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



# Visualization for Data Science DS-4630 / CS-5630 / CS-6630

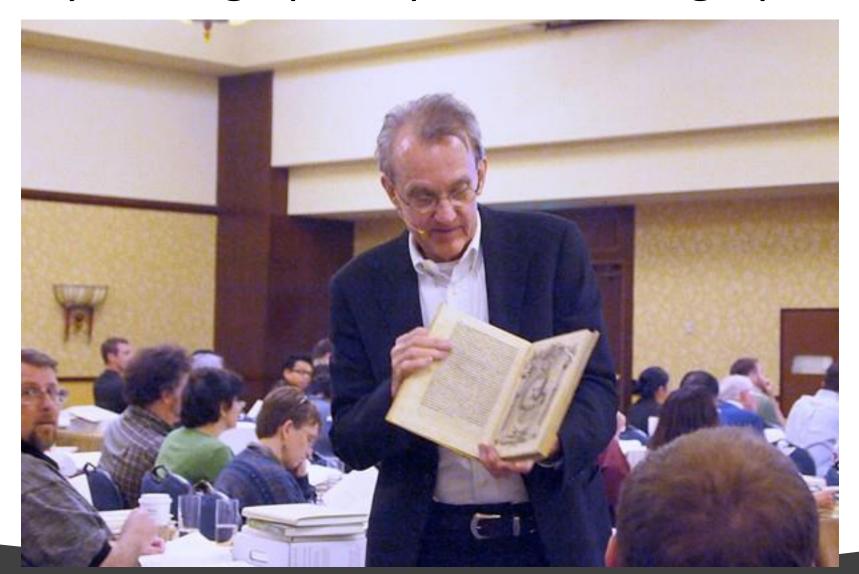
Visual Design and Dark Patterns

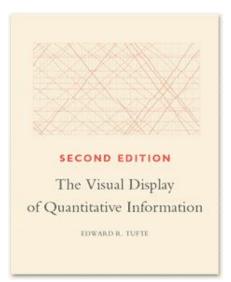
# TUFTE Design excellence

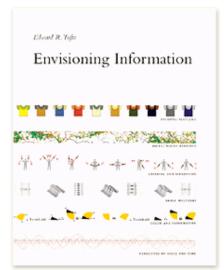


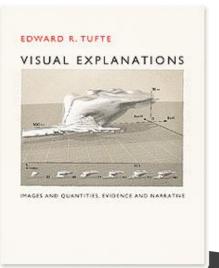
#### TUFTE'S LESSONS

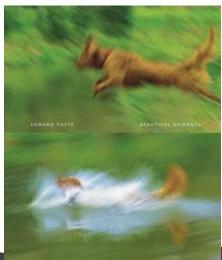
- practice—graphical integrity and excellence
- theory—design principles for data graphics













# 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."

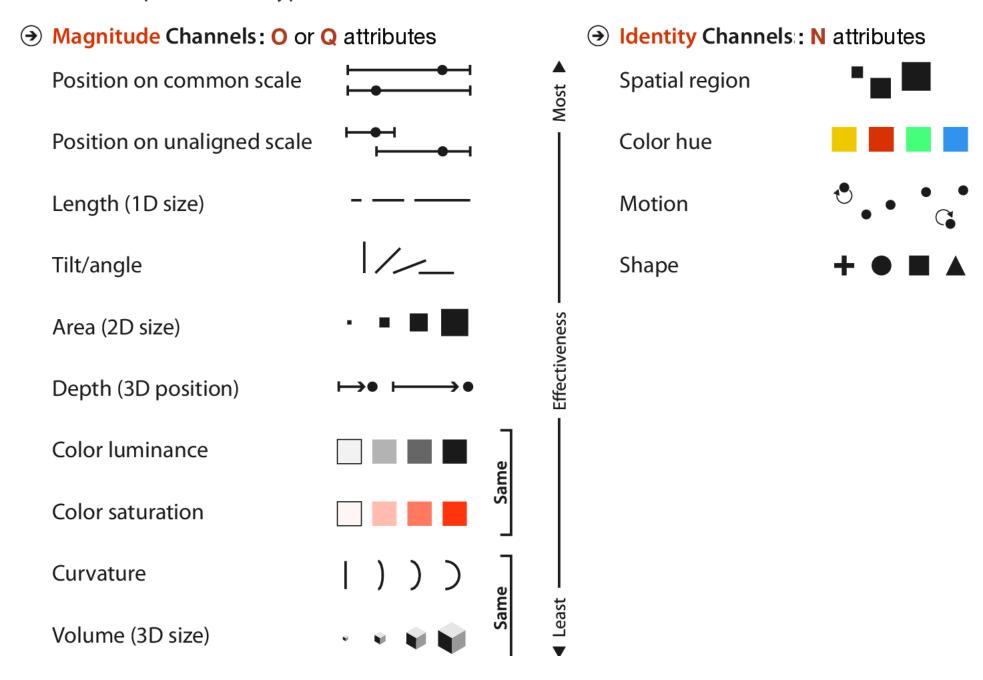


# Effective Encoding





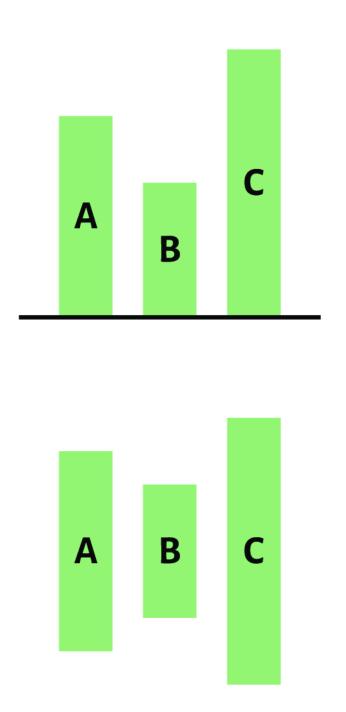
#### **Channels:** Expressiveness Types and Effectiveness Ranks





#### **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 Effectiveness Area (2D size) Depth (3D position) Color luminance Color saturation Curvature Volume (3D size)



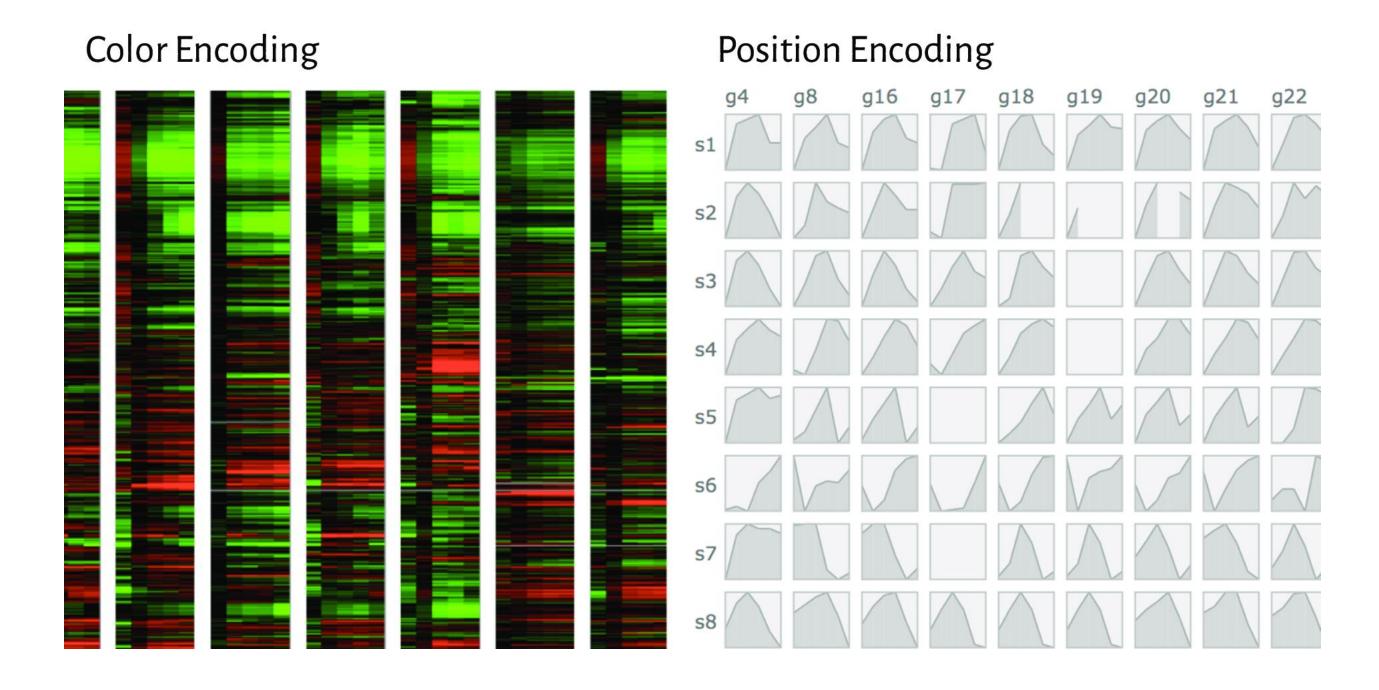


#### **Channels:** Expressiveness Types and Effectiveness Ranks

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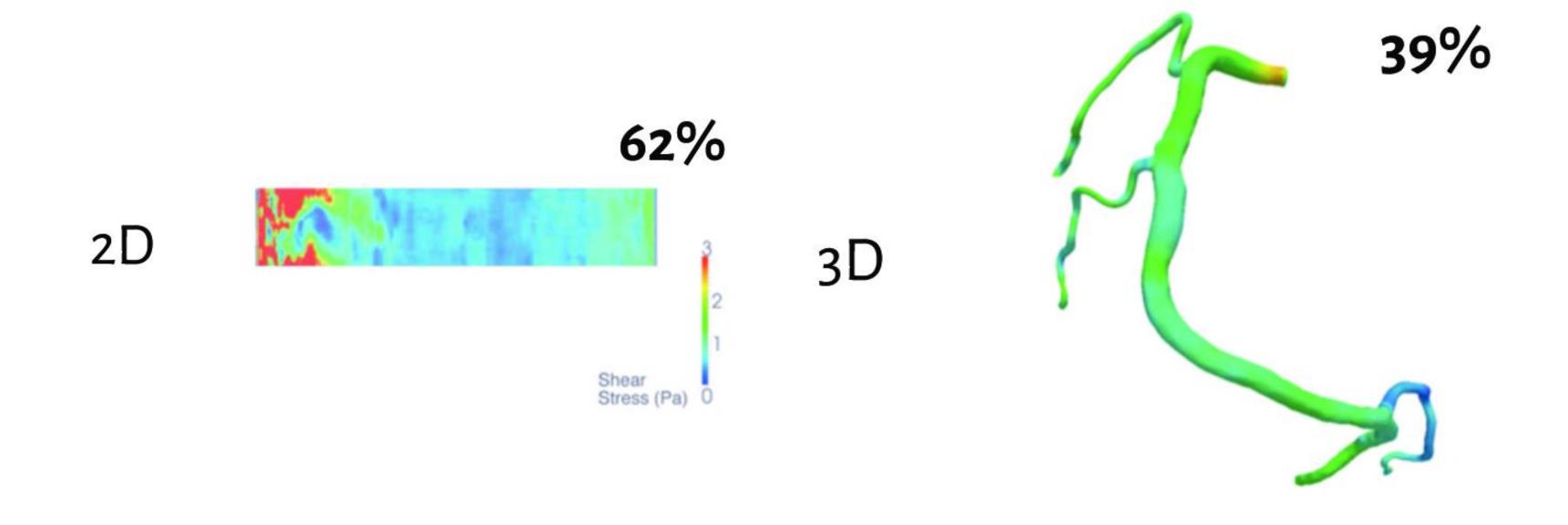
#### Gene Expression Time-Series [Meyer et al. '10]







