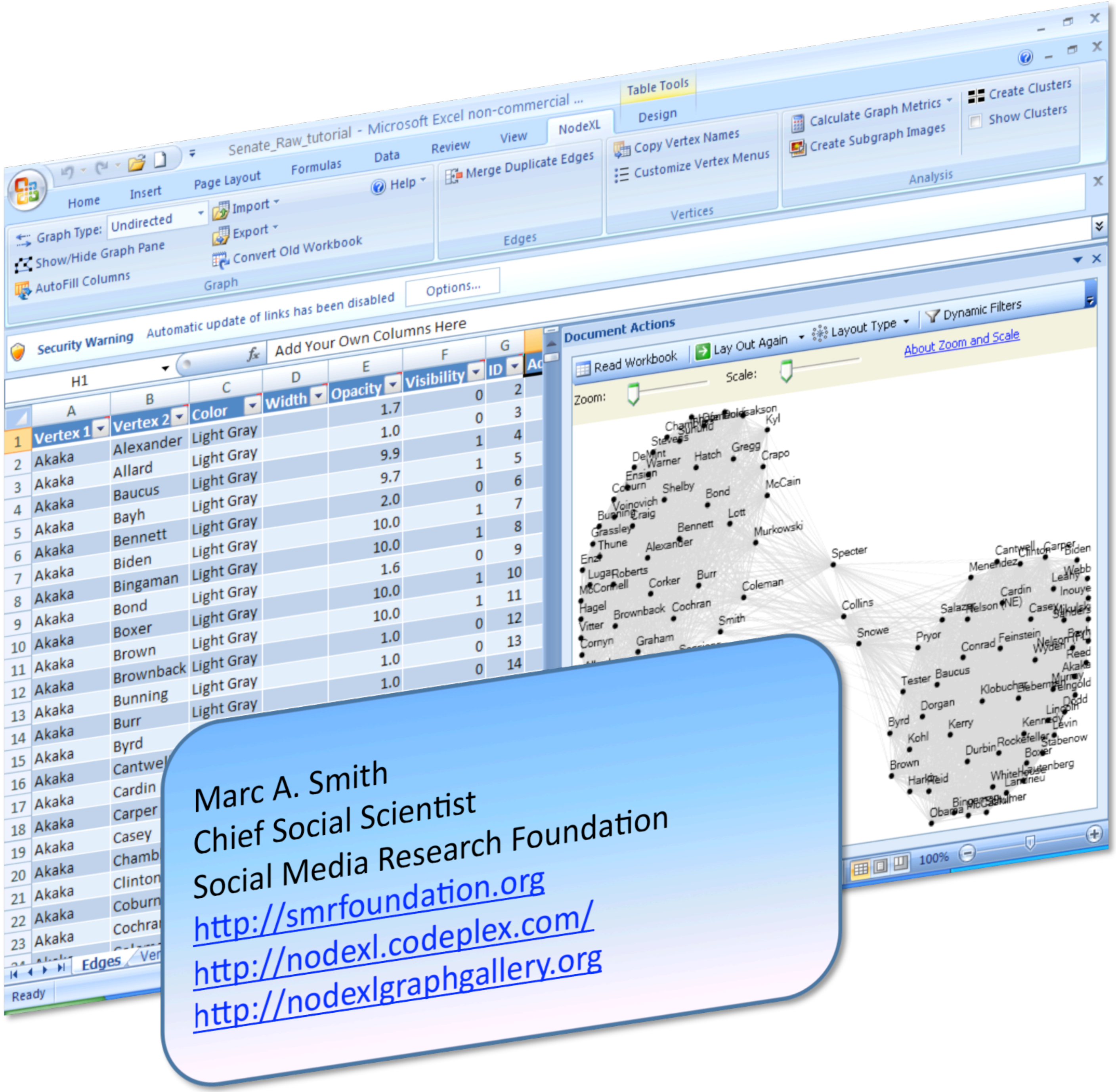
Map Social Media Connections with Excel & NodeXL

Mapping social media networks
to find
Influencers, Groups & Key Topics



Marc A. Smith
Chief Social Scientist
Social Media Research Foundation
http://smrfoundation.org
http://nodexl.codeplex.com/
http://nodexlgraphgallery.org

socialmedia
RESEARCH FOUNDATION

A project from the Social Media Research Foundation: http://www.smrfoundation.org

About Me

Introductions

Marc A. Smith
Chief Social Scientist / Director
Social Media Research Foundation

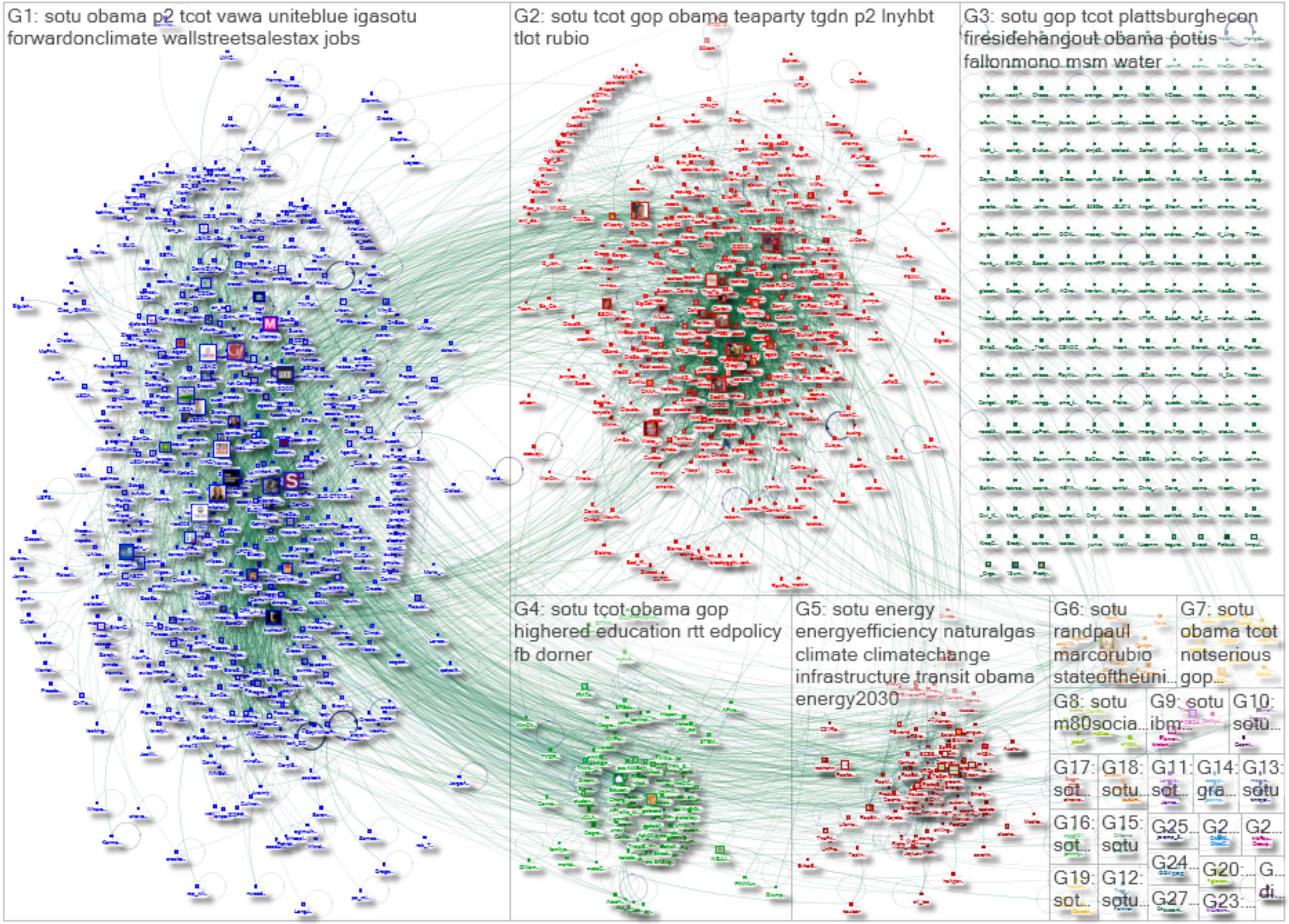
marc@smrfoundation.org
http://www.smrfoundation.org
http://www.codeplex.com/nodexl
http://www.twitter.com/marc_smith
http://www.linkedin.com/in/marcasmith
http://www.slideshare.net/Marc_A_Smith
http://www.flickr.com/photos/marc_smith
http://www.facebook.com/marc.smith.sociologist

Crowds matter

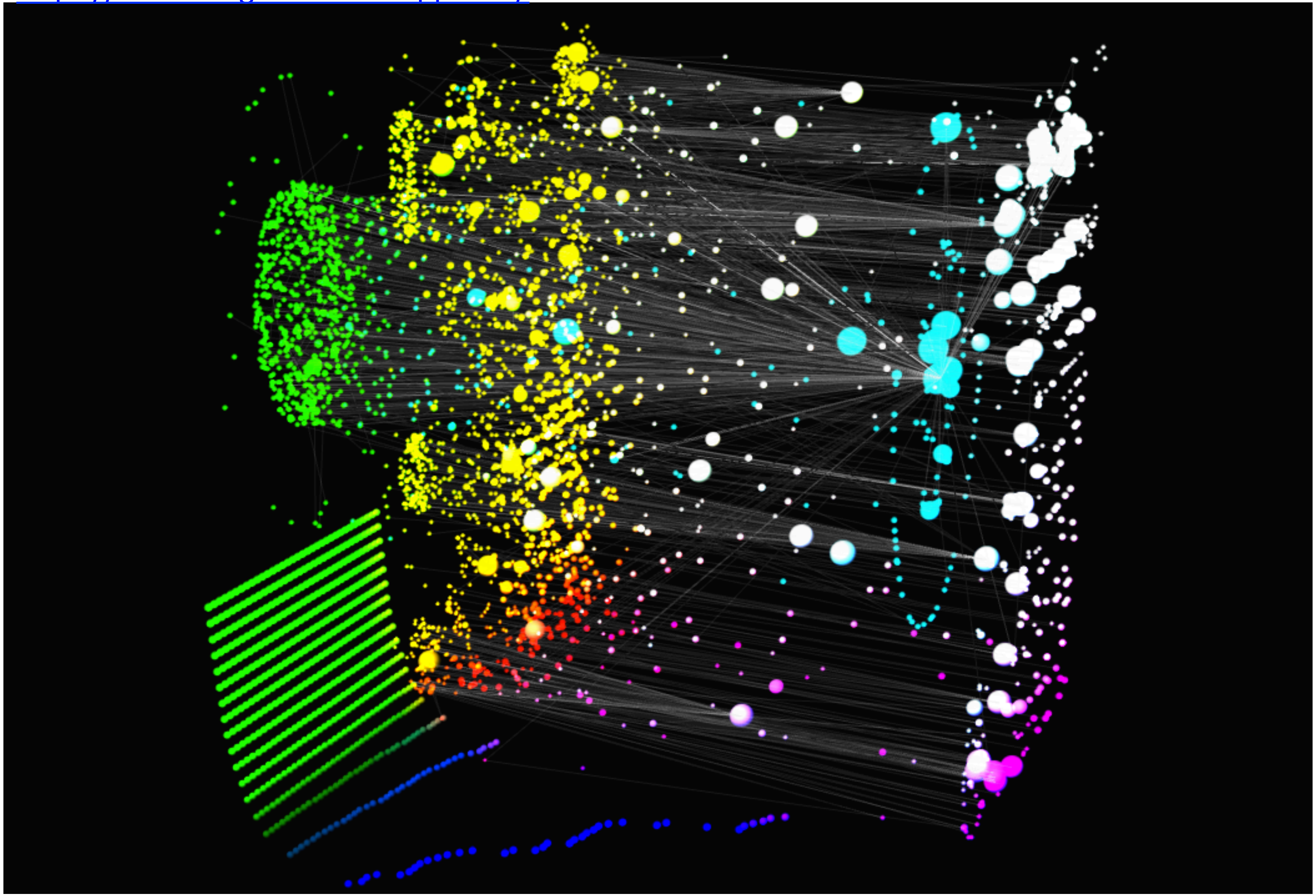
Crowds in social media matter

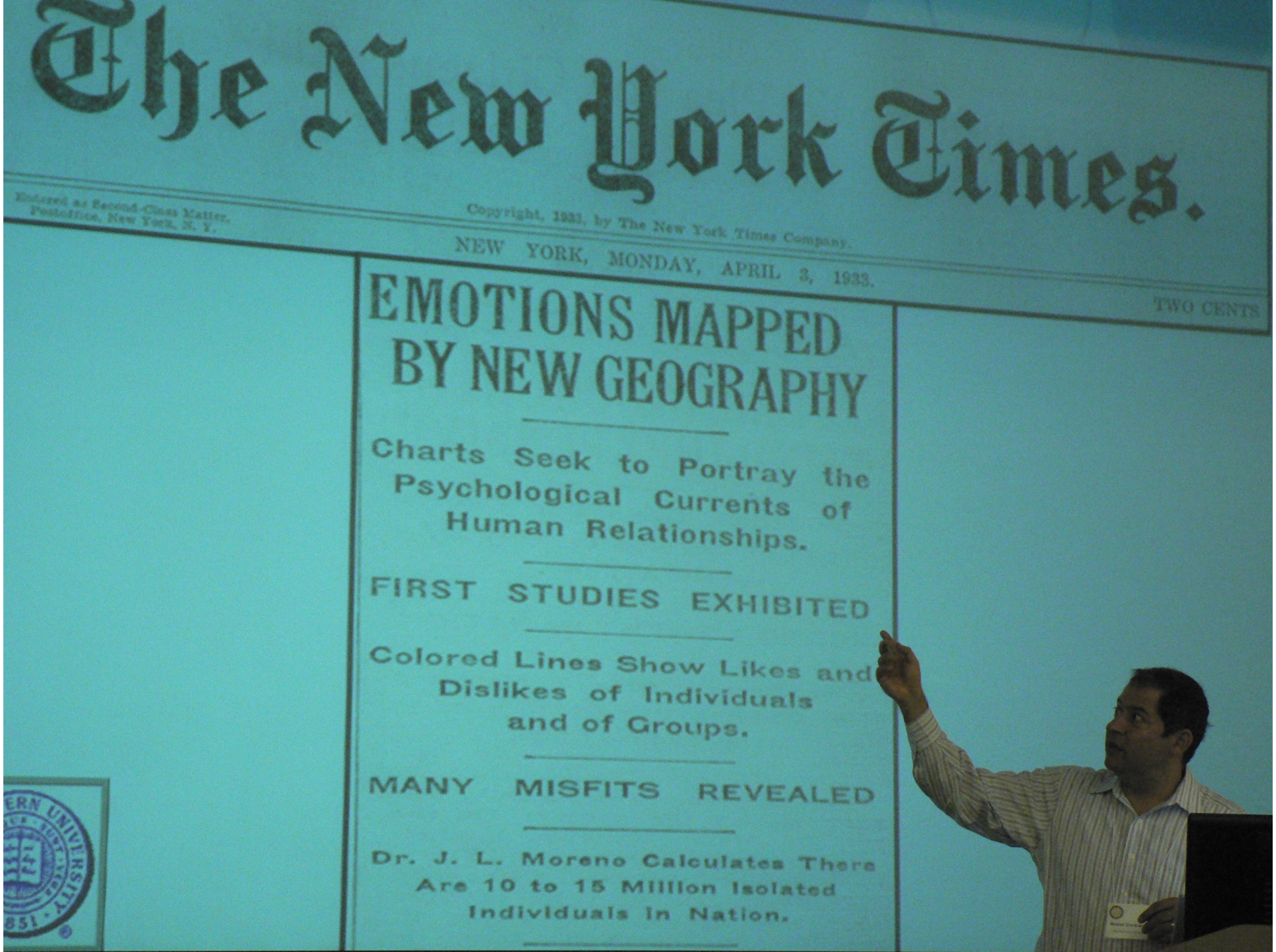
http://www.flickr.com/photos/amycgx/3119640267/

Crowds in social media have a hidden structure



https://demo-3dg-viz.herokuapp.com/

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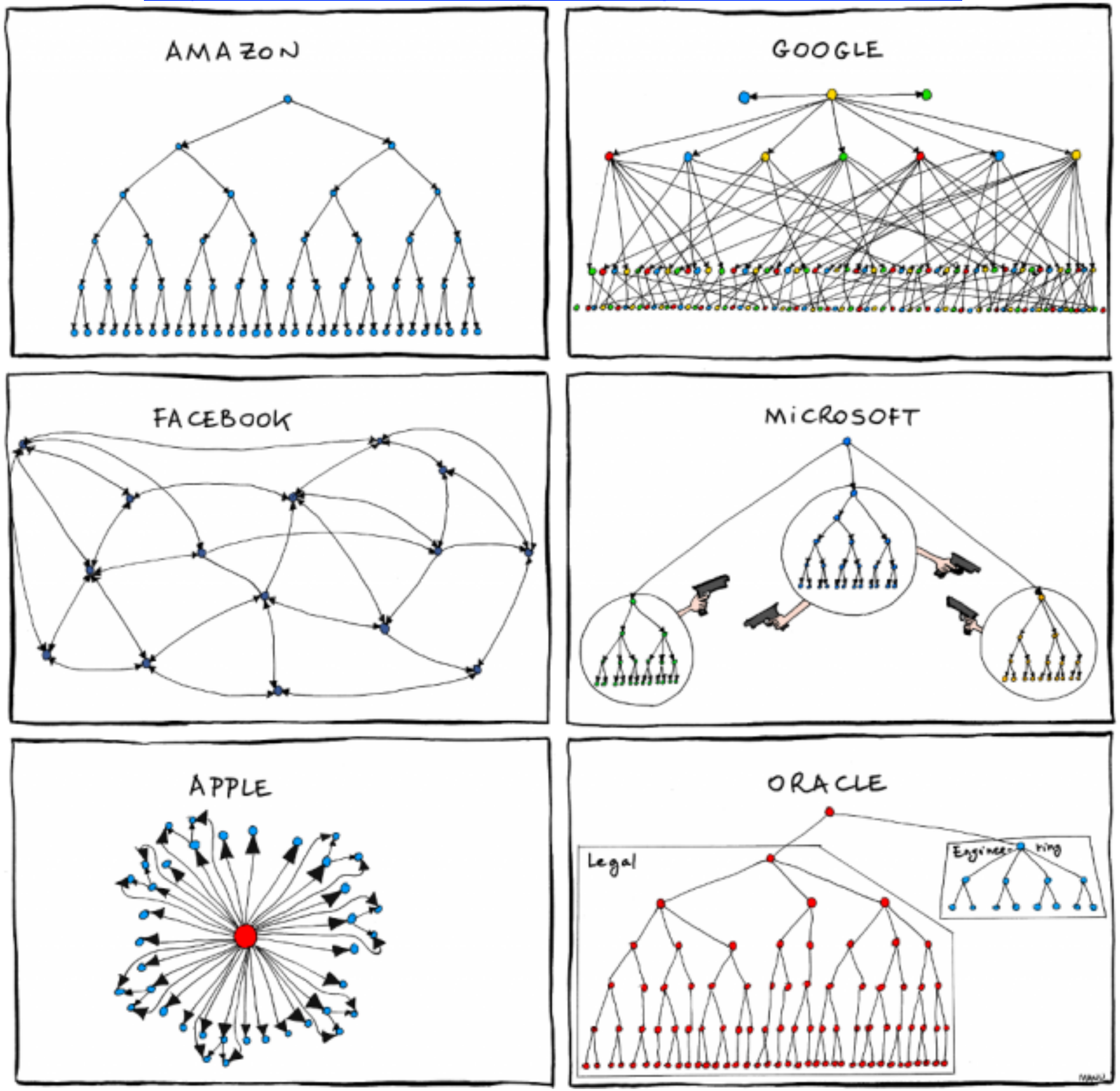
TWO CENTS
EMOTIONS MAPPED BY NEW GEOGRAPHY
Charts Seek to Portray the Psychological Currents of Human Relationships.
FIRST STUDIES EXHIBITED
Colored Lines Show Likes and Dislikes of Individuals and of Groups.
MANY MISFITS REVEALED
Dr. J. L. Moreno Calculates There Are 10 to 15 Million Isolated Individuals in Nation.

