CS-5630 / CS-6630 Visualization for Data Science
The Visualization Alphabet: Marks and Channels

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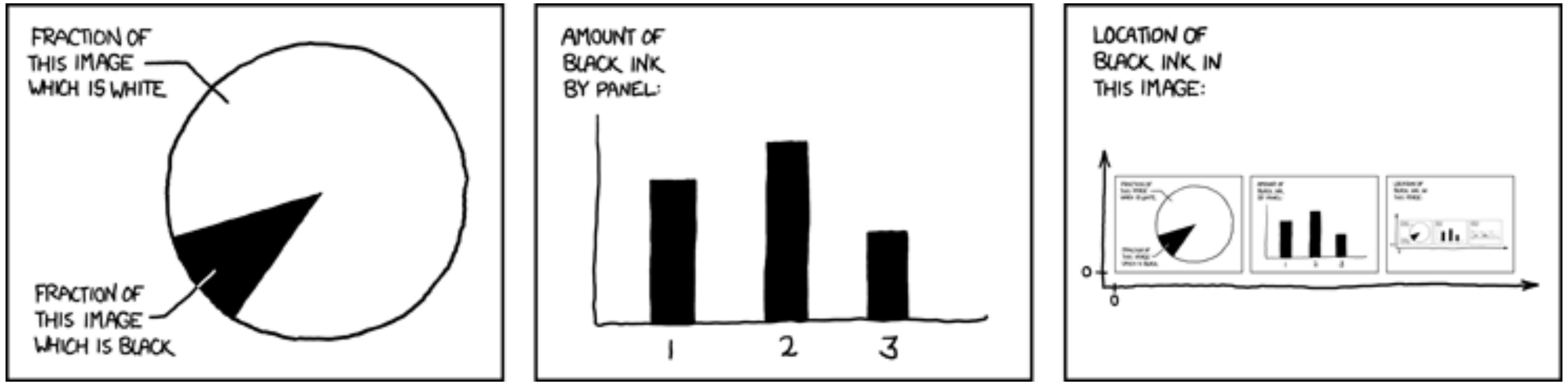
THE UNIVERSITY OF UTAH



[xkcd]

How can I visually represent two numbers, e.g.,

4 and 8

Marks & Channels

Marks: represent **items** or **links**

Channels: change **appearance** based on **attribute**

Channel = Visual Variable

Marks for Items

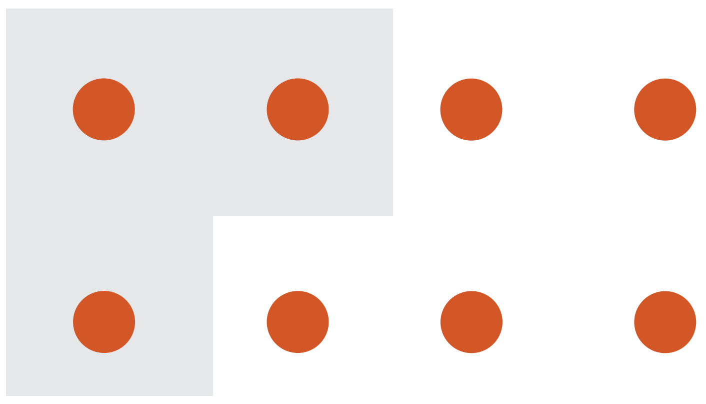
Basic geometric elements

0D 1D 2D

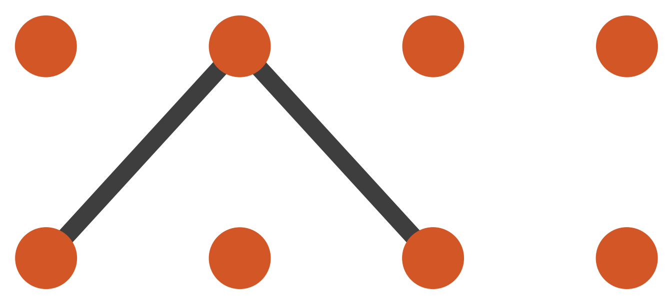
3D mark: Volume, but rarely used

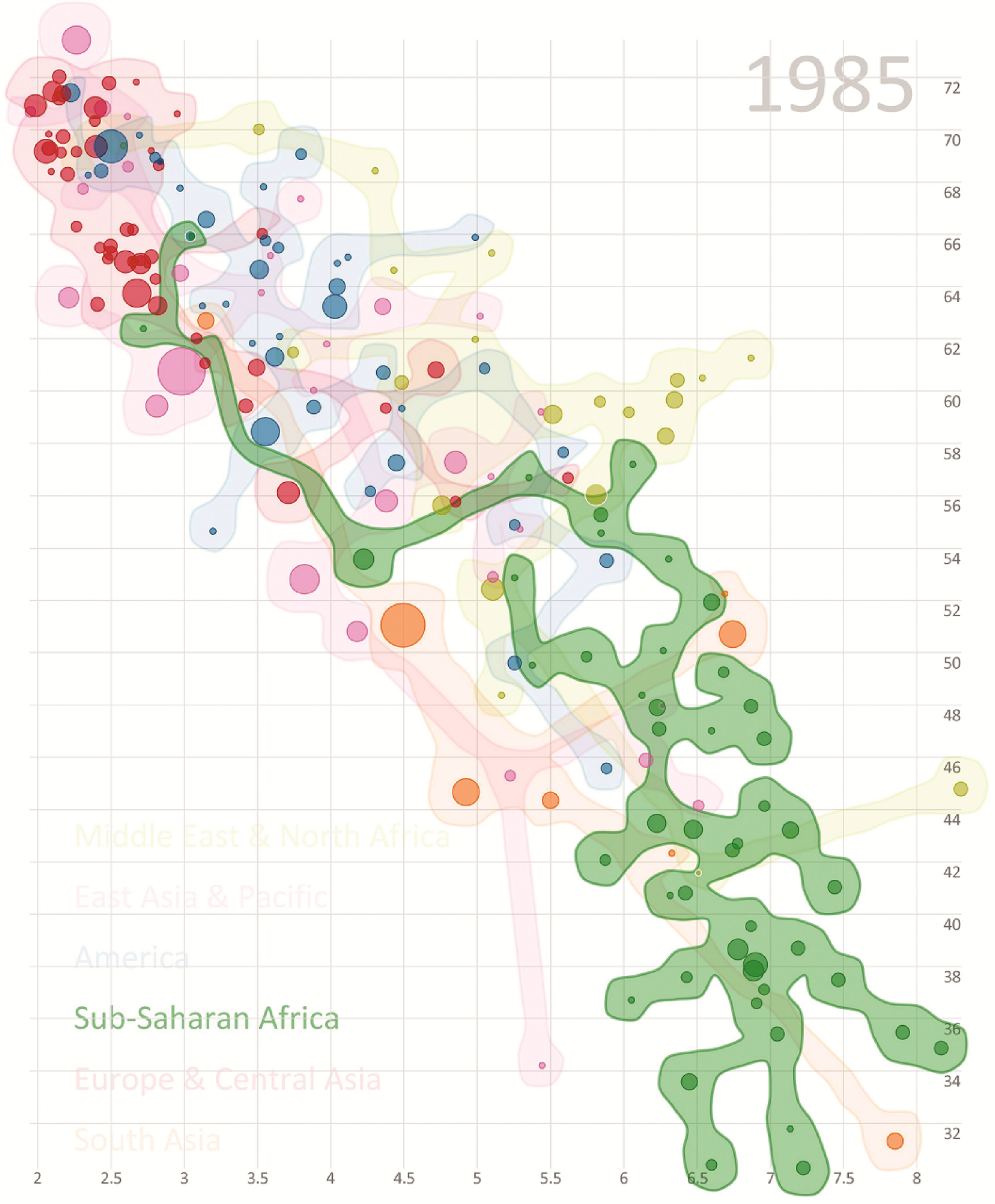
Marks for Links

➔ Containment

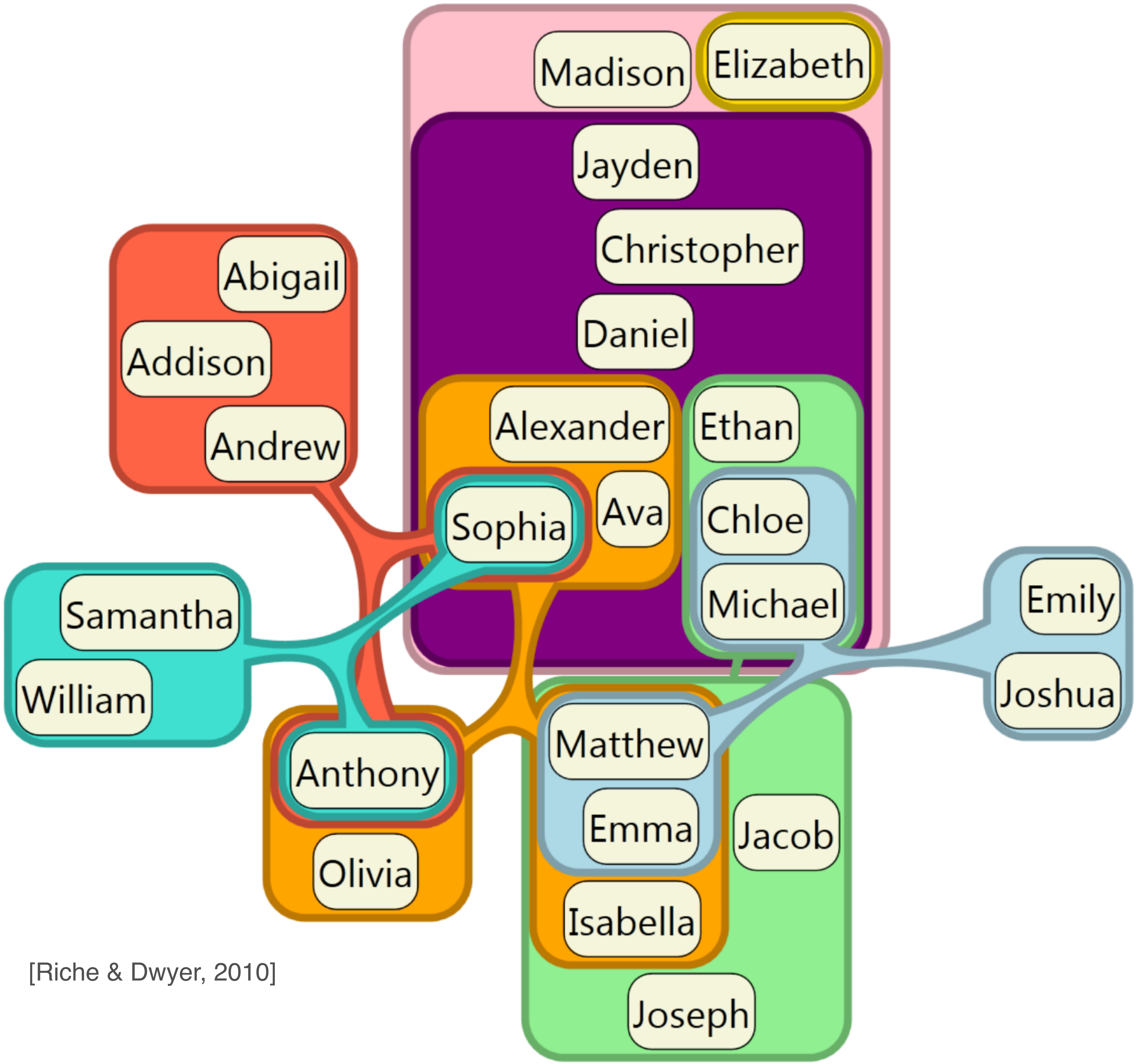


➔ Connection





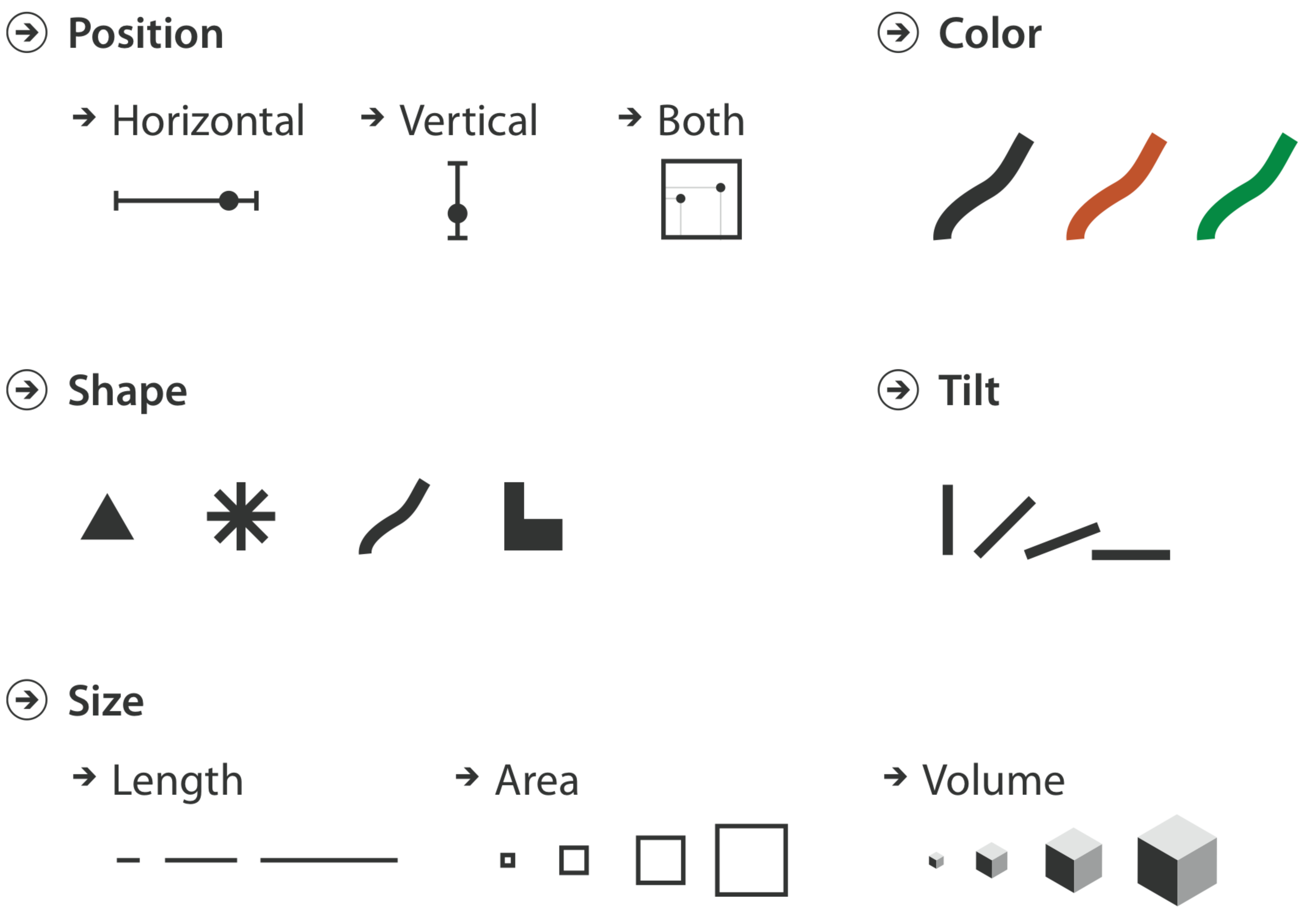
Containment can be nested



[Riche & Dwyer, 2010]

Channels (aka Visual Variables)

Control appearance proportional to or based on attributes



Jacques Bertin

French cartographer
[1918-2010]

Semiology of Graphics [1967]

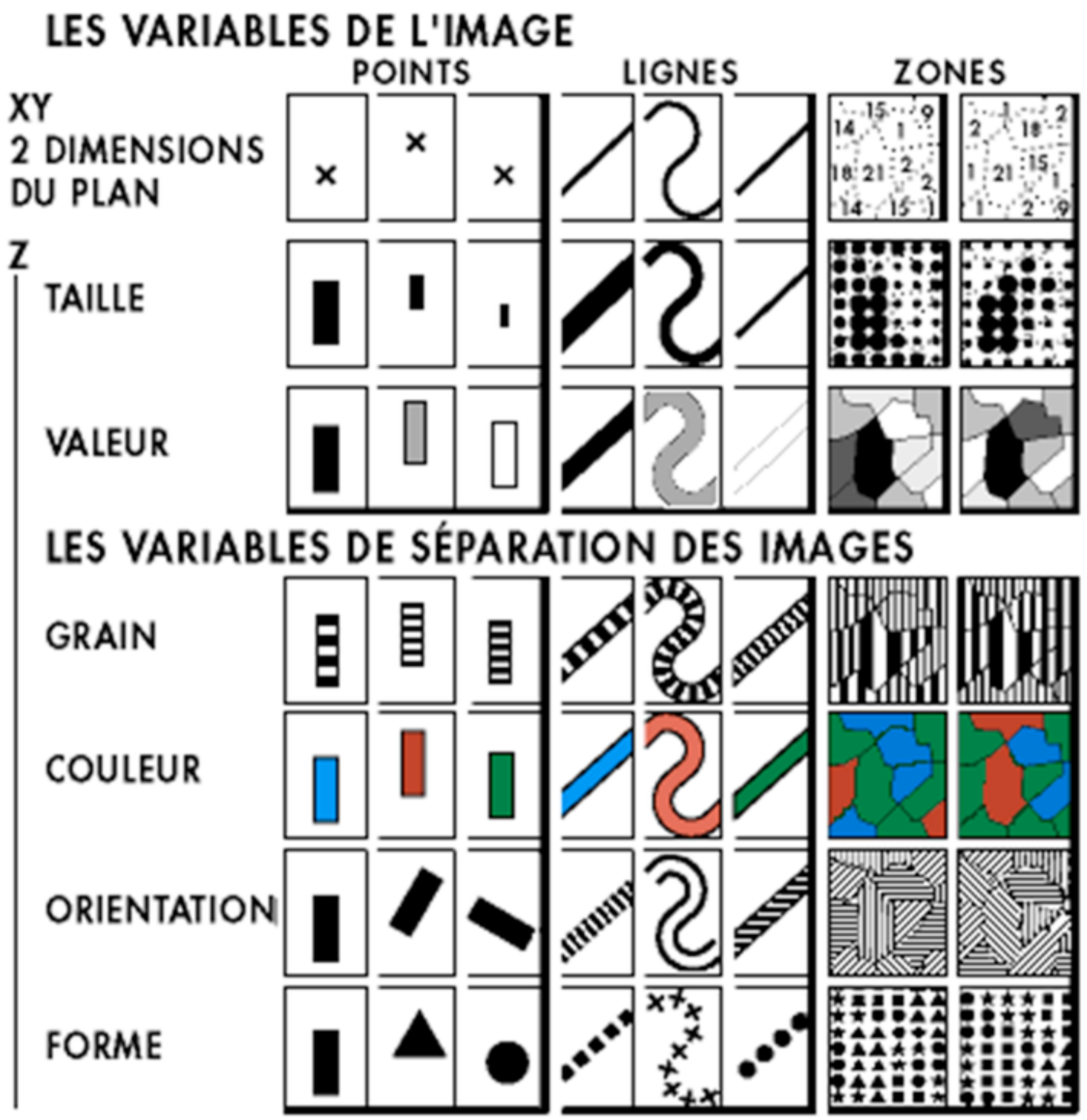
Theoretical principles for visual encodings