## Artery Visualization [Borkin et al. '11]





## Scales



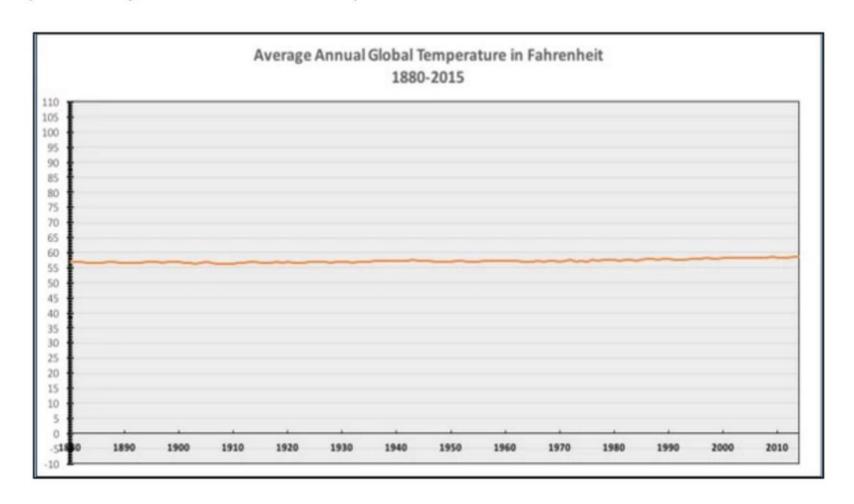






The only #climatechange chart you need to see. natl.re/wPKpro

#### (h/t @powerlineUS)



RETWEETS 408

LIKES 322









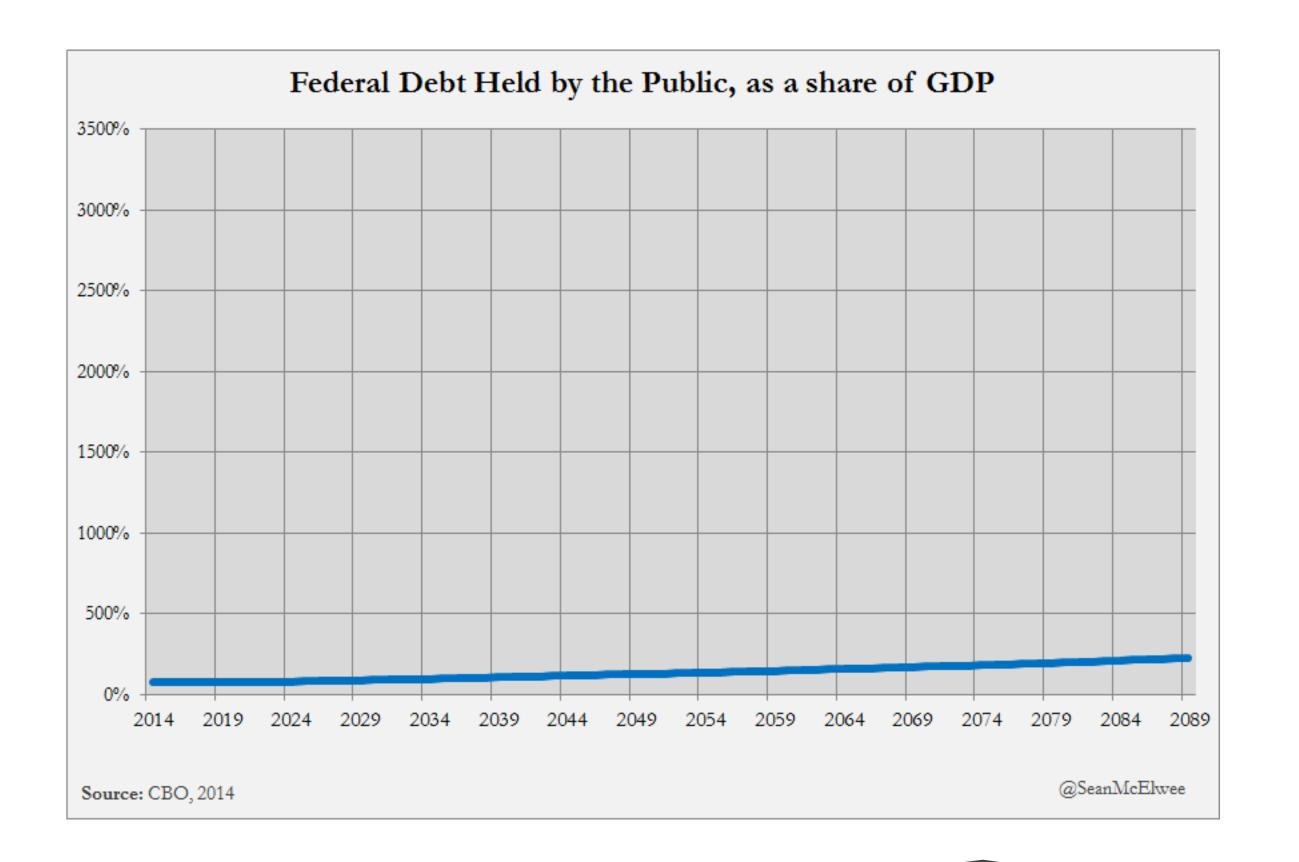
1:36 PM - 14 Dec 2015



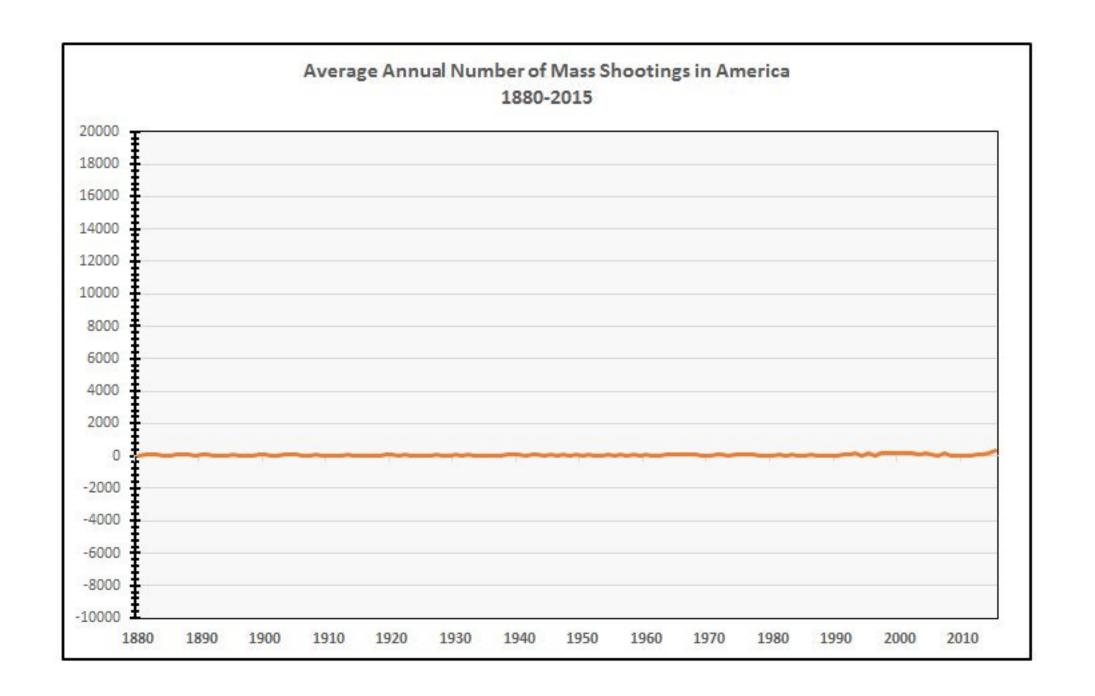






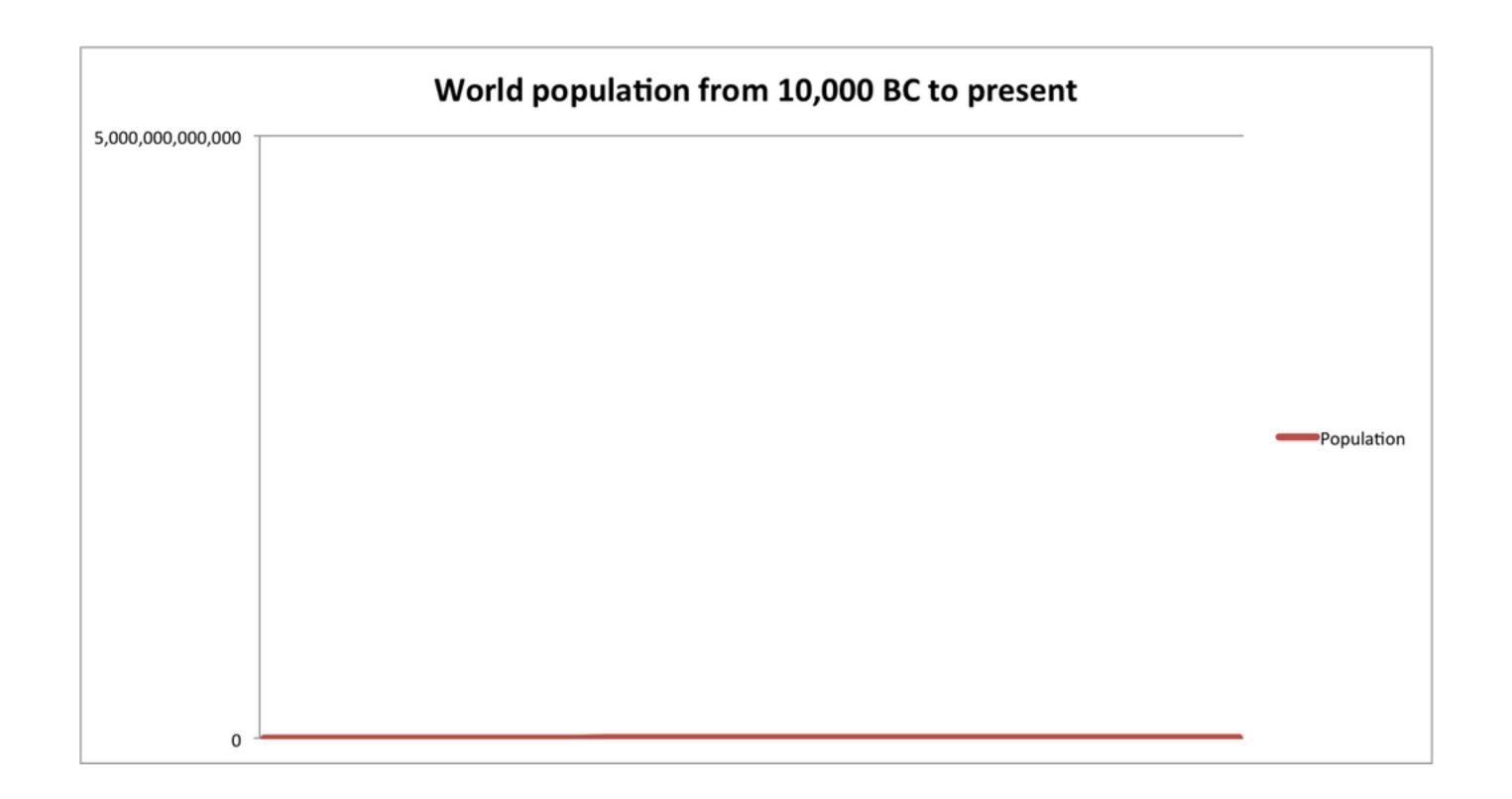








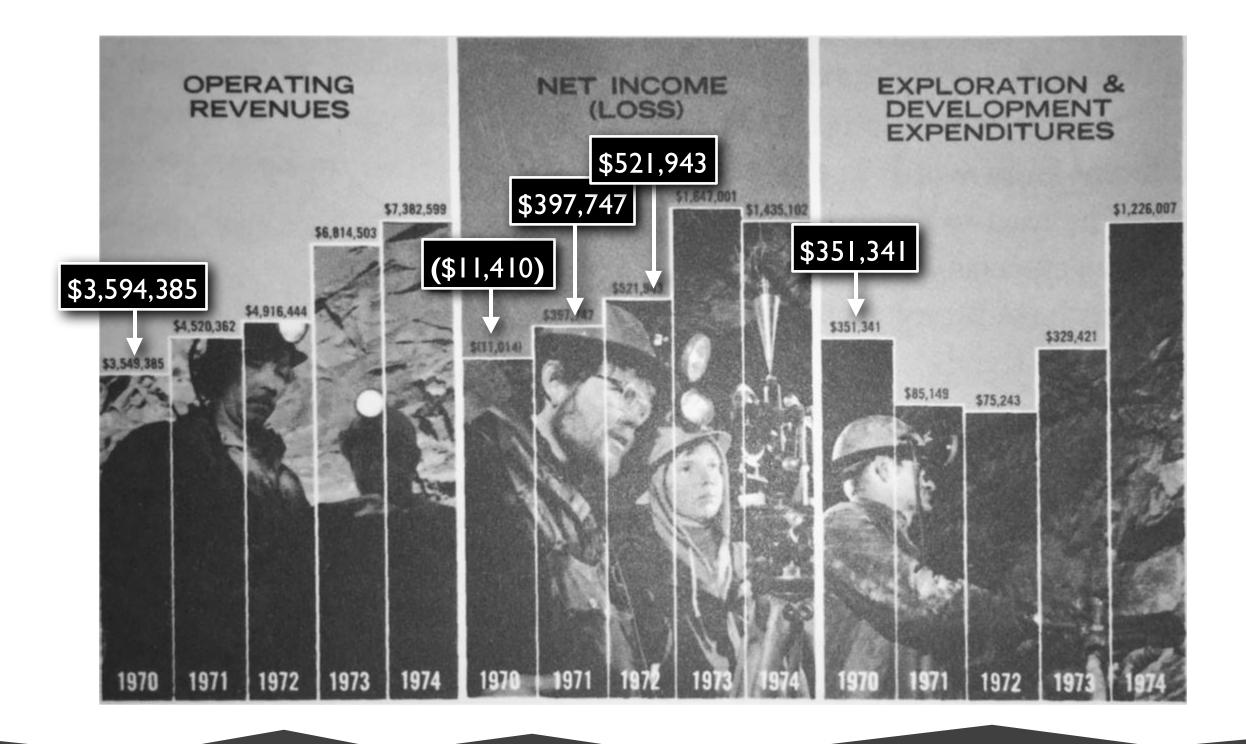






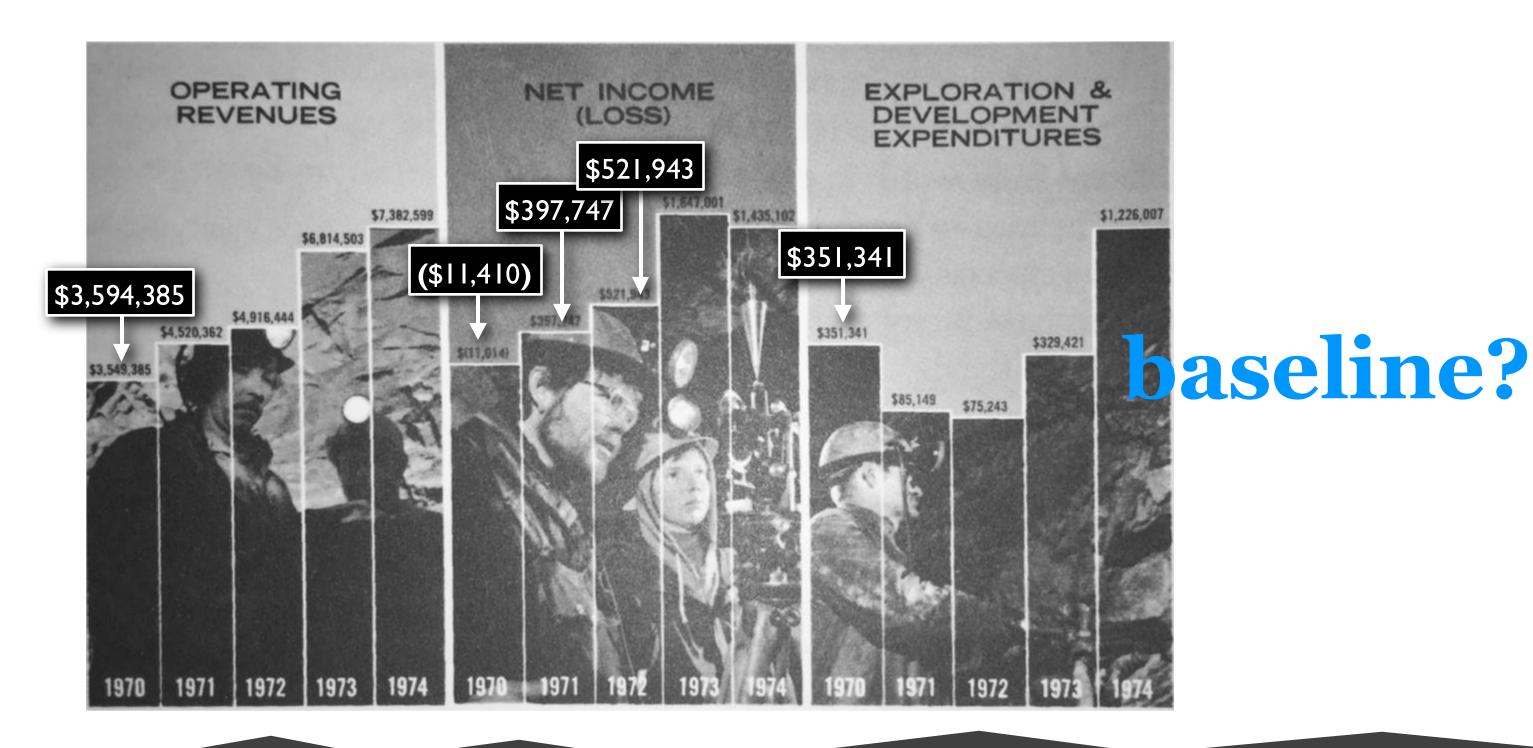


#### MISSING SCALES





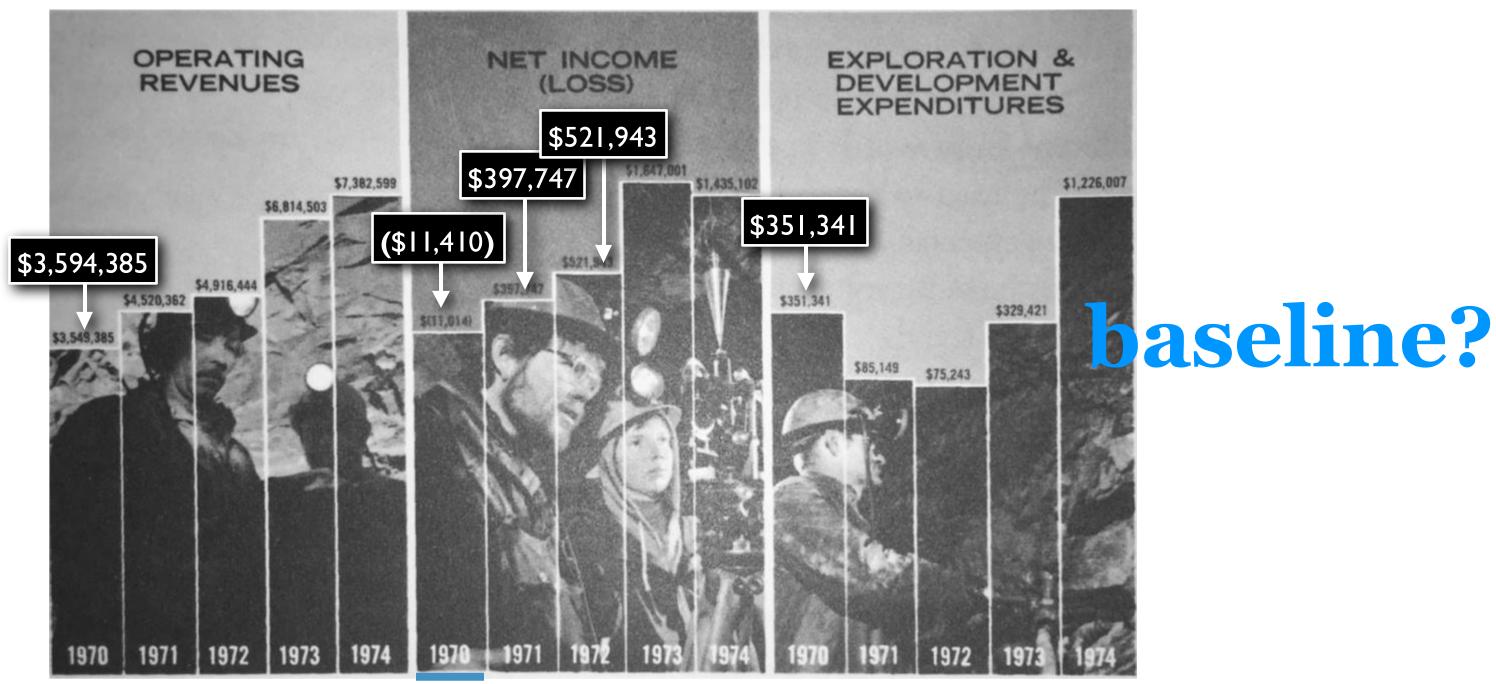
#### MISSING SCALES





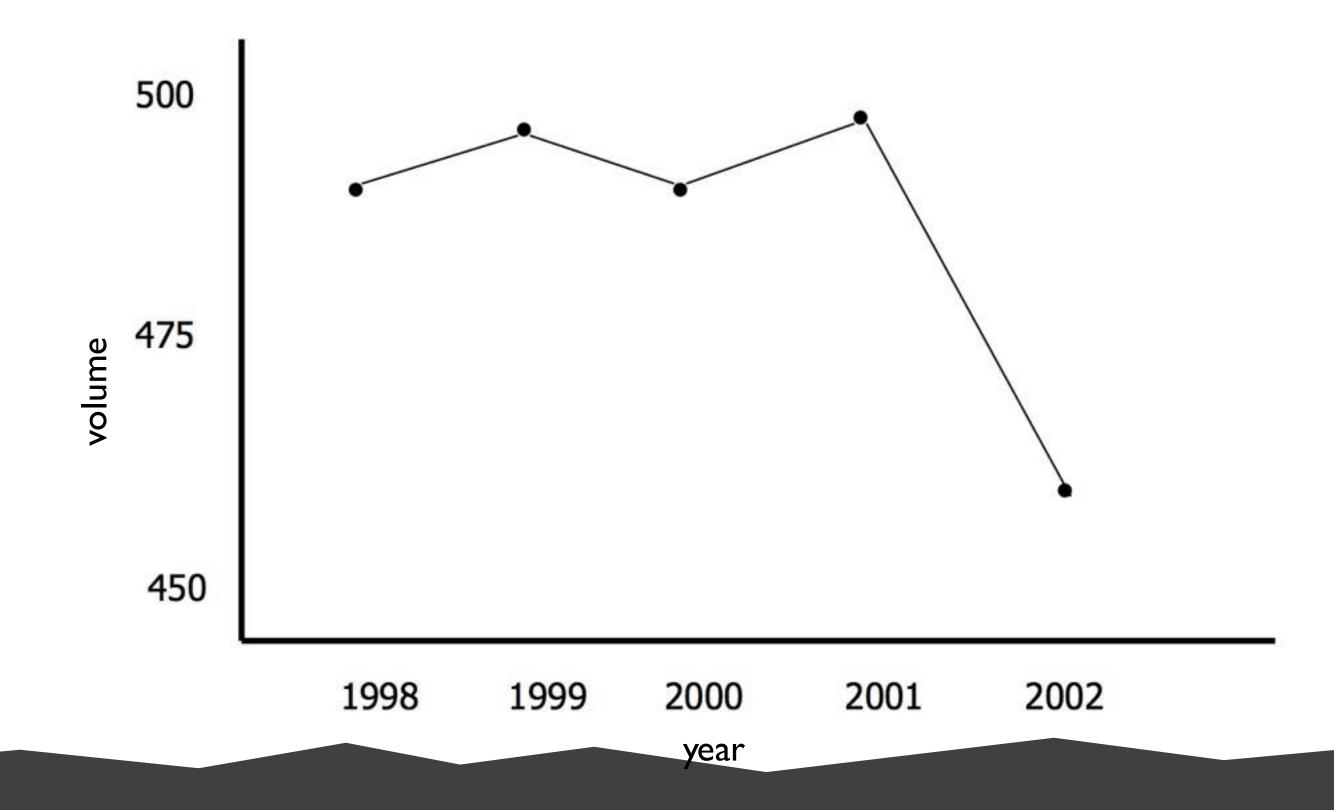


#### MISSING SCALES

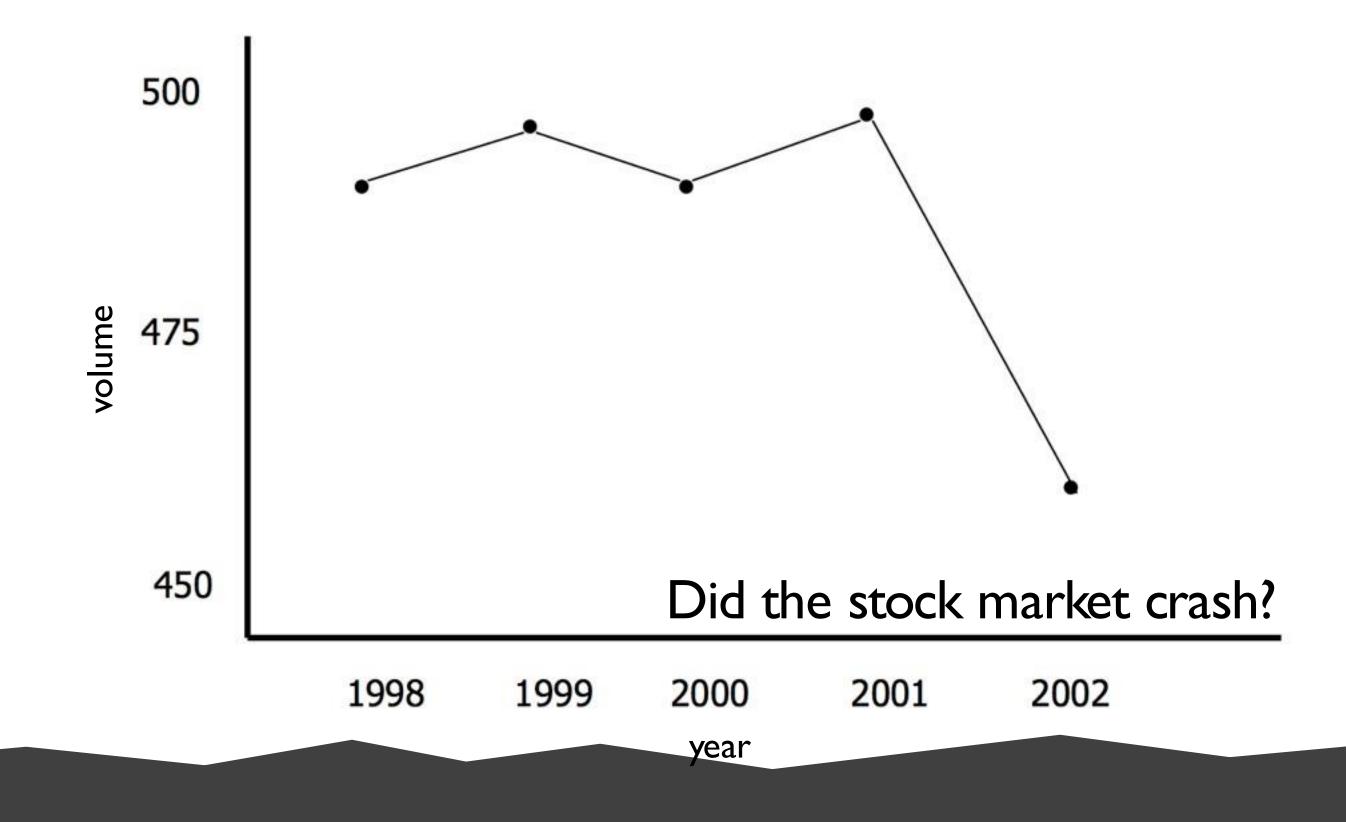




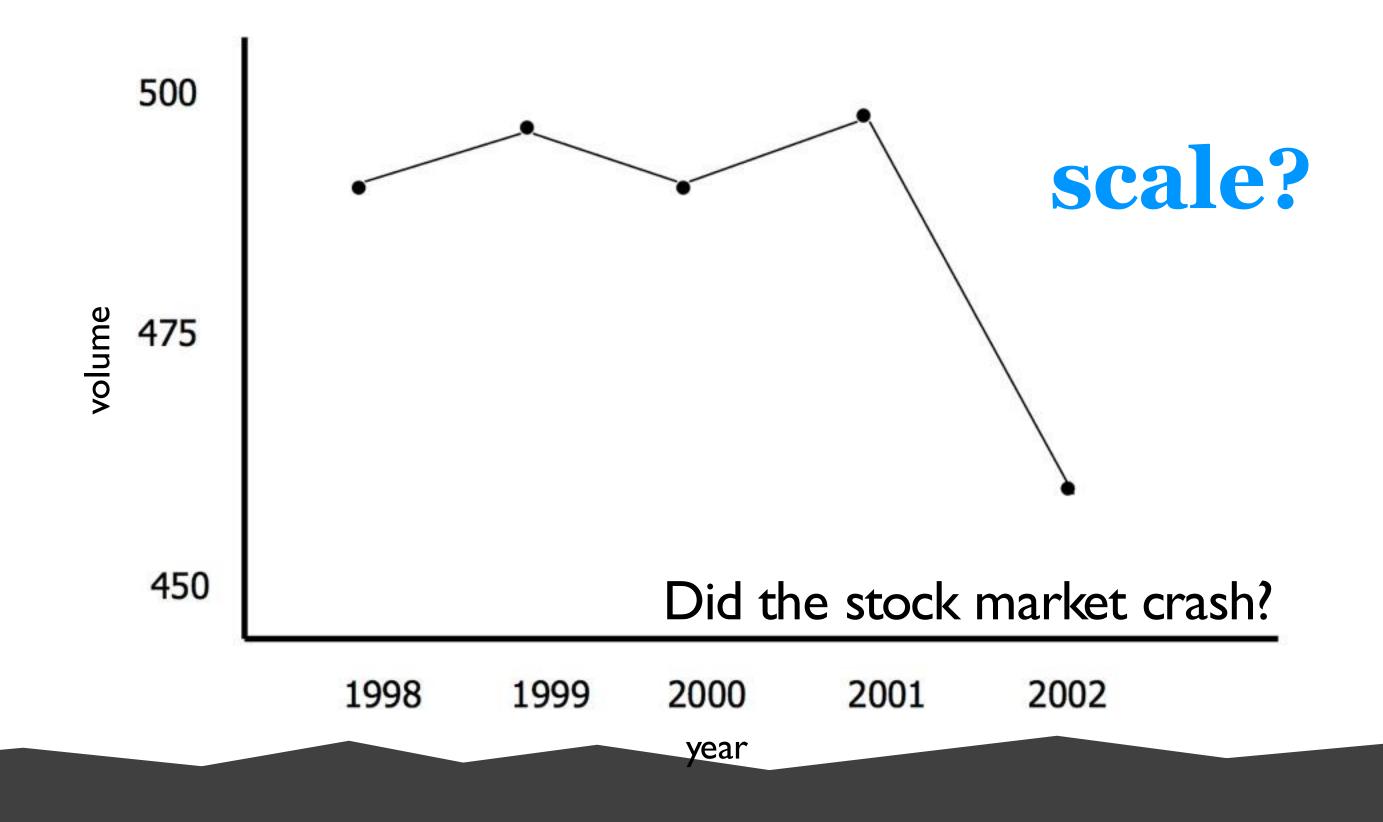




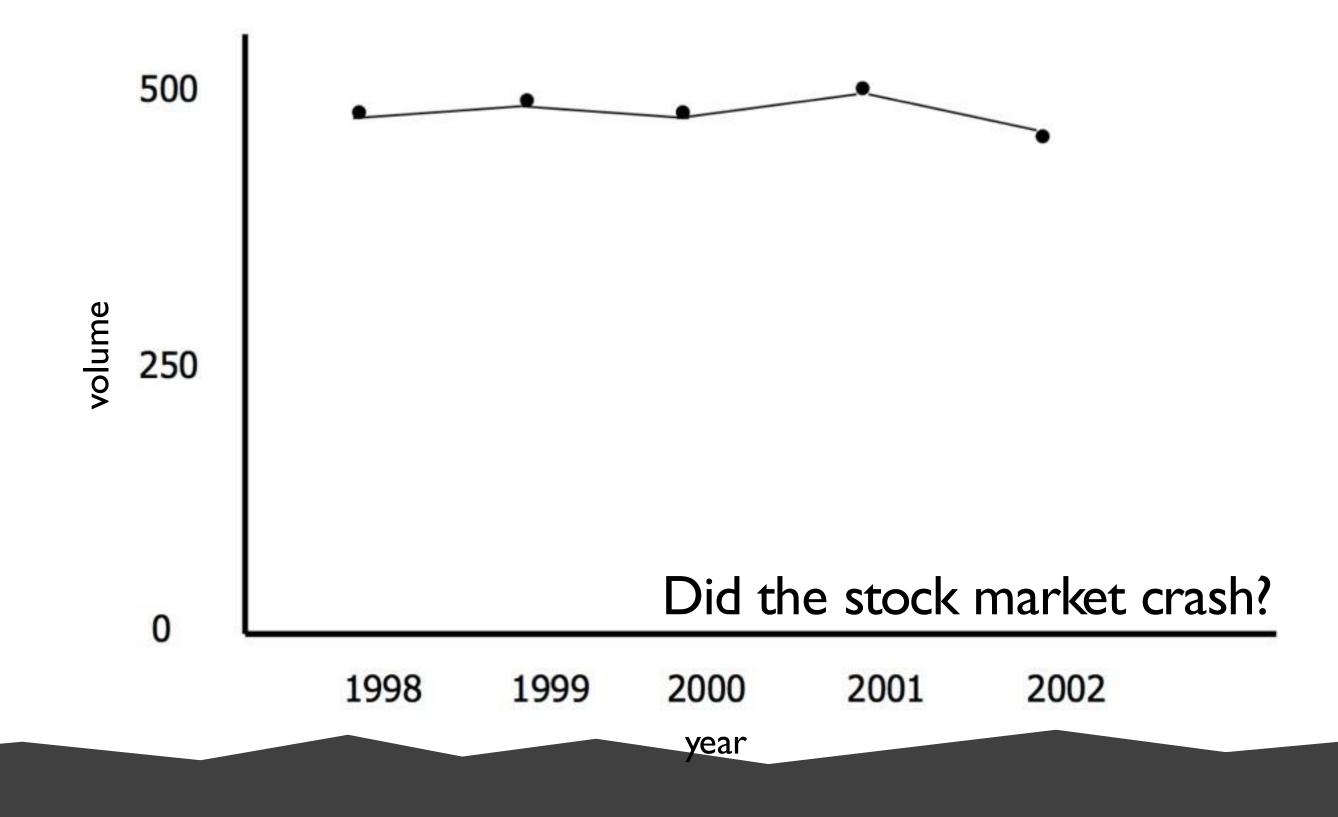




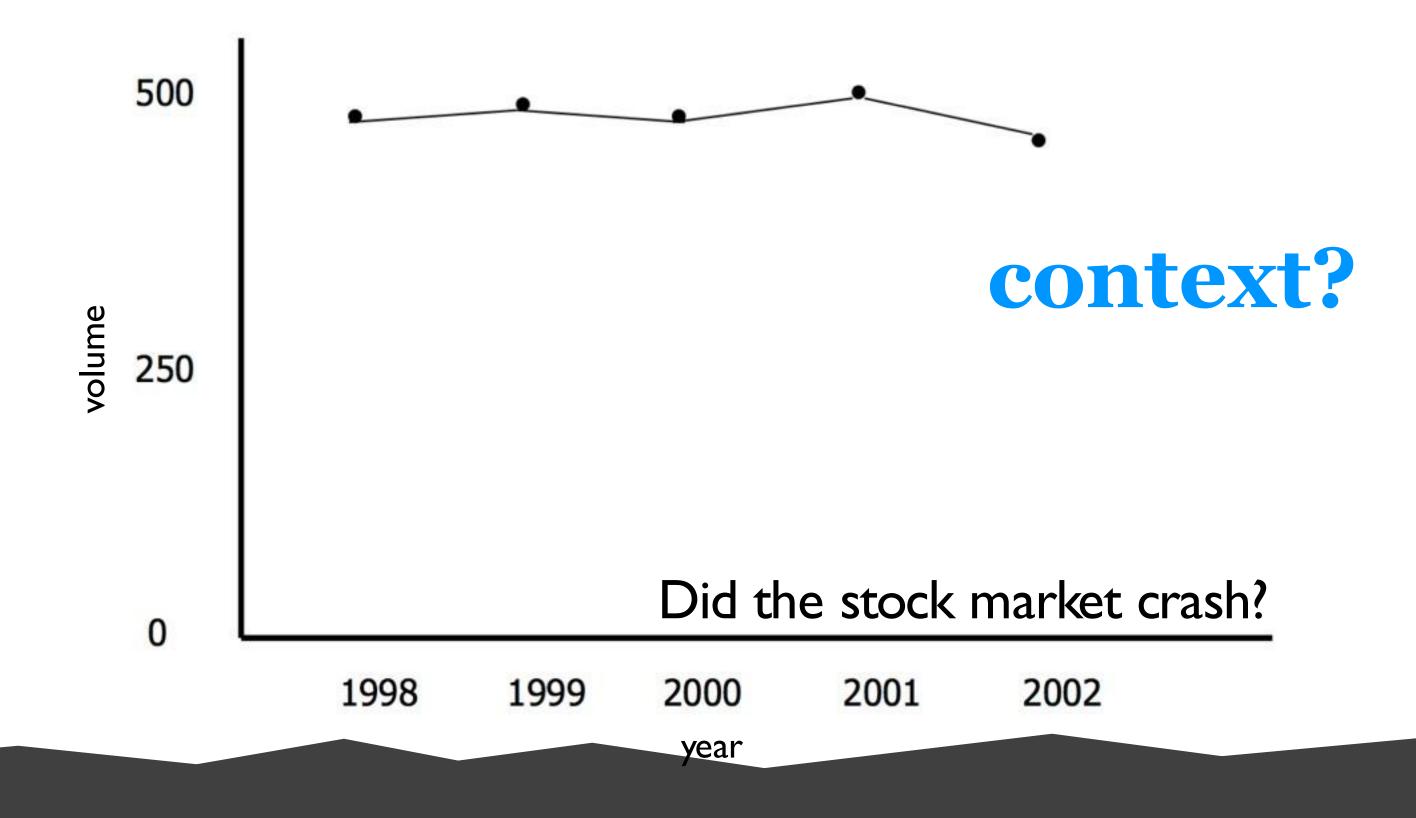




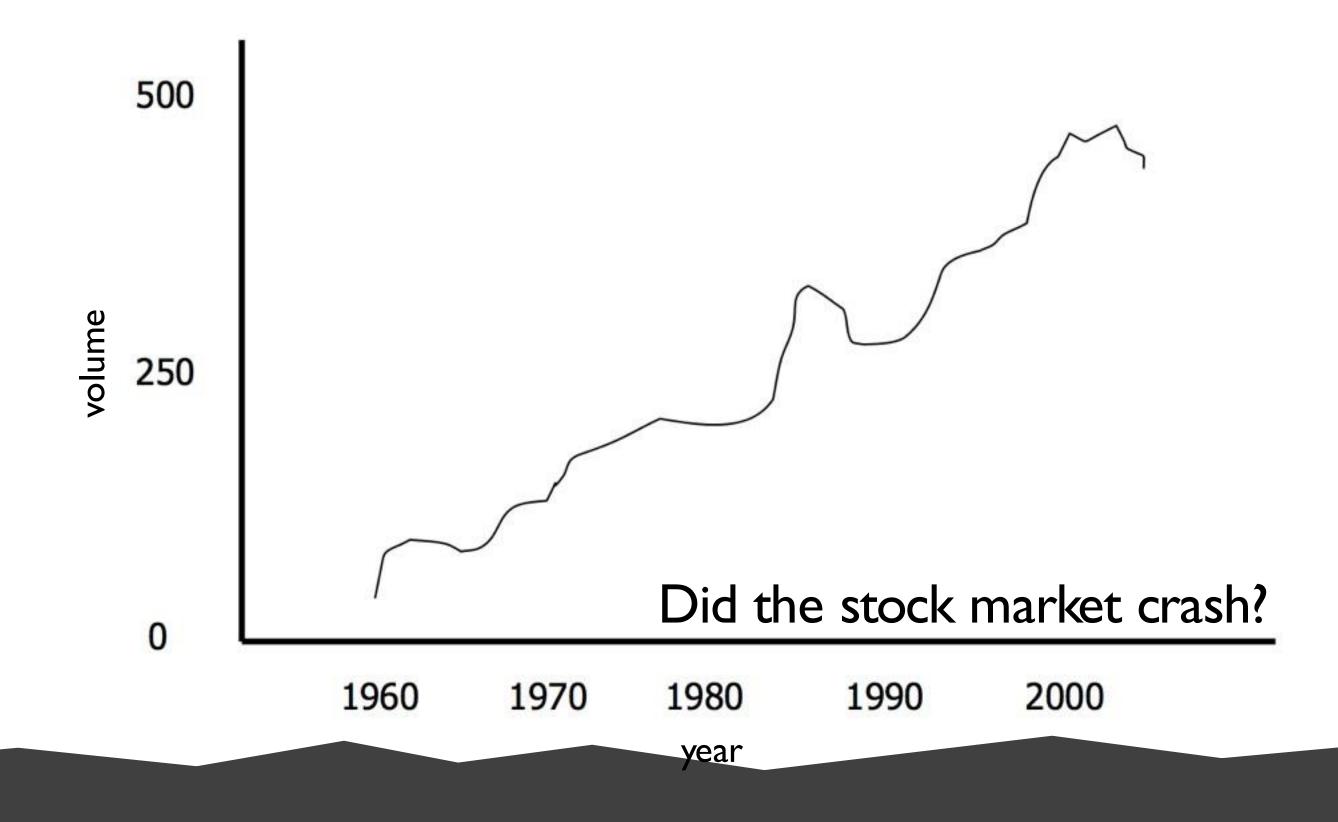




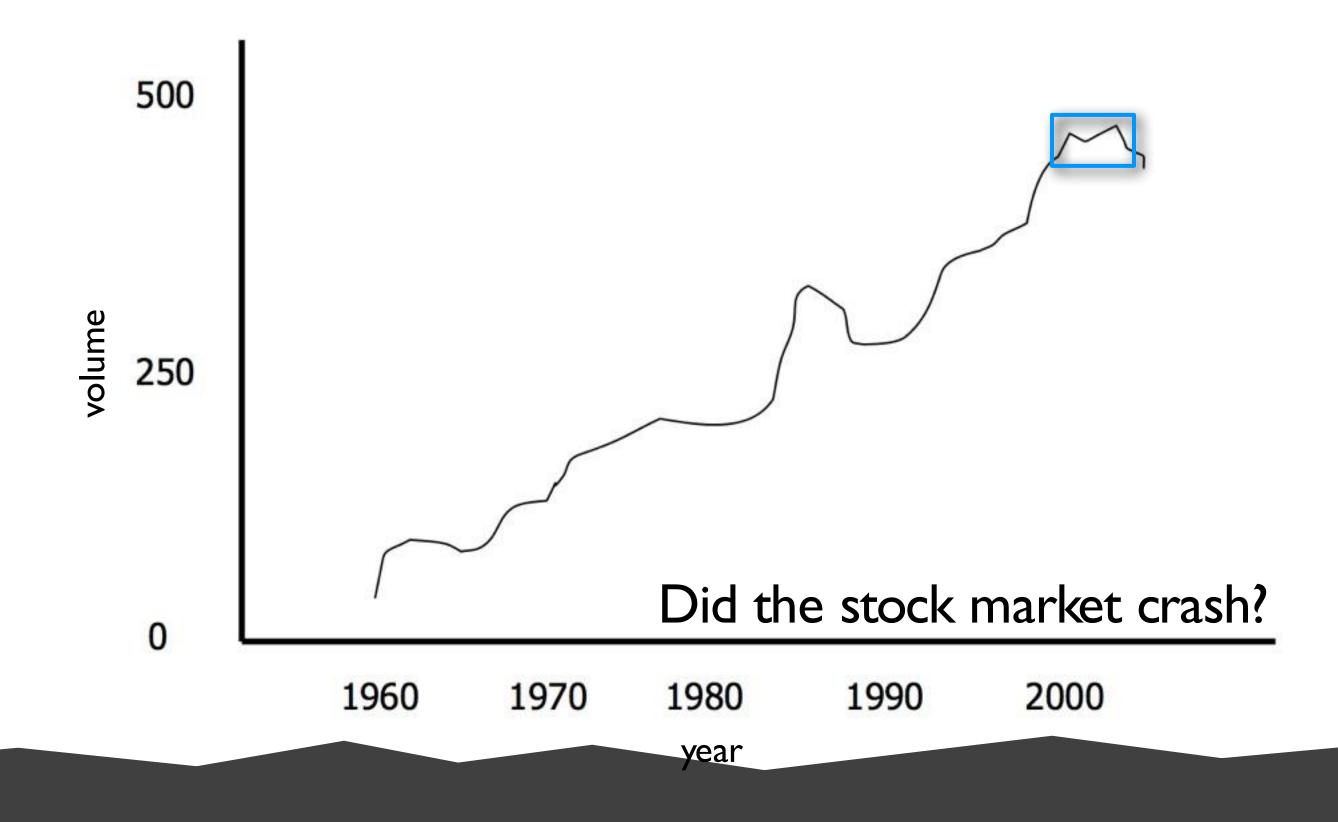






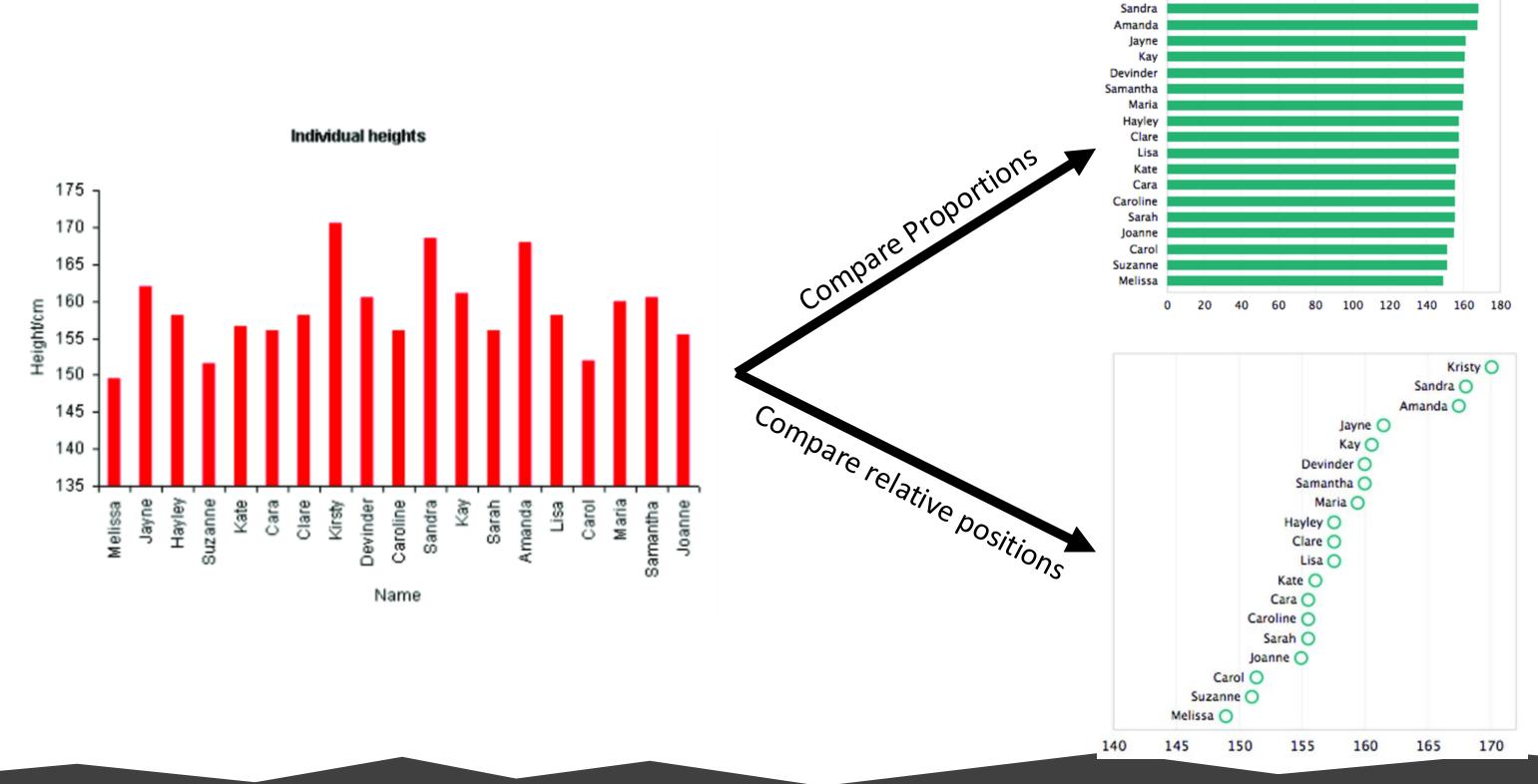








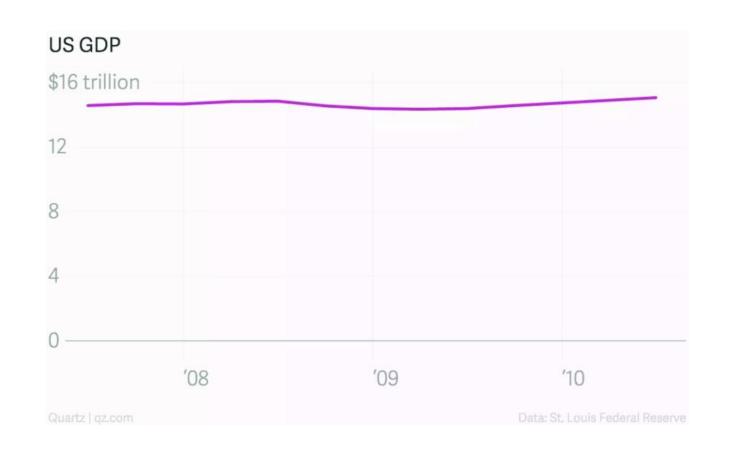
#### Zero Baseline

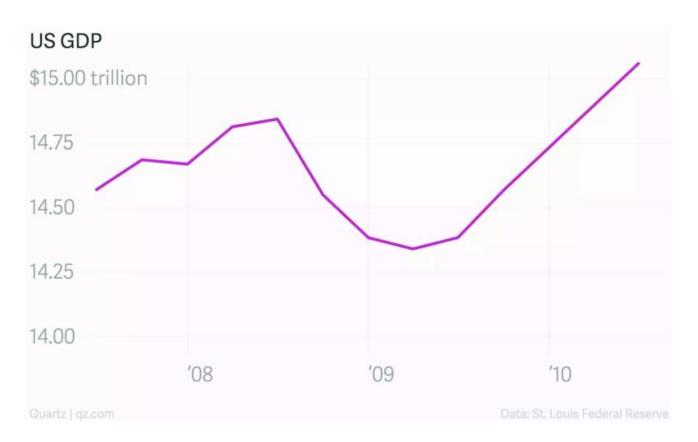


Kristy



