

Visual analytics for Data Quality

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whoami

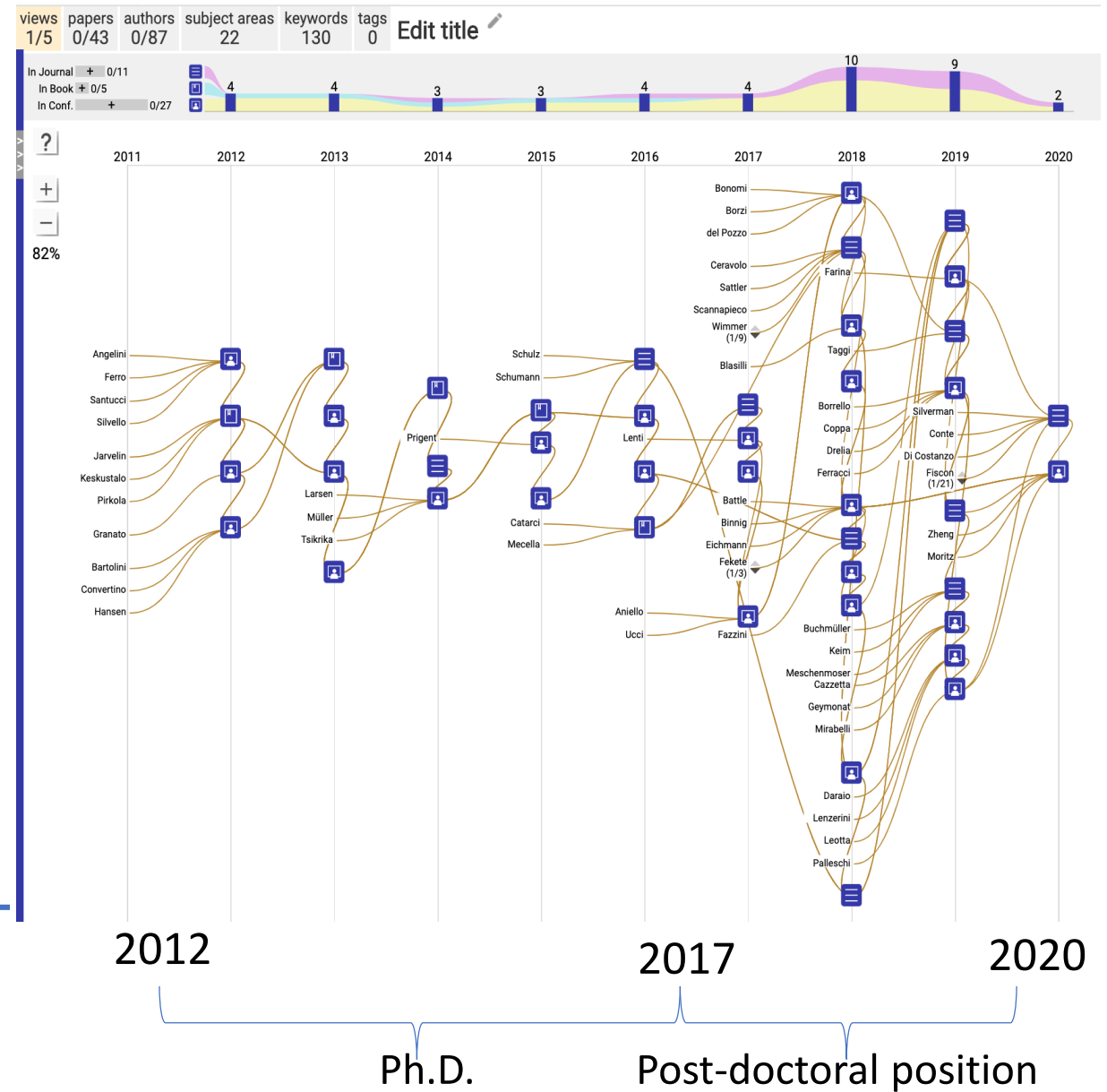
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A (very) simple question

- How many 3s?
- You have 4 seconds to answer.....

Game over!



So ?

- Time was not sufficient?
- You can answer this question in less than 0.2 seconds!
- Let's try again...

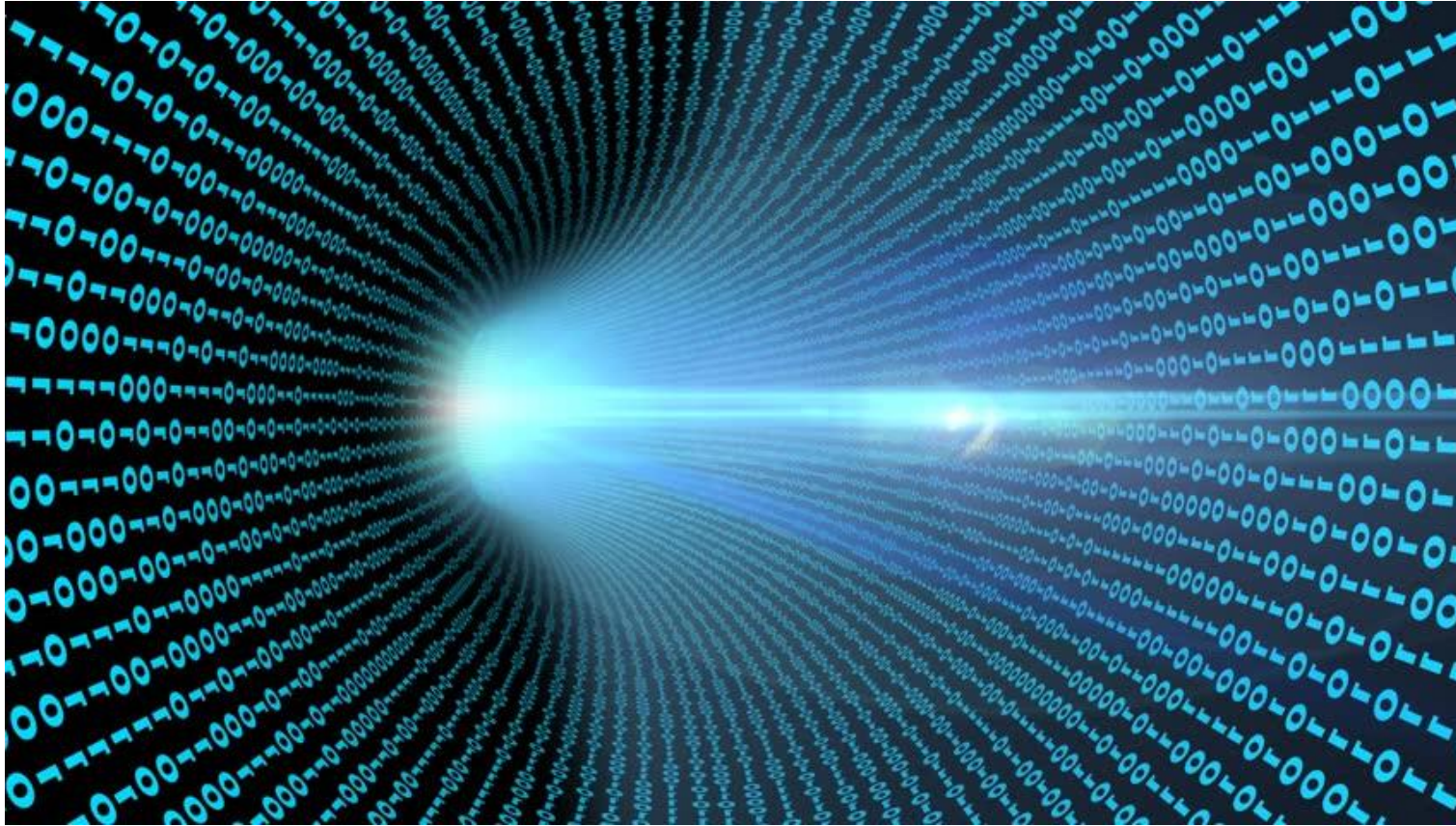


458757626808609928083982698028
747976296262867897187743671947
746588786758967329667287682085

- Color is pre-attentive(it pops up)
- It does not require any cognitive effort



Lots of Data!



Ben Chams - Fotolia



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Data Quality

- Understanding the gross structure of the datasets (how many columns, how many rows, etc.)
- How big is the dataset, how many attributes, how is the data organized, etc?
- Internalizing the dataset attributes (columns)
 - what type of data is in each column?
 - Is it categorical, quantitative, and ordinal, etc?
 - What are the most frequent values?
- Discovering relationships among the attributes and structure within the table
 - how are the columns related?
 - Are there duplications among the columns, implicit relationships, and implicit structure within the table?



Data Quality

- Finding invalid and missing values,
 - Invalid values occur when items are miss-keyed, when data is carelessly entered, or when data is inconsistently collected.
 - Missing values occur when data attributes are dropped as part of the data extraction process, important fields are ignored and not populated by data entry clerks, or when data tables are expanded as part of system maintenance but never populated.
- Discovering zeros and other suspicious values such as 99 or 99999. These values are often indicative of coding problems in the data collection process and may require manual investigation.
- Identifying duplicated rows and column. Errors in data extraction routines often manifest themselves by



Data Quality

Data profiling

Data Quality
Measurement

Data cleansing

Data Quality
Monitoring

- Accuracy
- Completeness
- Coherence
- Relevance
- Timeliness
- Accessibility
- interpretability

Type	Issue	Detection Method(s)
Missing	Missing record	Outlier Detection Residuals then Moving Average w/ Hampel X84
		Frequency Outlier Detection Hampel X84
Inconsistent	Missing value	Find NULL/empty values
	Measurement units	Clustering Euclidean Distance
		Outlier Detection z-score, Hampel X84
	Misspelling	Clustering Levenshtein Distance
	Ordering	Clustering Atomic Strings
Incorrect	Representation	Clustering Structure Extraction
	Special characters	Clustering Structure Extraction
	Erroneous entry	Outlier Detection z-score, Hampel X84
	Extraneous data	Type Verification Function
	Misfielded	Type Verification Function
Extreme	Wrong physical data type	Type Verification Function
	Numeric outliers	Outlier Detection z-score, Hampel X84, Mahalanobis distance
	Time-series outliers	Outlier Detection Residuals vs. Moving Average then Hampel X84
Schema	Primary key violation	Frequency Outlier Detection Unique Value Ratio



You saw a lot of it during these days....



How can an analyst be helped ?

- Managing complexity of this workflow
- Some of the indicator are easy to compute but requires explanation to a user
- Some of the indicators need analyzing data in detail and recognize the behavior
- Exploring data require good skills

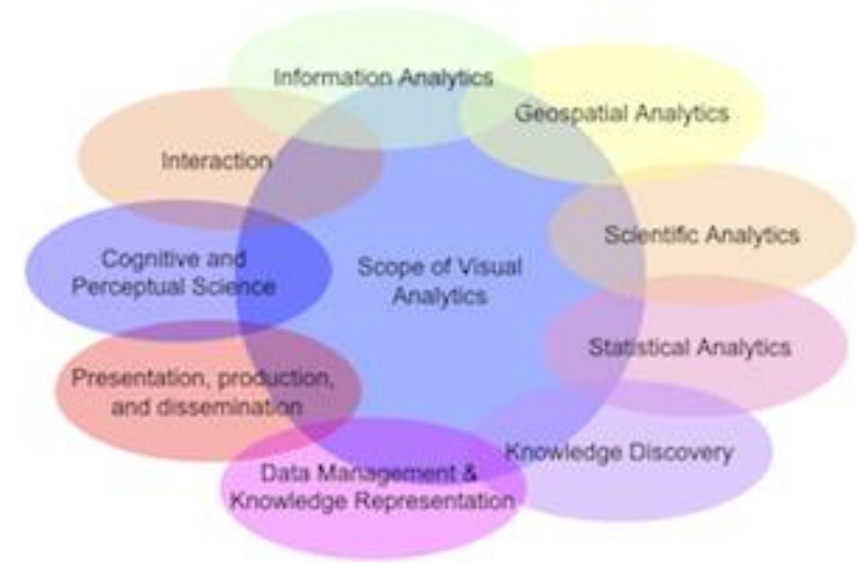


Visual Analytics: definition

Visual Analytics is the science of analytical reasoning supported by interactive visual interfaces. the complex nature of many problems makes it indispensable to include human intelligence at an early stage in the data analysis process.

Visual Analytics methods allow decision makers to combine their human flexibility, creativity, and background knowledge with the enormous storage and processing capacities of today's computers to gain insight into complex problems.

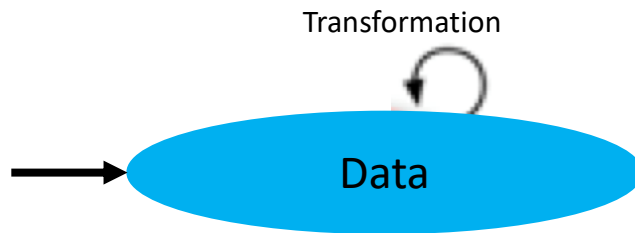
Using advanced visual interfaces, humans may directly interact with the data analysis capabilities of today's computer, allowing them to make well-informed decisions in complex situations.



Thomas, J., Cook, K.: Illuminating the Path: Research and Development Agenda for Visual Analytics. IEEE-Press (2005)



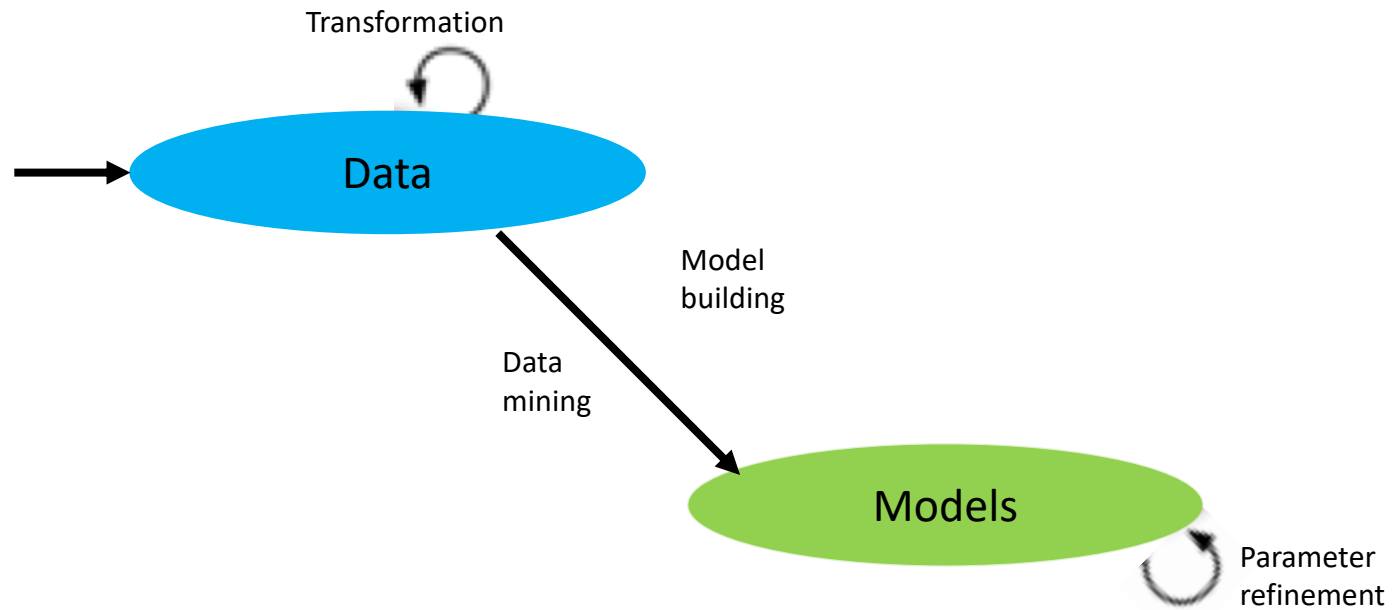
Visual Analytics



Data are ~~beautiful~~ ugly



Visual Analytics



Variables and indicators

The Analytics

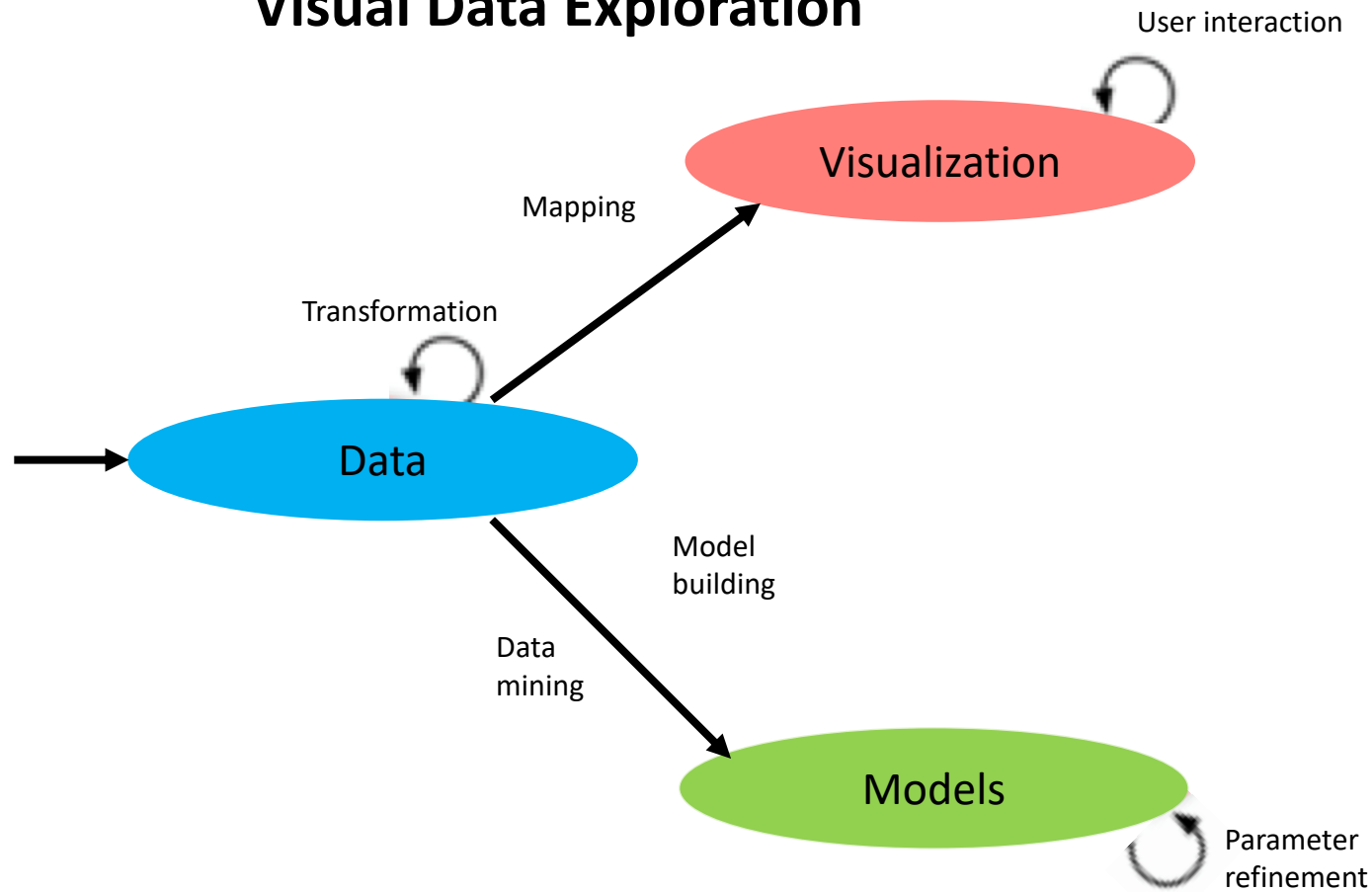
Innovation			Education			Research		
INPUT	OUTPUT	ENV. VAR.	INPUT	OUTPUT	ENV. VAR.	INPUT	OUTPUT	ENV. VAR.
% pop with higher education	GDP per capita	Foundation year	Total number of enrolled students ISCED5-8	Graduates at ISCED 5-7 (national, foreign and total graduates)	University hospital	Total academic staff (Full Time Equivalent)	Total number of documents published in scholarly journals indexed in Scopus	Ph.D. intensity (students ISCED8/student s ISCED5-8)
business R&D exp	patent number	Region of establishment (NUTS3; NUTS 2 and country)	Total academic staff (Full Time Equivalent)	Graduates at ISCED 5-7 area F09 (medicine)	Ph.D. intensity (students ISCED8/student s ISCED5-8) in FoE 09 Medicine	Total academic staff (HC)	Normalized Impact	Ph.D. intensity (students ISCED8/student s ISCED5-8) in FoE 09 Medicine
% pop lifelong learning activities	revenues		Students enrolled at ISCED 5-7 (national, foreign and total students)	Graduates at ISCED 8—area F 09 (medicine)	Ratio foreign/national students ISCED5-7	Academic staff—ISCED-F 09 (HC)	High Quality Publications Ratio of publications that an institution publishes in the most influential scholarly journals of the world	Total students enrolled/Total academic staff (HC)
high-tech empl in manuf	added value of high-tech industries		Students enrolled at ISCED 8— (distinguished in national, foreign and total students enrolled)		Ph.D. intensity (students ISCED8/student s ISCED5-8)	Number of administrative staff (FTE)	Excellence rate indicates the amount (in %) of an institution's scientific output that is included into the set of the 10% of the most cited papers	

Models

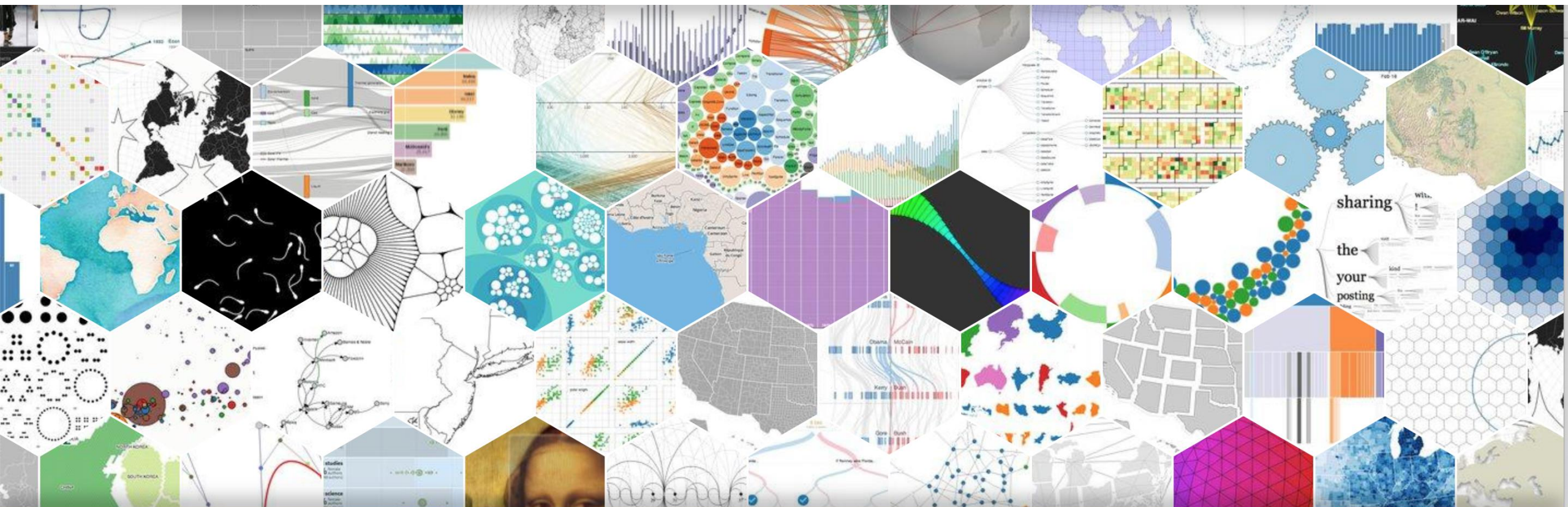


Visual Analytics

Visual Data Exploration

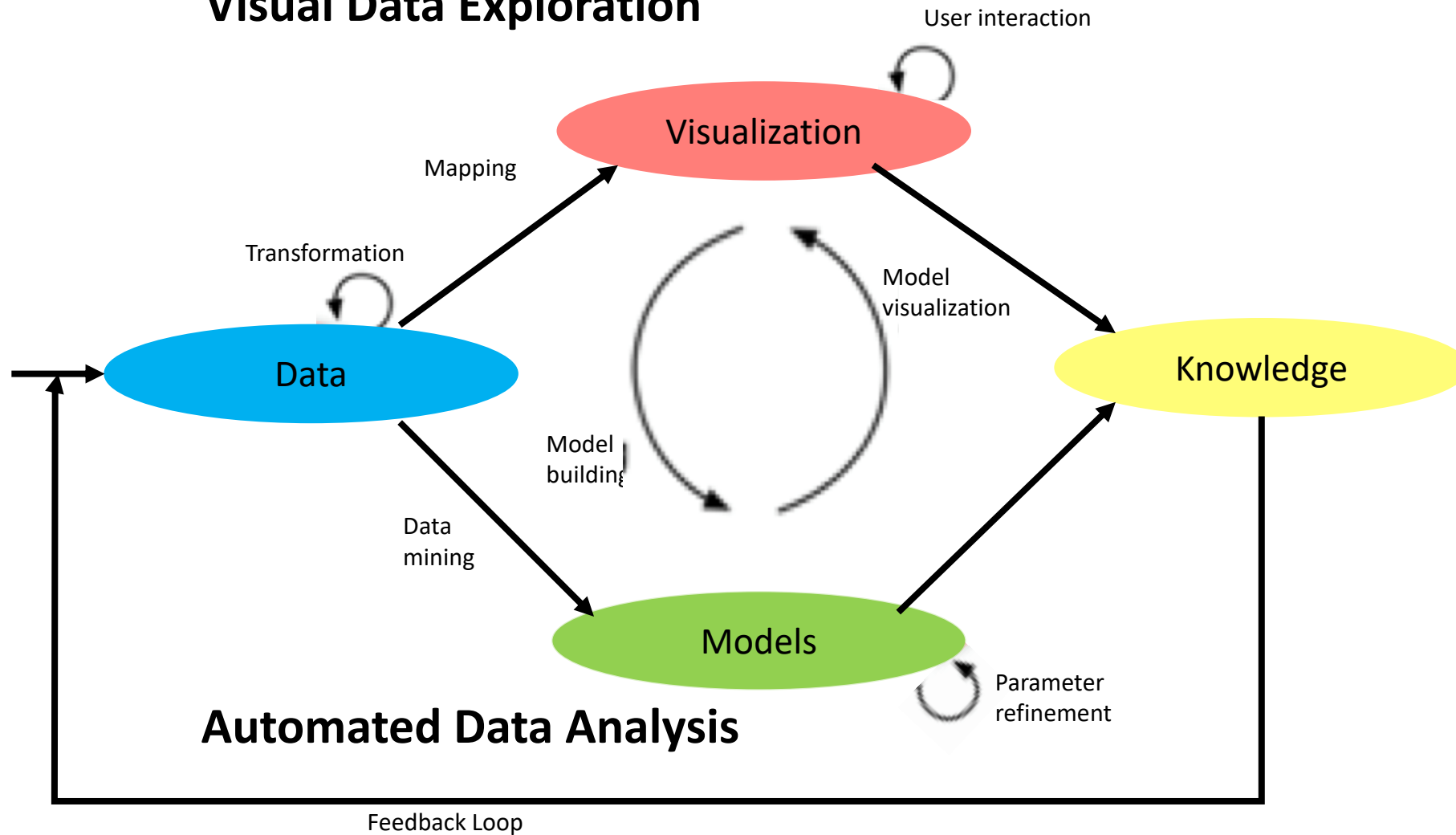


Visualization



Visual Analytics

Visual Data Exploration



Data Quality: a survey

667 software tools dedicated to “data quality” (still emerging market)

- half (50.82 %) of the DQ tools were domain specific, which means they were either dedicated to specific types of data or built to measure the DQ of a proprietary tool.
- 16.67 % of the DQ tools focused on data cleansing without a proper DQ measurement strategy
- Most surveyed tools supported data profiling to some extent
- did not find a tool that implements a wider range of DQ metrics for the most important DQ dimensions as proposed in research.
- Identified metric implementations have several drawbacks: some are only applicable on attribute-level (e.g., no aggregation), some require a gold standard that might not exist, and some have implementation errors.

