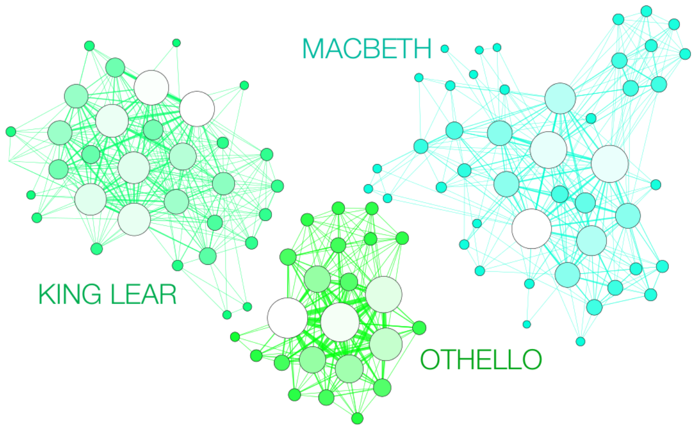
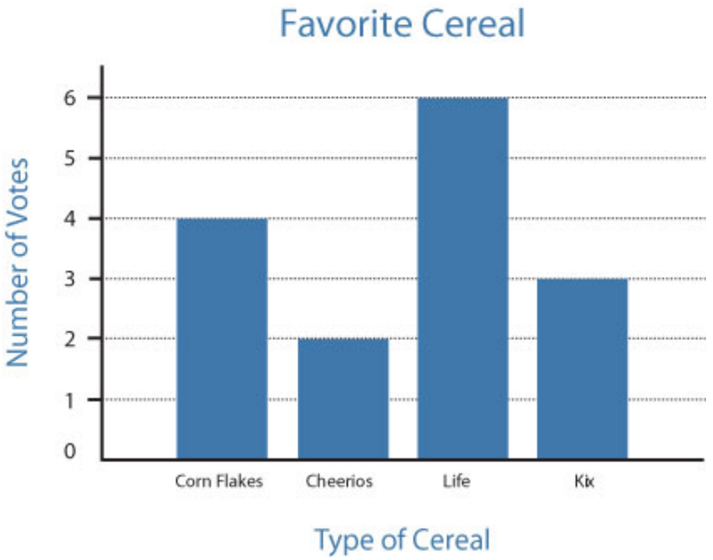
What is InfoVis?

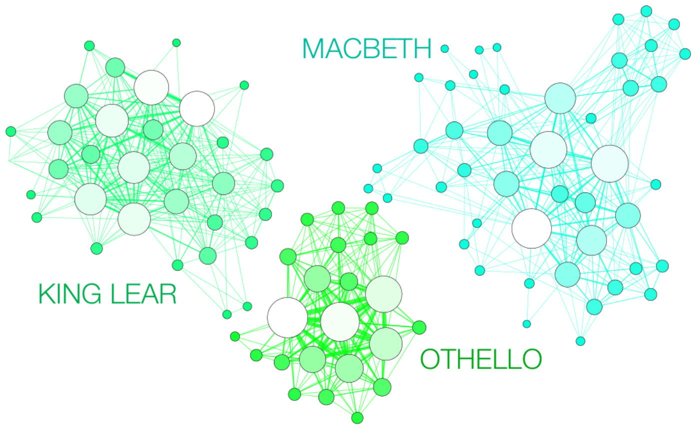
- Computer based visualizations are representations of data

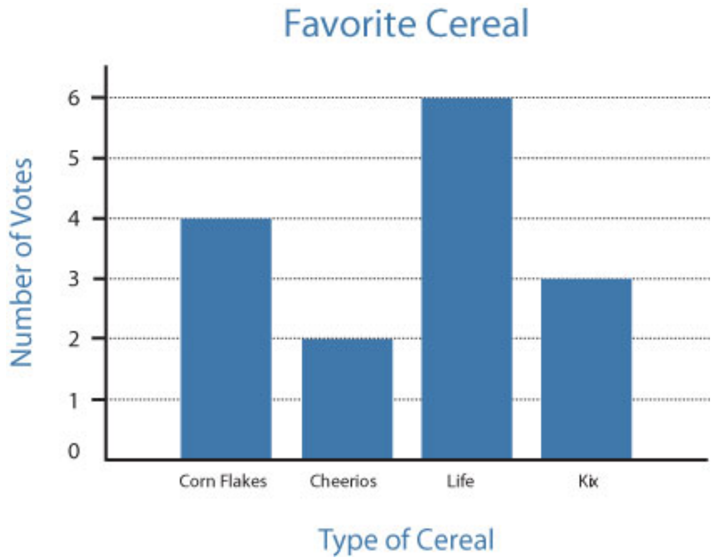




What is InfoVis?

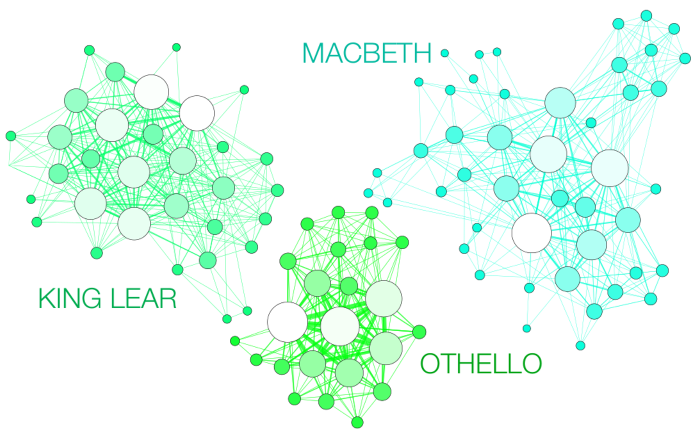
- Computer based visualizations are representations of data, that facilitate cognitive interaction

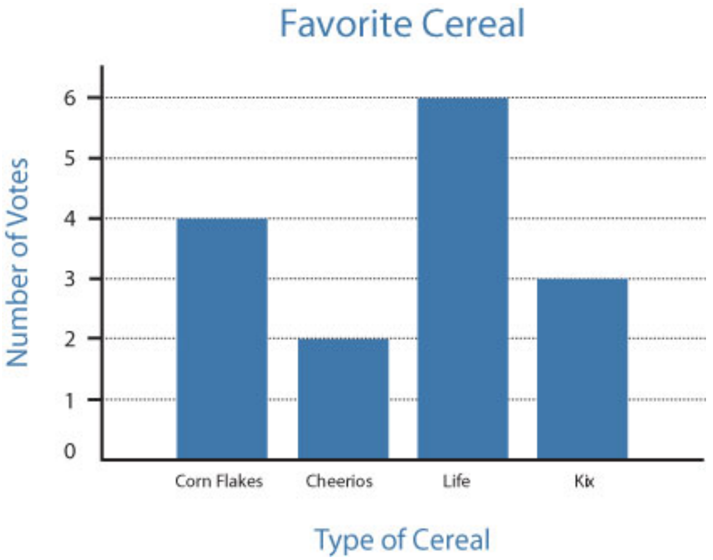




What is InfoVis?

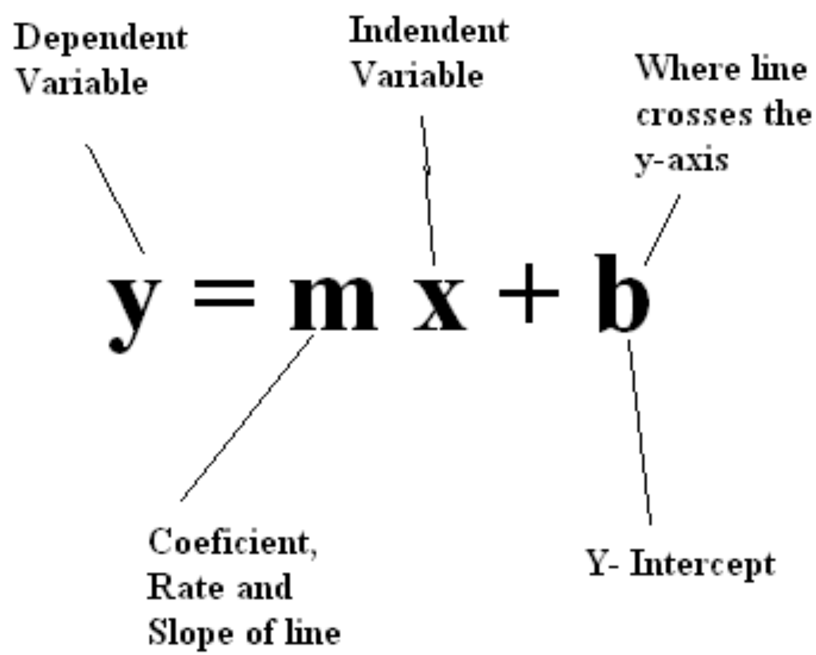
- Computer based visualizations are representations of data, that facilitate cognitive interaction, and help people carry out tasks more effectively.





