

# Data Visualization: Choosing the Right Visualization

```
$ echo "Data Science Institute"
```

# Agenda for today

- Go through slide deck #4: Choosing the right visualization
- Start on slide deck #6: Subplots and combining visualizations

# Review feedback from last time

# We're going to...

- Explore how to choose the right data visualization for a given situation
- Explore [Chapter 3 \( On Rational, Scientific, Objective Viewpoints from Mythical, Imaginary, Impossible Standpoints \) of D'Ignazio and Klein \(2020\). Data Feminism. MIT Press.](#)
- Discuss how ideas of neutrality and objectivity apply to data visualization
- Understand how different elements and types of data visualization are generally perceived, and use this understanding to decide what kind of visualization we should use for a particular situation

- So far, we have learned how to make and modify different types of data visualizations
- How do we decide which of these types of data visualization to use, and when?
- If we are accurately and honestly displaying our data, does the type of visualization even matter?

**How do we choose the 'right' visualization?**

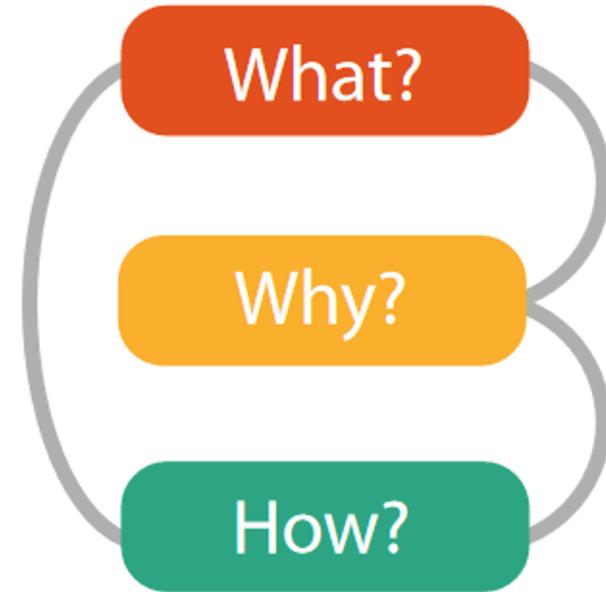
# The Visualization Process



What data is the user seeing?

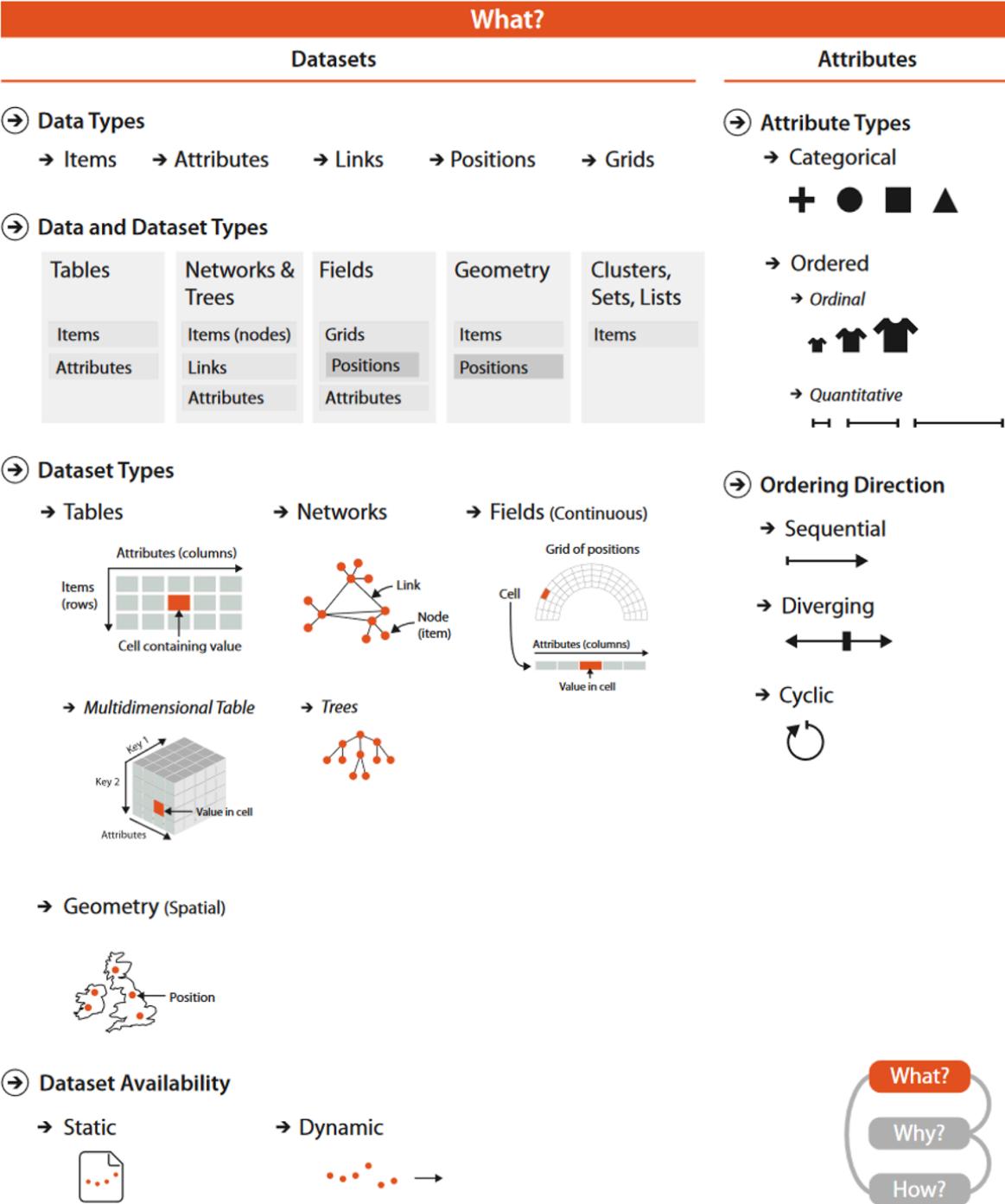
Why are people using the visualization (what is their goal?)

How is the visualization being designed?

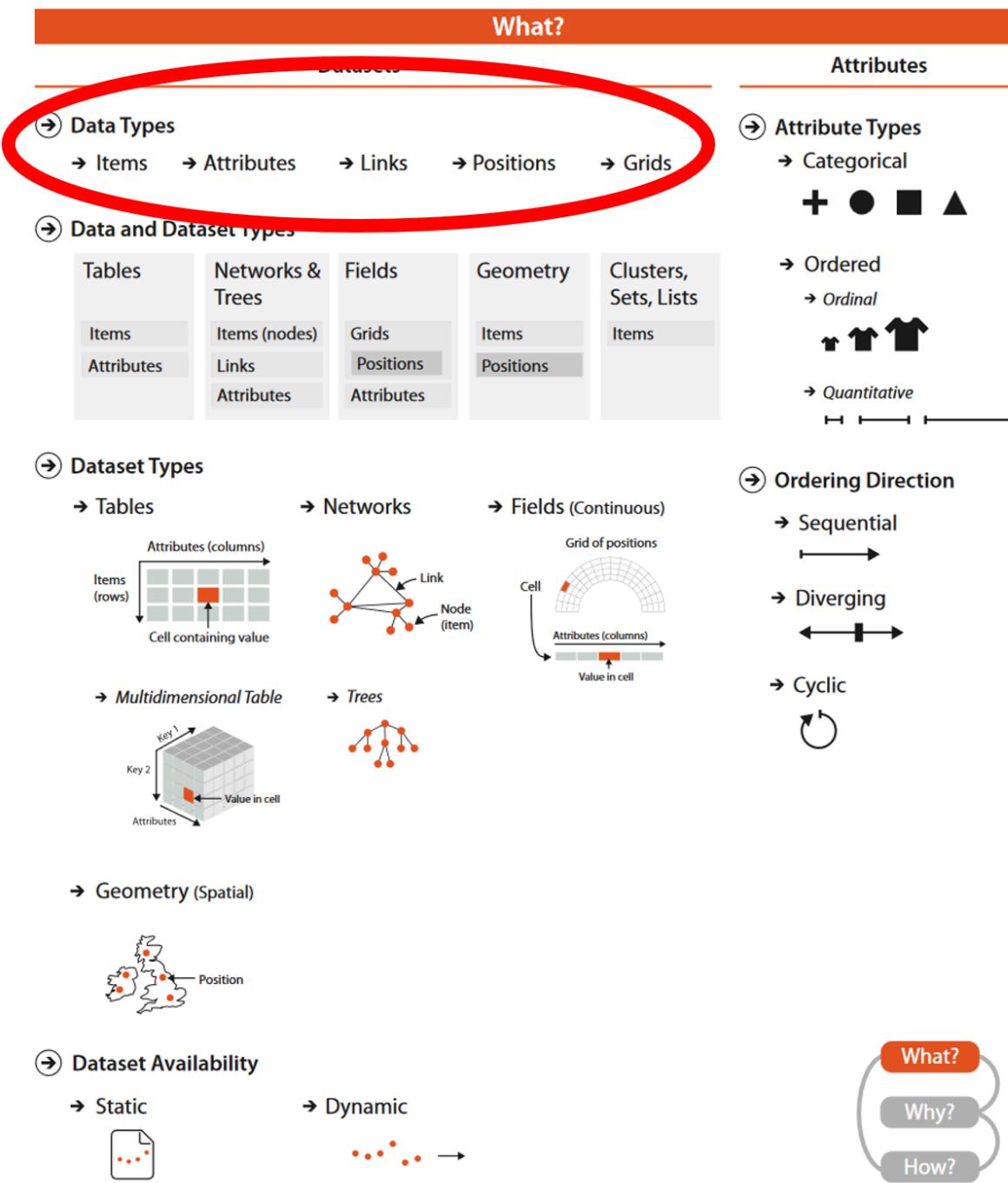


This figure shows *what* can be visualized.

Let's review it one-by-one

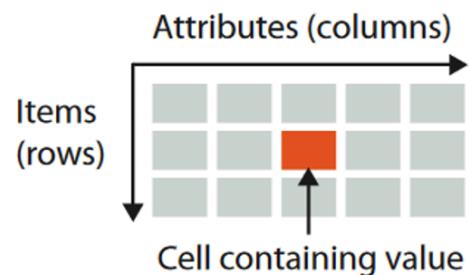


- In order to analyze the kind of dataset you're using, you must be familiar with data types.