Lisa Ehrlinger^{1, 2}, Elisa Rusz¹, and Wolfram Wöß¹, A SURVEY OF DATA QUALITY MEASUREMENT AND MONITORING TOOLS, Preprint, 2019



Data Quality & visualization: survey

- Very low presence of visual environments (in contrast with other “fields”)
- the authors list 9 usability criteria for the GUI, but in the evaluation they only distinguish between (g) representing “not user friendly GUI” and a (G) for “user-friendly GUI” with drag and drop functionality.

Lisa Ehrlinger^{1, 2}, Elisa Rusz¹, and Wolfram Wöß¹, A SURVEY OF DATA QUALITY MEASUREMENT AND MONITORING TOOLS, Preprint, 2019



Visualization 4 Data Quality: Tables are kings...

	Total defects	A	B	C	D	E
A4636	131	37	21	28		45
A2524	86	20	24	21	1	20
A3713	75	17	13	18		27
A4452	73	5	33	17		18
A4088	72	14	16	12	2	28
A2103	68	14	13	14	1	26
A2156	68	16	13	19	2	18
A3681	66	12	16	9	1	28
A1366	50	11	15	12		12
A2610	39	5	7	12		15
Total	728					

	Total defects	A	B	C	D	E
A4636	131	37	21	28		45
A2524	86	20	24	21	1	20
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A2156	68	16	13	19	2	18
A3681	66	12	16	9	1	28
A1366	50	11	15	12		12
A2610	39	5	7	12		15
Total	728	151	171	162	7	237

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A2156	68	16	13	19	2	18
A3681	66	12	16	9	1	28
A1366	50	11	15	12		12
A2610	39	5	7	12		15
Total	728	151	171	162	7	237

Category	This Year Sales Status	Average Unit Price	Last Year Sales	This Year Sales	This Year Sales Goal
010-Womens	●	\$7.30	\$2,680,662	\$1,767,558	\$2,680,662
020-Mens	●	\$7.12	\$4,453,133	\$4,452,421	\$4,453,133
030-Kids	●	\$5.30	\$2,726,892	\$2,705,490	\$2,726,892
040-Juniors	●	\$7.00	\$3,105,550	\$2,930,385	\$3,105,550
050-Shoes	●	\$13.84	\$3,640,471	\$3,574,900	\$3,640,471
060-Intimate	●	\$4.28	\$955,370	\$852,329	\$955,370
070-Hosiery	●	\$3.69	\$573,604	\$466,106	\$573,604
080-Accessories	●	\$4.84	\$1,273,096	\$1,379,259	\$1,273,096
090-Home	●	\$3.93	\$2,913,647	\$3,053,326	\$2,913,647
100-Groceries	●	\$1.47	\$810,176	\$829,776	\$810,176
Total	●	\$5.49	\$23,132,601	\$22,051,952	\$23,132,601



...but with problems

- No overview provided (only planar indicators)
- Structured, but difficult to intercept the changes
- Scale very bad with data cardinality/dimensionality



A step back: Visualization literacy



Informal approach

- Rules for different kind of information
- Data quality has mostly predominant numerical information (e.g. indicators, ratios, etc..)
- ...with some exceptions

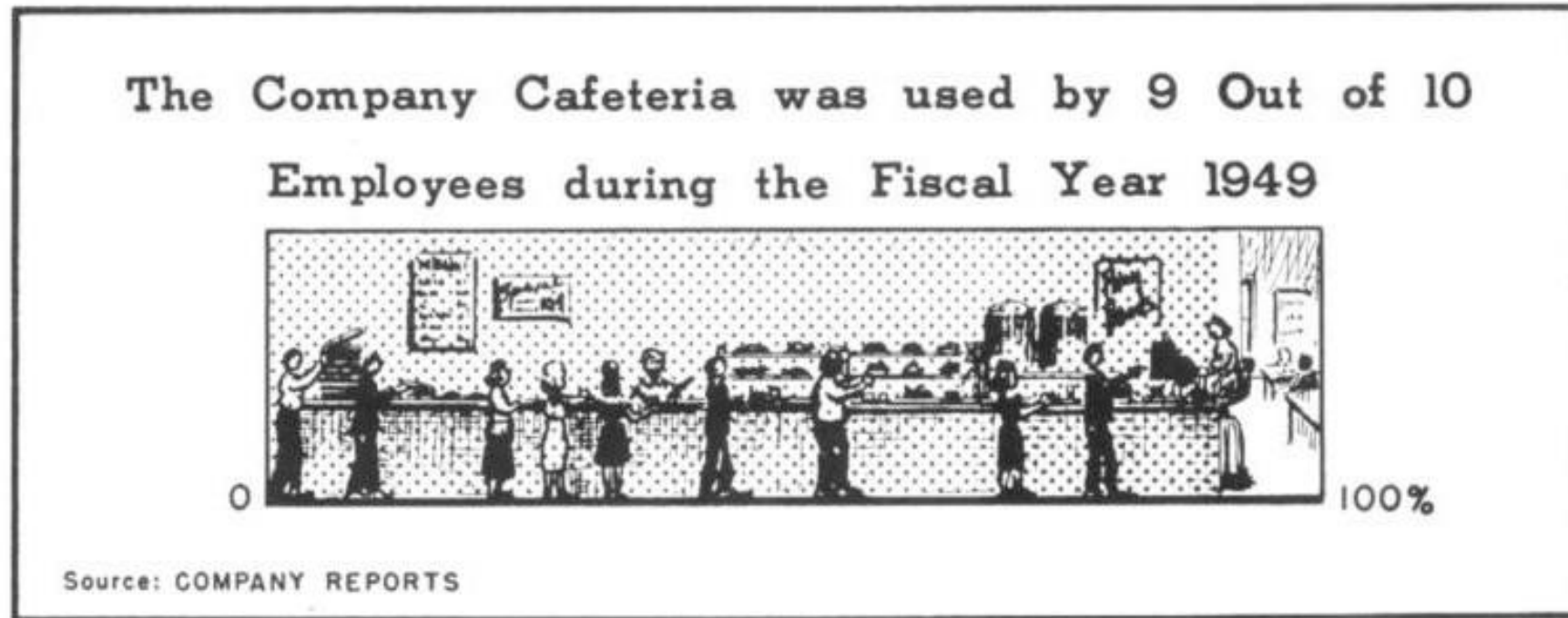


Numerical information: Rule 0

- **Do not use diagrams when handling few numbers**
- It does not make sense to use graphs to display very small amounts of data
- The human brain is quite capable of grasping one two, or even three values



Rule 0 violation (and also rule 2)



Rule 0 violation



Male 60%
Female 40%

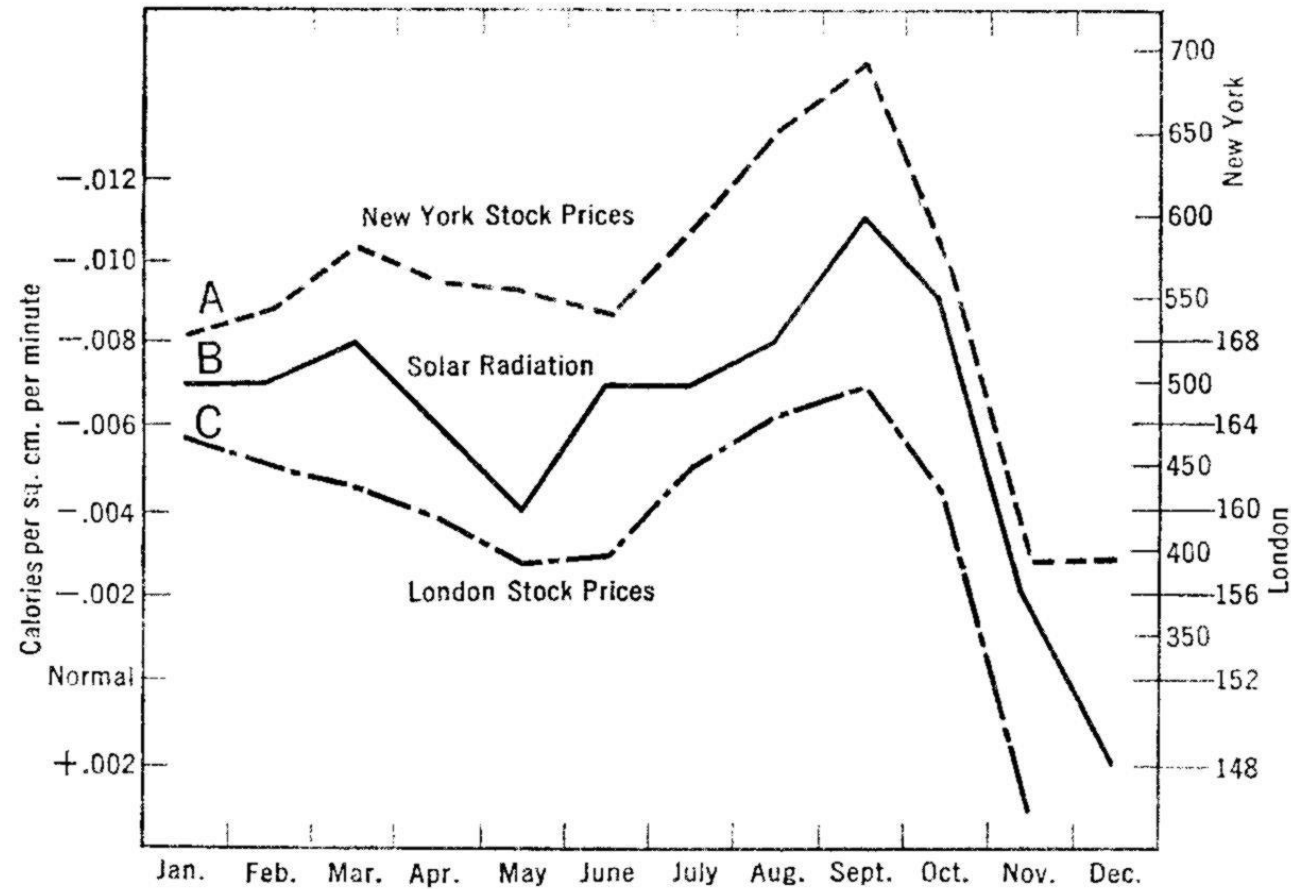


Numerical Information: Rule 1

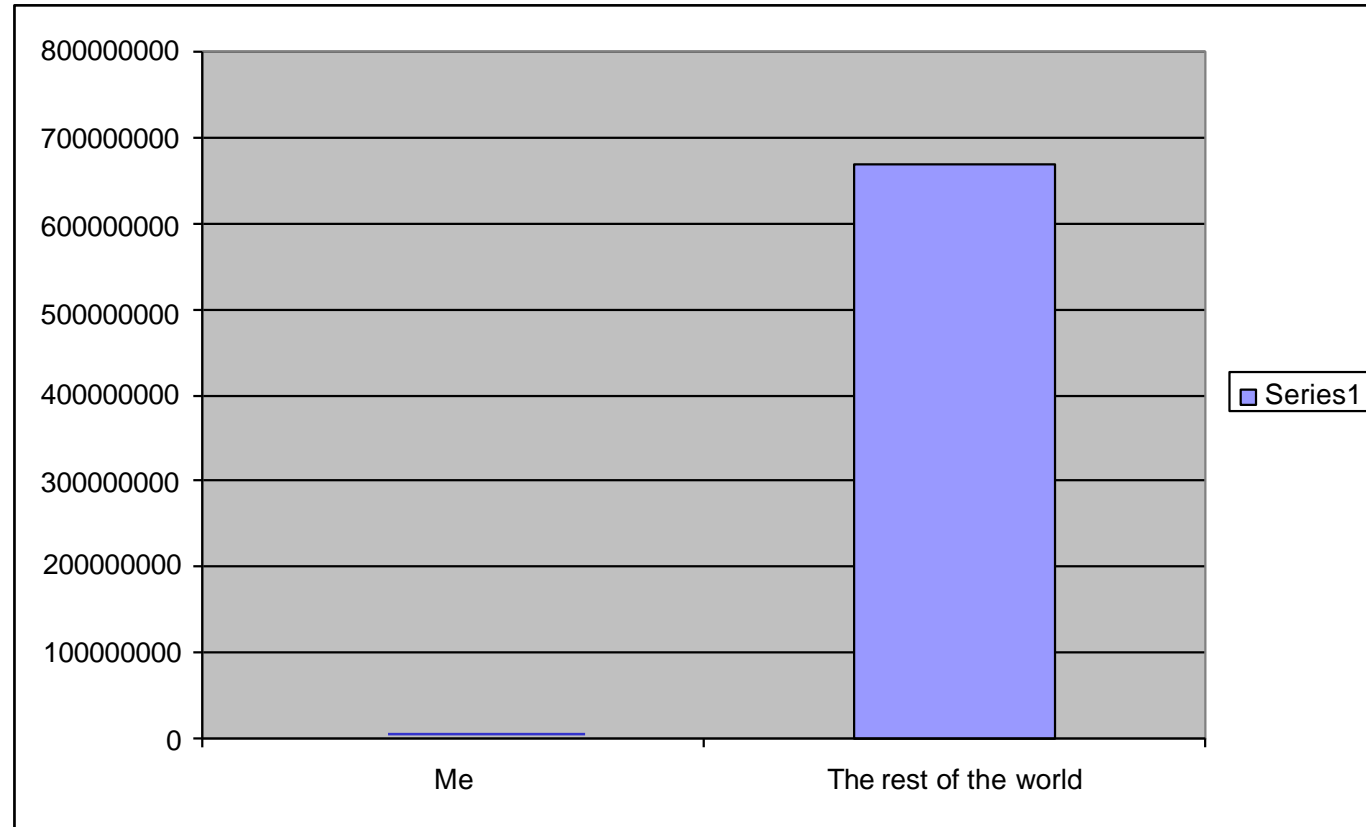
- **Insure data quality / significance**
- Graphs are only as good as the data they display
- No amount of creativity can produce a good graph from dubious or non relevant data



Rule 1 violation



Rule 1 violation (and also rule 0)



Not very significant data but a good example of distortion

Numerical Information: Rule 2:

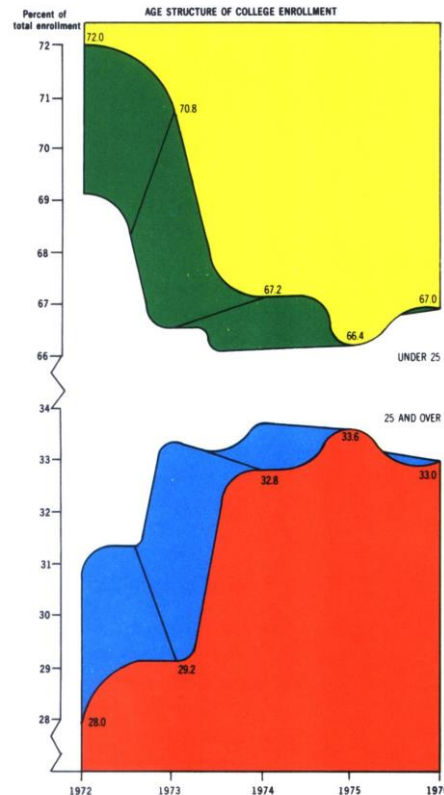
Insure chart simplicity

- Graphs should be no more complex than the data which they portray
- Unnecessary complexity can be introduced by
 - irrelevant decorations
 - colors
 - 3d effects
 - ...
- These are collectively known as “chart junk”
- For a very comprehensive set of chart junk effects look at Microsoft Excel
 - the more recent the version the larger the set !



Rule 2 violation (and also rule 3)

Rule 3 violation



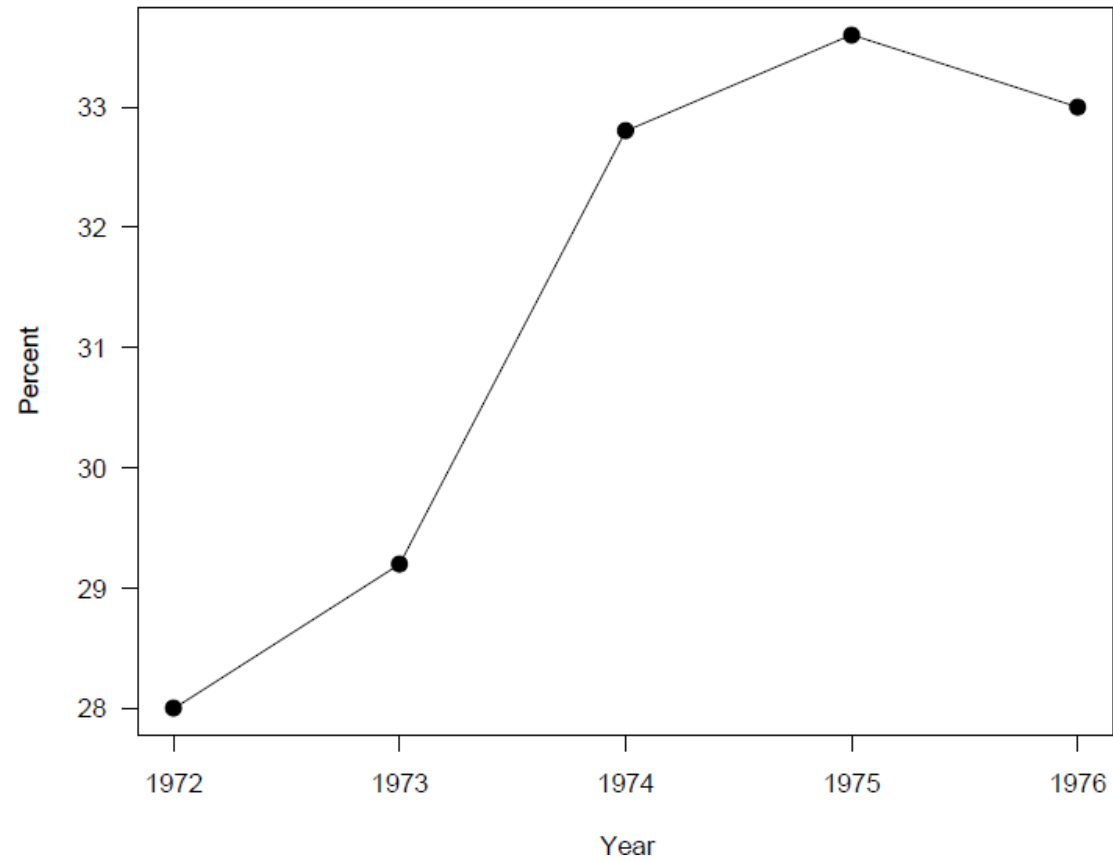
Age structure of College enrollment
(percentage of enrolled people above 25 years)

- A very good bad example!
- only 5 (!) numbers on it but
 - 4 meaningless colors
 - useless 3D
 - useless axes split
 - confusing and wrong visual attributes (size)
 - split y axis
 - odd interpolation
- Designers of this graph are now working in the Microsoft Excel's team, inspiring the new Excel's versions ...

Same data...

Age Structure of College Enrolment

Percent of Total Enrolment, Aged 25 and Over



The same data...

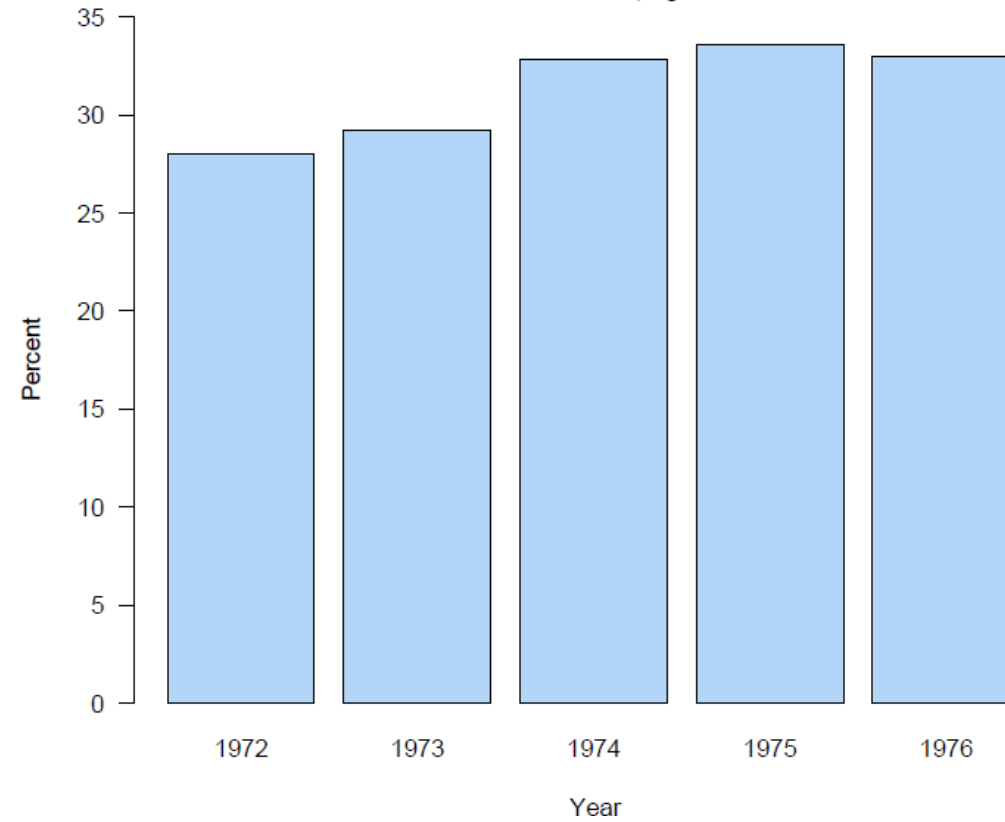
Year	Percentage above 25
1972	28.0
1973	29.2
1974	32.8
1975	33.6
1976	33.0



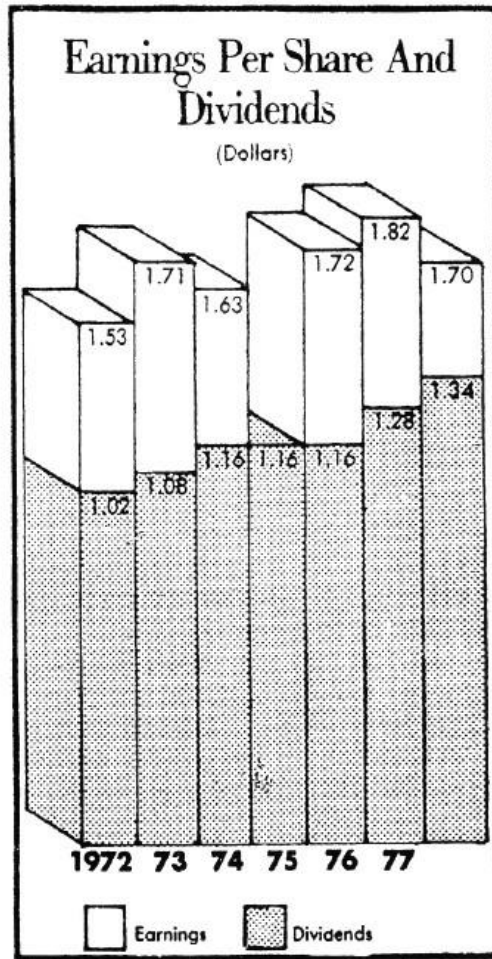
Same data...

Age Structure of College Enrolment

Percent of Total Enrolment, Aged 25 and Over



Rule 2 violation

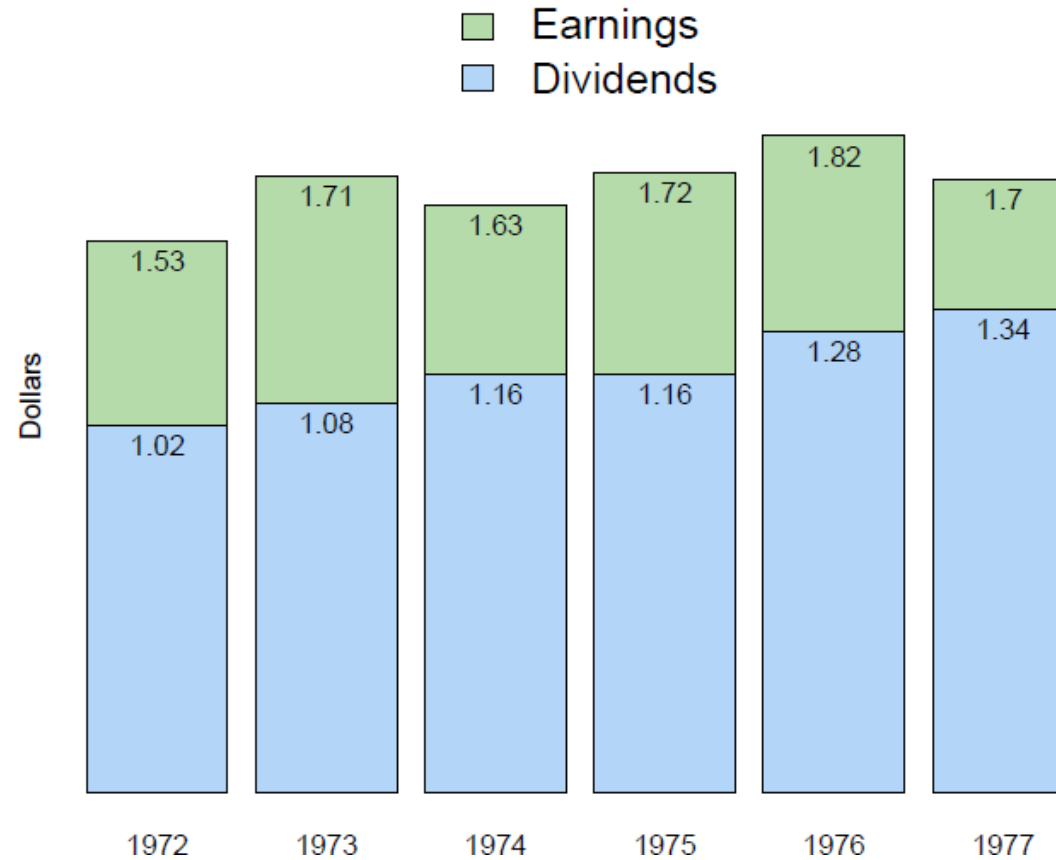


- Why 3D?
- The extra dimension used in this graph has confused even the person who created it..

The Washington Post, 1979

The same data...

Earnings Per Share and Dividends

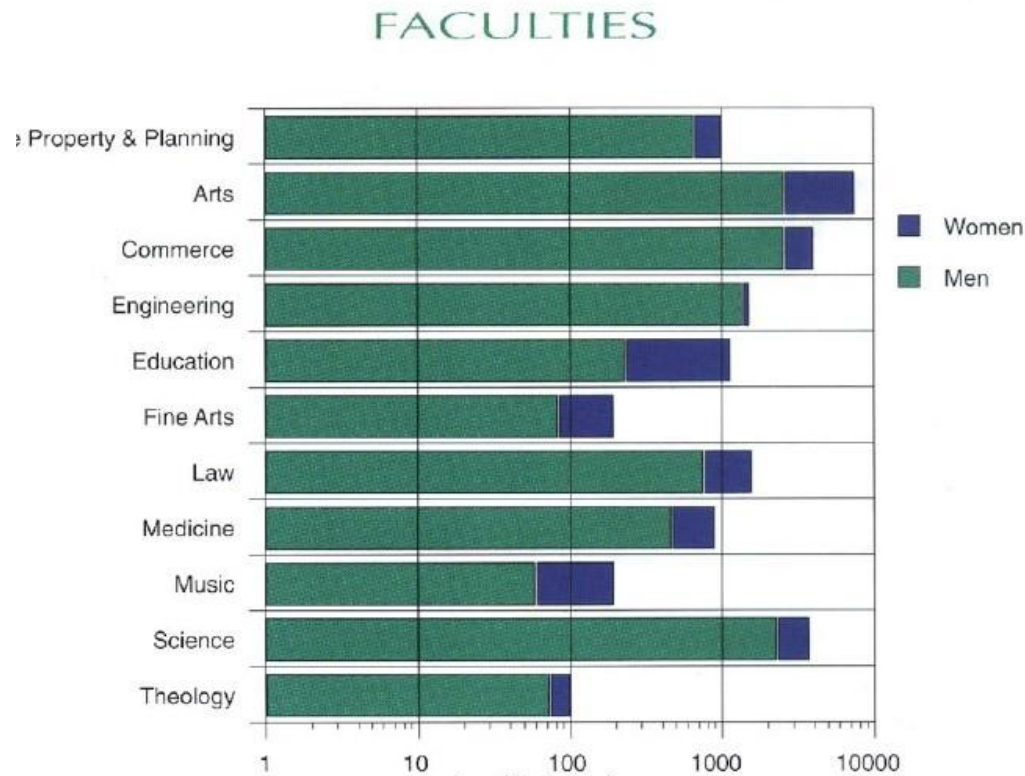


Numerical Information: Rule 3

- **Do not distort data in a confusing way**
- Graphs should not provide a distorted picture of the values they portray
- Distortion can be either deliberate or accidental
- Of course, it could be useful to know how to produce a graph which bends the truth...