http://www.bonkersworld.net/organizational-charts/



Kodak Brownie Snap-Shot Camera

The first
easy to use
point and shoot!

socialmedia
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ViviCam F128
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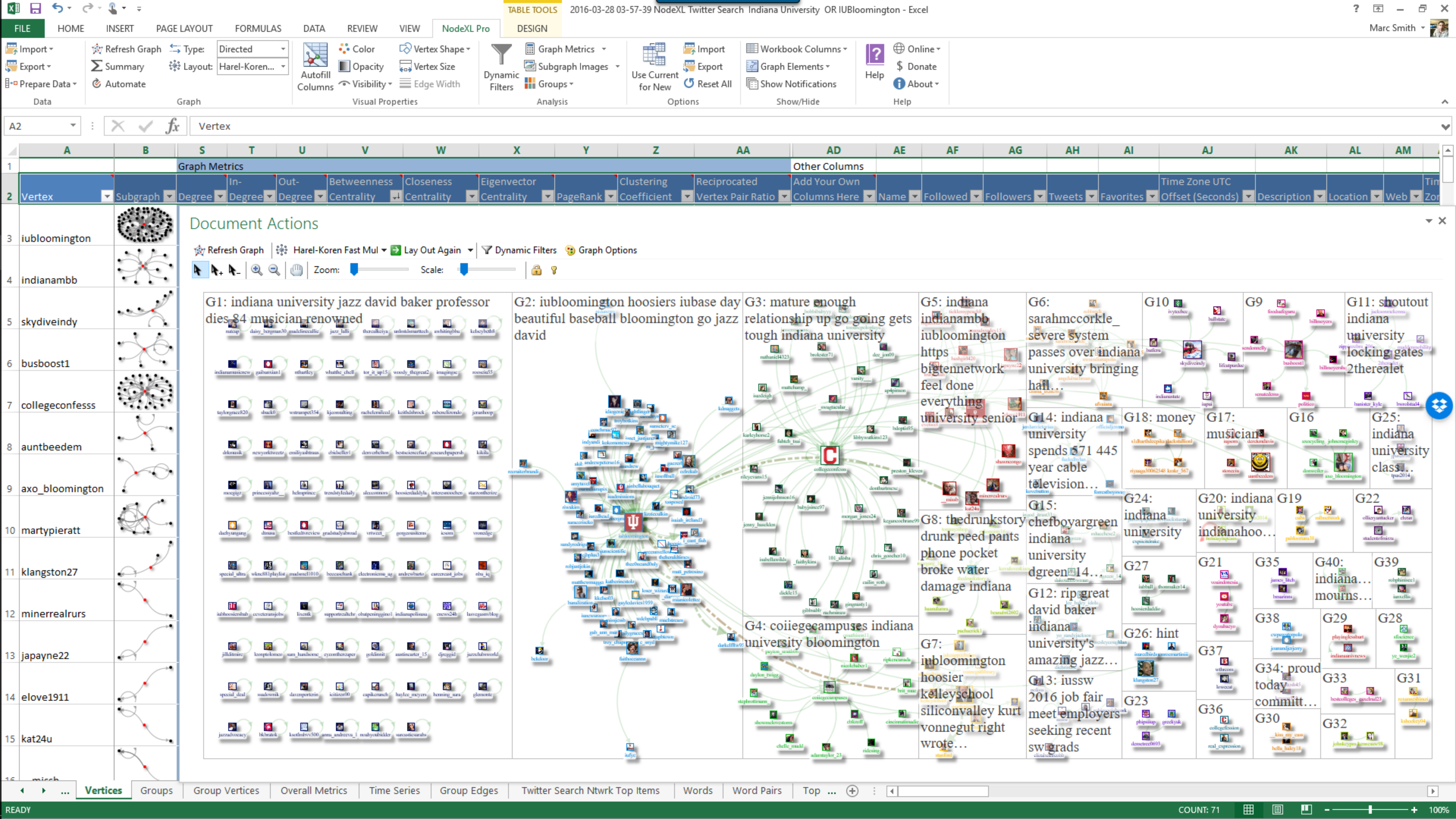
Camera


2016-03-28 03-57-39 NodeXL Twitter Search Indiana University OR IUBloomington - Excel
TABLE TOOLS
FILE HOME INSERT PAGE LAYOUT FORMULAS DATA REVIEW VIEW NodeXL Pro DESIGN
Marc Smith
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Data
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indianambb
skydiveindy
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G13: iussw 2016 job fair meet employers seeking recent sw grads
G14: indiana university spends 571 445 year cable television...
G15: chefboyargreen indiana university dgreen 14...
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COUNT: 71
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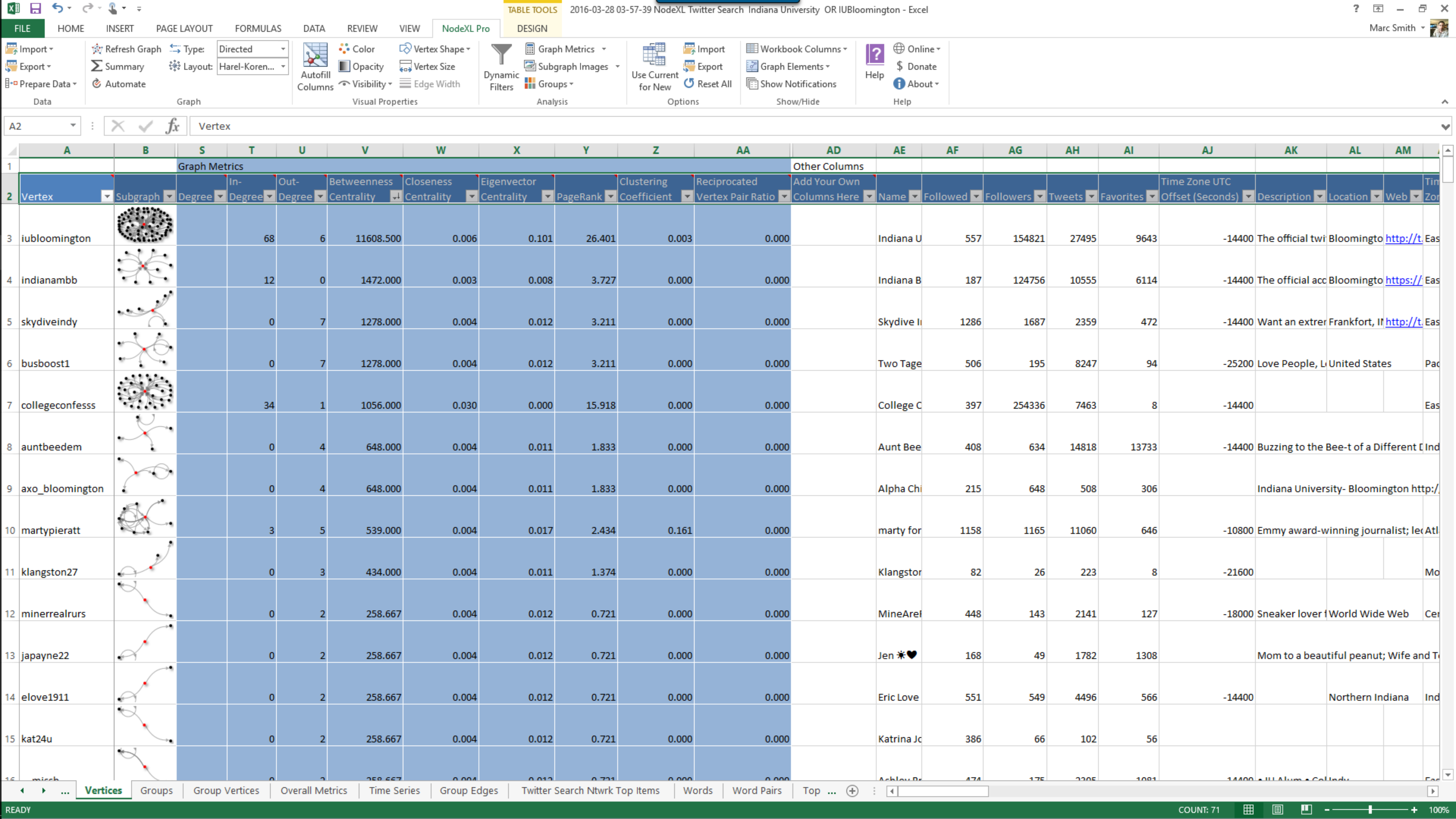

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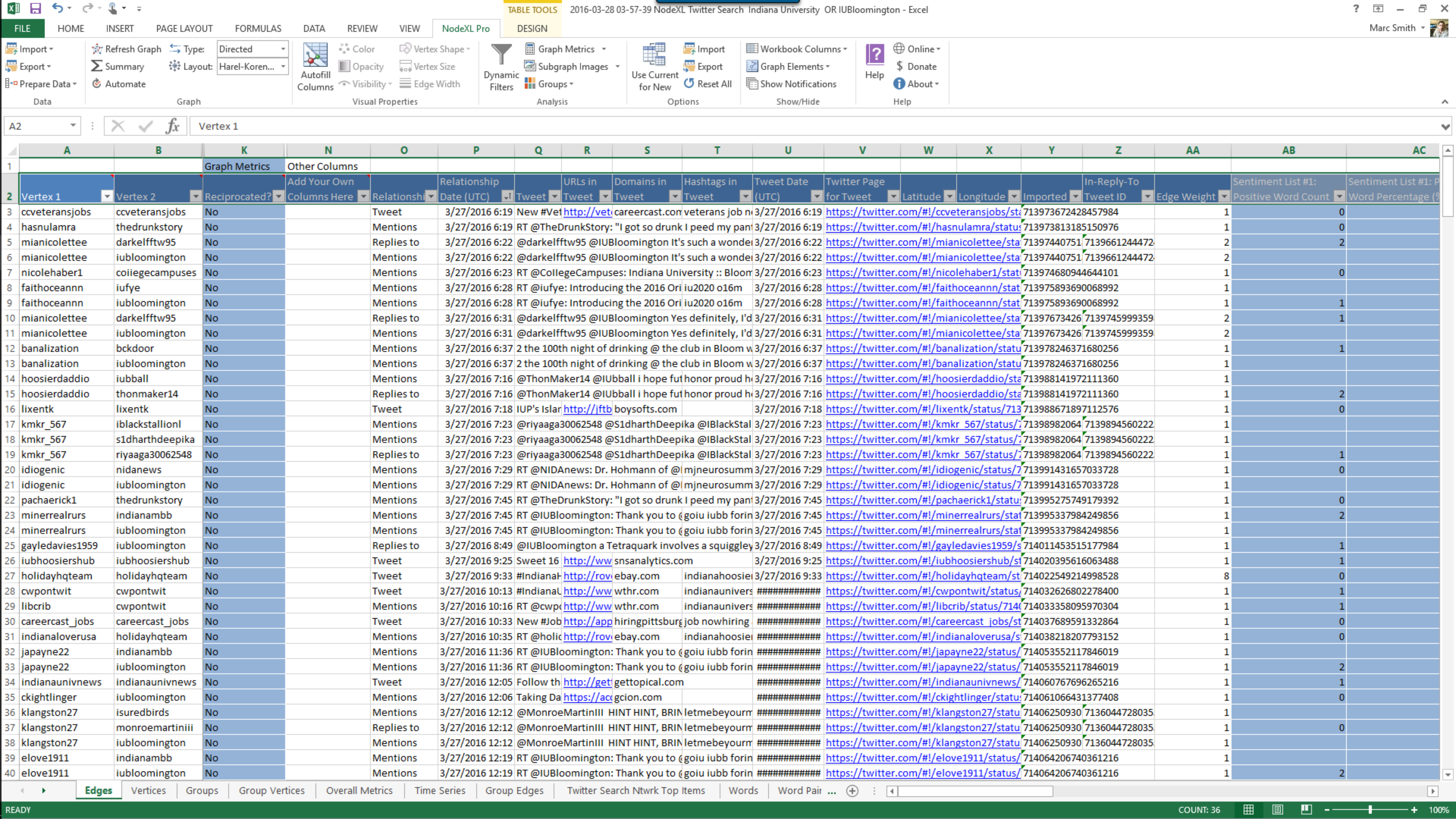

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3	ccveteransjobs	ccveteransjobs	No		Tweet	3/27/2016 6:19	New #Vet	http://vet	careercast.con	veterans job n	3/27/2016 6:19	https://twitter.com/#!/ccveteransjobs/sta			713973672428457984		1	0	
4	hasnulamra	thedrunkstory	No		Mentions	3/27/2016 6:19	RT @TheDrunkStory: "I got so drunk I peed my pant				3/27/2016 6:19	https://twitter.com/#!/hasnulamra/status			713973813185150976		1	0	
5	mianicolettee	darkelfftw95	No		Replies to	3/27/2016 6:22	@darkelfftw95 @IUBloomington It's such a wonder				3/27/2016 6:22	https://twitter.com/#!/mianicolettee/sta			71397440751	7139661244472	2	2	
6	mianicolettee	iubloomington	No		Mentions	3/27/2016 6:22	@darkelfftw95 @IUBloomington It's such a wonder				3/27/2016 6:22	https://twitter.com/#!/mianicolettee/sta			71397440751	7139661244472	2		
7	nicolehaber1	coiiegecampuses	No		Mentions	3/27/2016 6:23	RT @CollegeCampuses: Indiana University :: Bloom				3/27/2016 6:23	https://twitter.com/#!/nicolehaber1/stat			713974680944644101		1	0	
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12	banalization	bckdoor	No		Mentions	3/27/2016 6:37	2 the 100th night of drinking @ the club in Bloom w				3/27/2016 6:37	https://twitter.com/#!/banalization/statu			713978246371680256		1	1	
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15	hoosierdaddio	thonmaker14	No		Replies to	3/27/2016 7:16	@ThonMaker14 @IUbball i hope fut			honor proud h	3/27/2016 7:16	https://twitter.com/#!/hoosierdaddio/sta			713988141972111360		1	2	
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17	kmkr_567	iblackstallionl	No		Mentions	3/27/2016 7:23	@riyaaga30062548 @S1dharthDeepika @IBlackStal				3/27/2016 7:23	https://twitter.com/#!/kmkr_567/status/7			71398982064	7139894560222	1		
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25	gayledavies1959	iubloomington	No		Replies to	3/27/2016 8:49	@IUBloomington a Tetraquark involves a squiggley				3/27/2016 8:49	https://twitter.com/#!/gayledavies1959/s			714011453515177984		1	1	
26	iubhoosiershub	iubhoosiershub	No		Tweet	3/27/2016 9:25	Sweet 16	http://ww	snsanalytics.com		3/27/2016 9:25	https://twitter.com/#!/iubhoosiershub/st			714020395616063488		1	1	
27	holidayhqteam	holidayhqteam	No		Tweet	3/27/2016 9:33	#IndianaH	http://rov	ebay.com	indianahoosie	3/27/2016 9:33	https://twitter.com/#!/holidayhqteam/st			714022549214998528		8	0	
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32	japayne22	indianambb	No		Mentions	3/27/2016 11:36	RT @IUBloomington: Thank you to (			goiu iubb forin	############	https://twitter.com/#!/japayne22/status/			714053552117846019		1		
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34	indianaunivnews	indianaunivnews	No		Tweet	3/27/2016 12:05	Follow th	http://get	gettopical.com		############	https://twitter.com/#!/indianaunivnews/			714060767696265216		1	1	
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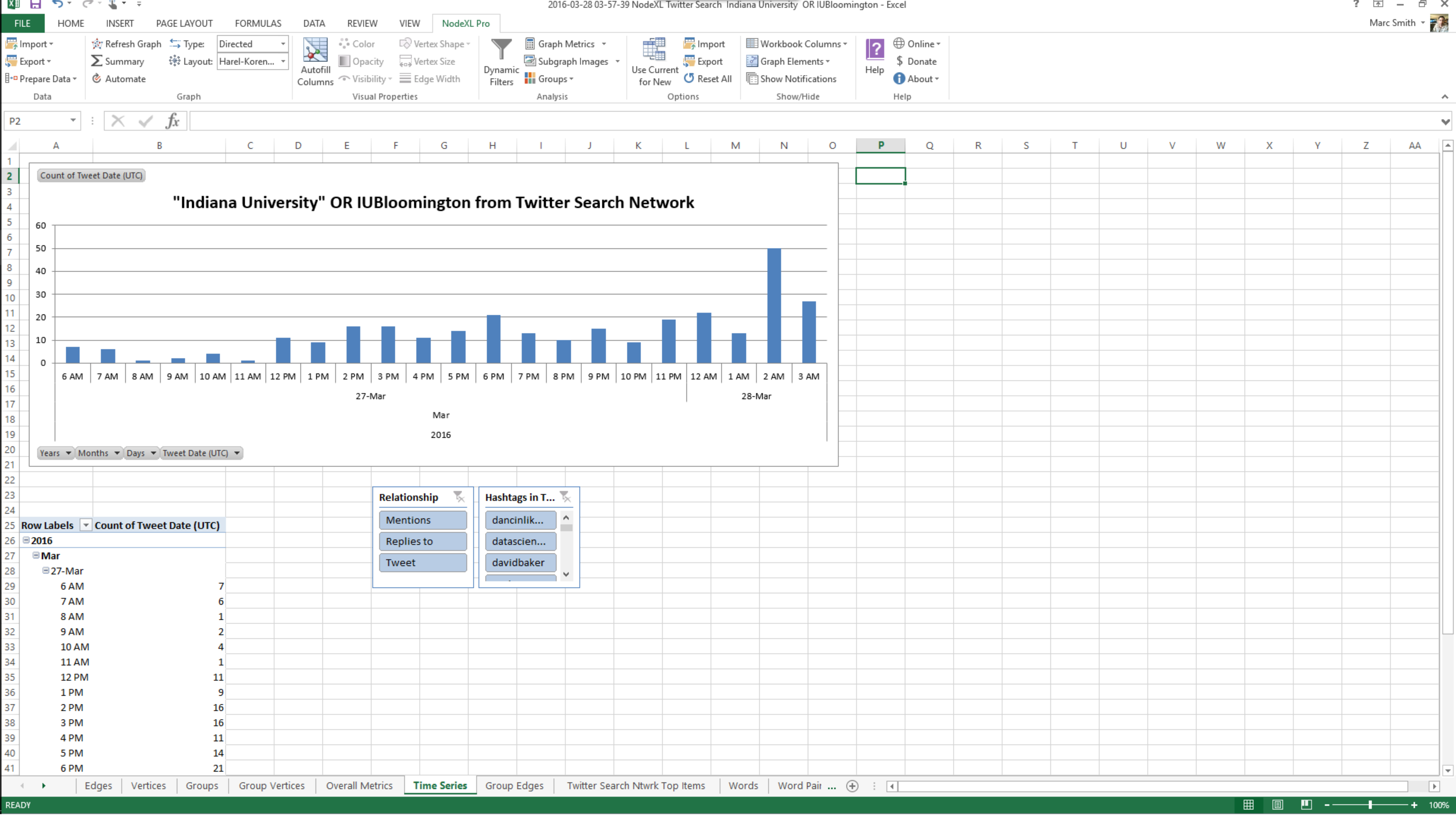
2016-03-28 03-57-39 NodeXL Twitter Search Indiana University OR IUBloomington - Excel
FILE
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Marc Smith
Import
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Prepare Data
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Layout: Harel-Koren...
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Vertex Shape
Vertex Size
Edge Width
Visual Properties
Dynamic Filters
Graph Metrics
Subgraph Images
Groups
Analysis
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Export
Reset All
Options
Workbook Columns
Graph Elements
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5 PM 14
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Edges
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Group Vertices
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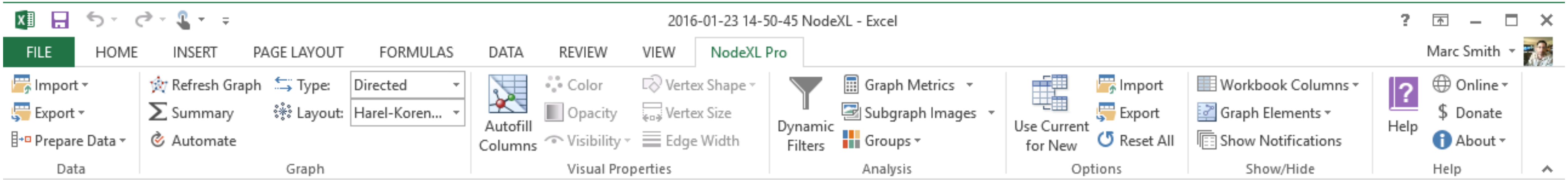
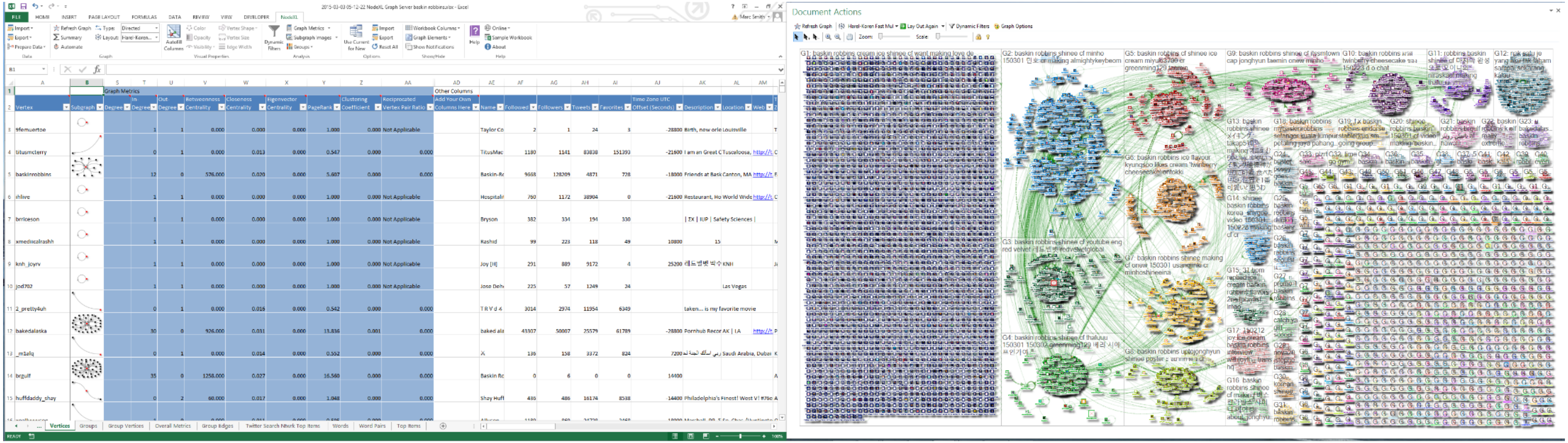
READY
100%

