VISUALIZING MULTI-ATTRIBUTE DATA

DATA TABLES

Petra Isenberg

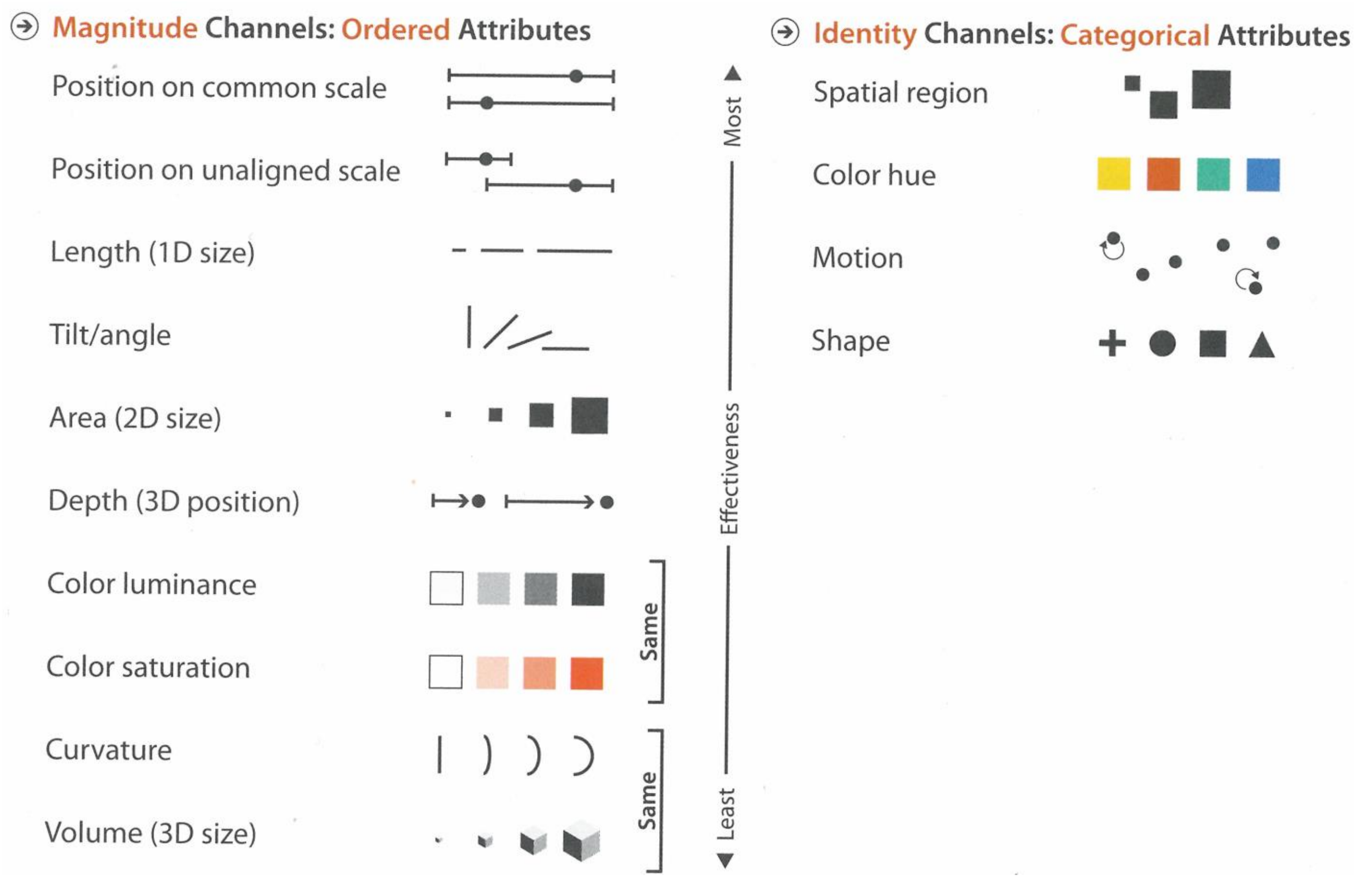
informatics mathematics

RECAP

you have learned about

- visual variables and marks
- that their perceptual properties matter

RECAP

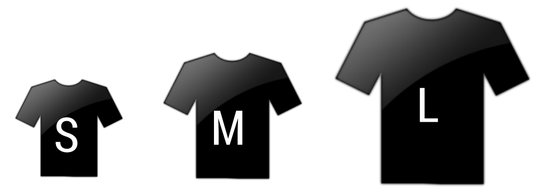


Magnitude Channels: Ordered Attributes
Position on common scale
Position on unaligned scale
Length (1D size)
Tilt/angle
Area (2D size)
Depth (3D position)
Color luminance
Color saturation
Curvature
Volume (3D size)
Same
Same
Most
Effectiveness
Least
Identity Channels: Categorical Attributes
Spatial region
Color hue
Motion
Shape

RECAP

DATA TYPES

ORDINAL (ranking)

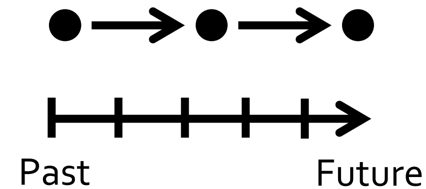


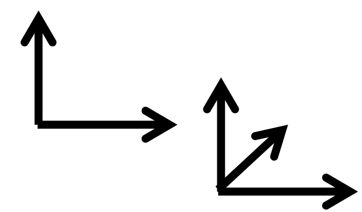
NOMINAL (categorical)

QUANTITATIVE (numerical)

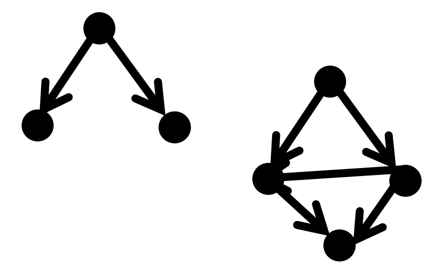

RECAP

- 1D (linear)
- Temporal
- 2D (maps)
- 3D
- nD (relational)
- Trees (hierarchies)
- Networks (graphs)



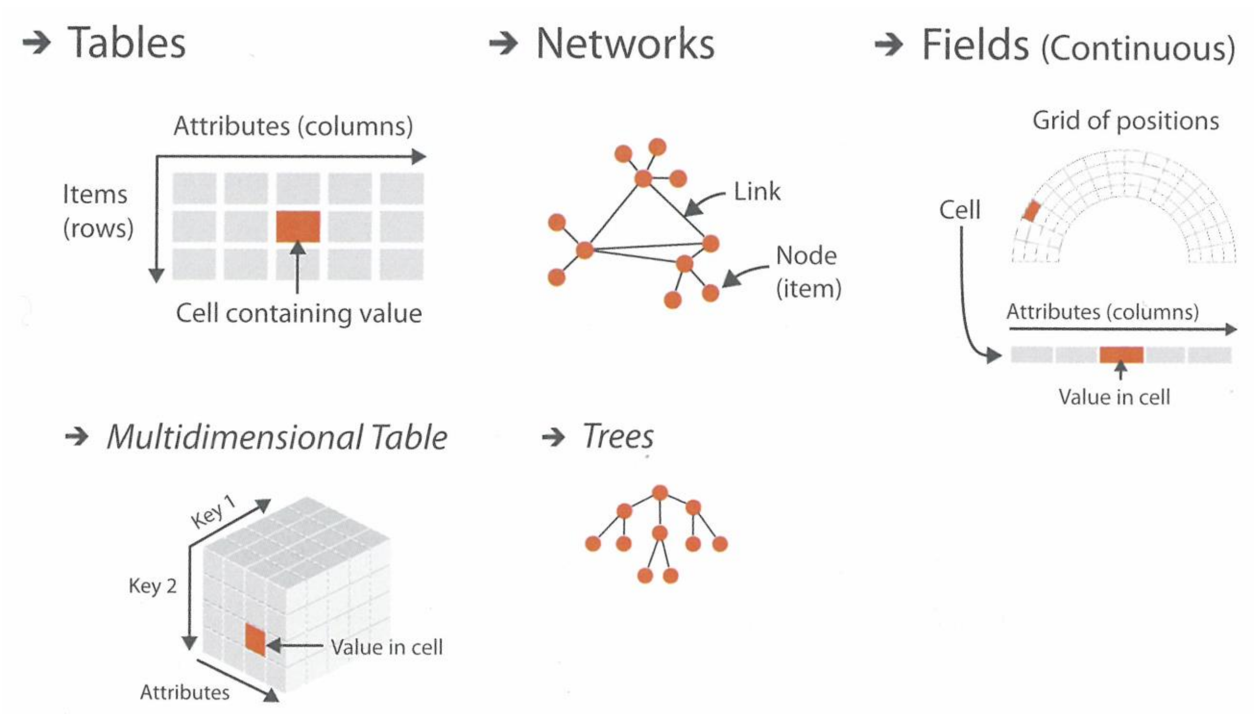


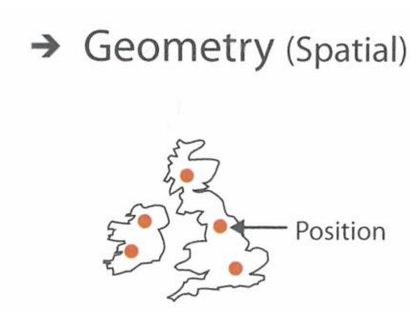
vis examples later

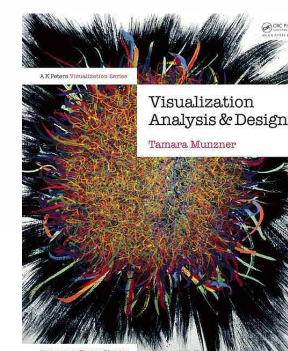


Shneiderman: The Eyes Have It

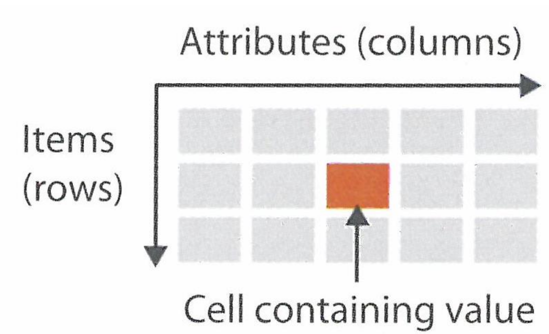
ANOTHER VIEW



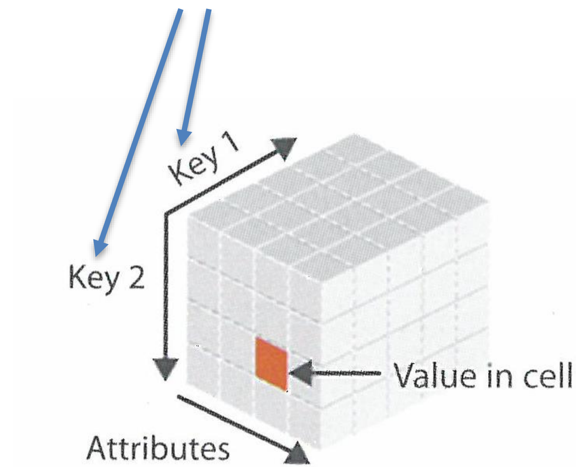




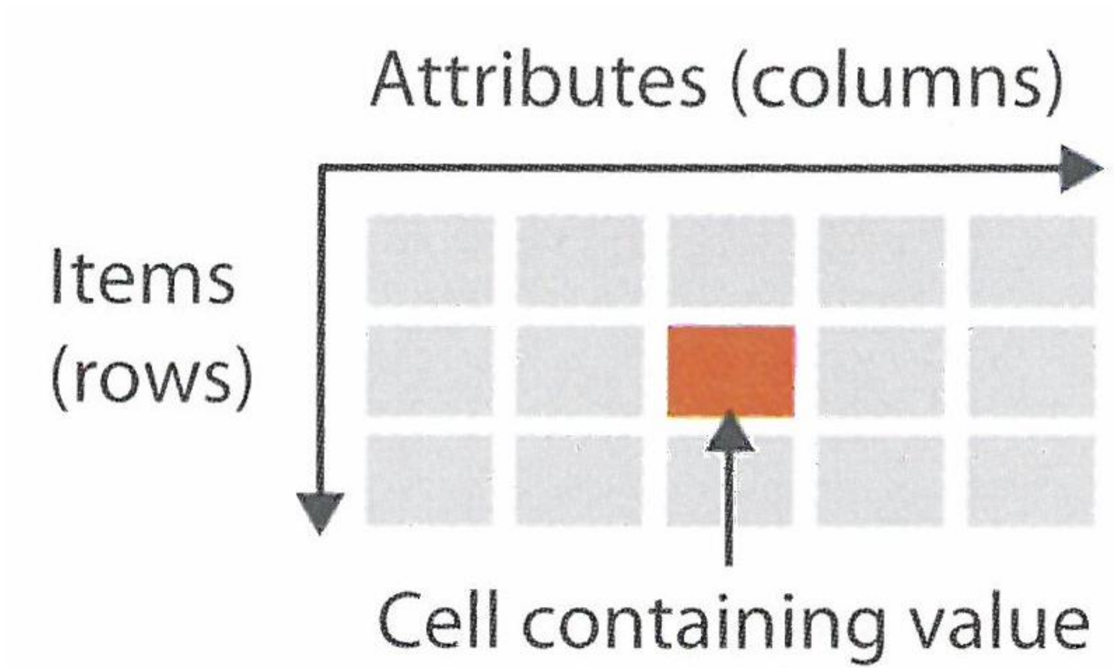
DATA TABLES - TERMINOLOGY



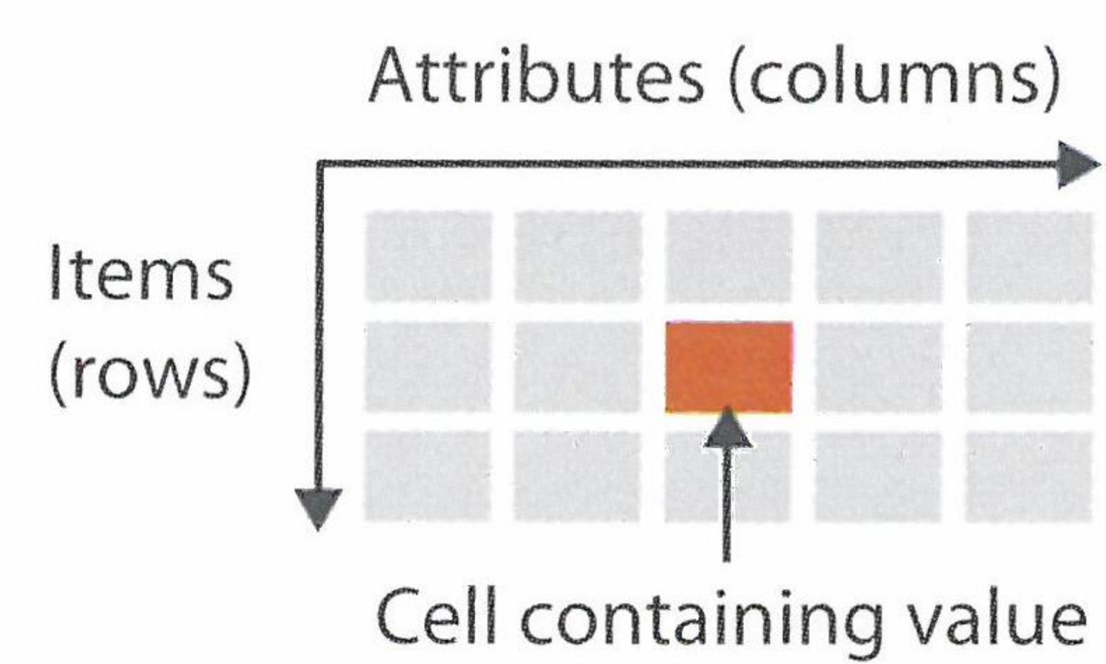
index to look up values



WHAT COULD BE THE KEY HERE?



WHAT DATA TYPE IS SUITABLE FOR A KEY?



KEYS VS. VALUES

key attributes are also sometimes called:

- independent attribute
- dimension

value attributes are also sometimes called:

- dependent attribute
- measure

LEVELS

= unique values for a categorical or ordered attribute

Abc Vispubdata-Grobid-min-c... Conference	# Vispubdata-... Year	Abc Vispubdata-Grobid-min-clean.... Paper.Title
InfoVis	2015	A comparative study ...
InfoVis	2015	A Linguistic Approach...
InfoVis	2015	A Psychophysical Inv...
InfoVis	2015	A Simple Approach fo...
InfoVis	2015	Acquired Codes of Me...
InfoVis	2015	AggreSet: Rich and Sc...
InfoVis	2015	AmbiguityVis: Visuali...
InfoVis	2015	Automatic Selection ...
InfoVis	2015	Beyond Memorability...
InfoVis	2015	Beyond Weber's Law:...
InfoVis	2015	Evaluation of Parallel...
InfoVis	2015	Guidelines for Effecti...
InfoVis	2015	High-Quality Ultra-Co...
InfoVis	2015	HOLA: Human-like Ort...
InfoVis	2015	How do People Make ...

CONFERENCE:
InfoVis, Vis, SciVis, VAST

YEAR:
1990 – 2015

PAPER.TITLE:
>2500 different

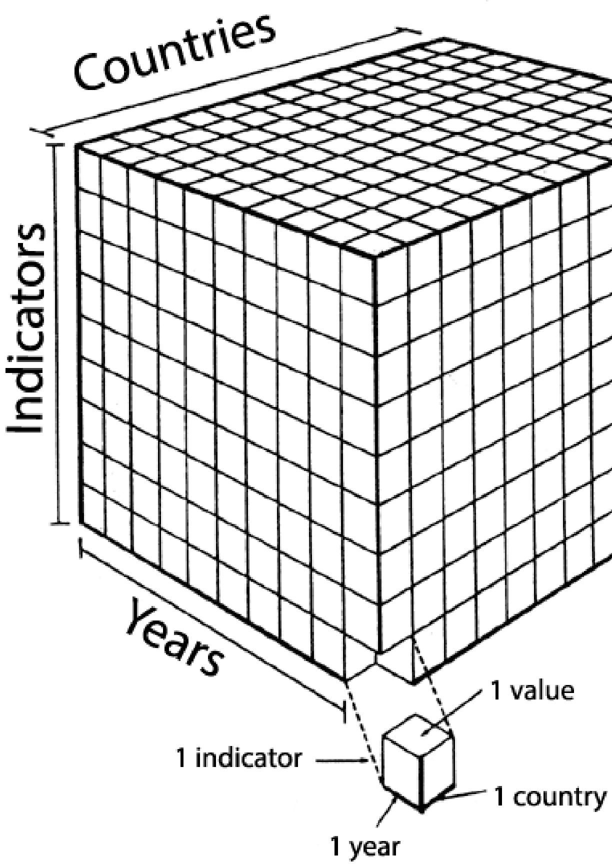
VISPUBDATA

ATTRIBUTES

ITEMS

C	Year	Paper.Title	Paper.DOI	Link	First.page	Last.page	Paper.type..C.conf...	Abstract	Author.Names	First.Author.Affilia...	Deduped.author.n...	References	Author.Keywords	OCR.Authors
In	2015	A comparative study ...	10.1109/TVCG.2015....	http://dx.doi.org/10....	619	628	J	RadViz and star coord...	Rubio-Sanchez, M.;Ra...	;;;	Rubio-Sanchez, M.;Ra...	10.1109/VAST.2010....	RadViz, Star coordina...	Rubio-S ´ Anchez,Ma...
In	2015	A Linguistic Approach...	10.1109/TVCG.2015....	http://dx.doi.org/10....	698	707	J	When data categorie...	Setlur, V.;Stone, M.C.	;	Setlur, V.;Stone, M.C.	null	linguistics, natural la...	Setlur,Vidya;Stone,M...
In	2015	A Psychophysical Inv...	10.1109/TVCG.2015....	http://dx.doi.org/10....	479	488	J	Physical visualization...	Jansen, Y.;Hornbaek, K.	Univ. of Copenhagen, ...	Jansen, Y.;Hornbaek, K.	10.1109/TVCG.2012....	Data physicalization, ...	Jansen,Yvonne;Hornb...
In	2015	A Simple Approach fo...	10.1109/TVCG.2015....	http://dx.doi.org/10....	678	687	J	General methods for ...	Simonetto, P.;Archam...	;;	Simonetto, P.;Archam...	10.1109/TVCG.2011....	Euler diagrams, Boun...	Simonetto,Paolo;Arc...
In	2015	Acquired Codes of Me...	10.1109/TVCG.2015....	http://dx.doi.org/10....	509	518	J	While information vis...	Byrne, L.;Angus, D.;W...	;;	Byrne, L.;Angus, D.;W...	10.1109/TVCG.2013....	Visual Design, Taxono...	Byrne,Lydia;Angus,D...
In	2015	AggreSet: Rich and Sc...	10.1109/TVCG.2015....	http://dx.doi.org/10....	688	697	J	Datasets commonly i...	Yalcin, M.A.;Elmqvist,...	Univ. of Maryland, Co...	Yalcin, M.A.;Elmqvist,...	10.1109/TVCG.2011....	Multi-valued attribut...	Adil Yalçın,M;Beders...
	2015	AmbiguityVis: Visuali...	10.1109/TVCG.2015....	http://dx.doi.org/10....	359	368	J	Node-link diagrams p...	Yong Wang;Qiaomu S...	;;;;;;	Yong Wang;Qiaomu S...	10.1109/TVCG.2006....	Visual Ambiguity, Vis...	Wang,Yong;Shen,Qia...
InfoVi	2015	Automatic Selection ...	10.1109/TVCG.2015....	http://dx.doi.org/10....	669	677	J	Effective small multi...	Anand, A.;Talbot, J.	;	Anand, A.;Talbot, J.	10.1109/VAST.2010....	Small multiple displa...	Anand,Anushka;Talbo...
InfoVis	2015	Beyond Memorability...	10.1109/TVCG.2015....	http://dx.doi.org/10....	519	528	J	In this paper we mov...	Borkin, M.A.;Bylinskii...	;;;;;;;	Borkin, M.;Bylinskii, Z...	10.1109/TVCG.2012....	Information visualiza...	null
InfoVis	2015	Beyond Weber's Law:...	10.1109/TVCG.2015....	http://dx.doi.org/10....	469	478	J	Models of human per...	Kay, M.;Heer, J.	;	Kay, M.;Heer, J.	10.1109/TVCG.2014....	Weber's law, percept...	Kay,Matthew;Heer,Je...
InfoVis	2015	Evaluation of Parallel...	10.1109/TVCG.2015....	http://dx.doi.org/10....	579	588	J	The parallel coordina...	Johansson, J.;Forsell,...	Norrkoping Visualiza...	Johansson, J.;Forsell,...	10.1109/TVCG.2014....	Survey, evaluation, g...	Johansson,Jimmy;For...
InfoVis	2015	Guidelines for Effecti...	10.1109/TVCG.2015....	http://dx.doi.org/10....	489	498	J	Semi-automatic text ...	Strobelt, H.;Oelke, D.;...	;;;;	Strobelt, H.;Oelke, D.;...	10.1109/TVCG.2012....	Text highlighting tec...	Strobelt,Hendrik;Oel...
InfoVis	2015	High-Quality Ultra-Co...	10.1109/TVCG.2015....	http://dx.doi.org/10....	339	348	J	Prior research into ne...	Yoghourdjian, V.;Dwy...	;;;;;	Yoghourdjian, V.;Dwy...	10.1109/TVCG.2008....	Network visualizatio...	Yoghourdjian,Vahan;...
InfoVis	2015	HOLA: Human-like Ort...	10.1109/TVCG.2015....	http://dx.doi.org/10....	349	358	J	Over the last 50 year...	Kieffer, S.;Dwyer, T.;...	;;;	Kieffer, S.;Dwyer, T.;...	10.1109/TVCG.2006....	Graph layout, orthog...	Kieffer,Steve;Dwyer,...
InfoVis	2015	How do People Make ...	10.1109/TVCG.2015....	http://dx.doi.org/10....	499	508	J	In this paper, we wou...	Sukwon Lee;Sung-He...	Sch. of Ind. Eng., Purd...	Sukwon Lee;Sung-He...	10.1109/TVCG.2013....	Sensemaking model, i...	Lee,Sukwon;Kim,Sun...
InfoVis	2015	Improving Bayesian R...	10.1109/TVCG.2015....	http://dx.doi.org/10....	529	538	J	Decades of research ...	Ottley, A.;Peck, E.M.;...	;;;;;;;	Ottley, A.;Peck, E.M.;...	10.1109/TVCG.2014....	Bayesian Reasoning, ...	Ottley,Alvitta;Peck,E...
InfoVis	2015	Matches, Mismatche...	10.1109/TVCG.2015....	http://dx.doi.org/10....	449	458	J	The energy performa...	Brehmer, M.;Ng, J.;Ta...	;;;	Brehmer, M.;Ng, J.;Ta...	10.1109/TVCG.2011....	Design study, design ...	Brehmer,Matthew;N...

THE DATA CUBE



Country	Year	Child mortality	Births per woman
Afghanistan	2014	68.1	4.8
Afghanistan	2013	69.9	5.1
France	2014	3.6	2.0
France	2013	3.6	2.0
USA	2014	5.7	5.9
USA	2013	1.9	1.9

MULTI-ATTRIBUTE DATA – OUR VIEW TODAY

n x d matrix

n attributes

d items (data points)

Country	Year	Child mortality	Births per woman
Afghanistan	2014	68.1	4.8
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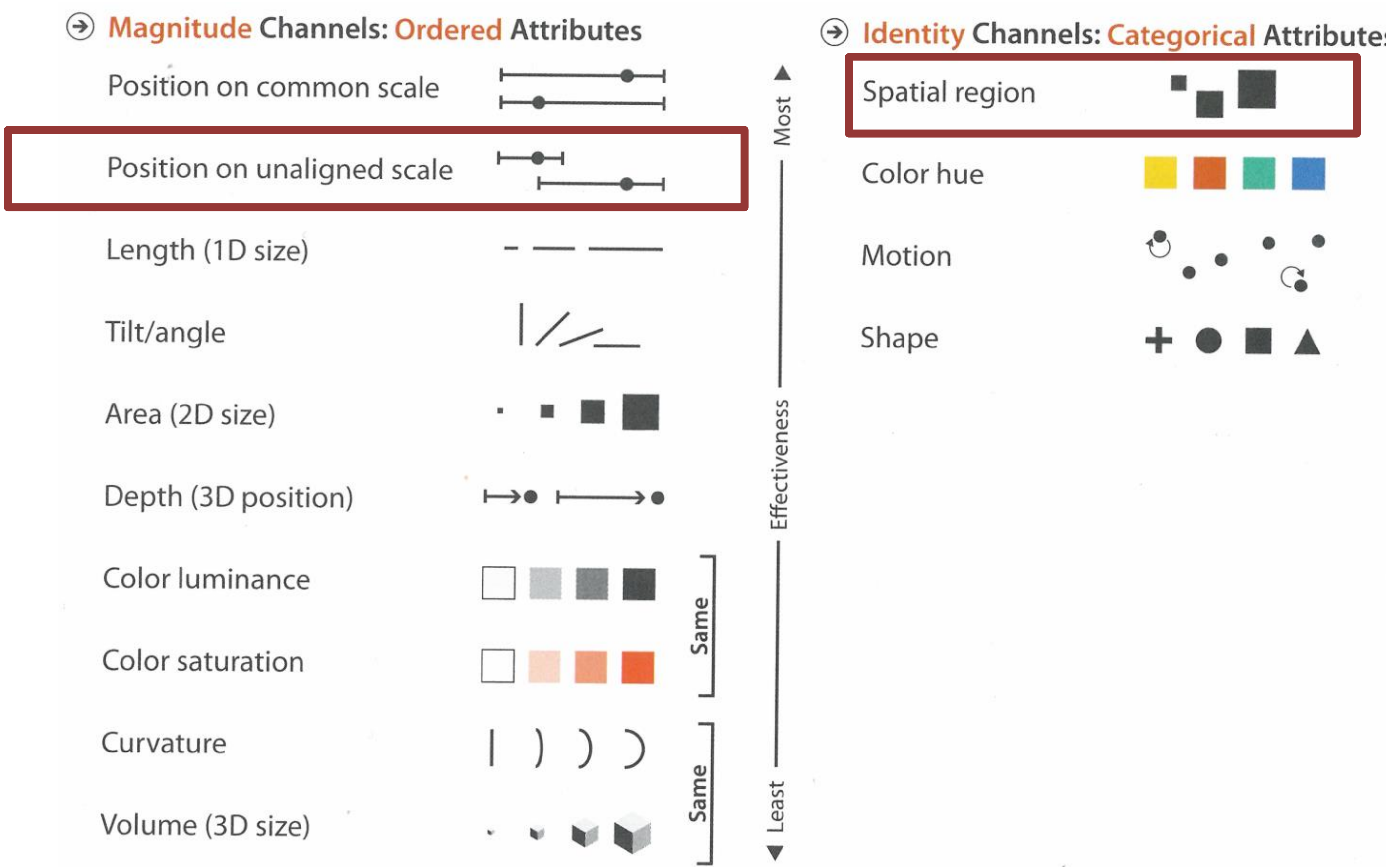
France	2013	3.6	2.0
USA	2014	5.7	5.9
USA	2013	1.9	1.9

ARRANGING TABULAR DATA

In Space

WHY ARRANGING DATA



QUANTITATIVE VALUES

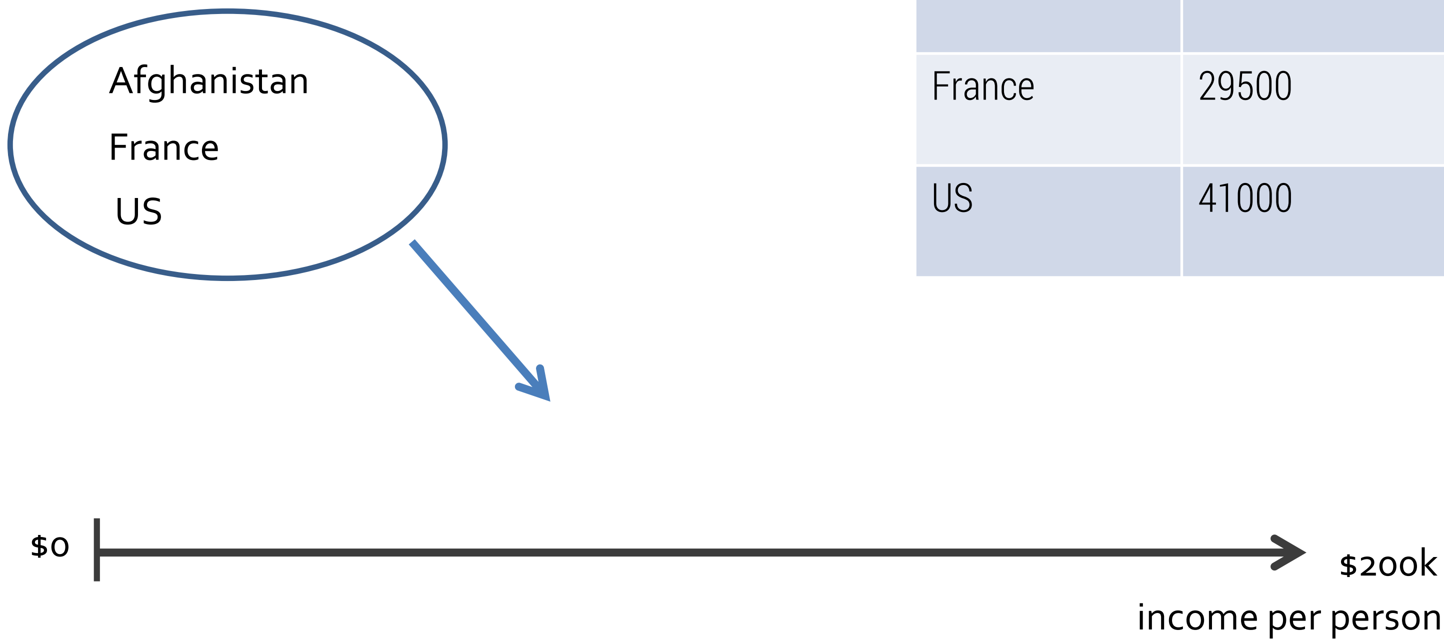
APPROACH

- Let's start with two attributes: country & income per person

Country	Income per person
Afghanistan	850
France	29500
US	41000

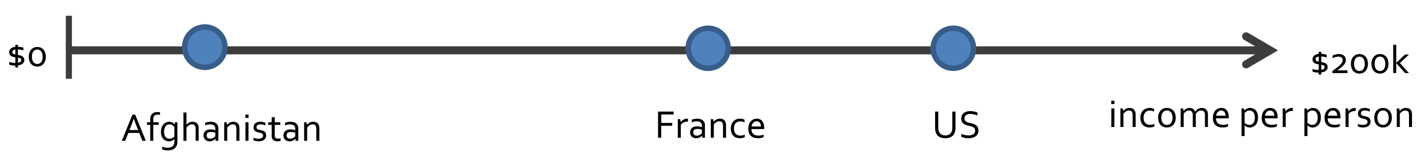
1. FIND A LAYOUT

Country	Income per person
Afghanistan	850
France	29500
US	41000



2. CHOOSE A VISUAL ENCODING & MARK

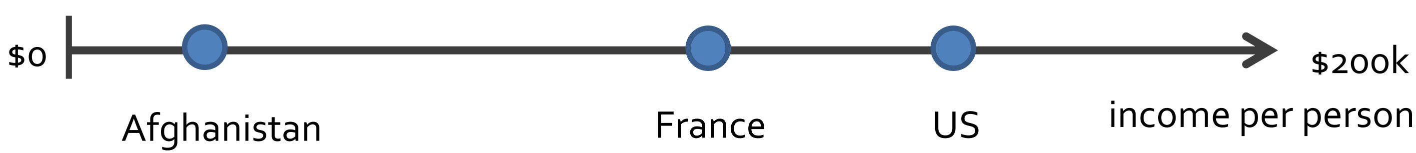
E.g. position + circle



1. FIND A LAYOUT

Country	Income per person	Life expectancy
Afghanistan	850	57
France	29500	81
US	41000	78

How do we extend this to 3 data attributes?