Bertin's Visual Variables

Marks: Points Lines Areas

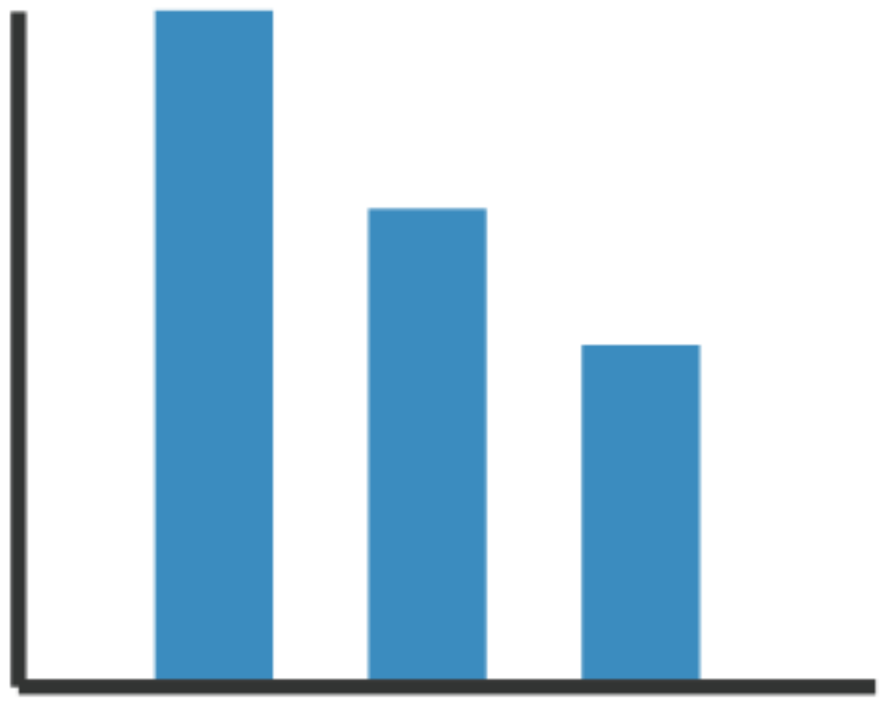
Position
Size
(Grey)Value

Texture
Color
Orientation
Shape



Semiology of Graphics [J. Bertin, 67]

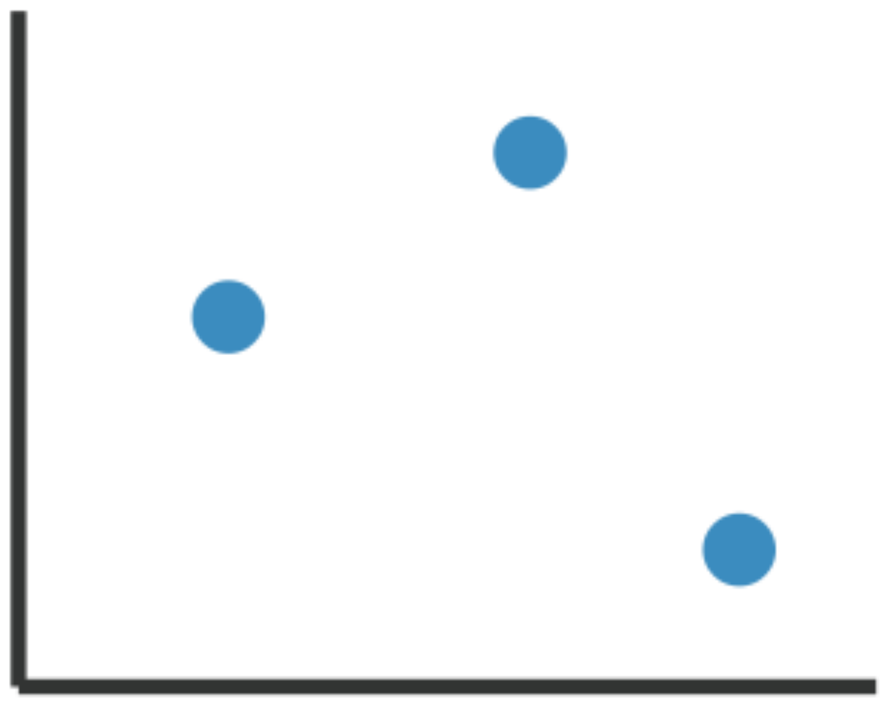
Using Marks and Channels



Mark: Line

Channel: Length, Position

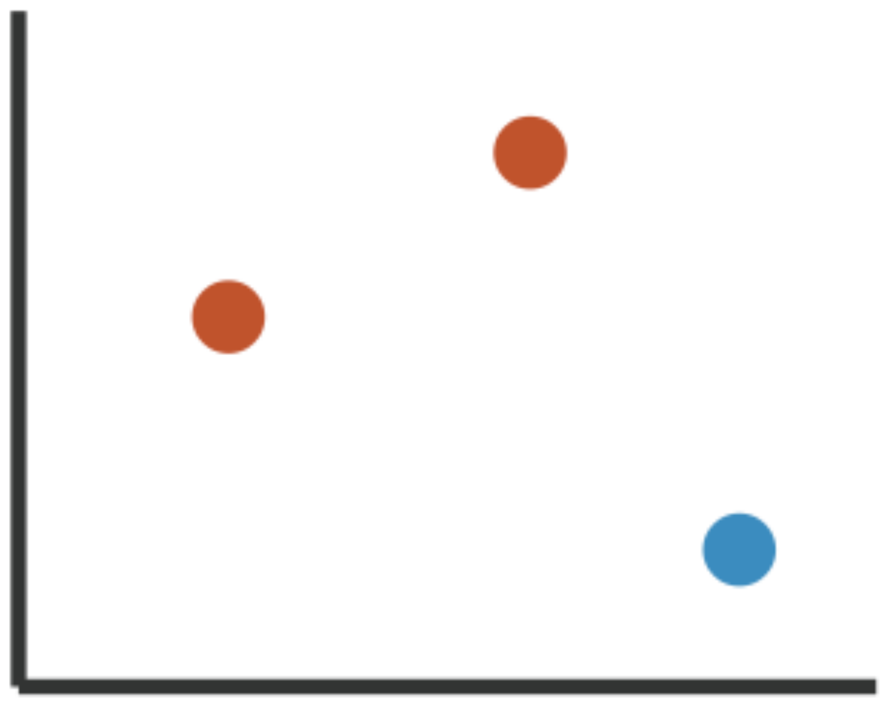
1 quantitative attribute



Mark: Point

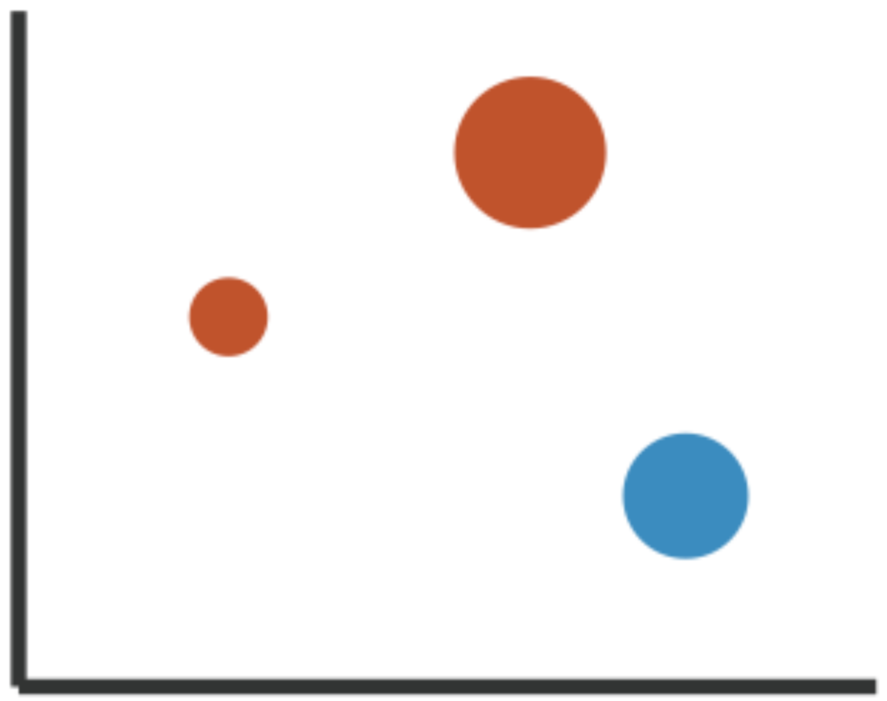
Channel: Position

2 quantitative attr.



Adding Hue

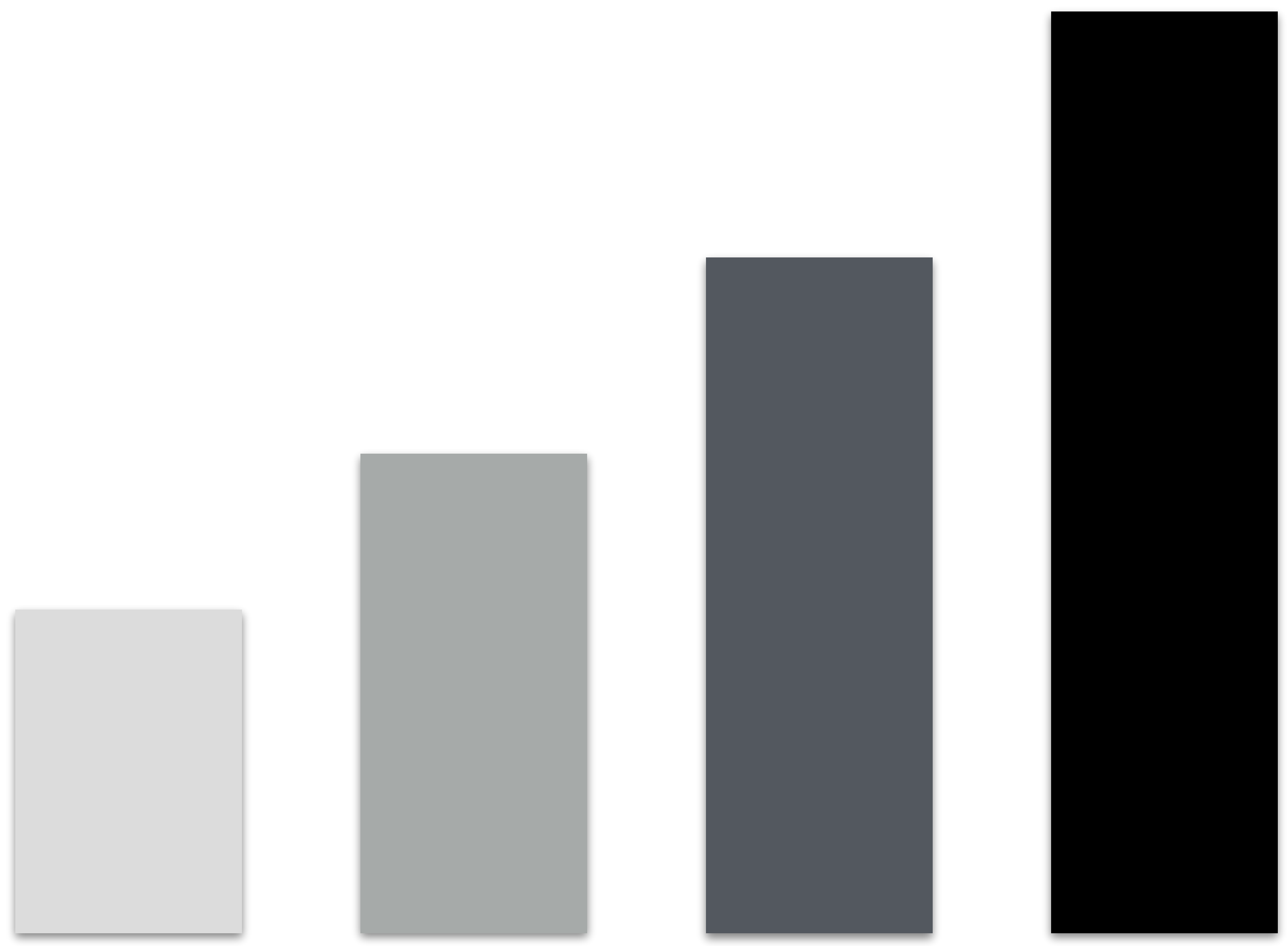
+1 categorical attr.



Adding Size

+1 quantitative attr.

Redundant encoding



Length, Position and Value

Good bar chart?

Rule: Use channel proportional to data!

https://twitter.com/ChaseThomason/status/1118478036507164672?s=19

Types of Channels

Magnitude Channels

How much? Which Rank?

Position

Length

Saturation …

Ordinal & Quantitative Data

Identity Channels

What?

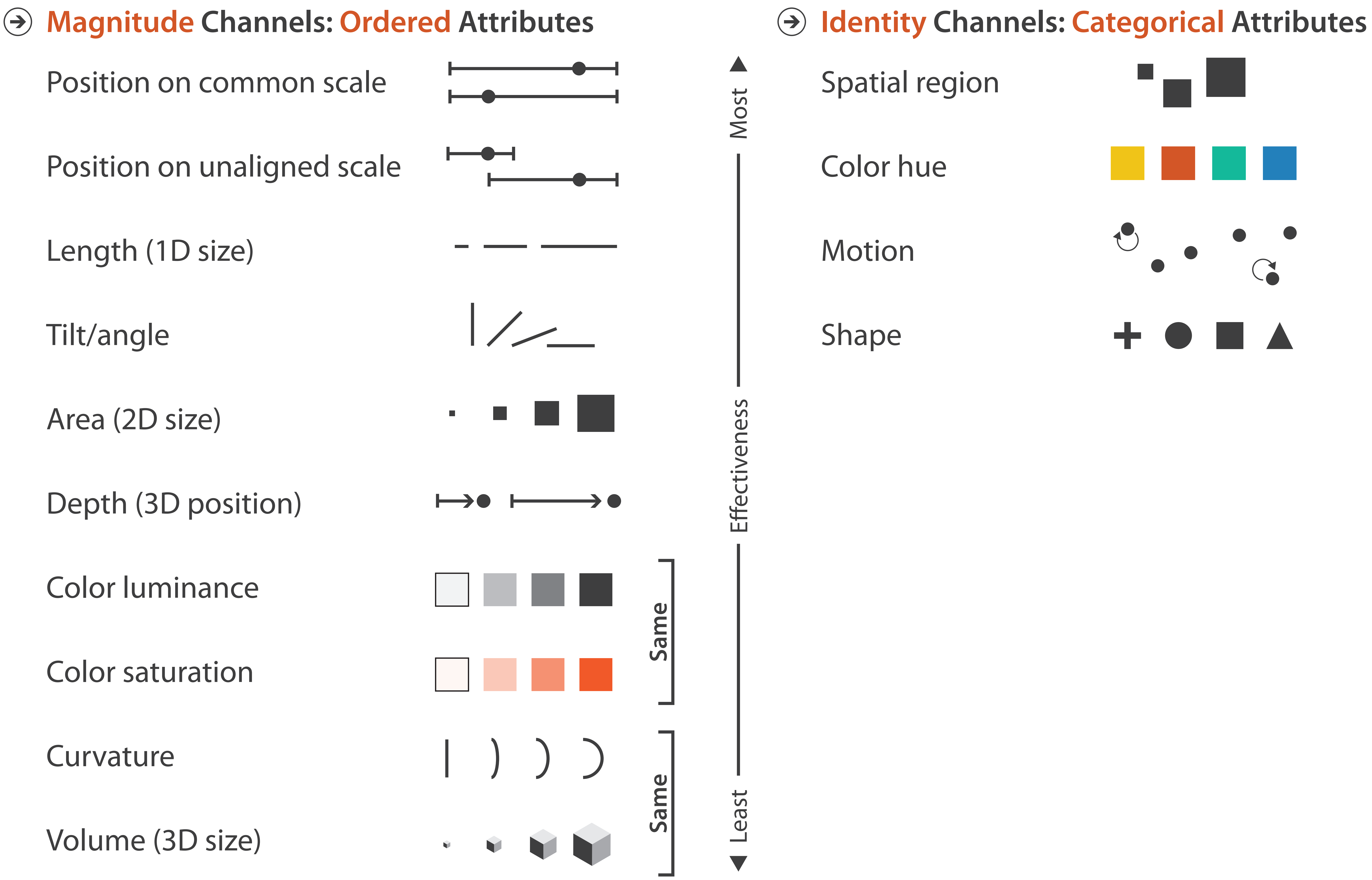
Shape

Color (hue)

