



NETWORKS, CLUSTERS, INFLUENCERS

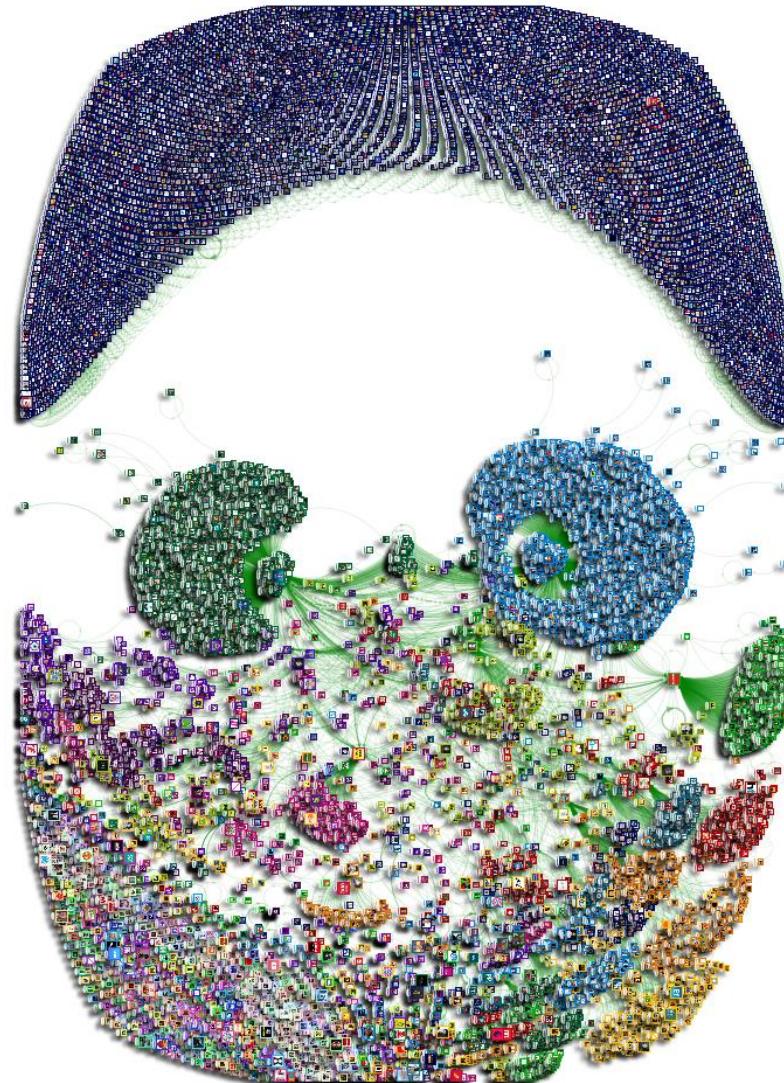
Introduction to Social Network
Analysis (SNA) for journalists

Dipl.-Geographer Harald Meier
harald@smrfoundation.org

June 9th, 2020

CONTENTS

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- 1. Social Network Analysis**
- 2. Social Media Networks**
- 3. Use cases for Journalists**
- 4. Tutorial Outlook and Preparation**
- 5. Q-and-A**

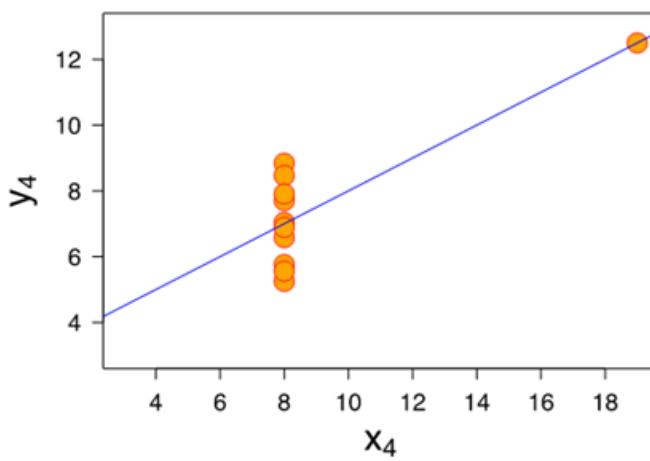
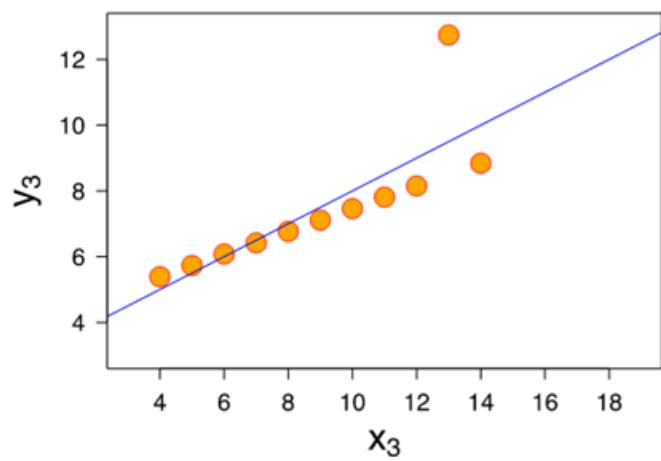
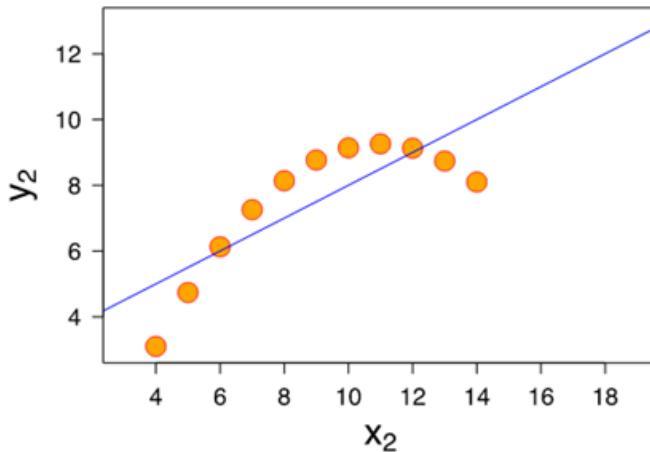
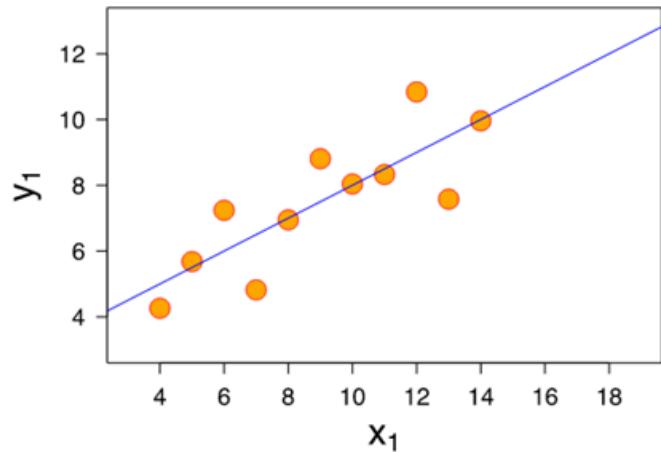
WHY DATAVIZ MATTERS

1		2		3		4	
x	y	x	y	x	y	x	y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

Anscombe's Quartet

Property	Value
Mean of x	9.0
Variance of x	11.0
Mean of y	7.5
Variance of y	4.12
Correlation	0.816
Linear regression	$y = 3 + 0.5x$

WHY DATAVIZ MATTERS



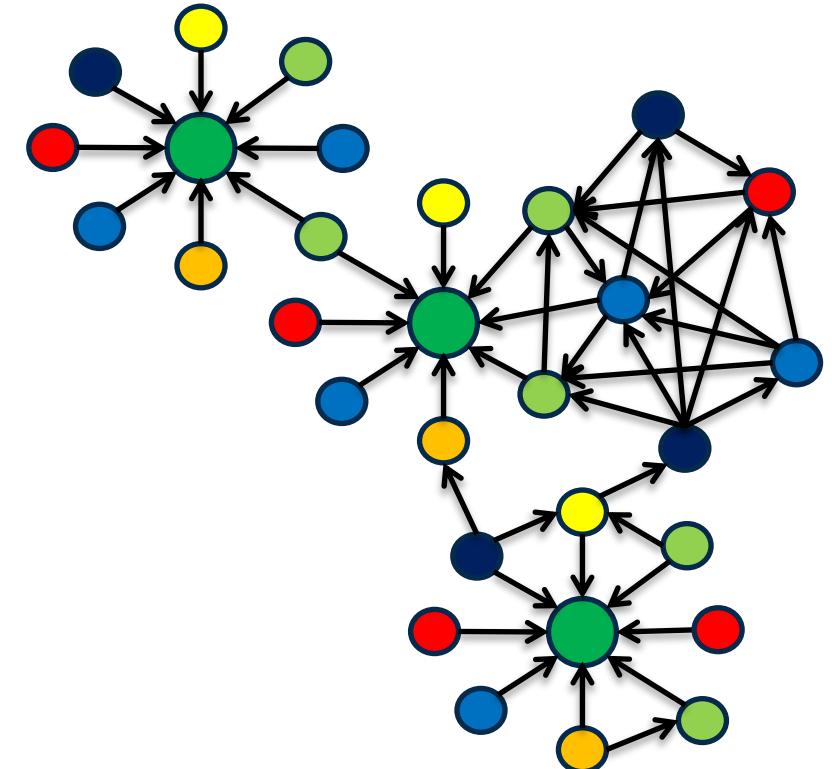
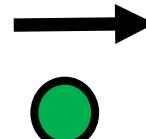
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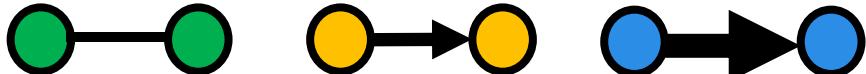
NETWORK BASICS

Network = collection of connections

- **Edge** = connection, relationship / like, retweet, ...
- **Vertex** = node, entity / person, user, company, ...
- **Cluster** = group of vertices
- **Graph** = network map



Undirected vs. **Directed** vs. **Weighted** networks



Single-mode vs. **multi-modal** networks



NETWORK TOOLS AND DATA

Tools

- NodeXL, Gephi, Socioviz, Netlytic, Neo4J, ...

File types

- Excel, csv
- GEXF, GDF, GraphML, UCINET, Pajek

Network Data Sources

- Social Media Platform APIs
- Digital Methods Initiative (DMI)
- databases / leaked data

All you need:

	A	B
1	Vertex 1	Vertex 2
2	Lenny	Carl
3	Carl	Barney
4	Barney	Moe
5	Monty	Waylon
6	Homer	Marge
7

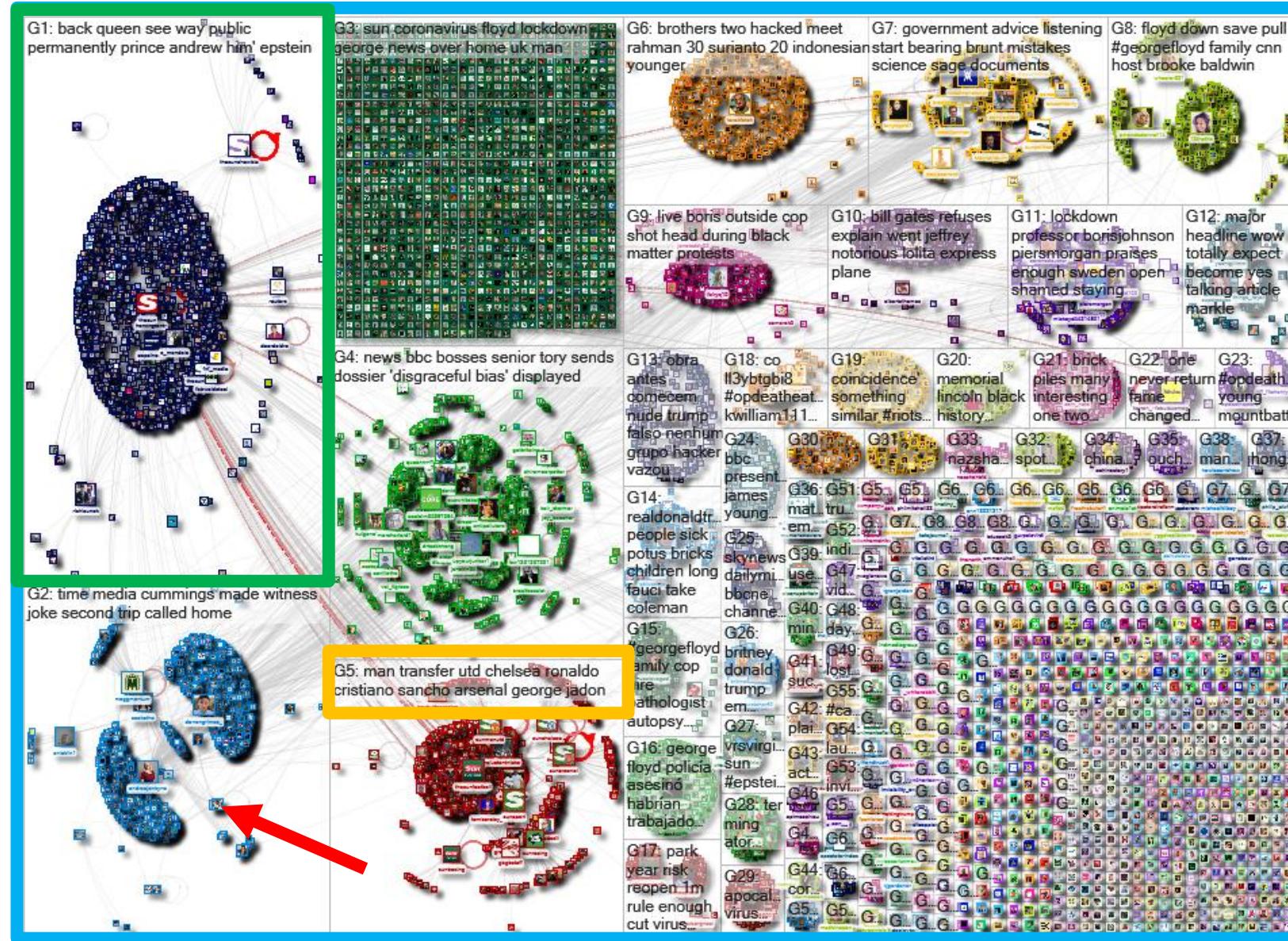
Edge table

	A
1	Vertex
2	Lenny
3	Carl
4	Maggie
5	Monty
6	Waylon
7	...

(Vertex table)

Additional columns = Metadata (!)

SOCIAL NETWORK ANALYSIS



Search term url:thesun.co.uk on June 3, 2020: <https://nodexlgraphgallery.org/Pages/Graph.aspx?graphID=228728>

Network Overview

- Size / Density / Modularity

Cluster Analysis

- Cluster Algorithm
 - Density

Vertex Metrics

- Centrality: Degree, Betweenness, Closeness, Eigenvector, ...

Content Analysis

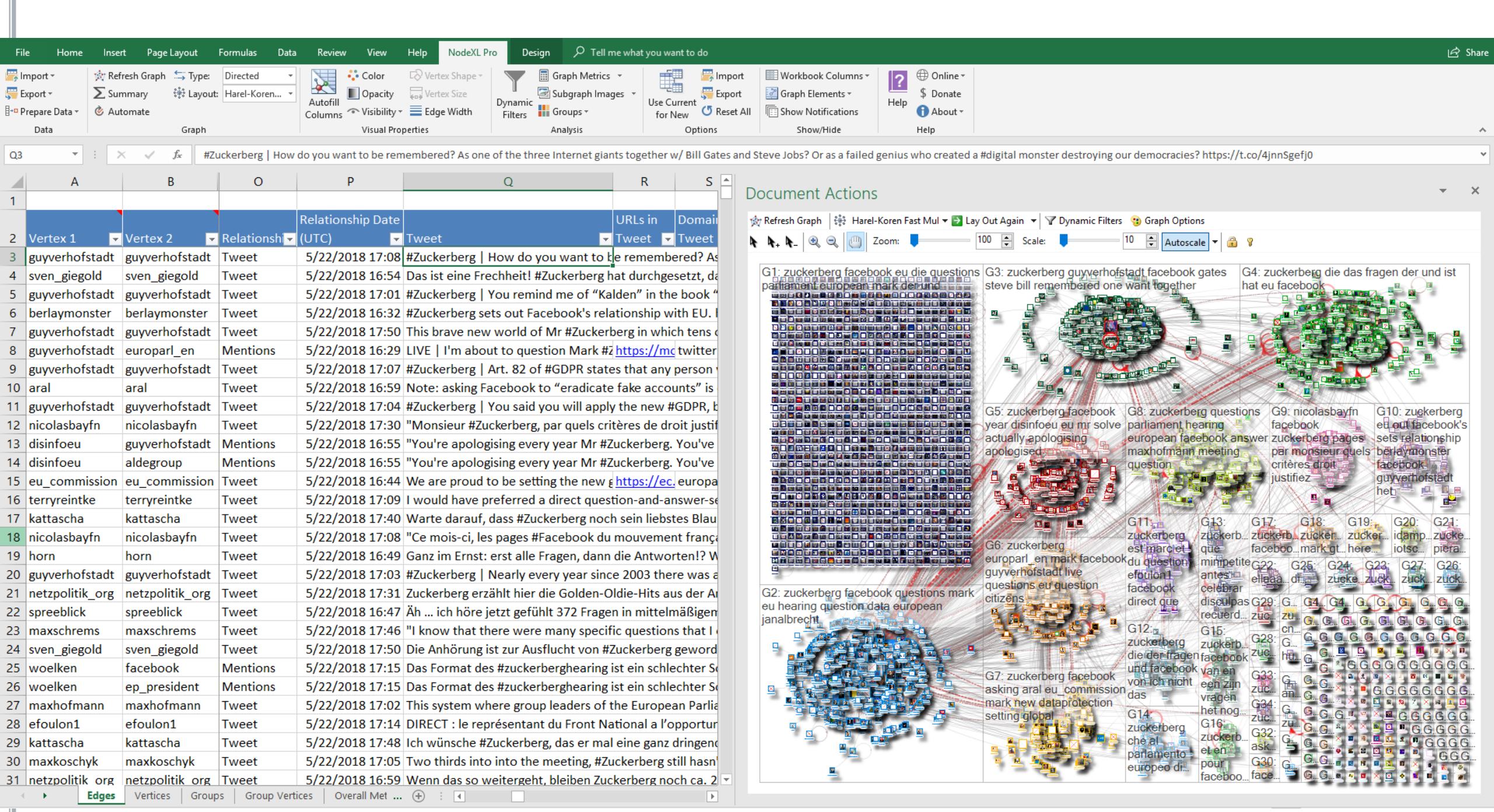
- Top hashtags, words, URLs, ...
 - Sentiment, time series

Visual Analysis

- Layout Algorithms
 - Group-In-A-Box: Treemap
 - Harel-Koren Fast Multiscale

$$\begin{aligned}
Q &= \frac{1}{2m} \sum_{vw} \left[A_{vw} - \frac{k_v k_w}{2m} \right] \sum_i \delta(c_v, i) \delta(c_w, i) \\
&= \sum_i \left[\frac{1}{2m} \sum_{vw} A_{vw} \delta(c_v, i) \delta(c_w, i) \right. \\
&\quad \left. - \frac{1}{2m} \sum_v k_v \delta(c_v, i) \frac{1}{2m} \sum_w k_w \delta(c_w, i) \right] \\
&= \sum_i (e_{ii} - a_i^2).
\end{aligned} \tag{7}$$

Clauset, Newman, Moore (2004)



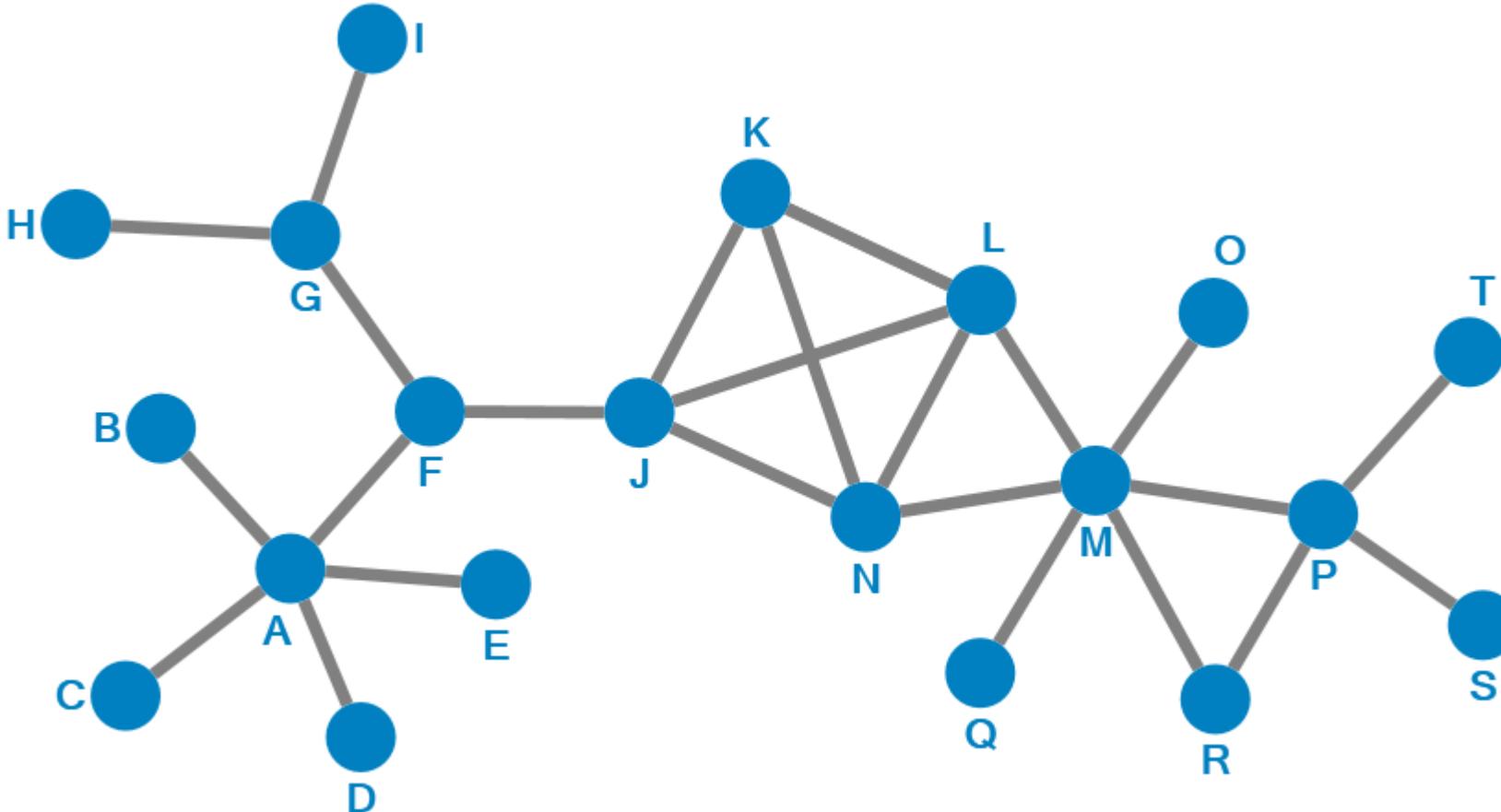
This screenshot illustrates the integration of NodeXL Pro with Microsoft Excel for network analysis. The top navigation bar shows the NodeXL Pro ribbon tab is active. The main interface consists of two primary components: a data table on the left and a network graph on the right.

Data Table (Left): The table displays "Graph Metrics" for 23 vertices. The columns include Vertex, In-Degree, Out-Degree, Betweenness Centrality, Closeness Centrality, Eigenvector Centrality, and PageRank. The vertex "facebook" is highlighted in yellow, and a tooltip indicates it is the active vertex. The table also includes a "Vertices" tab at the bottom.

	A	S	T	U	V	W	X
1	Graph Metrics						
2	Vertex	In-Degree	Out-Degree	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality	PageRank
3	guyverhofstadt	606	2	4226649.571	0.000	0.025	163.407
4	disinfoeu	112	12	1298638.567	0.000	0.004	28.878
5	europarl_en	267	0	1260917.790	0.000	0.009	56.940
6	sven_giegold	173	3	1069336.016	0.000	0.002	46.161
7	facebook	198	0	953820.097	0.000	0.006	40.519
8	nicolab	138	1	884252.900	0.000	0.000	57.442
9	netzpoli	131	7	840702.633	0.000	0.003	33.535
10	ep_president	120	0	758494.887	0.000	0.004	23.413
11	eu_commission	95	1	664007.646	0.000	0.001	27.302
12	janalbrecht	133	4	558006.663	0.000	0.004	25.308
13	berlaymonster	104	2	550244.967	0.000	0.002	29.270
14	aral	97	3	516235.416	0.000	0.002	27.645
15	kate_hammer	1	53	494504.455	0.000	0.003	10.518
16	mokomokai	0	42	462746.160	0.000	0.003	8.199
17	sandoly	0	58	437823.552	0.000	0.003	11.789
18	maxhofmann	84	1	362303.306	0.000	0.002	19.493
19	efoulon1	45	2	340678.356	0.000	0.000	18.025
20	greensep	101	8	329055.291	0.000	0.003	19.952
21	maxsattonnay	0	11	306241.747	0.000	0.002	2.544
22	samhufton1	3	26	271650.285	0.000	0.003	5.629
23	manfredweber	70	0	262375.866	0.000	0.002	13.454

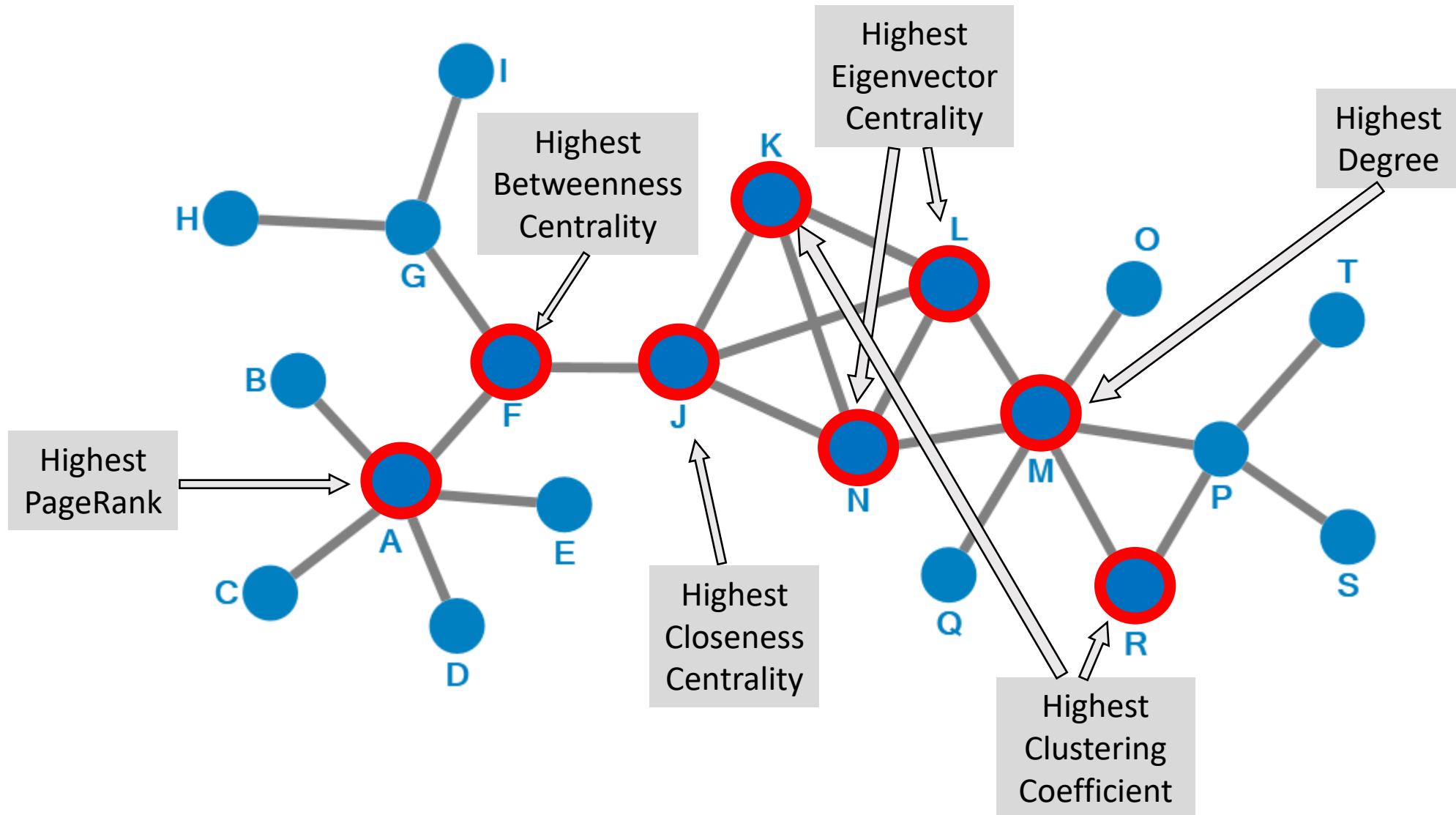
Network Graph (Right): The graph displays a complex network structure with nodes representing entities and edges representing relationships. Nodes are color-coded by group and have small icons next to them. A tooltip for node G1 provides context: "G1: zuckerberg facebook eu die questions parlament european mark der und". The graph includes various controls for layout, zoom, and selection.

