

Paul Rosen

paul.rosen@utah.edu
@paulrosenphd
<https://cspaul.com>



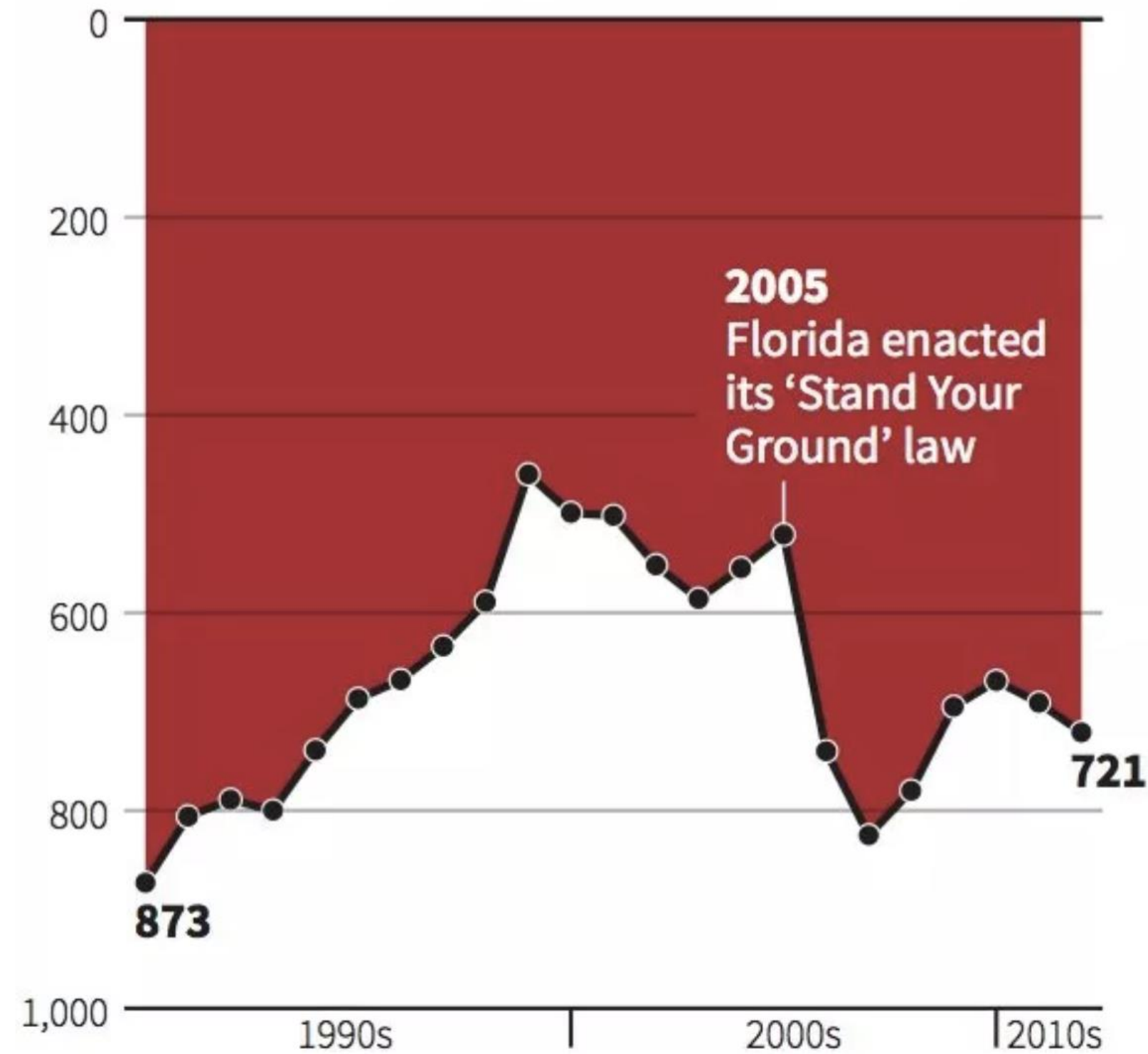
Visualization for Data Science

DS-4630 / CS-5630

Visual Design and Dark Patterns

Gun deaths in Florida

Number of murders committed using firearms



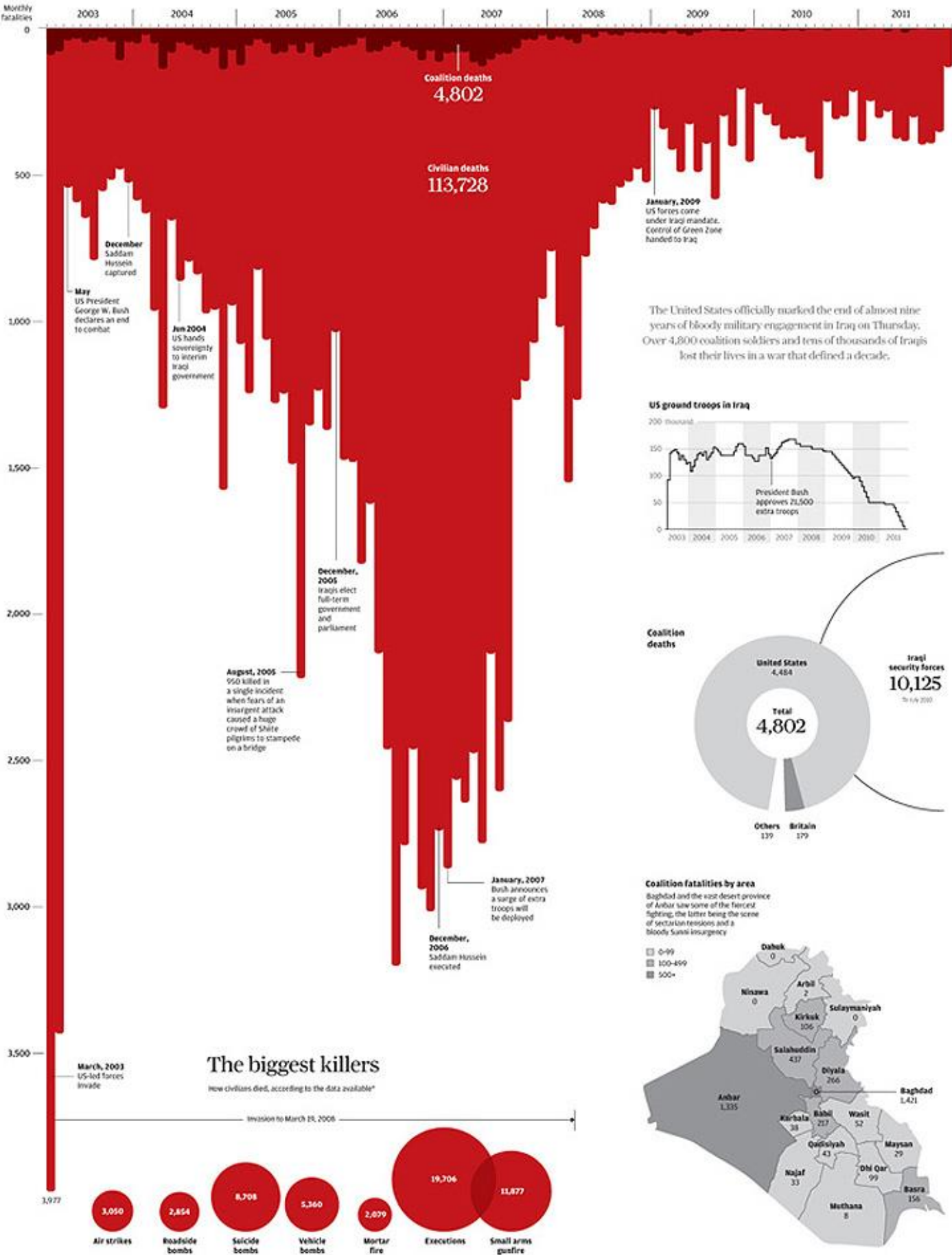
Source: Florida Department of Law Enforcement

C. Chan 16/02/2014

REUTERS

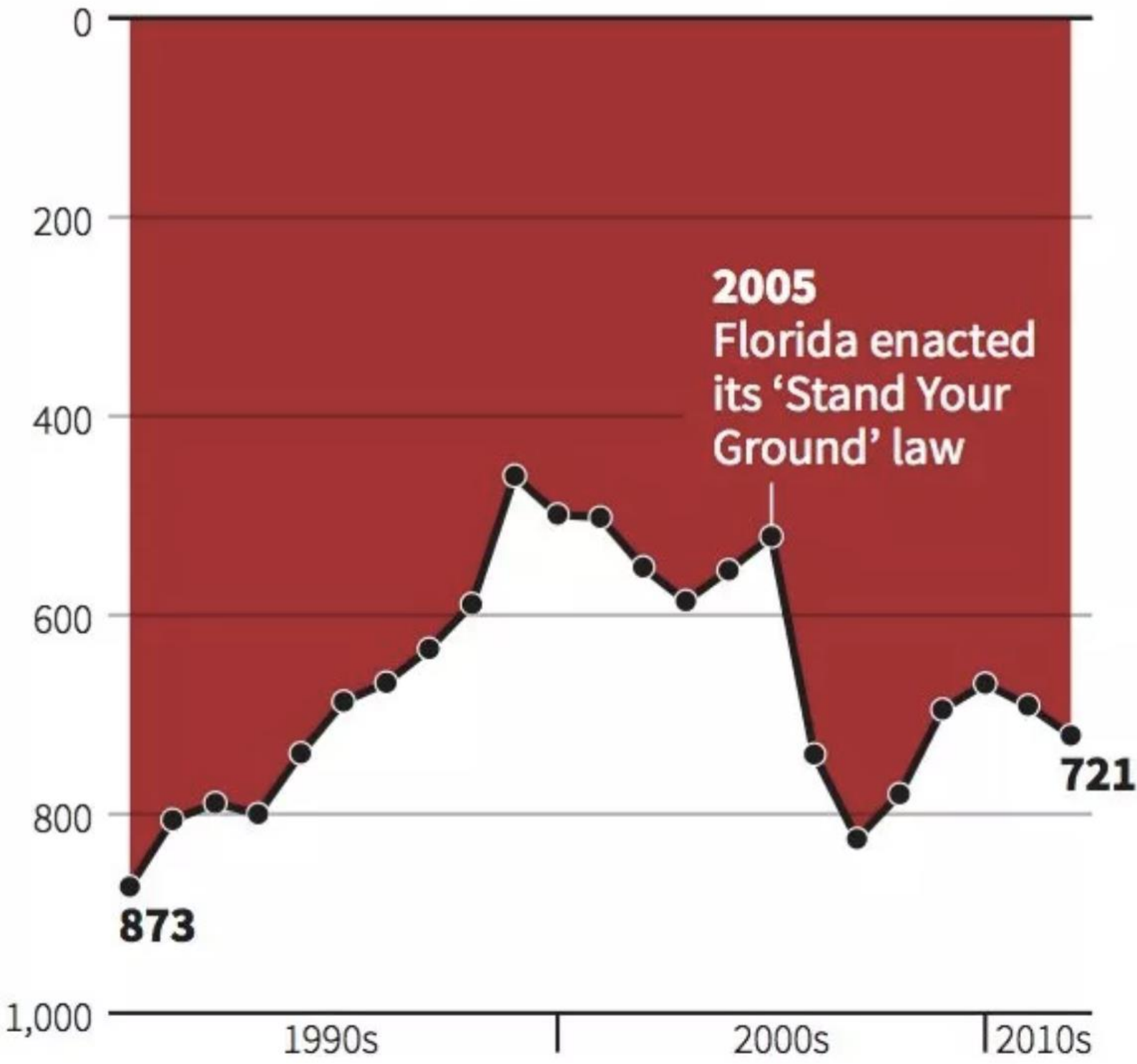


Iraq's bloody toll



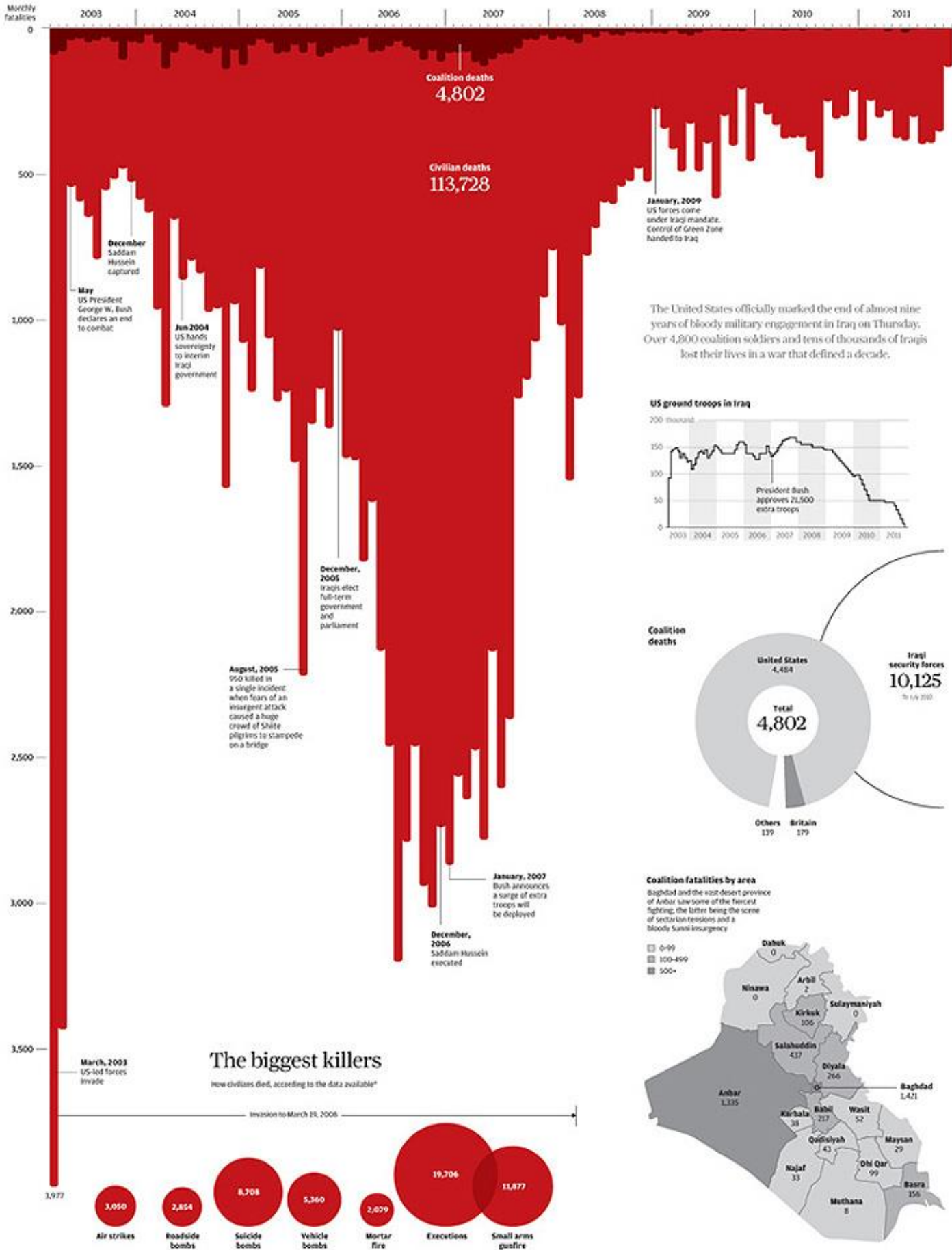
Gun deaths in Florida

Number of murders committed using firearms



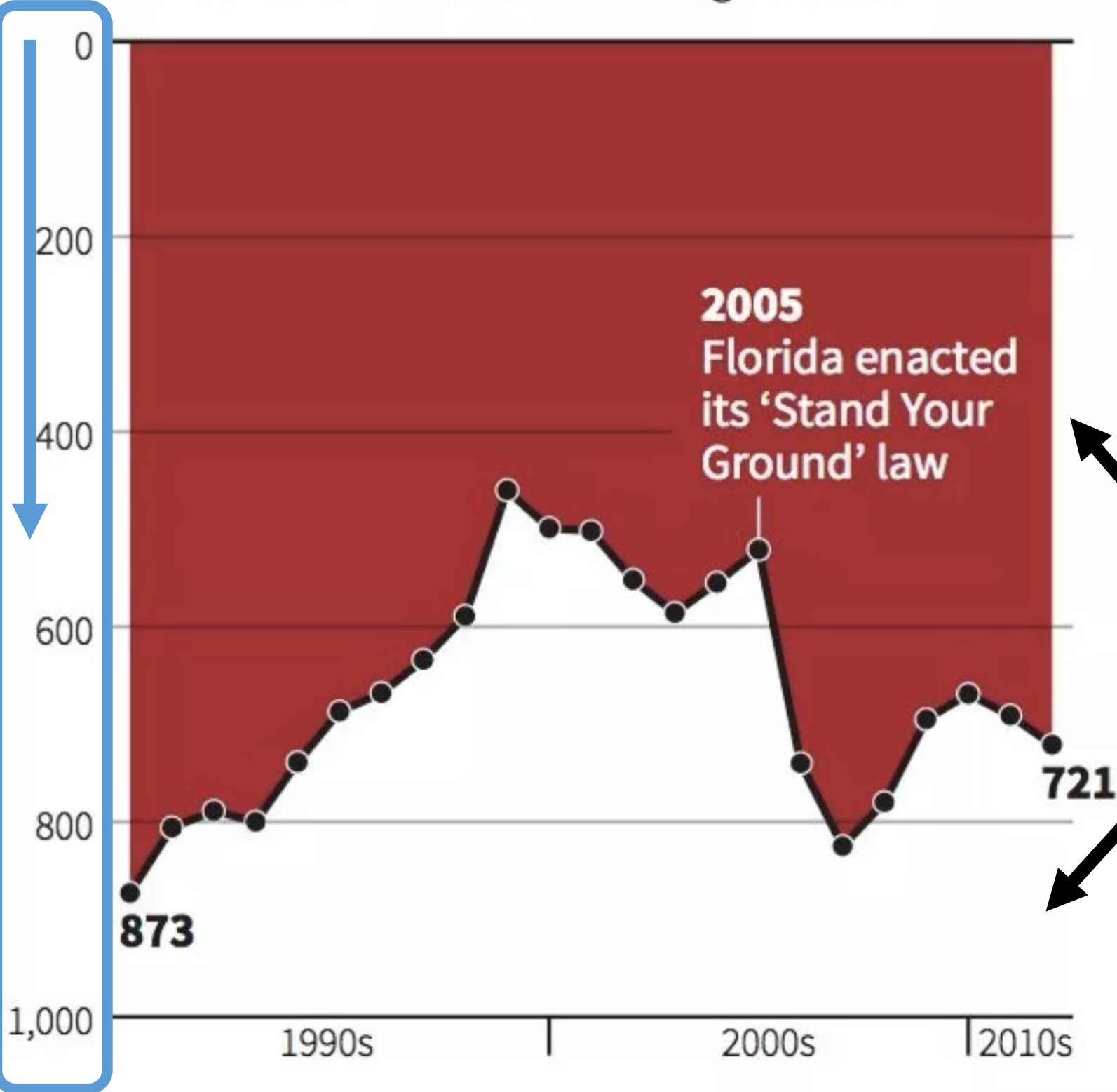
Source: Florida Department of Law Enforcement

Iraq's bloody toll



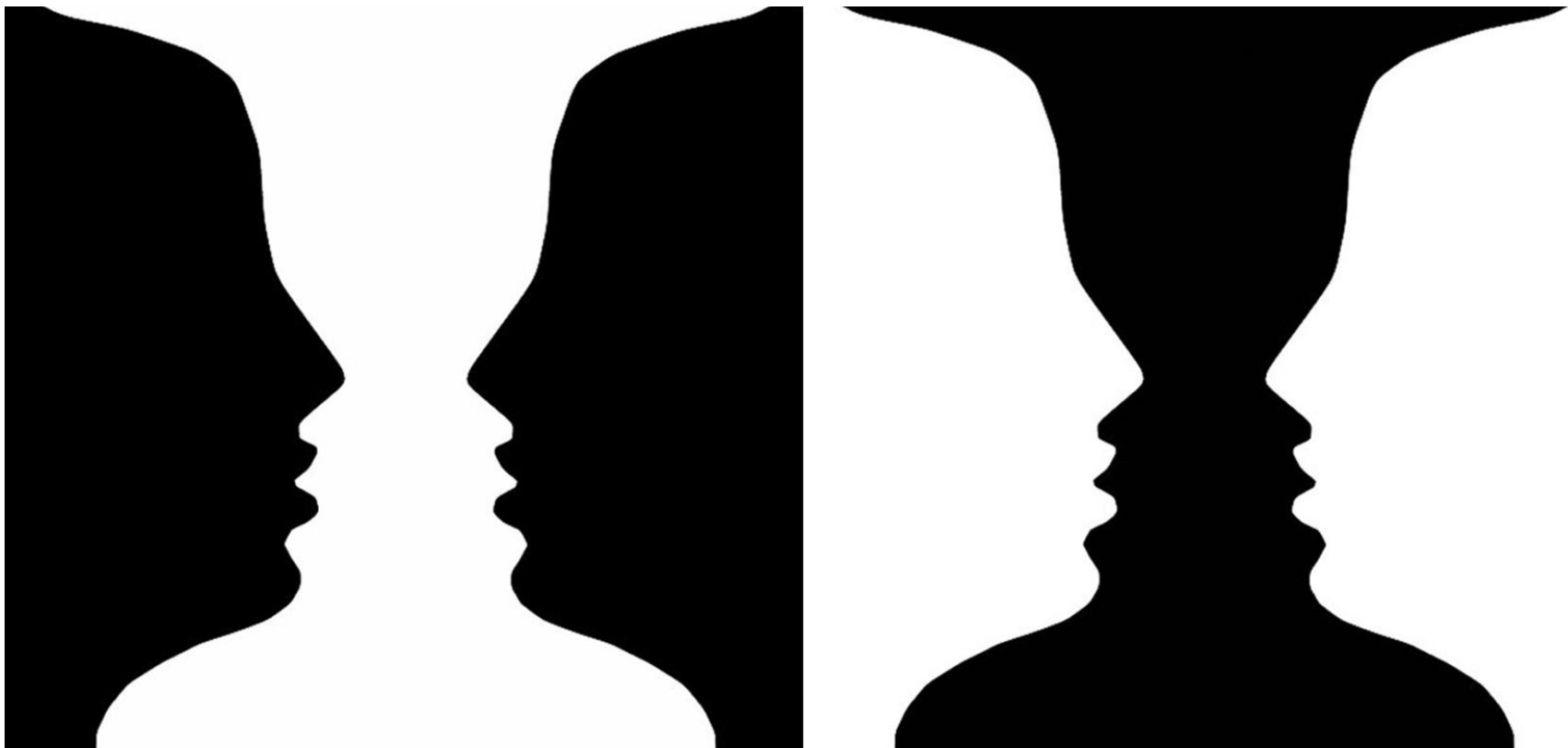
Gun deaths in Florida

Number of murders committed using firearms



Source: Florida Department of Law Enforcement

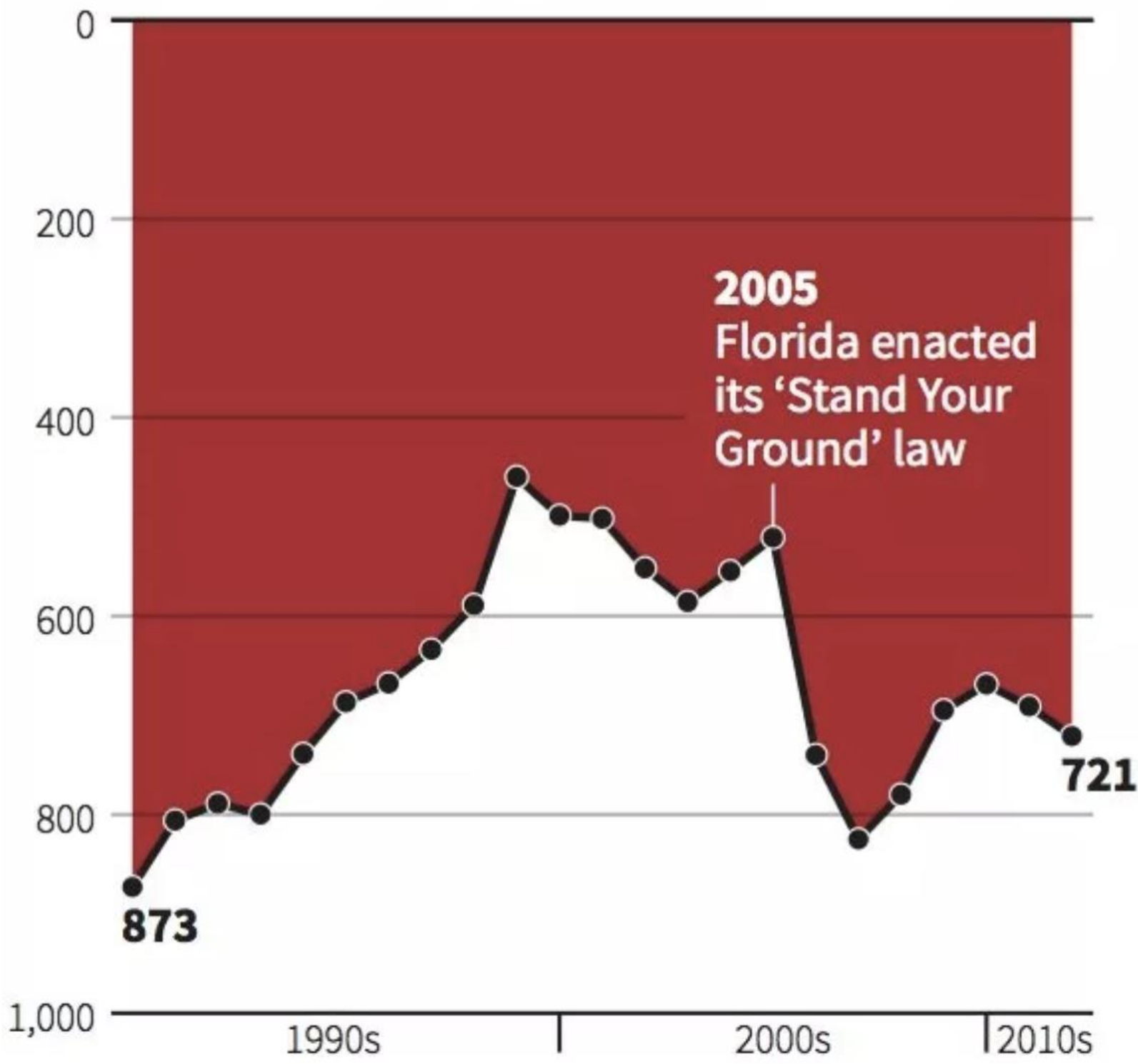
Gestalt Figure—Ground Principle



Which one is the data?

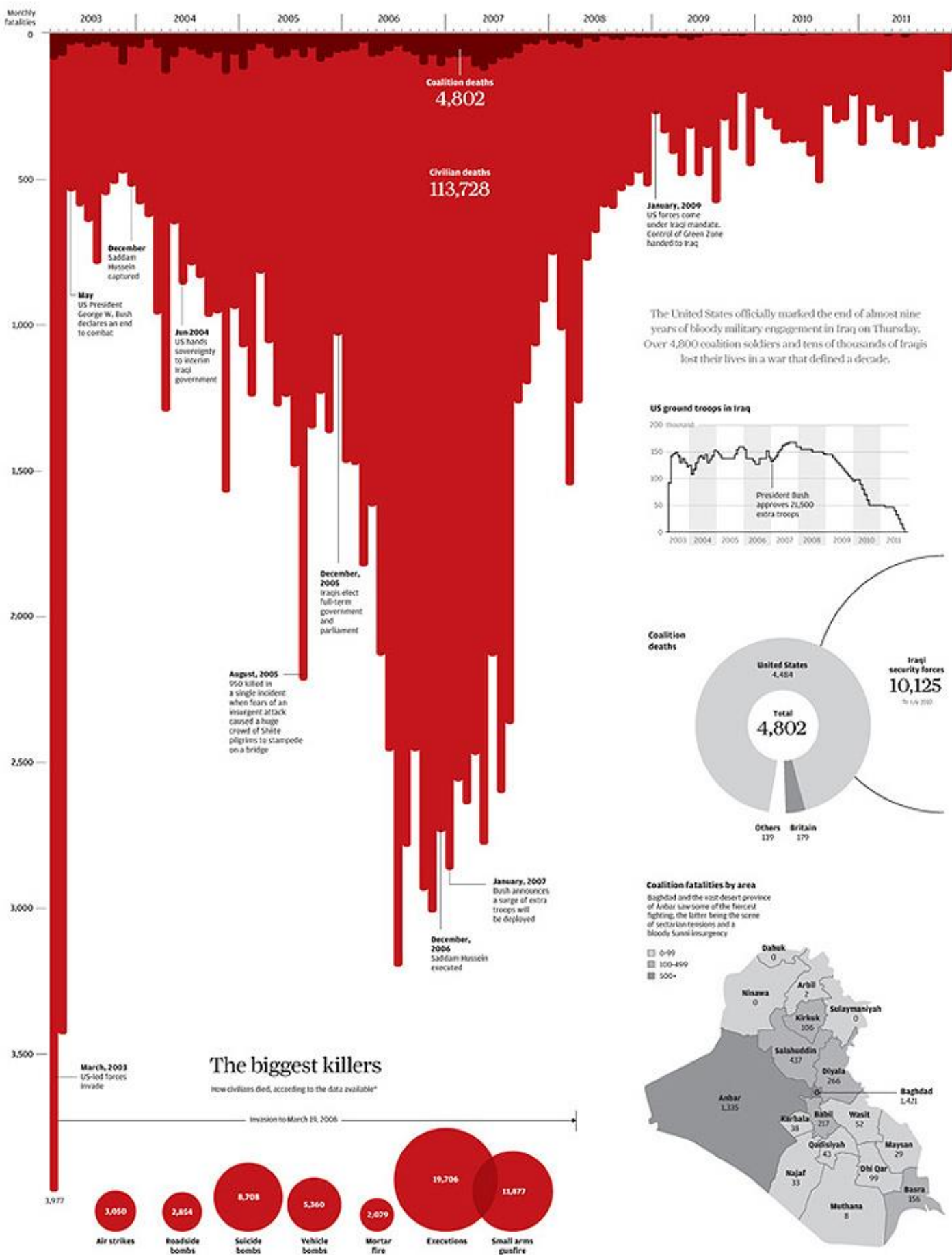
Gun deaths in Florida

Number of murders committed using firearms



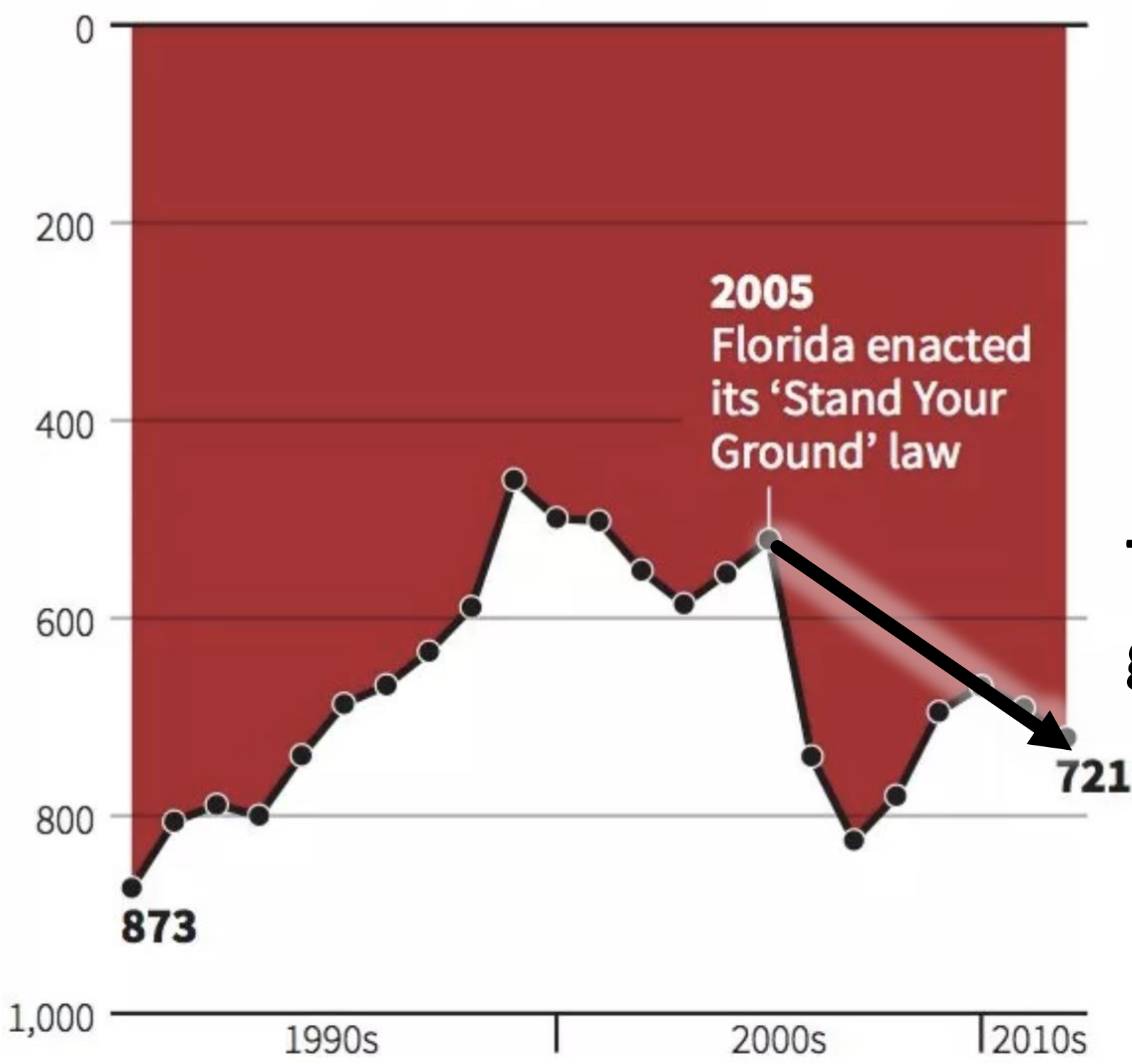
Source: Florida Department of Law Enforcement

Iraq's bloody toll



Gun deaths in Florida

Number of murders committed using firearms



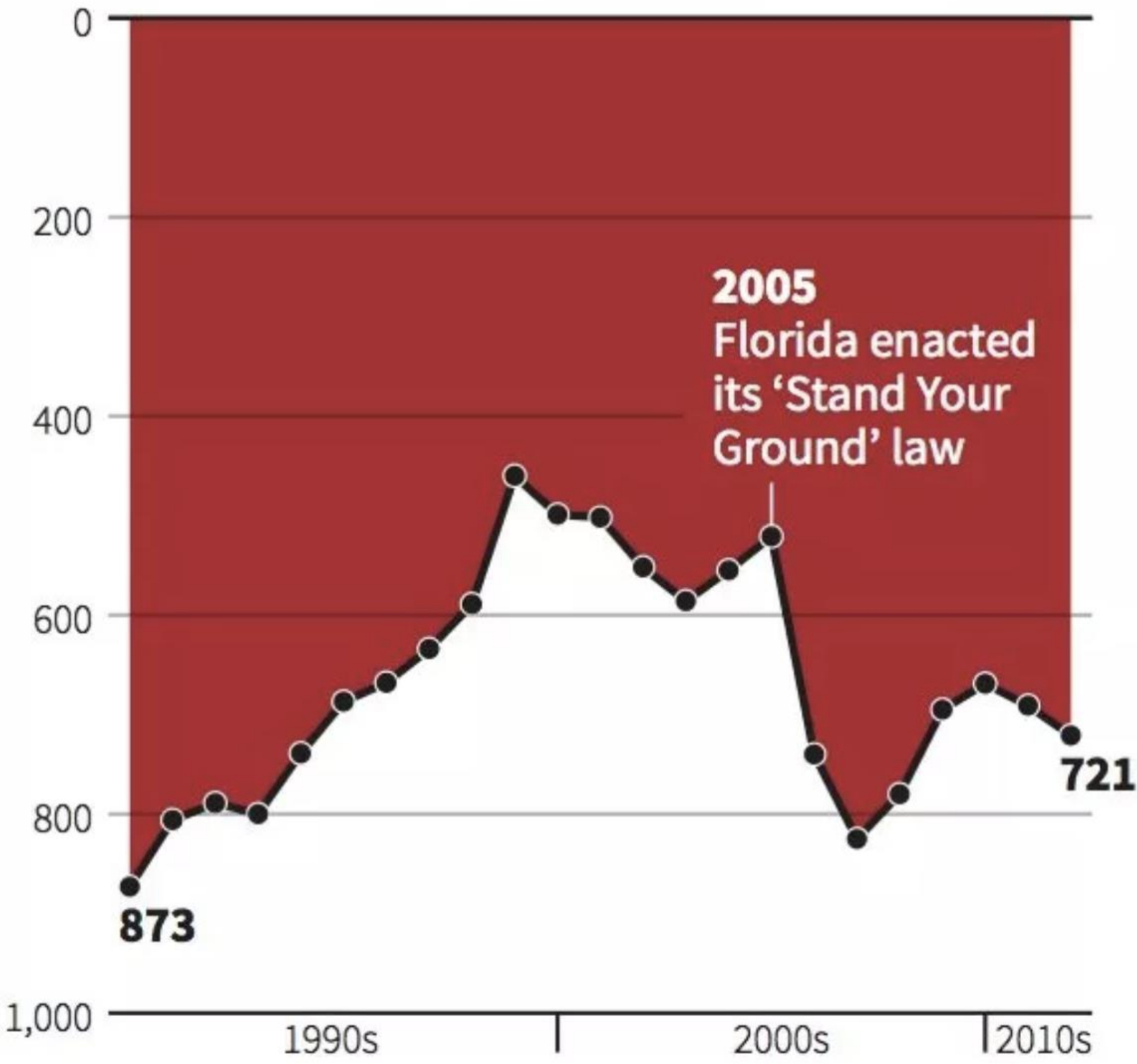
Source: Florida Department of Law Enforcement

Cognitive Misalignment

GREEN
YELLOW
RED
BLUE

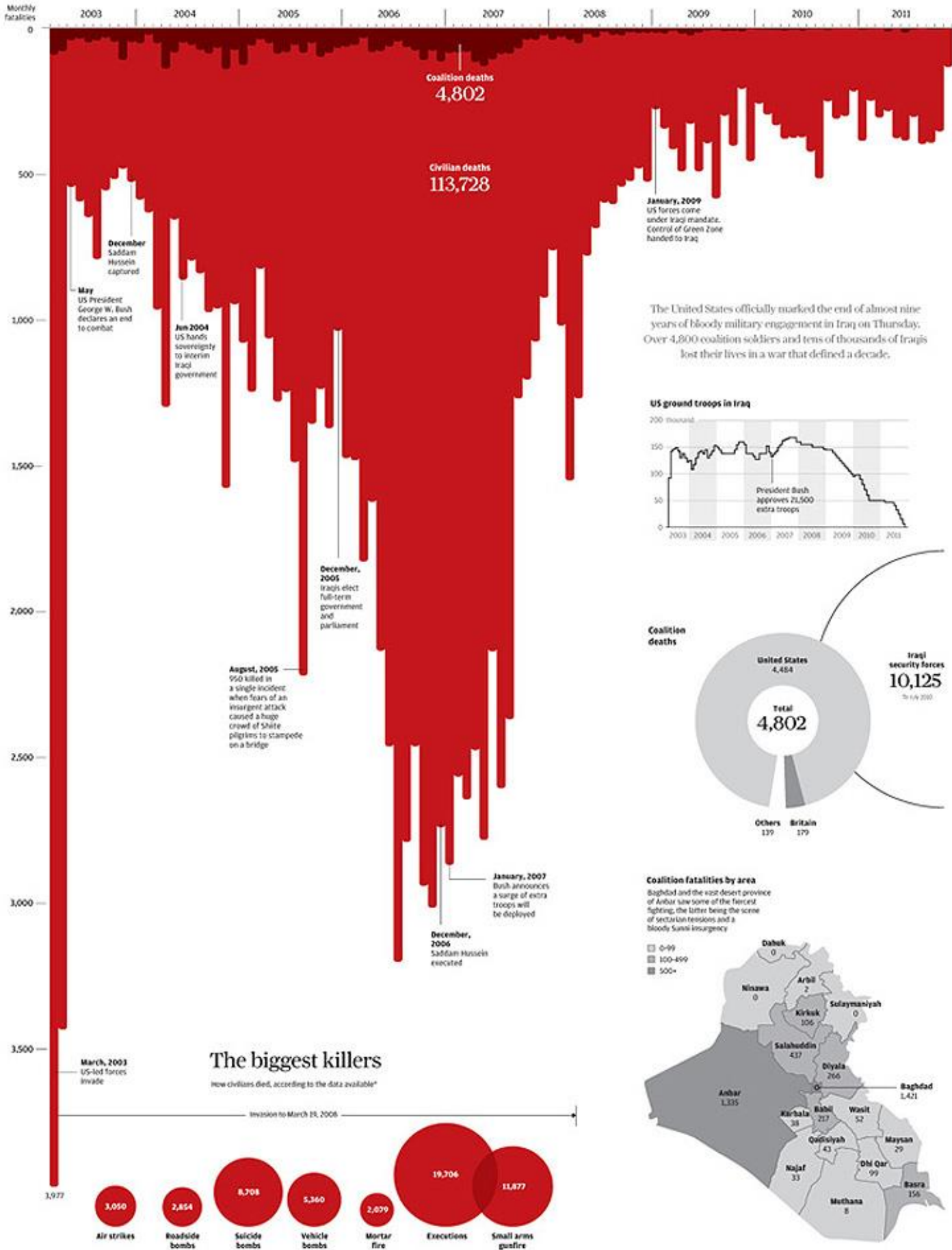
Gun deaths in Florida

Number of murders committed using firearms



Source: Florida Department of Law Enforcement

Iraq's bloody toll



Not a problem for me,
I use good design practice!

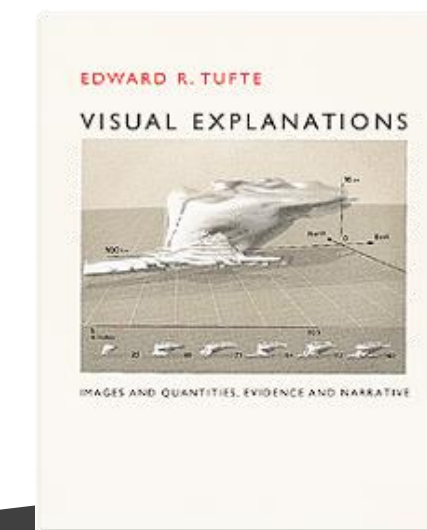
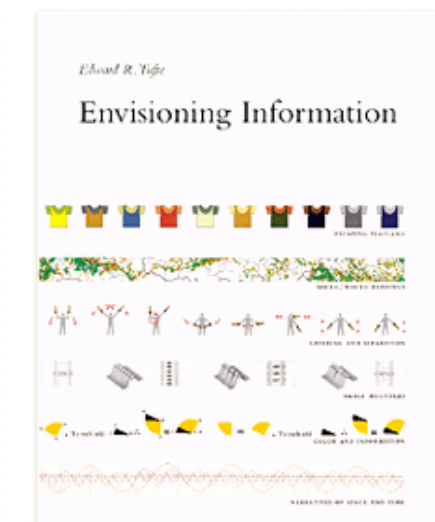
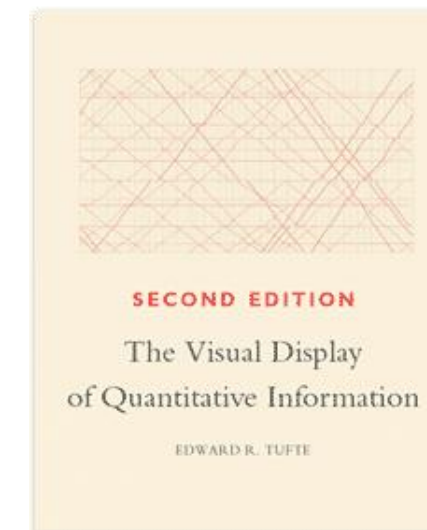
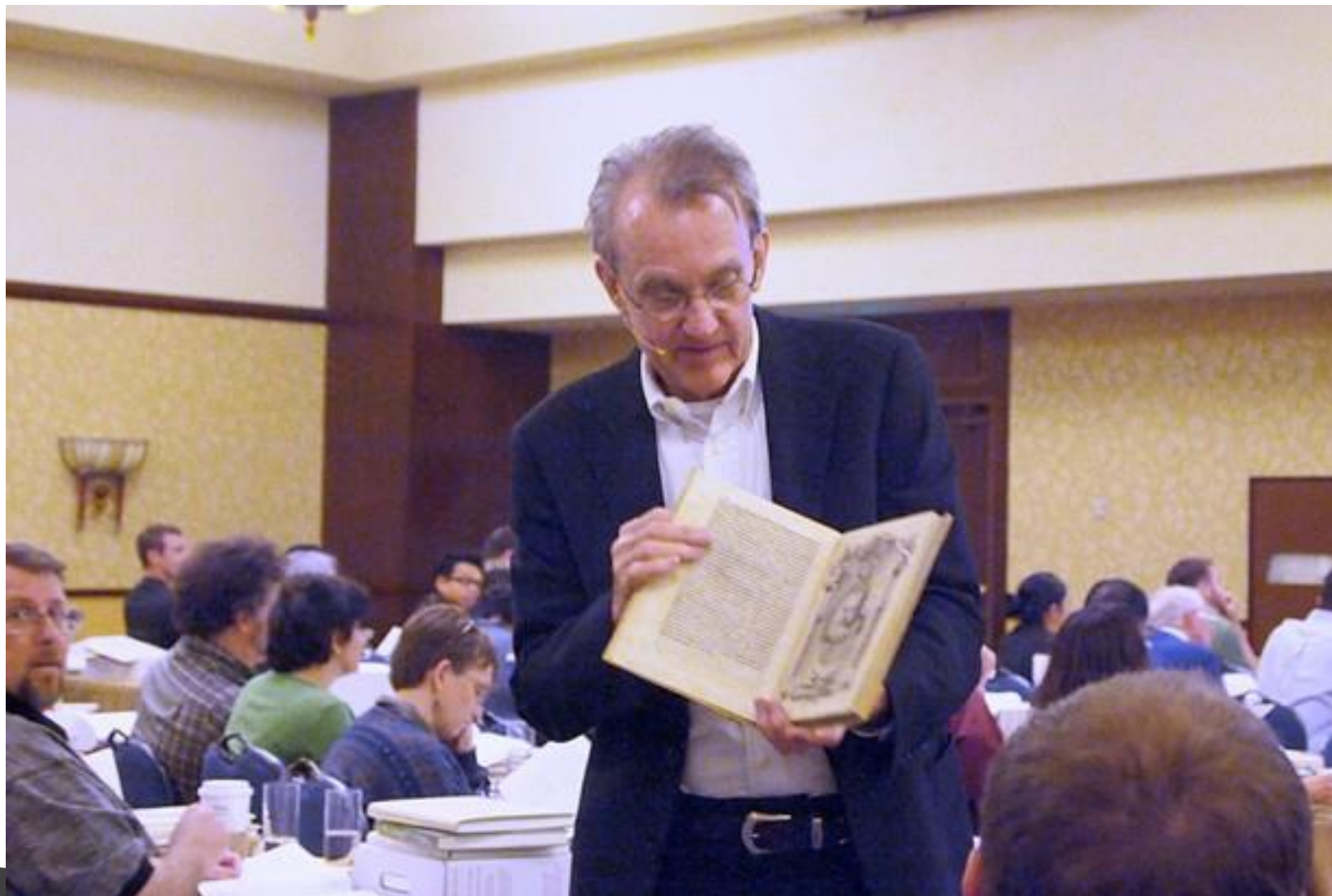


TUFTE

Design excellence

TUFTE'S LESSONS

- practice—graphical integrity and excellence
- theory—design principles for data graphics



GRAPHICAL INTEGRITY

clear, detailed, and thorough labeling
should be used to defeat graphical
distortion and ambiguity

Graphical excellence

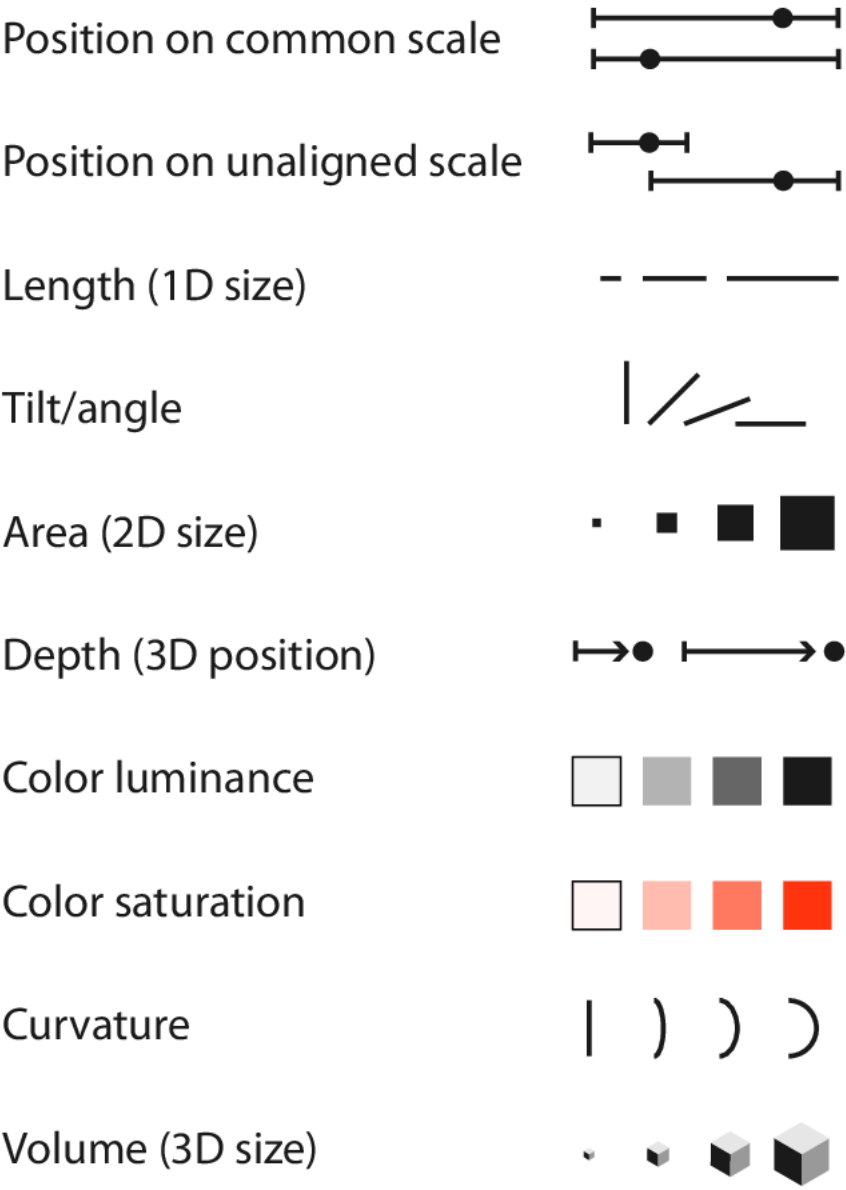
- Design a visualization that gives the viewer:
 - the greatest number of ideas,
 - in the shortest time,
 - with the least ink, and
 - in the smallest space.