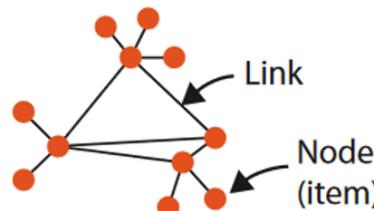


## → Dataset Types

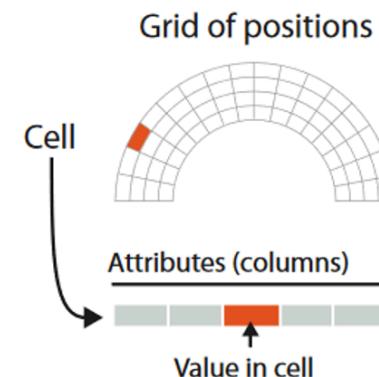
### → Tables



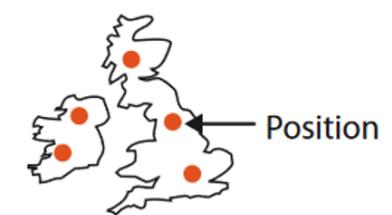
### → Networks



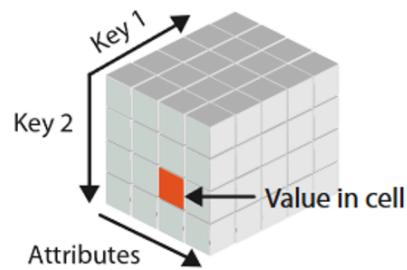
### → Fields (Continuous)



### → Geometry (Spatial)



### → Multidimensional Table

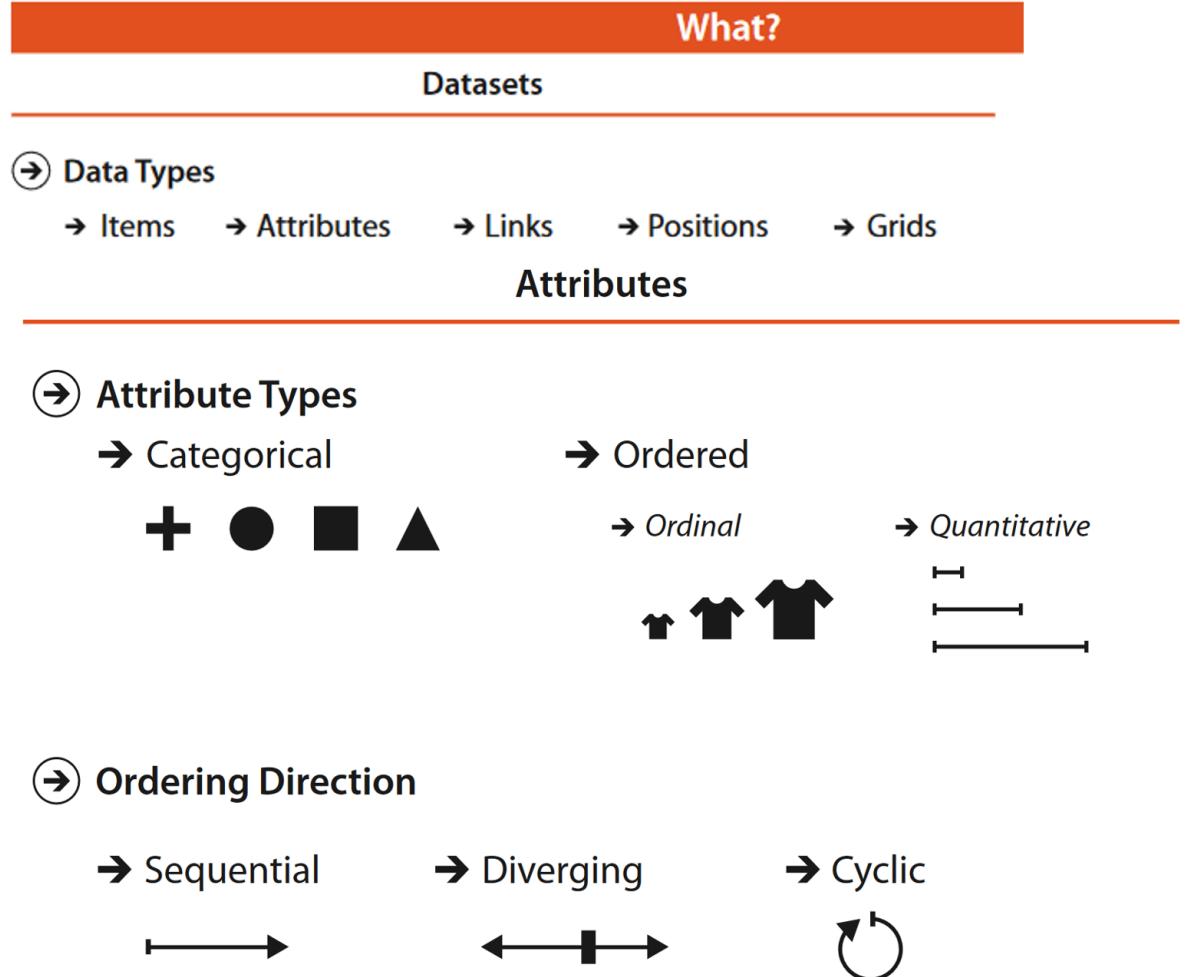


### → Trees

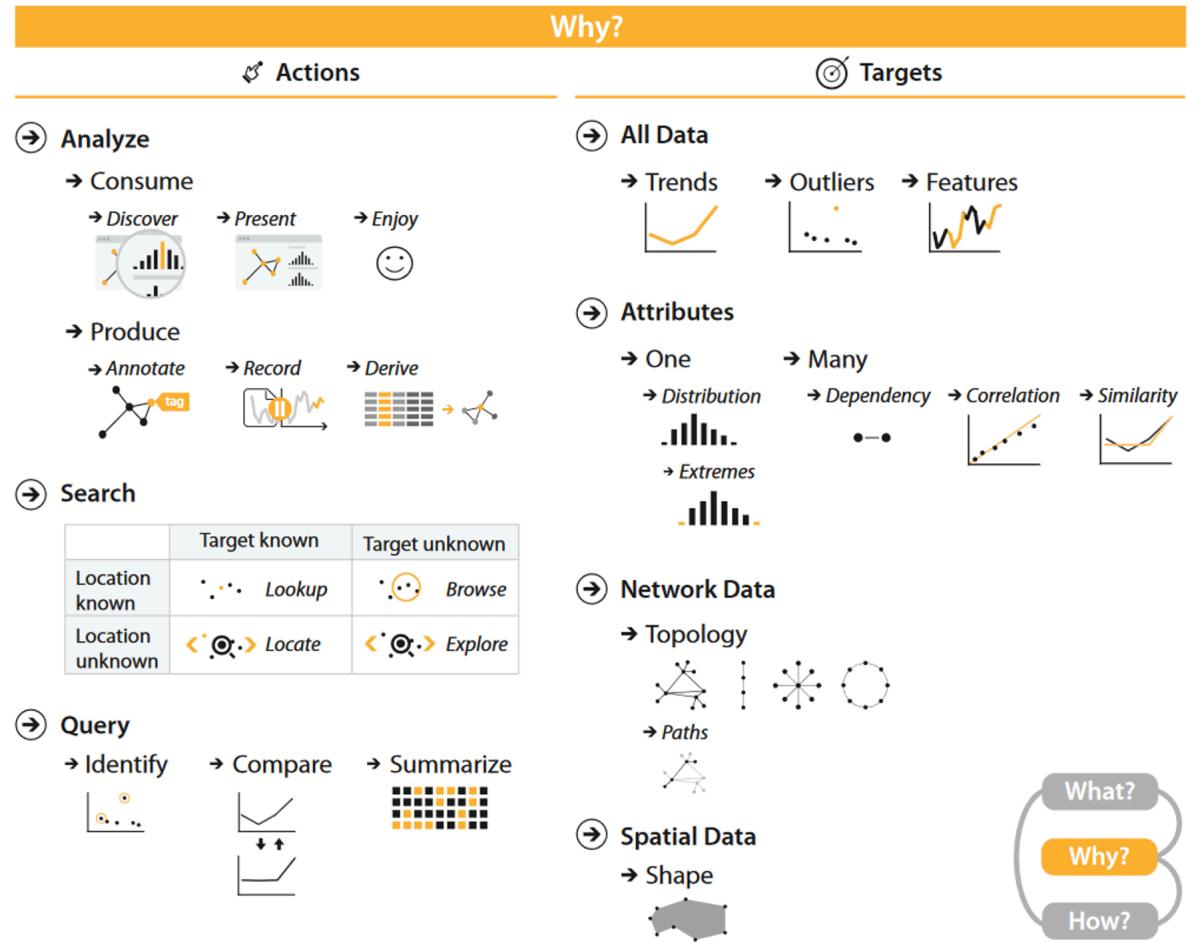


- Tables, networks, fields, and geometries are four basic dataset types.
- For any of these dataset types, the full dataset could be available immediately as a static file or it might be dynamic data processed gradually in the form of a stream.

- Identifying the attribute types for our data will help us make choices about how to visualize it.
- (We'll get to that in a few slides)



This figure helps us decompose different reasons *why* a person may use a visualization (i.e., what task they perform).



 Analyze

→ Consume

→ Discover



→ Present



→ Enjoy



→ Produce

→ Annotate



→ Record



→ Derive


 Search

	Target known	Target unknown
Location known	 Lookup	 Browse
Location unknown	   Locate	   Explore

 Query

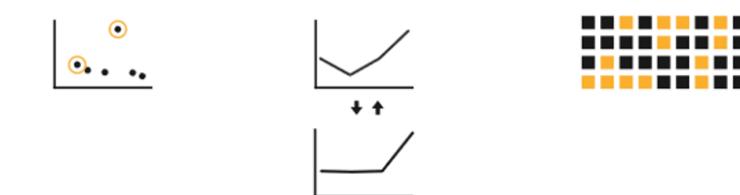
→ Identify



→ Compare



→ Summarize

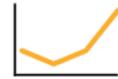


- There are 3 levels of action
- Analyze is high level, search is medium level, and query is low level

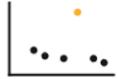
- Targets are “some aspect of the data that is of interest to the user”.
- For some tasks, this is more explicit than with others (but still relevant!).

 All Data

→ Trends



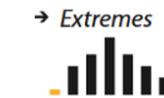
→ Outliers



→ Features


 Attributes

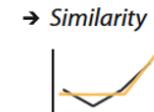
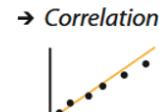
→ One



→ Many

→ Dependency

...