Why do we use InfoVis?

- Many times, all we need is an analysis or a computational mechanism to solve problems.



Why do we use InfoVis?

- But many other times, this isn’t sufficient information…

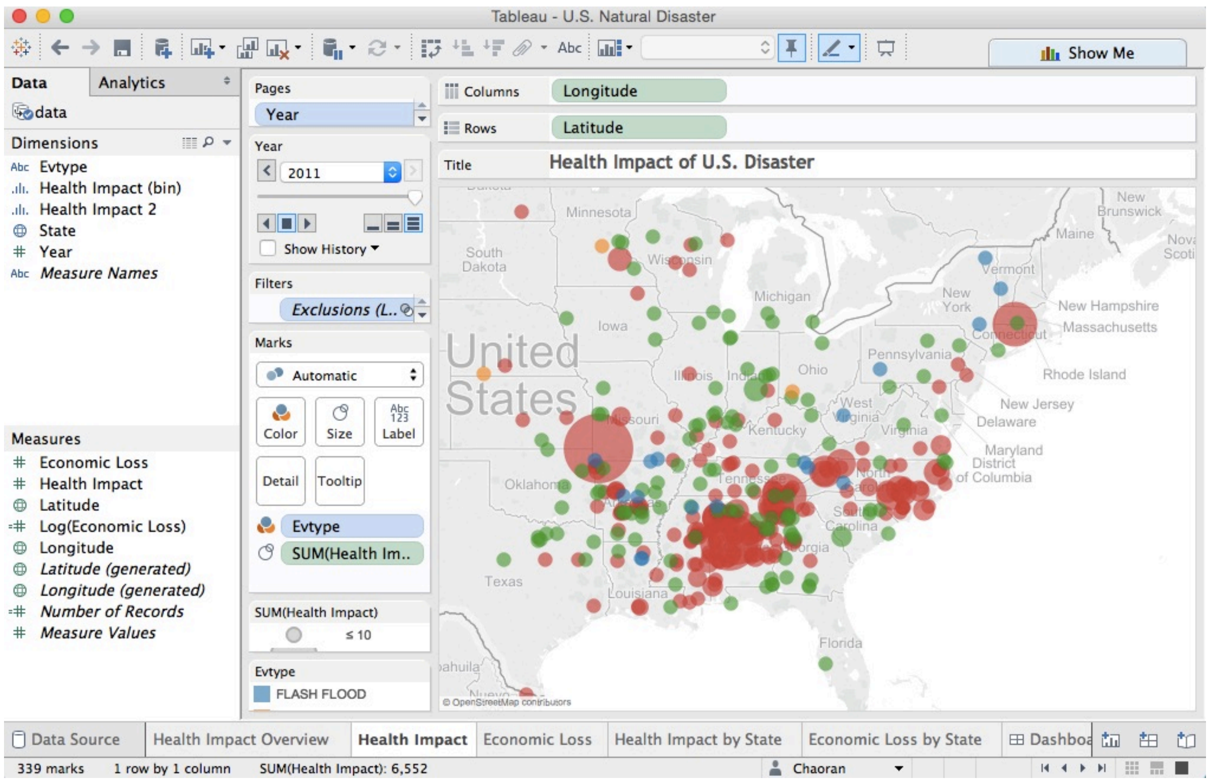
Why do we use InfoVis?

- Sometimes, we don't know what question to ask…

	A	B	C	D	E	F	G	H	I	J	K
1	Region	Group	ID Number	# Mailed	# Responded	Response Rate	# of New Accounts	Current Household Balance	Change in Balances	% Change in Balances	New Account Balance
2	East	A	1001	59	1	1.69%	1	$2,269,314	($207,326)	-8%	$160,612.00
3	East	A	1001	66	2	3.03%	4	$1,880,533	$165,561	10%	$78,944.00
4	East	A	1003	55	1	1.82%	1	$2,425,743	($375,908)	-13%	$354,235.00
5	East	A	1004	56	2	3.57%	2	$16,730,821	($4,541,020)	-21%	$63,208.00
6	East	B	1005	168	3	1.79%	5	$5,038,407	($815,558)	-14%	$111,960.00
7	East	C	1006	82	5	6.10%	5	$2,389,399	$103,972	-5%	$789,047.00
8	East	C	1007	90	5	5.56%	5	$3,186,964	($326,907)	-9%	$1,453,269.00
9	East	C	1008	79	2	2.53%	2	$2,838,031	($575,330)	-17%	$130,491.00
10	East	D	1009	75	3	4.00%	3	$1,428,805	($14,209)	-1%	$235,164.00
11	East	D	1010	69	5	7.25%	6	$1,710,499	$41,575	-2%	$157,442.00
12	East	D	1011	79	3	3.80%	4	$1,358,527	$34,001	-3%	$92,021.00
13	West	A	1001	126	2	1.59%	5	$12,171,434	$188,440	-8%	$12,359,874.00
14	West	A	1001	123	9	7.32%	10	$19,575,457	$15,129	10%	$19,590,586.00
15	West	A	1003	163	10	6.13%	2	$14,019,192	$3,406	-13%	$14,022,598.00
16	West	A	1004	219	3	1.37%	1	$7,829,874	$72,680	-21%	$7,902,554.00
17	West	B	1005	87	4	4.60%	10	$2,822,361	$96,426	-14%	$2,918,787.00
		C	1006	179	5	2.79%	3	$13,487,320	$192,905	-5%	$13,680,225.00
		C	1007	87	5	5.75%	5	$2,160,866	$168,703	-9%	$2,329,569.00
		C	1008	82	5	6.10%	2	$6,859,273	($12,778)	-17%	$6,846,495.00
		D	1009	200	5	2.50%	1	$11,571,973	($4,513)	-1%	$11,567,460.00
		D	1010	180	6	3.33%	10	$19,396,108	$103,140	-2%	$19,499,248.00
		D	1011	135	6	4.44%	5	$5,004,086	$31,464	-3%	$5,035,550.00
		A	1011	171	5	2.92%	5	$10,414,570	$91,696	-3%	$10,506,266.00
		A	1012	239	3	1.26%	4	$4,426,418	$28,851	97%	$4,455,269.00
		A	1013	137	3	2.19%	5	$14,527,150	$191,328	197%	$14,718,478.00
		A	1014	69	2	2.90%	5	$9,603,142	$192,871	297%	$9,796,013.00
		B	1015	190	2	1.05%	10	$6,335,228	$65,948	397%	$6,401,176.00
		C	1016	189	1	0.53%	3	$1,476,368	($8,395)	497%	$1,467,973.00
		C	1017	166	1	0.60%	3	$16,972,527	$7,376	597%	$16,979,903.00
		C	1018	62	3	4.84%	9	$6,419,181	$72,770	697%	$6,491,951.00
		D	1019	213	5	2.35%	1	$9,142,091	$103,105	797%	$9,245,196.00
		D	1020	197	8	4.06%	4	$17,959,916	$185,237	897%	$18,145,153.00
		D	1021	58	3	5.17%	3	$7,725,291	$102,193	997%	$7,827,484.00