1. FIND A LAYOUT

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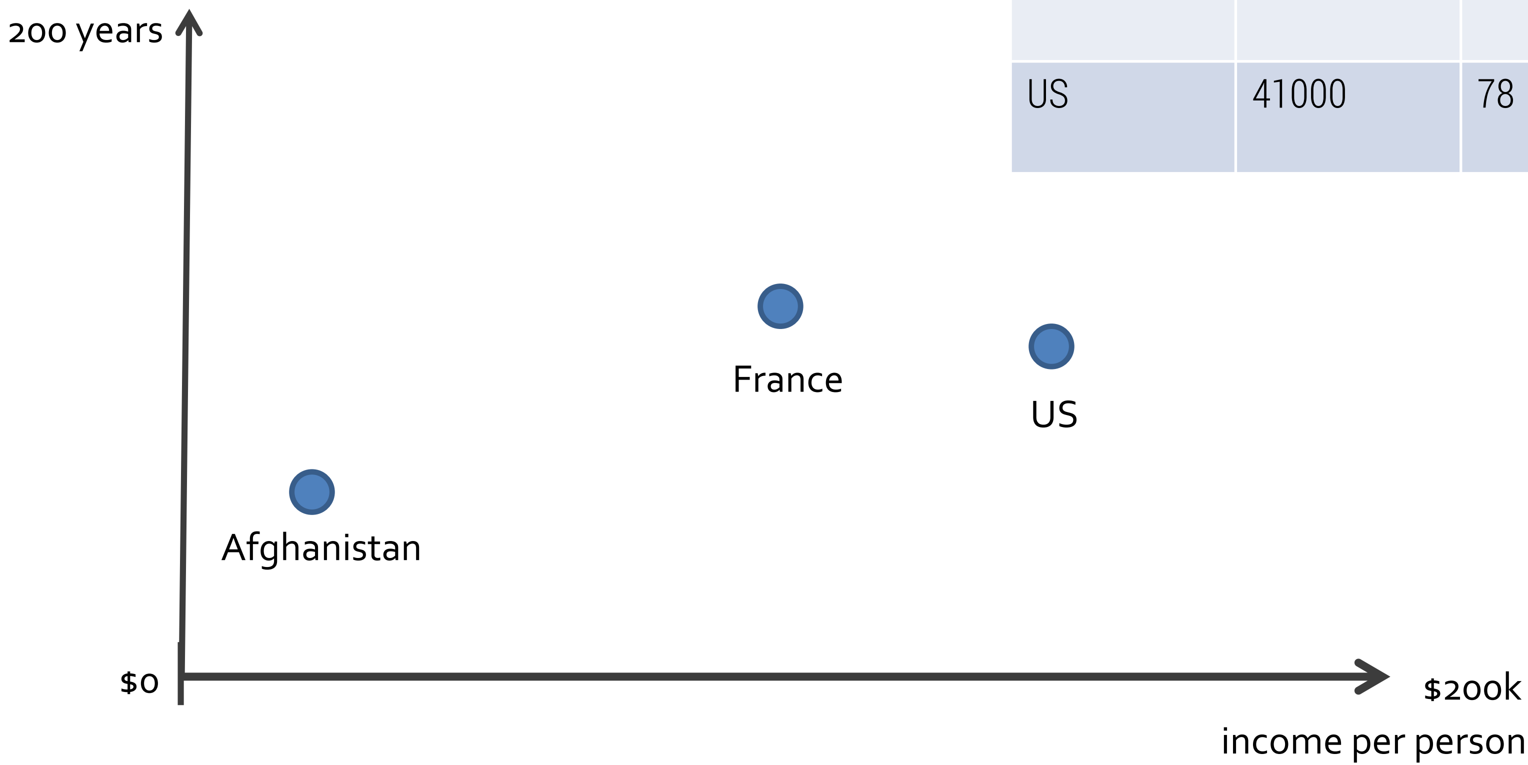
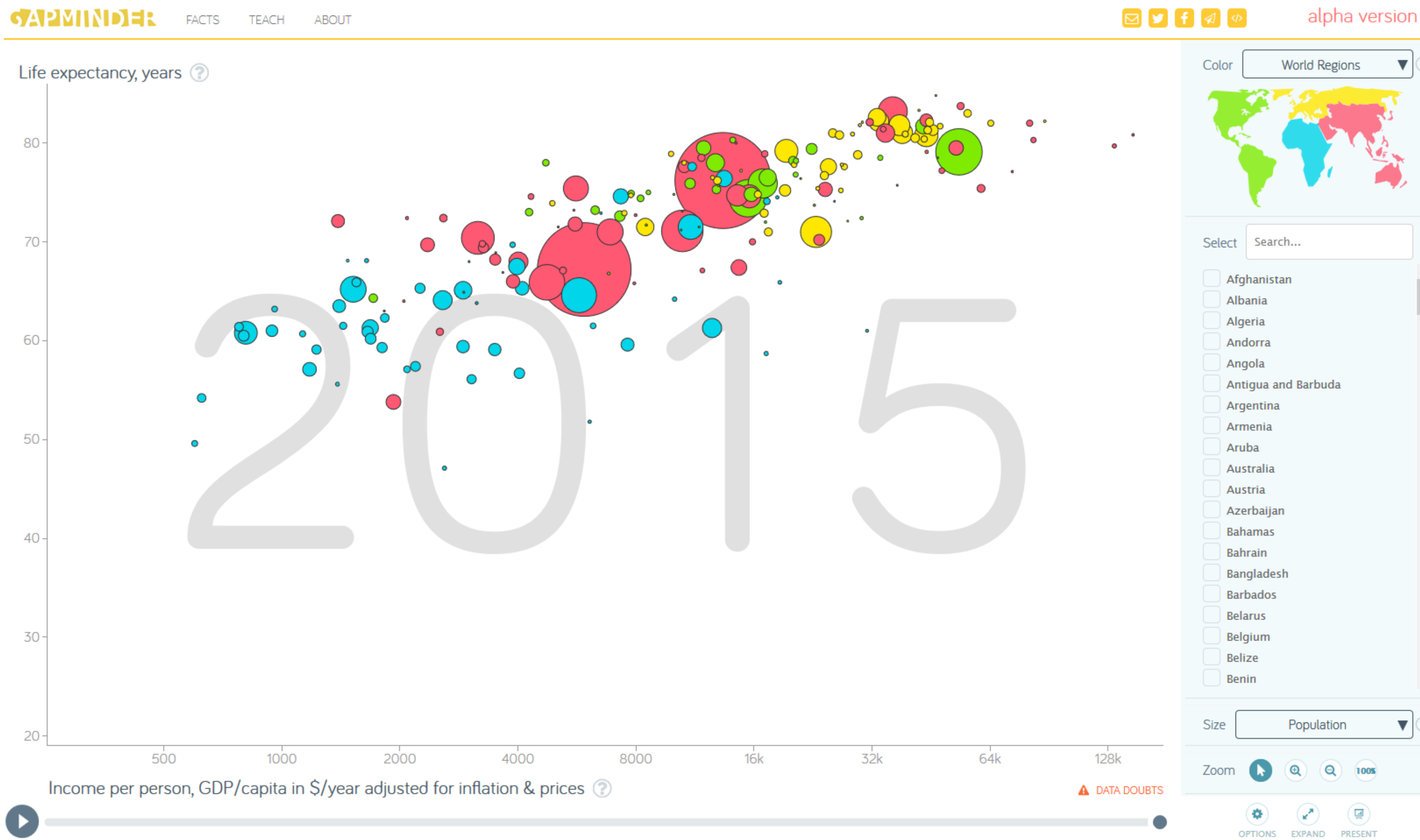


SCATTERPLOTS

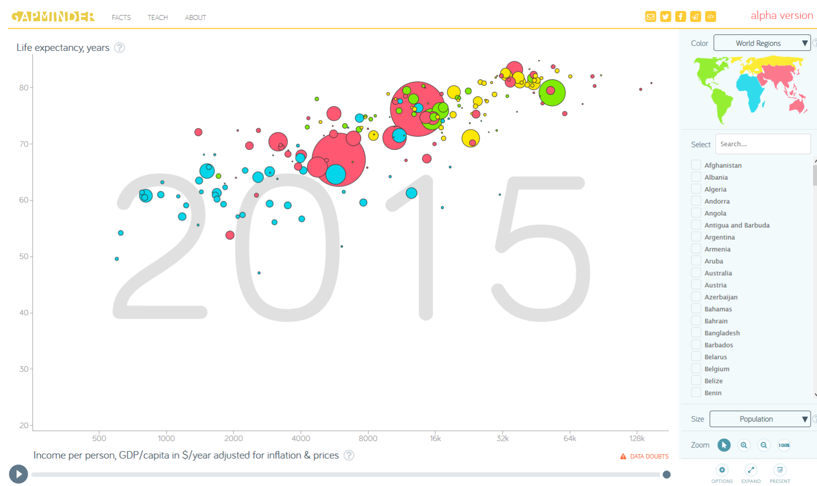
- two quantitative values
- horizontal and vertical spatial dimensions
- mark type = point



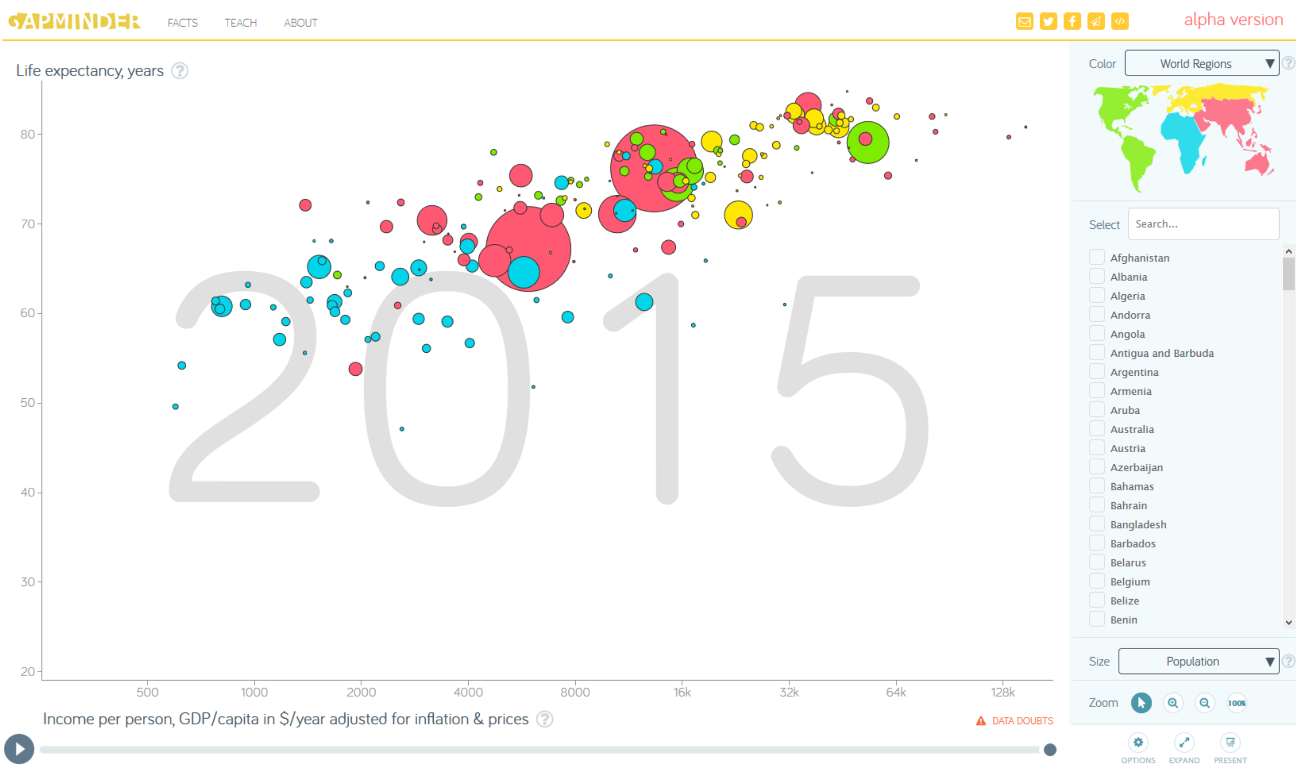
when marks are sized, the chart is often called a bubble chart or bubble plot

TASKS

- find trends
- find outliers
- show distribution
- show correlation
- locate clusters

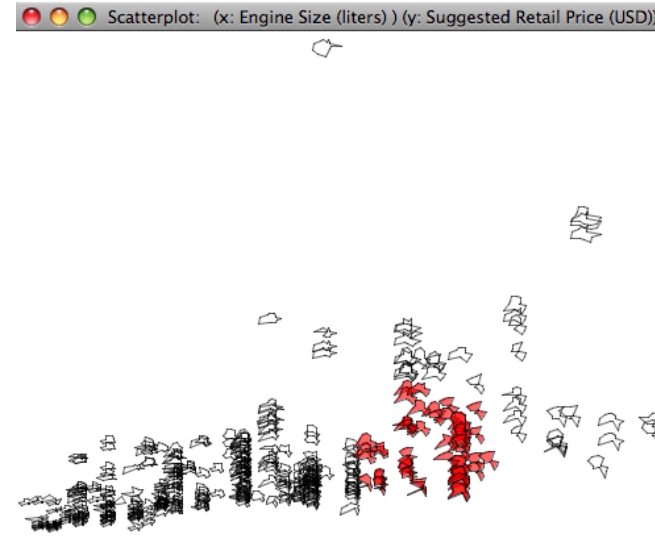


how many items are reasonable to put on a scatterplot?



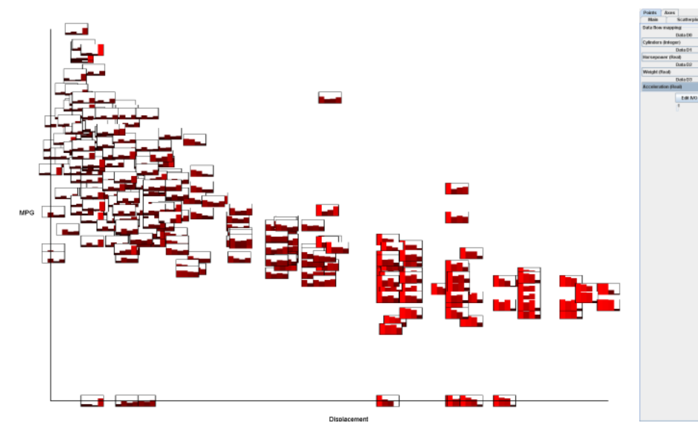
GLYPHS

marks can be replaced with glyphs



http://rosuda.org/software/Gauguin/gauguin.html

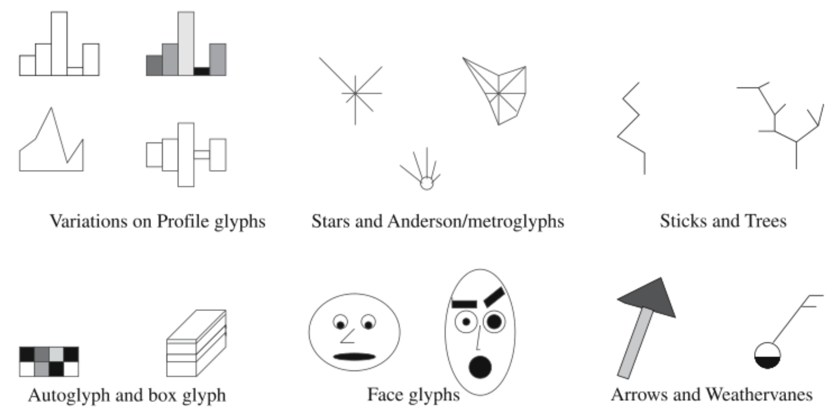
glyphs are themselves composed of multiple marks



https://engineering.purdue.edu/~elm/projects/gpuvis.html

GLYPHS

- Small composite visual representations of multi-dimensional data points
- Characterized generally by lack of reference structures (grid lines, axes labels, …)



From Ward, 2002
A taxonomy of glyph placement strategies for multidimensional data visualization

EXAMPLE: CHERNOFF FACES

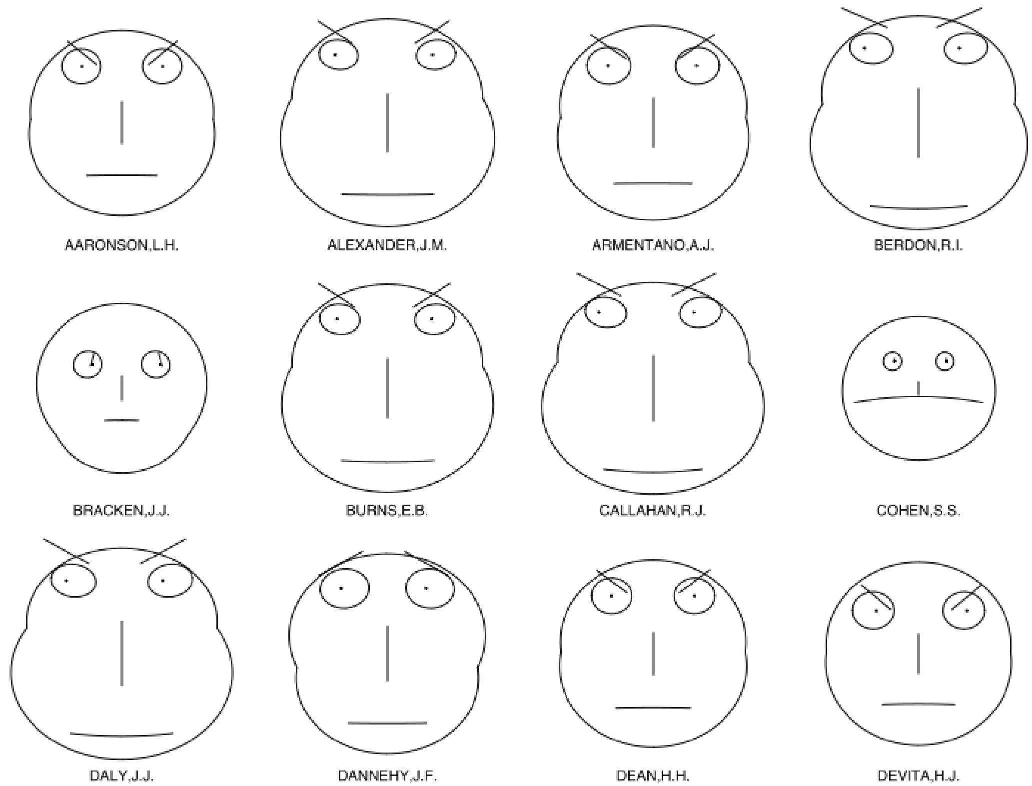
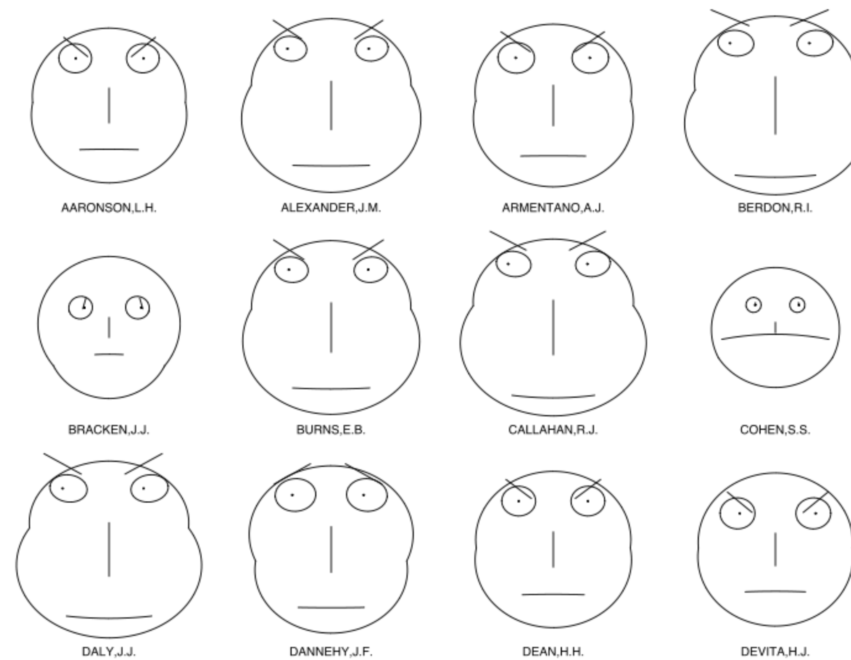


Image source: Wikipedia

Herman Chernoff, [The Use of Faces to Represent Points in K-Dimensional Space Graphically](), 1973.

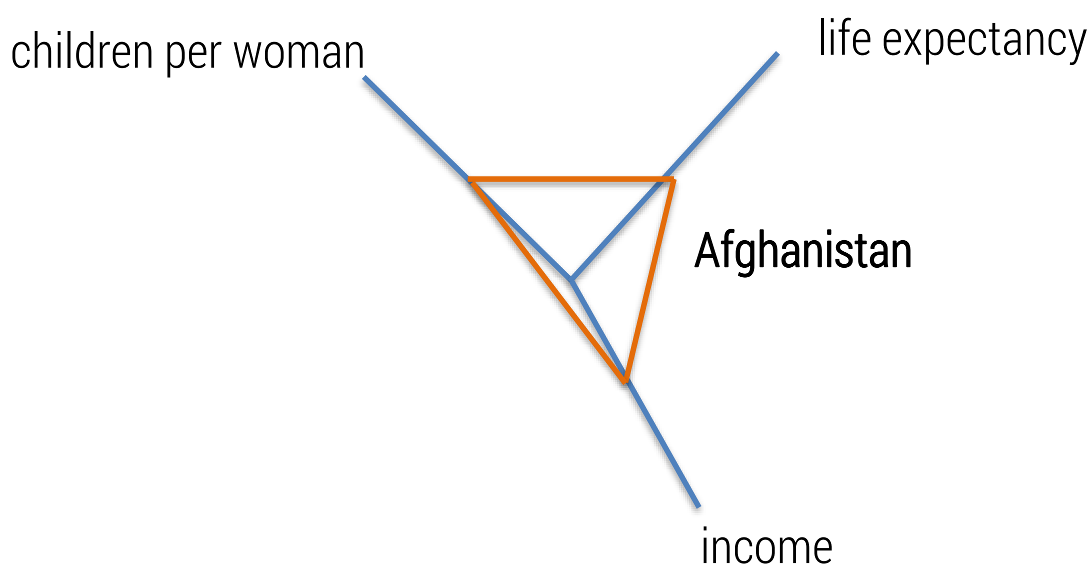
CHERNOFF FACES

- features of a human face encode data values (e.g. slant of eye brows, size of eyes, …)
- reasoning: humans are good at differentiating faces and reading face features
- problem: chernoff faces have generally been found not to be very effective



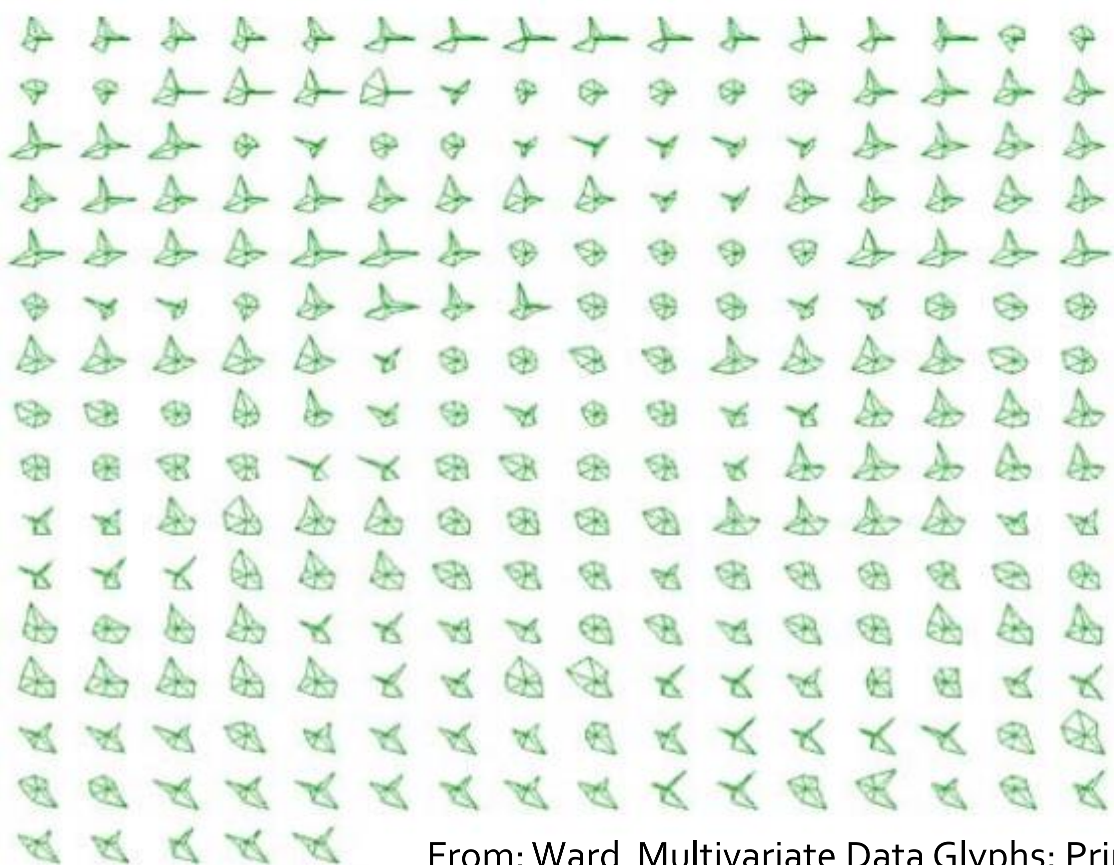
EXAMPLE: STAR GLYPHS

- Lay out dimension in radial fashion
- Draw each point as a ring



(not real data, here)

STAR GLYPHS



From: Ward Multivariate Data Glyphs: Principles and Practice. Handbook of Data Visualization (2008)

SHOW CATEGORICAL REGIONS

Separate, Order, and Align

CATEGORICAL VALUES

- spatial position is an ordered magnitude visual channel
- categorical attributes are unordered identities (no magnitude)

→cannot be encoded with spatial position

- BUT: can be differentiated with a spatial region

REGIONS

- contiguous bounded areas
- distinct from one another
- need to be separated, ordered, and aligned

LIST ALIGNMENT

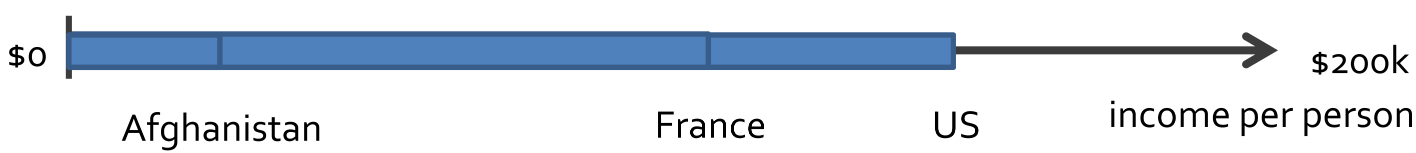
ONE KEY

LIST ALIGNMENT

separate into regions by key

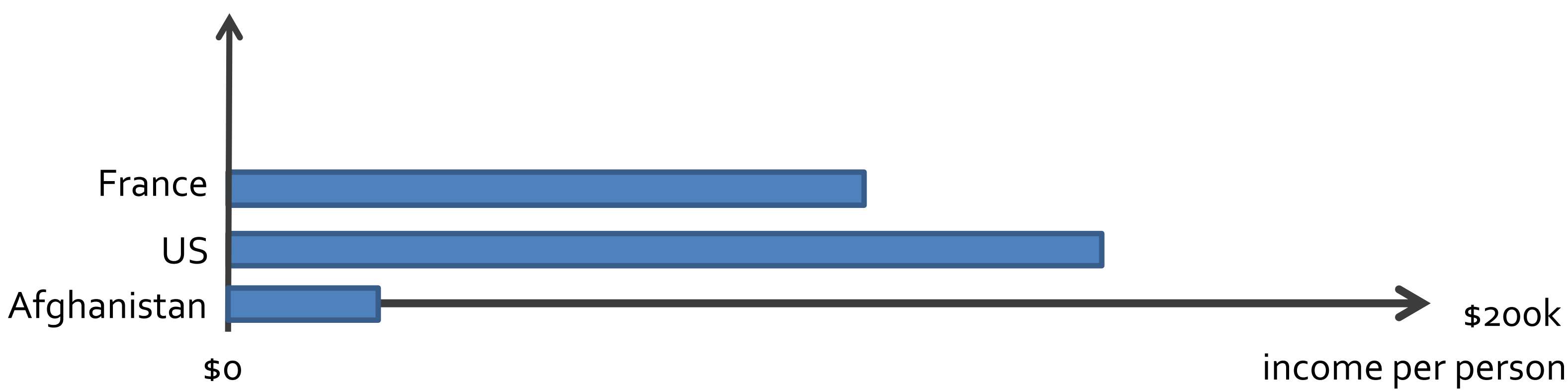
E.g. length + rectangle

Ok, this is weird



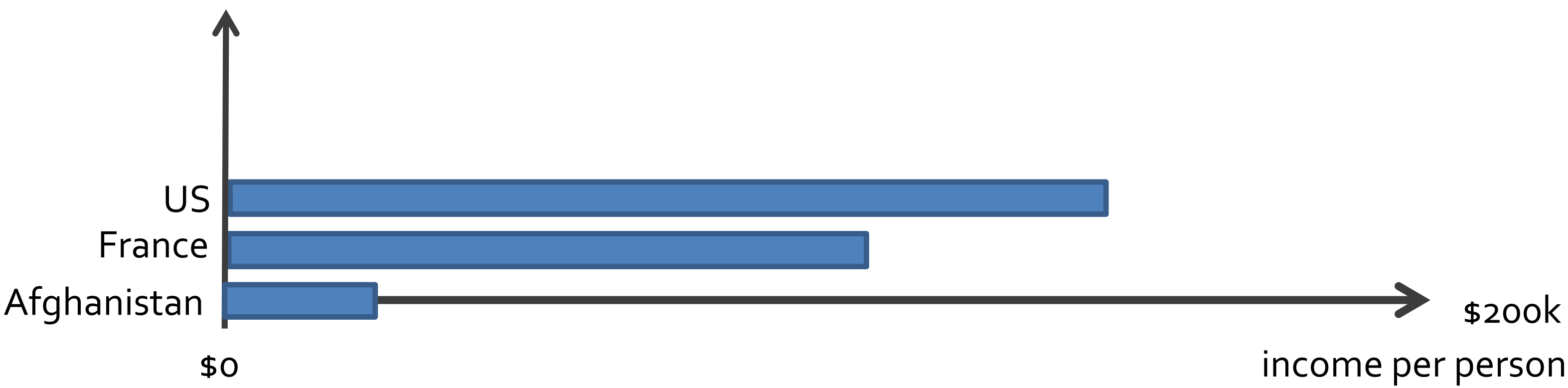
ALIGN

align regions of key categorical values along one axis in a common frame



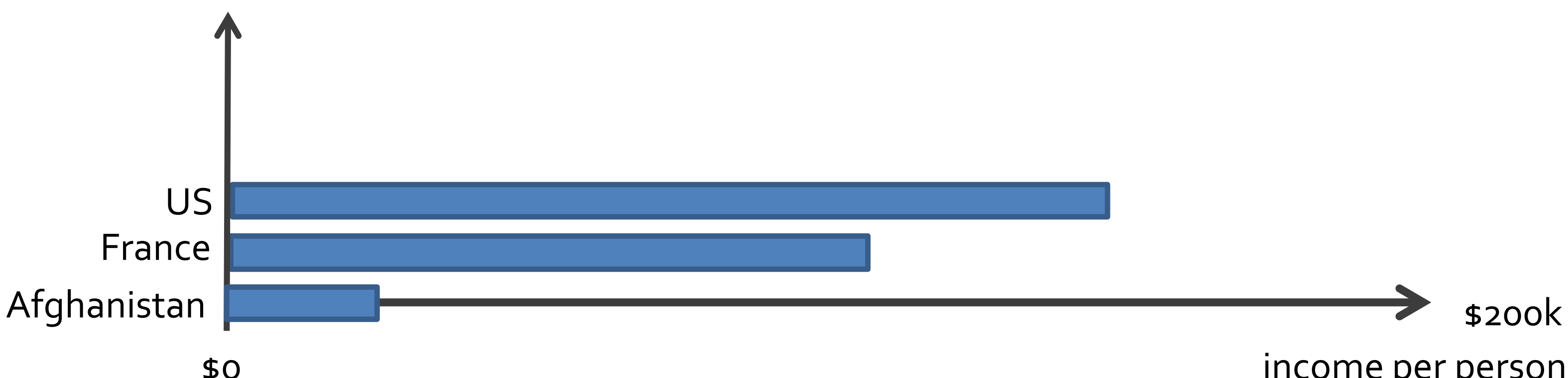
ORDER

- using a derived attribute such as alphabet
- and/or using dependent data values