A. Einstein, “An explanation should be as simple as possible, but no simpler.”

Effective Encoding

Channels: Expressiveness Types and Effectiveness Ranks

➔ **Magnitude Channels:** **O** or **Q** attributes

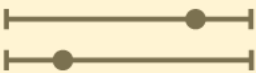


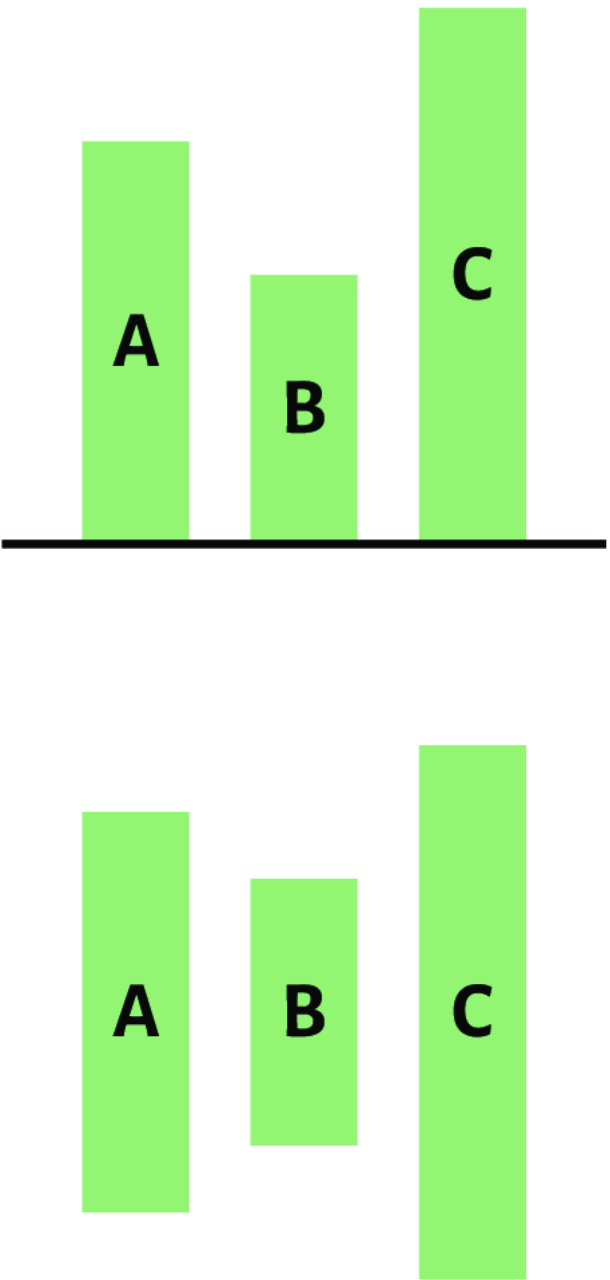
➔ **Identity Channels:** **N** attributes



Channels: Expressiveness Types and Effectiveness Ranks

➔ **Magnitude Channels:** **O** or **Q** attributes

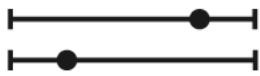
Position on common scale	
Position on unaligned scale	
Length (1D size)	
Tilt/angle	
Area (2D size)	
Depth (3D position)	
Color luminance	
Color saturation	
Curvature	
Volume (3D size)	



Channels: Expressiveness Types and Effectiveness Ranks

➔ **Magnitude Channels: O or Q** attributes

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)



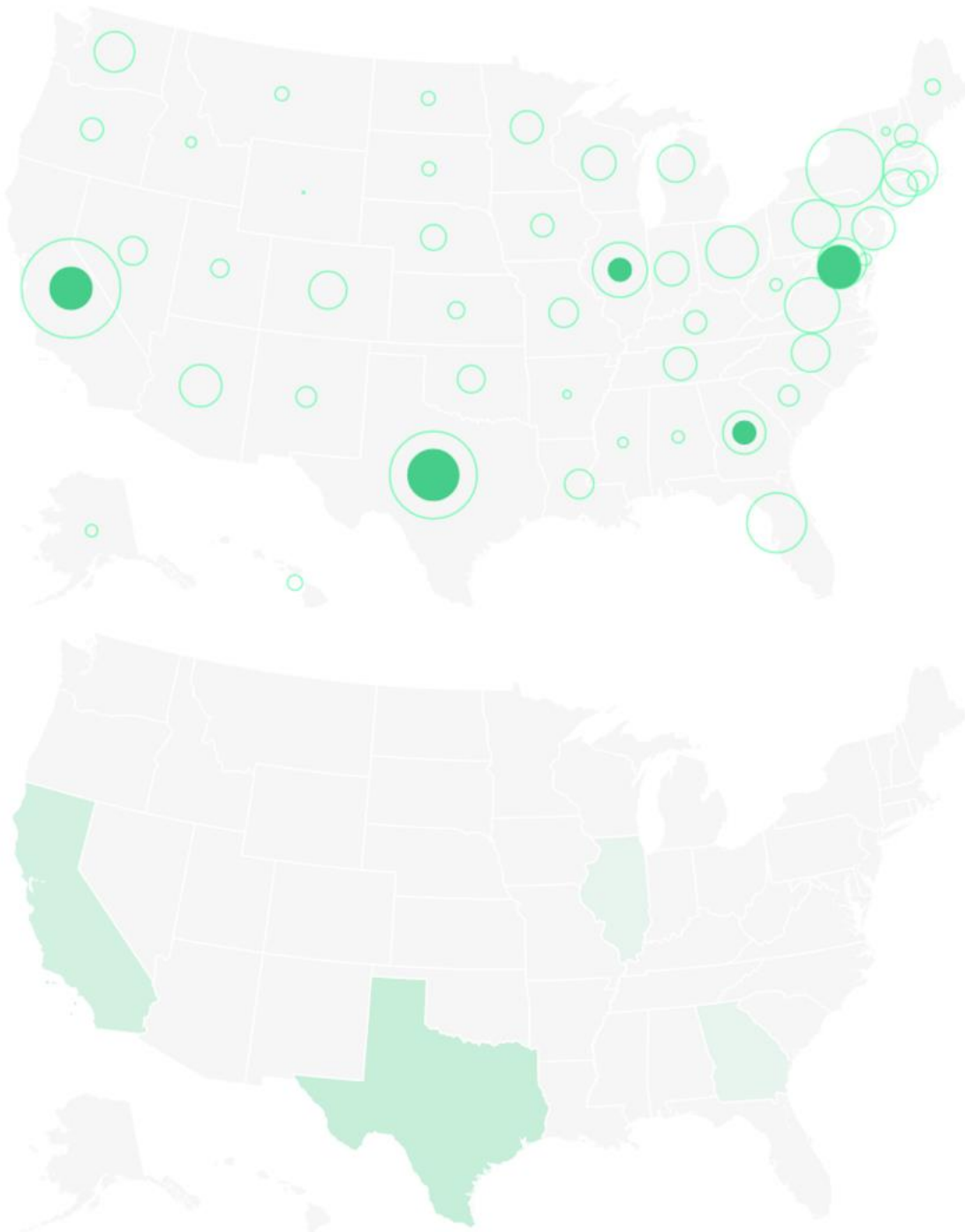
Same

Same

Most

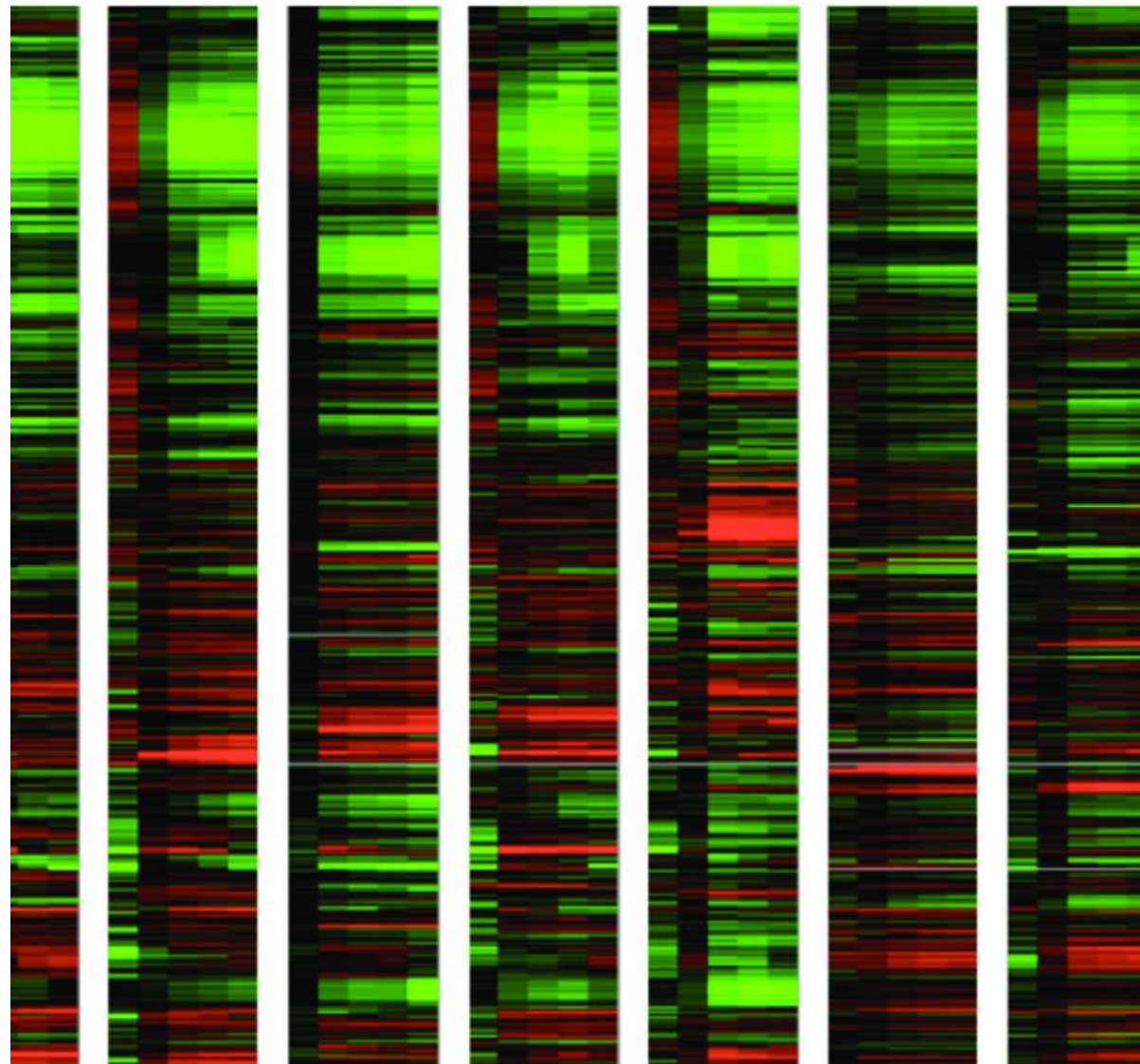
Effectiveness

Least

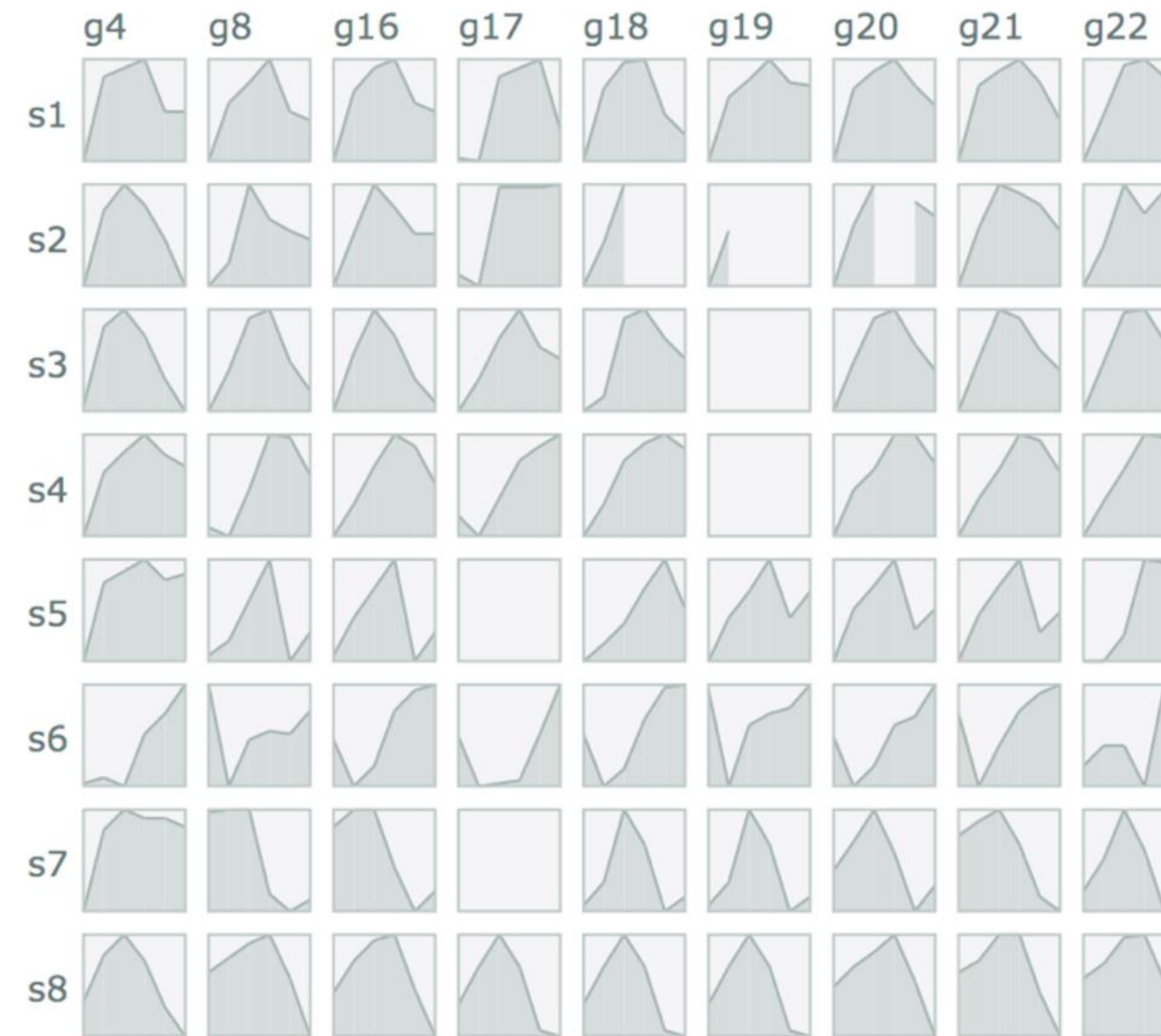


Gene Expression Time-Series [Meyer et al. '10]

Color Encoding



Position Encoding



Artery Visualization [Borkin et al. '11]

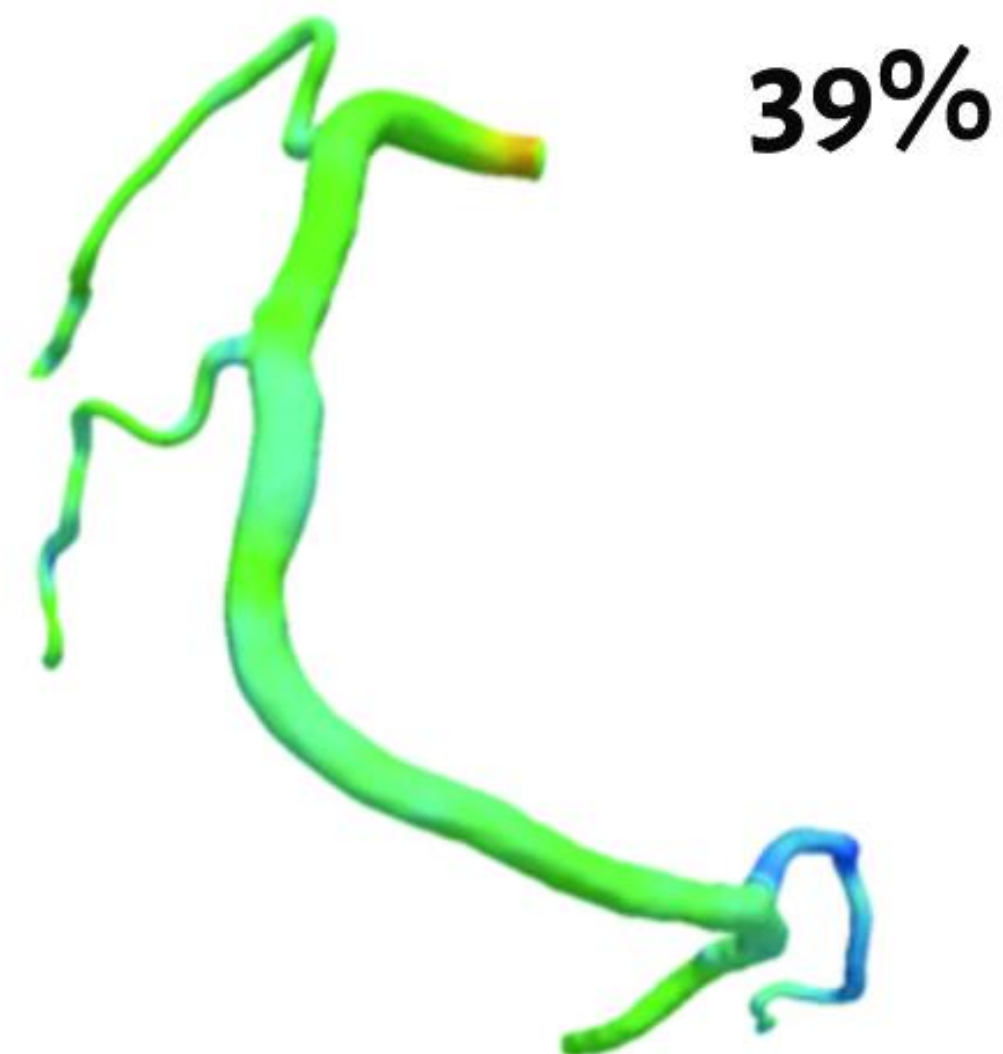
2D



62%



3D

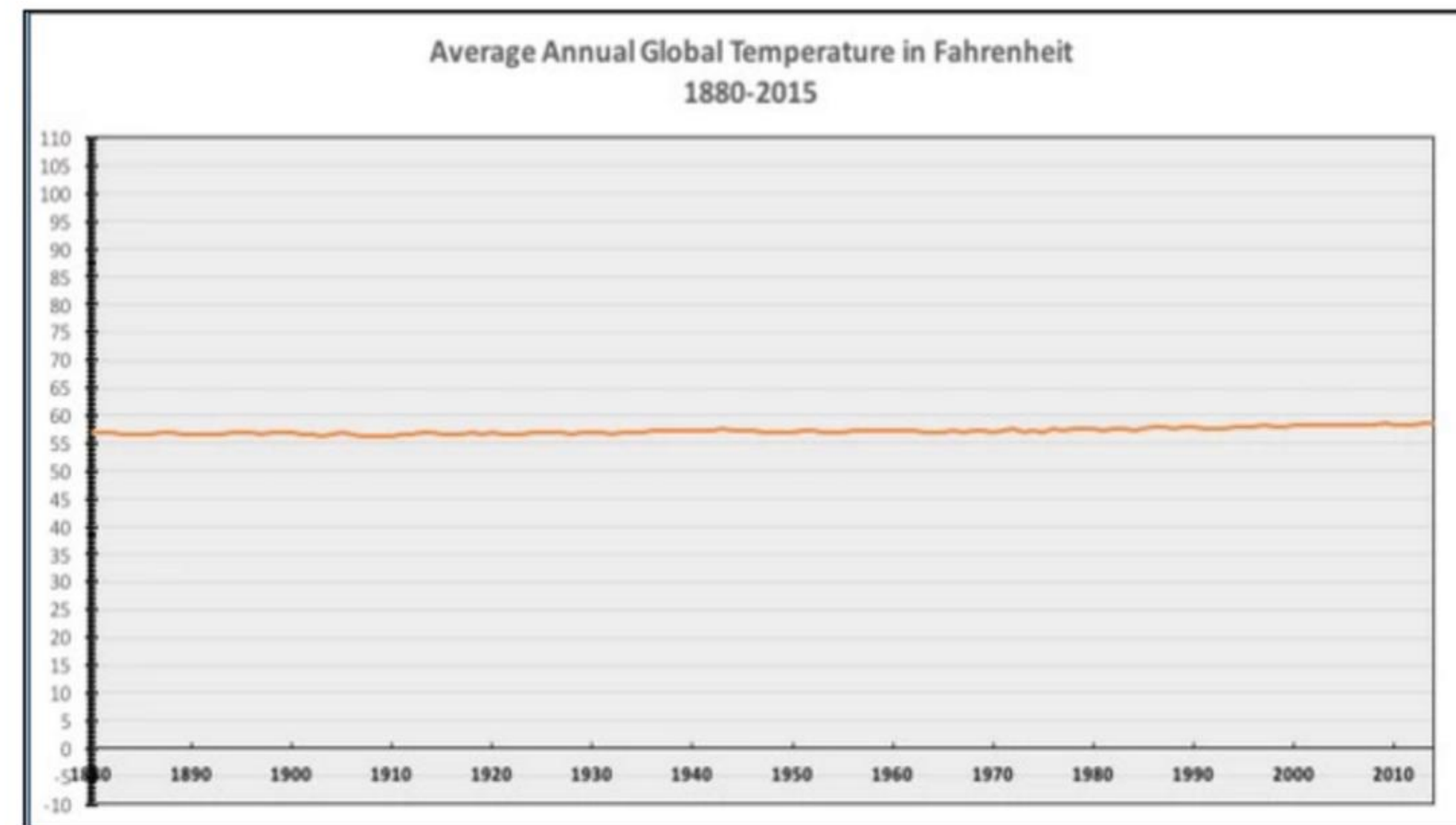


39%

Scales

The only [#climatechange](#) chart you need to see. natl.re/wPKpro

(h/t [@powerlineUS](#))



RETWEETS
408

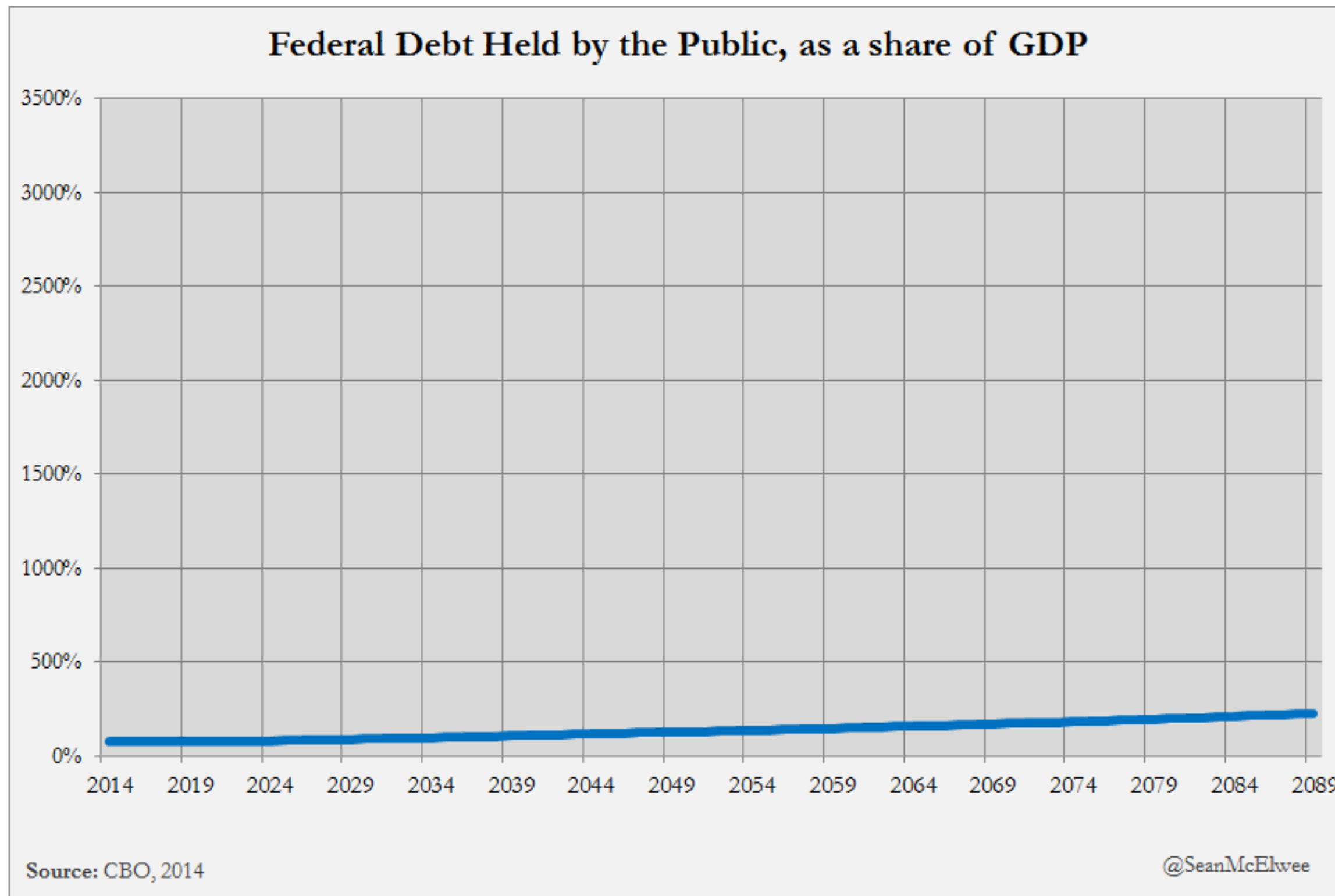
LIKES
322

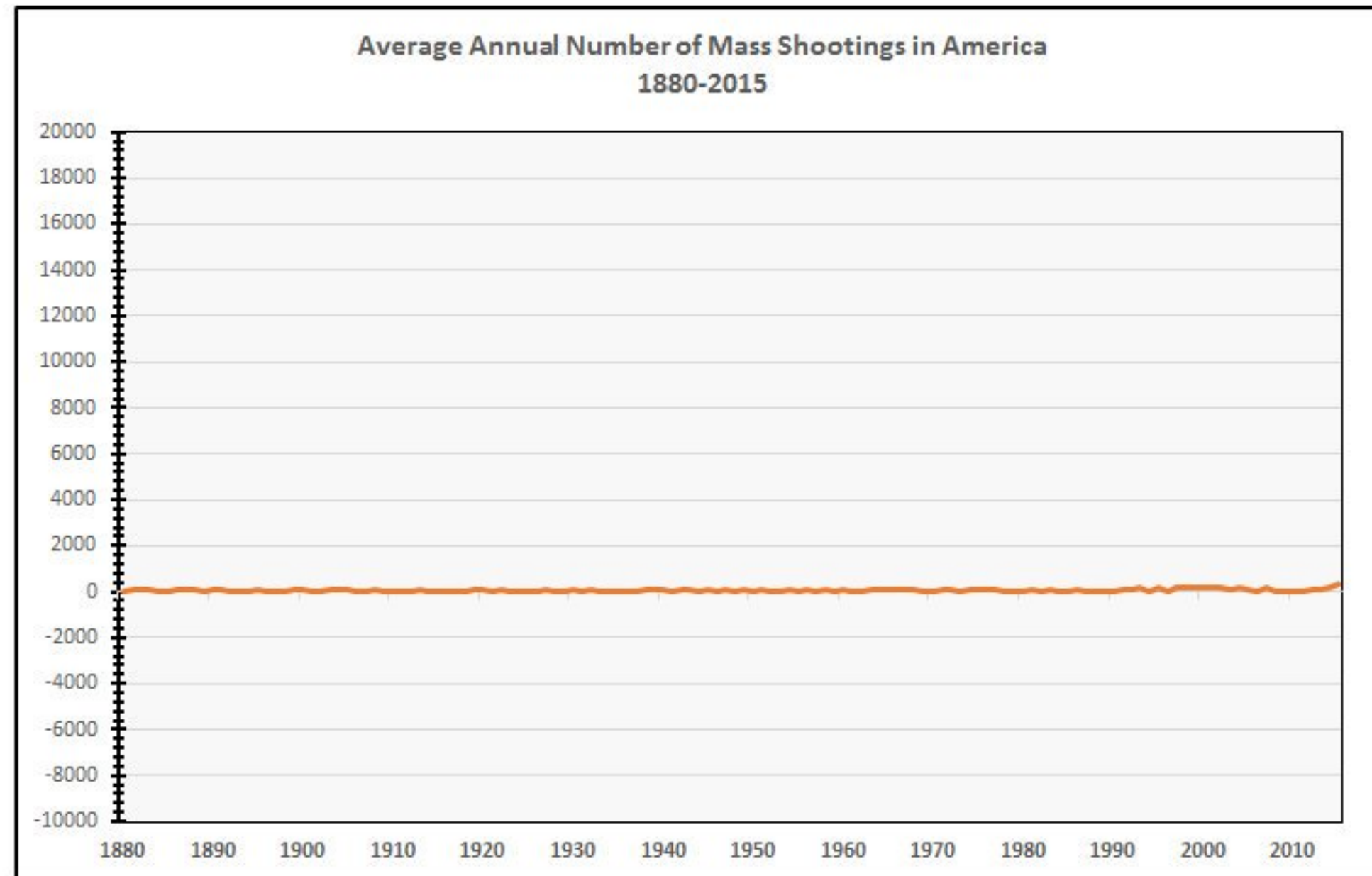


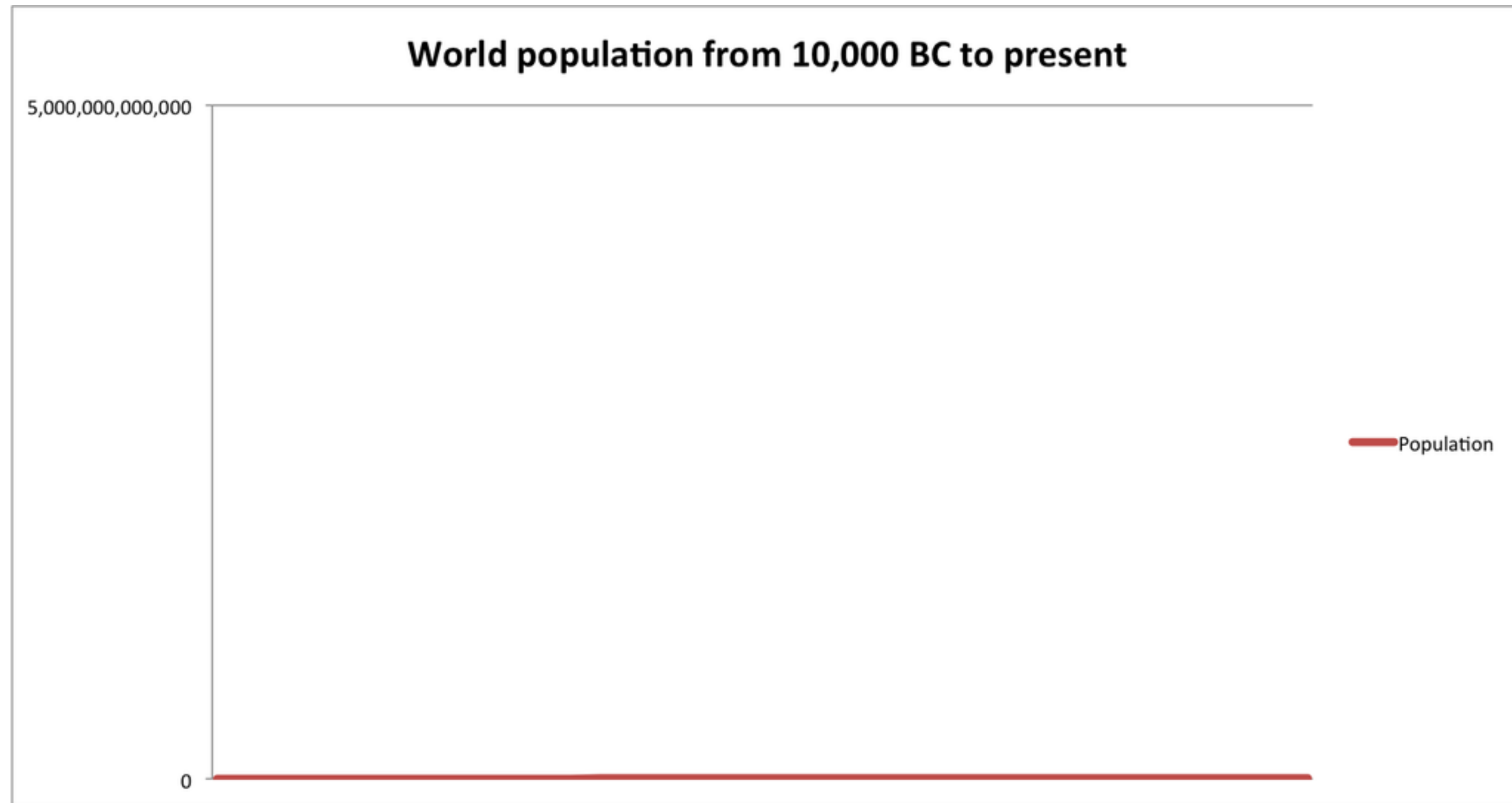
1:36 PM - 14 Dec 2015



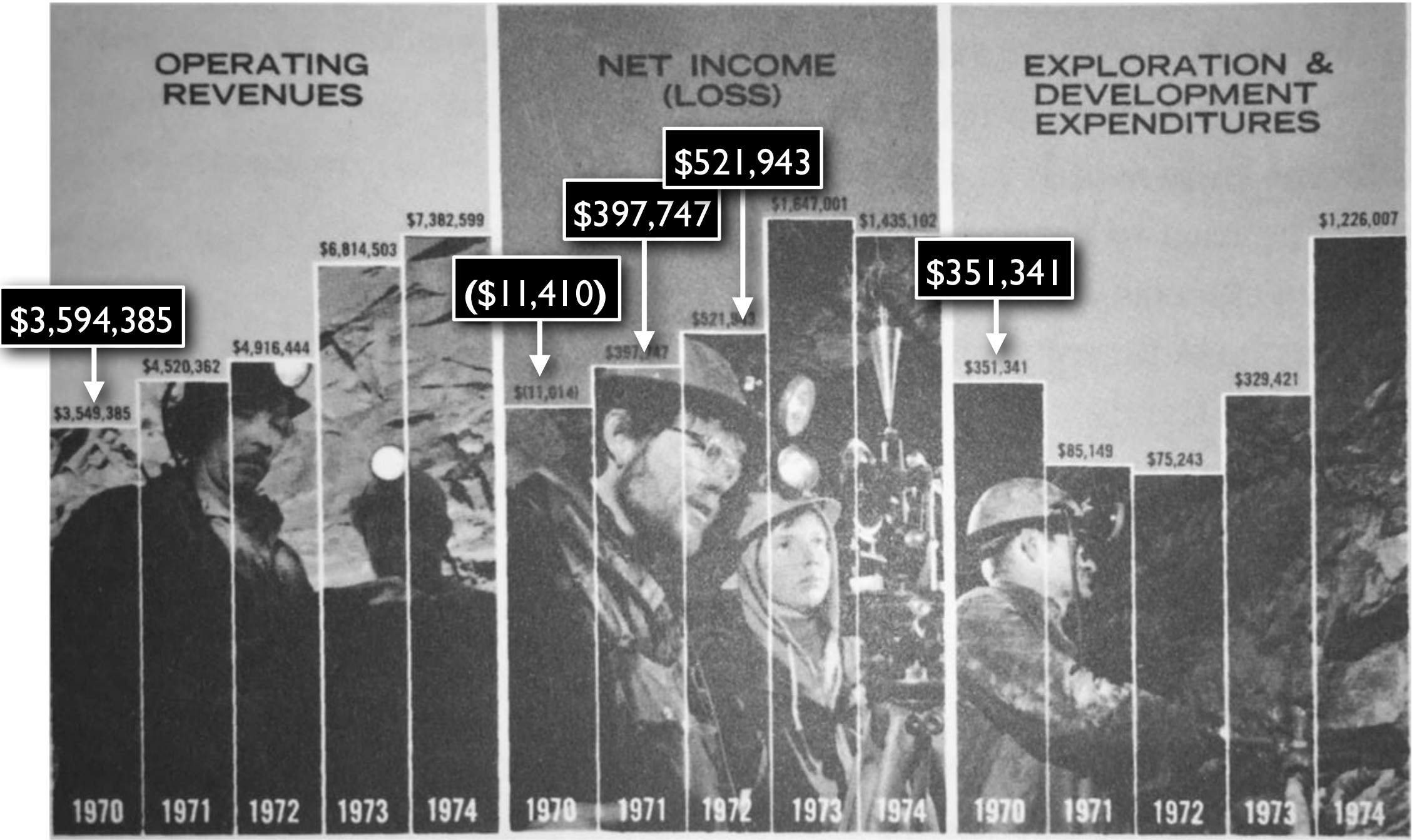
<http://www.vislies.org/>



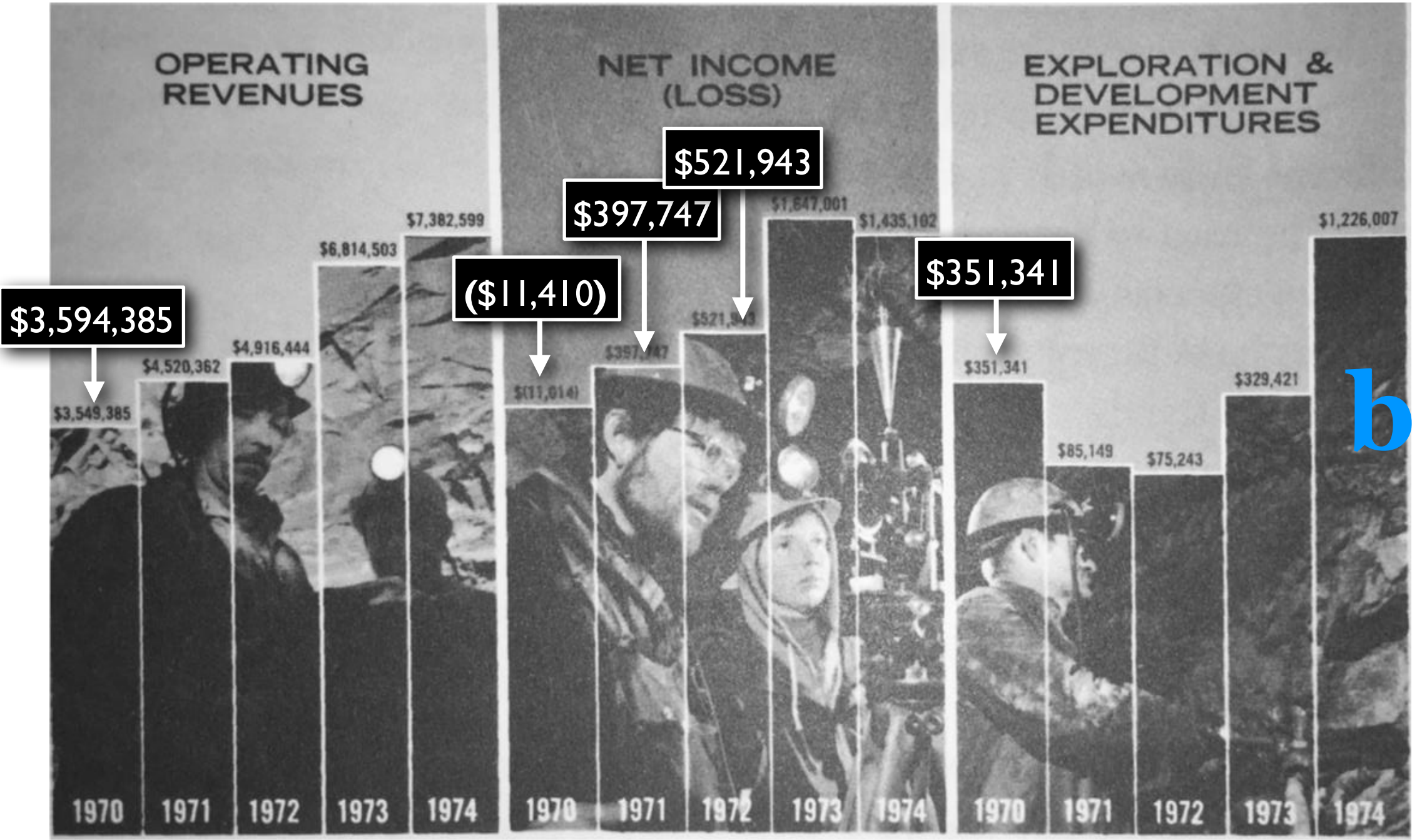




MISSING SCALES

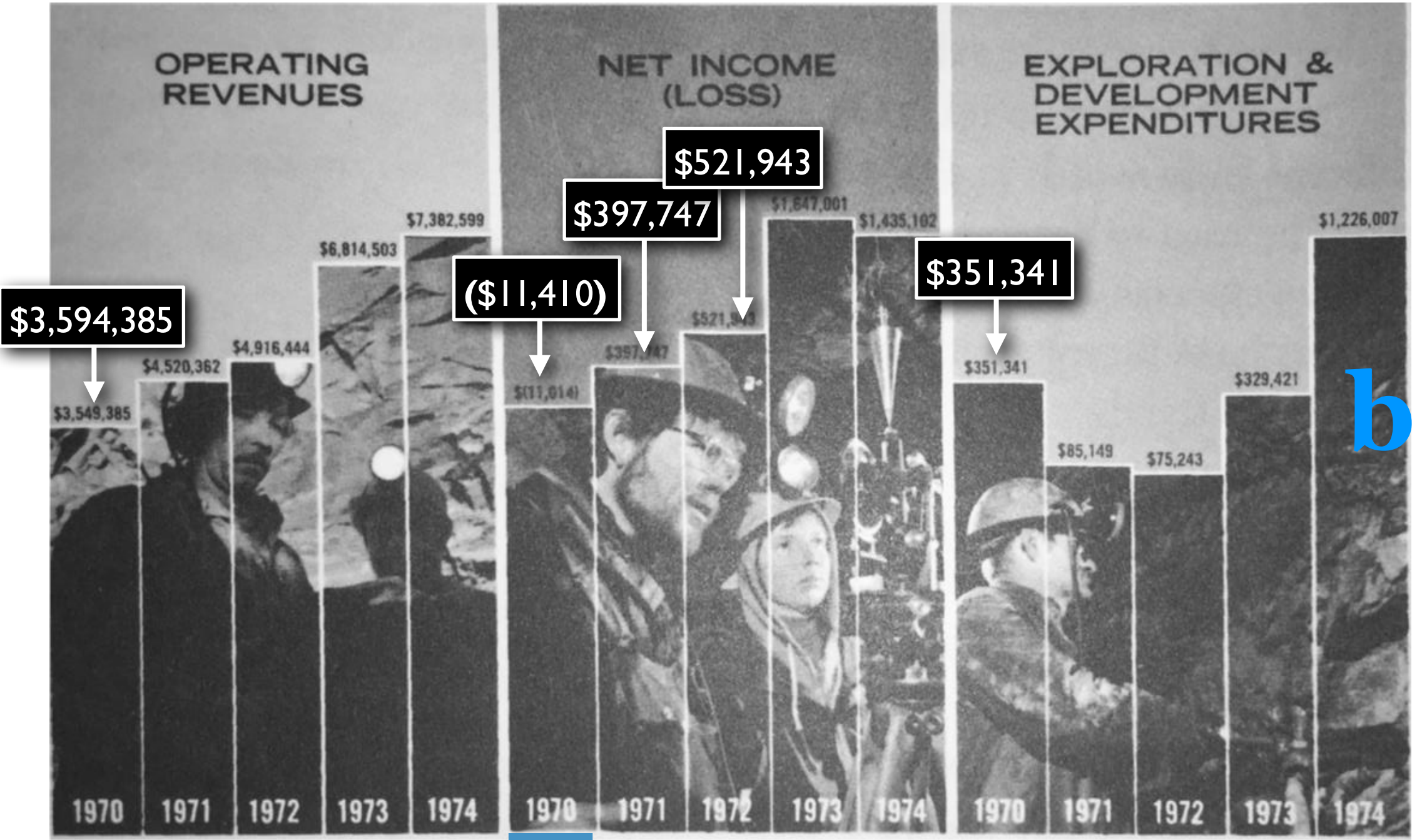


MISSING SCALES



baseline?