 Network Data

→ Topology



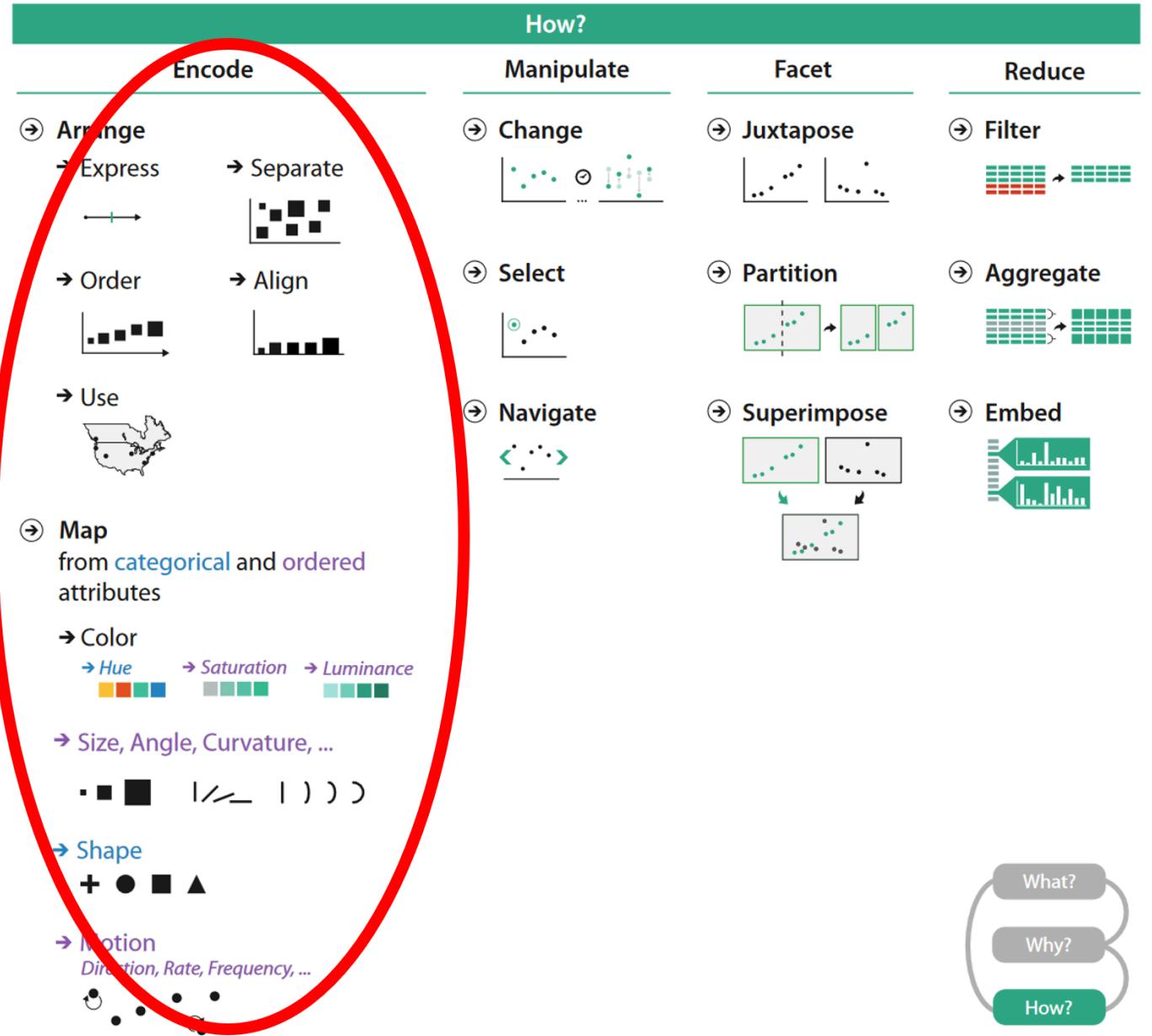
→ Paths


 Spatial Data

→ Shape

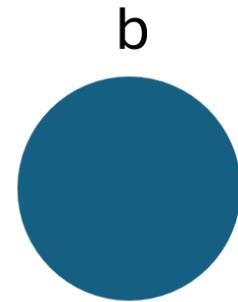
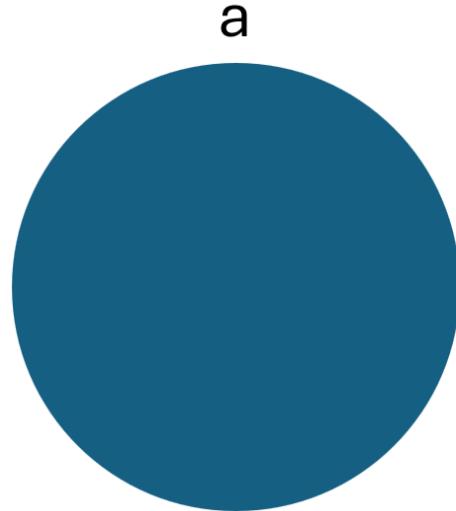


- Last part of the framework is 'how' the visualization is designed
- We will focus on 'encode'



# How do we visualize?

# Activity: How much bigger is a?



# How to visualize: Marks

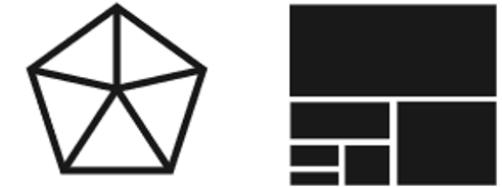
→ Points



→ Lines



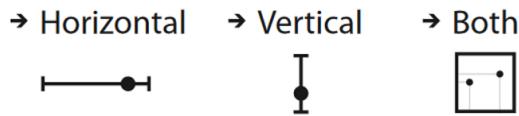
→ Areas



MARKS: Geometric objects, basic graphical elements (dot, circle, etc.)

# How to visualize: Channels

## ④ Position



## ④ Color



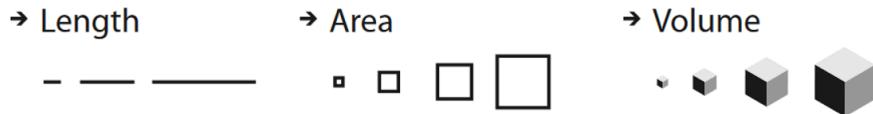
## ④ Shape



## ④ Tilt

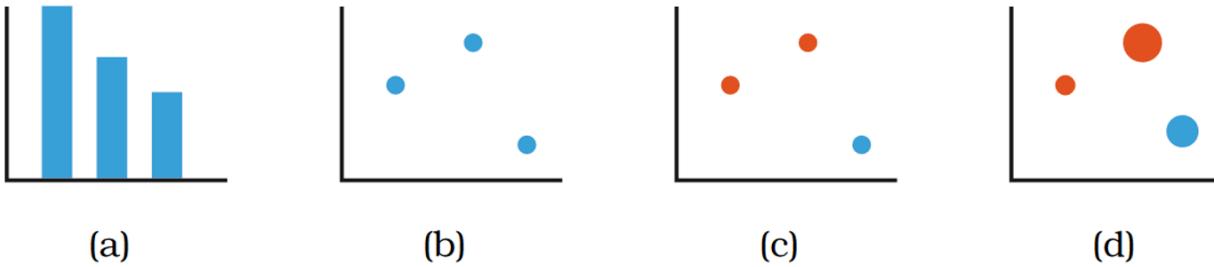


## ④ Size



CHANNELS: Way to control appearance of marks

# How to visualize: Encodings



**Figure 5.4.** Using marks and channels. (a) Bar charts encode two attributes using a line mark with the vertical spatial position channel for the quantitative attribute, and the horizontal spatial position channel for the categorical attribute. (b) Scatterplots encode two quantitative attributes using point marks and both vertical and horizontal spatial position. (c) A third categorical attribute is encoded by adding color to the scatterplot. (d) Adding the visual channel of size encodes a fourth quantitative attribute as well.

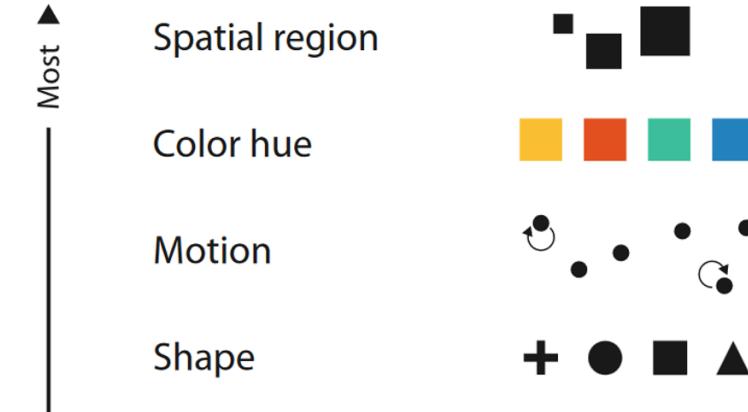
**ENCODINGS:** Mapping between data and visual attributes. For example, the bar chart maps frequency (data) with height (visual attribute).

## Channels: Expressiveness Types and Effectiveness Ranks

### ④ Magnitude Channels: Ordered 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)	

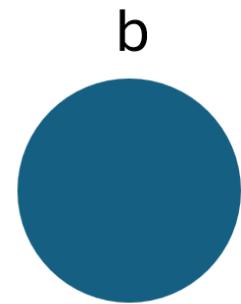
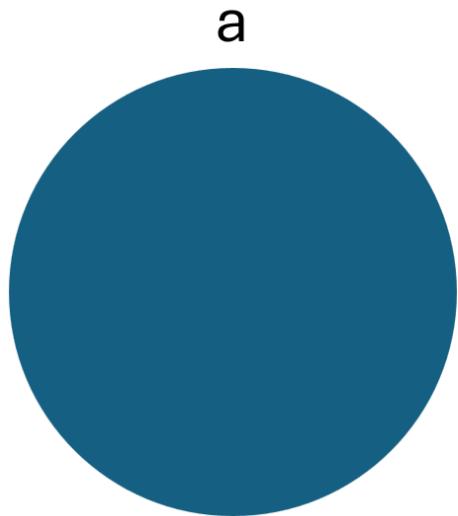
### ④ Identity Channels: Categorical Attributes



**Effectiveness principle:** Match most important attribute with most important effective channel

**Expressiveness principle:** Match channel to data characteristics

# Remember this activity?

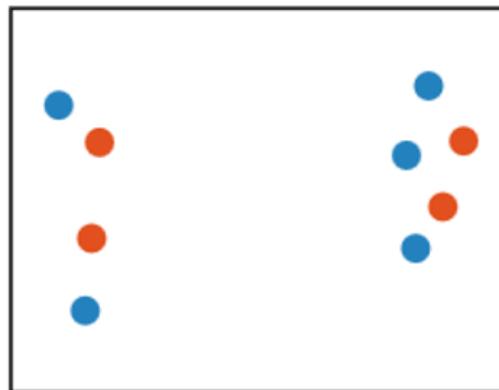


# How did the channel effectiveness ranking get established?

- Channels can be analyzed according to these criteria:
  - Accuracy
  - Discriminability
  - Separability
  - Ability to provide visual popout
  - Ability to provide perceptual groupings

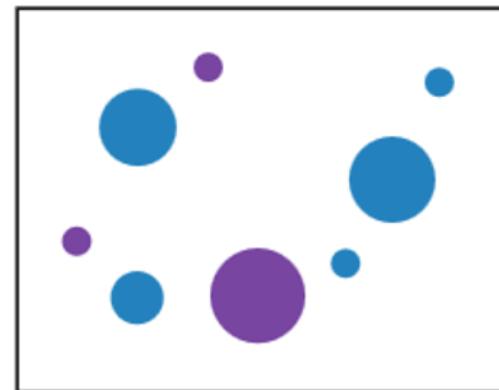
# Channels have dependencies & interactions

Position  
+ Hue (Color)



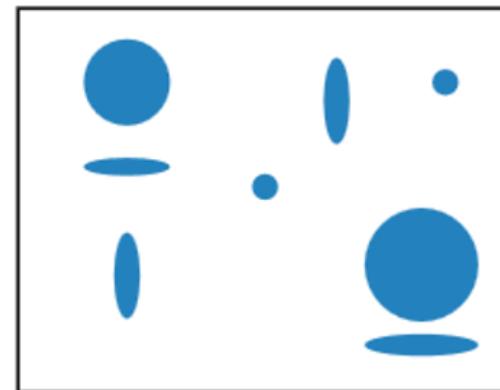
Fully separable

Size  
+ Hue (Color)



