Visualization

CS 347
Michael Bernstein

Last time

Design principles provide strong guides for content creation tools: (1) **identify design principles** in expert output based on **cognition/perception**, and (2) **instantiate them into algorithms** to aid content creators, and (3) **evaluate principles** through user studies

Approach generalizes across a wide range of categories, ranging from digital illustration to audio, video, instructions and exploded views

Software and Tools

Unit 4

human-centered AI
tools and toolkits
content creation

Cognition

Unit 5

cognitive models
visualization
(and don't forget the design cognition that we already covered)

Today

Data, marks, visual attributes and encodings

Graphical perception

Frontiers of visualization research

Anscombe's Quartet [Anscombe 1973]

Set A X	Set A Y	Set B X	Set B Y	Set C X	Set C Y	Set D X	Set D Y
10	8.04	10	9.14	10	7.46	8	6.58
8	6.95	8	8.14	8	6.77	8	5.76
13	7.58	13	8.74	13	12.74	8	7.71
9	8.81	9	8.77	9	7.11	8	8.84
11	8.33	11	9.26	11	7.81	8	8.47
14	9.96	14	8.1	14	8.84	8	7.04
6	7.24	6	6.13	6	6.08	8	5.25
4	4.26	4	3.1	4	5.39	19	12.5
12	10.84	12	9.11	12	8.15	8	5.56
7	4.82	7	7.26	7	6.42	8	7.91
5	5.68	5	4.74	5	5.73	8	6.89

