

# Visualization

CS 347

Maneesh Agrawala

# Last time

Low-level cognitive models create **computational proxies of human mental behavior**, to help us characterize and understand how we will engage with a piece of technology

Model human processor, GOMS, KLM

Thinking in the world requires an understanding of cognition as well: **embodied cognition** emphasizes how we think with our bodies, whereas **distributed cognition** emphasizes how we think with the environment and other people in it

When our cognition is overloaded, performance decreases

# Today

Choosing the right representation

Data, marks, visual attributes and encodings

Graphical perception

Frontiers of visualization research

# Choosing the right representation

# Cognitive amplification

Visualization can help, but ultimately this power comes from better **representation**. By better understanding human cognition, we can design technology that makes us smarter.

“The powers of cognition come from abstraction and representation: the ability to represent perceptions, experiences, and thoughts in some medium other than that in which they have occurred, abstracted away from irrelevant details.” [Norman '94, Simon '81]

# Example: Number scrabble

[Simon 1988]

Take turns picking numbers in 1,2,3,4,5,6,7,8,9 without replacement

Win if any **three** of your numbers add up to **15**.

It's OK if you have extra numbers in your hand, as long as three of them add up to exactly 15.

YOU READ THIS

# Ready, set, go!

YOU READ THIS

I will show the series of moves from players A and B so far. Raise your hand when you know what B's best next move should be.

A takes 4

B takes 9

A takes 2

B takes 8

A takes 5

What should B do?

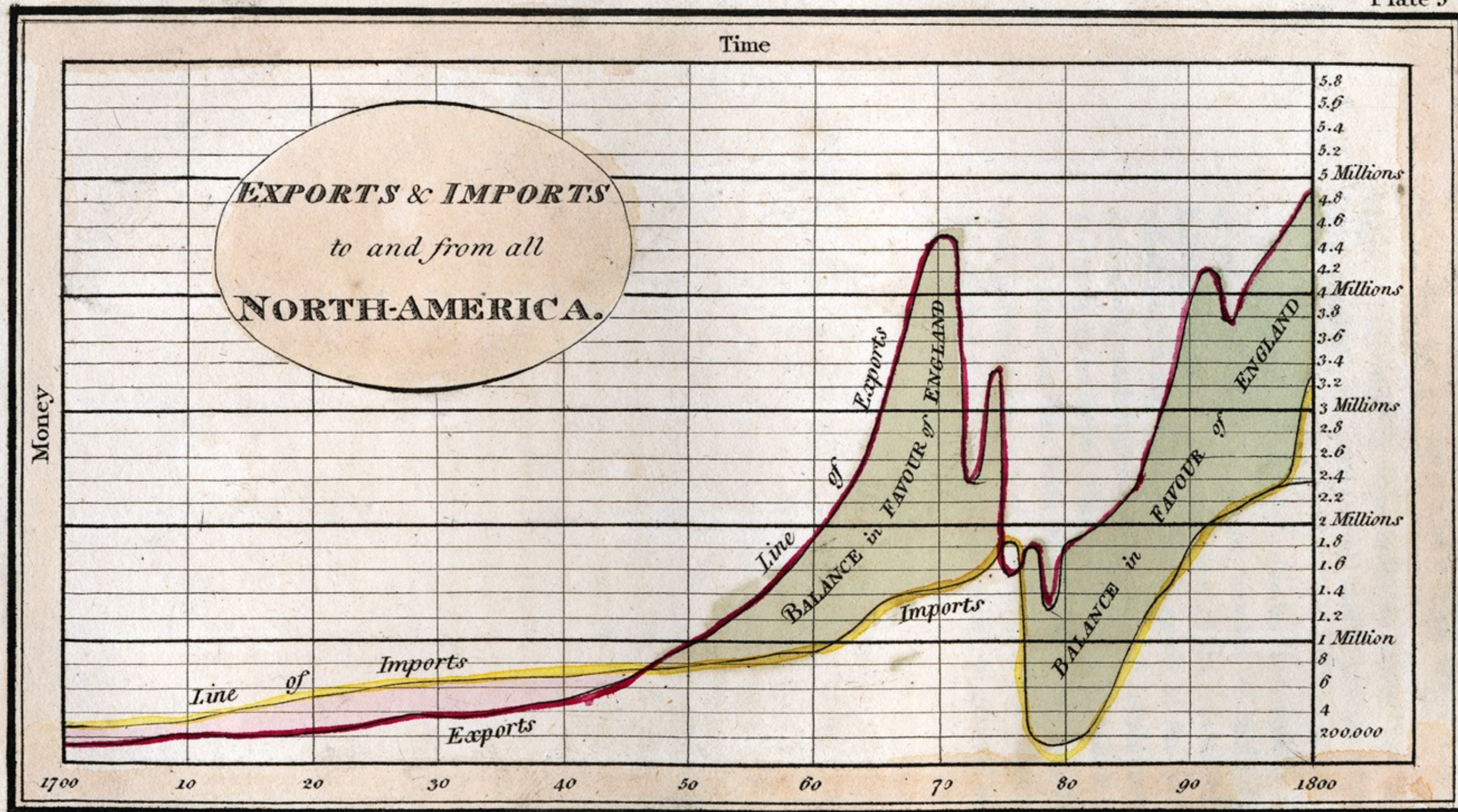
# Re-encoding number scrabble

YOU READ THIS

A4	B9	A2
3	A5	7
B8		6

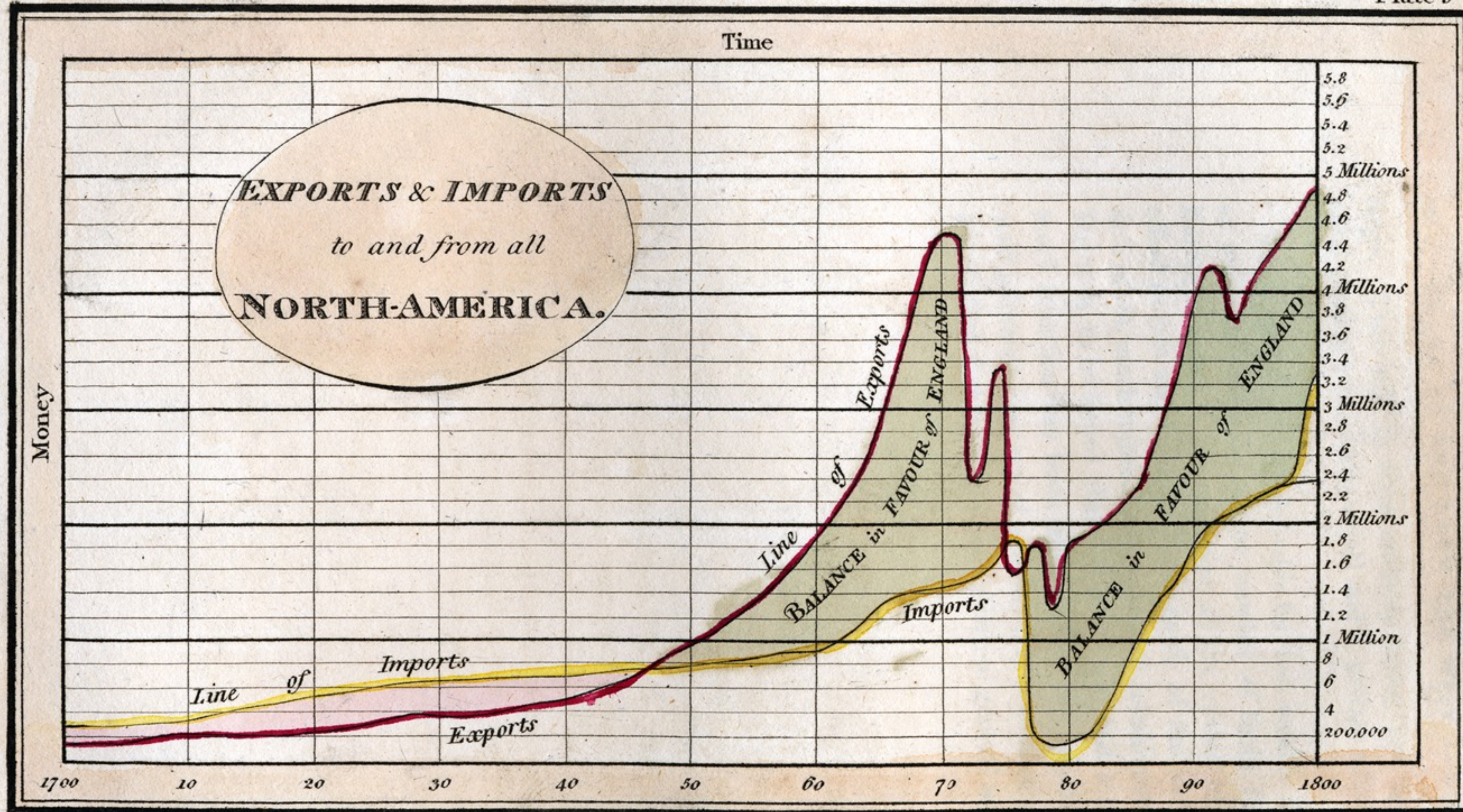
**Representation:** Changing representation to spatial tic-tac-toe board facilitates choice





Exports and Imports to and from all North America [Playfair 1786-1801]

User's task: Understand balance of trade between England and North America over time



Neale sc. Strand.

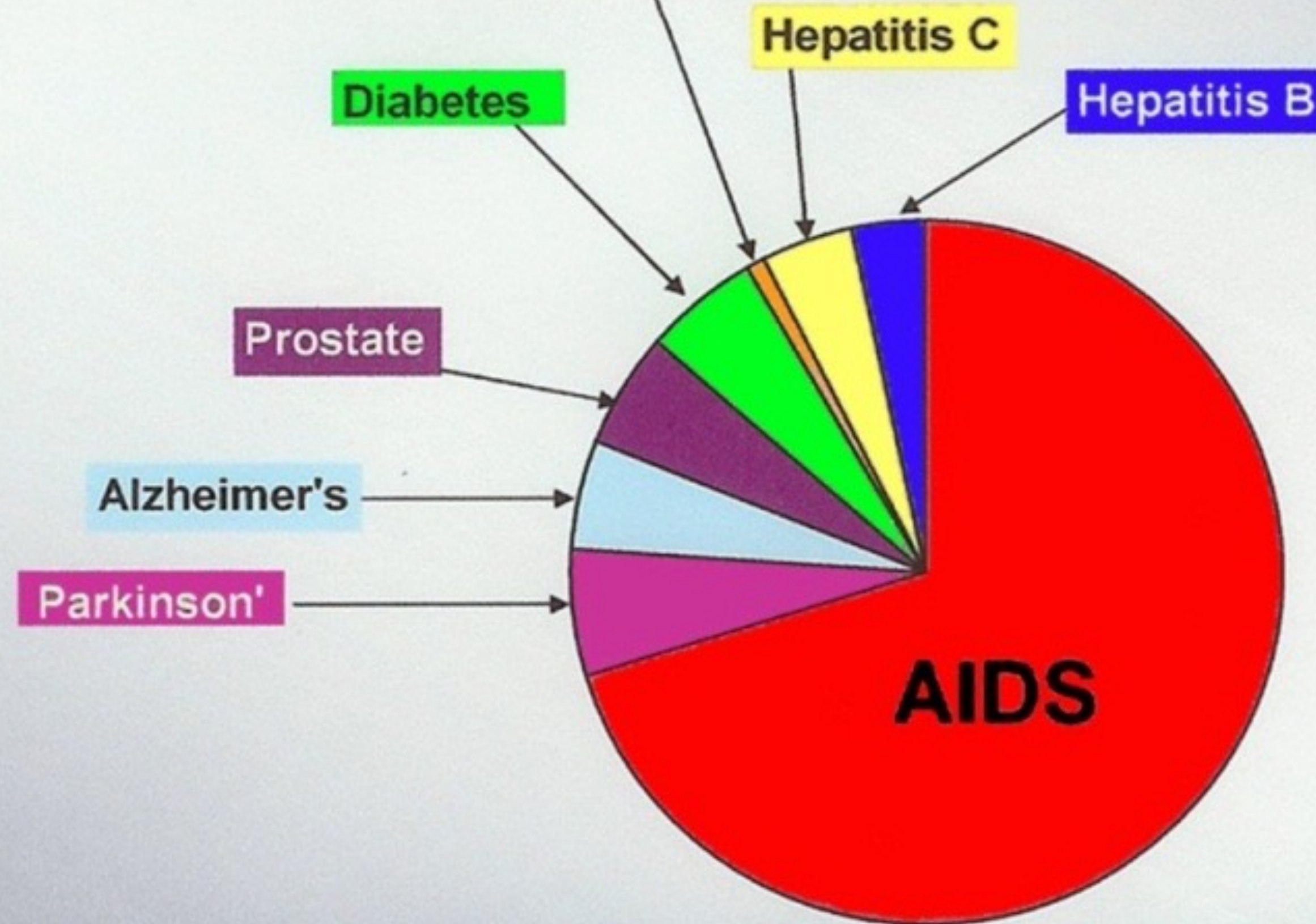
**Exports and Imports to and from all North America** [Playfair 1786-1801]

**Important Information:** Historical differences between exports and imports

**Representation:** Superimpose line charts of exports and imports to show historical pattern  
Shade differences between lines to highlight balance against/in favor

## 2005 NIH Research Budget per Death

Cardiovascular (CVD = Heart & Stroke)



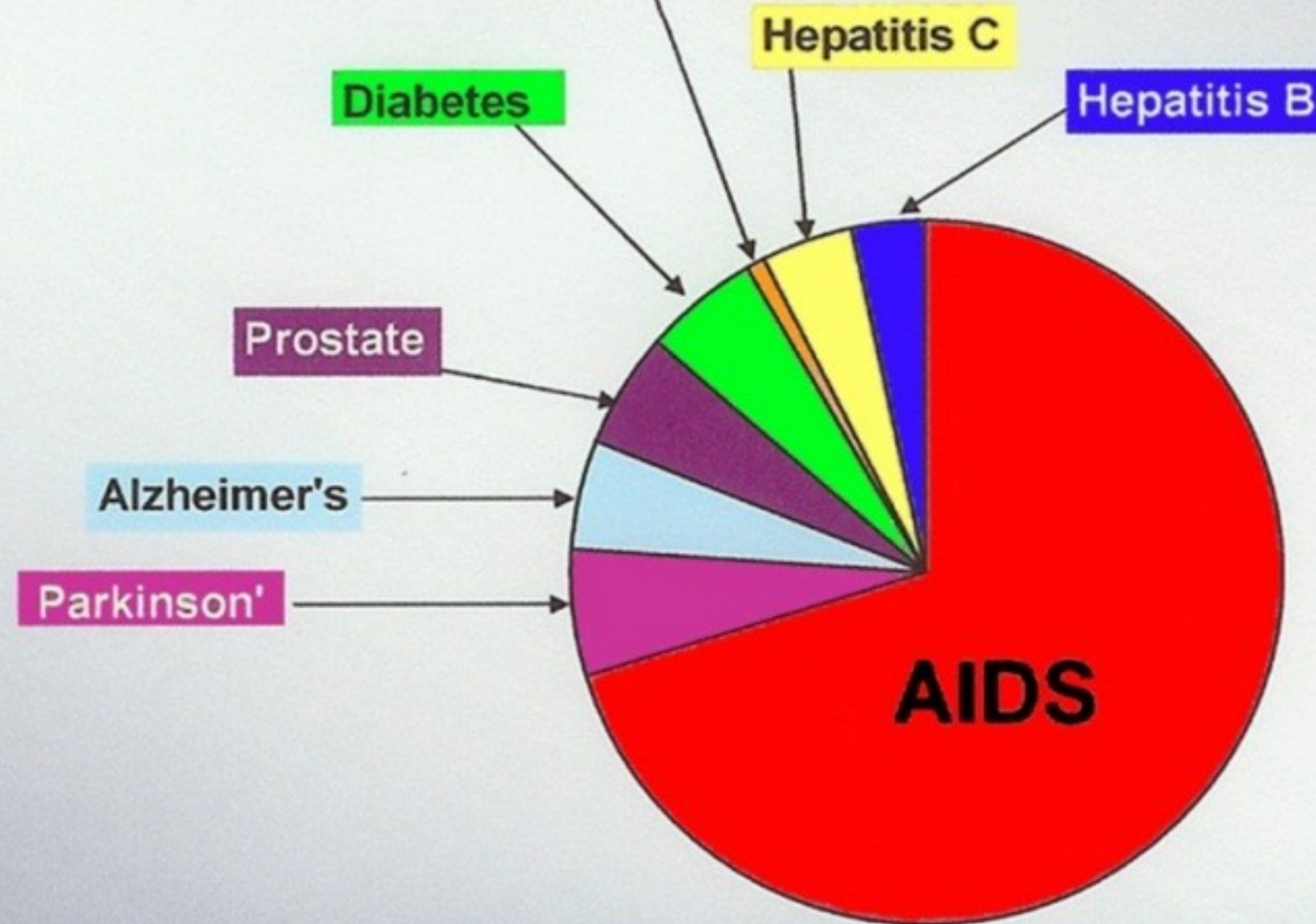
© Copyright FAIR Foundation 2004

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

**User's task:** Understand overall proportion of budget allocated to each disease  
Compare proportion of budget allocated to each disease

## 2005 NIH Research Budget per Death

Cardiovascular (CVD = Heart & Stroke)



