

Data.Europa Academy • Visualising data for impact

Foundations of Effective Data Visualization

Alberto Cairo

OpenVisualizationAcademy.com

Information design

The intentional presentation of information within a certain set of constraints with the goal of aiding thought.

Data visualization

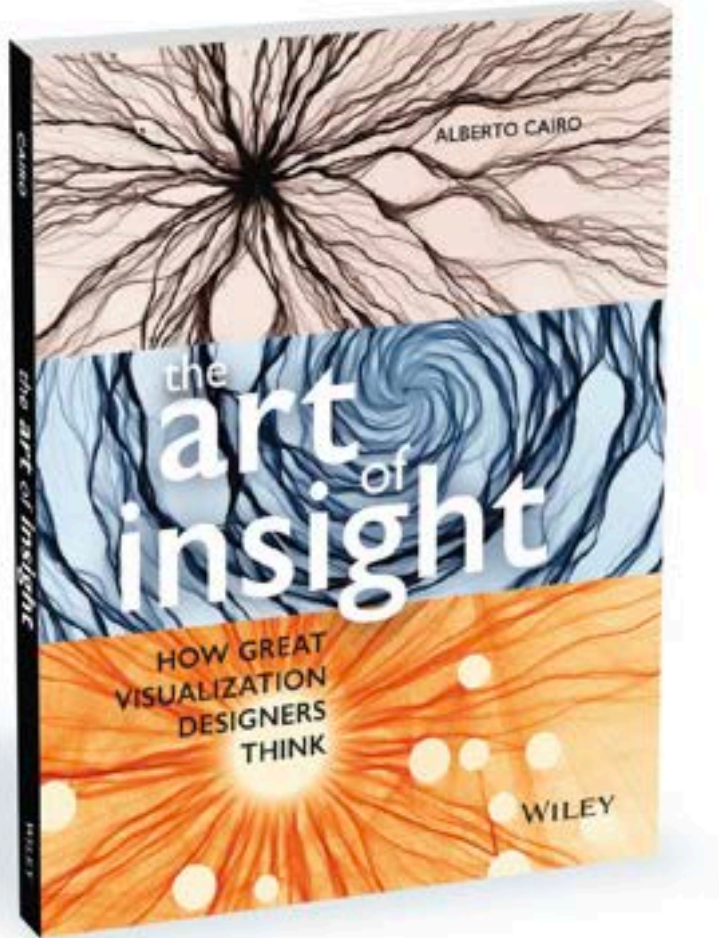
A branch of information design that focuses on the graphical encoding and presentation of data.

A bit about me

Teaching

CAIRO

Visualization design,
training, and consulting



Latest book

The Art of Insight:
How Great Visualization
Designers Think

Data visualization books don't typically transport you to new worlds. Alberto Cairo's *The Art of Insight* delves into the lives of numerous designers and what has shaped them. Each chapter showcases stunning examples, but also life stories and the motivations that informed choices. I laughed, I cried, I cheered, but perhaps most importantly, I caught glimpses of myself and my own story. —Bridget Cogley, co-author of *Functional Aesthetics for Data Visualization* and Chief Visualization Officer at Versalytix.

Order *The Art of Insight*

WILEY


BARNES & NOBLE

AMAZON

SCHOOL of
COMMUNICATION

ABOUT ADMISSIONS PROGRAMS STUDENTS OUR WORK FRIENDS

Alberto Cairo



Associate Professor,
Knight Chair in
Visual Journalism

Office
CIB 5051-L

Phone

Alberto Cairo is a journalist and designer with many years of experience leading graphics and visualization teams in several countries. He joined the School of Communication in January 2012. He teaches courses on infographics and data visualization. He is also director of the Center for Visualization, Data Communication & Information Design at UM's Institute for Data Science and Computing, and a Faculty Fellow at the Abess Center for Ecosystem Science and Policy.

Cairo has been described by Microsoft as always "in the vanguard of visual journalism". He is author of the books *How Charts Lie: Getting Smarter About Visual Information* (W.W. Norton, 2019), *The Truthful Art: Data, Charts, and Maps for Communication* (Peachpit Press, 2016), and *The Functional Art: an Introduction to Information Graphics and Visualization* (Peachpit Press 2012). His next book, which deals with ethics and moral reasoning in visualization design, will be published by Wiley in 2021.




Cairo has also written for *The New York Times* and *Scientific American* magazine.


Cairo has a popular visualization weblog, <http://www.thefunctionalart.com/>, and his Twitter account, <https://twitter.com/AlbertoCairo>, is followed by more than 50,000 people interested in visualization and data journalism.

Open
Visualization
Academy

by alberto cairo

Home About News Articles





Open
Visualization
Academy

by alberto cairo

Coming in 2025

The Open Visualization Academy is an open source repository of
knowledge about information design and data visualization.

Stay in the loop!

www.albertocairo.com

<https://com.miami.edu/profile/alberto-cairo/>

<https://openvisualizationacademy.org/>

Consulting, training, art direction

Google Trends

HomeExploreTrending now

United States

Explore what United States is searching for right now


Aaron Rodgers

Explore


Search interest, past 24 hours

Why is Aaron Rodgers trending?


Search it



Aaron Rodgers to Derwin James after Chargers-Jets: "Give me a..."
7 hours ago • NBC Sports - NFL



Aaron Rodgers hints at Jets return after loss to Chargers
7 hours ago • Fox News



Aaron Rodgers Dropped Another Hint About His Future After Jets...
8 hours ago • Newsweek

Congressional Budget Office

Nonpartisan Analysis for the U.S. Congress

About CBOTopicsCost EstimatesDataInteractivesFAQsBlog



FEATURED

[Long-Term Implications of the 2024 Future Years Defense Program](#)

[Estimated Budgetary Effects of the Israel Security Supplemental Appropriations Act, 2024](#)

[Monthly Budget Review: September 2023](#)

[Federal Subsidies for Health Insurance: 2023 to 2033](#)

[Federal Budgetary Effects of the Activities of the Center for Medicare & Medicaid Innovation](#)

[Communities at Risk of Flooding](#)


Short-Term Spending and Long-Term Dynamic Effects

Federal policies related to health care, education, infrastructure, the environment, and research and development often involve short-term expenditures that give rise to economic and budgetary effects far in the future. CBO's conventional cost estimates project the budgetary effects of proposed legislation over a 10-year period and incorporate the assumption that nominal gross domestic product (GDP) remains unchanged.

THE WORLD BANK

WHO WE AREWHAT WE DOWHERE WE WORKUNDERSTANDING POVERTYWORK WITH US

WE LIVE



"A world free of poverty on a livable planet."

A landmark speech by Ajay Banga on our ambitious new vision. One challenge cannot be solved without solving the others. They demand an expanded vision of the World Bank.

[WATCH SPEECH >](#)[READ SPEECH >](#)

European Union

Log inEnglish


Publications Office of the European Union

SearchAll collectionsSearch


Advanced searchBrowse by subjectExpert Search

Publications Office


EU lawEuropean dataEU tendersEU research resultsEU WhoiswhoEU publications




EU law
EU law, national law and related information




European data
Data from EU institutions and European countries




EU tenders
Business opportunities in the European Union and beyond




EUR-Lex online learning section
Check it out and become a EUR-Lex pro!



EU research results
Information about the results of



EU Whoiswho
The directory of the European



EU publications
Publications of the EU institutions

EVENTS

2025

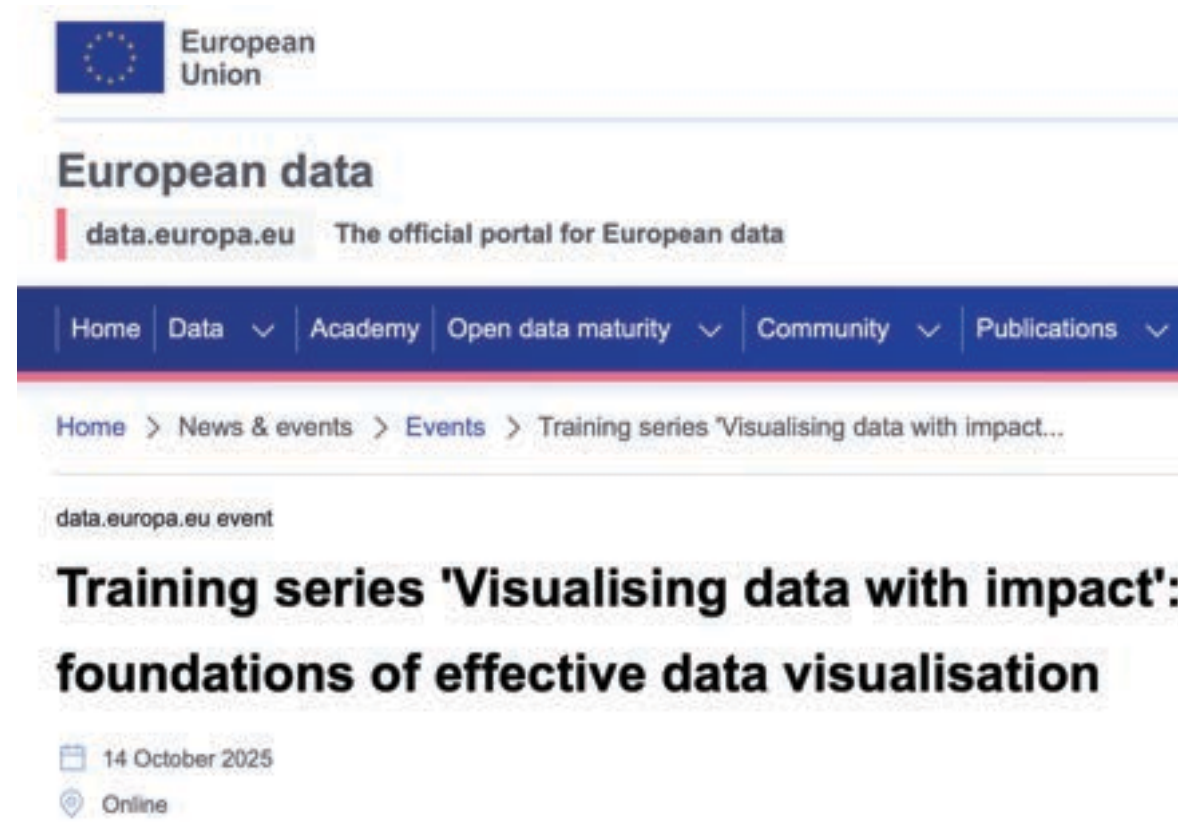
27 - 28 NOV

TED-together – Joint meeting for eSender, Reuser, eProcurement Ontology and ESPD communities

Books



Housekeeping



Episode ONE - October 14

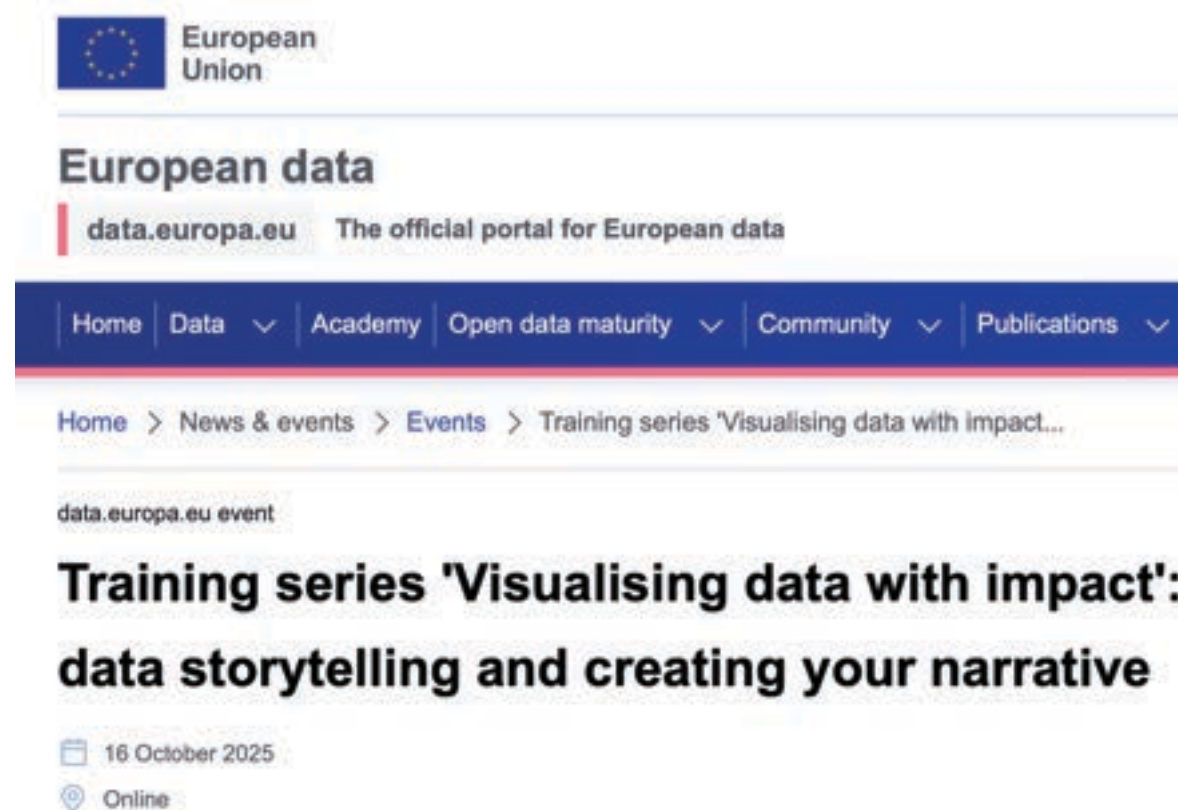
Today's webinar

<https://data.europa.eu/en/news-events/events/training-data-visualisation-session-1-foundations-effective-data-visualisation>



Episode TWO - October 15

<https://data.europa.eu/en/news-events/events/data-visualisation-training-session-2-designing-integrity>



Episode THREE - October 16

<https://data.europa.eu/en/news-events/events/data-visualisation-training-session-3-data-storytelling-and-creating-your>

EPISODE ONE: Foundations of effective data visualization

Defining information design and data visualization

Exploration, exposition, explanation, expression in visualization

Why do we visualize? The basics

The grammar of graphics

“Rules” versus decision-making

EPISODE TWO: Designing with integrity

Myths of visualization: From “A picture is worth a thousand words” to “the data should speak for itself”

The role of mental models

Why and when do charts “lie”, and what to do about it?

A structured way for thinking about visualization and minimizing misunderstanding

EPISODE THREE: Data storytelling and creating your narrative

Structuring a layout

Building a narrative

Considering visual design

Creative visualization

What comes next in visualization?

EPISODE ONE: Foundations of effective data visualization

Defining information design and data visualization

Exploration, exposition, explanation, expression in visualization

Why do we visualize? The basics

The grammar of graphics

“Rules” versus decision-making

EPISODE TWO: Designing with integrity

Myths of visualization: From “A picture is worth a thousand words” to “the data should speak for itself”

The role of mental models

Why and when do charts “lie”, and what to do about it?

A structured way for thinking about visualization and minimizing misunderstanding

EPISODE THREE: Data storytelling and creating your narrative

Structuring a layout

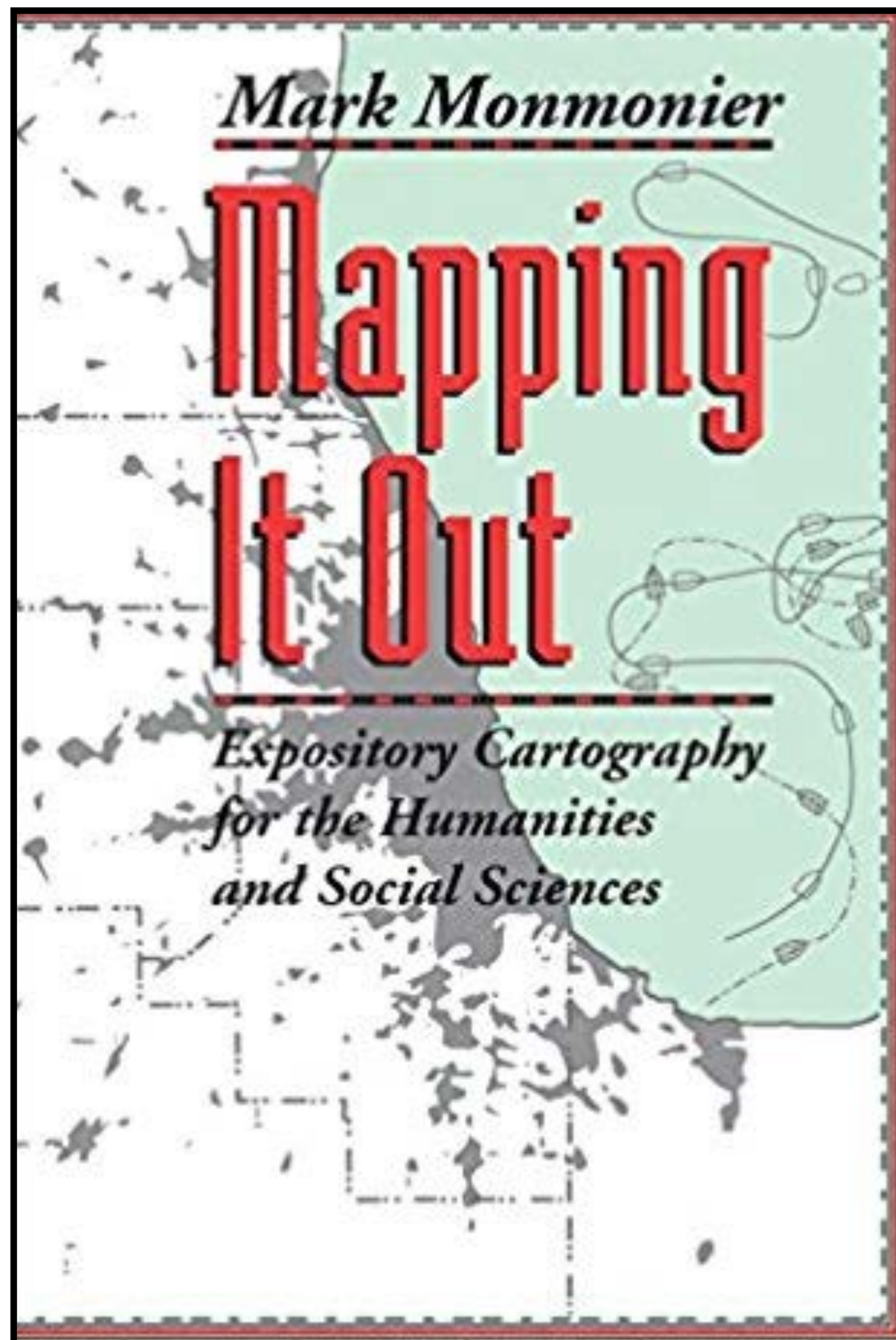
Building a narrative

Considering visual design

Creative visualization

What comes next in visualization?

— Everybody can (should!) design —



Modern literacy:

- Literacy
- Articulacy
- Numeracy
- Graphicacy

The same way that anyone can learn to **write** well,
anyone can learn to **design** and **visualize** well

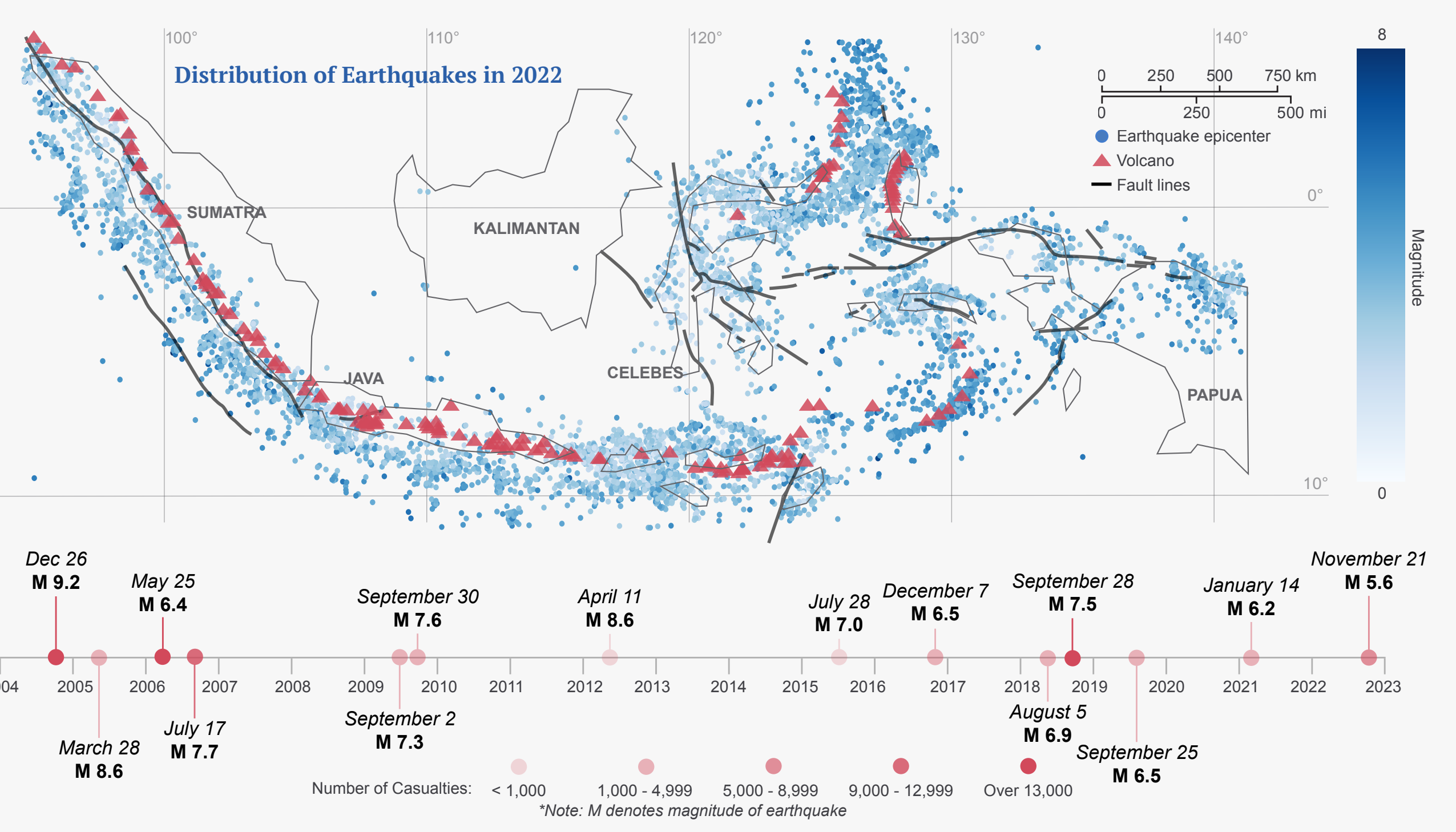
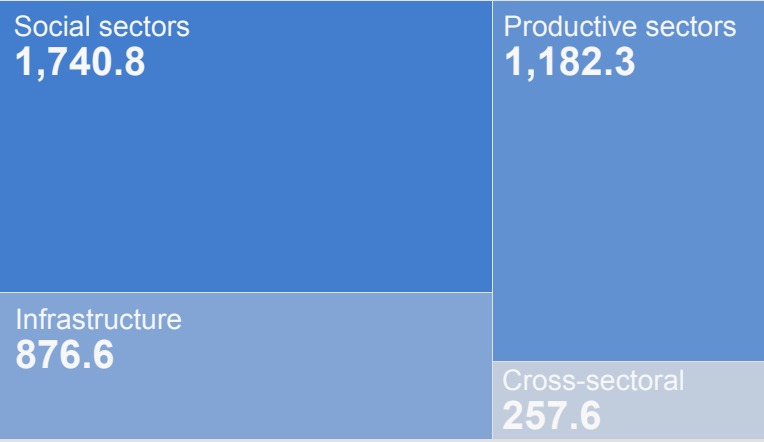
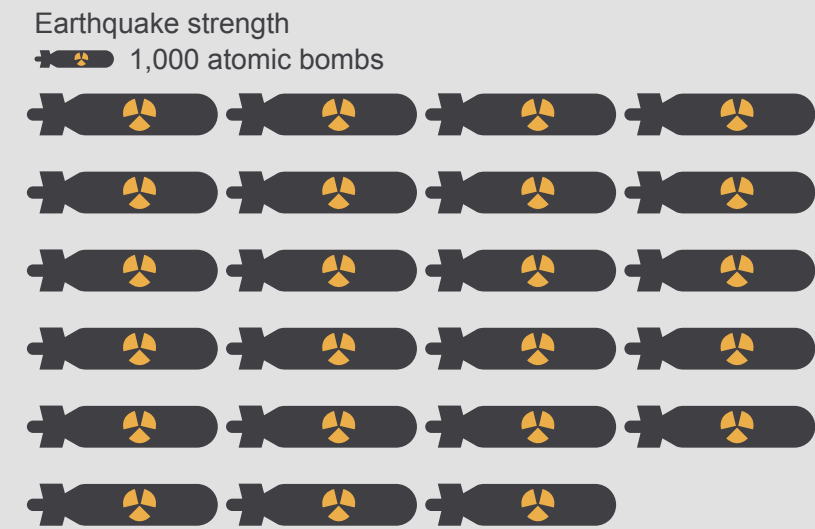
NAVIGATING INDONESIA'S EARTHQUAKES

Indonesia is positioned on active fault lines within the Ring of Fire, a semi-circle of volcanoes and shifting plates along the Pacific Ocean's edge. There have been numerous earthquakes, volcanic activities, and tsunamis in the region due to ongoing geological pressures. In 2022, The Meteorology, Climatology, and Geophysics Agency (BMKG.go.id) recorded 10,792 earthquakes. The severity of these earthquakes varies, with the most intense occurring in 2004, reaching a magnitude of 9.2.

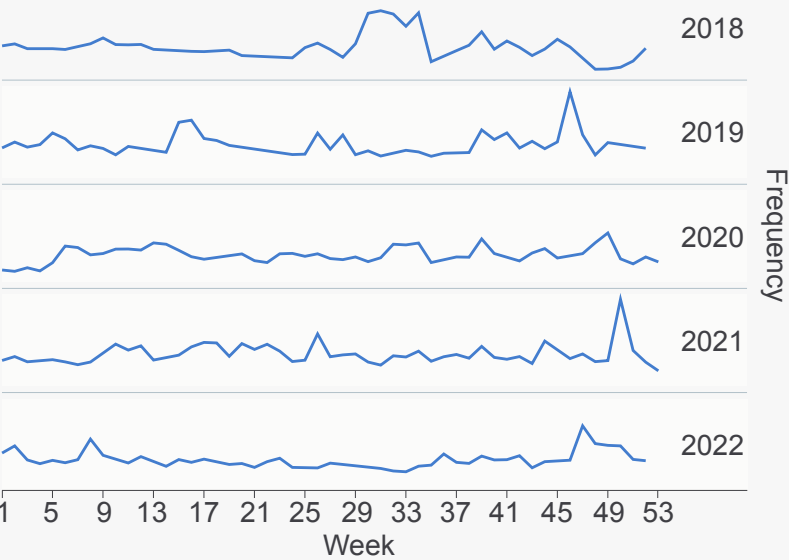
What impact do earthquakes have?



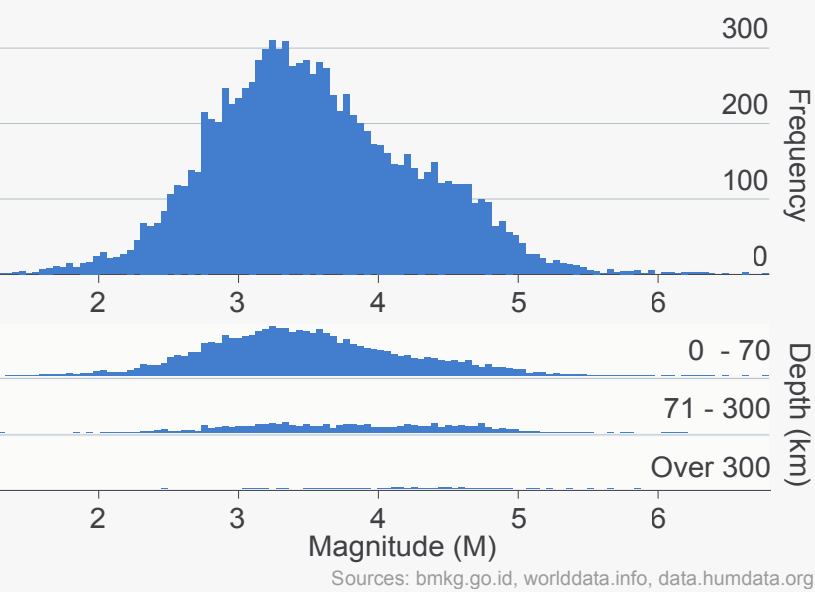
Most Devastating Earthquake in Indonesia: December 26, 2004



Are earthquakes seasonal?



How severe were earthquakes in 2022?

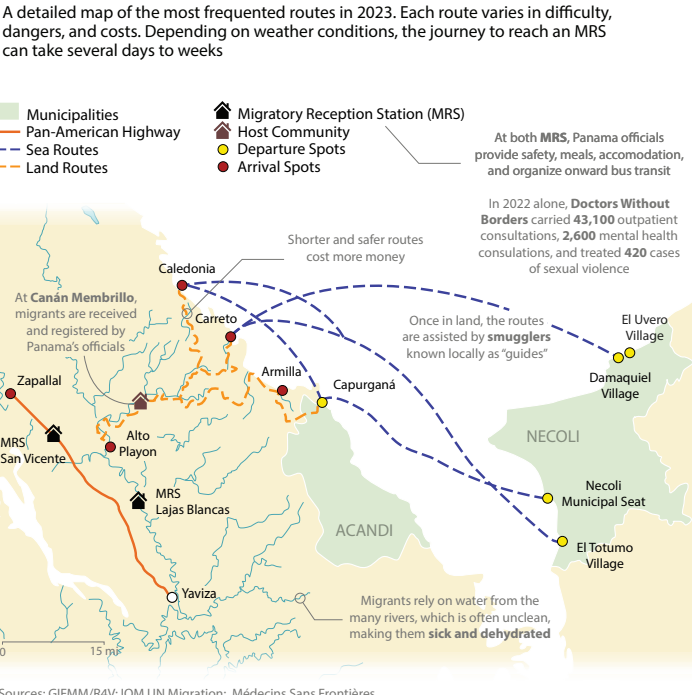


Defying death

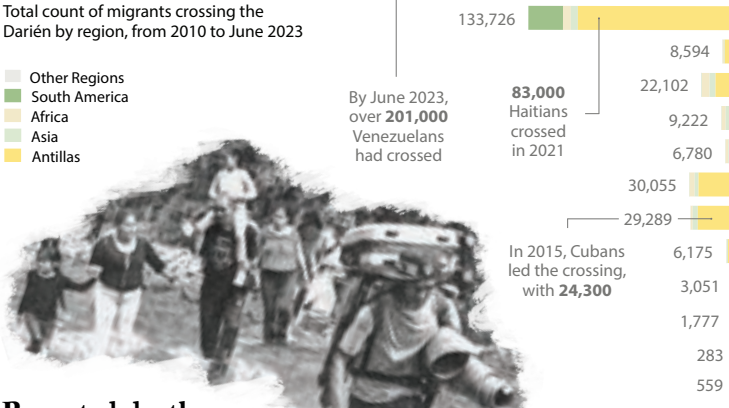
This year, over 400,000 migrants and asylum seekers have traversed the challenging expanse of the Central American jungle known as the Darién Gap, as reported by the government of Panama. Despite the formidable dangers and obstacles within the jungle, it stands as the sole terrestrial route linking South America to Central America. Those undertaking this journey face numerous human rights violations, including sexual violence, homicides, disappearances, trafficking, robbery, and intimidation perpetrated by organized criminal groups.



