Communicating Through Data Visualization

Eytan Adar

Population Dynamics and Health Program Workshop
June 25, 2025

https://github.com/eytanadar/pdhp2025

1

A bit about me…

2

A bit about you…

3

A bit about what we'll do today…

1) Infovis, perception, and cognition
   - Why visualizations work, what they're good for, choosing the right ones, (also a bunch of vocabulary)
2) Communication through infovis
   - How to achieve communicative intents
3) Unconventional approaches
   - Beyond the bar chart

4

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Infovis (what it is/isn't)

6

The use of computer-supported, interactive, visual representations of data to amplify cognition.

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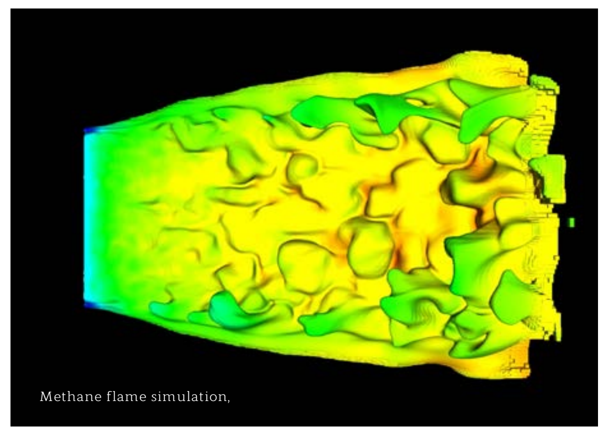

Methane flame simulation,

8

Visualization

The use of computer-supported, interactive, visual representations of data to amplify cognition.

9

Information Visualization

The use of computer-supported, interactive, visual representations of data to amplify cognition.

abstract

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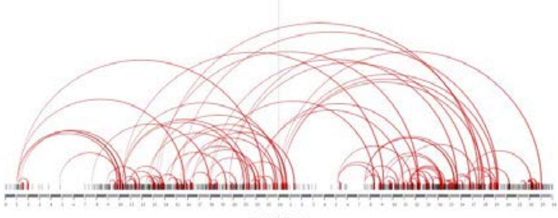

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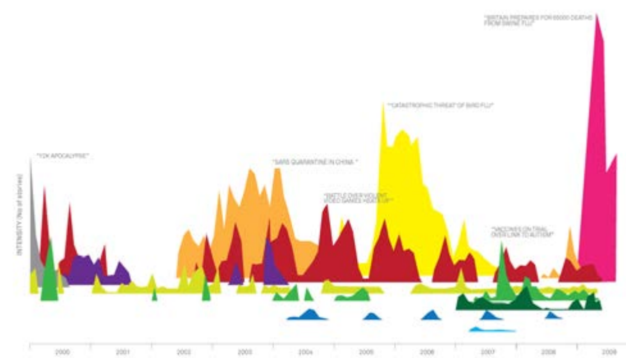

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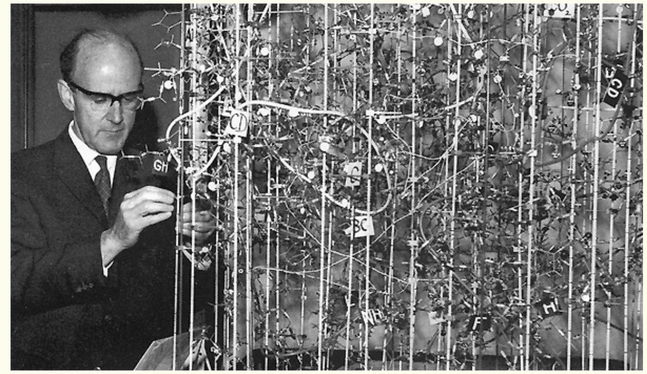
Our focus will mostly be digital,
“on a screen,” flat, but…

13



http://dataphys.org/list/proteine-visualizations/

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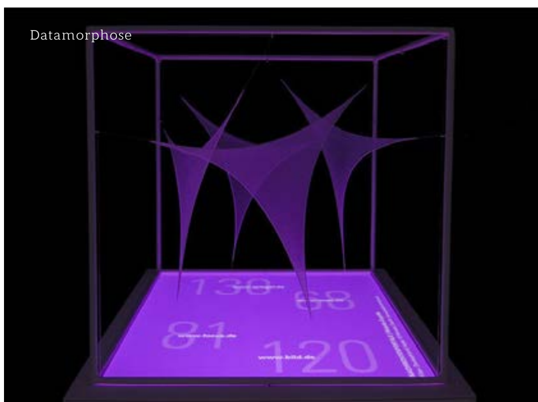

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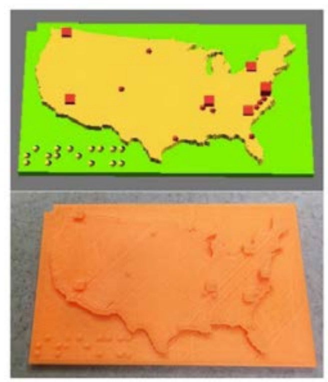

Kane & Bigham (2014)

Brown & Hurst (2012)

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Why interactive/dynamic?

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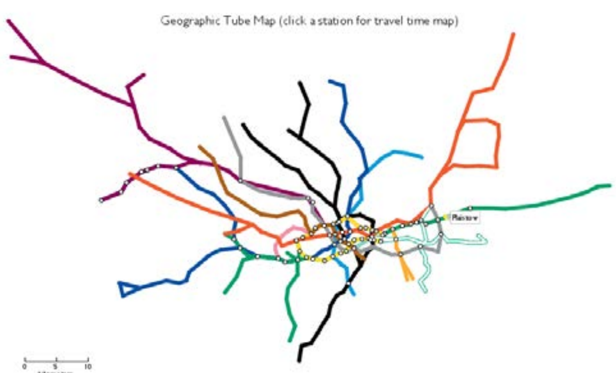
London Tube

18



London Tube, Geographic layout
http://www.tom-carden.co.uk/p5/tube_map_travel_times/applet/

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London Tube, Time to travel layout
http://www.tom-carden.co.uk/p5/tube_map_travel_times/applet/

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Related: Cartography

22

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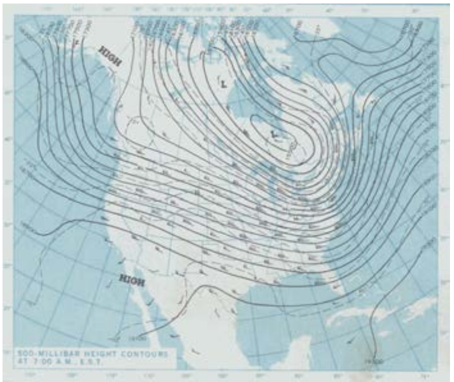

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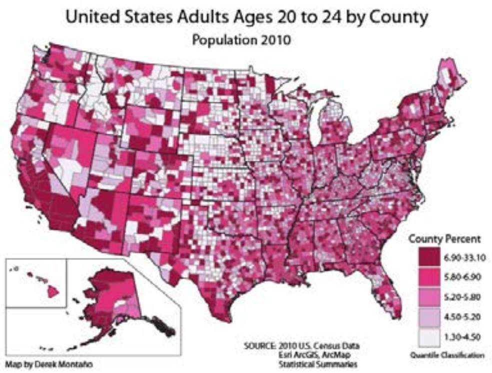

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Related: Statistical Graphics/Charts

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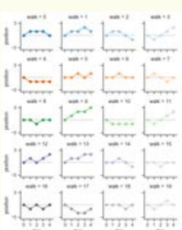
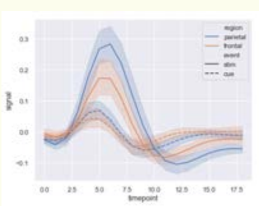
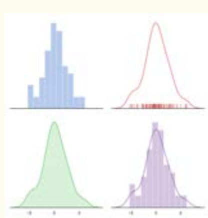
Statistical Graphics







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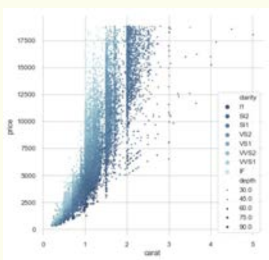
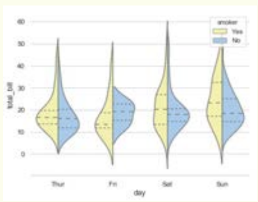
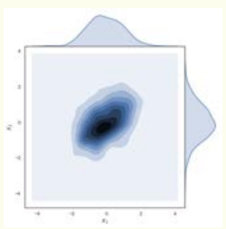
Statistical Graphics







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Statistical Charts/Graphics

- Often…
  - … static
  - … require training for use
  - … highly focused on narrow tasks
- Information visualization will often…
  - … leverage statistical chart techniques
  - … combine and augment them

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Related: Infographics

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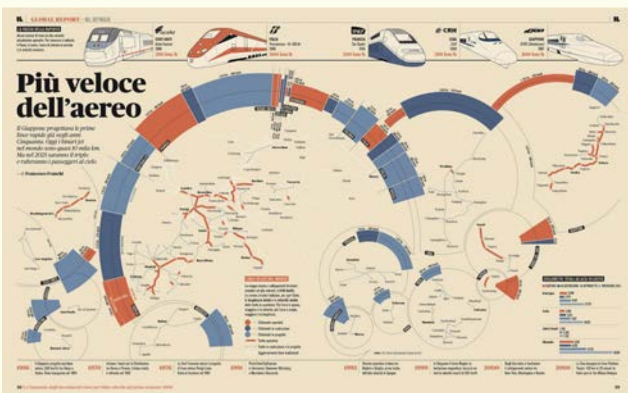

Francesco Franch

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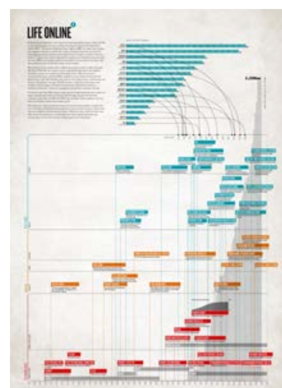

Paul Button

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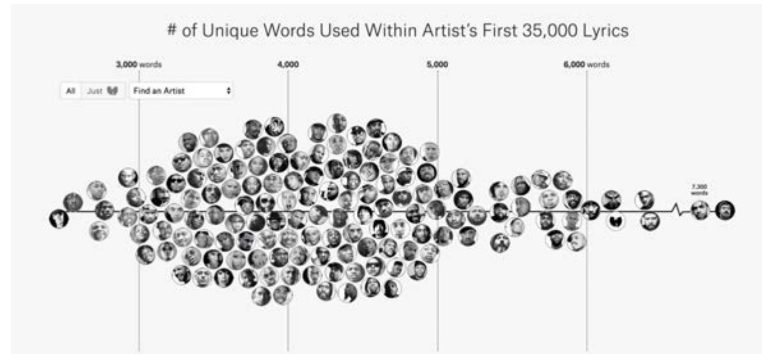
https://www.nytimes.com/interactive/2018/03/19/upshot/race-class-white-and-black-men.html

33



https://pudding.cool/projects/vocabulary/

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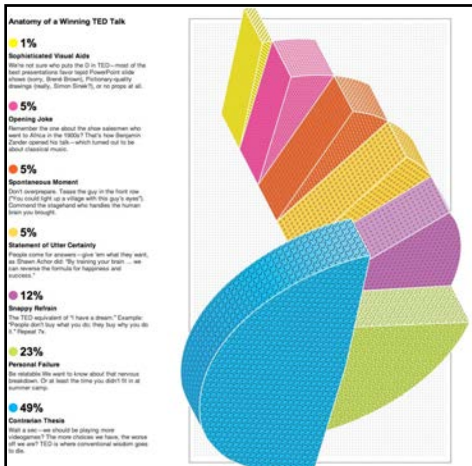

http://wtfviz.net/

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Infographics

- Tend to be:
  - Elaborate
  - Explanatory
  - Self-contained
  - Frequently static (non-interactive)
- May use infovis techniques
- We can learn from this approach
  - Especially for communicative vis

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Infovis, what is it good for?

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Why visualize?

- Exploratory Data Analysis
- Decision support
- Graphical calculation
- Pattern detection
- Storytelling
- Contextualization
- Memory expansion
- Inspiration

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Anscombe's Quartet

I		II		III		IV	
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

x mean = 9, x variance = 11,
y mean = 7.5, y variance = 4.12
Correlation = 0.816

Regression: y = 3 + .5x

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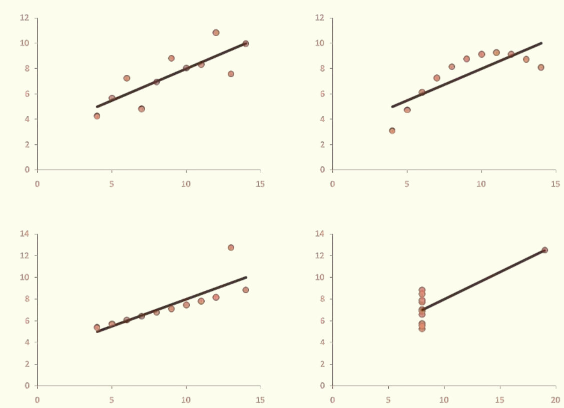

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"A computer should make both calculations and graphs. Both sorts of output should be studied; each will contribute to understanding"

– F. J. Anscombe (1973)

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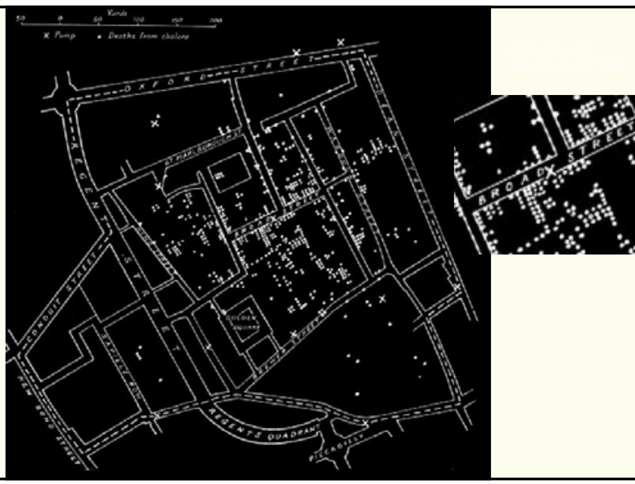

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High level functions

- Recording Tasks
- Analysis Tasks
- Communicative Tasks

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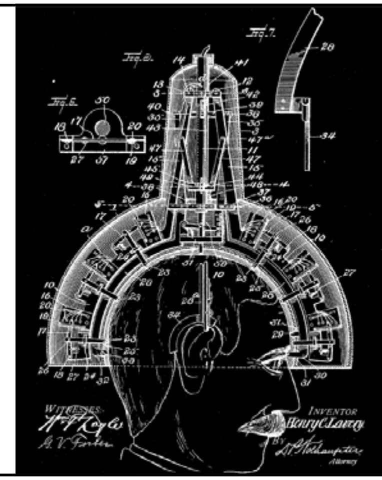
Record

45

Anatomical Measuring and
Recording Machine
Lavery, Patented Apr. 1905



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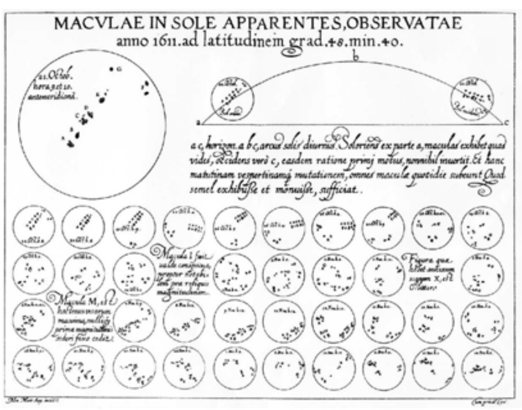

Sunspot change. 1626

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Analyst Tasks

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Memory aid

$$\begin{array}{r} 42 \\ \times\ \ 37 \\ \hline \overset{1}{2}94 \\ 126 \\ \hline 1554 \end{array}$$

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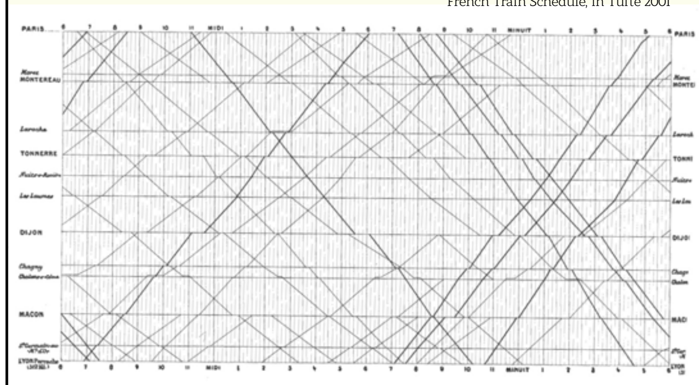
French Train Schedule, in Tufte 2001



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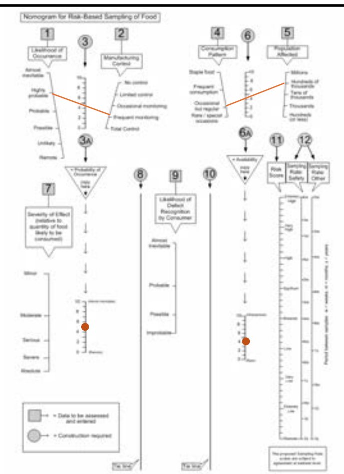
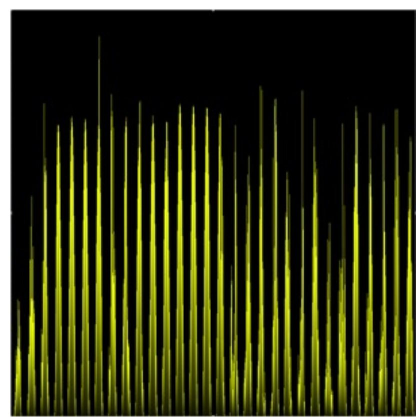


Nomogram
UK Food Standards Agency

51



Visualizing Time
Series on Spirals

Weber et al.

2001

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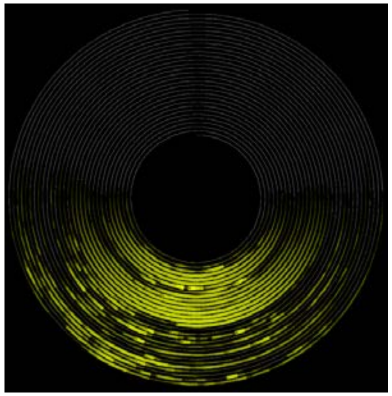
Visualizing Time Series on Spirals

Weber et al.

2001



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The goal of analytical visualization is to find patterns

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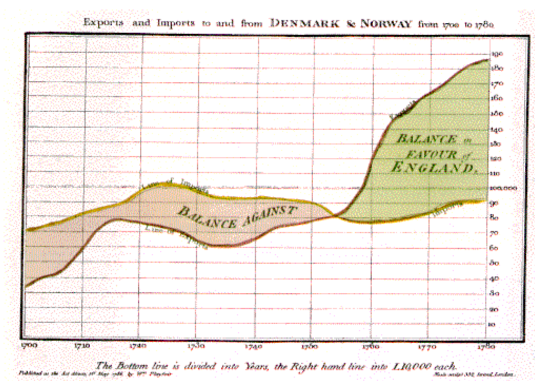
Communicative Tasks

55

Playfair, Exports & Imports, 1786



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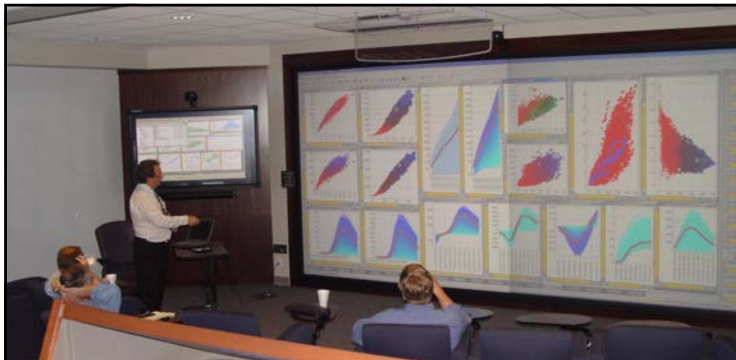

Spotfire session, From Ben Shneiderman
https://wiki.cs.umd.edu/cmsc734_09/index.php?title=Syllabus

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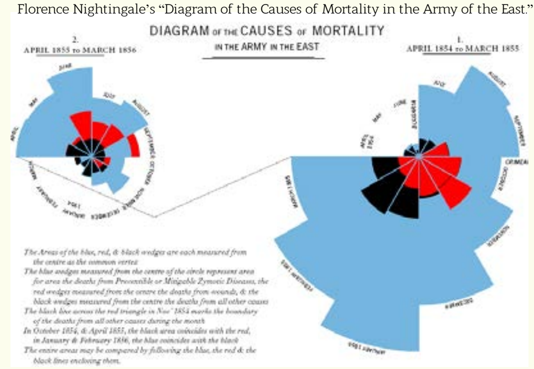
Florence Nightingale's "Diagram of the Causes of Mortality in the Army of the East."



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Opte Project, 2001

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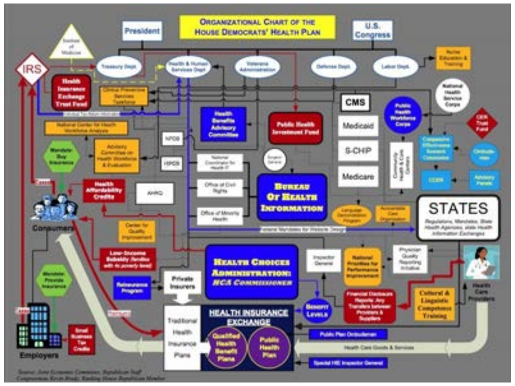
http://senatecharts.tumblr.com

60



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The goal of communicative visualization is to teach something (or at least support some teaching)

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At the root…

- At the root of almost all visualization tasks is: comparison
  - The visual system is comparing things
    - Bigger/Smaller
    - Up/Down
    - There/Not there
    - Like a pattern/Not like a pattern
    - Etc.