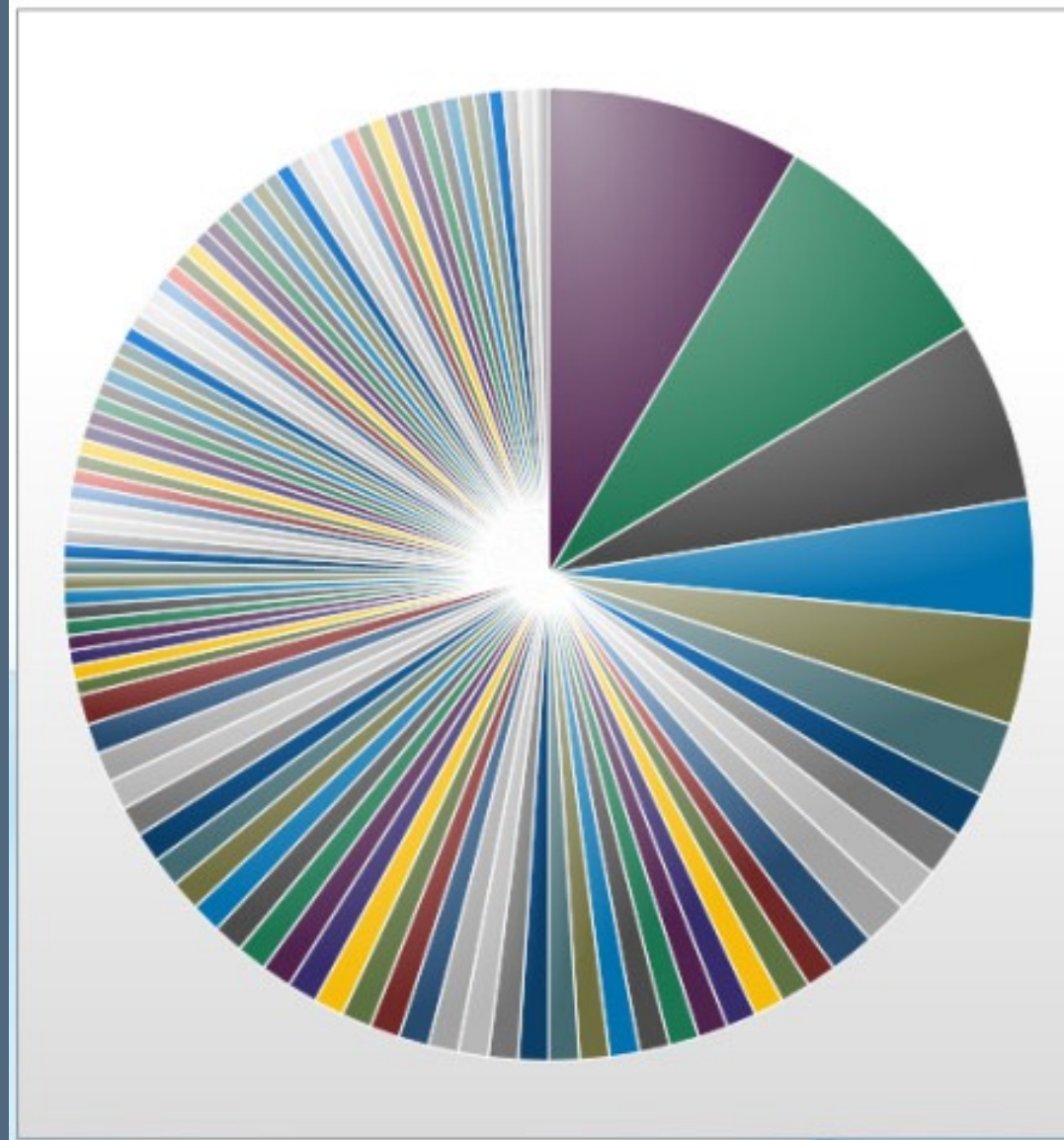
© Copyright FAIR Foundation 2004

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

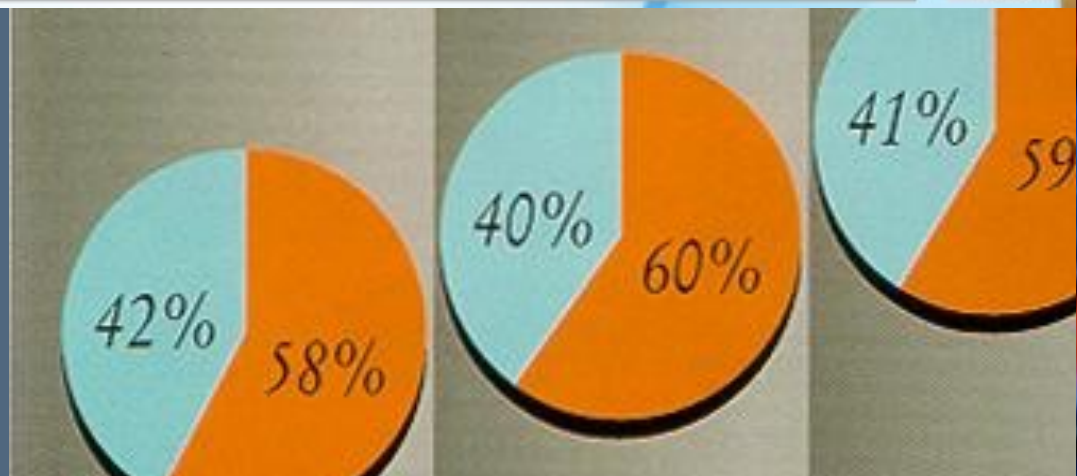
**Important Information:** Percentage of budget allocated to each disease

**Representation:** Encode budget using pie chart to emphasize part-to-whole relationship

~~Allow comparison between diseases by comparing pie slices (angles or areas)~~



- download11
- suhd
- iggym
- paviles
- System
- silverfi
- saurabi
- giograp
- DianaK
- dotnets
- jefisanc
- LukCAL
- inkhead
- alexpui
- phpcan
- MSExp
- hashajz
- marxw
- del\_jav
- james\_
- mmark
- katrienc
- enginee
- ch9
- flashbra
- irhctori
- Jungch
- niceout
- jrose
- BrianB
- Tunis
- pt\_shar
- skroski
- Crisp
- timhe
- jorgega
- JimDeg
- iBlend
- xgluxv
- peidk
- Ivanlo



## 2012 PRESIDENTIAL RUN

### GOP CANDIDATES

**BACK PALIN 70%**

**BACK ROMNEY 60%**

**BACK HUCKABEE 63%**

**SOURCE: OPINIONS DYNAMIC**

**FOX 47'**

## ITHACA NEWS

Planning Board approves  
Widewater development

10 students occupy Job Hall

Cayuga Vocal Ensemble  
ushers in the holidays with  
"Judas Maccabaeus"

## A Real Pie Chart

Results of a nationwide poll by Schwan's Consumer Brands North America, the makers of the Mrs. Smith's brand of pie products.\*

### What are your three most favorite types of pie?

\*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

### THE SHRINKING FAMILY DOCTOR In California

Percentage of Doctors Devoted Solely to Family Practice

1964	1975	1990
27%	16.0%	12.0%

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-*

<b>Average Sedan</b>	4 Capacity 27 Miles per gallon 0.37 Gallons per mile 05:50 Time to travel 350 miles at 60 mph	
<b>Average Hybrid</b>	4 Capacity 46 Miles per gallon 0.22 Gallons per mile 05:50 Time to travel 350 miles at 60 mph	
<b>Motorcycle</b>	1 Capacity 58 Miles per gallon 0.17 Gallons per mile 05:50 Time to travel 350 miles at 60 mph	
<b>Bicycle</b>	1 Capacity 912 Miles per gallon (caloric conversion) 0.001 Gallons per mile (caloric conversion) 23:20 Time to travel 350 miles at 15 mph	(or  x 16)
<b>Walking</b>	1 Capacity 211 Miles per gallon (caloric conversion) 0.005 Gallons per mile (caloric conversion) 100 Time to travel 350 miles at 3.5 mph	(or  x 48)

FUEL USAGE for driver alone  
 FUEL USAGE for driver plus one passenger  
 FUEL USAGE for driver plus three passengers  
 WHOPPER with cheese is 770 calories.  
 GOOD neither endorses nor denounces the consumption of Whoppers.  
 WE'RE EFFICIENT One gallon of gas equals approximately 31,000 calories. We only need about 2,000 calories a day.  
 CYCLIST A 175-pound rider, biking 15 miles per hour, and burning 0.40 calories per pound per minute.  
 WALKER A 175-pound pedestrian, walking at 3.5 miles per hour, and burning 0.35 calories per pound per minute.  
 NOTE Capacity, fuel economy, and speed numbers are, in some cases, averages or estimates.  
 good is Transparency

**Data, marks, visual  
attributes and encodings**



On the theory of  
scales of measurements  
S. S. Stevens, 1946

# Data Types

## **N - Nominal (labels)**

Fruits: Apples, oranges, ...

Operations: =, ≠

## **O - Ordered**

Quality of eggs: Grade AA, A, B

Operations: =, ≠, <, >

## **Q - Interval (location of zero arbitrary)**

Dates: Jan, 19, 2016; Loc.: (LAT 33.98, LON -118.45)

Like a geometric point. Cannot compare directly

Only differences (i.e. intervals) may be compared

Operations: =, ≠, <, >, -

## **Q - Ratio (location of zero fixed)**

Physical measurement: Length, Mass, ...

Counts and amounts

Like a geometric vector, origin is meaningful

Operations: =, ≠, <, >, -, ÷

# U.S. Census Data

**People Count:** # of people in group  
**Year:** 1850 – 2000 (every decade)  
**Age:** 0 – 90+  
**Sex:** Male, Female  
**Marital Status:** Single, Married, Divorced, ...

2348 data points

	A	B	C	D	E
1	year	age	marst	sex	people
2	1850	0	0	1	1483789
3	1850	0	0	2	1450376
4	1850	5	0	1	1411067
5	1850	5	0	2	1359668
6	1850	10	0	1	1260099
7	1850	10	0	2	1216114
8	1850	15	0	1	1077133
9	1850	15	0	2	1110619
10	1850	20	0	1	1017281
11	1850	20	0	2	1003841
12	1850	25	0	1	862547
13	1850	25	0	2	799482
14	1850	30	0	1	730638
15	1850	30	0	2	639636
16	1850	35	0	1	588487
17	1850	35	0	2	505012
18	1850	40	0	1	475911
19	1850	40	0	2	428185
20	1850	45	0	1	384211
21	1850	45	0	2	341254
22	1850	50	0	1	321343
23	1850	50	0	2	286580
24	1850	55	0	1	194080
25	1850	55	0	2	187208
26	1850	60	0	1	174976



# Census N, O, Q

People Count: Q-Ratio

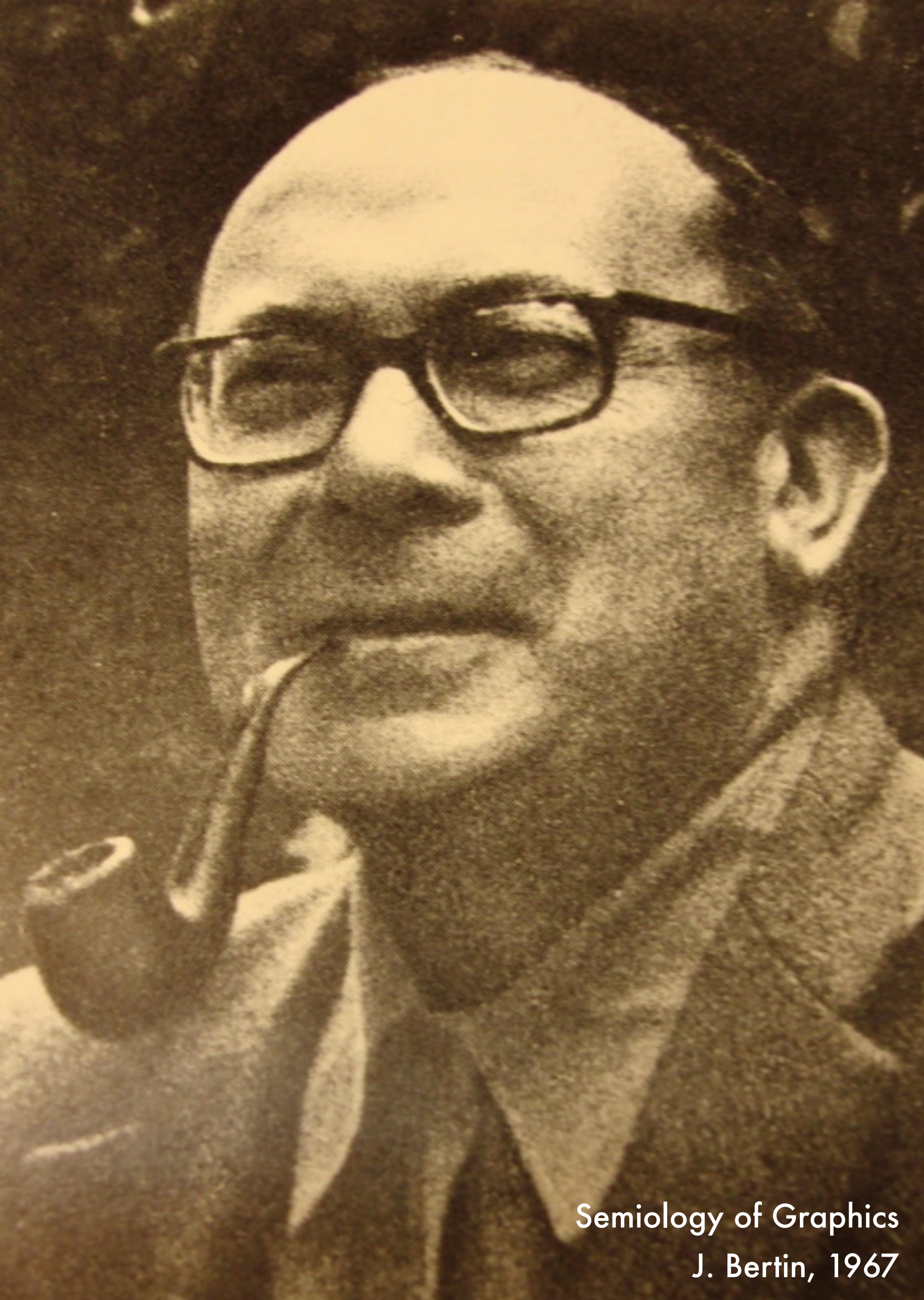
Year: Q-Interval (maybe O)

Age: Q-Ratio (maybe O)

Sex: N

Marital Status: N

	A	B	C	D	E
1	year	age	marst	sex	people
2	1850	0	0	1	1483789
3	1850	0	0	2	1450376
4	1850	5	0	1	1411067
5	1850	5	0	2	1359668
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25	1850	55	0	2	187208
26	1850	60	0	1	174976



# Marks & Visual Attributes

**Marks:** geometric primitives



**Visual Attributes:** control mark appearance

Position (2x)

Size

Value

Texture

Color

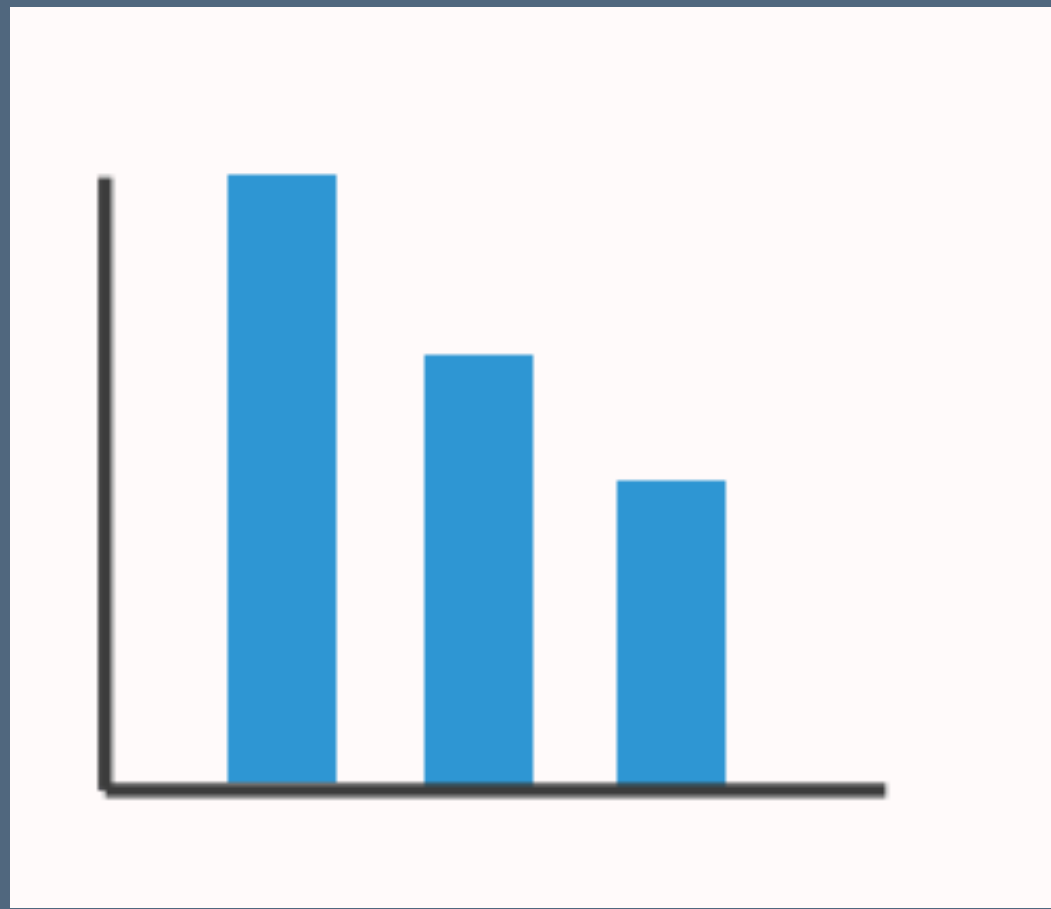
Orientation

Shape

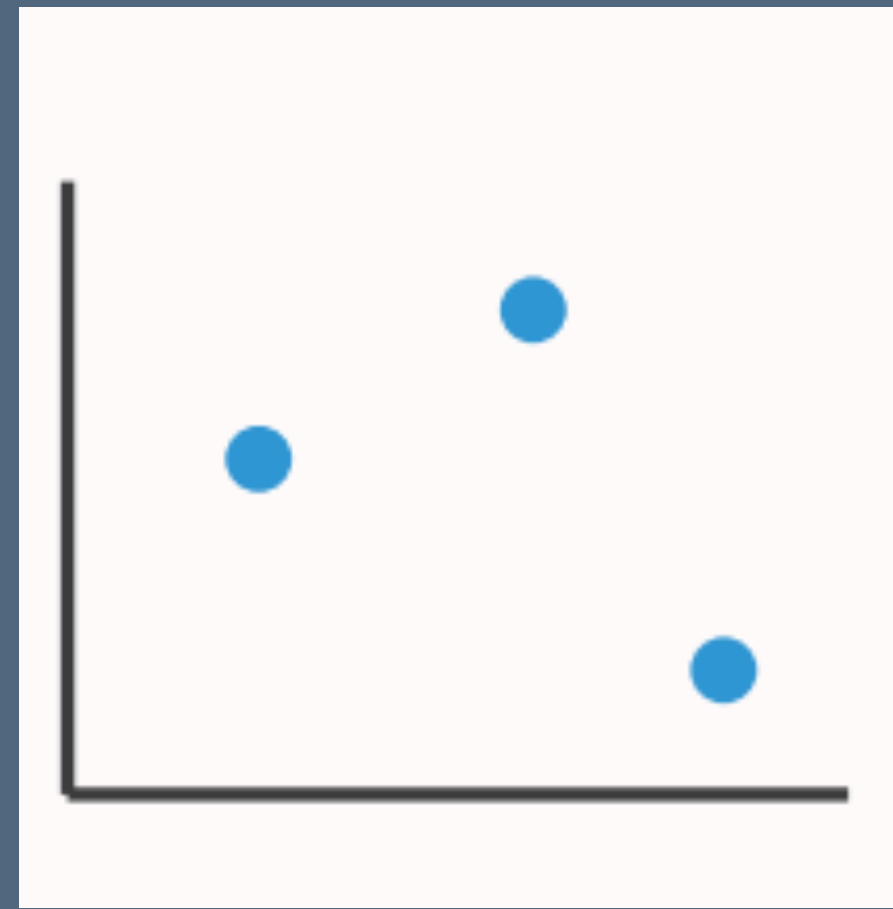
	POINTS	LIGNES	ZONES
XY 2 DIMENSIONS DU PLAN	x x x	/ ~ /	14 15 9 16 21 2 14 15 1    2 18 2 21 15
Z TAILLE	▬ ▬ ▬	/ ~ /	▬ ▬ ▬
VALEUR	▬ ▬ ▬	/ ~ /	▬ ▬ ▬
LES VARIABLES DE SÉPARATION DES IMAGES			
GRAIN	▬ ▬ ▬	/ ~ /	▬ ▬ ▬
COULEUR	▬ ▬ ▬	/ ~ /	▬ ▬ ▬
ORIENTATION	▬ ▬ ▬	/ ~ /	▬ ▬ ▬
FORME	▬ ▬ ▬	/ ~ /	▬ ▬ ▬