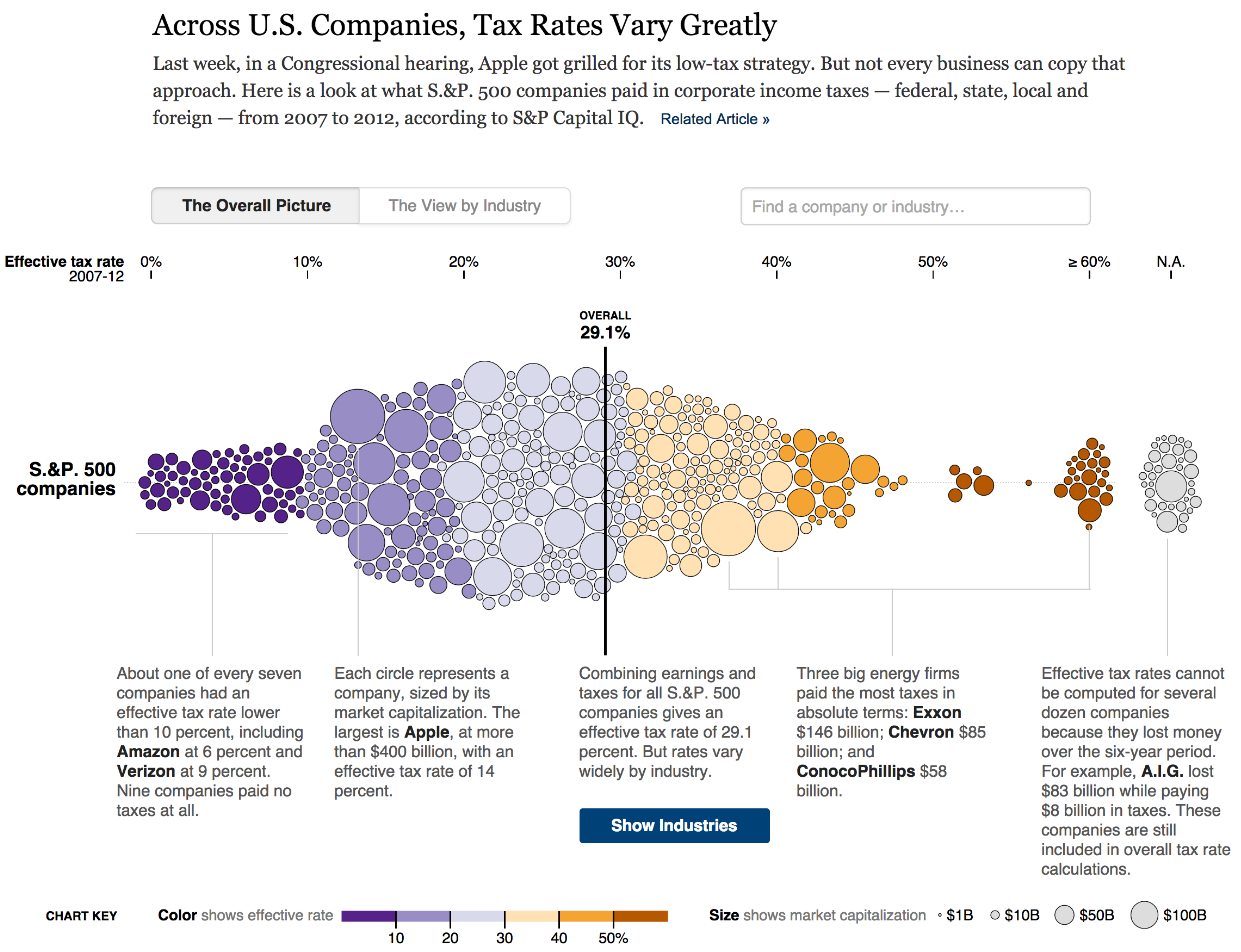
Spatial region …

Categorical Data

Channels: Expressiveness Types and Effectiveness Ranks



What visual variables are used?



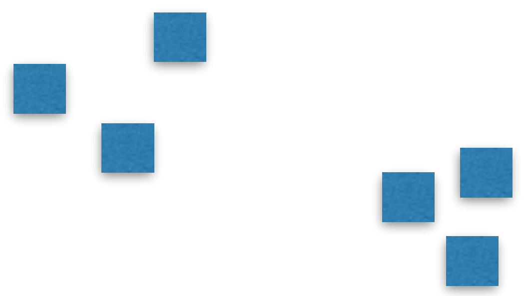
http://www.nytimes.com/interactive/2013/05/25/sunday-review/corporate-taxes.html

Characteristics of Channels

Selective

Is a mark distinct from other marks?

Can we make out the difference between two marks?

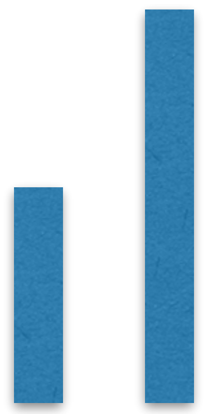


Associative

Does it support grouping?

Quantitative (Magnitude vs Identity Channels)

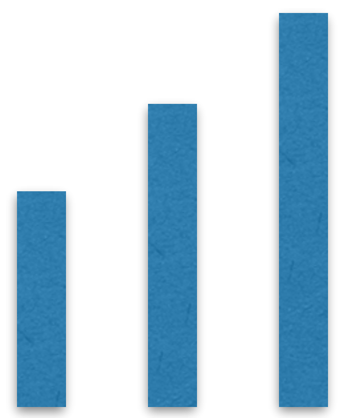
Can we quantify the difference between two marks?



Characteristics of Channels

Order (Magnitude vs Identity)

- Can we see a change in order?



Length

- How many unique marks can we make?

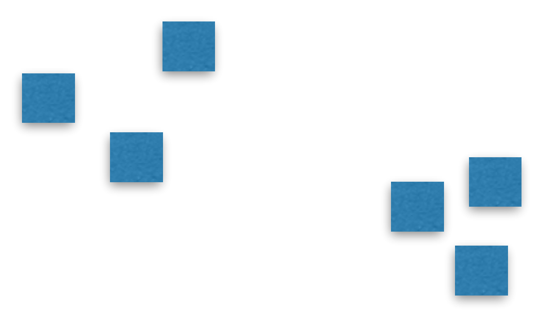
Position

Strongest visual variable

Suitable for all data types

Problems:

- Sometimes not available (spatial data)
- Cluttering



Selective: yes

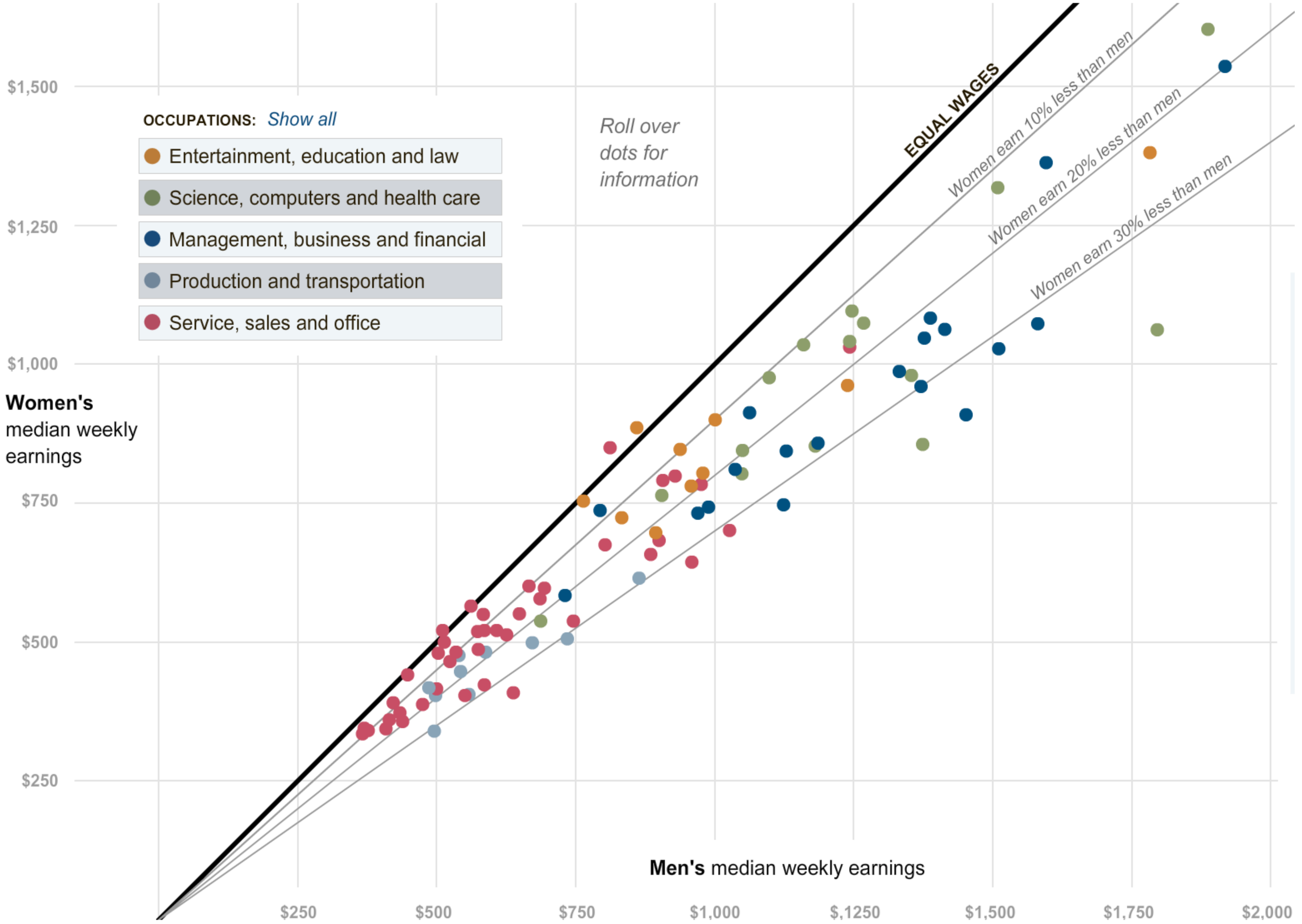
Associative: yes

Quantitative: yes

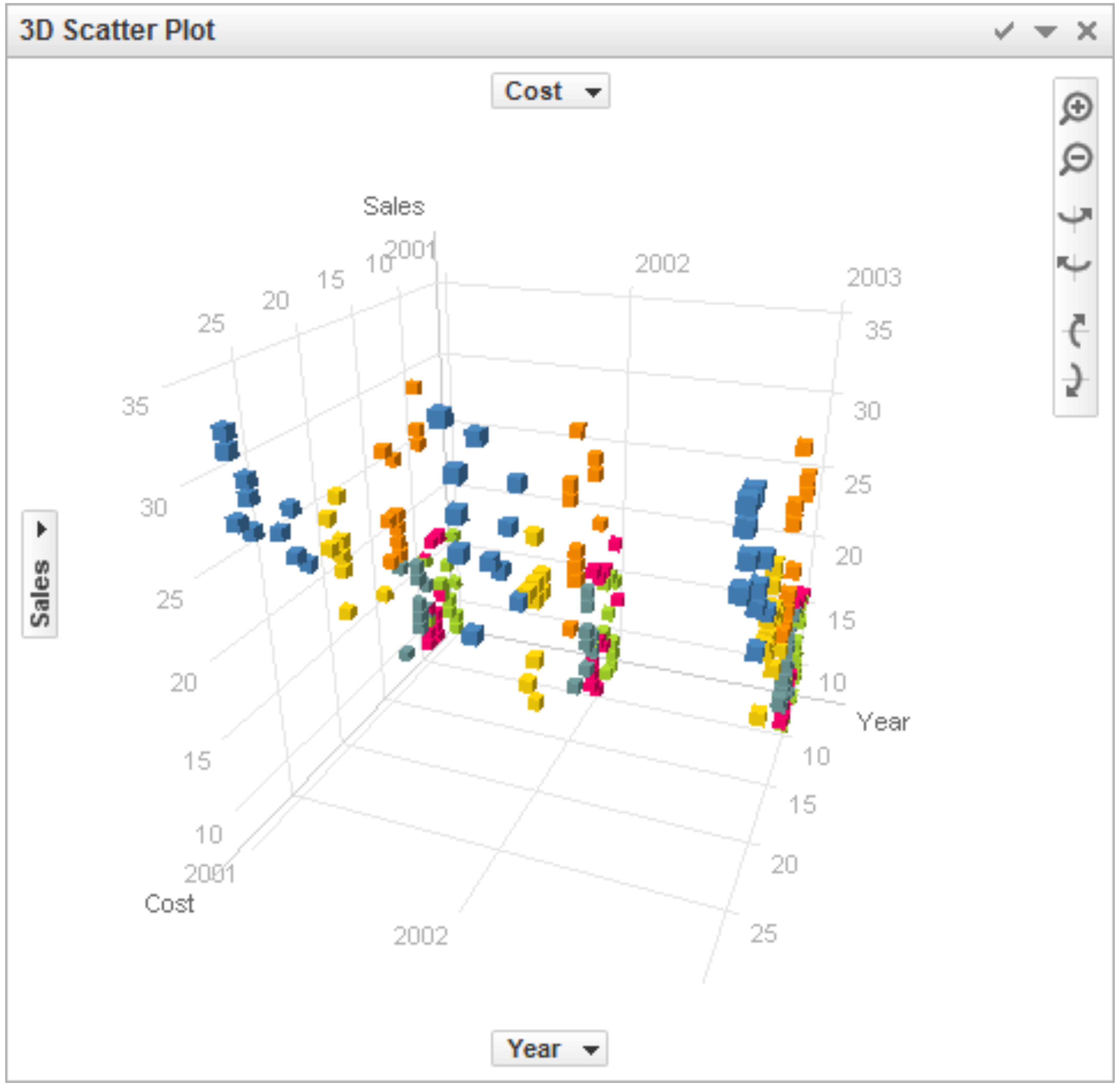
Order: yes

Length: fairly big

Example: Scatterplot



Position in 3D?



[Spotfire]

Length & Size

Good for 1D, OK for 2D, Bad for 3D

Easy to see whether one is bigger

Aligned bars use position redundantly

For 1D length:

Selective: yes

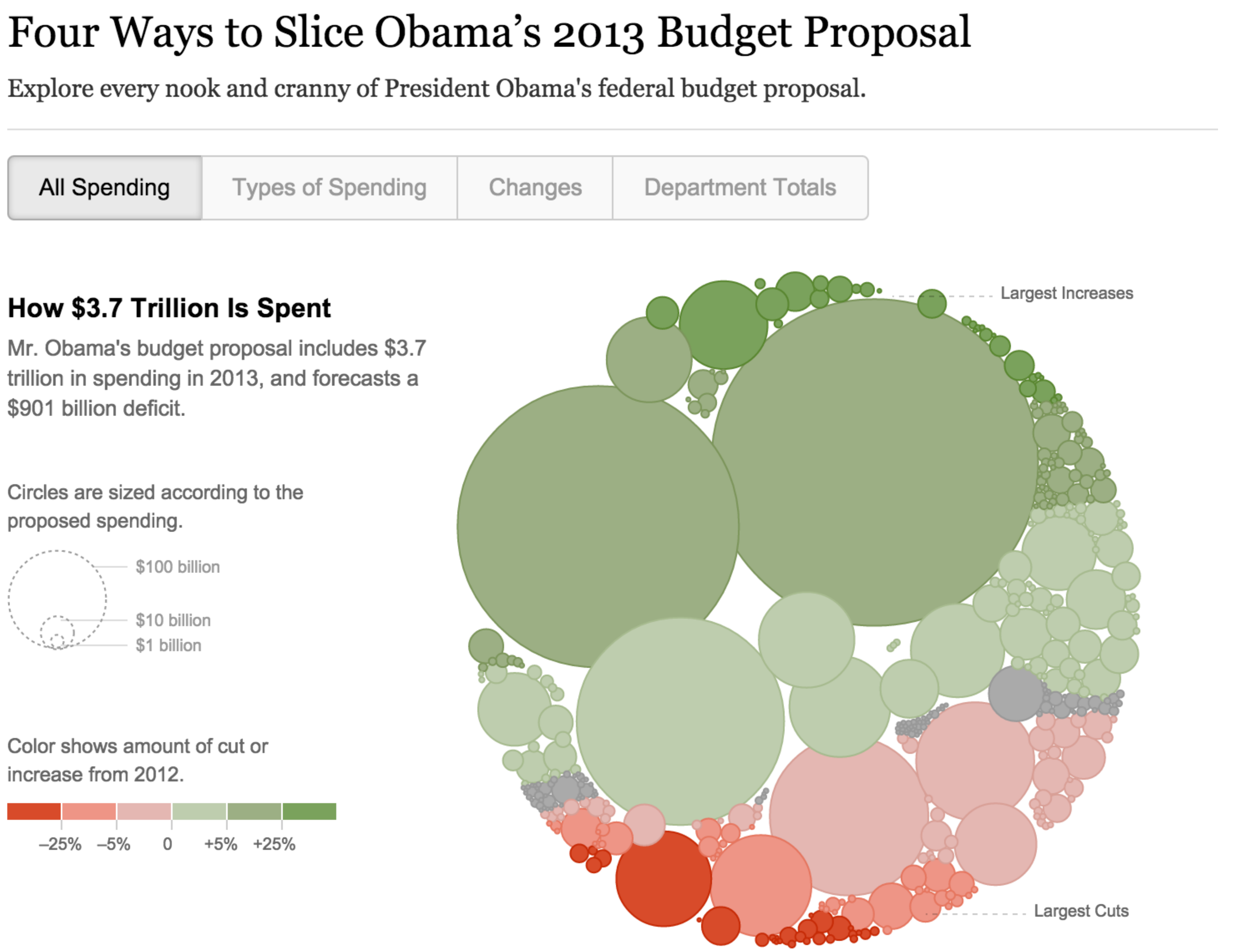
Associative: yes

Quantitative: yes

Order: yes

Length: high

Example 2D Size: Bubbles



Value/Luminance/Saturation

OK for quantitative data when length & size are used.