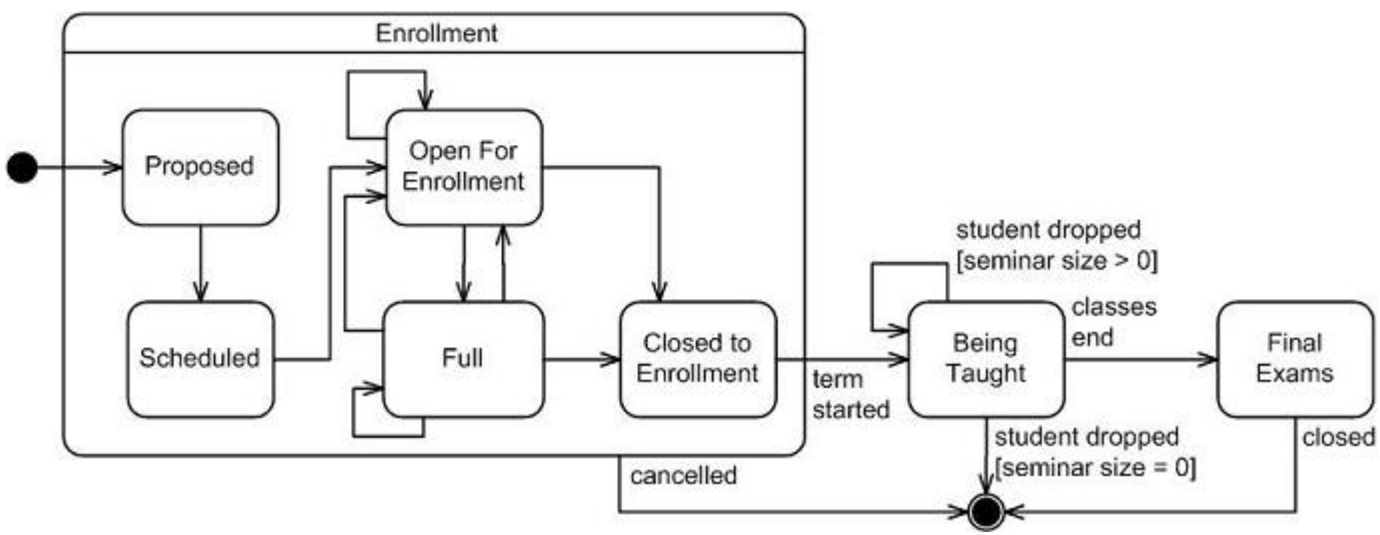
Why do we use InfoVis?

- Sometimes, we want to do long term, exploratory analyses…



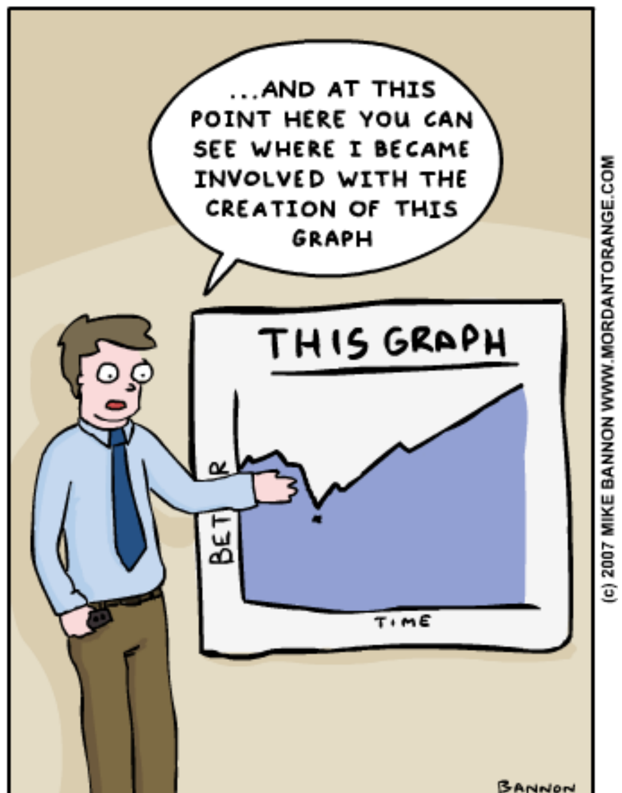
Why do we use InfoVis?

- Sometimes, we need to automate a process or work towards refining its components…



Why do we use InfoVis?

- Sometimes, we need to present our findings in a clear, concise way…



How to think about Visualization?

- Visualizations support the natural inferences that humans make with our cognitive systems

How to think about Visualization?

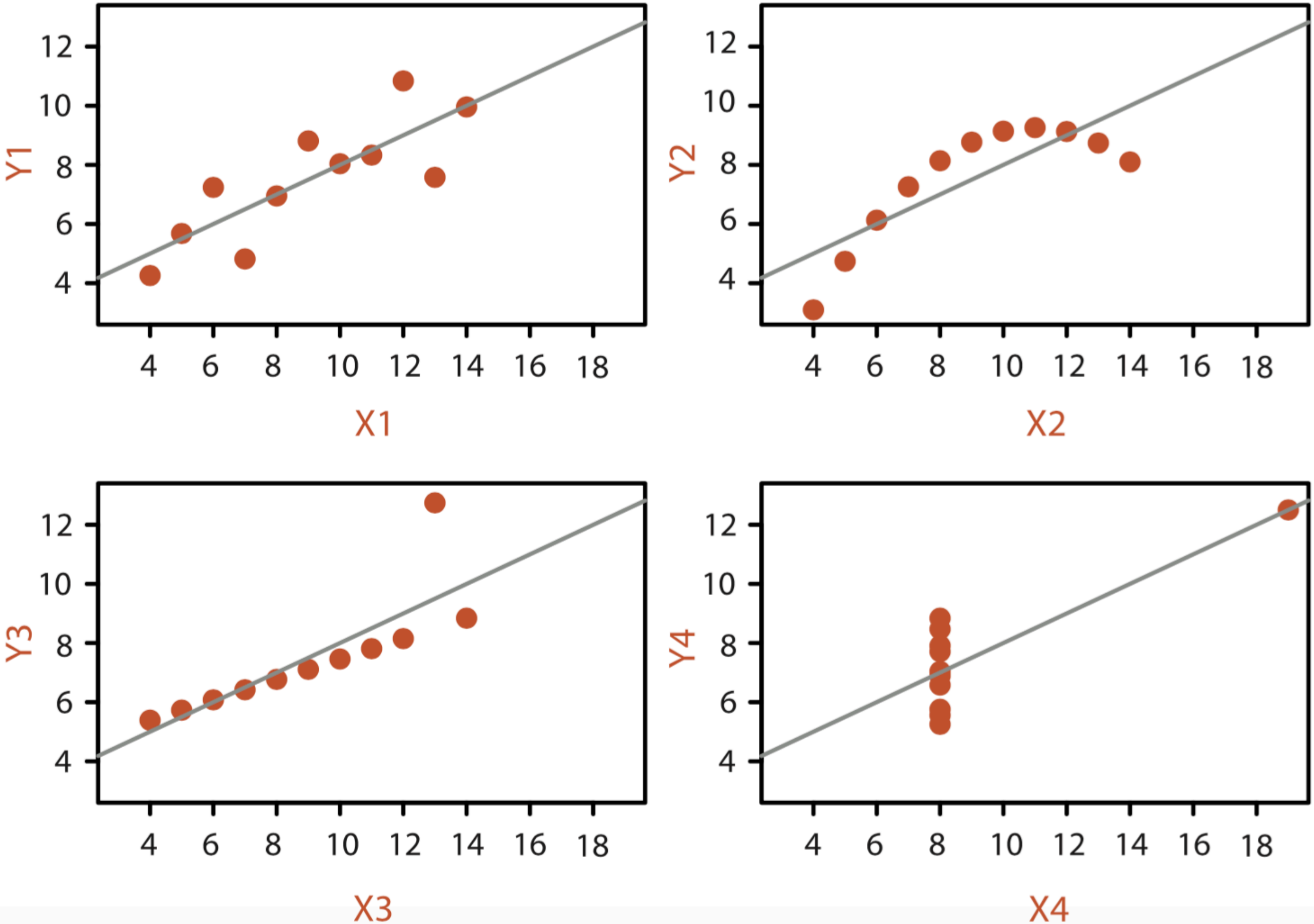
- Why rely on the visual system to communicate information?
  - Because, as we all know, vision is awesome!

