Data Visualization: Choosing the Right Visualization

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$ echo "Data Science Institute"
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Agenda for today

- Go through slide deck #4: Choosing the right visualization
- Discuss assignment 2

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?

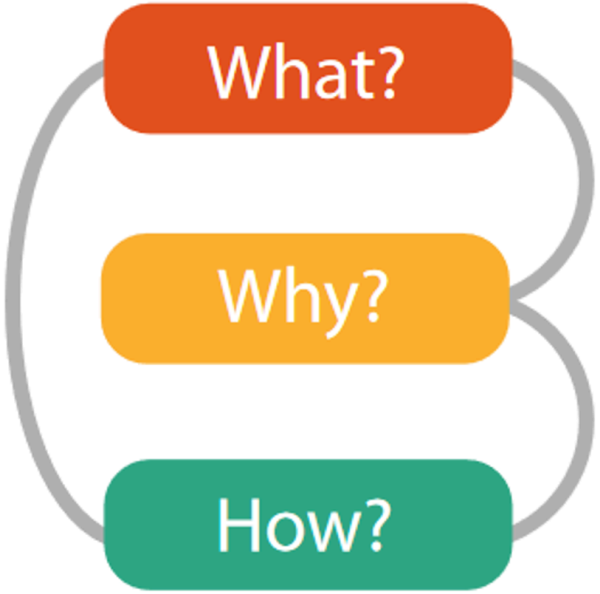
How do we choose the 'right' visualization?

The Visualization Process

What data is the user seeing?

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

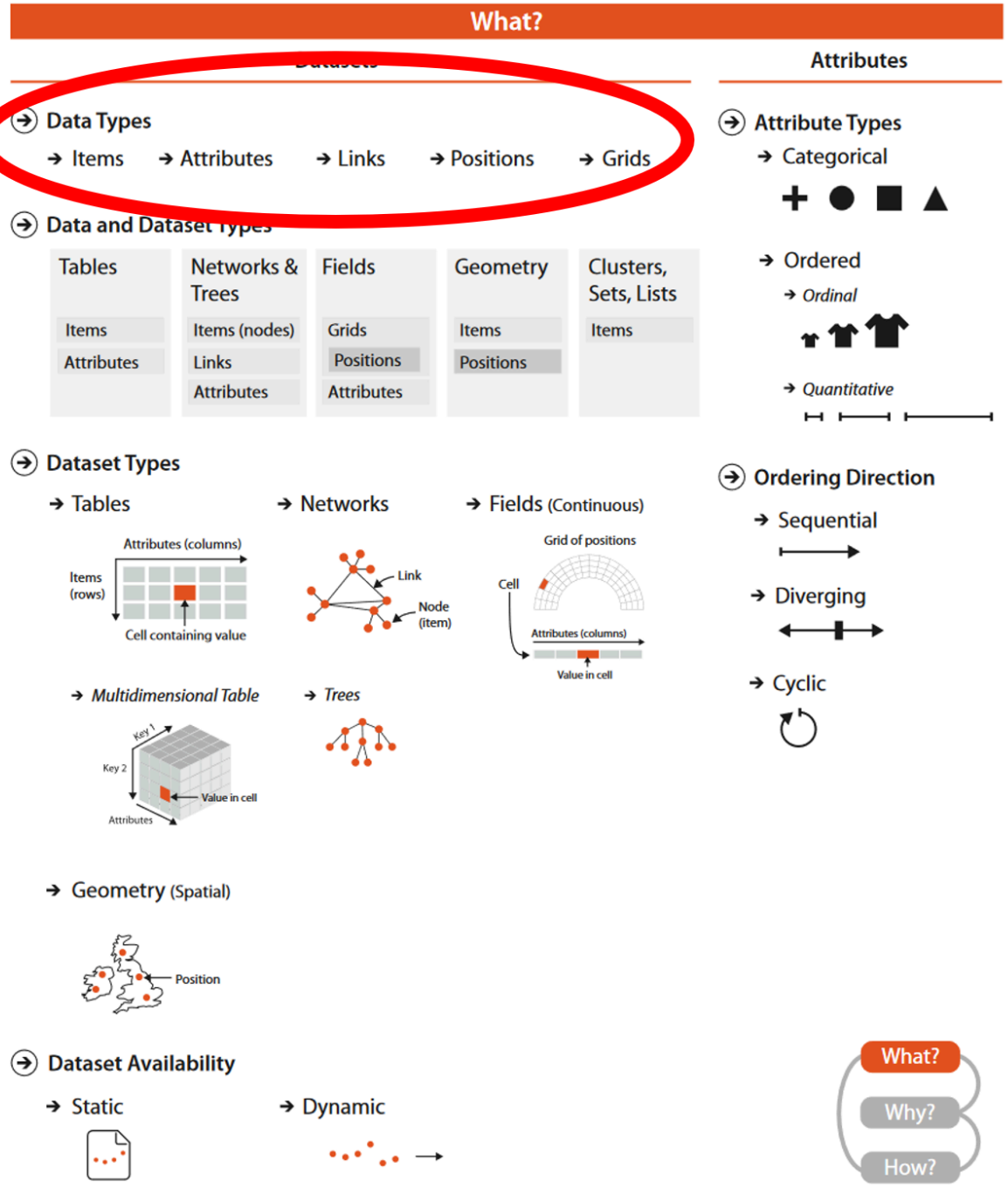
How is the visualization being designed?



This figure shows *what* can be visualized.

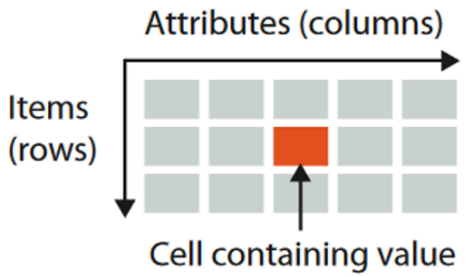
Let's review it one-by-one

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

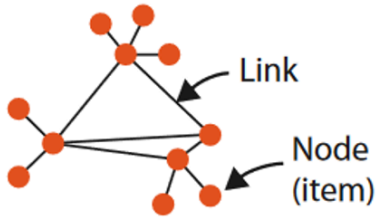


Dataset Types

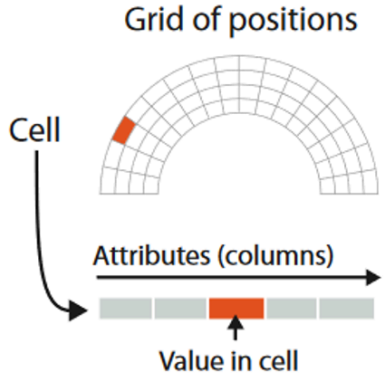
Tables



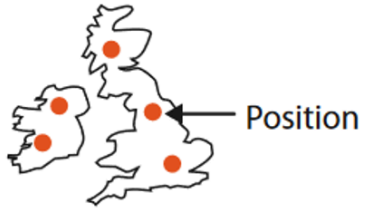
Networks



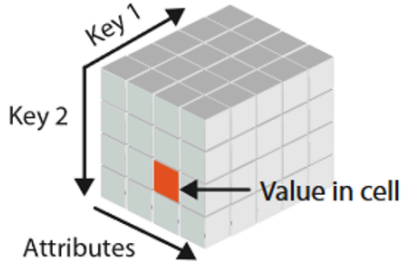
Fields (Continuous)



Geometry (Spatial)



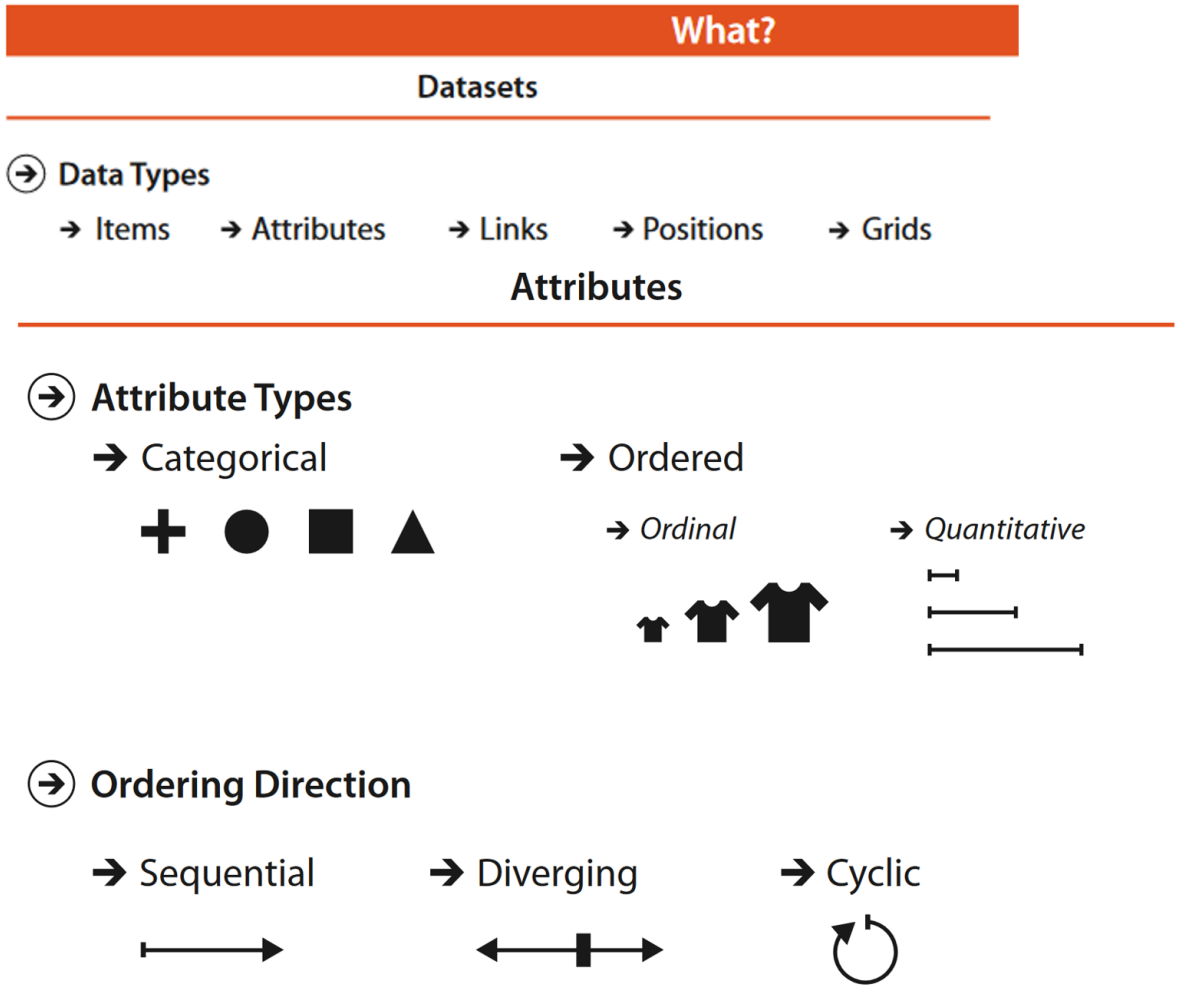
Multidimensional Table



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)