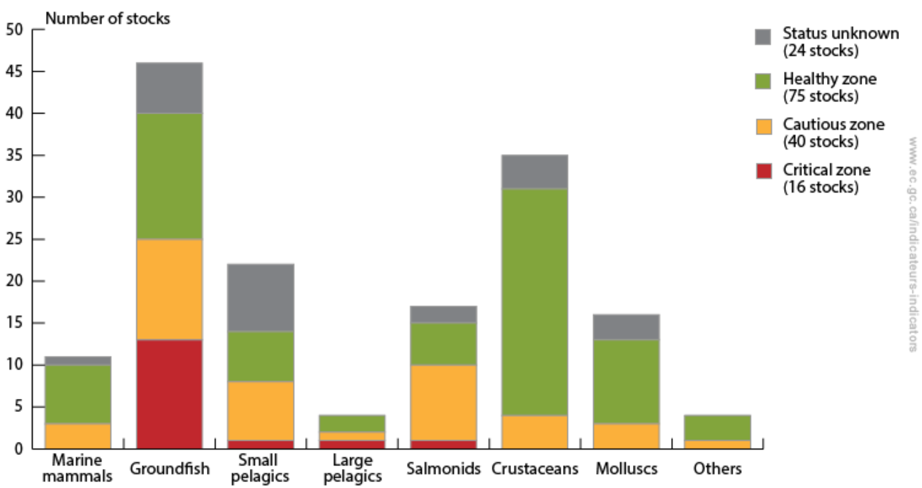


BAR CHARTS

DATA	one quantitative value attribute, one categorical key attribute
ENCODE	line marks, express value attribute with aligned vertical position (length), separate key attribute with horizontal position
TASK	lookup and compare values
SCALE	key attribute: dozens to hundreds of levels



ALTERNATIVE

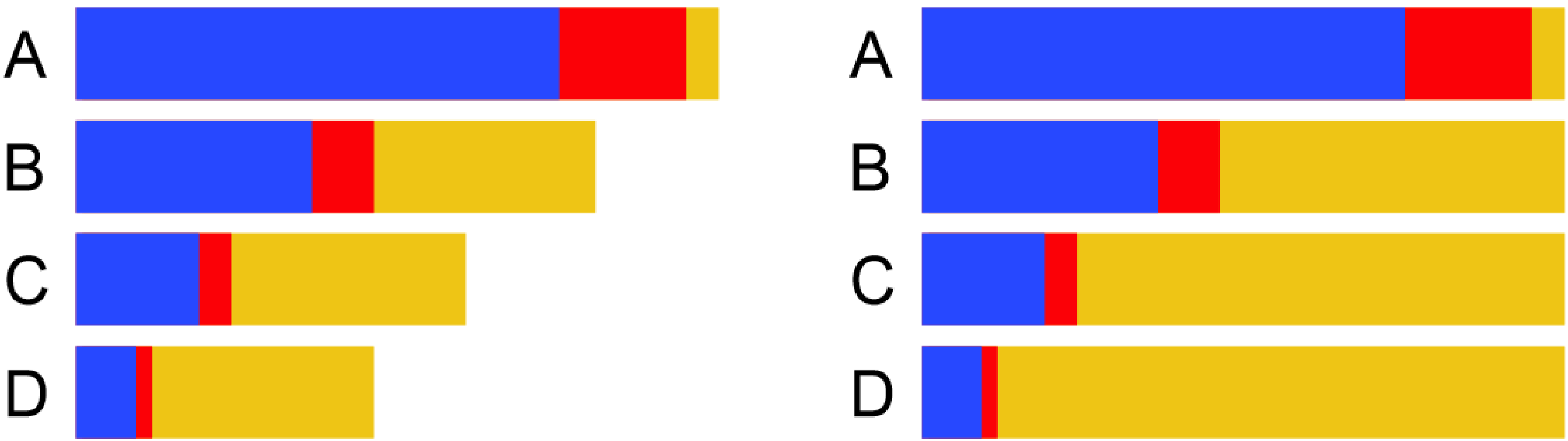


https://www.ec.gc.ca/indicateurs-indicators/default.asp?lang=en&n=1BCD421B-1

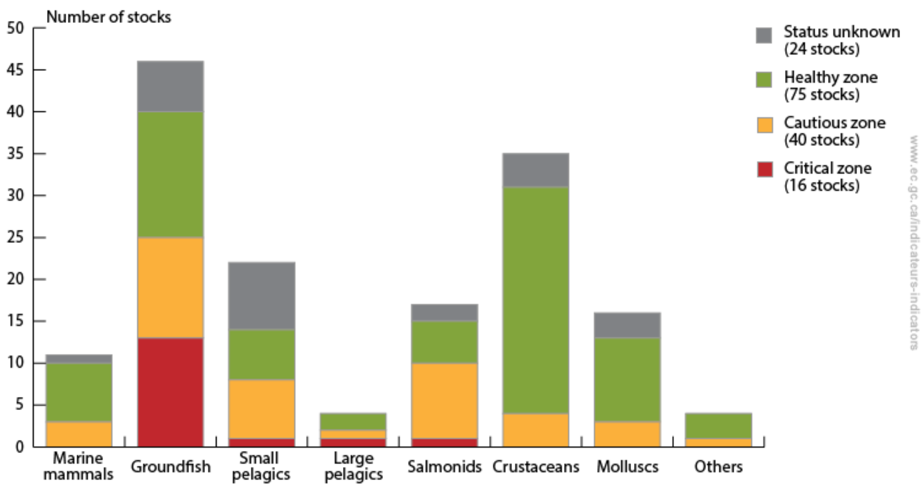
Stacked bar chart

- each bar is a composite glyph
- each bar part encodes a value
- composite glyphs arranged as a list according to primary key
- color used to distinguish secondary key
- typically used for absolute values (use a normalized stacked bar for proportions)

STACKED BARS VS. NORMALIZED STACKED BARS



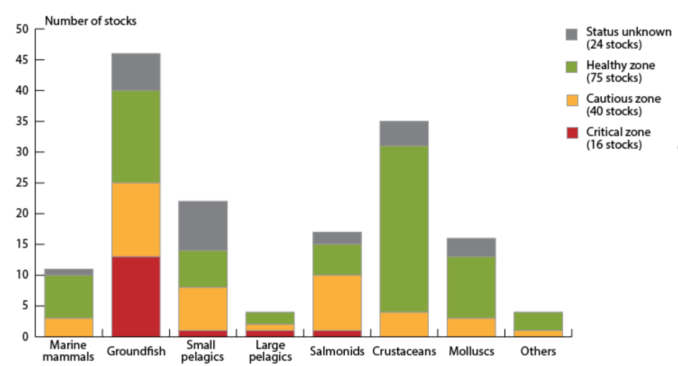
STACKED BARS



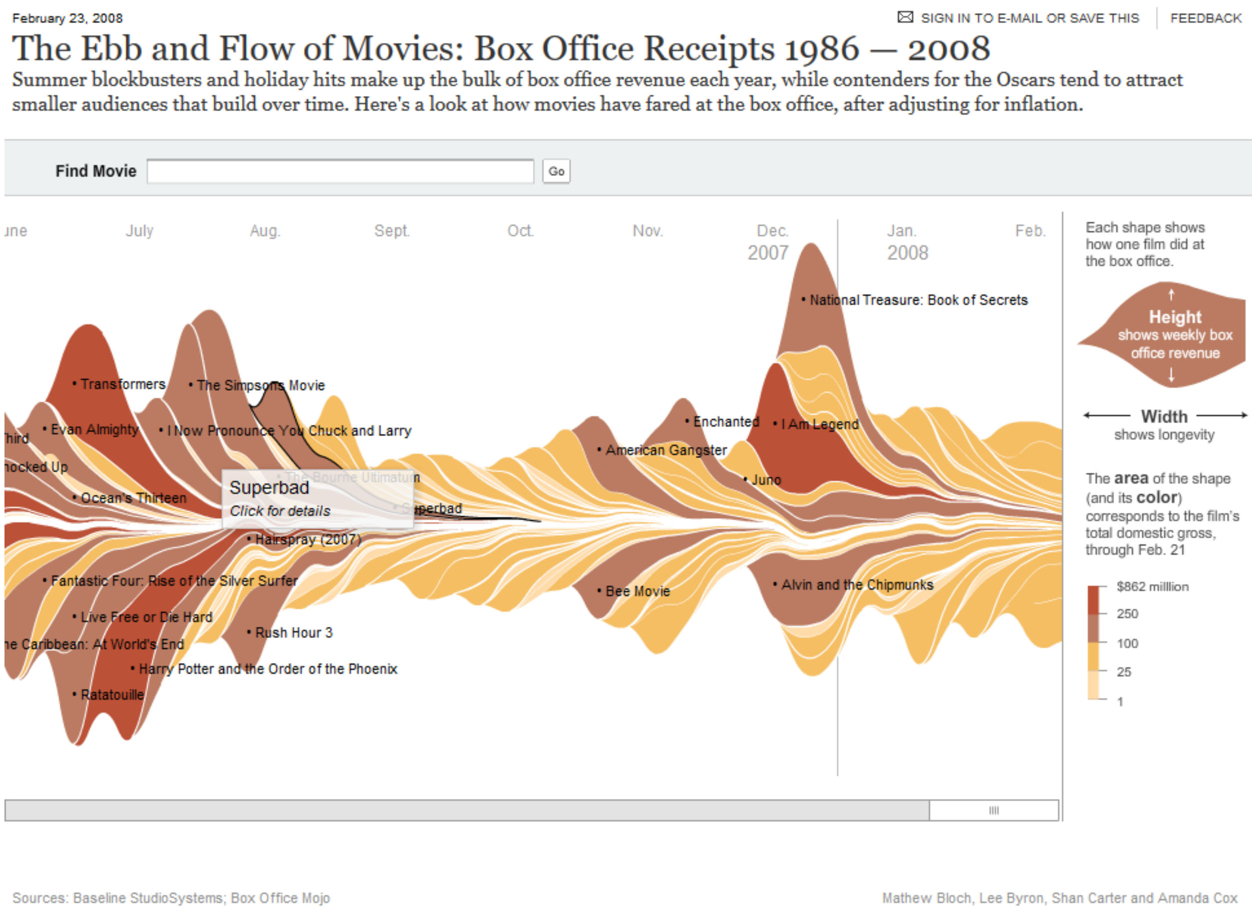
- ADVANTAGE
  - can compare totals and lowest level well
- DISADVANTAGE
  - upper levels of secondary key require comparison against non-aligned scale

STACKED BARS

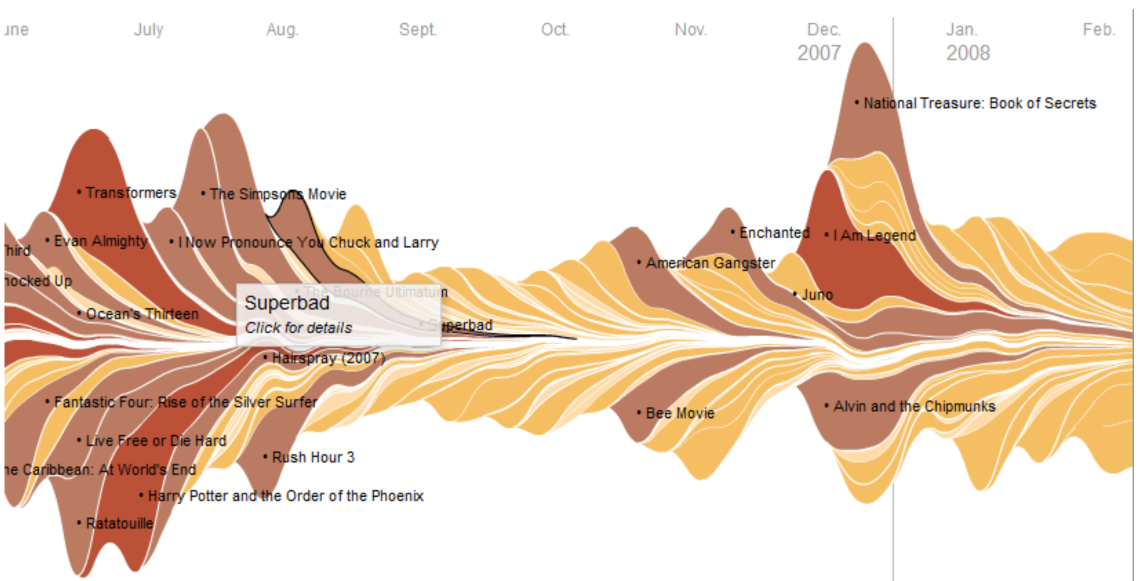
DATA	MD table; one quantitative value attribute, two categorical key attributes
ENCODE	bar glyph: length-encoded subcomponents for each level of secondary key attribute separate bars by category of primary key
TASK	part-to-whole relationship, lookup values, find trends
SCALE	key attribute (main axis): dozens to hundreds of levels key attribute (stacked glyph axis): several to one dozen

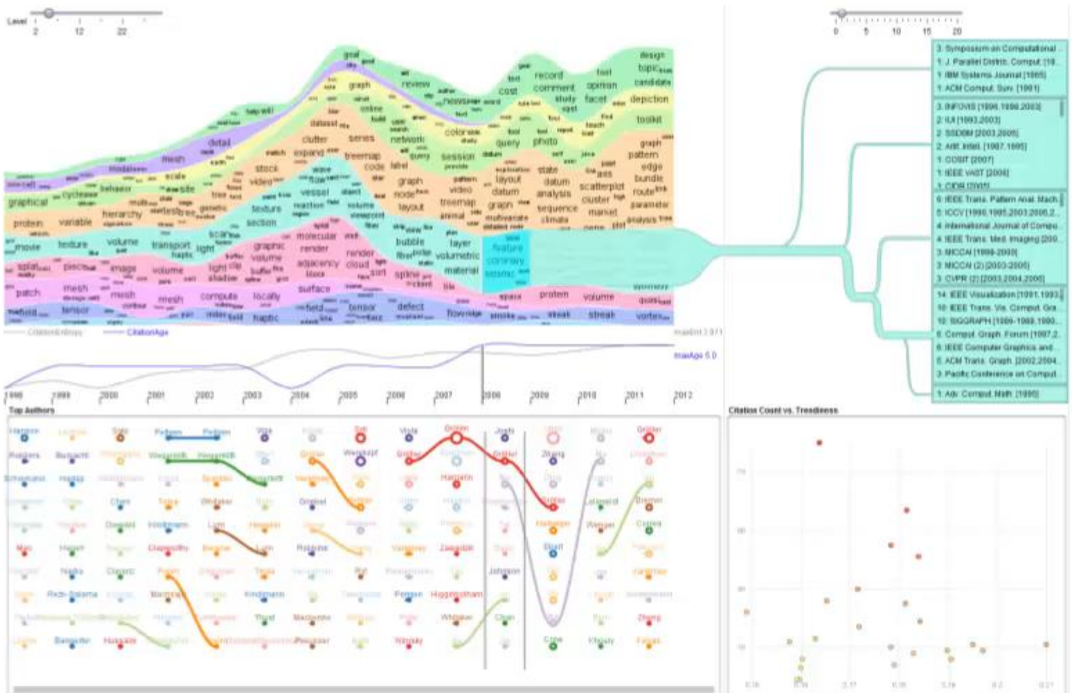


STREAMGRAPH



DATA	MD table; one quantitative value attribute (e.g. counts), one ordered key attribute (e.g. time), one categorical key attribute (e.g. film)
DERIVE	order of layers is derived from a quantitative attribute
ENCODE	use derived geometry to show layers across time, layer height encodes count
SCALE	key attributes (time, main axis): hundreds of time points key attributes (short axis): dozens to hundreds





CiteRivers

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Steffen Koch, Thomas Ertl

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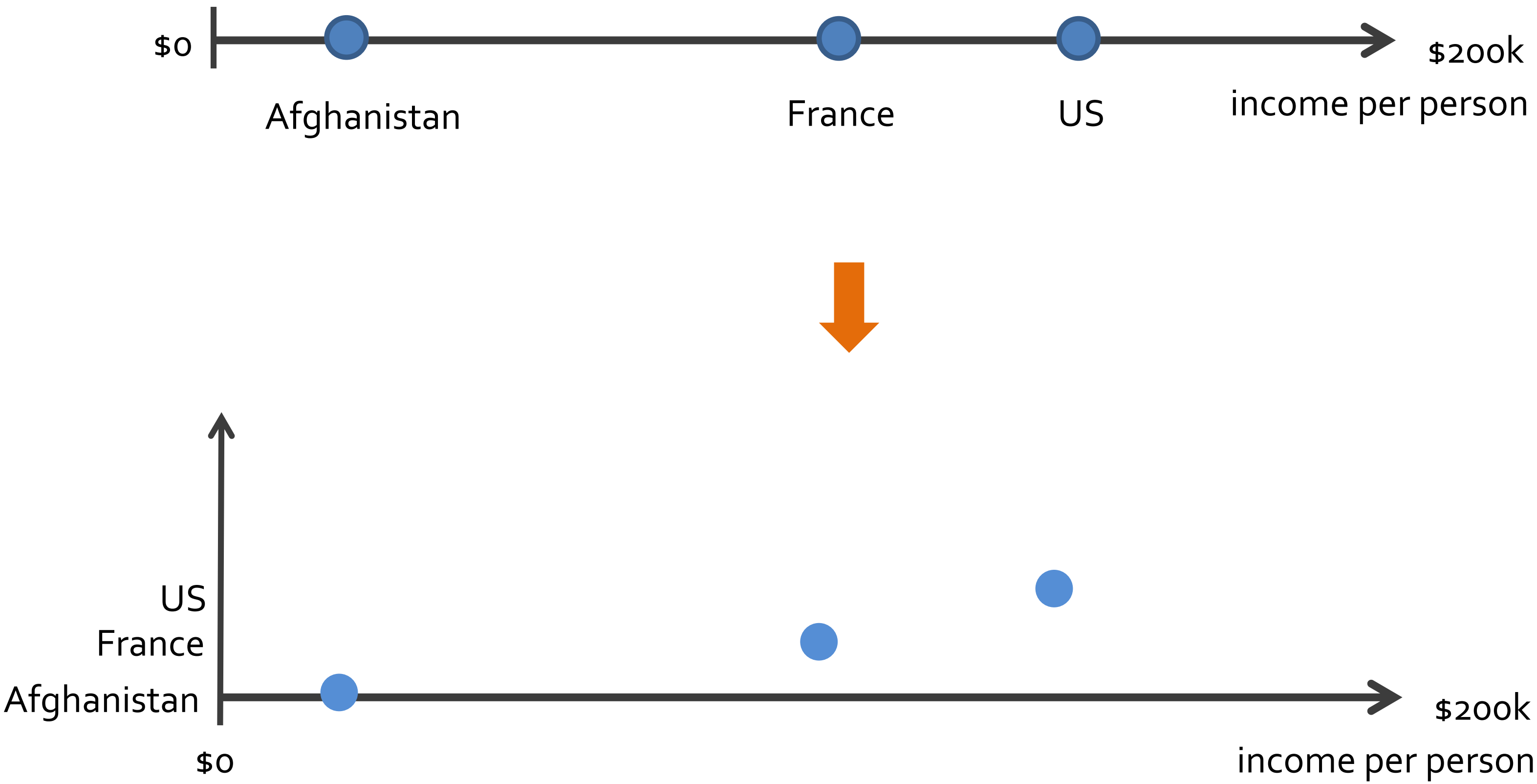
IEEE VAST 2015

Institute for Visualization
and Interactive Systems

DOT CHART/PLOT

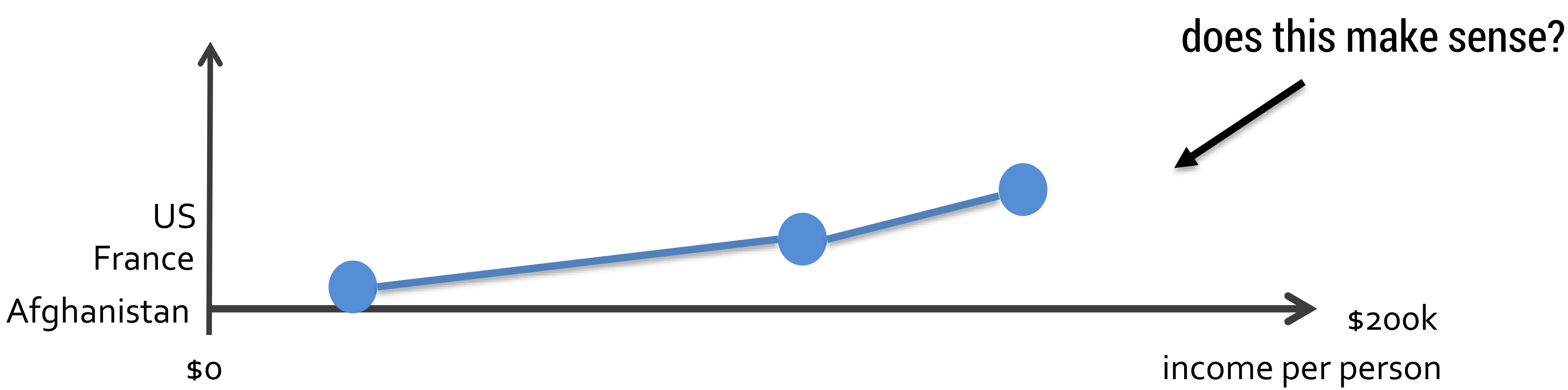


LINE CHART

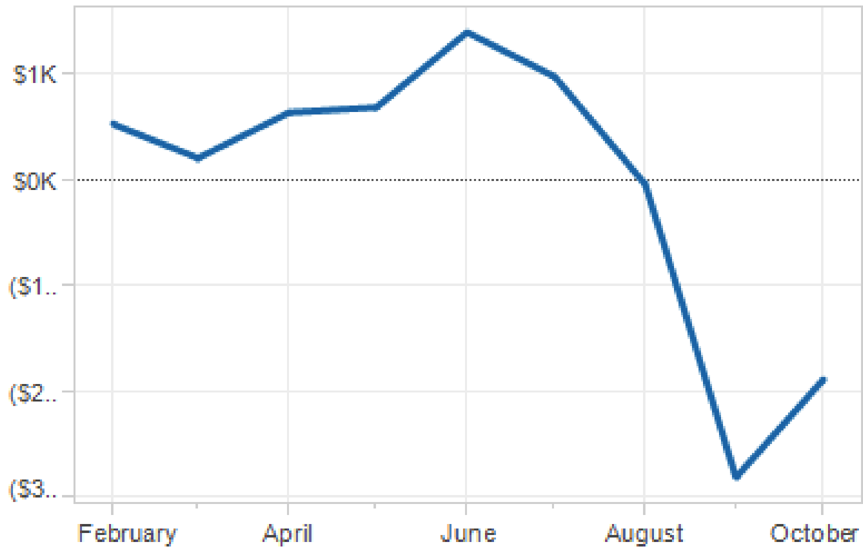
augment with line connection marks

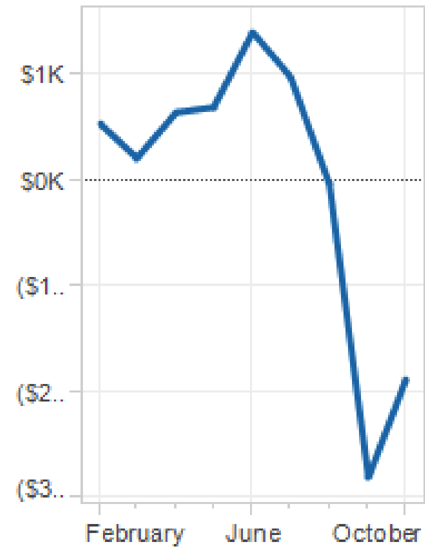
emphasize the ordering and show trends

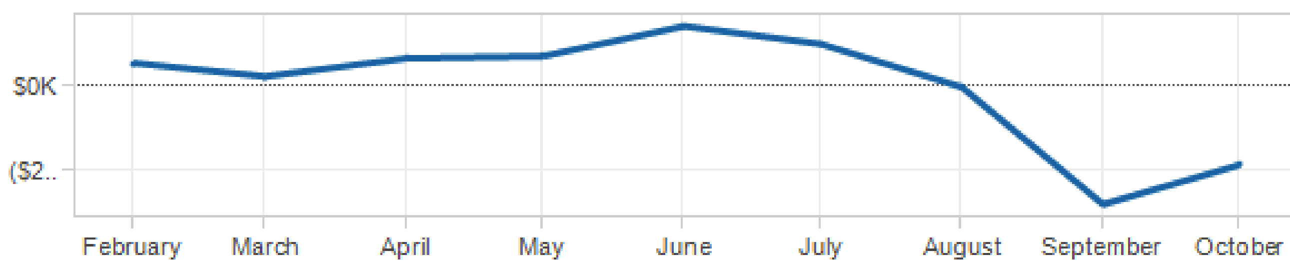
should not be used with categorical keys



ASPECT RATIO SELECTION



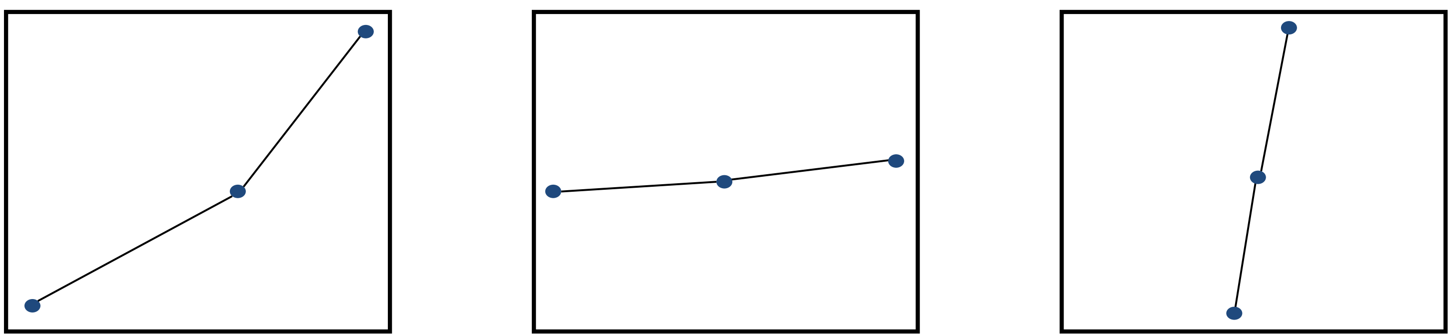




BANKING TO 45°

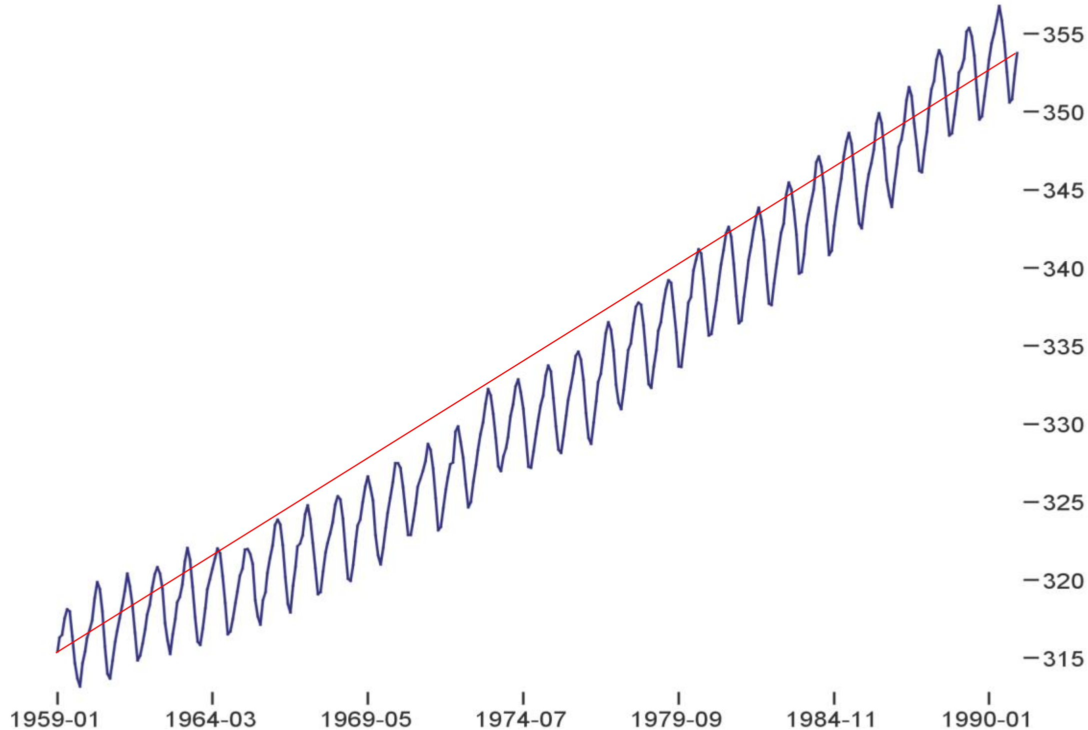
[Cleveland]

TO FACILITATE PERCEPTION OF TRENDS, MAXIMIZE THE DISCRIMINABILITY OF LINE SEGMENT ORIENTATIONS

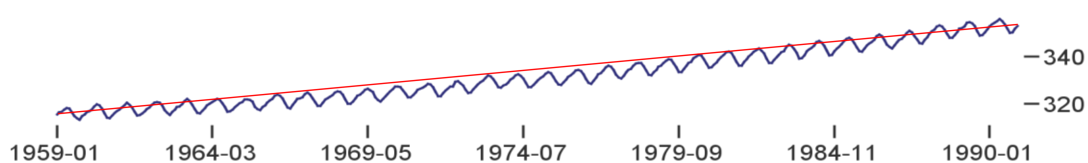


TWO SEGMENTS ARE MAXIMALLY DISCRIMINABLE WHEN THEIR AVG ABSOLUTE ANGLE IS 45°

OPTIMIZE THE *ASPECT RATIO* TO BANK TO 45°

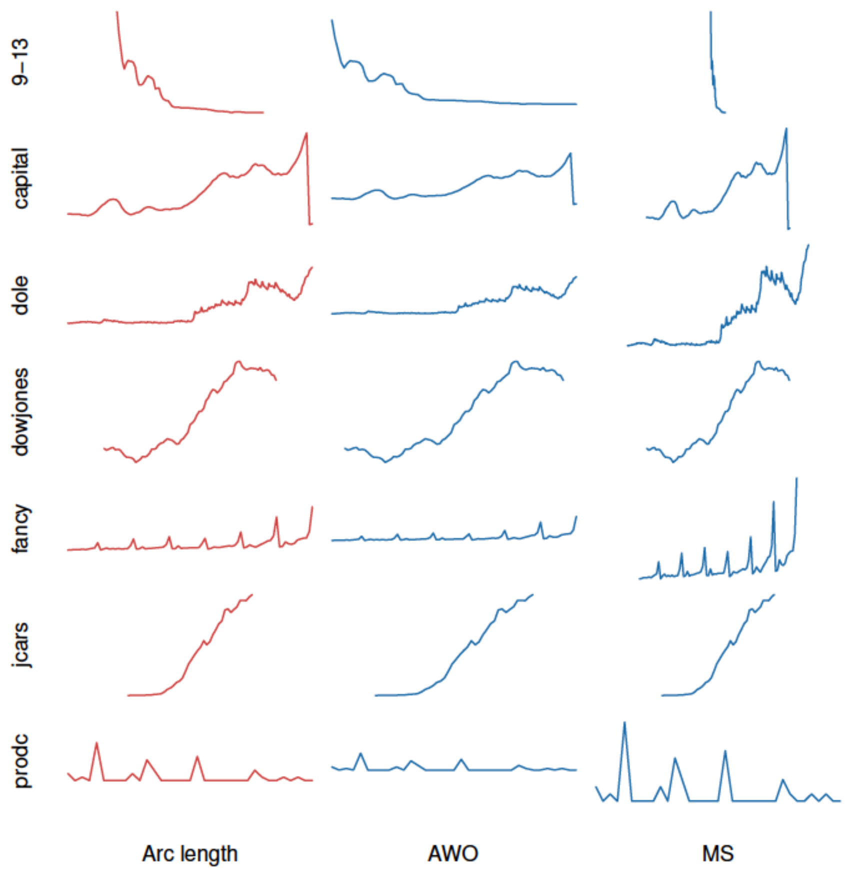


ASPECT RATIO = 1.17



ASPECT RATIO = 7.87

ALTERNATIVE METHODS



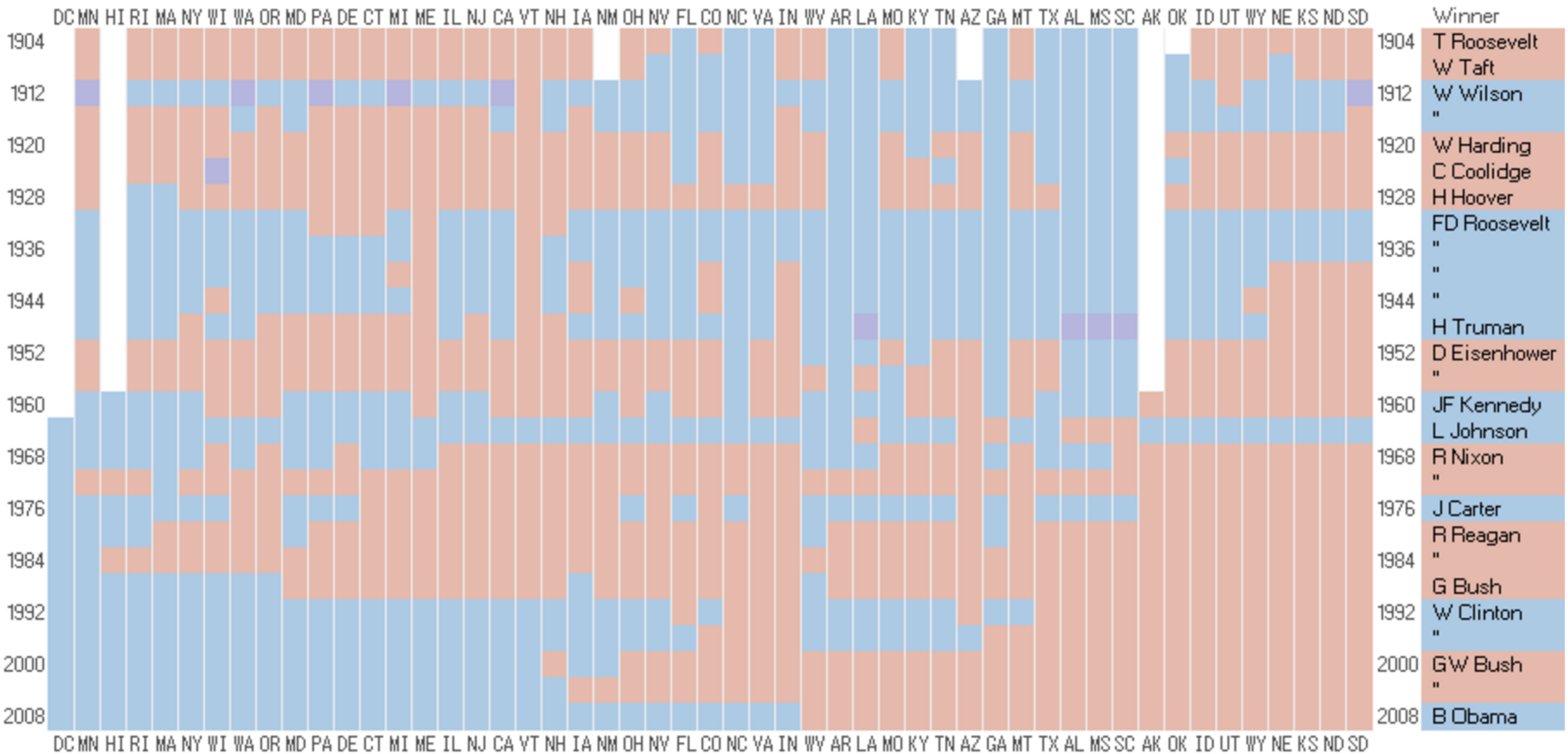
Practical advice:

CHOOSE AN ASPECT RATIO THAT EMPHASIZES THE IMPORTANT DETAILS FOR <u>YOUR</u> TASK

[TALBOT ET AL, 2011]

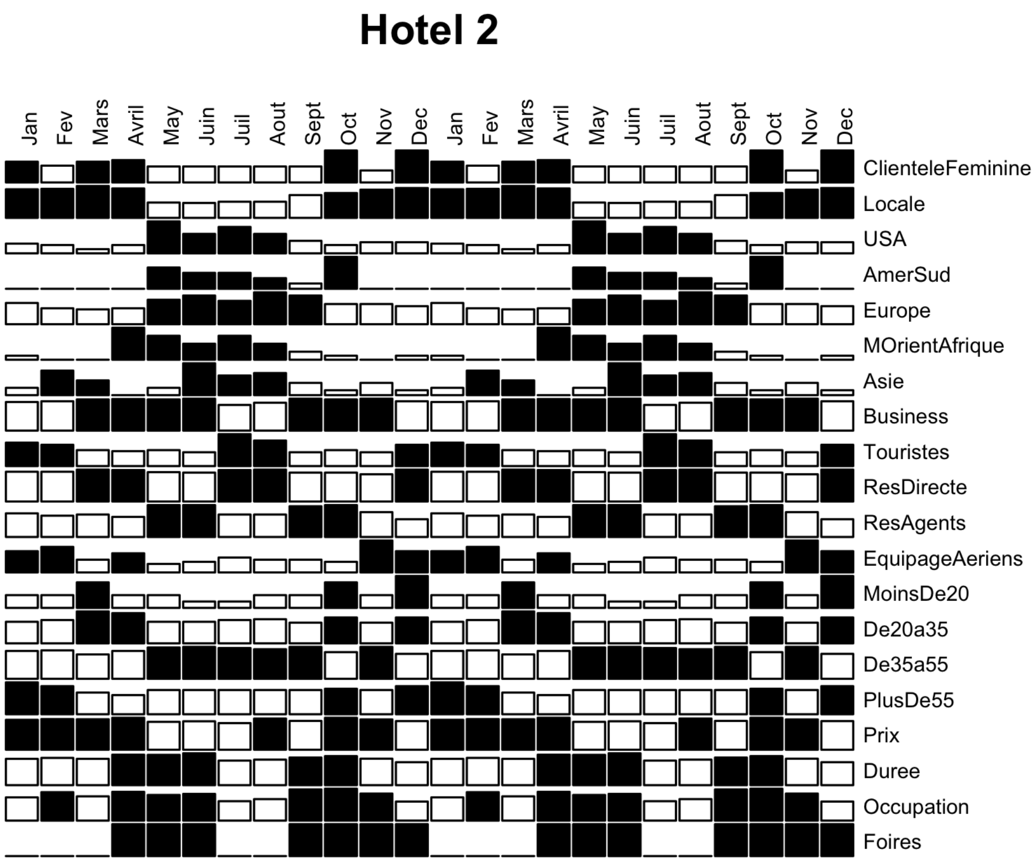
MATRIX ALIGNMENT

Two keys

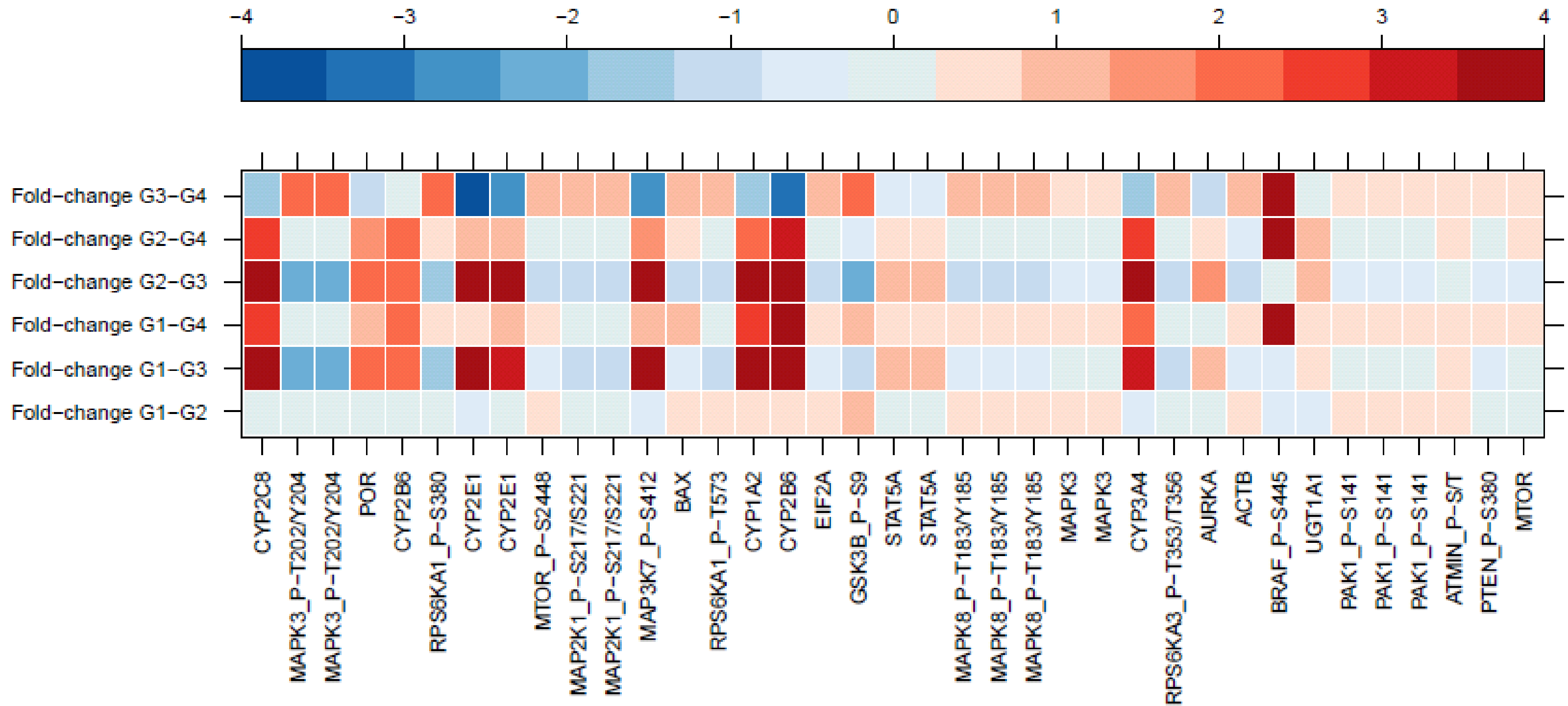


https://ldld.samizdat.cc/2016/tag/catalog/

HEATMAP


Hotel 2
Jan
Fev
Mars
Avril
May
Juin
Juil
Aout
Sept
Oct
Nov
Dec
Jan
Fev
Mars
Avril
May
Juin
Juil
Aout
Sept
Oct
Nov
Dec
ClienteleFeminine
Locale
USA
AmerSud
Europe
MOrientAfrique
Asie
Business
Touristes
ResDirecte
ResAgents
EquipageAeriens
MoinsDe20
De20a35
De35a55
PlusDe55
Prix
Duree
Occupation
Foires

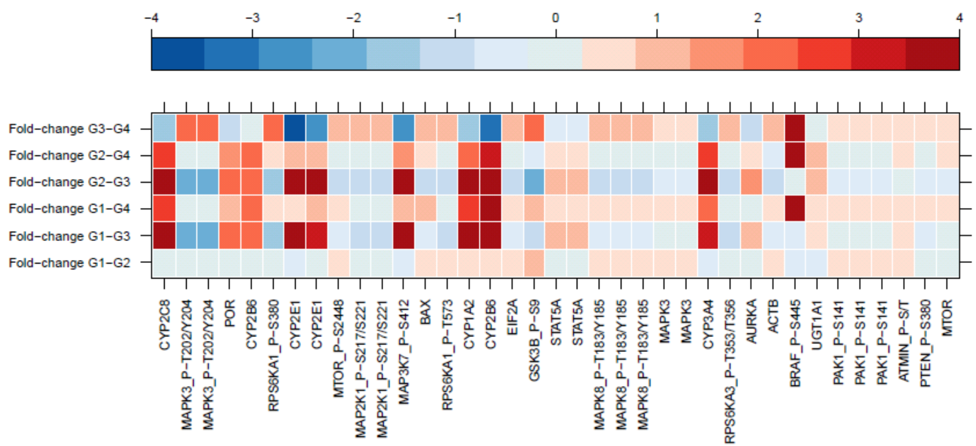
HEATMAP



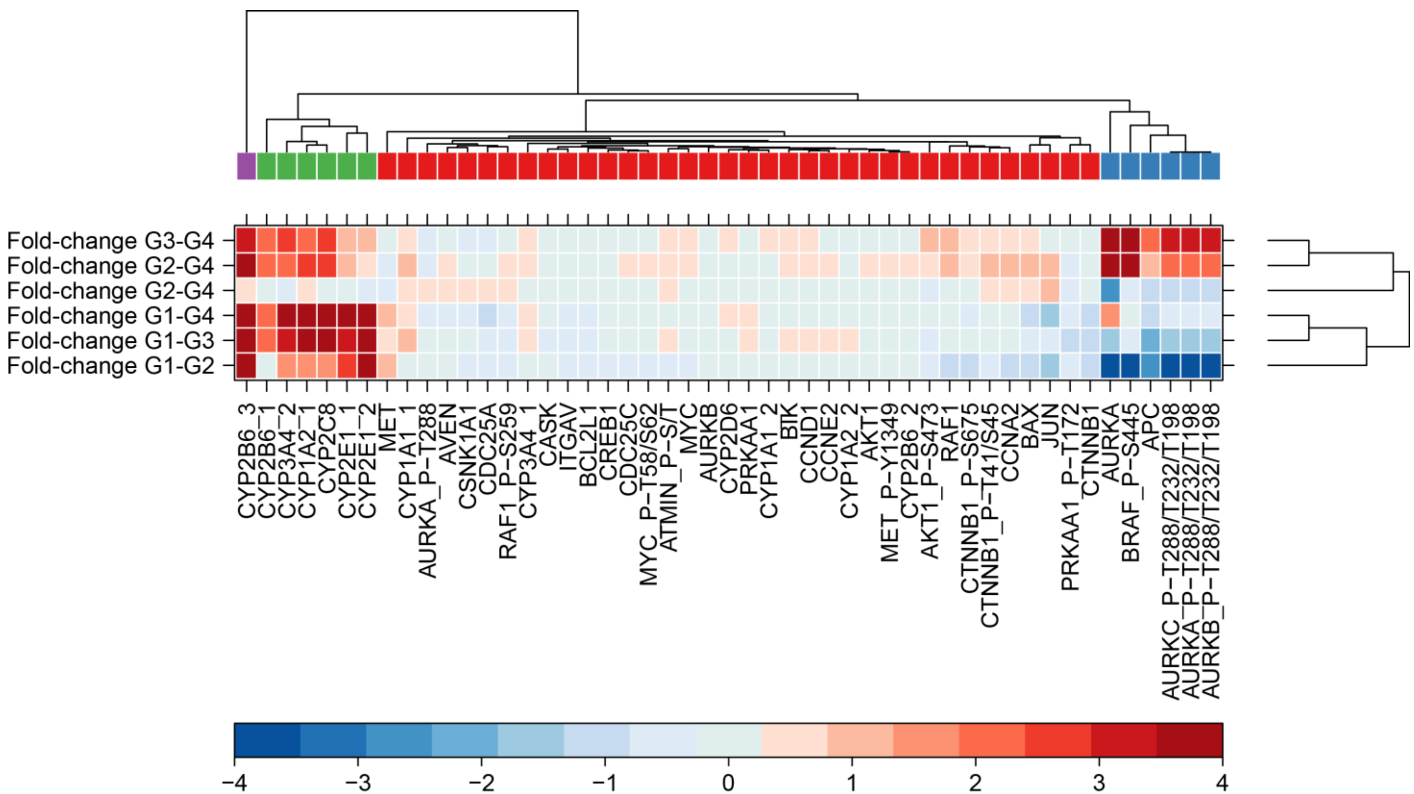
http://www.ra.cs.uni-tuebingen.de/software/RPPApipe/doc/documentation.htm

HEATMAP

DATA	Table; two categorical key attributes, one quantitative value attribute
ENCODE	2D matrix alignment of area marks, e.g. with diverging color map
TASK	find clusters, outliers; summarize
SCALE	items: ~1 million (on 1000x1000px), categorical attribute levels: hundreds, quantitative attribute levels: 3-11



CLUSTERED HEATMAP



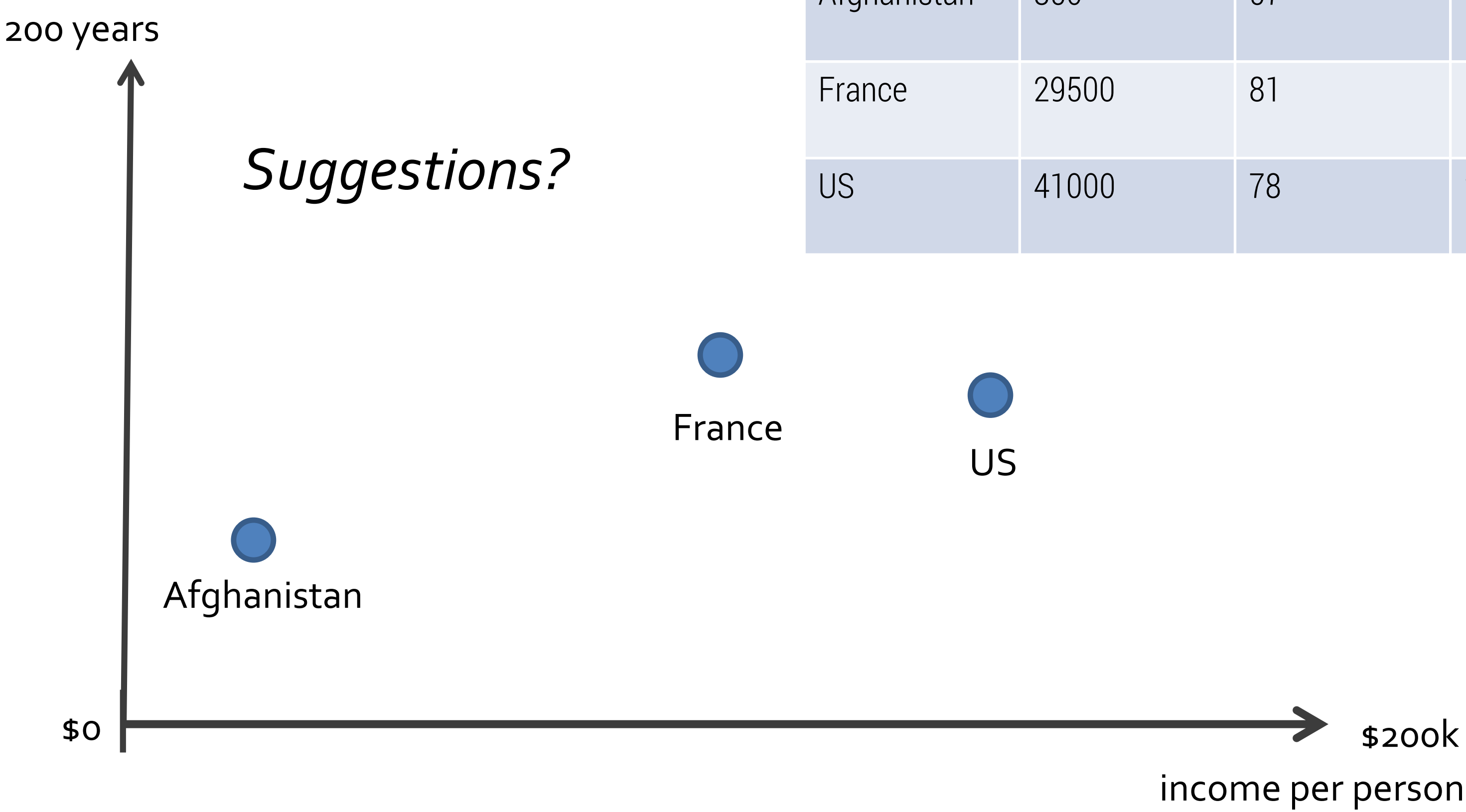
http://www.ra.cs.uni-tuebingen.de/software/RPPApipe/doc/documentation.htm

BACK TO OUR ORIGINAL EXAMPLE

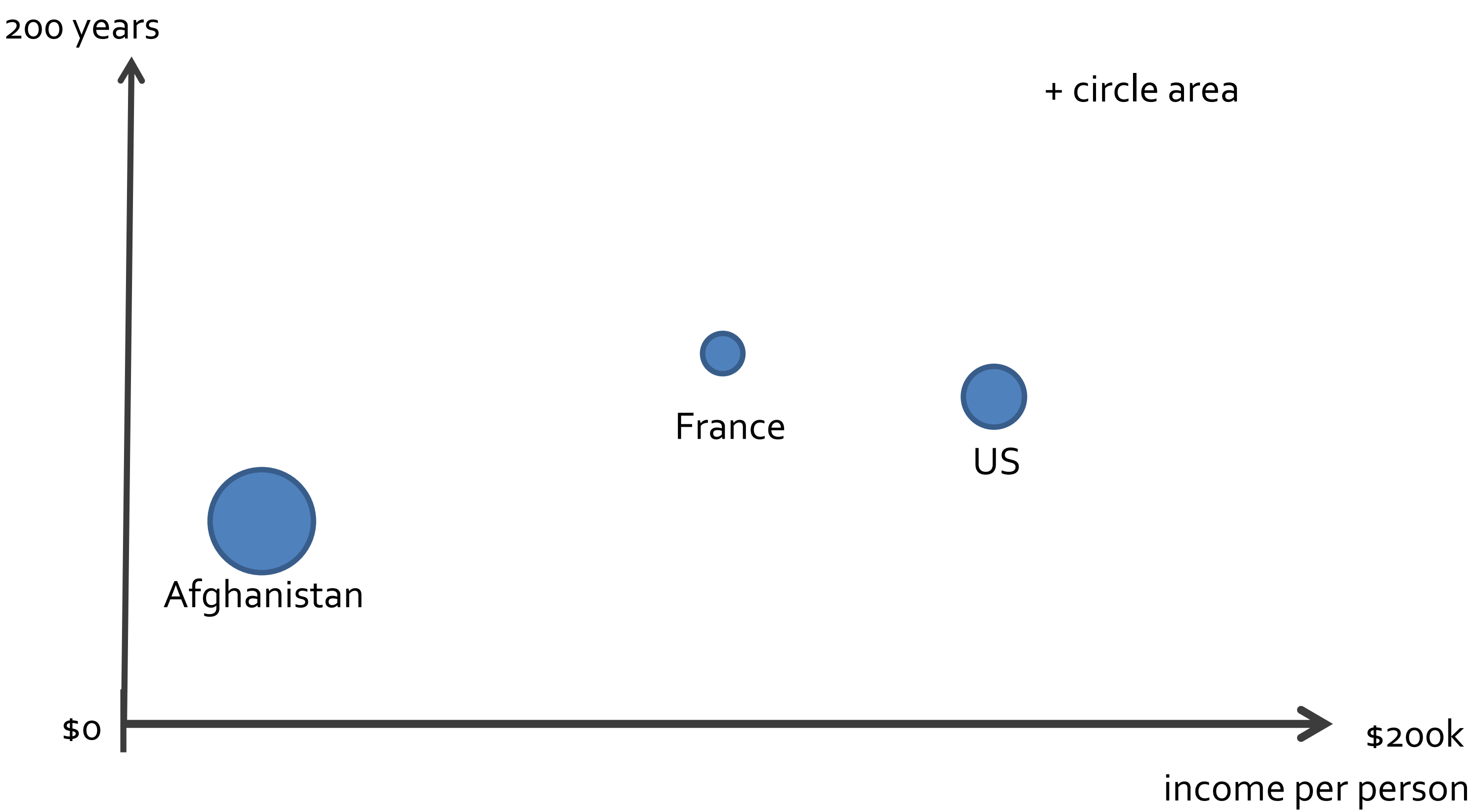
Country	Income per person	Life expectancy	Children per woman
Afghanistan	850	57	7.1
France	29500	81	1.9
US	41000	78	2.1

now with 4 attributes

Country	Income per person	Life expectancy	Children per woman
Afghanistan	850	57	7.1
France	29500	81	1.9
US	41000	78	2.1

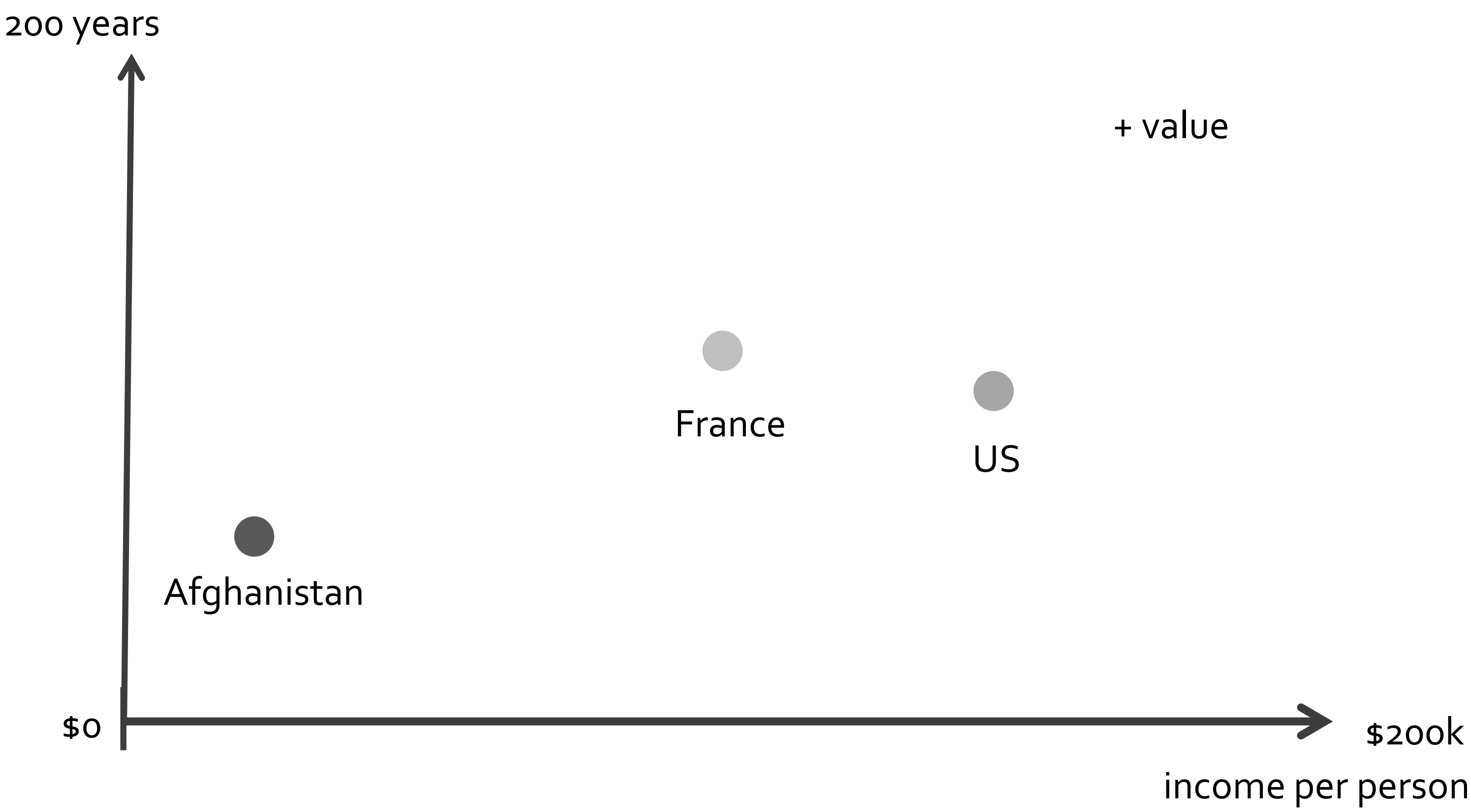


ADD ANOTHER VISUAL ENCODING



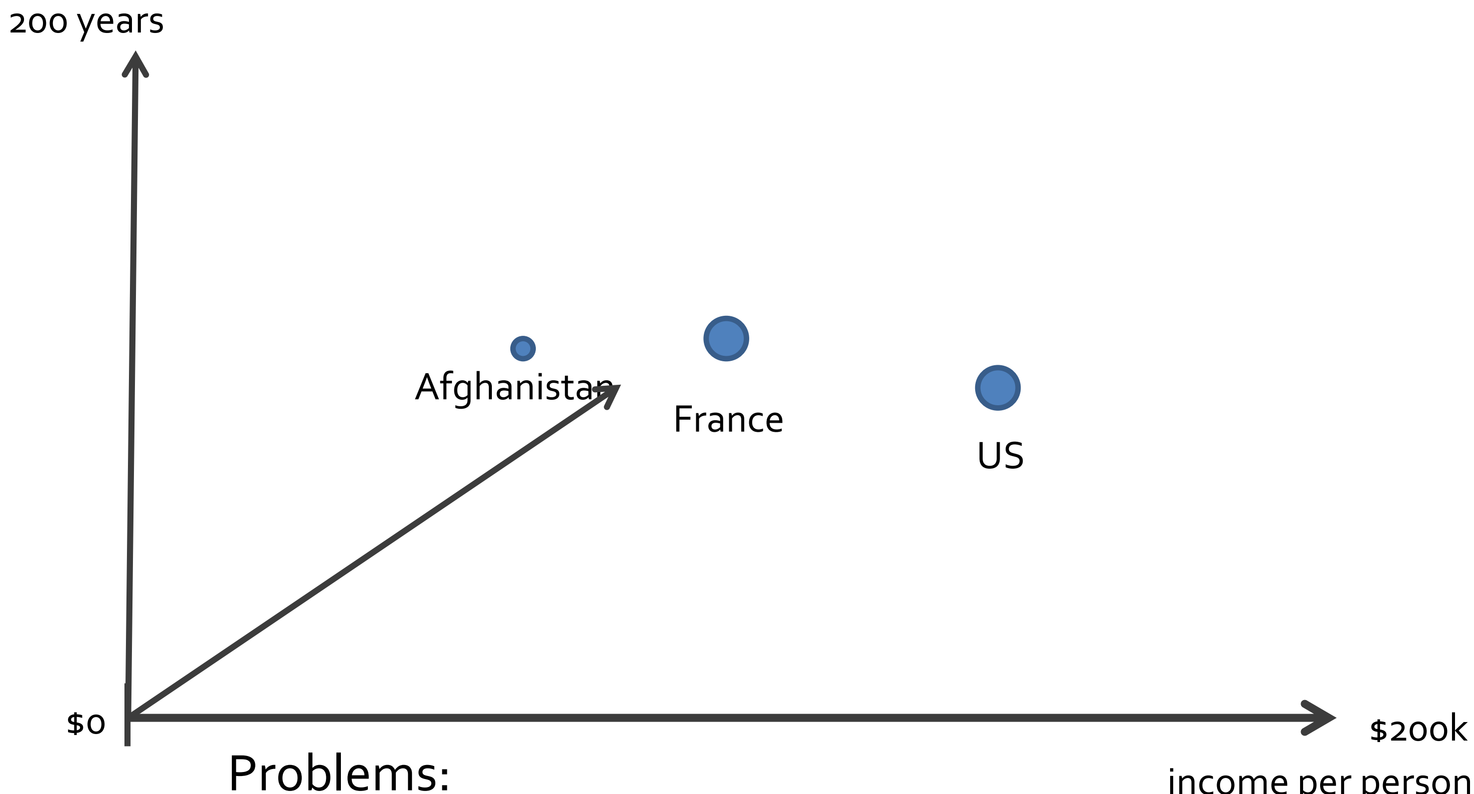
Problem:
Does not scale well to more attributes

ADD ANOTHER VISUAL ENCODING



Problem:
Does not scale well to more attributes

ADD AN AXIS

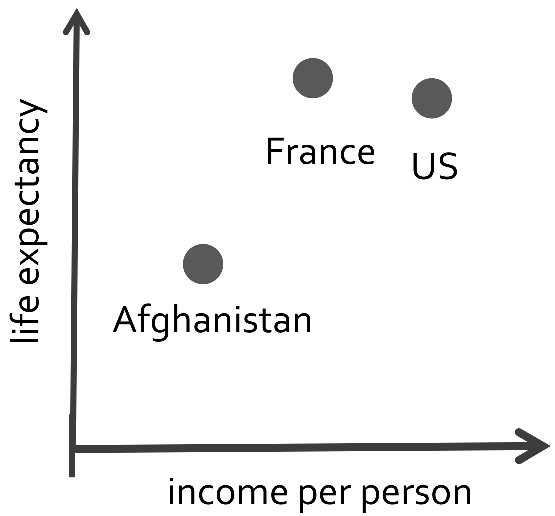


Problems:

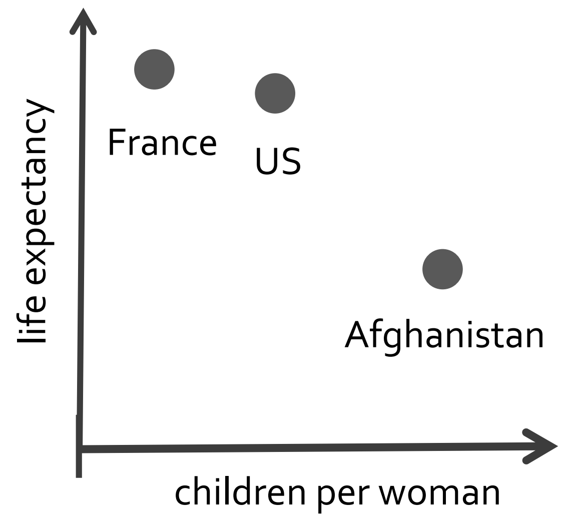
Occlusion, perspective distortion, does not scale