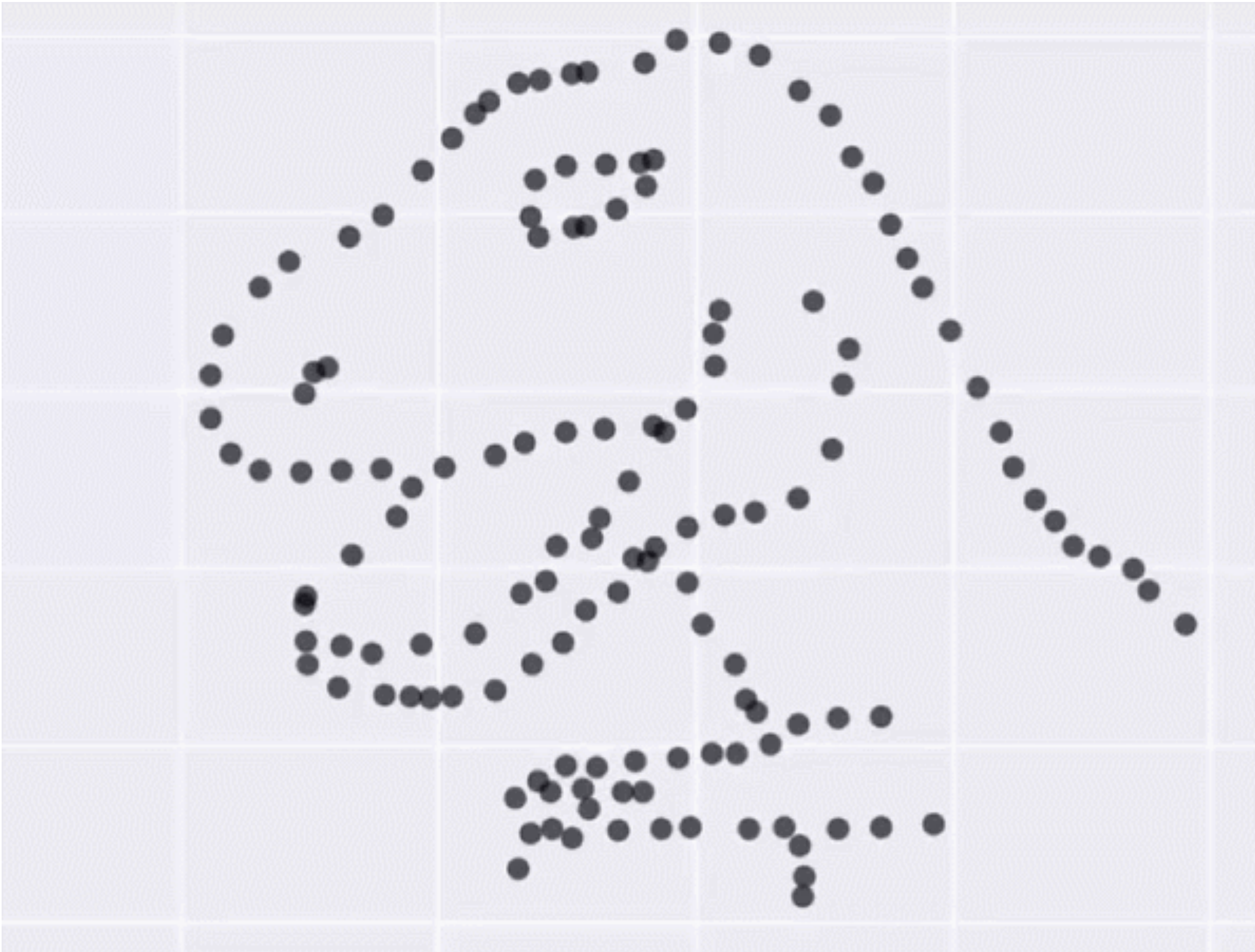
How to think about Visualization?

- Why rely on the visual system to communicate information?
  - Because, as we all know, vision is awesome!
  - The field of vision science has provided tons of empirical phenomena to capitalize on in the creation of visualizations.

Anscombe's Quartet: Raw Data

	1		2		3		4	
	X	Y	X	Y	X	Y	X	Y
	10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
	8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
	13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
	9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
	11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
	14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
	6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
	4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
	12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
	7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
	5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89
Mean	9.0	7.5	9.0	7.5	9.0	7.5	9.0	7.5
Variance	10.0	3.75	10.0	3.75	10.0	3.75	10.0	3.75
Correlation	0.816		0.816		0.816		0.816	


Y1
X1
Y2
X2
Y3
X3
Y4
X4
4
6
8
10
12
14
16
18



What else is Visualization used for?

- Consulting groups

What else is Visualization used for?

- Consulting groups
- Analytics (data science, finance, etc.)

What else is Visualization used for?

- Consulting groups
- Analytics (data science, finance, etc.)
- Software development

tableau®


Airline Flights and Delays
By State
By Airline
Southwest
Delta
American
US Airlines
United
AirTran
Continental
JetBlue
Alaska
Northwest
Frontier
Hawaiian
Number of Flights
Number of Planes
Fleet age
Flight Date
Airline
Avg. Delay
10.9 min
Section
Blog
Community
Examples
Register
Training
User-generated
Time on Page
Visits

What can Vision Scientists contribute to InfoVis?

- A lot !!!

What can Vision Scientists contribute to InfoVis?

- Primarily:
  - Methodologies…

What can Vision Scientists contribute to InfoVis?

- Primarily:
  - Methodologies…
  - Phenomena

What can Vision Scientists contribute to InfoVis?

- Primarily:
  - Methodologies…
  - Phenomena
  - Tasks and Paradigms

What can Vision Scientists contribute to InfoVis?

- Primarily:
  - Methodologies…
  - Phenomena
  - Tasks and Paradigms
  - Theories and models

What can Vision Scientists contribute to InfoVis?

- Primarily:
  - Methodologies…
  - Phenomena
  - Tasks and Paradigms
  - Theories and models

- Basically, they need the same things we need.

IEEE Vis

The Shaping of Information by Visual Metaphors

Caroline Ziemkiewicz and Robert Kosara

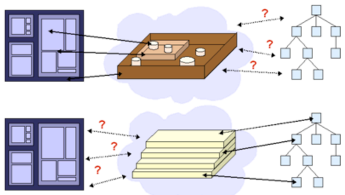
Abstract—The nature of an information visualization can be considered to lie in the visual metaphors it uses to structure information. The process of understanding a visualization therefore involves an interaction between these external visual metaphors and the user's internal knowledge representations. To investigate this claim, we conducted an experiment to test the effects of visual metaphor and verbal metaphor on the understanding of tree visualizations. Participants answered simple data comprehension questions while viewing either a treemap or a node-link diagram. Questions were worded to reflect a verbal metaphor that was either compatible or incompatible with the visualization a participant was using. The results (based on correctness and response time) suggest that the visual metaphor indeed affects how a user derives information from a visualization. Additionally, we found that the degree to which a user is affected by the metaphor is strongly correlated with the user's ability to answer task questions correctly. These findings are a first step towards illuminating how visual metaphors shape user understanding and have significant implications for the evaluation, application, and theory of visualization.

Index Terms—Cognition, visualization theory, metaphors, hierarchies, evaluation.

1 Introduction

Different information visualizations may present the same data in vastly different forms, as in the great variety of tree and graph visualizations. While these methods are often capable of showing the same information, it is widely recognized that any given method is better for some applications and worse for others. In cases where visualizations present equivalent information, it is the structural differences between methods that give rise to these differences in how the information they present can be used.

Understanding visualization, therefore, requires understanding how visualizations shape information, not only what information they present. A potential framework for this understanding is the formulation of a visualization as a set of visual metaphors. Metaphors are commonly used as a way of understanding how subtle differences in the form of language can suggest different interpretations of the same



How do People Make Sense of Unfamiliar Visualizations?: A Grounded Model of Novice's Information Visualization Sensemaking

Sukwon Lee, Sung-Hee Kim, Ya-Hsin Hung,
Heidi Lam, *Member, IEEE*, Youn-ah Kang, and Ji Soo Yi, *Member, IEEE*

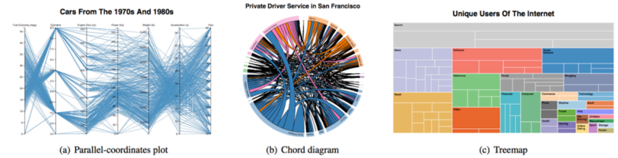


Fig. 1. The three unfamiliar information visualizations that were used in this study: (a) the parallel-coordinates plot (PCP), (b) the chord diagram (CD), and (c) the treemap (TM).