MEASURING INFLUENCE: VERTEX METRICS



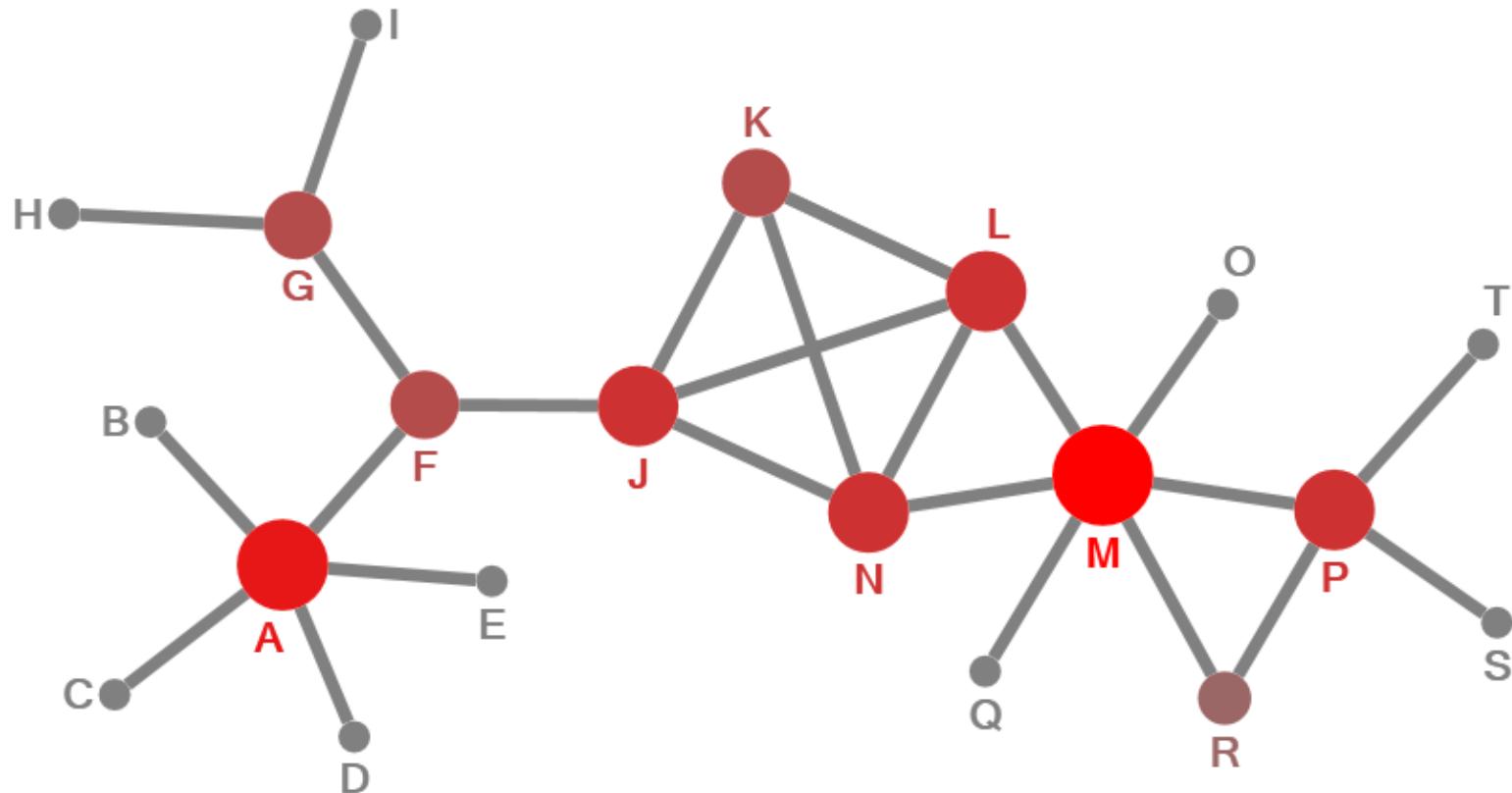
Derived from Borgatti (2006)

MEASURING INFLUENCE: VERTEX METRICS



DEGREE

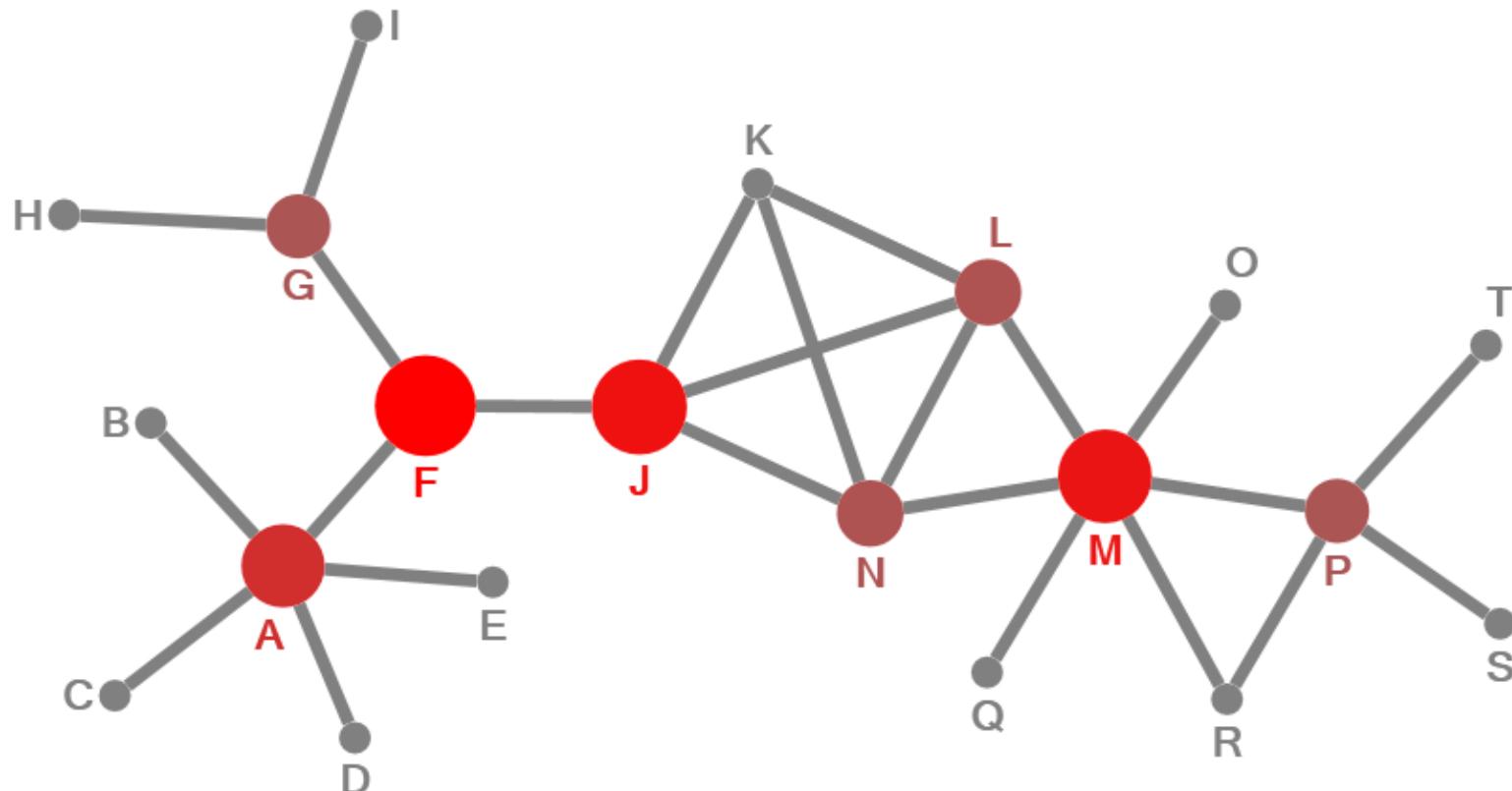
Vertex	Degree
M	6
A	5
L	4
N	4
J	4
P	4
K	3
G	3
F	3
R	2



Derived from Borgatti (2006)

BETWEENNESS CENTRALITY

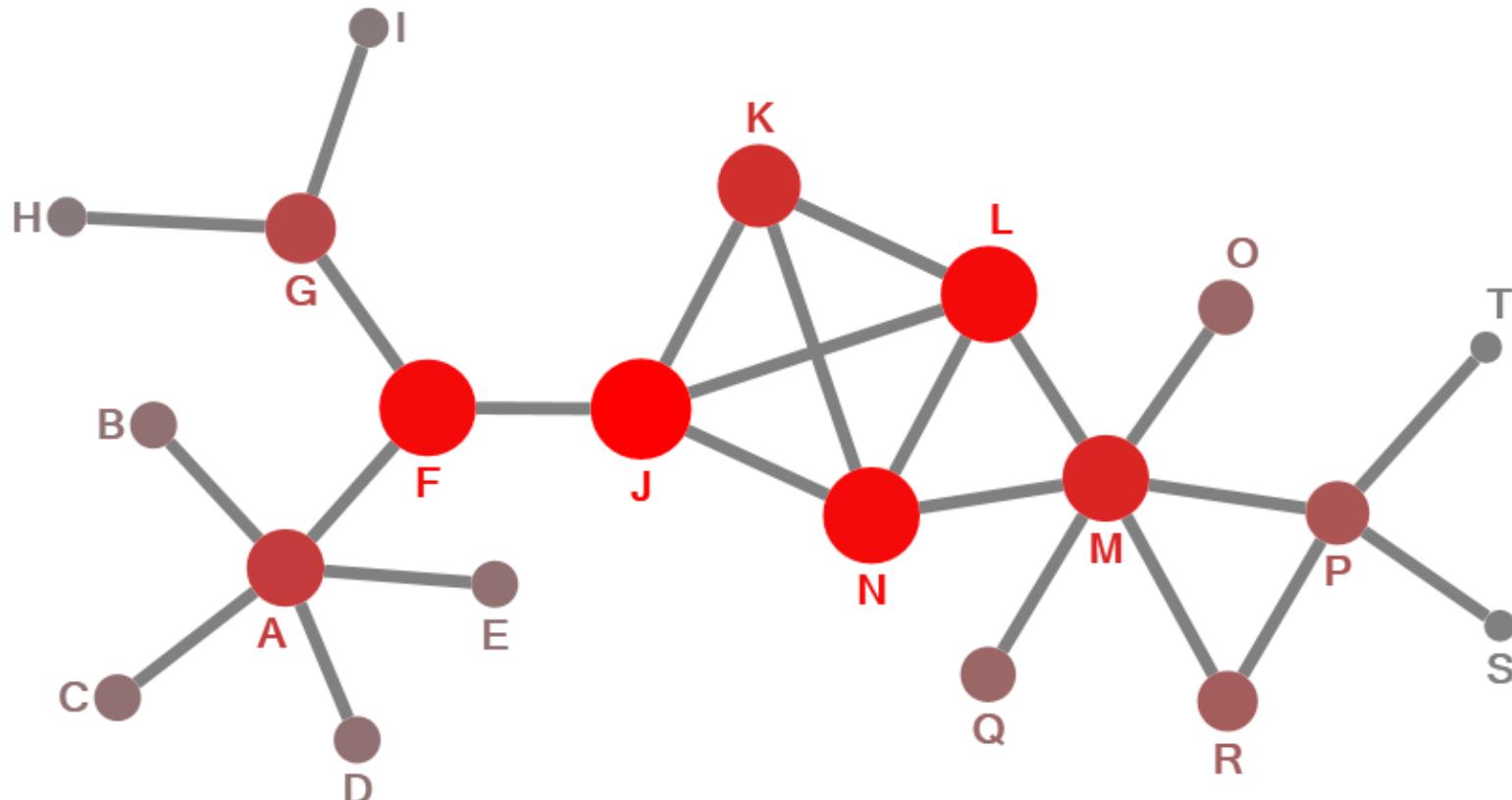
Vertex	Betweenness Centrality
F	103.000
J	90.000
M	87.000
A	66.000
L	38.500
N	38.500
P	35.000
G	35.000
K	0.000
R	0.000



Derived from Borgatti (2006)

CLOSENESS CENTRALITY

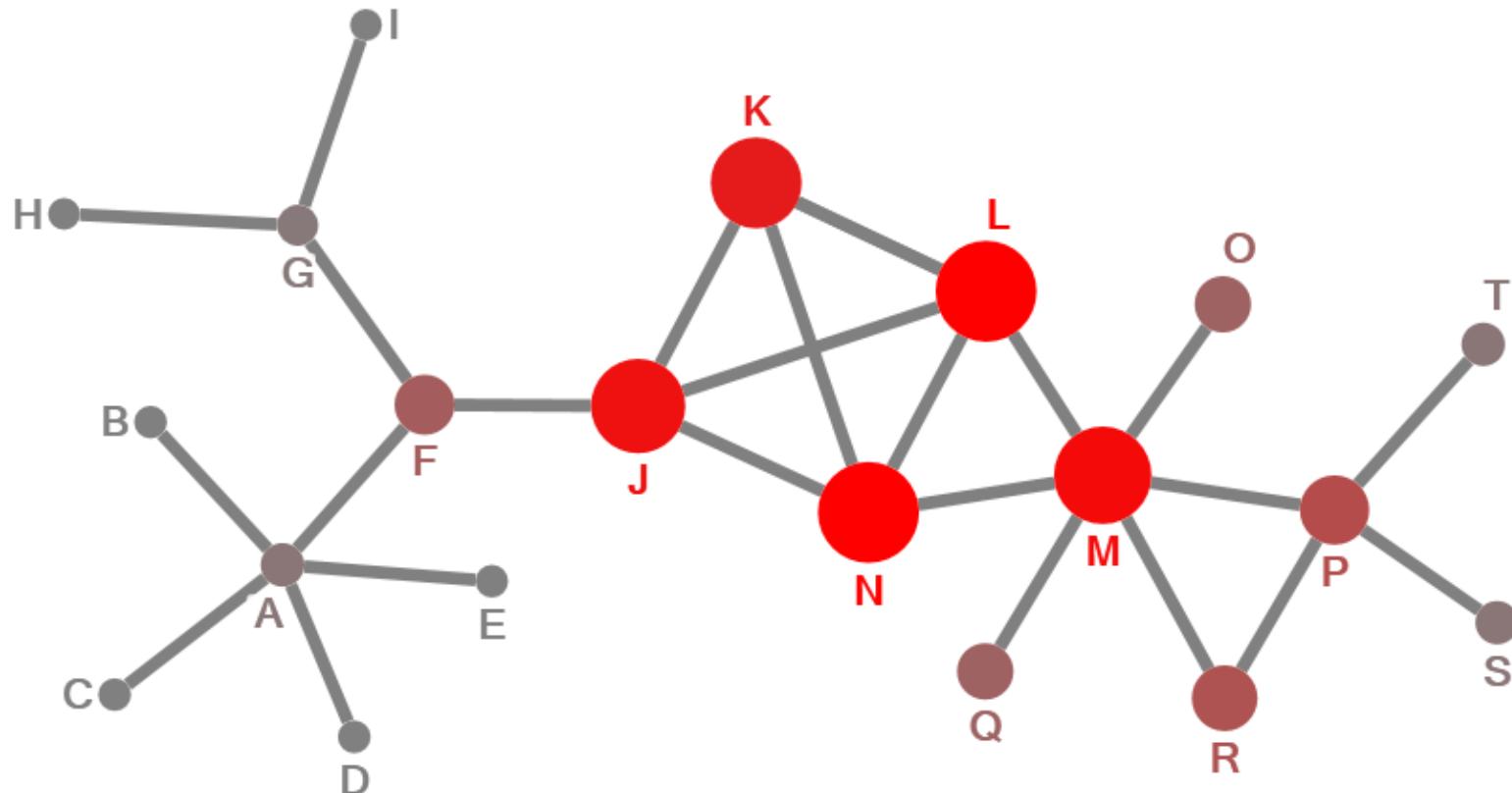
Vertex	Closeness Centrality
J	0.021
F	0.020
L	0.020
N	0.020
M	0.018
K	0.018
A	0.017
G	0.016
P	0.015
R	0.014



Derived from Borgatti (2006)

EIGENVECTOR CENTRALITY

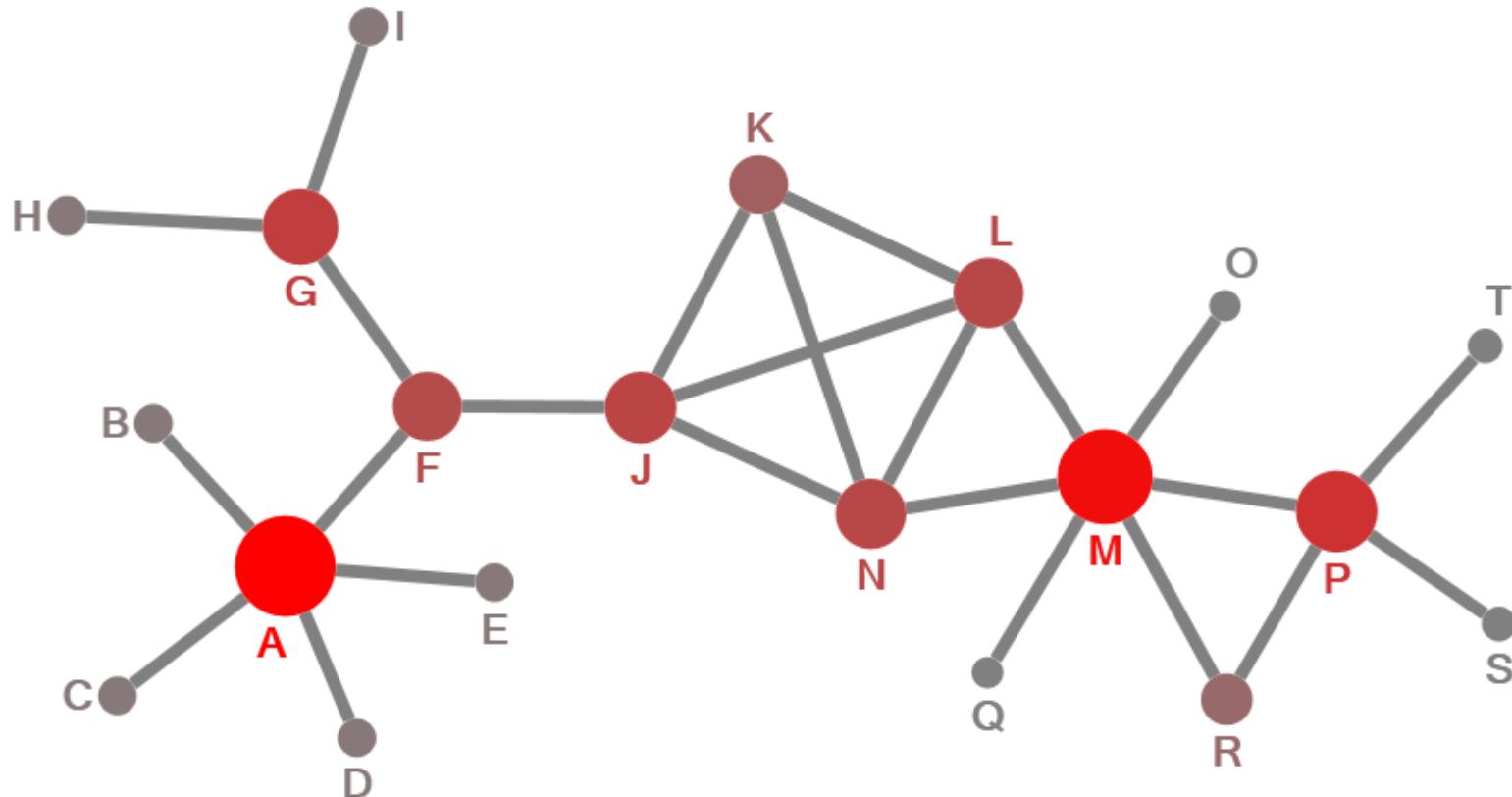
Vertex	Eigenvector Centrality
L	0.146
N	0.146
M	0.135
J	0.126
K	0.116
P	0.063
R	0.055
F	0.044
O	0.038
Q	0.038



Derived from Borgatti (2006)

PAGE RANK

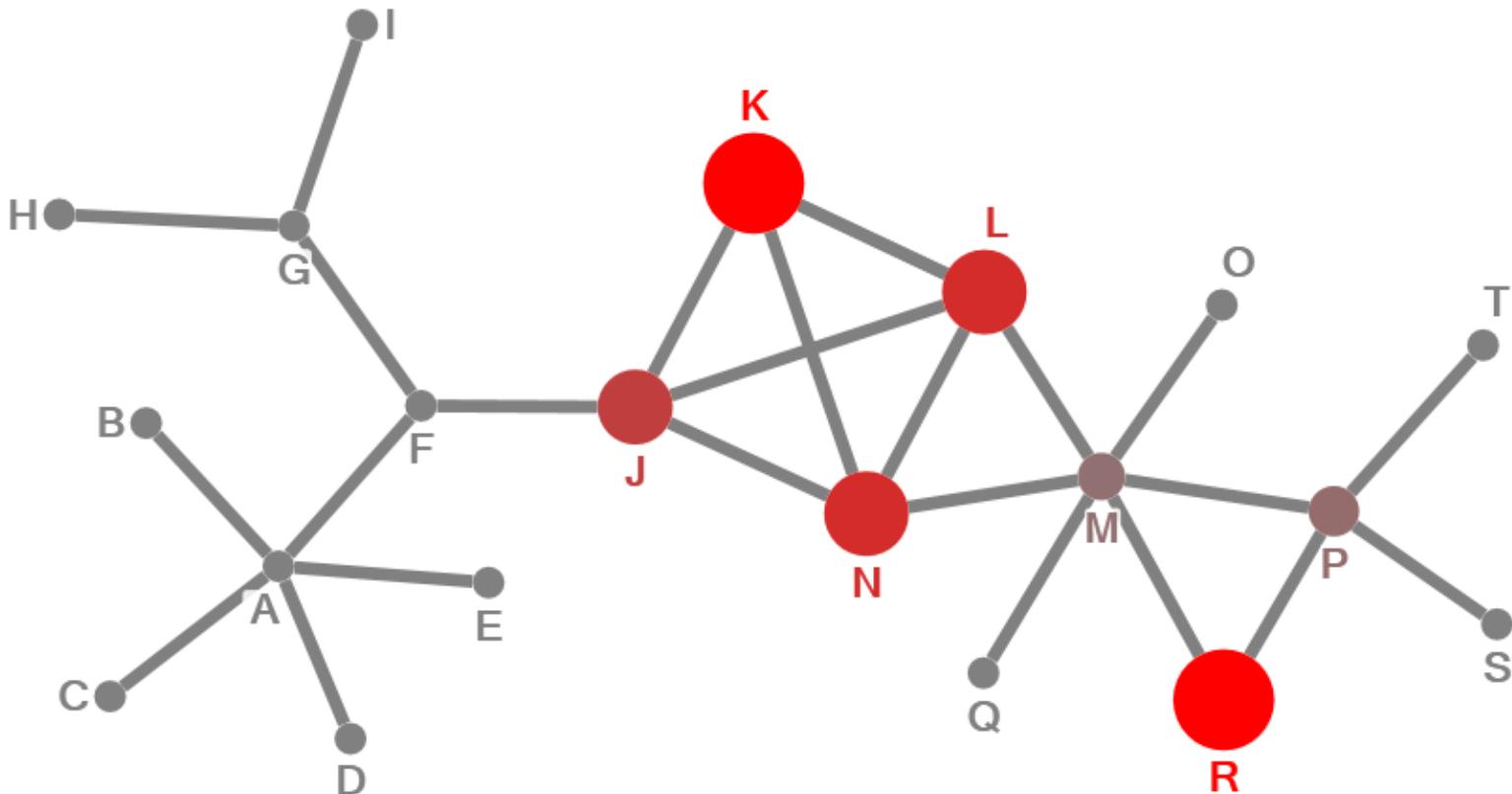
Vertex	PageRank
A	2.410
M	2.177
P	1.656
G	1.471
J	1.338
L	1.298
N	1.298
F	1.261
K	0.986
R	0.810



Derived from Borgatti (2006)

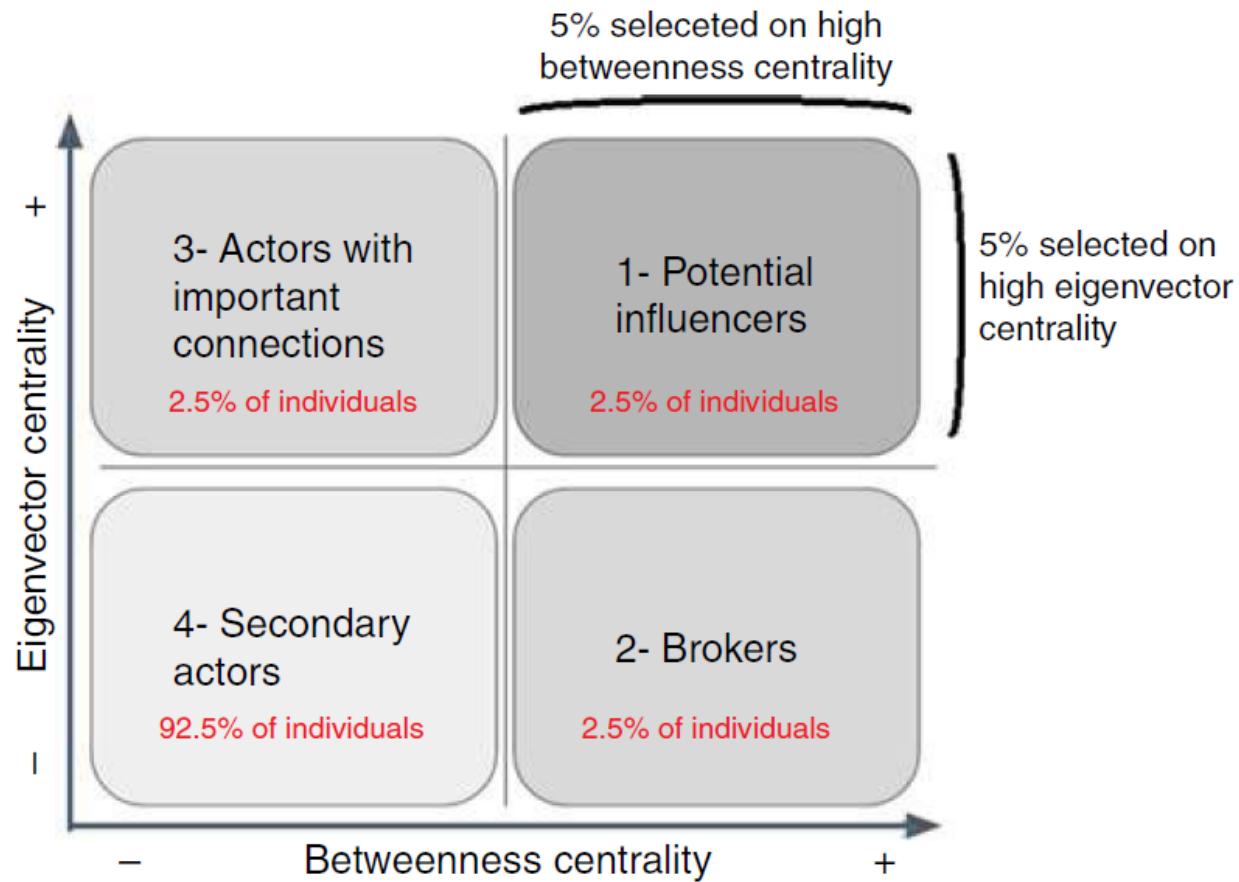
CLUSTERING COEFFICIENT

Vertex	Clustering Coefficient
K	1.000
R	1.000
L	0.667
N	0.667
J	0.500
P	0.167
M	0.133
A	0.000
G	0.000
F	0.000