→ Not usually recommended

ADD AN AXIS



life expectancy
France
US
Afghanistan
income per person



life expectancy
France
US
Afghanistan
children per woman

SCATTERPLOT MATRIX

This idea scales relatively well

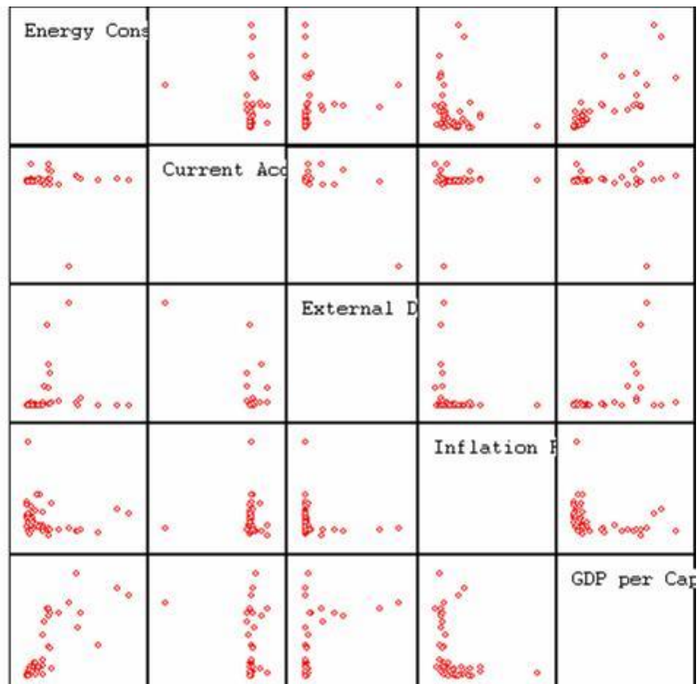
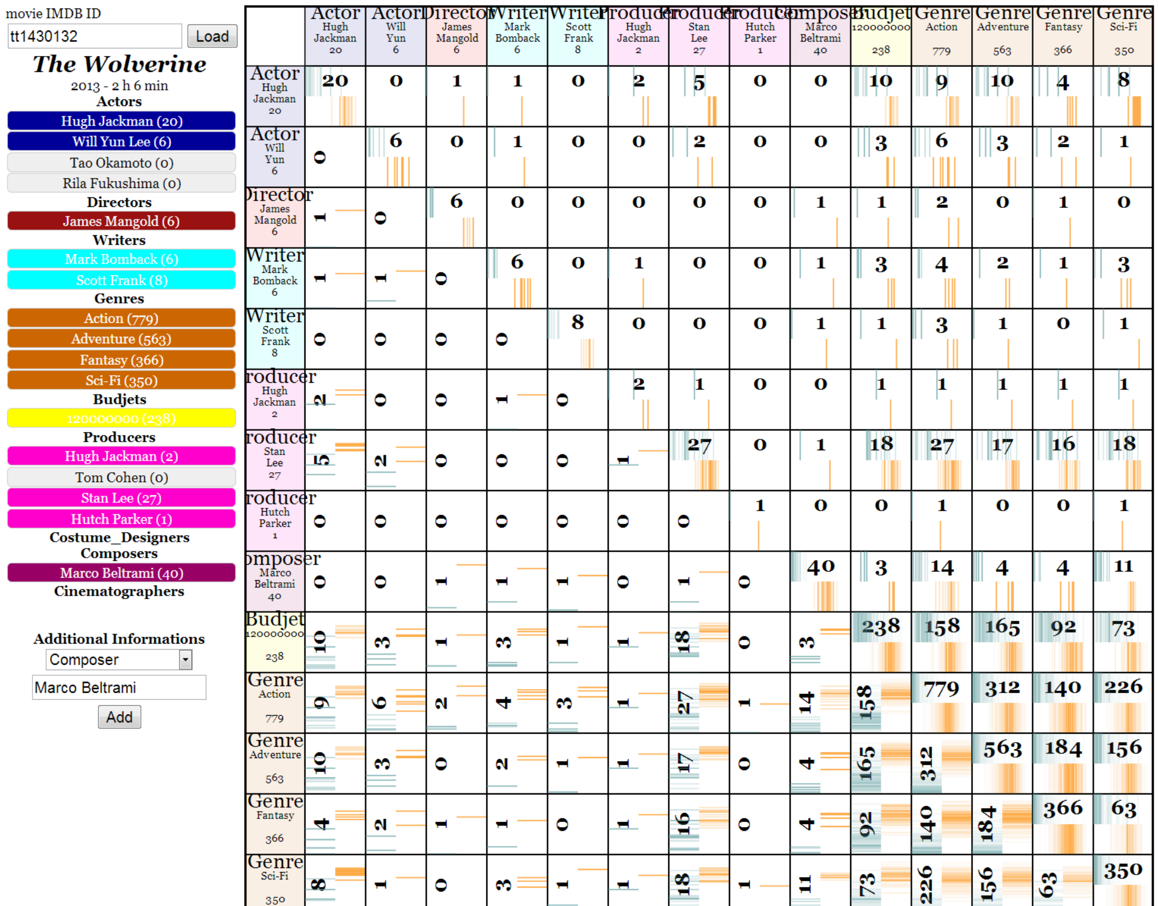


Image Source: Wikipedia

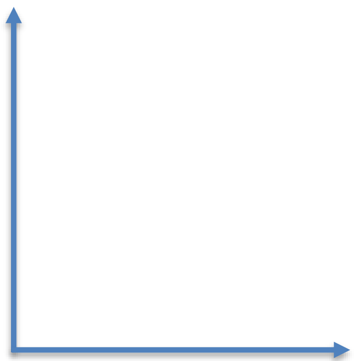
SCATTERPLOT MATRIX



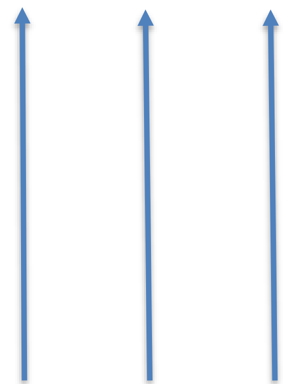
By Charles Perin

SPATIAL AXIS ORIENTATION

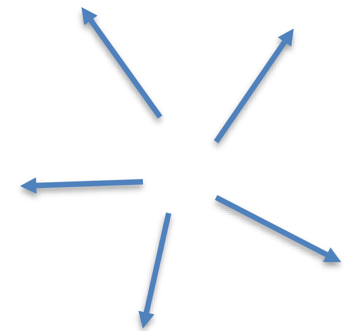
An additional design choice



rectilinear



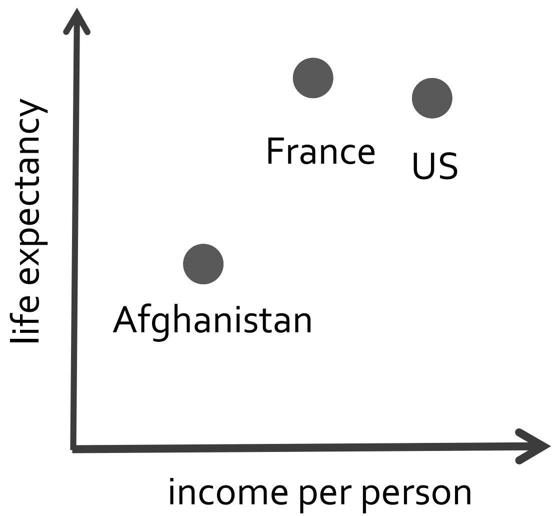
parallel



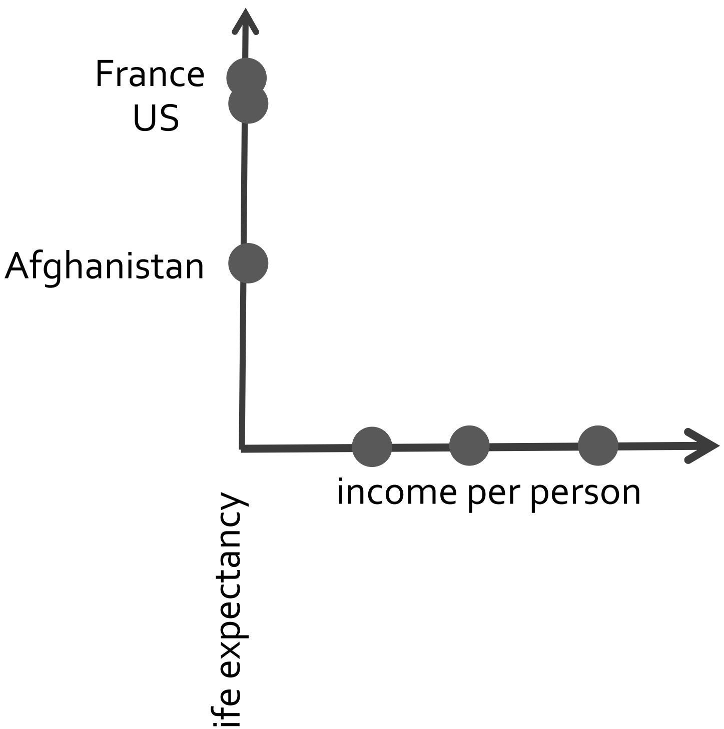
radial

parallel coordinates

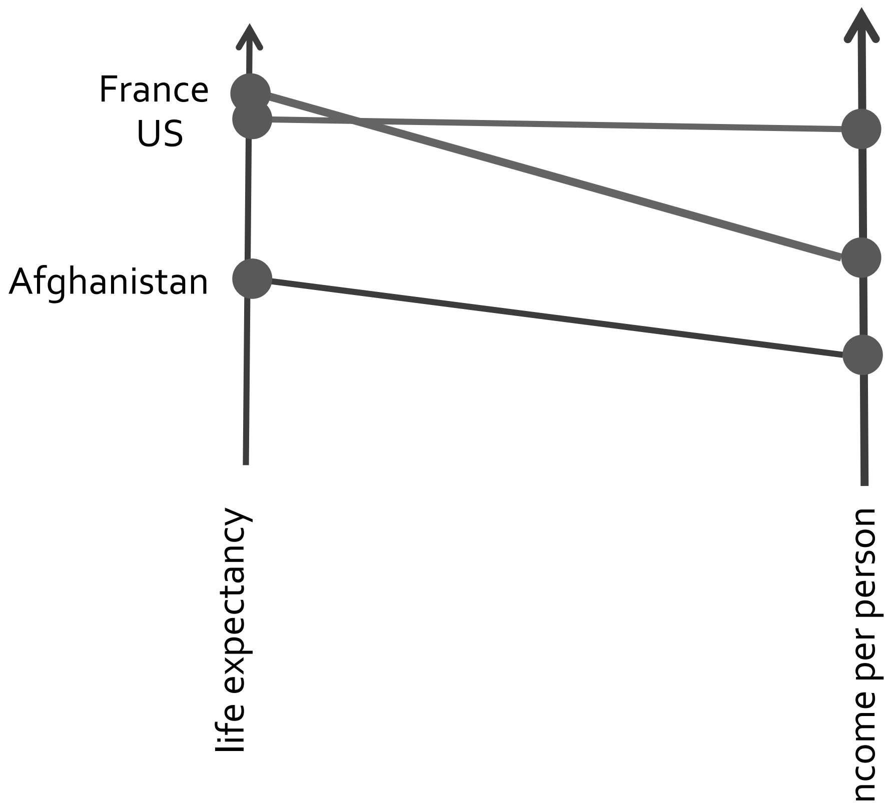
Back to our original example



Parallel Coordinates



parallel coordinates



- show correlations between neighboring axes

MULTIDIMENSIONAL DETECTIVE

Alfred Inselberg*, Multidimensional Graphs Ltd†
&
Computer Science Department
Tel Aviv University, Israel
aiisreal@math.tau.ac.il

Abstract

The display of multivariate datasets in parallel coordinates, transforms the search for *relations* among the variables into a 2-D pattern recognition problem. This is the basis for the application to *Visual Data Mining*. The Knowledge Discovery process together with some general guidelines are illustrated on a dataset from the production of a VLSI chip. The special strength of parallel coordinates is in modeling **relations**. As an example, a simplified Economic Model is constructed with data from various economic sectors of a real country. The visual model shows the interelationship and dependencies between the sectors, circumstances where there is competition for the same resource, and feasible economic policies. Interactively, the model can be used to do trade-off analyses, discover sensitivities, do approximate optimization, monitor (as in a Process) and Decision Support.

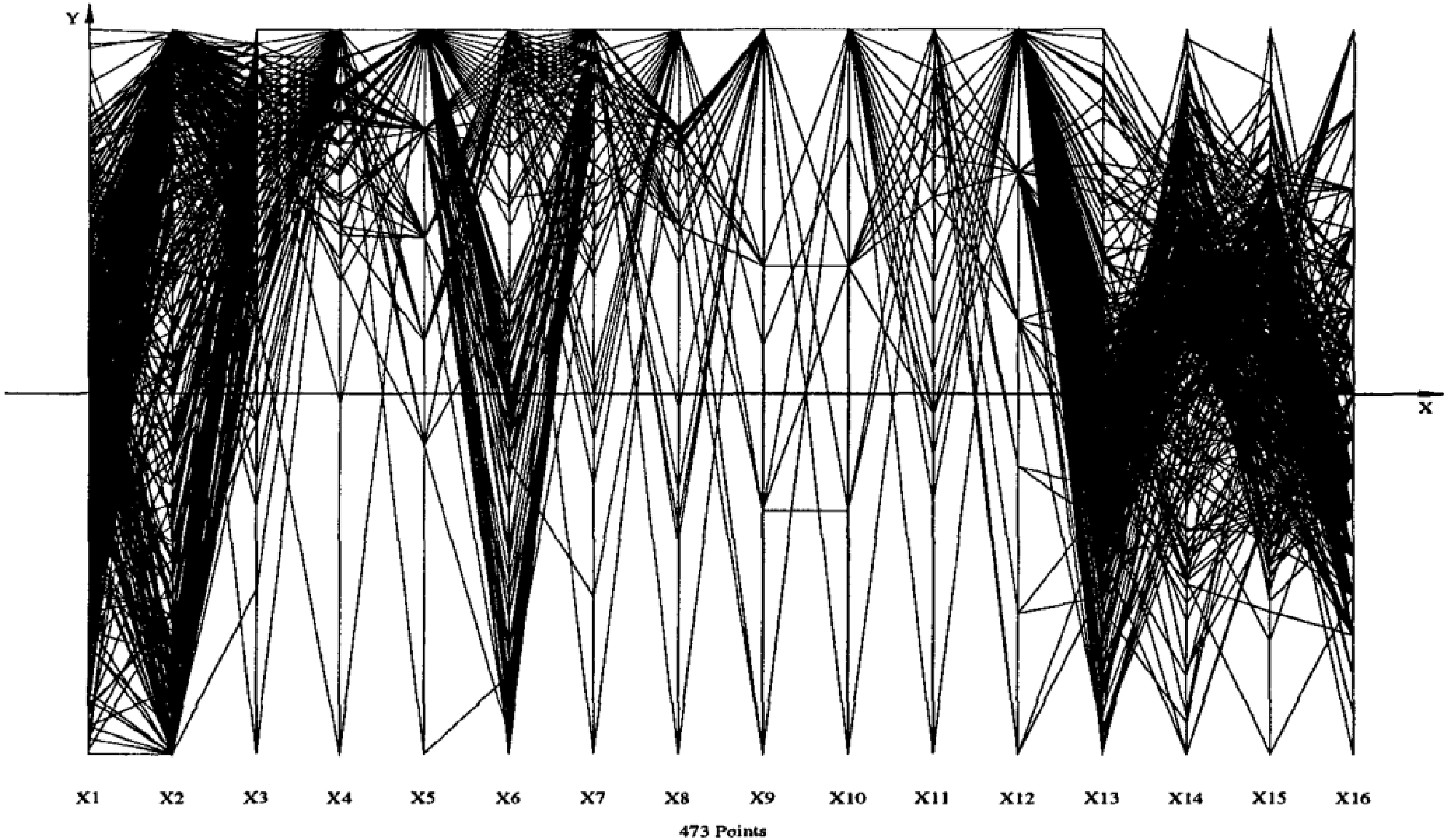
Introduction

In Geometry parallelism, which does not require a notion of angle, rather than orthogonality is the more fundamental concept. This, together with the fact that orthogonality "uses-up" the plane very fast, was the inspiration in 1959 for "Parallel" Coordinates. The systematic development began in 1977 [4]. The goals of the program were and still are (see [6] and [5] for short reviews) the visualization of multivariate/multidimensional problems without loss of information and having the properties:

1. Low representational complexity. Since the number of axes, N equals the number of dimensions (variables) the complexity is $O(N)$,
2. Works for any N,
3. Every variable is treated uniformly (unlike "Chernoff Faces" and various types of "glyphs"),
4. The displayed object can be recognized under projective transformations (i.e. rotation, translation, scaling, perspective),
5. The display easily/intuitively conveys information on the properties of the N-dimensional object it represents,
6. The methodology is based on rigorous mathematical and algorithmic results.

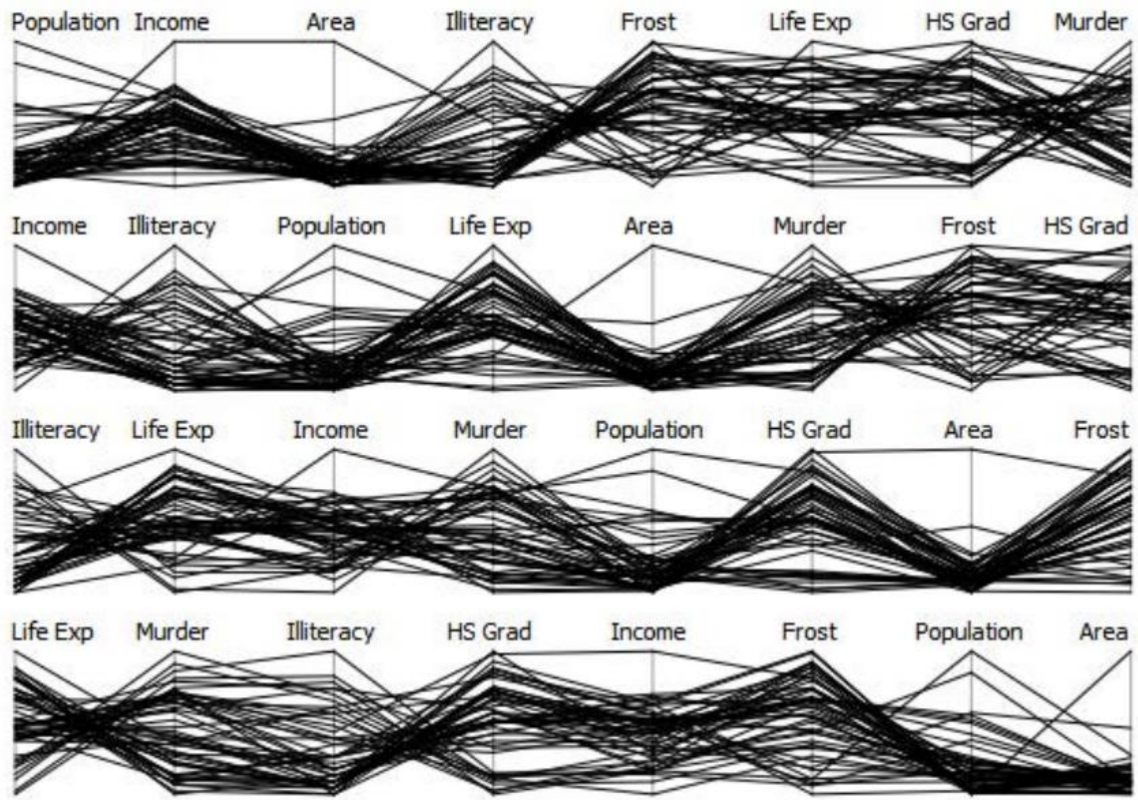
Parallel coordinates (abbr.||-coords) transform multivariate relations into 2-D patterns, a property that is well suited for Visual Data Mining.

*Senior Fellow San Diego SuperComputing Center
†36A Yehuda Halevy Street, Raanana 43556, Israel



Original Example from Inselberg 1997

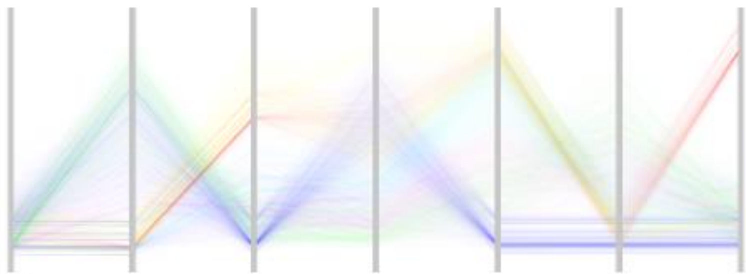
THE ORDER OF AXES MATTERS



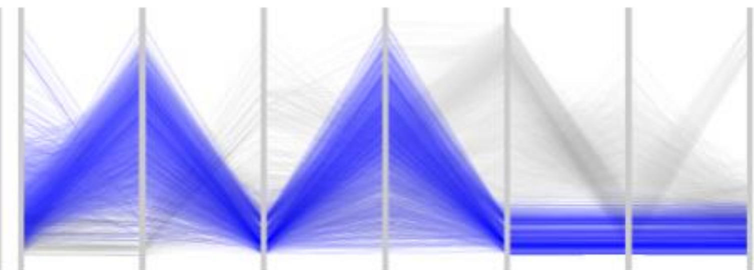
Eurographics 2013, STAR Report
J. Heinrich, D. Weiskopf

REDUCE CLUTTER - HIGHLIGHT CLUSTERS

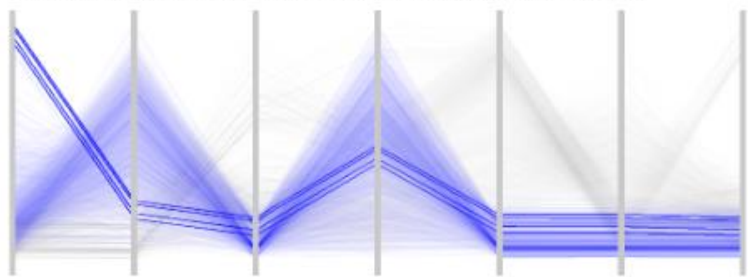
Lots of work on this. For example:



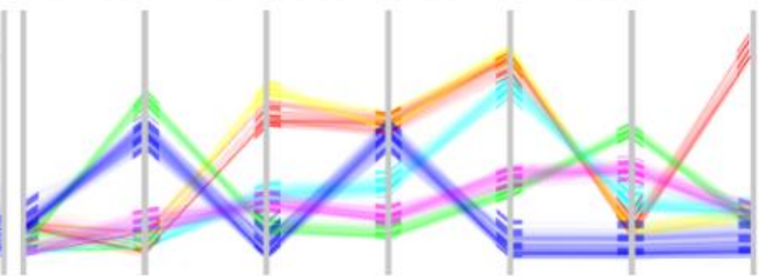
(a) A linear transfer function has been applied to the high-precision texture in order to prevent cluttering and to provide overview of the data.



(b) A logarithmic transfer function is applied to a selected cluster. The structure is preserved and emphasis is put on the low density regions.



(c) Local cluster outliers are enhanced. A square root transfer function is used and the outliers are visible even through high-density regions.

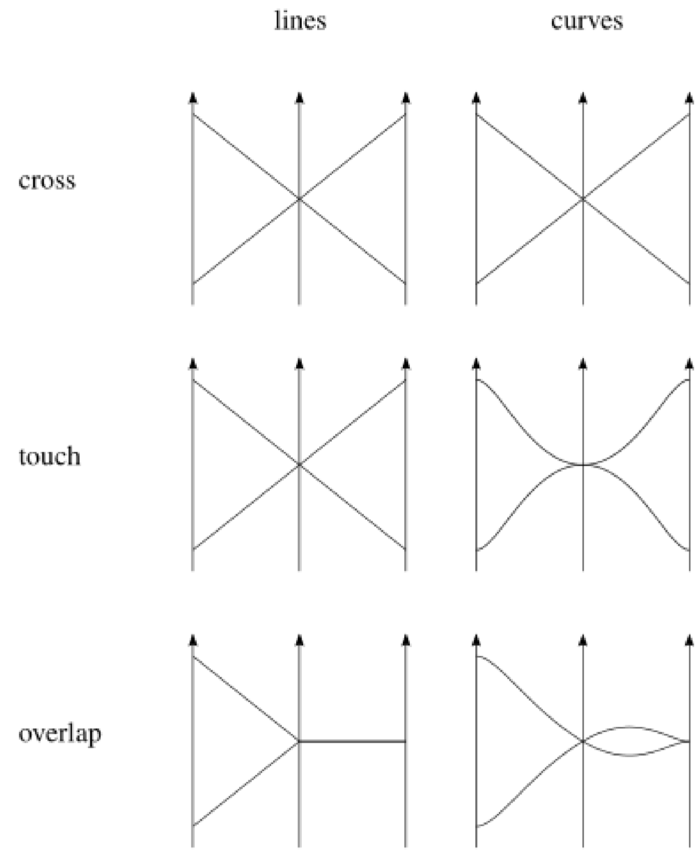


(d) A complementary view of the clusters with uniform bands. 'Feature animation' presents statistics about the clusters and acts as a guidance.

Revealing Structure within Clustered Parallel Coordinates Displays, InfoVis 2005

HOW TO DRAW THE LINES

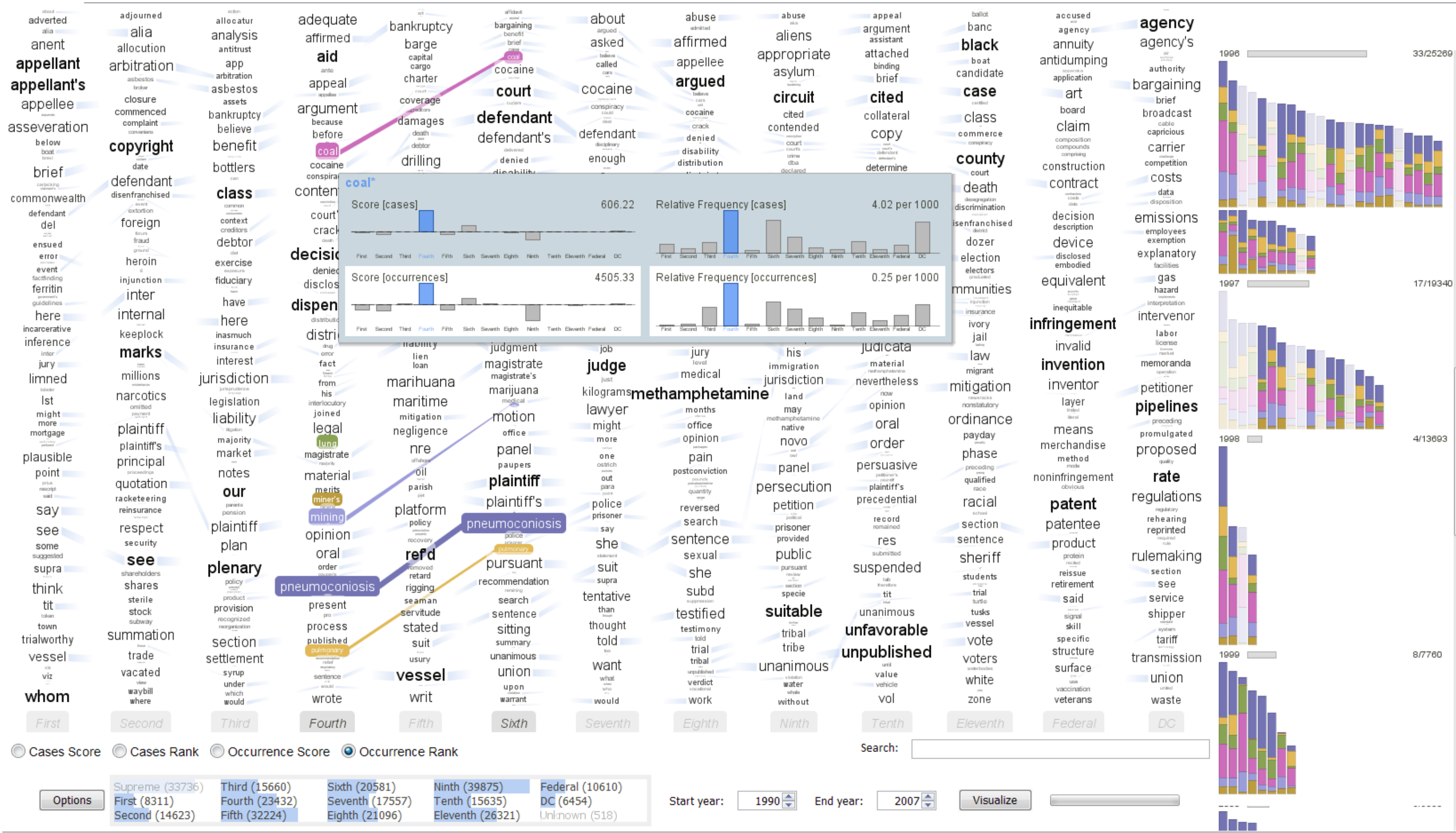
Goal: avoid ambiguity



Eurographics 2013, STAR Report
J. Heinrich, D. Weiskopf

COMBINE WITH OTHER VISUALIZATION TECHNIQUES

Parallel Tag Clouds to Explore Faceted Text Corpora (Collins et al., VAST 2009)



THERE IS MUCH MORE ON THIS…

Start here if you want more information

State of the Art of Parallel Coordinates

J. Heinrich and D. Weiskopf

Visualization Research Center, University of Stuttgart

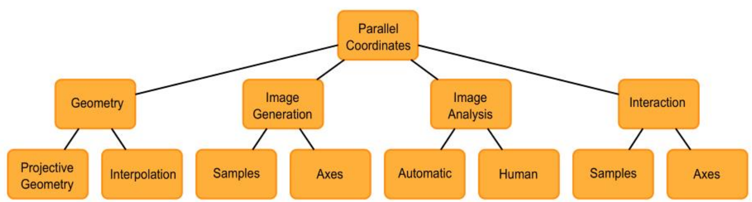


Figure 1: Taxonomy of topics for parallel coordinates in the scientific literature. The first-level nodes each represent a section in this paper, where the scope and definition of each topic will be explained.

Abstract

This work presents a survey of the current state of the art of visualization techniques for parallel coordinates. It covers geometric models for constructing parallel coordinates and reviews methods for creating and understanding visual representations of parallel coordinates. The classification of these methods is based on a taxonomy that was established from the literature and is aimed at guiding researchers to find existing techniques and identifying white spots that require further research. The techniques covered in this survey are further related to an established taxonomy of knowledge-discovery tasks to support users of parallel coordinates in choosing a technique for their problem at hand. Finally, we discuss the challenges in constructing and understanding parallel-coordinates plots and provide some examples from different application domains.