# Encodings

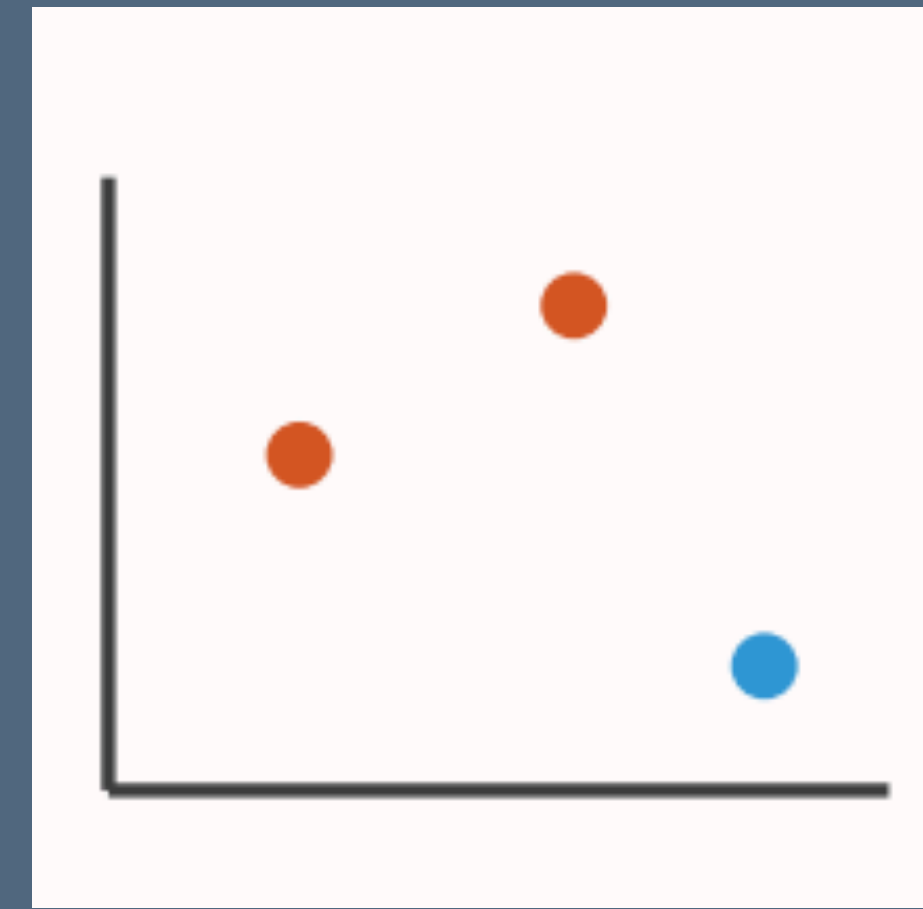
A map from data to visual attributes of marks



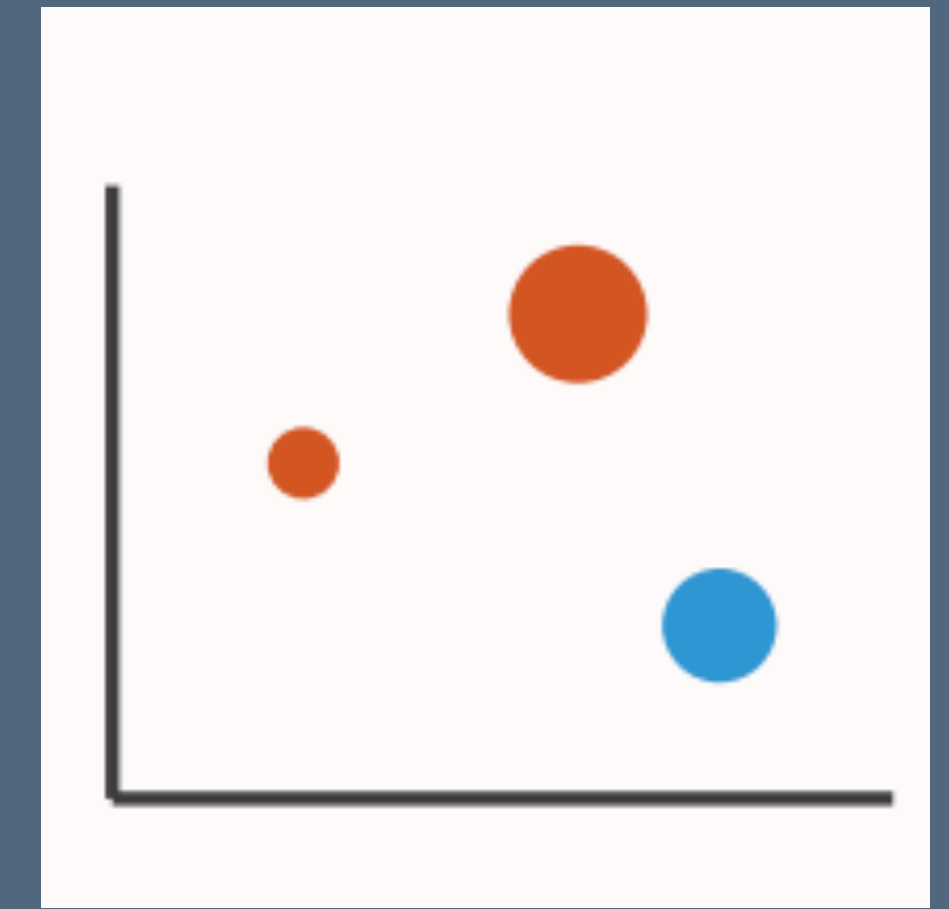
Mark: lines  
county(N)  $\rightarrow$  x  
population(Q)  $\rightarrow$  size or length



Mark: point  
acreage(Q)  $\rightarrow$  x  
population(Q)  $\rightarrow$  y



Mark: point  
acreage(Q)  $\rightarrow$  x  
population(Q)  $\rightarrow$  y  
county(N)  $\rightarrow$  color

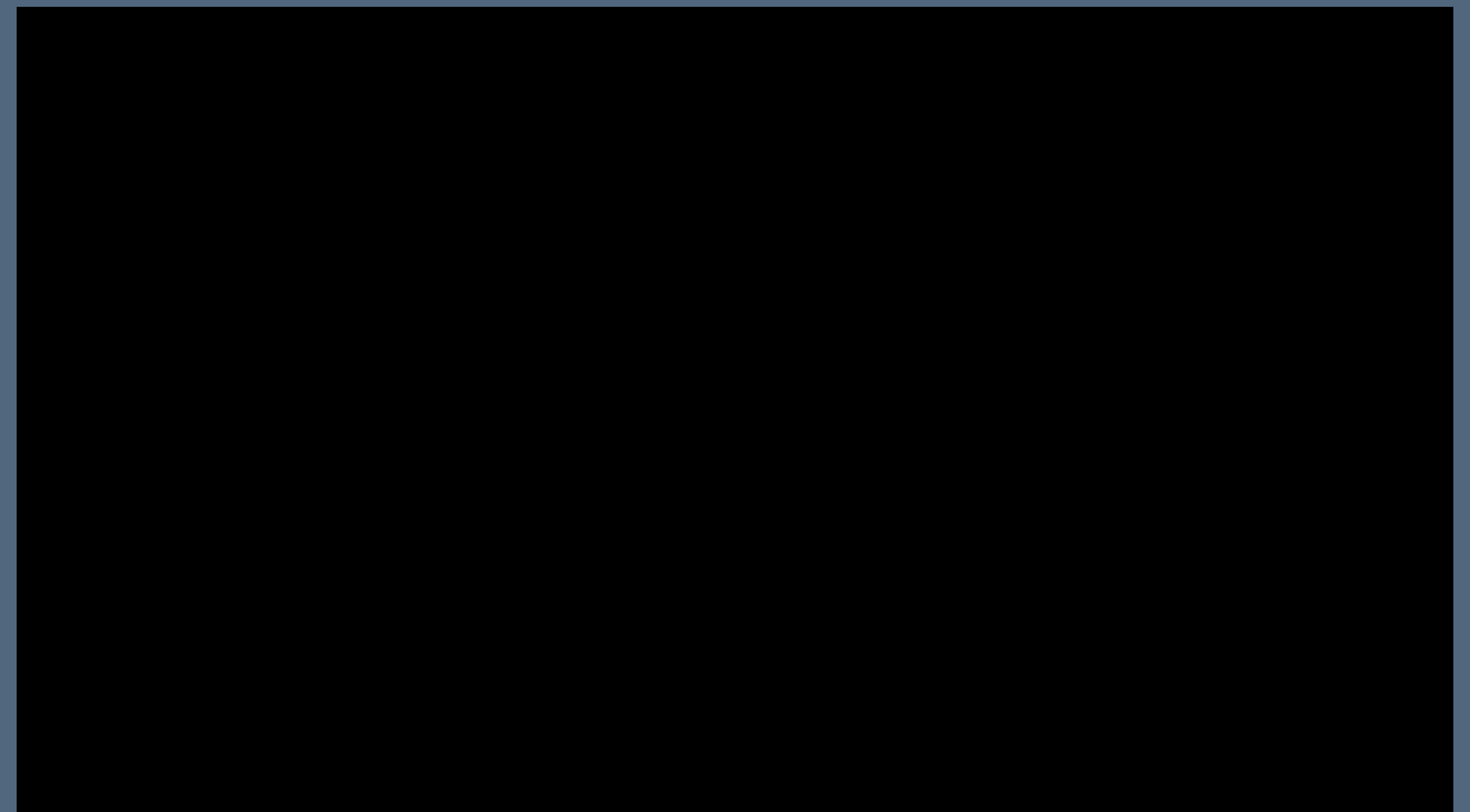


Mark: point  
acreage(Q)  $\rightarrow$  x  
population(Q)  $\rightarrow$  y  
county(N)  $\rightarrow$  color  
avg\_income(Q)  $\rightarrow$  size

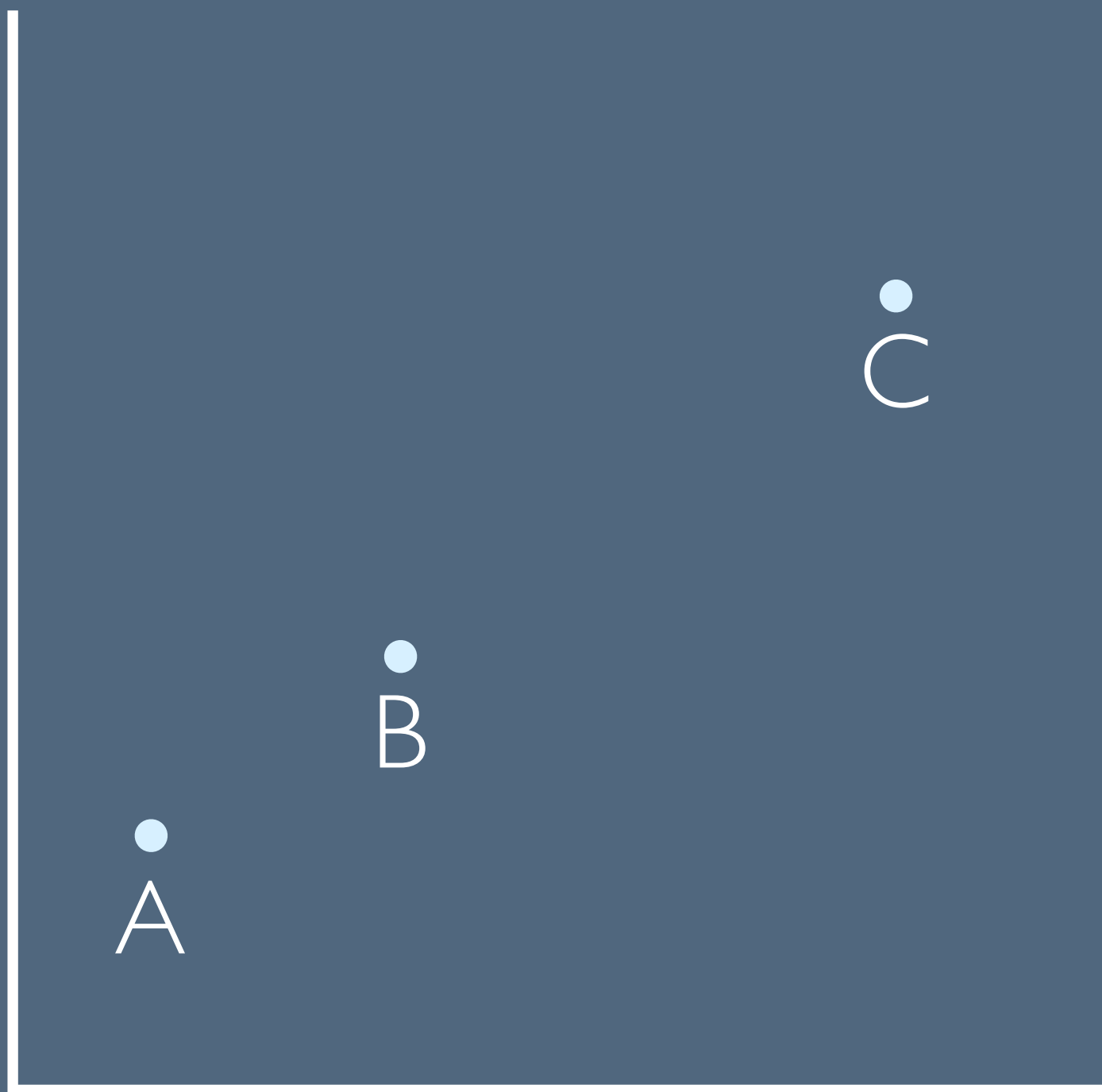
“Best” encoding based on **perceptual effectiveness** of visual attribute for data type

