Lecture 12: Visualization for Communication

DS4200 Spring 2023

Prof. Ab Mosca (they/them)

Today

- Visualization for communication
- Intro to Visualization Research

What is visualization for communication?

Visualization

Visualization (in CS)

Visualization (in CS)

Data Analysis Pipeline

Visualization (in CS)

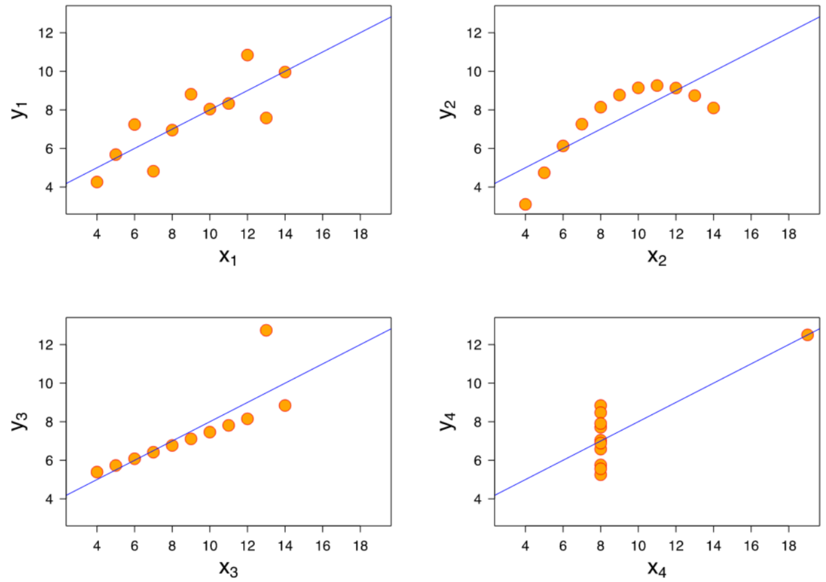
Data Analysis Pipeline -- Validation

Visualization (in CS)

Data Analysis Pipeline -- Validation

Anscombe's Data								
Observation	x1	y1	x2	y2	x3	y3	x4	y4
1	10	8.04	10	9.14	10	7.46	8	6.58
2	8	6.95	8	8.14	8	6.77	8	5.76
3	13	7.58	13	8.74	13	12.74	8	7.71
4	9	8.81	9	8.77	9	7.11	8	8.84
5	11	8.33	11	9.26	11	7.81	8	8.47
6	14	9.96	14	8.1	14	8.84	8	7.04
7	6	7.24	6	6.13	6	6.08	8	5.25
8	4	4.26	4	3.1	4	5.39	19	12.5
9	12	10.84	12	9.13	12	8.15	8	5.56
10	7	4.82	7	7.26	7	6.42	8	7.91
11	5	5.68	5	4.74	5	5.73	8	6.89
				Summary Statistics				
N	11	11	11	11	11	11	11	11
mean	9.00	7.50	9.00	7.500909	9.00	7.50	9.00	7.50
SD	3.16	1.94	3.16	1.94	3.16	1.94	3.16	1.94
r	0.82		0.82		0.82		0.82	

https://towardsdatascience.com/importance-of-data-visualization-anscombes-quartet-way-a325148b9fd2



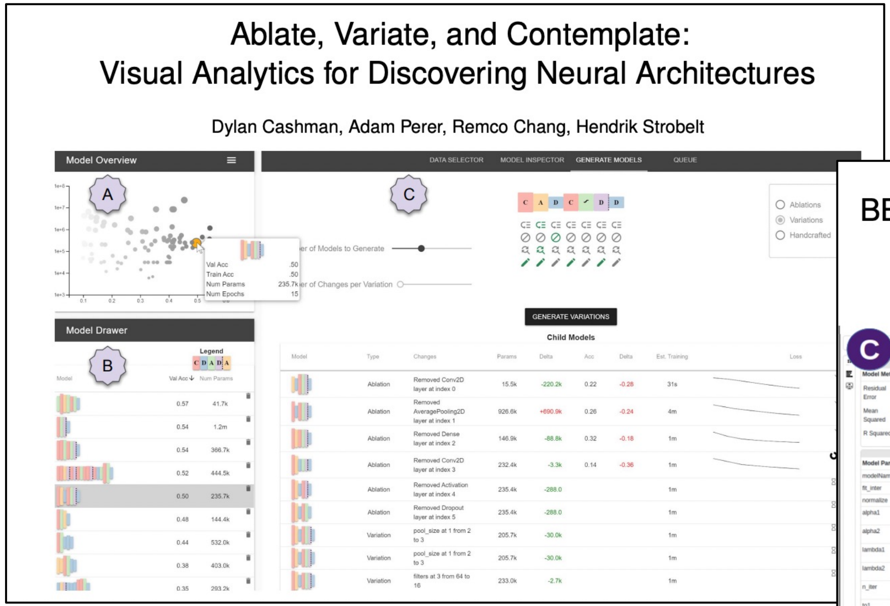
https://heap.io/blog/data-stories/anscombes-quartet-and-why-summary-statistics-dont-tell-the-whole-story

Visualization (in CS)

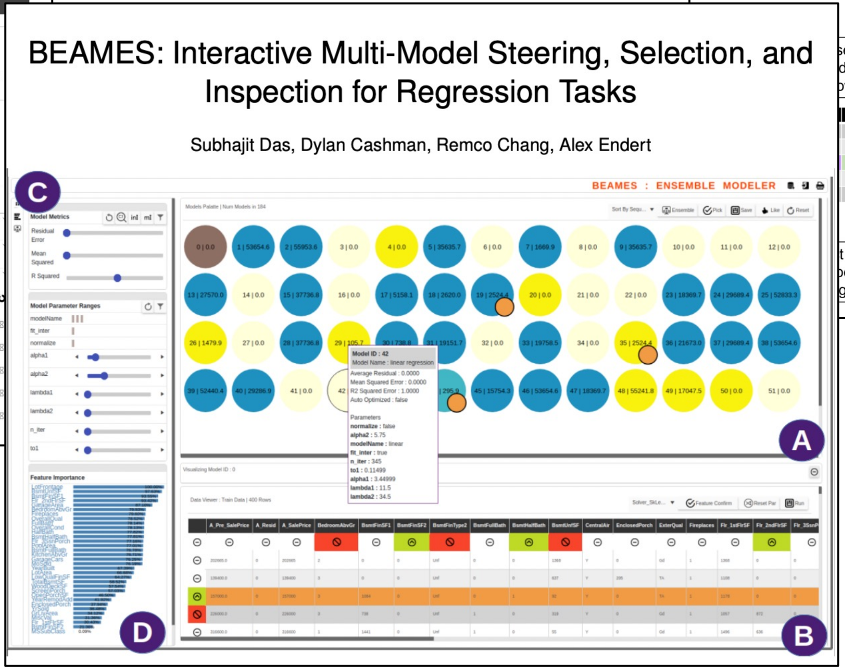
$\boxed{\text{Data Analysis Pipeline}}$ -- Modeling

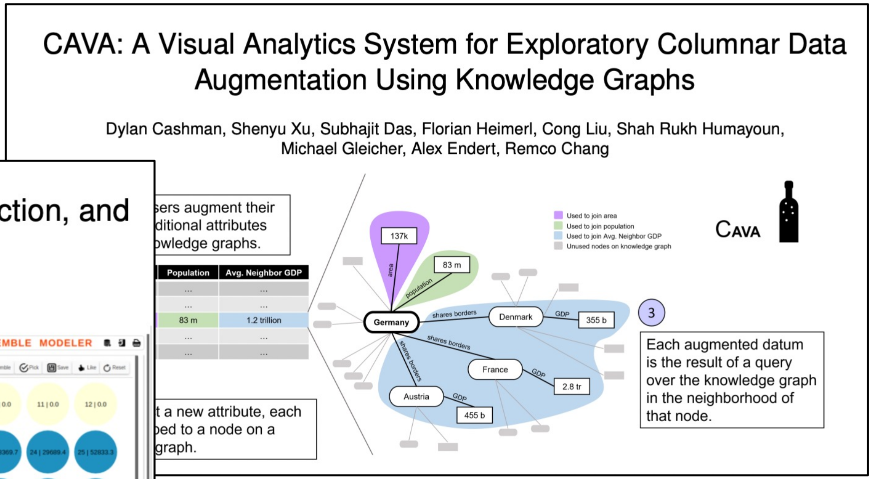
Visualization (in CS)

Data Analysis Pipeline -- Modeling



https://dylancashman.github.io/public/docs/remap.pdf





https://dylancashman.github.io/public/docs/cava.pdf

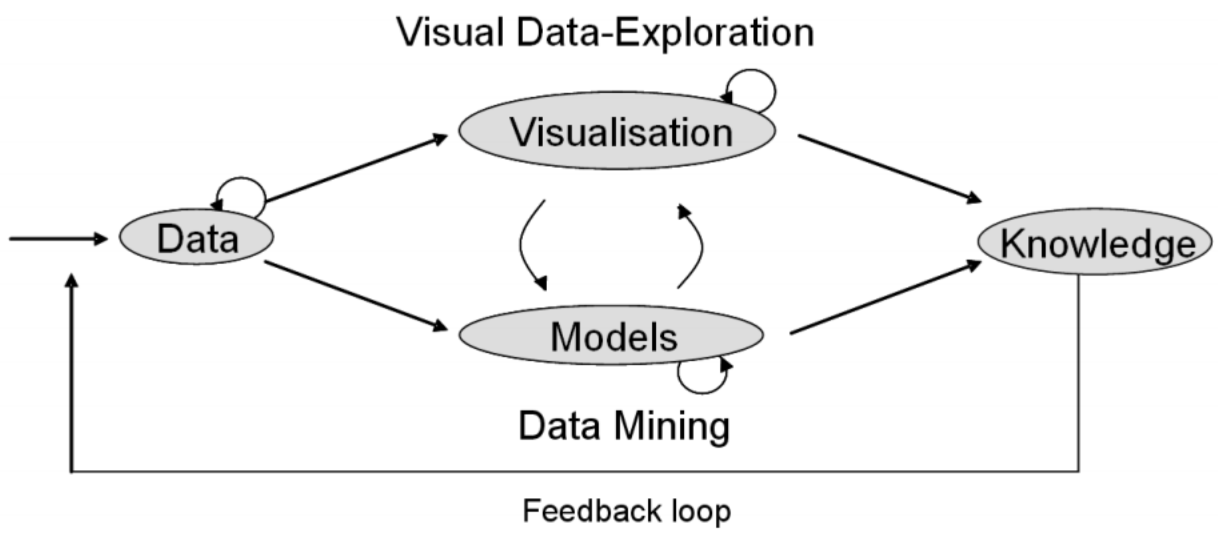
https://dylancashman.github.io/public/docs/das_vds_2018_gaggle.pdf

Visualization (in CS)

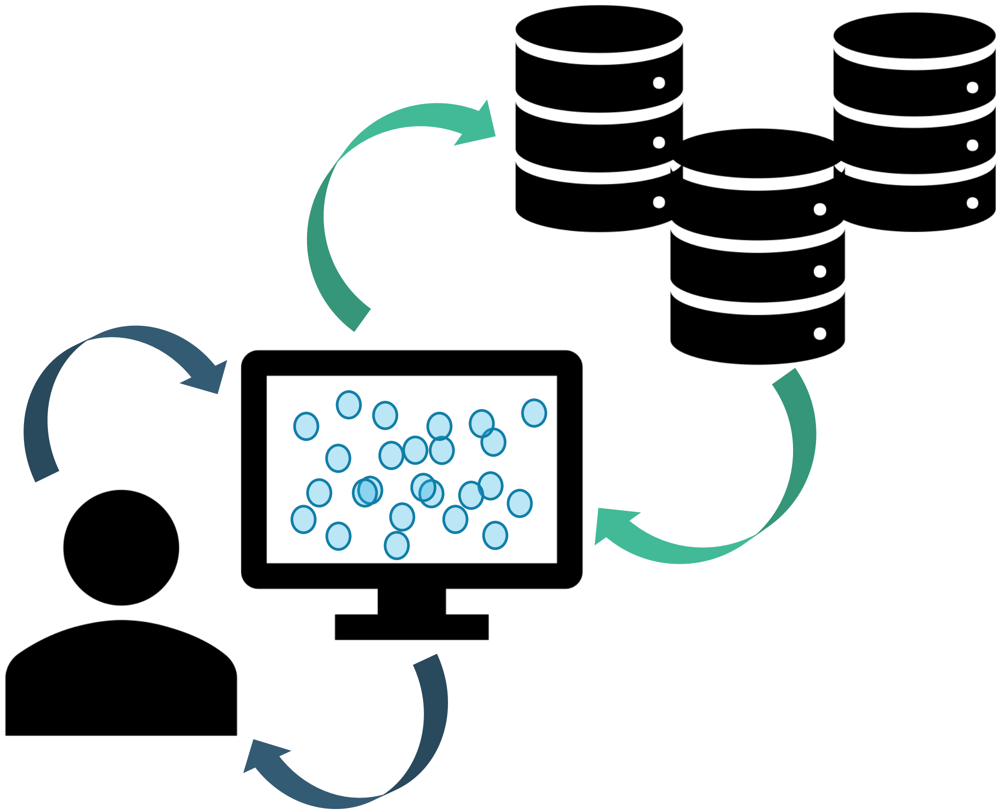
Data Analysis Pipeline -- Exploratory Data Analysis

Visualization (in CS)

Data Analysis Pipeline -- Exploratory Data Analysis



Keim et al.. Visual Analytics: Definition, Process and Challenges (2008).



Visualization (in CS)

Medium of Communication

As an alternative to written communication or numerical communication

Visualization (in CS)

Medium of Communication

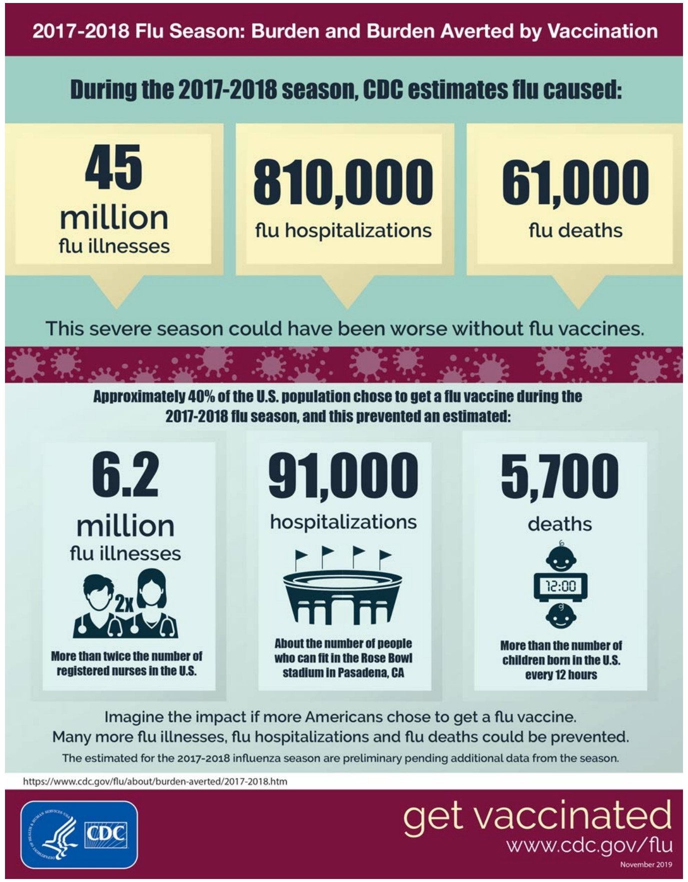
Examples?

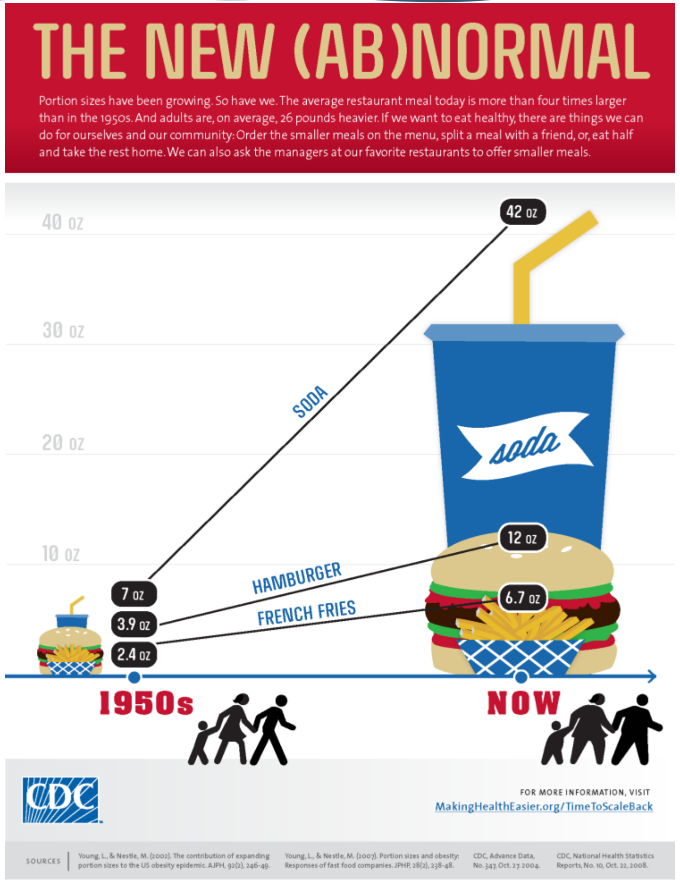
Visualization (in CS)

$\boxed{\text{Medium of Communication}}$ -- Public Health

Visualization (in CS)

Medium of Communication -- Public Health





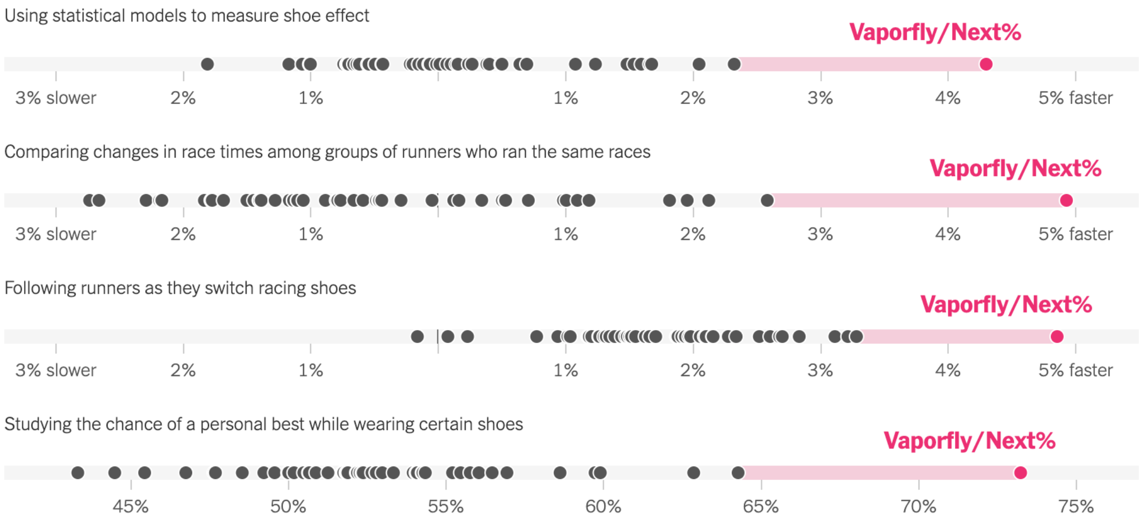
Visualization (in CS)

$\boxed{\text{Medium of Communication}}$ -- News reporting

Visualization (in CS)

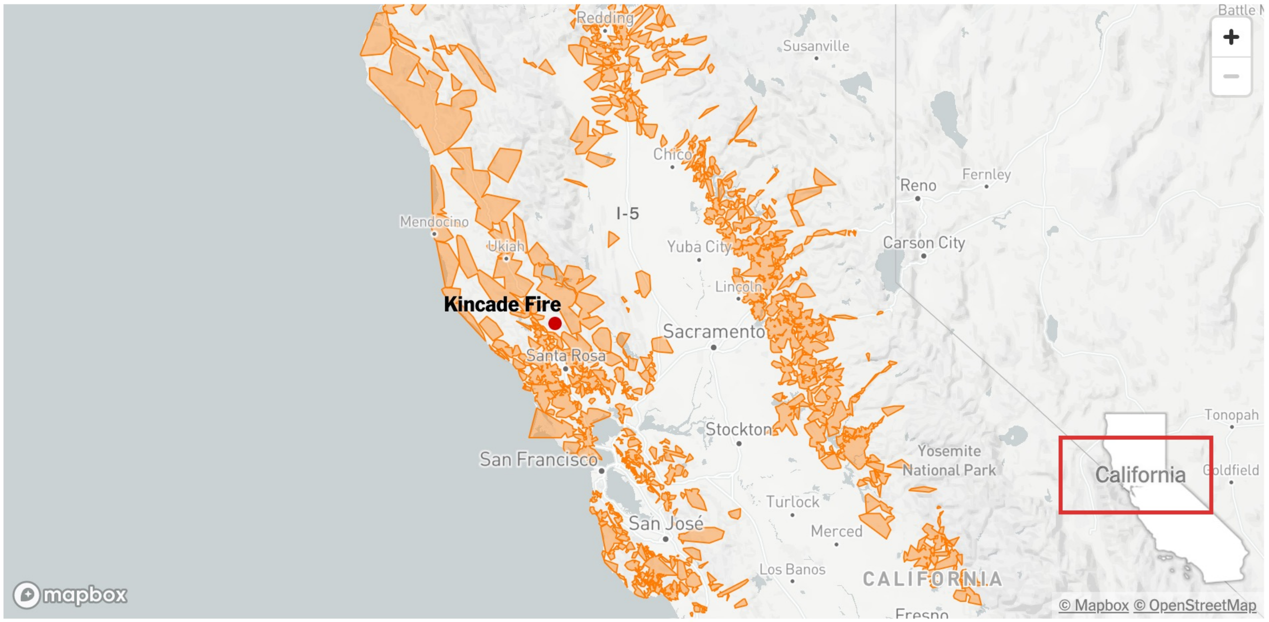
Medium of Communication -- News reporting

How Vaporflys and Next% shoes compare with other popular running shoes:



https://www.nytimes.com/interactive/2019/12/13/upshot/nike-vaporfly-next-percent-shoe-estimates.html

Power Outage Areas



Map shows outages for fire hazard mitigation from Oct. 27 to Oct. 29. | Source: Pacific Gas and Electric

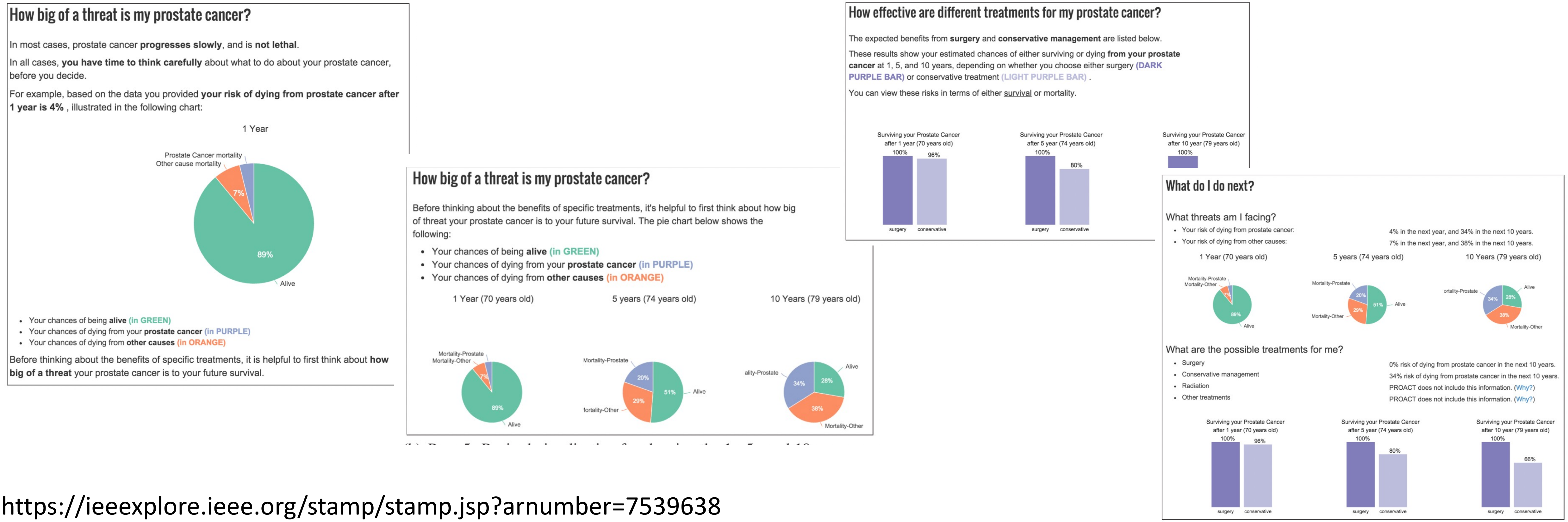
https://www.nytimes.com/interactive/2019/10/25/us/california-fire-map.html

Visualization (in CS)

$\boxed{\text{Medium of Communication}}$ -- Medical communication

Visualization (in CS)

Medium of Communication -- Medical communication



https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=7539638

Visualization (in CS)

Medium of Communication

-- Public Health
-- News Reporting
-- Medical communication
-- etc.

Use visualization as an alternative to written communication or numerical communication

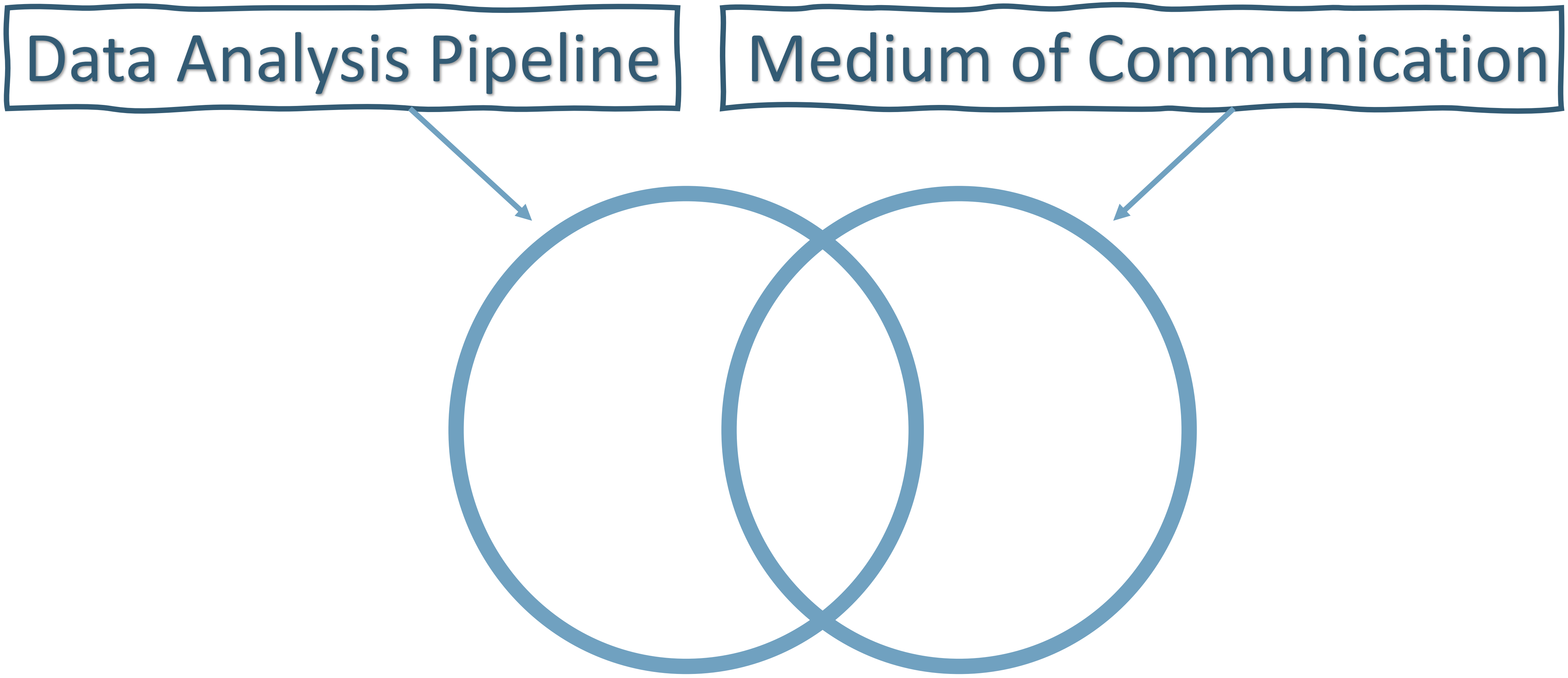
How does visualization for communication differ from other types of visualization?

