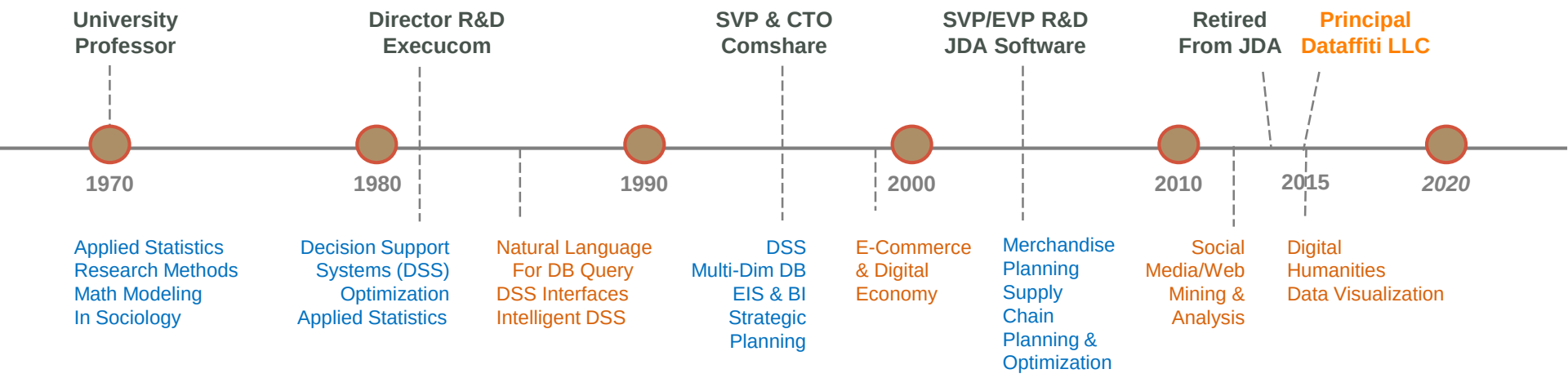
VISUAL ANALYSIS & MINING OF SOCIAL MEDIA – PART 1

Dave King
HICSS 48
2015

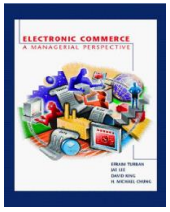
Agenda

- Definitions
- Example 1: Quantification of Self
- Visual Framework(s)
- Example 2: Text analysis of Rap lyrics
- Example 3: Social Network Analysis

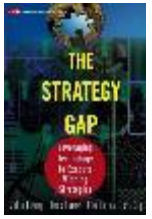
Biography



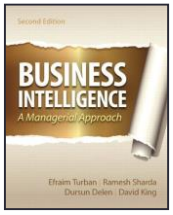
- Formal Positions
- Work Focus
- Research Focus
- Books



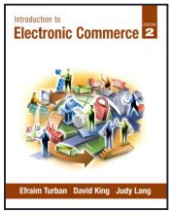
1st Edition '99



'08



2nd Edition '11



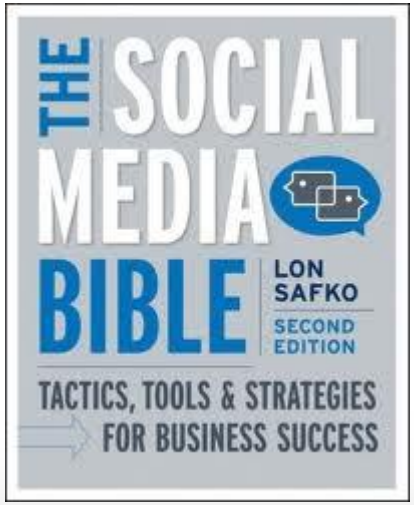
3rd Edition '11

8st Edition '15

DEFINITIONS

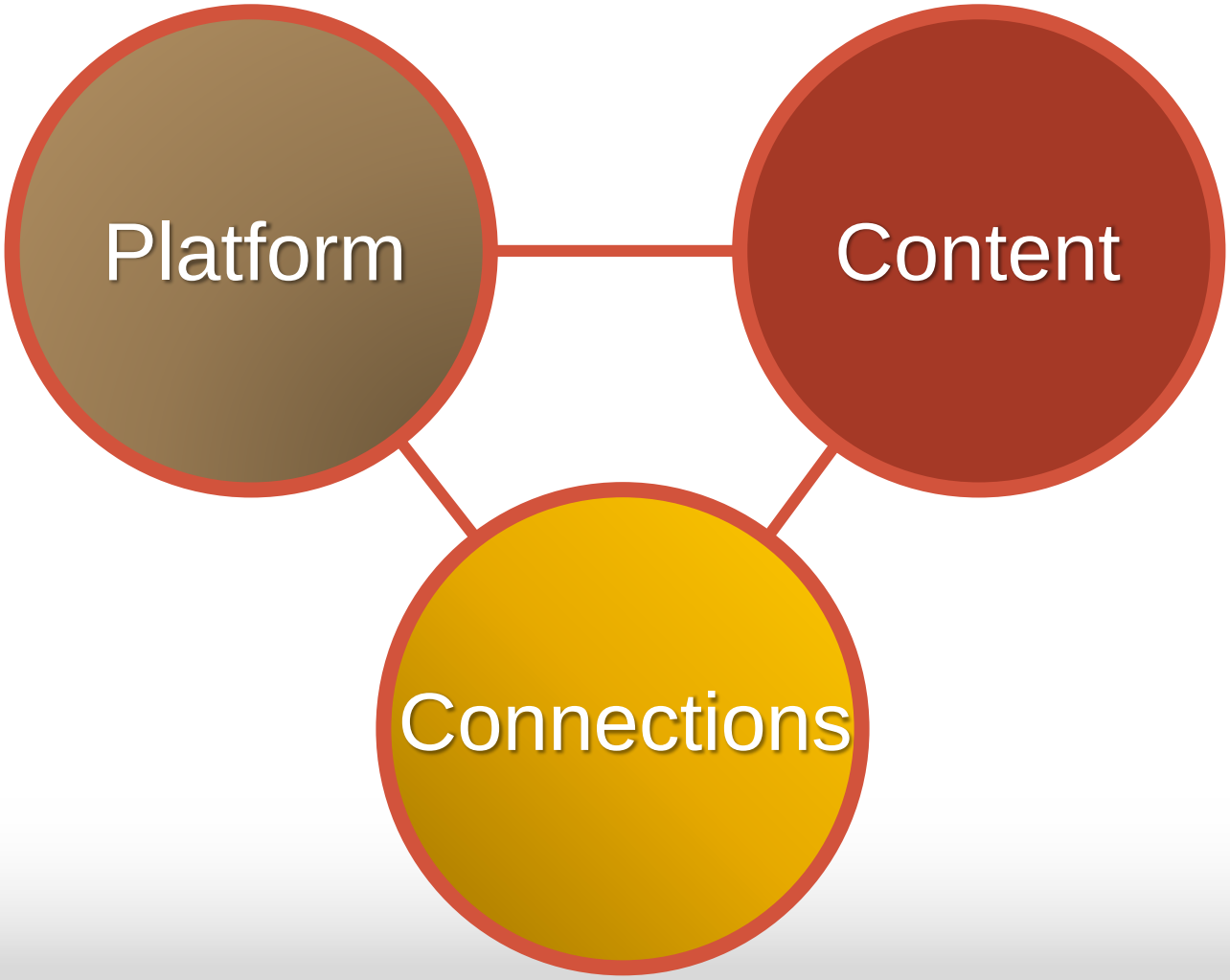
Social Media, Data Mining & Visualization

Defined



is the media we use to be social. That's it.

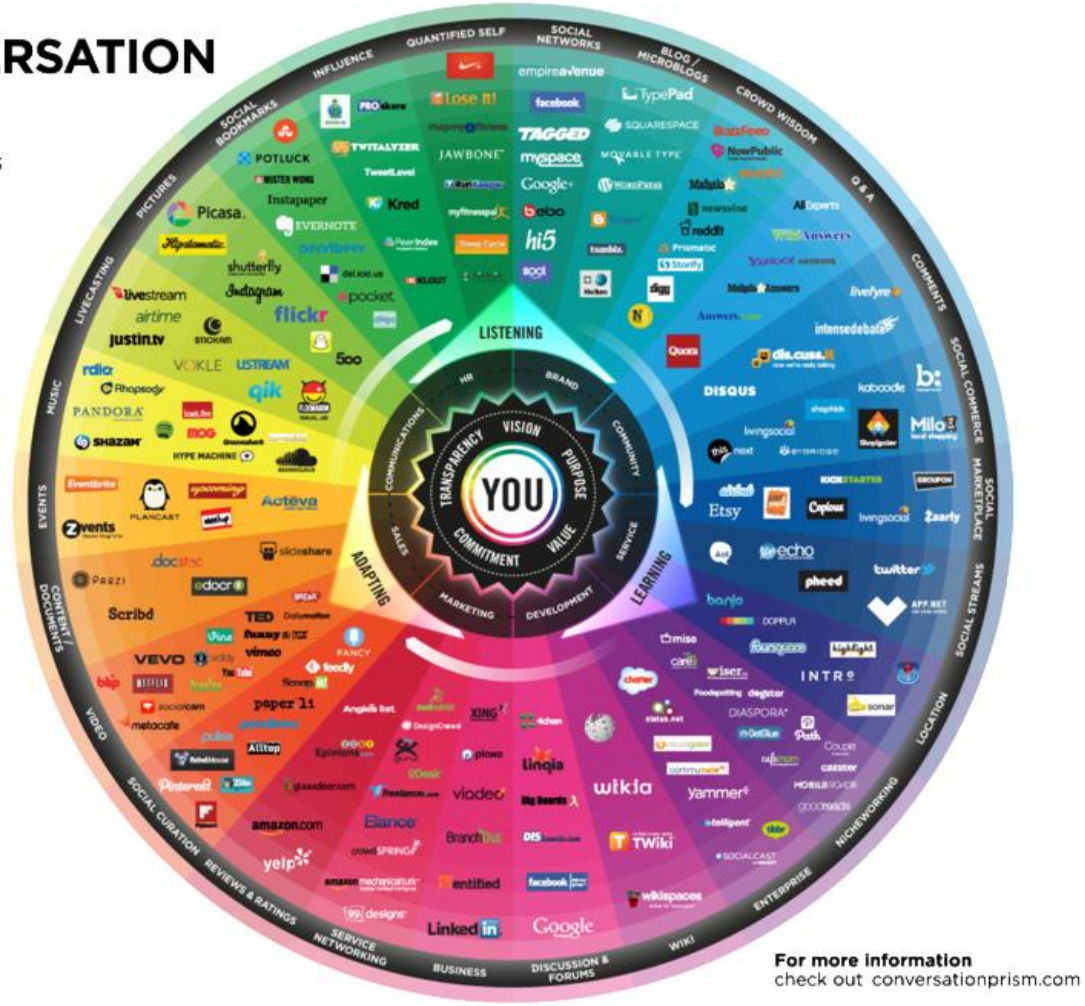
Media elements



Social media defined

- A group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, which allows the creation and exchange of user-generated content (Kaplan & Haenlein, 2008)
- Media for social interaction, using highly accessible and scalable publishing techniques (Morgan et al., 2012)
- The means of interaction among people in which information is created, shared, and exchanged, most often in virtual communities and digital networks (Paolo Ciuccarelli et al., 2014)

Social media landscape (2013)



Mining and analyzing social media:

Key elements

Content

Connections

Social media content:

Text, tags, profiles, location, images, video & sound

Social media connections:

Roles and relationships

Family Friends Groups

Followers

Senders

Contacts

Recipients

Authors

Participants

Readers

Answerers

Repliers Subscribers Collaborators

Social media mining defined

The process of representing, analyzing, and extracting (actionable) patterns from social media content, relations, and interactions.

Mining and analyzing:
Social media content

Data Mining
Discovering meaningful patterns from large data sets using pattern recognition technologies

Web Mining
Data Mining focused on the analysis of Web usage, structure & content

Text Mining
Using natural language processing & data mining to discover patterns in a collection of “documents

Image/Video Mining
Using image/video processing & analysis to uncover patterns in collections of images/videos

Some data mining models…

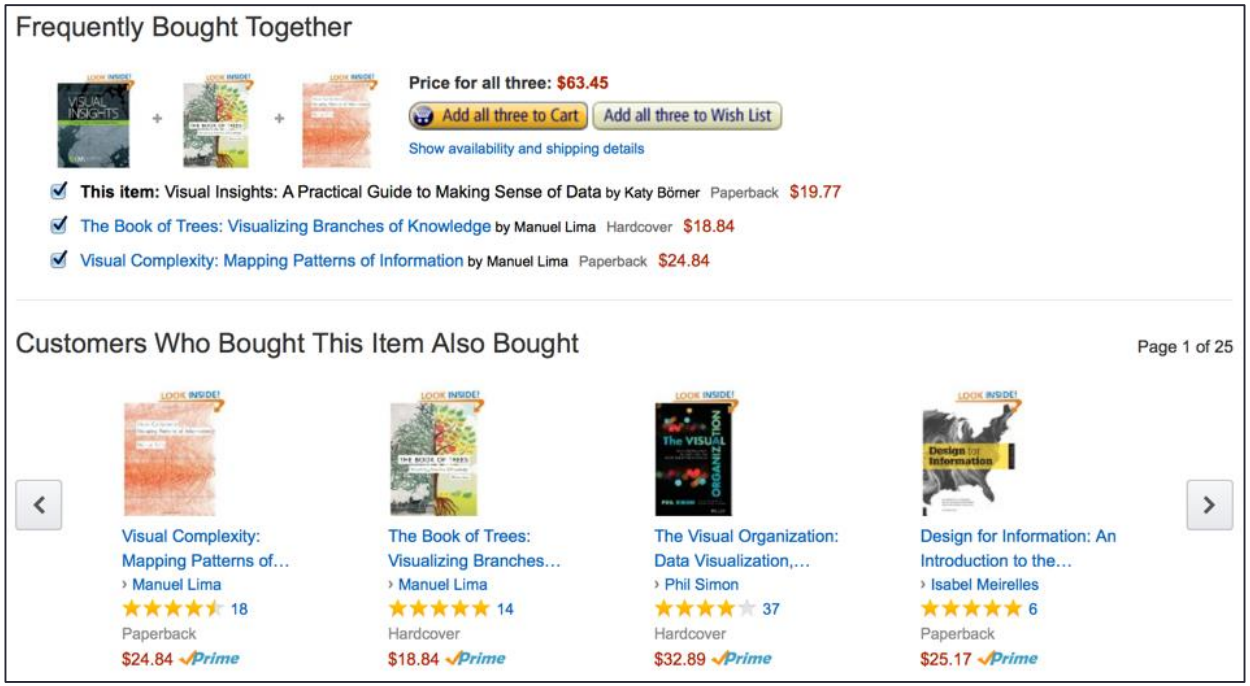
- Summarization
- Regression
- Anomaly Detection
- Association Rule Learning
- Clustering
- Classification

Data mining models assume the data is…

- Structured
- Transformed
- Well-formed

Data mining example:

Affinity analysis

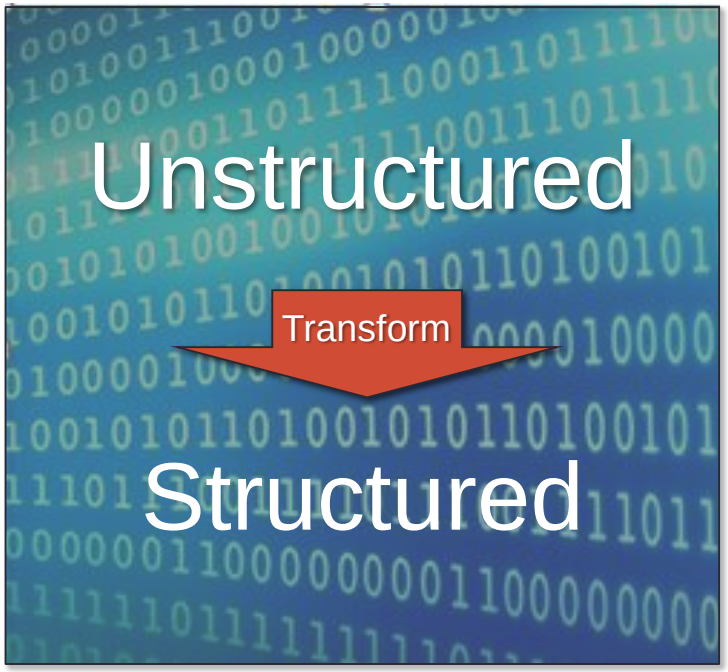


Transaction Records → Association Rules

Social media content is usually…

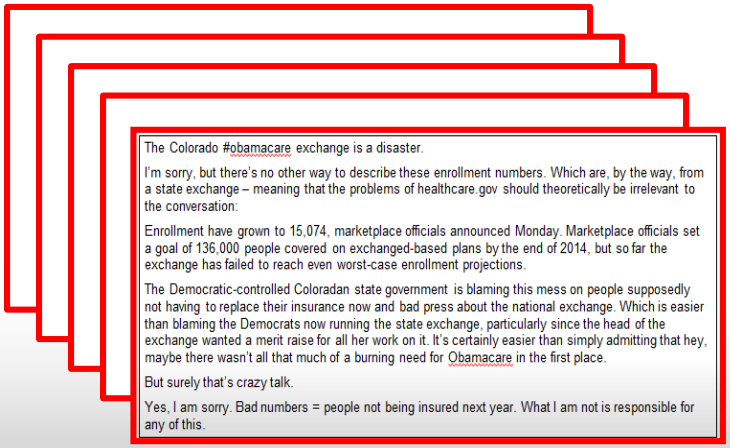
Mining and analyzing Content

requires…

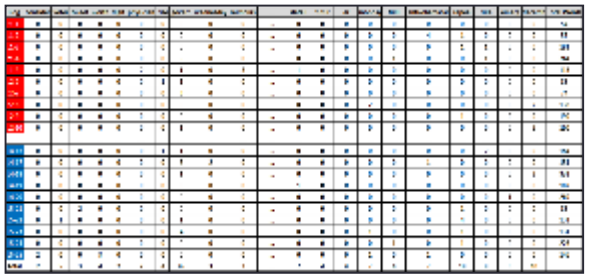


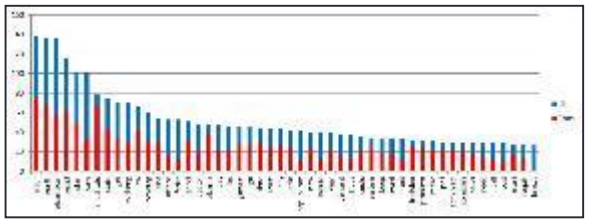
Mining social media content

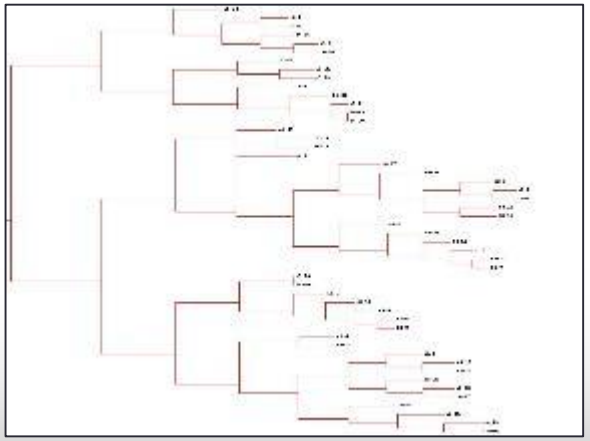
Simple example – political blog text



Data Transformation



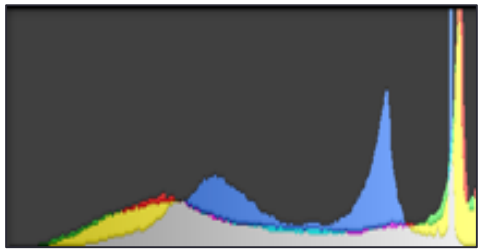


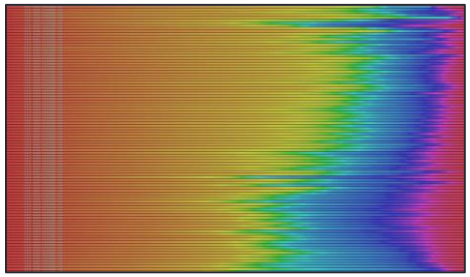


Mining social media content

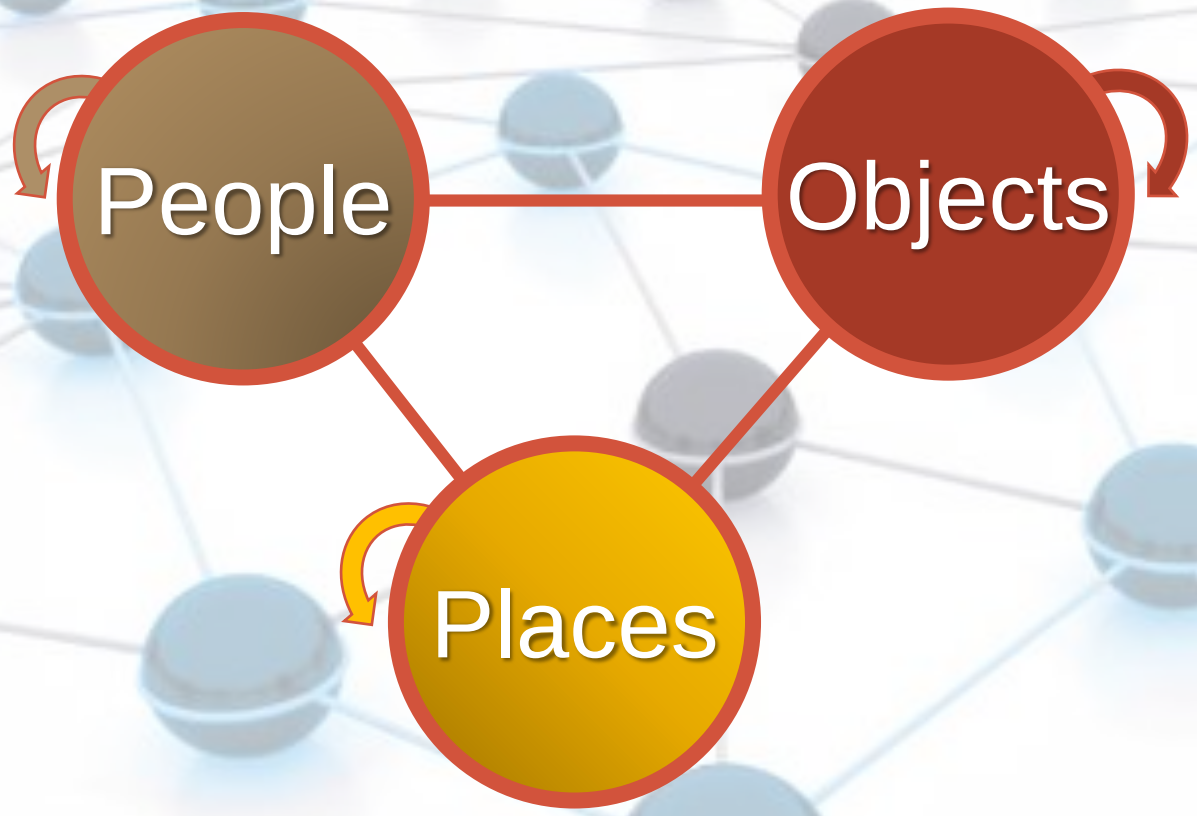
Simple example – graffiti collection

Data Transformation





Mining and analyzing Connections



…you just need to learn to recognize and analyze it

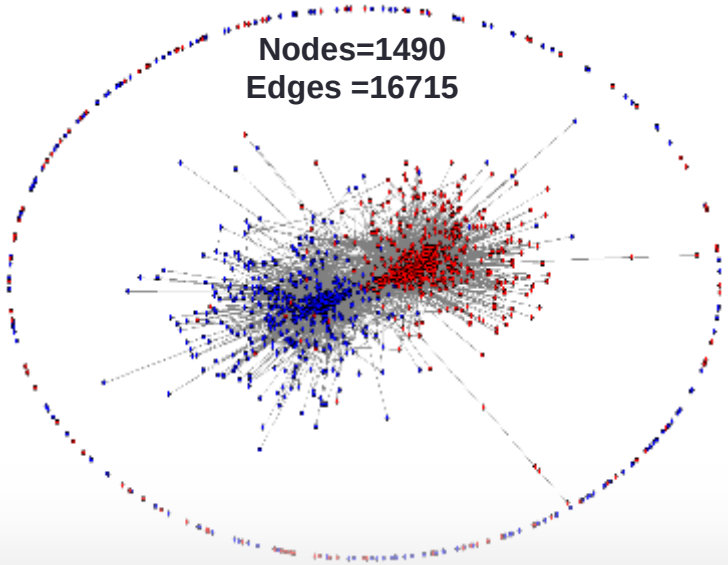
Mining social media connections

Simple example – political blogrolls test

Individual
Political Blogrolls

Data Transformation

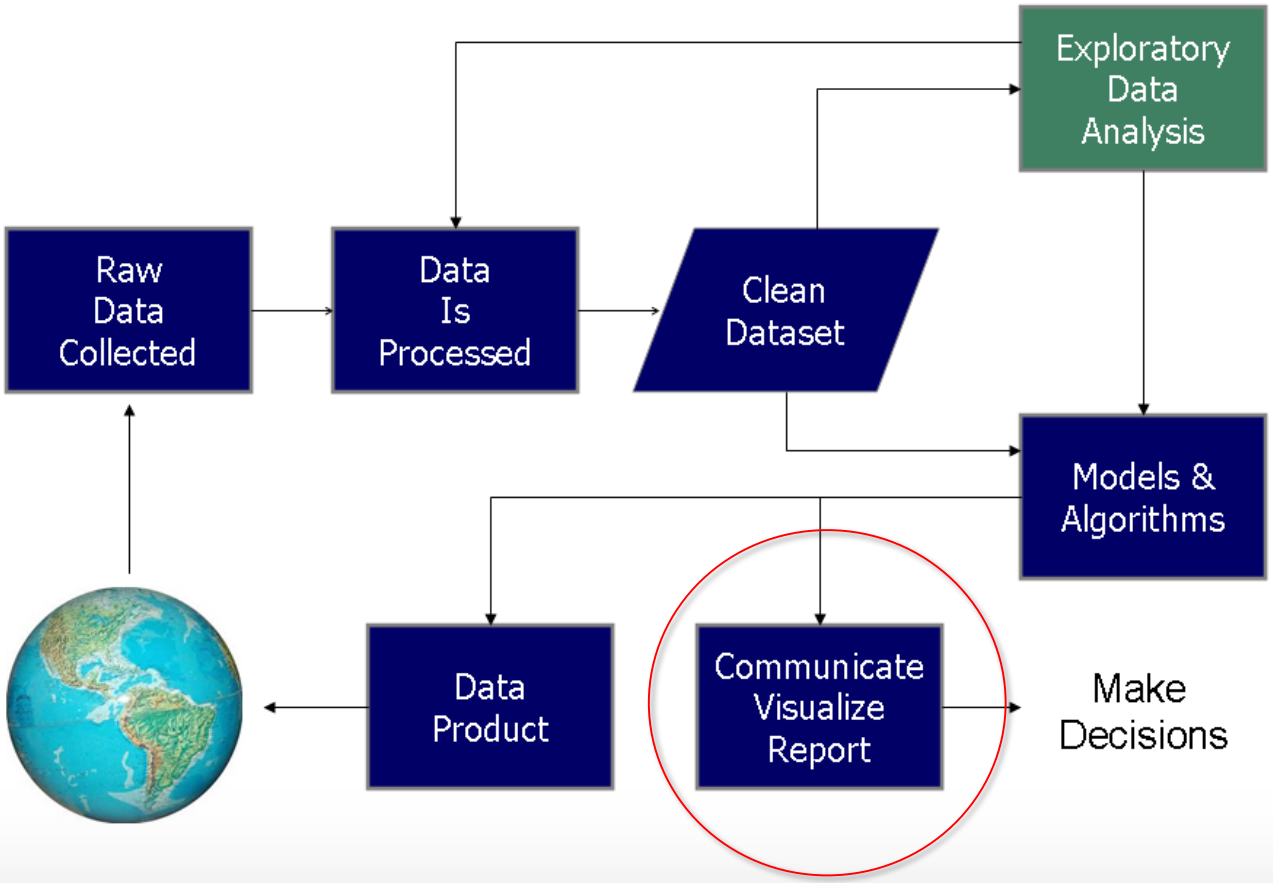
	Blog1	Blog2	Blog3	Blog4	...	BlogN
Blog1	-	1	0	0	...	0
Blog2	1	-	0	1	...	0
Blog3	0	0	-	1	...	1
Blog4	0	1	1	-	...	1
...	...	...	...	...	-	...
BlogN	0	0	1	1	...	-



Who links to whom?

Data Science Process

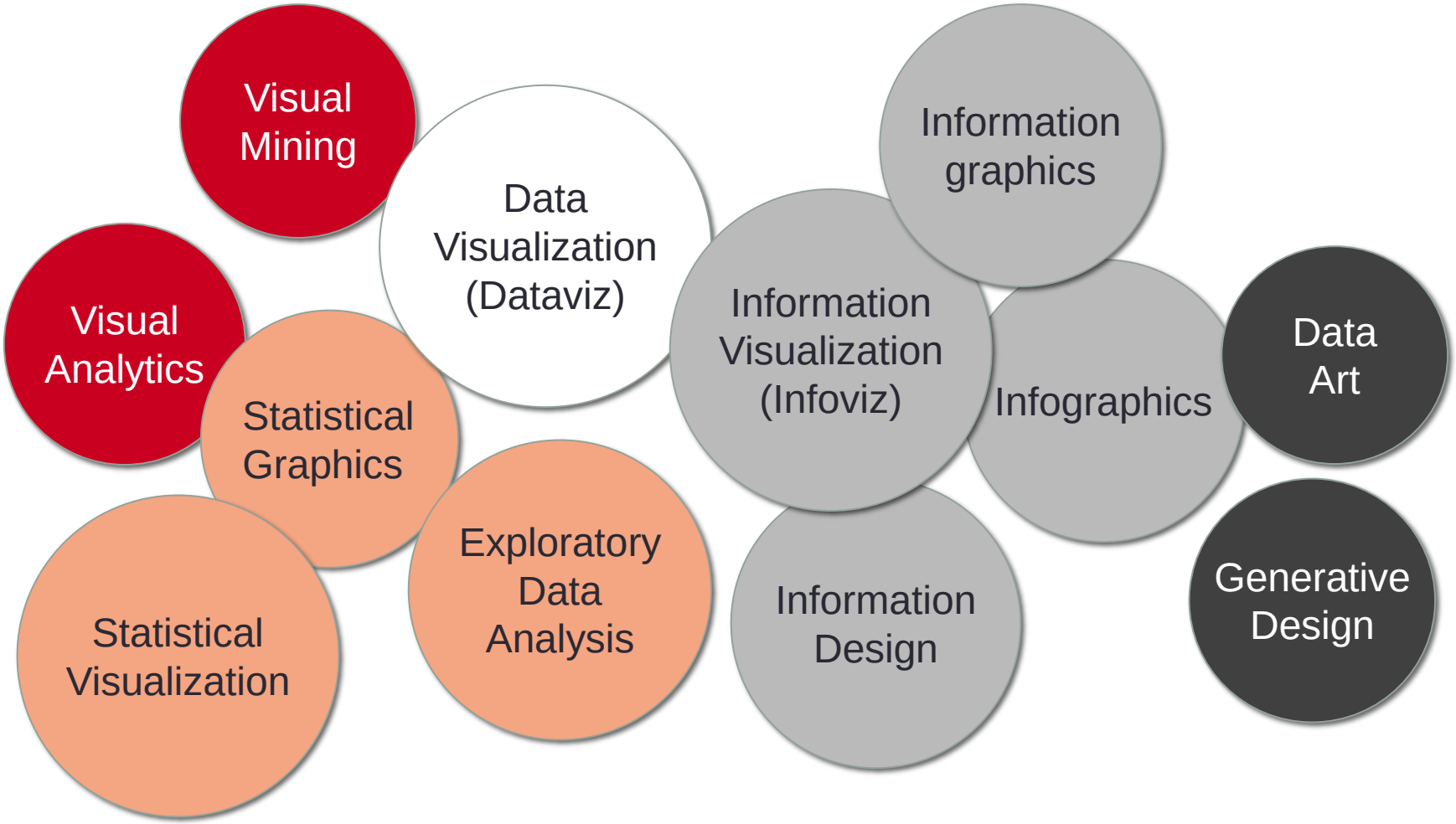
Mining and analysis workflow



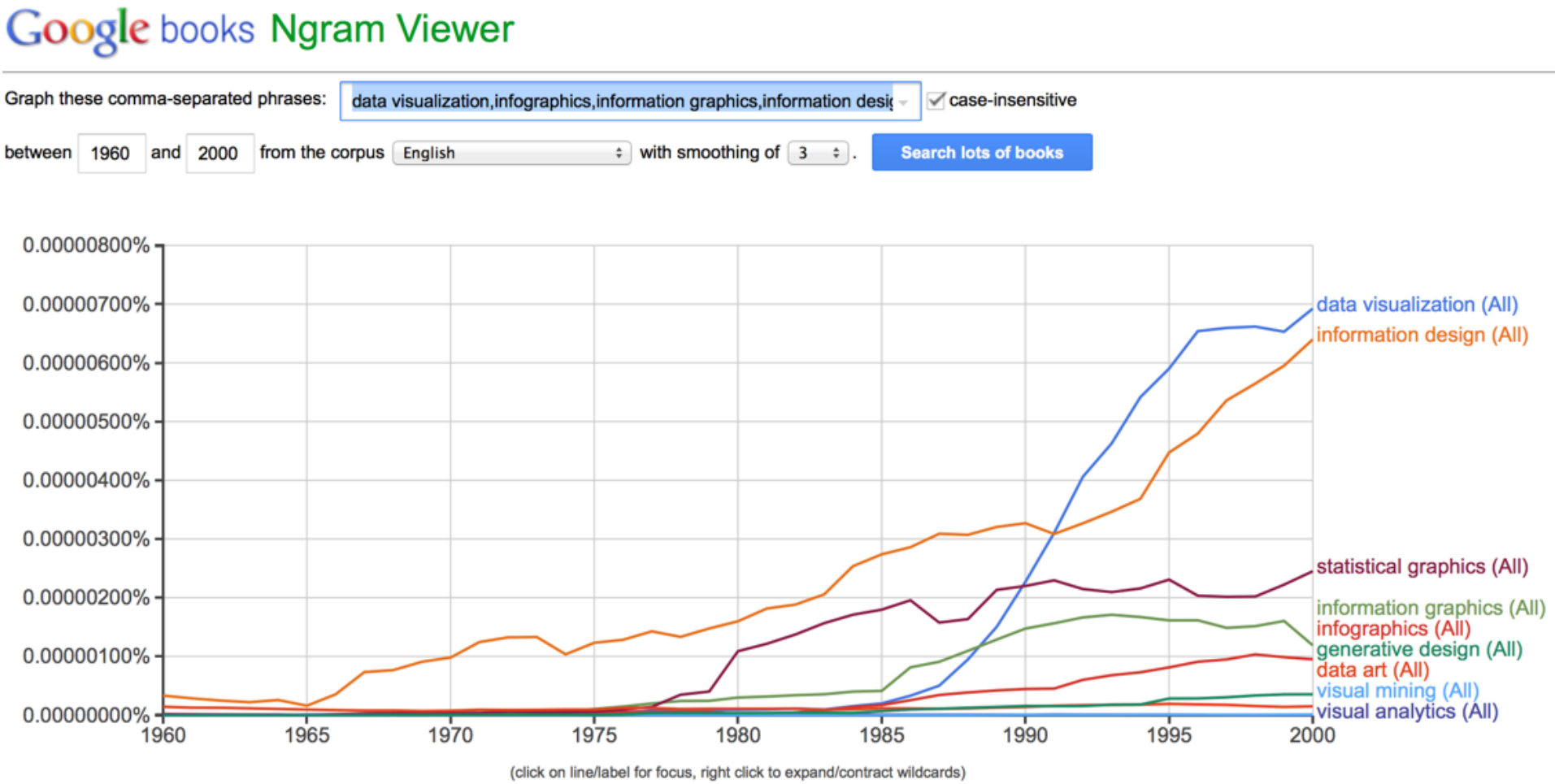
en.wikipedia.org/wiki/Data_visualization

Visualization by any other name…

Multiple terms with multiple definitions



Interest in visualization et al.



Interest in visualization et al.

Google Ngrams + XKCD | About | Source Code | Culturomics

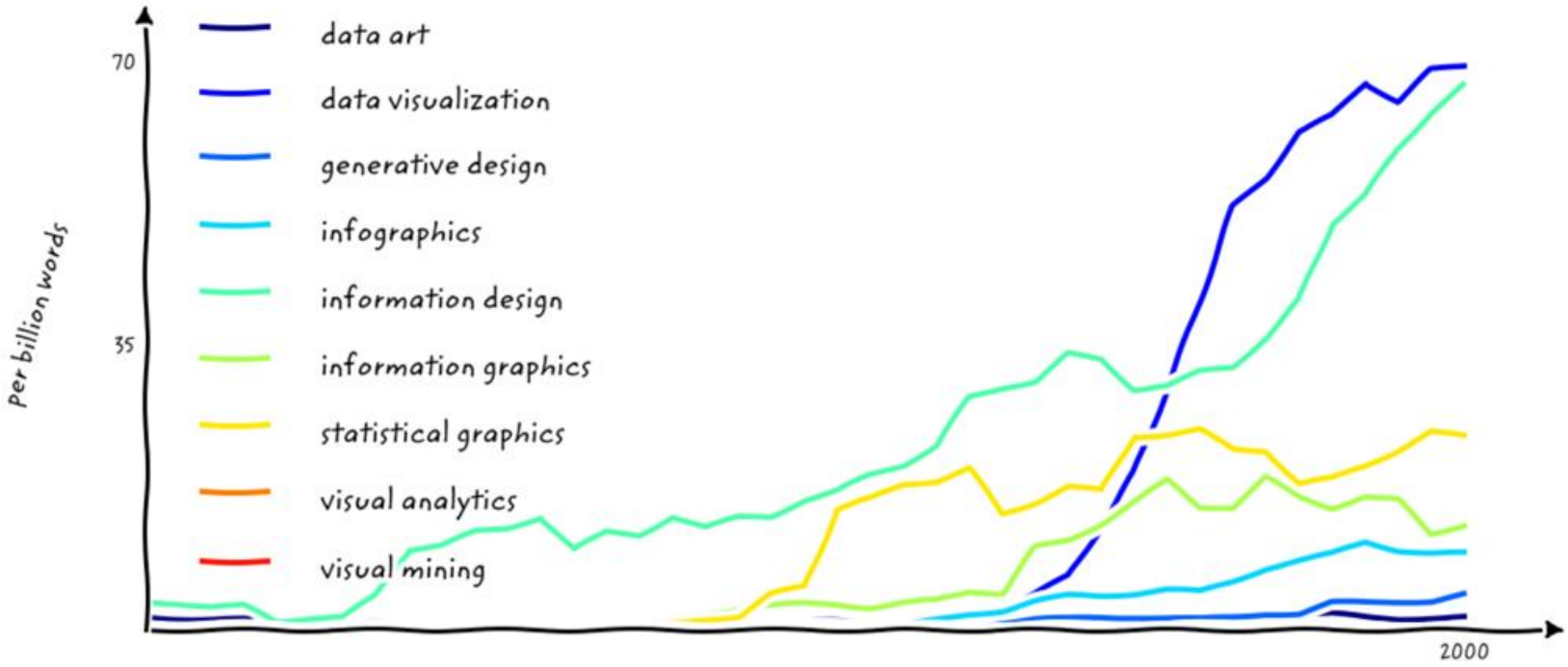
Plot Google Ngrams in XKCD Style

Graph these comma-separated phrases:

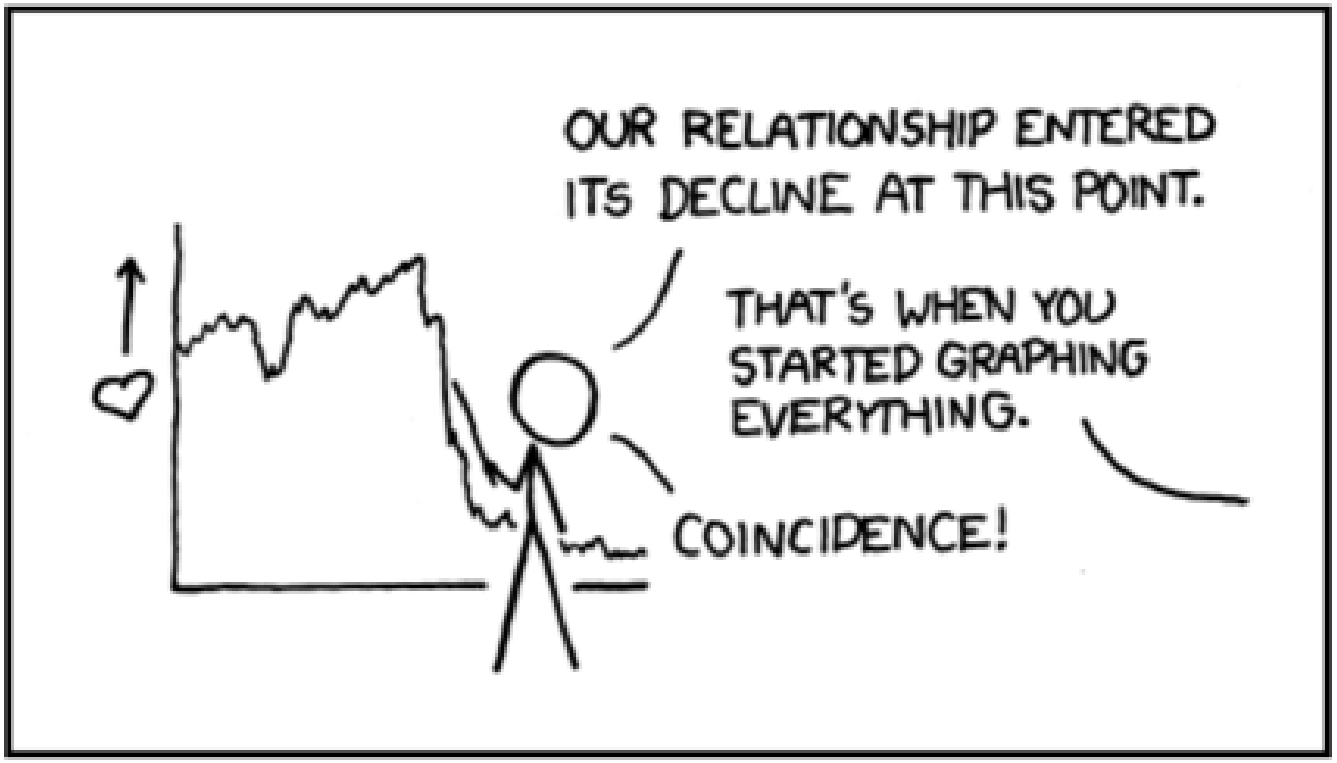
data visualization,infographics,information graphics,information design,visual analytics,statistical graphics,visual mining,data art,generative d

case-insensitive

between 1960 and 2000 from the corpus English with smoothing of 2 Search lots of books