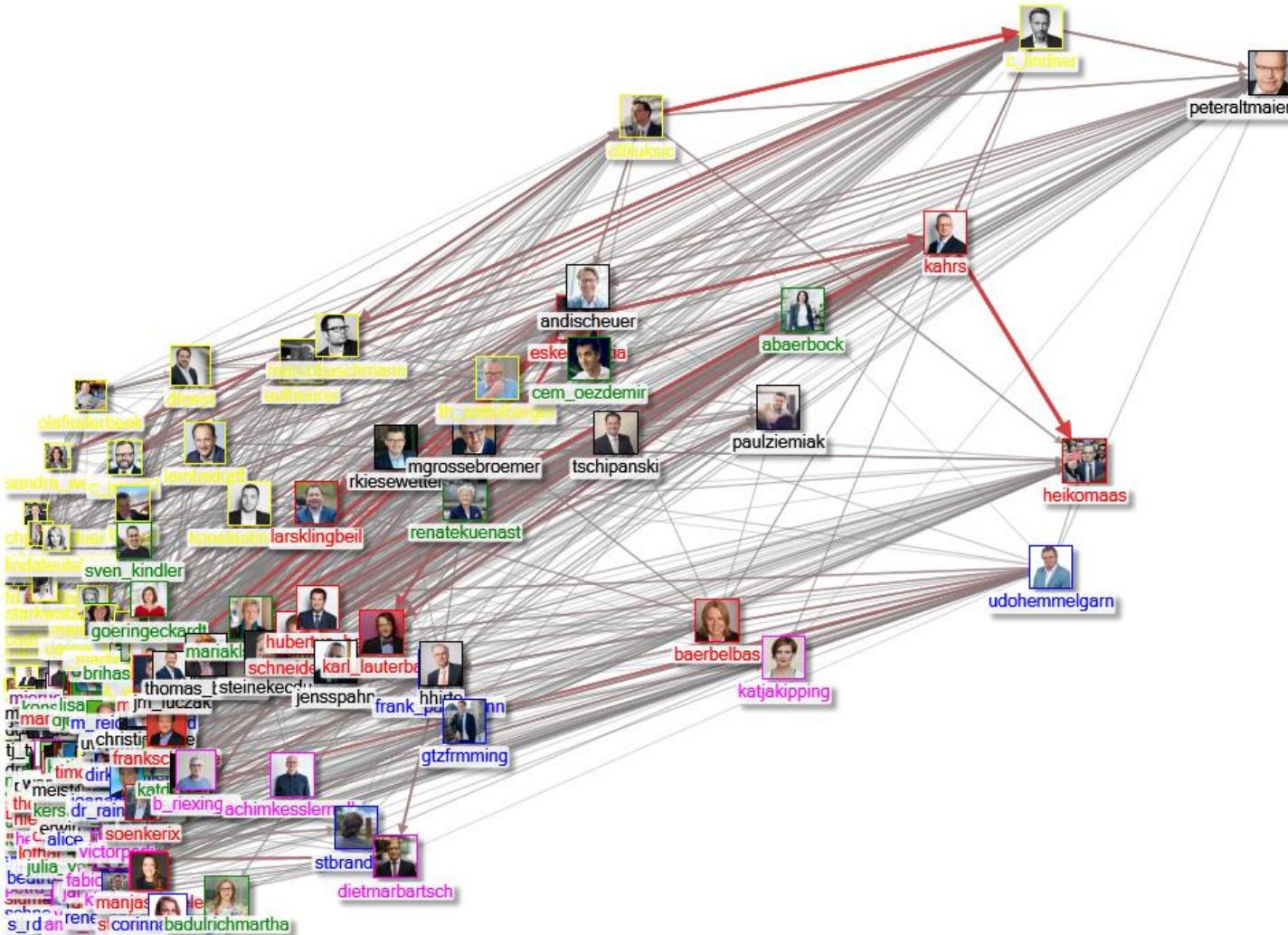


Derived from Borgatti (2006)

MEASURING INFLUENCE: VERTEX METRICS



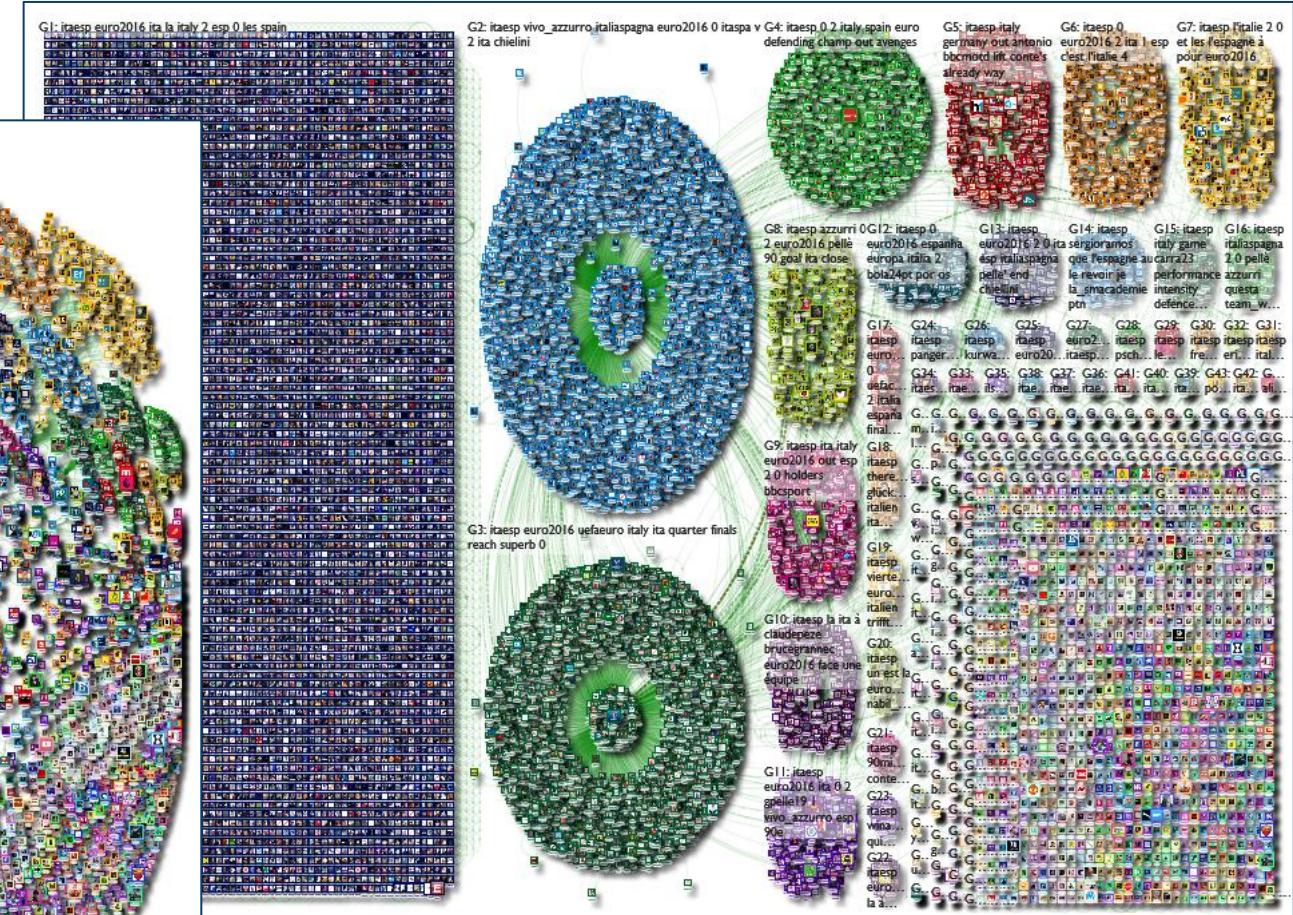
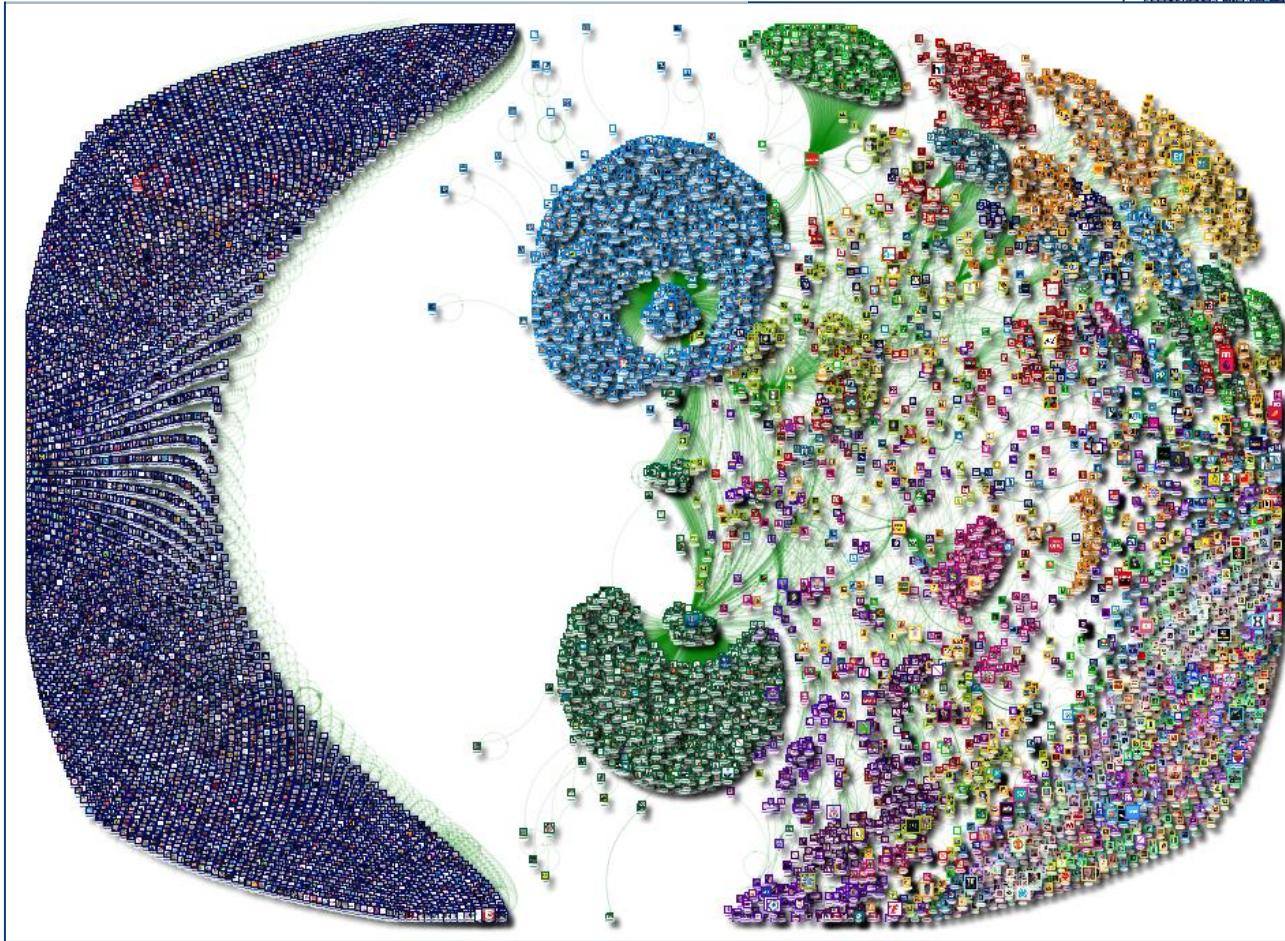
MEASURING INFLUENCE: VERTEX METRICS



MdB Influencer Layout August 2019: <https://nodexlgraphgallery.org/Pages/Graph.aspx?graphID=209098>

VISUAL ANALYSIS: LAYOUT OPTIONS

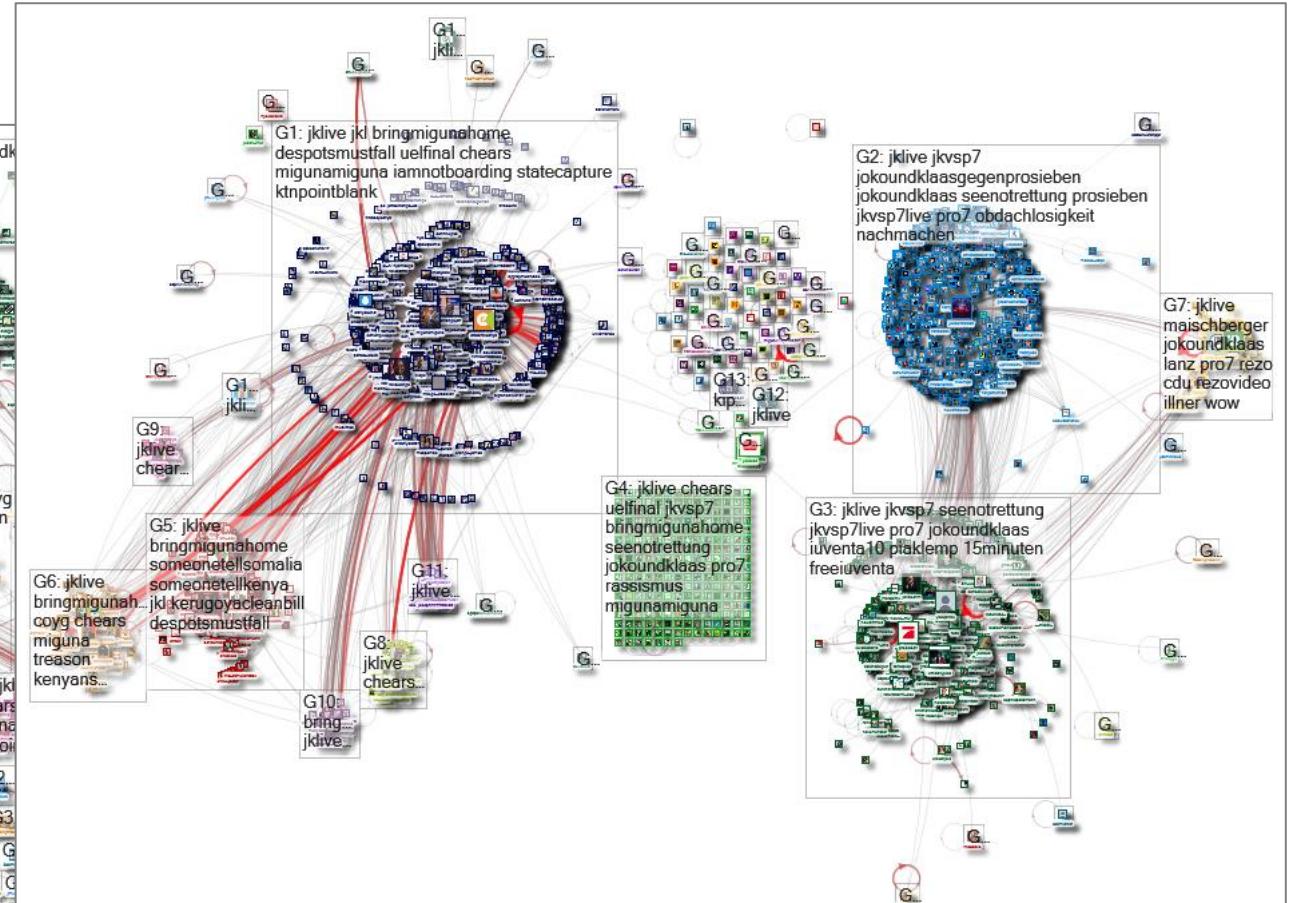
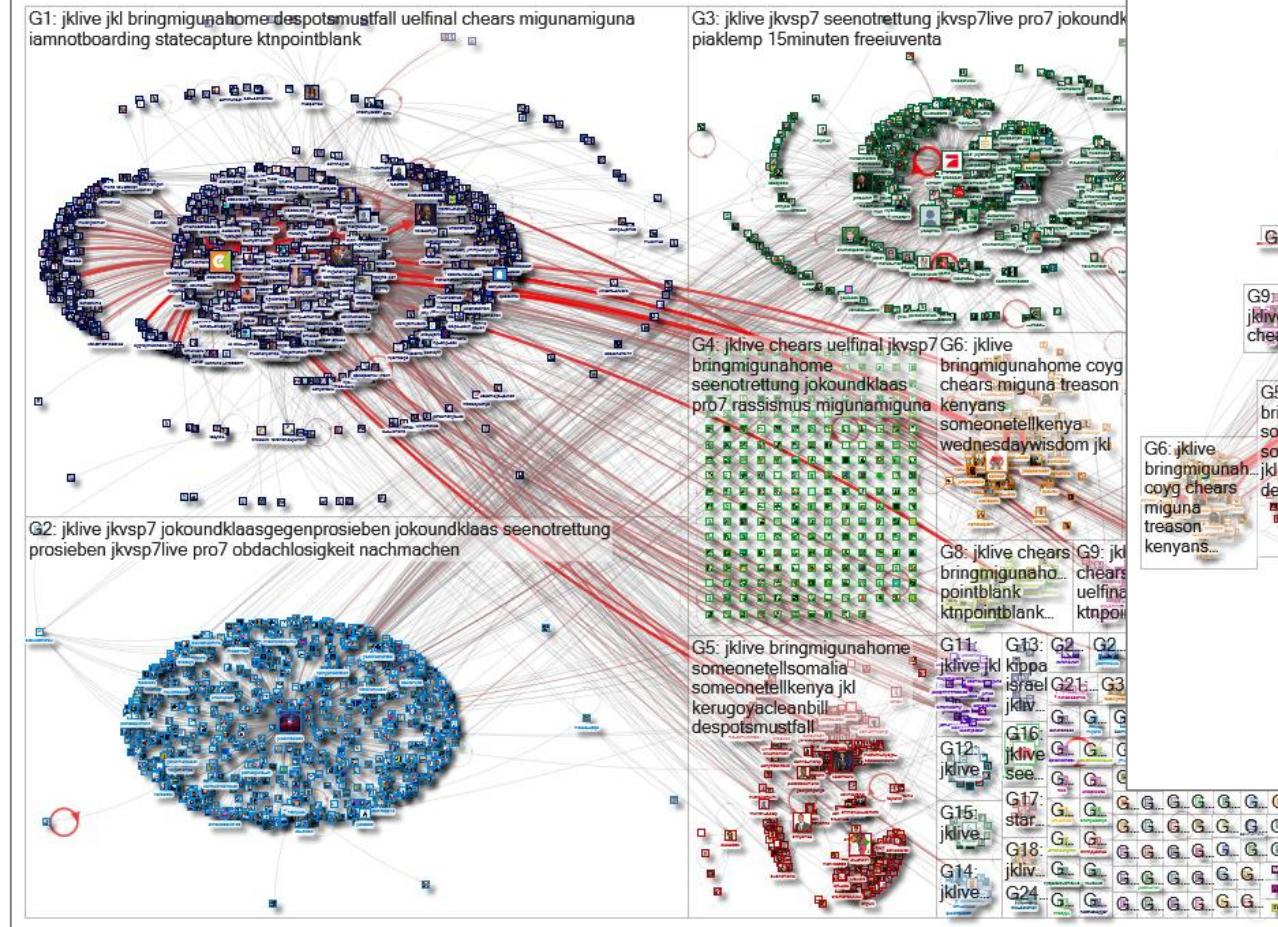
Entire Graph Layout



Group-In-A-Box Layout

VISUAL ANALYSIS: LAYOUT OPTIONS

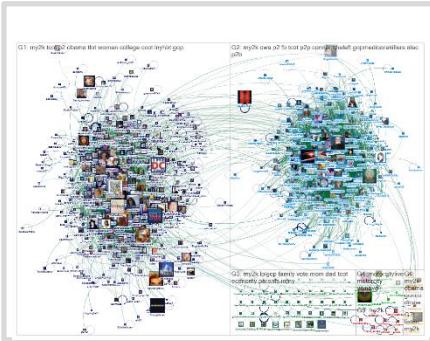
Treemap layout



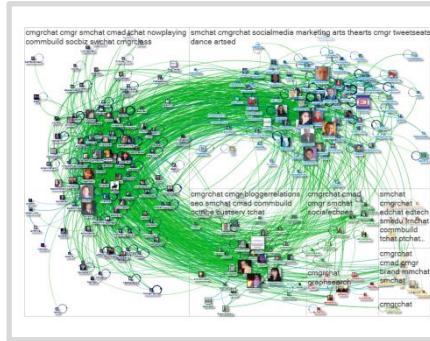
Force-directed layout

NETWORK SHAPES

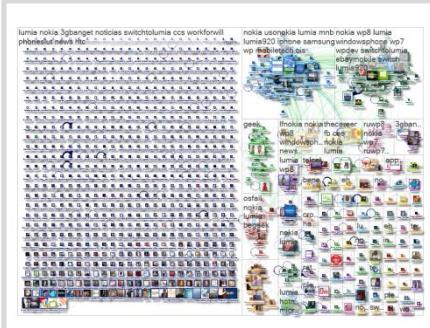
[Divided]
Polarized Crowds



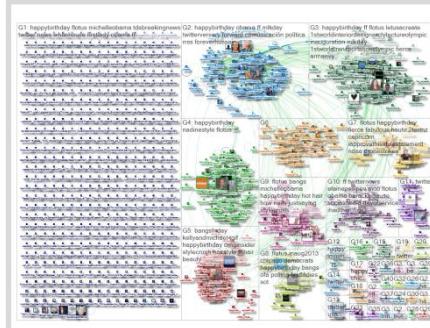
[Unified]
Tight Crowd



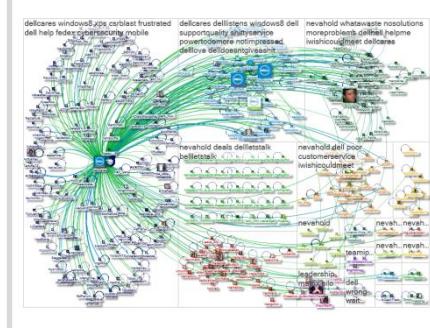
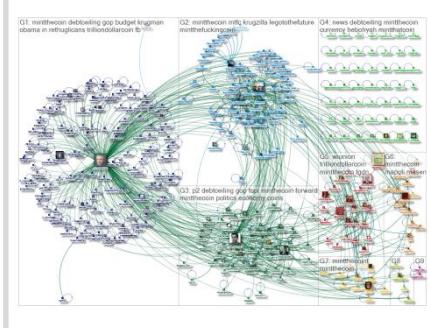
[Fragmented]
Brand Clusters



[Clustered]
Community Clusters



[In-Hub & Spoke]
Broadcast Network

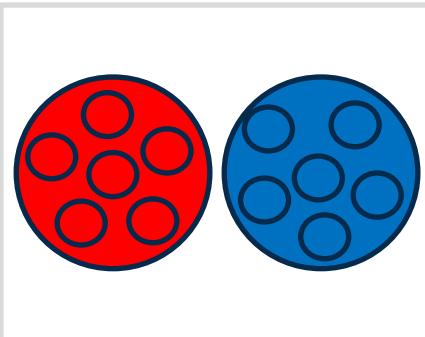


[Out-Hub & Spoke]
Support Network

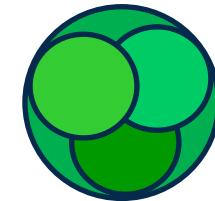
SOCIAL MEDIA NETWORK SHAPES

1

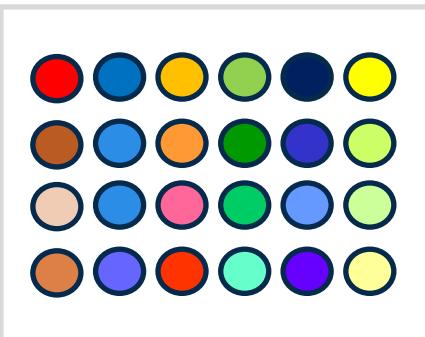
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Polarized Crowds



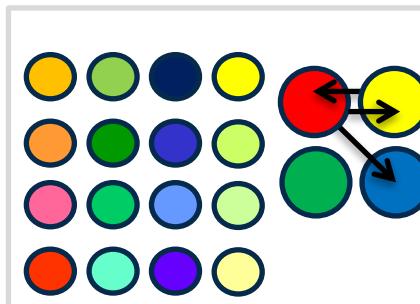
[Unified]
Tight Crowd



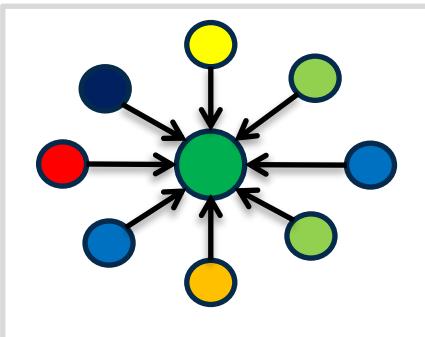
[Fragmented]
Brand Clusters



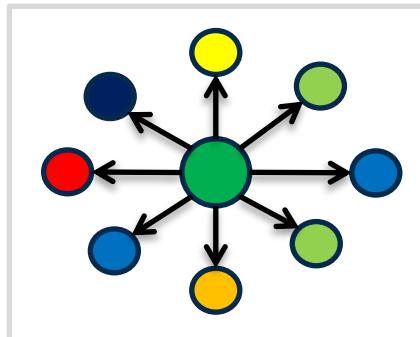
[Clustered]
Community Clusters



[In-Hub & Spoke]
Broadcast Network



[Out-Hub & Spoke]
Support Network



SOCIAL MEDIA NETWORK SHAPES

PewResearch Internet Project

U.S. POLITICS | MEDIA & NEWS | SOCIAL TRENDS | RELIGION | INTERNET & TECH | HISPANICS | GLOBAL

PUBLICATIONS TOPICS PRESENTATIONS INTERACTIVES KEY INDICATORS DATASETS ABOUT

REPORT

FEBRUARY 20, 2014 f t x e +

Mapping Twitter Topic Networks: From Polarized Crowds to Community Clusters

BY MARC A. SMITH, LEE RAINIE, BEN SCHNEIDERMAN AND ITAI HIMELBOIM

Summary of Findings

Polarized Crowds: Political conversations on Twitter

Conversations on Twitter create networks with identifiable contours as people reply to and mention one another in their tweets. These conversational structures differ, depending on the subject and the people driving the conversation. Six structures are regularly observed: divided, unified, fragmented, clustered, and inward and outward hub and spoke structures. These are created as individuals choose whom to reply to or mention in their Twitter messages and the structures tell a story about the nature of the conversation.