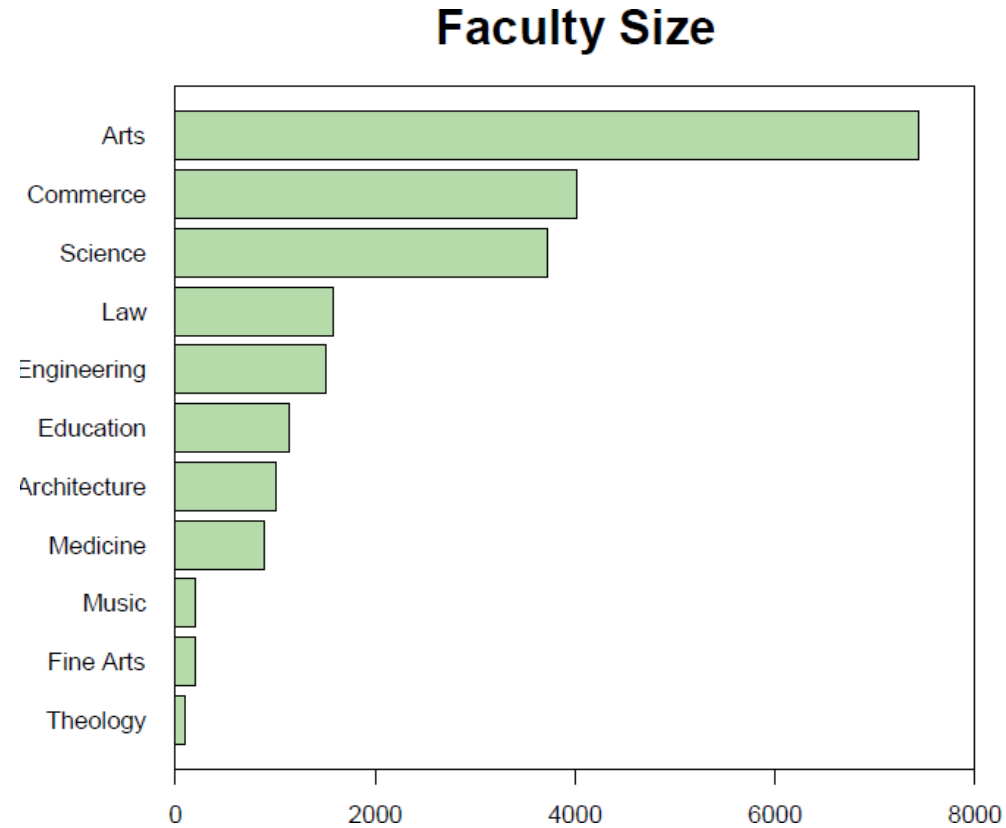


Rule 3 violation

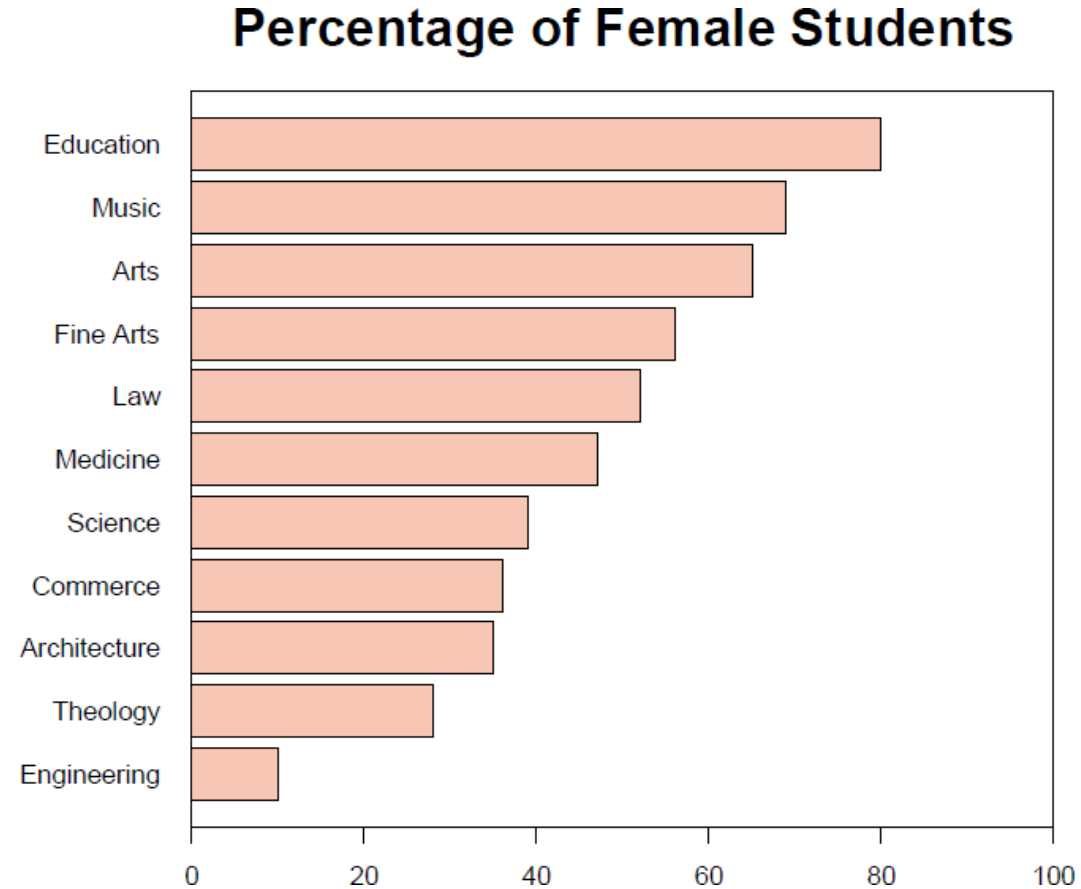


- At a very quick glance:
 - balanced faculty population
 - most male students
- What is wrong with this graph?
- The X scale is logarithmic!

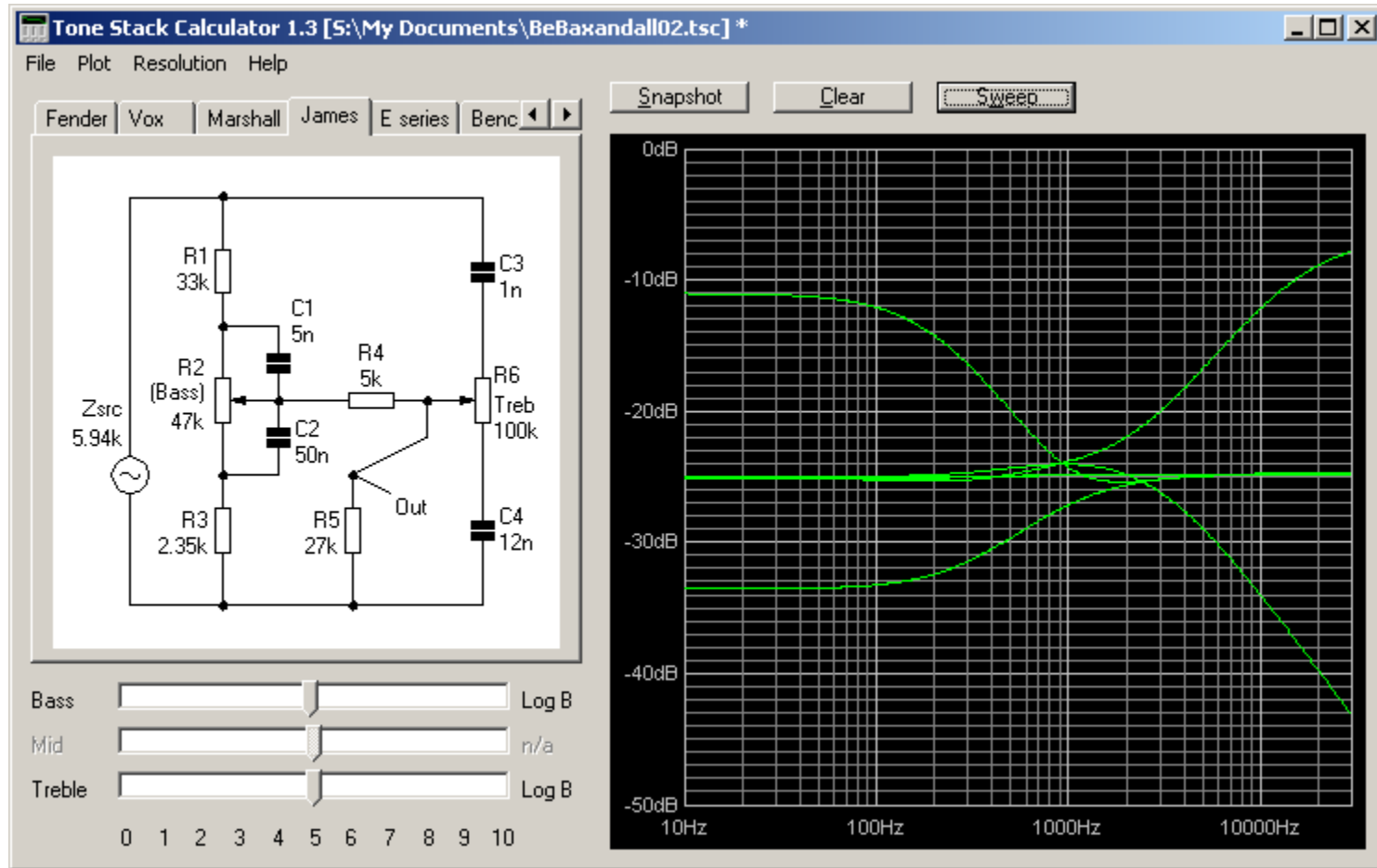
The truth : population size



The truth : female /male ratio



In other cases distortion is ok...

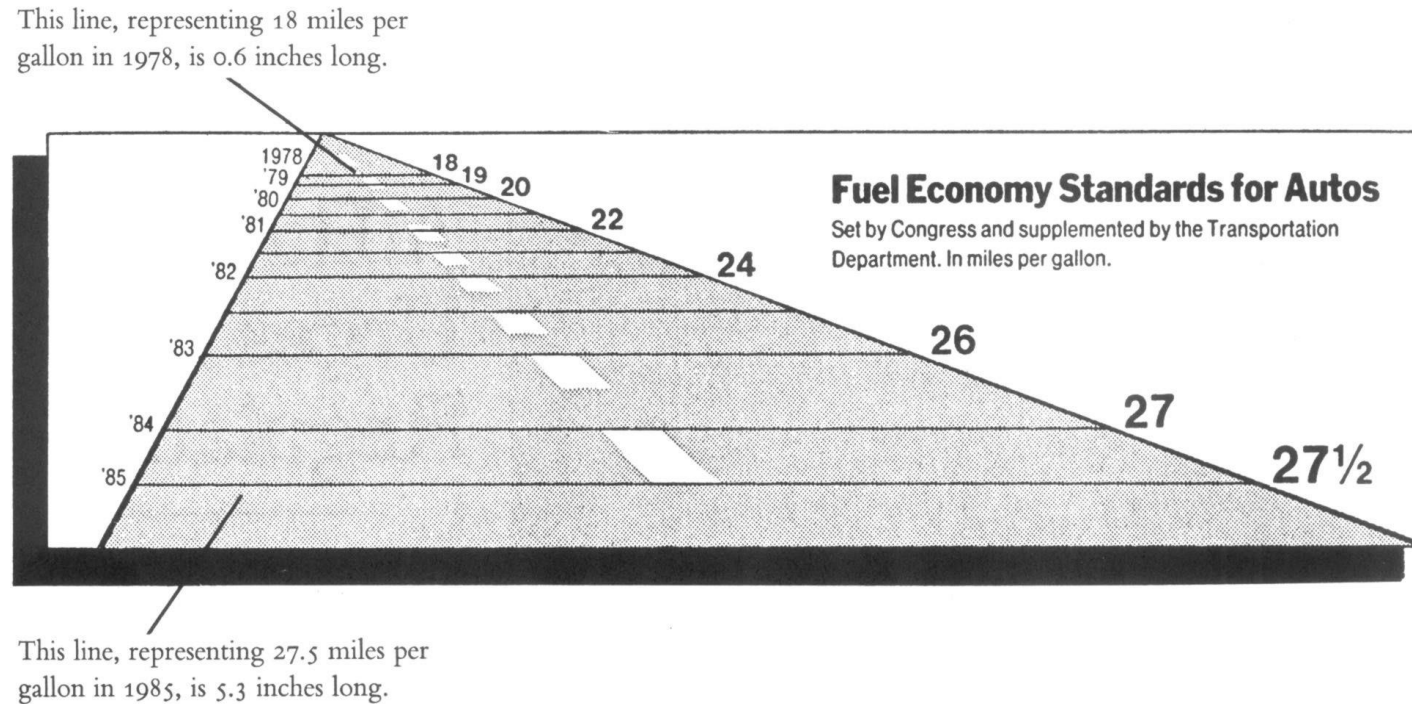


The lie factor

- The visual pioneer Ed Tufte of Yale University has defined a “lie factor” as a measure of the amount of distortion in a graph
- The lie factor is defined to be: $\text{Lie Factor} = \frac{\text{size of effect in graphic}}{\text{size of effect in data}}$
- If the lie factor of a graph is greater than 1, the graph is exaggerating the size of the effect



Measuring distortion through the lie factor



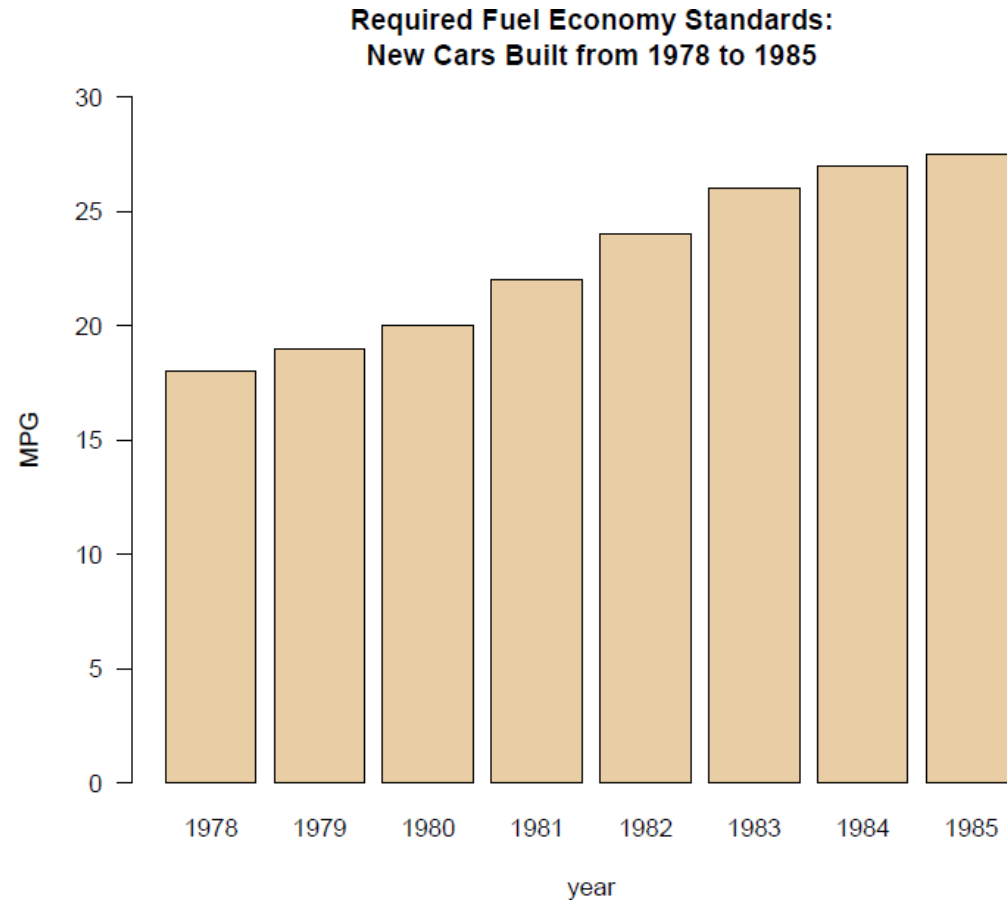
$$\text{Graph effect} = 5.3/0.6=8.8$$

$$\text{Data effect} = 27.5/18=1.52$$

$$\text{Lie Factor} = 8.8/1.52 = \mathbf{5.8}$$

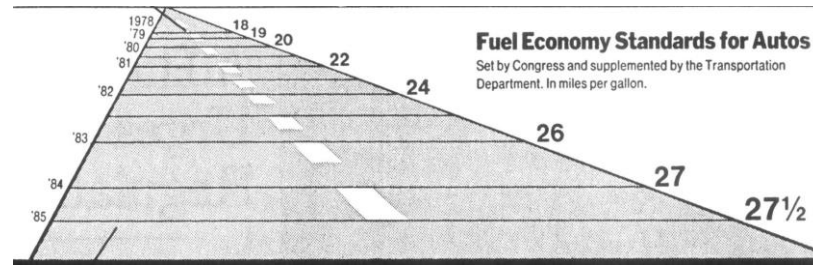


The same data with **lie** factor=1



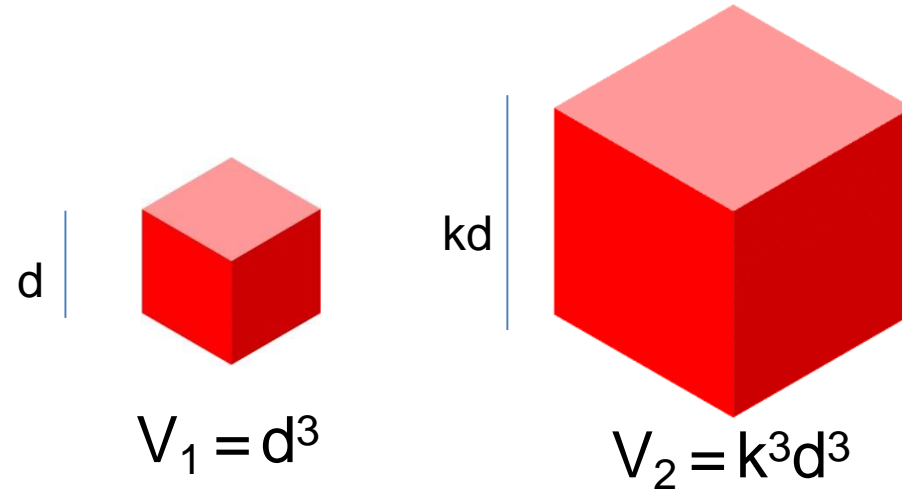
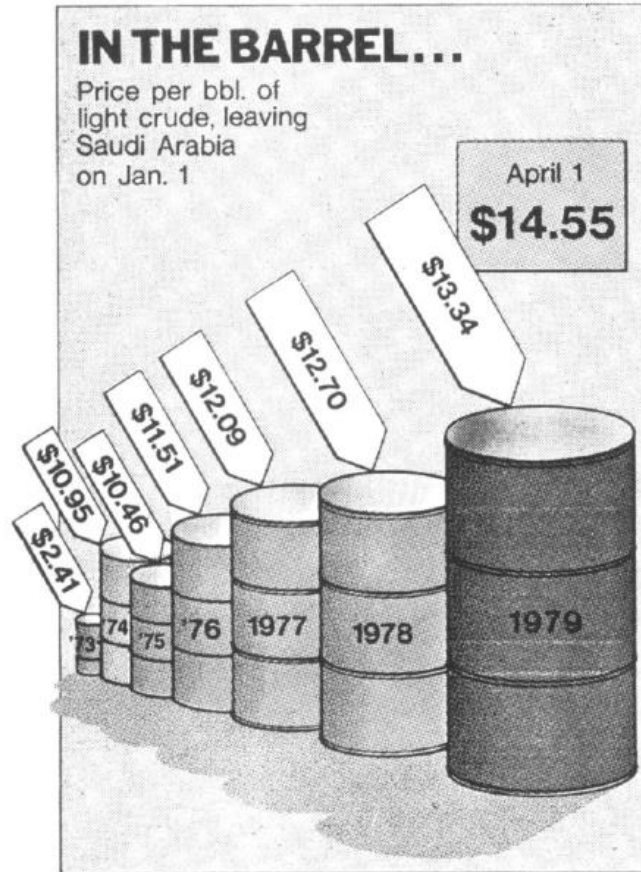
Common Sources of Distortion

- The use of image perspective is a common source of distortions in graphs



- Another common source is the inappropriate (or deliberate?) use of linear scaling when using area or volume to represent values

Distortion through non linear volumes



$$\text{Graph effect} = V_2/V_1 = k^3d^3/d^3 = \mathbf{k^3}$$

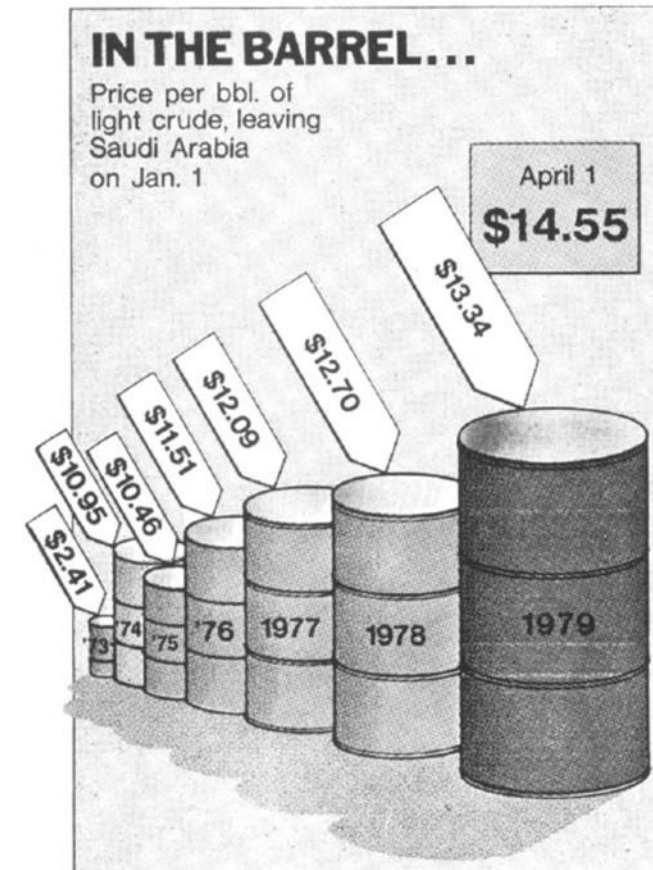
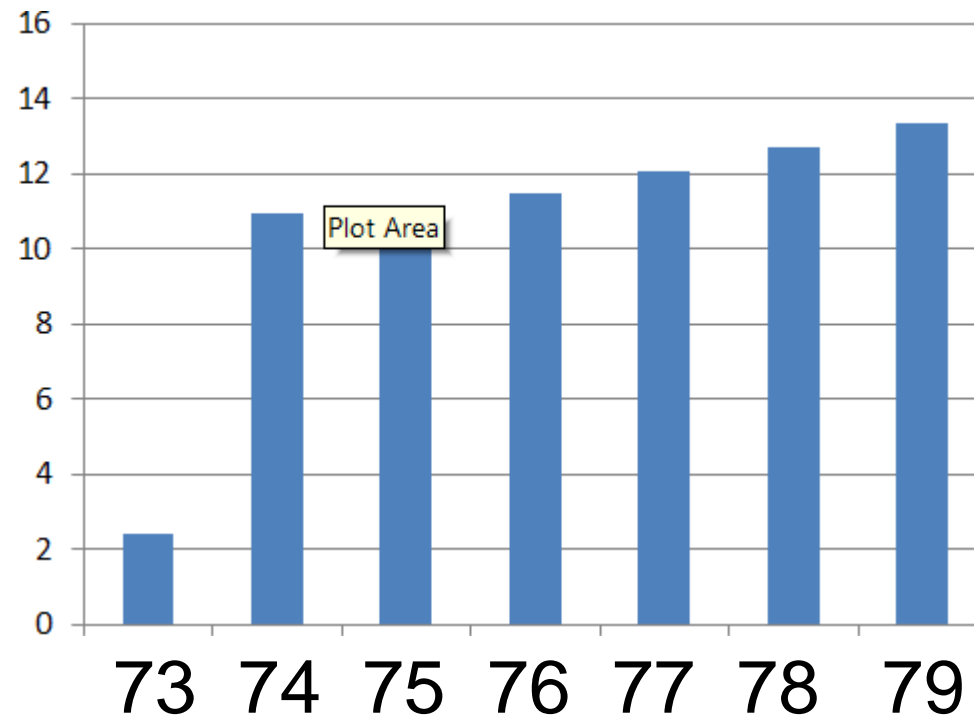
$$\text{Data effect} = kd/d = \mathbf{k}$$

$$\text{Lie Factor} = k^3/k = \mathbf{k^2}$$

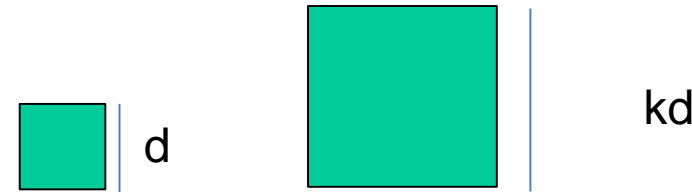
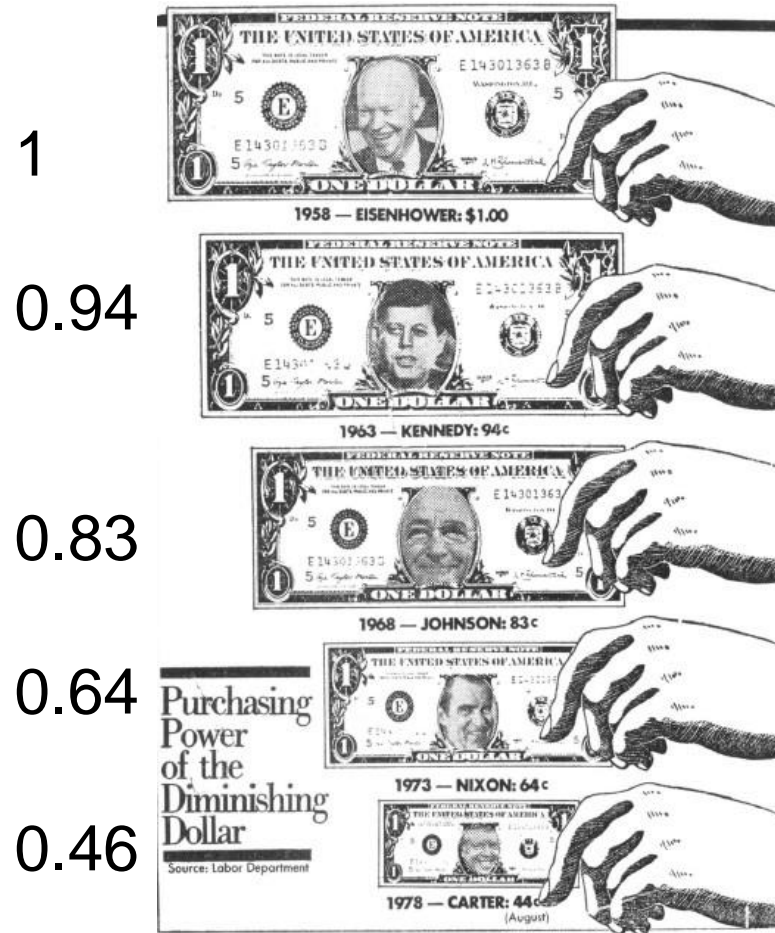
$$\text{Lie Factor} = \mathbf{\text{Data effect}^2}$$

$$\text{Lie factor} = (14.55/2.41)^2 = 6^2 = 36$$

The same data



Distortion through areas

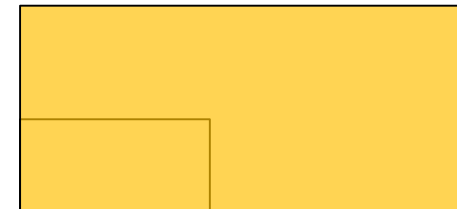


$$\text{Graph effect} = A_2/A_1 = k^2 d^2/d^2 = k^2$$

$$\text{Data effect} = kd/d = k$$

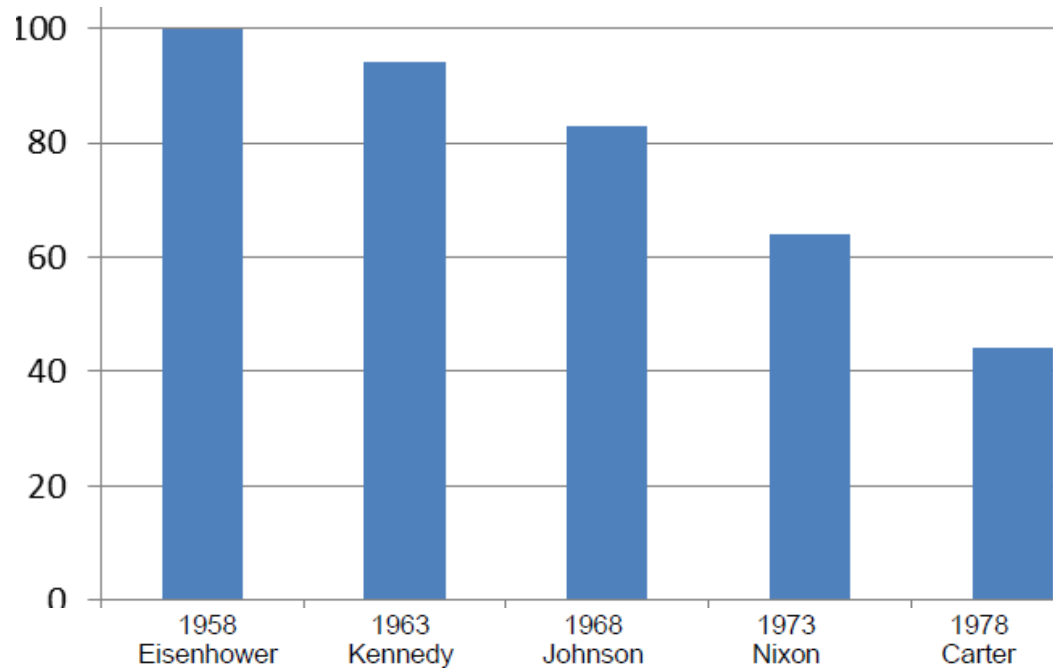
$$\text{Lie Factor} = k^2/k = k$$

$$\text{Lie factor} = \text{Data effect}$$



Is the bottom dollar roughly half the size of the top one?