Interest in Data Visualization and Infographics

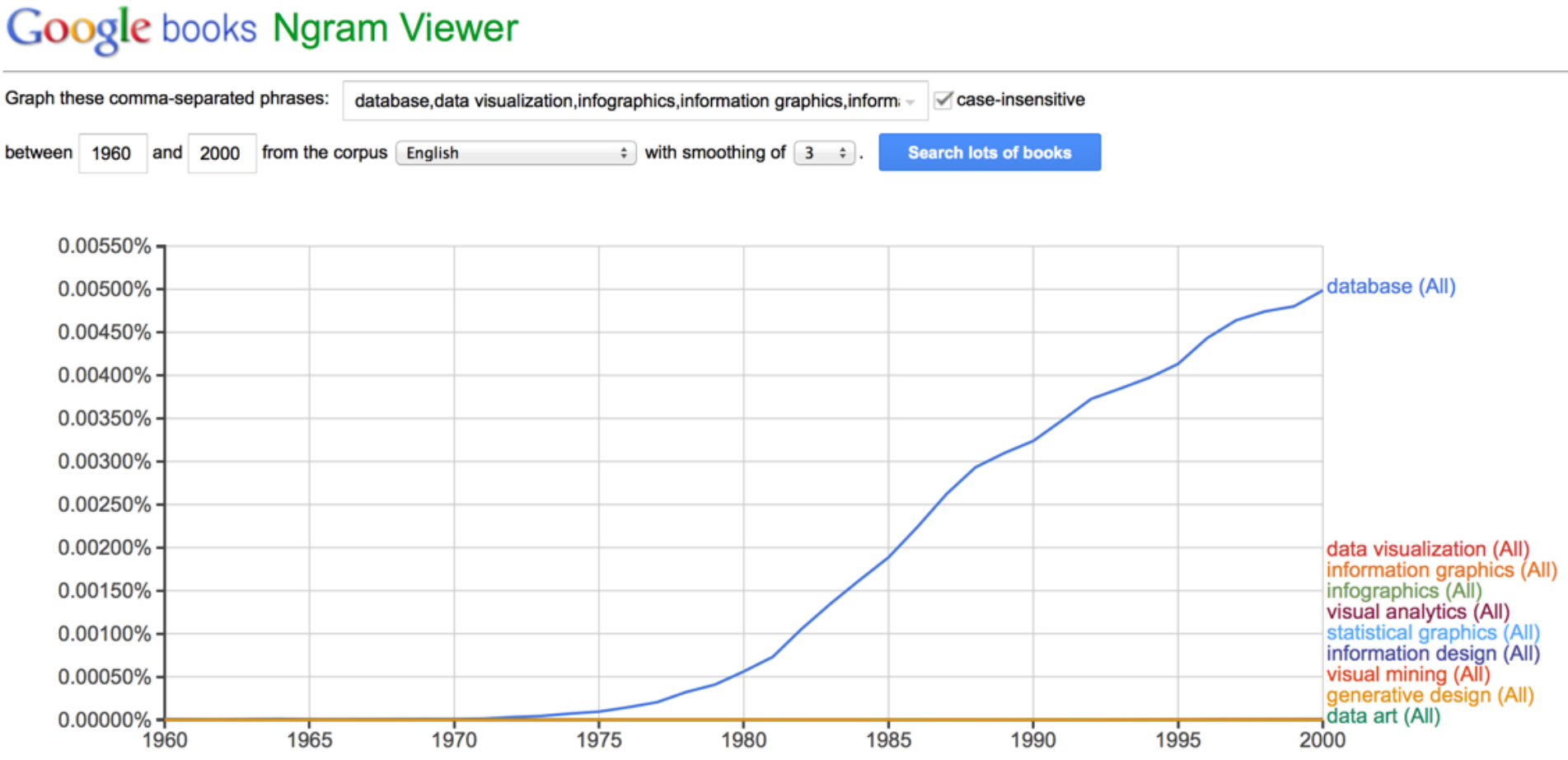


http://xkcd.com/523/

Randall

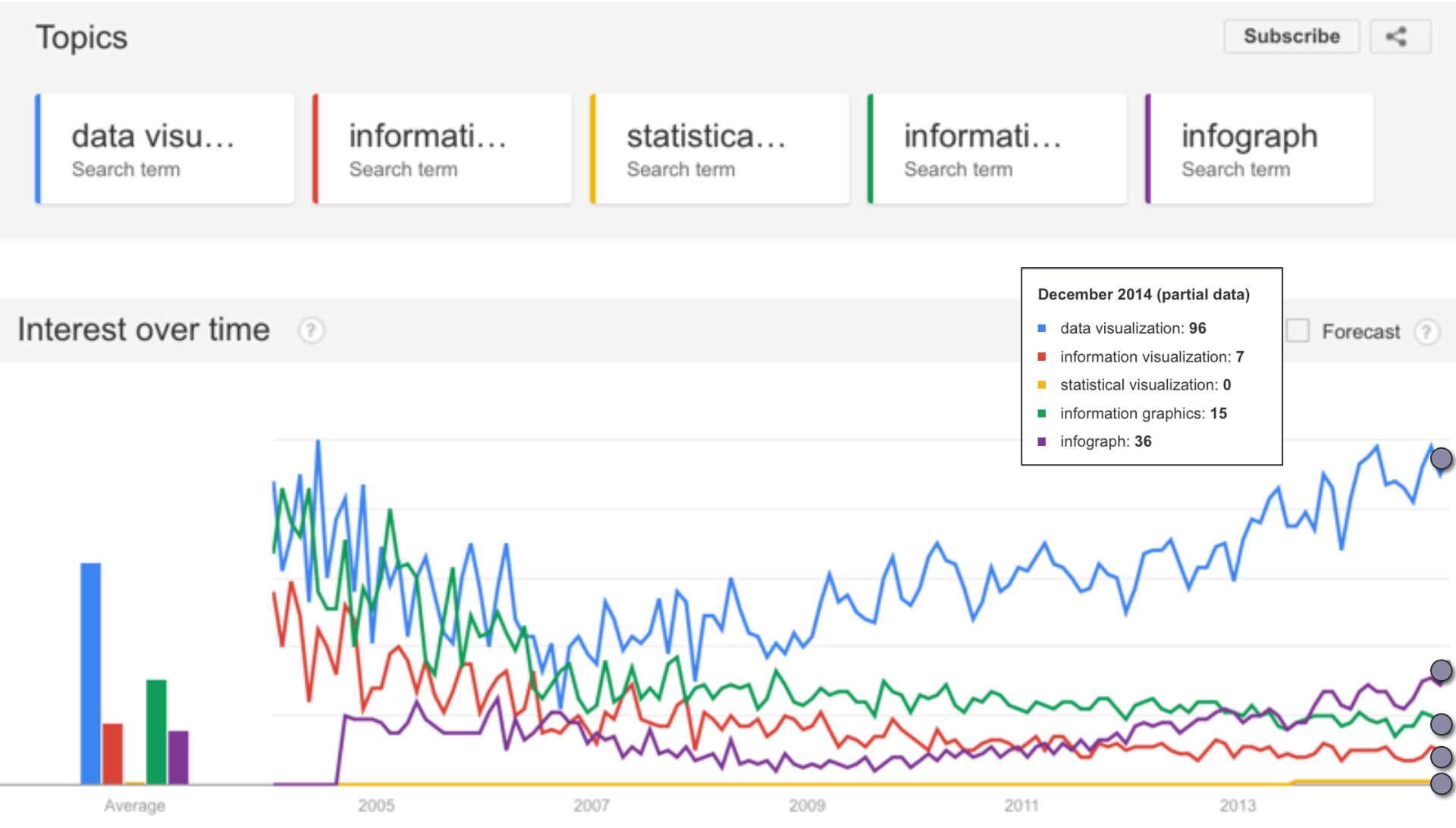
Interest in visualization et al.

a bit of perspective



Interest in visualization

Google Trends



Take one example

Data Visualization - same term, multiple definitions

- General term that describes any effort to help people understand the significance of data by placing it in a visual context.
- Overarching word for both the visual representation of data and the study of the presentation of data in a visual way.
- Pictorial representation of data that may take the form of an animation, a cloud, a map, a chart, or a simple picture.
- Study of the visual representation of data, meaning "information that has been abstracted in some schematic form, including attributes or variables for the units of information".
- Data visualization and information visualization refer to the use of computer-supported, interactive, visual representations of abstract data to amplify cognition

Take one example

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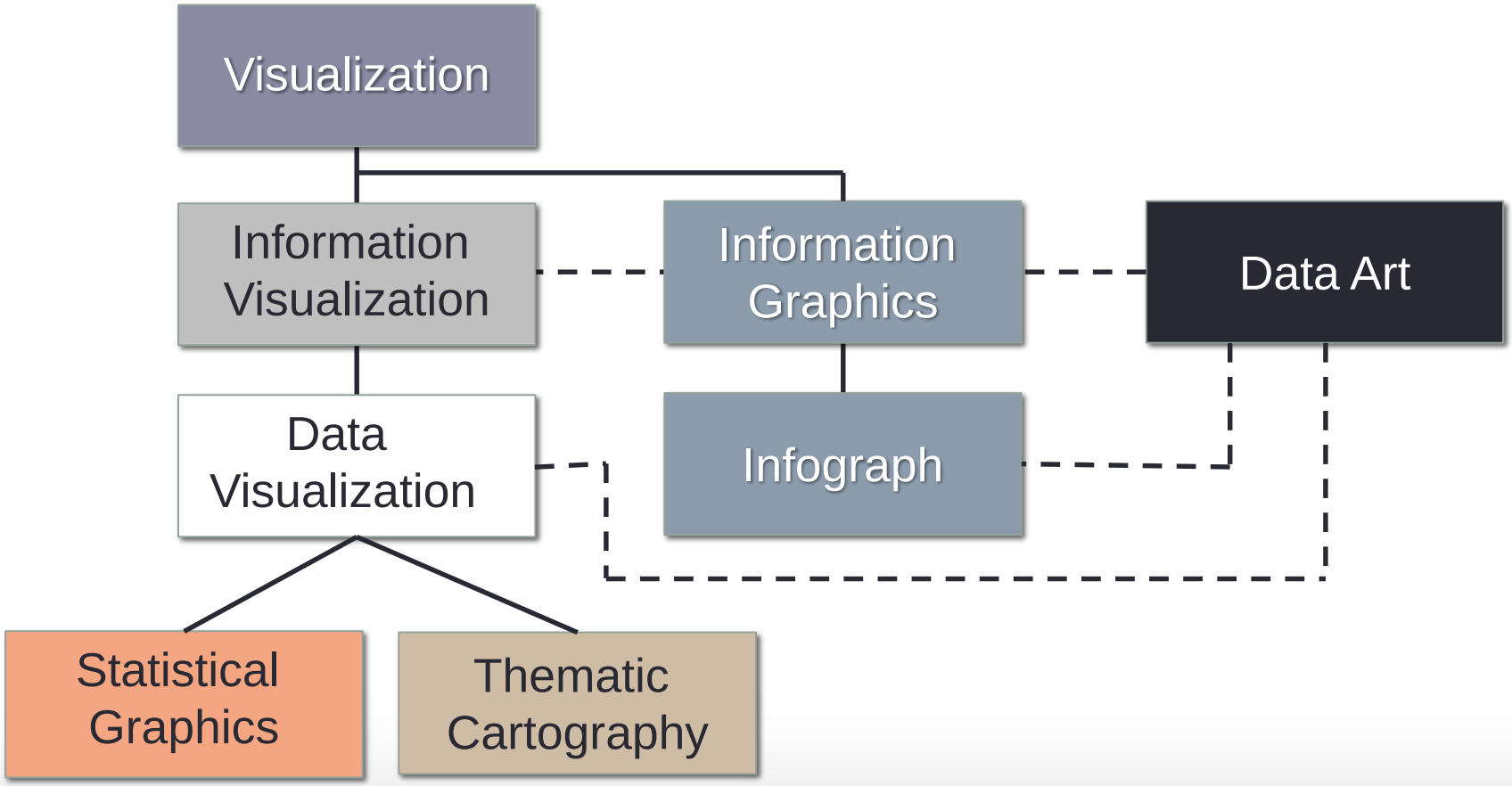
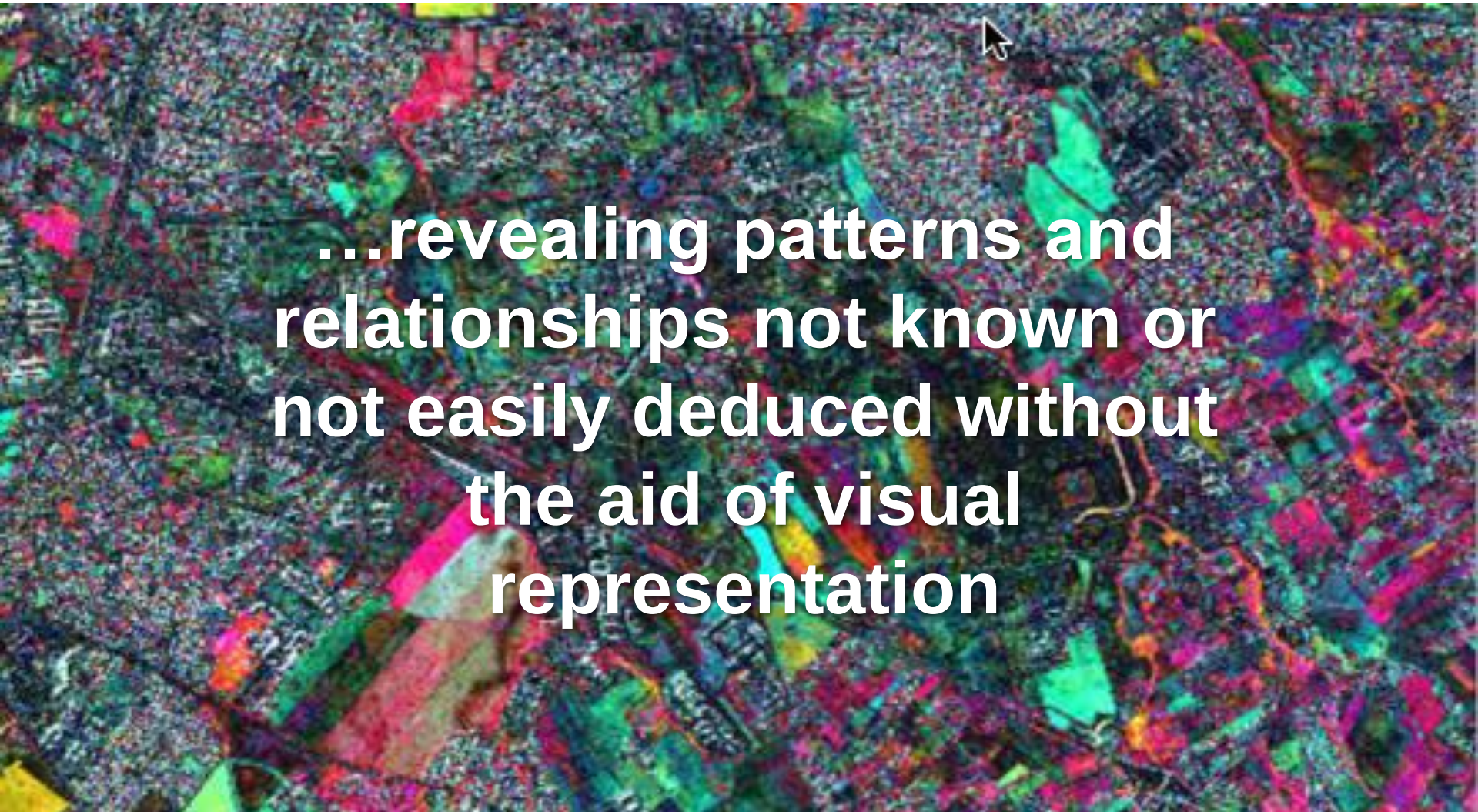
Interrelated Terms

One viewpoint



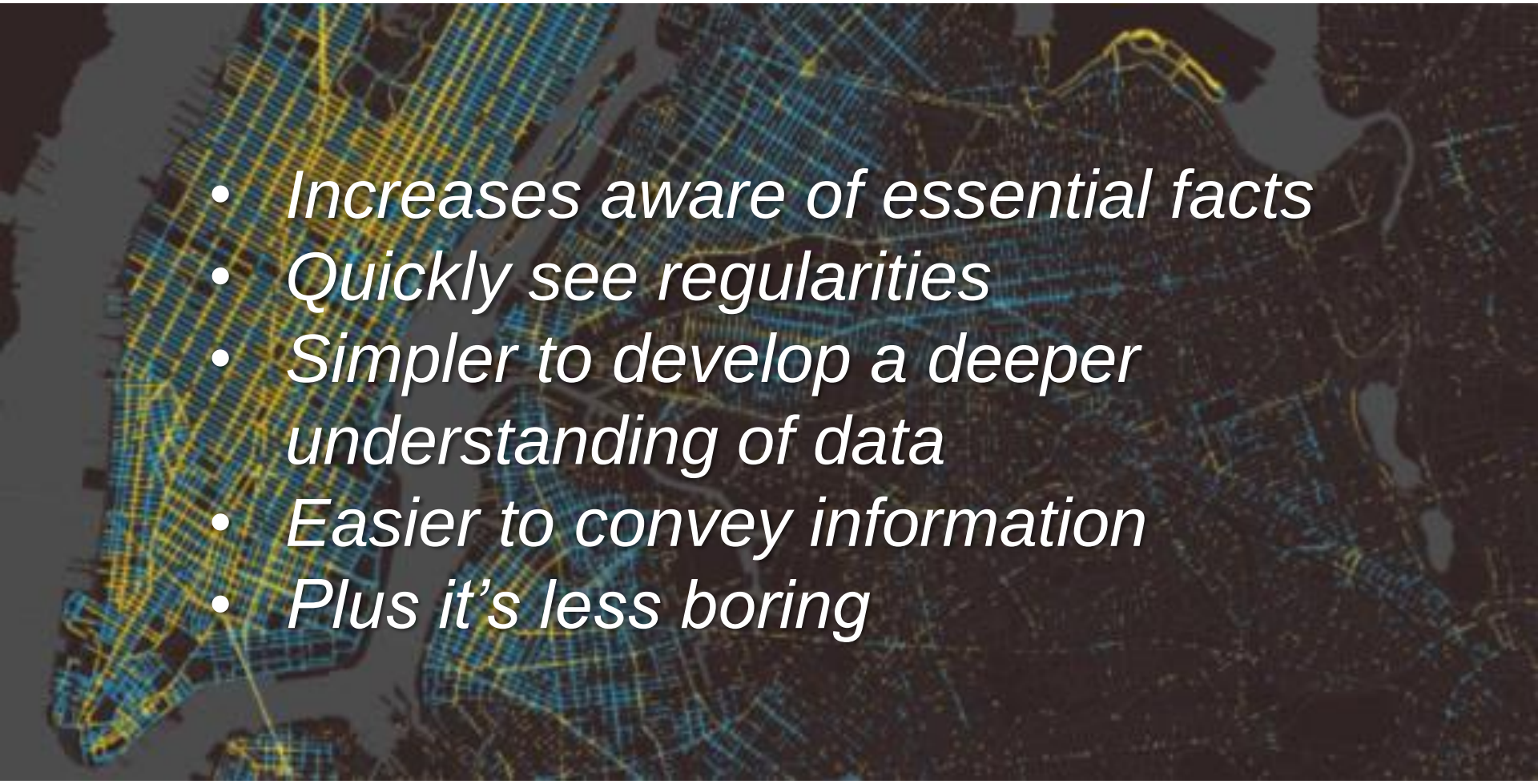
Purpose of Visualization

"…Insight, not art"



Benefits of Data Visualization

Some claims



- *Increases aware of essential facts*
- *Quickly see regularities*
- *Simpler to develop a deeper understanding of data*
- *Easier to convey information*
- *Plus it's less boring*

A <object1> is worth <#><object2>

A Drawing = 10 Pages in a Book

A Look = 1000 Words

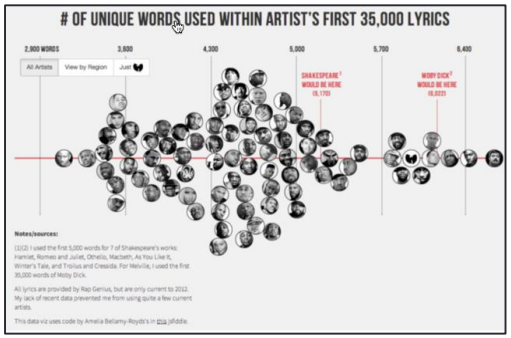
A Look = 100 Personal Letters/Ads

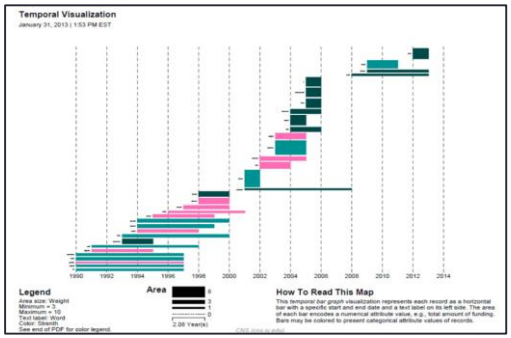
A Picture = 10,000 Words

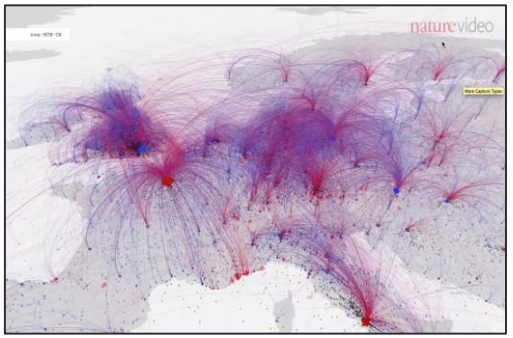
A Picture = 84.1 Words

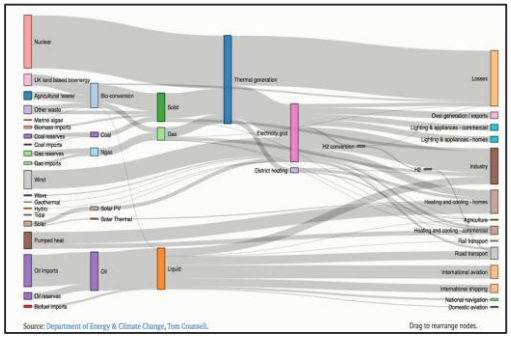
A picture tells a story just as well, or better, as a large amount of descriptive text.

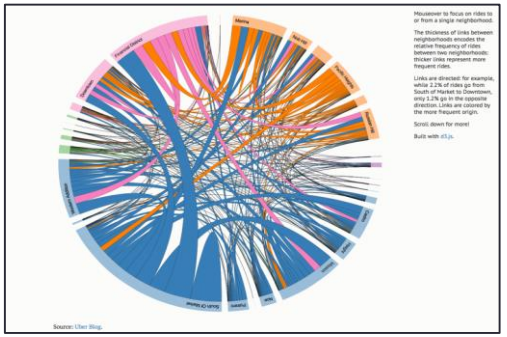
Is a visualization worth a 1000, 10000, 100000, … of words, links, numbers,…?

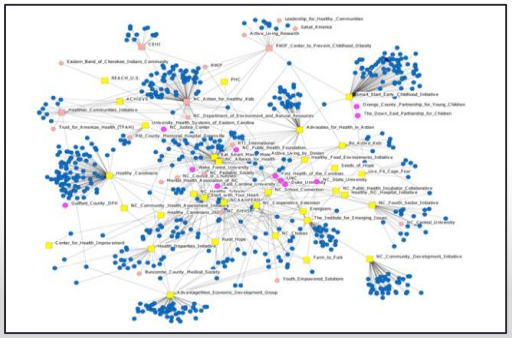


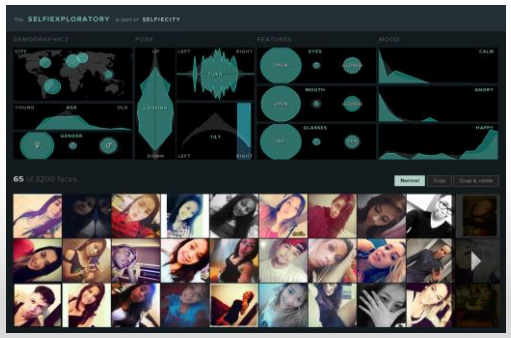


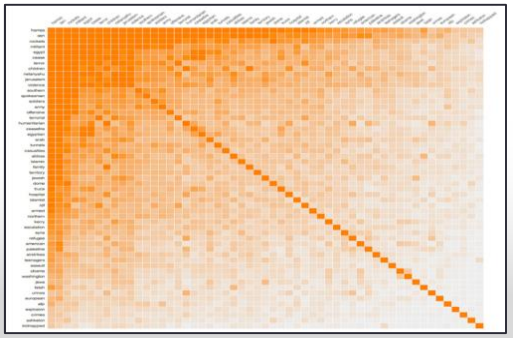












Some simple questions

Michelson-Morley data

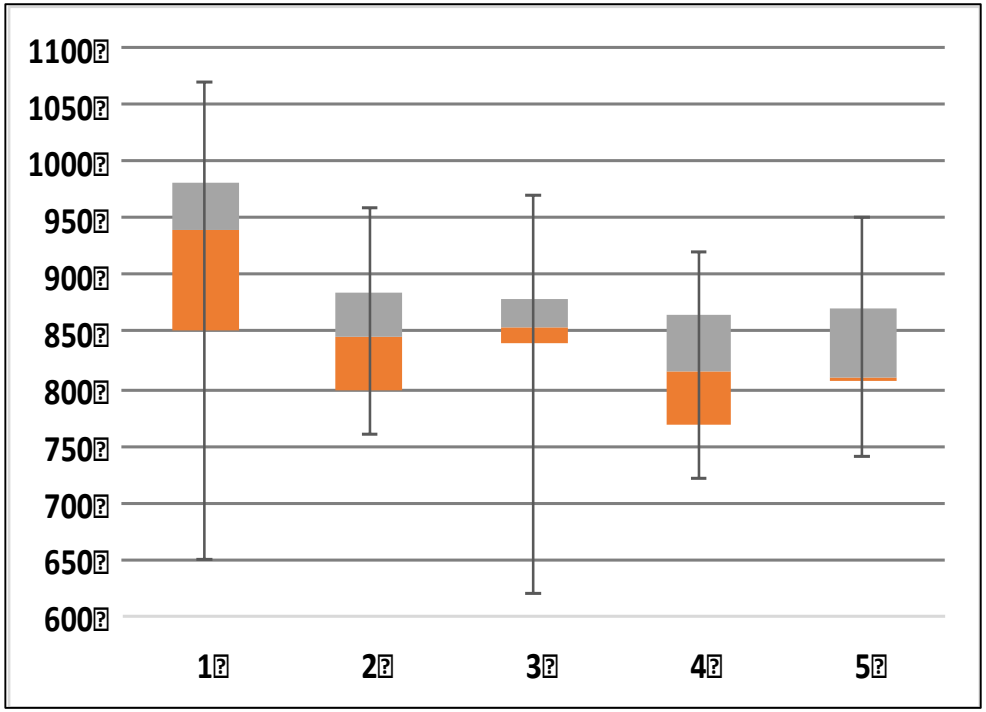
Run 1	Run 2	Run 3	Run 4	Run 5
850	960	880	890	890
740	940	880	810	840
900	960	880	810	780
1070	940	860	820	810
930	880	720	800	760
850	800	720	770	810
950	850	620	760	790
980	880	860	740	810
980	900	970	750	820
880	840	950	760	850
1000	830	880	910	870
980	790	910	920	870
930	810	850	890	810
650	880	870	860	740
760	880	840	880	810
810	830	840	720	940
1000	800	850	840	950
1000	790	840	850	800
960	760	840	850	810
960	800	840	780	870

What is the:

- Median value of Run 1?
- Minimum of Run 3? Max of Run 5?
- Which Run has the widest range?
- Which Run has the smallest interquartile range?
- …

http://nathanbrixius.wordpress.com/2014/03/10/beautiful-box-plots-in-excel-2013/

Some simple questions



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- …

http://nathanbrixius.wordpress.com/2014/03/10/beautiful-box-plots-in-excel-2013/

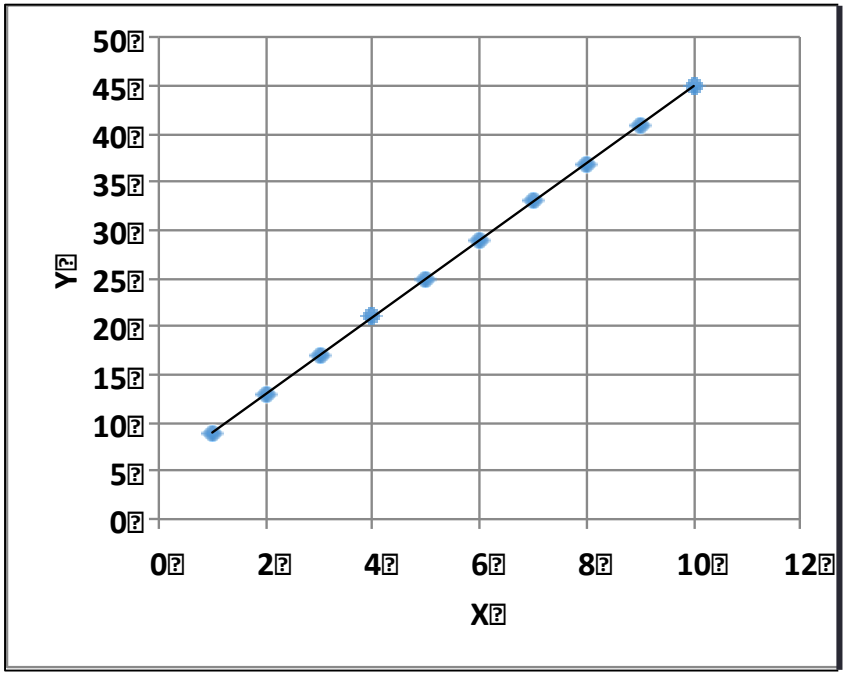
Some additional simple questions

X	Y
1	9
10	45
2	13
9	41
3	17
8	37
4	21
7	33
5	25
6	29

What is the relationship between X&Y?

- Upward linear
- Downward linear
- Curvilinear
- Basically random

Some additional simple questions



What is the relationship between X&Y?

- Upward linear
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Power of visualization

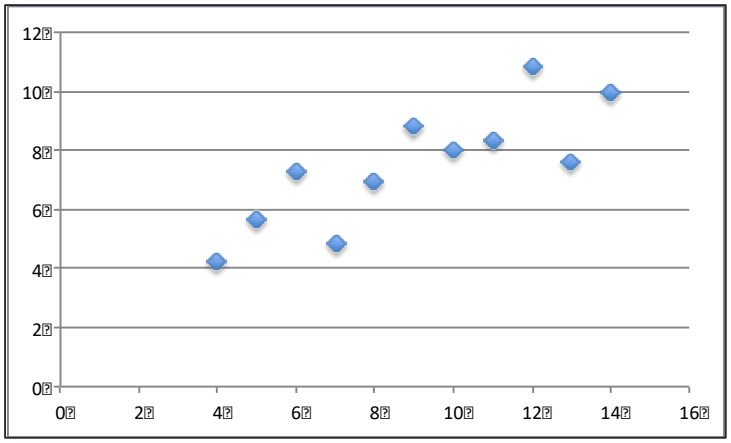
Are you familiar with this data?

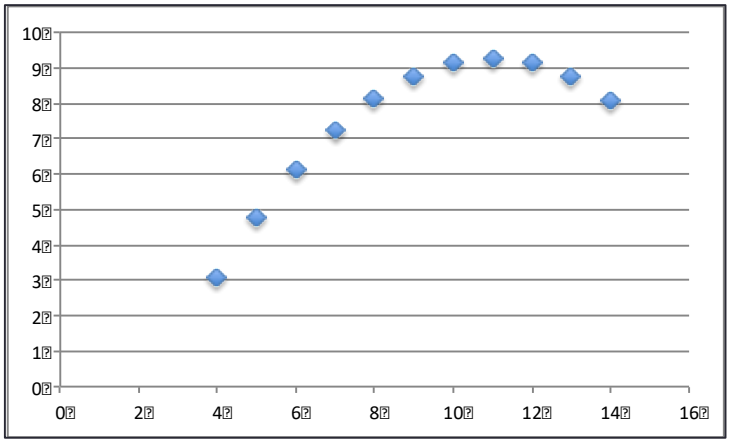
	DataSet1		DataSet2		DataSet3		DataSet4	
	X1	Y1	X2	Y2	X3	Y3	X4	X4
	10	8.04	10	9.14	10	7.46	8	6.58
	8	6.95	8	8.14	8	6.77	8	5.76
	13	7.58	13	8.74	13	12.74	8	7.71
	9	8.81	9	8.77	9	7.11	8	8.84
	11	8.33	11	9.26	11	7.81	8	8.47
	14	9.96	14	8.1	14	8.84	8	7.04
	6	7.24	6	6.13	6	6.08	8	5.25
	4	4.26	4	3.1	4	5.39	19	12.5
	12	10.84	12	9.13	12	8.15	8	5.56
	7	4.82	7	7.26	7	6.42	8	7.91
	5	5.68	5	4.74	5	5.73	8	6.89
Mean	9.00	7.50	9.00	7.50	9.00	7.50	9.00	7.50
Std.Dev.	3.16	1.94	3.16	1.94	3.16	1.94	3.16	1.94
Correlation	0.82		0.82		0.82		0.82	

The answer

Anscombe's Quartet (1973)

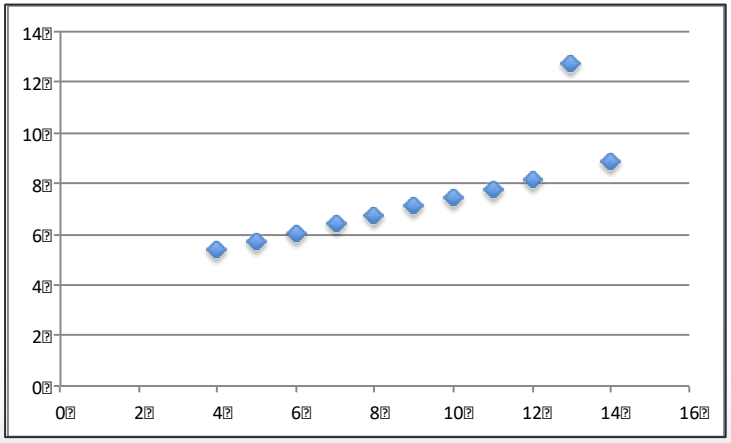
1

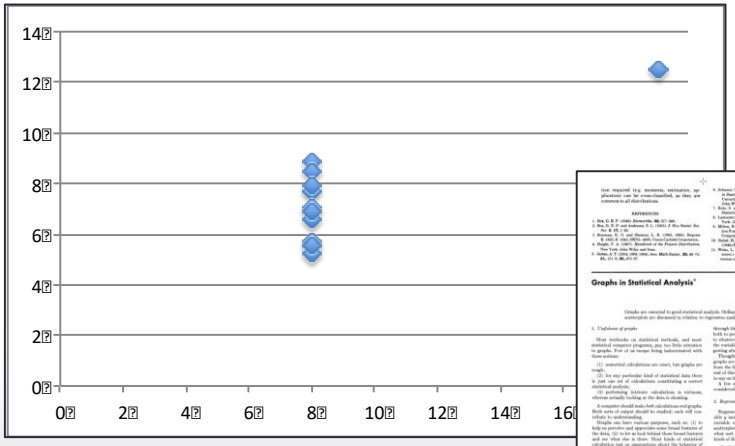




2

3





4

Graphs in Statistical Analysis*

F. J. ANSCOMBE**

A Picture is Worth a Thousand Numbers

Posted on July 10, 2014 by CFOC Admin

By Douglas A. Glenn, Deputy Chief Financial Officer, Department of the Interior

There is no doubt the Federal financial industry has made great gains in financial reporting since the passage of the CFO Act and Government Management Reform Act. Material weaknesses are less than half of what they were in the mid-1990s and all but one CFO Act Agency has achieved an audit opinion. I am extremely proud of our industry's accomplishments. What makes me even more proud is the unsung value our industry provides the American people. The cumulative, government-wide, cost of the Federal Financial Community totaled billions of dollars including our IT and audit friends - critical partners in our industry's success. If you compare this cost to the total budget we execute, we cost less than 1/3 of 1% of the total. I am confident that our internal controls, reconciliations, audit support, and other efforts have prevented Billions of dollars in fraud, waste, and abuse. Just imagine the fraud, waste, and abuse that would occur if we weren't reconciling, reviewing, comparing, approving, and reporting Federal financial activity. We offer a significant return on investment to the American taxpayers and we take significant pride in that accomplishment.

Reporting is a key part of our community and with the recent passage of the DATA Act, there have been many discussions about what our industry reports as key financial data and an equally important consideration on how we report the information. Typically we use spreadsheets and slide decks to share information but as fascinating as spreadsheets and slide decks are, they are cumbersome at best. At the Department of the Interior (DOI), we are pushing the boundaries of communicating quantitative information and are fans of the concept that "A picture is worth a thousand numbers". For example, with one picture we can show where our 2013 expenditures went, who they went to, and what they were for (see http://www.doi.gov/pfm/afr/2013/maps/index.cfm). It is a "heat map" of the United States where each State is shaded based on the DOI funding disbursed to that State. If you run your cursor over a State, you can see the total expenditures to that State, the top object classes related to those expenditures, or who were the top recipients (i.e., vendors) of our disbursements.

News/Events
- Blog
- Events
- News

Archives
- November 2014
- October 2014
- August 2014
- July 2014
- June 2014
- May 2014
- April 2014
- January 2014
- December 2013

A Picture is Worth a Thousand Numbers | The Chief Financial Officers Council

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A Picture is Worth a Thousand Numbers

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Posted on July 10, 2014 by CFOC Admin

By Douglas A. Glenn, Deputy Chief Financial Officer, Department of the Interior

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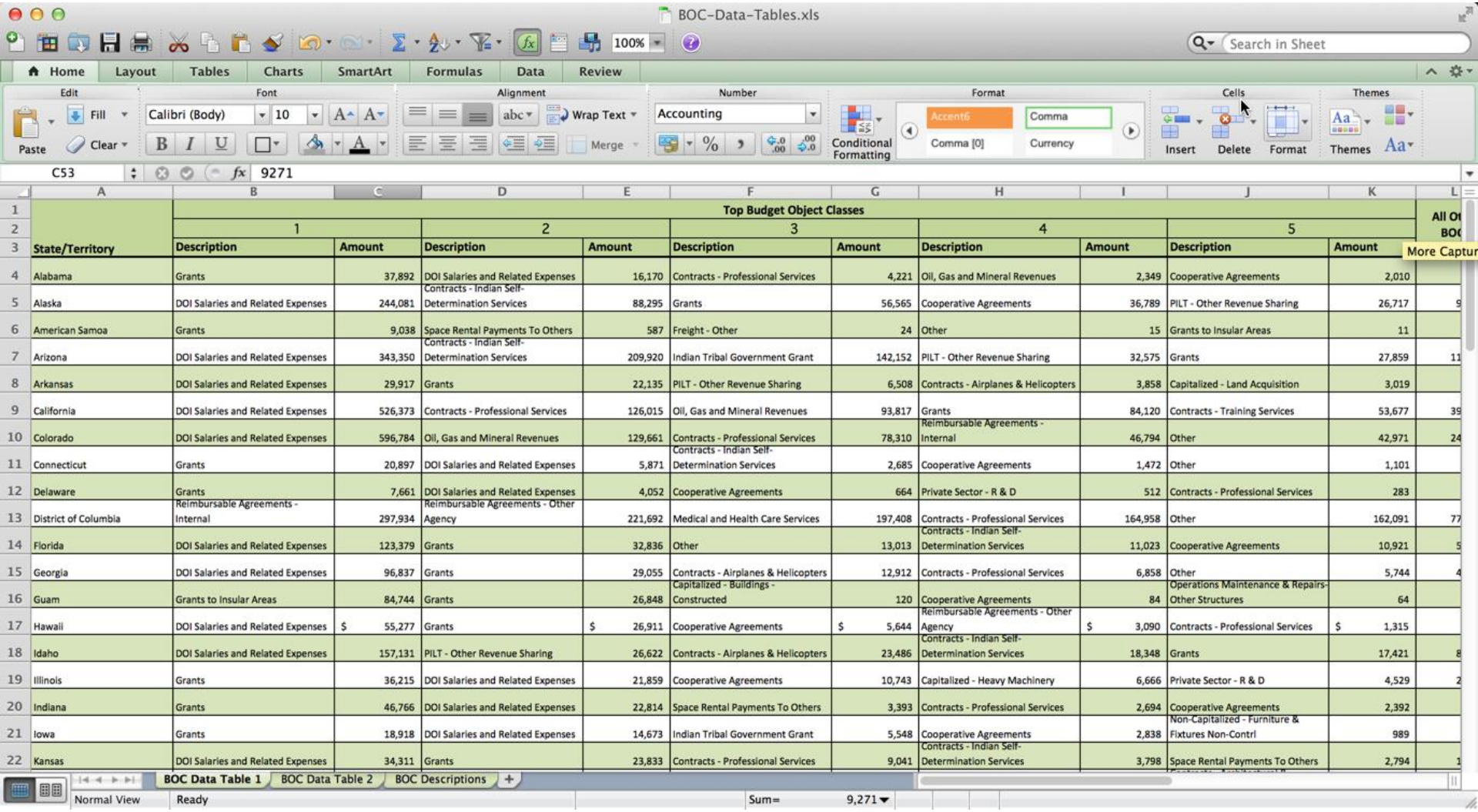
News/Events

- Blog
- Events
- News

- January 2014
- December 2013

To illustrate the value of pictures versus spreadsheets, I handed out the 60 row spreadsheet that supports the picture in the heat map noted above and asked a room of 25 accountants: "Who were the top 10 states receiving DOI disbursements?" They dutifully scanned their spreadsheets and after 106 seconds, the first brave hand was raised and the accountant correctly answered the question. Next a previously selected volunteer was pulled (back) into the room, shown the heat map, and asked the same question. The one volunteer (versus 25 other accountants with spreadsheets) reached the same conclusion, to the same question, in 1/3 of the time. Such is the power of pictures versus spreadsheets.