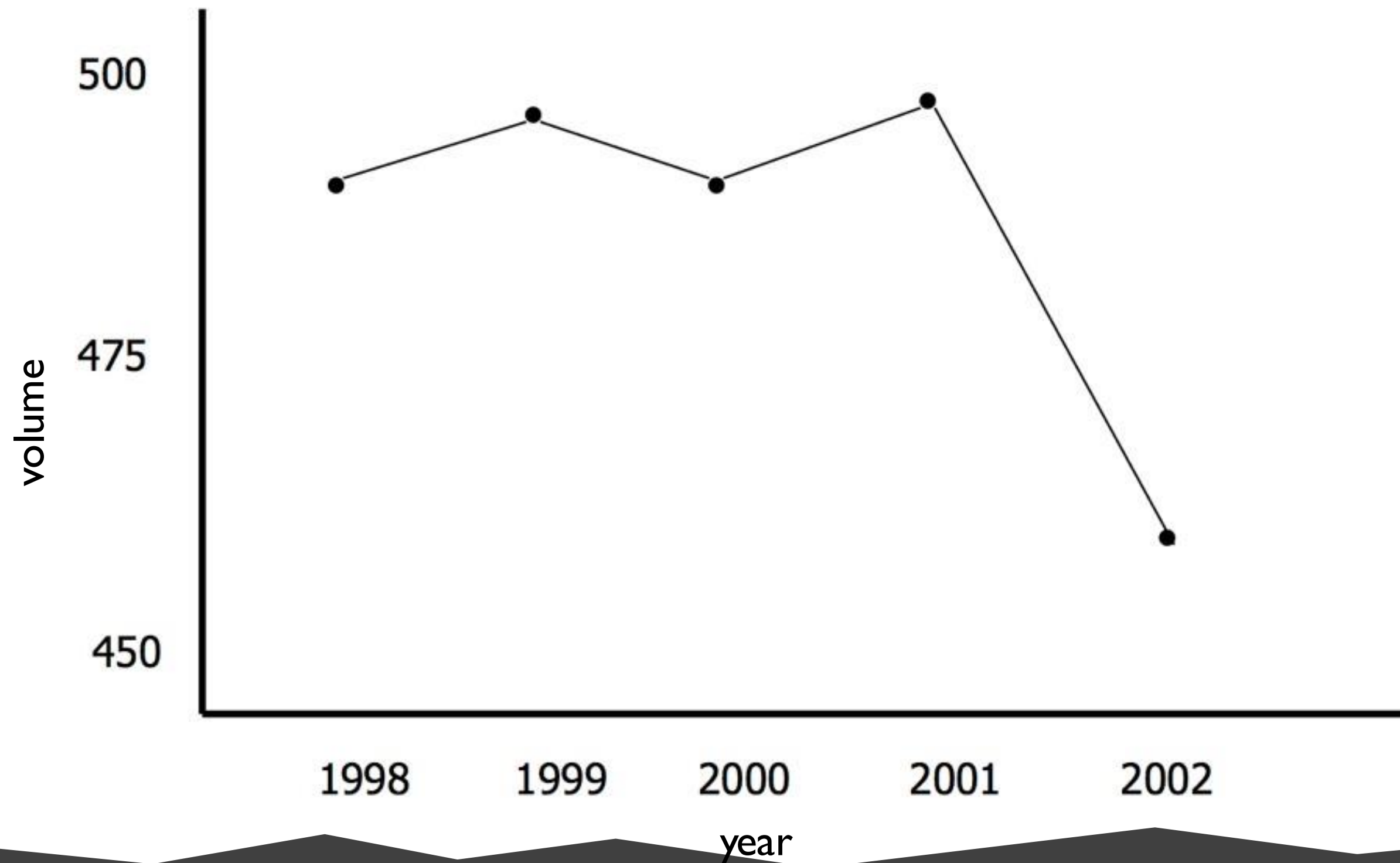
MISSING SCALES



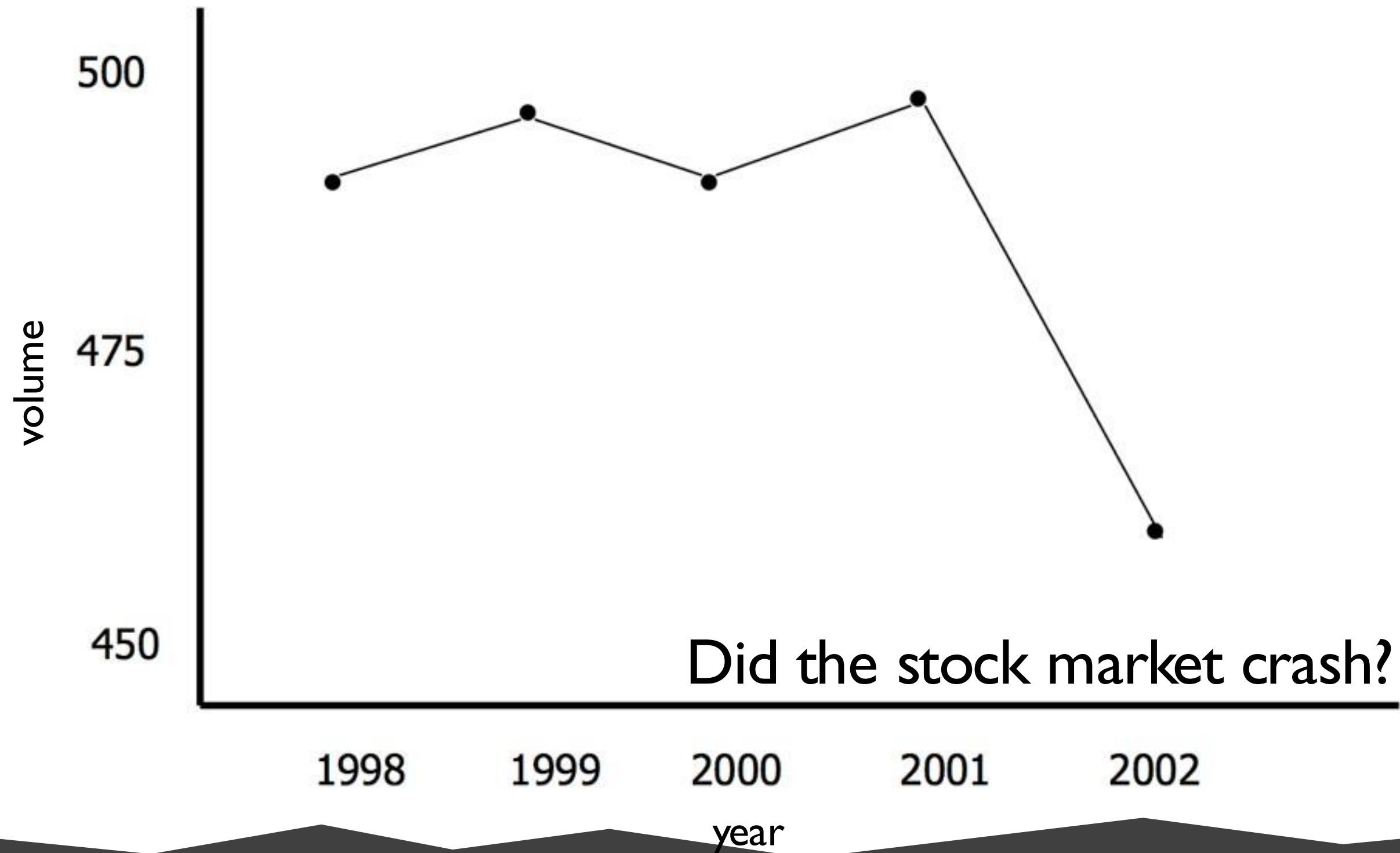
baseline?

-\$4,200,000

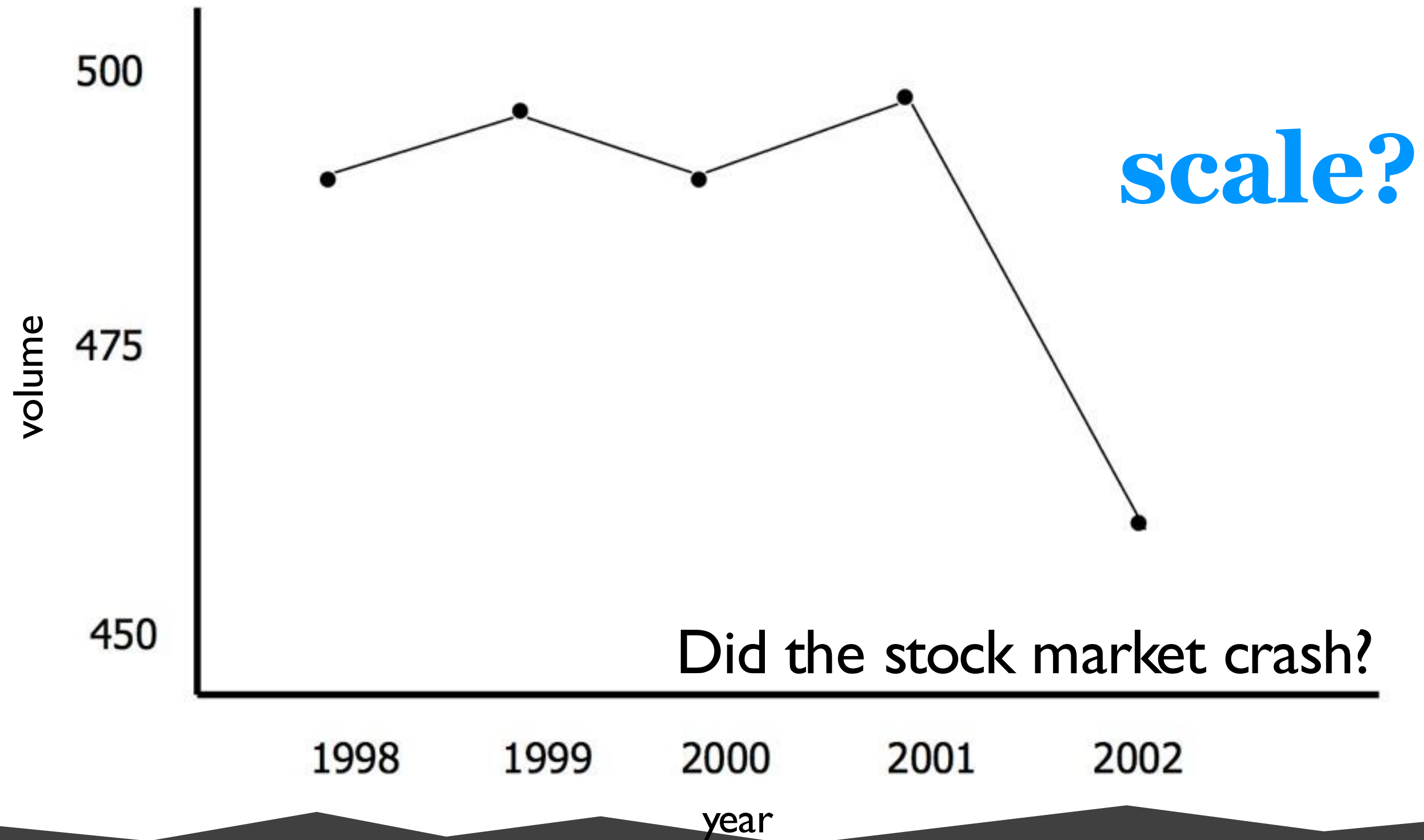
SCALE DISTORTION



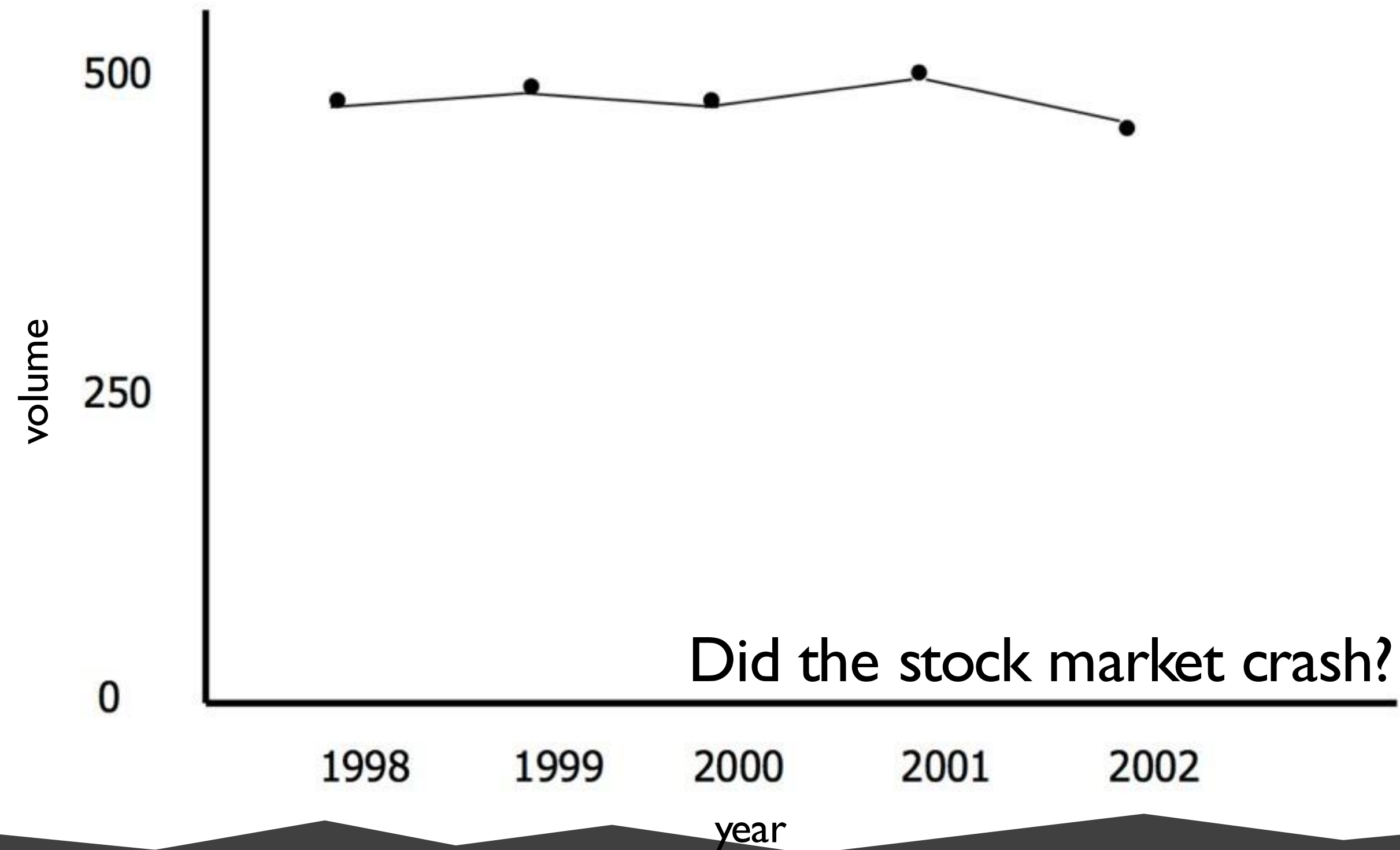
SCALE DISTORTION



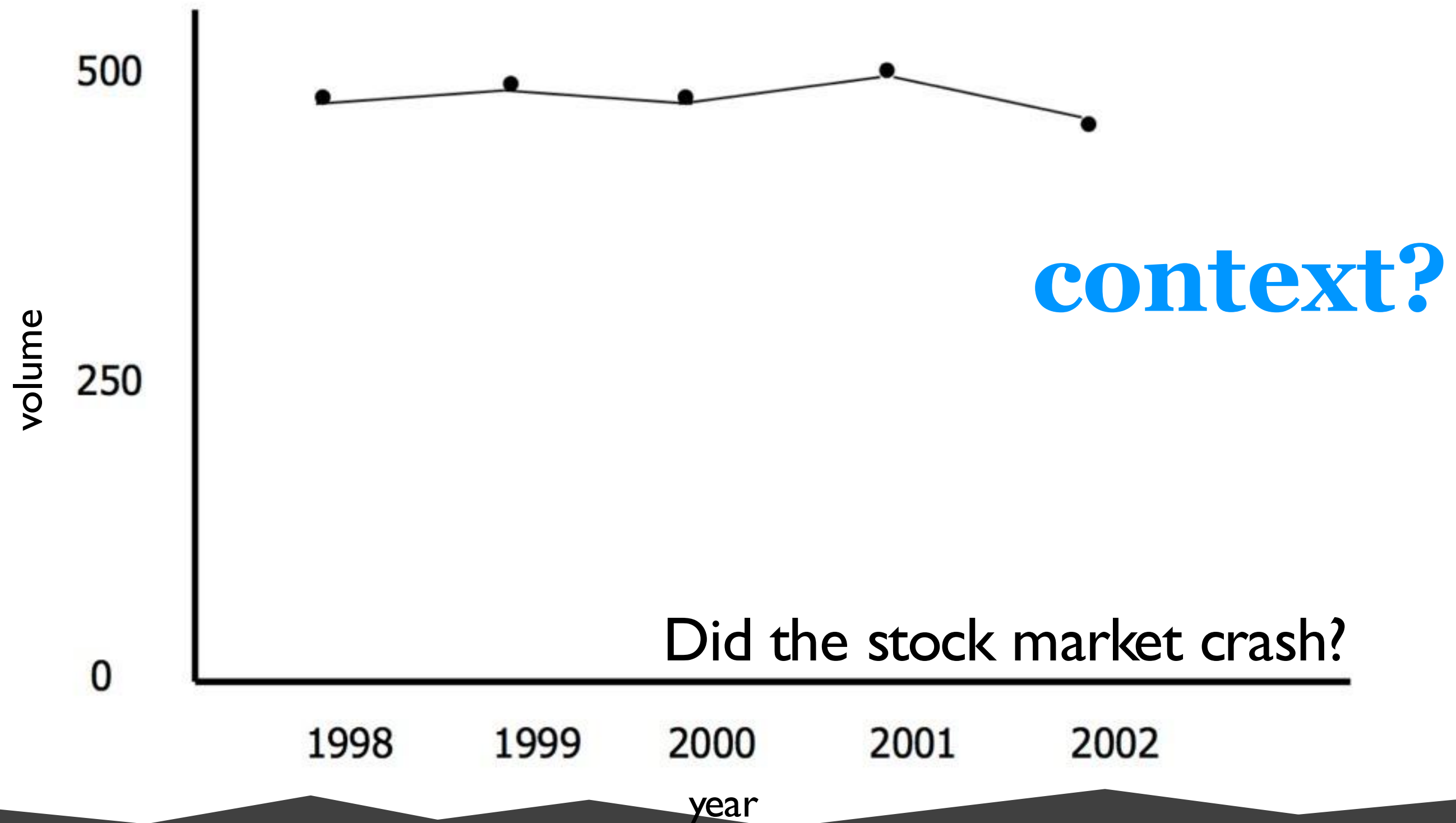
SCALE DISTORTION



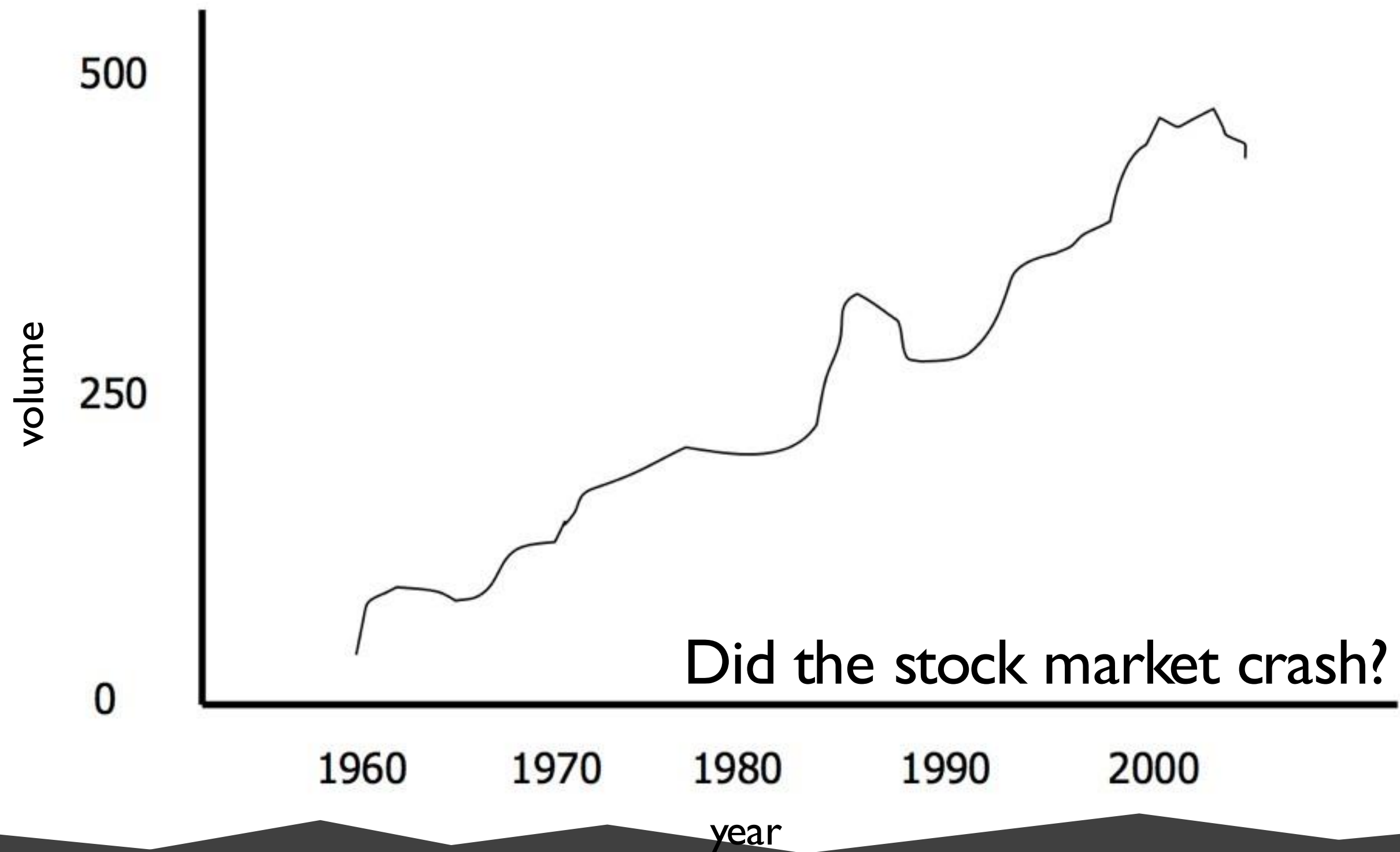
SCALE DISTORTION



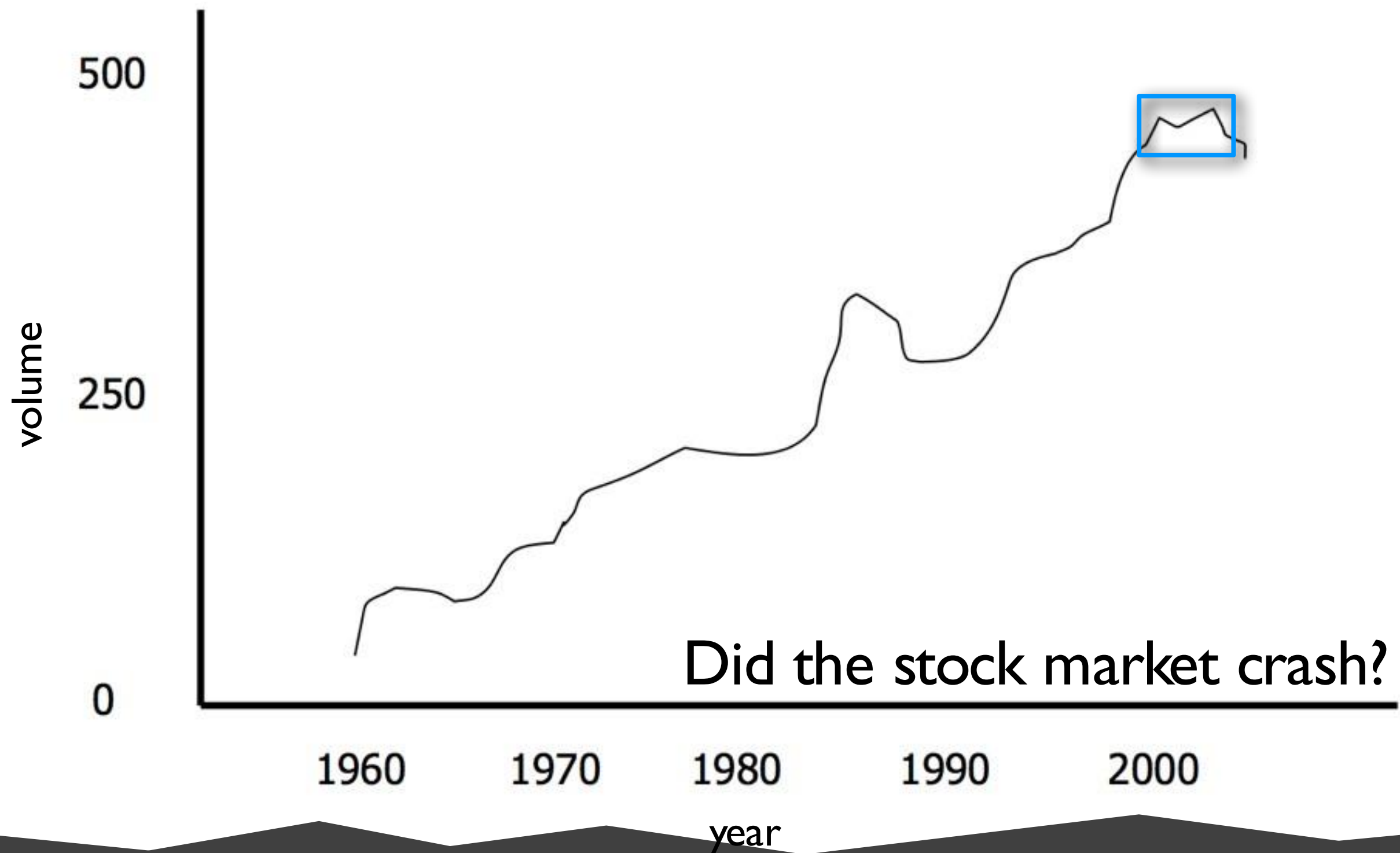
SCALE DISTORTION



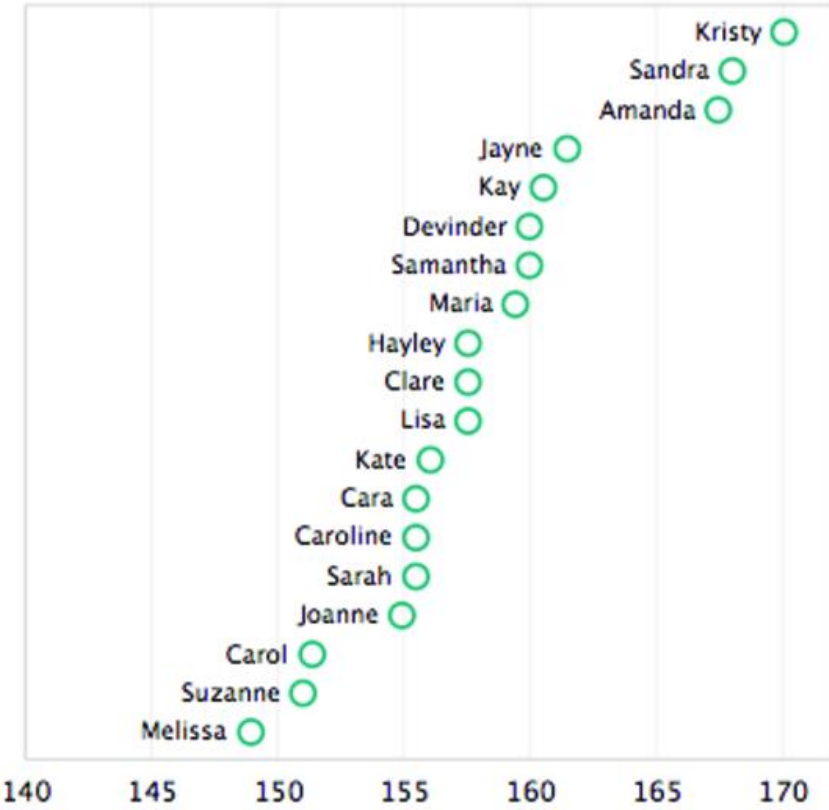
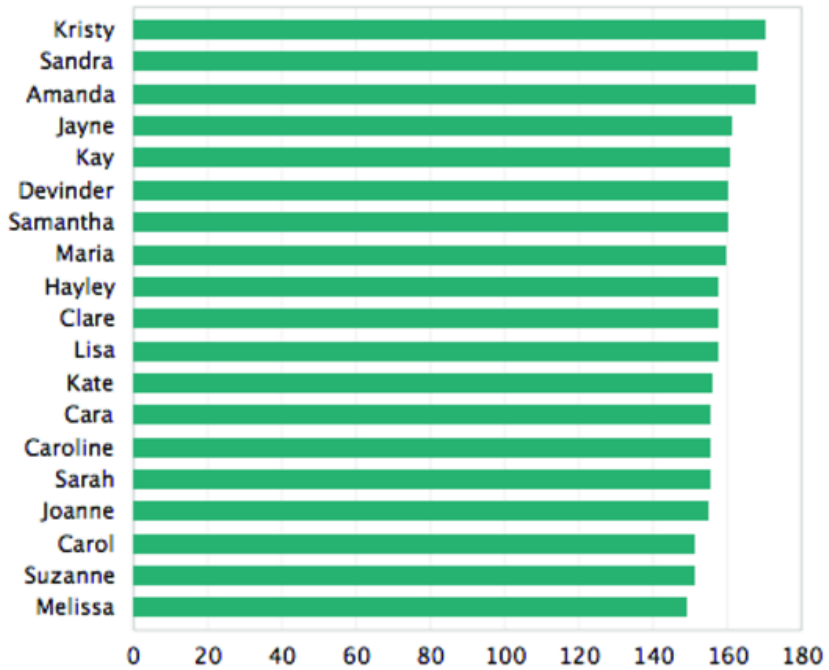
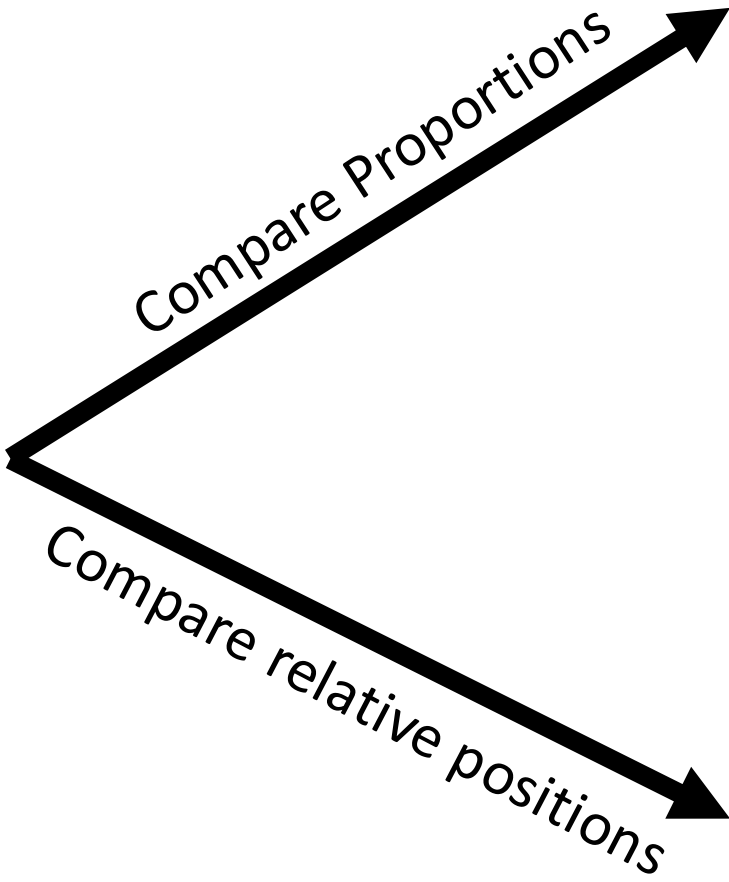
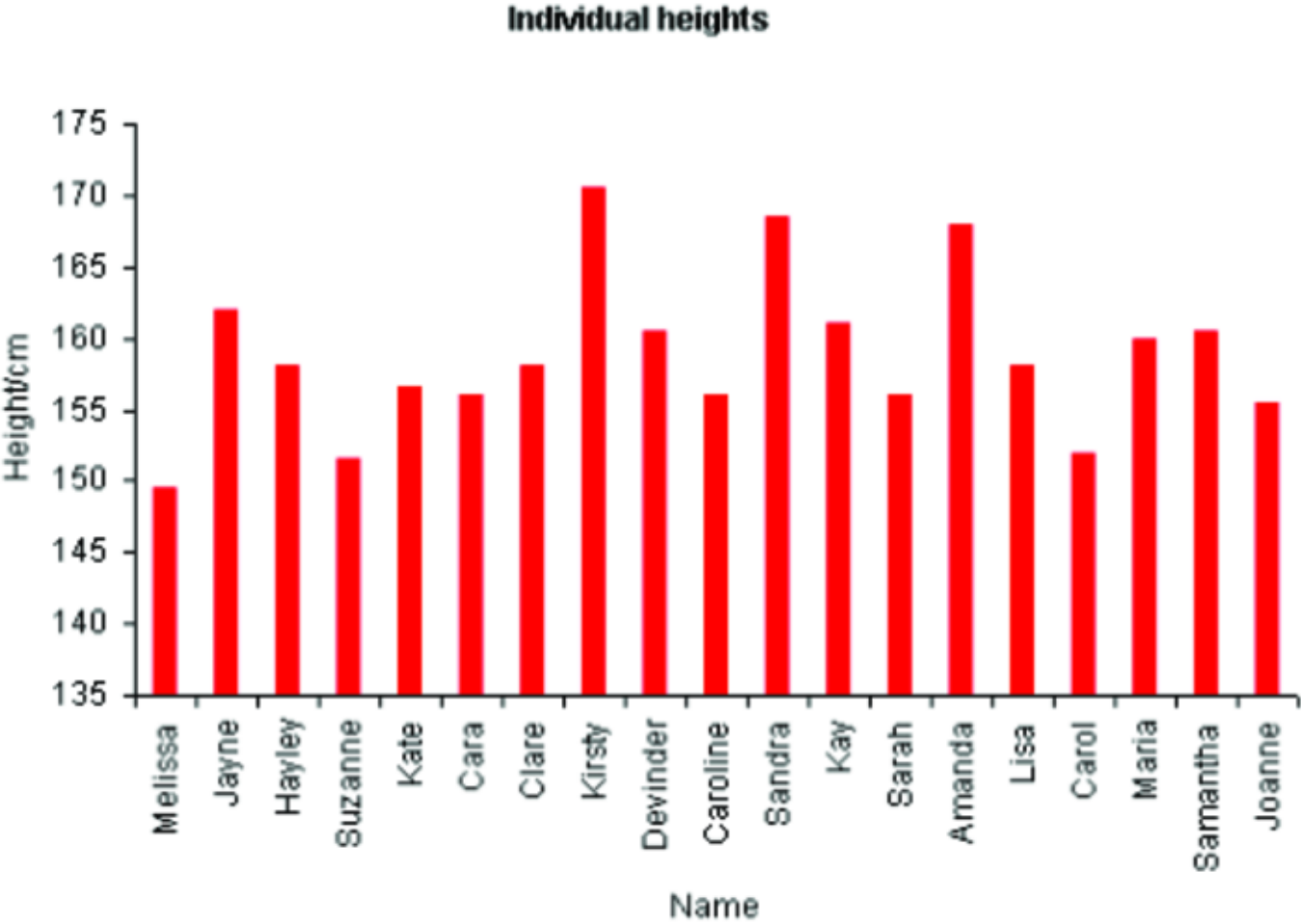
SCALE DISTORTION



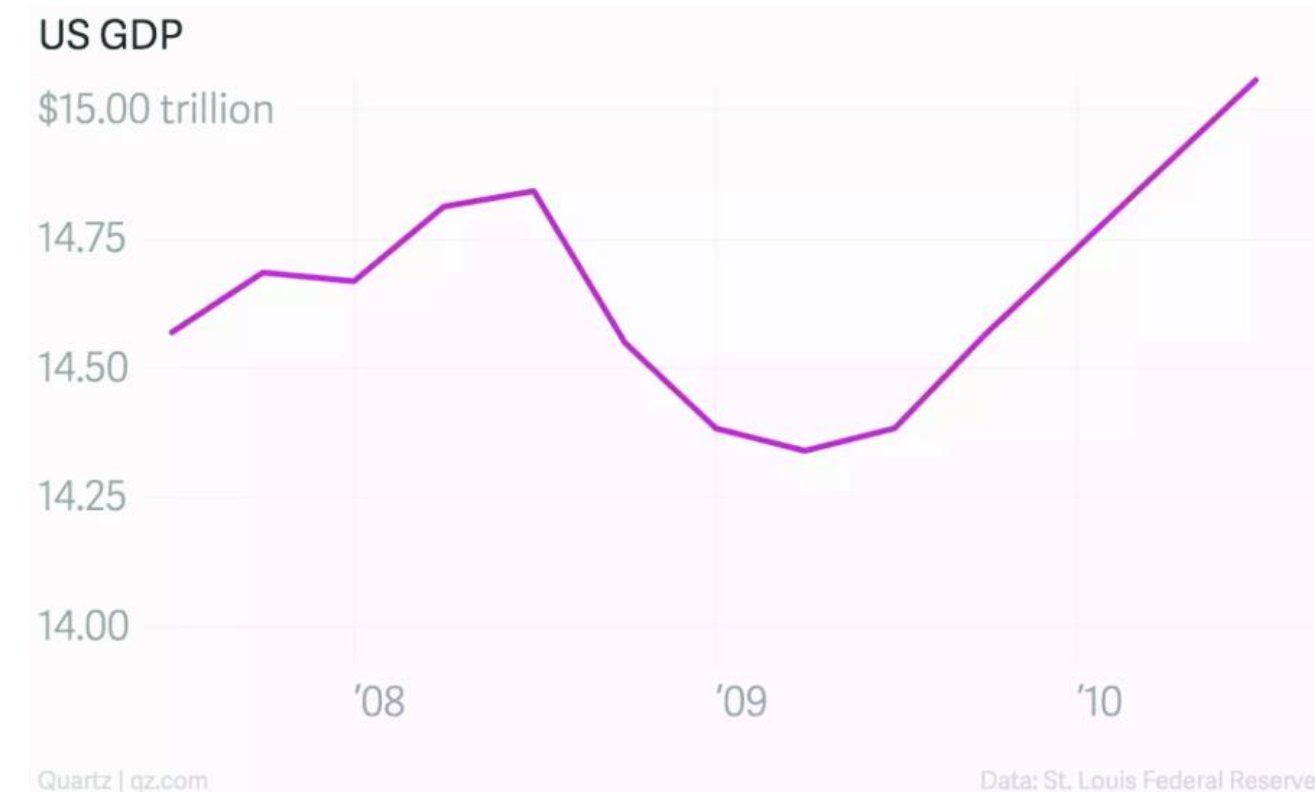
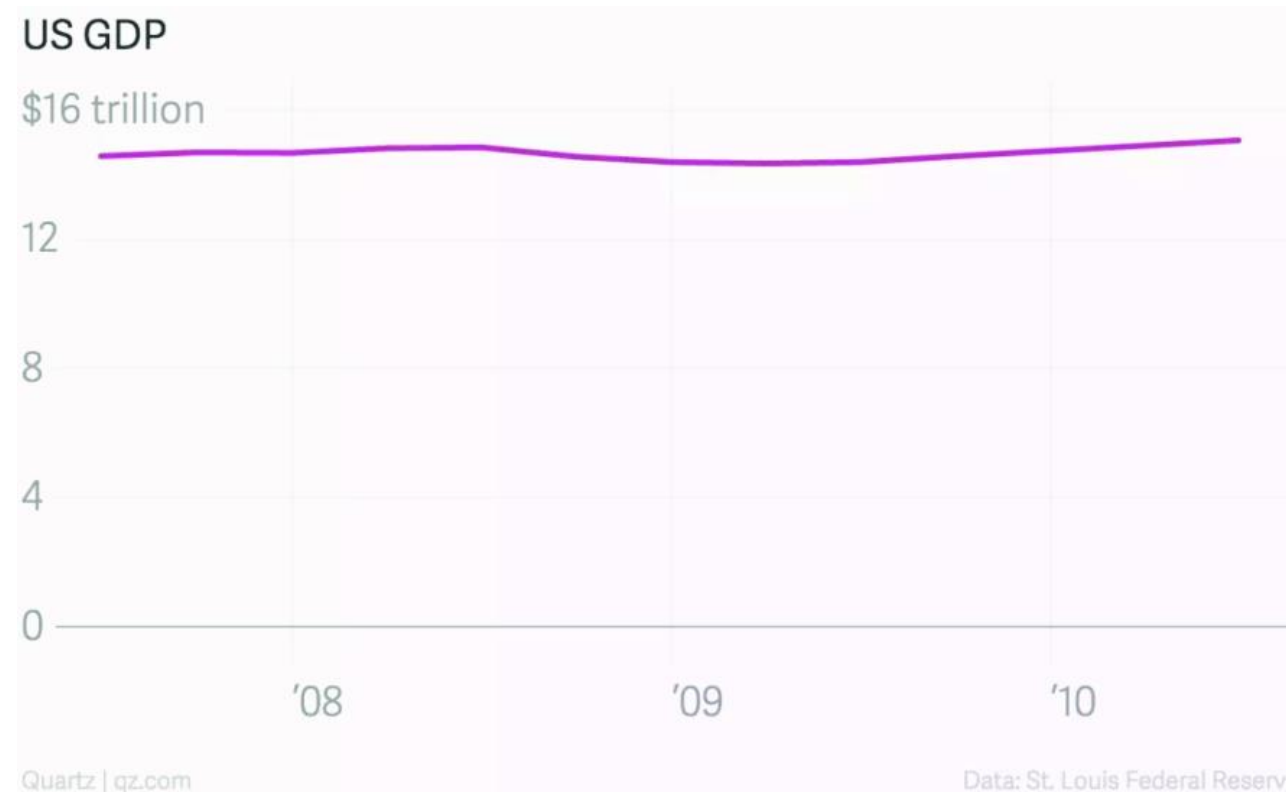
SCALE DISTORTION



Zero Baseline



Zero Baseline

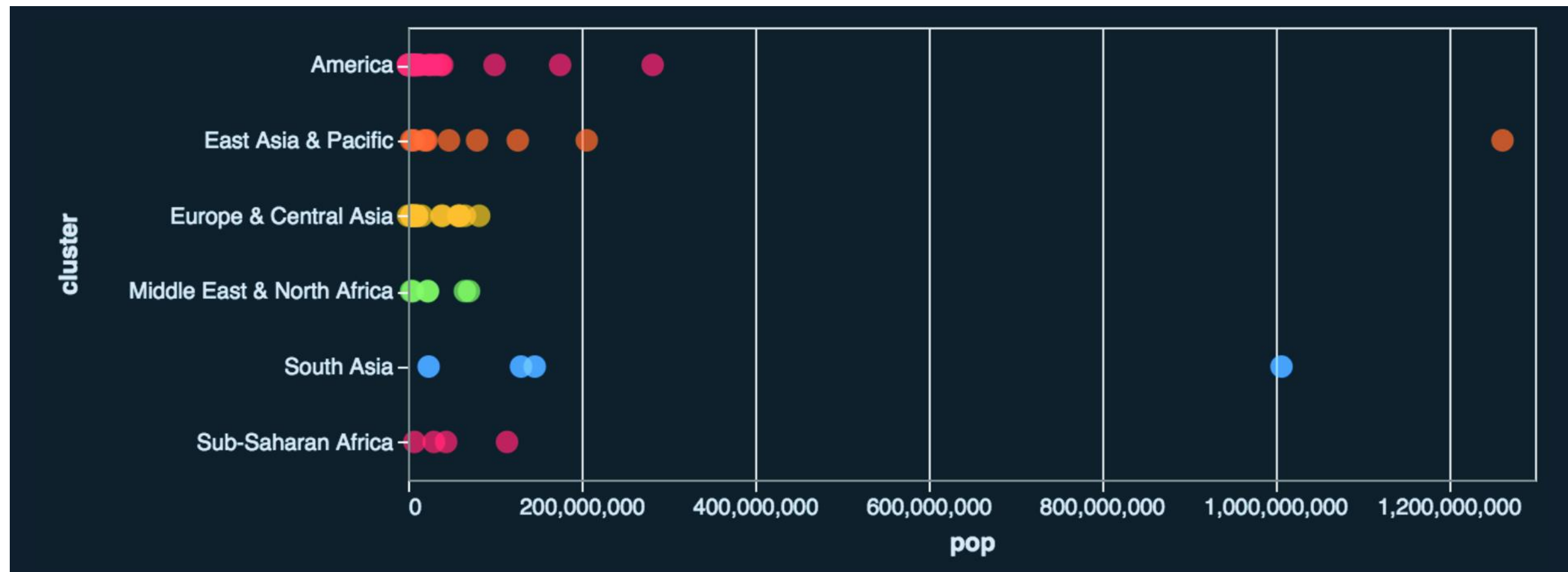


- Truncate the y-axis:
 - If the zero doesn't make sense
 - To emphasize the relative position comparisons
 - If it is the norm (e.g., stock charts)