The same data with lie factor=1
Note that in a histogram you are
comparing **lengths**, not **areas**

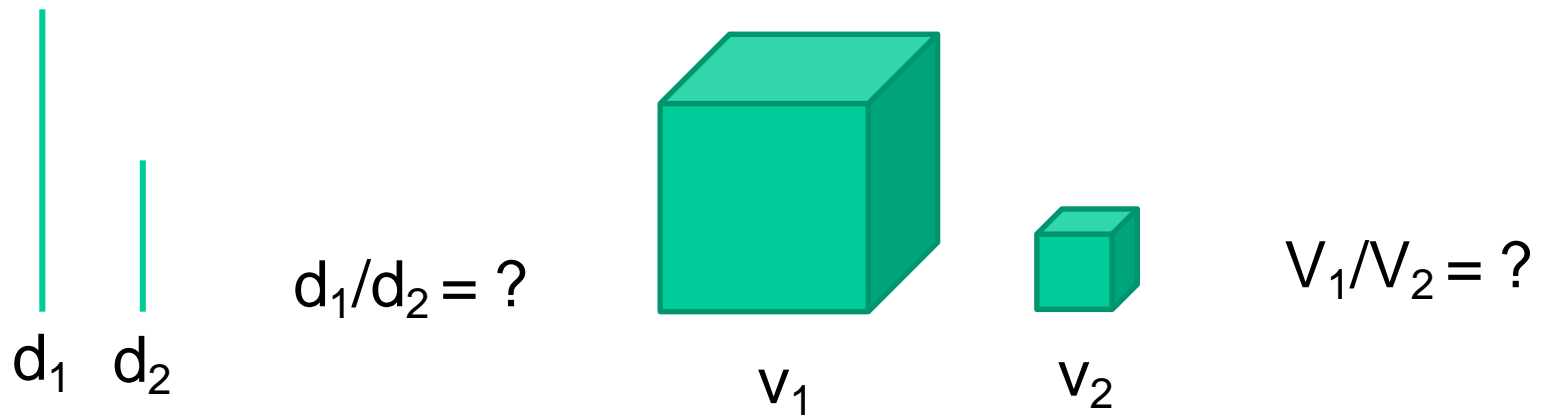


This is why it is
better to use
thin bars...



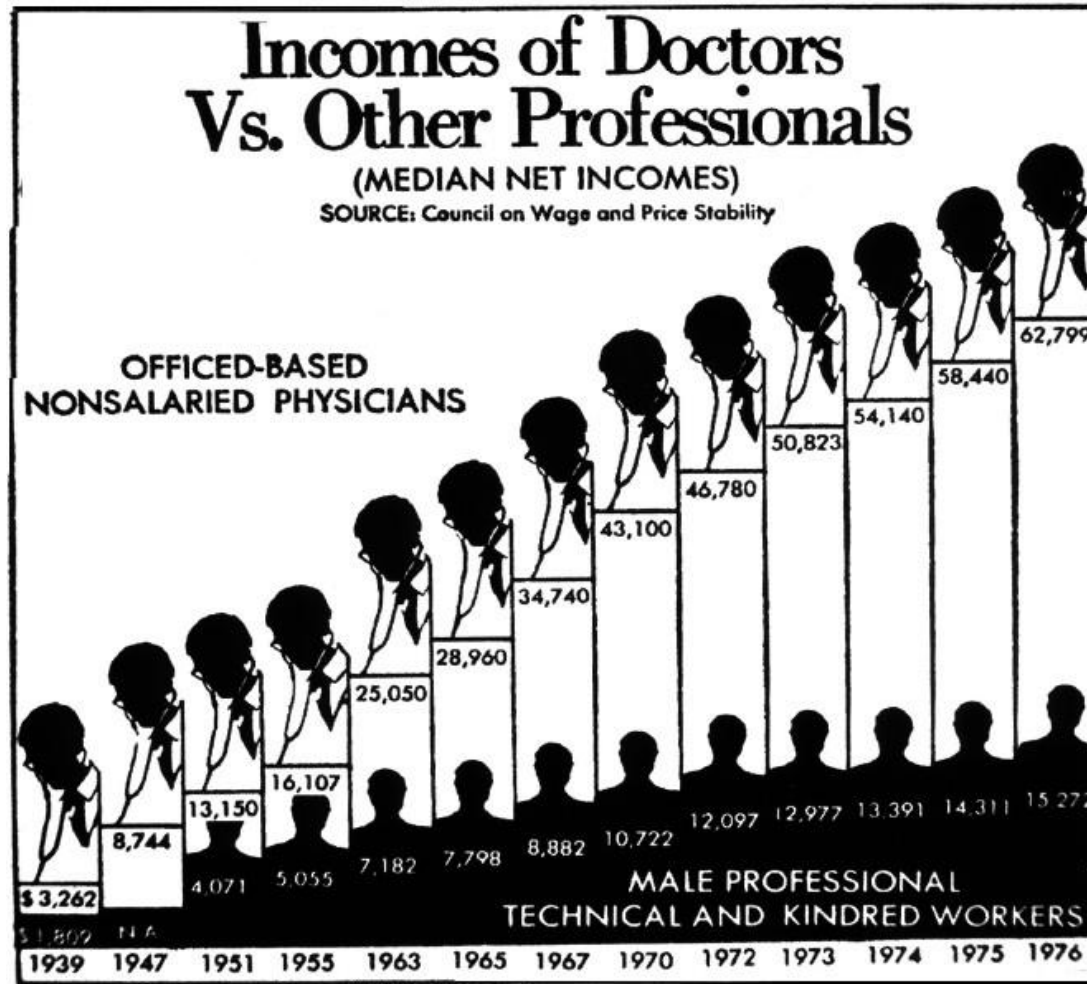
Encoding numerical values

- Human beings are better in comparing lengths than areas or volumes



- So, using volume or area **instead** of length is **wrong**!
- Or it is an intentional lie!

Distortion (deliberate?)

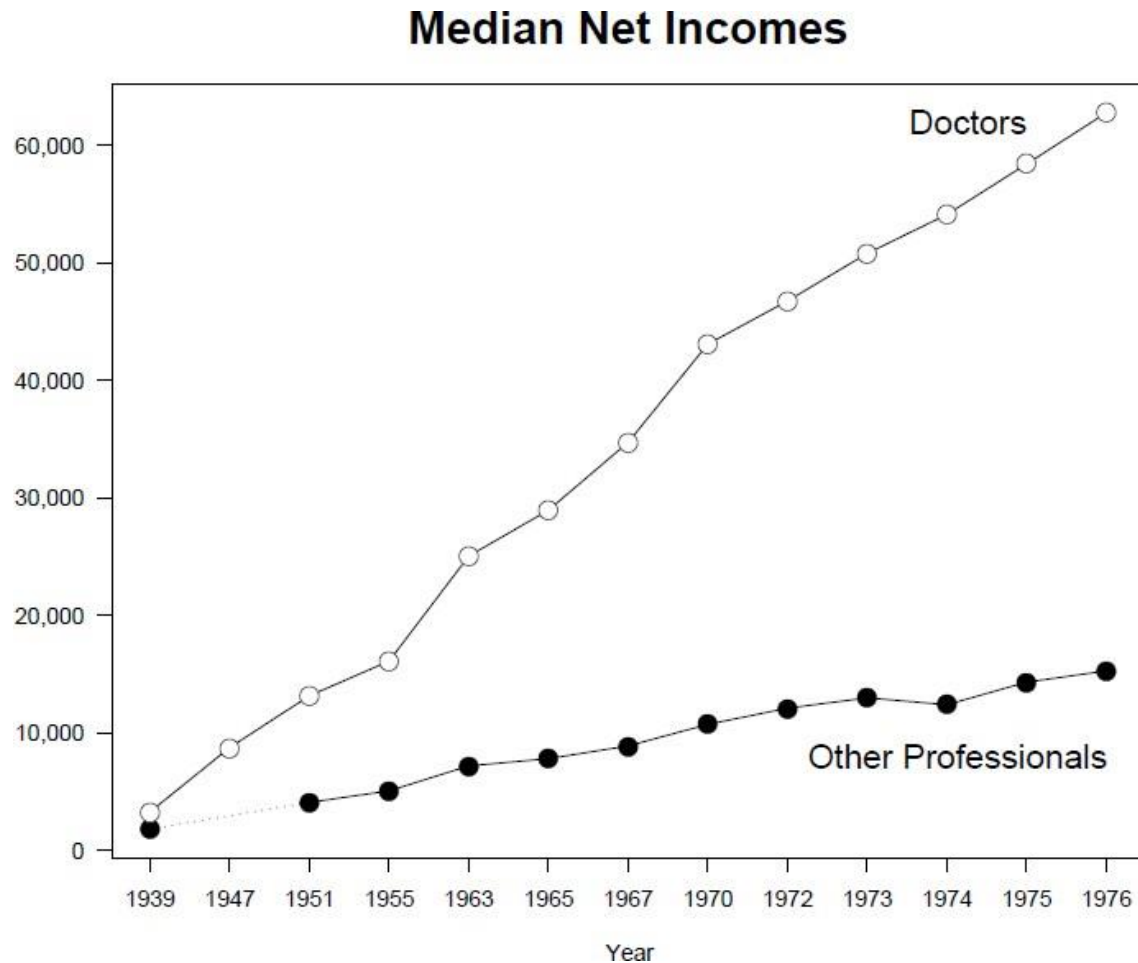


What's wrong
with this graph?

A part of the
chart junk



Presented data



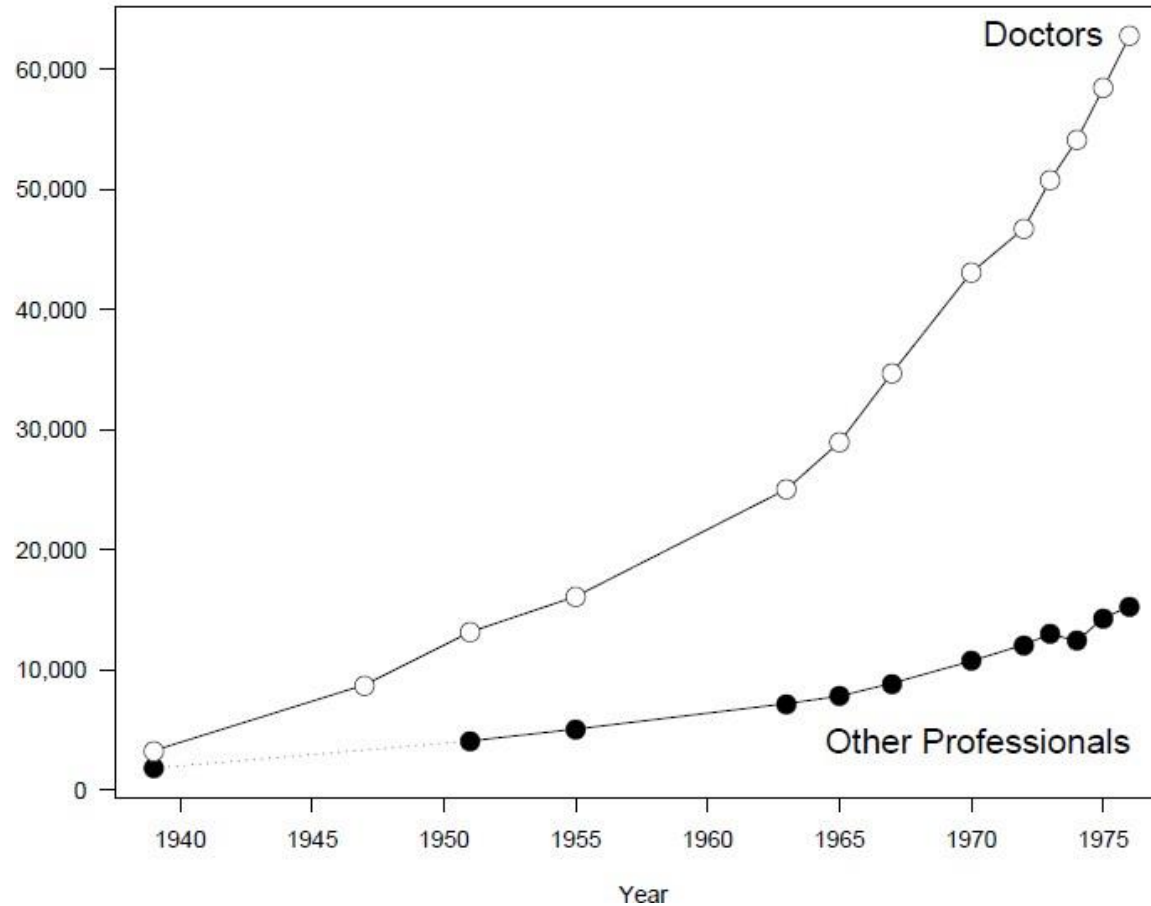
It suggests
a linear trend

What is wrong
with it?



Real data...

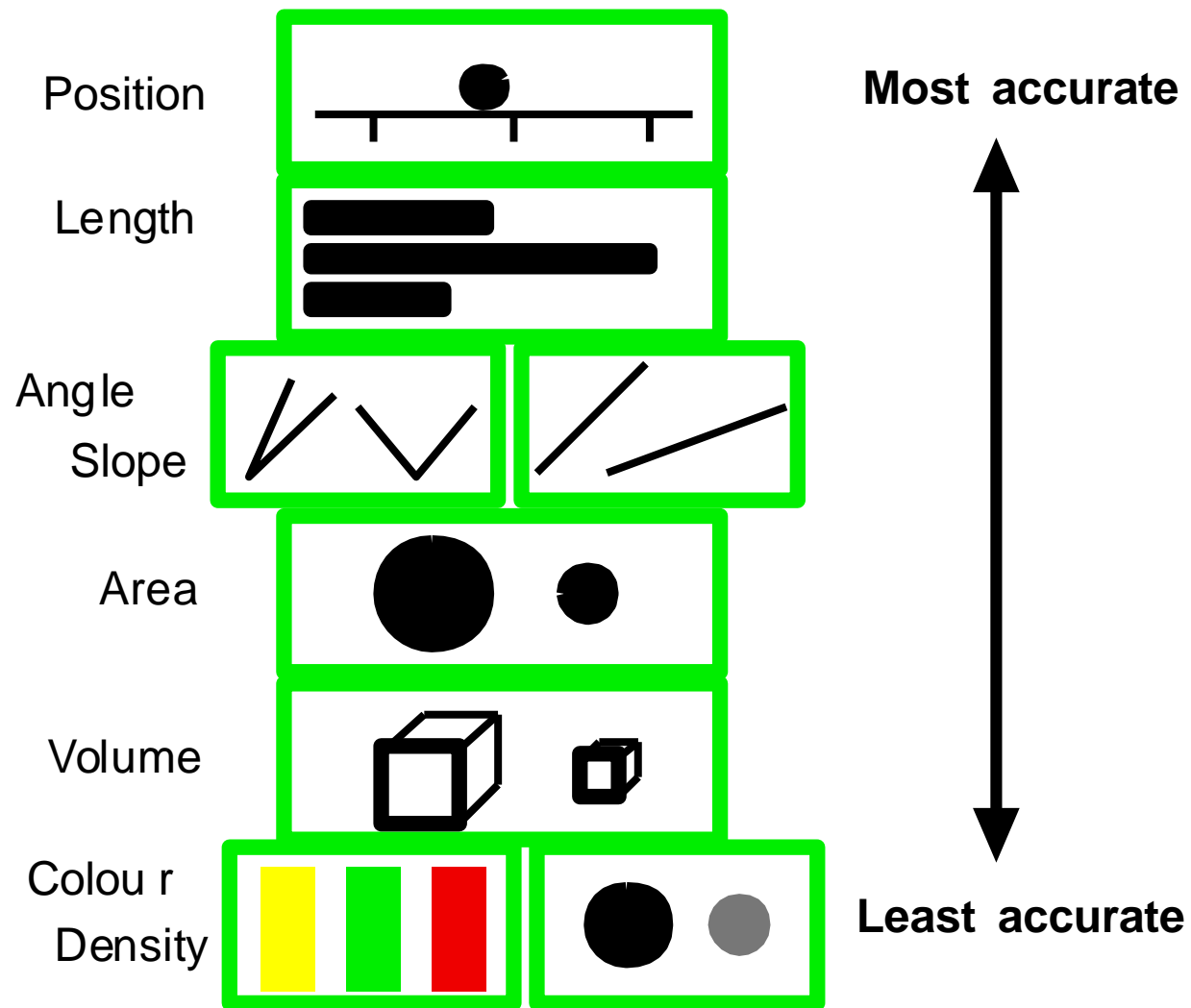
Median Net Incomes



The time scale
was not uniform!

Now the exponential
trend is clear

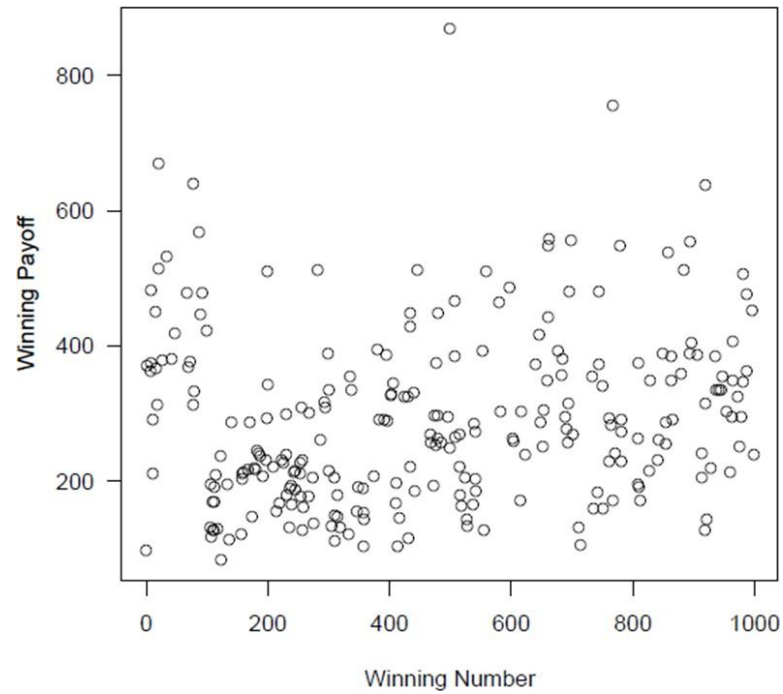




The relative difficulty of assessing **quantitative** value as a function of encoding mechanism, as established by Cleveland and McGill

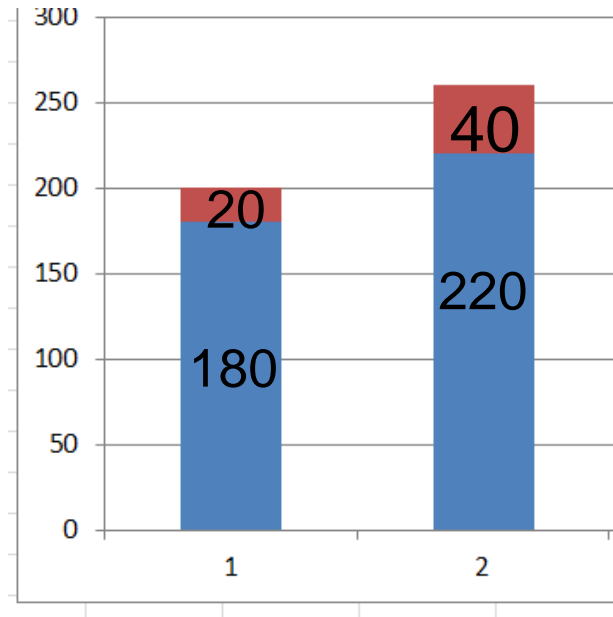
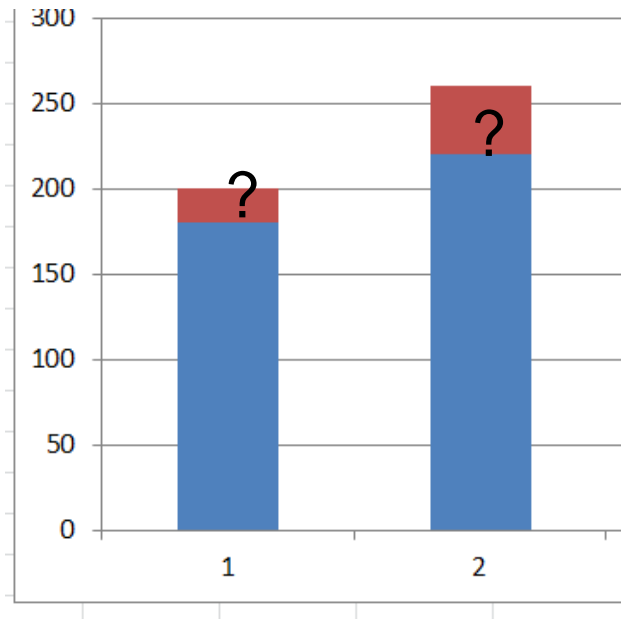
Position

- It works fine



Length?

- The lookup of precise number might be difficult if the position is not evident (e.g., stacked bar chart)

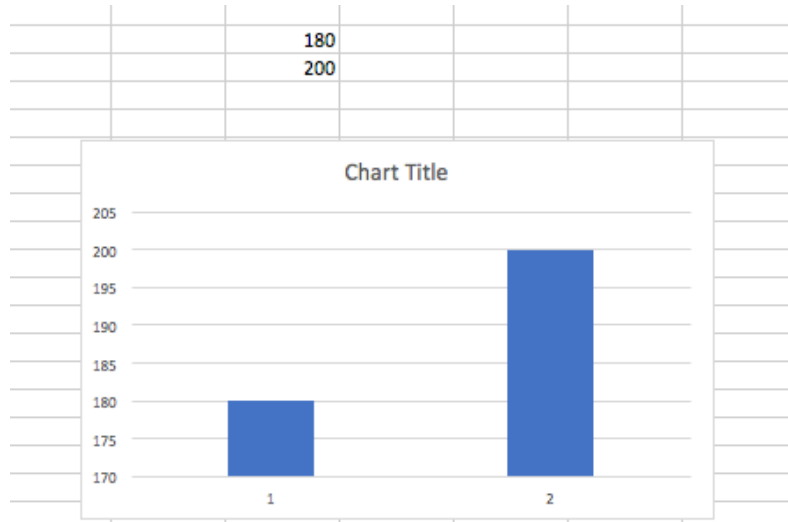


It makes sense to explicitly add figures

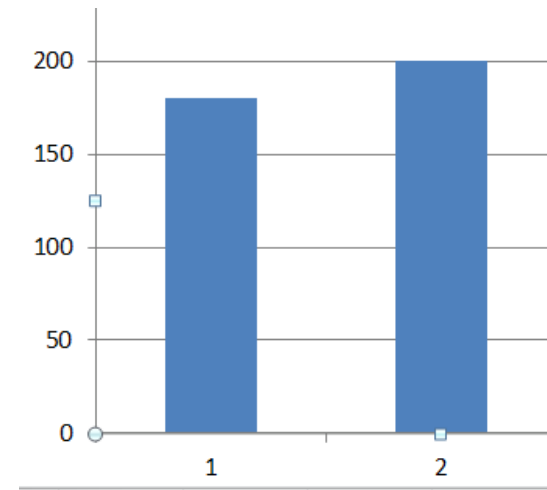


Length?

- Length is fine as well , but use the right scale!



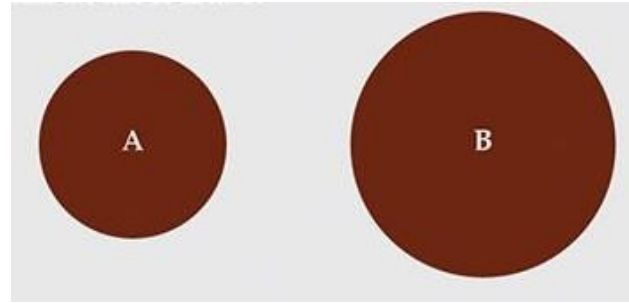
Automatically produced
by Excel



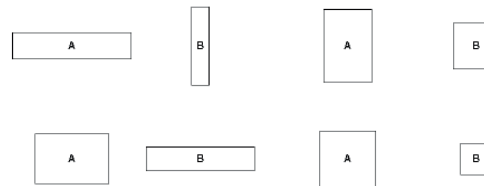
The reality

Areas: some new surprising issues

- Human beings are very bad at estimating area ratios



- What is the ratio between these two circles A/B ?
25% 35% 40% 45% 50% 55% 60% 70% ?
- What is the shape that produces the biggest error?



- The square!**
- Perceptual Guidelines for Creating Rectangular Treemaps (Nicholas Kong et al., Infovis 2010)

Colors / Numerical data

- Someone already thought how to associate quantitative values to colors and different choices are available
- Do not reinvent the wheel
- The rainbow scale does not work!!!)
- It is a very common error (I did it as well, 20 years ago...)



