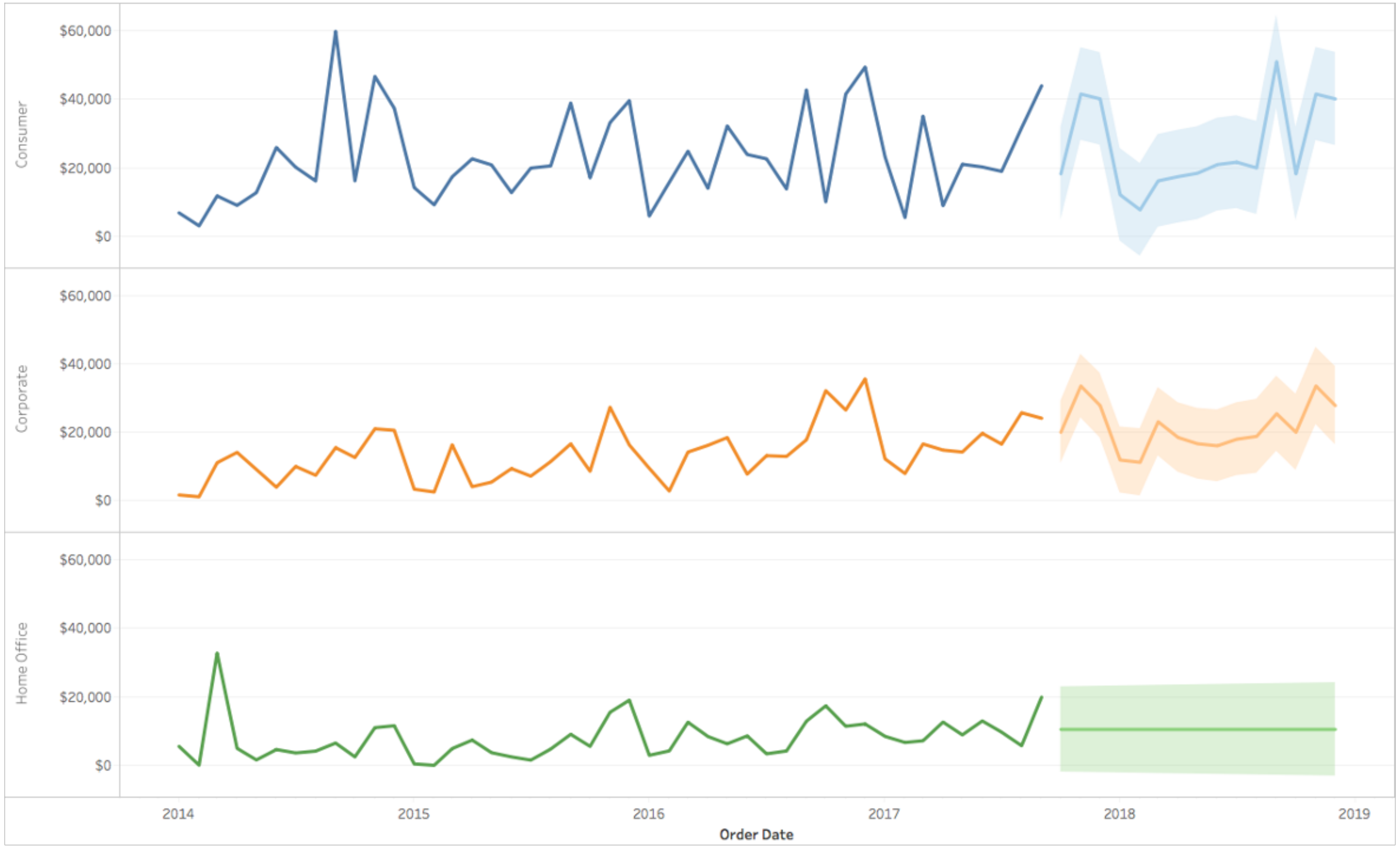
Visualizing Uncertainty

Model uncertainty in Tableau

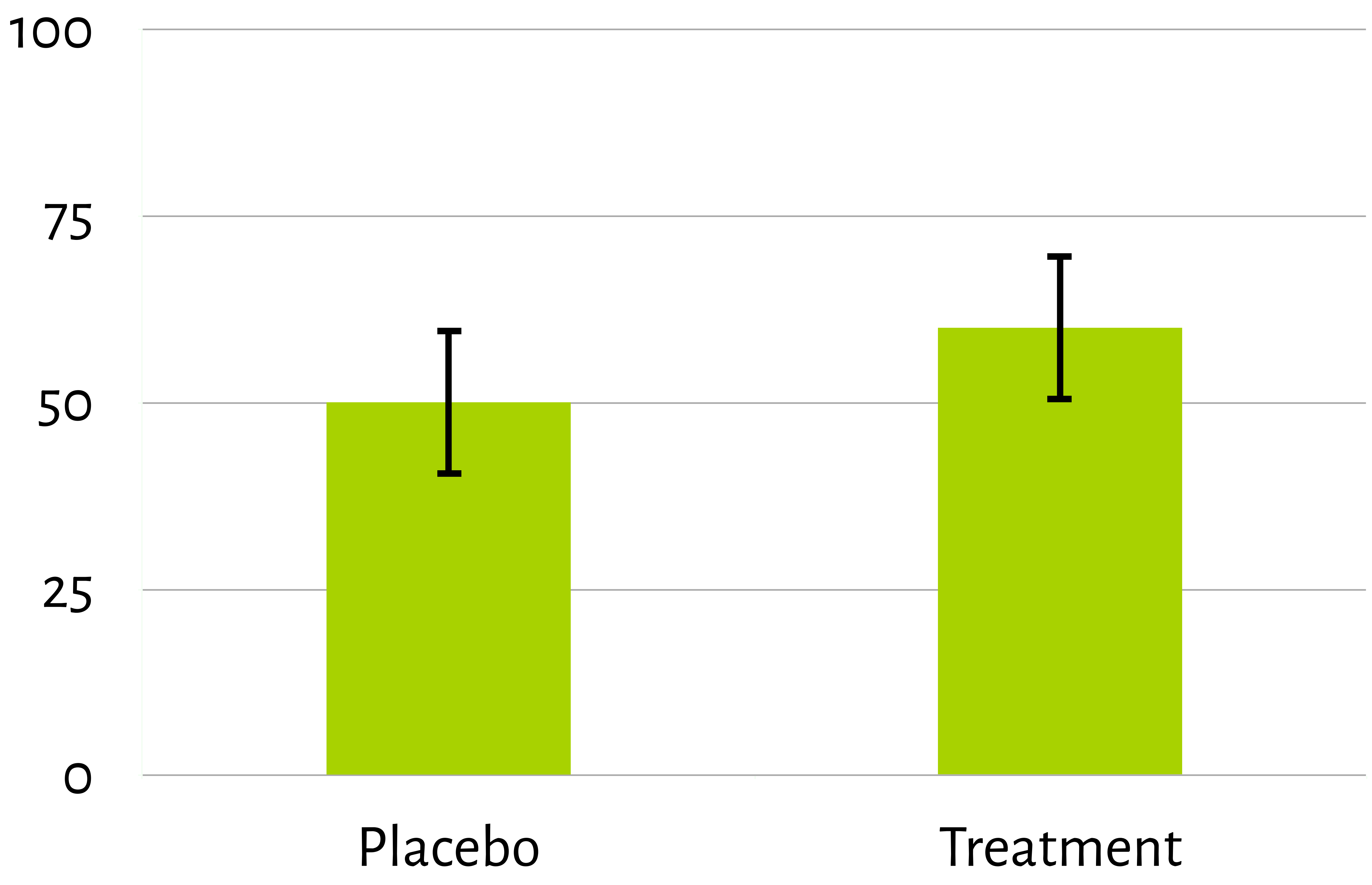


Visualizing Uncertainty

Forecast uncertainty in Tableau

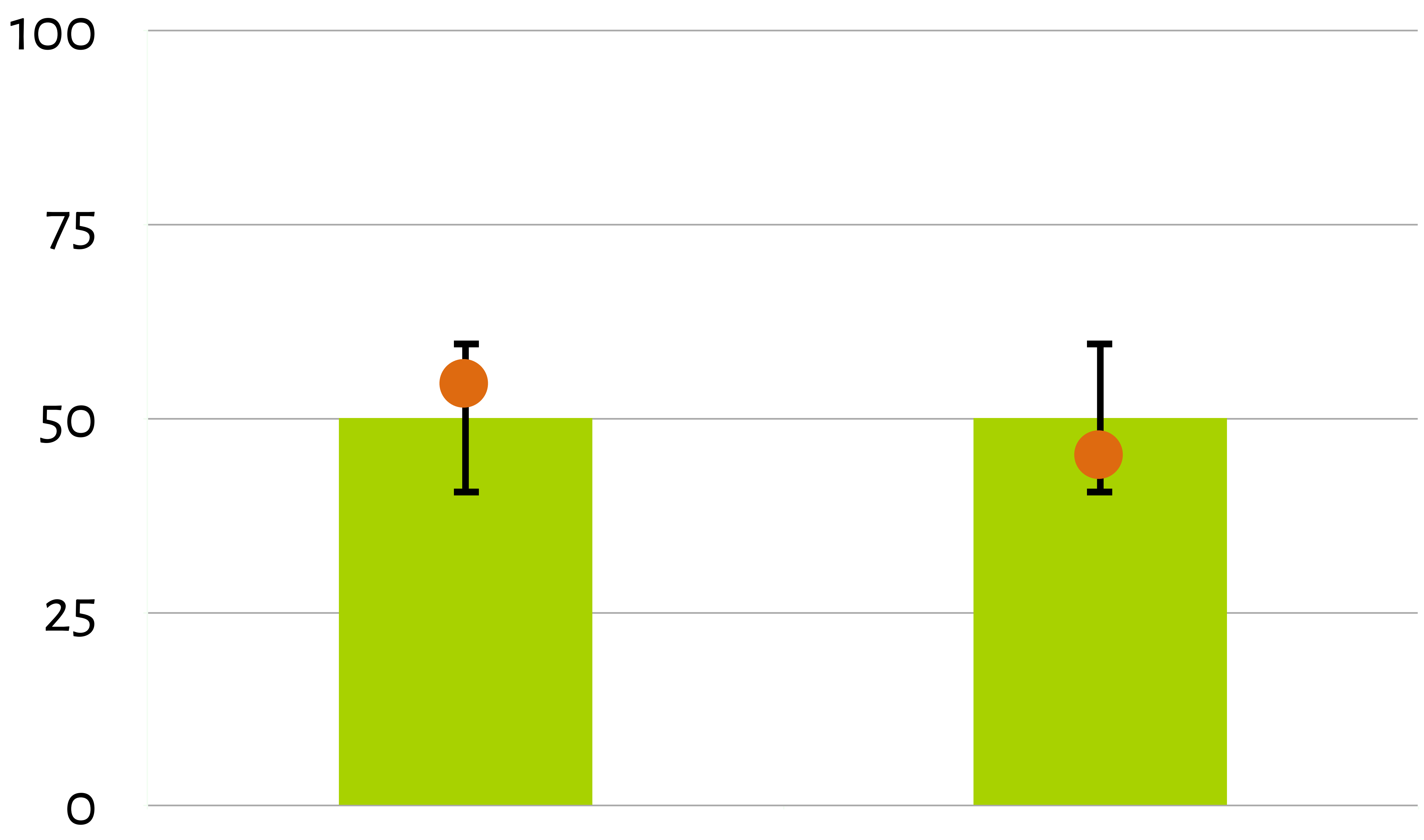


Visualizing Uncertainty: Glyphs



✘ Error bars **aren't consistently used** to visualize the same measure (standard deviation, standard error, IQR, 95% CI).

