

Critically engaging with social media research tools

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<https://snacda.com>

- Dr Steven McDermott, London College of Communications, University of the Arts London.
- TAGS; Yourtwapperkeeper; DMI-TCAT; Gephi; Leximancer; for collecting, archiving, analysing, visualising and disseminating social data collected from Twitter, YouTube and text based data.

Surveillance Capitalism

“The ugly truth here is that much of “big data” is plucked from our lives without our knowledge or informed consent. It is the fruit of a rich array of surveillance practices designed to be invisible and undetectable as we make our way across the virtual and real worlds.”(Zuboff, 2016)

The goal of big data analytics is to change people's behaviour at scale.

A Chief Data Scientist of a Silicon Valley company that develops applications to improve students' learning states that...

*“The goal of everything we do is to change people's actual behavior at scale. When people use our app, we can capture their behaviors, identify good and bad behaviors, and develop ways to **reward the good and punish the bad**. We can test how actionable our cues are for them and how profitable for us.” (Zuboff, 2016)*

Future Research Plans

Choose Your Targets Carefully

- **Big Data Scientists as Knowledge Creators** - [An Ethnography of Data Scientists of 2016](#) A searchable and interactive network graph of Data Scientists archived in February 2016 - **the digital environment and how it affects individuals and societal groups behaviour in the way they take decisions and seek information**
- **Mapping the 1%** - [The Forbes Billionaire List and their Connections – 2015](#) The Forbes 2015's Billionaires (2015). Forbes ranks more than 1,800 billionaires and their companies, and affiliations with Government Bodies. **Political, cultural and economic conflicts reproduce or extend in digital networks.**
- **Graphs of Wikipedia: Influential Thinkers** - [Interactive Graph of Wikipedia: Influential Thinkers](#) – assessing how social inclusion inequalities, class, gender, race, and disability manifest in digital networks.
- **Members of Parliament in the Digital Environment** - How are members of the political class exchanging information [UK MPs on Twitter August 2014](#)



By Martin Hawksey

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Get TAGS

To start using TAGS select one of the versions below then follow the steps below:

TAGS v6.0

TAGS v6.1

Which version? If you've not used TAGS before I recommend TAGS v6.1 which has an easy setup. If you've setup TAGS v6.0 you can keep on using that version, your existing archives will keep collecting tweets using your existing authentication. Some [background in this post](#).

1. After your copy has been made open TAGS > Setup Twitter Access and follow the onscreen instructions (when selecting this option you'll be promoted to authorize the script to run several services).
Important: In the new version of TAGS you only need to run the setup once
2. Enter what data you want to collect on the Readme/Settings sheet and hit TAGS > Run Now!

What's new

Search Forums

Search

Recent Topics

- [Last date tweet of every follower](#)
5 days, 19 hours ago
- [Twitter Mentions to GSheet](#)
6 days, 16 hours ago
- [Automating cut and export of data](#)
2 weeks, 5 days ago
- [Date-Time range](#)
1 month, 1 week ago
- [Too many tweets retrieved!](#)
1 month, 2 weeks ago

News

- [Social Media Analytics: Using Data to Understand Public Conversations \(course feat. TAGS\) #FLsocmed](#) July 18, 2016

Twitter Authorisation

Please be aware that if you are logged into multiple Google accounts your access details will be saved with you default account.

By clicking 'Sign in with Twitter' you agree to abide by the [Twitter Policy on 3rd party access](#)











Sign in with Twitter

 Sign in with Twitter

Your TwapperKeeper

archive your own tweets

Archive ID	Keyword / Hashtag	Description	Tags	Screen Name	Count	Create Time	
22	#bigdata	preliminary scrape	research	soci	1040644	Tue, 30 Jun 2015 12:39:44 +0000	
23	#analytics	secondary scrape	research	soci	403748	Tue, 30 Jun 2015 13:17:30 +0000	
24	#iot	secondary scrape	research	soci	1051596	Tue, 30 Jun 2015 13:17:47 +0000	
25	#datascience	secondary scrape	research	soci	179621	Tue, 30 Jun 2015 13:18:14 +0000	
26	#deeplearning	secondary scrape	research	soci	113215	Tue, 30 Jun 2015 13:18:47 +0000	
27	#data	secondary scrape	research	soci	463725	Tue, 30 Jun 2015 13:19:06 +0000	
28	#machinelearning	secondary scrape	research	soci	139813	Tue, 30 Jun 2015 13:20:25 +0000	
29	#internetofthings	secondary scrape	research	soci	169557	Tue, 30 Jun 2015 17:57:39 +0000	

Bills



Date: August 2016

[Download CSV](#) [Print](#)

Summary	Amount
AWS Service Charges	\$55.53
▶ Usage Charges and Recurring Fees View Invoices	\$55.53
Other Details	
▶ Payment Summary	\$55.53
▶ Tax Invoices View Invoices	
Total	\$55.53

[+ Expand All](#)

Details	Total
AWS Service Charges	\$55.53
▶ Data Transfer	\$0.05
▶ Elastic Compute Cloud	\$46.24
▶ CT to be collected	\$0.00
▶ GST to be collected	\$0.00
▶ US Sales Tax to be collected	\$0.00
▶ VAT to be collected	\$9.24



AWS ▾

Services ▾

Edit ▾

Steven McDermott ▾

N. Virginia ▾

Support ▾

Amazon Web Services

Compute

**EC2**
Virtual Servers in the Cloud**EC2 Container Service**
Run and Manage Docker Containers**Elastic Beanstalk**
Run and Manage Web Apps**Lambda**
Run Code without Thinking about Servers

Storage & Content Delivery

**S3**
Scalable Storage in the Cloud**CloudFront**
Global Content Delivery Network**Elastic File System**
Fully Managed File System for EC2**Glacier**
Archive Storage in the Cloud**Snowball**
Large Scale Data Transport**Storage Gateway**
Hybrid Storage Integration

Database

**RDS**
Managed Relational Database Service**DynamoDB**
Managed NoSQL Database**ElastiCache**
In-Memory Cache**Redshift**
Fast, Simple, Cost-Effective Data Warehousing**DMS**
Managed Database Migration Service

Developer Tools

**CodeCommit**
Store Code in Private Git Repositories**CodeDeploy**
Automate Code Deployments**CodePipeline**
Release Software using Continuous Delivery

Management Tools

**CloudWatch**
Monitor Resources and Applications**CloudFormation**
Create and Manage Resources with Templates**CloudTrail**
Track User Activity and API Usage**Config**
Track Resource Inventory and Changes**OpsWorks**
Automate Operations with Chef**Service Catalog**
Create and Use Standardized Products**Trusted Advisor**
Optimize Performance and Security

Security & Identity

**Identity & Access Management**
Manage User Access and Encryption Keys**Directory Service**
Host and Manage Active Directory**Inspector**
Analyze Application Security**WAF**
Filter Malicious Web Traffic**Certificate Manager**
Provision, Manage, and Deploy SSL/TLS Certificates

Internet of Things

**AWS IoT**
Connect Devices to the Cloud

Game Development

**GameLift**
Deploy and Scale Session-based Multiplayer Games

Mobile Services

**Mobile Hub**
Build, Test, and Monitor Mobile Apps**Cognito**
User Identity and App Data Synchronization**Device Farm**
Test Android, iOS, and Web Apps on Real Devices in the Cloud**Mobile Analytics**
Collect, View and Export App Analytics**SNS**
Push Notification Service

Application Services

**API Gateway**
Build, Deploy and Manage APIs**AppStream**
Low Latency Application Streaming**CloudSearch**
Managed Search Service**Elastic Transcoder**
Easy-to-Use Scalable Media Transcoding**SES**
Email Sending and Receiving Service**SQS**
Message Queue Service**SWF**
Workflow Service for Coordinating Application Components

Resource Groups

[Learn more](#)

A resource group is a collection of resources that share one or more tags. Create a group for each project, application, or environment in your account.