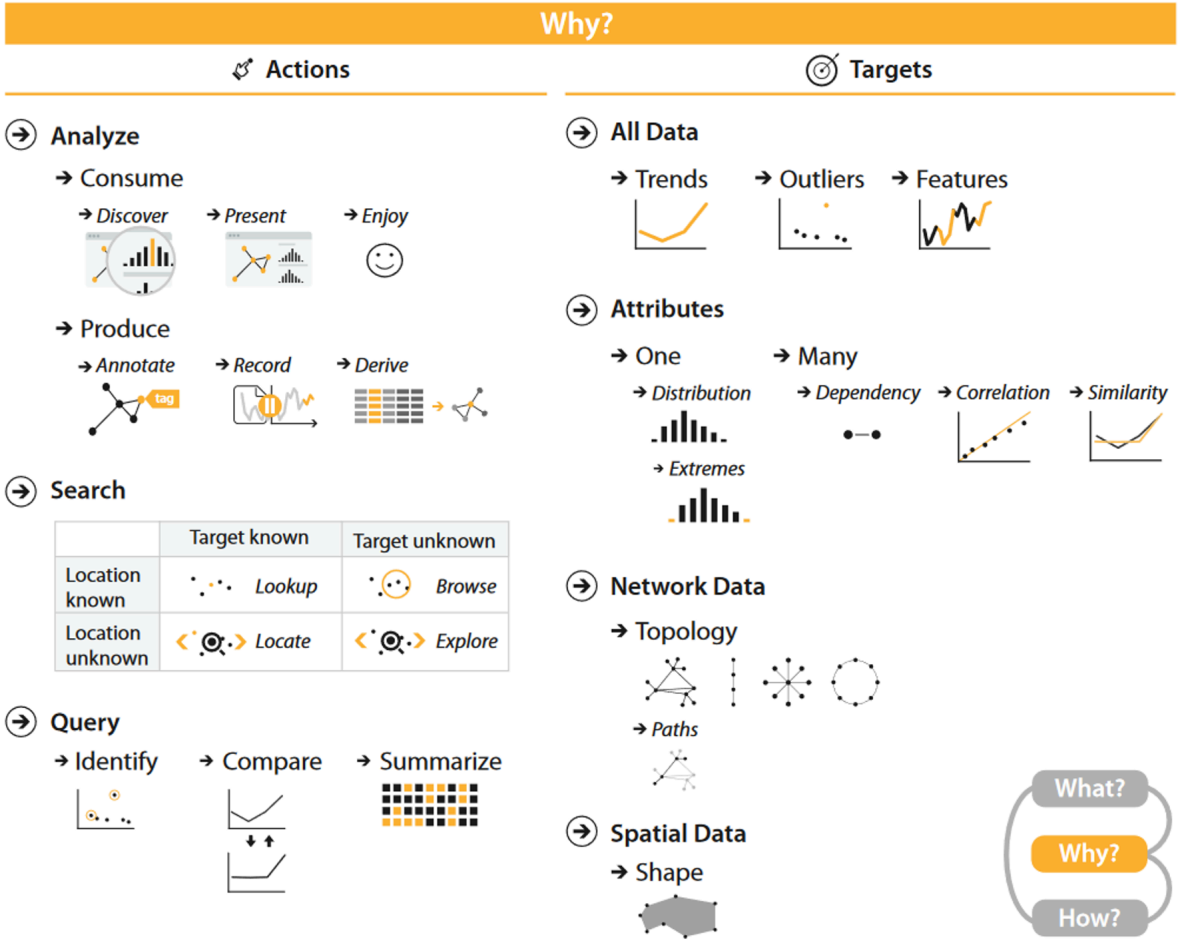


Quick Check-in

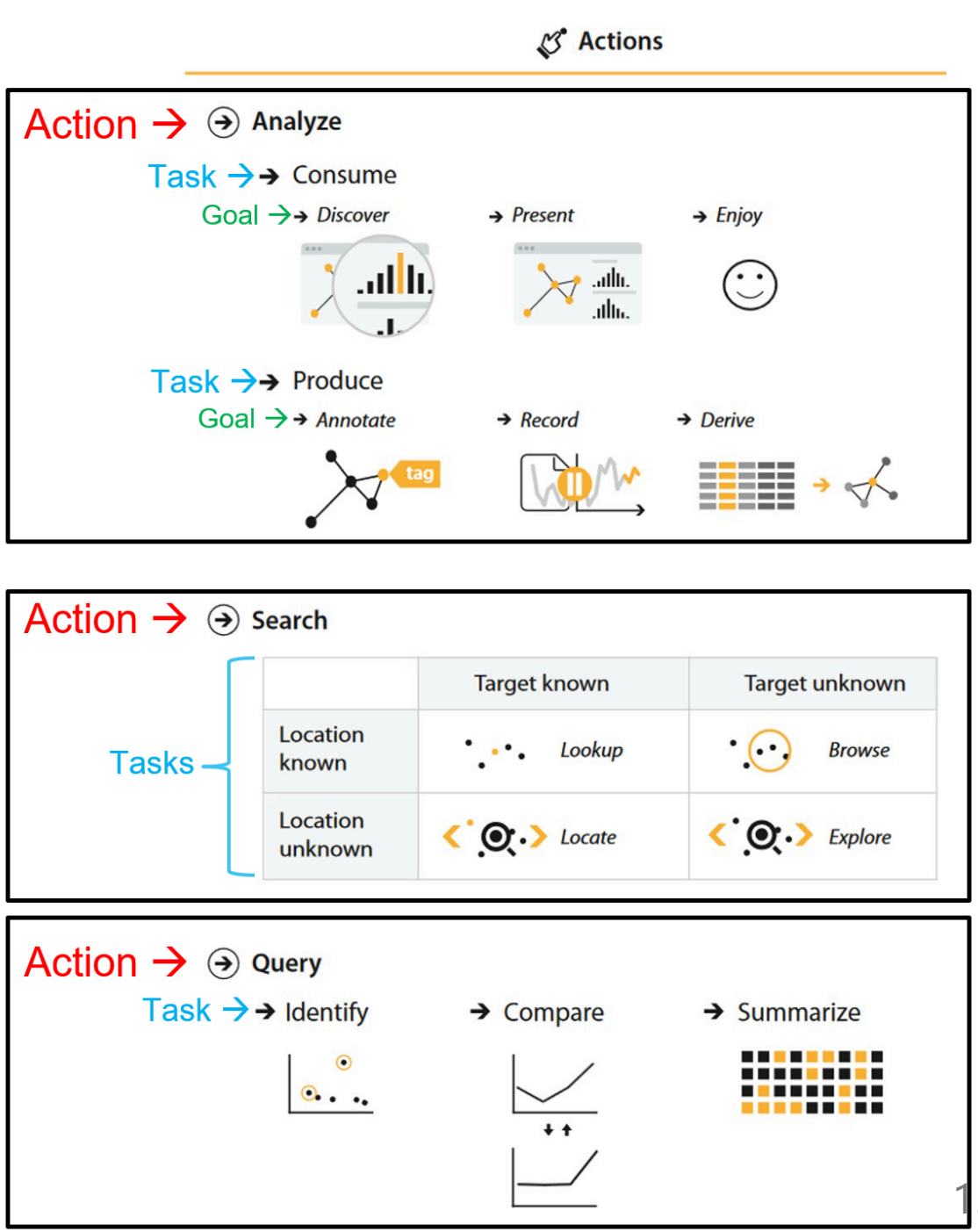
If we had to abstract our data and translate from domain-specific language to generic visualization language, we would ask:

- A) **What** are the data types?
- B) How are the data types structured (i.e, **what** is the dataset type?)
- C) **What** are my attribute types?
- D) All of the above
- E) None of the above

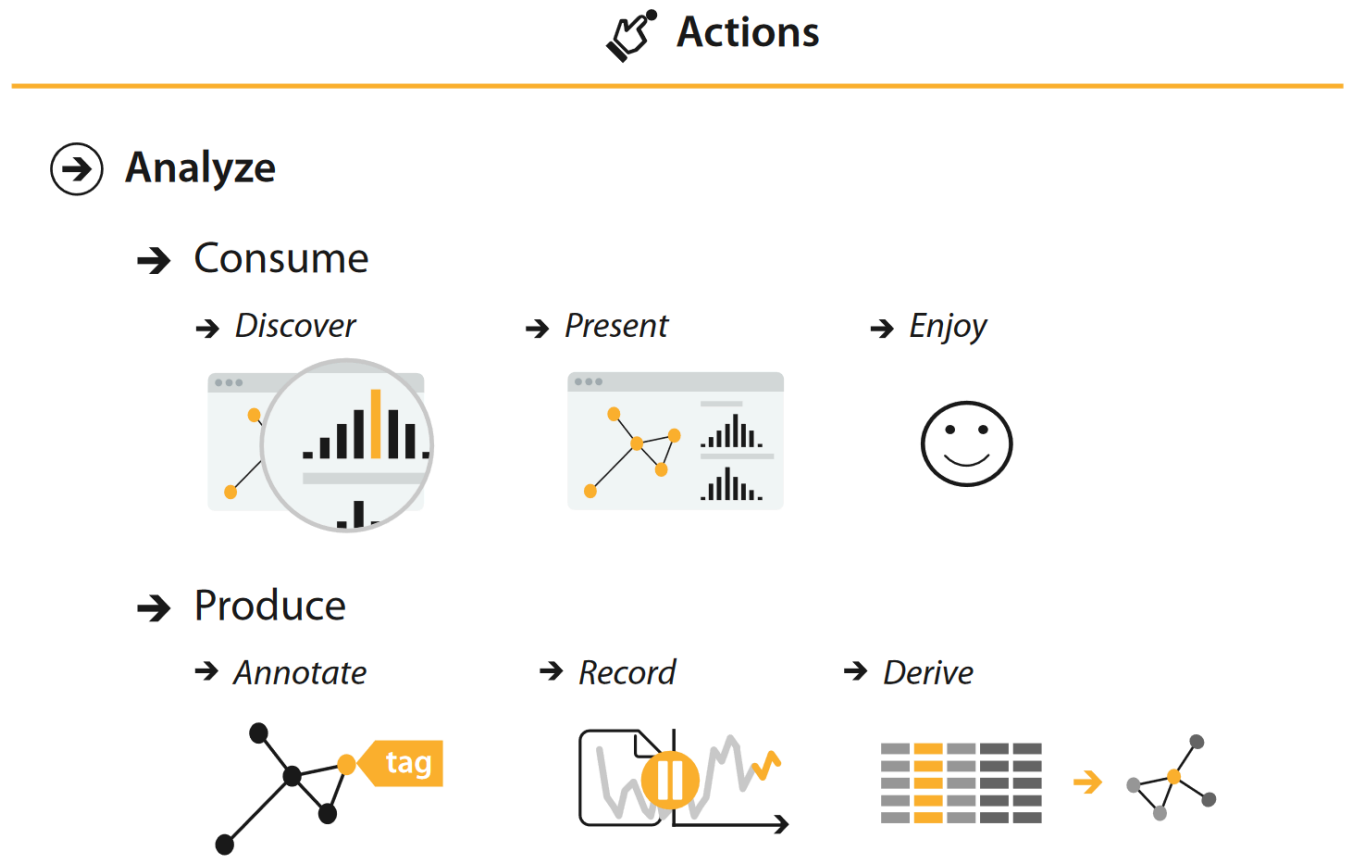
This figure helps us decompose different reasons *why* a person may use a visualization (i.e., what task they perform).



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



- Action → Analyze
- Task is either to consume data or produce additional data
- Consume or produce tasks can be performed to achieve different goals.



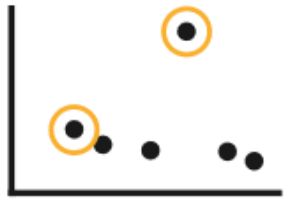
Search

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

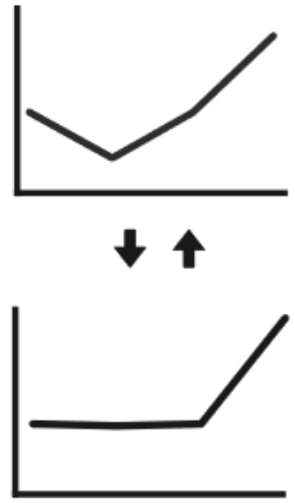
- Action → Search
- Task (lookup, browse, locate, explore) will depend on whether location and target are unknown or known

Query

→ Identify



→ Compare



→ Summarize

- Action → Query
- Task (identify, compare, summarize) will depend on **how much of the data** matters for you to do a particular task