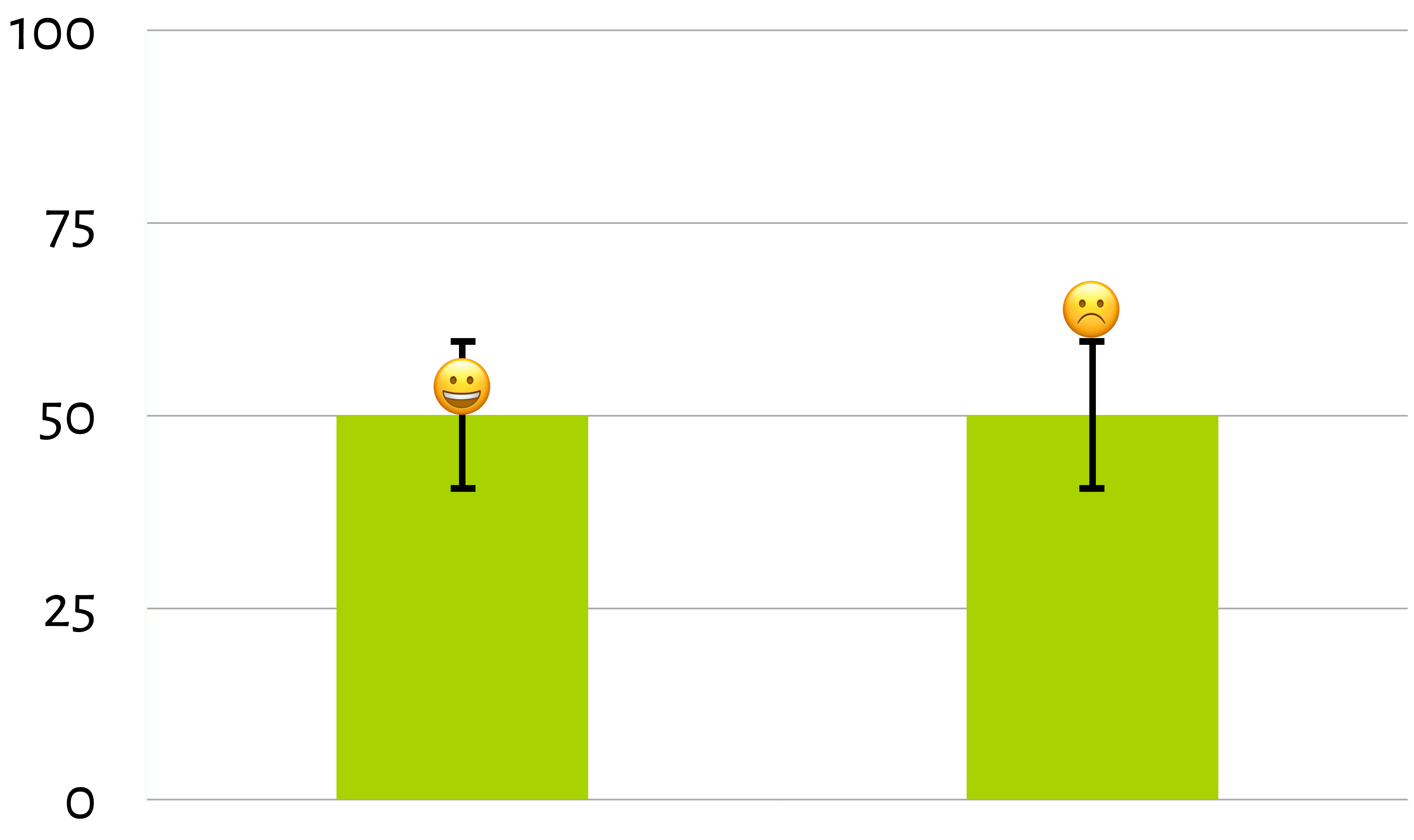
Visualizing Uncertainty: Glyphs



- ✘ Error bars **aren't consistently used** to visualize the same measure (standard deviation, standard error, IQR, 95% CI).
- ✘ **Within-the-bar bias**: people perceive points falling within the bar as more likely than those that lie outside.

[Newman & Scholl, 2012]
[Correll & Gleicher, 2014]

Visualizing Uncertainty: Glyphs



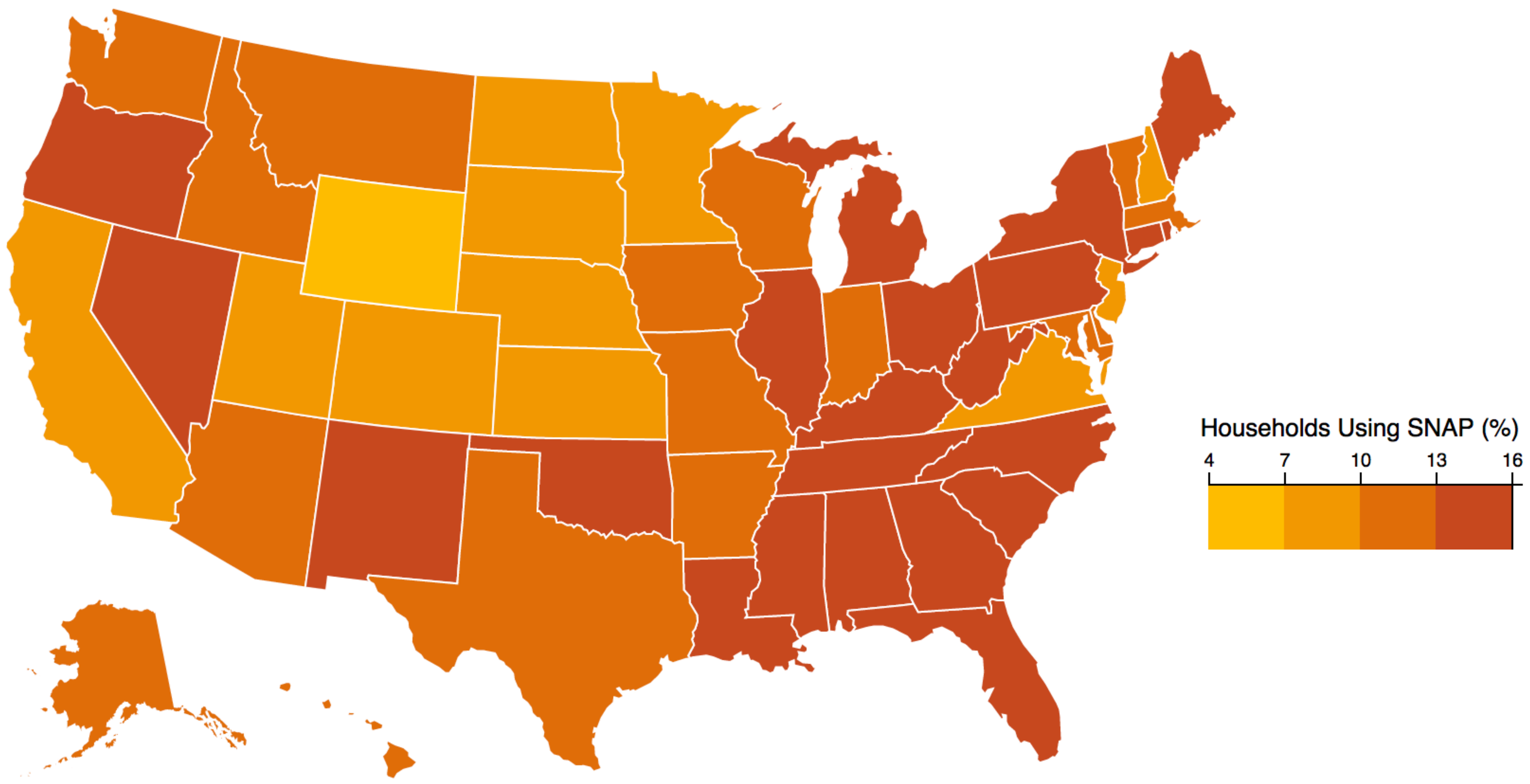
- ✘ Error bars **aren't consistently used** to visualize the same measure (standard deviation, standard error, IQR, 95% CI).
- ✘ **Within-the-bar bias**: people perceive points falling within the bar as more likely than those that lie outside.
- ✘ **Binary bias**: people perceive values to either be in or out of the margins of error.