DOI Spreadsheet


BOC-Data-Tables.xls

Search in Sheet

Home | Layout | Tables | Charts | SmartArt | Formulas | Data | Review

Edit | Font | Alignment | Number | Format | Cells | Themes

Paste | Fill | Clear | Calibri (Body) | 10 | Wrap Text | Merge | Accounting | Conditional Formatting | Accent6 | Comma | Comma [0] | Currency | Insert | Delete | Format | Themes

C53 | 9271

	A	B	C	D	E	F	G	H	I	J	K	L
1		Top Budget Object Classes										All Ot
2		1		2		3		4		5		BOC
3	State/Territory	Description	Amount	Description	Amount	Description	Amount	Description	Amount	Description	Amount	More Captur
4	Alabama	Grants	37,892	DOI Salaries and Related Expenses	16,170	Contracts - Professional Services	4,221	Oil, Gas and Mineral Revenues	2,349	Cooperative Agreements	2,010	
5	Alaska	DOI Salaries and Related Expenses	244,081	Contracts - Indian Self-Determination Services	88,295	Grants	56,565	Cooperative Agreements	36,789	PILT - Other Revenue Sharing	26,717	9
6	American Samoa	Grants	9,038	Space Rental Payments To Others	587	Freight - Other	24	Other	15	Grants to Insular Areas	11	
7	Arizona	DOI Salaries and Related Expenses	343,350	Contracts - Indian Self-Determination Services	209,920	Indian Tribal Government Grant	142,152	PILT - Other Revenue Sharing	32,575	Grants	27,859	11
8	Arkansas	DOI Salaries and Related Expenses	29,917	Grants	22,135	PILT - Other Revenue Sharing	6,508	Contracts - Airplanes & Helicopters	3,858	Capitalized - Land Acquisition	3,019	
9	California	DOI Salaries and Related Expenses	526,373	Contracts - Professional Services	126,015	Oil, Gas and Mineral Revenues	93,817	Grants	84,120	Contracts - Training Services	53,677	39
10	Colorado	DOI Salaries and Related Expenses	596,784	Oil, Gas and Mineral Revenues	129,661	Contracts - Professional Services	78,310	Reimbursable Agreements - Internal	46,794	Other	42,971	24
11	Connecticut	Grants	20,897	DOI Salaries and Related Expenses	5,871	Contracts - Indian Self-Determination Services	2,685	Cooperative Agreements	1,472	Other	1,101	
12	Delaware	Grants	7,661	DOI Salaries and Related Expenses	4,052	Cooperative Agreements	664	Private Sector - R & D	512	Contracts - Professional Services	283	
13	District of Columbia	Reimbursable Agreements - Internal	297,934	Reimbursable Agreements - Other Agency	221,692	Medical and Health Care Services	197,408	Contracts - Professional Services	164,958	Other	162,091	77
14	Florida	DOI Salaries and Related Expenses	123,379	Grants	32,836	Other	13,013	Contracts - Indian Self-Determination Services	11,023	Cooperative Agreements	10,921	5
15	Georgia	DOI Salaries and Related Expenses	96,837	Grants	29,055	Contracts - Airplanes & Helicopters	12,912	Contracts - Professional Services	6,858	Other	5,744	4
16	Guam	Grants to Insular Areas	84,744	Grants	26,848	Capitalized - Buildings - Constructed	120	Cooperative Agreements	84	Operations Maintenance & Repairs-Other Structures	64	
17	Hawaii	DOI Salaries and Related Expenses	$ 55,277	Grants	$ 26,911	Cooperative Agreements	$ 5,644	Reimbursable Agreements - Other Agency	$ 3,090	Contracts - Professional Services	$ 1,315	
18	Idaho	DOI Salaries and Related Expenses	157,131	PILT - Other Revenue Sharing	26,622	Contracts - Airplanes & Helicopters	23,486	Contracts - Indian Self-Determination Services	18,348	Grants	17,421	8
19	Illinois	Grants	36,215	DOI Salaries and Related Expenses	21,859	Cooperative Agreements	10,743	Capitalized - Heavy Machinery	6,666	Private Sector - R & D	4,529	2
20	Indiana	Grants	46,766	DOI Salaries and Related Expenses	22,814	Space Rental Payments To Others	3,393	Contracts - Professional Services	2,694	Cooperative Agreements	2,392	
21	Iowa	Grants	18,918	DOI Salaries and Related Expenses	14,673	Indian Tribal Government Grant	5,548	Cooperative Agreements	2,838	Non-Capitalized - Furniture & Fixtures Non-Contrl	989	
22	Kansas	DOI Salaries and Related Expenses	34,311	Grants	23,833	Contracts - Professional Services	9,041	Contracts - Indian Self-Determination Services	3,798	Space Rental Payments To Others	2,794	1

BOC Data Table 1 | BOC Data Table 2 | BOC Descriptions

Normal View | Ready | Sum= 9,271

FY 2013 Department of the Interior Data Maps

www.doi.gov/pfm/afr/2013/maps/index.cfm

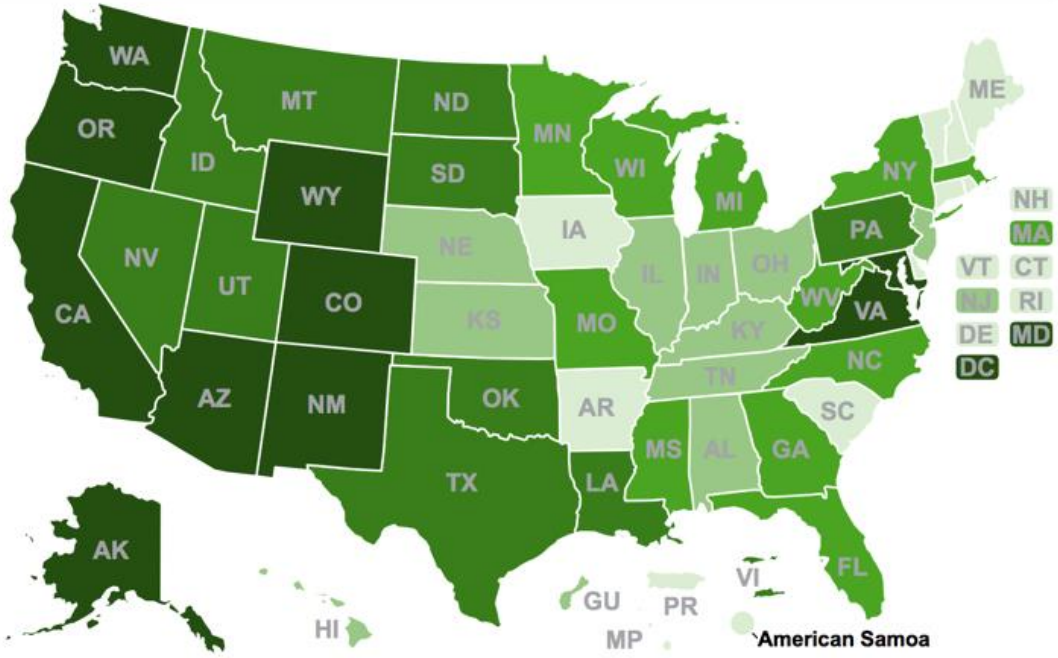
Web Slice Gallery Apple Bing Google Yahoo st luke's m...oogle Search

A Picture is Worth a Thousand Numbers | The Chief Financi... | FY 2013 Department of the Interior Data Maps | FY 2013 Department of the Interior Data Maps

FY 2013 Department of the Interior Data Maps

Select Map Data:

Expenditures by Budget Object Class | **Expenditures by Recipient** | **Oil and Gas Petroleum Royalties**



Domestic Expenditures by State and Budget Object Class (in thousands)

$0 --- $72,000	$72,001 --- $119,000	$119,001 --- $257,000	$257,001 --- $450,000	$450,001 --- $1,819,000

FY 2013 Department of the Interior Data Maps

Select Map Data:

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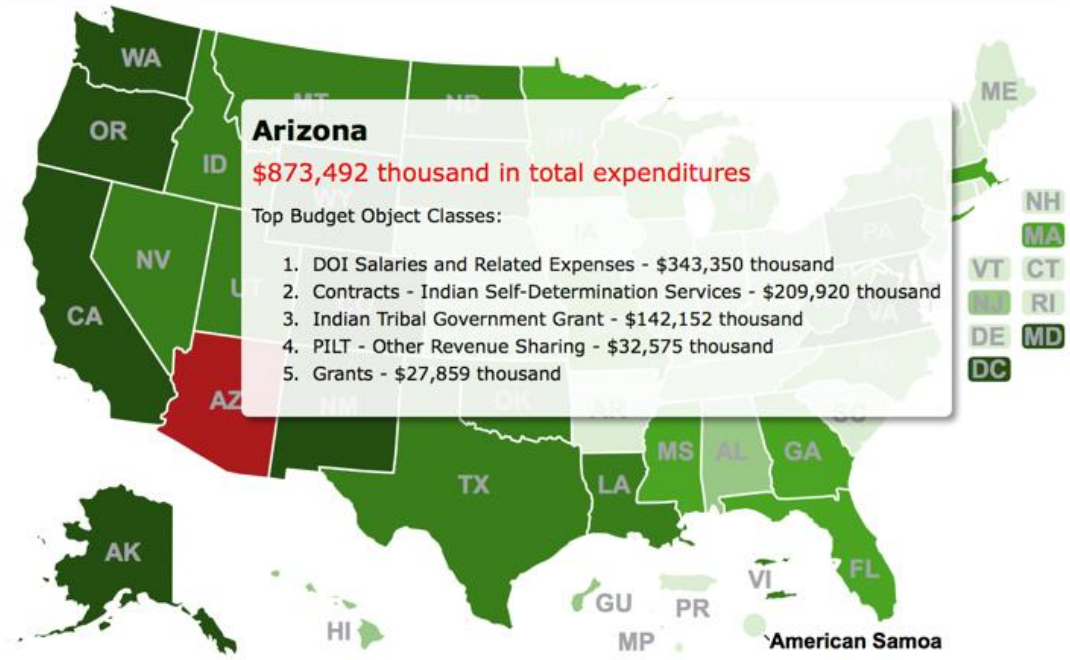

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$0 --- $72,000	$72,001 --- $119,000	$119,001 --- $257,000	$257,001 --- $450,000	$450,001 --- $1,819,000

A visualization is worth a 100 words, but a few numbers are worth 1 visualization?

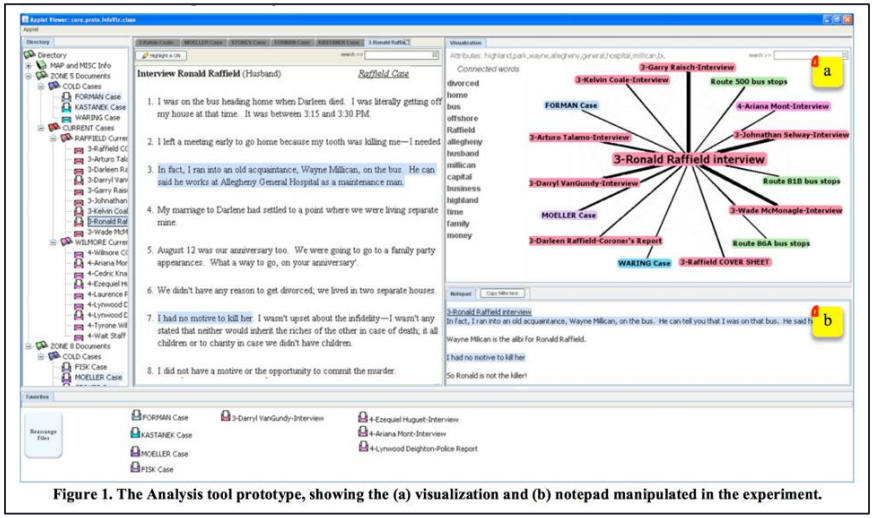


Figure 1. The Analysis tool prototype, showing the (a) visualization and (b) notepad manipulated in the experiment.

Feature	Serial Killer Identification (%)	Clue Recall (0 to 9)	Relationship Detection (0 to 1)	Time Spent on Features (%)	Perceived Feature Usefulness (0 to 5)
Vis. Only	**90** (SD=10)	**4.5** (SD=0.34)	**0.85** (SD=0.07)	12.61 (SD=1.97)	3.66 (SD=0.44)
Notepad Only	30 (SD=15)	1.4 (SD=0.47)	0.35 (SD=0.10)	8.64 (SD=2.82)	3.90 (SD=0.37)
Visualization and Notepad	70 (SD=15)	3.9 (SD=0.73)	0.60 (SD=0.10)	V:**16.11** (SD=5.98) N:14.61 (SD=6.01)	V:**4.30** (SD=0.21) N:3.70 (SD=0.42)
Control	50 (SD=16)	2.0 (SD=0.63)	0.35 (SD=0.10)	N/A	N/A

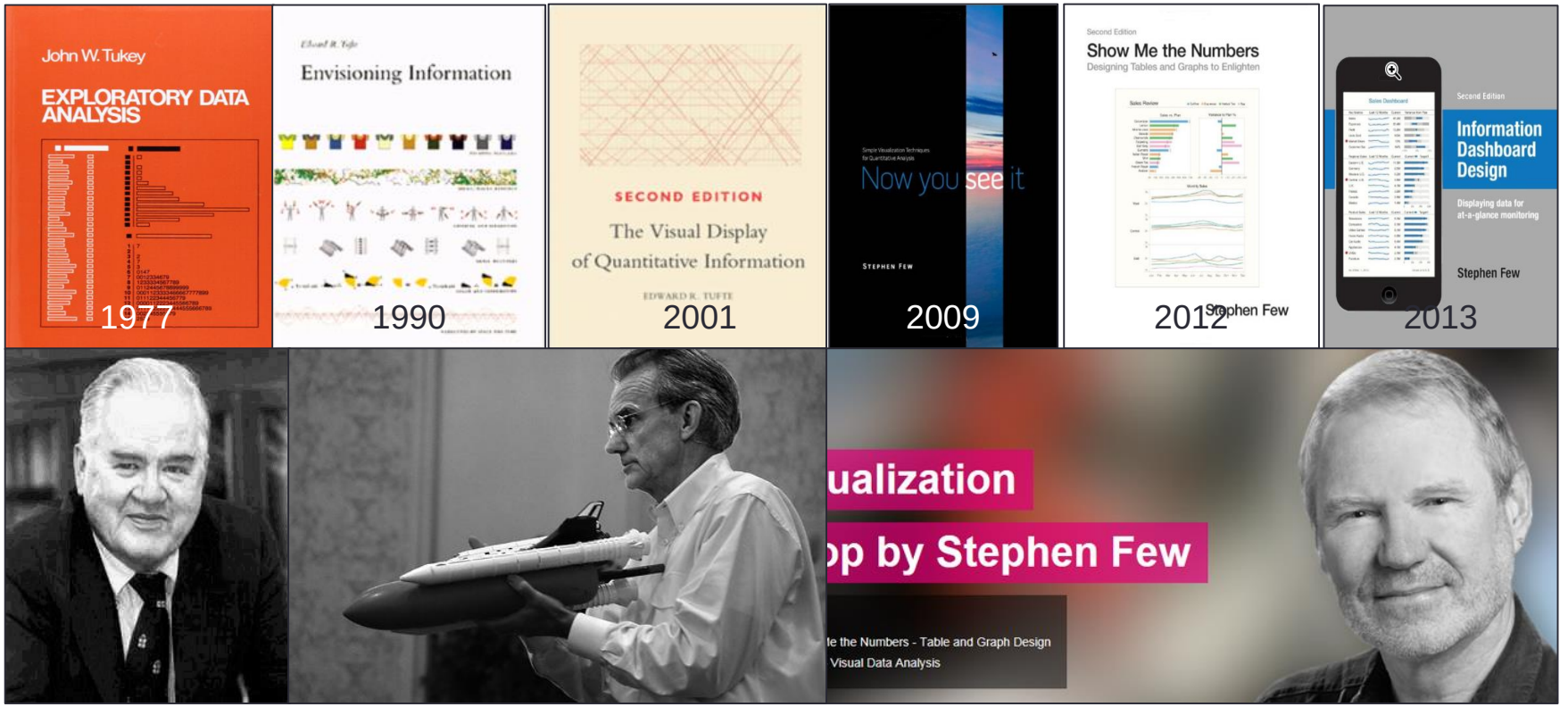
Table 1 Descriptive Summary (Means and Std. Deviations) across the four conditions for the five measures

Effects of Visualization and Note-Taking on Sensemaking and Analysis. Nitesh Goyal et al. (CHI 2013)

A fundamental clash
Data Art vs. Data Visualization

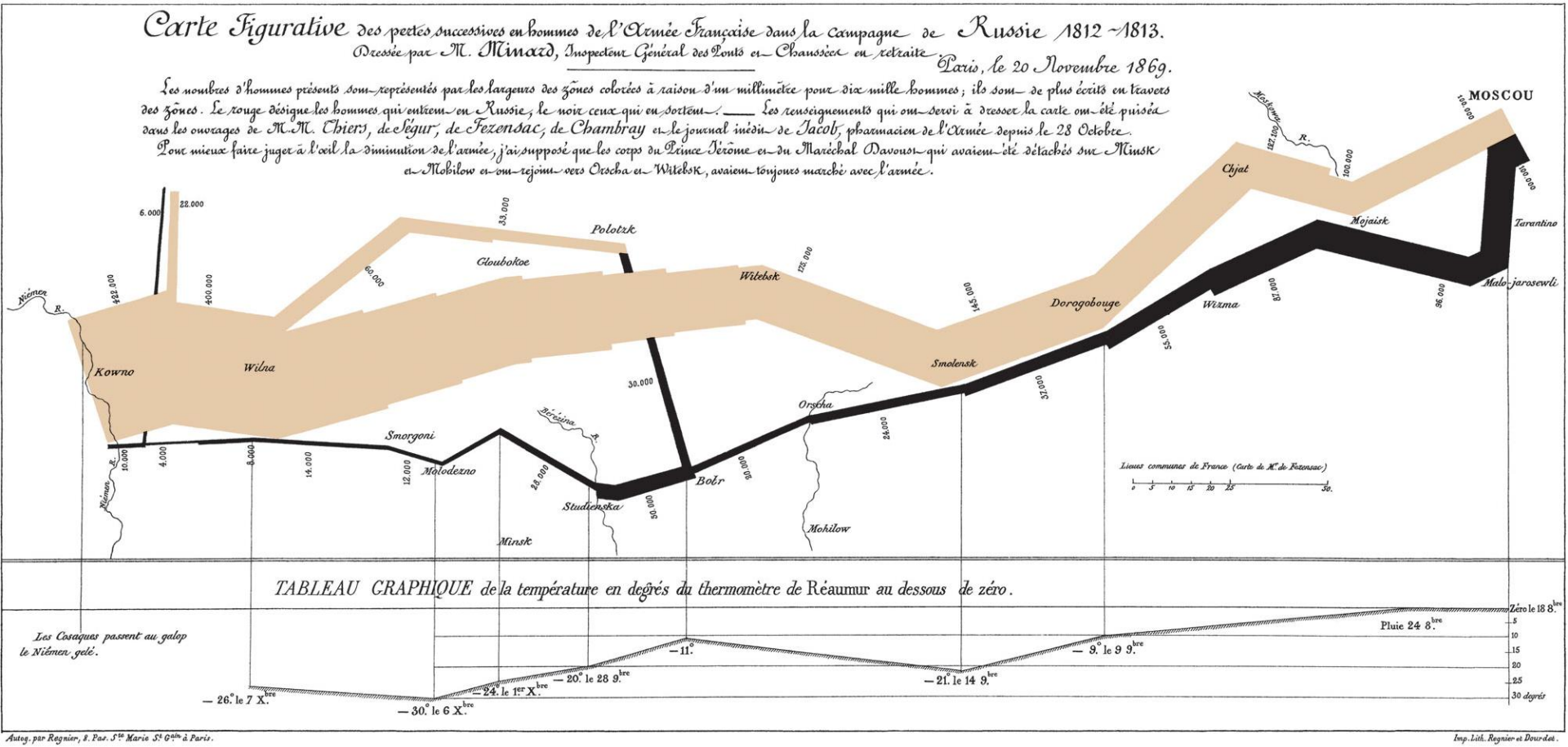
- There has always been a fundamental clash in information graphics and visualization between those who favor a rational, scientific approach to the profession, emphasizing functionality, and those who consider themselves “artists,” placing emphasis on emotion and esthetics (Albert Cairo)
- Two distinct approaches to presenting data graphically exist today—data visualization and data art—and rarely do the twain meet. They differ in purpose and in design. When we fail to distinguish them from one another, we not only create confusion, but do great harm as well (Stephen Few)
-

On one side

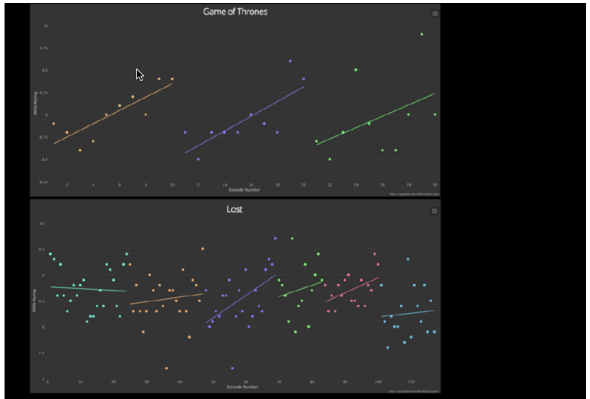

John W. Tukey
EXPLORATORY DATA ANALYSIS
1977
Envisioning Information
1990
SECOND EDITION
The Visual Display of Quantitative Information
EDWARD R. TUFTE
2001
Now you see it
STEPHEN FEW
2009
Second Edition
Show Me the Numbers
Designing Tables and Graphs to Enlighten
Stephen Few
2012
Second Edition
Information Dashboard Design
Displaying data for at-a-glance monitoring
Stephen Few
2013
ualization
op by Stephen Few
e the Numbers - Table and Graph Design
Visual Data Analysis

The perfect information graphic

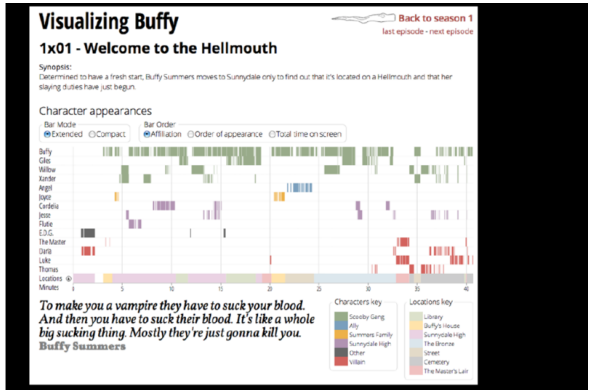
The designer and how many variables?



The imperfect visualizations



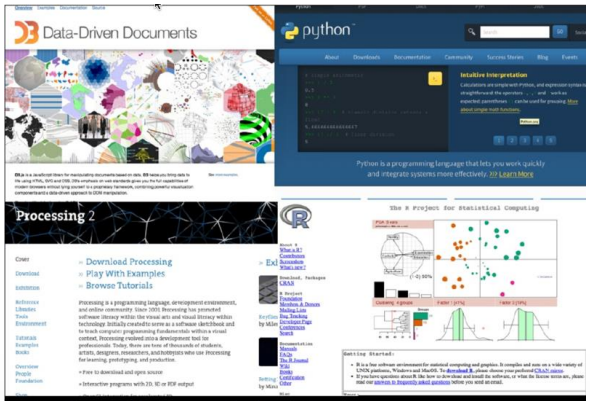
http://graphtv.kevinformatics.com/



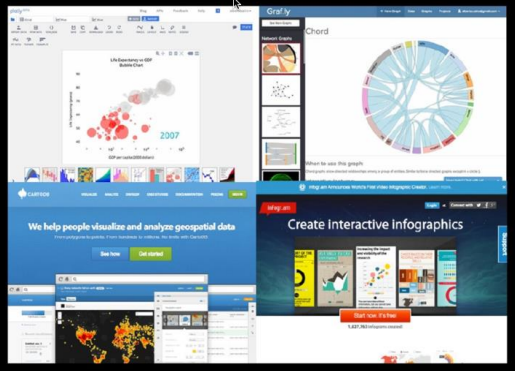
Esteve Boix http://visualizingbuffy.com/

do projects like this represent the future of visualization?

front the point of view of tools, sure, but…



Aren't we talking too much about these?



Or about these?

But I think that the future of visualization doesn't depend on the tools we use, but on solid principles

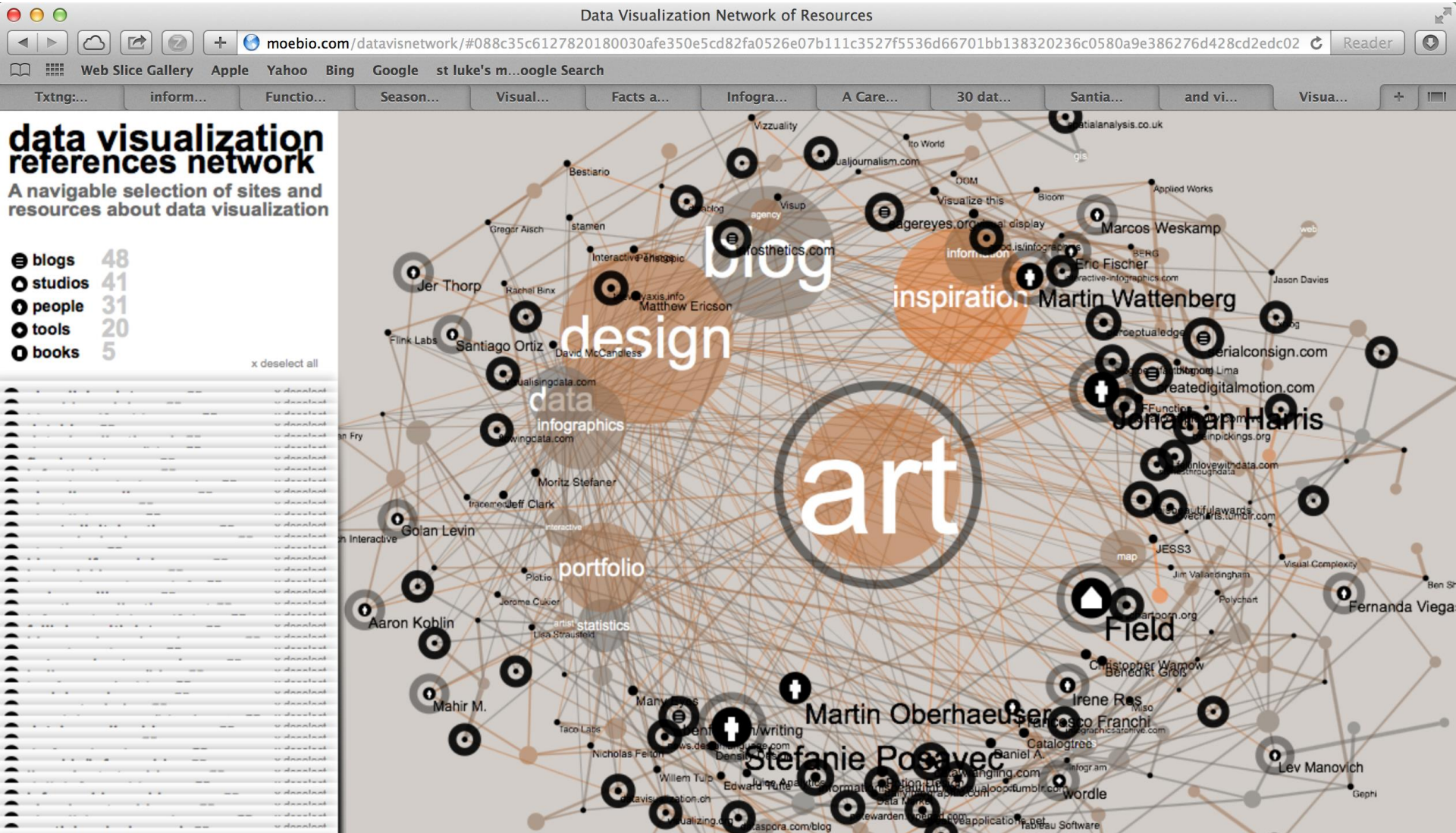
Instead of thinking what the future of visualization will be, I perhaps should talk about what I would like the future of news visualization to be

What's the harm?

- It suggests that data cannot be visualized without training in the graphic arts. As such, it works against the democratization of data
- It features ineffective practices as exemplars of data visualization
- It keeps the practice of data visualization spinning its wheels, never able to progress beyond the mistakes of the past.

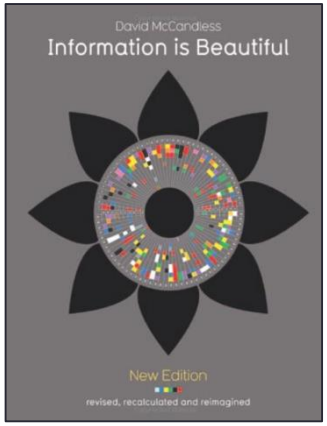
On the other side

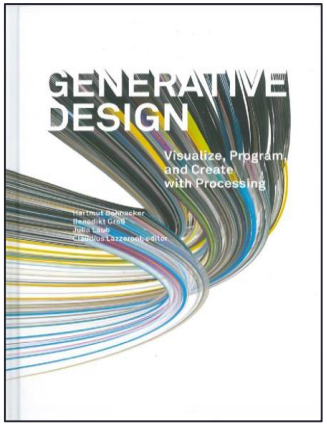
Proponents of Data Art

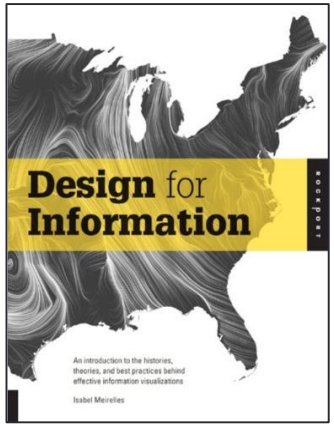


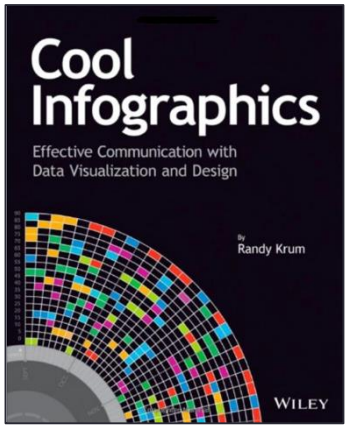
On the other side

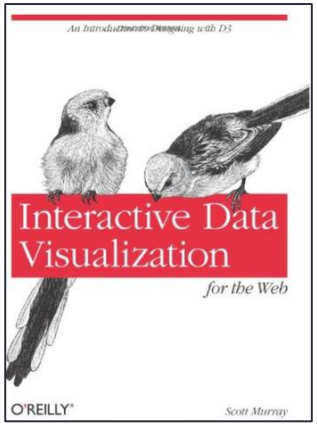
Proponents of (some variation of) Data Art

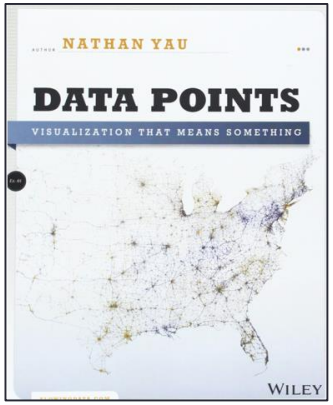


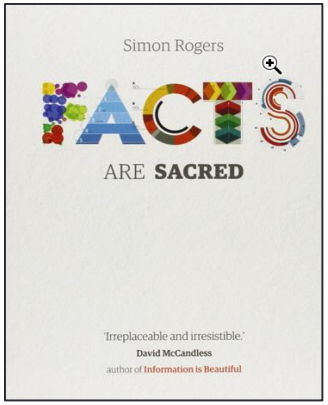


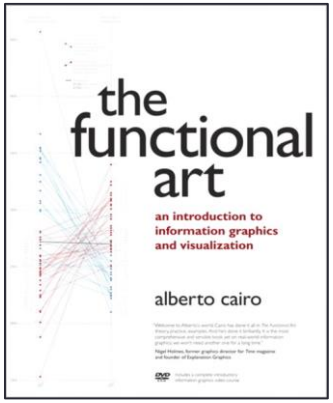


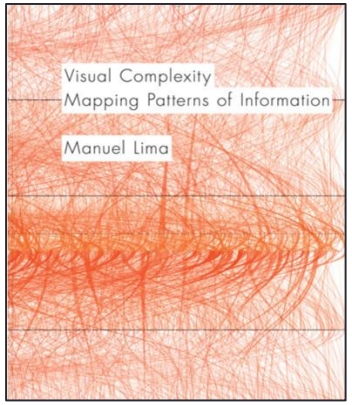


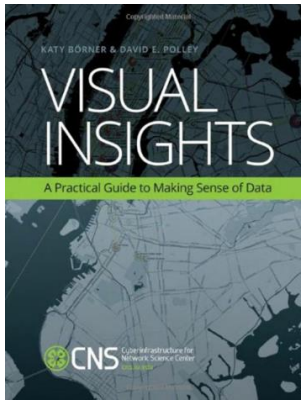












Artifying Data

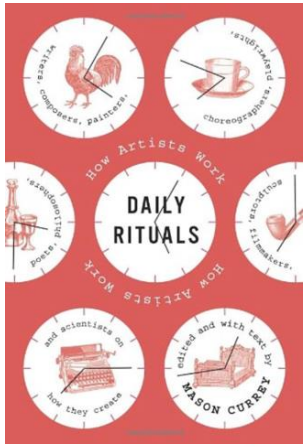
It's more than just "Chartjunk"

- More than adornment (or ornamentation)
- Applying artistic techniques to design choices
  - Strengthen by learning basic art elements and design principles
- Expand and enrich the experience
- Open new ways of seeing the world around us
- Encourage others and share ideas with fresh new vision

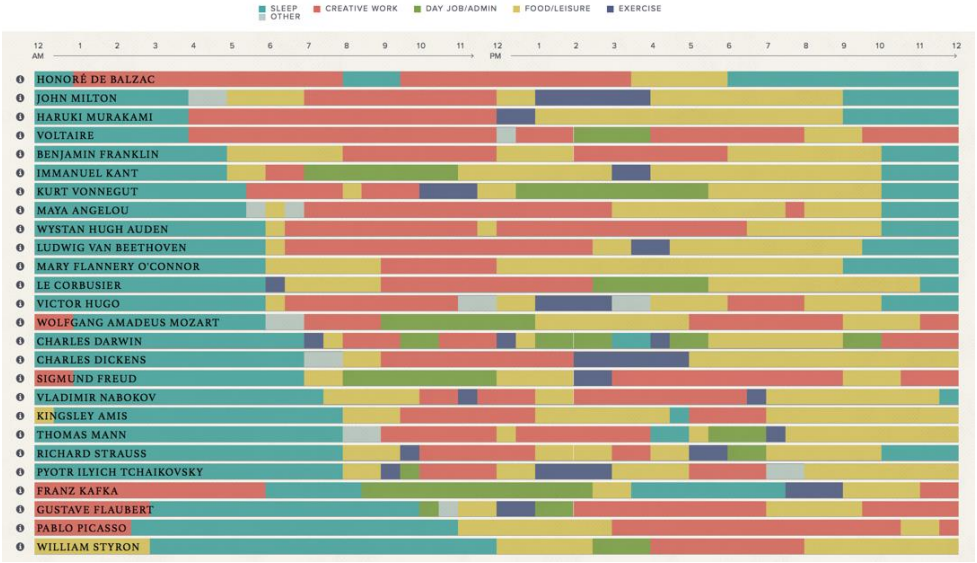
SIMPLE EXAMPLE: QUANTIFICATION OF SELF

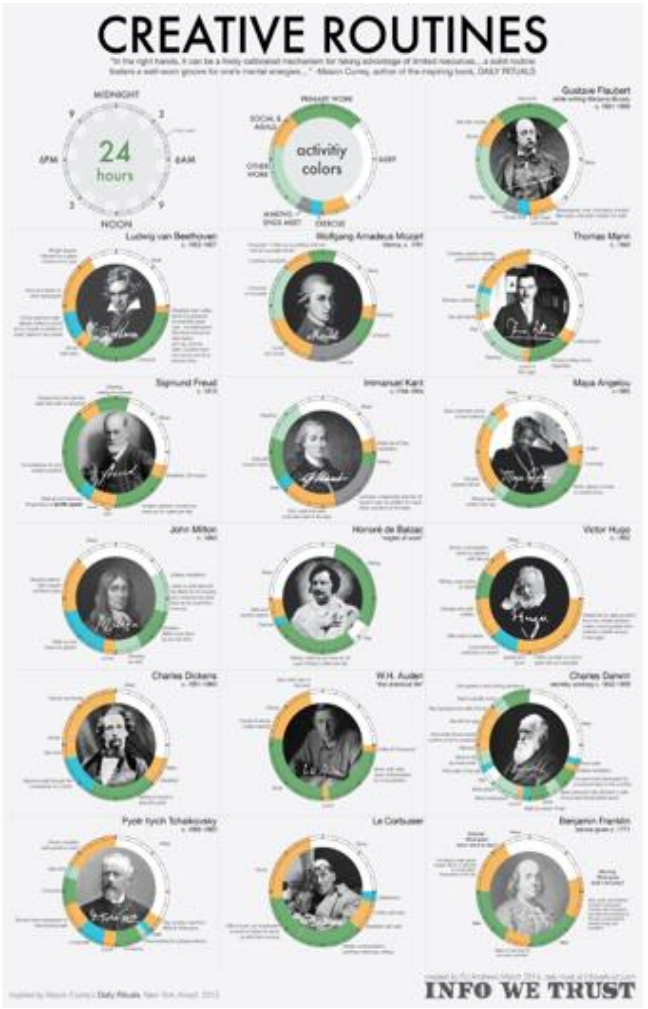
Daily rituals of how (161) artists work

Mason Currey



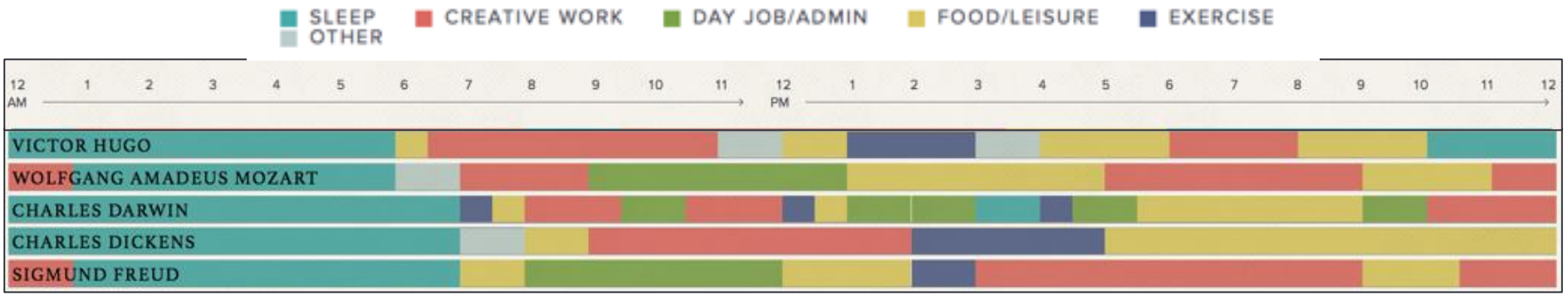
It's about the circumstances of creative activity, not the product; it deals with manufacturing rather than meaning.





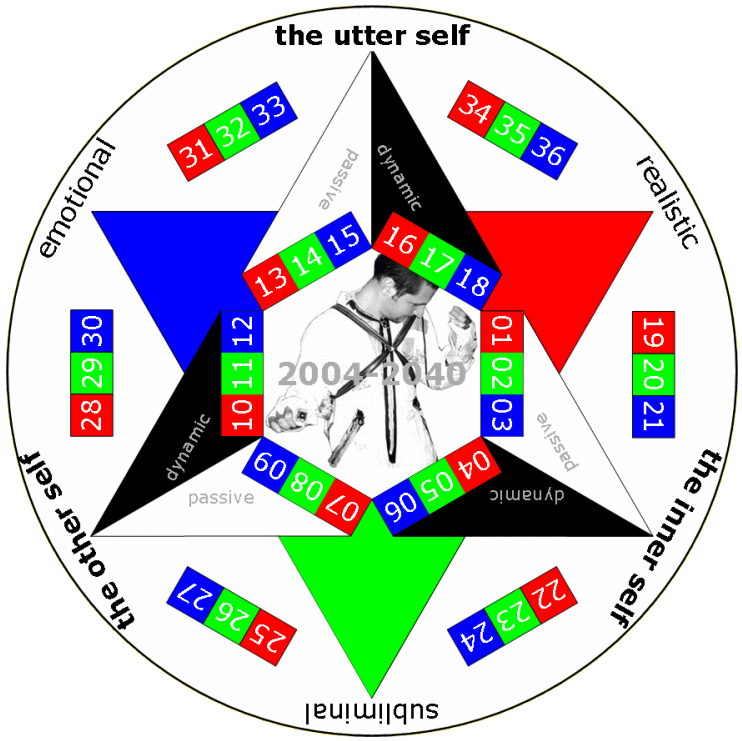
Daily rituals of how (161) artists work

Some simple questions



You've heard of "My Left Foot"

How about Albert Frigo's Right Hand?



It has been more then 10 years since I have started that project, to be precise today the 11th of May 2014, is my 3.882nd day I have been photographing every object my right hand uses.

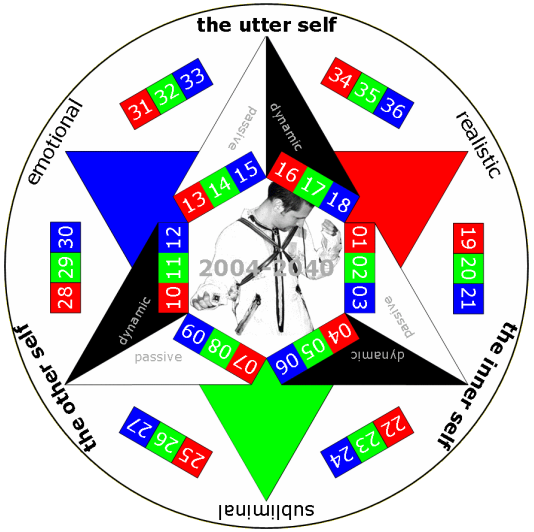
www.2004-2040.com/30_we.htm

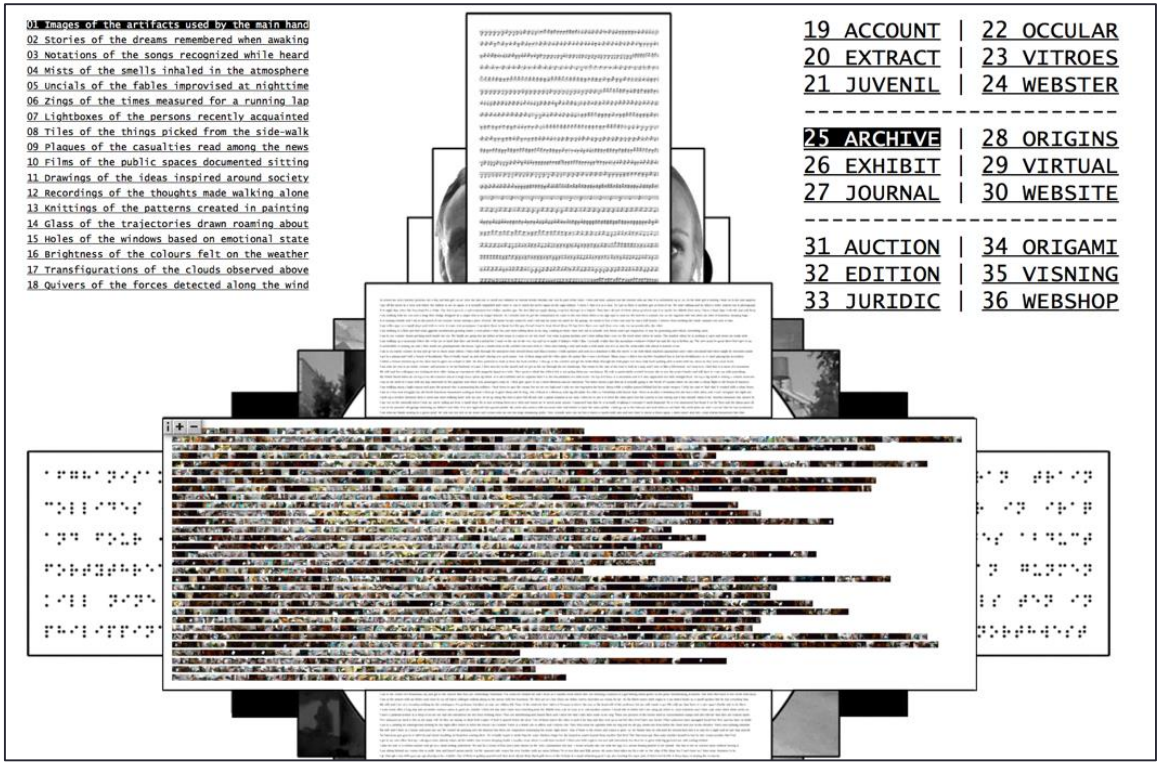
Alfredo Frigo

Pause in the action

If he had been left handed, he'd be taking a picture right now.