[Create a Group](#)[Tag Editor](#)

Additional Resources

[Getting Started](#)

Read our [documentation](#) or view our [training](#) to learn more about AWS.

[AWS Console Mobile App](#)

View your resources on the go with our AWS Console mobile app, available from Amazon Appstore, Google Play, or iTunes.

[AWS Marketplace](#)

Find and buy software, launch with 1-Click and pay by the hour.

[AWS re:Invent Announcements](#)

Explore the next generation of AWS cloud capabilities. [See what's new](#)

Service Health

🟢 All services operating normally.

Updated: Sep 20 2016 13:19:01 GMT+0100

[Service Health Dashboard](#)

Data selection

Select the dataset:

digitalhealth --- 149.330 tweets from 2016-06-21 14:00:00 to 2016-08-08 17:32:43 ▼

160.486 tweets archived so far (and counting)

Select parameters:

Query: (empty: containing any text*)

Exclude: (empty: exclude nothing*)

From user: (empty: from any user*)

From twitter client: (empty: from any client*)

(Part of) URL: (empty: any or all URLs*)

Startdate (UTC): (YYYY-MM-DD or YYYY-MM-DD HH:MM:SS)

Enddate (UTC): (YYYY-MM-DD or YYYY-MM-DD HH:MM:SS)

[update overview](#)

* You can also do AND or OR queries, although you cannot mix AND and OR in the same query.

Overview of your selection

Dataset: digitalhealth (#digihealthcapital, #digitalhealth, #patient, #patients, 'patient voice', 'patient voices', digitalhealth, mHealth)

Search query:

Comments:

Exclude:

From user:

From twitter client:

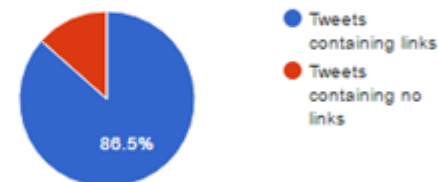
(Part of) URL:

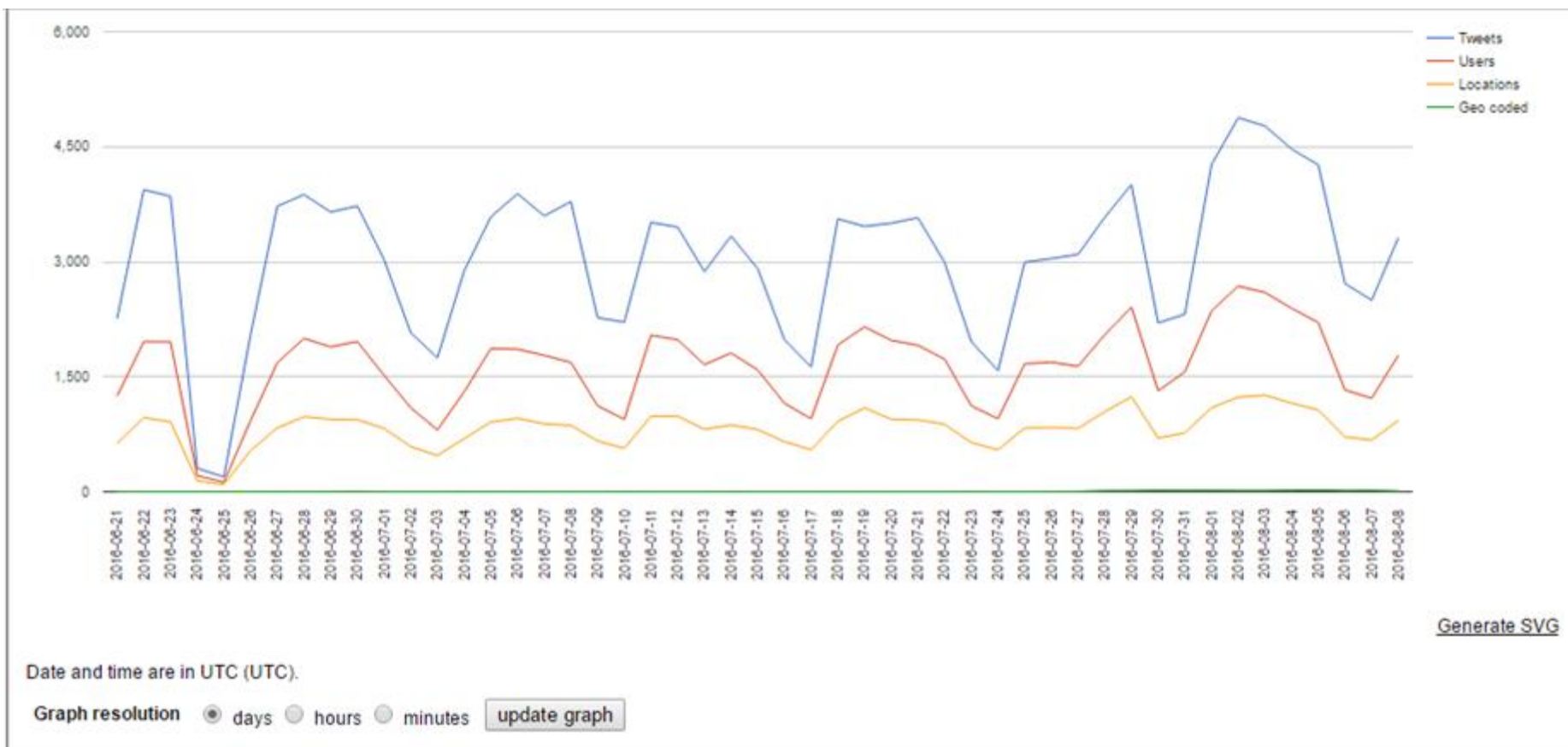
Startdate: 2016-06-21

Enddate: 2016-08-08

Number of tweets: 149.330

Number of distinct users: 33.050





All statistics and activity metrics come as a row file which you can open in Excel or similar

Here you can select from the statistics which to group:

> overall > per hour > per day > per week > per month > per year > custom

YYYY-MM-DD YYYY-MM-DD YYYY-MM-DD

Tweet stats

Contains the number of tweets, number of tweets with links, number of tweets with hashtags, number of tweets with mentions, number of retweets, and number of replies

Use: get a feel for the overall character of your data set.