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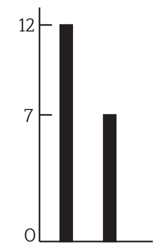
It's all about choice…

64

12, 7

65

12, 7



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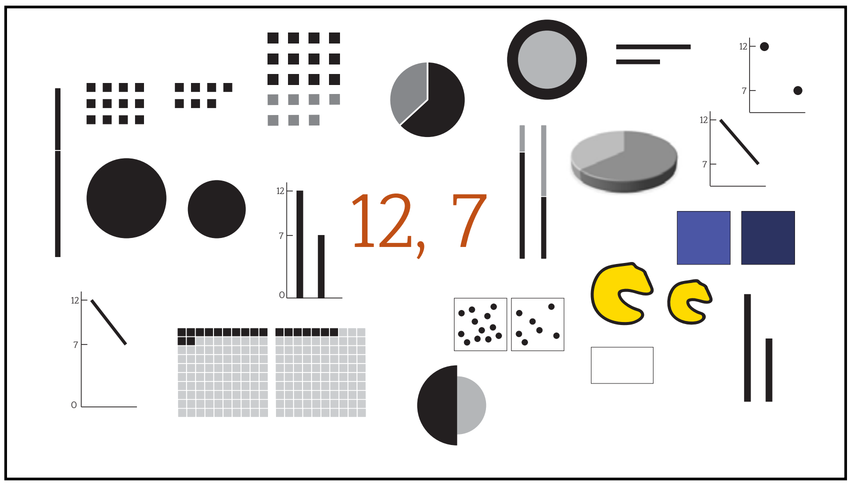

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How do we think about design?

- It's a puzzle!
- We're going to take pieces that describe the "domain" task
- We'll then fit them solutions
- Goal of the course: finding the right pieces.

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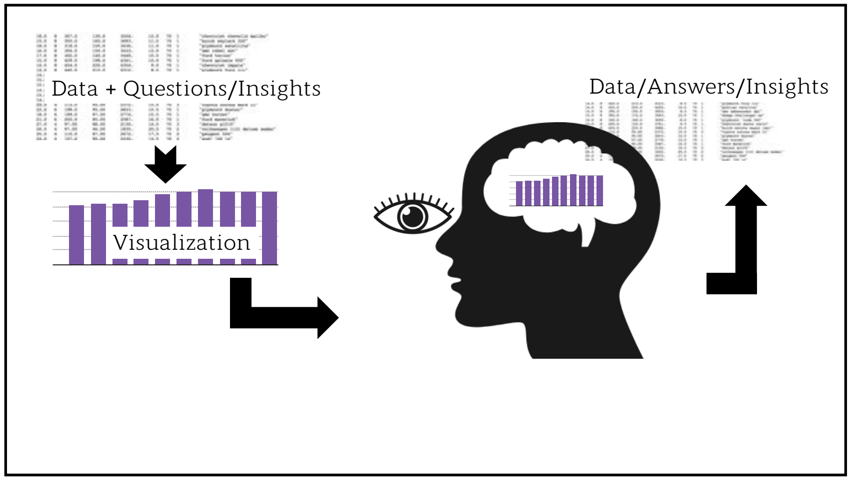

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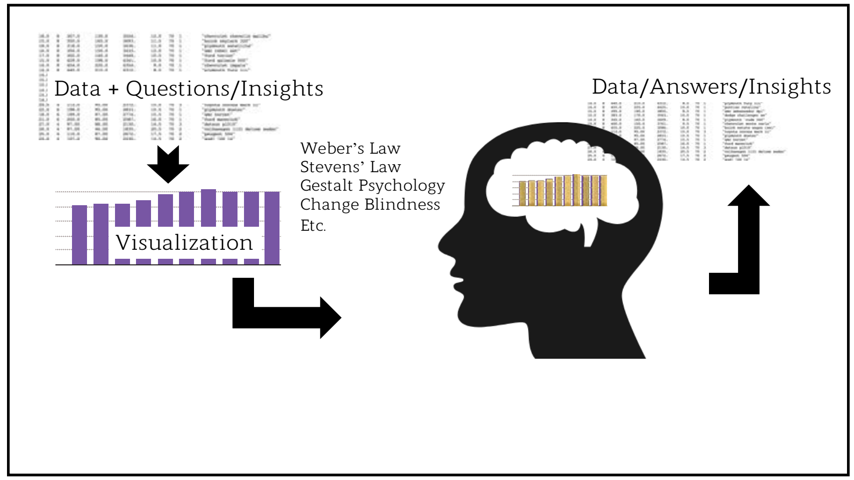

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Before we start…
(notation)

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Attribute Quality

- Nominal
  - Labels (unordered)
- Ordinal
  - Ordered
- Interval
  - Gap comparison
  - Distance metric
- Ratio
  - Size comparison
  - Interval with zero

Nominal (= and ≠)

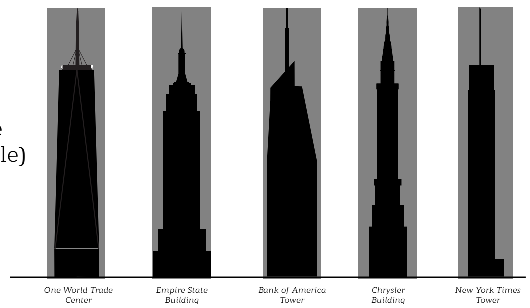
Ordinal (<)

Quantitative (+,-,x, etc.)

Stevens, On the Theory of Scales of Measurement

72

Nominal
Not to scale
(and no scale)



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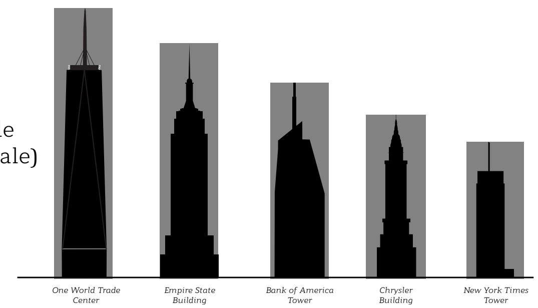
Ordinal
Not to scale
(and no scale)



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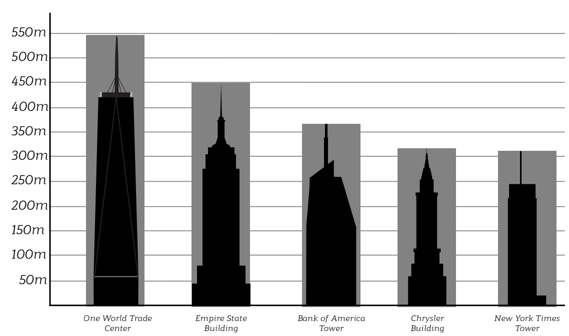

Quantitative
To scale

75

Attribute Quality

- Nominal
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Nominal (= and ≠)

Ordinal (<) &

& Quantitative (+,-,x, etc.)

Stevens, On the Theory of Scales of Measurement

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Key principle: communicate data by *encoding* it in *marks*

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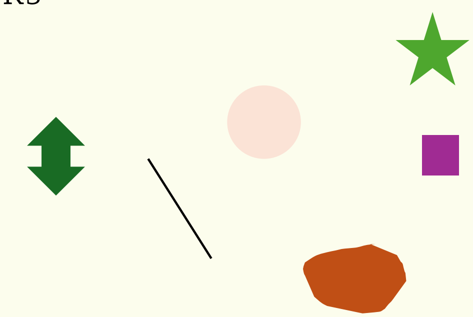
Marks



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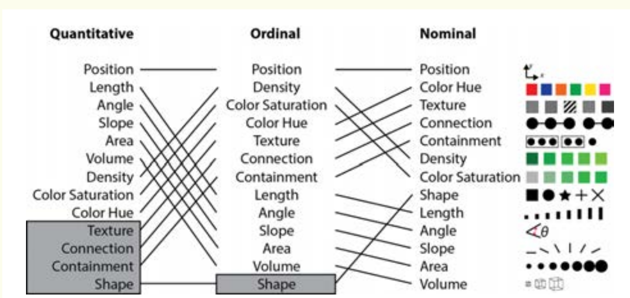
Properties of marks



From Mackinlay

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What do marks represent?

- Entities
  - "things"
    - person/place/company/etc.
  - "properties of things"
    - weight/population/etc.
- Relationships
  - Is a friend, is a parent, is in the same club, is after, etc.

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What do marks represent?

- Entities
  - “things”
    - Alice and Bob, Males/Females, etc.
  - “properties of things”
    - Height of Alice and Bob
- Relationships
  - Is a friend, is a parent, is in the same club, is after, etc.

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The marks will *express* some information

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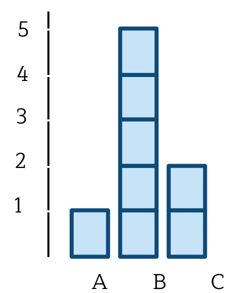
Name	Score
A	1
B	5
C	2

Insights

Vis expresses
1. A is 1, B is 5, C is 2
2. B is 5 times larger than A
3. C is 2 times larger than A

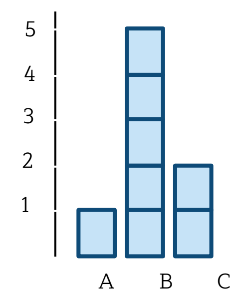


83

Name	Score
A	1
B	5
C	2

Answers

Vis expresses
1. What is the distribution of values?
2. What is the largest value?
3. What is the smallest?



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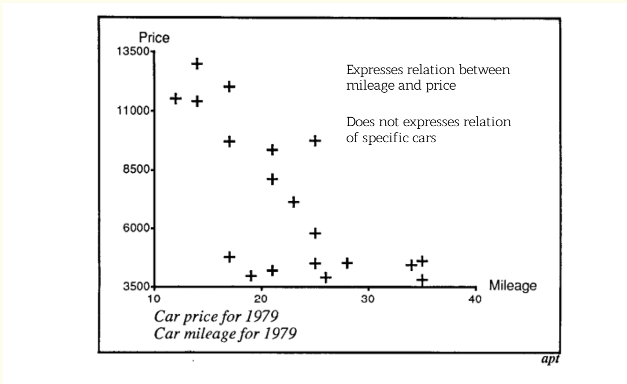

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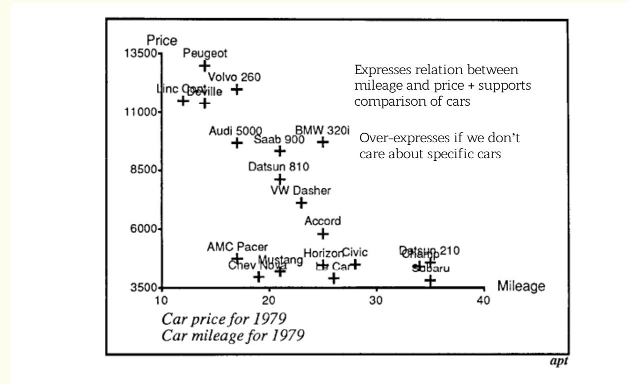

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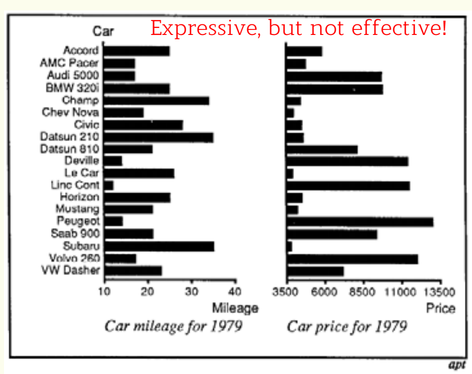

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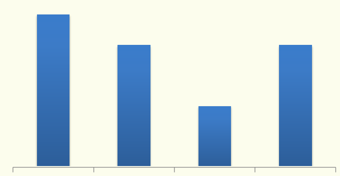
What is expressed here?
What is *not* expressed here?



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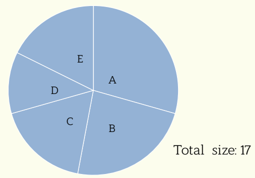
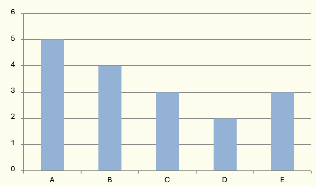
- Which is more expressive (expresses more facts)?
- Which is more effective?





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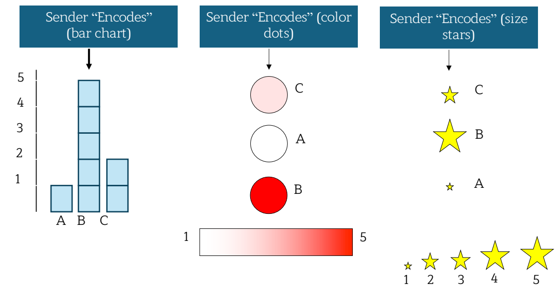
Which is better?

99% of visualization is on making the right choice…



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Answering the question

- The power (and limits) of perception
- The perception pipeline
- Ability to detect/estimate
- Gestalt psychology
- Multiple encodings
- Change blindness
- Color
- Context

91

Why is something effective?

(this will really tell us *what* is effective)

92

“All models are wrong, but some are useful.”

Attributed to George Box

93

Human visual system→ powerful but constrained

94

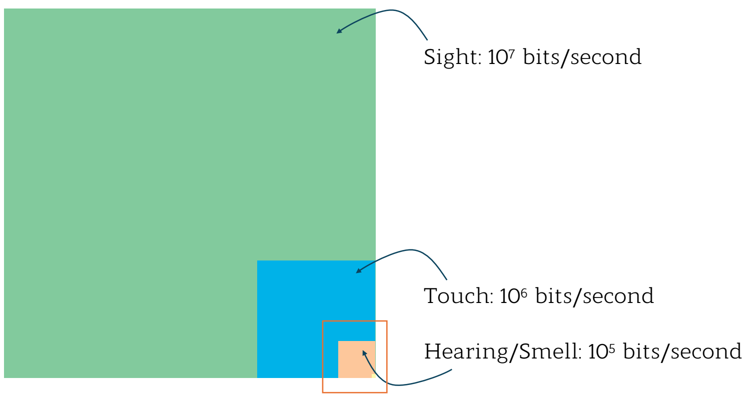
To remember:
1) Visual channel is high bandwidth & accurate (relatively)

95

Bandwidth of the senses in bits/second

Zimmerman, 1989

96



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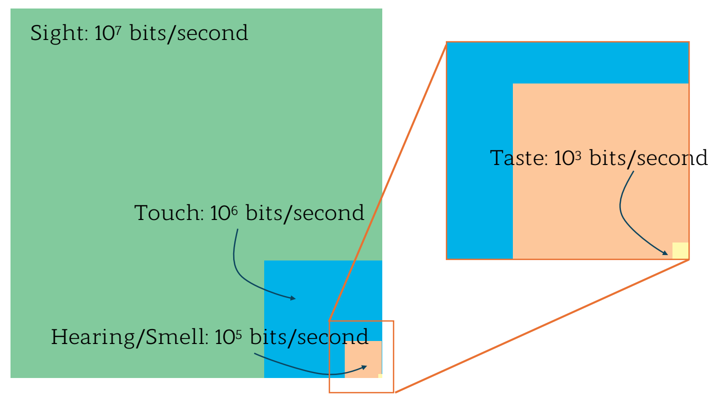

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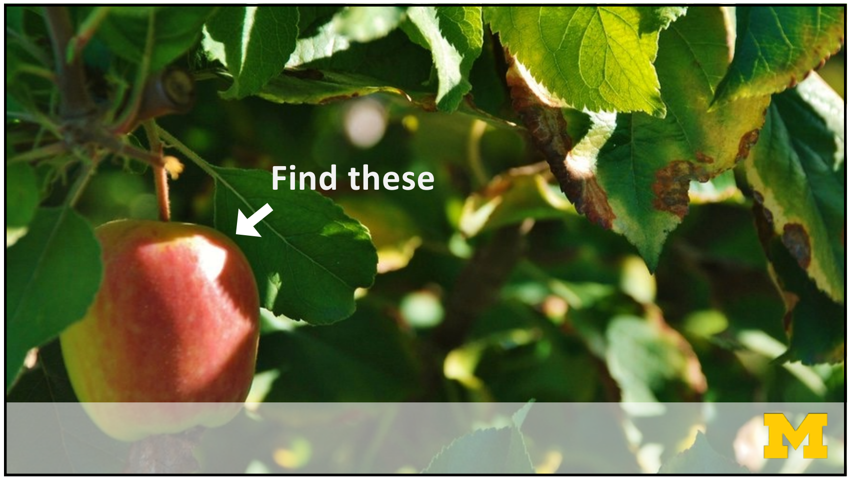
To remember:
1) Visual channel is high bandwidth & accurate (relatively)
2) Visual channel is primary

99

100

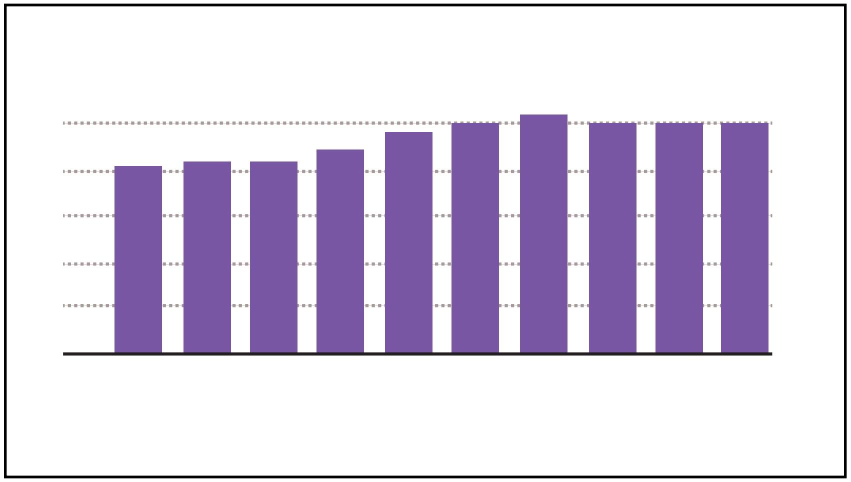
To remember:
1) Visual channel is high bandwidth & accurate (relatively)
2) Visual channel is primary
3) Visual channel is evolved

101



102

103



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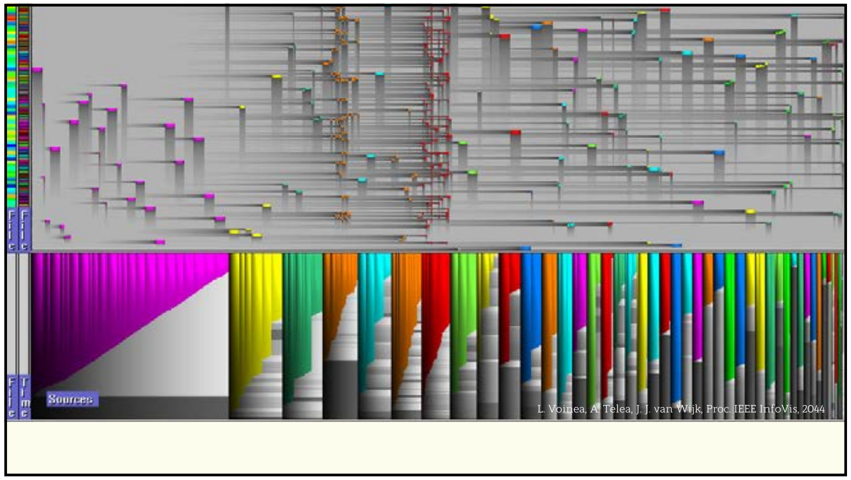

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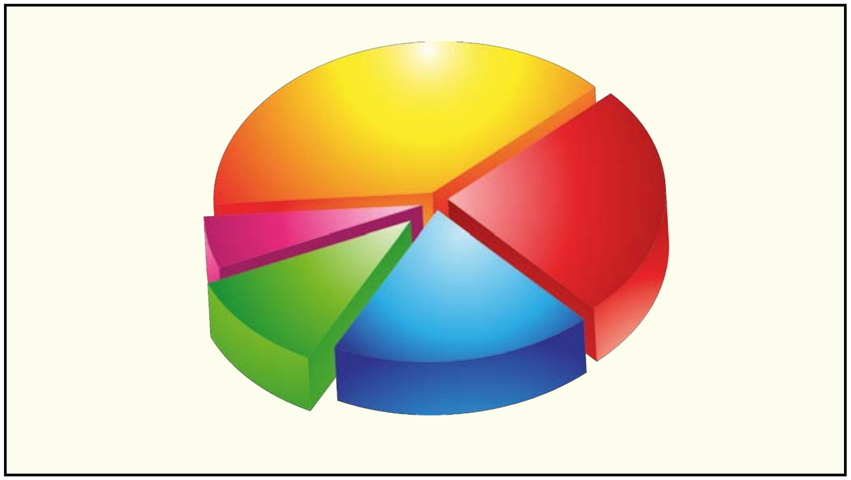

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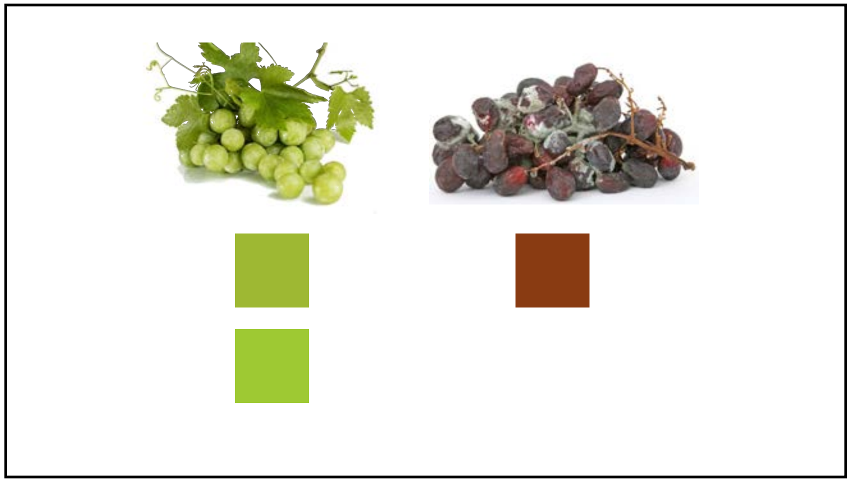

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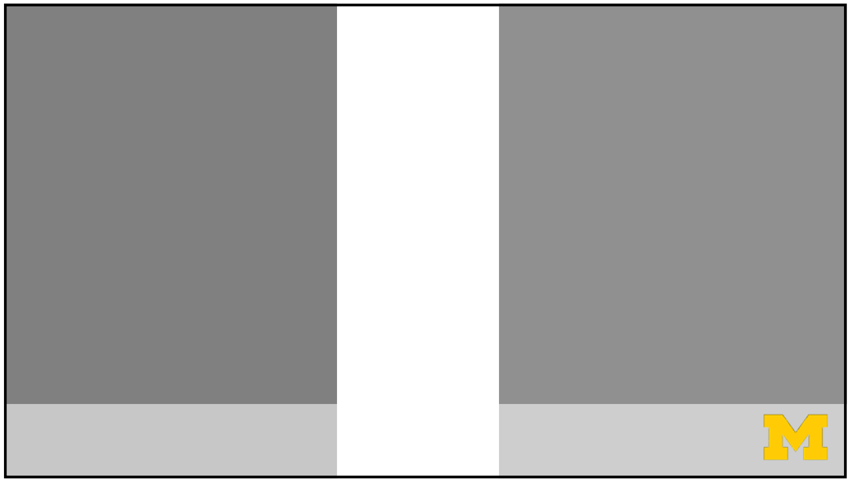