NodeXL Ribbon in Excel





NodeXL in Excel

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We envision hundreds of NodeXL data collectors around the world collectively generating an archive of social media network snapshots on a wide range of topics.

http://msnbcmedia.msn.com/i/msnbc/Components/Photos/071012/071012_telescope_hmed_3p.jpg

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http://www.smrfoundation.org

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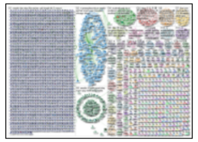
NodeXL GraphGallery
The Social Media Research Foundation

Search

These are network graphs created with NodeXL, a template for graphing network data in Excel® (2007, 2010, 2013 and 2016).

Recent graphs: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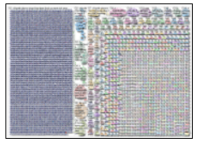
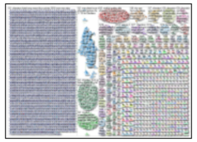

Chipotle_2016-01-22_20-...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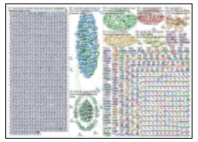
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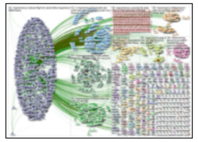
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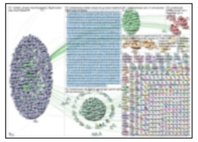
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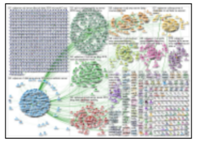
%22air miles%22 OR %22f...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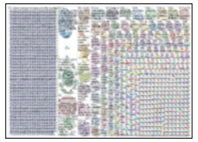
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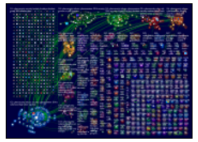
SkollWorldForum OR jeff...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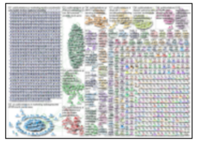
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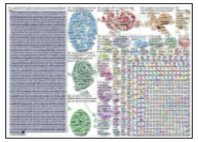
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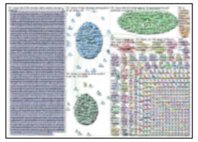
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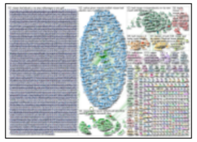
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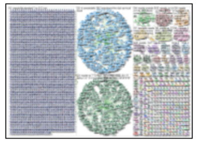
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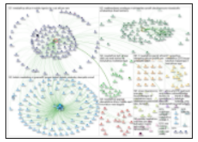
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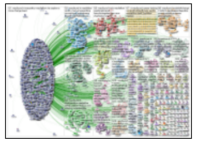
macfound_2016-01-22_06-...


Coalition to Protect Am...

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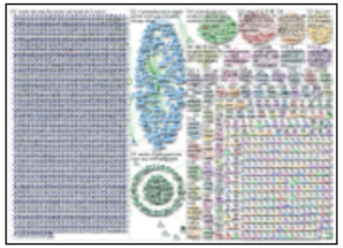
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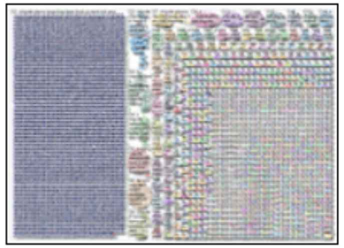
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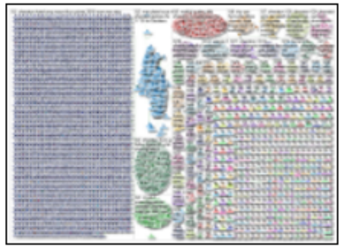
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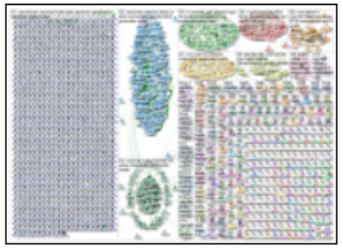
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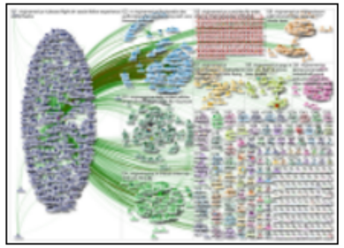
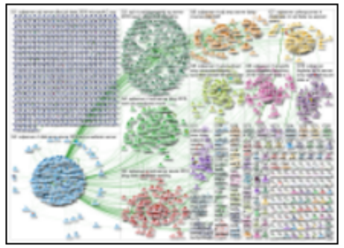

VirginAmerica_2016-01-2...


lufthansa_2016-01-22_17...


BritishAirways_2016-01-...


@klm_2016-01-22_17-17-1...


%22air miles%22 OR %22f...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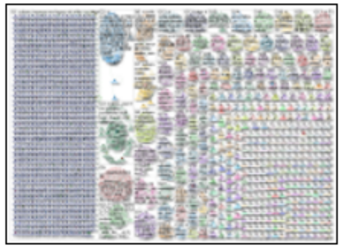
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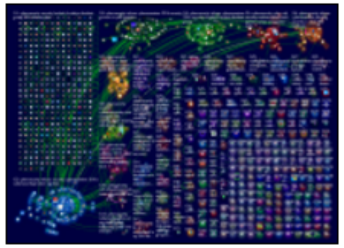
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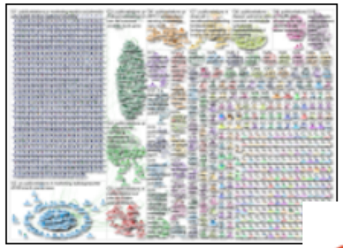
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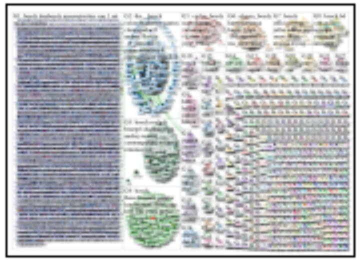

Bosch Twitter NodeXL SN...

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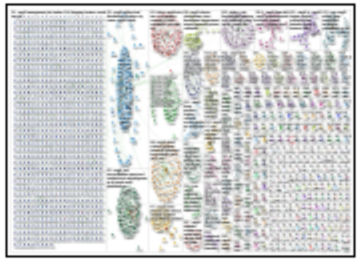

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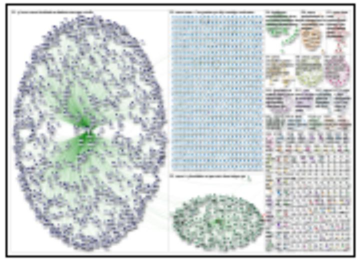

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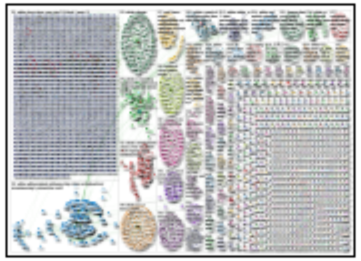
dataviz OR datavis_2016...

datascientist_2016-01-2...

NodeXL Twitter Network ...



adidas Twitter NodeXL S...

Garmin Twitter NodeXL ...

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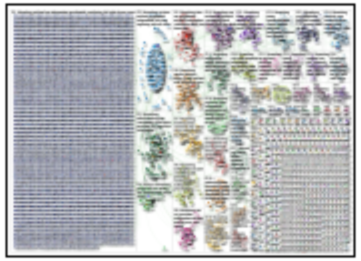

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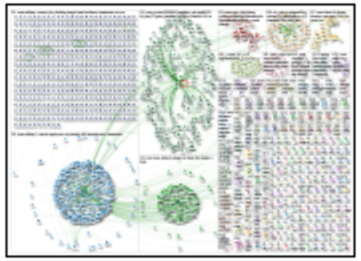

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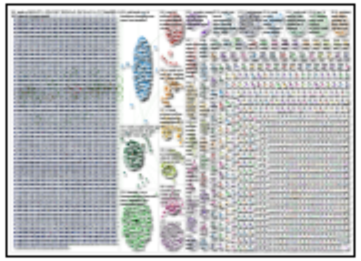

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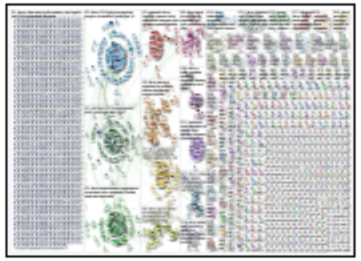

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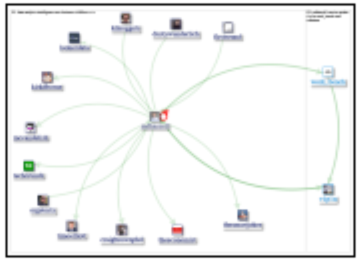

mdhassell Twitter NodeX...

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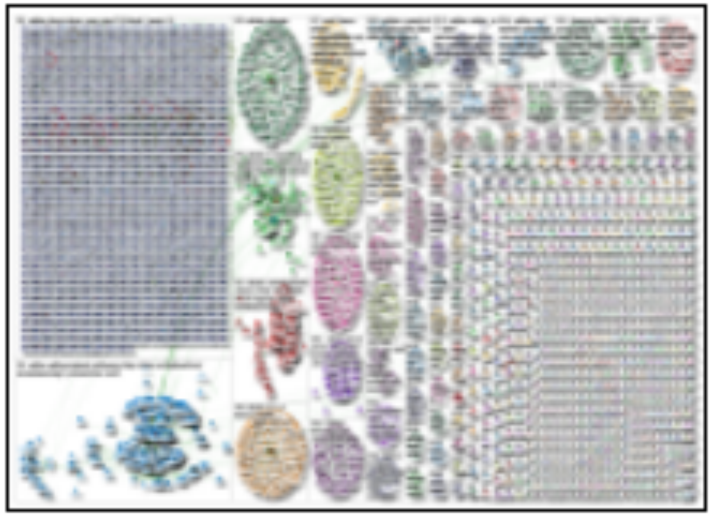
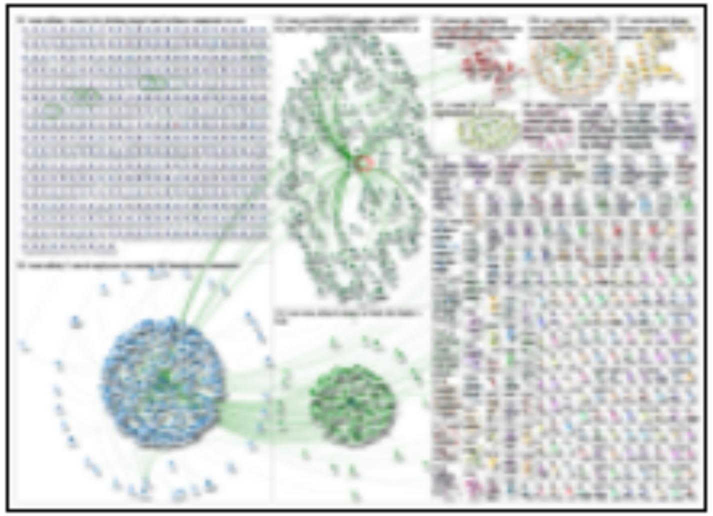


adidas Twitter NodeXL S...

Garmin Twitter NodeXL ...



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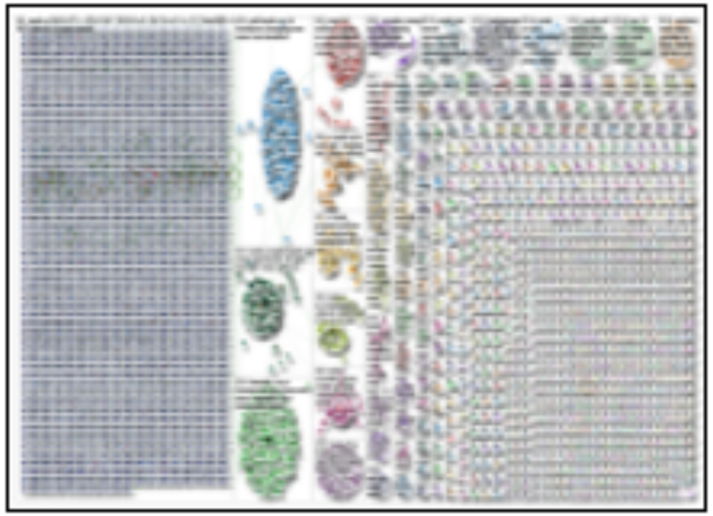

E*TRADE Twitter NodeXL...

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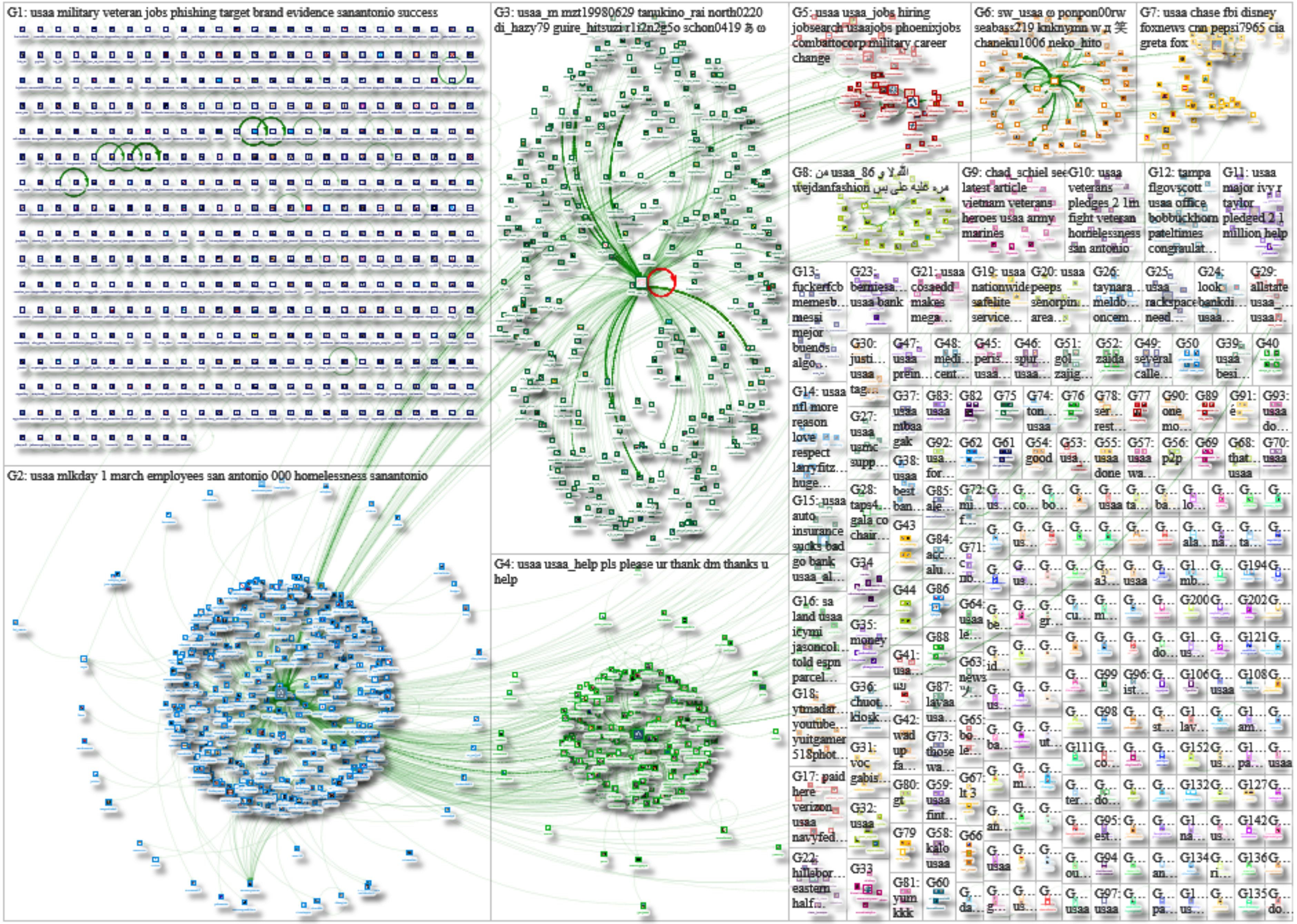