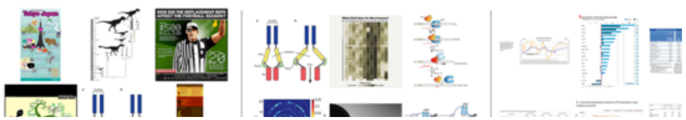
How Capacity Limits of Attention Influence Information Visualization Effectiveness

Steve Haroz and David Whitney

Fig. 1. These images each have one colored square that is unique within that image. How long does it take you to find each? How many color categories are there in each panel? Why does grouping make both tasks substantially easier?

What Makes a Visualization Memorable?

Michelle A. Borkin, *Student Member, IEEE*, Azalea A. Vo, Zoya Bylinskii, Phillip Isola, *Stude*
Shashank Sunkavalli, Aude Oliva, and Hanspeter Pfister, *Senior Member, IE*



Implied Dynamics in Information Visualizatio

Caroline Ziemkiewicz
UNC Charlotte
9201 University City Blvd
Charlotte, NC 28262
caziemki@uncc.edu

Robert Kosara
UNC Charlotte
9201 University City Blvd
Charlotte, NC 28262
rkosara@uncc.edu

ABSTRACT

Information visualization is a powerful method for understanding and working with data. However, we still have an incomplete understanding of how people use visualization to think about information. We propose that people use visualization to support comprehension and reasoning by viewing abstract visual representations as physical scenes with a set of implied dynamics between objects. Inferences based on these implied dynamics are metaphorically extended to form inferences about the represented information. This view predicts that even seemingly meaningless properties of a visualization, including such minor design elements as borders, background areas, and the connectedness of parts, may affect how people perceive semantic aspects of data by suggesting different potential dynamics between data points. We present a study that supports this claim and discuss the design implications of this theory of information visualization.

Categories and Subject Descriptors

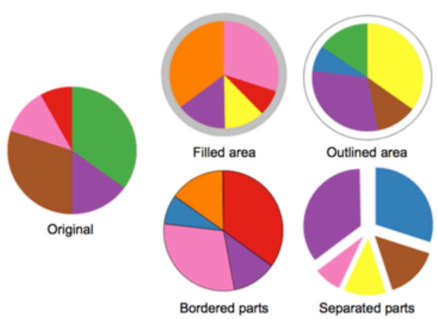


Figure 1: A pie chart in five different design configurations.

Beyond Memorability: Visualization Recognition and Recall

Michelle A. Borkin*, *Member, IEEE*, Zoya Bylinskii*, Nam Wook Kim, Constance May Bainbridge,
Chelsea S. Yeh, Daniel Borkin, Hanspeter Pfister, *Senior Member, IEEE*, and Aude Oliva

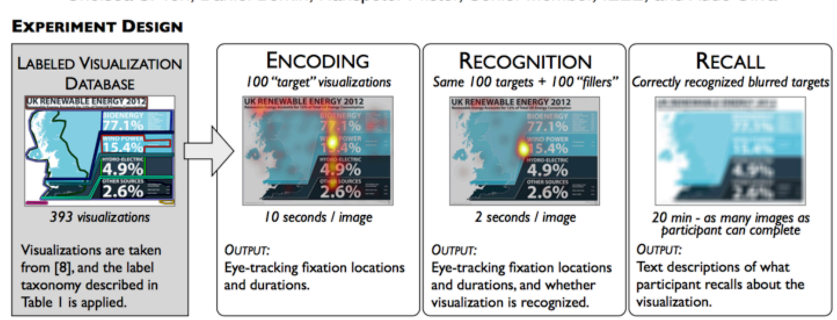
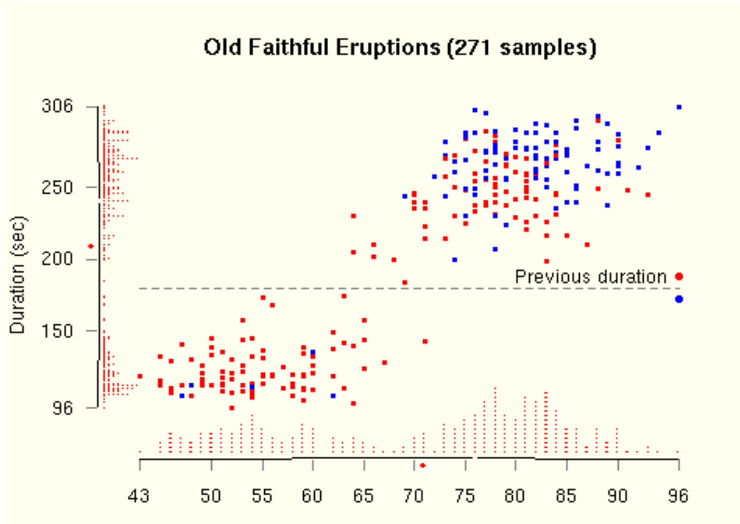
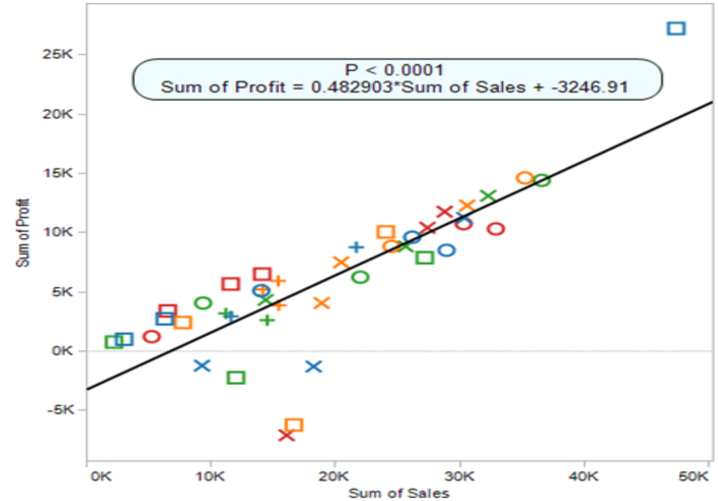
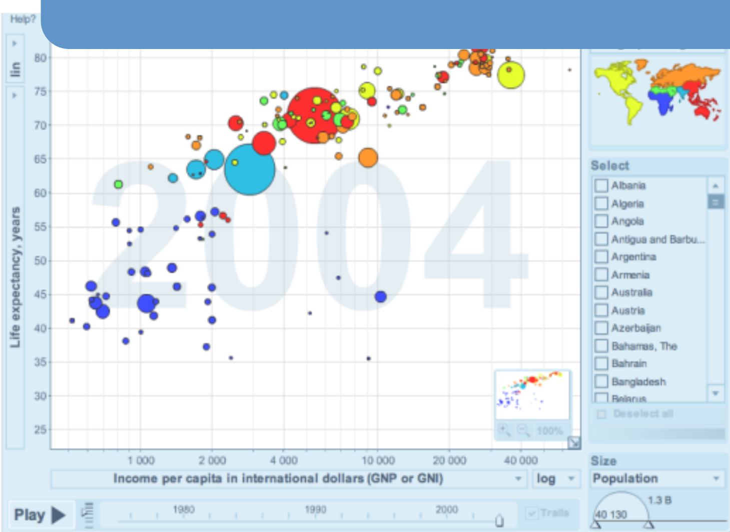


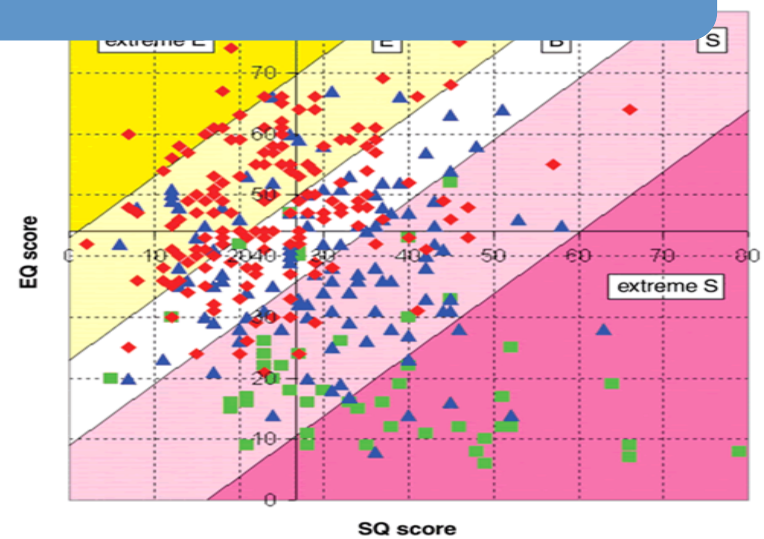
Fig. 1. Illustrative diagram of the experiment design. From left to right: the elements of the visualizations are labeled and categorized, eye-tracking fixations are gathered for 10 seconds of "encoding", eye-tracking fixations are gathered while visualization recognizability is measured, and finally participants provide text descriptions of the visualizations based on blurred representations to gauge recall.