Actions

Action → Analyze

Task → Consume

Goal → *Discover* → *Present* → *Enjoy*

Task → Produce

Goal → *Annotate* → *Record* → *Derive*

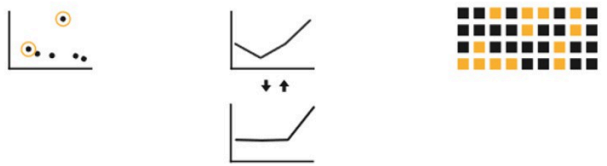
Action → Search

Tasks

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

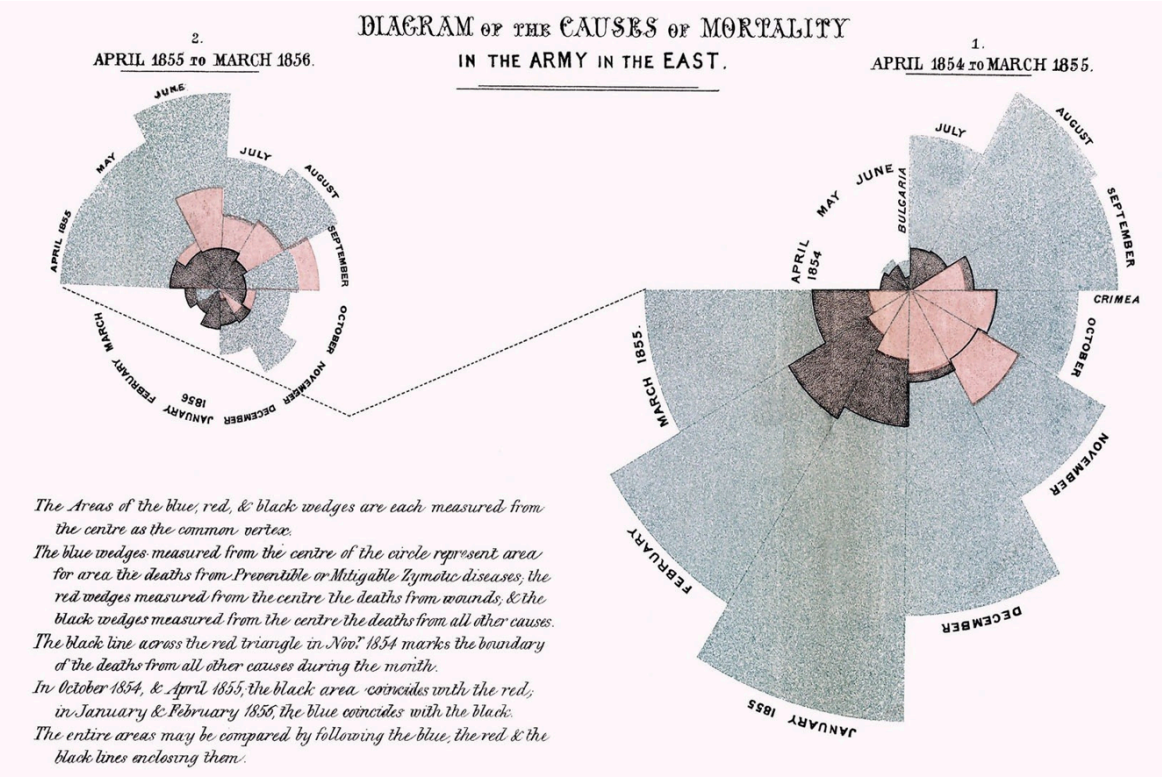
Action → Query

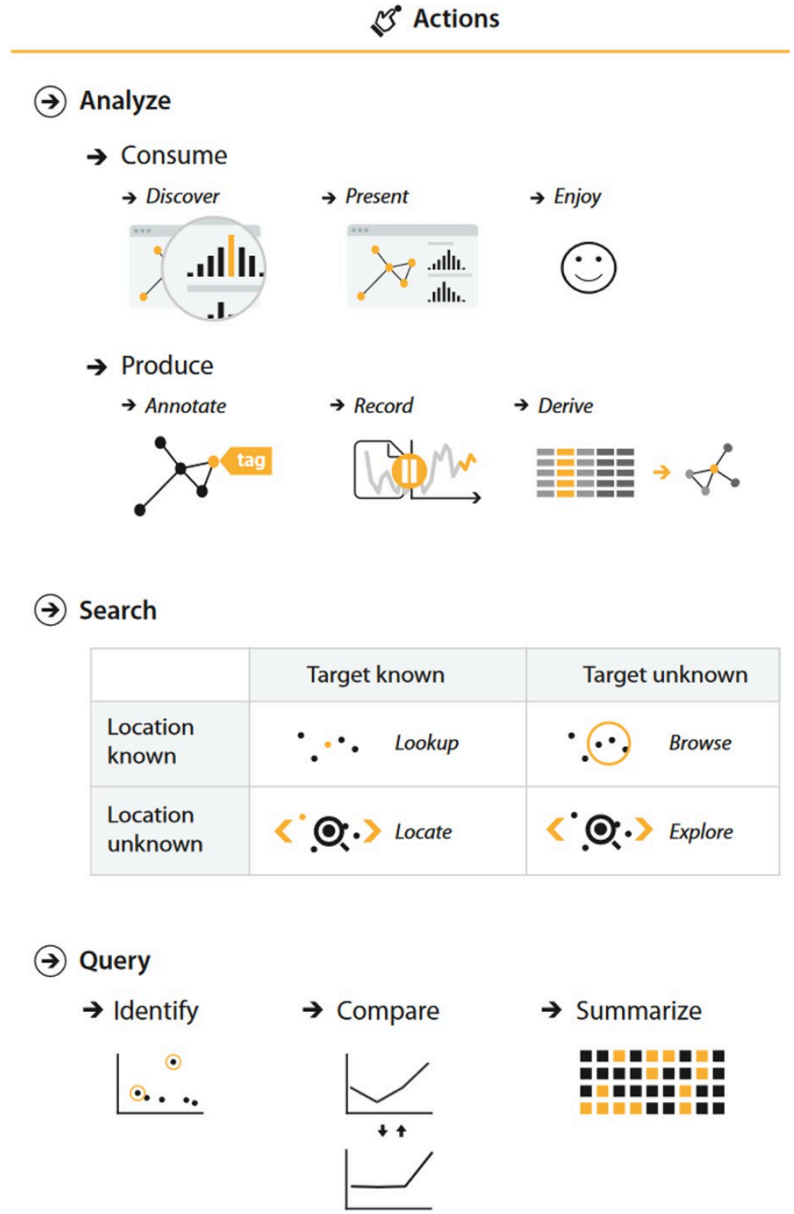
Task → Identify → Compare → Summarize



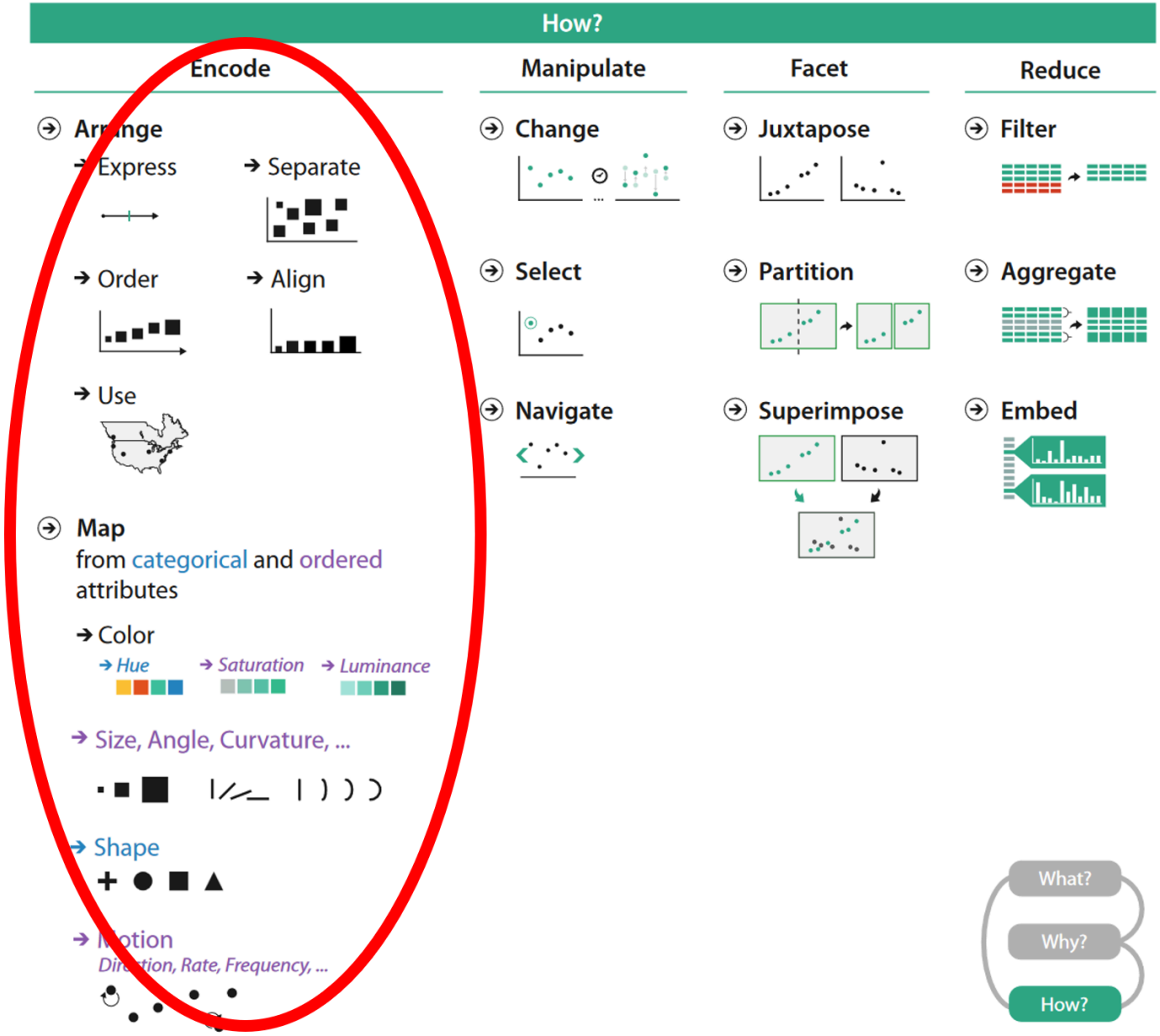
- Targets are “some aspect of the data that is of interest to the user”.
- For some tasks, this is more explicit than with others (but still relevant!).

ACTIVITY: Let's revisit a graph from the previous class...



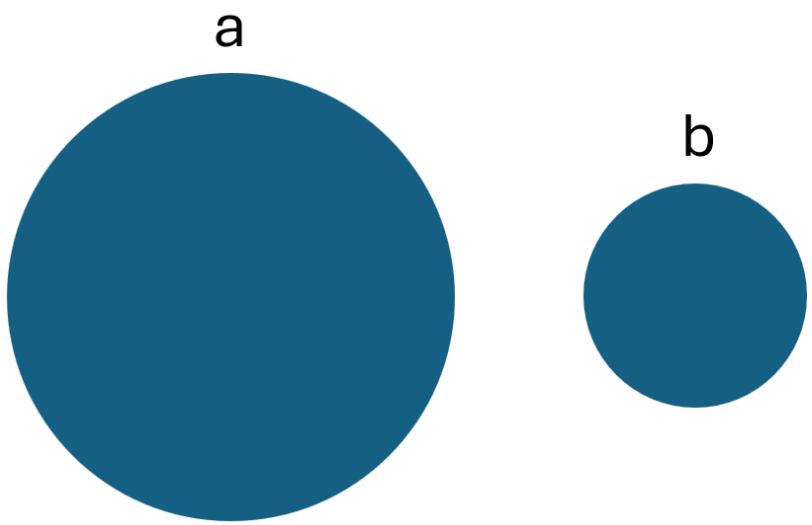


- Last part of the framework is 'how' the visualization is designed
- We will focus on 'encode'



How do we visualize?

Activity: How much bigger is a?



How to visualize: Marks

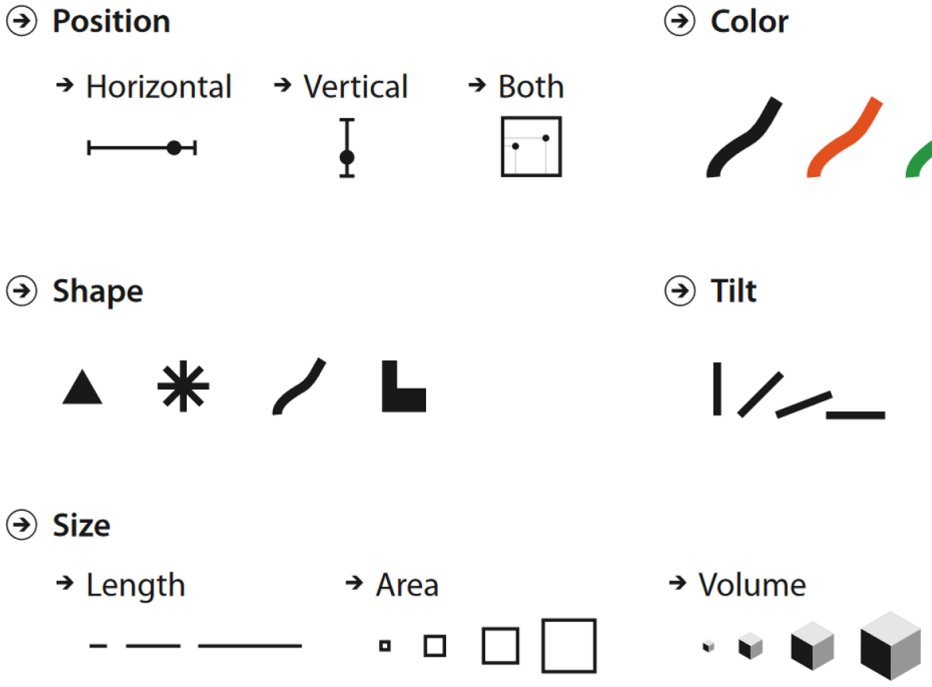
Points

Lines

Areas

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

How to visualize: Channels



CHANNELS: Way to control appearance of marks

How to visualize: Encodings

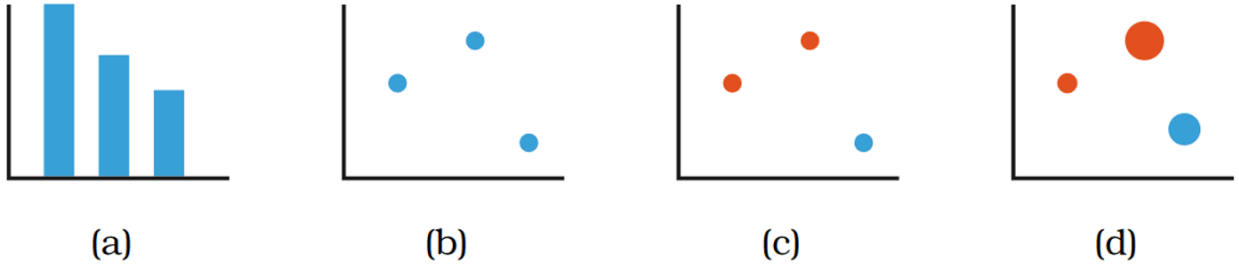
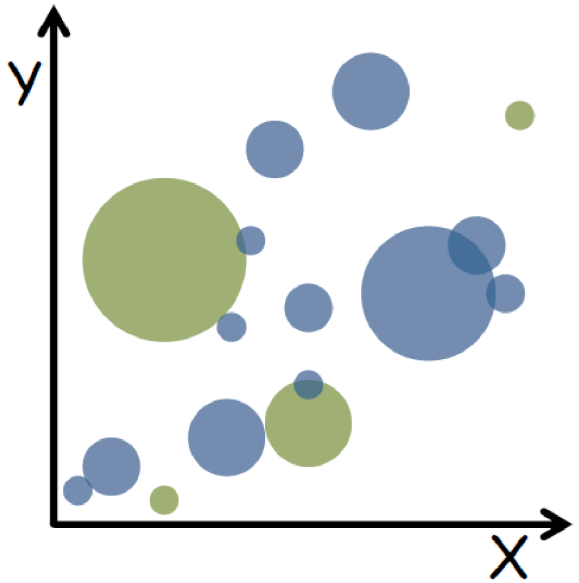


Figure 5.4. Using marks and channels. (a) Bar charts encode two attributes using a line mark with the vertical spatial position channel for the quantitative attribute, and the horizontal spatial position channel for the categorical attribute. (b) Scatterplots encode two quantitative attributes using 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).