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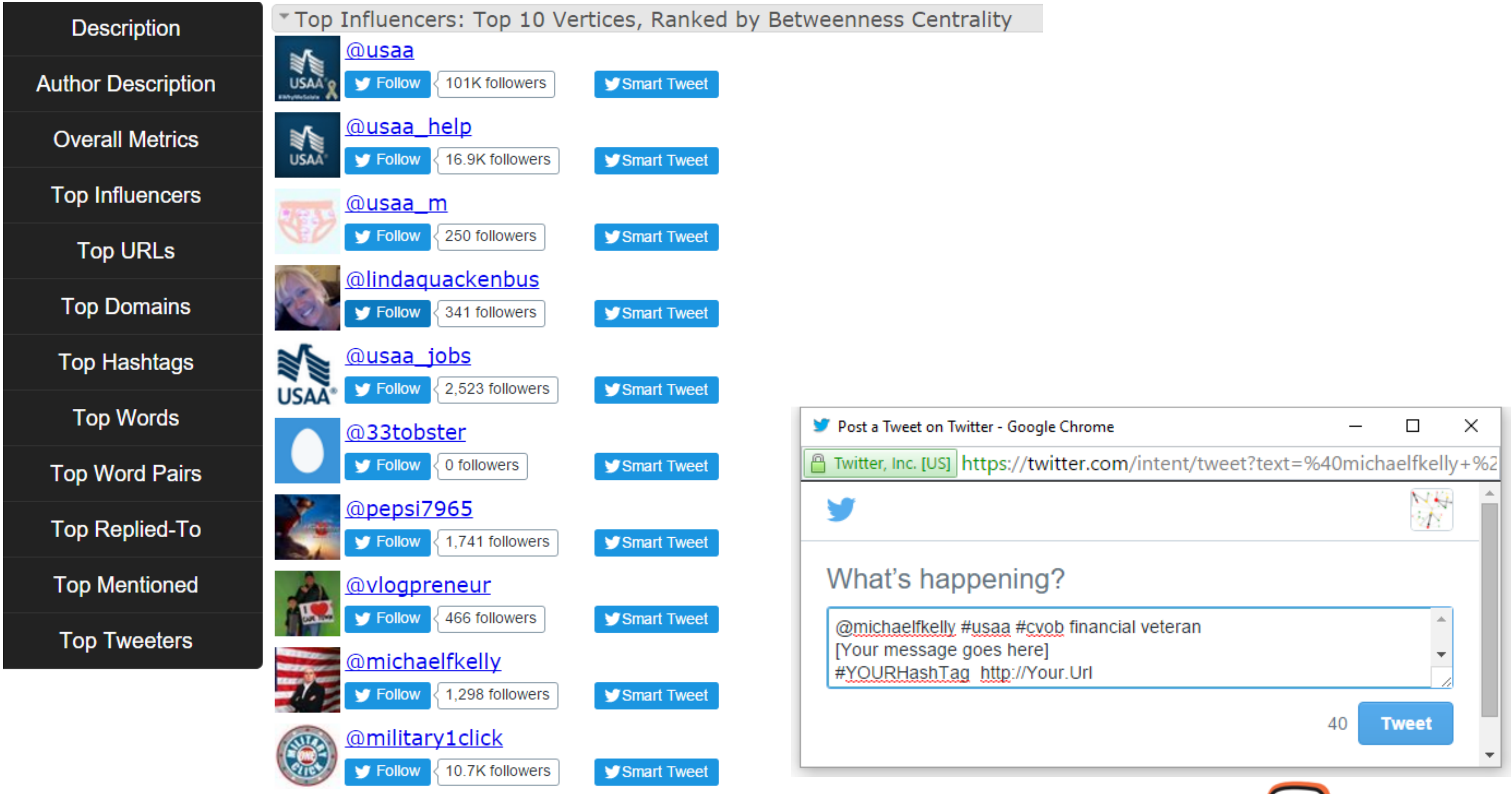

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- Description
- Author Description
- Overall Metrics
- Top Influencers
- Top URLs
- Top Domains
- Top Hashtags
- Top Words
- Top Word Pairs
- Top Replied-To
- Top Mentioned
- Top Tweeters

Top Hashtags

Top Hashtags in Tweet in Entire Graph:

[214] usaa
[158] sanantonio
[126] mlkday
[106] military
[90] jobs
[79] phishing
[74] veterans
[68] success
[66] veteran
[60] job

Top Hashtags in Tweet in G1:

[126] usaa
[104] military
[75] phishing
[69] sanantonio
[68] jobs
[68] success
[64] veteran
[52] job
[44] veterans
[36] podcast

Top Hashtags in Tweet in G2:

[121] mlkday
[61] sanantonio
[58] armynavy
[28] legacy
[28] dream
[28] honor
[25] homelessness
[13] usaaserves
[11] nbavote
[8] salutetoservice

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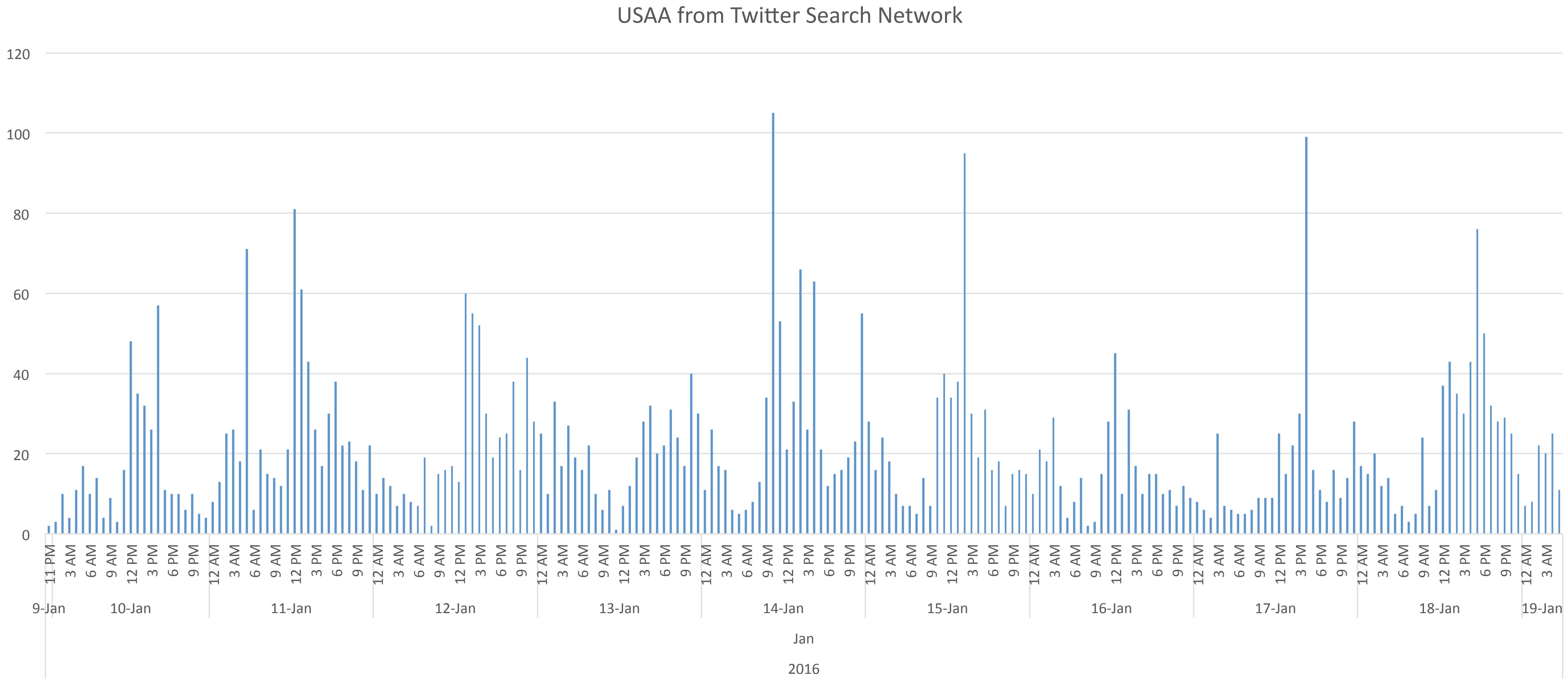

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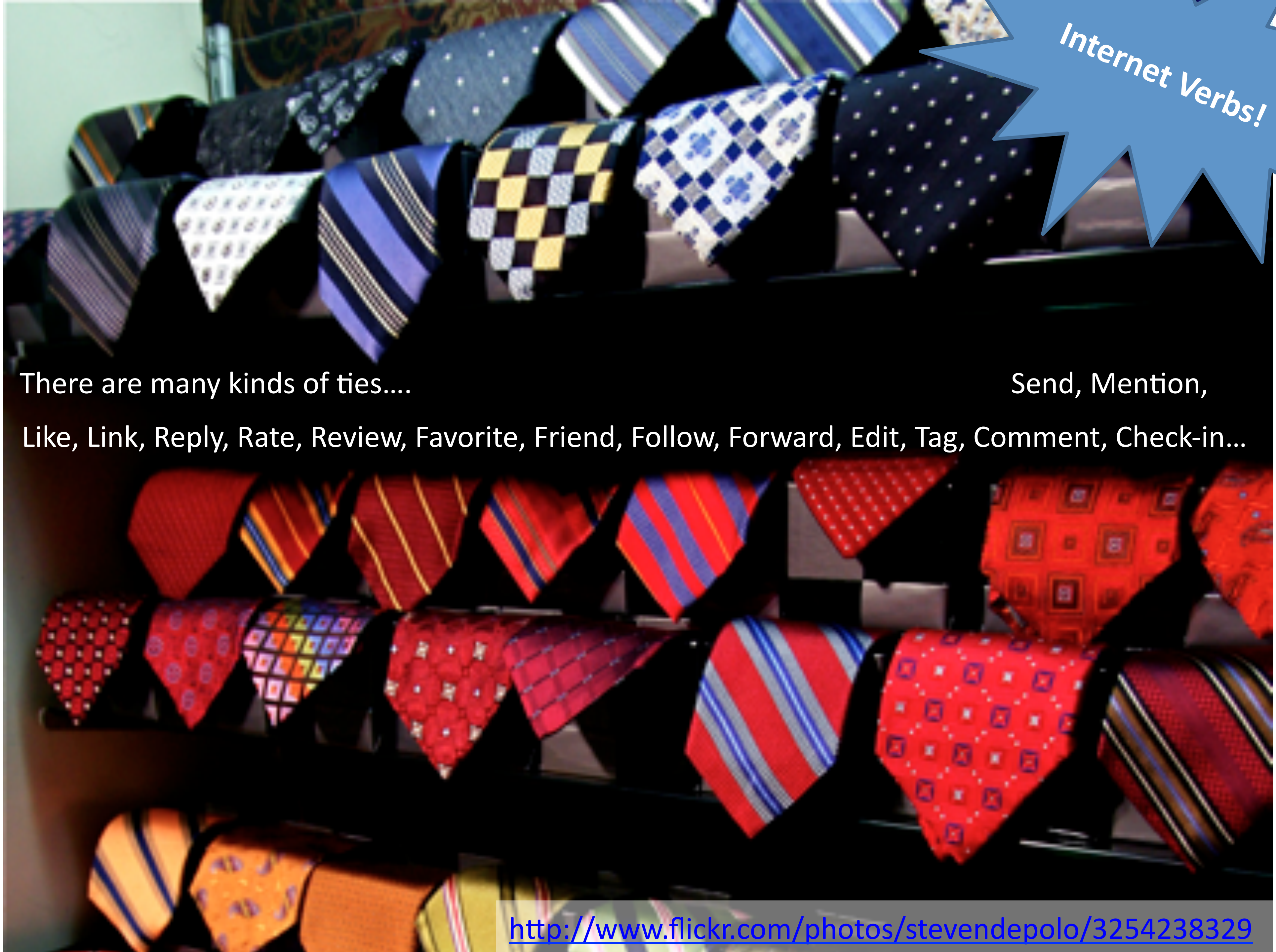
Social Media
(email, Facebook,
Twitter, YouTube, &
more) is all about
connections
from people
to people.


Patterns are
left
behind



Internet Verbs!

There are many kinds of ties.... Send, Mention,

Like, Link, Reply, Rate, Review, Favorite, Friend, Follow, Forward, Edit, Tag, Comment, Check-in...

http://www.flickr.com/photos/stevendepolo/3254238329

Crowds in social media form networks

twitter

facebook

VOSON

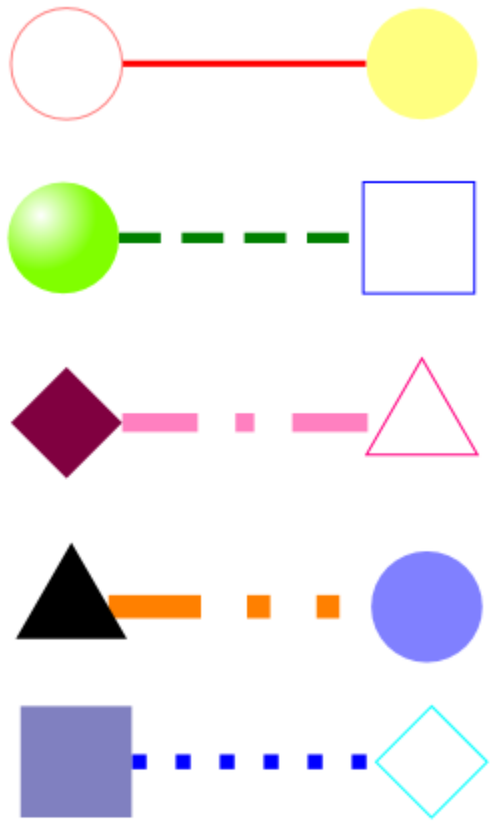
World Wide Web

flickr from YAHOO!

YouTube

WIKIPEDIA

Social media must contain one or more social networks



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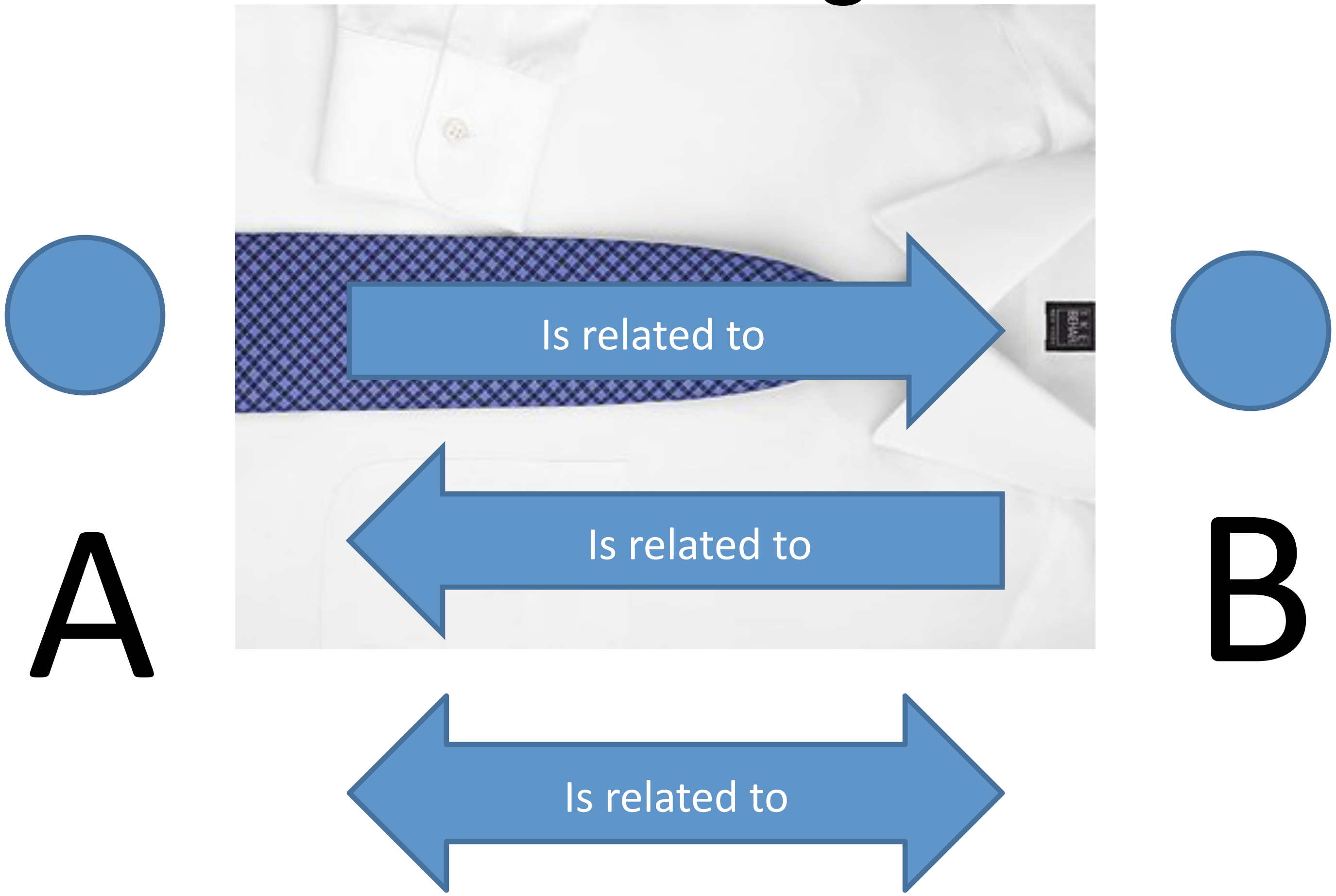
“Think Link”

Nodes & Edges



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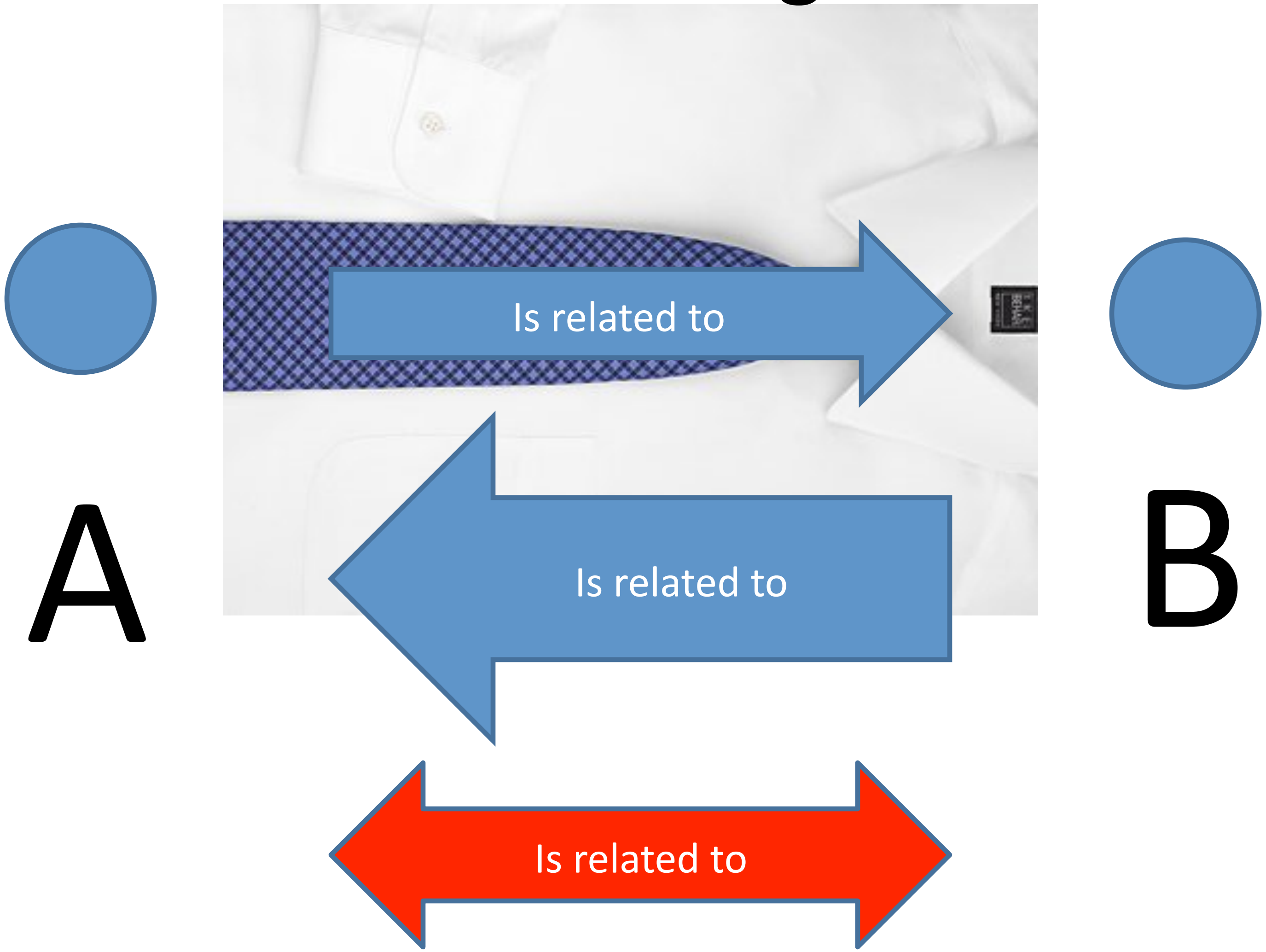
“Think Link”