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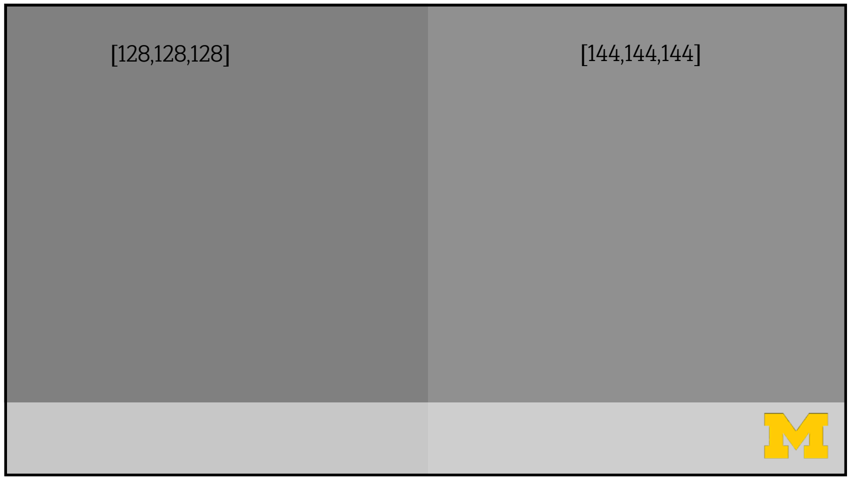

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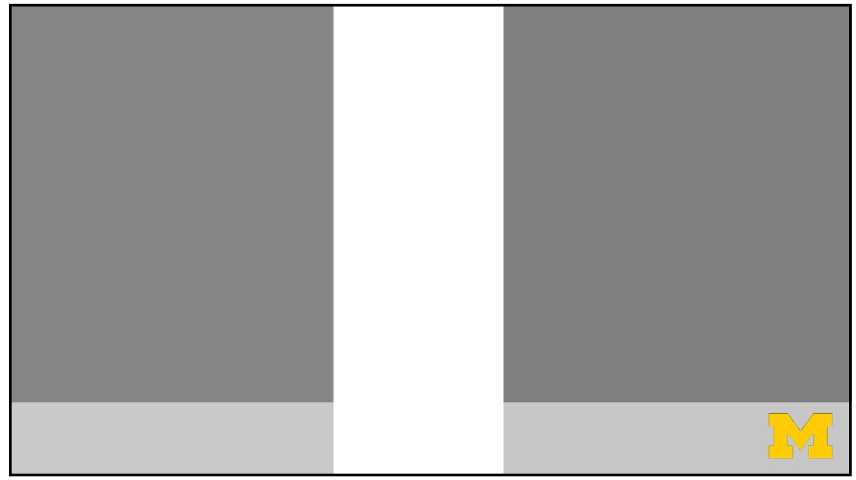

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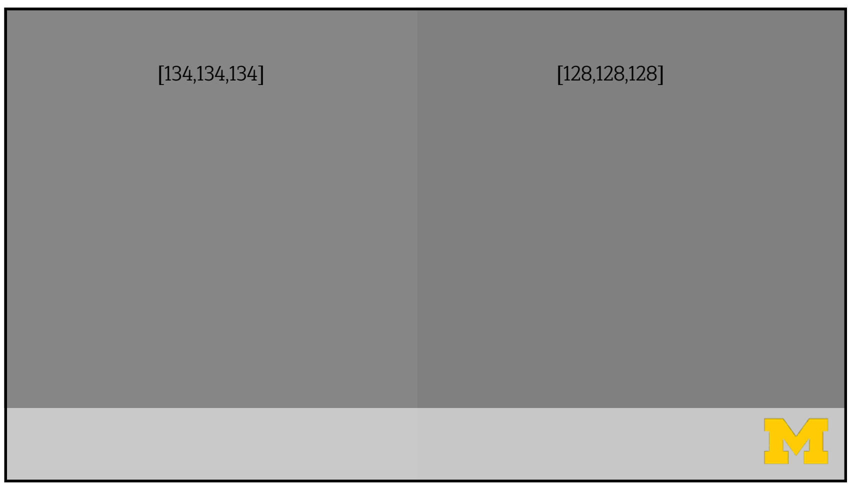
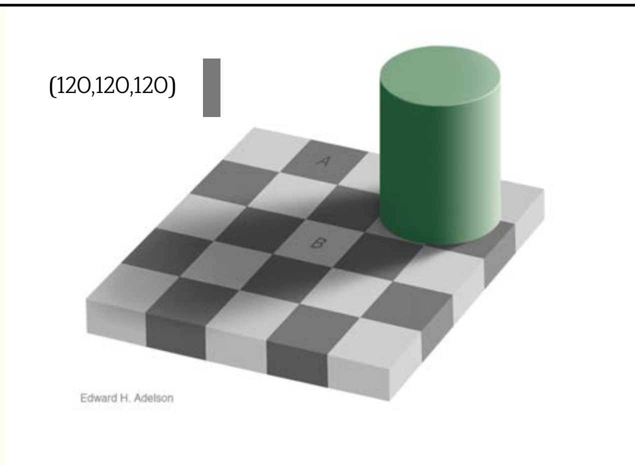


111

To remember:
1) Visual channel is high bandwidth & accurate (relatively)
2) Visual channel is primary
3) Visual channel is evolved
4) We prefer simple explanations

112



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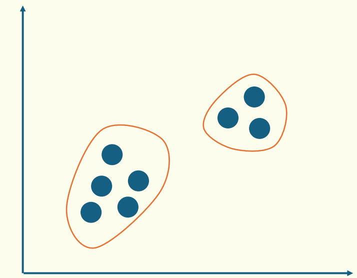


114

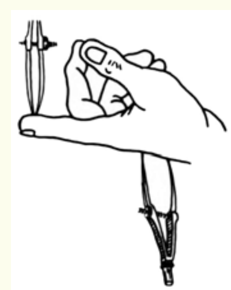
To remember:
1) Visual channel is high bandwidth & accurate (relatively)
2) Visual channel is primary
3) Visual channel is evolved
4) We prefer simple explanations

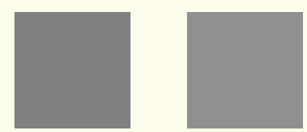
Visualization needs to work within the constraints of the system

115

Just Noticeable Difference

Increment where change is detected





116

Just Noticeable Difference

- Weber's law: $k = \frac{\Delta I}{I}$

Change in intensity

Intensity

Constant

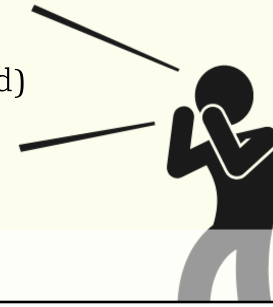
If $k = 1$ and $I = 2$ (quiet)
then $\Delta I = 2$

117

Just Noticeable Difference

- Weber's law: $k = \frac{\Delta I}{I}$

If $k = 1$ and $I = 100$ (loud)
then $\Delta I = 100$!



118

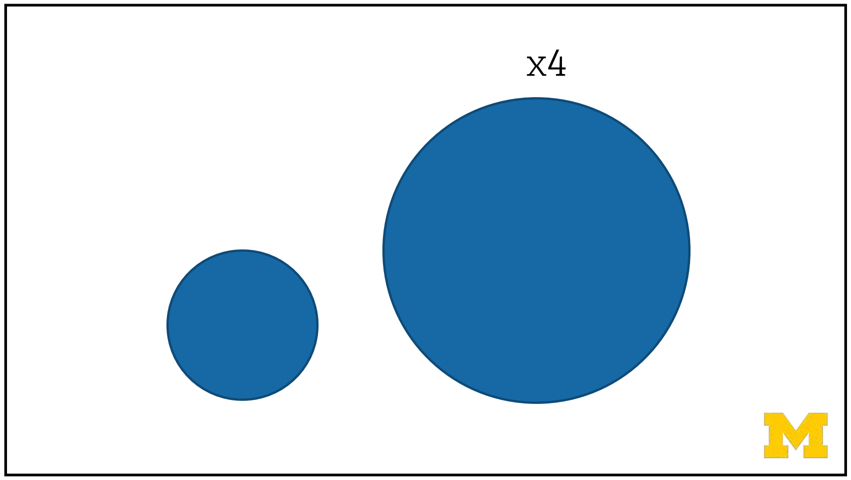
Just Noticeable Difference

- Most continuous data perceived discretely

119

Estimation…

120



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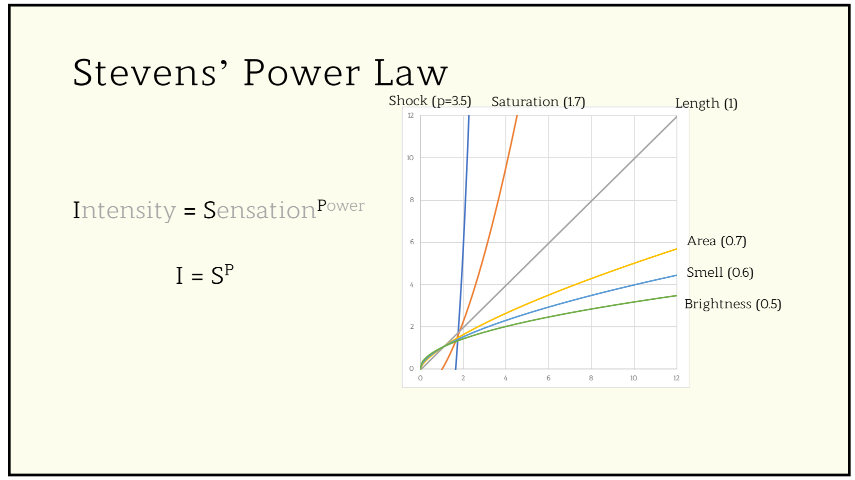

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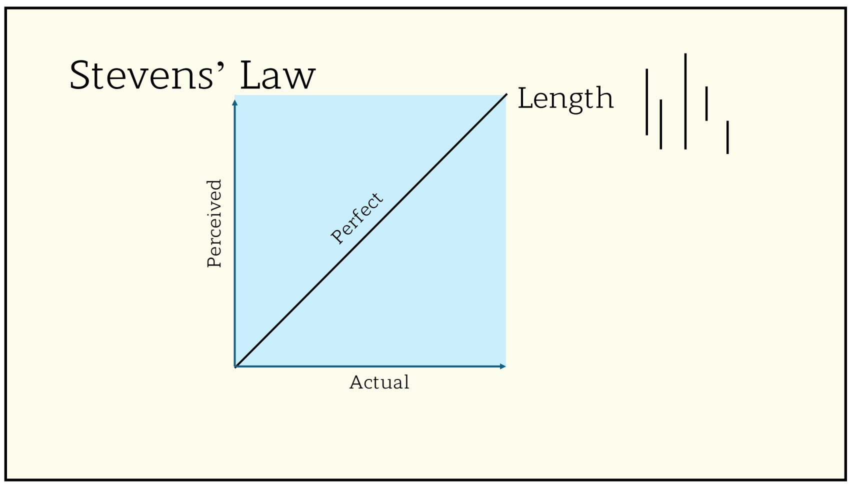

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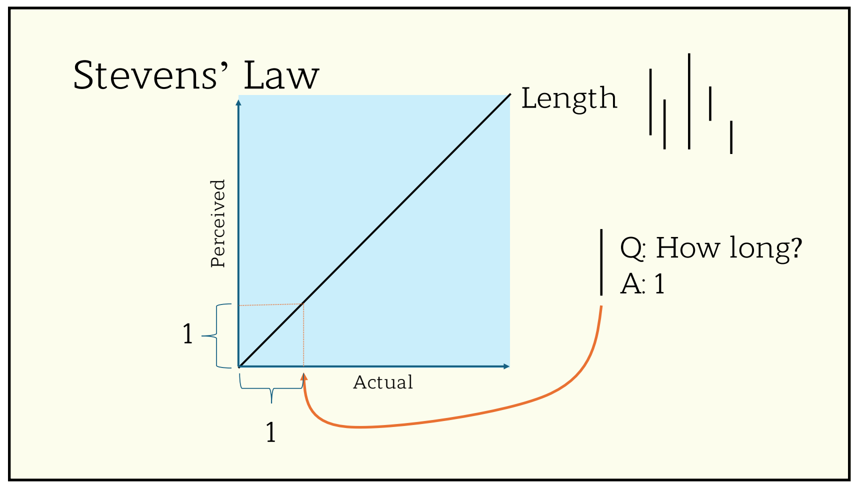

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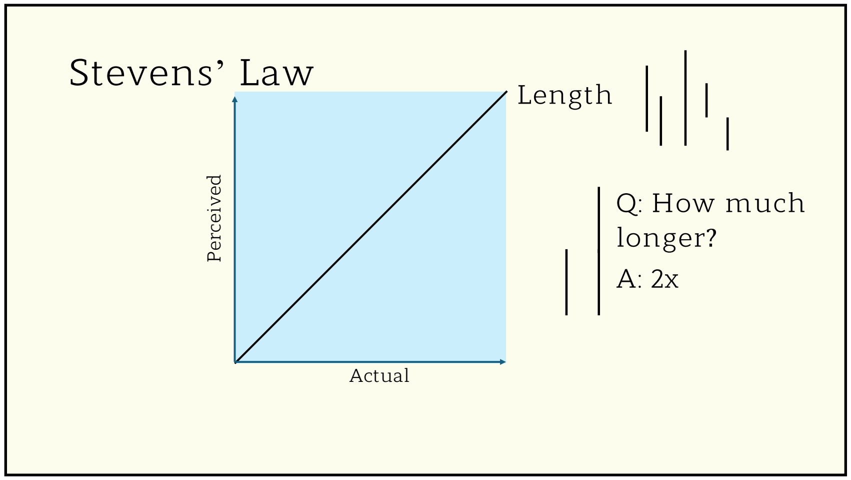

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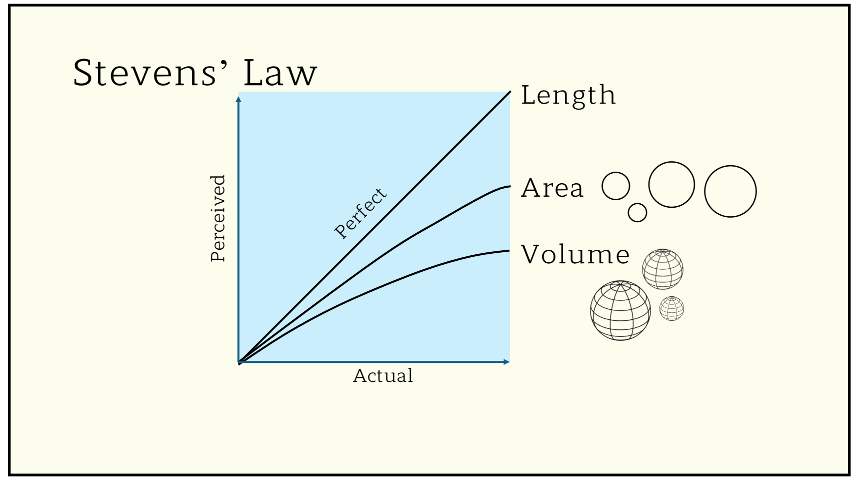

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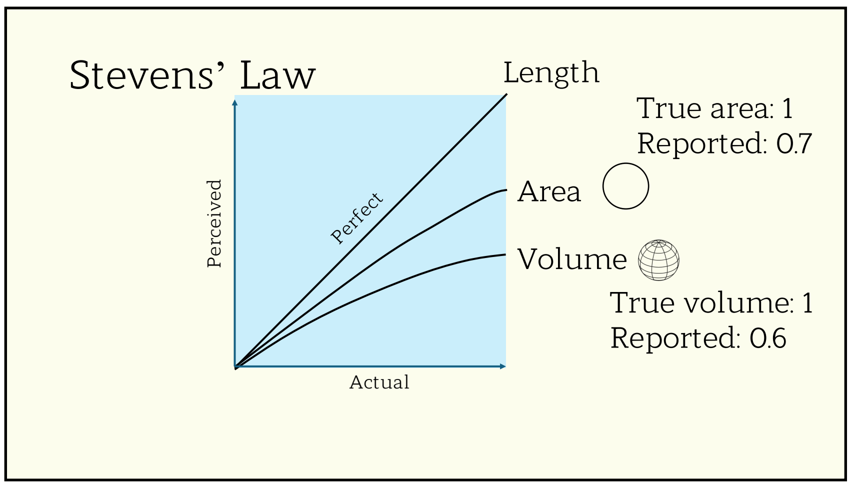

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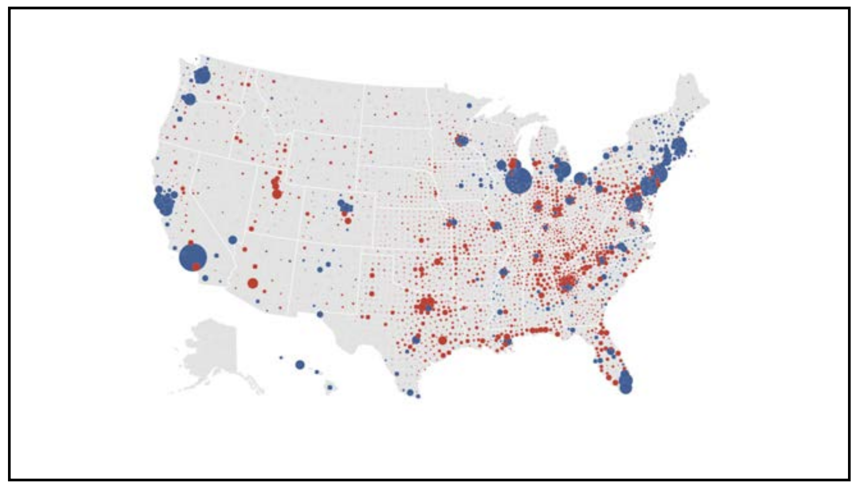

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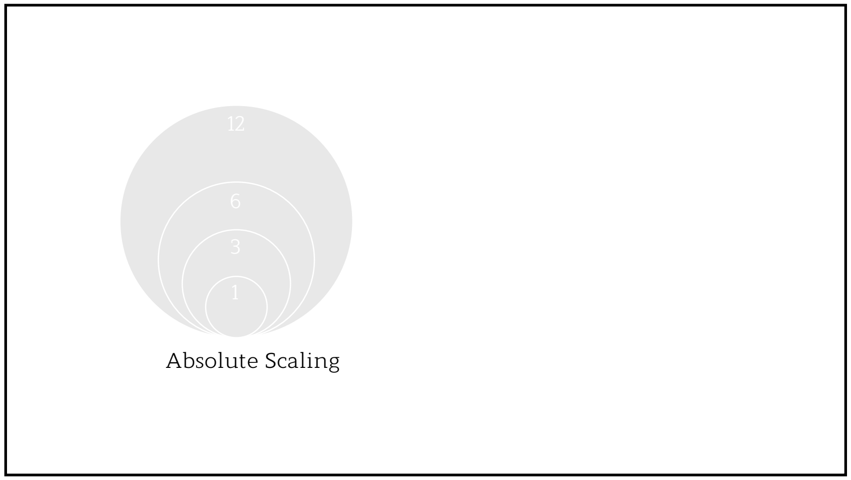

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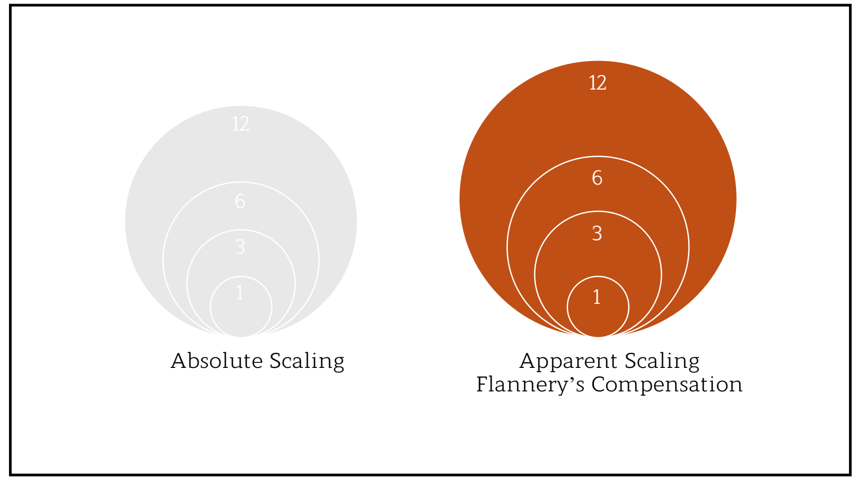

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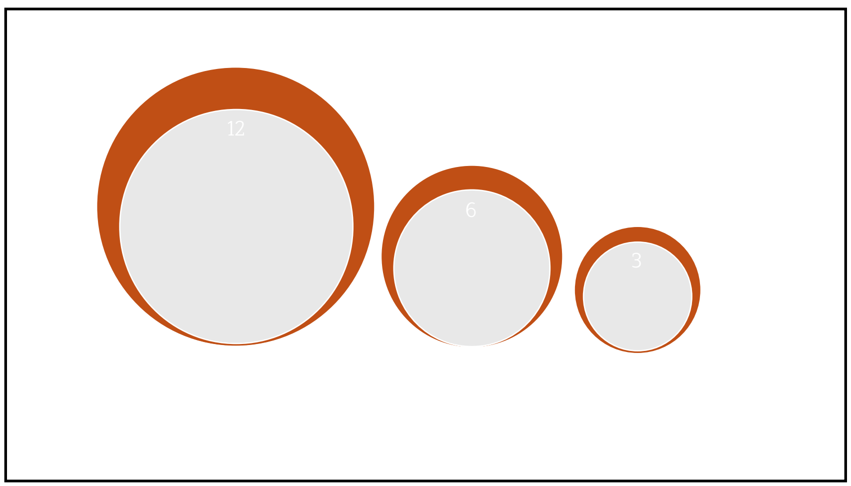

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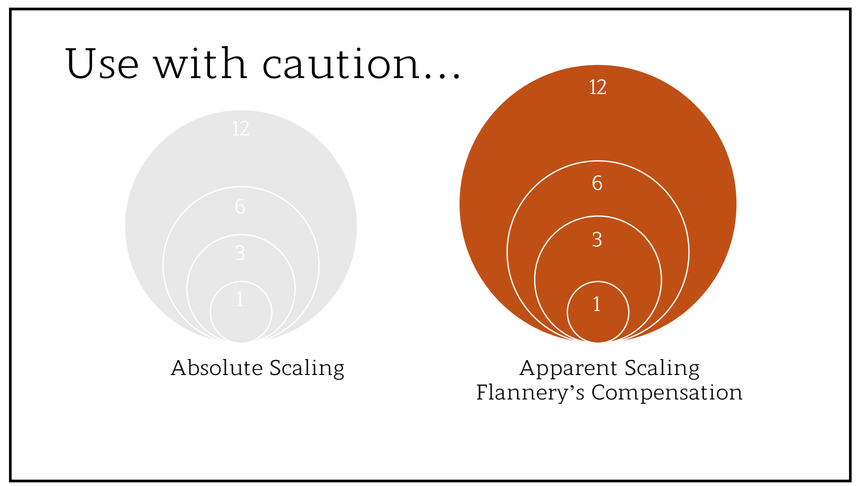

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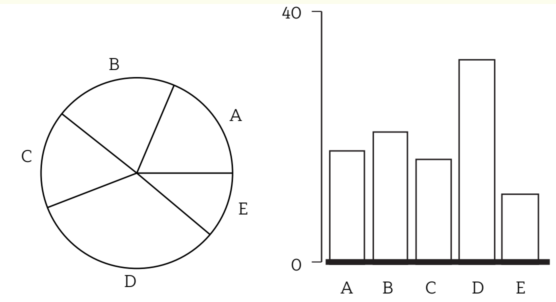
Takeaways

- Perception limits our ability to determine differences (JND/Weber's)
- Input signal != perception (Stevens')
- Impacts the accuracy of our reading of data
- Corrections should be used with caution (Flannery)

133

Cleveland/McGill

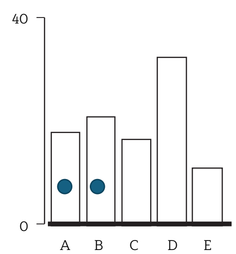


134

Cleveland/McGill

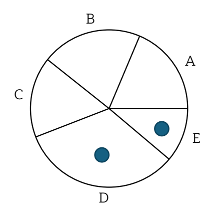
Q1: Which is bigger, A or B?