Comparison

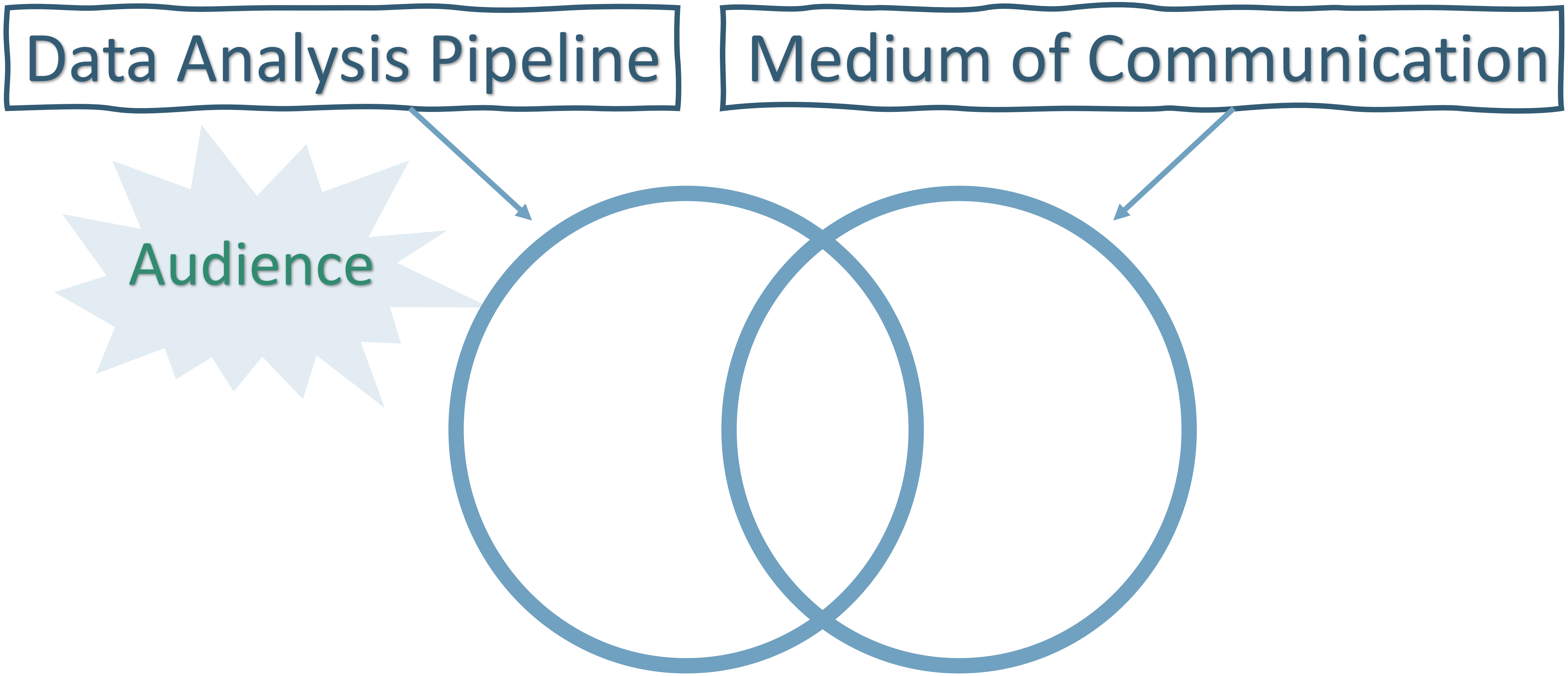
Data Analysis Pipeline

Medium of Communication

Comparison



Comparison

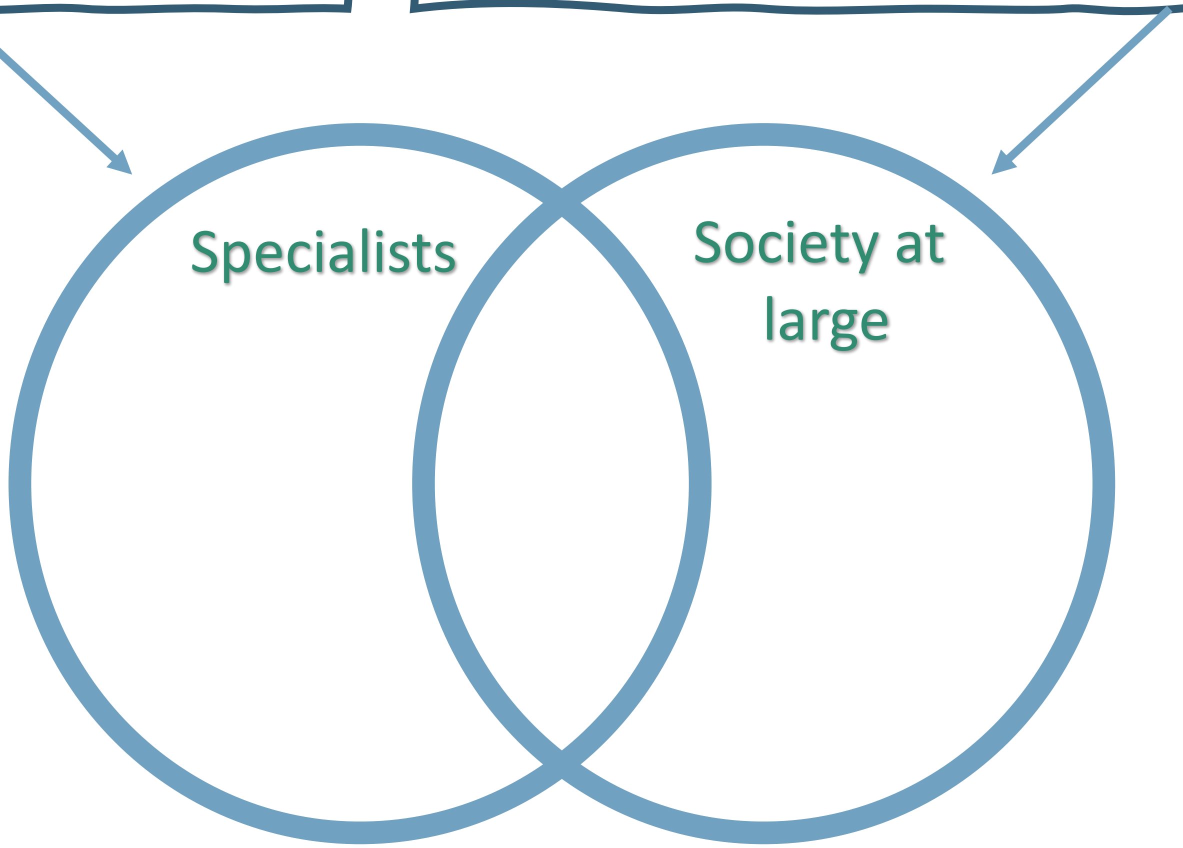


Comparison

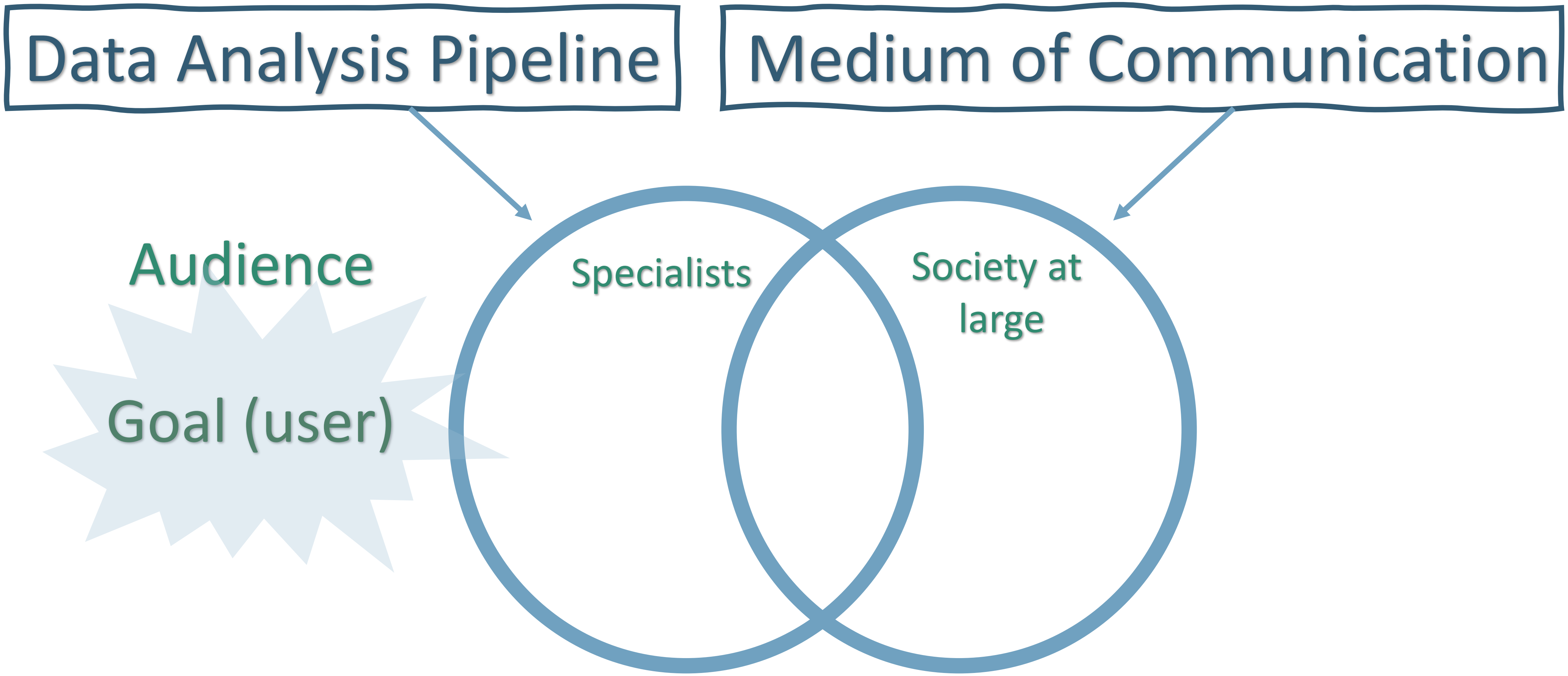
Data Analysis Pipeline

Medium of Communication

Audience



Comparison



Data Analysis Pipeline
Medium of Communication
Audience
Goal (user)
Specialists
Society at large

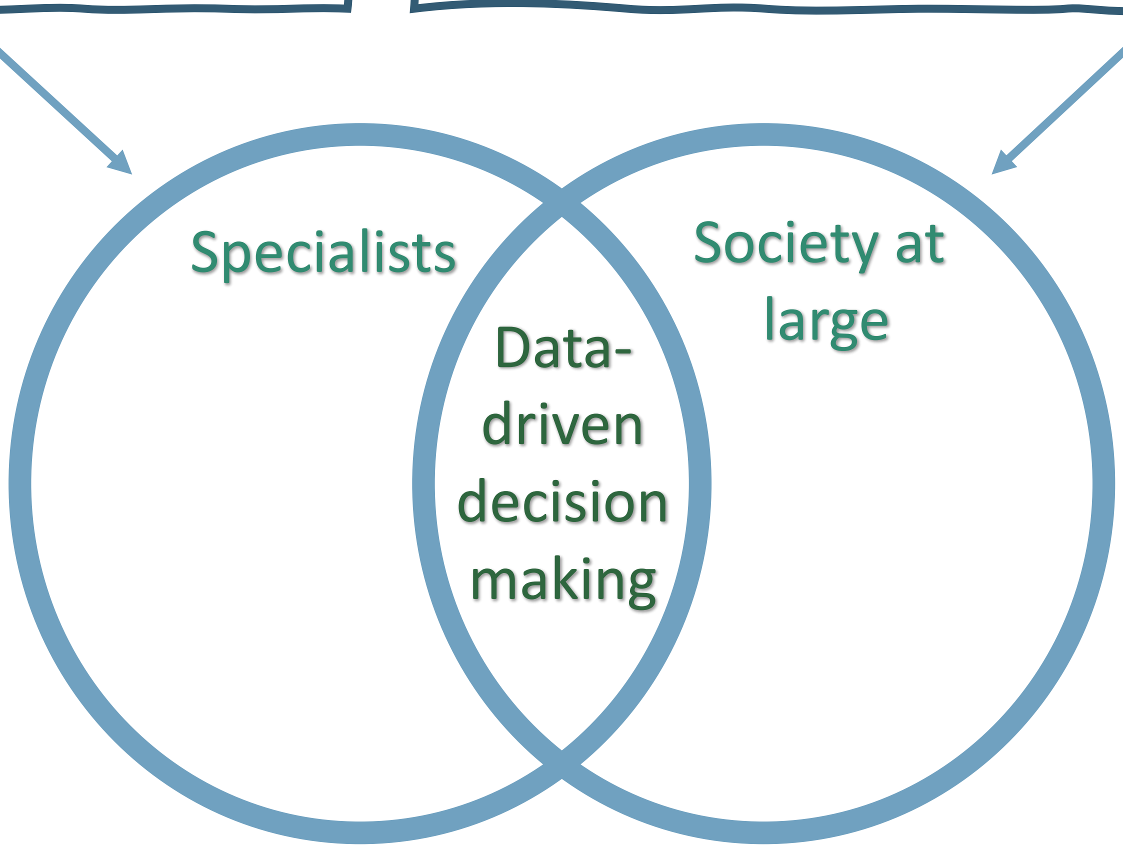
Comparison

Data Analysis Pipeline

Medium of Communication

Audience

Goal (user)



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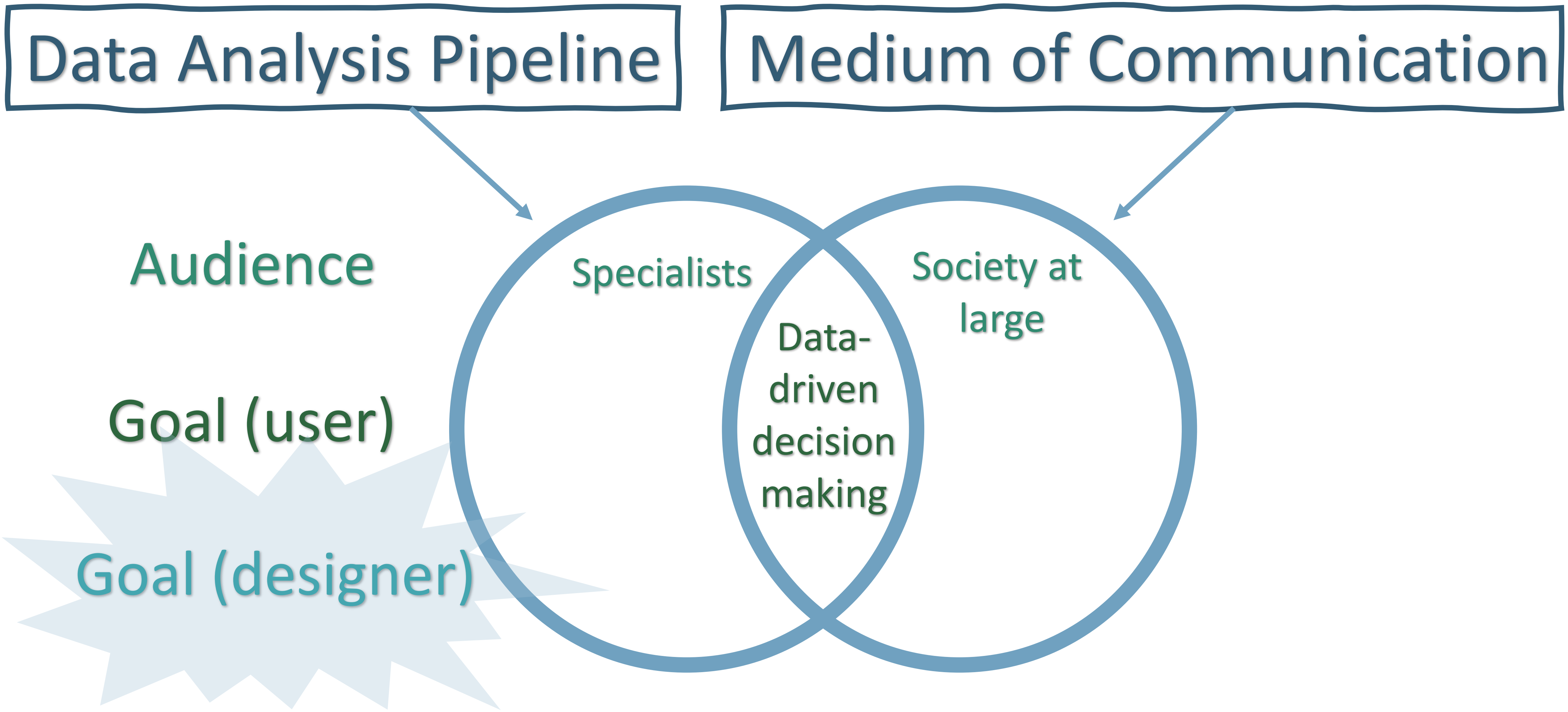
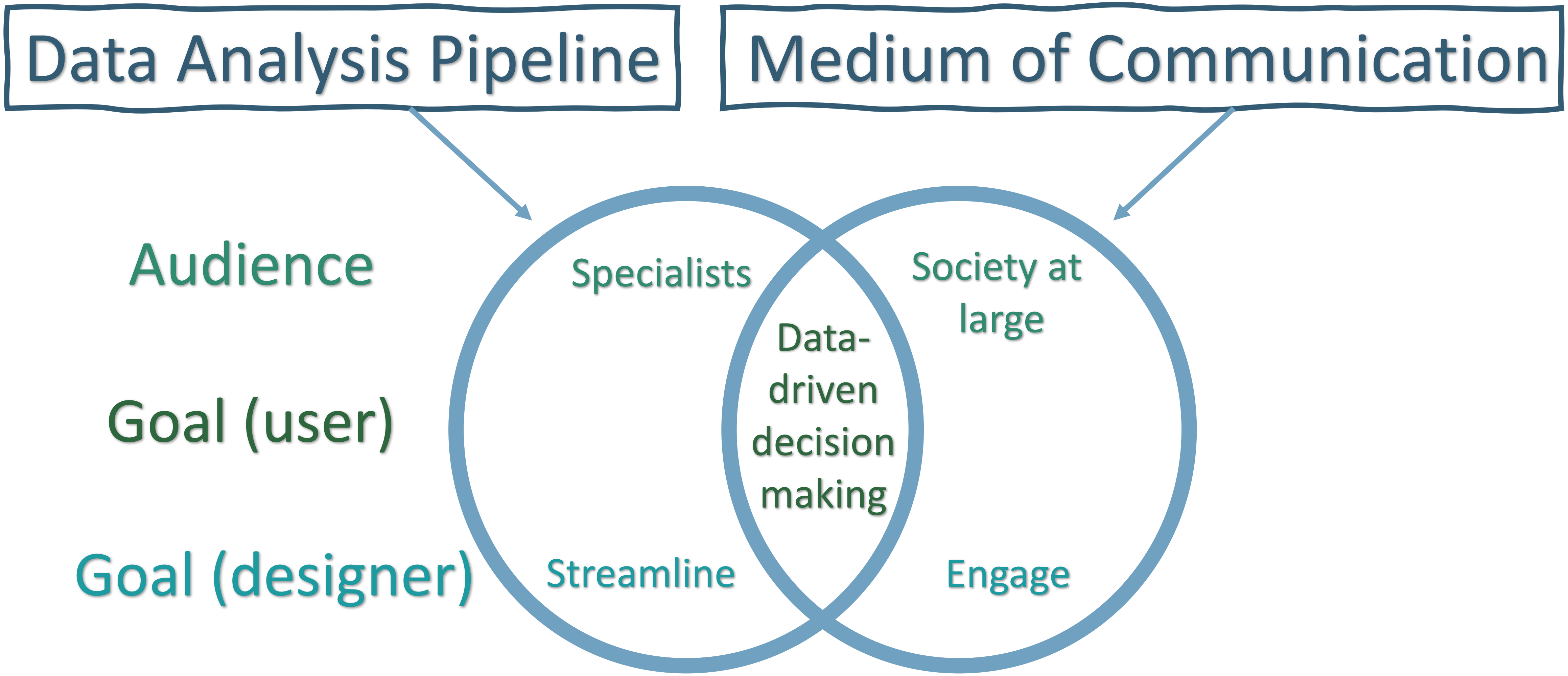

Data Analysis Pipeline
Medium of Communication
Audience
Goal (user)
Goal (designer)
Specialists
Data-driven decision making
Society at large

Comparison


Data Analysis Pipeline
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Goal (user)
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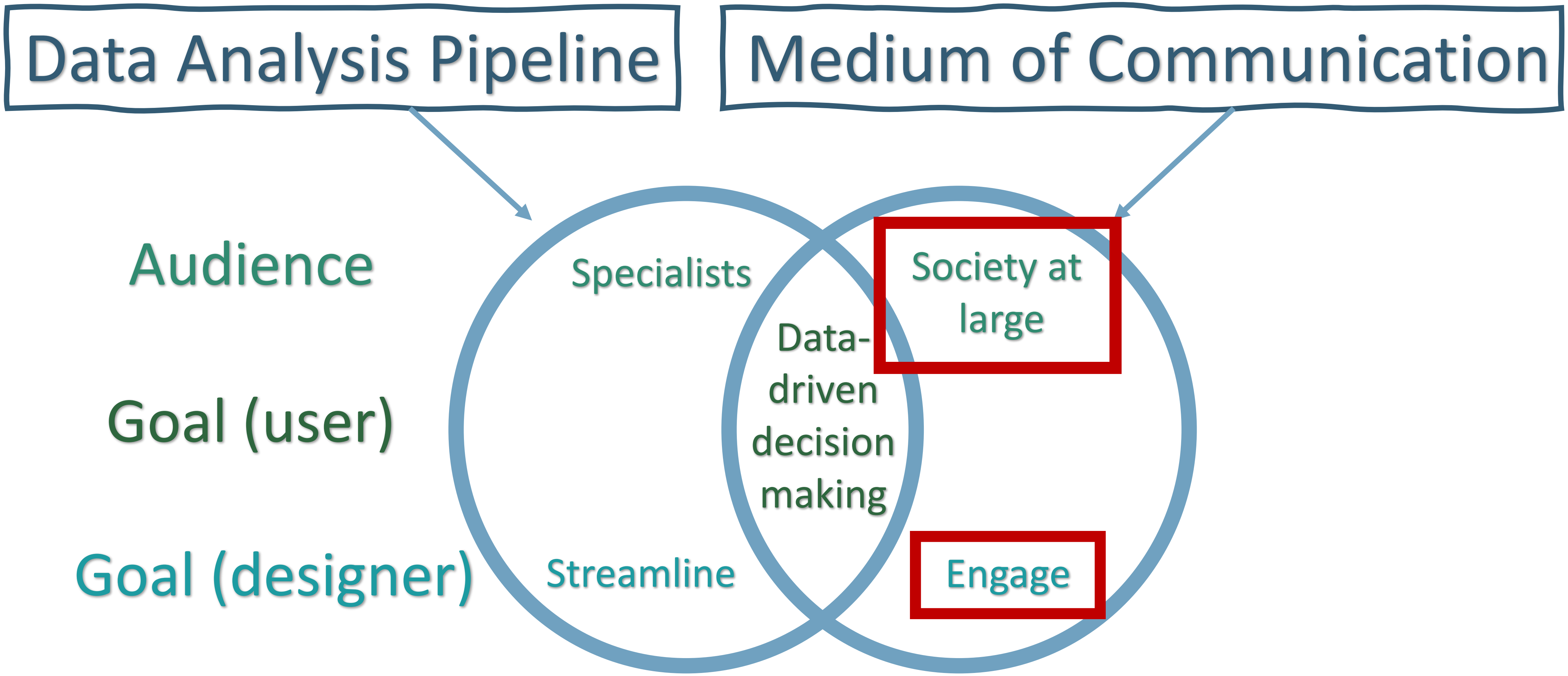
Specialists
Streamline
Data-driven decision making
Society at large
Engage

Comparison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Audience
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Engage

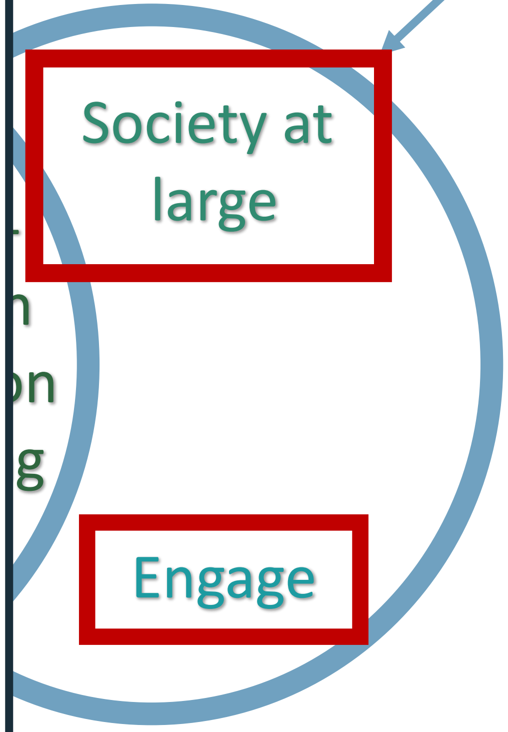
Comparison

Data Analysis Pipeline

Medium of Communication

Data Visualization Literacy:

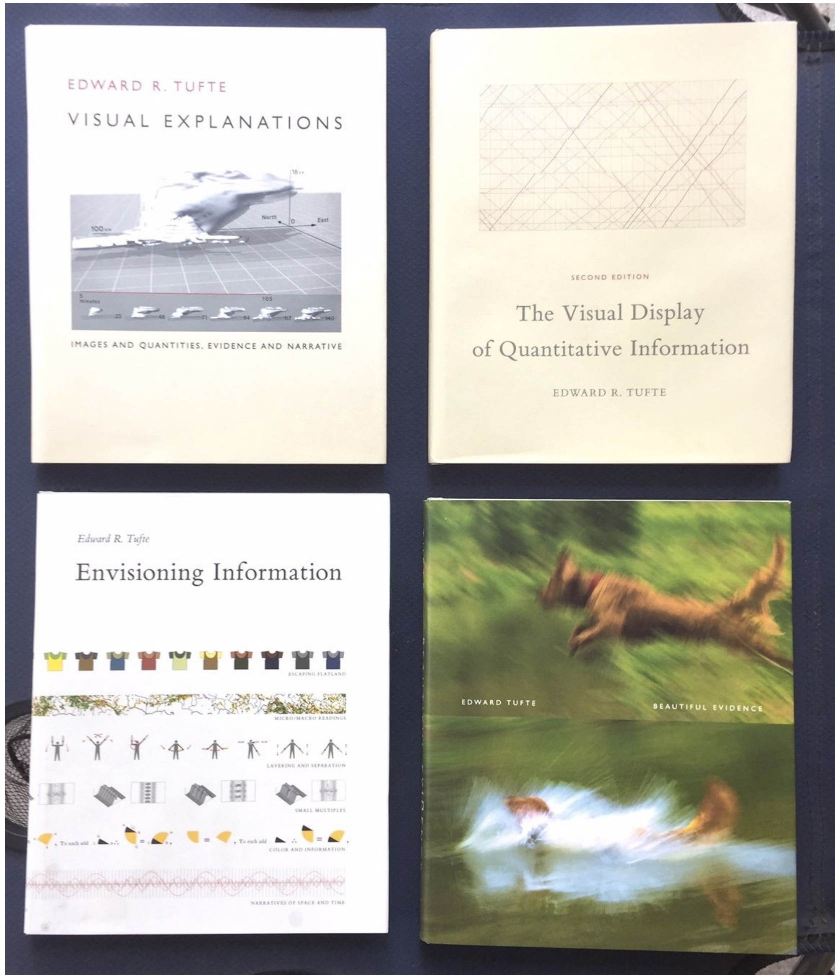
- “the ability to confidently use a given data visualization to translate questions specified in the data domain into visual queries in the visual domain, as well as interpreting visual patterns in the visual domain as properties in the data domain” (Boy et al., 2014);
- “the ability and skill to read and interpret visually represented data in and to extract information from data visualizations” (Lee et al., 2017); and
- “the ability to make meaning from and interpret patterns, trends, and correlations in visual representations of data” (Börner et al., 2016).