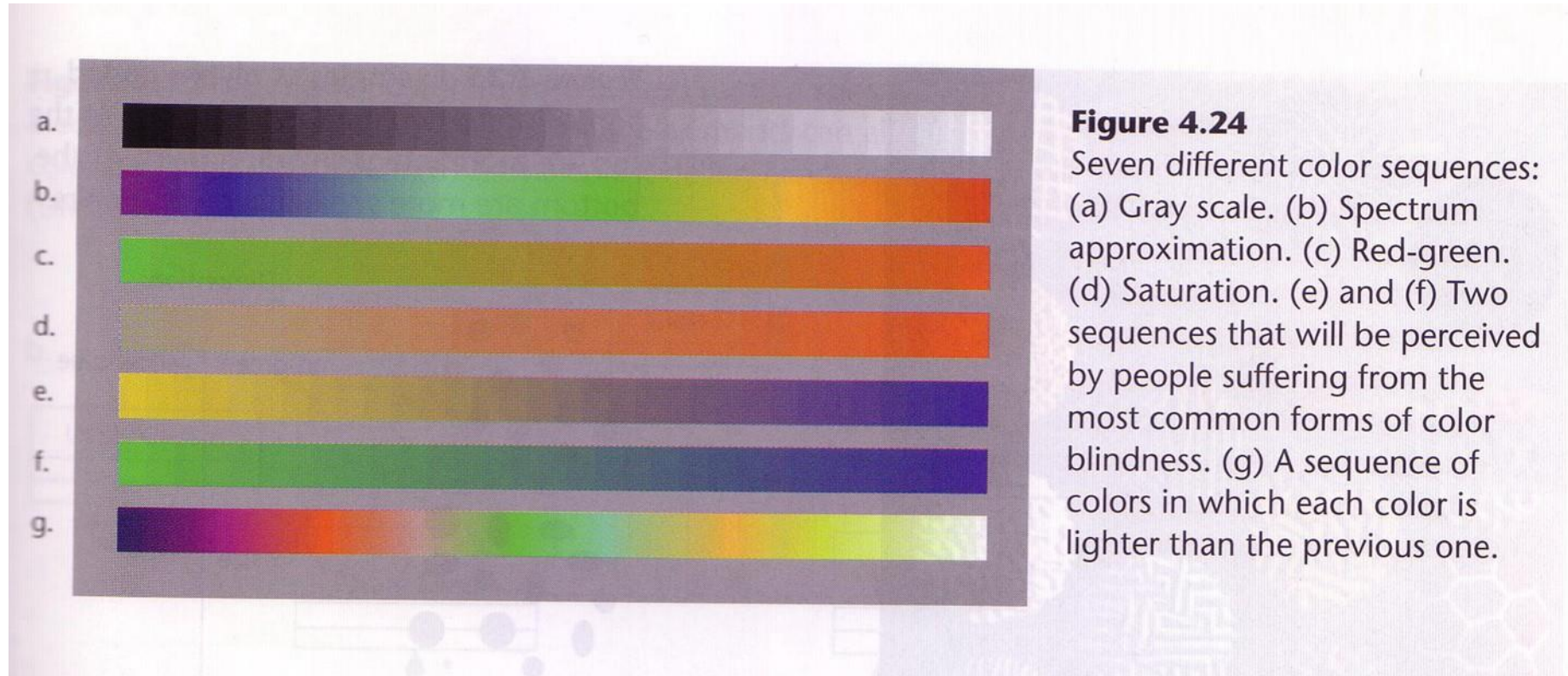
rainbow scale



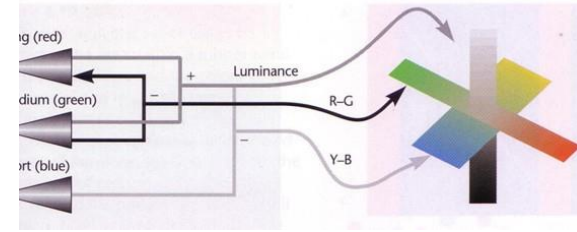
HSI color model

(Keim and Kriegel) - Issues in visualizing large databases. Proc. of the IFIP working conference on Visual database Systems, 1995

Other choices (Colin Ware)

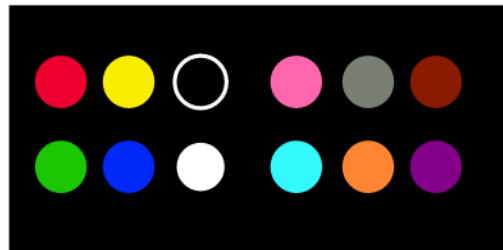


Colors /Categorical



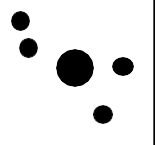

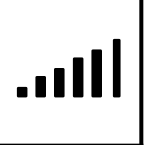
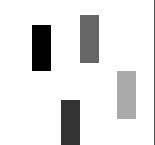
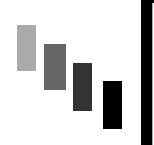
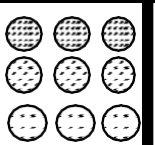
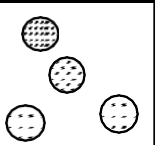
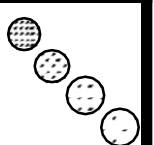
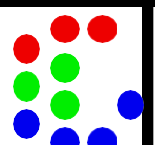
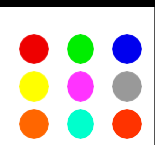


- Colors are fine with categorical data
- Do not reinvent the wheel (again)
- The Ewald Hering idea is that there are only 6 elementary colors arranged in three pairs
 - black-white
 - red-green
 - yellow-blue

- That gives us up to



easily distinguishable (11!)

12 Colors
for labeling

	Association The marks can be perceived as SIMILAR	Selection The marks are perceived as DIFFERENT, forming families	Order The marks are perceived as ORDERED	Quantity The marks are perceived as PROPORTIONAL to each other
Size				
Value				
Texture				
Colour				
Orientation				
Shape				

Interpretation of Bertin's guidance regarding the suitability of various encoding methods to support common tasks

Some new considerations

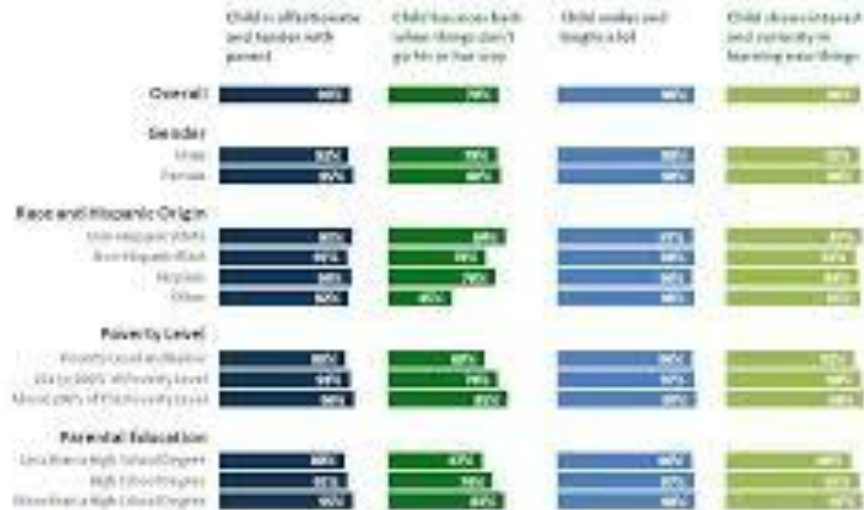
- Chartjunk is not the unique enemy...
- Before PCs building graphs was a matter of paper and pencil
 - requiring time and effort
 - pushing you to better understand :
 - the meaning of numbers
 - the graph purpose
 - the graph organization
 - ...
- now, with Excel (or Matplotlib, or general chart software you can produce graphs so fast that you might loose control...
 - you select predefined solutions
 - you might not understand how the graph is built (row, columns, headings, ...)
 - you can make mistakes (e.g., missing a row...)



Visualization literacy: better tables

Measures of Flourishing

Percentage of children, ages six months through five years, whose parents indicated they "usually" or "always" showed selected "flourishing" behaviors.



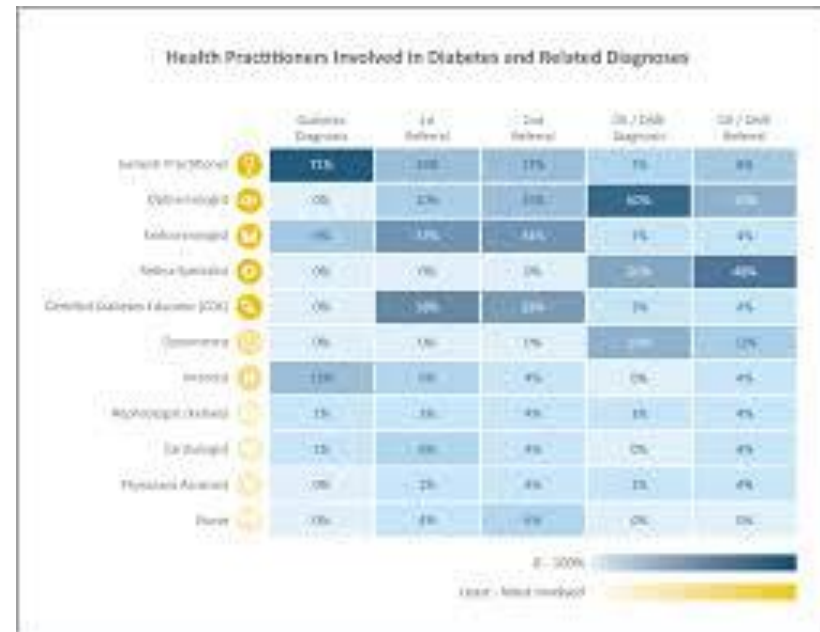
Data from <https://www.bls.gov/news.release/archives/011501177.htm>

Visualization: Alan Becker

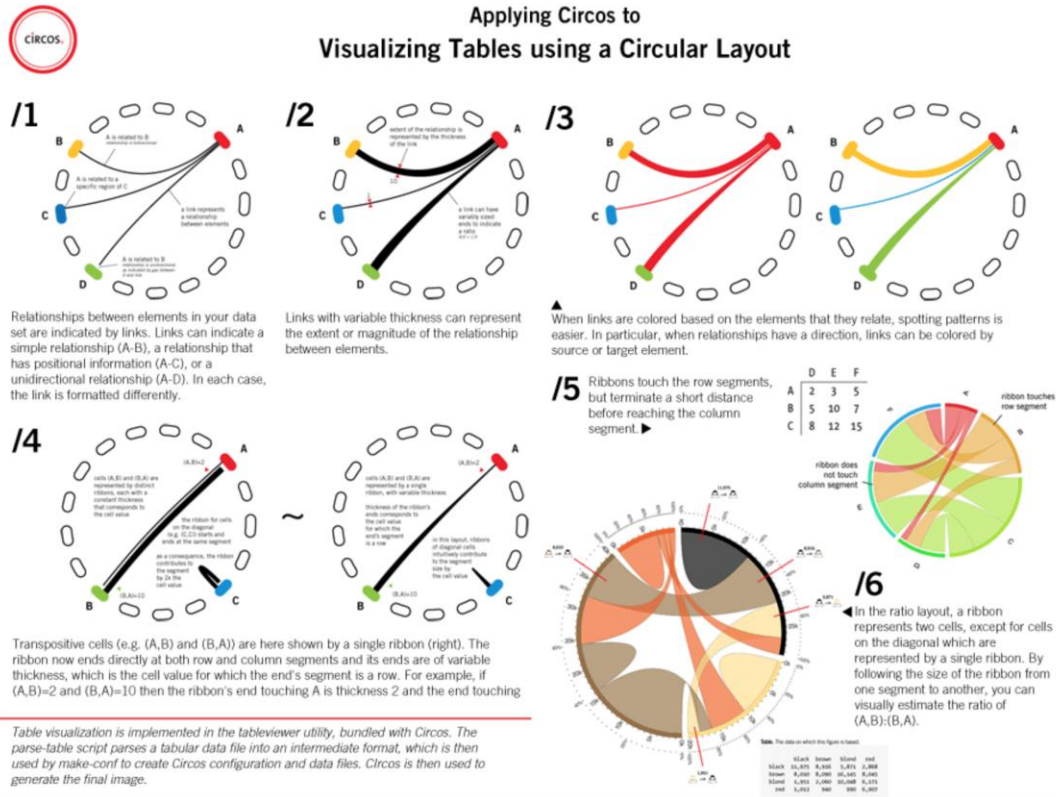
Open menu

The screenshot shows a data visualization tool interface. The main table displays sales data with columns for ID, Latest ID, Lifetime Order, and Average Sale. The sidebar on the right contains settings for Plot, Series, and Formatting, including options like Truncate Text, Show Full Field Name, and Size Columns to Fit. A 'CUSTOMIZATIONS' section lists various filters and sorting options.

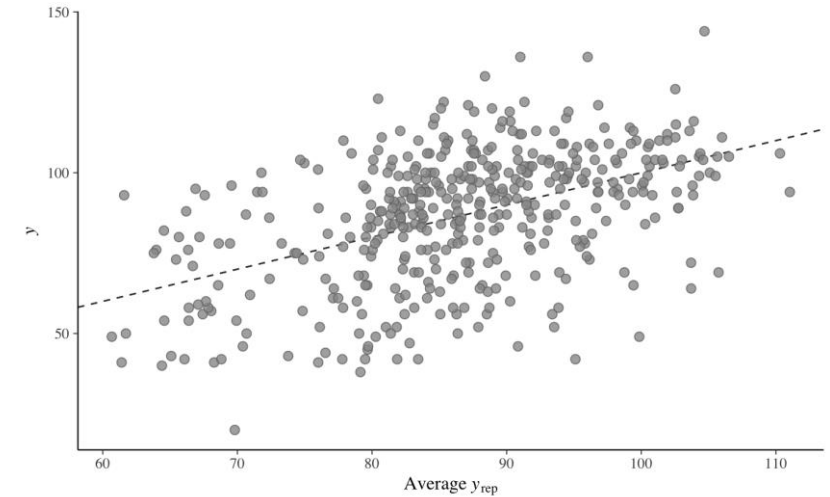
ID	Latest ID	Lifetime Order	Average Sale
75057	2000-07-01	1	\$44.74
70744	2000-07-01	1	\$14.54
86426	2000-07-01	2	\$91.46
61528	2000-07-01	2	\$64.86
94554	2000-07-01	3	\$65.30
57882	2000-07-01	4	\$26.16
43228	2000-07-01	8	\$42.63
44355	2000-07-01	8	\$47.62
32252	2000-07-01	7	\$57.15
55062	2000-07-01	4	\$44.78
41982	2000-07-01	3	\$52.67
58362	2000-07-01	5	\$54.78
32927	2000-07-01	12	\$79.28
54187	2000-07-01	5	\$25.99



Visualization literacy: better **THAN** tables



Chords: relations



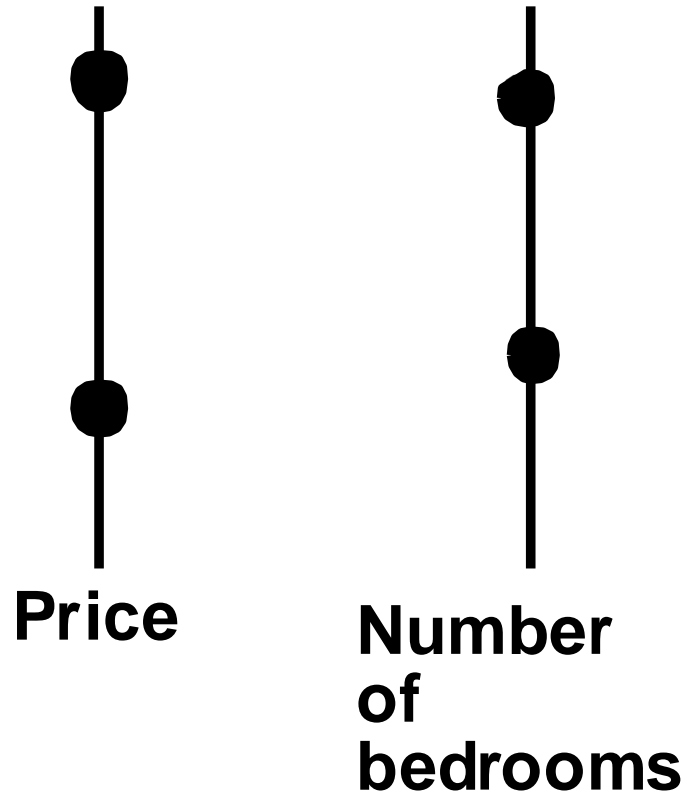
Scatterplots: correlations

Greece €47.89	Luxembourg €31.20	Hungary €21.60	Spain €19.83		United
	Sweden €27.22				
France €43.70	Romania €26.99	Austria €18.85			
		Portugal €18.57			
Italy €35.93	Denmark €25.58		Germany €12.84		
		Finland €17.74	Poland		
Malta €32.71	Slovakia €24.72	Czech Republic €16.57	Lithuania		

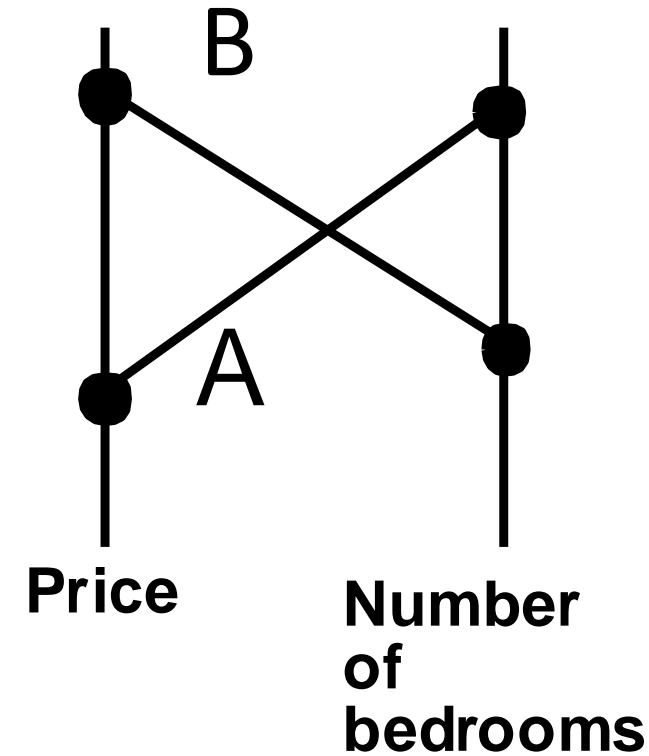
Treemaps: hierarchy / part to whole



Parallel coordinates



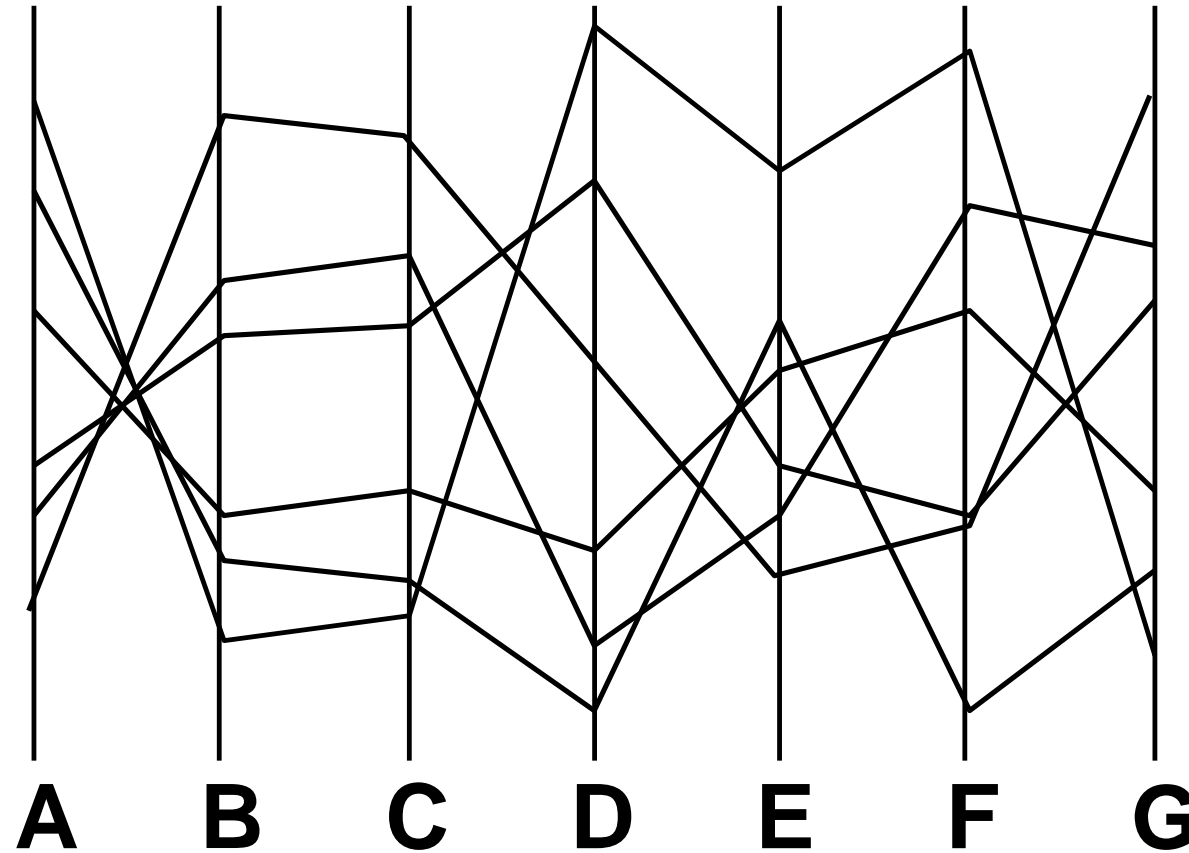
An alternative representation to the scatterplot in which the two attribute scales are presented in parallel, thereby requiring two points to represent each house



To avoid ambiguity the pair of points representing a house are joined and labelled

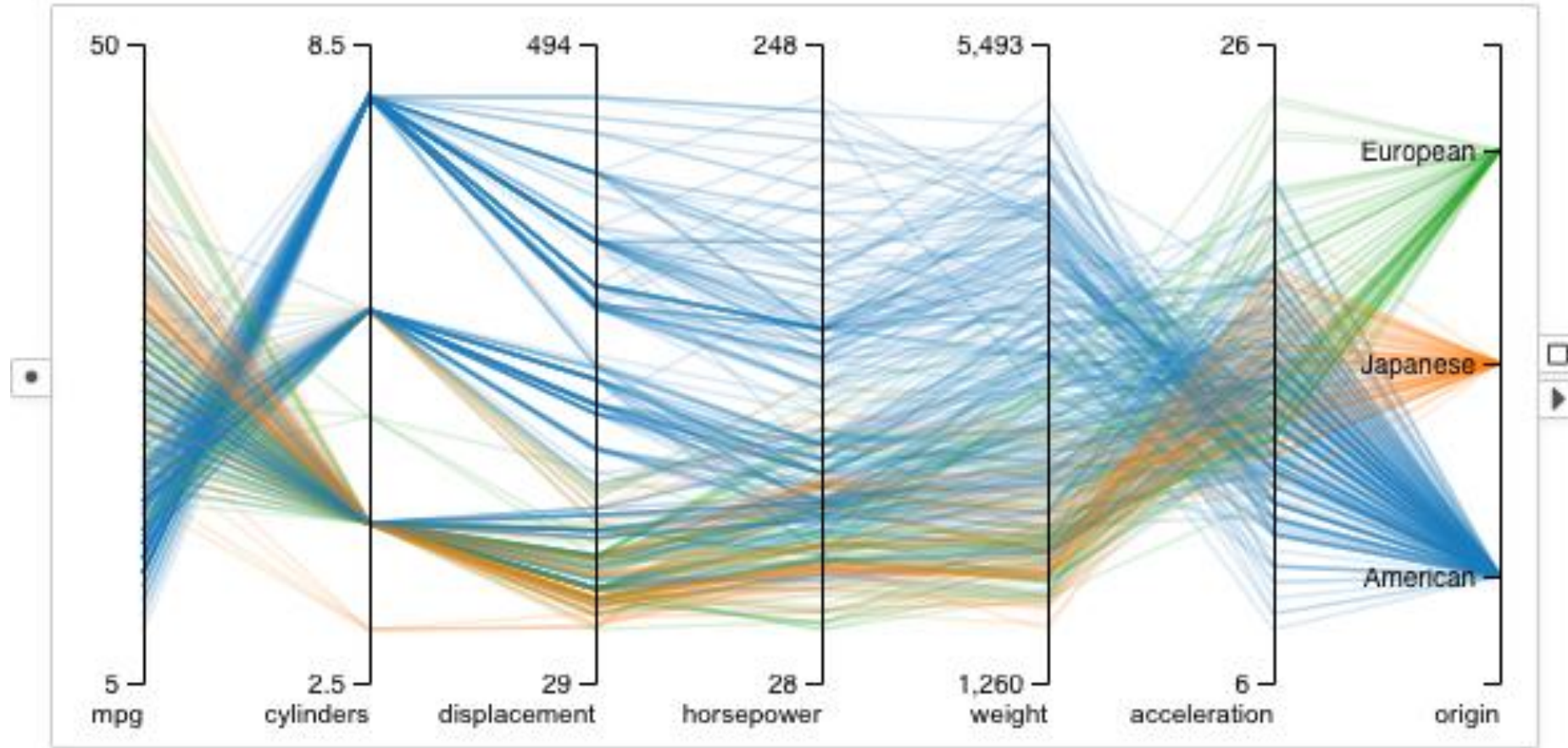


Parallel coordinates

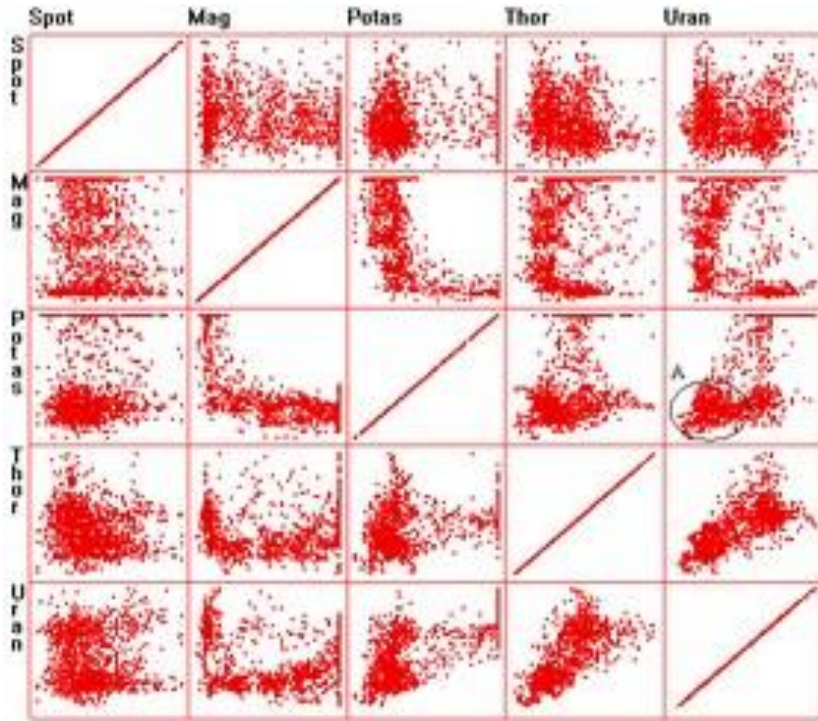


A parallel coordinate plot for six objects, each characterised by seven attributes. The trade-off between A and B, and the correlation between B and C, are immediately apparent. The trade-off between B and E, and the correlation between C and G, are not

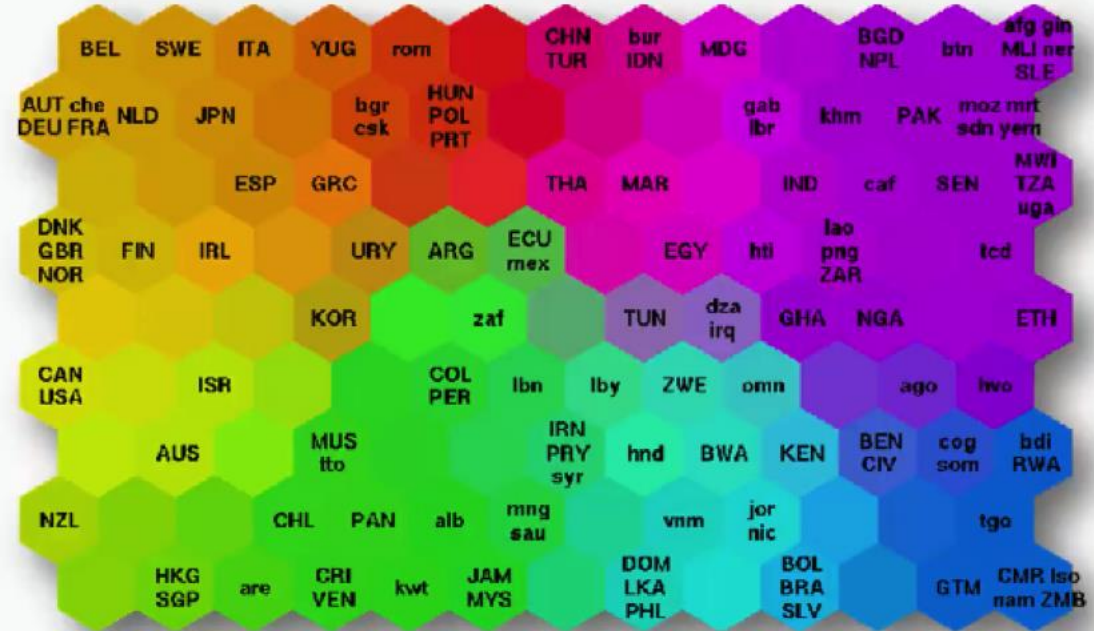
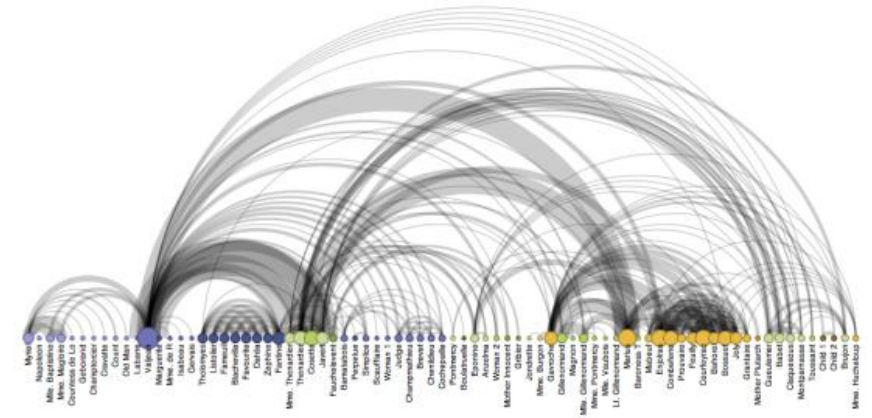
Parallel coordinates