Q2: How much bigger?



135

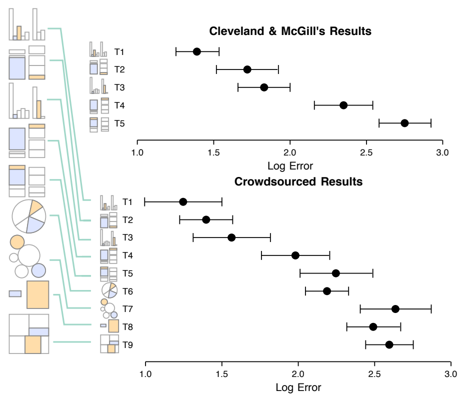
Cleveland/McGill



Q1: Which is bigger, E or D?

Q2: How much bigger?

136



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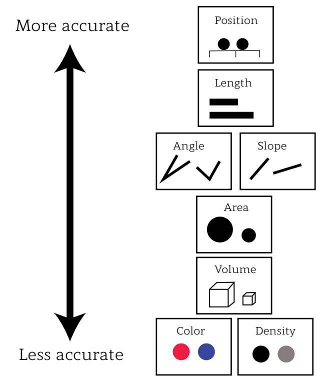

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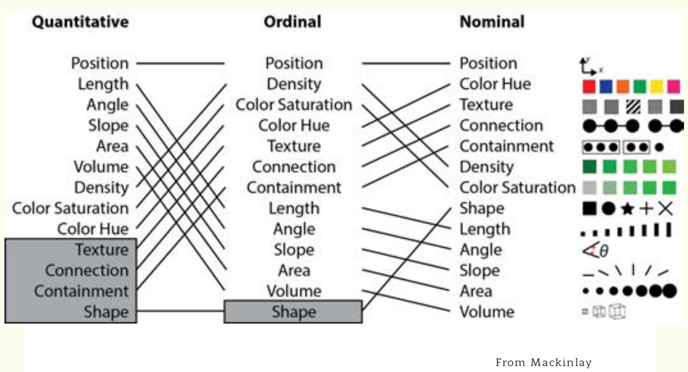


139

Takeaways

- Key findings in perception allow us:
  - Rank different "retinal variables"
  - Evaluate new techniques

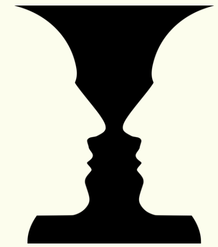
140

The simplest and most stable interpretations are favored

Law of Prägnanz

141

Principles – Figure and Ground



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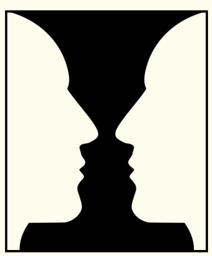
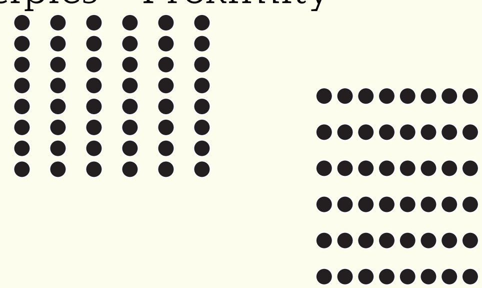
Principles – Figure and Ground



143

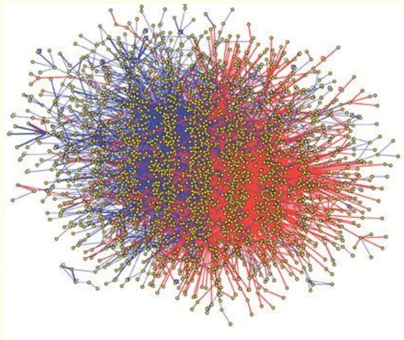
Principles – Proximity



http://www.aber.ac.uk/media/Modules/MC10220/visper07.html

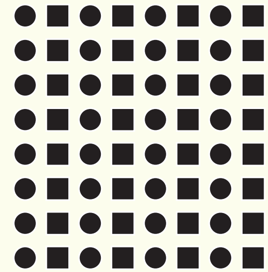
144

Principles – Proximity



145

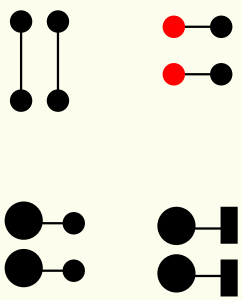
Principles –Similarity



http://www.aber.ac.uk/media/Modules/MC10220/visper07.html

146

Principles - Connectedness



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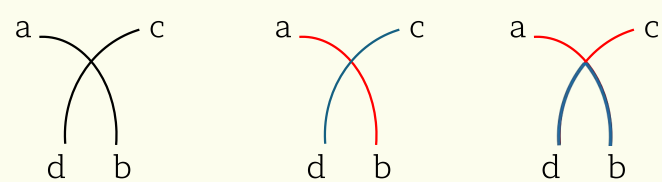
147

Principles - Continuation



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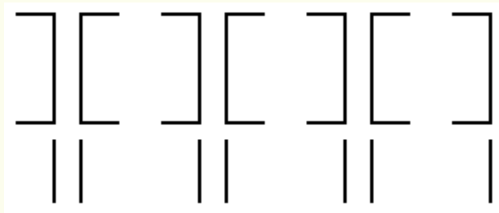
148

Principles –Closure



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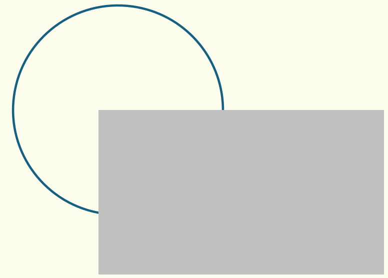
149

Principles – Closure



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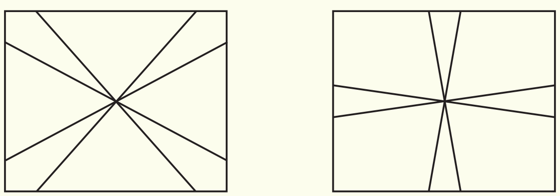
150

Principles – Smallness



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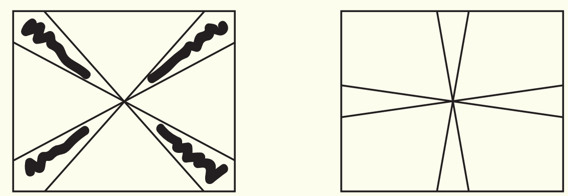
151

Principles – Smallness



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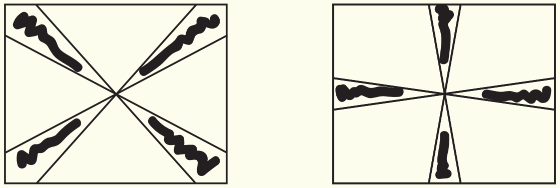
Principles – Smallness



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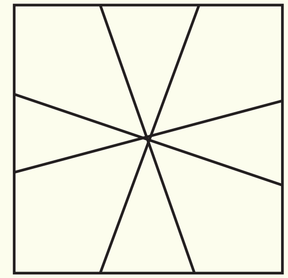
Principles – Smallness



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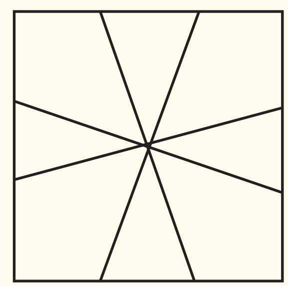
154

Principles – Smallness

http://www.aber.ac.uk/media/Modules/MC10220/visper07.html

155

Principles – Smallness



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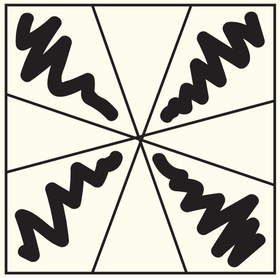
156

Principles – Smallness



http://www.aber.ac.uk/media/Modules/MC10220/visper07.html

157

Principles –Surroundedness

http://www.aber.ac.uk/media/Modules/MC10220/visper07.html

158

Principles –Surroundedness

http://www.aber.ac.uk/media/Modules/MC10220/visper07.html

159

The simplest and most stable interpretations are favored

Law of Prägnanz

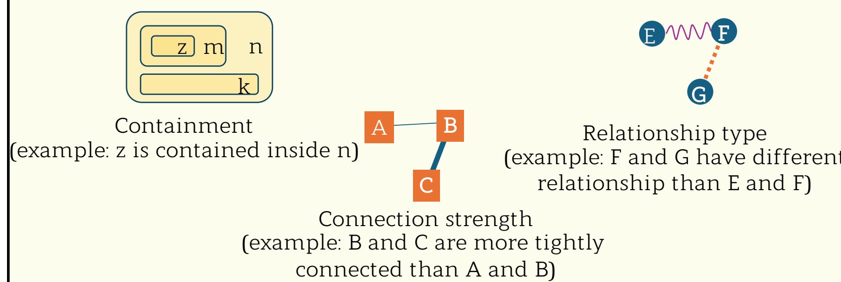
160

Takeaways

- Gestalt psychology indicates we focus on simple explanations
- Specific laws/principles around this
- Can be used to our advantage but can also create problems

161

Semantics and metaphor



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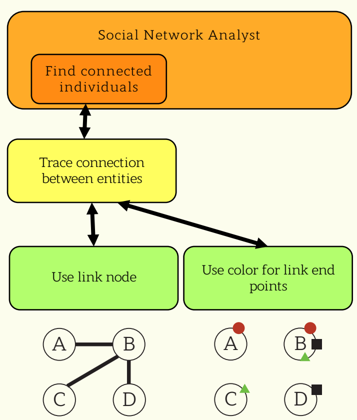

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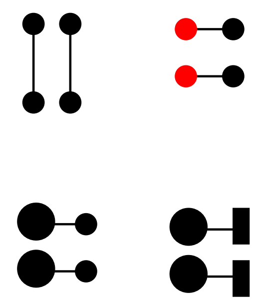
An aside: precedence

164

Principles

- Remember this?



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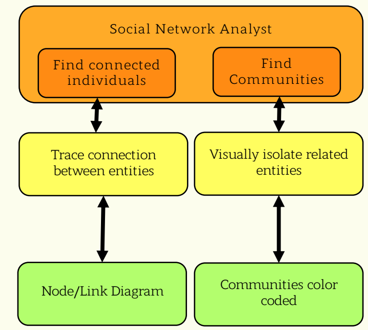

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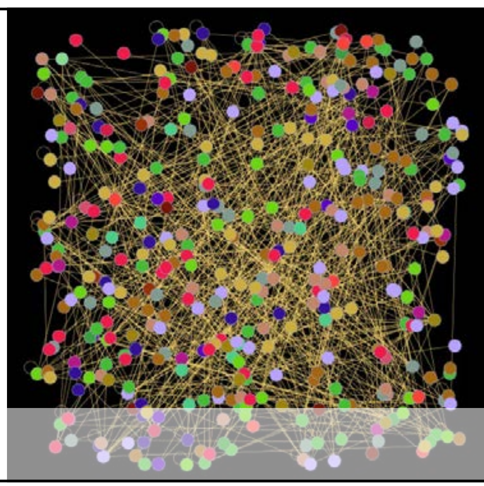

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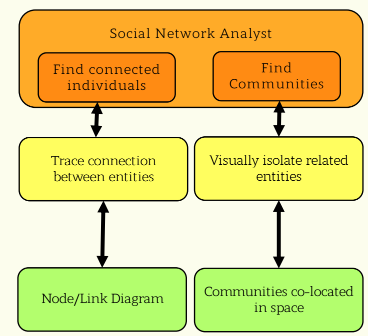

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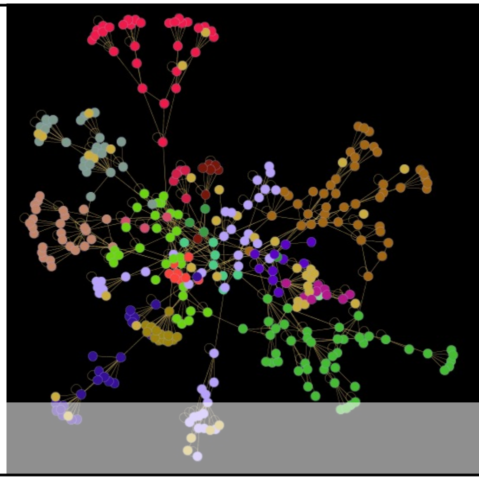

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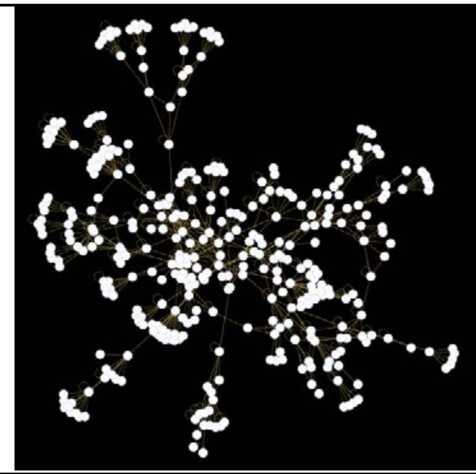

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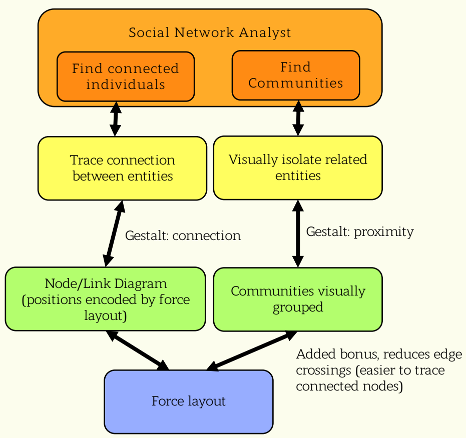

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Takeaways

- Gestalt principles can be applied to building (and understanding) visualizations
- Critical feature: focus on simple explanations

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Change Blindness
(what's different?)

173

174

175

176

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178

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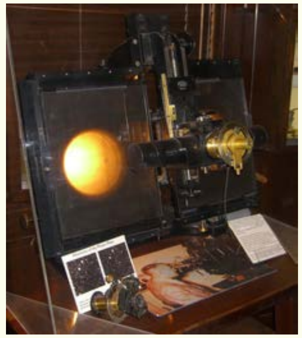
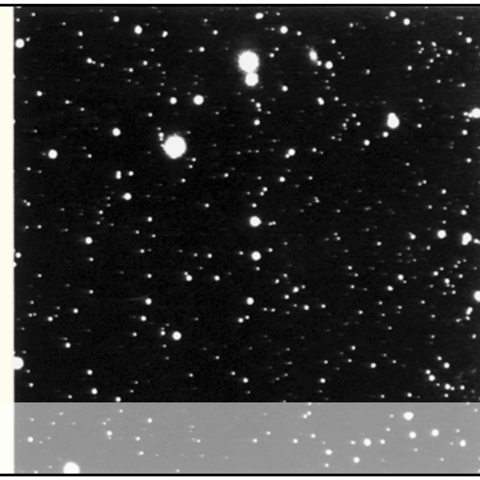
Relation to visualization:
Change Blindness ←→ Change Detection

180



How Tombaugh found Pluto

181



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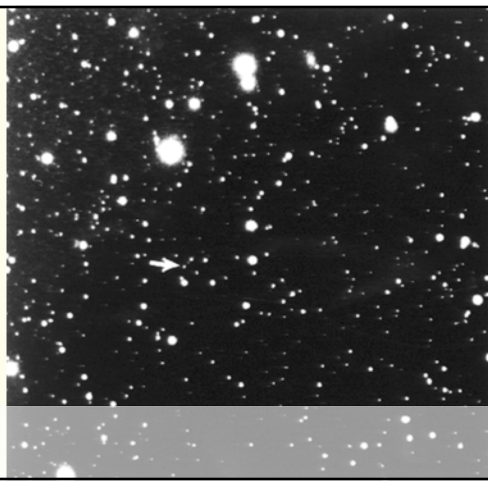

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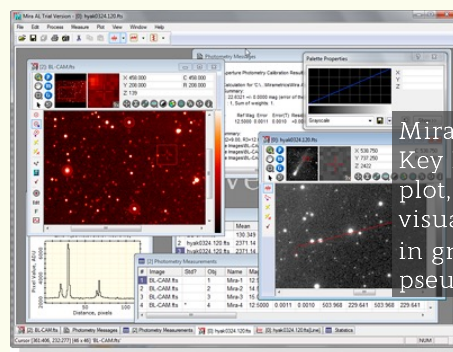

Mira AL
Key Features: “Display, plot, animate, blink, and visually enhance images in grayscale, color, and pseudo-color.”

184

185

Takeaways

- Change is good for detecting interesting data features
- Change *blindness* can impact comparisons
- Caution needed when designing software

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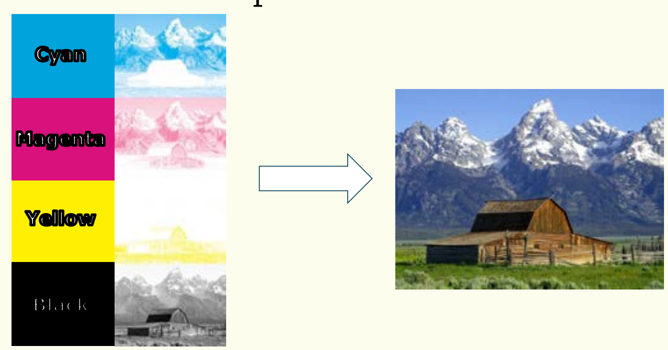
Color spaces

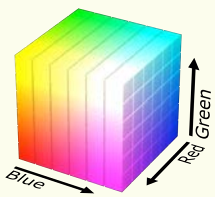
187

CMYK Color Space



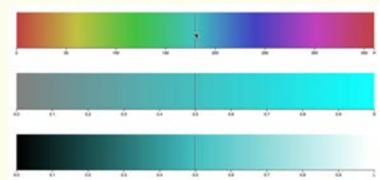
188

RGB Color Space



189

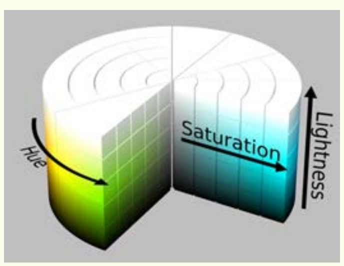
HSL Color Space



- H – Hue (the color, 0-360)
- S – Saturation (from neutral gray to full saturation – muted to vivid)
- L – Lightness (from black to white)

190

HSL Color Space

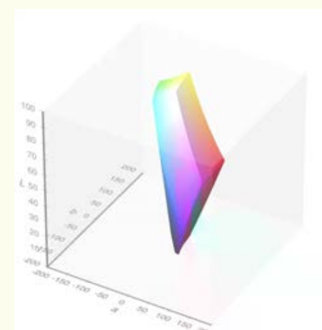


- H – Hue (the color, 0-360)
- S – Saturation (from neutral gray to full saturation)
- L – Lightness (from black to white)

191

CIELAB Color Space

- Better models perception
- l* - lightness (0 to 100)
- a* - red to green (negative to positive)
- b* - yellow to blue (negative to positive)
- Non-linear, 3D but *perceptual* distances preserved



192

Which one to work with

- RGB/CMYK – easier to think about but device dependent
- Lab – hard to reason about, but more accurate to human perception
- HSL – designed to be aligned to perception but distances inaccurate

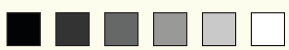
193

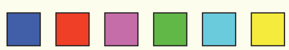
Picking colors

194

Picking colors

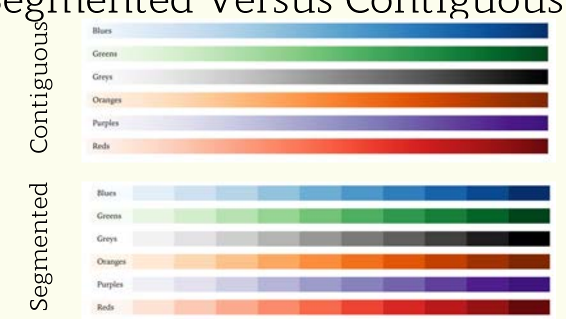
- For ordered data –
  - Luminance in HSL space
  - (Possibly not grayscale)
  - Saturation can work
    - not as easily discernable and interacts
- For nominal data
  - Hue





195

Segmented Versus Contiguous

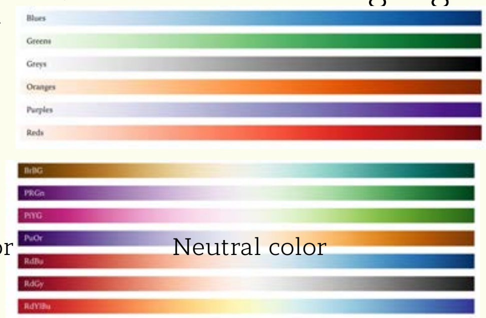


196

Sequential versus Diverging

Sequential

Start color



End color

Diverging

Start color

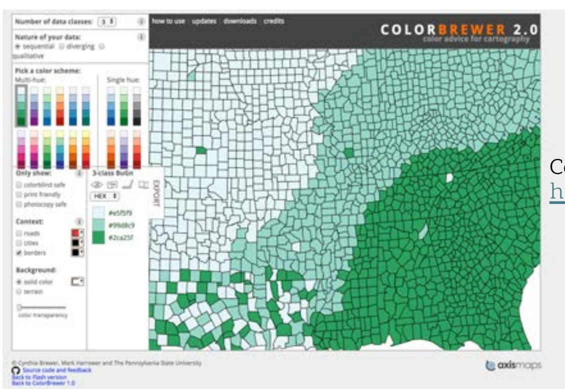
Neutral color

End color

197

Tools

198

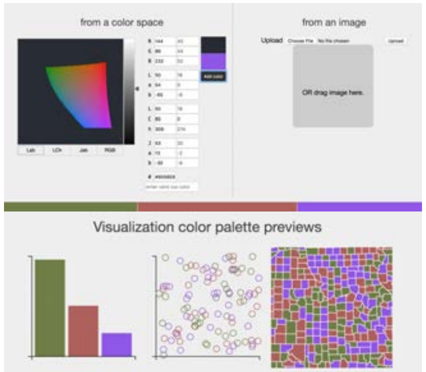


Color Brewer 2.0
http://colorbrewer2.org

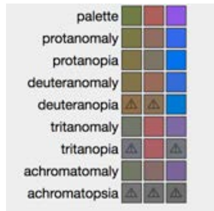
199

Color Picker for Data
http://tristen.ca/hcl-picker/

200



Chromaticity
http://gramaz.io/chromaticity/



201

A bit about what we'll do today…

1) Infovis, perception, and cognition
   - Why visualizations work, what they're good for, choosing the right ones, (also a bunch of vocabulary)
2) Communication through infovis
   - How to achieve communicative intents
3) Unconventional approaches
   - Beyond the bar chart

202

A bit about what we'll do today…

1) Infovis, perception, and cognition
   - Why visualizations work, what they're good for, choosing the right ones, (also a bunch of vocabulary)
2) Communication through infovis
   - How to achieve communicative intents
3) Unconventional approaches
   - Beyond the bar chart

Elsie Lee-Robbins
https://elsiejlee.com/

203

Distinction between

- High level goals
  - What are we trying to communicate? Did we do a good job?
- Specific strategies
  - Design, annotations, etc.