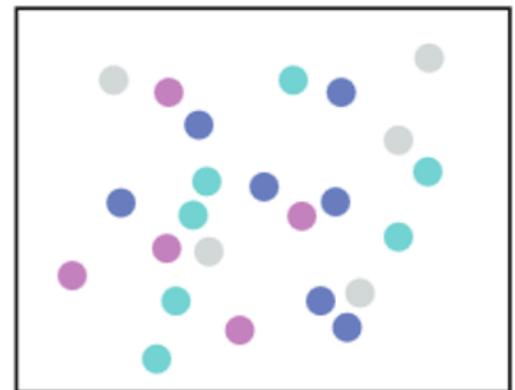
Some interference

Width  
+ Height



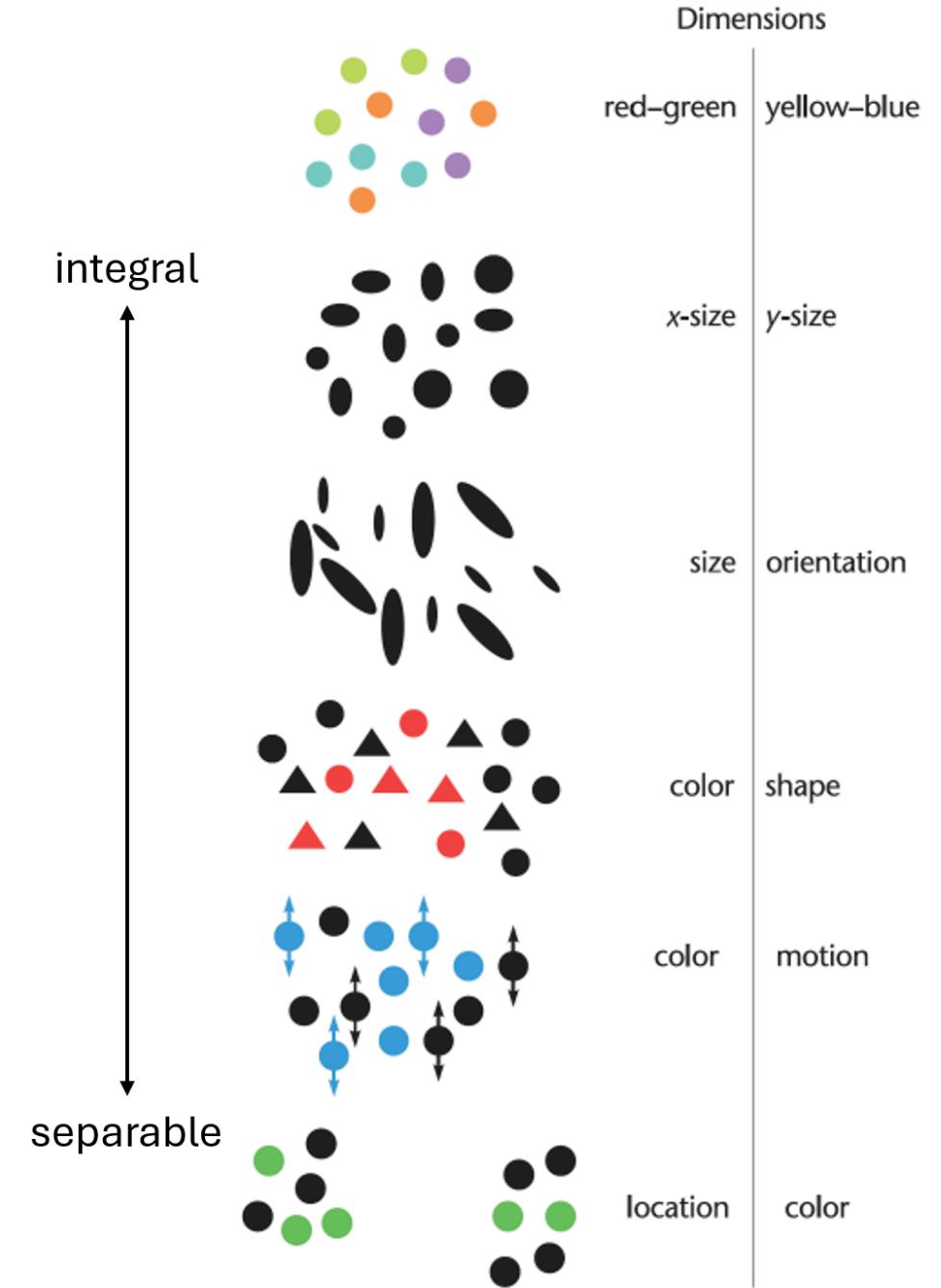
Some/significant  
interference

Red  
+ Green

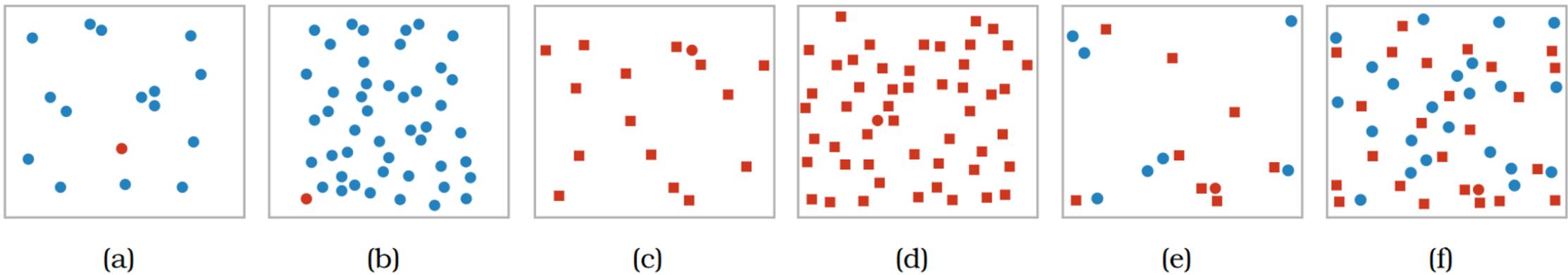


Major interference

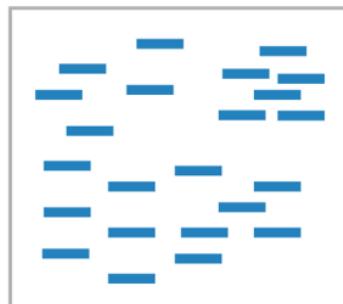
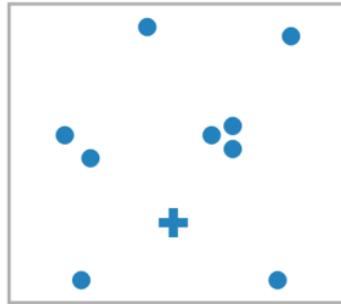
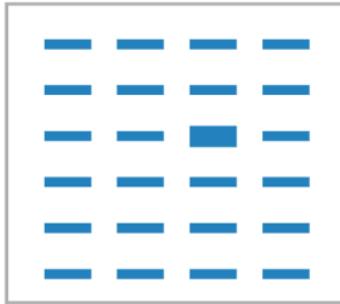
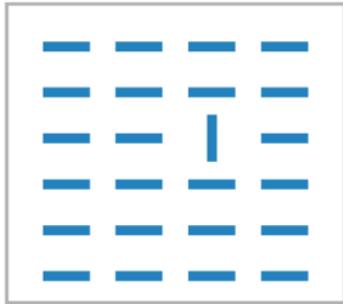
Channels have  
dependencies &  
interactions



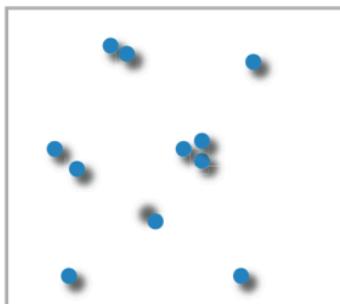
# Some channels provide visual popout



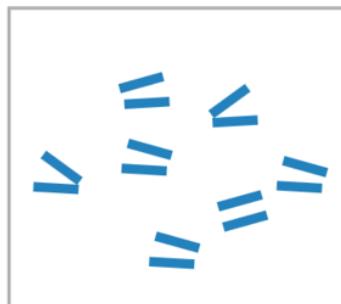
# Some channels provide visual popout



(d)



(e)

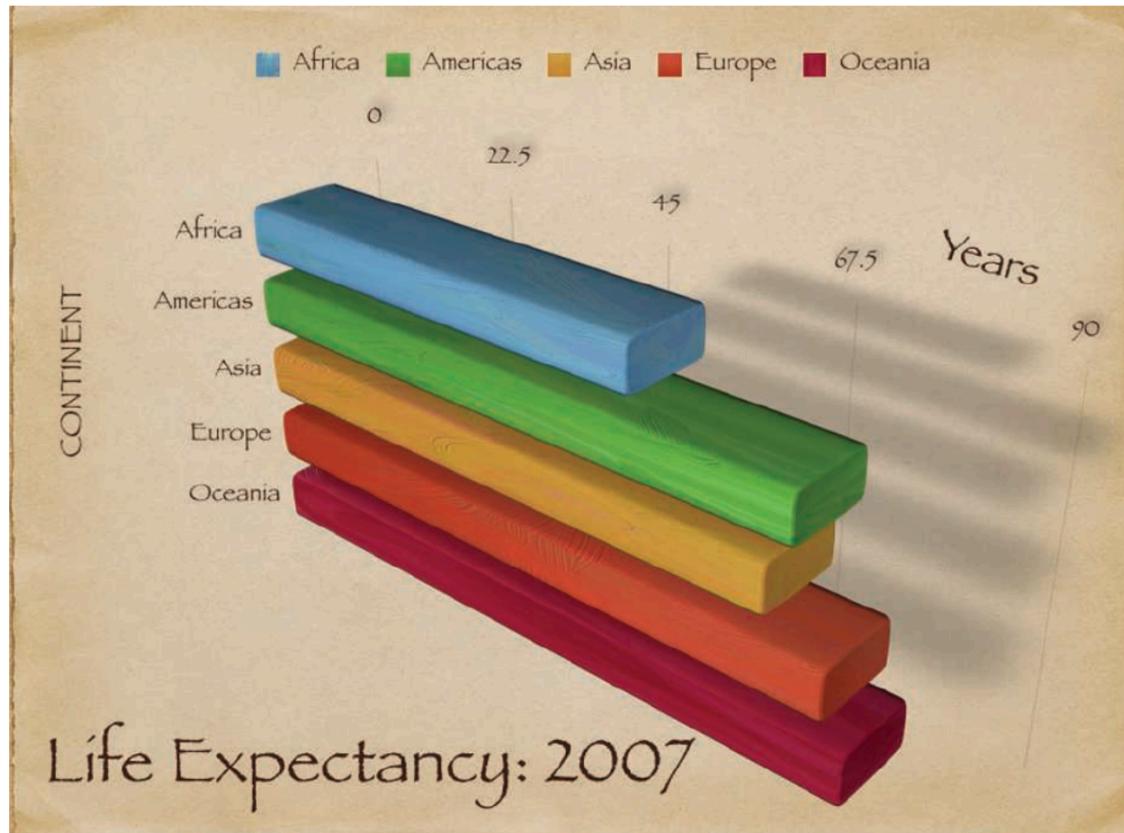


(f)