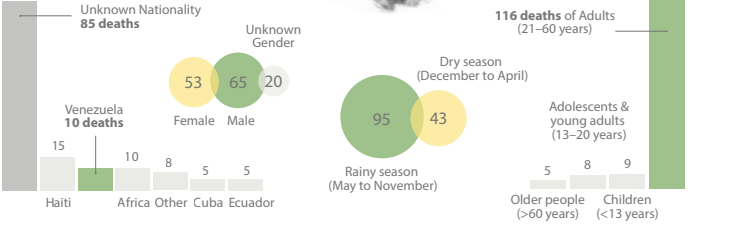
Major routes taken to cross the Darién Gap



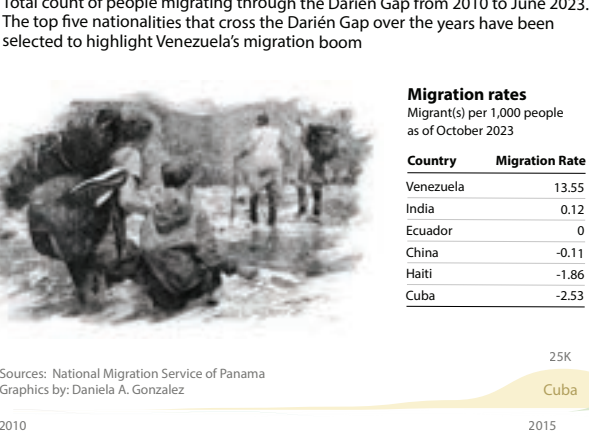
Transit throughout the years



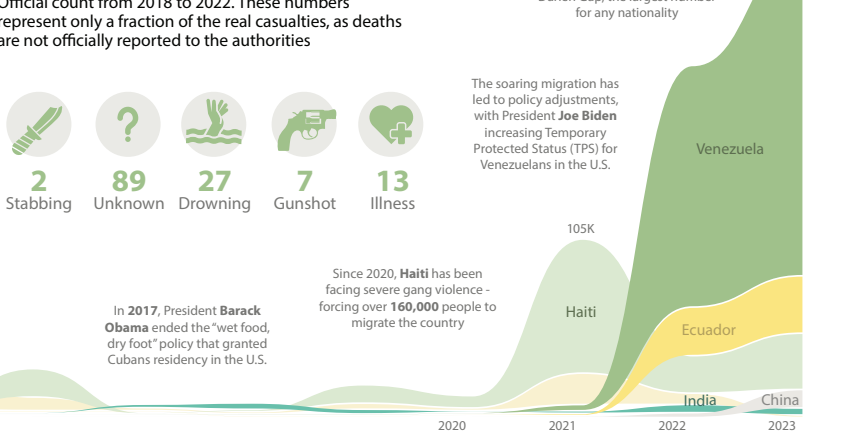
Reported deaths



Venezuela's migration rates lead the Darién



Main death causes



Poster by Michela Effendi

Poster by Daniela González

The same way that anyone can learn to **write** well,
anyone can learn to **design** and **visualize** well

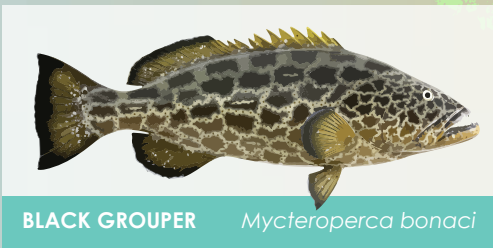
POPULAR GROUPER of the Florida Keys

Grouper are woven into the fabric of South Florida culture and life. Regionally, grouper is one of the most important fish commercially, recreationally, & economically. They are a heavily targeted fishery and are well known by anglers for their impressive fighting strength and ability to steal bait. They also make excellent table fare with their light buttery flavor, flakey texture, and delicate soft white meat.

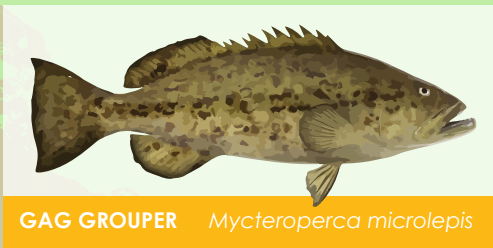
In the ocean, they are curious fish and an inspiring site to witness . They easily glide through the water with power, grace, and speed. Every year, thouns of snorkelers and divers visit Sanctuary Preservation Areas (SPA) and other special marine protected areas that facilitate dive tourism and offer refuge for all species of fish to grow and reproduce without the threat of fishing. In addition to other sea life, grouper are a star attraction in these areas.

Grouper populations have declined historically due to over-fishing, habitat loss and degradation, and poor water quality. Though not currently considered overfished by NOAA. They are still at high-risk of exploitation due to those same historic threats. The three grouper species shown are the most sought after in The Florida Keys.

In the map to the right, all three species of grouper were added together and then the density values were calculated per kilometer. For example, This means that for the color category between 7 to 13, for a square kilometer area over the past 23 years, there are on average 7 to 13 grouper in that area and they could be either Black, Gag, or Red Grouper. Exact proportions vary from site to site, but are roughly 47.5% Black, 47.5% Red, & 5% Gag Grouper.



BLACK GROUPER *Mycteroperca bonaci*

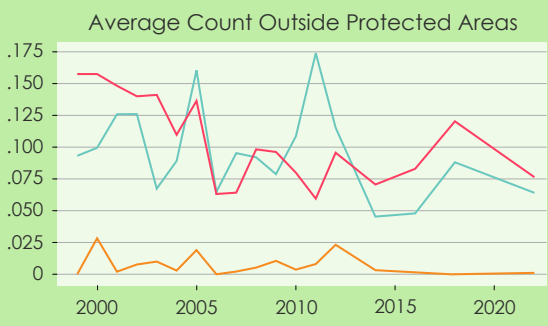
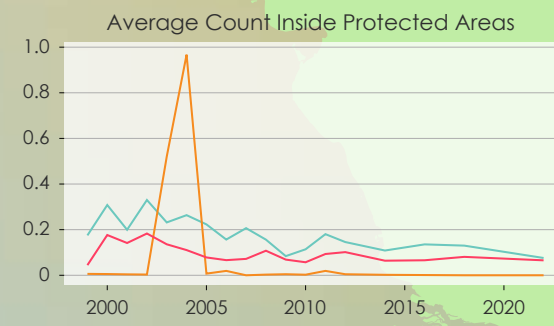
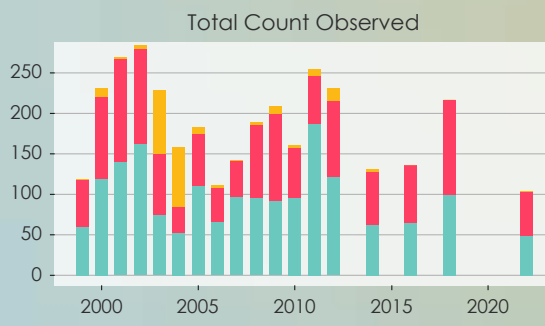


GAG GROUPER *Mycteroperca microlepis*

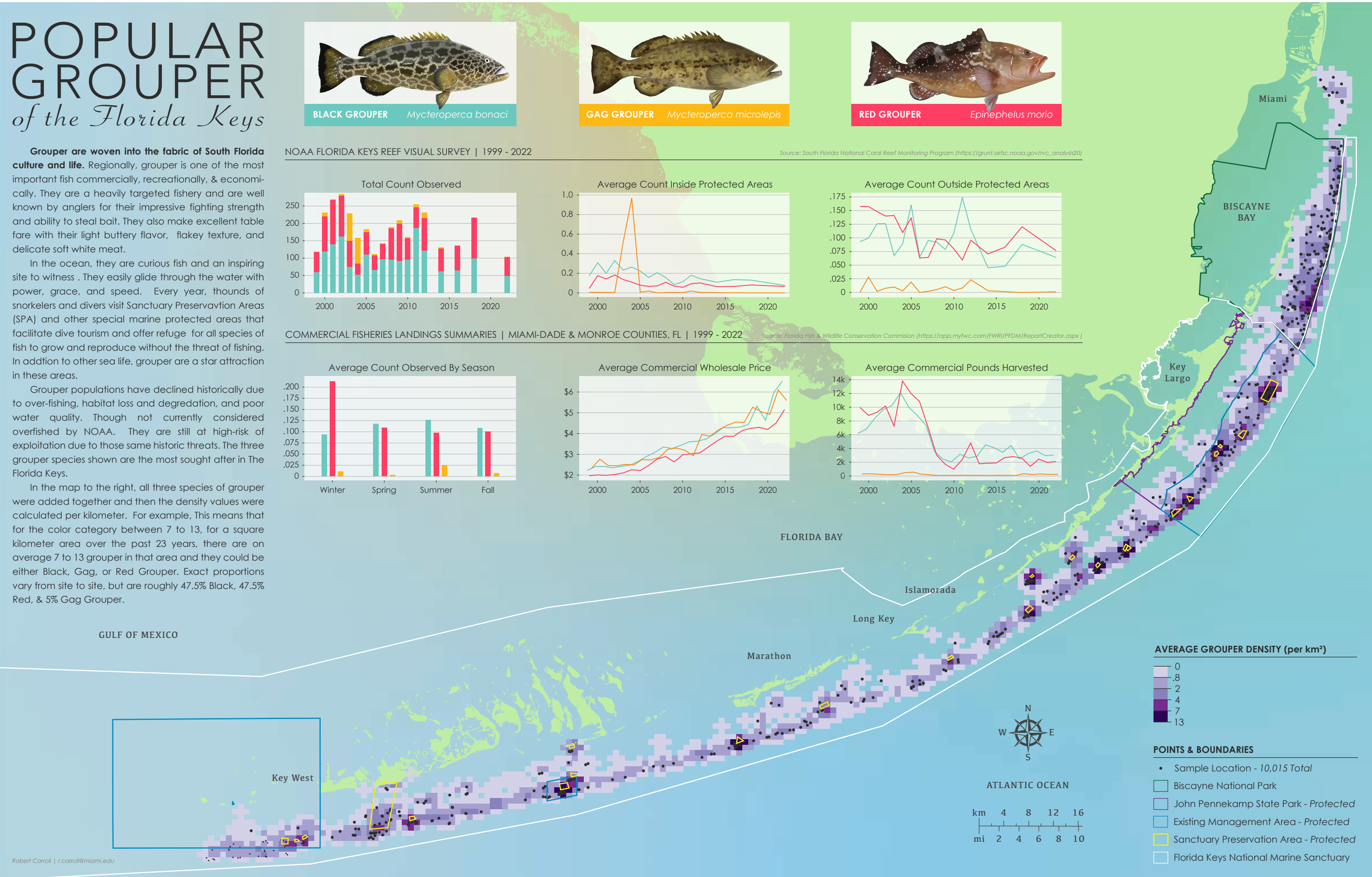
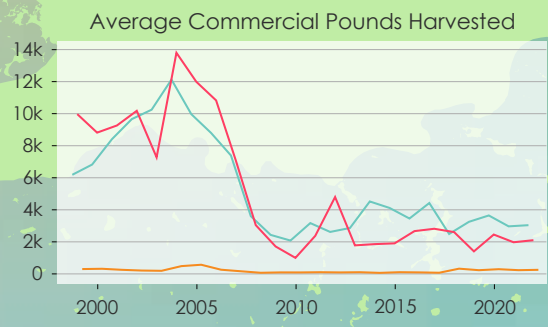
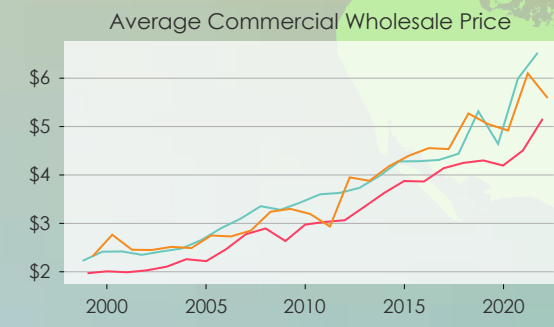
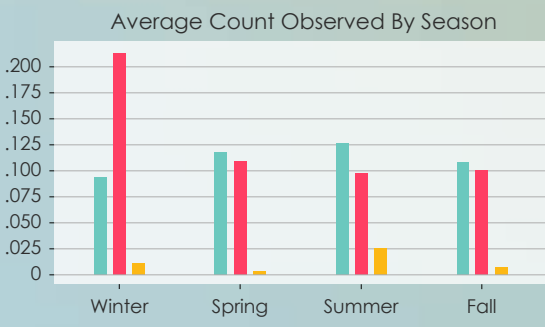


RED GROUPER *Epinephelus morio*

NOAA FLORIDA KEYS REEF VISUAL SURVEY | 1999 - 2022



COMMERCIAL FISHERIES LANDINGS SUMMARIES | MIAMI-DADE & MONROE COUNTIES, FL | 1999 - 2022



Robert Carroll | r.carroll@miami.edu

Poster by Robert Carroll



Antibiotic-Induced Shifts in Coral Cell Populations

Shara Sookhoo, Aliyah True, and Nikki Traylor-Knowles
Rosenstiel School of Marine, Atmospheric and Earth Science, University of Miami, FL
sys25@miami.edu



Summary

Antibiotics are commonly used to treat **Stony Coral Tissue Loss Disease (SCTLD)** but can compromise the coral's long-term resilience. The goal of this study was to evaluate the side effects of antibiotic treatment at the **cellular level**. This study showed that **antibiotics reduce cell death and stress in the short-term**. This suggests that antibiotics decrease the pathogenic bacterial load. Future studies will address the long-term effects of antibiotics on corals at the cellular level.

Methods

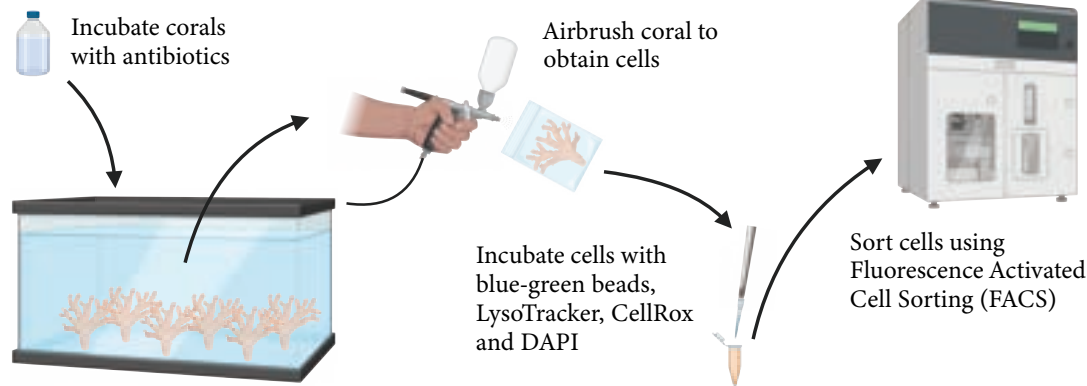


Figure 2: Corals are either exposed to antibiotics for 2.5 days (n=3) or 4.5 days (n=6). Corals are then airbrushed to obtain cells and incubated with blue-green beads to identify phagocytes. Cells are also incubated with LysoTracker which stains lysosomes, CellRox which stains reactive oxygen species and DAPI which stains the DNA of dead cells. Cells are sorted into different populations based on inherent properties or marker intensity.

Introduction

- Coral reefs are biological hotspots and provide many ecosystem services.
- Stony Coral Tissue Loss Disease (SCTLD) decimated Caribbean reefs.
- Treatment with antibiotics is 95% effective^[1] but reduces coral microbiome diversity which lowers host resilience^[2].
- **Research Motivation:** Little is known about the impact of antibiotics on corals at the cellular level.



Figure 1: Left shows white SCTLD lesion on coral colony. Right shows treatment of lesion margin with antibiotic infused epoxy

Goals

To identify distinct coral cell populations and determine whether their abundances are impacted by the addition of antibiotics.

Discussion

- Reduction in dead cells and cellular stress markers (lysosomal production and phagocytic activity) suggest that **antibiotics have a positive effect on corals at the cellular level**.
- The next step is to determine if cell populations have distinct microbiomes and ascertain whether they are differentially impacted by antibiotics.
- Future studies will investigate the long-term impact of antibiotics on coral cell populations and indetify whether these effects can be mitigated by the addition of beneficial micro-organisms.

Acknowledgements

I would like to thank PhD candidate Aliyah True for guiding me through this project. I would also like to thank my advisor Dr. Nikki Traylor Knowles and the other members of my senior thesis committee: Dr. Douglas Crawford and Dr. Grace Klings. Thank you to the family of Dr. Linda Farmer for providing the financial support to conduct this research.

References



QR codes are provides for references [1], [2] and [3] from left to right. Images were taken from the National Park Service. Figure 2 was created using Biorender.

Results: 5 out of 9 Cell Types are Significantly Impacted by Antibiotics

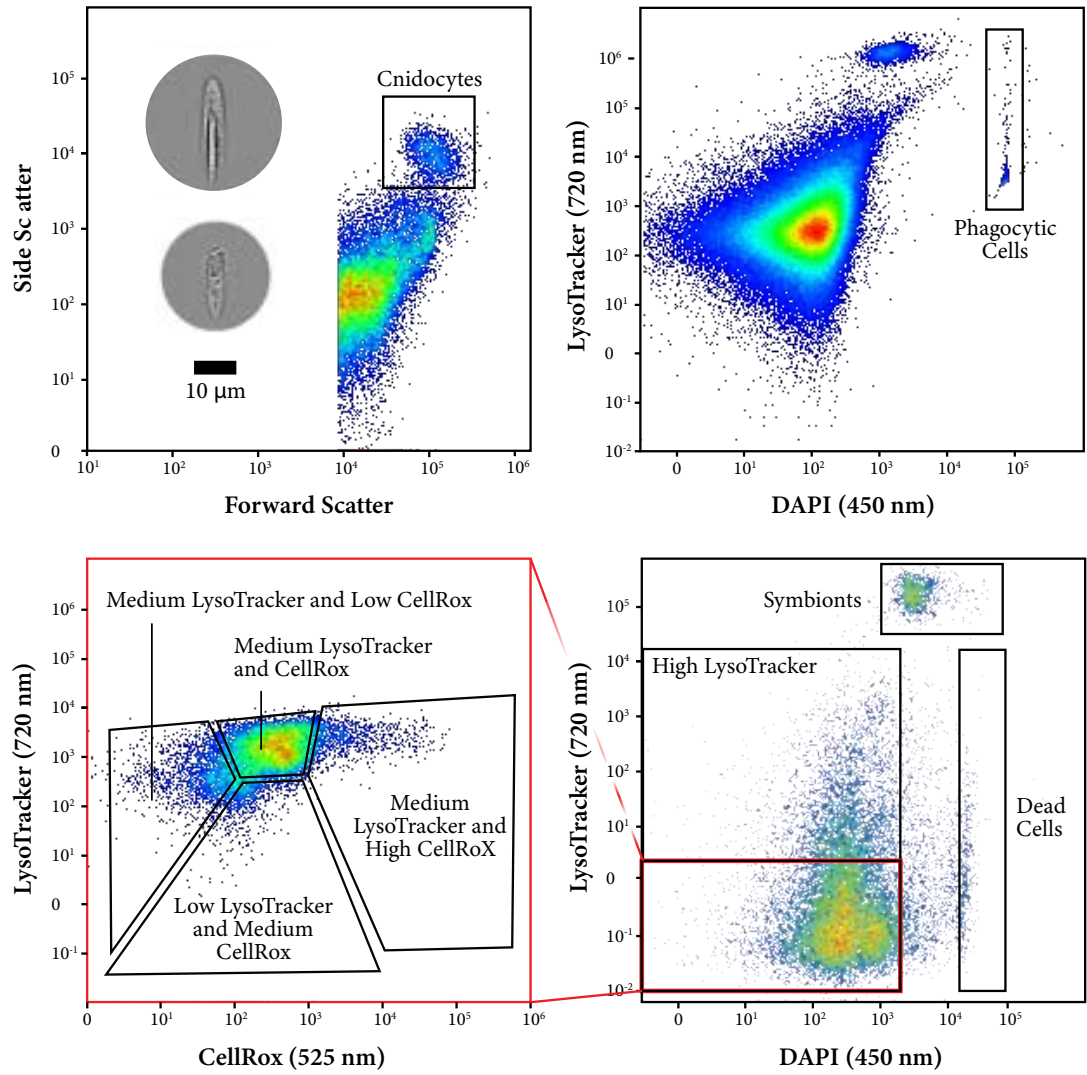


Figure 3: 9 cell populations identified using FACS based on inherent cell properties or the intensity of the non-specific cell markers^[3]. Images taken via image flow cytometry are provided for cnidocytes.

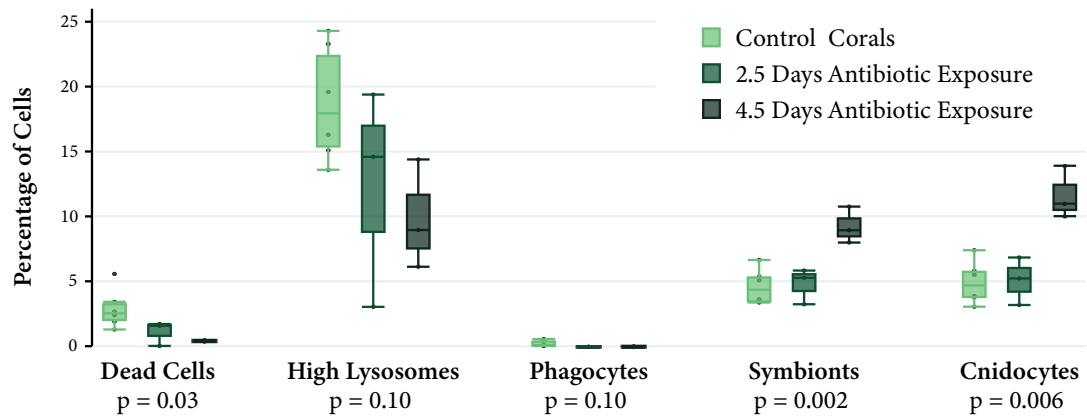


Figure 4: Boxplots showing the change in the significantly affected cell population due to antibiotic exposure. p values are given for ANOVAs.

Poster by Shara Sookhoo

The same way that anyone can learn to **write** well,
anyone can learn to **design** and **visualize** well

POPULAR GROUPE

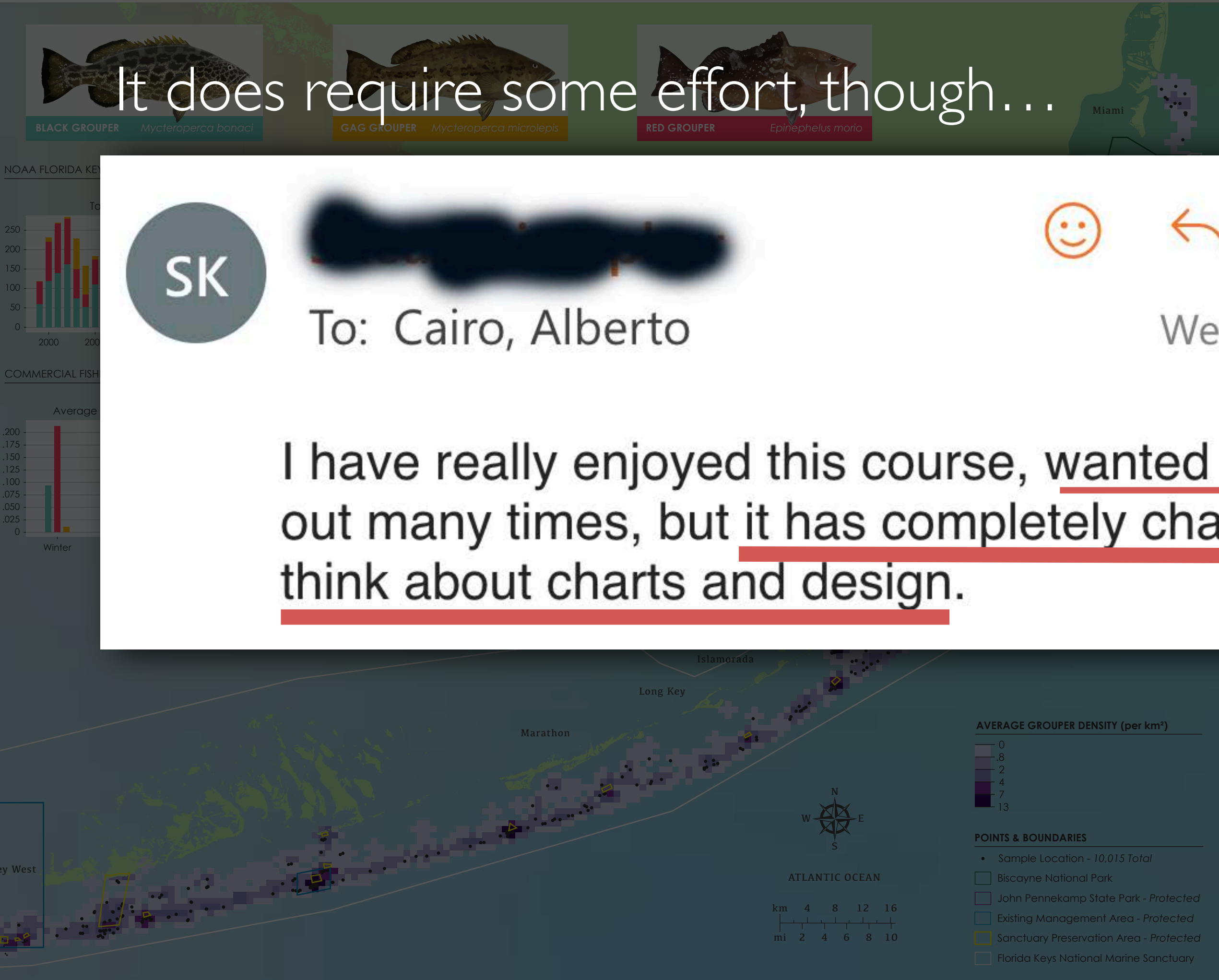
of the Florida Keys

Grouper are woven into the fabric of South Florida culture and life. Regionally, grouper is one of the most important fish commercially, recreationally, & economically. They are a heavily targeted fishery and are well known by anglers for their impressive fighting strength and ability to steal bait. They also make excellent table fare with their light buttery flavor, flakey texture, and delicate soft white meat.

In the ocean, they are curious fish and an inspiring site to witness . They easily glide through the water with power, grace, and speed. Every year, thounds of snorkelers and divers visit Sanctuary Preservavtion Areas (SPA) and other special marine protected areas that facilitate dive tourism and offer refuge for all species of fish to grow and reproduce without the threat of fishing. In addition to other sea life, grouper are a star attraction in these areas.

Grouper populations have declined historically due to over-fishing, habitat loss and degradation, and poor water quality. Though not currently considered overfished by NOAA. They are still at high-risk of exploitation due to those same historic threats. The three grouper species shown are the most sought after in The Florida Keys.

In the map to the right, all three species of grouper were added together and then the density values were calculated per kilometer. For example, This means that for the color category between 7 to 13, for a square kilometer area over the past 23 years, there are on average 7 to 13 grouper in that area and they could be either Black, Gag, or Red Grouper. Exact proportions vary from site to site, but are roughly 47.5% Black, 47.5% Red, & 5% Gag Grouper.



It does require some effort, though...



To: Cairo, Alberto

Wed 4/26/2023 5:08 PM

I have really enjoyed this course, wanted to pull my hair out many times, but it has completely changed the way I think about charts and design.



Antibiotic-Induced Shifts in Coral Cell Populations

Shara Sookhoo, Aliyah True, and Nikki Traylor-Knowles
Rosenstiel School of Marine, Atmospheric and Earth Science, University of Miami, FL
sys25@miami.edu



Summary

Antibiotics are commonly used to treat **Stony Coral Tissue Loss Disease (SCTLD)** but can compromise the coral's long-term resilience. The goal of this study was to evaluate the side effects of antibiotic treatment at the **cellular level**. This study showed that **antibiotics reduce cell death and stress in the short-term**. This suggests that antibiotics decrease the pathogenic bacterial load. Future studies will address the long-term effects of antibiotics on corals at the cellular level.

Introduction

- Coral reefs are biological hotspots and provide many ecosystem services.
- Stony Coral Tissue Loss Disease (SCTLD) decimated Caribbean reefs.
- Treatment with antibiotics is 95% effective^[1] but reduces coral microbiome diversity which lowers host resilience^[2].
- Research Motivation:** Little is known

Methods

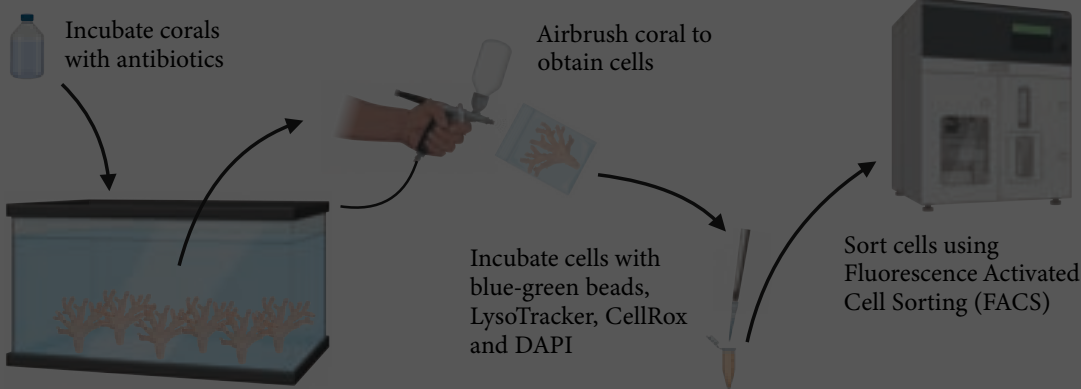


Figure 2: Corals are either exposed to antibiotics for 2.5 days (n=3) or 4.5 days (n=6). Corals are then airbrushed to obtain cells and incubated with blue-green beads to identify phagocytes. Cells are also incubated with LysoTracker which stains lysosomes, CellRox which stains reactive oxygen species and DAPI which stains the DNA of dead cells. Cells are sorted into different populations based on inherent properties or marker intensity.

Results: 5 out of 9 Cell Types are Significantly Impacted by Antibiotics

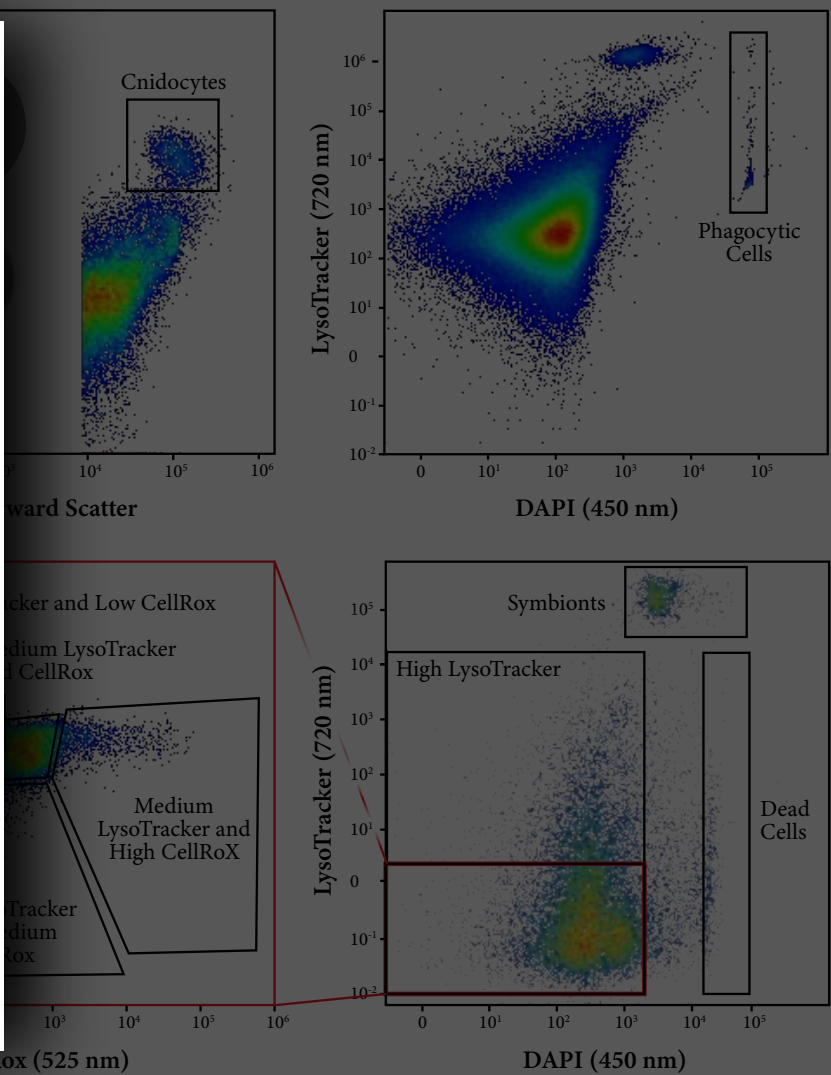


Figure 3: 9 cell populations identified using FACS based on inherent cell properties or the intensity of the non-specific cell markers^[3]. Images taken via image flow cytometry are provided for cnidocytes.

Acknowledgements

I would like to thank PhD candidate Aliyah True for guiding me through this project. I would also like to thank my advisor Dr. Nikki Traylor Knowles and the other members of my senior thesis committee: Dr. Douglas Crawford and Dr. Grace Klings. Thank you to the family of Dr. Linda Farmer for providing the financial support to conduct this research.

References



QR codes are provides for references [1], [2] and [3] from left to right. Images were taken from the National Park Service. Figure 2 was created using Biorender.