Summary Statistics

$u_X = 9.0$ $\sigma_X = 3.317$

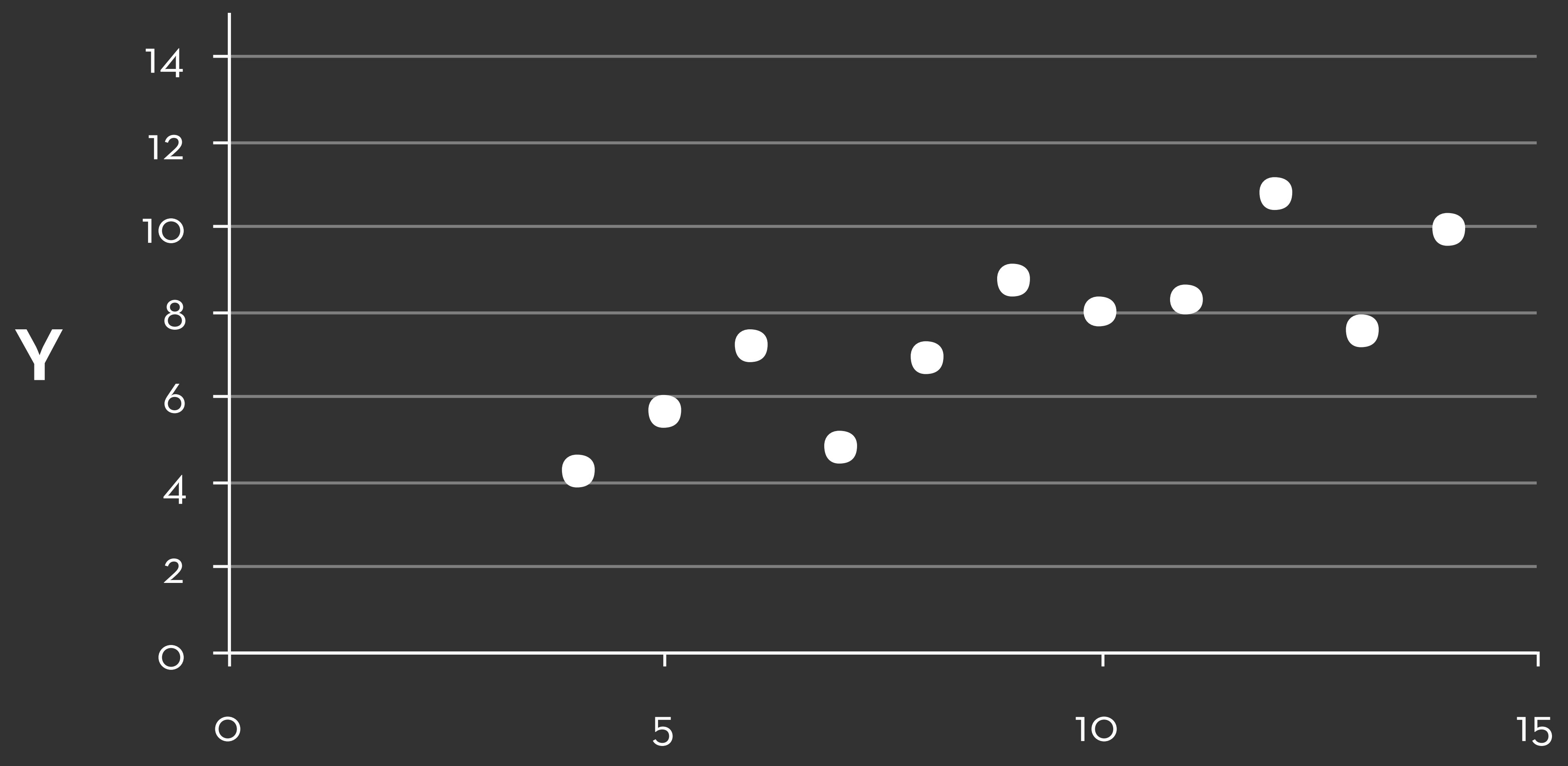
$u_Y = 7.5$ $\sigma_Y = 2.03$

Linear Regression

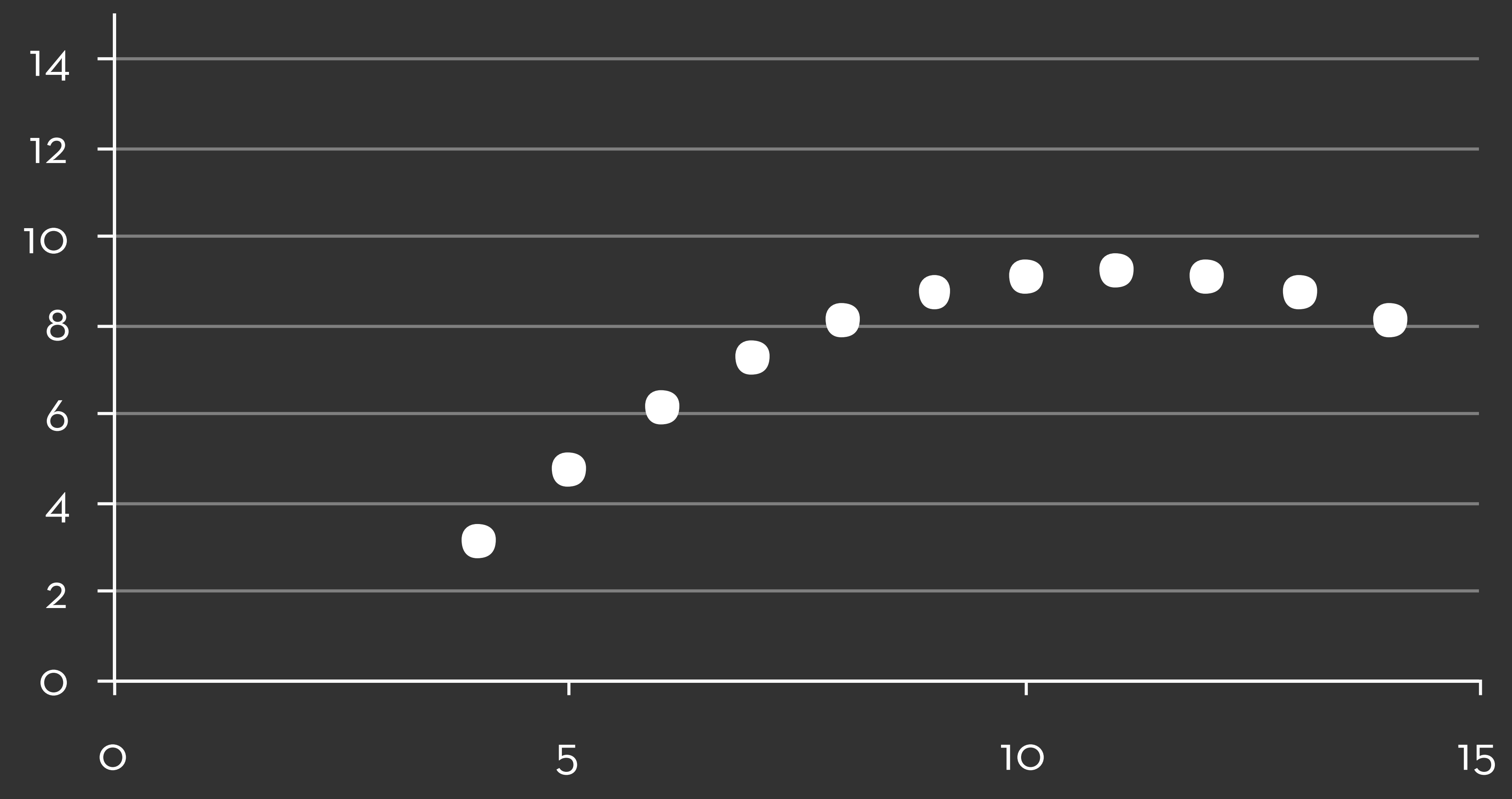
$Y = 3 + 0.5\ X$

$R^2 = 0.67$

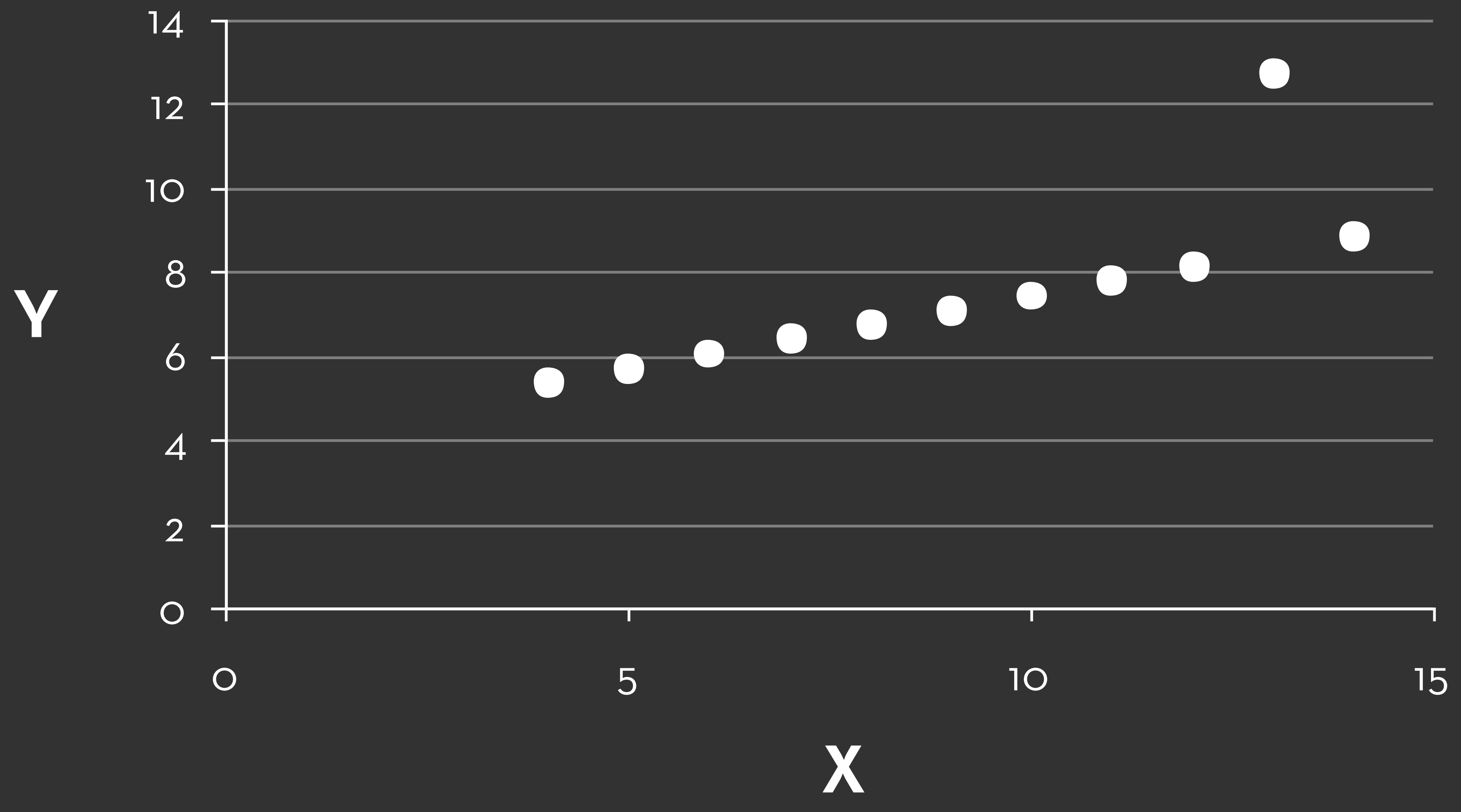
Set A



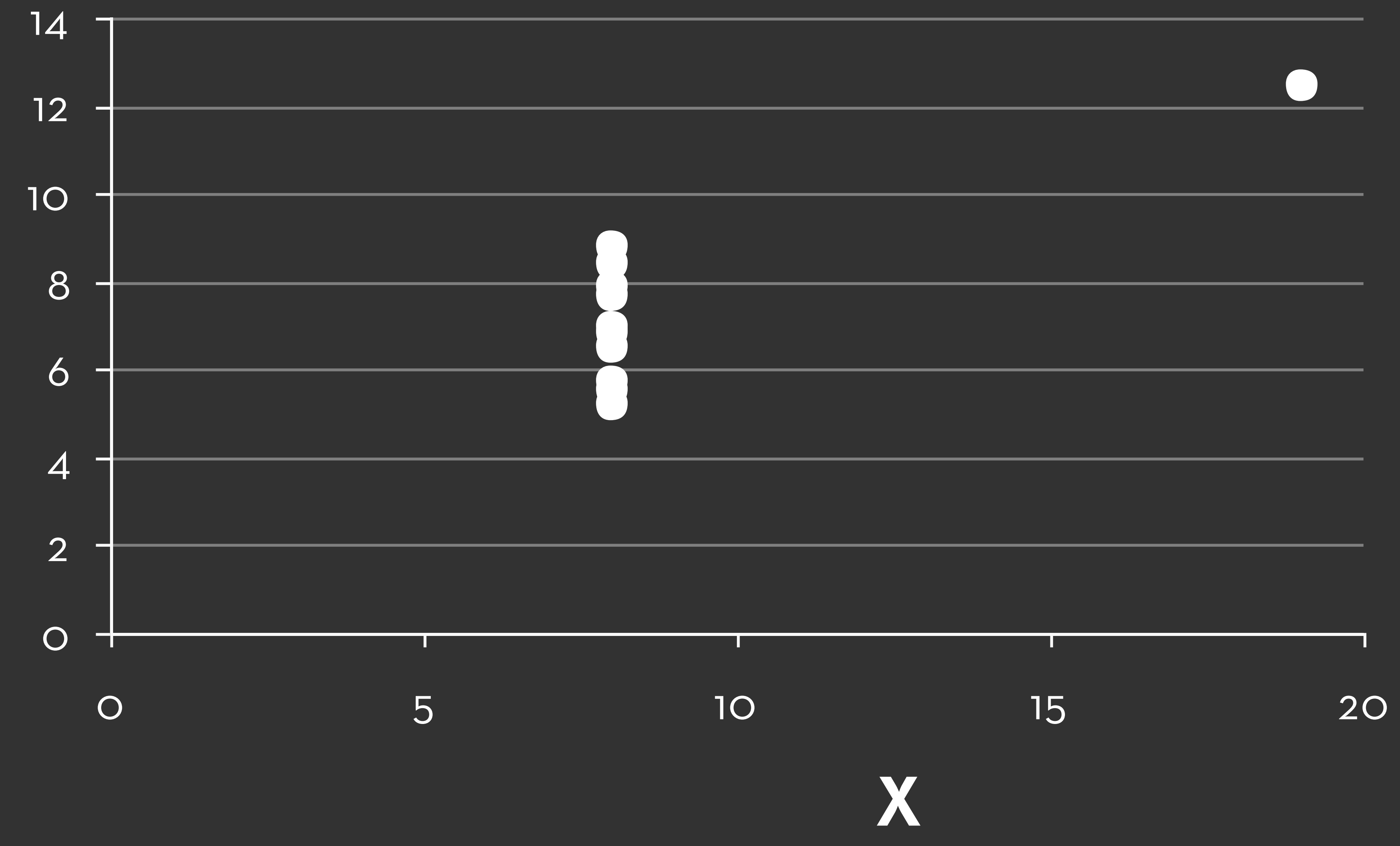
Set B

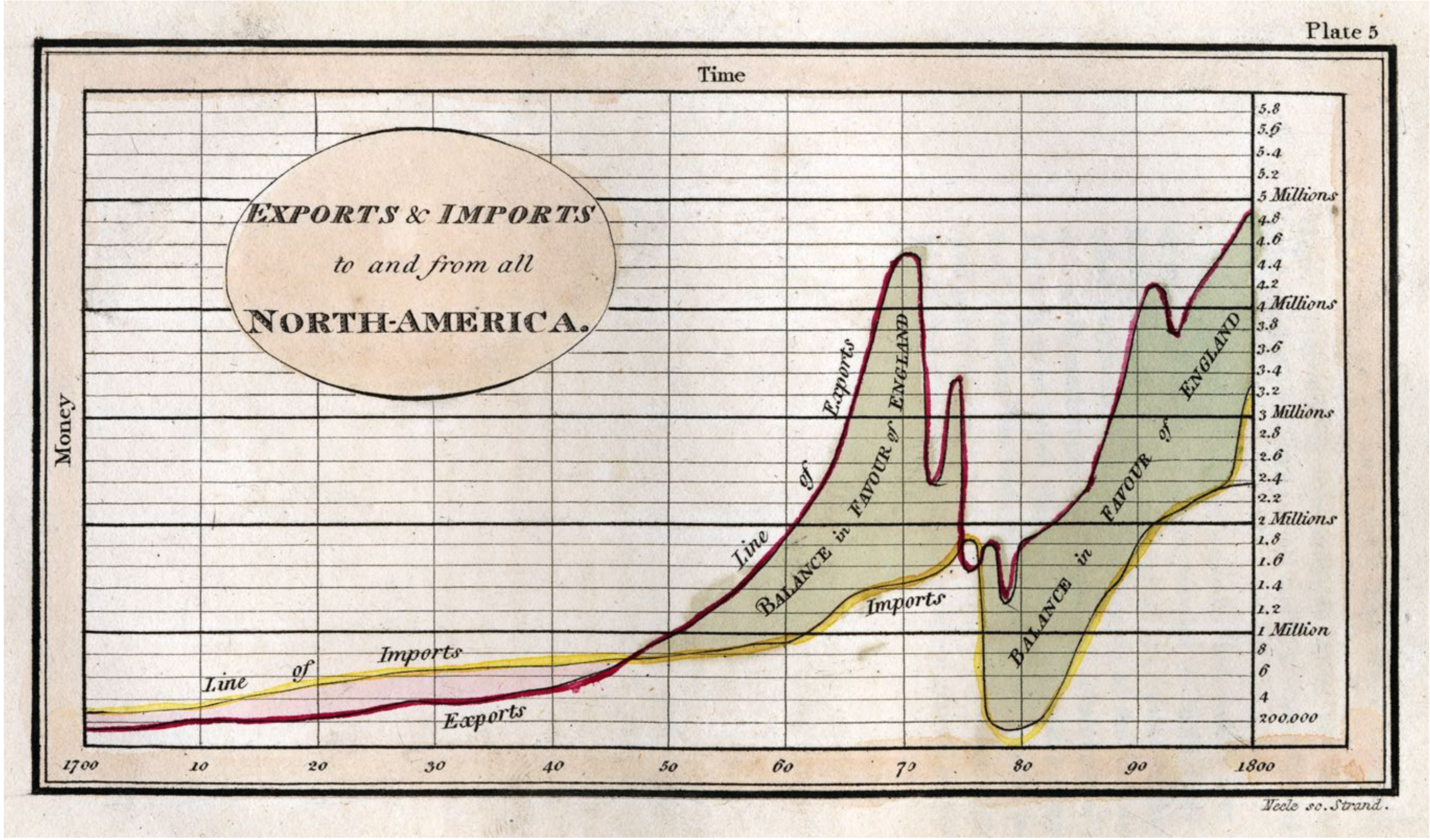


Set C



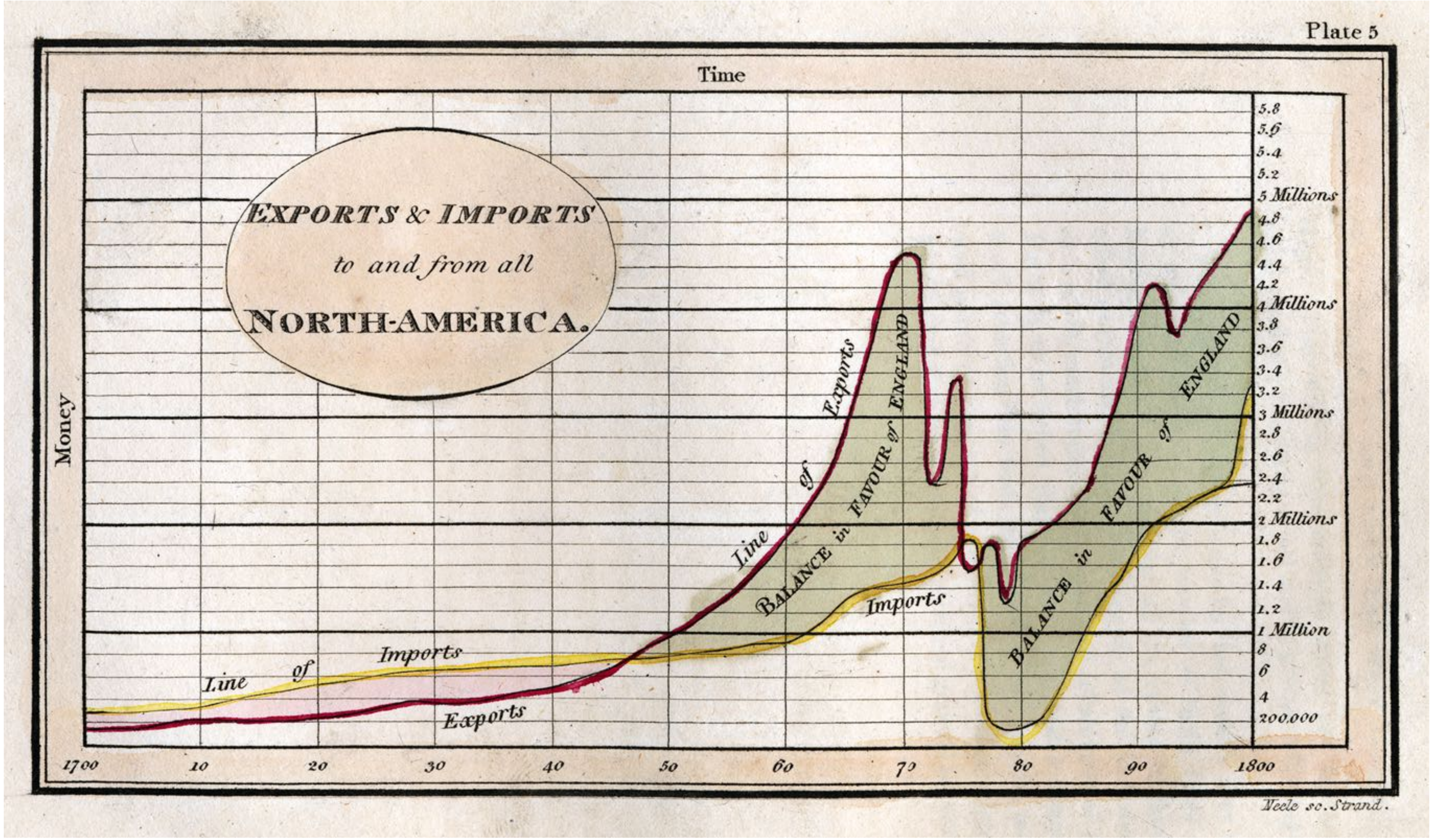
Set D





Exports and Imports to and from all North America [Playfair 1786]

Important information: differences between exports and imports

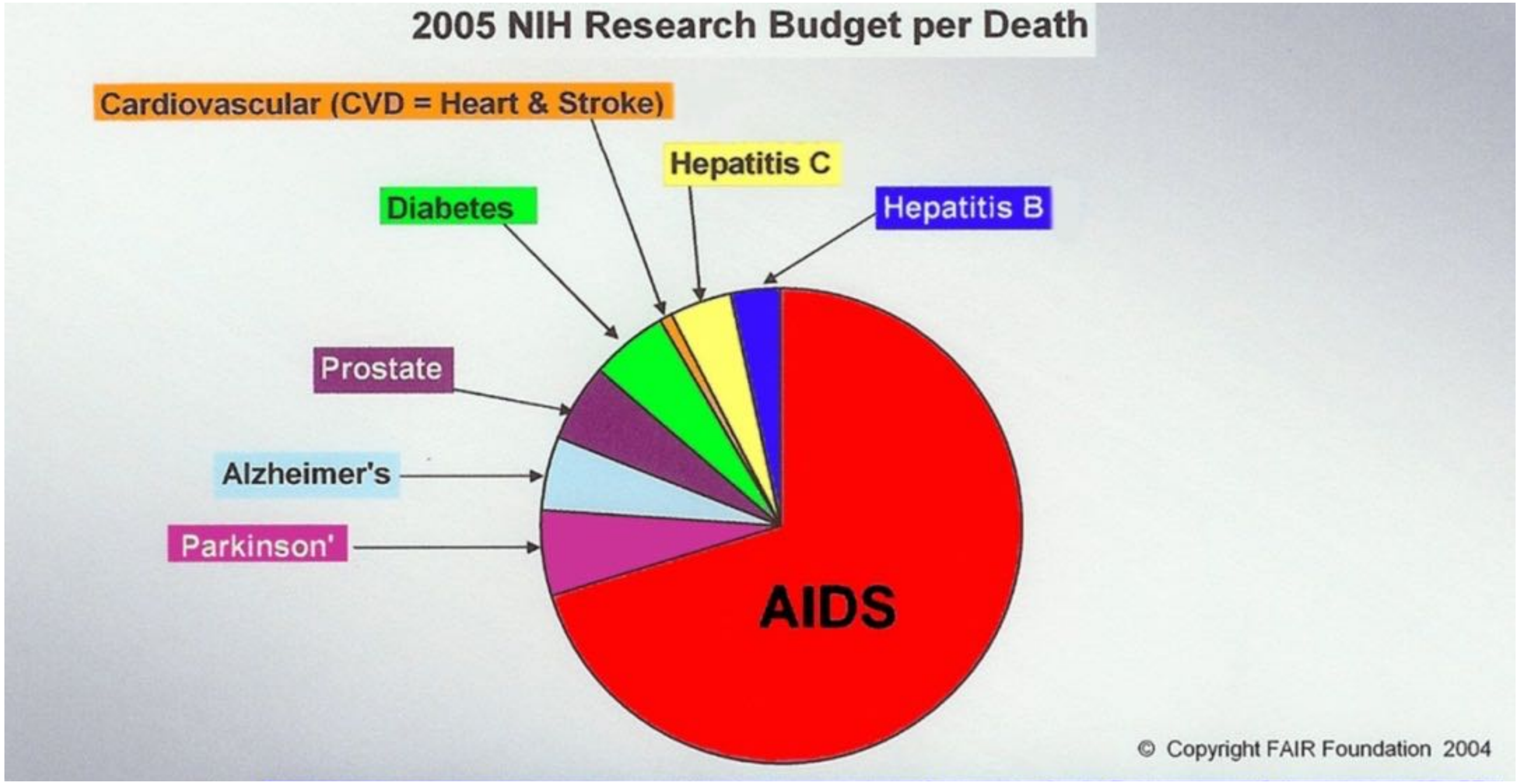


Design principle: shade areas between lines to highlight differences

Charles Minard [1869]

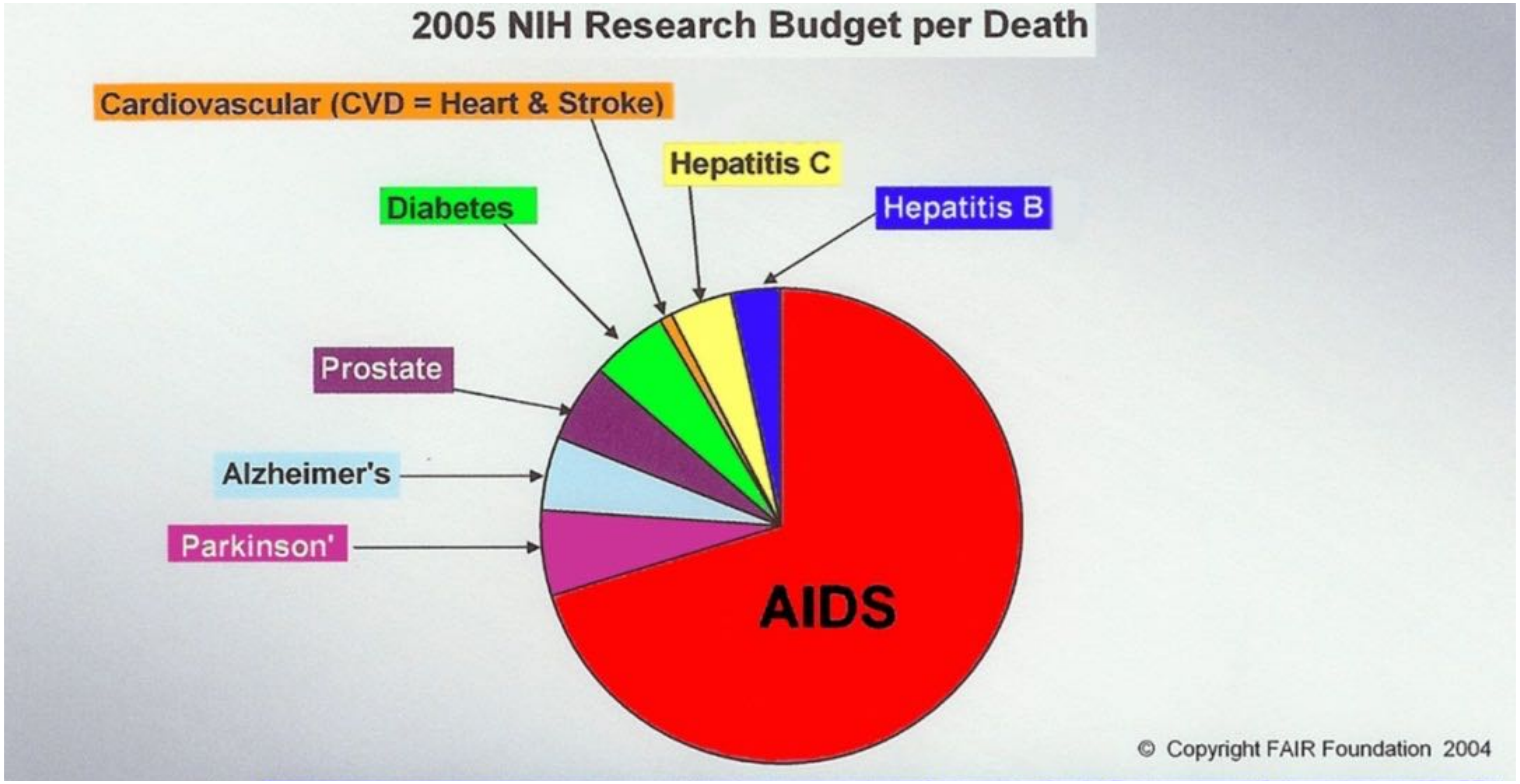
Important information: army size decreasing as Napoleon marches

Design principle: use flow diagram width to convey the drop in army size



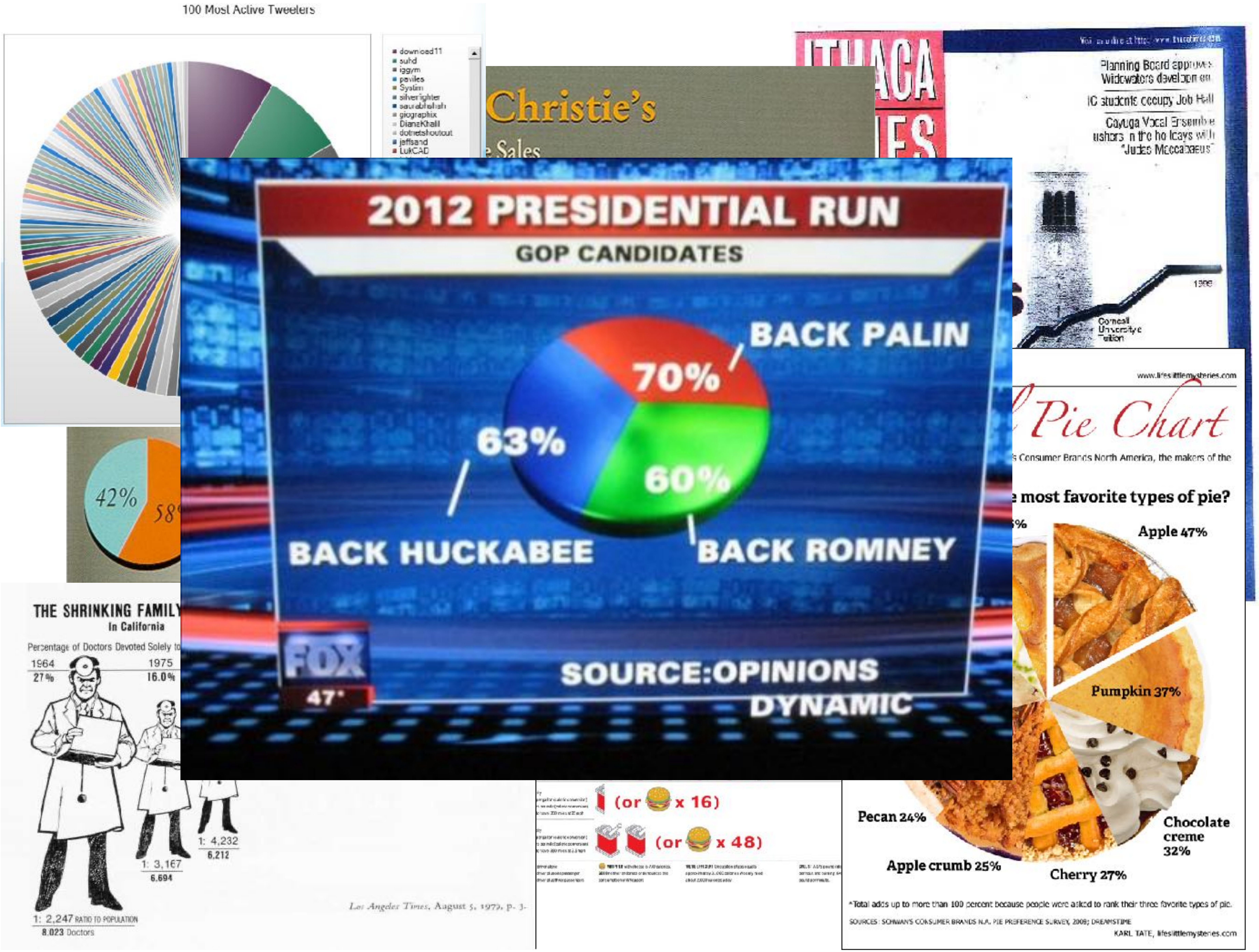
Estimated 2005 NIH Research Budget per Death [FAIR Foundation 04]

User's task: Understand proportion of budget allocated to each disease, and compare proportion of budget allocated to each disease



Representation: pie chart to emphasizes part-to-whole relationship

But, a failure: doesn't easily comparison between diseases by comparing pie slices (angles or areas)


100 Most Active Tweeters
downloed11
suhd
iggym
paviles
System
silverfighter
saurabhshah
glographix
DianeKhalil
dotnetshoutout
jeffsand
LukCAD
Christie's
Sales
Planning Board approves
IC students occupy Job Hall
Cayuga Vocal Ensemble
"Judas Maccabaeus"
2012 PRESIDENTIAL RUN
GOP CANDIDATES
BACK PALIN
70%
63%
60%
BACK HUCKABEE
BACK ROMNEY
FOX
47°
SOURCE:OPINIONS DYNAMIC
42%
www.lifeslittlemysteries.com
Pie Chart
most favorite types of pie?
Apple 47%
Pumpkin 37%
Pecan 24%
Apple crumb 25%
Cherry 27%
Chocolate creme 32%
*Total adds up to more than 100 percent because people were asked to rank their three favorite types of pie.
SOURCES: SCHWAN'S CONSUMER BRANDS N.A. PIE PREFERENCE SURVEY, 2008; DREAMSTIME
KARL TATE, lifeslittlemysteries.com
(or x 16)
(or x 48)
THE SHRINKING FAMILY
In California
Percentage of Doctors Devoted Solely to
1964
27%
1975
16.0%
1: 2,247 RATIO TO POPULATION
8,023 Doctors
1: 3,167
6,694
1: 4,232
6,212
Los Angeles Times, August 5, 1979, p. 3.

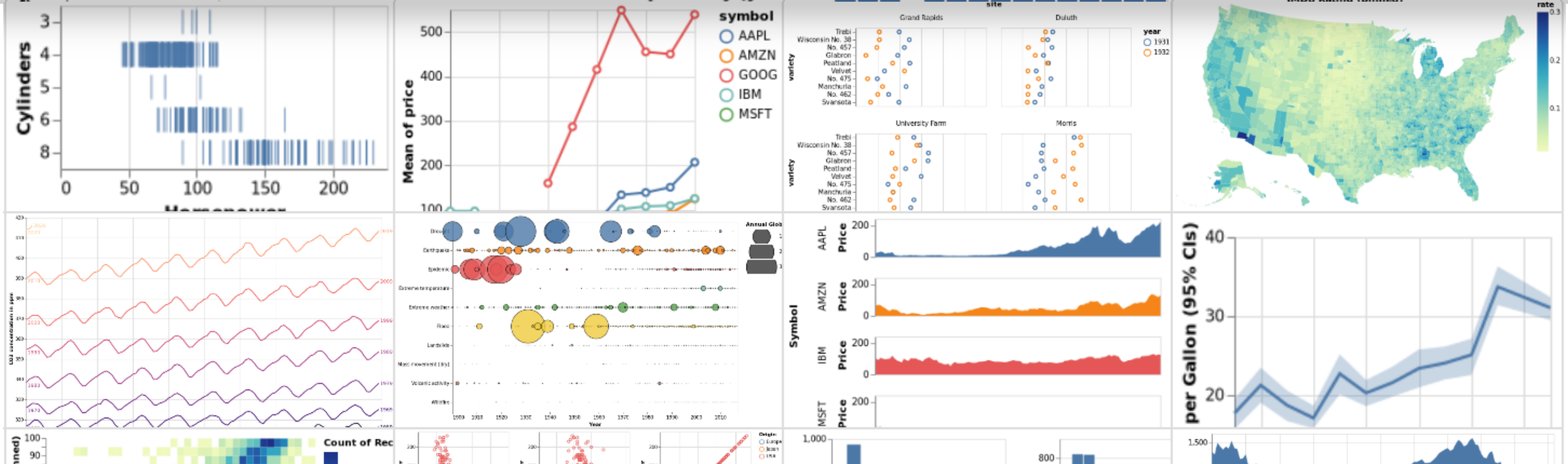
What is visualization?