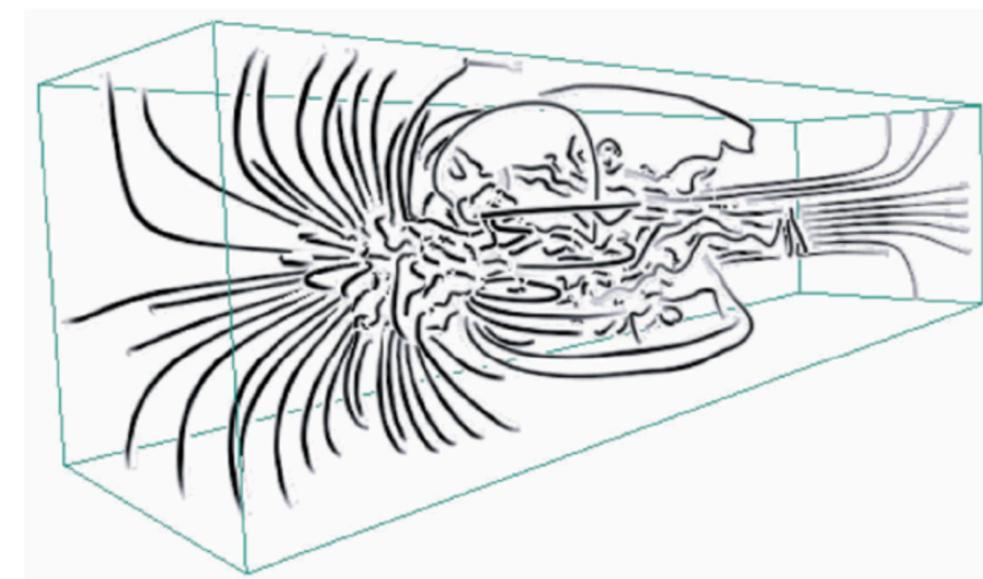
# Best Practices

- 3 of 8 shown

# No 3D without Cause



VS



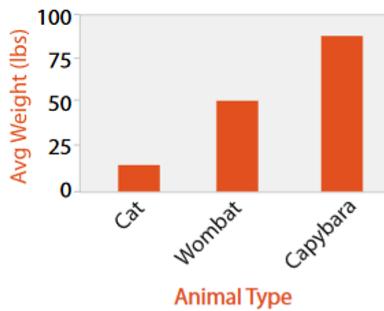
# Cognition over Memory

- Working memory is limited!
- It's better to show side-by-side views than using our memory

# Overview then zoom then details

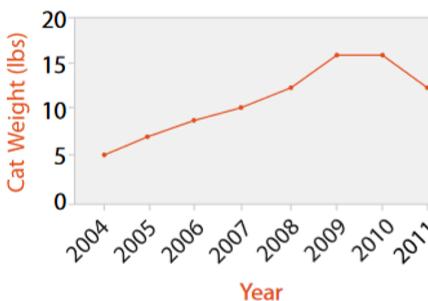
- **Overview:** see overall patterns, trends
- **Zoom:** see a smaller subset of the data
- **Filter:** see a subset based on values, etc.
- **Details on demand:** see values of objects when interactively selected

# Visualization Idioms



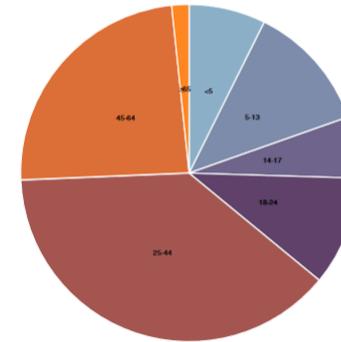
## Bar Chart

- Data: one quantitative, one categorical
- Task: lookup and compare values



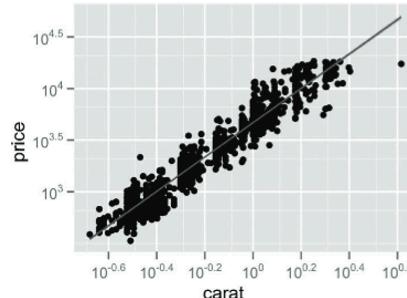
## Line Graph

- Data: one quantitative, one ordered
- Task: Show trend



## Pie Chart

- Data: one quantitative, one categorical
- Task: part-whole relationship



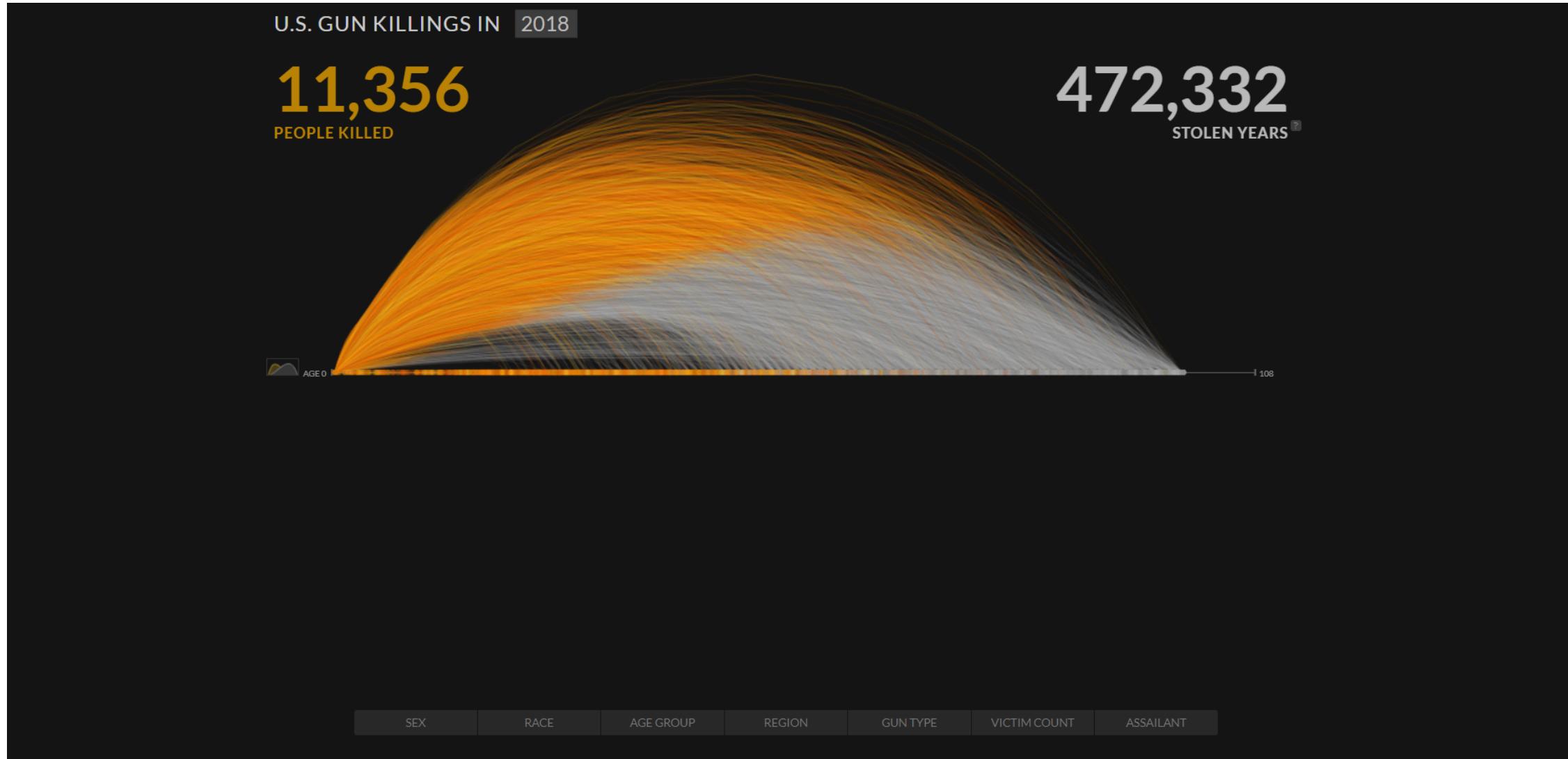
## Scatterplot

- Data: 2 quantitative
- Task: Find correlation, trends, outliers, locate clusters

# Activity

- We will explore two data visualizations, each showing similar datasets with different techniques
- For each visualization, discuss the following questions:
  - What information can we learn from this visualization?
  - Is this an example of objective, neutral data visualization? Why or why not?

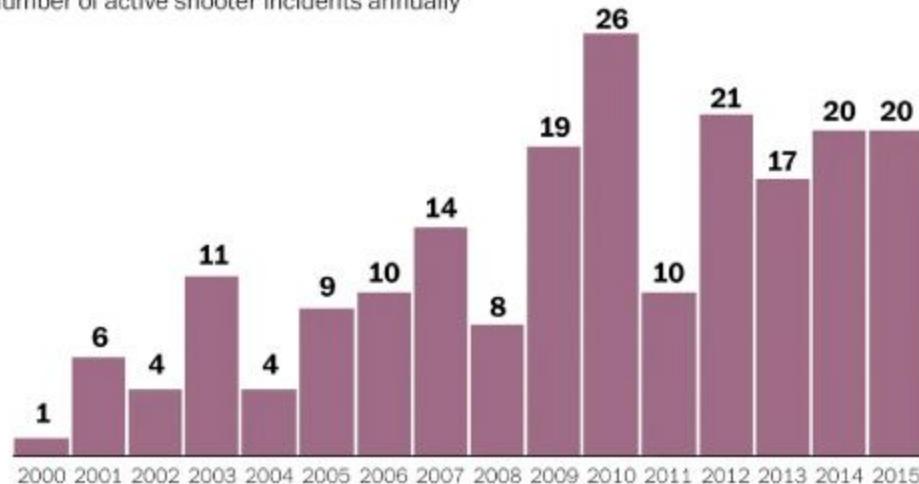
# Visualization #1: US Gun Killings in 2018



# Visualization #2: Washington Post Active Shooters

## The era of “active shooters”

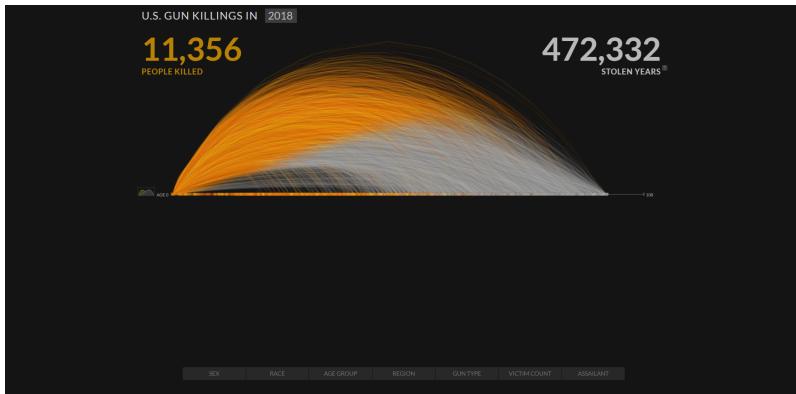
Number of active shooter incidents annually



