

# Storytelling with Data

**Module 7: The storytelling process continued, and visual perception**

**Scott Spencer**  
Faculty and Lecturer  
Columbia University

# Agenda

Upcoming deliverable – *final storyboard*

Today's objectives

Storytelling process continued

Group work on storyboards and project

Perception in visual narrative

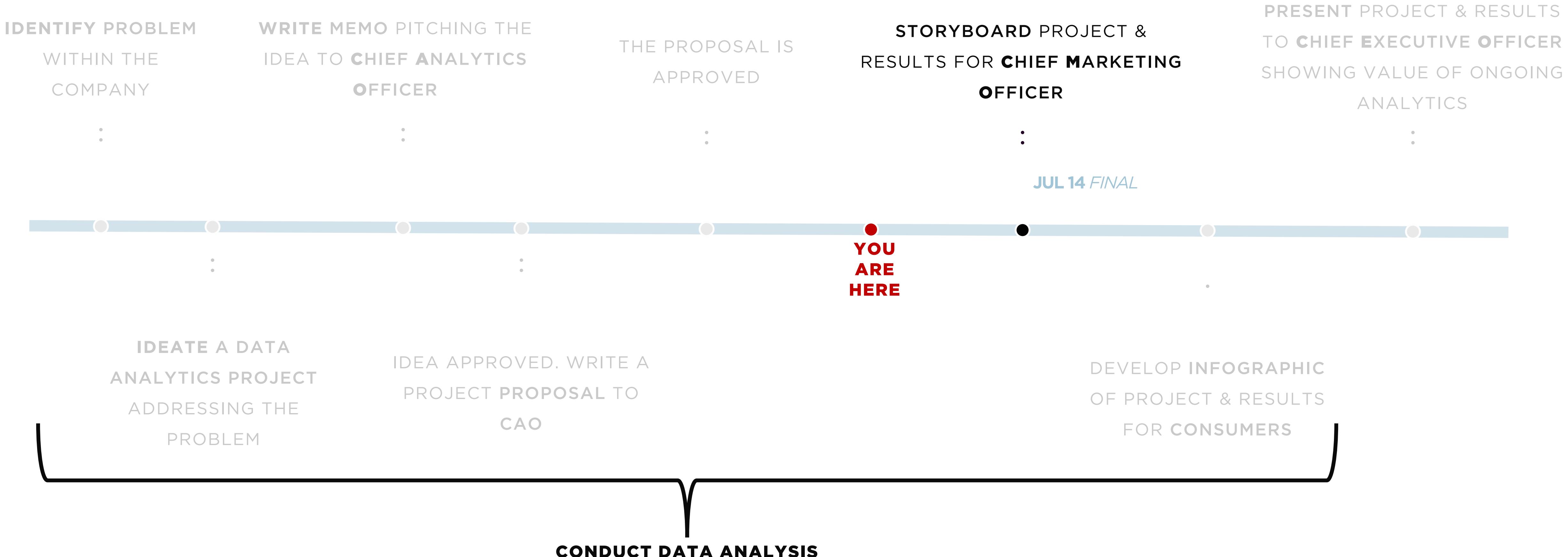
# Questions or suggestions?

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# Upcoming deliverable

# Upcoming deliverable

In **Storyboard** form – describe (1) your project, (2) preliminary results or insights so far, and (3) why those results are interesting for the marketing team. Use a distinct narrative arc (beginning, middle, and end), be clear and accessible for the **CMO**.



# Today's Objectives

# Objectives

1

Explain importance of  
effectively framing a story

2

Group work on  
storyboards and projects

3

Consider audience perception  
of visual components of a story

# The storytelling process, continued

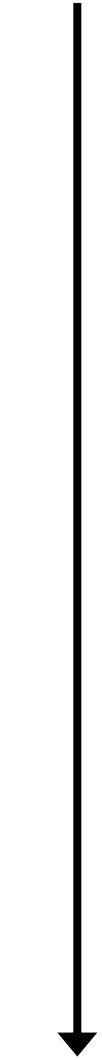


# See, Think, Design, Produce

*Corum*

A former student of Edward Tufte at Yale, Jonathan is science graphics editor at The New York Times and has won 28 awards from the Society for News Design and 18 medals from the international Malofiej competition, including Best of Show.

His projects for an audience of NYT readers ...



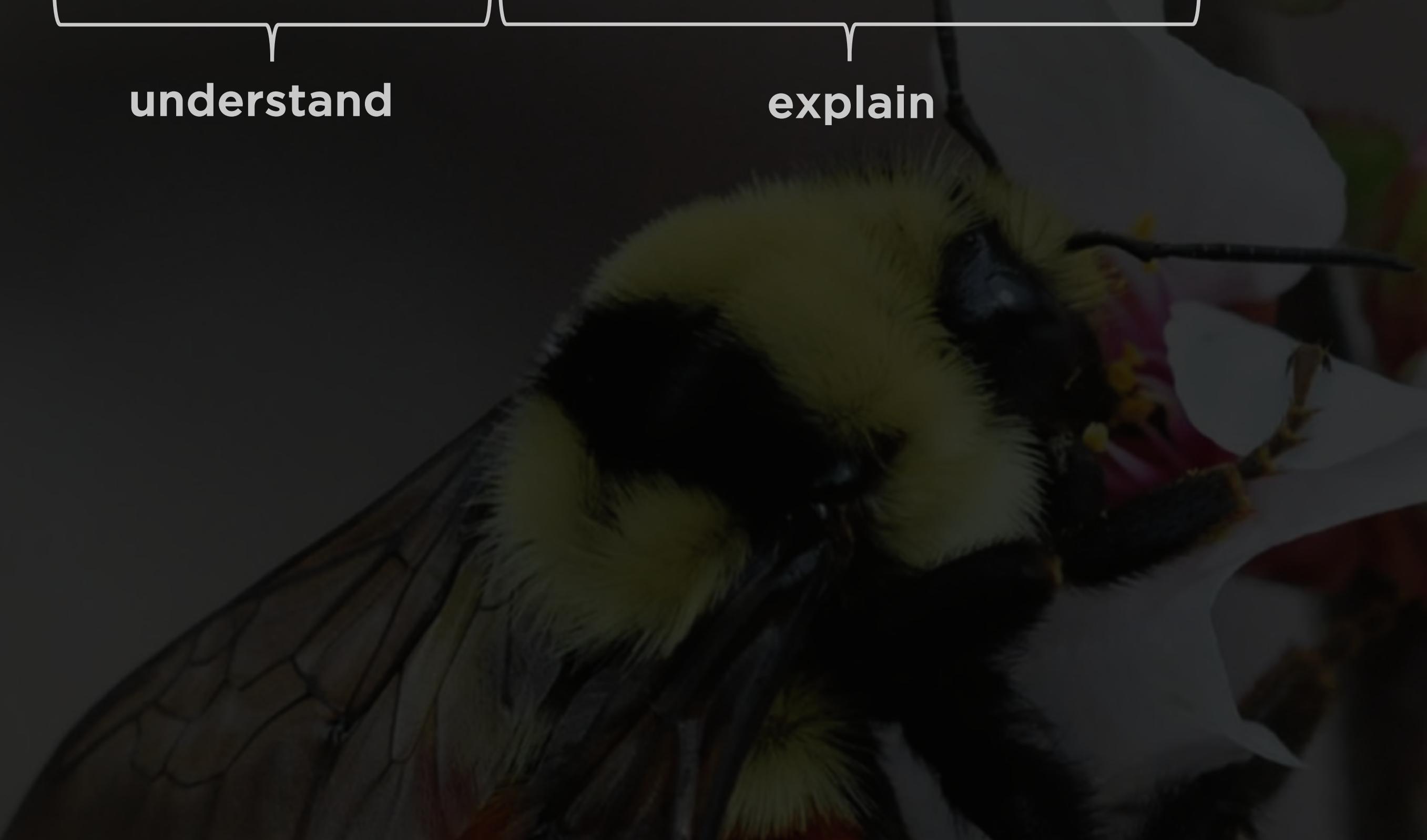
13pt style.org



# See, Think, Design, Produce

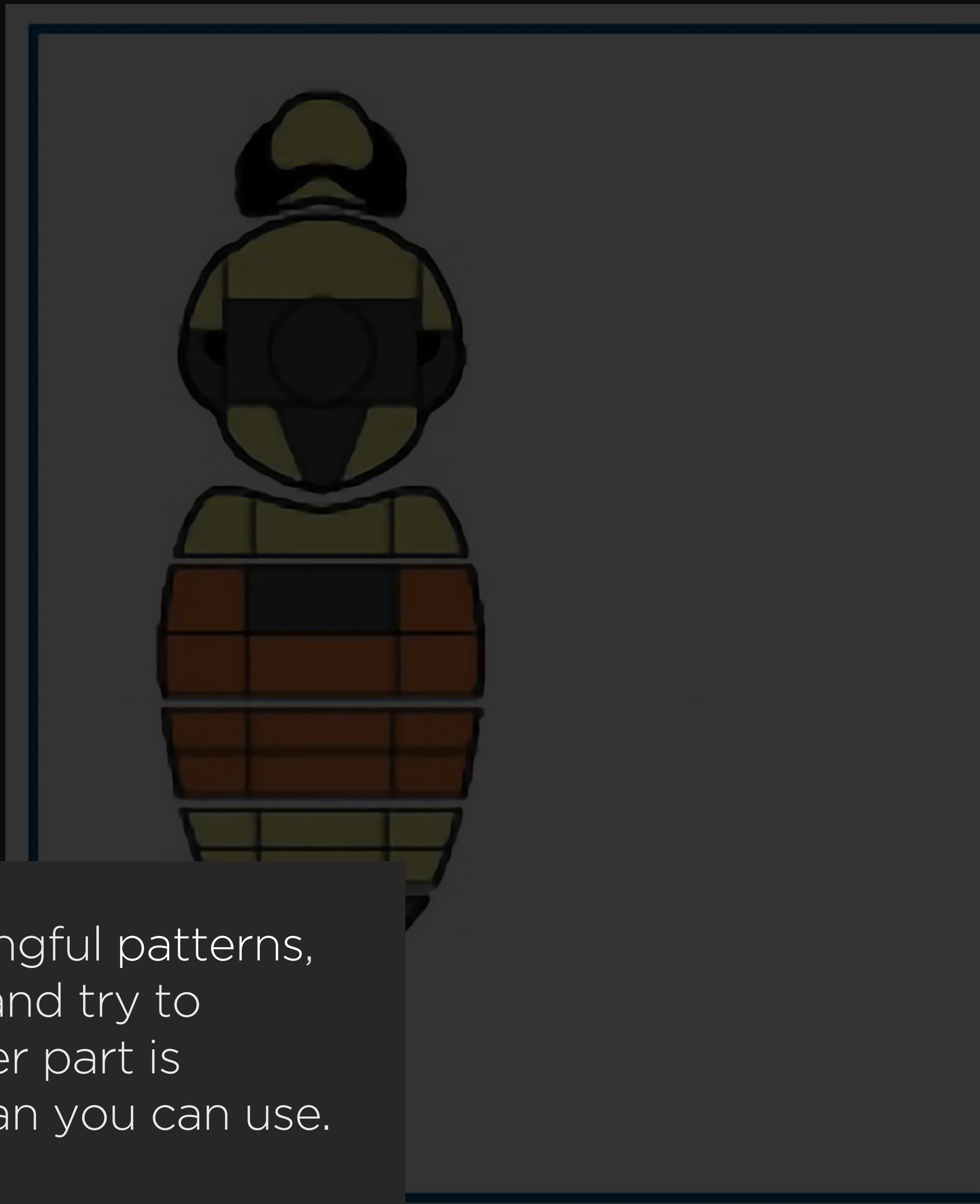
understand

explain



**Search for  
patterns  
by comparing**

Visualization is not counting. Search for meaningful patterns, try to understand **patterns**, visualize patterns and try to explain them. Part of this is **comparing**. Another part is finding what's **possible**. Look at more ideas than you can use.



# See, Think, Design, Produce

understand

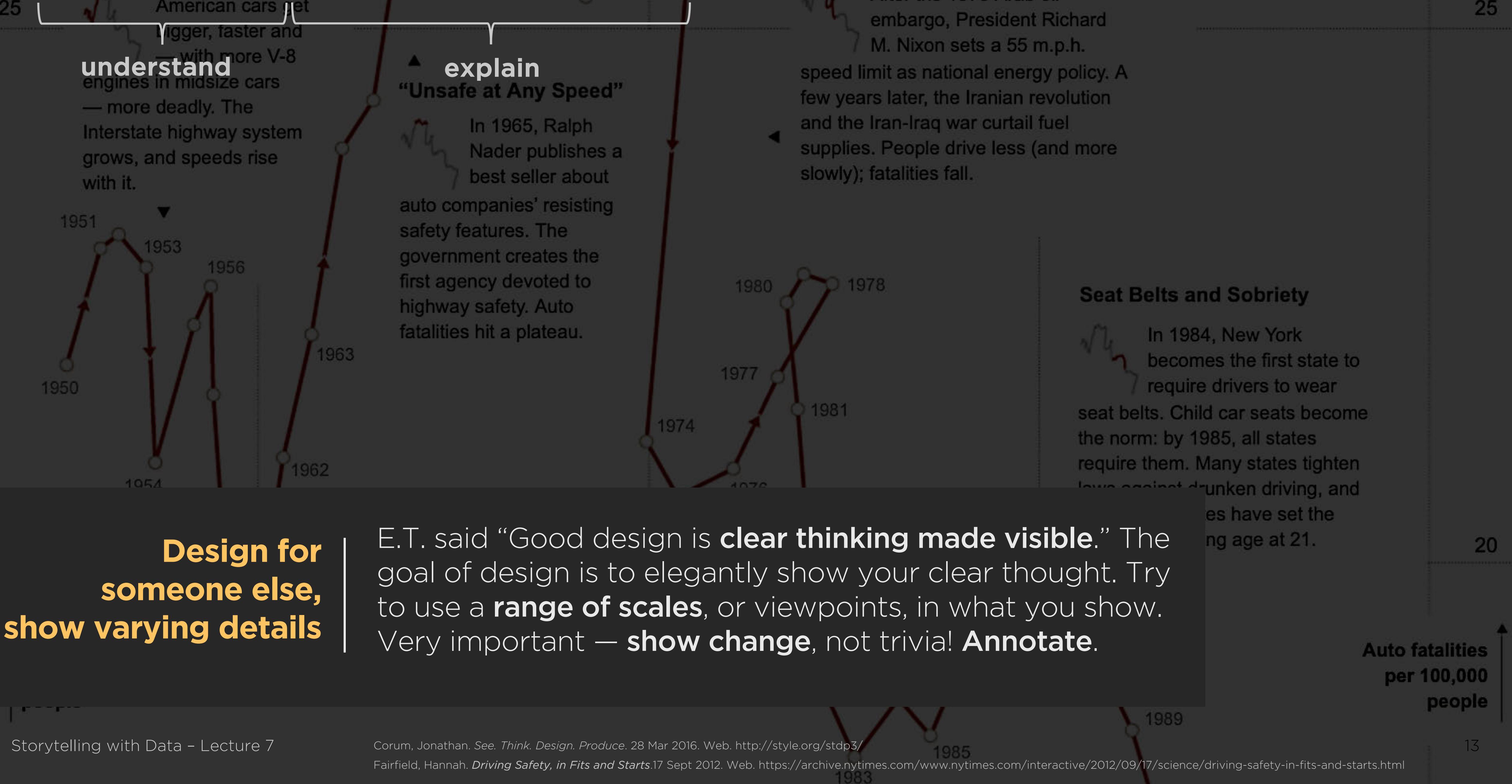
explain



Sketch  
until your  
aha! moment

Finding a **clear thought** through visualization can begin with **sketching**, on either paper or screen. Sketching is visual problem solving, not a commitment. It's much easier to begin with an ugly sketch and make it prettier as you work on design.

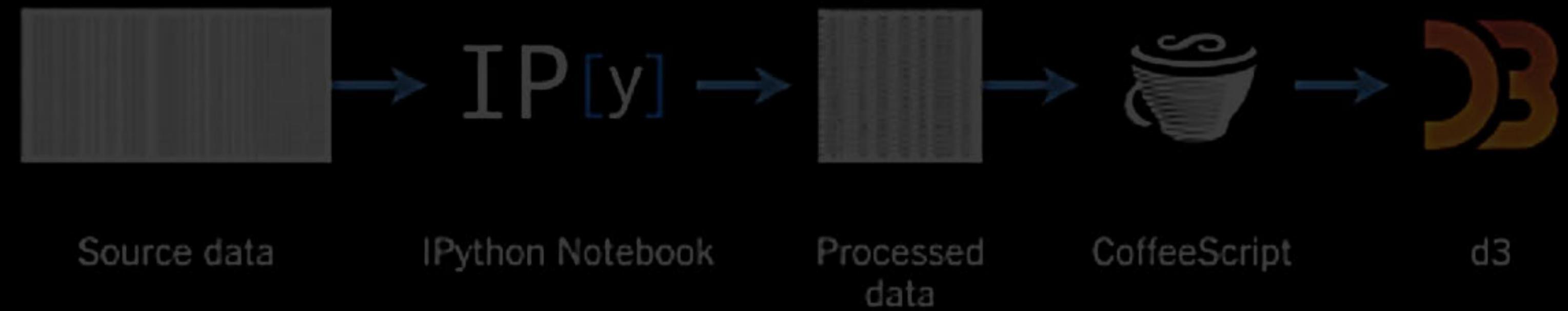
# See, Think, Design, Produce



# See, Think, Design, Produce

# understand

# explain



# Hone ideas Within limitations

**Embrace limitations;** use them to **hone your ideas.** Understand every step—leave nothing to magic—in your production. Design is **cumulative decision making.**

# Questions for discussion.

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What did you find interesting or helpful in the way Jonathan described his process of visual storytelling?

Which of his examples were most vivid, most memorable, to you? What made them so?

# **Group work on storyboards and projects**

# Help your colleagues

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Pair up, take turns providing feedback. Look for:

narrative and messaging

consideration of audience

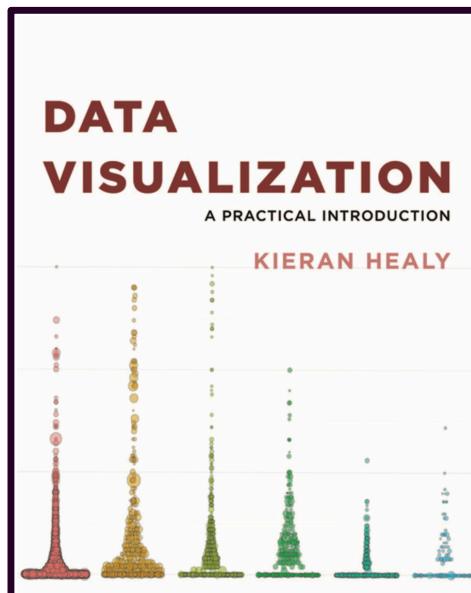
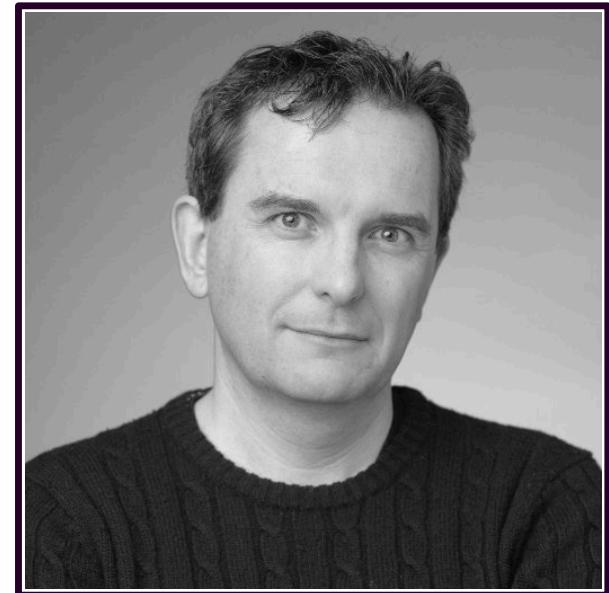
coherence in design, combining words and graphics

# Audience (mis)perception of data graphics

# Data Visualization: a practical introduction

*Healy*

A PhD graduate from Princeton, Kieran is associate professor of sociology at Duke University. His book has been described as “covering the ‘why do’ as well as the ‘how to’ of data visualization.” — Andrew Gelman



## Issues when visually encoding data

### Aesthetic

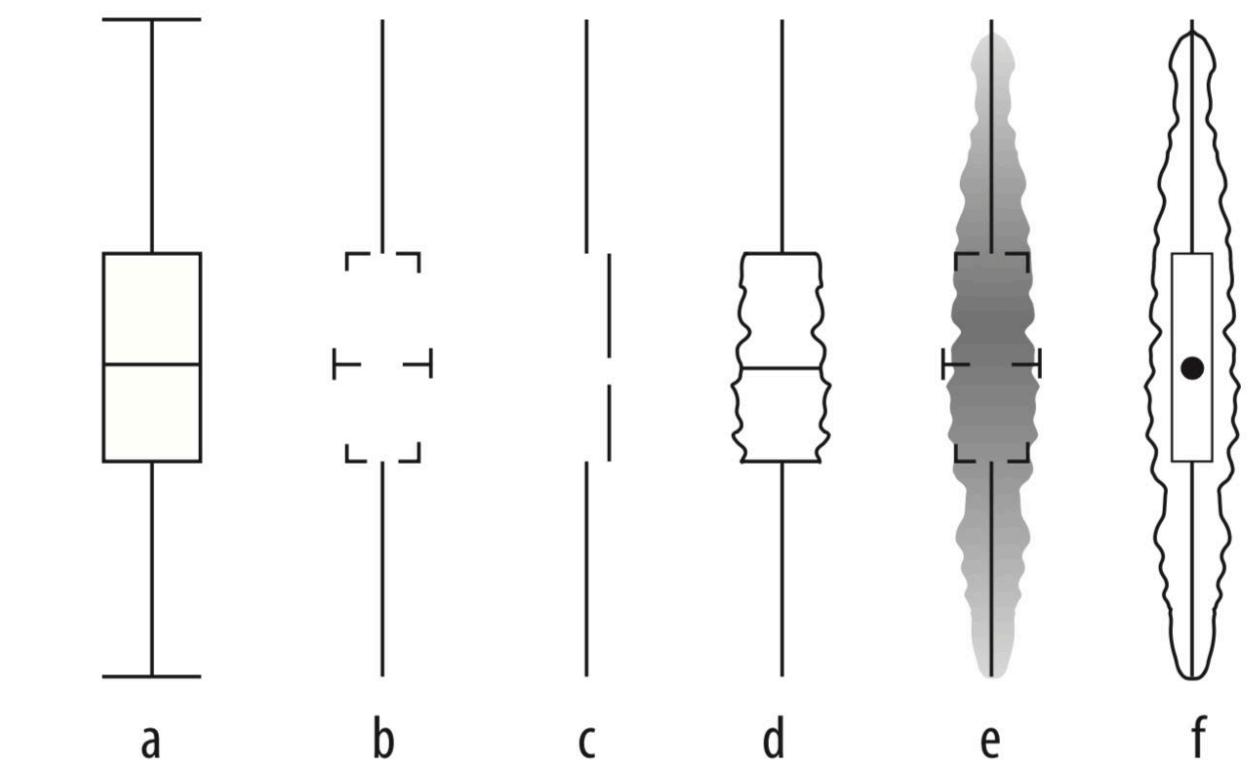
**Aesthetic**  
Substantive  
Perceptual

Consider whether every mark, color, and luminance on a statistical graph conveys information and supports messaging.