#### 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)

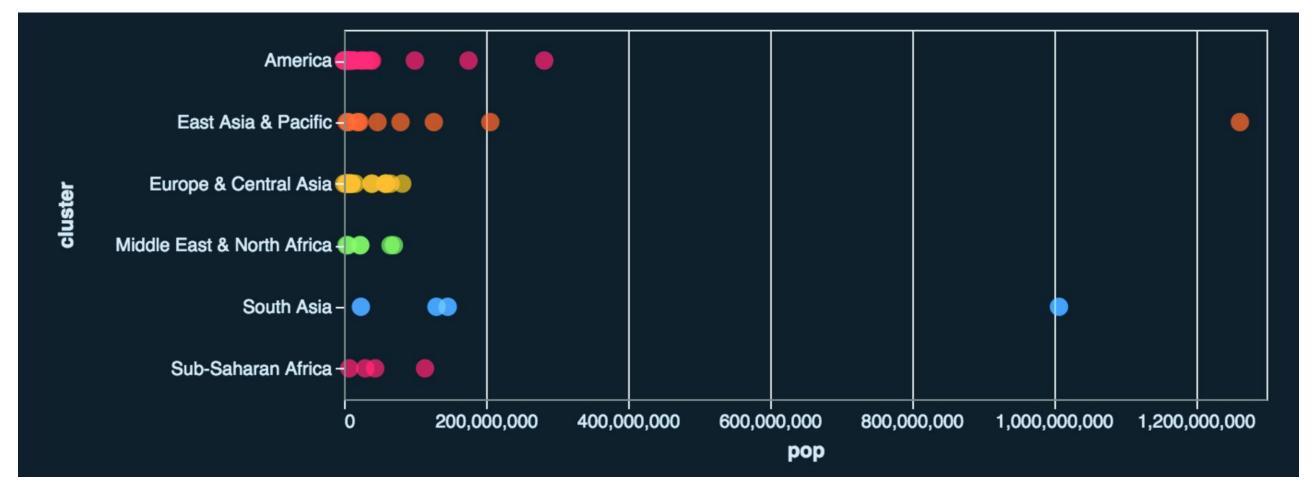






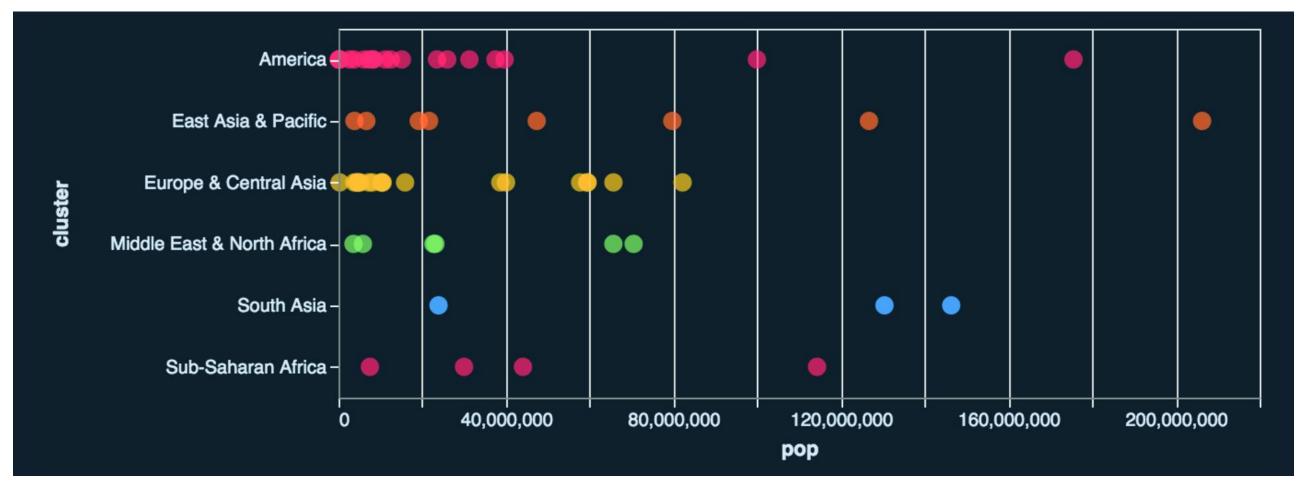


• Option #1: Clip them out



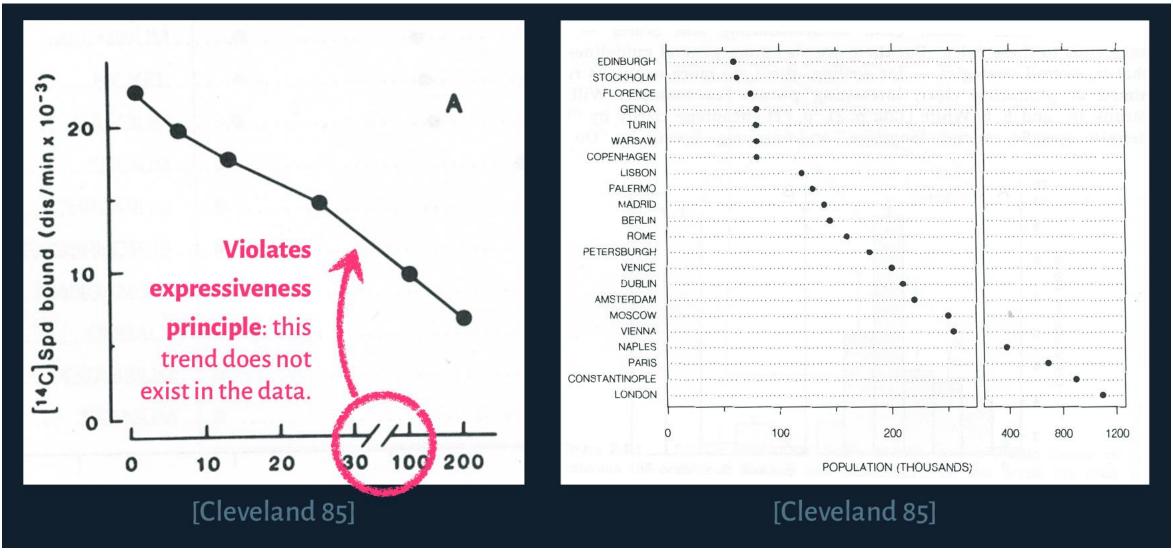


• Option #1: Clip them out





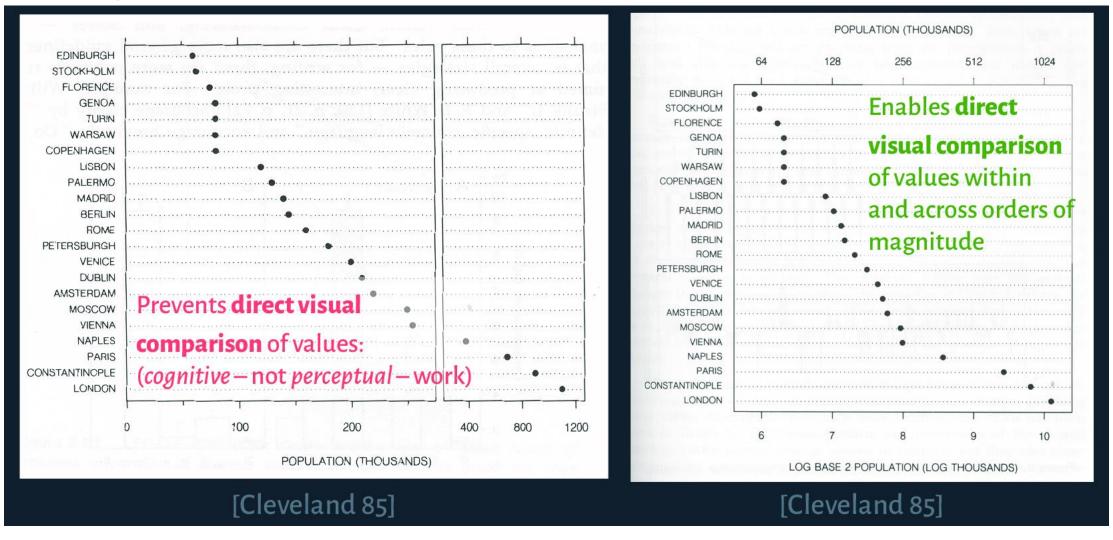
Option #2: Scale Breaks







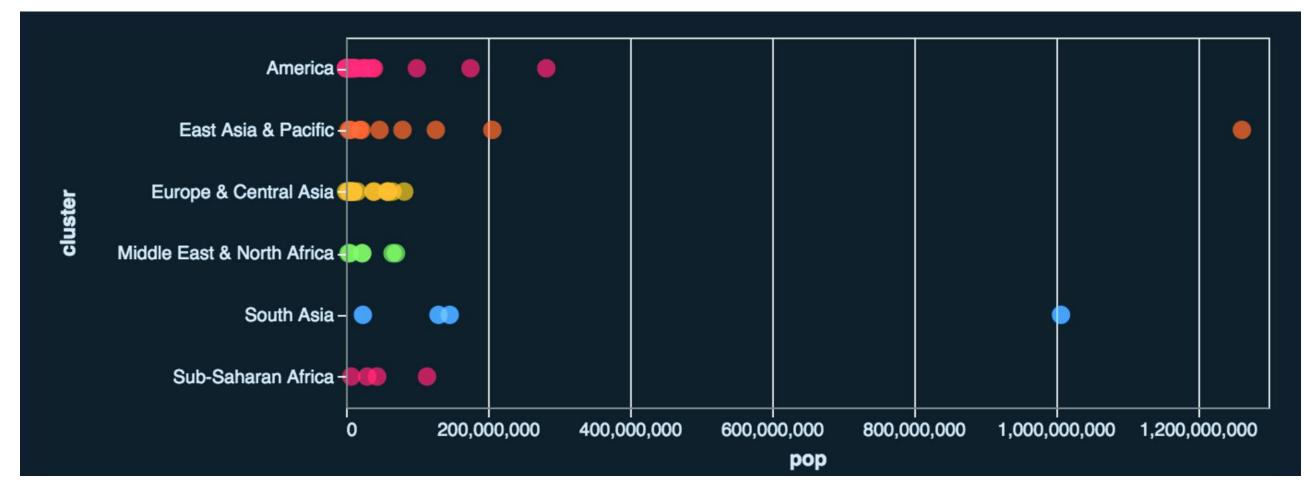
Option #3: Log Scales





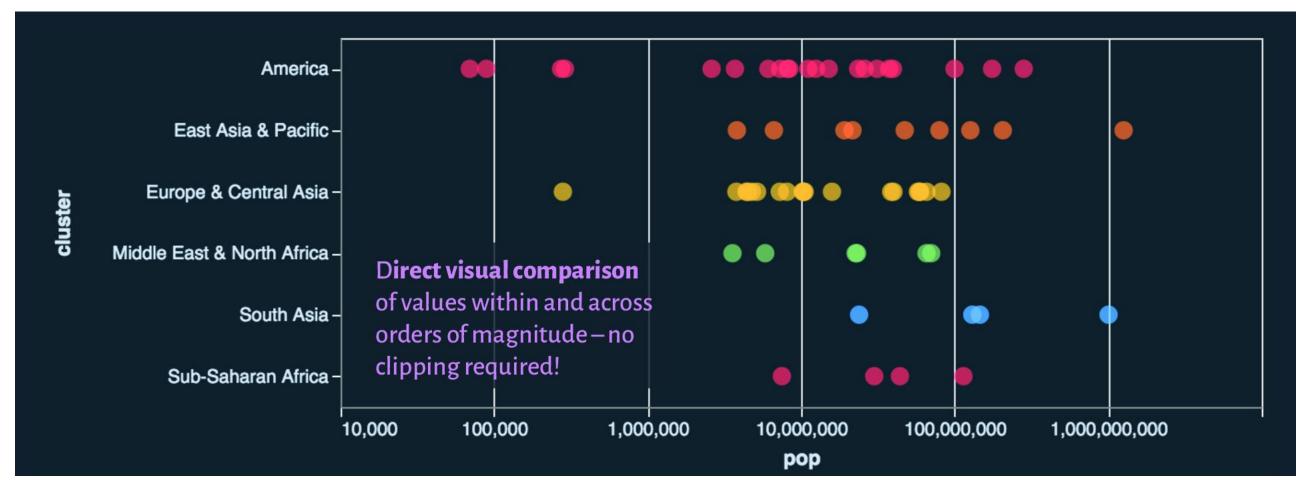


• Option #3: Log Scales



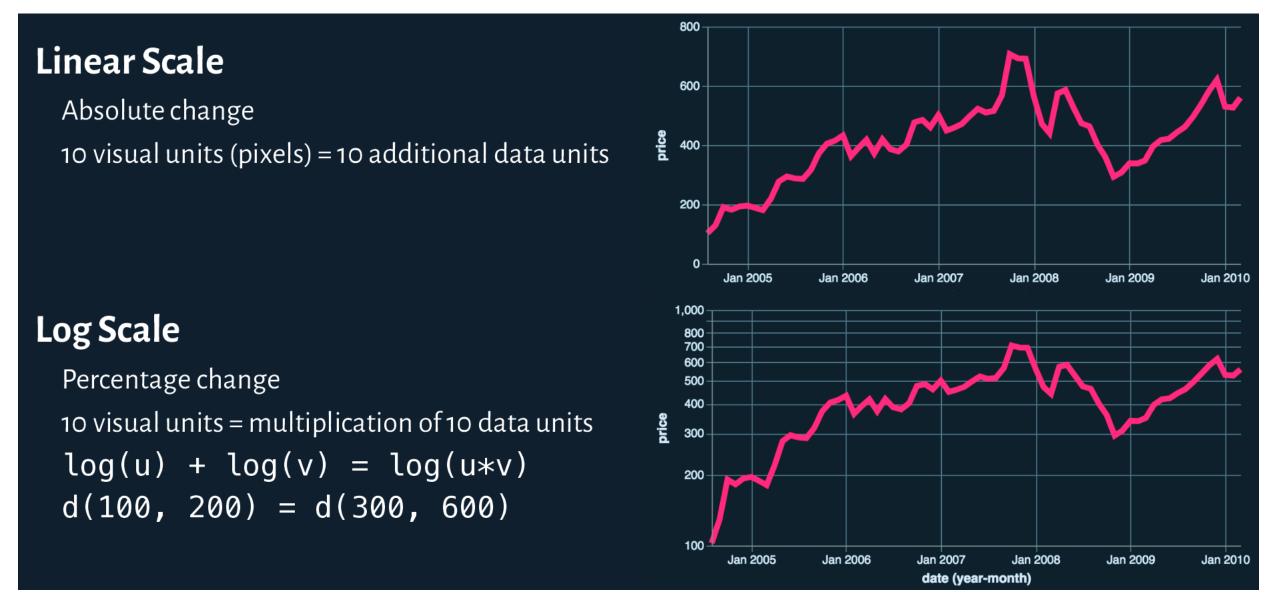


Option #3: Log Scales





Option #3: Log Scales





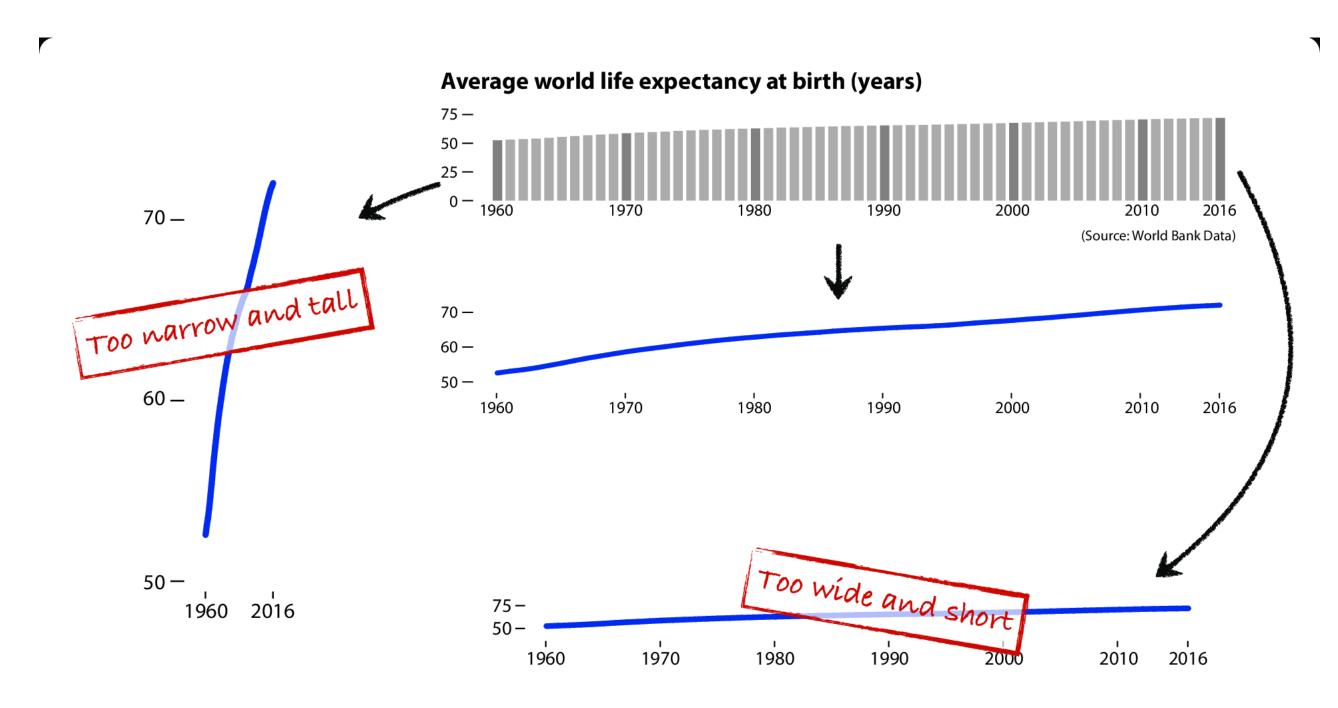
#### Outliers

Option #3: Log Scales









[Alberto Cairo. How Charts Lie, 2019]



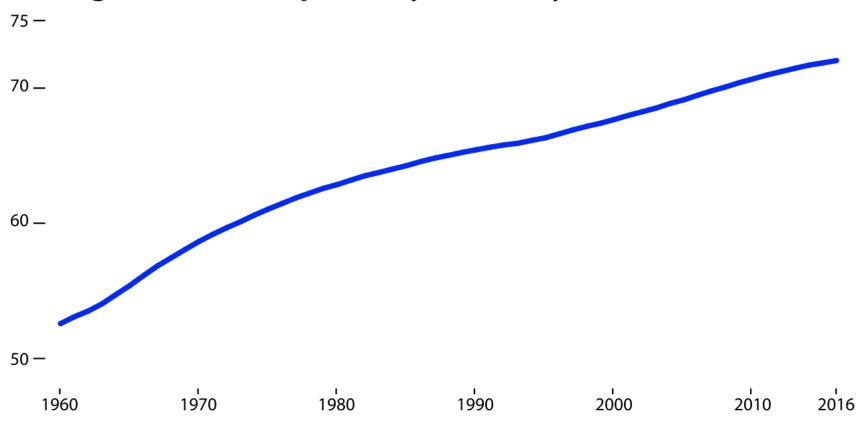
1



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

35% increase ≈ 1/3rd ≈ 3:1 aspect ratio

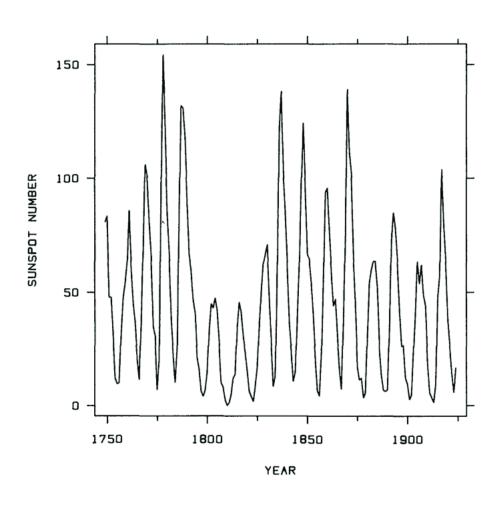
#### Average world life expectancy at birth (years)

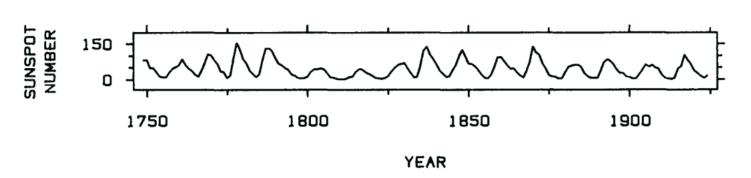


[Alberto Cairo. How Charts Lie, 2019]



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