> [help](#)

User stats (overall)

Contains the min, max, average, Q1, median, Q3, and trimmed mean for: number of tweets per user, rets per user, number of followers, number of friends, or of tweets, unique users per time interval

Use: get a better feel for the users in your data set.

> [help](#)

User stats (individual)

Lists users and their number of tweets, number of followers, number of friends, how many times they are listed, their UTC time offset, whether the user has a verified account and how many times they appear in the data set.

Use: get a better feel for the users in your data set.

> [help](#)

Hashtag frequency

Contains hashtag frequencies.

Use: find out which hashtags are most often associated with your subject.

> [help](#)

Hashtag-user activity

Lists hashtags, the number of tweets with that hashtag, the number of distinct users tweeting with that hashtag, the number of distinct mentions tweeted together with the hashtag, and the total number of mentions tweeted together with the hashtag

Use: explore user-hashtag activity

> [help](#)

User variability (mention frequency)

Lists usernames and the number of times they were mentioned by others.

Use: find out which users are "influencers".

> [help](#)

User activity (tweet frequency)

Lists usernames and the amount of tweets posted.

Use: find the most active tweeters, see if the dataset is dominated by certain relations.

> [help](#)

User activity + variability (tweet+mention frequency)

Lists usernames with both tweet and mention counts.

Use: see whether the users mentioned are also those who tweet a lot.

> [help](#)

Twitter client frequency

List the frequency of tweet software sources per interval.

> [help](#)

URL frequency

Contains the frequencies of tweeted URLs.

Use: find out which contents (articles, videos, etc.) are referenced most often.

> [help](#)

Real name frequency

Contains the frequencies of tweeted domain names.

Use: find out which sources (media, platforms, etc.) are referenced most often.

> [help](#)

Identical tweet frequency

Contains tweets and the number of times they have been (re)tweeted identically.

Use: get a grasp of the most "popular" content.

> [help](#)

Word frequency

Contains words and the number of times they have been used.

Use: get a grasp of the most used language.

> [help](#)

Media frequency

Contains media URLs and the number of times they have been used.

Use: get a grasp of the most popular media.

> [help](#)

Export an estimation of the number of rate limited tweets in your data

Exports a spreadsheet with an estimation of the amount of rate-limited tweets in your query due to relative occurrence.

Use: gain insight in possible missing data due to hitting the Twitter API's rate limits.

> [help](#)

Export data with potential gaps in your data

Exports a spreadsheet with all known data gaps in your current query during which TCAT was not running or capturing data for this file.

Use: Gain insight in possible missing data due to outages

> [help](#)

Networks

All network exports come as a .gexf or .gdf file which you can open in [Gexf](#) or similar.

Social graph by mentions

Produces a [directed graph](#) based on interactions between users. If a user mentions another one, a directed link is created. The more often a user mentions another, the stronger the link ("link weight"). The "count" value contains the number of tweets for each user in the specified period.

Use: analyze patterns in communication, find "hubs" and "communities", categorize user accounts.

> [help](#)

Social graph by re_reply_to_status_id

Produces a [directed graph](#) based on interactions between users. If a tweet was written in reply to another one, a directed link is created.

Use: analyze patterns in communication, find "hubs" and "communities", categorize user accounts.

> [help](#)

Co-hashtag graph

Produces an [undirected graph](#) based on co-occurrence analysis of hashtags. If two hashtags appear in the same tweet, they are linked. The more often they appear together, the stronger the link ("link weight").

Use: explore the relations between hashtags, find and analyze subcommunities, distinguish between different types of hashtags (event related, questions, etc.).

> [help](#) (set minimum frequency)

> [help](#) (get top hashtags)

Bipartite hashtag-user graph

Produces a [bipartite graph](#) based on co-occurrence of hashtags and users. If a user wrote a tweet with a certain hashtag, there will be a link between that user and the hashtag. The more often they appear together, the stronger the link ("link weight").

Use: explore the relations between users and hashtags, find and analyze which users group around which topics.

> [help](#)

Bipartite hashtag-mention graph

Produces a [bipartite graph](#) based on co-occurrence of hashtags and @mentions. If an @mention co-occurs in a tweet with a certain hashtag, there will be a link between that @mention and the hashtag. The more often they appear together, the stronger the link ("link weight").

Use: explore the relational activity between mentioned users and hashtags, find and analyze which users are considered experts around which topics.

> [help](#)

Bipartite hashtag-source graph

Produces a [bipartite graph](#) based on co-occurrence of hashtags and "sources" (the client a tweet was sent from in its source). If a hashtag is associated with a particular client, there will be a link between that client and the hashtag. The more often they appear together, the stronger the link ("link weight").

Use: explore the relations between clients and hashtags, find and analyze which clients are related to which topics.

> [help](#)

Bipartite URL-user graph

Produces a [bipartite graph](#) based on co-occurrence of URLs and users. If a user wrote a tweet with a certain URL, there will be a link between that user and the URL. The more often they appear together, the stronger the link ("link weight").

Use: explore the relations between users and URLs, find and analyze which users group around which topics.

> [help](#)

Bipartite hashtag-URL graph

Creates a row file that contains URLs and the number of times they have co-occurred with a particular hashtag.

Creates a .gexf file that contains a [bipartite graph](#) (.gexf), open in [gexf](#) based on co-occurrence of URLs and hashtags. If a URL co-occurs with a certain hashtag, there will be a link between that URL and the hashtag. The more often they appear together, the stronger the link ("link weight").

Use: get a grasp of how info are qualified.

> [help](#)