Memorable,  
but hard to read.  
“Junk chart”



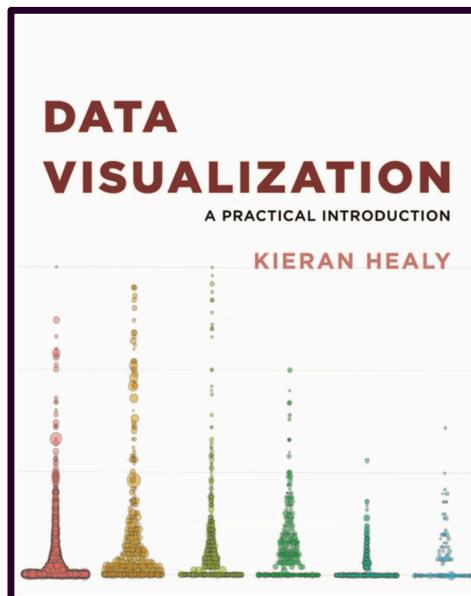
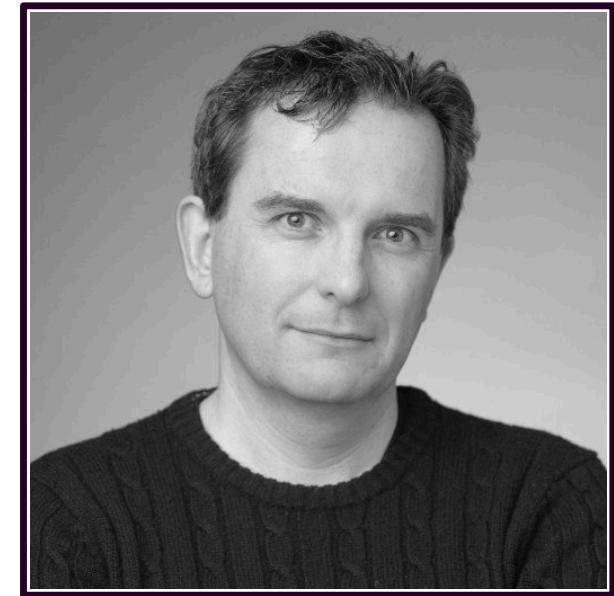
Consider the audience when erasing non- or redundant-data ink



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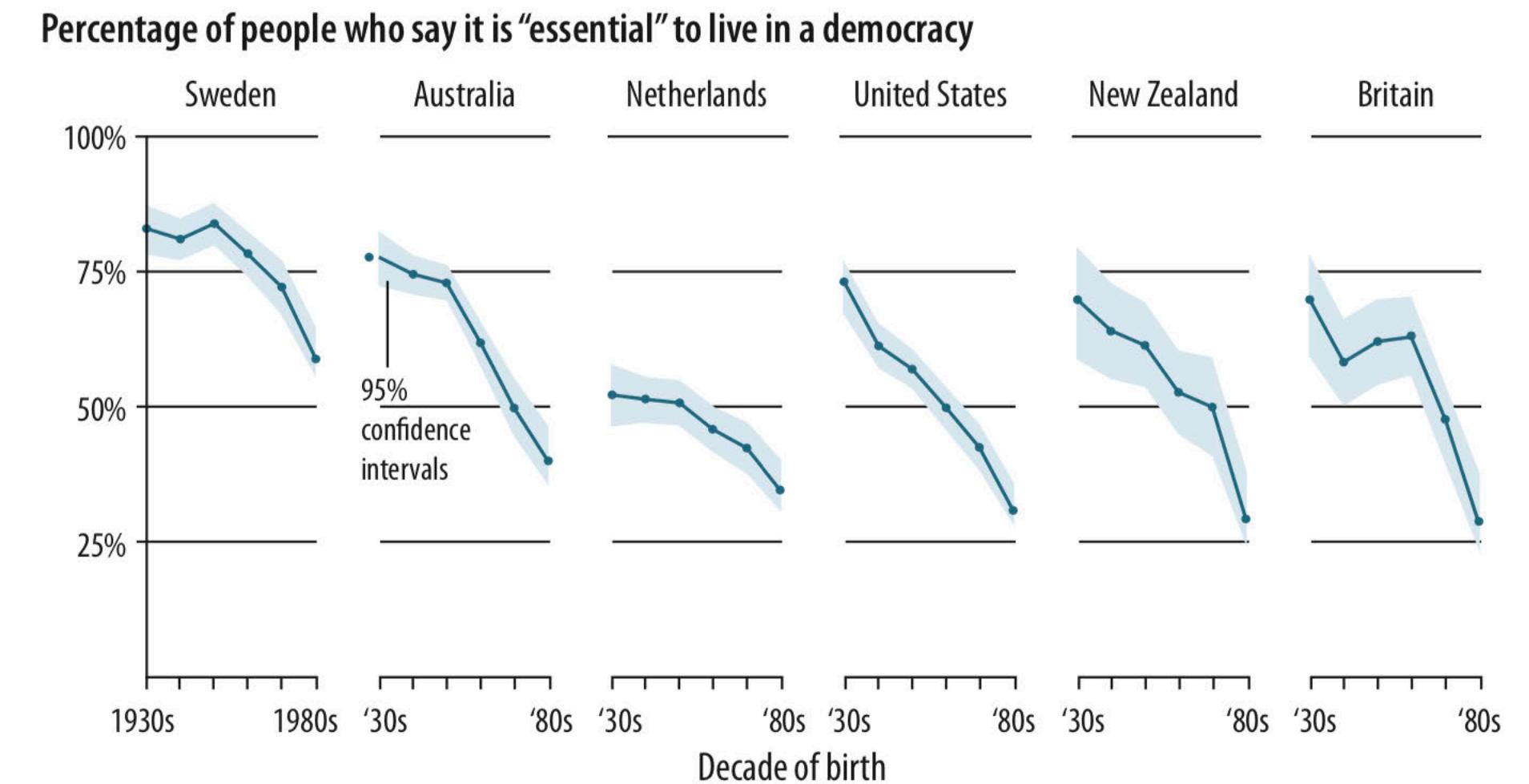
## Issues when visually encoding data

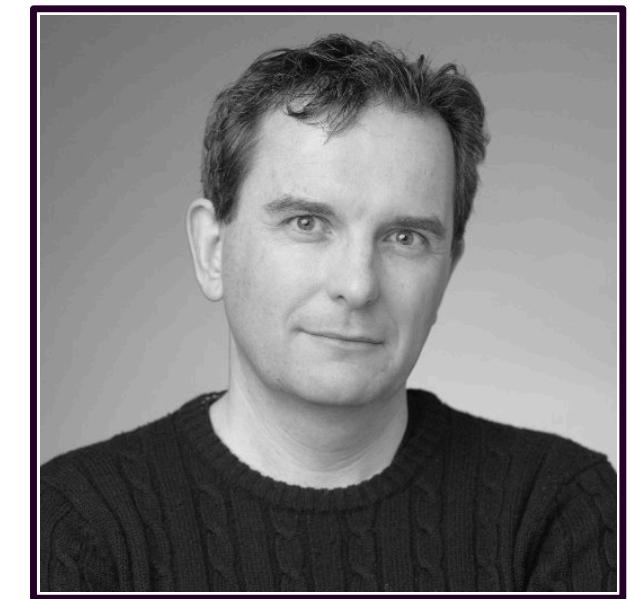
Aesthetic  
**Substantive**  
Perceptual

### Substantive

Consider whether your data honestly and fairly represent your message.

The original chart below graphed the relative change in response of respondents who selected 10 on a 10 point scale.

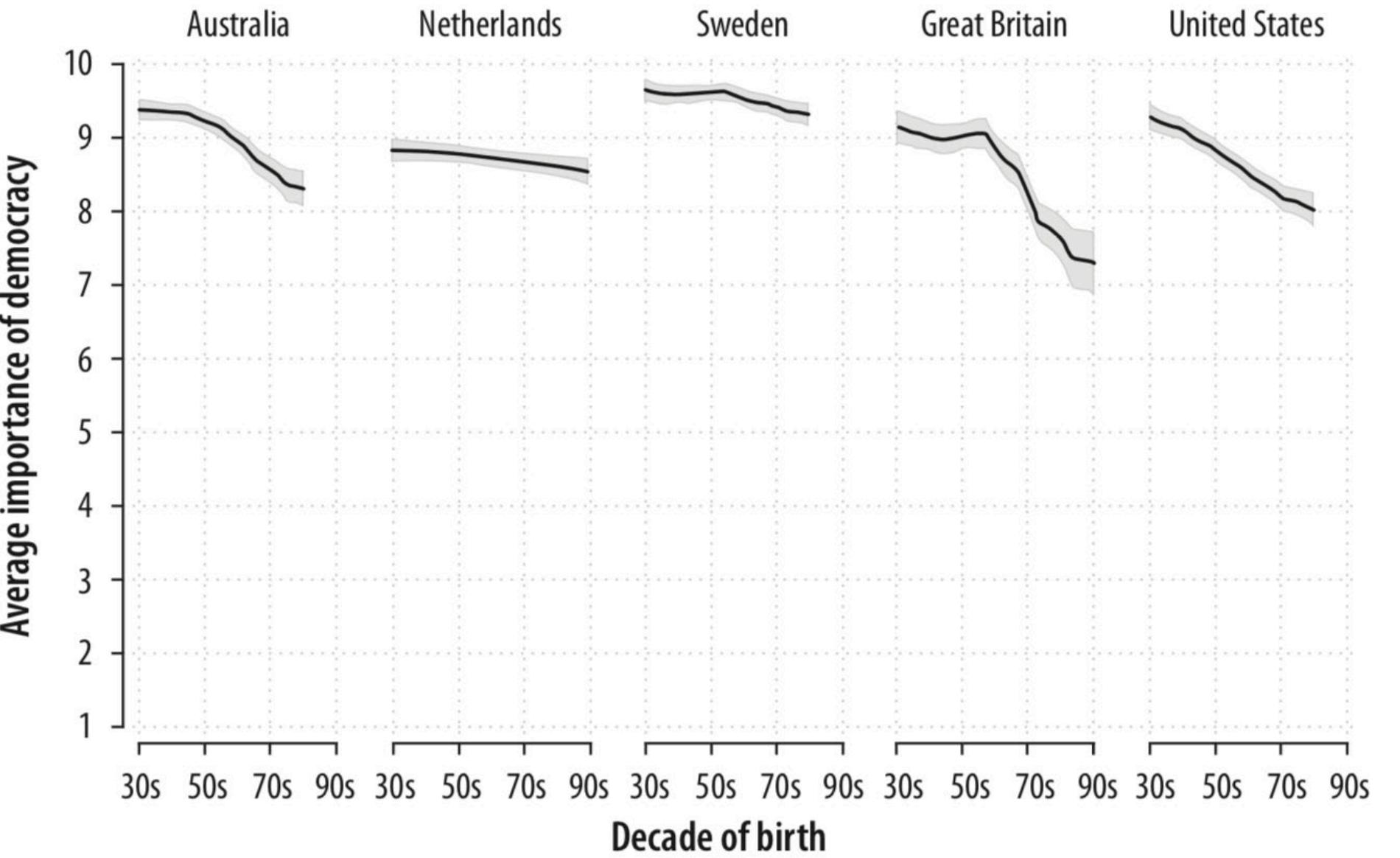
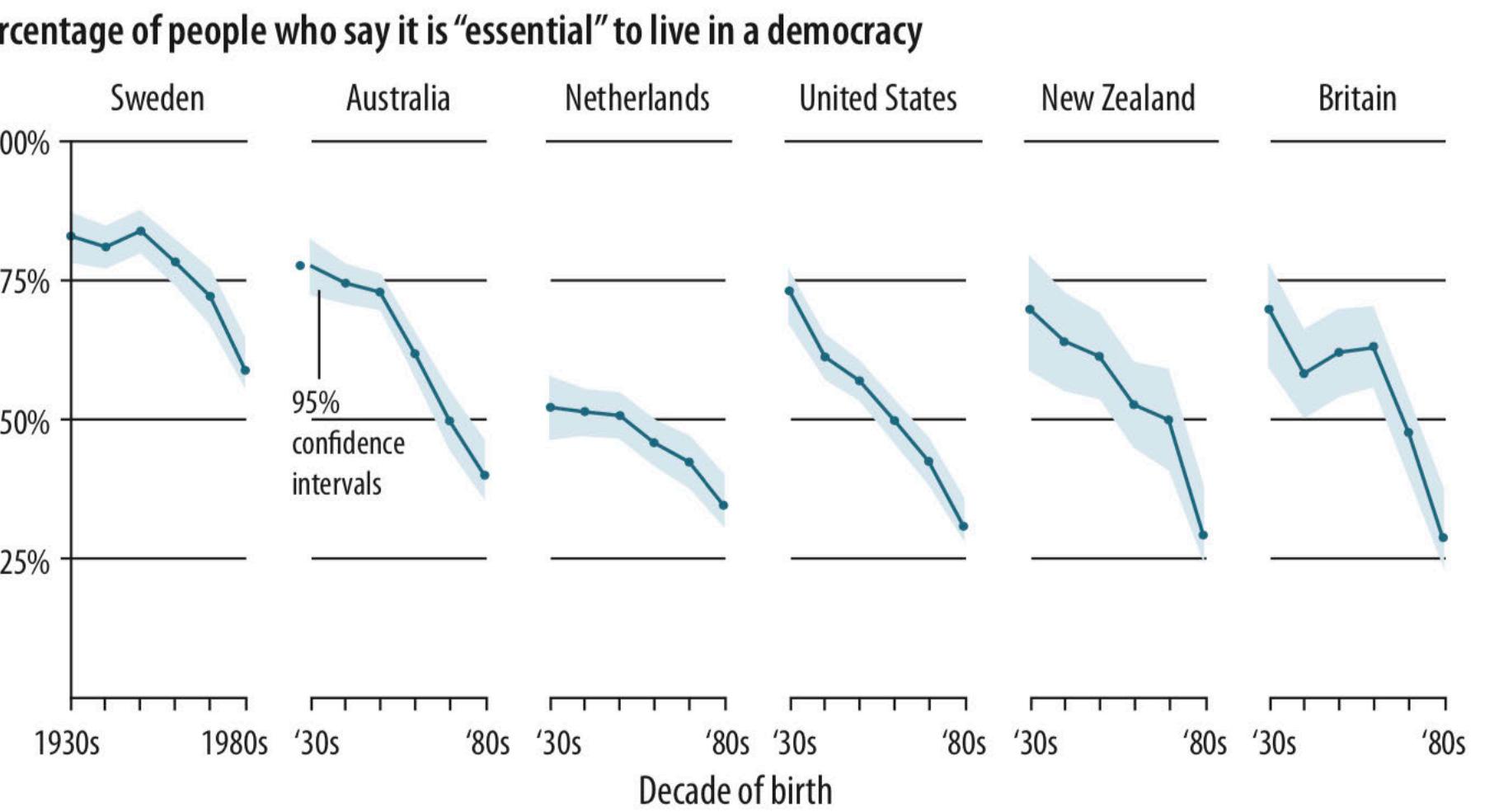




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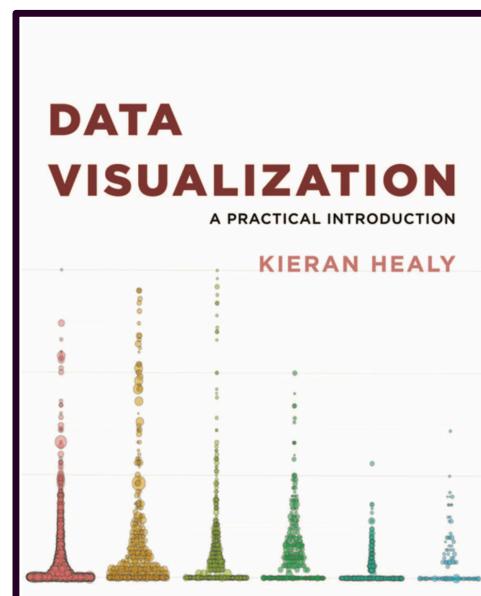
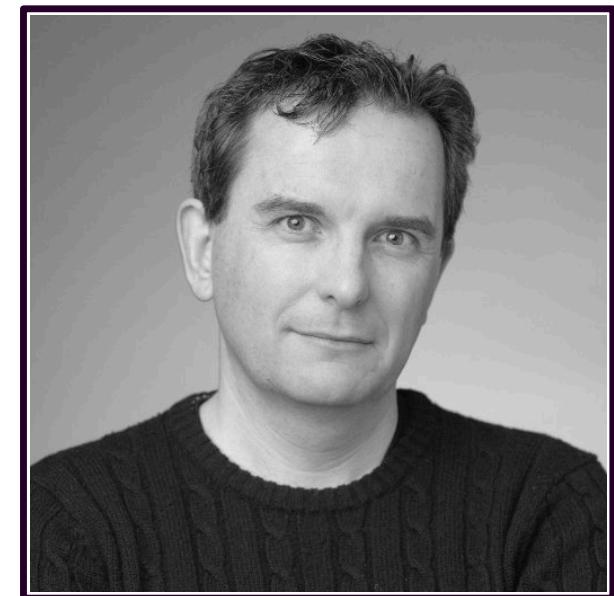