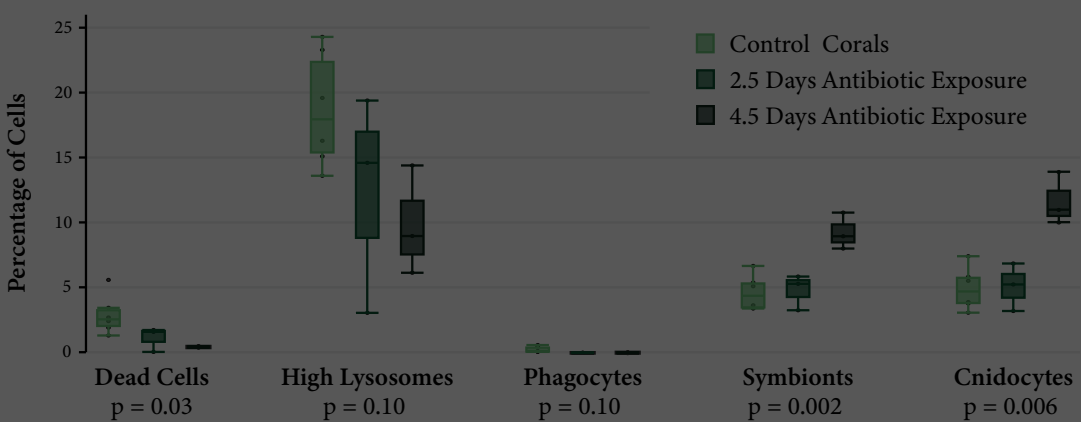


Figure 4: Boxplots showing the change in the significantly affected cell population due to antibiotic exposure. p values are given for ANOVAs.

Poster by Robert Carroll

Poster by Shara Sookhoo

“...It has completely changed
the way I think about charts and design.”

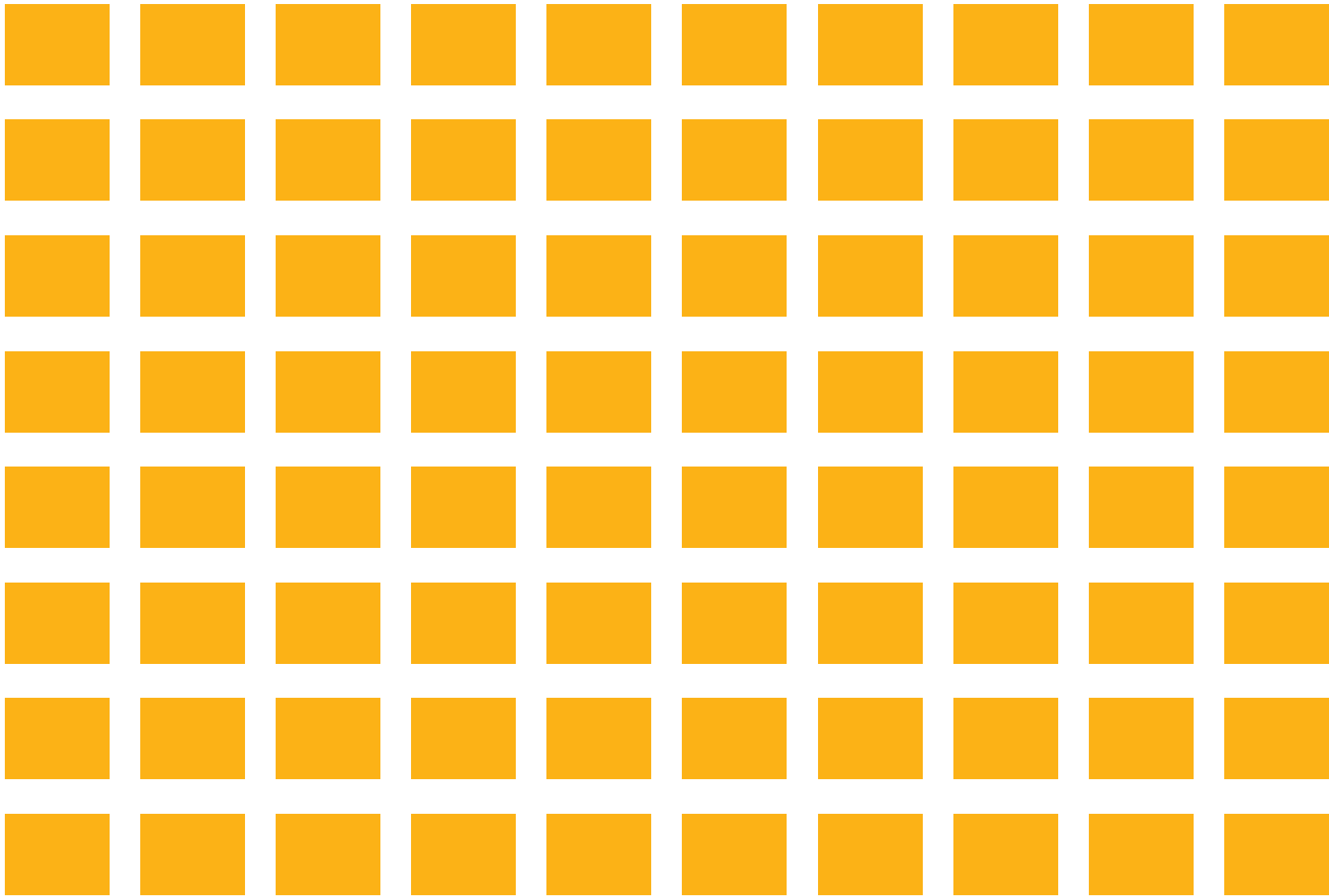
Spoiler alert: Like the class that changed this student’s mind, these three webinars aren’t about ***how to*** make visualizations.

They are about ***how I, an individual designer,*** makes visualizations.

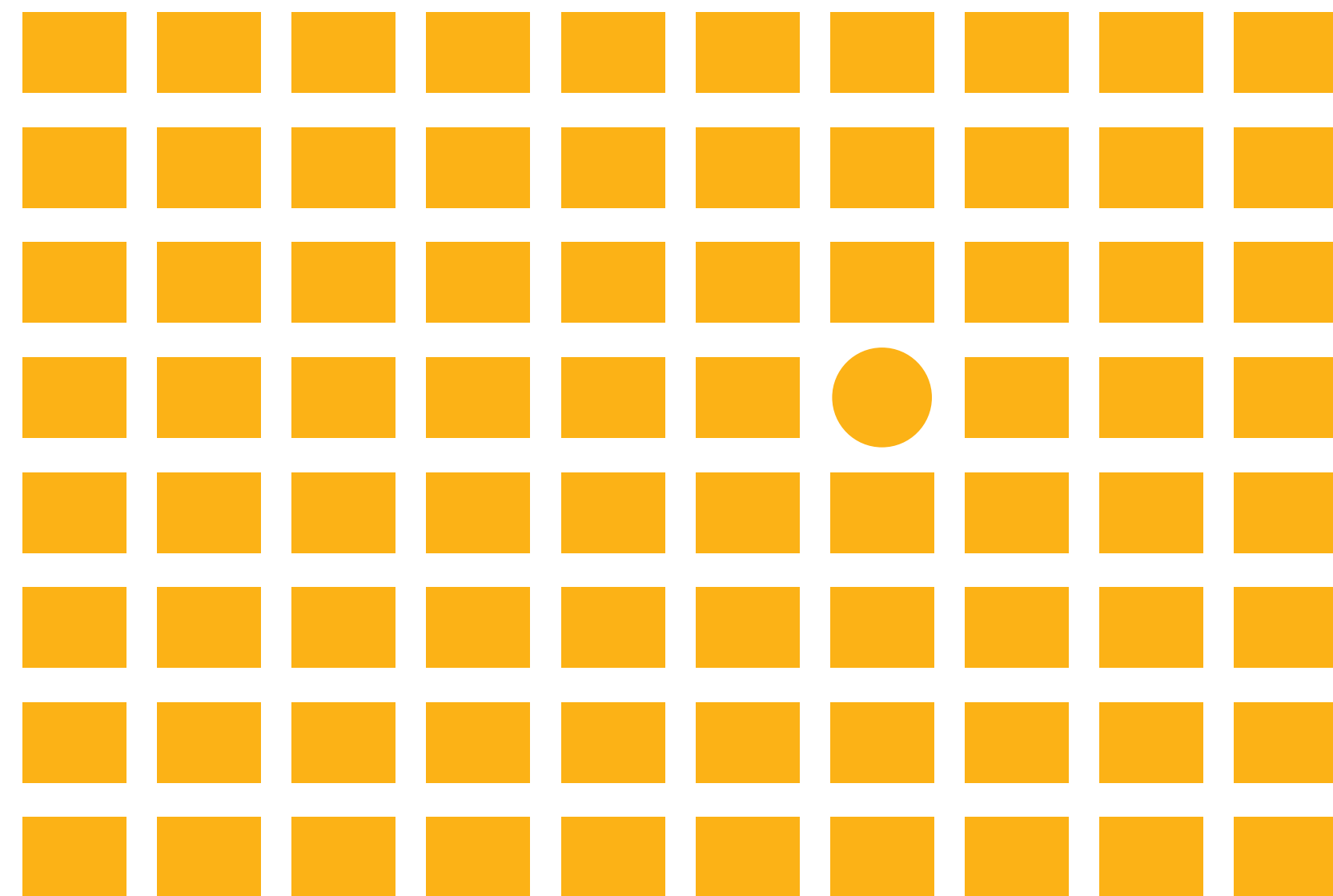
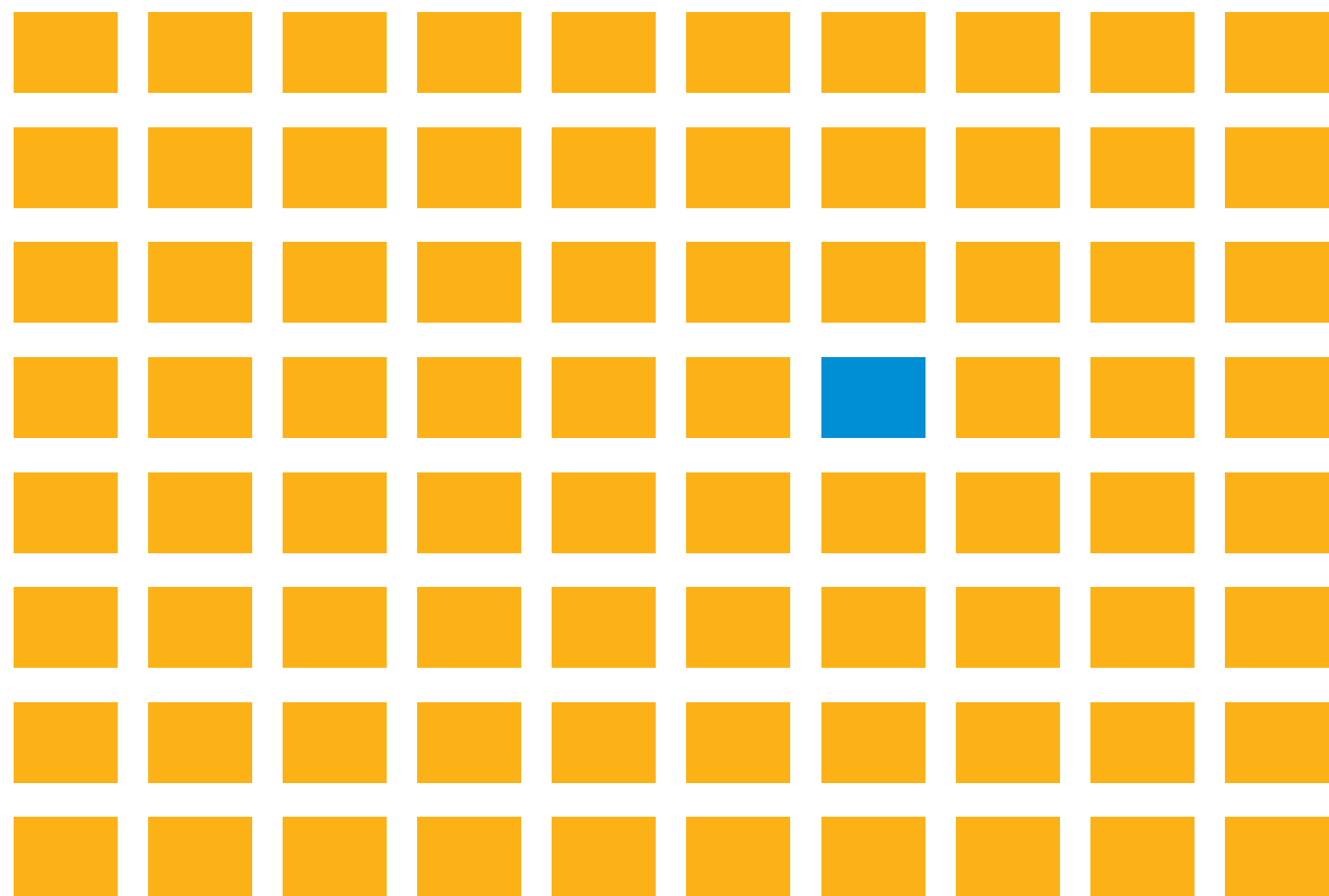
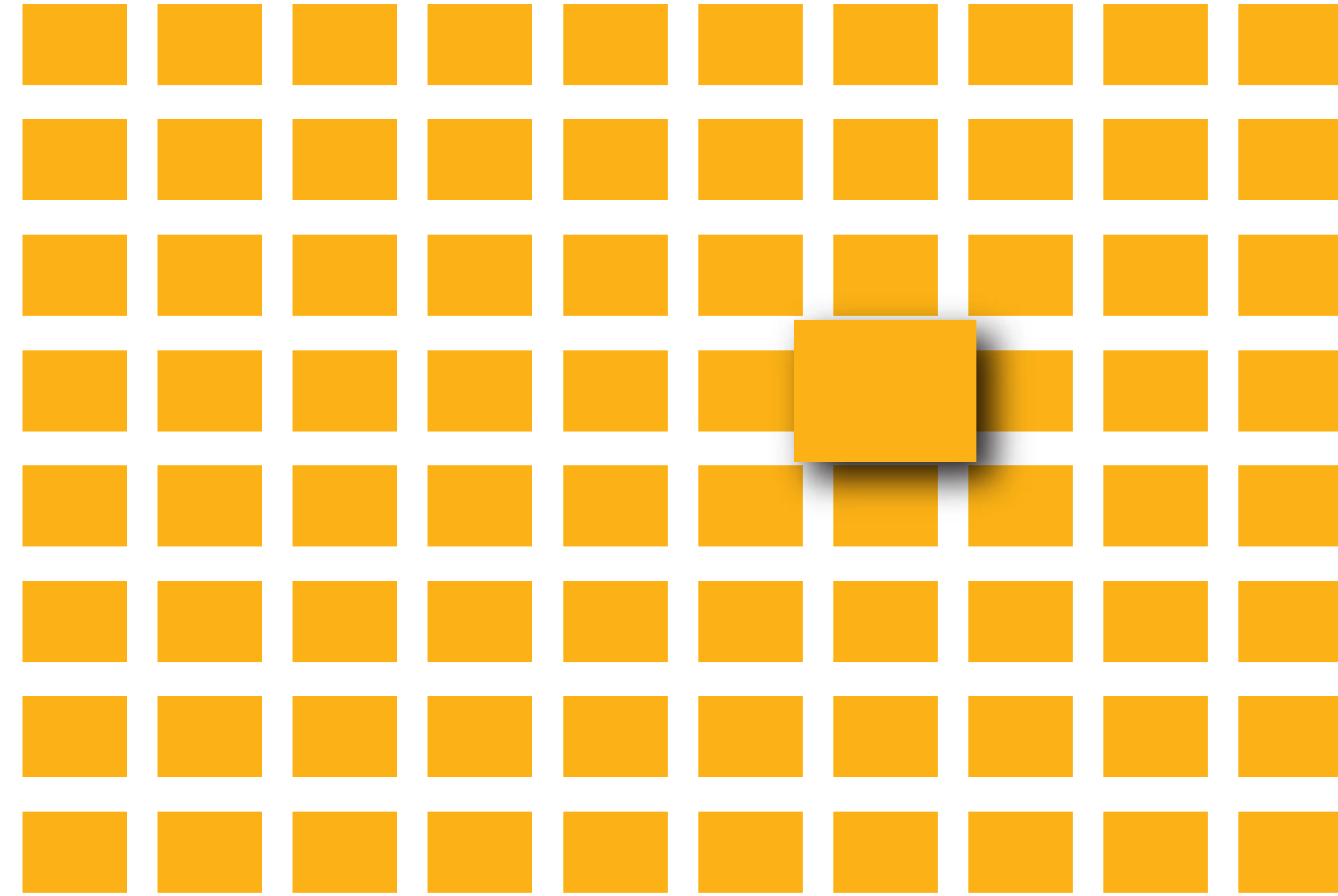
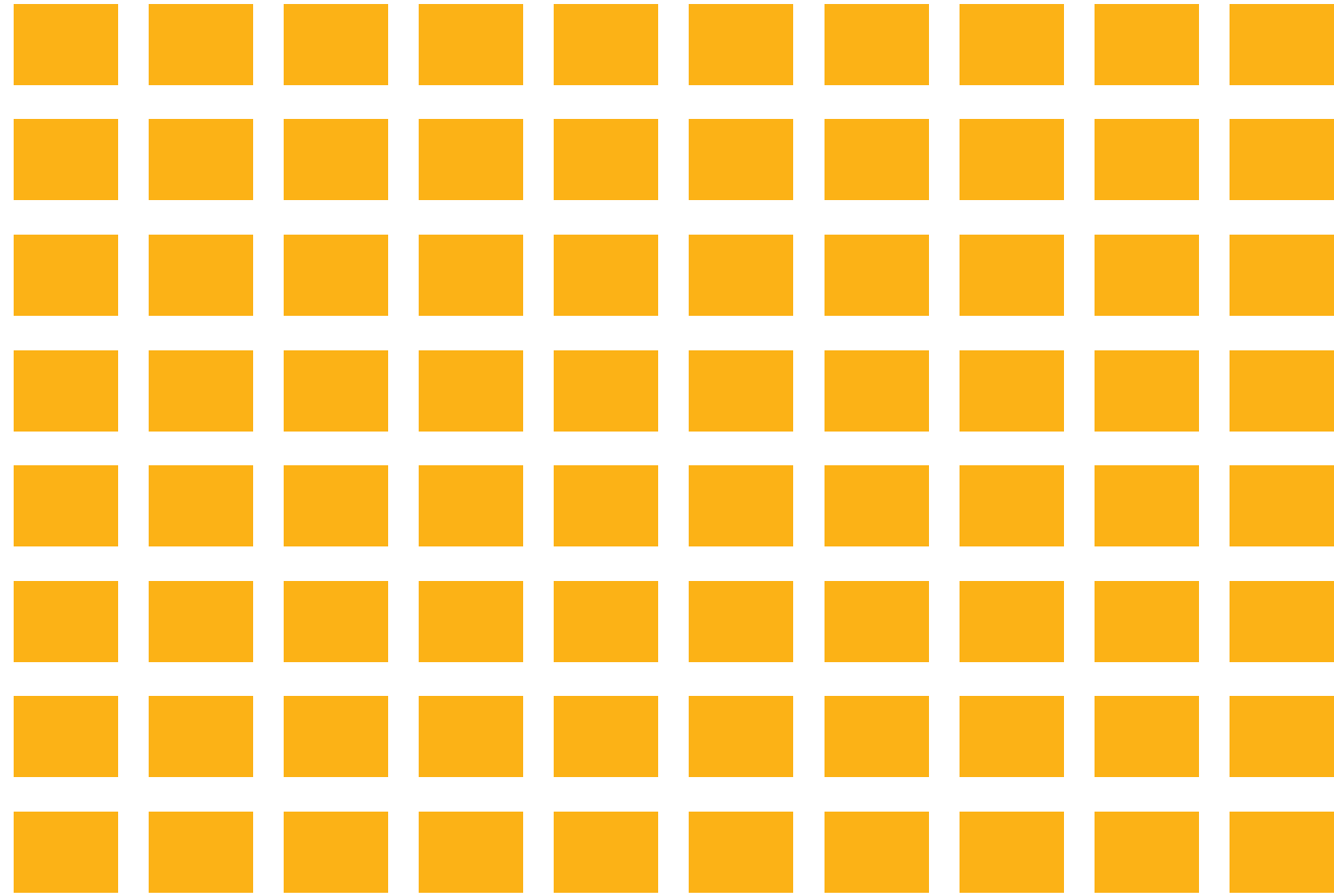
— The basics of visualization —

The type of visualizations I typically design are graphical displays intended to enable either **exploration, discovery**, or **communication** by letting us see what we cannot normally see.

We visualize because the human visual brain evolved to detect **patterns**...

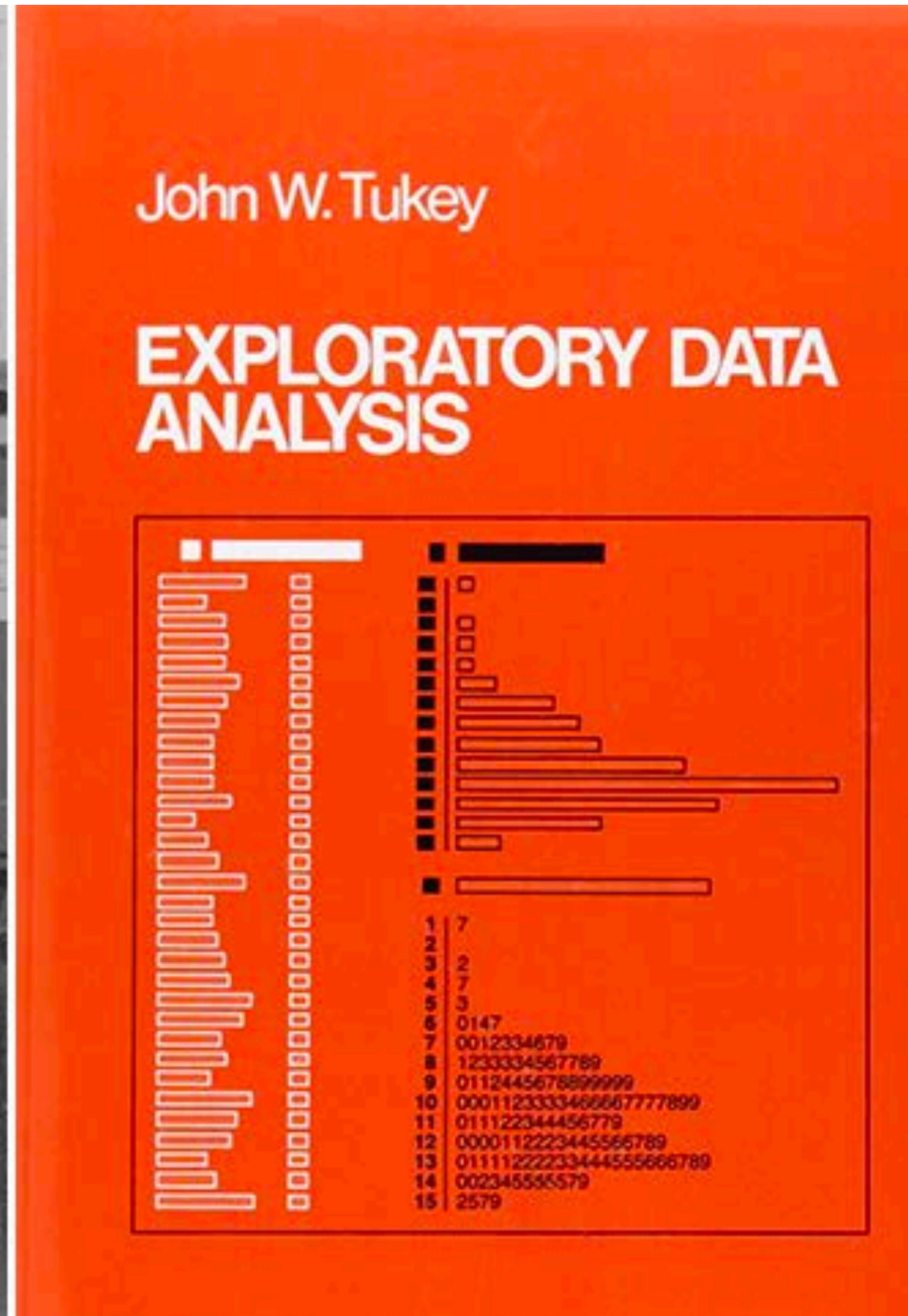
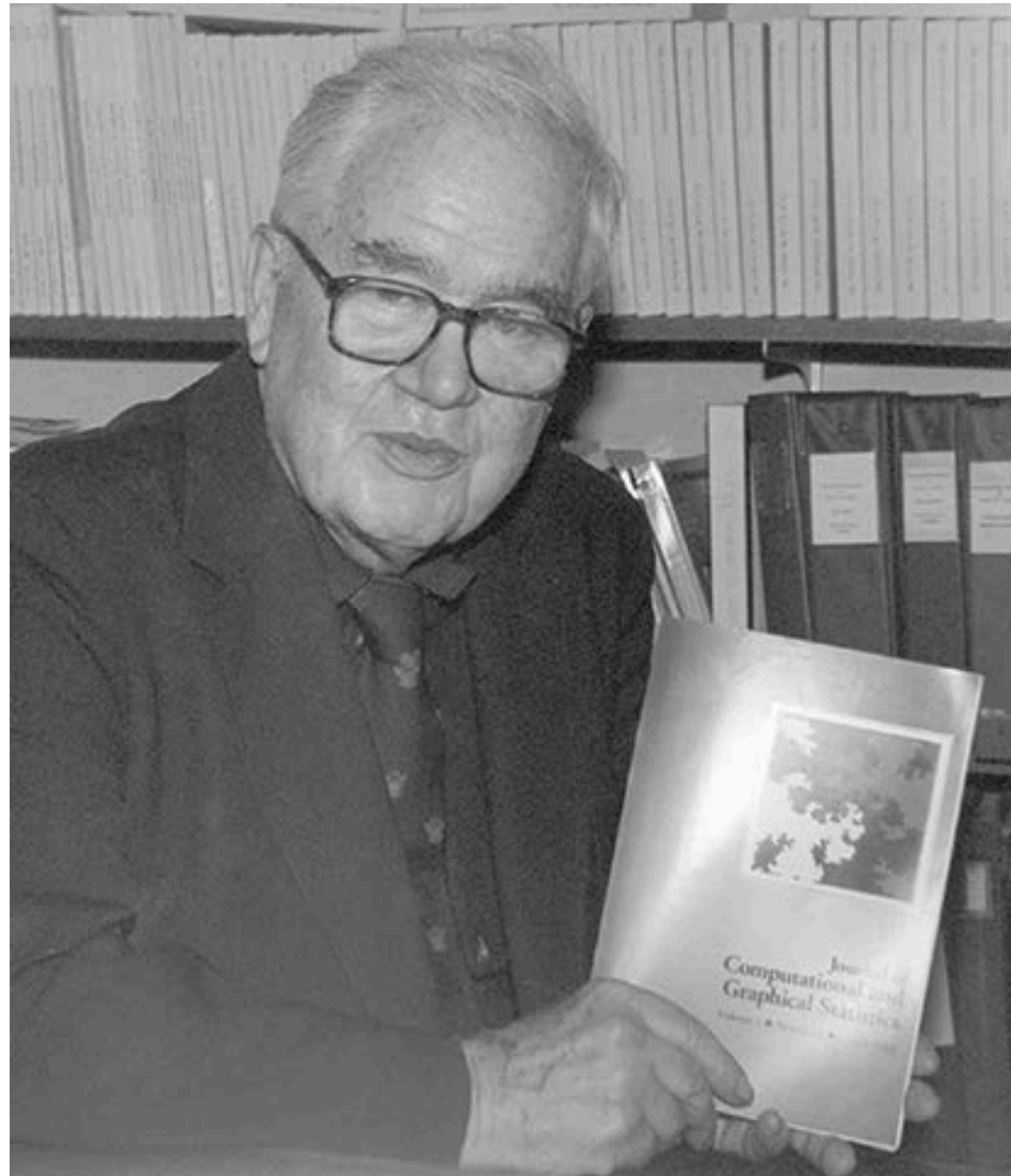


We visualize because the human visual brain evolved to detect **patterns**...



...and the
exceptions to
those patterns.

The relationship between patterns and their exceptions is a key principle of data exploration: to reveal **patterns and trends**, but also the **exceptions** to them.



“The greatest value of a picture is when it forces us to notice what we never expected to see.”

John W. Tukey

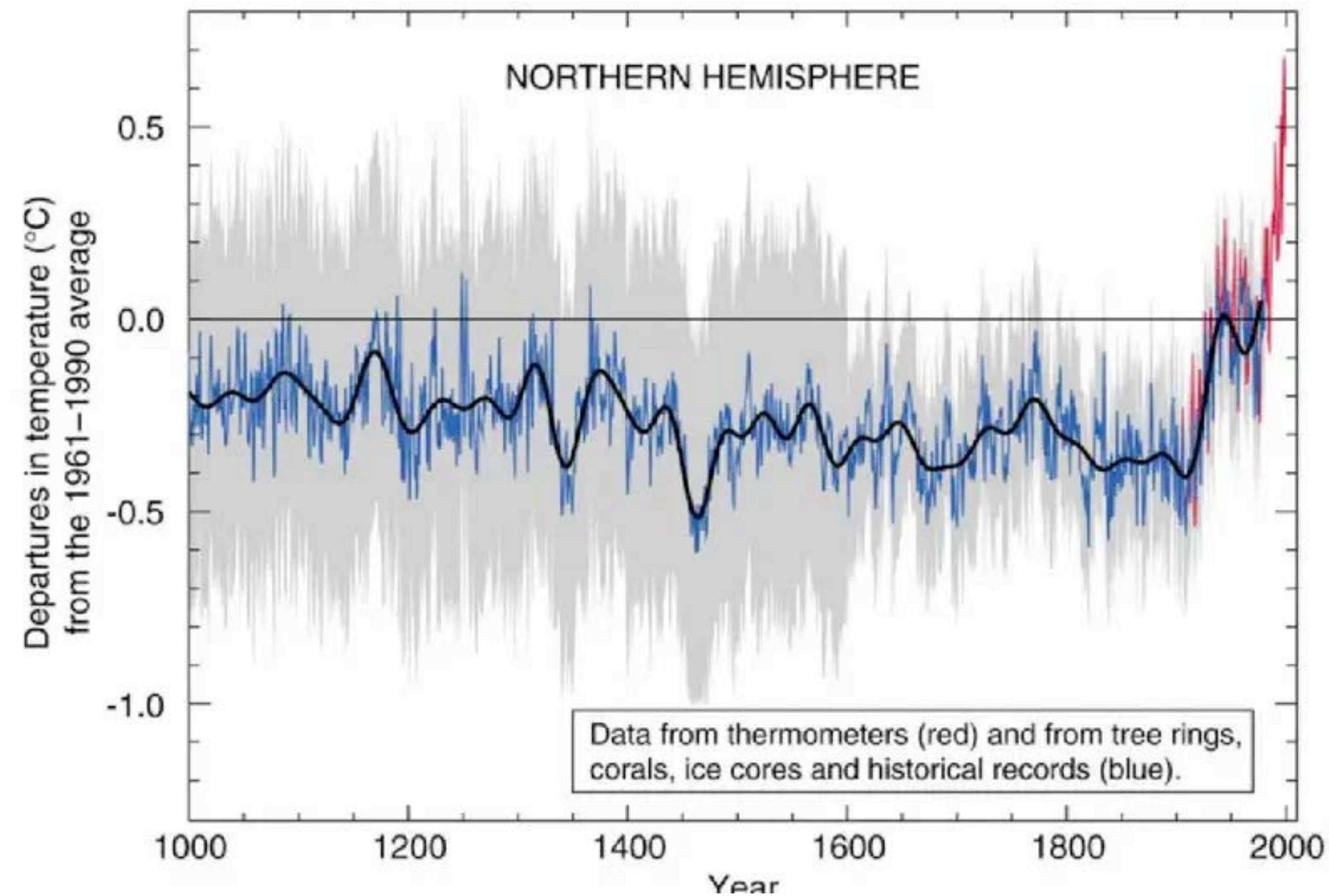
If we want to see each value, show each value...