More advanced visualizations



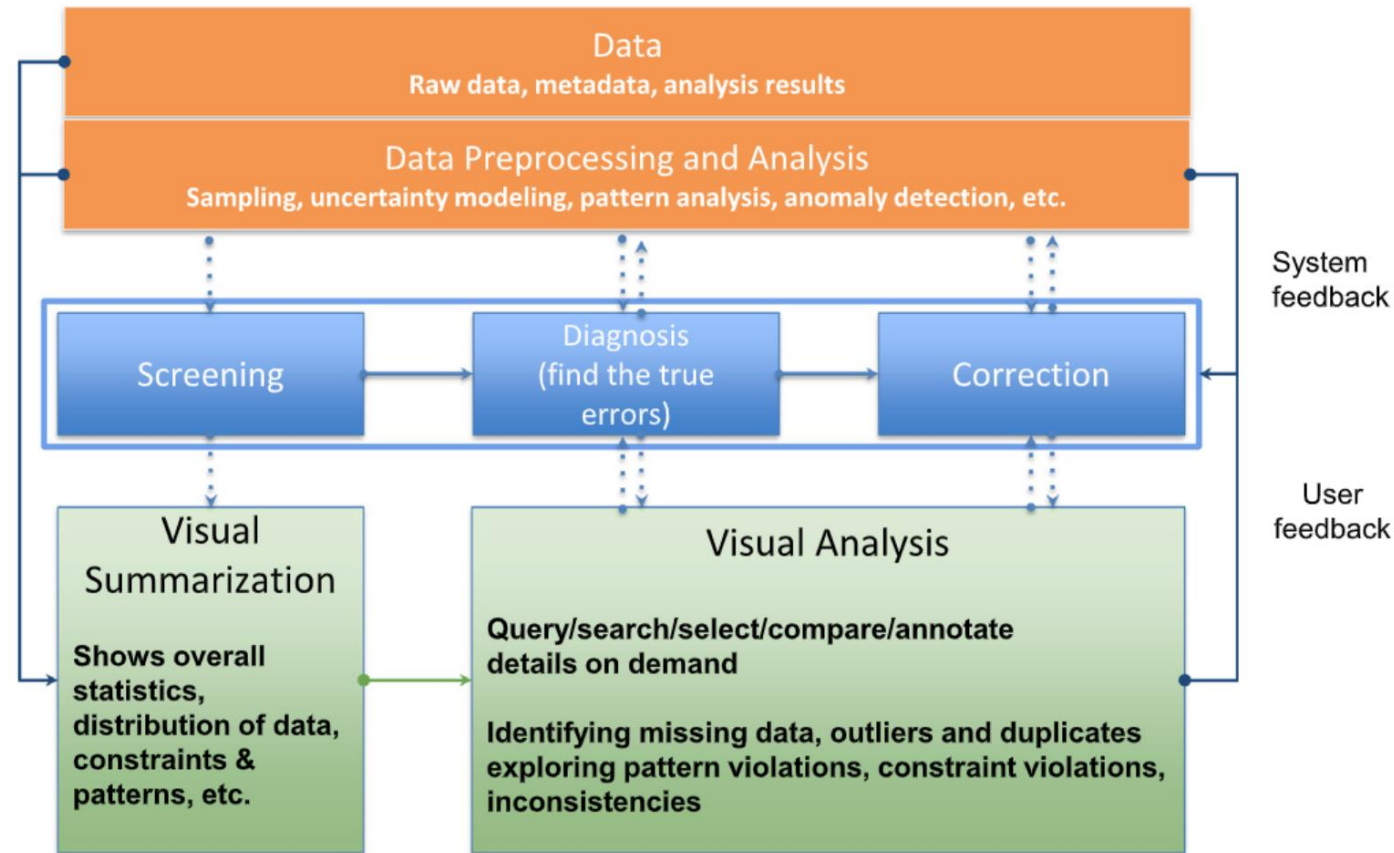
Scatterplot-matrix



Self
Organizing
Maps



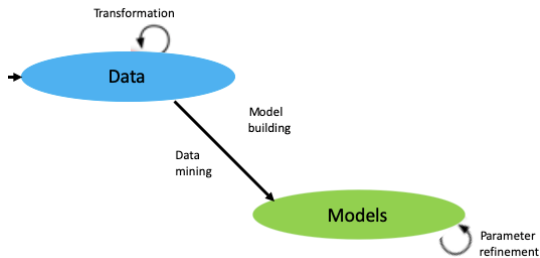
Visual Analytics 4 Data Quality (VA4DQ): an overview



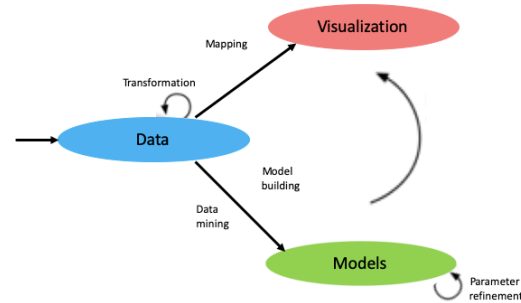
Liu, S., Andrienko, G., Wu, Y., Cao, N., Jiang, L., Shi, C., ... & Hong, S. (2018). **Steering data quality with visual analytics: The complexity challenge.** *Visual Informatics*, 2(4), 191-197.

VA4DQ: an overview

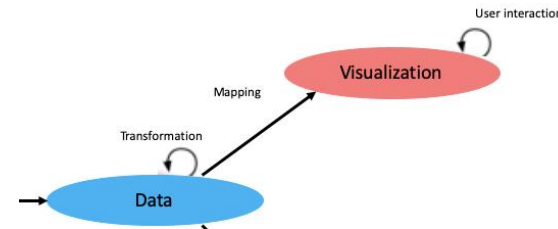
The flavor of integration can be quite different



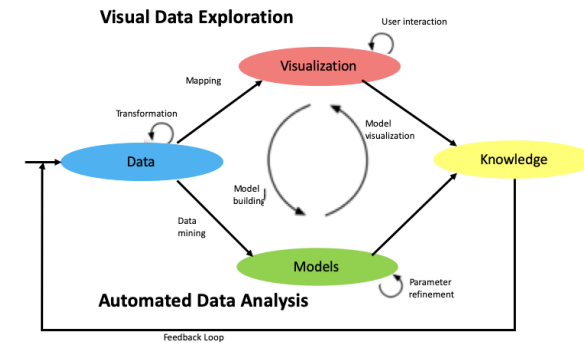
Only numerical



Visualization of results



Visualization with
Basic interaction



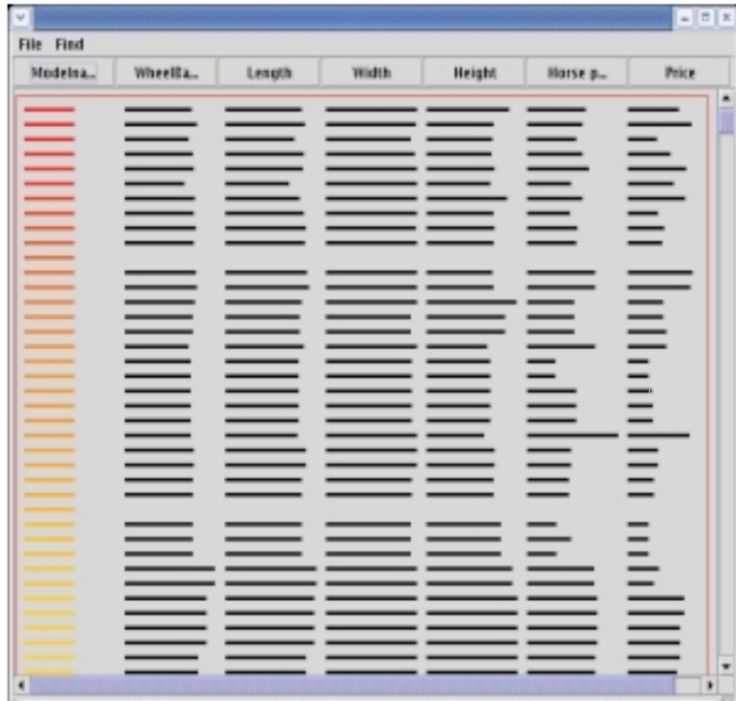
Visual Analytics



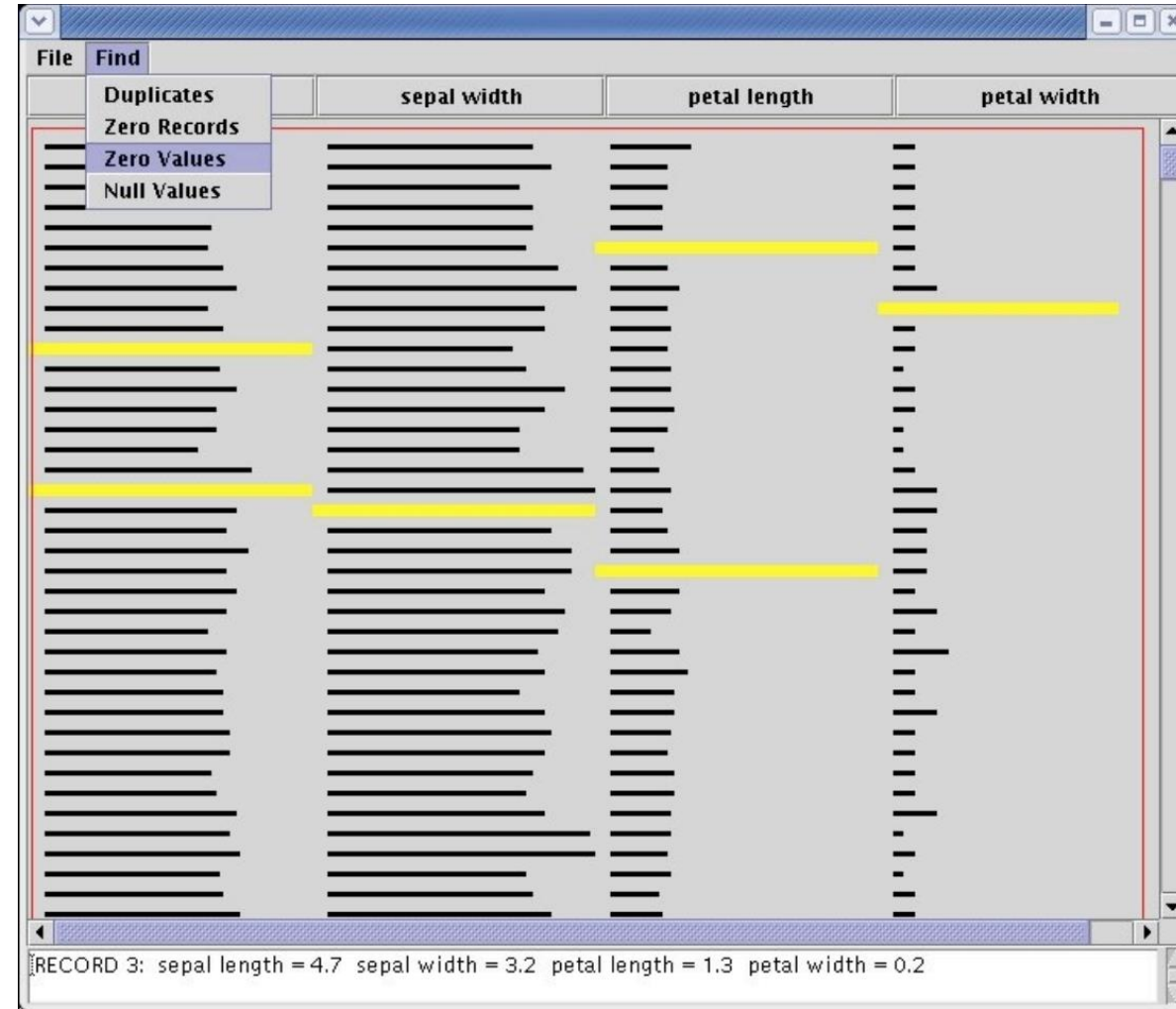
What state-of-the-art research
proposes for "Data Quality" ?



DaVis: a tool for visualizing Data Quality



Sulo, Rajmonda, Stephen Eick, and Robert Grossman.
"DaVis: a tool for visualizing data quality." *Posters
Compendium of InfoVis 2005* (2005): 45-46.



Yellow represents zero values



Visual Data Quality Dashboard

- It uses R for computing indicators
- Strongly oriented at reporting
- Still oriented at tables (less scalability)



DATA QUALITY ASSESSMENT

SYNTHETIC HEALTH DATABASE

Results generated at 2019-08-22 14:15:06 in 29 mins

	Verification				Validation				Total			
	Pass	Fail	Total	% Pass	Pass	Fail	Total	% Pass	Pass	Fail	Total	% Pass
Plausibility	159	21	180	88%	283	0	283	100%	442	21	463	95%
Conformance	637	34	671	95%	104	0	104	100%	741	34	775	96%
Completeness	369	17	386	96%	5	10	15	33%	374	27	401	93%
Total	1165	72	1237	94%	392	10	402	98%	1557	82	1639	95%

<https://github.com/OHDSI/DataQualityDashboard>



Profiler

Type	Issue	Detection Method(s)	Visualization
Missing	Missing record	Outlier Detection Residuals then Moving Average w/ Hampel X84	Histogram, Area Chart
		Frequency Outlier Detection Hampel X84	Histogram, Area Chart
Inconsistent	Missing value	Find NULL/empty values	Quality Bar
	Measurement units	Clustering Euclidean Distance	Histogram, Scatter Plot
		Outlier Detection z-score, Hampel X84	Histogram, Scatter Plot
	Misspelling	Clustering Levenshtein Distance	Grouped Bar Chart
	Ordering	Clustering Atomic Strings	Grouped Bar Chart
	Representation	Clustering Structure Extraction	Grouped Bar Chart
	Special characters	Clustering Structure Extraction	Grouped Bar Chart
Incorrect	Erroneous entry	Outlier Detection z-score, Hampel X84	Histogram
	Extraneous data	Type Verification Function	Quality Bar
	Misfielded	Type Verification Function	Quality Bar
	Wrong physical data type	Type Verification Function	Quality Bar
Extreme	Numeric outliers	Outlier Detection z-score, Hampel X84, Mahalanobis distance	Histogram, Scatter Plot
	Time-series outliers	Outlier Detection Residuals vs. Moving Average then Hampel X84	Area Chart
Schema	Primary key violation	Frequency Outlier Detection Unique Value Ratio	Bar Chart

Sean Kandel, Ravi Parikh, Andreas Paepcke, Joseph M. Hellerstein, and Jeffrey Heer. 2012. Profiler: integrated statistical analysis and visualization for data quality assessment. In Proceedings of the International Working Conference on Advanced Visual Interfaces (AVI '12). Association for Computing Machinery, New York, NY, USA, 547–554. DOI:<https://doi.org/10.1145/2254556.2254659>



Profiler

Schema Browser

- Creative Type
- Distributor
- IMDB Rating
- IMDB Votes
- MPAA Rating
- Major Genre
- Production Budget

Related Views: Anomalies

Anomaly Browser

Missing (6)

MPAA Rating

Creative Type

Source

Major Genre

Distributor

Release Location

Error (2)

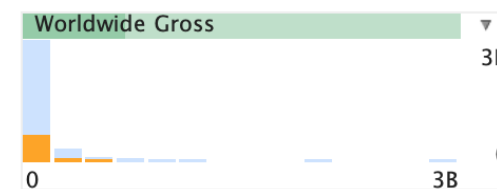
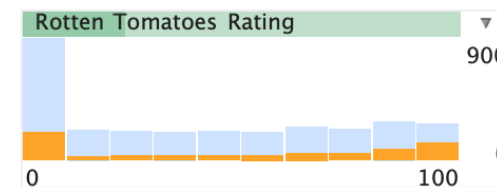
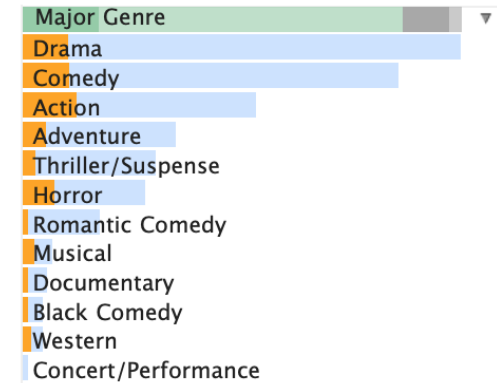
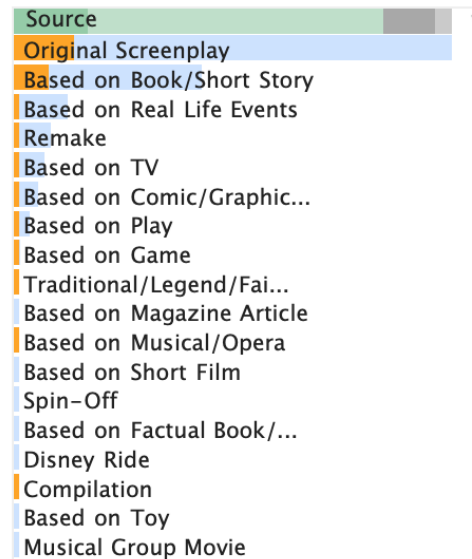
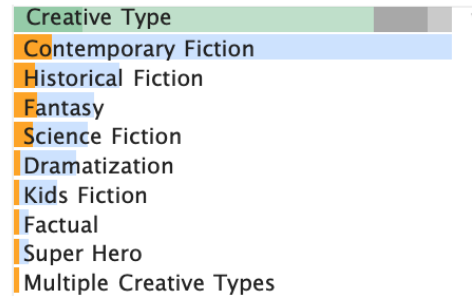
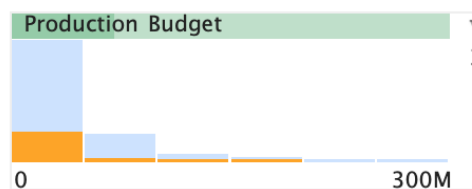
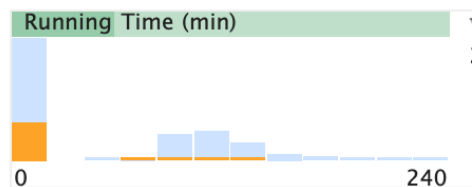
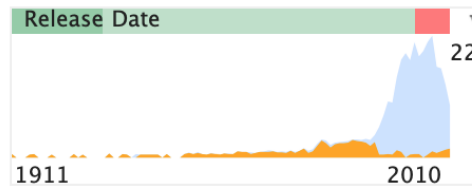
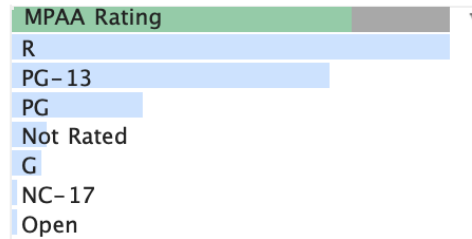
Extreme (7)

Inconsistent (3)

Distributor (Levenshtein)

Source (Levenshtein)

Transform:



General Environments: Tableau

Data Quality Indicators

Universe	Data Accuracy	Data Completeness	Data Conformity
CDAG	●	●	●
CPE	●	●	●
FA	●	●	●
ODAG	●	●	●
SNP MOC	●	●	●

Valori misure

93,43% 96,27%

Month

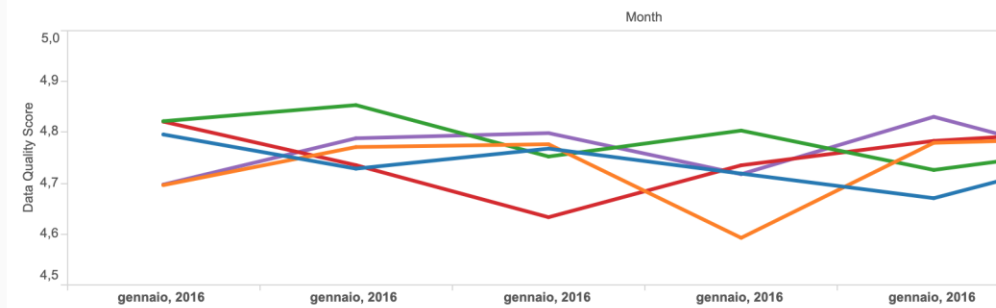
- ☒ (Tutti)
- ☒ gennaio, 2016
- ☒ gennaio, 2016
- ☒ gennaio, 2016
- ☒ gennaio, 2016
- ☒ gennaio, 2016
- ☒ gennaio, 2016
- ☒ gennaio, 2016

Data Accuracy: indicated by % of records with all fields having valid values

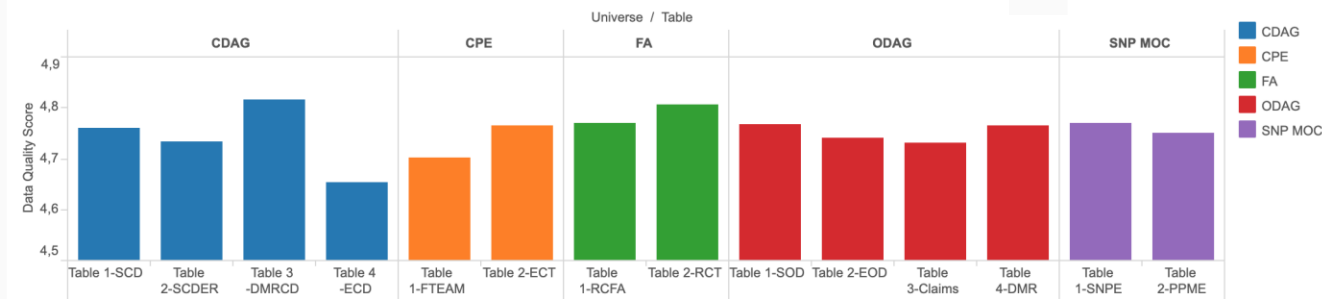
Data Completeness: indicated by % of records with all fields being not null

Data Conformity: indicated by % of records with all fields

Data Quality Score Monthly Trend



Data Quality Score per Universe Table



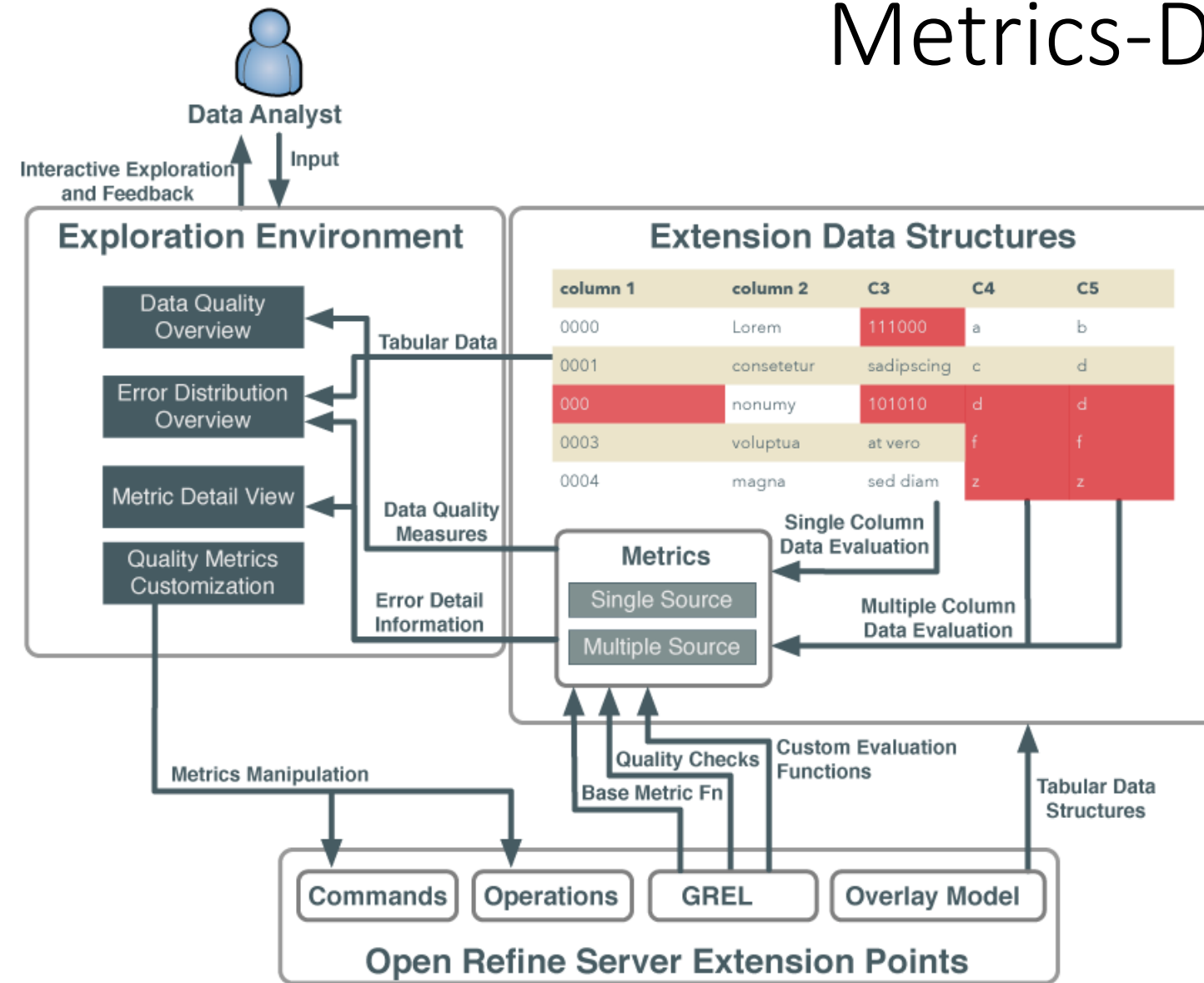
Data Quality Indicators

Universe	Data Accuracy	Data Completeness	Data Conformity
CDAG	●	●	●
CPE	●	●	●
FA	●	●	●
ODAG	●	●	●
SNP MOC	●	●	●

https://public.tableau.com/views/DataQualityDashboards/Dashboard1?:embed=y&:showVizHome=no&:display_count=y&:display_static_image=y&:bootstrapWhenNotified=true