Graph by Erik Voeten, based on WVS 5

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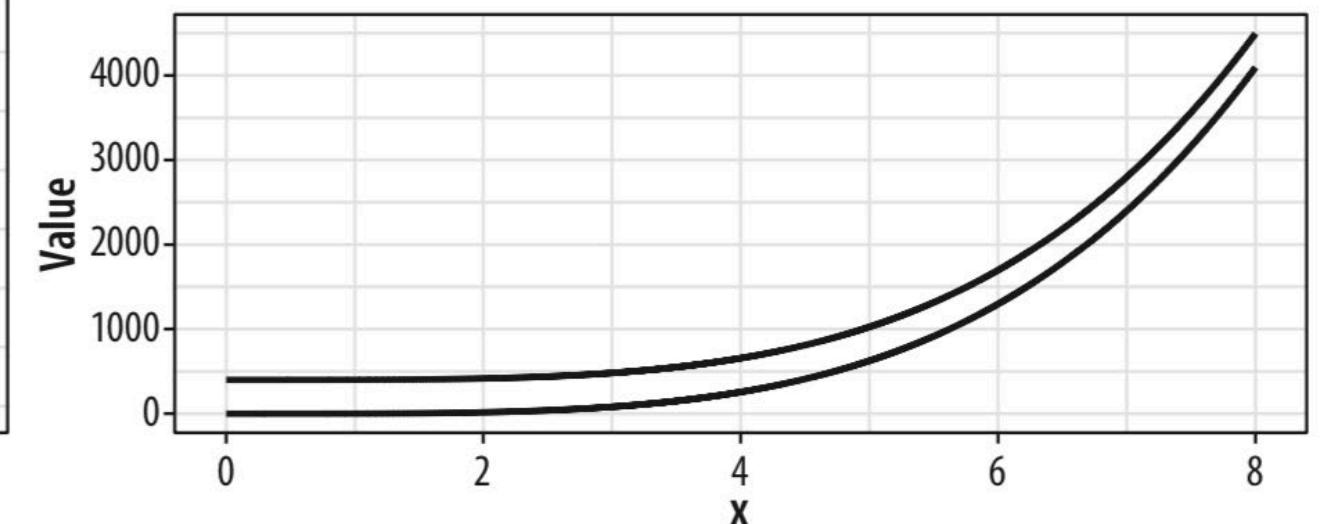
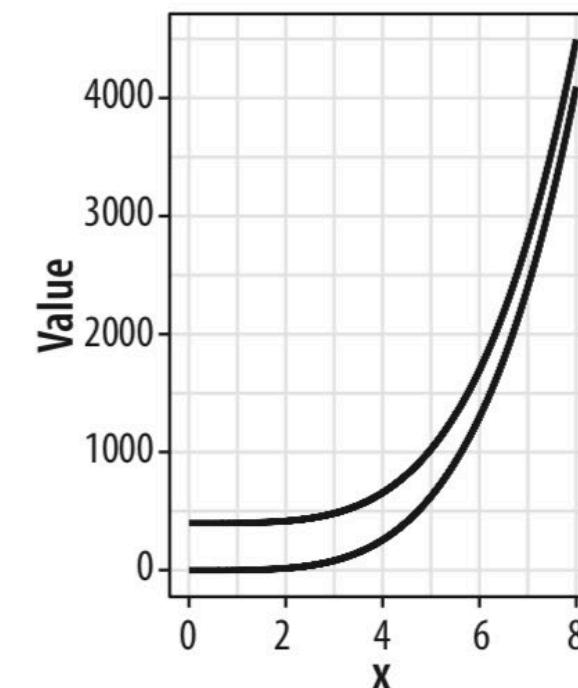
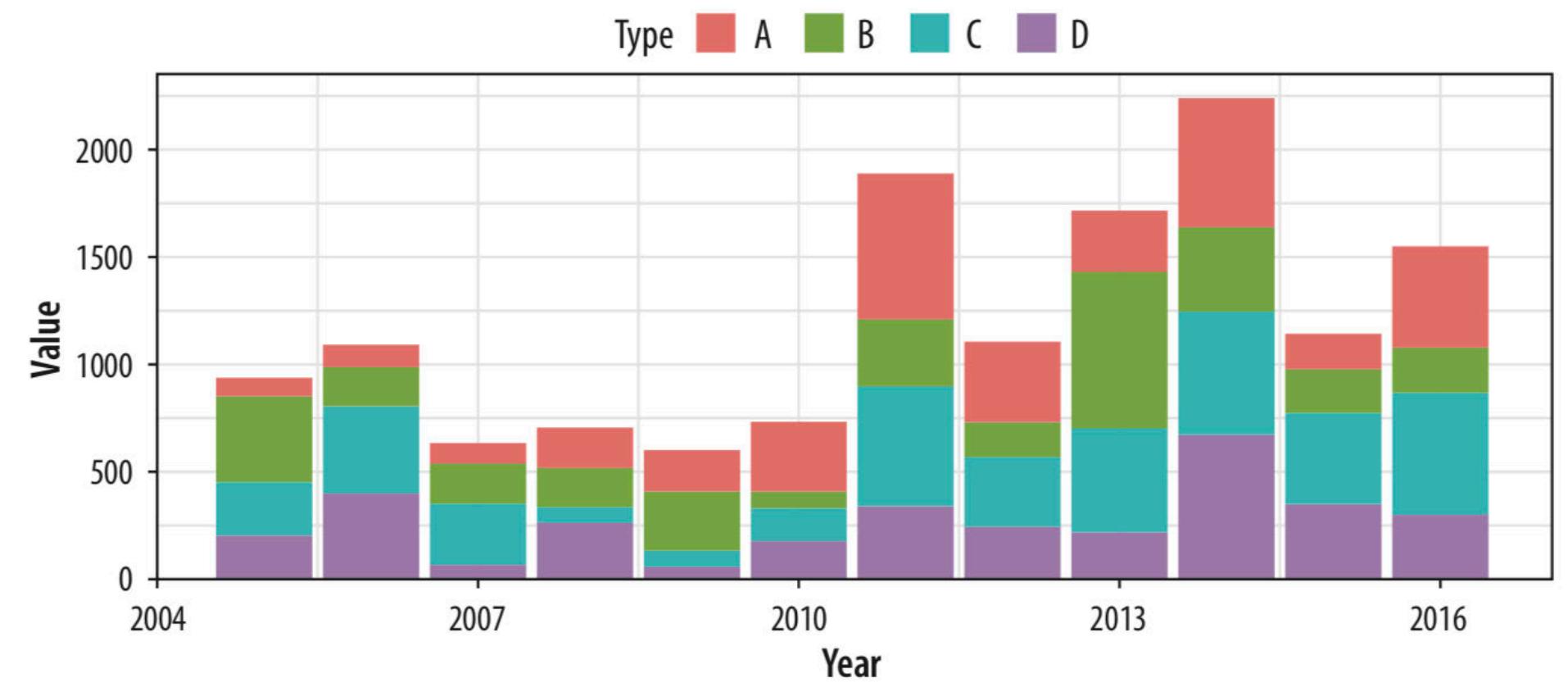


## Issues when visually encoding data

Aesthetic  
Substantive  
**Perceptual**

### Perceptual

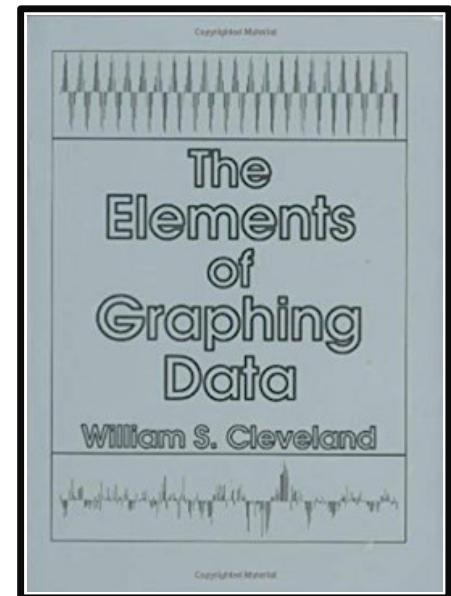
Even with a reasonably-high data-ink ratio, you must choose an encoding that most naturally guides the audience to understand and compare the data. The graphs below have perceptual issues.



# The Elements of Graphing Data

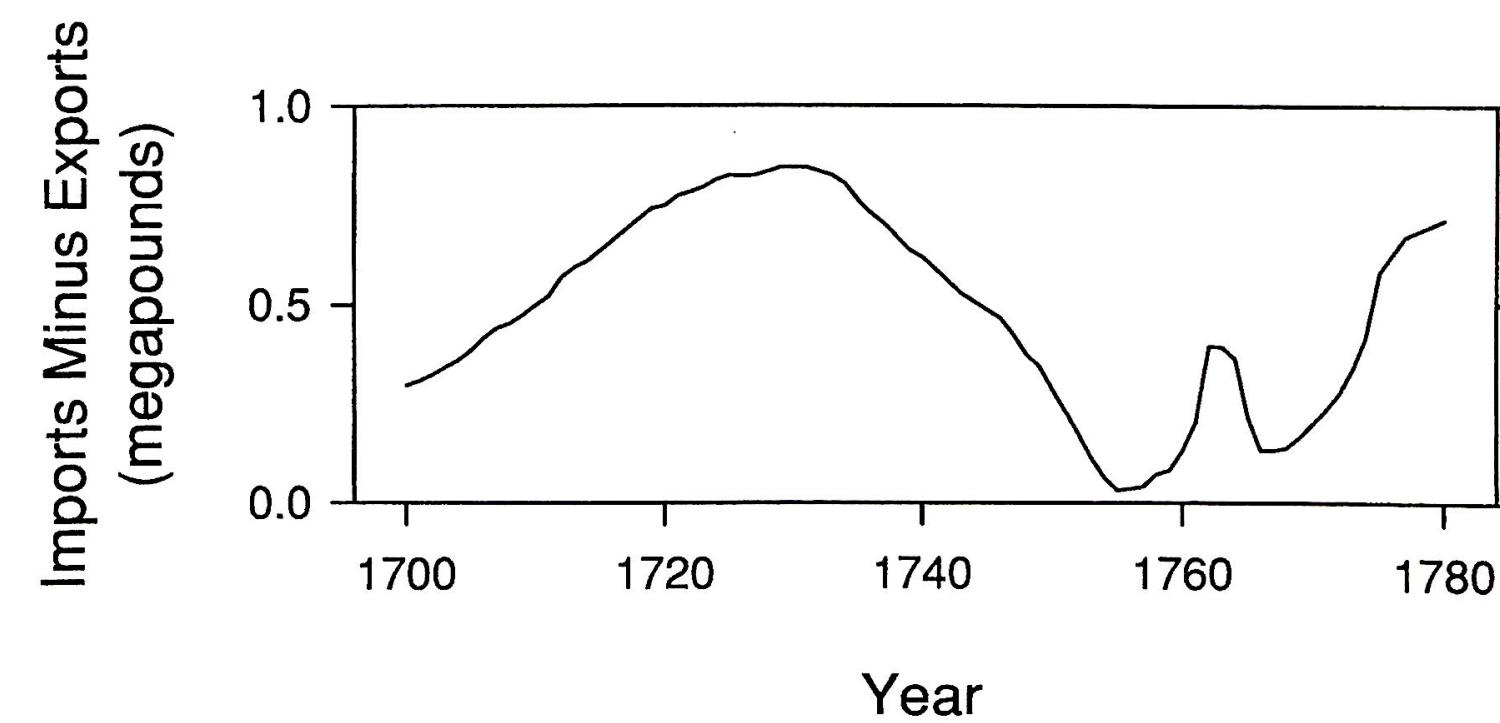
*Cleveland*

A graduate of Princeton, William is a computer scientist and Professor of Statistics and Professor of Computer Science at Purdue University, known for his work on data visualization, particularly on nonparametric regression and local regression.



## Superposed curves have a decoding problem

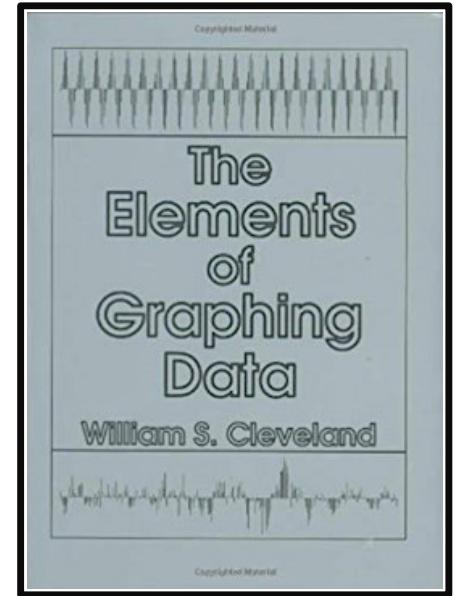
Decoding differences between two lines or curves on a graph can be inaccurate because we naturally compare the shortest distance between the lines instead of the vertical distance between the lines.



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We need a fixed percentage change in something to detect a difference

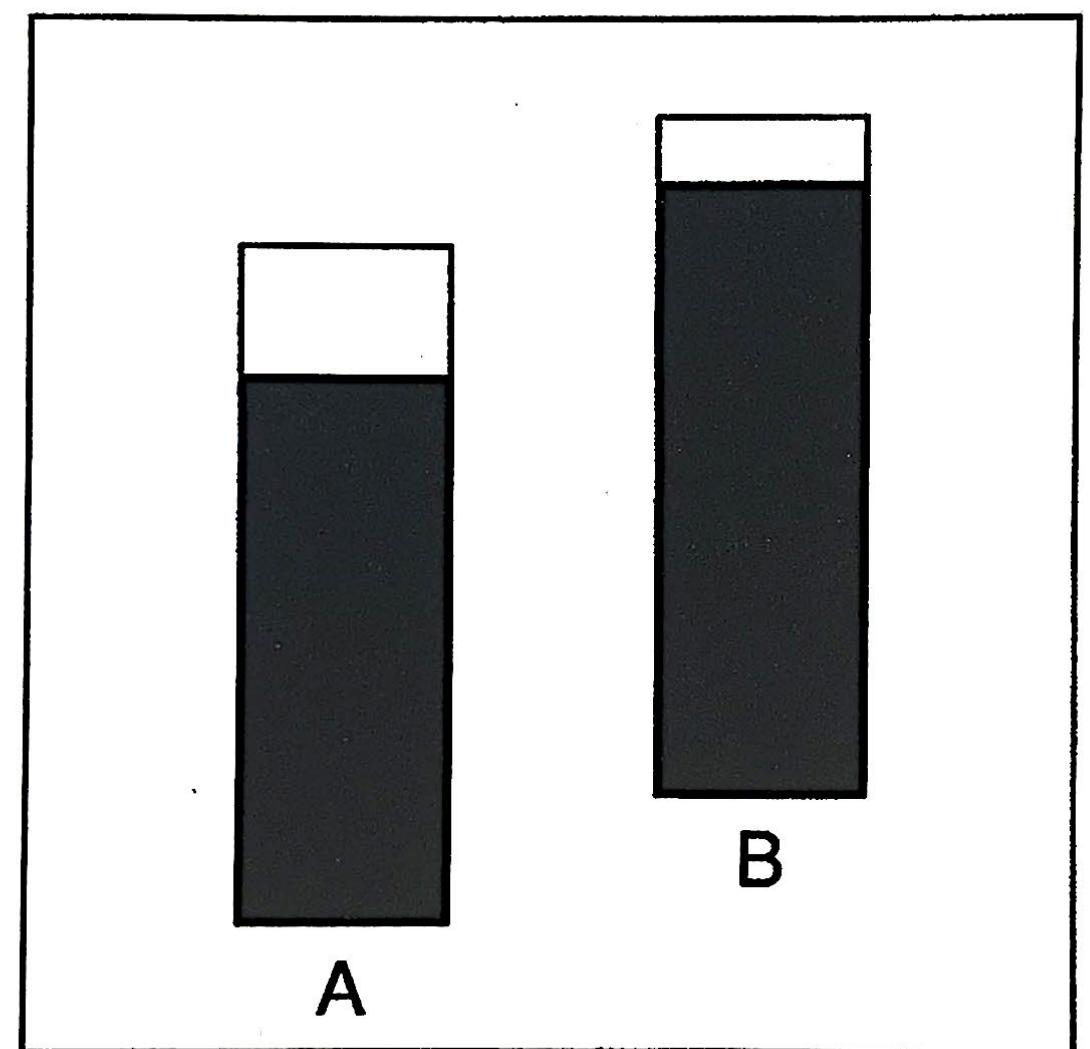
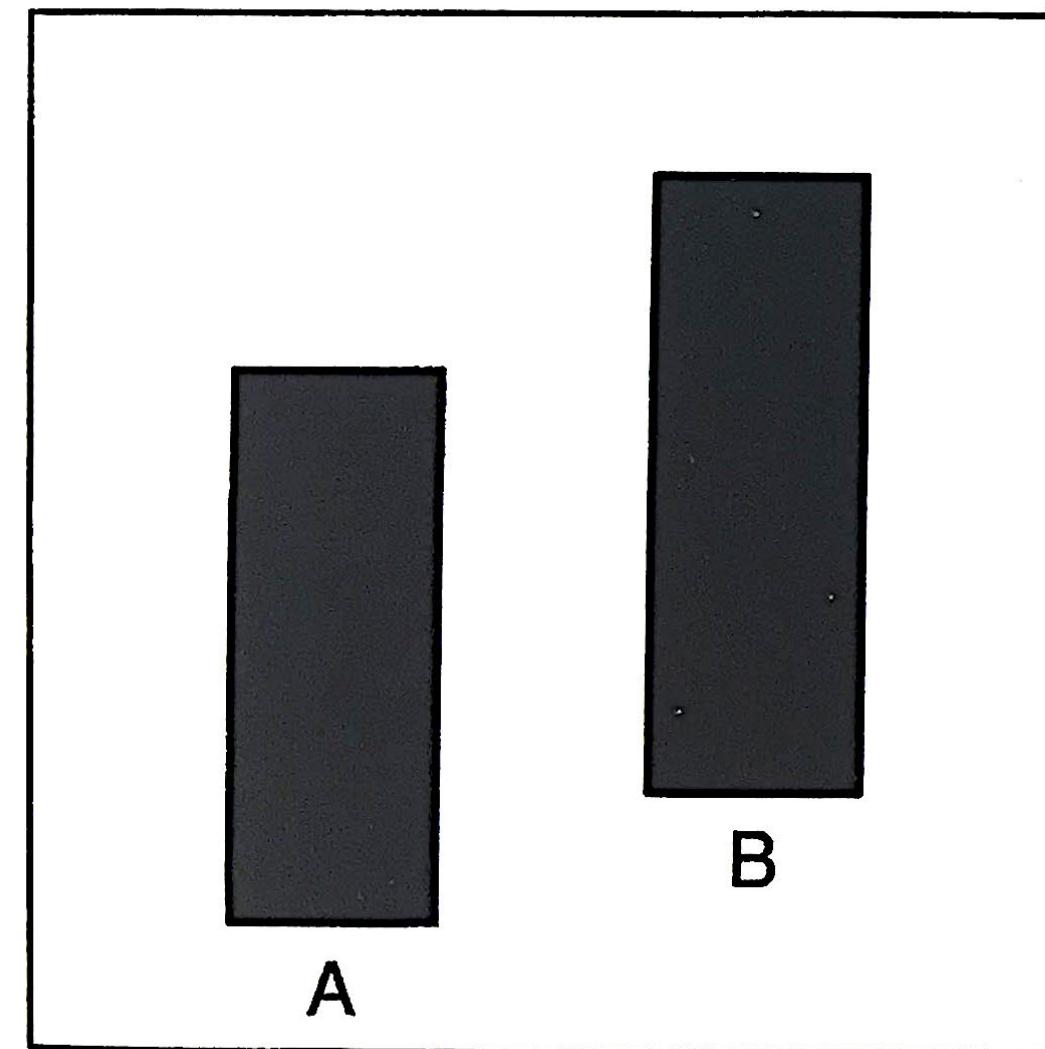
Our visual perception of differences can be stated mathematically, as Weber's Law.

If  $x$  is the magnitude of a physical attribute, say, length of a line segment, and  $w_p(x)$  is a positive number such that a line of length

$$x + w_p(x)$$

is discriminated with probability  $p$  to be longer than the line of length  $x$  then,

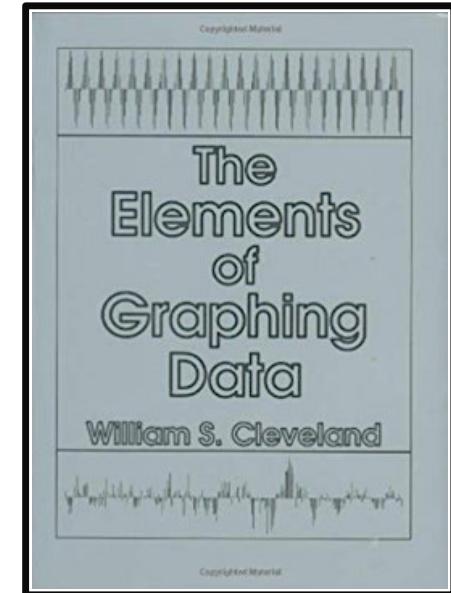
$$w_p(x) = k_p x$$



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## Consider (only) using reference grids in aid of Weber's Law

Reference grids can help us perceive the differences between two measurements, but they can also distract. Consider only using reference lines that guide your audience to the relevant point of your message.

And a little goes a long way: for any needed reference lines, consider making them, say, very faint gray or otherwise distinguish them from the data.

## How did we do in the example proposal for the Dodgers?

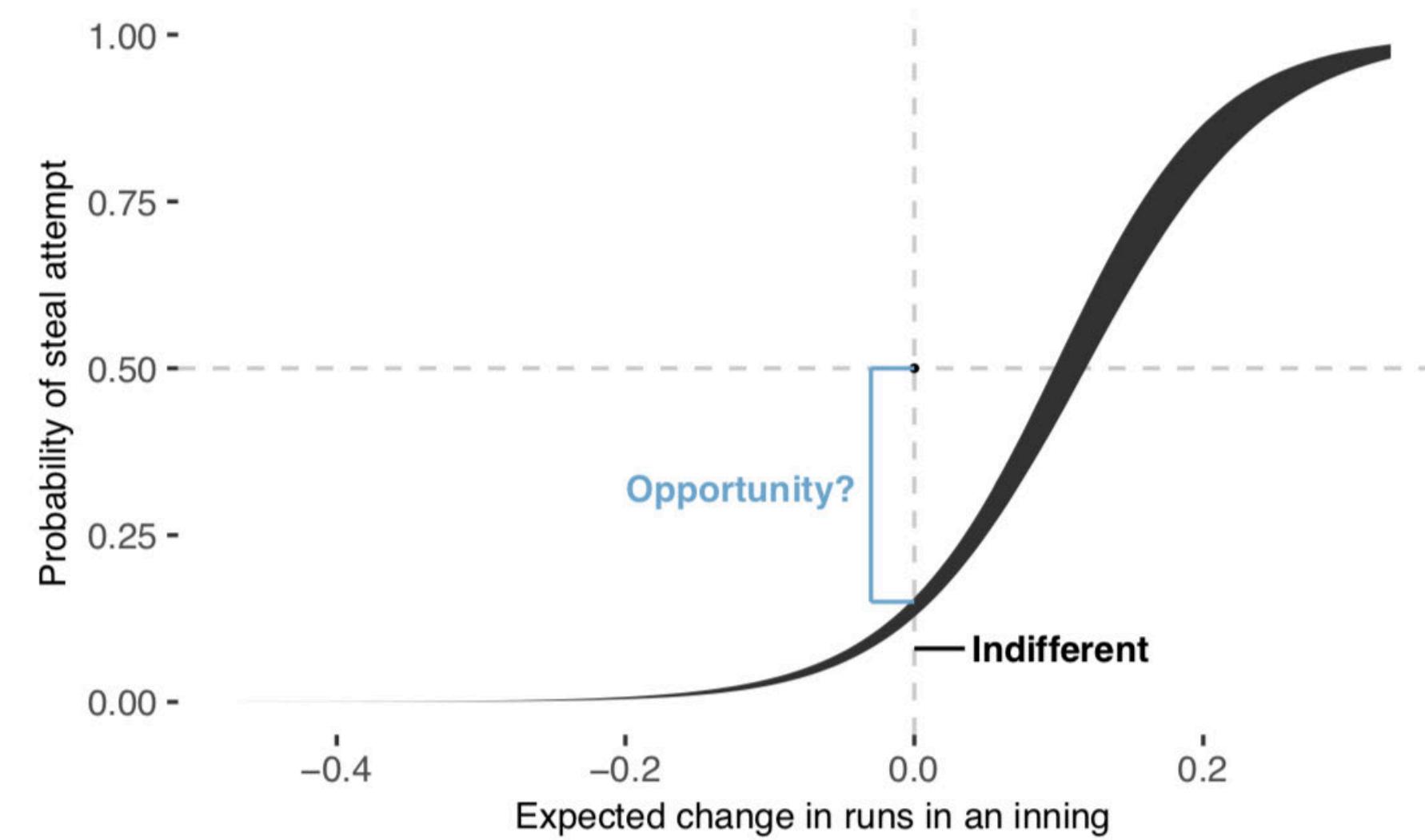


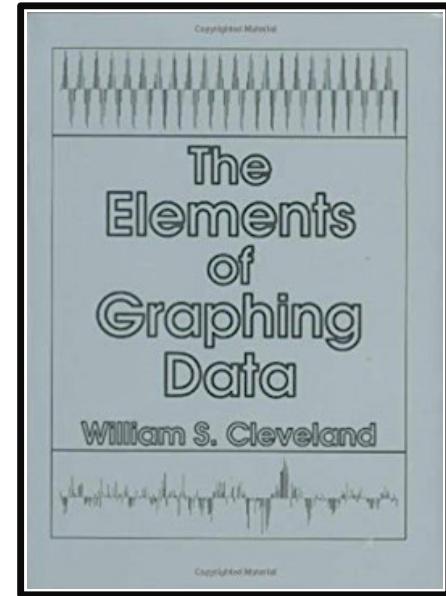
Figure 2. When the change in expected runs is zero, managers should be indifferent to attempted steals, saying go half the time.