WAPOTST/WONKBLOG

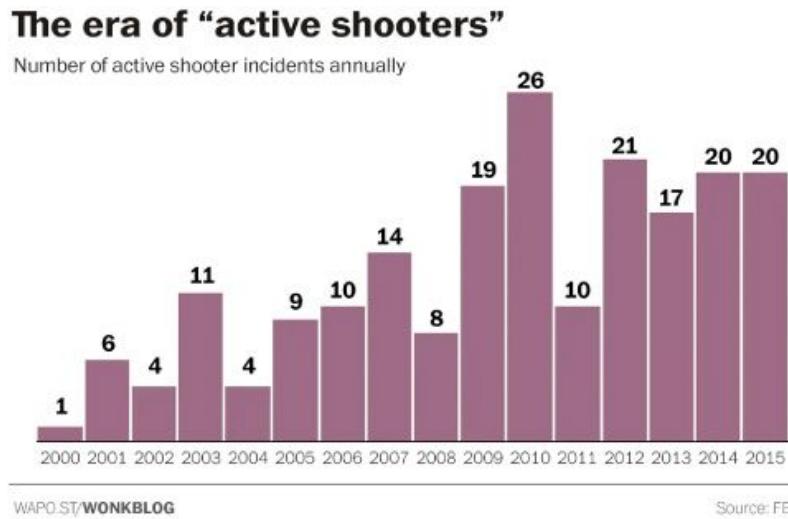
Source: FBI

# Visualization #1: US Gun Killings in 2018



- Periscopic's animated visualization shows the expected years of life lost to gun violence in the United States in 2018
- It emphasizes an emotion: a sense of loss
- This visualization has been criticized as "[actively \[shaping\] data to support a cause](#)" (in this case, highlighting a lack of gun control in the United States)

# Visualization #2: Washington Post Active Shooters

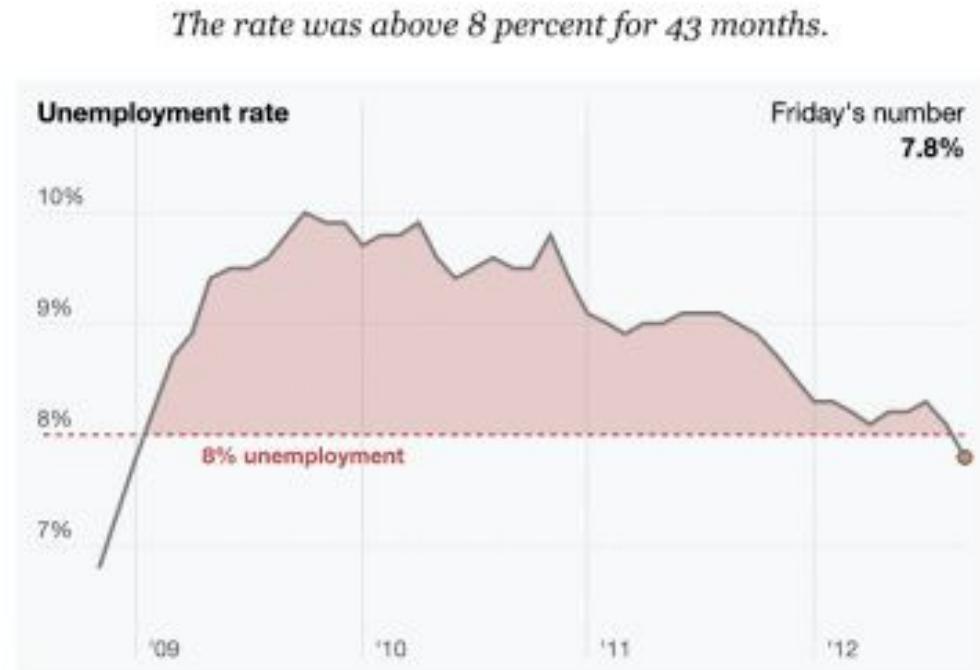


- The next visualization shows a related dataset (about gun violence in the United States)
- Viewers will likely reach a similar conclusion as in Visualization #1, but this plot is intended to present *“a deliberately neutral emotional field, a blank page in effect, upon which viewers are more free to choose their own response to the information”*

**What qualities or visual elements of Visualization #2 help to make it a “blank page”?**

# A blank page

- Some of the same design elements from our 'blank page' Visualization #2 can be seen in this New York Times visualization of the September 2012 Jobs Report
- The clean, 2D layout is designed to avoid conveying an emotional narrative to the audience

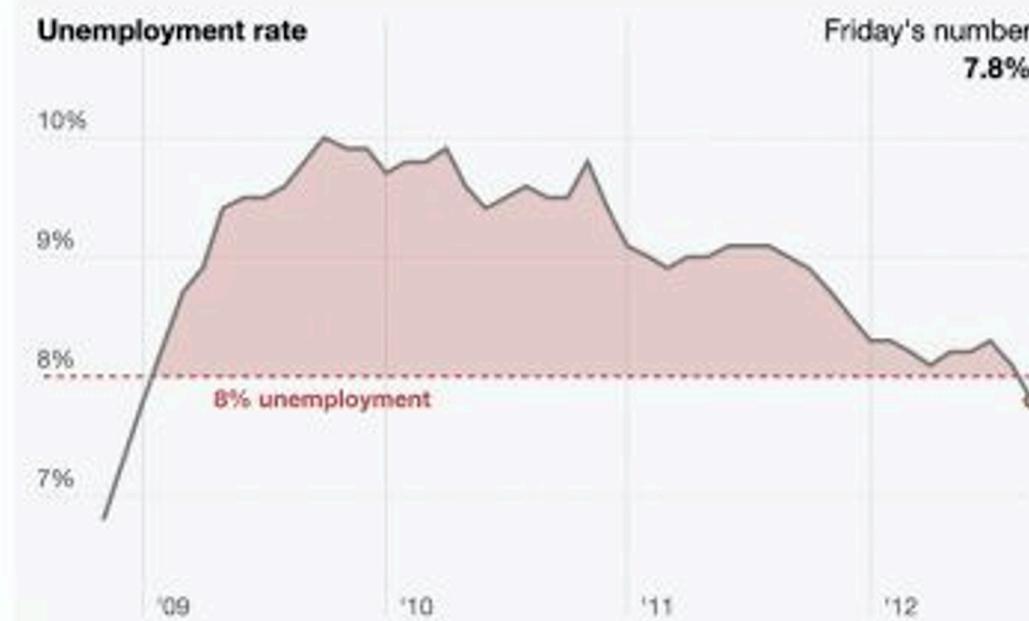


# A blank page... right?

- The Jobs Report graphic was published alongside another image:

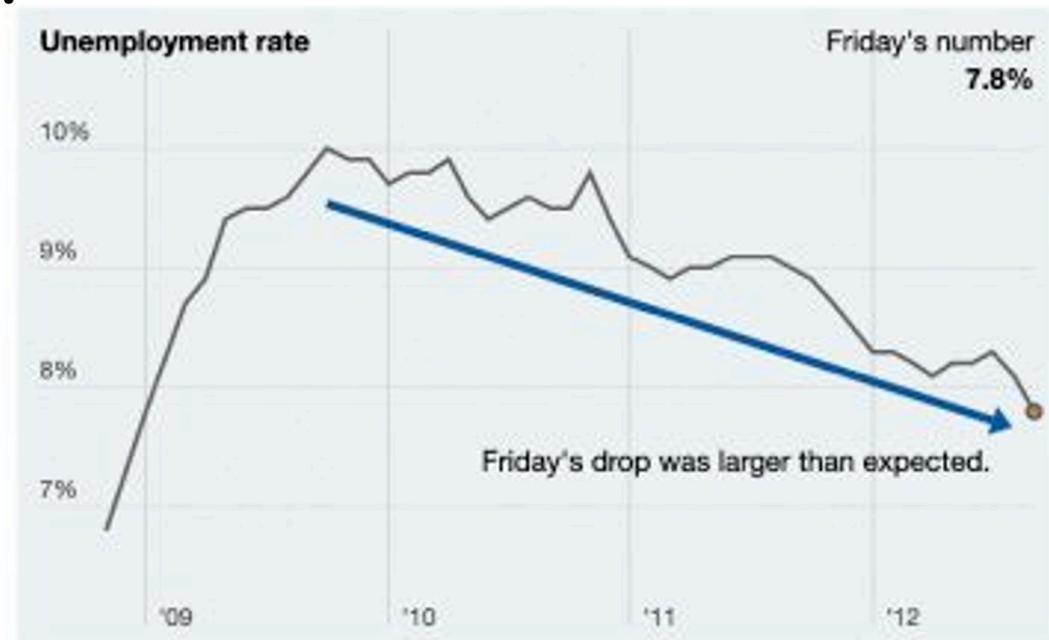
A.

*The rate was above 8 percent for 43 months.*



B.

*The rate has fallen more than 2 points since its recent peak.*

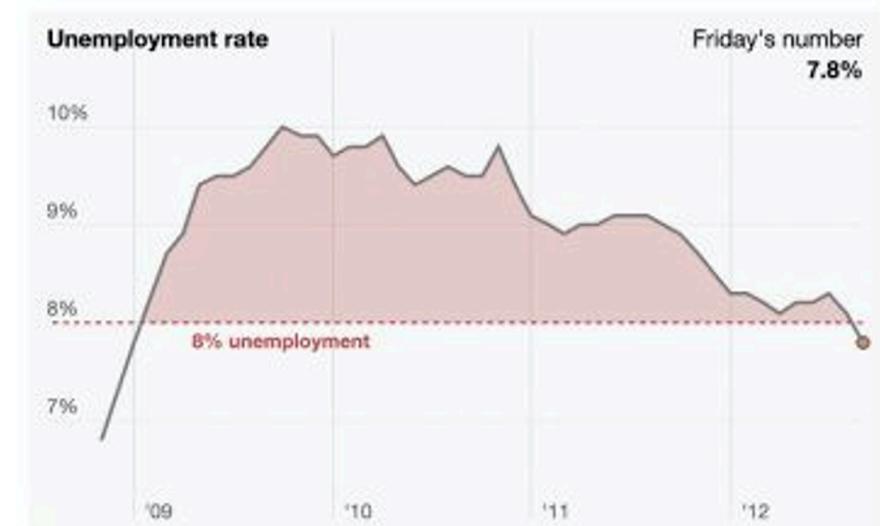


# A blank page

- Images A and B were designed to show the exact same data from the perspectives of Republicans and Democrats, respectively
- Image A emphasizes the unemployment rate staying above 8%, while Image B emphasizes the rate's decline
- Neither is technically dishonest!