Visualizing the Right Hand



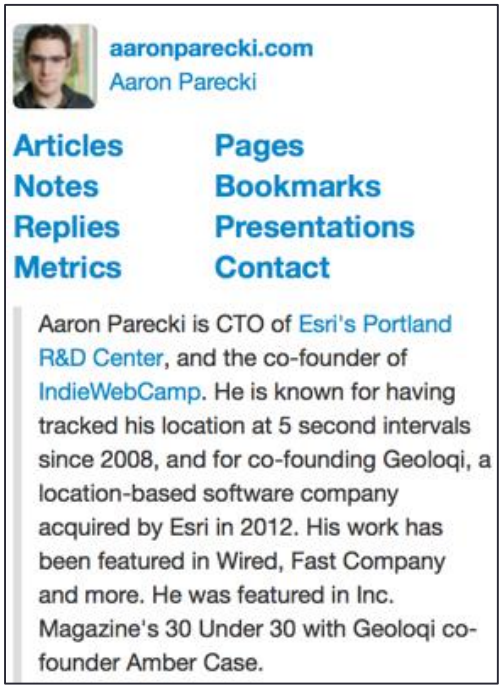


Larger Movements

- Health, Wellness & Fitness
- Personal and Professional Productivity
- Education and Learning
- Gamification
- Child Rearing (Quantified Babies)
- …

Lifelogging Visualizations

Mapping movements from 2008-2012



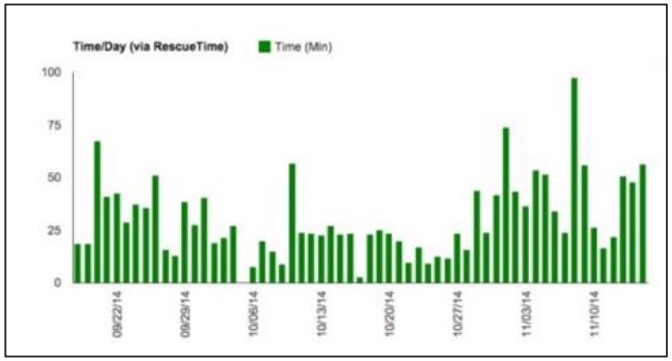
Lifelogging Visualization

Mapping movements from 2008-2012

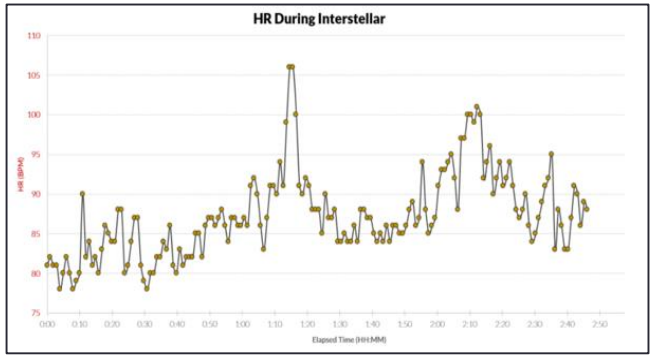
2.5 million GPS points over 31/ 2 years between 2008 and 2012, about one point every 2 to 6 mins

Lifelogging Visualizations *BAPPS*

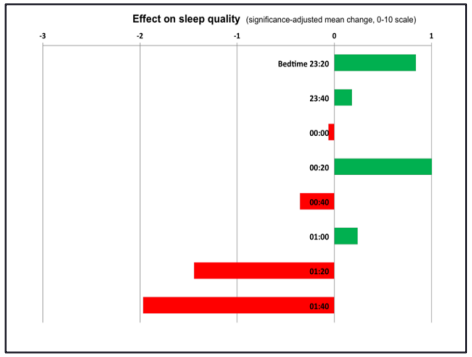
Mins Writing - Daily

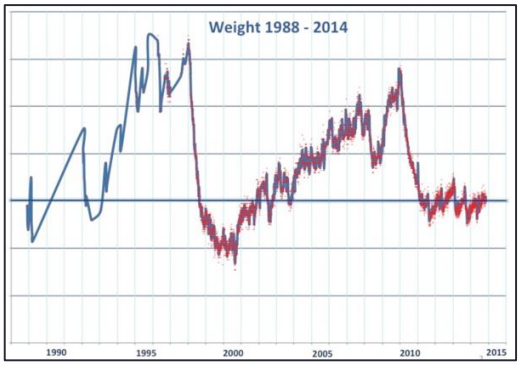


Heart Rate - Mins

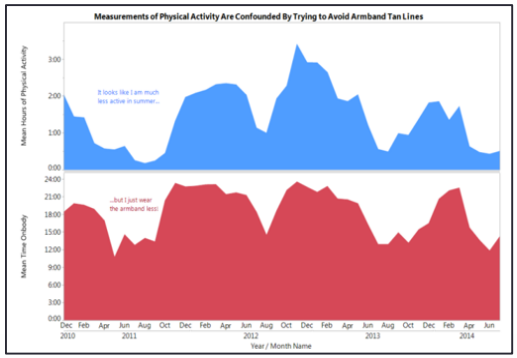


Sleep Quality - Hourly

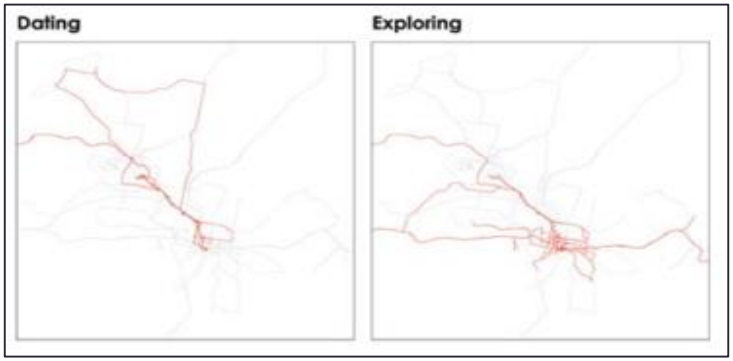




Mins Writing - Daily

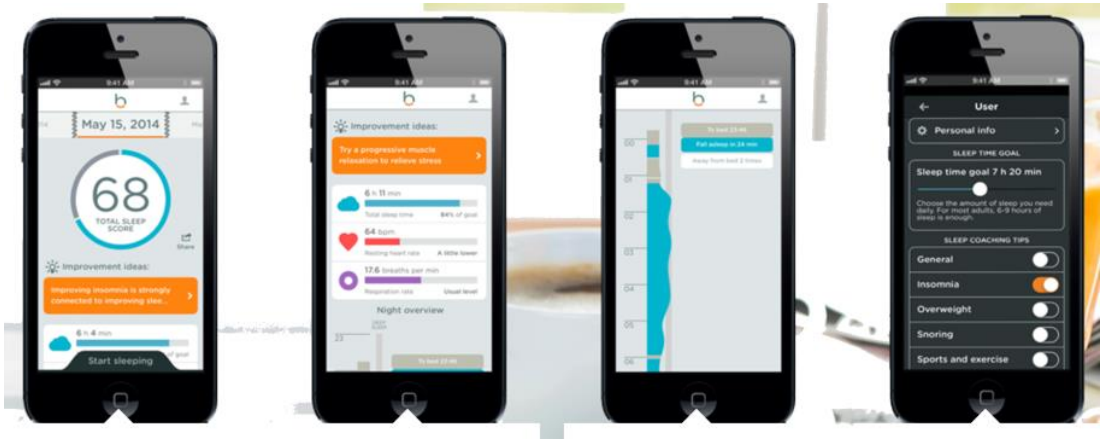


Avg HRs Phy Act - Mnth

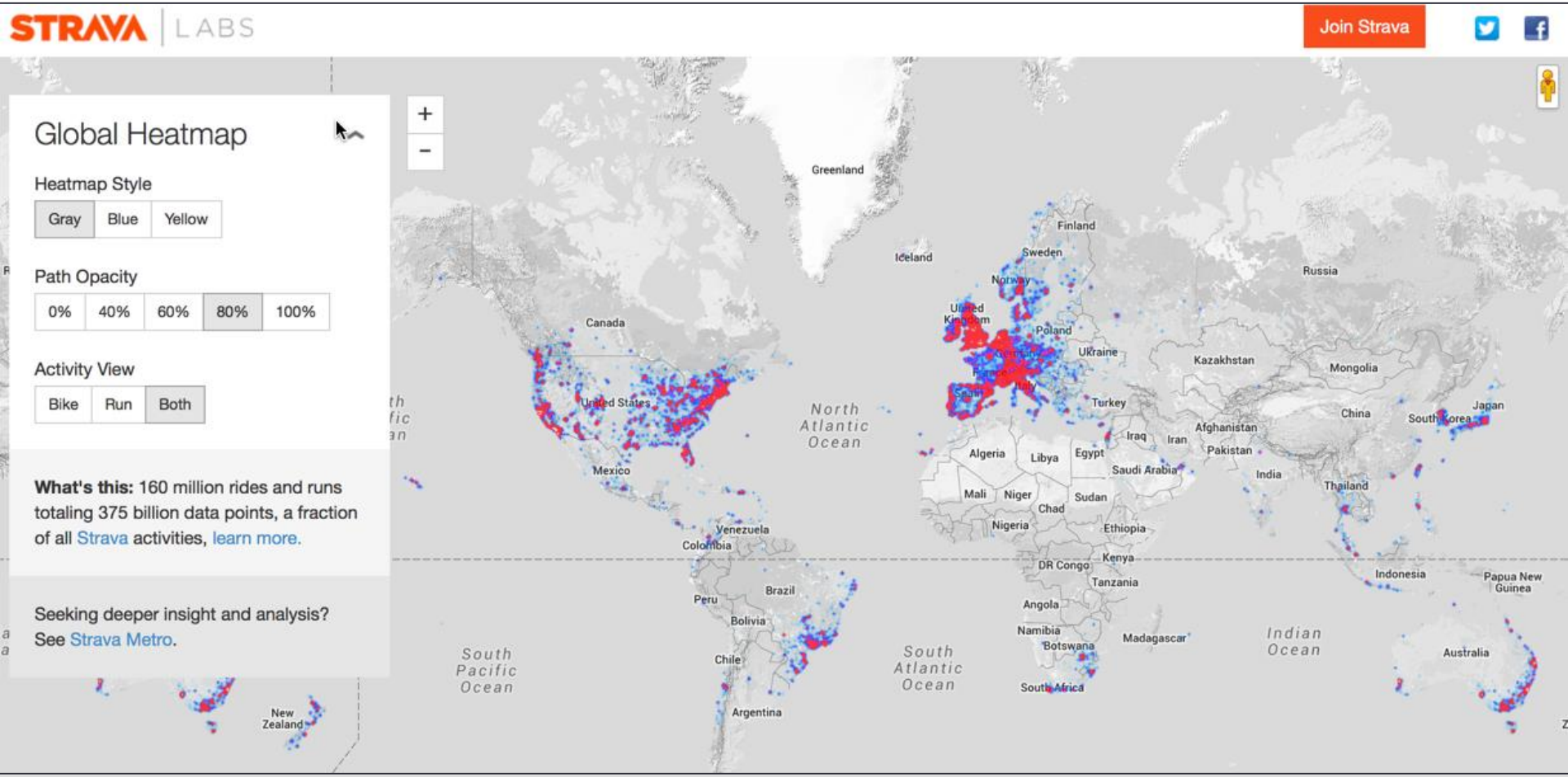


GPS Traces for 200 Days

Lifelogging Visualizations *APPSA*



A view of 160 million rides and runs

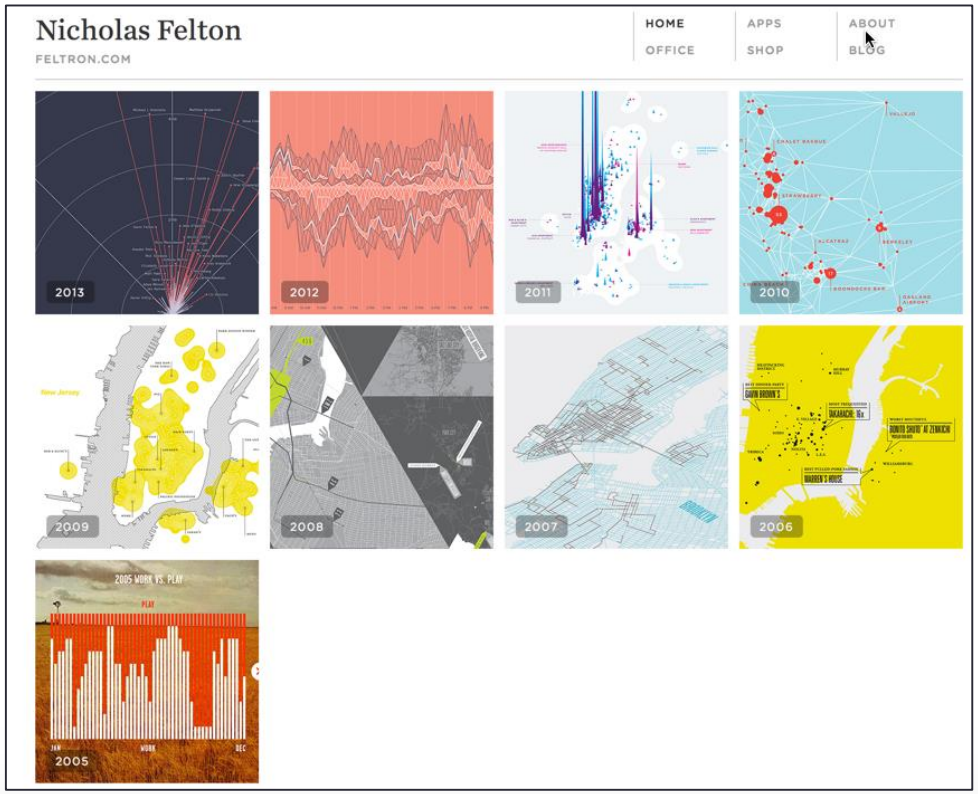


Lifelogging Visualization

Infographing a year of activities

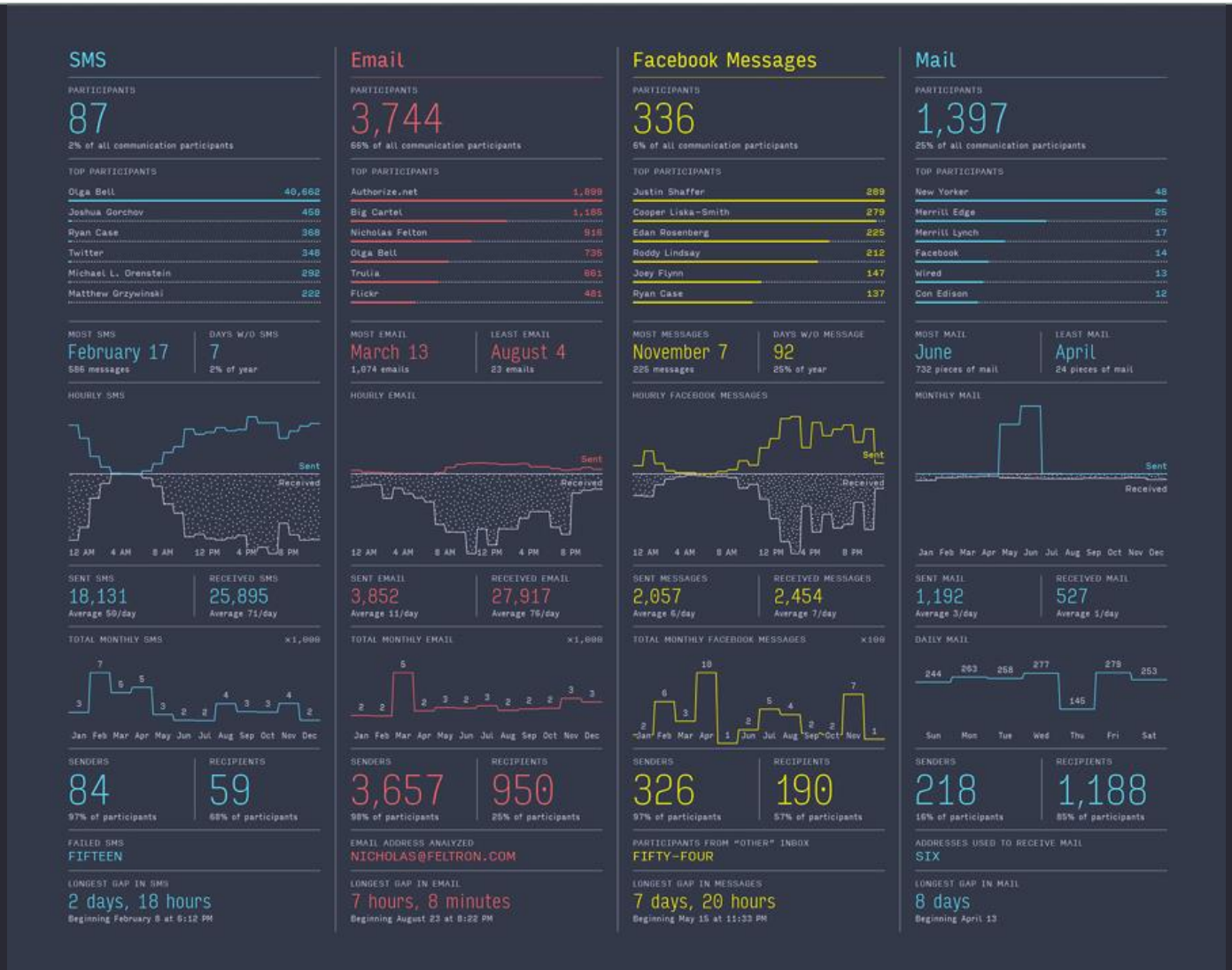
Biography

Nicholas Felton spends much of his time thinking about data, charts and our daily routines. He is the author of many Personal Annual Reports that weave numerous measurements into a tapestry of graphs, maps and statistics reflecting the year's activities. He was one of the lead designers of Facebook's timeline and the co-founder of Daytum.com. His most recent product is Reporter, an iPhone app designed to record and visualize subtle aspects of our lives. His work is a part of the permanent collection at MoMA. He has also been profiled by the Wall Street Journal, Wired and Good Magazine and recognized as one of the 50 most influential designers in America by Fast Company.



Lifelogging Visualization

Felton's 2013 Annual Report



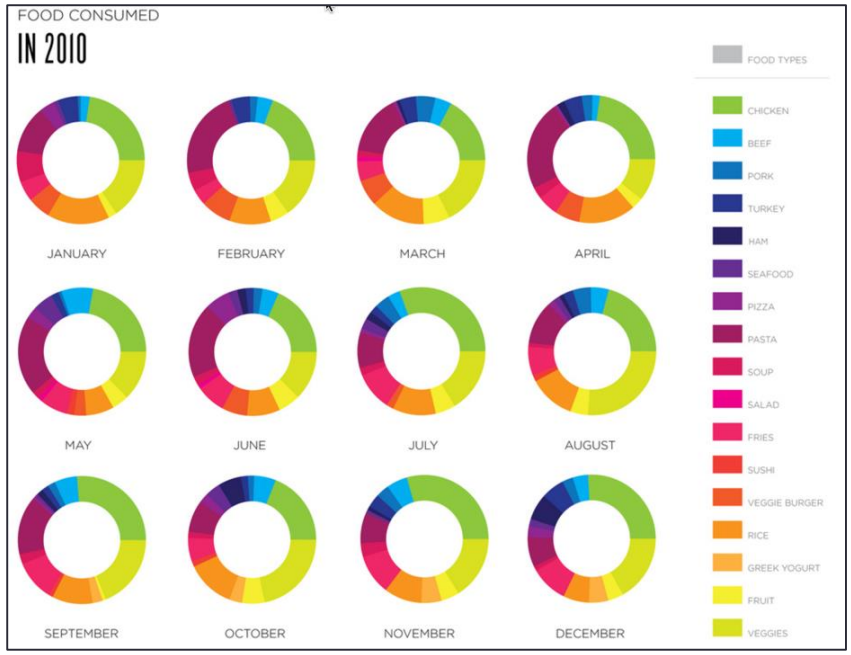
Lifelogging Visualization

Felton's 2013 Annual Report

Lauren Manning

Food consumed in 2010

Date	Meal	Food Type
1-Jan	Breakfast	Yogurt
1-Jan	Breakfast	Banana
1-Jan	Lunch	Salad
1-Jan	Lunch	Chicken
1-Jan	Dinner	Shrimp
1-Jan	Dinner	Pasta
1-Jan	Dinner	Zucchini
…		
31-Dec	Breakfast	Yogurt
31-Dec	Breakfast	Strawberries
31-Dec	Lunch	Turkey Sandwich
31-Dec	Lunch	Tomato Soup
31-Dec	Dinner	Miso Soup
31-Dec	Dinner	Mixed Salad
31-Dec	Dinner	Sashimi



Lauren Manning

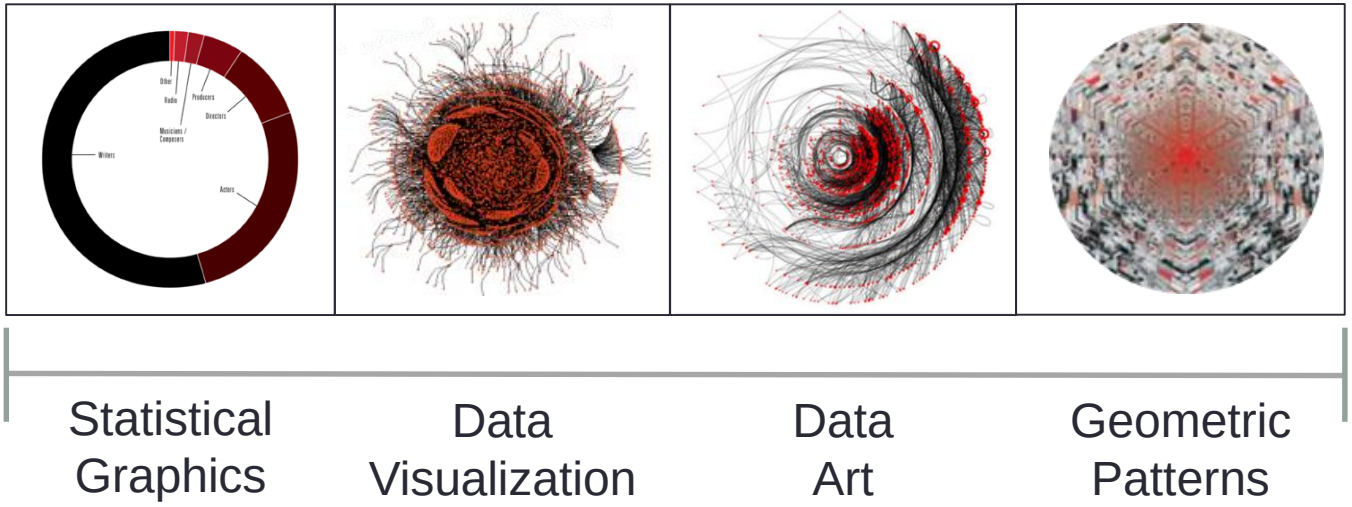
40 ways to love your liver (or chicken, or ham…)

"It's like comparing apples to oranges." … For the designer, its easy to find good visualizations and bad ones, but how to apply the successful elements of particular designs to one's own data set starts to get a little more complicated

Lauren Manning

Visualizing Yearly Food Consumption

Data Visualization



"You can think of visualization as a continuous spectrum that stretches from statistical graphics to data art"

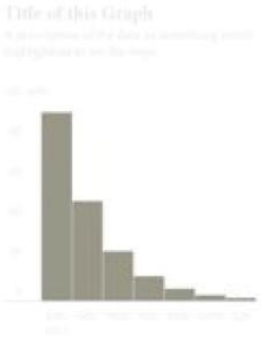
Yau, Data Points (2013)

VISUALIZATION FRAMEWORK

Components of a data visualization

Working parts

Several pieces work together to make a graph. Sometimes these are explicitly shown in the visualization and other times they form a visual in the background. They all depend on the data.

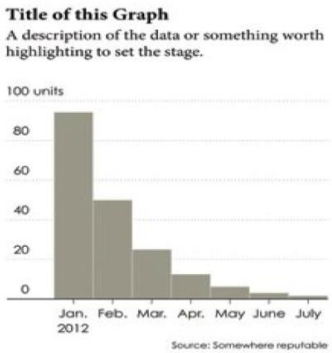


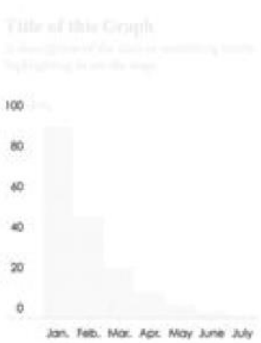
Visual Cues

Visualization involves encoding data with shapes, colors, and sizes. Which cues you choose depends on your data and your goals.

Coordinate System

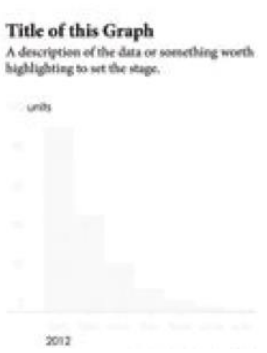
You map data differently with a scatterplot than you do with a pie chart. It's x- and y-coordinates in one and angles with the other; it's cartesian versus polar.





Scale

Increments that make sense can increase readability, as well as shift focus.



Context

If your audience is unfamiliar with the data, it's your job to clarify what values represent and explain how people should read your visualization.

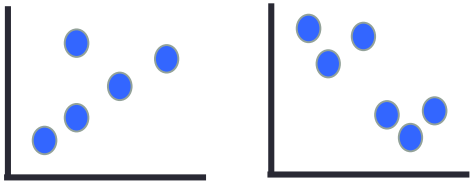
Each visualization, regardless of where it is on the spectrum, is built on data and these five components.

Visual cues

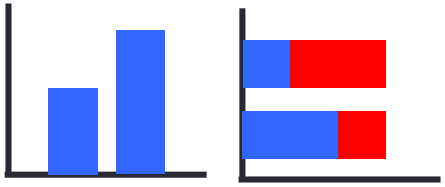
More Accurate

Less Accurate

Position

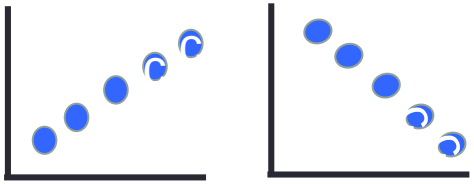


Length



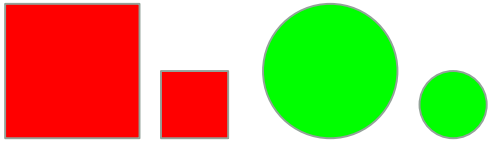
Angle

Direction

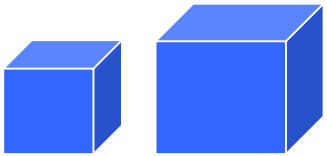


Shapes

Area



Volume



Color (Saturation)

Color (Hue)

Cleveland & McGill

How many __’s are there?

7	9	2	5	8	5	0	4	1	5	9	0	1	0	0
2	2	3	6	1	0	6	0	6	7	0	7	6	9	5
9	4	8	4	6	1	4	2	9	2	8	6	4	6	8
0	9	1	3	1	1	7	6	7	5	2	5	9	4	1

6’s

7	9	2	5	8	5	0	4	1	5	9	0	1	0	0
2	2	3	**6**	1	0	**6**	0	**6**	7	0	7	**6**	9	5
9	4	8	4	**6**	1	4	2	9	2	8	**6**	4	**6**	8
0	9	1	3	1	1	7	**6**	7	5	2	5	9	4	1

2’s

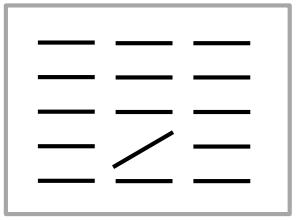
7	9	2	5	8	5	0	4	1	5	9	0	1	0	0
2	2	3	6	1	0	6	0	6	7	0	7	6	9	5
9	4	8	4	6	1	4	2	9	2	8	6	4	6	8
0	9	1	3	1	1	7	6	7	5	2	5	9	4	1

1’s

7	9	2	5	8	5	0	4	1	5	9	0	1	0	0
2	2	3	6	1	0	6	0	6	7	0	7	6	9	5
9	4	8	4	6	1	4	2	9	2	8	6	4	6	8
0	9	1	3	1	1	7	6	7	5	2	5	9	4	1

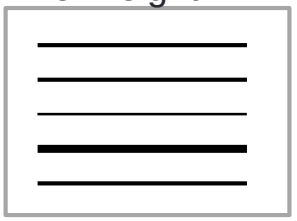
Detection and Recognition

Line Orientation

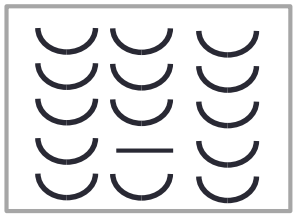


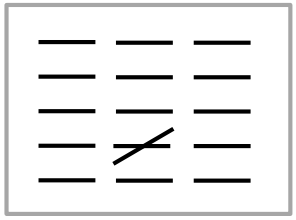
Line Length

Line Weight

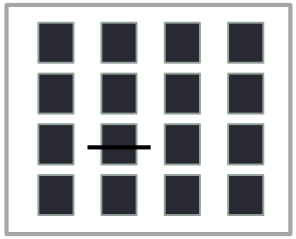


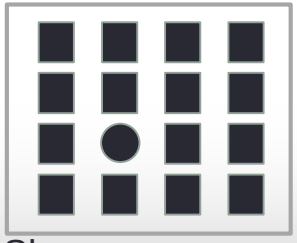
Curvature



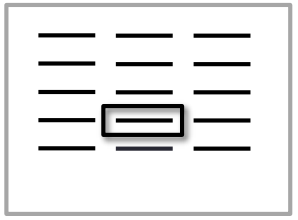


Added Markers

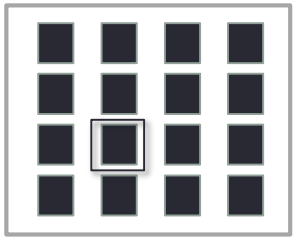




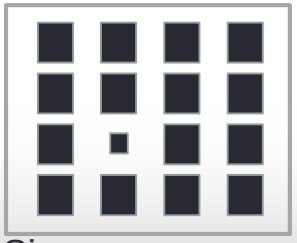
Shape

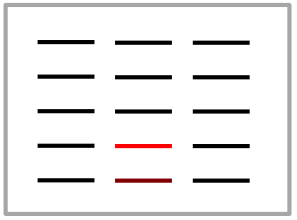


Enclosure

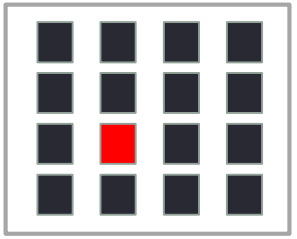


Size

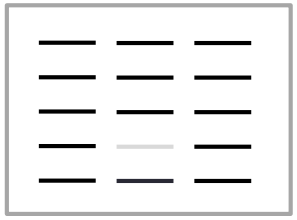




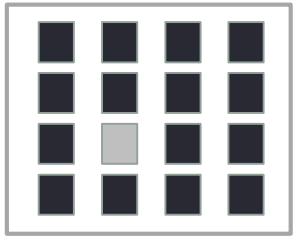
Color/Hue



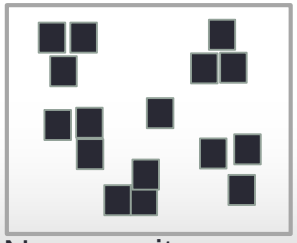
Sharpness



Intensity/Value



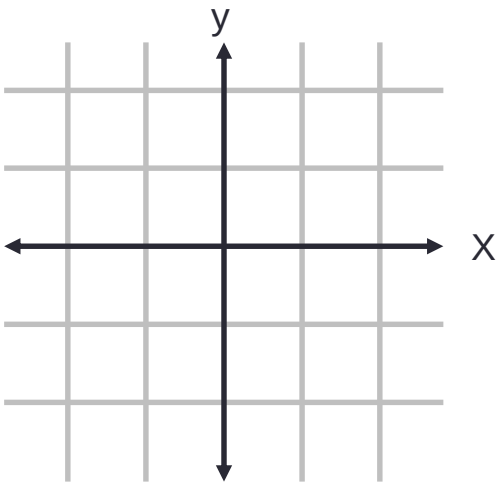
Numerosity



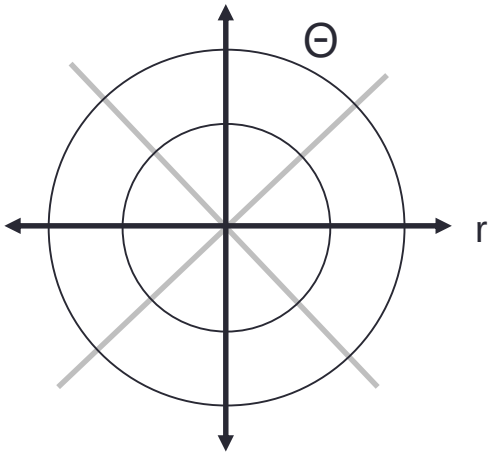
Coordinate Systems

Most common

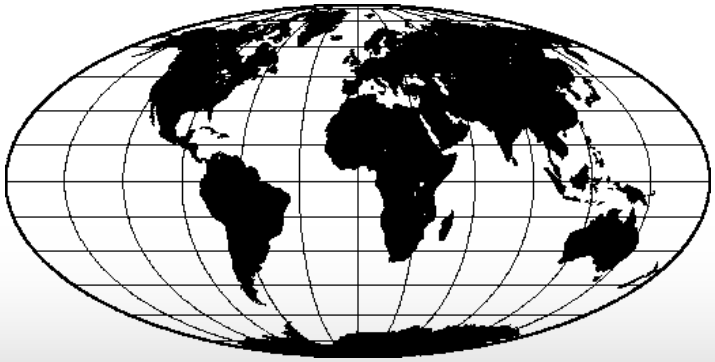
Cartesian



Polar



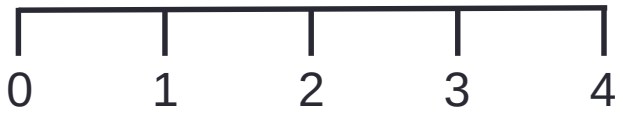
Geographic Projection



Scale

Most common

Linear (even space)



Logarithmic (% change)

Categorical (discrete)

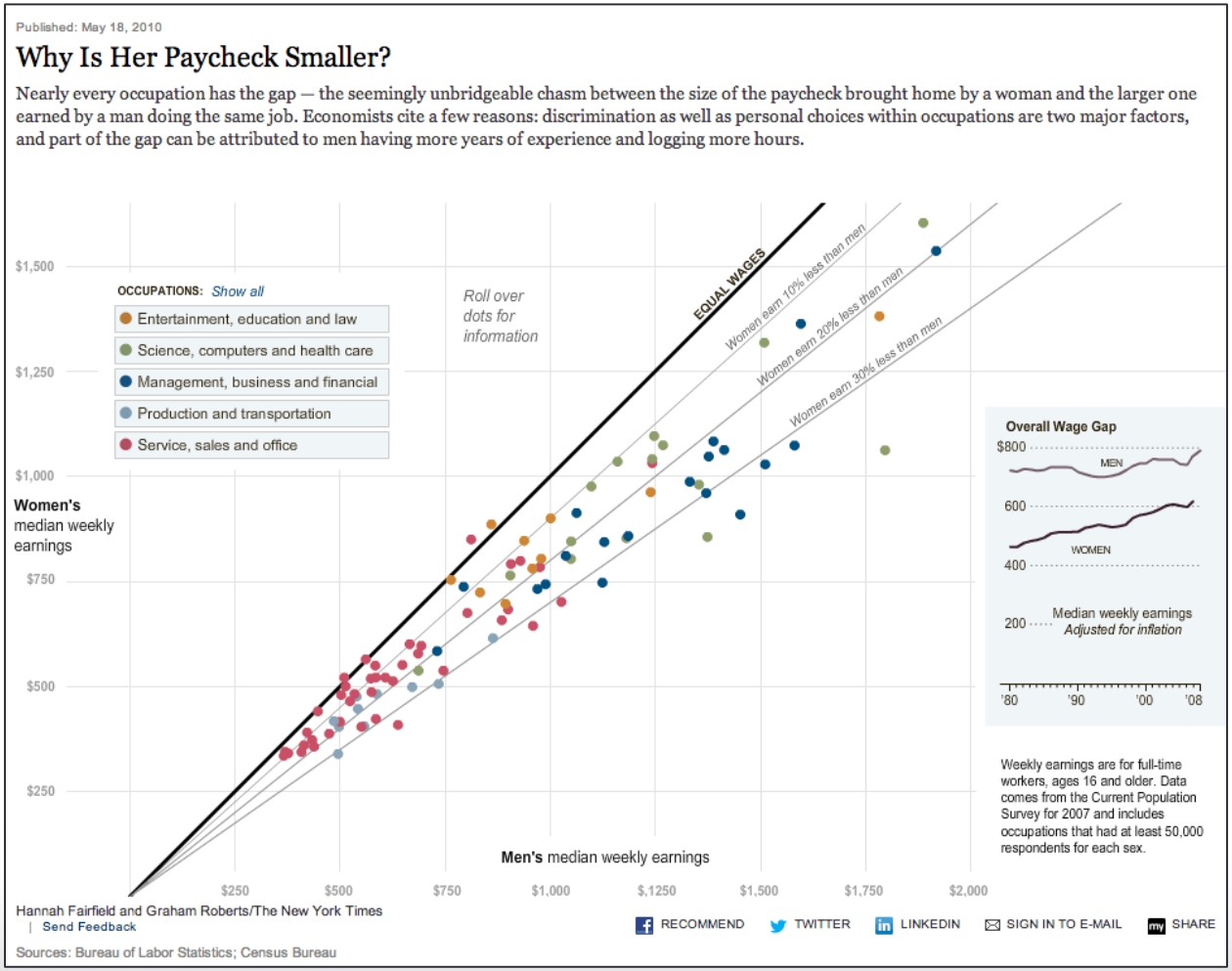
Ordinal (ranked categories)

Percent (of whole)

Time (hours, days, mnths, years …)

The role of context

1 word is worth …



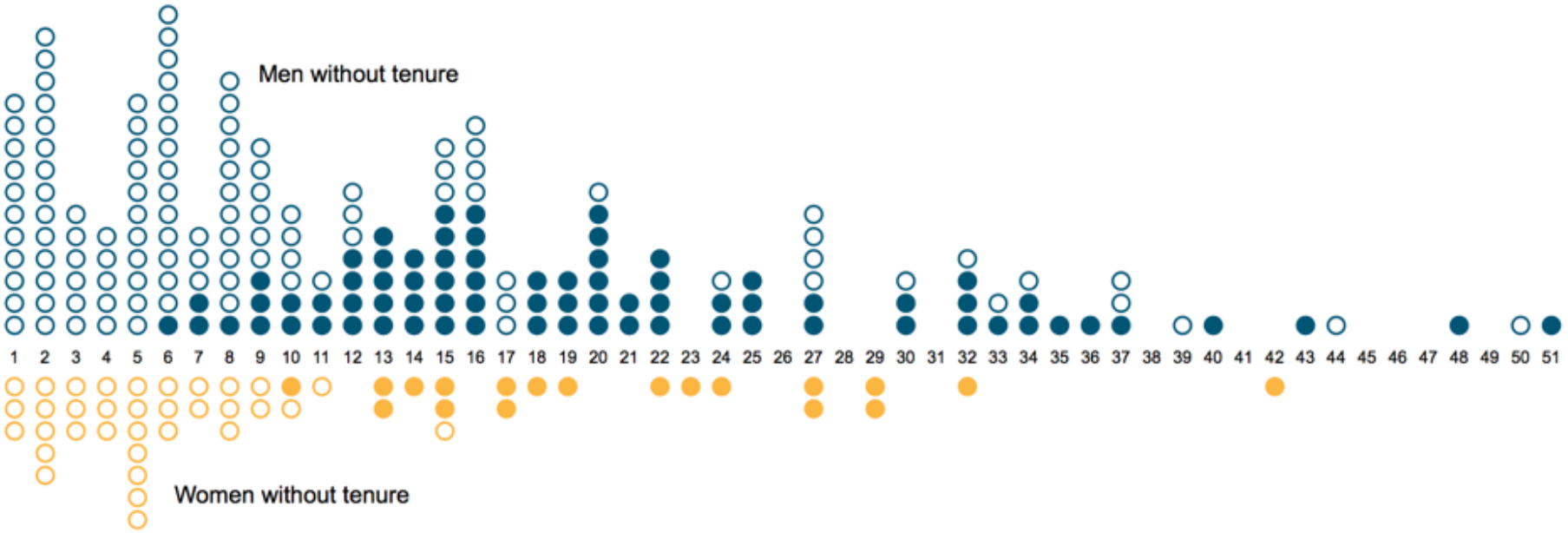
Context

1 word is worth …

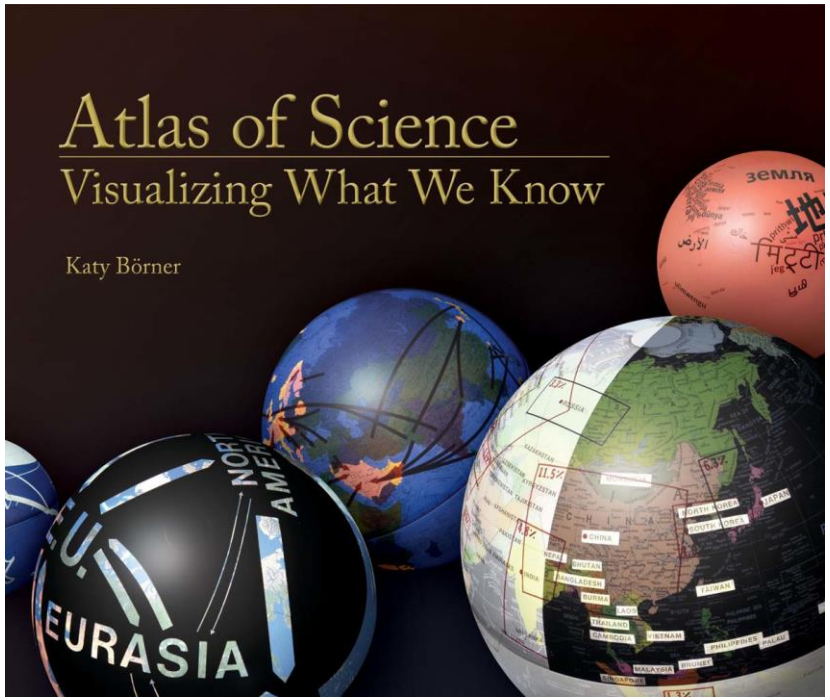
The Tenure Pipeline at Harvard Business School

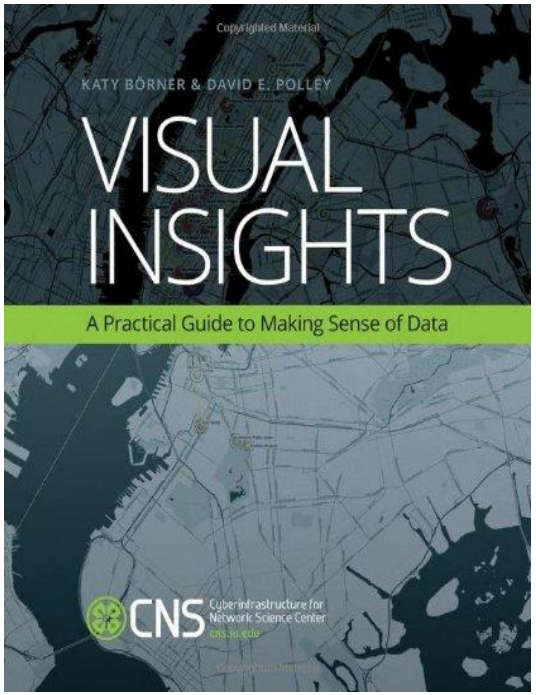
1 2 3 4 **5** NEXT >

But **the pipeline for women is small**. Fewer than a third of untenured faculty members are women, making it unlikely that the gender imbalance in tenured faculty will shift in the near future.