Nodes & Edges



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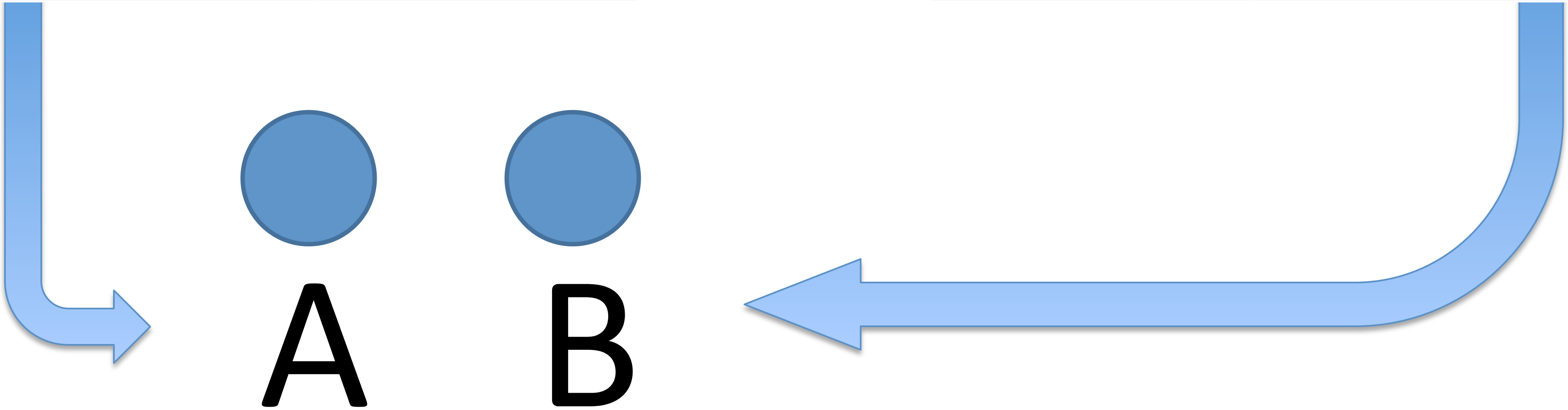
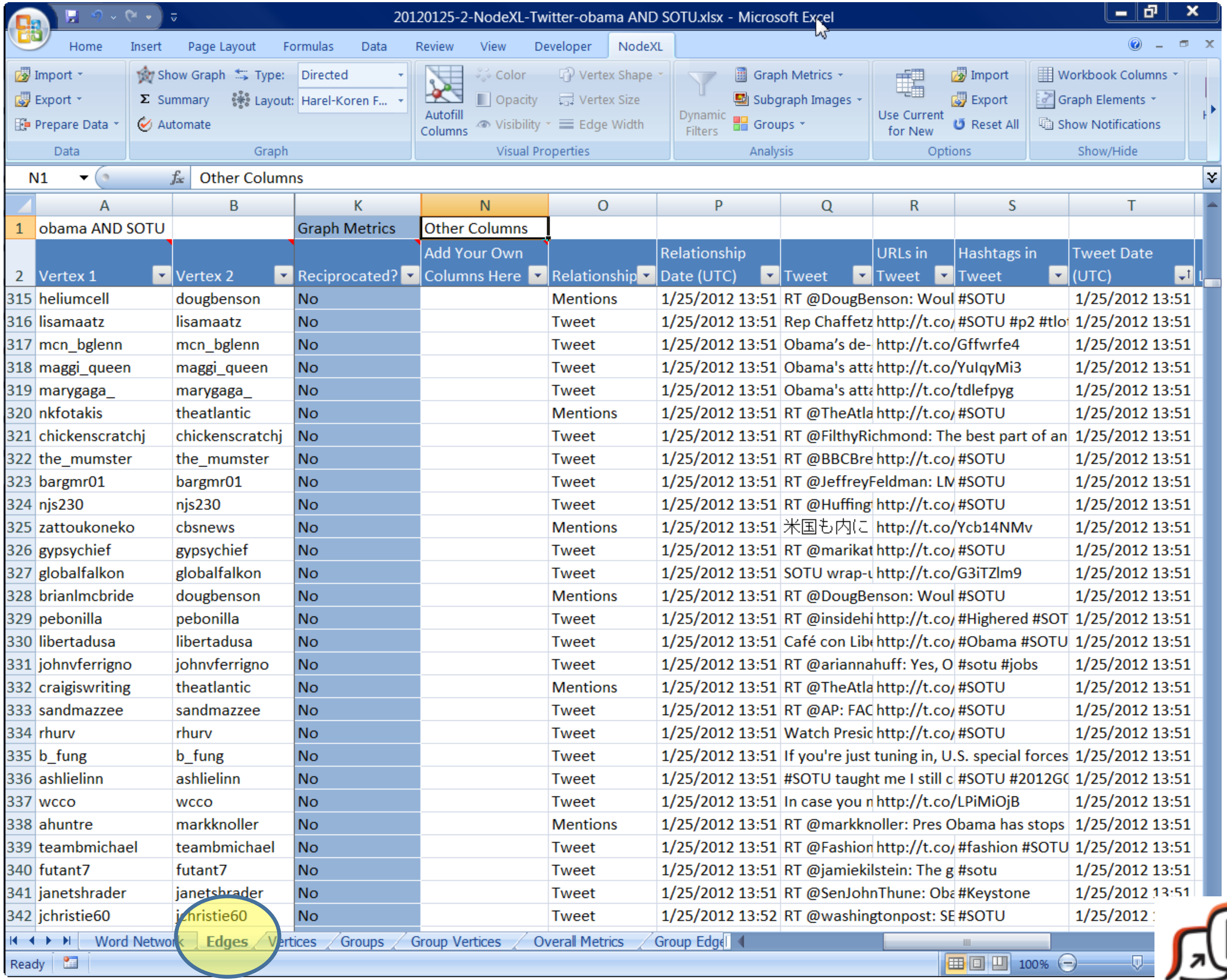
A network is born whenever two GUIDs are joined.

Username	Attributes
@UserName1	Value, value

Username	Attributes
@UserName2	Value, value



Vertex1	Vertex 2	“Edge” Attribute	“Vertex1” Attribute	“Vertex2” Attribute
@UserName1	@UserName2	value	value	value



	Vertex 1	Vertex 2	Reciprocated?	Add Your Own Columns Here	Relationship	Relationship Date (UTC)	Tweet	URLs in Tweet	Hashtags in Tweet	Tweet Date (UTC)
315	heliumcell	dougbenson	No		Mentions	1/25/2012 13:51	RT @DougBenson: Woul		#SOTU	1/25/2012 13:51
316	lisamaatz	lisamaatz	No		Tweet	1/25/2012 13:51	Rep Chaffetz	http://t.co/	#SOTU #p2 #tlo	1/25/2012 13:51
317	mcn_bglenn	mcn_bglenn	No		Tweet	1/25/2012 13:51	Obama's de-	http://t.co/Gffwrfe4		1/25/2012 13:51
318	maggi_queen	maggi_queen	No		Tweet	1/25/2012 13:51	Obama's atta	http://t.co/YuIqyMi3		1/25/2012 13:51
319	marygaga_	marygaga_	No		Tweet	1/25/2012 13:51	Obama's atta	http://t.co/tdlefpyg		1/25/2012 13:51
320	nkfotakis	theatlantic	No		Mentions	1/25/2012 13:51	RT @TheAtla	http://t.co/	#SOTU	1/25/2012 13:51
321	chickenscratchj	chickenscratchj	No		Tweet	1/25/2012 13:51	RT @FilthyRichmond: The best part of an			1/25/2012 13:51
322	the_mumster	the_mumster	No		Tweet	1/25/2012 13:51	RT @BBCBre	http://t.co/	#SOTU	1/25/2012 13:51
323	bargmr01	bargmr01	No		Tweet	1/25/2012 13:51	RT @JeffreyFeldman: LM		#SOTU	1/25/2012 13:51
324	njs230	njs230	No		Tweet	1/25/2012 13:51	RT @Huffing	http://t.co/	#SOTU	1/25/2012 13:51
325	zattoukoneko	cbsnews	No		Mentions	1/25/2012 13:51	米国も内に	http://t.co/Ycb14NMv		1/25/2012 13:51
326	gypsychief	gypsychief	No		Tweet	1/25/2012 13:51	RT @marikat	http://t.co/	#SOTU	1/25/2012 13:51
327	globalfalkon	globalfalkon	No		Tweet	1/25/2012 13:51	SOTU wrap-u	http://t.co/G3iTZlm9		1/25/2012 13:51
328	brianlmcbride	dougbenson	No		Mentions	1/25/2012 13:51	RT @DougBenson: Woul		#SOTU	1/25/2012 13:51
329	pebonilla	pebonilla	No		Tweet	1/25/2012 13:51	RT @insidehi	http://t.co/	#Highered #SOT	1/25/2012 13:51
330	libertadusa	libertadusa	No		Tweet	1/25/2012 13:51	Café con Lib	http://t.co/	#Obama #SOTU	1/25/2012 13:51
331	johnvferrigno	johnvferrigno	No		Tweet	1/25/2012 13:51	RT @ariannahuff: Yes, O		#sotu #jobs	1/25/2012 13:51
332	craigiswriting	theatlantic	No		Mentions	1/25/2012 13:51	RT @TheAtla	http://t.co/	#SOTU	1/25/2012 13:51
333	sandmazzee	sandmazzee	No		Tweet	1/25/2012 13:51	RT @AP: FAC	http://t.co/	#SOTU	1/25/2012 13:51
334	rhurv	rhurv	No		Tweet	1/25/2012 13:51	Watch Presic	http://t.co/	#SOTU	1/25/2012 13:51
335	b_fung	b_fung	No		Tweet	1/25/2012 13:51	If you're just tuning in, U.S. special forces			1/25/2012 13:51
336	ashlielinn	ashlielinn	No		Tweet	1/25/2012 13:51	#SOTU taught me I still c		#SOTU #2012G(	1/25/2012 13:51
337	wcco	wcco	No		Tweet	1/25/2012 13:51	In case you r	http://t.co/LPiMiOjB		1/25/2012 13:51
338	ahuntre	markknoller	No		Mentions	1/25/2012 13:51	RT @markknoller: Pres Obama has stops			1/25/2012 13:51
339	teambmichael	teambmichael	No		Tweet	1/25/2012 13:51	RT @Fashion	http://t.co/	#fashion #SOTU	1/25/2012 13:51
340	futant7	futant7	No		Tweet	1/25/2012 13:51	RT @jamiekilstein: The g		#sotu	1/25/2012 13:51
341	janetshrader	janetshrader	No		Tweet	1/25/2012 13:51	RT @SenJohnThune: Oba		#Keystone	1/25/2012 13:51
342	jchristie60	jchristie60	No		Tweet	1/25/2012 13:52	RT @washingtonpost: SE		#SOTU	1/25/2012

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NodeXL imports “edges” from social media data sources

6 kinds of Twitter social media networks

[Divided]
Polarized Crowds

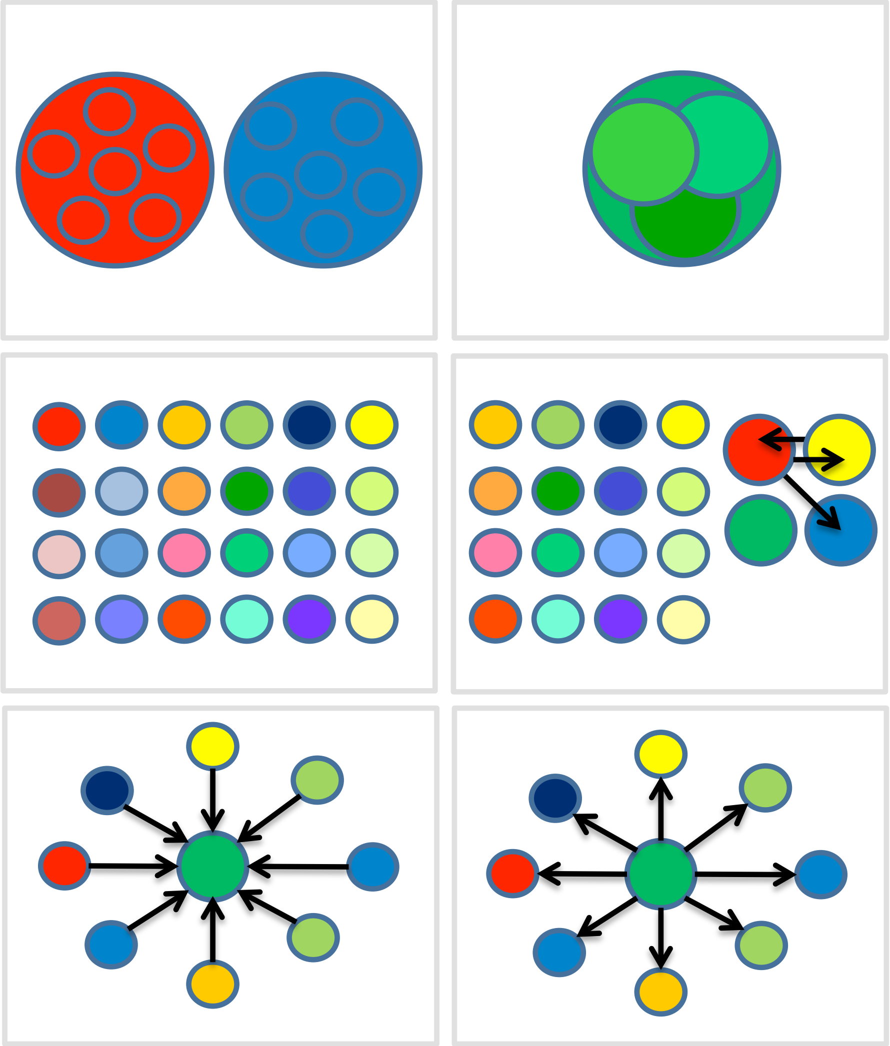
[Unified]
Tight Crowd

[Fragmented]
Brand Clusters

[Clustered]
Community Clusters

[In-Hub & Spoke]
Broadcast Network

[Out-Hub & Spoke]
Support Network



REPORT

FEBRUARY 20, 2014

Mapping Twitter Topic Networks: From Polarized Crowds to Community Clusters

BY MARC A. SMITH, LEE RAINIE, BEN SHNEIDERMAN 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.

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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

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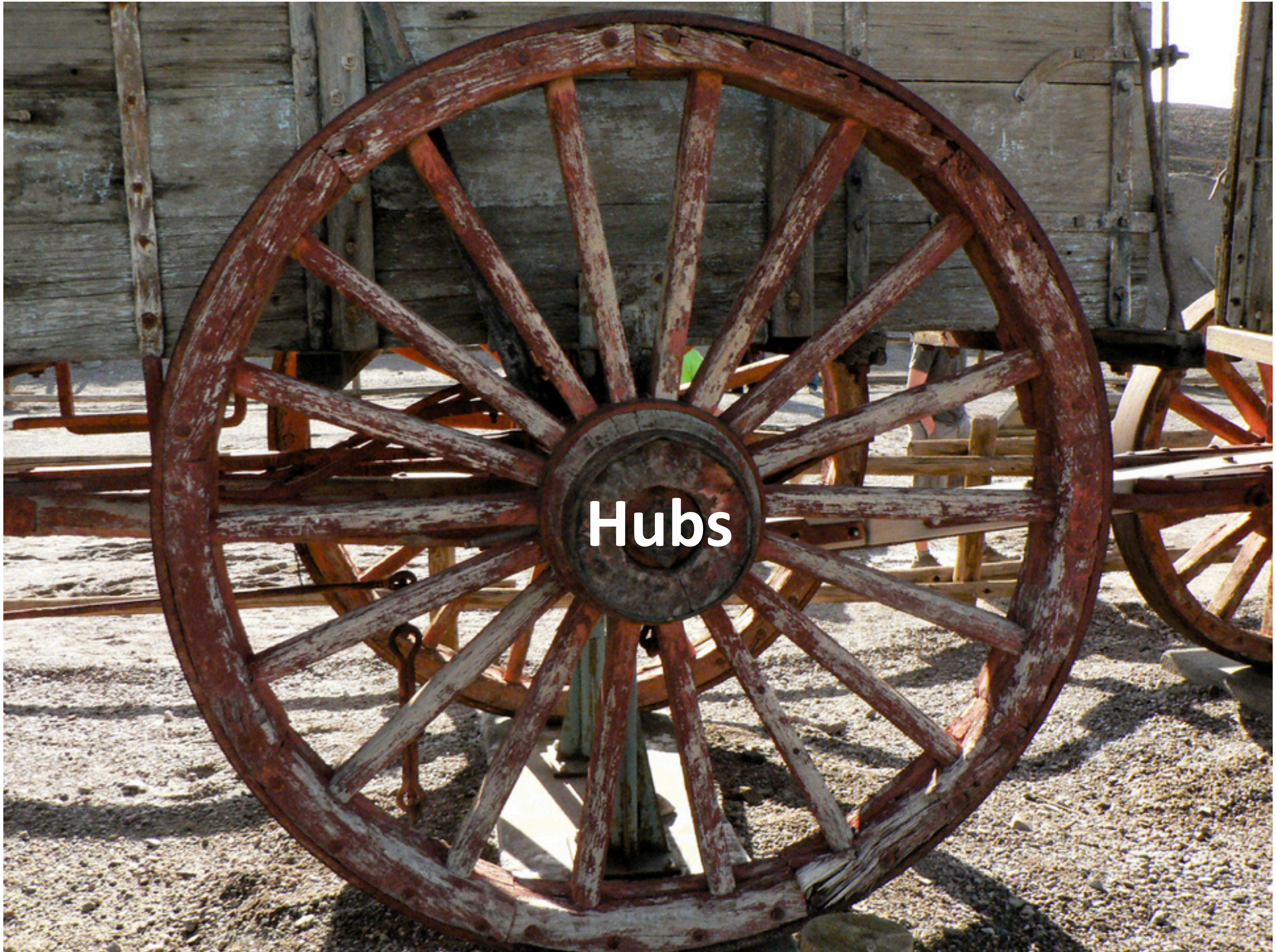
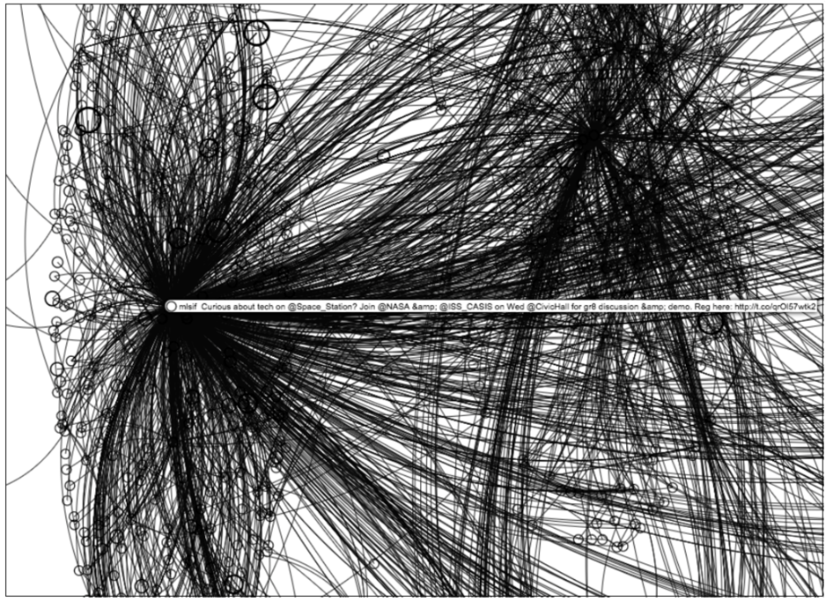
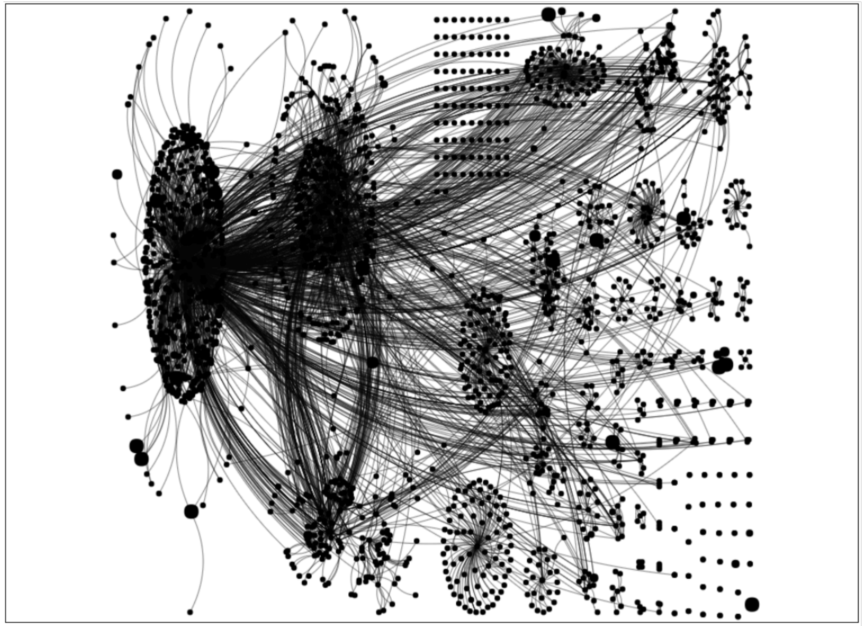