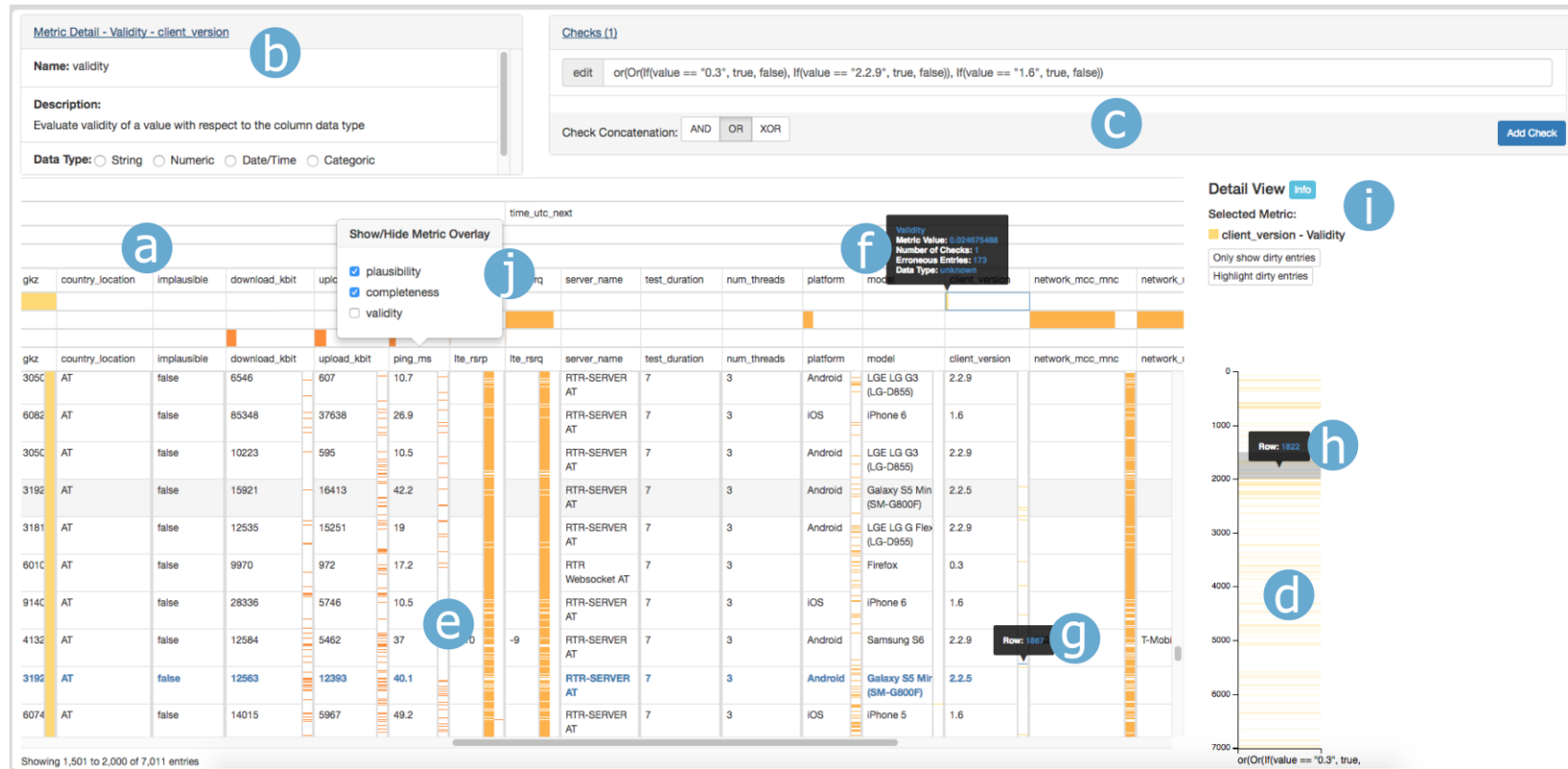
Metrics-Doc



Christian Bors, Theresia Gschwandtner, Simone Kriglstein, Silvia Miksch, and Margit Pohl. 2018. Visual Interactive Creation, Customization, and Analysis of Data Quality Metrics. *J. Data and Information Quality* 10, 1, Article 3 (May 2018), 26 pages.
DOI:<https://doi.org/10.1145/3190578>



Metrics-Doc



(a) *quality metrics overview*
distribution heatmaps

(b) the metric information view and
(c) customization tabs
(d) the *metric detail view*

(e) the tabular *raw data view* enhanced with *error*

(f) mouseover tooltips provide detail information on
(g) metrics
(h) data errors

(j) metric distribution heatmaps can be enabled and disabled individually



Integrated VA environment

High level analysis of data:

- Looking for correlation among data column
- Spotting outliers
- Exploiting coordination for understanding trends
- On research production data

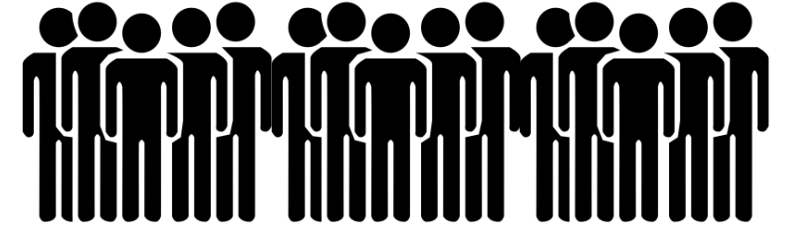


Introduction

Research evaluation

- transition from a traditional evaluation model, based on bibliometric indicators of publications and citations
- modern evaluation, characterized by a multiplicity of distinct, complementary dimensions

Demand side (those that ask for research assessment) including an increase of institutional and internal assessments



Supply side (those that offer research assessment) including proliferation of rankings, development of Altmetrics, open access repositories, new assessment tools and desktop bibliometrics

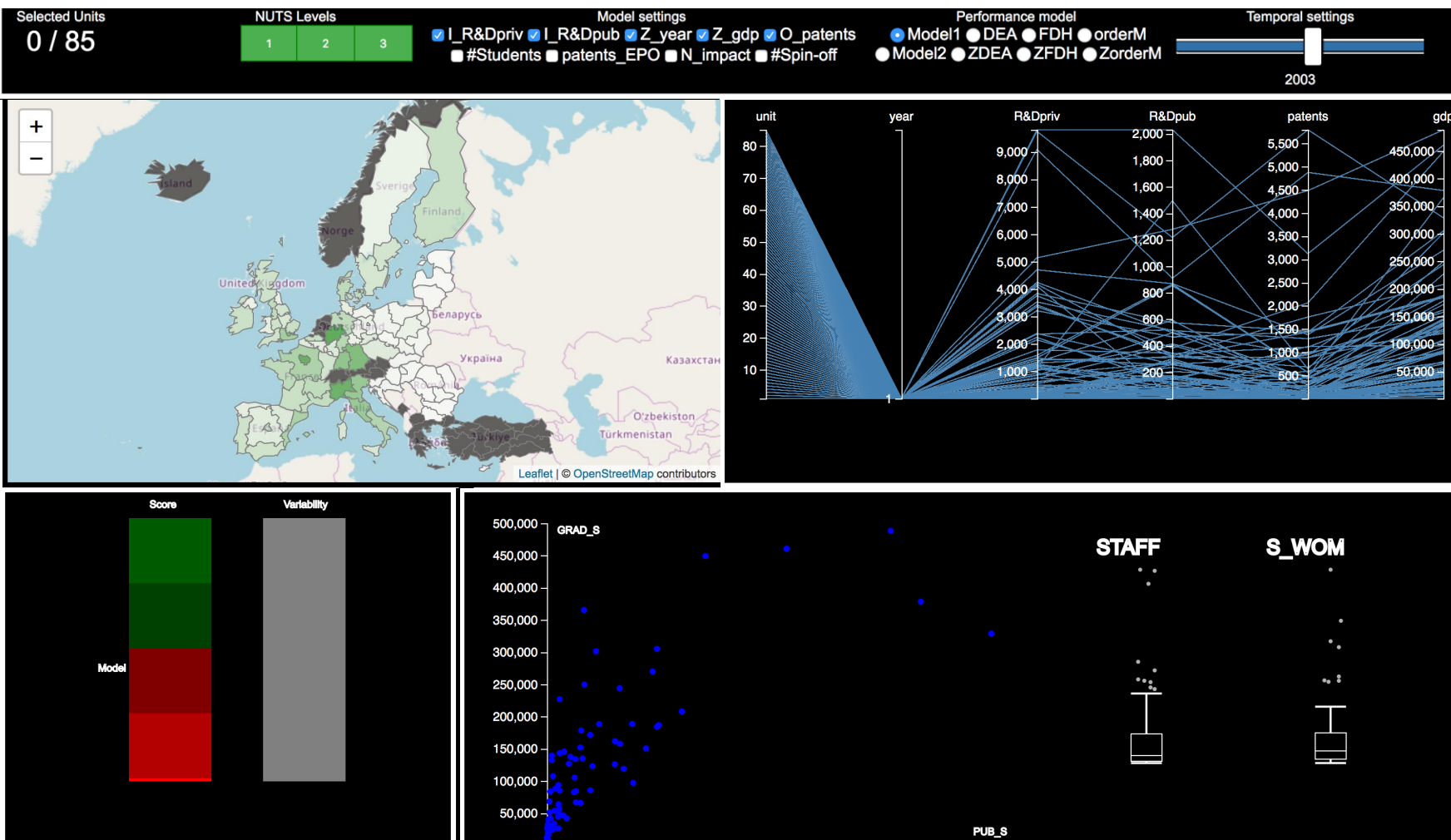


Scholars the increase of “publish or perish” pressure, impact on:

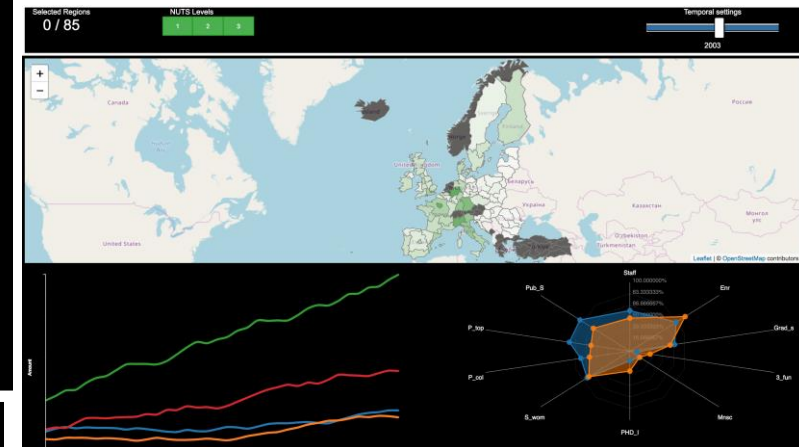
- incentives, behaviour and misconduct, and increasing critics against traditional bibliometric indicators
- the assessment process (increasing the complexity of the research assessment)
- the indicators’ development.



Visualization



Visualization



Angelini, M., Daraio, C., Lenzerini, M. *et al.* Performance model's development: a novel approach encompassing ontology-based data access and visual analytics. *Scientometrics* (2020). <https://doi.org/10.1007/s11192-020-03689-x>



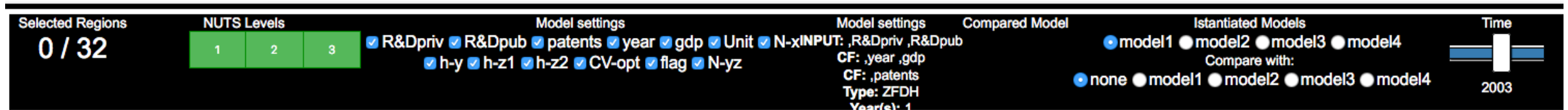
SAPIENZA
UNIVERSITÀ DI ROMA

Command bar


Selected model characteristics

Compared model characteristics

Temporal slider



units



NUTS level
Selector



Selectable dimensions:

(add/remove dimensions
In the Parallel coordinates
For better readability)

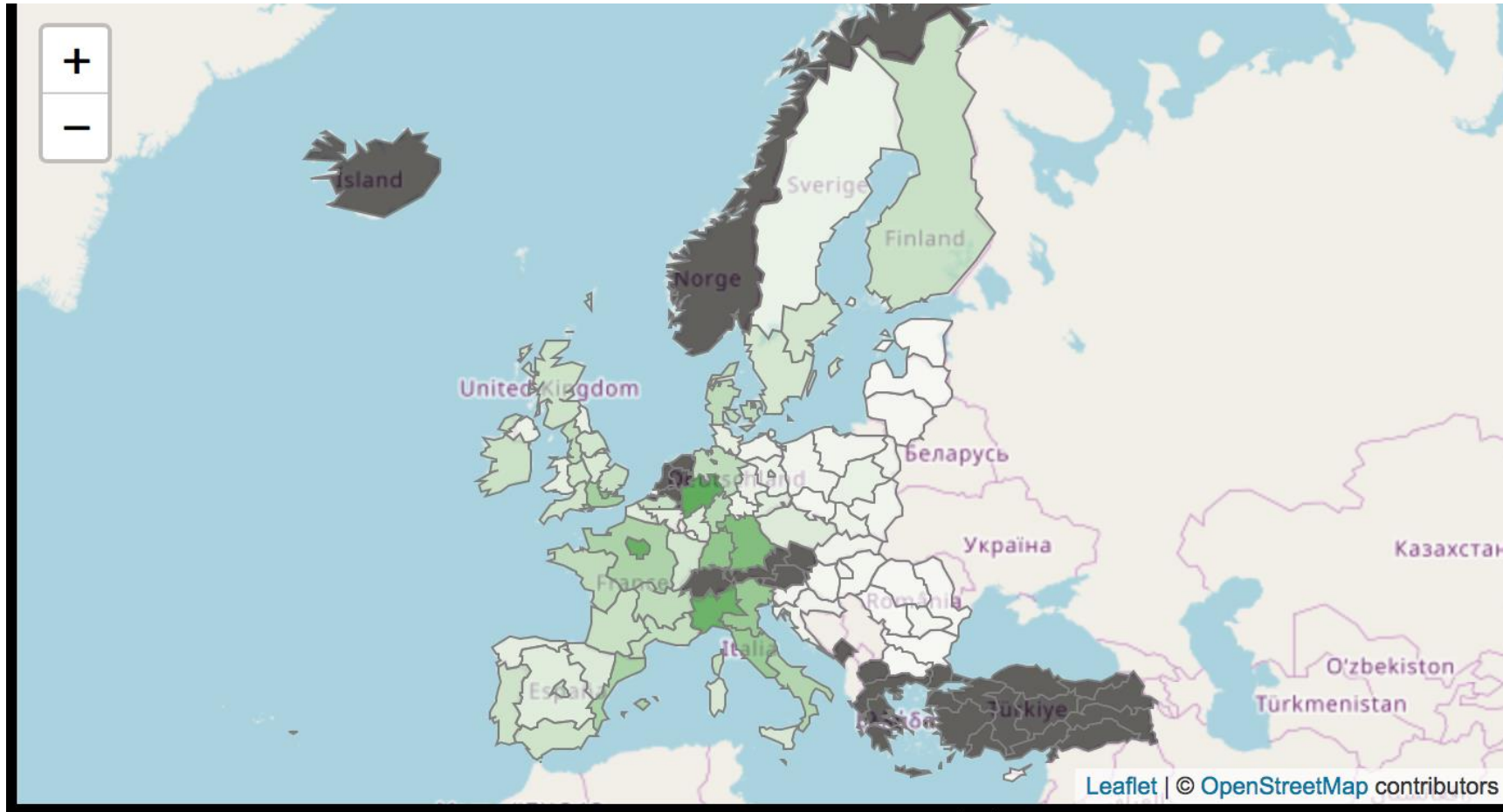


Selectable models; TOP: **actual** model used

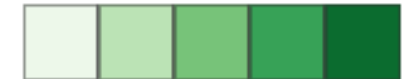
BOTTOM (Compare with). A model that stay Fixed and will be compared with the **actual** one.

If you choose «none», no comparison will
Be made

Visualization: geographic view



- The user can see one dimension, mapped with a color scale, for the right geographic aggregation level (NUTS levels)



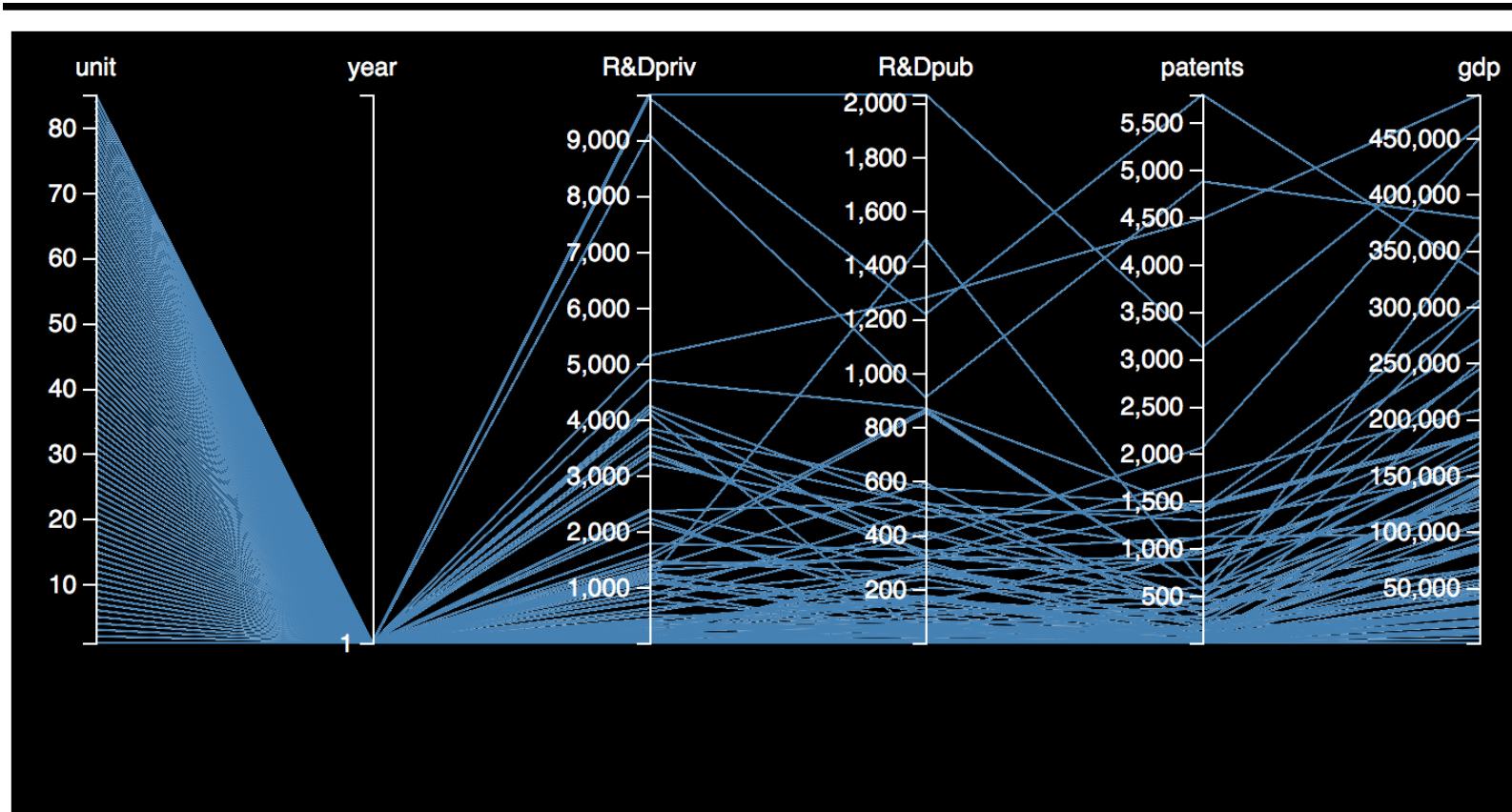
low

high



= no value

Visualization: parallel coordinates

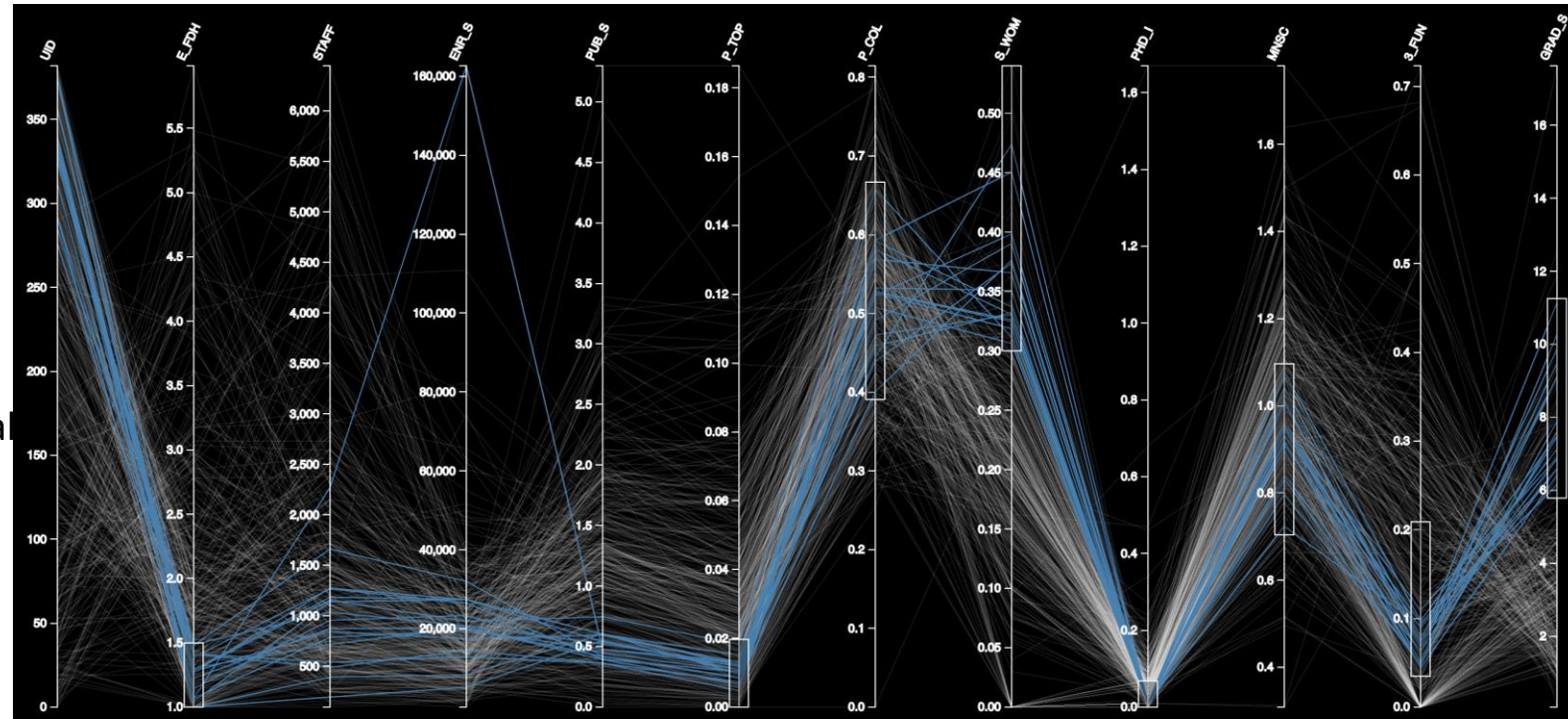


- Each dimension is represented as a vertical axis
- Each tuple is a line (in blue) that pass for the value of each dimension
- We can see ALL the data (a lot) in a Compact view
- We can inspect for correlation between dimensions

Example: relations among dimensions

Axes (12 dimensions)

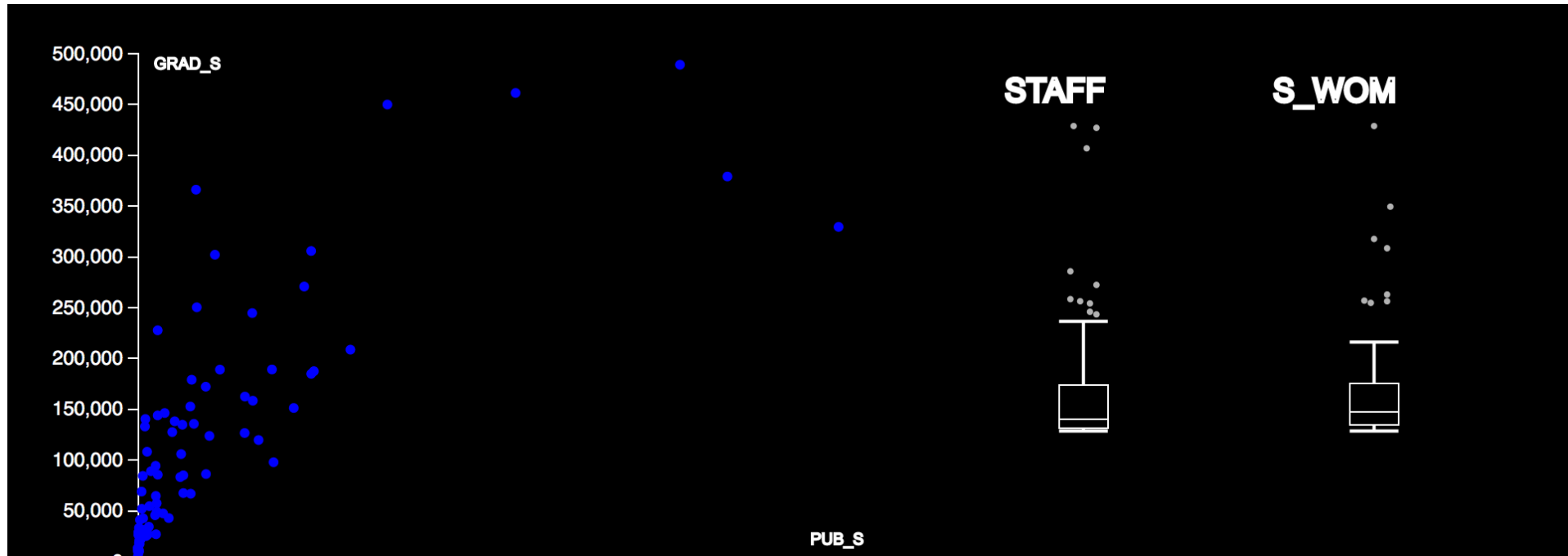
- UID institution id
- E_FDH is the FDH (in)efficiency score
- STAFF number of academic staff
- ENR_S enrolled students per academic staff
- PUB_S number of publications in WoS (fractional count) per academic staff
- P_TOP number of publications in top 10% of highly cited journals per academic staff
- P_COL percentage of papers done with international collaborations
- S_WOM share of women professors on total academic staff
- PHD_I PhD intensity
- MNCS Mean Normalized Citation
- 3_FUN share of third party funds
- GRAD_S is total number of graduates per academic staff



Among the most efficient units in teaching and research (i.e. $E_FDH = [1 \ 1.5]$) there are those teaching oriented institutions (with the highest values of $GRAD_S$) in which the S_WOM is the highest ($[0.30-0.50]$): these are universities with almost zero PhD intensity that are able nevertheless to produce a small fraction of P_TOP publications with MNCS around the world average

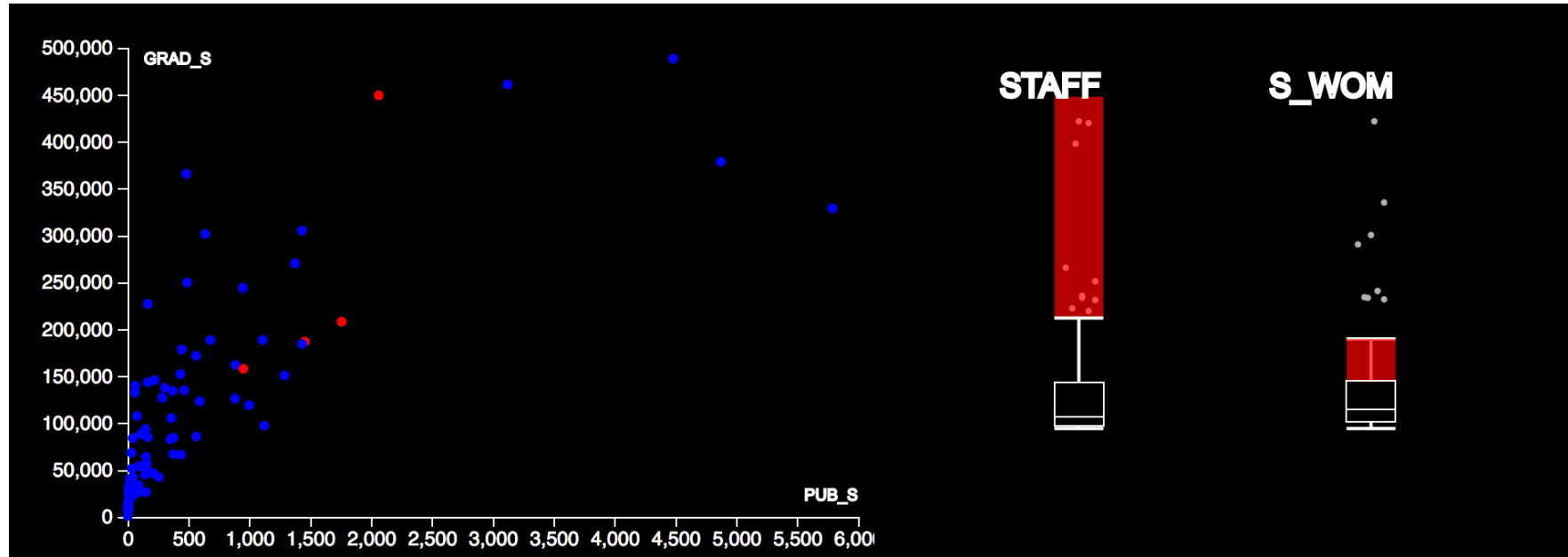


Visualization: scatterplot + boxplot



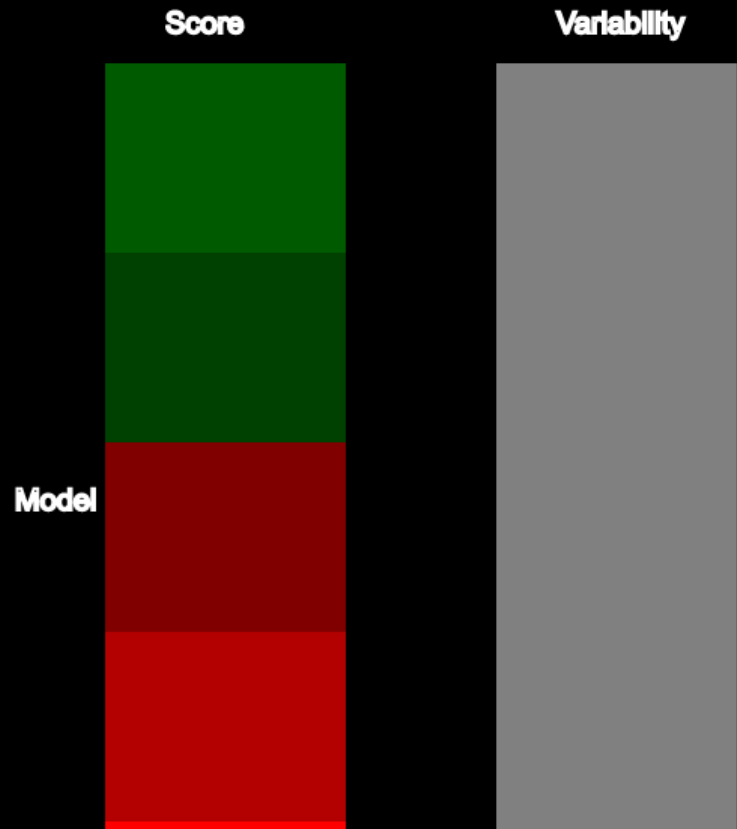
- The user see a 2D scatterplot looking again for correlation among couples of dimensions
- She can filter from the boxplot (on the right) instantiated on different dimensions from the ones in the scatterplot

Example: relations among entities



Example of data filtering: with respect to all the units, the selection is composed by high outliers for academic staff (STAFF) and the 4th quartile for percentage of women staff (S_WOM); the resulting points are highlighted in red in the scatter plot, and the unit can be identified by mouse-hover.