Outliers

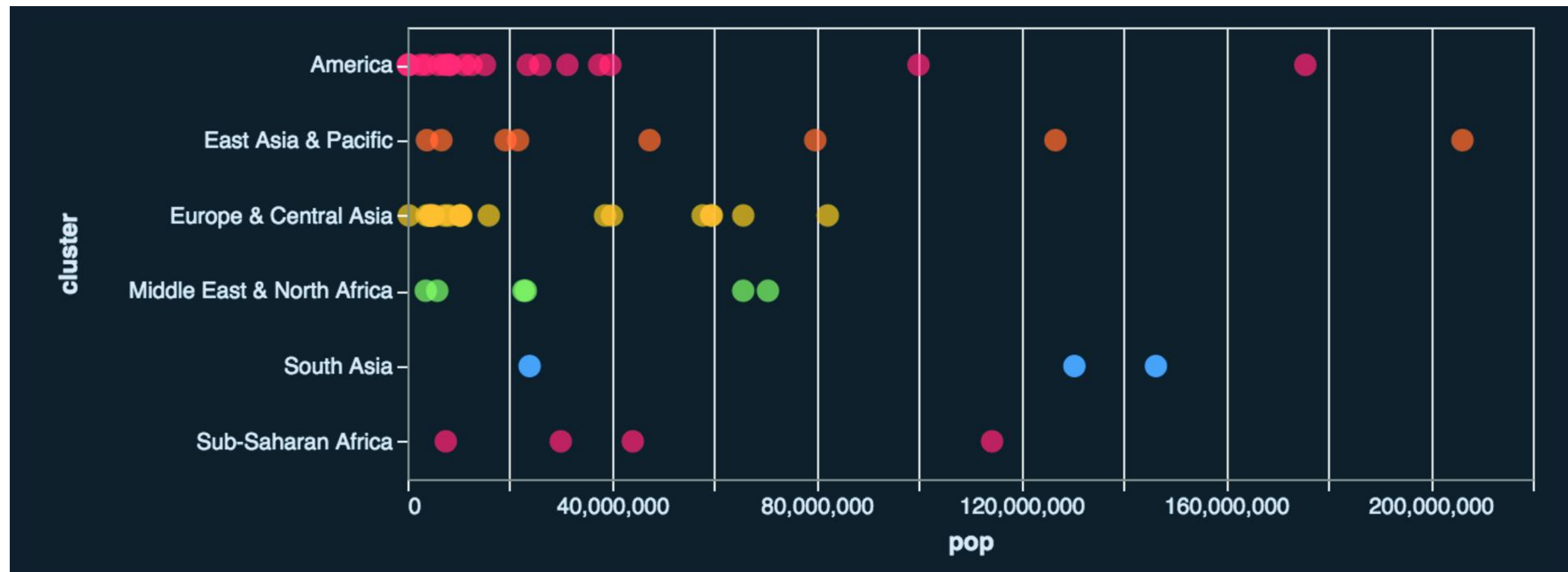
Outliers

- Option #1: Clip them out



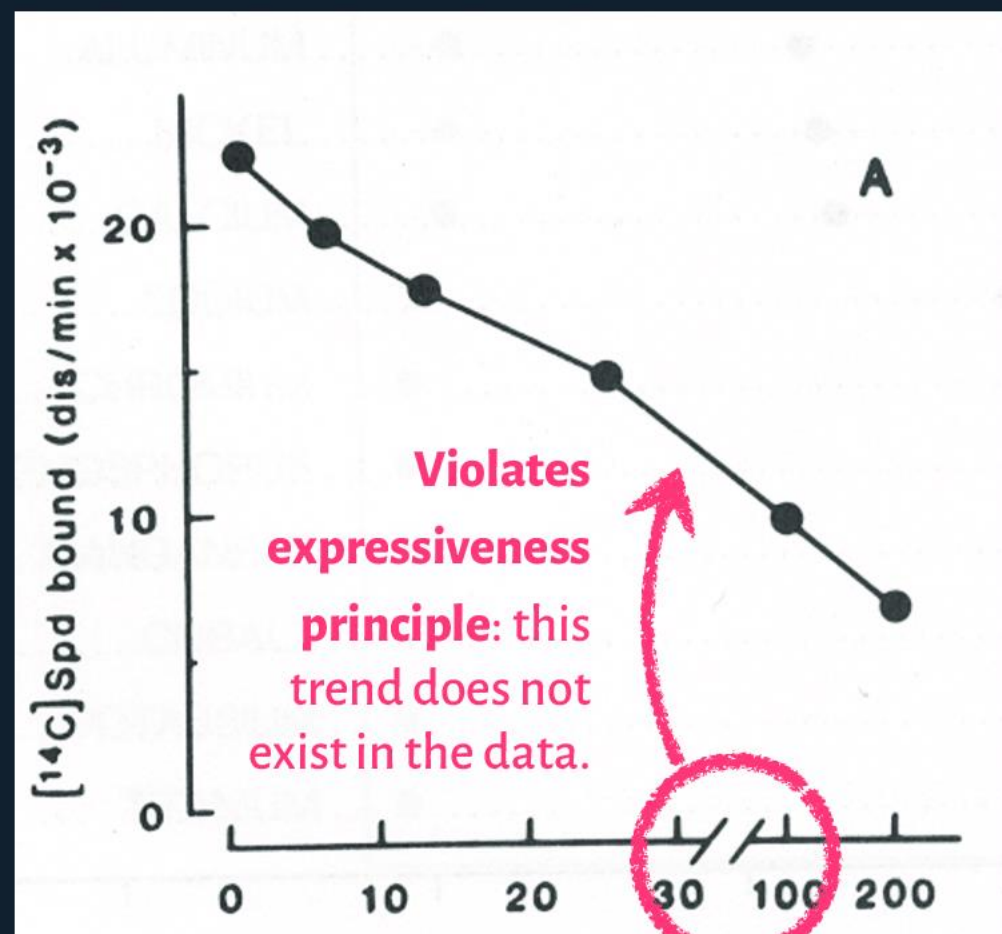
Outliers

- Option #1: Clip them out

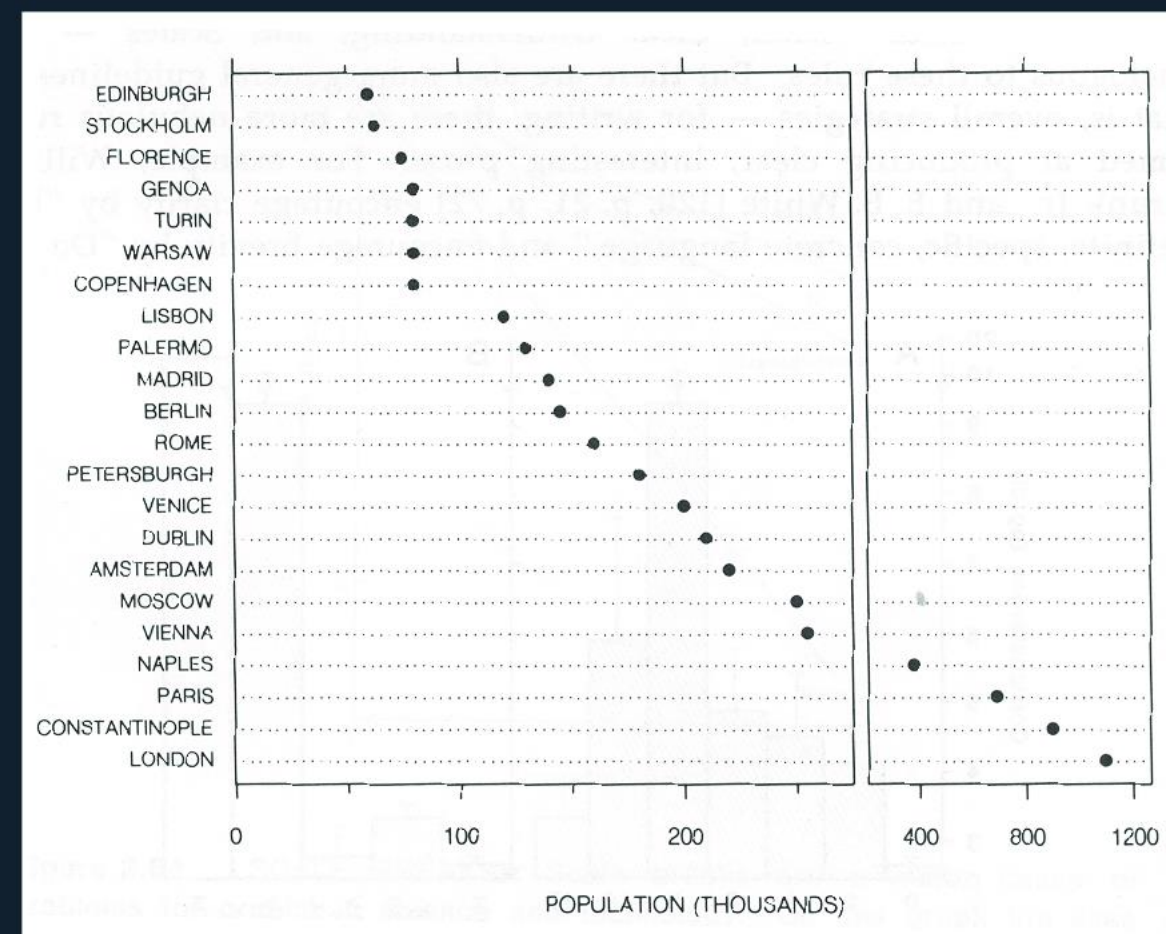


Outliers

- Option #2: Scale Breaks



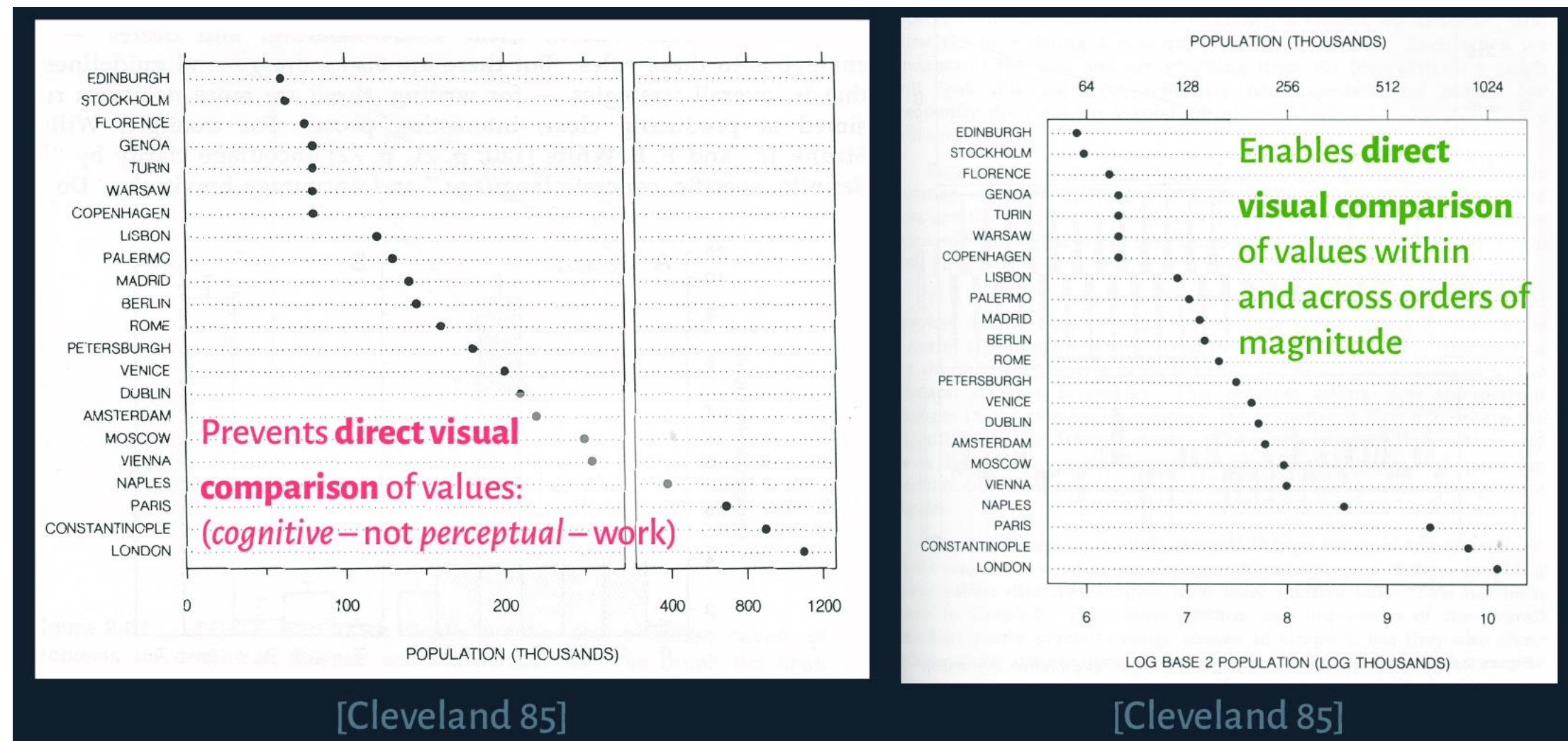
[Cleveland 85]



[Cleveland 85]

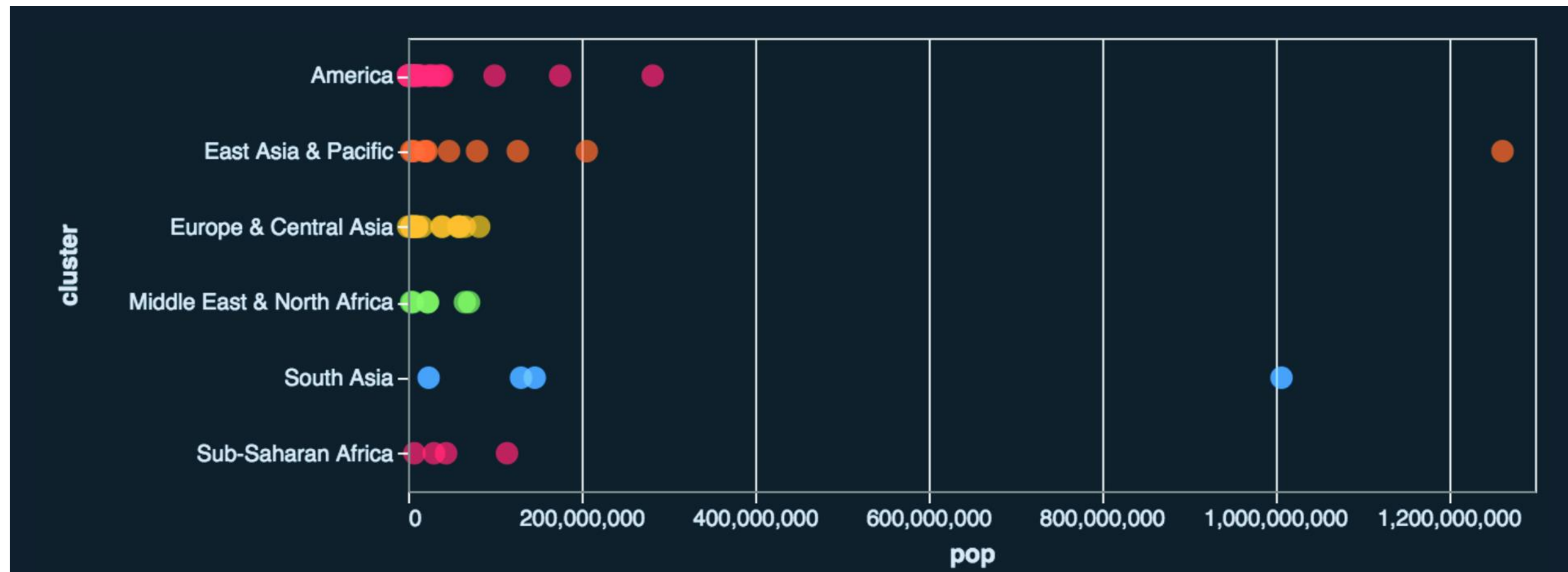
Outliers

- Option #3: Log Scales



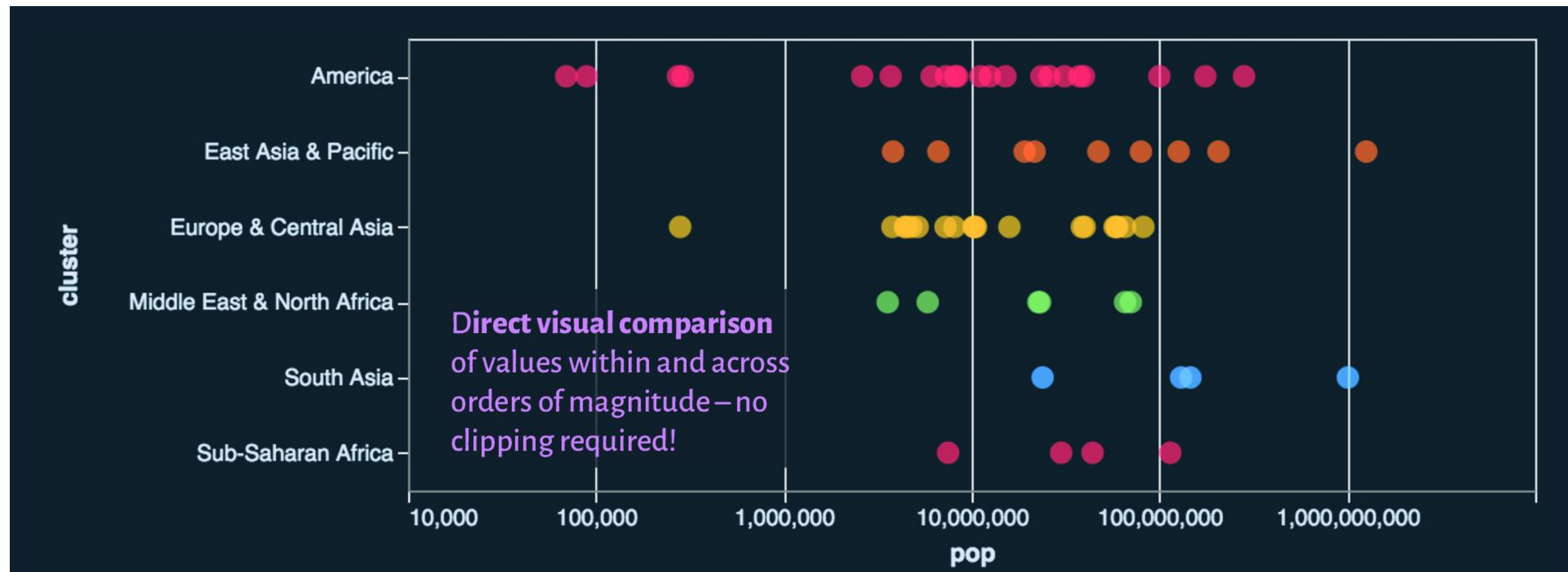
Outliers

- Option #3: Log Scales



Outliers

- Option #3: Log Scales



Outliers

- Option #3: Log Scales

Linear Scale

Absolute change

10 visual units (pixels) = 10 additional data units

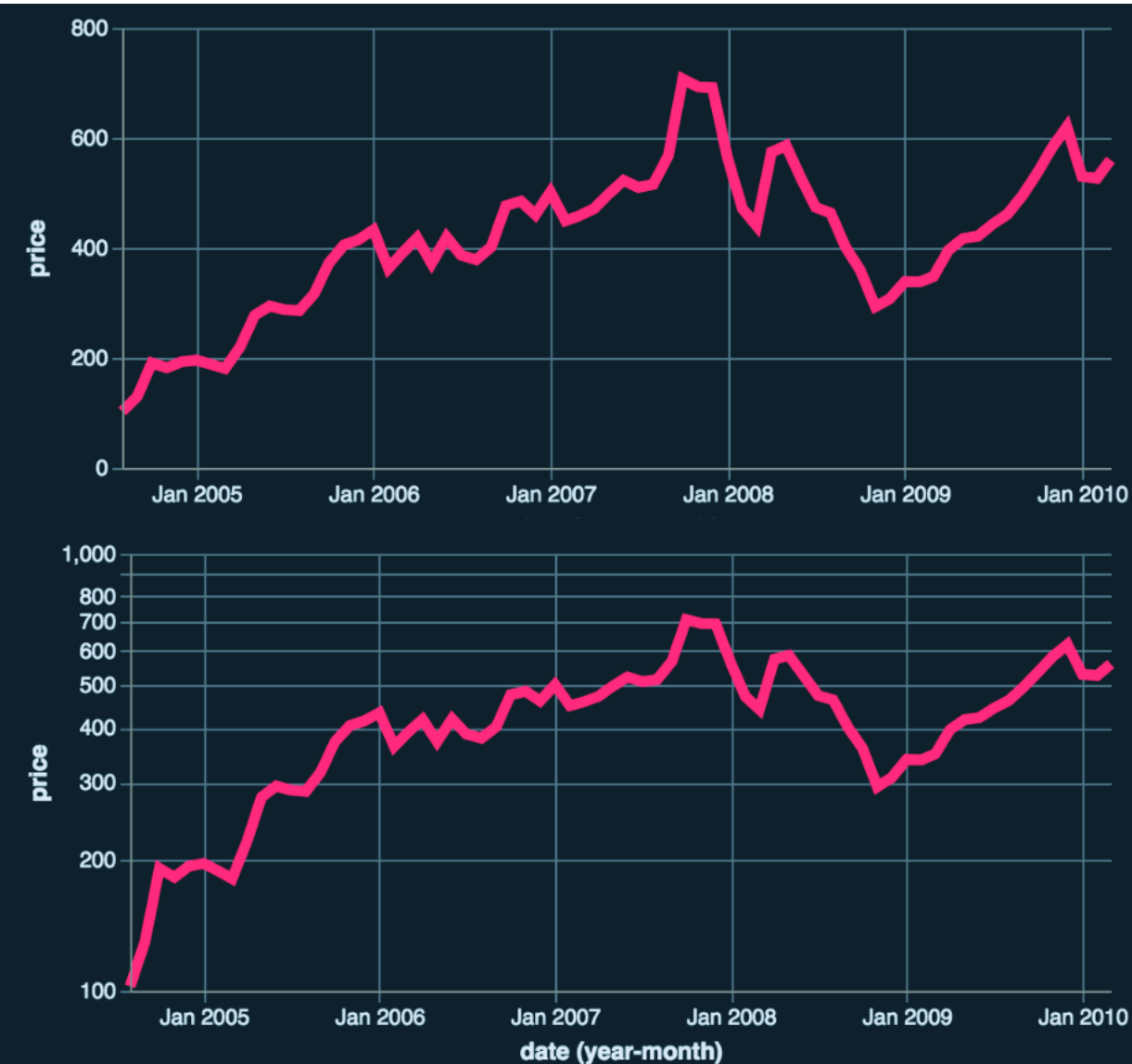
Log Scale

Percentage change

10 visual units = multiplication of 10 data units

$\log(u) + \log(v) = \log(u*v)$

$d(100, 200) = d(300, 600)$



Outliers

- Option #3: Log Scales

Log Scale

Percentage change

10 visual units = multiplication of 10 data units

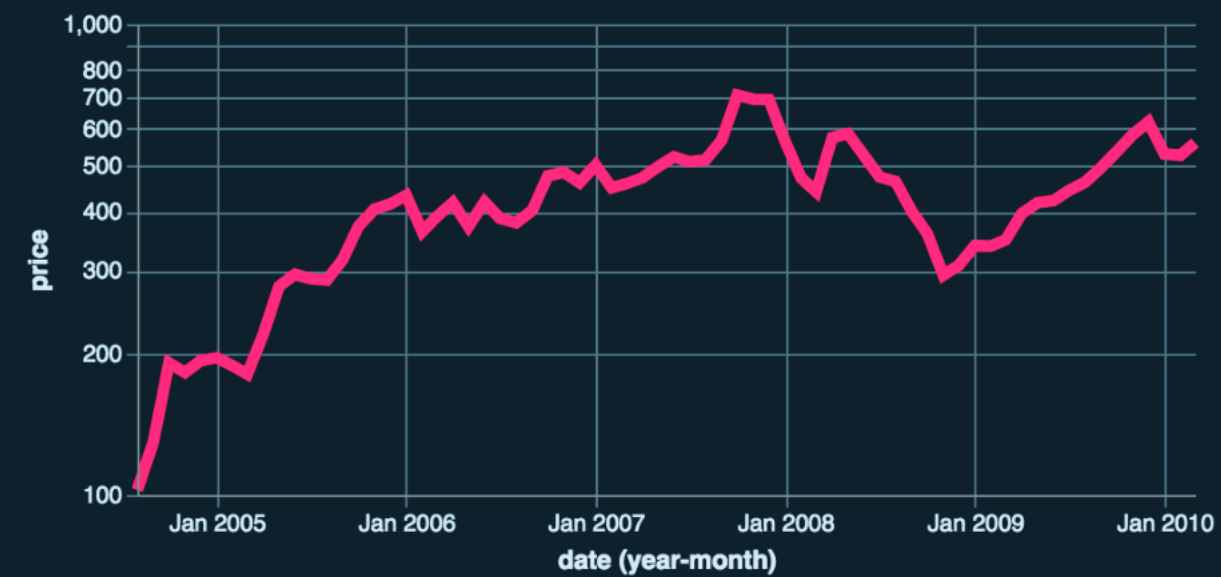
$$\log(u) + \log(v) = \log(u*v)$$

$$d(100, 200) = d(300, 600)$$

Constraints

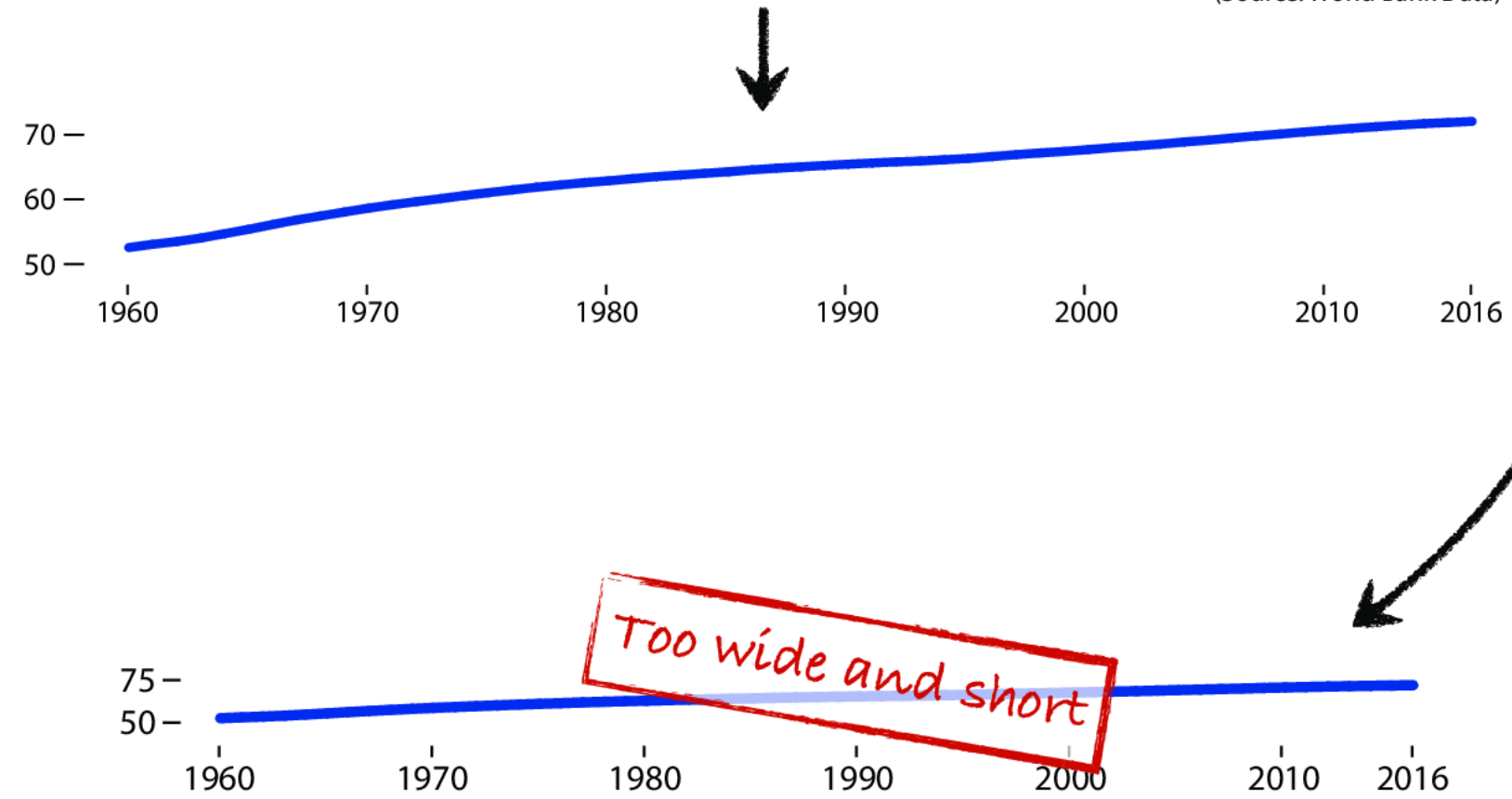
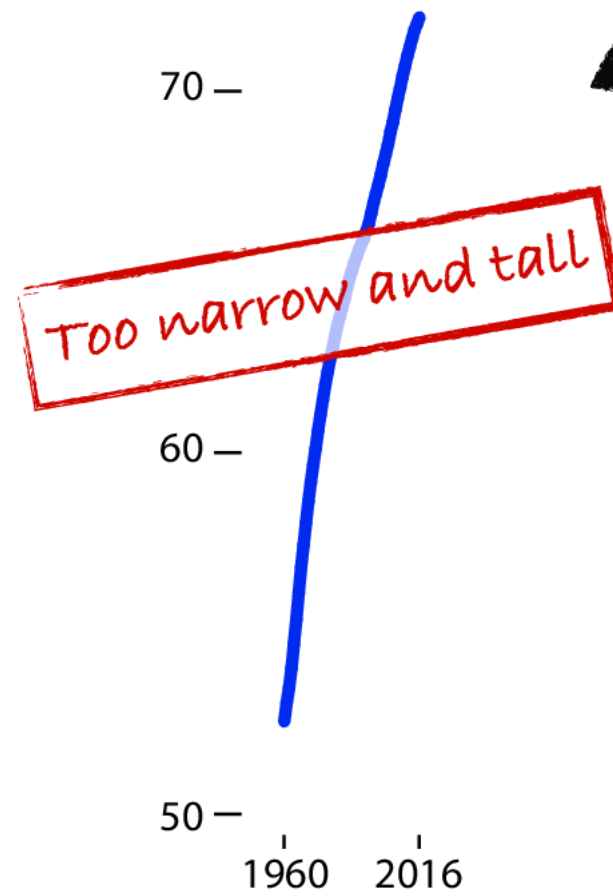
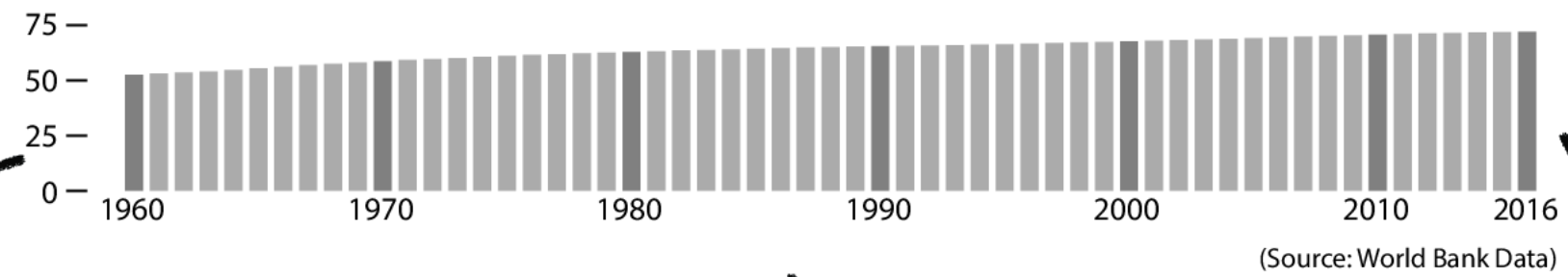
Positive, non-zero values

Audience familiarity?



Aspect Ratio

Average world life expectancy at birth (years)



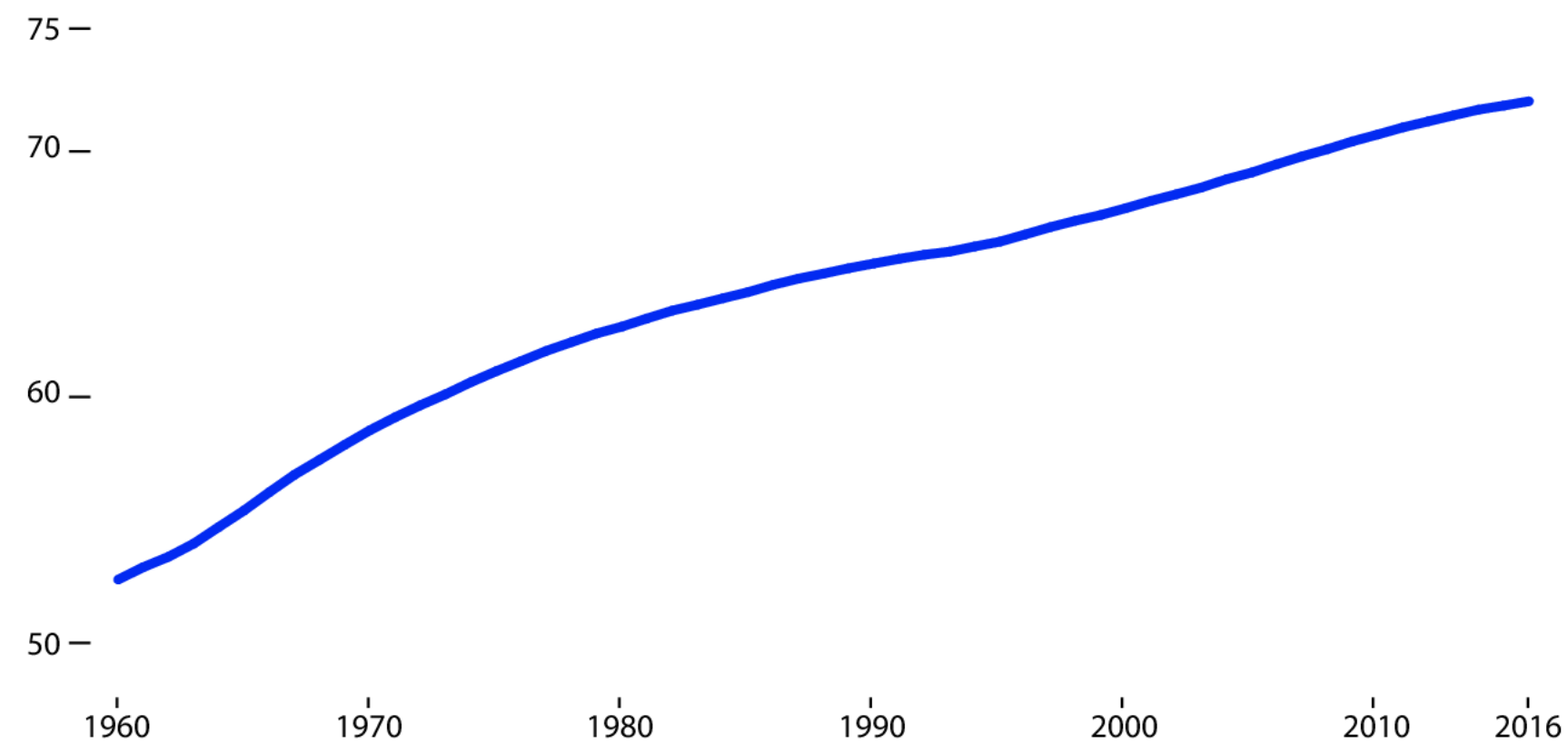
[Alberto Cairo. *How Charts Lie*, 2019]

Aspect Ratio

Approximate the proportion of the chart to match the depicted trend.

35% increase $\approx 1/3$ rd
 $\approx 3:1$ aspect ratio

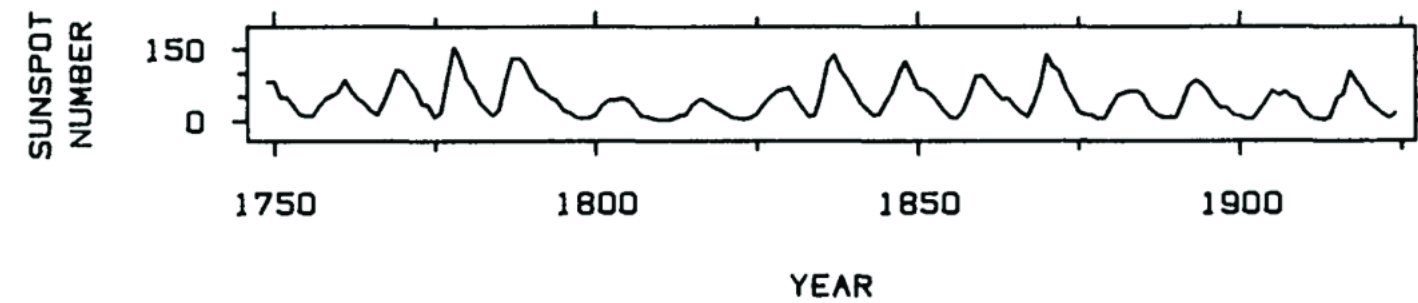
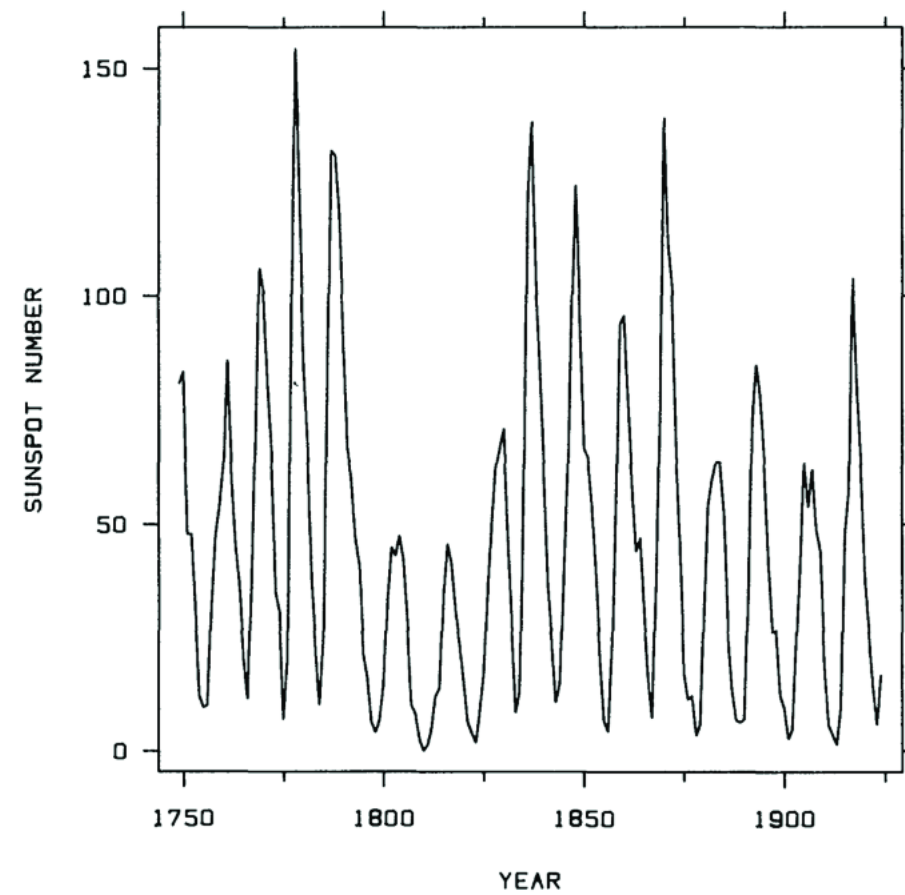
Average world life expectancy at birth (years)



[Alberto Cairo. *How Charts Lie*, 2019]

Aspect Ratio

Approximate the proportion of the chart to match the depicted trend.

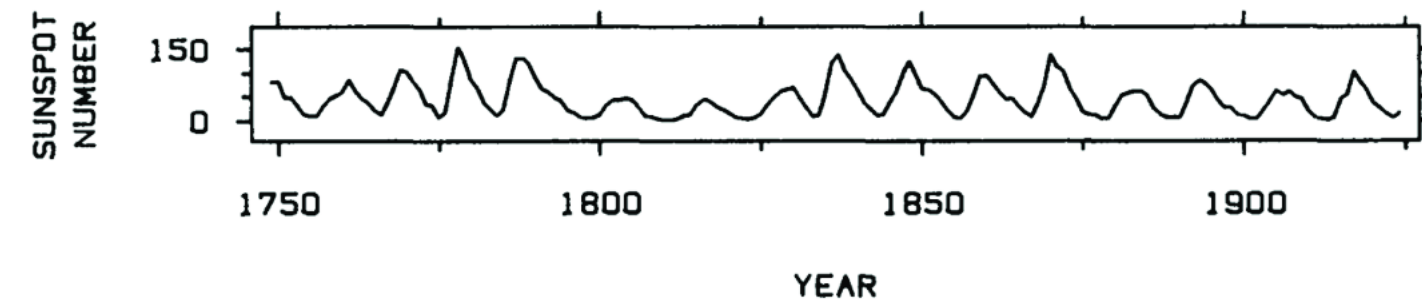
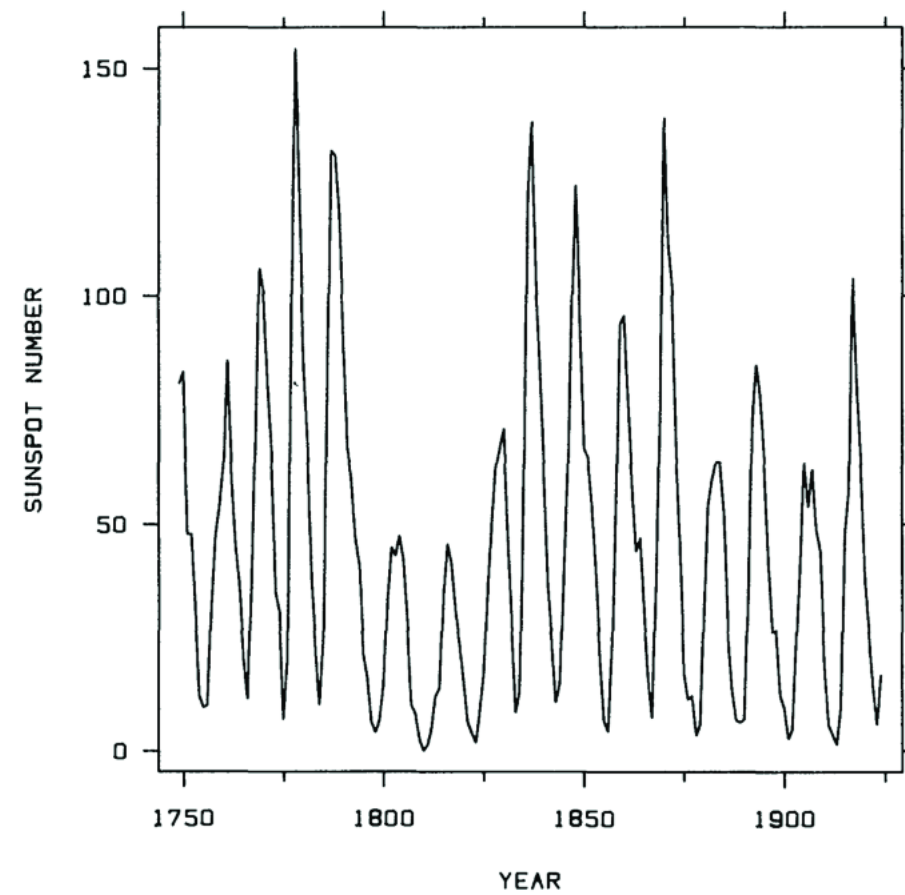


[Cleveland & McGill, 1987]

Aspect Ratio

(1) Approximate proportion of the chart to match the depicted trend.

(2) *Bank to 45°*: aspect ratios with 45° avg. line segment orientation.

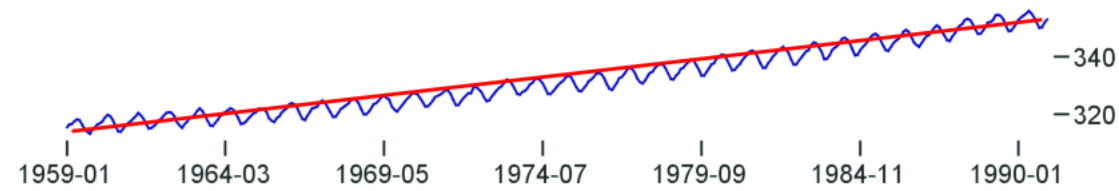


[Cleveland & McGill, 1987]

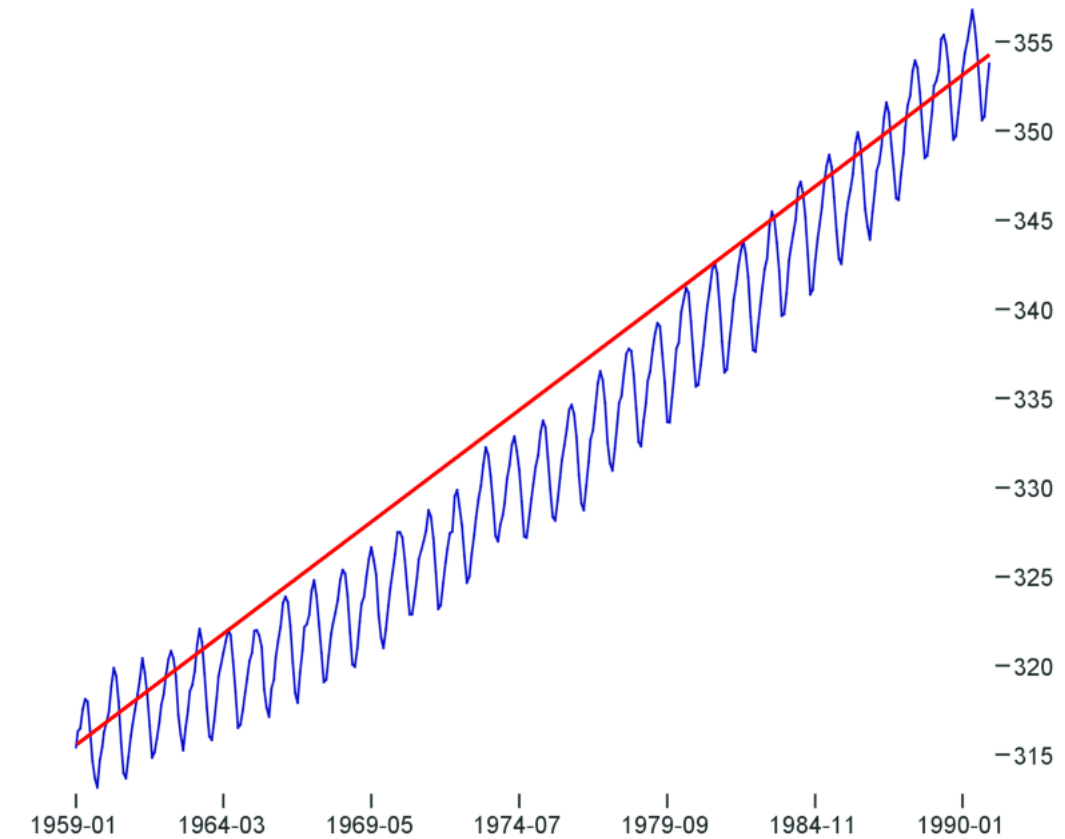
Aspect Ratio

(1) Approximate proportion of the chart to match the depicted trend.

(2) *Bank to 45°*: aspect ratios with 45° avg. line segment orientation.