Hubs

https://flic.kr/p/4Z6GHv



#pdf15 OR #wegov OR pdmteam OR @techpresident OR %22personal democracy%22 OR Mlsif
Twitter NodeXL SN (experimental version)



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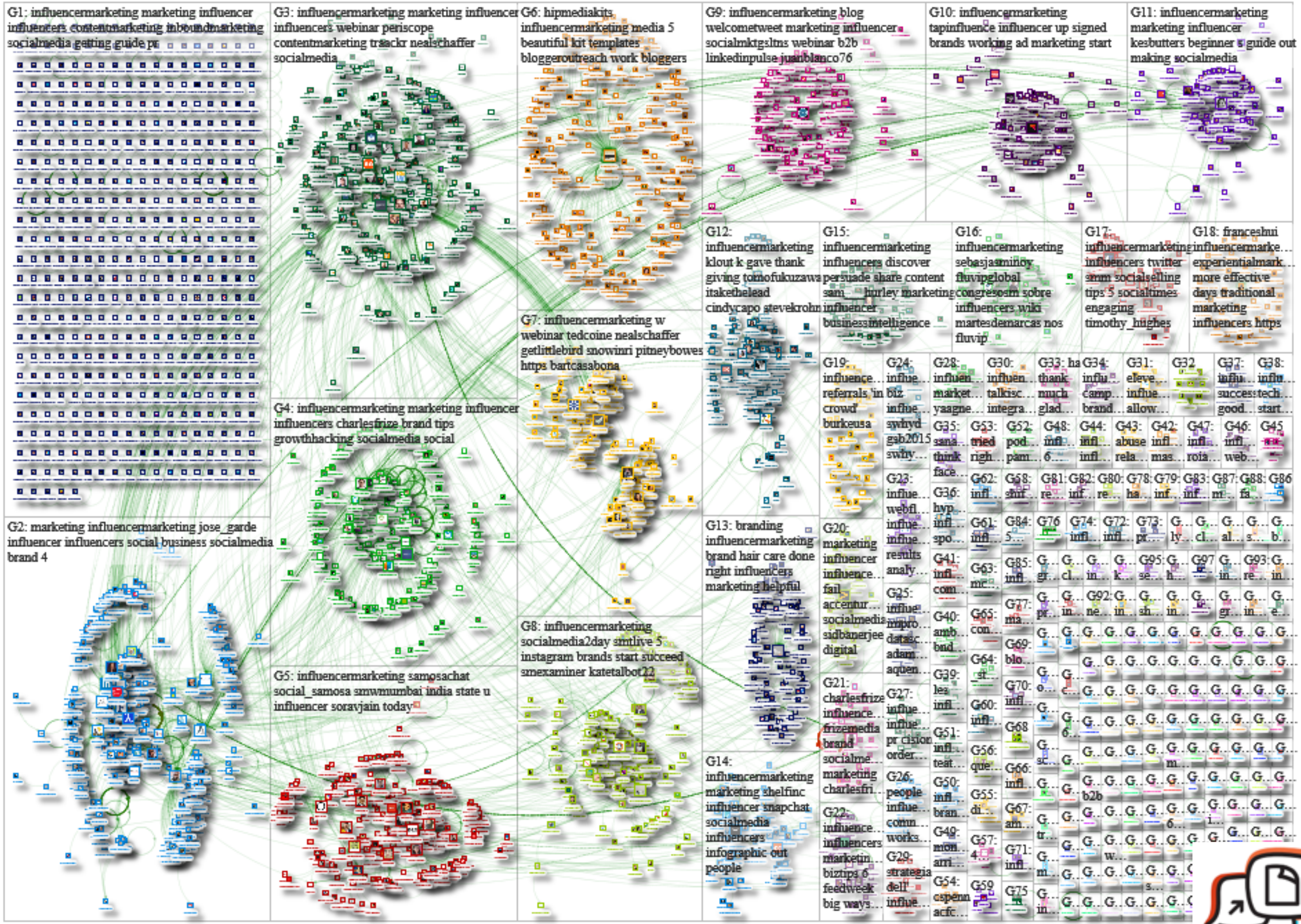
Twitter NodeXL SN (experimental version)

https://flic.kr/p/etEmeR


Bridges


Islands
http://www.flickr.com/photos/storm-crypt/3047698741

#influencermarketing Twitter NodeXL SNA Map and Report for Wednesday, 25 November 2015 at 05:09 UTC



https://www.nodexlgraphgallery.org/Pages/Graph.aspx?graphID=57696

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InfluencerMarketing

Top Influencers: Top 10 Vertices, Ranked by Betweenness Centrality

@iconnectim
Follow | 20.1K followers | Smart > | Tweet

@recuweb
Follow | 8,807 followers | Smart > | Tweet

@jose_garde
Follow | 23.6K followers | Smart > | Tweet

@hipmediakits
Follow | 2,024 followers | Smart > | Tweet

@socialmktgsltns
Follow | 32.2K followers | Smart > | Tweet

@tapinfluence
Follow | 10.4K followers | Smart > | Tweet

@kesbutters
Follow | 227K followers | Smart > | Tweet

@juntaedelane
Follow | 275K followers | Smart > | Tweet

@socialmedia2day
Follow | 508K followers | Smart > | Tweet

@adfresco_media
Follow | 1,163 followers | Smart > | Tweet

https://www.nodexlgraphgallery.org/Pages/Graph.aspx?graphID=57696#headerTopVertices

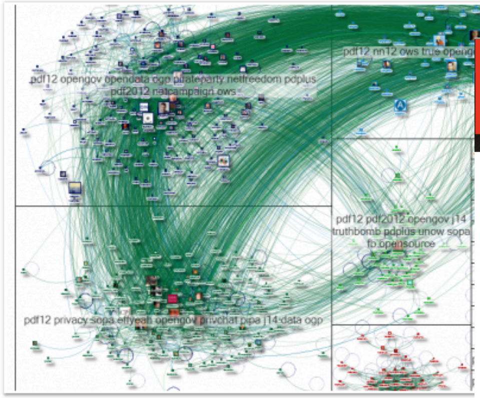
Top Hashtags in Tweet in Entire Graph:
[10001] influencermarketing
[2381] marketing
[652] socialmedia
[553] brand
[541] klout
[501] socialmediamarketing
[404] contentmarketing
[377] frizemedia
[332] influencers
[300] charlesfriedofrize

https://www.nodexlgraphgallery.org/Pages/Graph.aspx?graphID=57696#headerTopHashtags

TECHPRESIDENT BETA

Beyond 'Bitter Twitter': Crowd-Photography for the Cyber-Tahrir Square

BY MICAH L. SIFRY | Tuesday, July 10 2012



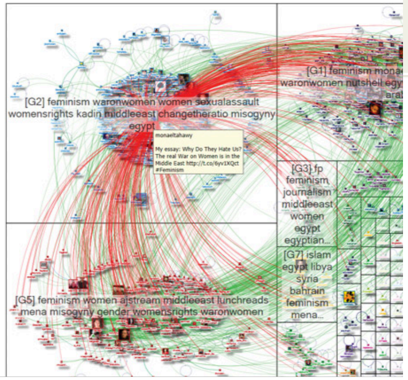
http://techpresident.com/news/22538/crowd-photography-cyber-tahrir-square

FP

Visualizing the War on Women Debate

A look at how the most popular cover story in Foreign Policy's history ricocheted across Twitter.

BY LOIS FARROW PARSHLEY | JUNE 18, 2012



http://foreignpolicy.com/2012/06/18/visualizing-the-war-on-women-debate/

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

Mapping Twitter Topic Networks: From Polarized Crowds to Community Clusters

BY MARC A. SMITH, LEE RAINIE, BEN SHNEIDERMAN 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.

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- Complete Report
- Press Release
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- **Infographic:** The six types of Twitter conversations

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http://www.pewinternet.org/2014/02/20/mapping-twitter-topic-networks-from-polarized-crowds-to-community-clusters/

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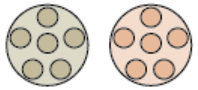
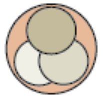
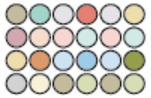
Social media network analysis

- Social media is inherently made of networks,
  - which are created when people link and reply.
- Collections of connections have an emergent shape,
  - Some shapes are better than others.
- Some people are located in strategic locations in these shapes,
  - Centrally located people are more influential than others.

http://www.pewresearch.org/fact-tank/2014/02/20/the-six-types-of-twitter-conversations/

The Six Structures of Twitter Conversation Networks

NETWORK TYPE			GROUPS	EXAMPLES
Divided 1		**POLARIZED CROWDS** This type illustrates different groups of Twitter users who discuss polarizing topics. They often rely on different sources of information and commonly do not interact with groups that disagree with them.	**2 large**	Politics or divisive topics that display separate "echo chamber" structures
Unified 2		**TIGHT CROWDS** This type captures close communities, such as conferences, professional topics and hobby groups, where participants strongly connect to one another for information, ideas and opinions.	**2-6 medium**	Hobbies, professional topics, conferences. No outsiders, all participants are members
Fragmented 3		**BRAND CLUSTERS** This type is formed around products and celebrities. These popular topics attract large fragmented Twitter populations, generating mass interest, but little connectivity.	**Many small**	Brands, public events, popular subjects
Clustered 4		**COMMUNITY CLUSTERS** These groups are created around global news events and popular topics. Communities form around multiple news sources. These community clusters are mostly disconnected from one another.	**Many small and medium**	Global news events
In-Hub & Spoke 5		**BROADCAST NETWORK** This type is often triggered by news media outlets and pundits who have loyal followers who retweet them. These communities are often star-shaped, as little interaction exists among members of the audience.	**1 large, some secondary**	News pundits and media outlets, famous individuals
Out-Hub & Spoke 6		**SUPPORT NETWORK** This type is created when companies, government agencies or organizations respond to complaints and customer requests. The company, or hub, account replies to many disconnected users, creating outward spokes.	**1 large, some secondary**	Companies and services with customer support

PEW RESEARCH CENTER in association with Social Media Research Foundation

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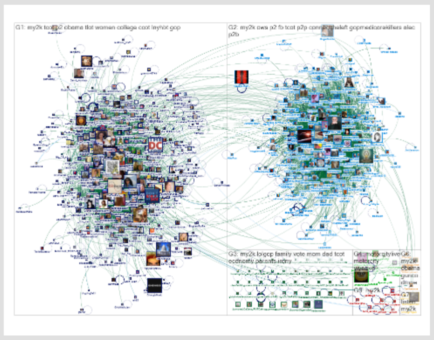
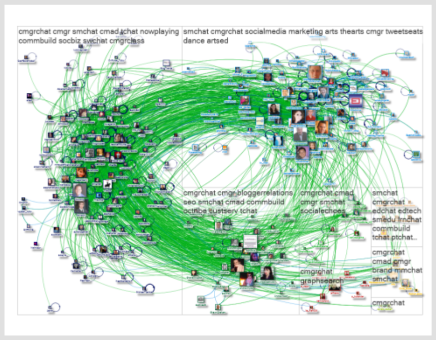
6 kinds of Twitter social media networks

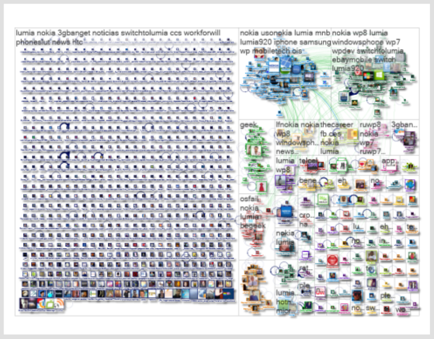
[Divided]
Polarized Crowds

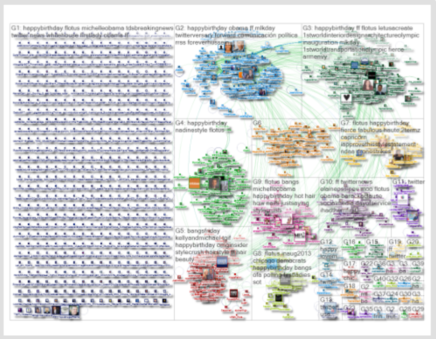




[Unified]
Tight Crowd

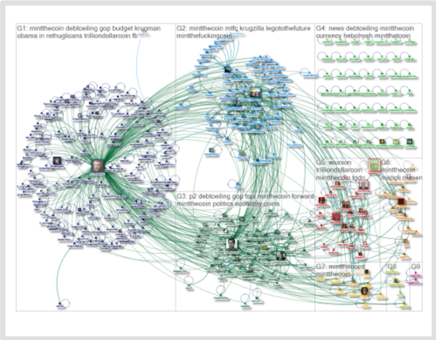
[Fragmented]
Brand Clusters

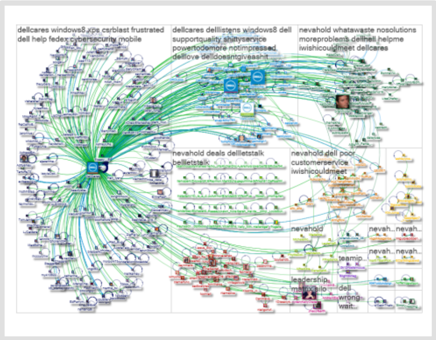




[Clustered]
Community Clusters

[In-Hub & Spoke]
Broadcast Network





[Out-Hub & Spoke]
Support Network

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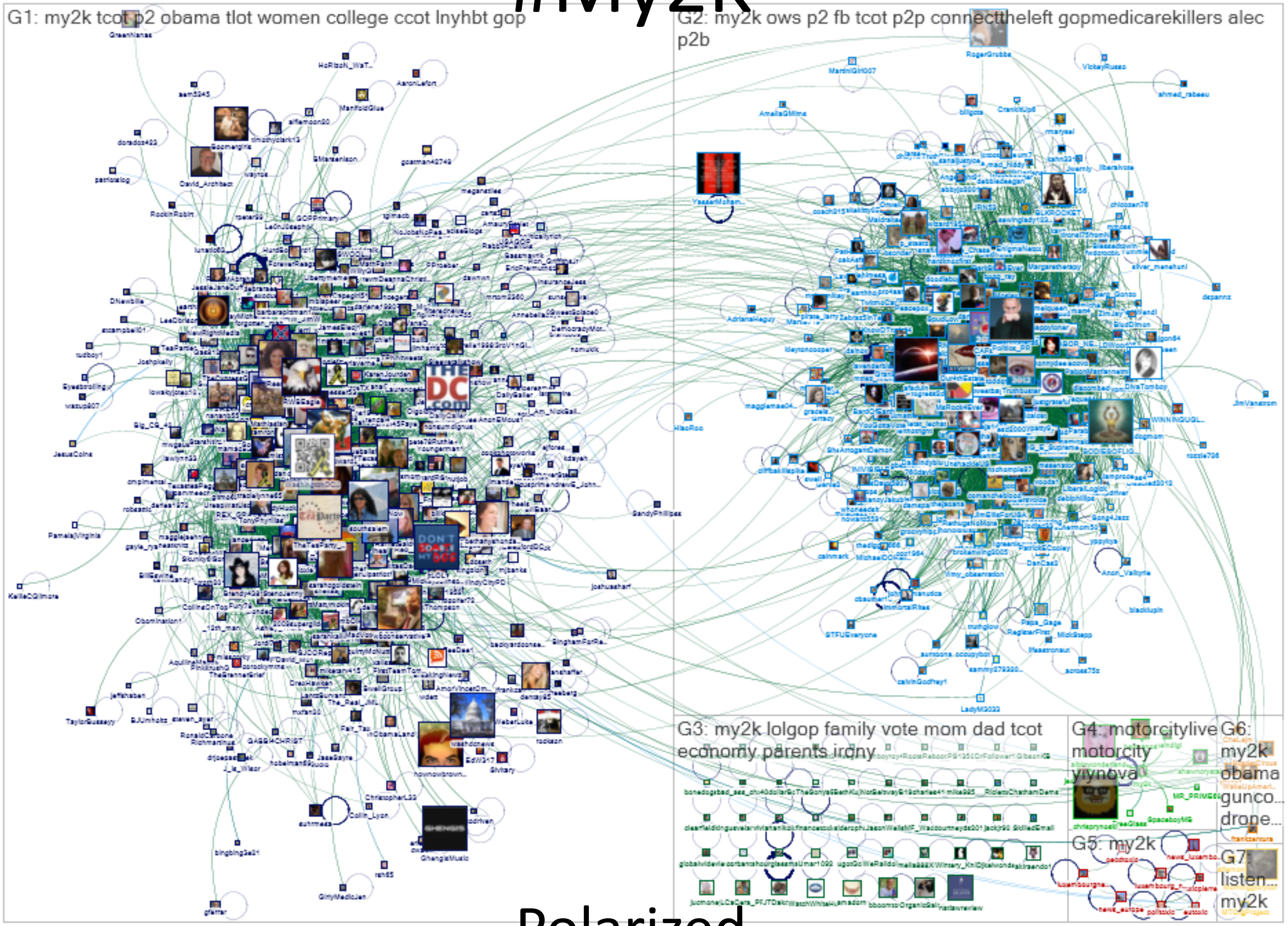
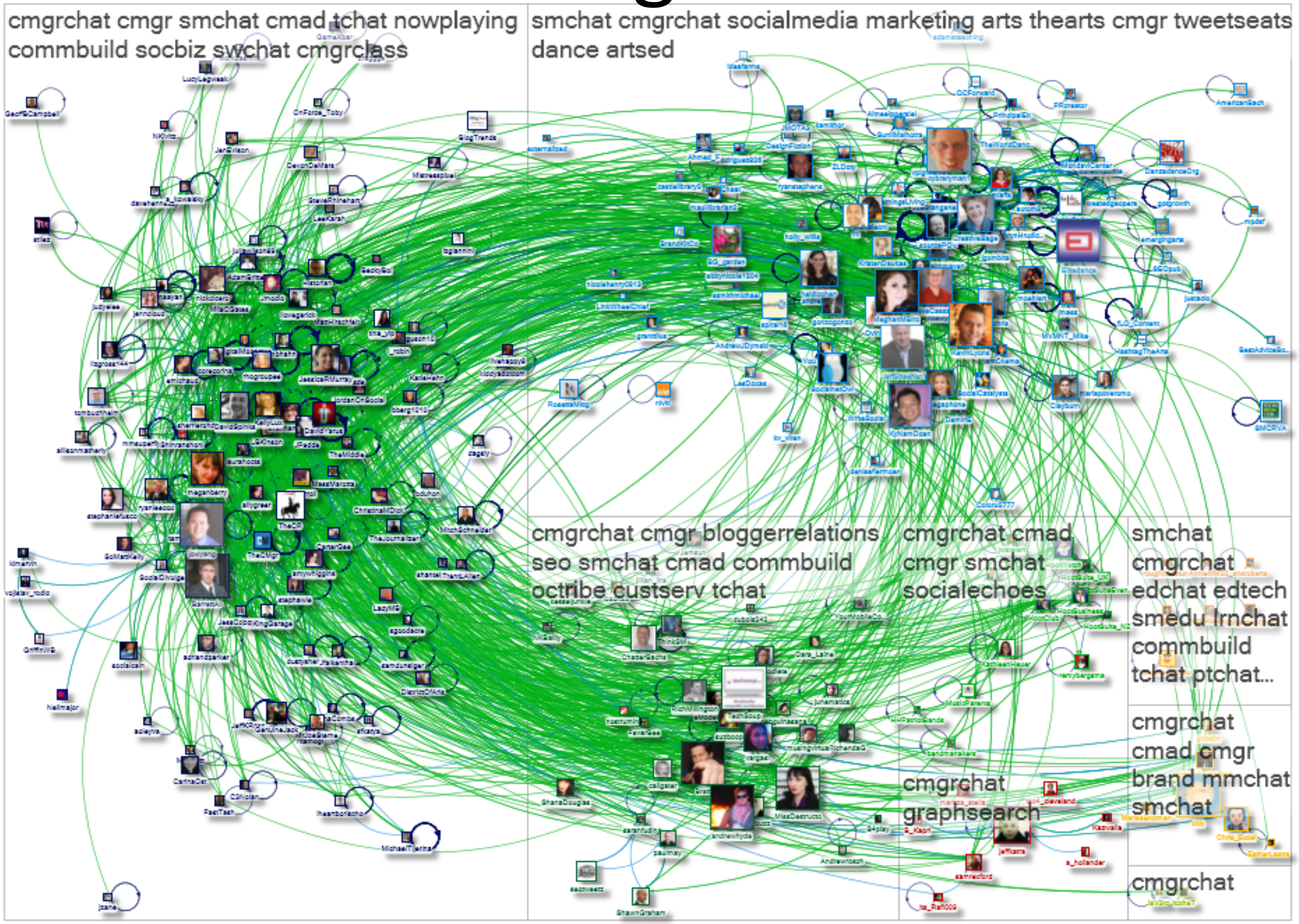
#My2K