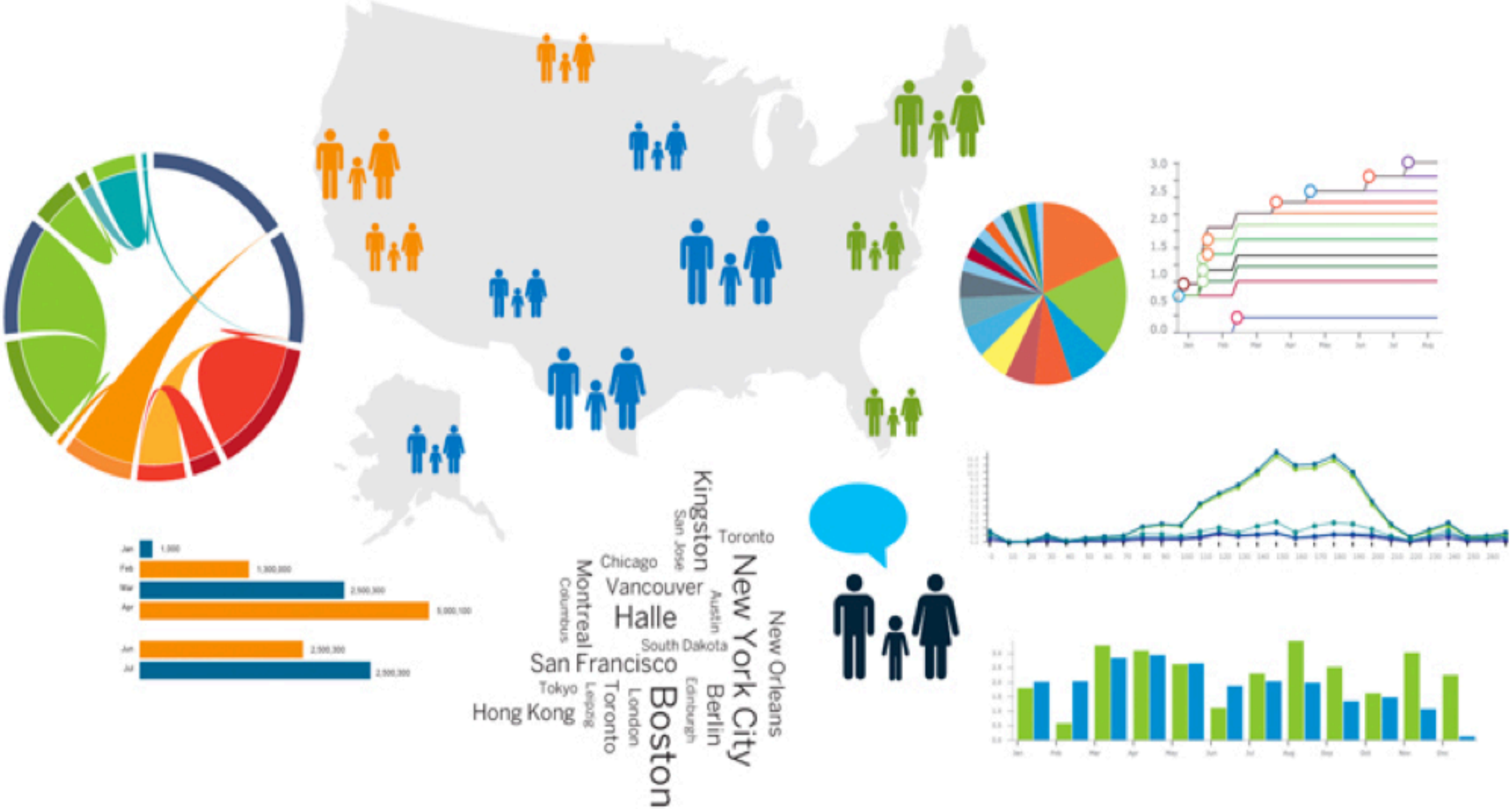


How to Study a Data Visualization?



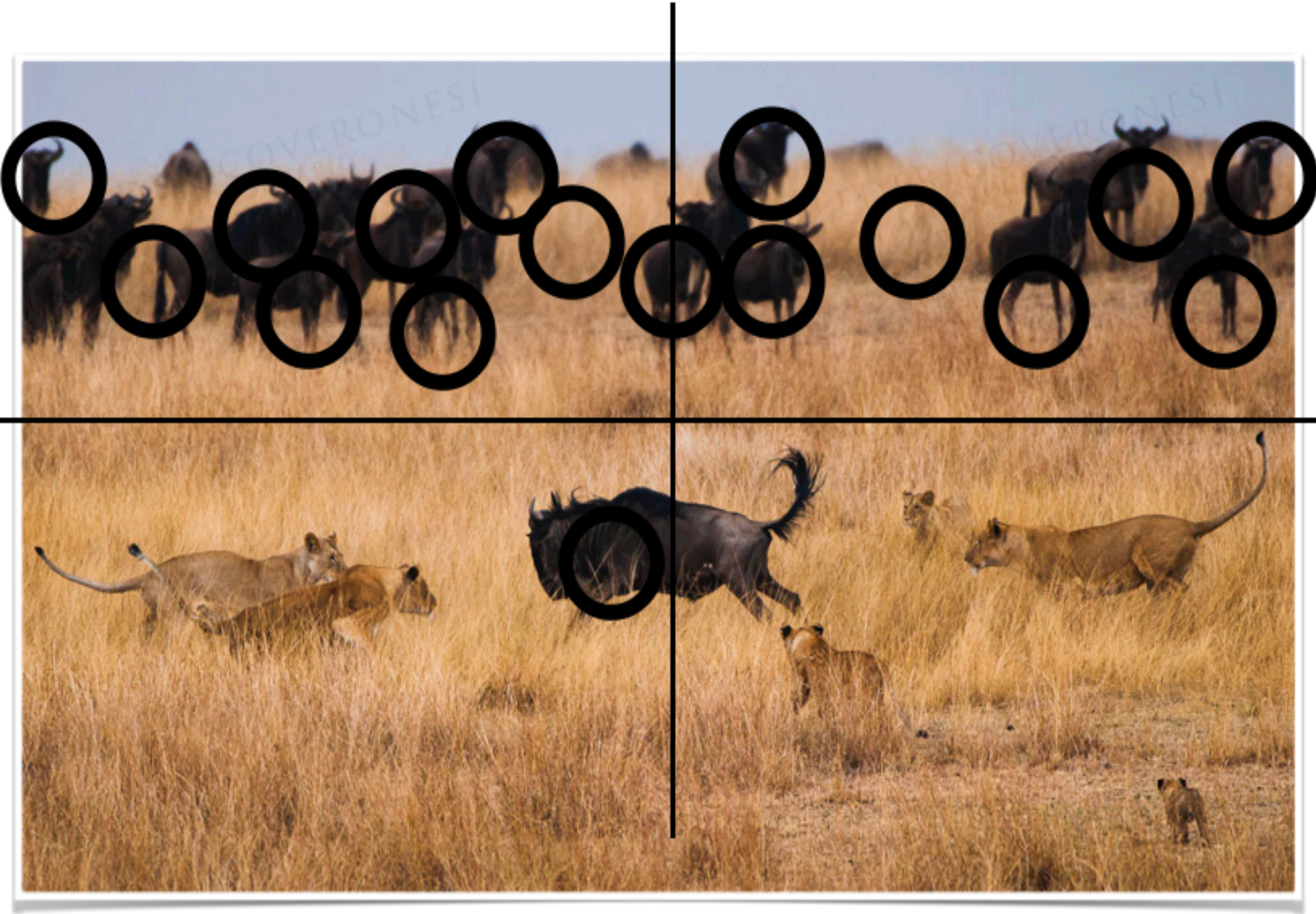


Where do we start?