# 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

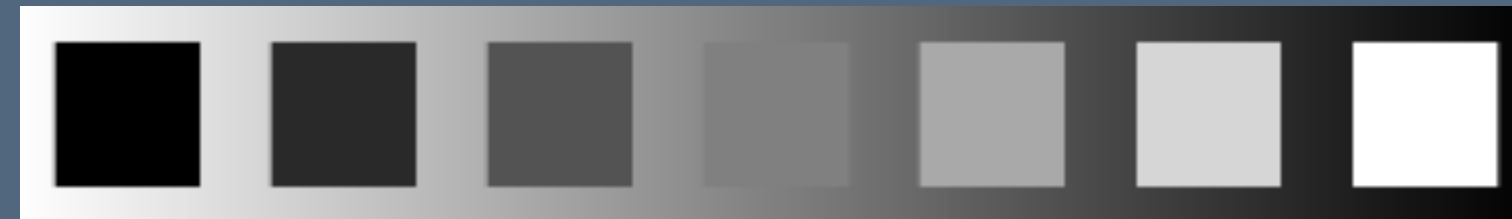
BC is twice as long as AB

**Position encodes quantitative data well**

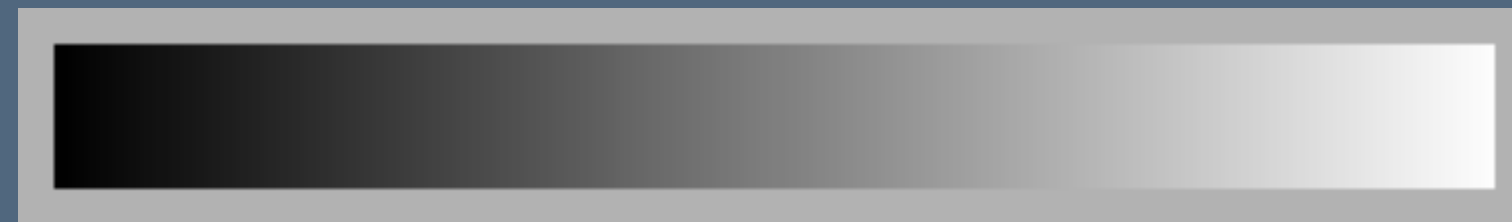
# Color

## Value or gray level is perceived as ordered

So, it encodes ordinal data well



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



## Hue is typically perceived as unordered

So, hue encodes nominal data well

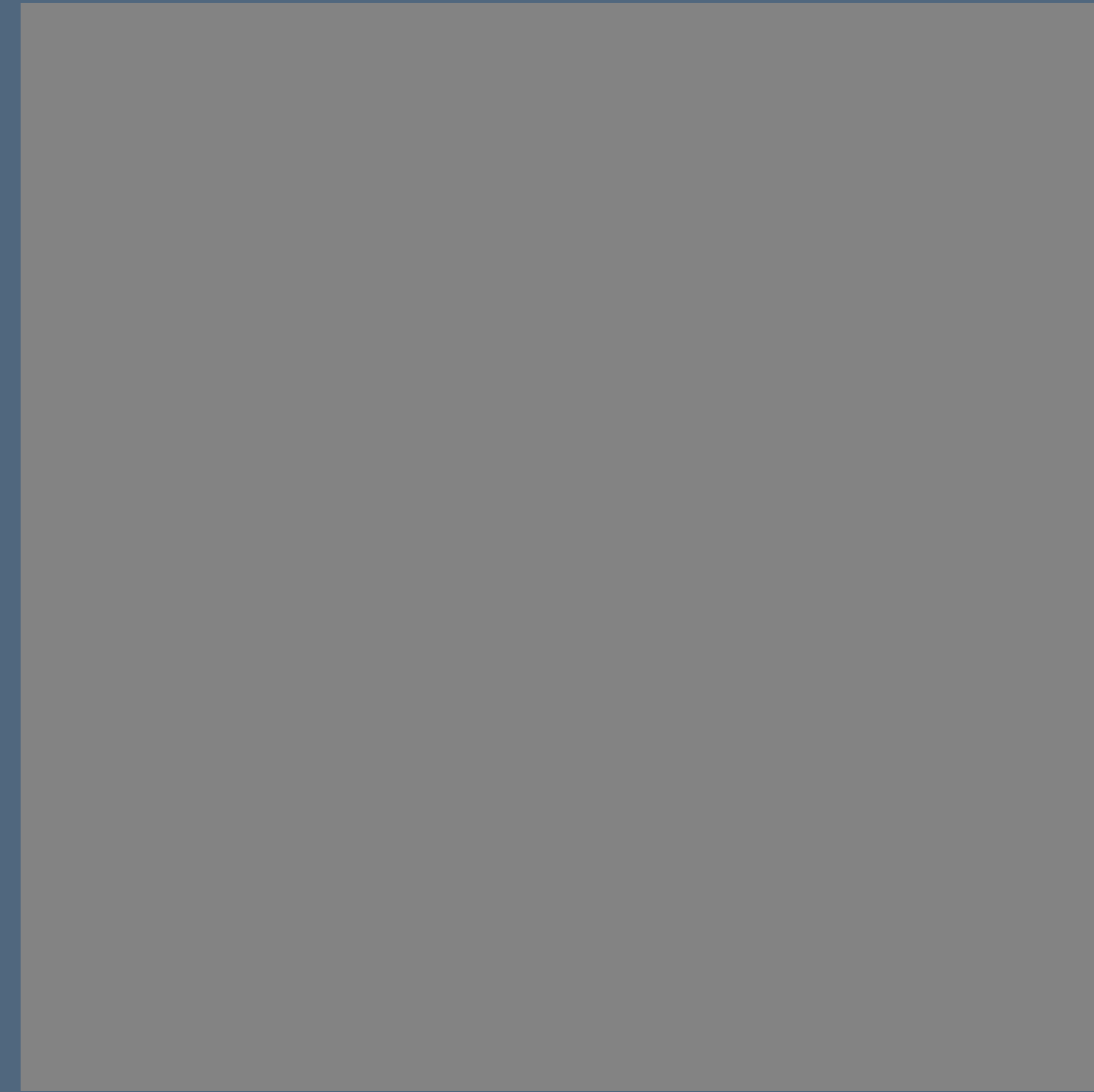
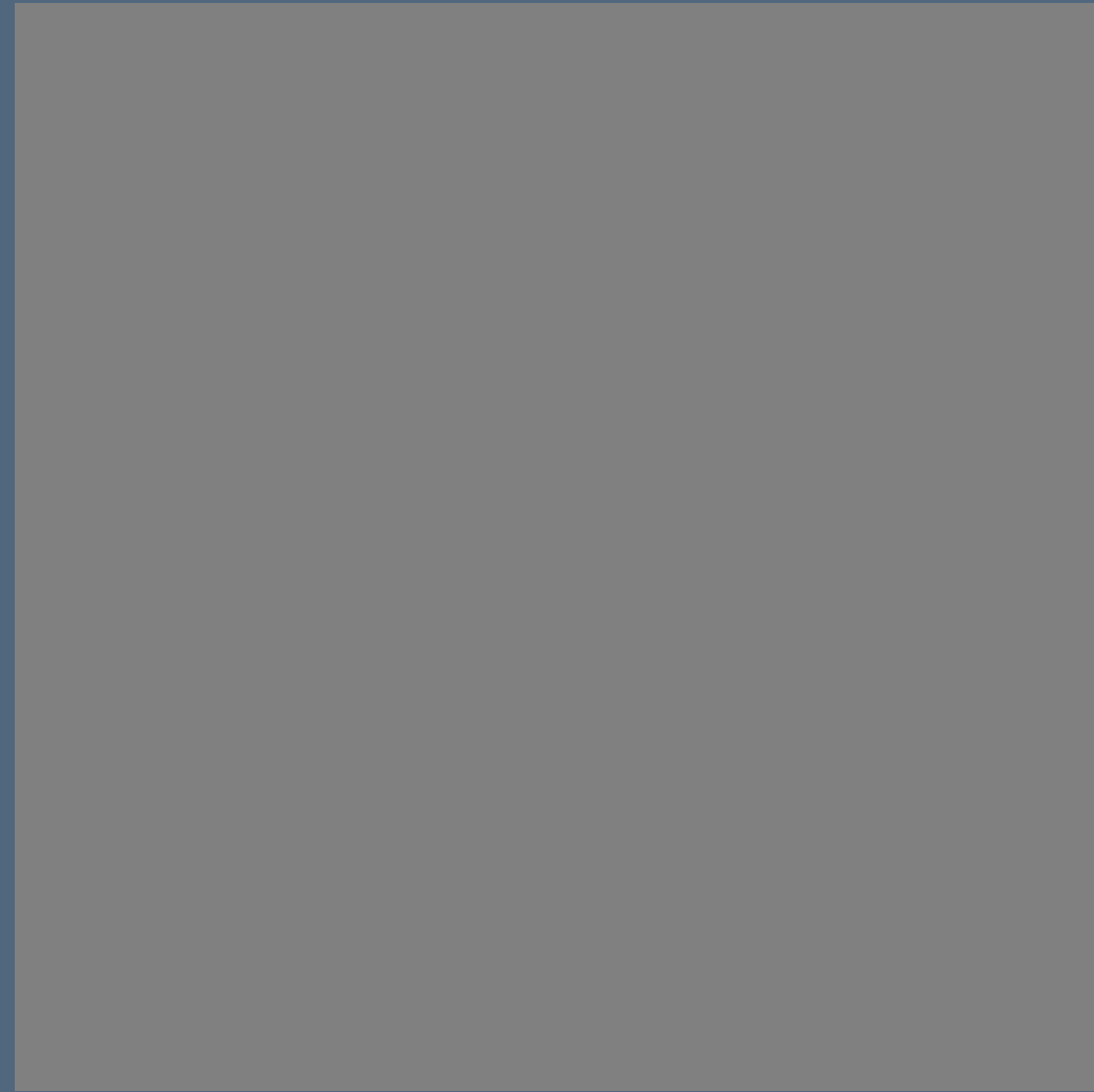


# Bertin's "Levels of Organization"

<b>Position</b>	<b>N</b>	<b>O</b>	<b>Q</b>	<b>N</b>	<b>Nominal</b>
<b>Size</b>	<b>N</b>	<b>O</b>	<b>Q</b>	<b>O</b>	<b>Ordered</b>
<b>Value</b>	<b>N</b>	<b>O</b>	<b>Q</b>	<b>Q</b>	<b>Quantitative</b>
<b>Texture</b>	<b>N</b>	<b>o</b>			
<b>Color</b>	<b>N</b>				
<b>Orientation</b>	<b>N</b>				
<b>Shape</b>	<b>N</b>				



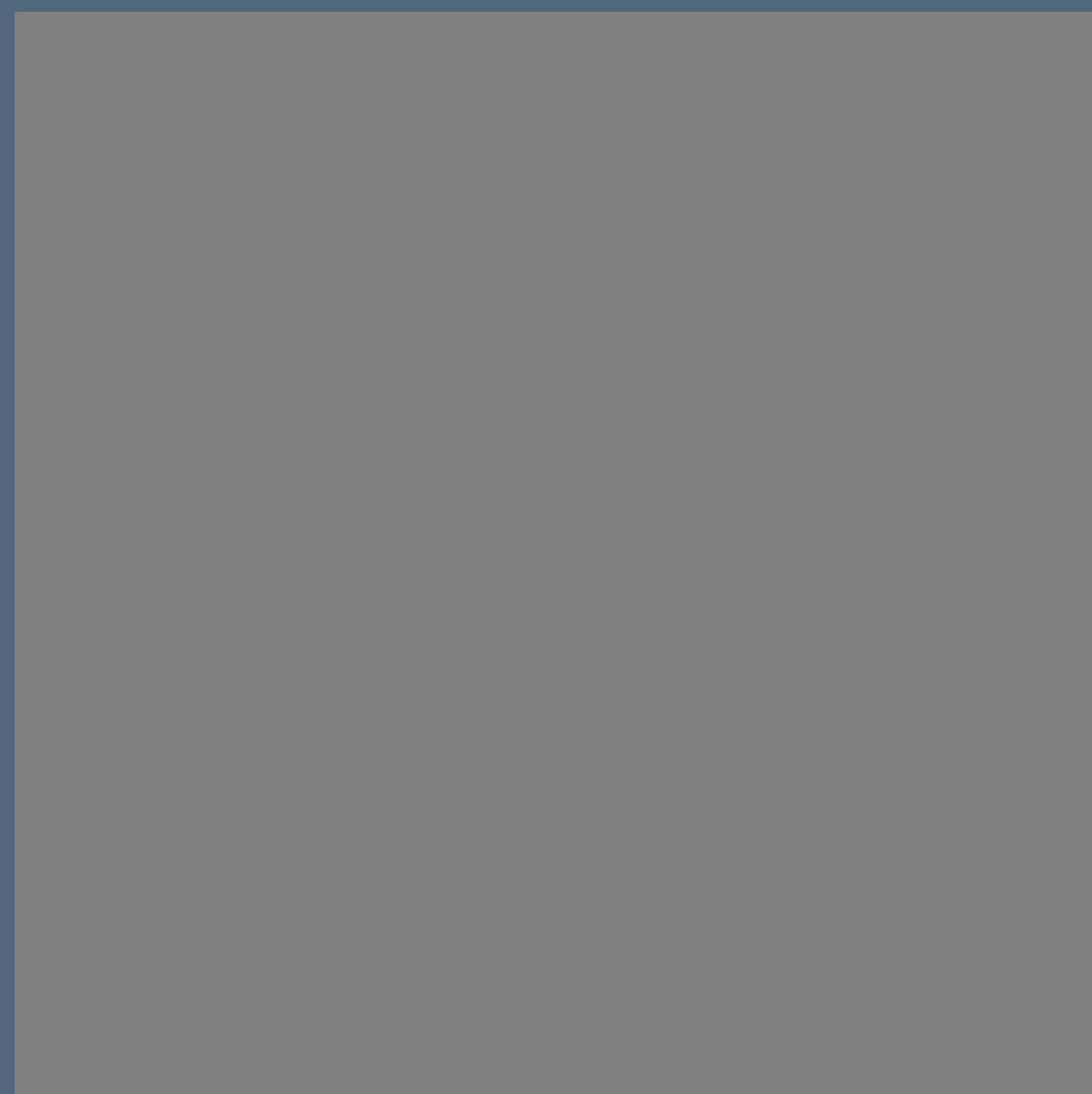




**Which is brighter?**



**(128, 128, 128)**



**(130, 130, 130)**



**Which is brighter?**

# Just Noticeable Differences

JND (Weber's Law)

$$\Delta S = k \frac{\Delta I}{I}$$

- Ratios more important than magnitude
- Most continuous variations in stimuli are perceived in discrete steps







**Compare areas of circles**





Compare lengths of bars

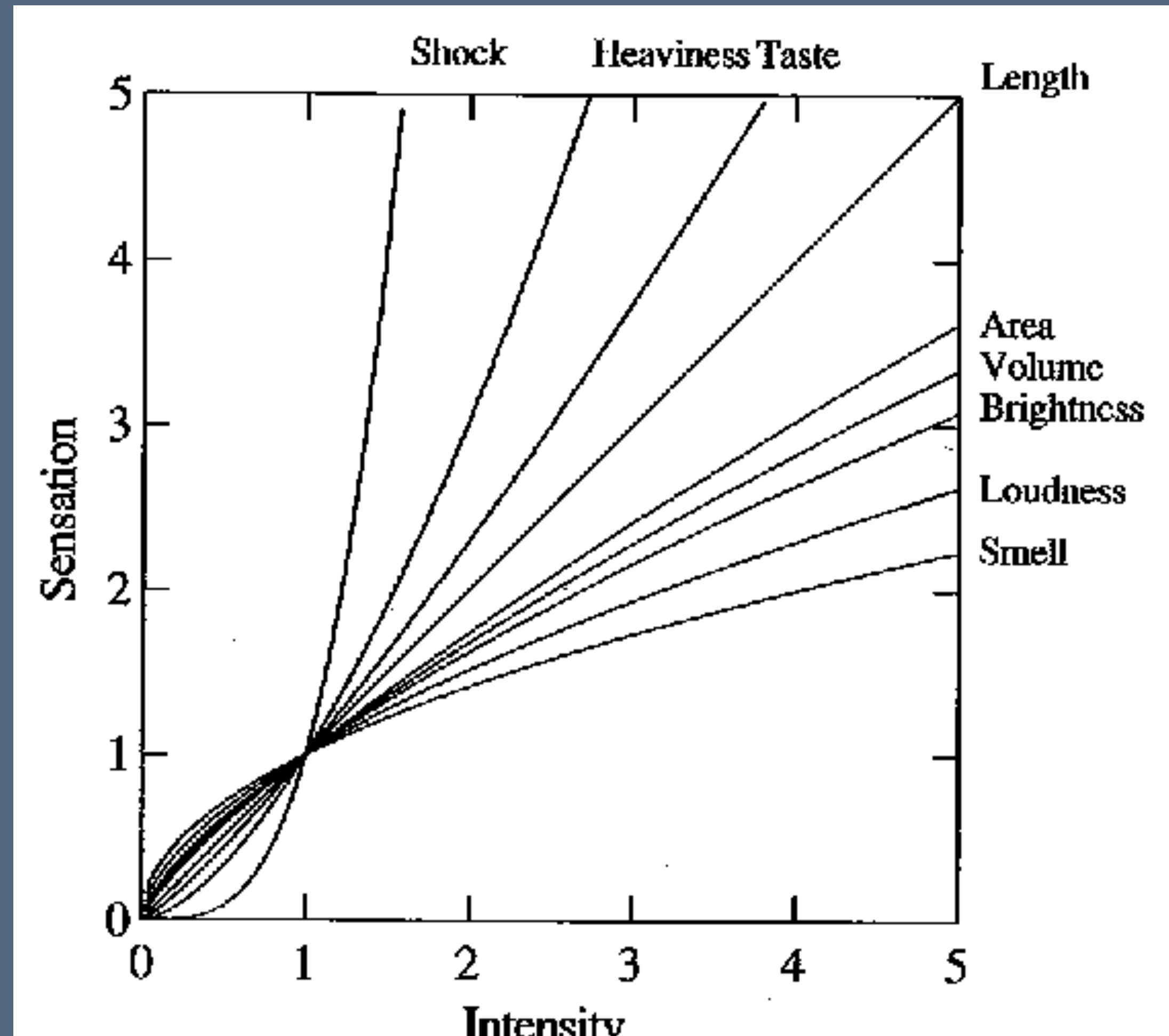




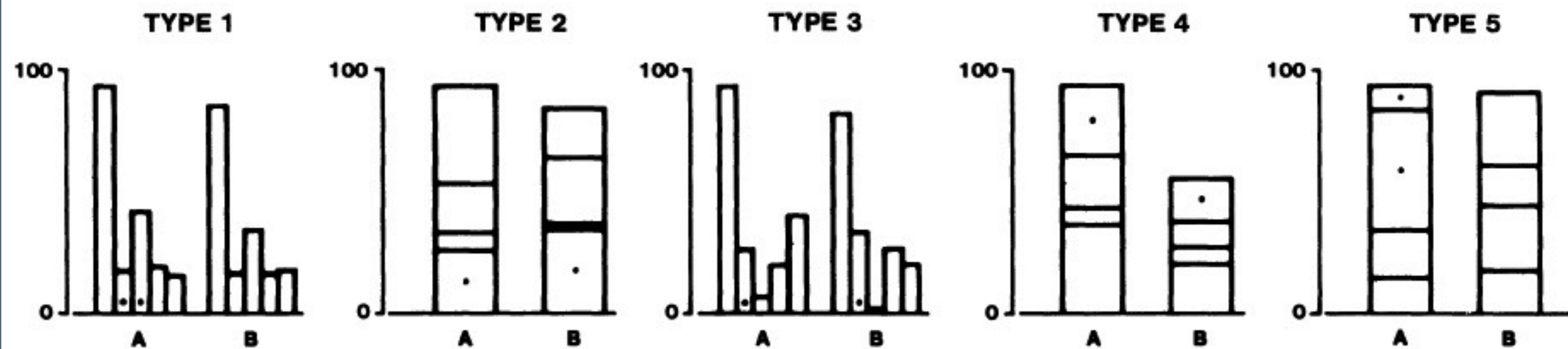
# Steven's Power Law

$$S = kI^p$$

$p < 1$  : underestimate  
 $p > 1$  : overestimate



[graph from Wilkinson 99, based on Stevens 61]