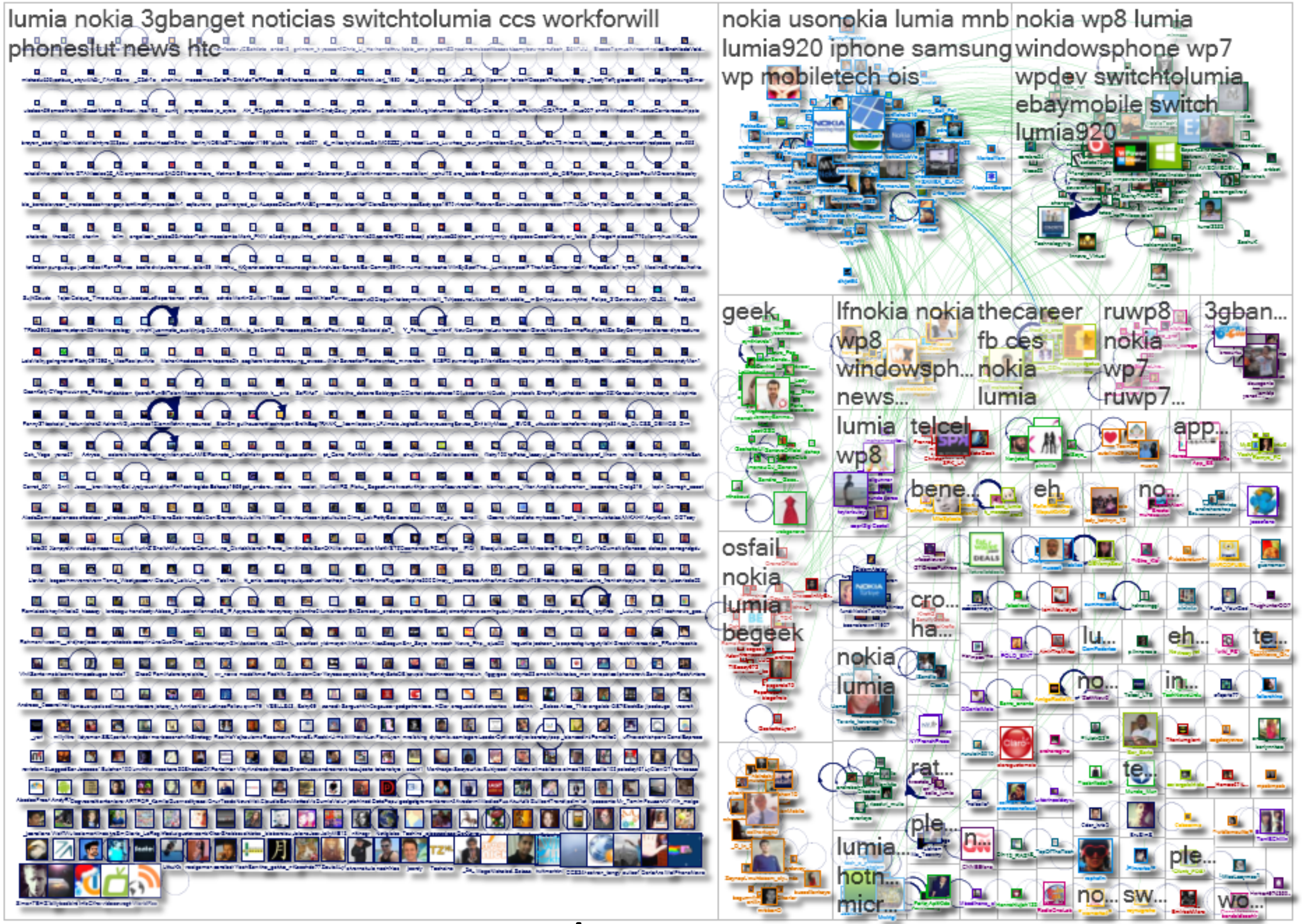
Polarized

#CMgrChat



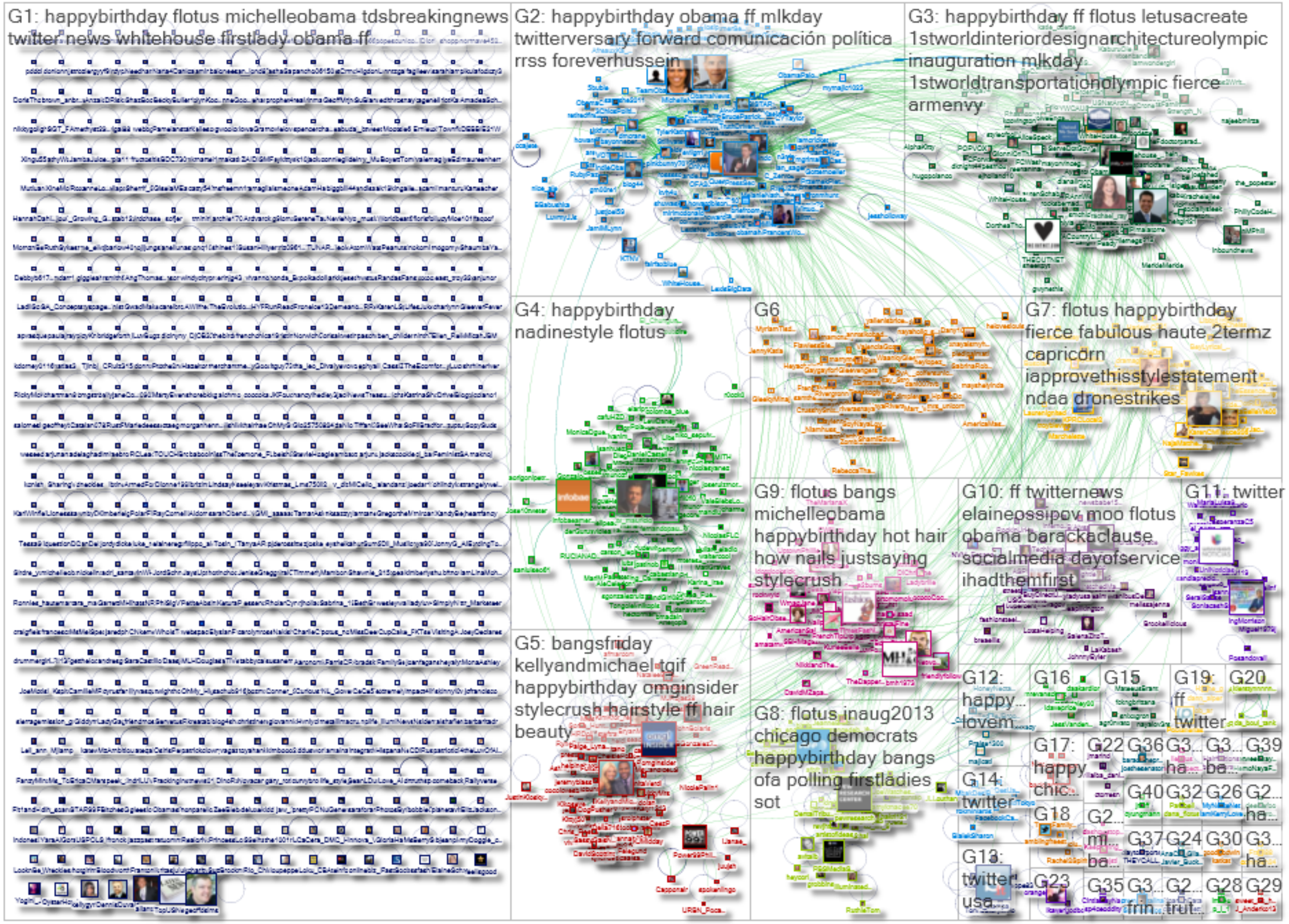
In-group / Community

Lumia



Brand / Public Topic

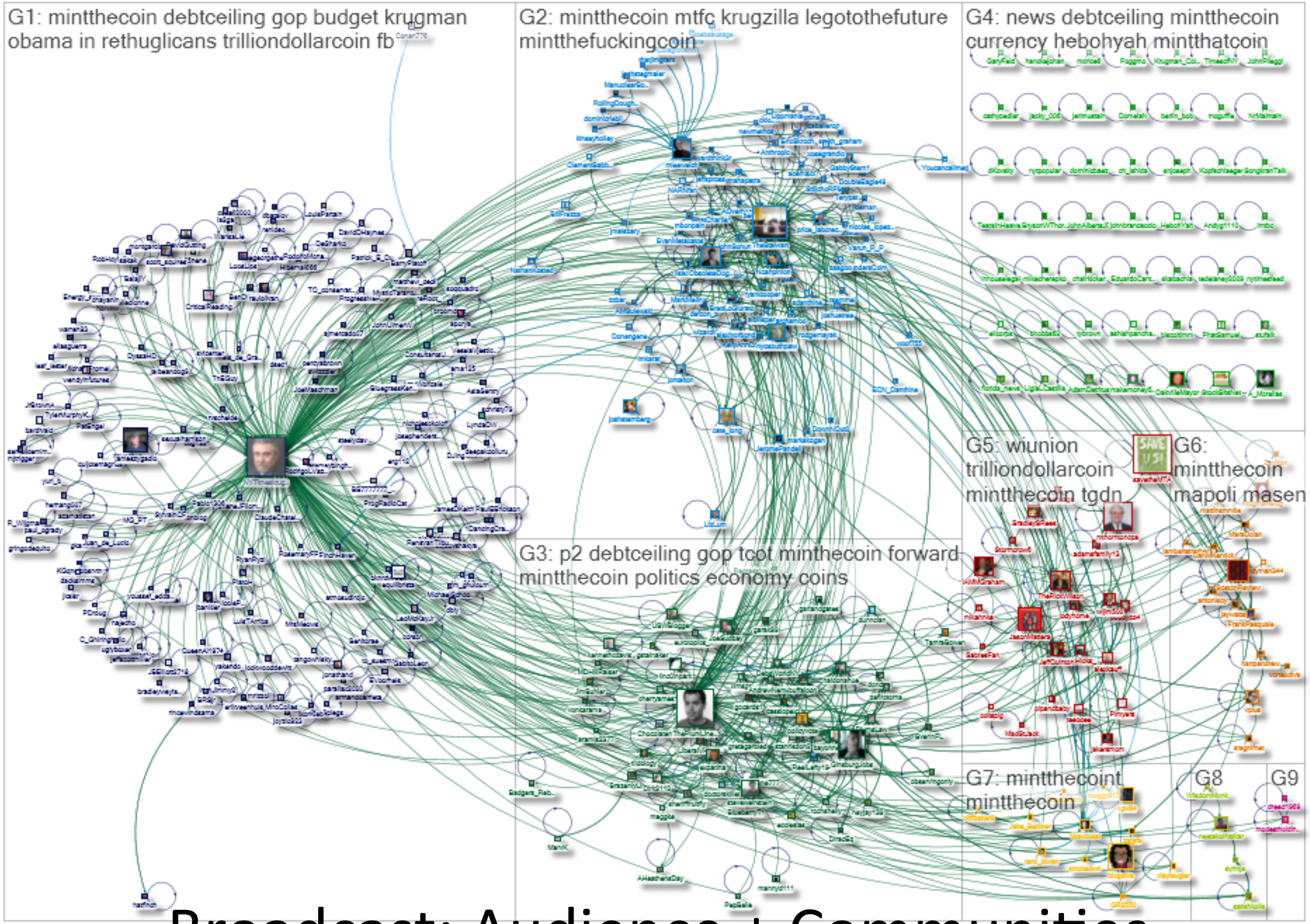
#FLOTUS



Bazaar

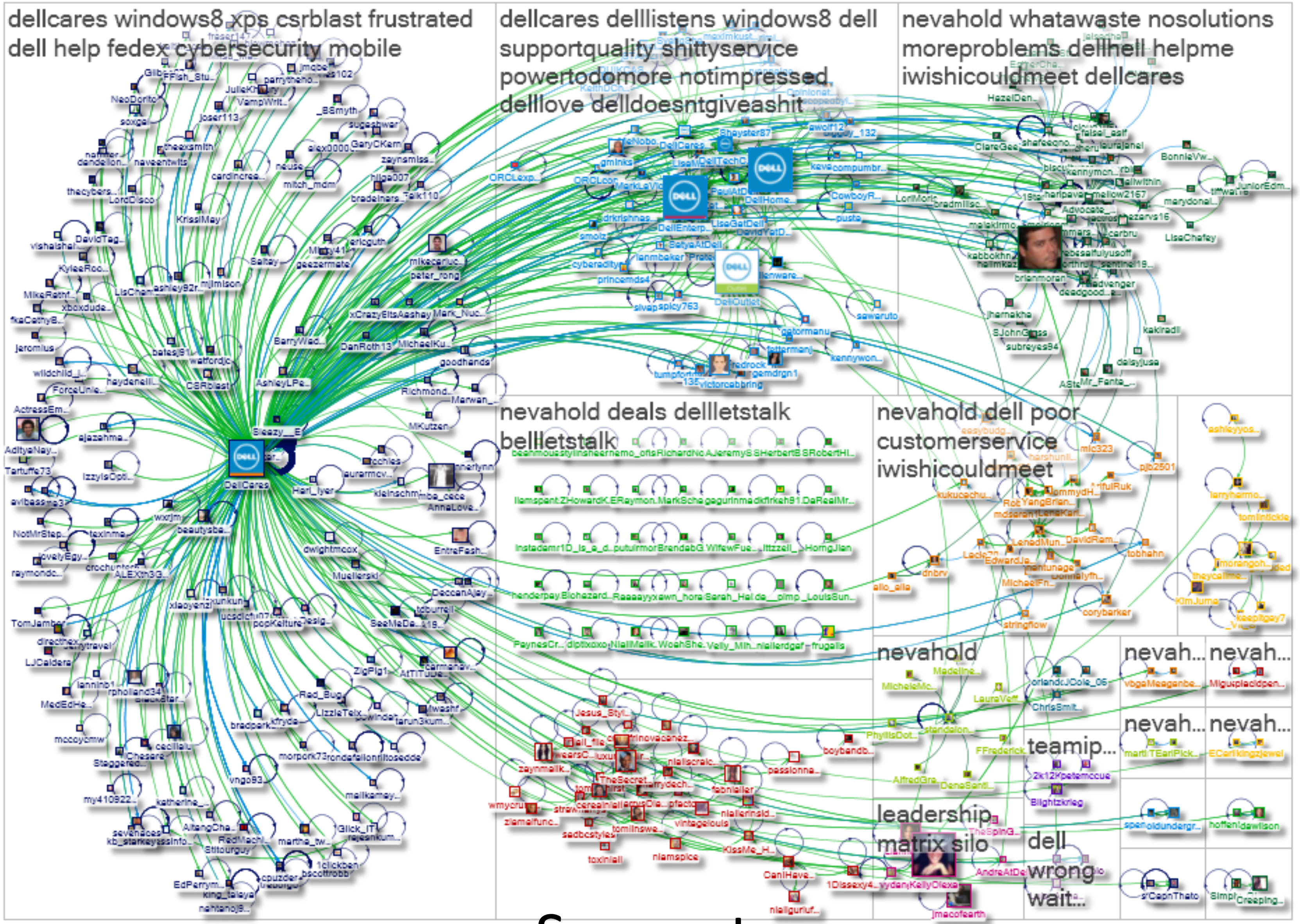
New York Times Article

Paul Krugman



Broadcast: Audience + Communities

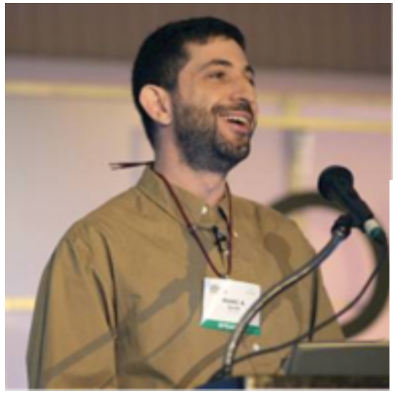
Dell Listens/Dellcares



Support

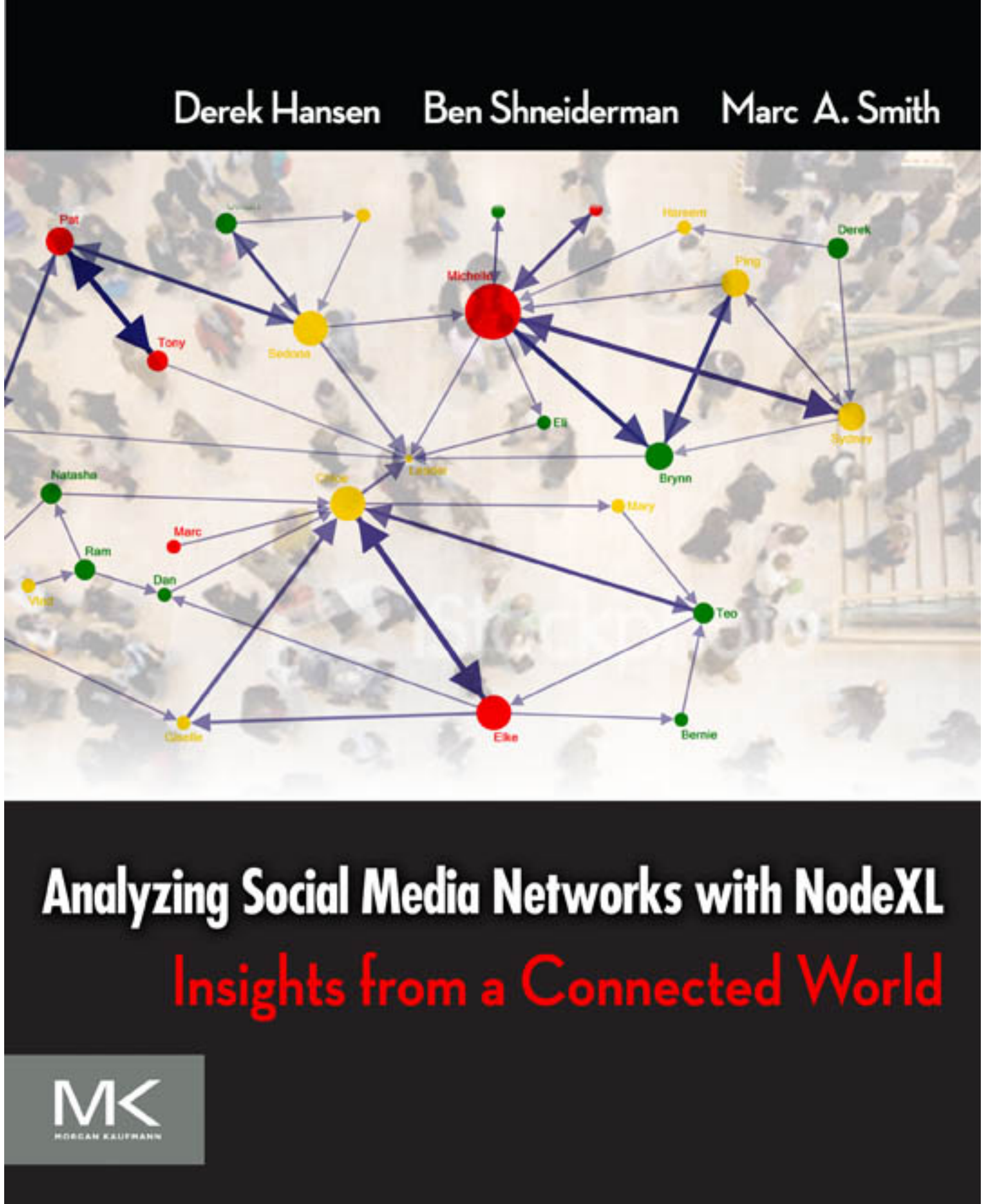
UNIVERSITY OF MARYLAND

HCIL Human-Computer Interaction Lab University of Maryland



Connected

Action



New Book in Progress!