Visualization for communication design

Historically – Tufte's "Graphical Integrity"

- Essentially, Tufte's Design Rules of Thumb
- Widely known, but not always adhered to



Historically – Tufte's "Graphical Integrity"

To achieve graphical "excellence":

1. Above all else show the data.
2. Maximize data to ink ratio.
3. Erase non-data ink.
4. Erase redundant data ink.
5. Revise and edit.

Tufte, "Visual Display of Quantitative Information" (1983)

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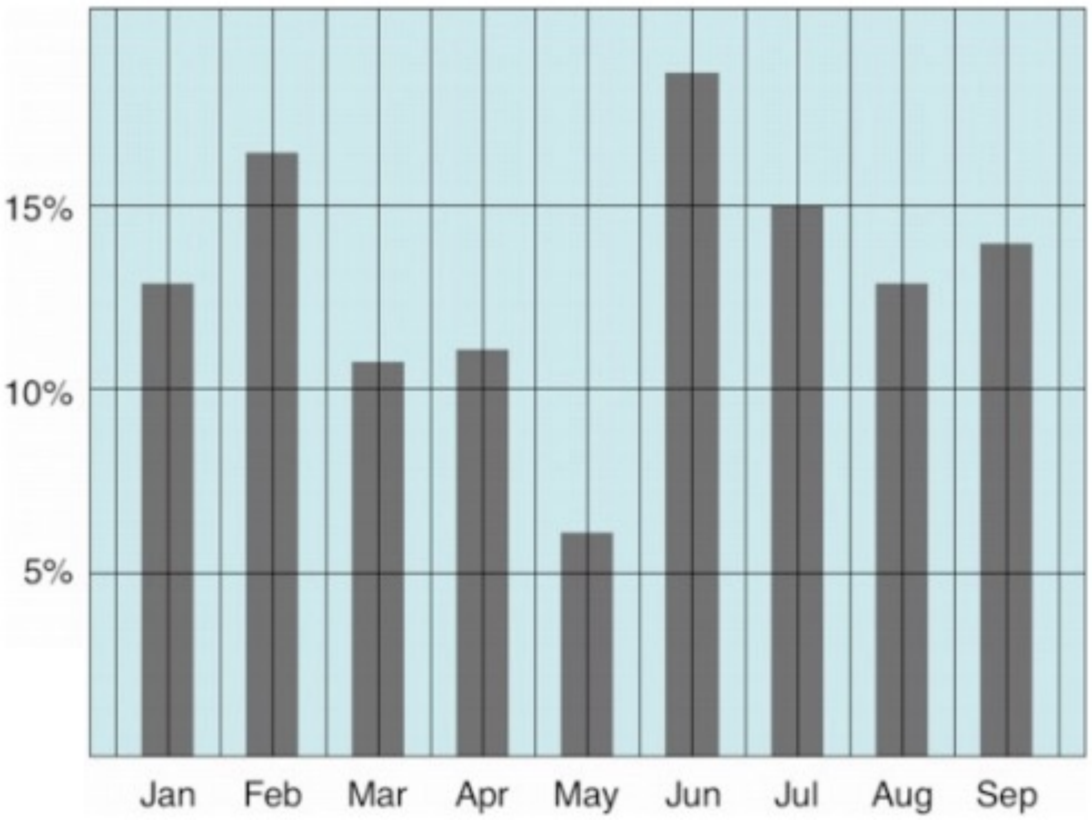

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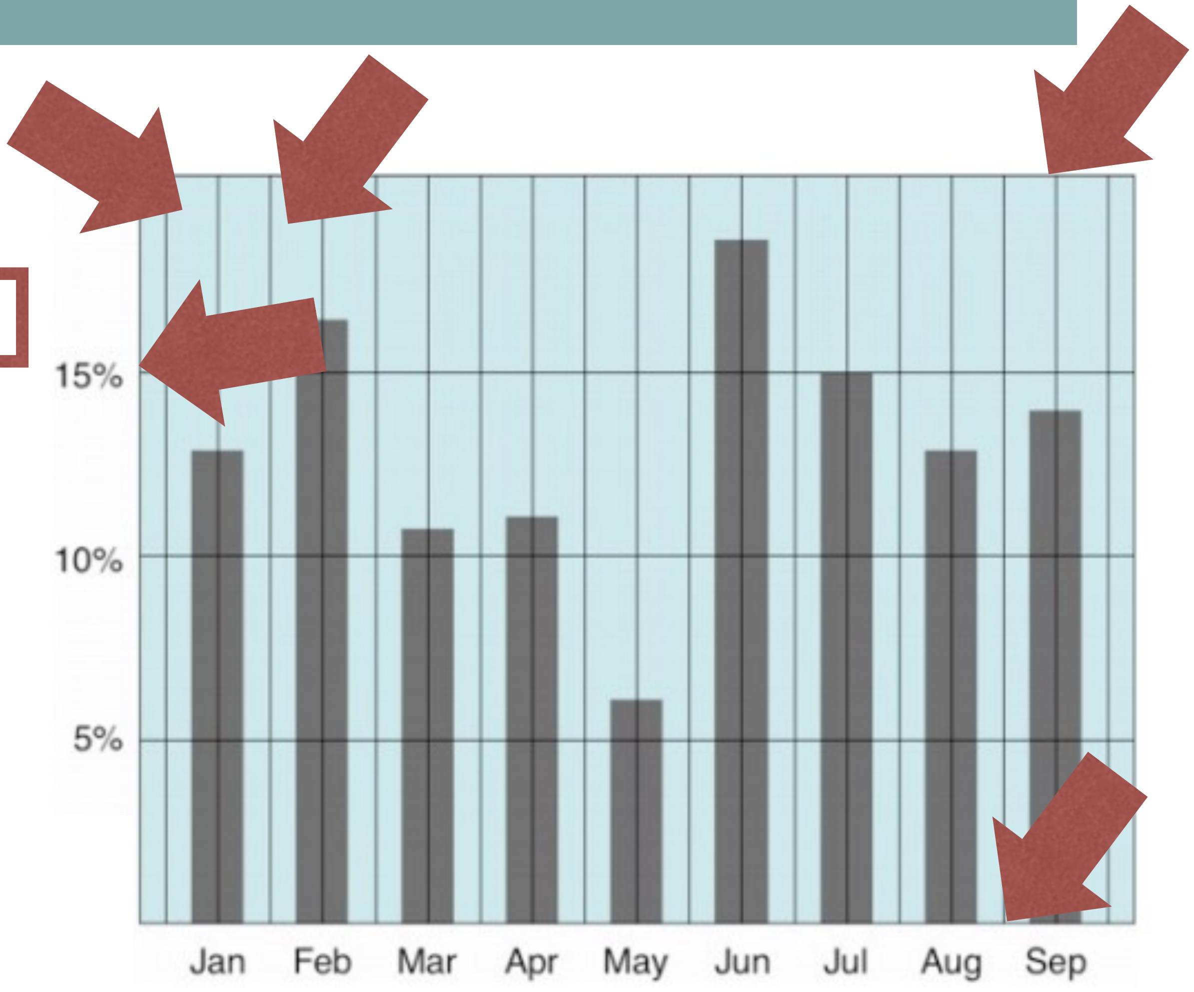

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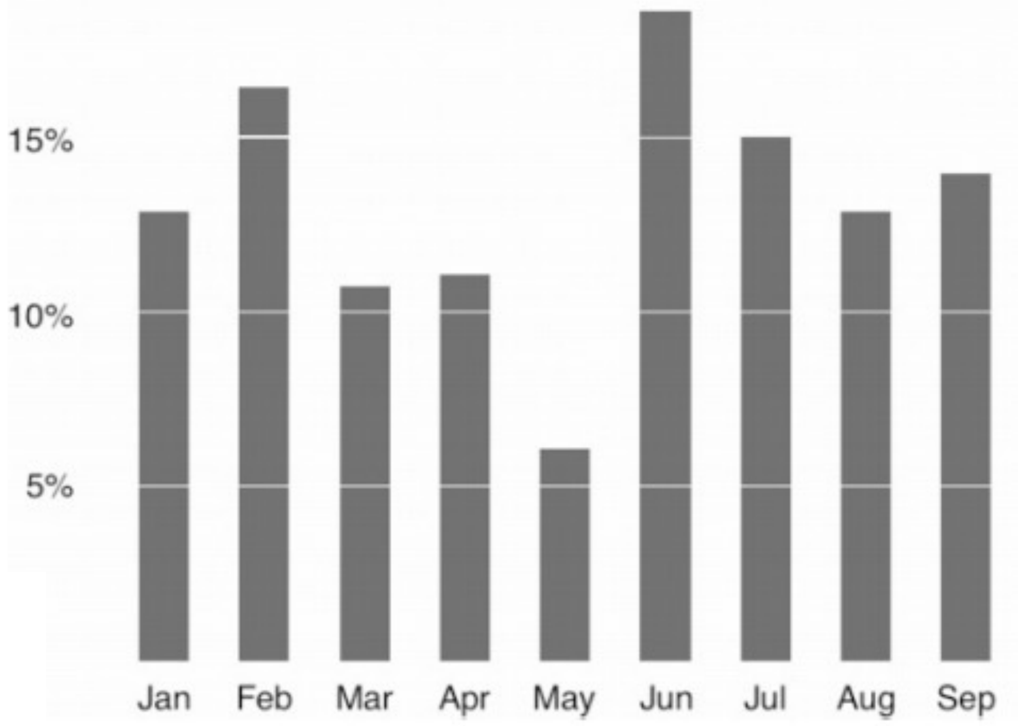

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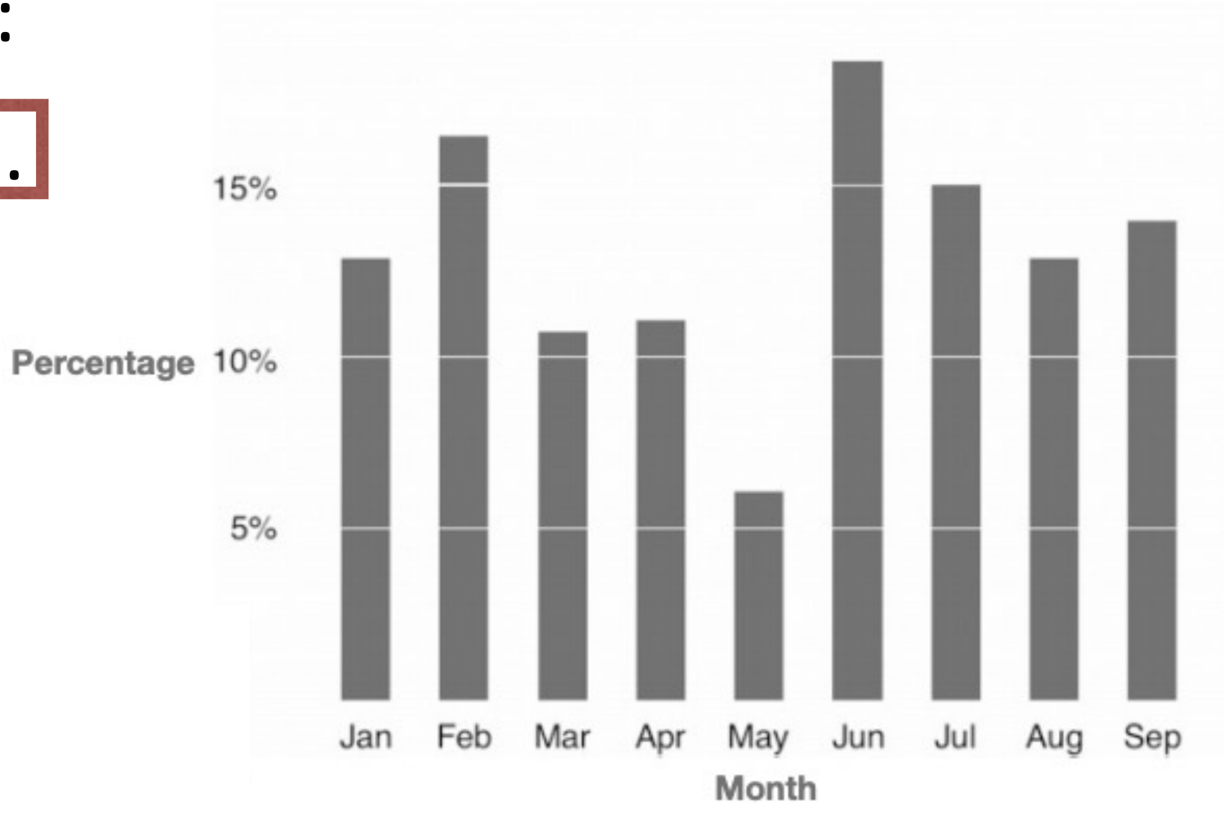

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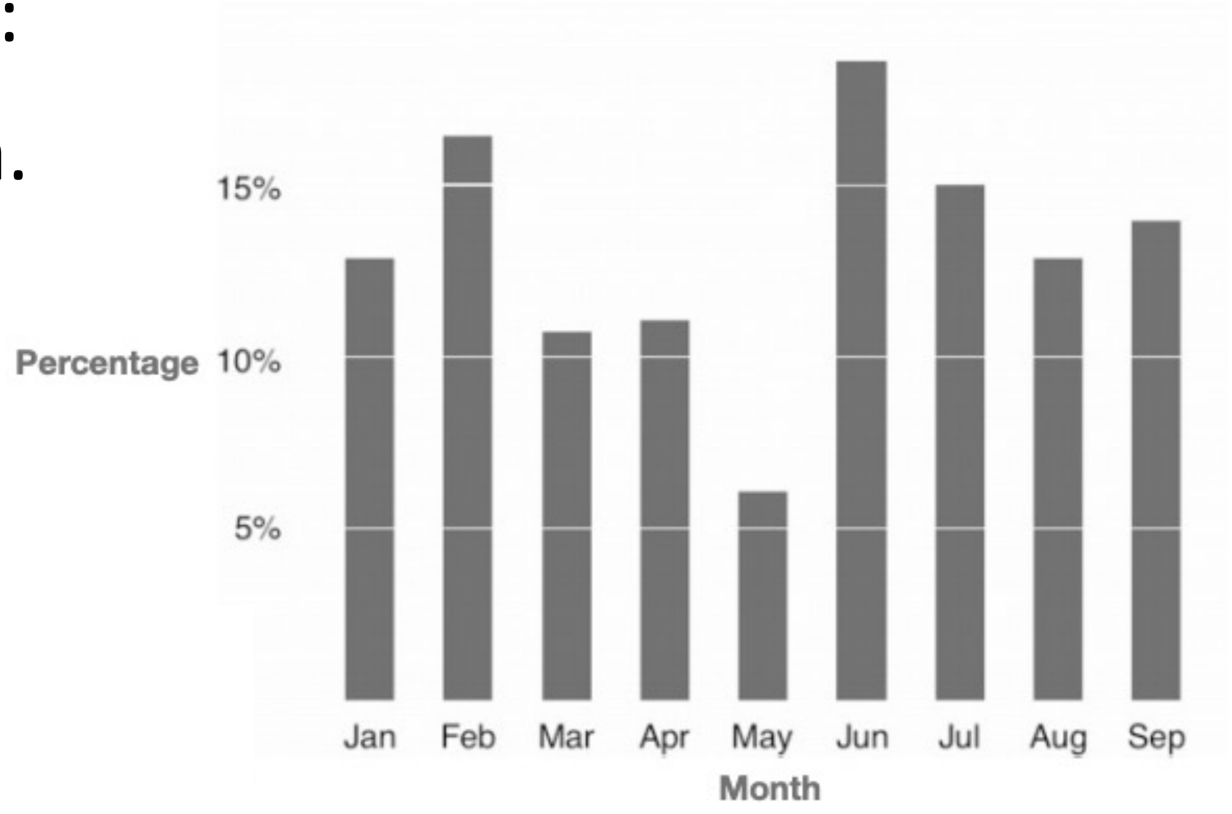

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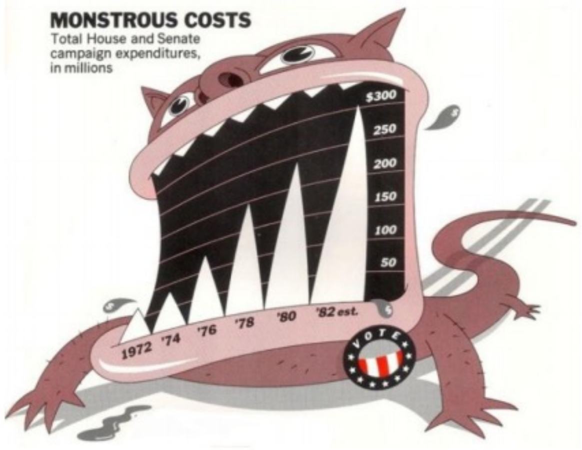
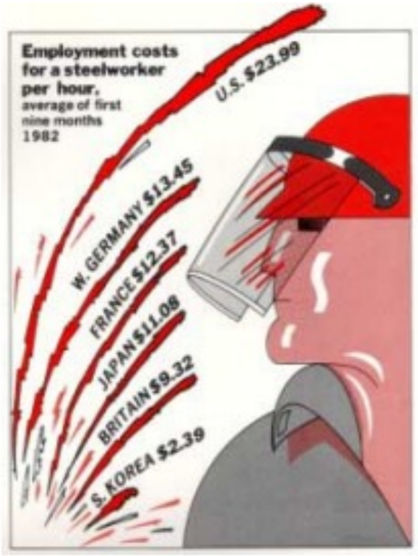
No "Chart Junk" i.e. no elements that do not communicate data.

Tufte, "Visual Display of Quantitative Information" (1983)

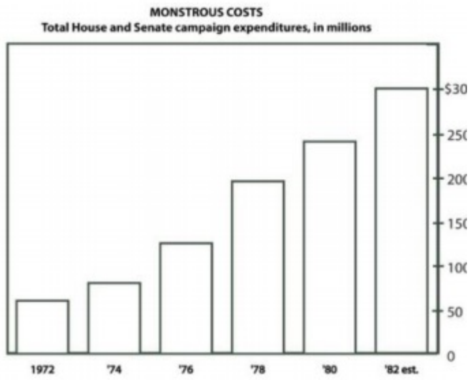
Open Question – Chart Junk

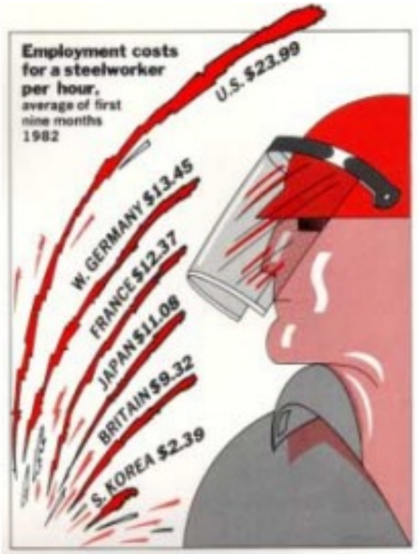


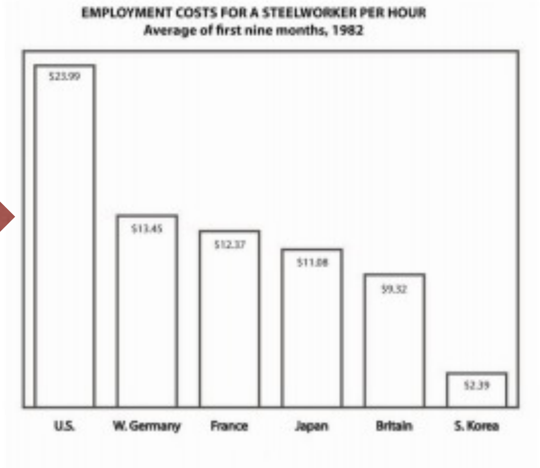


Useful Junk? The effects of visual embellishment on comprehension and memorability of charts. Bateman et al.

Open Question – Chart Junk







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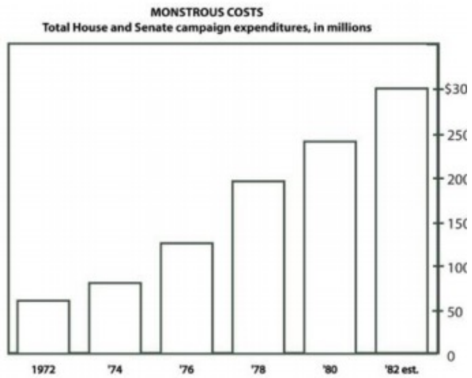
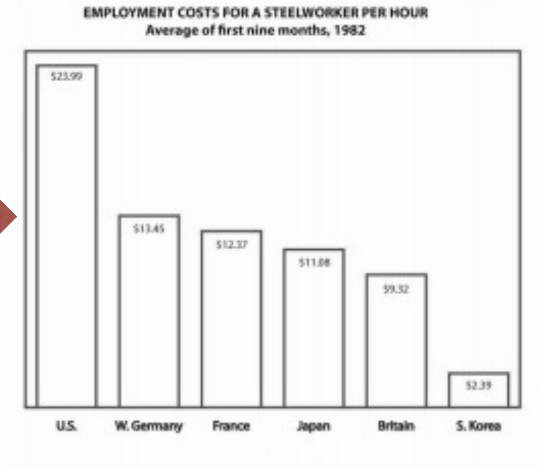




Debate Amongst Contemporary Researchers

\+ Cart junk has been shown to persuade, help with memorability, engage users

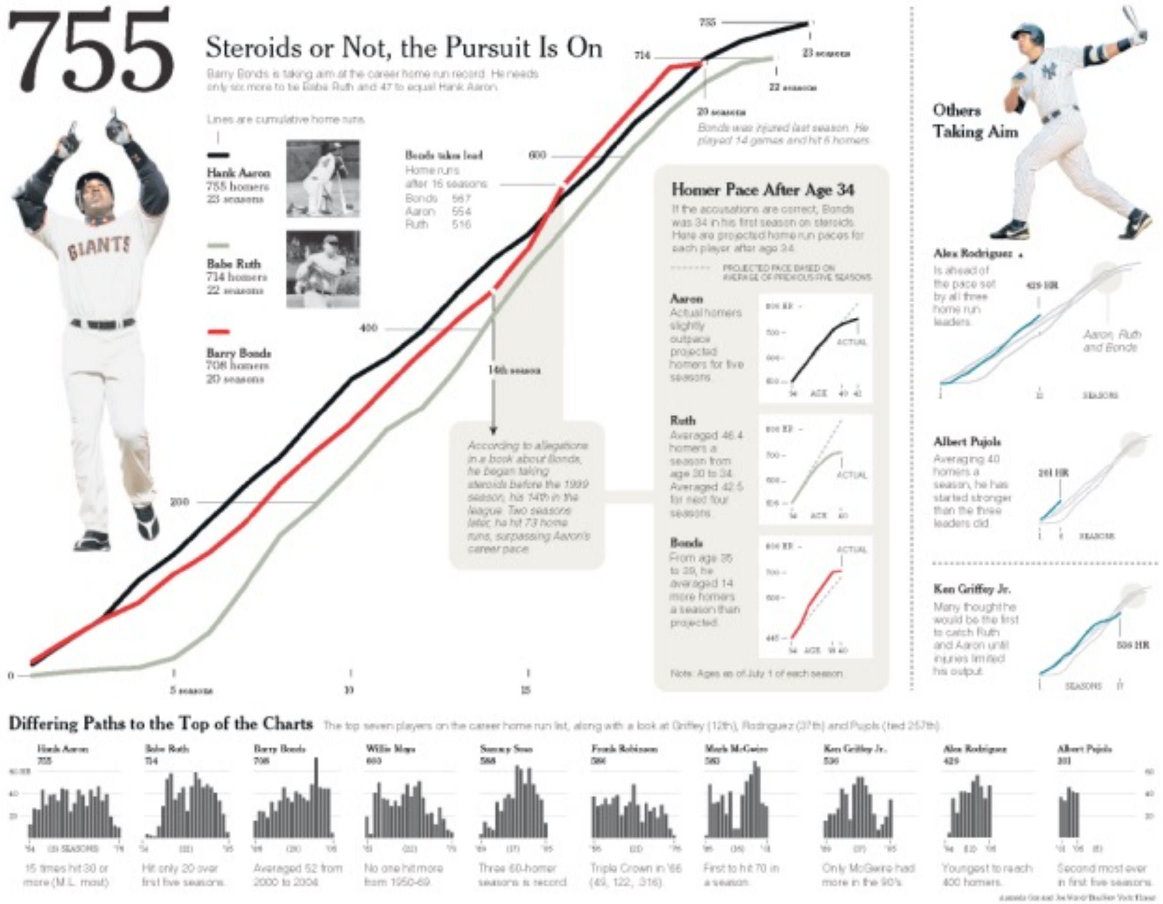
\- Chart junk has been shown to cause bias, reduce data-ink ratio, clutter, degrade user trust

Useful Junk? The effects of visual embellishment on comprehension and memorability of charts. Bateman et al.