"Transformation of the symbolic into the geometric" [McCormick et al. 1987]

"…finding the artificial memory that best supports our natural means of perception." [Bertin 1967]

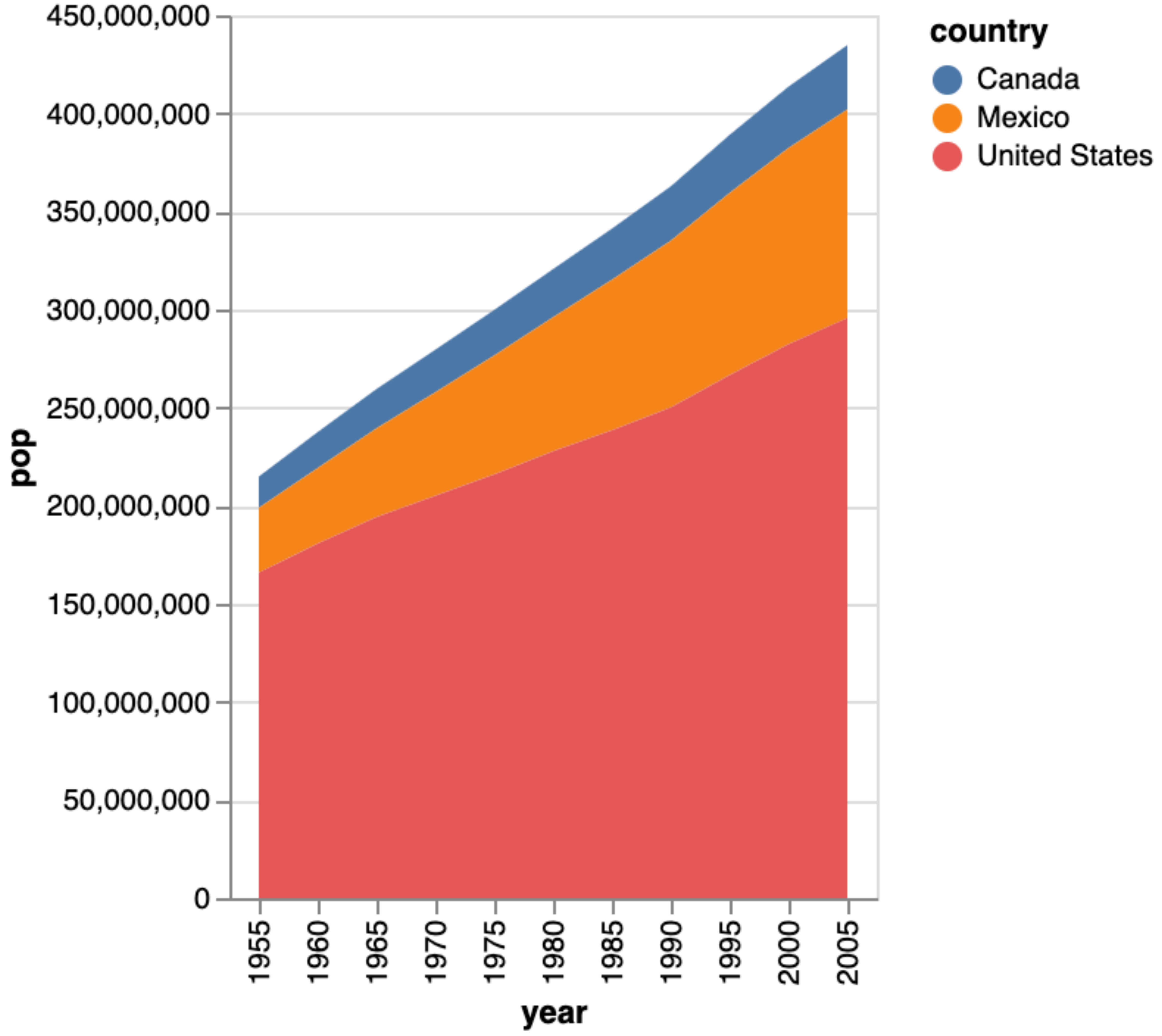
"The use of computer-generated, interactive, visual representations of data to amplify cognition." [Card, Mackinlay, and Shneiderman 1999]

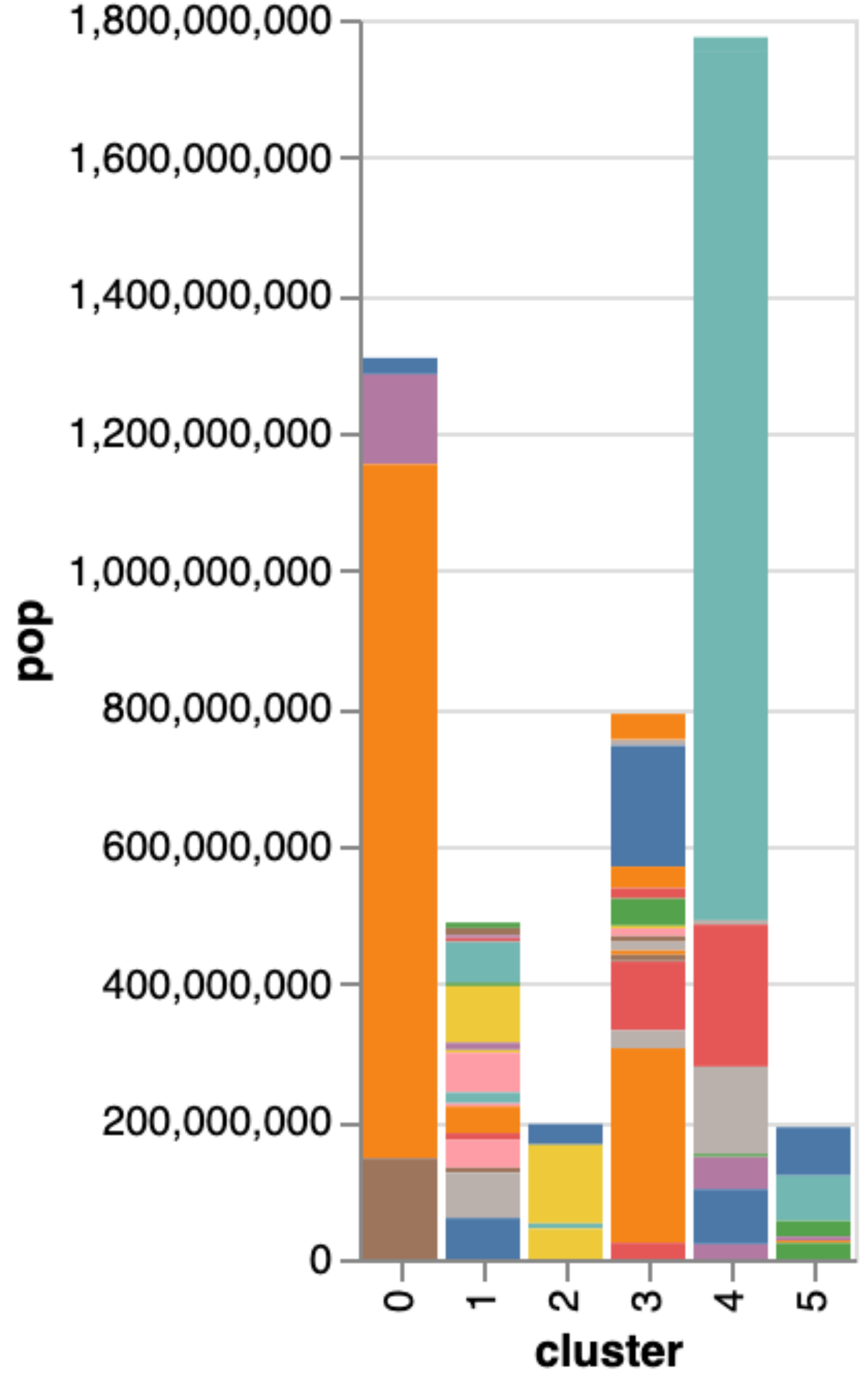
Data, marks, visual attributes and encodings



What unifies and describes visualizations?

Examples from Vega Lite





What precisely makes these visualizations—of the same dataset—different?

[Heer 2021]

Anatomy of a visualization

Visualizations comprise a few main elements:

Data: the information to be visualized

Marks: geometric primitives, e.g., points, lines, areas

Visual attributes: transformations on the marks, e.g., size

Encodings: functions that map from data onto marks and visual variables

Let's introduce each of these in turn.

Data: types of data [Stevens 1946]

Nominal: category labels, no inherent ordering

e.g., apples, oranges | operations: =, ≠

Ordinal: ordered, but no notion of "distance"

e.g., freshman, sophomore, junior, senior | operations: =, ≠, <, >, ≤, ≥

Quantitative: can be compared via differences or ratios

intervals, e.g., dates, lat/lon | operations: =, ≠, <, >, ≤, ≥, -

ratios, e.g., length, mass, temperature | operations: =, ≠, <, >, ≤, ≥, -, ÷

Same info, different type

Floating point numbers: 32.5, 54.0, -17.3

plus

Conceptual model: temperature

equals

Different possible data types:

- Nominal: burned or not burned
- Ordinal: cold, warm, hot
- Quantitative: °F

U.S. Census Data

People Count: # of people in group

Year: 1850 – 2000 (every decade)

Age: 0 – 90+

Sex: Male, Female (Census classification)

Marital Status: Single, Married, Divorced, …

A	B	C	D	E
year	age	marst	sex	people
1850	0	0	1	1483789
1850	0	0	2	1450376
1850	5	0	1	1411067
1850	5	0	2	1359668
1850	10	0	1	1260099
1850	10	0	2	1216114
1850	15	0	1	1077133
1850	15	0	2	1110619
1850	20	0	1	1017281
1850	20	0	2	1003841
1850	25	0	1	862547
1850	25	0	2	799482
1850	30	0	1	730638
1850	30	0	2	639636
1850	35	0	1	588487
1850	35	0	2	505012
1850	40	0	1	475911
1850	40	0	2	428185
1850	45	0	1	384211
1850	45	0	2	341254
1850	50	0	1	321343
1850	50	0	2	286580
1850	55	0	1	194080
1850	55	0	2	187208
1850	60	0	1	174976

Census

People Count:	Quantitative
Year:	Quantitative
Age:	Quantitative
Sex:	Nominal
Marital Status:	Nominal

A	B	C	D	E
year	age	marst	sex	people
1850	0	0	1	1483789
1850	0	0	2	1450376
1850	5	0	1	1411067
1850	5	0	2	1359668
1850	10	0	1	1260099
1850	10	0	2	1216114
1850	15	0	1	1077133
1850	15	0	2	1110619
1850	20	0	1	1017281
1850	20	0	2	1003841
1850	25	0	1	862547
1850	25	0	2	799482
1850	30	0	1	730638
1850	30	0	2	639636
1850	35	0	1	588487
1850	35	0	2	505012
1850	40	0	1	475911
1850	40	0	2	428185
1850	45	0	1	384211
1850	45	0	2	341254
1850	50	0	1	321343
1850	50	0	2	286580
1850	55	0	1	194080
1850	55	0	2	187208
1850	60	0	1	174976

Marks and visual variables

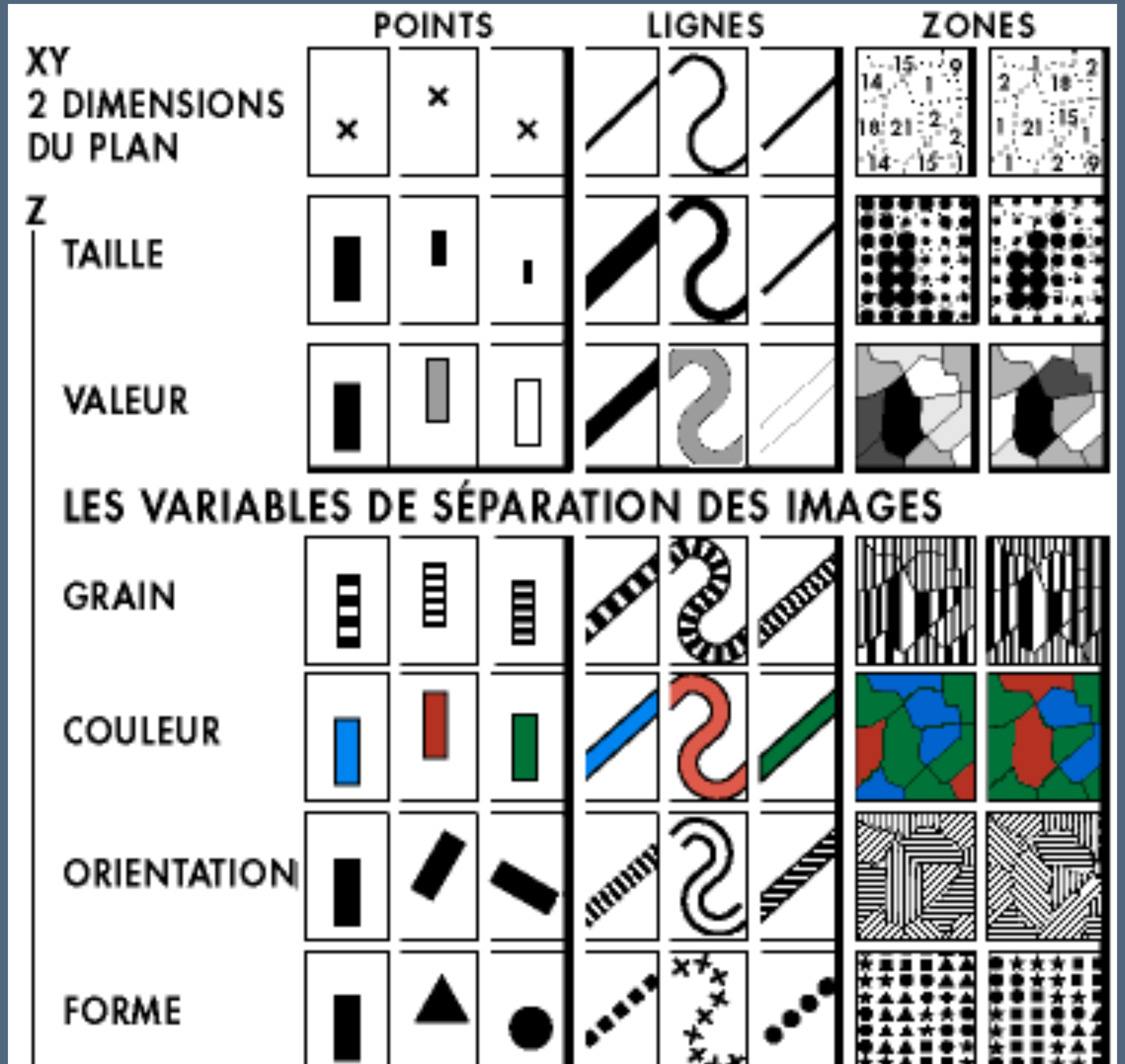
[Bertin 1967]

Marks: geometric primitives

Points Lines Areas

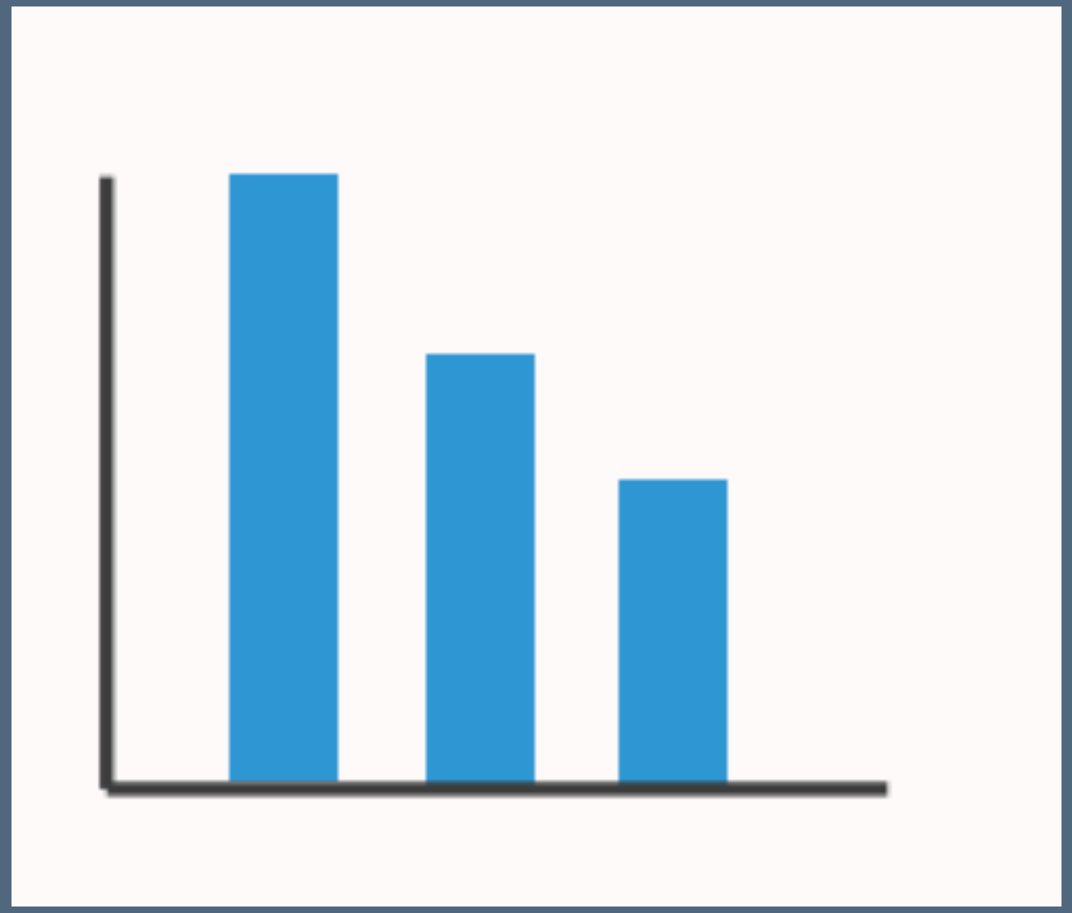
Visual attributes: control mark appearance