TYPE 1 (POSITION)



TYPE 2 (POSITION)



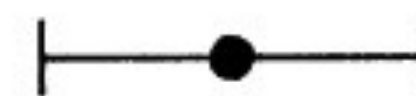
TYPE 3 (POSITION)



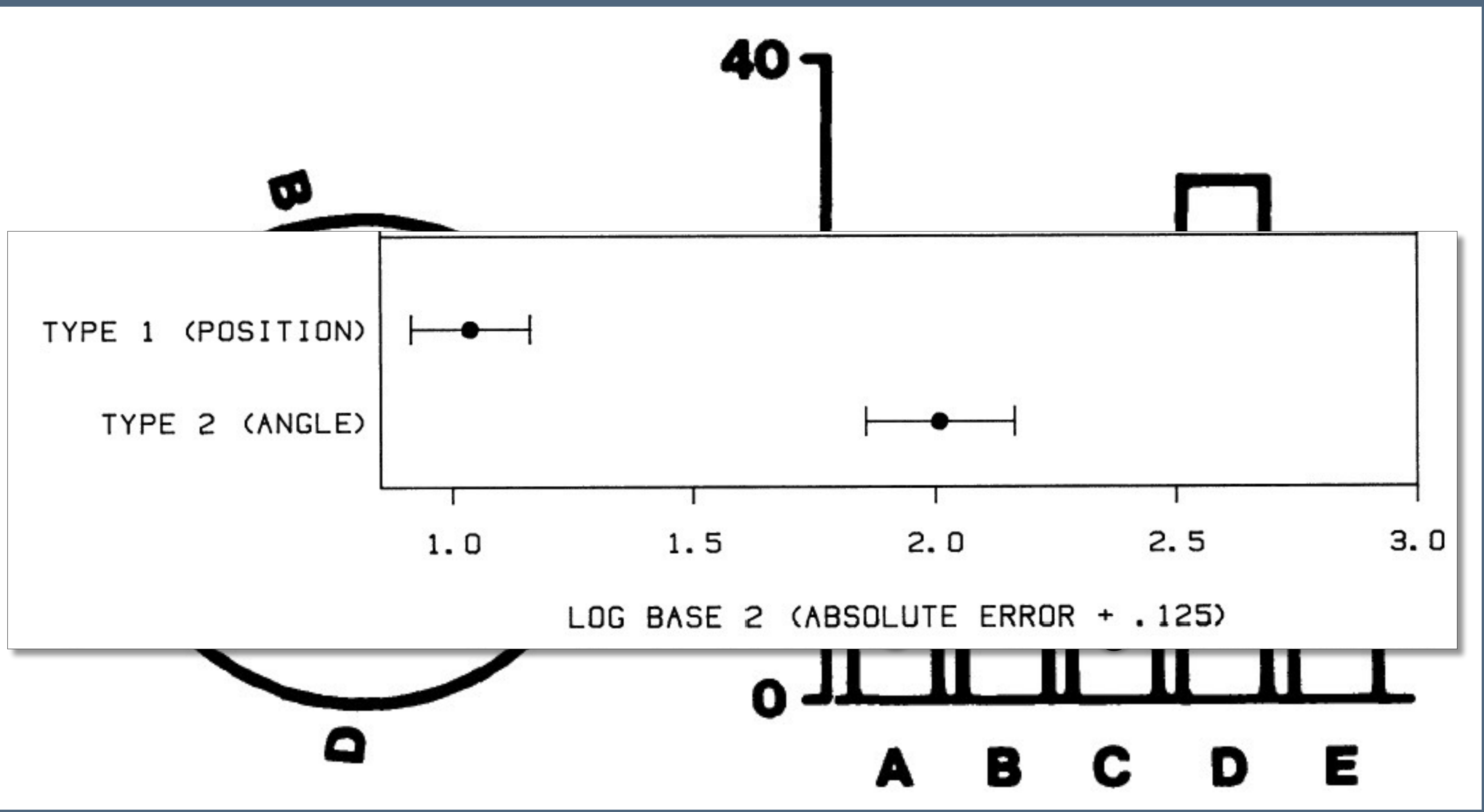
TYPE 4 (LENGTH)



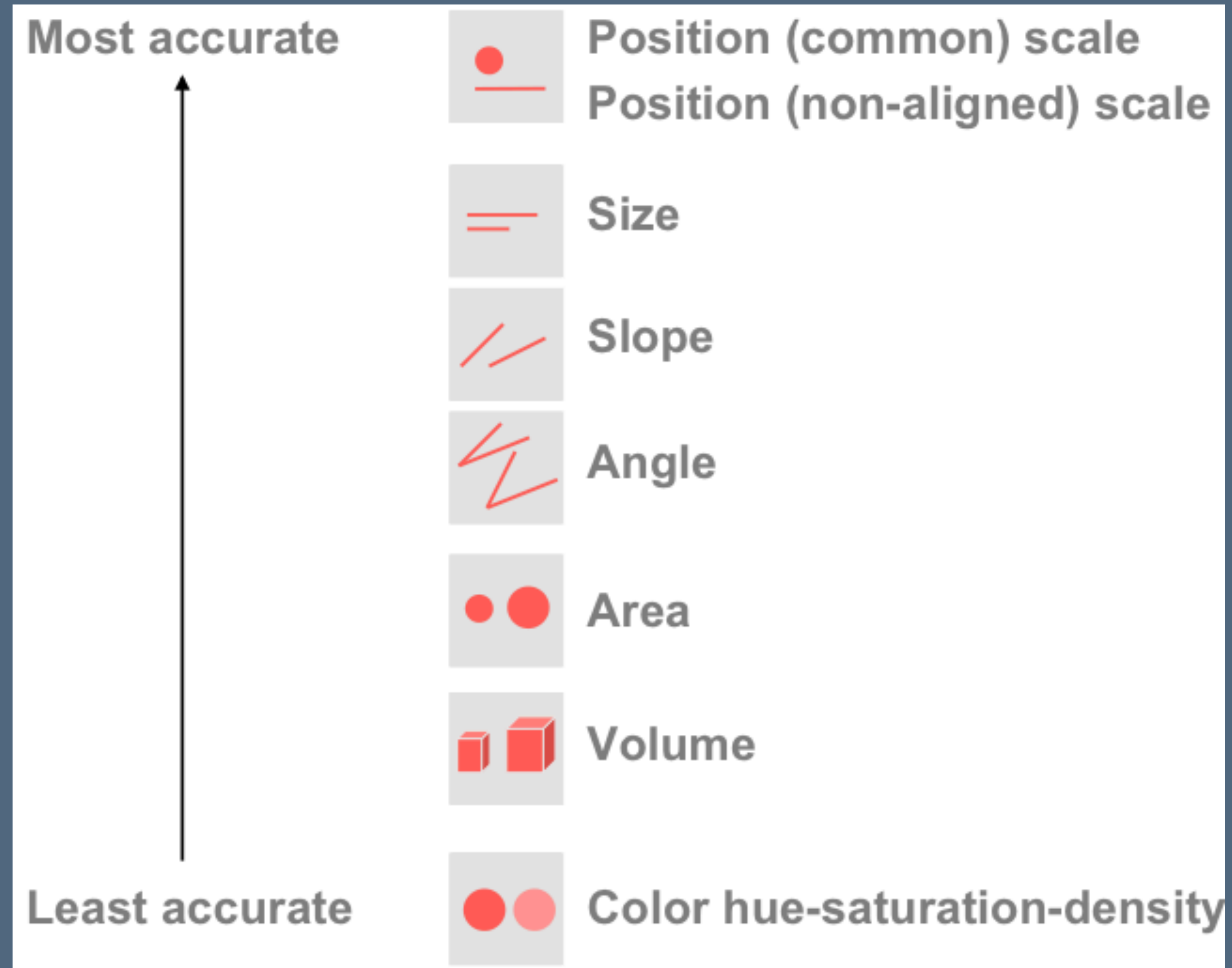
TYPE 5 (LENGTH)



LOG BASE 2 (ABSOLUTE ERROR + .125)



# Relative Magnitude Estimation



# Mackinlay's ranking [1986]

## Quantitative

Position  
Length  
Angle  
Slope  
Area  
Volume  
Density  
Color saturation  
Color hue  
Texture  
Connection



## Ordinal

Position  
Density  
Color saturation  
Color hue  
Texture  
Connection  
Containment  
Length  
Angle  
Slope  
Area  
Volume  
Shape

## Nominal

Position  
Color hue  
Texture  
Connection  
Containment  
Density  
Color saturation  
Shape  
Length  
Angle  
Slope  
Area  
Volume



Automating the design of graphical presentation of relational information  
J. Mackinlay, 1986

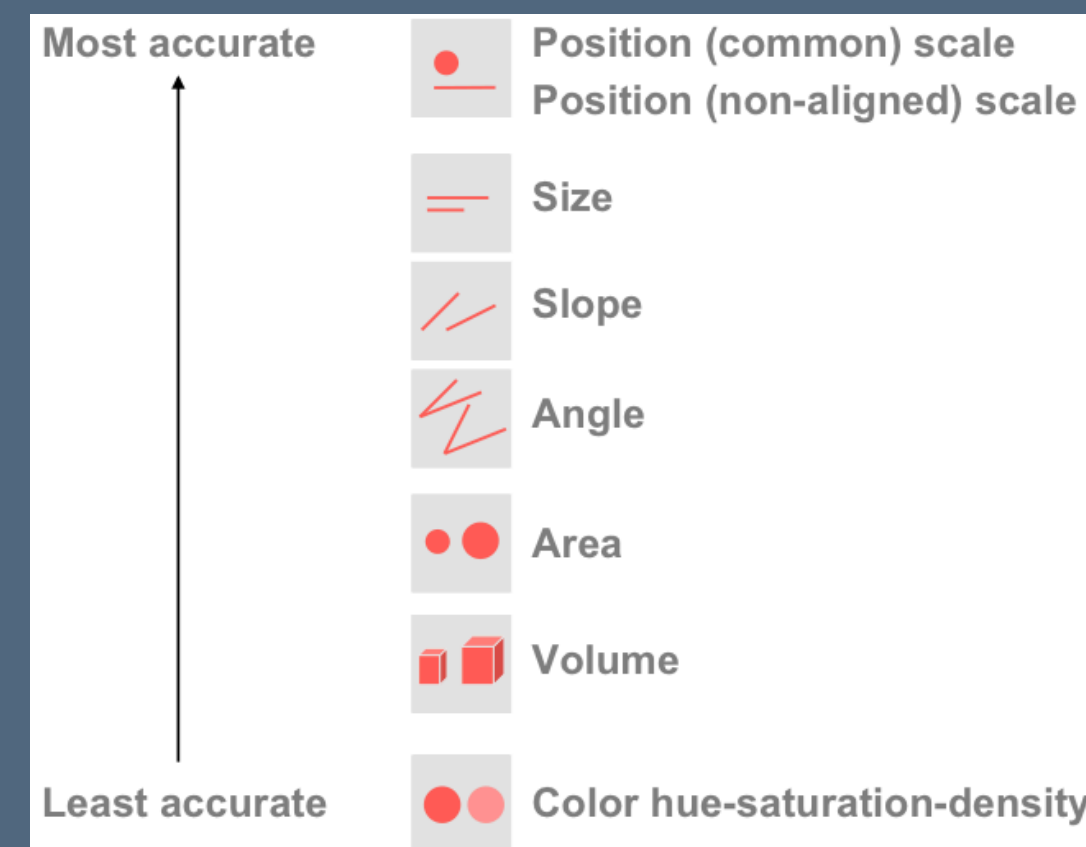
# Algorithm for Chart Construction

Encode most important data using highest ranking visual variable for the data type

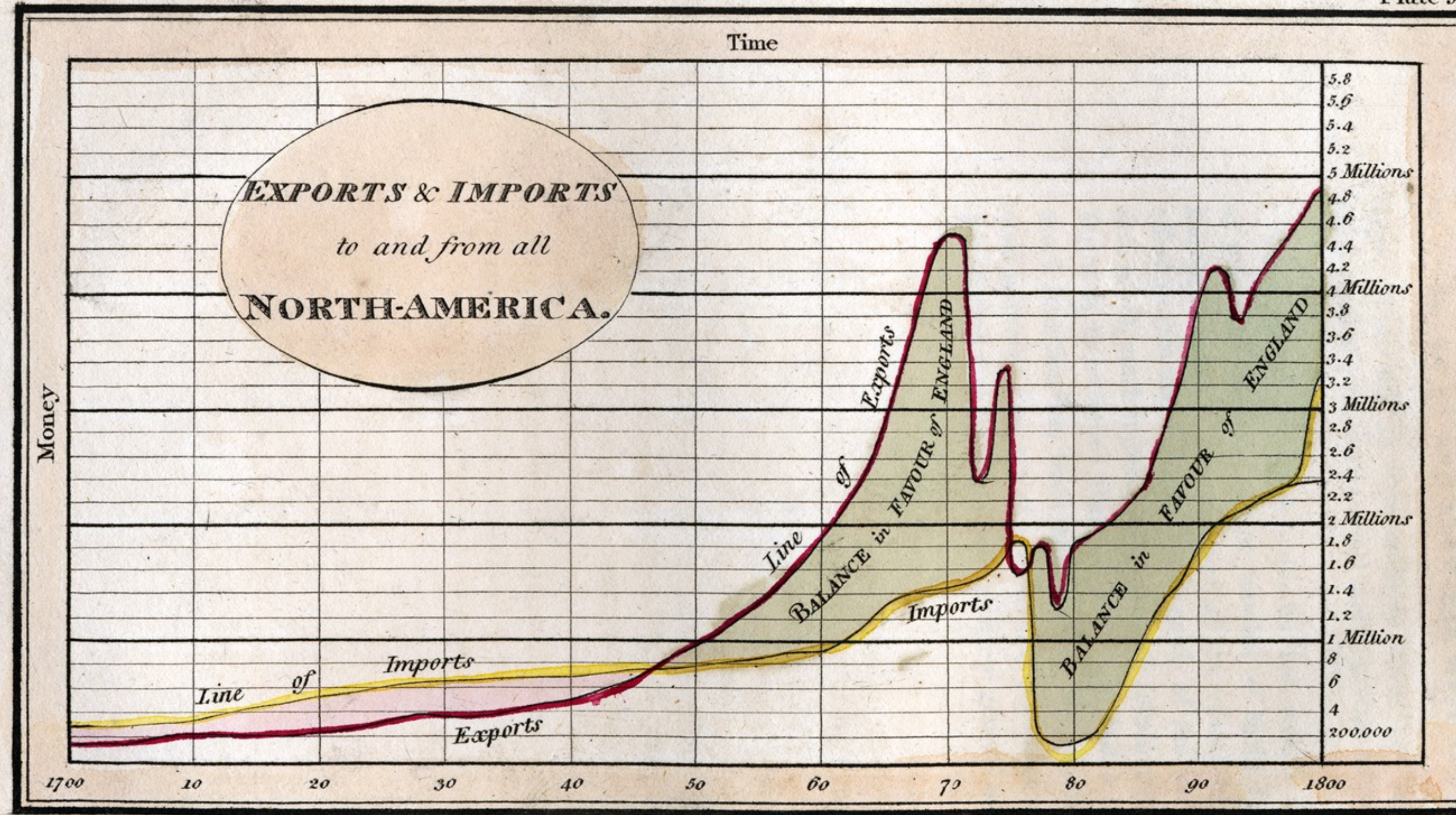
Year	Exports	Imports
1700	170,000	300,000
1701	171,000	302,000
1702	176,000	303,000
...	...	...



1. Year (Q)
2. Exports (Q)
3. Imports (Q)



**mark: lines**  
**Year (Q) → x-pos**  
**Exports (Q) → y-pos**  
**Imports (Q) → y-pos**



Neale sc. Strand.

## Data

Year	Exports	Imports
1700	170,000	300,000
1701	171,000	302,000
1702	176,000	303,000
1703	180,000	312,000
1704	187,000	319,000
...	...	...