Contemporary – Narrative Visualization

Storytelling – Narrative Visualization

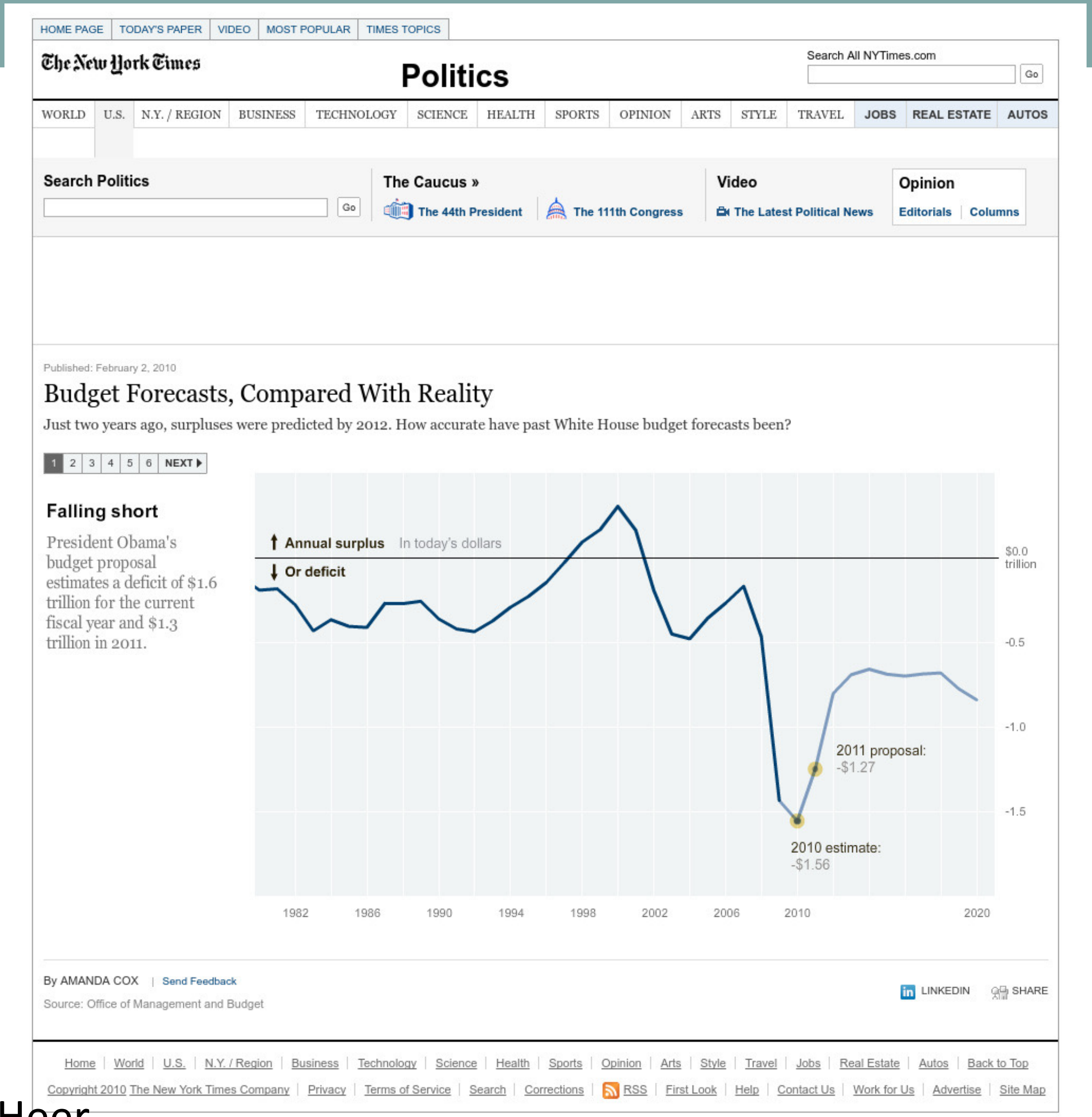
Visualizations that combine narratives with interactive graphics.



Narrative Visualization: Telling Stories with Data. Segel and Heer.

Storytelling – Narrative Visualization

Visualizations that combine narratives with interactive graphics.



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Storytelling – Narrative Visualization

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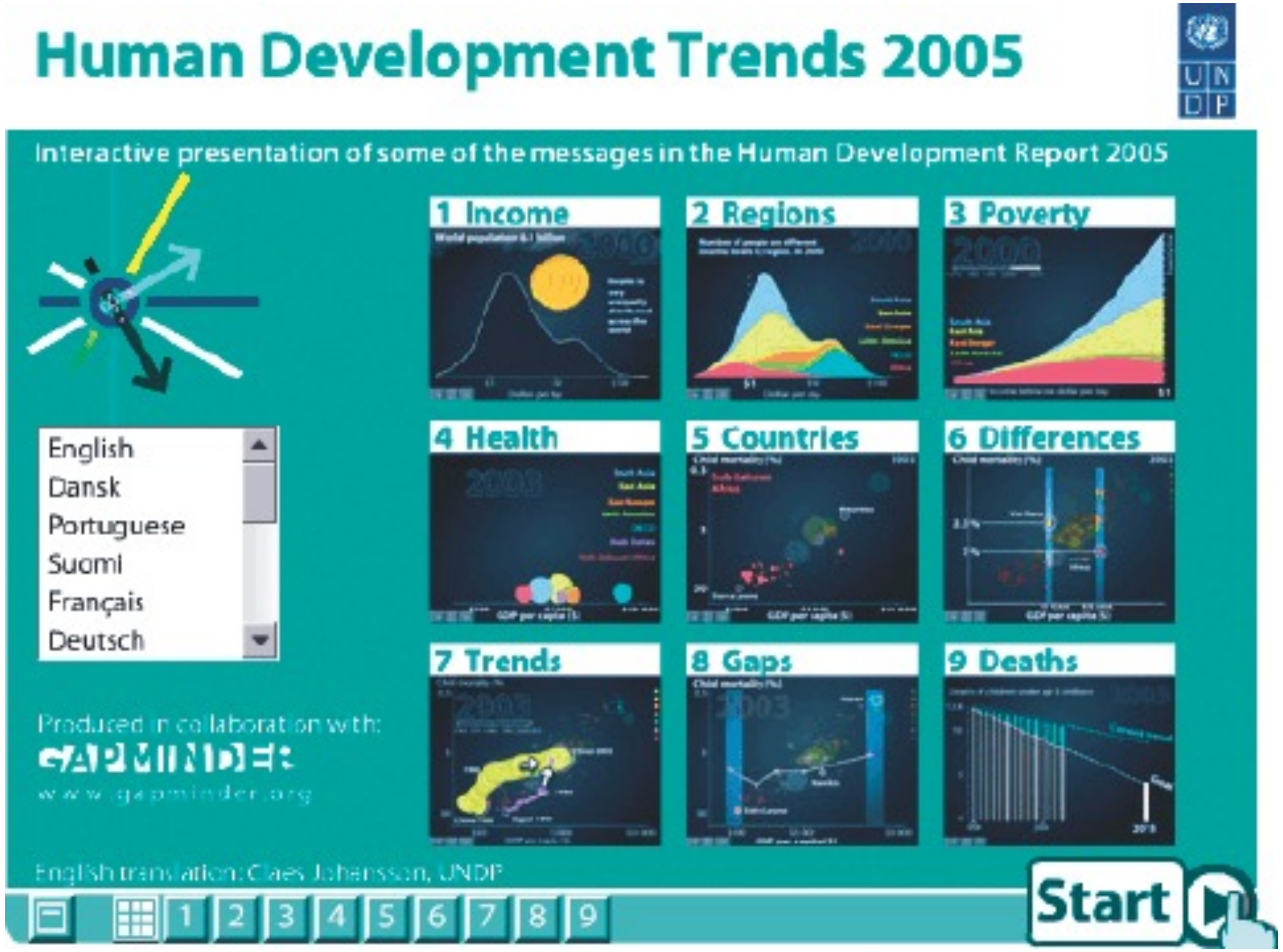

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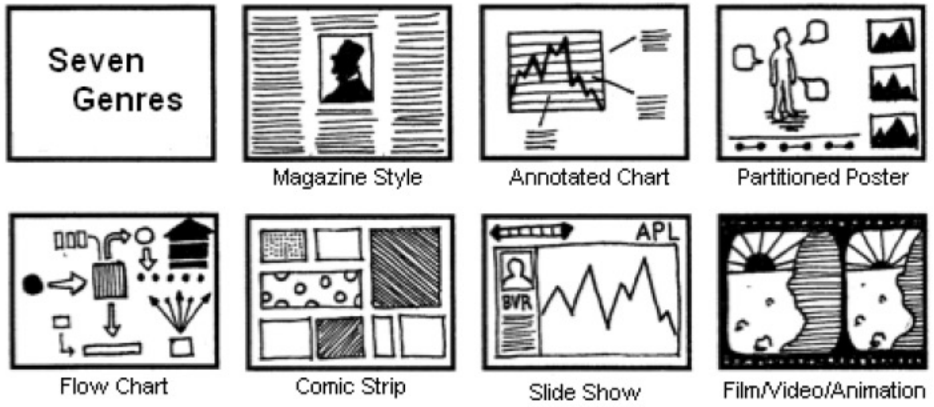
Storytelling – Narrative Visualization



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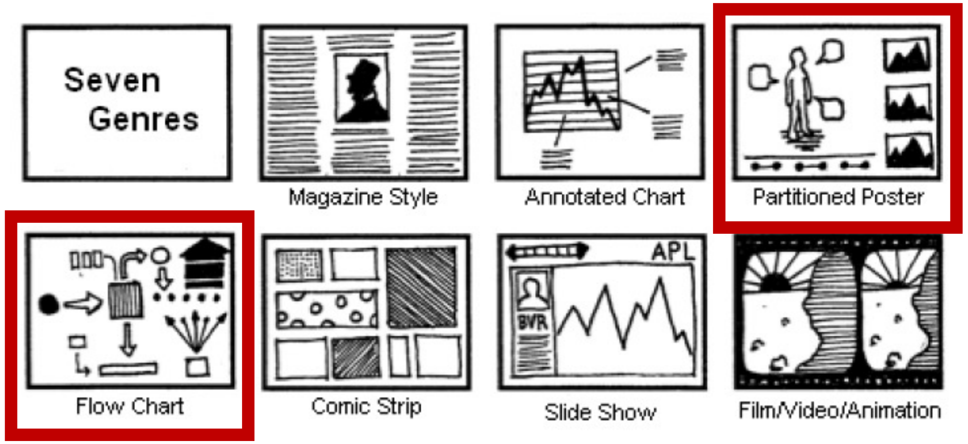

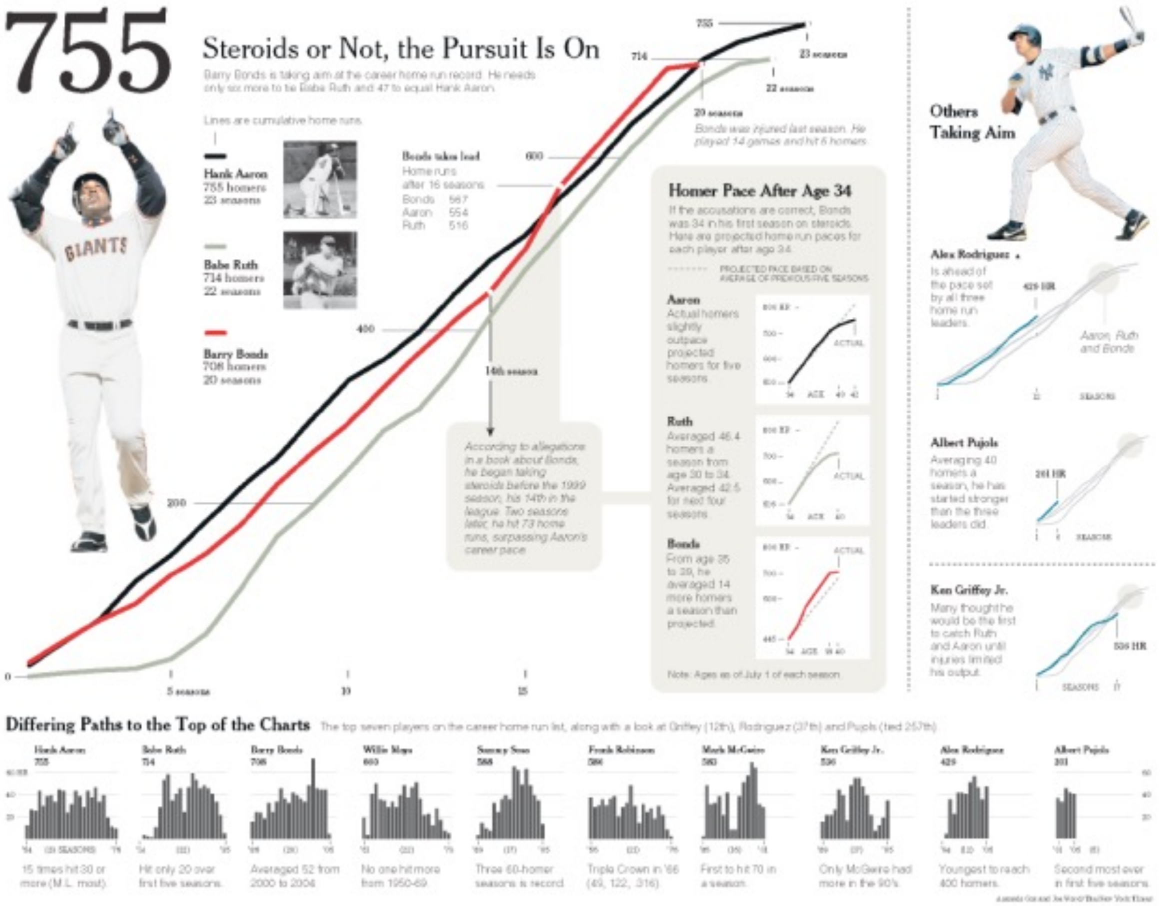

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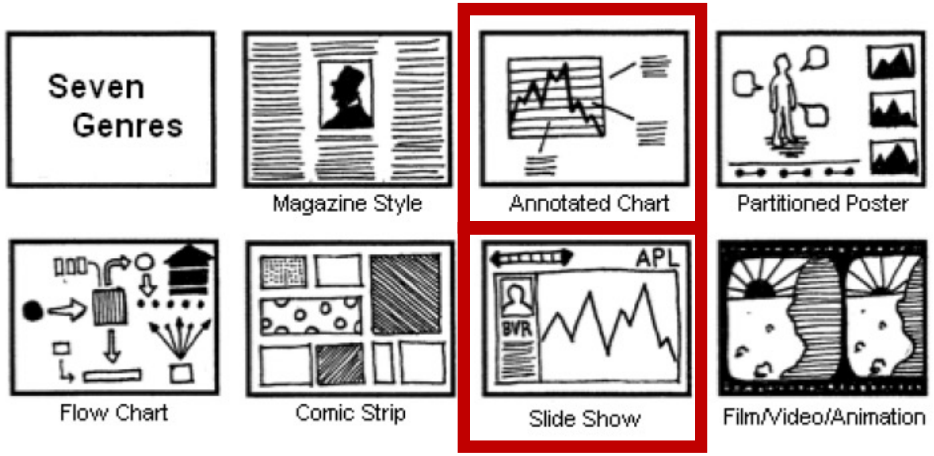
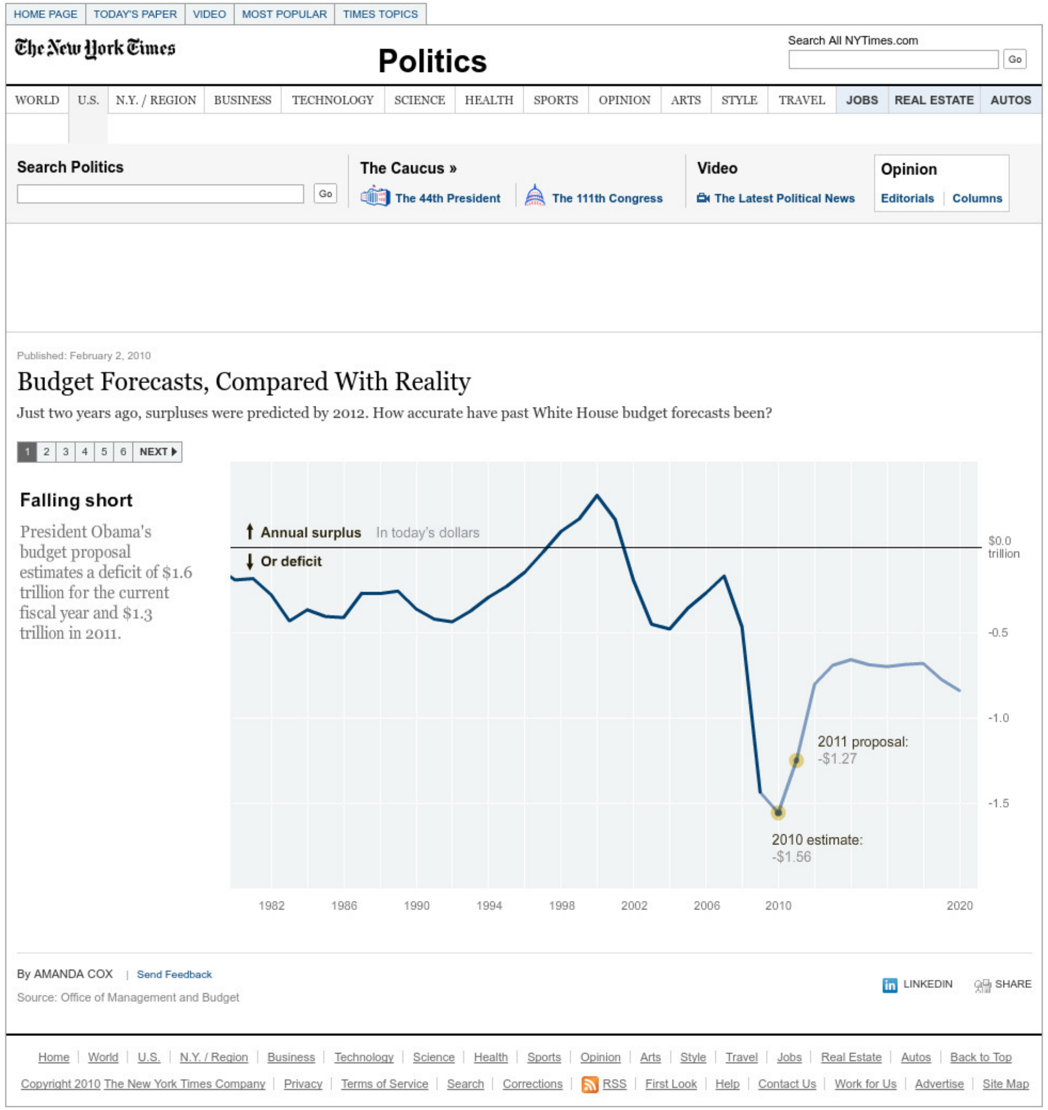
Storytelling – Narrative Visualization





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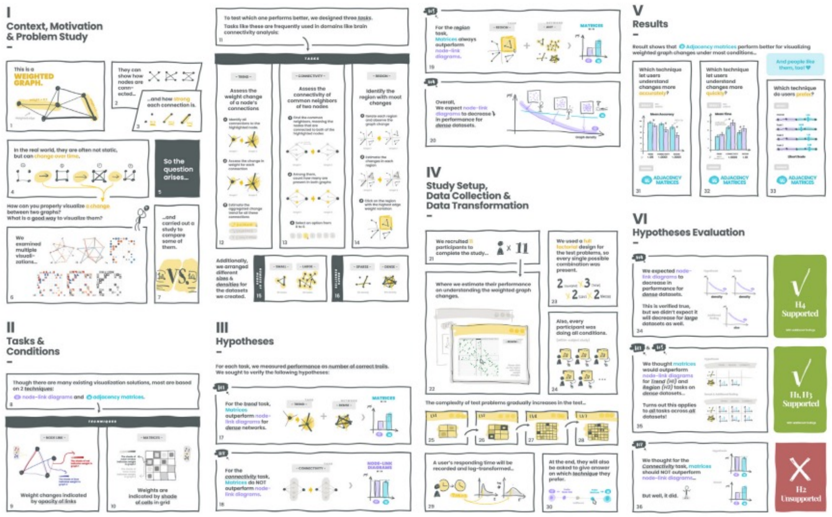
Storytelling – Narrative Visualization

Author Driven

Reader Driven

Narrative Visualization: Telling Stories with Data. Segel and Heer.

Storytelling – Narrative Visualization



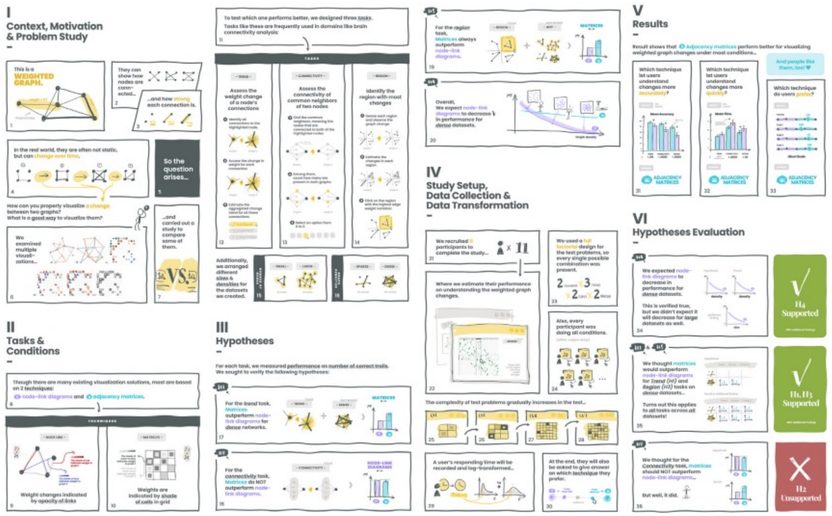
Data Comics

- Strict linear ordering of scenes
- Heavy messaging
- No interactivity

Author Driven | Reader Driven

Narrative Visualization: Telling Stories with Data. Segel and Heer.

Storytelling – Narrative Visualization



Data Comics

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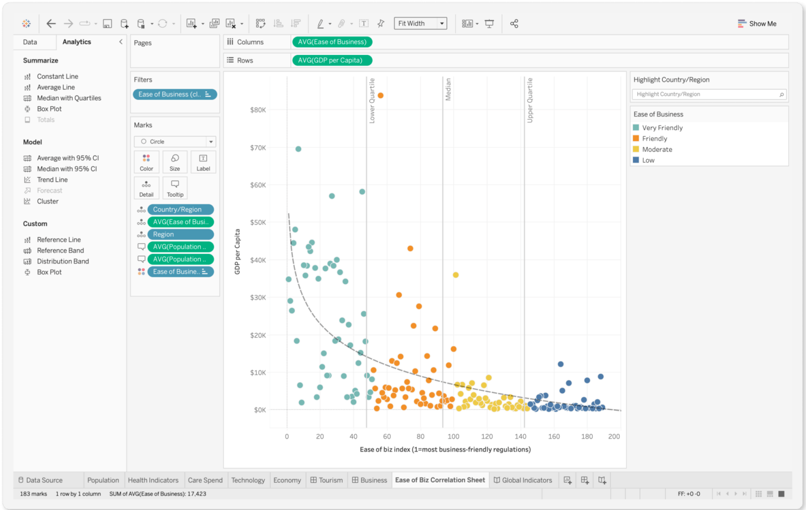


Tableau

- No prescribed ordering
- No messaging
- Free interactivity

Author Driven ⟷ Reader Driven

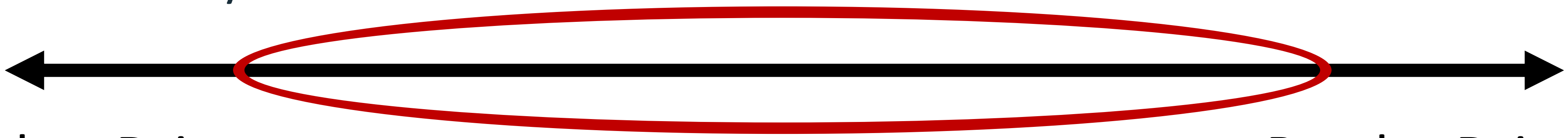
Narrative Visualization: Telling Stories with Data. Segel and Heer.

Storytelling – Narrative Visualization

Martini Glass Structure
Interactive Slideshow
Drill-Down Story

- Strict linear ordering of scenes
- Heavy messaging
- No interactivity

- No prescribed ordering
- No messaging
- Free interactivity



Author Driven

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Storytelling – Narrative Visualization

Martini Glass Structure
Interactive Slideshow
Drill-Down Story

In groups, brainstorm what each of these structures might look like. Sketch a (simple) example to illustrate your thoughts.

- Strict linear ordering of scenes
- Heavy messaging
- No interactivity

- No prescribed ordering
- No messaging
- Free interactivity

Author Driven

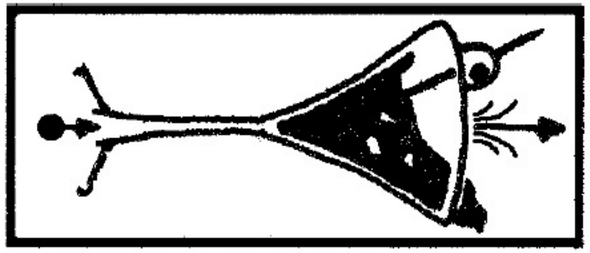
Reader Driven

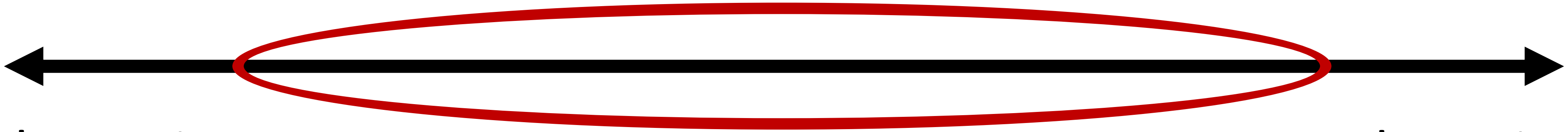
Narrative Visualization: Telling Stories with Data. Segel and Heer.

Storytelling – Narrative Visualization

Martini Glass Structure

- Starts with an author-driven approach, then opens to a reader-driven stage





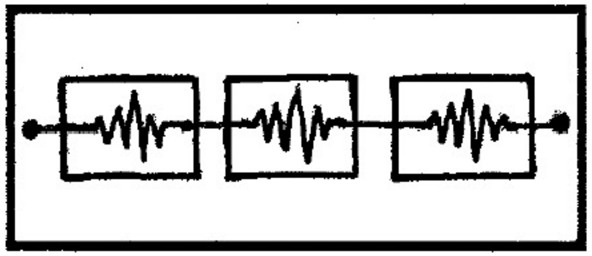
Author Driven — Reader Driven

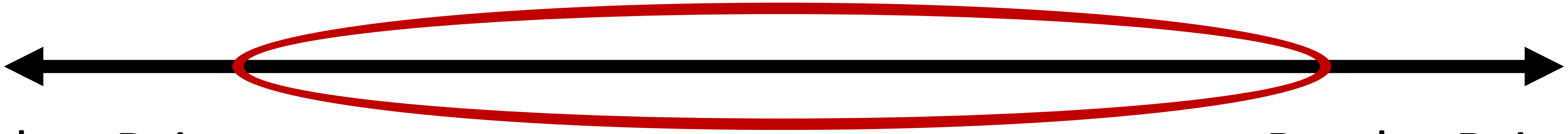
Narrative Visualization: Telling Stories with Data. Segel and Heer.

Storytelling – Narrative Visualization

Interactive Slideshow

- Slideshow that incorporates interaction within each slide
- More even mix of author-driven and reader-driven





Author Driven

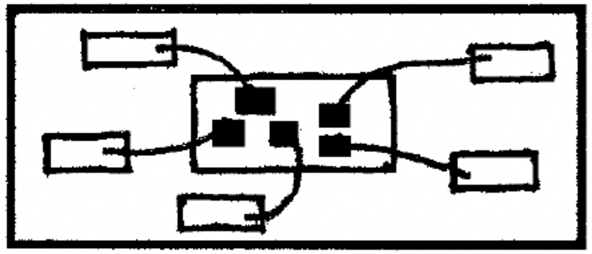
Reader Driven

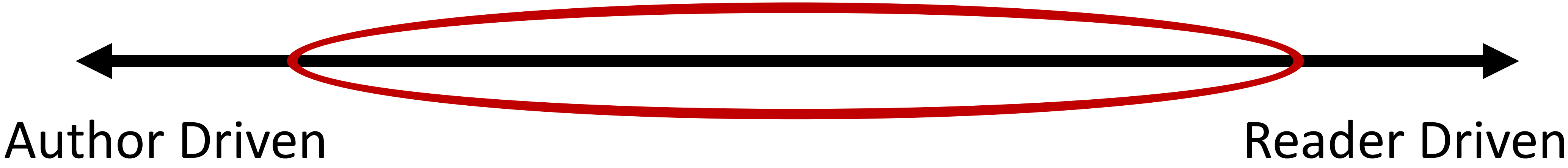
Narrative Visualization: Telling Stories with Data. Segel and Heer.