[Newman & Scholl, 2012]
[Correll & Gleicher, 2014]

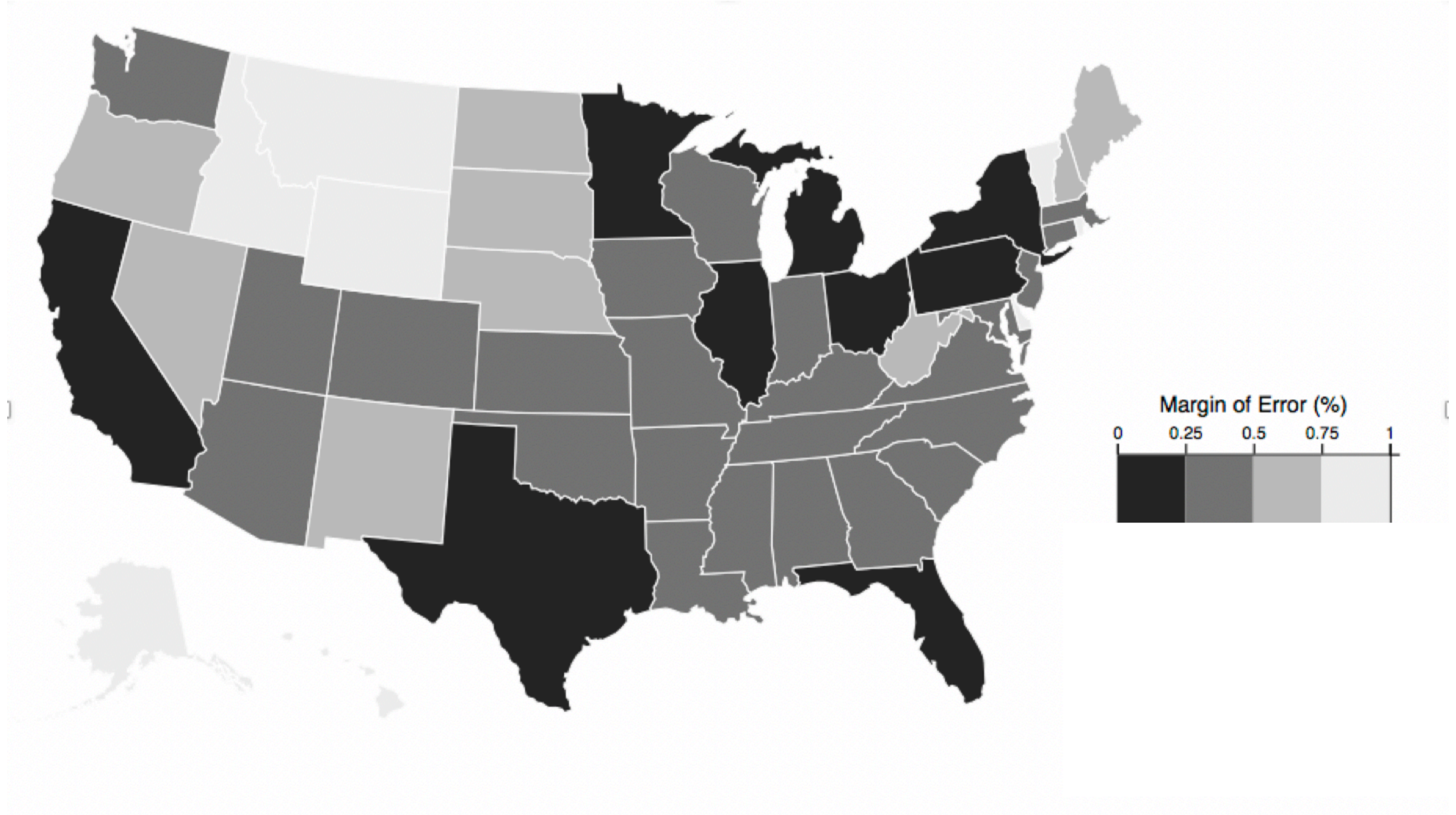
Visualizing Uncertainty: Visual Variables

[Matejka & Fitzmaurice, 2017]
[Correll & Gleicher, 2014]

Visualizing Uncertainty: Visual Variables



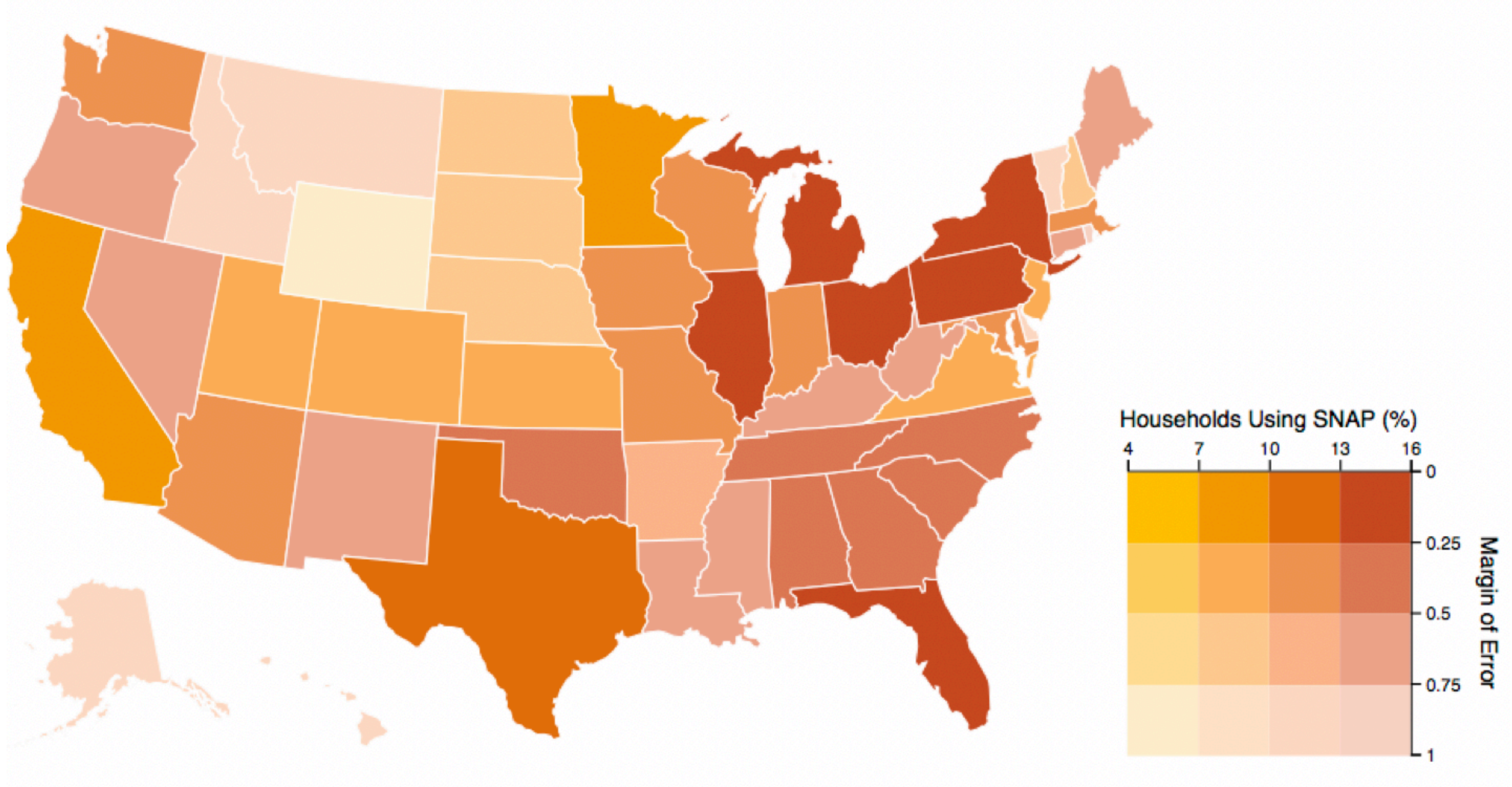
Data Map



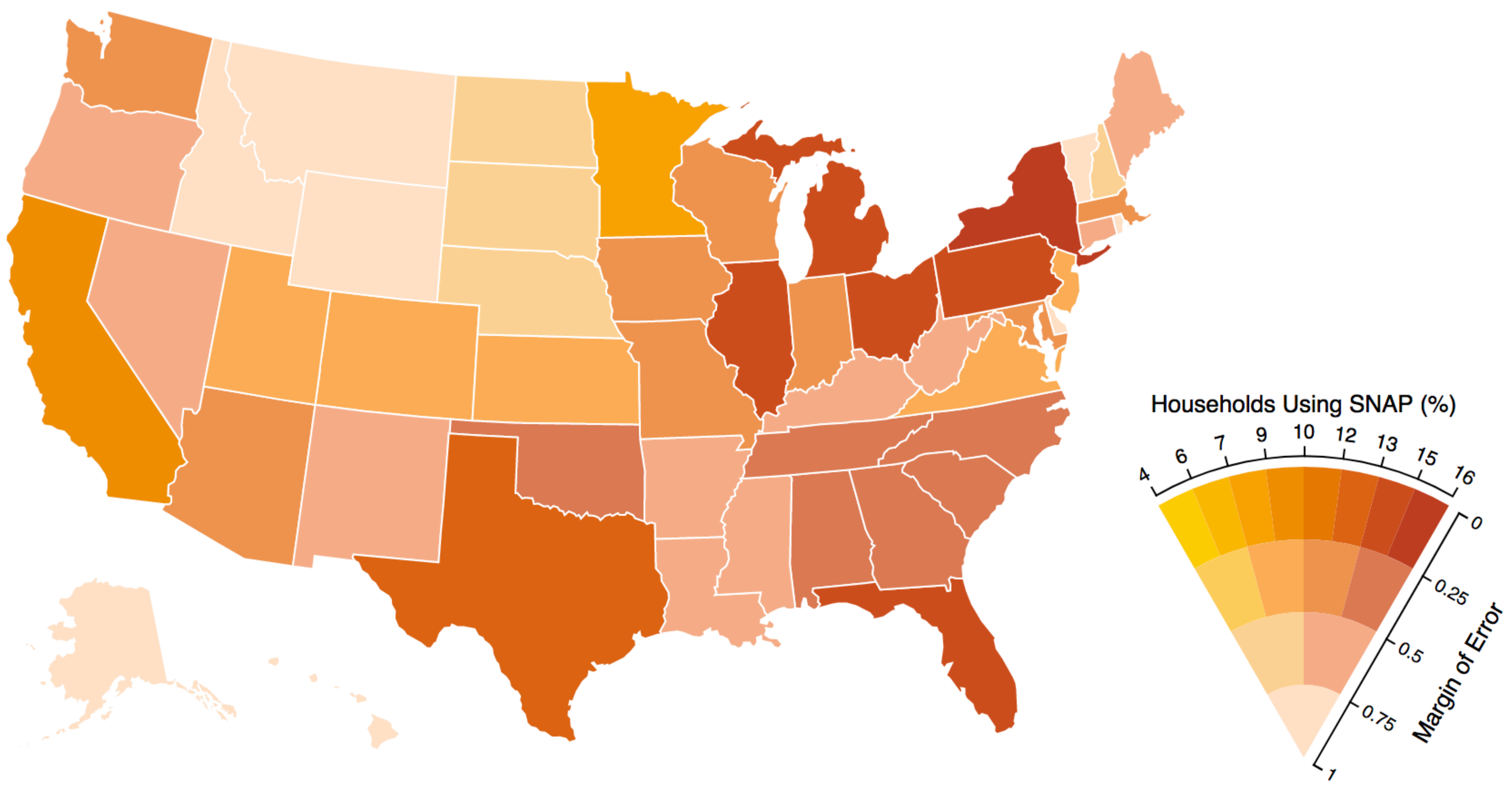
Uncertainty Map

[Correll, Moritz, & Heer, 2018]