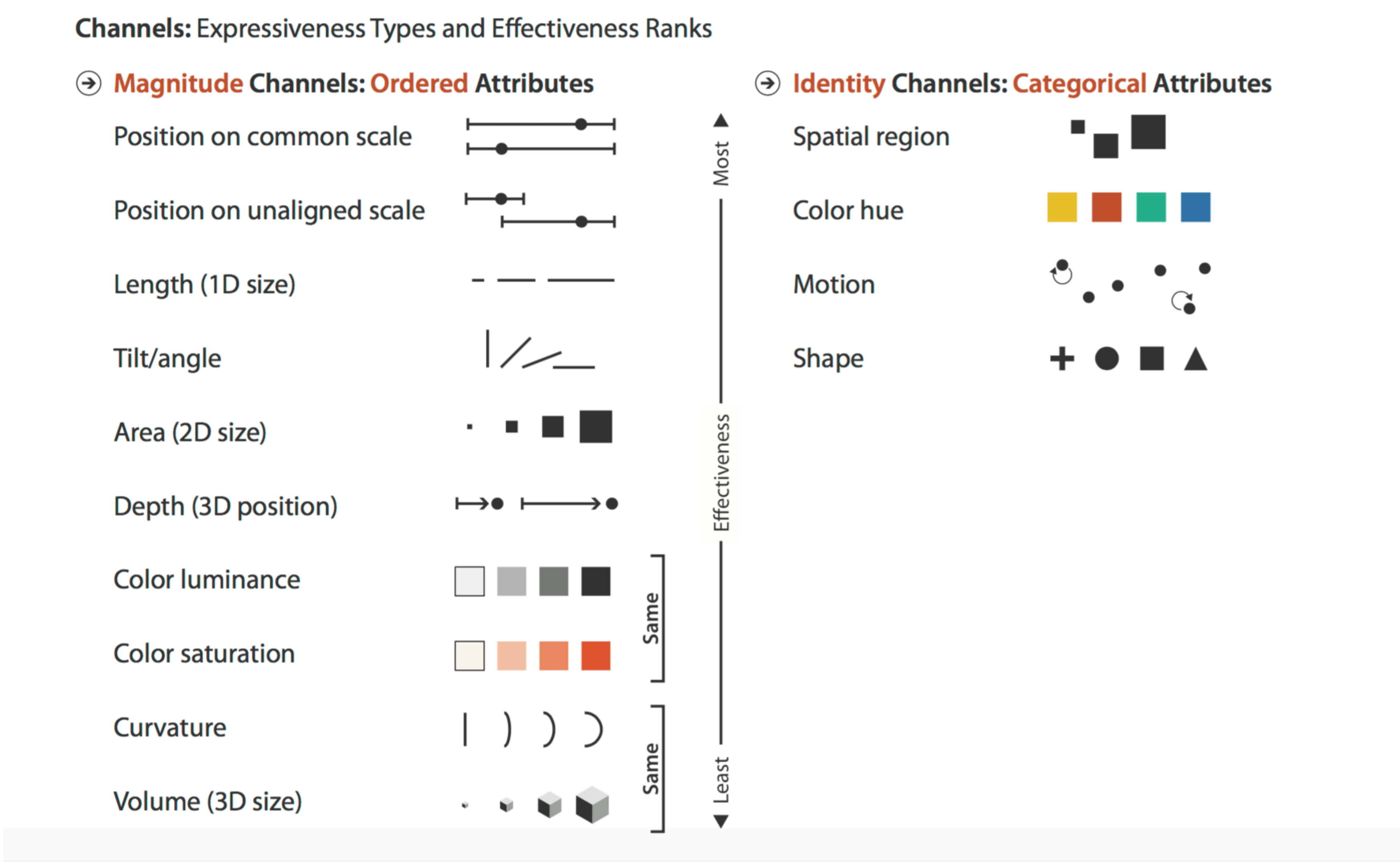


the artificial world

the natural world

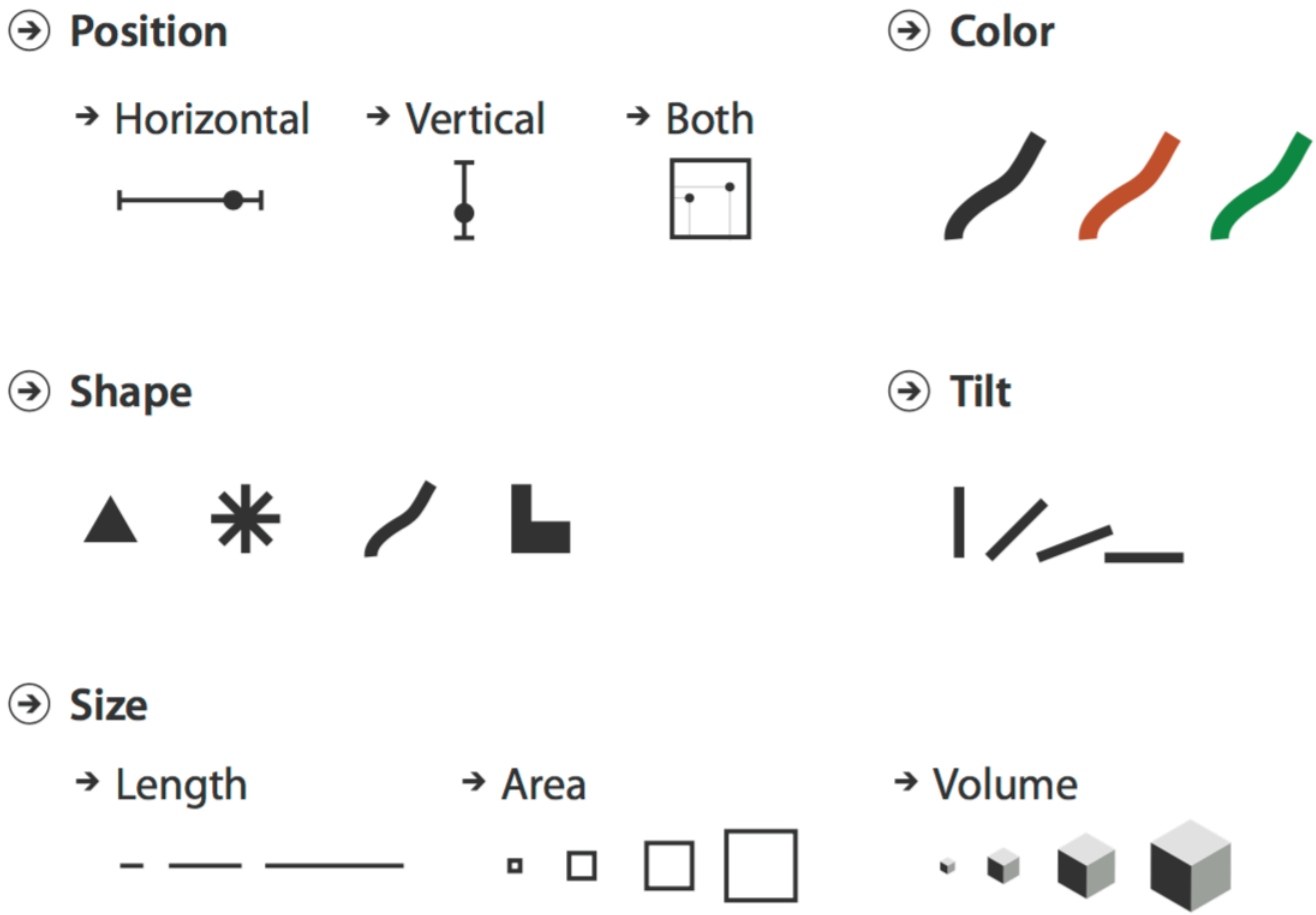


Graphs as stimuli



Munzner, T. (2014). *Visualization analysis and design*. CRC Press.

Graphs as stimuli



Munzner, T. (2014). *Visualization analysis and design*. CRC Press.

Graphs as stimuli

These are visual features!

Munzner, T. (2014). *Visualization analysis and design*. CRC Press.

Vision Science

+ Data Visualization

= A Science of Visualization

Vision Science

\+ Data Visualization

= A Science of Visualization

…which is still, basically, Vision Science.