Workbook1							
Home Layout Tables Charts SmartArt Formulas Data Review							
Edit Font Alignment Number Conditional Formatting							
H6							
	A	B	C	D	E	F	G
1	YEAR	TEMP	YEAR	1 SIGMA	2 SIGMA		
2	1000	0.0659	1000	0.240346	0.480693	0.206137	0.123588
3	1001	-0.1241	1001	0.240347	0.480694	0.206137	0.123589
4	1002	-0.1208	1002	0.240346	0.480692	0.206136	0.123588
5	1003	-0.1801	1003	0.240347	0.480694	0.206137	0.123589
6	1004	-0.0711	1004	0.240347	0.480693	0.206137	0.123588
7	1005	-0.1334	1005	0.240346	0.480692	0.206136	0.123588
8	1006	-0.0644	1006	0.240346	0.480693	0.206137	0.123588
9	1007	0.0042	1007	0.240347	0.480693	0.206137	0.123588
10	1008	-0.1288	1008	0.240347	0.480693	0.206137	0.123588
11	1009	-0.0296	1009	0.240347	0.480693	0.206137	0.123588
12	1010	0.1187	1010	0.240347	0.480694	0.206137	0.123589
13	1011	-0.1252	1011	0.240346	0.480692	0.206136	0.123588
14	1012	-0.1634	1012	0.240347	0.480694	0.206137	0.123588
15	1013	-0.0791	1013	0.240347	0.480693	0.206137	0.123588
16	1014	-0.1120	1014	0.240347	0.480693	0.206137	0.123588
17	1015	-0.1146	1015	0.240346	0.480692	0.206136	0.123588
18	1016	-0.1206	1016	0.240346	0.480692	0.206136	0.123588
19	1017	-0.0815	1017	0.240347	0.480693	0.206137	0.123588
20	1018	-0.2031	1018	0.240346	0.480693	0.206137	0.123588
21	1019	0.0305	1019	0.240347	0.480693	0.206137	0.123588
22	1020	0.1098	1020	0.240347	0.480694	0.206137	0.123589
23	1021	0.0244	1021	0.240347	0.480693	0.206137	0.123588
24	1022	-0.0743	1022	0.240347	0.480693	0.206137	0.123588
25	1023	-0.0323	1023	0.240347	0.480693	0.206137	0.123588
26	1024	-0.0434	1024	0.240346	0.480693	0.206137	0.123588

Workbook1							
Home Layout Tables Charts SmartArt Formulas Data Review							
Edit Font Alignment Number Format Conditional Formatting							
H6							
	A	B	C	D	E	F	G
878	1876	-0.1891	1876	0.113228	0.226456	8.25297E-02	7.75207E-02
879	1877	-0.0140	1877	0.113228	0.226457	8.25299E-02	7.75209E-02
880	1878	-0.0873	1878	0.113228	0.226457	8.25298E-02	7.75209E-02
881	1879	-0.2959	1879	0.113229	0.226458	8.25302E-02	7.75212E-02
882	1880	-0.2368	1880	0.113229	0.226457	8.25300E-02	7.75210E-02
883	1881	-0.1977	1881	0.113229	0.226458	8.25302E-02	7.75212E-02
884	1882	-0.2036	1882	0.113229	0.226457	8.25300E-02	7.75210E-02
885	1883	-0.2489	1883	0.113228	0.226455	8.25293E-02	7.75204E-02
886	1884	-0.2125	1884	0.113229	0.226457	8.25301E-02	7.75211E-02
887	1885	-0.1896	1885	0.113228	0.226457	8.25299E-02	7.75210E-02
888	1886	-0.1084	1886	0.113228	0.226456	8.25298E-02	7.75208E-02
889	1887	-0.3265	1887	0.113228	0.226456	8.25296E-02	7.75206E-02
890	1888	-0.1694	1888	0.113228	0.226457	8.25298E-02	7.75209E-02
891	1889	-0.1339	1889	0.113228	0.226456	8.25298E-02	7.75208E-02
892	1890	-0.3107	1890	0.113229	0.226457	8.25301E-02	7.75211E-02
893	1891	-0.1754	1891	0.113229	0.226457	8.25300E-02	7.75210E-02
894	1892	-0.3186	1892	0.113228	0.226456	8.25295E-02	7.75205E-02
895	1893	-0.3236	1893	0.113228	0.226456	8.25297E-02	7.75207E-02
896	1894	-0.1970	1894	0.113228	0.226456	8.25295E-02	7.75205E-02
897	1895	-0.1578	1895	0.113228	0.226456	8.25297E-02	7.75207E-02
898	1896	-0.0804	1896	0.113228	0.226456	8.25298E-02	7.75208E-02
899	1897	-0.0537	1897	0.113228	0.226456	8.25298E-02	7.75208E-02
900	1898	-0.2195	1898	0.113229	0.226457	8.25301E-02	7.75211E-02
901	1899	-0.3486	1899	0.113228	0.226456	8.25297E-02	7.75207E-02
902	1900	-0.1253	1900	0.113229	0.226457	8.25300E-02	7.75210E-02
903	1901	-0.1575	1901	0.113228	0.226456	8.25296E-02	7.75206E-02

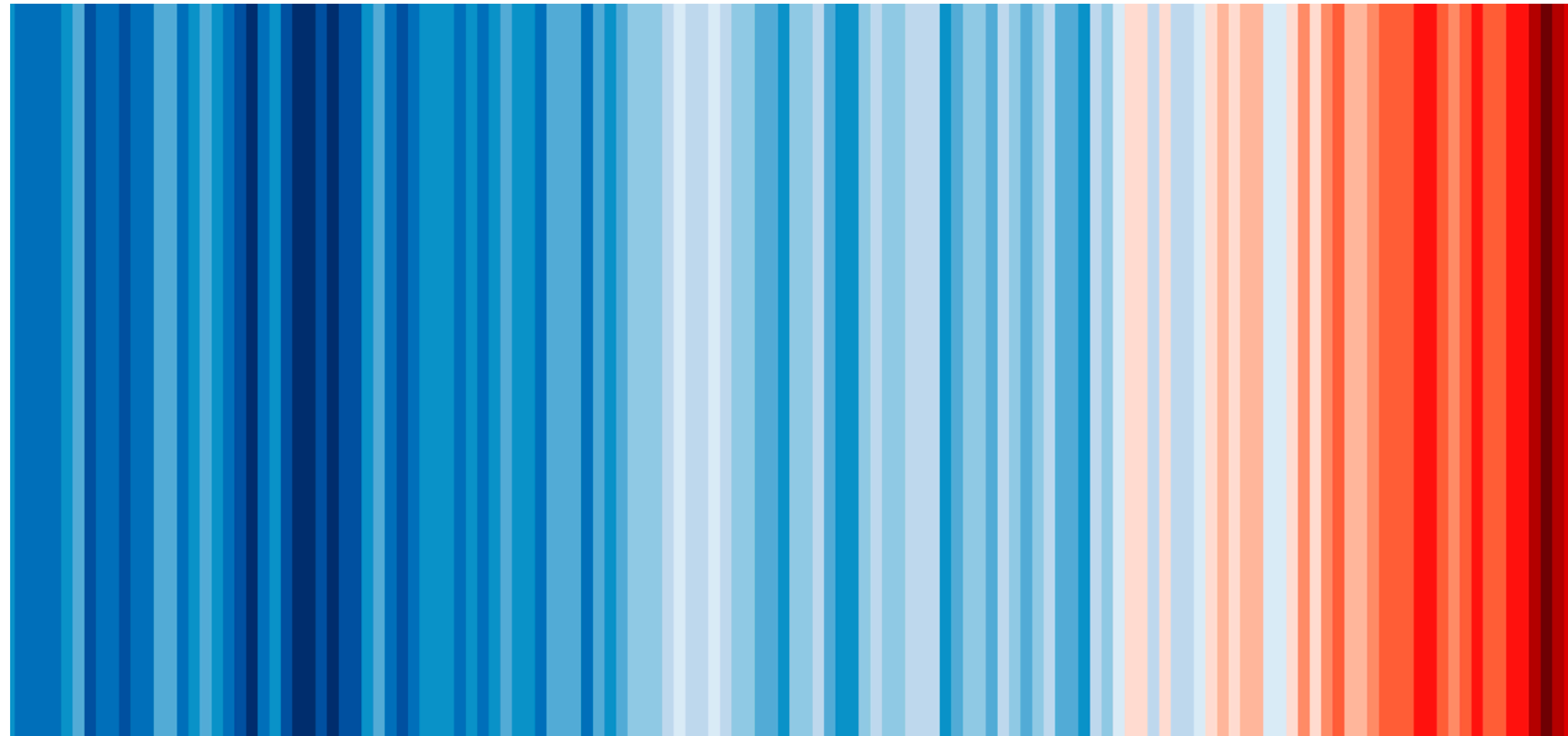
...but if we care more about general patterns and trends than we care about individual values, then we should think about visualizations

The hockey stick chart

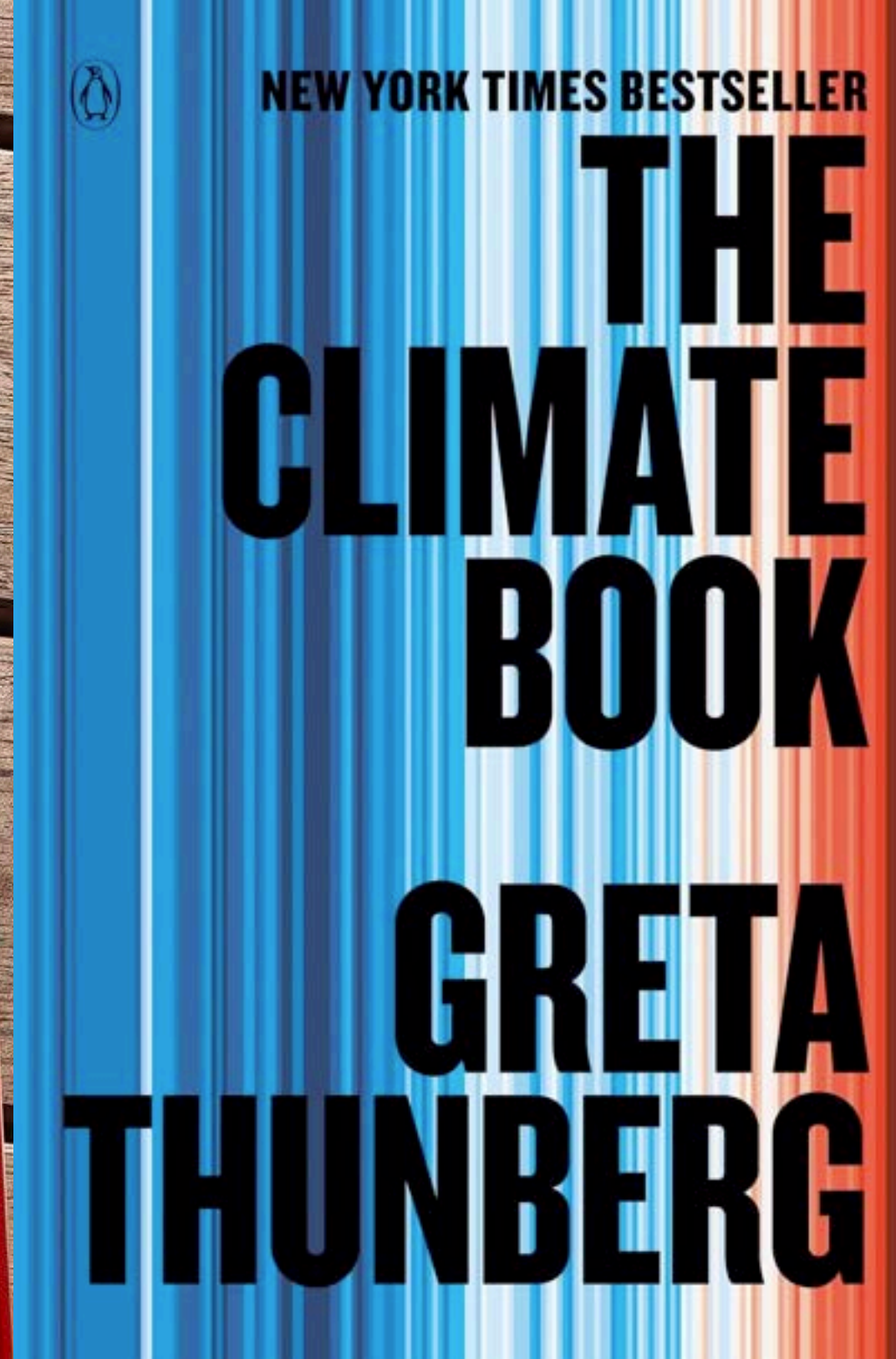


Michael E. Mann, Raymond S. Bradley, and Malcolm K. Hughes
Intergovernmental Panel on Climate Change (IPCC), Third Report, 2001

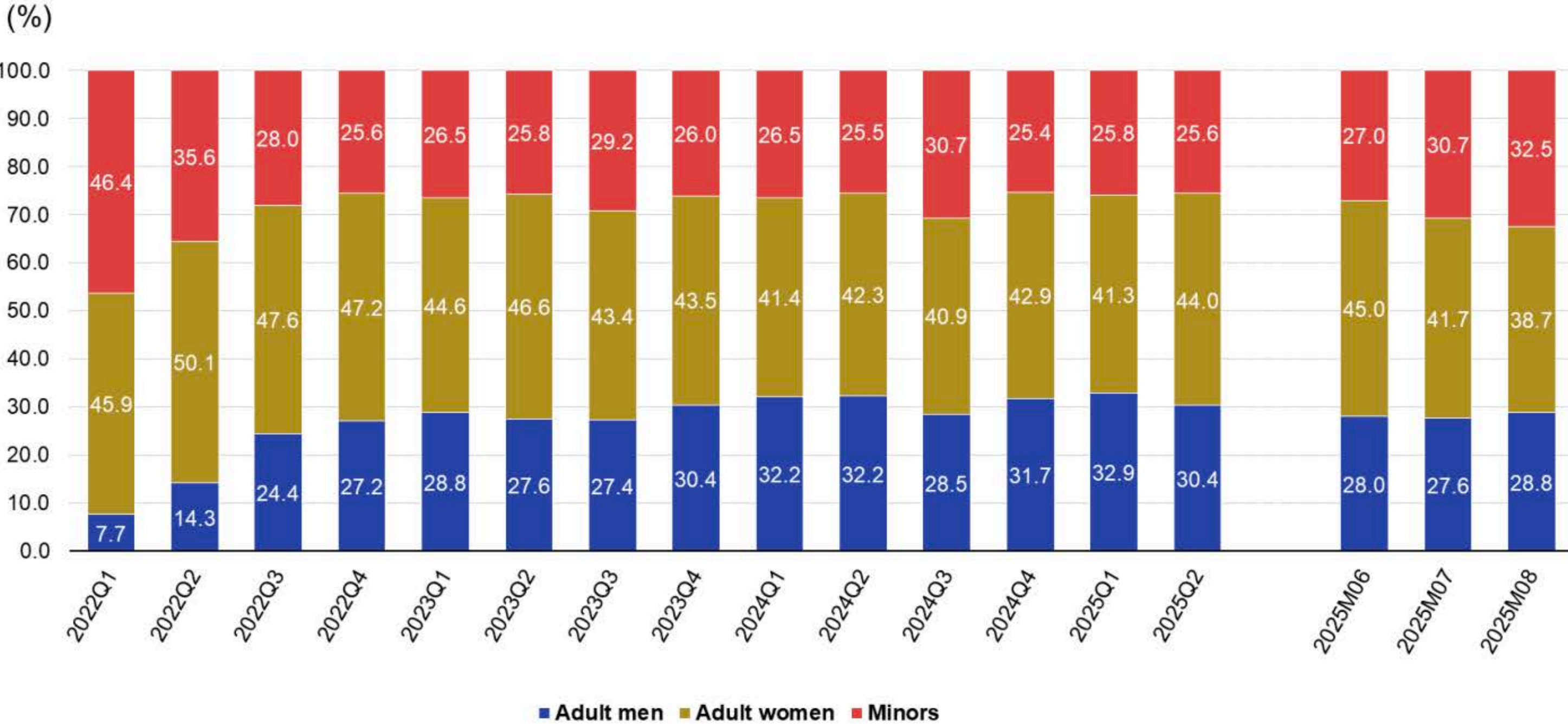
Ed Hawkins's 'Warming Stripes'



<https://showyourstripes.info/s/globe>



Quarterly and monthly shares of main population groups among people granted temporary protection, EU



Note:
EU total excluding:
Hungary - data by age group not available until December 2024.
France - data for minors generally not included.
Source: Eurostat (migr_asytpfq, migr_asytpfm)

eurostat 

Figure 3: Quarterly and monthly shares of main population groups among people granted temporary protection, EU

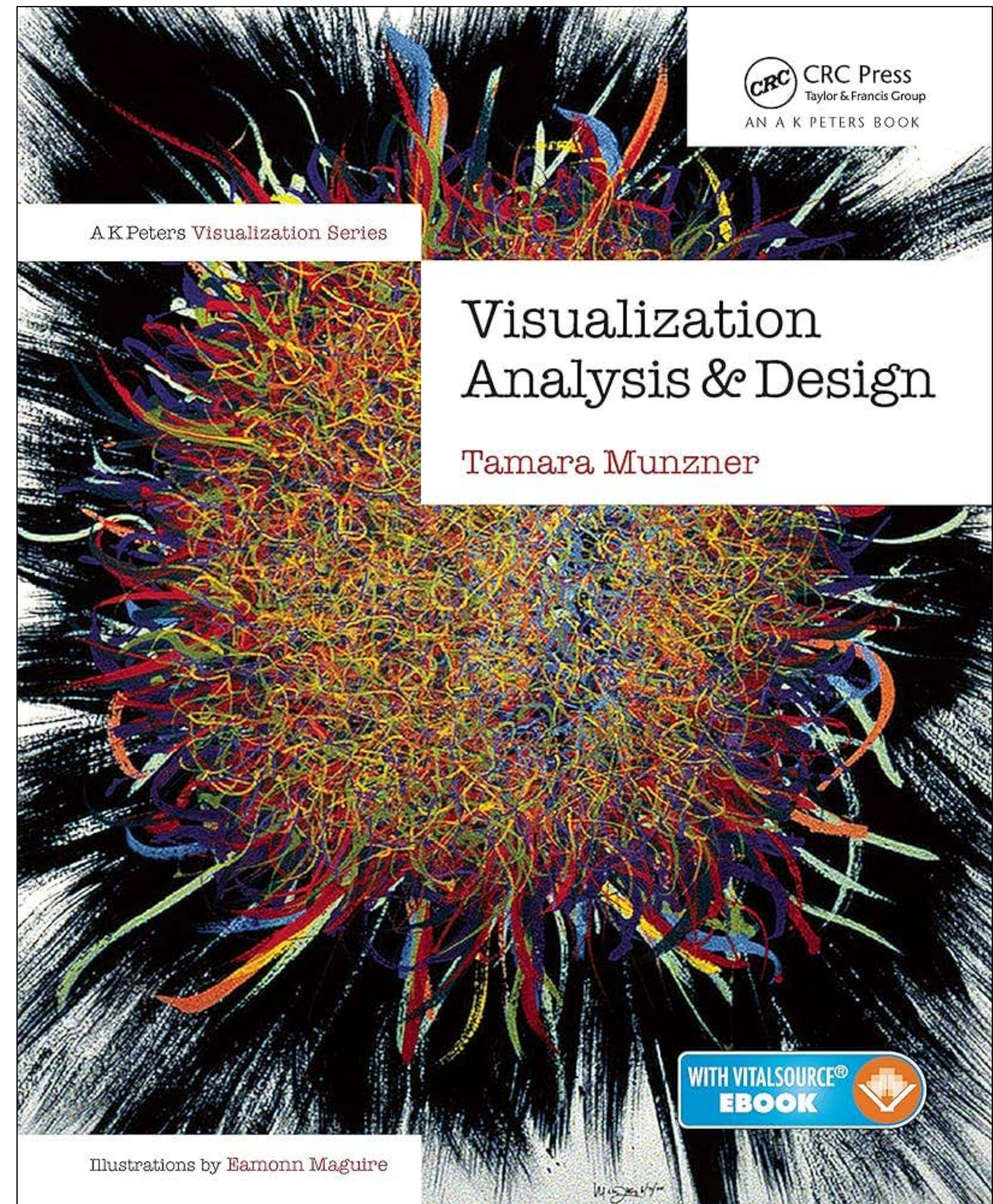
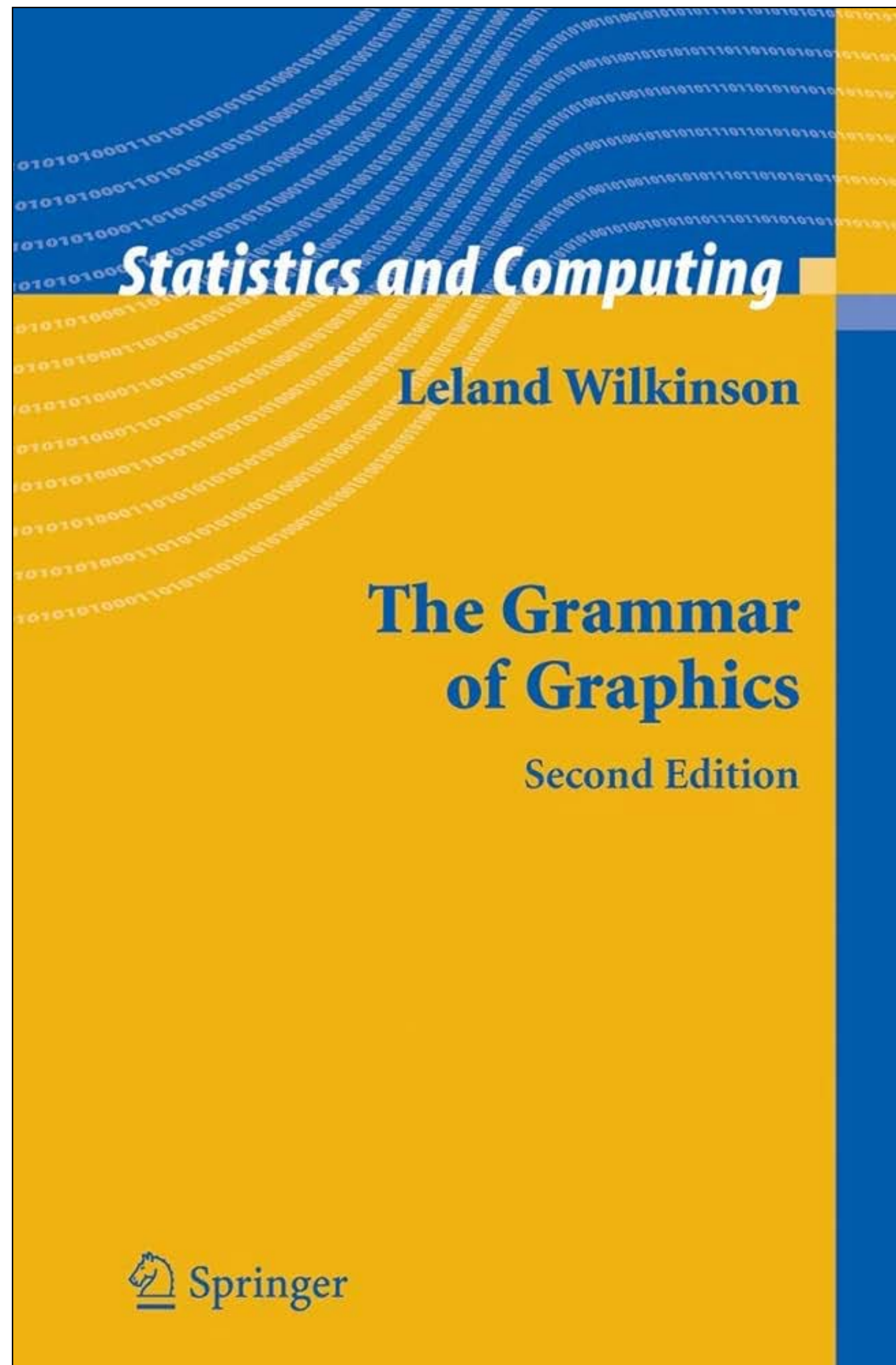
Source: Eurostat ([migr_asytpfm](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Temporary_protection_for_persons_fleeing_Ukraine_-_monthly_statistics))

Should we include all figures in a chart? I'd say: Only if we have a very good reason to.

If not, it's better to design a table.

https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Temporary_protection_for_persons_fleeing_Ukraine_-_monthly_statistics

— The grammar of graphics —



Marks



Rectangles



Circles



Triangles

Encoding data

Data visualization consists of mapping data onto attributes of objects—commonly abstract shapes, called **“marks”**.

Marks



Rectangles



Circles



Triangles

Encoding data

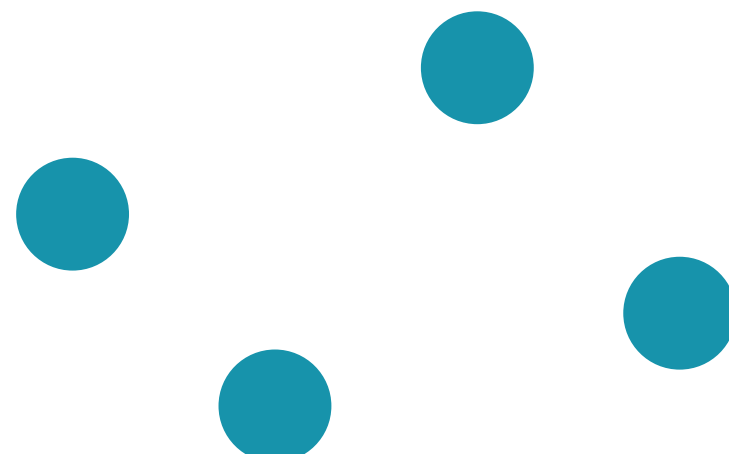
Data visualization consists of mapping data onto attributes of objects—commonly abstract shapes, called **“marks”**.

These attributes that vary in relation to the data are called **“visual channels”**.