Aspect ratio = 7.87

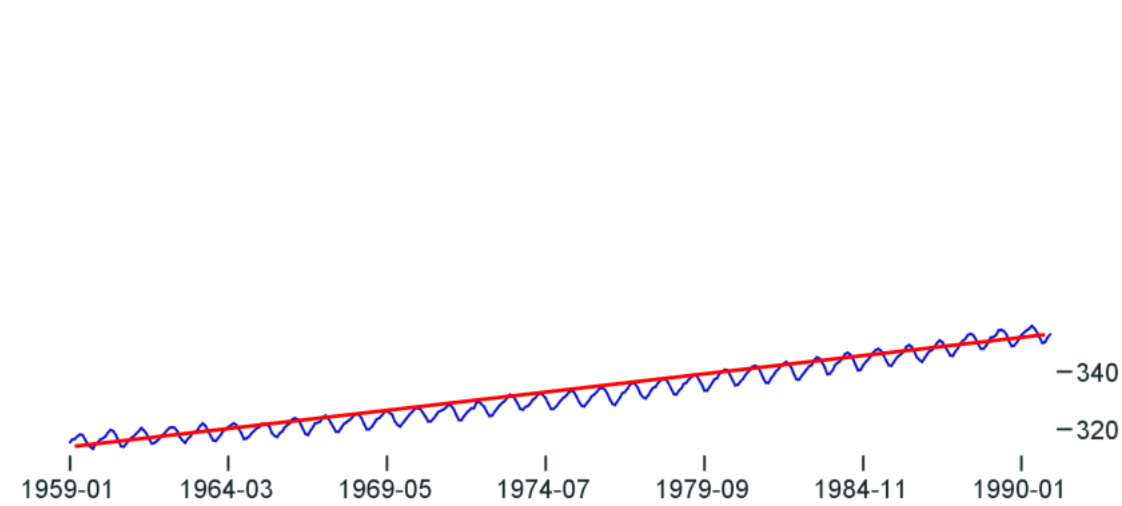


Aspect ratio = 1.17

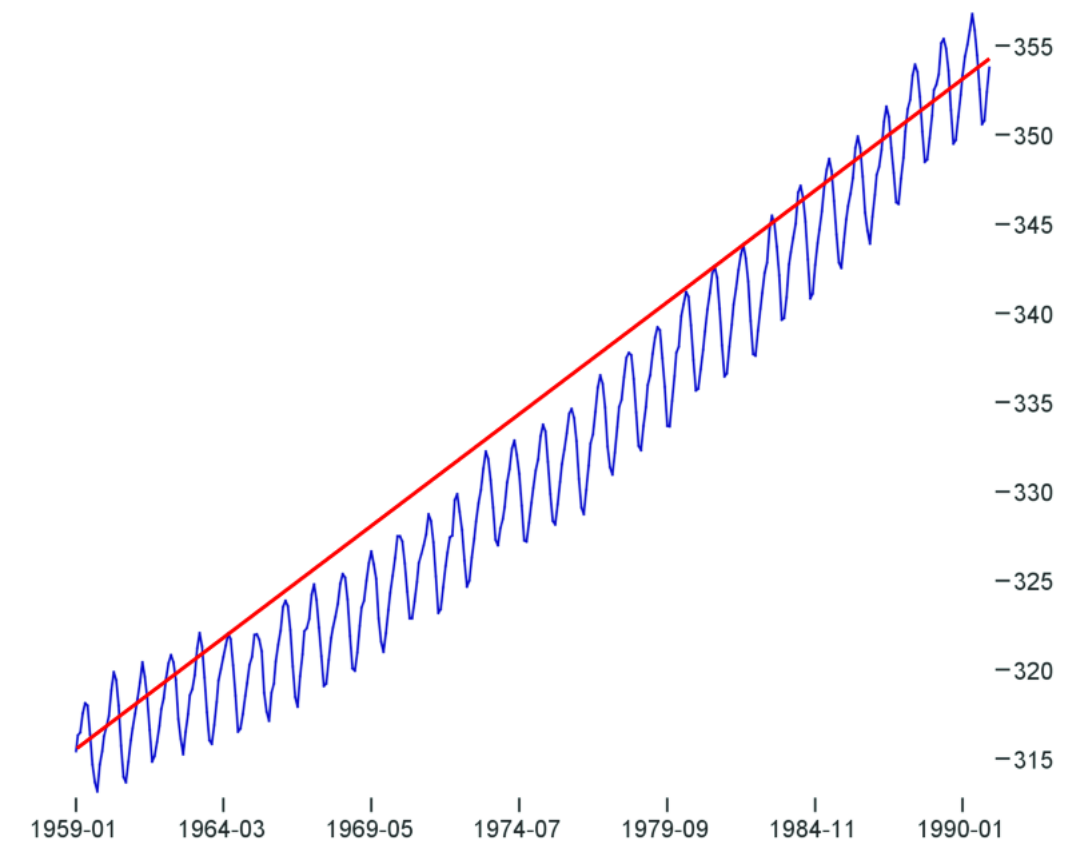
[Heer & Agrawala, 2006]

Aspect Ratio

- (1) Approximate proportion of the chart to match the depicted trend.
- (2) *Bank to 45°*: original data **or** fitted trend lines.



Aspect ratio = 7.87



Aspect ratio = 1.17

[Heer & Agrawala, 2006]

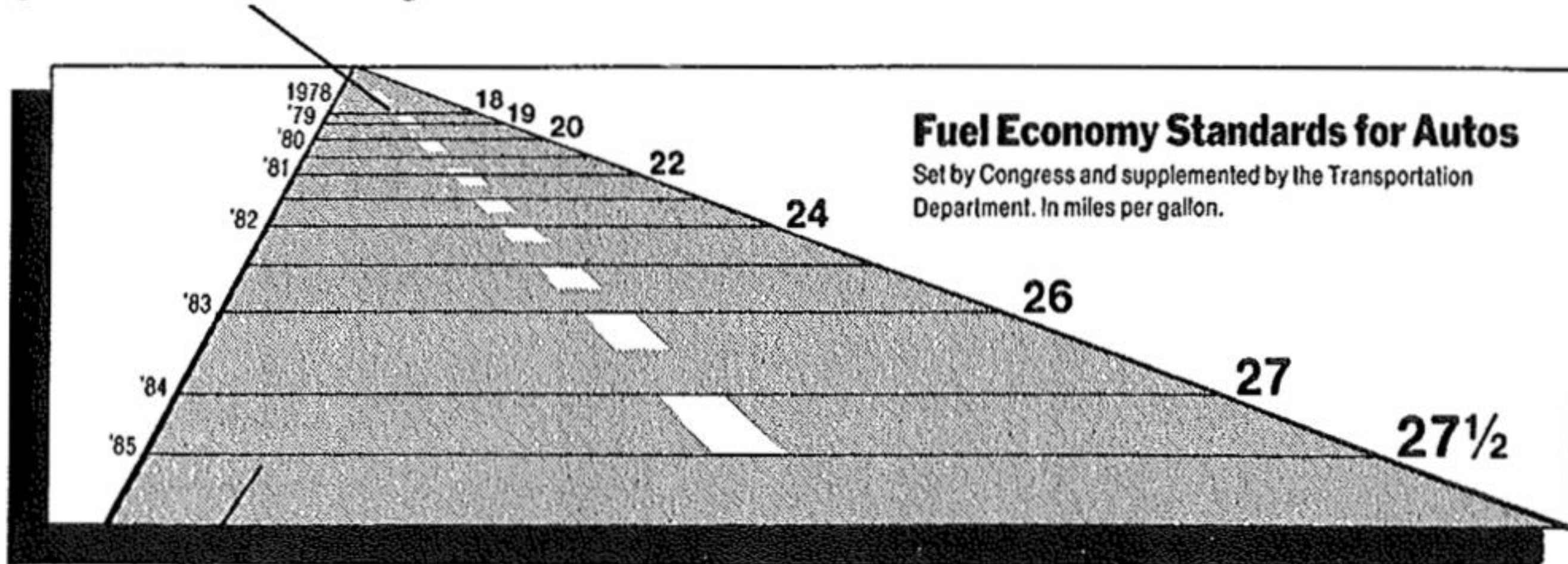
Tufte's integrity principles

- the representation of numbers, as physically measured on the surface of the graphic itself, should be directly proportional to the numerical quantities represented.

$$\text{The Lie Factor} = \frac{\text{size of effect shown in graphic}}{\text{size of effect in data}}$$

DISTORTION

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

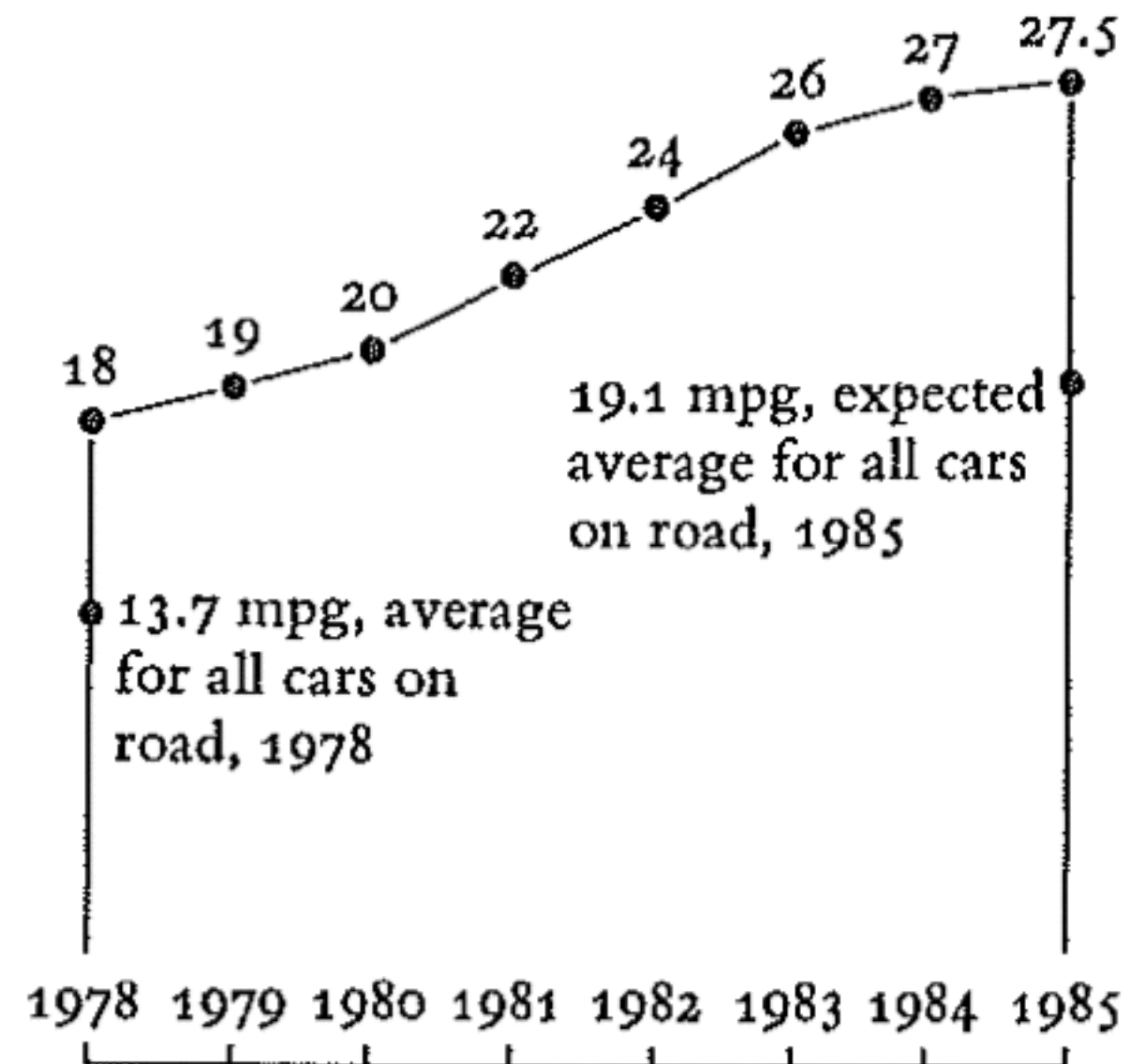


This line, representing 27.5 miles per gallon in 1985, is 5.3 inches long.

Lie factor for the percent increase from 1978 to 1985

$$\Rightarrow \frac{\frac{5.3}{0.6}}{\frac{27.5}{18}} = \frac{8.83}{1.53} = 5.8$$

REQUIRED FUEL ECONOMY STANDARDS:
NEW CARS BUILT FROM 1978 TO 1985



D = 2.0, A = PI
D = 1.6, A = 0.65*PI

Area Ratio = 0.65 (67%/43.5%)
Diameter Ratio = 0.8 (67%/53.6%)

D = 1.05, A = 0.28*PI
D = 0.8, A = 0.16*PI

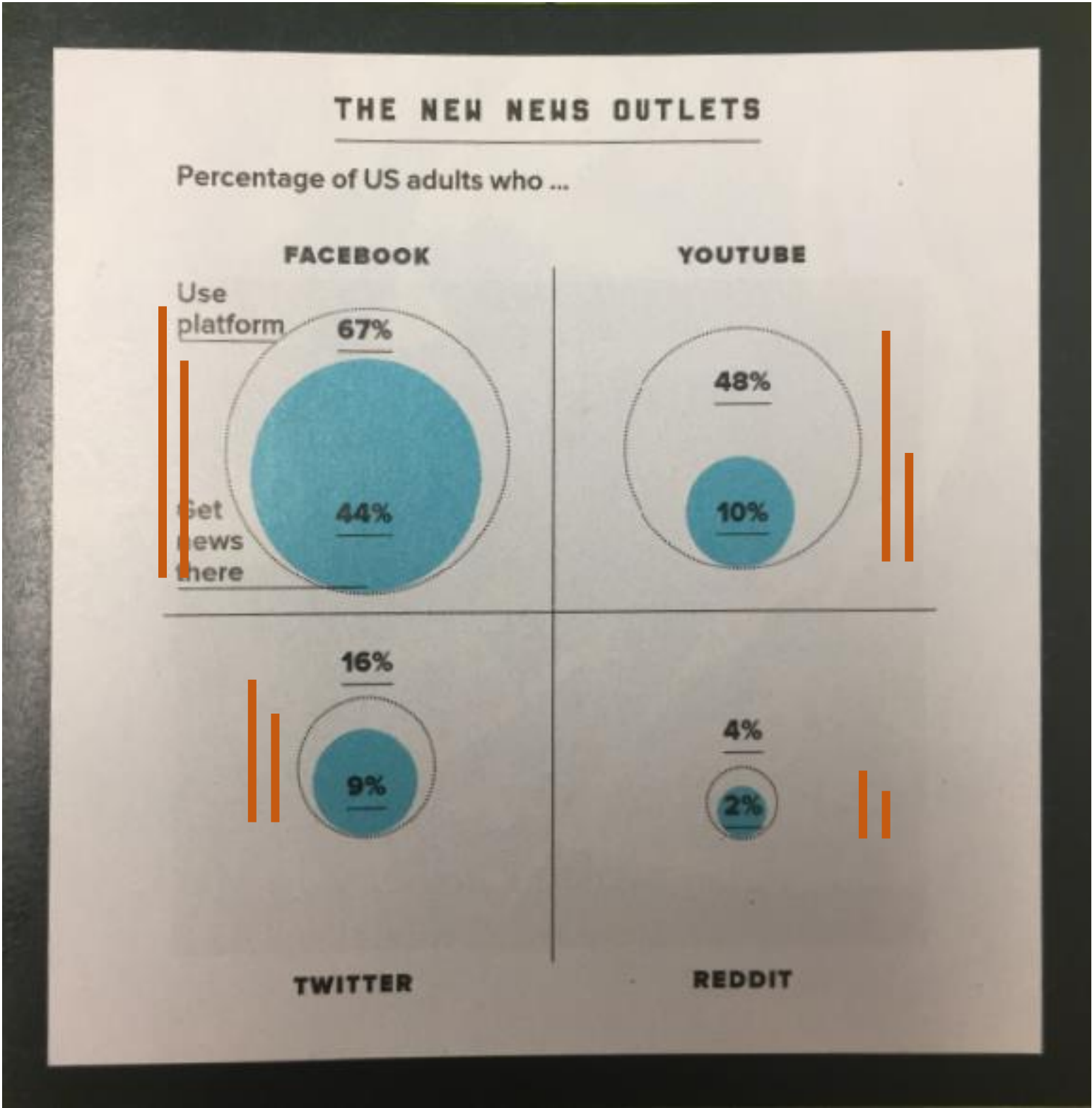
Area Ratio = 0.57 (16%/9.1%)
Diameter Ratio = 0.76 (16%/12.1%)

D = 1.7, A = 0.73*PI
D = 0.8, A = 0.16*PI

Area Ratio = 0.21 (48%/10.1%)
Diameter Ratio = 0.47 (48%/22.6%)

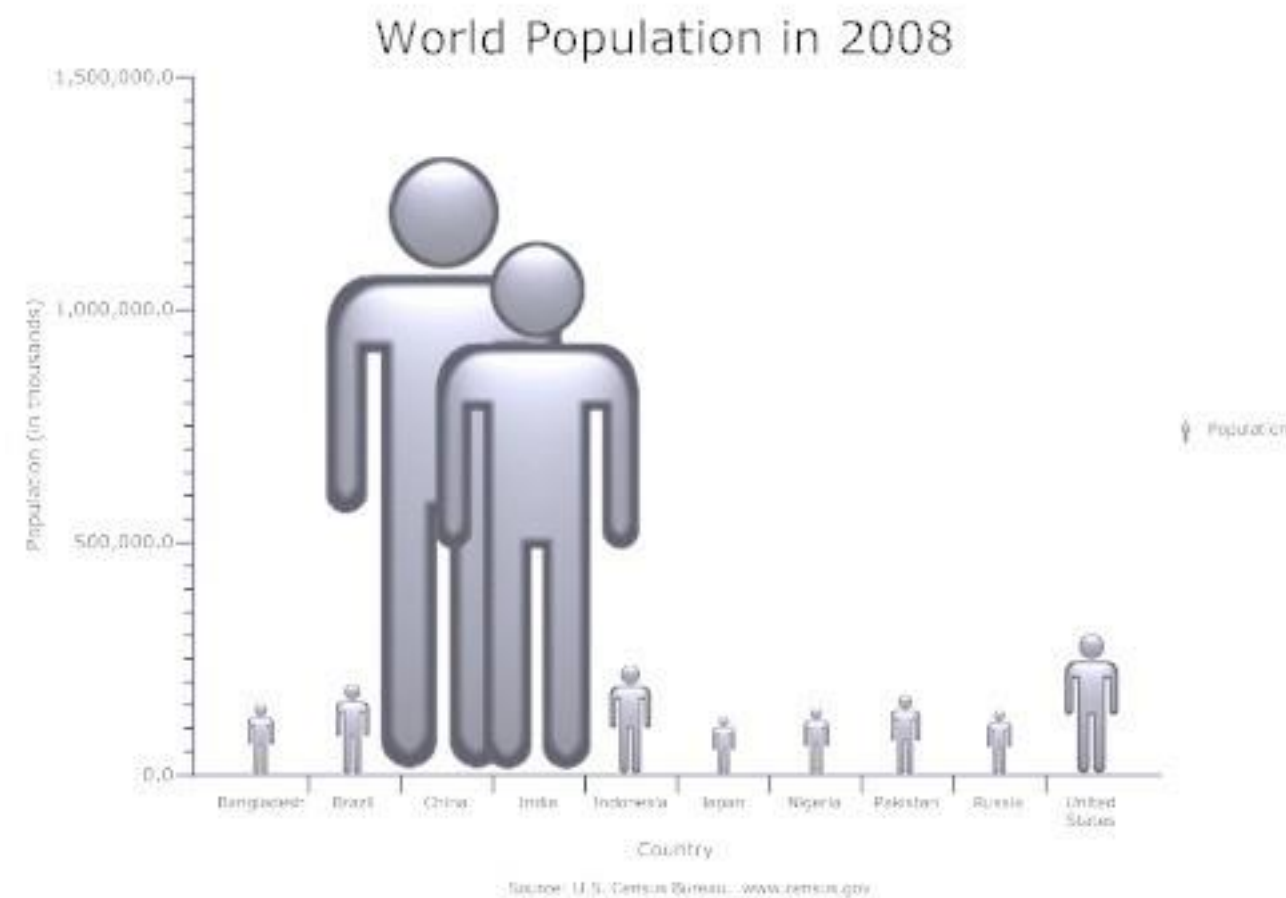
D = 0.5, A = 0.06*PI
D = 0.35, A = 0.03*PI

Area Ratio = 0.5 (4%/2%)
Diameter Ratio = 0.7 (4%/2.8%)

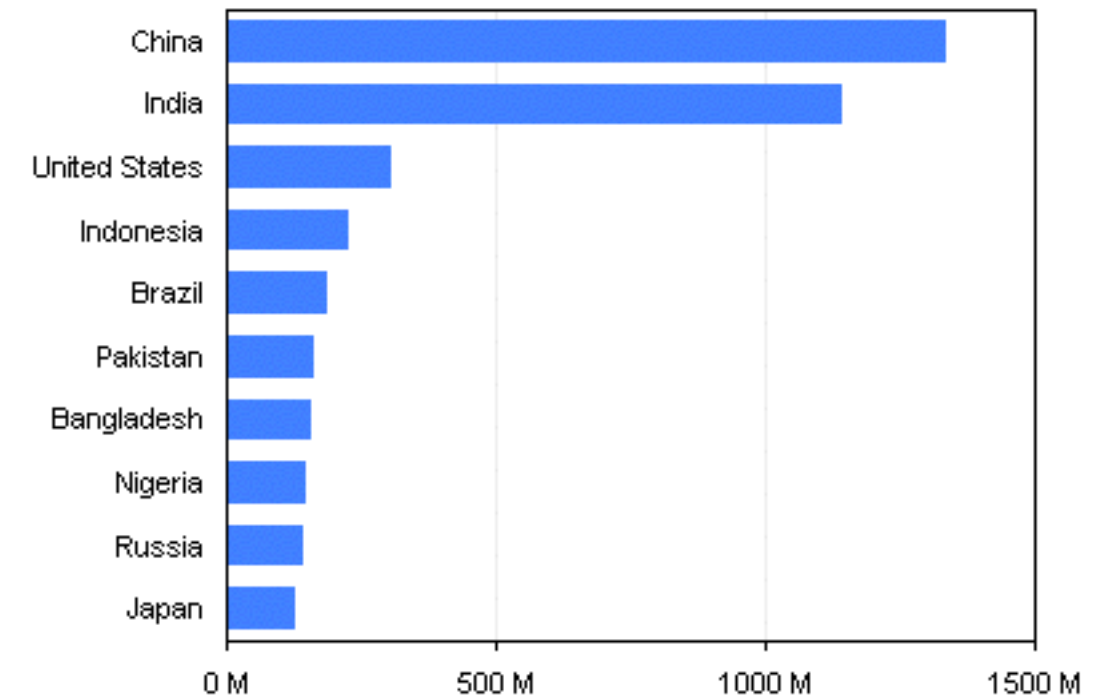
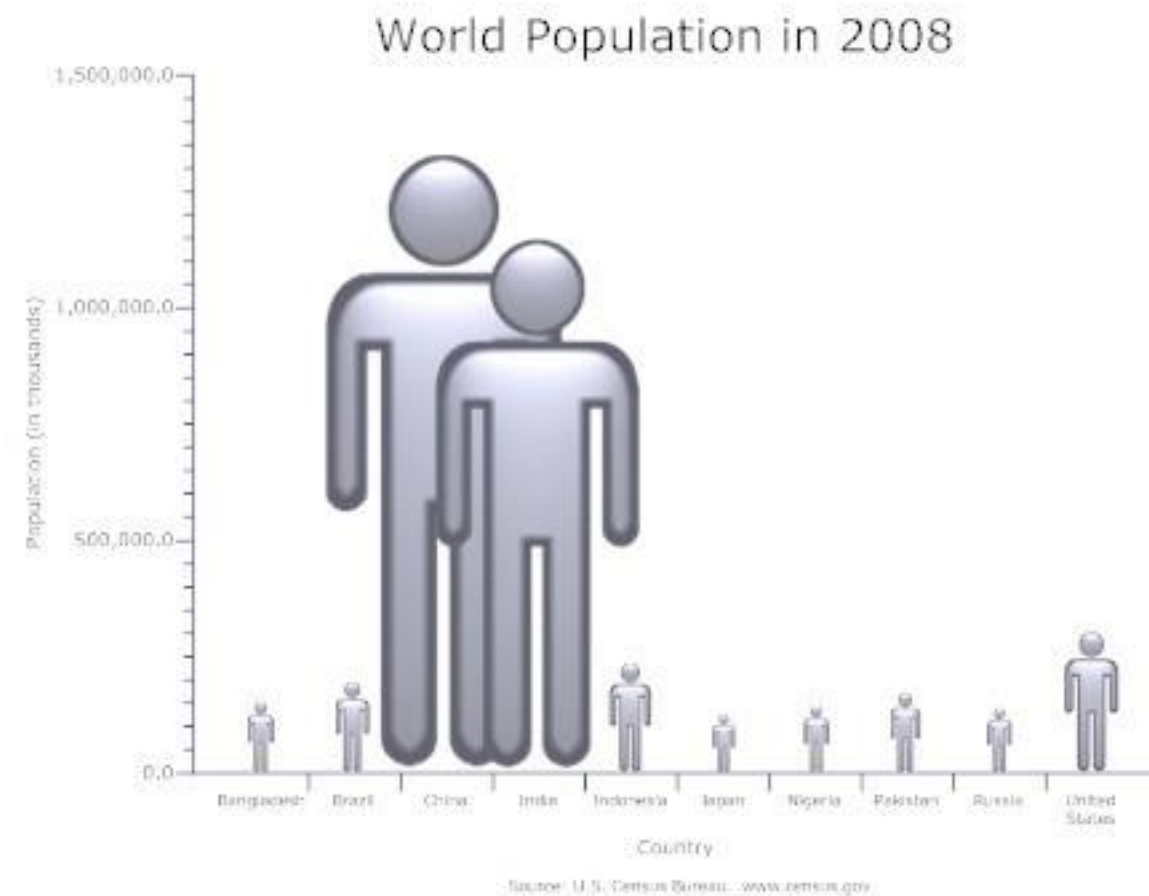


Tufte's integrity principles
show *data* variation, not *design*
variation

UNINTENDED SIZE CODING



UNINTENDED SIZE CODING

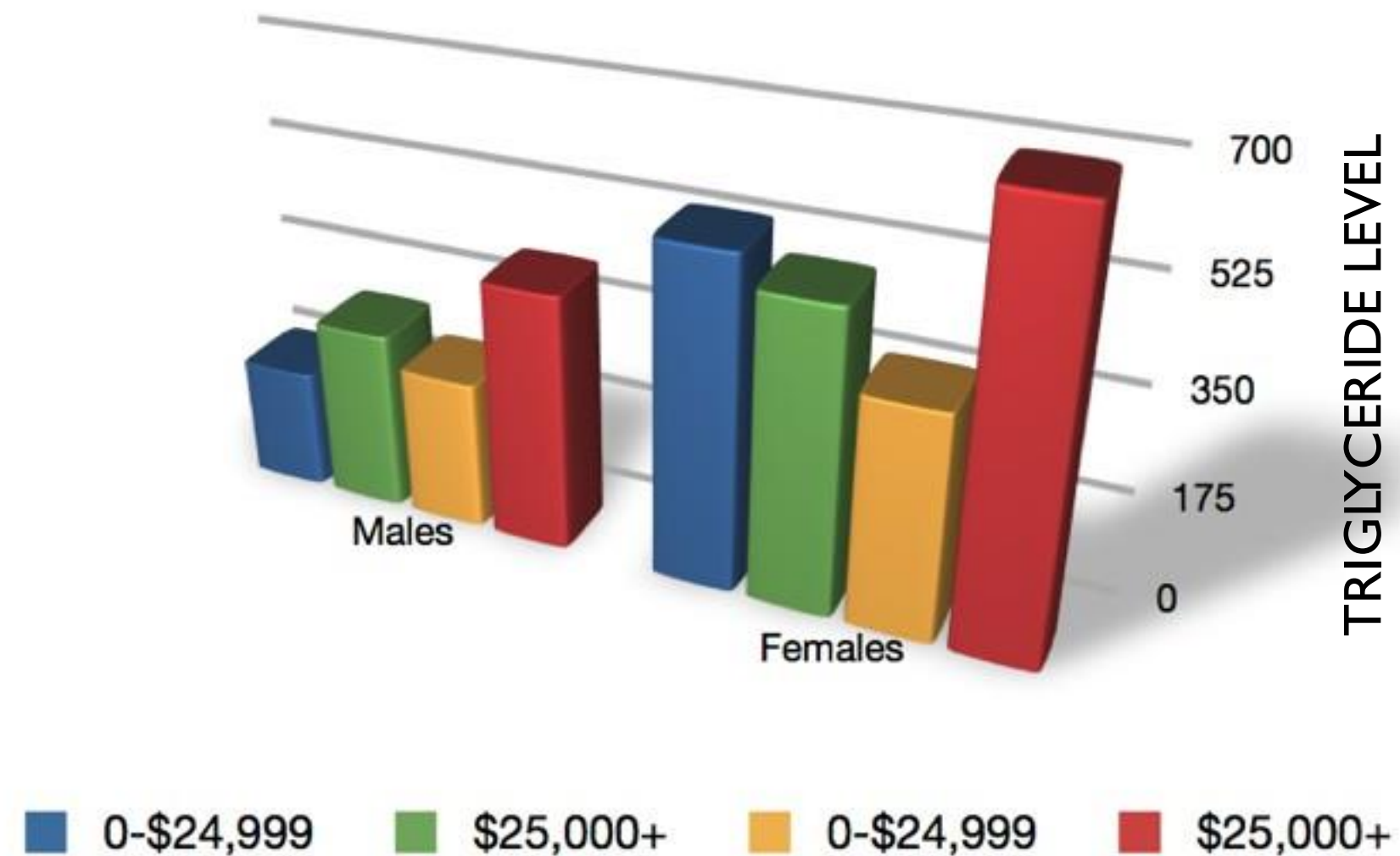


DESIGN PRINCIPLES

(or how to achieve integrity and
excellence)

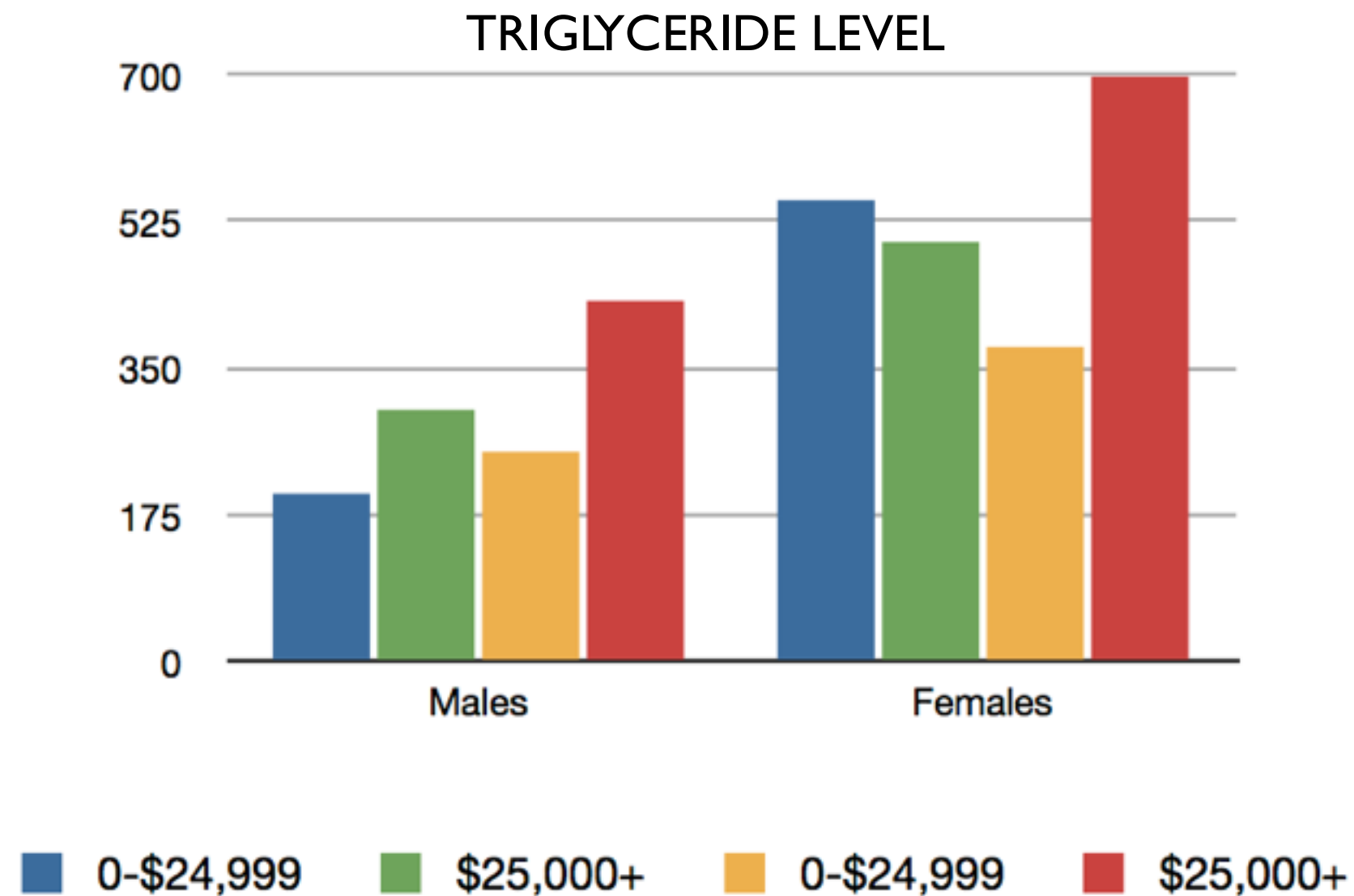
maximize the

$$\text{Data-ink Ratio} = \frac{\text{data-ink}}{\text{total ink used in graphic}}$$



maximize the

$$\text{Data-ink Ratio} = \frac{\text{data-ink}}{\text{total ink used in graphic}}$$

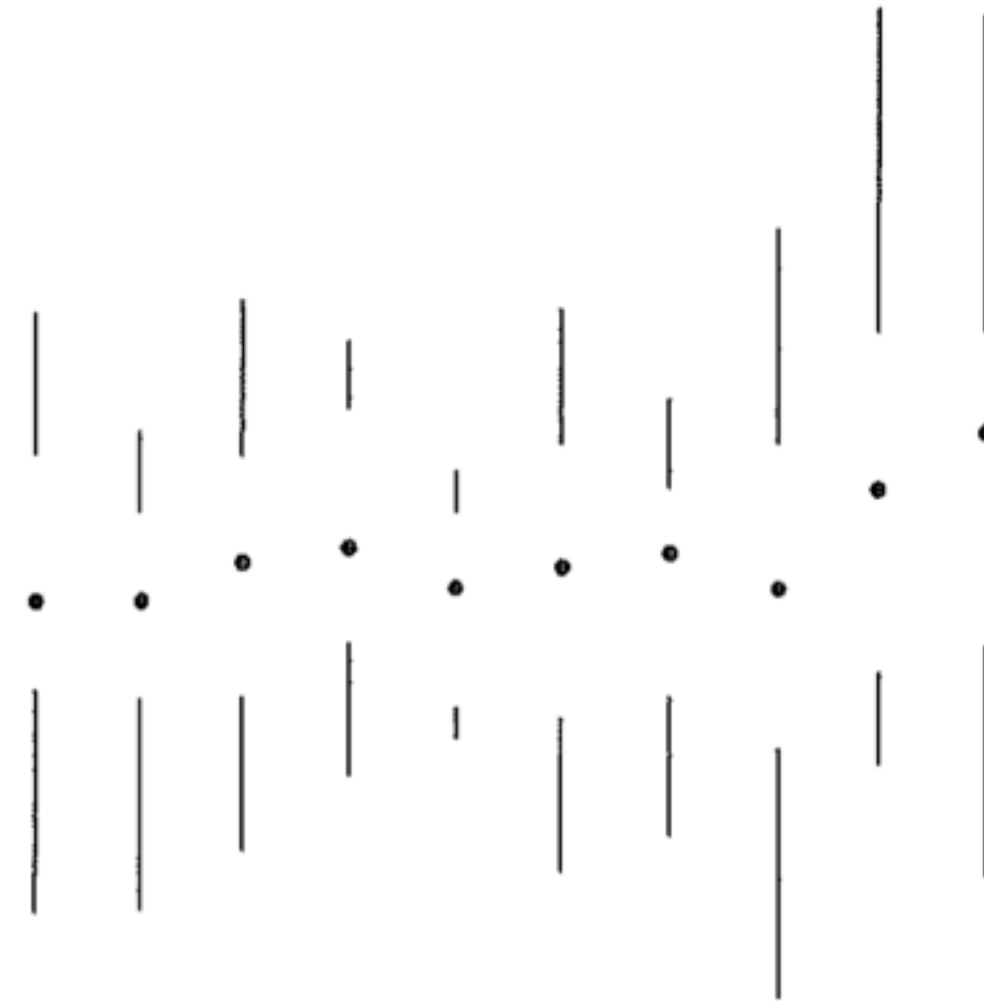
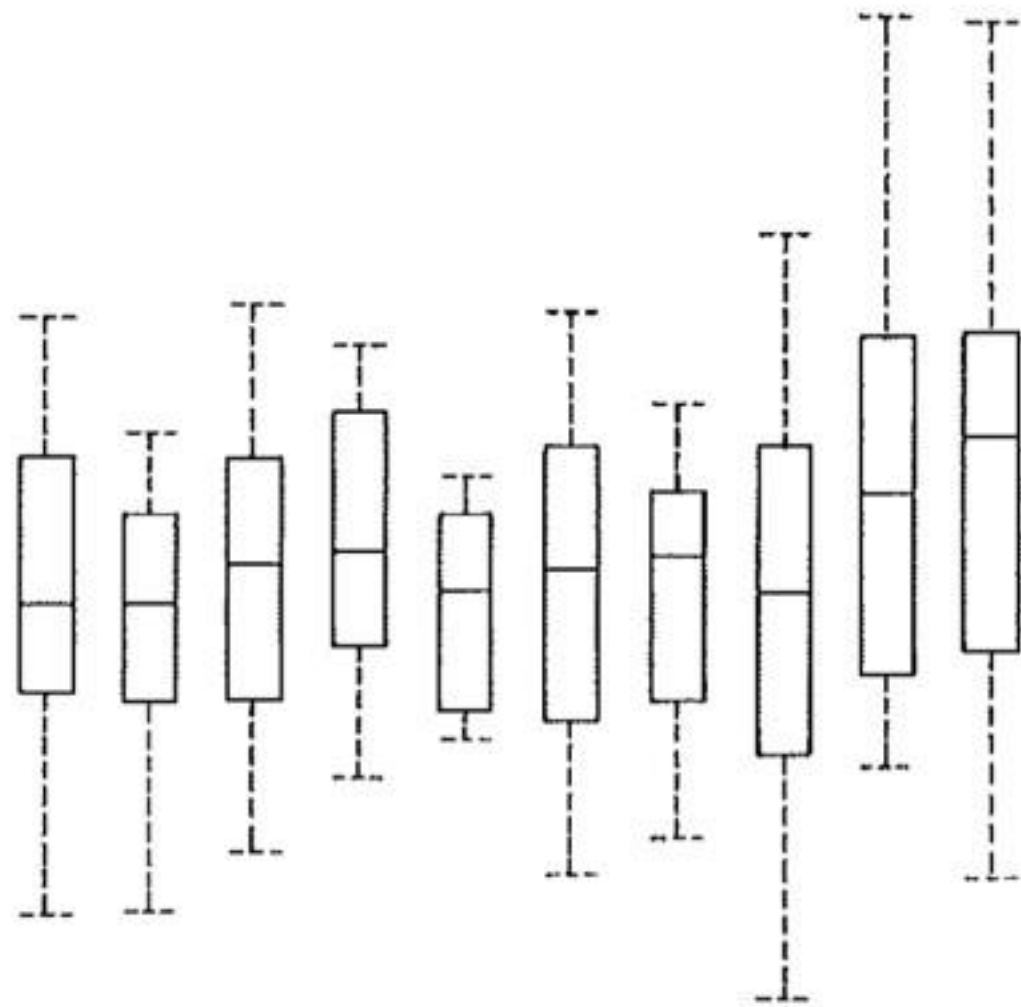


maximize the

Data-ink Ratio =

data-ink

total ink used in graphic



A User Study of Visualization Effectiveness Using EEG and Cognitive Load

E. W. Anderson¹, K. C. Potter¹, L. E. Matzen², J. F. Shepherd², G. A. Preston³, and C. T. Silva¹

¹SCI Institute, University of Utah, USA

²Sandia National Laboratories, USA

³Utah State Hospital, USA

Abstract

Effectively evaluating visualization techniques is a difficult task often assessed through feedback from user studies and expert evaluations. This work presents an alternative approach to visualization evaluation in which brain

COUNTER-POINT

information is processed to provide insight into the cognitive load imposed on the viewer. This paper describes the design of the user study performed, the extraction of cognitive load measures from EEG data, and how those measures are used to quantitatively evaluate the effectiveness of visualizations.

Categories and Subject Descriptors (according to ACM CCS): I.3.3 [Computer Graphics]: General—Human Factors, Evaluation, Electroencephalography

1. Introduction

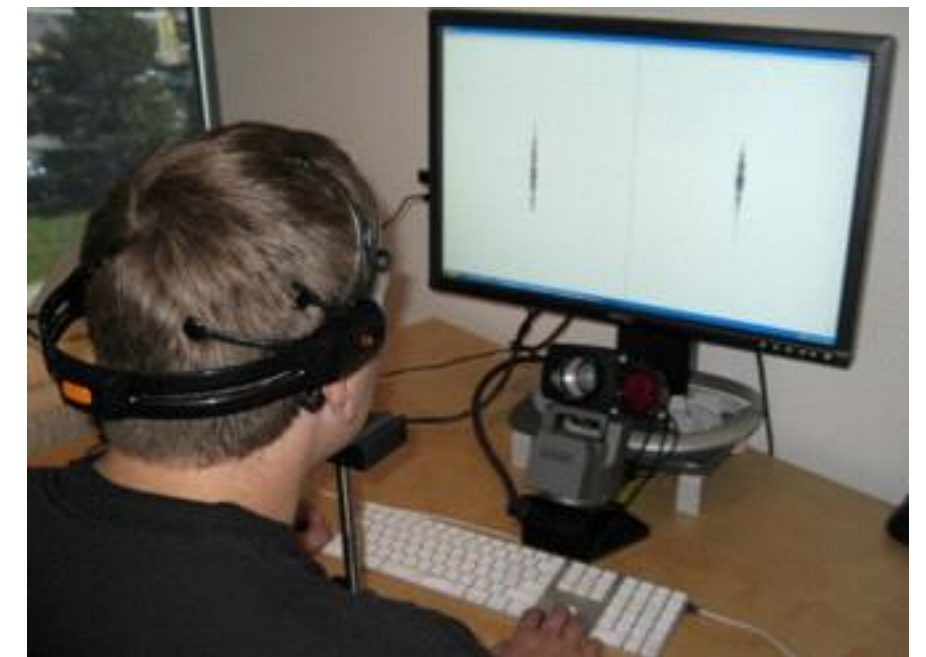
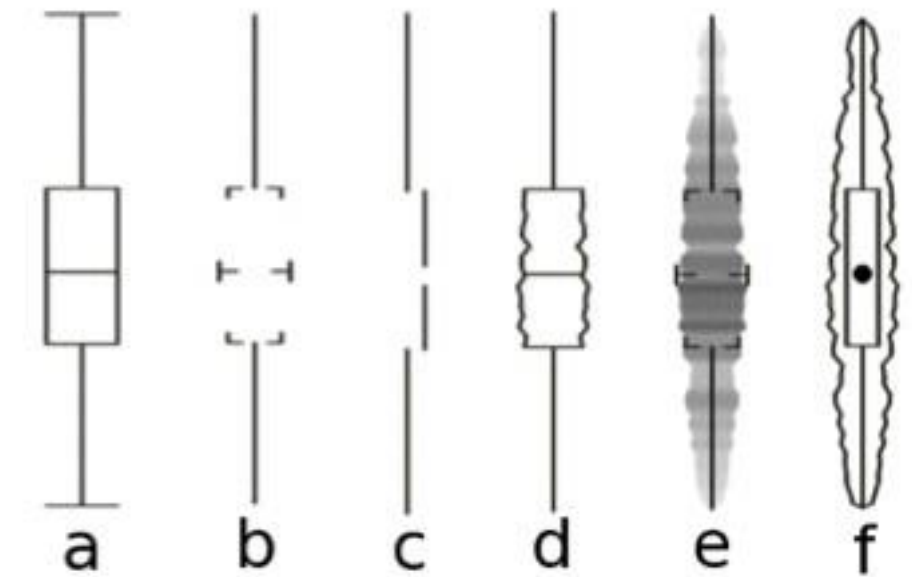
Efficient visualizations facilitate the understanding of data sets through an appropriate choice of visual metaphor.

this paper strives to evaluate visualization techniques objectively by using passive, non-invasive monitoring devices to measure the burden placed on a user's cognitive resources.



EXPERIMENT

- asked participants to choose box plot with largest range from a set
- varied representation
- measured cognitive load from EEG brain waves



EXPERIMENTAL RESULTS

- studies showed that the simplest (highest data-ink ratio) box plot is hardest to interpret
- paper focused on cognitive load as an evaluation method

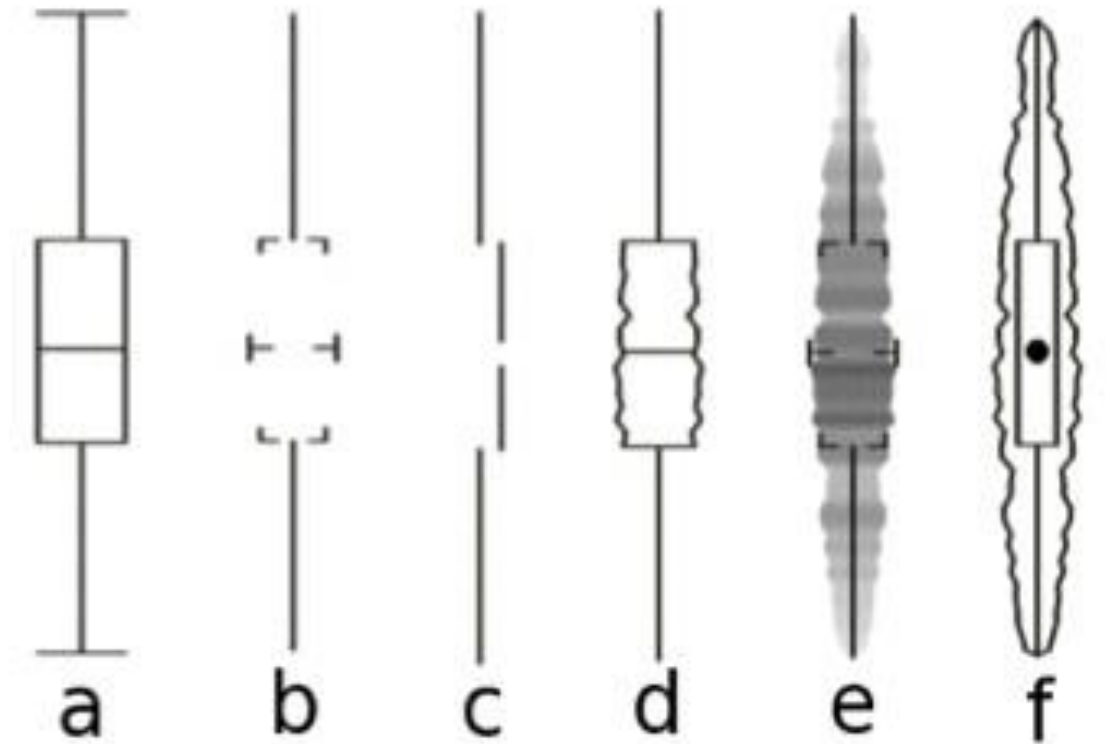


Chart Junk: attraction or distraction?