Visualizing Uncertainty: Visual Variables



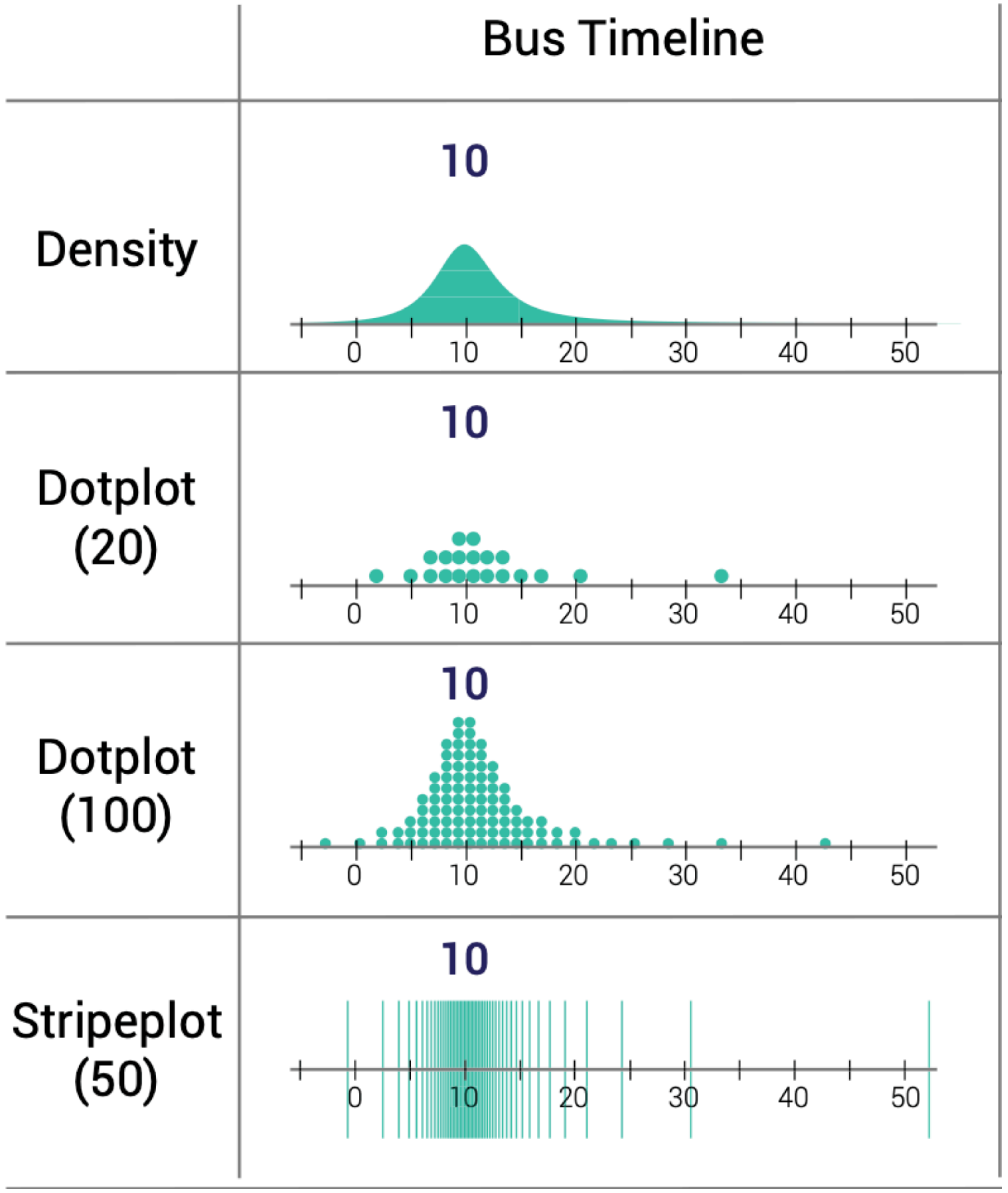
Bivariate Map (Data + Uncertainty)

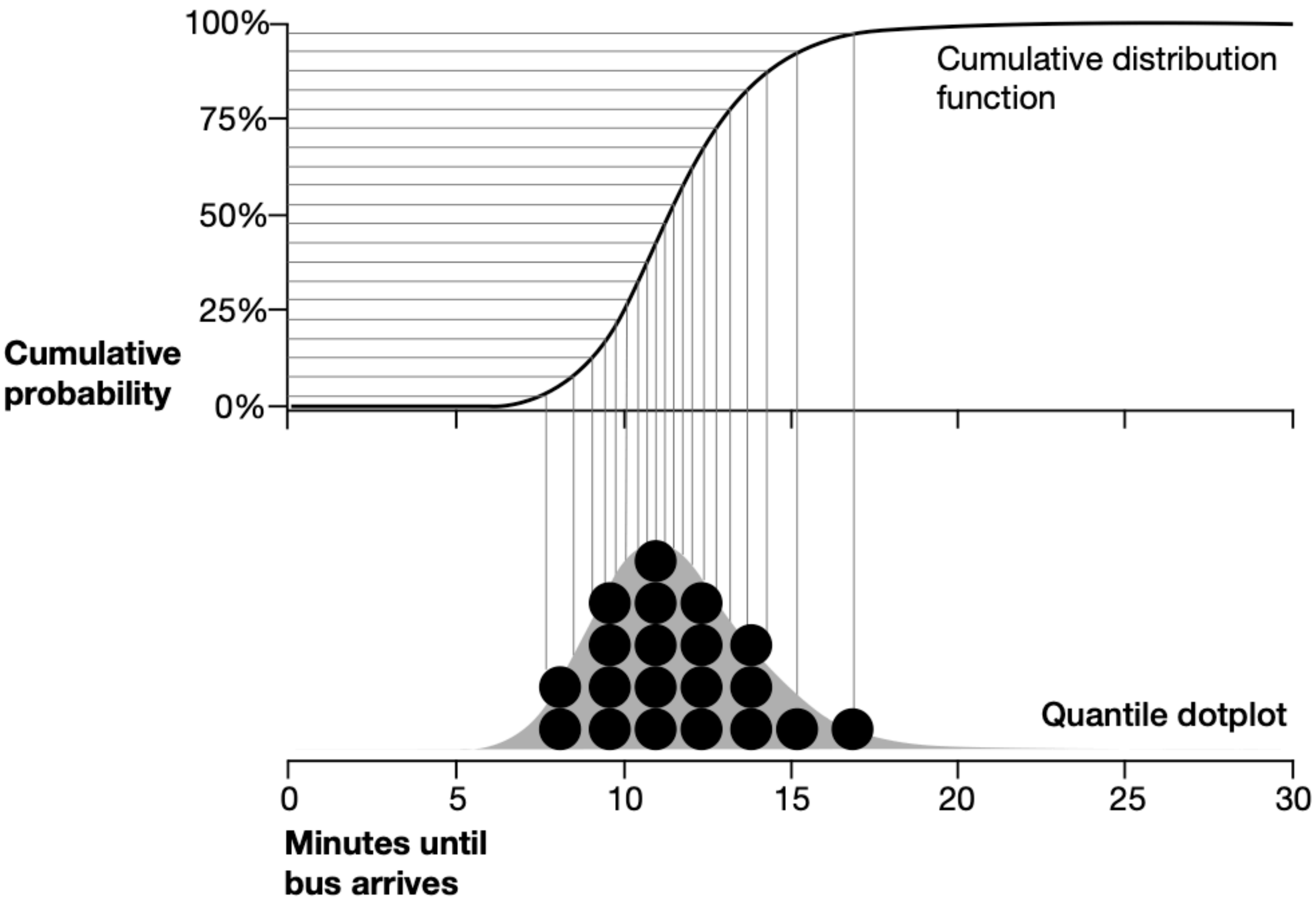


Value-Suppressing Uncertainty Map

[Correll, Moritz, & Heer, 2018]

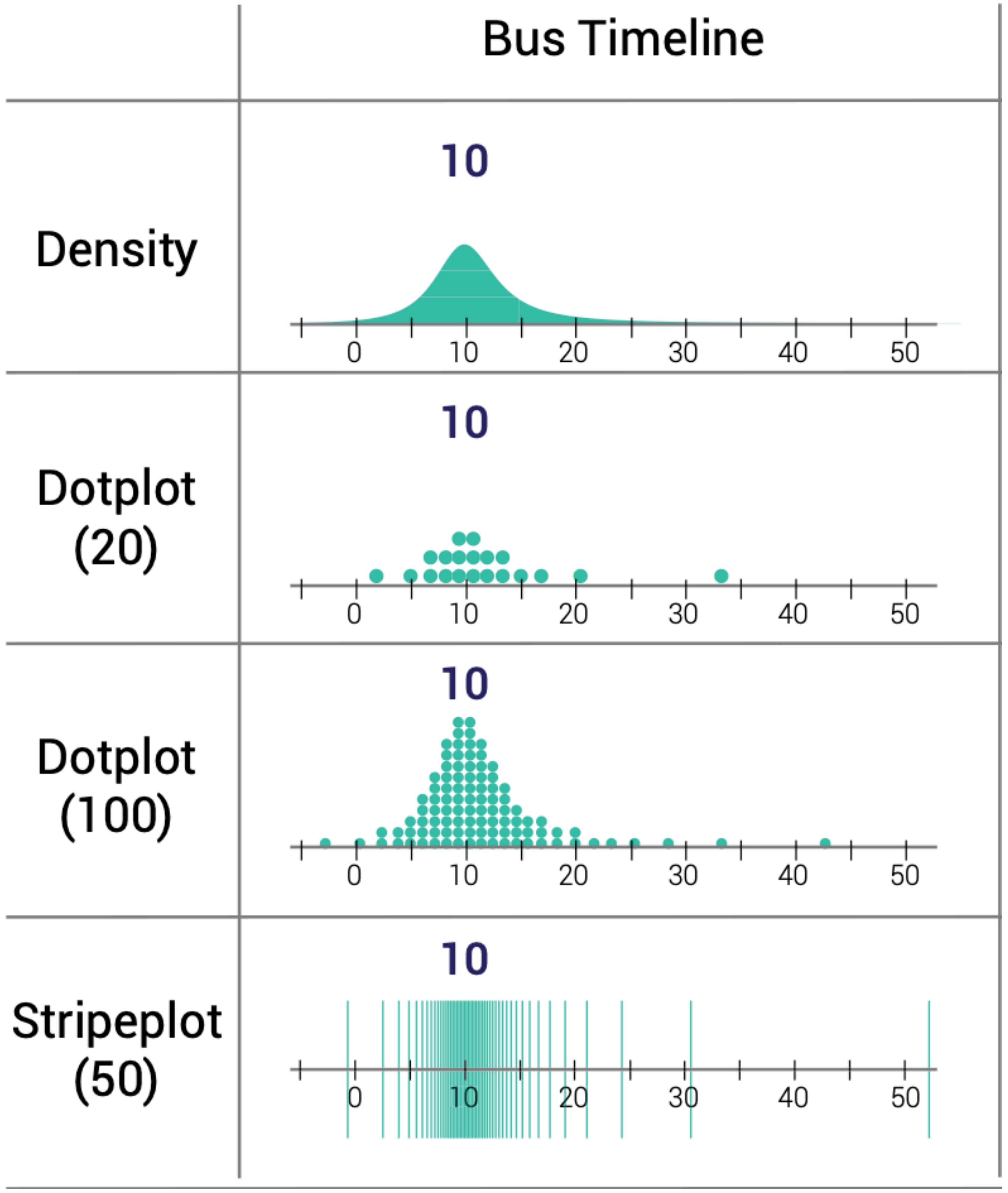
Visualizing Uncertainty: Set of "Draws"