Storytelling – Narrative Visualization

Drill-Down Story

- Presents a general theme, then allows the user to explore specific instances of that theme
- More emphasis on reader-driven

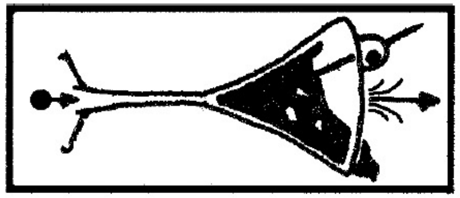




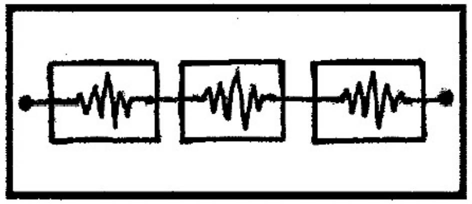
Narrative Visualization: Telling Stories with Data. Segel and Heer.

Storytelling – Narrative Visualization

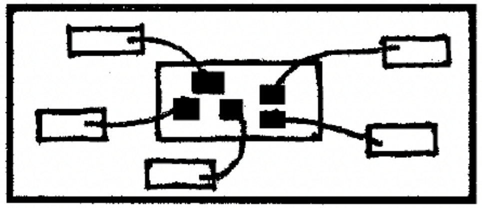
Martini Glass Structure



Interactive Slideshow

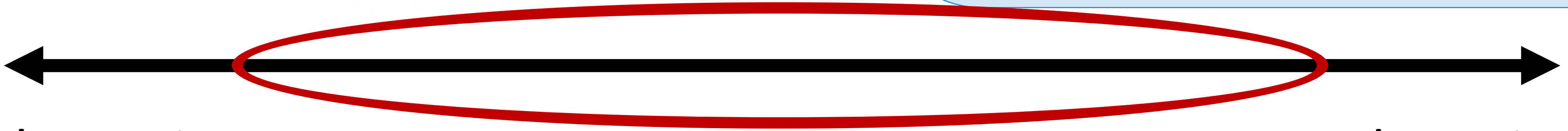


Drill-Down Story



In groups, find an example of each story structure. Add your examples to the Narrative-Vis Jamboard.

(Try looking on New York Times, Washington Post, FiveThirtyEight, Boston Globe, etc.)



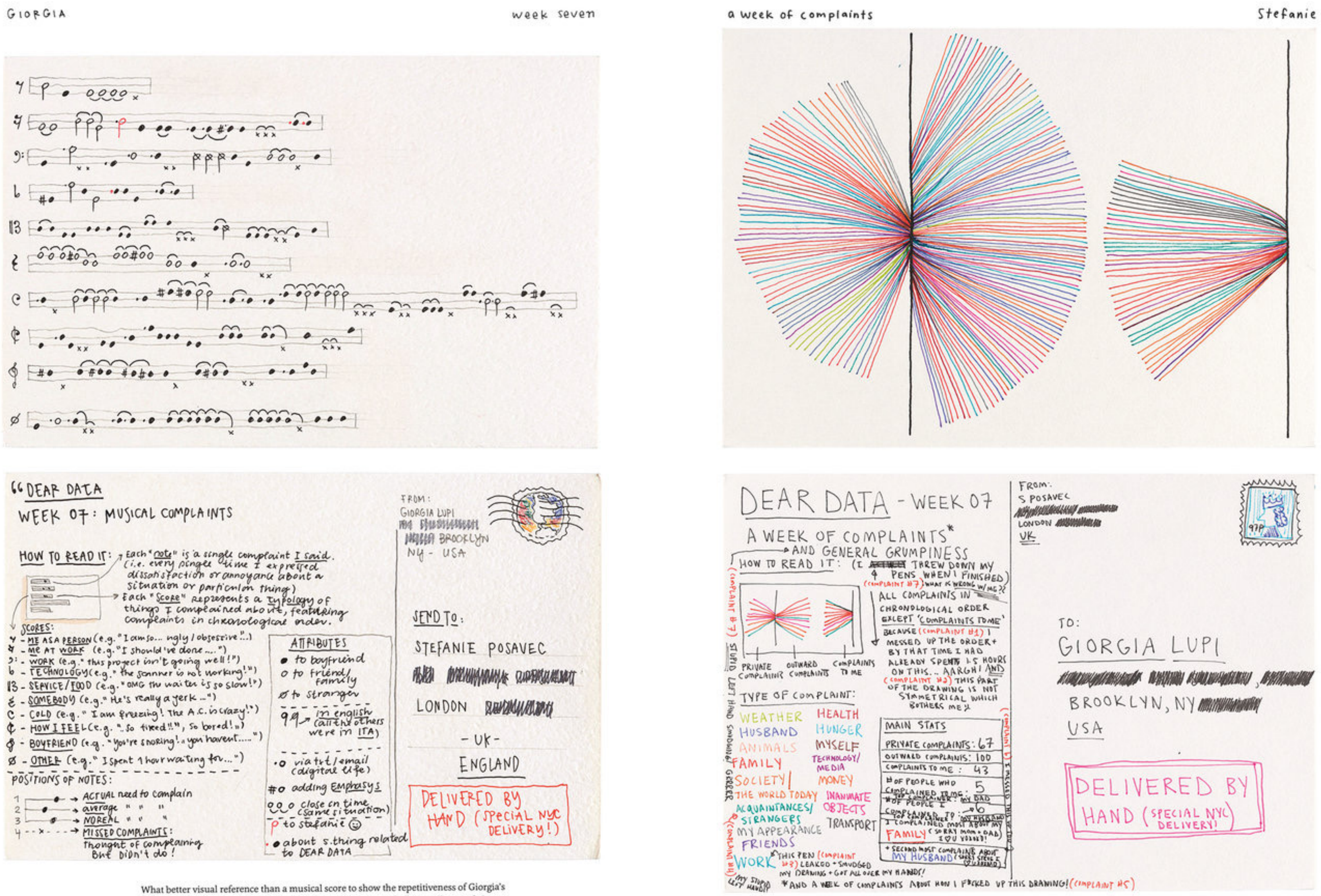
Author Driven

Reader Driven

Narrative Visualization: Telling Stories with Data. Segel and Heer.

A more artistic approach

Giorgia Lupi – Dear Data

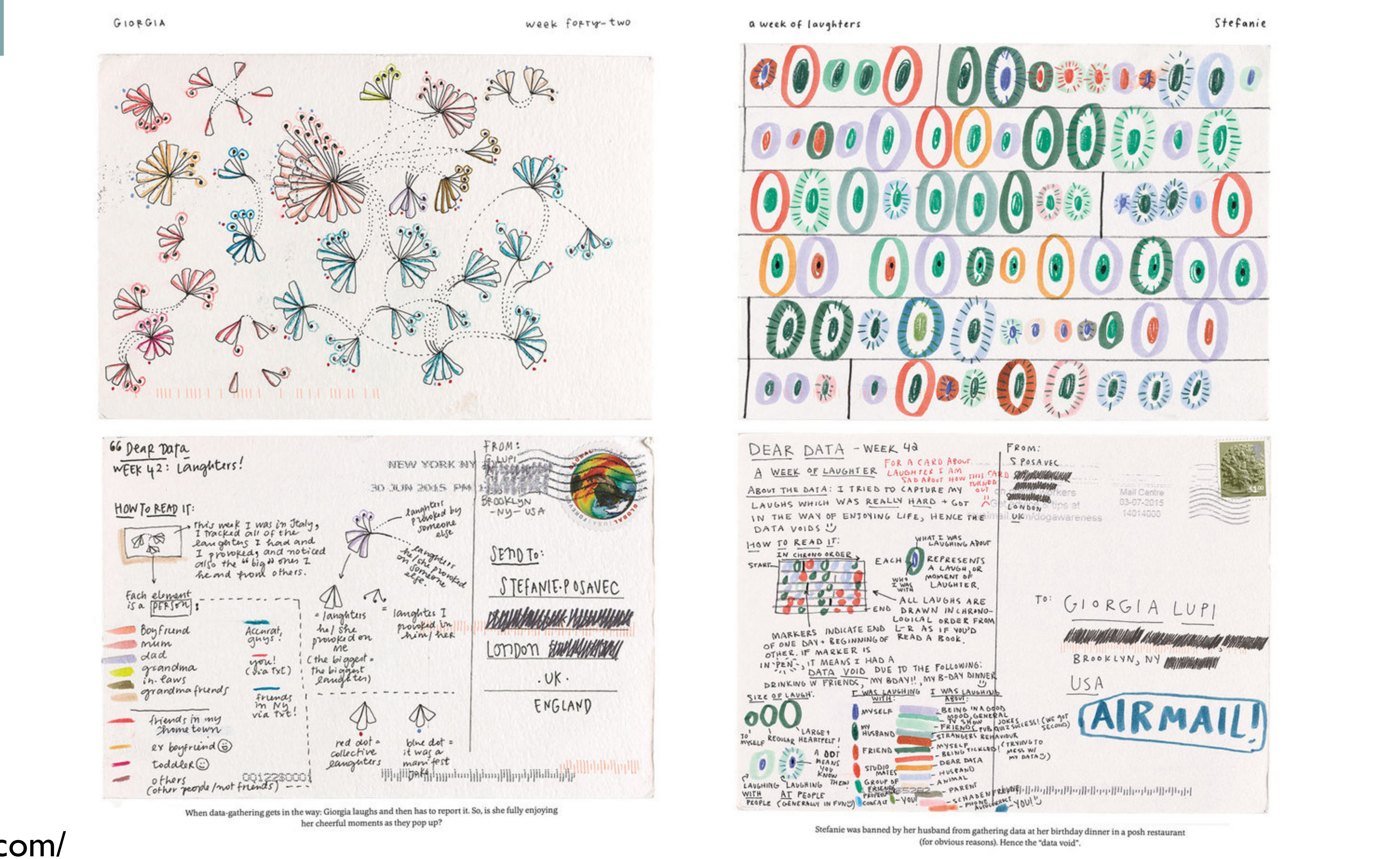


What better visual reference than a musical score to show the repetitiveness of Giorgia's protests and the "level" of complaint: whether they are justified or totally out of place.

Note the hand-drawn stamps: these postcards were delivered in person in New York!

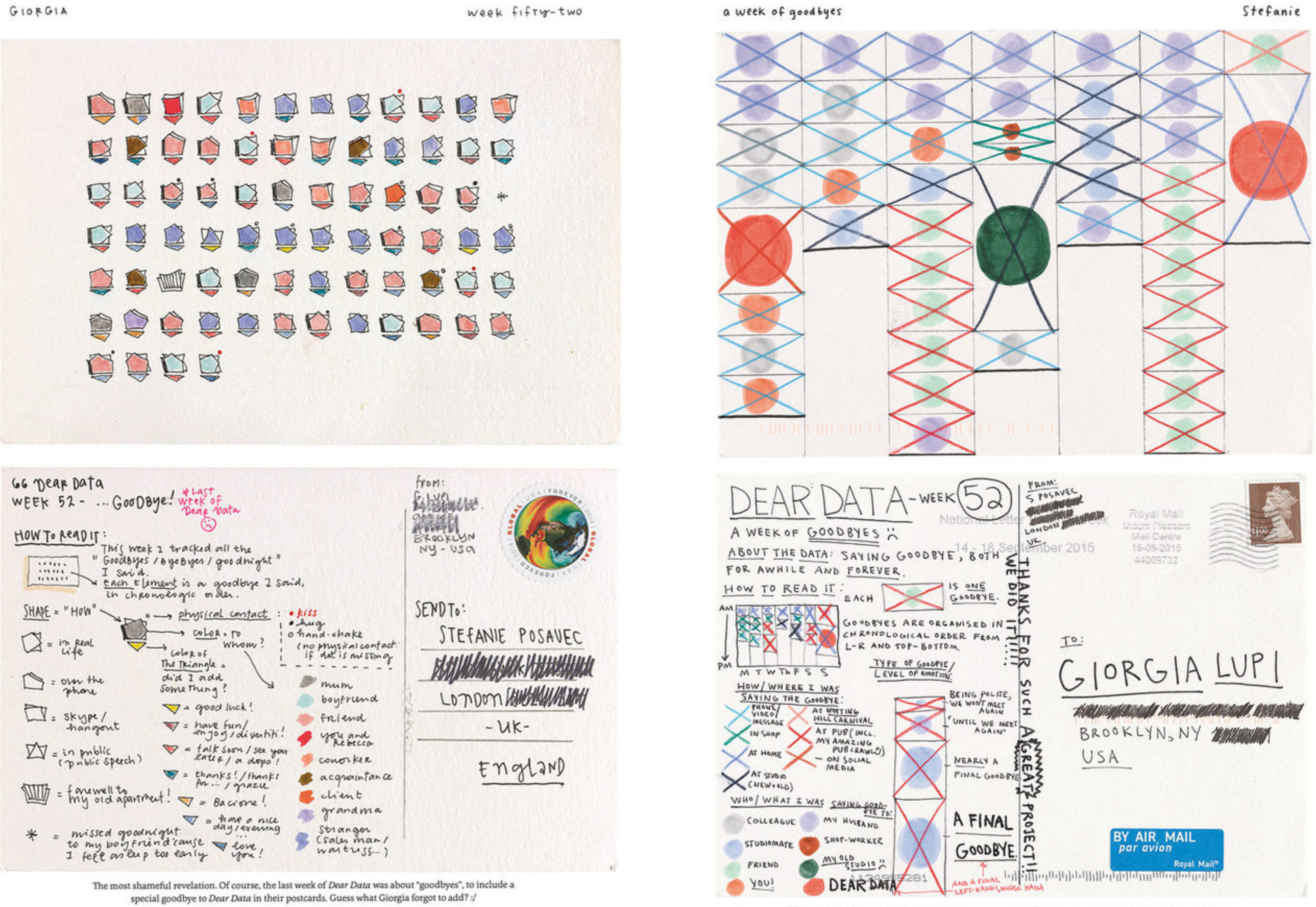
http://giorgialupi.com/

Giorgia Lupi – Dear Data



http://giorgialupi.com/

Giorgia Lupi – Dear Data



The most shameful revelation. Of course, the last week of *Dear Data* was about "goodbyes", to include a special goodbye to *Dear Data* in their postcards. Guess what Giorgia forgot to add? :/

"My amazing pub crawl": Stefanie hit ten pubs in an afternoon and was feeling pretty proud. "My old studio": the pub crawl was in honour of the disbanding of the studio she shared with friends.

http://giorgialupi.com/

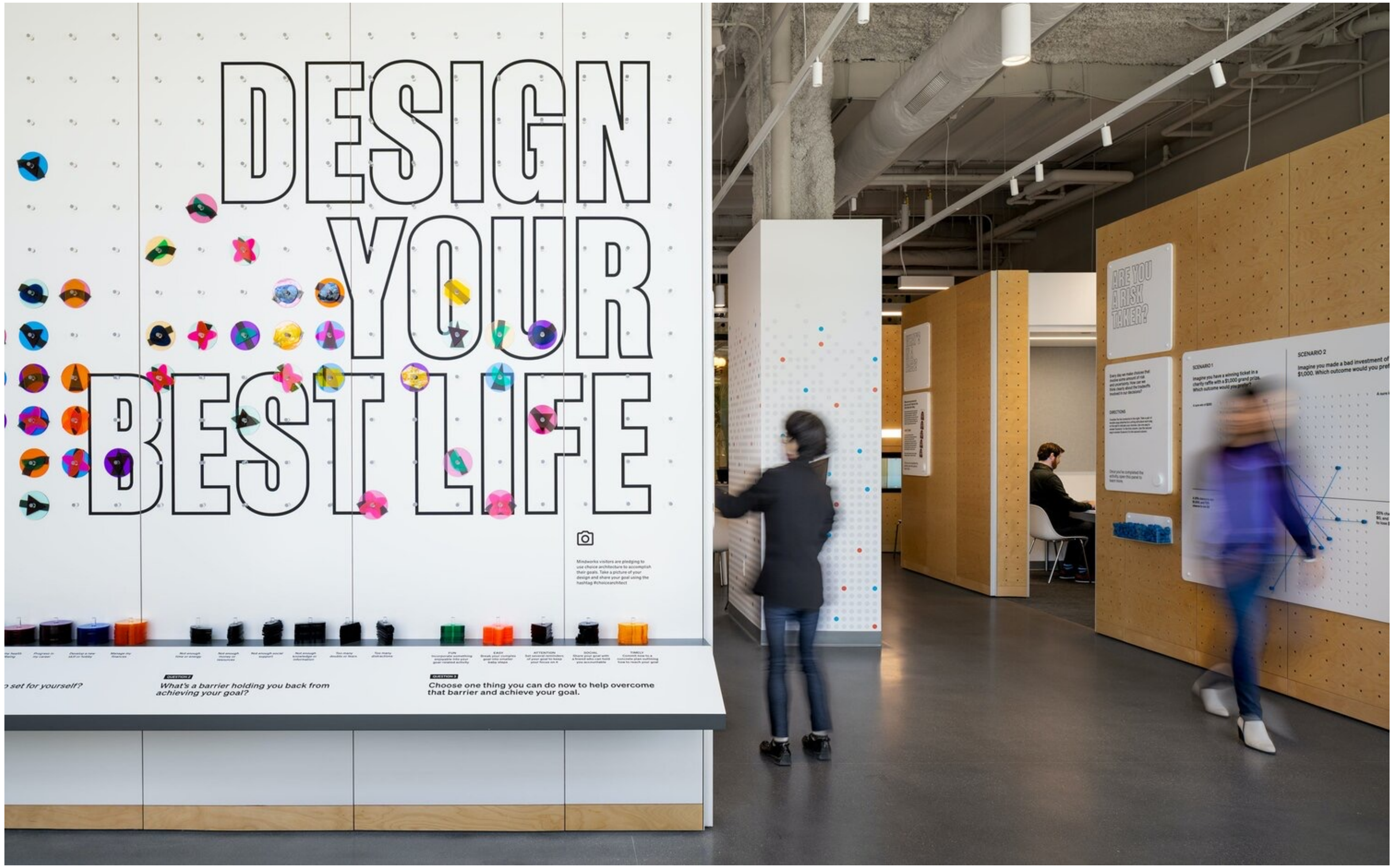
Giorgia Lupi

What sets Giorgia apart is her humanistic approach to the world of data. Data is considered to be impersonal, boring, and clinical, but her work proves the opposite.

She uses data as a lens to better understand our human nature and every aspect of our society. By distilling our personal experiences (our activities, thoughts, behaviors, relationships) into what we so coldly call data, and by actively building her datasets and expressing them as a designer and artist, she seeks to grasp glimpses of humanity and discover overlooked details.

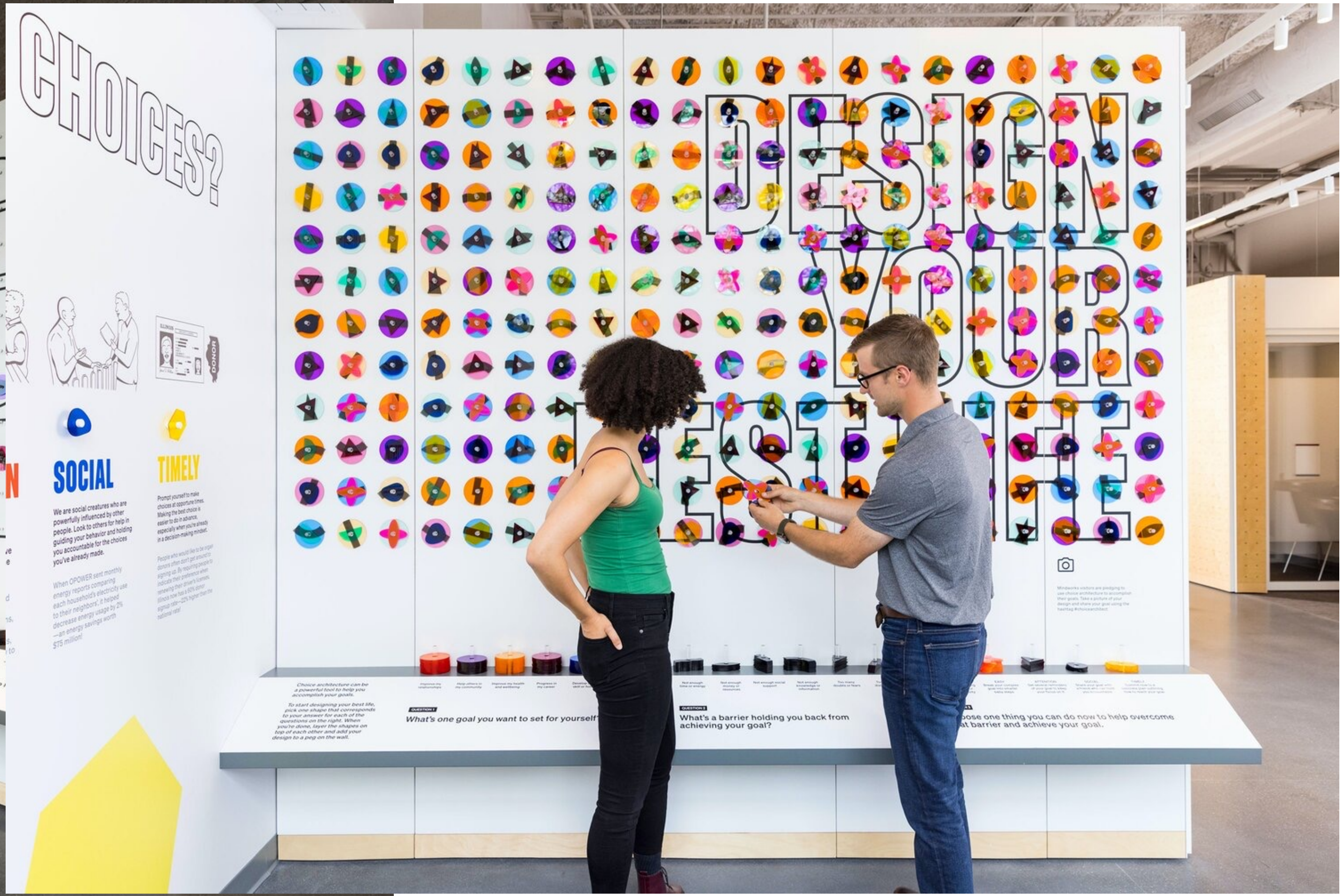
When Giorgia is presented with data, she seeks to humanize it, to make it speak our language and represent our human nature, because, in her opinion, this is the ultimate goal of any design work, especially with data. She often combines the original data with layers of softer and more qualitative information that renders and presents its more nuanced and more human aspects of us.