The **black band** represents the range of variation across managers' decisions. At the intersection of **indifference**, managers tend to say steal only **10 percent** of the time, leaving opportunity.

# The Elements of Graphing Data

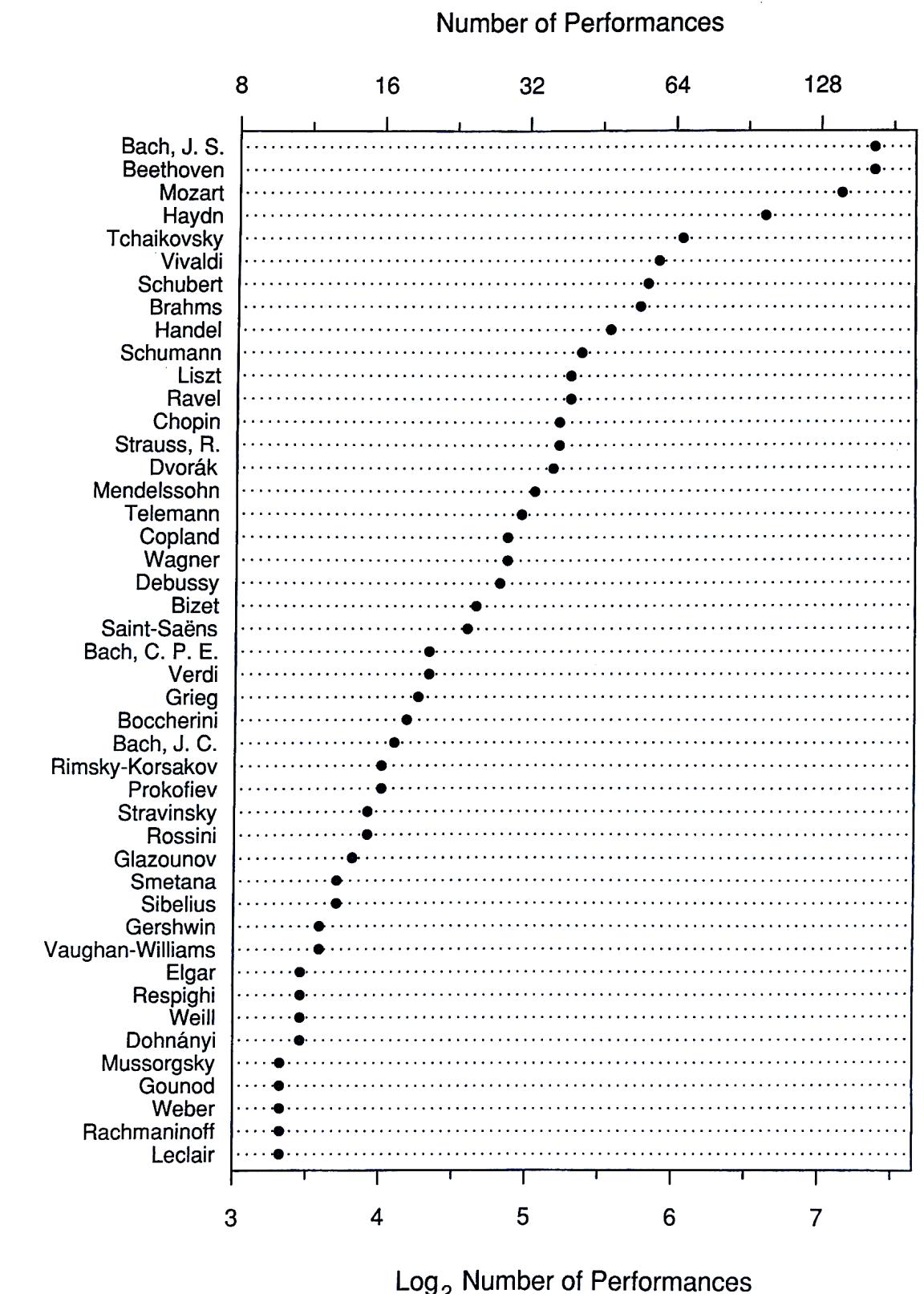
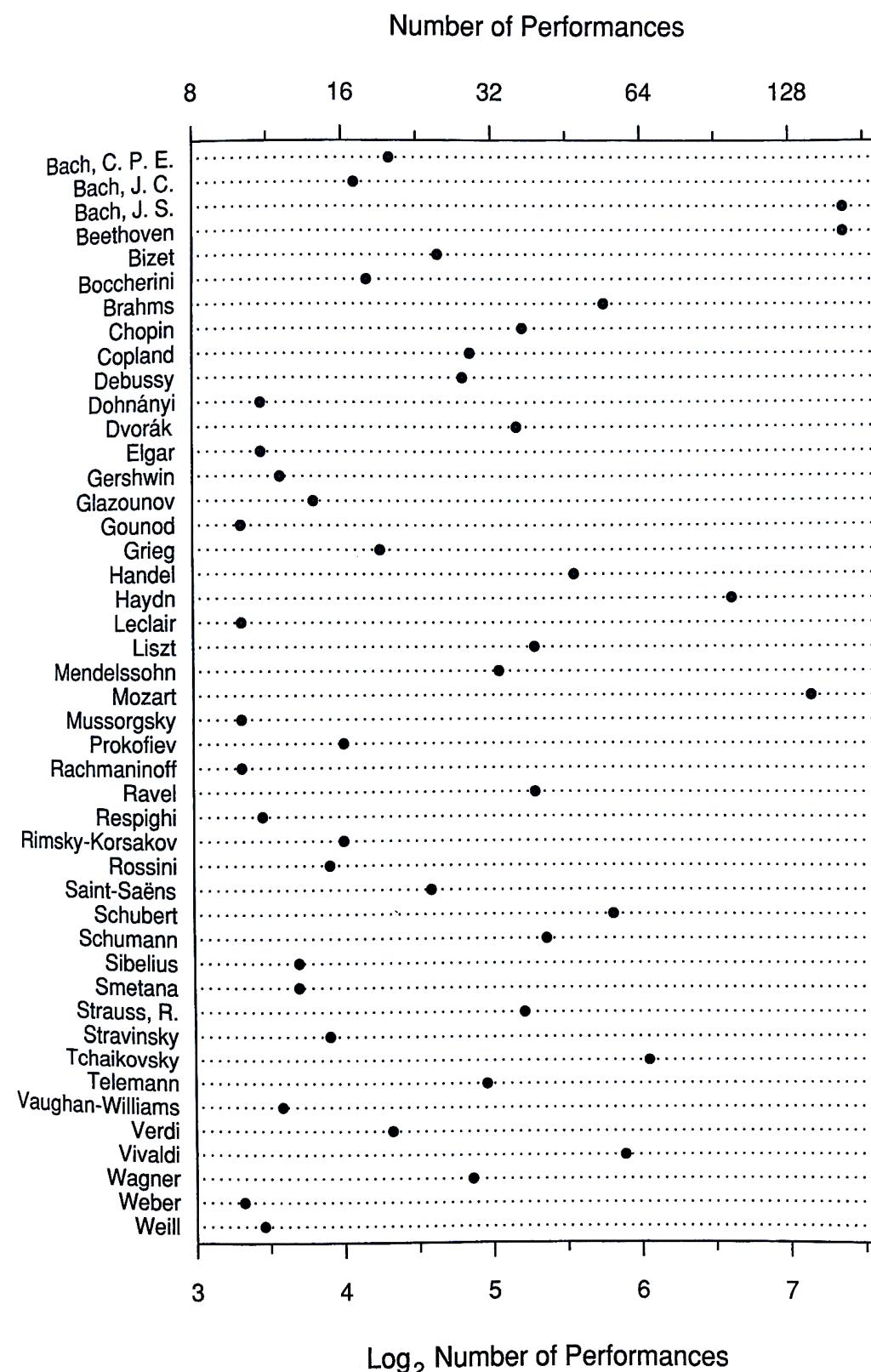
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**Ordering for categorical variables substantially affects our visual decoding**

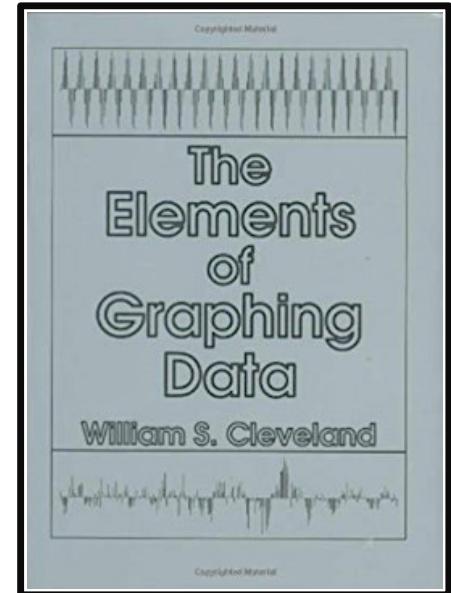
Ordering from, say, smallest to largest enhances our visual decoding of the distribution of values along the measurement scale.



# The Elements of Graphing Data

*Cleveland*

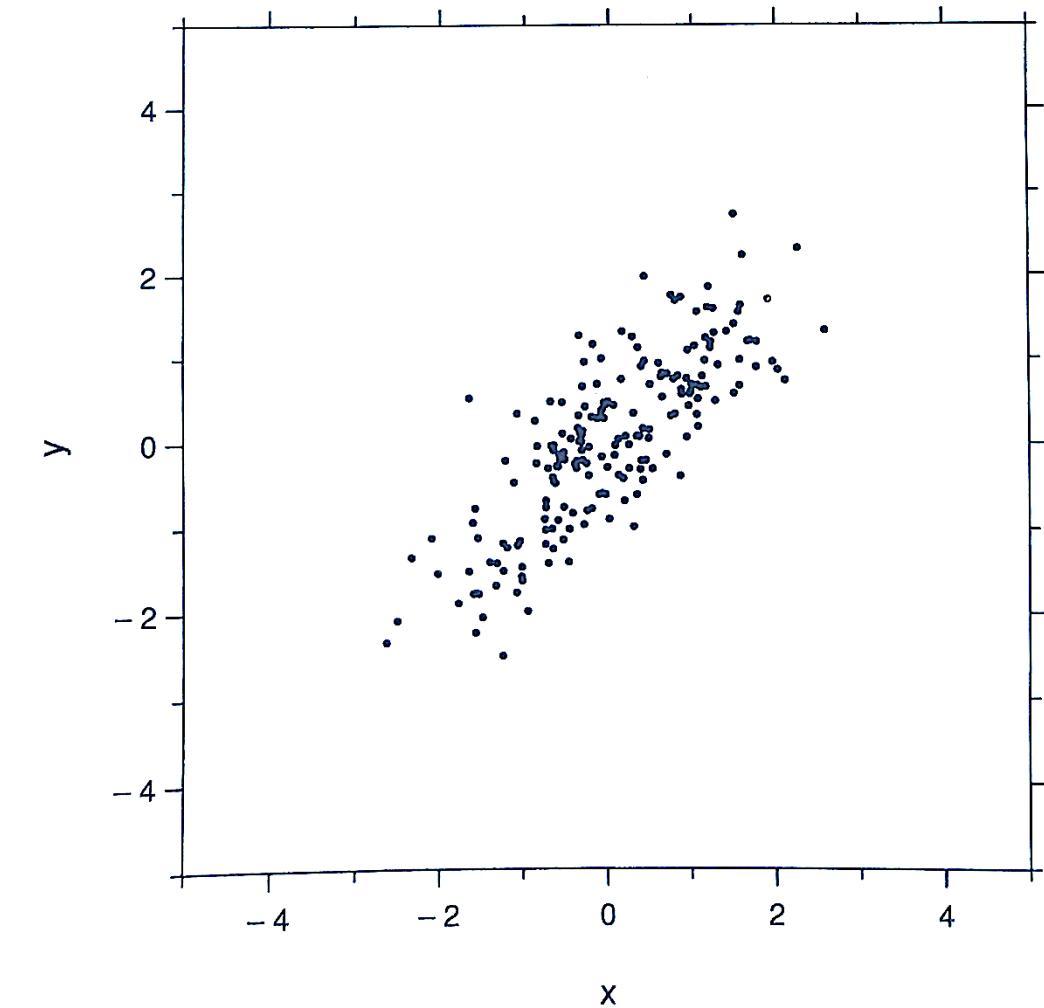
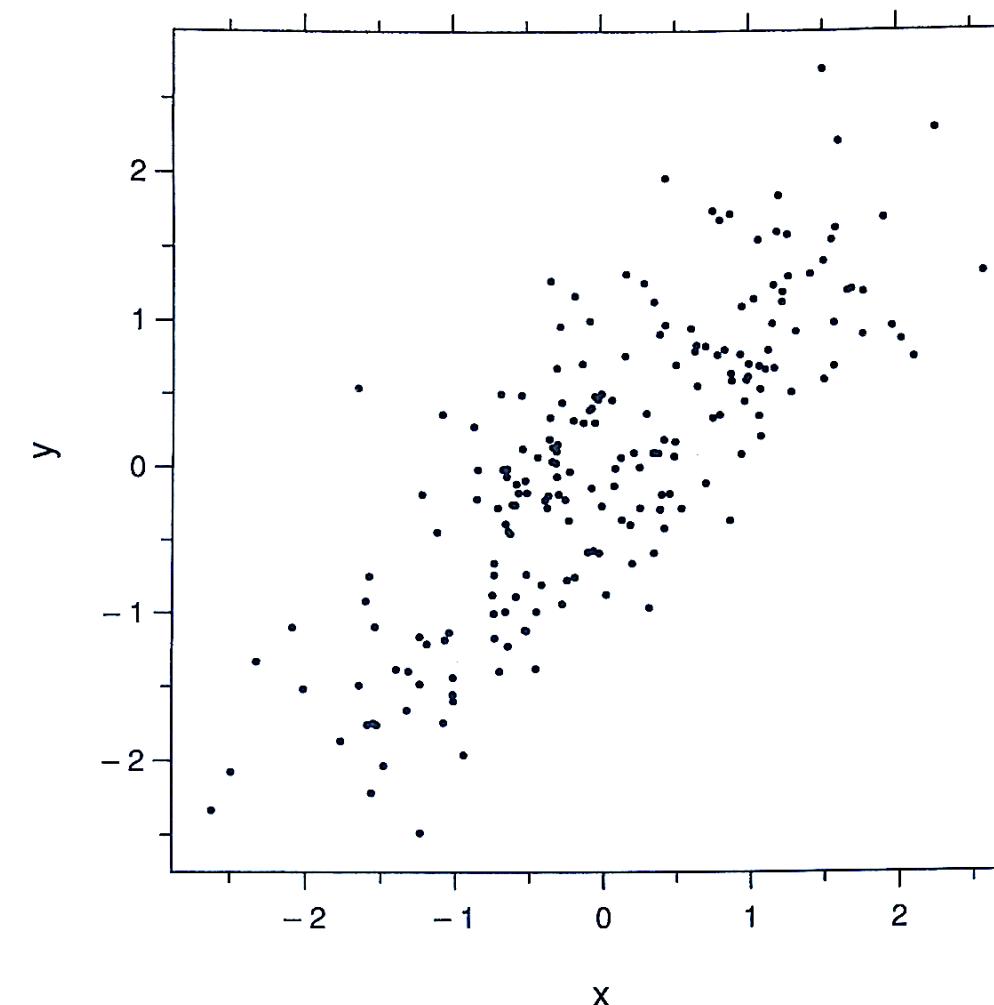
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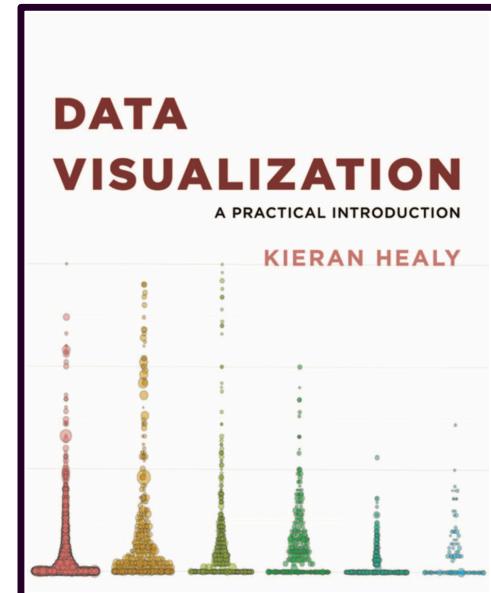
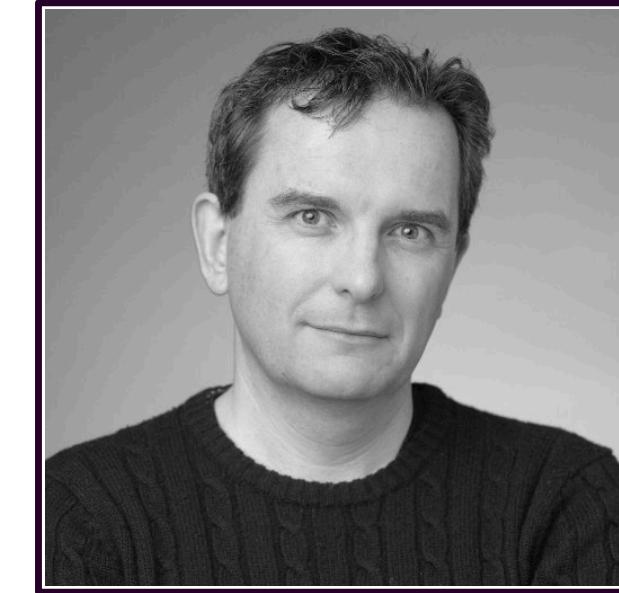
## Perceived correlation depends on ratio of plot area to data area

Our estimation of correlation is affected by the area of the data rectangle divided by the area of the scale-line rectangle.

Showing the same data, the left panel displays a 1 to 1 ratio, while in the right panel displays the data rectangle as much smaller than the scale-line rectangle.