Visual channels



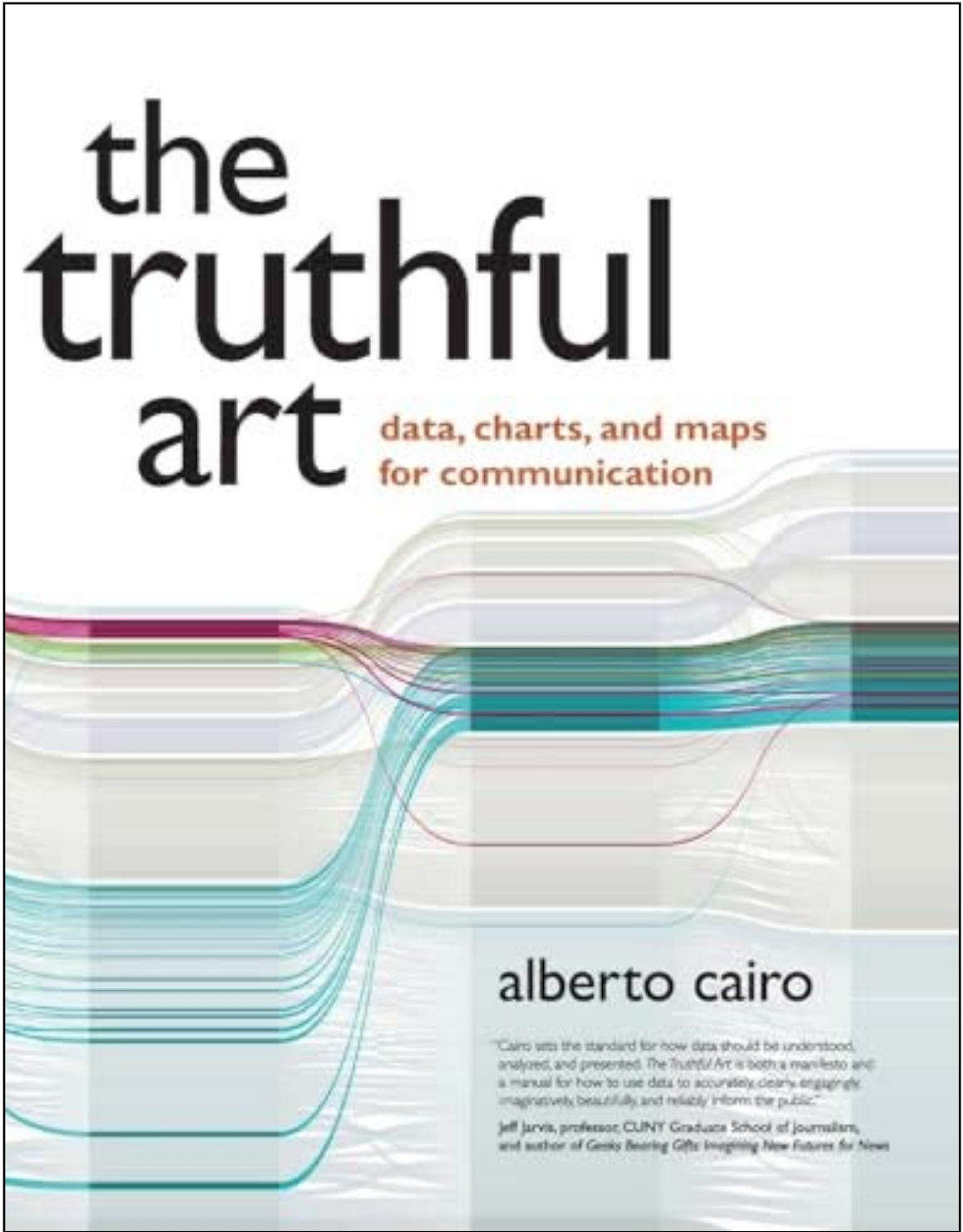
Height



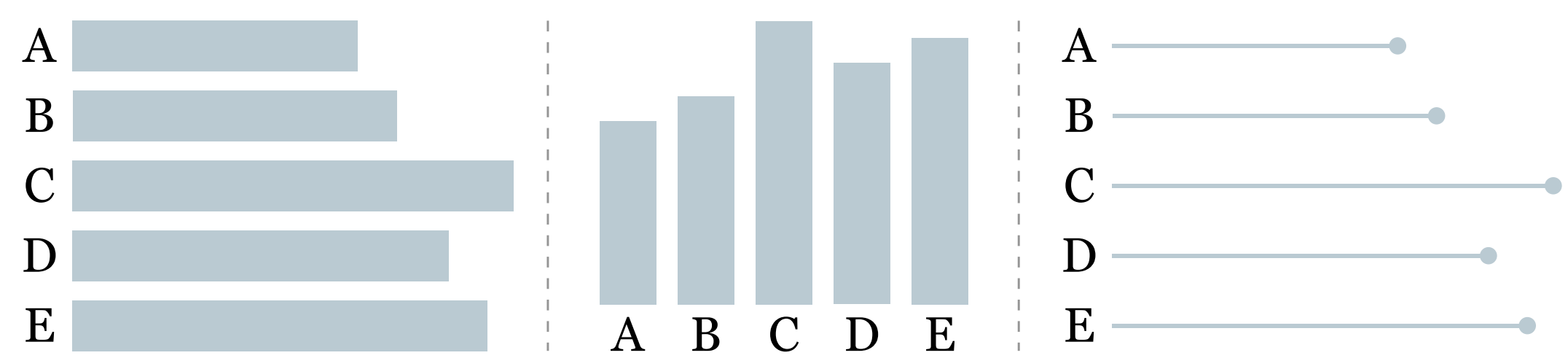
Position



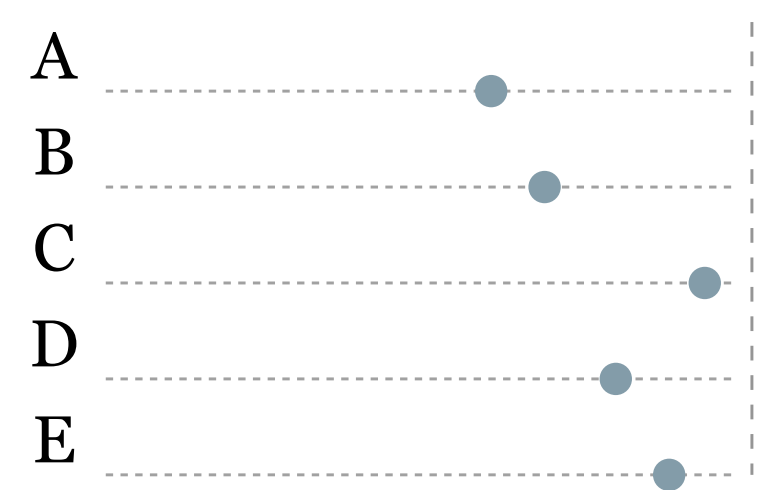
Color hue



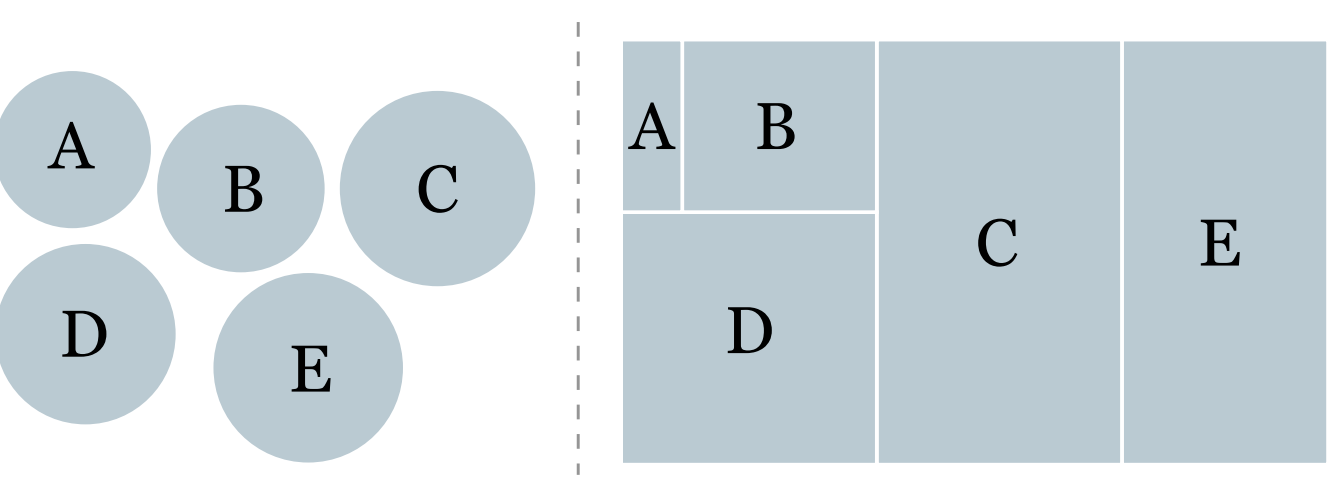
Length or height



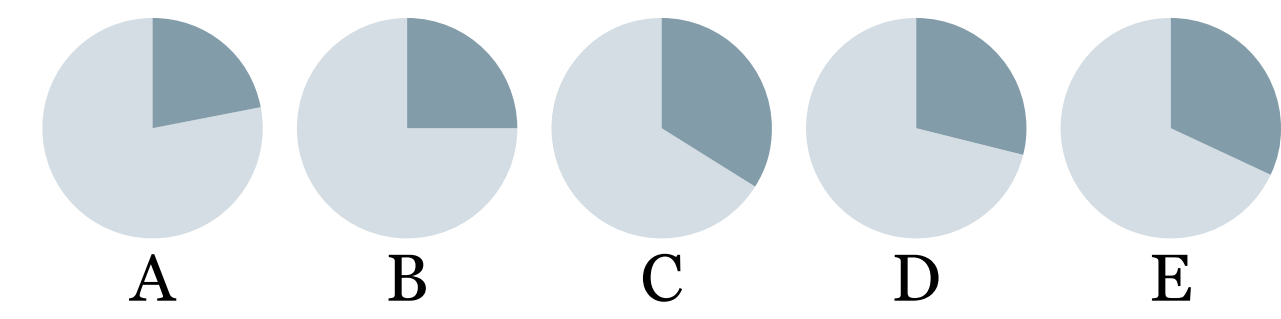
Position



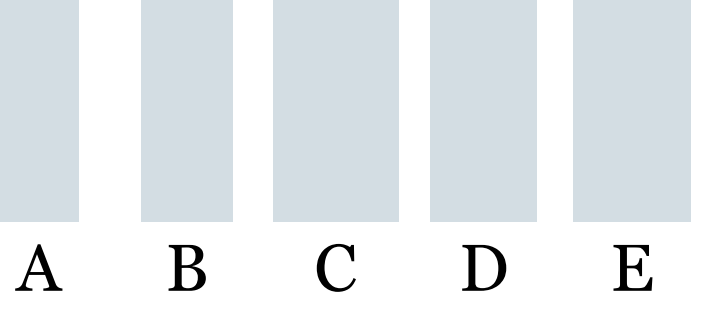
Area



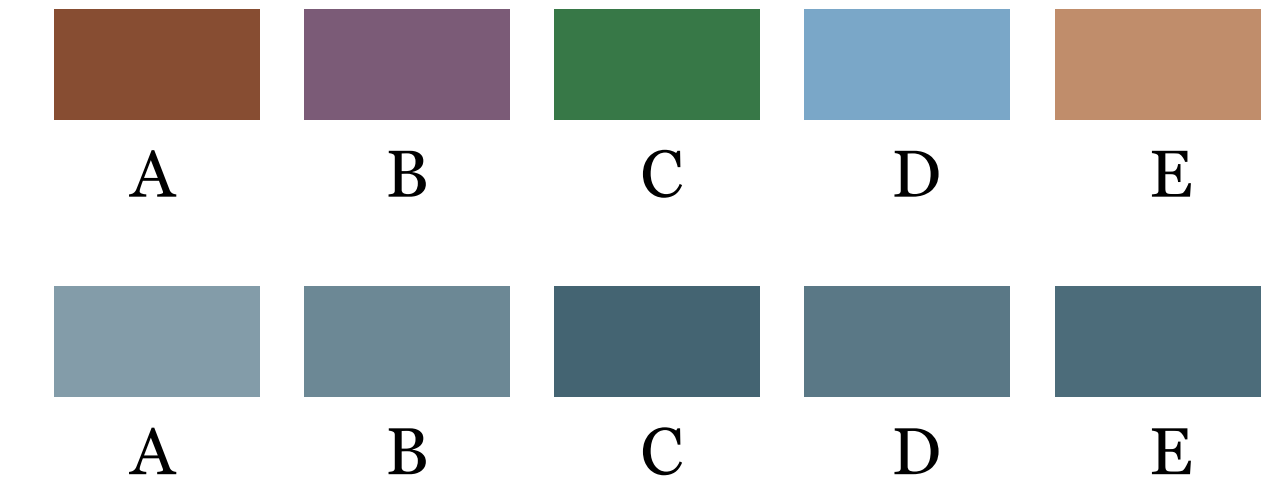
Angle/area



Line weight



Hue and shade



Figures represented
in all these graphics:
22%, 25%, 34%, 29%, 32%

Encoding data

Data visualization consists of mapping data onto attributes of objects—commonly abstract shapes, called **“marks”**.

These attributes that vary in relation to the data are called **“visual channels”**.

What visual channels do you see here?

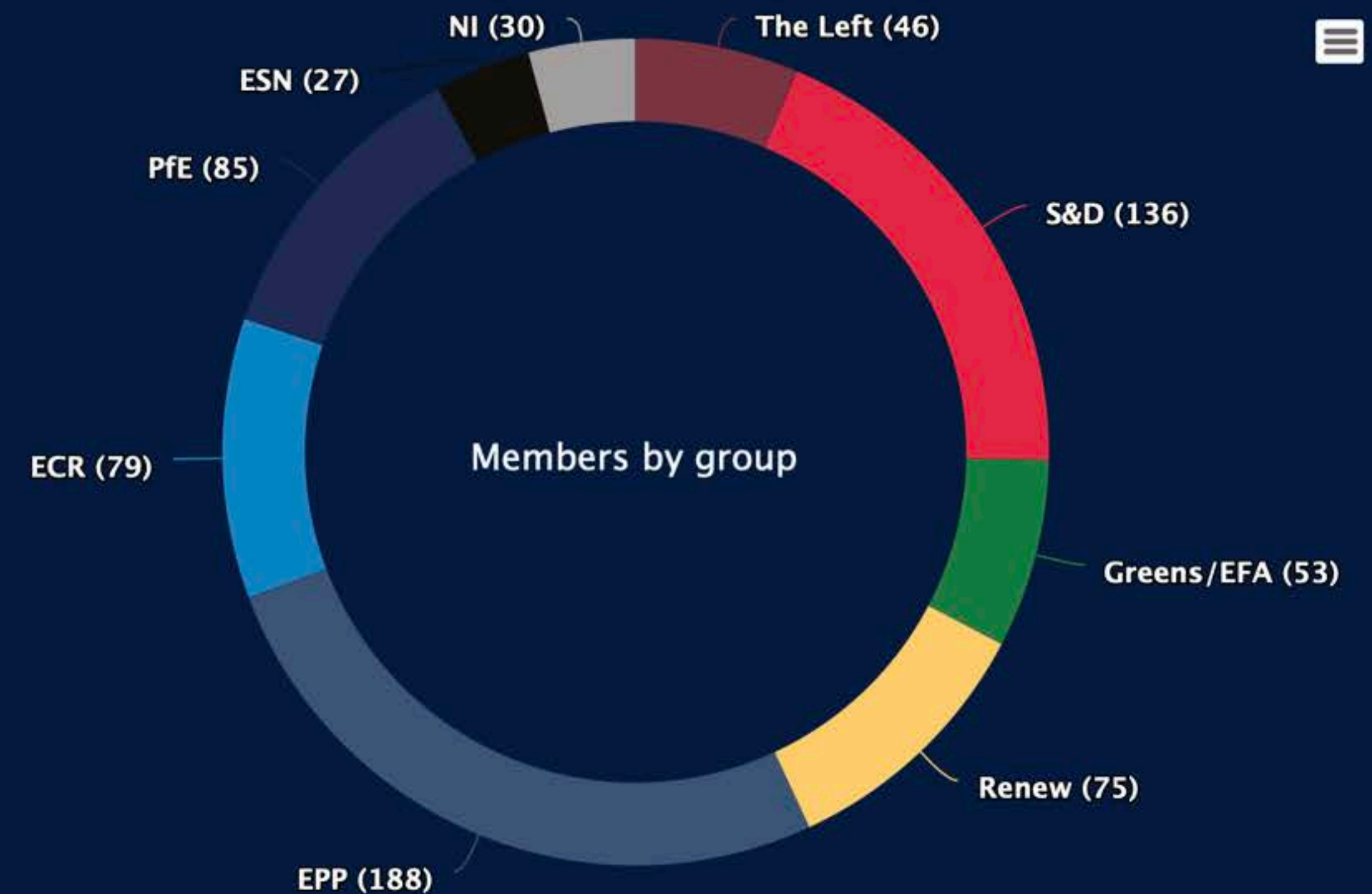
Political groups: size, composition by country and national political party of their MEPs

Selected date : 10th term - October 2025

This graph details the composition of the European Parliament for the selected legislative term. Move your mouse over any political group; you will be shown the share that the MEPs of that group represent in terms of the total number of MEPs. If you select a political group, you will see the MEPs of that group, divided by Member State. By clicking on a given country, you will see the number of national political parties within the selected political group and Member State. A final click on the graph will display the names of the MEPs belonging to that national political party in that Member State.

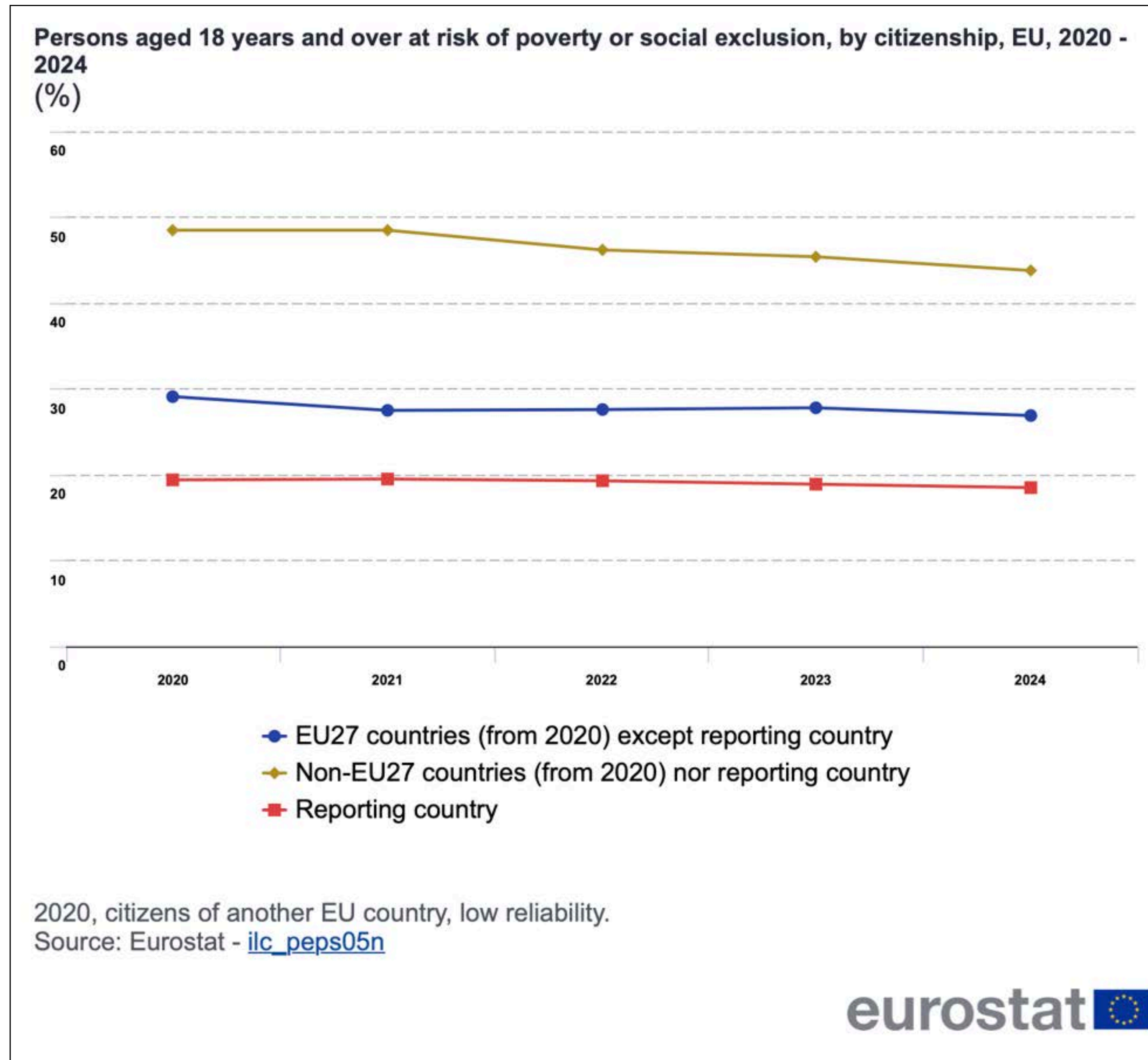
Three question marks means there are no data for the given item.

Source: European Parliament



<https://facts-and-figures.europarl.europa.eu/snapshot/term-10/current>

What visual channels do you see here?



Something I hear often:

“OK, let’s cut to the chase: What are the rules of data visualization?”

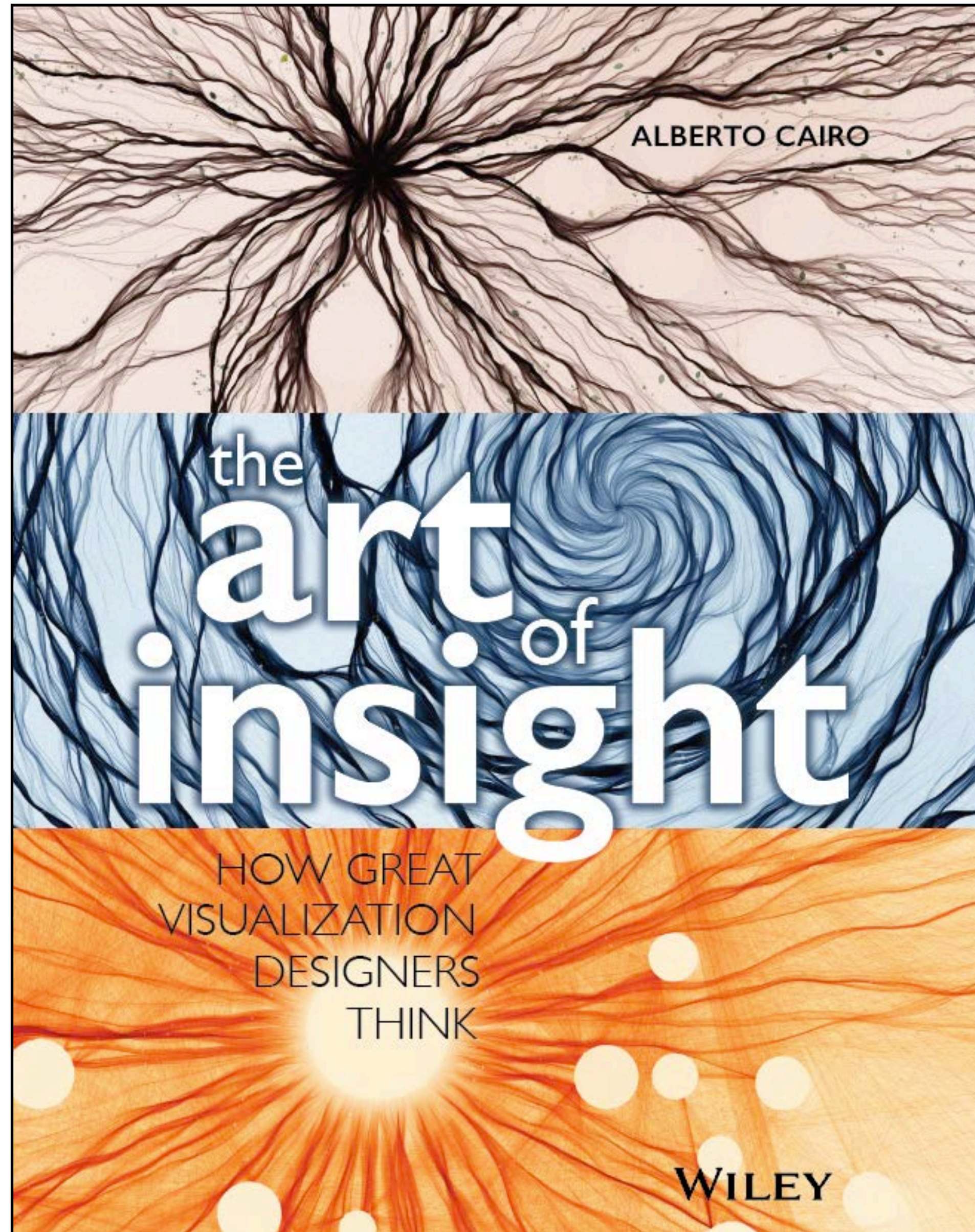
Visualization is **similar to writing** in many ways.

First, it's based on a vocabulary and a grammar.

Second, **there are few “rules” that are set in stone and that can be memorized** when it comes to designing visualizations. **It's not that easy!**

Like writing, this is a craft takes time, dedication, study, and practice to master.

Third —again like writing— visualization **can be used for many purposes:**
Communication, reasoning, exploration, or even artistic expression.



Visualization design consists of **reasoning** about possible **choices** by considering the interplay between:

1. **Content:** The nature, origin, and limitations of the data.
2. **People:** Your audience.
3. **Intent:** The purpose(s) that we define.
4. **Constraints:** The limitations that we may face.
5. **Outcomes:** How the graphic is received.

Every design choice must be **deliberate**.

It is inevitably **subjective**, but it should never be **arbitrary**.

Aside: Reading recommendation

A digital publication that...
creates **visual essays with data**

The Pudding

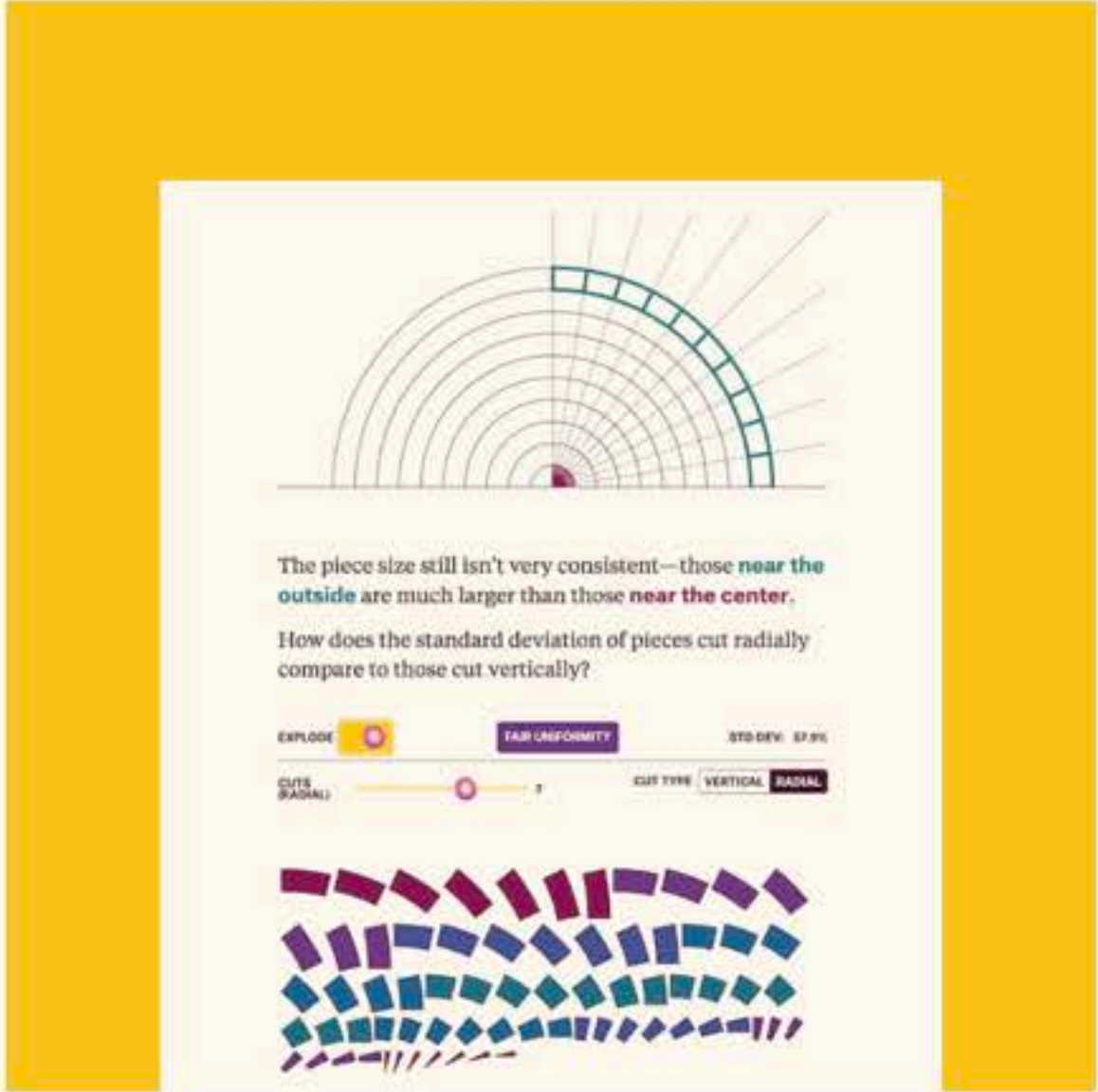
ABOUT SUBSCRIBE MORE

Find a story...

OUR FAVES POPULAR UPDATING YOUR INPUT VIDEO AUDIO

#210

AUG 2025



The piece size still isn't very consistent—those **near the outside** are much larger than those **near the center**.
How does the standard deviation of pieces cut radially compare to those cut vertically?

EXPLORE TAB UNIFORMITY STD DEV: 37.9%

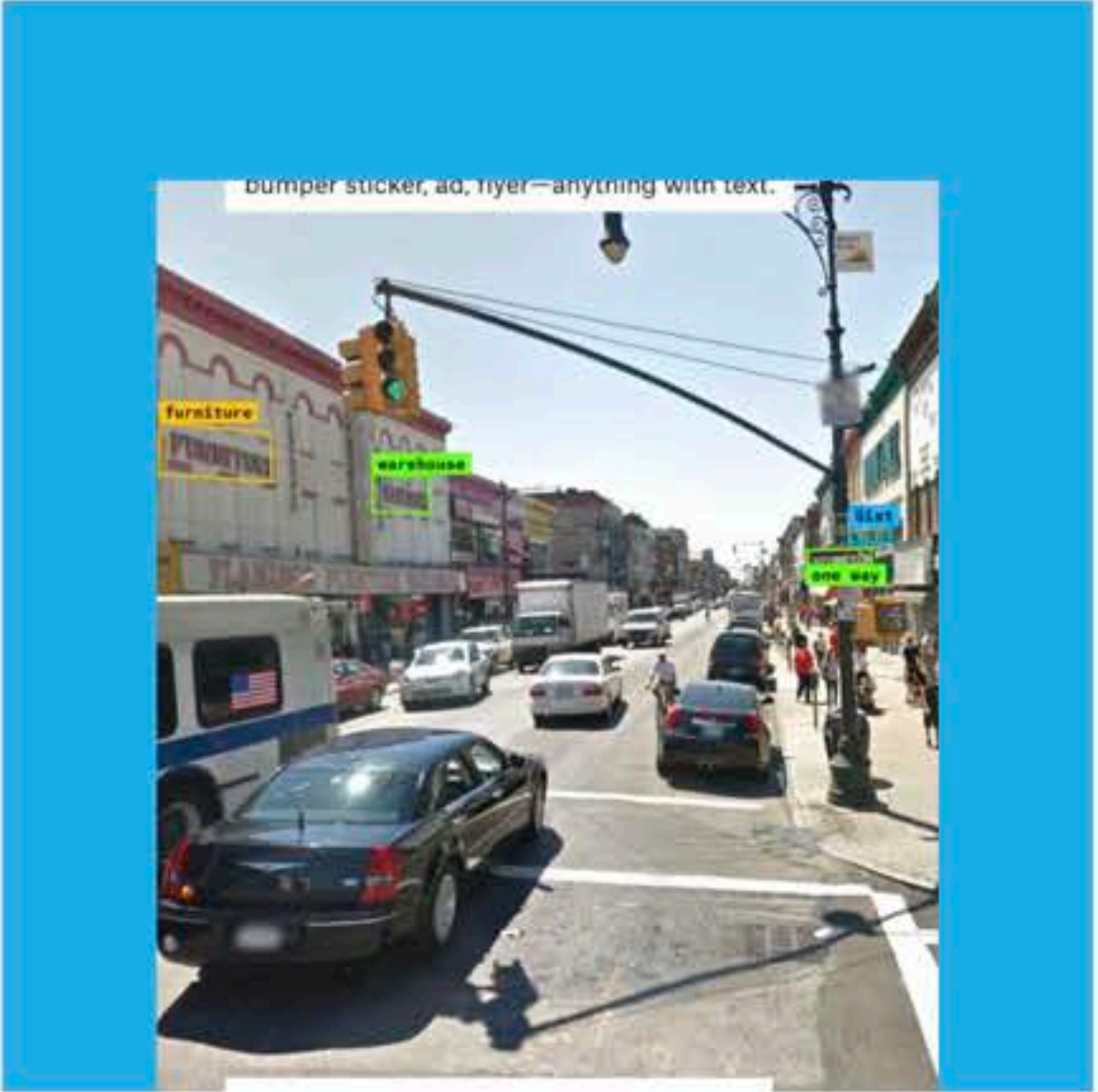
CUTS (RADIAL) CUT TYPE VERTICAL RADIAL

dicing onions

What is the best way to dice an onion to get the most uniform piece sizes?

#209

JUL 2025



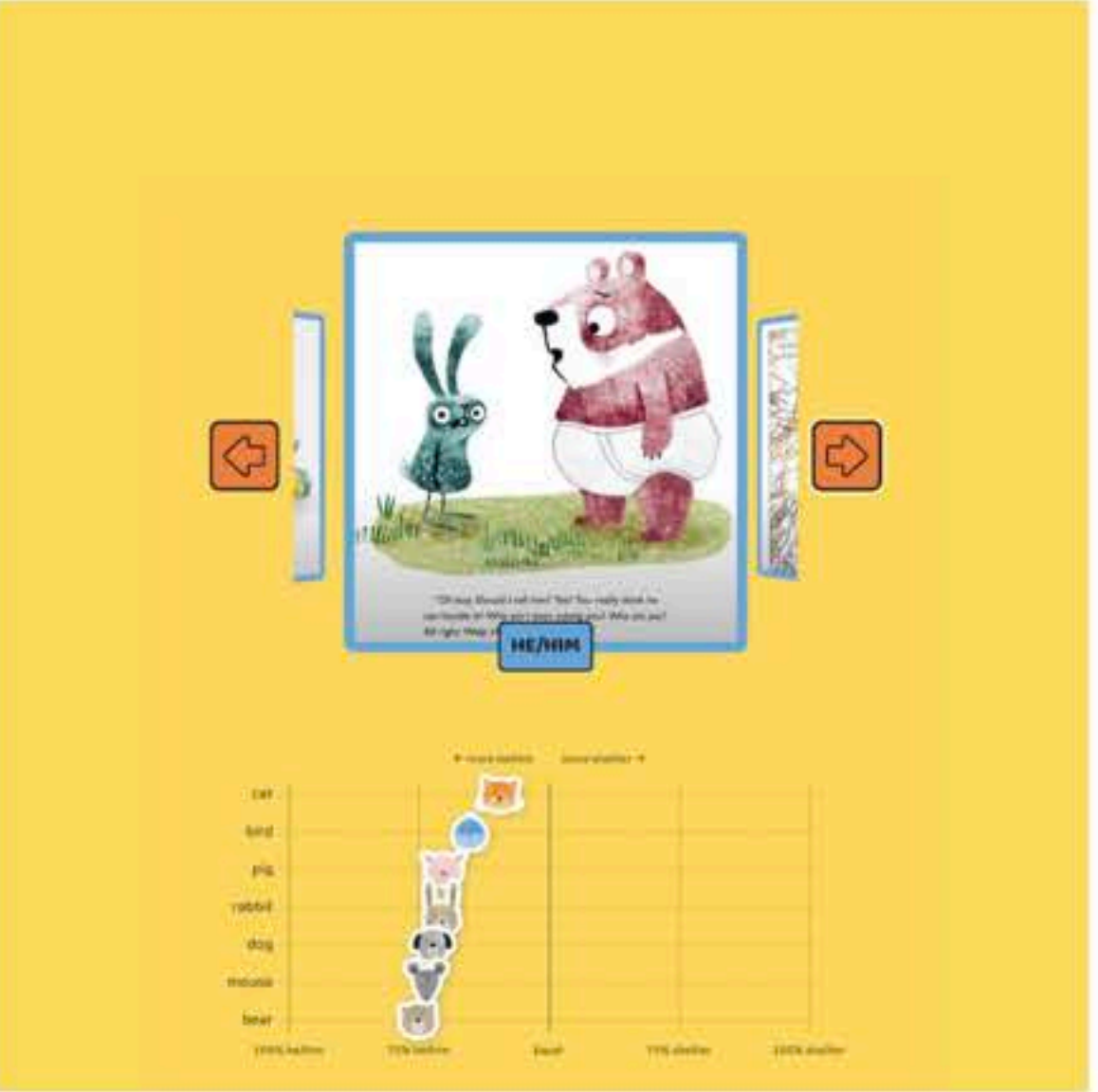
bumper sticker, ad, flyer—anything with text.

nyc street view

What if you could search every visible word on New York City's streets?

#208

JUL 2025



HE/HIM

kids book animals

How and why do we gender animals in stories?