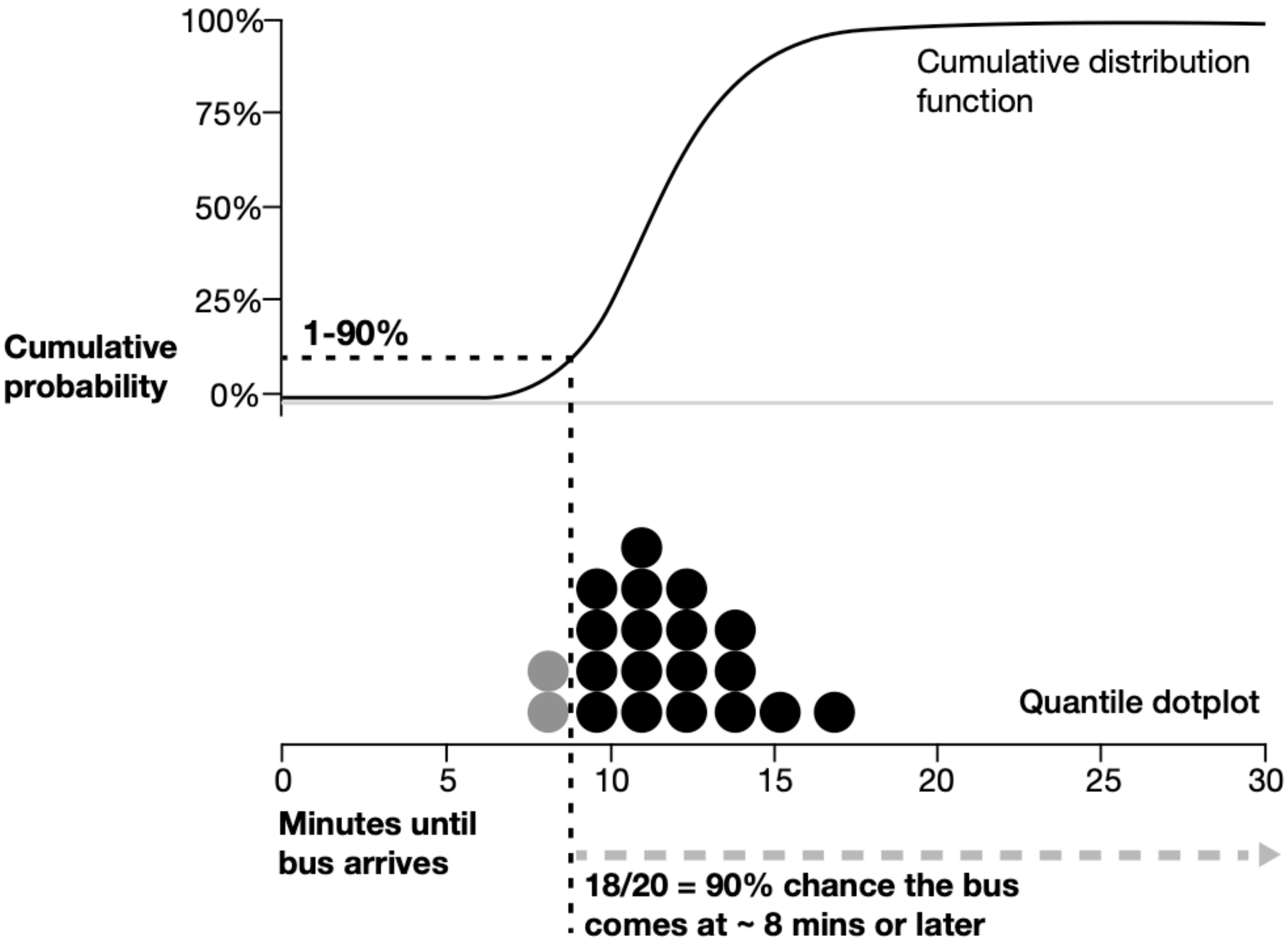




[Kay et al., 2016]

Visualizing Uncertainty: Set of "Draws"





[Kay et al., 2016]


P
S
H
National overview
FiveThirtyEight 2020
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.
Trump wins
10 in 100
Biden wins
89 in 100
+300
ELECTORAL VOTE MARGIN
+200
+100
TIE
+100
+200
+300
Trump win
Biden win
No Electoral College majority, House decides election
Don't count the underdog out! Upset wins are surprising but not impossible.


P
S
H
National overview
FiveThirtyEight 2020
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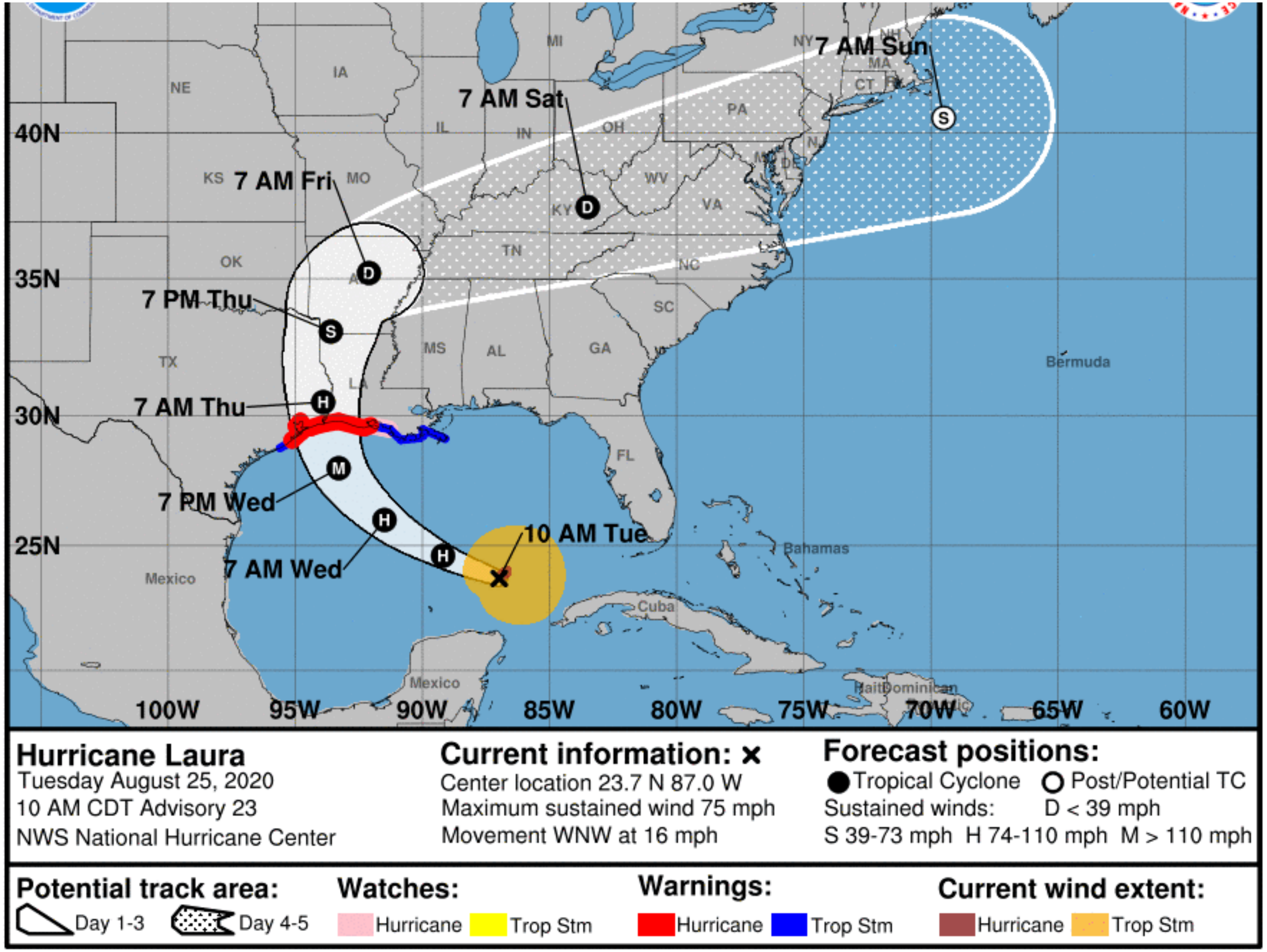
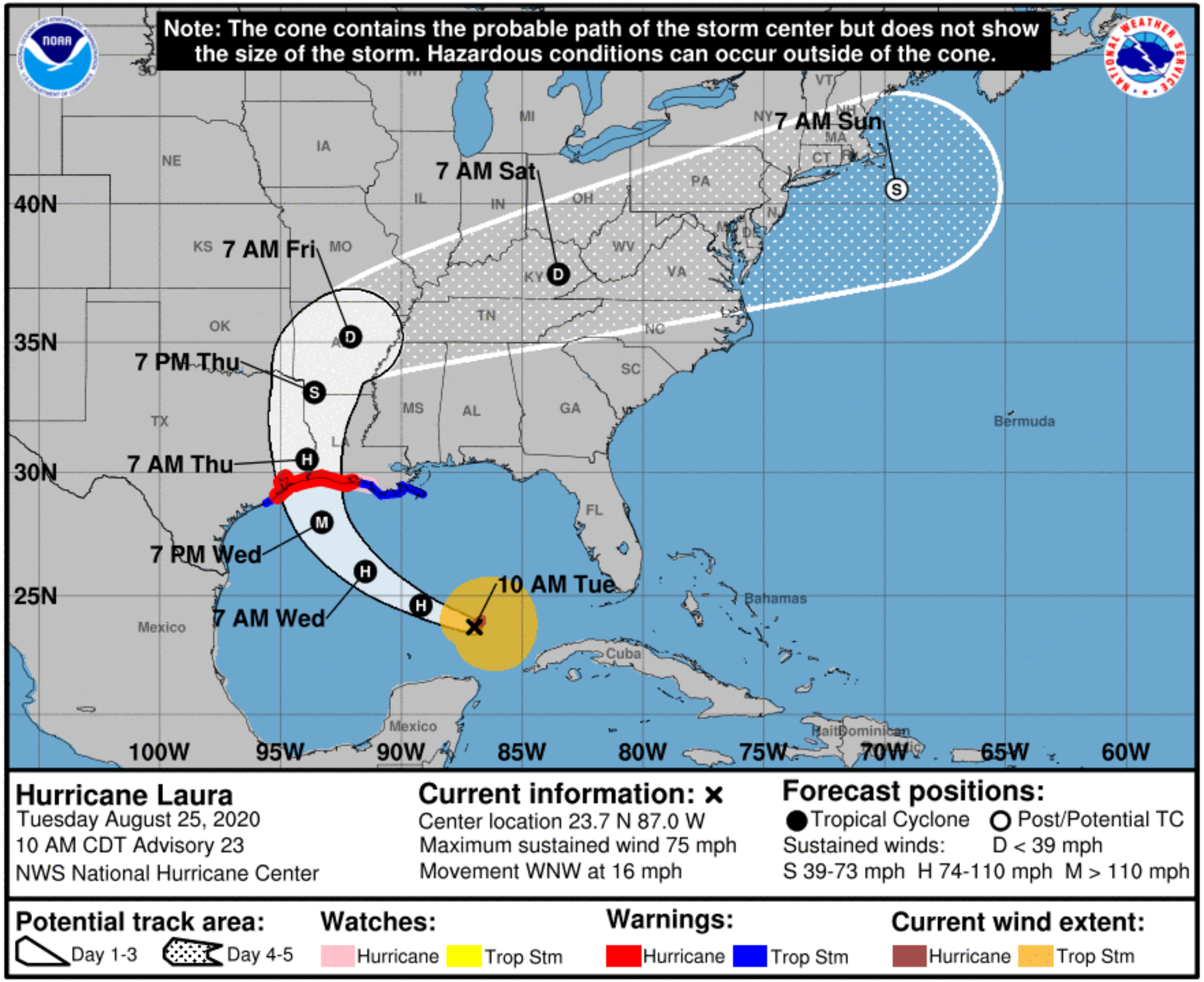
+100
+300
Don't count the underdog out! Upset wins are surprising but not impossible.
No Electoral Colle
tion
ELECTORAL VOTES
Biden ✓ 306
Trump 232