Check-in: Marks, Channels, and Encodings

Question 1: What mark(s) are being used?

- a) Points/dots
- b) Lines
- c) Areas
- d) All of the above
- e) None of the above

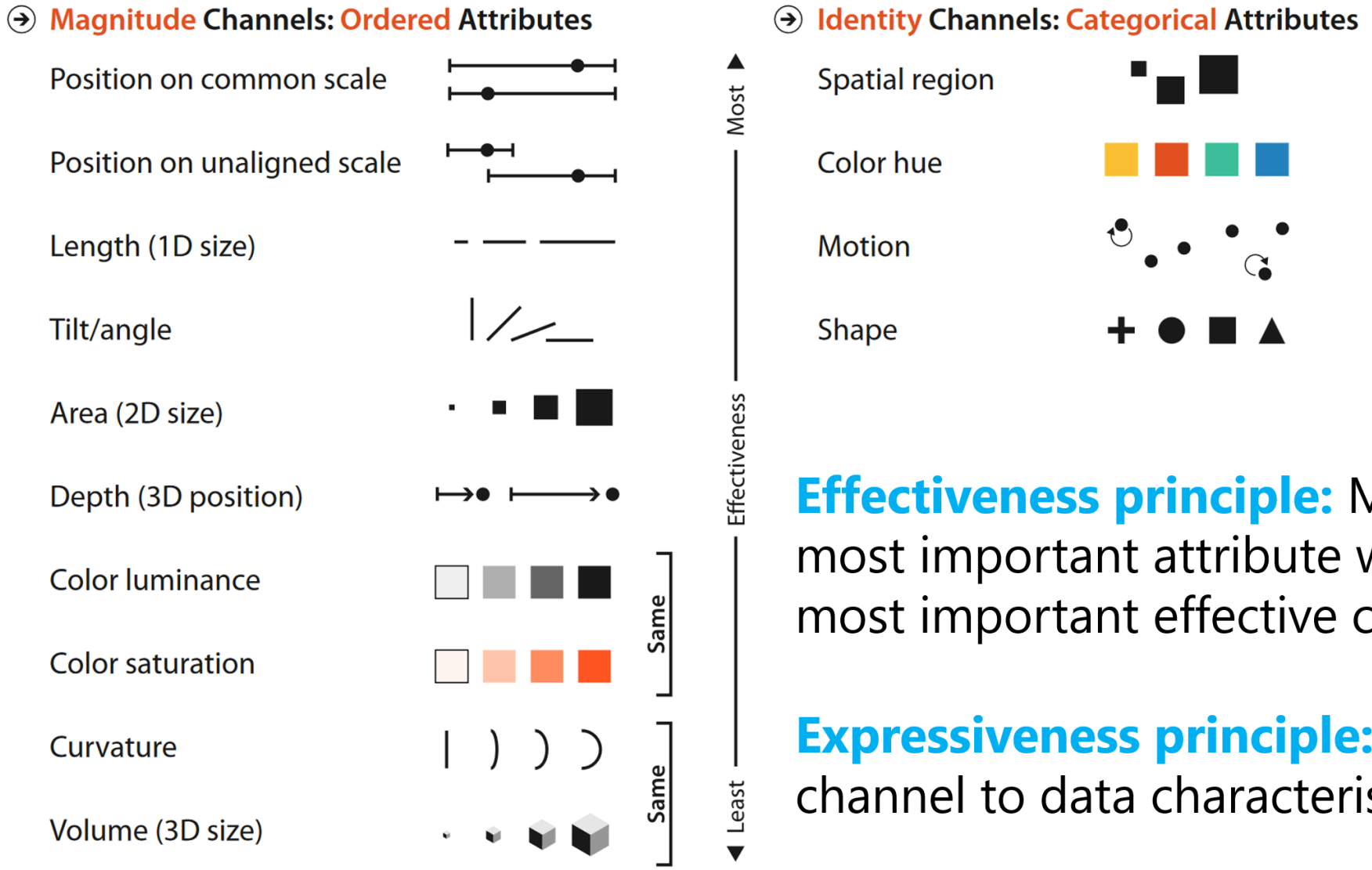
Question 2: What channel(s) are being used?

- a) Horizontal position
- b) Vertical position
- c) Colour
- d) Area
- e) All of the above

Question 3: How many attributes are encoded?

- a) 1
- b) 2
- c) 3
- d) 4
- e) 5

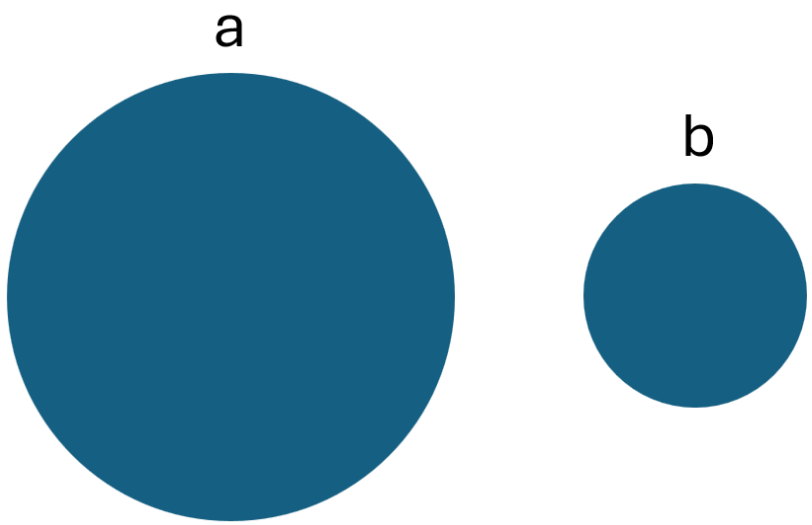
Channels: Expressiveness Types and Effectiveness Ranks



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

Expressiveness principle: Match channel to data characteristics

Remember this activity?

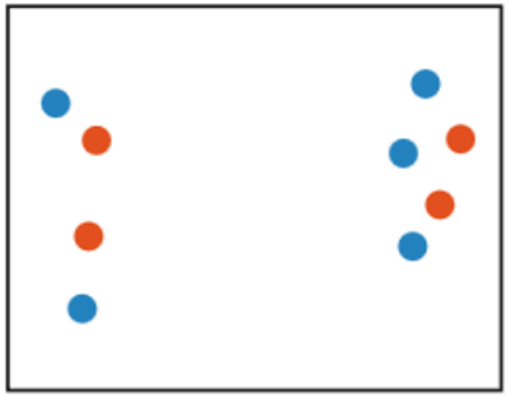


How did the channel effectiveness ranking get established?

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

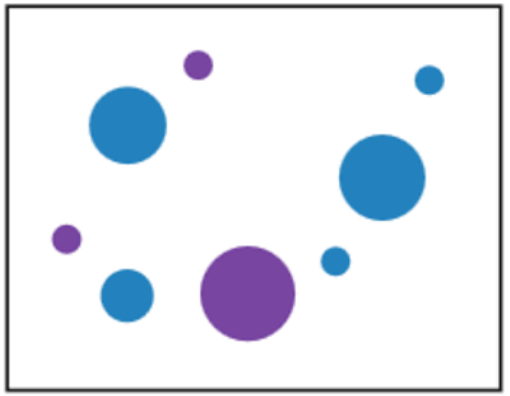
Channels have dependencies & interactions

Position
+ Hue (Color)



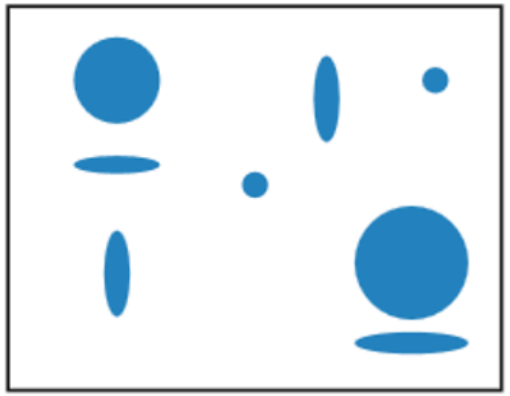
Fully separable

Size
+ Hue (Color)