<https://pudding.cool/>

Aside: Reading recommendation

Polygraph

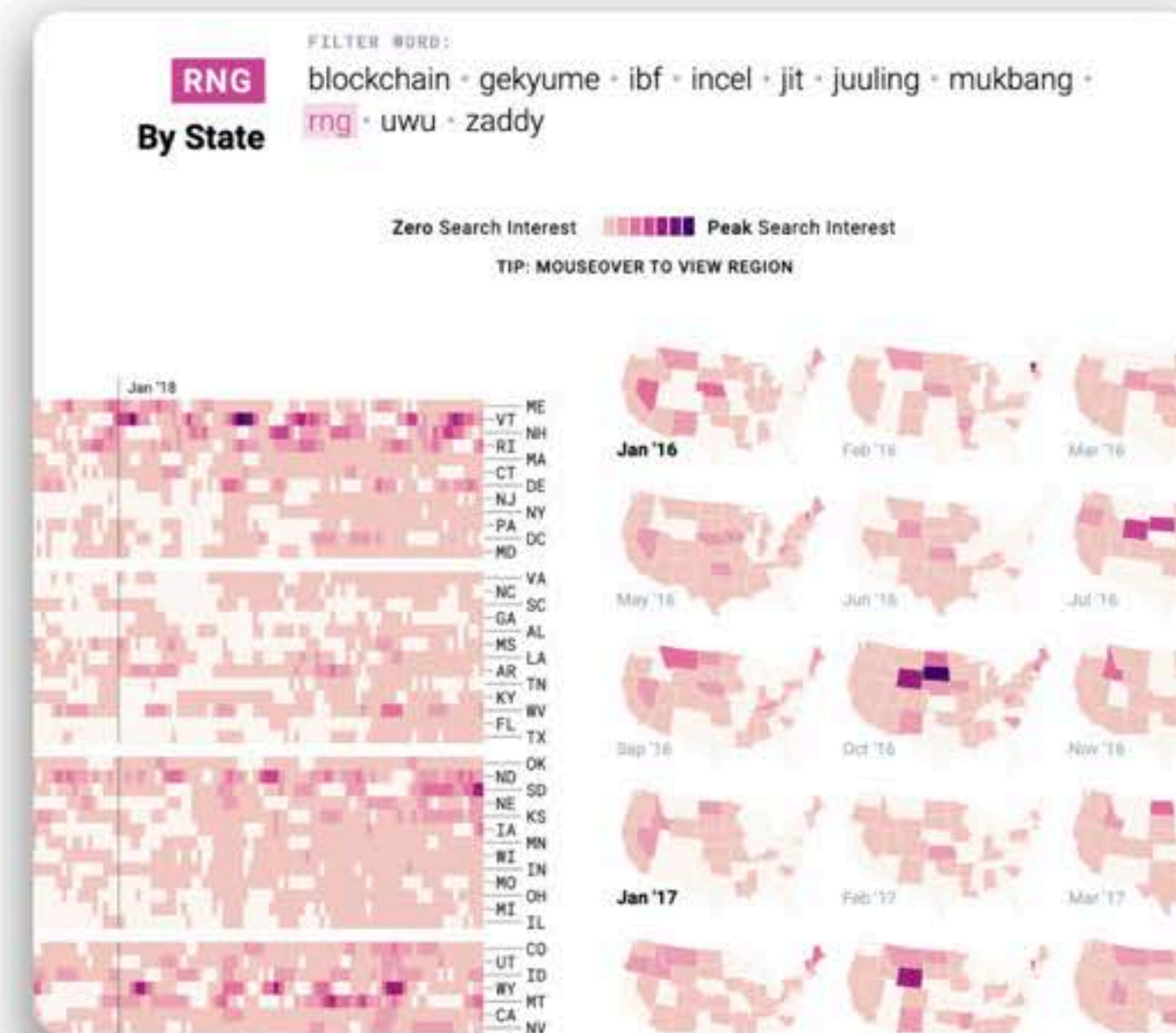
CATEGORY

Polygraph is a studio composed of the same team behind [The Pudding](#). We're your favorite in-house data journalism team, with an eye for translating complex information into visual content.

GOOGLE TRENDS

THE YEAR IN LANGUAGE

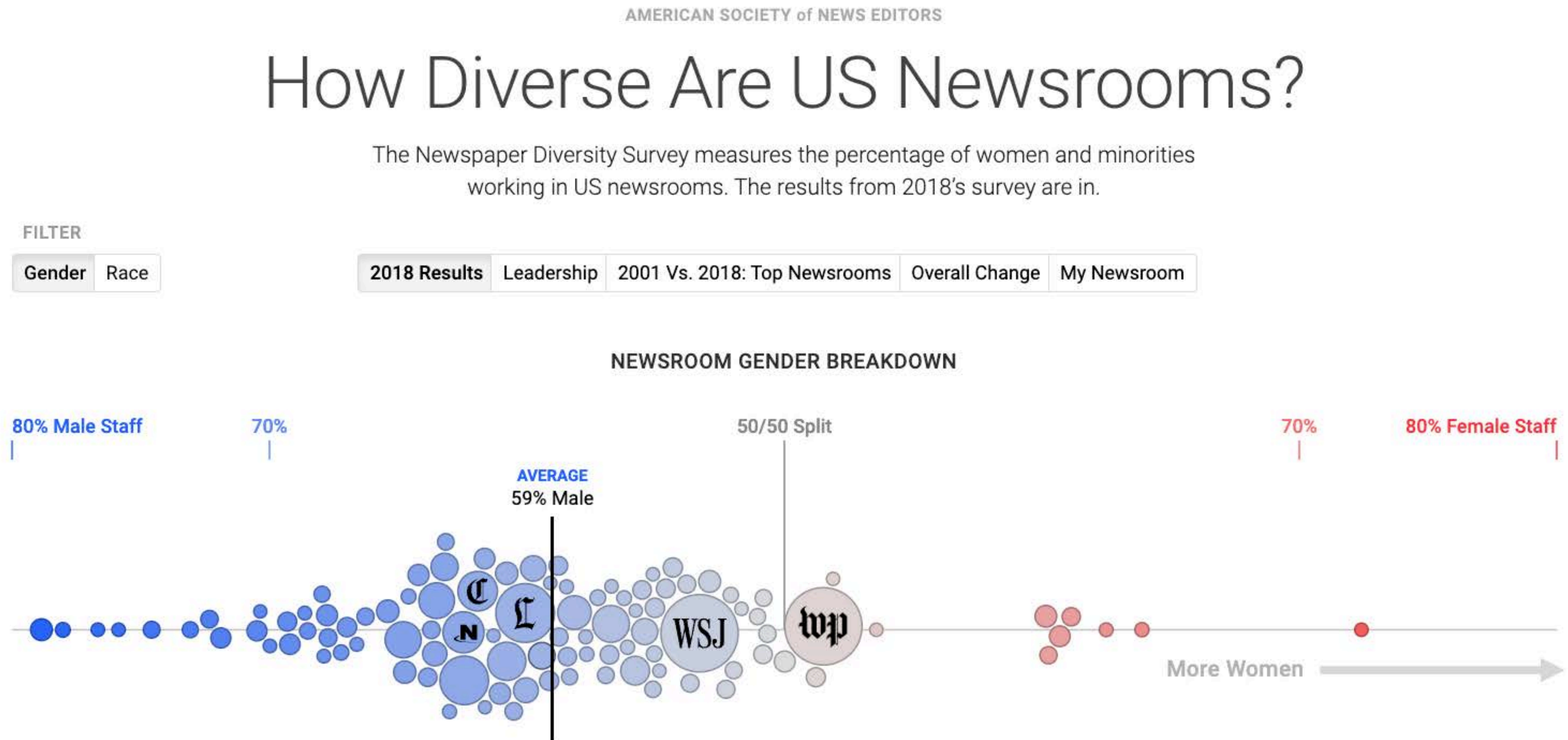
We identified 2018's rising words by ranking search interest growth for their definitions (e.g., searches for "woke definition," "define woke"). This project was also the subject of an NBC video series.

[VIEW THE PROJECT ↗](#)

<https://polygraph.cool/>

A good exercise: To reverse-engineer existing visualizations

“If I were the designer who created this, what choices would lead me to this solution?”



<https://googletrends.github.io/asne/>

How Diverse Are US Newsrooms?

The Newspaper Diversity Survey measures the percentage of women and minorities working in US newsrooms. The results from 2018's survey are in.

FILTER

Gender Race

2018 Results

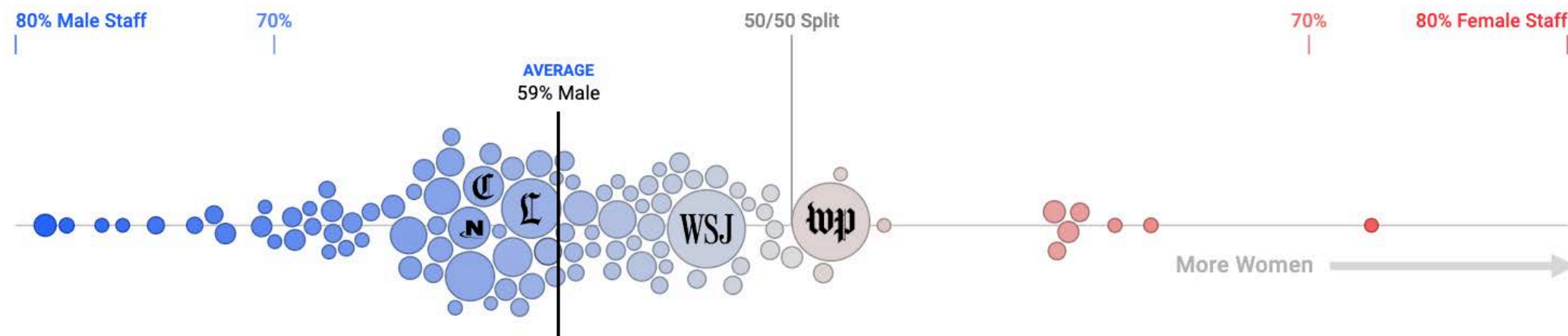
Leadership

2011 Vs. 2018: Top Newsrooms

Overall Change

My Newsroom

NEWSROOM GENDER BREAKDOWN

80%
Male Staff

70%

Average:
59% Male50/50
split

70%

80%
Female Staff

How Diverse Are US Newsrooms?

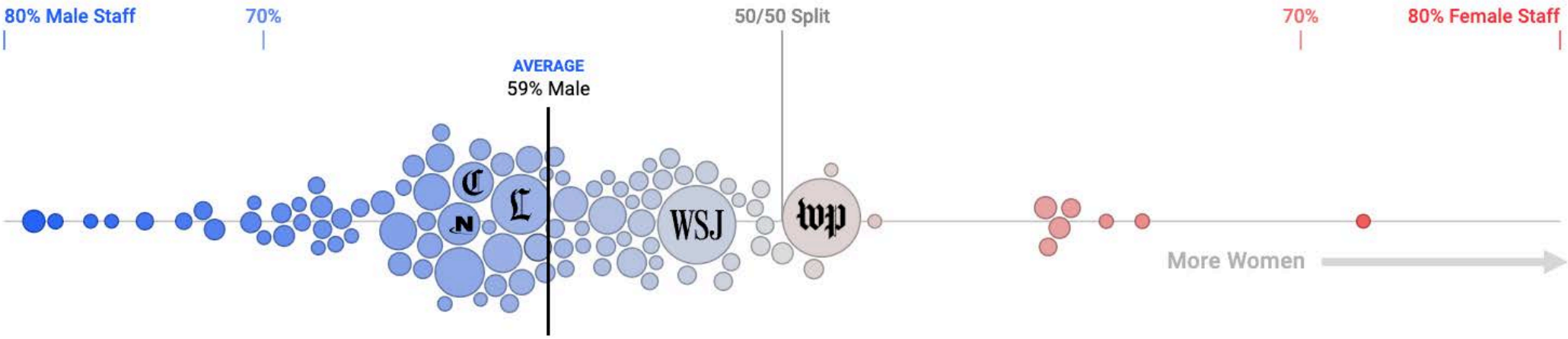
The Newspaper Diversity Survey measures the percentage of women and minorities working in US newsrooms. The results from 2018's survey are in.

FILTER

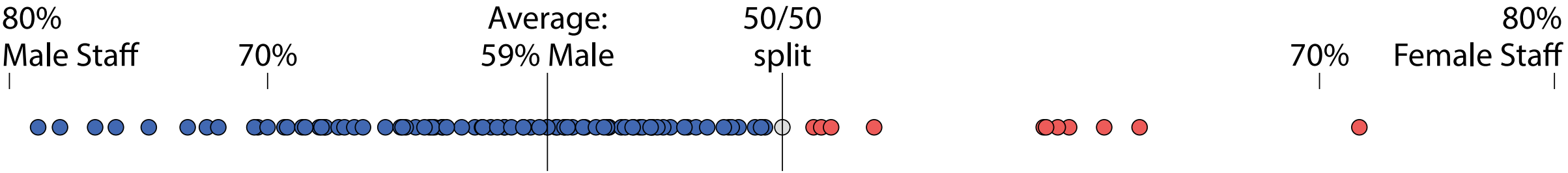
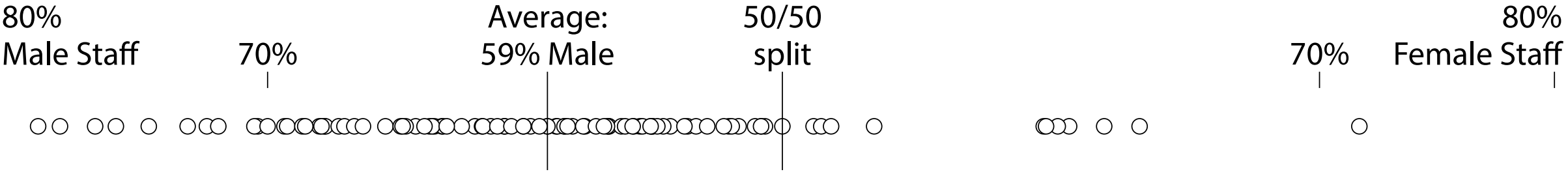
Gender Race

2018 Results Leadership 2001 Vs. 2018: Top Newsrooms Overall Change My Newsroom

NEWSROOM GENDER BREAKDOWN



Strip plot



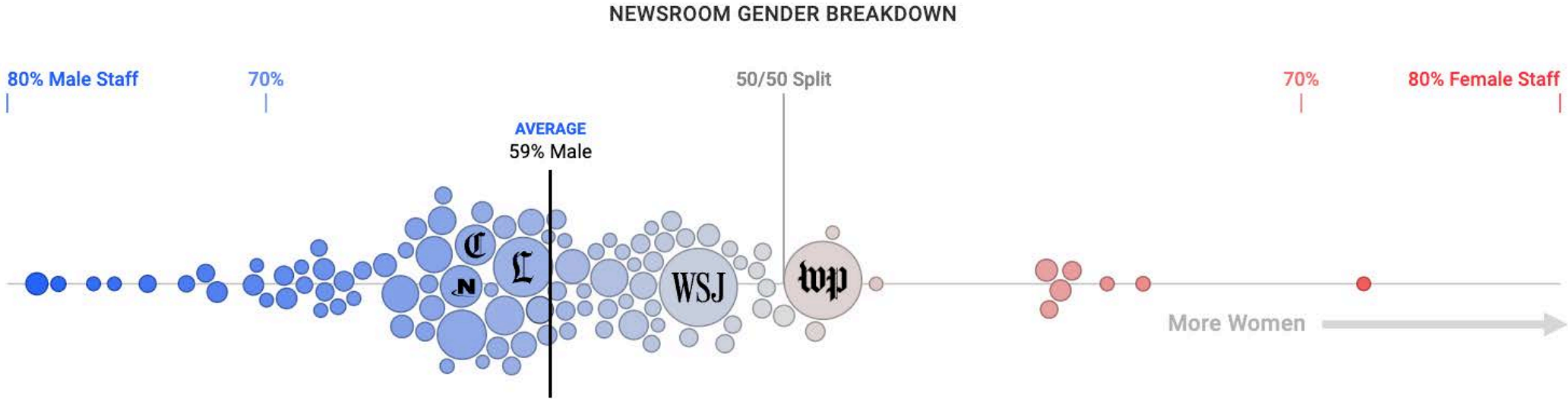
How Diverse Are US Newsrooms?

The Newspaper Diversity Survey measures the percentage of women and minorities working in US newsrooms. The results from 2018's survey are in.

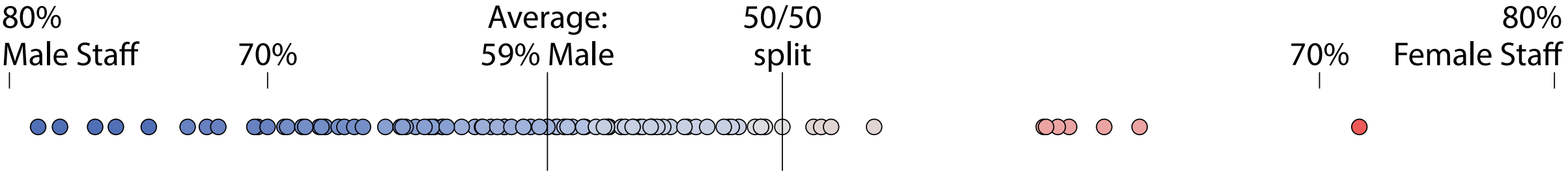
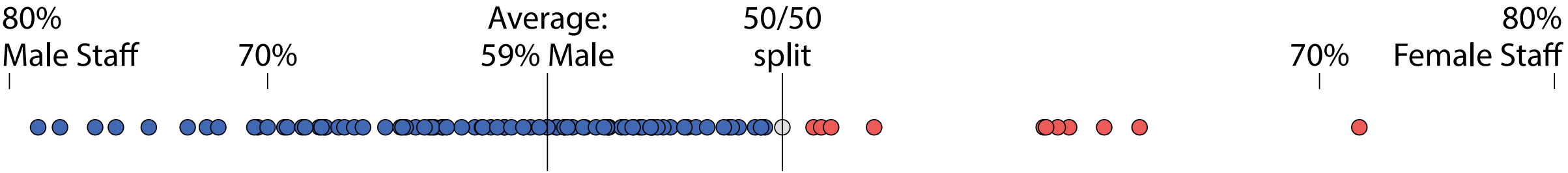
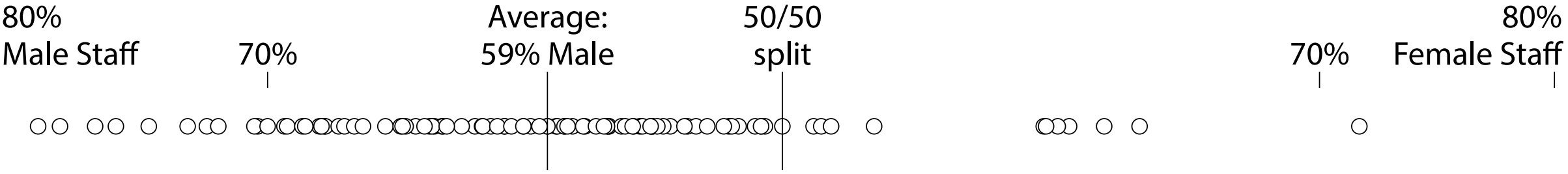
FILTER

Gender Race

2018 Results Leadership 2001 Vs. 2018: Top Newsrooms Overall Change My Newsroom



Strip plot



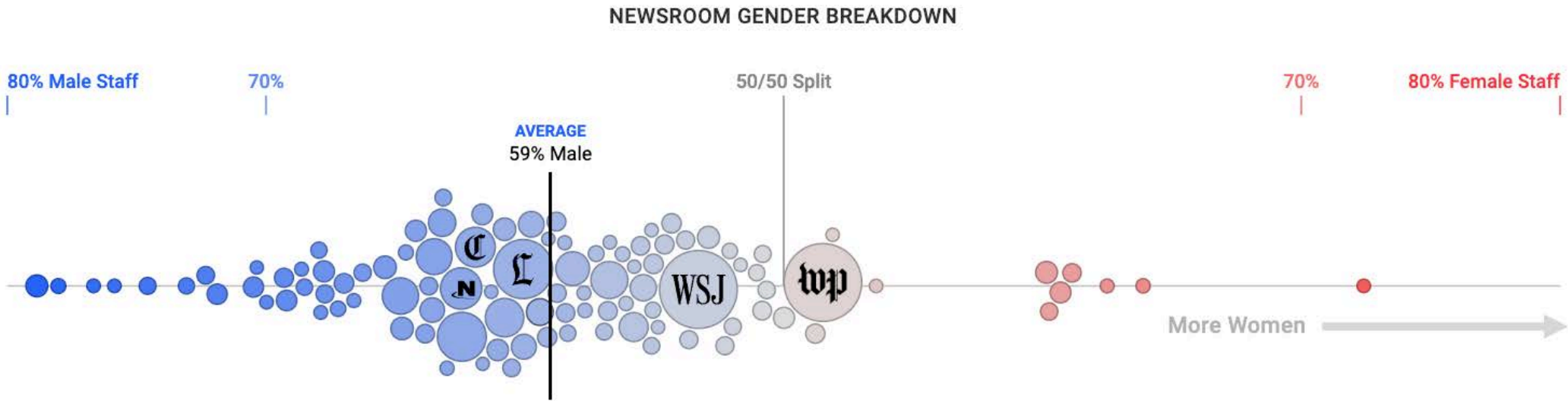
How Diverse Are US Newsrooms?

The Newspaper Diversity Survey measures the percentage of women and minorities working in US newsrooms. The results from 2018's survey are in.

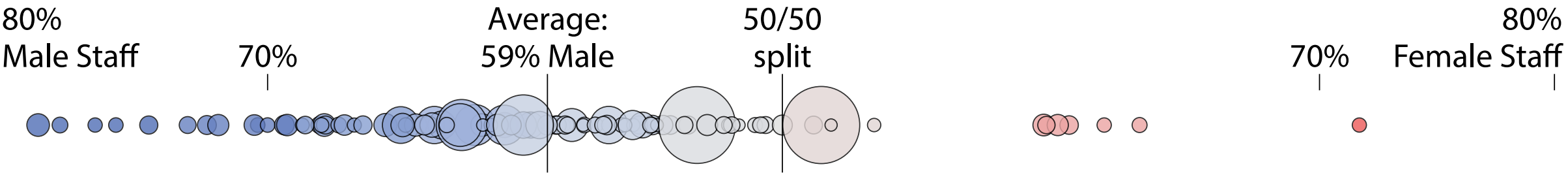
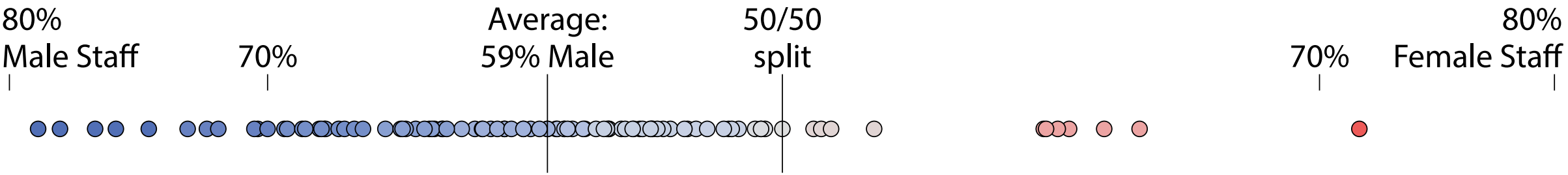
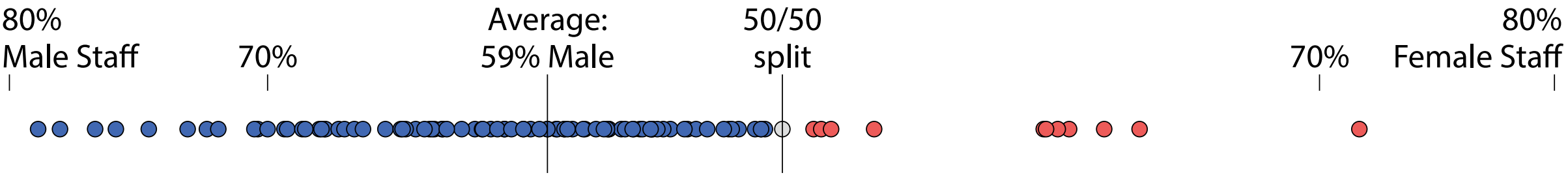
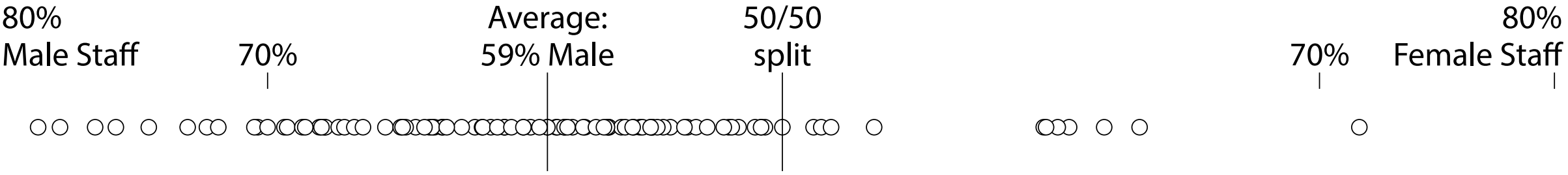
FILTER

Gender Race

2018 Results Leadership 2001 Vs. 2018: Top Newsrooms Overall Change My Newsroom



Strip plot



How Diverse Are US Newsrooms?

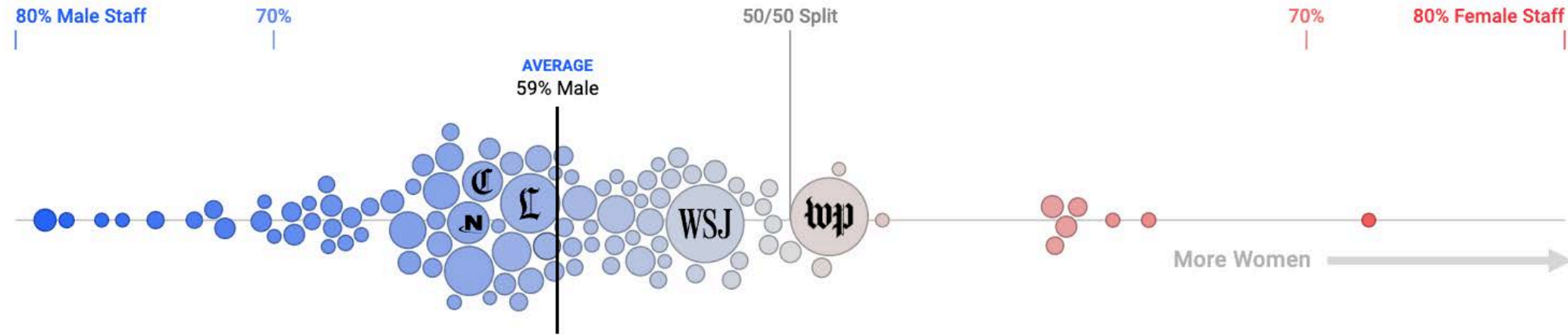
The Newspaper Diversity Survey measures the percentage of women and minorities working in US newsrooms. The results from 2018's survey are in.

FILTER

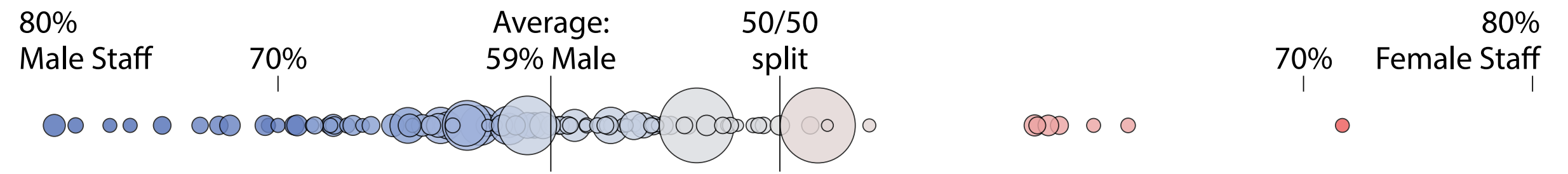
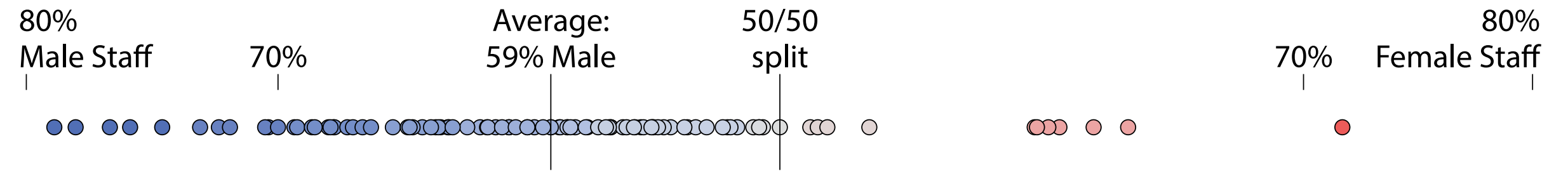
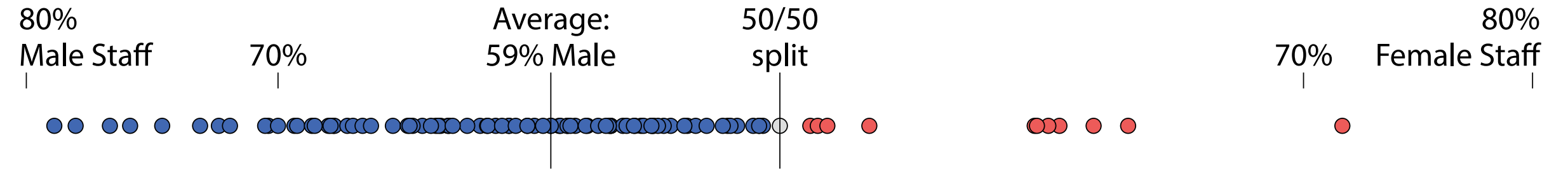
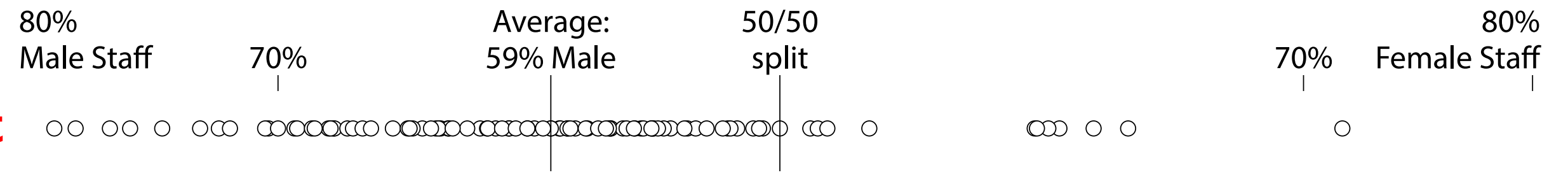
Gender Race

2018 Results Leadership 2001 Vs. 2018: Top Newsrooms Overall Change My Newsroom

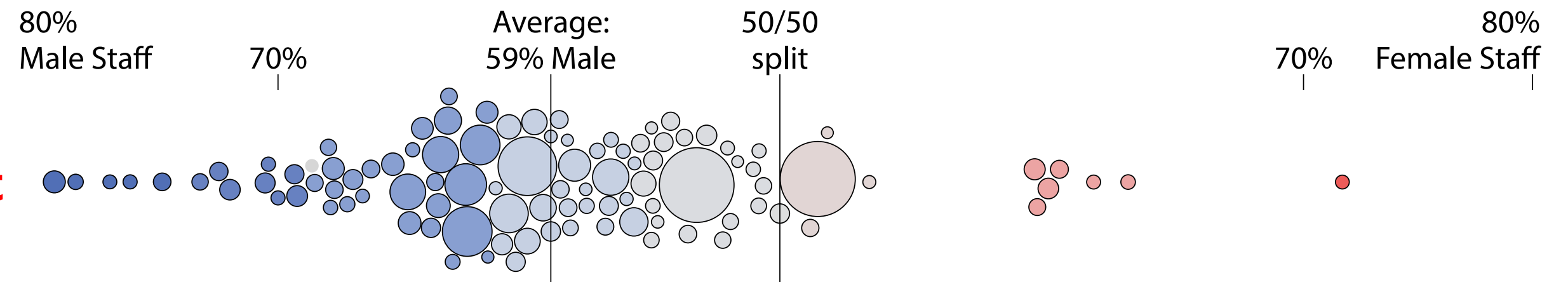
NEWSROOM GENDER BREAKDOWN



Strip plot



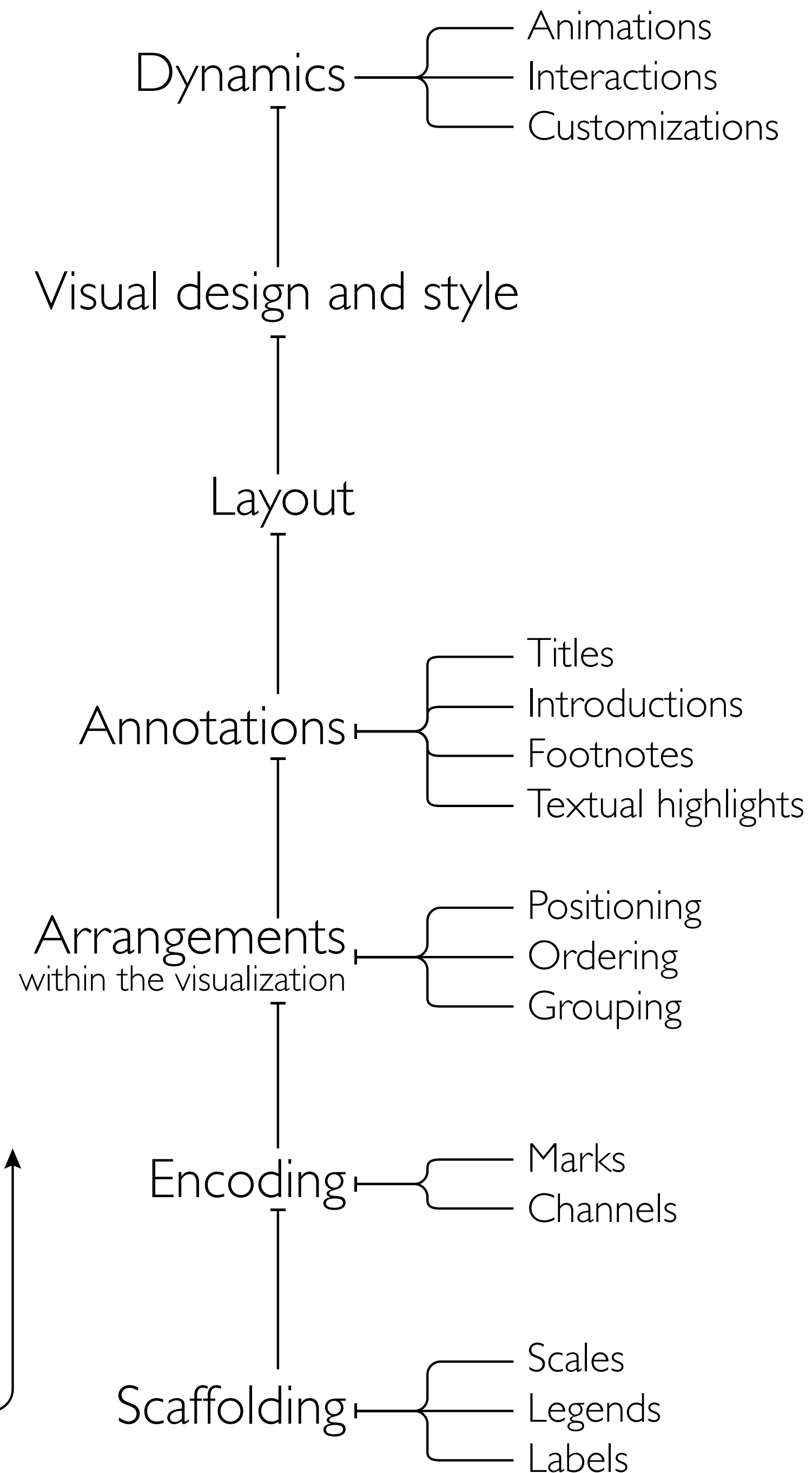
Beeswarm plot



Visualization: Layers and elements to think about

The nature of the data to
be visualized influences
everything else

**Read from
the bottom-up**



Reasoning based on our intent

Learning objectives framework

The reader will [verb][noun]

Papers by Elsie Lee-Robbins et al. <https://elsieleerobbins.com/publications.html>

Communicative Visualizations as a Learning Problem

Eytan Adar and Elsie Lee

The diagram on the left shows the extended Bloom Taxonomy with levels 1 through 7. The diagram on the right shows a visualization of the Phillips curve with a red line and a blue line, and a text box explaining the viewer's task.