What is being visualized?

What are the strengths and weaknesses of this visualization?



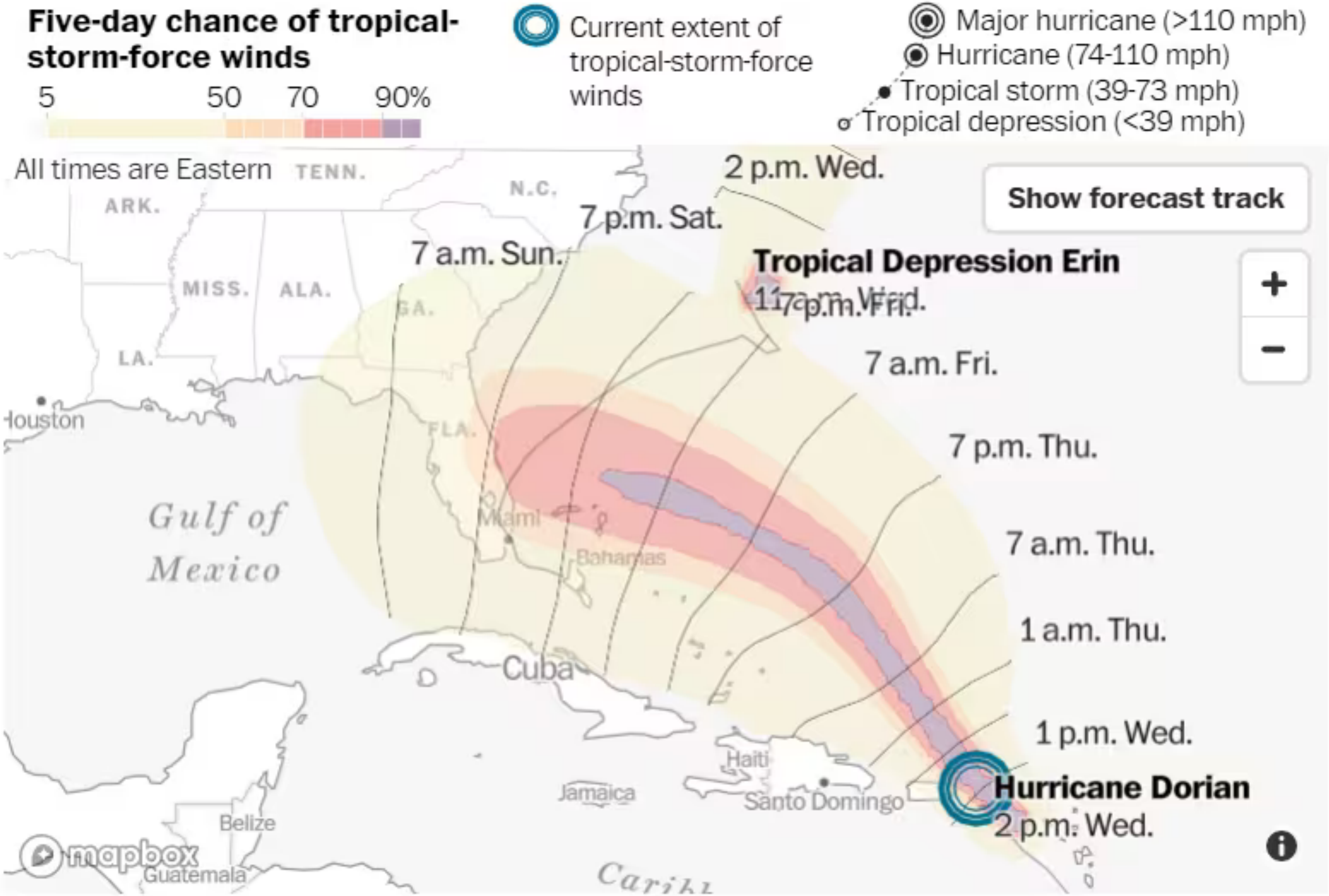
What is being visualized?

What are the strengths and weaknesses of this visualization?

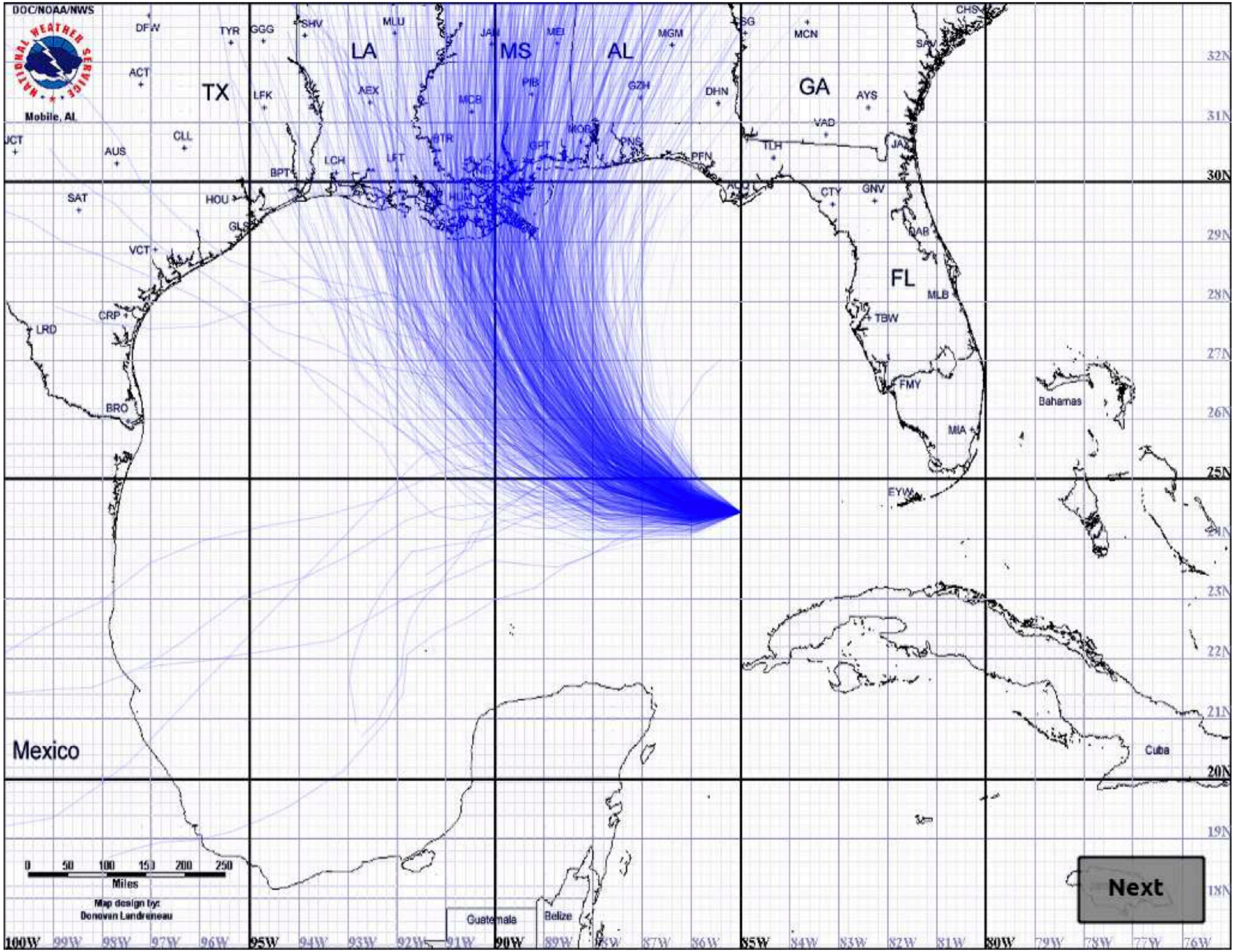

FOX4 HURRICANE IAN
5:00 AM ADVISORY
SAT 2:00 AM
40 MPH
FRI 2:00 AM
90 MPH
THU 2:00 AM
115 MPH
WED 2:00 PM
130 MPH
WED 2:00 AM
140 MPH
FORT MYERS
NAPLES
CURRENT LOCATION: 90 MI SW OF G