Visualization Framework & Workflow

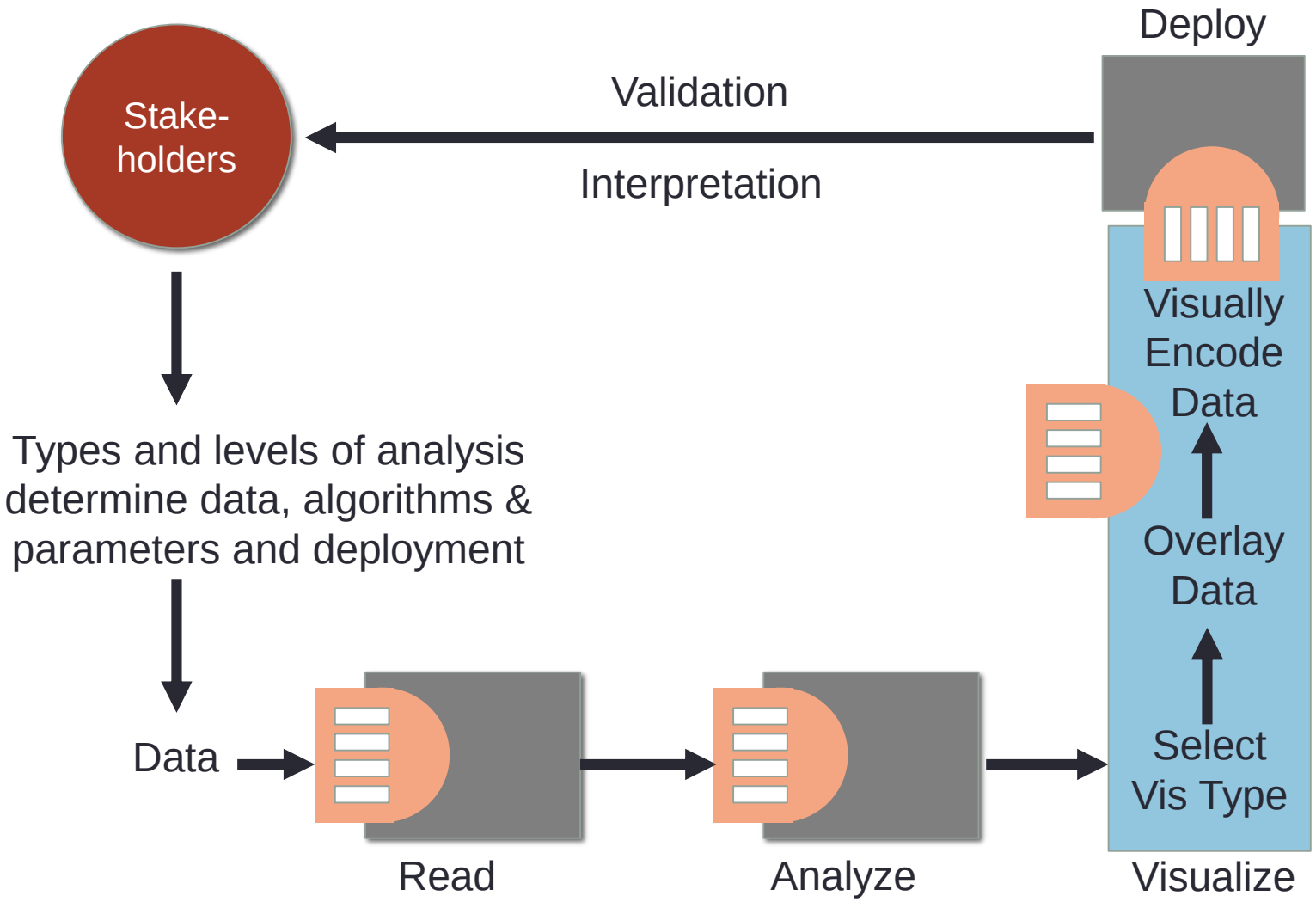




cns.iu.edu/home.html

ella.slis.indiana.edu/~katy/

Visualization Framework & Workflow

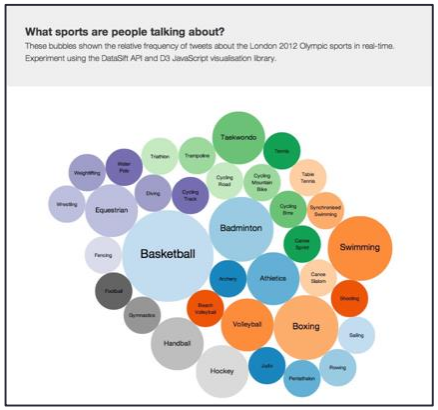


Analysis: Type vs. Level

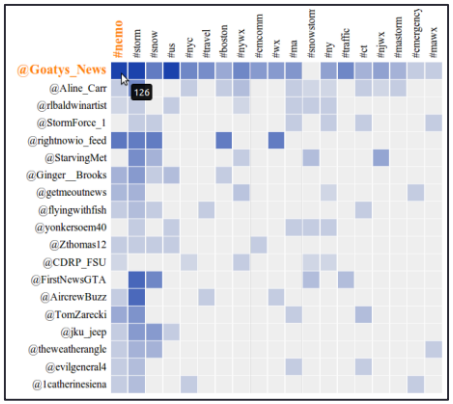
Types of Analysis	Levels of Analysis		
	Micro/Individual 1-100 records	Meso/Local 101-10,000 records	Macro/Global 10,000+ records
Statistical Analysis/Profiling			
Temporal Analysis (When)			
Geospatial Analysis (Where)			
Topical Analysis (What)			
Network Analysis (with Whom)			

Visualization Types

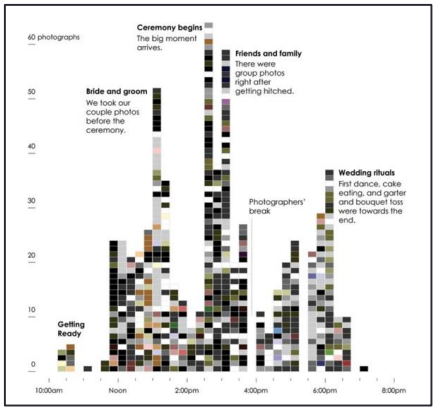
Charts



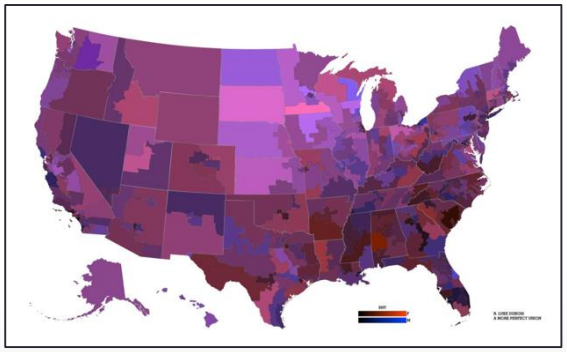
Tables



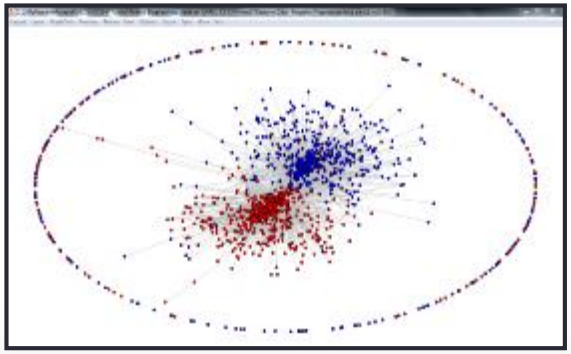
Graphs



Geospatial Maps



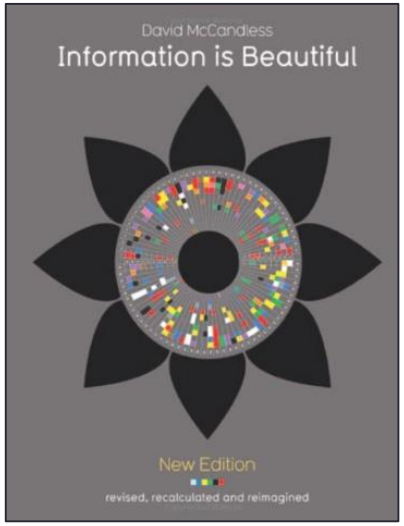
Network Graphs

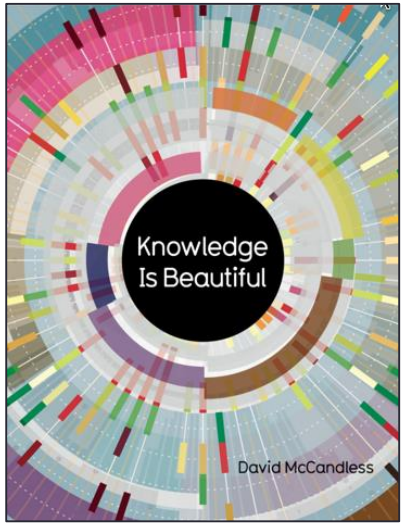


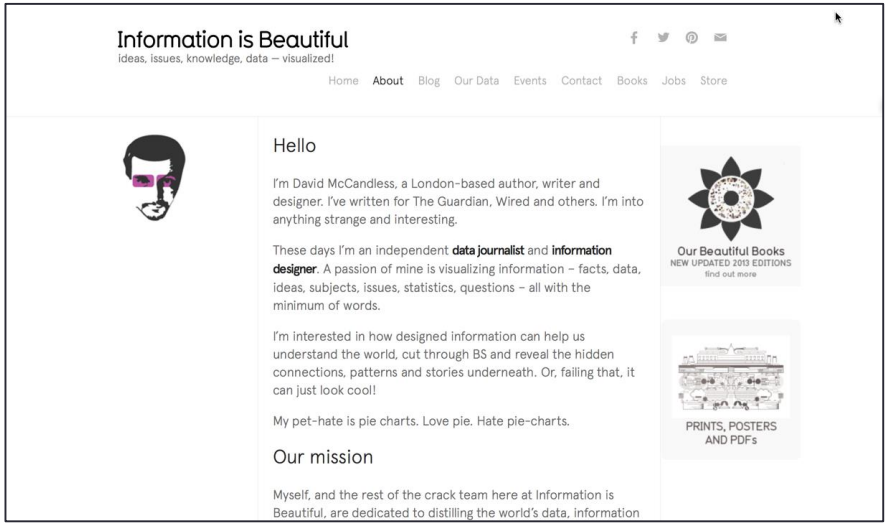
EXAMPLE: RAP LYRICS

Example

Analyzing the lyrics of Rap/Hip Hop songs



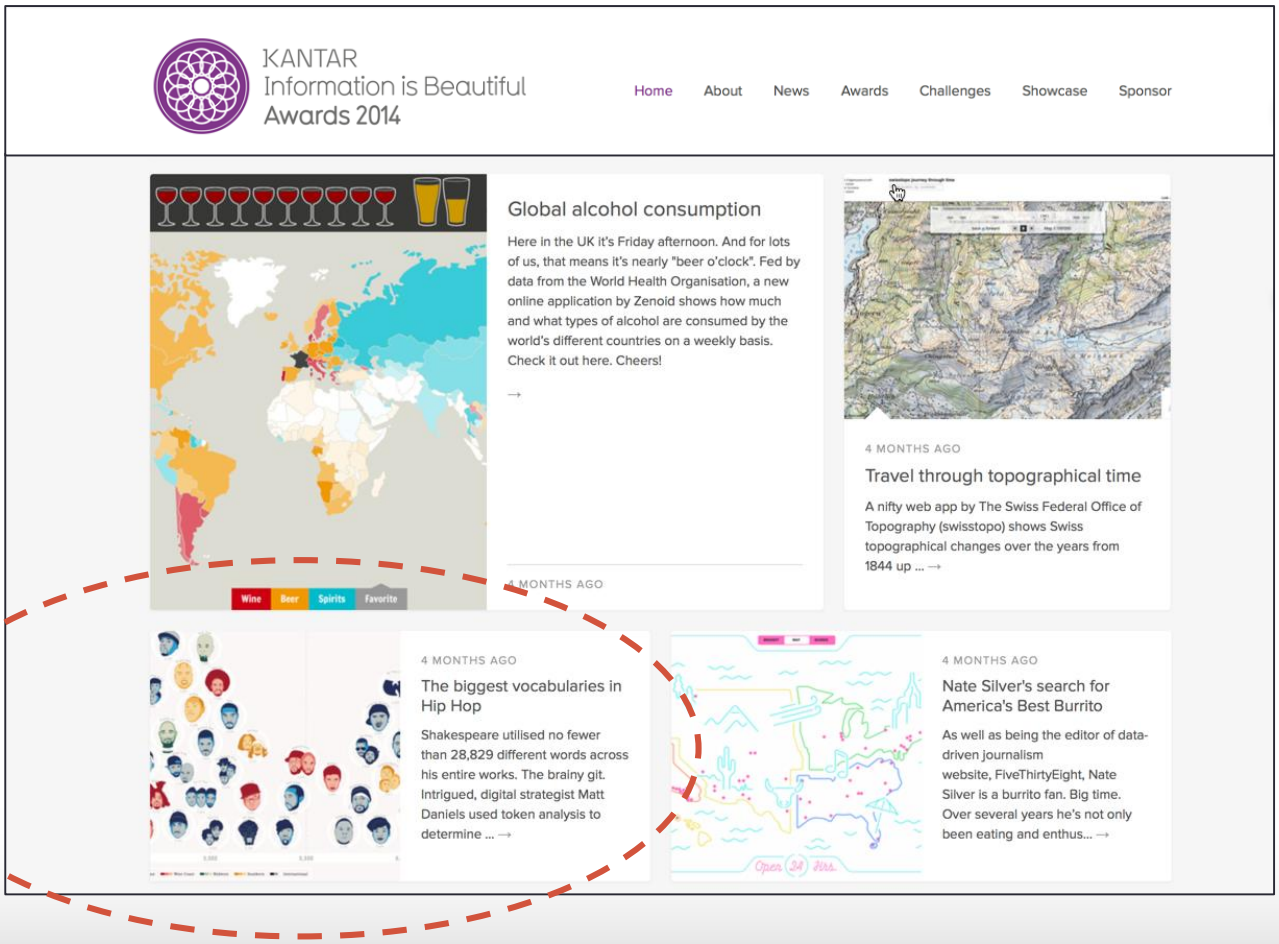




David McCandless – Informationisbeautiful.net

Example

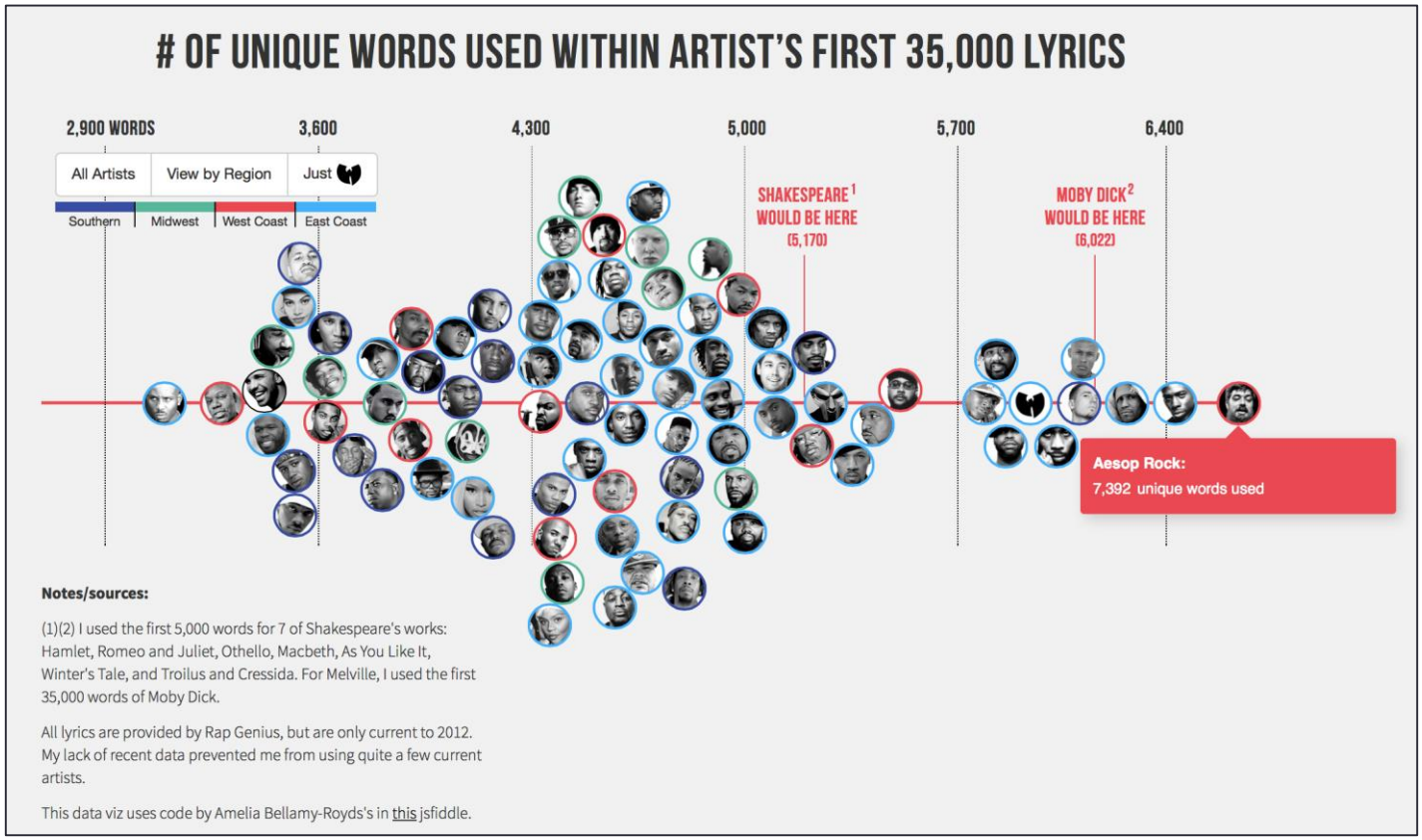
Analyzing the lyrics of Rap/Hip Hop songs



Informationisbeautifulawards.net

Example: Lyrics of Rap Songs

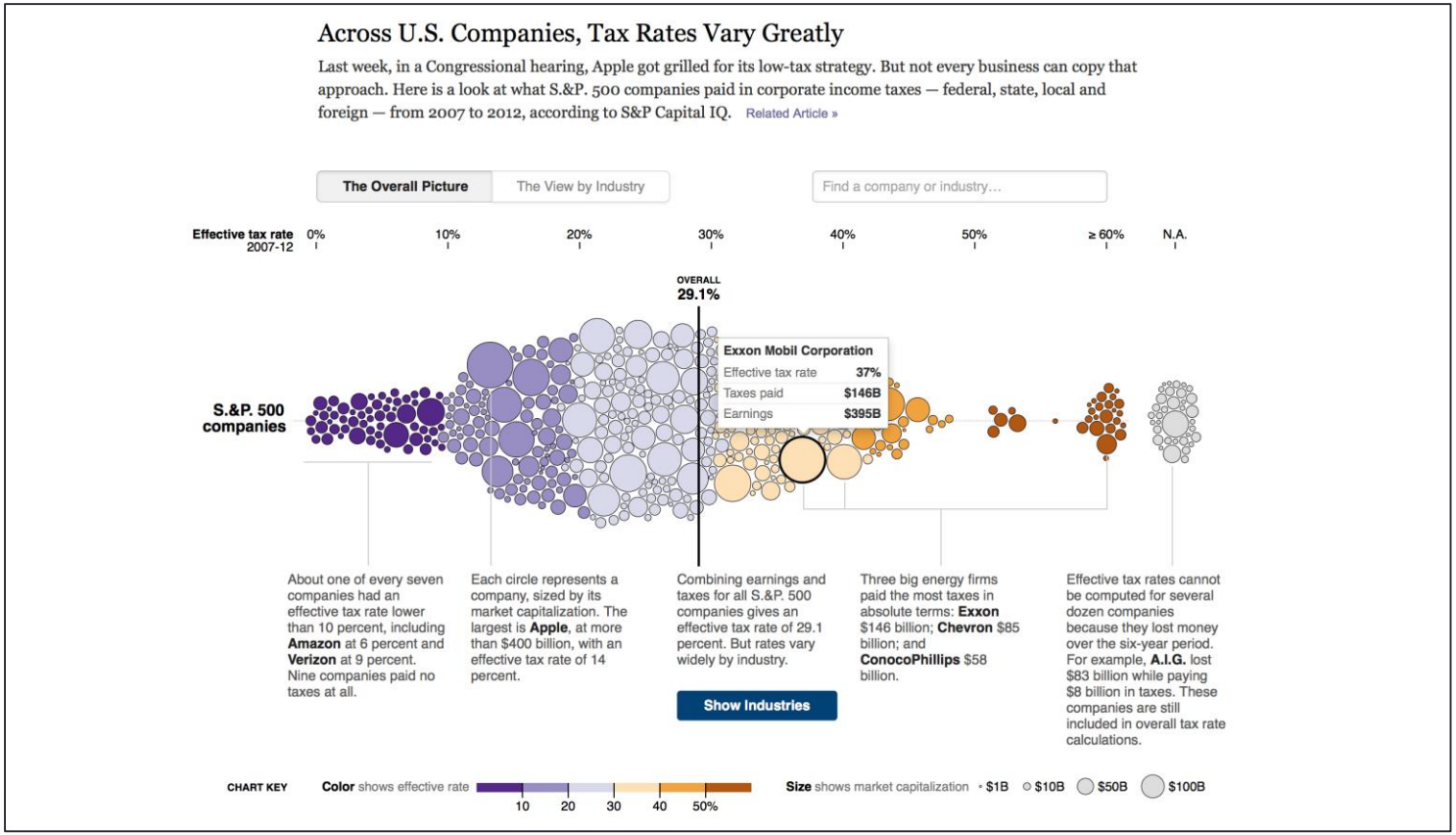
Biggest Vocabularies and Unique Words



Research by: Matt Daniels, mdaniels.com
Visualization by: Amelia Bellamy-Royds, fiddle.jshell.net/6cW9u/8/

Example: Lyrics of Rap Songs

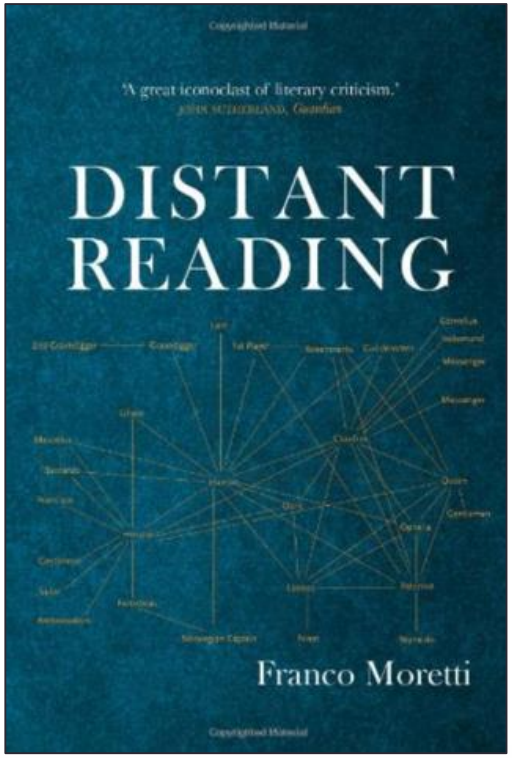
Visualization inspired by…

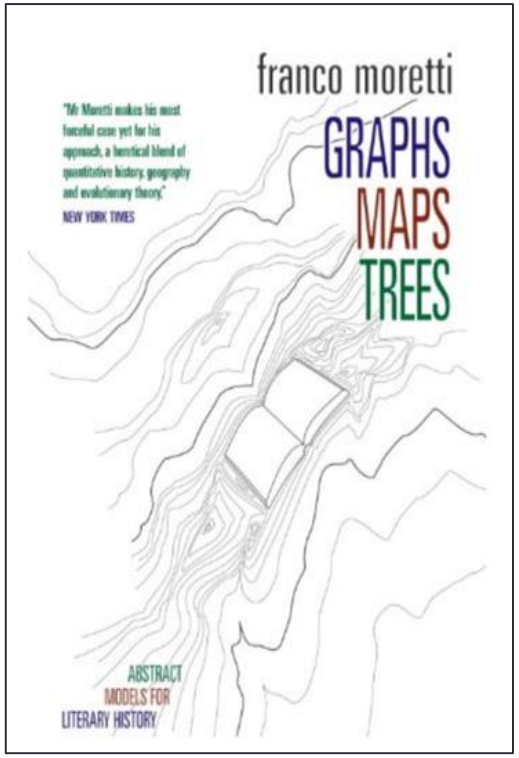


Inspired by: nytimes.com/interactive/2013/05/25/sunday-review/corporate-taxes.html?_r=2&

Example: Lyrics of Rap Songs

In the same vein as …

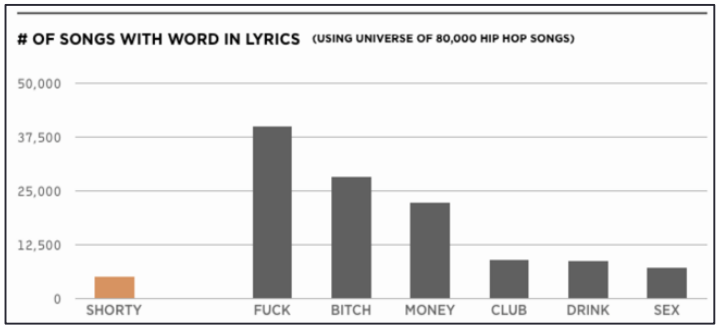


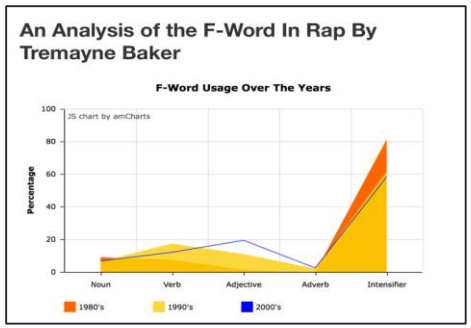


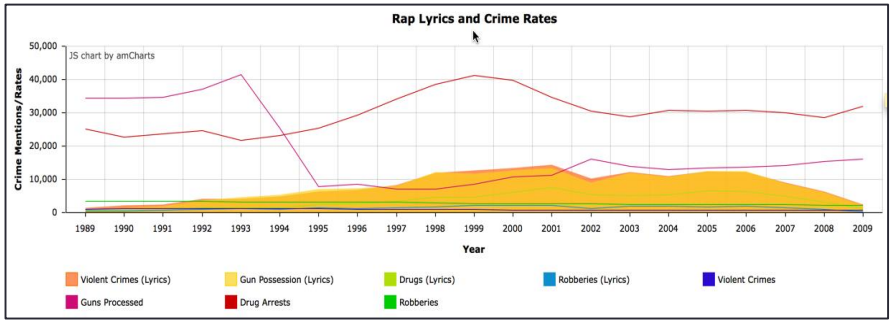
Literature scholars should stop reading books and start counting, graphing, and mapping them instead.

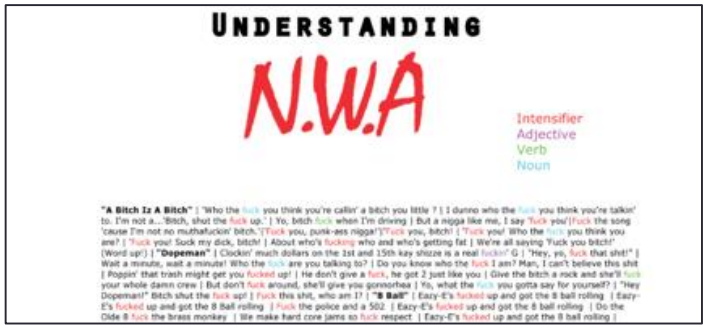
Example: Lyrics of Rap Songs

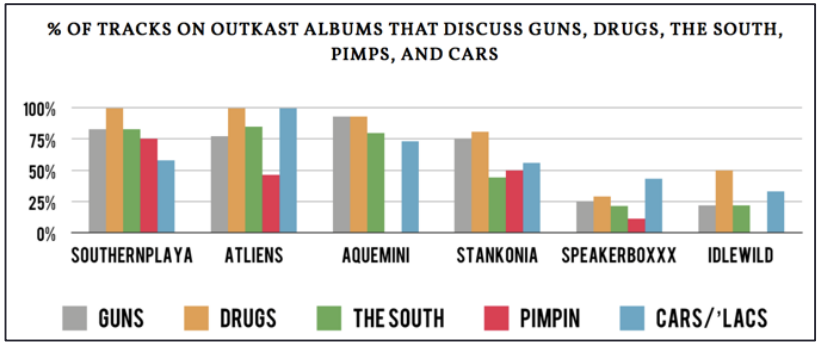
Types of analyses – word or topic frequency

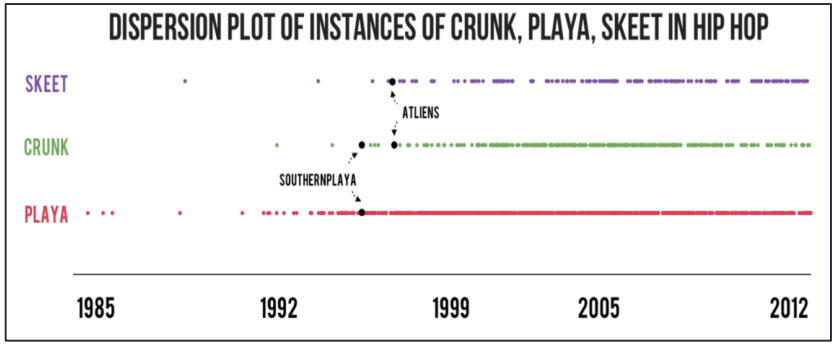






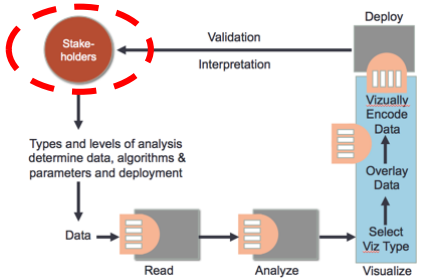






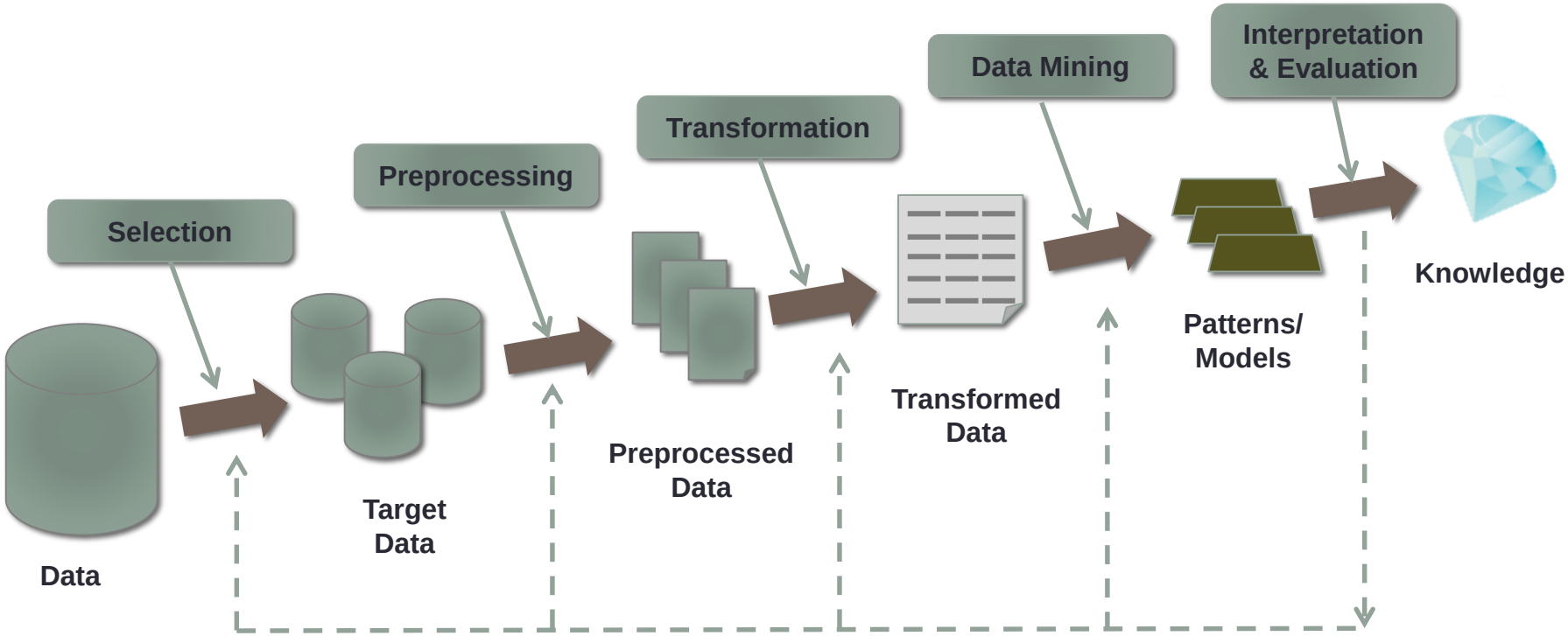
Example: Lyrics of Rap Songs

Textual analysis – the interest



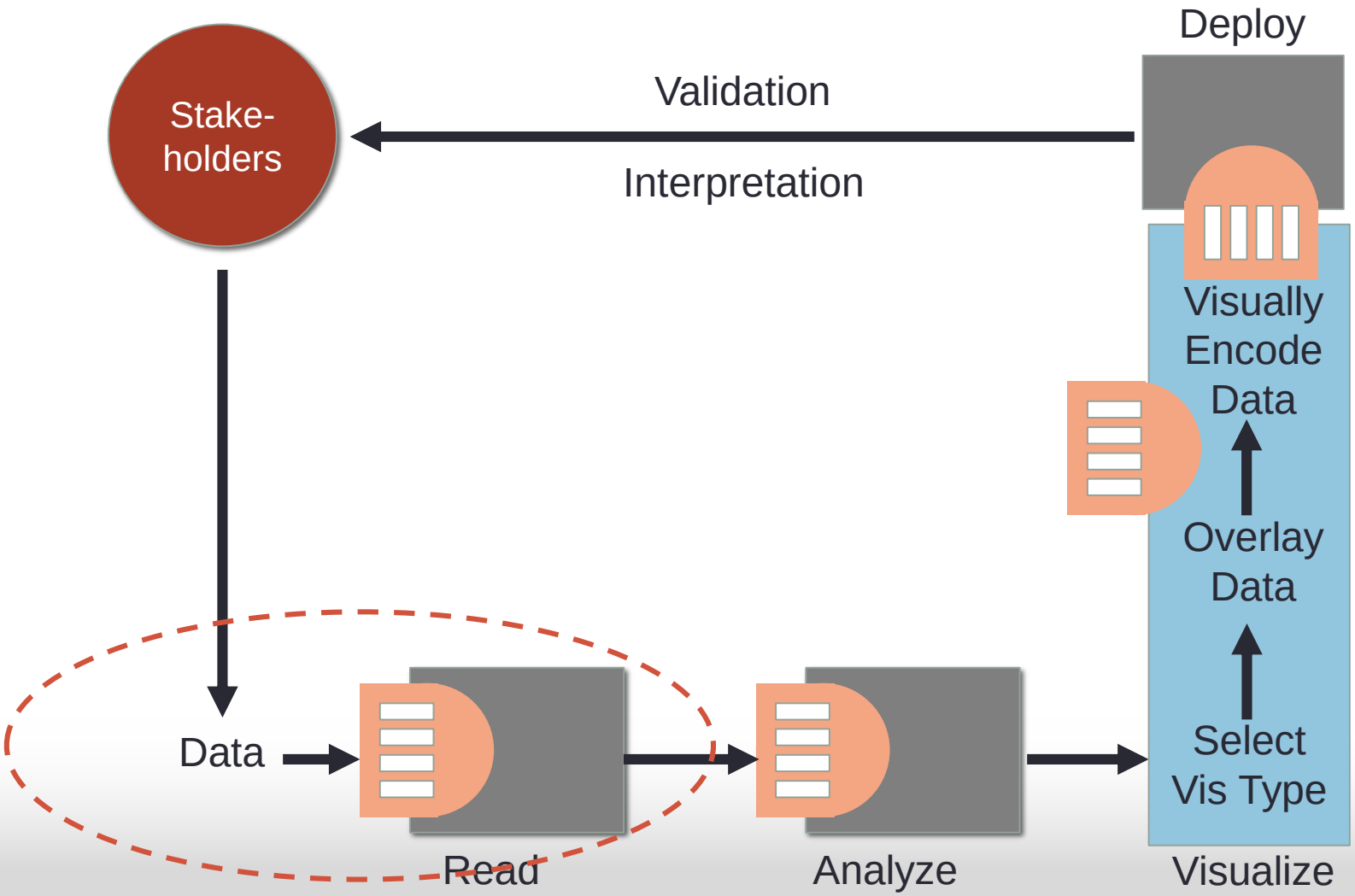
kickstarter.com/projects/1801076626/the-hip-hop-word-count-a-searchable-rap-almanac

Example: Lyrics of Rap Songs
CRISP Data Mining Process



Example: Lyrics of Rap Songs

Difficult part is turning text into analyzable data



Example: Lyrics of Rap Songs

Moving from lyrics to…

Everybody just rock it, don't stop it
You gotta rock it, don't stop
Keep tickin' and tockin', work it all around the clock
Everybody keep rockin' and clockin' and shockin' and rockin', go house

Da leaders, lookin straight charming in our Giorgio Armani's
You wanna harm me and Nas you gots ta conquer through a whole army
The cee-lo rollers, money folders, sippin' Bolla, holdin mad payola
Slangin that Coke without the Cola
Me and black don't fake jacks but we might sling one
It ain't no shame in our game we do our thing son

[Chorus – Eminem (repeat 2x):]
'Cause I'm Slim Shady, yes I'm the real Shady
All you other Slim Shadys are just imitating
So won't the real Slim Shady please stand up,
Please stand up, please stand up?

They were jammin off a record that said it best:
"Now what you hear is not a test!"

Aowowowowowowowowowowowo!
A-hunga-hunga-hunga-hunga
Aowowowowowowowowowowowo!
Aowowowowowowowowowowowo!

Form(at) amenable to mathematical/statistical analysis and visual display

Example: Lyrics of Rap Songs

Issues with rap/hip hop lyrics

- No specified format
- Variable length
- Variable spelling
- Punctuation and non-alphanumeric characters
- No predefined content or predefined set of values
- Slang, made up and misspelled words.
- Repetitive content(e.g. choruses)
- Some sources embed annotation (who is singing, how often to repeat a phrase, …)

Example: Lyrics of Rap Songs

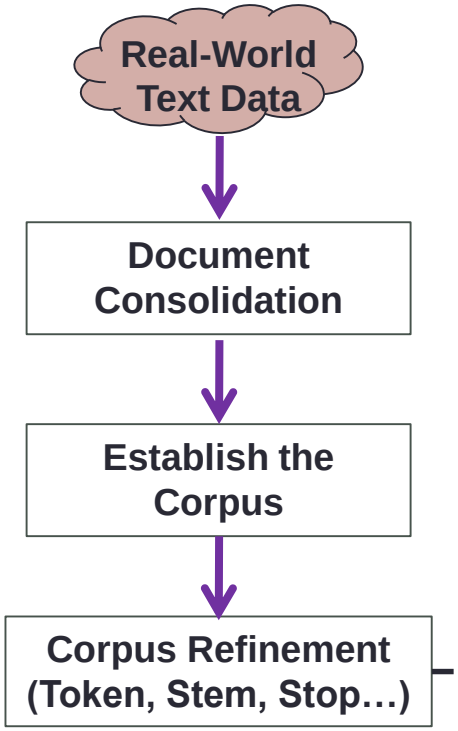
General approach

The overarching goal is, essentially, to turn text into data for analysis, via application of natural language processing (NLP) and analytical methods.

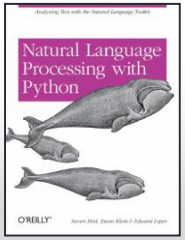
It is often assumed that documents are a *bag of words*, where order does not inform our analyses… If this assumption is unpalatable, we can retain some word order by including bigrams (word pairs) or trigrams.

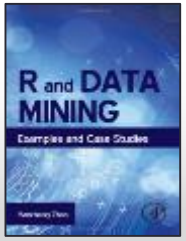
Example: Lyrics of Rap Songs

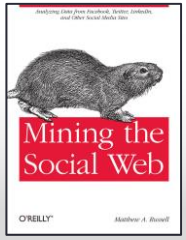
Text conversion process

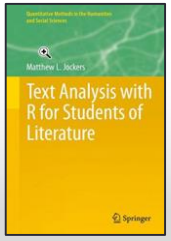


- **Tokenization** —Parse the text to generate terms. Sophisticated analyzers can also extract phrases from the text.
- **Normalize** — Convert them to lowercase.
- **Eliminate stop words** — Eliminate terms that appear very often (e.g. the, and, …).
- **Stemming** — Convert the terms into their stemmed form— remove plurals and different word forms (e.g. achieve, achieves, achieved – achiev) [note: word about synonyms – WordNet Synset]



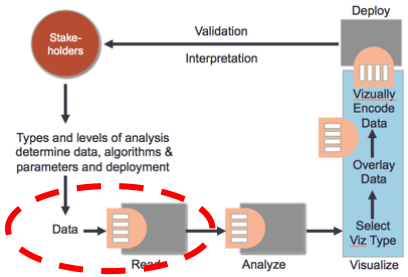


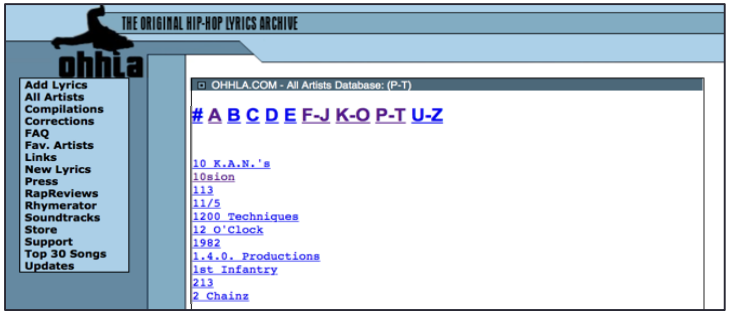


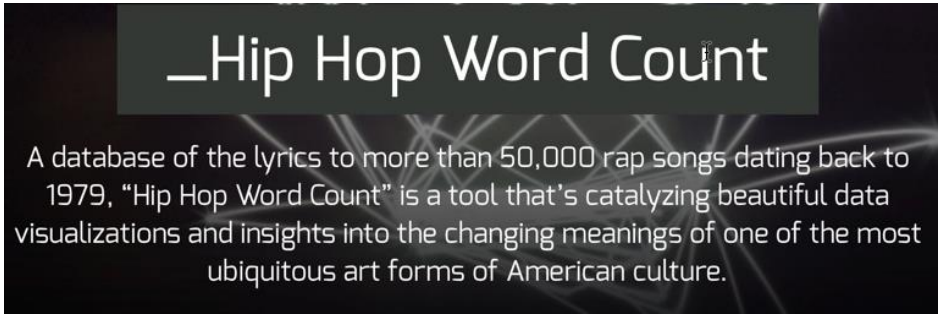


Example: Lyrics of Rap Songs

Text conversion process - Corpus

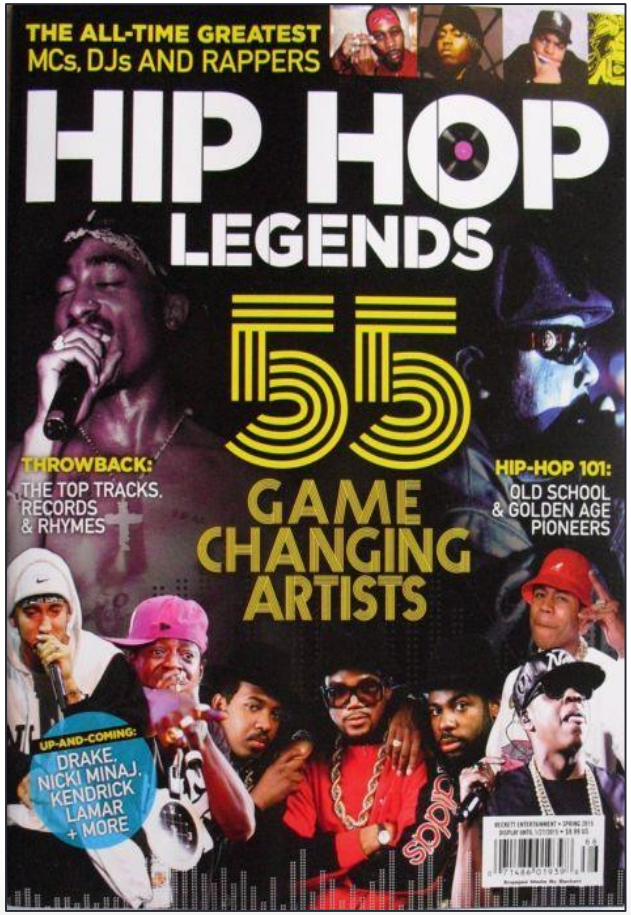






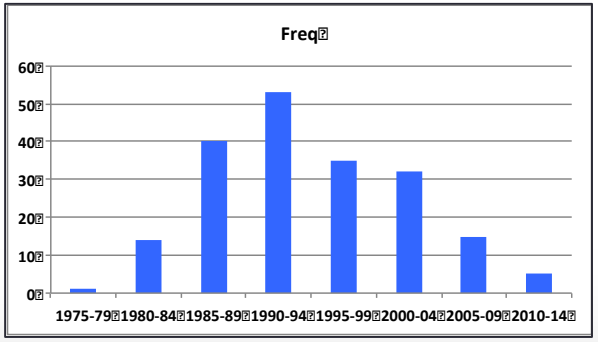
Example: Lyrics of Rap Songs

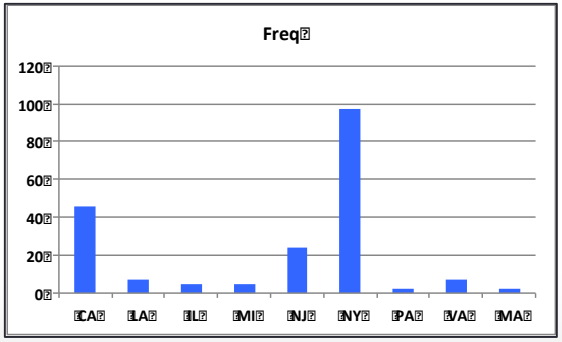
Text conversion process – Hip Hop corpus



195 Hip Hot Artists (Individuals & Groups)							
Old School	**15**	**Golden Age**	**86**	**Gangsta Rap**	**62**	**Millennium**	**32**
Afrika Bambaataa	3	2 Live Crew	6	2PAC	5	Eminem	5
Grandmaster Flash & The Furious Five	1	ATCQ	4	Dr. DRE	6	Jay-Z	8
Kook G Rap	2	Beastie Boys	6	Ice Cube	8	Kanye West	5
Kool Moe Dee & Treacherous Three	2	Big Daddy Kane	2	Ice-T	6	Lil Wayne	7
Kurtis Blow	4	Biz Markie	2	Lil' Kim	5	Missy Elliott	7
Sugar Hill Gang	3	Busta Rhymes	7	N.W.A	6		
		De La Soul	4	NAS	5		
		DJ Jazzy & The Fresh Prince	2	Puff Daddy, P. Diddy	6		
		Eric B. & Rakim	7	Snoop Dogg	5		
		Gang Starr	2	The Notorious Big	5		
		KRS-One	4	Wu-Tang Clan	5		
		LL Cool J	9				
		MC Hammer	4				
		Public Enemy	7				
		Queen Latifah	6				
		Run-D.M.C.	7				
		Salt-N-Pepa	5				
		Slick Rick	2				

195 Songs By 40 Artists





Example: Lyrics of Rap Songs

Text conversion process – Hip Hop corpus

```
Something's Got to Give
wish for peace between the races
Someday we shall all be one
Why fight yourself?
This one's called 'Rectify'
There's something coming to the su
There's fire all around but this i
I've seen better days than this on
I've seen better nights than this
Tension is rebuilding
Something's got to give
Something's got to give
Someday we shall all be one
Jesus Christ, we're nice
```

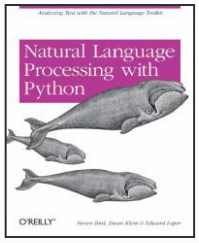
Words - 69/45
['wish', 'for', 'peace', 'between', 'the', 'races', 'Someday', 'we', 'shall', 'all', 'be', 'one', 'Why', 'fight', 'yourself', 'This', 'ones', 'called', 'Rectify', 'Theres', 'something', 'coming', 'to', 'the', 'surface', 'Theres', 'fire', 'all', 'around', 'but', 'this', 'is', 'all', 'illusion', 'Ive', 'seen', 'better', 'days', 'than', 'this', 'one', 'Ive', 'seen', 'better', 'nights', 'than', 'this', 'one', 'Tension', 'is', 'rebuilding', 'Somethings', 'got', 'to', 'give', 'Somethings', 'got', 'to', 'give', 'Someday', 'we', 'shall', 'all', 'be', 'one', 'Jesus', 'Christ', 'were', 'nice']

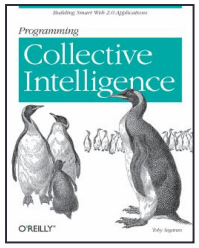
Lowers - 69/44
['wish', 'for', 'peace', 'between', 'the', 'races', 'someday', 'we', 'shall', 'all', 'be', 'one', 'why', 'fight', 'yourself', 'this', 'ones', 'called', 'rectify', 'theres', 'something', 'coming', 'to', 'the', 'surface', 'theres', 'fire', 'all', 'around', 'but', 'this', 'is', 'all', 'illusion', 'ive', 'seen', 'better', 'days', 'than', 'this', 'one', 'ive', 'seen', 'better', 'nights', 'than', 'this', 'one', 'tension', 'is', 'rebuilding', 'somethings', 'got', 'to', 'give', 'somethings', 'got', 'to', 'give', 'someday', 'we', 'shall', 'all', 'be', 'one', 'jesus', 'christ', 'were', 'nice']