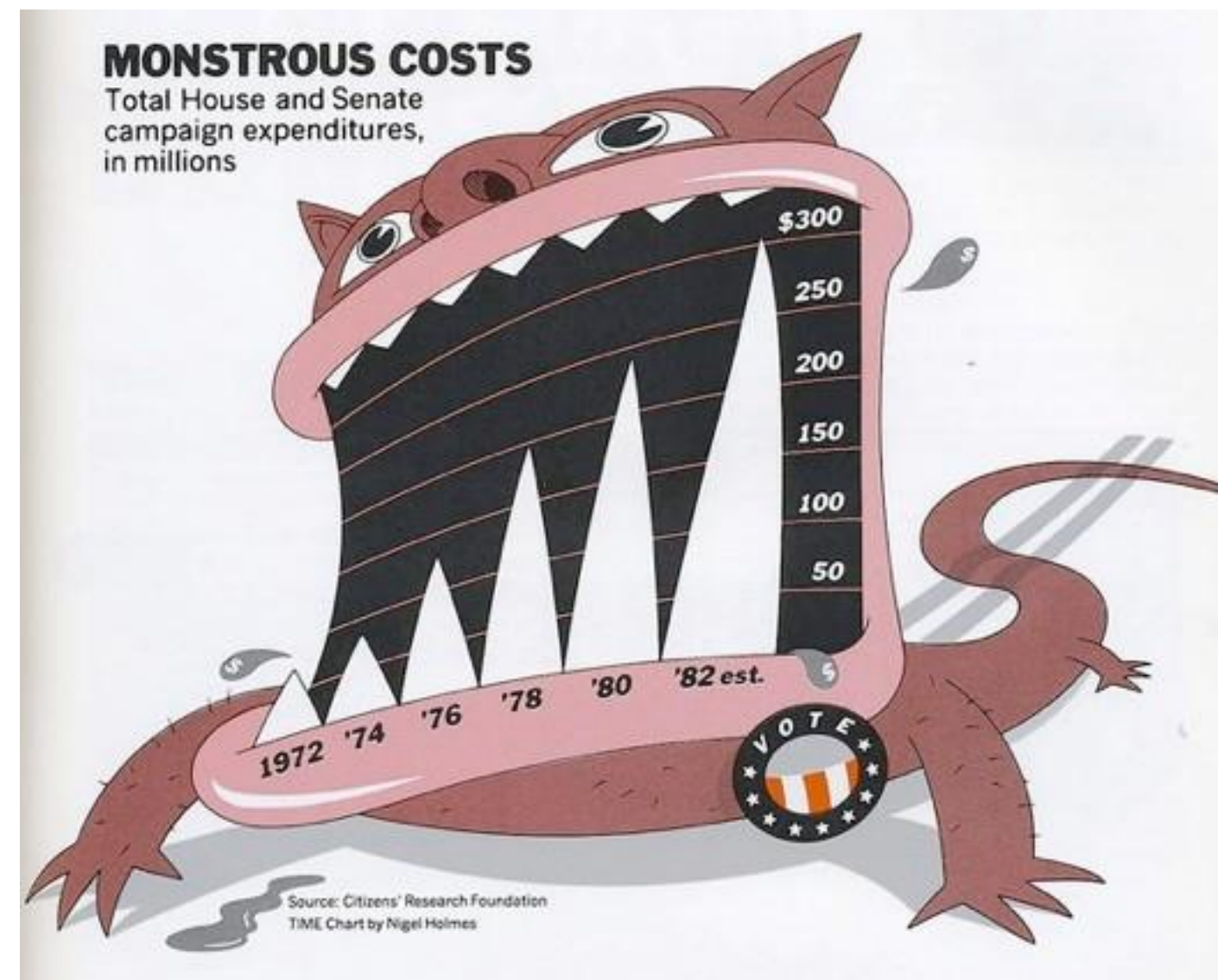
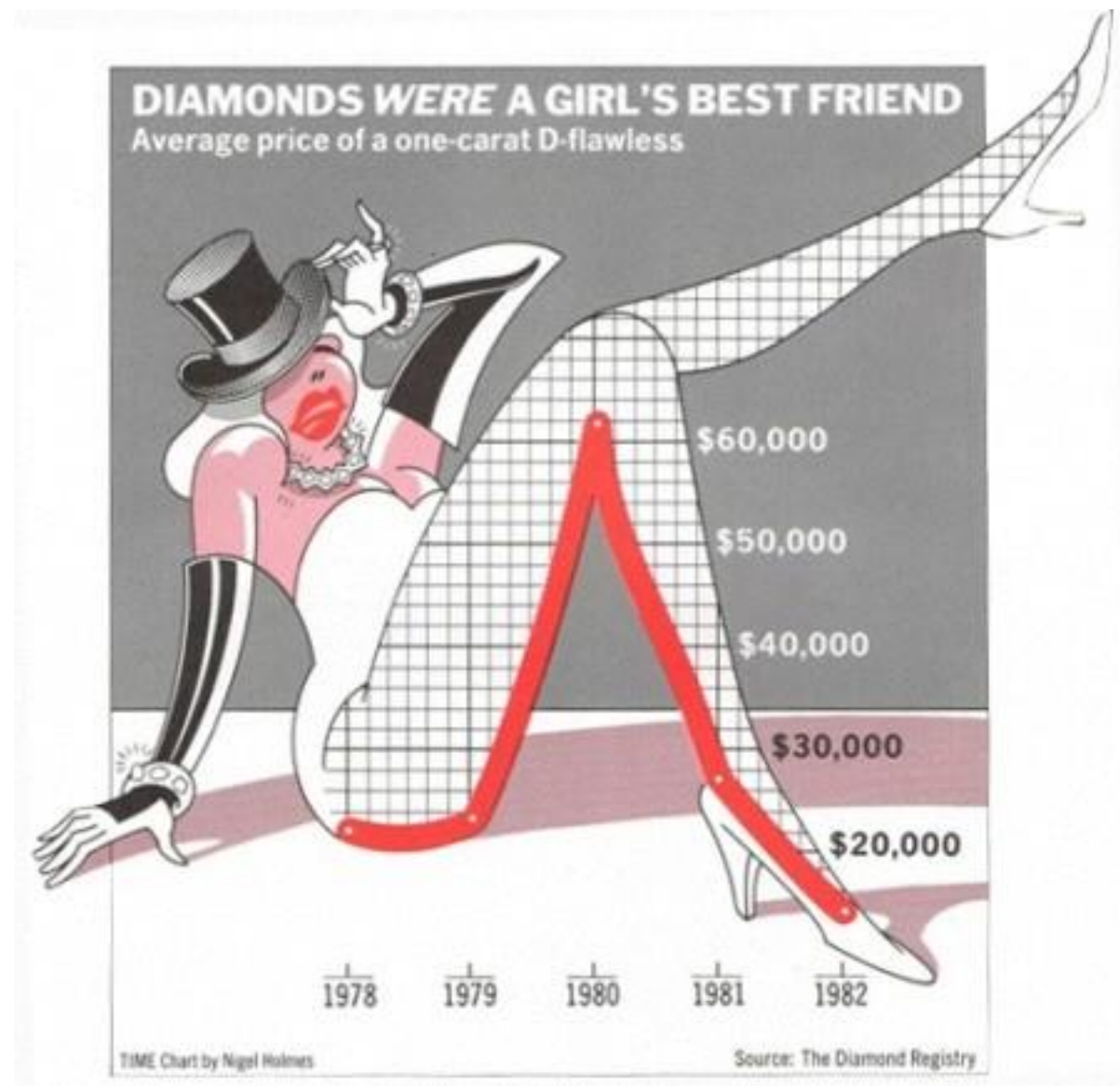


Chart Junk

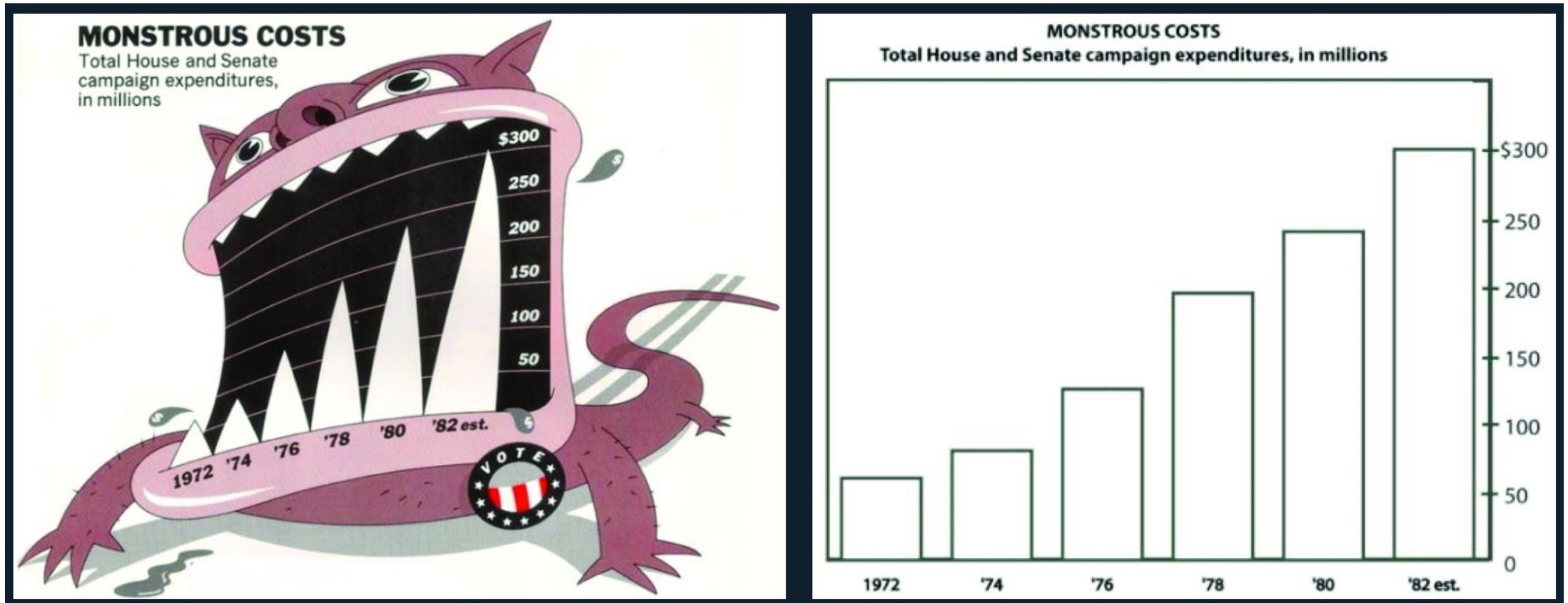


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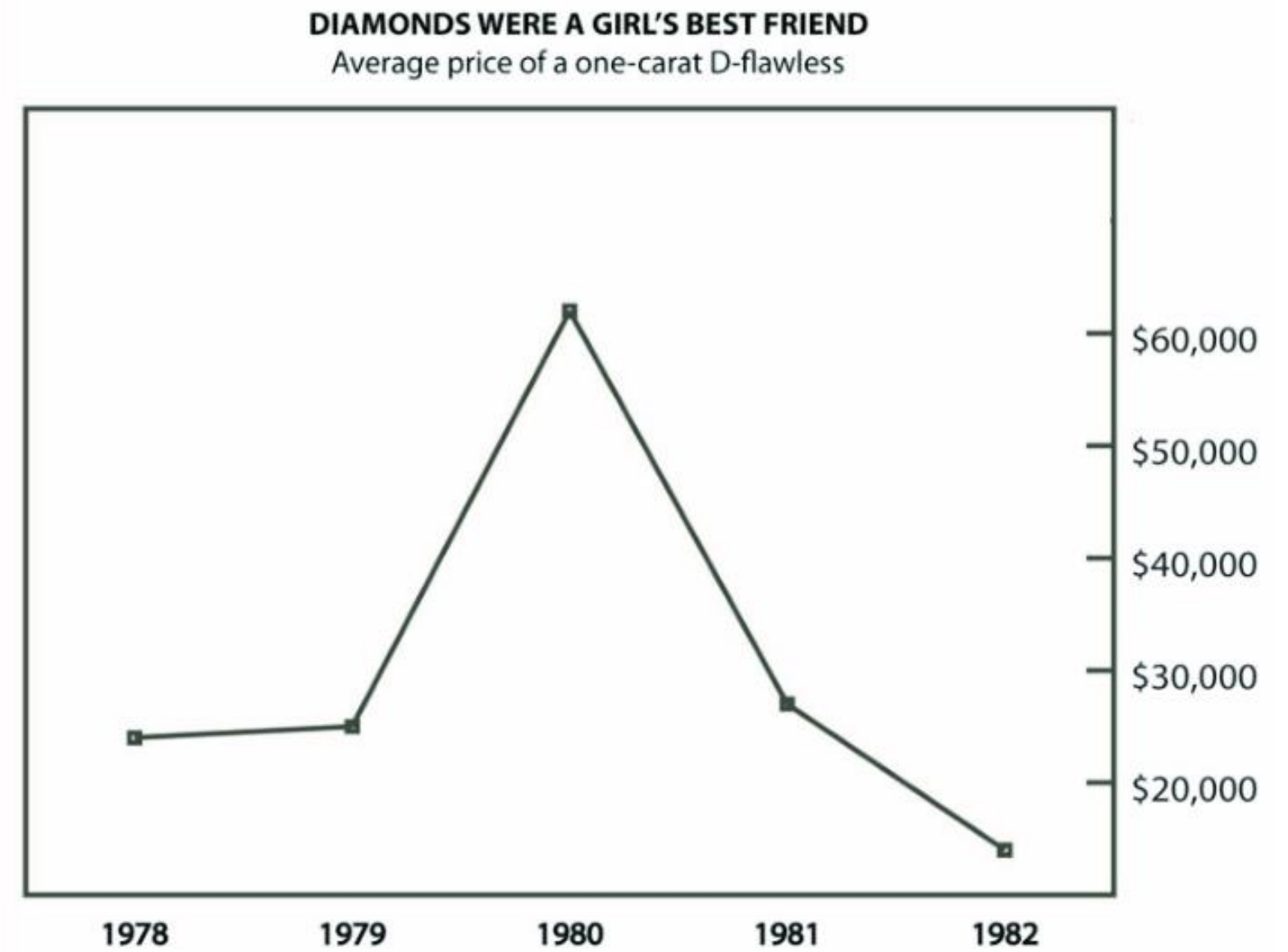
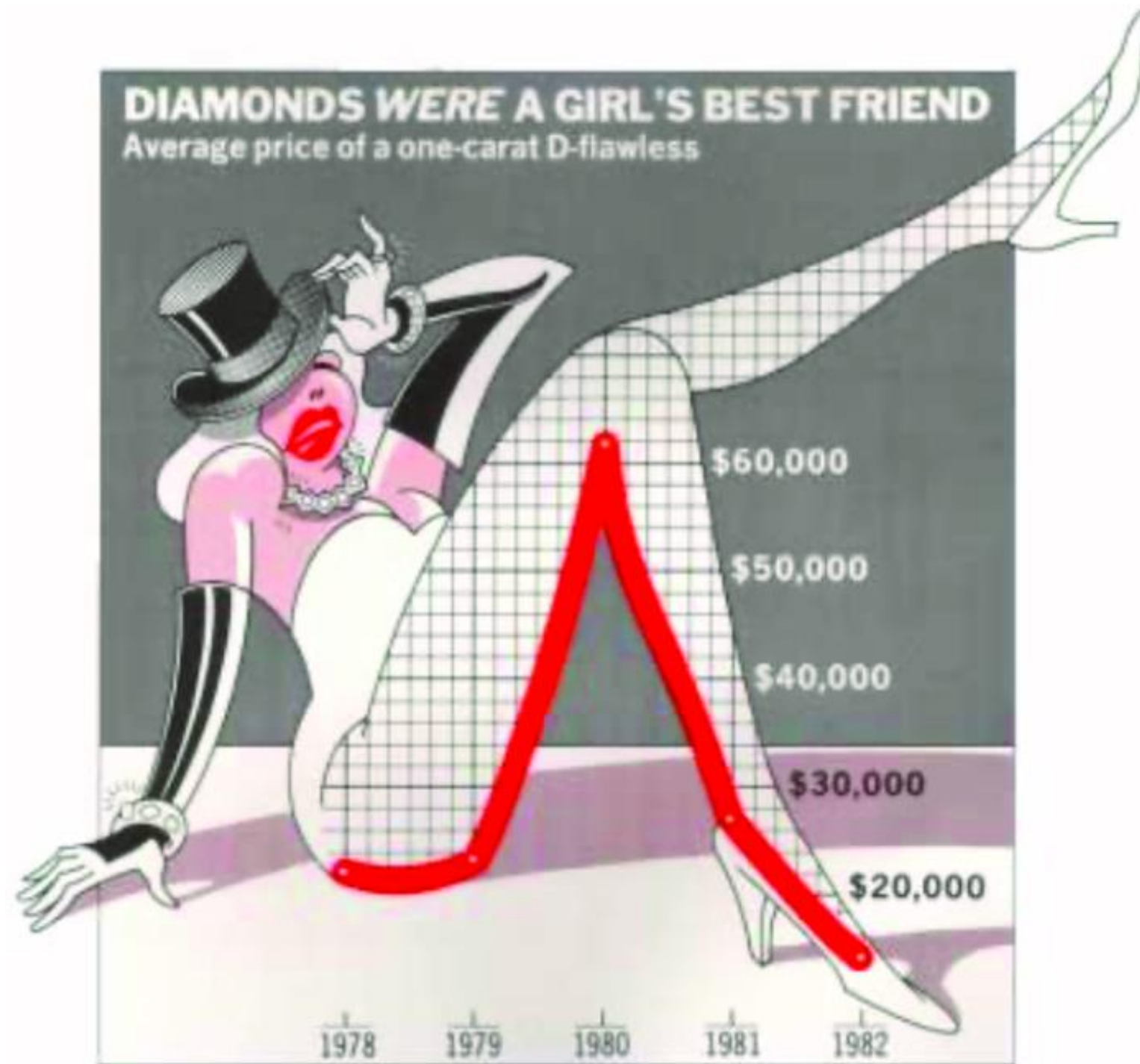


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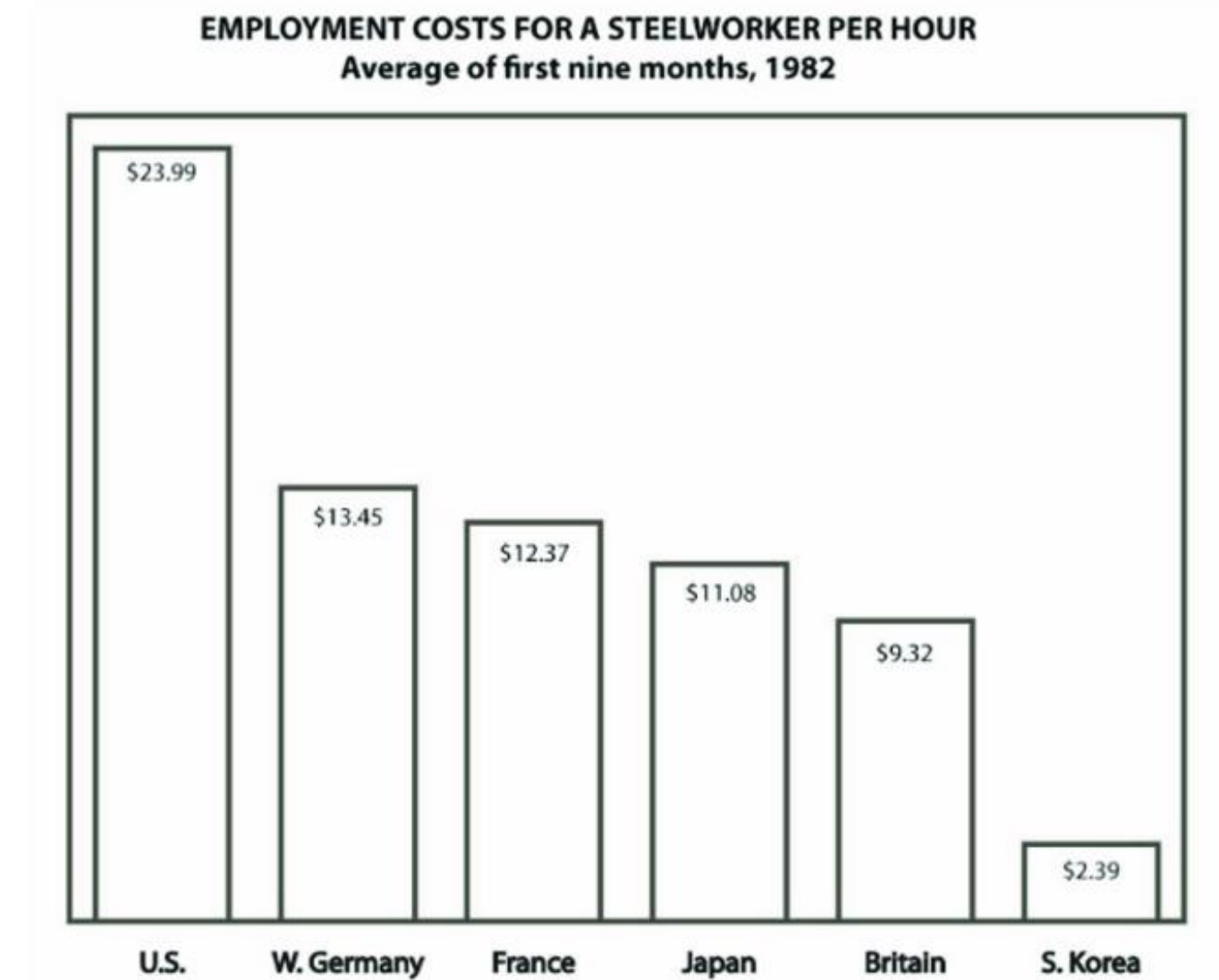
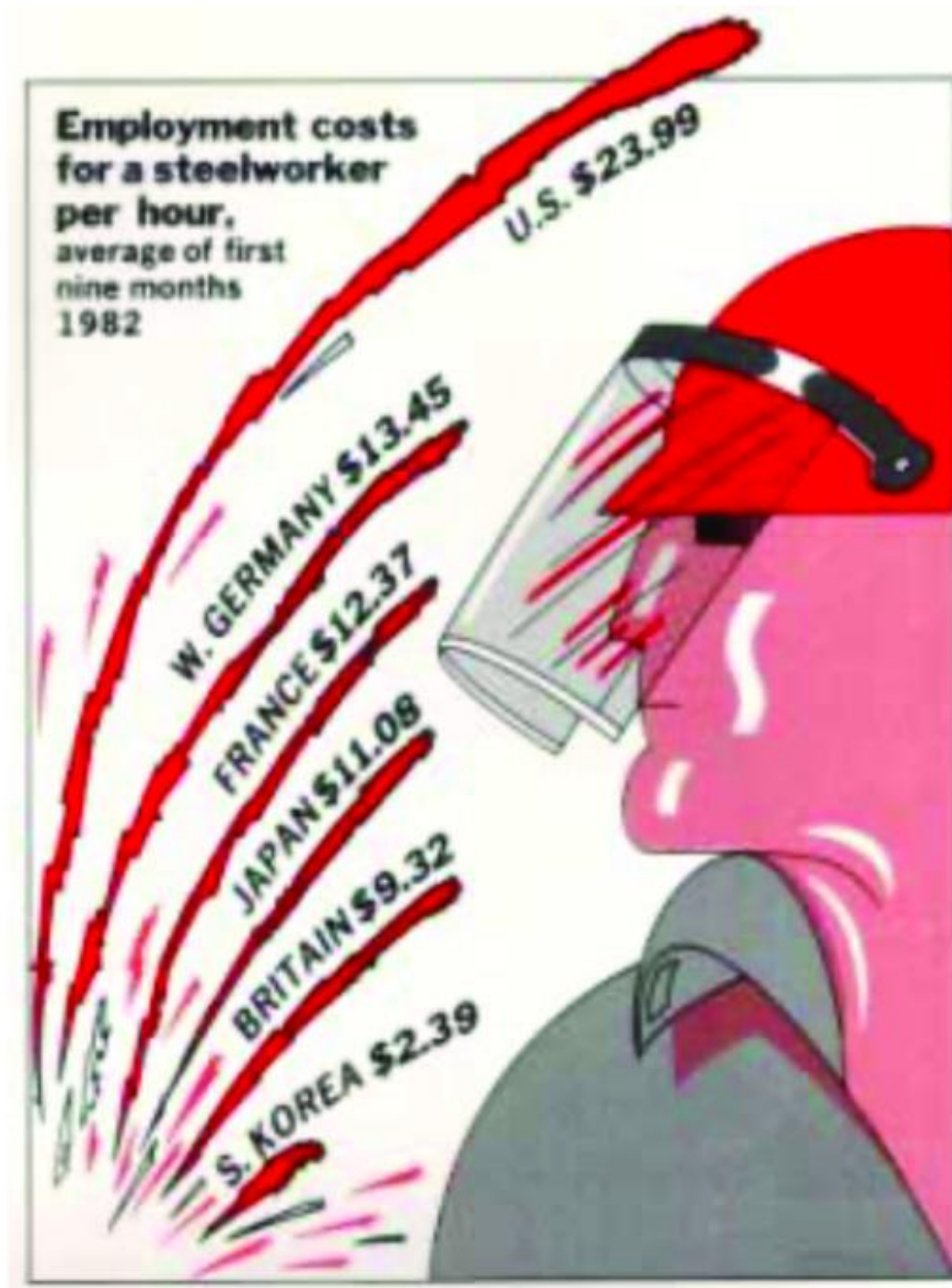


Chart Junk

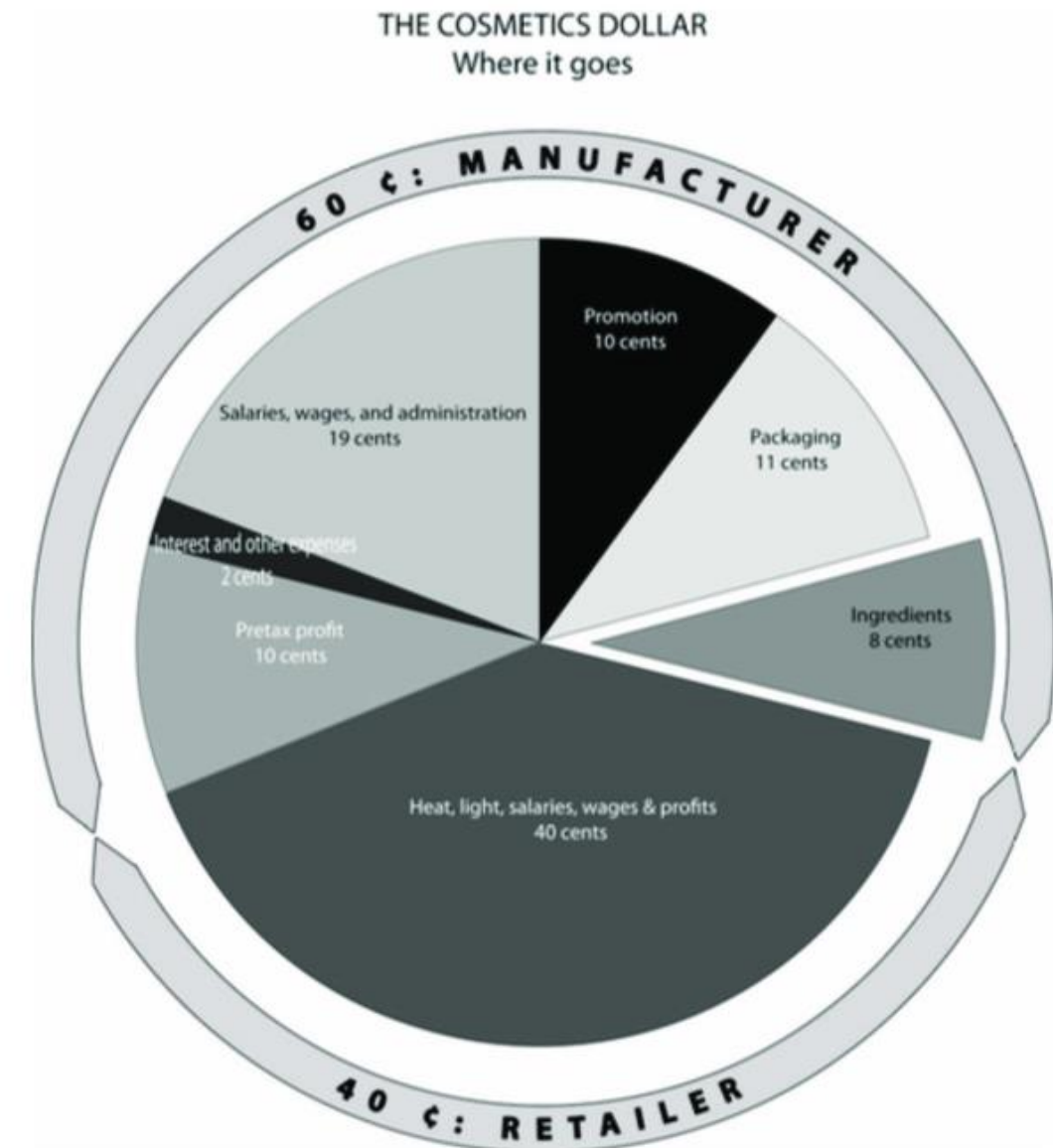
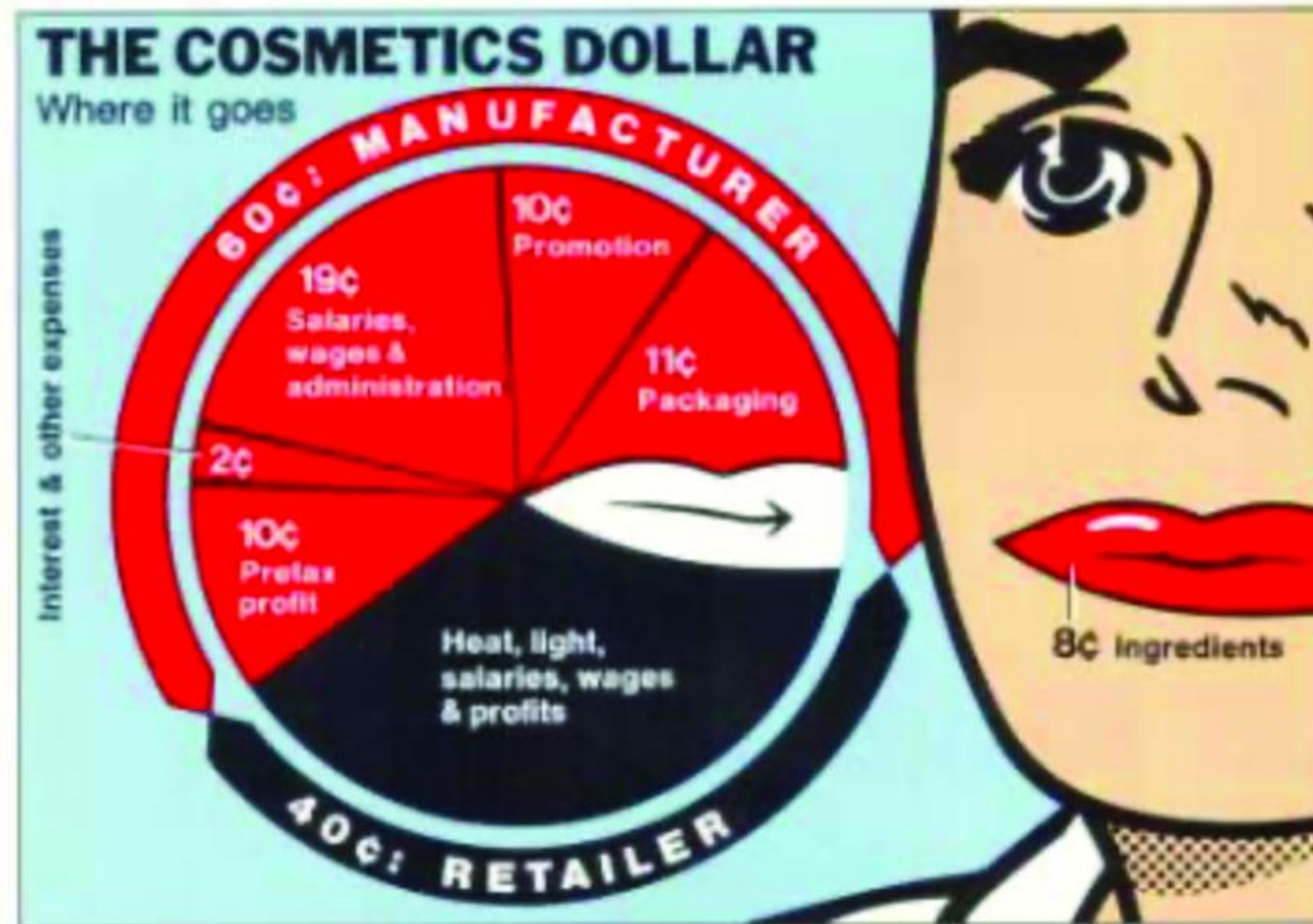
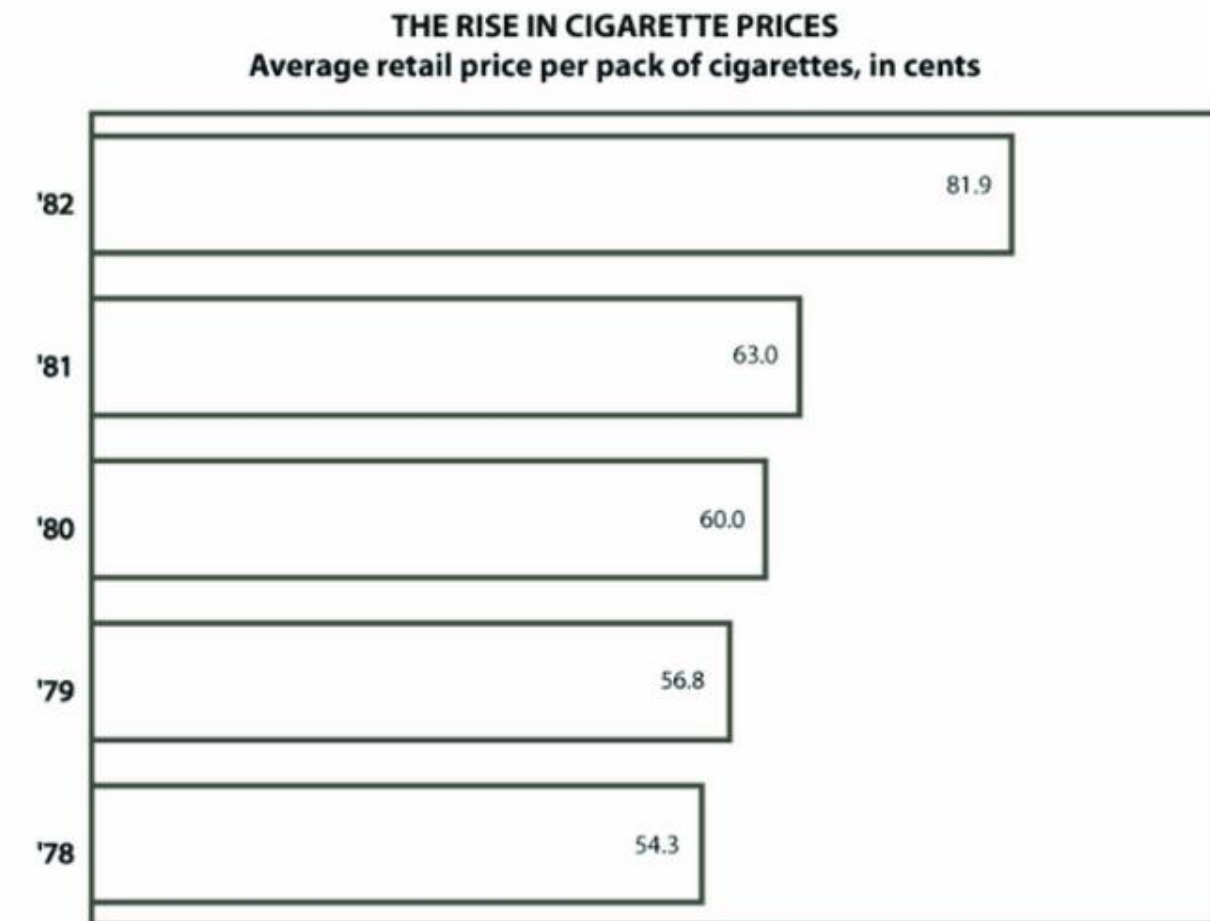
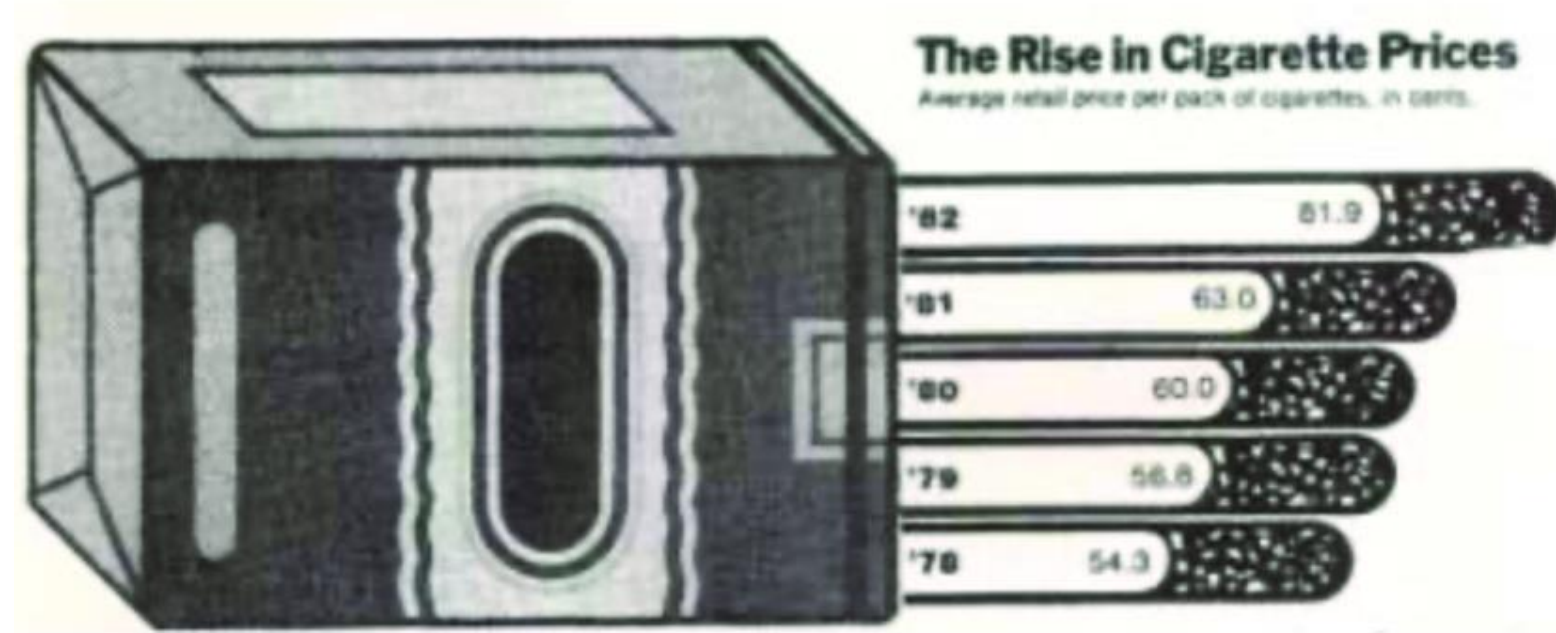
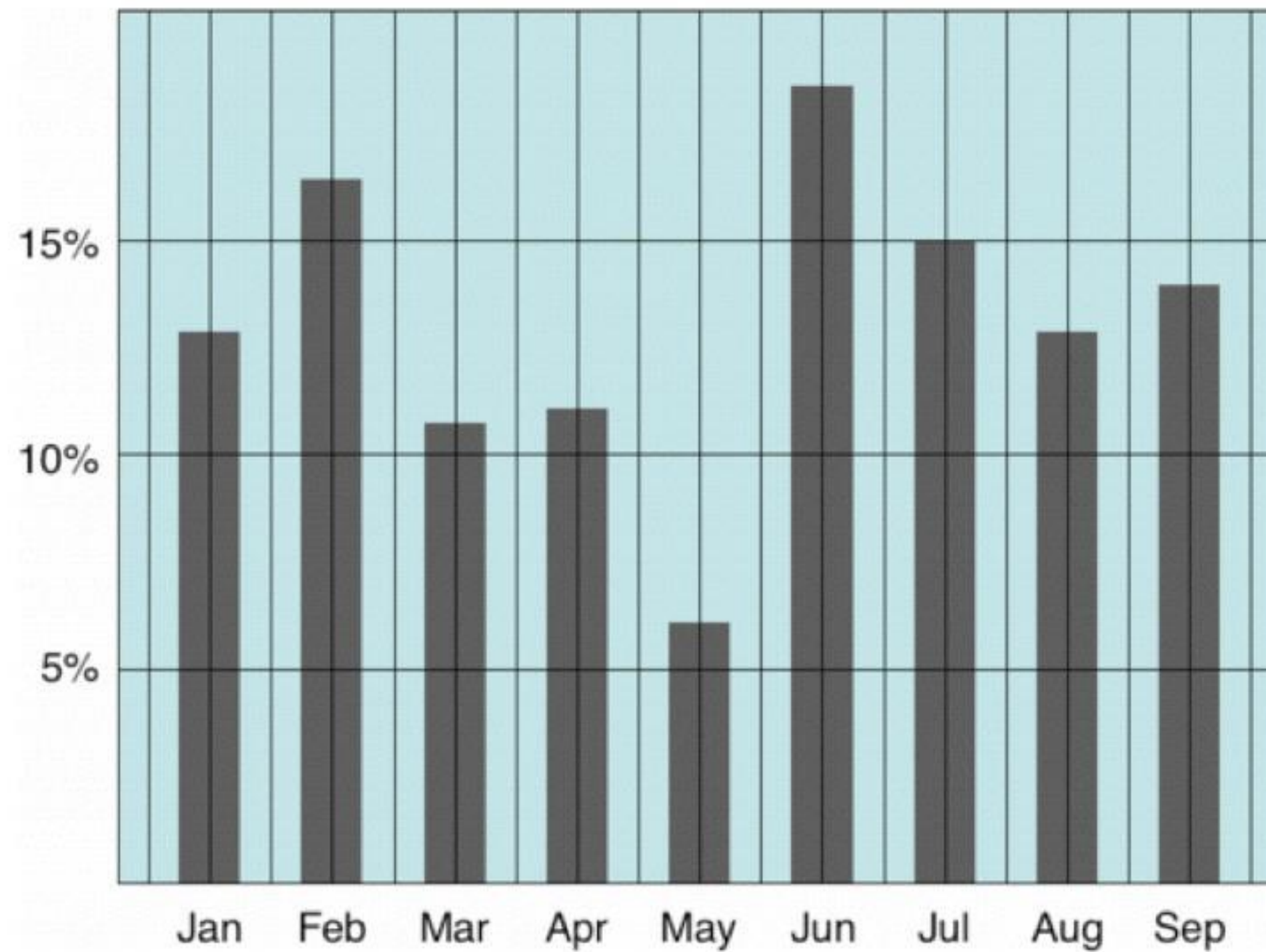