Giorgia Lupi – Physical Visualizations



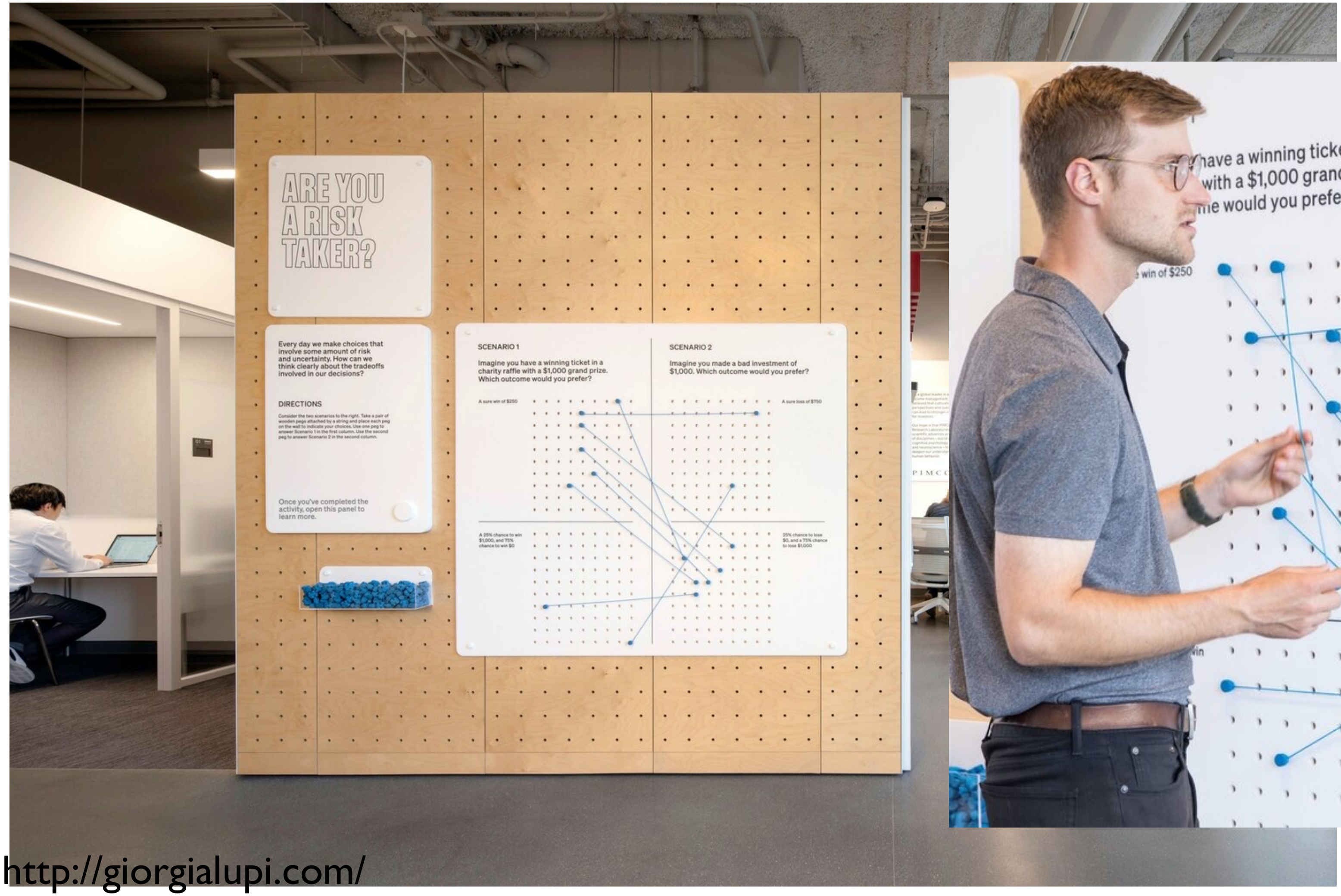
http://giorgialupi.com/

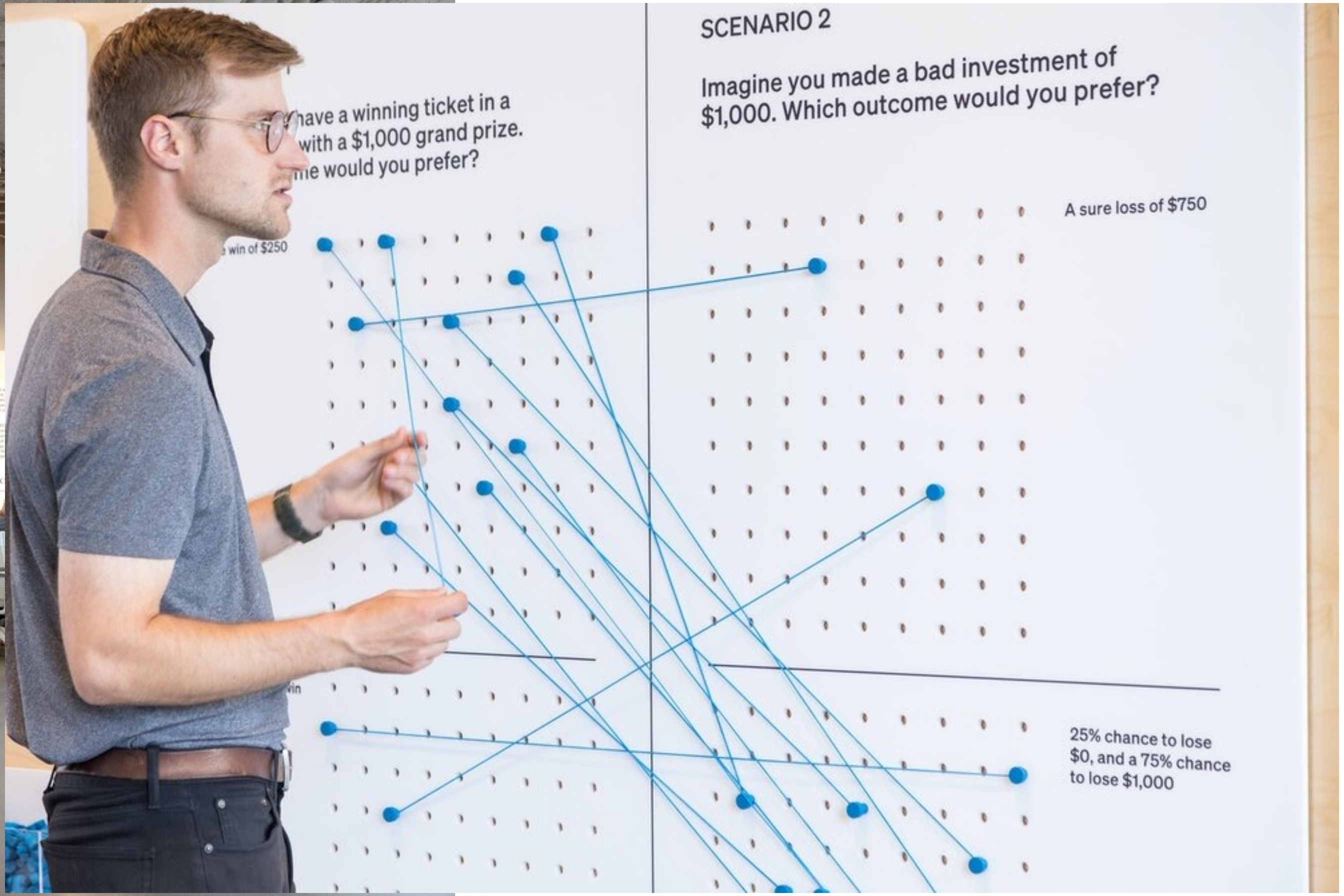
Giorgia Lupi – Physical Visualizations



http://giorgialupi.com/

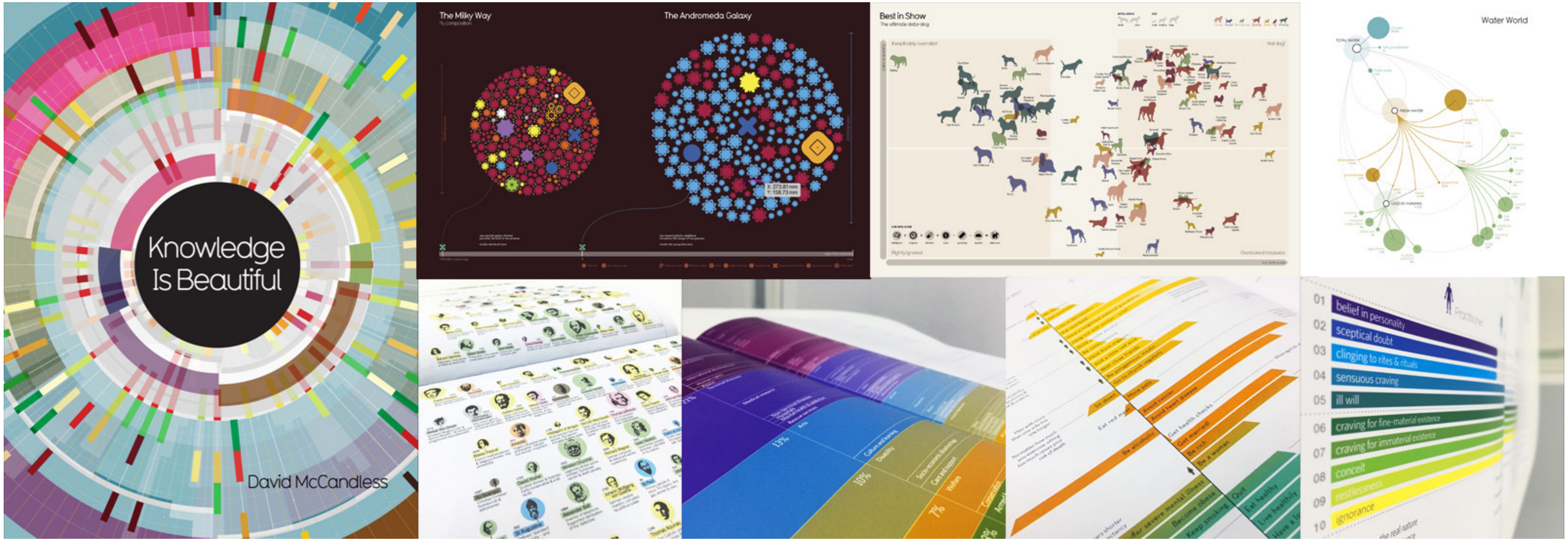
Giorgia Lupi – Physical Visualizations





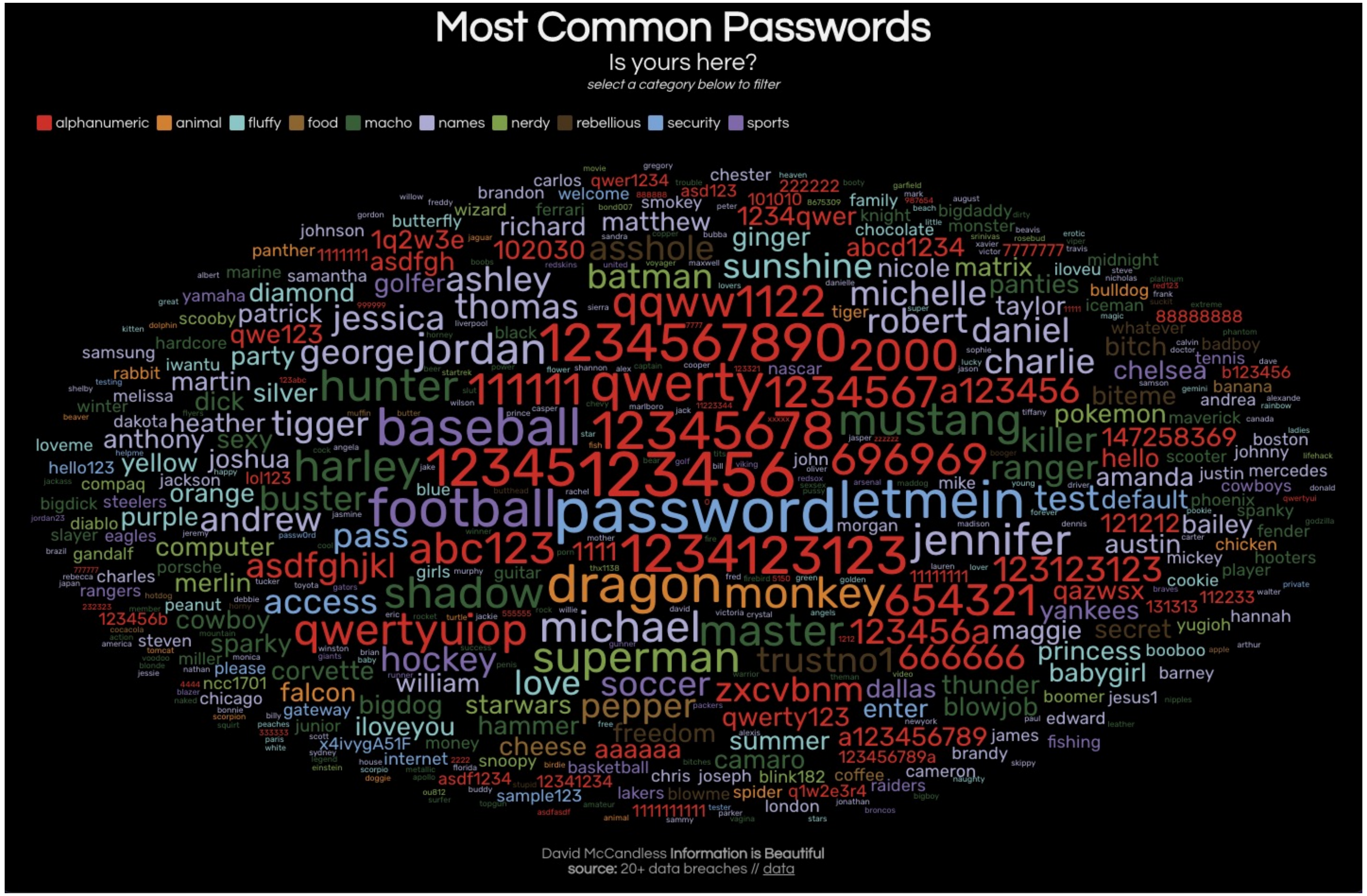
http://giorgialupi.com/

information is beautiful



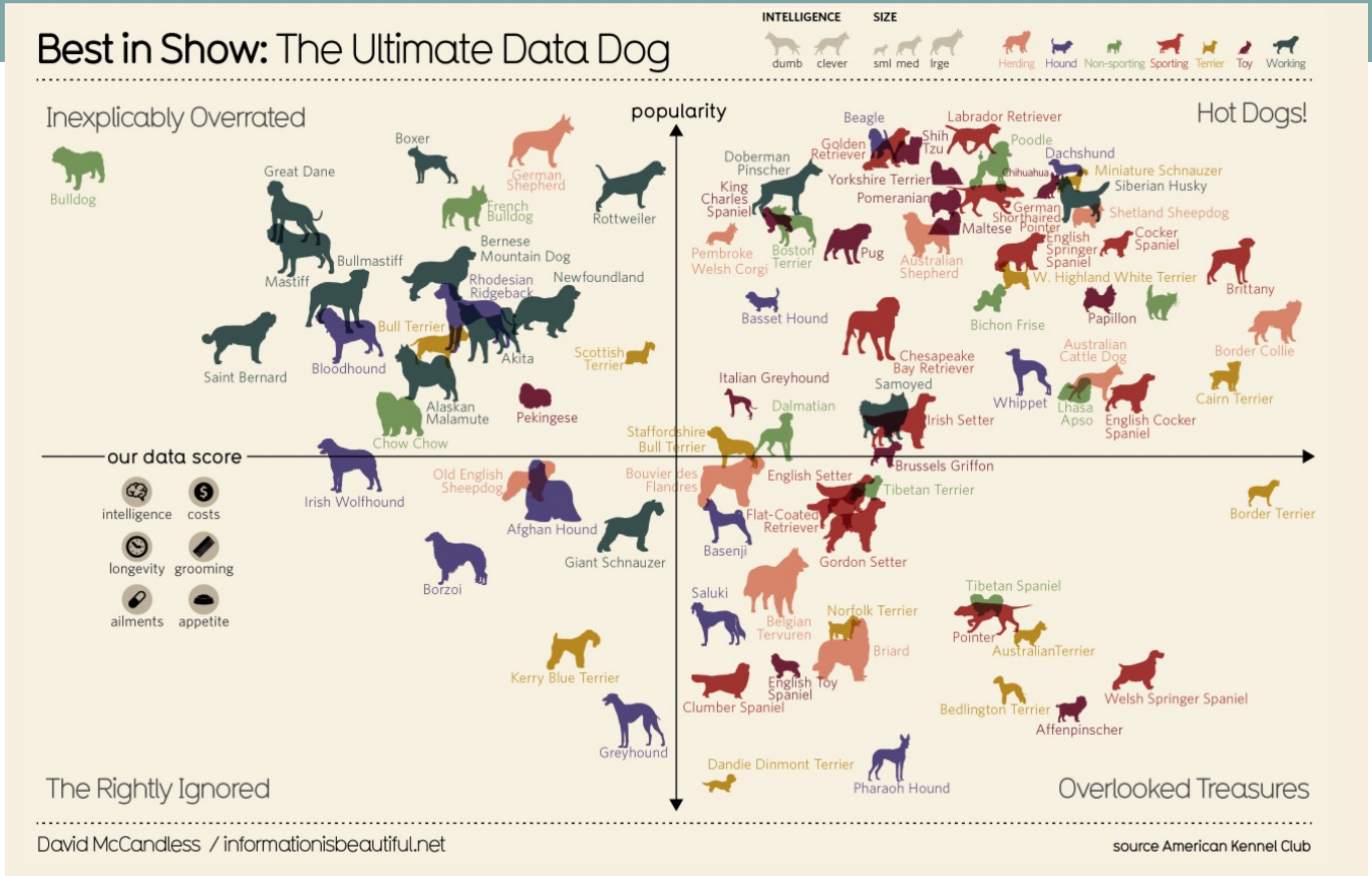
https://informationisbeautiful.net/books/

information is beautiful



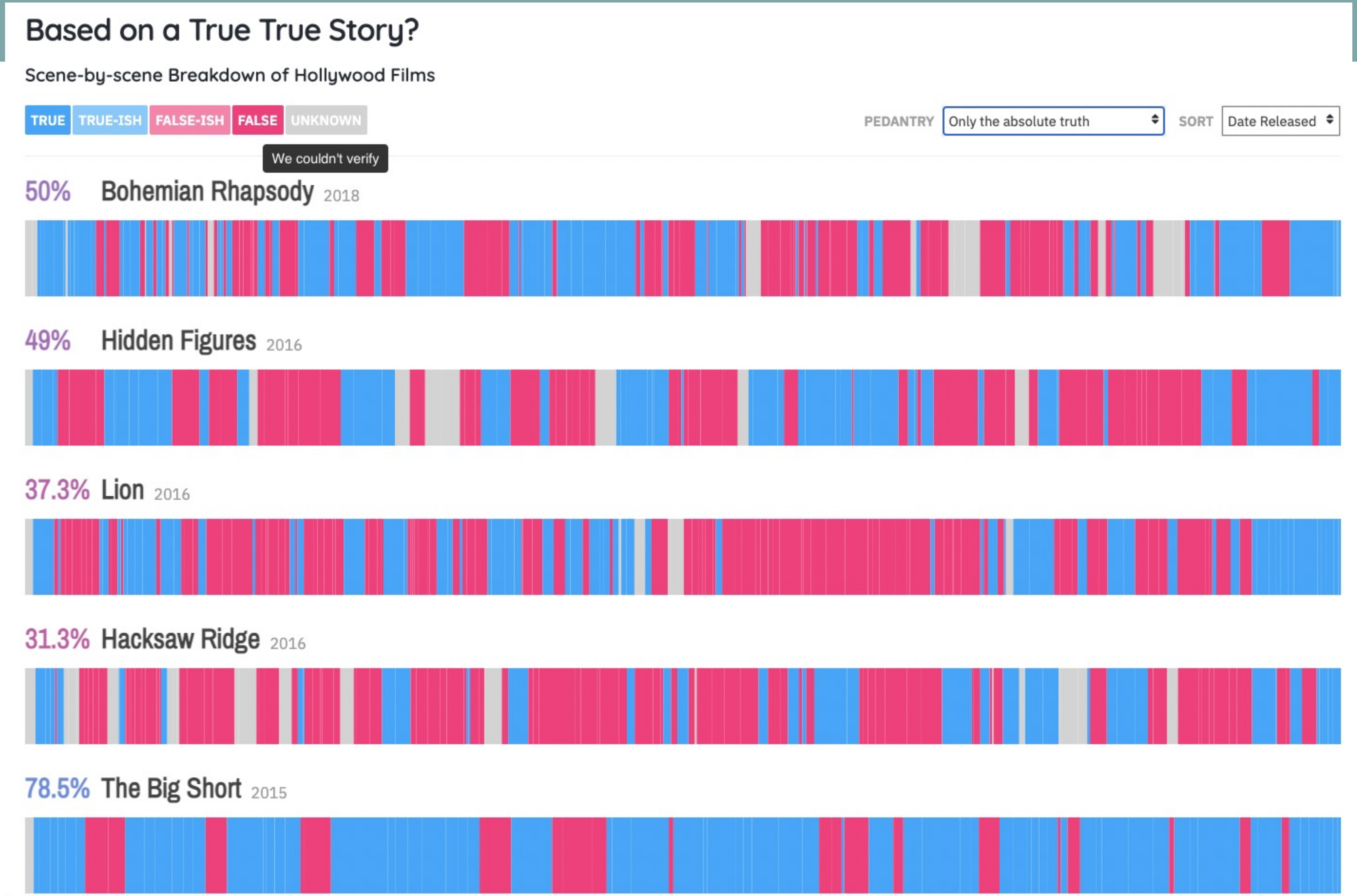
https://informationisbeautiful.net/visualizations/top-500-passwords-visualized/

information is beautiful



https://informationisbeautiful.net/visualizations/best-in-show-whats-the-top-data-dog/

information is beautiful

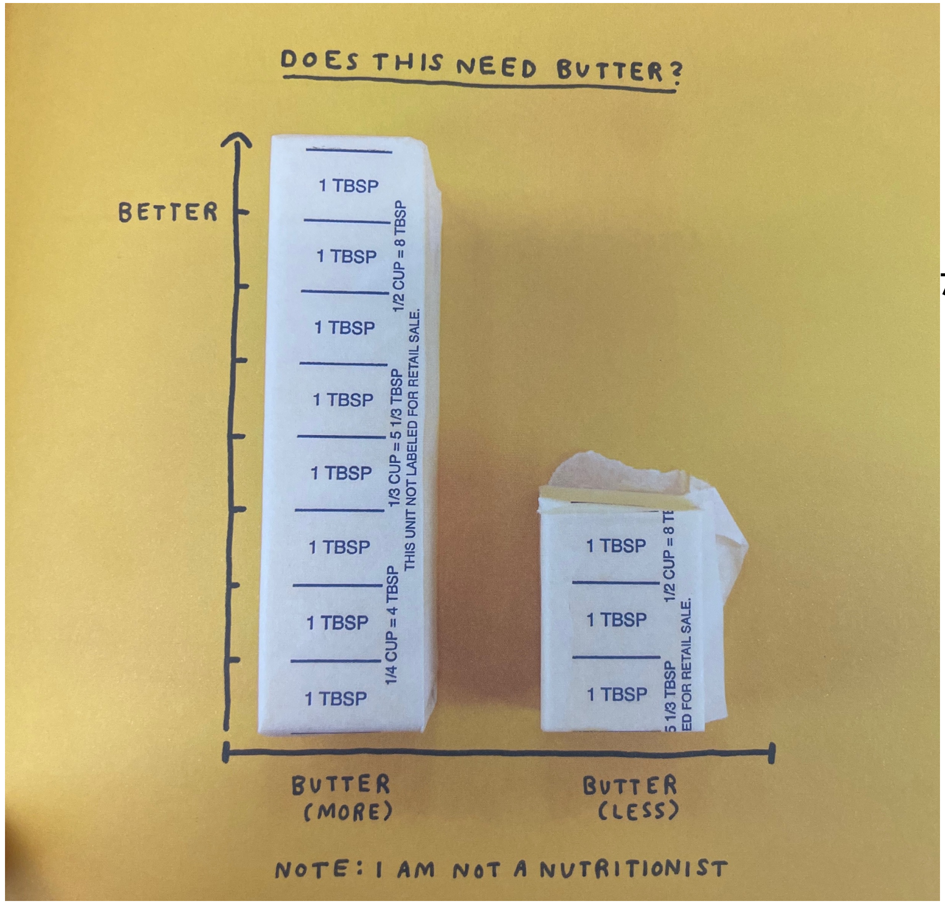


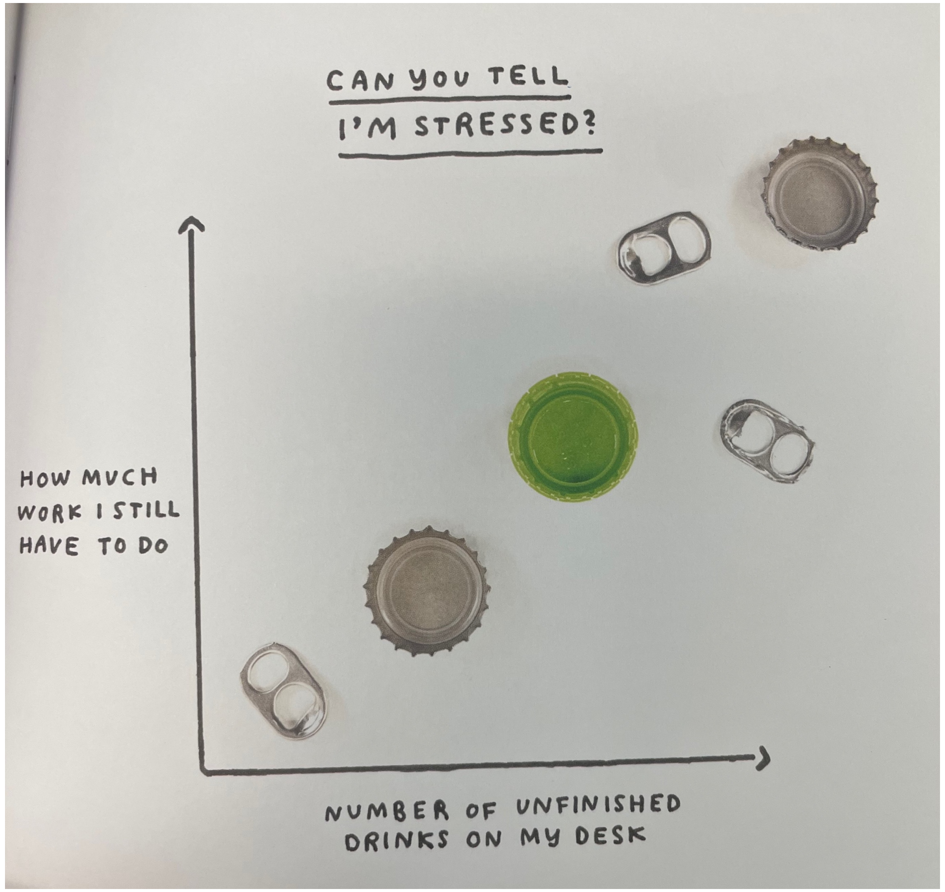
https://informationisbeautiful.net/visualizations/based-on-a-true-true-story/

Michelle Rial

https://www.michellerial.com/

Michelle Rial – Am I Overthinking This?

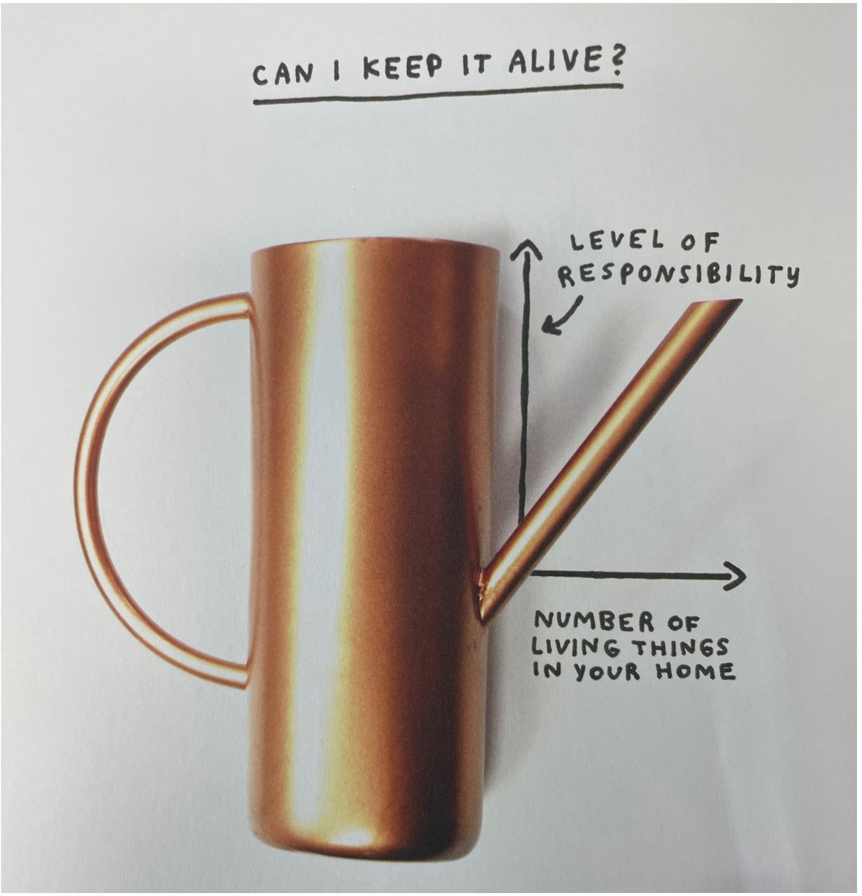




https://www.michellerial.com/

Michelle Rial – Am I Overthinking This?

75



https://www.michellerial.com/

10 minute break, get up if you need to

Intro to Visualization Research

Medical Risk Communication

Bayesian Reasoning

The probability of breast cancer is 1% for women at age forty who participate in routine screening. If a woman has breast cancer, the probability is 80% that she will get a positive mammography. If a woman does not have breast cancer, the probability is 9.6% that she will also get a positive mammography.

A woman in this age group had a positive mammography in a routine screening. What is the probability that she actually has breast cancer?

Bayesian Reasoning

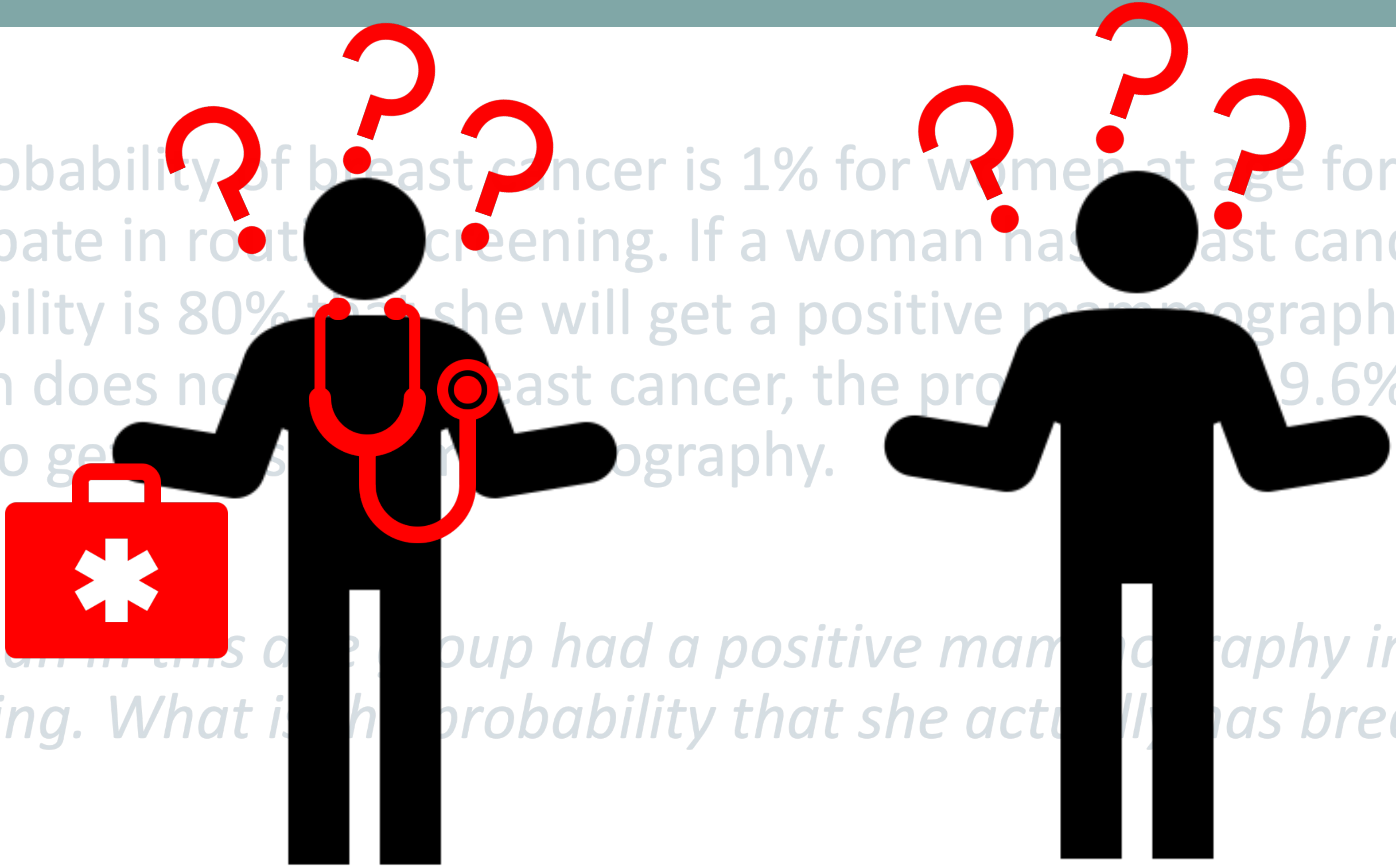
$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

https://miro.medium.com/max/1468/1*LB-G6WBuswEfpg20FMighA.png

Bayesian Reasoning

The probabilit[illegible]of b[illegible]east [illegible]ncer is 1% for w[illegible]men at a[illegible]e forty who participate in ro[illegible]creening. If a woman has [illegible]ast cancer, the probability is 80% [illegible] she will get a positive m[illegible]ography. If a woman does no[illegible]east cancer, the pro[illegible]9.6% that she will also ge[illegible]ography.