Not very many shades recognizable

Selective: yes

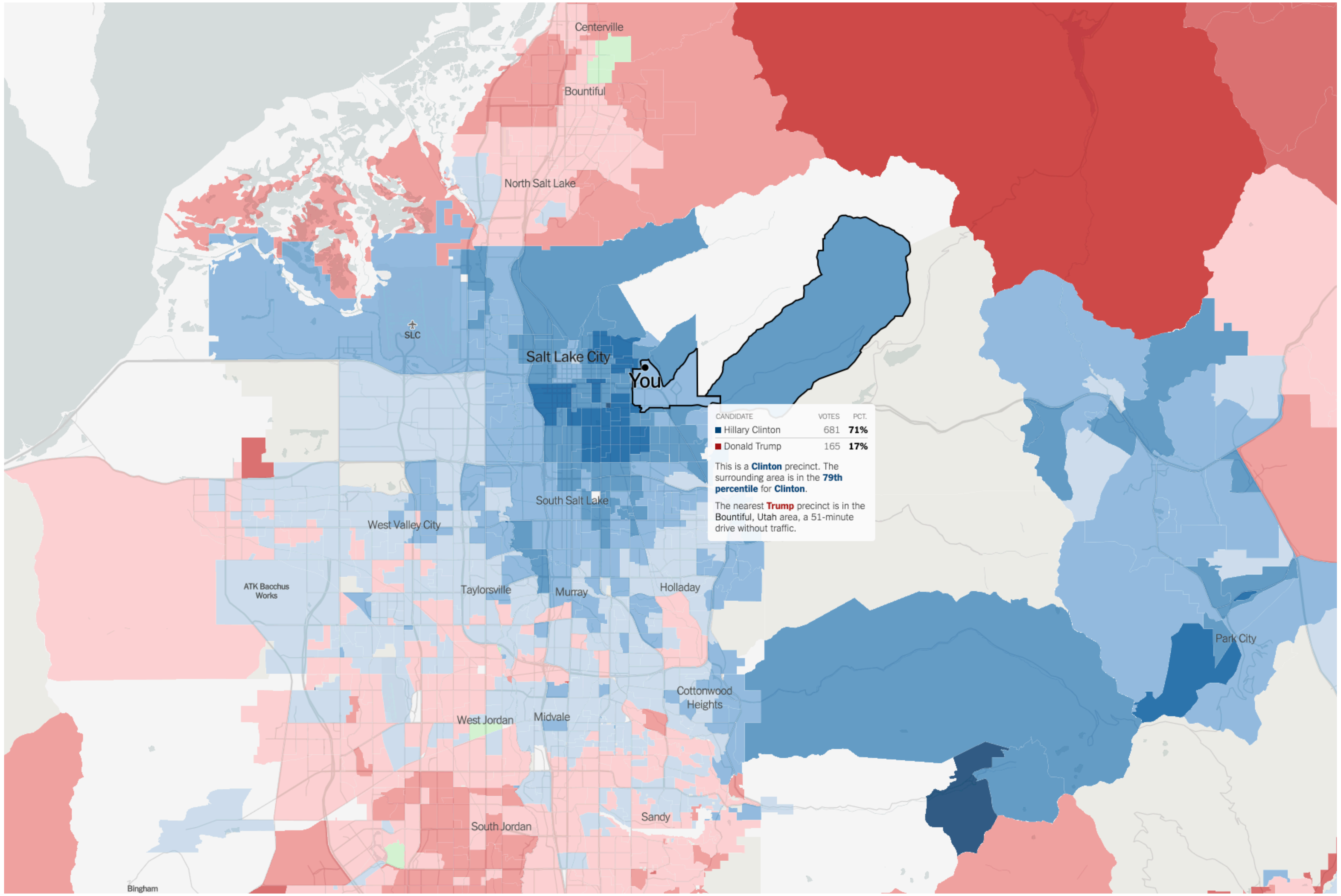
Associative: yes

Quantitative: somewhat (with problems)

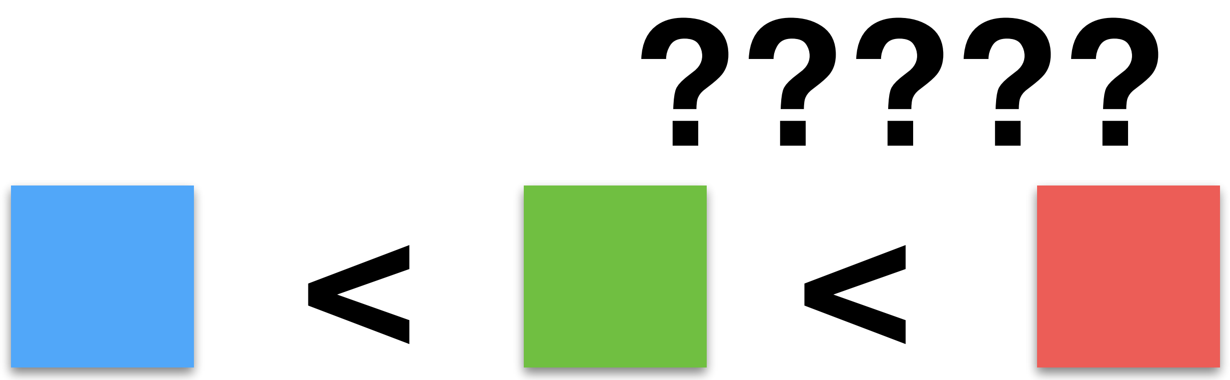
Order: yes

Length: limited

Example: Diverging Value-Scale



Color



Good for qualitative data (identity channel)

Limited number of classes/length (~7-10!)

Does not work for quantitative data!

Lots of pitfalls! Be careful!

My rule:

- minimize color use for encoding data
- use for brushing

Selective: yes

Associative: yes

Quantitative: no

Order: no

Length: limited

Color: Bad Example

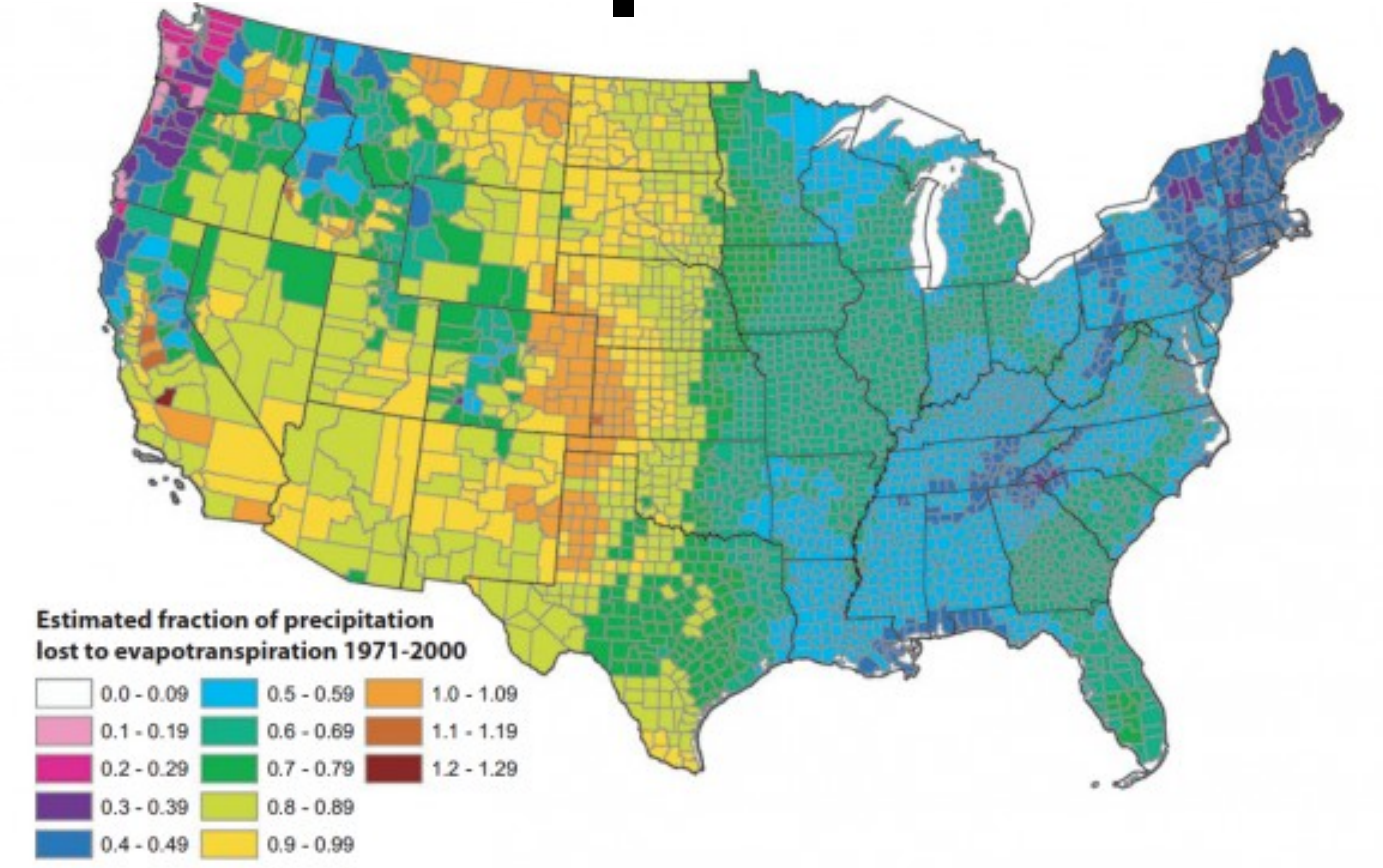
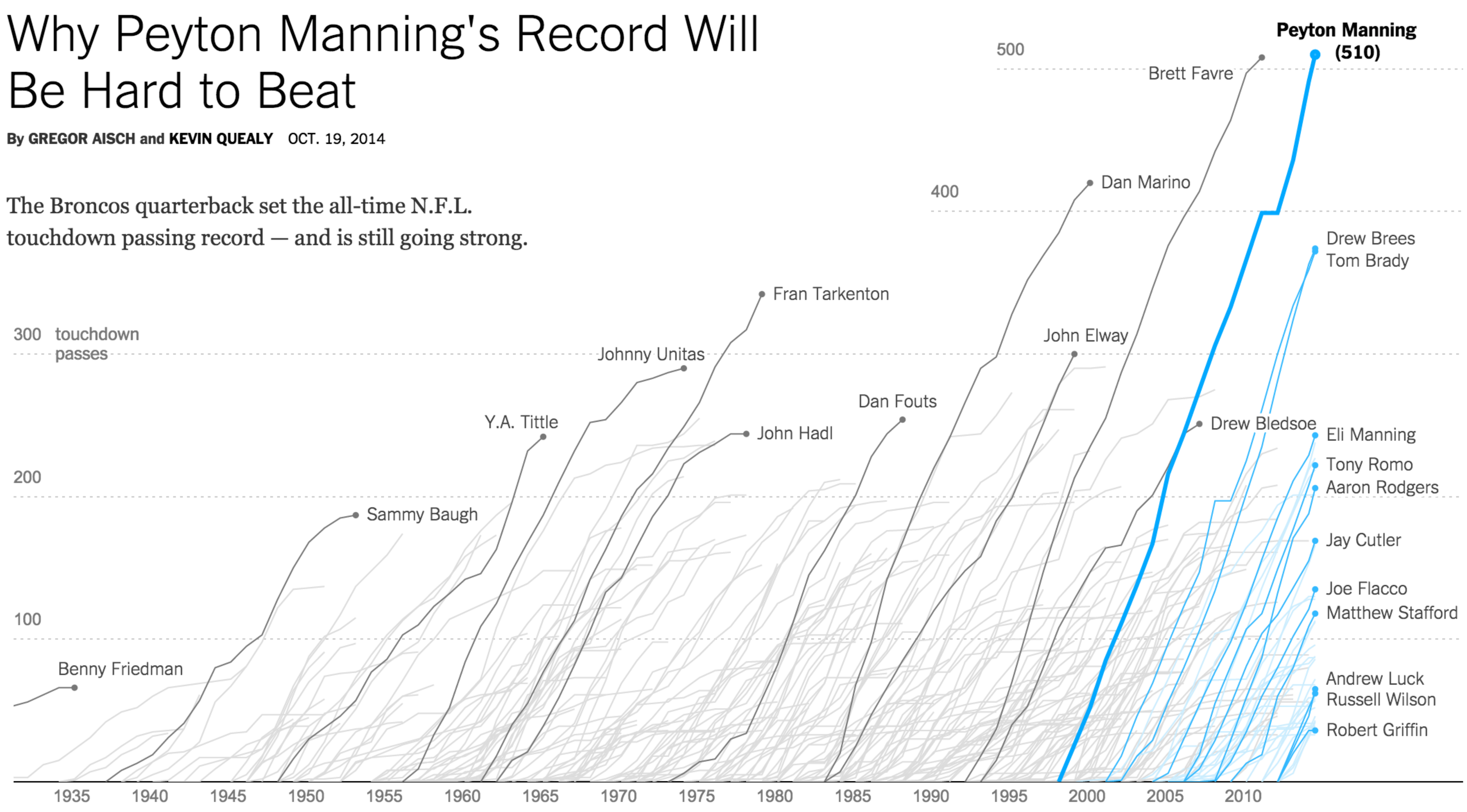


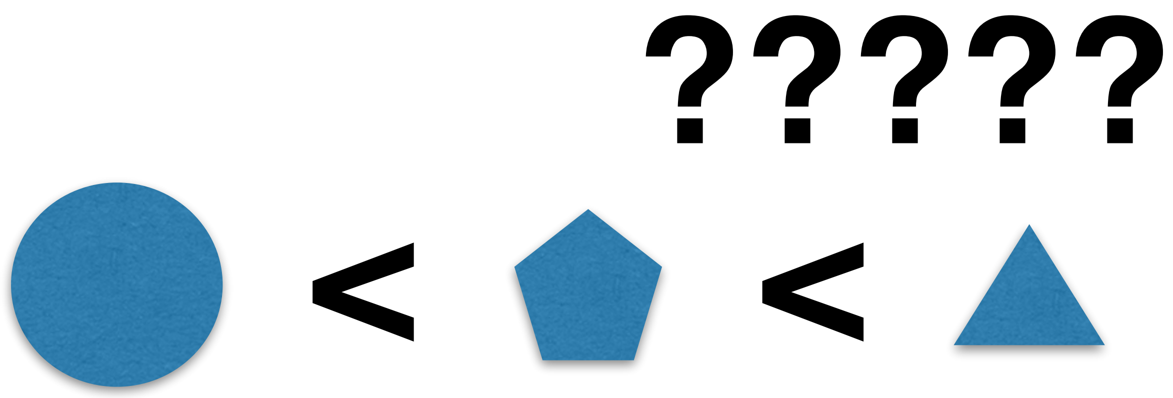
FIGURE 13. Estimated Mean Annual Ratio of Actual Evapotranspiration (ET) to Precipitation (*P*) for the Conterminous U.S. for the Period 1971-2000. Estimates are based on the regression equation in Table 1 that includes land cover. Calculations of ET/*P* were made first at the 800-m resolution of the PRISM climate data. The mean values for the counties (shown) were then calculated by averaging the 800-m values within each county. Areas with fractions >1 are agricultural counties that either import surface water or mine deep groundwater.

Cliff Mass

Color: Good Example



Shape



Great to recognize many classes.

No grouping, ordering.