# (In)accuracy in decoding visuals



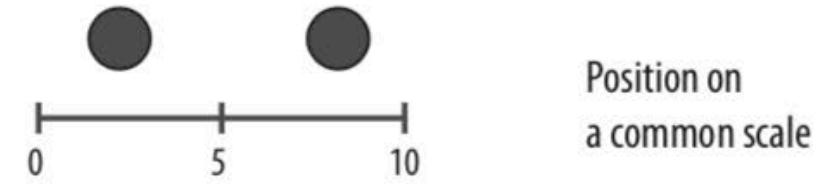
# Data Visualization: a practical introduction

*Healy*

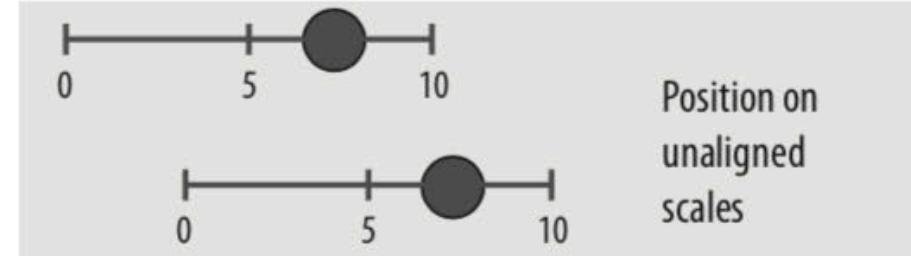
A PhD graduate from Princeton, Kieran is associate professor of sociology at Duke University. His book has been described as “covering the ‘why do’ as well as the ‘how to’ of data visualization.” — Andrew Gelman

Most accurate

Least accurate



Position on a common scale



Position on unaligned scales



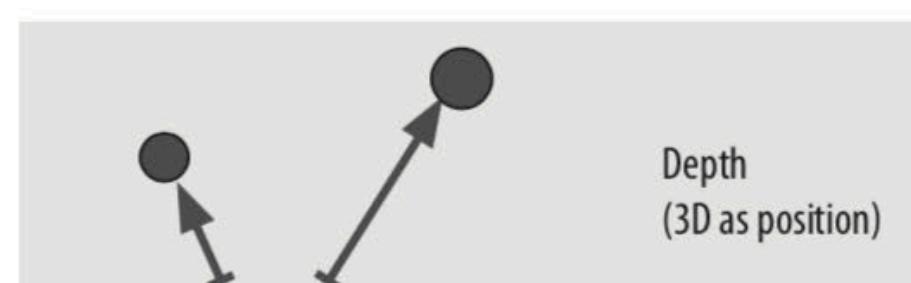
Length



Tilt or Angle



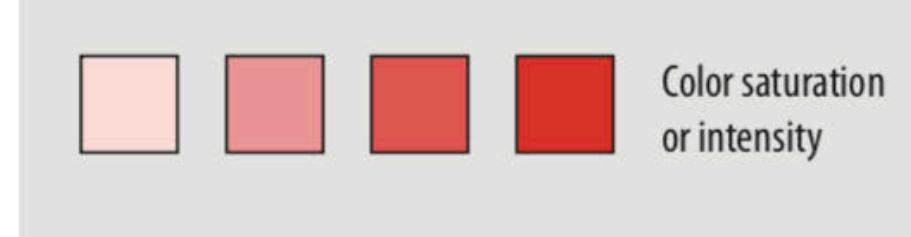
Area (2D as size)



Depth (3D as position)



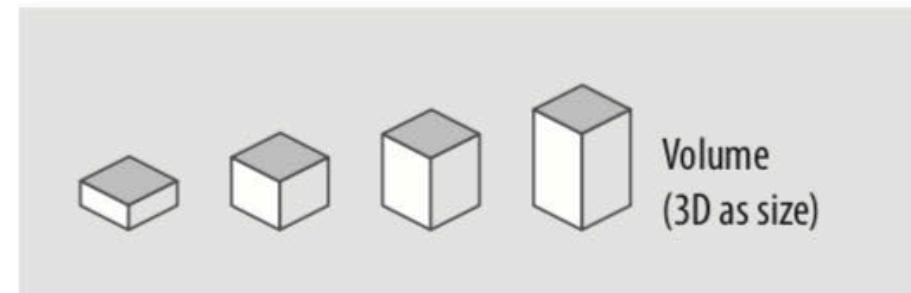
Color luminance or brightness



Color saturation or intensity

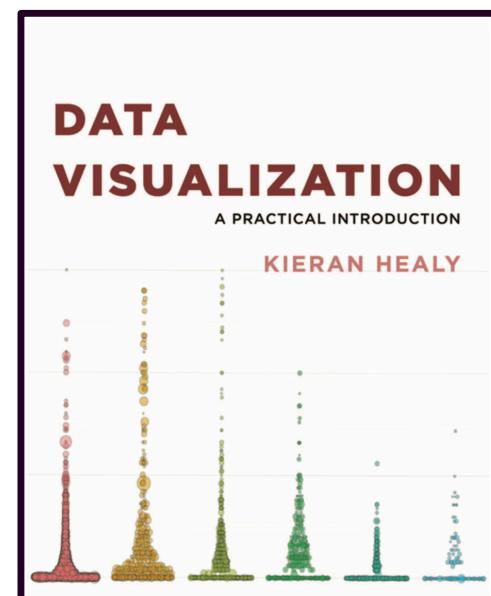
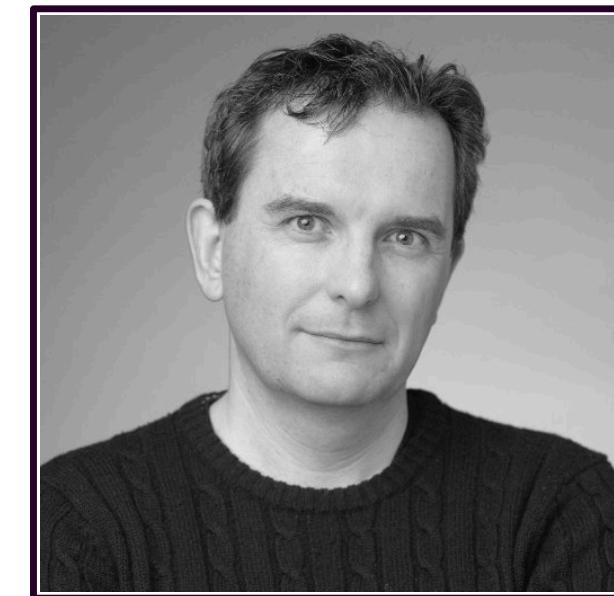


Curvature



Volume (3D as size)

# Focusing visual attention



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## Help your audience with Gestault principles

Our eyes automatically search for (grouping), difference and change.

**Proximity:** Things that are spatially near to one another seem to be related.

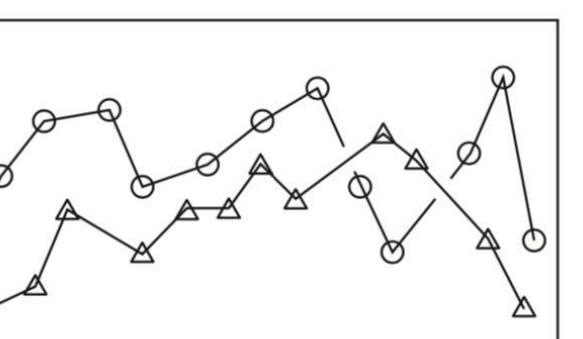
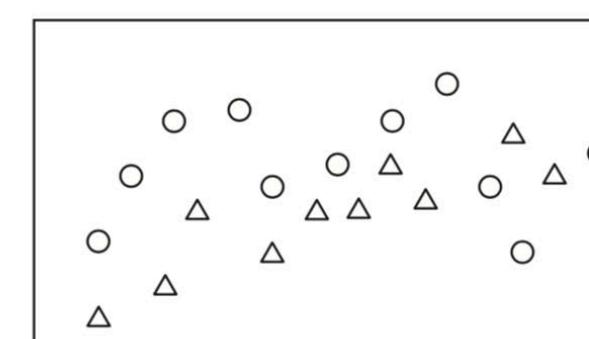
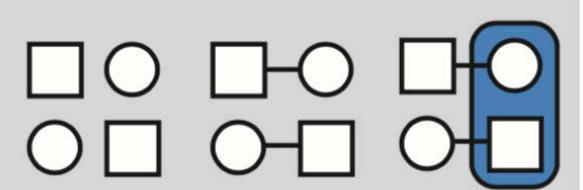
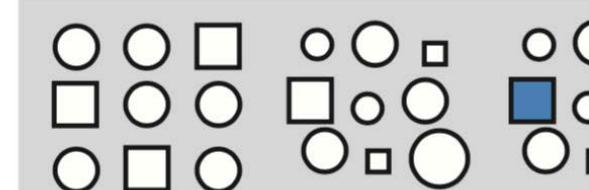
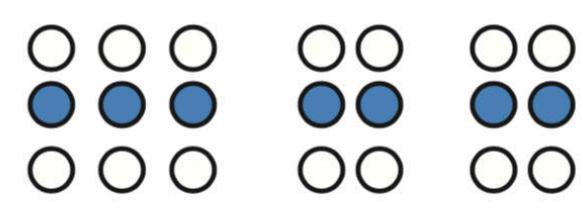
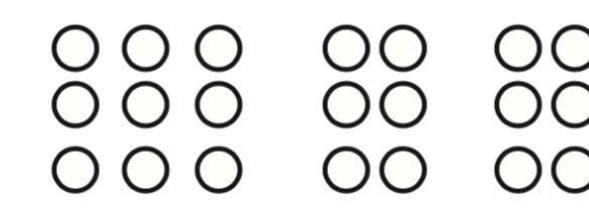
**Similarity:** Things that look alike seem to be related.

**Connection:** Things that are visually tied to one another seem to be related.

**Continuity:** Partially hidden objects are completed into familiar shapes.

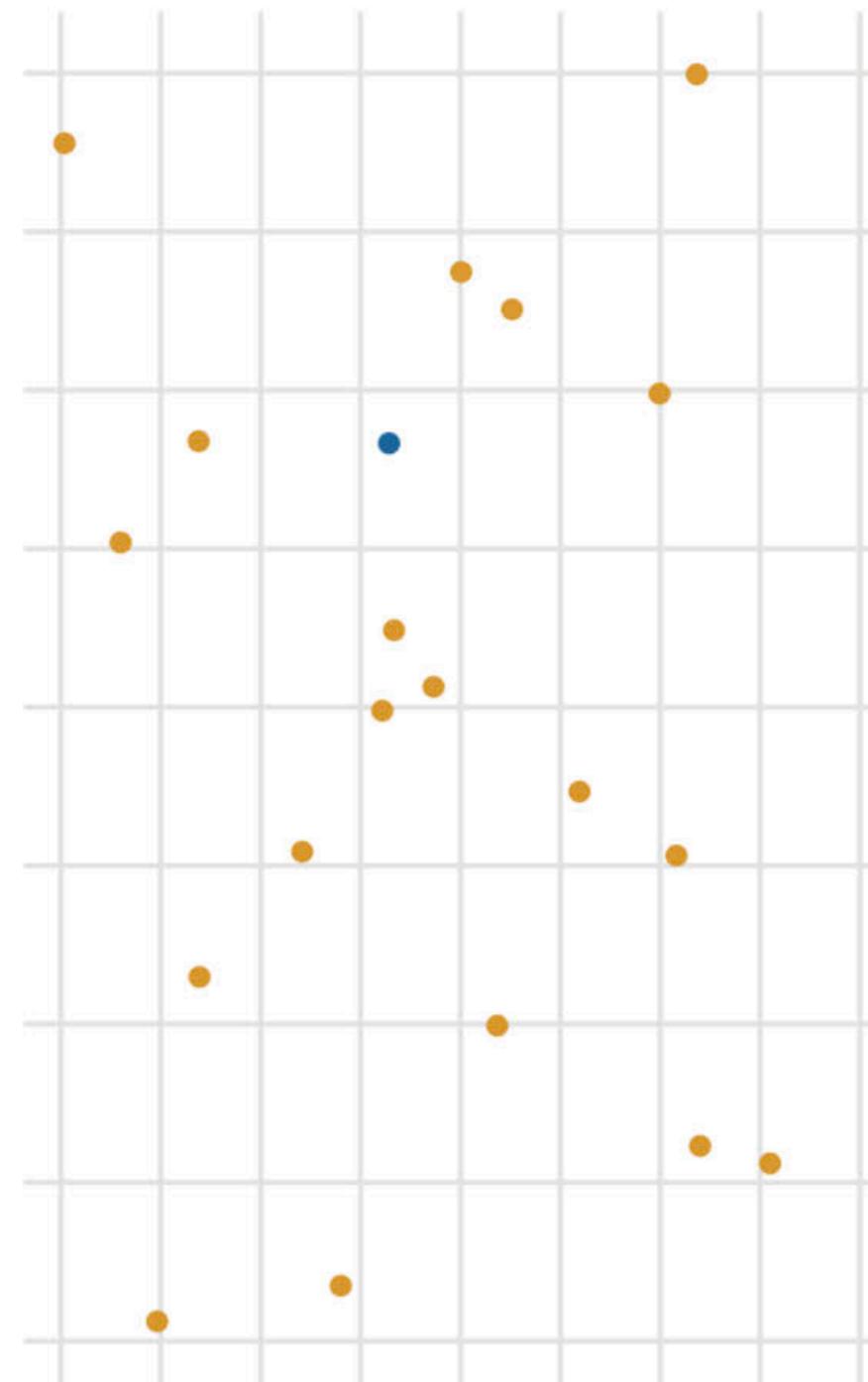
**Closure:** Incomplete shapes are perceived as complete.

**Figure and ground:** Visual elements are taken to be either in the foreground or in the background.

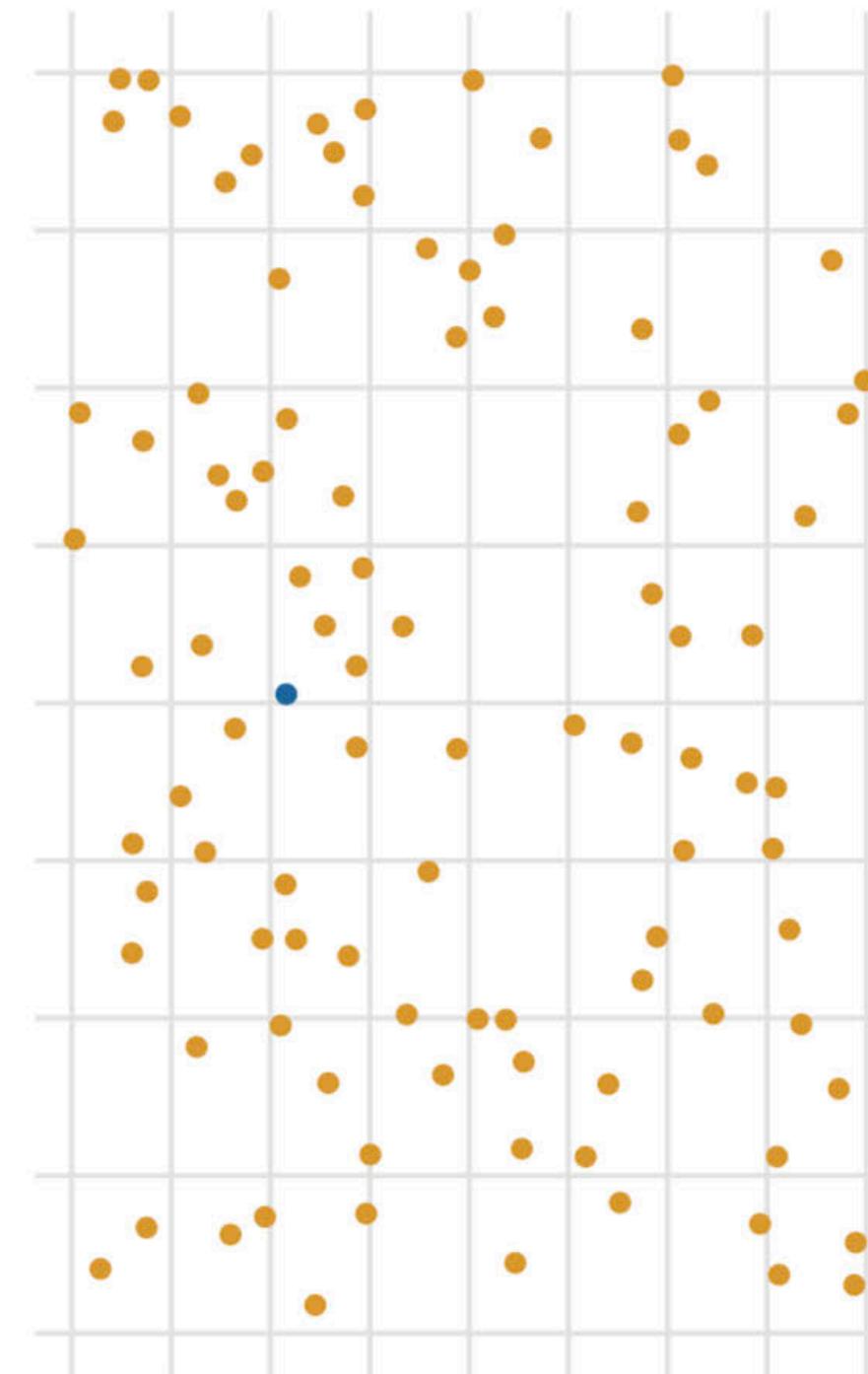


Consider Gestault principles when trying—as an audience—to find the blue circle.