Categories and Subject Descriptors (according to ACM CCS): I.3.3 [Computer Graphics]: Picture/Image Generation—Line and curve generation

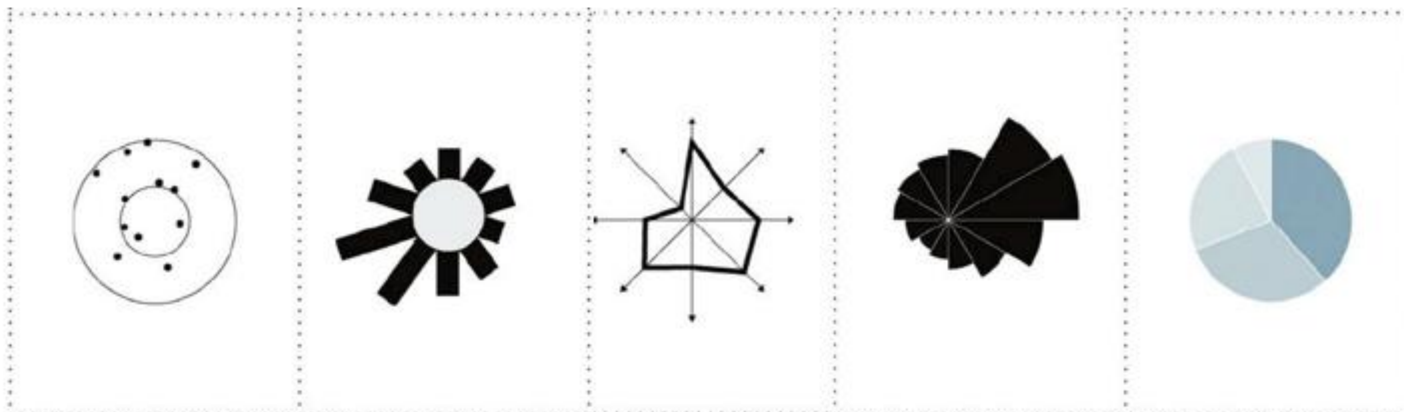
Scattering Points in Parallel Coordinates

Xiaoru Yuan[1], Peihong Guo[1], He Xiao[1], Hong Zhou[2], Huamin Qu[2]

1. Key Laboratary of Machine Perception (MOE), School of EECS, Peking University
2. Department of Computer Science and Engineering at Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong

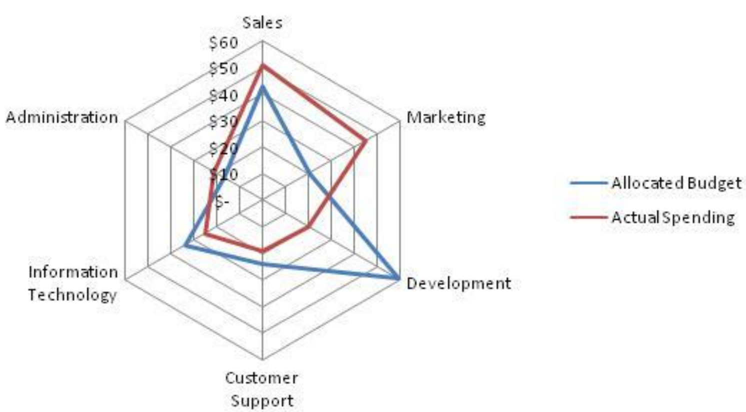
RADIAL AXES

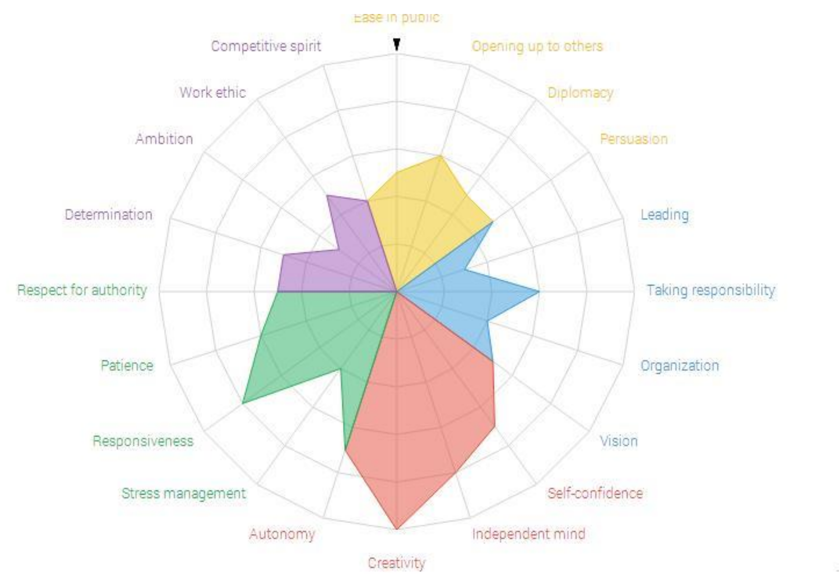
Polar



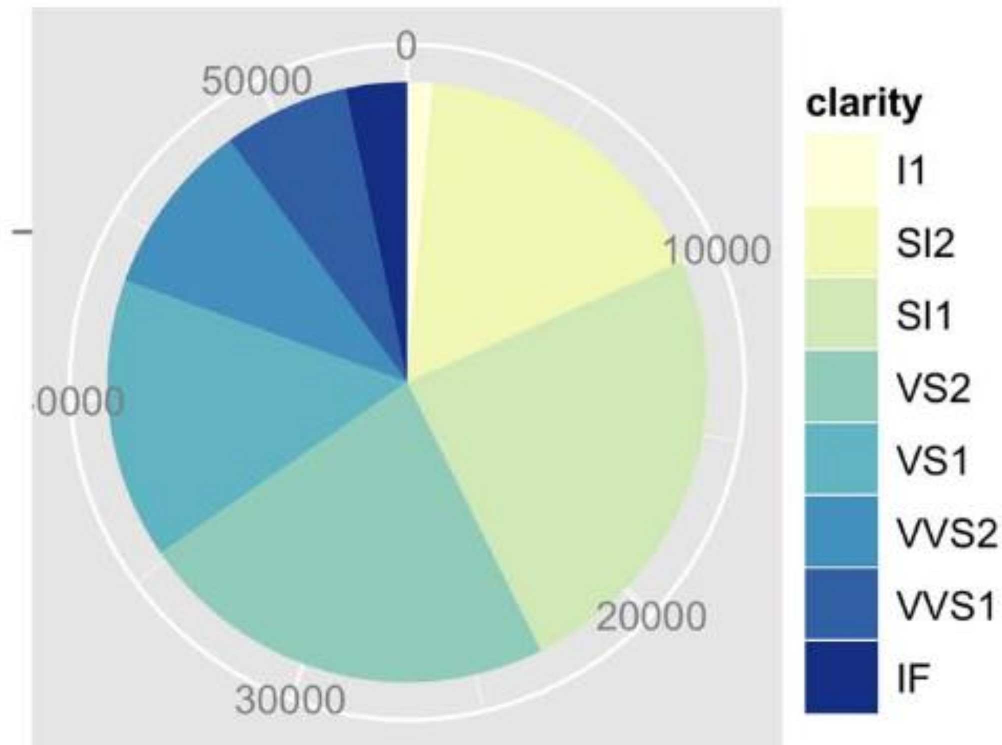
EXAMPLE: STAR PLOT

- = radial line chart

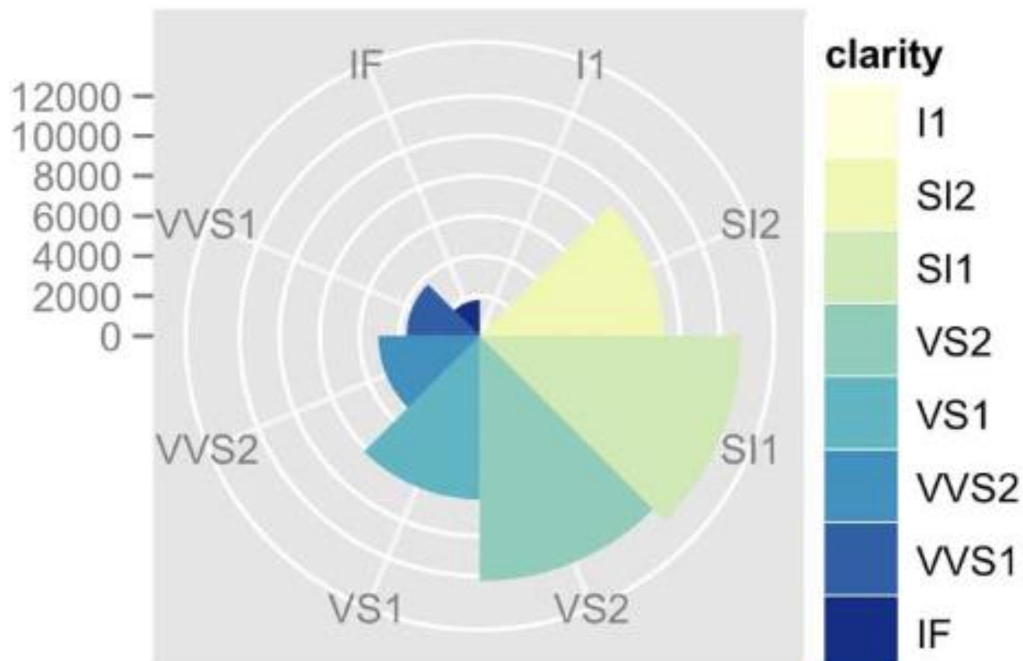




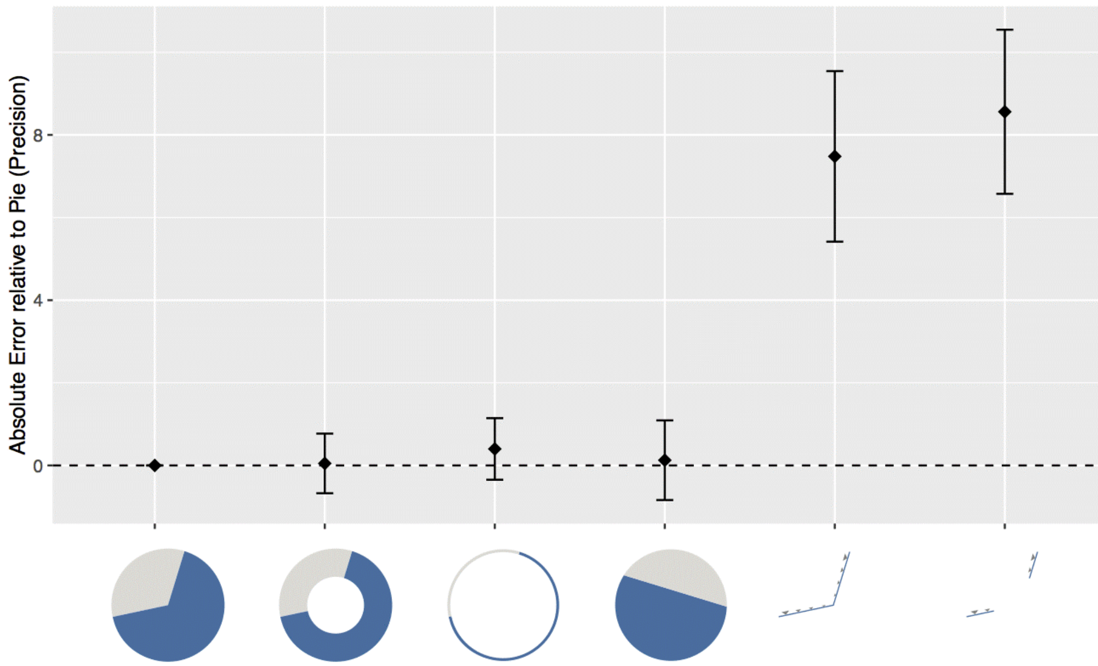
PIE CHARTS


0
50000
10000
0000
20000
30000
clarity
I1
SI2
SI1
VS2
VS1
VVS2
VVS1
IF

POLAR AREA CHARTS

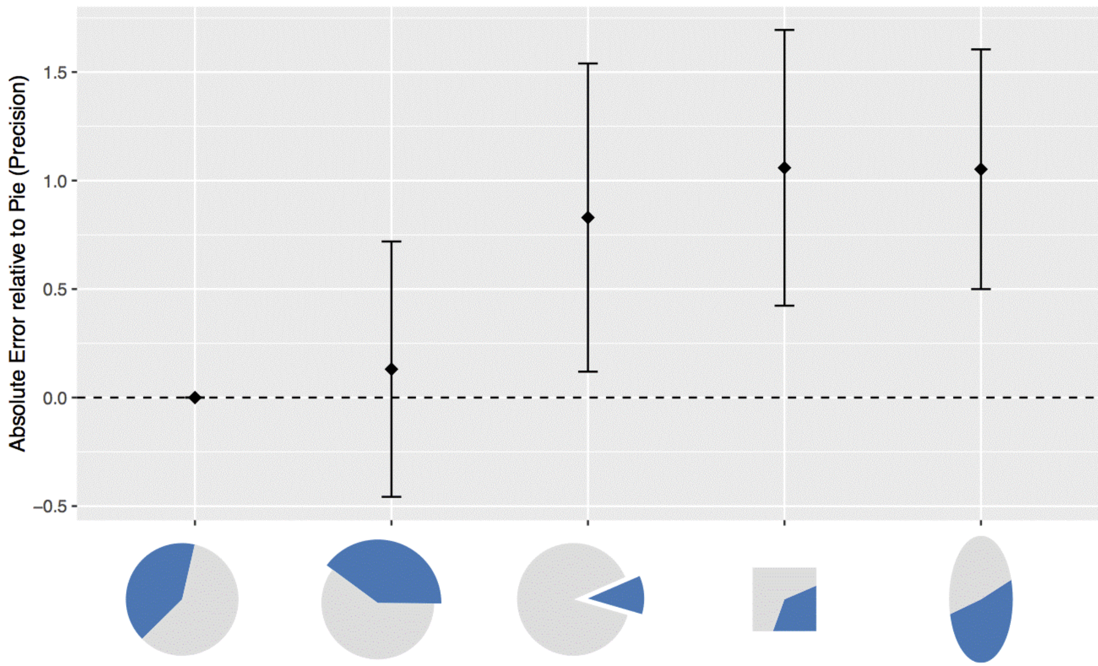


HOW DO PEOPLE READ PIE CHARTS?



https://eagereyes.org/blog/2016/an-illustrated-tour-of-the-pie-chart-study-results

HOW DO PEOPLE READ PIE CHARTS?



https://eagereyes.org/blog/2016/an-illustrated-tour-of-the-pie-chart-study-results

WHAT IT ONE DIMENSION IS TIME?

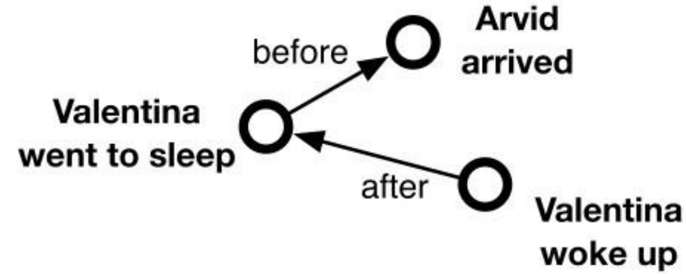
TIME…

- …IS JUST ANOTHER DATA DIMENSION
- WHY BOTHER?

- WHAT DATA TYPE IS IT?
  - NOMINAL?
  - ORDINAL?
  - QUANTITATIVE?

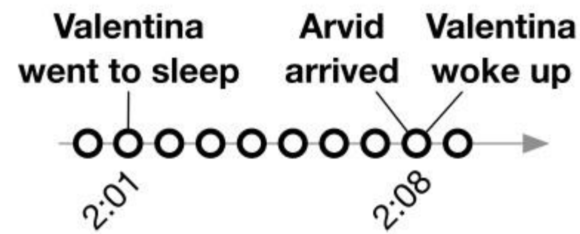
DATA TYPE

ORDINAL



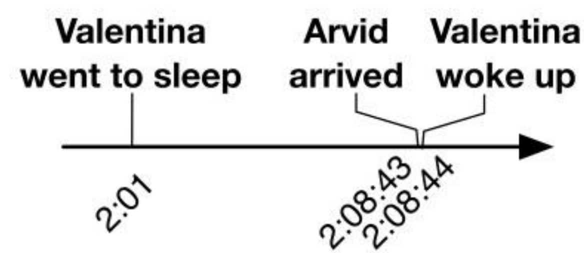
QUANTITATIVE

DISCRETE



CONTINUOUS

(WITHIN THE LIMITS OF A COMPUTER)



AIGNIER ET AL 2011

TIME IS PARTICULAR

- **PERIODICITY**
  - NATURAL: DAYS, SEASONS
  - SOCIAL: WORKING HOURS, HOLIDAYS
  - BIOLOGICAL: SLEEP, ETC.
- **MANY SUBDIVISIONS** (UNITS)
  - YEARS, MONTHS, DAYS, WEEKS, H, M, S
- **SPECIFIC MEANING**
  - NOT CAPTURED BY DATA TYPE
  - ASSOCIATIONS, CONVENTIONS
  - TIME VISUALIZATIONS OFTEN CONSIDERED AS A SEPARATE TYPE

TIME IS PARTICULAR

- SHNEIDERMAN'S TAXONOMY OF DATA TYPES
  - 1D DATA
  - 2D DATA
  - 3D DATA
  - TEMPORAL DATA
  - MULTI-DIMENSIONAL DATA
  - TREE DATA
  - NETWORK DATA

VISUALIZING TIME

Of 4000 randomly sampled graphics from 15 newspapers and magazines ('74-'80), **75%** were time series.

EDWARD TUFTE

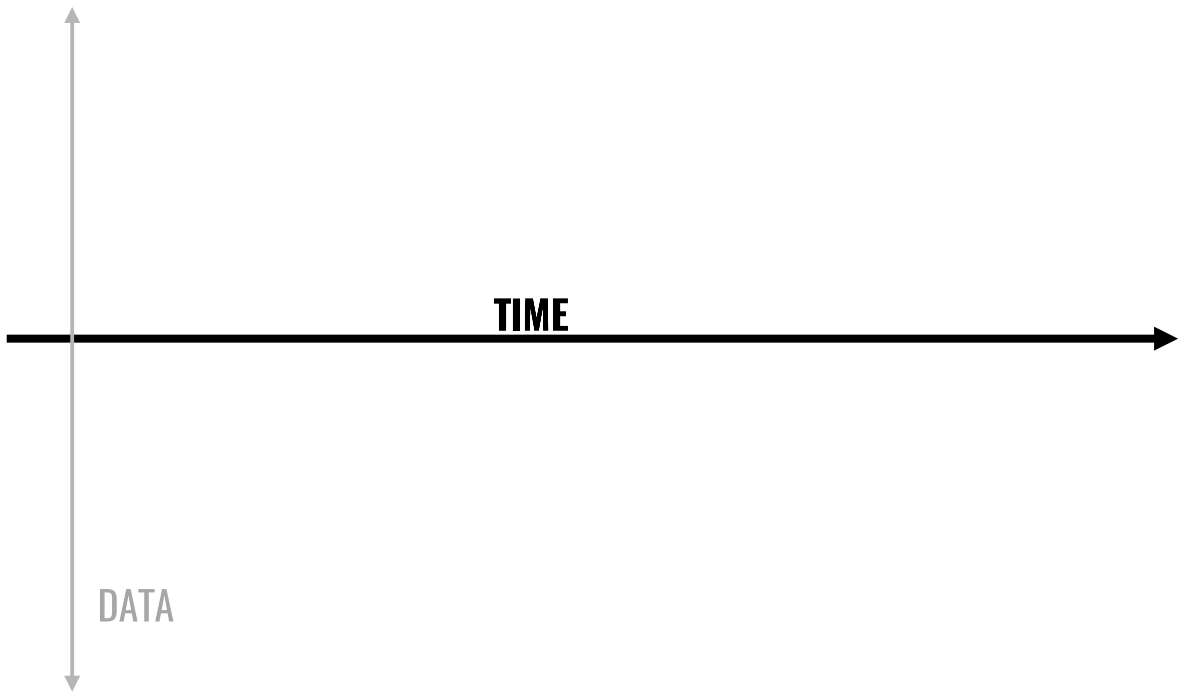
DEFINITION

A TIME SERIES IS A SEQUENCE OF DATA POINTS, MEASURED (TYPICALLY) AT SUCCESSIVE POINTS IN TIME (OFTEN) SPACED AT UNIFORM TIME INTERVALS.

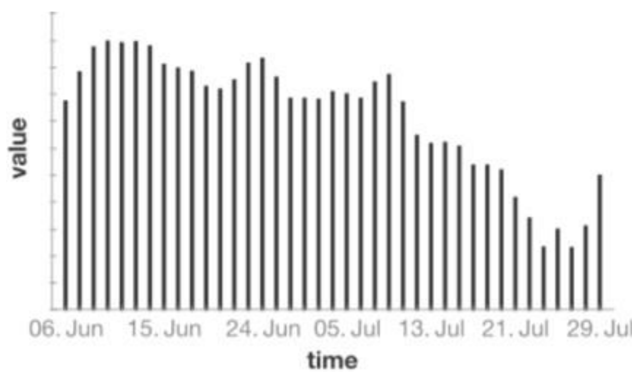
A SET OF OBSERVATIONS X_T, EACH ONE BEING RECORDED AT A SPECIFIC TIME T

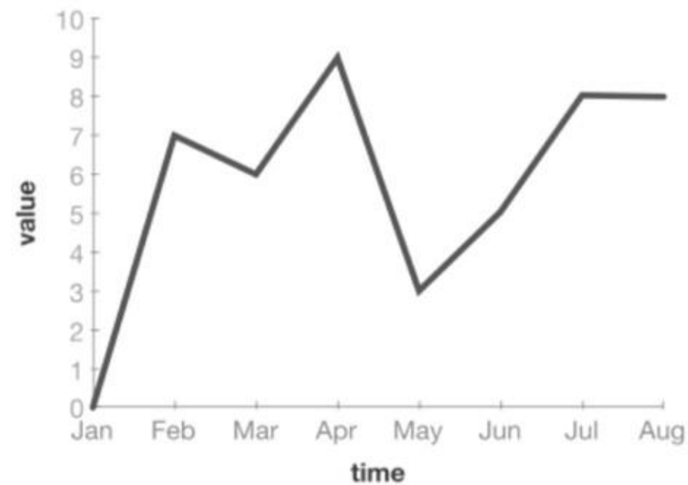
MAPPING DATA TO AN AXIS

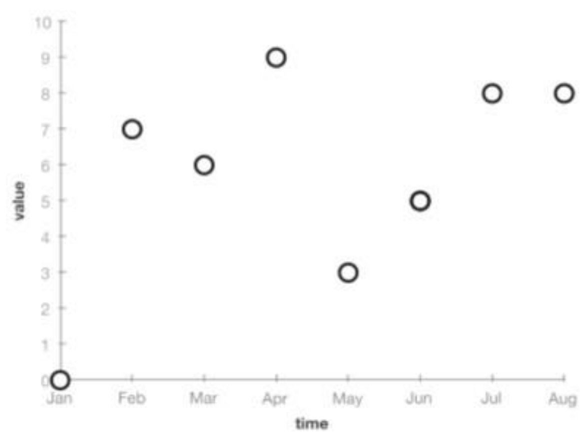
MAPPING TIME TO AN AXIS

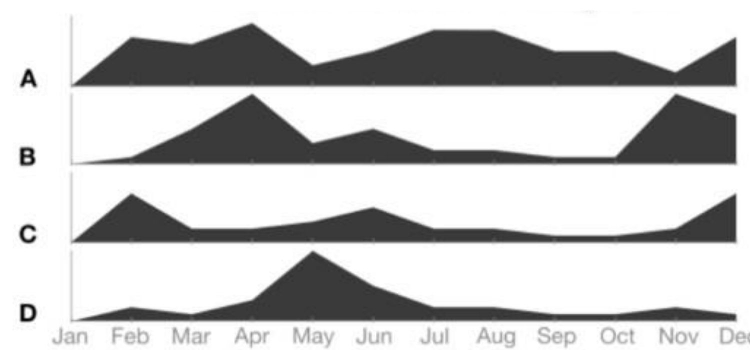


SIMPLE CHARTS

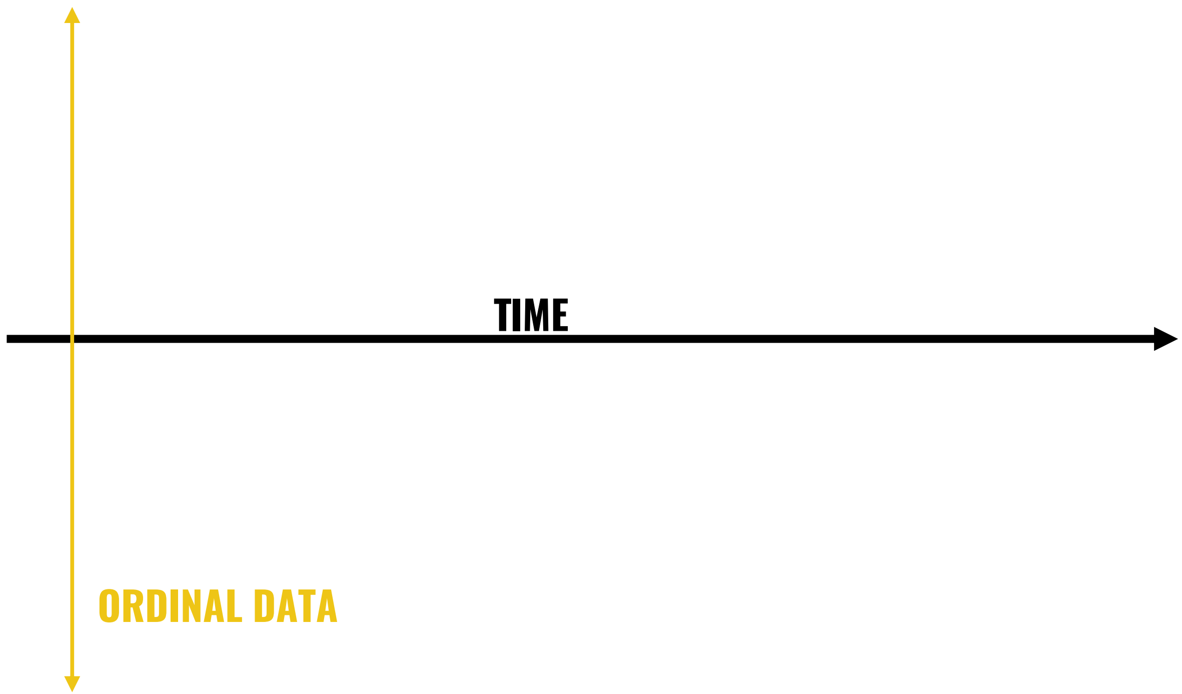








OTHER DATA TYPES



OTHER DATA TYPES - ORDINAL

RANK CHART

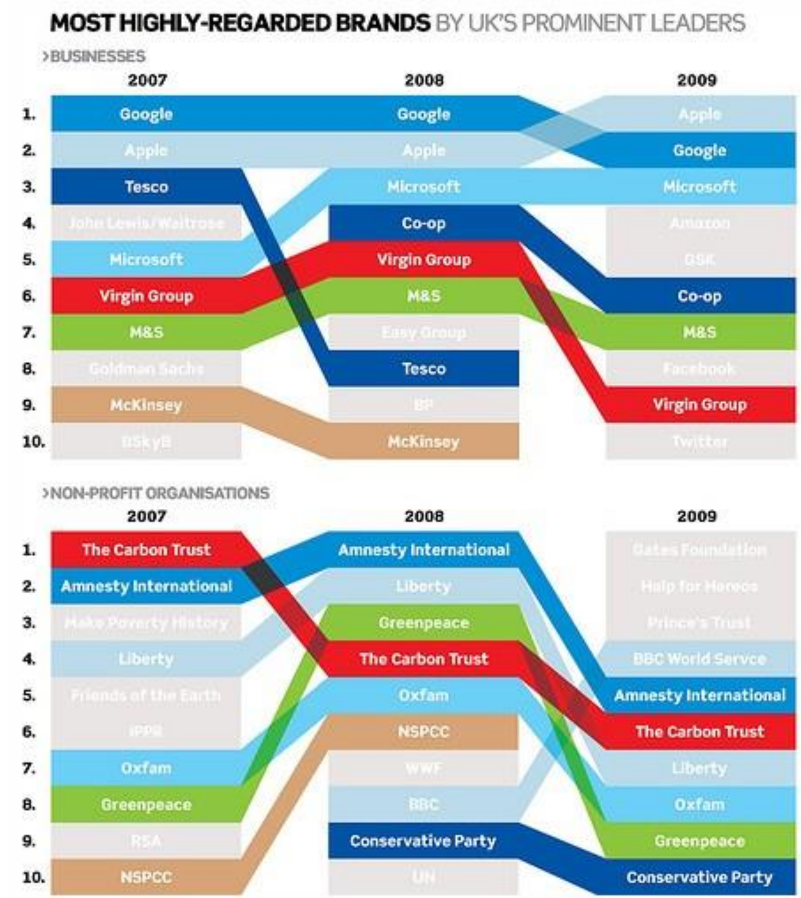
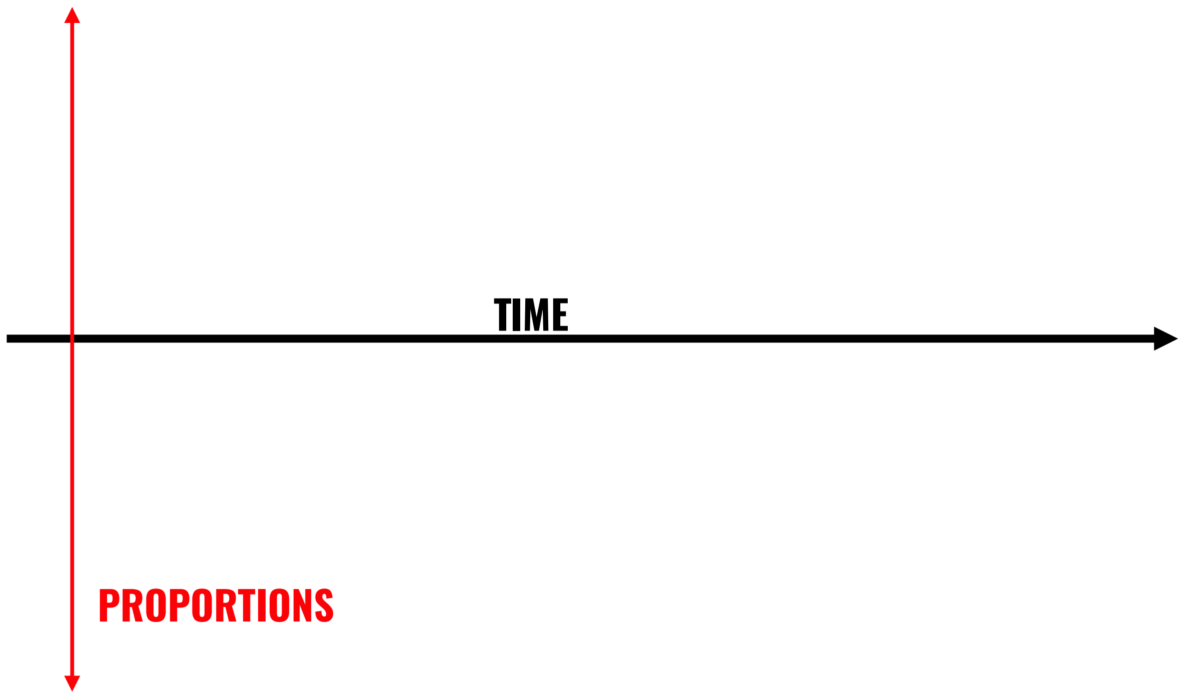