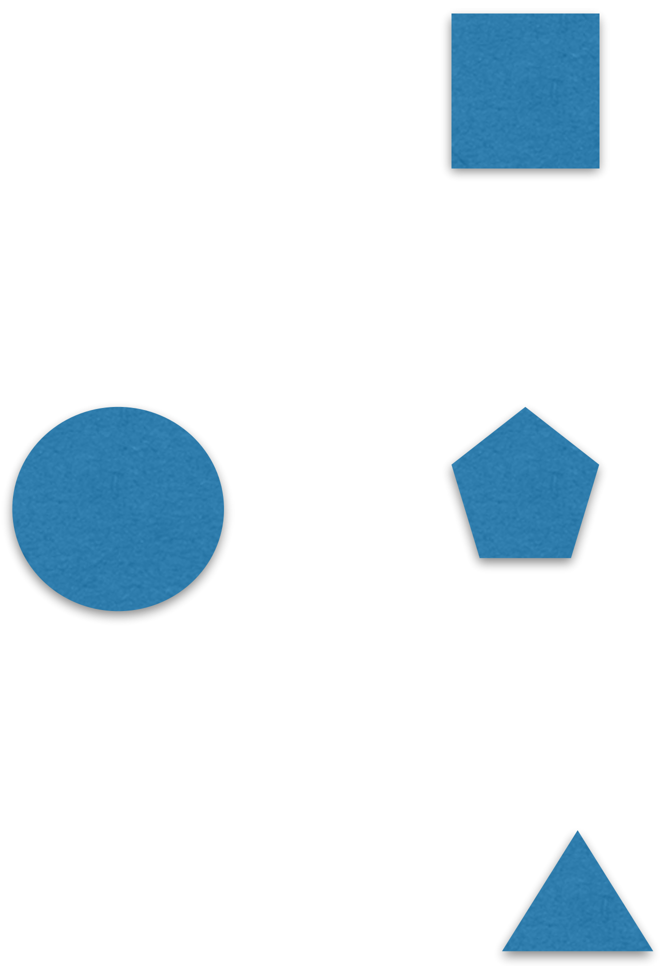
Selective: yes

Associative: limited

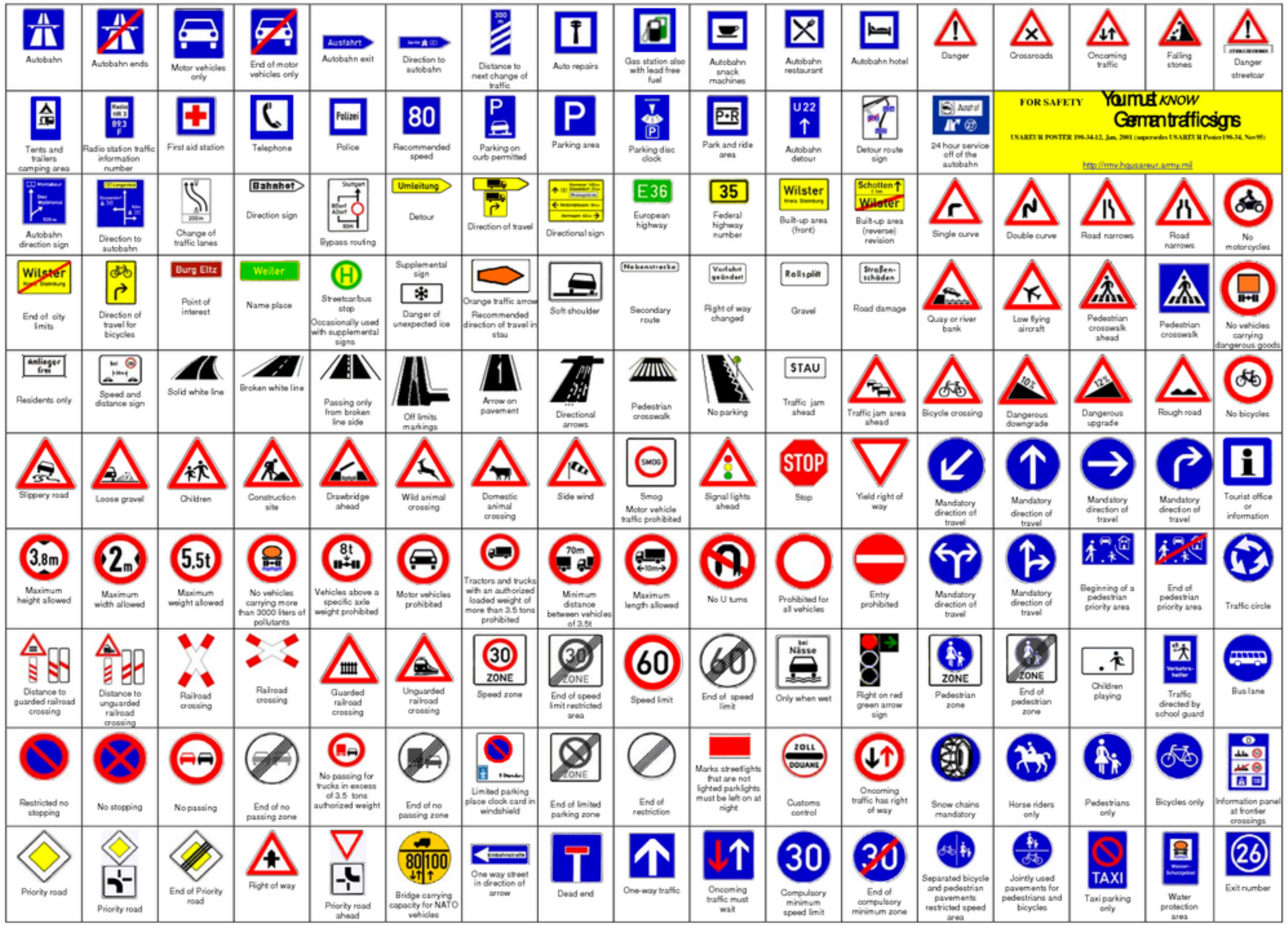
Quantitative: no

Order: no

Length: vast



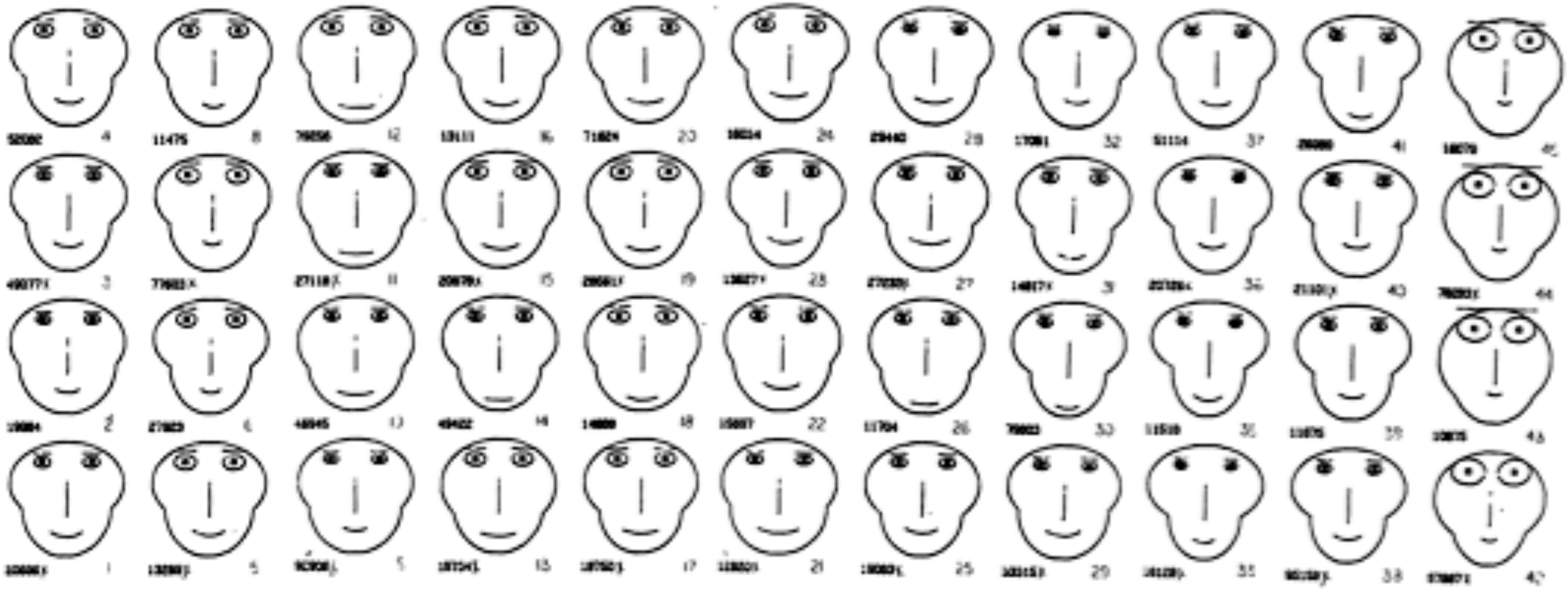
ALFA ROMEO
ACURA
ASTON MARTIN
ASTON MARTIN
BENTLEY
Audi
BMW
MITSUBISHI
MOTORS
Ferrari
Photoshop plugins



FOR SAFETY
You must KNOW
German traffic signs
STOP
TAXI

Chernoff Faces

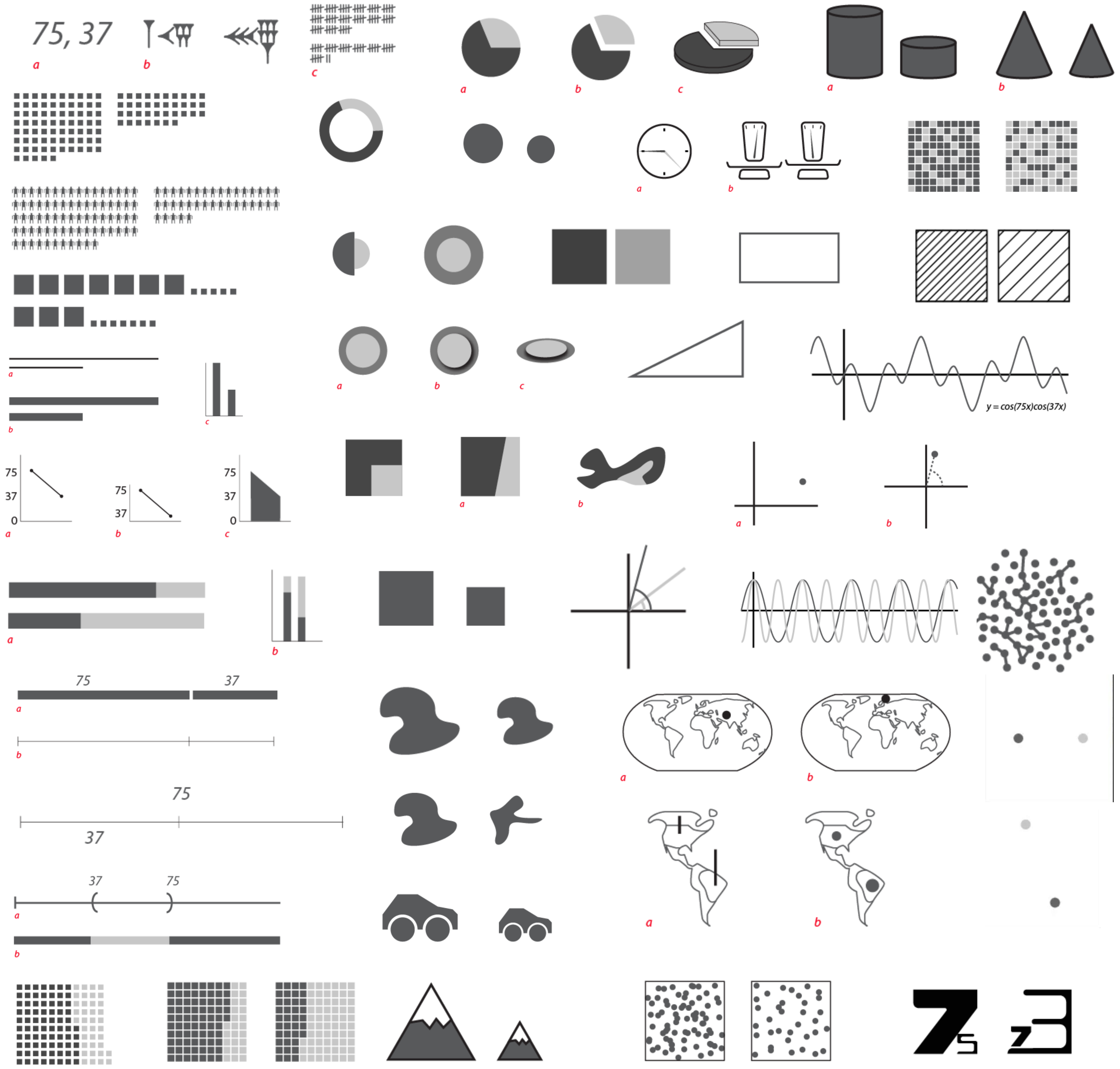
Idea: use facial parameters to map quantitative data



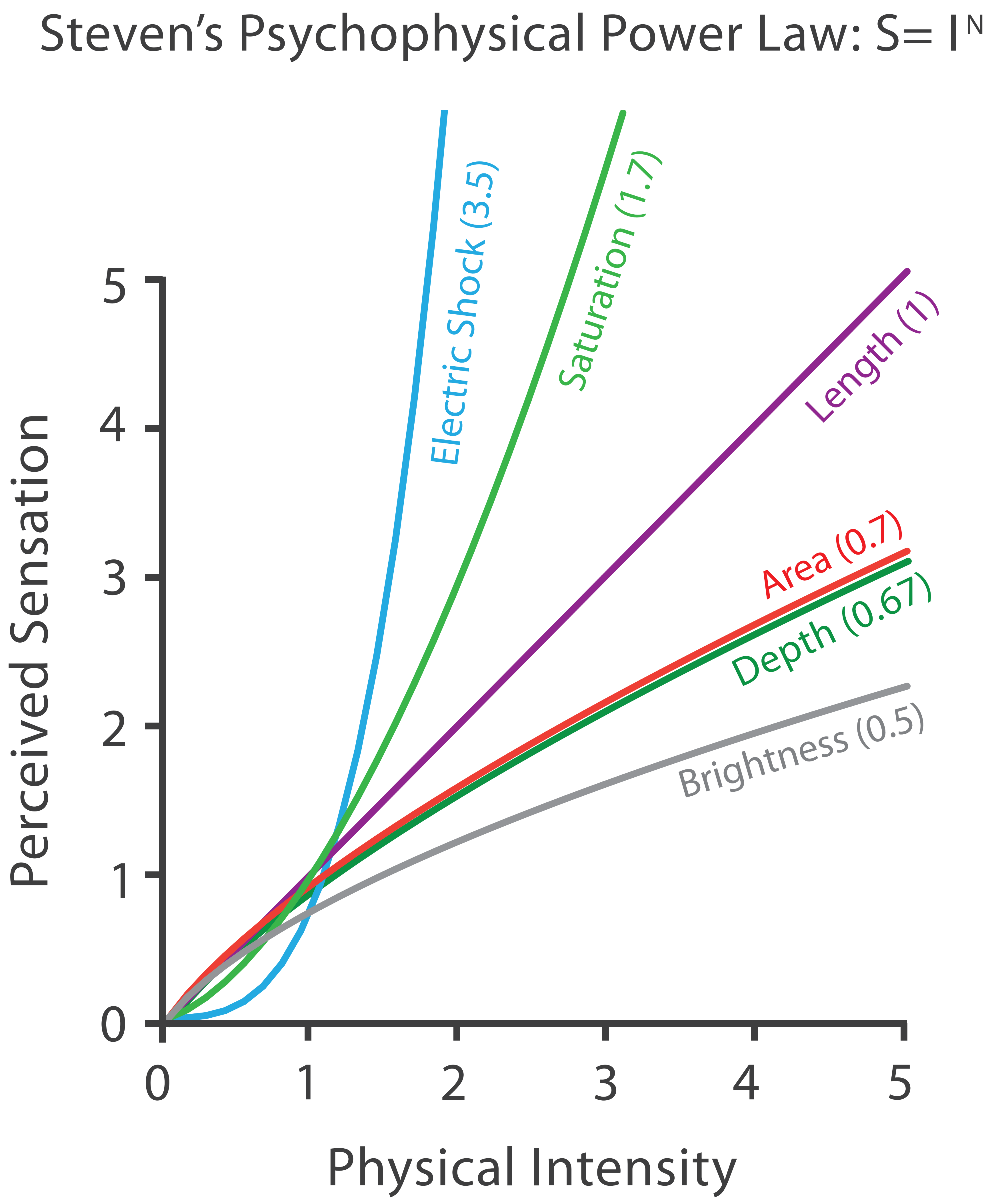
Does it work?
Not really!

Critique: https://eagereyes.org/criticism/chernoff-faces

More Channels

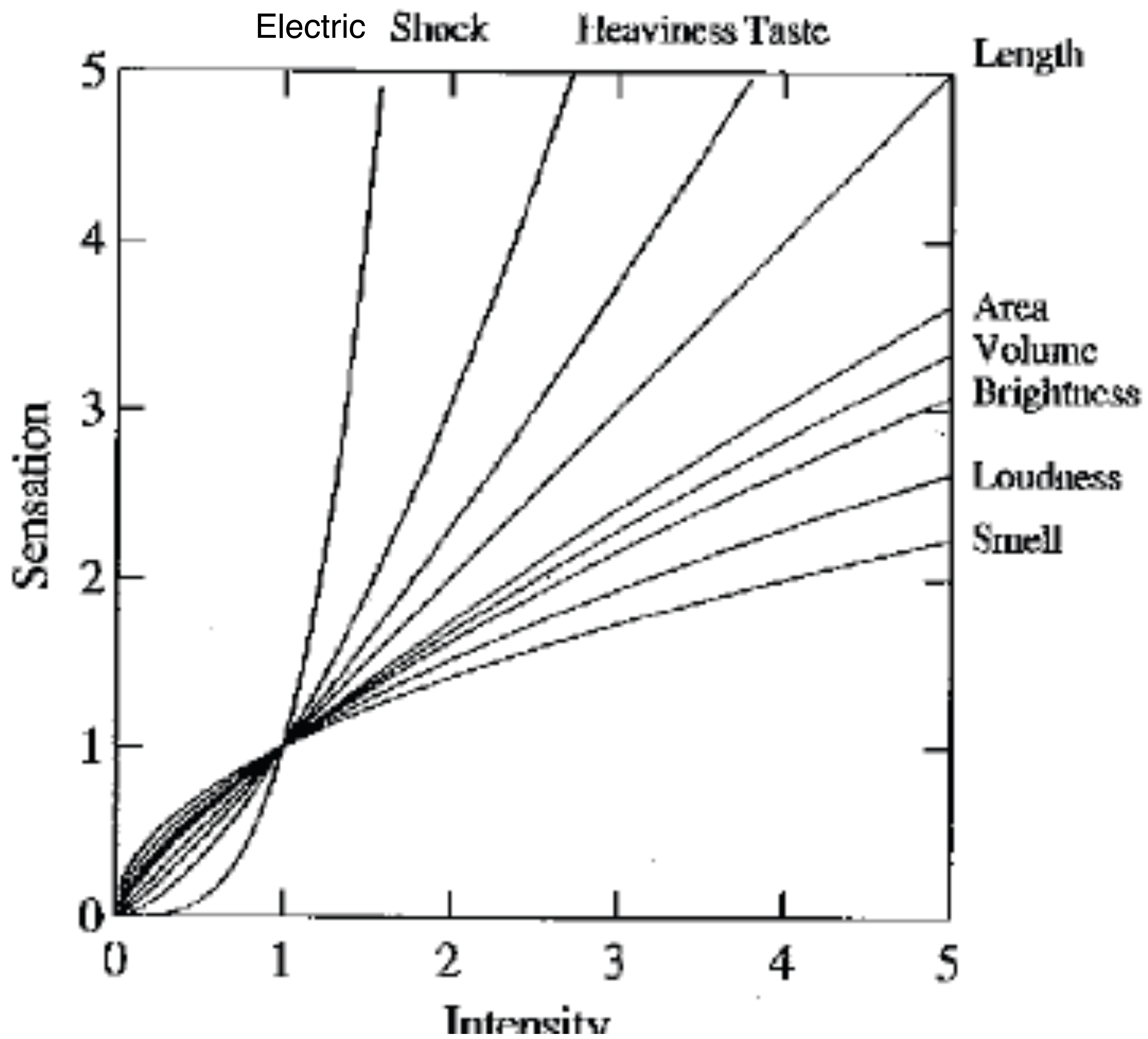


Why are quantitative channels different?