Fig. 1. The extended Bloom Taxonomy (left) and a visualization of the Phillips curve (right) [32]. Learning objectives, and visual support for them, link the two images.

Abstract—Significant research has provided robust task and evaluation languages for the analysis of exploratory visualizations. Unfortunately, these taxonomies fail when applied to communicative visualizations. Instead, designers often resort to evaluating communicative visualizations from the cognitive efficiency perspective: “can the recipient accurately decode my message/insight?” However, designers are unlikely to be satisfied if the message went “in one ear and out the other.” The consequence of this inconsistency is that it is difficult to design or select between competing options in a principled way. The problem we address is the fundamental mismatch between how designers want to describe their intent, and the language they have. We argue that visualization designers can address this limitation through a learning lens: that the recipient is a student and the designer a teacher. By using learning objectives, designers can better define, assess, and compare communicative visualizations. We illustrate how the learning-based approach provides a framework for understanding a wide array of communicative goals. To understand how the framework can be applied (and its limitations), we surveyed and interviewed members of the Data Visualization Society using their own visualizations as a probe. Through this study we identified the broad range of objectives in communicative visualizations and the prevalence of certain objective types.

Index Terms—Learning objectives, communicative visualization, visualization design

1 INTRODUCTION

Communicative visualizations represent the bulk of exposure any individual has to visualizations. We experience the messages of data journalists, scientists, instructors, designers, and analysts as charts, graphs, and in many other forms. In each case, the person creating the visualization or context (the thing—a paper, article, etc.—in which the visualization was embedded) has a specific set of intents. The intents are as unique as the visualizations with which they are associated: A journalist may seek to explain an insight; a scientist or analyst to convey evidence or to support a decision; an instructor to teach the relationship between two interacting chemicals. The main question we tackle here is: *how do we formally describe communicative intent in visualizations?* We propose that using *cognitive learning objectives* as a frame will encourage a better way of building communicative visualizations.

With apologies to Bloom [13], learning objectives may help address our problem because they are, “explicit formulations of the ways in which [viewers (i.e., students)] are expected to be *changed* by [communicative visualizations (i.e., the educative process)].” In their role as “educational tools”, communicative visualizations must be designed as “*intentional and reasoned act[s]*” [9]. Doing so requires a formal language to allow a designer to explicitly formulate their expectations and intents.

Given the prevalence of advice and taxonomies for visualization designers, it is worth asking why we even need such an “intent language”? Significant literature already exists to ensure that our viewer can *read* our encoding of data accurately and effectively—a success, if that was really the designer’s intent. However, knowing that the visualization will support finding *X*, or the encoding will allow the viewer to accurately decode *Y*, is poor proxy for knowing if the visualization satisfied our communicative intent. A designer would not, and should not, be satisfied if the message was, “in one ear and out the other.” Knowing the message was communicated clearly and interpreted accurately may be necessary, but is not sufficient.

Existing task and evaluation taxonomies are not refined enough to describe the intent behind a communicative visualization. Take as a simple example the plot in Figure 2 which we may encounter reading a technical paper, webpage, or textbook. The plot shows the Sum of Squares Distances between entities as a function of the number of clusters. It is used in k-means clustering for the “elbow method” of determining an optimal *k* [24] (roughly, that one should pick the number of clusters where there is a “kink” in the plot, e.g., 4 clusters). The plot in our context is communicative—it was produced by someone else to tell us, the readers, “*something*”. That “something” reflects the designer’s many possible intents. This may be to convince us that a choice of *k* = 4 was correct; to relay the insight that 4 was significantly better than *k* = 3 or *k* = 5; to critique a bad choice of *k*; to teach us what the term “elbow” means; to demonstrate how to read or create a plot suitable for an elbow method analysis; to contrast it to an alternative (e.g., the silhouette plot, Fig. 2B); or to lead us to create alternatives.

All these are possible—in fact, likely—intents. But how does the designer know that the visualization is successful? The mechanisms for evaluating are as varied as the intents: Can the viewer recall which *k* was picked? Can they define an elbow point? Can they read a new plot? Can they produce a similar plot for their own data? Can they critique

• Eytan Adar and Elsie Lee are with the University of Michigan. E-mail: {eadar, elsielee}@umich.edu.

Manuscript received xx xxx. 201x; accepted xx xxx. 201x. Date of Publication xx xxx. 201x; date of current version xx xxx. 201x. For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org. Digital Object Identifier: xx.xxxx/TVCG.201x.xxxxxxx

Learning Objectives, Insights, and Assessments: How Specification Formats Impact Design

Elsie Lee-Robbins, Shiqing He, and Eytan Adar

The diagram shows three specification formats: Learning objective, Insight, and Assessment. Each format is linked to a set of visualization designs (Vis #1 to Vis #7) and a “Most preferred design” label. The designs are ordered from most effective to least effective.

Fig. 1. Example of three specifications (learning objective, insight, and assessment) with the most preferred visualization design identified for each specification. The seven visualization designs are ordered from most effective to least effective.

Abstract—Despite the ubiquity of communicative visualizations, specifying communicative intent during design is ad hoc. Whether we are selecting from a set of visualizations, commissioning someone to produce them, or creating them ourselves, an effective way of specifying intent can help guide this process. Ideally, we would have a concise and shared specification language. In previous work, we have argued that communicative intents can be viewed as a learning/assessment problem (i.e., what should the reader learn and what test should they do well on). Learning-based specification formats are linked (e.g., assessments are derived from objectives) but some may more effectively specify communicative intent. Through a large-scale experiment, we studied three specification types: learning objectives, insights, and assessments. Participants, guided by one of these specifications, rated their preferences for a set of visualization designs. Then, we evaluated the set of visualization designs to assess which specification led participants to prefer the most effective visualizations. We find that while all specification types have benefits over no-specification, each format has its own advantages. Our results show that learning objective-based specifications helped participants the most in visualization selection. We also identify situations in which specifications may be insufficient and assessments are vital.

Index Terms—Communicative visualization, evaluation, visualization specification.

1 INTRODUCTION

Communicative visualizations are omnipresent. They exist in everything from news articles to scientific papers and from Web pages to television broadcasts. The people involved in the visualization design process must make design decisions based on their intents or goals. Unfortunately, most design guidelines do not connect communicative intent to the actual design. Instead, there is a significant amount of information on what makes communicative visualizations effective perceptually, focusing on making the visualization readable. However,

this low-level information often fails to account for what kind of impact people would ultimately like to make: to influence the viewer cognitively (i.e., to have them learn something) or affectively (e.g., to have them believe something) [12,25].

Current design literature is often biased towards low-level cognitive efficiency [7,17,36,37,40]. This literature is built on significant academic foundations [38] that have allowed us to identify which encodings can be read accurately and quickly. However, if designers only rely on cognitive efficiency evaluation methods, such as how fast a viewer can decode the visualization, they might fail to consider higher-level communication goals for what they want their reader to be able to know or do. In most instances, being able to read the visualization is only the first step and may not even be the most crucial [12,25]. A designer may also want the viewer to remember the message, take personal action, or generate hypotheses. If the reader only reads the visualization but does not take any of these next steps, it would not be considered a good design. In addition to focusing on low-level cognitive efficiency, identifying higher-level communicative goals would benefit everyone involved in the design process.

• Elsie Lee-Robbins, Shiqing He, and Eytan Adar are with University of Michigan, School of Information. E-mail: {elsielee, hesiqing, eadar}@umich.edu.

Manuscript received xx xxx. 201x; accepted xx xxx. 201x. Date of Publication xx xxx. 201x; date of current version xx xxx. 201x. For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org. Digital Object Identifier: xx.xxxx/TVCG.201x.xxxxxxx

Affective Learning Objectives for Communicative Visualizations

Elsie Lee-Robbins and Eytan Adar

The diagram shows the relationship between learning objectives, insights, and assessments. It includes a flowchart and a table of visualization designs.

Abstract—When designing communicative visualizations, we often focus on goals that seek to convey patterns, relations, or comparisons (cognitive learning objectives). We pay less attention to affective intents—those that seek to influence or leverage the audience’s opinions, attitudes, or values in some way. Affective objectives may range in outcomes from making the viewer care about the subject, strengthening a stance on an opinion, or leading them to take further action. Because such goals are often considered a violation of perceived ‘neutrality’ or are ‘political’, designers may resist or be unable to describe these intents, let alone formalize them as learning objectives. While there are notable exceptions—such as advocacy visualizations or persuasive cartography—we find that visualization designers rarely acknowledge or formalize affective objectives. Through interviews with visualization designers, we expand on prior work on using learning objectives as a framework for describing and assessing communicative intent. Specifically, we extend and revise the framework to include a set of affective learning objectives. This structured taxonomy can help designers identify and declare their goals and compare and assess designs in a more principled way. Additionally, the taxonomy can enable external critique and analysis of visualizations. We illustrate the use of the taxonomy with a critical analysis of an affective visualization.

Index Terms—Affective visualization, communicative visualization, learning objectives.

1 INTRODUCTION

Data visualization designers often emphasize their goal of conveying facts, insights, comparisons, and patterns to their audience through communicative visualizations. Goals of this type are commonly viewed as “cognitive objectives” (e.g., recall that group X’s unemployment is greater than group Y’s). By modeling the designer as “teacher” and viewer as “student” it is possible to state intents as learning objectives [1]. Using a learning objectives framework, a designer can explicitly state their objective (e.g., “the viewer will analyze the impact of different policy ‘bundles’ on global temperature”) and assess whether a visualization successfully supports this outcome. Most attention in the data visualization field—both from researchers and practitioners—focuses on the cognitive domain. However, data visualization practitioners also have goals that go beyond the cognitive domain—they want their audience to have a *reaction* or a *response* to their visualization. For example, a designer may want their viewer to consider that Obamacare is a bad system if they show a chaotic diagram [37] (or a good one if they show an organized one [61]). The cognitive intent becomes limited in these visualizations; the designer doesn’t need the viewer to remember how Obamacare works or critique its particular features. Rather, the designer may want their audience to agree with an appraisal (e.g., Obamacare is bad), accept an attitude (e.g., hospitals should be for-profit), or believe in a value (e.g., small government). These goals are *affective* intents, and cognitive learning objectives do not cover them.

Affective intents are most obvious in data visualizations that are created for advocacy reasons. With these, designers are clearly trying to raise awareness or have a call to action. Advocates for a cause are not trying to hide the fact that they are taking these positions and that they want you to care about their cause too. The visualization “U.S. Gun Deaths” created by Periscope is a very clear example of an affective visualization [64]. Among other features, the visualization animates a tally of “stolen years” due to gun violence. The cognitive aspect of the visualization—how many people were killed—is important, but not the main takeaway of the visualization. Periscope co-founder Kim Rees reflects, “We need people to react. We need people to sort of get riled up about things, get excited about things, and want to make change in the world” ([72], 5:30). At a minimum, the goal of “U.S. Gun Deaths”

is to create interest in the topic. Ideally, the visualization will evoke empathy within the audience for the victims. The affective response, not the cognitive component, is the main intent of the visualization.

However, even in domains other than advocacy and social justice, designers have affective goals. They want the viewer to care about the topic, strengthen an attitude, or take further action. A visualization of a family tree might have you consider your own family ties. A visualization about sleep patterns might lead you to value sleep. A visualization about blood donations might inspire you to donate blood. Unfortunately, because of the lack of attention in this area, designers may not even realize or consider that they have affective goals. Given the focus on “neutrality” (or related concepts), persuasive data visualizations are often controversial, which might make designers try to hide the fact that they have affective goals. Even if a designer acknowledges that they have affective goals, they may not have the vocabulary or framework to articulate their goals.

In this paper, we extend our previous research on cognitive learning objectives to the affective domain, adapting the affective taxonomy from the education realm to work for data visualizations. We conceptualize *affective intents* as goals regarding an audience’s *reaction* or *response* to appraisals, attitudes, or values. We begin by adapting the (so-called) Bloom’s affective taxonomy [43] to provide a framework for communicative data visualization intent. We conducted an interview study to learn more about data visualization practitioners’ affective goals, how they conceptualize their intent, and how they could use learning objectives. Based on this study, we revised the affective taxonomy to better align with visualization intents. A language for describing affective intents will not only benefit designers, but will also enable new kinds of critique. We also draw a distinction between affective rhetorical techniques (i.e., “pathos”) in contrast to affective intents. Specifically, we contribute: an affective learning objectives taxonomy for data visualization, a qualitative analysis of an interview study of 12 designers, and a critical analysis of an affective visualization with associated learning objectives to illustrate the taxonomy’s use. Data visualization designers will be able to apply this framework to their own work to consider their affective intents.

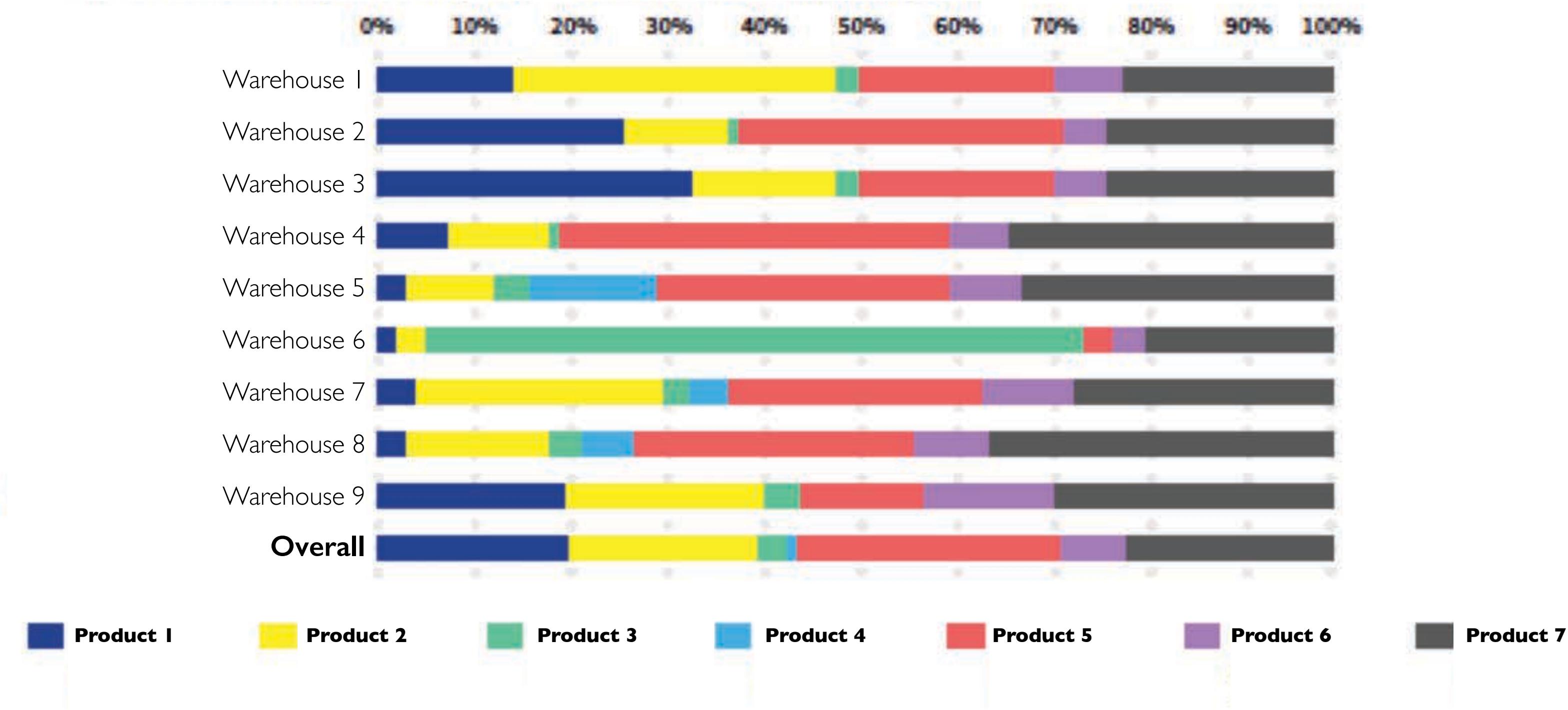
2 BACKGROUND

Data visualizations are not neutral, even though designers and viewers might want them to be. To create a data visualization, designers must make choices that will shape how the audience will interpret the data. Intentionally or unintentionally, designers have biases, backgrounds, and personal opinions and preferences that will influence their design decisions. Strategically, designers employ logical (logos), emotional (pathos), and credibility (ethos) elements that are designed to evoke emotion in the audience (e.g., visual imagery). In many cases, these pathos-based techniques, such as humanizing data, coincide with trying

• Elsie Lee-Robbins and Eytan Adar are with the University of Michigan. E-mail: {elsielee, eadar}@umich.edu.

Manuscript received xx xxx. 201x; accepted xx xxx. 201x. Date of Publication xx xxx. 201x; date of current version xx xxx. 201x. For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org. Digital Object Identifier: xx.xxxx/TVCG.201x.xxxxxxx

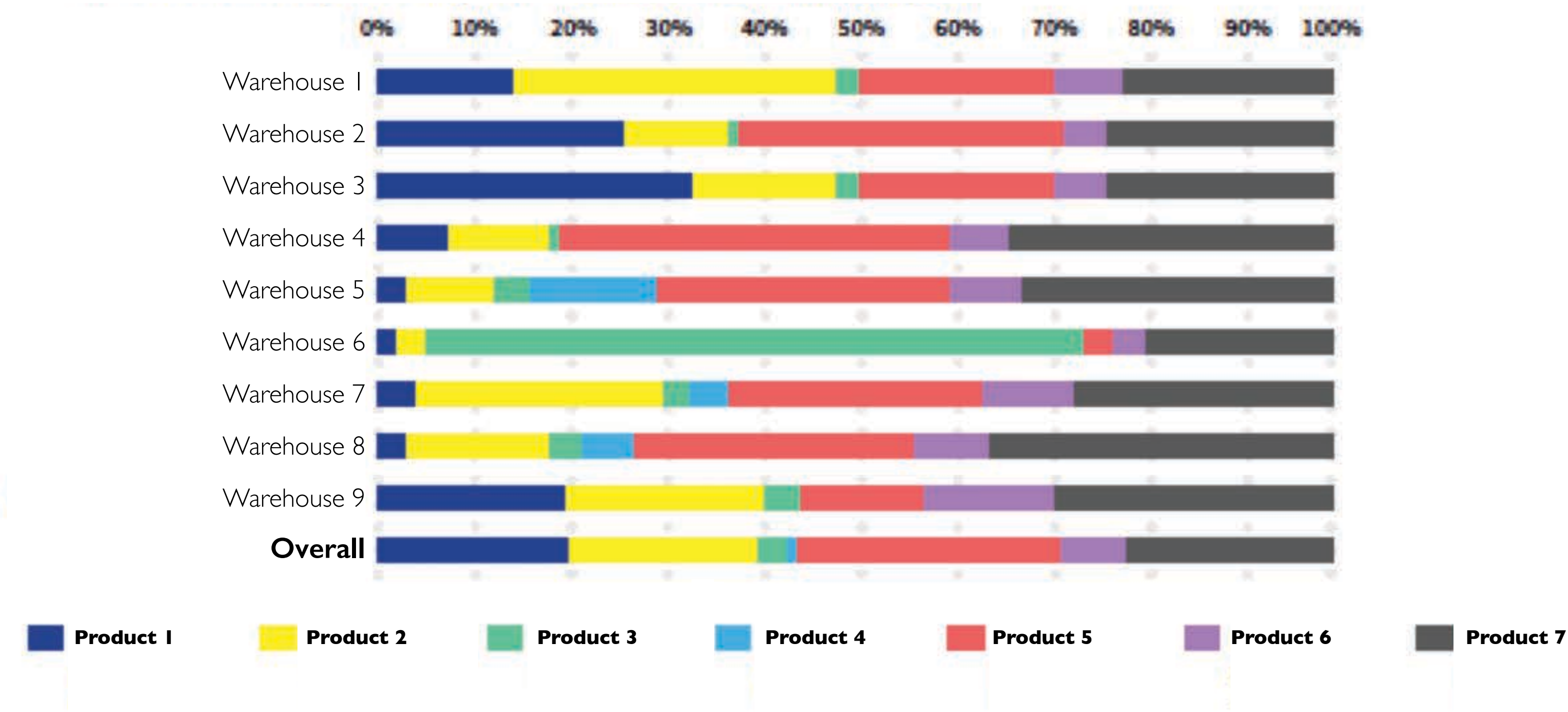
PROPORTION OF PRODUCTS SOLD PER WAREHOUSE



The reader will see that the data corresponding to each category adds up to 100%.

The reader will get a general (not very precise) impression of the portions of that total.

PROPORTION OF PRODUCTS SOLD PER WAREHOUSE

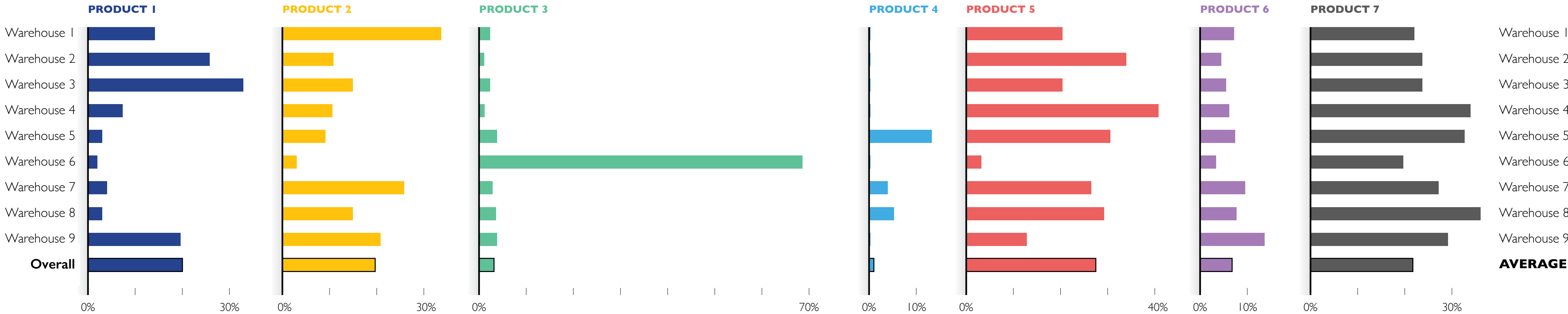
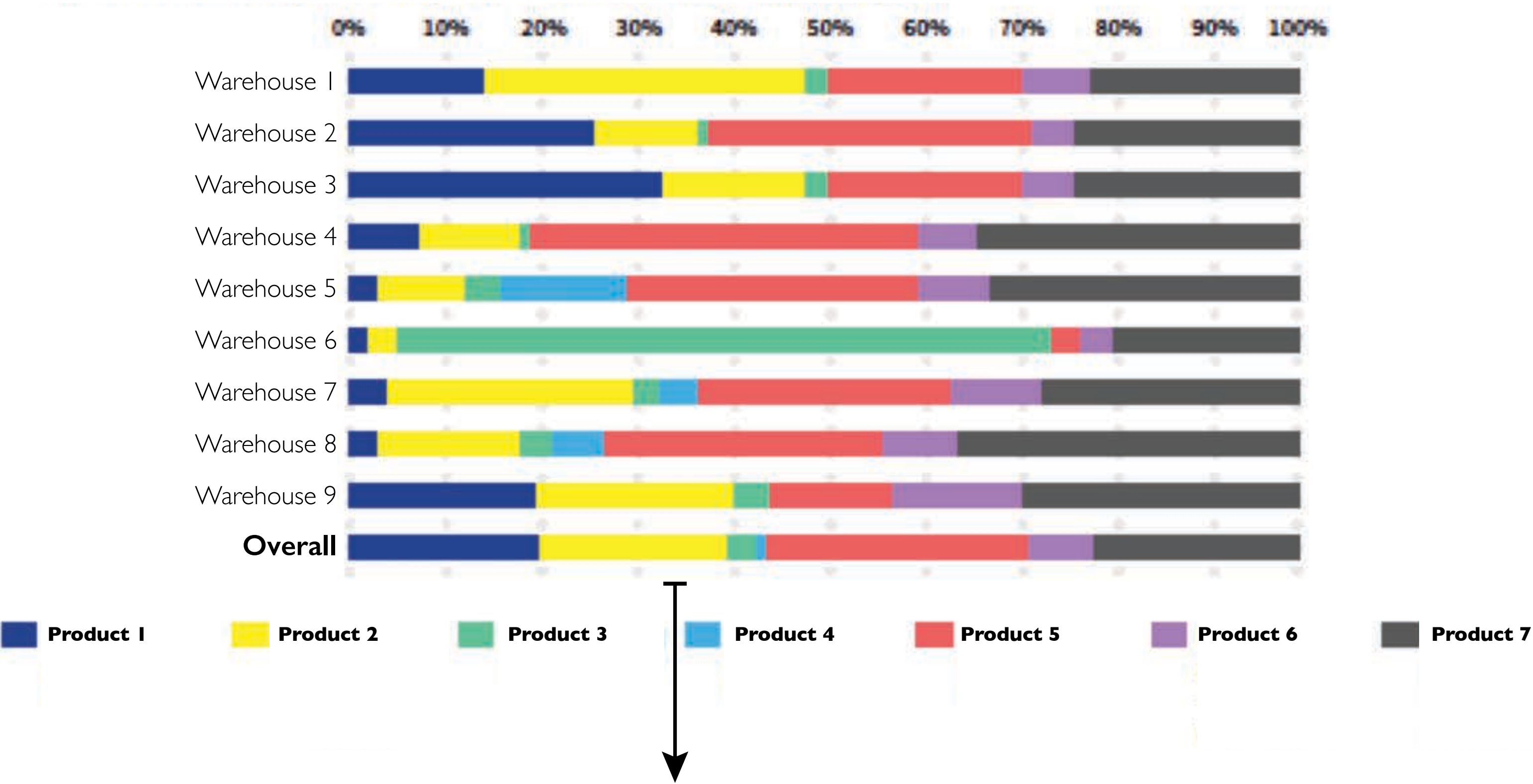


The viewer will see that the data corresponding to each category adds up to 100%.

The viewer will get a general (not very precise) impression of the portions of that total.

The reader will be able to compare percentages within each category of products.

PROPORTION OF PRODUCTS SOLD PER WAREHOUSE



— An example of decision-making —

You are the jury

(Probably the largest one in history!)



Photo by Mariakray

<https://pixabay.com/users/mariakray-23567841/>

Take two companies, **Company A** —our client; the one suing
—and **Company B**—the one being sued.

Take two companies, **Company A** —our client; the one suing —and **Company B**—the one being sued.

Beginning in **January of 2017**, Company B manufactured certain components for products (machinery) produced by Company A. For a while, fewer than 0.5% of these components were defective.

Take two companies, **Company A** —our client; the one suing —and **Company B**—the one being sued.

Beginning in **January of 2017**, Company B manufactured certain components for products (machinery) produced by Company A. For a while, fewer than 0.5% of these components were defective.

Between mid-2018 and early 2019, a substantial percentage of components —up to **more than one third in February of 2019**—made by Company B began failing, making an equal rate of Company A's machinery fail, as well.

Take two companies, **Company A** —our client; the one suing —and **Company B**—the one being sued.

Beginning in **January of 2017**, Company B manufactured certain components for products (machinery) produced by Company A. For a while, fewer than 0.5% of these components were defective.

Between mid-2018 and early 2019, a substantial percentage of components —up to **more than one third in February of 2019**—made by Company B began failing, making an equal rate of Company A's machinery fail, as well.

Our client, Company A, obtained tentative evidence suggesting that, at least since **June 2018**, there was a defect in the equipment that Company B was using to produce the components.

Take two companies, **Company A** —our client; the one suing —and **Company B**—the one being sued.

Beginning in **January of 2017**, Company B manufactured certain components for products (machinery) produced by Company A. For a while, fewer than 0.5% of these components were defective.

Between mid-2018 and early 2019, a substantial percentage of components —up to **more than one third in February of 2019**—made by Company B began failing, making an equal rate of Company A's machinery fail, as well.

Our client, Company A, obtained tentative evidence suggesting that, at least since **June 2018**, there was a defect in the equipment that Company B was using to produce the components.

Company B denied this defect in its production equipment. They blamed our client, arguing, among other things, that it wasn't assembling the components correctly.

Take two companies, **Company A** —our client; the one suing —and **Company B**—the one being sued.

Beginning in **January of 2017**, Company B manufactured certain components for products (machinery) produced by Company A. For a while, fewer than 0.5% of these components were defective.

Between mid-2018 and early 2019, a substantial percentage of components —up to **more than one third in February of 2019**—made by Company B began failing, making an equal rate of Company A's machinery fail, as well.

Our client, Company A, obtained tentative evidence suggesting that, at least since **June 2018**, there was a defect in the equipment that Company B was using to produce the components.

Company B denied this defect in its production equipment. They blamed our client, arguing, among other things, that it wasn't assembling the components correctly.

However, without telling Company A, Company B purchased new production equipment, which was put in use on **May 2nd, 2019**.

Take two companies, **Company A** —our client; the one suing —and **Company B**—the one being sued.

Beginning in **January of 2017**, Company B manufactured certain components for products (machinery) produced by Company A. For a while, fewer than 0.5% of these components were defective.

Between mid-2018 and early 2019, a substantial percentage of components —up to **more than one third in February of 2019**—made by Company B began failing, making an equal rate of Company A's machinery fail, as well.

Our client, Company A, obtained tentative evidence suggesting that, at least since **June 2018**, there was a defect in the equipment that Company B was using to produce the components.

Company B denied this defect in its production equipment. They blamed our client, arguing, among other things, that it wasn't assembling the components correctly.

However, without telling Company A, Company B purchased new production equipment, which was put in use on **May 2nd, 2019**.

After the new production equipment was in place, the percentage of defective components dropped sharply, eventually going back to <0.5%.

Take two companies, **Company A** —our client; the one suing—and **Company B**—the one being sued.

Beginning in January of 2017, Company B manufactured certain components for products (machinery) produced by Company A. For a while, fewer than 0.5% of these components were defective.

Between mid-2018 and early 2019, a substantial percentage of components—up to **more than one third in February of 2019**—made by Company B began failing, making an equal rate of Company A’s machinery fail, as well.