Alphas - 69/44
['wish', 'for', 'peace', 'between', 'the', 'races', 'someday', 'we', 'shall', 'all', 'be', 'one', 'why', 'fight', 'yourself', 'this', 'ones', 'called', 'rectify', 'theres', 'something', 'coming', 'to', 'the', 'surface', 'theres', 'fire', 'all', 'around', 'but', 'this', 'is', 'all', 'illusion', 'ive', 'seen', 'better', 'days', 'than', 'this', 'one', 'ive', 'seen', 'better', 'nights', 'than', 'this', 'one', 'tension', 'is', 'rebuilding', 'somethings', 'got', 'to', 'give', 'somethings', 'got', 'to', 'give', 'someday', 'we', 'shall', 'all', 'be', 'one', 'jesus', 'christ', 'were', 'nice']

NonStops - 42/30
['wish', 'peace', 'races', 'someday', 'shall', 'one', 'fight', 'ones', 'called', 'rectify', 'theres', 'something', 'coming', 'surface', 'theres', 'fire', 'around', 'illusion', 'ive', 'seen', 'better', 'days', 'one', 'ive', 'seen', 'better', 'nights', 'one', 'tension', 'rebuilding', 'somethings', 'got', 'give', 'somethings', 'got', 'give', 'someday', 'shall', 'one', 'jesus', 'christ', 'nice']

Stems - 42/28
['wish', 'peac', 'race', 'someday', 'shall', 'one', 'fight', 'one', 'call', 'rectifi', 'there', 'someth', 'come', 'surfac', 'there', 'fire', 'around', 'illus', 'ive', 'seen', 'better', 'day', 'one', 'ive', 'seen', 'better', 'night', 'one', 'tension', 'rebuild', 'someth', 'got', 'give', 'someth', 'got', 'give', 'someday', 'shall', 'one', 'jesu', 'christ', 'nice']





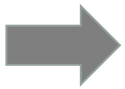
Analysis from Python NLTK Program

Example: Lyrics of Rap Songs

Text conversion process – Hip Hop corpus

```
Something's Got to Give
wish for peace between the races
Someday we shall all be one
Why fight yourself?
This one's called 'Rectify'
There's something coming to the
There's fire all around but this
I've seen better days than this
I've seen better nights than thi
Tension is rebuilding
Something's got to give
Something's got to give
Someday we shall all be one
Jesus Christ, we're nice
```

"Bag of Words, Terms, Tokens, Stems, …"



wordsCnts
{'all': 4, 'Christ': 1, 'rebuilding': 1, 'is': 2, 'Somethings': 2, 'surface': 1, 'yourself': 1, 'something': 1, 'seen': 2, 'Jesus': 1, 'fire': 1, 'Tension': 1, 'nights': 1, 'for': 1, 'peace': 1, 'fight': 1, 'better': 2, 'to': 3, 'Ive': 2, 'between': 1, 'got': 2, 'Why': 1, 'nice': 1, 'be': 2, 'we': 2, 'around': 1, 'shall': 2, 'This': 1, 'but': 1, 'ones': 1, 'coming': 1, 'one': 4, 'than': 2, 'Theres': 2, 'Someday': 2, 'give': 2, 'Rectify': 1, 'this': 3, 'wish': 1, 'days': 1, 'illusion': 1, 'races': 1, 'were': 1, 'the': 2, 'called': 1}
lowerCnts
{'someday': 2, 'all': 4, 'rectify': 1, 'is': 2, 'surface': 1, 'yourself': 1, 'ive': 2, 'something': 1, 'seen': 2, 'jesus': 1, 'nights': 1, 'christ': 1, 'for': 1, 'peace': 1, 'somethings': 2, 'fight': 1, 'better': 2, 'to': 3, 'between': 1, 'got': 2, 'illusion': 1, 'nice': 1, 'be': 2, 'we': 2, 'around': 1, 'than': 2, 'shall': 2, 'fire': 1, 'rebuilding': 1, 'but': 1, 'ones': 1, 'coming': 1, 'one': 4, 'why': 1, 'give': 2, 'this': 4, 'wish': 1, 'days': 1, 'tension': 1, 'races': 1, 'were': 1, 'the': 2, 'called': 1, 'theres': 2}
alphasCnts
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nonstopsCnts
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stemsCnts
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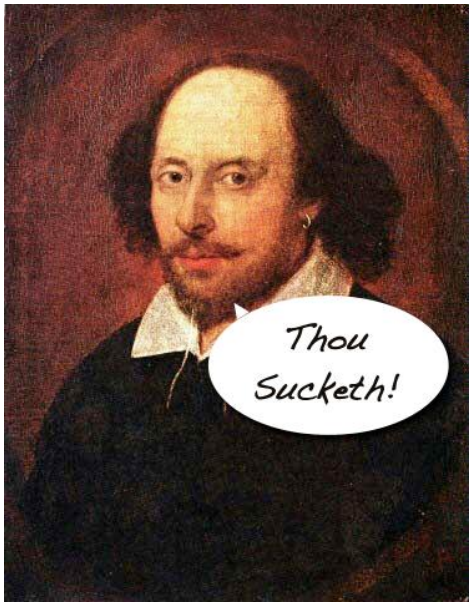
Example: Lyrics of Rap Songs

Text conversion process – structural features



	Words	Alphas	Stems
Total	127643	120263	52094
TotUniq	12521	10182	7675
NumLines	16412	16412	16412
Chars	495063	487265	247340
AvgWrd/Ln	7.8	7.3	3.2
AvgCh/Word	3.9	4.1	4.7
LexDiv	10.2	11.8	6.8

Author	WordLen	AvgWords/Sent	Words/Voca
austen-emma.txt	4	21	26
austen-persuasion.txt	4	23	16
austen-sense.txt	4	24	22
bible-kjv.txt	4	33	79
blake-poems.txt	4	18	5
bryant-stories.txt	4	17	14
burgess-busterbrown.txt	4	14	12
carroll-alice.txt	4	16	12
chesterton-ball.txt	4	17	11
chesterton-brown.txt	4	19	11
chesterton-thursday.txt	4	16	10
edgeworth-parents.txt	4	18	24
melville-moby_dick.txt	4	24	15
milton-paradise.txt	4	52	10
shakespeare-caesar.txt	4	12	8
shakespeare-hamlet.txt	4	13	7
shakespeare-macbeth.txt	4	13	6
whitman-leaves.txt	4	35	12

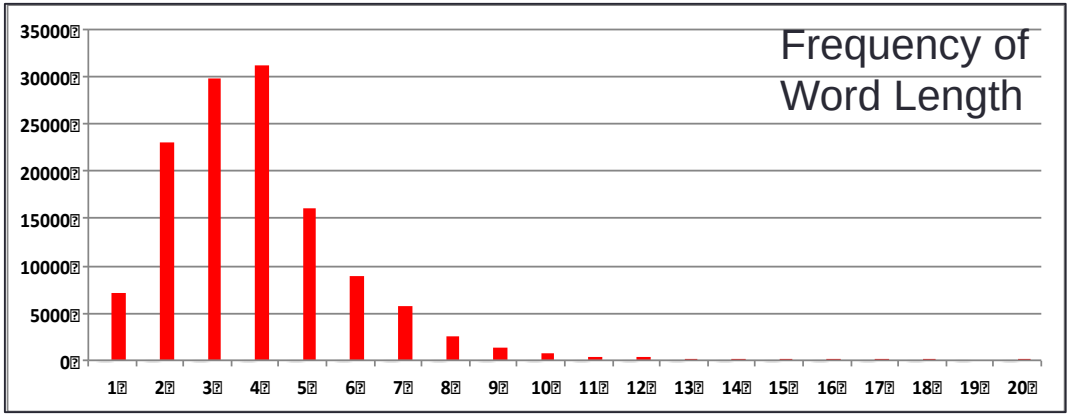
Example: Lyrics of Rap Songs

Text conversion process – structural features

…
Final answer "not to be", "not to be" is right!
Next question - to build winged shoes or autophagy
Silk screen band tees, take apart a vcr, ringer off, canned peas
Cabin fever mi amor
Patiently adhering to the chandelier ta key-in-door
To usher in the understated anarchy of leisureforce
Led a purple tongue and ratty caballeros
Up over the black rainbow into the house of mirrors
To become a thousand zeroes
Echoing a twisted alchemy, freak flags, fluttering to circadian free jazz
Sleep apnea scratching "bring that beat back"
I doze off, clothes on, noise in the feedbag
Shhh.. om nom nom, blinds drawn
Compost thrown to the spine pile, bygones, mangy
Intimately spaced pylons on a plot of inhospitable terrain
Hi mom!
…
(from Leisureforce)

Example: Lyrics of Rap Songs

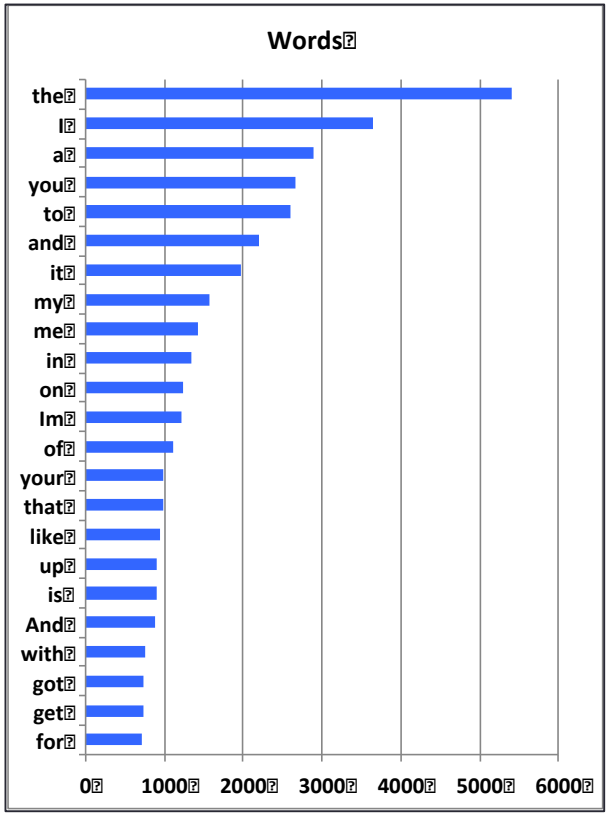
Text conversion process – word length

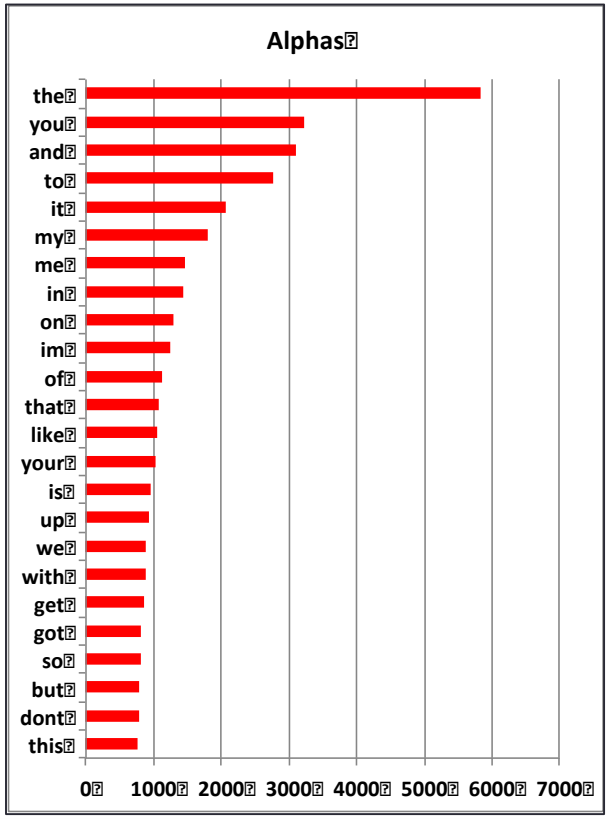


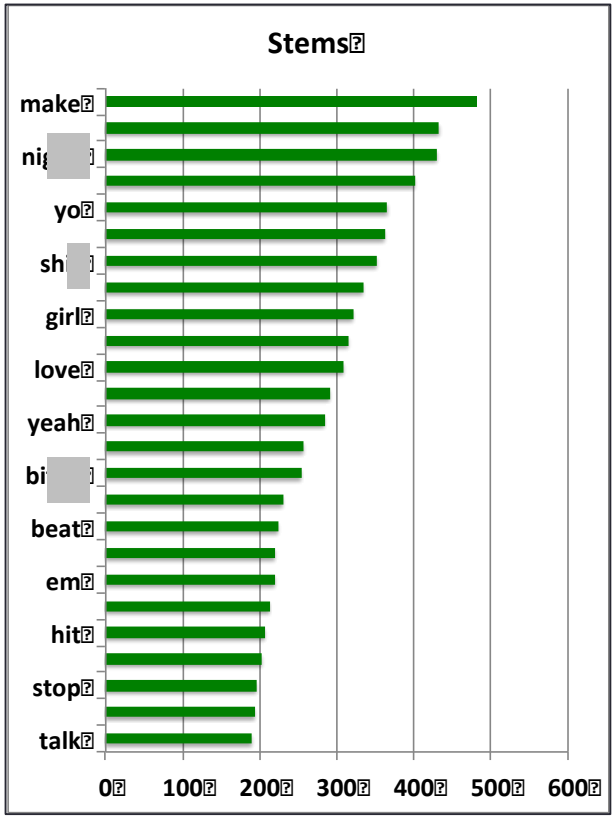
Word	Freq	Length	Word	Freq	Length
EeeyiyiyiyiyeahtheDoggPoundsinthehouowwowse	1	43	Ratatatatatatatatata	1	20
EeeyiyiyiyiyahtheDoggPoundsinthehouowwse	1	40	Whatwhawhatwhatwhats	1	20
Wooooooooooooooooooooooeeeeeeeeeeeee	1	39	rrrrrrrrrrrrrrrah	1	18
Wowowowowowowowowowowowowowowow	1	34	EazymotherfuckingE	1	18
MisterImTooGoodToCallOrWriteMyFans	1	34	wowowowowowowowowo	1	18
supercalifragilisticexpialidocious	1	34	CharlieBakerDenver	1	18
Checkchcheckcheckcheckchcheck	1	29	Heyheyheyheyheyhey	1	18
checkchcheckcheckcheckchcheck	1	29	moneymakinmachines	1	18
yaauhhhaaaauhhhhahhhauhhhhll	1	28	YouknowhatImsayin	1	17
bowwowwowyippyyoyoyoyoyo	1	26	Wowowowowowowowow	1	17
Rockthaithaiotoyothaithai	1	25	youknowhatImsayin	1	17
Bowwowwowyippyyoyippyyay	1	24	BedfordStuyvesant	1	17
Workwaworkworkworkwawork	1	24	whoahhhhhhhhhhhh	1	17
Whythaithaiotoyothaithai	1	24	Checkacheckacheck	1	17
Aowowowowowowowowowowo	1	24	yaknowhatImsayin	2	16
ooooooooooooooooooooo	1	23	bowwowwowyippyyo	1	16
HeyyyeyyyeEYEYyyyEYYYY	1	22	crossedSyndicate	1	16
Ahungahungahungahunga	1	21	Incomprehensible	1	16
FUNNNNNNNNNNNNNNNNNN	1	21	doodoodoodadahhh	1	16
hippahoppadippaboppa	1	20	Micmicmicrophone	1	16
Awowowowowowowowowow	1	20	Extraterrestrial	1	16
GreGreGreGreGreatest	1	20	Aftermathematics	1	16
WHODIWHOOOOOOOOOOOOO	1	20	multimillionaire	1	16

Example: Lyrics of Rap Songs

Text conversion process – frequencies

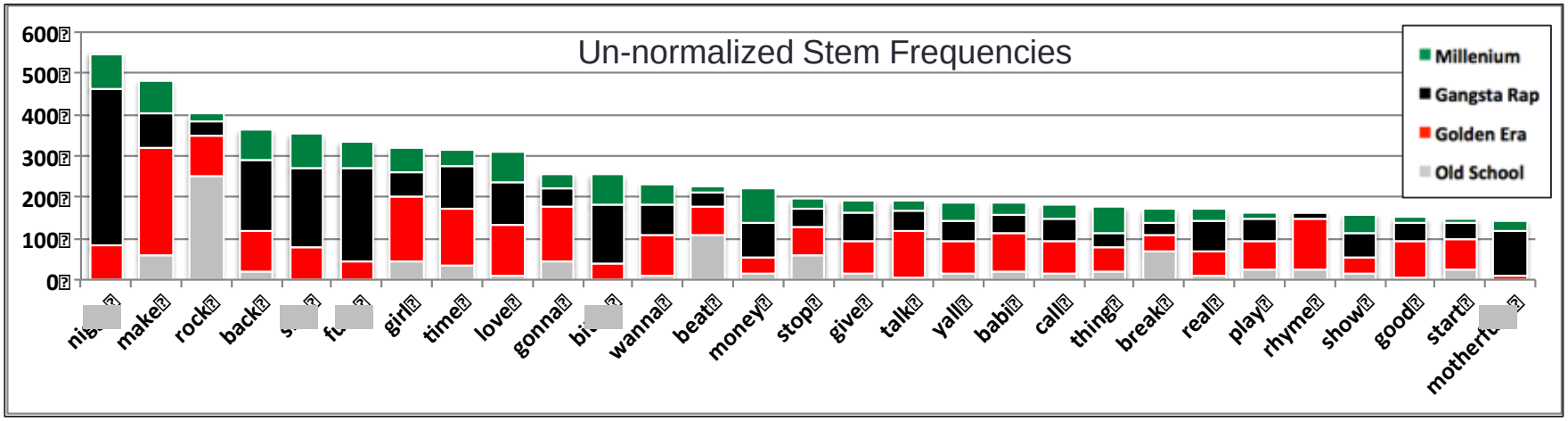


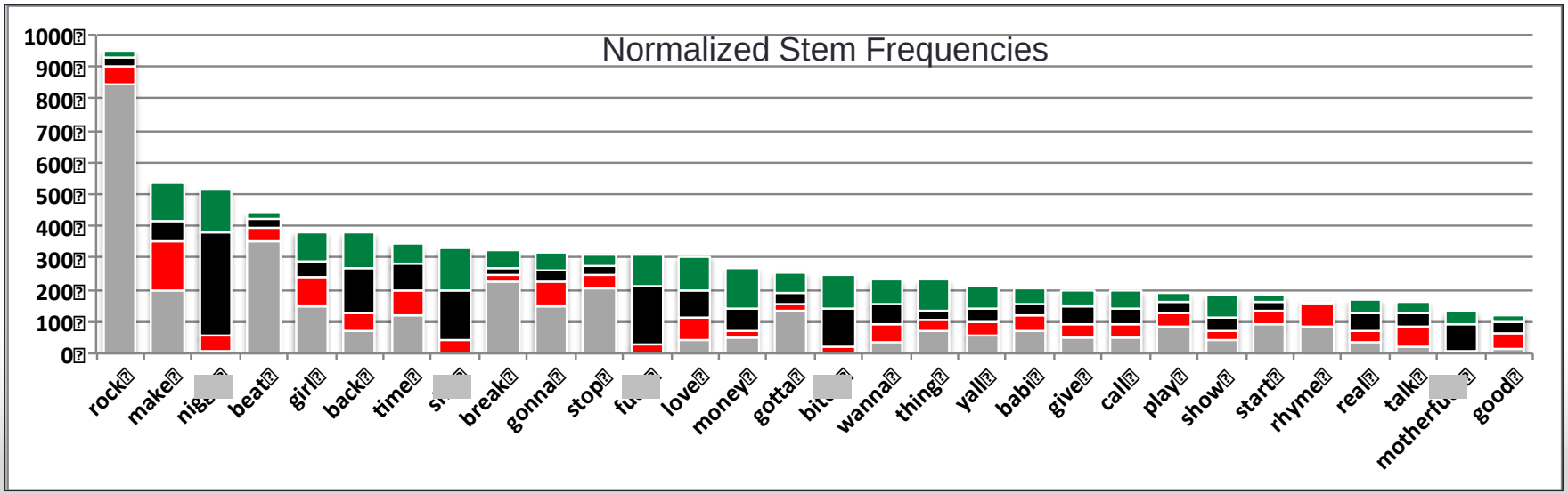




Example: Lyrics of Rap Songs

Text analysis process – stem frequencies by era

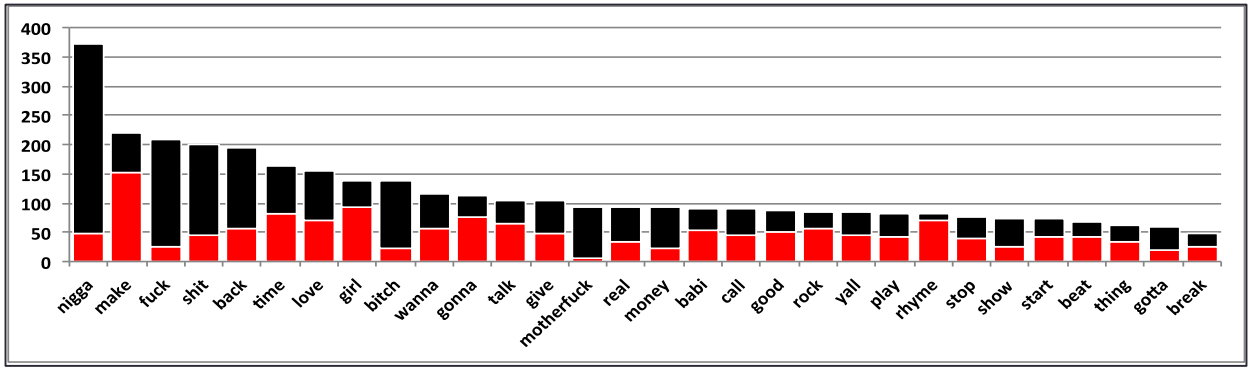


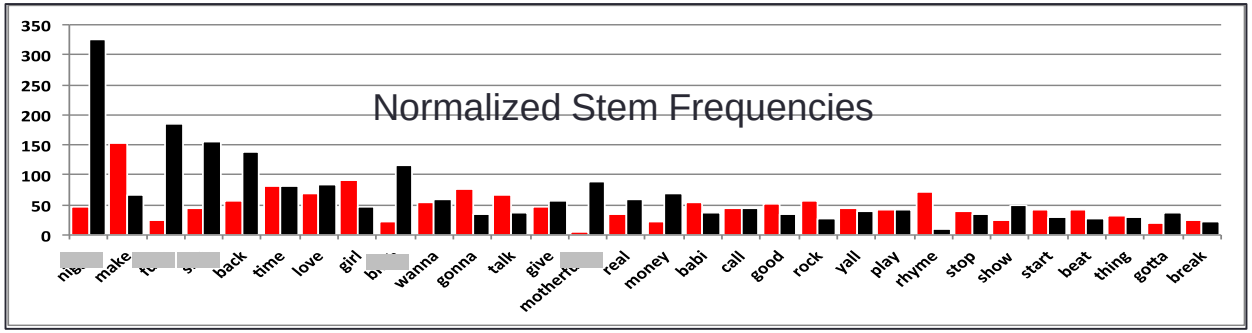


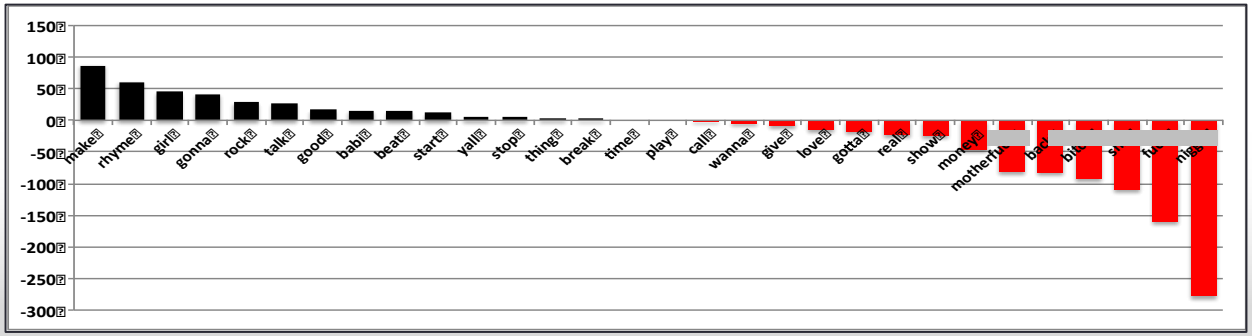
Example: Lyrics of Rap Songs

Text analysis process – stem frequencies by era

Normalized Stem Frequencies

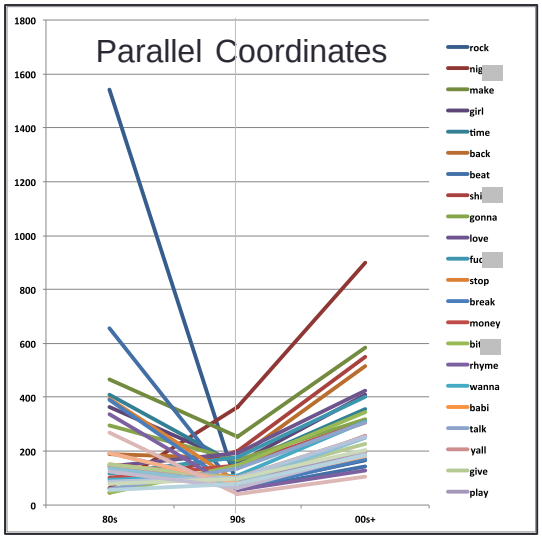


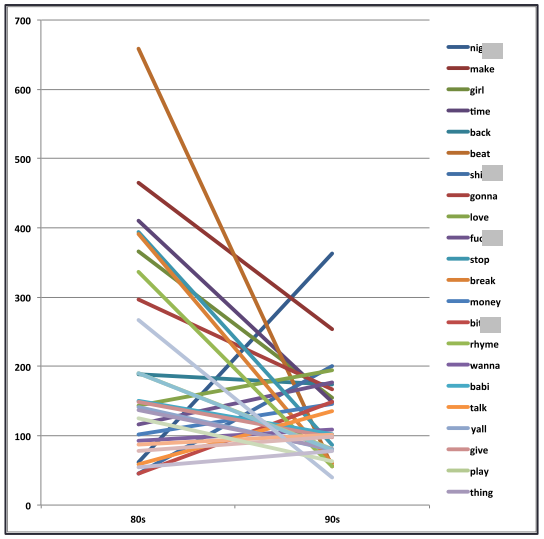


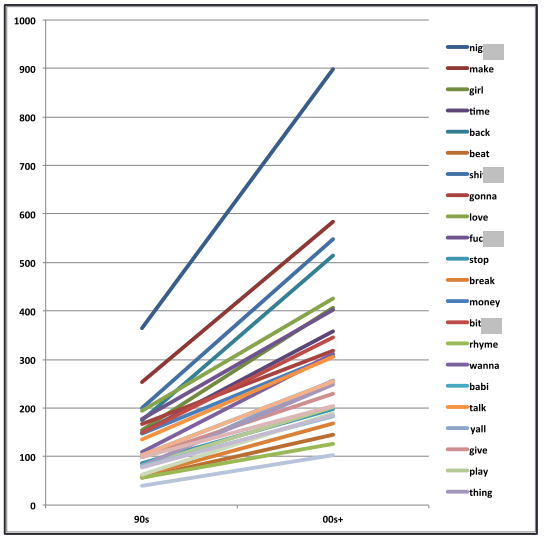


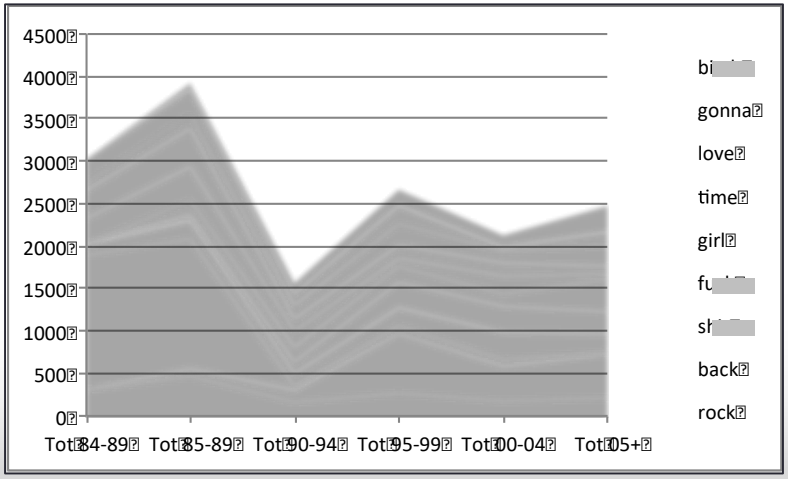
Example: Lyrics of Rap Songs

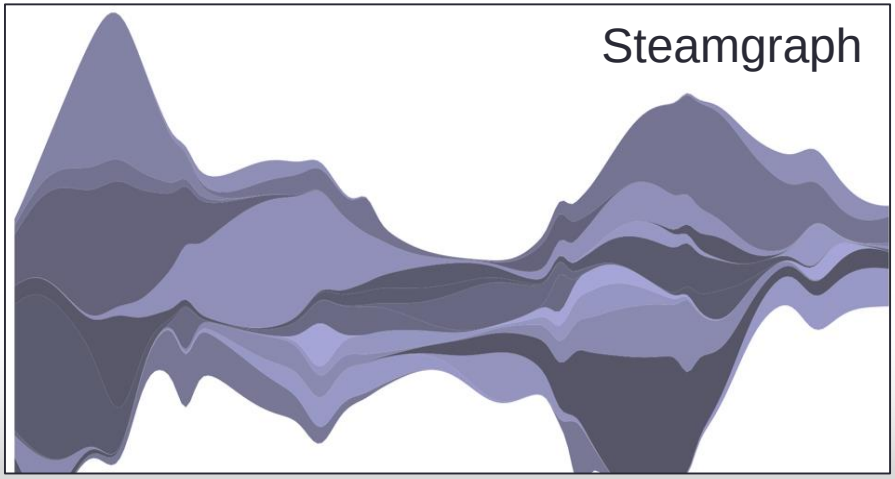
Text analysis process – stem frequencies by time











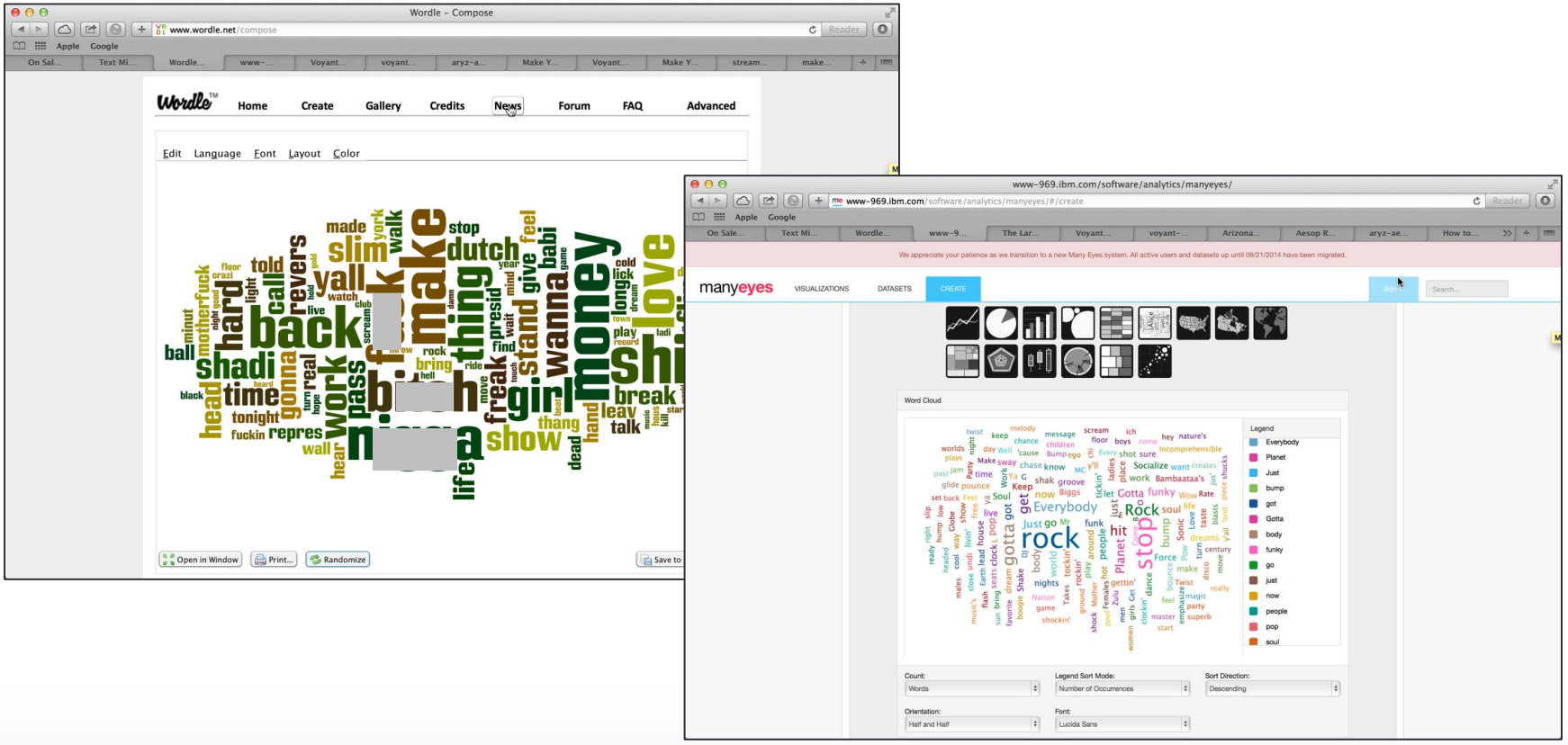
Example: Lyrics of Rap Songs

Text analysis process – frequencies with less precision

Word Clouds – They're everywhere along with subway maps, periodic charts…

Example: Lyrics of Rap Songs

Text analysis process – frequencies with less precision



Word Clouds – They're everywhere along with subway maps, periodic charts…

Example: Lyrics of Rap Songs

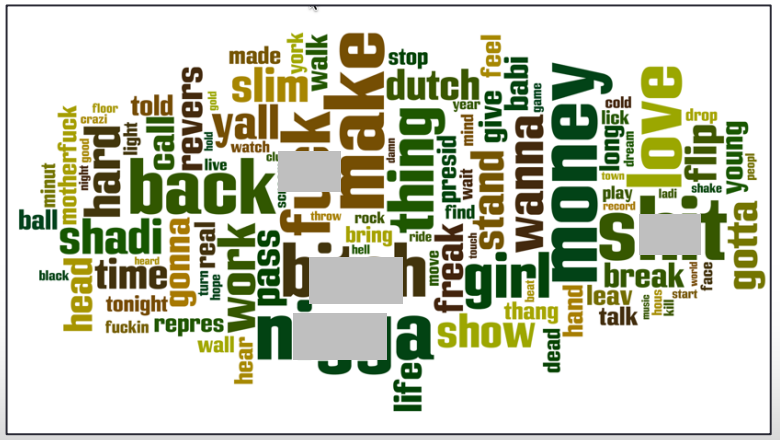
Text analysis process – frequencies with less precision

Old School

Golden Era

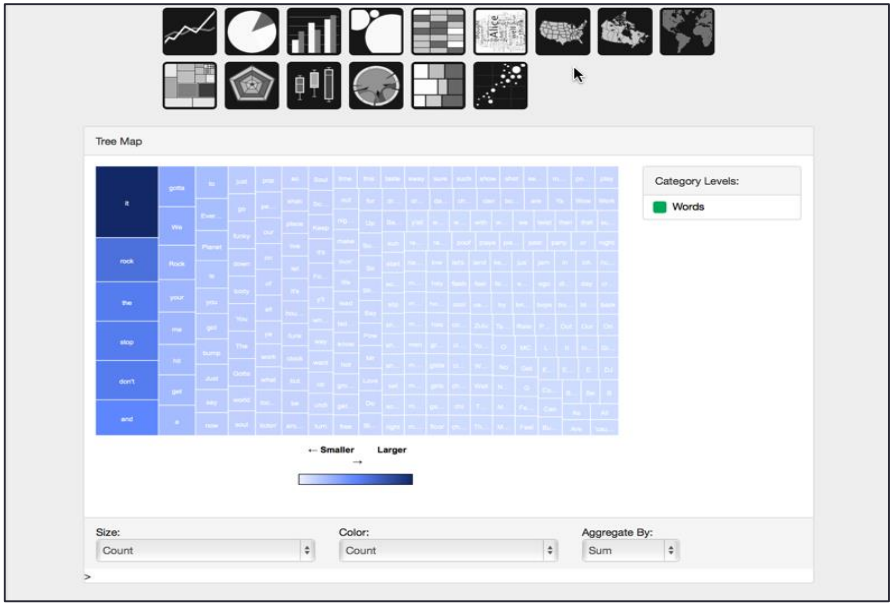
Gangsta

Millenium



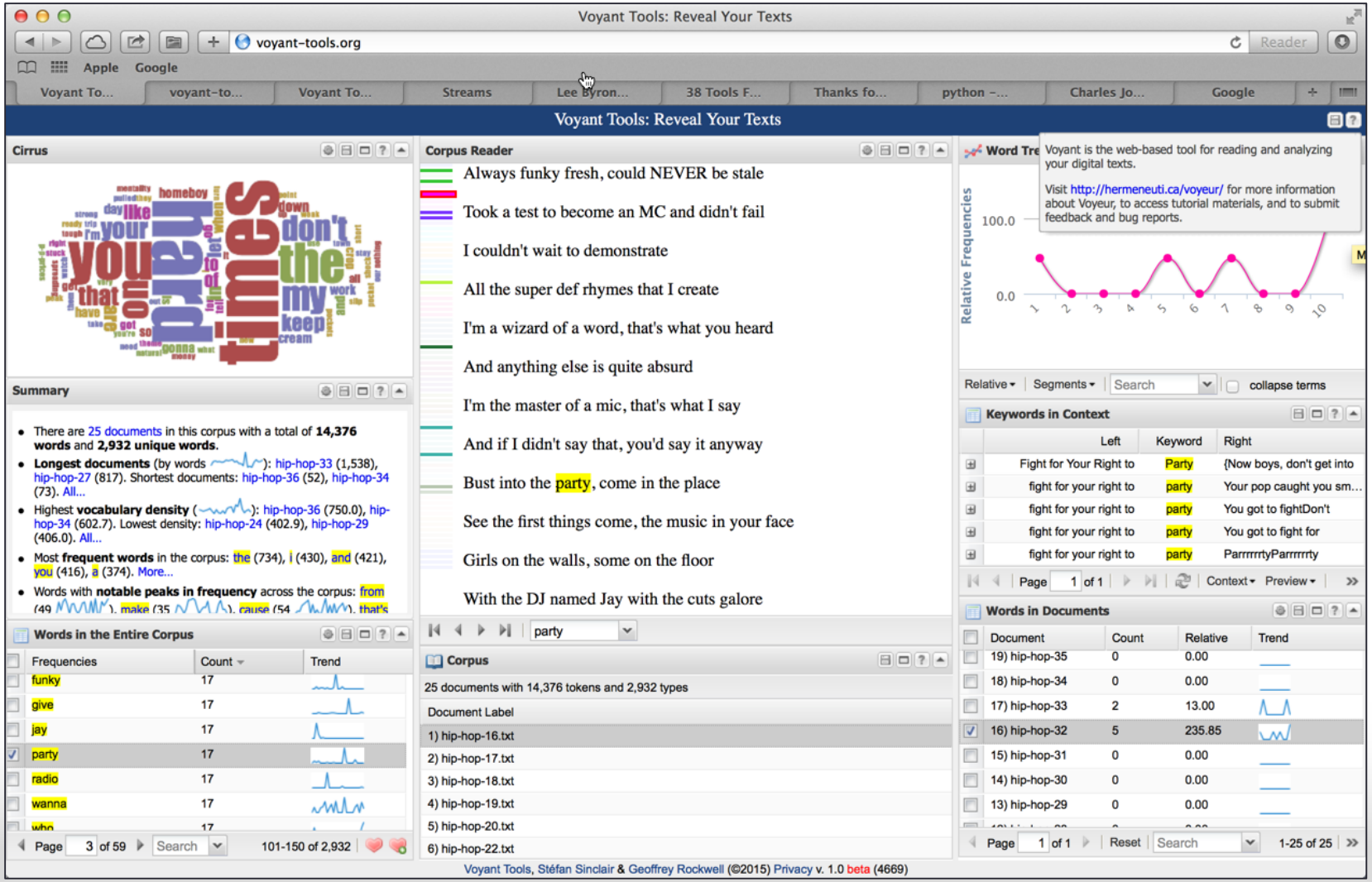
Example: Lyrics of Rap Songs

Text analysis process – frequencies with less precision



Example: Lyrics of Rap Songs

Text analysis process – general interactive platform

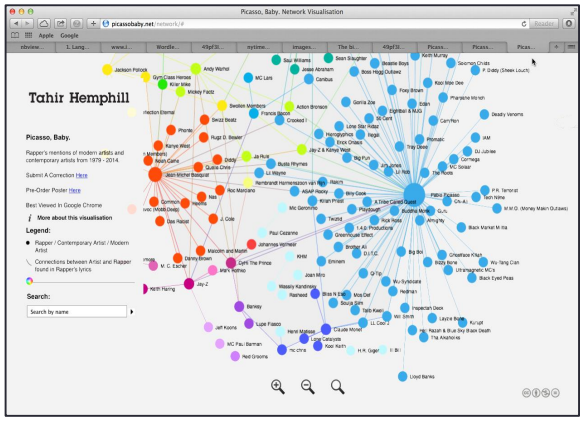


Example: Lyrics of Rap Songs

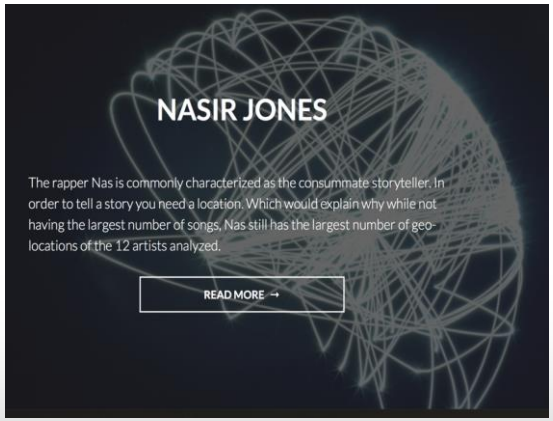
Types of (visual) analysis

Cluster/Classification

Network

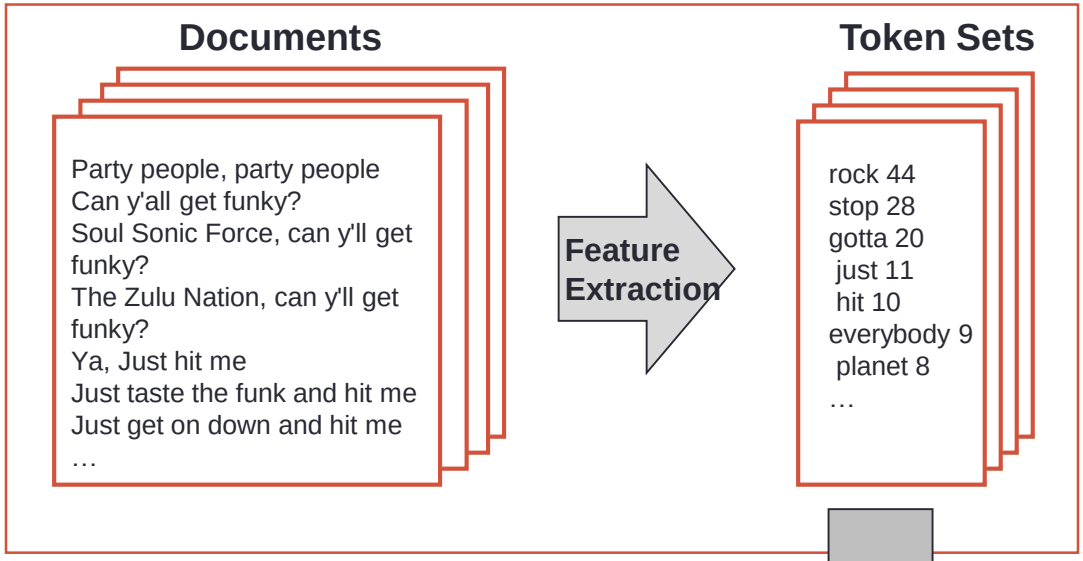


Geospatial



Example: Lyrics of Rap Songs

Text analysis process – Role of Document-Term Matrix



Feature Extraction & Weighting

"Bag of Words, Terms or Tokens"

Doc/Token Matrix:
Vectors of Words, Terms or Tokens by Doc

	Token1	Token2	Token3	Token4	…
Doc1	1	2	2	4	
Doc2	4	2	3	0	
Doc3	1	1	1	0	
Doc4	1	1	1	2	
…					

"Bag of Words" (BOW) or Vector Space Model (VSM): Words or Tokens are attributes and documents are examples