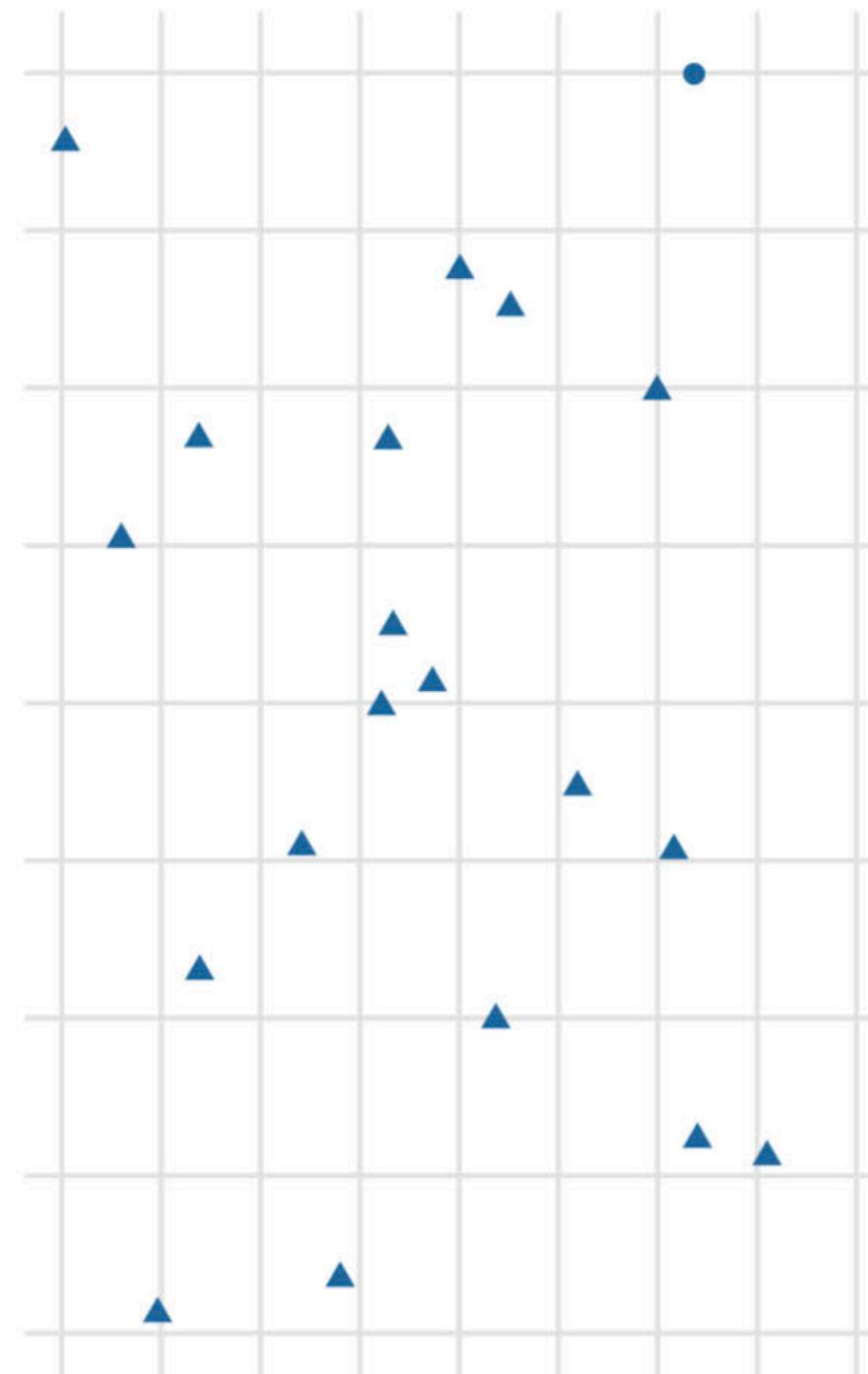
Color only,  $N = 20$



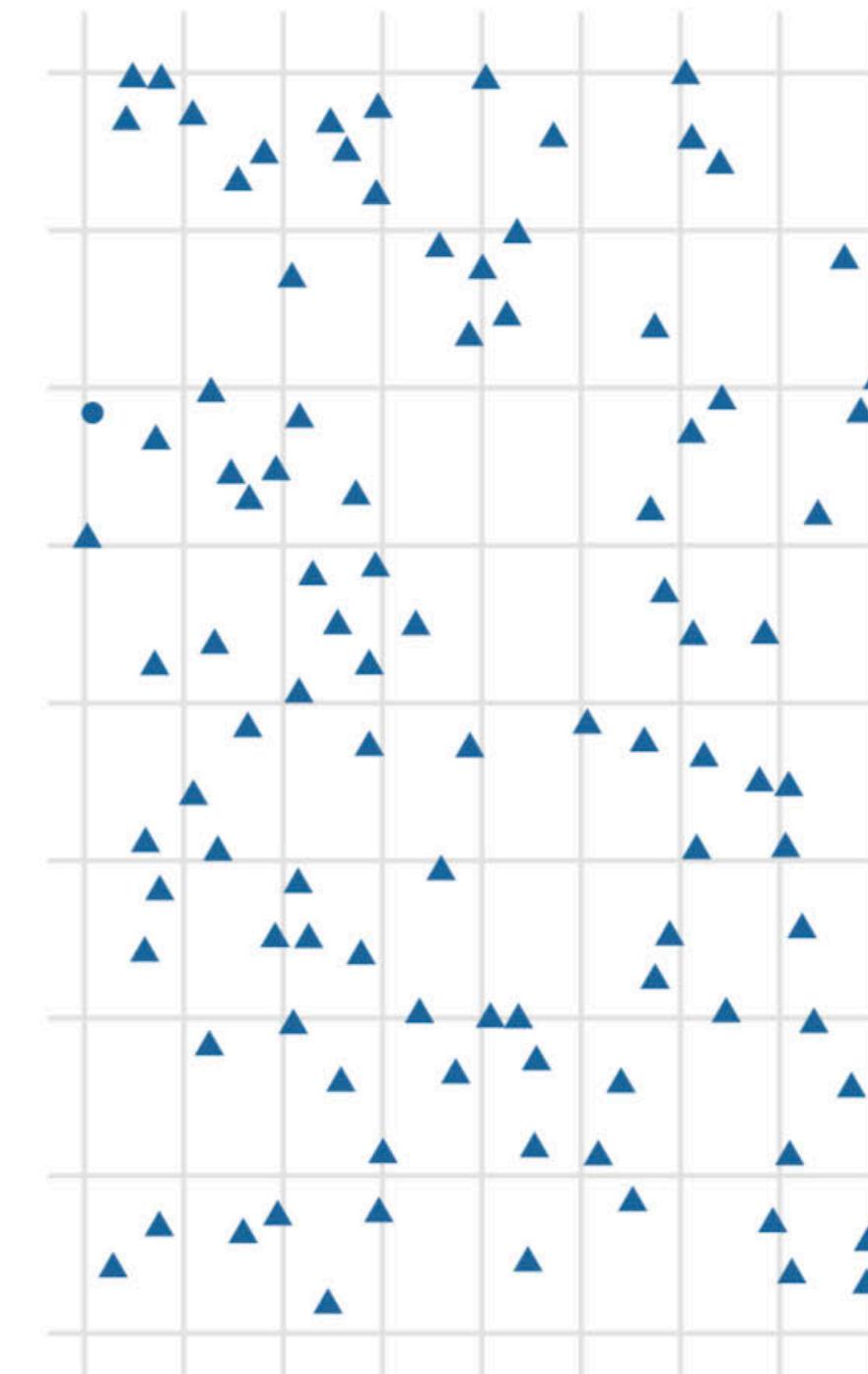
Color only,  $N = 100$



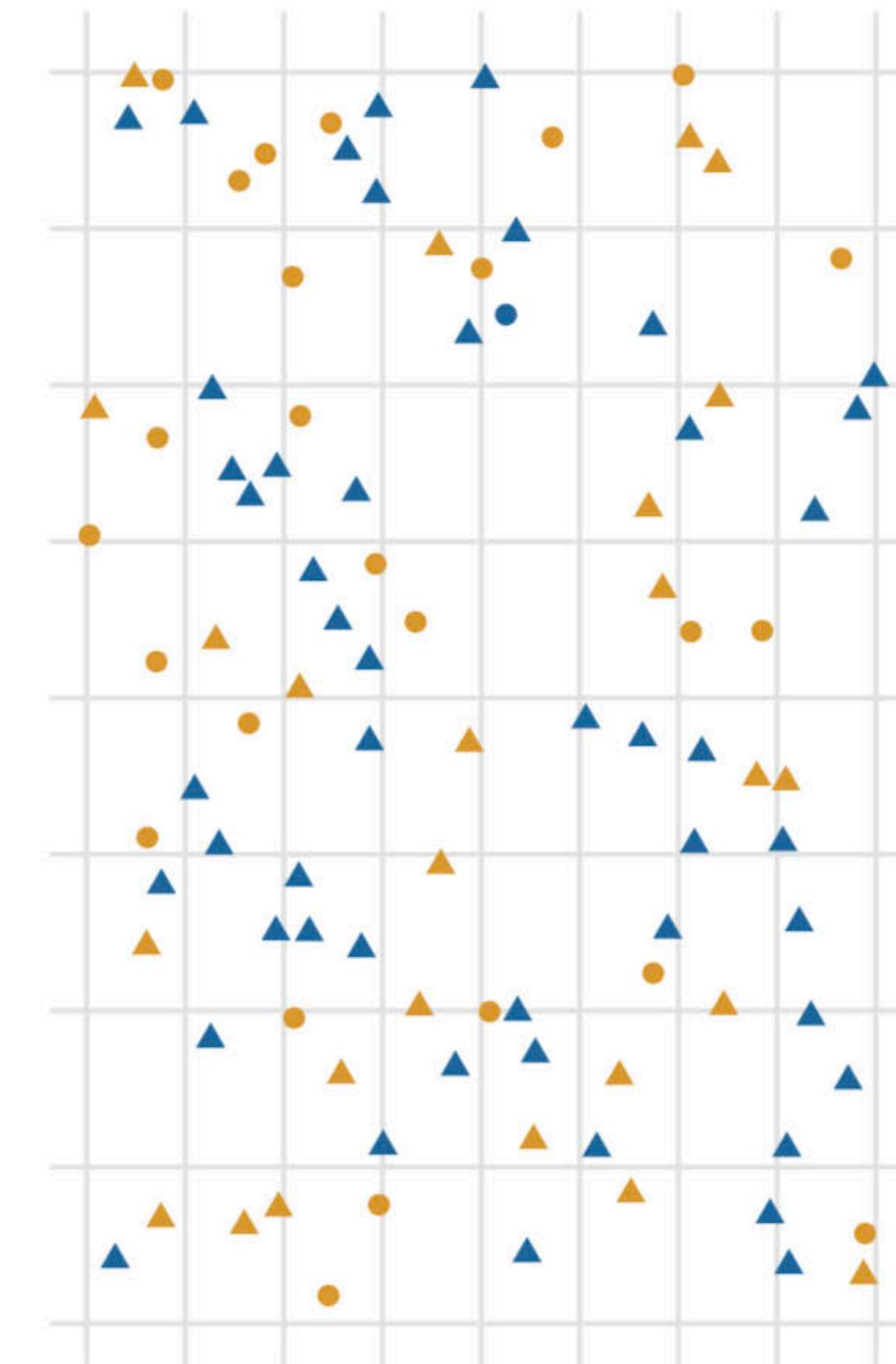
Shape only,  $N = 20$



Shape only,  $N = 100$

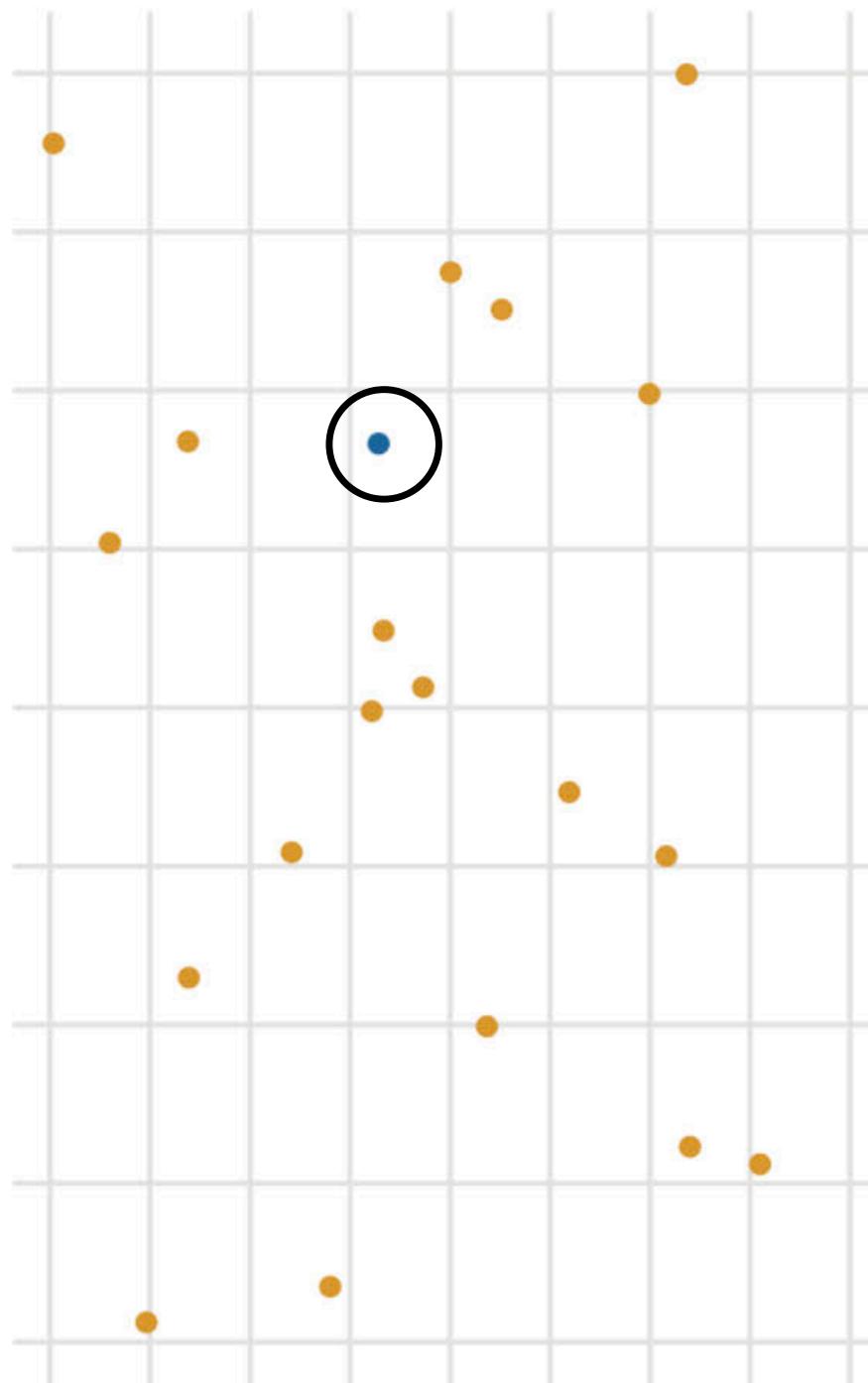


Color & shape,  $N = 100$

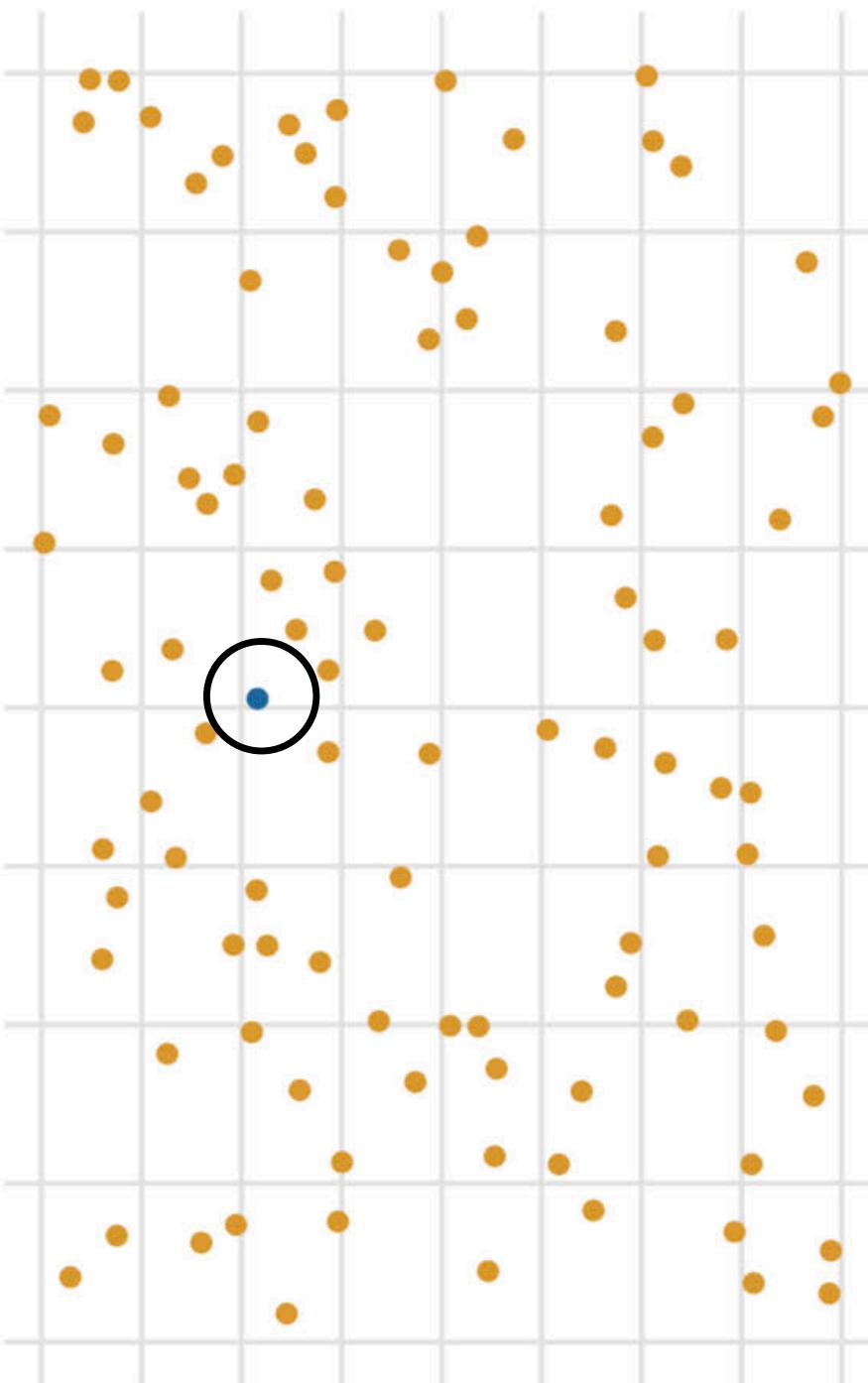


**For these, another choice (enclosure) is more effective, which draw the eye instantly.**

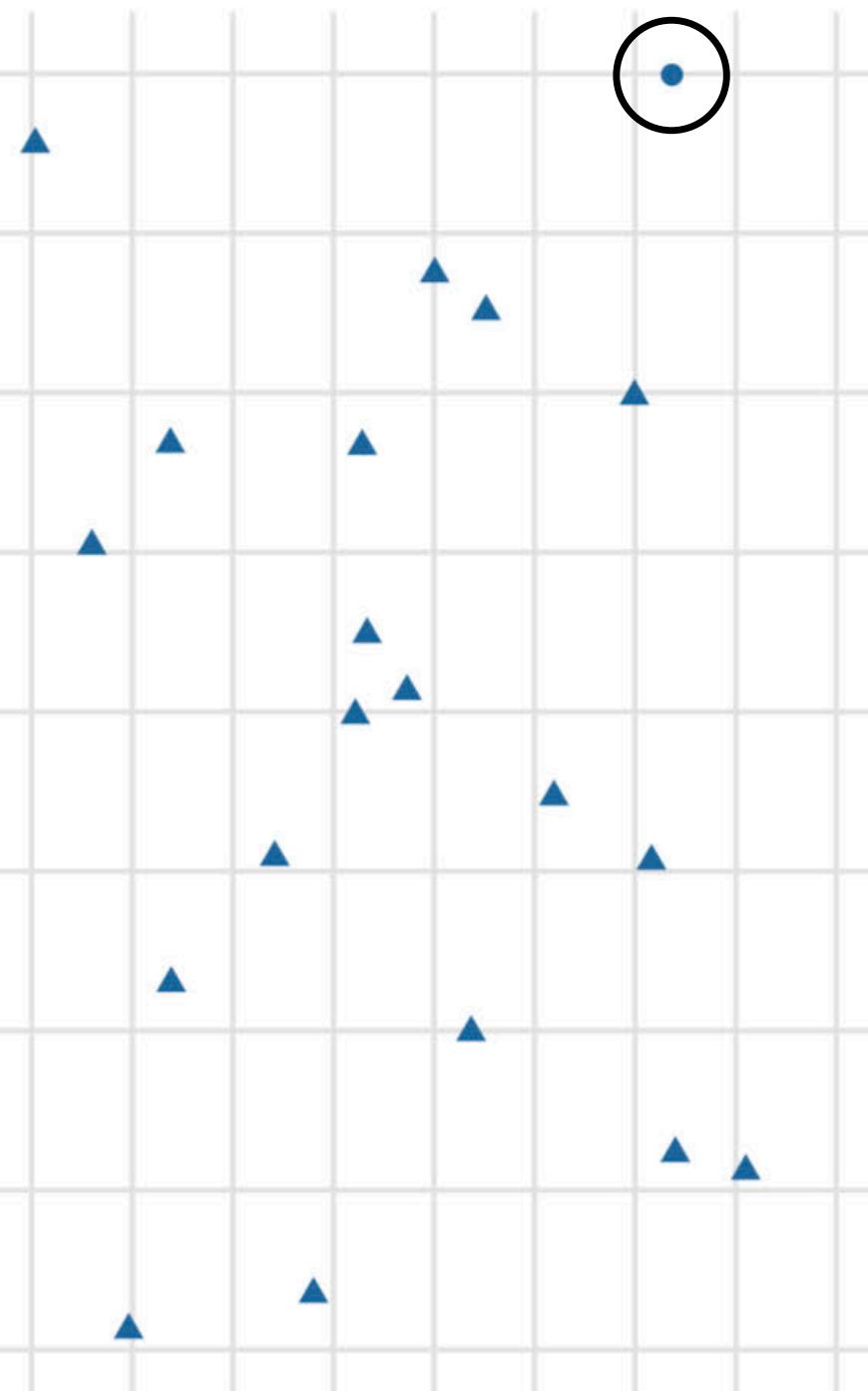
Color only,  $N = 20$



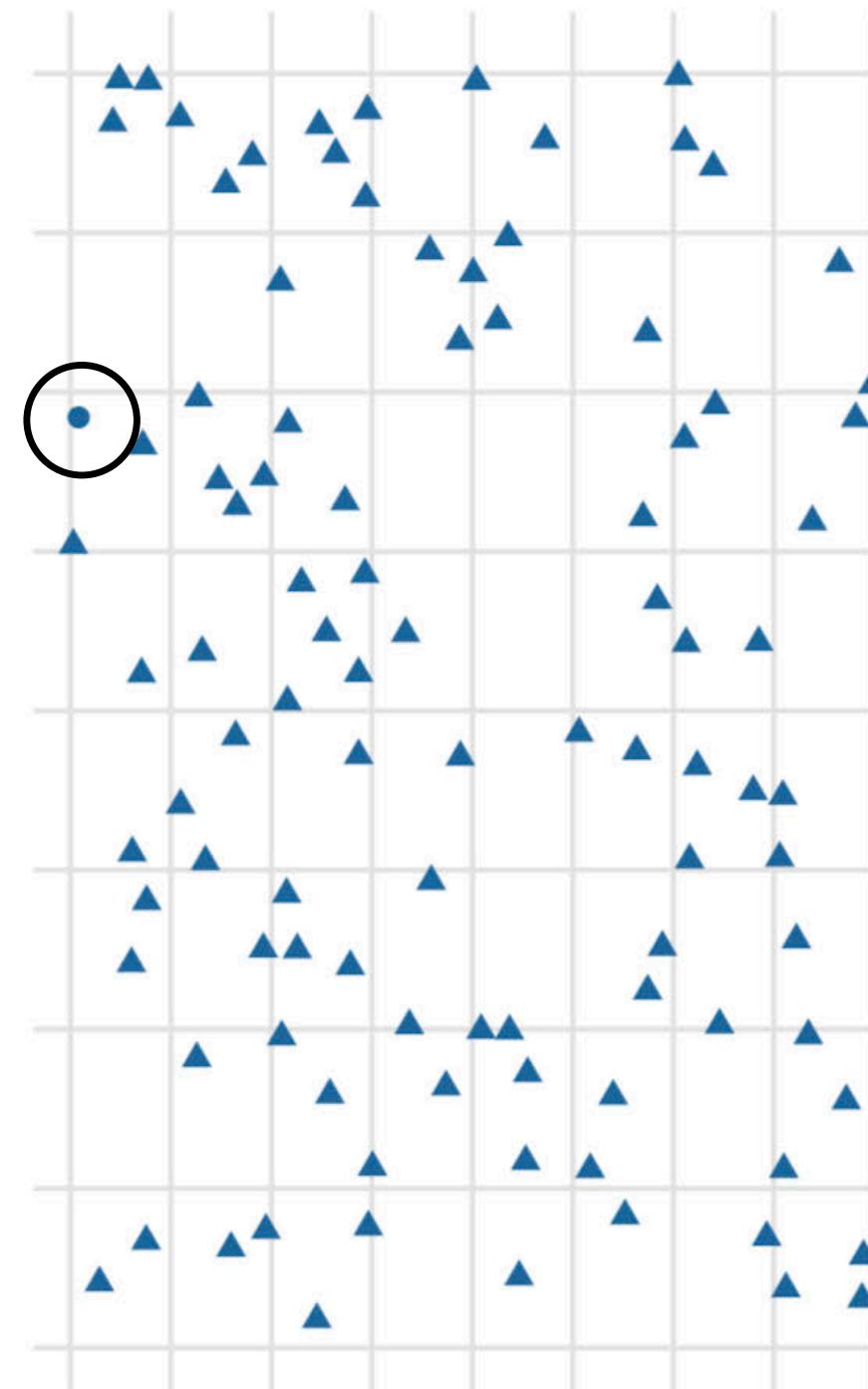
Color only,  $N = 100$



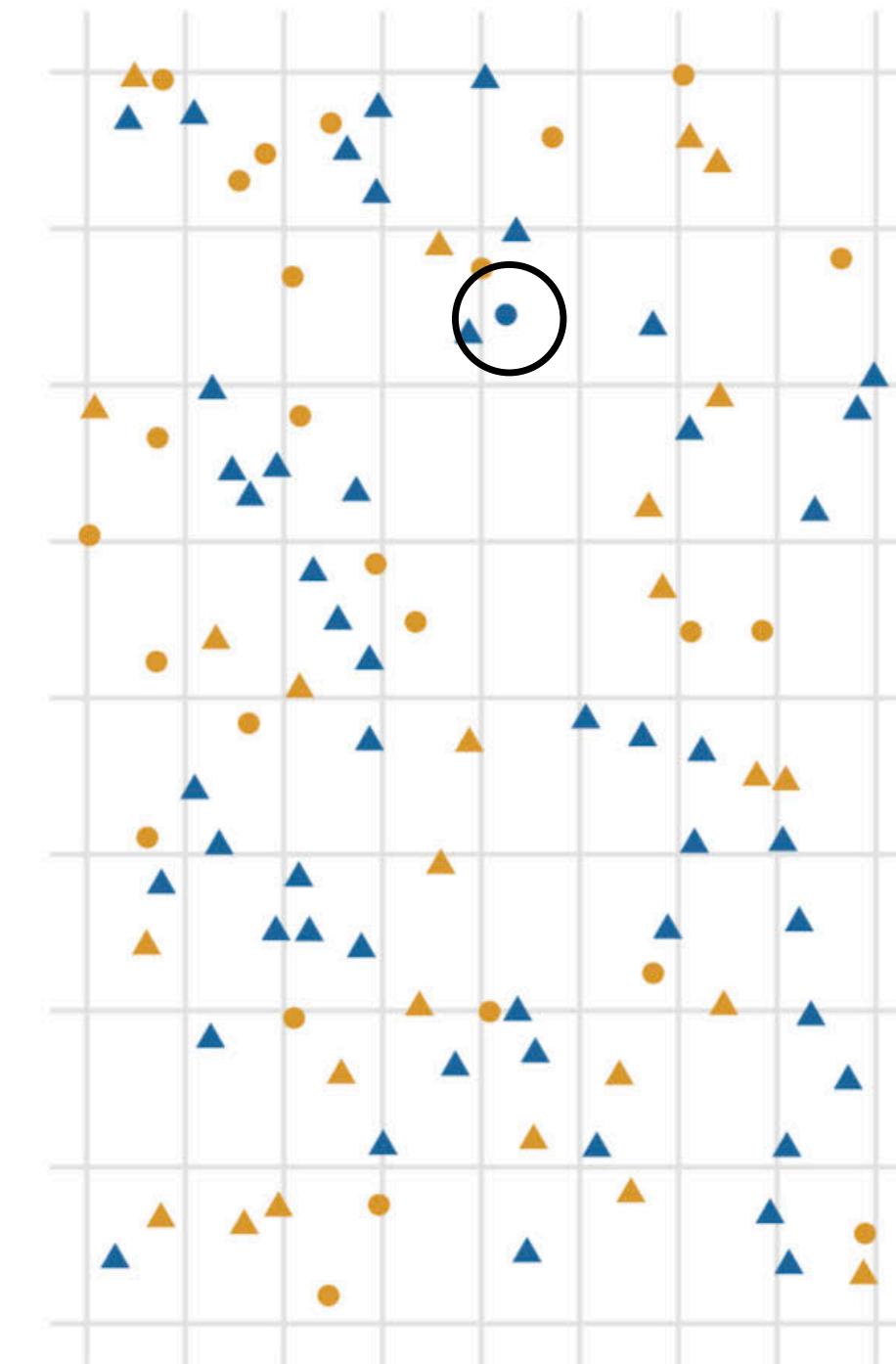
Shape only,  $N = 20$



Shape only,  $N = 100$



Color & shape,  $N = 100$

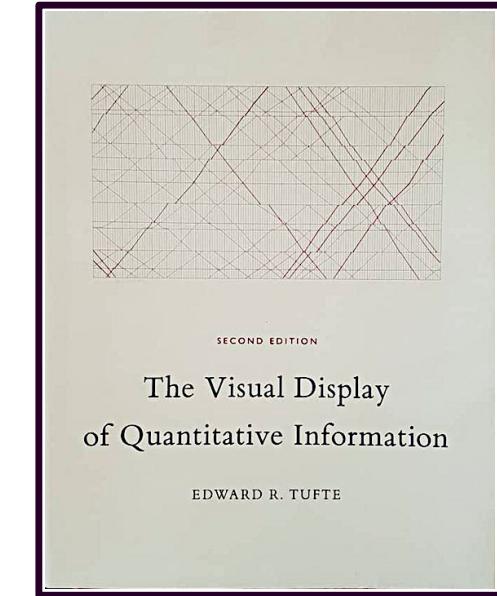
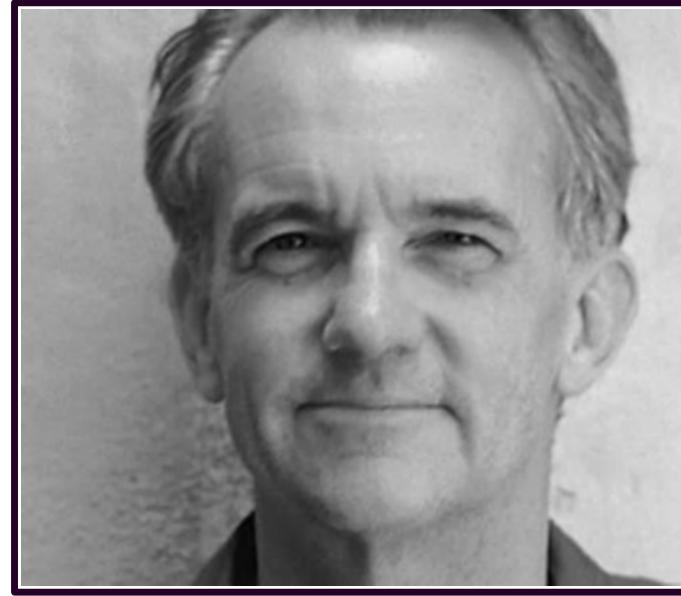


# **From default visual to visual narrative**

# The Visual Display of Quantitative Information

*Tufte*

Hailed "The Leonardo da Vinci of data" by the New York Times. He is professor emeritus of Political Science, Statistics, and Computer Science at Yale University.



## Simplicity of design, complexity of data

## Words and pictures belong together

## Proportion and scale: the shape of graphics

Graphical excellence is often found in simplicity of design and complexity of data.

Viewers need the help that words can provide. **Words on graphics are data-ink**, making effective use of the space freed up by erasing redundant and non-data-ink.

Note, the **size of type** on and around graphics can be quite **small**, since the phrases and sentences are usually not too long.

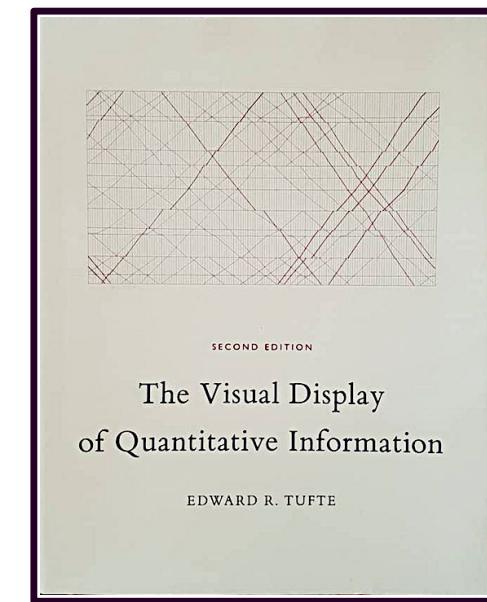
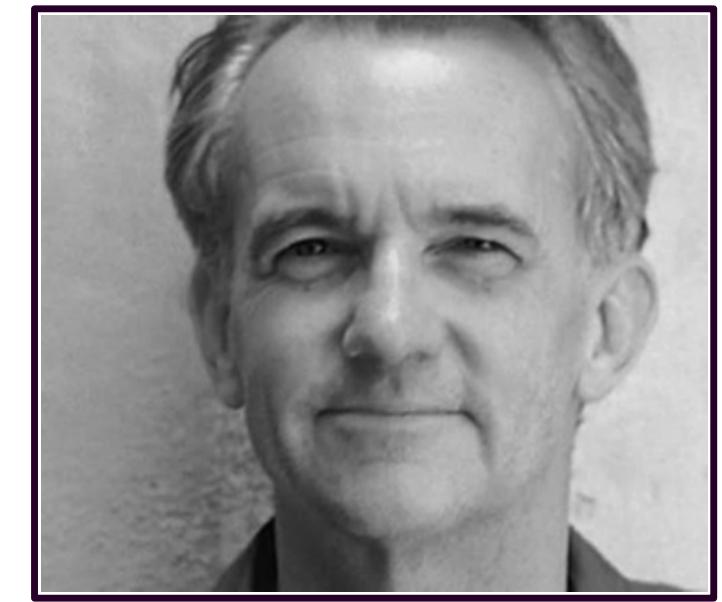
The principle of data/text integration is: data **graphics are paragraphs about data** and should be treated as such.

Our eye is naturally practiced in detecting **deviations from the horizon**.

Horizontally shaped plots tend to make it **easier to directly label** and explain the data.

Tradition places the effect vertically, the cause horizontally.

The empirically studied **Golden Rectangle**, a  $1.0 \times 1.618$  ratio is aesthetically pleasing.