A wom[illegible]oup had a positive mam[illegible]aphy in a routine screening. What i[illegible]robability that she act[illegible]as breast cancer?



Visual Data Analysis Group
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Bayesian Reasoning

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Visual Data Analysis Group

Bayesian Reasoning

Probability -> Frequency

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A woman in this age group had a positive mammography in a routine screening. What is the probability that she actually has breast cancer?

Bayesian Reasoning

Probability -> Frequency

$\boxed{\text{10 out of every 1,000}}$ women at age forty who participate in routine screening have breast cancer. $\boxed{\text{8 of every 10}}$ women with breast cancer will get a positive mammography. $\boxed{\text{95 out of every 990}}$ women without breast cancer will also get a positive mammography.

A woman in this age group had a positive mammography in a routine screening. What is the probability that she actually has breast cancer?

Bayesian Reasoning

10 out of every 1,000 women at age forty who participate in routine screening have breast cancer. 8 of every 10 women with breast cancer will get a positive mammography. 95 out of every 990 women without breast cancer will also get a positive mammography.

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Bayesian Reasoning

Use a probe question

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Imagine 1000 people are tested for the disease.

(a) How many people will test positive?

(b) Of those who test positive, how many will actually have the disease?

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Bayesian Reasoning

Use visualization

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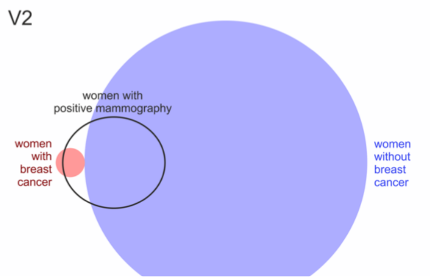
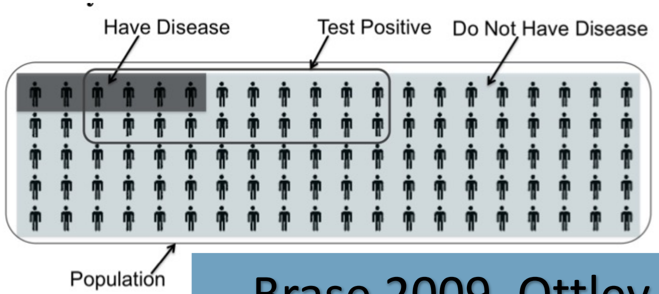
Bayesian Reasoning

Use visualization

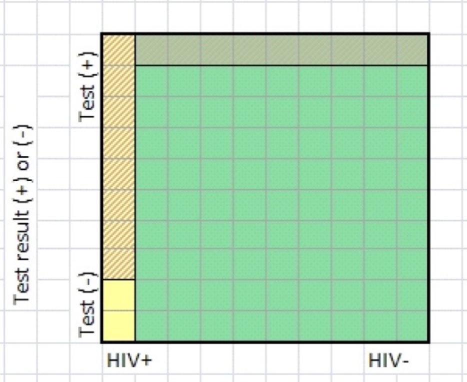
- Euler diagrams
- Frequency grids or icon arrays
- Decision trees
- “Beam cut" diagrams
- Probability curves
- Contingency tables
- Doubletrees
- Flow charts
- Pipe diagrams
- Sankey diagrams
- Unit squares



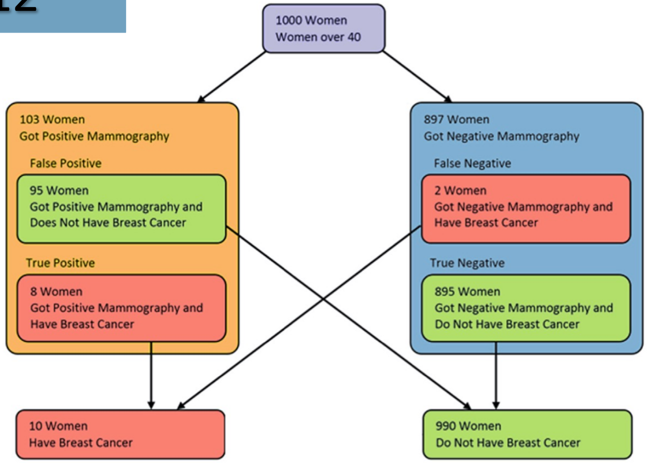
Micallef et al. 2012



Brase 2009, Ottley et al. 2016



Tsai et al. 2011



Khan et al. 2015

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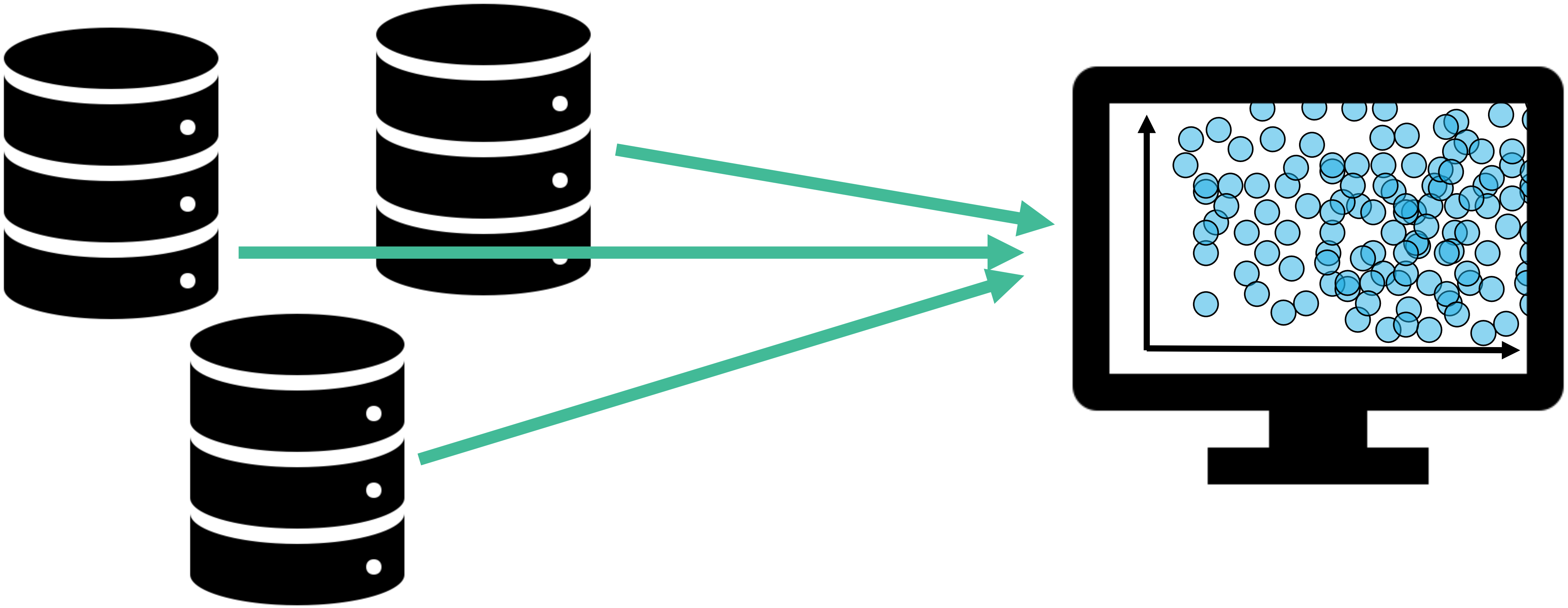
[v]alt

Can interaction help?

Large Data Exploration



Visual Data Analysis Group

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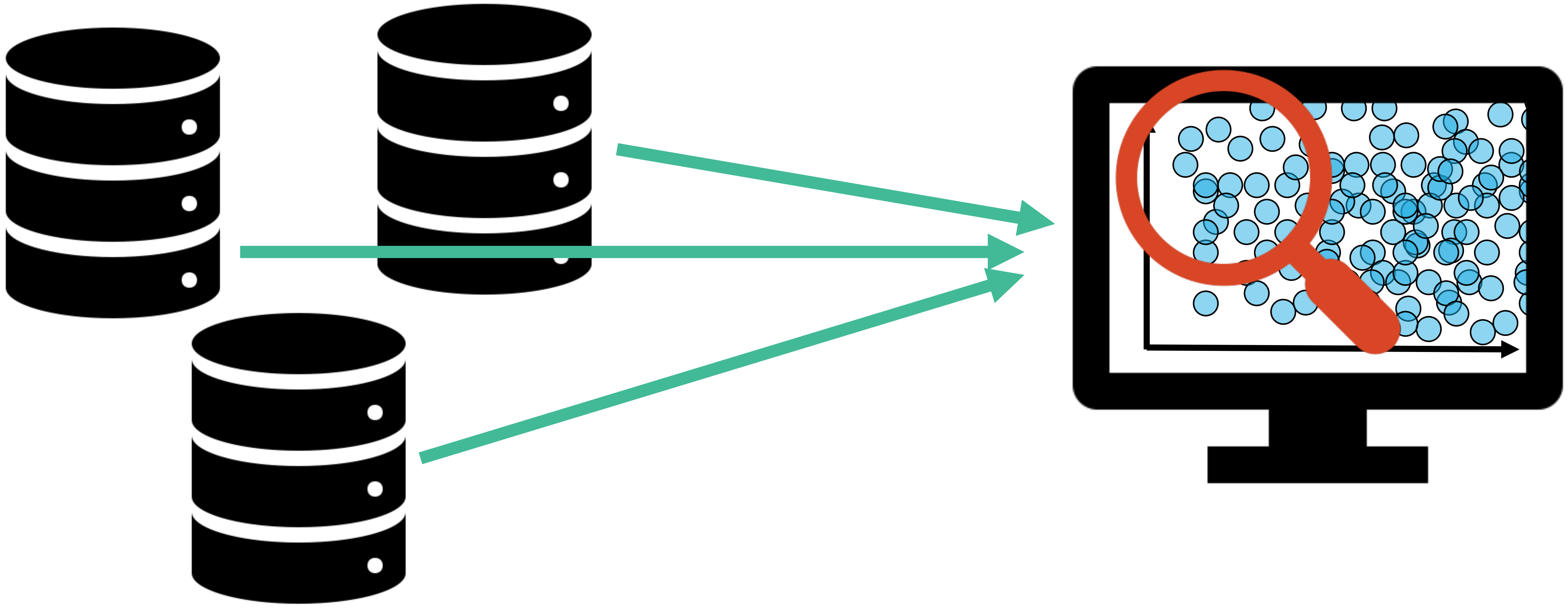
Large Data Exploration



Visual Data Analysis Group
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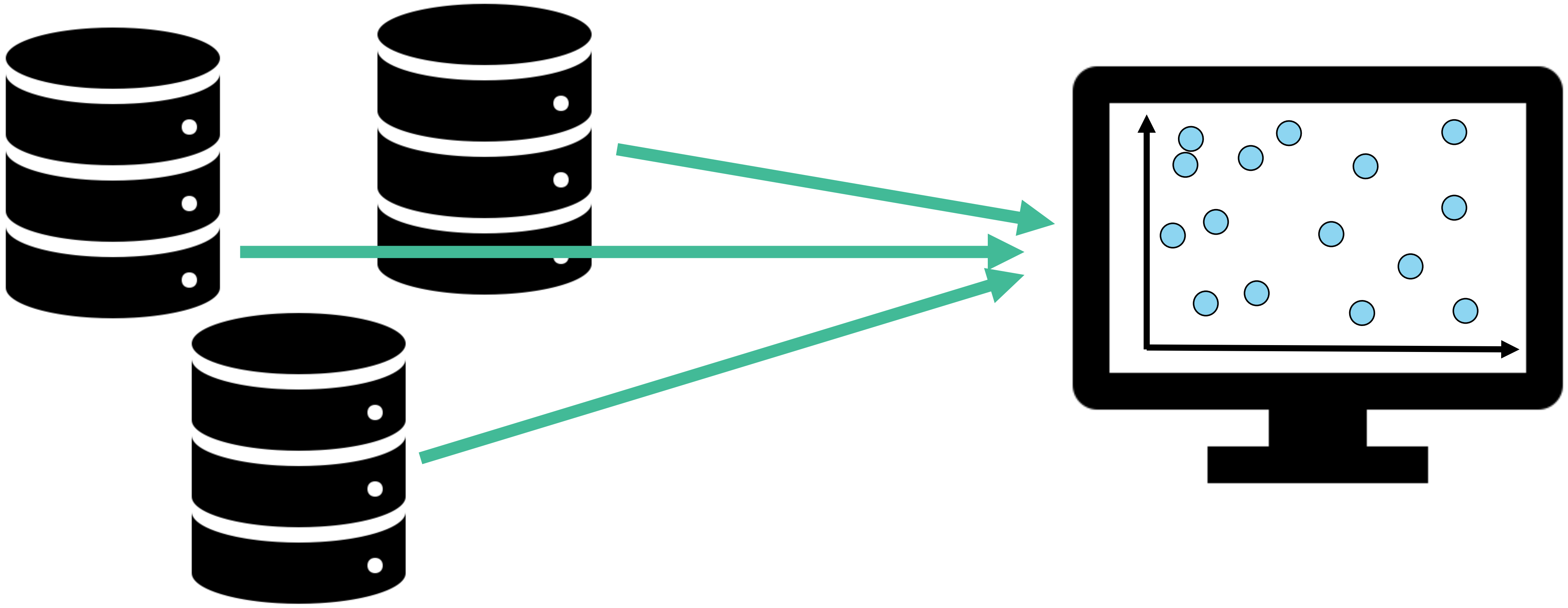
Large Data Exploration



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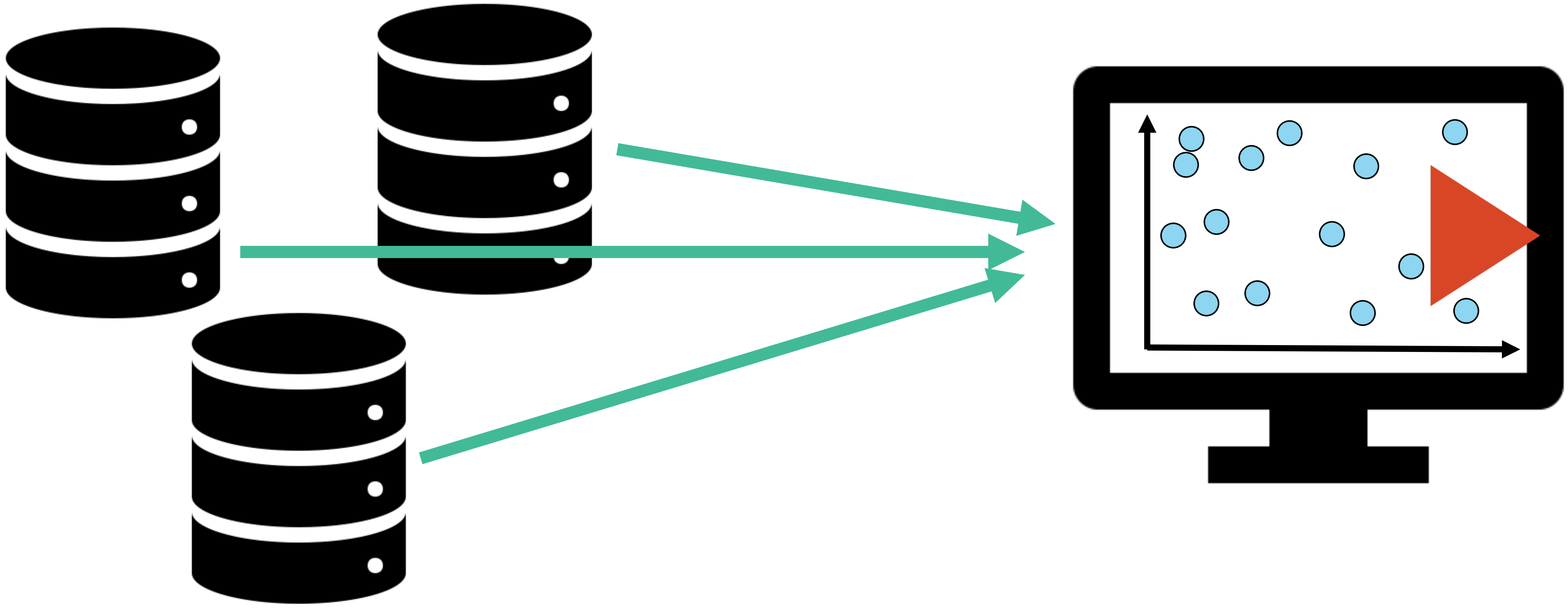
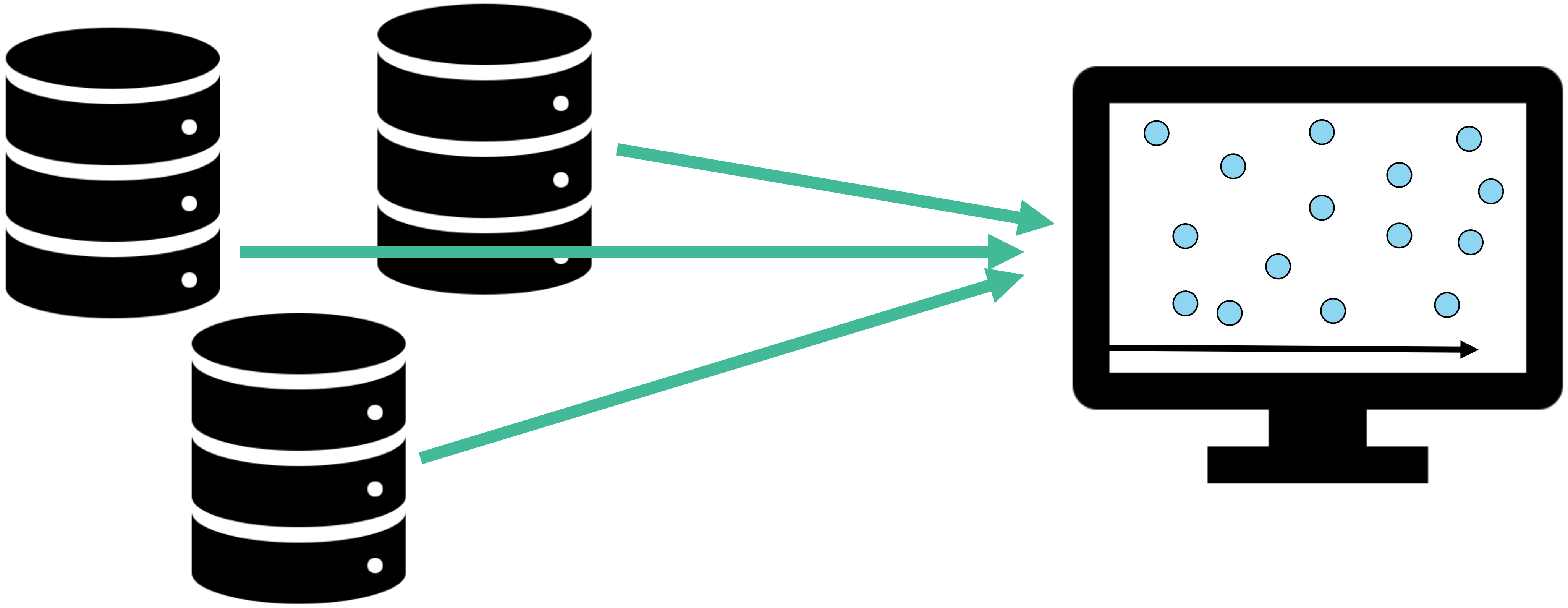
Large Data Exploration



Visual Data Analysis Group

Large Data Exploration



Visual Data Analysis Group

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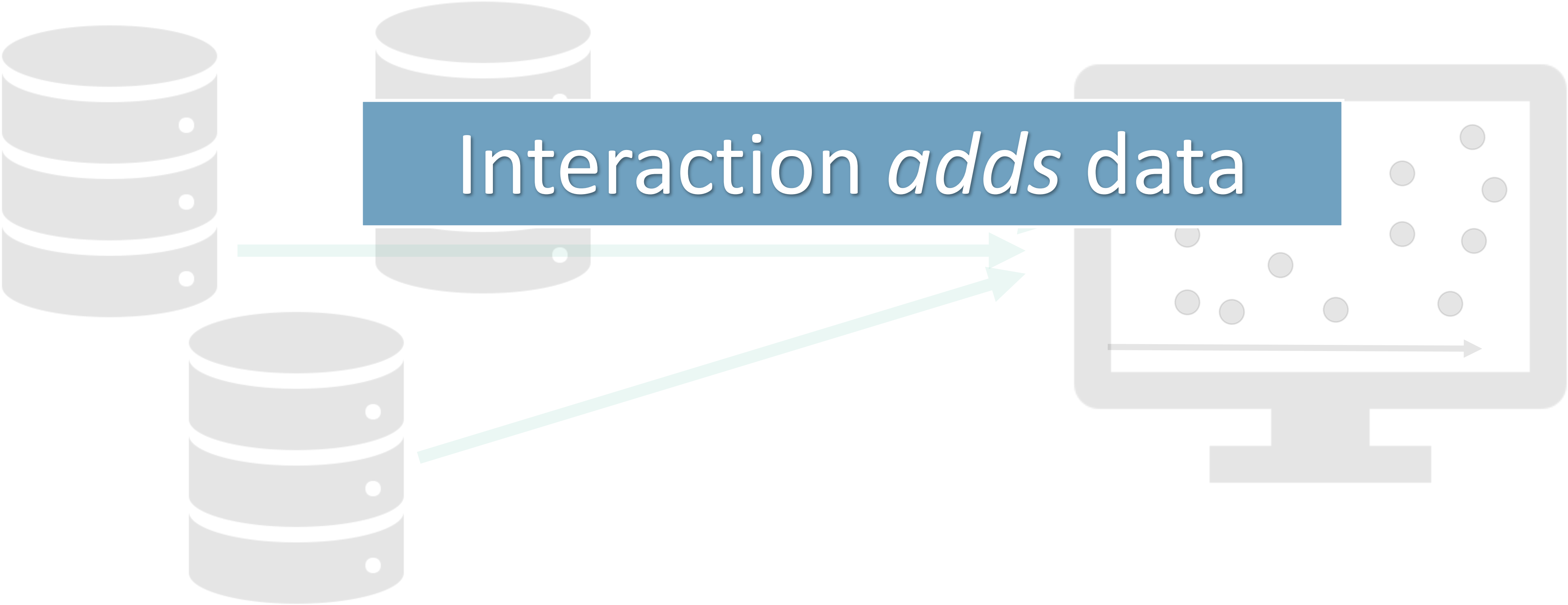
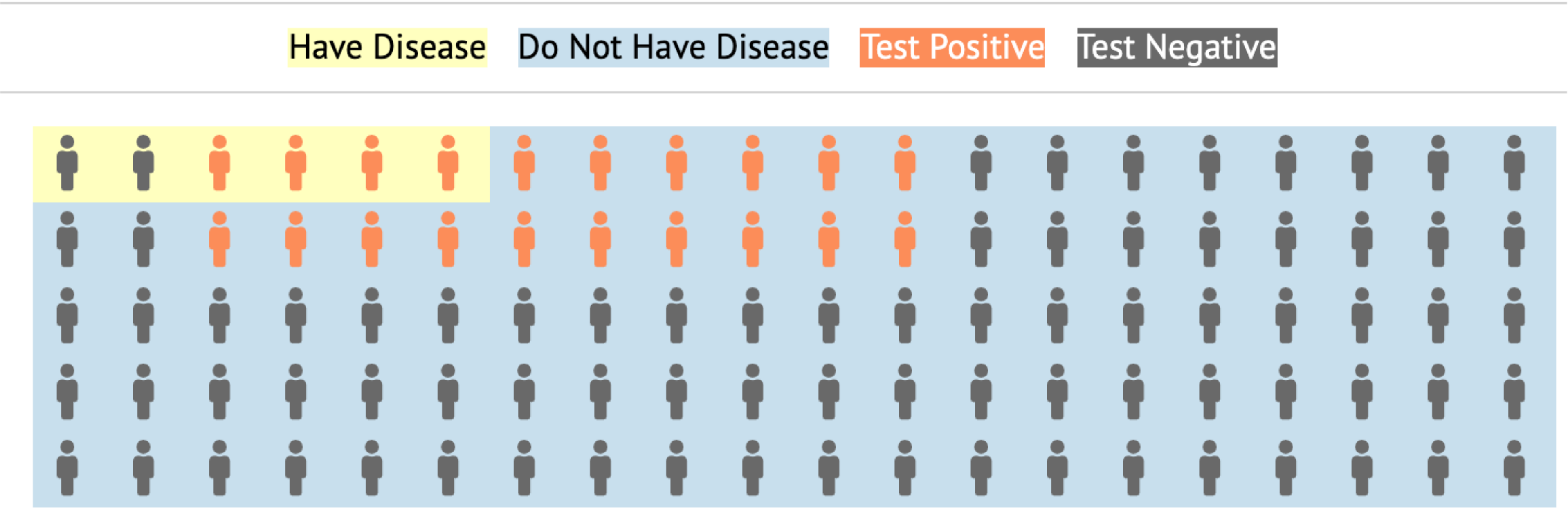
Large Data Exploration