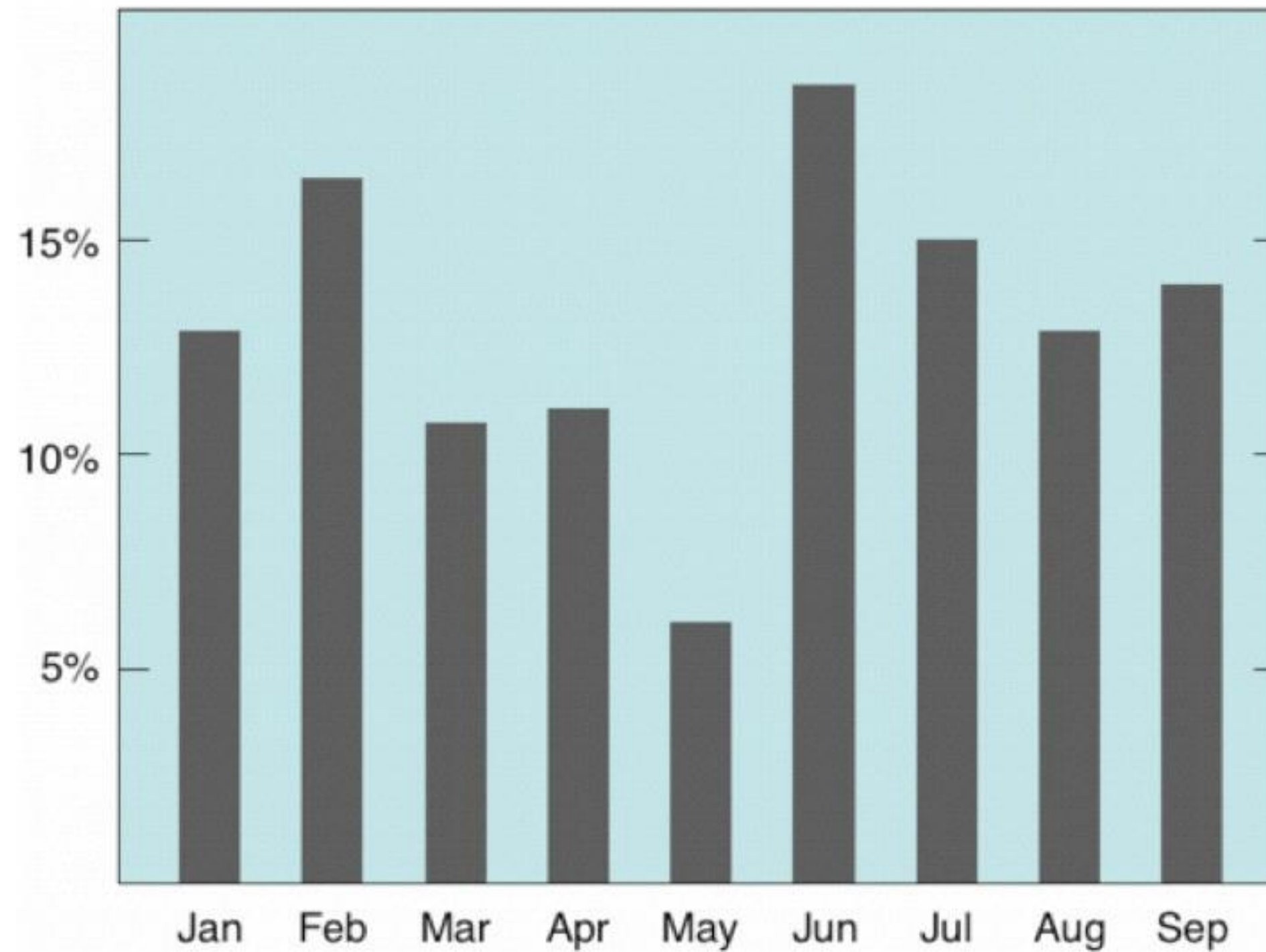
Chart Junk



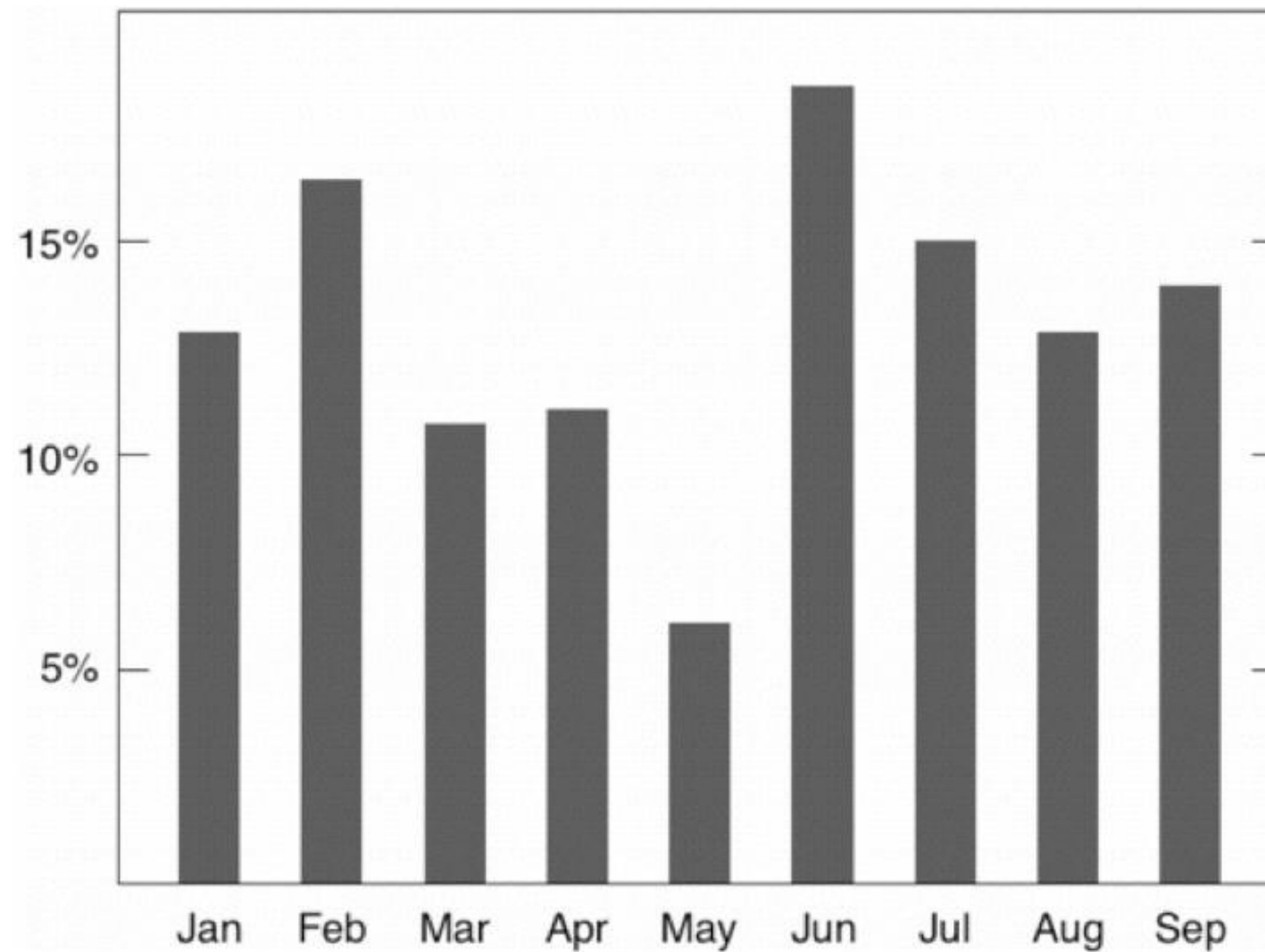
AVOID CHART JUNK



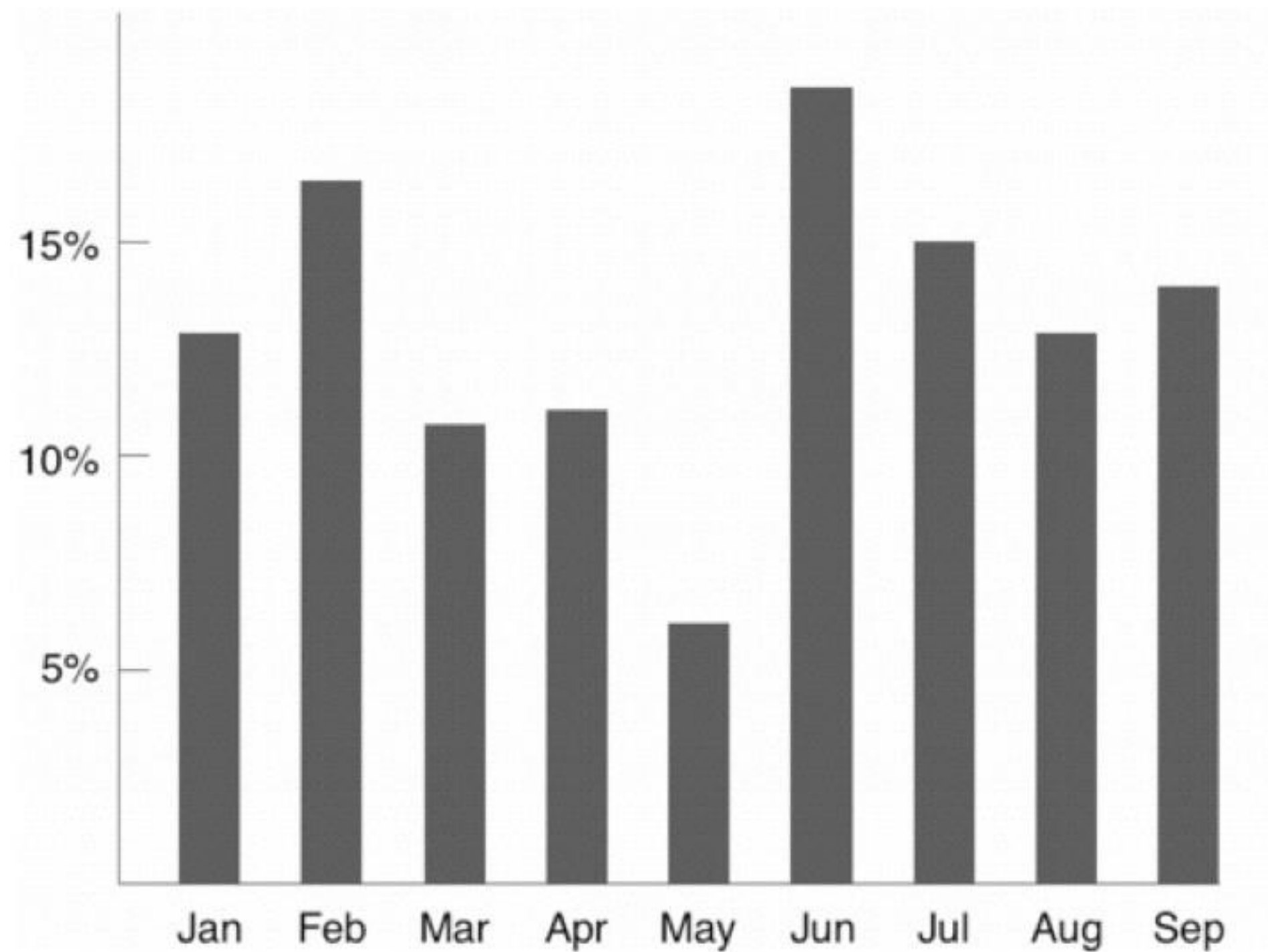
AVOID CHART JUNK



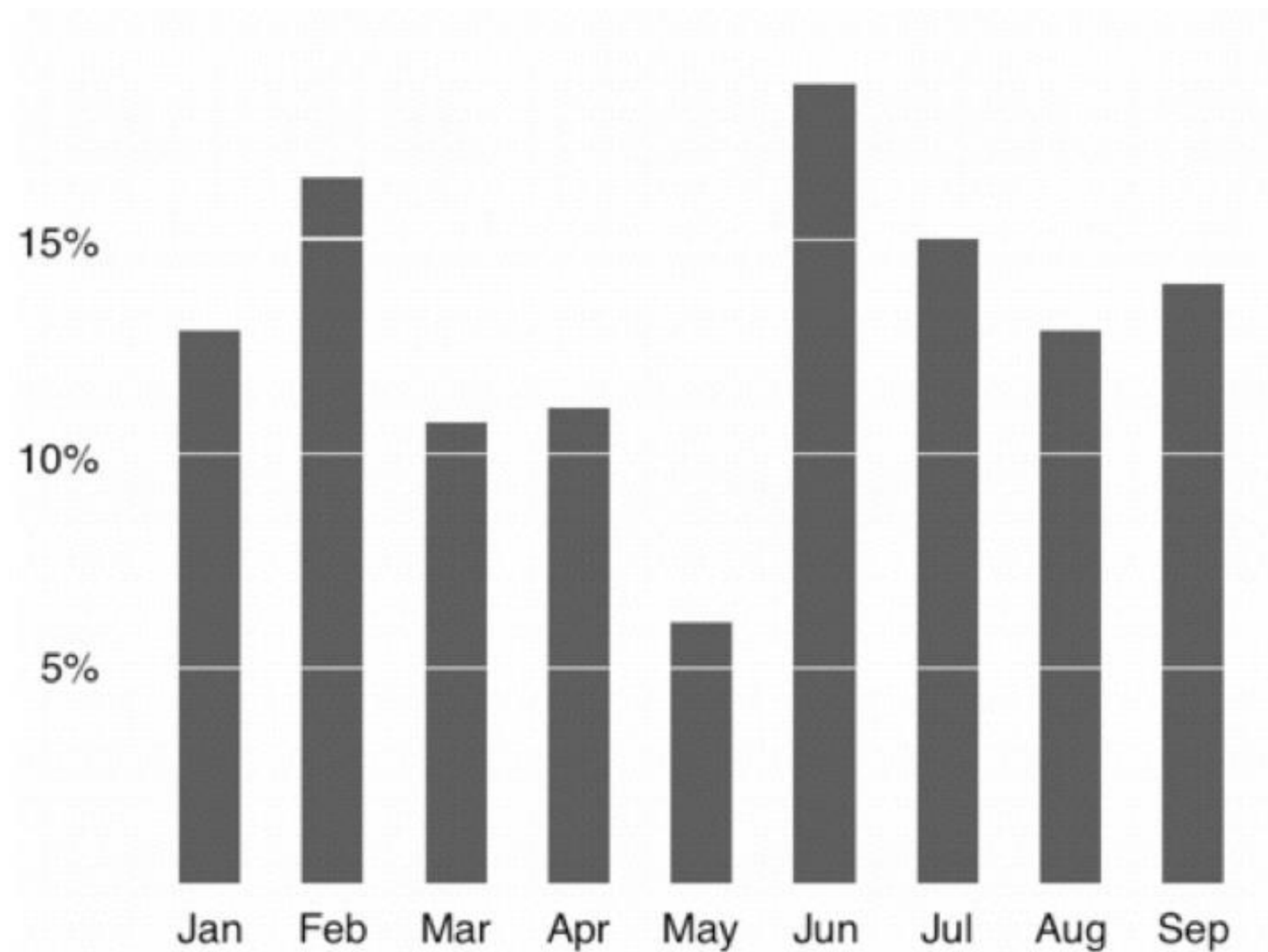
AVOID CHART JUNK



AVOID CHART JUNK



AVOID CHART JUNK



COUNTER-POINTS

CHI 2010: Graphs

April 10–15, 2010, Atlanta, GA, USA

Useful Junk? The Effects of Visual Embellishment on Comprehension and Memorability of Charts

Scott Bateman, Regan L. Mandryk, Carl Gutwin,
Aaron Genest, David McDine, Christopher Brooks

Department of Computer Science, University of Saskatchewan, Saskatoon, Saskatchewan, Canada
scott.bateman@usask.ca, regan@cs.usask.ca, gutwin@cs.usask.ca,
aaron.genest@usask.ca, dam085@mail.usask.ca, cab938@mail.usask.ca

ABSTRACT

Guidelines for designing information charts often state that the presentation should reduce ‘chart junk’ – visual embellishments that are not essential to understanding the data. In contrast, some popular chart designers wrap the presented data in detailed and elaborate imagery, raising the questions of whether this imagery is really as detrimental to understanding as has been proposed, and whether the visual embellishment may have other benefits. To investigate these issues, we conducted an experiment that compared embellished charts with plain ones, and measured both interpretation accuracy and long-term recall. We found that people’s accuracy in describing the embellished charts was no worse than for plain charts, and that their recall after a two-to-three-week gap was significantly better. Although we are cautious about recommending that all charts be produced in this style, our results question some of the premises of the minimalist approach to chart design.

Author Keywords

Charts, information visualization, imagery, memorability.

Despite these minimalist guidelines, many designers include a wide variety of visual embellishments in their charts, from small decorations to large images and visual backgrounds. One well-known proponent of visual embellishment in charts is the graphic artist Nigel Holmes, whose work regularly incorporates strong visual imagery into the fabric of the chart [7] (e.g., Figure 1).



What Makes a Visualization Memorable?

Michelle A. Borkin, *Student Member, IEEE*, Azalea A. Vo, Zoya Bylinskii, Phillip Isola, *Student Member, IEEE*, Shashank Sunkavalli, Aude Oliva, and Hanspeter Pfister, *Senior Member, IEEE*

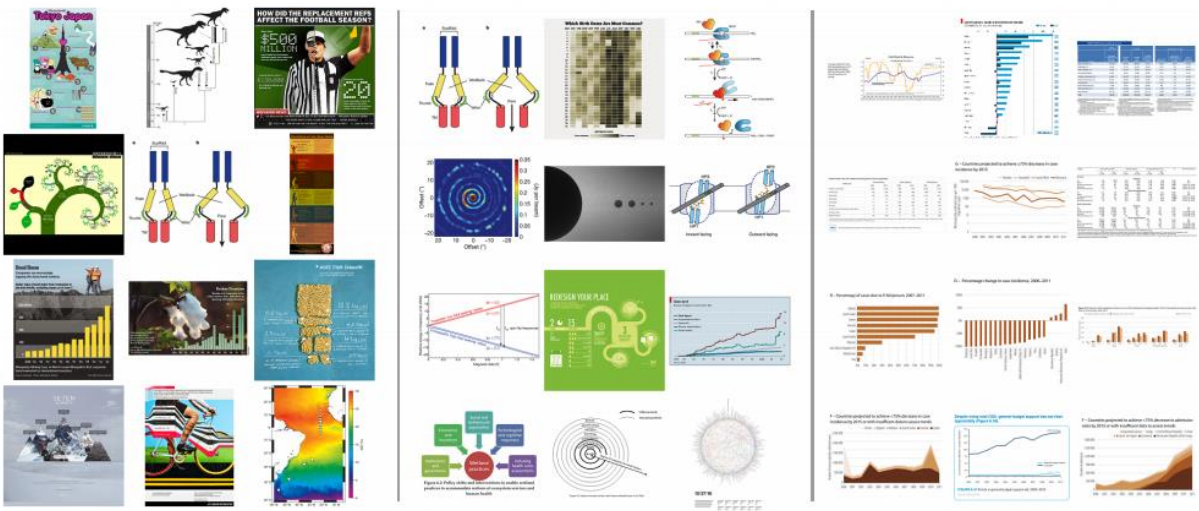


Fig. 1. **Left:** The top twelve overall most memorable visualizations from our experiment (most to least memorable from top left to bottom right). **Middle:** The top twelve most memorable visualizations from our experiment when visualizations containing human recognizable cartoons or images are removed (most to least memorable from top left to bottom right). **Right:** The twelve least memorable visualizations from our experiment (most to least memorable from top left to bottom right).

Abstract—An ongoing debate in the Visualization community concerns the role that visualization types play in data understanding. In human cognition, understanding and memorability are intertwined. As a first step towards being able to ask questions about impact and effectiveness, here we ask: “What makes a visualization memorable?” We ran the largest scale visualization study to date using 2,070 single-panel visualizations, categorized with visualization type (e.g., bar chart, line graph, etc.), collected from news media sites, government reports, scientific journals, and infographic sources. Each visualization was annotated with additional attributes, including ratings for data-ink ratios and visual densities. Using Amazon’s Mechanical Turk, we collected memorability scores for hundreds of these visualizations, and discovered that observers are consistent in which visualizations they find memorable and forgettable. We find intuitive results (e.g., attributes like color and the inclusion of a human recognizable object enhance memorability) and less intuitive results (e.g., common graphs are less memorable than unique visualization types). Altogether our findings suggest that quantifying memorability is a general metric of the utility of information, an essential step towards determining how to design effective visualizations.

Index Terms—Visualization taxonomy, information visualization, memorability

Useful Junk? The Effects of Visual Embellishment on Comprehension and Memorability of Charts

Scott Bateman, Regan L. Mandryk, Carl Gutwin,
Aaron Genest, David McDine, Christopher Brooks

Department of Computer Science, University of Saskatchewan, Saskatoon, Saskatchewan, Canada
scott.bateman@usask.ca, regan@cs.usask.ca, gutwin@cs.usask.ca,
aaron.genest@usask.ca, dam085@mail.usask.ca, cab938@mail.usask.ca

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MONSTROUS COSTS

Total House and Senate
campaign expenditures,
in millions



EXPERIMENTAL QUESTIONS

- do visual embellishments cause comprehension problems?
- do embellishments provide additional information that is valuable for the reader?

EXPERIMENTAL RESULTS

- No significant difference between plain and embellished charts for interactive interpretation accuracy
- No significant difference in recall accuracy after a five-minute gap

EXPERIMENTAL RESULTS

- Significantly better recall for embellished charts of both the chart topic and the details (categories and trend) after long-term gap (2-3 weeks)
- Participants saw value messages in the embellished charts significantly more often than in the plain charts
- Participants found the embellished charts more attractive, most enjoyed them, and found that they were easiest and fastest to remember

What Makes a Visualization Memorable?

Michelle A. Borkin, *Student Member, IEEE*, Azalea A. Vo, Zoya Bylinskii, Phillip Isola, *Student Member, IEEE*, Shashank Sunkavalli, Aude Oliva, and Hanspeter Pfister, *Senior Member, IEEE*

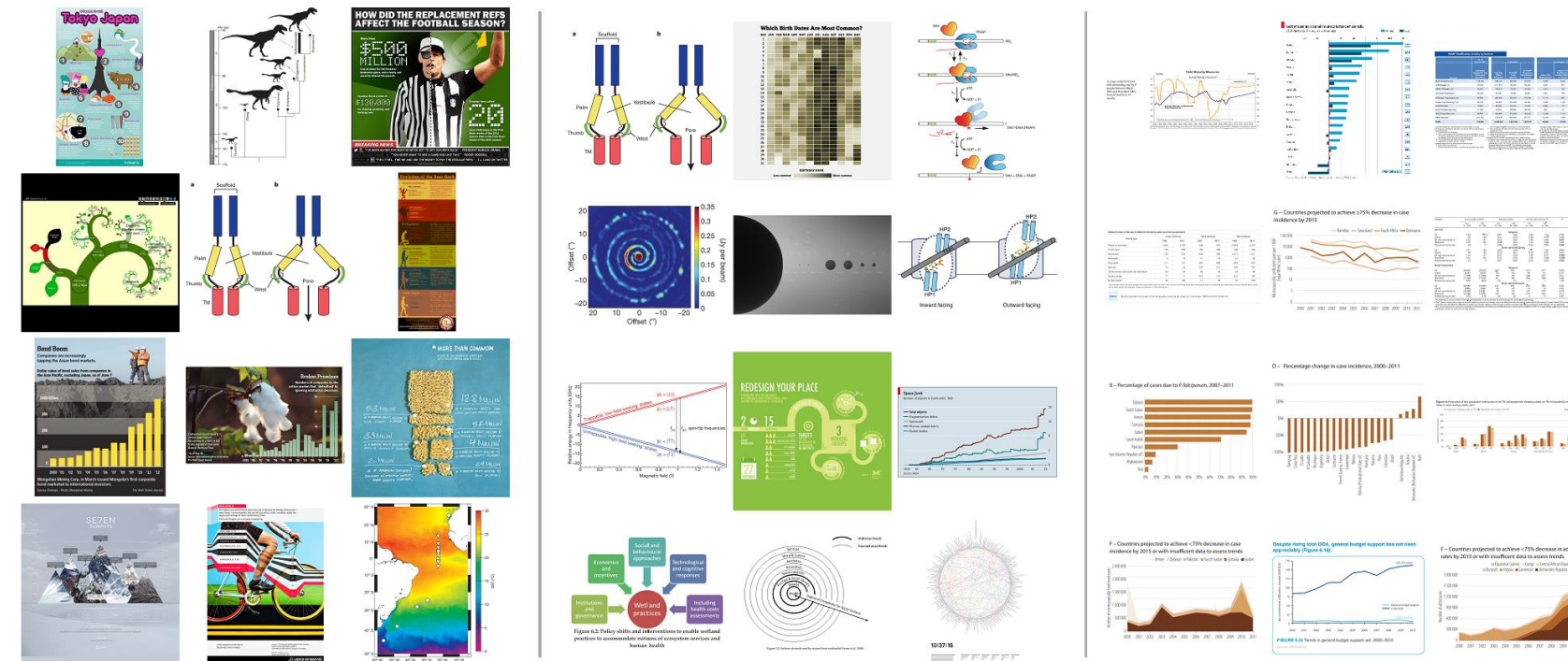


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Index Terms—Visualization taxonomy, information visualization, memorability

Results

- color and human recognizable objects enhance memorability
- common graphs are less memorable than unique visualization types

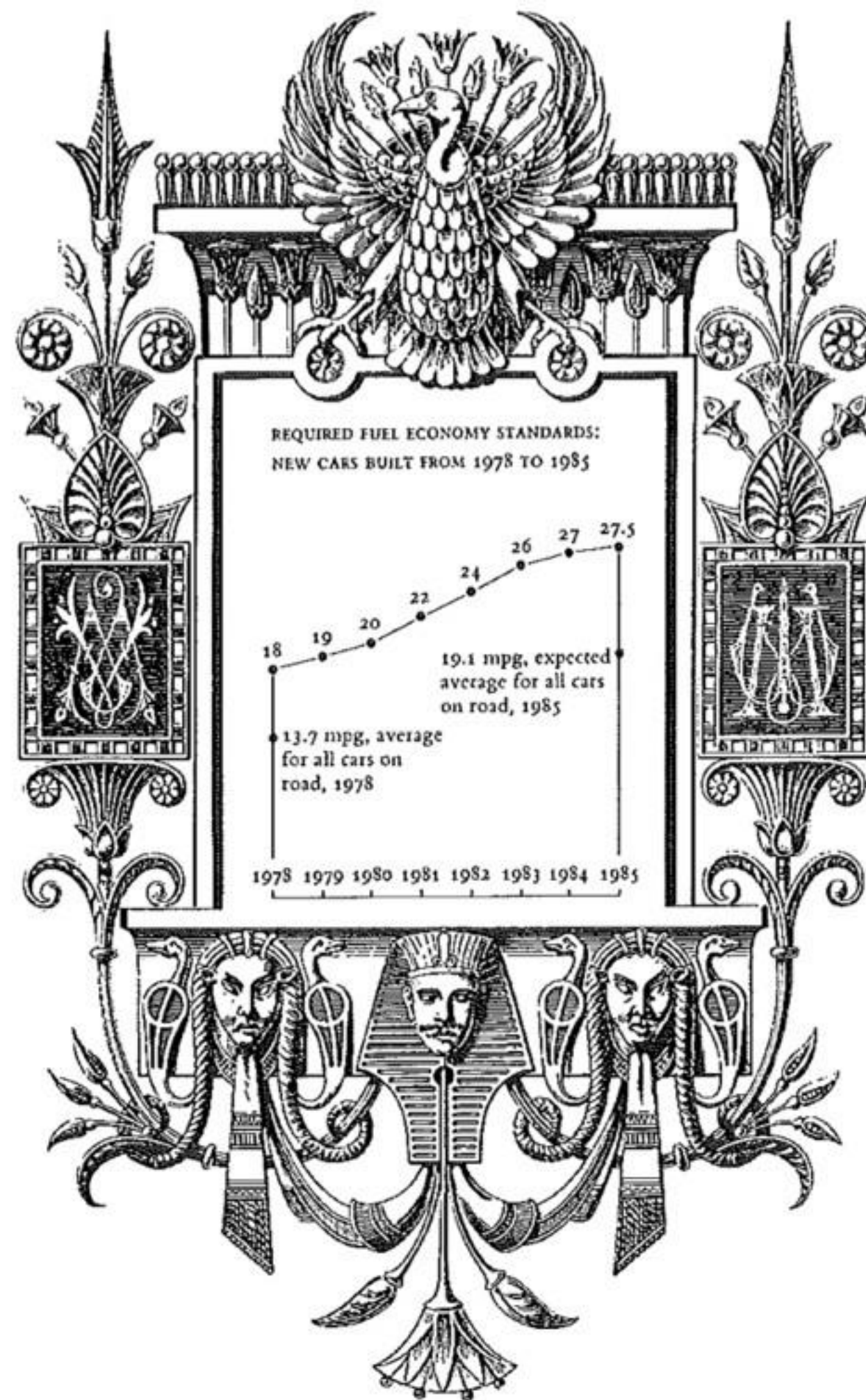
CHART JUNK? IT DEPENDS

- persuasion
- memorability
- engagement

PROS

- unbiased analysis
- trustworthiness
- interpretability
- space efficiency

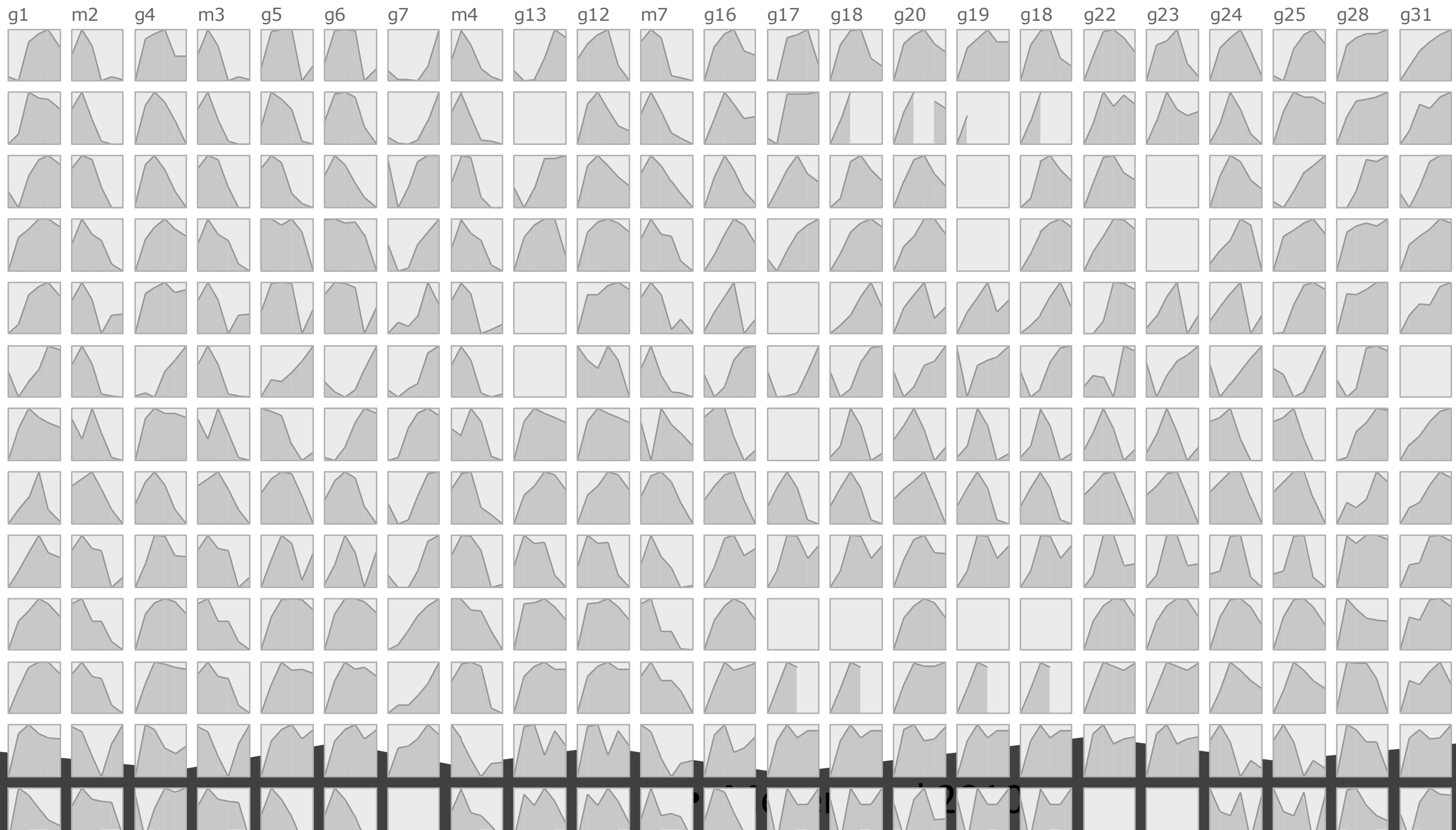
CONS



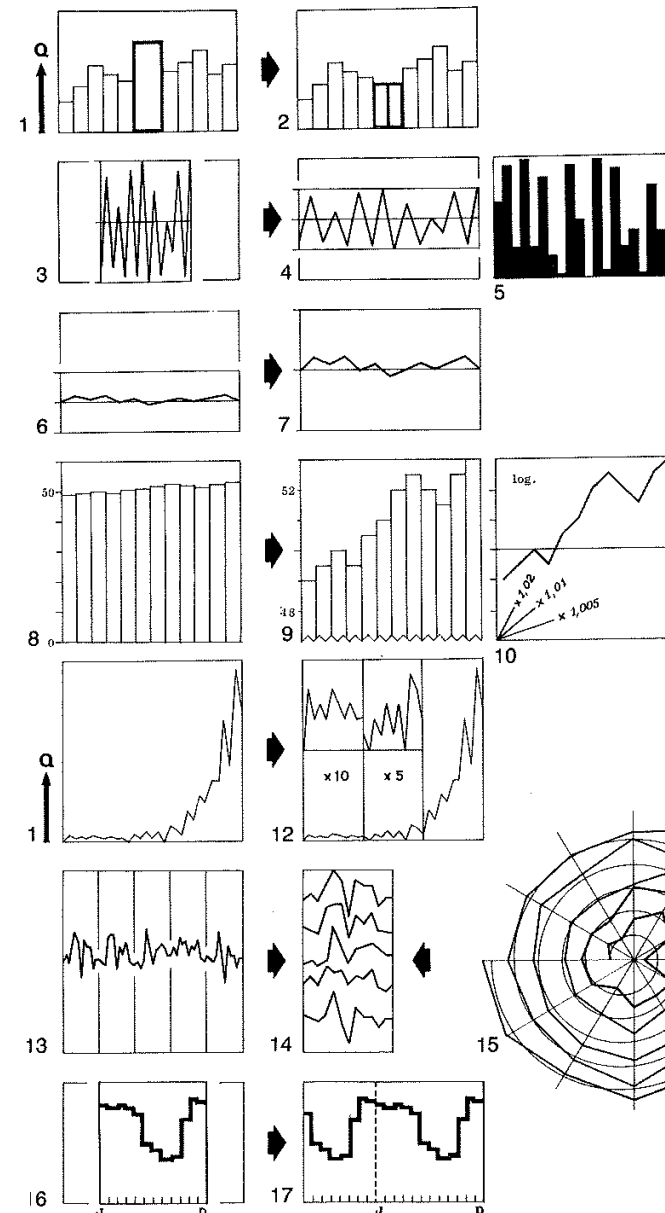
maximize the

$$\text{Data Density} = \frac{\text{number of entries in data array}}{\text{area of data graphic}}$$

SHRINK THE GRAPHICS – with small multiples



SHRINK THE GRAPHICS



GRAPHIC PROBLEMS POSED BY TIME SERIES

Scale in years

With a scale in years, a two-year total (figure 1) should be divided by 2 (figure 2). A total for six months should be multiplied by 2.

Pointed curves

For overly pointed curves (figure 3), the scale of the Q should be reduced; optimum angular perceptibility occurs at around 70 degrees (figure 4).

If the curve is not reducible (large and small variations), filled columns can be used (figure 5).

Flat curves

For overly flat curves (figure 6), the scale of the Q should be increased (figure 7).

Small variations

For small variations in relation to the total (figure 8), the total loses its importance, and the zero point can be eliminated, provided the reader is made aware of this elimination (figure 9). The graphic can be interpreted as an acceleration if a precise study of the variations is necessary; here, we use a logarithmic scale (figure 10). (See also page 240.)

Large range

For a very large range between the extreme numbers (figure 11), we must either:

- (1) leave out the smallest variations;
- (2) be concerned only with relative differences (logarithmic scale), without knowing the absolute quantities;
- (3) select different parts (periods) within the ordered component and treat them on different scales above the common scale (figure 12).

Obvious periodicity

If there is obvious periodicity (figure 13), and the study involves a comparison of the phases of each cycle, it is preferable to break up the cycles in order to superimpose them (figure 14). A polar construction can be used, preferably in a spiral shape (figure 15), but we should not begin with too small a circle. As striking as it seems, it is less efficient than an orthogonal construction.

Annual curves

For annual curves of rainfall or temperature, if a cycle has two phases (figure 17), why depict only one (figure 16)?

A contrast

Unlike what we see in figure 18, the pertinent or "new" information must be separated from the background or "reference" information. The background involves: (a) the invariant, highlighted by a heading (Port St. Michel); (b) the highly visible identification of each component (tonnage and dates). The new information (the curve) must stand out from the background (figure 19).

Reference points

It is impossible to utilize a graphic such as figure 20, except in a general manner. There is confusion concerning the position of the points, and no potential comparison is possible, as it is in figure 21.

Precision reading

A precision reading (utilization on the elementary level, as in figure 24) is difficult in figure 22, which results in a poor reading of the order of the points, and in figure 23, where there is ambiguity concerning the position of the points. On the other hand, figure 22 does favor overall vision (correlation).

Null boxes

Curves accommodate null boxes poorly (figure 25). Columns (figure 26) are preferable.

Unknown boxes

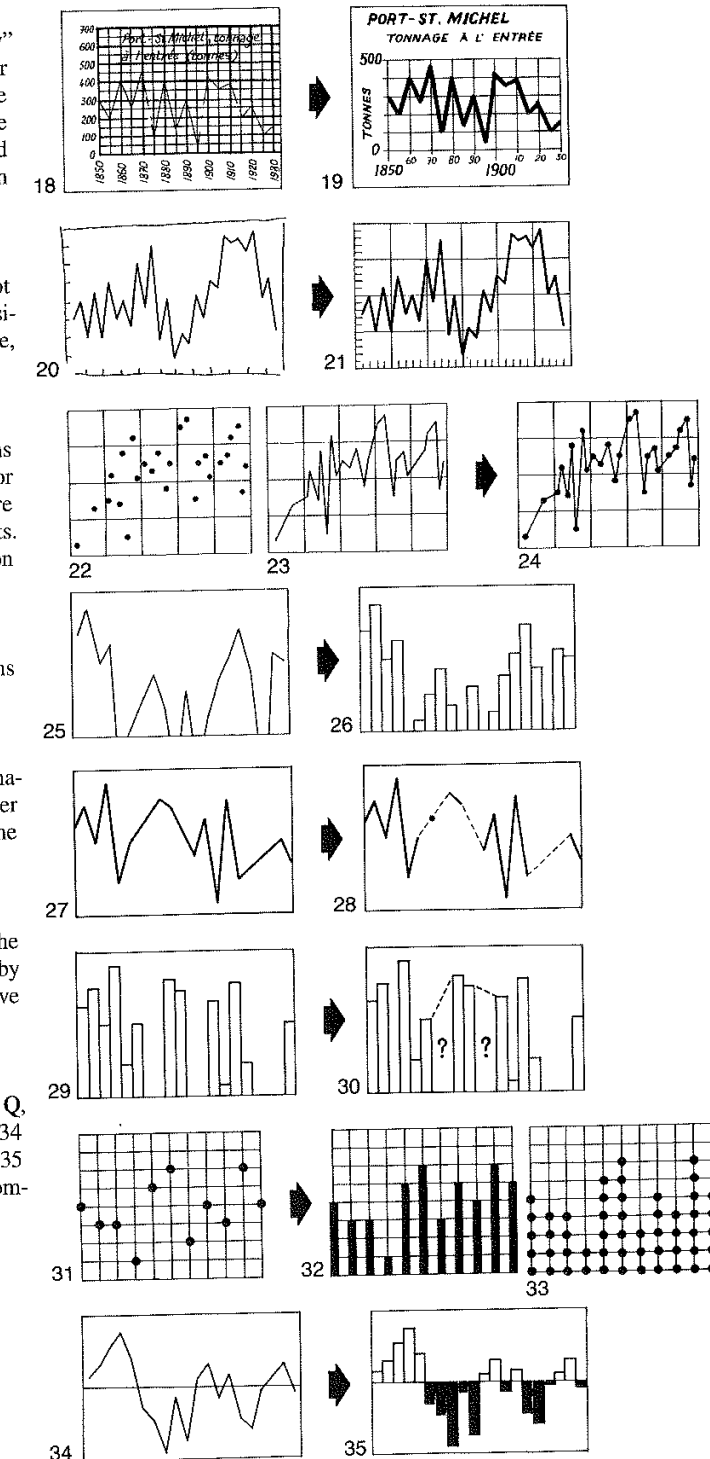
The drawing must indicate the unknowns of the information in an unambiguous way (figures 28 and 30). The reader might interpret figure 27 as a change in the structure of the curve and figure 29 as involving null values.

Very small quantities

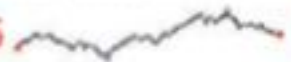
Except in seeking a correlation (quite improbable here) the number of ships entering into a port is represented better by figure 33 than by figures 31 or 32. The reader can perceive the numerical values at first glance.

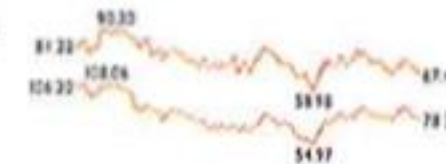
Positive-negative variation

This is in fact a problem involving three components O , Q , $\neq (+, -)$, and it must be visually treated as such. Figure 34 can be improved by utilizing a retinal variable (in figure 35 a value difference: black-white) to differentiate the $\neq$ component and thus highlight positive-negative variation.



SHRINK THE GRAPHICS – with sparklines

Dequantification In exchange for an enormous increase in graphical resolving power, the wordlike size of sparklines precludes the overt labels and scaling of conventional statistical displays. Most of our examples have, however, depicted *contextual methods* for quantifying sparklines: the gray bar for normal limits and the red encoding to link data points in sparklines to exact numbers  glucose 6.6 ; global scale bars and labels for sparkline clusters; and, probably best of all, surrounding a sparkline with an implicit data-scaling box formed by nearby numbers that label key data points (such as beginning/end, high/low) 1.1025  1.1907 1.0783 1.2858. And now and then sparklines might be scaled by very small type:



Production methods Data lines produced by conventional statistical graphics programs must be gathered together, rescaled, and resized into sparklines. Sometimes this can be quickly done by cutting and pasting data lines, then resizing the printed output to sparkline resolutions. To produce and display really elegant sparklines, however, currently requires elaborate software: (1) a *page layout* program, (2) a *graphic design* program that gives complete control over type, tables, linework, and (3) a *statistical analysis* program to generate hundreds of chartjunk-free sparklines for export into design and layout operations. Once the basic templates for sparklines are worked out, then ongoing production and

Small Multiples

alfisol



entisol



histosol



inceptisol



mollisol

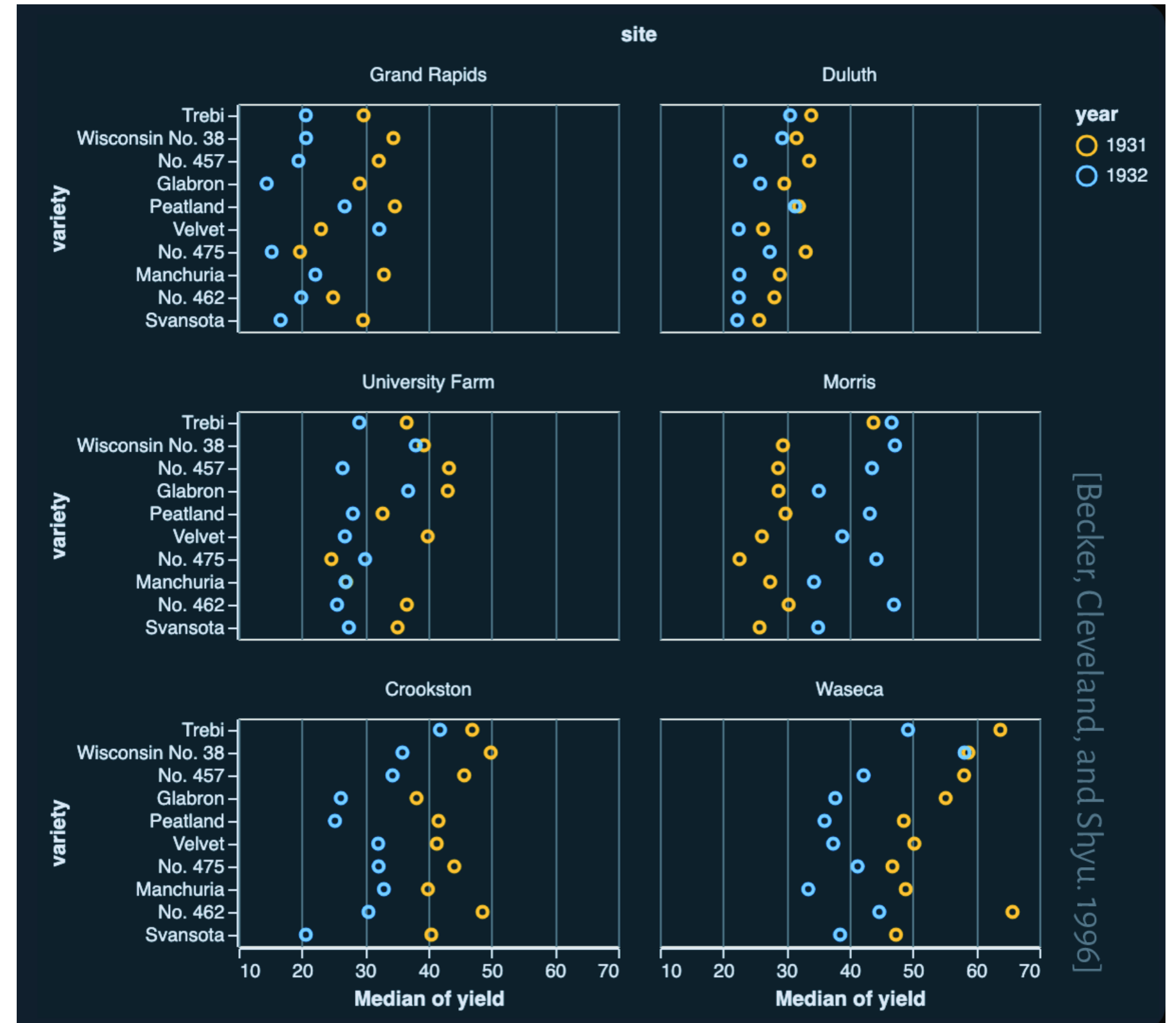


ultisol



Trellis Plots

- Subdivide space to enable comparison across multiple plots
- Typically, nominal or ordinal variables are used as dimensions for subdivision.