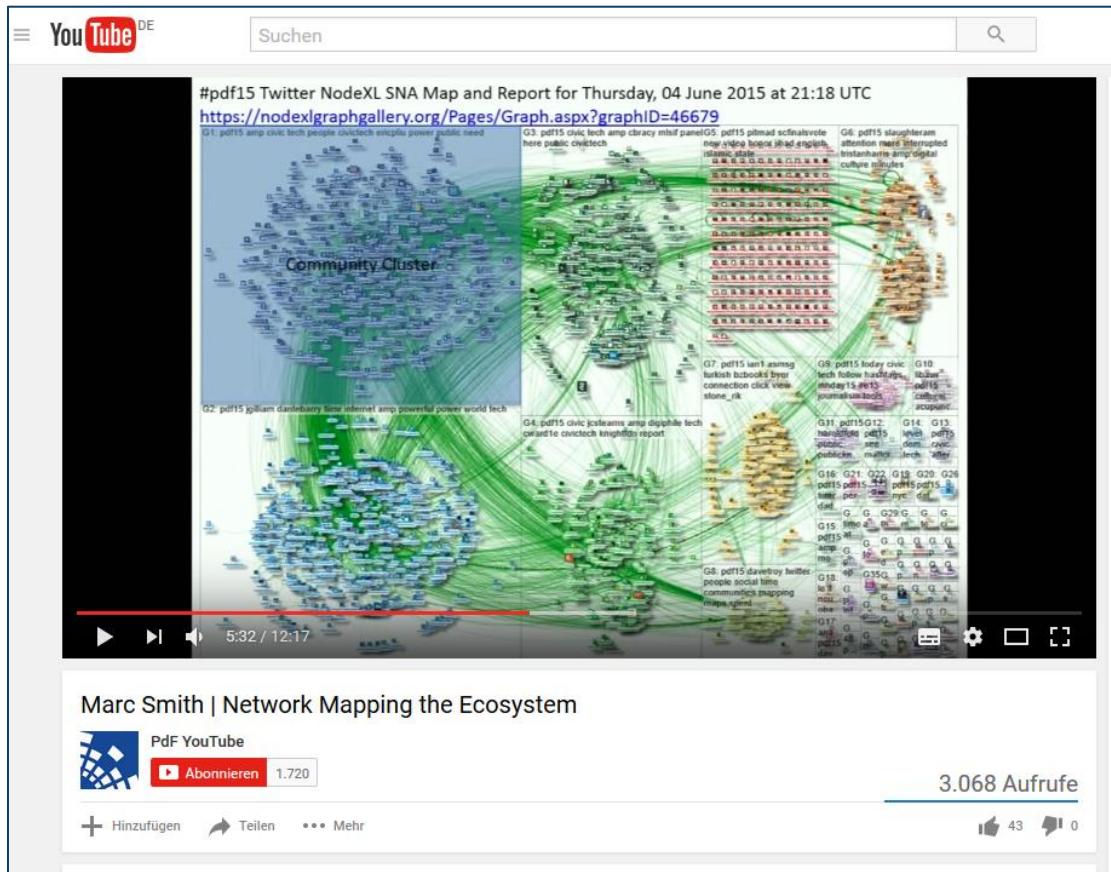
If a topic is political, it is common to see two separate, polarized crowds take shape. They form two distinct discussion groups that mostly do not interact with each other. Frequently these are recognizably liberal or conservative groups. The participants within each separate group commonly mention very different collections of website URLs and use distinct hashtags and words. The split is clearly evident in many highly controversial discussions: people in clusters that we identified as liberal used URLs for mainstream news websites, while groups we identified as conservative used links to conservative news websites and commentary sources. At the center of each group are discussion leaders, the

REPORT MATERIALS

- Complete Report
- Press Release
- Data gallery: Examples of six kinds of Twitter social media networks
- How we did it: Analyzing Twitter social media networks with NodeXL
- Fact Tank: Q/A: How Pew Research mapped the conversations on Twitter
- Infographic: The six types of Twitter conversations

TABLE OF CONTENTS

- Overview
- Summary of Findings
- Polarized Crowds: Political



PEW Report: Mapping Twitter Topic Networks: From Polarized Crowds to Community Clusters. PEW Research Report 2014:
<http://www.pewinternet.org/2014/02/20/mapping-twitter-topic-networks-from-polarized-crowds-to-community-clusters/>

Video: SMRF Director Marc Smith | Network Mapping the Ecosystem: <https://www.youtube.com/watch?v=kDiGI-2m868>

YOUTUBE NETWORKS

Video network

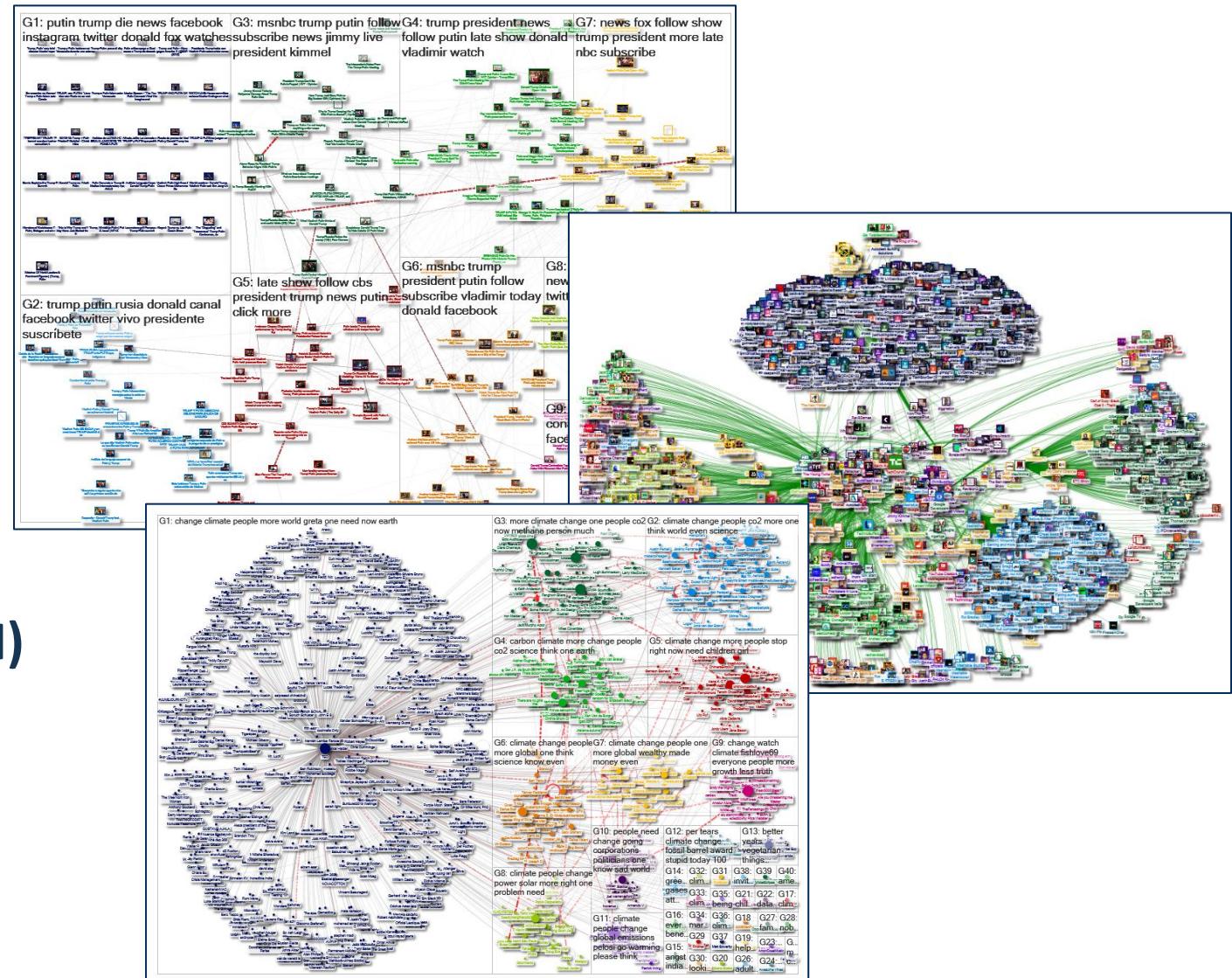
- Vertex: Video
- Edge creation: same commenter

User network

- Vertex: Youtube User
- Edge creation: subscribed to

User network (Netlytic data, DMI)

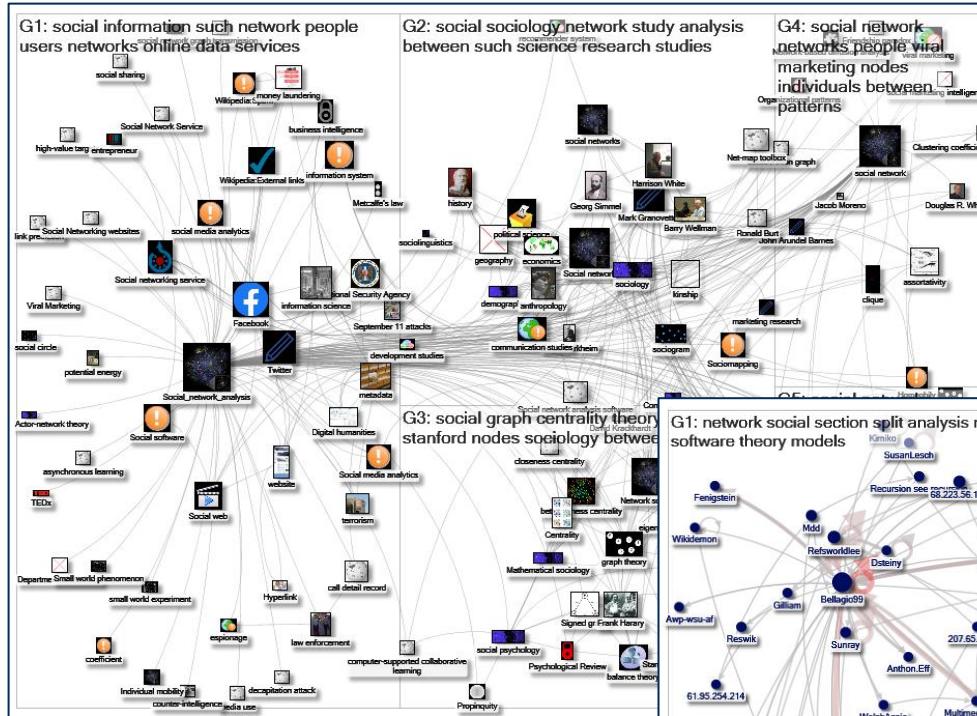
- Vertex: Youtube User
- Edge creation: comment, reply



WIKIPEDIA NETWORKS

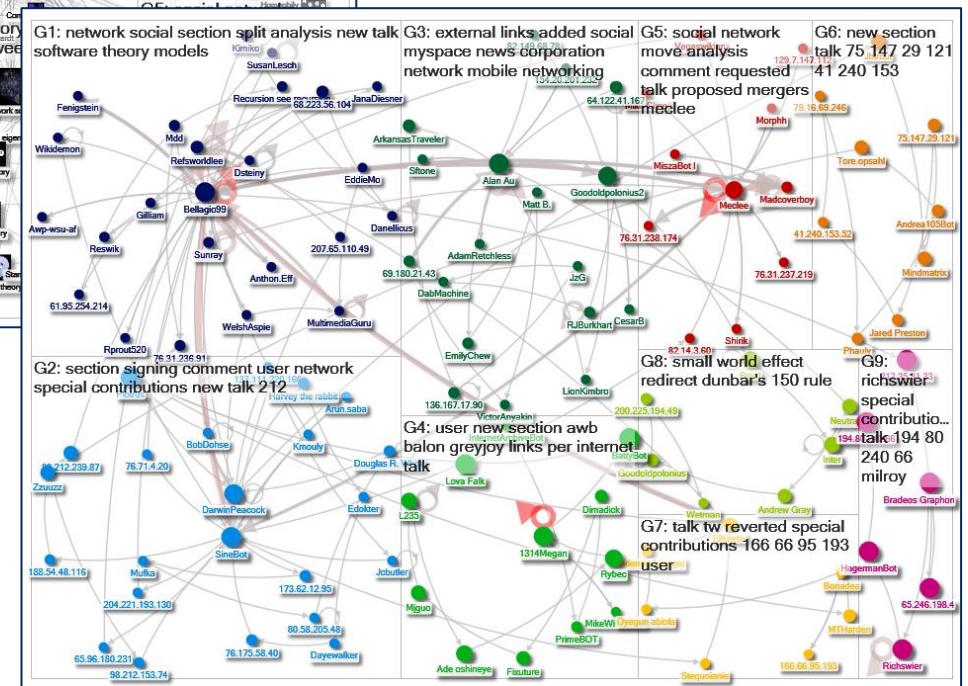
Page network

- Vertex: Page
- Edge creation: page link



User network

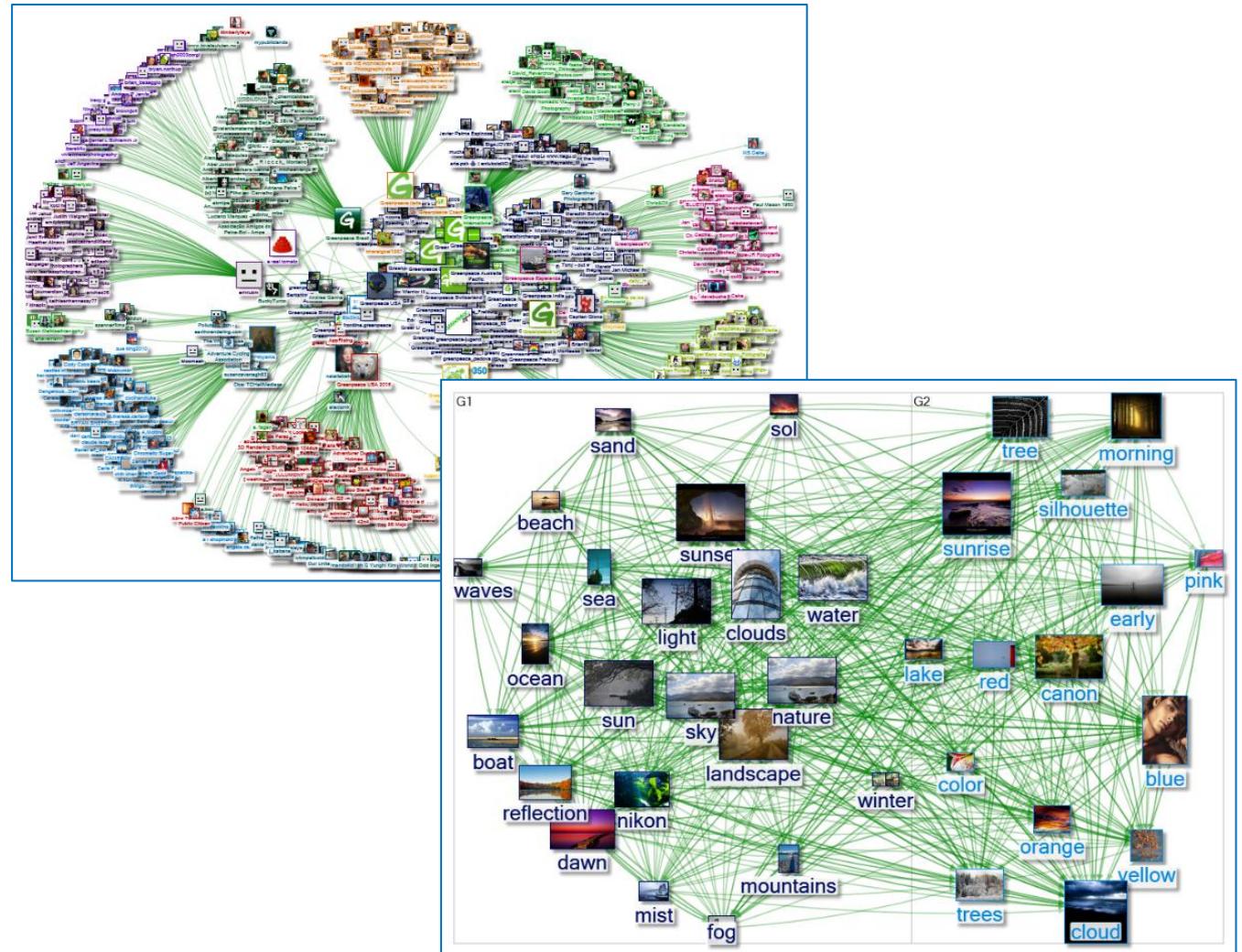
- Vertex: User
- Edge creation: Discussion, Coauthorship



FLICKR NETWORKS

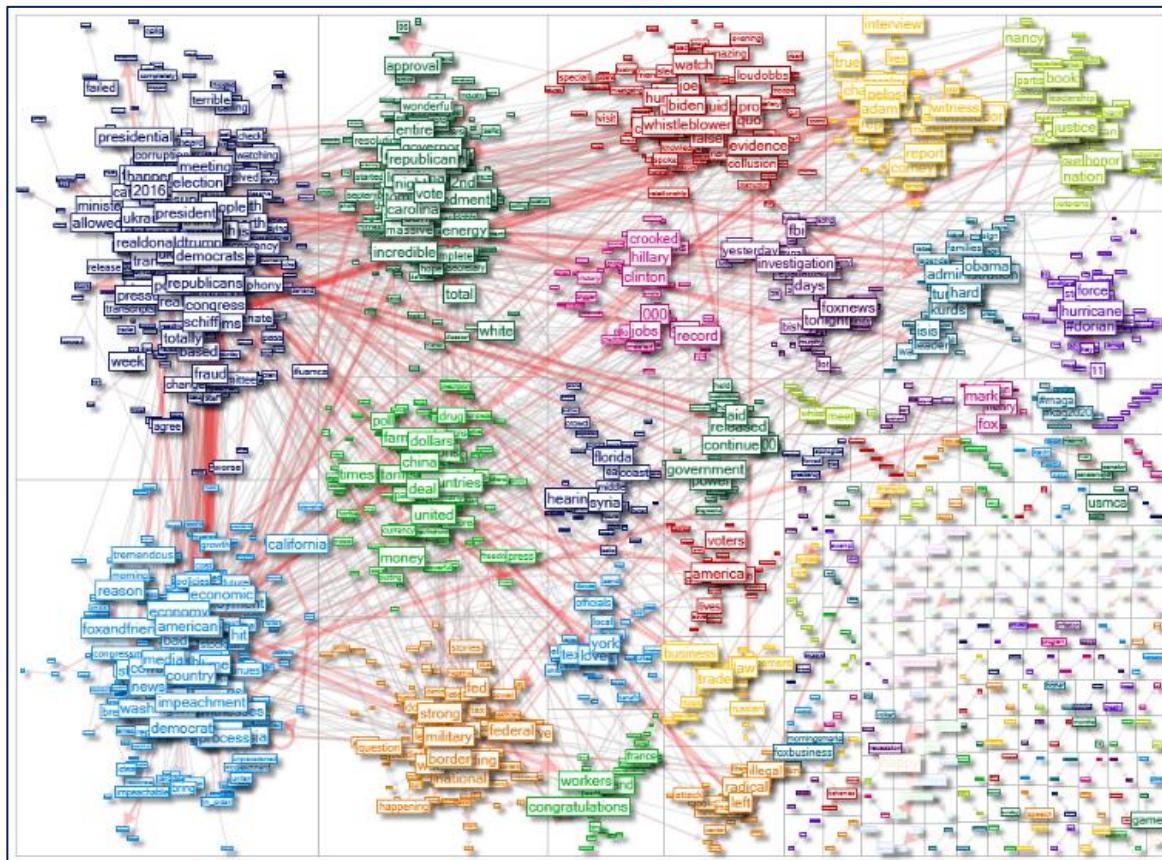
User network

- Vertex: Flickr User
- Edge creation: contact, comment



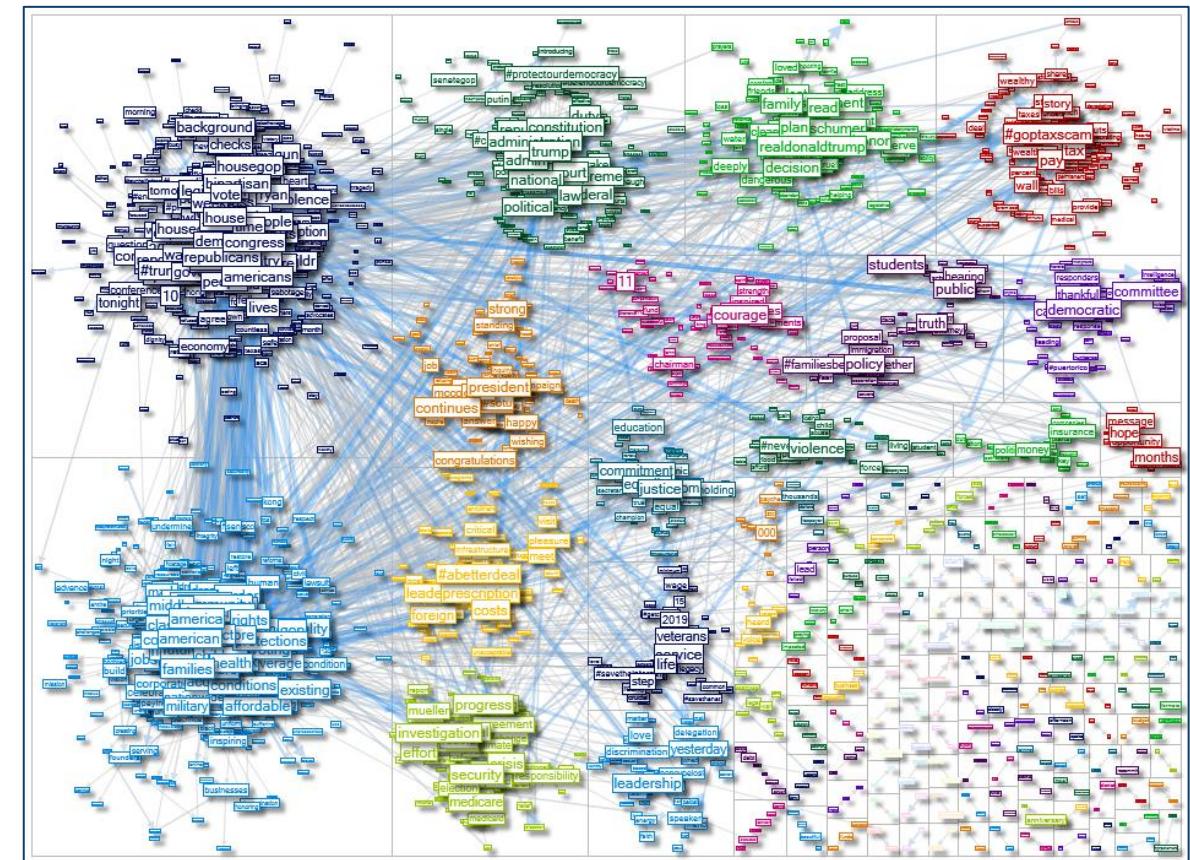
SEMANTIC NETWORKS

- Vertex: Hashtag / Word
 - Edge creation: Co-mentions of hashtags / words in a tweet



Realdonaldtrump:

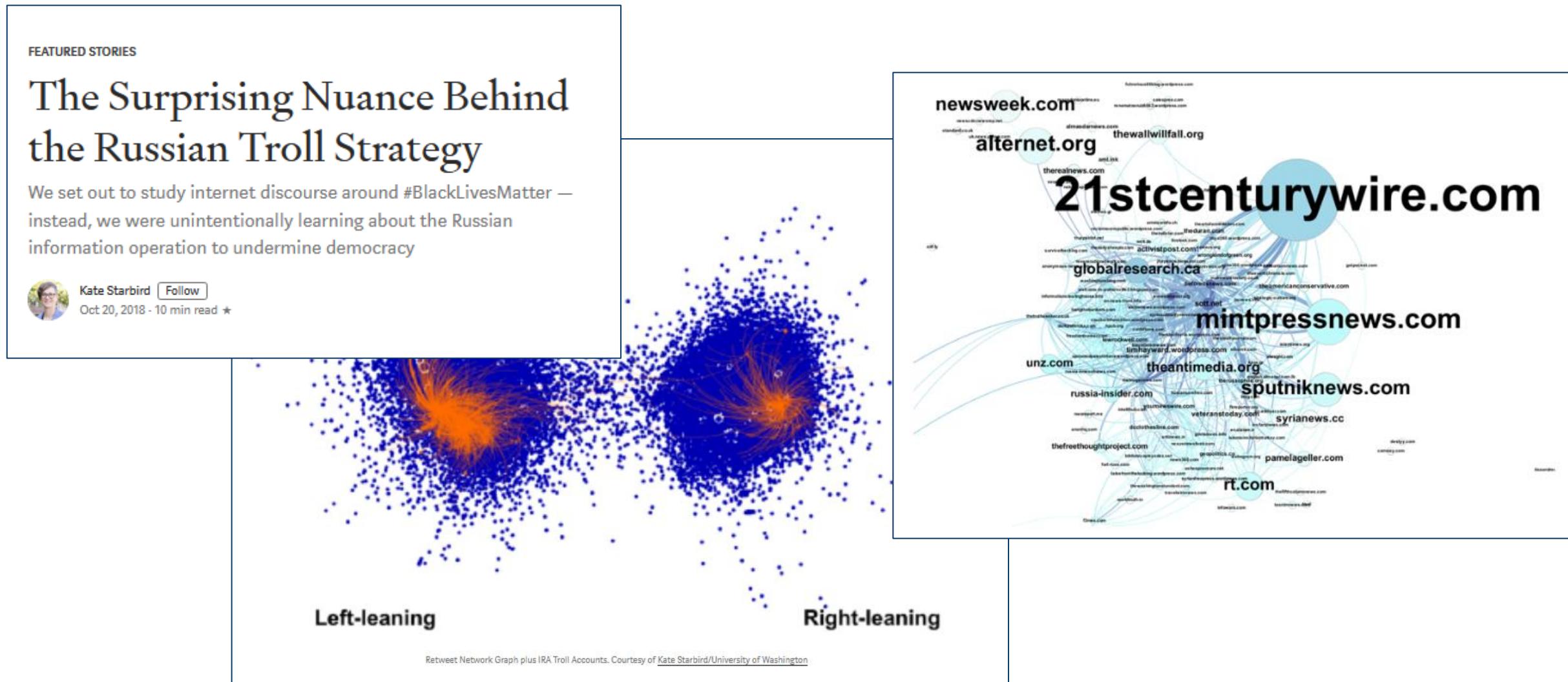
<https://nodexlgraphgallery.org/Pages/Graph.aspx?graphID=217493>



SpeakerPelosi:

<https://nodexlgraphgallery.org/Pages/Graph.aspx?graphID=2174>

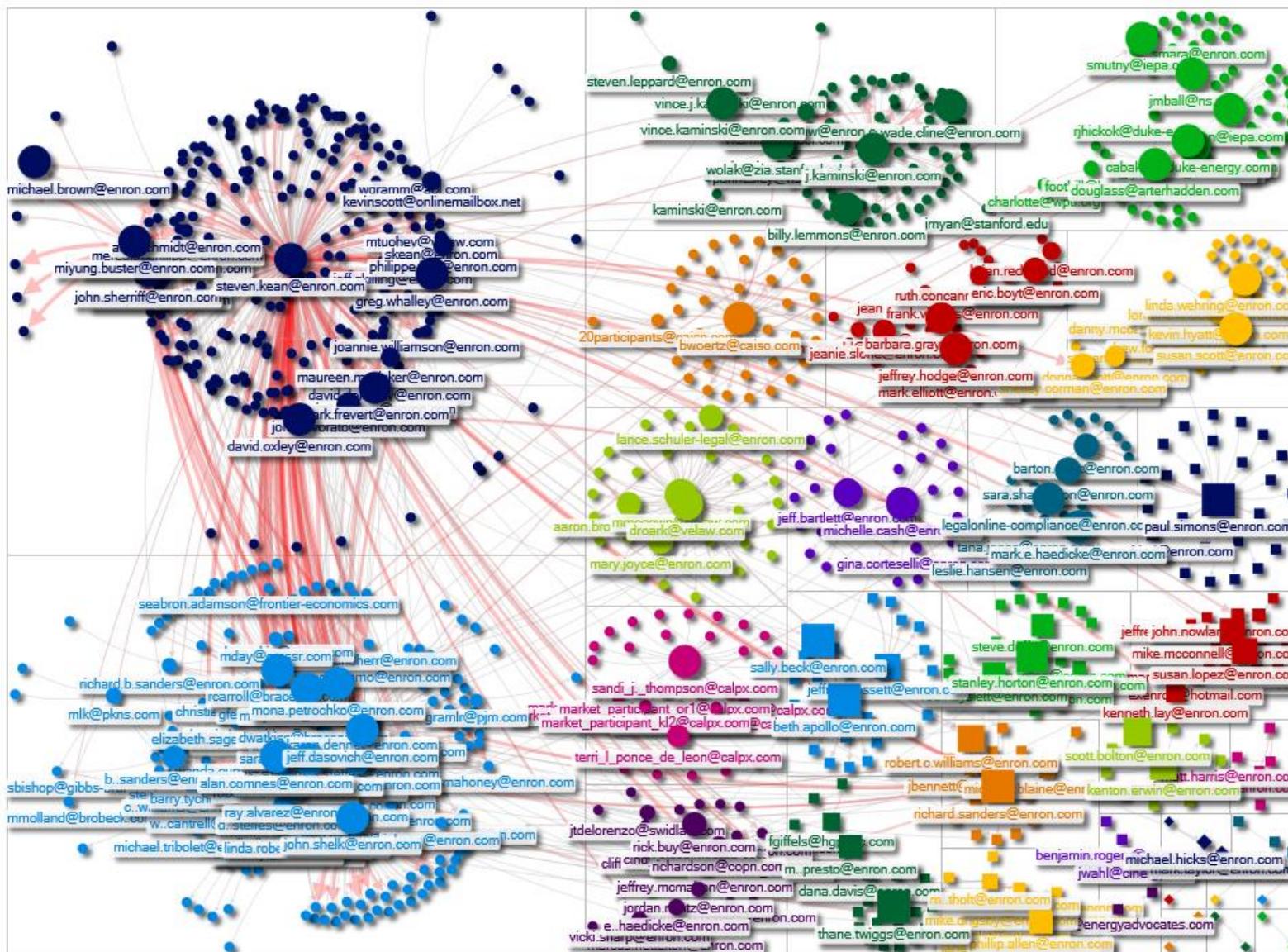
SNA AS INVESTIGATIVE TOOL



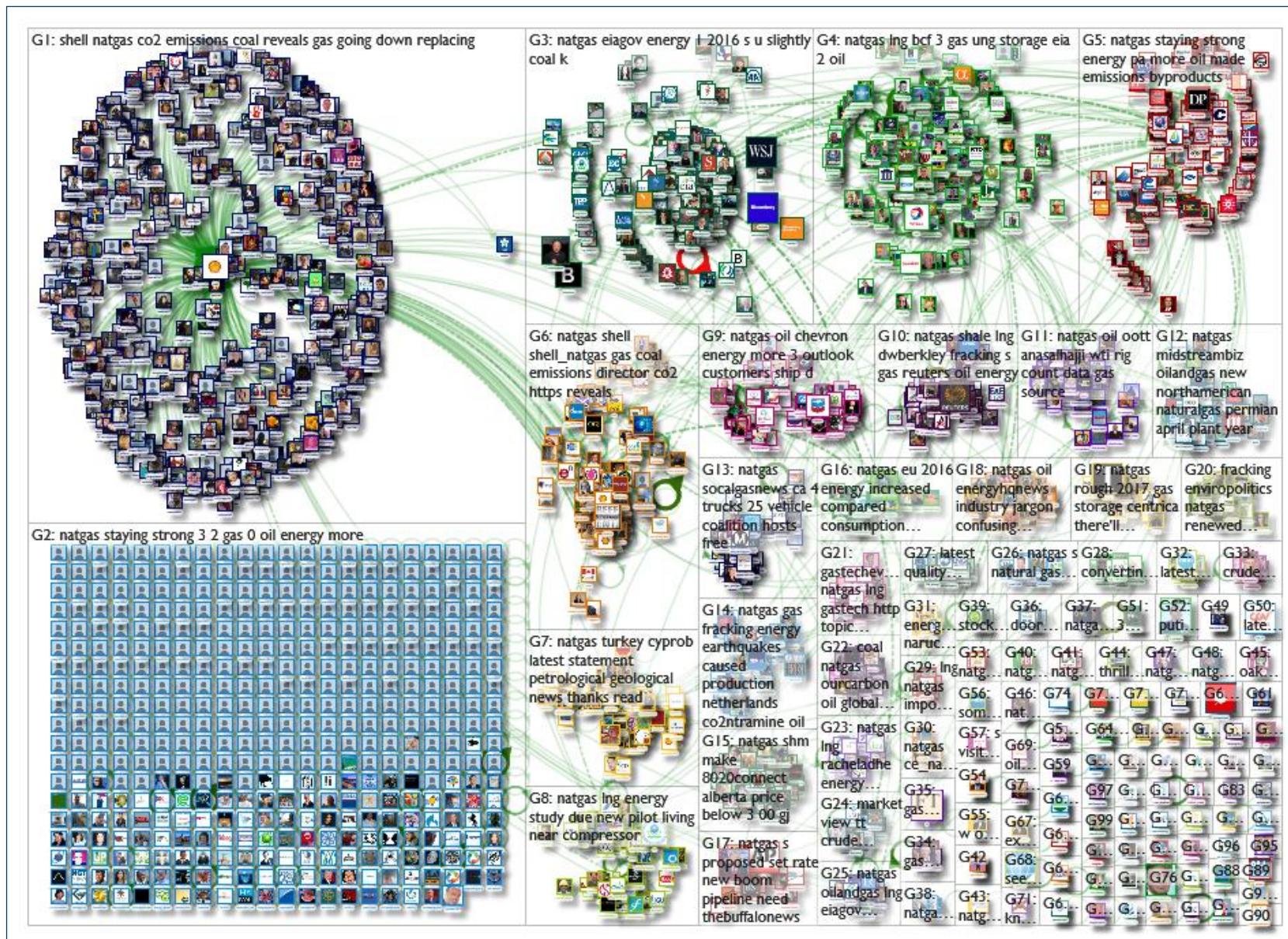
<https://medium.com/s/story/the-trolls-within-how-russian-information-operations-infiltrated-online-communities-691fb969b9e4>

https://faculty.washington.edu/kstarbi/StarbirdArifWilson_DisinformationsCollaborativeWork-CameraReady-Preprint.pdf

SNA AS INVESTIGATIVE TOOL



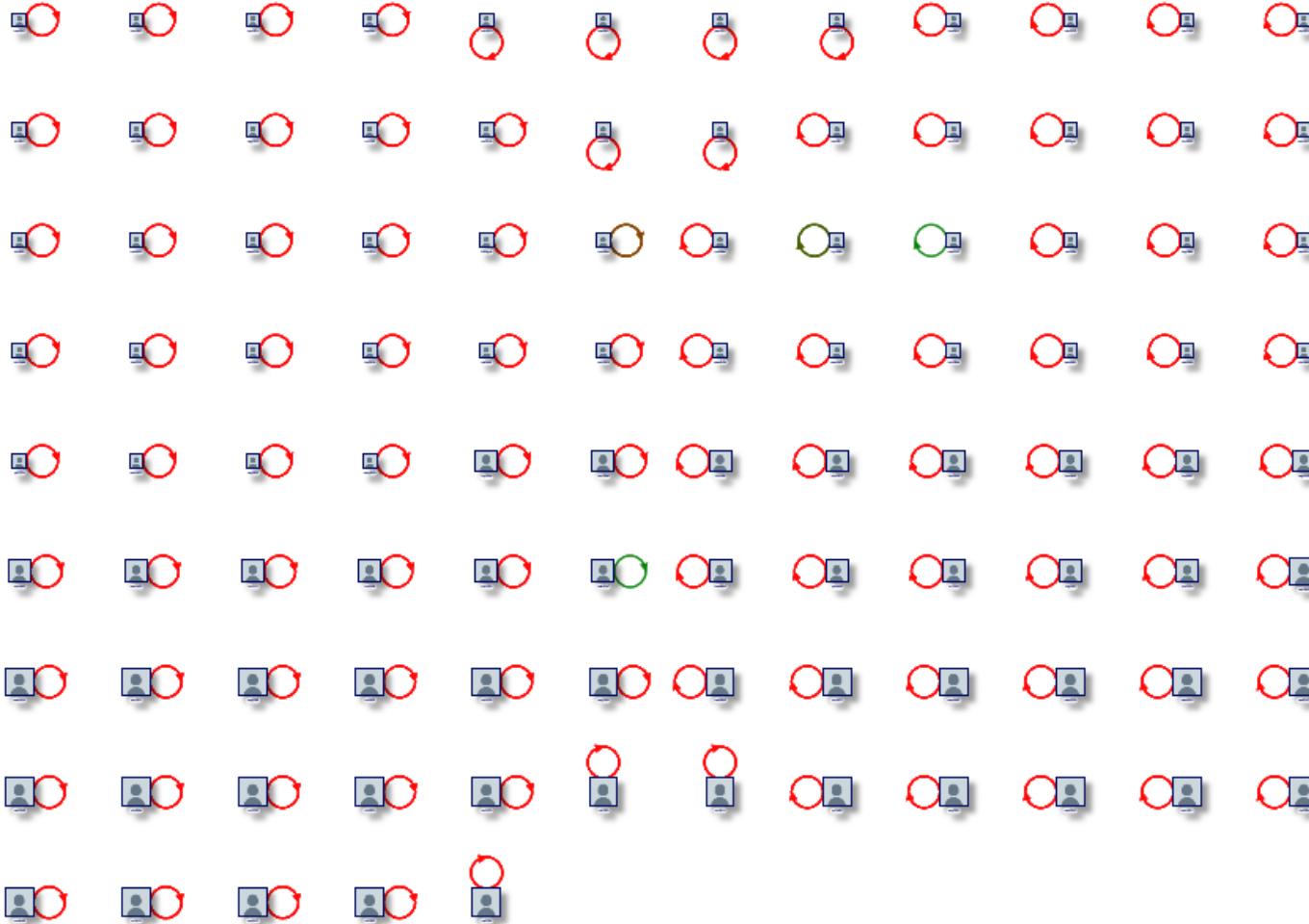
BOT NETWORK: SEARCH NETWORK #NATGAS



BOT NETWORK: #NATGAS USER NETWORK - INTERNAL

32

GI: best 20 coolsculpting fat removal ready summer rates results look



▼ Top URLs

Top URLs in Tweet in Entire Graph:

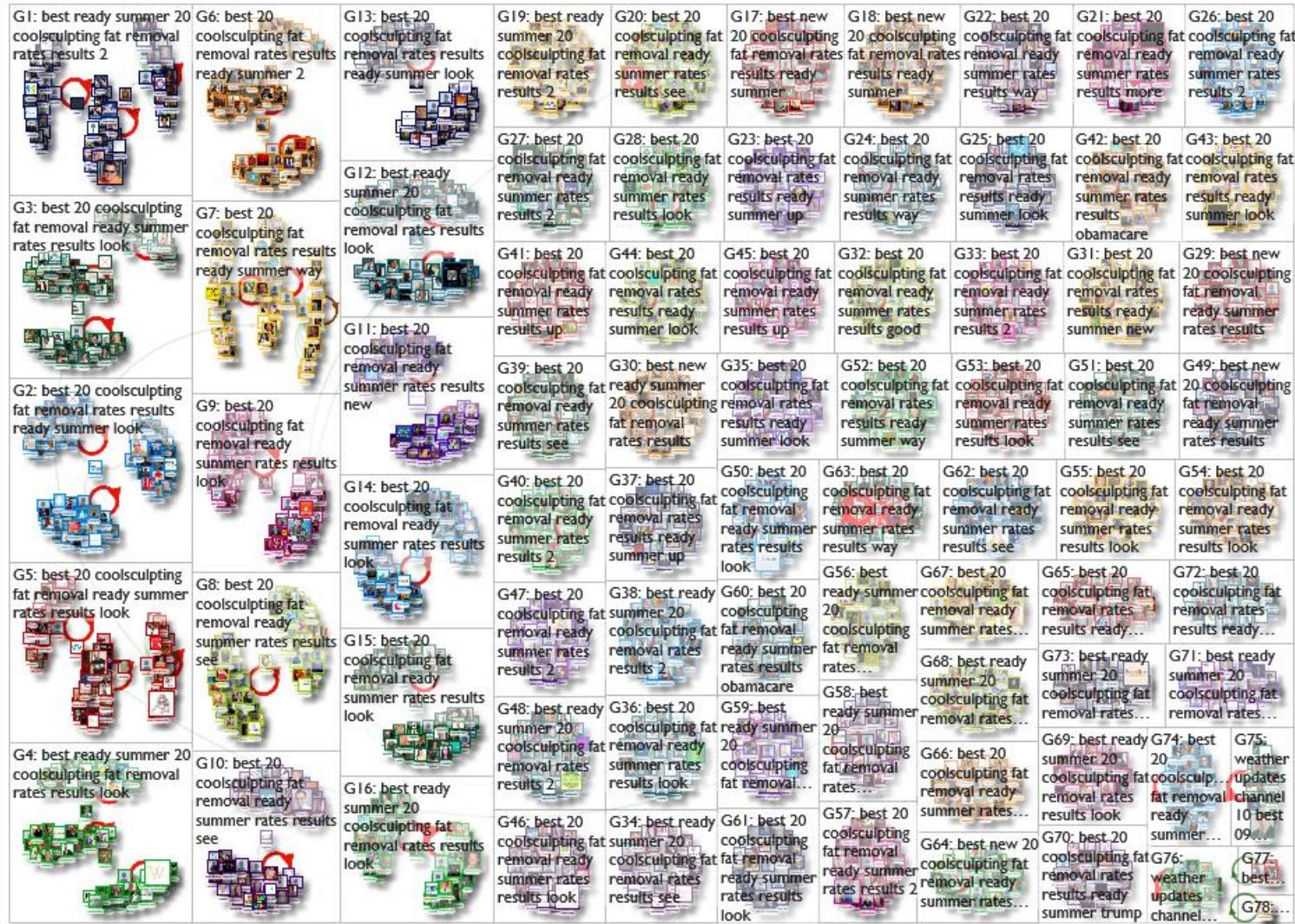
- [452] <http://uberdeal5.com/Doctor/>
- [233] <http://bingomillionsforcharity.com/Doctor/>
- [224] <http://bingobullion.com/Doctor/>
- [208] <http://bingoangels.org/Doctor/>
- [135] <http://toptweetdeals5.com/Doctor/>
- [128] <http://uberdeal4.com/Doctor/>
- [113] <http://uberdeal3.com/Doctor/>
- [81] <http://uberdeal1.com/Doctor/>
- [79] <http://tweet4topdeals2.com/Doctor/>
- [77] <http://tweet4topdeals3.com/Doctor/>

▼ Top Hashtags

Top Hashtags in Tweet in Entire Graph:

- [322] [trump](#)
- [240] [crudeoil](#)
- [212] [natgas](#)
- [180] [healthcare](#)
- [148] [laborparticipation](#)
- [137] [gdp](#)
- [135] [samsung](#)
- [127] [bryant](#)
- [122] [spurs](#)
- [119] [dow](#)

BOT NETWORK: #NATGAS USER NETWORK



▼ Top URLs

Top URLs in Tweet in Entire Graph:

- [452] <http://uberdeal5.com/Doctor/>
- [233] <http://bingomillionsforcharity.com/Doctor/>
- [224] <http://bingobullion.com/Doctor/>
- [208] <http://bingoangels.org/Doctor/>
- [135] <http://toptweetdeals5.com/Doctor/>
- [128] <http://uberdeal4.com/Doctor/>
- [113] <http://uberdeal3.com/Doctor/>
- [81] <http://uberdeal1.com/Doctor/>
- [79] <http://tweet4topdeals2.com/Doctor/>
- [77] <http://tweet4topdeals3.com/Doctor/>

▼ Top Hashtags

Top Hashtags in Tweet in Entire Graph:

- [322] [trump](#)
- [240] [crudeoil](#)
- [212] [natgas](#)
- [180] [healthcare](#)
- [148] [laborparticipation](#)
- [137] [gdp](#)
- [135] [samsung](#)
- [127] [bryant](#)
- [122] [spurs](#)
- [119] [dow](#)

BOT NETWORK: NODEXL „6 TYPES OF“

 **Harry Miller**
@Harry_Robots

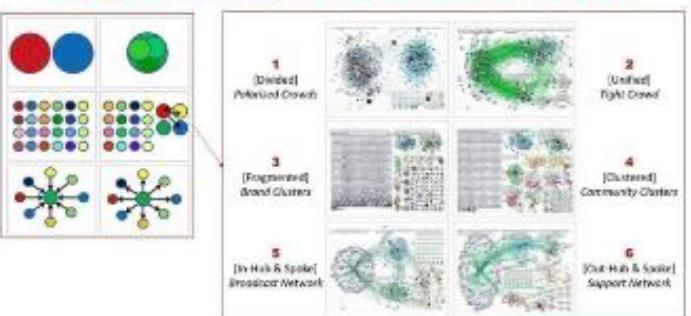
[Follow](#)

6 Types of Twitter Social Media Networks
[\[INFOGRAPHICS\]](#)
by [@nodexl](#) |

#IoT #InternetOfThings #DigitalMarketing
#BigData #Analytics #DataScience
#DataScientists #SocialNetworks #RT

Cc: @MikeQuindazzi CC @mikequindazzi
#BigData #MachineLearning #AI #IoT
#infographic #DeepL

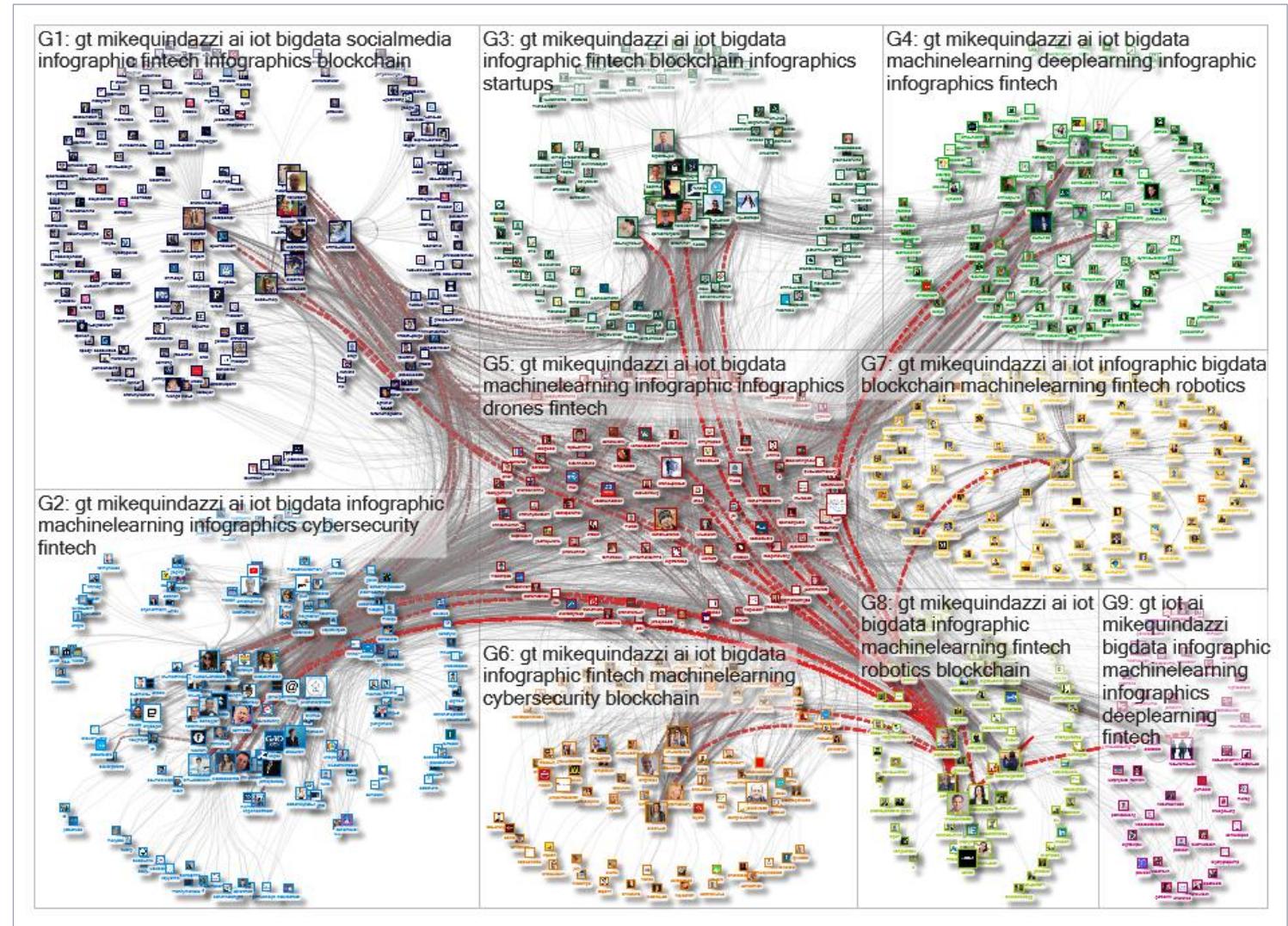
6 Types of Twitter Social Media Networks



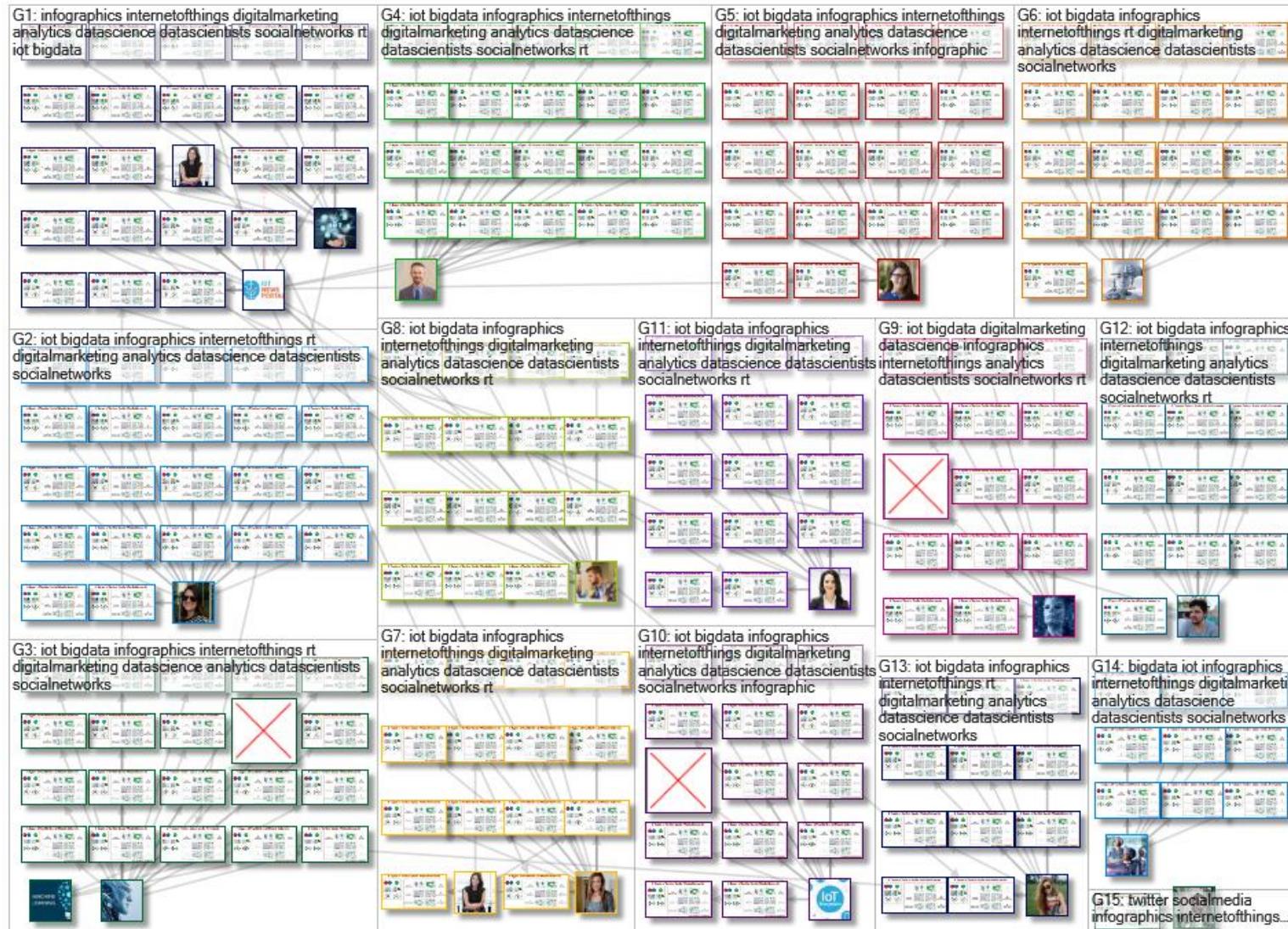
source connected action via @mikequindazzi

1:24 AM - 27 Aug 2018

13 Retweets 16 Likes



MULTIMODAL NETWORKS: USER - MEDIA

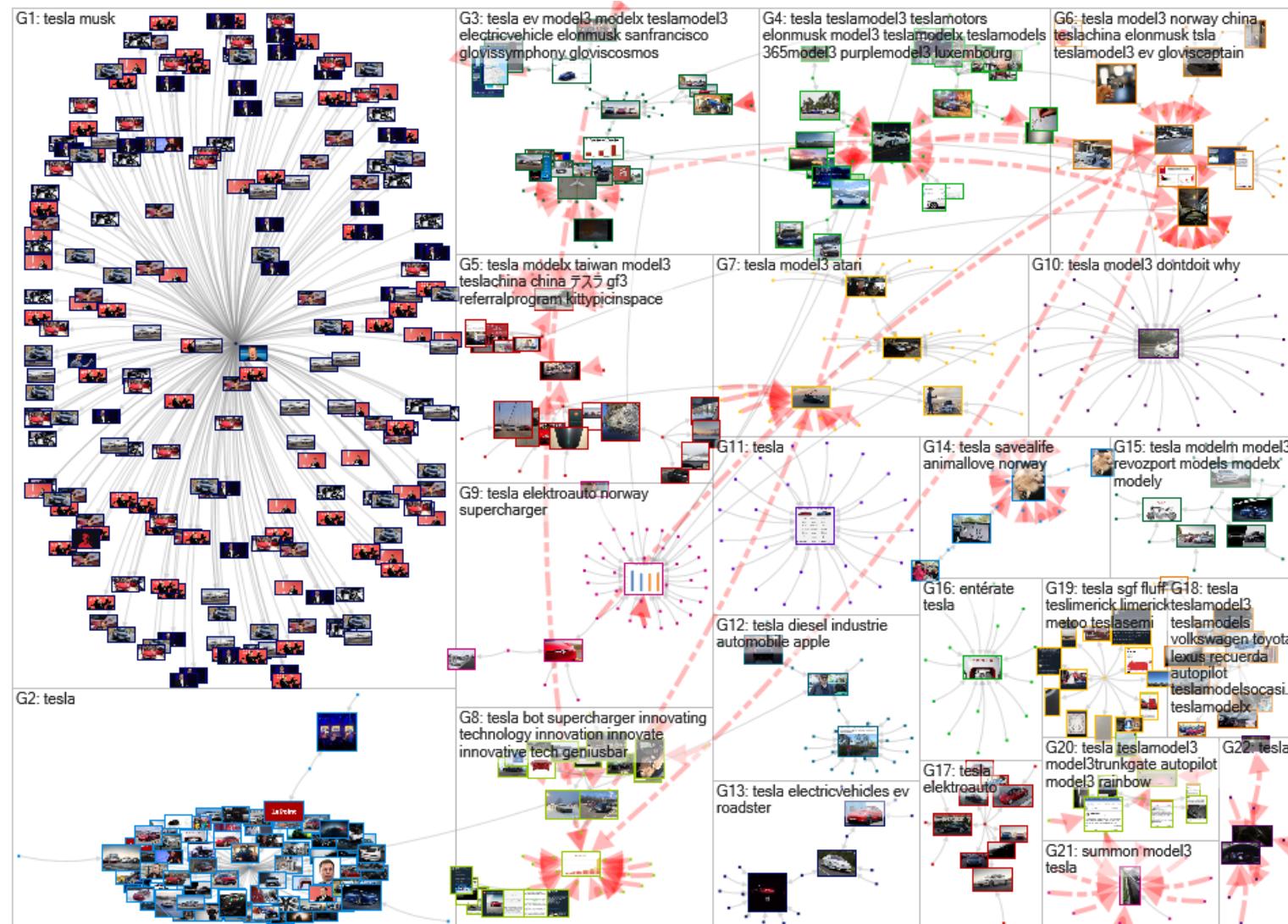


Top Hashtags

Top Hashtags in Tweet in Entire Graph:

- [308] iot ↗
- [303] bigdata ↗
- [242] infographics ↗
- [242] internetofthings ↗
- [236] digitalmarketing ↗
- [236] datascience ↗
- [234] analytics ↗
- [234] datascientists ↗
- [234] socialnetworks ↗
- [232] rt ↗