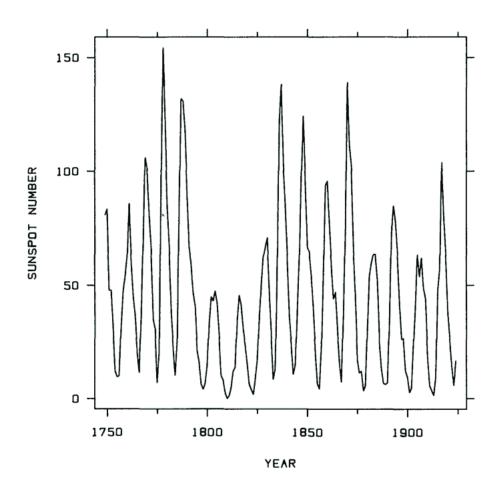


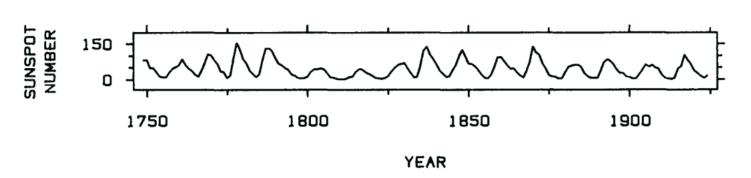


[Cleveland & McGill, 1987]



- (1) Approximate proportion of the chart to match the depicted trend.
- (2) **Bank to 45**°: aspect ratios with 45° avg. line segment orientation.

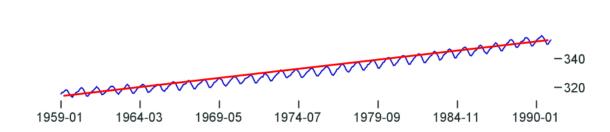




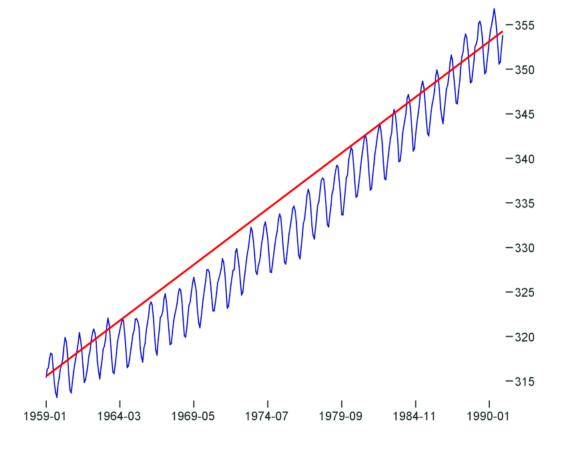
[Cleveland & McGill, 1987]



- (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



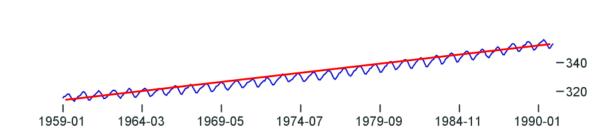
Aspect ratio = 1.17

[Heer & Agrawala, 2006]

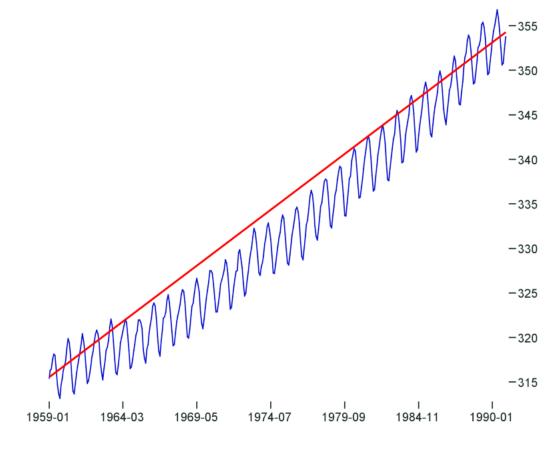




- (1) Approximate proportion of the chart to match the depicted trend.
- (2) *Bank to 45*°: original data *or* fitted trend lines.



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.

The Lie Factor =

size of effect shown in graphic

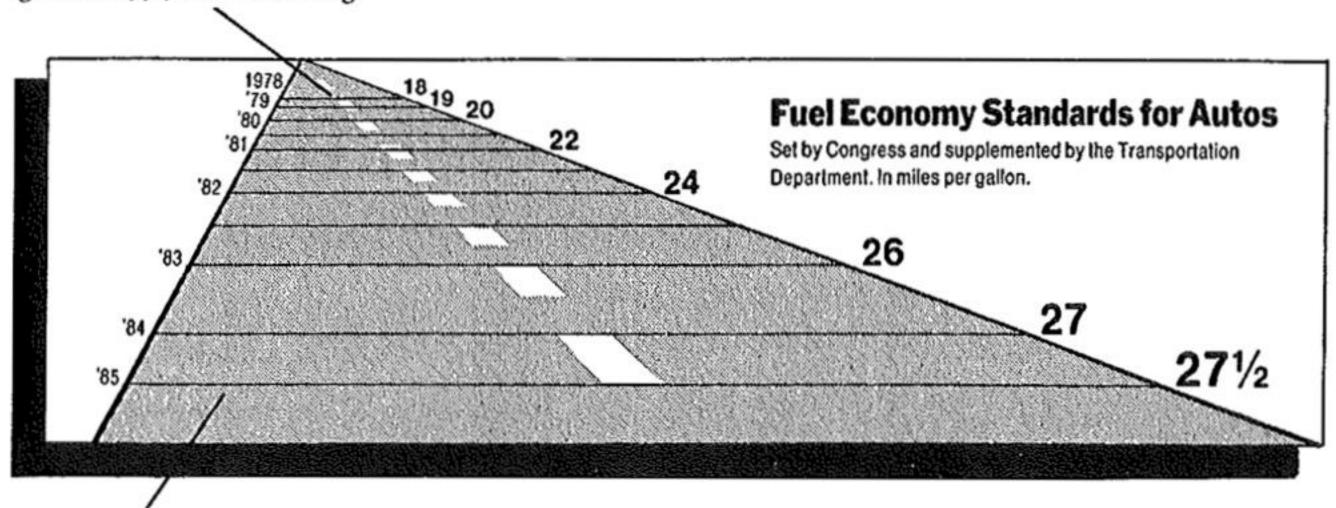
size of effect in data





#### DISTORTION

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

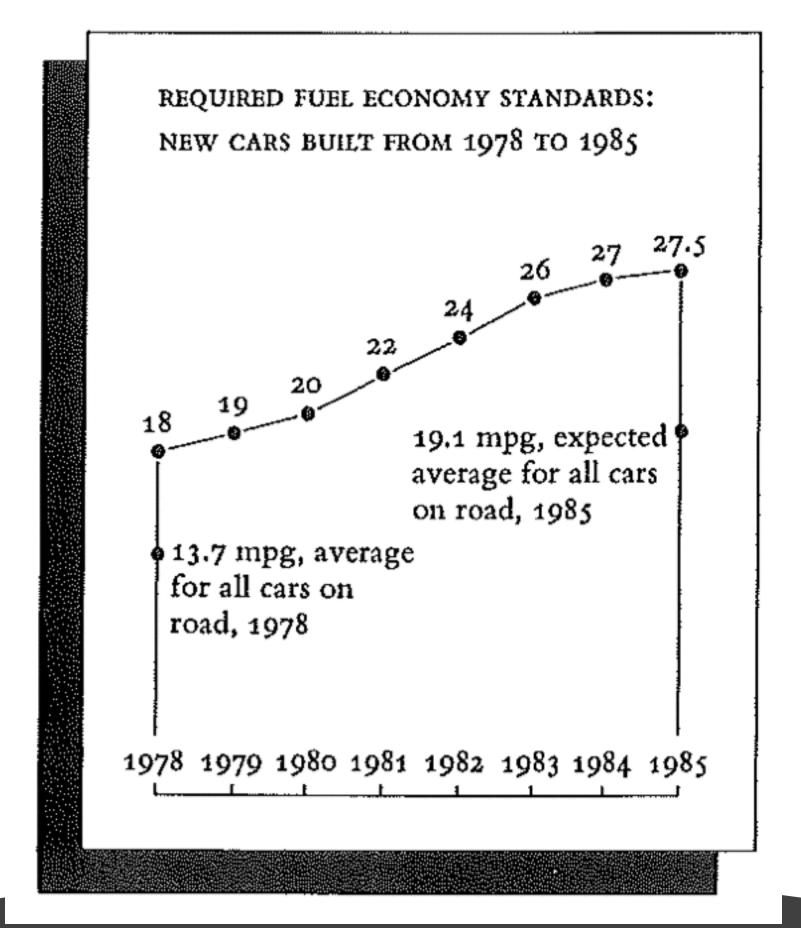


This line, representing 27.5 miles per gallon in 1985, is 5.3 inches long.