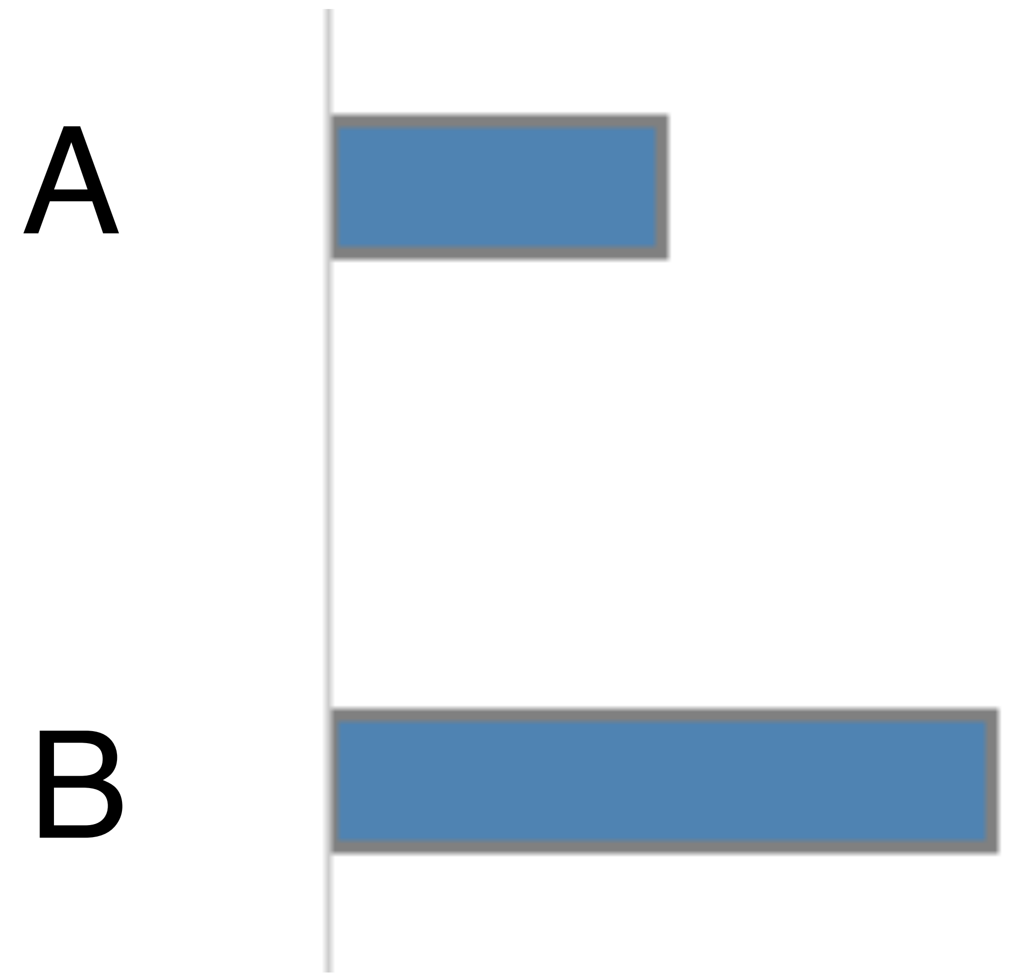
S = sensation
I = intensity

Steven’s Power Law, 1961



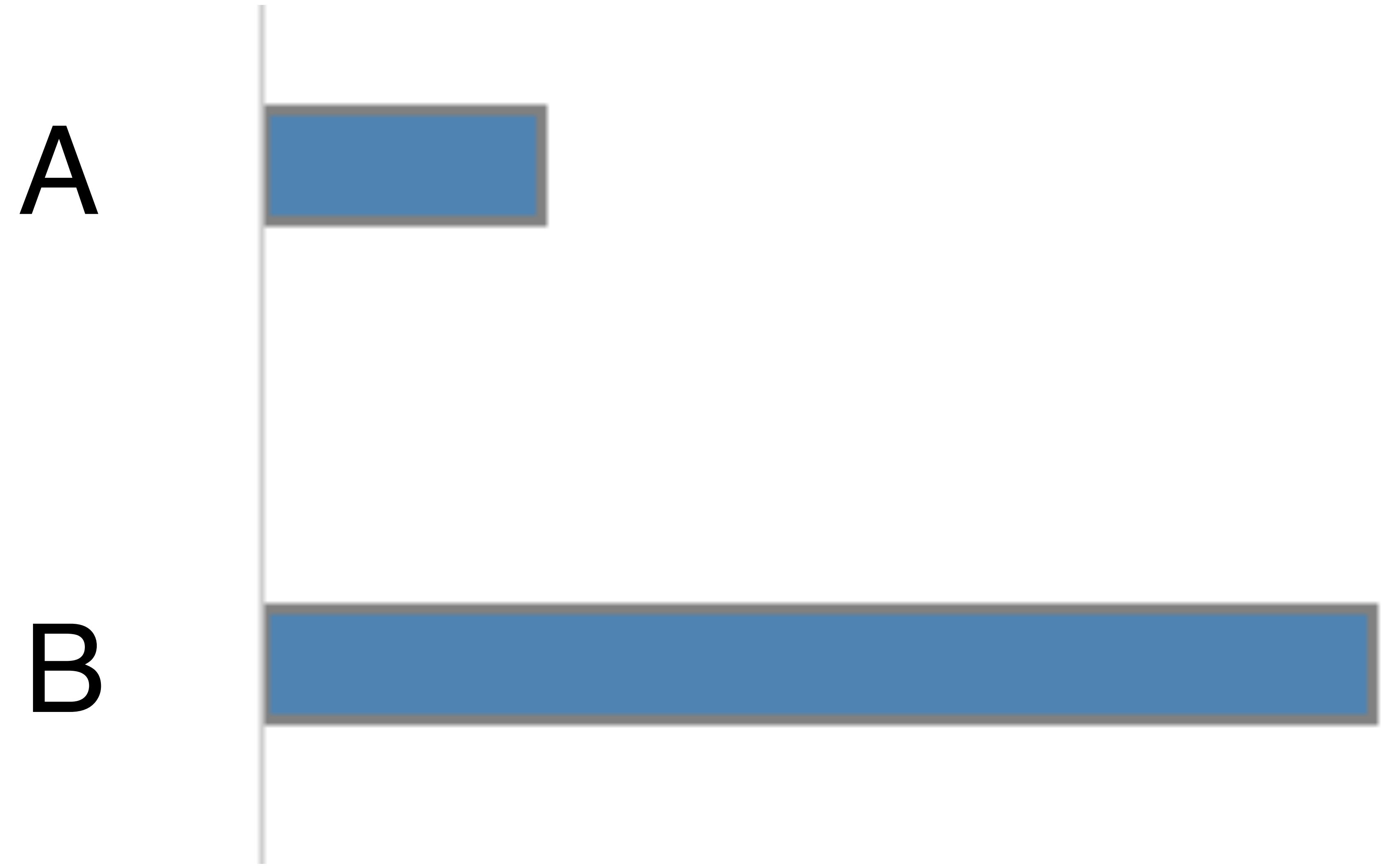
From Wilkinson 99, based on Stevens 61

How much longer?



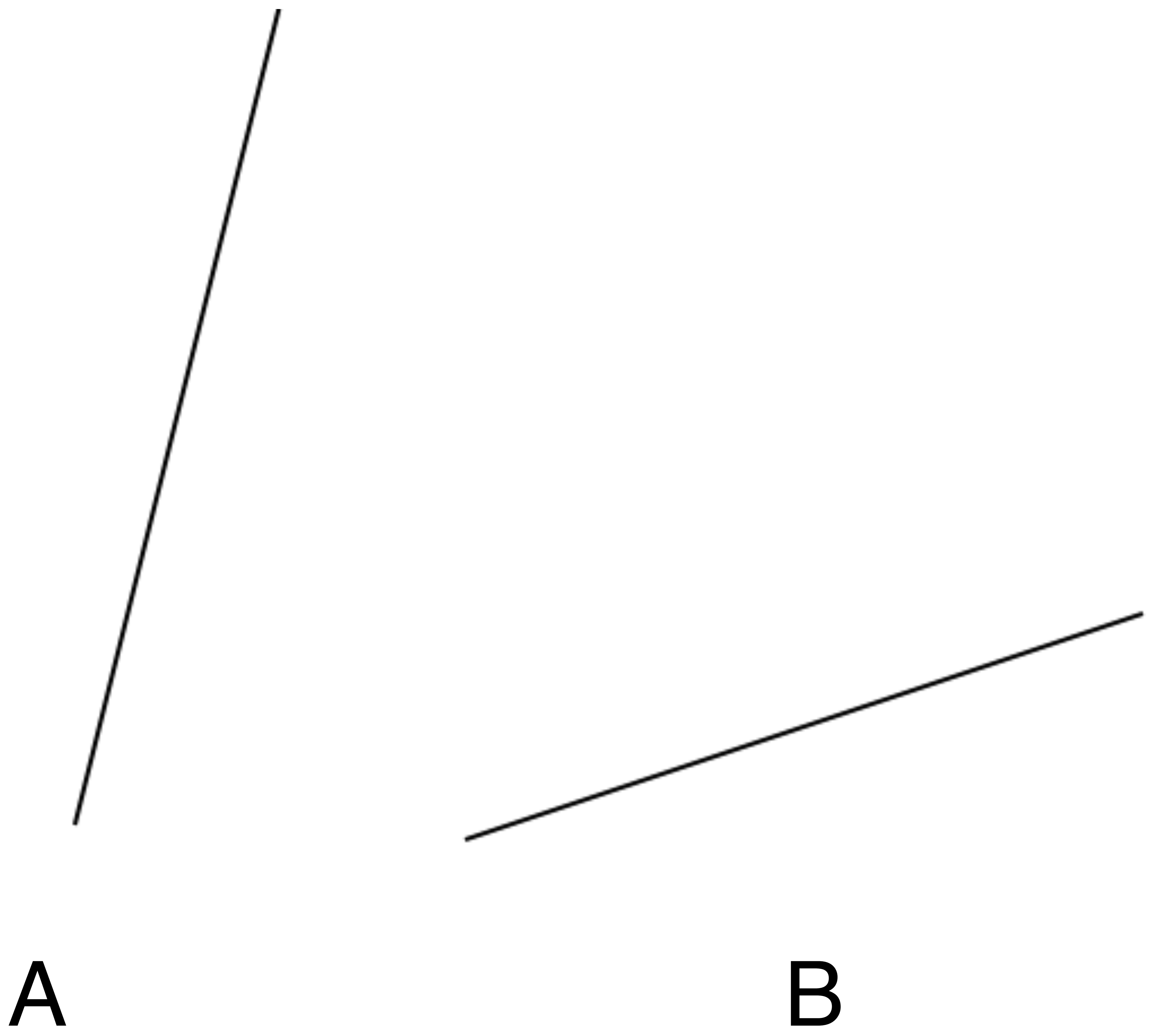
2x

How much longer?



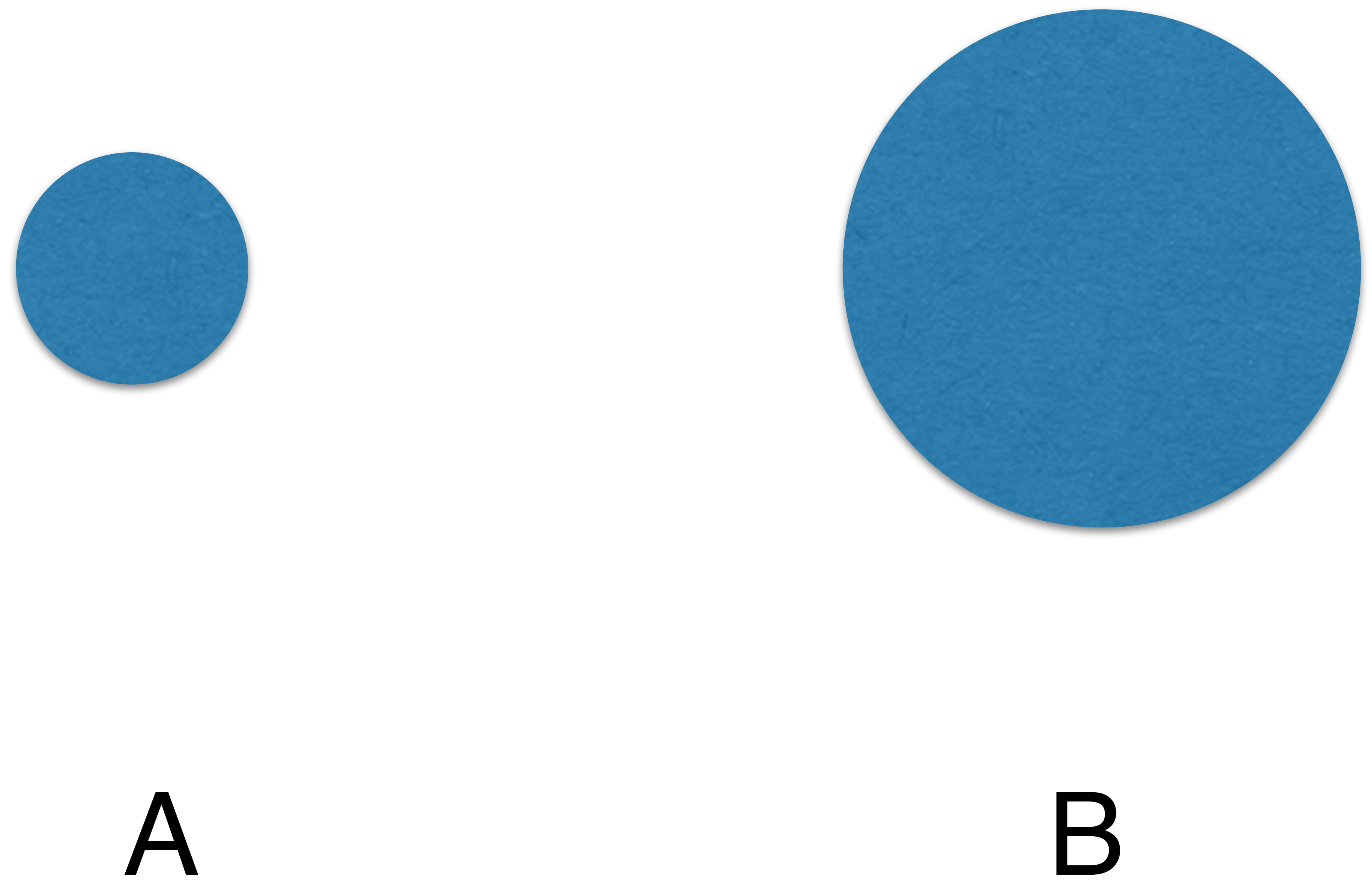
4x

How much steeper?



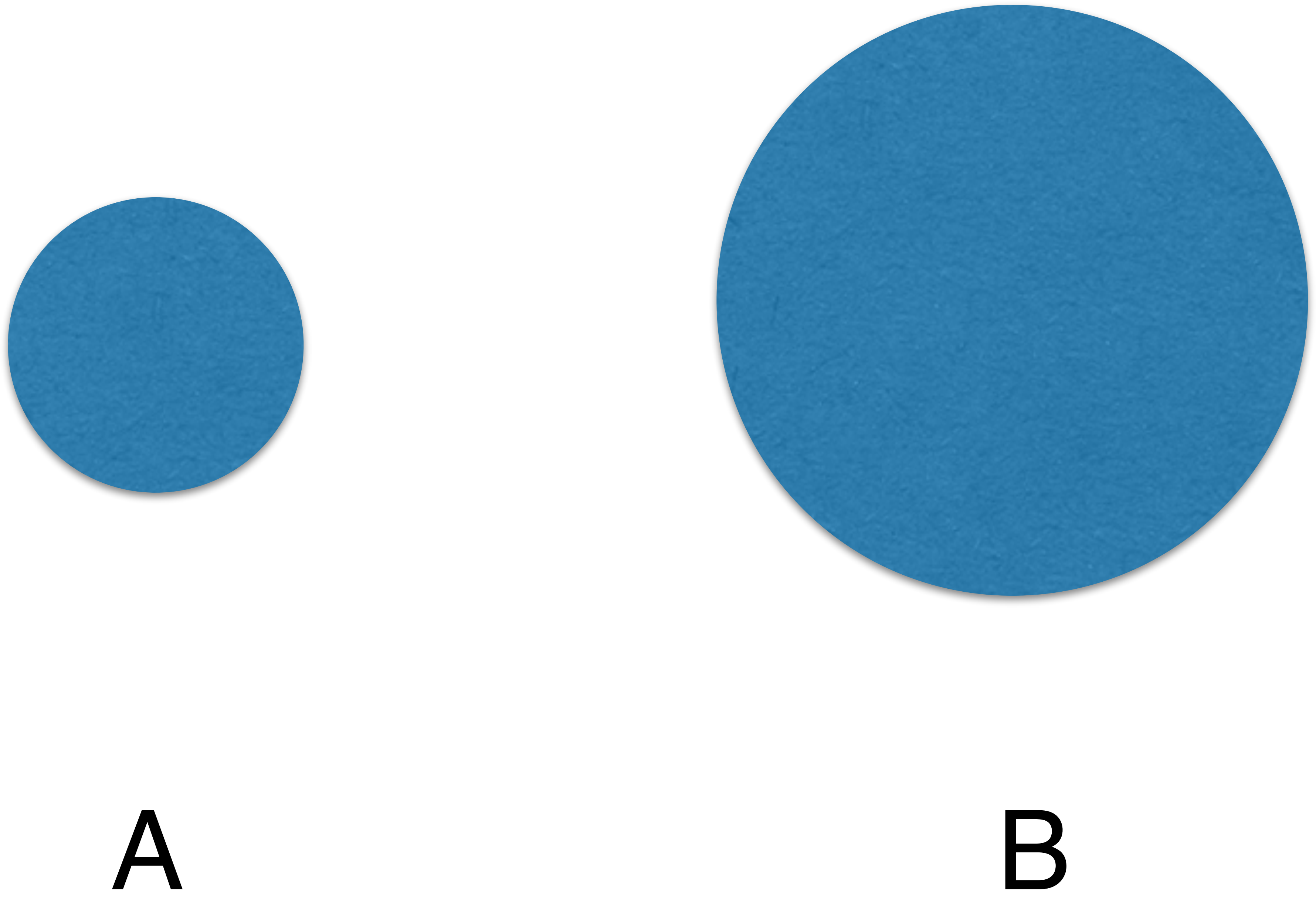
~4x

How much larger?



5x

How much larger?



2x diameter

4x area

area is proportional to diameter squared

How much larger (area)?

A B

3x

How much darker?