Visualization: model performance



- Units are ordered (from top to bottom with respect to their performance score according to the selected model)
- The color (green: GOOD scores, red=BAD scores) tell us How the units behave according to the model
- The second bargram (GREY) is used to calculate the variability of the model (how much the scores change if we perturb the model removing or changing one of its Parameters)

GREEN= good changes
RED= bad changes

For the same units!



All together: Demo



The Knowledge from both worlds

Data exploration: allowing comprehension of analyzed data

Knowledge

Additional analysis possible, e.g. Comparative analysis:

Identify inputs causing most uncertainty – direct research or information gathering

- Check the effect of model assumptions on model output
- Model simplification - identify inputs that do not affect the output, therefore redundant
- Better understanding of the model - what causes what.
- Corroboration or falsification
- Identifying errors - are there unexpected relationships between inputs and outputs?

assist with the decision making process

What-if analysis (testing different models/performance indicators/combinations of them)



Integrated VA environment: limitations

- Still working on completing data quality checks
- Modifications to dataset must be done outside of the tool
- Management of the data schema to improve
- Still in development



Visualization is a vast discipline



Cornsweet effect

- Suitable shading creates edges and difference in lightness
- What is the darker side?



Cornsweet effect

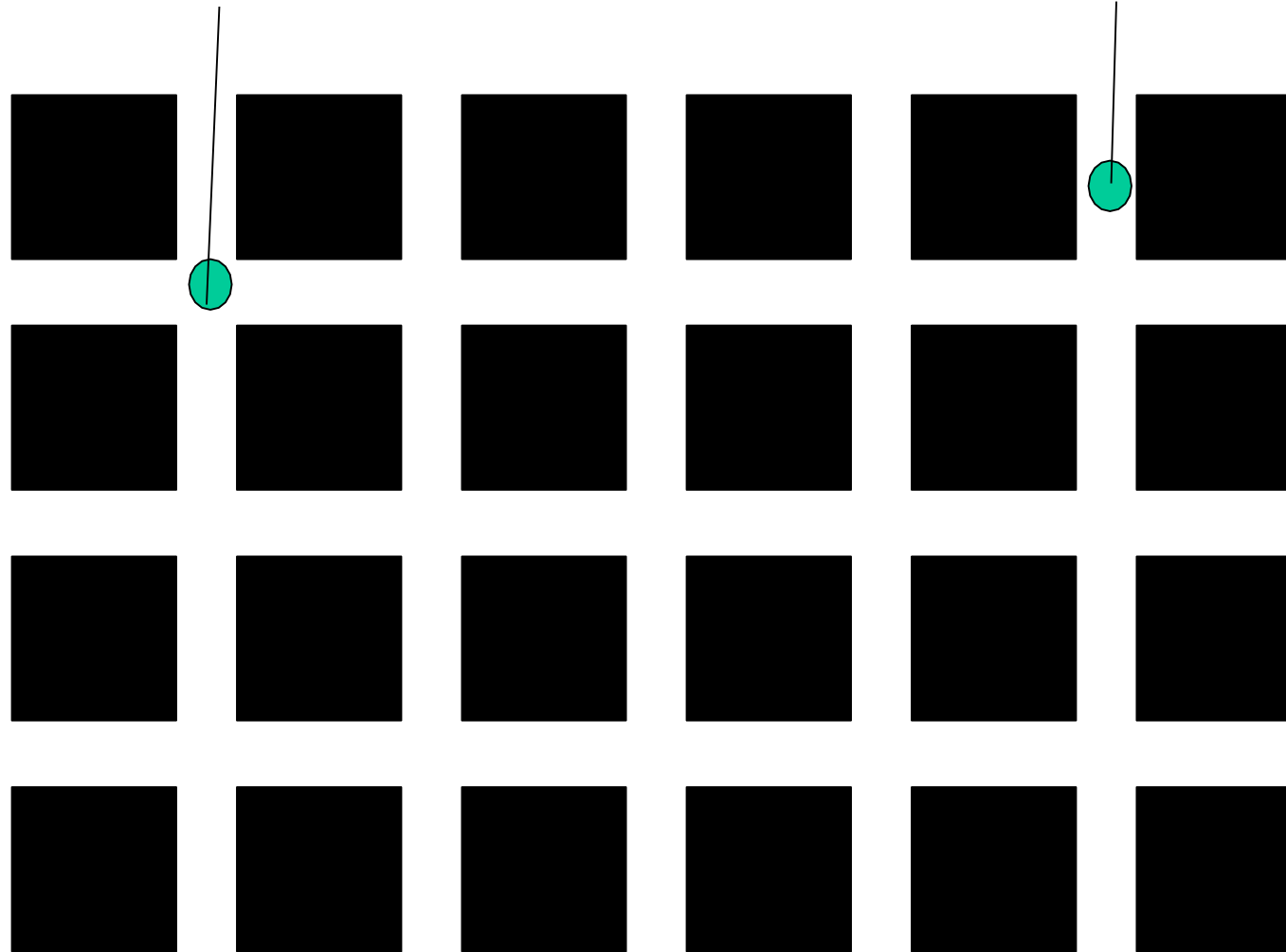
- No one...



Human perceptual
errors

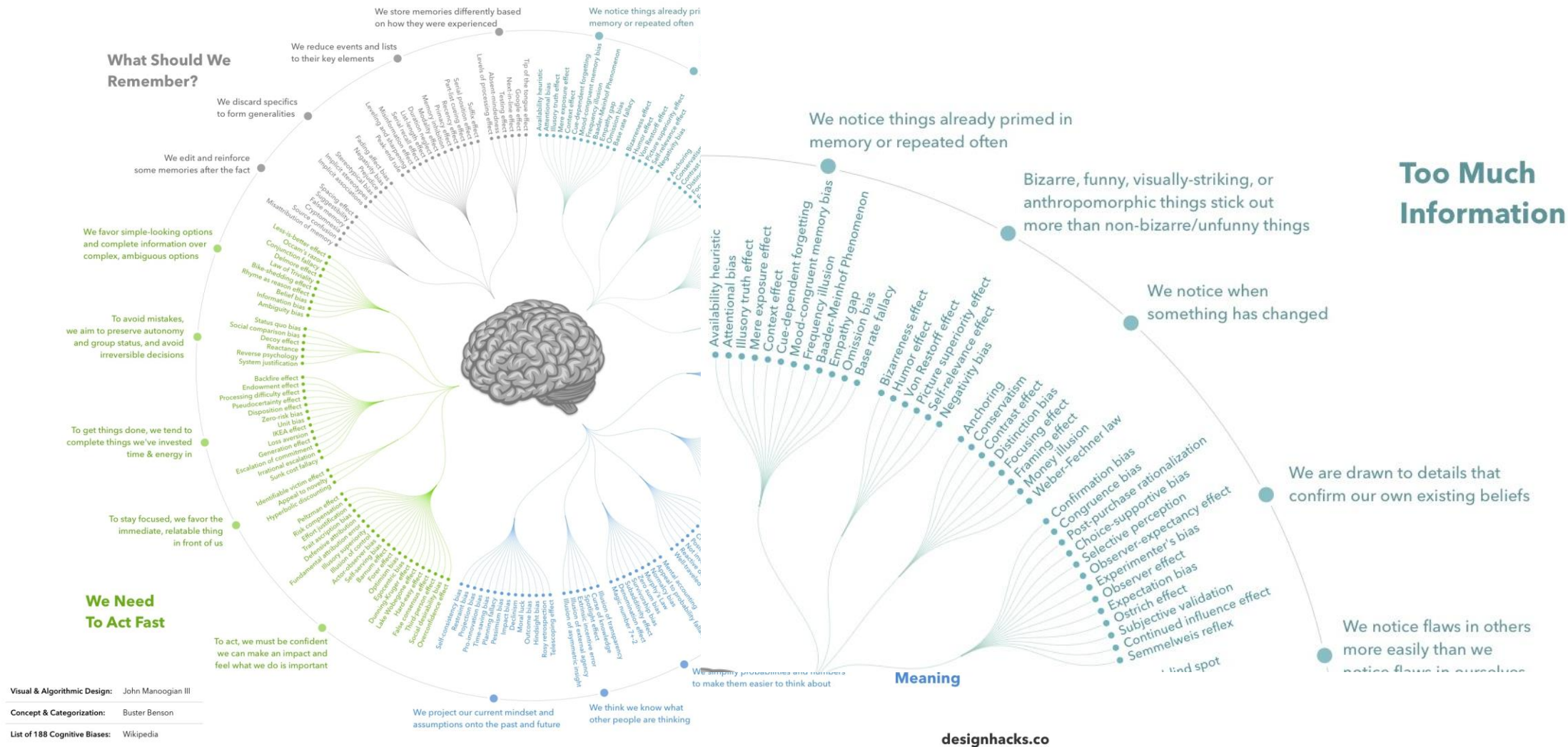
Less inhibition

More inhibition



Human cognitive biases

COGNITIVE BIAS CODEX



Research Challenges

Monitoring the Data quality evolution during time

Move from numeric representation (tables) to more exploratory analysis

- requirement of different visual paradigms to support different tasks

Better support Human intervention into the analysis (not just reporting)

Better support explanation of results



Research Challenges

- **Scalability:** existing visual data cleansing methods cannot be scaled to large scale datasets.
 - sample only a small subset of the whole training set. The challenge here is how to develop effective sampling methods that can both keep the data density and preserve important data such as influential points, outliers, and exceptions.
- there is a lack of effective quality metrics to measure the quality of different types of data such as textual data, images, videos, graph data, and trajectory data
- the analyst often needs to examine multiple types of data and correct the errors among them.
 - designing an integrated interface to visually illustrate the distributions of different types of data



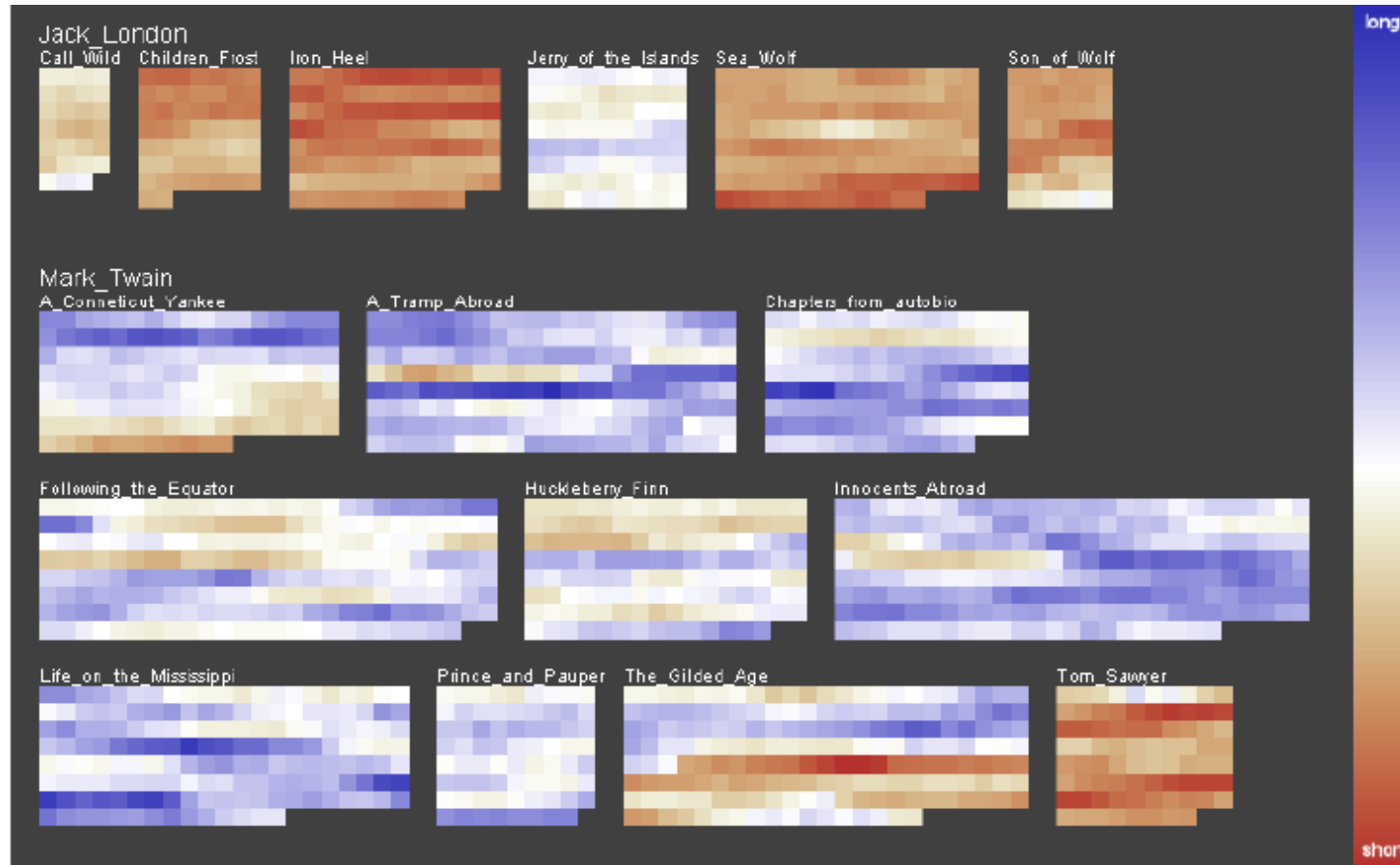
Research Challenges

Textual data

- Although textual data is widely used in many lines of work, data quality problems for such type of unstructured data remain largely unexplored.
 - This is because, due to the unstructured nature of textual documents, quality management for textual data is challenging.
- textual data often contains several data fields and mixes the useful information with irrelevant information.
- Therefore, it is important to remove the irrelevant information, which is still a hot research topic in the area of information retrieval.
- text corpora may contain text strings of different distributions, such as different lengths and language usages.
- Another challenge is how to effectively improve the quality of a text corpora with inconsistent data distributions

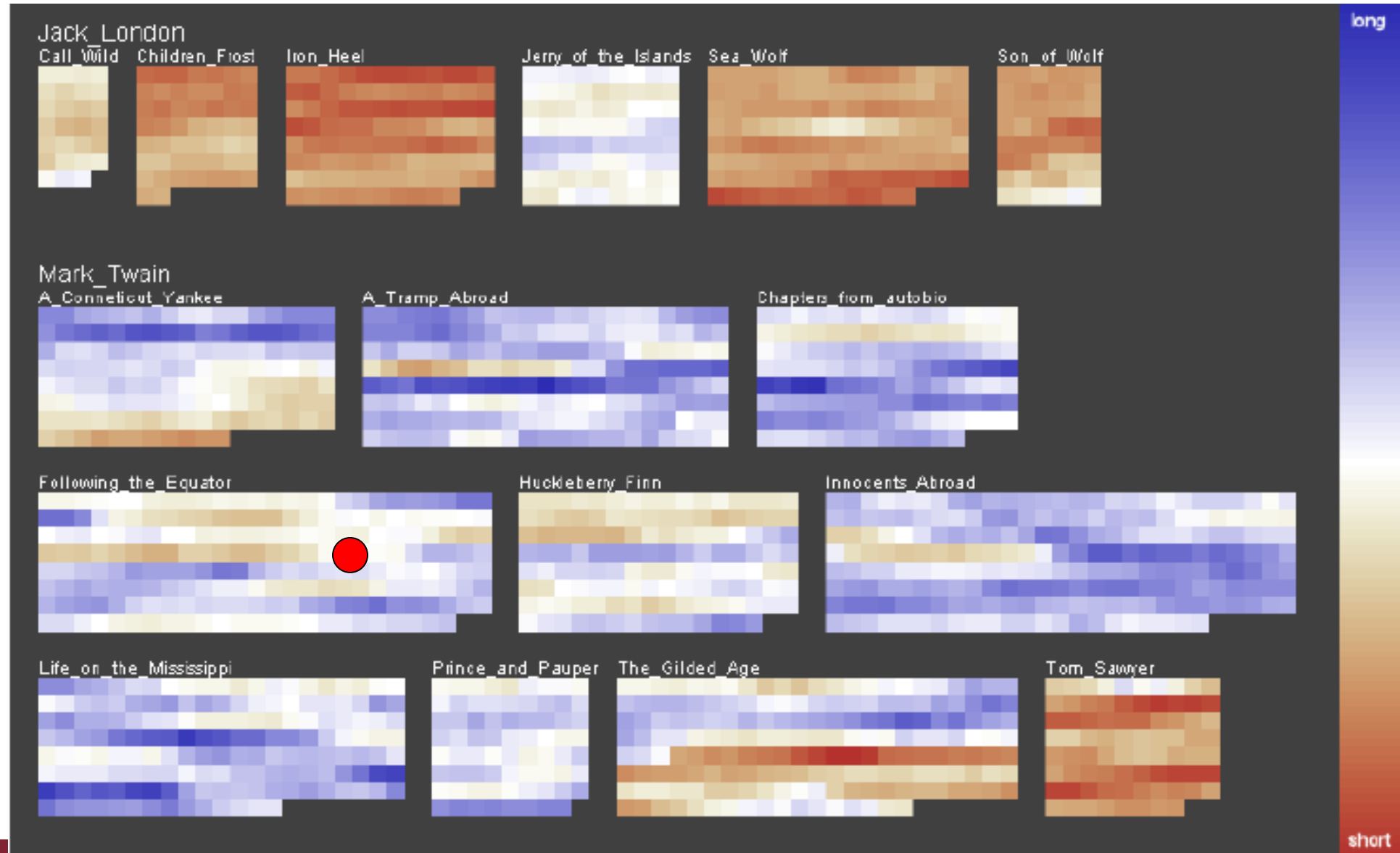


J.London vs M.Twain average sentence lengths

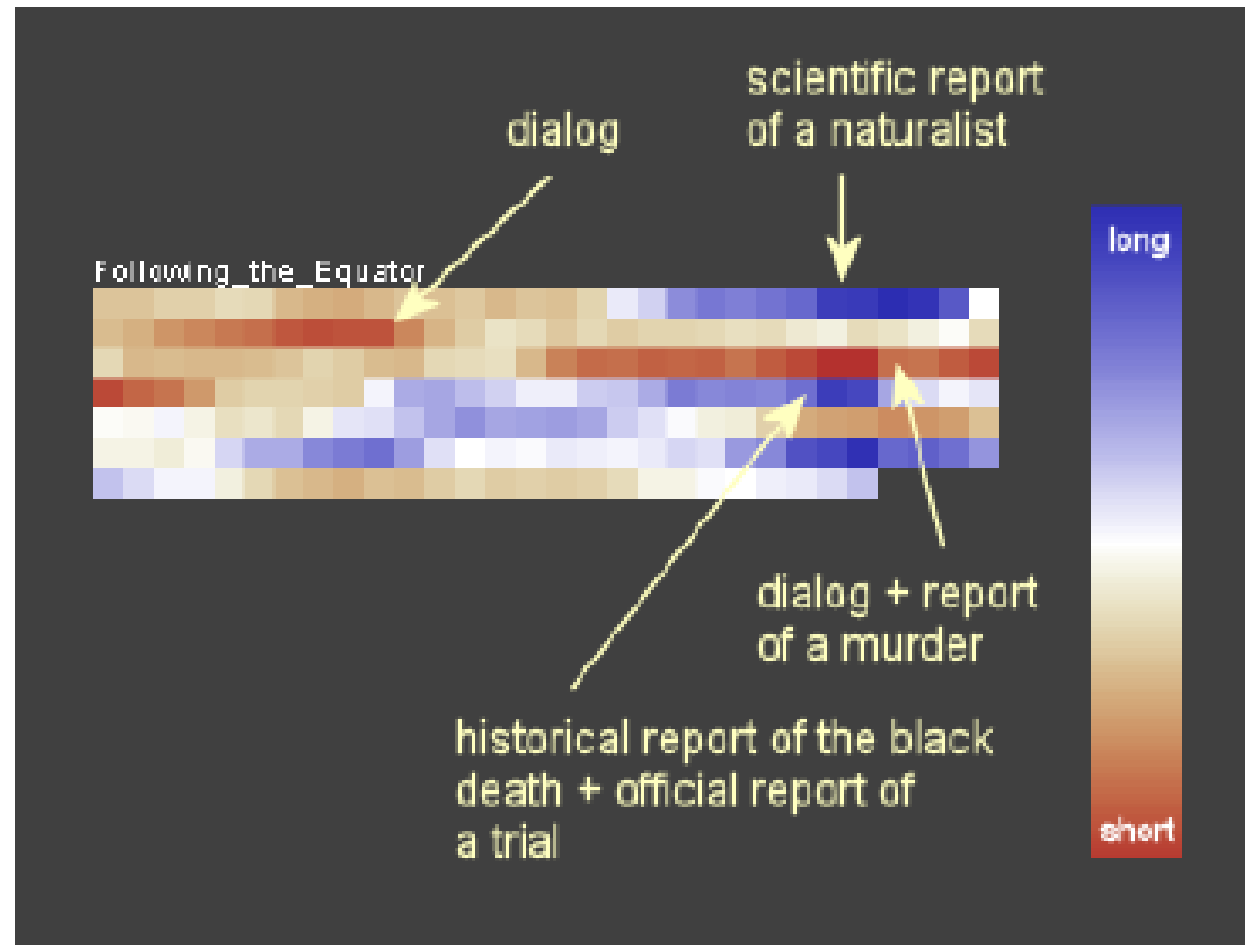


Keim, Daniel A., and Daniela Oelke. "Literature fingerprinting: A new method for visual literary analysis." 2007 *IEEE Symposium on Visual Analytics Science and Technology*. IEEE, 2007.

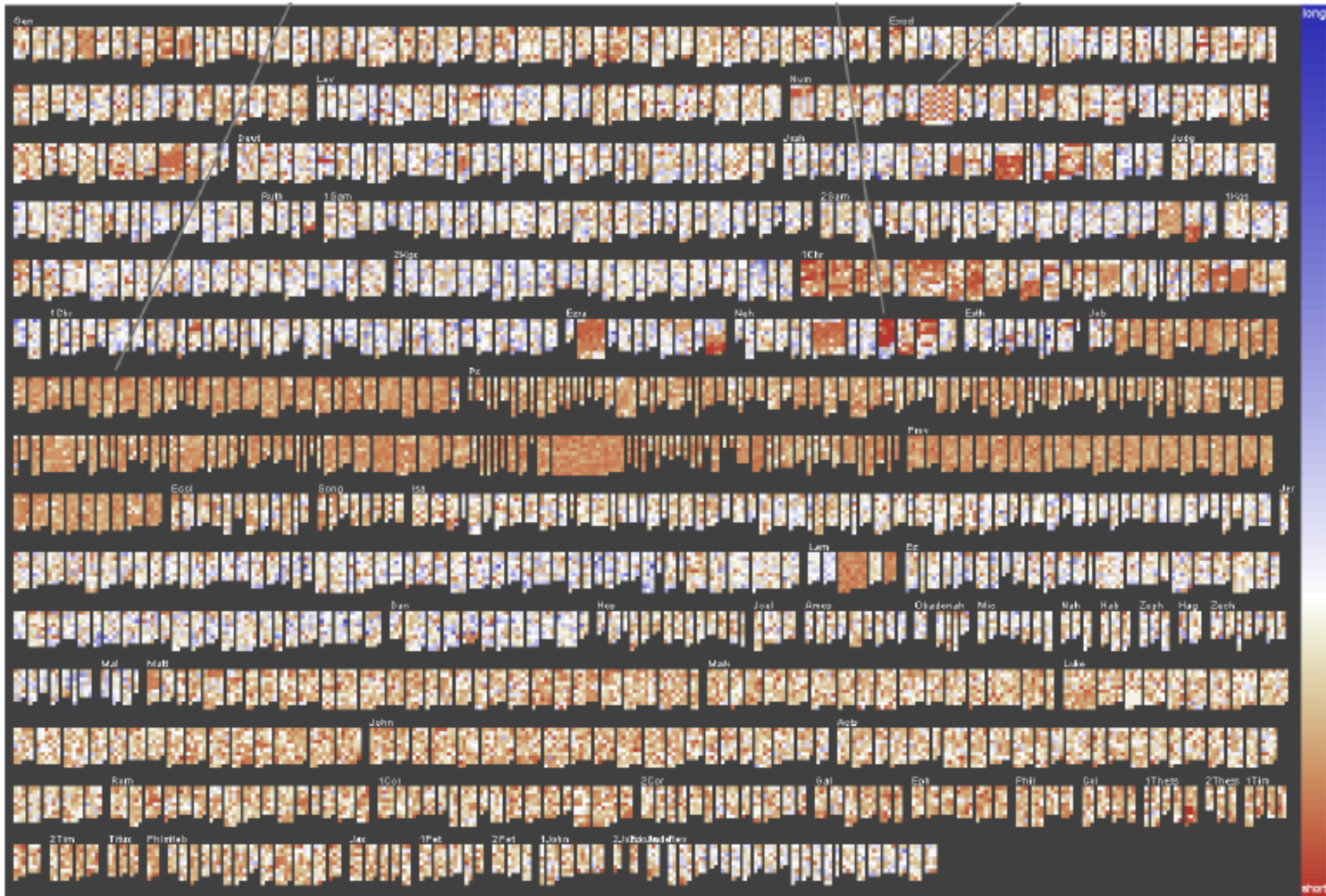
User interaction (a non uniform book?)



Details of a book



What about the Bible?



Research Challenges

Limitations of perception/cognition.

- limitations on visual perception and cognition (restricted field of view) limited working memory in cognition
- explore a mixed initiative mechanism which seamlessly integrates system initiative guidance and user initiative guidance for better human machine intelligence,

Difficulty in understanding uncertainty and its implications.

- Uncertainty might arise in any stage of a data cleaning process, and propagate in subsequent stages
- understanding the uncertainty and its implications would be generally difficult without a proper visual guidance.



Thank you for your attention !

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ANY QUESTIONS?



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