Lie factor for the percent increase from 1978 to 1985 
$$\Rightarrow \frac{\frac{5.3}{0.6}}{\frac{27.5}{1.8}} = \frac{8.83}{1.53} = 5.8$$







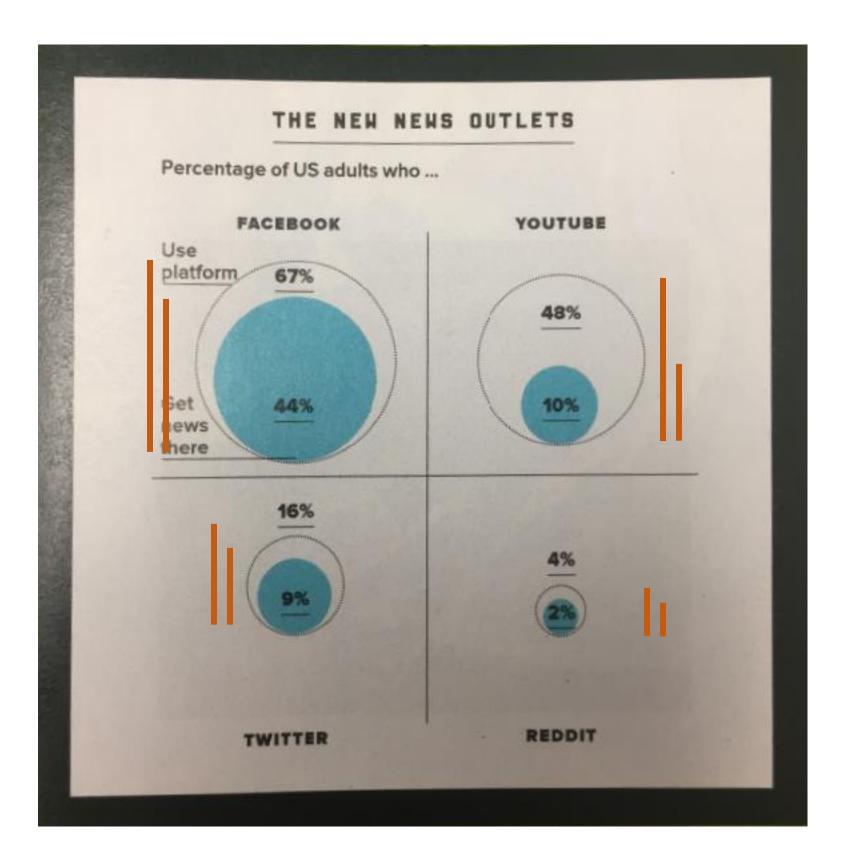


D = 2.0, A = PI D = 1.6, A = 0.65\*PI

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%)

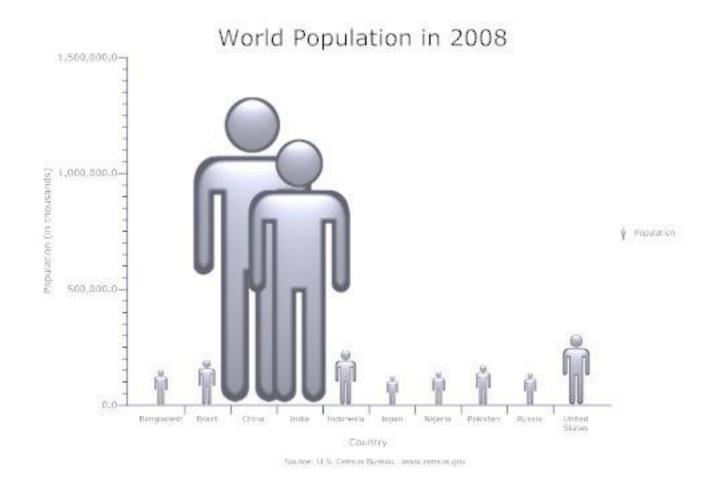
D = 0.5, A = 0.06\*PI D = 0.35, A = 0.03\*PI

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

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

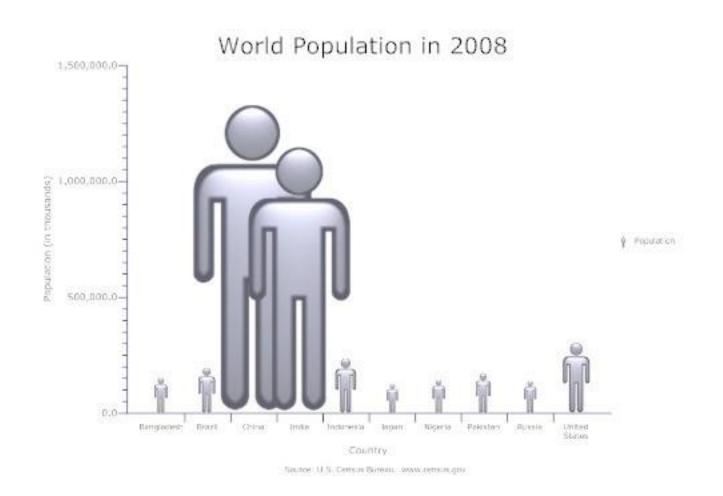


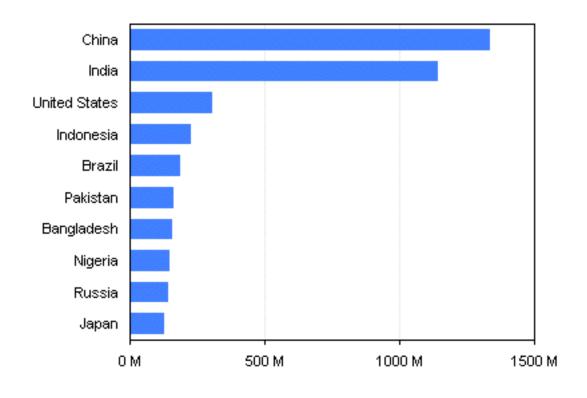
#### UNINTENDED SIZE CODING





#### UNINTENDED SIZE CODING







# DESIGN PRINCIPLES (or how to achieve integrity and excellence)

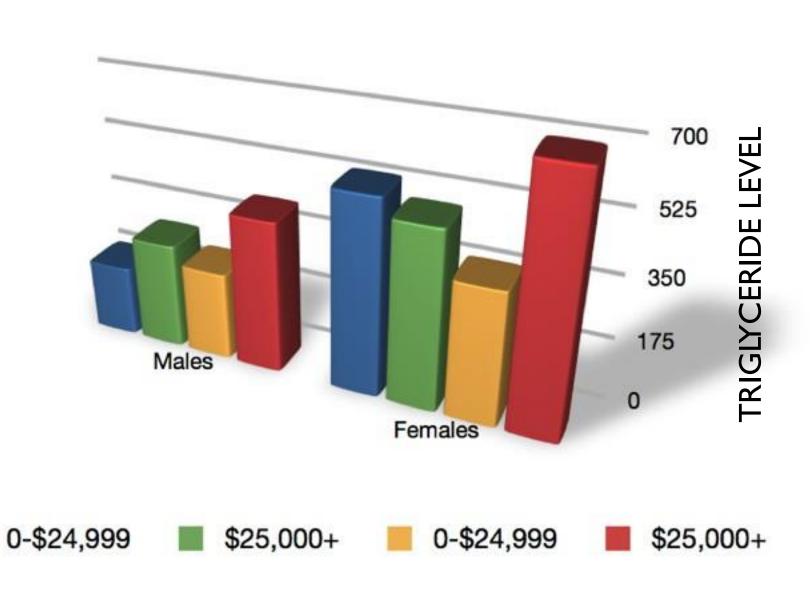


maximize the

#### **Data-ink Ratio =**

#### data-ink

#### total ink used in graphic



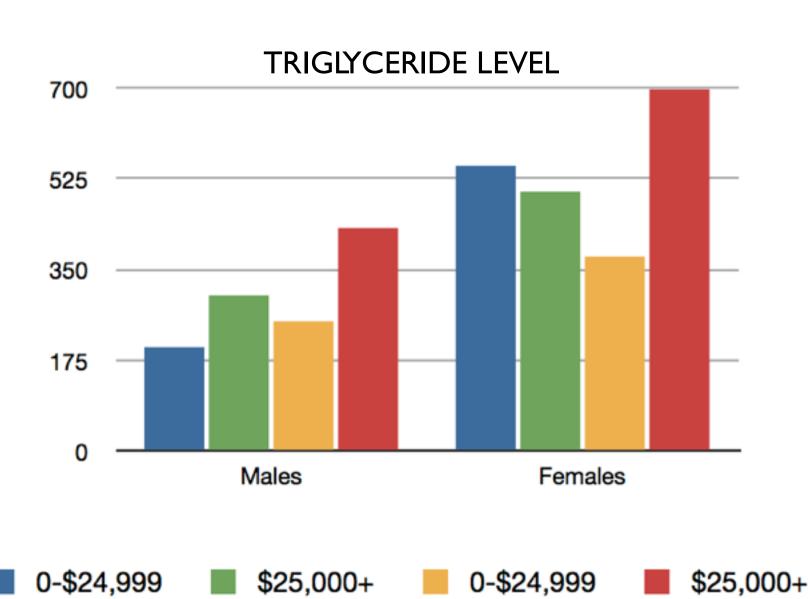


maximize the

#### Data-ink Ratio =

#### data-ink

#### total ink used in graphic



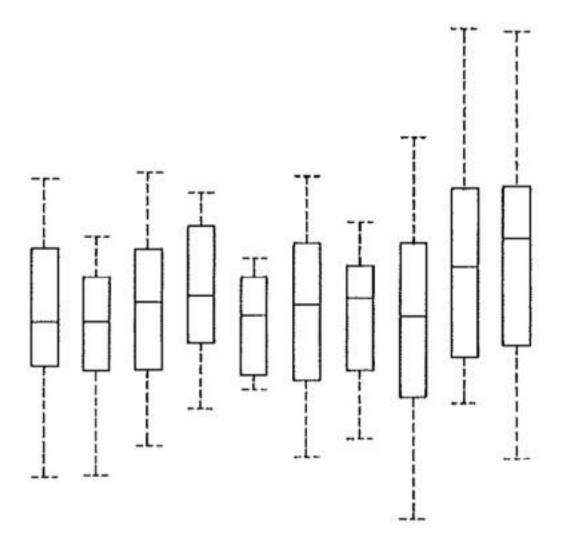


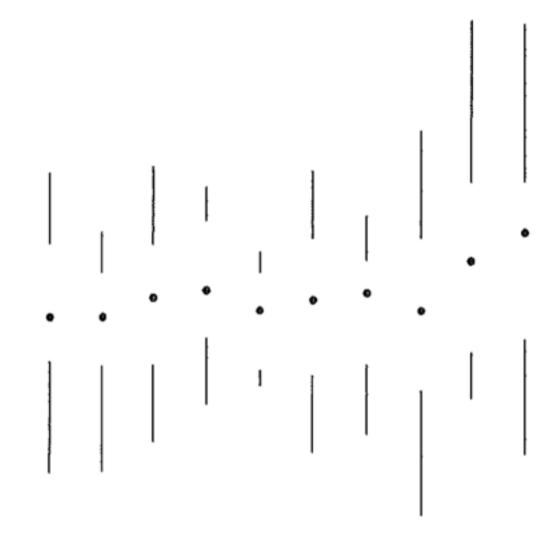
maximize the

#### **Data-ink Ratio =**

#### data-ink

#### total ink used in graphic







#### A User Study of Visualization Effectiveness Using EEG and Cognitive Load

E. W. Anderson<sup>1</sup>, K. C. Potter<sup>1</sup>, L. E. Matzen<sup>2</sup>, J. F. Shepherd<sup>2</sup>, G. A. Preston<sup>3</sup>, and C. T. Silva<sup>1</sup>

<sup>1</sup>SCI Institute, University of Utah, USA <sup>2</sup>Sandia National Laboratories, USA <sup>3</sup>Utah State Hospital, USA

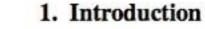
#### Abstract

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

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

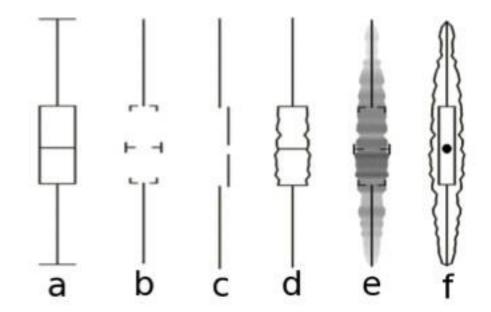


Efficient visualizations facilitate the understanding of data

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

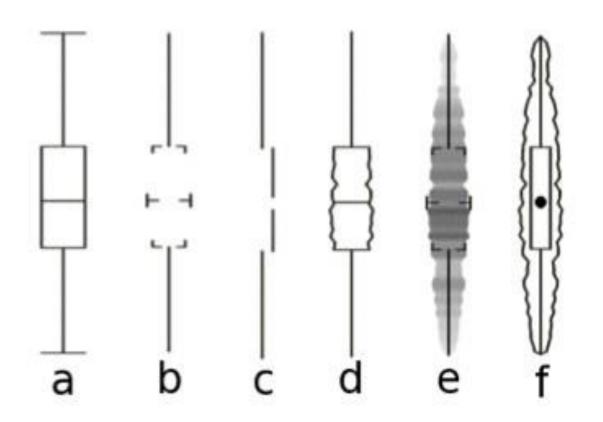






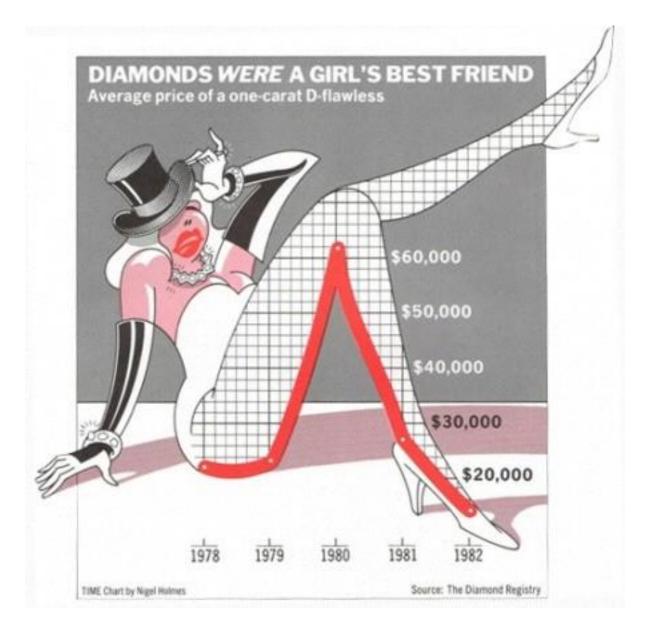
#### EXPERIMENTAL RESULTS

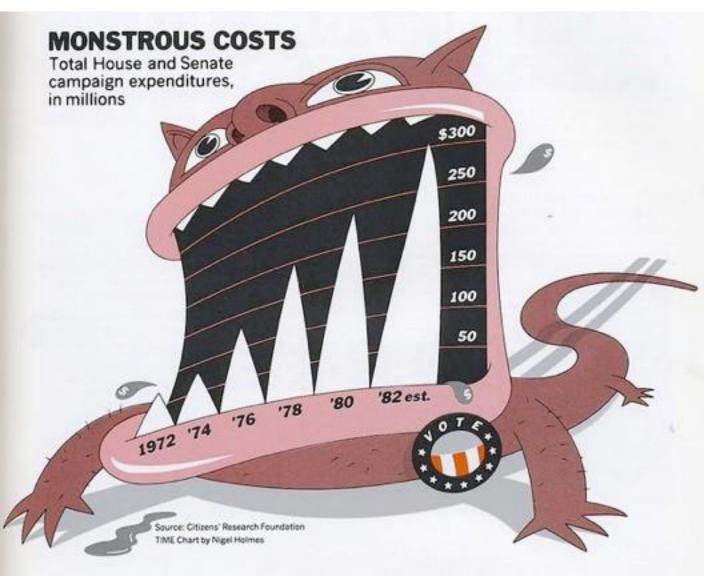
- studies showed that the simplest (highest data-ink ratio) box plot is hardest to interpret
- paper focused on cognitive load as an evaluation method