A

B

2x

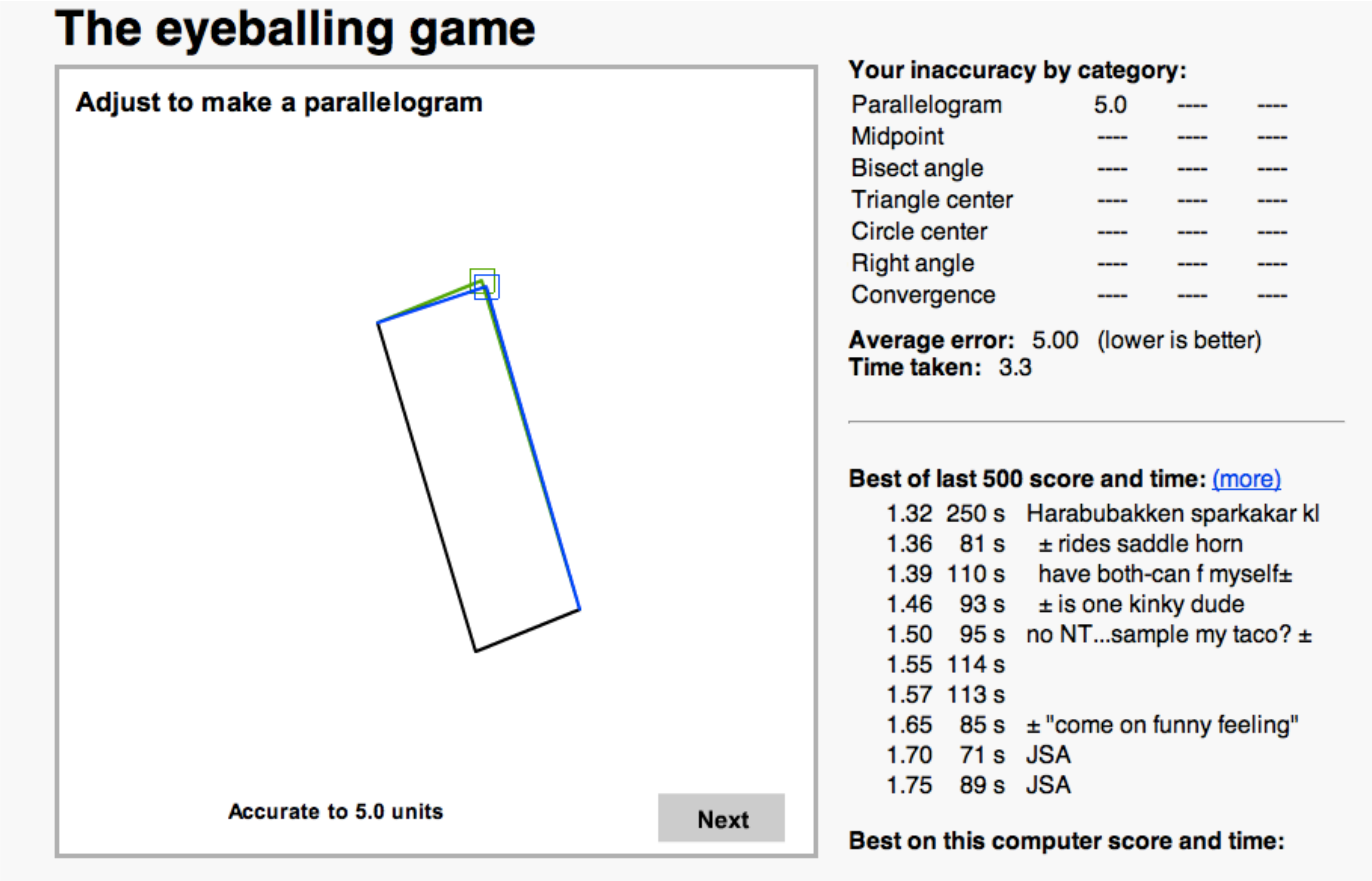
How much darker?

A

B

3x

Position, Length & Angle



Other Factors Affecting Accuracy

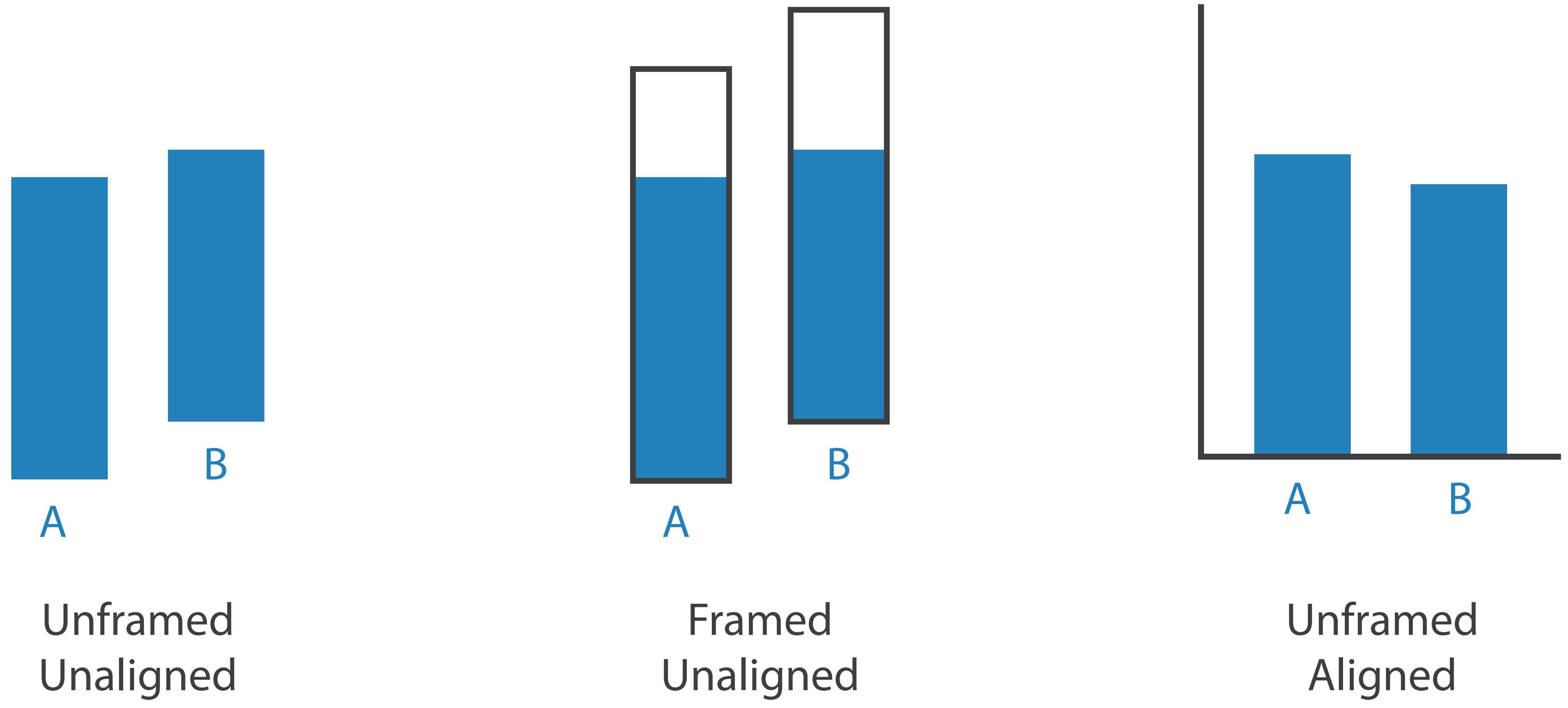
Alignment

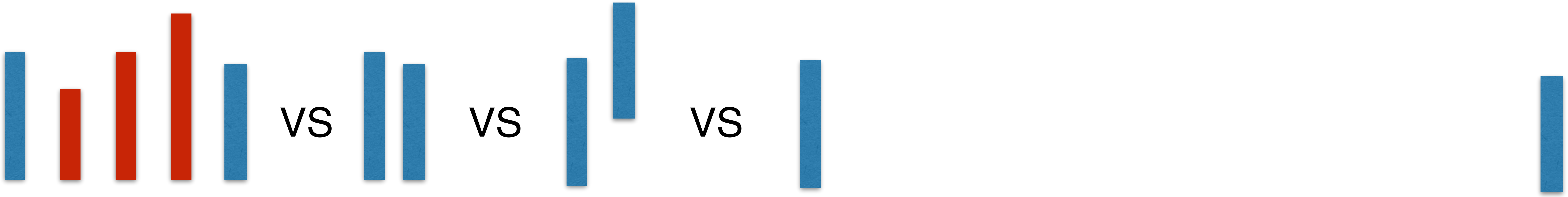
Distractors

Distance

Common scale

…





Cleveland / McGill, 1984

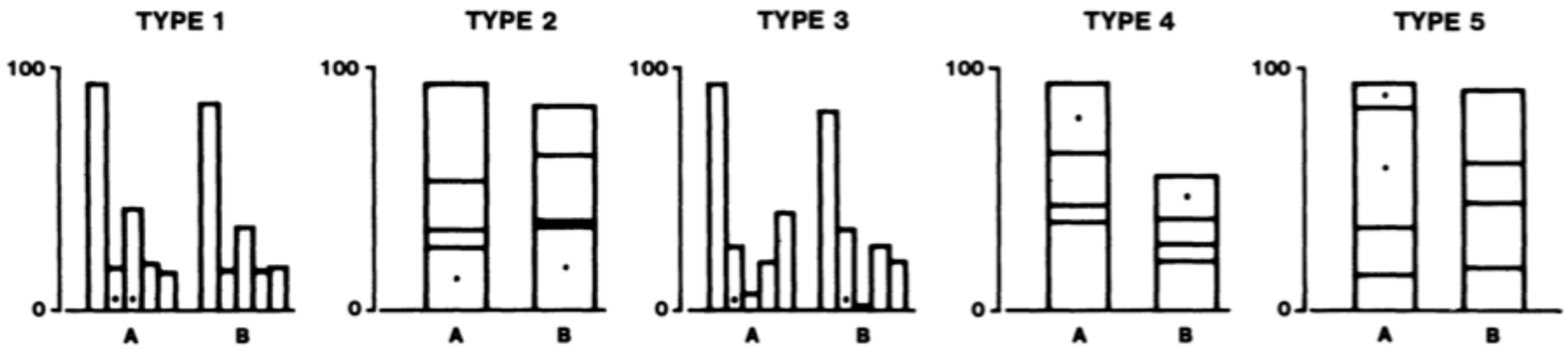


Figure 4. Graphs from position–length experiment.

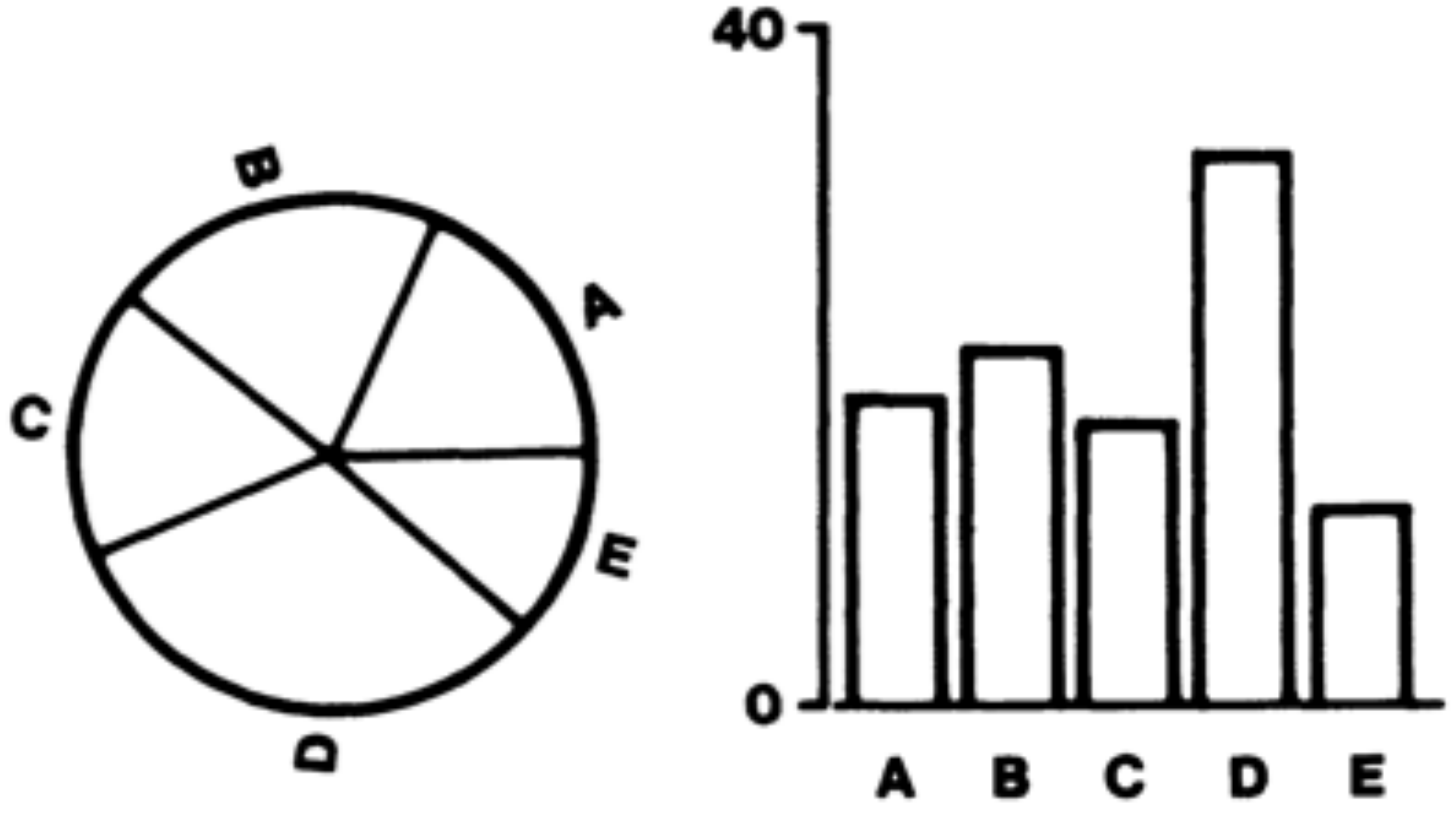
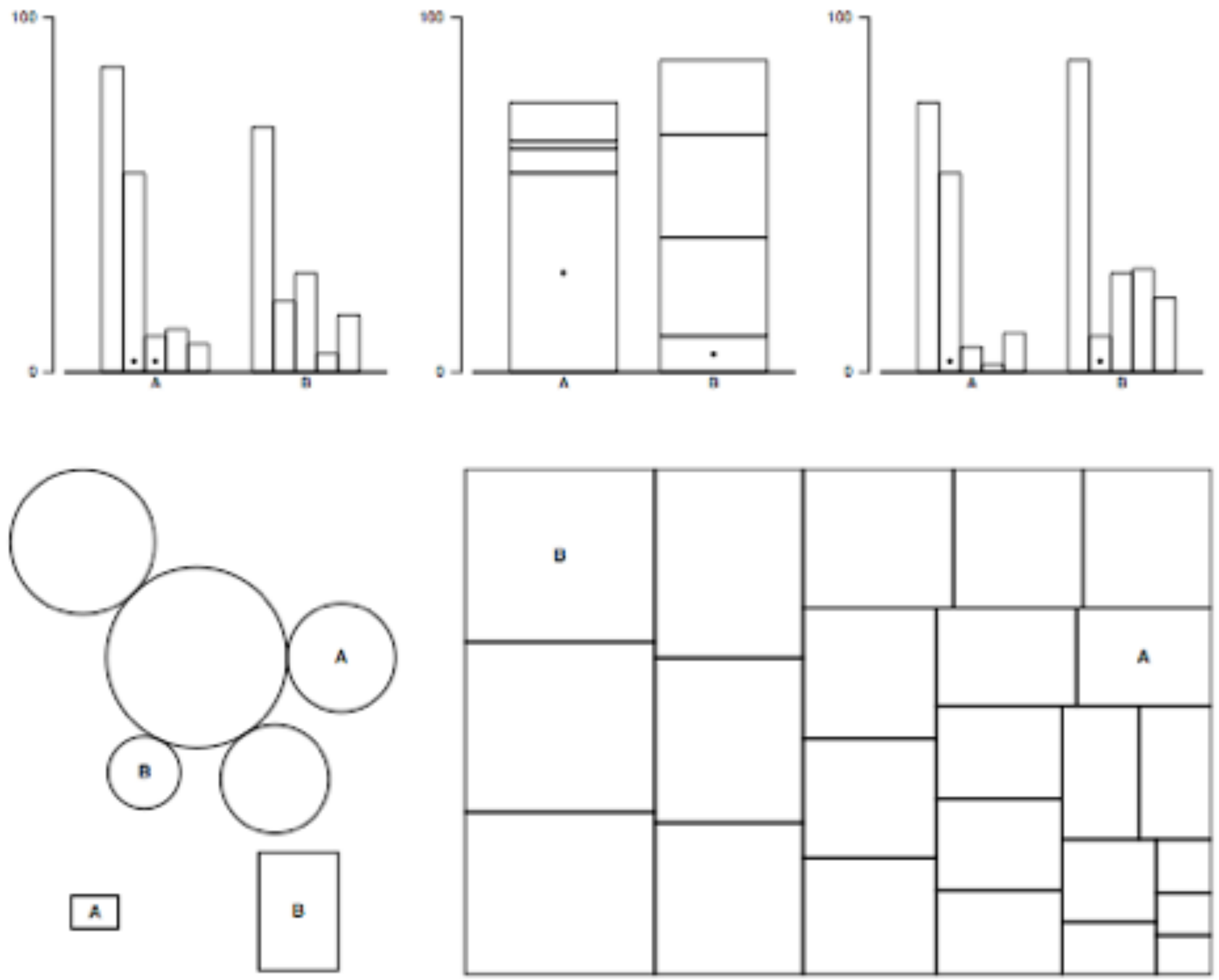
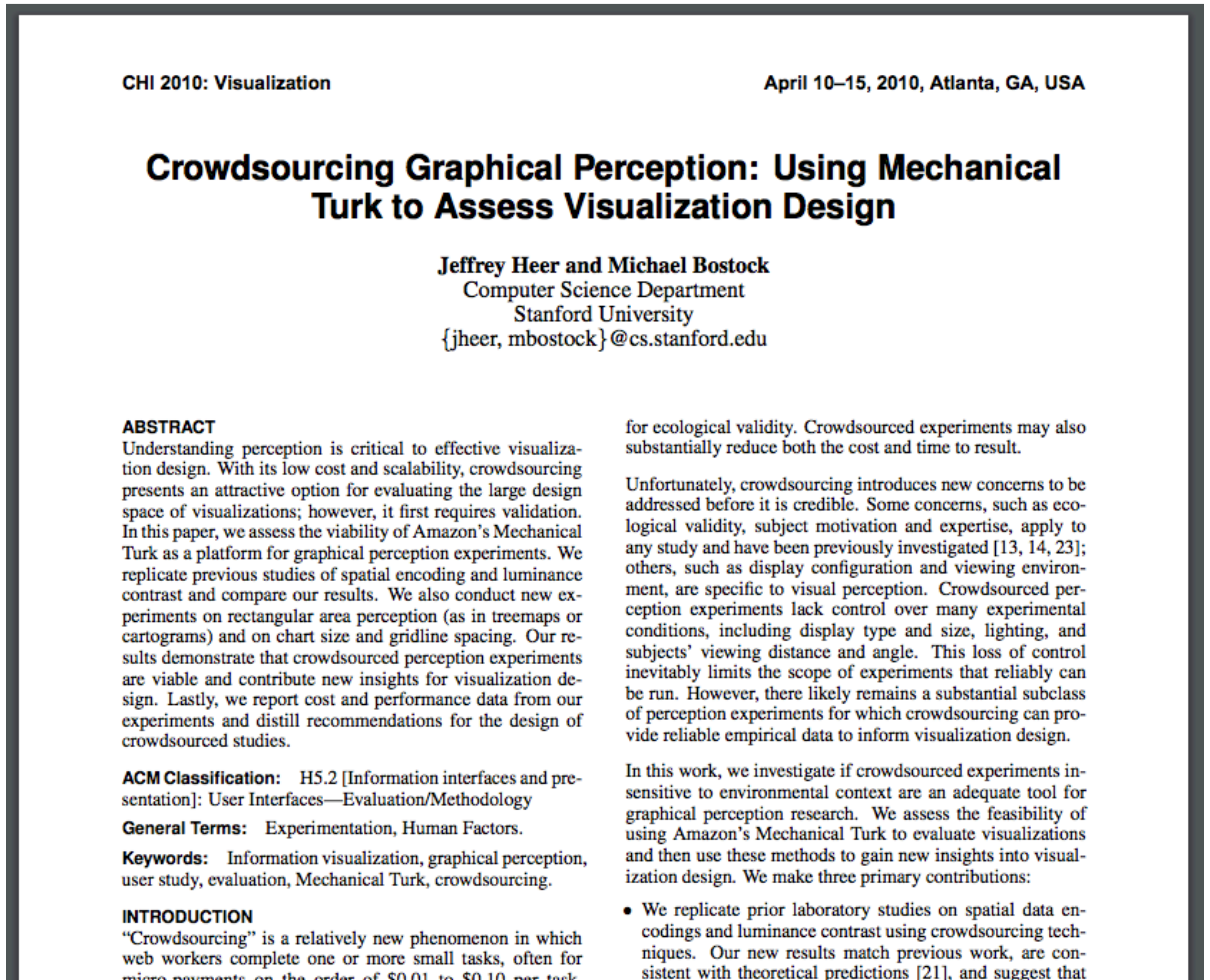


Figure 3. Graphs from position–angle experiment.