Position (x, y)
Size
Value
Texture
Color
Orientation
Shape

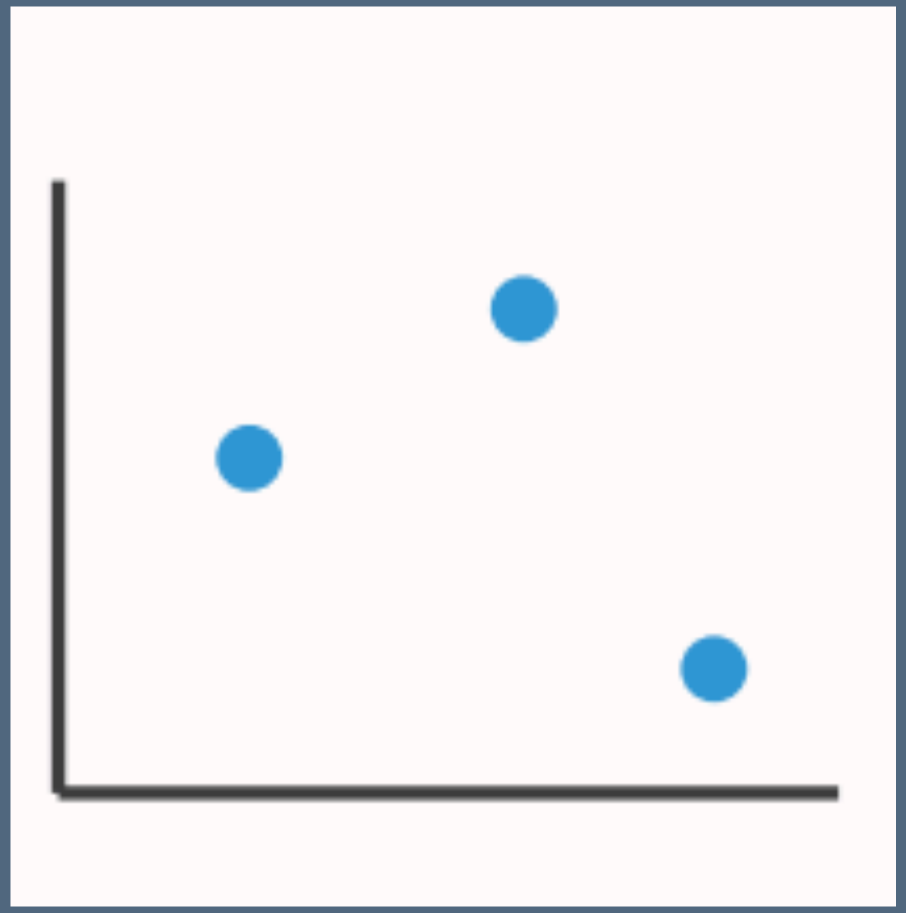


Encodings

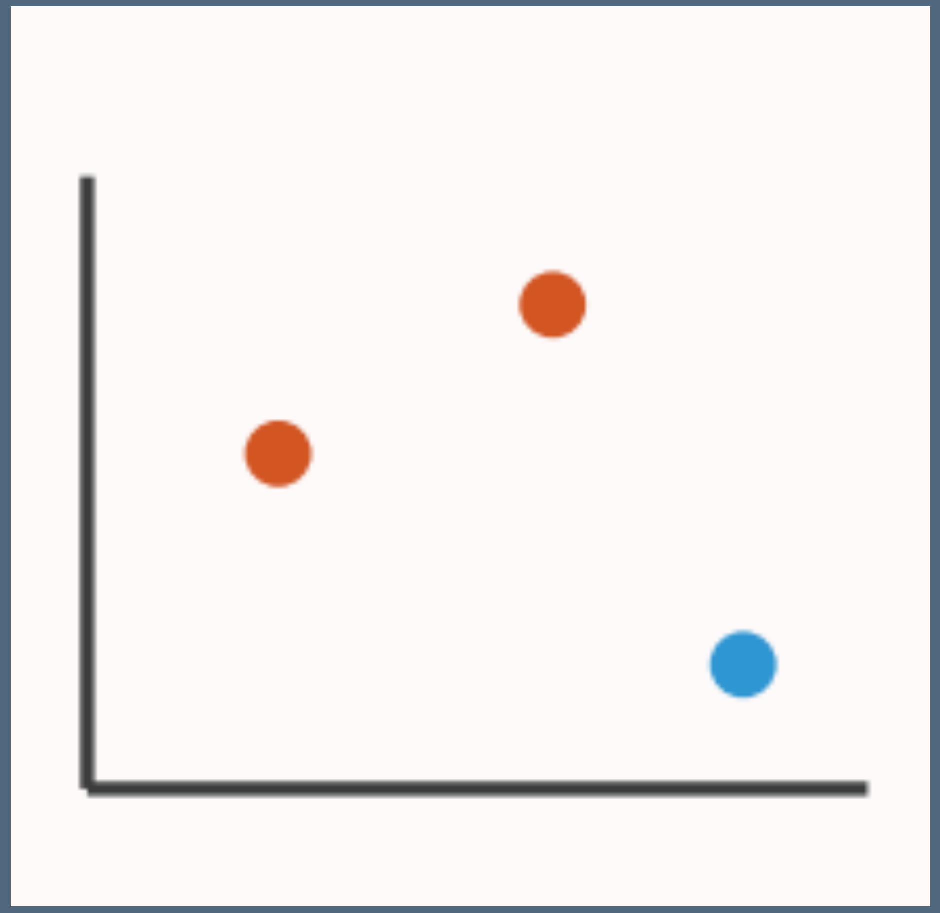
A map from data to visual attributes of marks



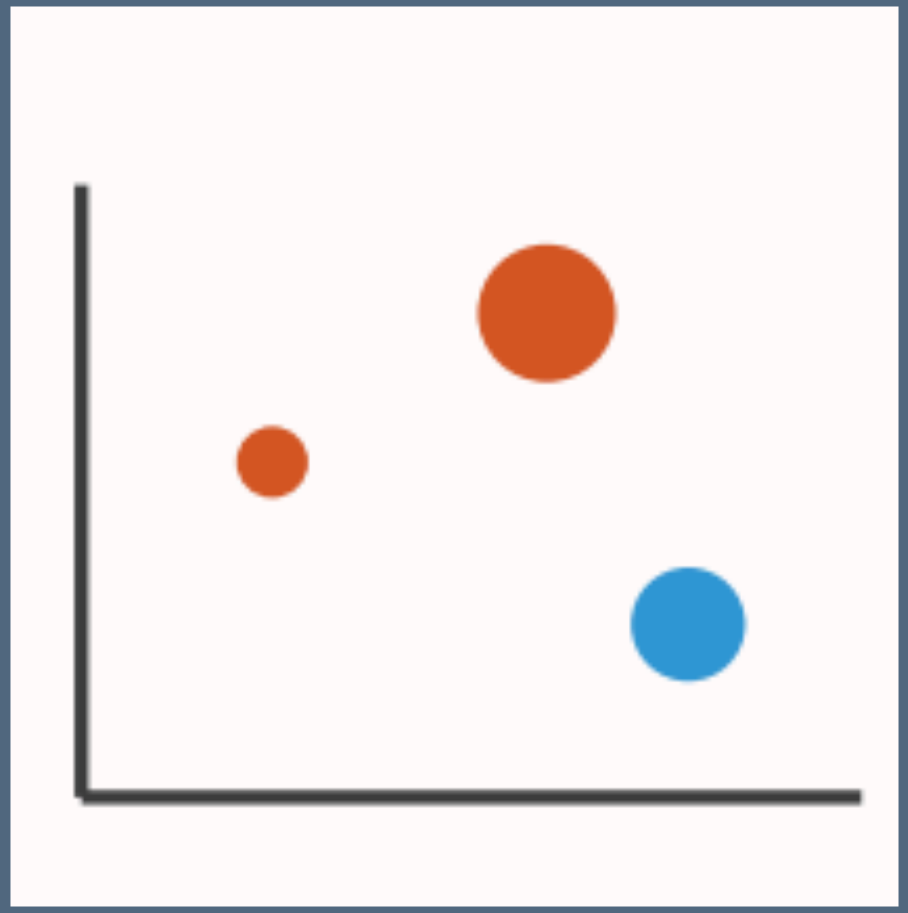
Mark: bar
county(nominal) → x
population(quant) → size or length



Mark: point
acreage(quant) → x
population(quant) → y

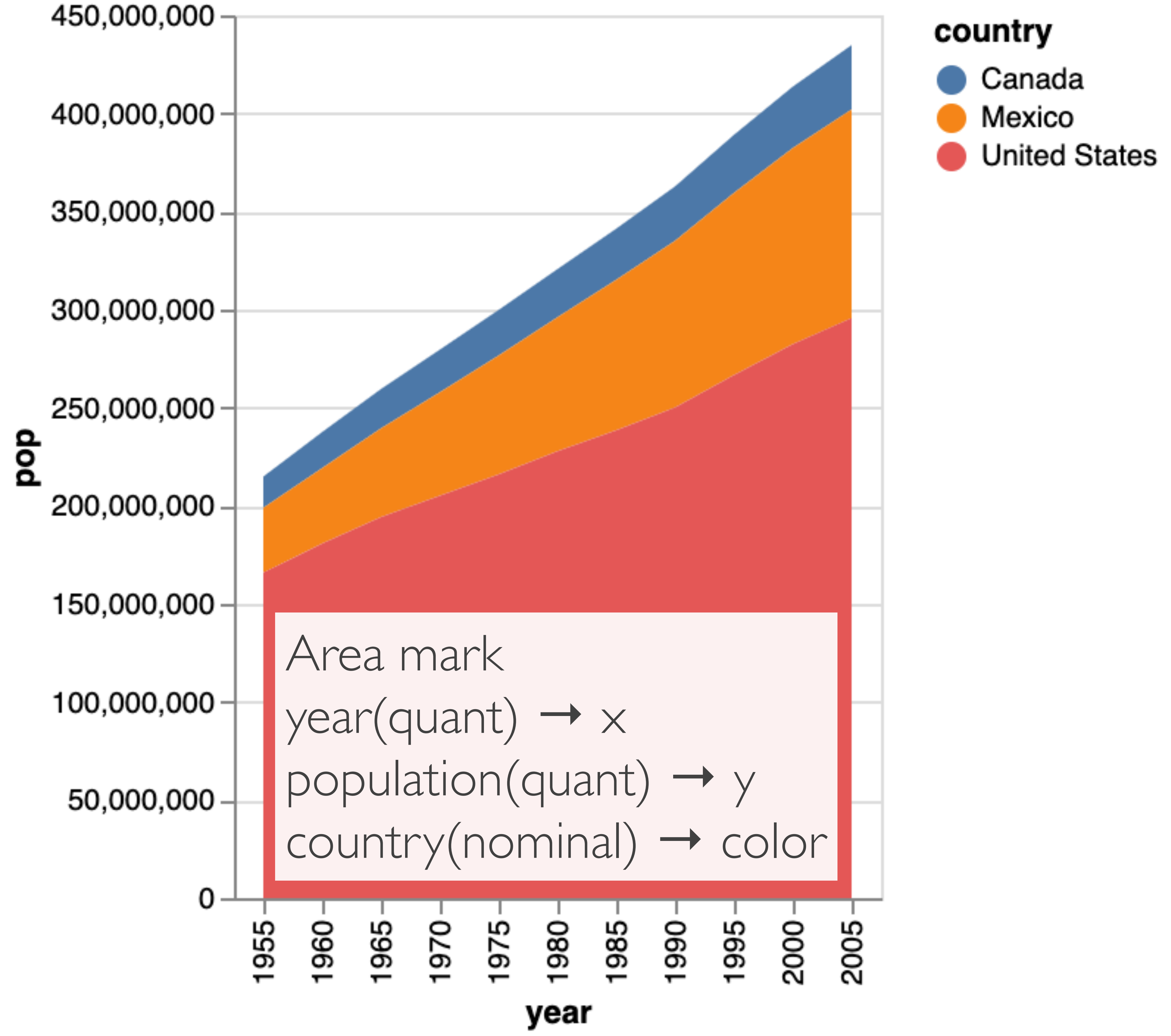


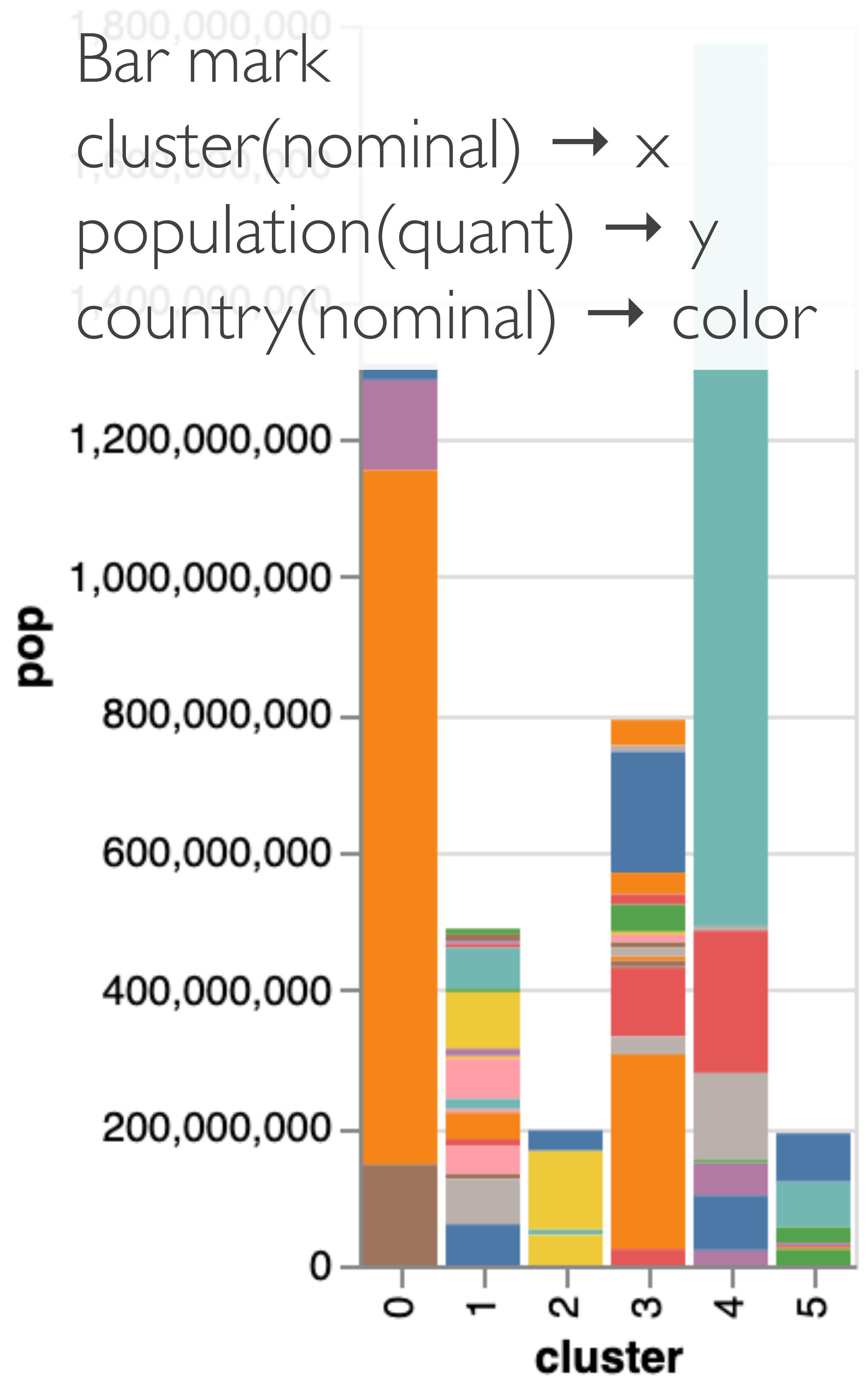
Mark: point
acreage(quant) → x
population(quant) → y
county(nominal) → color



Mark: point
acreage(quant) → x
population(quant) → y
county(nominal) → color
avg_income(quant) → size

"Best" encoding based on **perceptual effectiveness** of visual attribute for data type

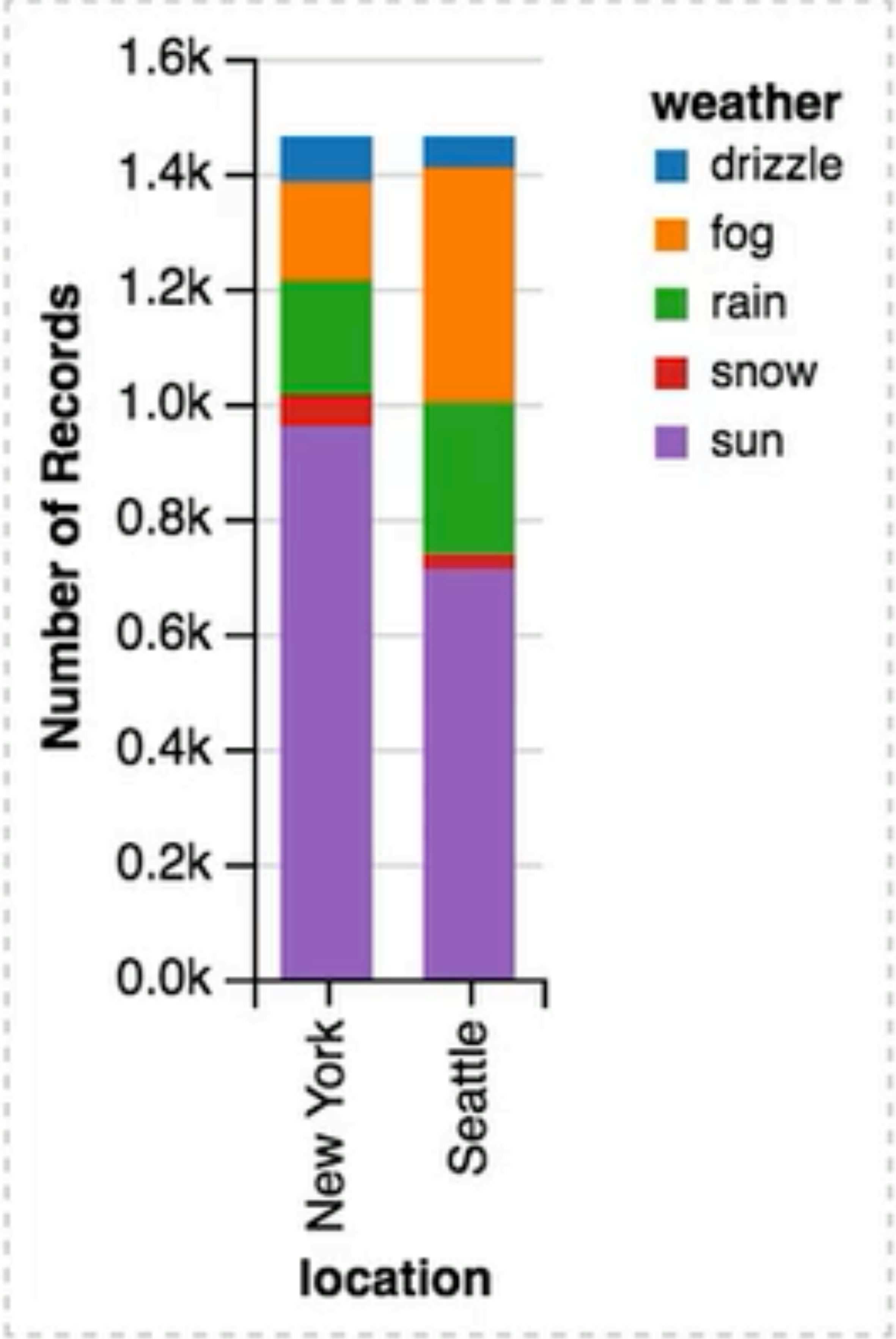




What precisely makes these visualizations—of the same dataset—different?