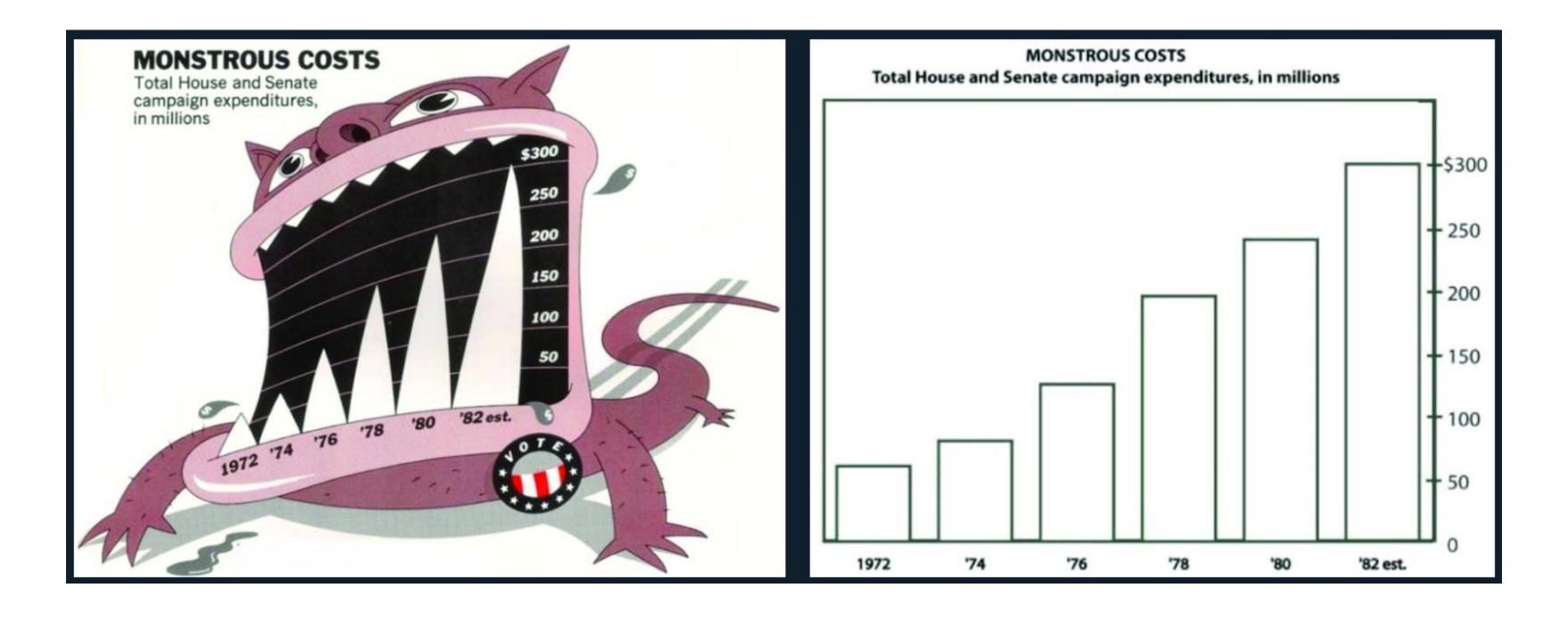


#### Chart Junk: attraction or distraction?

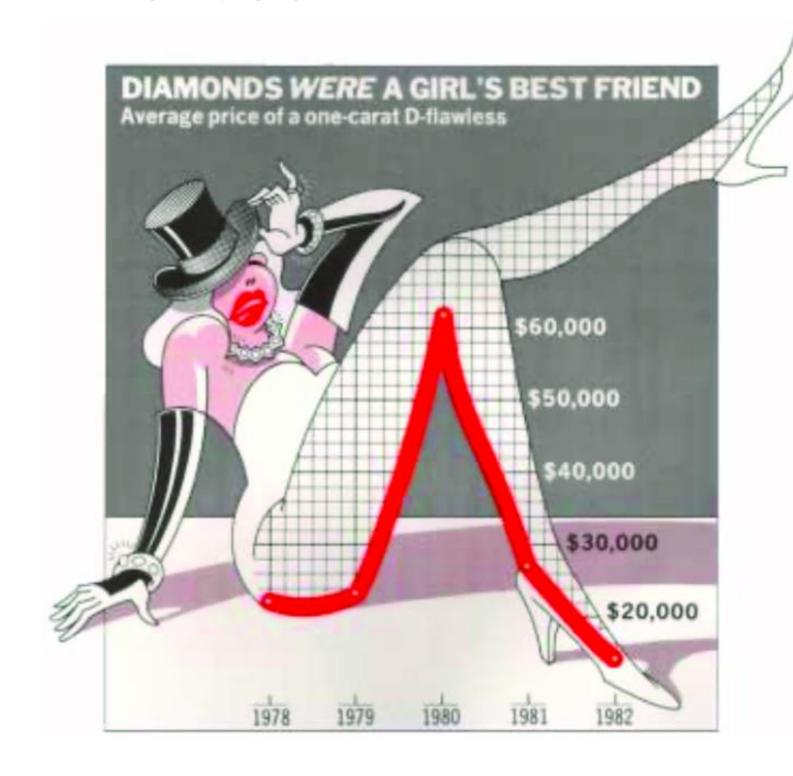


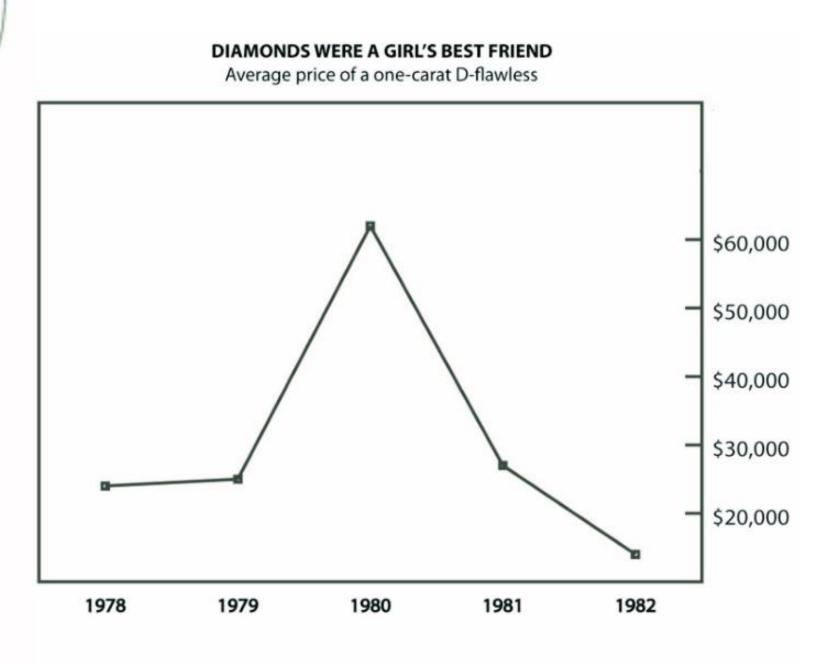




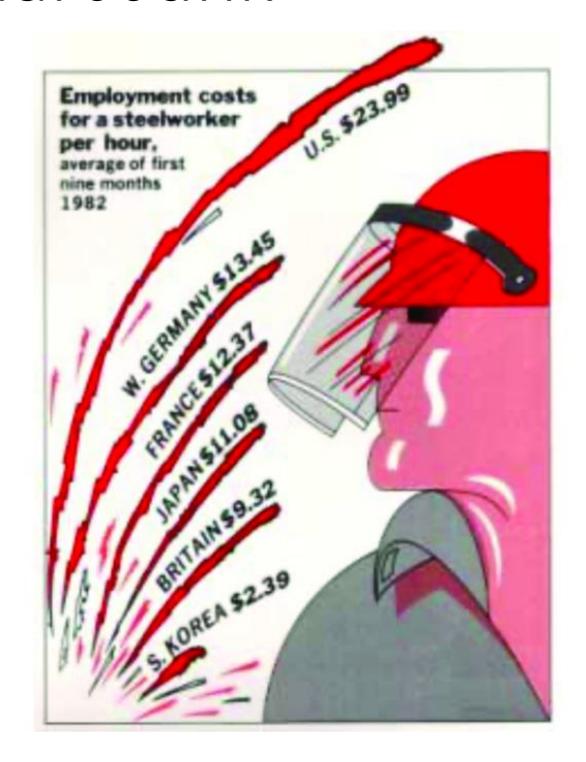


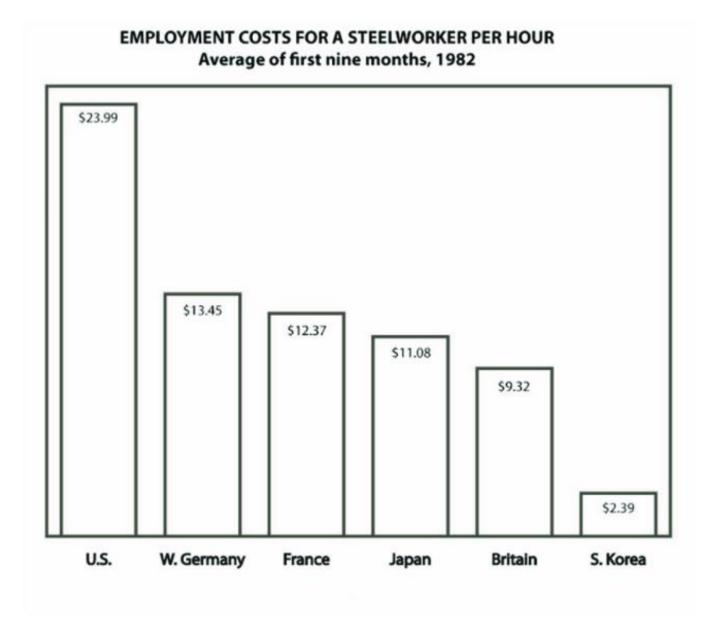






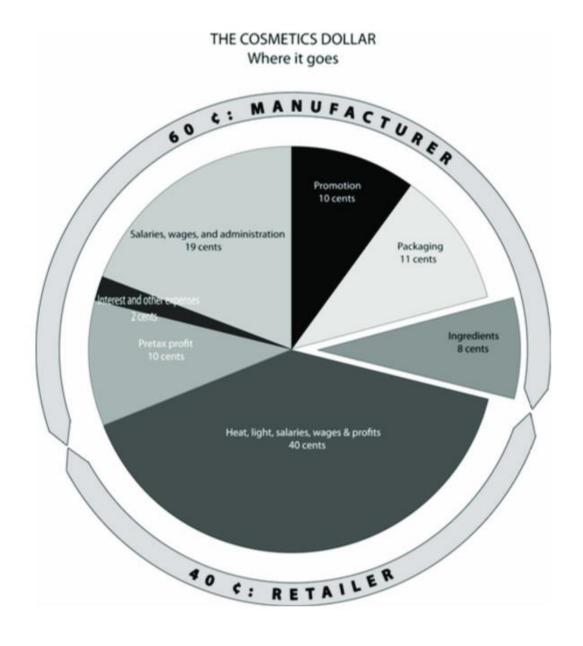






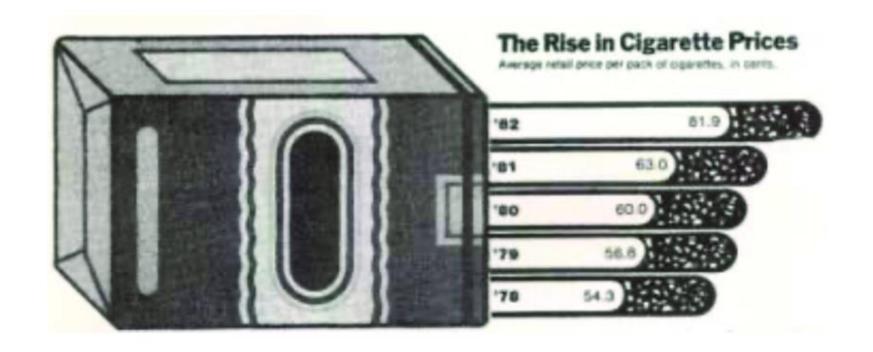




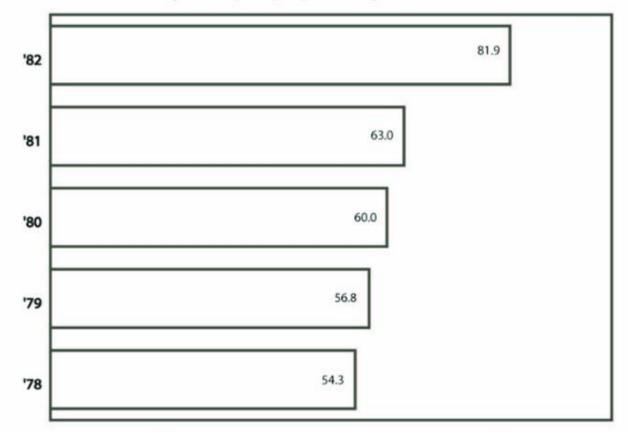




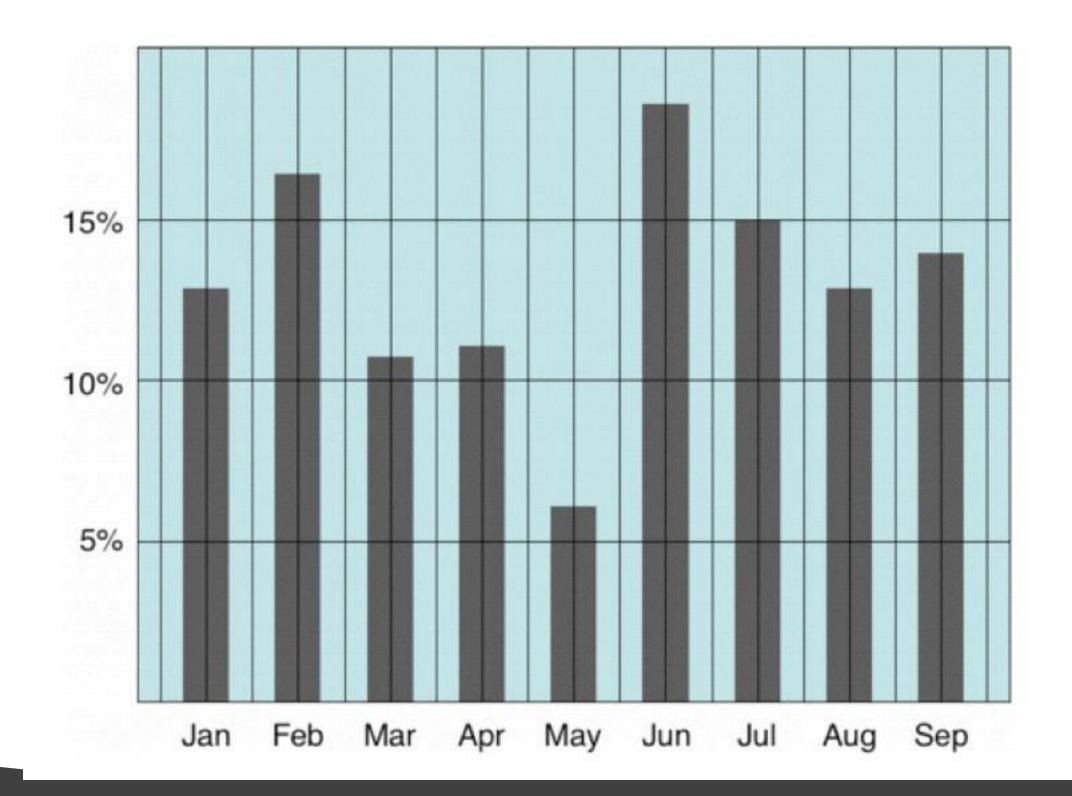




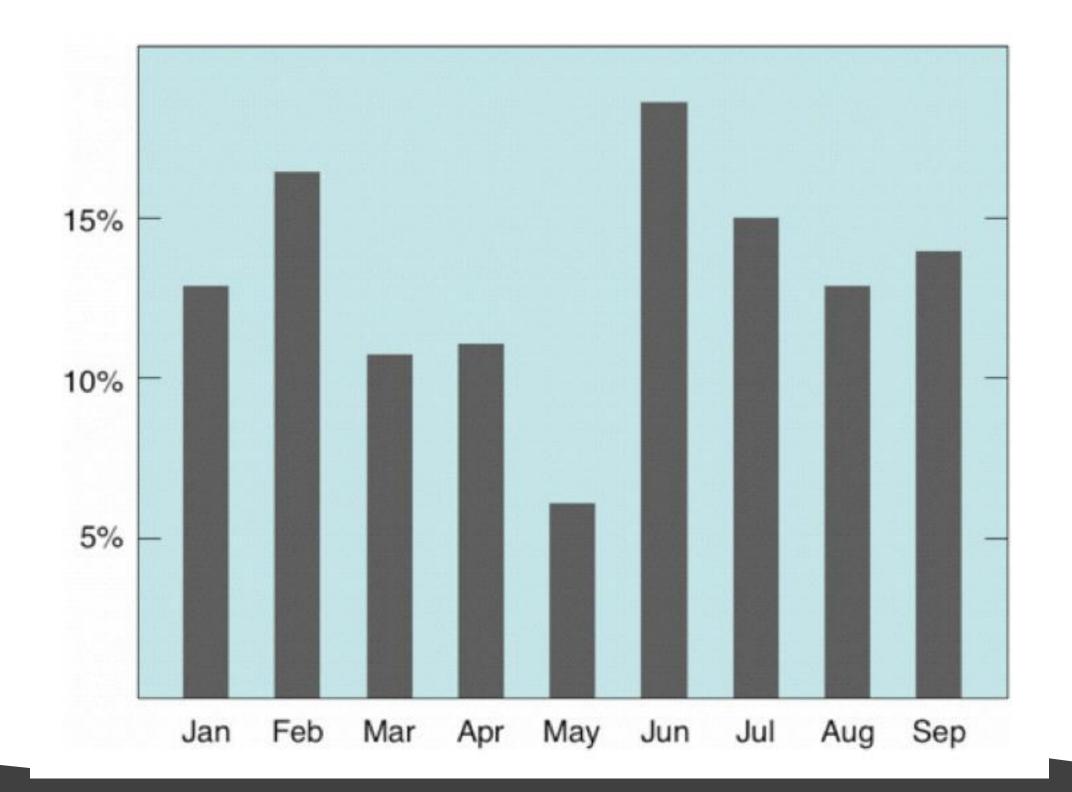
#### THE RISE IN CIGARETTE PRICES Average retail price per pack of cigarettes, in cents



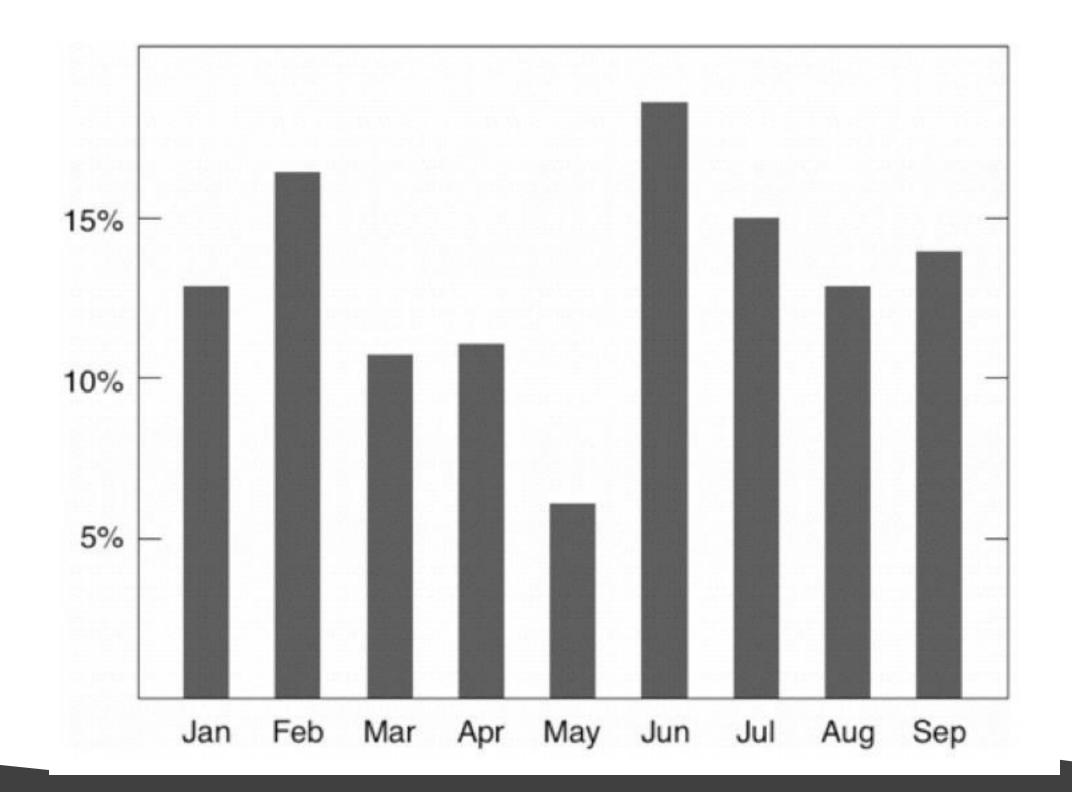




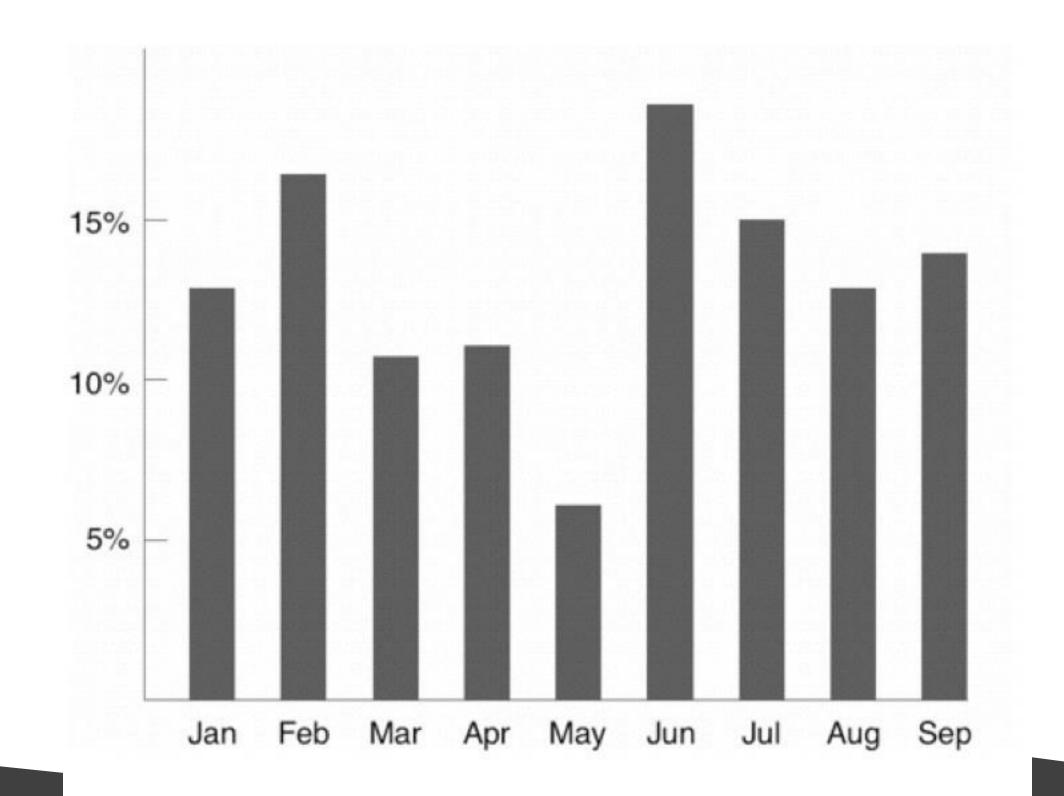




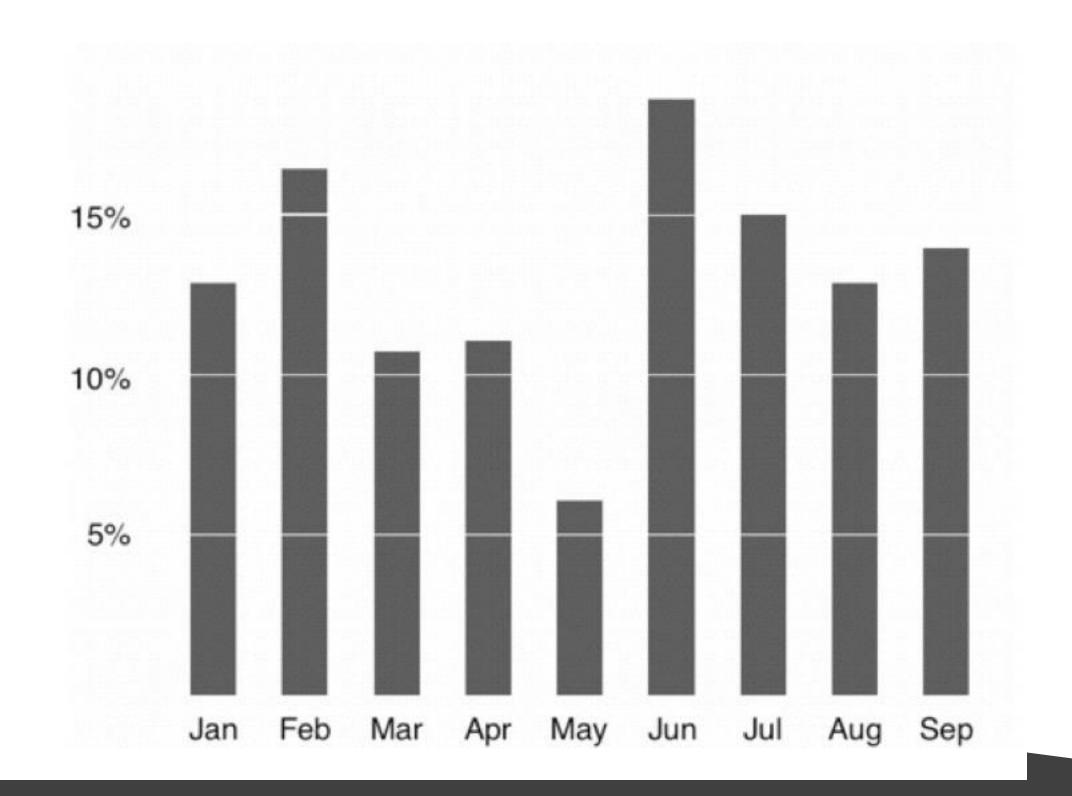














#### COUNTER-POINTS

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

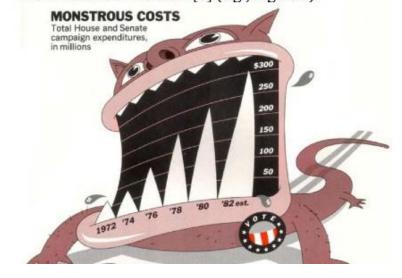
#### ABSTRACT

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

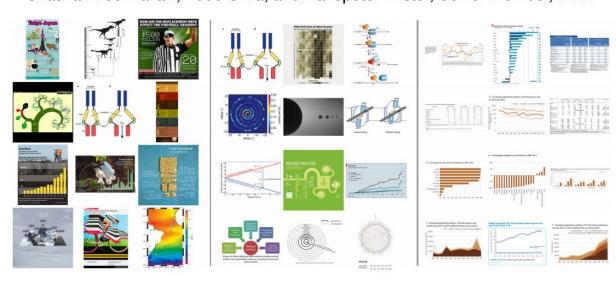


Fig. 1. Left: The top twelve overall most memorable visualizations from our experiment (most to least memorable from top left to bottom right). Middle: The top twelve most memorable visualizations from our experiment when visualizations containing human recognizable cartoons or images are removed (most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



#### CHI 2010: Graphs

## 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

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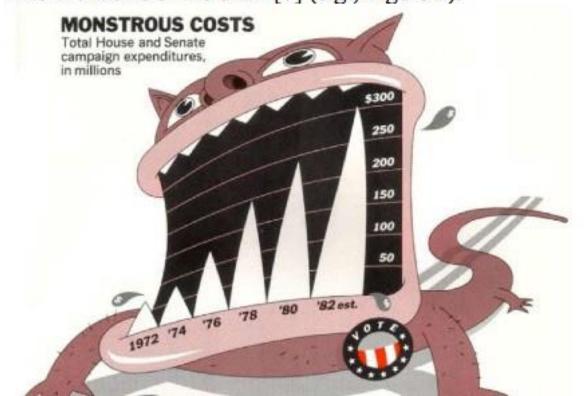
#### ABSTRACT

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).