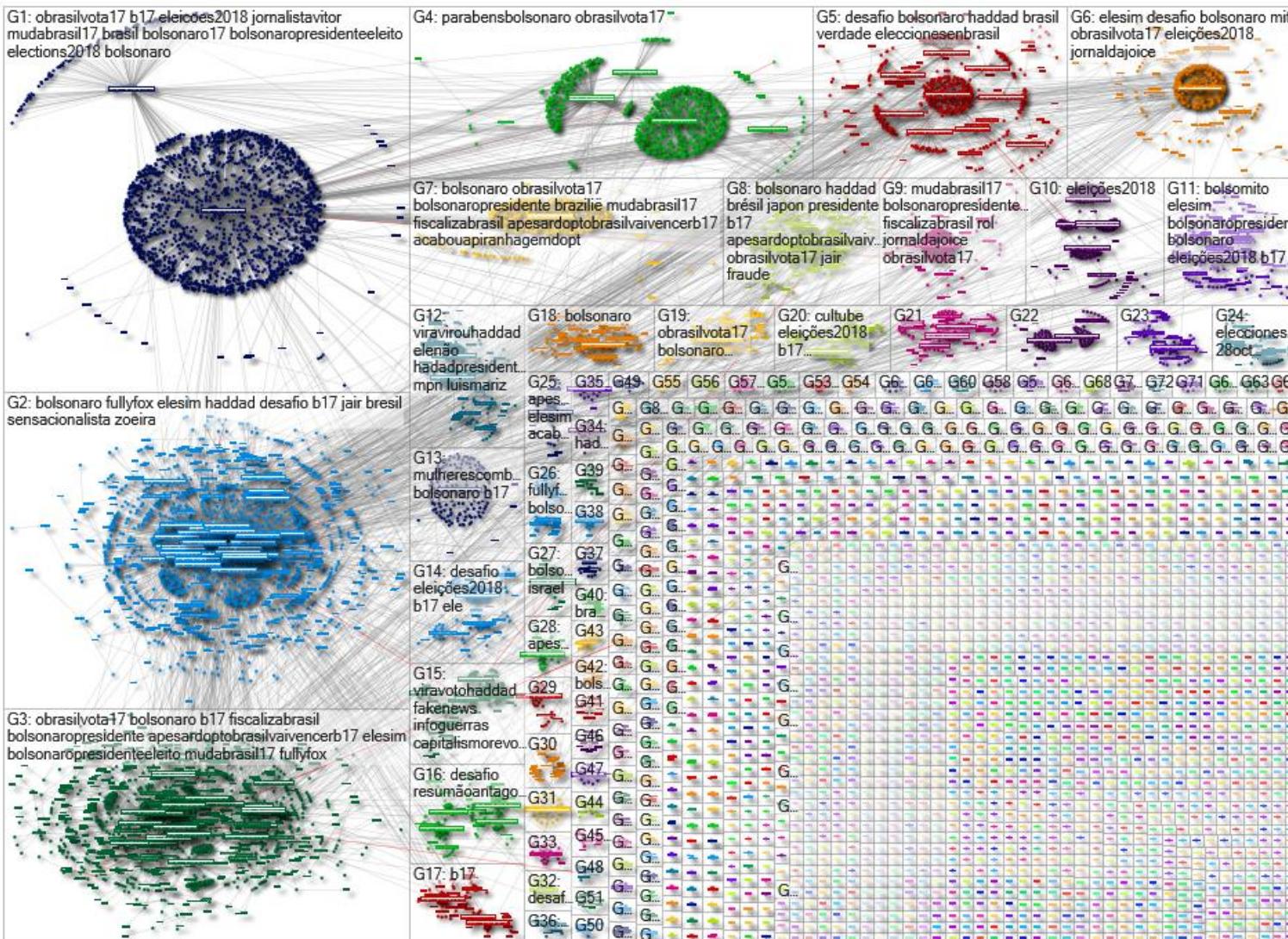
MULTIMODAL NETWORKS: USER - MEDIA



#Tesla Twitter User-to-Media File Network G1-G22 Monday, 04 February 2019

<https://nodexlgraphgallery.org/Pages/Graph.aspx?graphID=185277>

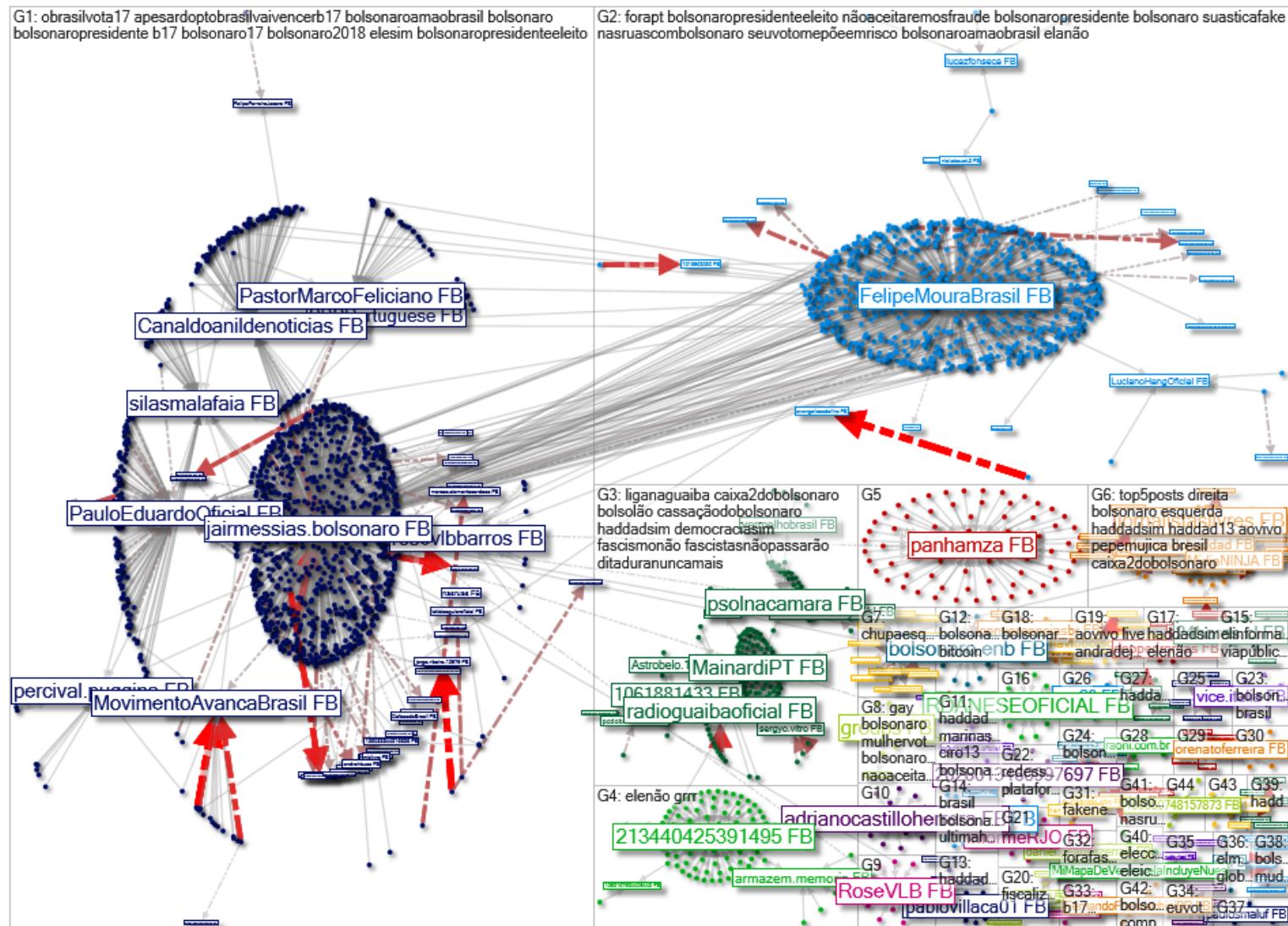
CROSS-PLATFORM ANALYSIS: TWITTER-YOUTUBE



Bolsonaro (youtube OR youtube.com OR youtu.be) user-url network until:2018-10-28

<https://nodexlgraphgallery.org/Pages/Graph.aspx?graphID=185579>

CROSS-PLATFORM ANALYSIS: TWITTER-FACEBOOK



Bolsonaro (facebook.com OR fb.com OR fb.me) until:2018-10-22

<https://nodexlgraphgallery.org/Pages/Graph.aspx?graphID=185533>

USER ACCOUNT INVESTIGATION



<https://theguardiansofdemocracy.com/trump-schedules-last-minute-meetings-based-whatever-saw-fox-friends-report/>
<https://www.vanityfair.com/news/2017/06/trump-says-he-wont-stop-tweeting>

EXAMPLE: USER ACCOUNT ANALYSIS

Donald J. Trump

@realDonaldTrump

45th President of the United States of America

Washington, DC

Instagram.com/realDonaldTrump

Joined March 2009

Tweets 38K Following 46 Followers 53M Likes 25 Moments 6

Follow

Ronna McDaniel

@GOPChairwoman

GOP Chairwoman | Wife, mother of two

Follow

Brad Parscale

@parscale

Campaign Manager for @realdonaldtrump 2020 Presidential Campaign.

Follow

Tucker Carlson

@TuckerCarlson

Host of "Tucker Carlson Tonight", weeknights at 8 PM ET @FoxNews. My new book #ShipOfFools is available for preorder below! Re-tweets are...

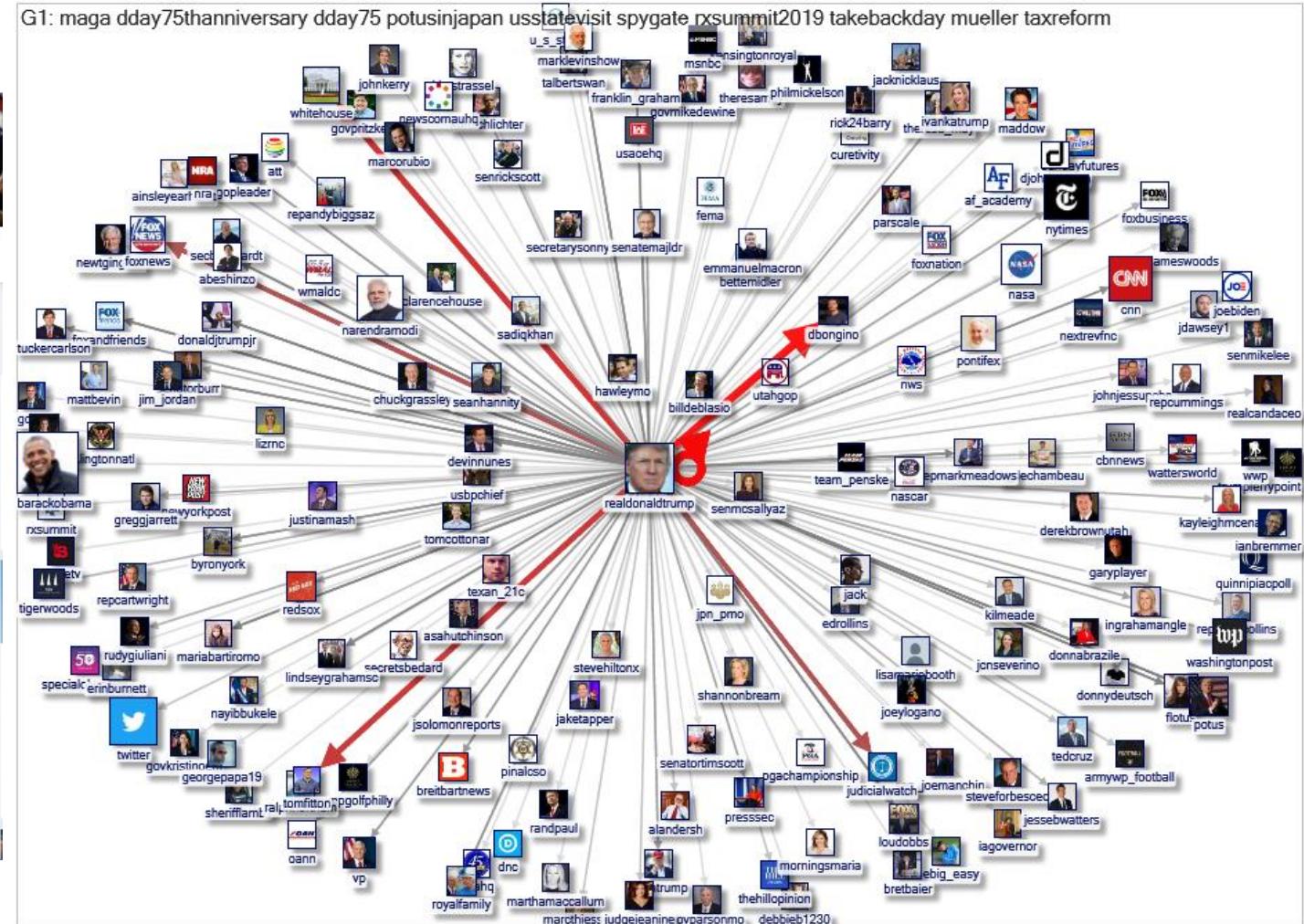
Follow

Jesse Watters

@JesseBWatters

Co-Host of "The Five" & Host of "Watters' World" on Fox News Channel. Speaking engagements here [premierespeakers.com/jesse_watters/...](http://premierespeakers.com/jesse_watters/)

Follow



realdonaldtrump Userlist 1000 2019-06-09

<https://nodexlgraphgallery.org/Pages/Graph.aspx?graphID=199512>

EXAMPLE: USER ACCOUNT ANALYSIS

Donald J. Trump • @realDonaldTrump
45th President of the United States of America
📍 Washington, DC
🔗 Instagram.com/realdonaldtrump
Joined March 2009

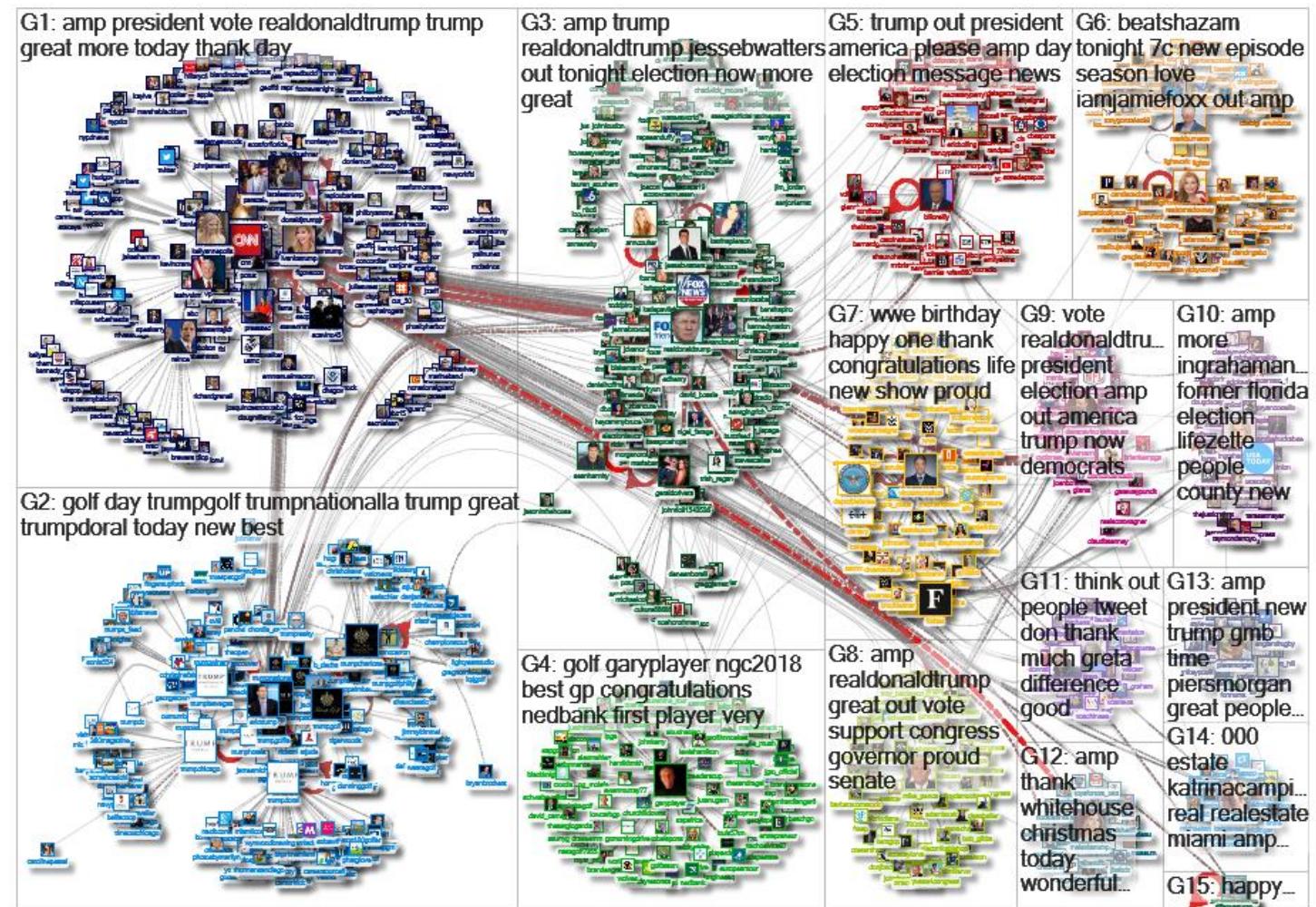
Tweets 38K Following 46 Followers 53M Likes 25 Moments 6

Ronna McDaniel • @GOPChairwoman
Chairwoman | Wife, mother of two

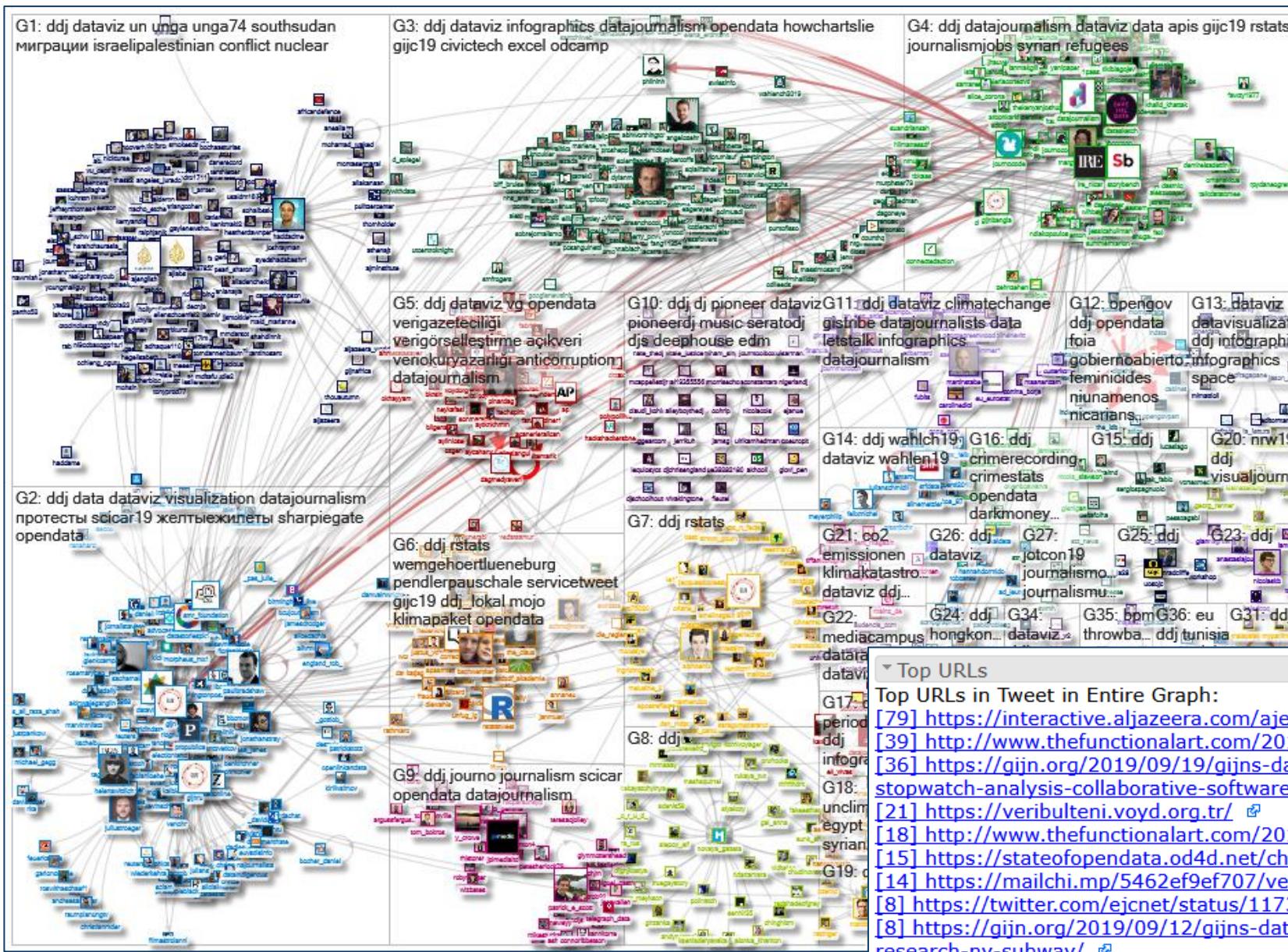
Brad Parscale • @parscale
Campaign Manager for @realdonaldtrump 2020 Presidential Campaign.

Tucker Carlson • @TuckerCarlson
Host of "Tucker Carlson Tonight", weeknights at 8 PM ET @FoxNews. My new book #ShipOfFools is available for preorder below! Re-tweets are...

Jesse Watters • @JesseBWatters
Co-Host of "The Five" & Host of "Watters' World" on Fox News Channel. Speaking engagements here premierespeakers.com/jesse_watters/



Based on Twitter users followed by @realdonaldtrump
<https://nodexlgraphgallery.org/Pages/Graph.aspx?graphID=174922>



Summarize and explore

Search term: #ddj

Top Hashtags

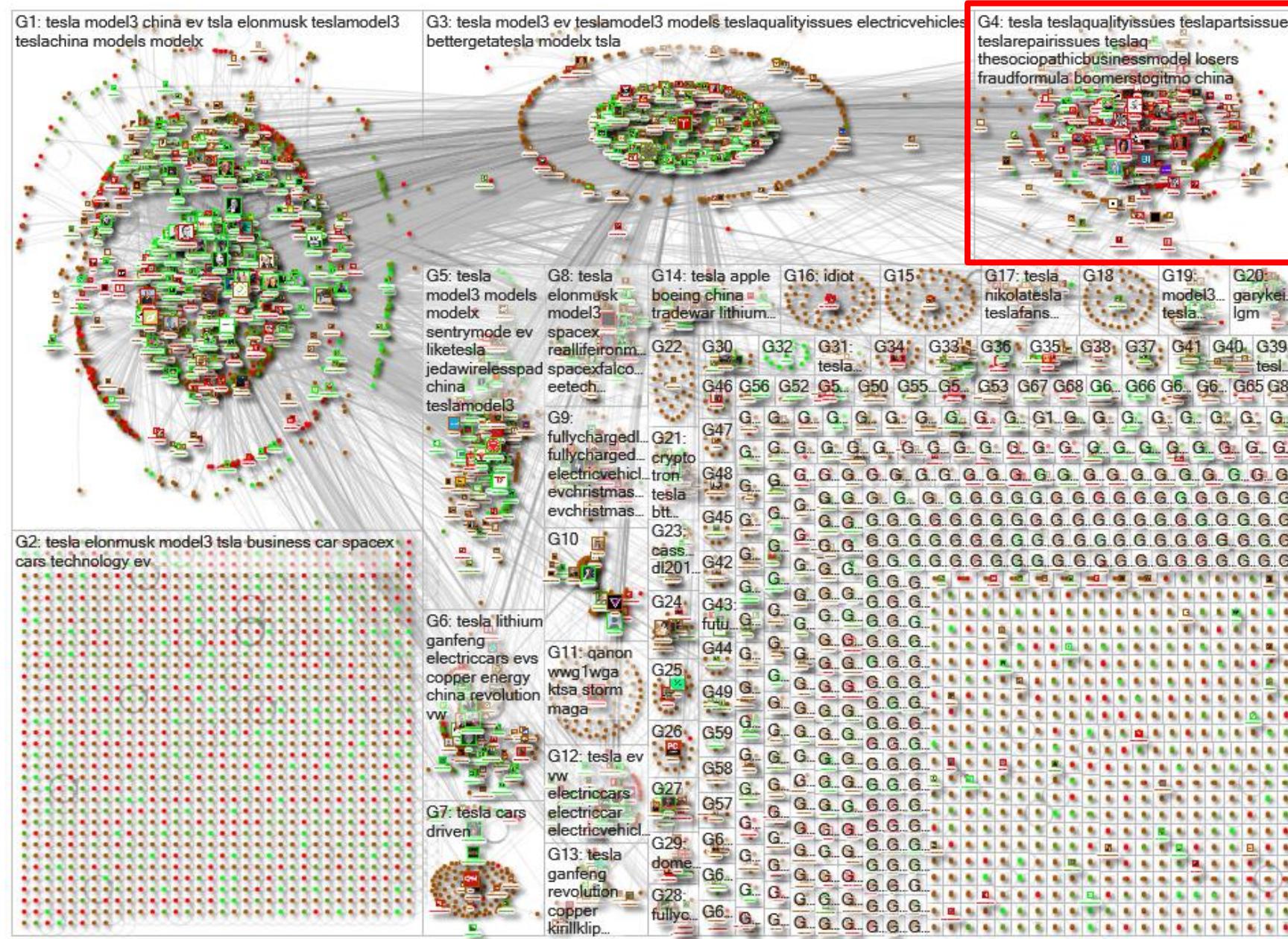
Top Hashtags in Tweet in Entire Graph:

- [602] ddj ↗
- [301] dataviz ↗
- [105] datajournalism ↗
- [74] infographics ↗
- [56] opendata ↗
- [47] vg ↗
- [32] data ↗
- [31] verigazeteciliği ↗
- [31] verigörselleştirme ↗
- [25] un ↗

Top URLs

Top URLs in Tweet in Entire Graph:

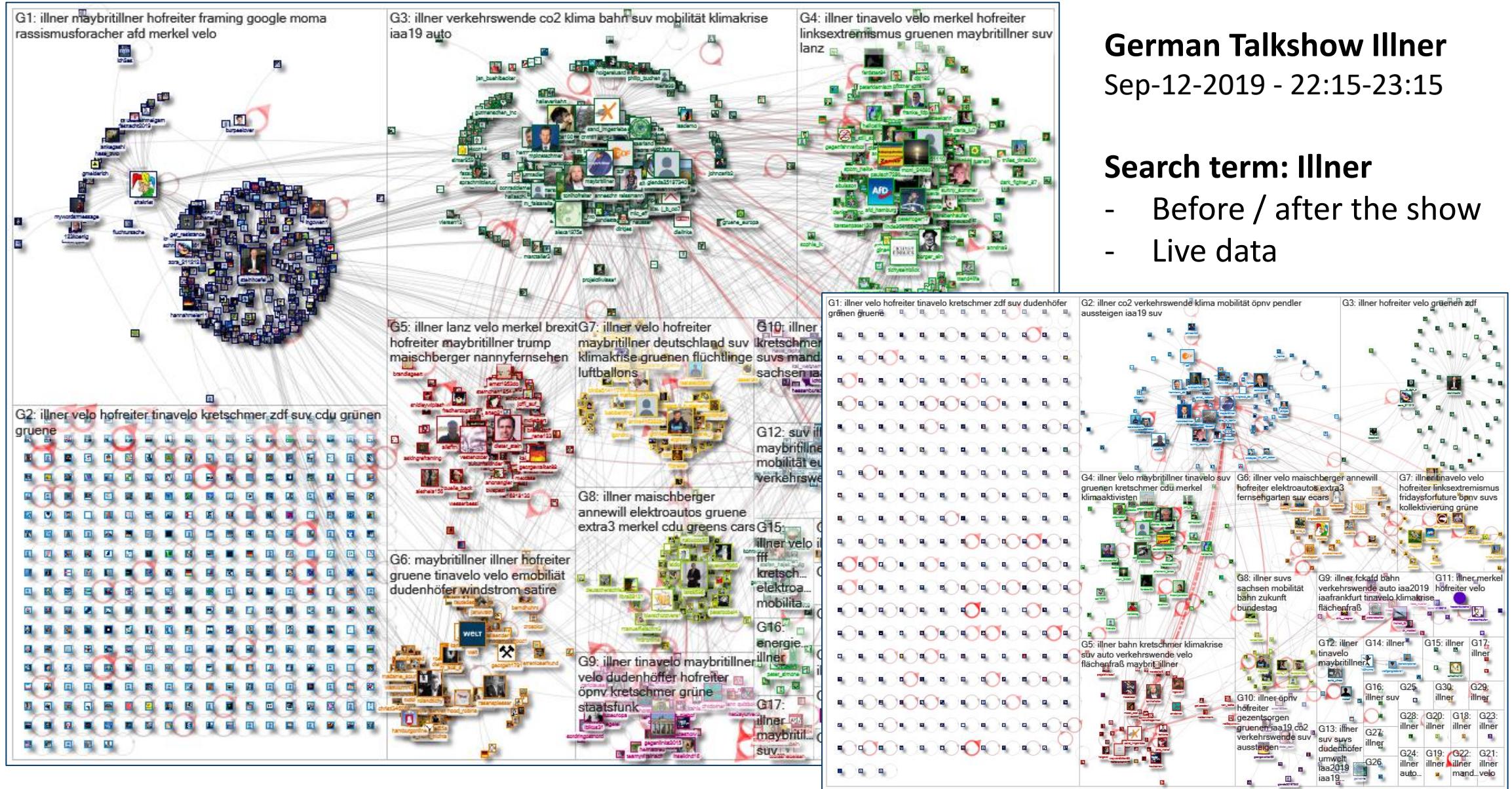
- [79] <https://interactive.aljazeera.com/aje/2019/how-has-my-country-voted-at-unga/index.html>
- [39] <http://www.thefunctionalart.com/2019/09/new-data-journalism-and-visualization.html> ↗
- [36] <https://gijn.org/2019/09/19/gijns-data-journalism-top-10-plastic-mountains-sharpiegate-stopwatch-analysis-collaborative-software/> ↗
- [21] <https://veribulteni.voyd.org.tr/> ↗
- [18] <http://www.thefunctionalart.com/2019/09/how-to-build-data-narrative.html> ↗
- [15] <https://stateofopendata.od4d.net/chapters/sectors/accountability.html> ↗
- [14] <https://mailchi.mp/5462ef9ef707/veri-bulteni47> ↗
- [8] <https://twitter.com/ejcnet/status/1173587534745673734> ↗
- [8] <https://gijn.org/2019/09/12/gijns-data-journalism-top-10-3d-animation-brexit-borders-bad-research-ny-subway/> ↗
- [6] <https://wid.world/> ↗