William S. Cleveland; Robert McGill , "Graphical Perception: Theory, Experimentation, and Application to the Development of Graphical Methods." 1984

Heer & Bostock, 2010





CHI 2010: Visualization

April 10–15, 2010, Atlanta, GA, USA

Crowdsourcing Graphical Perception: Using Mechanical Turk to Assess Visualization Design

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Computer Science Department
Stanford University
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ABSTRACT
Understanding perception is critical to effective visualization design. With its low cost and scalability, crowdsourcing presents an attractive option for evaluating the large design space of visualizations; however, it first requires validation. In this paper, we assess the viability of Amazon's Mechanical Turk as a platform for graphical perception experiments. We replicate previous studies of spatial encoding and luminance contrast and compare our results. We also conduct new experiments on rectangular area perception (as in treemaps or cartograms) and on chart size and gridline spacing. Our results demonstrate that crowdsourced perception experiments are viable and contribute new insights for visualization design. Lastly, we report cost and performance data from our experiments and distill recommendations for the design of crowdsourced studies.

ACM Classification: H5.2 [Information interfaces and presentation]: User Interfaces—Evaluation/Methodology

General Terms: Experimentation, Human Factors.

Keywords: Information visualization, graphical perception, user study, evaluation, Mechanical Turk, crowdsourcing.

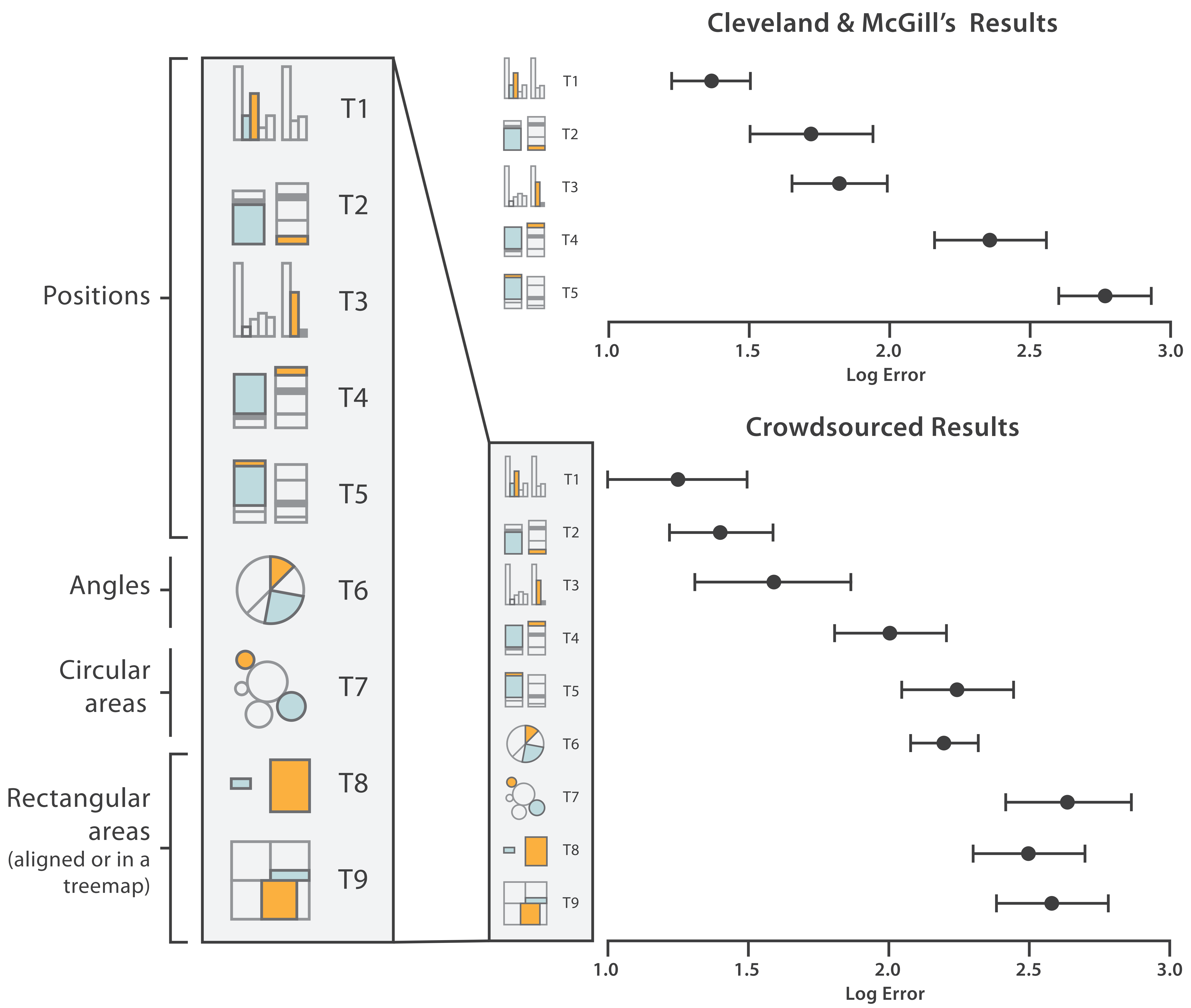
INTRODUCTION
"Crowdsourcing" is a relatively new phenomenon in which web workers complete one or more small tasks, often for

for ecological validity. Crowdsourced experiments may also substantially reduce both the cost and time to result.

Unfortunately, crowdsourcing introduces new concerns to be addressed before it is credible. Some concerns, such as ecological validity, subject motivation and expertise, apply to any study and have been previously investigated [13, 14, 23]; others, such as display configuration and viewing environment, are specific to visual perception. Crowdsourced perception experiments lack control over many experimental conditions, including display type and size, lighting, and subjects' viewing distance and angle. This loss of control inevitably limits the scope of experiments that reliably can be run. However, there likely remains a substantial subclass of perception experiments for which crowdsourcing can provide reliable empirical data to inform visualization design.

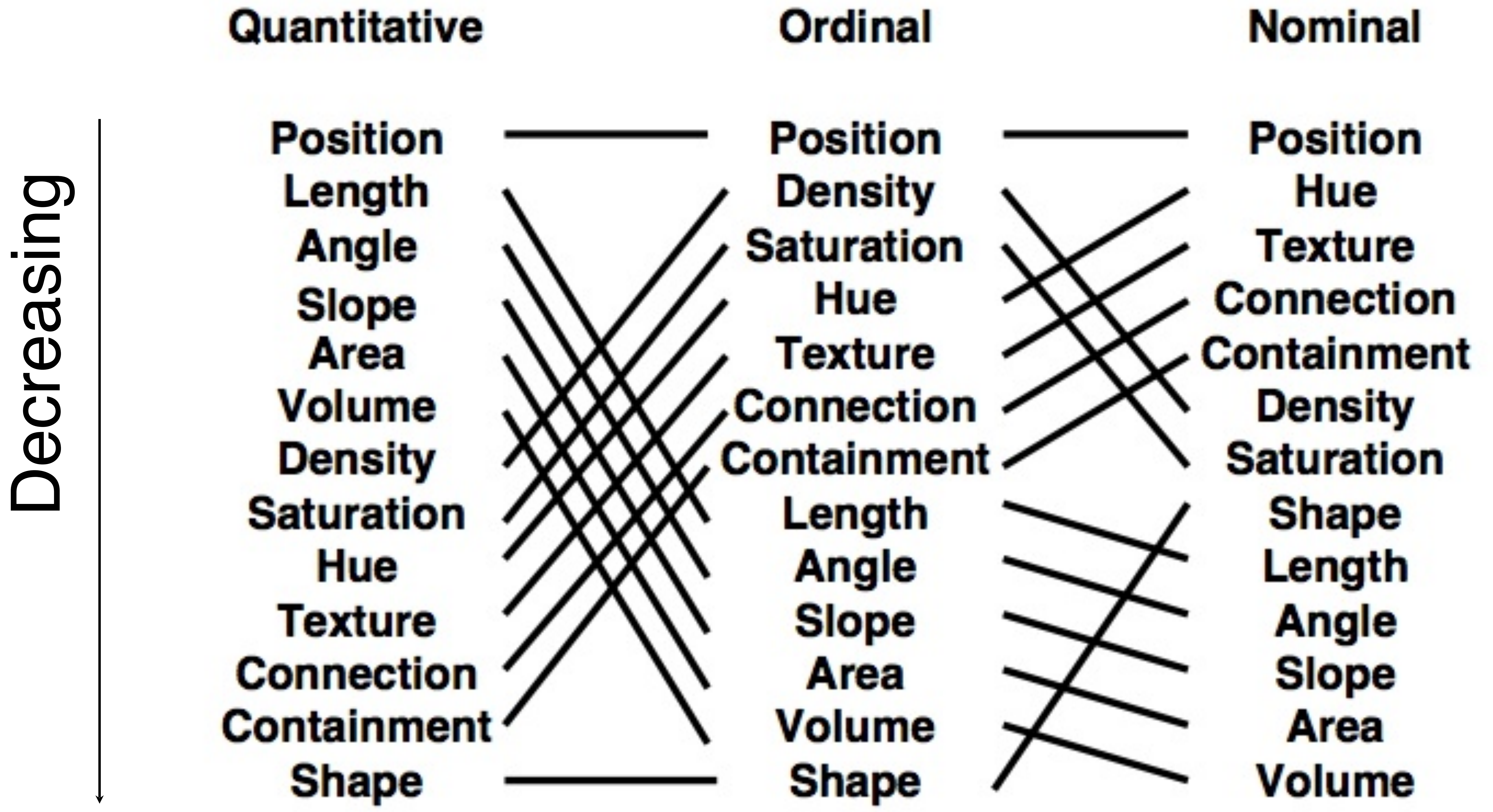
In this work, we investigate if crowdsourced experiments insensitive to environmental context are an adequate tool for graphical perception research. We assess the feasibility of using Amazon's Mechanical Turk to evaluate visualizations and then use these methods to gain new insights into visualization design. We make three primary contributions:

- We replicate prior laboratory studies on spatial data encodings and luminance contrast using crowdsourcing techniques. Our new results match previous work, are consistent with theoretical predictions [21], and suggest that



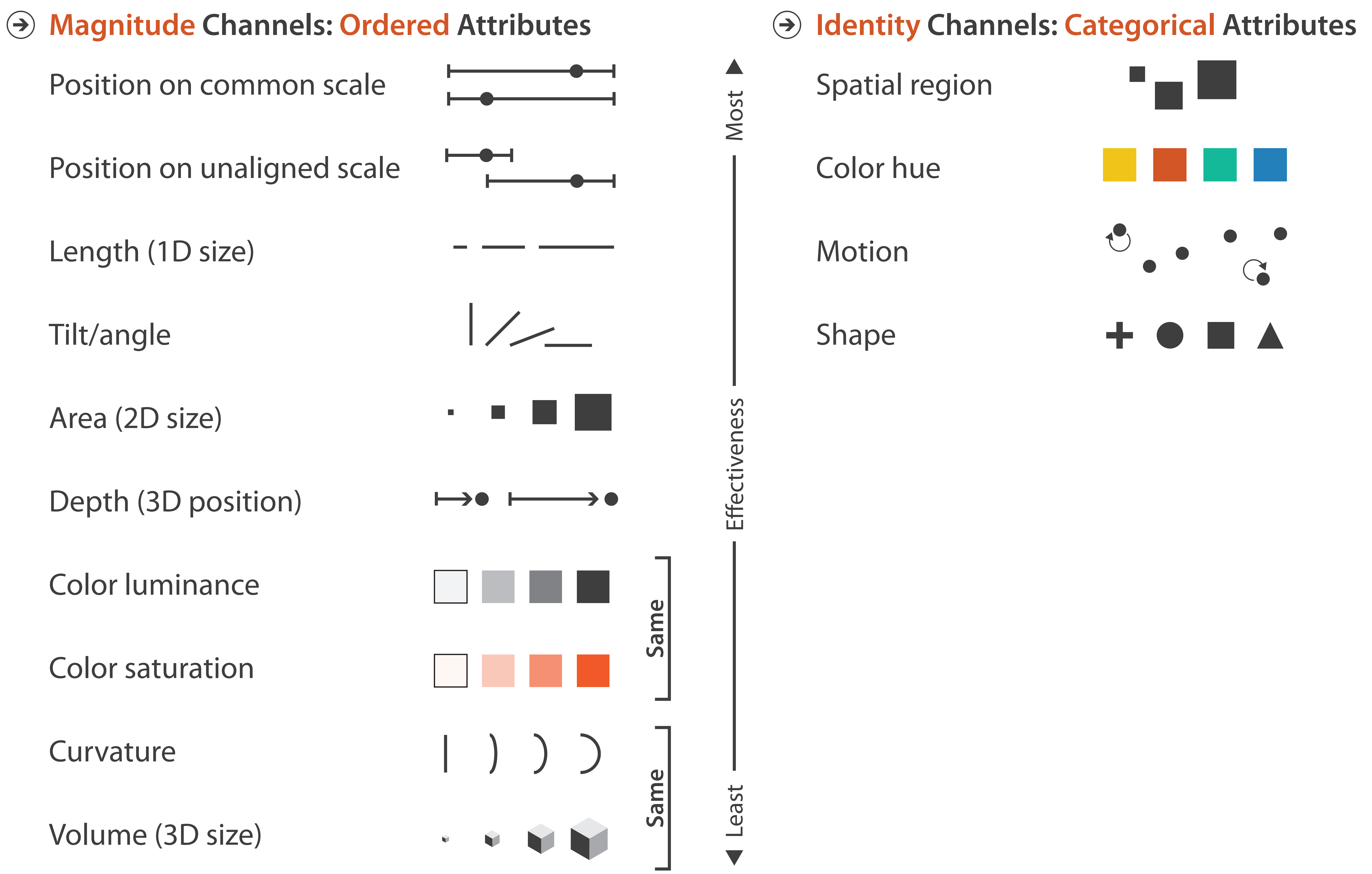
Log Error = log2(judged percent - true percent + 1/8)

Jock Mackinlay, 1986



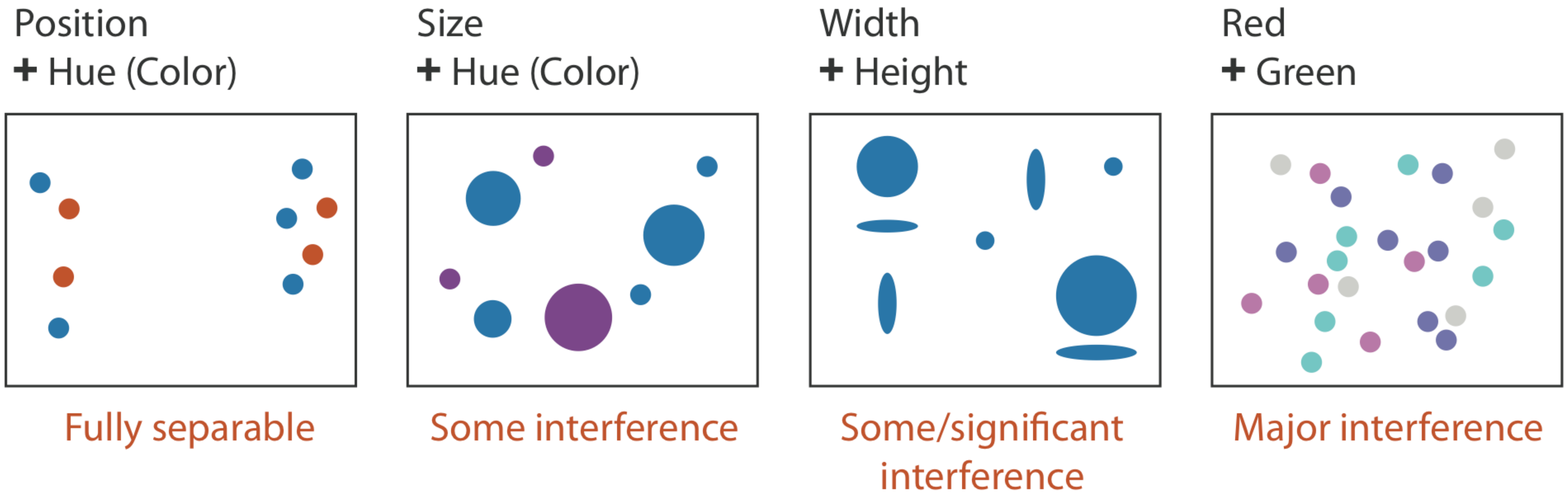
[Mackinlay, Automating the Design of Graphical Presentations of Relational Information, 1986]

Channels: Expressiveness Types and Effectiveness Ranks



Separability of Attributes

Can we combine multiple visual variables?



T. Munzner, Visualization Analysis and Design, 2014