Some interference

Width
+ Height

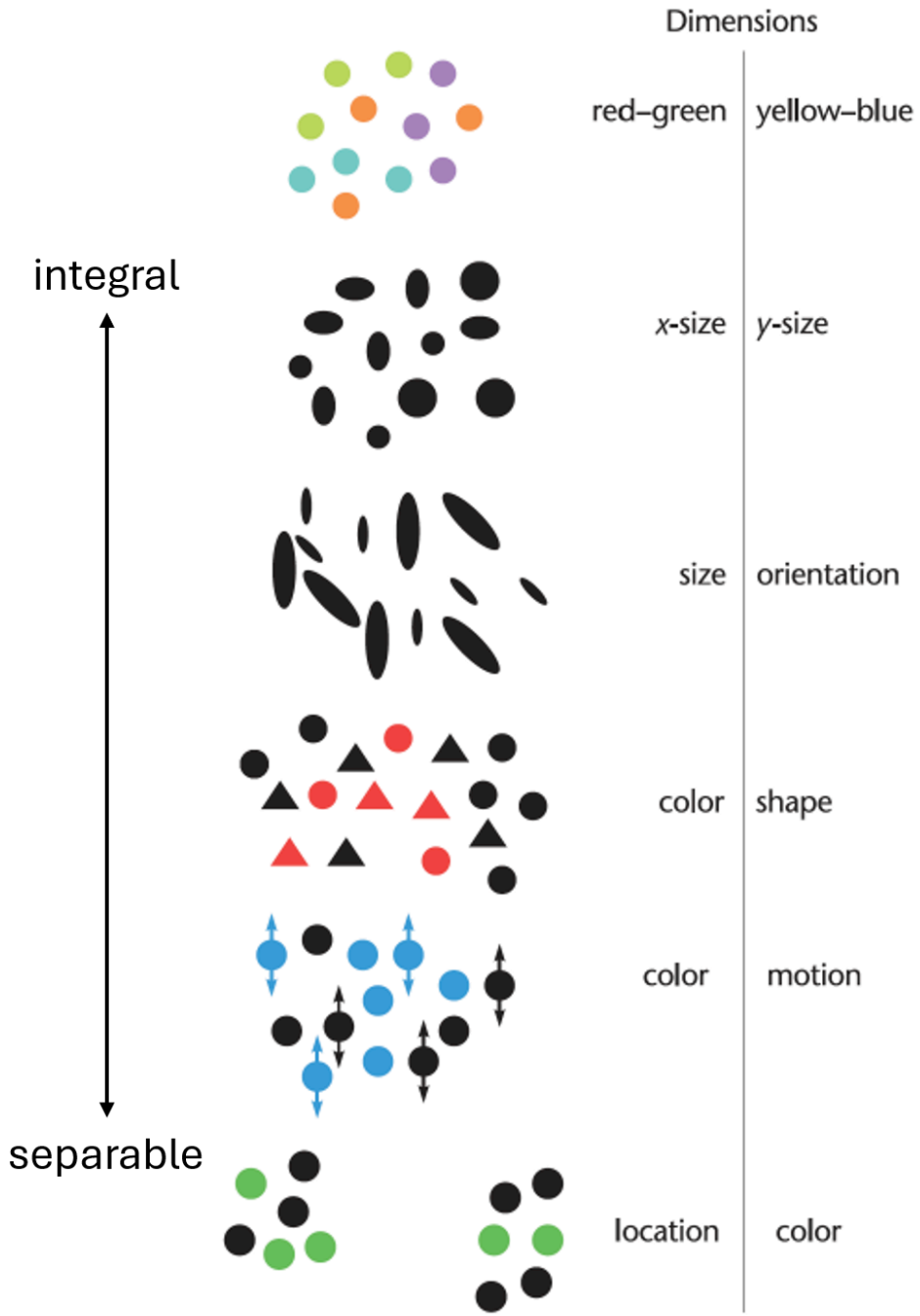


Some/significant interference

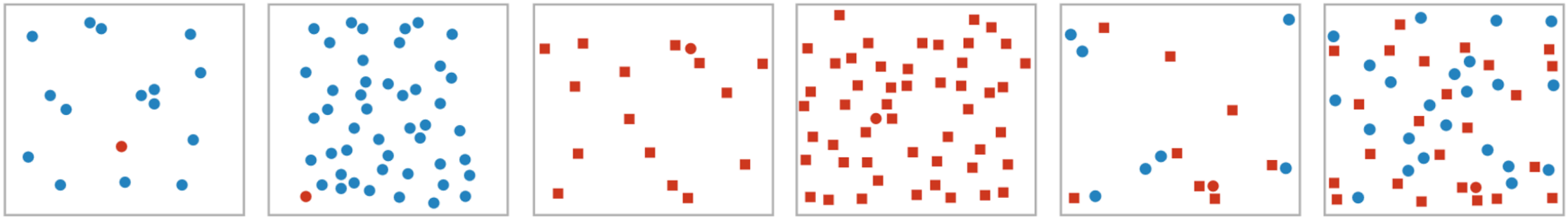
Red
+ Green

Major interference

Channels have dependencies & interactions



Some channels provide visual popout



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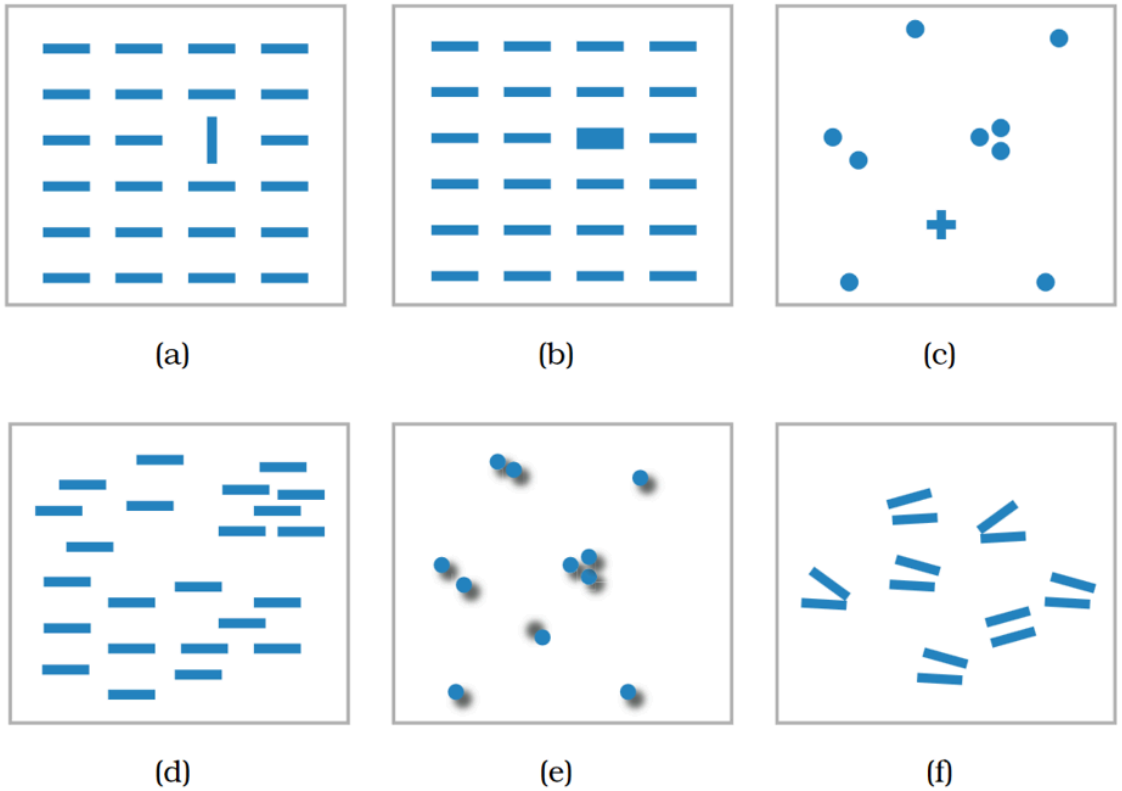
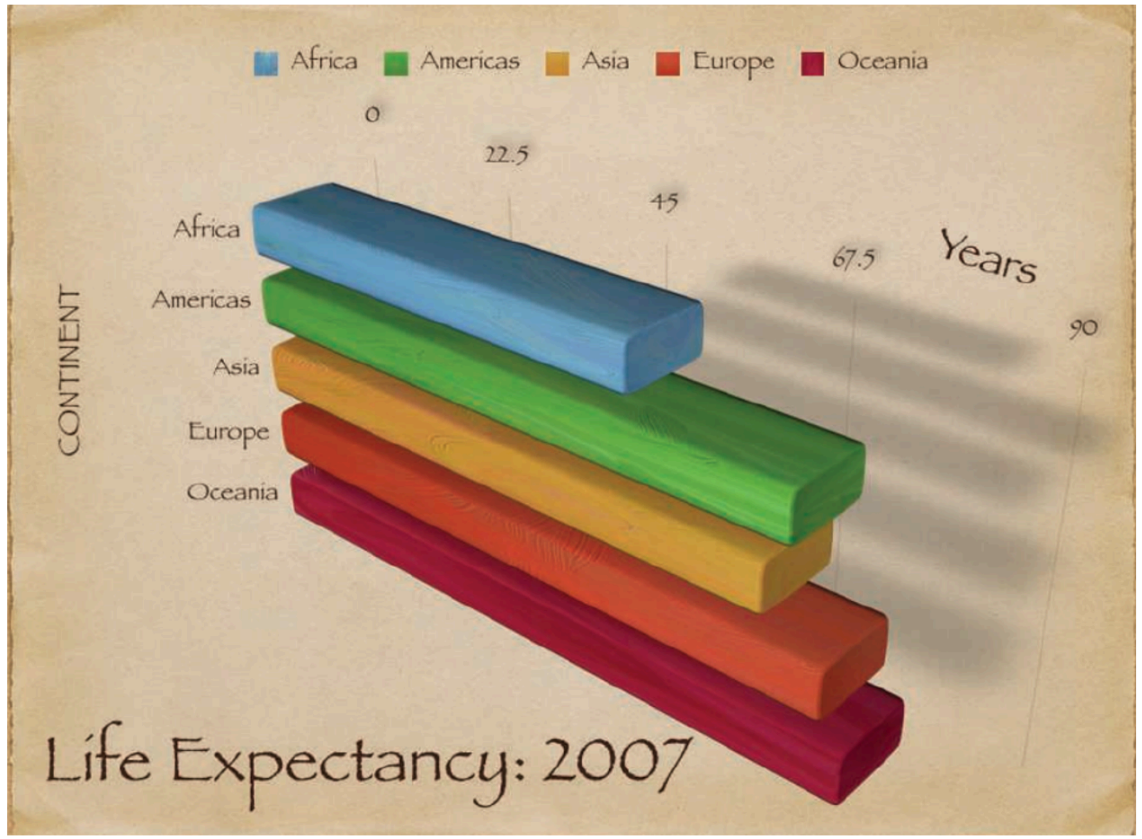


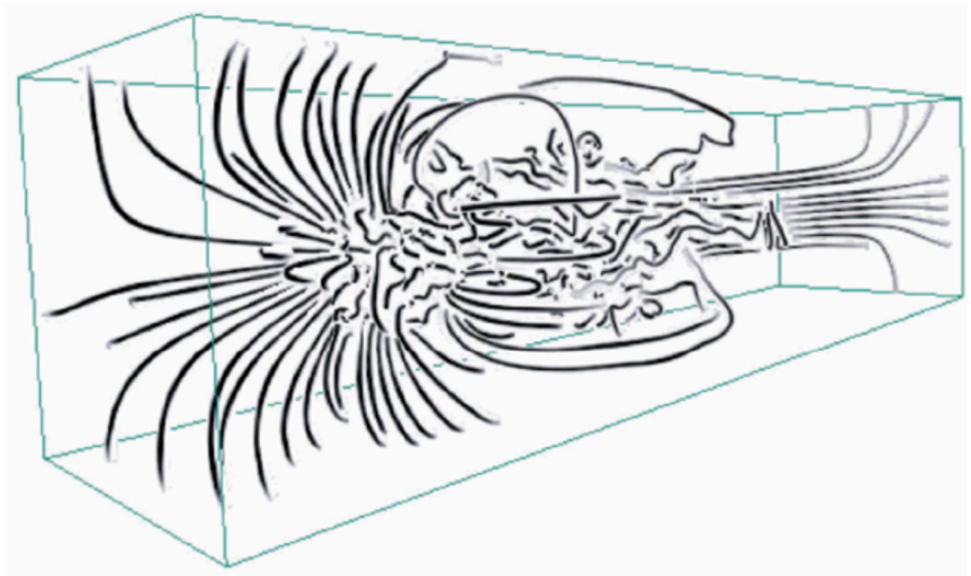
Best Practices

- 3 of 8 shown

No 3D without Cause



vs



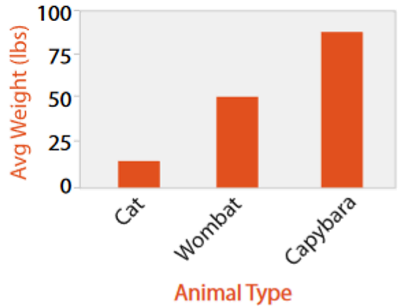
Cognition over Memory

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

Overview then zoom then details

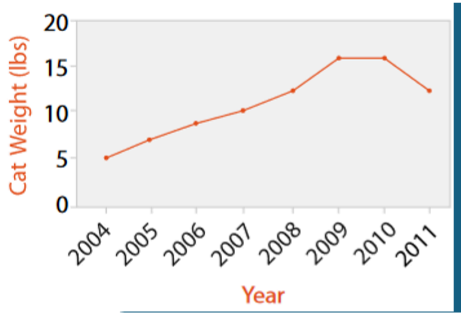
- **Overview:** see overall patterns, trends
- **Zoom:** see a smaller subset of the data
- **Filter:** see a subset based on values, etc.
- **Details on demand:** see values of objects when interactively selected