#### 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

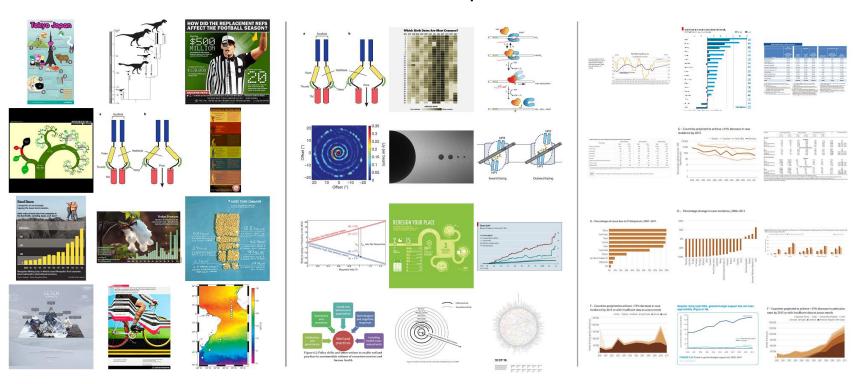


Fig. 1. Left: The top twelve overall most memorable visualizations from our experiment (most to least memorable from top left to bottom right). Middle: The top twelve most memorable visualizations from our experiment when visualizations containing human recognizable cartoons or images are removed (most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



### Results

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



### CHART JUNK? IT DEPENDS

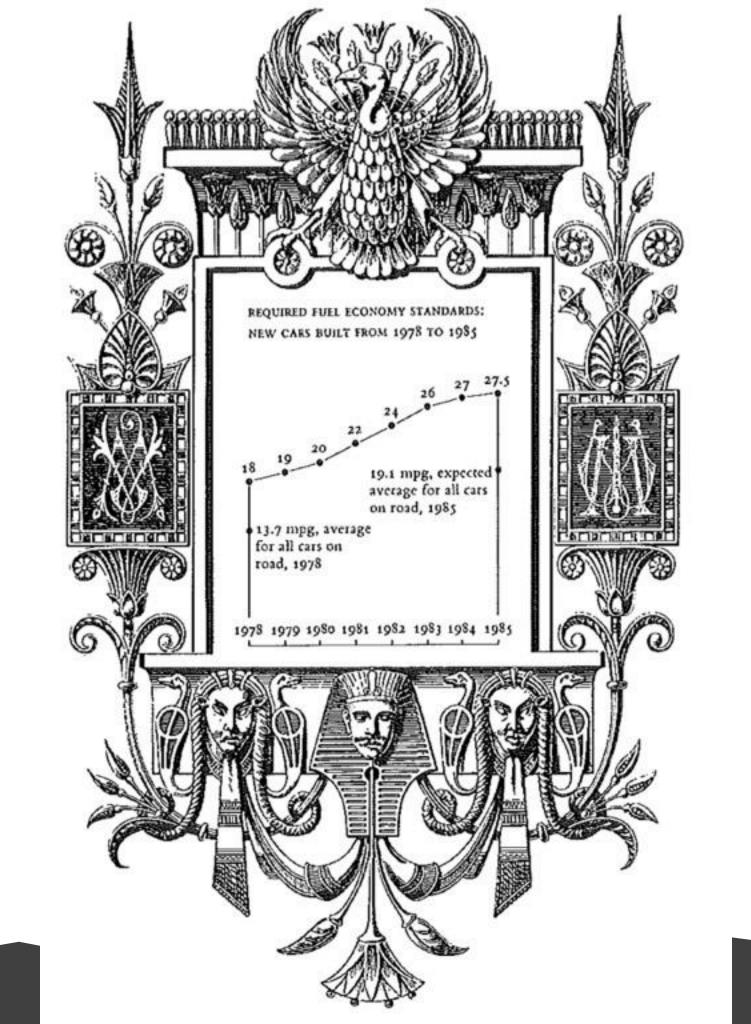
- persuasion
- memorability
- engagement

**PROS** 

- unbiased analysis
- trustworthiness
- interpretability
- space efficiency

**CONS** 







maximize the

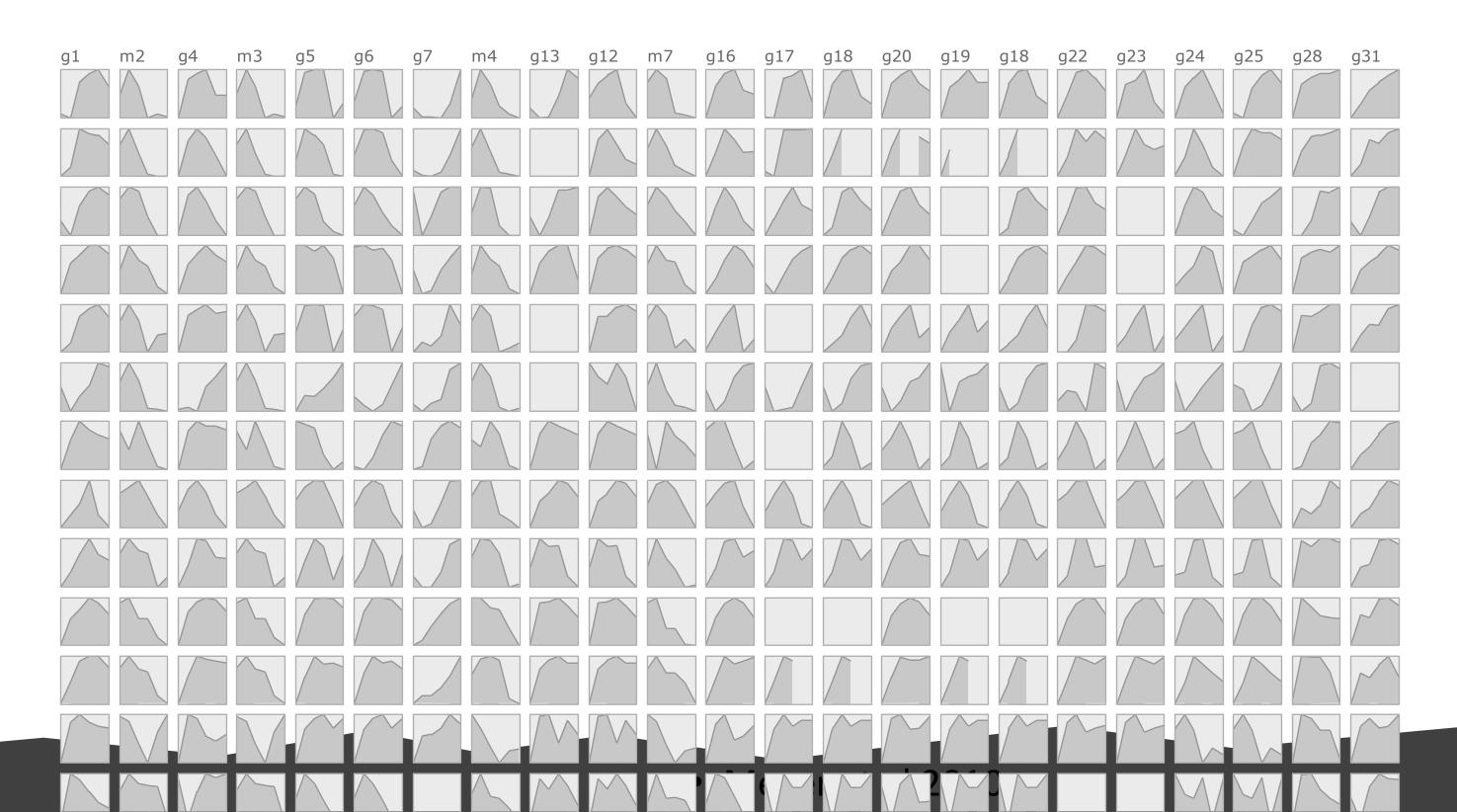
**Data Density =** 

number of entries in data array

area of data graphic

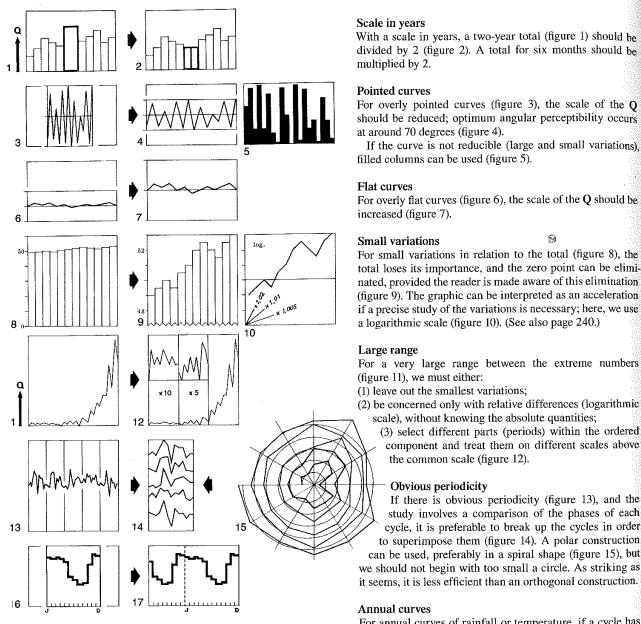


# SHRINK THE GRAPHICS – with small multiples





### SHRINK THE GRAPHICS



#### GRAPHIC PROBLEMS POSED BY TIME SERIES

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

For overly pointed curves (figure 3), the scale of the O 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).

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.)

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

#### Annual curves

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

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).

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

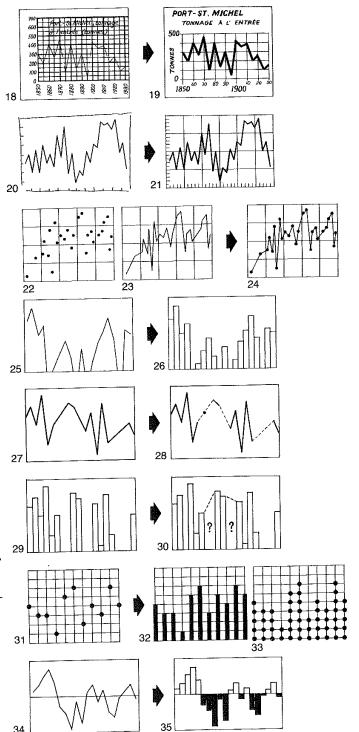
The drawing must indicate the unknowns of the information in an unambiguous way (figures 28 and 30). The reader might interpret figure 27 as a change in the structure of the curve and figure 29 as involving null values.

#### 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 ≠ component and thus highlight positive-negative variation.



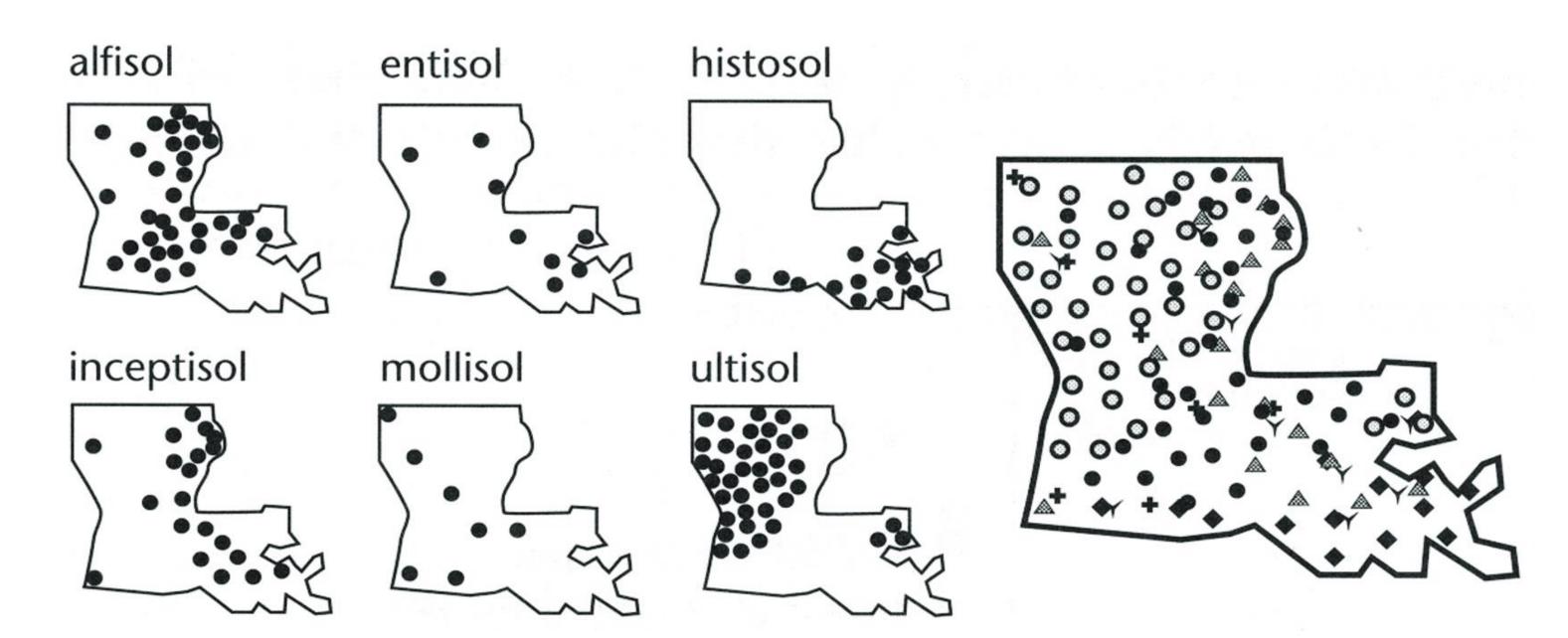
# SHRINK THE GRAPHICS – with sparklines

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 of 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



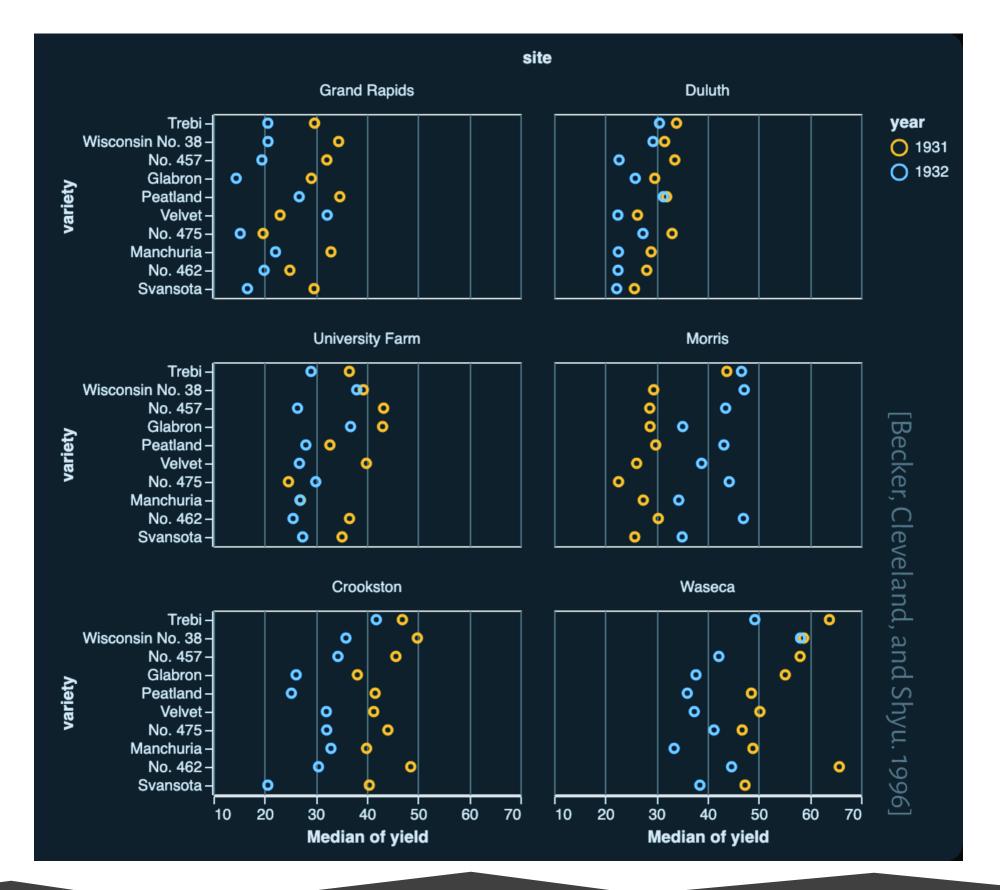
# Small Multiples





### 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

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Roger Fidler
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#### 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 specifics 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