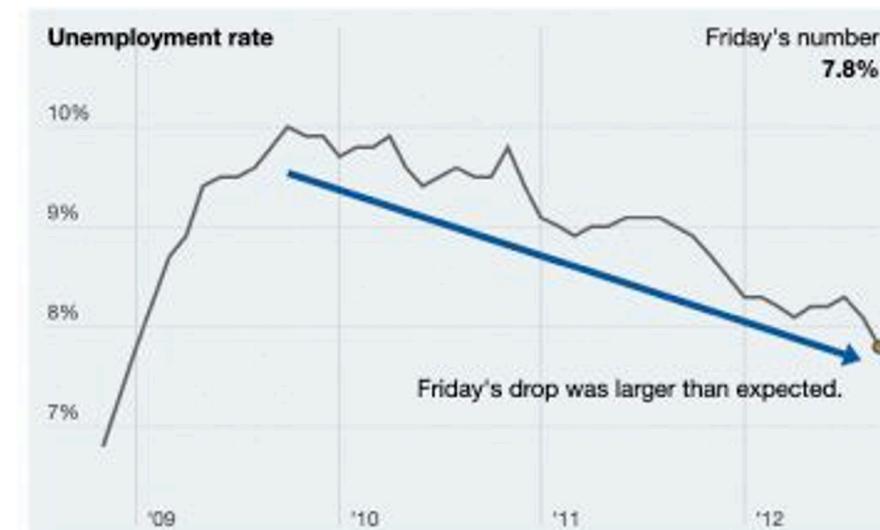
*The rate was above 8 percent for 43 months.*

**A.**



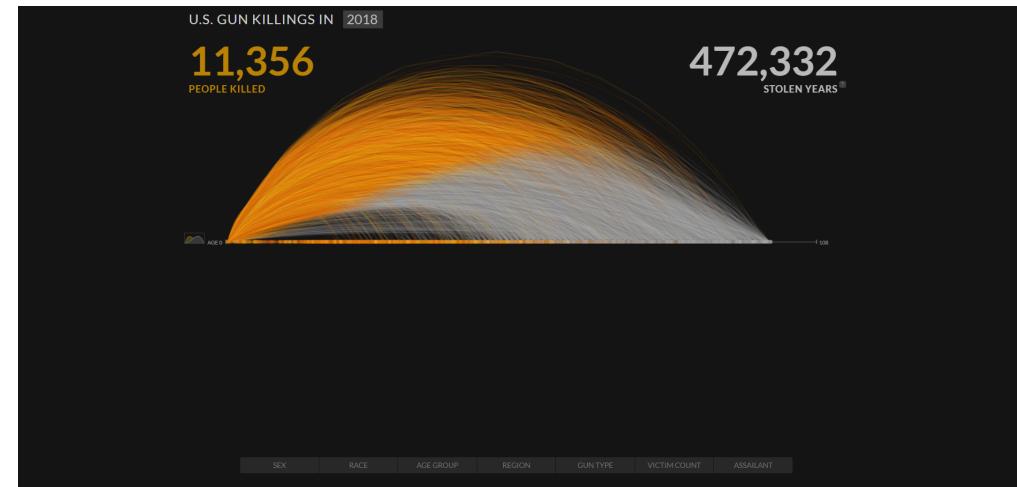
*The rate has fallen more than 2 points since its recent peak.*

**B.**



# Supporting a cause

- Periscope's Gun Killings visualization won several year-end information visualization awards
- This visualization is not neutral, and conveys an emotional narrative to the audience...
- ...**But this visualization is not dishonest either!**



**So where does this leave us in our search for neutral, objective data visualization?**

**Can data visualization be neutral?**

**Short answer:**

NO!

**“The constraints of truth leave a very wide space for interpretation...”**

**(Stray, 2016)**

# Data visualizations as rhetorical objects

- Rhetoric is the act of communicating effectively and persuasively
- From D'Ignazio and Klein (2020),

“Any communicating object that reflects choices about the selection and representation of reality is a rhetorical object. Whether or not it is rhetorical (it always is) has nothing to do with whether or not it is true (it may or may not be).”
- That is, **we make choices about how to visualize our data, so these visualizations are not neutral...**
- ...**BUT data visualizations can be factual without being neutral**

Data visualization as an interpretative, rhetorical act is not necessarily a bad thing, but one that we should be aware of.

# Recall

- Three important qualities of data visualization:
  - Is the visualization pleasing to look at? → **Aesthetic**
  - Does the visualization accurately and honestly present data? → **Substantive**
  - Can we understand what message the maker of the visualization is attempting to convey? → **Perceptual**

- Two data visualizations can share the same substantive qualities while, intentionally or not, being perceived completely differently
- When we are aware of the choices we make while creating data visualizations, we can design data visualizations that are suited to the situation at hand (perceptual qualities) without sacrificing honesty and accuracy (substantive qualities)

# What do we want our data visualization to do?

# Intended purpose



Persuading



Comparison

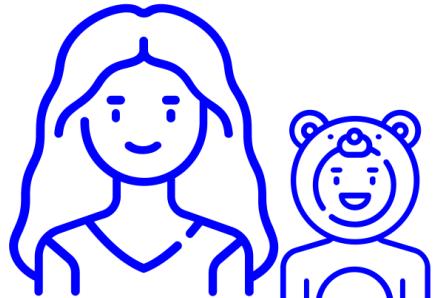


Evaluating



Exploring

# Intended audience



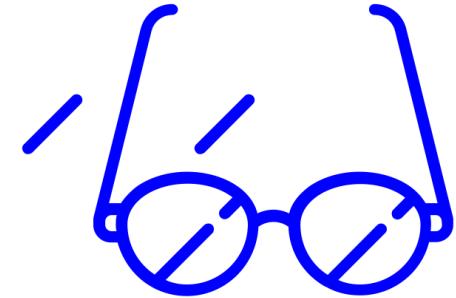
Age



Education

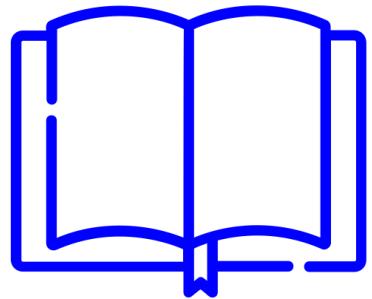


Expertise



Accessibility

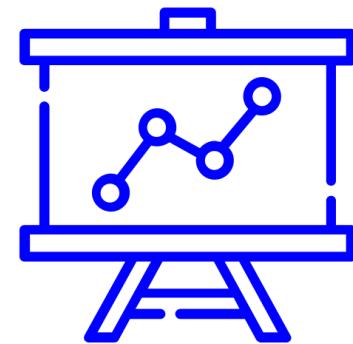
# Intended medium



Print



Web



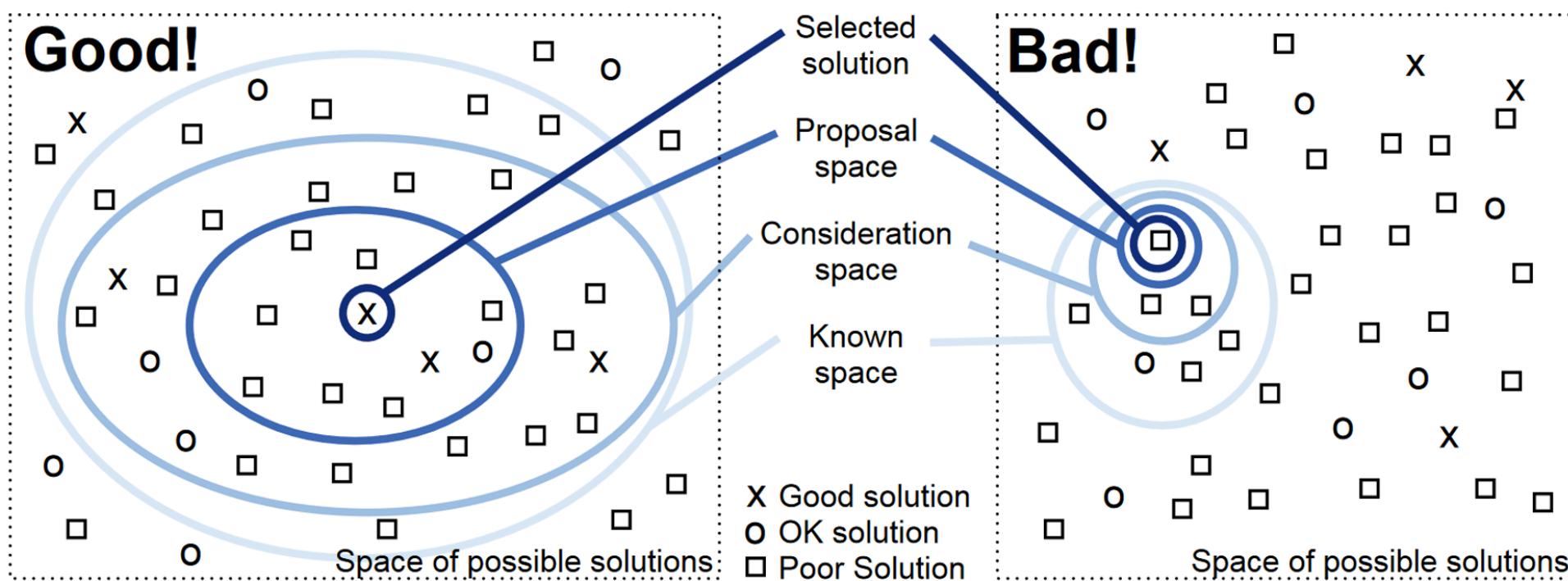
Poster



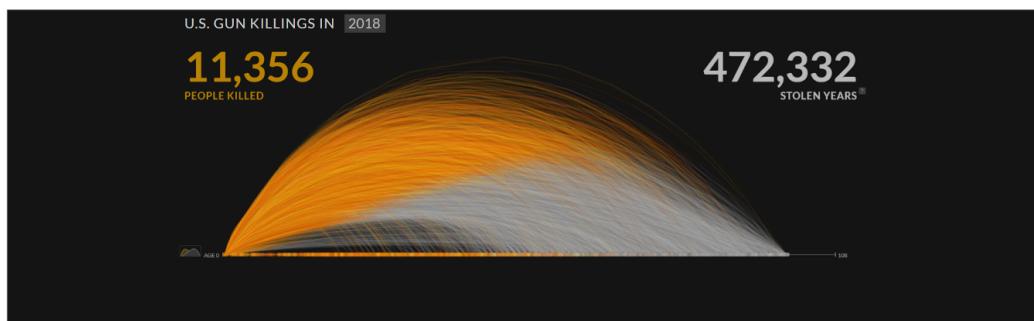
Presentation

# Effective Visualization

- Depends on purpose, audience, and medium!
- A good goal is to satisfy: “to find one of the many possible good solutions rather than one of the even larger number of bad ones”