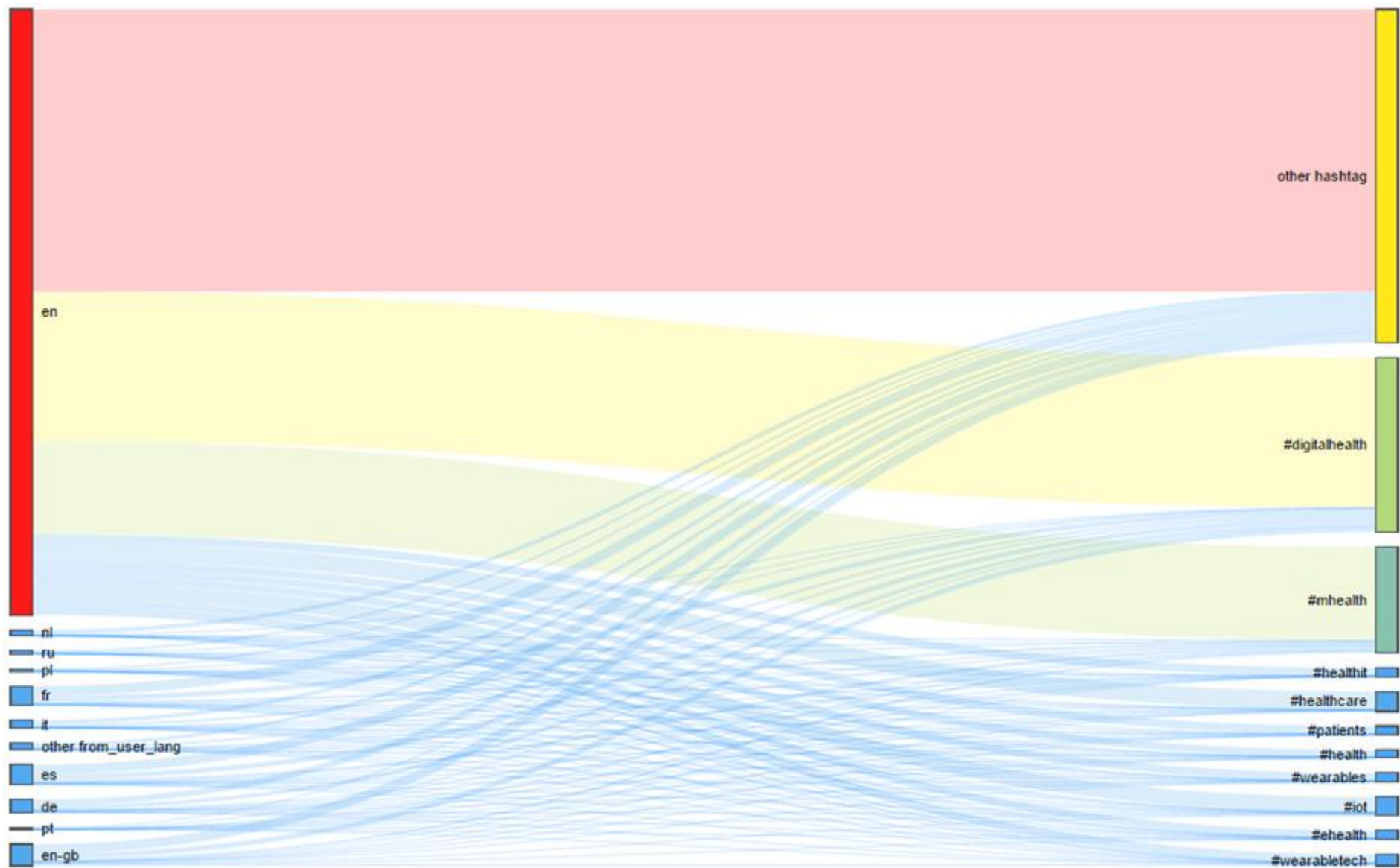
Bipartite hashtag-retweet graph

Creates a row file that contains tweets and the number of times they have co-occurred with a particular hashtag.

Creates a .gexf file that contains a [bipartite graph](#) (.gexf), open in [gexf](#) based on co-occurrence of tweets and hashtags. If a tweet co-occurs with a certain hashtag, there will be a link between that tweet and the hashtag. The more often they appear together, the stronger the link ("link weight").

Use: get a grasp of how tweets are qualified.

> [help](#)



The Open Graph Viz Platform

Gephi is the leading visualization and exploration software for all kinds of graphs and networks. Gephi is open-source and free.

Runs on Windows, Mac OS X and Linux.

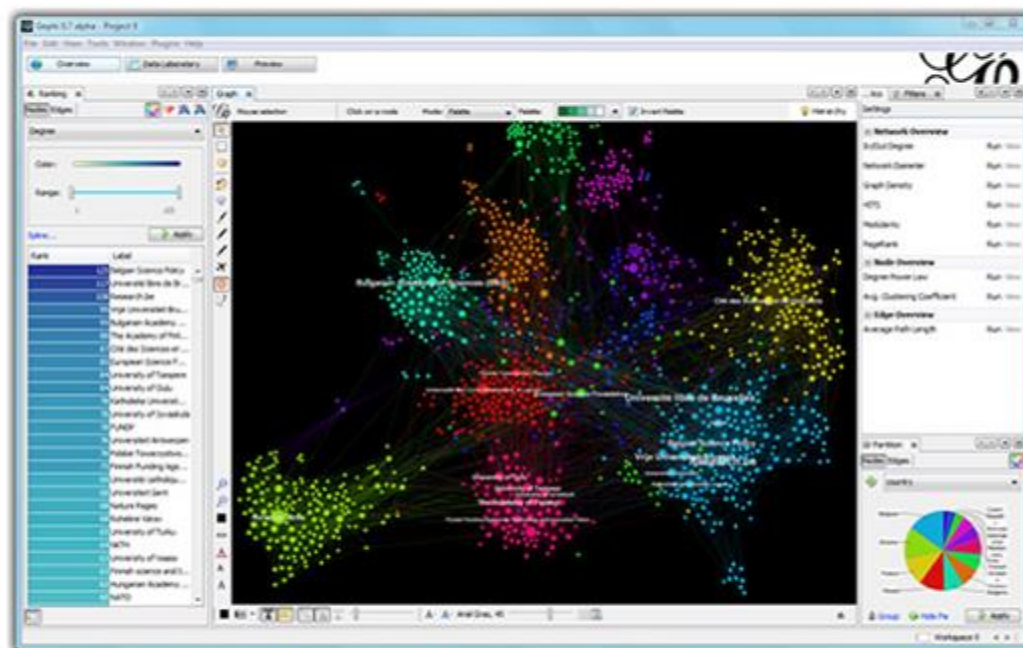
[Learn More on Gephi Platform »](#)



[Release Notes](#) | [System Requirements](#)

► [Features](#)
► [Quick start](#)

► [Screenshots](#)
► [Videos](#)



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APPLICATIONS

✓ **Exploratory Data Analysis:** intuition-oriented

Like Photoshop™ for graphs.

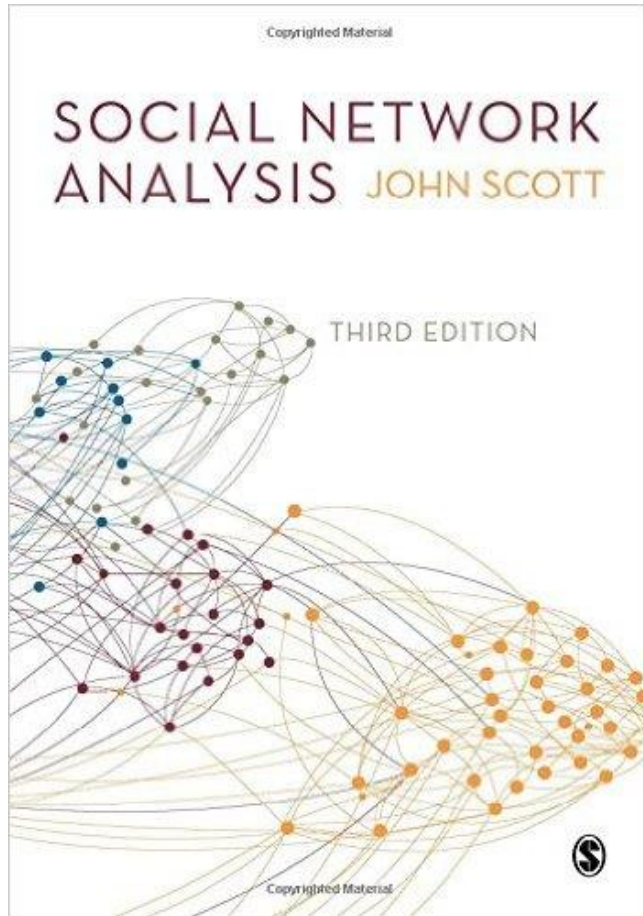
PAPERS

[Gephi 2.0: An Open Graph Visualization Platform](#)

The Various Algorithms to Choose From...