Omaha
Cincinnati
Washington
St. Louis
FIRST WARNING WEATHER
HURRICANE DORIAN
Atlanta
Jacksonville
Wednesday 8:00 AM EDT
75 mph
Tuesday 8:00 AM EDT
125 mph
Monday 8:00 AM EDT
140 mph
Sunday 8:00 AM EDT
130 mph
Saturday 8:00 AM EDT
125 mph
Location: 24.5°N, 69.8°W
Wind: 110 mph
Gusts: 130 mph
Movement: NW at 10 mph
Pressure: 28.70 in


NOAA
Hurricane Dorian Forecast Track and Intensity
Note: The cone contains the probable path of the storm center but does not show the size of the storm. Hazardous conditions can occur outside of the cone.
8 AM Tue
8 AM Sun
8 AM Sat
8 PM Fri
8 AM Fri
11 AM Thu
8 AM Mon
30N
25N
20N
90W
85W
80W
75W
70W
65W
60W
Hurricane Dorian
Thursday August 29, 2019
11 AM AST Advisory 21
NWS National Hurricane Center
Current information: ×
Center location 21.4 N 67.2 W
Maximum sustained wind 85 mph
Movement NW at 13 mph
Forecast positions:
Tropical Cyclone
Post/Potential TC
Sustained winds:
D < 39 mph
S 39-73 mph H 74-110 mph M > 110 mph
Potential track area:
Day 1-3
Day 4-5
Watches:
Hurricane
Trop Stm
Warnings:
Hurricane
Trop Stm
Current wind extent:
Hurricane
Trop Stm

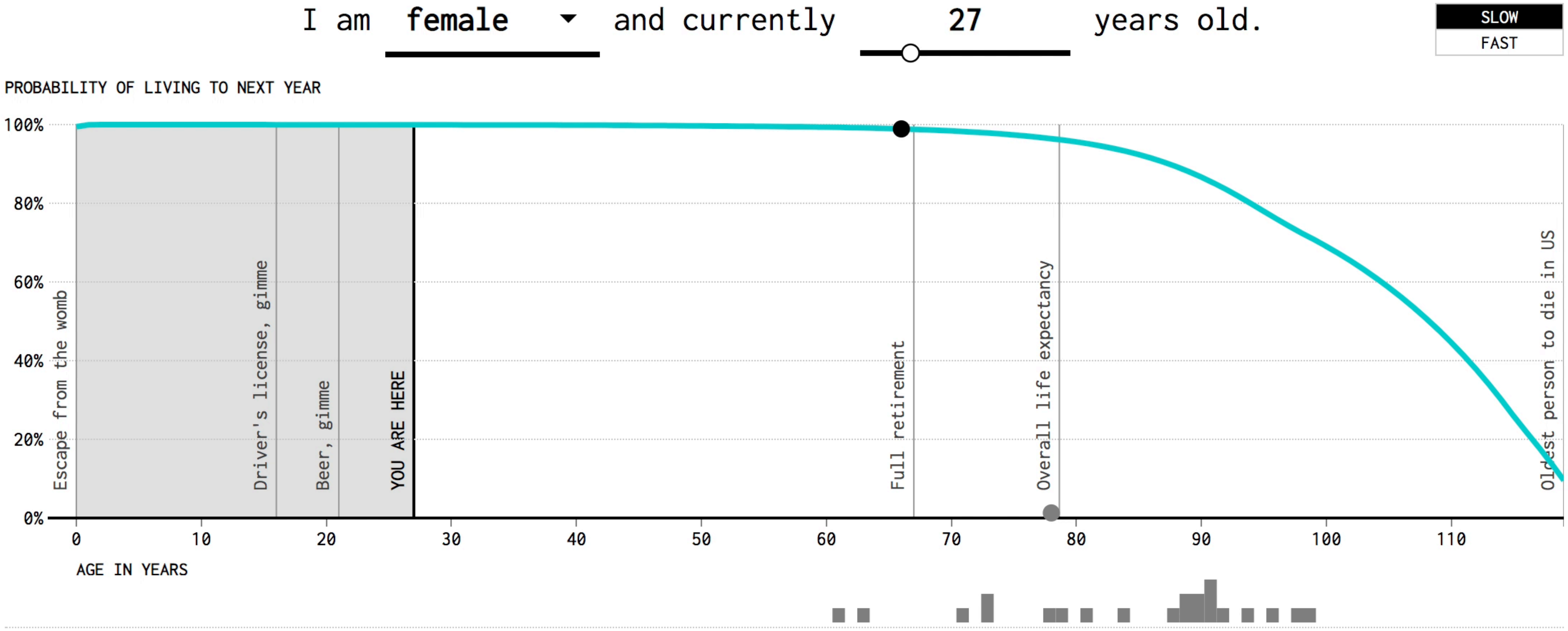


Source: National Weather Service. Note: Impact lines represent the earliest reasonable arrival time of tropical-storm-force winds.



[Cox et al., 2013]

Visualizing Uncertainty: Set of "Draws"



Probabilities For Years Left to Live

0 to 9	10 to 19	20 to 29	30 to 39	40 to 49	50 or more
0%	0%	0%	9%	14%	77%
(0)	(0)	(0)	(2)	(3)	(17)

[Yau, 2015]

Visualizing Uncertainty: Set of “Draws”

The New York Times

TheUpshot

STATISTICAL NOISE

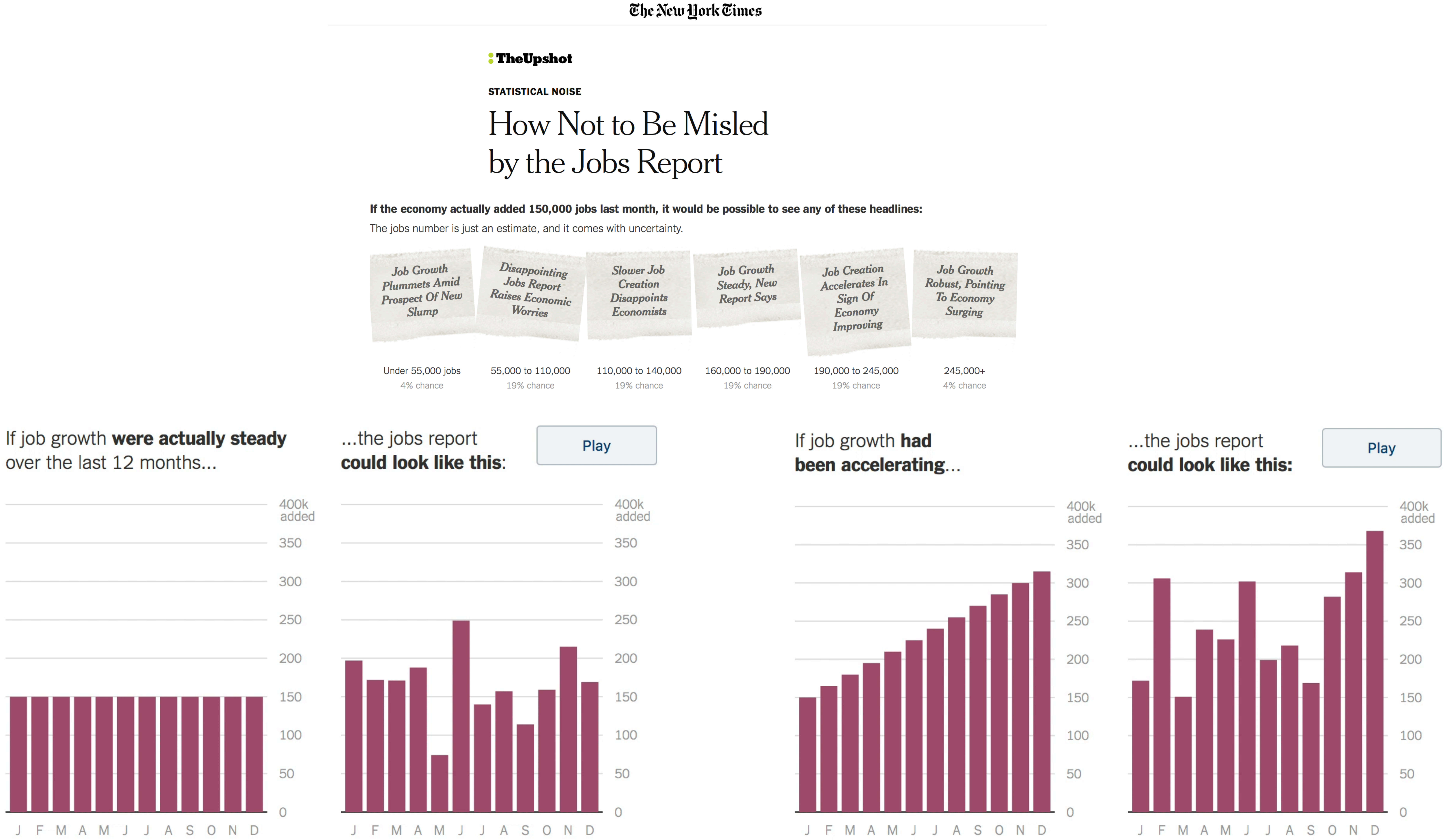
How Not to Be Misled by the Jobs Report

If the economy actually added 150,000 jobs last month, it would be possible to see any of these headlines:

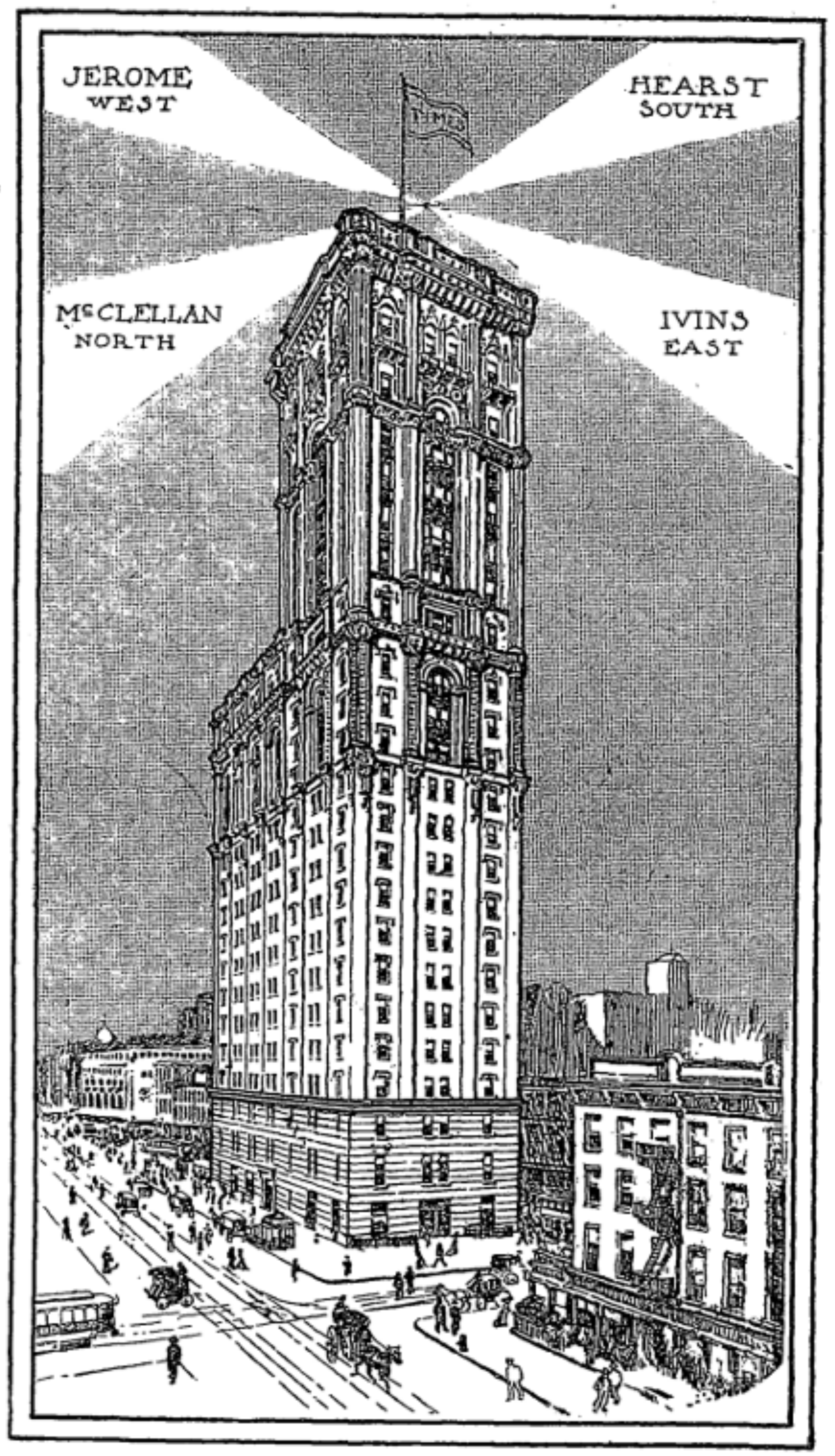
The jobs number is just an estimate, and it comes with uncertainty.

Job Growth Plummets Amid Prospect Of New Slump	*Disappointing Jobs Report Raises Economic Worries*	*Slower Job Creation Disappoints Economists*	*Job Growth Steady, New Report Says*	*Job Creation Accelerates In Sign Of Economy Improving*	*Job Growth Robust, Pointing To Economy Surging*
Under 55,000 jobs	55,000 to 110,000	110,000 to 140,000	160,000 to 190,000	190,000 to 245,000	245,000+
4% chance	19% chance	19% chance	19% chance	19% chance	4% chance

Visualizing Uncertainty: Set of “Draws”



ELECTION RESULTS BY SEARCHLIGHT.



The Times Election Searchlight Code.

News Will Be Flashed from the Tower of The Times Building on Tuesday Night.

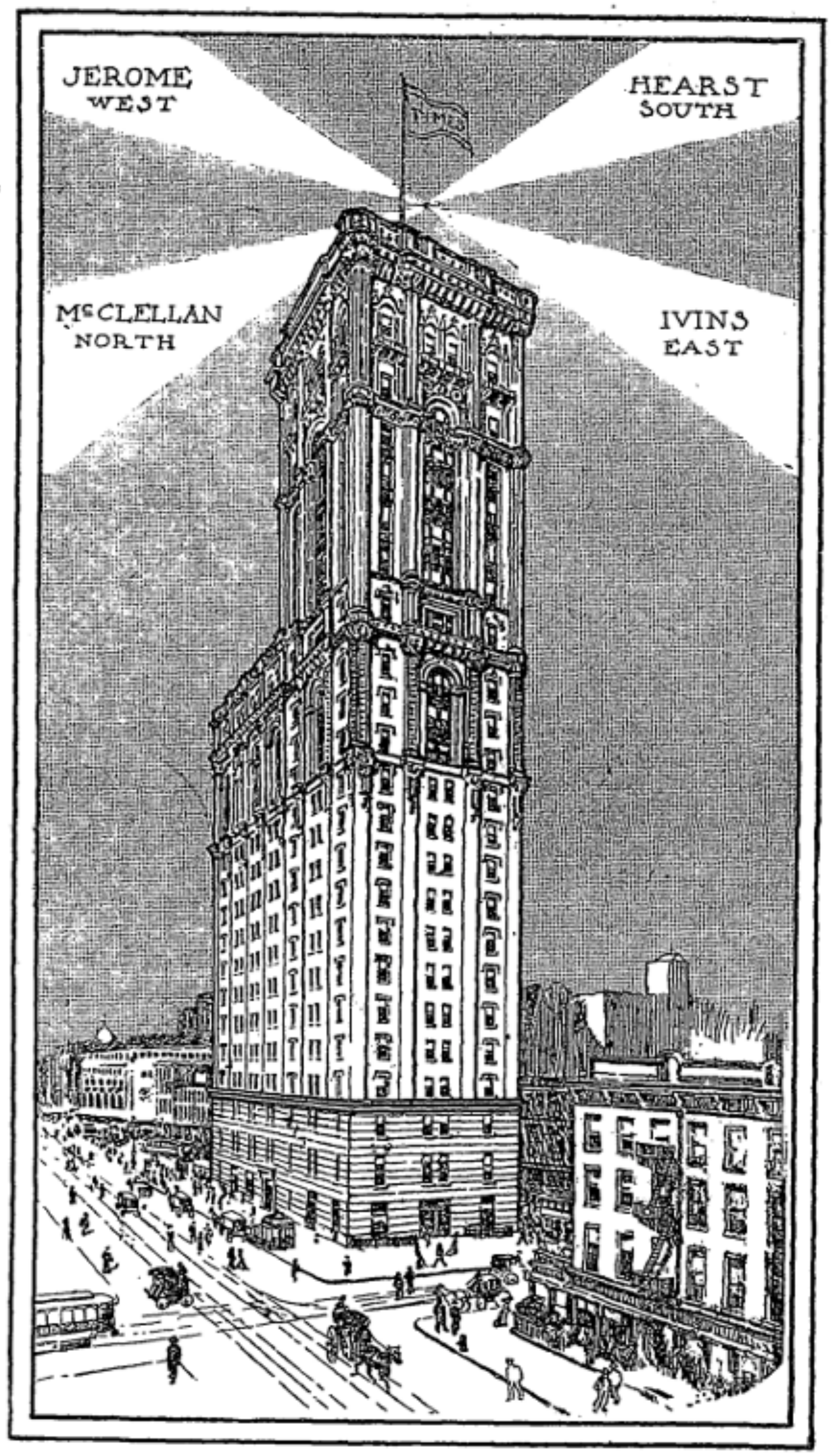
The results of the election next Tuesday night will be flashed by electric light from the tower of the Times Building, so that for miles around people will be able to tell which of the candidates has won.

This will be entirely separate and distinct from the elaborate bulletin service which THE TIMES will also maintain. To display the detailed bulletins so that the crowds can see them easily and comfortably, a stereopticon machine will be set up in the triangle north of the Times Building and the bulletins displayed on canvas stretched from the north side of the building. There will be a similar service at the Harlem office of THE TIMES, 129 West 125th Street.

The electric signals from the tower of the Times Building will be flashed from a point 365 feet above the street level. A steady light to the north will show that McClellan has been elected; a steady light to the east will indicate Ivins's election, and a steady light to the south will indicate that Hearst has won.

Jerome's election will be indicated by a steady light to the west. A light to the north, waving from east to west, will indicate Osborne's election. A light to the south, waving from east to west, will indicate Shearn's election.

ELECTION RESULTS BY SEARCHLIGHT.



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Jerome's election will be indicated by a steady light to the west. A light to the north, waving from east to west, will indicate Osborne's election. A light to the south, waving from east to west, will indicate Shearn's election.

Election Bulletins

BY BOMBS.

TUESDAY NIGHT

THE TRIBUNE

will send up from the roof of the

GREAT NORTHERN HOTEL

hourly, shells containing blue and red stars—exactly on the hour—at 7, 8, 9, 10, 11 p. m. 12 midnight, 1 and 2 a. m. Wednesday morning, unless election is decided earlier, in which case twelve bombs will be sent up in rapid succession. Blue to indicate McKinley's election. Red to indicate Bryan's election.

SIX BOMBS EVERY HOUR.

The first bomb sent up, if blue, indicates the returns in **COOK COUNTY** at that hour are favorable to McKinley; if red, favorable to Bryan.

After sixty seconds two bombs will be sent up in rapid succession, and will indicate, if blue, that returns from **ILLINOIS** favor McKinley; if red, Bryan.

After sixty seconds more three bombs will be sent up in rapid succession, and if blue will indicate that at that hour returns from the **entire country** favor McKinley; if red, Bryan. Each bomb bursts high in the air, scattering a shower of stars.

PART THREE

Visualizing Uncertainty

Visualization, EVA, & Uncertainty

A Crash Course

Arvind Satyanarayan