# The Visual Display of Quantitative Information

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## Data-ink

The non-erasable core of a graphic, the non-redundant ink arranged in response to variation in the numbers represented. Annotations are part of the data-ink.

$$\text{data-ink ratio} = \frac{\text{data-ink}}{\text{total ink used to print the graphic}}$$

= proportion of a graphic's ink devoted to the non-redundant display of data-information

=  $1.0 - \text{proportion of a graphic that can be erased without loss of data-information}$

## Maximize within reason

Maximize the data-ink ratio, within reason.  
Erase non-data-ink, within reason.  
Erase redundant data-ink, within reason.

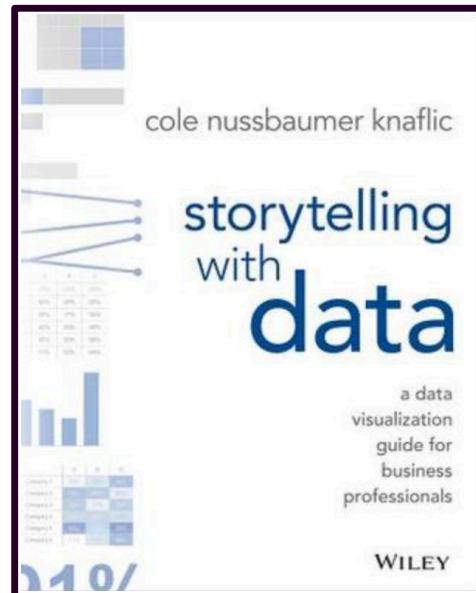
## Size graphics for legibility

As the quantity of data increases, data measures must shrink. . . . The way to increase data density other than by enlarging the data matrix is to reduce the area of a graphic.  
**Graphics can be shrunk way down.**

# Storytelling with data

*Knaflic*

The author is a consultant focused on visual displays. Her experience arose from human resources in Google where she applied theory learned as a student of Yale's Edward Tufte.



## Please approve the hire of 2 FTEs

to backfill those who quit in the past year

### Ticket volume over time



Data source: XYZ Dashboard, as of 12/31/2014 | A detailed analysis on tickets processed per person and time to resolve issues was undertaken to inform this request and can be provided if needed.

# Discussion: what differences do you see? What advice has she applied?

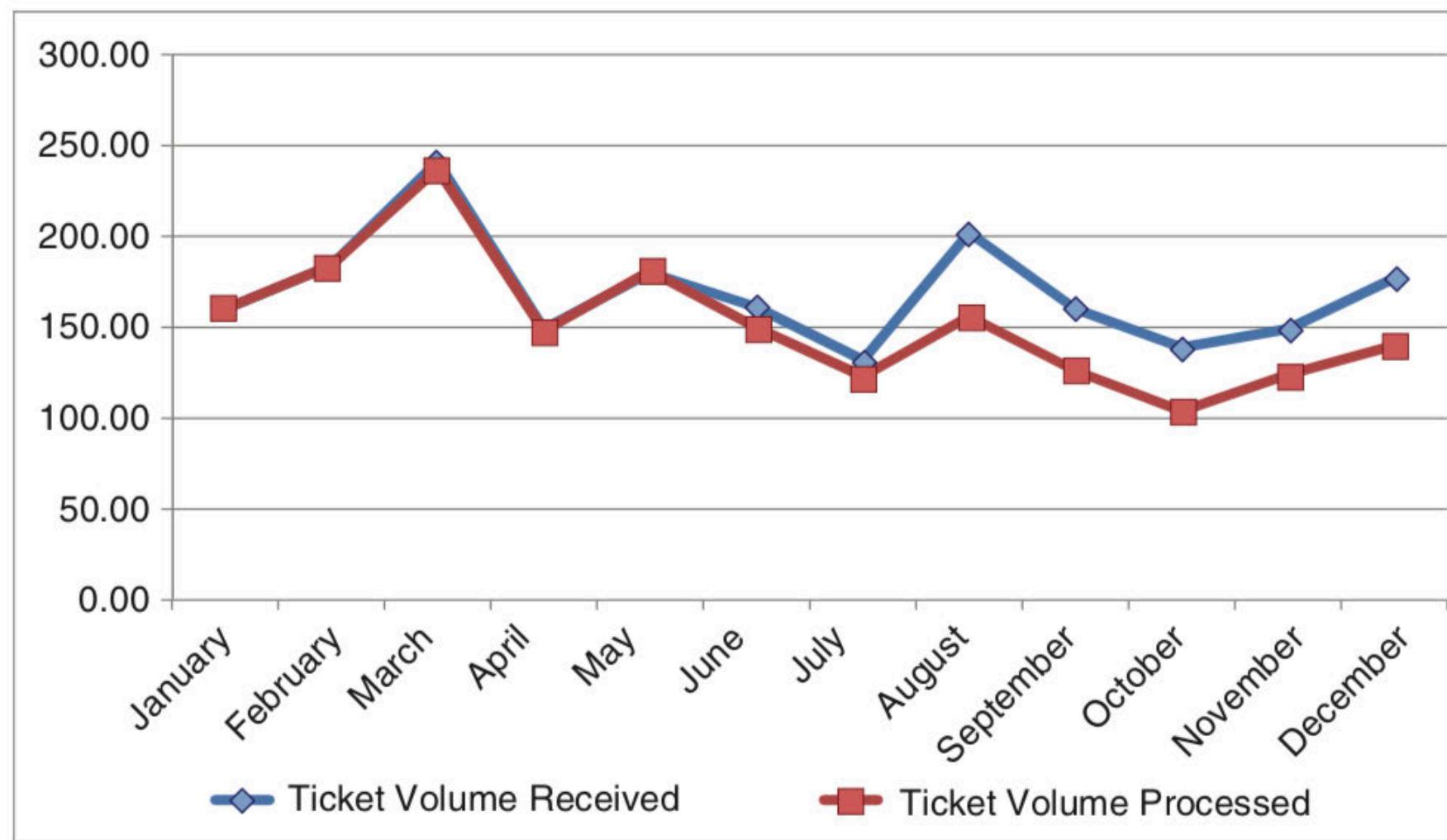
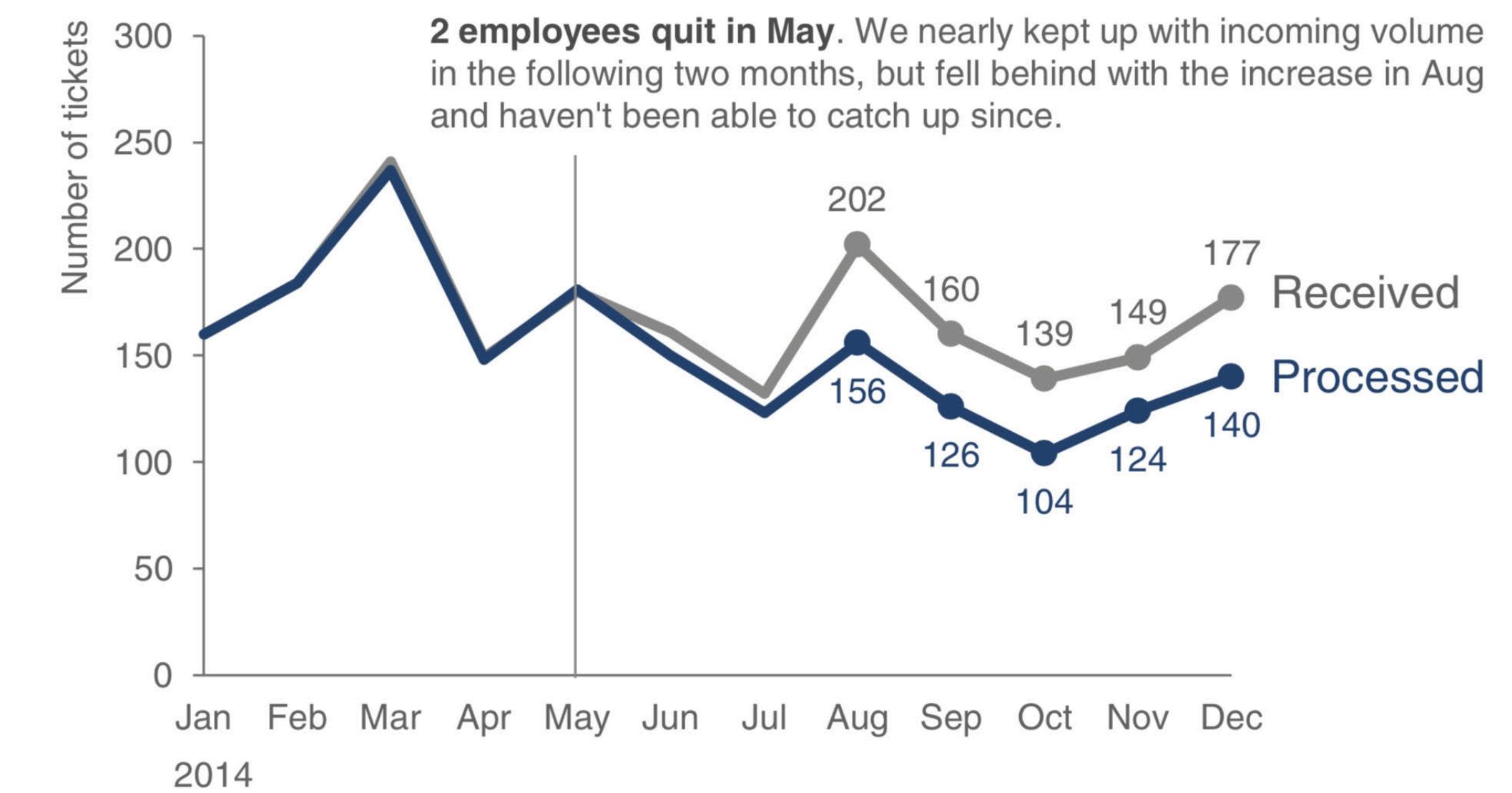


FIGURE 3.17 Original graph

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### Ticket volume over time



Data source: XYZ Dashboard, as of 12/31/2014 | A detailed analysis on tickets processed per person and time to resolve issues was undertaken to inform this request and can be provided if needed.