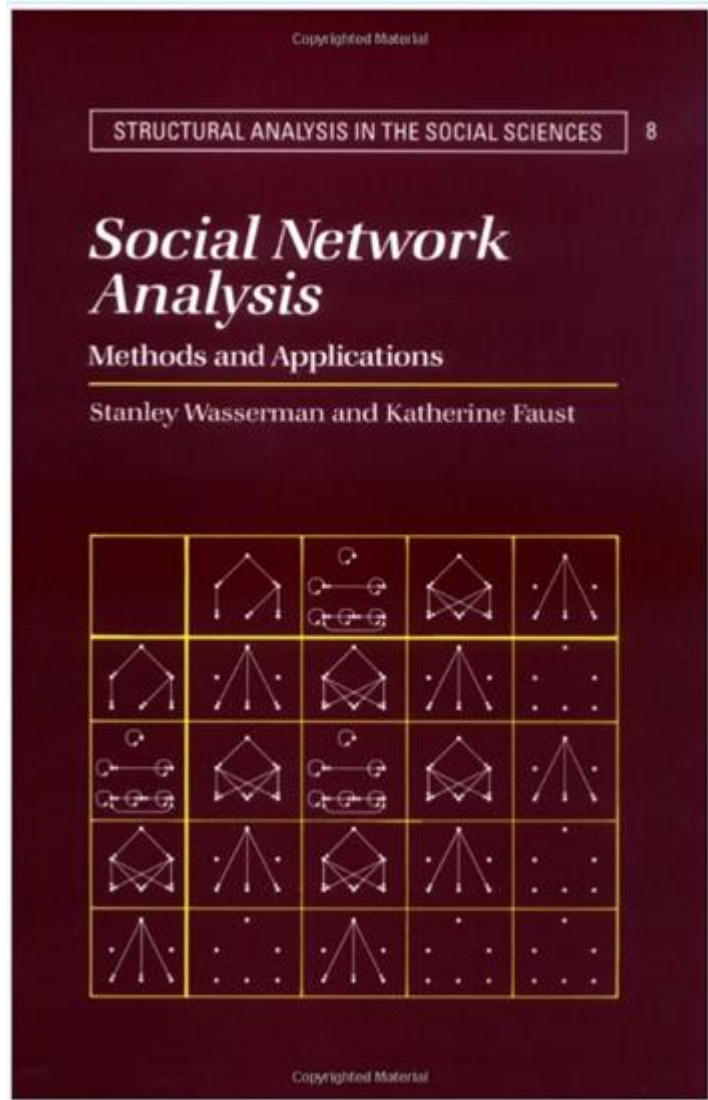
	id	label	timeset	indegree	outdegree	degree	weighted d	weighted i	weighted o	eccentricit	closeness	betweenes	authority	hub	modularity	componen	pageranks	harmonicc	clustering	triangles	eigencentralit
1																					
2	897	#healthcare		72	0	72	957	957	0	4	0.408613	0.108482	0.002091	0	6	1	0.001261	0.44089	0.033646	86	0.666603
3	290	#health		47	0	47	373	373	0	4	0.379455	0.072401	0.001375	0	30	1	0.000856	0.41325	0.026827	29	0.473737
4	117	@healthythinker		5	514	519	1708	76	1693	5	0.351963	0.055618	0.000172	0.015915	22	1	0.009896	0.372563	0.001509	202	1
5	8312	@healthranger		1	463	464	613	4	609	5	0.332176	0.054006	5.73E-05	0.005305	1	1	0.011183	0.351481	3.72E-05	4	0.443949
6	32	@		36	0	36	150	150	0	4	0.347737	0.0528	0.00106	0	0	1	0.000665	0.379914	0.02381	15	0.318074
7	4531	@jod_ehealth		1	386	387	1567	22	1567	5	0.335209	0.042413	5.73E-05	0.005305	4	1	0.008545	0.348872	0	0	0.505168
8	7447	@picardonhealth		3	380	383	1205	30	1202	5	0.329081	0.041943	0.000115	0.01061	14	1	0.008787	0.347148	0.000948	69	0.371479
9	333	@meglobalhealth		1	347	348	1095	21	1095	5	0.329585	0.041867	5.73E-05	0.005305	15	1	0.008407	0.343724	0.000183	11	0.305347
10	3491	@healthhydebate		1	367	368	1592	28	1592	5	0.334137	0.041493	5.73E-05	0.005305	14	1	0.008557	0.349583	0.00061	41	0.377999
11	9184	@helthihealthy		1	332	333	1290	123	1290	5	0.31885	0.040699	5.73E-05	0.005305	3	1	0.008761	0.336106	0	0	0.265454
12	8728	@dignityhealth		5	344	349	946	103	924	5	0.345461	0.03917	0.000172	0.015915	28	1	0.00767	0.360483	0.001342	81	0.471561
13	14354	@healthdata4all		2	369	371	4765	157	4764	5	0.33654	0.037179	8.59E-05	0.007958	19	1	0.007477	0.351246	0.000557	38	0.568403
14	4059	@dellhealth		5	253	258	1002	32	987	5	0.343485	0.035154	0.000172	0.015915	25	1	0.004849	0.357646	0.003496	115	0.535466
15	2373	@healthloop		5	360	365	2944	299	2898	5	0.342834	0.034383	0.000172	0.015915	19	1	0.006913	0.360259	0.003535	231	0.660325
16	7513	@smart_health		1	302	303	1323	23	1323	5	0.336961	0.033625	5.73E-05	0.005305	18	1	0.006819	0.349145	0.000682	31	0.416239
17	7733	@healthtech_talk		2	317	319	3176	24	3174	5	0.339506	0.033477	8.59E-05	0.007958	27	1	0.00677	0.356257	0.002156	108	0.539018
18	1468	#digitalhealth		48	0	48	982	982	0	6	0.362891	0.033129	0.001403	0	16	1	0.000826	0.398177	0.044326	50	0.49184
19	1373	@healthspafi		3	290	293	1094	39	1082	5	0.33272	0.032435	0.000115	0.01061	3	1	0.006687	0.346897	0.000565	24	0.369456
20	4015	@healthitcentral		1	330	331	2455	2	2455	5	0.343597	0.030915	5.73E-05	0.005305	33	1	0.006215	0.358078	0.002376	129	0.65792
21	9969	@healthware_intl		3	310	313	1460	99	1417	5	0.336464	0.030884	0.000115	0.01061	30	1	0.00622	0.349157	0.001357	65	0.454601
22	1116	@newhealthfr		1	256	257	1031	31	1031	5	0.316699	0.03034	5.73E-05	0.005305	34	1	0.006387	0.331502	0	0	0.21292
23	10845	@tincturehealth		2	335	337	3038	223	3026	5	0.337874	0.030248	8.59E-05	0.007958	19	1	0.006324	0.35514	0.002038	114	0.57498
24	4169	@digihealthhelp		3	289	292	809	12	797	5	0.33726	0.029908	0.000115	0.01061	16	1	0.005948	0.3553	0.00273	116	0.473344
25	3774	@healthmap		0	269	269	533	0	533	5	0.282092	0.029867	0	0.002653	15	1	0.006627	0.303288	0	0	0.16599
26	3234	@healthbankcoop		1	314	315	1323	118	1323	5	0.329776	0.028812	5.73E-05	0.005305	13	1	0.006186	0.343081	0	0	0.517346
27	12032	@arab_health		2	239	241	860	172	854	5	0.333071	0.028423	8.59E-05	0.007958	15	1	0.005835	0.343165	0.000244	7	0.236781
28	1724	@ibmhealthcare		4	262	266	1218	89	1200	5	0.34099	0.02802	0.000143	0.013263	22	1	0.005266	0.354522	0.002601	91	0.482919
29	11409	@ochsnerhealth		2	225	227	682	65	678	5	0.335969	0.027473	8.59E-05	0.007958	5	1	0.005415	0.345128	0.000551	14	0.212592
30	5668	@barnabas_health		1	224	225	1114	140	1114	5	0.313201	0.027456	5.73E-05	0.005305	21	1	0.0058	0.327501	0	0	0.148858
31	6561	@nexjhealth		1	249	250	945	28	945	5	0.330732	0.026219	5.73E-05	0.005305	26	1	0.005394	0.341336	0	0	0.336692
32	4343	@ehealthscotland		2	241	243	896	17	893	5	0.327902	0.026099	8.59E-05	0.007958	18	1	0.005308	0.341262	0.000754	22	0.315195