Visualization Idioms



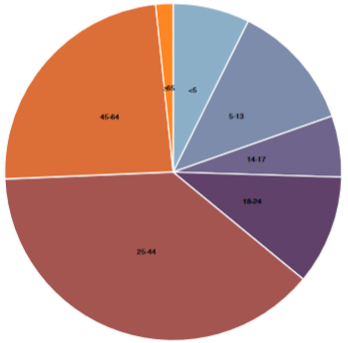
Bar Chart

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



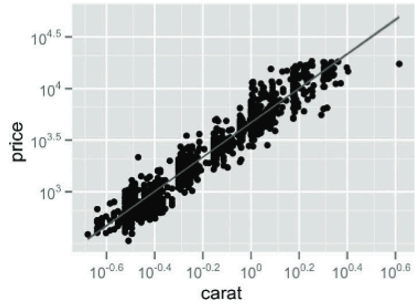
Line Graph

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



Pie Chart

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



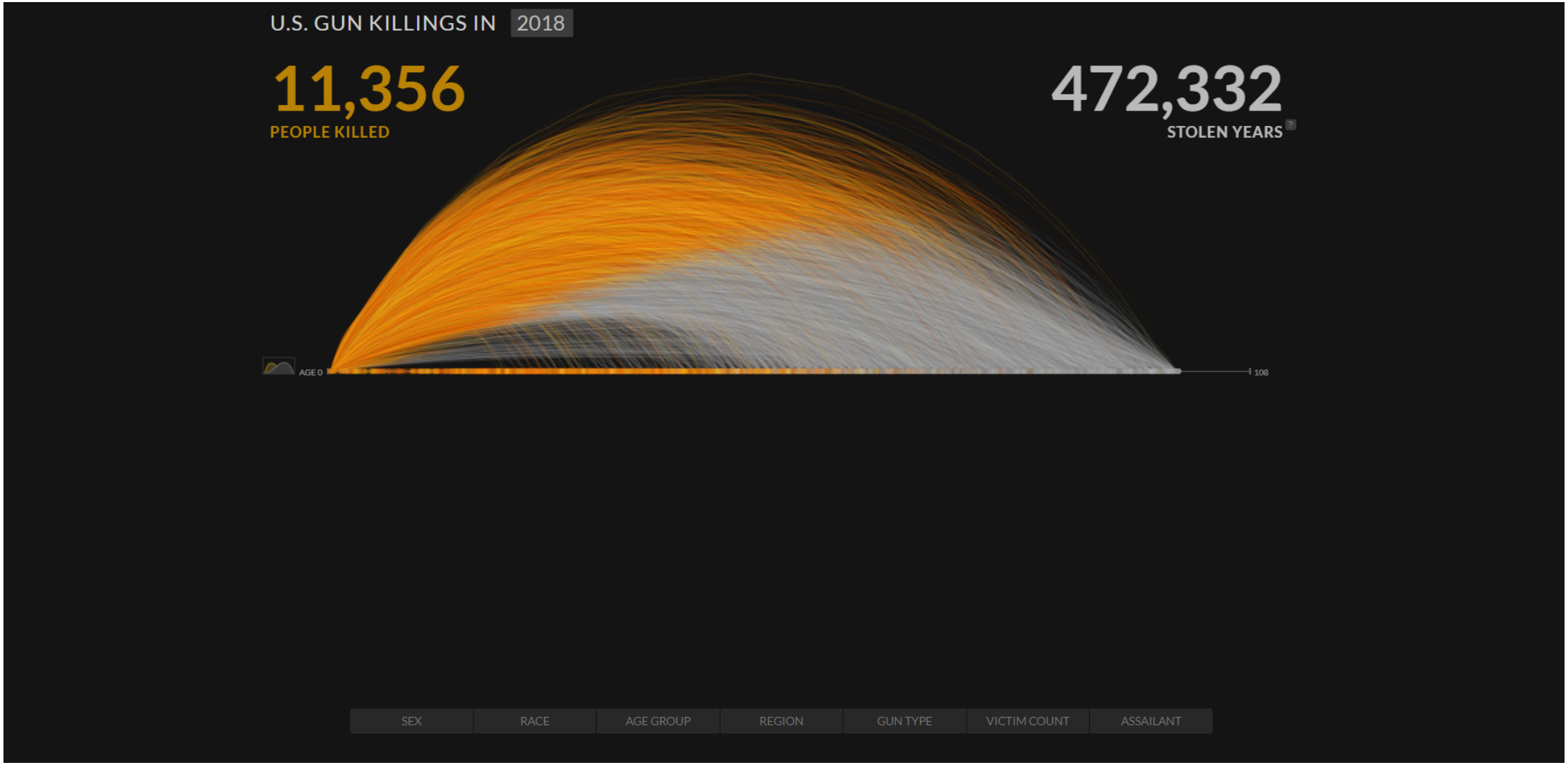
Scatterplot

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

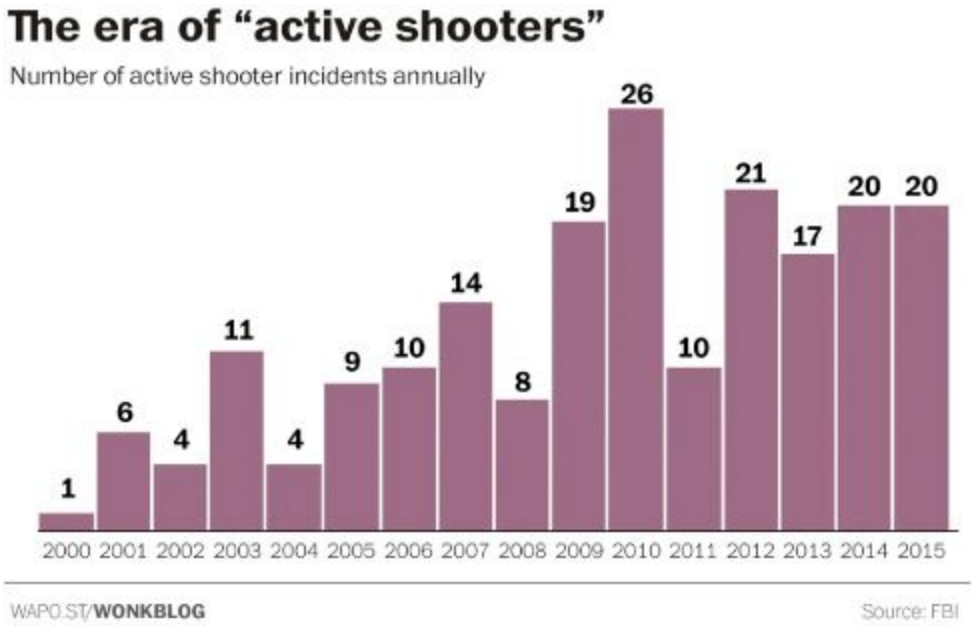
Activity

- 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?

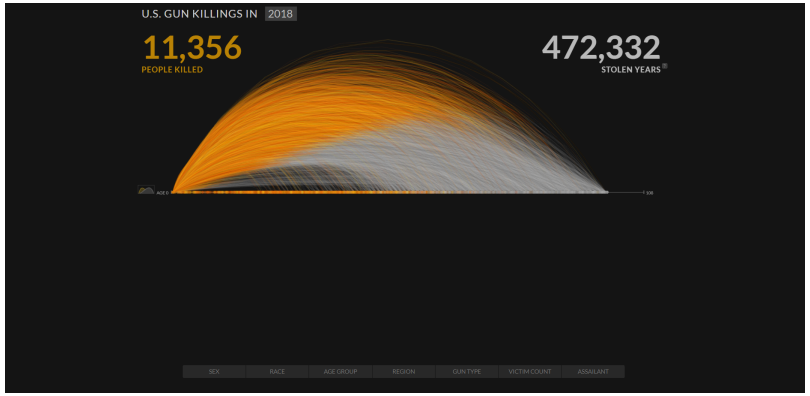
Visualization #1: US Gun Killings in 2018



Visualization #2: Washington Post Active Shooters

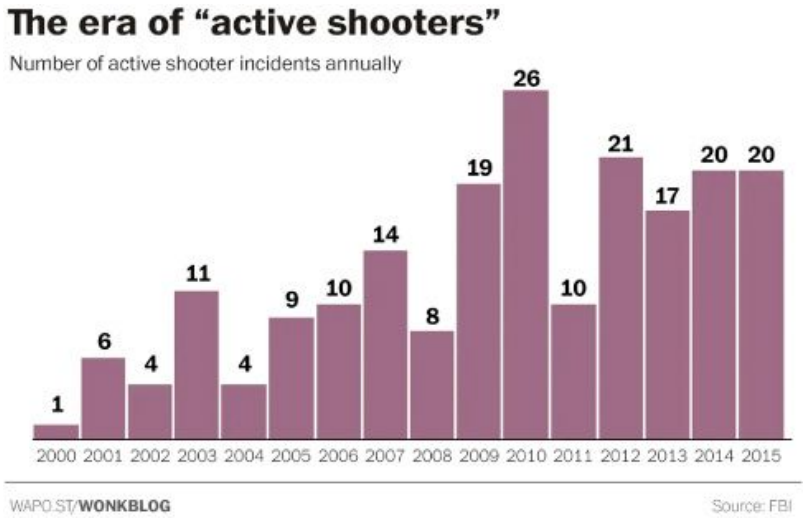


Visualization #1: US Gun Killings in 2018



- 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

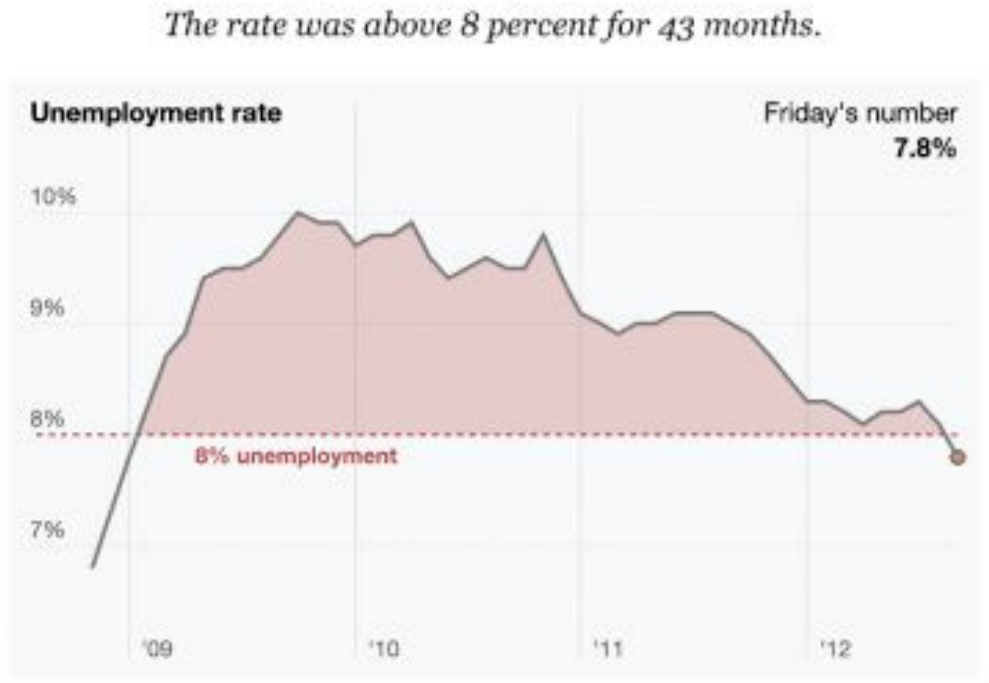


- The next visualization shows a related dataset (about gun violence in the United States)
- Viewers will likely reach a similar conclusion as in Visualization #1, but this plot is intended to present "a deliberately neutral emotional field, a blank page in effect, upon which viewers are more free to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

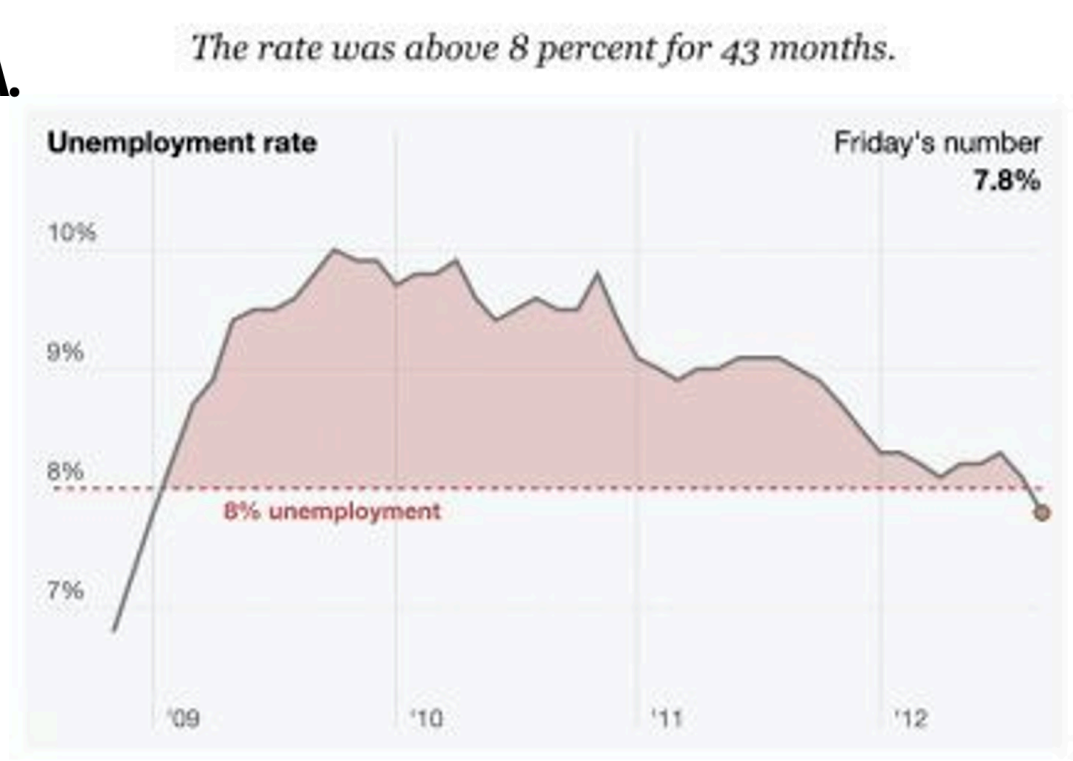
- Some of the same design elements from our ‘blank page’ Visualization #2 can be seen in this New York Times visualization of the September 2012 Jobs Report
- The clean, 2D layout is designed to avoid conveying an emotional narrative to the audience



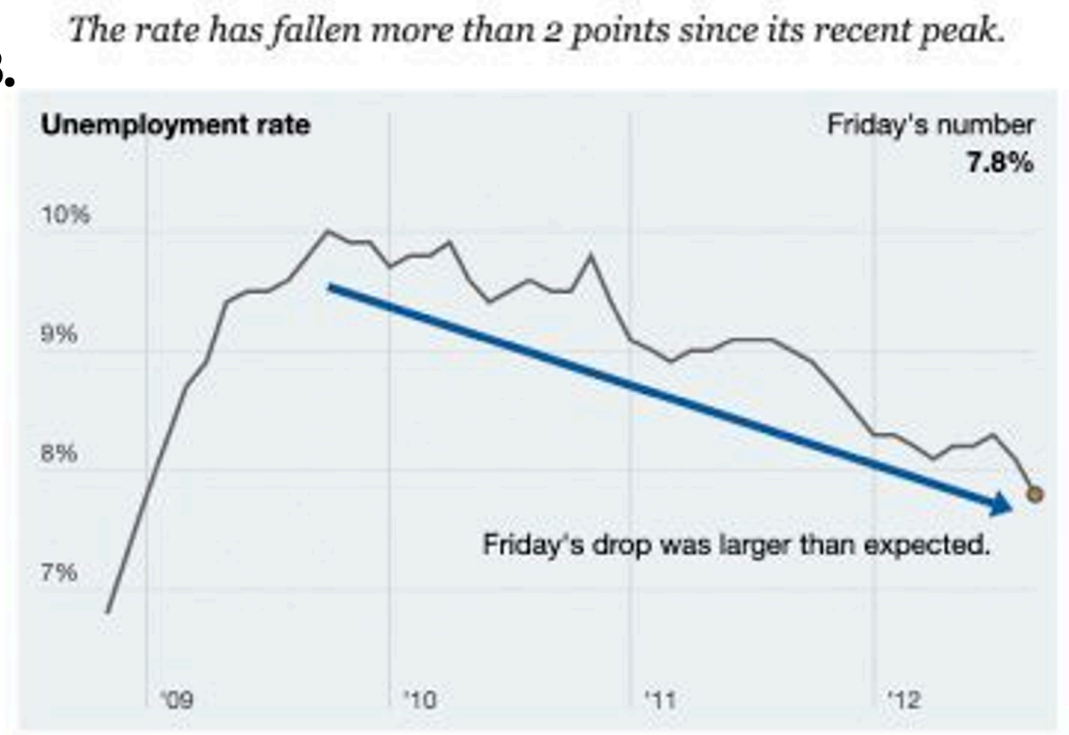
A blank page… right?