Visualizing Sentiment

Color by Language

Search term:
Tesla lang:en



German Talkshow Illner

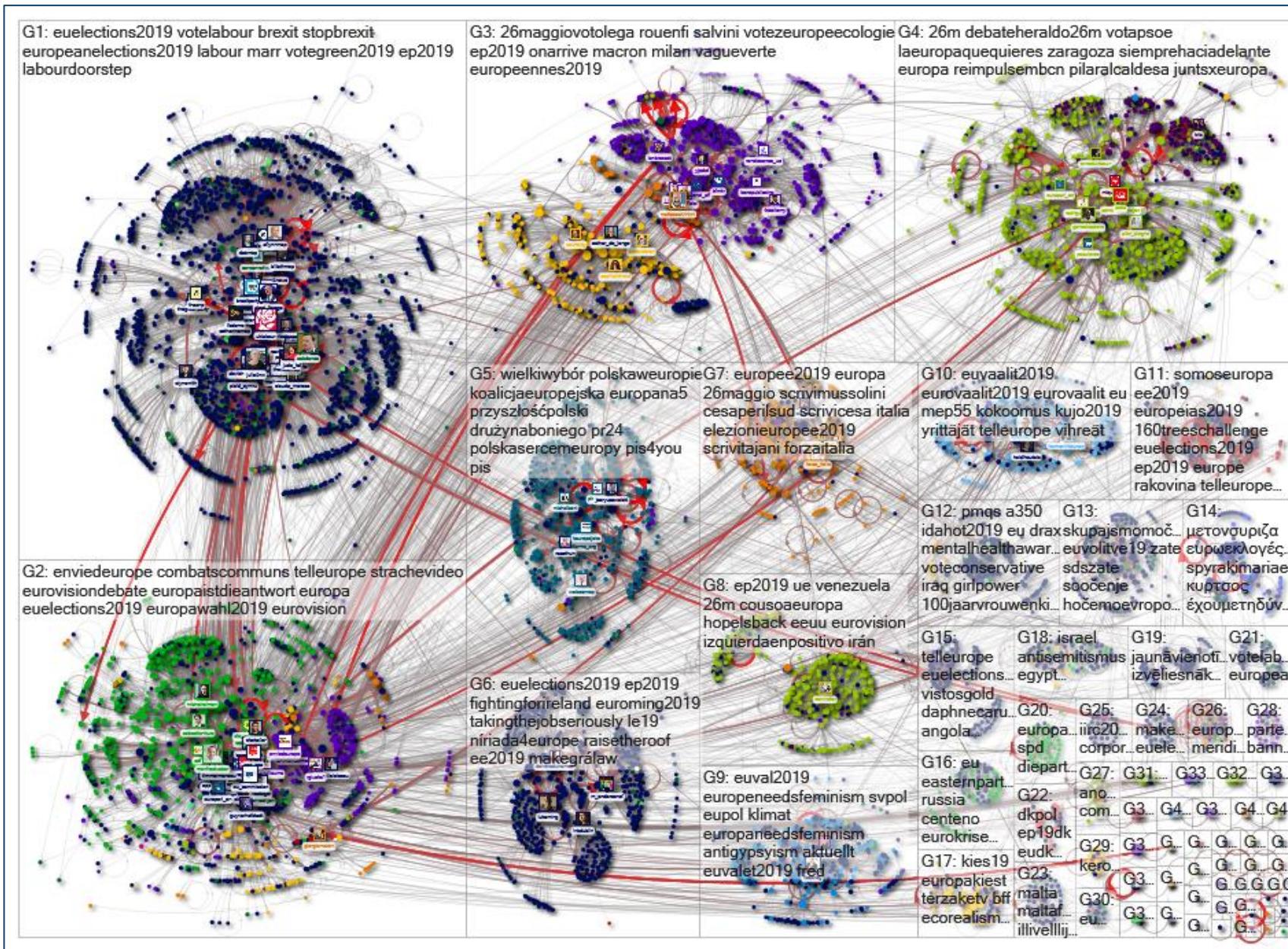
Sep-12-2019 - 22:15-23:15

Search term: Illner

- Before / after the show
 - Live data

<https://nodexlgraphgallery.org/Pages/Graph.aspx?graphID=209614>

<https://nodexlgraphgallery.org/Pages/Graph.aspx?graphID=209628>

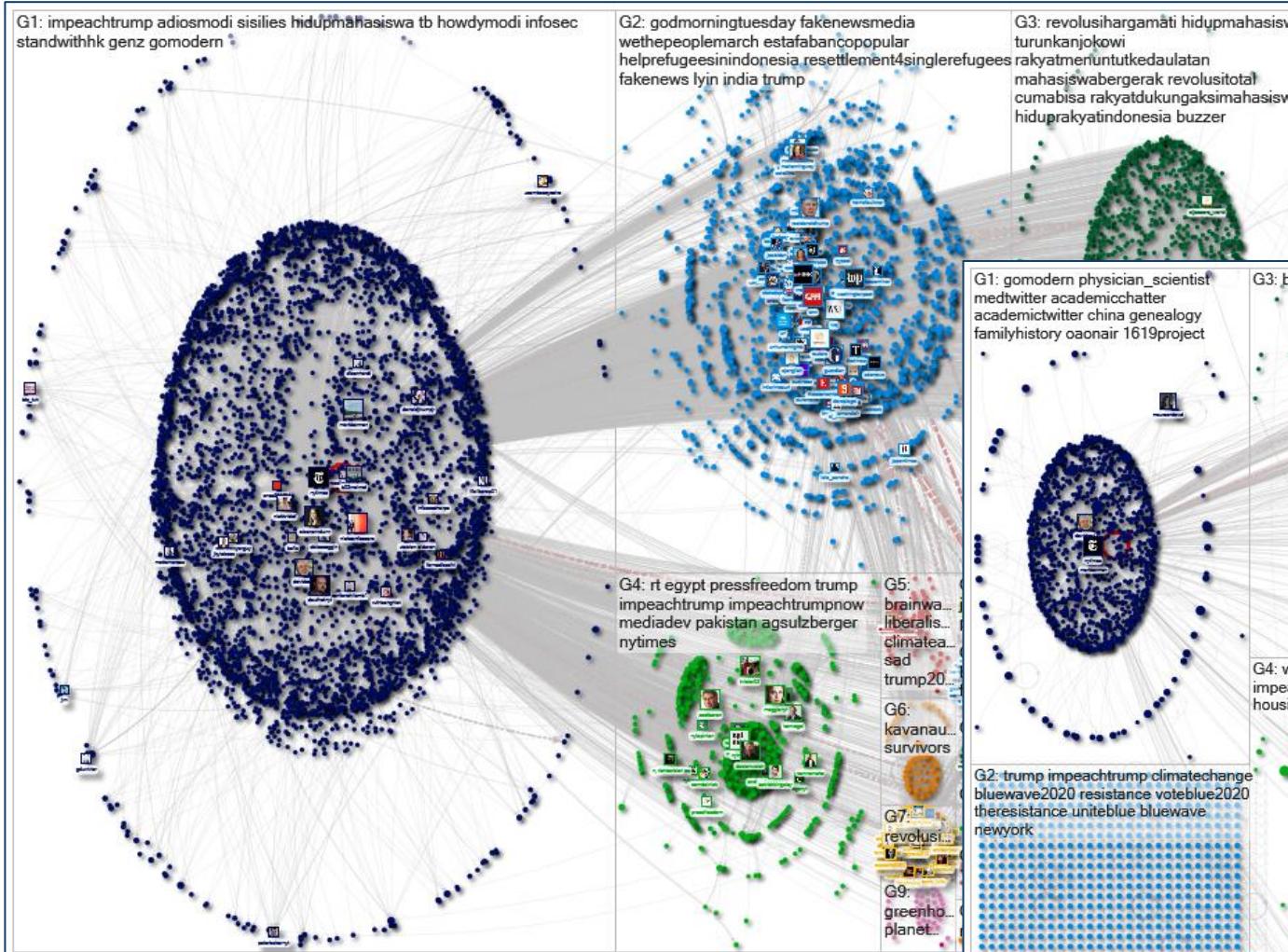


Members of the European Parliament before the European Elections 2019

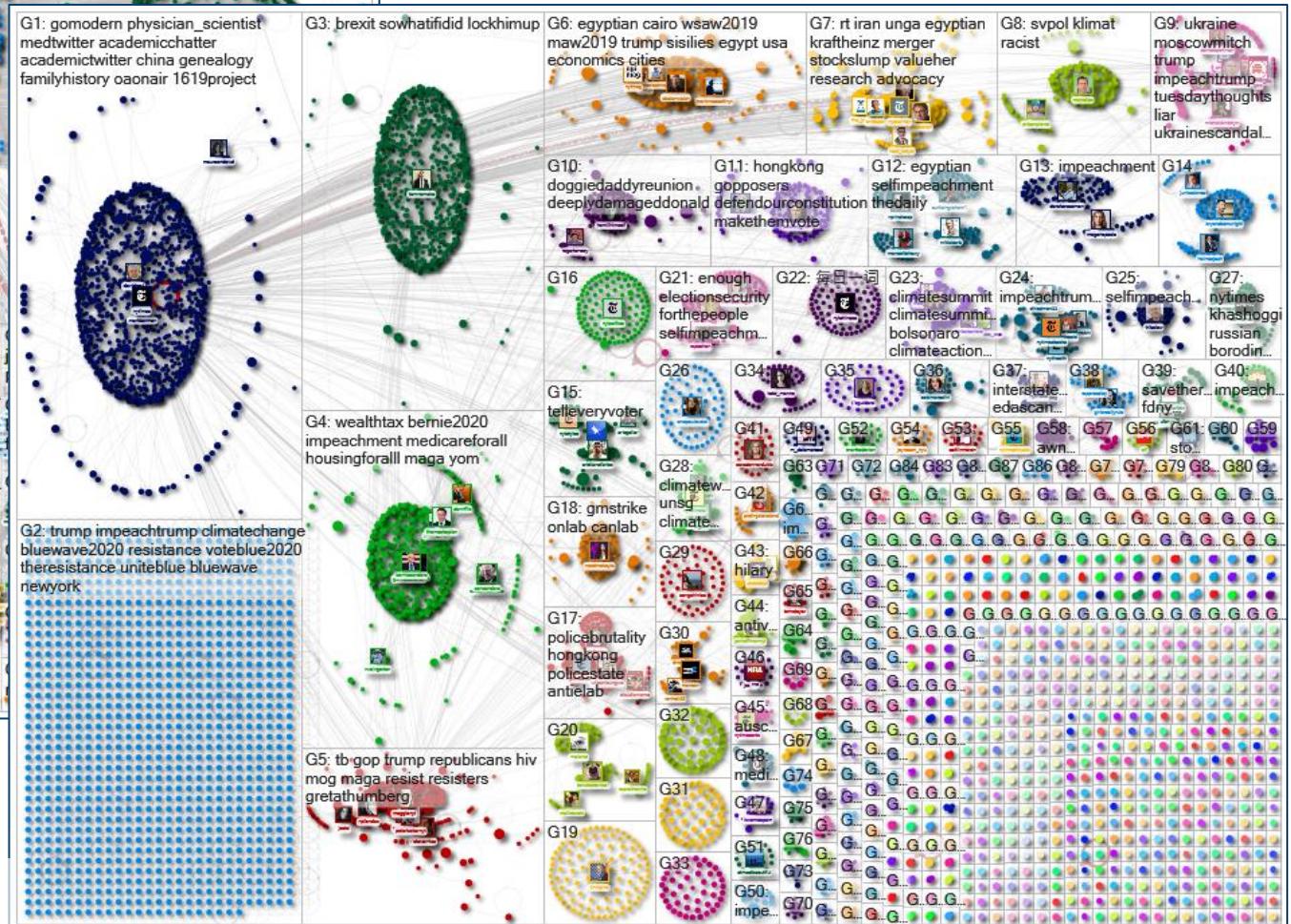
Color by Language

Search term:

list:Europarl_EN/all-meps-on-twitter



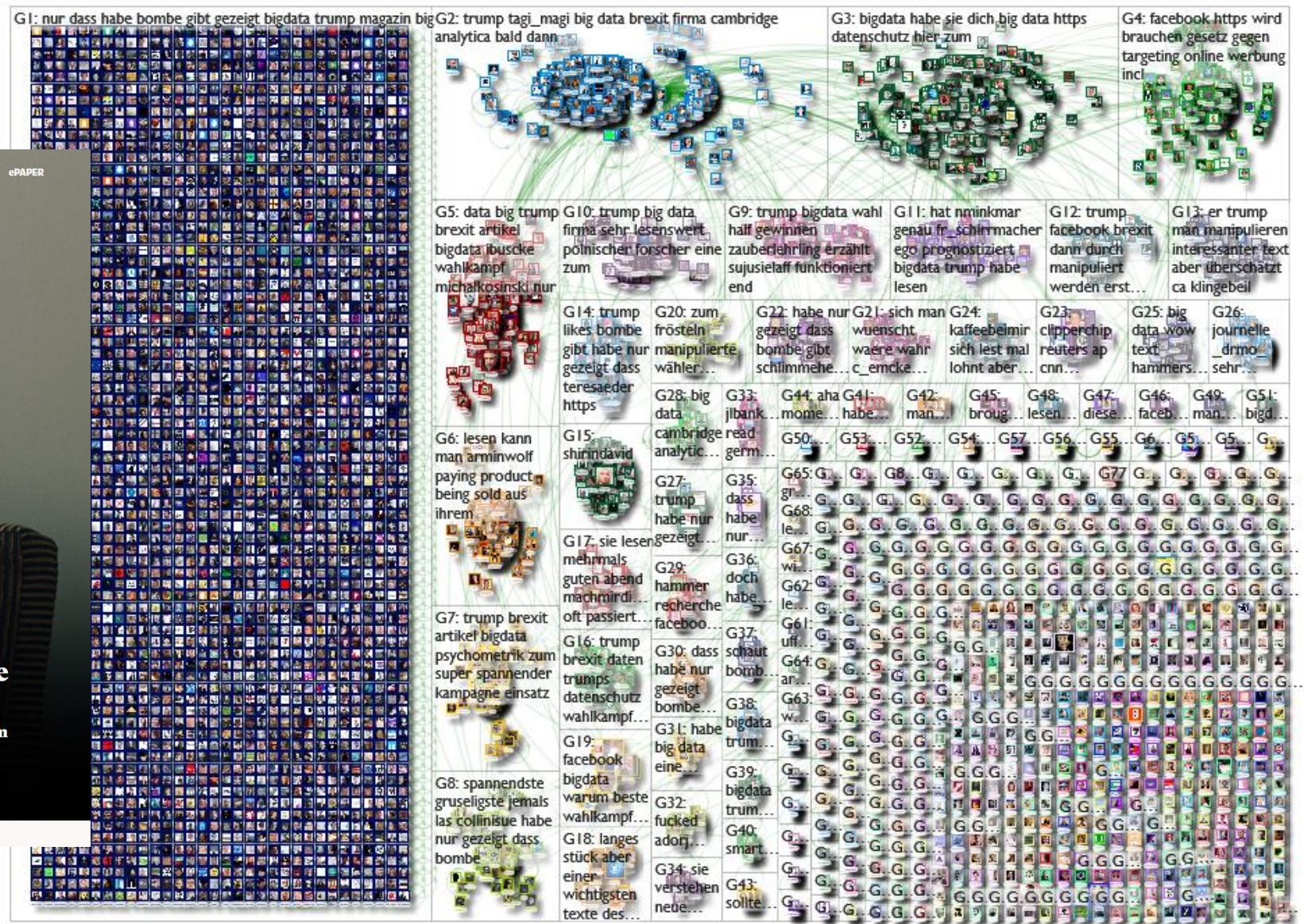
Search term: url:nytimes



Search term: @nytimes

Track articles and analyze audiences

Search term: dasmagazin.ch/2016/12/03/ich-habe-nur-gezeigt-dass-es-die-bombe-gibt



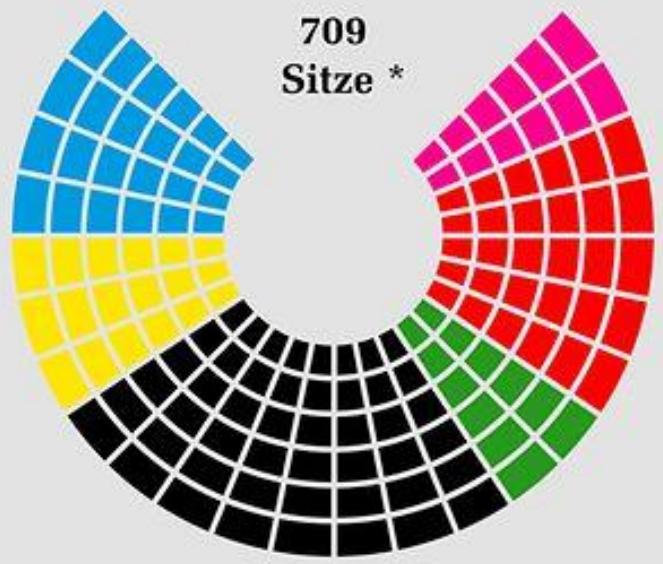
19. BUNDESTAG: TWITTER USEAGE



48

Sitzverteilung im 19. Deutschen Bundestag

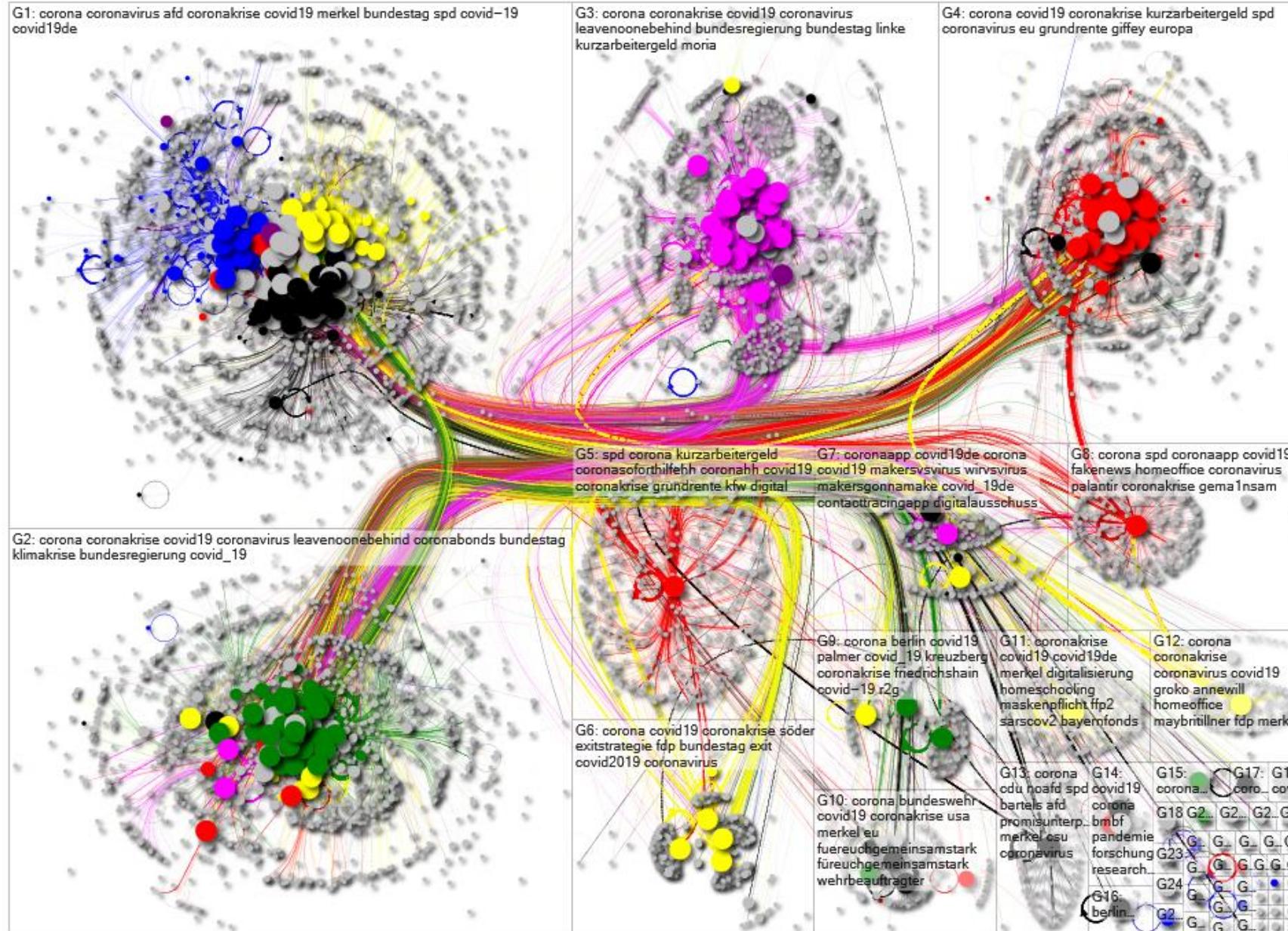
Stand: Oktober 2017



Party	Color	Seats	Twitter users	Twitter users per seat
CDU/CSU	Black	246	131	53 %
SPD	Red	153	123	80 %
AfD	Blue	92	85	92 %
FDP	Yellow	80	72	90 %
Die Linke	Pink	69	60	87 %
B90/Die Grünen	Green	67	64	96 %
no affiliation		2	2	100 %
All		709	537	76 %

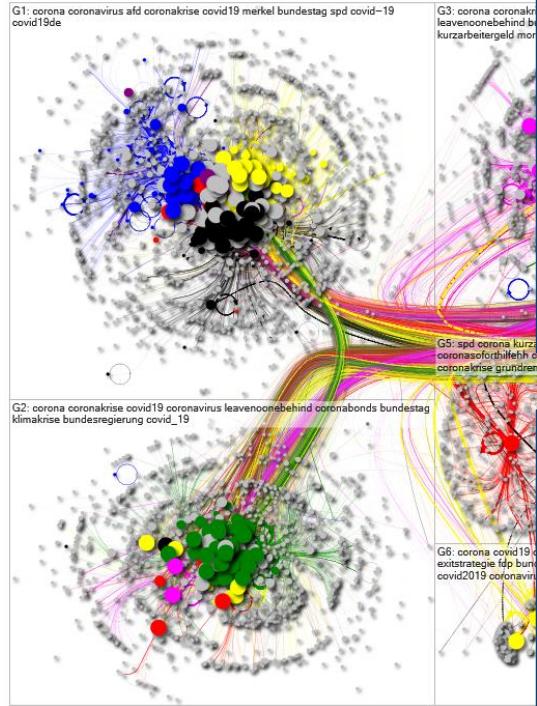
https://www.bundestag.de/parlament/plenum/sitzverteilung_19wp