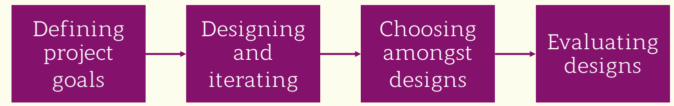
204

Distinction between

- High level goals
  - What are we trying to communicate? Did we do a good job?
- Specific strategies
  - Design, annotations, etc.

205

Data Visualization Design Process



http://visualobjectives.net/

206

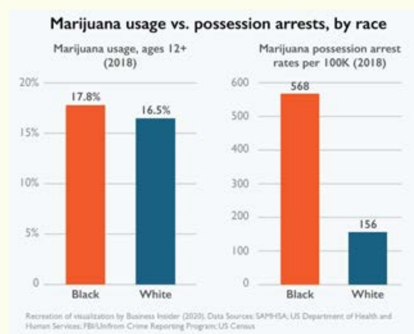
What is a Learning Objective?

- Outcomes of what the viewer should be able to know or do after viewing the visualization

http://visualobjectives.net/

207

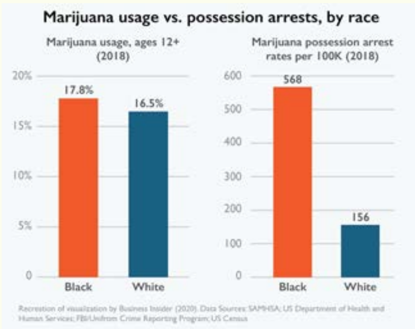
Examples of Learning Objectives



http://visualobjectives.net/

208

Examples of Learning Objectives



The viewer will **recall** the average rate of marijuana usage.

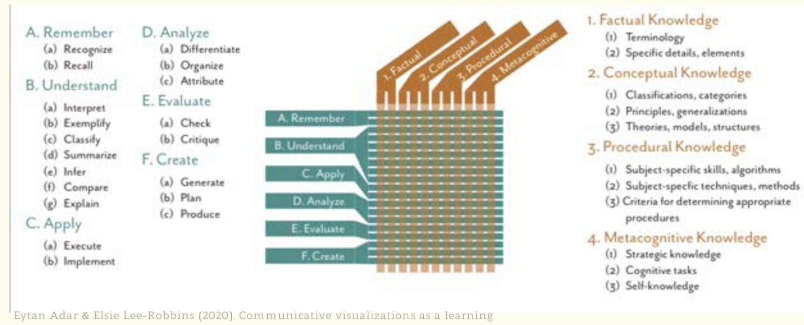
The viewer will **compare** the arrest rates for white and Black people.

The viewer will **attribute** the disparity to systemic racism.

http://visualobjectives.net/

209

Cognitive Learning Objectives Taxonomy



Eytan Adar & Elsie Lee-Robbins (2020). Communicative visualizations as a learning problem. IEEE Transactions on Visualization and Computer Graphics.

210

SMART Goals

- Specific
- Measurable
- Attainable
- Relevant
- Time-bound

http://visualobjectives.net/

211

Use specific and measurable verbs

- Avoid ambiguous, broad verbs, such as understand, learn, or know.
  - Vague: The viewer will understand marijuana usage and possession arrest rates by race.
  - Better: The viewer will infer disparities between marijuana usage and possession arrest rates by race."

http://visualobjectives.net/

212

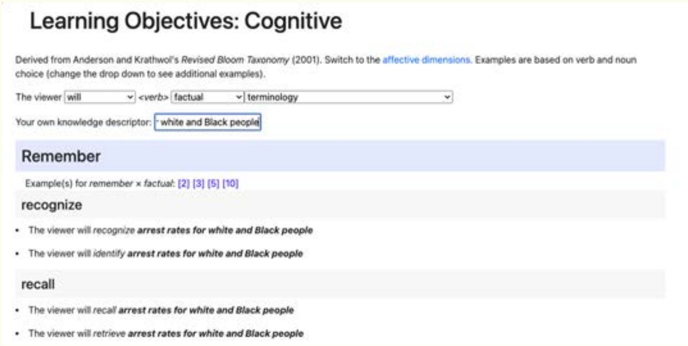
SMART Goals

- Specific
- Measurable
- Achievable
- Relevant
- Time-bound

http://visualobjectives.net/

213

http://visualobjectives.net/



214

Affective Learning Objectives

- Reaction or a response to an appraisal, attitude, or value

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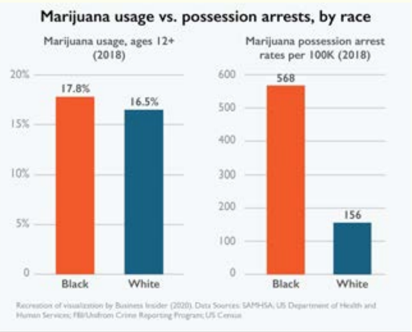
215

Examples of Learning Objectives



The viewer will **consider** the harm of racism.

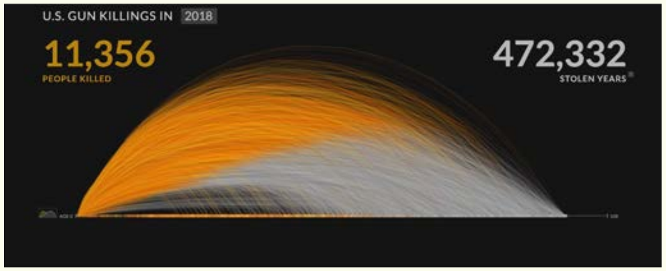
The viewer will **support** racial justice initiatives.

http://visualobjectives.net/

216

Affective Visualizations

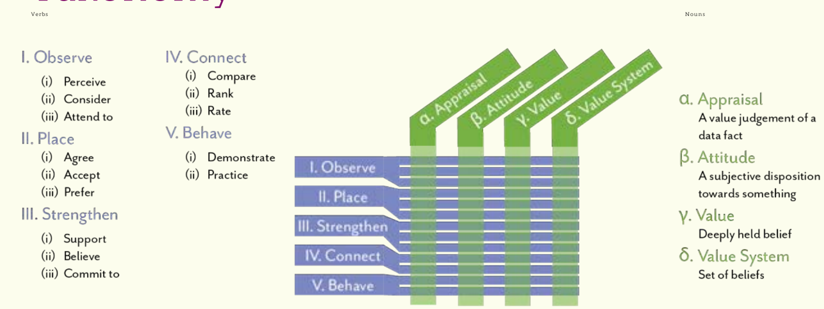
https://guns.periscopic.com



Periscopic. (2018). U.S. Gun Deaths.

217

Affective Learning Objectives Taxonomy



http://visualobjectives.net/

218

Common Mistakes and Difficulties

- Combining multiple goals into one learning objective
  - The viewer will compare the rates of marijuana usage and arrests and attribute the difference to systemic racism.

http://visualobjectives.net/

219

Common Mistakes and Difficulties

- Combining multiple goals into one learning objective
- Non-measurable verbs
- Match verbs to your goals
- Blurring the lines between cognitive and affective goals

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220

Programmatic Goals

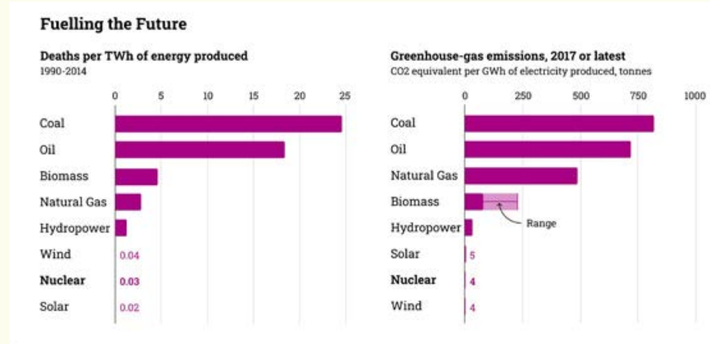
Broader goals that a designer aims to achieve over a longer period of time and over several or many visualizations.

- Single visualization learning objective: The viewer will observe the environmental impact of a chemical on an indigenous population.
- Programmatic learning objective: The viewer will agree that climate justice is an important issue.

http://visualobjectives.net/

221

Pop Quiz

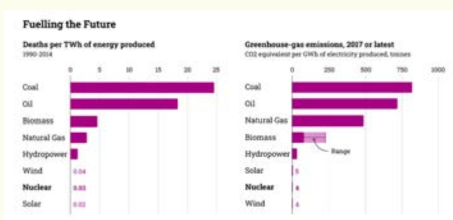


Recreated from The Economist, Data from Our World in Data

222

Pop Quiz

The viewer will **agree** that nuclear power is a safe and clean source of energy.



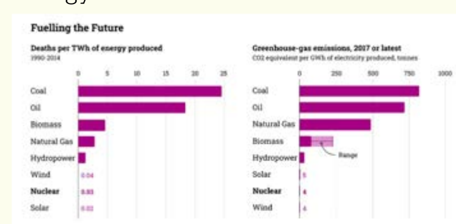
Recreated from The Economist, Data from Our World in Data

http://visualobjectives.net/

223

Pop Quiz

The viewer will **learn** about the greenhouse-gas emissions for popular energy sources.



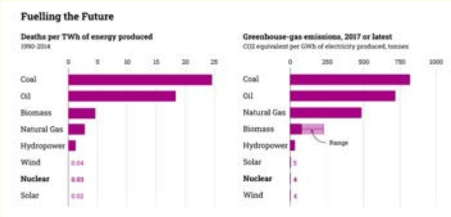
Recreated from The Economist, Data from Our World in Data

http://visualobjectives.net/

224

Pop Quiz

The viewer will **summarize** the relationship between greenhouse-gas emissions and deaths.



Recreated from The Economist, Data from Our World in Data

http://visualobjectives.net/

225

Why use learning objectives for dataviz?

- Communicate goal within a team or to external people
- Design better visualizations
- Create assessments for evaluation

http://visualobjectives.net/

226

What is a Learning Objective?

- Outcomes of what the viewer should be able to know or do after viewing the visualization
- The viewer will [verb] [noun].
  - The viewer will recall the percentage of plastic that gets recycled.
  - The viewer will compare the carbon footprint of beef compared to chicken.

http://visualobjectives.net/

227

Data Visualization Design Process

Defining project goals → Designing and iterating → Choosing amongst designs → Evaluating designs

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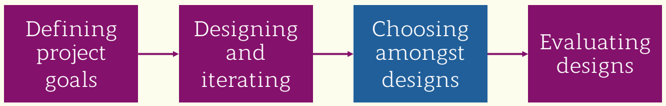
228

Data Visualization Design Process



http://visualobjectives.net/

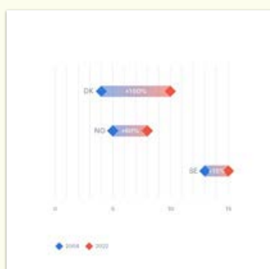
229

1 dataset. 100 visualizations.

Visualizations from Ferdio, https://100.datavizproject.com/

230

Which visualization is better?



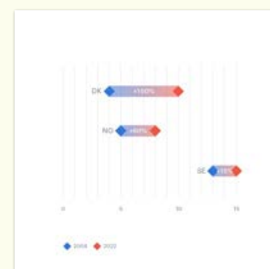
http://visualobjectives.net/

Visualizations from Ferdio, https://100.datavizproject.com/

231

Which visualization is better?

The viewer will compare the ranks of countries over time.



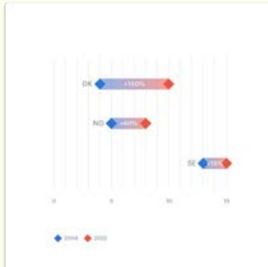
http://visualobjectives.net/

Visualizations from Ferdio, https://100.datavizproject.com/

232

Which visualization is better?

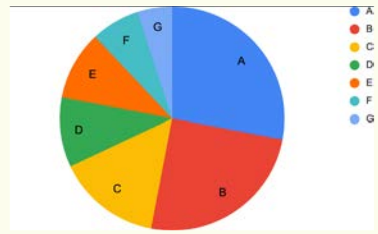
The viewer will recall the percentile change for each country.



http://visualobjectives.net/

Visualizations from Ferdio, https://100.datavizproject.com/

233



The viewer will recall that categories A and B together make up about 50% of the total.

234

The viewer will recall that categories A and B together make up about 50% of the total.

http://visualobjectives.net/

235

Categories A and B make up about 50% of the total.

The viewer will recall that categories A and B together make up about 50% of the total.

http://visualobjectives.net/

236

Pop Quiz

The viewer will recall the overall increase from 2004 to 2022.

http://visualobjectives.net/

Visualizations from Ferdio, https://100.datavizproject.com/

237

Why use learning objectives for infovis?

- Communicate goal within a team or to external people
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- Create assessments for evaluation

http://visualobjectives.net/

238

Data Visualization Design Process

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http://visualobjectives.net/

239

Data Visualization Design Process

Defining project goals → Designing and iterating → Choosing amongst designs → Evaluating designs

http://visualobjectives.net/

240

Assessing and Measuring Outcomes

- Number of clicks, number of shares, length of reading time
- Multiple-choice questions
- Interviews, focus groups, surveys

http://visualobjectives.net/

241

What is a Learning Objective?

- Outcomes of what the viewer should be able to know or do after viewing the visualization
- The viewer will compare the carbon footprint of beef to chicken.

http://visualobjectives.net/

242

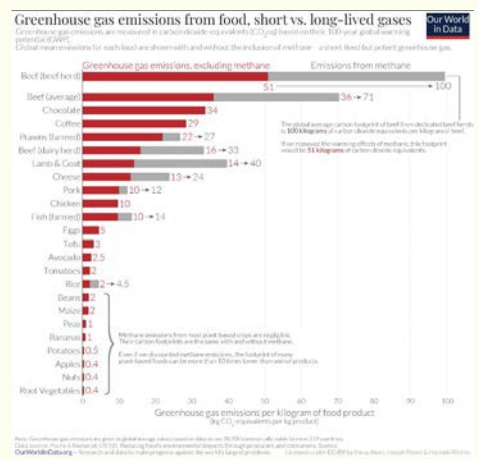
How to design multiple-choice questions

A multiple-choice question (MCQ) is composed of two parts:

- a stem that identifies the question or problem, and
- a set of alternatives that contain
  - the best answer to the question, and
  - a number of distractors that are plausible but incorrect answers to the question

http://visualobjectives.net/

243



244

Beef results in ______ times more greenhouse gas emissions compared to chicken.

- 3
- 6
- 10

245

Designing stems

- Express the full problem and put all relevant material in the stem.
- Eliminate excessive wording and irrelevant information from the stem.
- Avoid giving verbal association clues from the stem.
- Use familiar language.
- Check the alignment between the question and the goal.

246

Full information in the stem

Beef results in ____ times more greenhouse gas emissions.

- 3
- 6
- 10

3-4 alternatives

247

Too much text

When considering the environmental impacts of different types of meat, a kilogram of beef results in ______ times more greenhouse gas emissions compared to a kilogram of chicken.

- 3
- 6
- 10

248

Avoid hints at answer

Beef results in the highest ratio: ___ times more greenhouse gas emissions compared to chicken.

- 3
- 6
- 10

249

Avoid unfamiliar language

A kg of cattle results in ___ times more GHG compared to a kg of poultry.

- 3
- 6
- 10

250

The viewer will compare the carbon footprint of beef to chicken.

Alignment between objective and question

Beef results in ___ times more greenhouse gas emissions compared to chicken.

- 3
- 6
- 10

251

Designing alternatives

- Limit the number of alternatives.
- Make sure there is only one correct answer.
- Make the distractors appealing and plausible.
- Make the choices grammatically consistent with the stem.
- Place the choices in some meaningful order.

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252

Beef results in ___ greenhouse gas emissions compared to chicken.

- Half as much
- Three times as much
- Ten times as much

Don't pick language that is inconsistent with the visualization

253

Beef results in ___ times more greenhouse gas emissions compared to chicken.

- triple
- six
- ten-fold

Don't use obvious outliers (grammatical consistency)

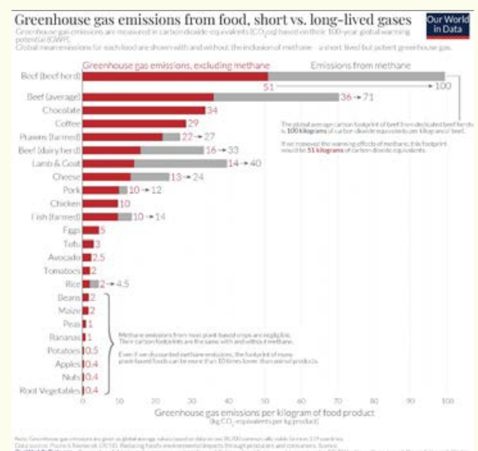
254

Beef results in ___ times more greenhouse gas emissions compared to chicken.

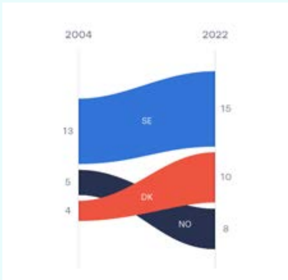
- 6
- 3
- 10

Avoid random order (use meaningful order)

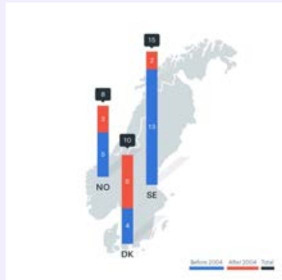
255



256



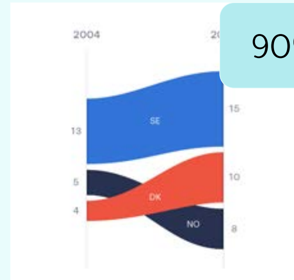
What country had the biggest increase from 2004 to 2022?



What country had the biggest increase from 2004 to 2022?

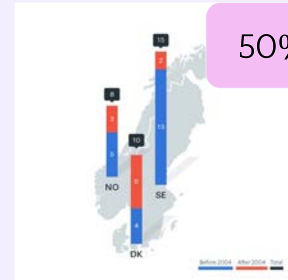
Visualizations from Ferdio, https://100.datavizproject.com/

257



90%

What country had the biggest increase from 2004 to 2022?



50%

What country had the biggest increase from 2004 to 2022?

Visualizations from Ferdio, https://100.datavizproject.com/

258

Open-ended question

What is the main takeaway this graph is communicating?

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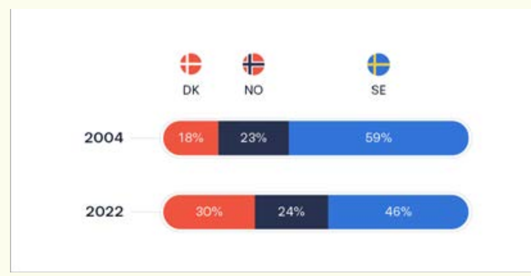
259

Pop Quiz

The viewer will recall that Sweden used to have over half of all sites and now has under half.



Visualization from Ferdio, https://100.datavizproject.com/

260

Pop Quiz

The viewer will recall that Sweden used to have over half of all sites and now has under half.

A: True or False? Sweden used to have over half of all sites and now has under half.
- True
- False

B: What percentage of sites did Sweden have in 2004 and 2022?
- 59% to 46%
- 46% to 59%
- 30% to 59%

C: Which country gained the most new sites between 2004 and 2022?
- Sweden
- Denmark
- Norway

http://visualobjectives.net/

261

Why use learning objectives for dataviz?