COUNTER-POINT

Unseen and Unaware: Implications of Recent Research on Failures of Visual Awareness for Human-Computer Interface Design

D. Alexander Varakin and Daniel T. Levin

Vanderbilt University

Roger Fidler

Kent State University

ABSTRACT

Because computers often rely on visual displays as a way to convey information to a user, recent research suggesting that people have detailed awareness of only a small subset of the visual environment has important implications for human-computer interface design. Equally important to basic limits of awareness is the fact that people often over-predict what they will see and become aware of. Together, basic failures of awareness and people's failure to intuitively understand



ILLUSIONS OF VISUAL BANDWIDTH

- people over-predict what they will see and become aware of

overestimate of breadth

- belief that viewers can take in all (or most) of the details of a scene at once
- adding extra visual features makes it harder to find specific bits of information

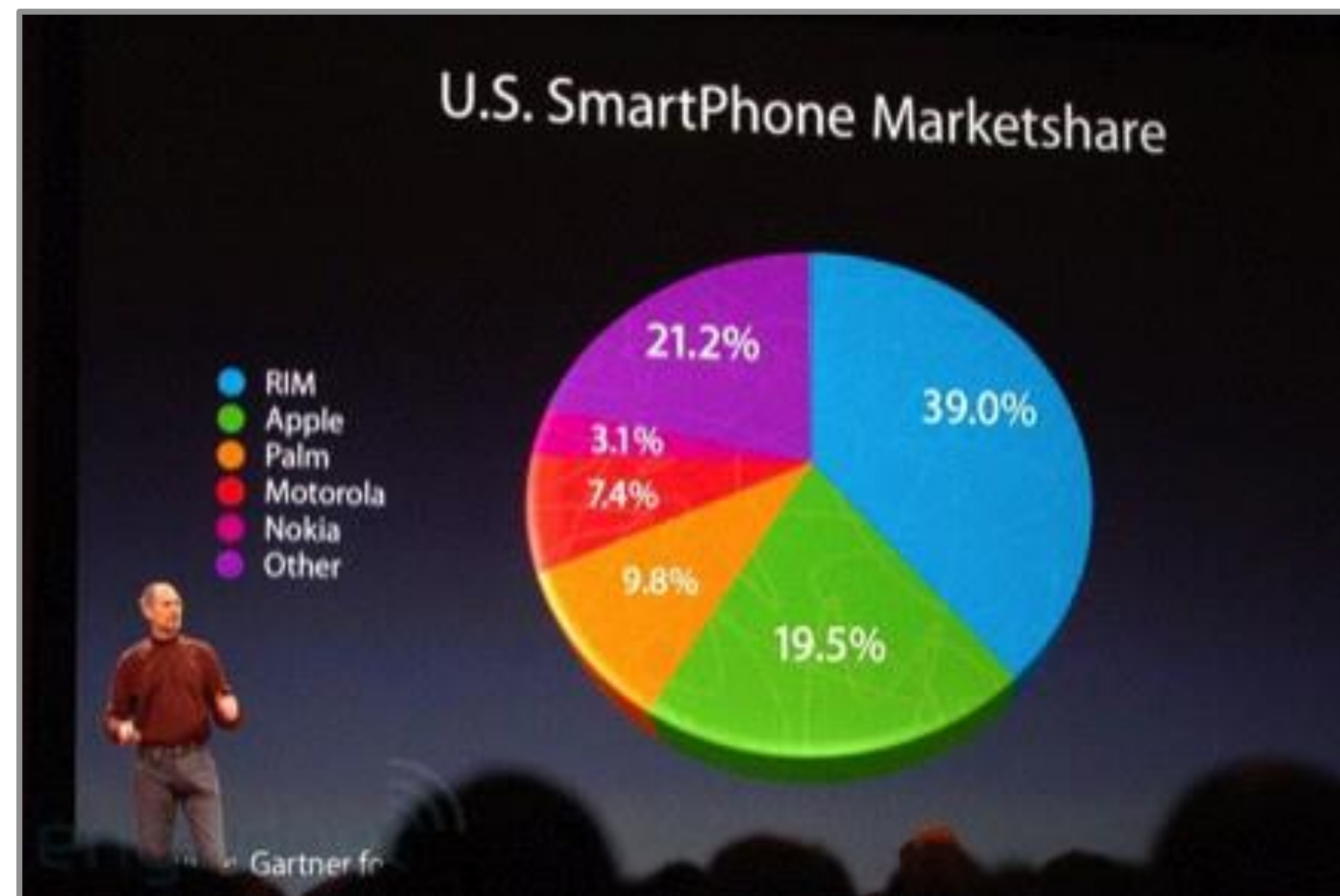
overestimate of countenance

- belief that user will attend to a higher proportion of the display than they do
- users typically have expectations about where in a display to look

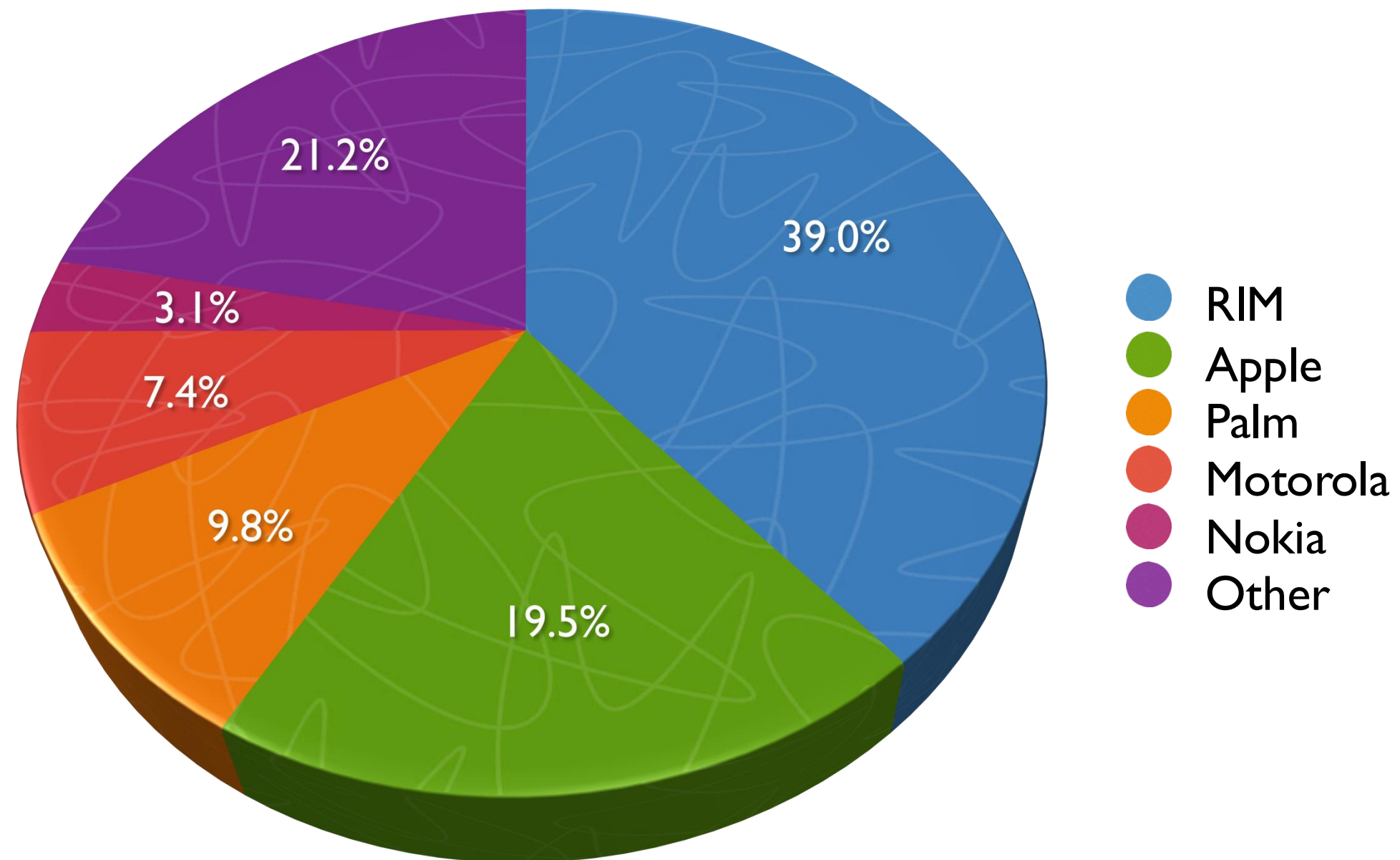
overestimate of depth

- belief that attending to an object leads to more complete and deep understanding than is the case

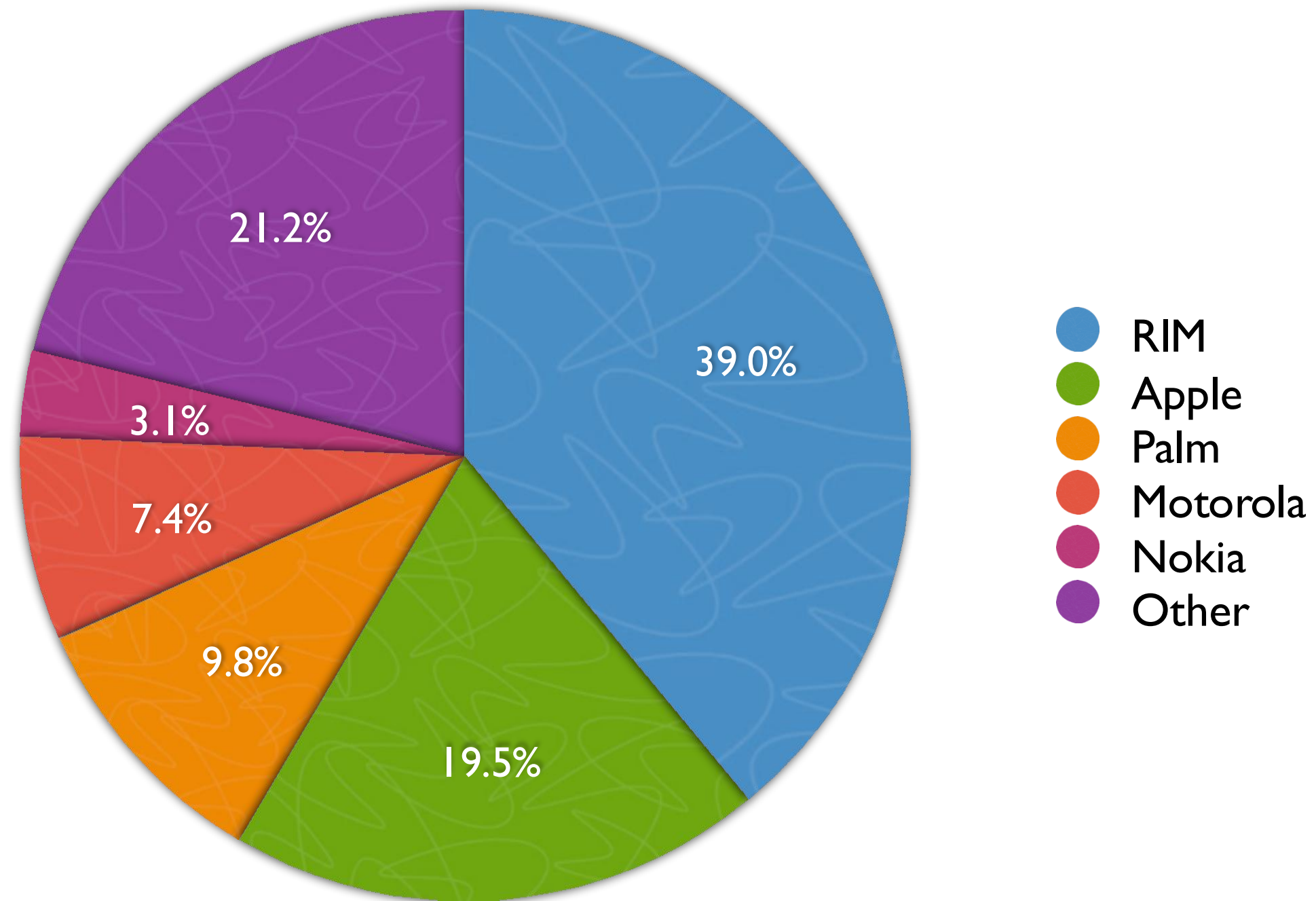
Misleading Encoding



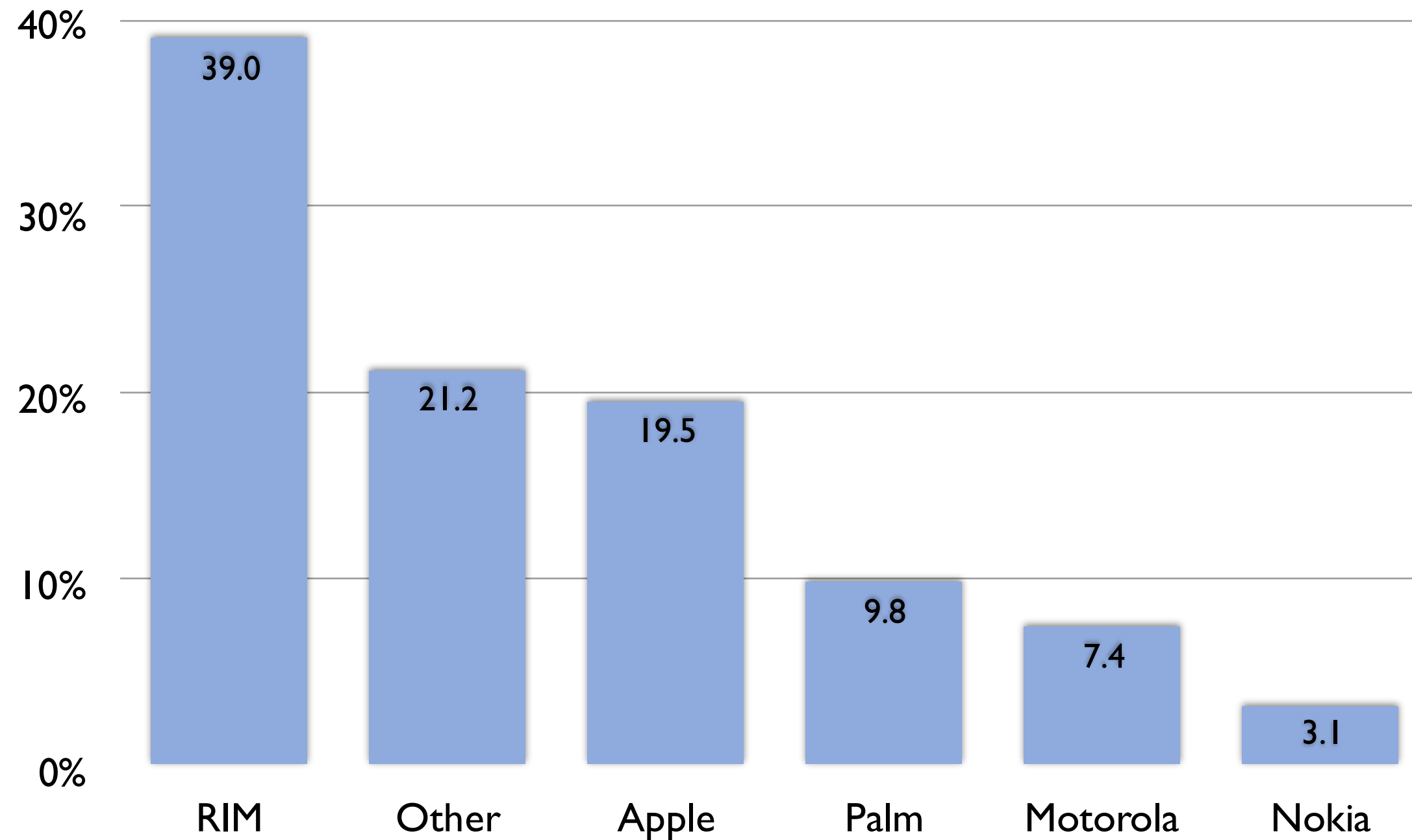
U.S. SmartPhone Marketshare



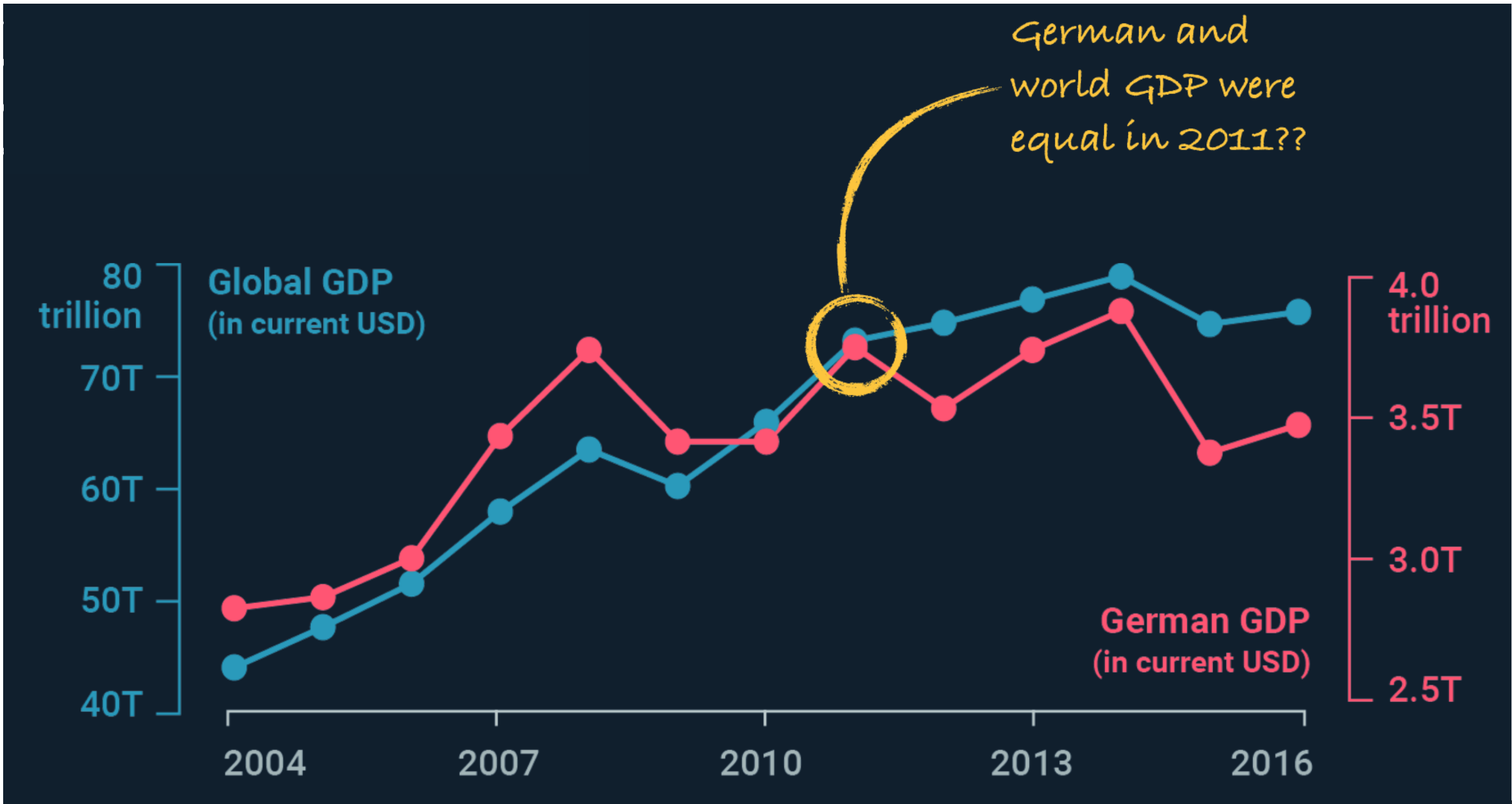
U.S. SmartPhone Marketshare



U.S. SmartPhone Marketshare



Dual Axis Charts



Dual Axis Charts



Orange steady,
Blue massively increasing.



Blue steady,
Orange increasing.



Both started at the same
level, but Orange increased
far more than Blue.



Both started at the same
level, but Blue increased far
more than Orange.

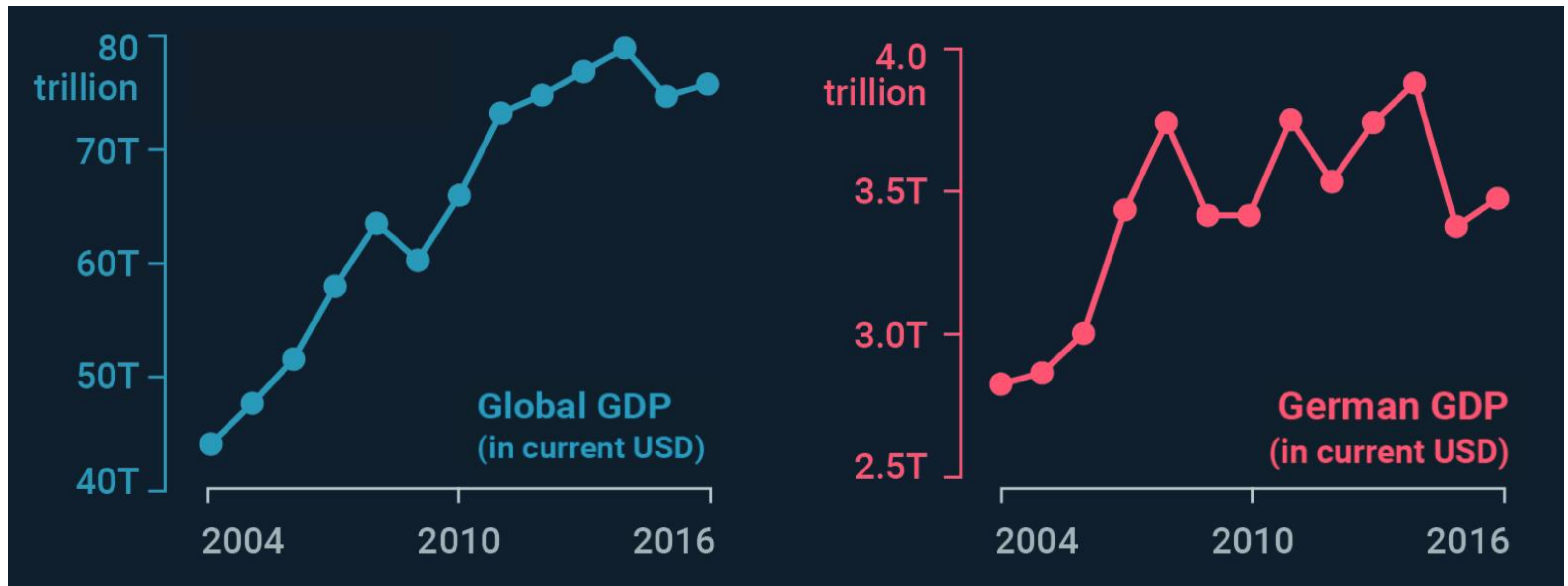


Both started with the
same increase, then Blue
raced to the top.

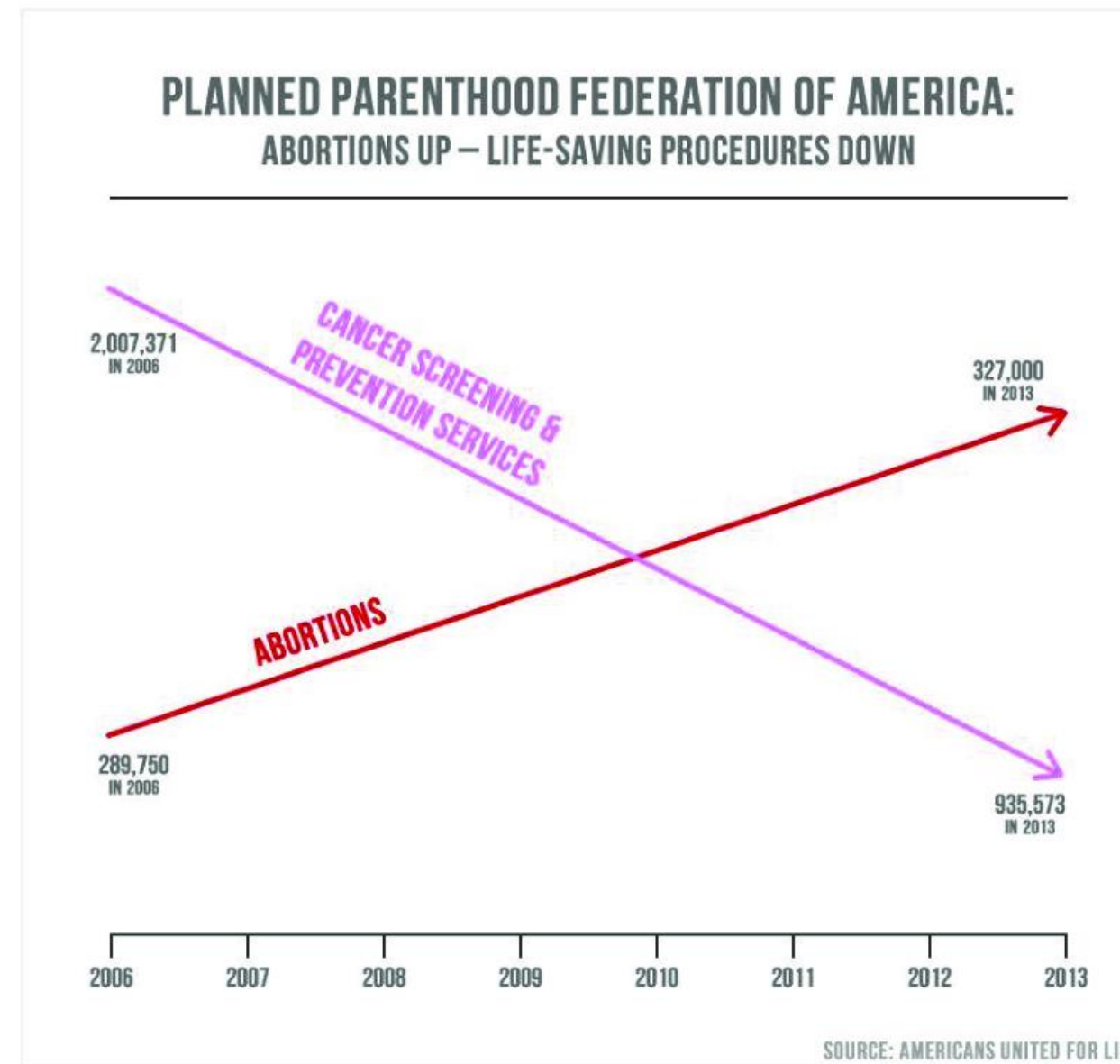


Both steady.

Dual Axis Charts

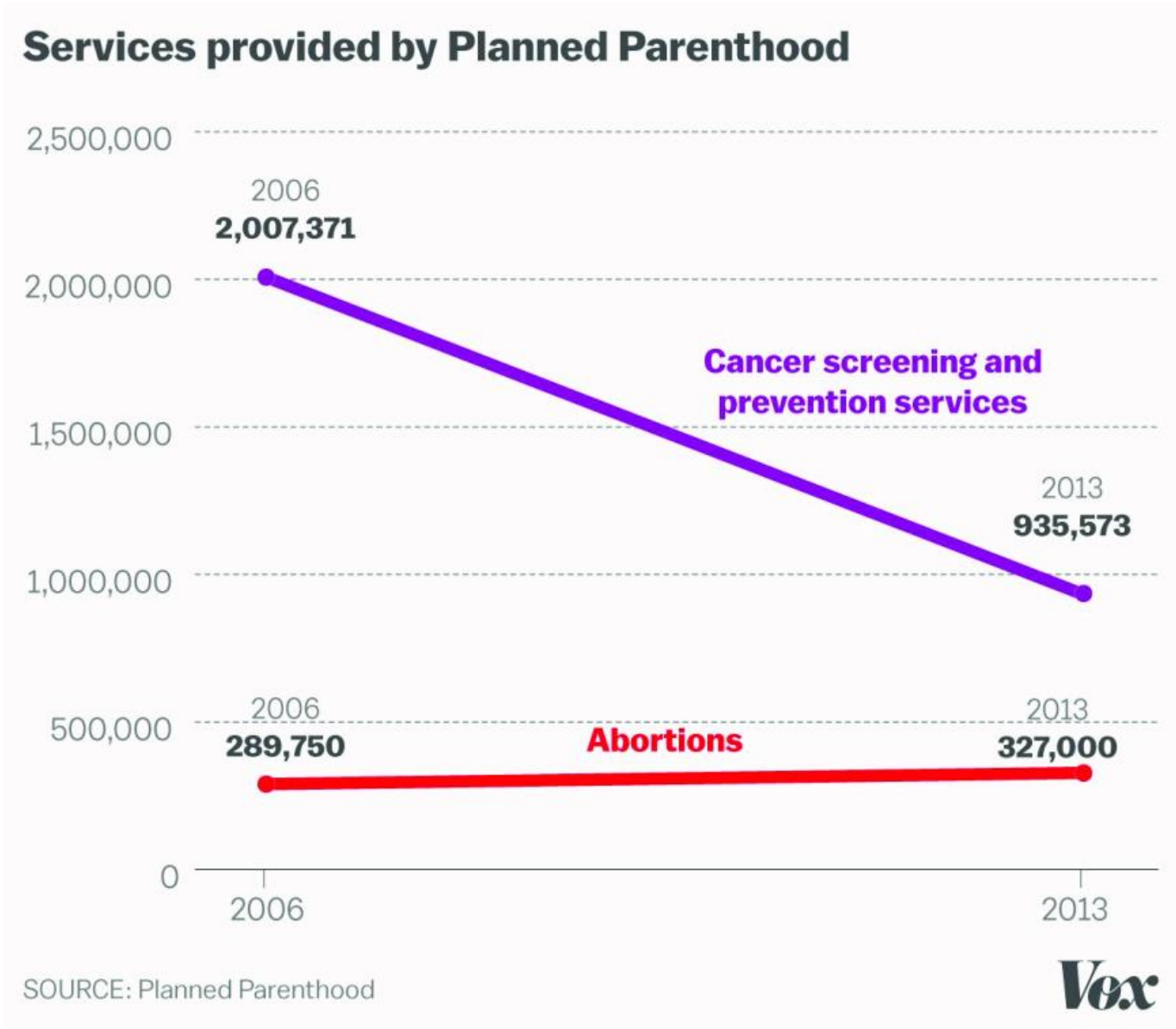
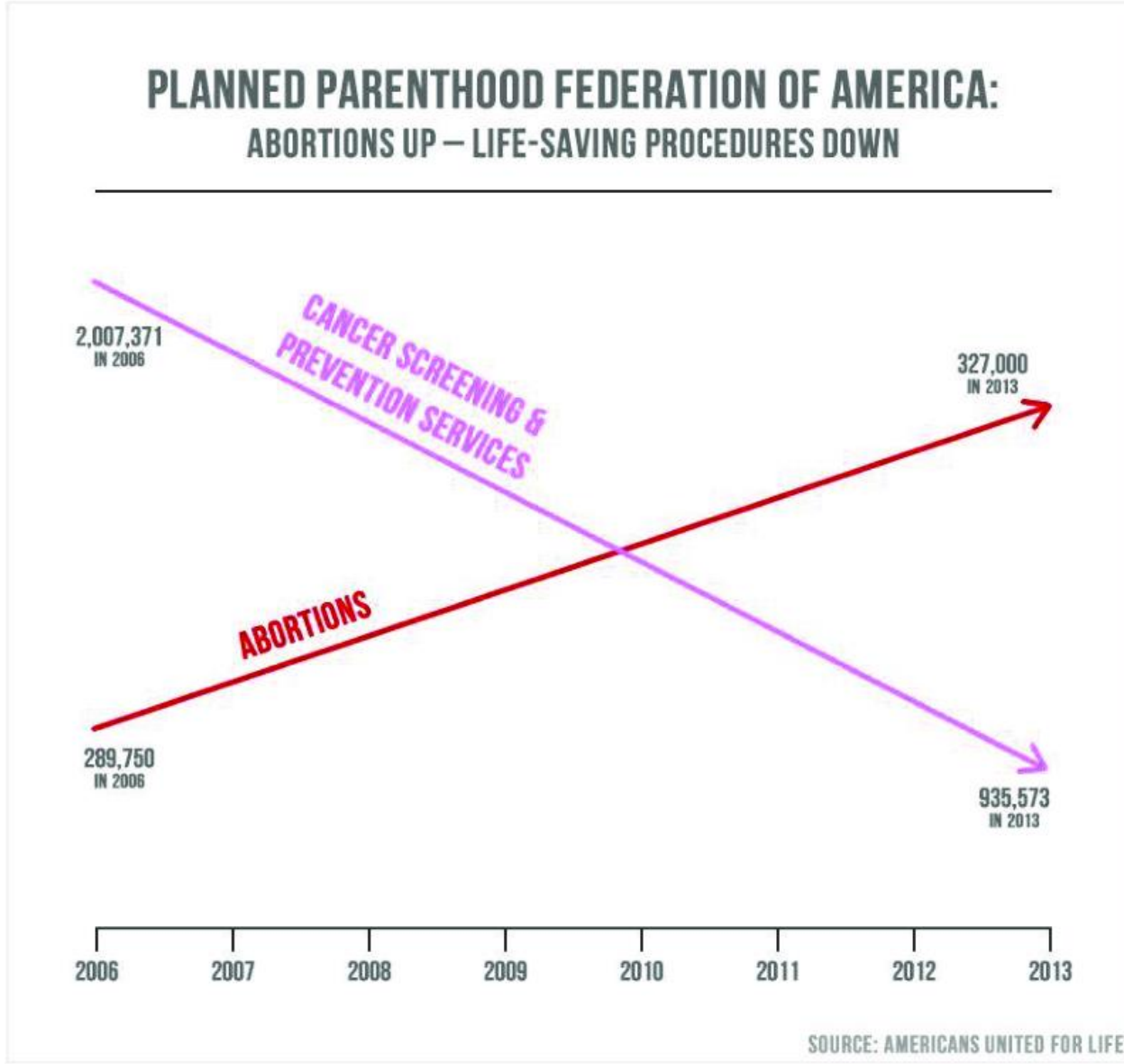


Dual Axis Charts



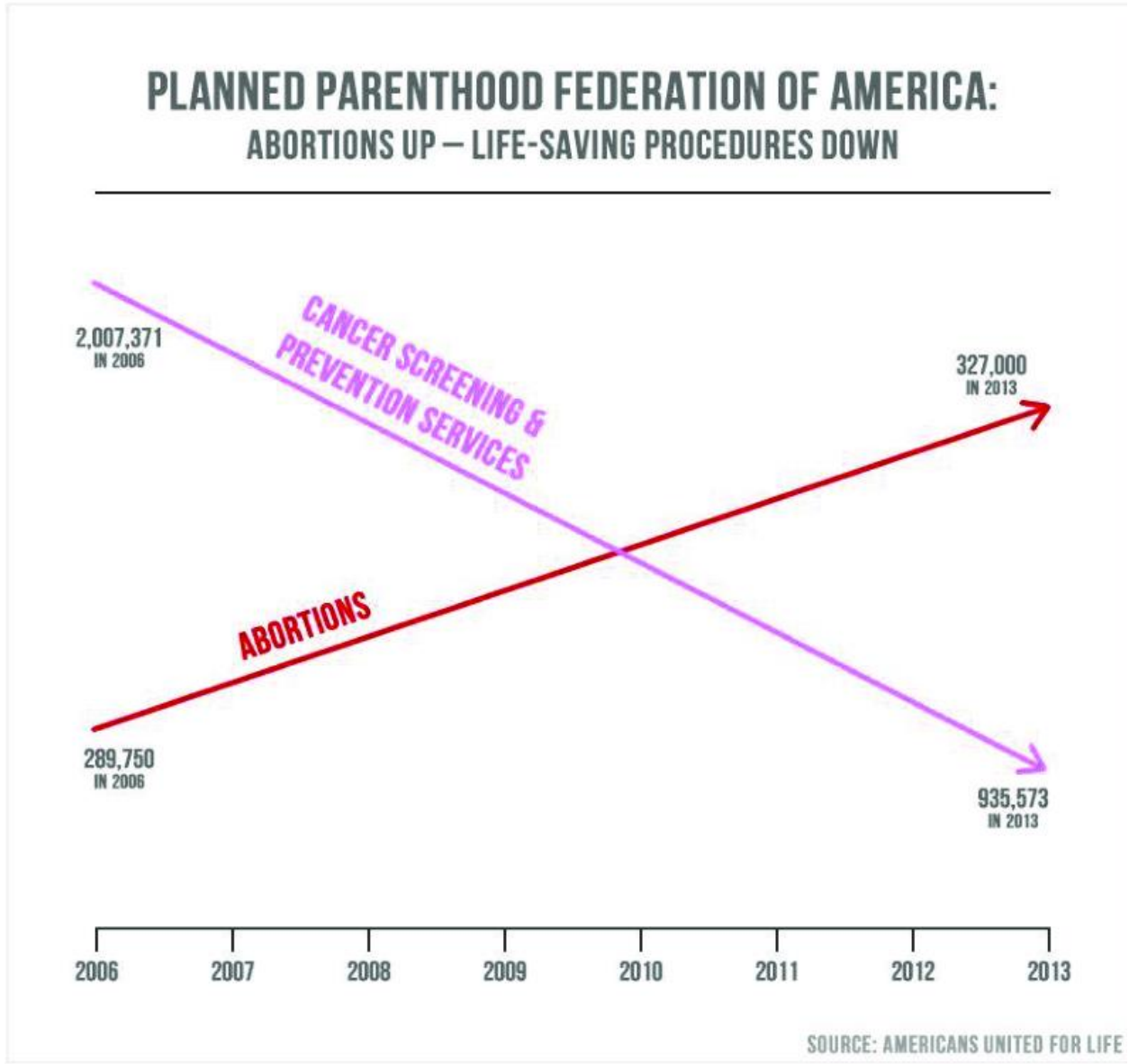
Presented by Rep. Jason Chaffetz. House Oversight Committee, Sept '15

Dual Axis Charts



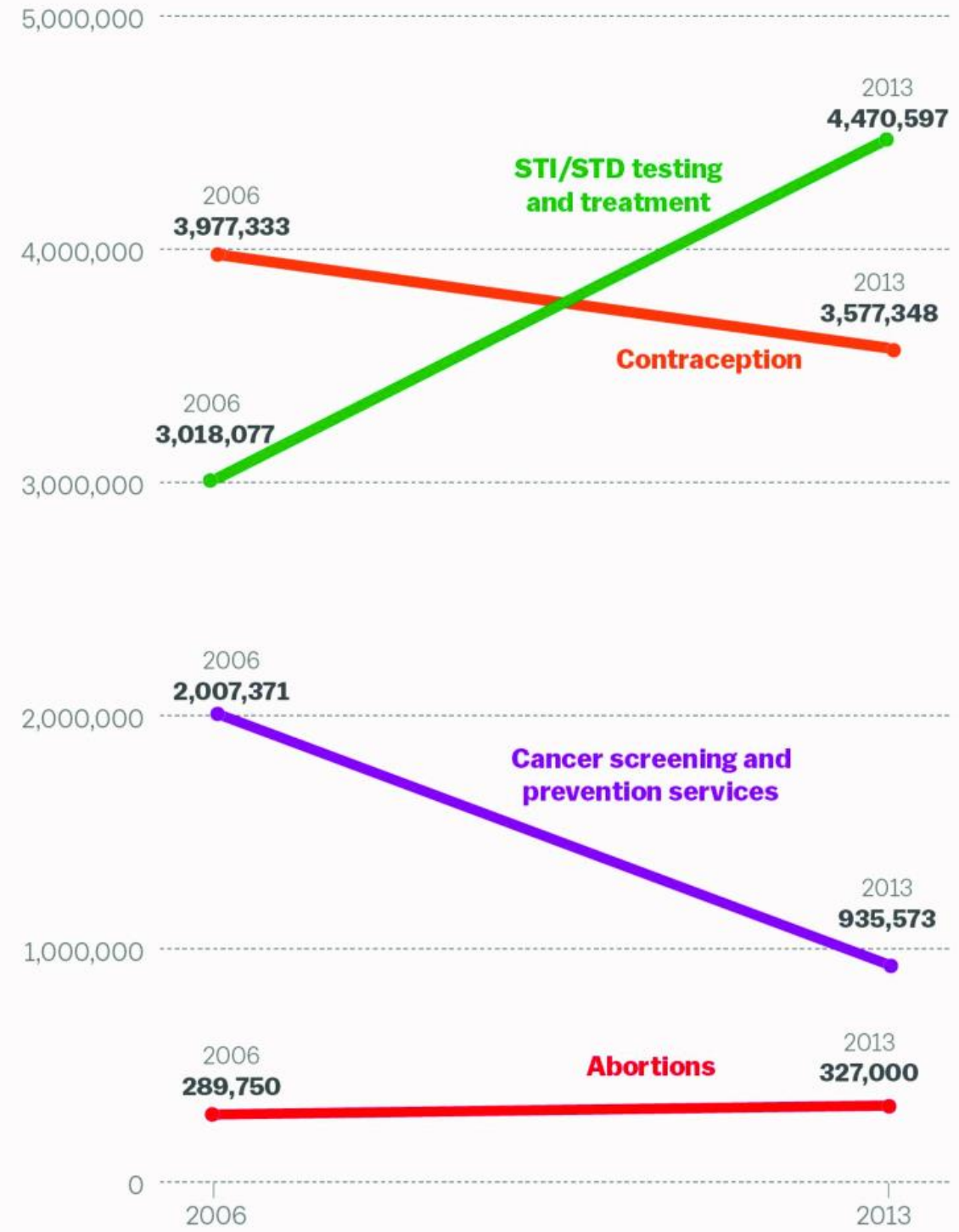
Presented by Rep. Jason Chaffetz. House Oversight Committee, Sept '15

Insufficient Context!



Presented by Rep. Jason Chaffetz. House Oversight Committee, Sept '15

Services provided by Planned Parenthood



SOURCE: Planned Parenthood

Vox

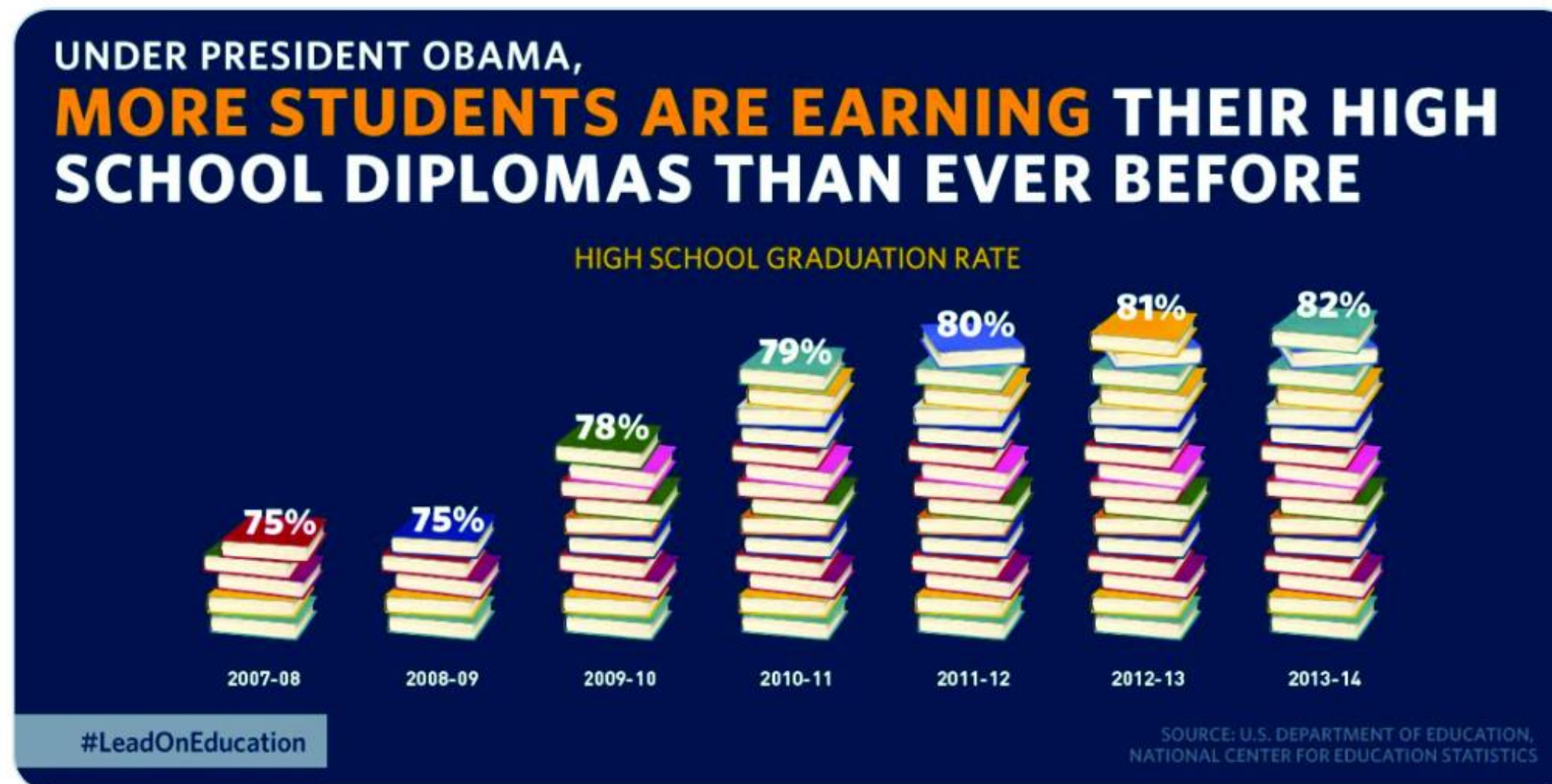
Insufficient Context



White House Archived ✓
@ObamaWhiteHouse



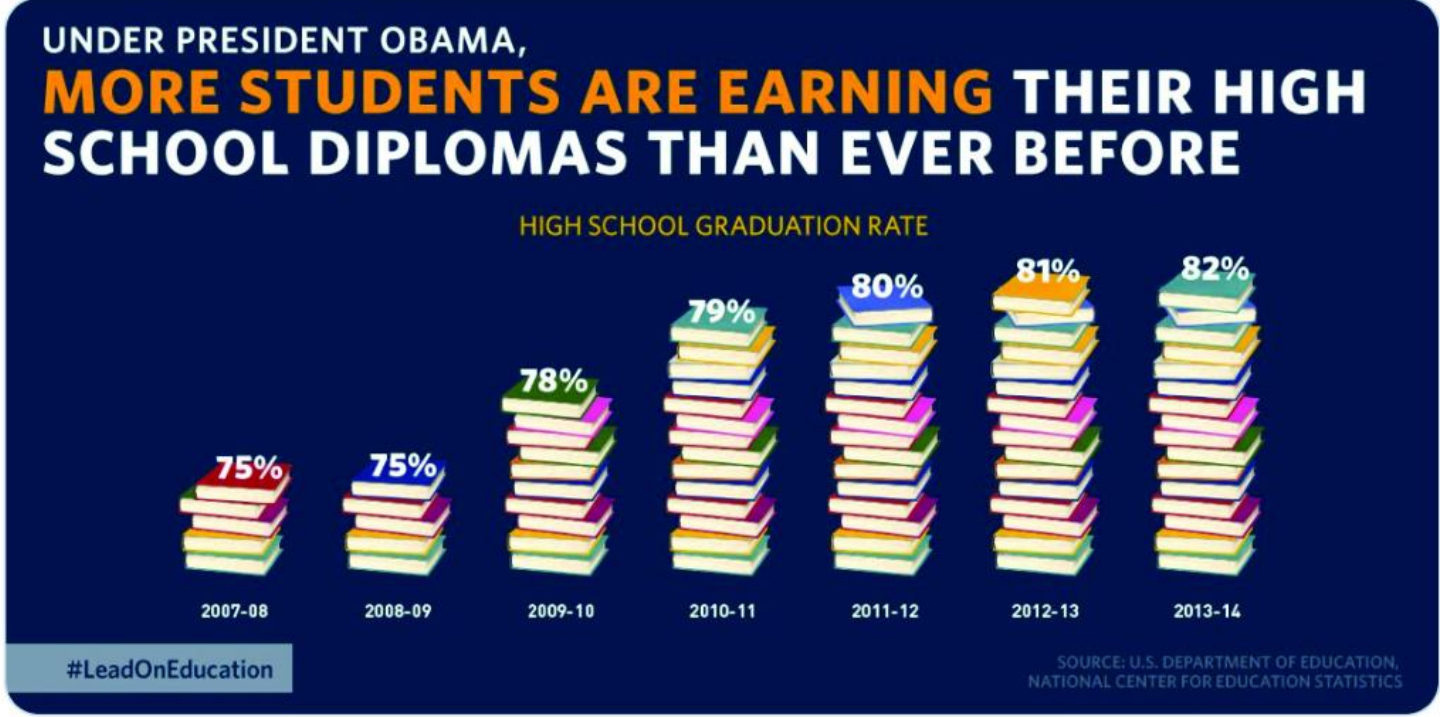
Good news: America's high school graduation rate has increased to an all-time high. 🎓 [wapo.st/1m40Mei](https://www.wapo.st/1m40Mei)



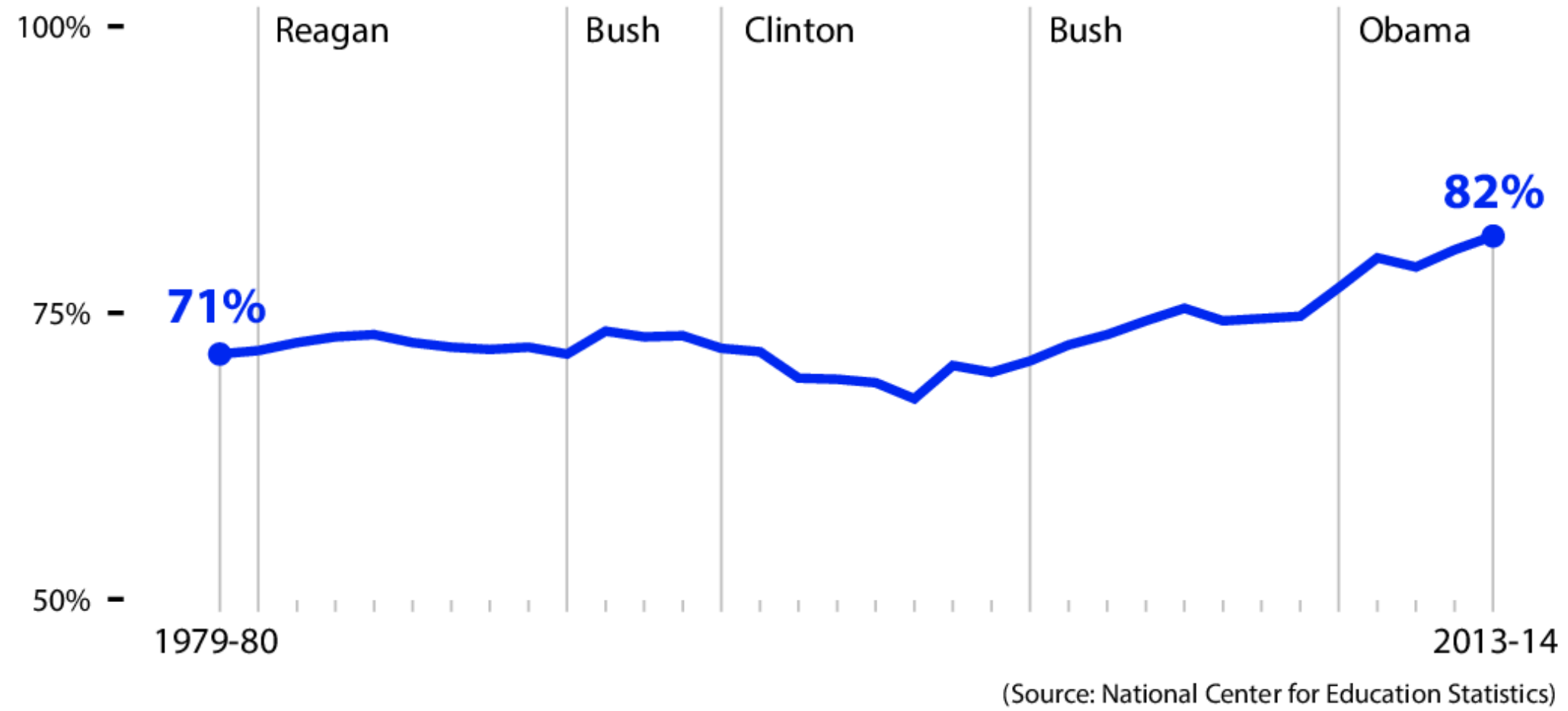
Insufficient Context



Good news: America's high school graduation rate has increased to an all-time high. [wapo.st/1m40Mei](https://www.wapo.st/1m40Mei)



High school graduation rates under each president



Insufficient Context

 **Donald J. Trump** ✓
@realDonaldTrump



♡ 236K 6:05 AM - Oct 1, 2019



 **Trey Yingst** ✓
@TreyYingst

Spotted: A map to be hung somewhere in the West Wing



♡ 8,013 9:03 AM - May 11, 2017



Insufficient Context

Share of the popular vote in the 2016 presidential election



Percentage of eligible voters