[Heer 2021]

```
{
  "data": {"url": "data/weather.csv","formatType": "csv"},
  "mark": "bar",
  "encoding": {
    "x": {"field": "location","type": "nominal"},
    "y": {
      "field": "*",
      "type": "quantitative",
      "aggregate": "count"
    },
    "color": {"field": "weather","type": "nominal"}
  }
}
```

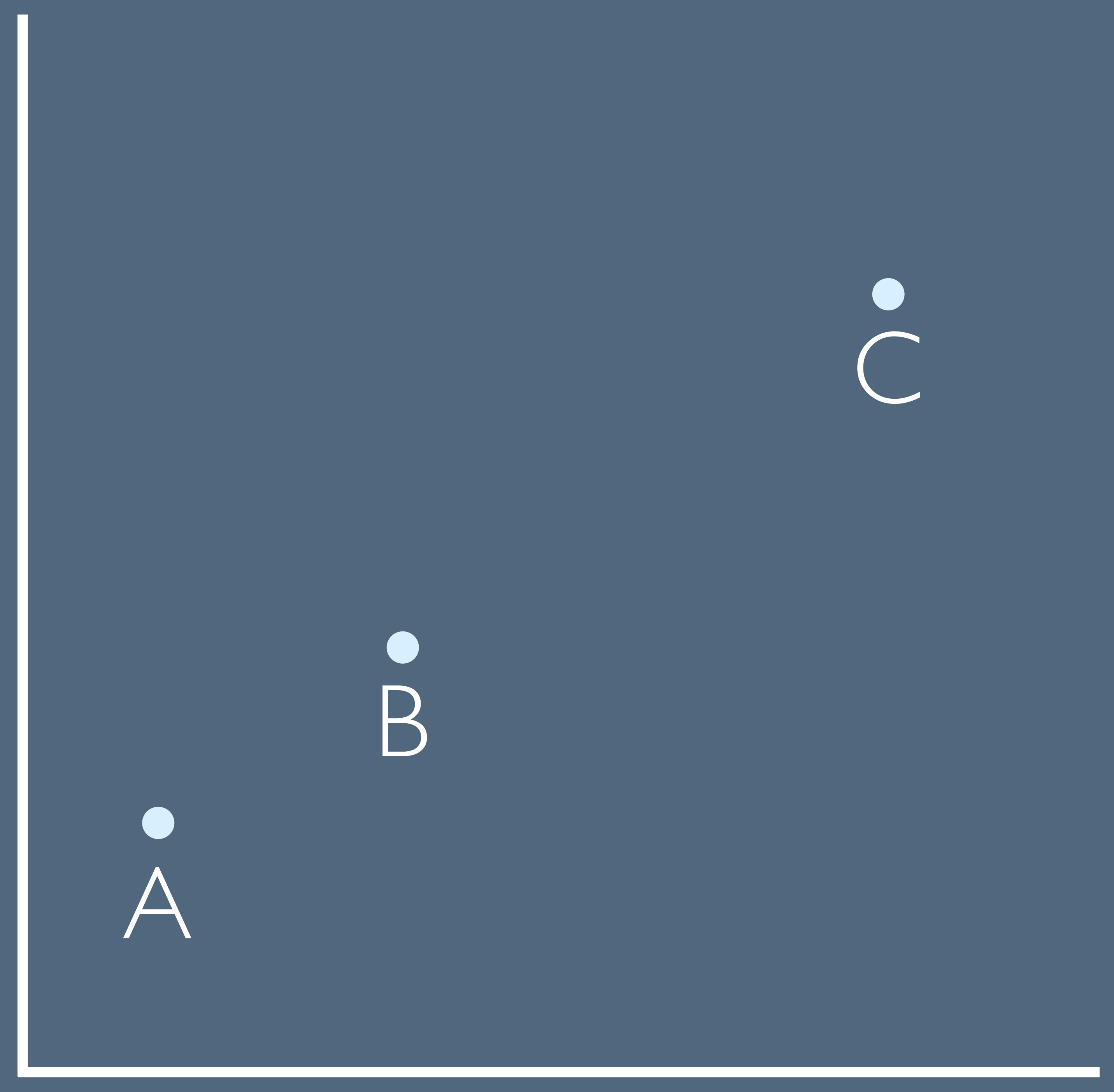


[Satyanarayan et al. 2016]

Graphical perception

How we look at graphs

Position



We immediately notice that:

- A, B, C are distinguishable
- Points are collinear. B is between A and C
- BC is twice as long as AB

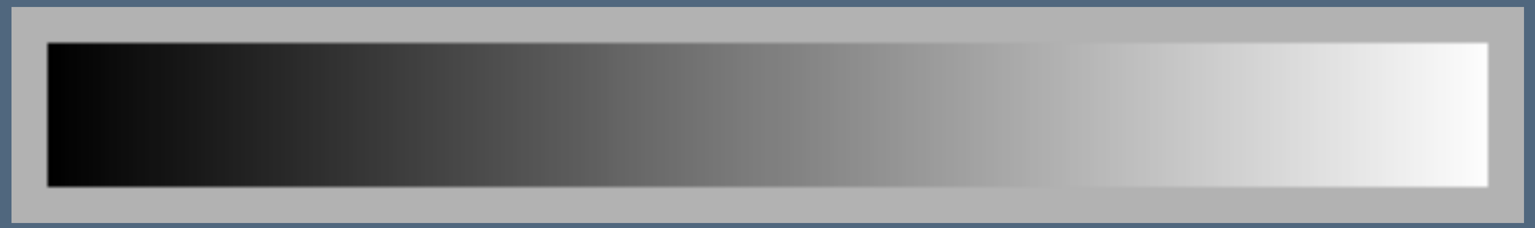
Position encodes quantitative data well

Color

Value or gray level is perceived as ordered

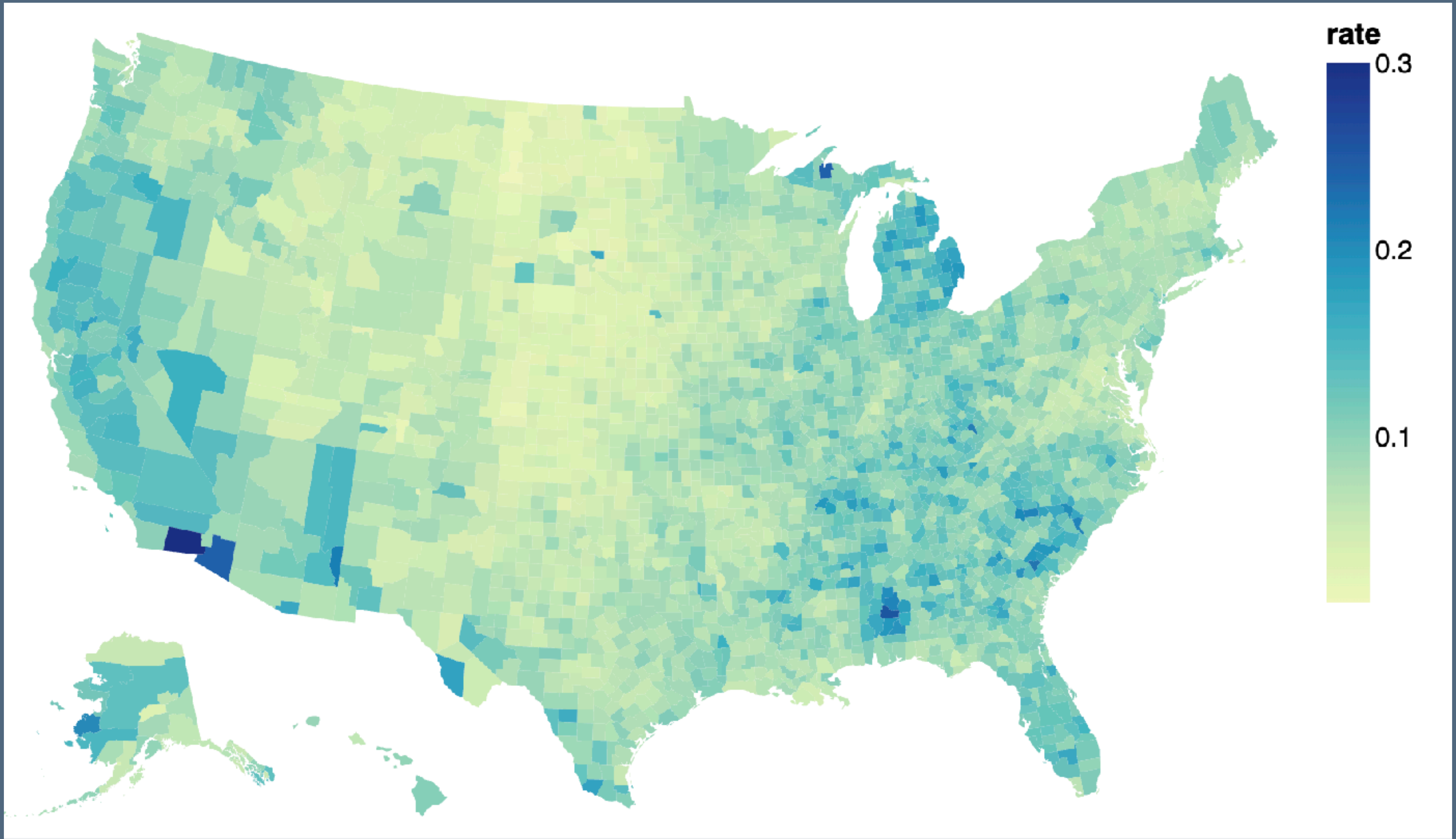
So, it encodes ordinal data well

But, fine differences hard to perceive, so encodes quantitative data less well



Hue is typically perceived as unordered

So, hue encodes nominal data well



We can perceive which areas have higher rates, but it takes effort to understand **how much** higher the rates are (2x? 3x?)

Bertin's "Levels of Organization"

[Bertin 1967]

Ranking of visual variables in terms of how well they can represent different kinds of data: e.g., position and size are good for all data types

Position	**Nominal**	**Ordinal**	**Quantitative**
Size	**Nominal**	**Ordinal**	**Quantitative**
Value	**Nominal**	**Ordinal**	(quantitative)
Texture	**Nominal**	(ordinal)	
Color	**Nominal**		
Orientation	**Nominal**		
Shape	**Nominal**		

Brightness

Which is brighter? With only a quick visual judgment:

Brightness

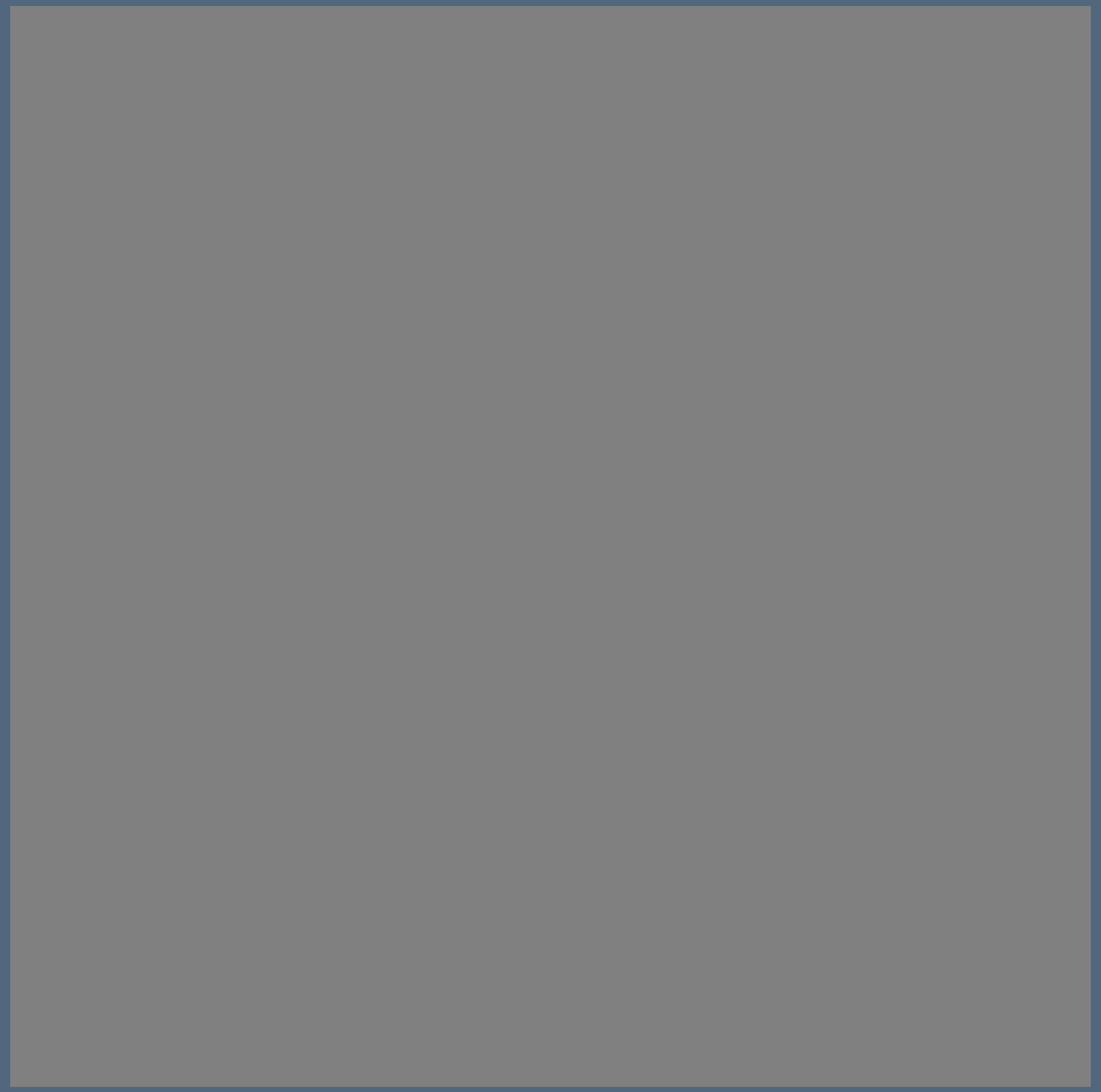
Which is brighter? With only a quick visual judgment:

Brightness

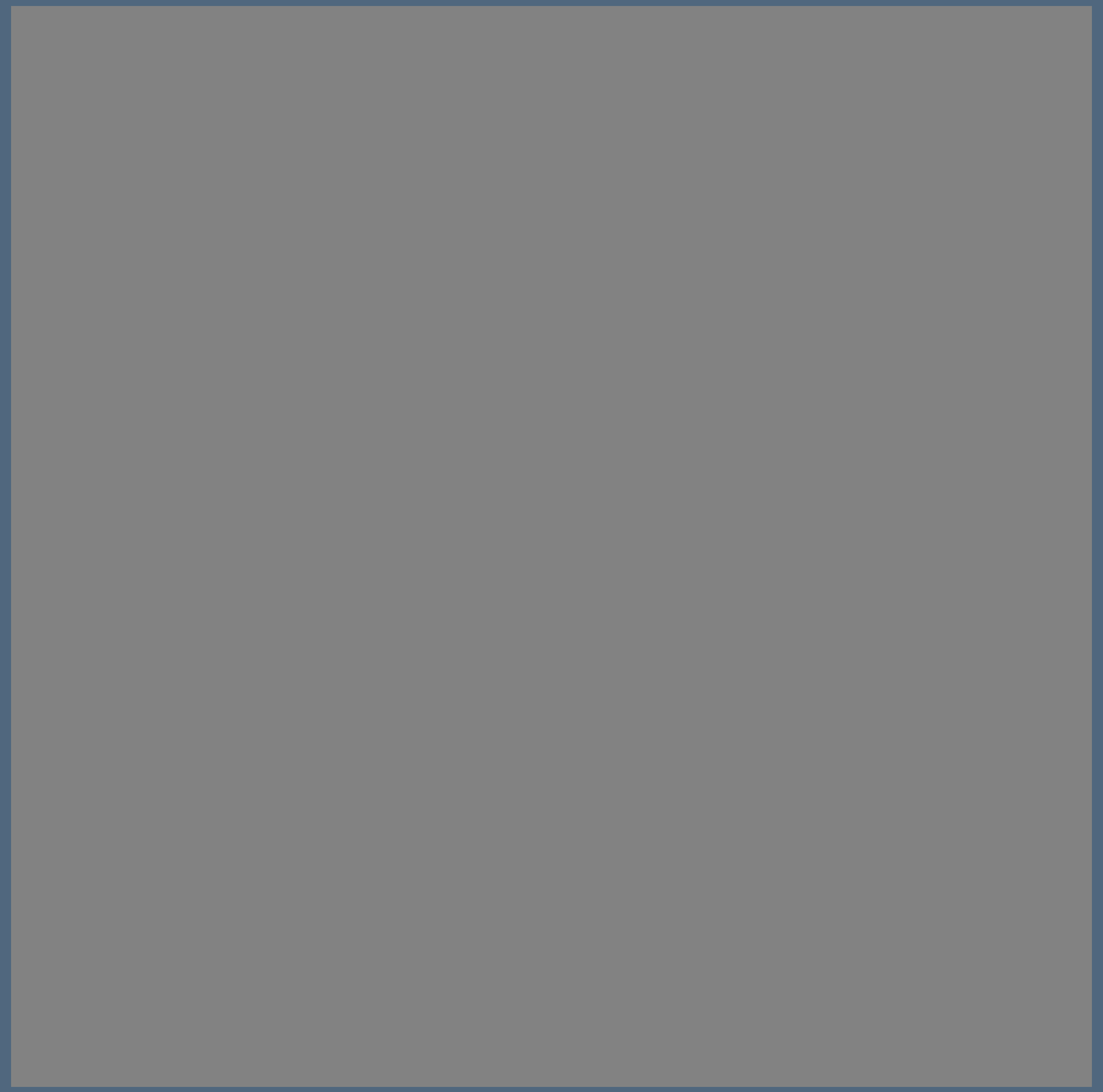
Which is brighter? With only a quick visual judgment:

Brightness

Which is brighter? With only a quick visual judgment:



(128, 128, 128)



(130, 130, 130)

Area

Which has greater area? With only a quick visual judgment:

Area

Which has greater area? With only a quick visual judgment:

Area

Which has greater area? With only a quick visual judgment:

Area

Which has greater area? With only a quick visual judgment:

10000π pixels 13924π pixels

Length

Re-encoding the same comparison as length rather than area:

Length

Re-encoding the same comparison as length rather than area:

Length

Re-encoding the same comparison as length rather than area:

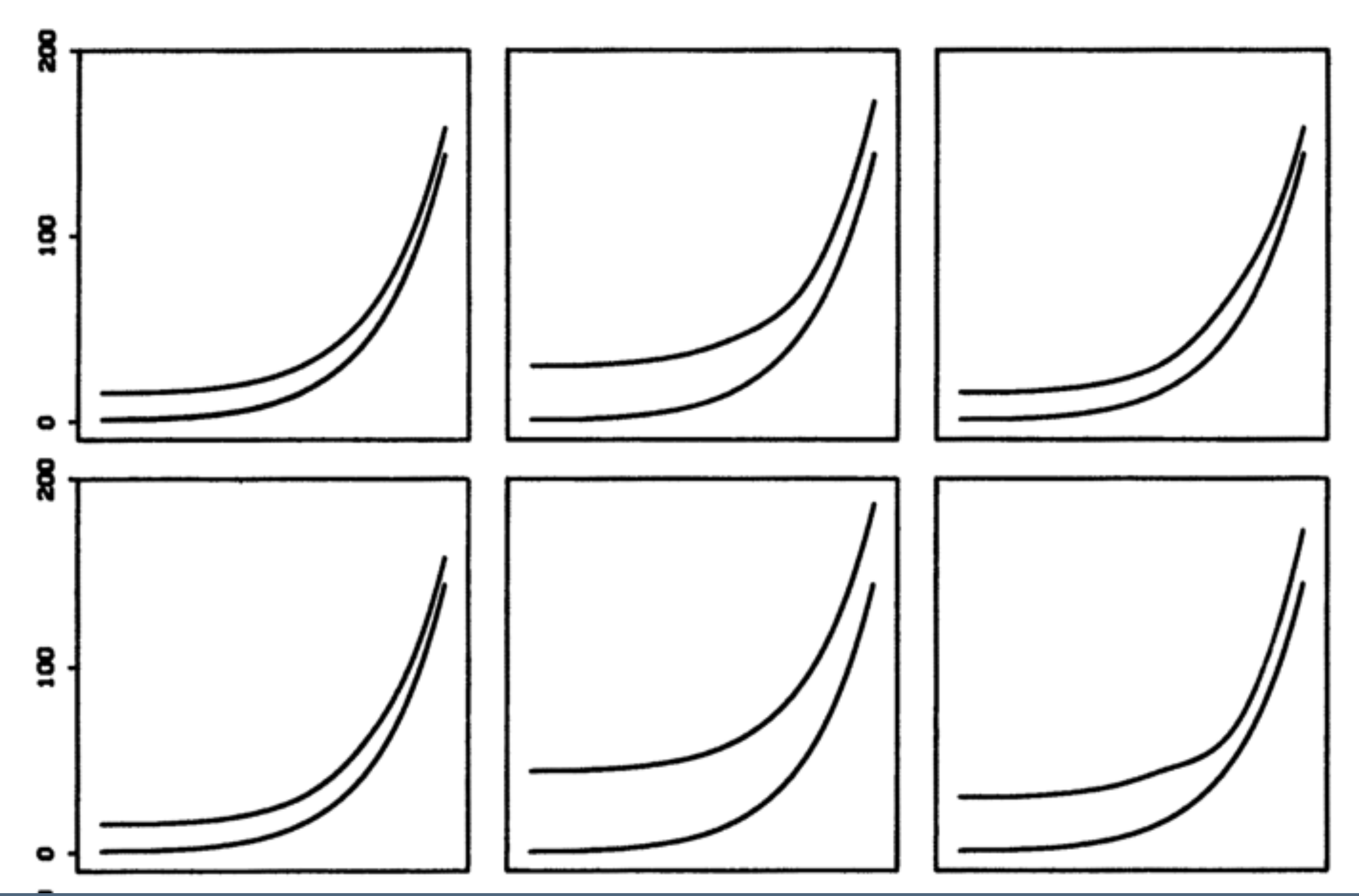
Length

Re-encoding the same comparison as length rather than area:

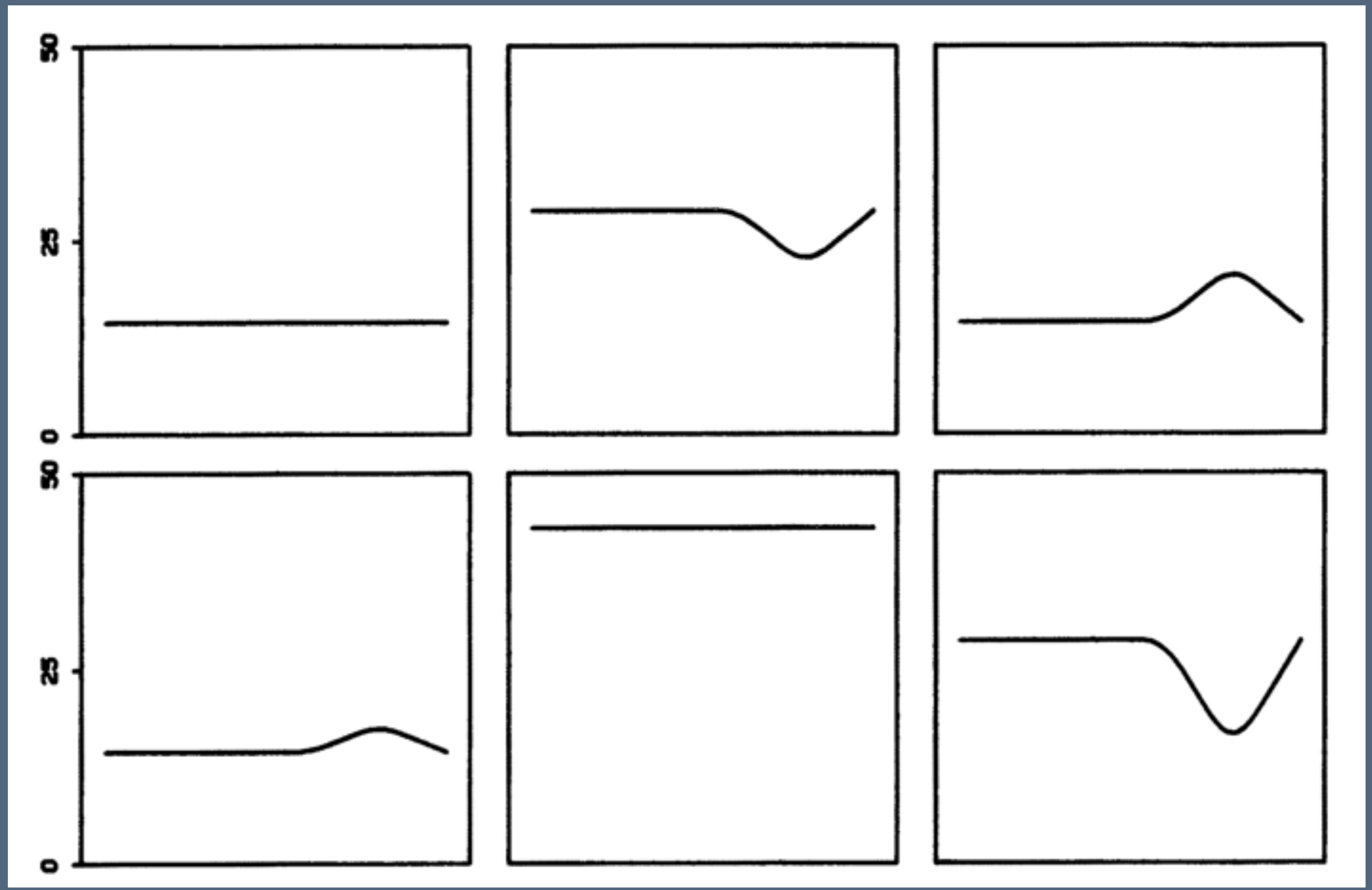
We are poor at perceiving (some) differences [Cleveland and McGill1984]

Classic result: experimental tests of the relationship between encodings and the accuracy of the differences that we perceive from those encodings

What are the distances between these lines?

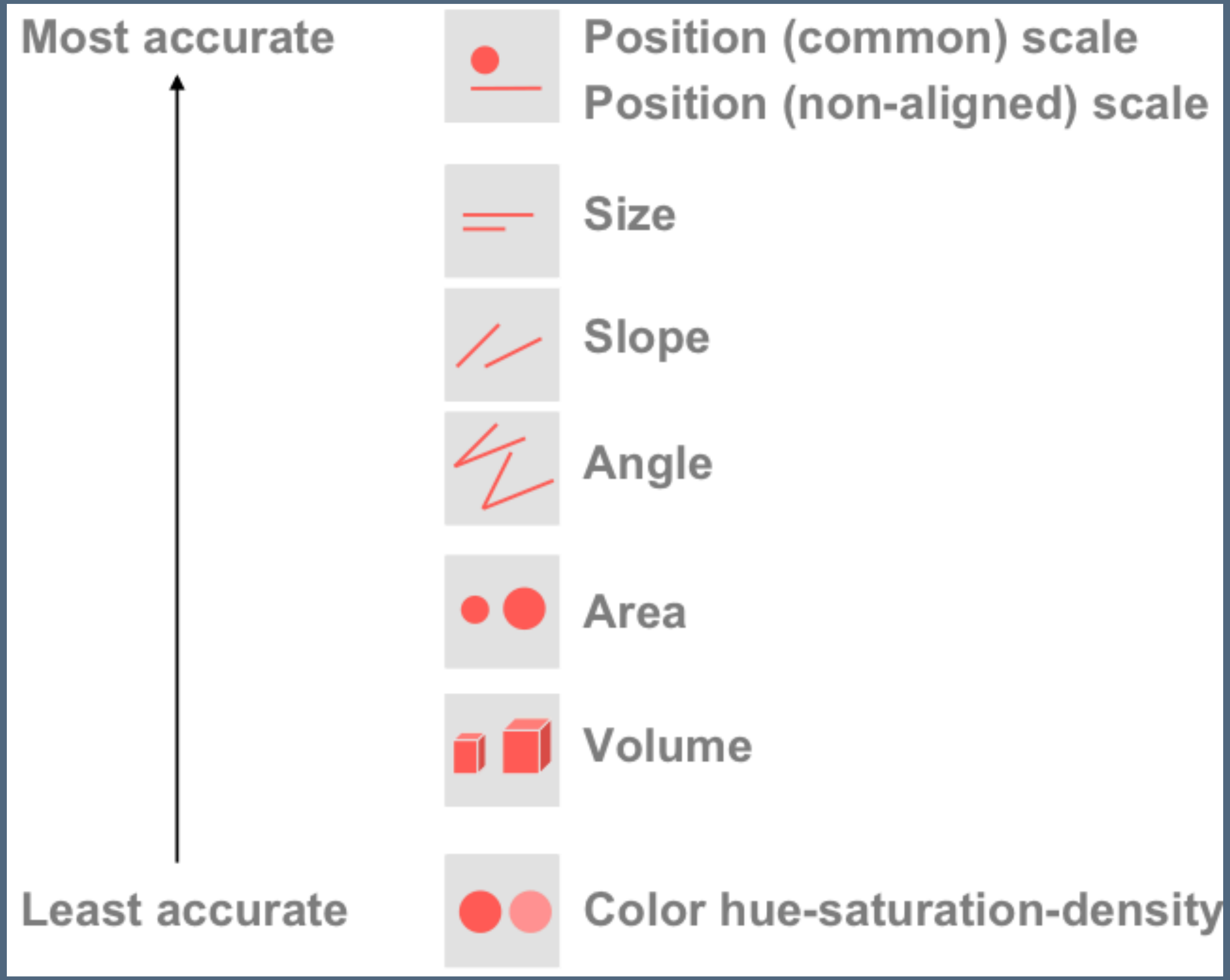


Answers — map onto each cell to the left:



Result of systematic experimentation

In comparing relative magnitude:



← Why pie charts get hate

Graphical perception enables chart construction

[Mackinlay 1986]

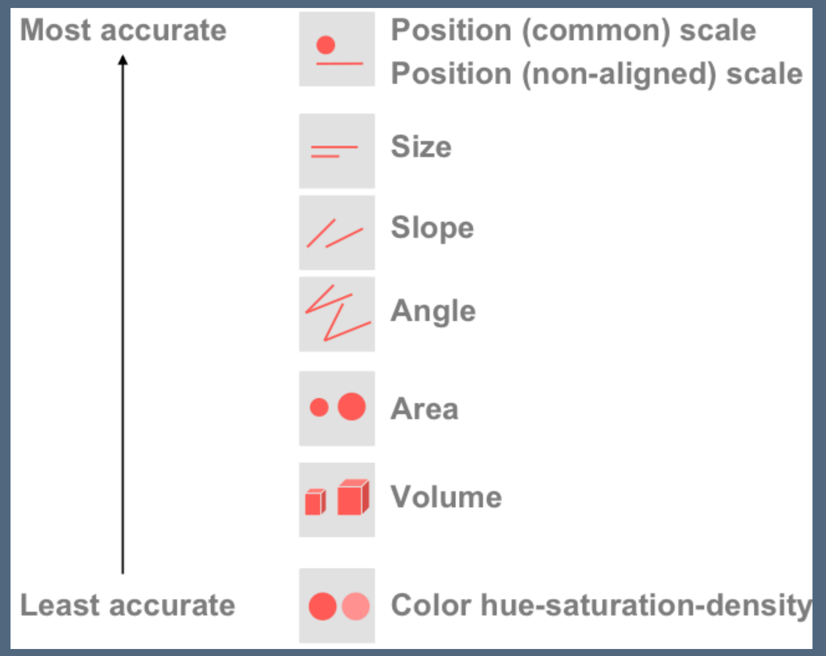
Algorithm: encode the most important data using the highest-ranking visual variable for the data type

Year	Exports	Imports
1700	170,000	300,000
1701	171,000	302,000
1702	176,000	303,000
...	...	...

→

1. quant(year)
2. quant(exports)
3. quant(imports)

→



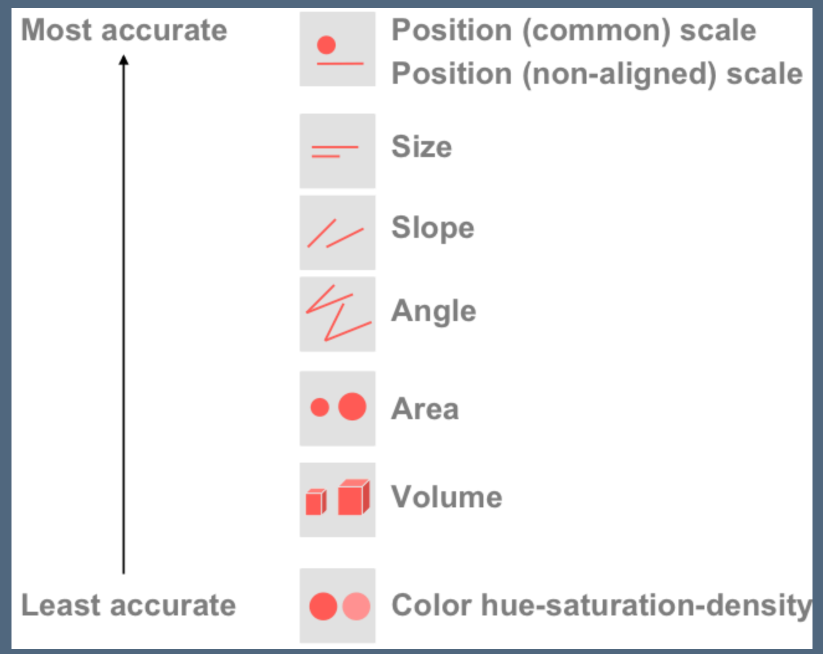
→

mark: lines
quant(year) → x
quant(exports) → y
quant(imports) → y

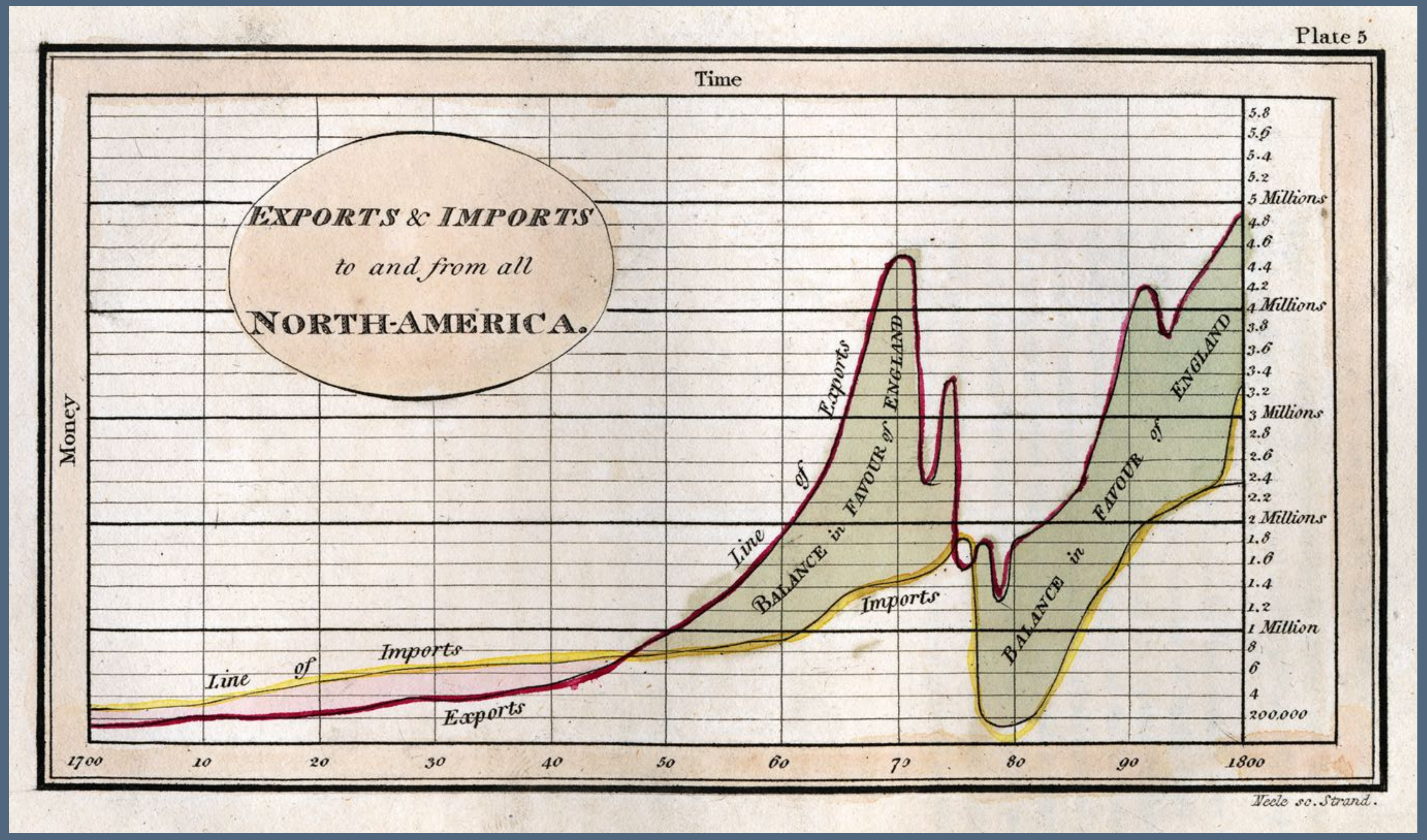
Graphical perception enables chart construction

[Mackinlay 1986]

Algorithm: encode the most important data using the highest-ranking visual variable for the data type

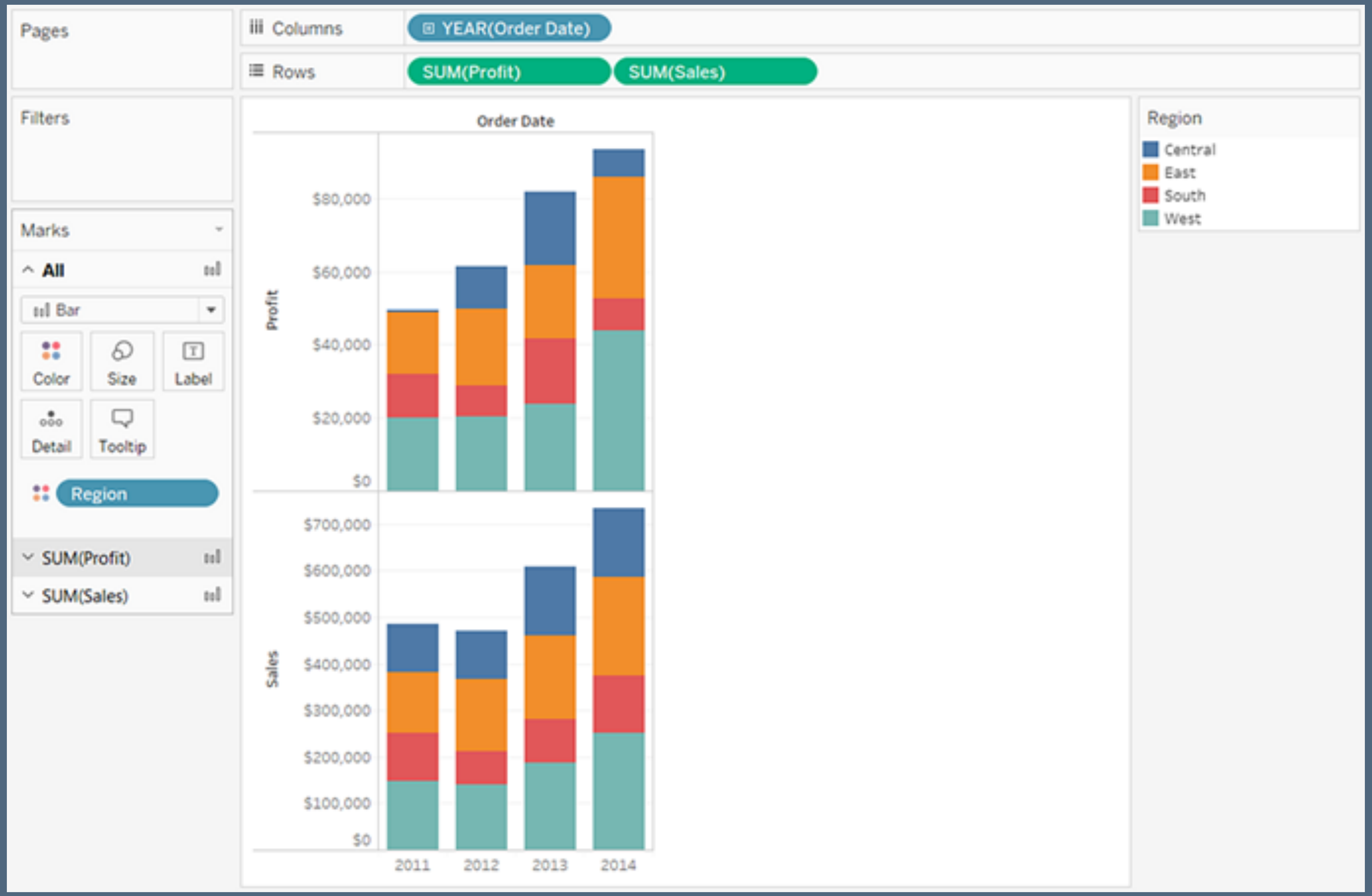


mark: lines
quant(year) → x
quant(exports) → y
quant(imports) → y



Impact

Mackinlay's algorithm gets extended by Chris Stolte and Pat Hanrahan into VizQL, which then becomes…