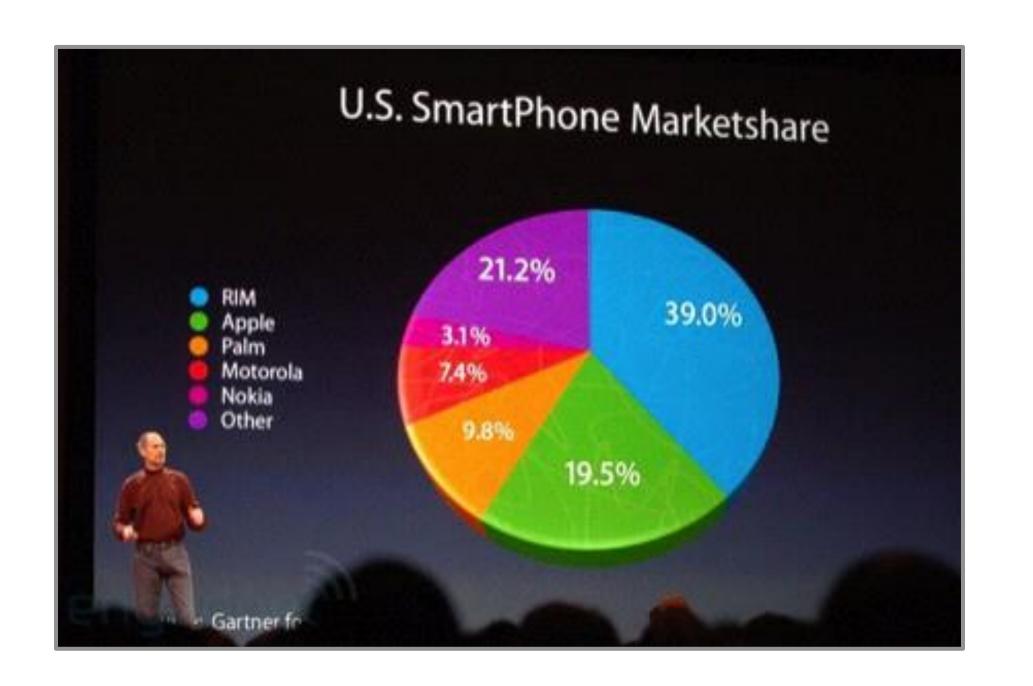
# overestimate of depth

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



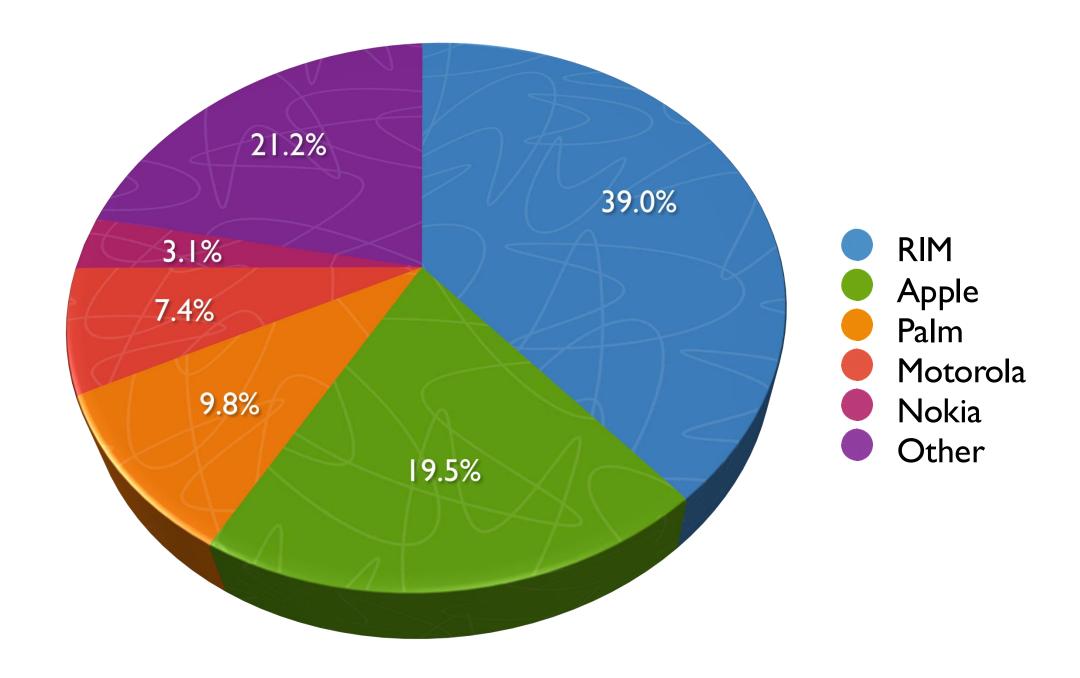
# Misleading Encoding





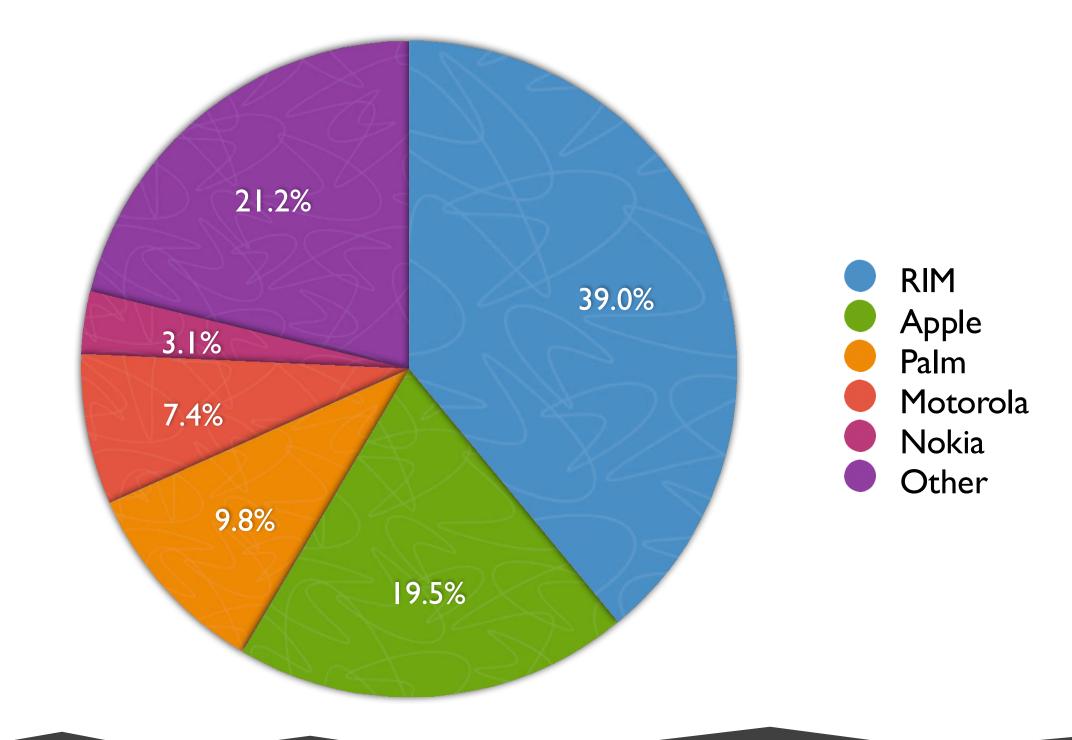


# U.S. SmartPhone Marketshare



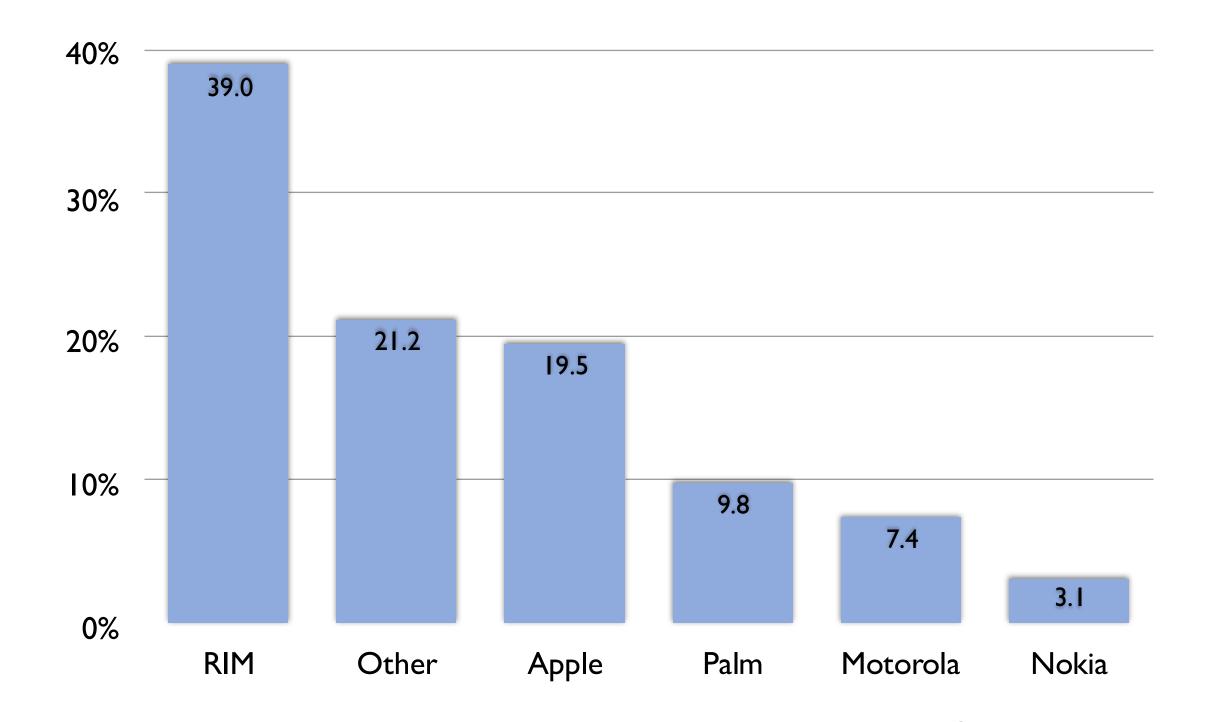


# U.S. SmartPhone Marketshare



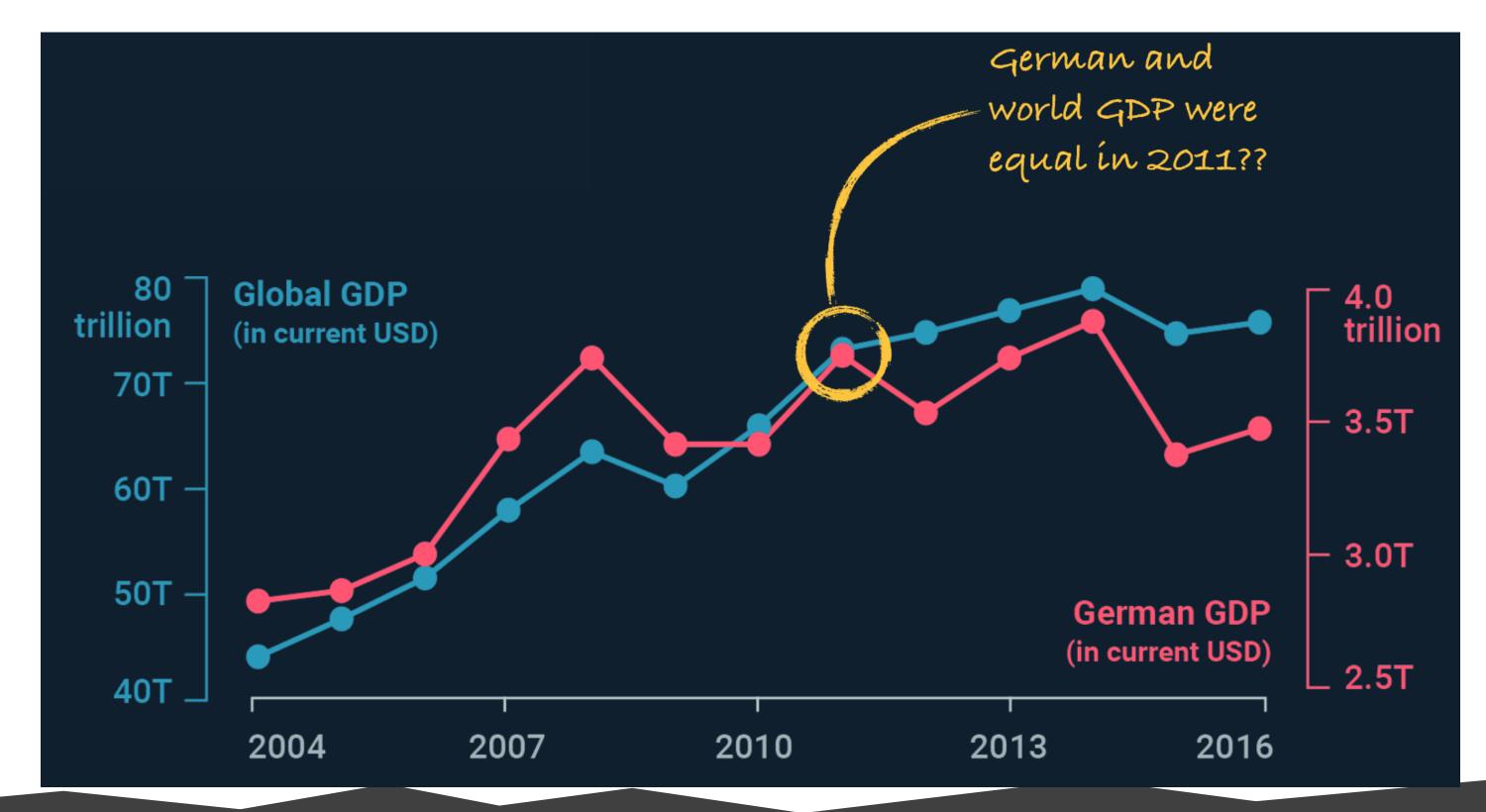


### U.S. SmartPhone Marketshare







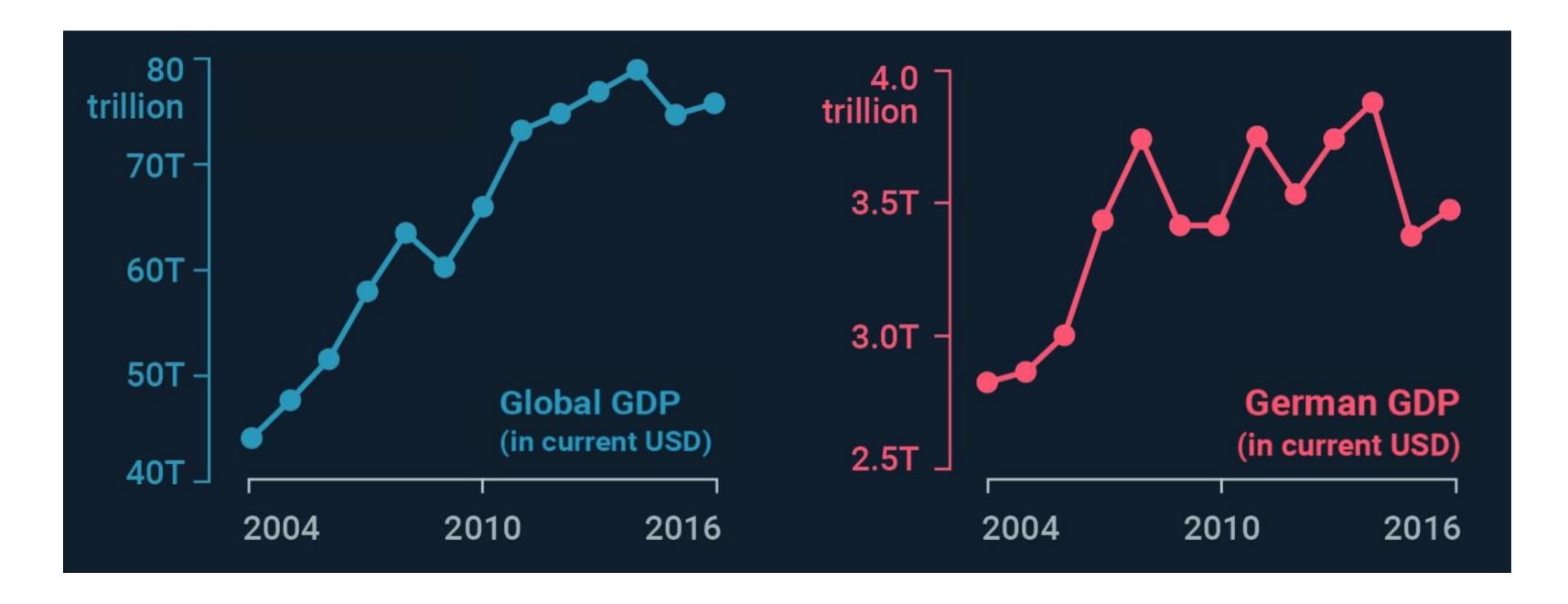






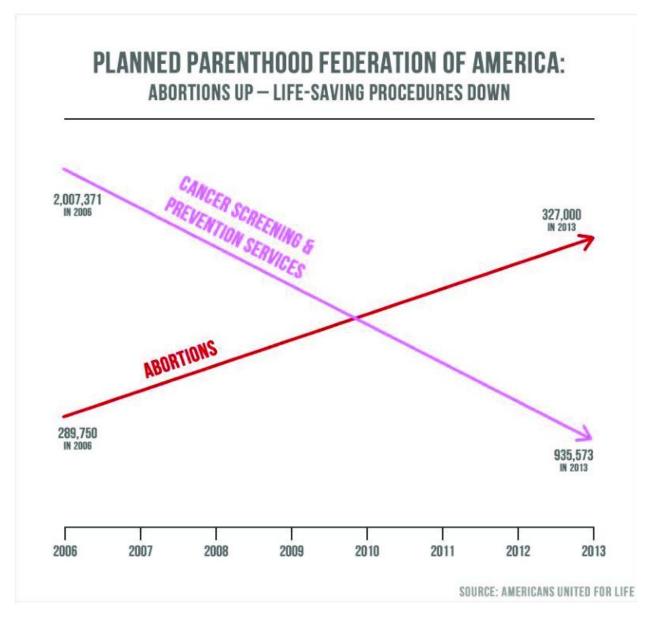






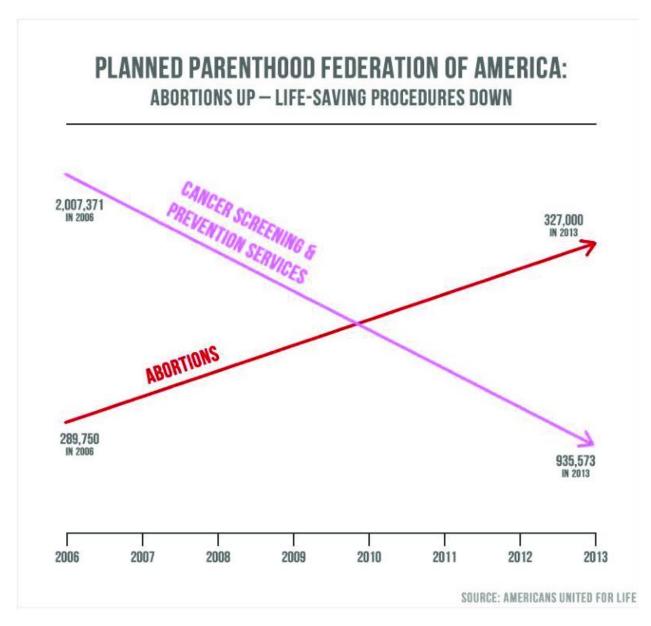




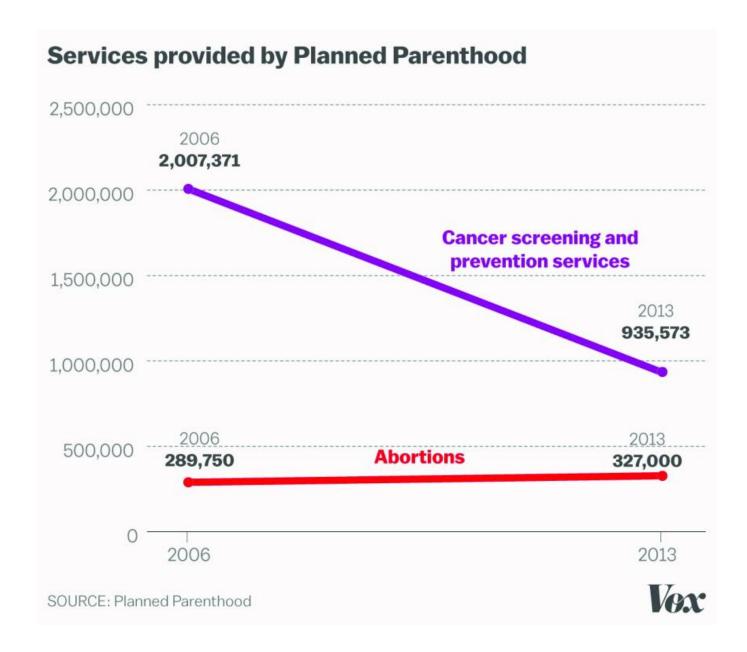


Presented by Rep. Jason Chaffetz. House Oversight Committee, Sept '15



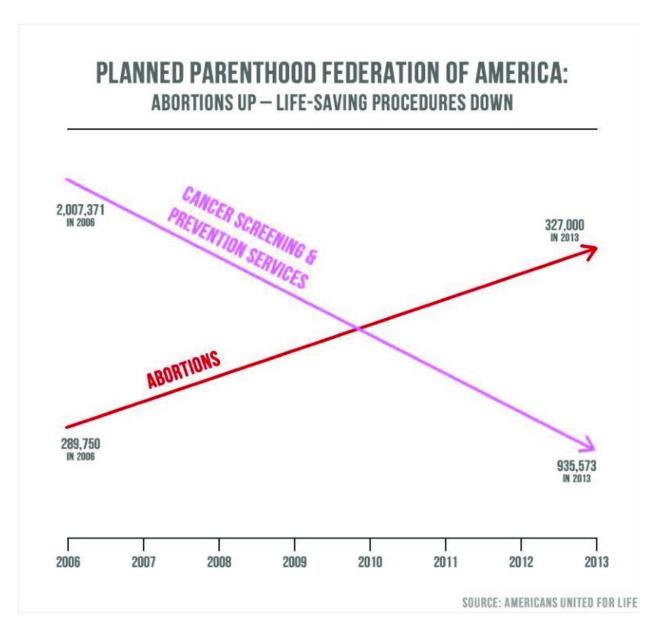


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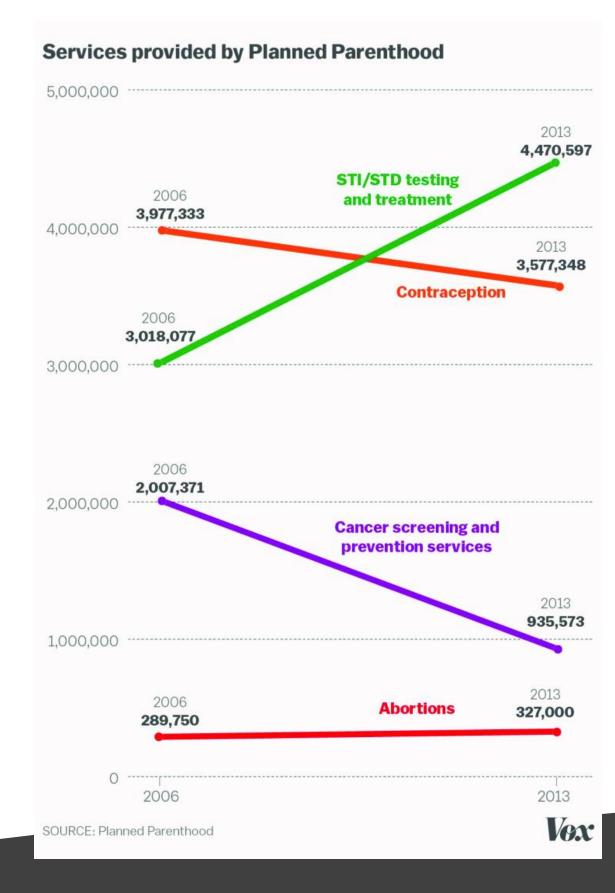








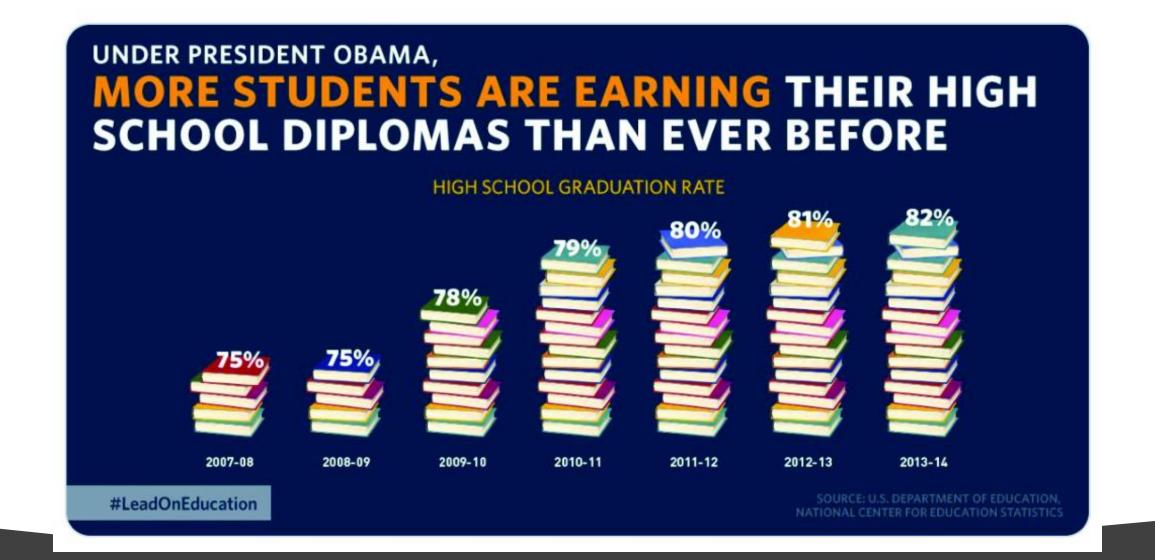
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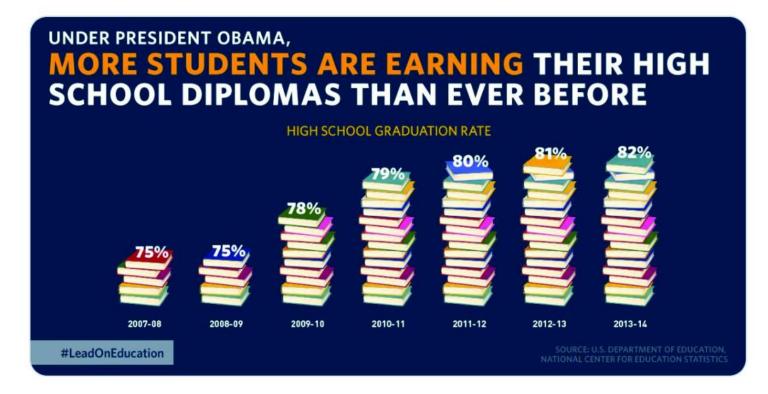
Good news: America's high school graduation rate has increased to an all-time high. wapo.st/1m40Mei



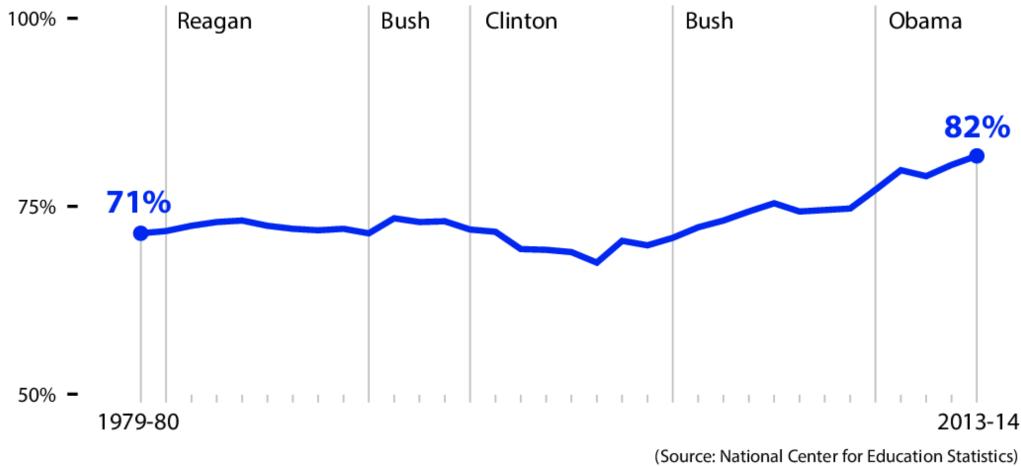


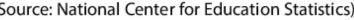


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#### High school graduation rates under each president













○ 236K 6:05 AM - Oct 1, 2019



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



○ 8,013 9:03 AM - May 11, 2017





#### Share of the popular vote in the 2016 presidential election