Social Network Analysis – By John Scott



Scott, J. (2012). *Social network analysis*. Sage.

Social Network Analysis – Methods and Applications



Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8). Cambridge university press.

TROPES

High Performance Text Analysis for Professional Users

Analysis of written or spoken texts requires that certain questions should be asked with regard to certain objectives. To obtain answers to these questions, texts must be reduced as far as possible to their essentials.

Designed for Information Science, Market Research, Sociological Analysis and Scientific studies, Tropes is a Natural Language Processing and Semantic Classification software that guarantees **pertinence and quality in Text Analysis**.



Extraction of Relevant Information

Tropes can immediately detect contexts, isolate themes and identify principal actors, through the application of **three levels of semantic classifications**. You can quickly determine who says what to whom; who does what, where and when; and with what purpose.

Qualitative Analysis and Categorization

Tropes identifies the **Text Style** in order to place it in context and rapidly compare it with other texts. Tropes uses **Semantic Meta-Categories** to group verbs, adjectives, adverbs, personal pronouns and conjunctions.

Chronological Analysis

Tropes carries out a **chronological analysis** of a text from which the principal episodes can be isolated, the discussion blocks visualized and the development of an idea followed up.

Products

COMMERCIAL

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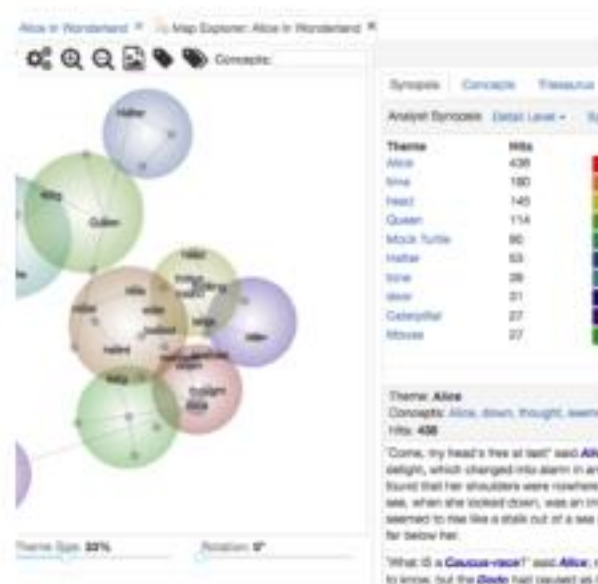
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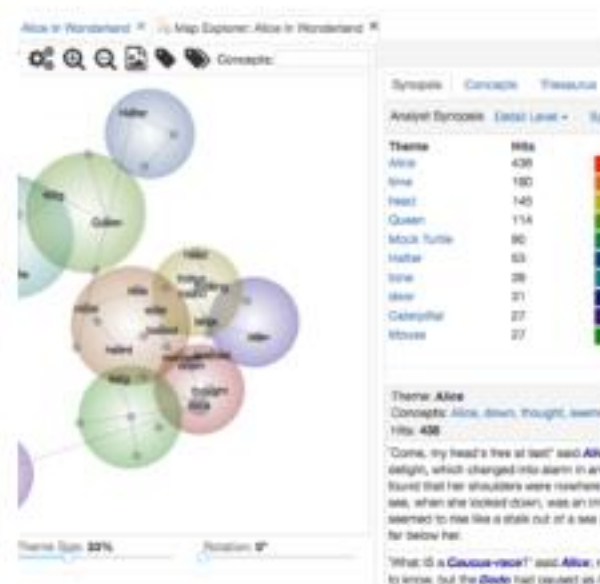
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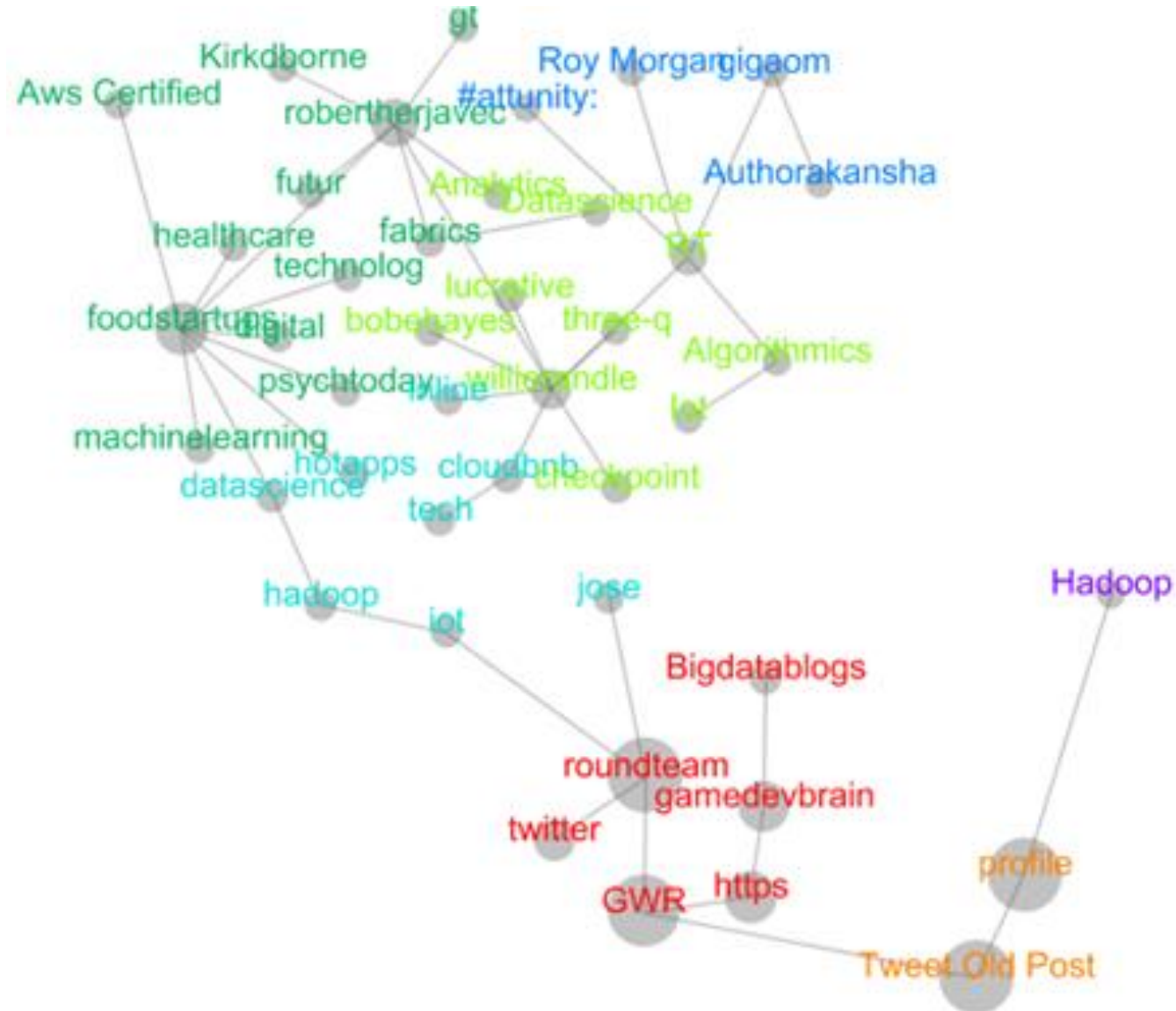
Leximancer is computer software that conducts quantitative content analysis using a machine learning technique. It learns what the main concepts are in a text and how they relate to each other. It conducts a thematic analysis and a relational analysis of the textual data. Leximancer provides word frequency counts and co-occurrence counts of concepts present in the tweets. It is:

[A] Method for transforming lexical co-occurrence information from natural language into semantic patterns in an unsupervised manner. It employs two stages of co-occurrence information extraction— semantic and relational—using a different algorithm for each stage. The algorithms used are statistical, but they employ nonlinear dynamics and machine learning.

Smith and Humphreys, p. 26

Once a concept has been identified by the machine learning process, Leximancer then creates a thesaurus of words that are associated with that concept giving the 'concept its semantic or definitional content'.

1,040,000 #BigData Tweets Analysed using Leximancer



Top Named Individuals

- @authorakansha - I'm 21 & I spent much of my time on Social Media & Photography. I'm also the author of a travel guide series
- @roymorganonline - Recognised leader in Social and Market Research, Melbourne, Australia - roymorgan.com
- @Kirkdborne - The Principal Data Scientist at [@BoozAllen](http://BoozAllen.com), PhD Astrophysicist, ♥ Data Science, Top Big Data Influencer. Ex-Professor <http://rocketdatascience.org/> - Booz Allen Hamilton
- @Robertherjavec - Dad. Founder of Herjavec Group. Shark on ABC's Shark Tank. Author of You Don't Have to Be a Shark: Creating Your Own Success. Wherever I need to be. RobertHerjavec.com
- @willierandle - Follow Me, I'll Follow You! Tweet on! El Paso, TX
- @bobehayes - B.O.B. is Chief Research Officer [@AnalyticsWeek](http://AnalyticsWeek.com). PhD in industrial-organizational psychology. Interests in #custexp #bigdata #statistics #analytics Seattle, WA • businessoverbroadway.com

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Tweets by @BoozAllen

Booz Allen Hamilton Holding Corporation

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Type	Public
Traded as	NYSE: BAH ↗
Industry	Management consulting Government contractor
Founded	1914; 102 years ago
Founder	Edwin G. Booz James L. Allen Carl L. Hamilton
Headquarters	Tysons Corner, Virginia, U.S. ^[1]
Key people	Horacio D. Rozanski, President & Chief Executive Officer ^[1] John Michael McConnell, Vice Chairman
Services	Management and Technology Consulting
Revenue	▲ US\$ 5.48 billion (2014) ^[2]
Net income	▲ US\$ 239.955 million (FY 2012) ^[2]
Number of employees	22,000 (2014)
Website	www.boozallen.com ↗

Edward Snowden was employed by Booz Allen Hamilton and the National Security Agency.

On Twitter the key influencer around the term #bigdata is a contractor who supplies staff to the NSA.

Data Mining, Social Network Analysis and Content Analysis

- What has been presented so far are a few of the techniques and tools of data mining and analytics – with machine learning and automation in Leximancer.
- Such insights that are born from the data and the application of algorithms need to be validated in the light of informed understanding of the '**never raw data**' position especially for matters related to health.
- The existence of this '**data**' is the result of a long chain of requirements, goals and a shift in the wider political economy.
- The 'insights' are at the macro level – devoid of context and therefore an immediate sense of meaning.

Calculated Data Patients/Scientists

- Data Science generates crude quantitative knowledge, or “calculated publics” (Gillespie, 2014).
- In order to interpret the visualisations requires human perception.
- Big data and social media analytics can not answer questions about data scientists, or patients on their own.
- Big data and social media analytics requires wider knowledge of context and debates surrounding the topic at hand.