# From default visual to visual narrative – erase clutter, add narrative annotation ...

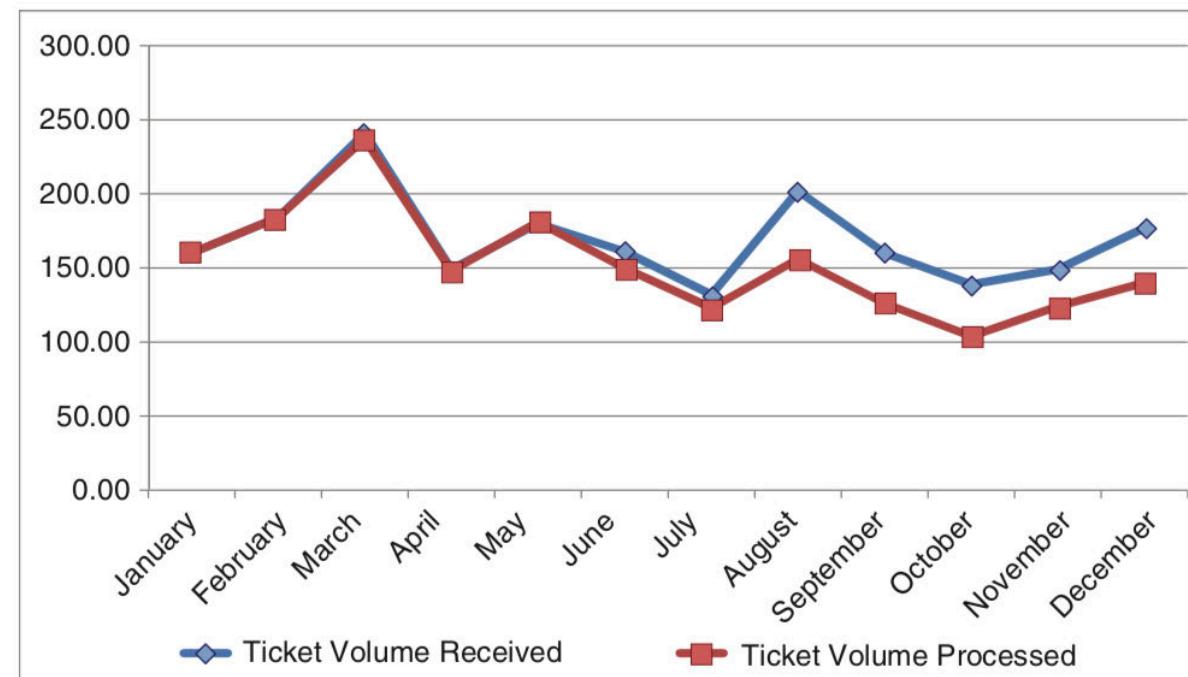


FIGURE 3.17 Original graph

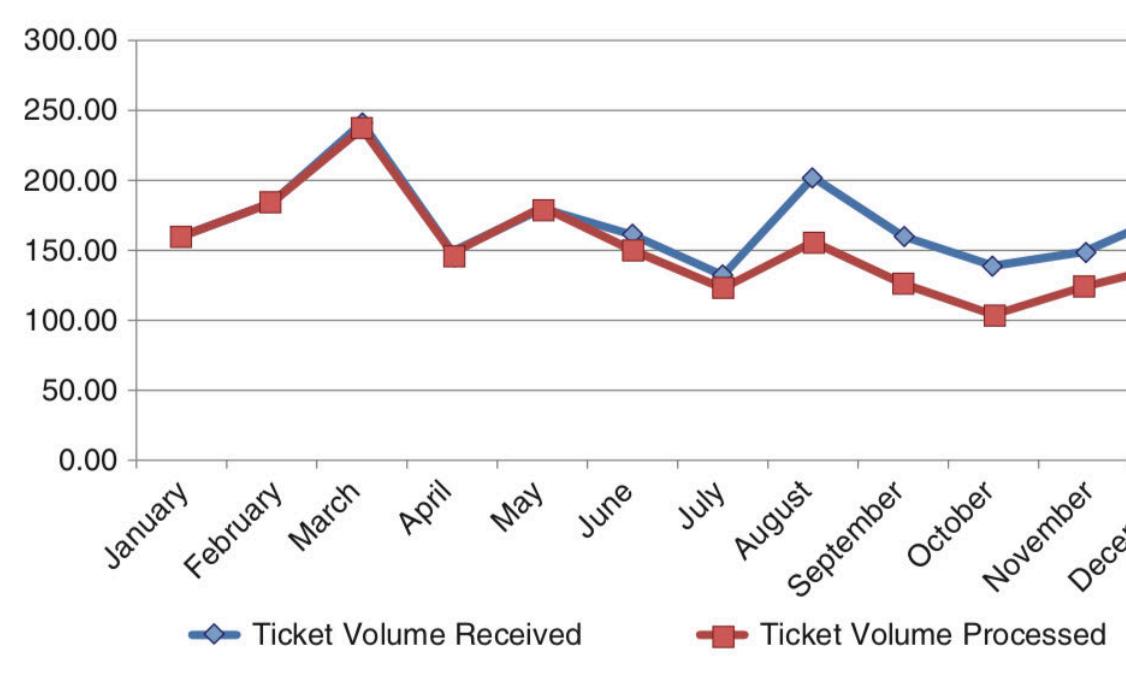


FIGURE 3.18 Remove chart border

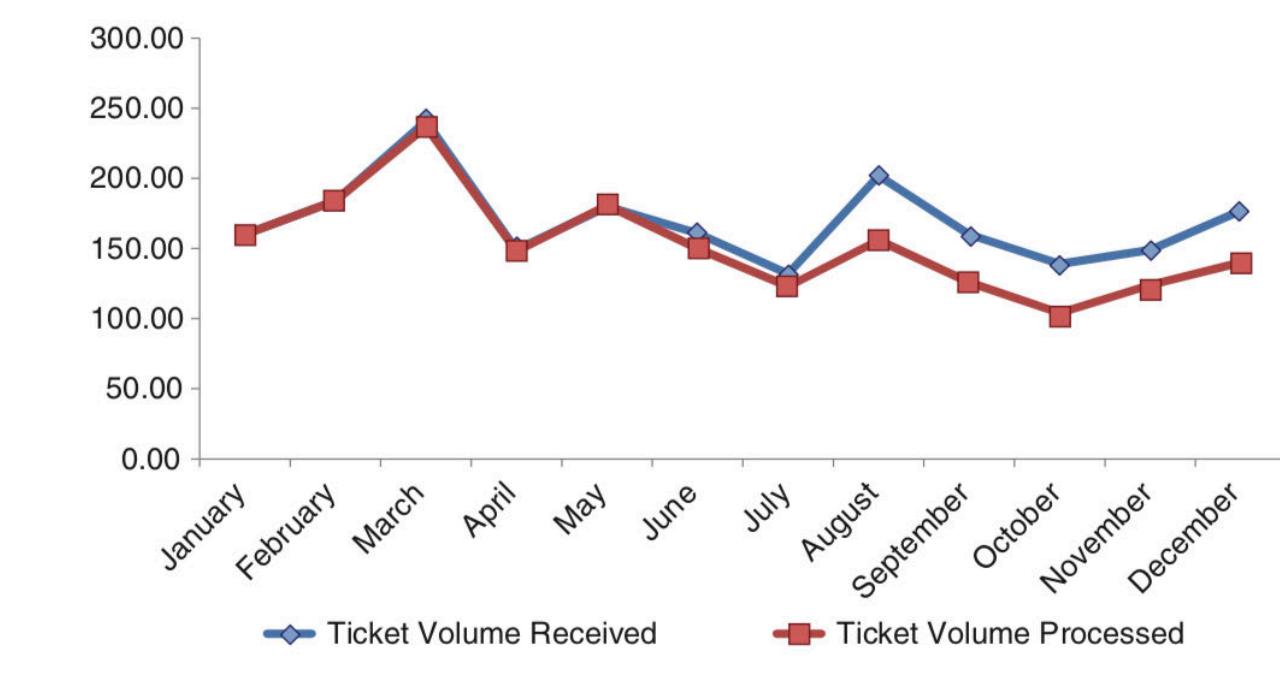


FIGURE 3.19 Remove gridlines

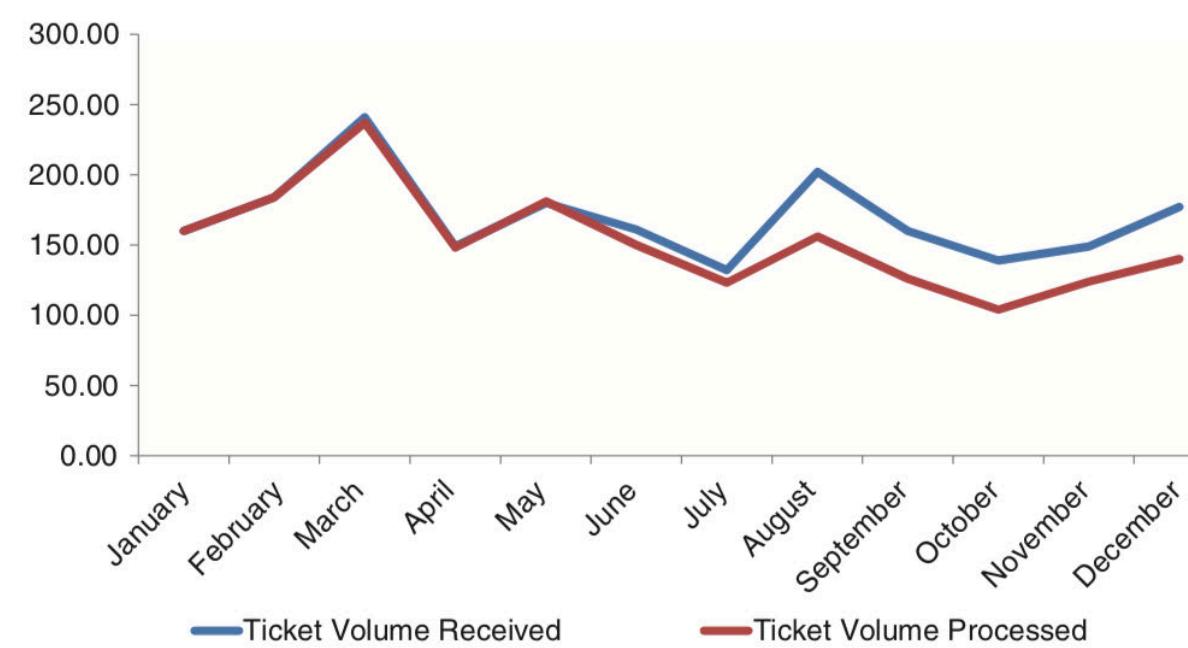


FIGURE 3.20 Remove data markers

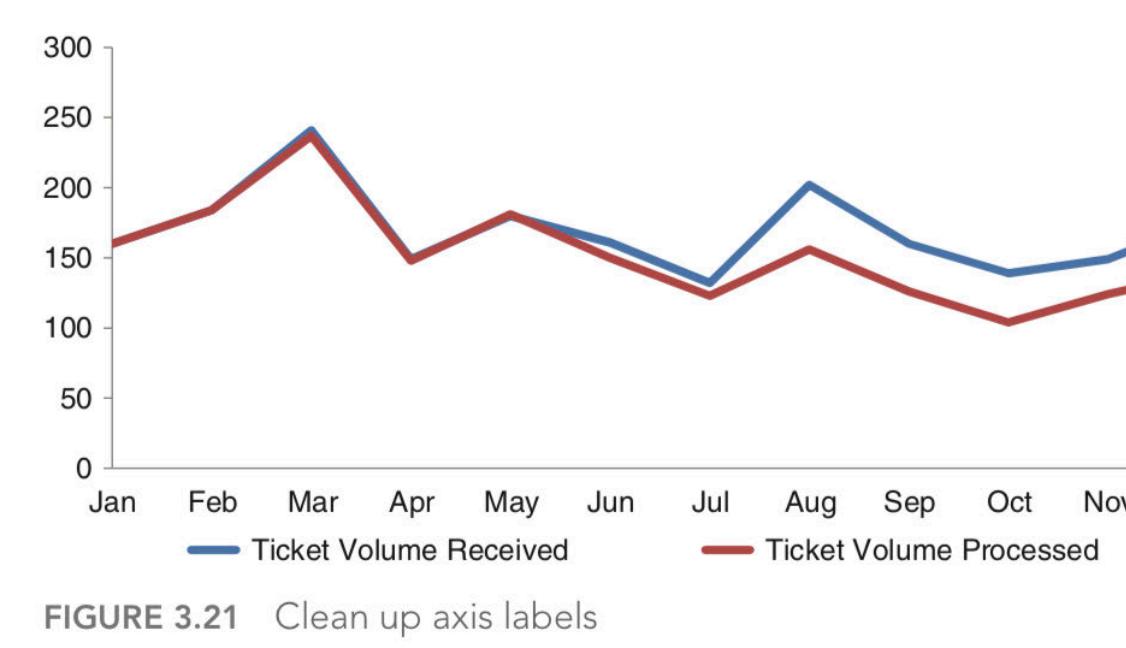


FIGURE 3.21 Clean up axis labels

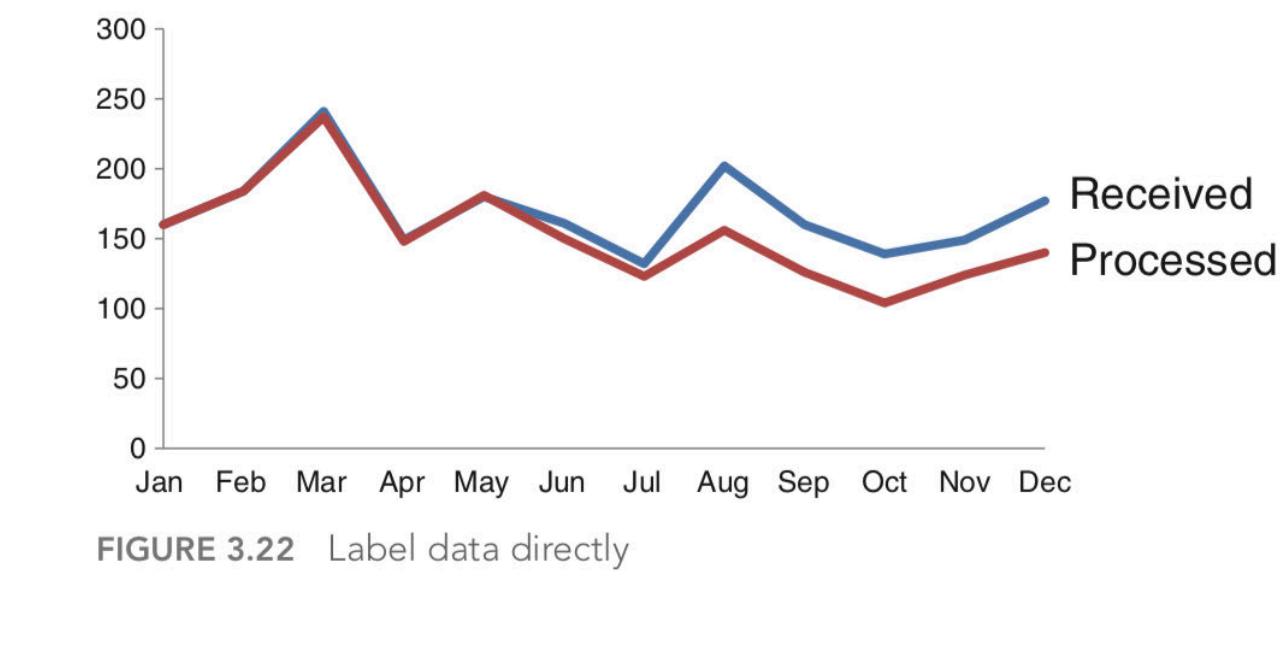


FIGURE 3.22 Label data directly

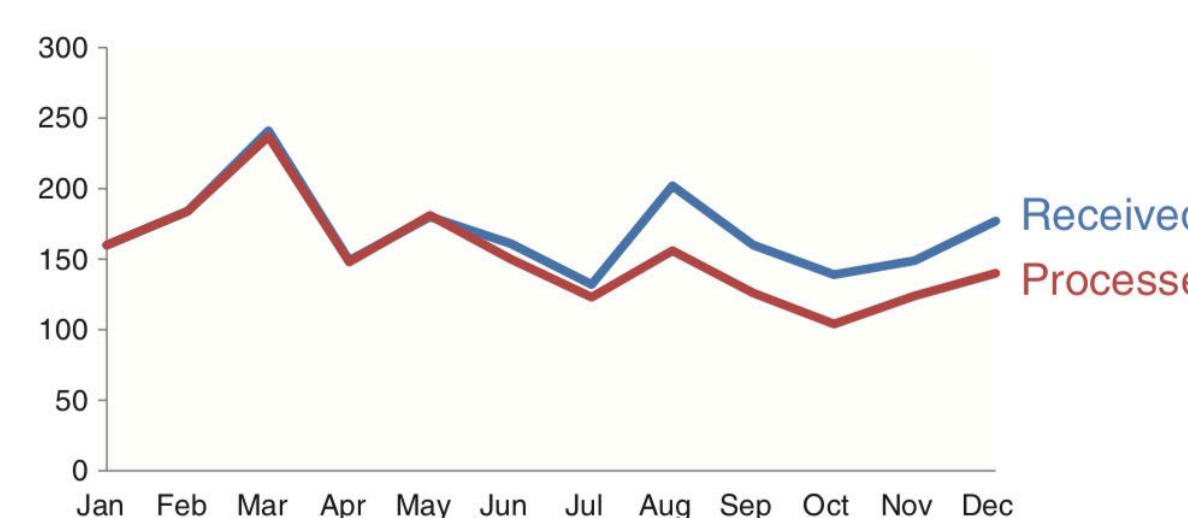


FIGURE 3.23 Leverage consistent color



FIGURE 4.11 First, push everything to the background

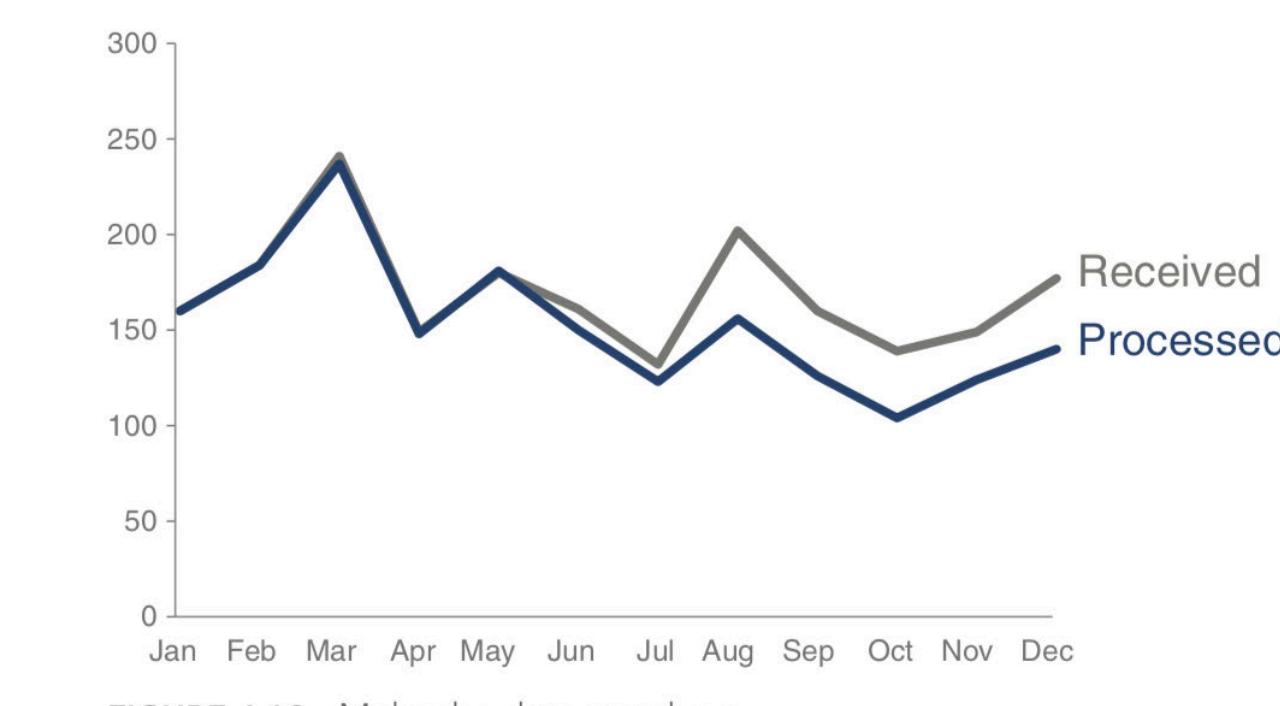


FIGURE 4.12 Make the data stand out



FIGURE 4.12 Make the data stand out

## Please approve the hire of 2 FTEs

to backfill those who quit in the past year

### Ticket volume over time



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FIGURE 5.10 Add action title and annotation



FIGURE 4.14 Data labels used sparingly help draw attention

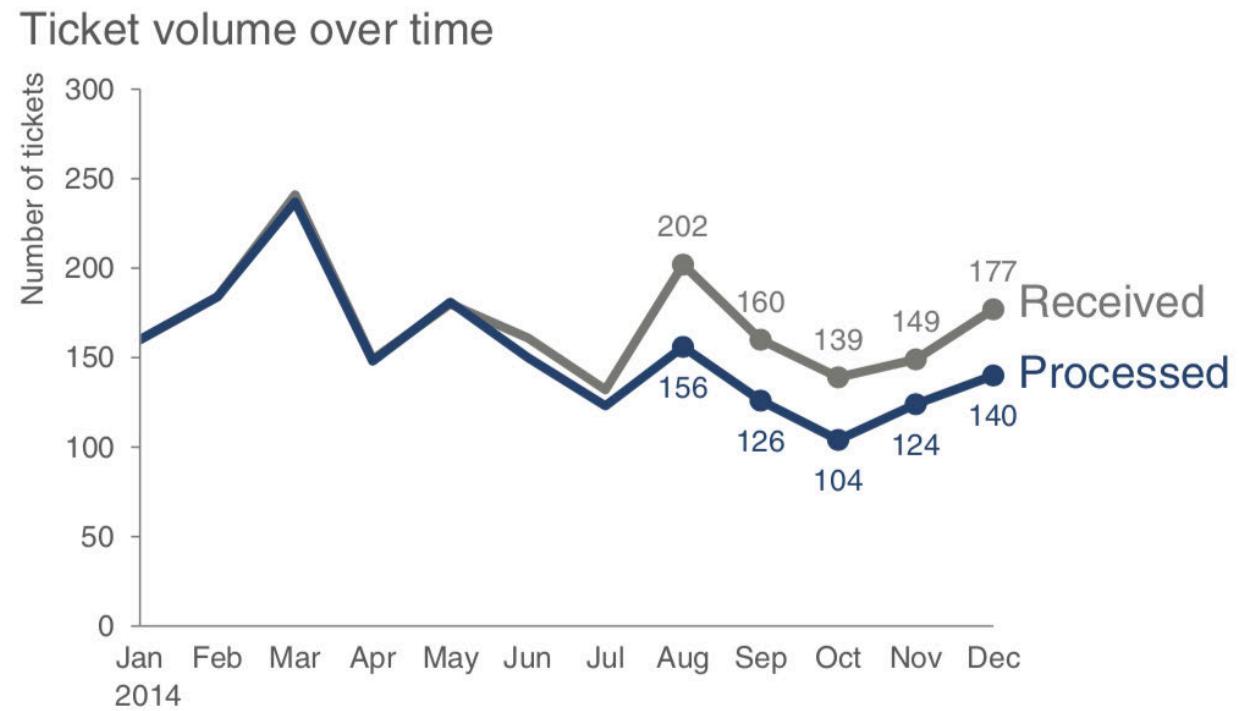


FIGURE 5.9 Use words to make the graph accessible

# **Between now and next class**

# For Next Week, Module 8:

## Agenda next week

### The minimum

Next deliverable, *final* storyboard

Theory and best practices for the visual components of your analytics project, continued

Hullman, Jessica et al. *Imagining Replications: Graphical Prediction & Discrete Visualizations Improve Recall & Estimation of Effect Uncertainty.* IEEE Transactions on Visualization and Computer Graphics 24.1 (2017): 446–456. Web.

How do audiences perceive uncertainty? Consider approaches to communicating uncertainty important to your messages about your projects.

Song, Hayeong, and Danielle Albers Szafir. *Where's My Data? Evaluating Visualizations with Missing Data.* IEEE Transactions on Visualization and Computer Graphics 25.1 (2018): 914–924. Web.

How should we reason, explore, visualize and communicate the implications of missing data?

Lupi, Giorgia. *The New Aesthetic of Data Narrative* in Chapter 3 of Bihanic, David. *New Challenges for Data Design.* Springer, 2015. Print.

Read to get a sense of how Lupi thinks through making a graphic.

# Feedback

**Visualize it**

Consider three ways you might visually represent the uncertainty you identified.

**Uncertain?**

What types of uncertainty have you identified in your project, and how might that be important for our different audiences?

**Coding?**

Was the example walk through of code to create the CitiBike visual helpful? Conceptually, what would you like code tutorials to cover?

See you  
next week!