Chart showing the top ten brands' standing over the last three years

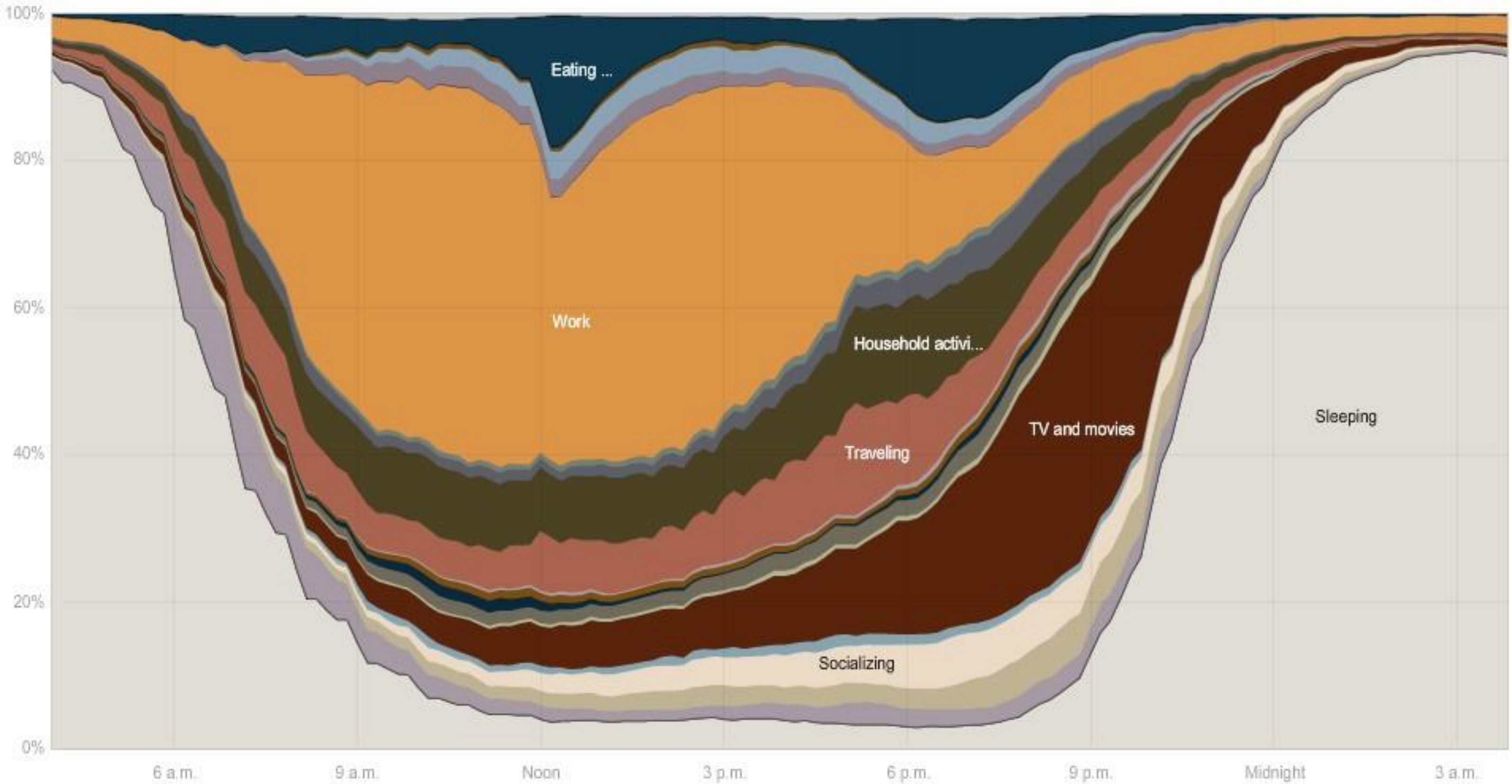
HUGUES, 2009

OTHER DATA TYPES



PROPORTIONS

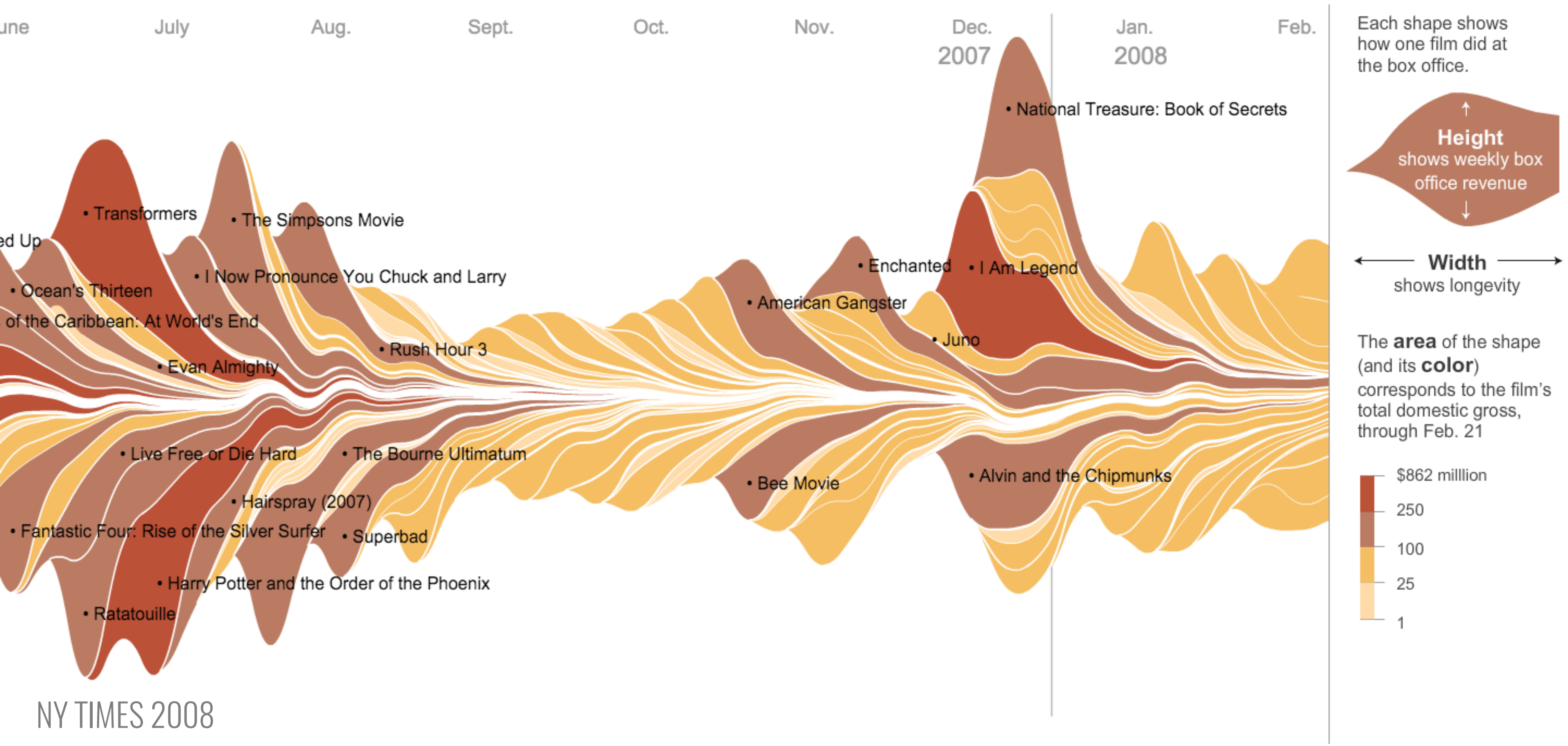
STACKED AREA CHART



NY TIMES 2009

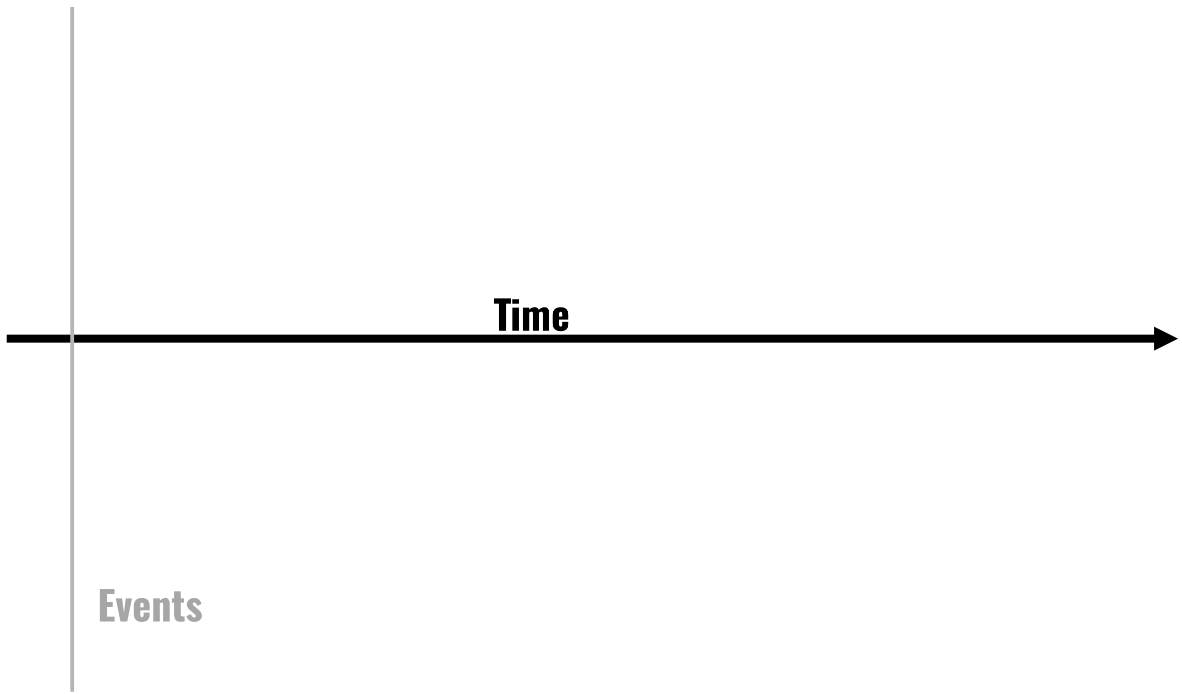
PROPORTIONS

STREAMGRAPHS



NY TIMES 2008

OTHER DATA TYPES



OTHER DATA TYPES - EVENTS

LIKE OBSERVATIONS IN TIME-SERIES

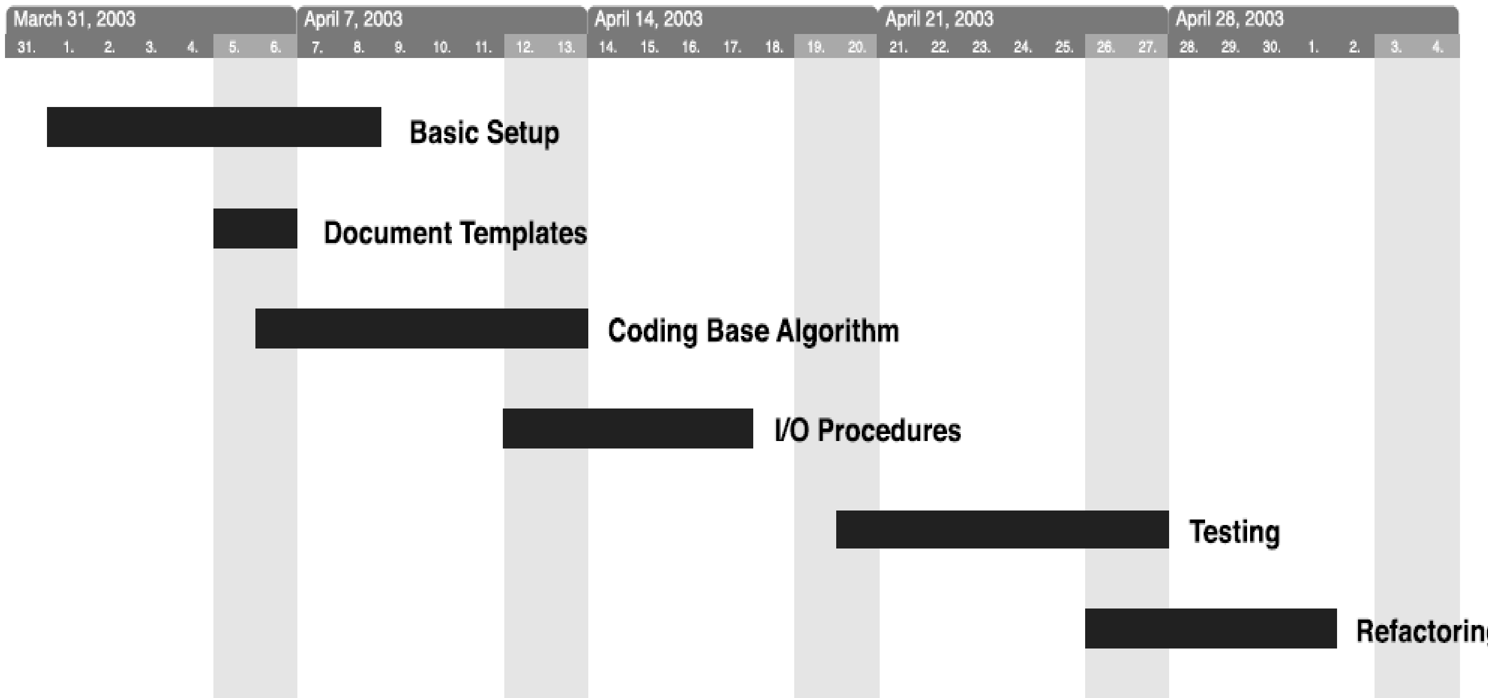
- DATA POINTS WITH A TIME STAMP

BUT

- MOST OFTEN SPARSE AND IRREGULAR
- DATA IS MOSTLY NOMINAL
- CAN HAVE A DURATION (START + END)
- OFTEN SUBJECTIVE / SOCIAL DATA RATHER THAN PHYSICAL MEASURES

EVENTS

PROJECT TIMELINE



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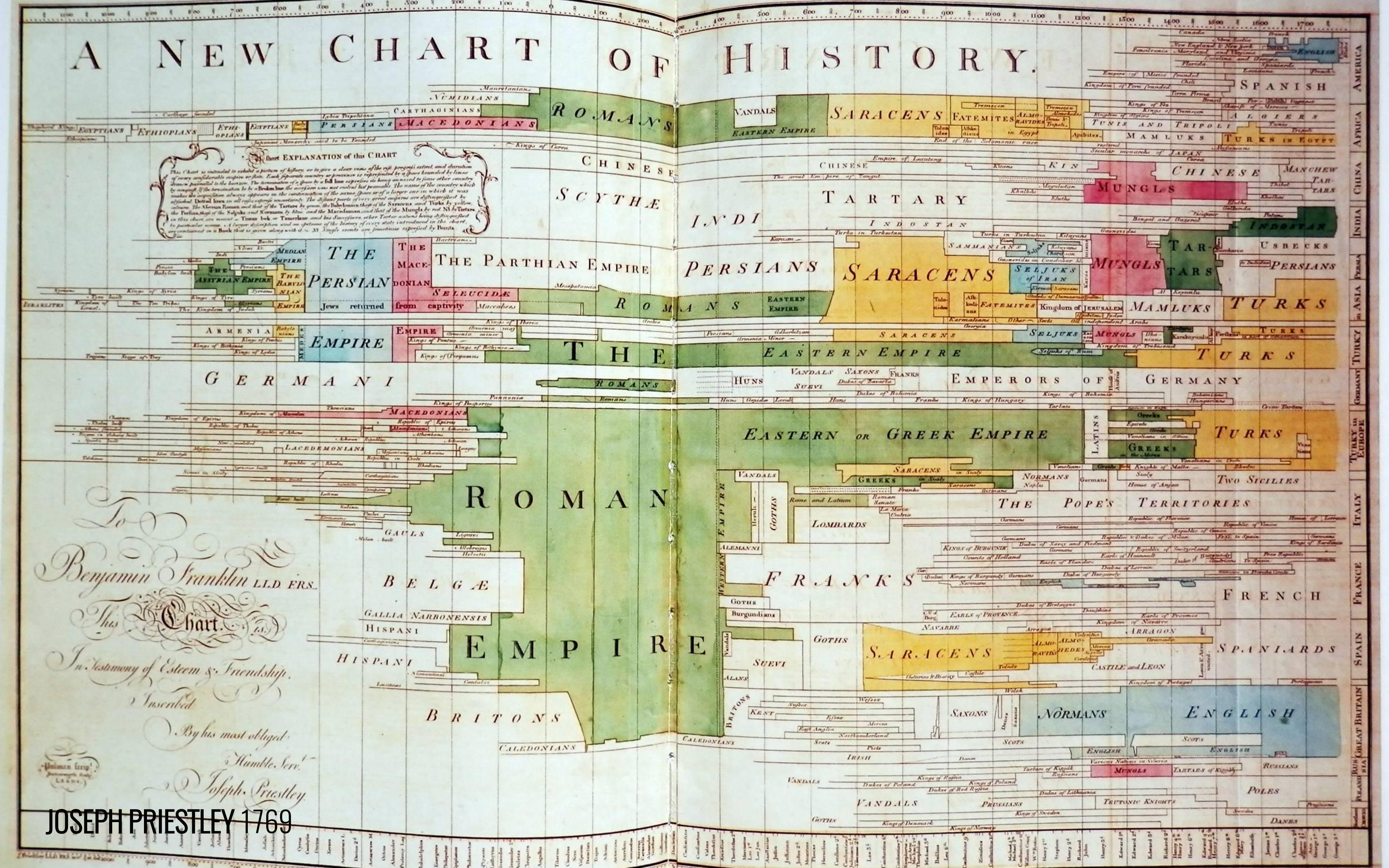
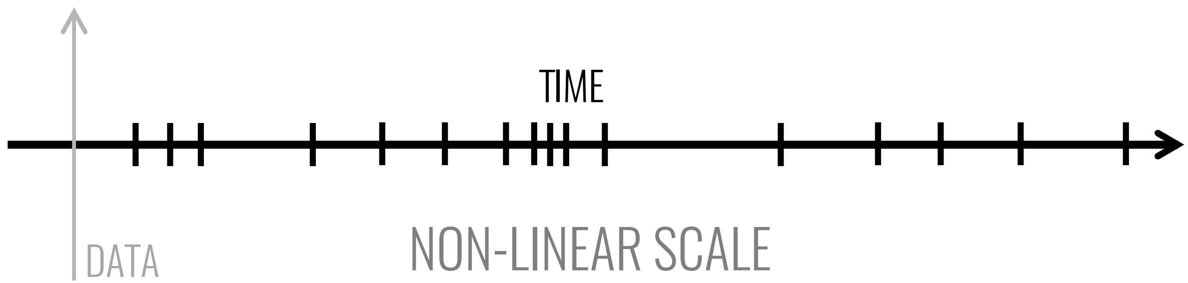
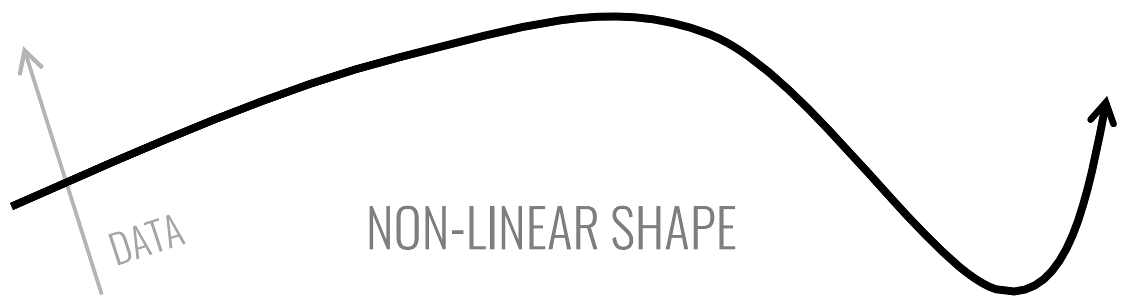


JOSEPH PRIESTLEY 1769

MAPPING TIME TO AN AXIS

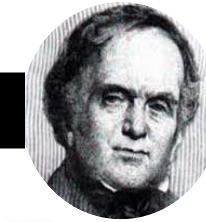
NON-LINEAR TIME AXES

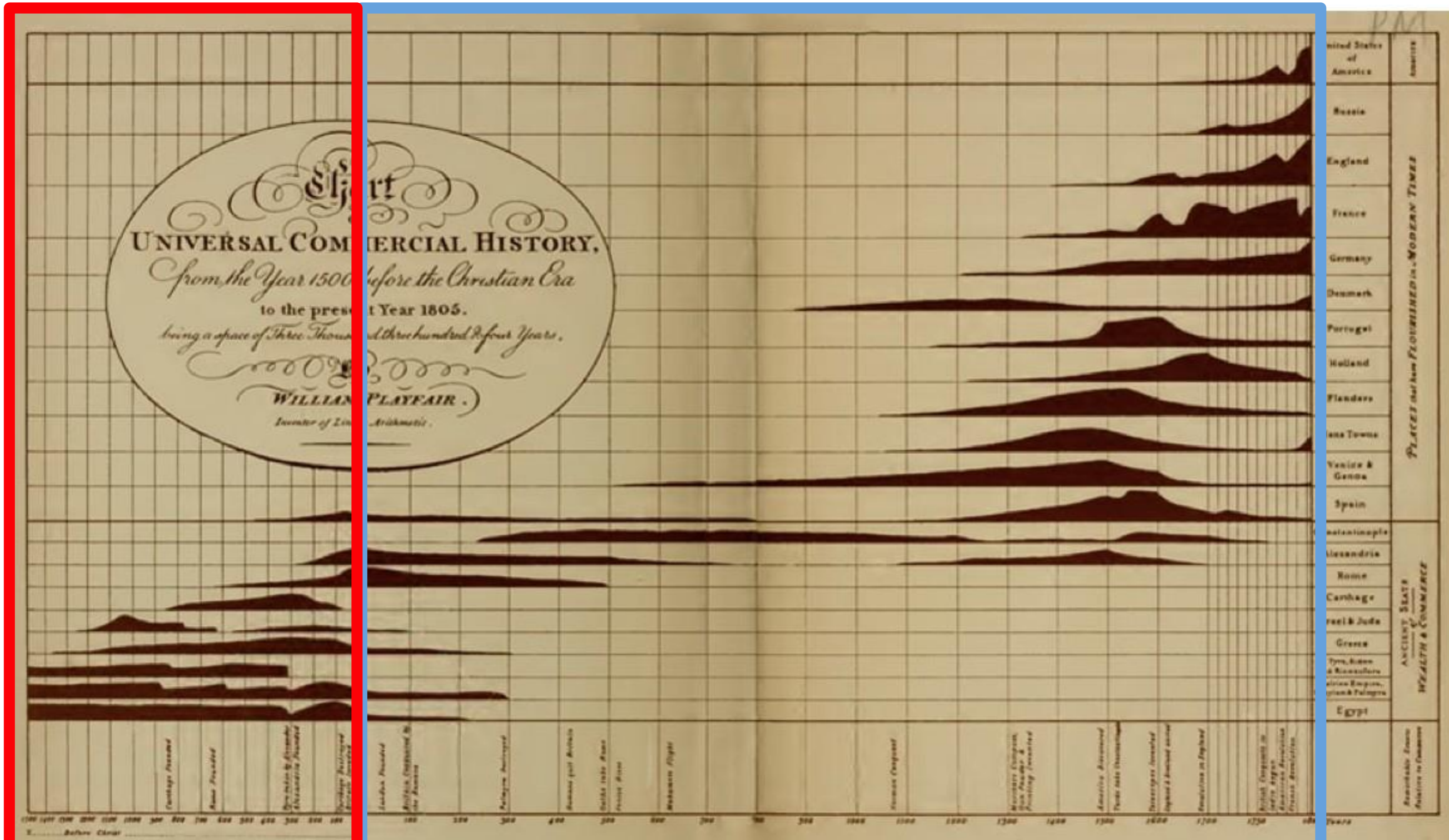




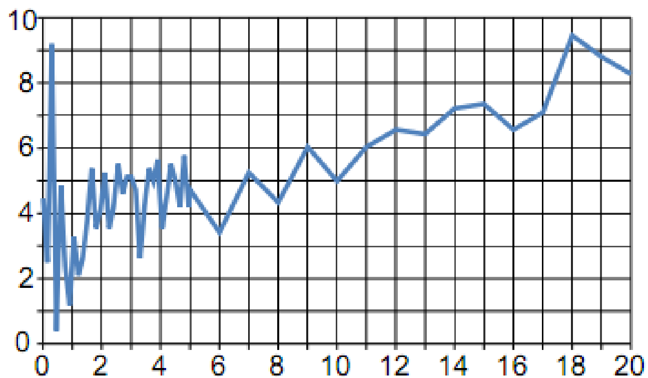
DUAL-SCALE CHARTS

WILLIAM PLAYFAIR
1805

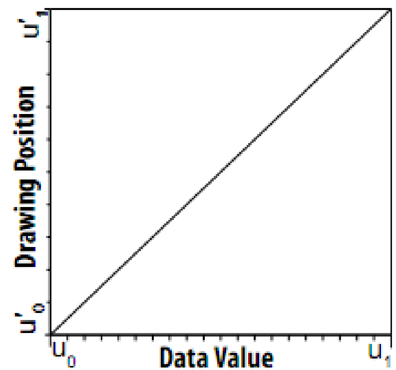


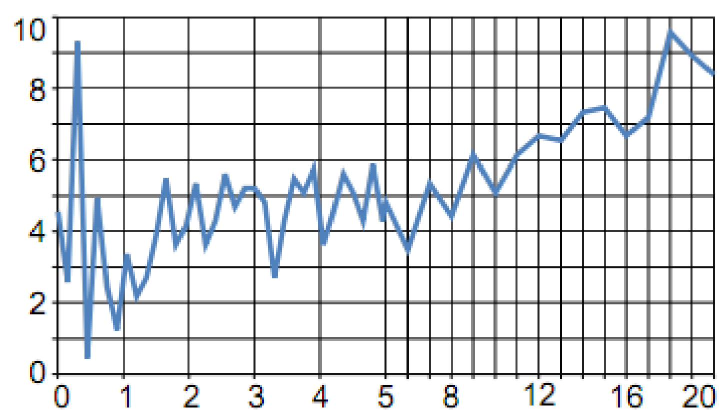


DUAL-SCALE CHARTS

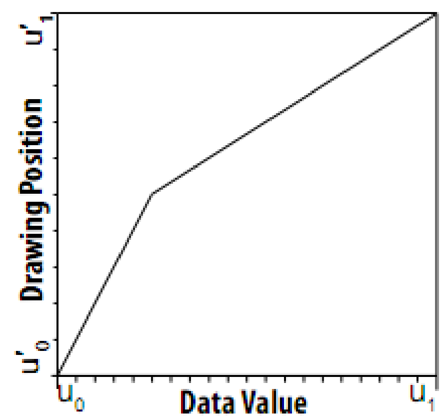


REGULAR CHART





BIFOCAL CHART



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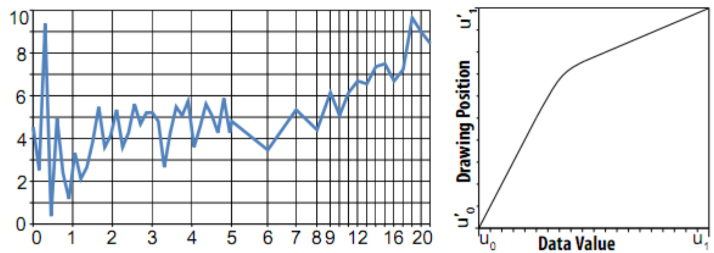
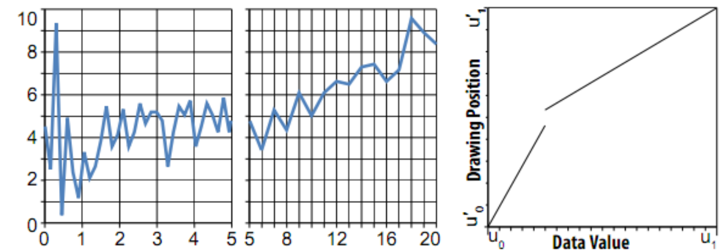
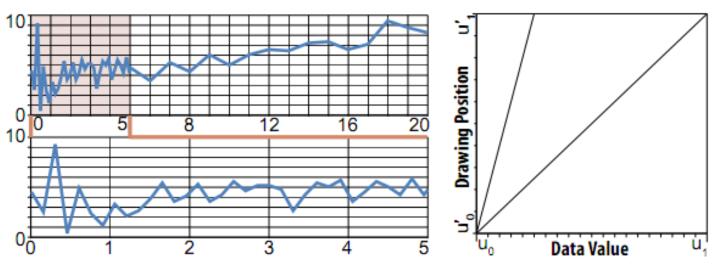
DUAL-SCALE CHARTS



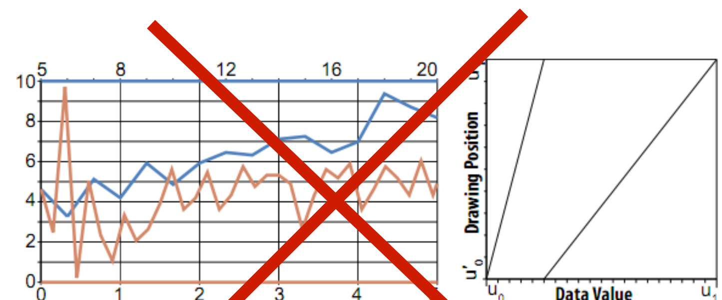
LENS CHART



BROKEN CHART



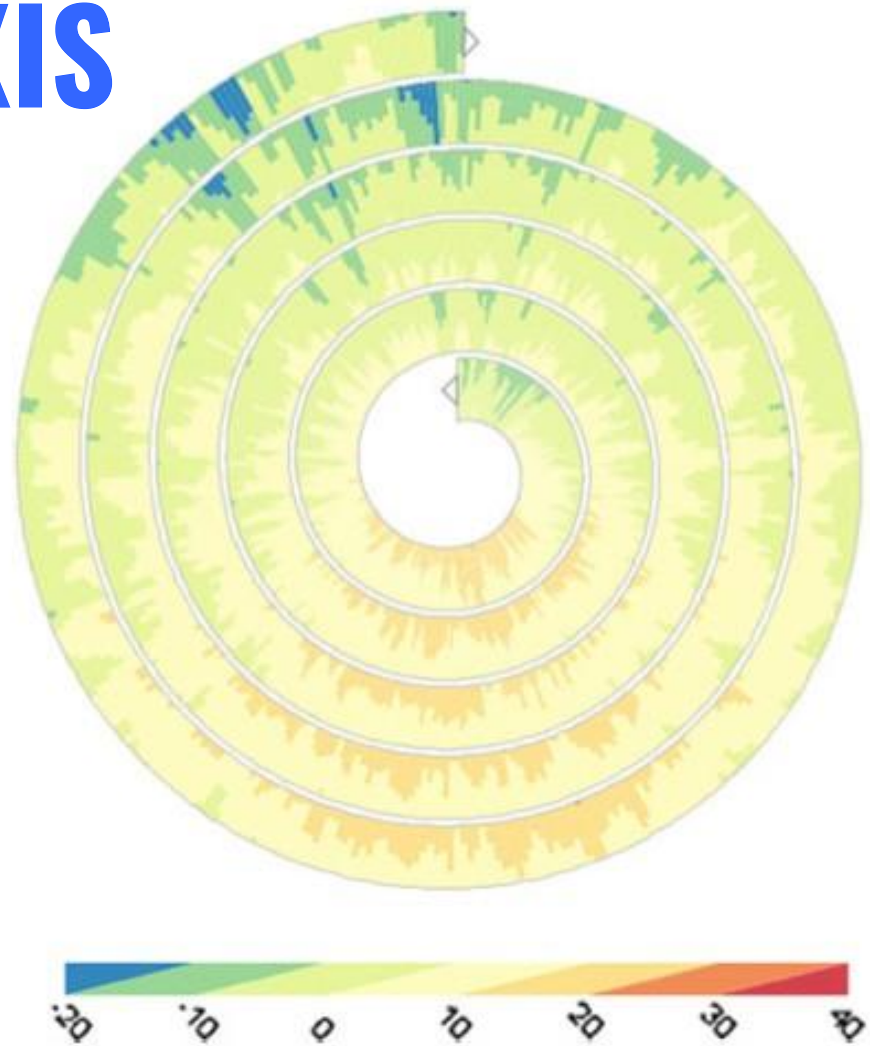
CUT-OUT CHART



SUPERIMPOSED CHART

ISENBERG ET AL 2011

SPIRAL AXIS



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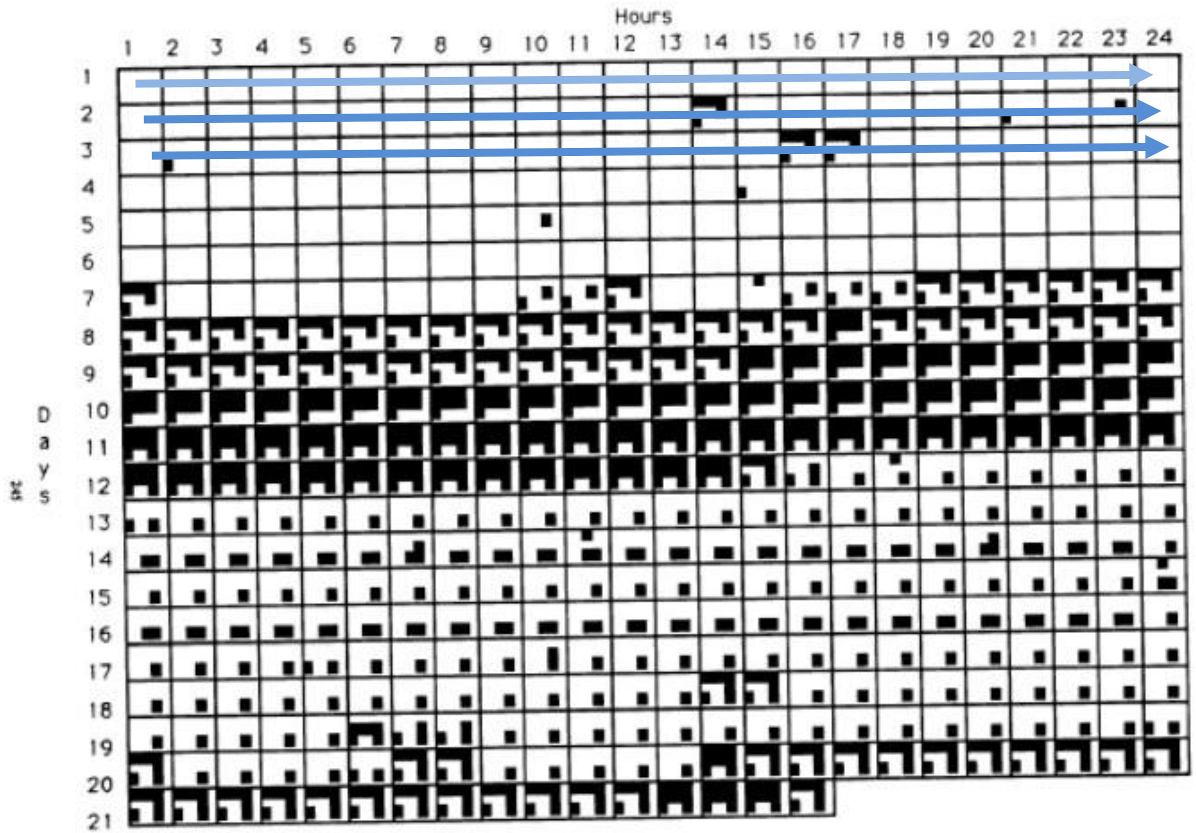
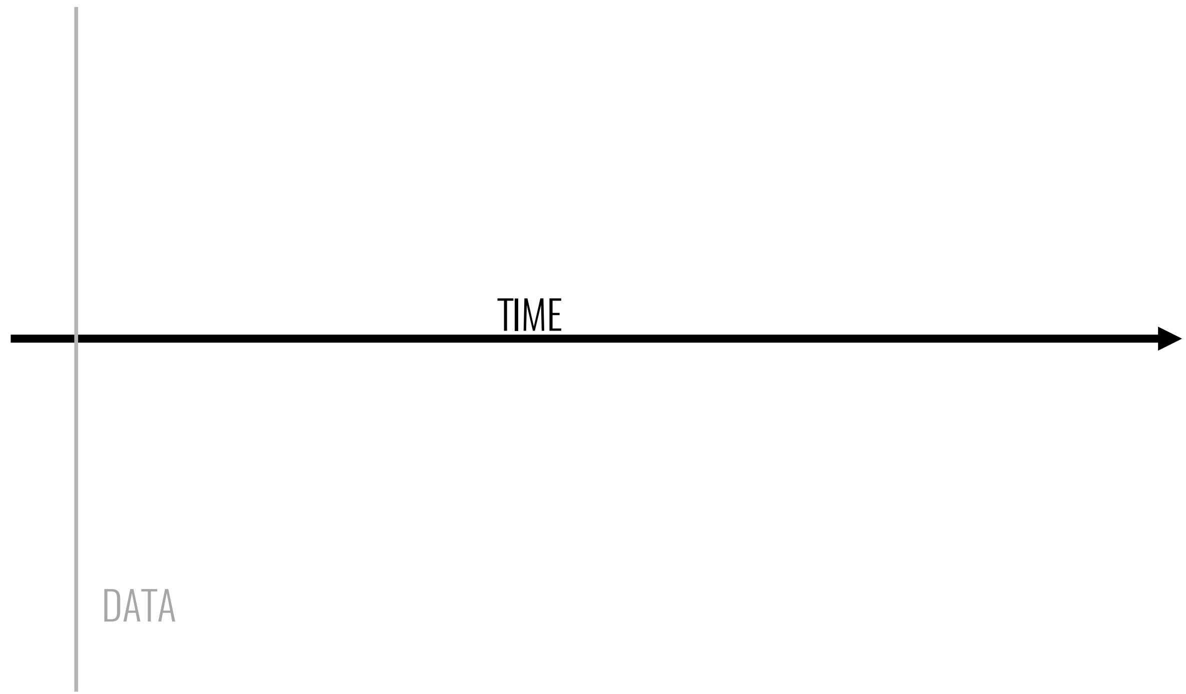
GRID AXIS