## Marks

## Mappings

mark: lines

Year → x-pos (Q)

Exports → y-pos (Q)

Imports → y-pos (Q)

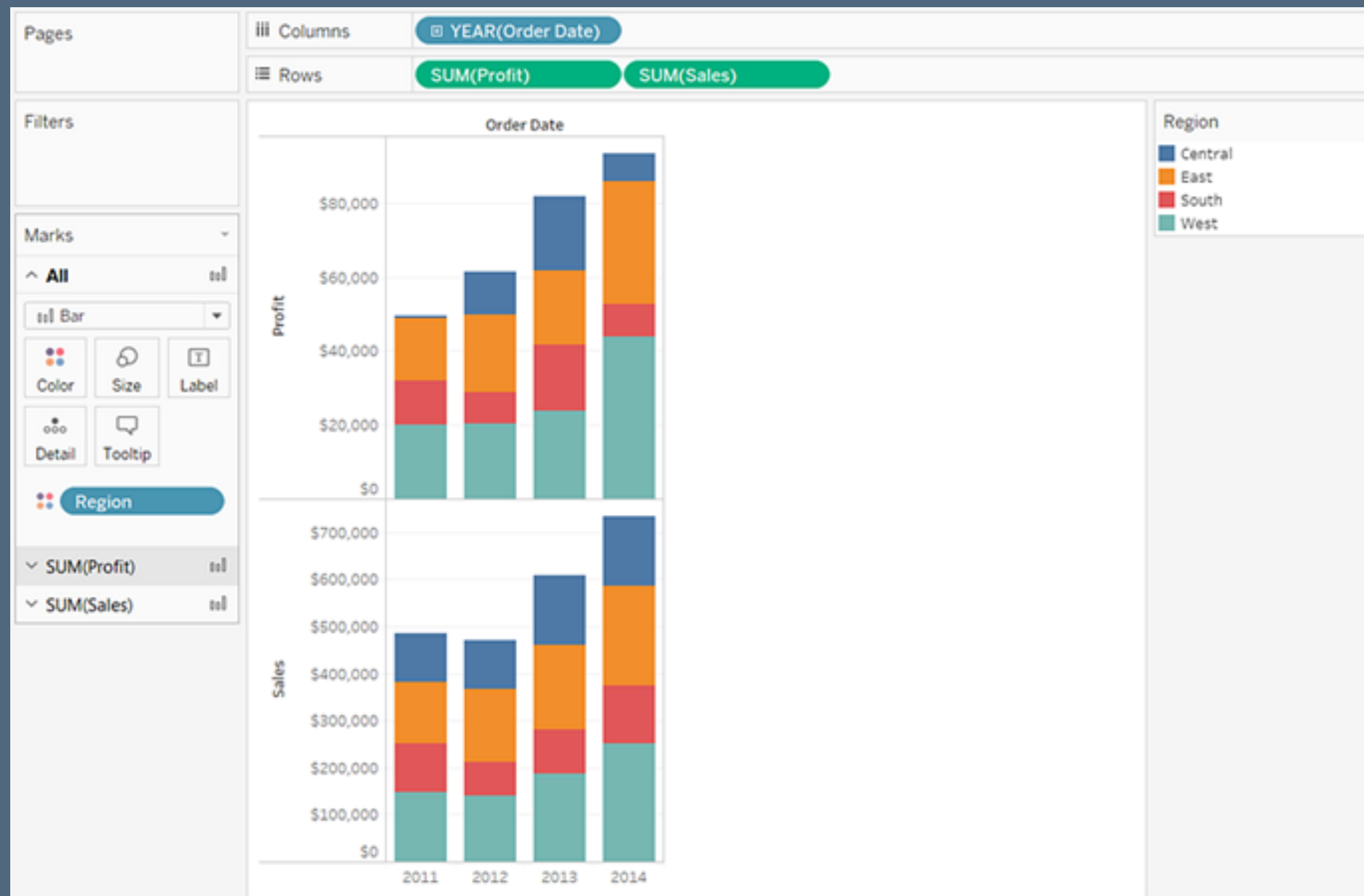
Exports → color (N)

Imports → color (N)



# Impact

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

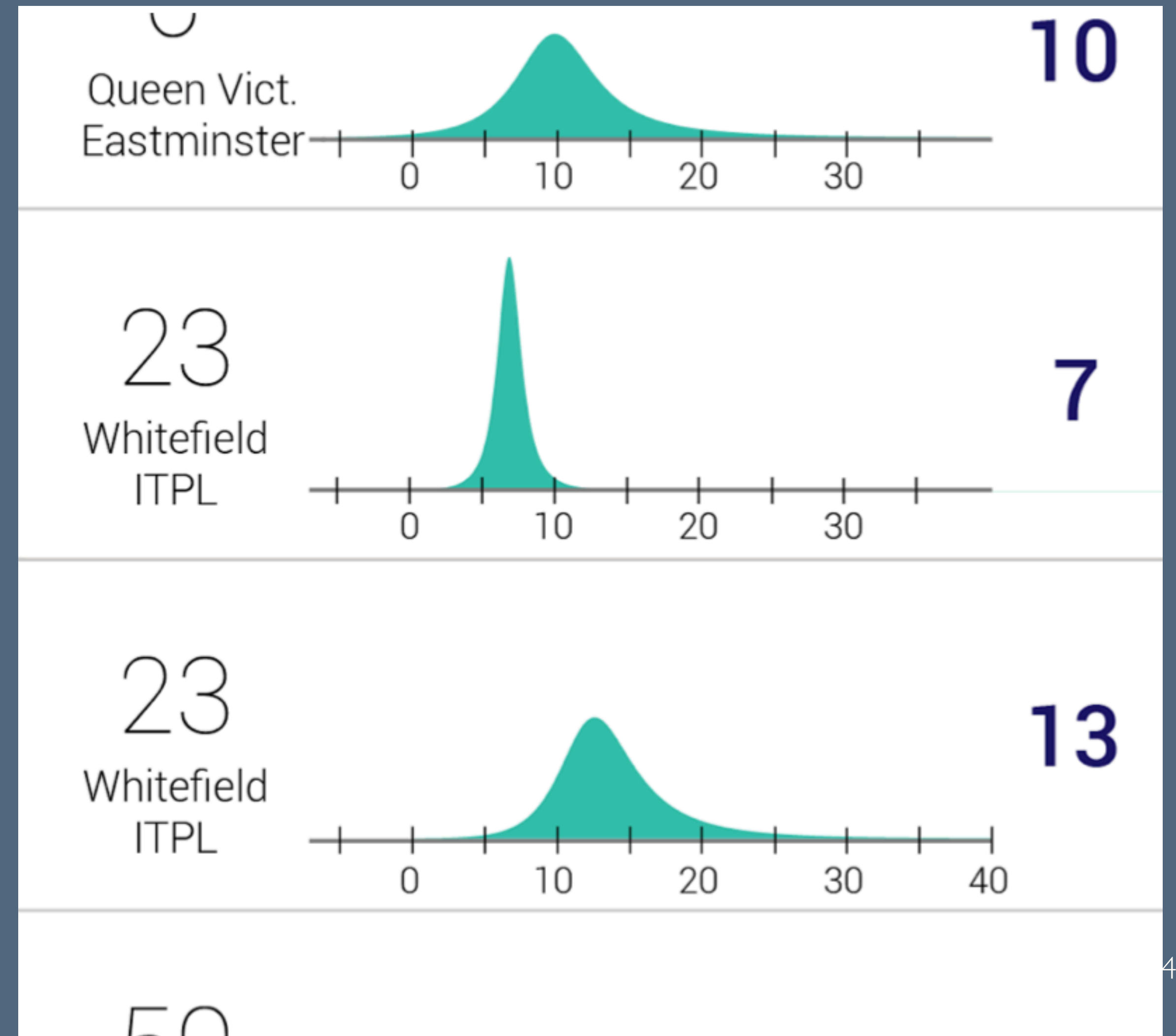


# Frontiers of Visualization Research

# 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

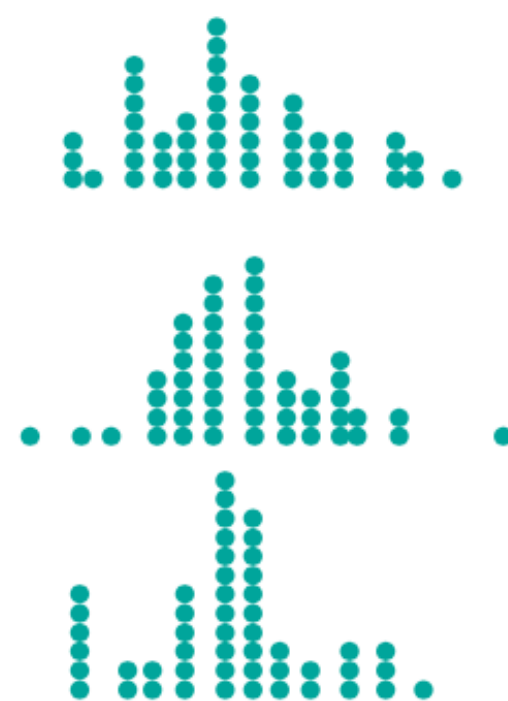
[Kay et al. 2016]

Suggestion: quantile dot plots

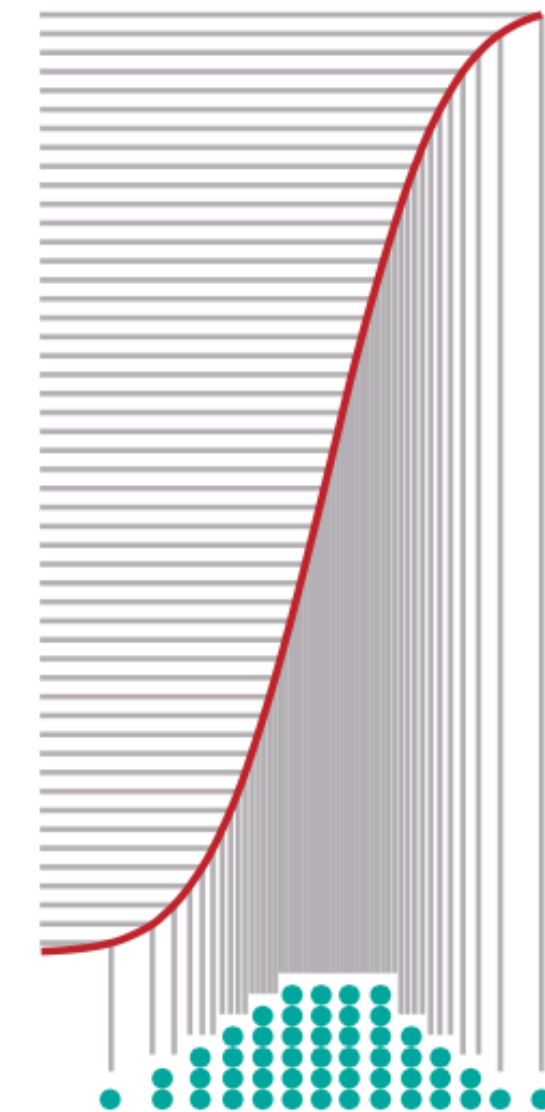
Probability density of Normal distribution



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.

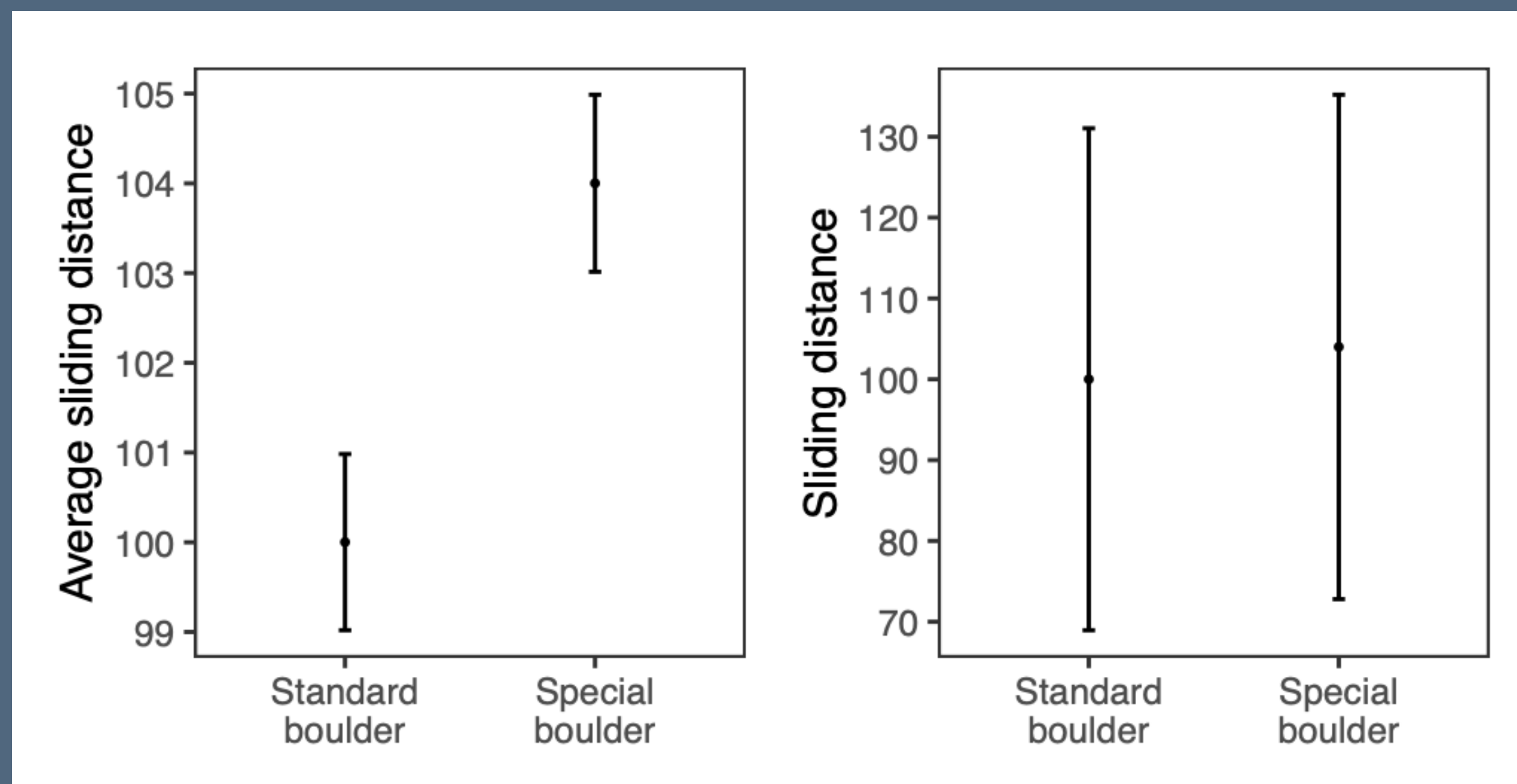
By using quantiles we facilitate interval estimation from frequencies: e.g., knowing there are 50 dots here, if we are willing to miss our bus **3/50** times, we can count **3 dots** from the left to get a one-sided **94% (1 - 3/50) prediction interval** corresponding to that risk tolerance.



# Interpretation errors

[Hofman, Goldstein, and Hullman 2020]

Two common visualizations of uncertainty:



Std. Error:  
uncertainty in the  
population mean

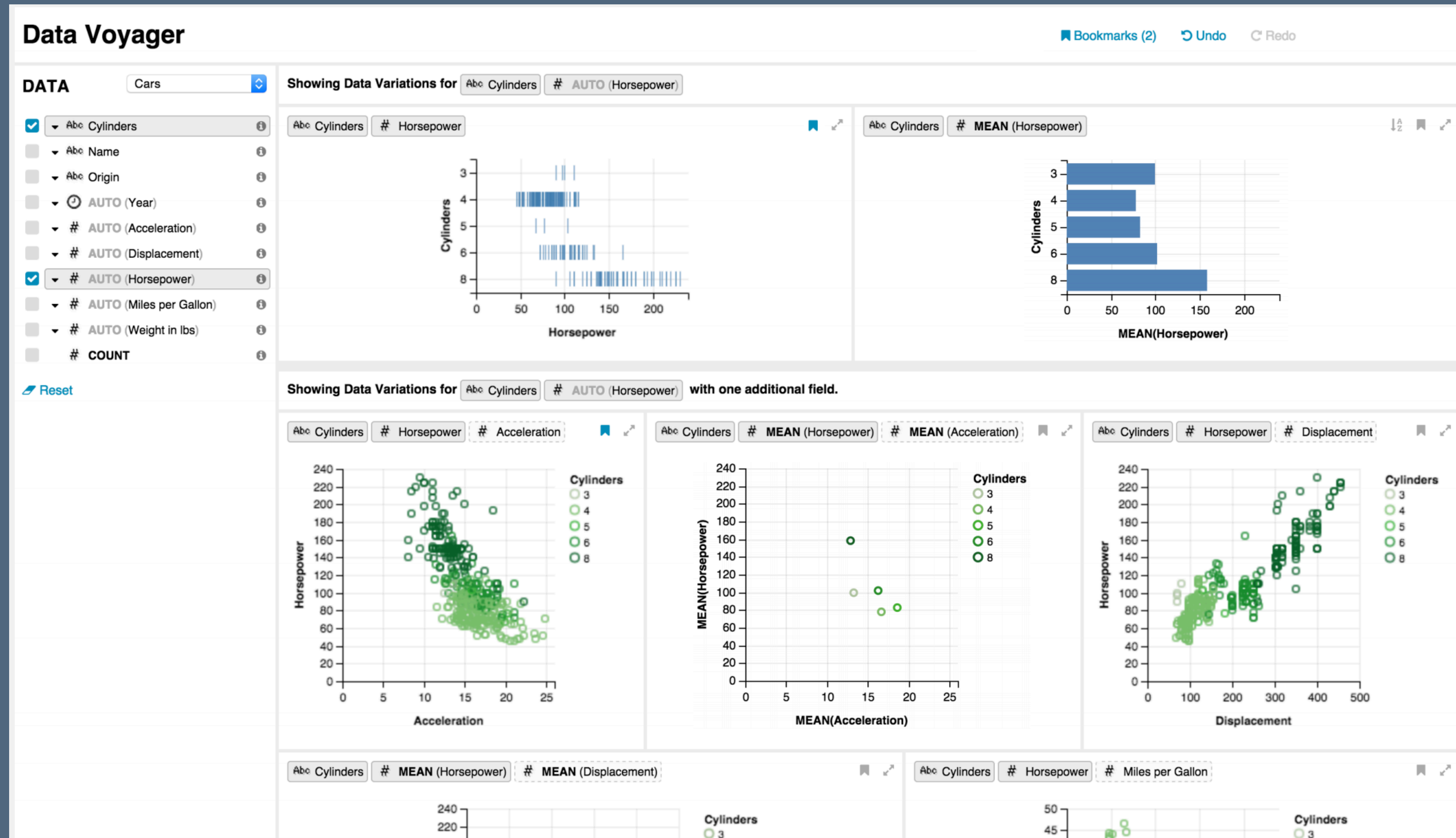
Std. Deviation:  
uncertainty in a  
single sample