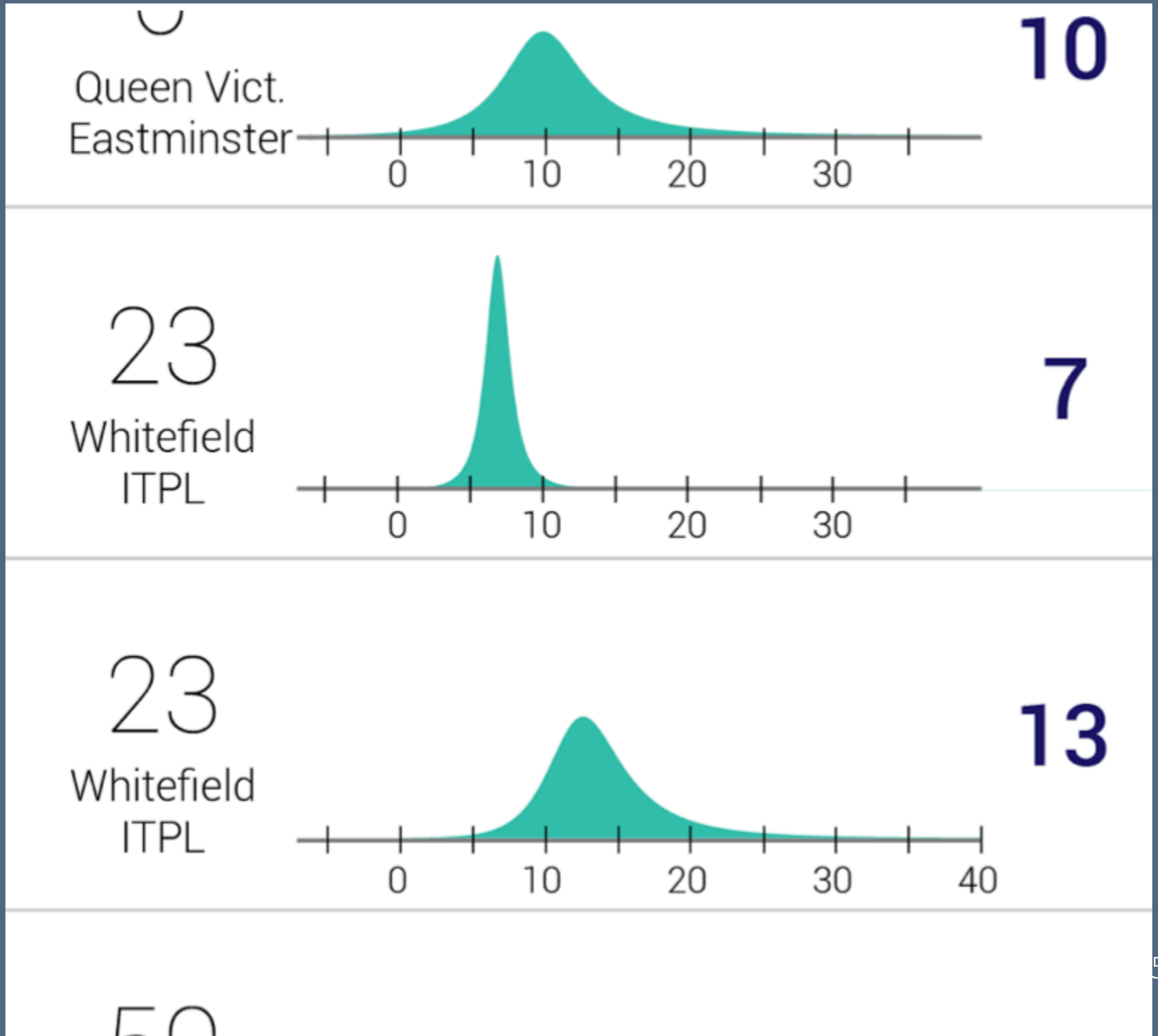
tableau® SOFTWARE

Frontiers of Visualization Research

Conveying uncertainty

[Kay et al. 2016]

We over-rely on point estimates. People simplify distributions and attend to point estimates on the right (10min until the bus comes)



Conveying uncertainty

[Kay et al. 2016]

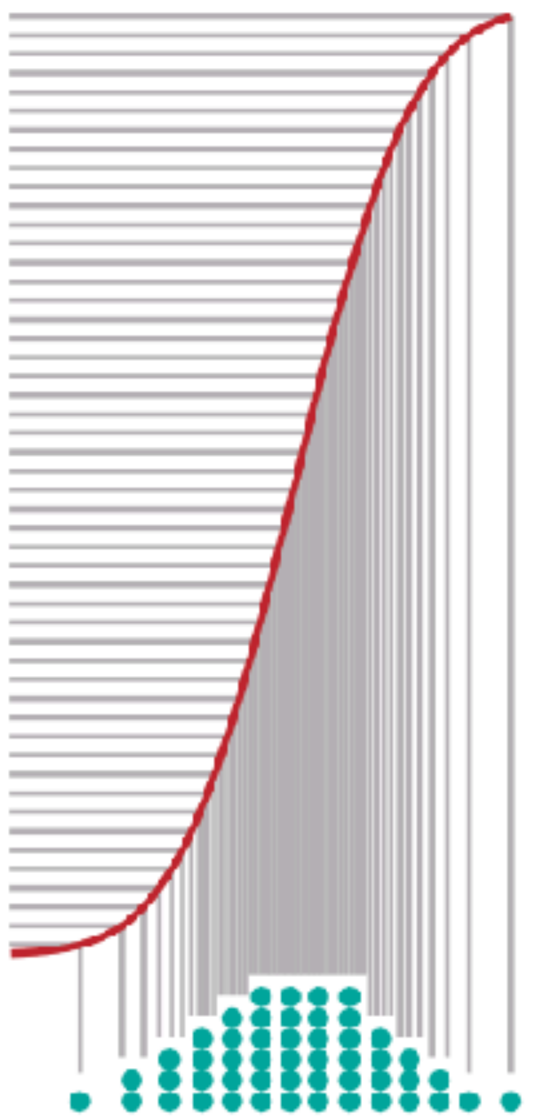
Suggestion: quantile dot plots

Probability density of Normal distribution

To generate a discrete plot of this distribution, we could try taking **random draws** from it. However, **this approach is noisy**: it may be very different from one instance to the next.

Instead, we use the **quantile function (inverse CDF)** of the distribution to generate “draws” from evenly-spaced quantiles.

We plot the quantile "draws" using a Wilkinsonian dotplot, yielding what we call a **quantile dotplot**: a consistent discrete representation of a probability distribution.

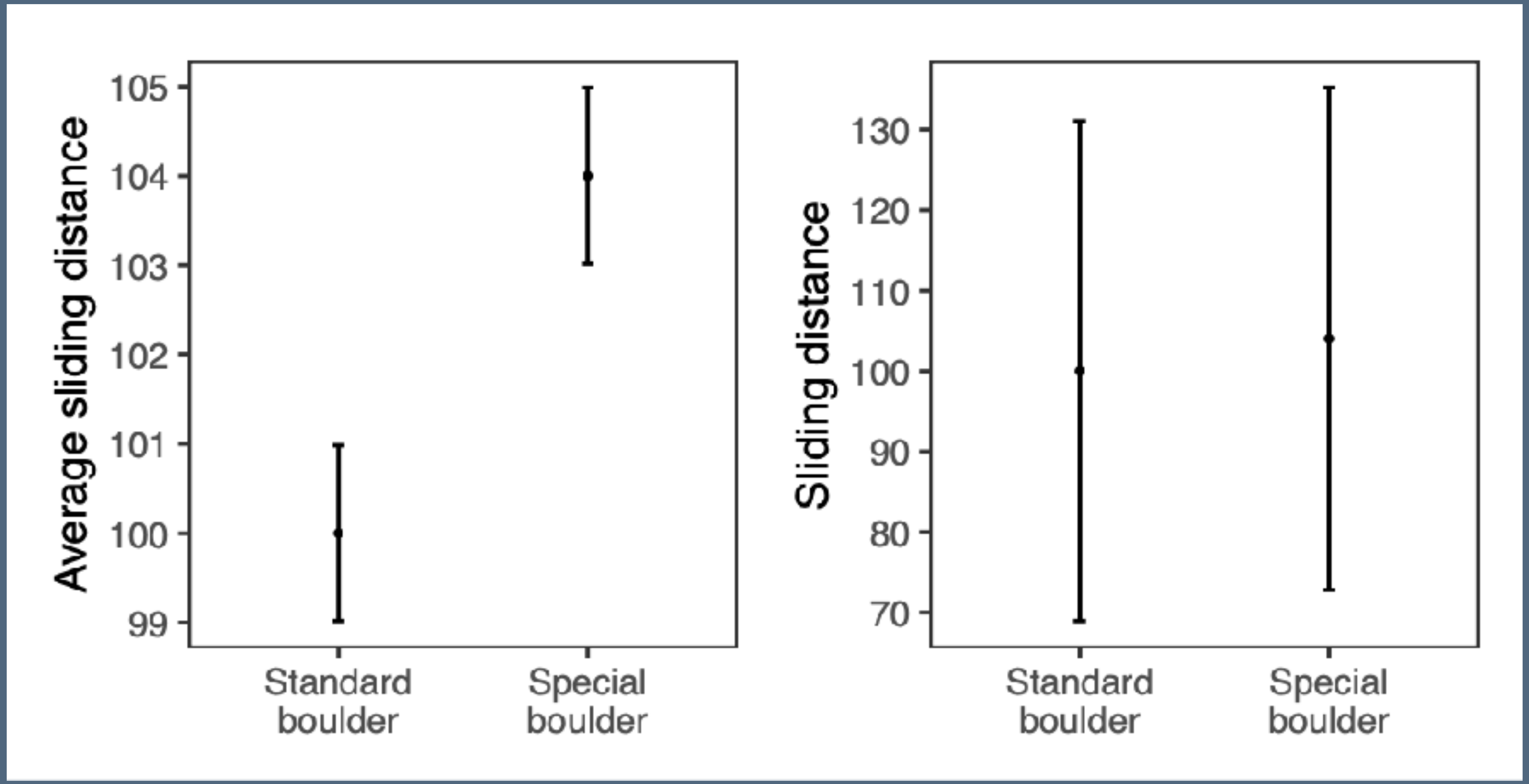


By using quantiles we facilitate interval estimation from frequencies: e.g., knowing there are 50 dots here, if we are willing to miss our bus **3/50** times, we can count **3 dots** from the left to get a one-sided **94% (1 – 3/50) prediction interval** corresponding to that risk tolerance.

Interpretation errors

[Hofman, Goldstein, and Hullman 2020]

Two common visualizations of uncertainty:



Std. Error: uncertainty in the population mean

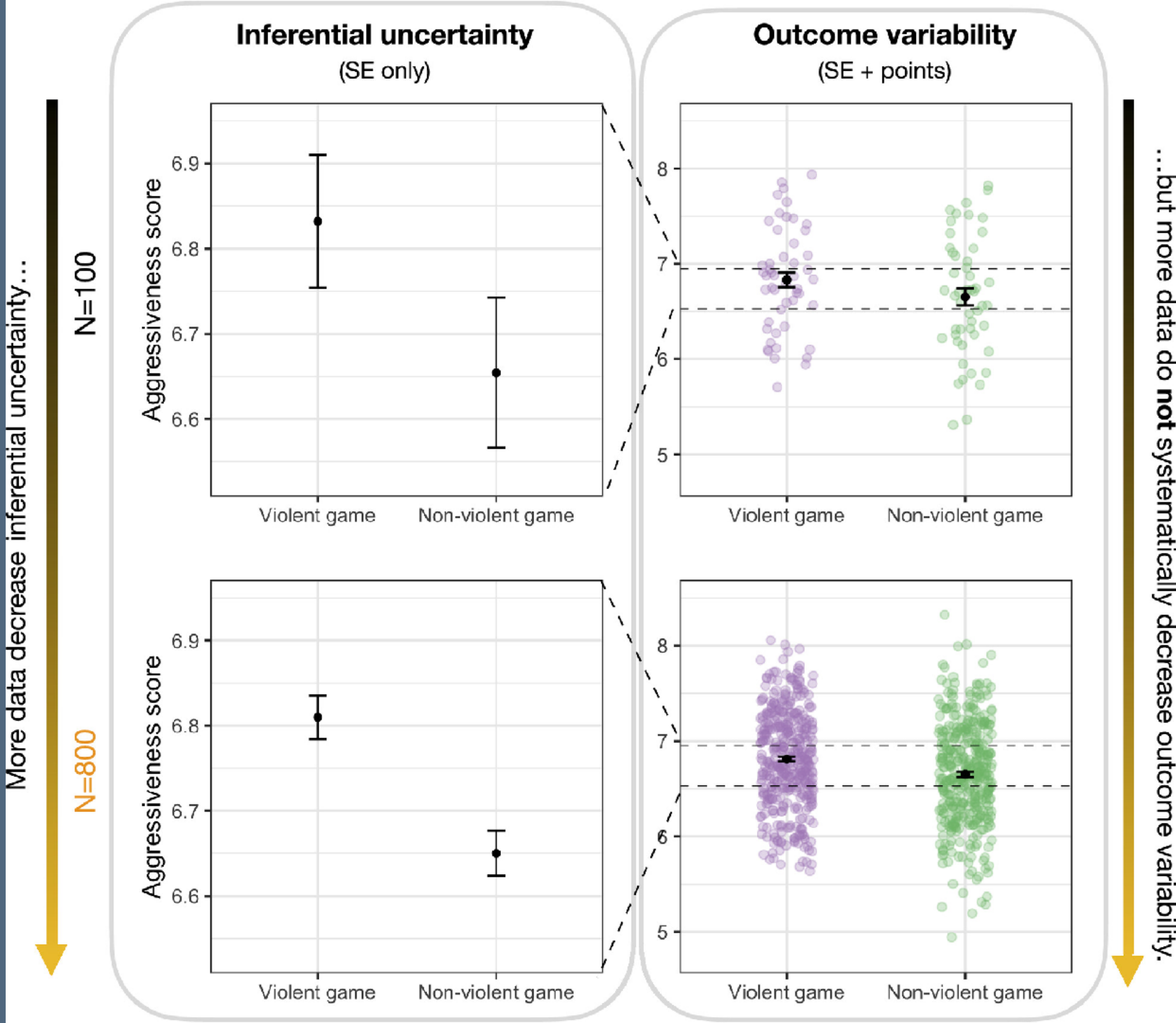
Std. Deviation: uncertainty in a single sample

Experiment: people overestimate treatment effects when shown standard errors instead of standard deviation

Uncertainty or variability?

[Zhang et al. 2023]

Even experts draw the wrong conclusions: "The prevalent form of visualizing only inferential uncertainty can lead to significant overestimates of treatment effects, even among highly trained experts."



Exploratory analysis

[Wongsuphasawat et al. 2015]

User inputs dataset and variables of interest, and recommender automatically generates visualizations of relevant other variables

Intentionally difficult?

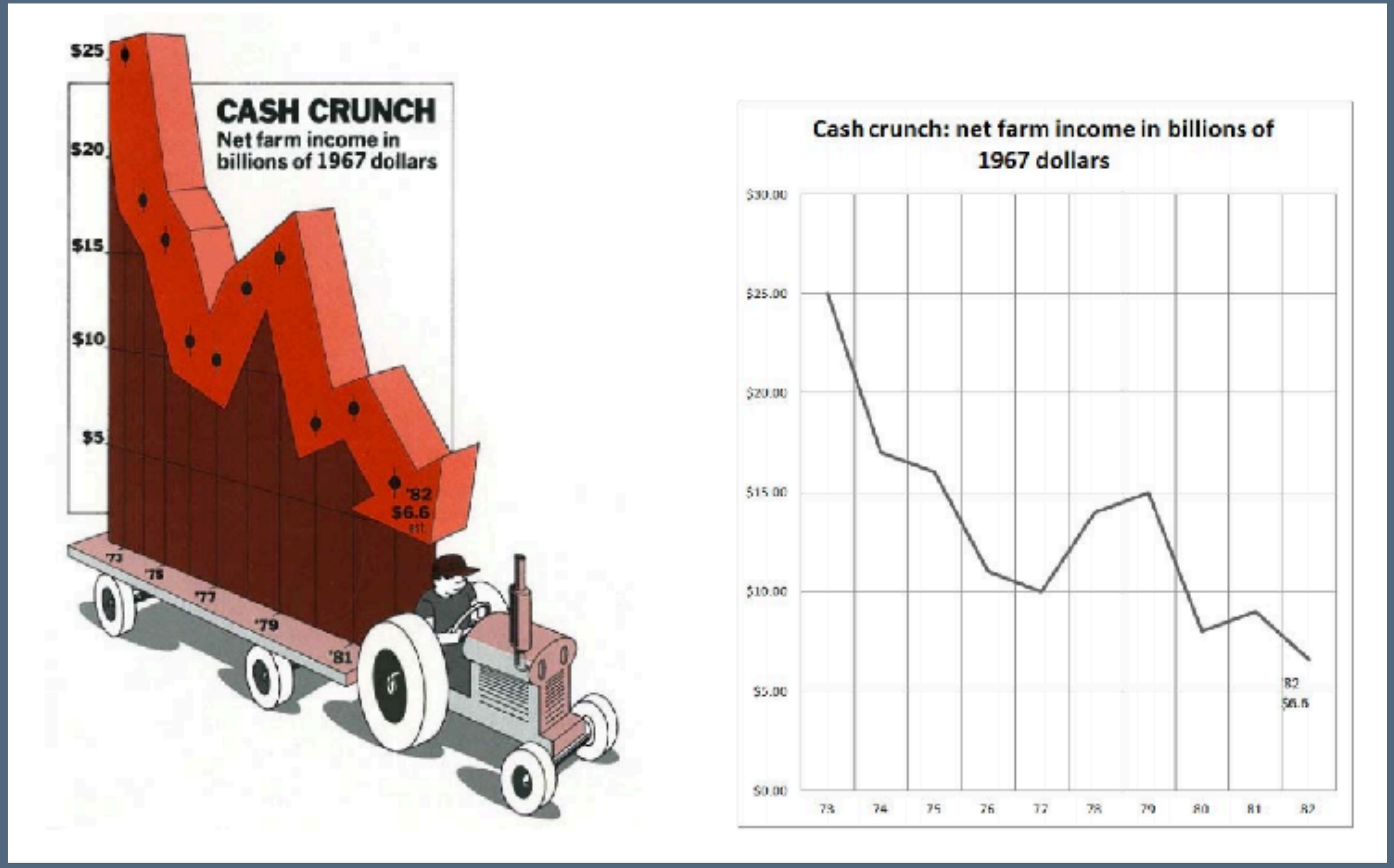
[Hullman and Adar 2011]

Generally, visualization (and HCI more broadly) argue optimizing for clear and correct interpretation

Yet difficult visualizations may support better comprehension and recall

Why? It induces active processing:

- Forcing active construction of meaning
- Disfluent learning experiences avoid heuristics and superficial reasoning