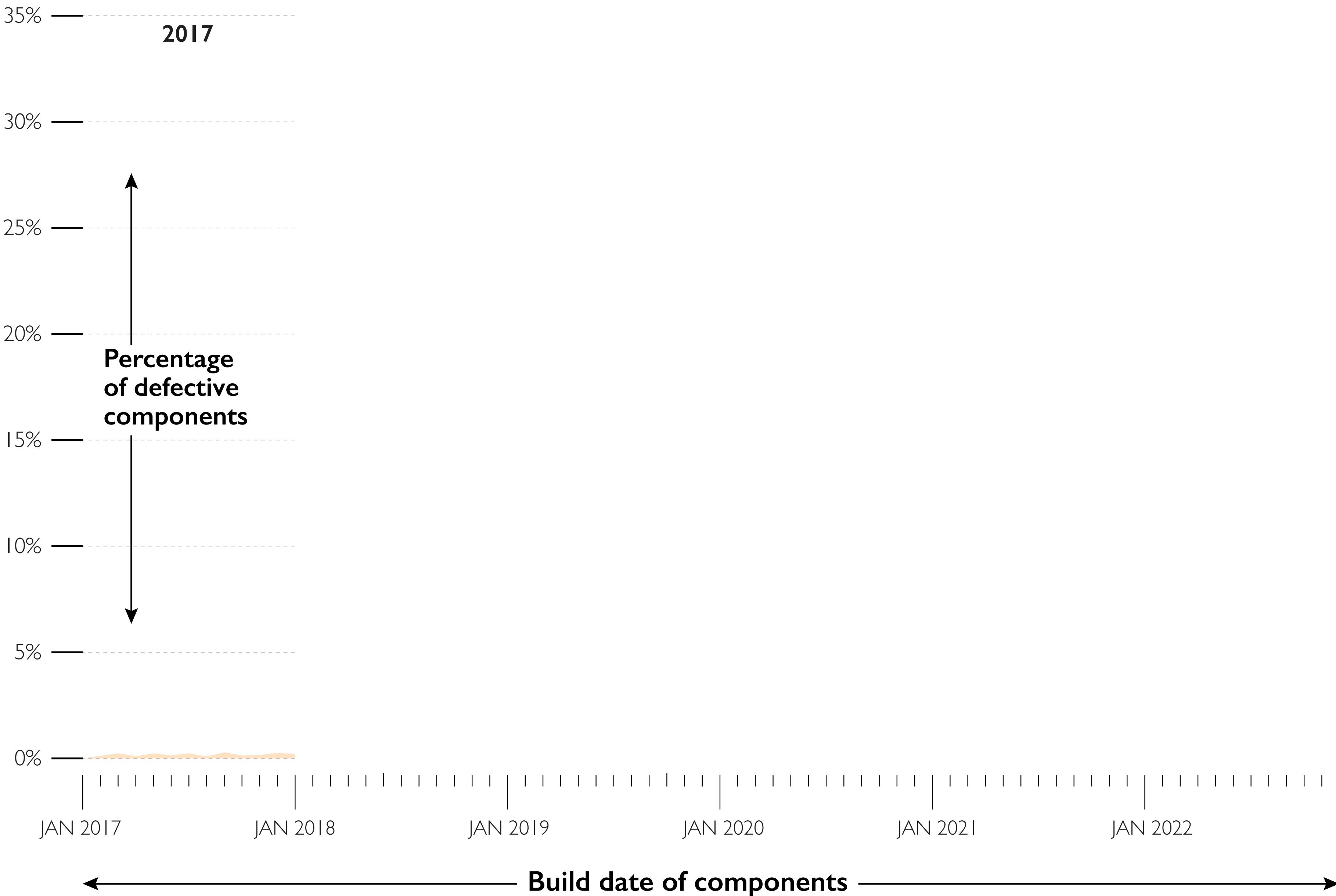
Our client, Company A, obtained tentative evidence suggesting that, at least since **June 2018**, there was a defect in the equipment that Company B was using to produce the components.

Company B denied this defect in its production equipment. They blamed our client, arguing, among other things, that it wasn’t assembling the components correctly.

However, without telling Company A, Company B purchased new production equipment, which was put in use on **May 2nd, 2019**.

After the new production equipment was in place, the percentage of defective components dropped sharply, eventually going back to <0.5%.

COMPONENTS MADE BY COMPANY B AND PURCHASED BY COMPANY A THAT FAILED BEFORE THEIR SERVICE LIFE



Take two companies, **Company A** —our client; the one suing—and **Company B**—the one being sued.

Beginning in January of 2017, Company B manufactured certain components for products (machinery) produced by Company A. For a while, fewer than 0.5% of these components were defective.

Between mid-2018 and early 2019, a substantial percentage of components—up to **more than one third in February of 2019**—made by Company B began failing, making an equal rate of Company A’s machinery fail, as well.

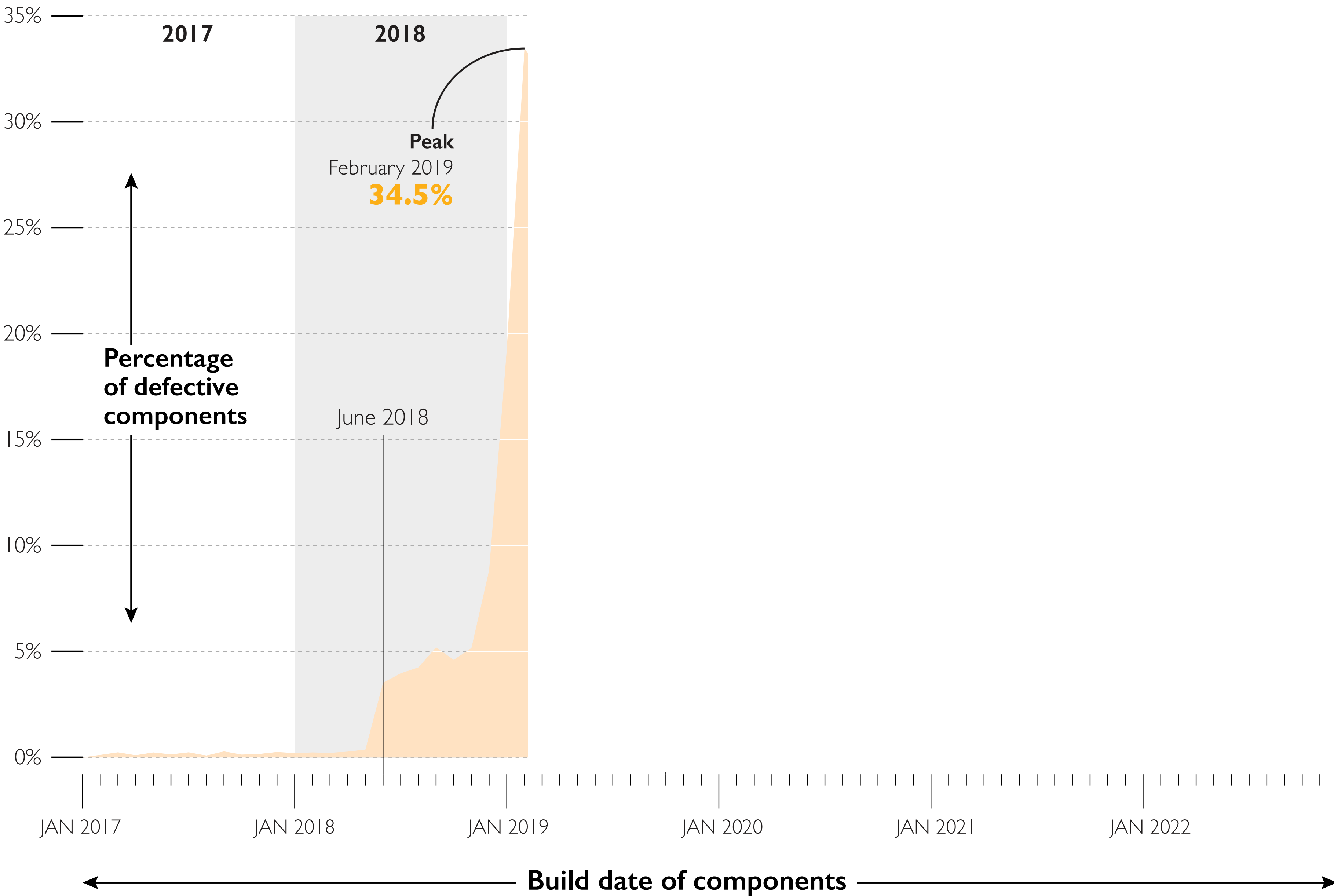
Our client, Company A, obtained tentative evidence suggesting that, at least since **June 2018**, there was a defect in the equipment that Company B was using to produce the components.

Company B denied this defect in its production equipment. They blamed our client, arguing, among other things, that it wasn’t assembling the components correctly.

However, without telling Company A, Company B purchased new production equipment, which was put in use on **May 2nd, 2019**.

After the new production equipment was in place, the percentage of defective components dropped sharply, eventually going back to <0.5%.

COMPONENTS MADE BY COMPANY B AND PURCHASED BY COMPANY A THAT FAILED BEFORE THEIR SERVICE LIFE



Take two companies, **Company A** —our client; the one suing—and **Company B**—the one being sued.

Beginning in January of 2017, Company B manufactured certain components for products (machinery) produced by Company A. For a while, fewer than 0.5% of these components were defective.

Between mid-2018 and early 2019, a substantial percentage of components—up to **more than one third in February of 2019**—made by Company B began failing, making an equal rate of Company A’s machinery fail, as well.

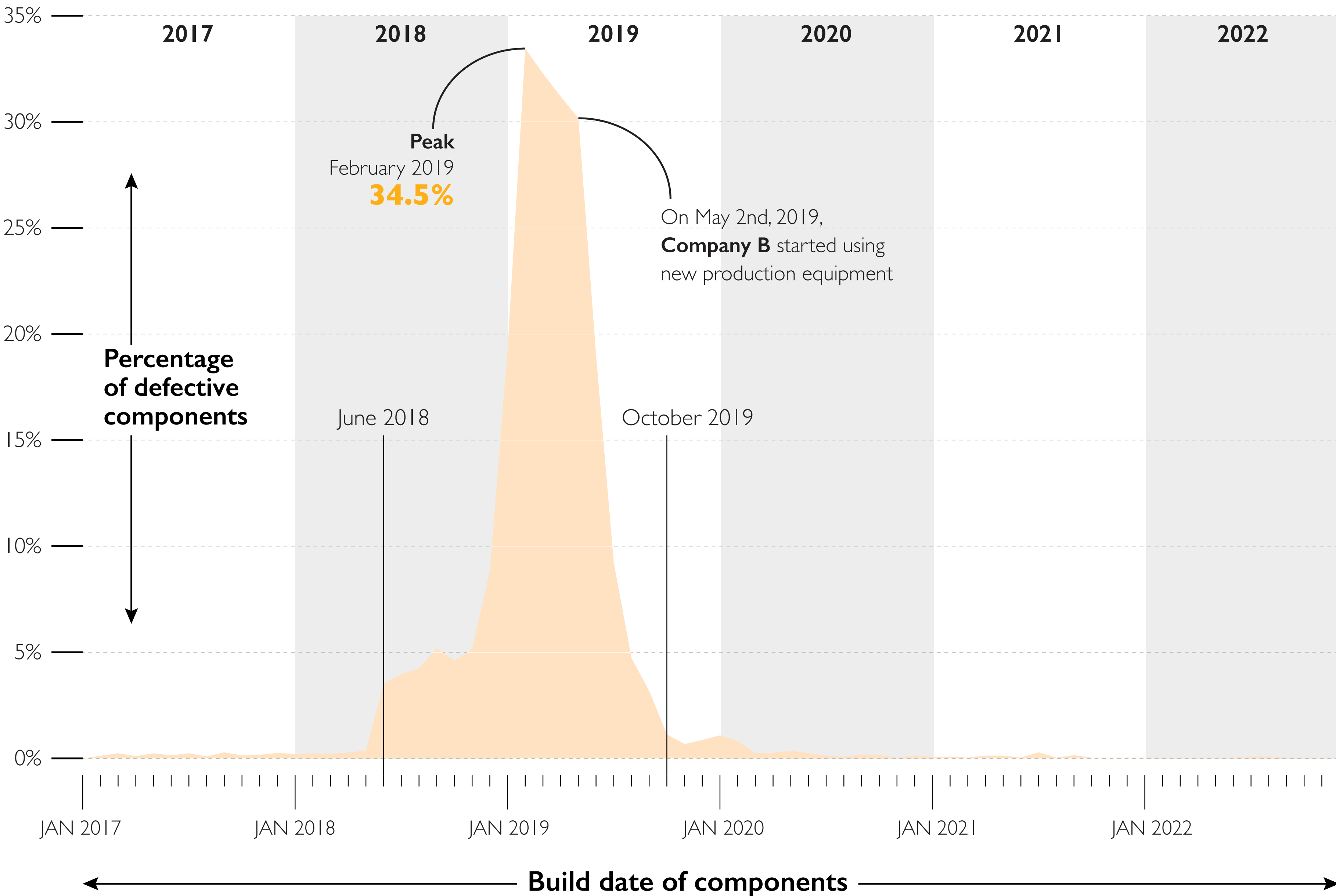
Our client, Company A, obtained tentative evidence suggesting that, at least since **June 2018**, there was a defect in the equipment that Company B was using to produce the components.

Company B denied this defect in its production equipment. They blamed our client, arguing, among other things, that it wasn’t assembling the components correctly.

However, without telling Company A, Company B purchased new production equipment, which was put in use on **May 2nd, 2019**.

After the new production equipment was in place, the percentage of defective components dropped sharply, eventually going back to <0.5%.

COMPONENTS MADE BY COMPANY B AND PURCHASED BY COMPANY A THAT FAILED BEFORE THEIR SERVICE LIFE



Take two companies, **Company A** —our client; the one suing—and **Company B**—the one being sued.

Beginning in January of 2017, Company B manufactured certain components for products (machinery) produced by Company A. For a while, fewer than 0.5% of these components were defective.

Between mid-2018 and early 2019, a substantial percentage of components—up to **more than one third in February of 2019**—made by Company B began failing, making an equal rate of Company A’s machinery fail, as well.

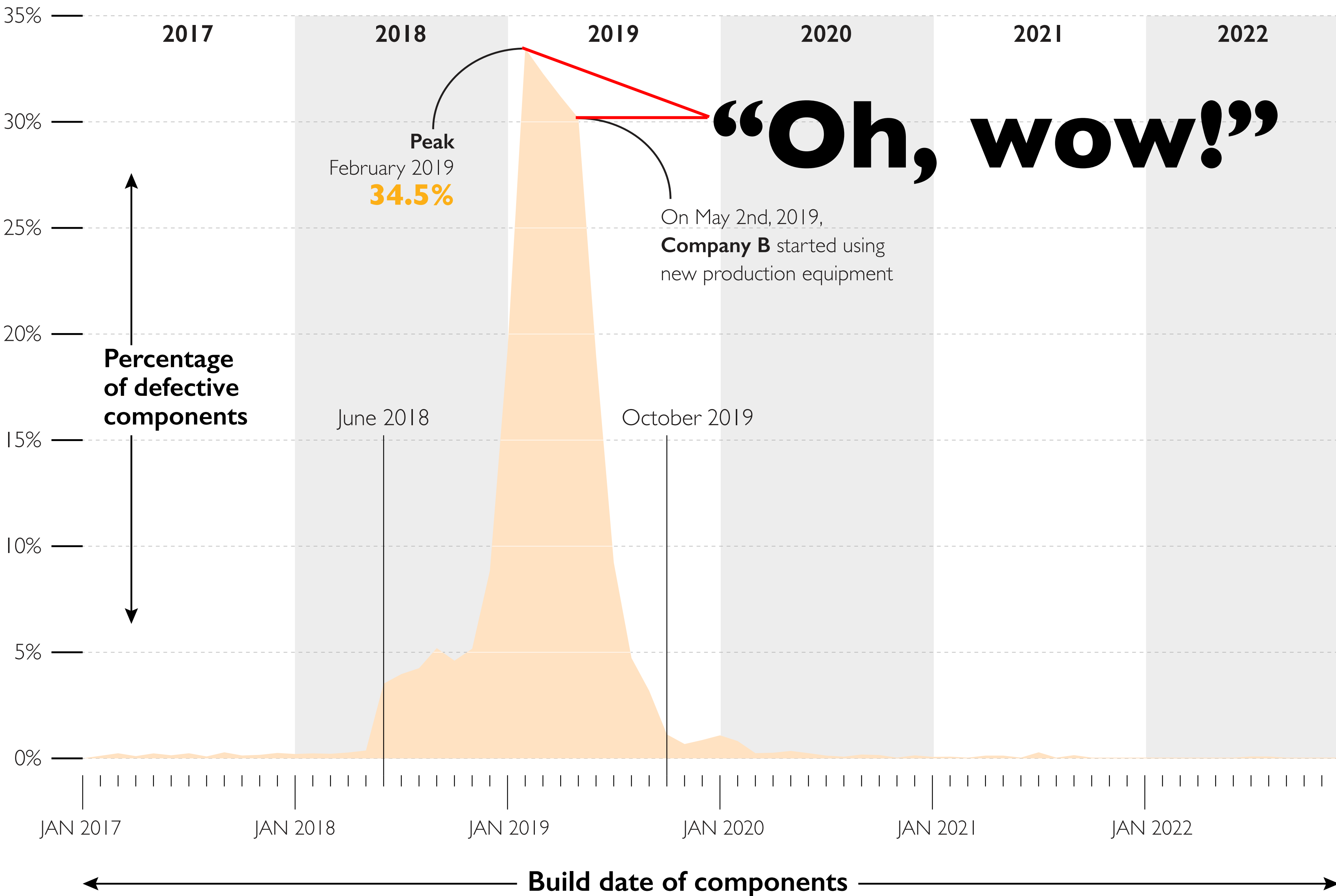
Our client, Company A, obtained tentative evidence suggesting that, at least since **June 2018**, there was a defect in the equipment that Company B was using to produce the components.

Company B denied this defect in its production equipment. They blamed our client, arguing, among other things, that it wasn’t assembling the components correctly.

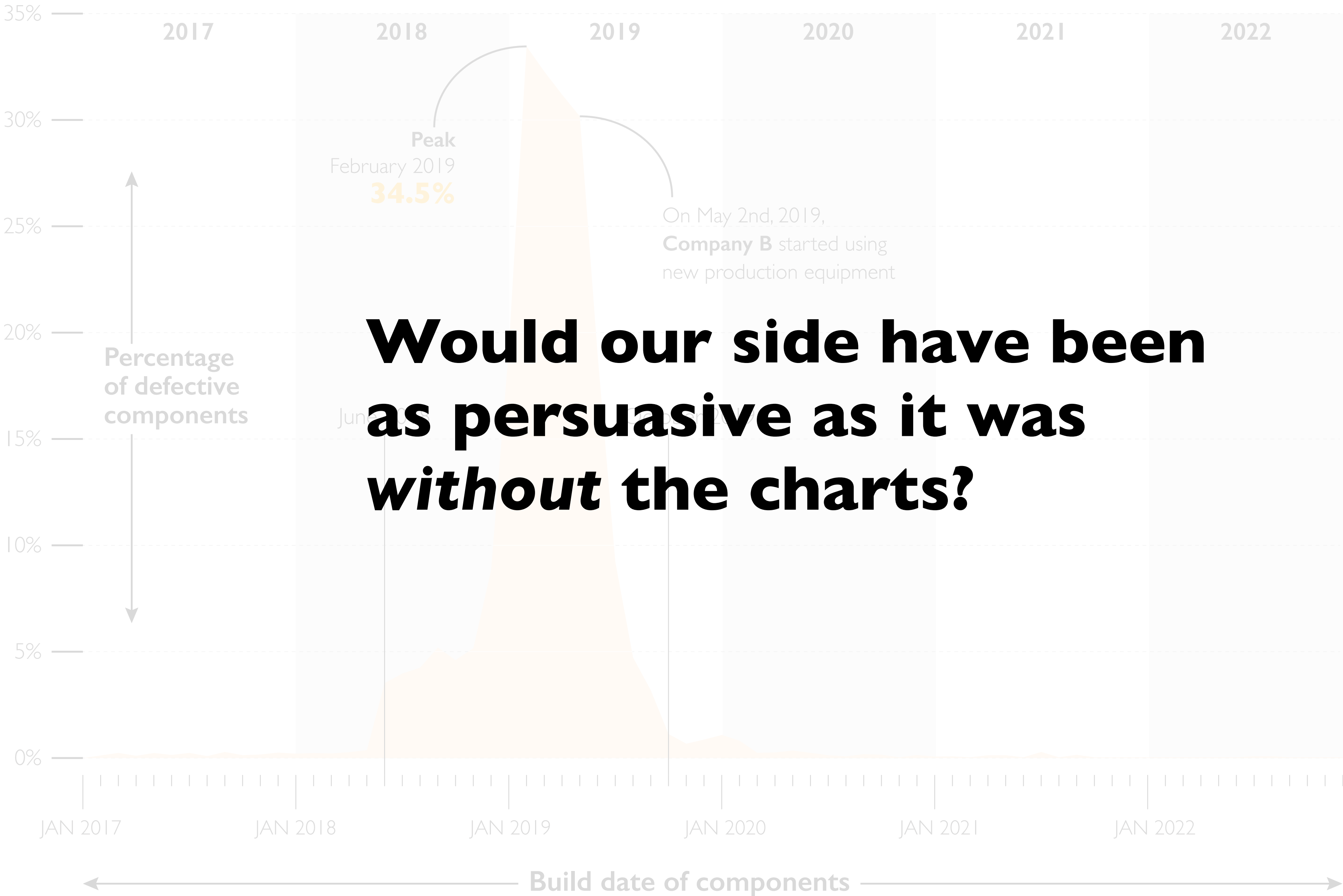
However, without telling Company A, Company B purchased new production equipment, which was put in use on **May 2nd, 2019**.

After the new production equipment was in place, the percentage of defective components dropped sharply, eventually going back to <0.5%.

COMPONENTS MADE BY COMPANY B AND PURCHASED BY COMPANY A THAT FAILED BEFORE THEIR SERVICE LIFE



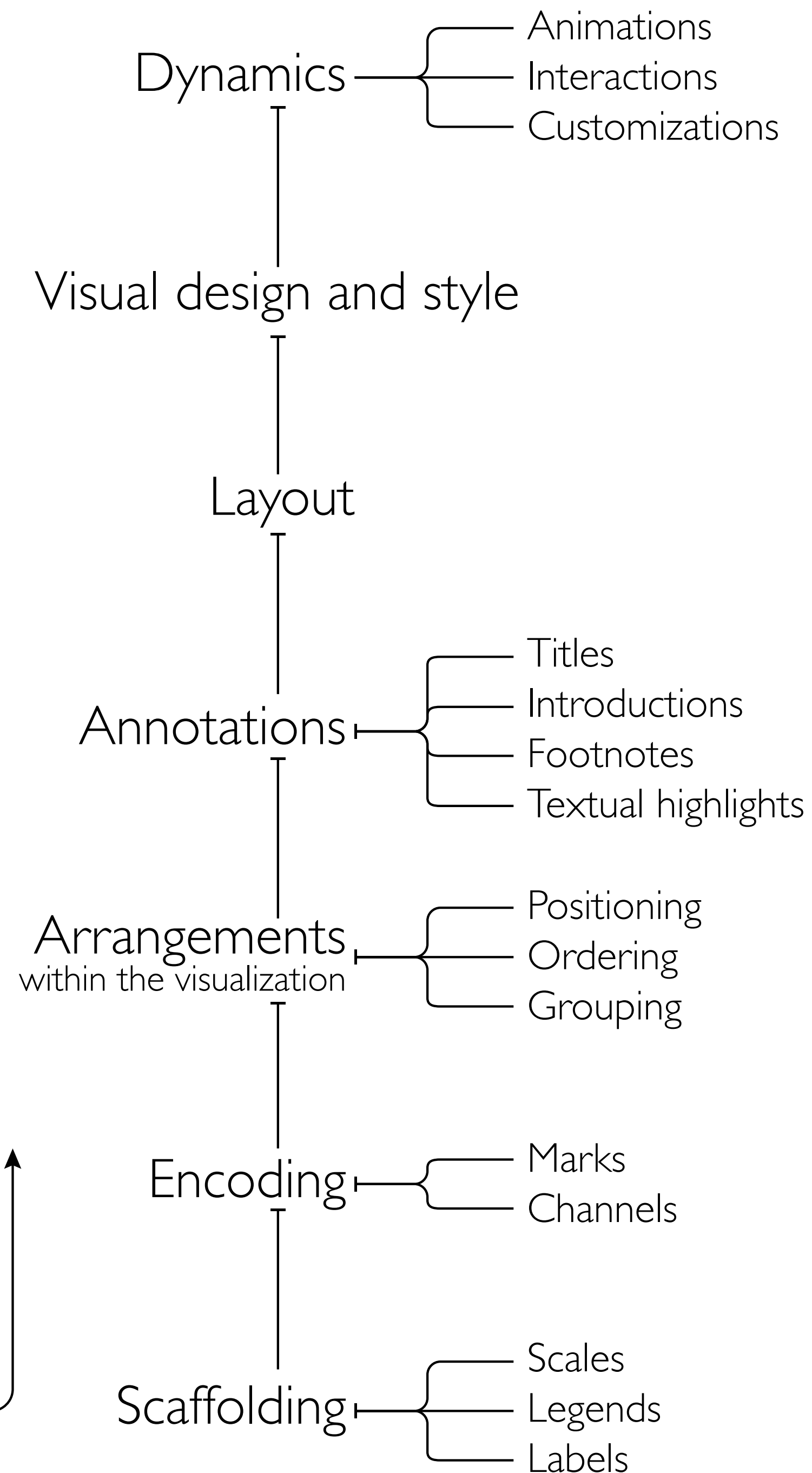
COMPONENTS MADE BY COMPANY B AND PURCHASED BY COMPANY A THAT FAILED BEFORE THEIR SERVICE LIFE

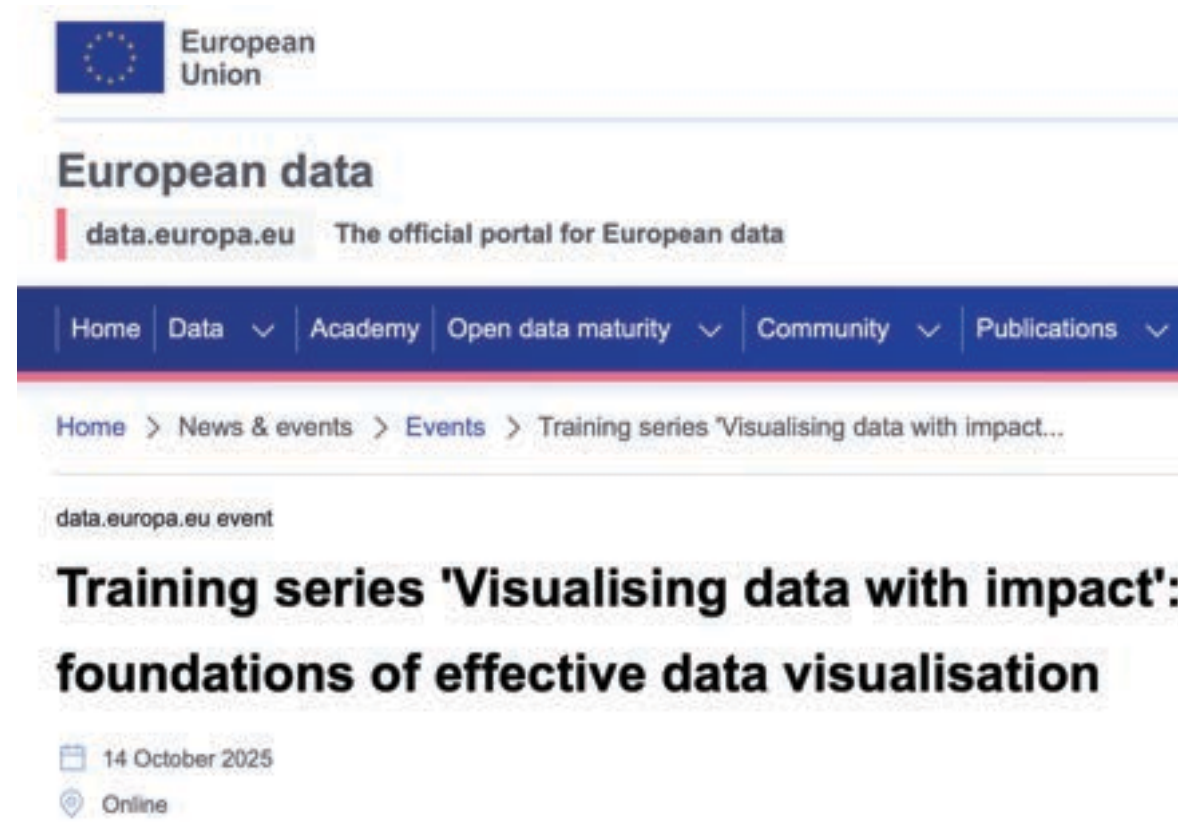


Visualization: Layers and elements to think about

The nature of the data to
be visualized influences
everything else

**Read from
the bottom-up**





Episode ONE - October 14

<https://data.europa.eu/en/news-events/events/training-data-visualisation-session-1-foundations-effective-data-visualisation>

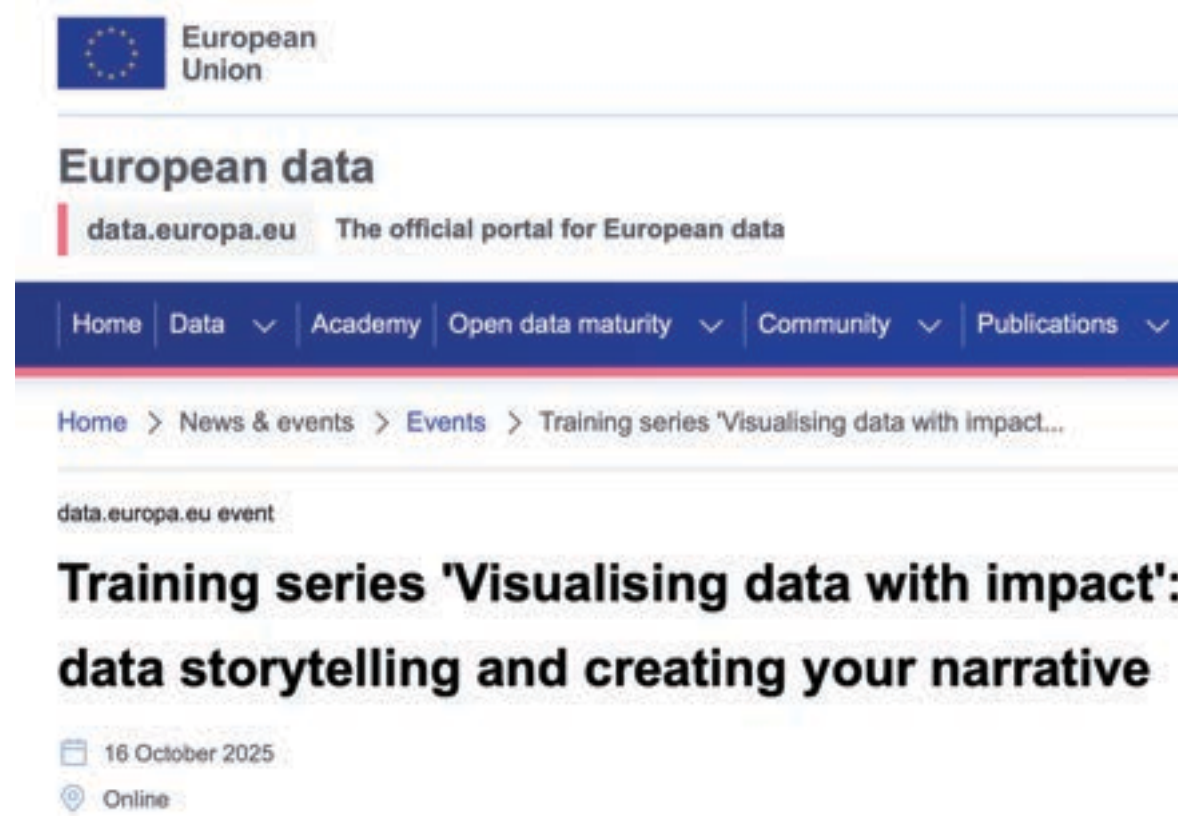


Episode TWO - October 15

Tomorrow's webinar




<https://data.europa.eu/en/news-events/events/data-visualisation-training-session-2-designing-integrity>



Episode THREE - October 16

<https://data.europa.eu/en/news-events/events/data-visualisation-training-session-3-data-storytelling-and-creating-your>

 1_The_Basics

 2_History

 3_Chart_Taxonomies

 4_Perception_and_Accessibility

 5_Visual_Design

 6_Annotations_And_Storytelling

 7_Uncertainty

 8_Maps

Extra readings

<https://tinyurl.com/mr2st327>

Foundations of Effective Data Visualization

Thank you!

Alberto Cairo

OpenVisualizationAcademy.com