Interaction *adds* data

Visual Data Analysis Group

Static Visualization



Visual Data Analysis Group

[v]alt

Static Visualization

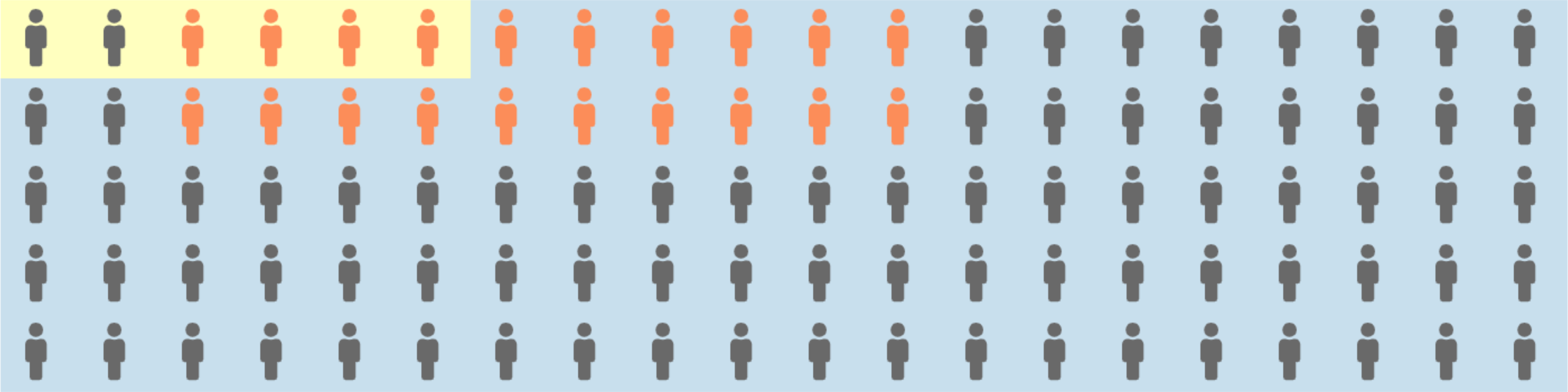
True Positive

True Negative

False Positive

False Negative

Have Disease | Do Not Have Disease | Test Positive | Test Negative



Visual Data Analysis Group

[v]alt

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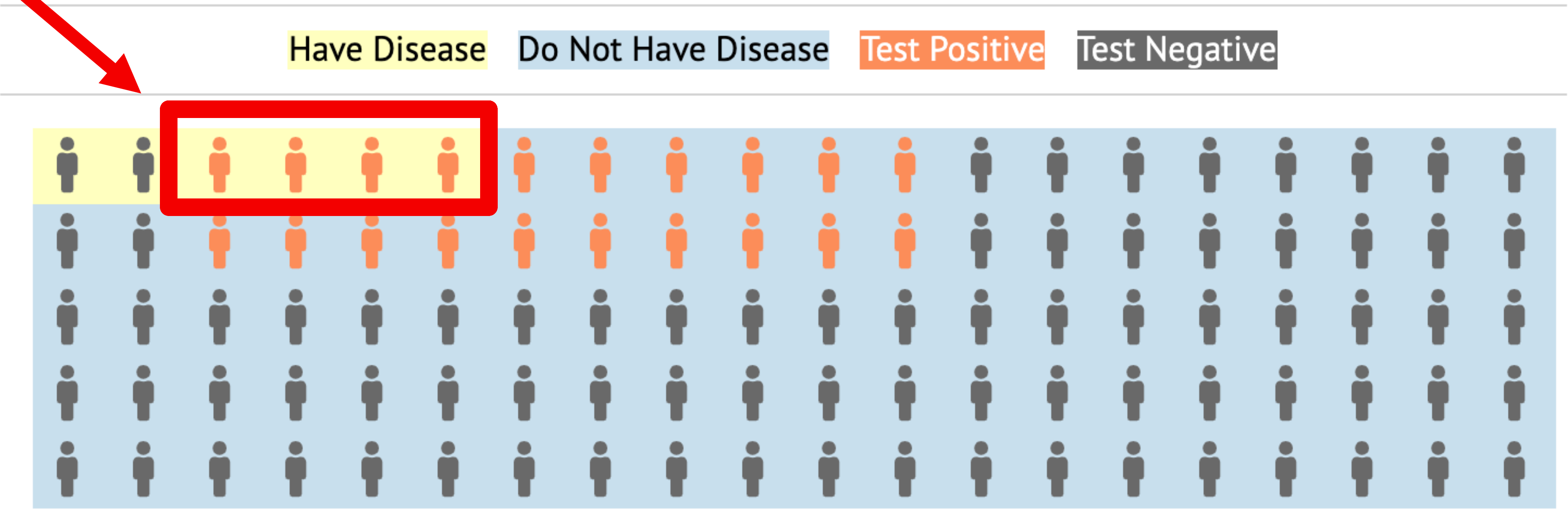

Visual Data Analysis Group

[v]alt

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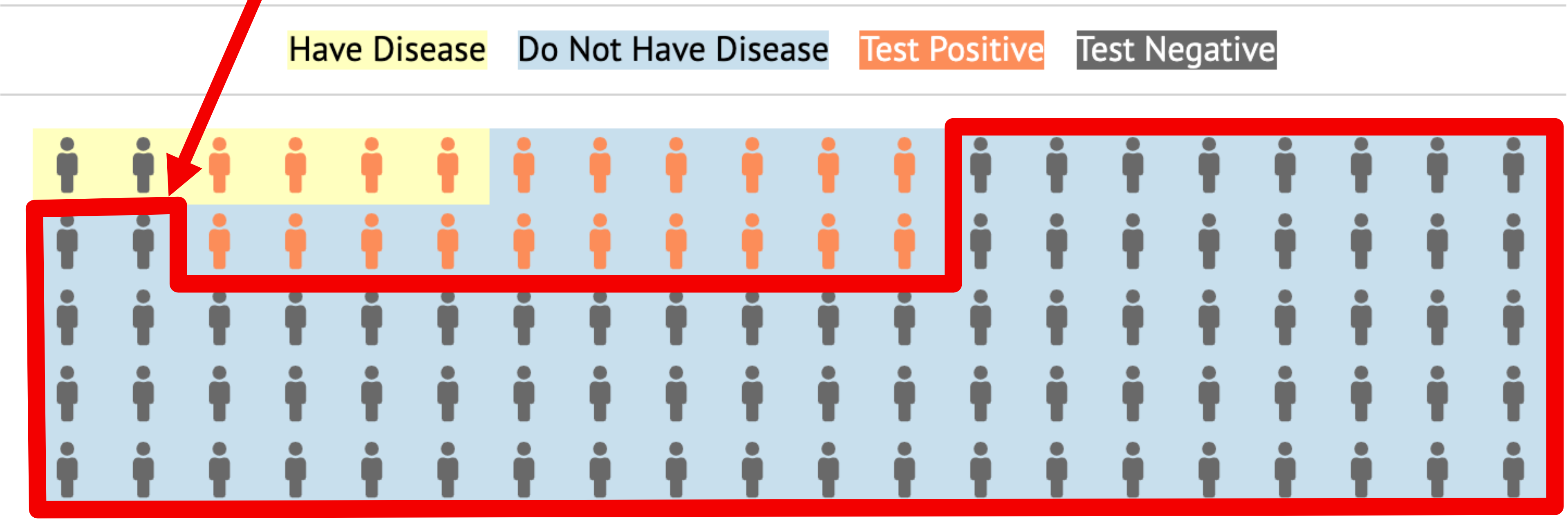

Visual Data Analysis Group
[v]alt

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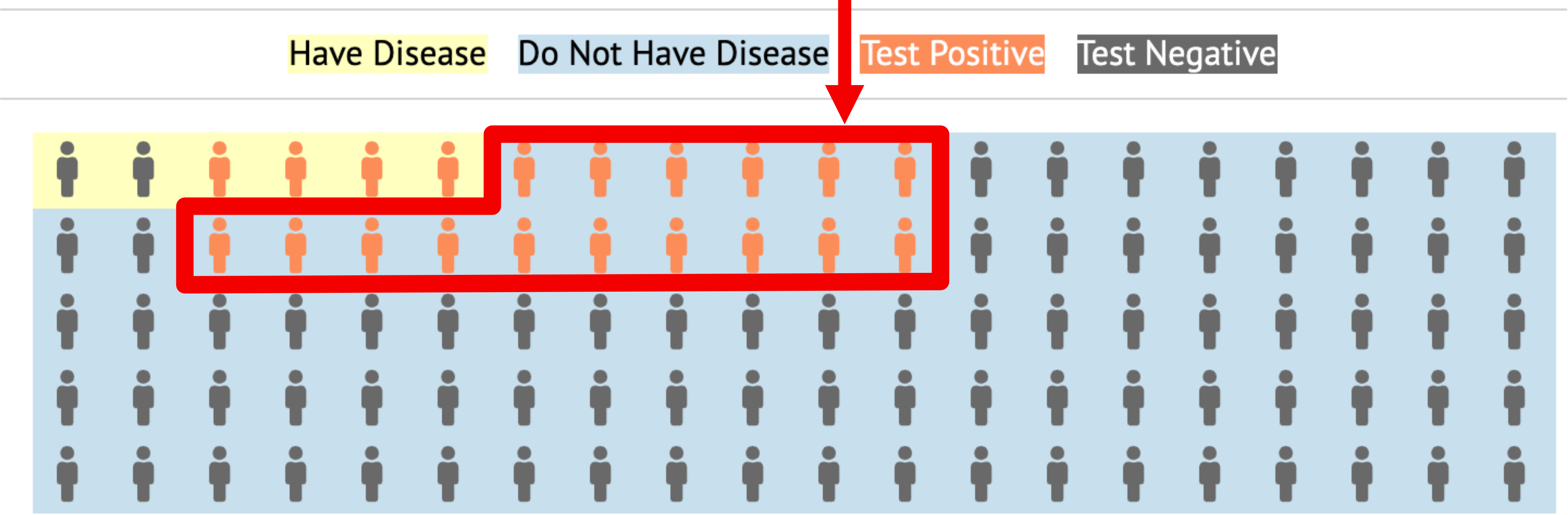


Visual Data Analysis Group

Static Visualization

True Positive

True Negative

False Positive

False Negative

Visual Data Analysis Group

[v]alt

Driving questions

1. Can we help people better perform Bayesian reasoning in the context of medical risk communication?

2. What is the value add of interaction to a *static Bayesian reasoning* visualization?

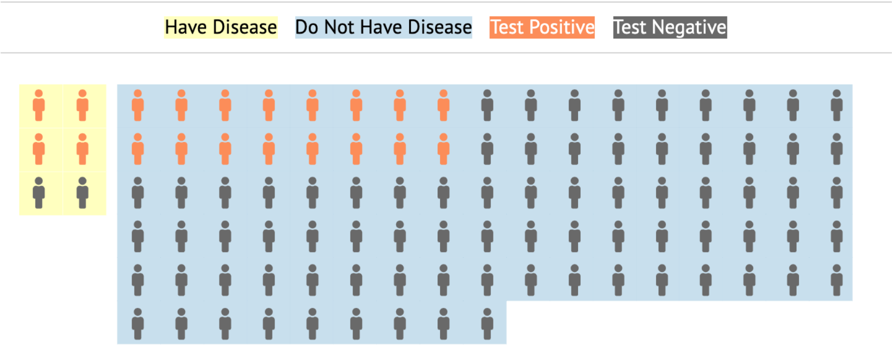
Visual Data Analysis Group
[v]alt

2 Human-subject Experiments

Visual Data Analysis Group
[v]alt

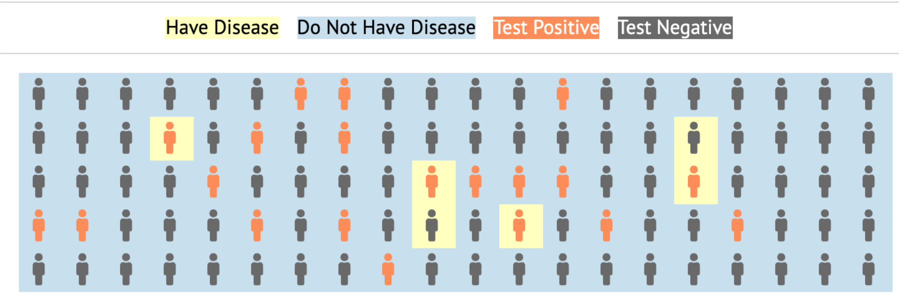
3 Base Visualization Designs

Grouped



Aligned

Randomized

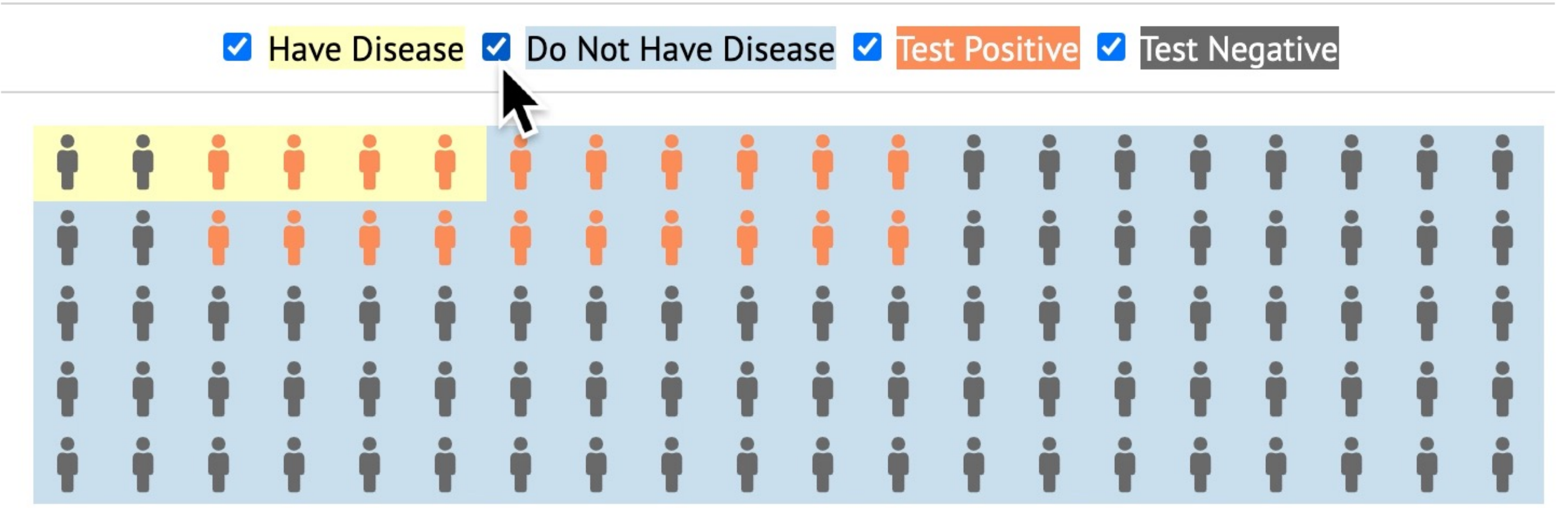


Visual Data Analysis Group
[v]alt

Interactive vs Static

Experiment 1

cbAll

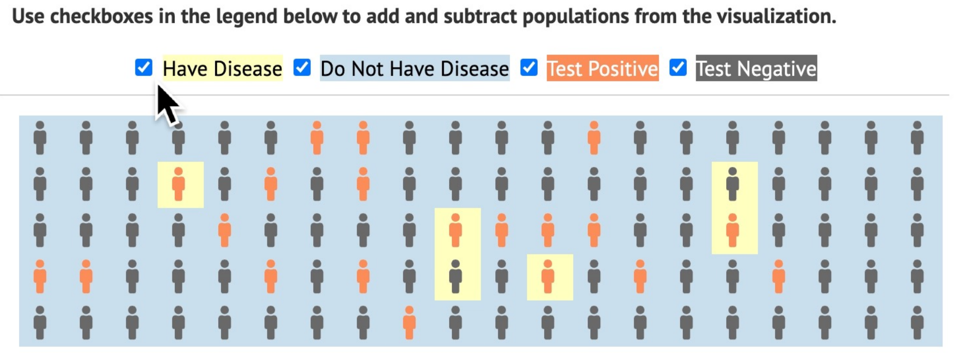


Visual Data Analysis Group
[v]alt

Interactive vs Static

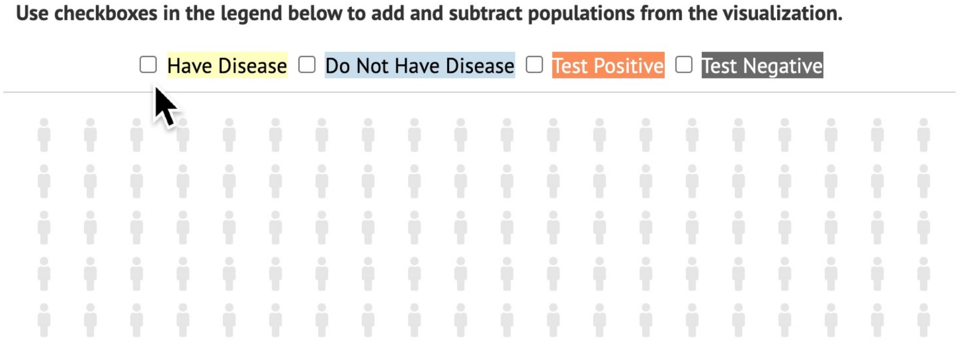
Experiment 2

cbAll



drag

cbNone

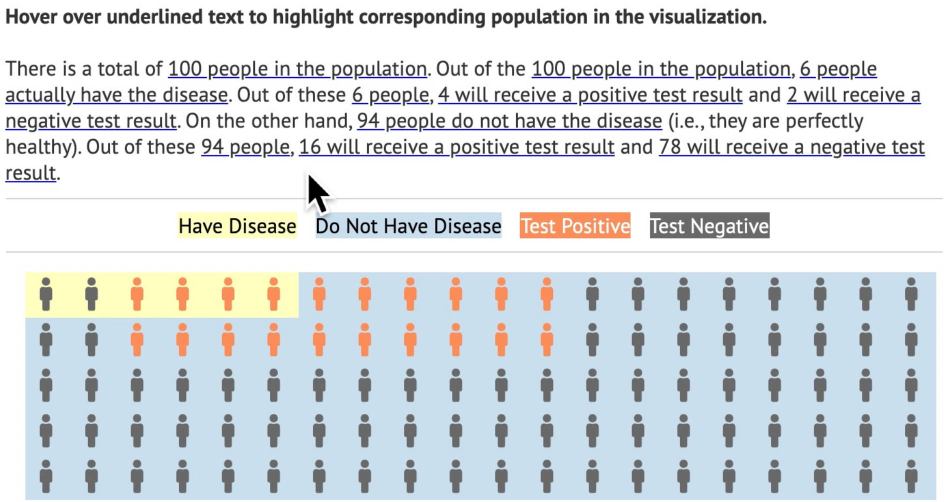


Visual Data Analysis Group

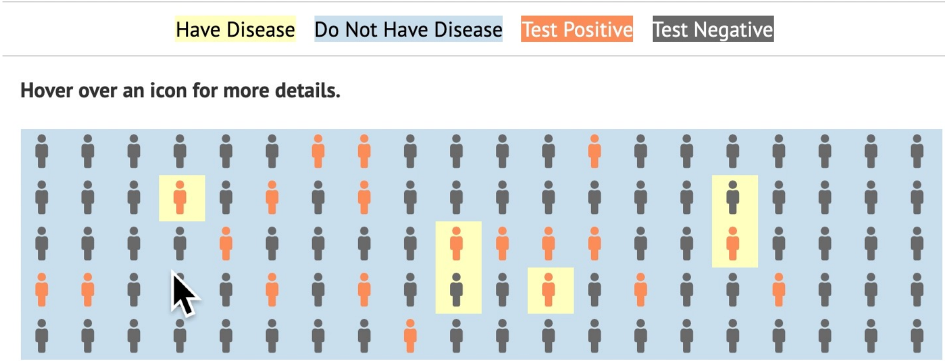
Interactive vs Static

Experiment 2

hover



tooltips



Visual Data Analysis Group

Experimental Task

Textual description: There is a newly discovered disease, Disease X, which is transmitted by a bacterial infection found in the population. There is a test to detect whether or not a person has the disease, but it is not perfect. Here is some information about the current research on Disease X and efforts to test for the infection that causes it.

There is a total of 100 people in the population. Out of the 100 people in the population, 6 people actually have the disease. Out of these 6 people, 4 will receive a positive test result and 2 will receive a negative test result. On the other hand, 94 people do not have the disease (i.e., they are perfectly healthy). Out of these 94 people, 16 will receive a positive test result and 78 will receive a negative test result.

Questions:

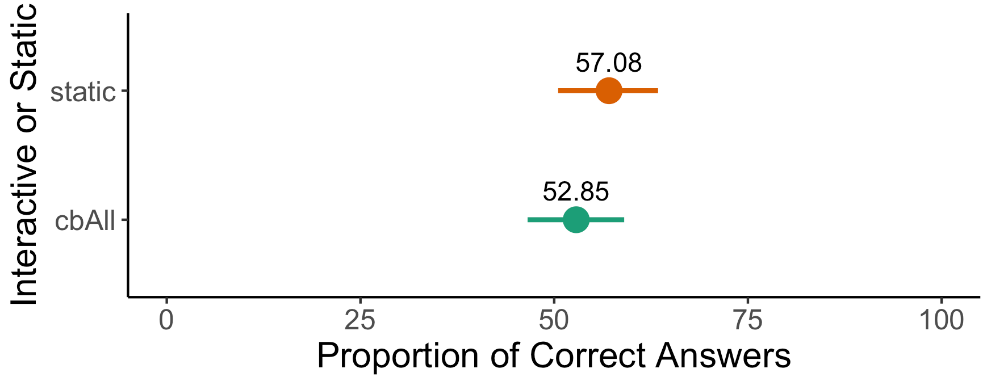
(a) How many people will test positive? _ _ _

(b) Of those who test positive, how many will actually have the disease? _ _ _

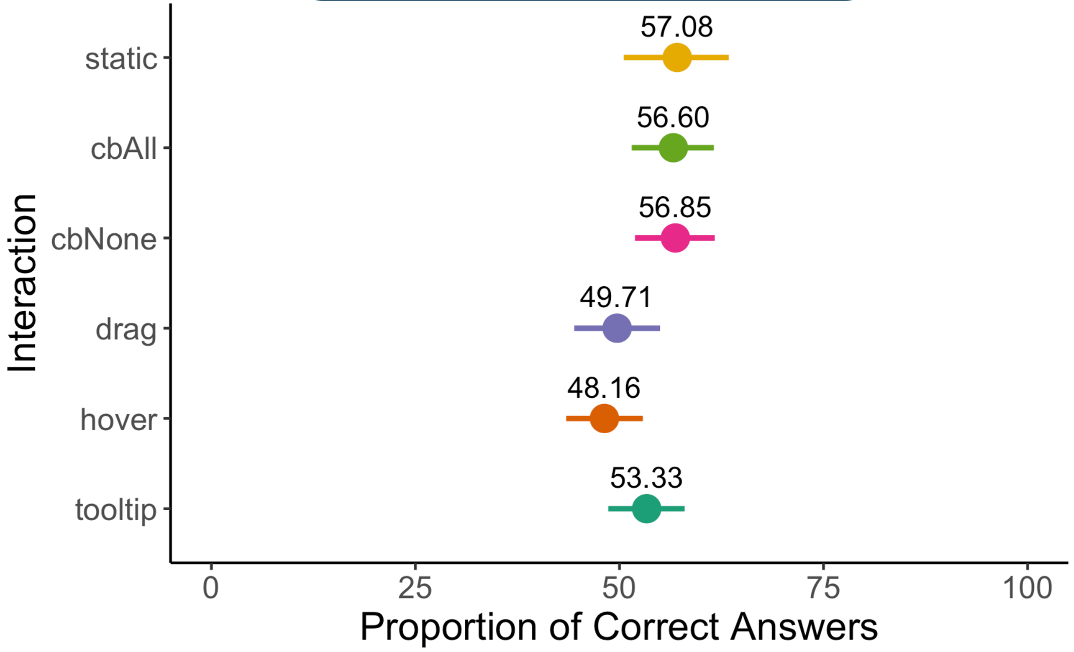
Findings

1. We **found no situations in which interaction improves performance** on the Bayesian Reasoning task.

Experiment 1



Experiment 2



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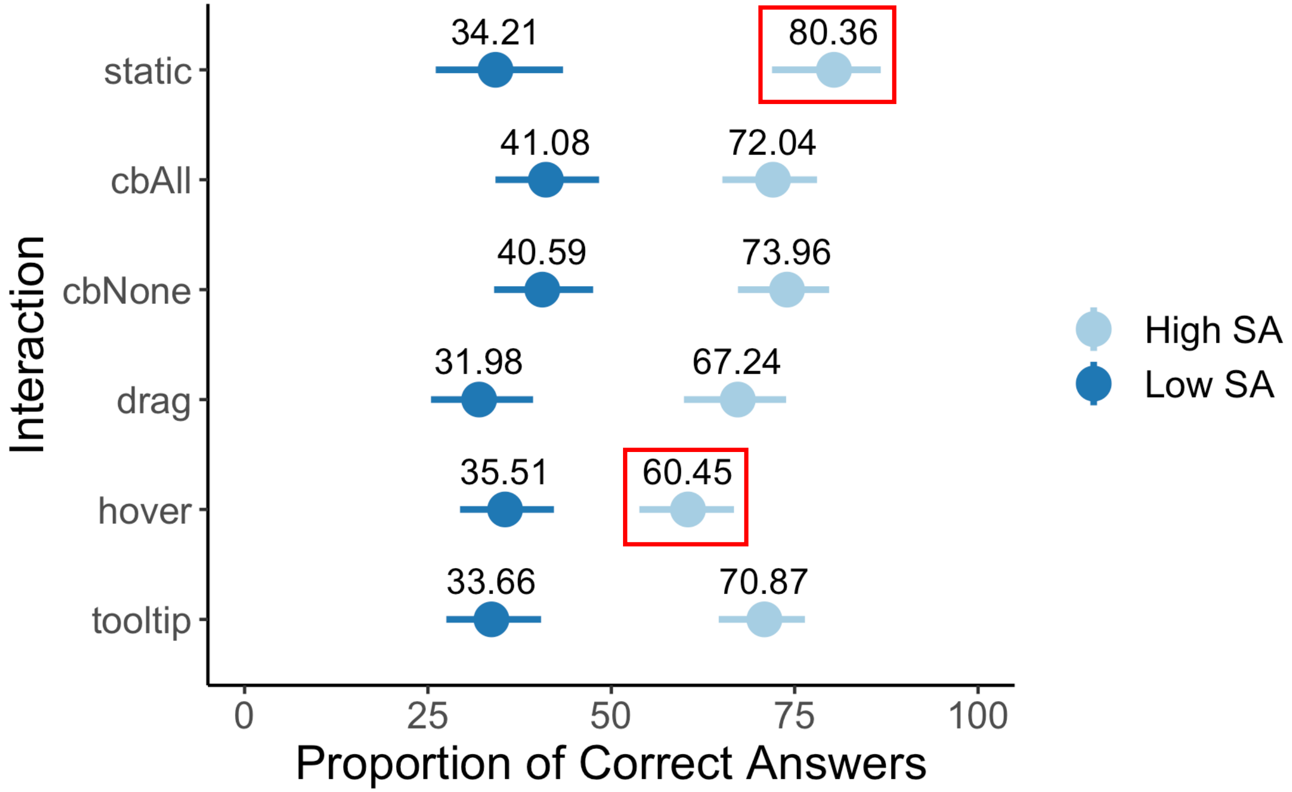
[v]alt

Findings

2. We observe that **in certain cases interaction** results in **significantly decreased accuracy** on the Bayesian reasoning task.

Experiment 2



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Driving questions

1. Can we help people better perform Bayesian reasoning in the context of medical risk communication?

2. What is the value add of interaction to a *static Bayesian reasoning* visualization?

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   Our results suggest interaction may not be the solution.

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[v]alt

Driving questions

1. Can we help people better perform Bayesian reasoning in the context of medical risk communication?

Our results suggest interaction may not be the solution.

2. What is the value add of interaction to a *static Bayesian reasoning* visualization?

Our results suggest interaction does not add value in terms of increased accuracy on a Bayesian reasoning task. But more research needs to be done! Interaction is a cost / benefit game and we don't understand all of the nuances yet :)

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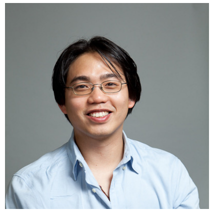
Does Interaction Improve Bayesian Reasoning with Visualization? (CHI 2021)

Alvitta Ottley,
Washington University in St. Louis

Remco Chang,
Tufts University



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Summary

Today we:

- Reviewed Visualization for Communication
- Took a look at a Visualization Research Project