- Communicate goal within a team or to external people
- Design better visualizations
- Create assessments for evaluation

http://visualobjectives.net/

262

Example redesign…

263

Some resources

- https://www.datavizstyleguide.com/
- https://brand.umich.edu/design-resources/
- https://www.rawgraphs.io/

264

Distinction between

- High level goals
  - What are we trying to communicate? Did we do a good job?
- Specific strategies
  - Design, annotations, etc.

265

Distinction between

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  - What are we trying to communicate? Did we do a good job?
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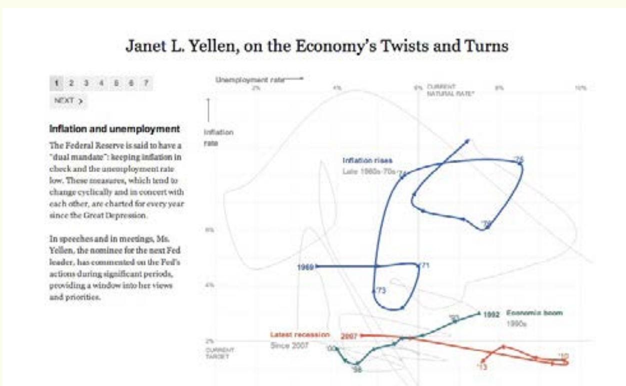
266

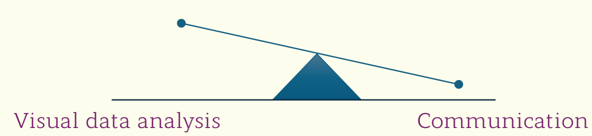


http://www.nytimes.com/interactive/2013/10/09/us/yellen-fed-chart.html

267

Communicative Vis in Context

- We want them to *learn* something
  - We (the designers) have insights/ideas/processes we want to communicate
- We want to get beyond "explore" (analysis)
- Storytelling helps:
  - More than "just annotation"
  - Engages: conflict, resolution, uncertainty

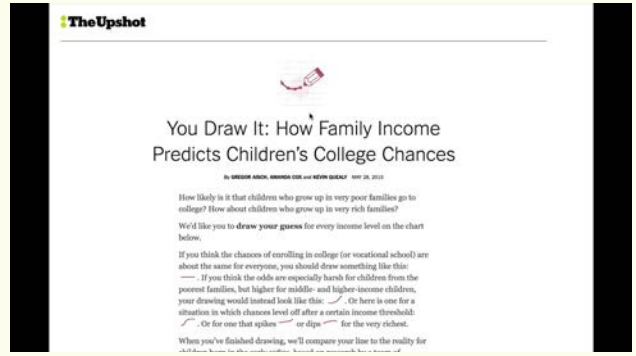


268

Let me tell you…

269

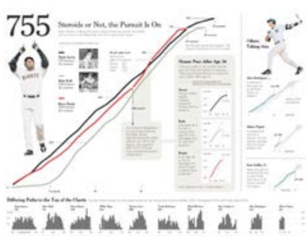
Draw Your Expectations…



270

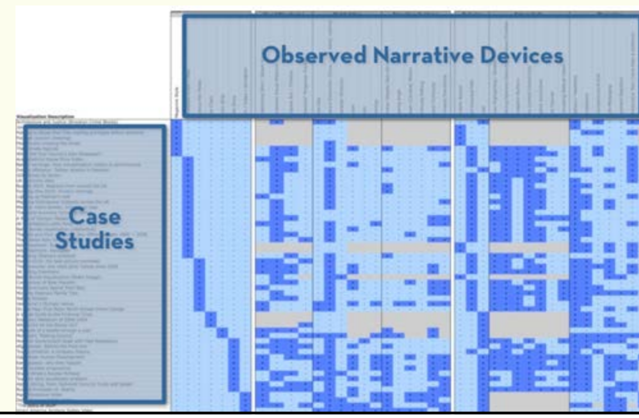
Narrative Visualization (Segel and Heer 2010)

- Studied 58 examples
- News media, blogs, instructional videos, research
- Characterizing the design space



271

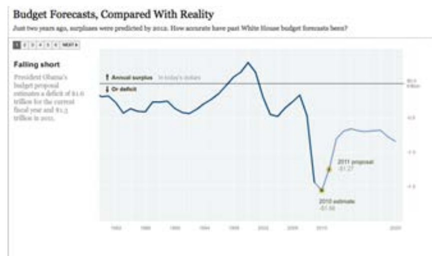
Narrative Visualization (Segel and Heer 2010)



272

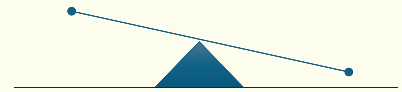
Narrative structure tactics

- Ordering
- Messaging
- Interactivity

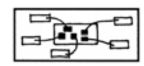


273

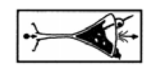
Author vs. reader driven stories



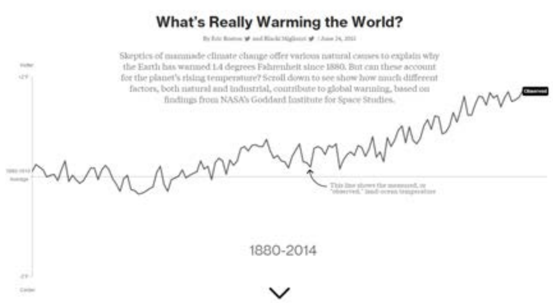
Reader driven	Author driven
Multiple orderings	Prescribed ordering
Less messaging	Stronger messaging
More open interactivity	Limited interactivity


Drill down story


Interactive Slide Show

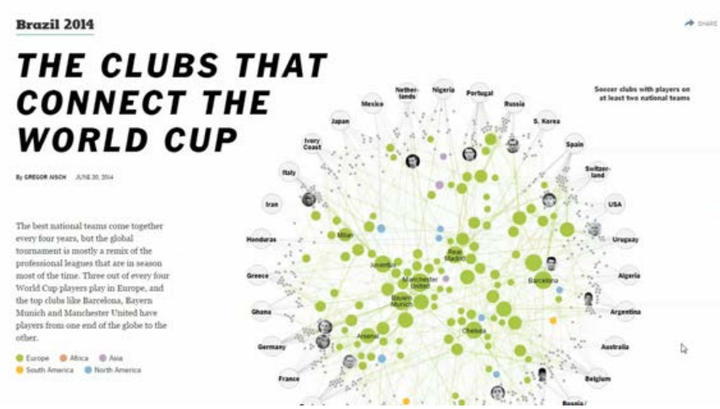

Martini Glass

274

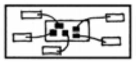


https://www.bloomberg.com/graphics/2015-whats-warming-the-world/

275

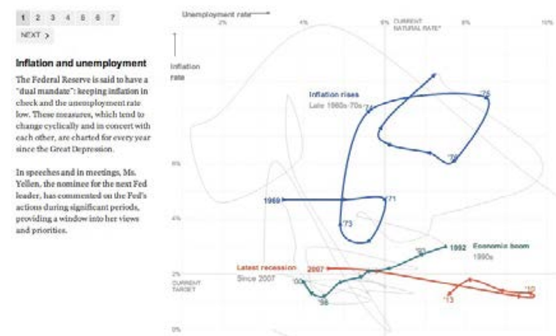


276



277

Janet L. Yellen, on the Economy's Twists and Turns



http://www.nytimes.com/interactive/2013/10/09/us/yellen-fed-chart.html

278

Design space dimensions: Genre

279

Designing narrative visualizations

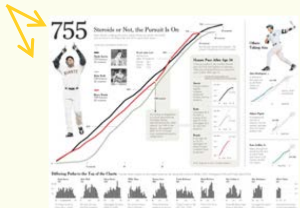
"require skills like those familiar to movie directors, beyond a technical expert's knowledge of computer science and engineering…."

Gershon and Page 2001

280

Visual narrative tactics

- Highlighting



- Transition guidance

281

Emphasis and control

https://www.youtube.com/watch?v=v4seDVfgwOg

282

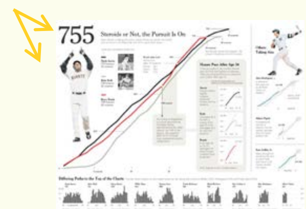
Montage / editing
- Prescribed order
- Where you look explicitly directed
- Little reader/viewer agency

Ensemble staging / direction
- Less prescribed order
- Salience, structure nudges you to look
- More reader/viewer agency

283

Visual narrative tactics

- Highlighting



- Transition guidance

284

Visual narrative tactics

- Highlighting
- Transition guidance

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Visualization rhetoric

Rhetoric / framing: How an interpretation arises from a representation, plus individual, social factors

Framing effects: small changes in presentation of an issue result in significant changes in opinion

- Hullman and Diakopoulos [2011]
  - 51 professional produced narrative visualizations
  - NYT, BBC, Economist, local news, political outlets
  - Iterative qualitative coding, seeded scheme with semiotics, persuasion concepts

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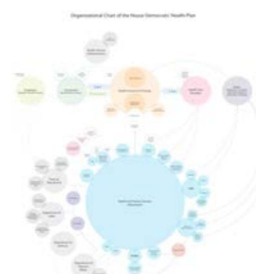
Visual/linguistic metaphor

287

Visual metaphor (mapping rhetoric)

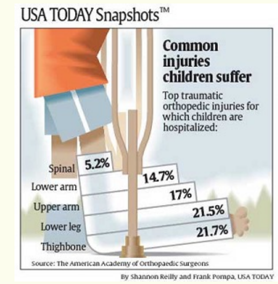


288

Labeling, sourcing (linguistic, provenance)

289

Consider your audience



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Annotations

- Annotations are a type of guide
- Draw your attention to the important things
- Tell you how to read the visualization

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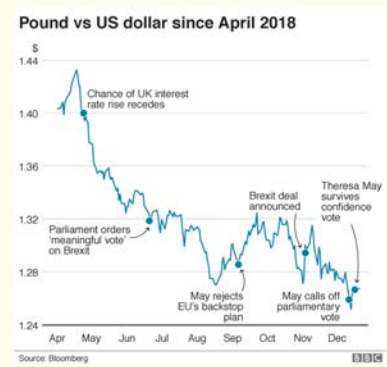
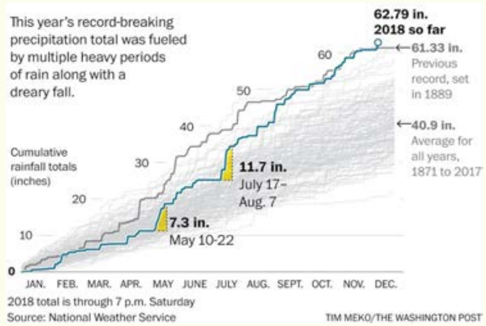
Annotations



https://www.visualisingdata.com/2016/03/little-visualisation-design/

292

Annotations



https://www.visualisingdata.com/2016/03/little-visualisation-design/

293

Annotations

https://www.visualisingdata.com/2016/03/little-visualisation-design/

294

Annotations

https://www.visualisingdata.com/2016/03/little-visualisation-design/

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Summary

- Communicative visualization is important type
- Often ignored in academic vis community
  - Less so in practice
- Think of what you want to teach
- Think of how you want to do it
- Create opportunities for learning

296

A bit about what we'll do today…

1) Infovis, perception, and cognition
   - Why visualizations work, what they're good for, choosing the right ones, (also a bunch of vocabulary)
2) Communication through infovis
   - How to achieve communicative intents
3) Unconventional approaches
   - Beyond the bar chart

297

A bit about what we'll do today…

1) Infovis, perception, and cognition
   - Why visualizations work, what they're good for, choosing the right ones, (also a bunch of vocabulary)
2) Communication through infovis
   - How to achieve communicative intents
3) Unconventional approaches
   - Beyond the bar chart

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Visualizing Time

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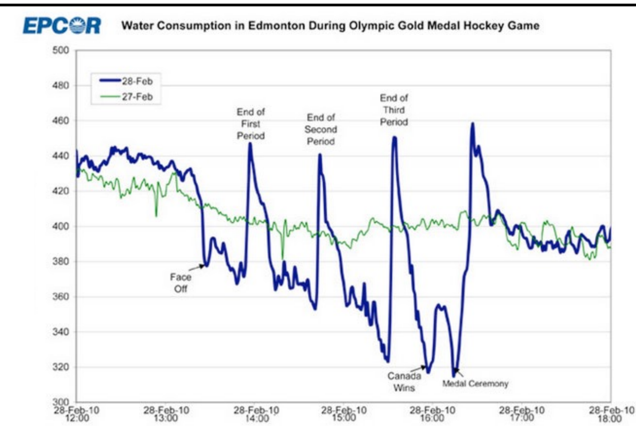
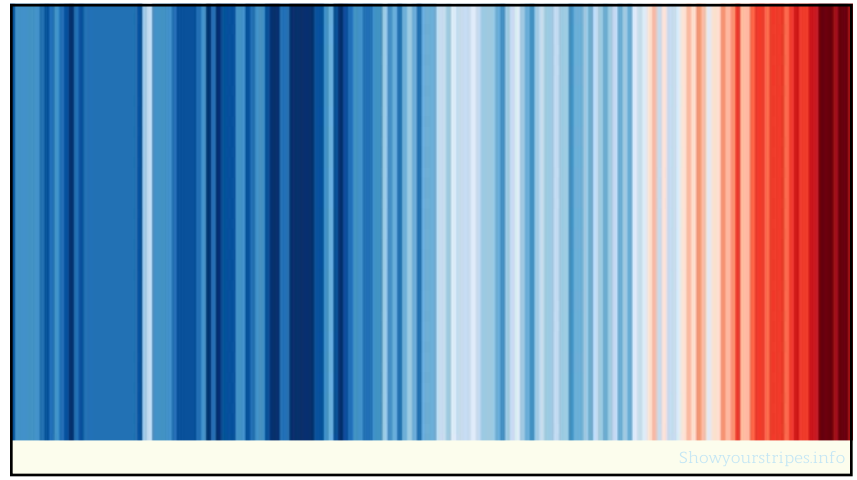


300

301



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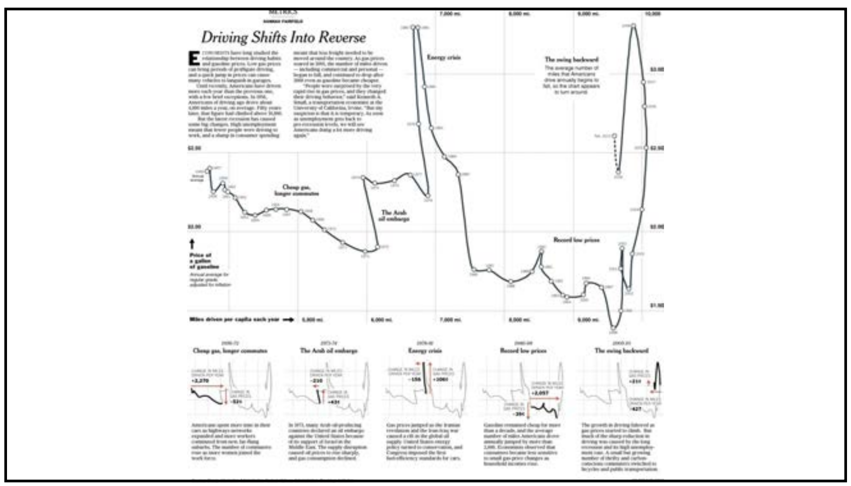

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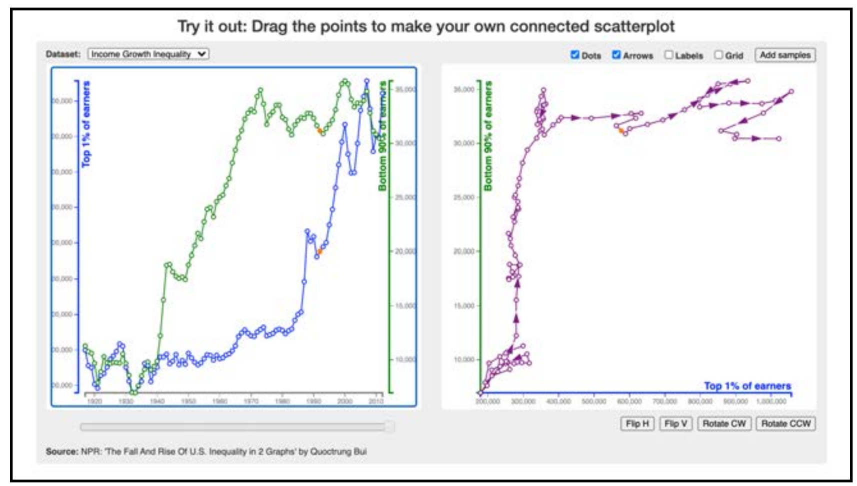

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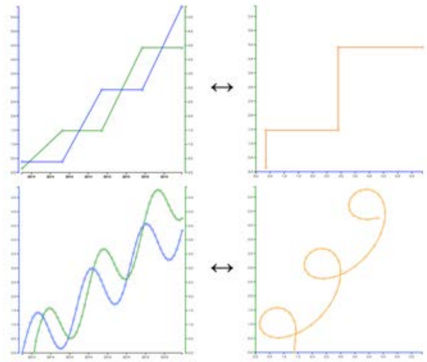
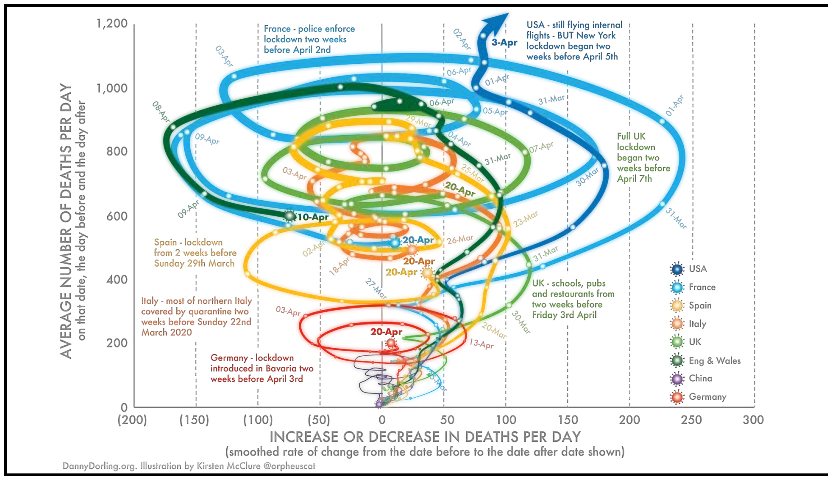


Fig. 4. (Top) A right angle indicates a sharp change in the rate of change of one series or a swap of the rates of change between series. (Bottom) Loops in the connected scatterplot are the result of similar patterns that are shifted by up to a quarter of the periodicity of the pattern (Section 2.2).

http://steveharoz.com/research/connected_scatterplot/

305



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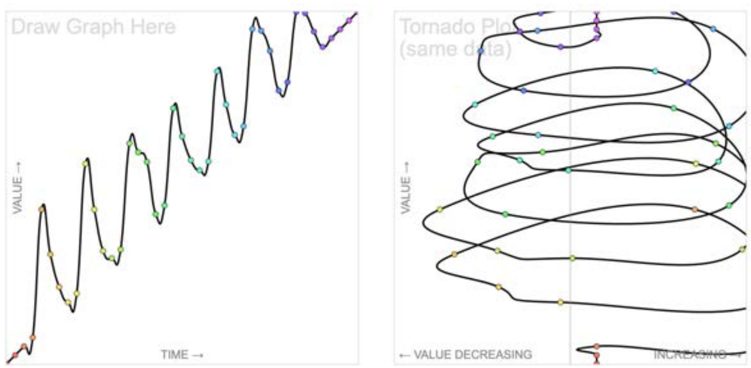
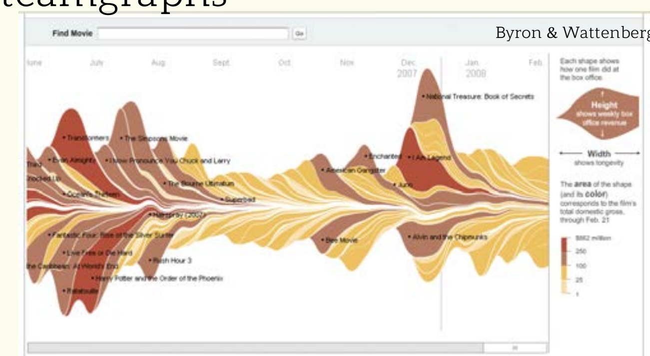


http://www.bewitched.com/demo/tornado/tornado.html

307

Steamgraphs



http://www.nytimes.com/interactive/2008/02/23/movies/20080223_REVENUE_GRAPHIC.htm

308

The problem with streamgraphs

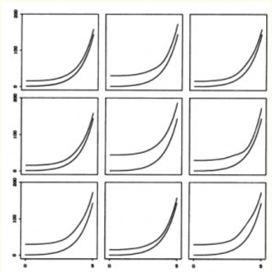
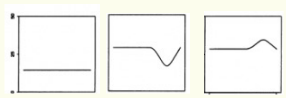


Figure 26. Curve-difference chart.



309

The problem with streamgraphs

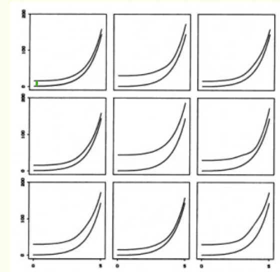


Figure 26. Curve-difference chart.

310

The problem with streamgraphs

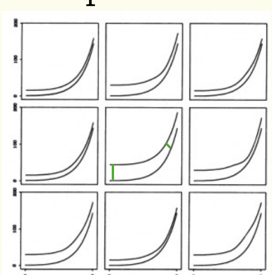


Figure 26. Curve-difference chart.

311

The problem with streamgraphs

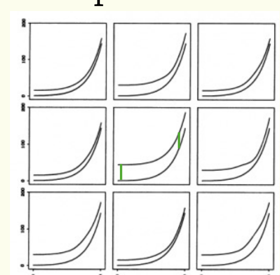


Figure 26. Curve-difference chart.

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Multidimensional data

313

Small Multiples I

	V1	V2	V3	V4	V5
D1	7	3	4	8	1
D2	2	7	6	3	4
D3	9	8	1	4	2

Easy to compare within

Harder to compare between

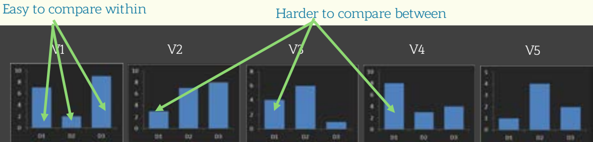
314

Small Multiples I

	V1	V2	V3	V4	V5
D1	7	3	4	8	1
D2	2	7	6	3	4
D3	9	8	1	4	2

Easy to compare within

Harder to compare between



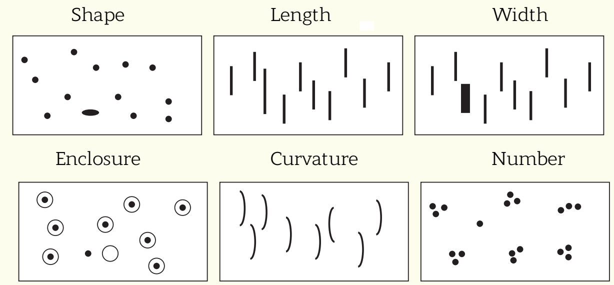
315

But… small can mean really small (details hard to pick out)

316

So why does this work?