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

# 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]

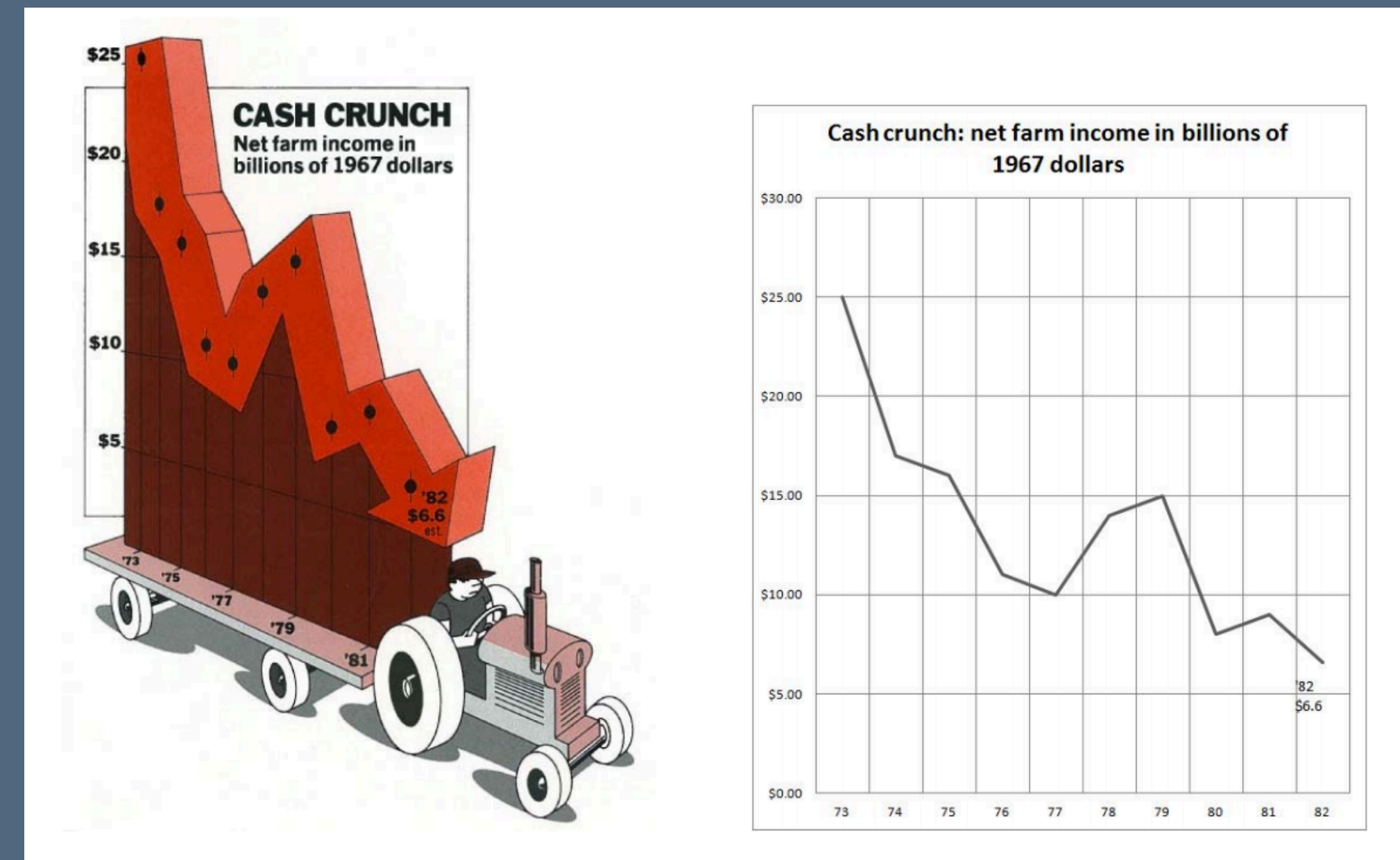
Generally, visualization (and HCI more broadly) argue optimizing for clear and correct interpretation

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

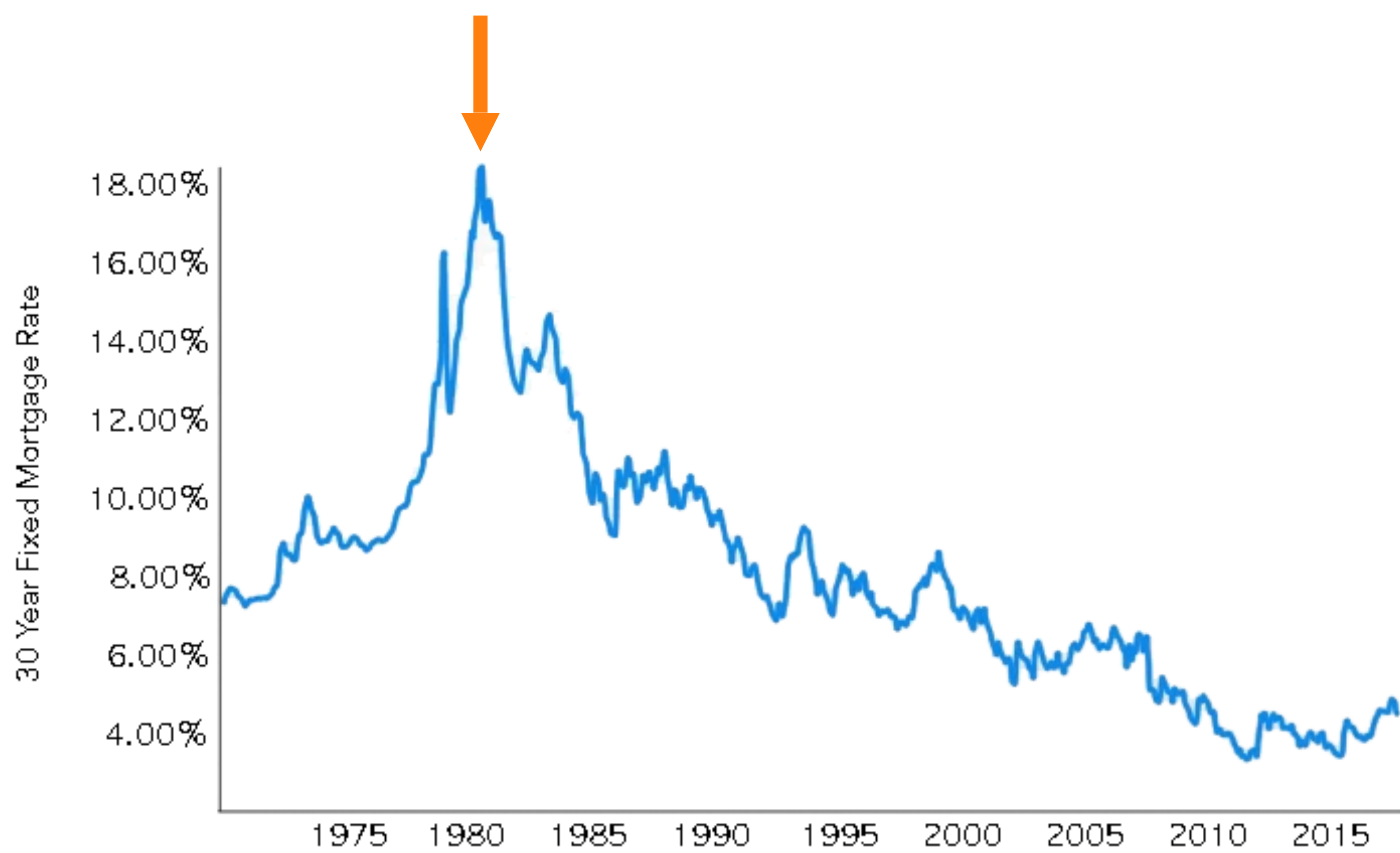


Difficult with chartjunk

Easy

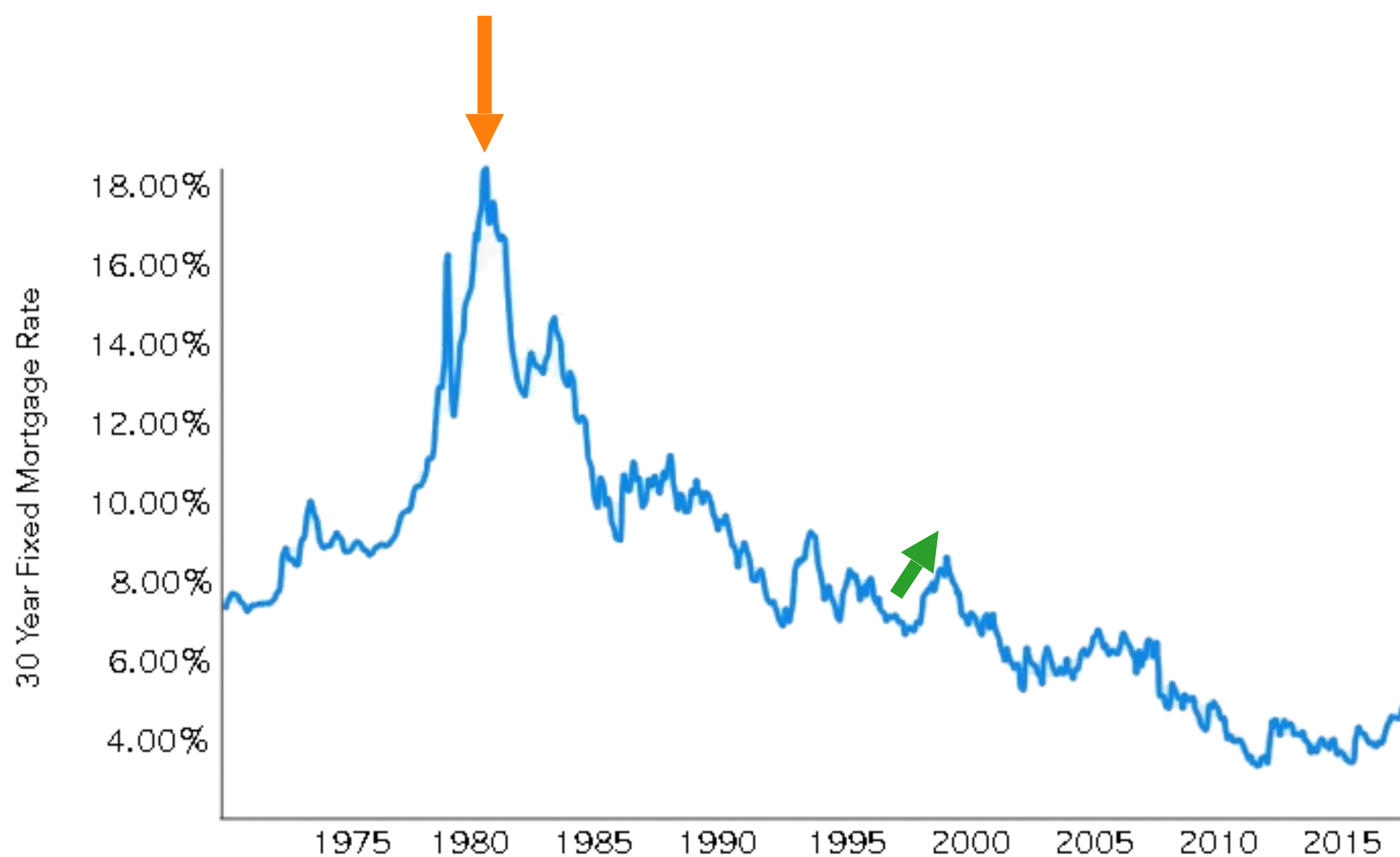




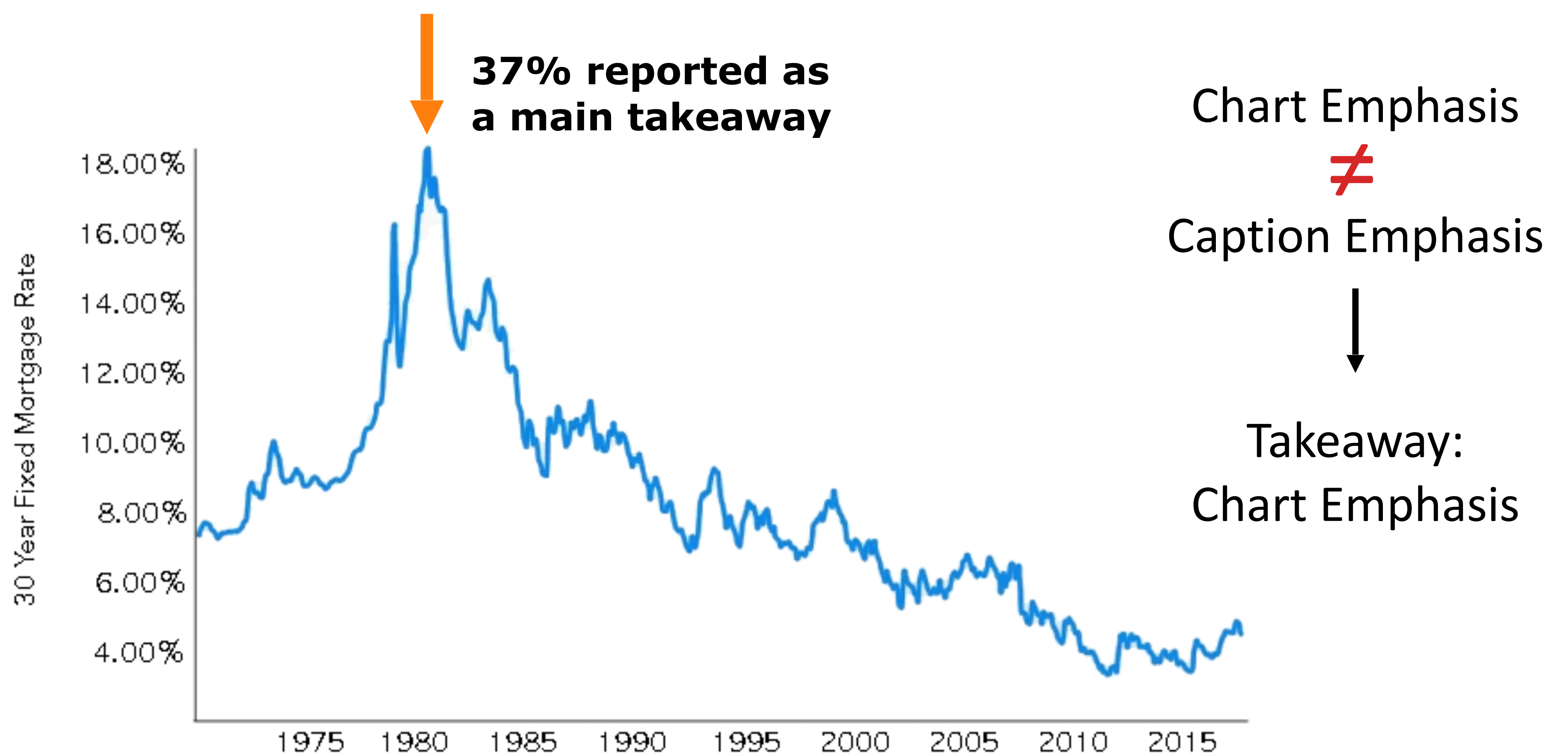




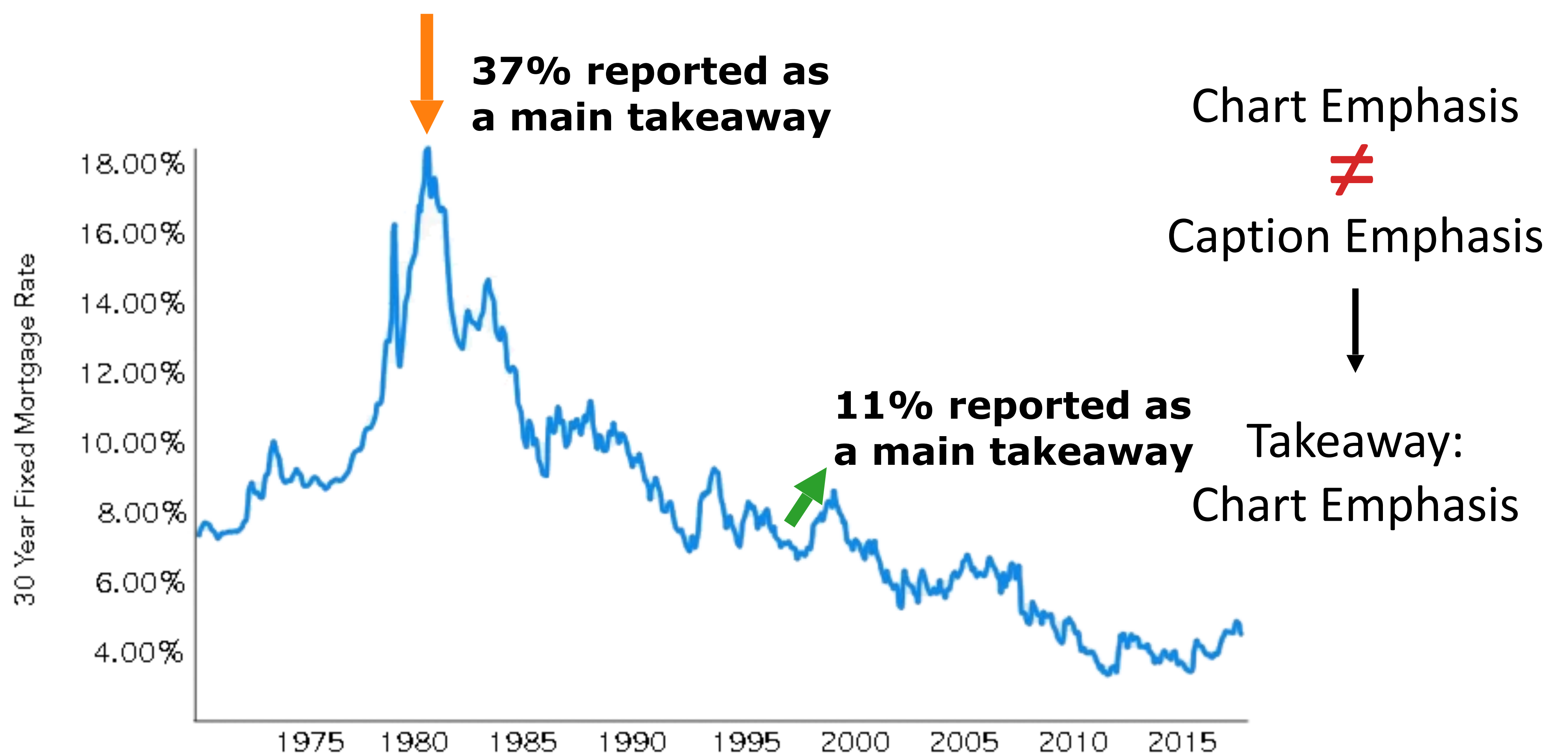
The 30-year fixed mortgage rate increased slightly from 1997 to 1999.