Example: Lyrics of Rap Songs

Text analysis process – Document-Term Matrix

SongCode	make	nigga	rock	back	shit	fuck	…	girl	sell	suck	sweat	thug	uhuh	week	worri	TotalStems
Song1-OS-NY-80s	3	0	43	1	0	0	…	1	0	0	0	0	0	0	0	193
Song2-OS-NY-80s	1	0	0	0	0	0	…	0	0	0	0	0	0	0	0	116
Song3-OS-NY-80s	3	0	8	0	0	0	…	1	0	0	0	0	0	0	0	174
Song4-OS-NY-80s	3	0	1	0	0	0	…	2	0	0	0	0	0	1	0	82
Song5-OS-NY-80s	0	0	1	1	0	0	…	3	0	0	0	0	0	0	0	166
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
Song16-GA-NY-80s	0	0	0	0	0	0	…	0	0	0	0	0	0	0	0	55
Song17-GA-NY-80s	2	0	2	3	0	0	…	3	0	0	0	0	0	0	0	93
Song18-GA-NY-80s	2	0	6	1	0	0	…	3	0	0	0	0	0	0	0	108
Song19-GA-NY-80s	1	0	10	1	0	0	…	0	1	0	0	0	0	1	0	98
Song20-GA-NY-80s	0	0	6	1	0	0	…	0	0	0	0	0	0	0	0	103
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
Song102-GR-NJ-90s	0	0	0	0	1	32	…	0	0	0	0	0	0	0	0	106
Song103-GR-NJ-90s	0	3	0	2	1	1	…	1	0	0	1	0	0	0	0	98
Song104-GR-NJ-80s	1	0	3	5	5	0	…	2	0	0	0	0	0	0	0	190
Song105-GR-NJ-80s	1	0	1	0	0	0	…	0	0	0	0	0	0	0	0	56
Song106-GR-NJ-90s	1	0	0	1	0	0	…	1	1	0	1	0	0	0	0	101
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
Song164-ML-LA-00s	9	4	0	6	1	0	…	0	0	0	0	6	0	0	0	123
Song165-ML-LA-00s	7	0	0	1	3	2	…	0	0	0	0	0	0	0	1	84
Song166-ML-LA-00s	0	0	0	1	0	0	…	0	0	0	0	0	0	0	0	49
Song167-ML-LA-00s	0	1	1	0	4	0	…	1	0	0	0	0	0	0	0	66
Song168-ML-LA-00s	0	6	0	3	2	1	…	0	0	0	0	0	0	0	0	77
TotalStems	482	430	401	362	352	334		321	31	31	31	31	31	31	31	

0	0
1	0
2	1
3	1
1	0
1	2
0	0
0	0
13	17
8	3
1	0
0	11
12	10

3	2
1	6
3	1
3	0
0	1
0	0
3	4
2	0
2	1
13	11
12	1
0	0
5	3

Song1-OS-N'	3	0	43	1	0	0	1	2	2	0	0	0	0	0	28	0	0	1
Song2-OS-N'	1	0	0	0	0	0	0	6	0	0	0	0	2	0	2	0	1	0

Song13-OS-	5	0	112	2	0	0	0	3	0	11	0	0	7	1	1	0	0	0
Song14-OS-	8	0	39	2	0	0	12	5	1	10	0	1	4	1	2	5	2	2

Which pair of song vectors is more correlated? (.05 vs .49)

Which pair of word vectors is more correlated? (.7 vs. .6)

Example: Lyrics of Rap Songs

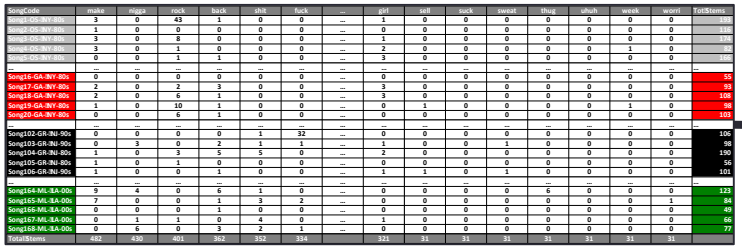
Text analysis process – Document-Term Matrix

Normalizing the data

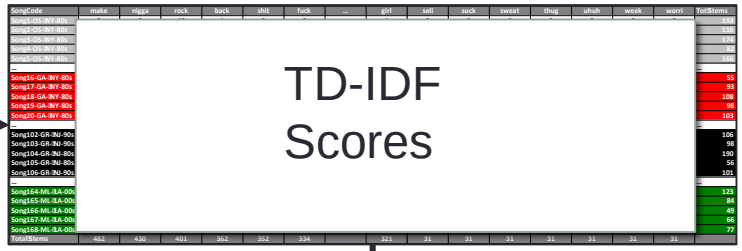
- Binary Frequencies: tf =1 for tf>0; otherwise 0
- Term Frequencies: tf(i,j)/Sum of tf(i,j) in Doc K
- Log Frequencies: 1 + log(tf) for tf>0; otherwise 0
- Normalized Frequencies: Divide each frequency by SQRT of Sum of Squares of the frequencies within the vector (column)
- Term Frequency–Inverse Document Frequency
  - TF: Freq of term for given doc/ sum of words for given doc
  - Inverse Document Frequency: log(N/(1+D)) where N is total number of docs and D is number with term
  - TF * IDF

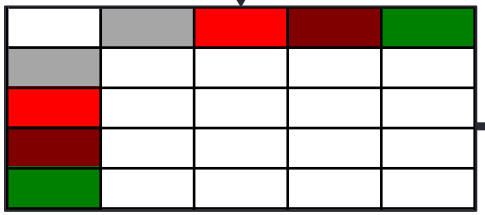
Example: Lyrics of Rap Songs

Text analysis process – Clustering



Doc-Term Matrix



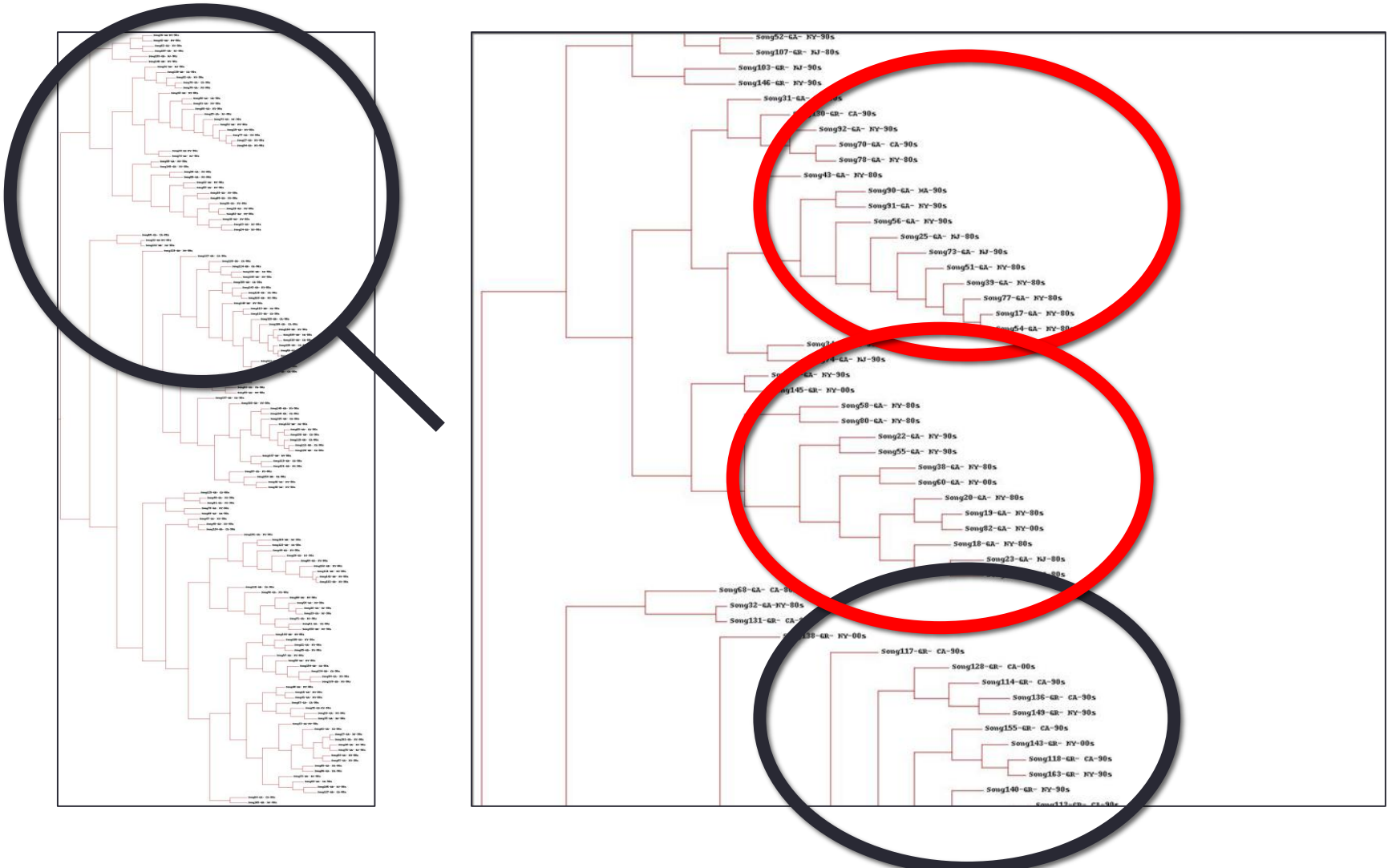


Correlation Matrix
(t x t or d x d)

Dendogram

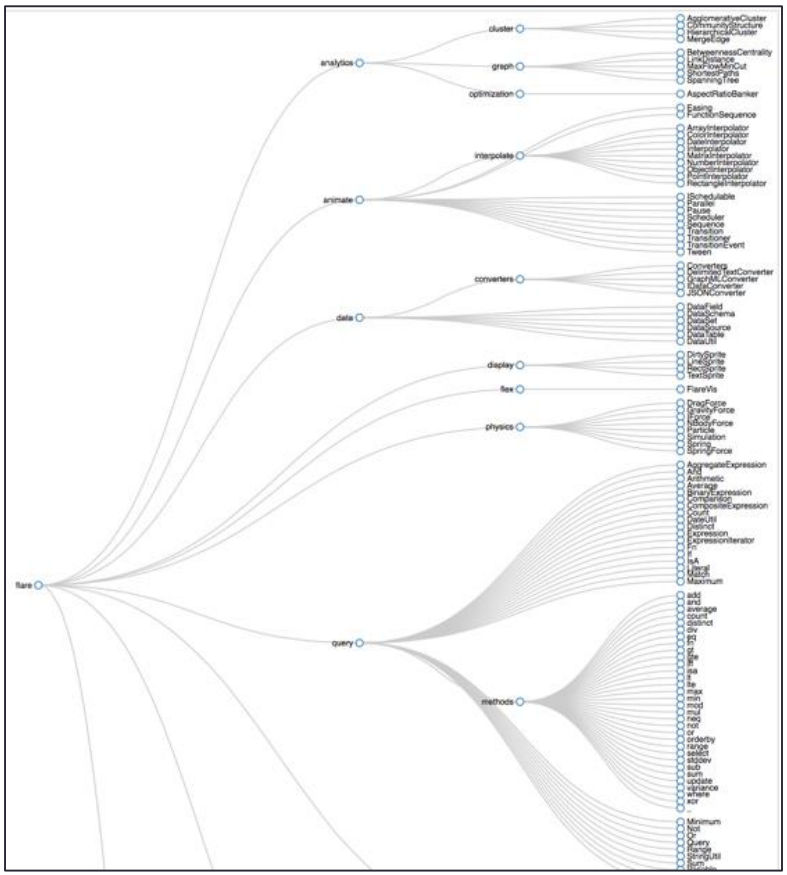
Example: Lyrics of Rap Songs

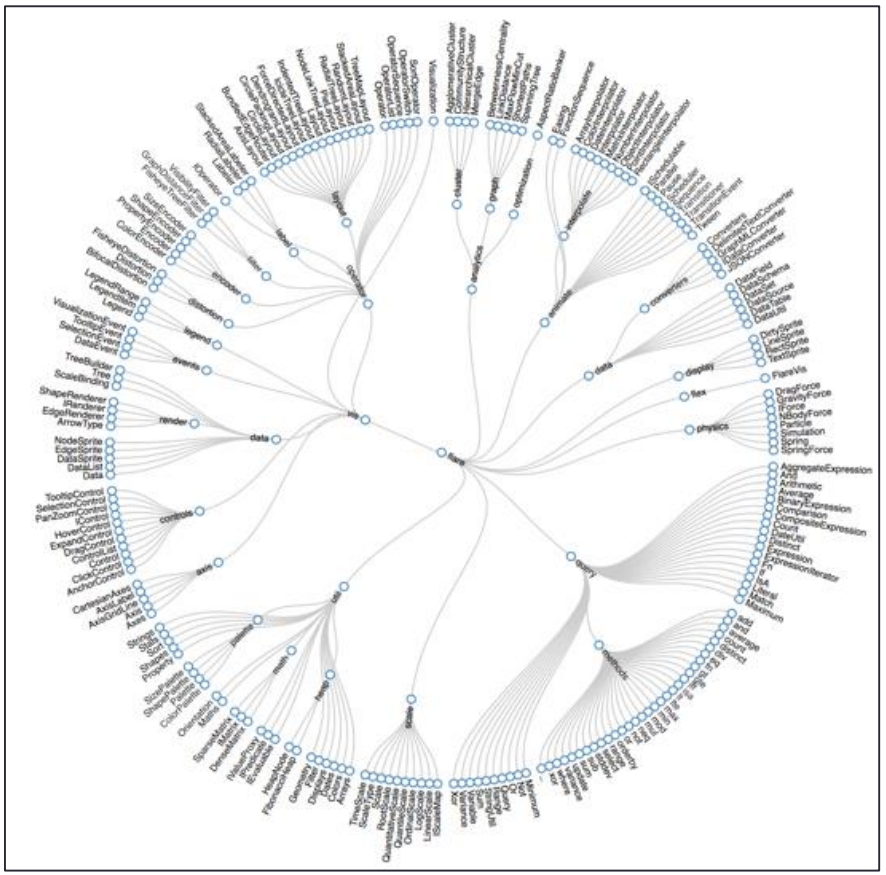
Text analysis process – Clustering



Example: Lyrics of Rap Songs

Text analysis process – Clustering



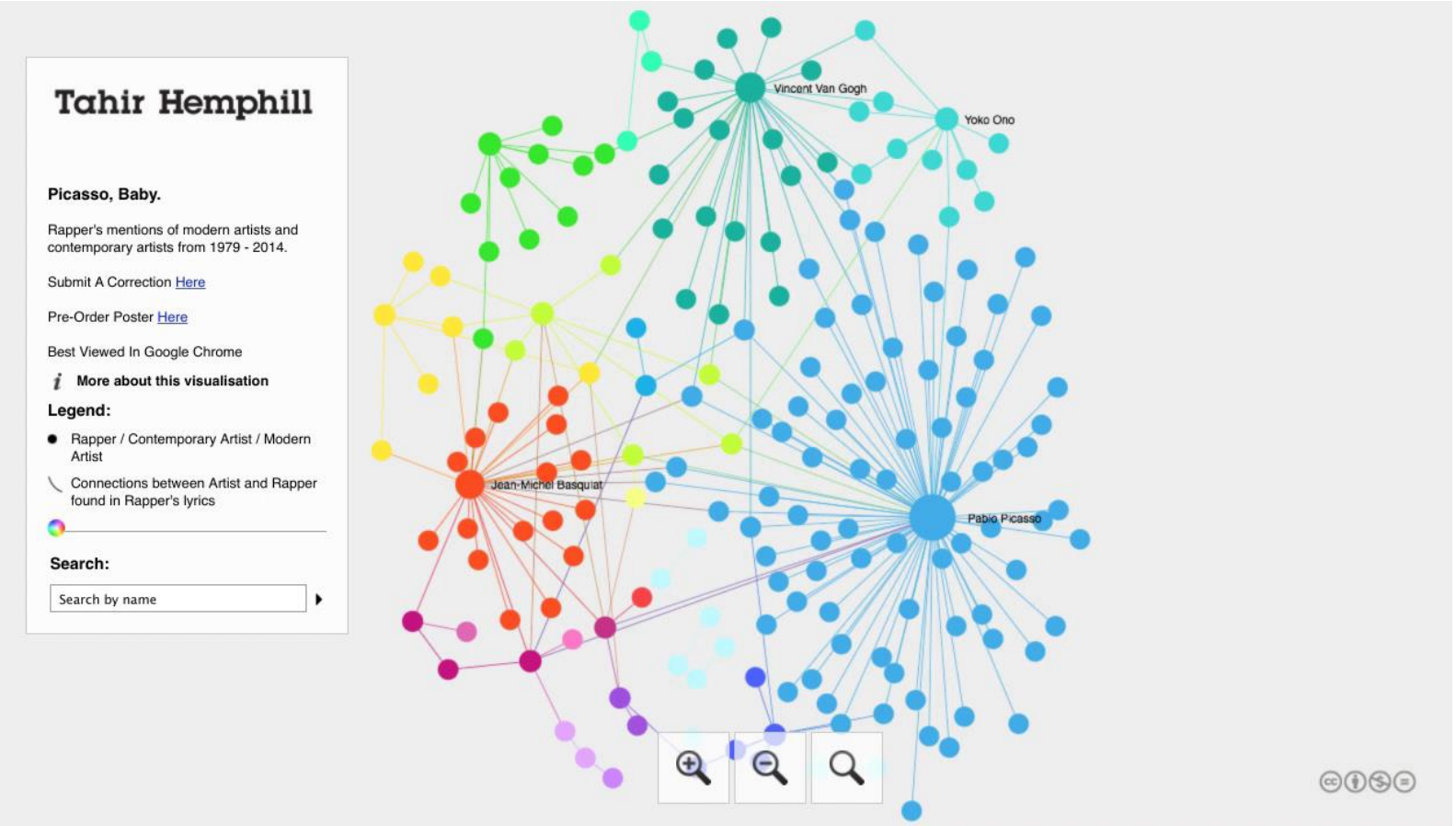


New Versions

EXAMPLE: SOCIAL NETWORK ANALYSIS

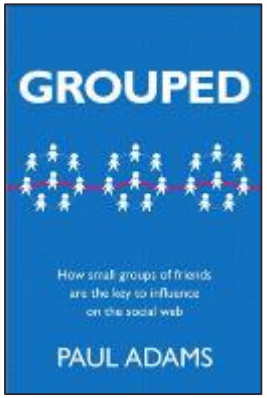
Example: Lyrics of Rap Songs

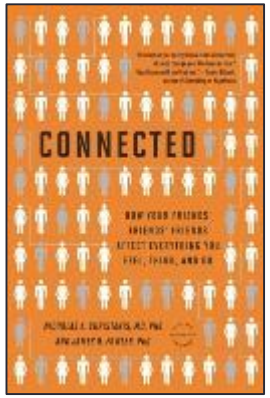
Network analysis

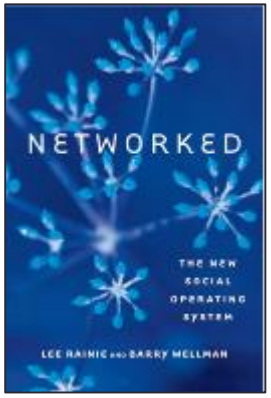


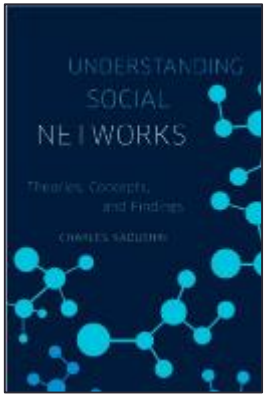
Social Network Analysis

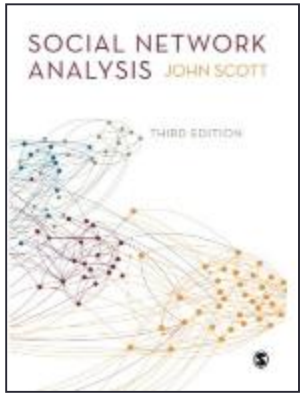
General Resources

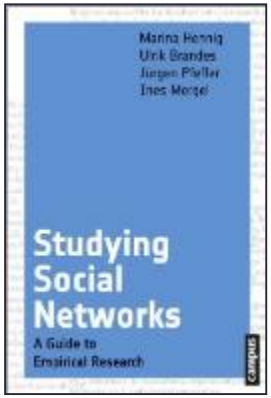


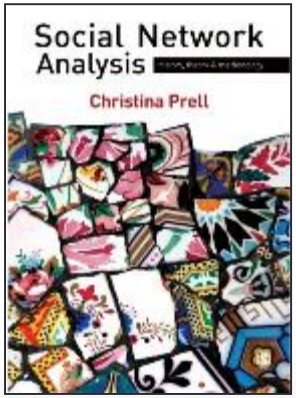


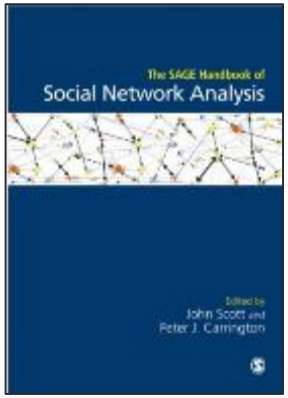


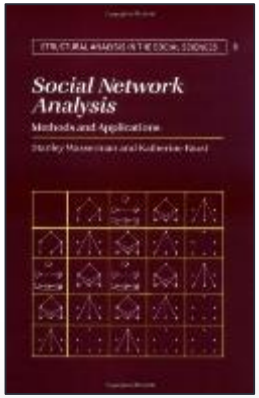


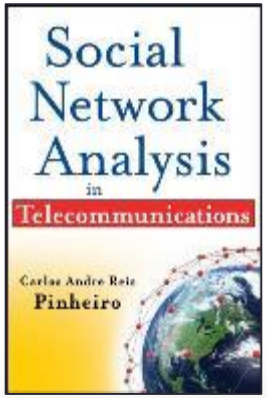


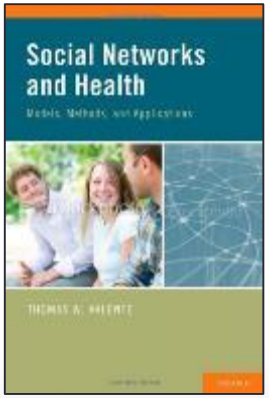


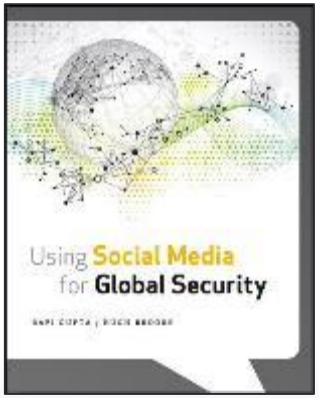






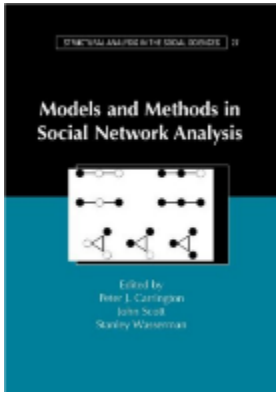


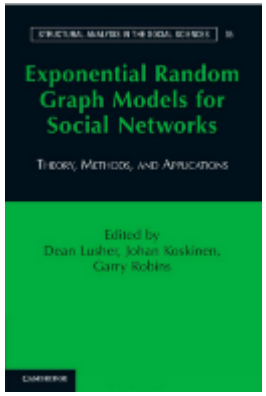


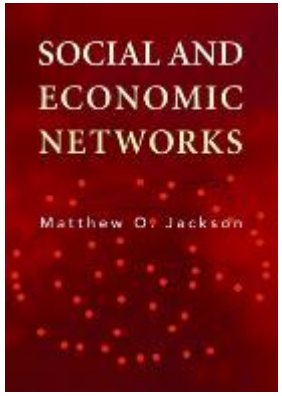


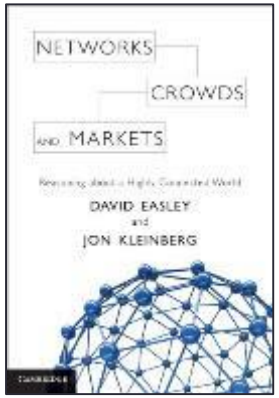
Social Network Analysis

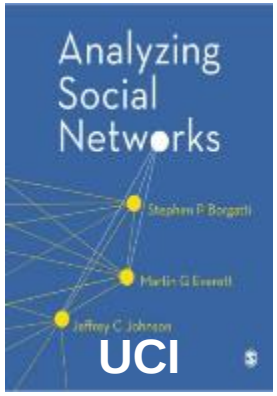
General Resources with Packages

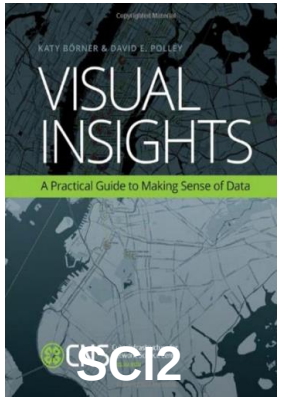


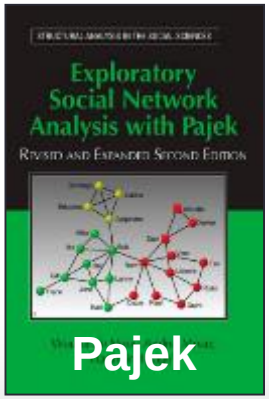


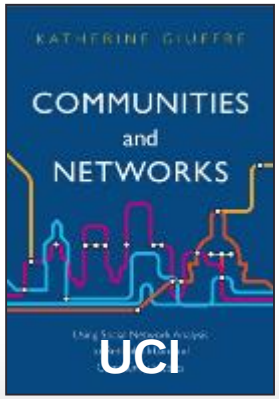


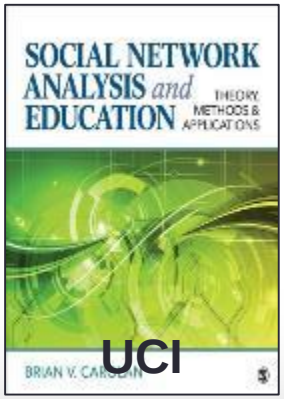


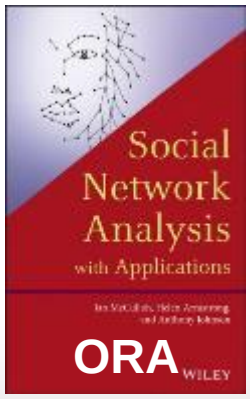


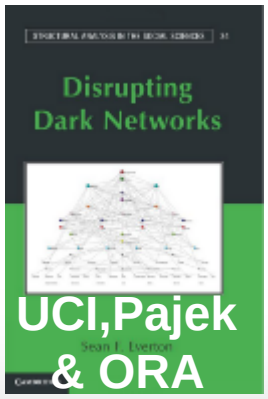


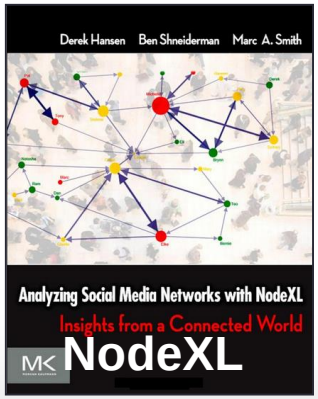








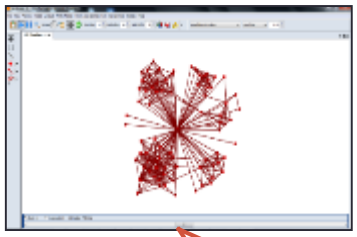
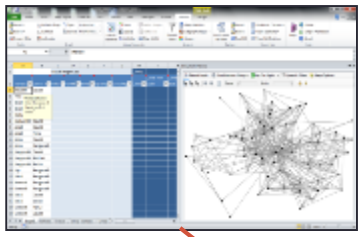
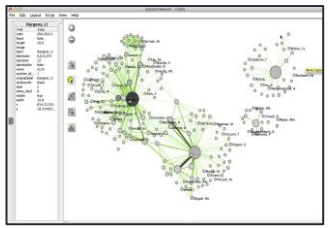


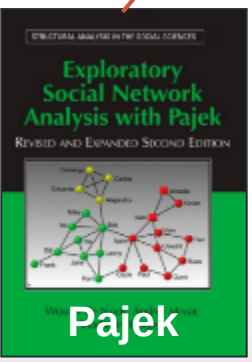


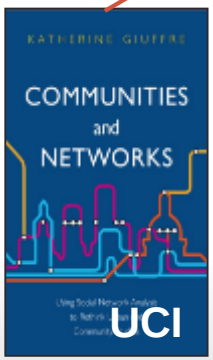
Social Network Analysis

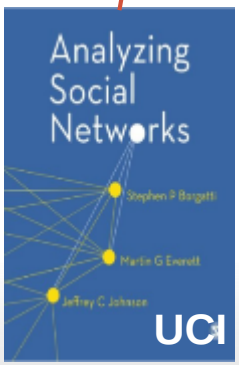
Social Network Packages

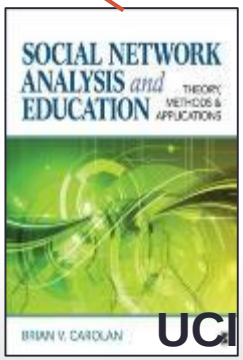


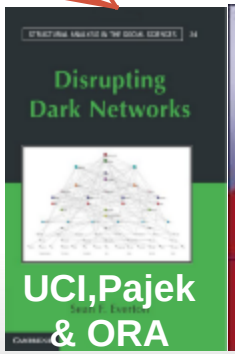




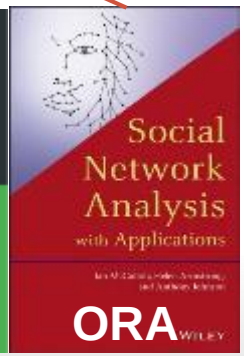


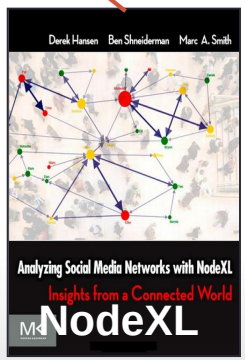


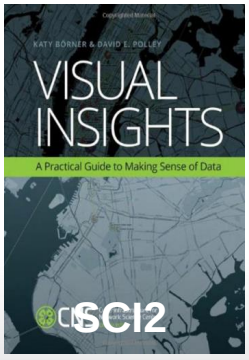






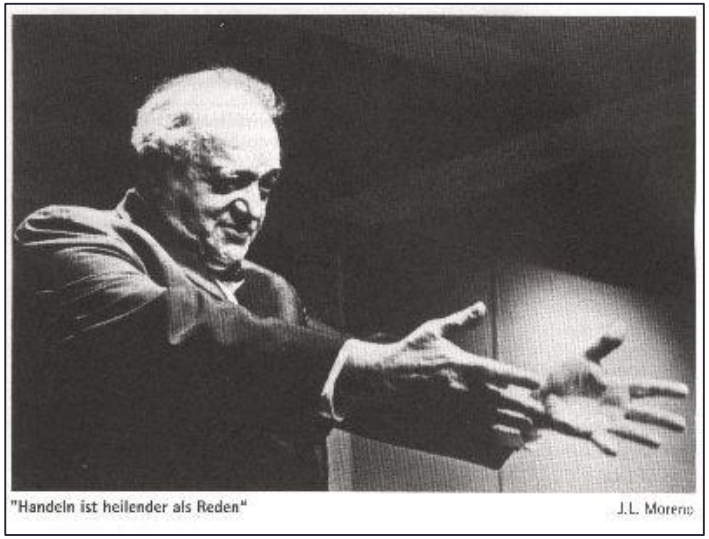




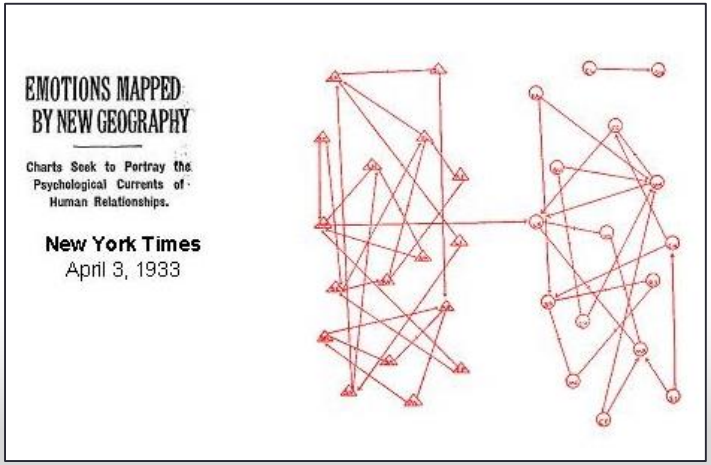


Social Network Analysis

Long tie to visualization



"Handeln ist heilender als Reden" J.L. Moreno



EMOTIONS MAPPED BY NEW GEOGRAPHY

Charts Seek to Portray the Psychological Currents of Human Relationships.

New York Times
April 3, 1933

Decade	Scholar(s)	Innovations
1900	Simmel	Dyads and Triads
1930	Jacob Moreno	Sociometry, Sociograms
1930	Mayo & Warner	Hawthorne Study
1940	Forsyth & Katz	(Adjacency) Matrix
1940	Luce & Festinger	Matrix Algebra, n-cliques
1940	Bavelas	Centrality, Centralization
1950	Radcliff-Browne	Social Structure as a Network of Social Relations
1950	Harary & Norman	Graph Theory, Structural Balance
1950	Manchester School	Ego Networks
1950	Bott	Connectedness, Density
1950	Barnes	Social Network'
1950	Homans	Social Exchange
1960	James Davis	Clustering, Transitivity
1960	Coleman	Diffusion in Social Networks
1960	Milgram	Small world
1970	Blau	Homophily
1970	White	Block models, Vacancy Chains
1970	Granovetter	Weak ties
1980	Holland & Leinhardt	Exponential Random Graph Models
1980	Frank & Strauss	Markov dependency grfaphs
1990	Friedkin	Social Influence Network Theory
1990	Bonacich	Eigenvector centrality, Power centrality
1990	Putnam	Social capital
1990	Watts & Strogatz	Small world simulation
2000	Snijders & Huisman	Longitudinal network data

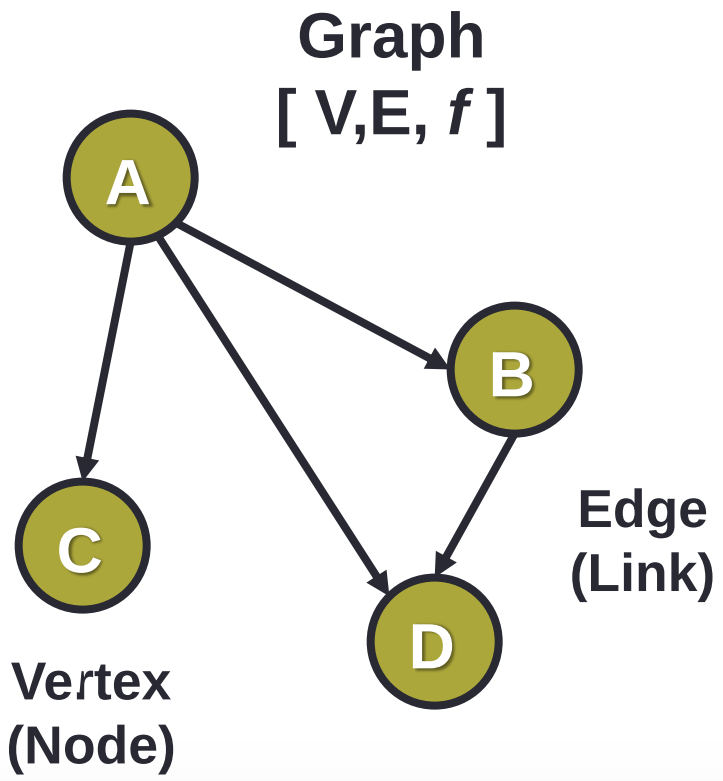
Social Network Analysis

Key Elements

Vertices or Nodes
The "things"

Edges or Links
The "relationships"

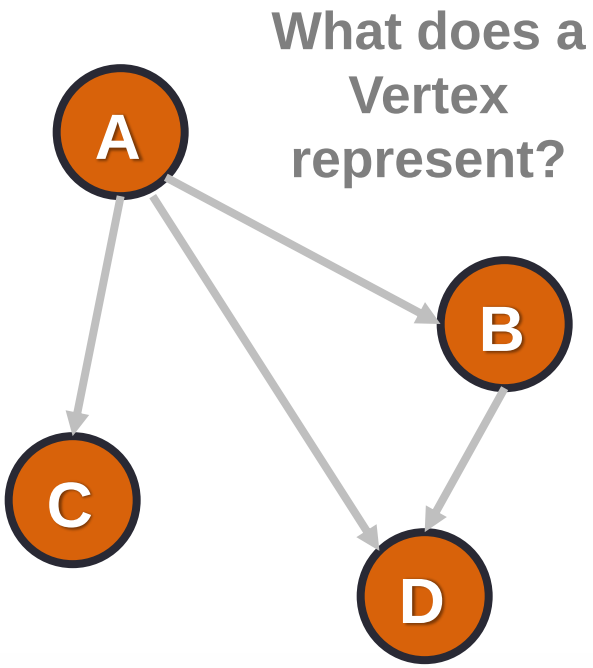
Graph or Network
The set of vertices/nodes, edges/links and the relationship/function connecting them.



Social Network Analysis

Types of Nodes or Vertices

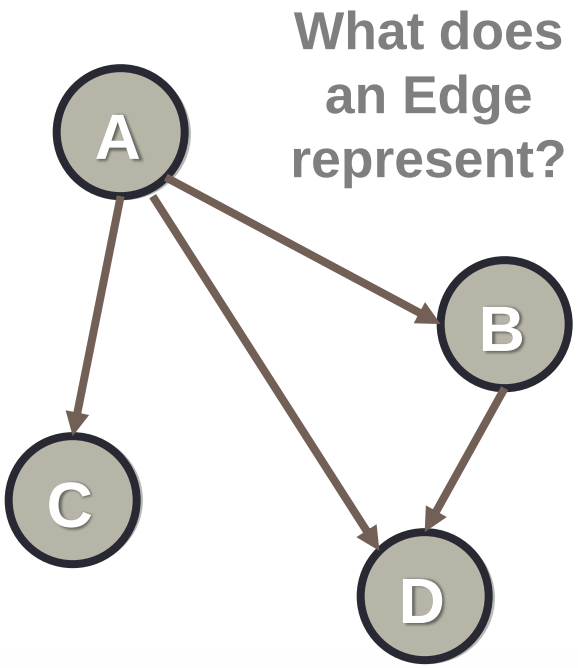
- Social Entities
  - People or social structures such as workgroups, teams, organizations, institutions, states, or even countries.
- Content
  - Web pages, keyword tags, or videos.
- Locations
  - Physical or virtual locations or events.
- Primary building blocks of social media
  - Friends in social networking sites, posts or authors in blogs, or pages in wikis.