Full Network - April 2020

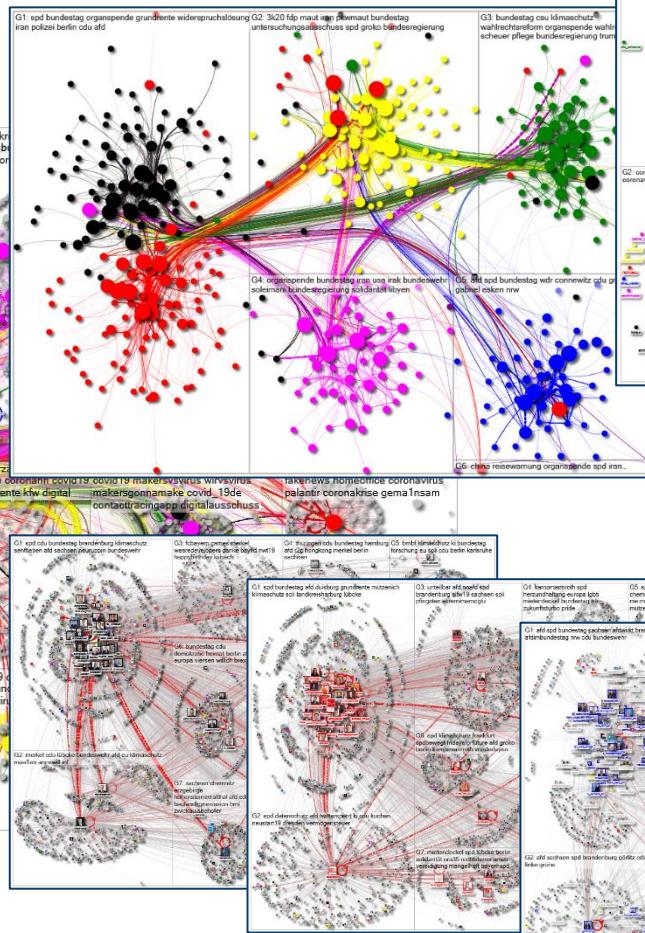


NETWORKS CREATED FROM ONE MONTHLY DATASET

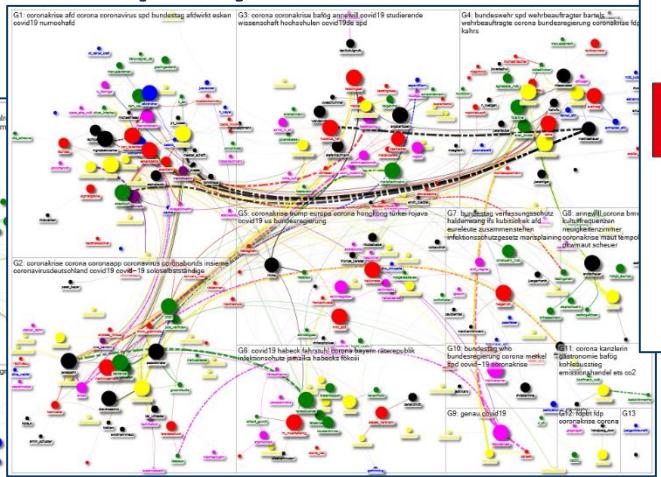
Full Network



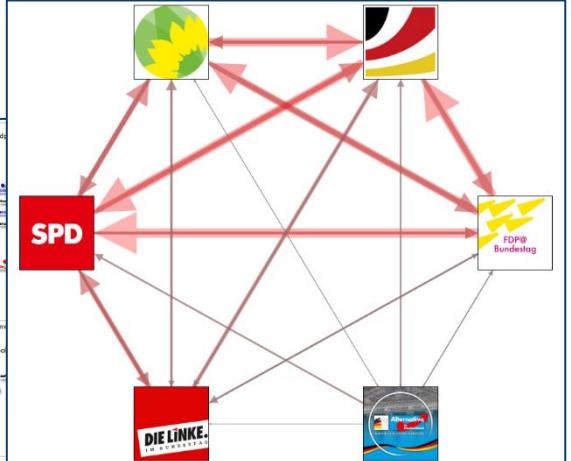
Internal Network



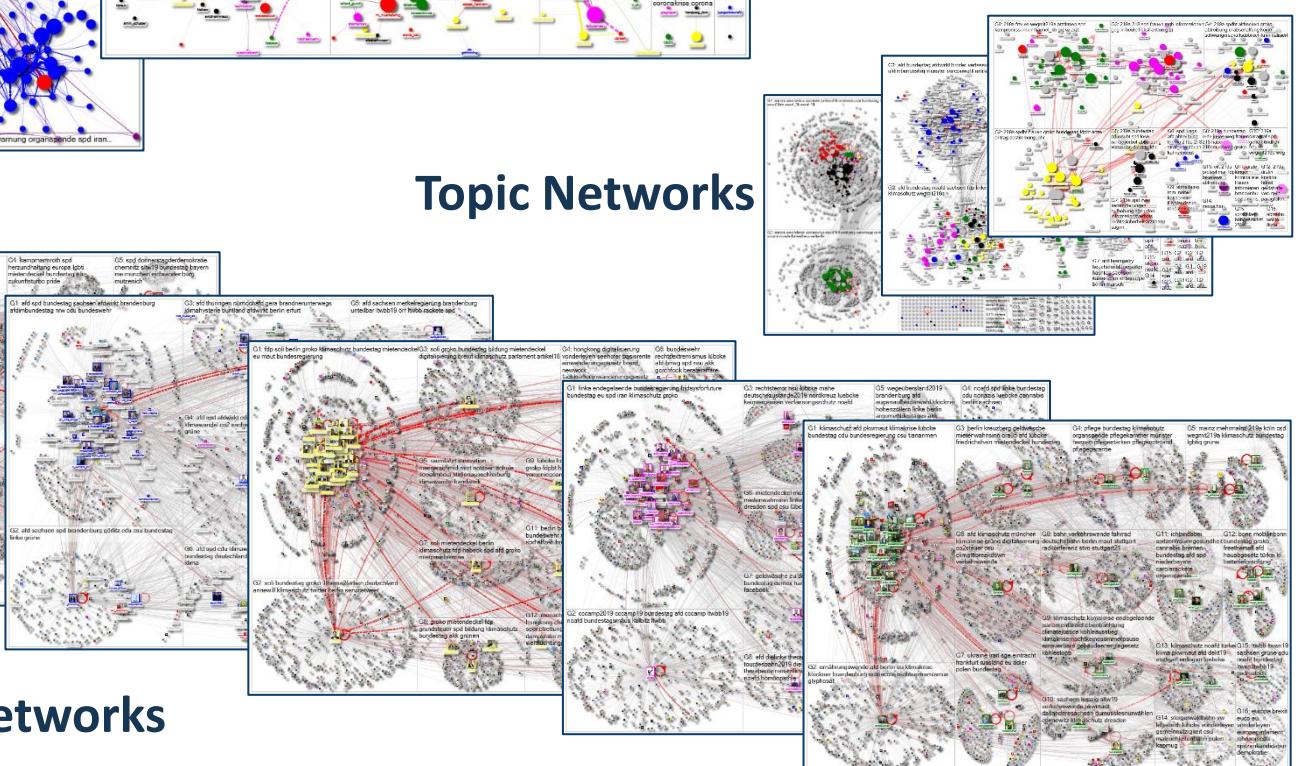
Cross-party Network



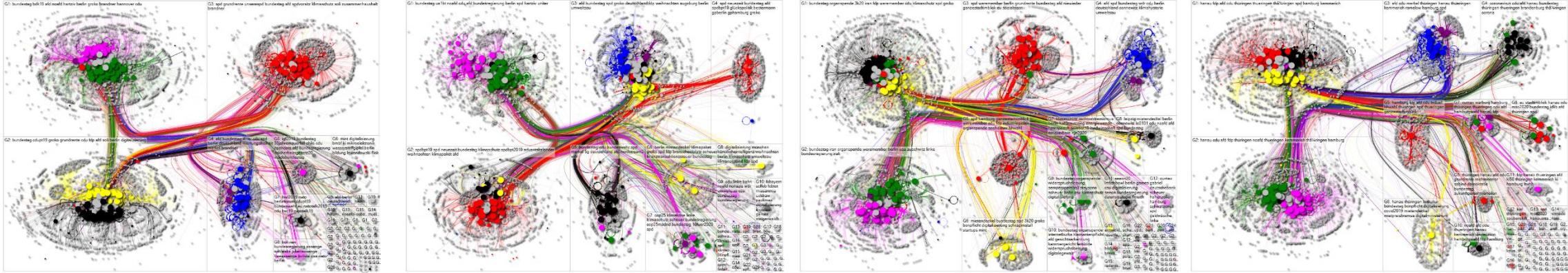
Party Interaction



Party Networks



COMPARING NETWORKS OVER TIME

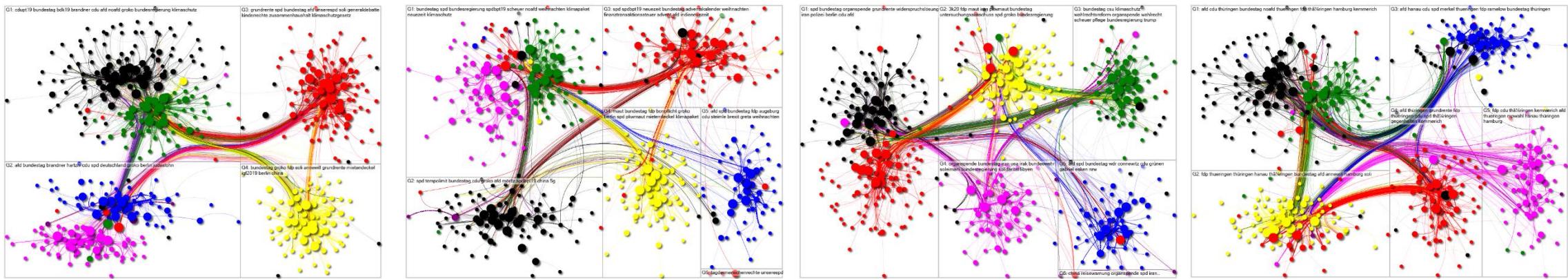


November 2019

December 2019

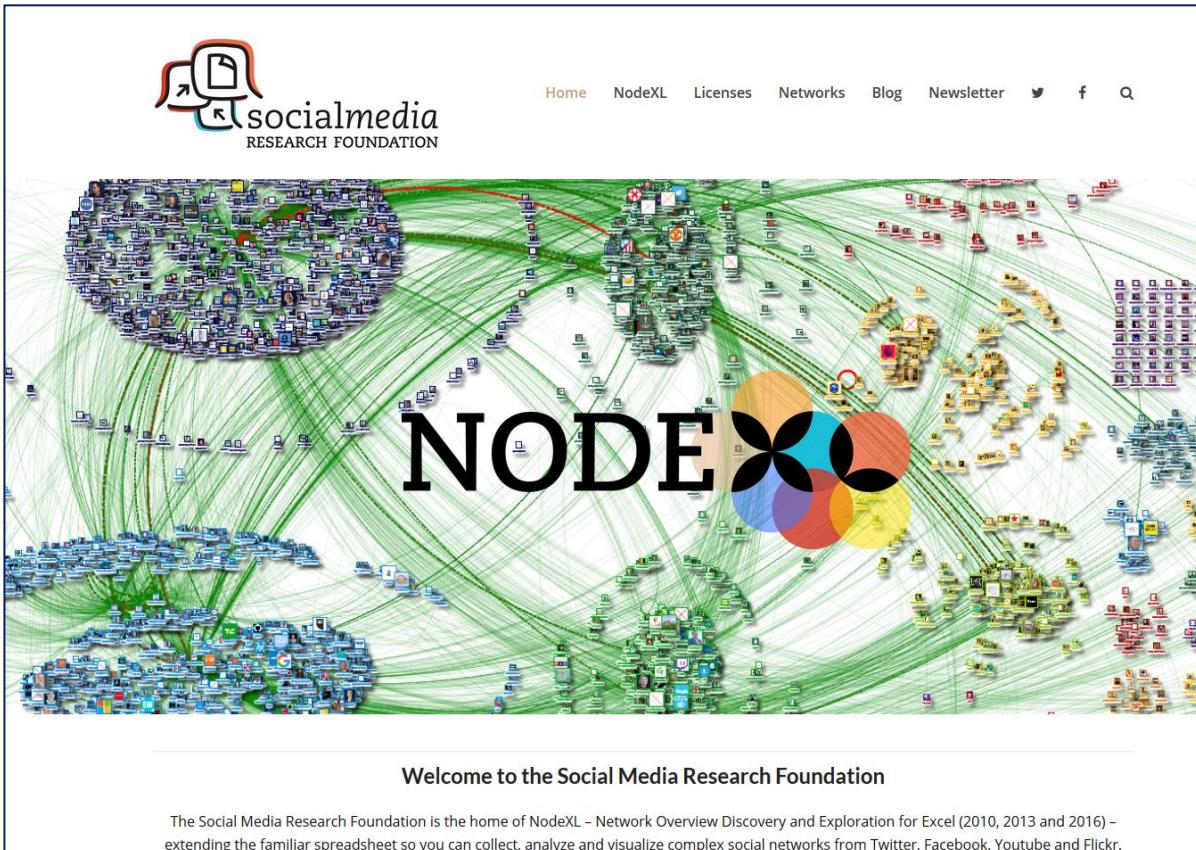
January 2020

February 2020



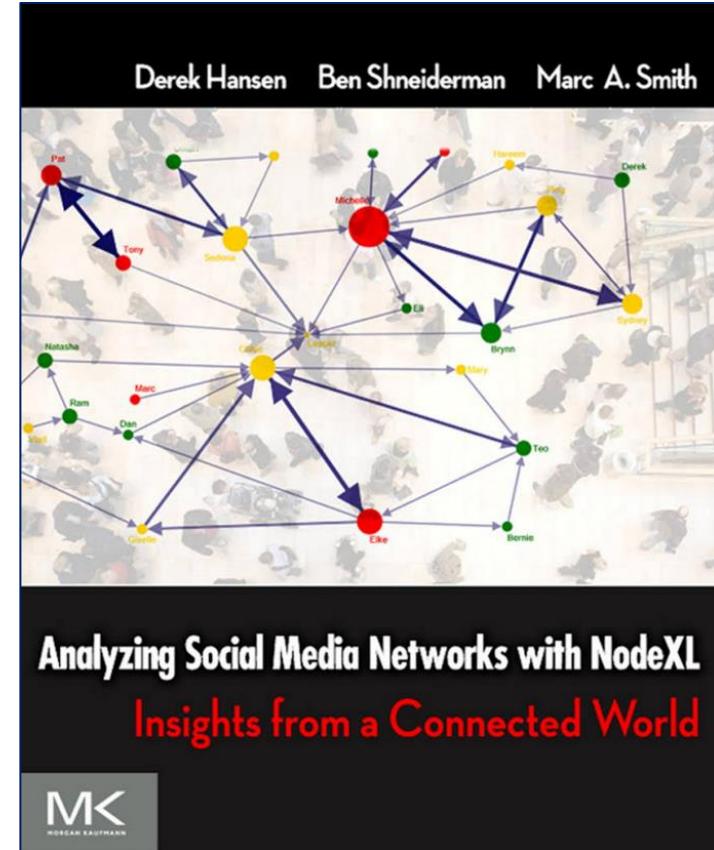
SOCIAL MEDIA RESEARCH FOUNDATION

52



<https://www.smrfoundation.org/>

<https://www.nodexlgraphgallery.org/>



Book: Derek Hansen, Ben Shneiderman and Marc Smith (2020):
Analyzing Social Media Networks with NodeXL:
<https://www.elsevier.com/books/analyzing-social-media-networks-with-nodexl/hansen/978-0-12-817756-3>

LITERATURE / LINKS

Social Media Research Foundation and NodeXL

- Social Media Research Foundation: <http://www.smrfoundation.org/>
- NodeXL Graph Gallery: <https://nodexlgraphgallery.org/>
- Marc Smith | Network Mapping the Ecosystem: <https://www.youtube.com/watch?v=kDiGI-2m868>
- How to Automate NodeXL Pro: <https://www.youtube.com/watch?v=mjAq8eA7uOM>
- Eduarda Mendes Rodrigues, Natasa Milic-Frayling, Marc Smith, Ben Shneiderman, Derek Hansen (2011): Group-in-a-box Layout for Multi-faceted Analysis of Communities. In: IEEE Third International Conference on Social Computing, October 9-11, 2011. Boston, MA: <https://www.cs.umd.edu/hcil/trs/2011-24/2011-24.pdf>
- Smith, Marc A., Lee Rainie, Ben Shneiderman and Itai Himelboim (2014): Mapping Twitter Topic Networks: From Polarized Crowds to Community Clusters. PEW Research Report: <https://www.pewinternet.org/2014/02/20/mapping-twitter-topic-networks-from-polarized-crowds-to-community-clusters/>
- Derek Hansen, Ben Shneiderman and Marc Smith (2009): Analyzing Social Media Networks with NodeXL: <https://www.elsevier.com/books/analyzing-social-media-networks-with-nodexl/hansen/978-0-12-382229-1>
- Itai Himelboim, Marc A. Smith, Lee Rainie, Ben Shneiderman and Camila Espina: Classifying Twitter Topic-Networks Using Social Network Analysis. In: Social Media + Society (January-March 2017: 1 –13). <https://journals.sagepub.com/doi/full/10.1177/2056305117691545>

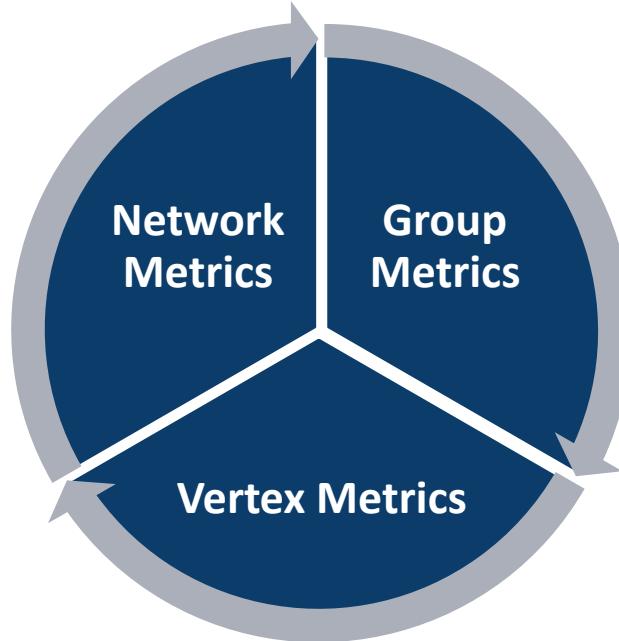
LITERATURE / LINKS

- Borgatti, Stephen P. (2006): Identifying sets of key players in a social network. In: Comput Math Organiz Theor (2006) 12: 21–34 [DOI 10.1007/s10588-006-7084-x]
- Castells, Manuel (1996): The Rise of the Network Society, Malden: Blackwell Publishers.
- Aaron Clauset, M. E. J. Newman, and Christopher Moore (2004): Finding community structure in very large networks. In: Phys. Rev. E 70.
- Litterio, Arnaldo M., et. al. (2017): "Marketing and social networks: a criterion for detecting opinion leaders", European Journal of Management and Business Economics, Vol. 26 Issue: 3, pp.347-366, <https://doi.org/10.1108/EJMBE-10-2017-020>
- Frank W. Takes, Eelke M. Heemskerk (2016): Centrality in the global network of corporate control. Social Network Analysis and Mining, December 2016, 6:97). Online unter: <https://link.springer.com/article/10.1007/s13278-016-0402-5>
- Tingting Yan, Thomas Y. Choi, Yusoon Kim, Yang Yang (2015): A Theory of the Nexus Supplier: A Critical Supplier From A Network Perspective. Journal of Supply Chain Management, 51-1 pp: 3-92. Online unter: <https://onlinelibrary.wiley.com/doi/abs/10.1111/jscm.12070>

KEY FEATURES OF NODEXL PRO

55

2. Network Analysis

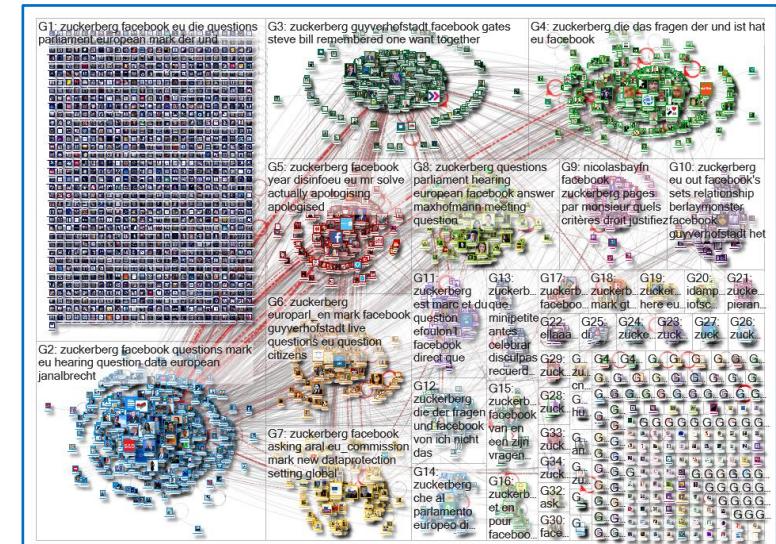


3. Content Analysis

Text Analysis

Top Contents Analysis

4. Visualization



1. Data Import



6. Automation with Data Recipes

5. Publish



KEY FEATURES OF NODEXL PRO

56

Data Import

Data formats
Excel/UCINET/GraphML/
Pajek/GEFX/GDF

Social media data



YouTube

Flickr

Network Analysis

Network Overview
Network size and composition
Graph density, modularity

Group Analysis
Group by cluster
e.g. Clauset-Newman-Moore
Group metrics

Vertex metrics
Degree/In-/OutDegree
Betweenness/Closeness/
Eigenvector/ PageRank

Path Analysis

Content Analysis

Text Analysis
Words and word pairs from
Tweets, Posts, Replies, ...

Sentiment Analysis
Positive/Negative Sentiment
Your list of Keywords

Top Content Summary
By entire network / by group
Top hashtags, URLs, domains
Top words and word pairs

Time Series Analysis
By minute/hour/day/...
By hashtag/word/language/...

Visualization

Customize
Shape, size, color, label of
vertices, edges and groups

Autofill Columns

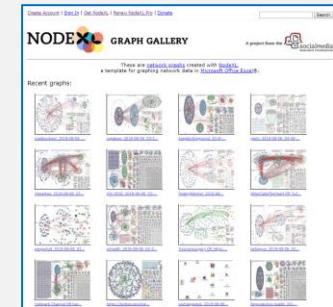
Graph Layout
Various layout algorithms
e.g. Harel-Koren Fast
Multiscale

Group-In-a-Box Layout
Treemap
Force-directed
Packed rectangles

Data Export

Data formats
Excel/UCINET/GraphML/
Pajek/GEFX/GDF

Publish to the web
NodeXL Graph Gallery



Export to Powerpoint
Export to Polinode

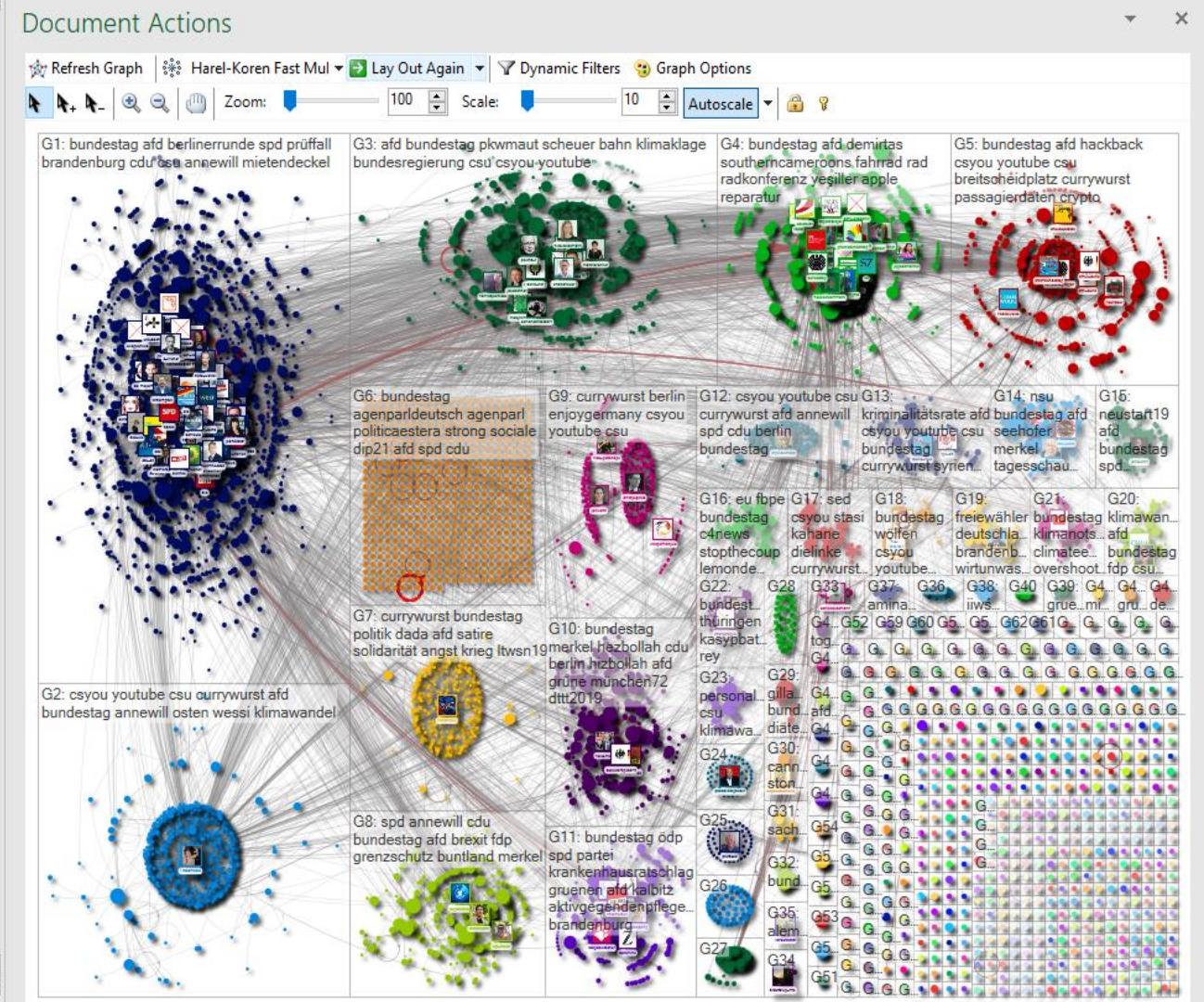
Automate Key Features with NodeXL Data Recipes

File Home Insert Page Layout Formulas Data Review View Help NodeXL Pro Table Design

Import Export Prepare Data Data Graph Visual Properties Analysis Options Show/Hide Help

A2 Vertex 1

	A	B	K	N	O	P	Q	R
1			Graph Metrics	Other Columns				
2	Vertex 1	Vertex 2	Reciprocated?	Add Your Own Columns Here	Relationship	Date (UTC)	Tweet	URLs
36045	andreasand	andreasand	No		Tweet	9/4/2019 13:15	Im Kampf gegen de https://t.co/...	
36046	andreasand	andreasand	No		Tweet	9/4/2019 13:16	Sofortige Freilassur https://t.co/...	
36047	andreasand	andreasand	No		Tweet	9/4/2019 13:16	Dialog und Deeskal: https://t.co/...	
36048	andreasand	andreasand	No		Retweet	9/4/2019 13:20	Dialog und Deeskal: https://t.co/...	
36049	andreasand	andreasand	No		Retweet	9/4/2019 13:20	Sofortige Freilassur https://t.co/...	
36050	andreasand	andreasand	No		Retweet	9/4/2019 13:20	Im Kampf gegen den Klima https://t.co/...	
36051	andreasand	andreasand	No		Retweet	9/4/2019 13:20	Katastrophe Zust: https://t.co/...	
36052	andreasand	andreasand	No		Retweet	9/4/2019 13:20	Cum-Ex-Prozess: G https://t.co/...	
36053	andreasand	andreasand	No		Retweet	9/4/2019 13:20	Neue Besen kehren https://t.co/...	
36054	tumalwas	andreasand	No		Retweet	8/29/2019 13:49	Grundlegender Kurswechs https://t.co/...	
36055	jagodamari	jagodamari	No		Tweet	8/29/2019 12:39	In Deutschland ist n https://t.co/...	
36056	jagodamari	jagodamari	No		Tweet	9/1/2019 20:42	Herr Gauland, fühlen Sie s https://t.co/...	
36057	tumalwas	jagodamari	No		Retweet	8/29/2019 16:02	In Deutschland ist noch so https://t.co/...	
36058	watch_unic	watch_unic	No		Tweet	8/23/2019 18:18	Ziemlich krass. Die : https://t.co/...	
36059	watch_unic	watch_unic	No		Tweet	8/26/2019 14:29	In den #USA würden wir d https://t.co/...	
36060	watch_unic	watch_unic	No		Tweet	8/30/2019 8:58	"Allein in der vergar https://t.co/...	
36061	watch_unic	watch_unic	No		Tweet	8/31/2019 12:44	Weil wahrscheinlich einig https://t.co/...	
36062	watch_unic	watch_unic	No		Retweet	8/31/2019 19:49	Nicht nur bei #YouTube ü https://t.co/...	
36063	tumalwas	watch_unic	No		Retweet	8/30/2019 9:03	"Allein in der vergangener https://t.co/...	
36064	tumalwas	korallenher	No		Mentions	9/1/2019 13:47	@elgrunwald @Korallenher https://t.co/...	
36065	tumalwas	elgrunwald	No		Replies to	9/1/2019 13:47	@elgrunwald @Korallenher https://t.co/...	
36066	franzi_chule	franzi_chule	No		Tweet	9/1/2019 16:42	Ralf Brinkhaus (Fraktions https://t.co/...	
36067	tumalwas	franzi_chule	No		Retweet	9/1/2019 16:49	Ralf Brinkhaus (Fraktions https://t.co/...	
36068	suse1603	cdcsubt	No		Mentions	9/1/2019 18:12	Gerade eben #ARD #Afd https://t.co/...	
36069	tumalwas	suse1603	No		Retweet	9/1/2019 18:26	Gerade eben #ARD #Afd https://t.co/...	
36070	tumalwas	cdcsubt	No		Mentions	9/1/2019 18:26	Gerade eben #ARD #Afd https://t.co/...	
36071	isegrimm_6	fdp	No		Mentions	9/4/2019 15:17	Ist das @fdp ... unc https://t.co/...	
36072	tumalwas	isegrimm_6	No		Retweet	9/4/2019 15:24	Ist das @fdp ... und kann https://t.co/...	
36073	tumalwas	fdp	No		Mentions	8/27/2019 12:14	Immobilien-Lobbyisten ha https://t.co/...	



TUTORIAL PREPARATION

NodeXL Pro requires:

- **User license:** You will receive an email with a NodeXL Pro Student Trial User license and installation instructions shortly.
- **OPERATING SYSTEM:** Microsoft Windows™(7, 8, 10)
- **SOFTWARE:** Microsoft Office™ (2007, 2010, 2013, 2016, 365)

Tutorial Requirements:

- To download data from Twitter, you need a Twitter account!

If you run into any installation issues, please have a look at this page:

<https://www.smrfoundation.org/nodexl/installation/>

Feel free to request tech support from team NodeXL by [filling out this form](#).

Session 1: For Mac / Linux Users: How to install a virtual machine via Amazon Web Services
(Amazon account is required; small costs may occur)

Topic: Node XL Pro - Technical Session: Installing Node plugin and getting started.

Time: Jun 16, 2020 11:00 AM London

Join Zoom Meeting <https://us02web.zoom.us/j/89012594289> Meeting ID: 890 1259 4289

Session 2: Topic: Node: NodeXL plugin workshop: How to create a social network and content analysis

Time: Jun 23, 2020 10:00 AM London

Join Zoom Meeting <https://us02web.zoom.us/j/85719168917> Meeting ID: 857 1916 8917