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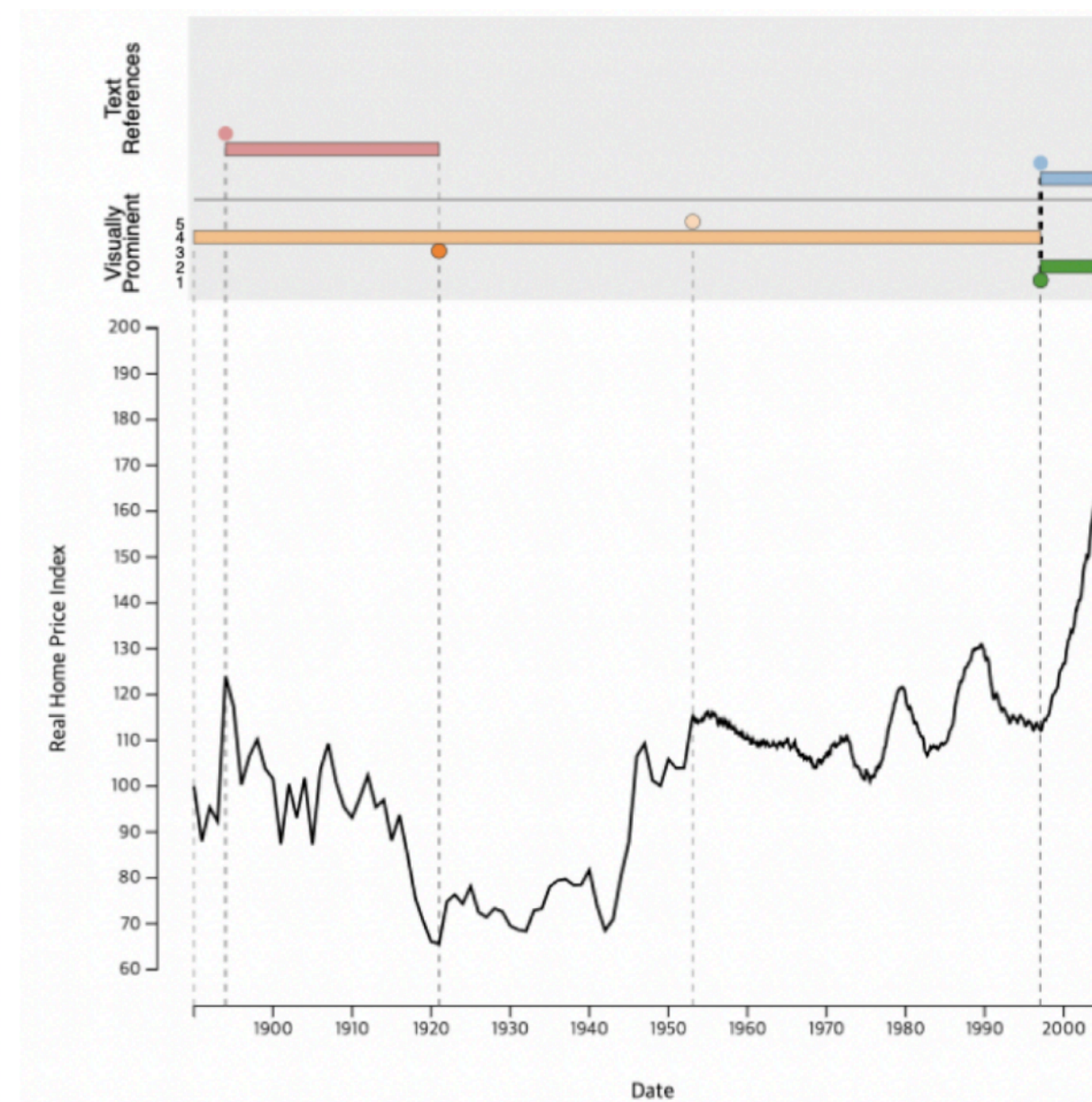
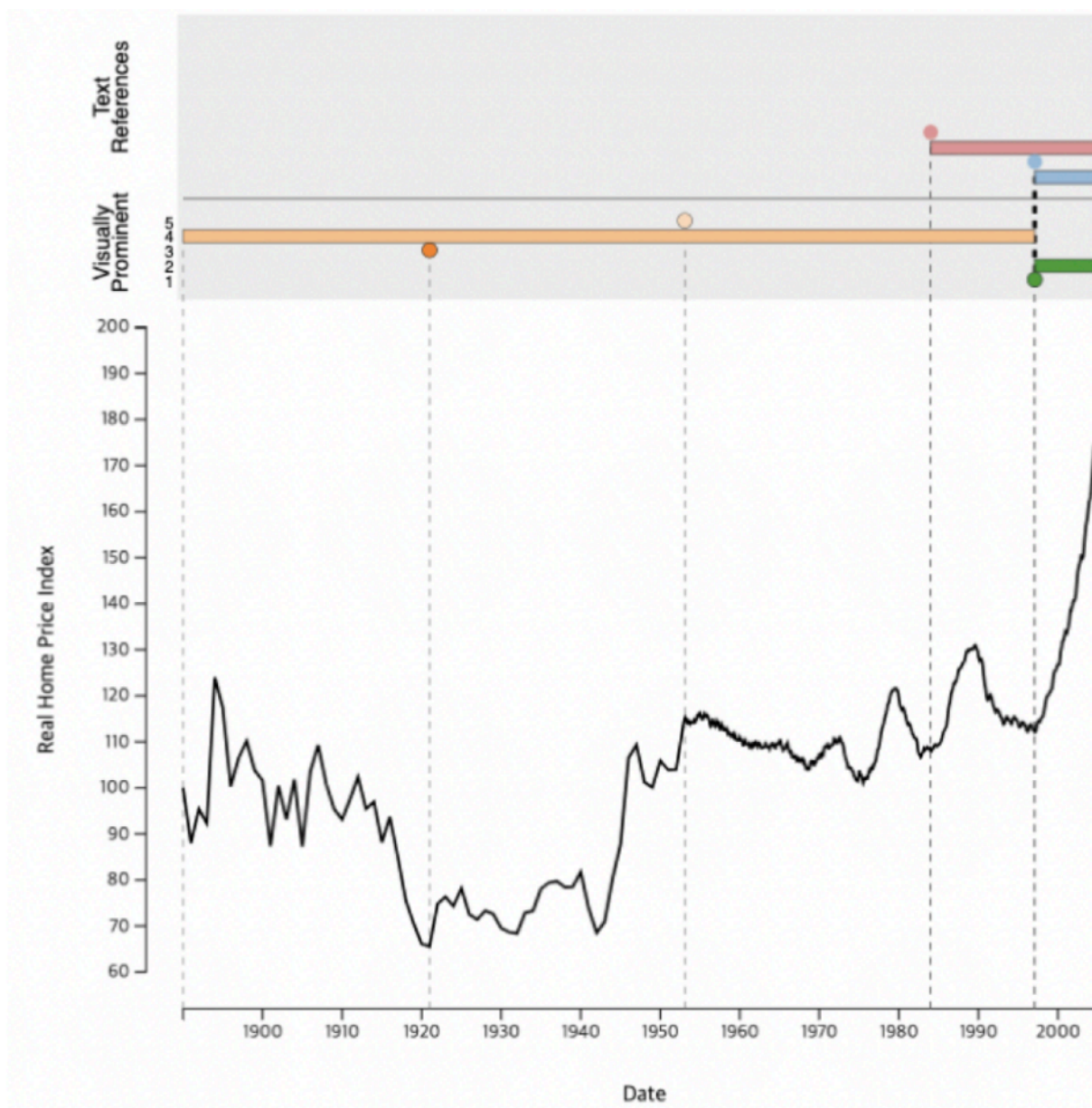
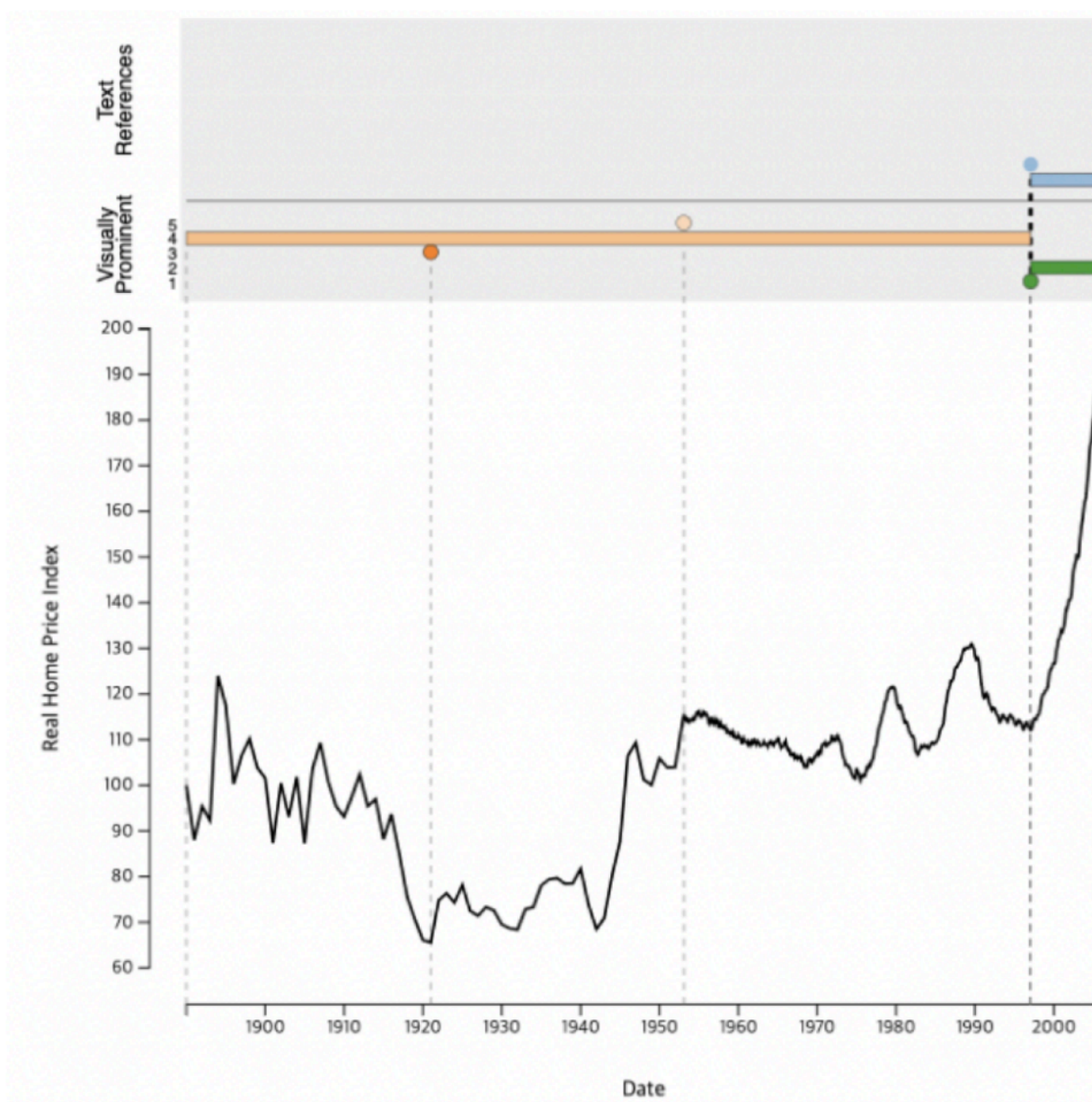
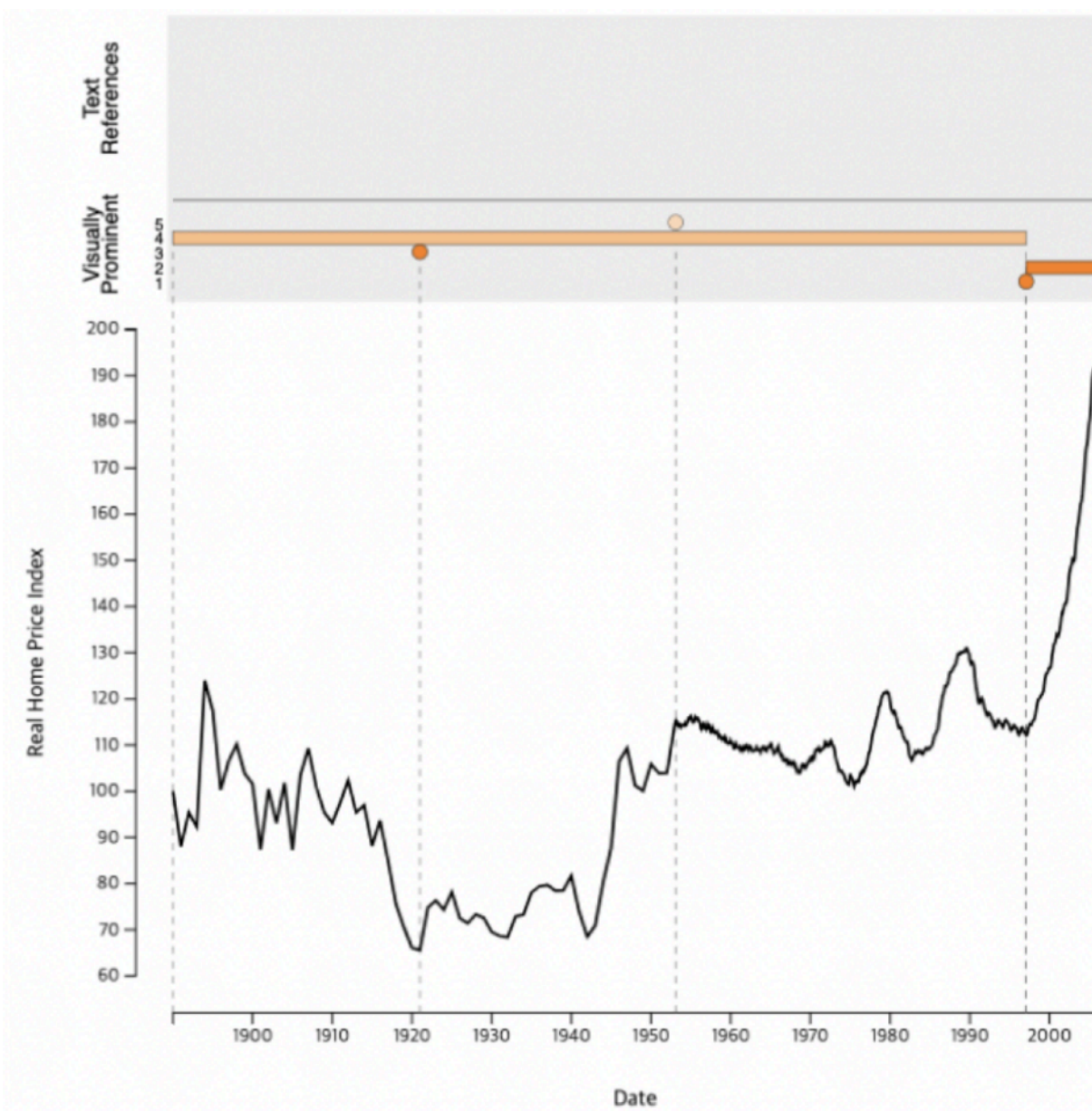


The 30-year fixed mortgage rate reached its peak of 18.5% in 1981.

# 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.



This chart shows the real home price index between 1890 and 2006.

This chart shows the real home price index between 1890 and 2006. The housing prices have skyrocketed starting around 1997 and we need to act.

This chart shows the real home price index between 1890 and 2006. The housing prices have skyrocketed starting around 1997 and we need to act. Looking back, they declined since 1984 with an increased housing supply as manufactured homes became available to the public.

This chart shows the real home price index between 1890 and 2006. The housing prices have skyrocketed starting around 1997 and we need to act. Looking back, they declined since 1894 with an increased housing supply as manufactured homes became available to the public. A similar supply-side solution is what we need.

(a) Prominent features & Basic caption

(b) Caption text about prominent feature

(c) Caption including false information

(d) Caption about less prominent feature



# 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

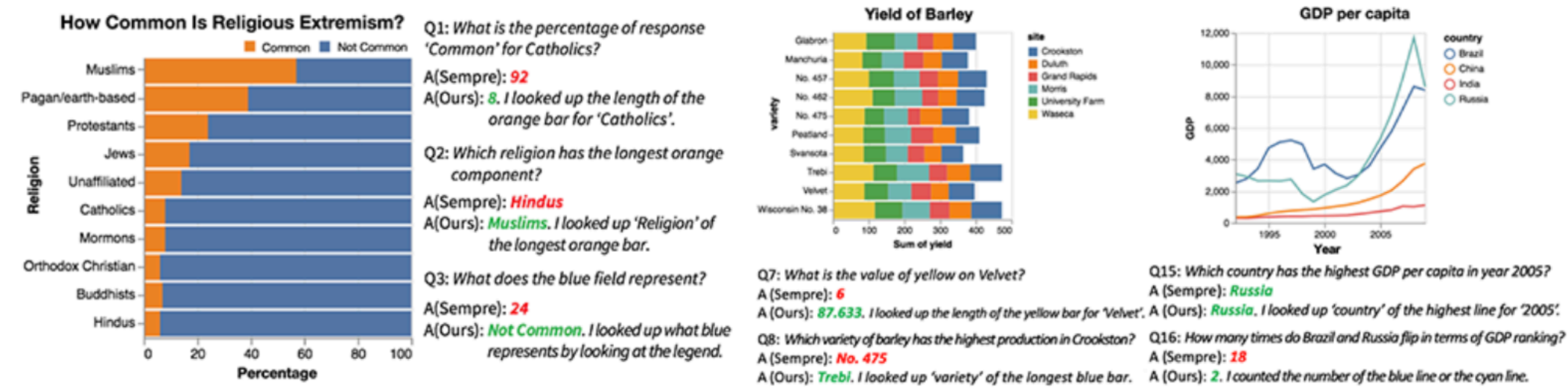
## SCHEDULE

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 Javascript 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

- 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.

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