Social Network Analysis

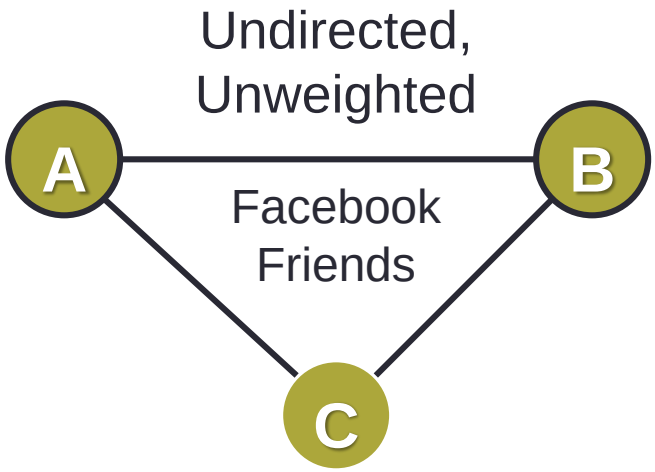
Types of Relations or Links

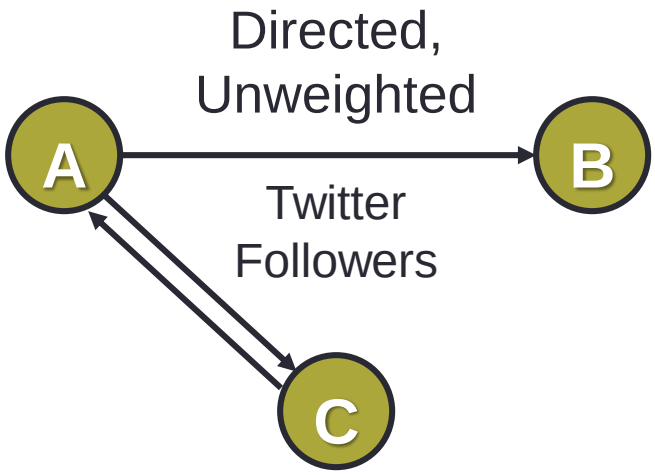
- Similarities
  - Location (same spatial and temporal space)
  - Participation (same club, same event, …)
  - Attributes (Age, gender, same attitudes, …)
- Relational Roles
  - Kinship (mother of, sibling of, …)
  - Other Roles (friend of, boss of, …)
- Relational Cognition
  - Affective (Likes, Hates…)
  - Perceptual (Knows, Knows of, …)
- Relational Events
  - Interactions (Sold to, talked to, helped, …)
  - Flows (Information, beliefs, money, …)

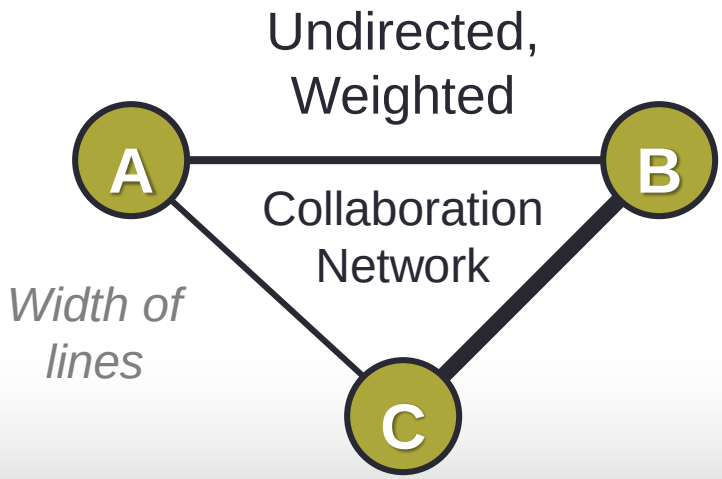


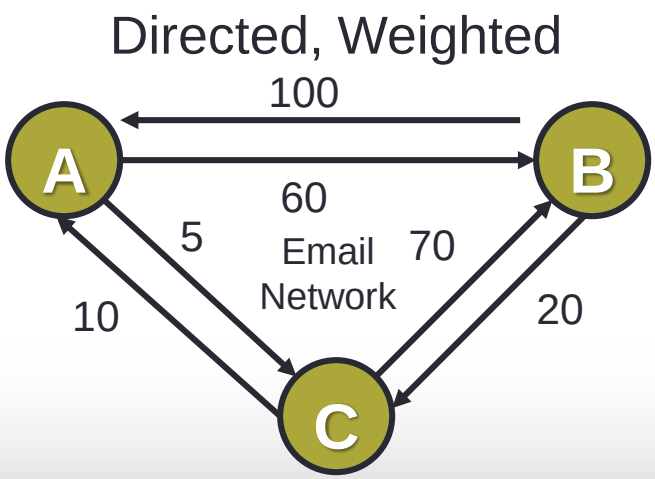
Social Network Analysis

Types of Edges or Links







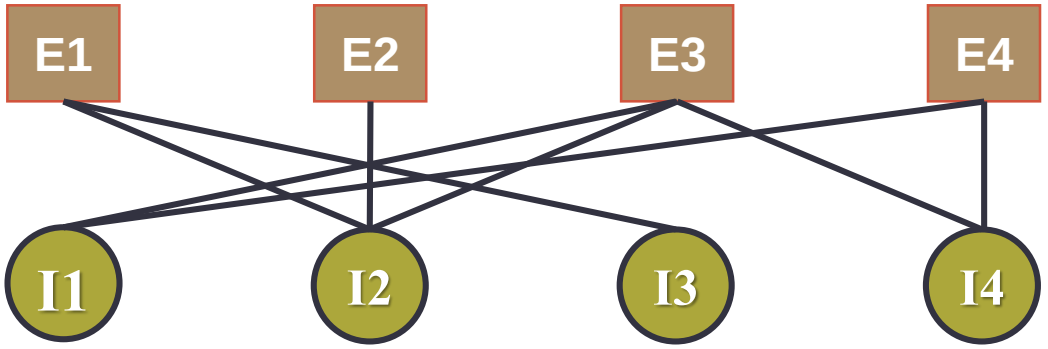


Social Network Analysis

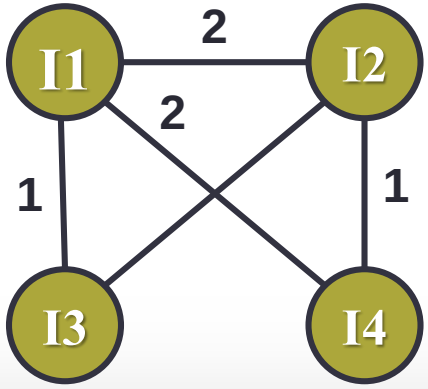
Bipartite or Bimodal Networks

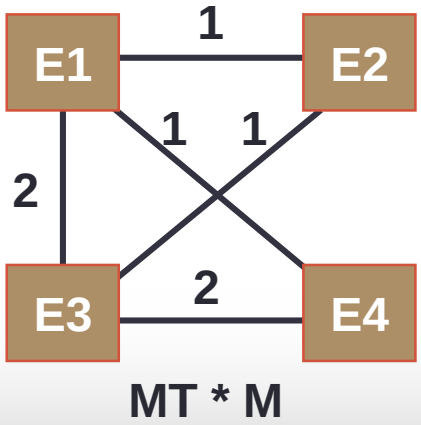
Bipartite or Bimodal Network
Linking individuals to events (participation, membership, topic, tag, post, …)

Examples:
Authors-to-papers (they authored)
Actors-to-Movies (they appeared in)
Users-to-Movies (they rated)
"Folded" networks:
Author collaboration networks
Movie co-rating networks



	E1	E2	E3	E4
I1	1	0	1	1
I2	1	1	1	0
I3	1	0	0	0
I4	0	0	1	1

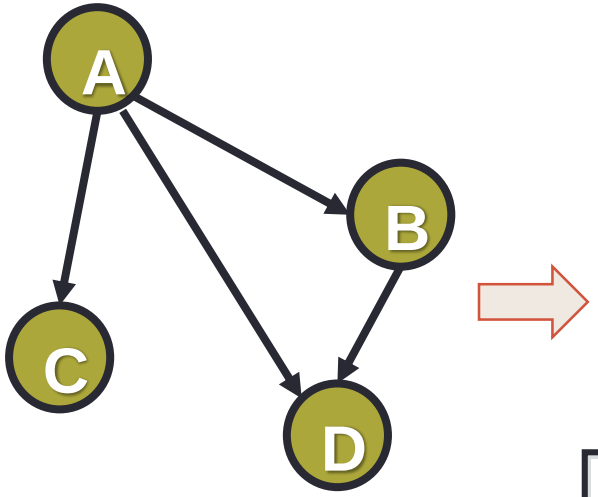




Social Network Analysis

Types of Alternative Representations

Graph



Edge List

A	B
A	C
A	D
B	D

Adjacency Matrix

	A	B	C	D
A	-	1	1	1
B	0	-	0	1
C	0	0	-	0
D	0	0	0	-

Adjacency List

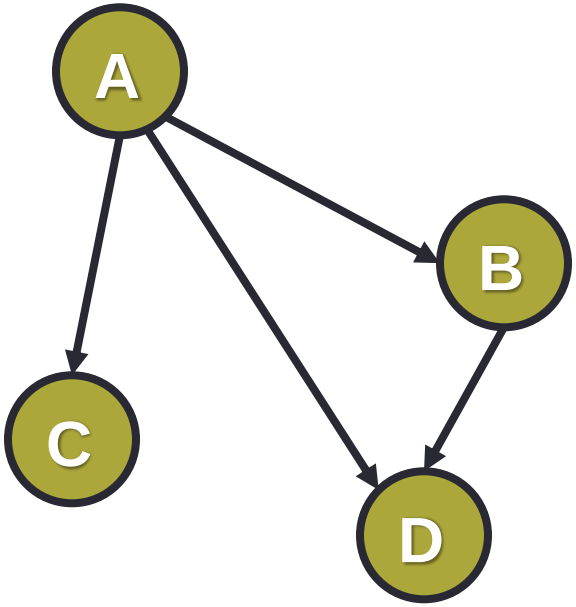
A	B, C, D
C	D

XML

```
<Node>
    <Label> A </Label>
    <Connection> B </Connection>
    <Connection> C </Connection>
    <Connection> D </Connection>
</Node>
<Node>
    <Label> C </Label>
    <Connection> D </Connection>
</Node>
```

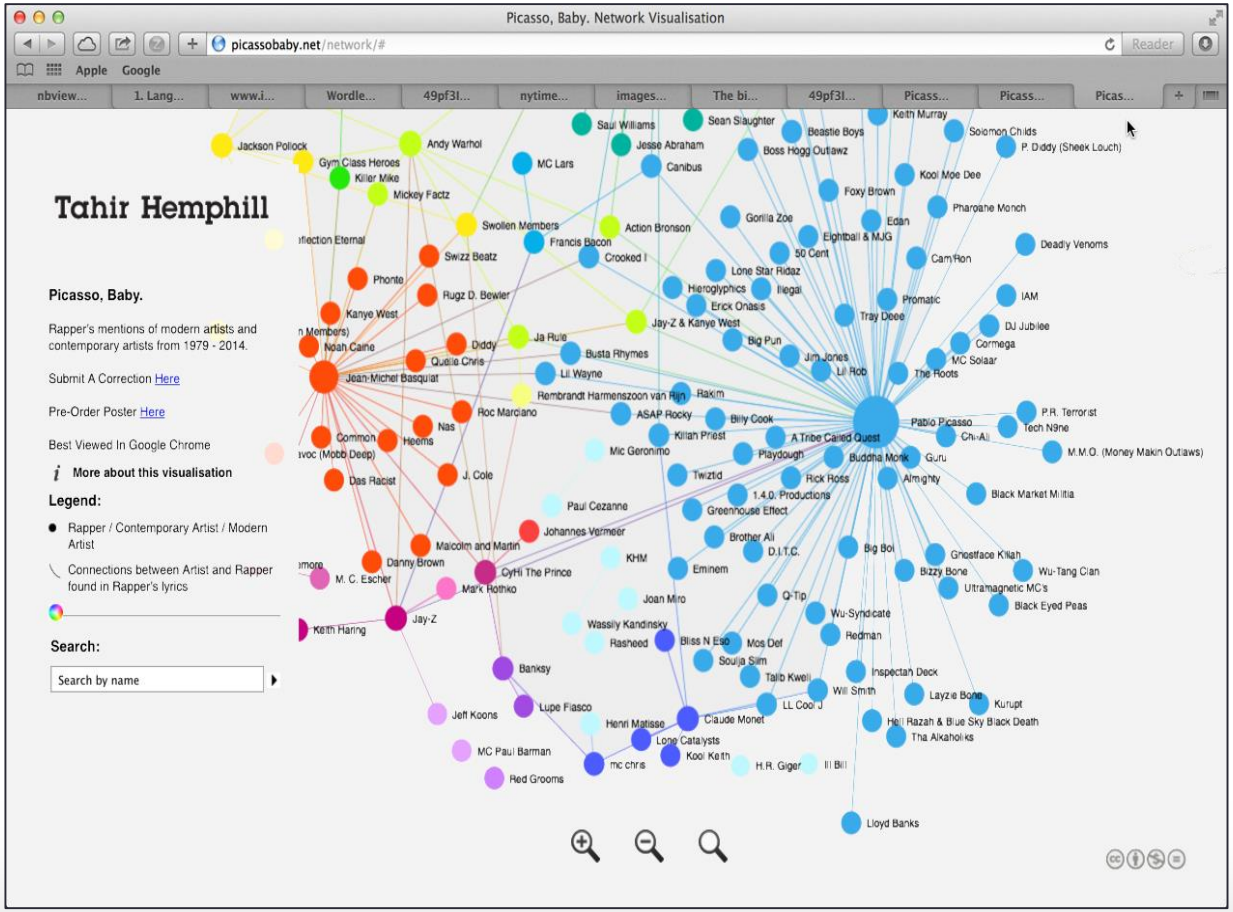
Social Network Analysis

How many variables can we represent?



Social Network Analysis

How many variables in this network?



Social Network Analysis

How many variables in this network?

Reducing the number of edges via pathfinder network scaling.

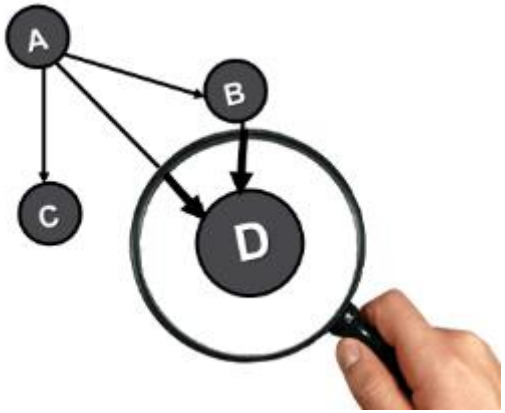
Co-word space of the top 50 highly frequent and bursty words used in the top 10% most highly cited PNAS publications in 1982-2001.

(*Mane & Börner, 2004*)

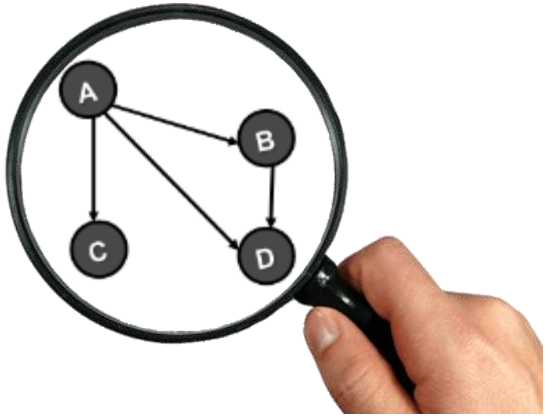
Social Network Analysis

Bifurcated measures

Local Measures



Global Measures



Social Network Analysis

Wide Variety of Metrics Available

Measures Manager

Select Measures | Set Measure Inputs

Contains

	Measure Title	Network Level	Node Level	Computation...	U
☐	Redundancy, Access	true	false	normal	fa
☐	Actual Workload	false	true	normal	fa
☐	Socio Economic Power, Agent	false	true	normal	fa
☐	Redundancy, Assignment	true	false	normal	fa
☐	Centrality, Authority	false	true	normal	tr
☐	Characteristic Path Length	true	false	normal	tr
☐	Speed, Average	true	false	normal	tr
☑	Centrality, Betweenness	false	true	normal	tr
☑	Network Centralization, Betweenness	true	false	normal	tr
☐	Centrality, Bonacich Power	false	true	normal	tr
☐	Capability	false	true	normal	tr
☐	Clique Count	false	true	normal	fa
☑	Centrality, Closeness	false	true	normal	tr
☑	Network Centralization, Closeness	true	false	normal	tr
☑	Density, Clustering Coefficient	true	true	normal	fa
☐	Cognitive Demand	false	true	normal	tr
☐	Cognitive Distinctiveness	false	true	normal	fa
☐	Cognitive Expertise	false	true	normal	fa
☐	Cognitive Resemblance	false	true	normal	fa
☐	Cognitive Similarity	false	true	normal	fa
☐	Breadth, Column	true	false	normal	fa
☐	Count, Column	true	false	normal	fa
☐	Centrality, Column Degree	false	true	normal	tr

Select All | Select Visible

13 / 160 Selected, 160 / 160 Visible

OK | Close

Social Network Analysis

Who is most influential

Measure	Definition	Interpretation	Reasoning
Degree	Number of edges or links. In degree- links in, Out-degree - links out	How connected is a node? How many people can this person reach directly?	Higher probability of receiving and transmitting information flows in the network. Nodes considered to have influence over larger number of nodes and or are capable of communicating quickly with the nodes in their neighborhood.
Betweenness	Number of times node or vertex lies on shortest path between 2 nodes divided by number of all the shortest paths	How important is a node in terms of connecting other nodes? How likely is this person to be the most direct route between two people in the network?	Degree to which node controls flow of information in the network. Those with high betweenness function as brokers. Useful where a network is vulnerable.
Closeness	1 over the average distance between a node and every other node in the network	How easily can a node reach other nodes? How fast can this person reach everyone in the network?	Measure of reach. Importance based on how close a node is located with respect to every other node in the network. Nodes able to reach most or be reached by most all other nodes in the network through geodesic paths.
Eigenvector	Proporational to the sum of the eigenvector centralities of all the nodes directly connected to it.	How important, central, or influential are a node's neighbors? How well is this person connected to other well-connected people?	Evaluates a player's popularity. Identifies centers of large cliques. Node with more connections to higher scoring nodes is more important.

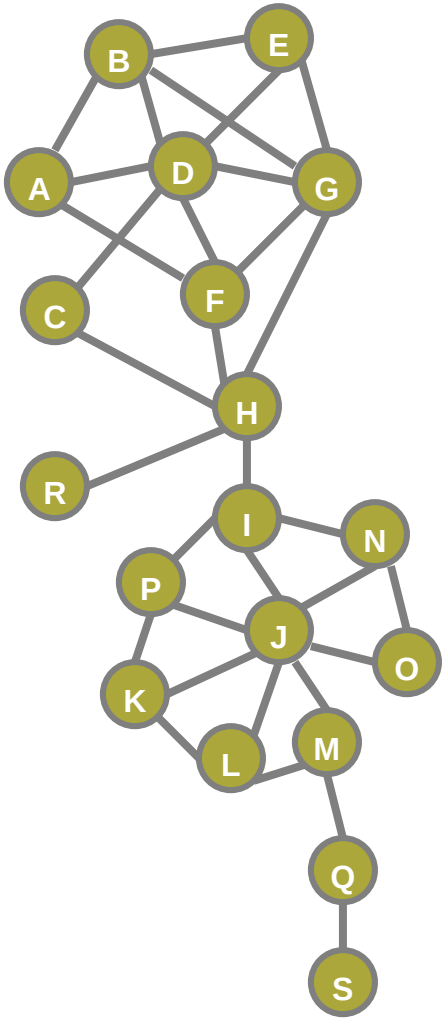
Social Network Analysis

How well connected is the network?

Cohesion	Definition	Interpretation	Reasoning
Density	Ratio of the number of edges in the network over the total number of possible edges between all pairs of nodes	How well connected is the overall network?	Perfectly connected network is called a "clique" and has a density of 1.
Clustering	A node's *clustering coefficient* is the density of it's 1.5 degree egocentric network (ratio of connecting among ego's alters). For entire network it is the average of all the coefficients for the individual nodes.	What proportion of ego's alters are connected? More technically, how many nodes form triangular subgraphs with their adjacent nodes?	Measures certain aspects of "cliquishness." Proportion of you friends that are also friends with each other. Another way to measure is to determine (in a undirected) graph the ratio of the number of times that two links eminating from the same node are also linked.
Average Path Length (Distance)	Average number of edges or links between any two nodes (along the shortest path)	On average, how far apart are any two nodes?	This is synonymous with the "degrees of separation" in a network.
Diameter	Longest (shortest path) between any two nodes	At most, how long will it take to reach any node in the network? Sparse networks usually have greater diameters.	Measure of the reach of the network
Centralization	Normalize ratio of the sum of the variances of the centrality of each node from the most central node to the maximum sum possible	Indicates how unequal the distribution of centrality is in a network.	Measures how much variance there is in the distribution of centrality in a network. The measure applies to all forms of centrality.

Social Network Analysis

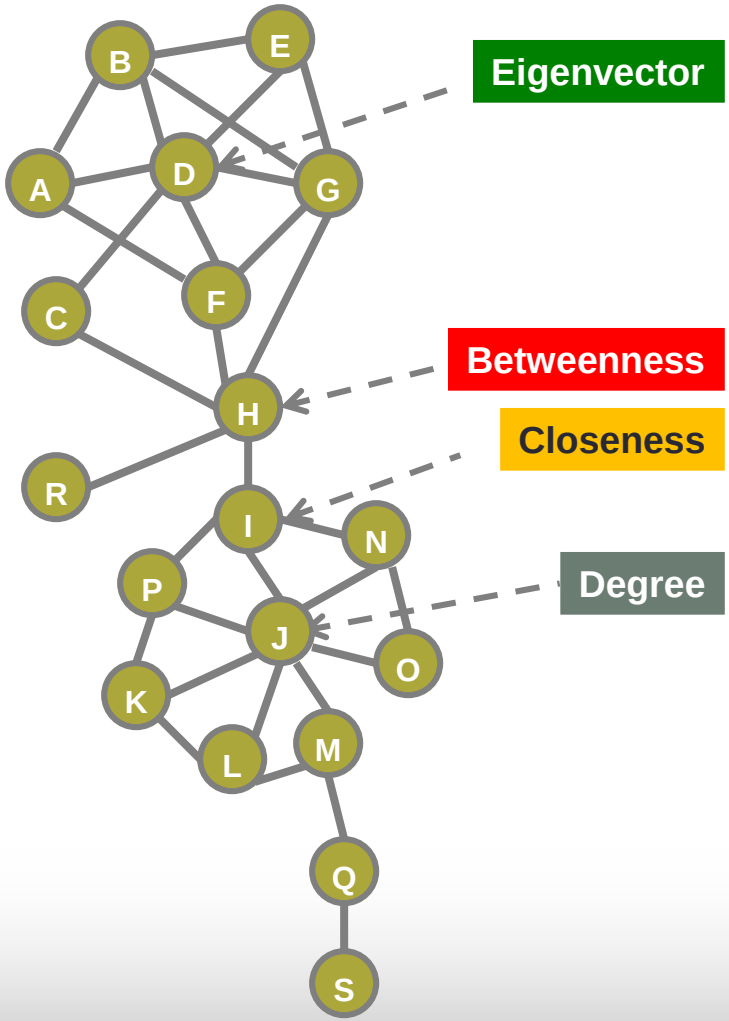
Generic Example



- For each of the nodes what is it's
  - Degree Centrality
  - Betweenness Centrality
  - Closeness Centrality
  - Eigenvector Centrality
- For the entire network what is it's
  - Degree Centralization
  - Betweenness Centralization
  - Closeness Centralization
  - Eigenvector Centralization

Social Network Analysis

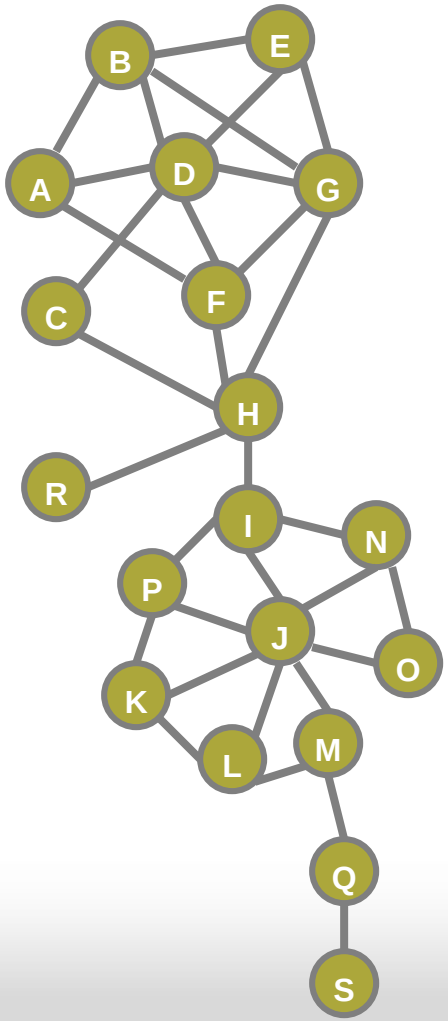
Who's most influential?



Node	Degree	Normed Degree	Betweenness	Closeness	Eigen Vector
A	3	0.17	0.00	0.29	0.29
B	4	0.22	0.01	0.30	0.36
C	2	0.11	0.03	0.35	0.18
D	6	0.33	0.04	0.31	0.46
E	3	0.17	0.00	0.29	0.30
F	4	0.22	0.11	0.36	0.35
G	5	0.28	0.19	0.37	0.43
H	5	0.28	0.58	0.45	0.28
I	4	0.22	0.53	0.46	0.13
J	7	0.39	0.43	0.43	0.12
K	3	0.17	0.00	0.32	0.06
L	3	0.17	0.01	0.33	0.05
M	3	0.17	0.21	0.33	0.04
N	3	0.17	0.03	0.38	0.07
O	2	0.11	0.00	0.31	0.05
P	3	0.17	0.03	0.38	0.08
Q	2	0.11	0.11	0.26	0.01
R	1	0.06	0.00	0.32	0.07
S	1	0.06	0.00	0.21	0.00

Correlations	Degree	Betweenness	Closeness	Eigenvector
Degree	-	0.57	0.59	0.59
Betweenness		-	0.79	0.07
Closeness			-	0.13
Eigenvector				-

Social Network Analysis
How cohesive is the network?



Measure	Value
Network Size	19
Average Degree	3.37
Degree Centralization	0.22
Betweenness Centralization	0.48
Closeness Centralization	0.27
Eigenvector Centralization	0.56
Clustering Coefficient	0.43
Density	0.19
Average Distance	3.06
Diameter	8
Number of Unreachable Nodes	0

Node	Clustering
A	0.67
B	0.67
C	0.00
D	0.40
E	1.00
F	0.50
G	0.50
H	0.10
I	0.33
J	0.29
K	0.67
L	0.67
M	0.33
N	0.67
O	1.00
P	0.67
Q	0.00
R	NA
S	NA

6

Frigyes Karinthy
1929

John Guare
1990

Stanley Milgram
1967

Duncan Watts
1998

Six Degrees of Kevin Bacon (1994)

Social Network Analysis

Who is the center of Hollywood?

The Center of the Hollywood Universe

Click on a name to see that person's table.

1. Harvey Keitel (2.848635)
2. Dennis Hopper (2.849329)
3. Robert De Niro (2.855810)
4. David Carradine (2.857729)
5. Martin Sheen (2.858291)
6. Udo Kier (2.859489)
7. Michael Madsen (I) (2.860010)
8. Donald Sutherland (I) (2.860447)
9. Michael Caine (I) (2.862189)
10. Eric Roberts (I) (2.867675)
11. Seymour Cassel (2.869415)
12. Malcolm McDowell (2.870208)
13. Max von Sydow (I) (2.872338)
14. Willem Dafoe (2.873805)
15. Samuel L. Jackson (2.873819)
16. Danny Trejo (2.876002)
17. John Hurt (2.878378)
18. Christopher Lee (I) (2.879217)
19. Harry Dean Stanton (2.880725)
20. Bruce Willis (2.886364)
21. Christopher Plummer (I) (2.886928)
22. John Malkovich (2.888575)
23. Morgan Freeman (I) (2.891003)
24. Christopher Walken (2.894212)
25. John Savage (I) (2.894873)

Kevin Bacon Number	# of People
0	1
1	2799
2	313045
3	1078865
4	276680
5	22296
6	2361
7	251
8	24

Total number of linkable actors: 1696322
Weighted total of linkable actors: 5099799
Average Kevin Bacon number: 3.006

Kyra Sedgwick Number	# of People
0	1
1	1353
2	229226
3	1083255
4	350117
5	29167
6	2845
7	331
8	27

Total number of linkable actors: 1696322
Weighted total of linkable actors: 5275476
Average Kyra Sedgwick number: 3.110

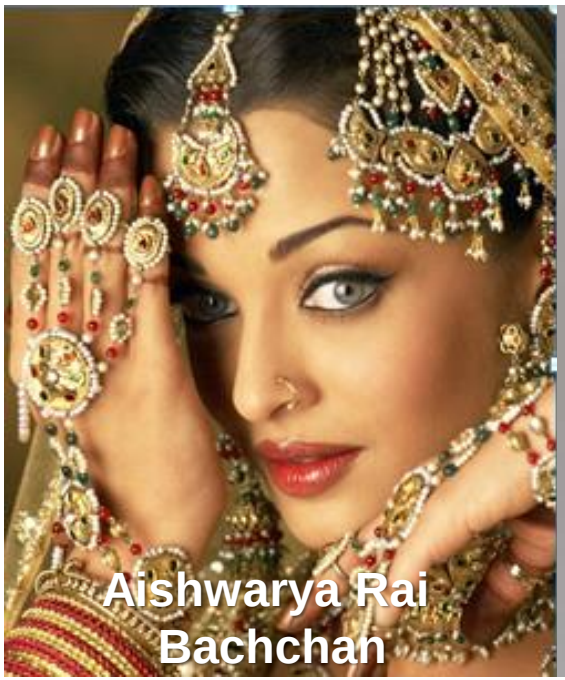
Harvey Keitel (I) Number	# of People
0	1
1	4128
2	454260
3	1051685
4	169704
5	14709
6	1679
7	141
8	15

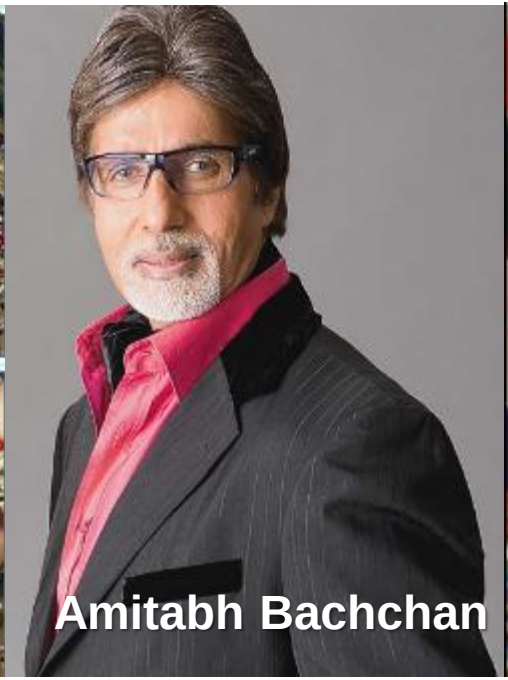
Total number of linkable actors: 1696322
Weighted total of linkable actors: 4831245
Average Harvey Keitel (I) number: 2.848

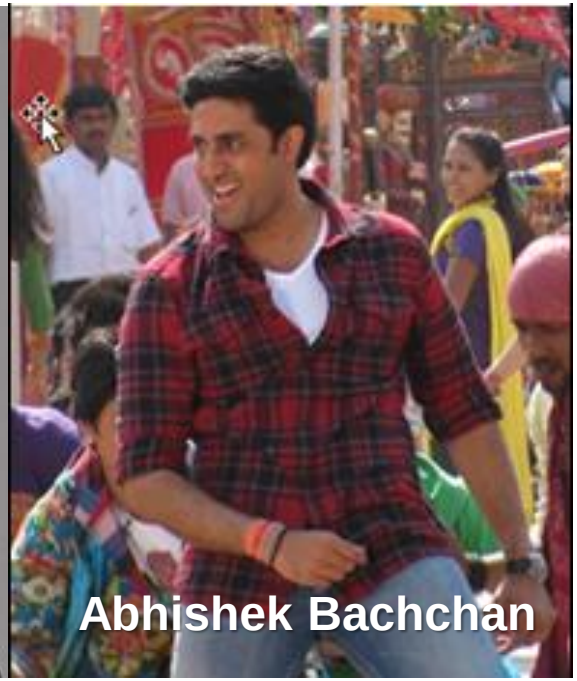
John Savage (I) Number	# of People
0	1
1	3766
2	408573
3	1073294
4	192718
5	16000
6	1764
7	195
8	11

Total number of linkable actors: 1696322
Weighted total of linkable actors: 4903703
Average John Savage (I) number: 2.891

Social Network Analysis Bollywood?







जुदाई की छह डिग्री

judā'ī kī chaha ḍigrī

Social Network Analysis

Source of Bollywood Data

Amitabh Bachchan - Goo | List of Bollywood films - V

en.wikipedia.org/wiki/List_of_Bollywood_films#2010s

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The Free Encyclopedia

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Contents
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Random article
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Help
About Wikipedia
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Recent changes
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Tools

Print/export

Languages
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Edit links

List of Bollywood films

From Wikipedia, the free encyclopedia

This article **does not cite any references or sources**. Please help improve this article by adding citations to reliable sources. Unsourced material may be challenged and removed. *(September 2012)*

This is a list of films produced by the Bollywood film industry of Mumbai ordered by year and decade of release and also contains the top ten or forty superhit films of respective years as the case may be. Although "Bollywood" films are generally listed under the Hindi language, most are in mixed Hindi, Urdu and Punjabi and occasionally other languages. There is a range of mixtures from mostly Urdu to mostly Hindi to mostly Punjabi. Speakers of Hindi, Urdu, and Punjabi understand the mixed language usage of Bollywood thus extending the viewership to people all over the Indian subcontinent (throughout India and its neighboring countries). Here are some examples - Partly Hindi: *Om Shanti Om*, *Dhoom 2*, *No Entry* and *Kabhi Alvida Naa Kehna*, Partly Urdu: *Jodhaa Akbar*, *Fanaa*, *Saawariya* and *Kurbaan*, Partly Punjabi: *Singh Is Kinng*, *Jab We Met*, *Patiala House* and *Rab Ne Bana Di Jodi*. The film *Veer Zaara* is an equal mix of Hindi, Punjabi and Urdu.

Contents [hide]

Alam Ara (1931), the first Indian sound film

2010s [edit]

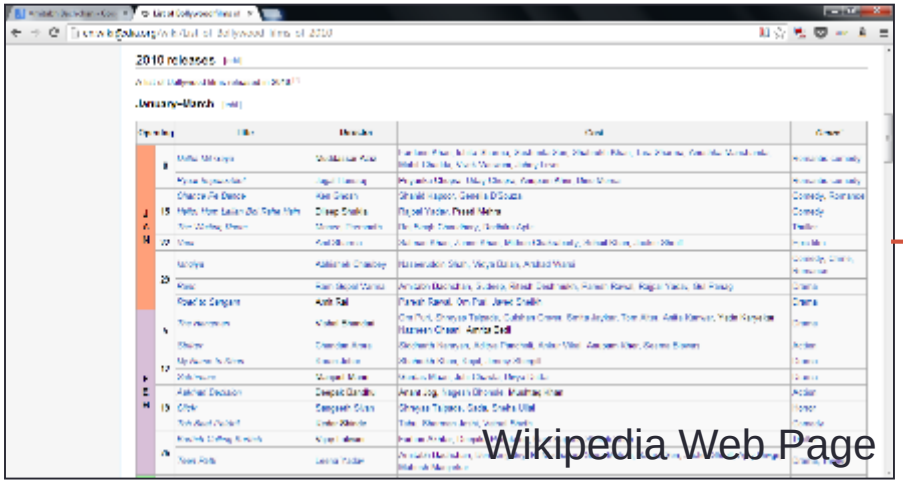
- List of Bollywood films of 2010
- List of Bollywood films of 2011
- List of Bollywood films of 2012
- List of Bollywood films of 2013
- List of Bollywood films of 2014

2000s [edit]

- List of Bollywood films of 2000

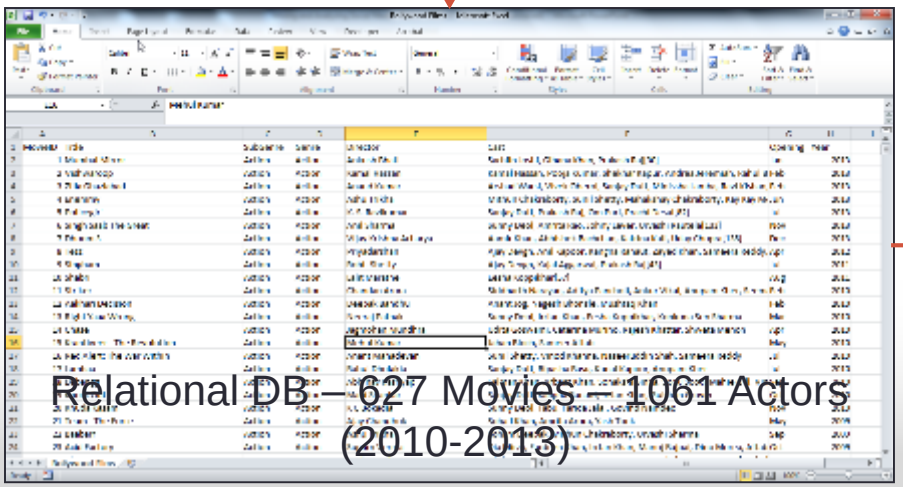
Social Network Analysis

Source of Bollywood Data



Wikipedia Web Page

HTML- Page Source



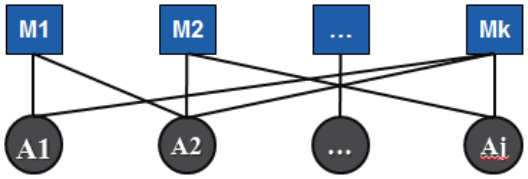
Relational DB – 627 Movies – 1061 Actors (2010-2013)

```
*Network bollywood.net [2-Mode]
*Vertices 1643 627
1 "Mumbai Mirror" 0.0000 0.0000 0.5000
2 "Vishwaroop" 0.0000 0.0000 0.5000
...
628 "A. K. Hangal" 0.0000 0.0000 0.5000
629 "Aamir Ali" 0.0000 0.0000 0.5000
...
*Arcs
*Edges
1 896 1
1 1220 1
...
627 856 1
627 1053 1
```

Pajek .NET File

Social Network Data

Bipartite Network – Movies and Actors



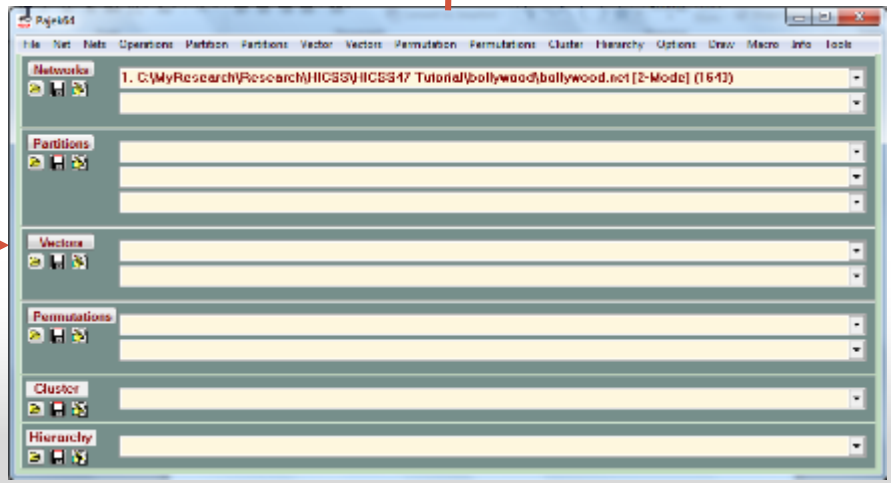
	M1	M2	...	Mk
A1	1	0		1
A2	1	1	...	1
...	...	...	...	...
Aj	0	1		1

	A1	A2	...	Aj
A1	-	2	...	1
A2	2	-	...	1
...	...	...	...	...
Aj	1	1	...	-

	M1	M2	...	Mk
M1	-	1	...	2
M2	1	-	...	2
...	...	...	...	...
Mk	2	2	...	-

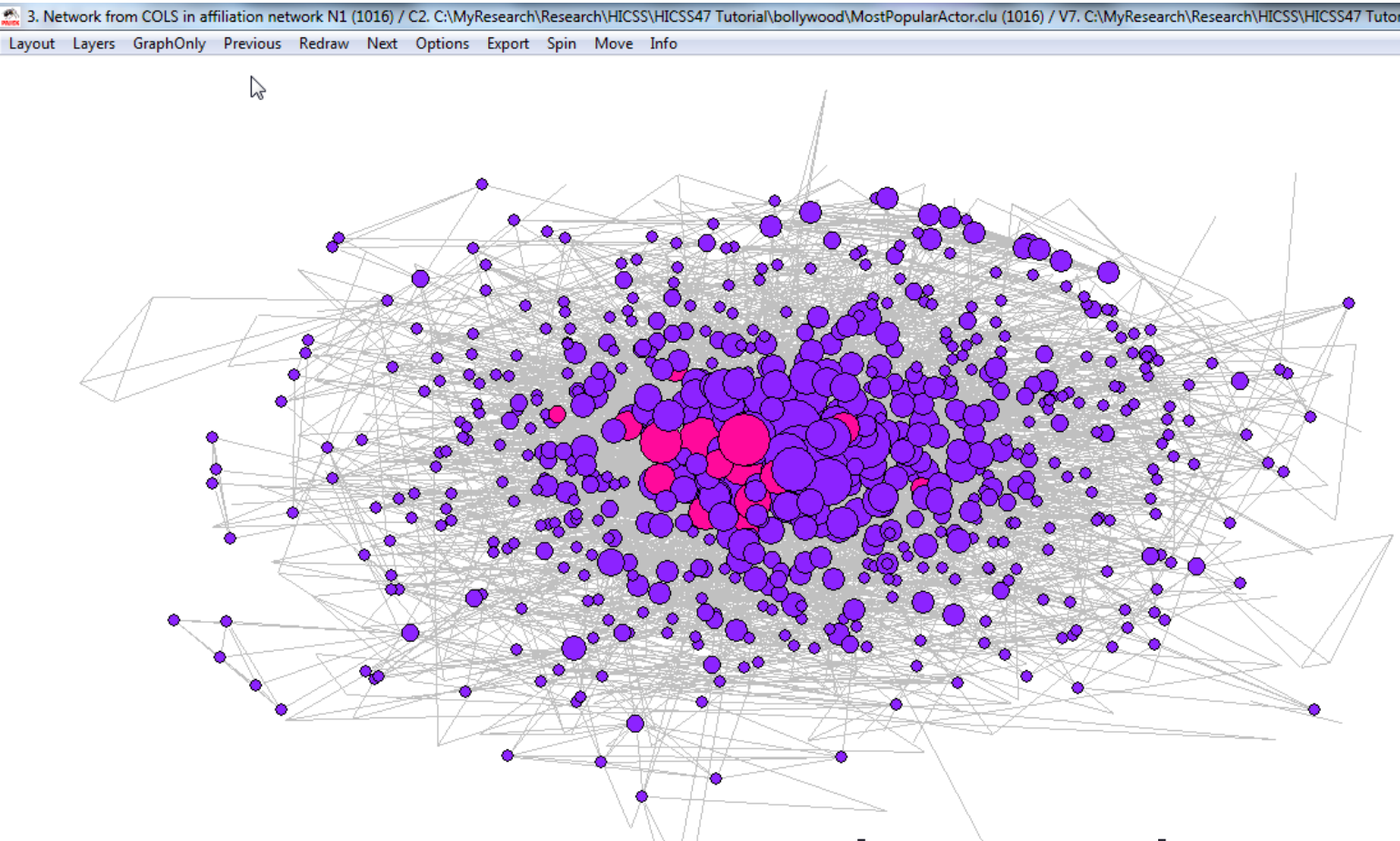
```
*Network bollywood.net [2-Mode]
*Vertices 1643 627
1 "Mumbai Mirror" 0.0000 0.0000 0.5000
2 "Vishwaroop" 0.0000 0.0000 0.5000
...
628 "A. K. Hangal" 0.0000 0.0000 0.5000
629 "Aamir Ali" 0.0000 0.0000 0.5000
...
*Arcs
*Edges
1 896 1
1 1220 1
...
627 856 1
627 1053 1
```

Pajek .NET File



Social Network Analysis

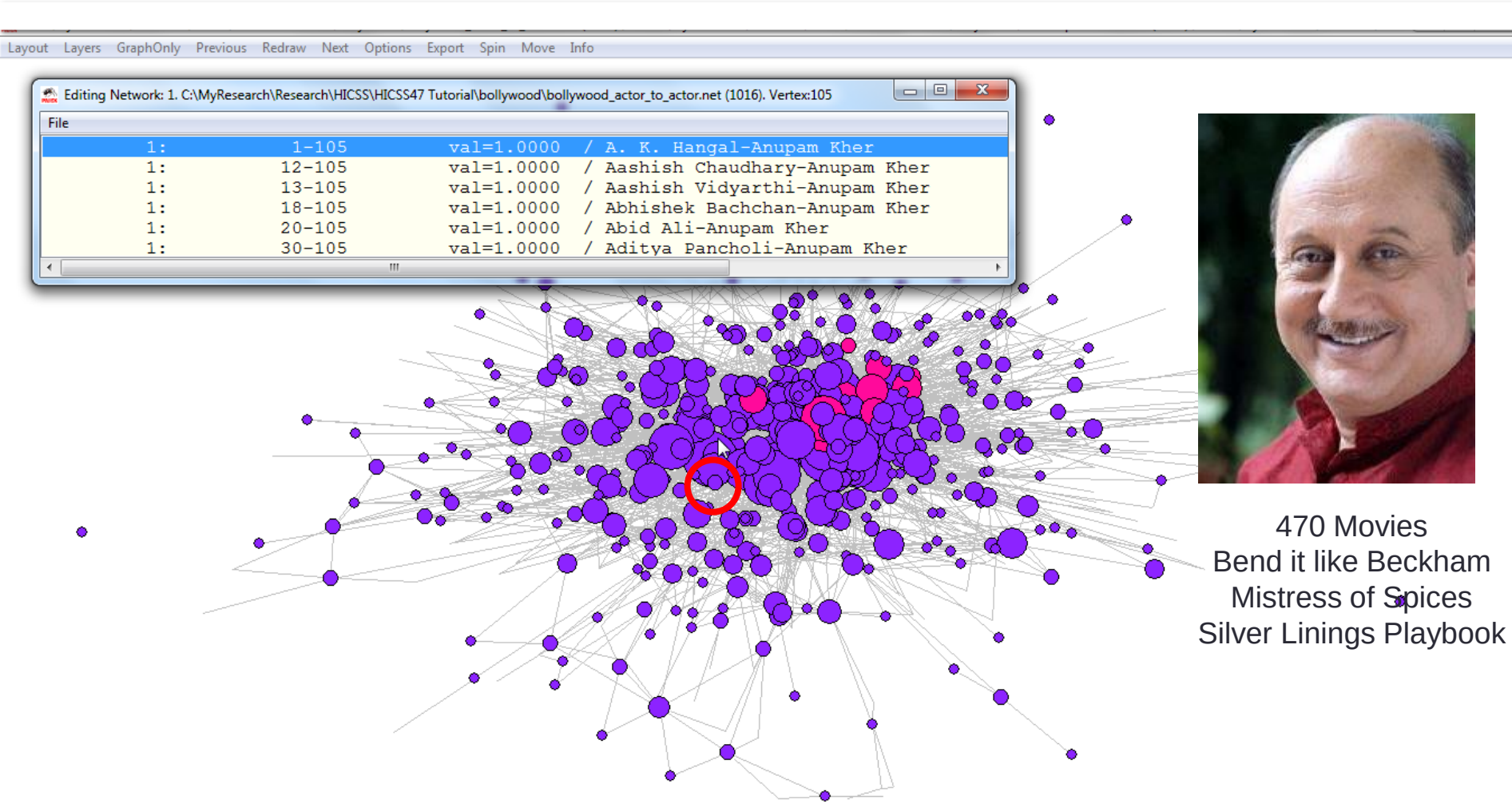
And the answer is…



Average Distance is 3.44

Social Network Analysis

and the center of Bollywood is

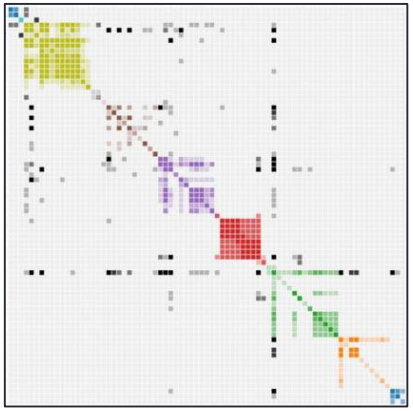


470 Movies
Bend it like Beckham
Mistress of Spices
Silver Linings Playbook

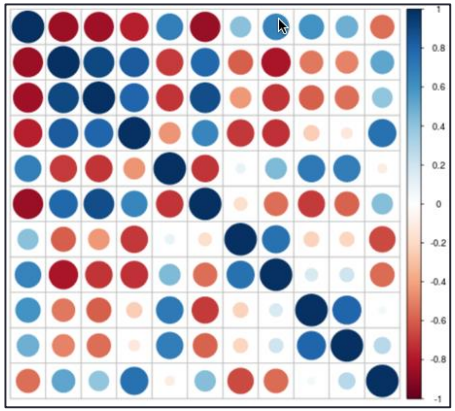
Alternative Visualizations

Once in matrix form …

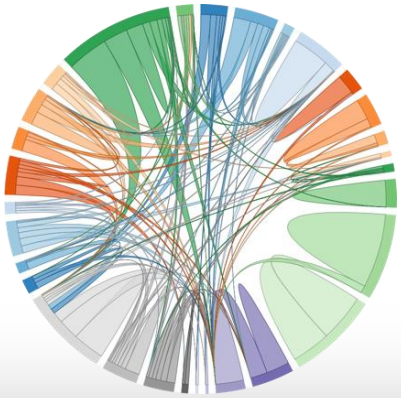
Co-occurrence



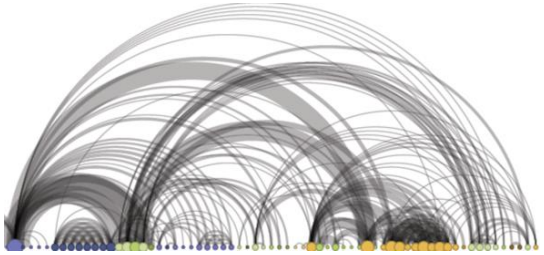
Corrplot



Chord



Arc



Alternative Visualizations

Chord Diagram