- The Jobs Report graphic was published alongside another image:

A.



B.

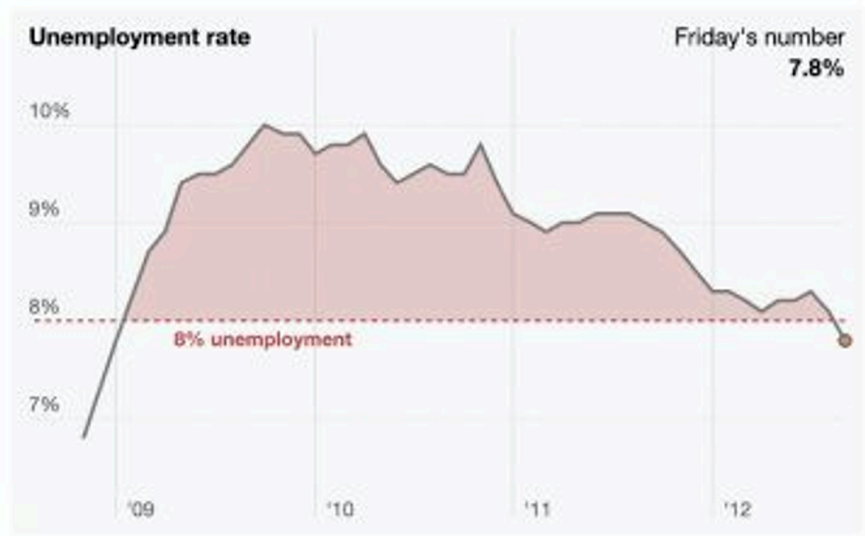


A blank page

- 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!**

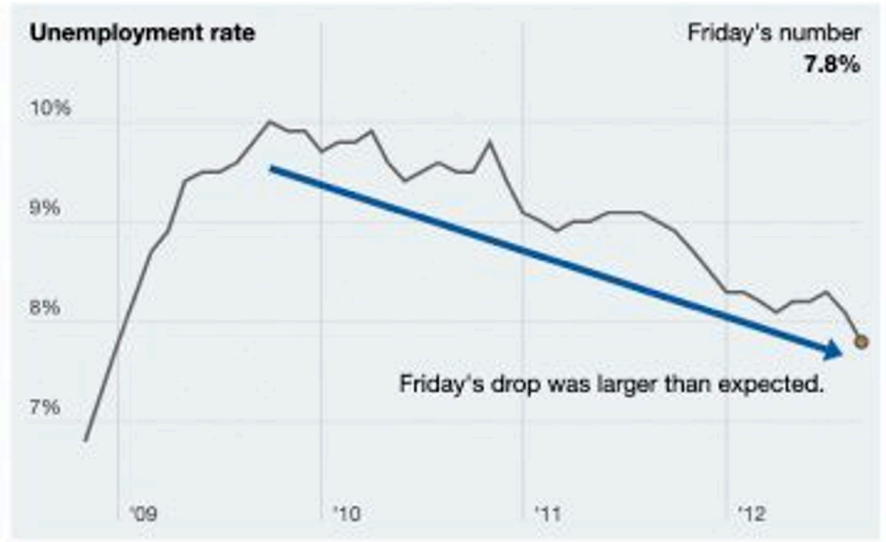
The rate was above 8 percent for 43 months.

A.



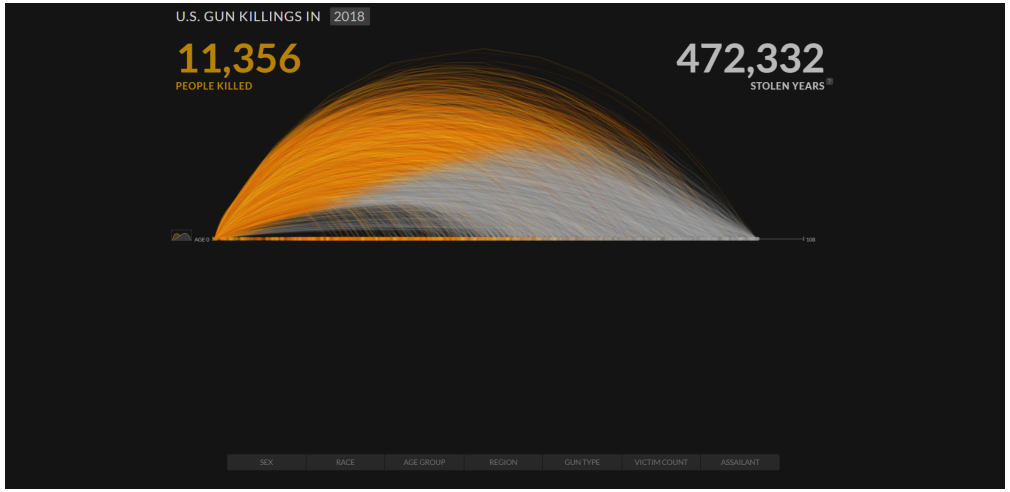
The rate has fallen more than 2 points since its recent peak.

B.



Supporting a cause

- Periscopic'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

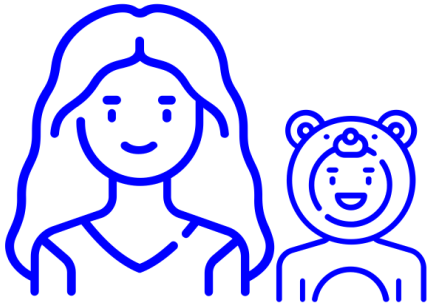
Persuading

Comparison

Evaluating

Exploring

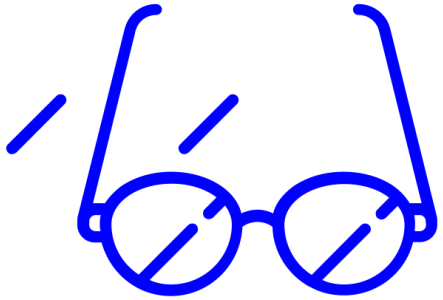
Intended audience



Age

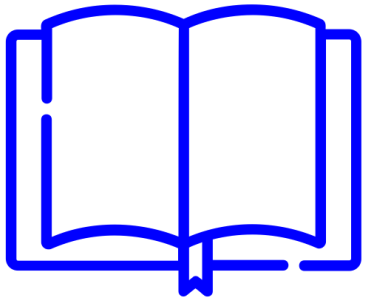
Education

Expertise



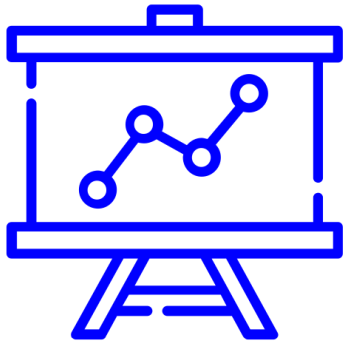
Accessibility

Intended medium



Print

Web

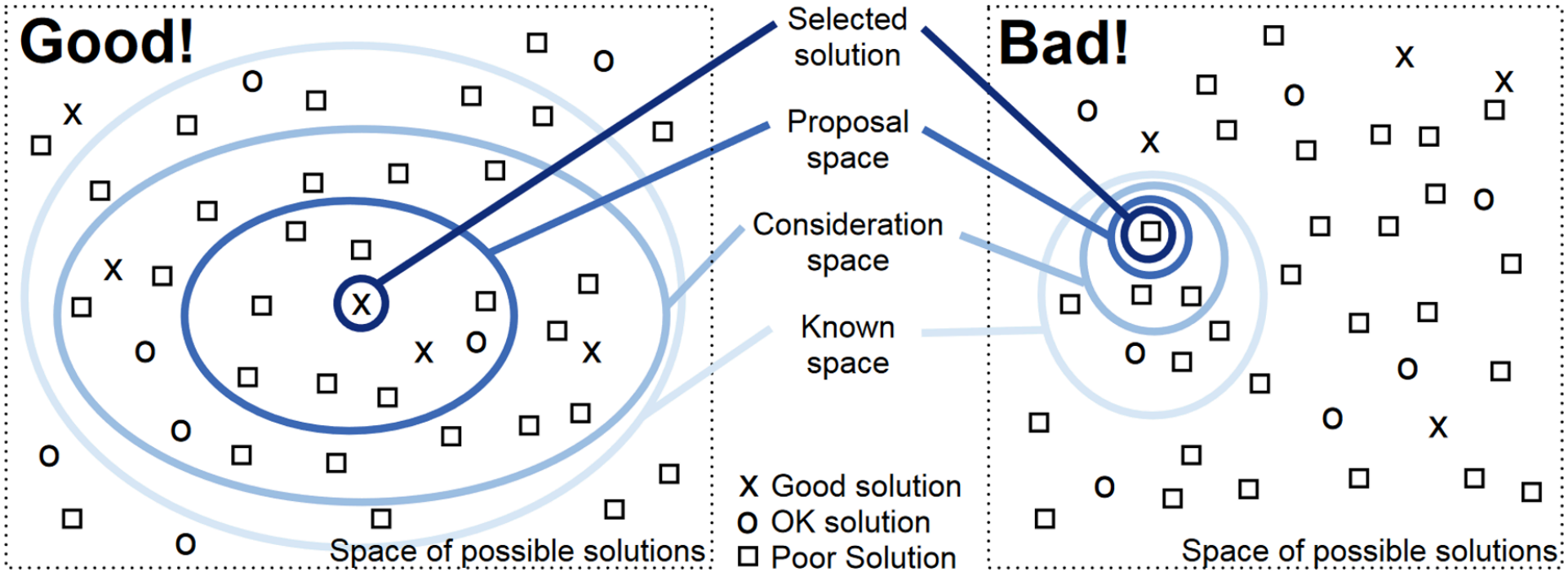


Poster

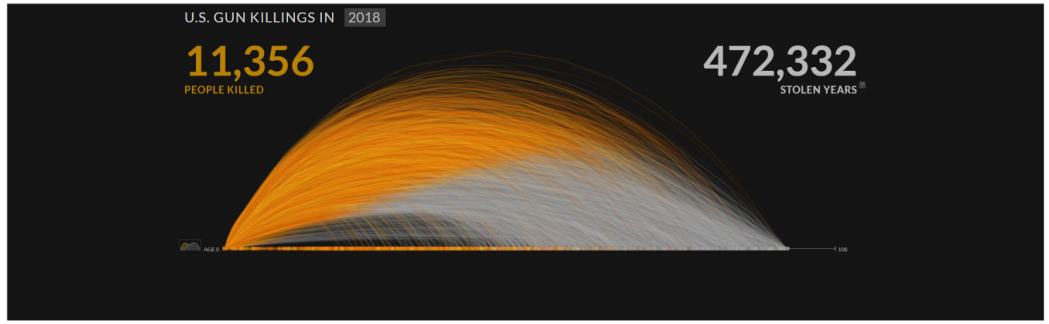
Presentation

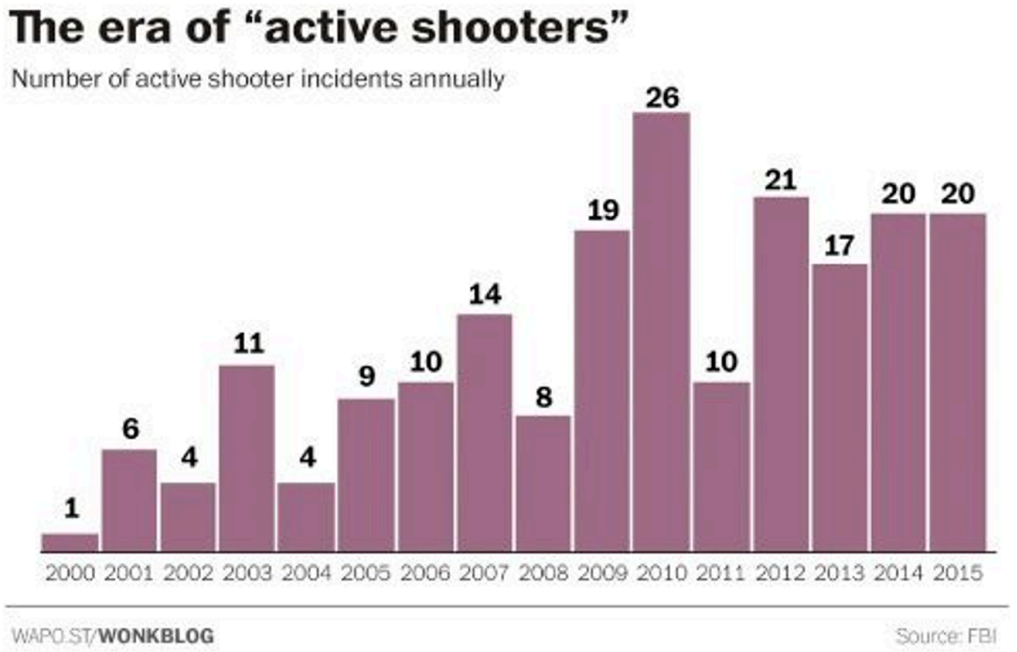
Effective Visualization

- 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





How is our data visualization perceived?