317



Small multiples works well when target is different from distractors

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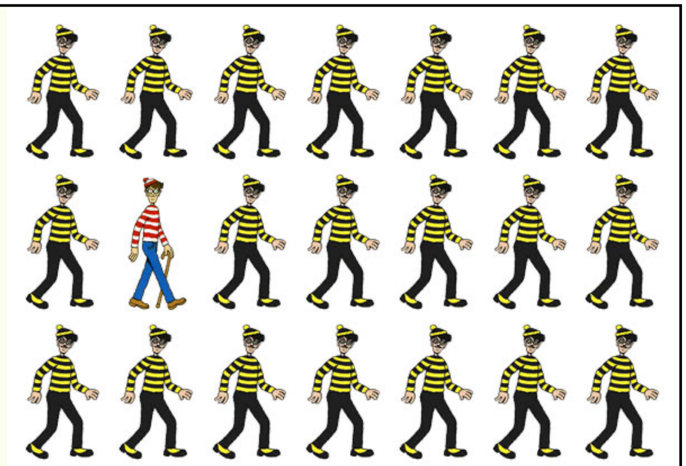
Easy



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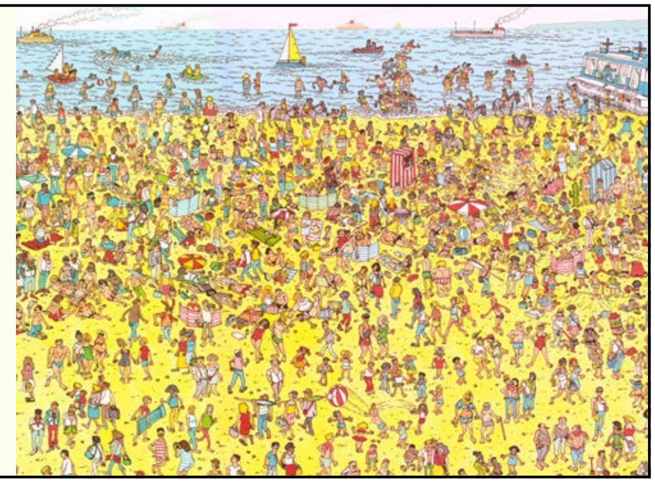
Not Easy



320

Parallel Coordinates

321

Parallel Coordinates (Inselberg)

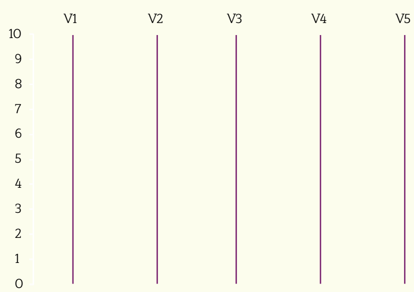
- 3 different pieces of data with 5 variables

	V1	V2	V3	V4	V5
D1	7	3	4	8	1
D2	2	7	6	3	4
D3	9	8	1	4	2

322

Construction

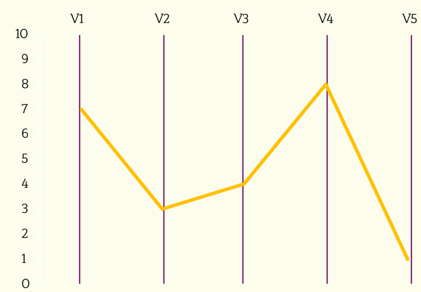
	V1	V2	V3	V4	V5



323

Construction

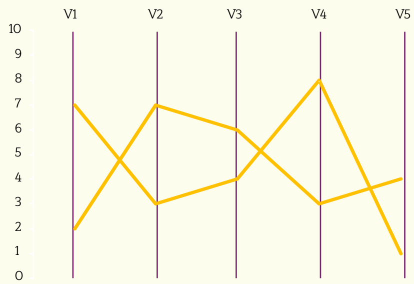
	V1	V2	V3	V4	V5
D1	7	3	4	8	1



324

Construction

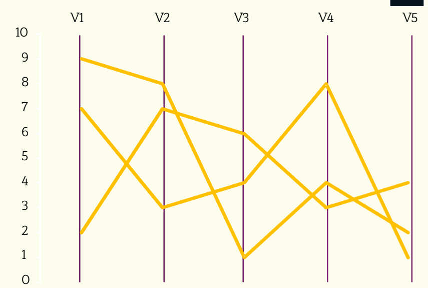
	V1	V2	V3	V4	V5
D1	7	3	4	8	1
D2	2	7	6	3	4



325

Construction

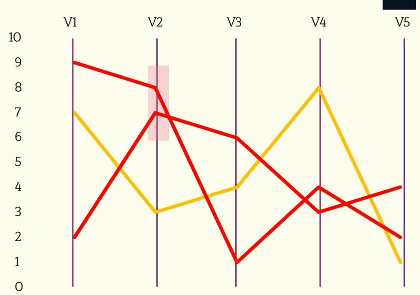
	V1	V2	V3	V4	V5
D1	7	3	4	8	1
D2	2	7	6	3	4
D3	9	8	1	4	2



326

Construction

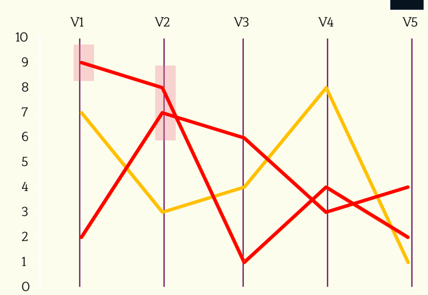
	V1	V2	V3	V4	V5
D1	7	3	4	8	1
D2	2	7	6	3	4
D3	9	8	1	4	2



327

Construction

	V1	V2	V3	V4	V5
D1	7	3	4	8	1
D2	2	7	6	3	4
D3	9	8	1	4	2



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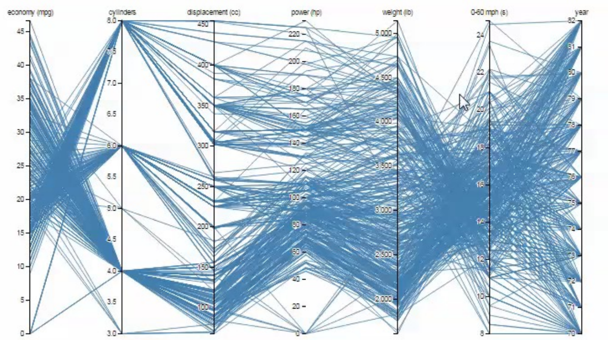

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Design Choices/Constraints

- Different variables with different ranges
  - Normalization (e.g., 0-1)
  - Ordering (top to bottom, bottom to top)
  - Ordering of axes
- Extensions
  - Categorical data
  - Independent axes

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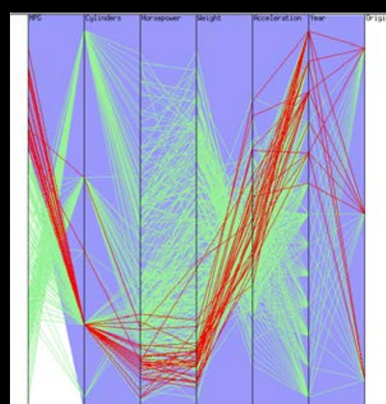
Free Options

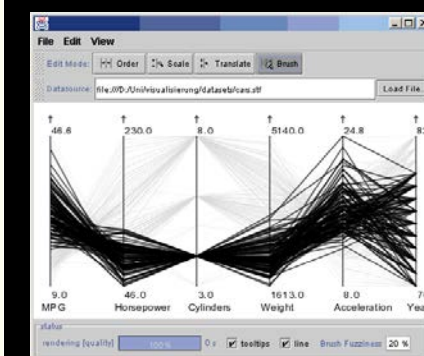
- XmdvTool
  - http://davis.wpi.edu/xmdv/



331

Free Options

- XmdvTool
  - http://davis.wpi.edu/xmdv/
- Parvis
  - http://www.mediavirus.org/parvis/



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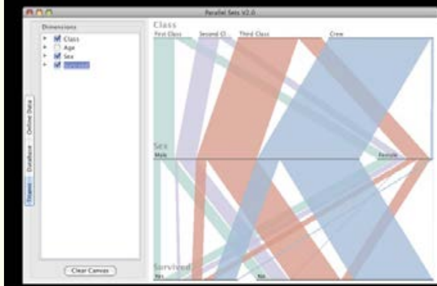
Free Options

- XmdvTool
  - http://davis.wpi.edu/xmdv/
- Parvis
  - http://www.mediavirus.org/parvis/
- Parallel Sets
  - http://code.google.com/p/parsets/



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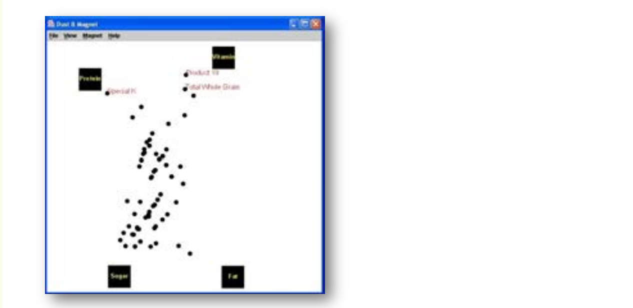
Reconfigure: Dust and Magnet



Yi, Melton, Stasko, and Jacko, (IV'05)

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Reconfigure: Dust and Magnet

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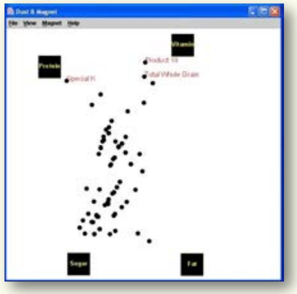
Dust and magnets

- Reconfiguring here is hard to follow
- Learning curve
  - Semantics
- Requires interactivity
  - Static representations limited



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LineUp

Gratzl et al., 2013

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Visualizing Sets

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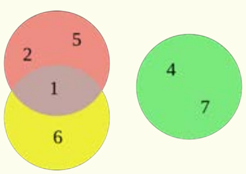

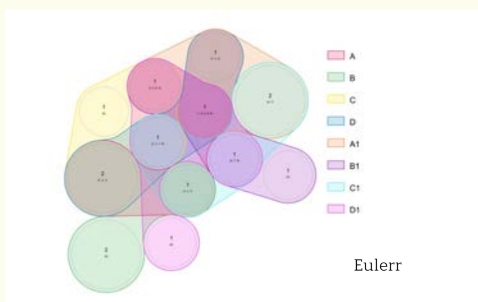

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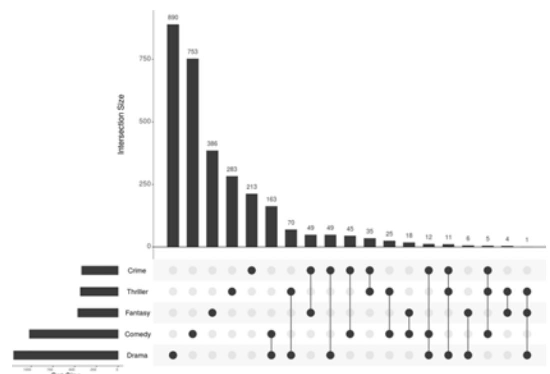
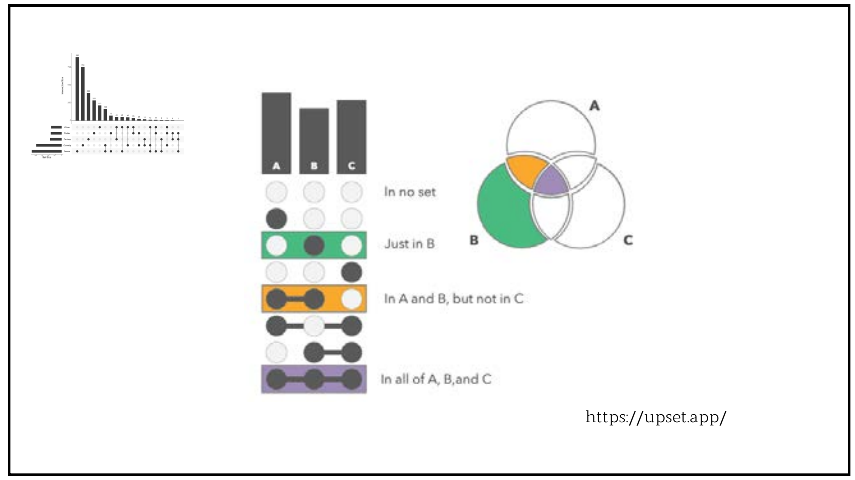
339



https://upset.app/

340

341



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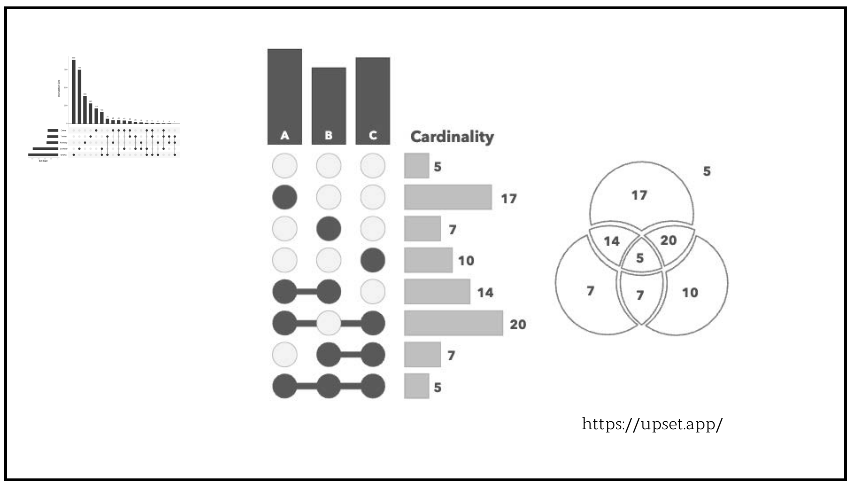

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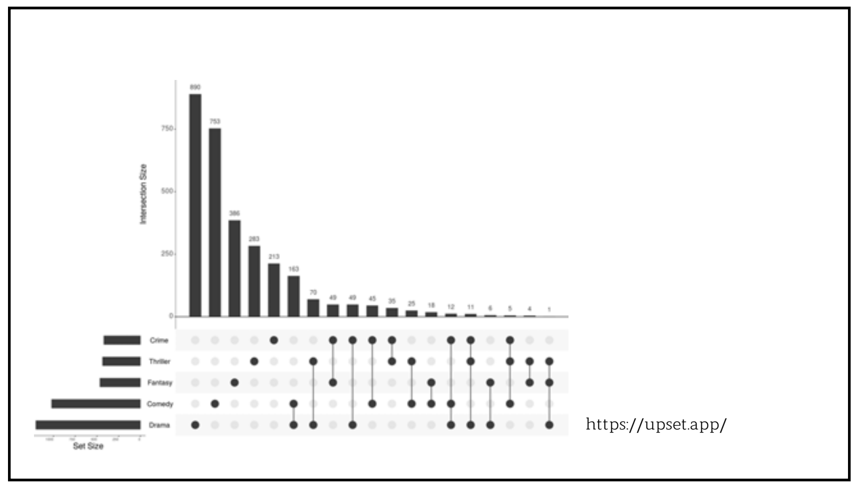

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Hierarchies and Networks

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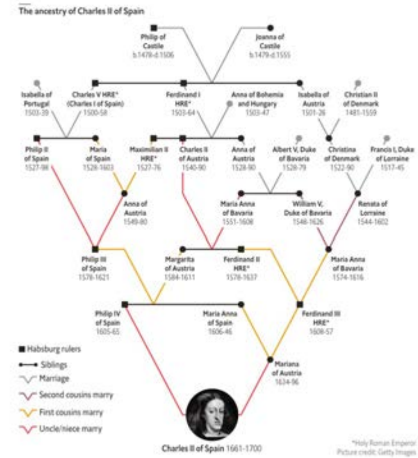

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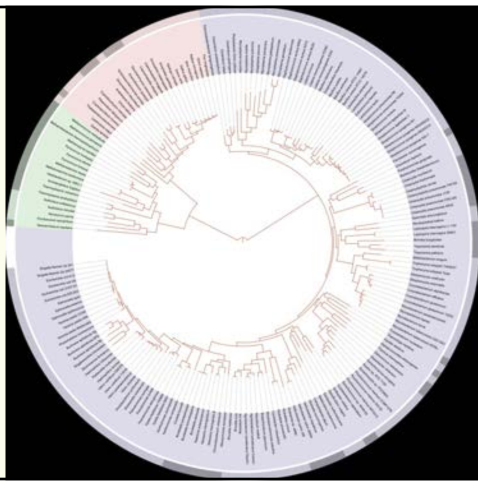
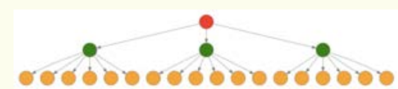


Letunic, I (2007)
Wikipedia

347

Hierarchical Vis

- Tasks
  - How much depth? How much fanning?
  - How far are two nodes?
  - How many subclasses?
  - How far down the hierarchy?
  - Which subtree contains entity?
  - Which subtree contains matches?
  - Which subtree contains more matching items than others?
  - Etc.
- Techniques
  - Trees + Space Filling



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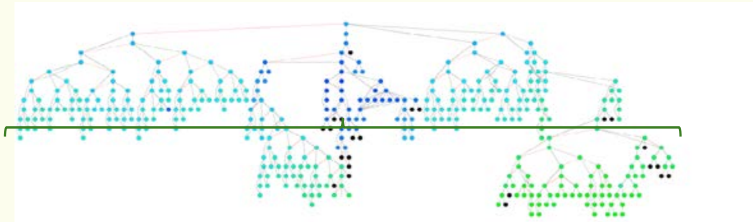
Tree Visualization

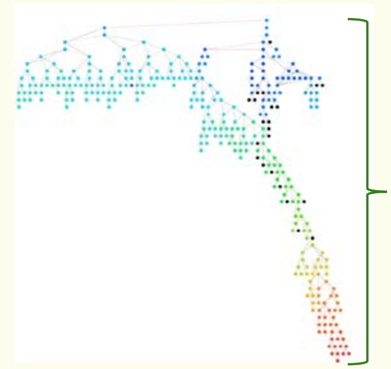


- Constraints/ problems of rendering?
  - Branching factor
  - Single branch depth

349

Tree Visualization

- Constraints/ problems of rendering?
  - Branching factor
  - Single branch depth



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Fish eye lens

- Hyperbolic transformations
  - Fisheye/focus+context

- Technique:
  - Lay out tree to hyperbolic plane
  - Map plane to disk
  - Start at center – salience to focus area
  - Animate to move in space – mental model preservation

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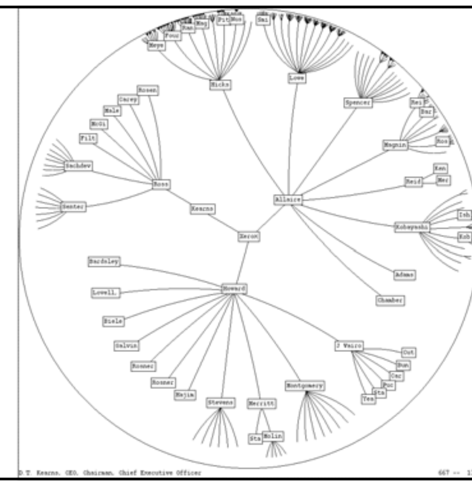

Up to 10x as many nodes regular tree vis

Lamping et al, 1995

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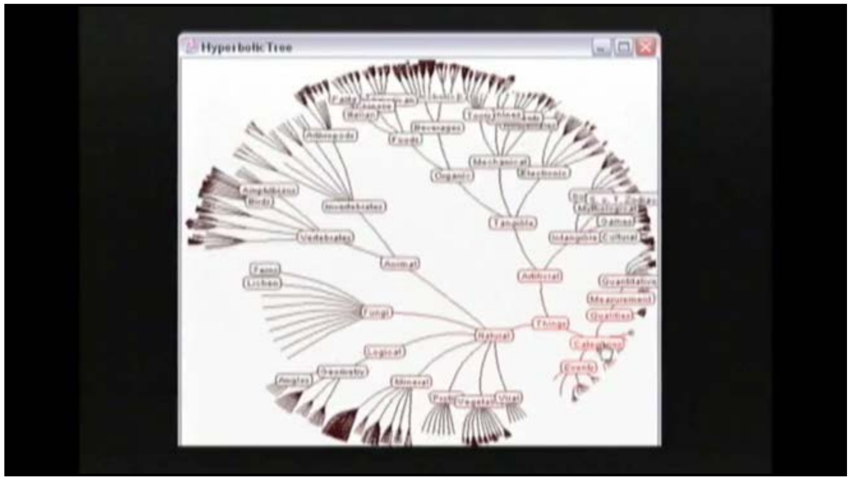

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Key Features

- Magnification on center
- Layout only depends on 2-3 levels out
  - Cheaper rendering (don't have to draw far stuff)
- Smooth animation for change

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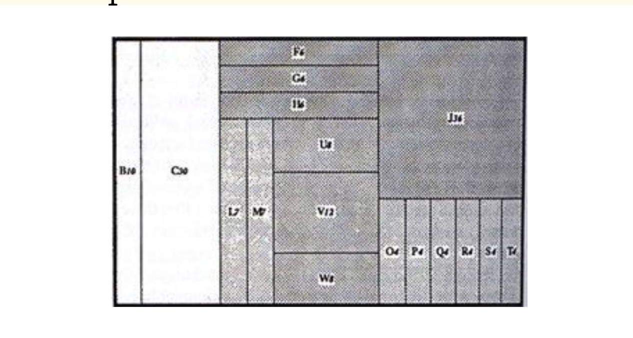
TreeMaps



Johnson + Shneiderman, 1991

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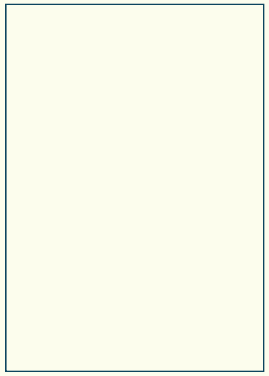
Example