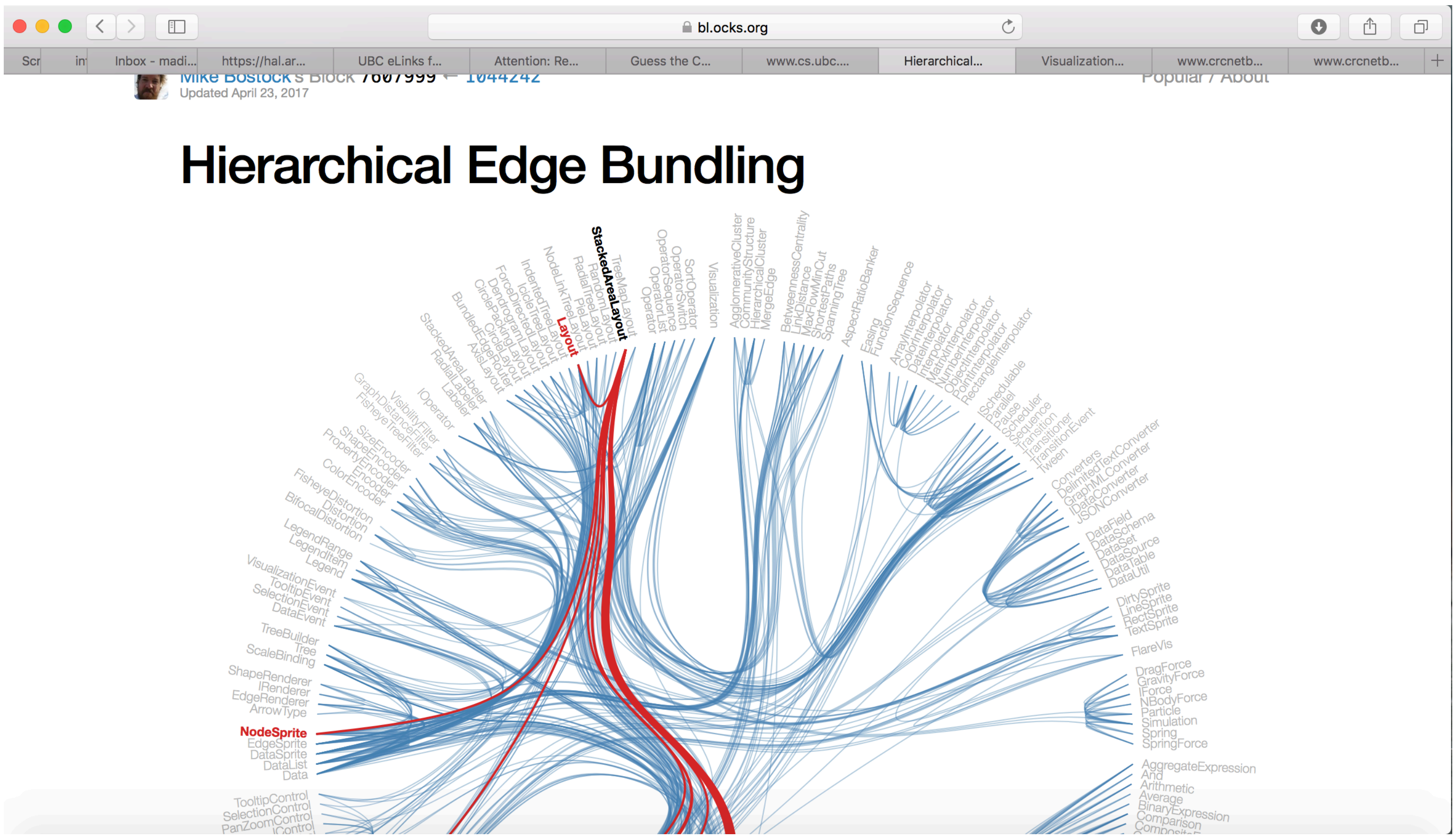
What can InfoVis contribute to Vision Science?

- Code sharing and version control

GitHub

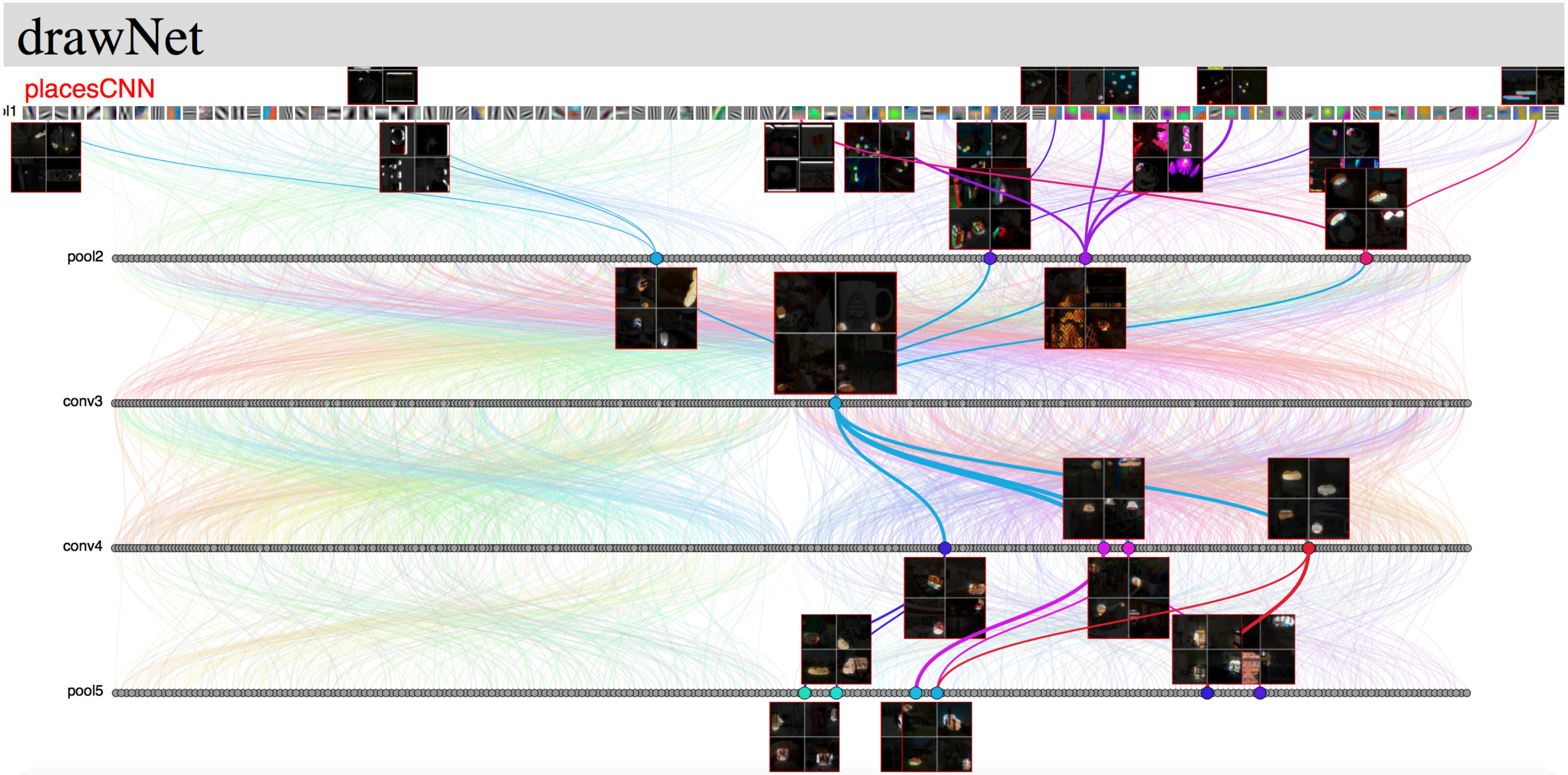
What can InfoVis contribute to Vision Science?

- Engineering transparency



What can InfoVis contribute to Vision Science?

- Computational modeling



Data Blitz!

- Presenters
  - Madison Elliott (UBC)
  - Christie Nothelfer (Northwestern)
  - Cindy Xiong (Northwestern)
  - Danielle Albers-Szafir (Colorado)
  - Zoya Bylinskii (MIT)