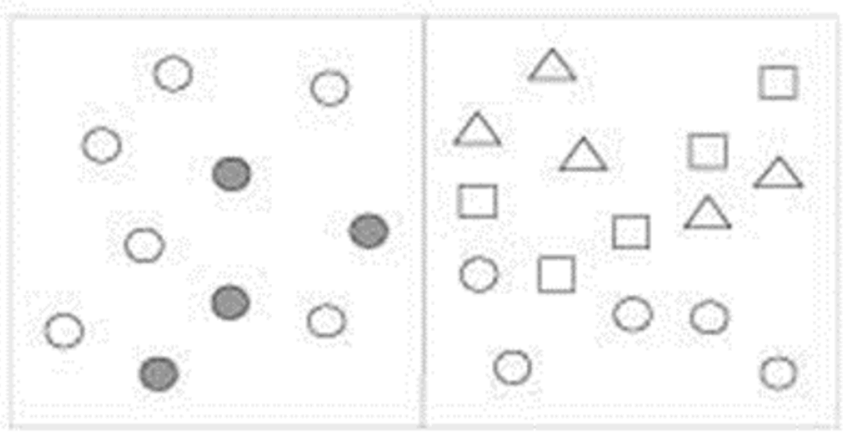
Taking advantage of cognitive psychology

- 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

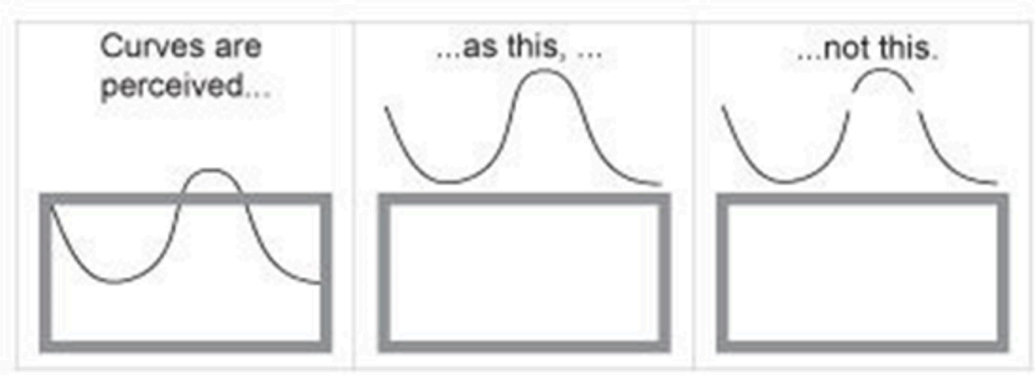
Objects that are close together are perceived as belonging to a group



Similarity

Similar objects are grouped, regardless of proximity

Gestalt principles



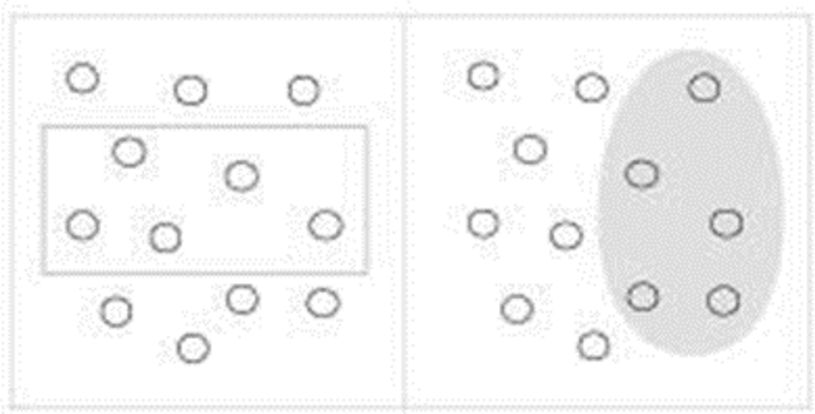
Continuity

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

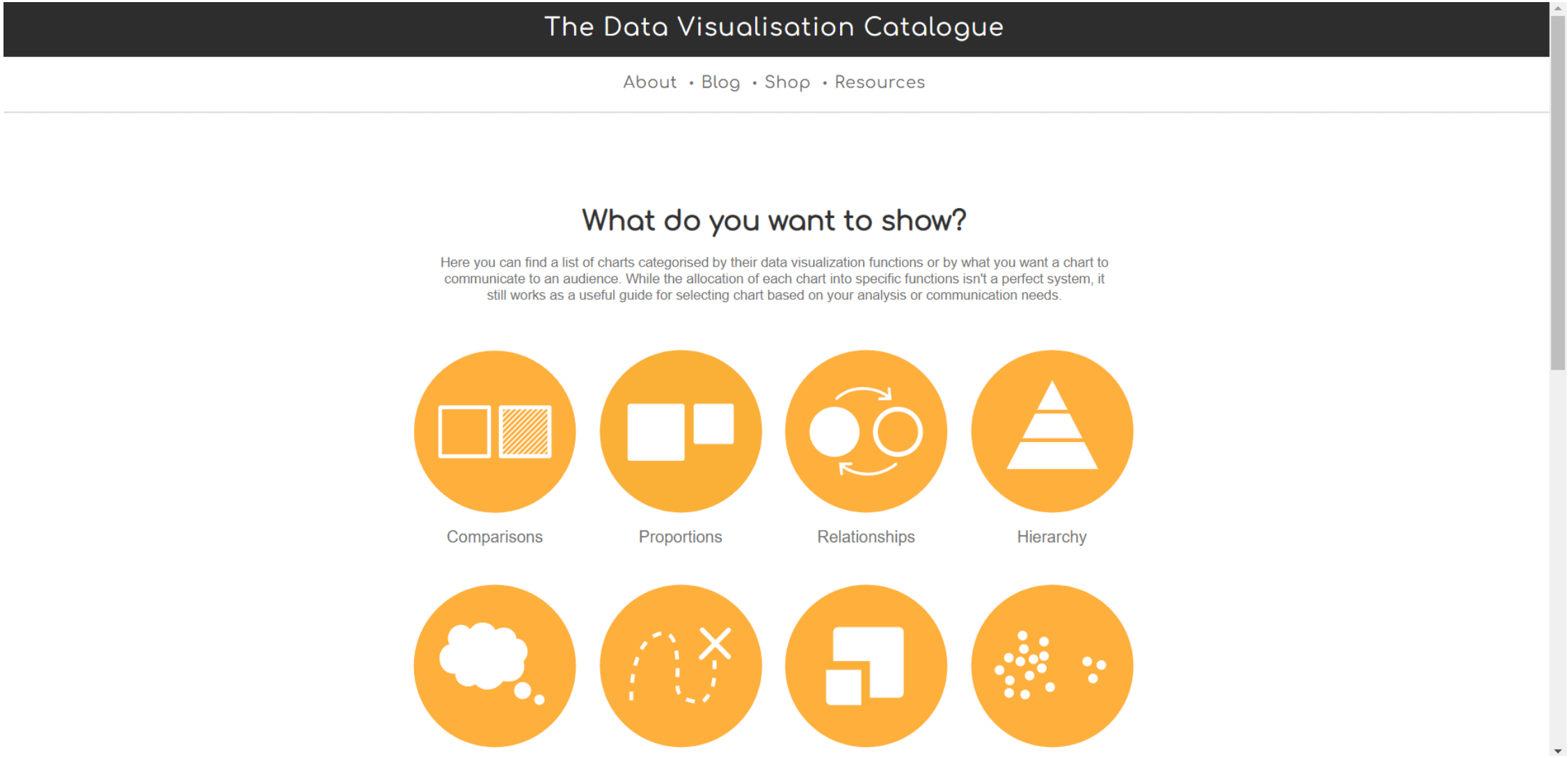
- Citing the source(s) of our data is not only best practice (reproducibility!), but also helps people to trust our data visualizations more
- **Provenance rhetoric** is the idea that the inclusion of a data source with our graphic signals "transparency and trustworthiness" to the audience
- This increases 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

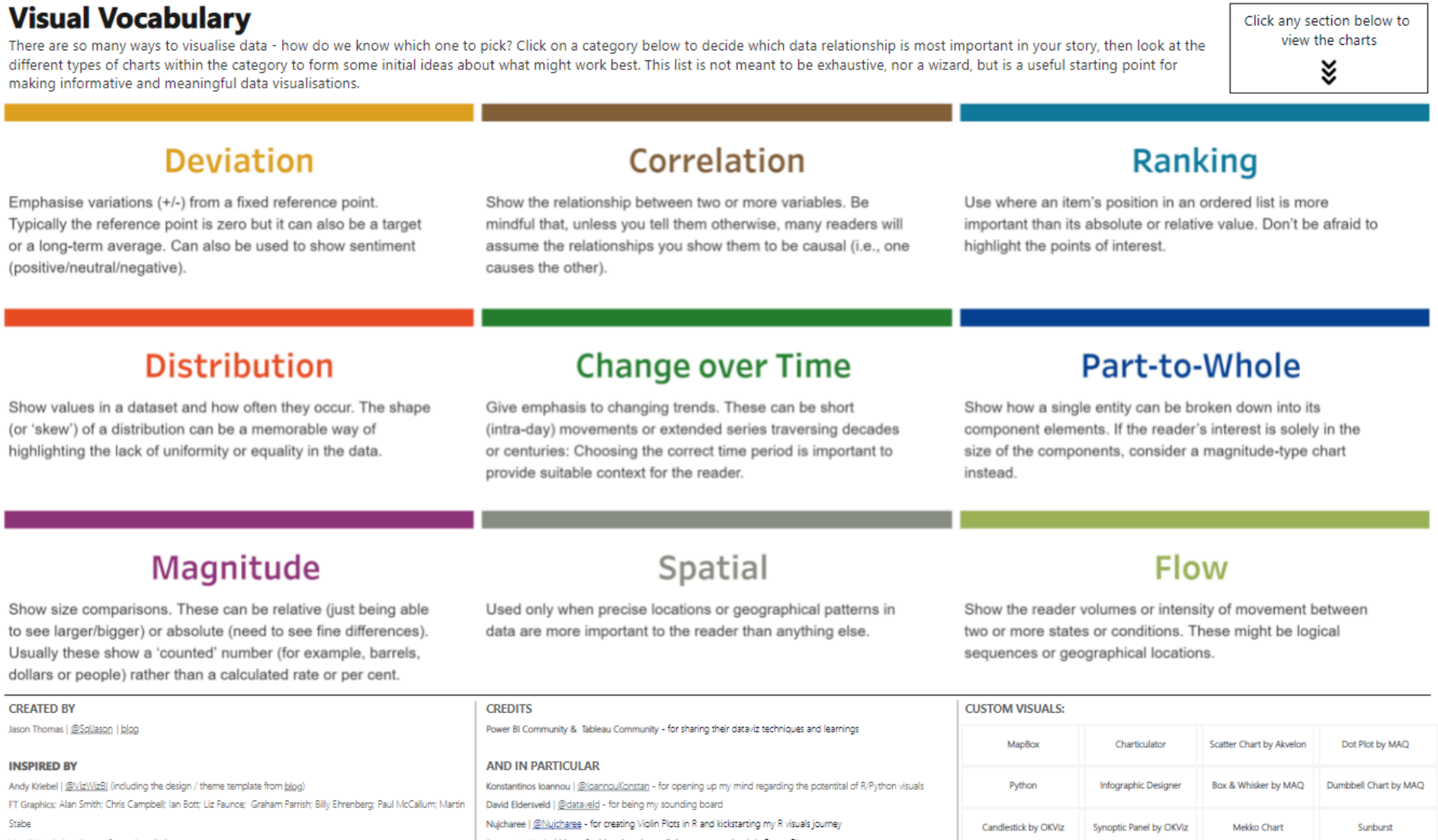


Financial Times Visual Vocabulary

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



Assignment 2

Feedback!

Next session, we'll discuss:

- What is reproducible data visualization?
- How can we incorporate ideas about reproducibility into our data visualization practices? (Ethics)
- More matplotlib!