Difficult with chartjunk Easy

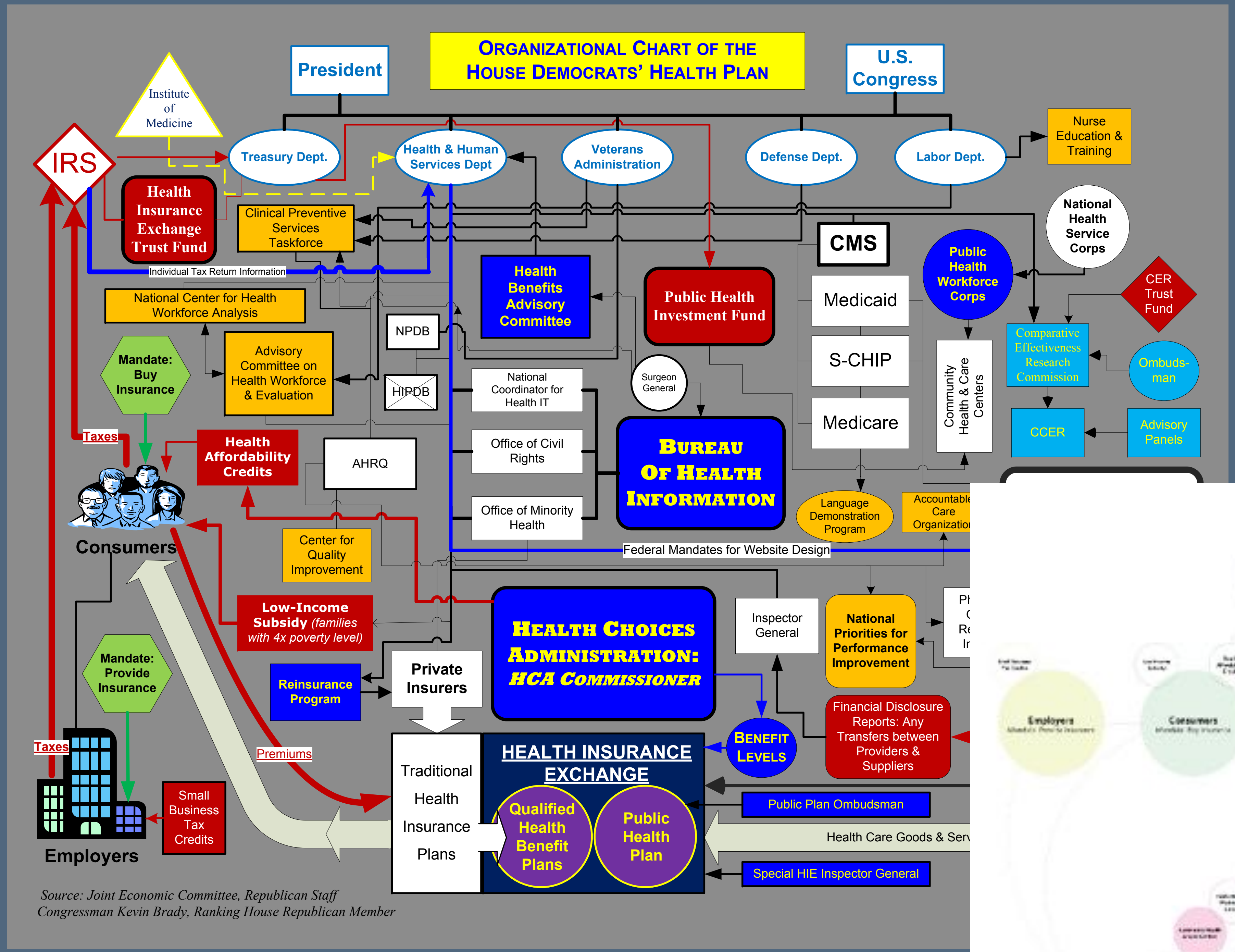
Rhetoric and visualization

[Hullman and Diakopoulos 2011]

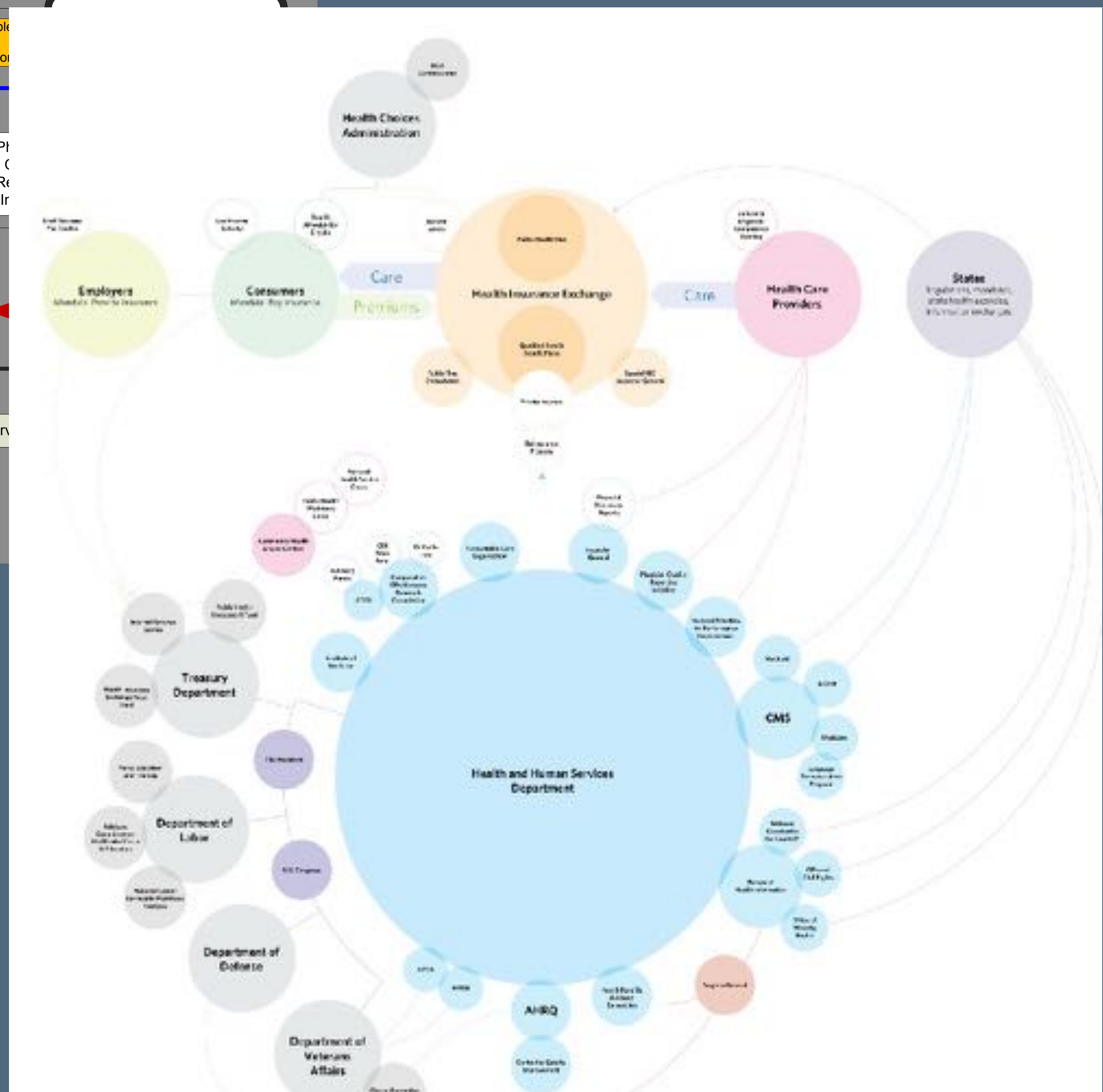
Visualizations embed rhetorical goals to tell a story

Semiotics: signs derive their meaning from culture and other signs placed near them

Rhetoric gets embedded by omission, by how we represent uncertainty, by visual metaphor (up and right = good), and others



House of Representatives graphic



"Do not %*#& with graphic designers" response by Robert Palmer

Conveying rhetoric visually

[Wu, Chung, and Adar 2023]

Draw on the control techniques described in the "Black Box" lecture to make visualizations that reflect some desired underlying narrative or semiotics

Remember the "visual blends" example? 

Is vis 'truth'? [Lee et al. 21]

Narrative visualization can be tuned to any goal: a group of scientific skeptics used the rhetorics of science and visualization to "follow the data" on COVID vaccines to its own conclusions

Visualization is not an objective process that always produces correct answers

Viral Visualizations: How Coronavirus Skeptics Use Orthodox Data Practices to Promote Unorthodox Science Online

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ABSTRACT

Controversial understandings of the coronavirus pandemic have turned data visualizations into a battleground. Defying public health officials, coronavirus skeptics on US social media spent much of 2020 creating data visualizations showing that the government's pandemic response was excessive and that the crisis was over. This paper investigates how pandemic visualizations circulated on social media, and shows that people who mistrust the scientific establishment often deploy the same rhetorics of data-driven decision-making used by experts, but to advocate for radical policy changes. Using a quantitative analysis of how visualizations spread on Twitter and an ethnographic approach to analyzing conversations about COVID data on Facebook, we document an epistemological gap that leads pro- and anti-mask groups to draw drastically different inferences from similar data. Ultimately, we argue that the deployment of COVID data visualizations reflect a deeper sociopolitical rift regarding the place of science in public life.

CCS CONCEPTS

• Human-centered computing → Empirical studies in visualization; Visualization theory, concepts and paradigms; Social and professional topics → Ethnographic studies.

1 INTRODUCTION

Throughout the coronavirus pandemic, researchers have held up the crisis as a "breakthrough moment" for data visualization research [91]: John Burn-Murdoch's line chart comparing infection rates across countries helped millions of people make sense of the pandemic's scale in the United States [44], and even top Trump administration officials seemed to rely heavily on the Johns Hopkins University COVID data dashboard [70]. Almost every US state now hosts a data dashboard on their health department website to show how the pandemic is unfolding. However, despite a preponderance of evidence that masks are crucial to reducing viral transmission [25, 29, 105], protestors across the United States have argued local governments to overturn their mask mandates and begin opening schools and businesses. A pandemic that affects a majority, they reason, should not impinge on the liberties of a ... go about life as usual. To support their arguments, these ... and activists have created thousands of their own visual... often using the same datasets as health officials.

This paper investigates how these activist networks use ... of scientific rigor to oppose these public health measures ... ignoring scientific evidence to argue for individual fre... maskers often engage deeply with public datasets and ... we call "counter-visualizations"—visualizations us... methods to make unorthodox arguments—to challeng... narratives that the pandemic is urgent and ongoi... community members to "follow the data," these g... data visualizations to support significant local cha... We examine the circulation of COVID-relate... both quantitative and qualitative ...

Towards Understanding How Readers Integrate Charts and Captions: A Case Study with Line Charts [Kim et al. 2021]

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The 30-year fixed mortgage rate increased slightly from 1997 to 1999.

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Chart Emphasis
≠
Caption Emphasis
↓
Takeaway:
Chart Emphasis

The 30-year fixed mortgage rate increased slightly from 1997 to 1999.

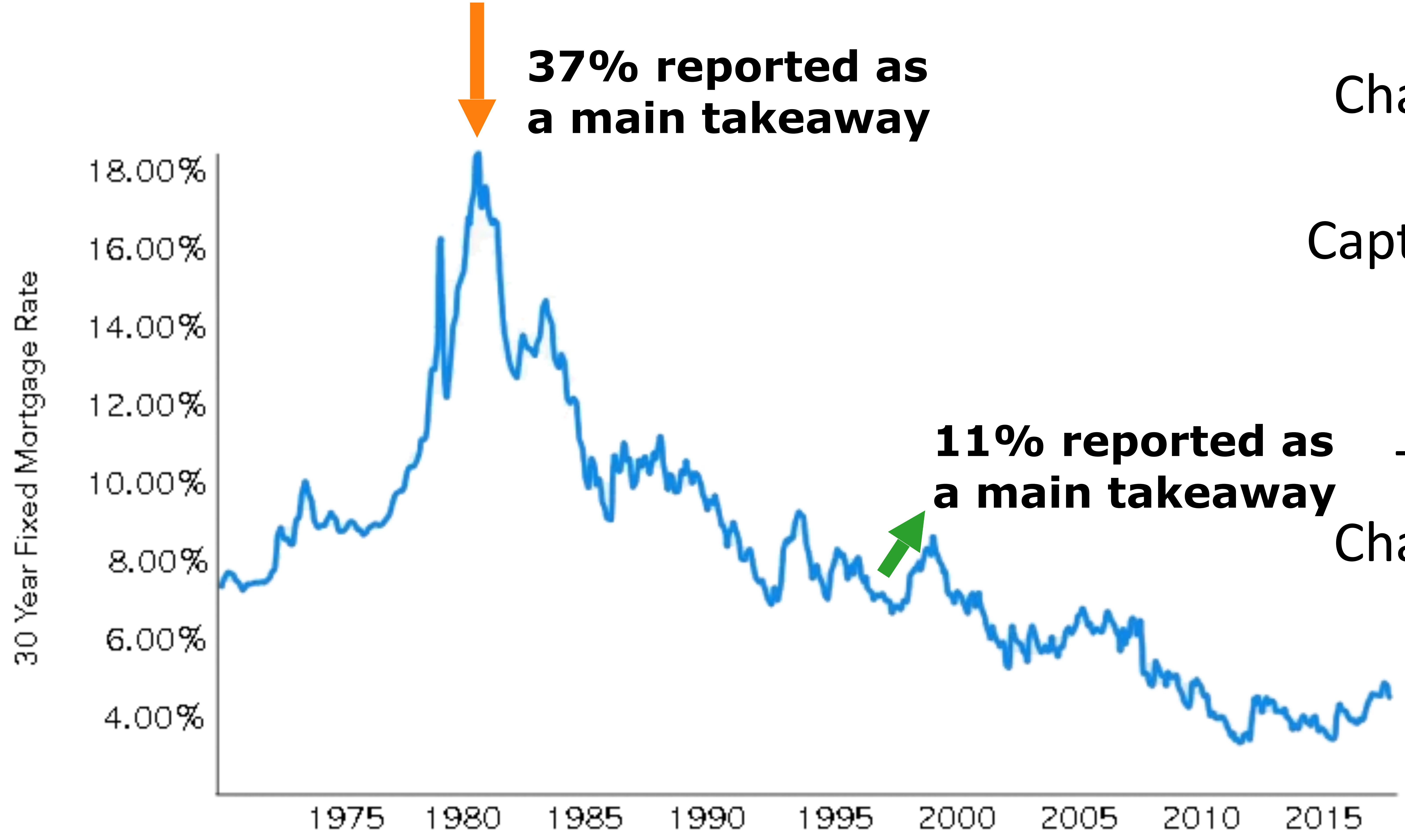

Chart Emphasis ≠ Caption Emphasis

↓

Takeaway: Chart Emphasis

The 30-year fixed mortgage rate increased slightly from 1997 to 1999.

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Chart Emphasis

=

Caption Emphasis

↓

Takeaway:

Chart Emphasis

The 30-year fixed mortgage rate reached its peak of 18.5% in 1981.

Towards Understanding How Readers Integrate Charts and Captions: A Case Study with Line Charts [Kim et al. 2021]

Reading Charts and Captions

[Kim et al. 2021]

When text and visualization emphasis **mismatch**, readers **rely more on the chart** and can miss information in the caption.

(a) Prominent features & Basic caption (b) Caption text about prominent feature (c) Caption including false information (d) Caption about less prominent feature

EmphasisChecker: A Tool for Guiding Chart and Caption Emphasis [Kim et al. 2023]

Summary

Visualizations can be represented as **encodings** that map from **data to marks & visual attributes** based on **data types**

Our **cognitive and perceptual systems determine which encodings are effective**: we (mis)read data if encoded poorly

Active research at frontiers investigating **how users can create effective visualizations** and **how readers take information away from them**

CS 448B Visualization

Stanford CS course on data visualization techniques (Fall 2021)

Location: Huang Eng. 18
Time: MW 11:30am-1pm

ABOUT

LEARNING GOALS

TEXTBOOKS/RESOURCES

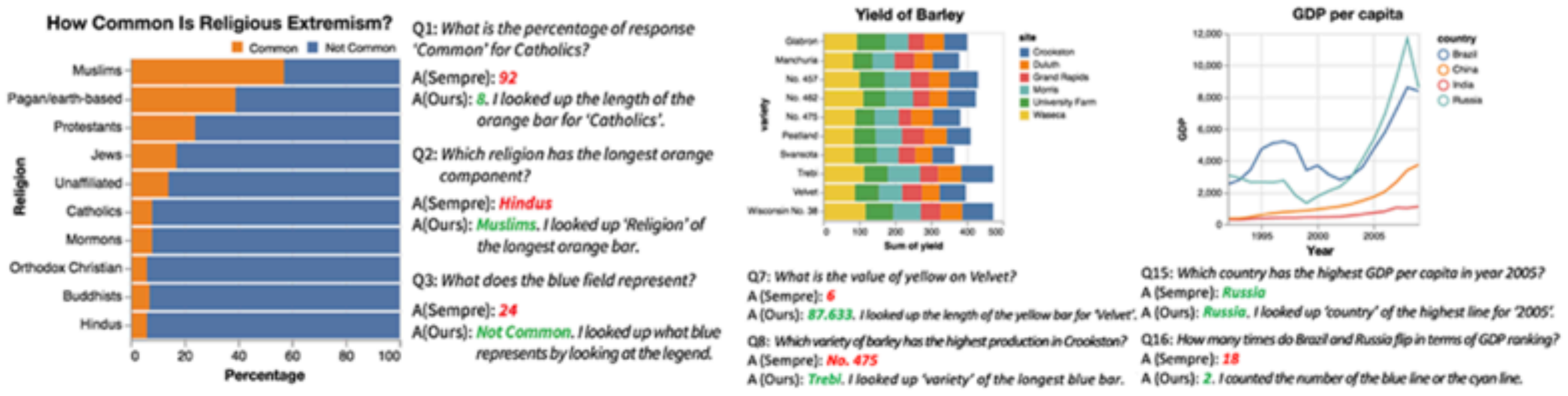
SCHEDULE

- Week 1
- Week 2
- Week 3
- Week 4
- Week 5
- Week 6
- Week 7
- Week 8
- Week 9
- Week 10

TEACHING STAFF

ASSIGNMENTS

- Class Participation
- Assignment 1
- Assignment 2
- Assignment 3
- Final Project



Well designed visualizations capitalize on human facilities for processing visual information and thereby improve comprehension, memory, inference, and decision making. In this course we will study techniques and algorithms for creating effective visualizations based on principles from graphic design, visual art, perceptual psychology and cognitive science. The course is targeted both towards students interested in using visualization in their own work, as well as students interested in building better visualization tools and systems.

There are no official prerequisites for the class, but familiarity with the material in CS147, CS148 and CS142 is especially useful. Most important is a basic working knowledge of, or willingness to learn, web-programming, especially JavaScript, Vega-Lite and D3.js. While we will cover a little bit of Vega-Lite and D3.js in class, we will also expect students learn some introductory material, especially about Javscript on their own, as necessary. Tutorials on Javascript are available on the web and we will help you find the relevant information as you need it.

*Contact us via Slack if you are worried about whether you have the background for the course.

Learning Goals

The goals of this course are to provide students with the foundations necessary for understanding and extending the current state of the art in visualization. By the end of the course, students will have:

- An understanding of key visualization techniques and theory, including data models, graphical perception and methods for visual encoding and interaction.
- Exposure to a number of common data domains and corresponding analysis tasks, including exploratory data analysis and network analysis.
- Practical experience building and evaluating visualization systems using Vega-Lite and D3.js.
- The ability to read and discuss research papers from the visualization literature.

Textbooks/Resources

1. The Visual Display of Quantitative Information (2nd Edition). E. Tufte. Graphics Press.
2. Envisioning Information. E. Tufte. Graphics Press.
3. ***Optional Textbook.*** Visualization Analysis and Design. Tamara Munzner. A K Peters Visualization Series. CRC Press.
4. ***Optional Reference.*** Interactive Data Visualization for the Web (2nd Edition). Scott Murray. O'Reilly Press. [Read Online] [Code Examples on Github]

Your best bet is to order them online. **Please order soon. Readings will be assigned in the first week of class.**

To learn more about visualization consider taking **CS 448B: Fall 2025**

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