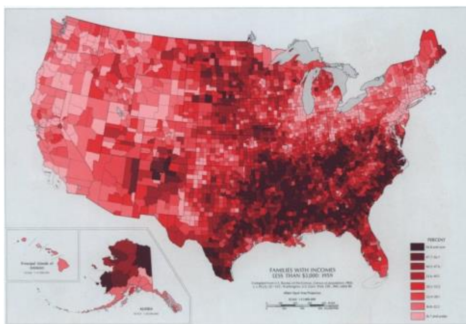


Day by Hour: Thirteen Parameters of Magnetosphere and Solar Wind Data

BEDDOW 1990

MAPPING TIME AND SPACE


TIME
DATA

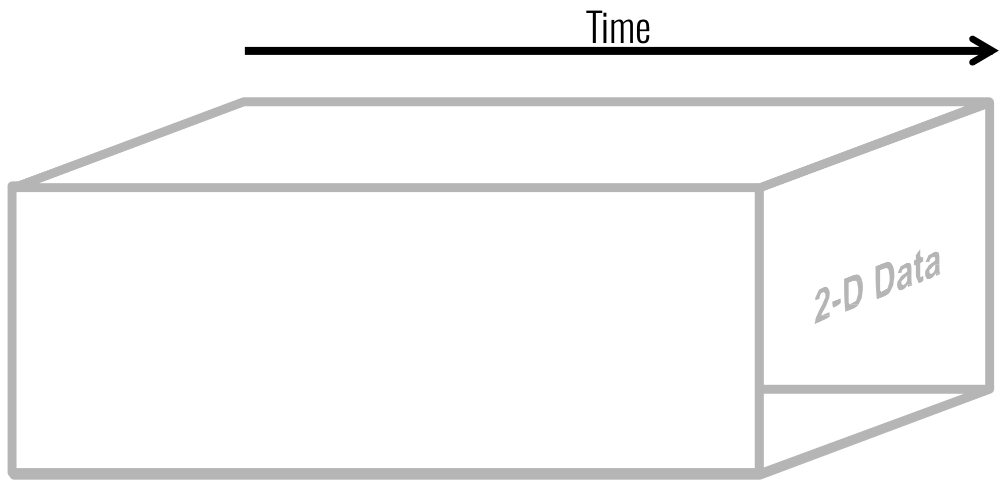


TIME

DATA

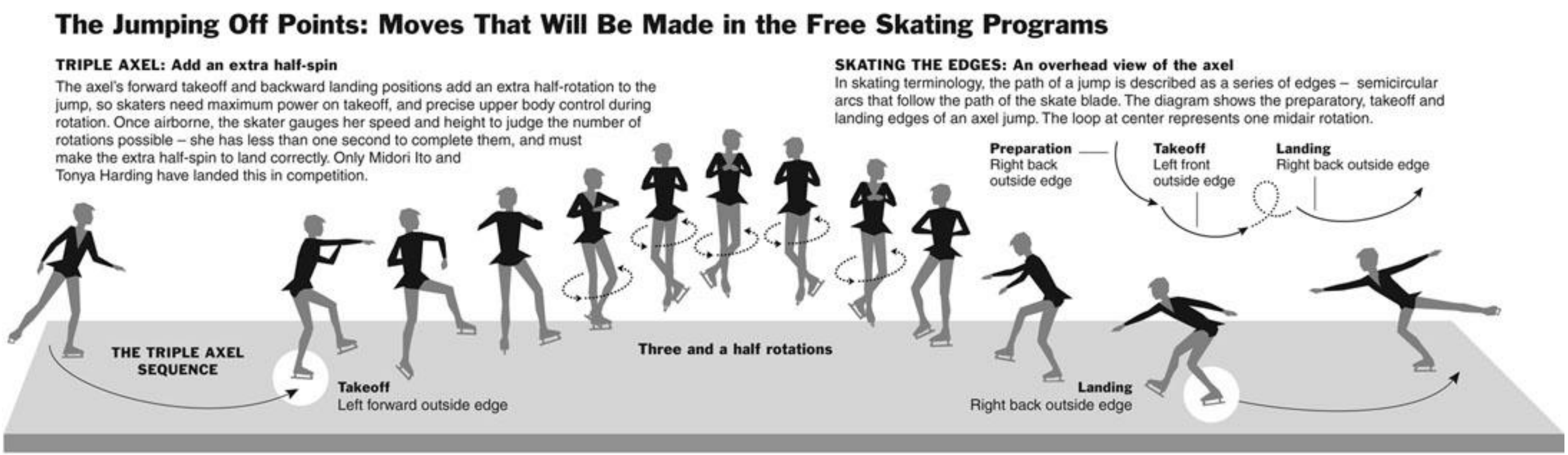
2D + TIME

SPACE-TIME CUBE MODEL



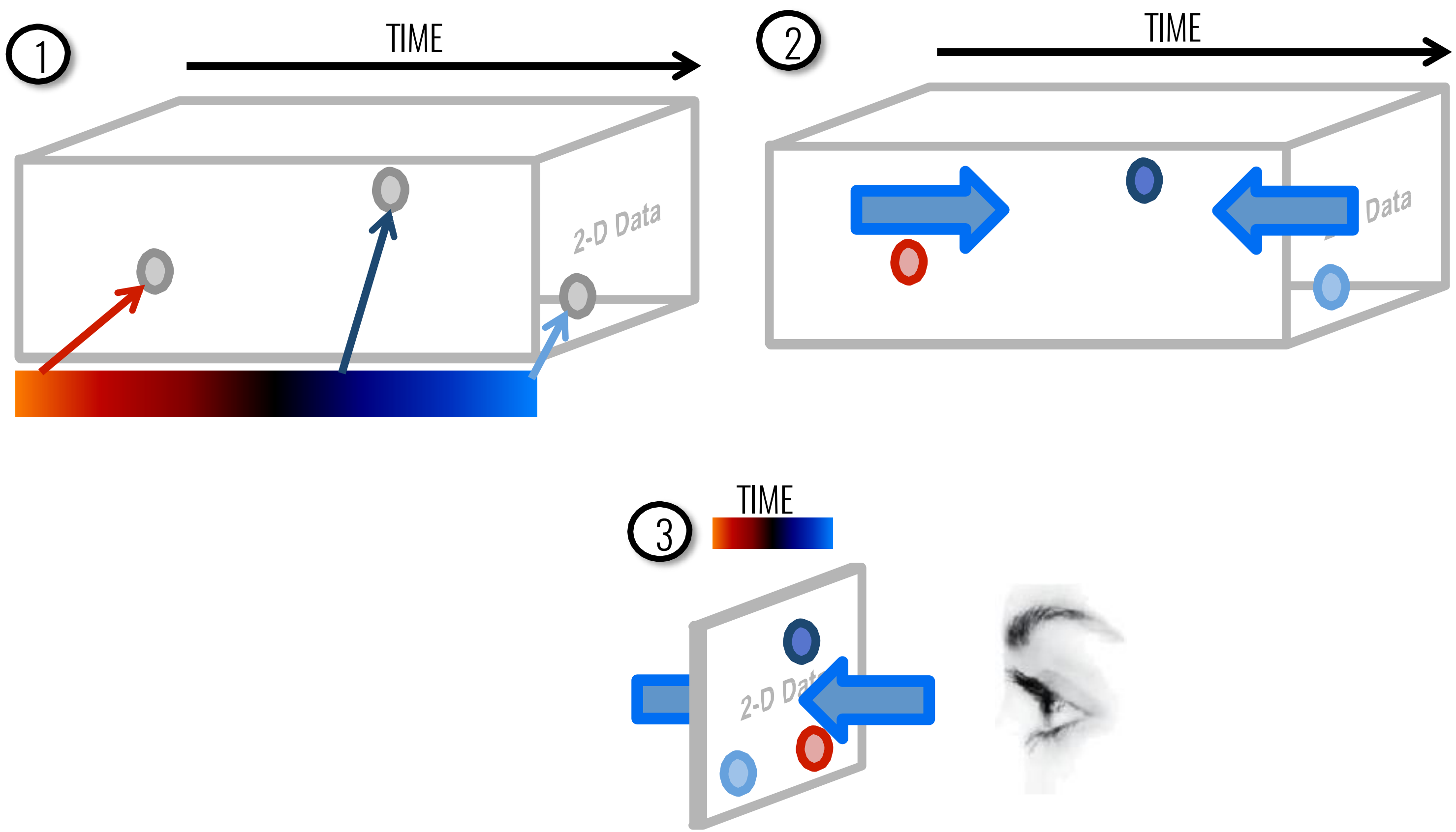
DISCRETE TIME FLATTENING

SEQUENCES



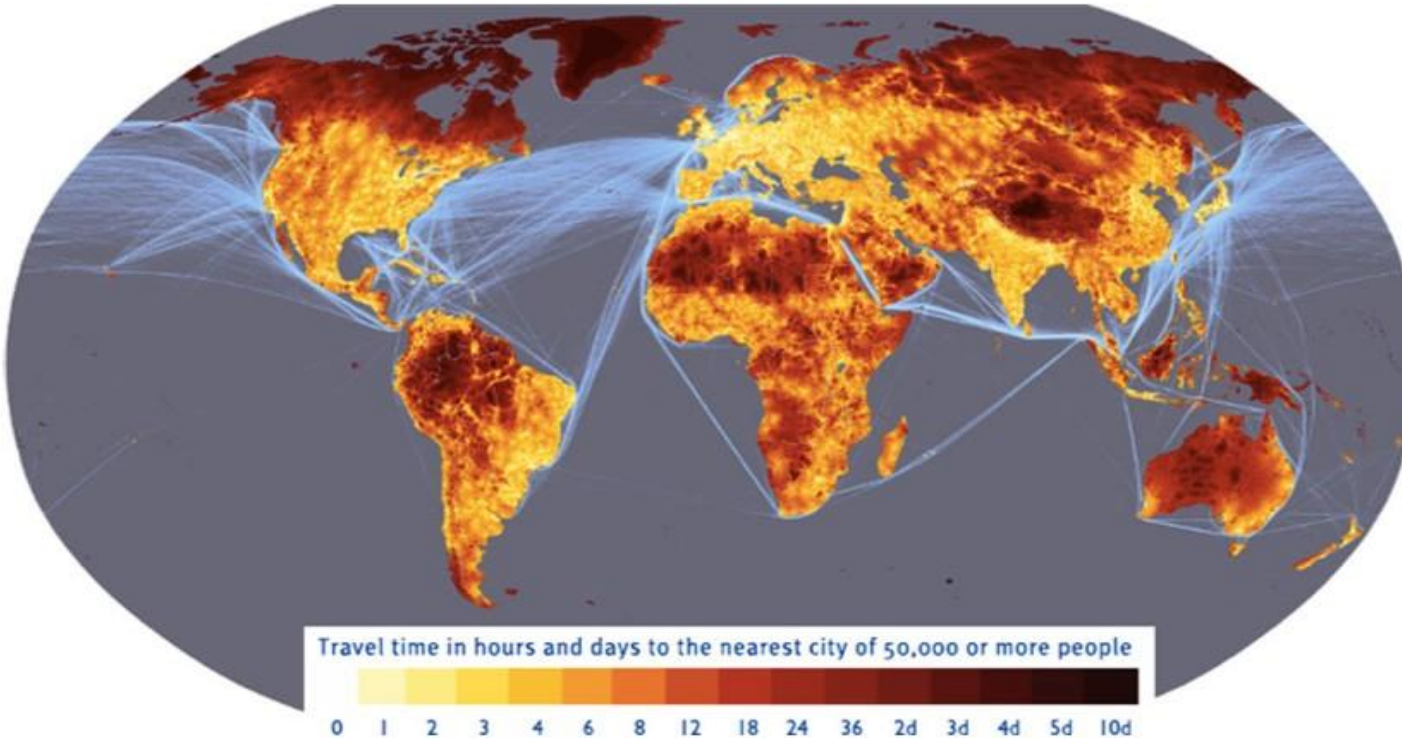
MEGAN JAEGERMAN

COLORED TIME FLATTENING



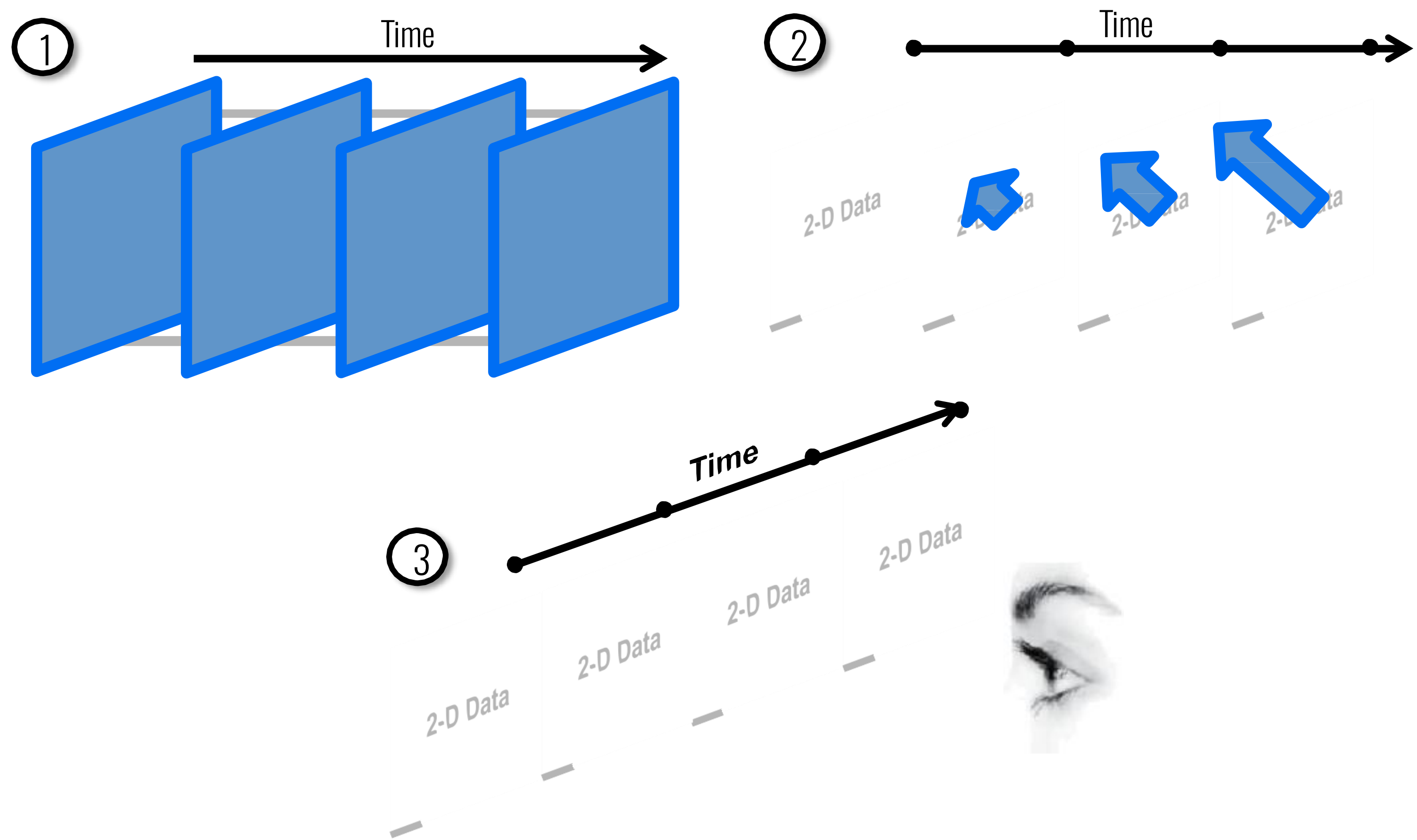
COLORED TIME FLATTENING

TRAVEL TIMES



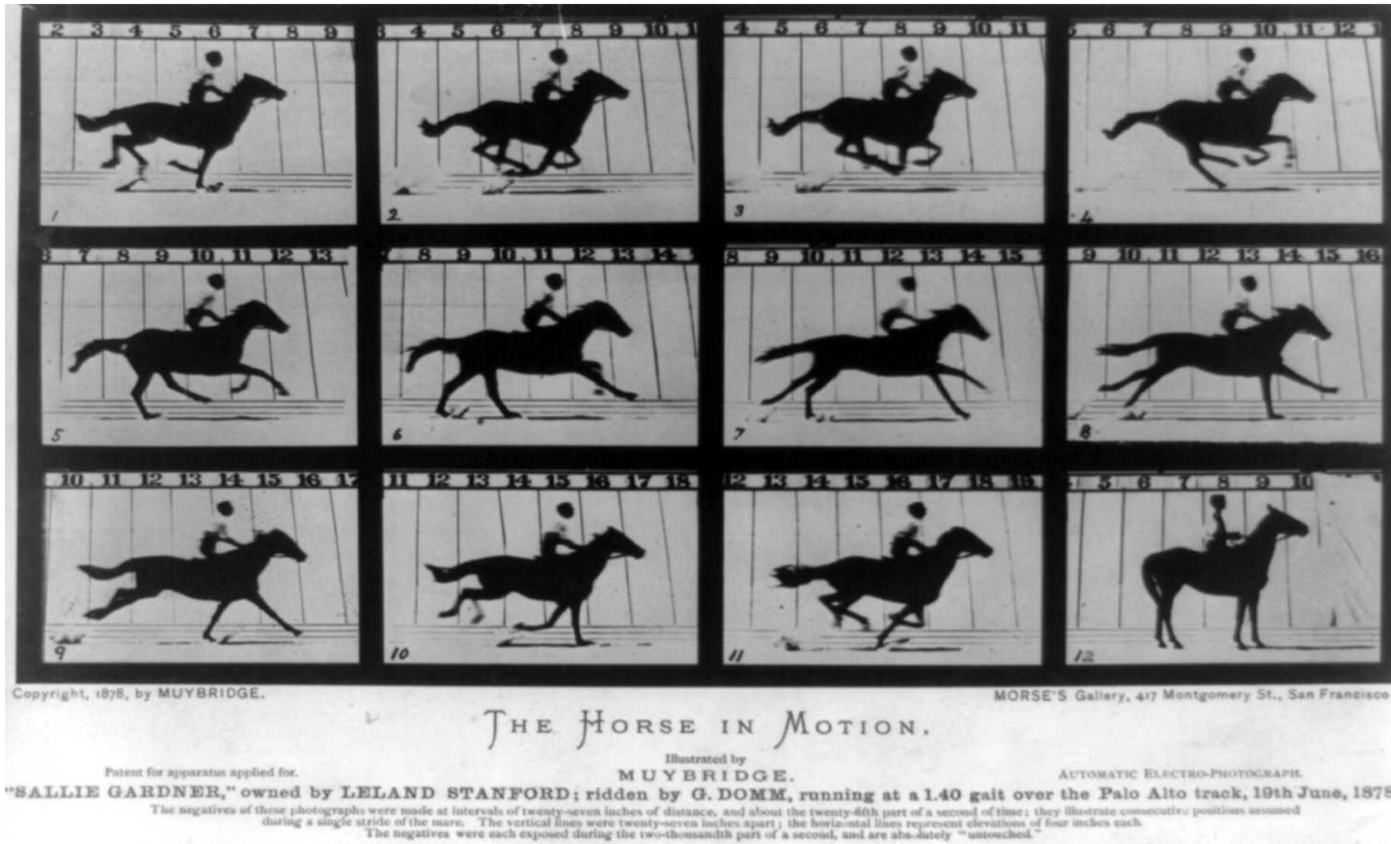
NELSON 2008

TIME JUXTAPOSING



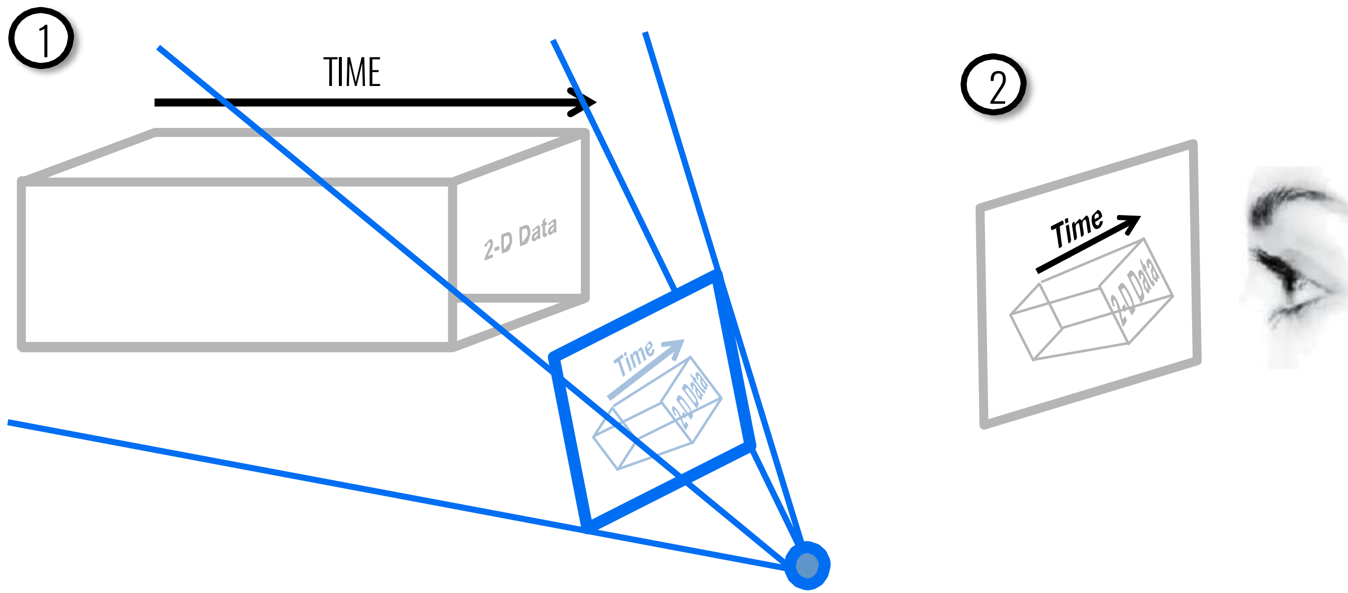
TIME JUXTAPOSING

MUYBRIDGE'S CHRONOPHOTOGRAPHY TECHNIQUE



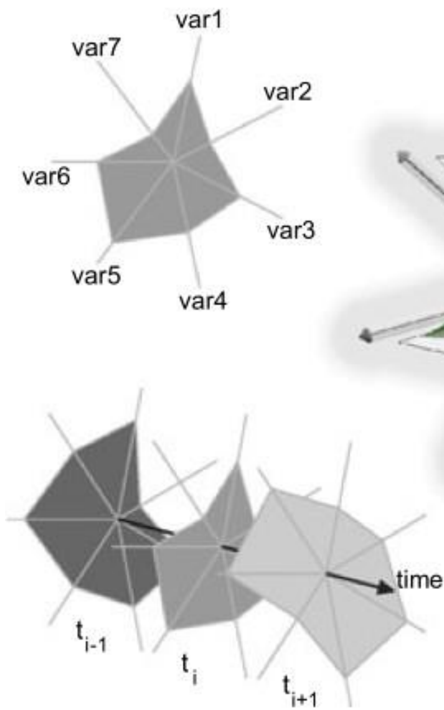
MUYBRIDGE 1878

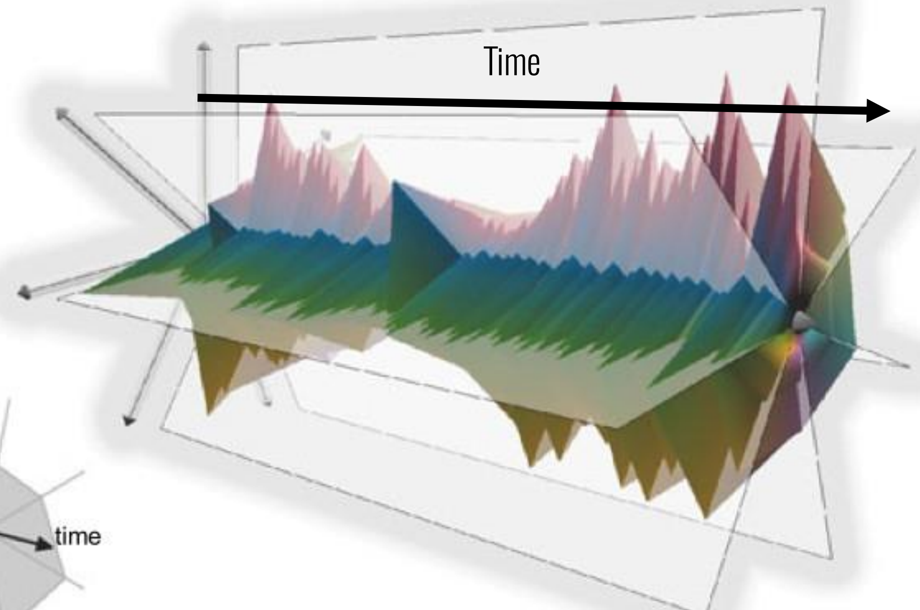
3D RENDERING



3D RENDERING

KIVIAT TUBE





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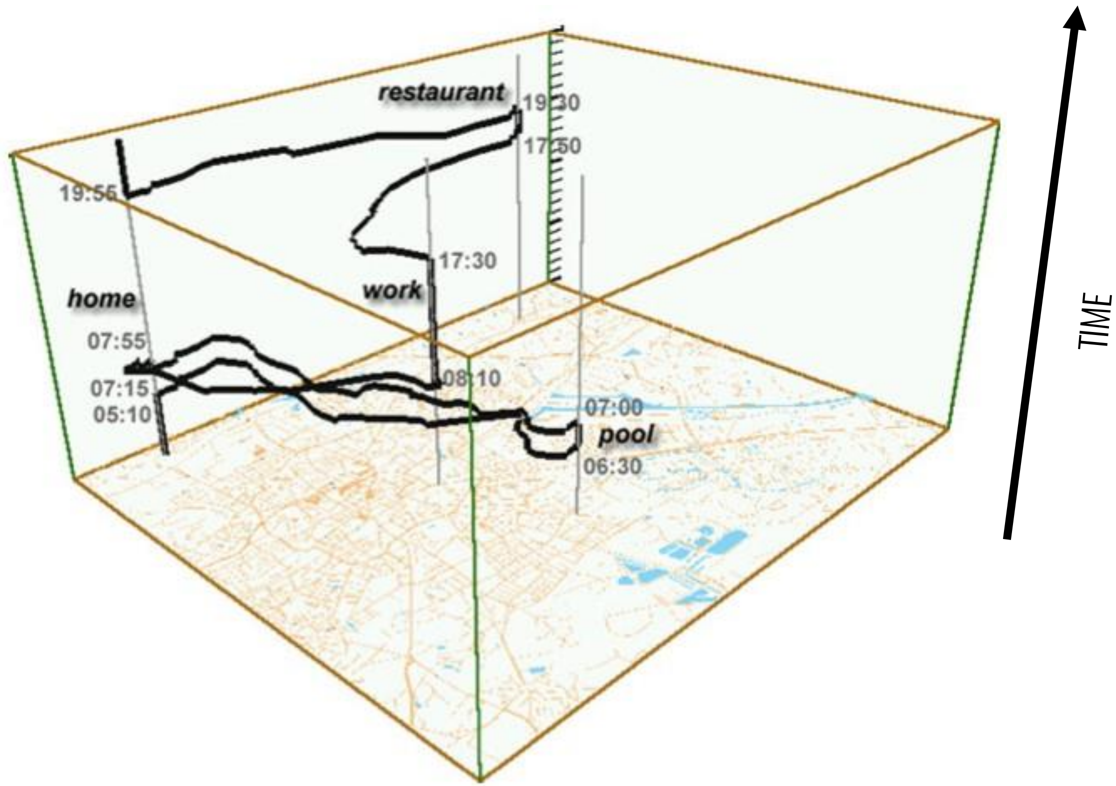
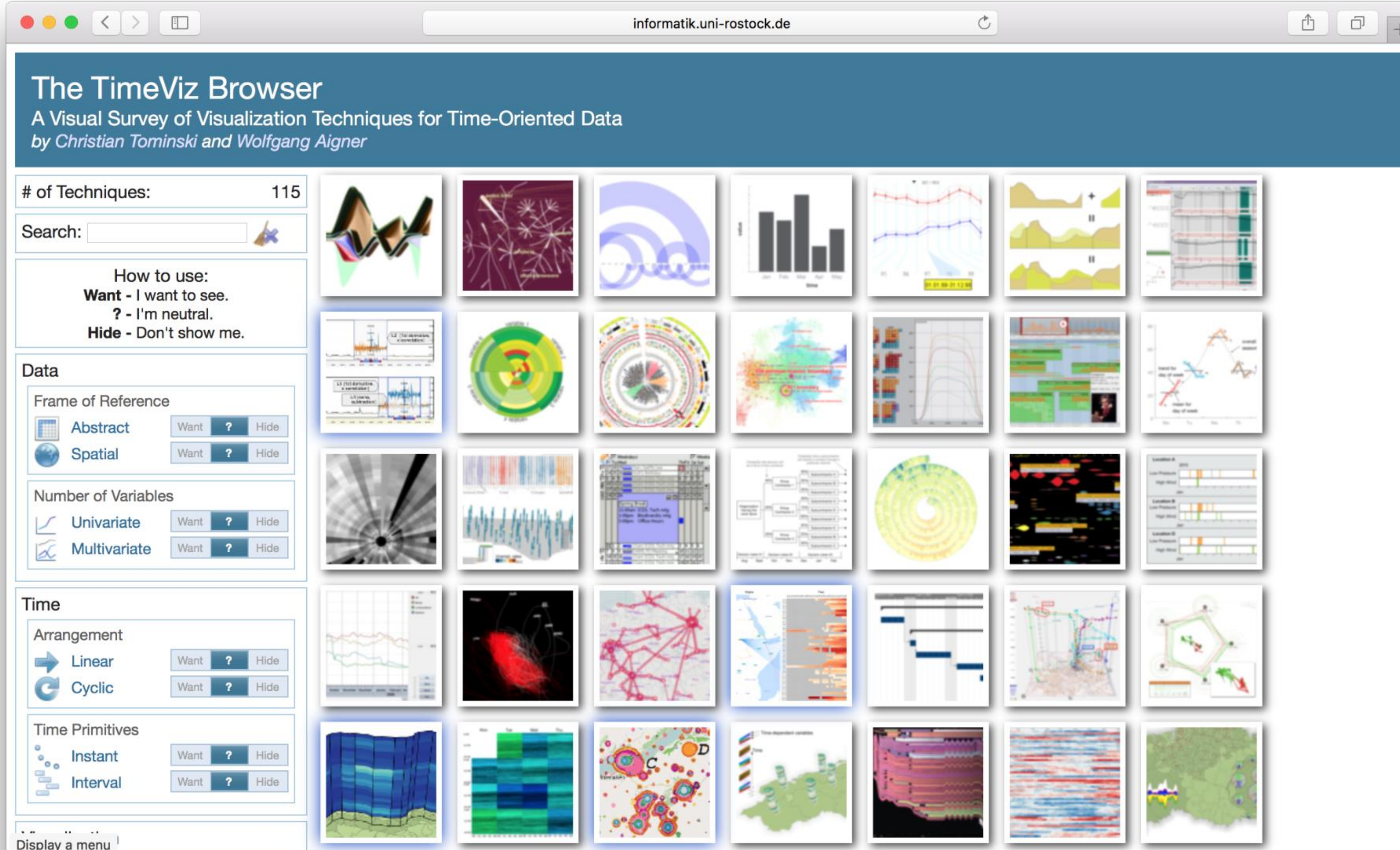
3D RENDERING

PATHS



KRAAK 2003

http://www.timeviz.net/



https://timelinestoryteller.com/

Microsoft

Timeline Storyteller

CONTACT US TOP

- Examples
- Preparing data
- How do I use it?
- Source code
- Acknowledgements

Project Team:

- Matthew Brehmer
- Bongshin Lee
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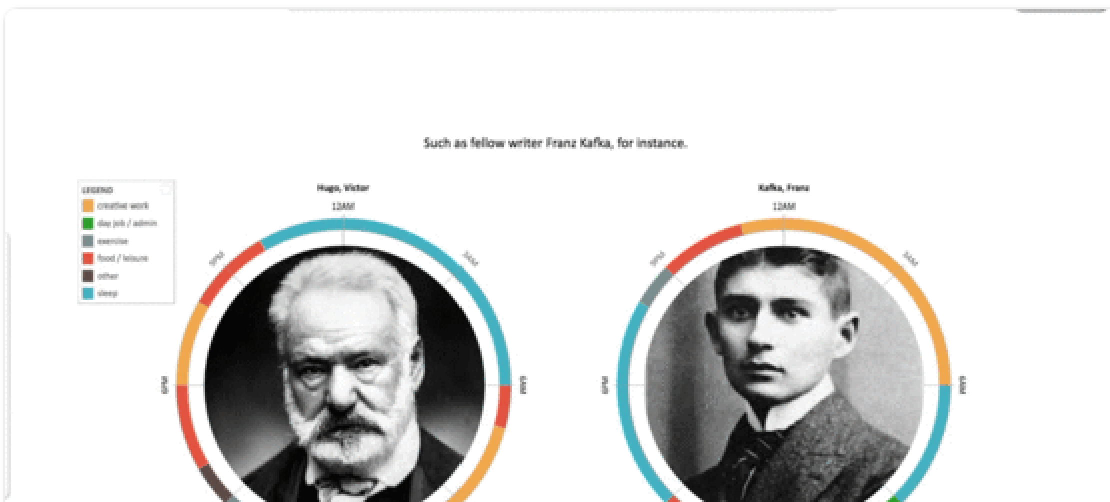
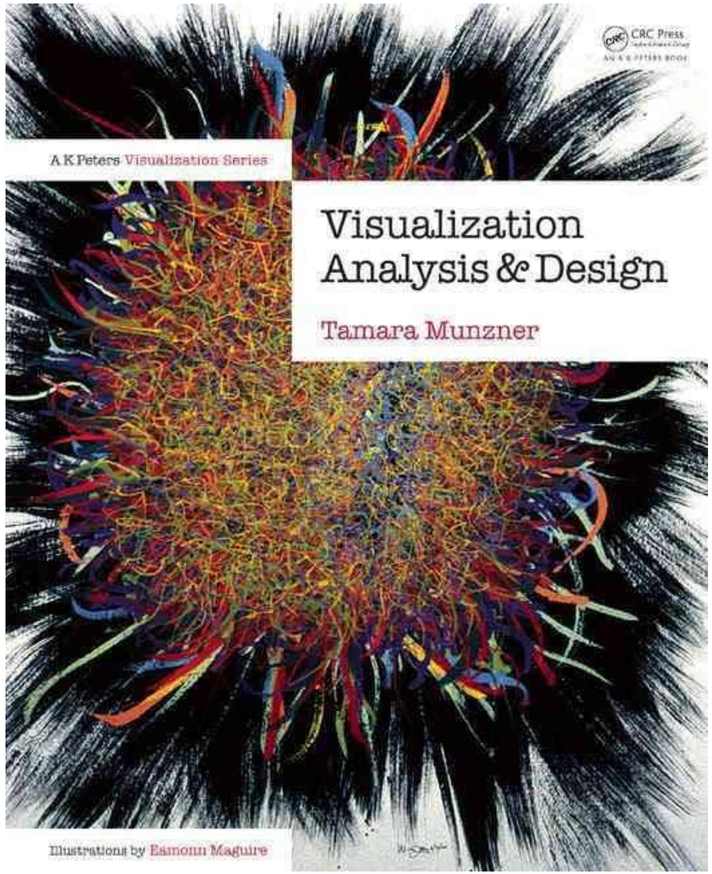
- Darren Edge
- Christopher White
- Kate Lytvynets
- David Tittsworth

Timeline Storyteller is an open-source expressive visual storytelling environment for presenting timelines in the browser or in Microsoft Power BI.

Use it to present different aspects of timeline data using a palette of timeline representations, scales, and layouts, as well as controls for filtering, highlighting, and annotation.



READINGS


CRC Press
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