- Total sales
  - Fruit
    - Apples ($100)
    - Cherries ($100)
    - Strawberries ($200)
    - Grapes ($200)
  - Meat
    - Chicken ($400)
    - Beef ($200)
    - Pork ($200)
  - Dairy
    - Milk ($300)
    - Cheese ($300)

356

Example

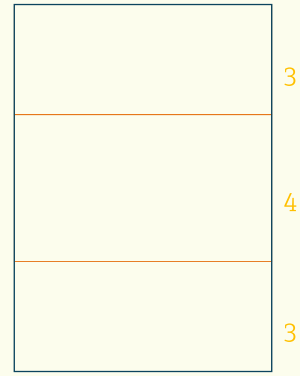
- Total sales ($2000)
  - Fruit ($600)
    - Apples ($100)
    - Cherries ($100)
    - Strawberries ($200)
    - Grapes ($200)
  - Meat ($800)
    - Chicken ($400)
    - Beef ($200)
    - Pork ($200)
  - Dairy ($600)
    - Milk ($300)
    - Cheese ($300)



357

Example

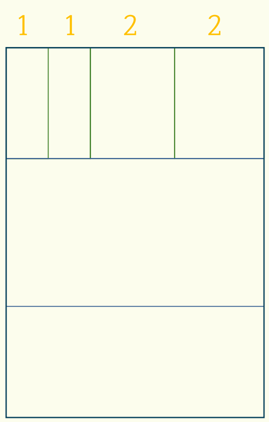
- Total sales ($2000)
  - Fruit ($600)
    - Apples ($100)
    - Cherries ($100)
    - Strawberries ($200)
    - Grapes ($200)
  - Meat ($800)
    - Chicken ($400)
    - Beef ($200)
    - Pork ($200)
  - Dairy ($600)
    - Milk ($300)
    - Cheese ($300)



358

Example

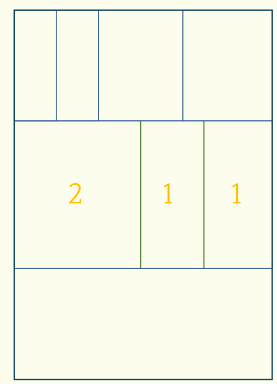
- Total sales ($2000)
  - Fruit ($600)
    - Apples ($100)
    - Cherries ($100)
    - Strawberries ($200)
    - Grapes ($200)
  - Meat ($800)
    - Chicken ($400)
    - Beef ($200)
    - Pork ($200)
  - Dairy ($600)
    - Milk ($300)
    - Cheese ($300)



359

Example

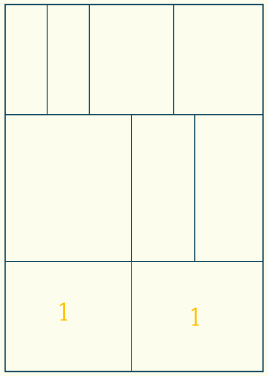
- Total sales ($2000)
  - Fruit ($600)
    - Apples ($100)
    - Cherries ($100)
    - Strawberries ($200)
    - Grapes ($200)
  - Meat ($800)
    - Chicken ($400)
    - Beef ($200)
    - Pork ($200)
  - Dairy ($600)
    - Milk ($300)
    - Cheese ($300)



360

Example

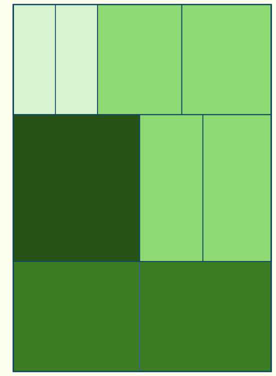
- Total sales ($2000)
  - Fruit ($600)
    - Apples ($100)
    - Cherries ($100)
    - Strawberries ($200)
    - Grapes ($200)
  - Meat ($800)
    - Chicken ($400)
    - Beef ($200)
    - Pork ($200)
  - Dairy ($600)
    - Milk ($300)
    - Cheese ($300)



361

Example
(color for double encoding)

- Total sales ($2000)
  - Fruit ($600)
    - Apples ($100)
    - Cherries ($100)
    - Strawberries ($200)
    - Grapes ($200)
  - Meat ($800)
    - Chicken ($400)
    - Beef ($200)
    - Pork ($200)
  - Dairy ($600)
    - Milk ($300)
    - Cheese ($300)



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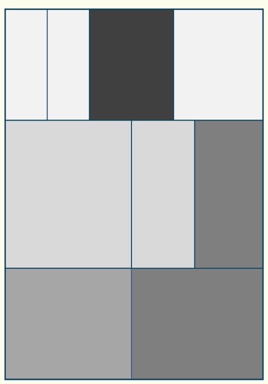
Example
(color for extra variable)

- Total sales
  - Fruit
    - Apples ($100,10)
    - Cherries ($100,10)
    - Strawberries ($200,100)
    - Grapes ($200,10)
  - Meat
    - Chicken ($400,20)
    - Beef ($200,20)
    - Pork ($200,60)
  - Dairy
    - Milk ($300,40)
    - Cheese ($300,60)



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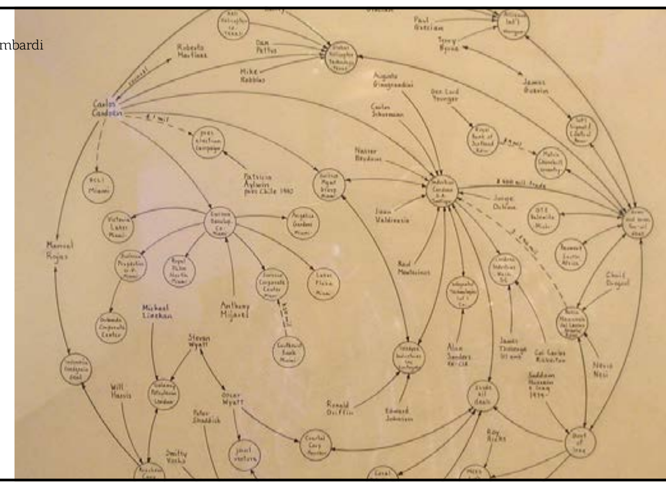
Mark Lombardi



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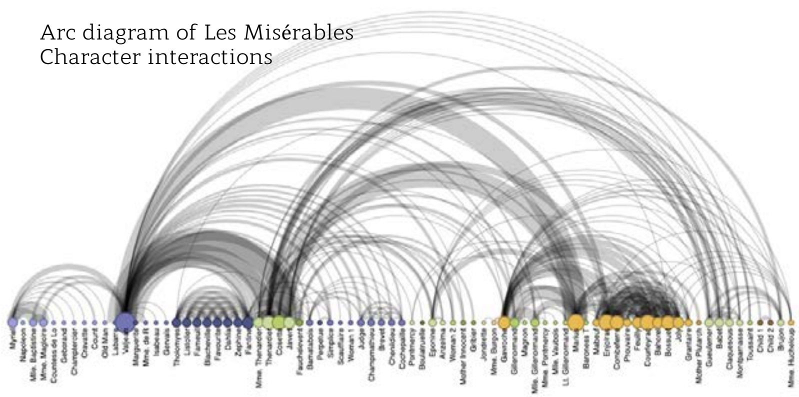
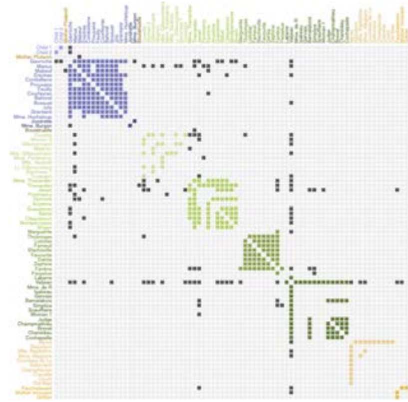


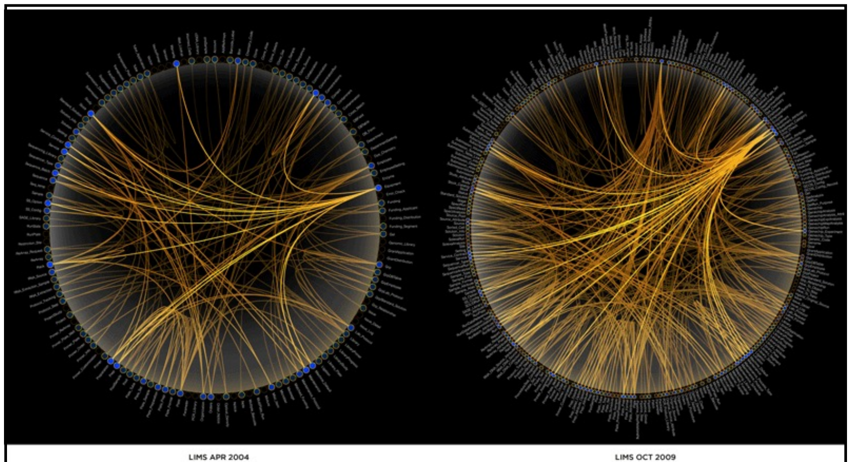
Arc diagram of Les Misérables
Character interactions

365



Matrix representation of
Les Misérables character
interactions

366



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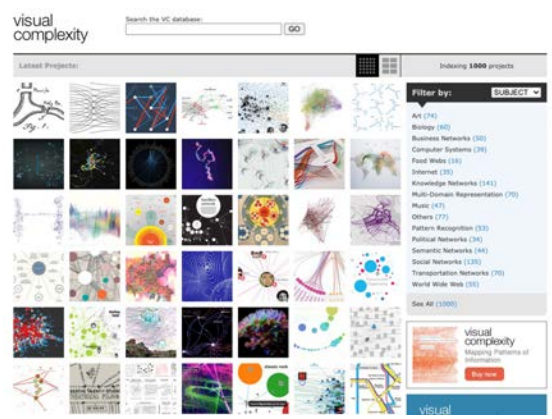

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Some alternatives…

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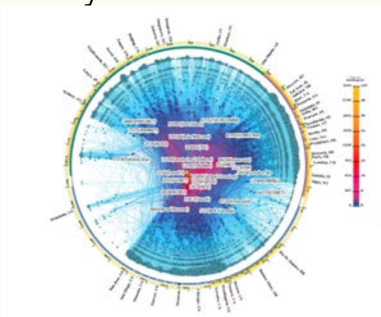
Attribute Driven Layouts - Skitter

- Angle
  - Longitude of node location
- Radius
  - Function of out-degree (more, closer in)



http://www.caida.org/research/topology/as_core_network/

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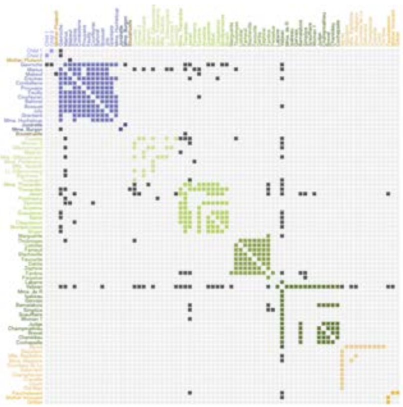

Matrix representation of Les Misérables character interactions

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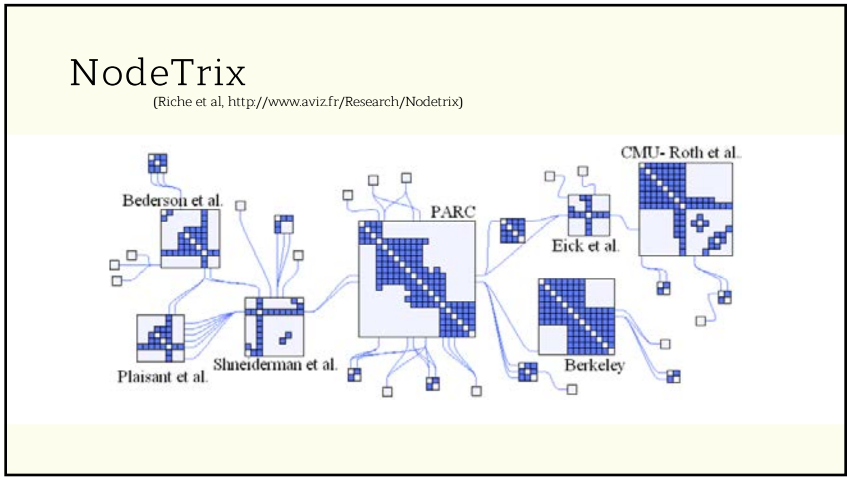

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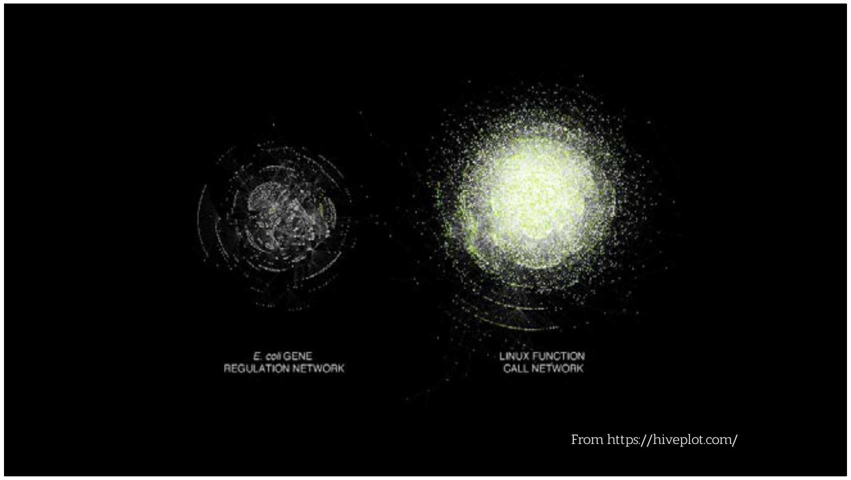

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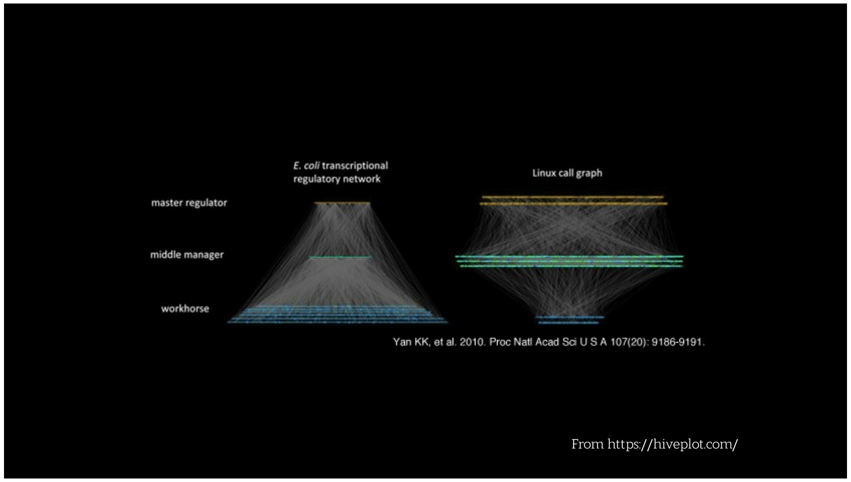

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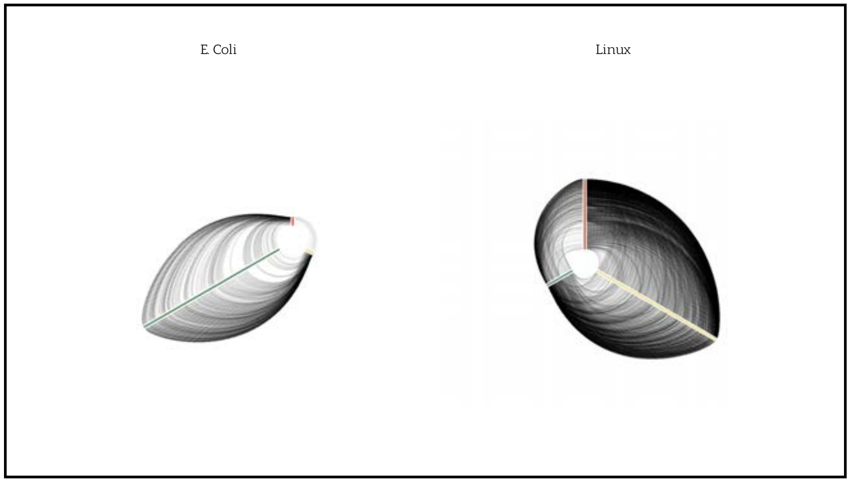

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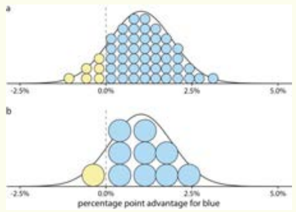
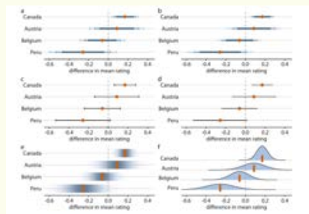
Uncertainty...





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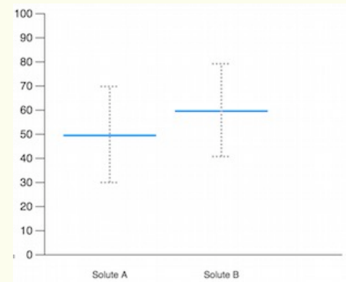
Hypothetical Outcome Plots



HOPS, Jessica Hullman, Paul Resnick, Eytan Adar

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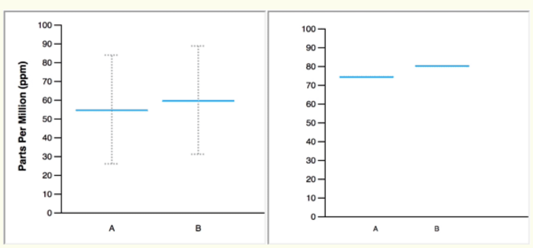
Hypothetical Outcome Plots



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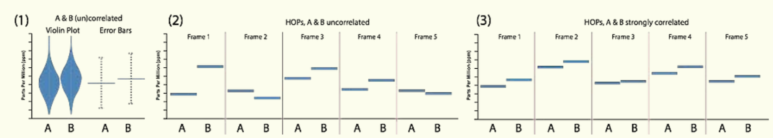
Hypothetical Outcome Plots



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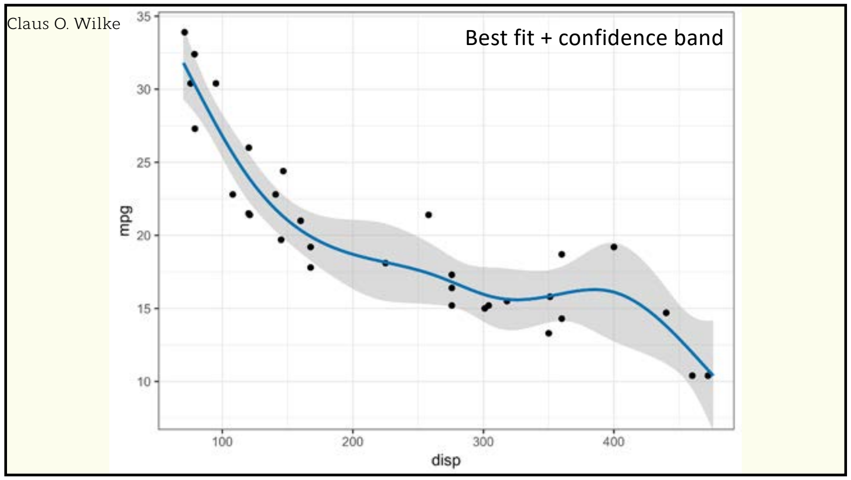

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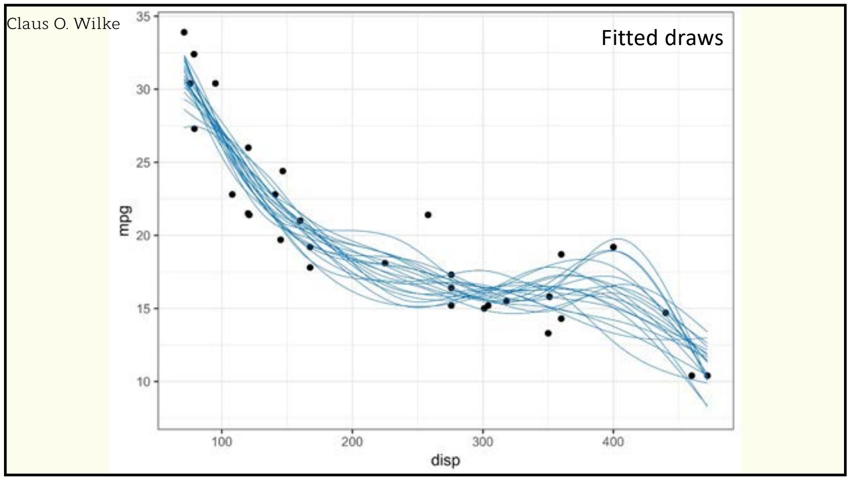

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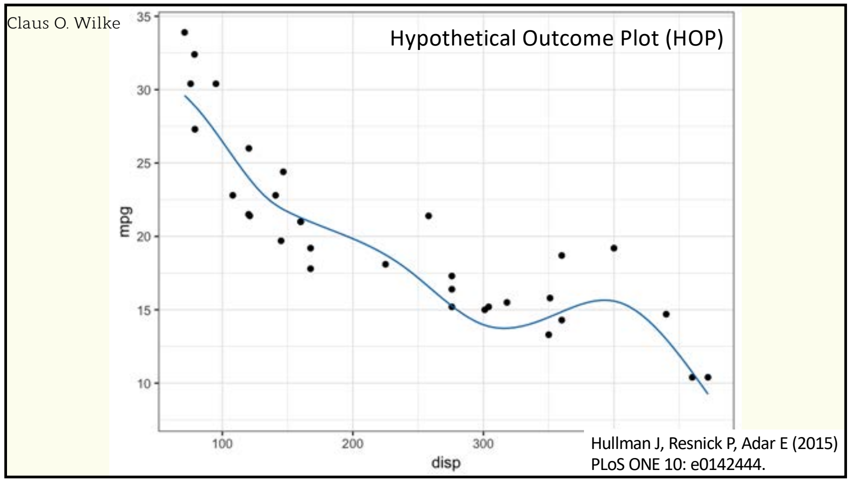

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Wrap up

- Bar charts, pie charts, time series, etc. are a great place to start
- There are many specialized tools
  - Target narrower sets of tasks
  - Have a learning curve
  - Should be in your toolbox

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