Defined, managed, and governed

- Big/Social data does not represent what we think they do.
- Nonetheless it does represent *something*, and this *something* is certainly something worthy of our consideration.
- “That a census or a social survey is a *snapshot of the way our societies are regulated* is rarely remarked on and instead emphasis is given to the presumed objectivity of the categories and their data. This is the ideology of the small data era in action – the claim that it is science and not society that we are seeing through such instruments.”
- Even if the referent of population data is not the population itself, we are still dealing with reference and meaning; we are glimpsing not a population in its totality, but the *various ways in which that population is defined, managed, and governed.*

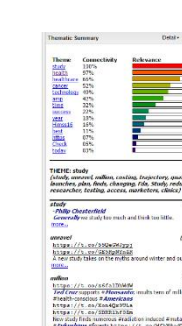
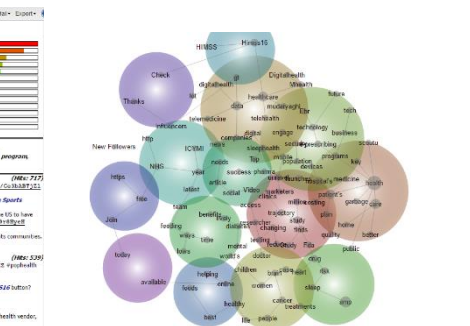
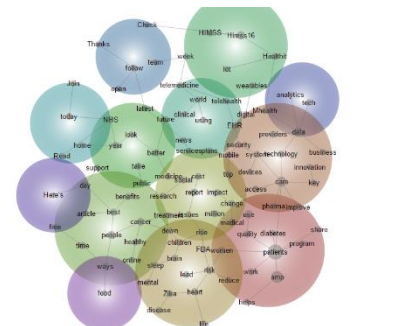
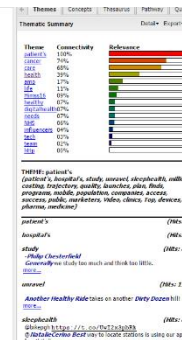
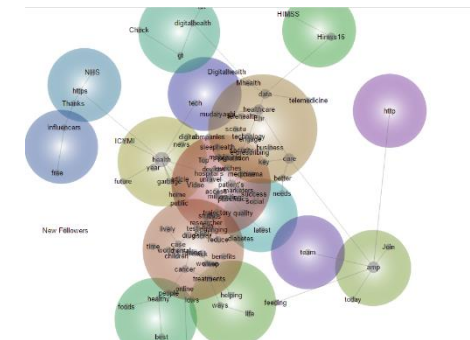
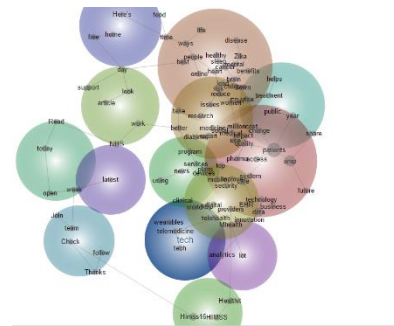
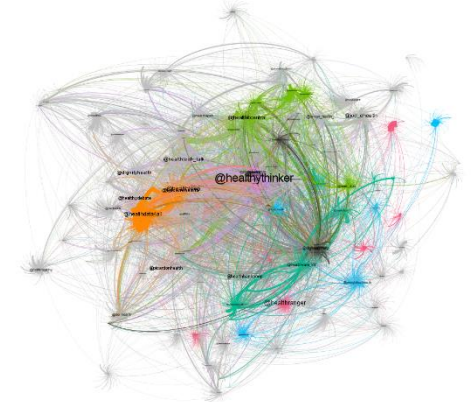
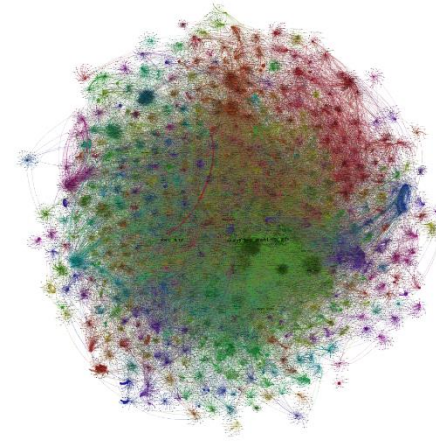
In Order to Interpret Data – Context and Critique are Crucial

- There are those within the Data Science discipline who are prepared to acknowledge the utility of human interpretation of data over algorithmic accounts.
- The Principal Data Scientist at @BoozAllen, (PhD Astrophysicist, Kirk Borne) recently stated that only using computer algorithms for visualisation...

“[...] can miss salient (explanatory) features of the data [therefore] a data analytics approach that combines the best of both worlds (machine algorithms and human perception) will enable efficient and effective exploration of large high-dimensional data”.

<http://rocketdatascience.org/?p=567>

- Unsupervised concept and theme modelling is denaturalising and unfamiliar – but crucially they are not objective, unbiased or neutral.
- They are fictions.
- The modelling algorithm knows nothing about letters, nothing about narrative form, nothing about health.
- All it can tell us is that 1) this string of tokens (in our case, words) co-occur together more than we would expect, all things being equal, and 2) some particular documents (in this case, Tweets) are composed of a certain number of tokens (words) with a relatively high probability of belonging to this topic.



- The algorithm's lack of knowledge of semantic meaning, and particularly its lack of knowledge of the social media as a form or genre, lets it point us to a very different model of the social.
- Such 'Reading Machines' are engaged in datafication of the social.

Datafication

- Datafication as defined by Kenneth Cukier and Viktor Mayor-Schoenberger (2013) refers to: ‘the ability to render into data many aspects of the world that have not been quantified before’.
- This is importantly ‘not the same as digitization, which takes analog content – books, films, photographs -and converts it into digital information, a sequence of ones and zeros that computers can read.
- Datafication is a far broader activity: taking all aspects of life and turn them into data’ (Cukier & Mayor-Schoenberger, 2013). It includes ‘behavioural metadata, such as those automatically derived from smartphones, like time stamps and GPS-inferred locations’ and may be used for a range of purposes ranging from surveillance to citizen empowerment (Kennedy, Poell and van Dijck 2015).

Data is NOT Objective NOT Incontrovertible

- The concern with the notion of **datafication** is that as it attempts to describe a certain state of affairs, as it occurs in one moment, it also flattens human experience, in a way that ethnography always defies, by acknowledging and insisting that whatever we label as 'data' is 'rich' and 'lively', rather than fixed, frozen or representing something 'true' about the world.

- Data, particularly that which is derived from huge conglomerate sources, is becoming increasingly a material or source for driving questions for and informing design practice. This is worrying in many ways - metrics derived through Big Data always represent a partial and non-representative sample (Baym, 2013) and thus do not accurately or adequately represent how people engage with and experience the world.
- While some might fall back on the positivist argument that we simply need to improve our measures, people –as everyday designers– will intentionally or unintentionally ensure that data is incomplete, dispersed and unfinished.

- There are growing movements towards data as fiction – embodied within data is an ideology.
- More recently for example the unfitbits online initiative (<http://www.unfitbits.com/>)
- Yet what is perhaps more worrying is that designers, developers, and policy makers will continue to take Big/Social Data at face value, as an object or representation of a truth that can be extracted from and that reflects the social.
- We are glimpsing the *various ways in which we are defined, managed, and governed.*