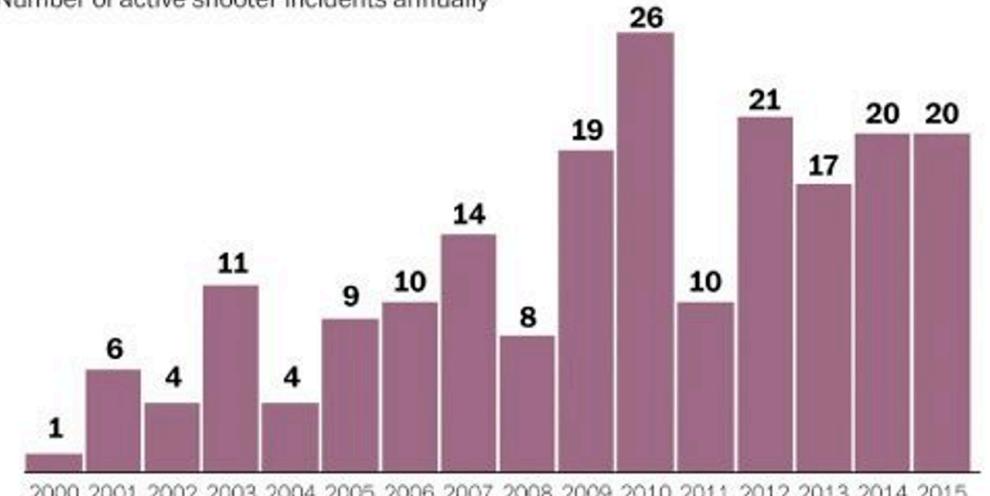


# Different purpose, different results



## The era of “active shooters”

Number of active shooter incidents annually



WAPO-ST/WONKBLOG

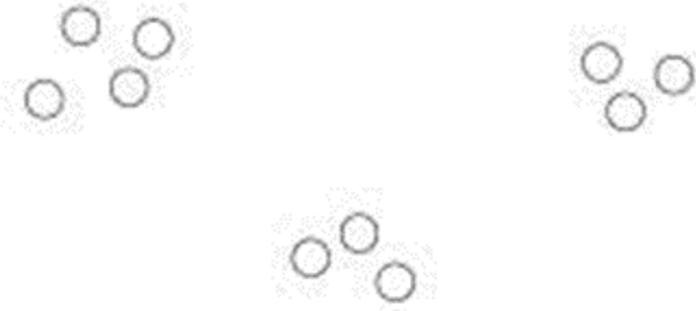
Source: FBI

# How is our data visualization perceived?

# Taking advantage of cognitive psychology

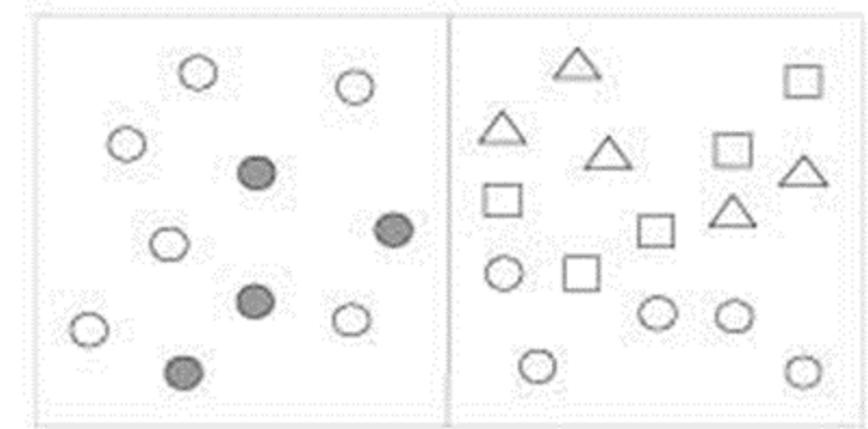
- In general, data visualization takes advantage of human cognition to help us understand data more intuitively than we can if it is presented to us as a list or a table ([Li, 2020](#))
- By learning about how humans tend to process visual information, we can communicate more effectively with our graphs. For example...
- **Gestalt principles** (Gestalt is German for shape) are a set of cognitive theories for how people tend to organize visual information; and are commonly used in UX design and data visualization ([Wong, 2010](#))

# Gestalt principles



## Proximity

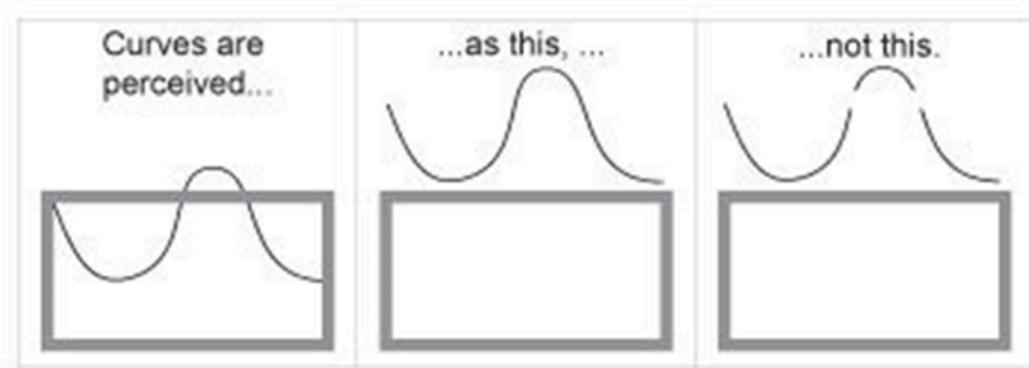
Objects that are close together are perceived as belonging to a group



## Similarity

Similar objects are grouped, regardless of proximity

# Gestalt principles



## Continuity

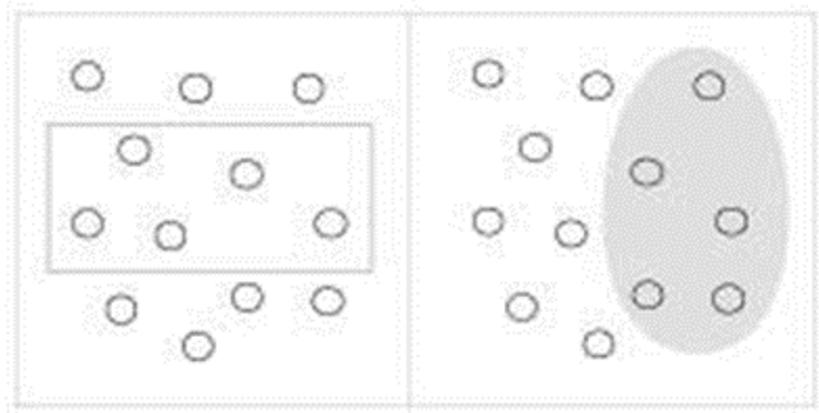
Aligned objects or objects that appear to continue are perceived as a group



## Closure

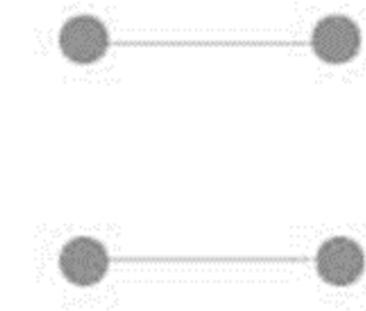
Open structures are perceived as closed/complete (our brains fill in the gaps)

# Gestalt principles



## Enclosure

Objects with a boundary around them are perceived as a group



## Connection

Connected objects are perceived as related/as a group

# Cognitive load

- It can also be helpful to consider **cognitive load** , or the amount of work required to take in new information
- Cognitive load can be divided into:
  - **Intrinsic**(the intrinsic complexity of the new information)
  - **Germane**(the audience's familiarity with the information)
  - **Extraneous**(complexity from how the information is presented)
- In a data visualization context, extraneous cognitive load is most within our control

# Cognitive load

- Elements of a visualization that can affect cognitive load include:
  - **Familiar vs. Rare chart types** → rare types increase cognitive load
  - **Accurate vs. Approximate interpretation** → relational values or areas (approximate) increase cognitive load compared to absolute values or position (accurate)
  - **Concise vs. Detailed composition** → more visual elements increases cognitive load
  - **Explanatory vs. Exploratory composition** → a chart that the audience navigates alone increases cognitive load compared to a chart that they are guided through step-by-step

# Perceived factual basis

- Sociologists Kennedy et al. (2016) find that adherence to **four conventions of data visualization** reinforces the perceived objectivity and factual basis of a visualization:
  - Two-dimensional image
  - Clean layouts
  - Geometric shapes and lines
  - Inclusion of data sources at the bottom of the image

# Provenance rhetoric

- Citing the source(s) of our data is not only best practice (reproducibility!), but also helps people to trust our data visualizations more
- **Provenance rhetoric** is the idea that the inclusion of a data source with our graphic signals “[transparency and trustworthiness](#)” to the audience
- This increases the persuasiveness of the visualization, since viewers are more likely to believe what they see

# Resources for choosing data visualization types

# Decision making tools

There are resources available online that incorporate visualization purpose and cognitive principles into reference guides to help us decide the most suitable data visualization in a given situation

# The Data Visualization Catalogue

The Data Visualisation Catalogue

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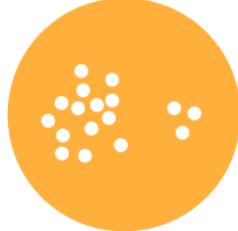
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## What do you want to show?

Here you can find a list of charts categorised by their data visualization functions or by what you want a chart to communicate to an audience. While the allocation of each chart into specific functions isn't a perfect system, it still works as a useful guide for selecting chart based on your analysis or communication needs.



Comparisons      Proportions      Relationships      Hierarchy



# Financial Times Visual Vocabulary

The Financial Times Visual Vocabulary help sheet is available in both [interactive](#) (online PowerBI dashboard) and [PDF](#) versions

In both forms, the Visual Vocabulary offers a list of potential functions of visualizations, and several corresponding chart types and examples for each

# Financial Times Visual Vocabulary

## Visual Vocabulary

There are so many ways to visualise data - how do we know which one to pick? Click on a category below to decide which data relationship is most important in your story, then look at the different types of charts within the category to form some initial ideas about what might work best. This list is not meant to be exhaustive, nor a wizard, but is a useful starting point for making informative and meaningful data visualisations.

Click any section below to view the charts



### Deviation

Emphasise variations (+/-) from a fixed reference point. Typically the reference point is zero but it can also be a target or a long-term average. Can also be used to show sentiment (positive/neutral/negative).

### Correlation

Show the relationship between two or more variables. Be mindful that, unless you tell them otherwise, many readers will assume the relationships you show them to be causal (i.e., one causes the other).

### Ranking

Use where an item's position in an ordered list is more important than its absolute or relative value. Don't be afraid to highlight the points of interest.

### Distribution

Show values in a dataset and how often they occur. The shape (or 'skew') of a distribution can be a memorable way of highlighting the lack of uniformity or equality in the data.

### Change over Time

Give emphasis to changing trends. These can be short (intra-day) movements or extended series traversing decades or centuries: Choosing the correct time period is important to provide suitable context for the reader.

### Part-to-Whole

Show how a single entity can be broken down into its component elements. If the reader's interest is solely in the size of the components, consider a magnitude-type chart instead.

### Magnitude

Show size comparisons. These can be relative (just being able to see larger/bigger) or absolute (need to see fine differences). Usually these show a 'counted' number (for example, barrels, dollars or people) rather than a calculated rate or per cent.

### Spatial

Used only when precise locations or geographical patterns in data are more important to the reader than anything else.

### Flow

Show the reader volumes or intensity of movement between two or more states or conditions. These might be logical sequences or geographical locations.

#### CREATED BY

Jason Thomas | [@Squigson](#) | [blog](#)

#### INSPIRED BY

Andy Kriebel | [@vizjones](#) | (including the design / theme template from [blog](#))

FT Graphics: Alan Smith; Chris Campbell; Ian Bott; Liz Faunce; Graham Parrish; Billy Ehrenberg; Paul McCallum; Martin Stabe

#### CREDITS

Power BI Community & Tableau Community - for sharing their dataviz techniques and learnings

#### AND IN PARTICULAR

Konstantinos Ioannou | [@kanouKonstan](#) - for opening up my mind regarding the potential of R/Python visuals

David Eldersveld | [@dataeld](#) - for being my sounding board

Nujcharae | [@Nujcharae](#) - for creating Violin Plots in R and kickstarting my R visuals journey

#### CUSTOM VISUALS:

MapBox	Chartulator	Scatter Chart by Akelon	Dot Plot by MAQ
Python	Infographic Designer	Box & Whisker by MAQ	Dumbbell Chart by MAQ
Candlestick by OKViz	Synoptic Panel by OKViz	Mekko Chart	Sunburst

## Next...

Subplots, multiple axes, and combining elements in matplotlib