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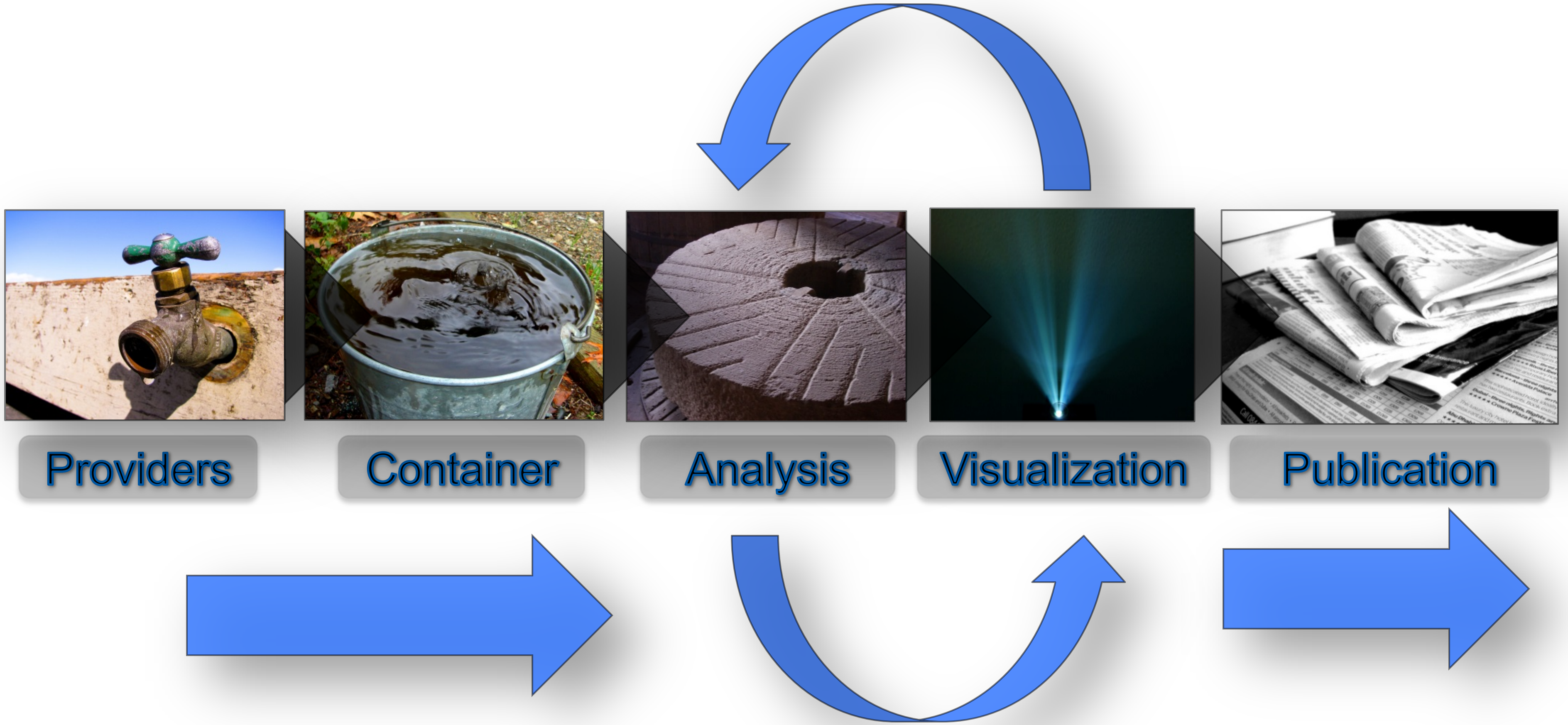
Network Analysis Data Flow



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Social Network Maps Reveal

Key influencers in any topic.

Sub-groups.

Bridges.

SNA questions for social media:

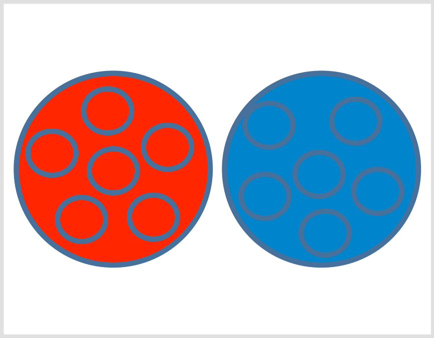
1. What does my topic network look like?
2. What does the topic I aspire to be look like?
3. What is the difference between #1 and #2?
4. How does my map change as I intervene?

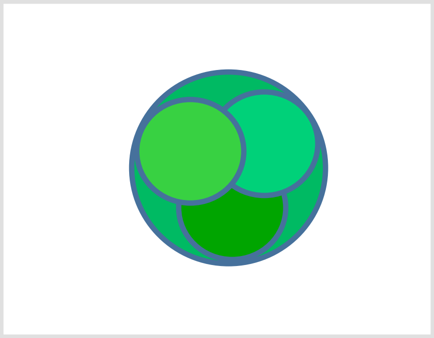
What does #YourHashtag look like?

Who is the mayor of #YourHashtag?

6 kinds of Twitter social media networks

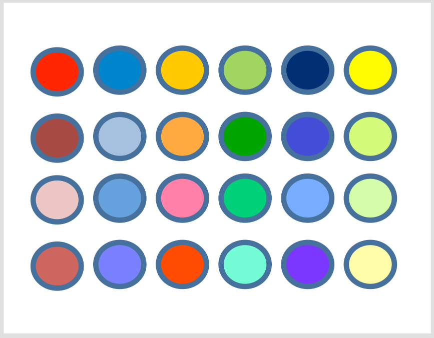
[Divided]
Polarized Crowds

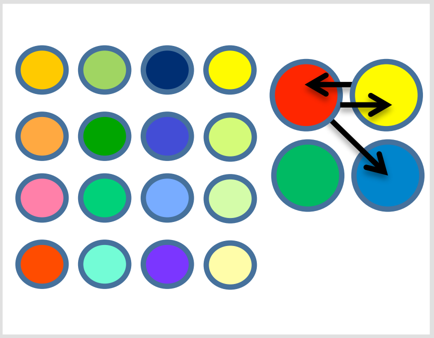




[Unified]
Tight Crowd

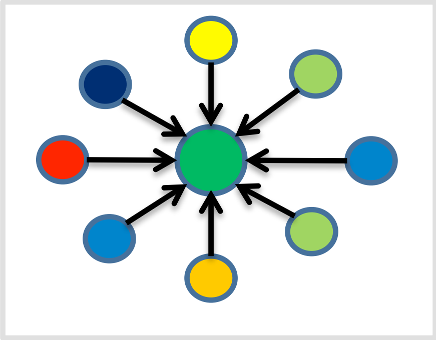
[Fragmented]
Brand Clusters

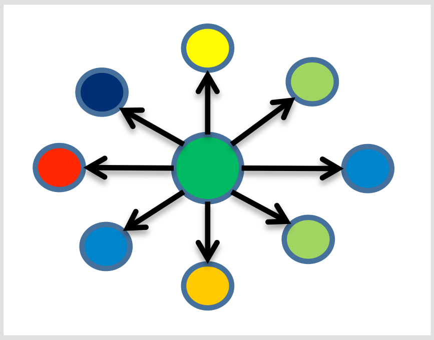




[Clustered]
Community Clusters

[In-Hub & Spoke]
Broadcast Network





[Out-Hub & Spoke]
Support Network

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Applying the insights of
social networks to social media:

Your social media audience is smaller…

…than the audiences of
ten influential voices.

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Build a collection of mayors

- Map multiple topics
  - Your brand and company names
  - Your competitor brands and company names
  - The names of the activities or locations related to your products
- Identify the top people in each topic
- Follow these people
  - 30-50% of the time they follow you back
- Re-tweet these people (if they did not follow you)
  - 30-50% of the time they follow you back

Speak the language of the mayors

- Use NodeXL content analysis to identify each users most salient:
  - Words
  - Word pairs
  - URLs
  - #Hashtags
- Mix the language of the Mayors with your brand's messages.

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Speak the language of the mayors

- The "perfect" tweet:

.@Theirname #Theirhashtag News about your brand using their words http://your.site #Yourhashtag

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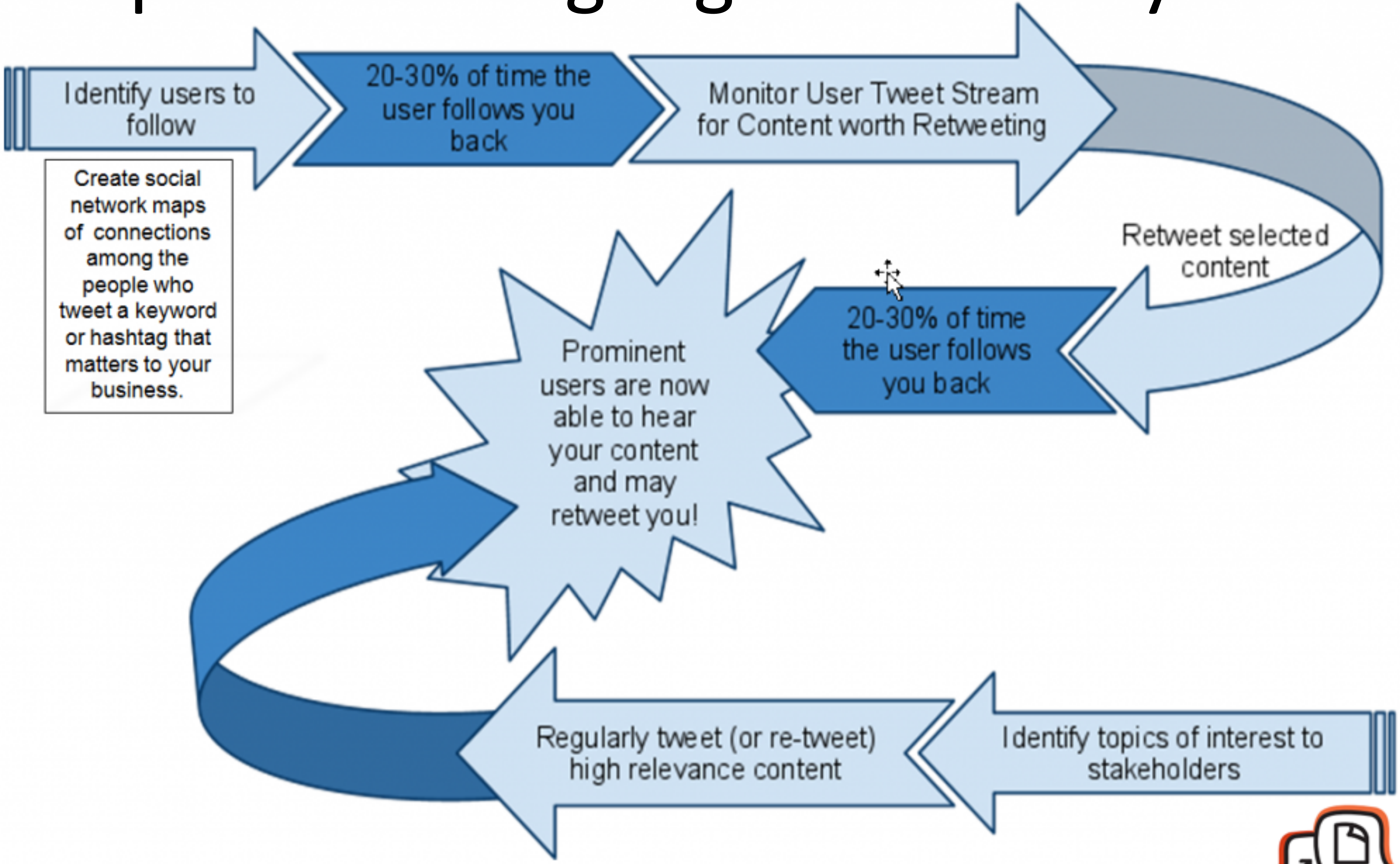
Speak the language of the mayors



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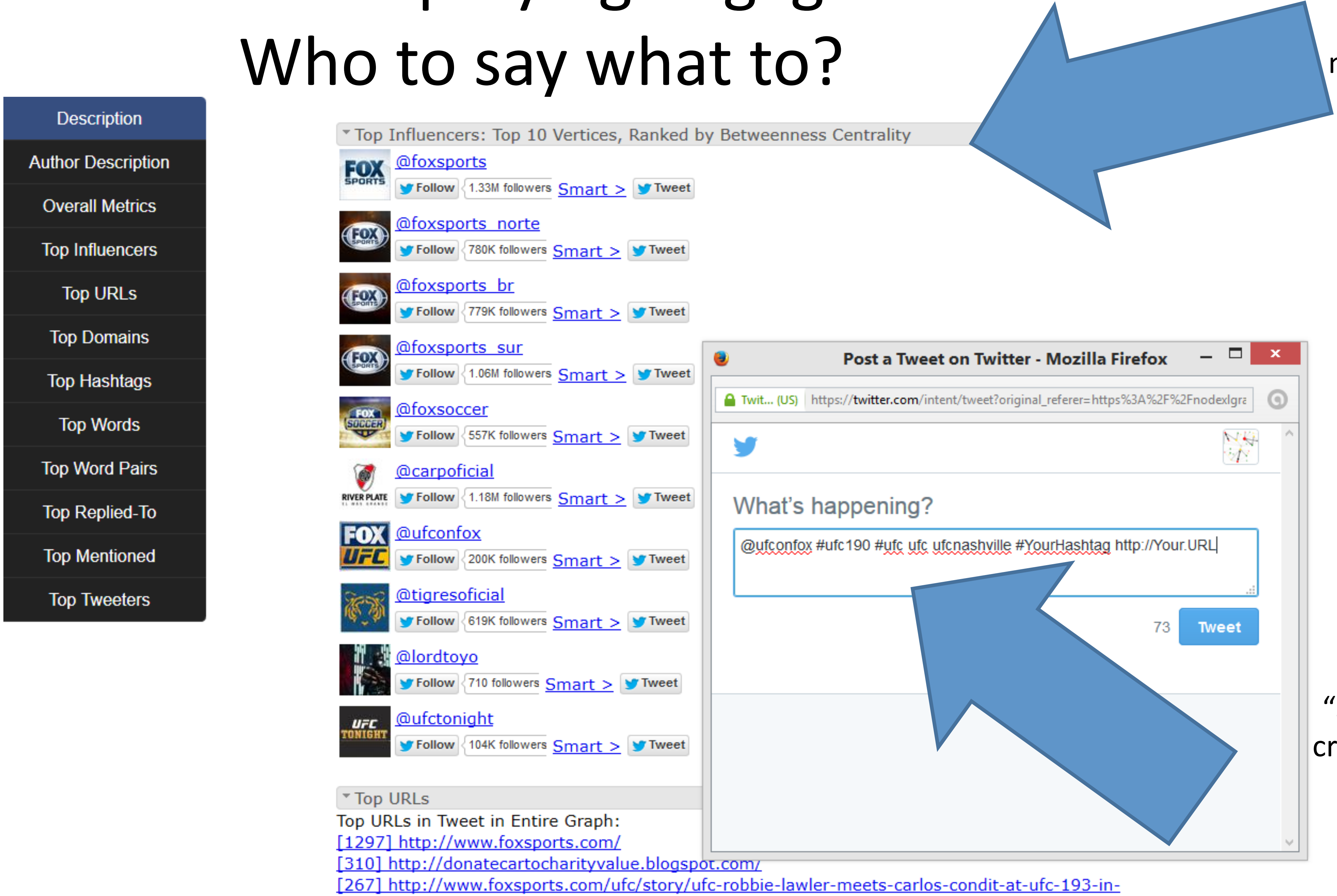
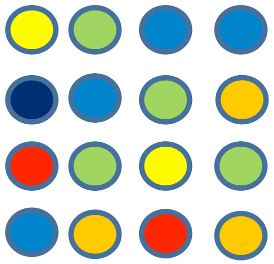
Tools for simplifying engagement: Who to say what to?

List the top "mayors" of the topics that matter to you.

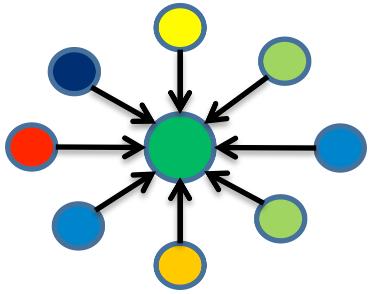


"Smart Tweet" creates content for best engagement.

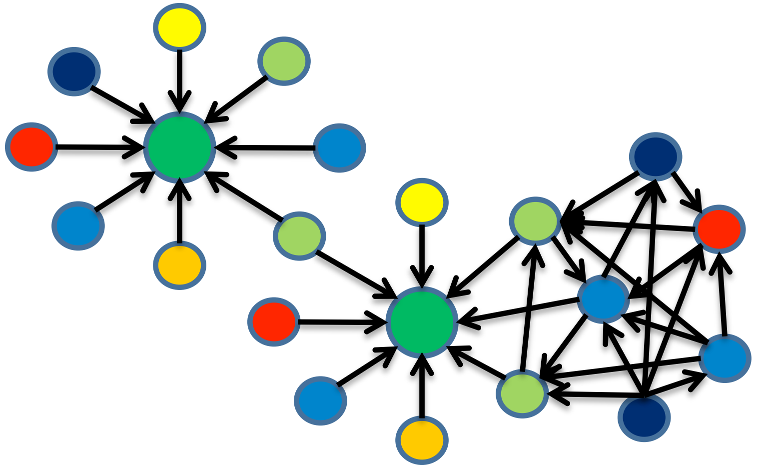
Network phases of social media success



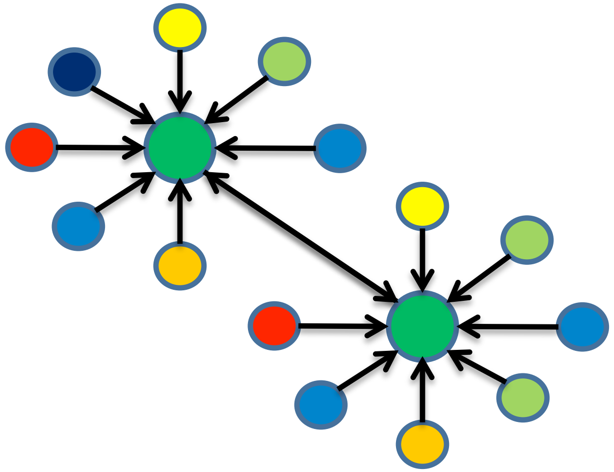
Phase 2a: People mention you



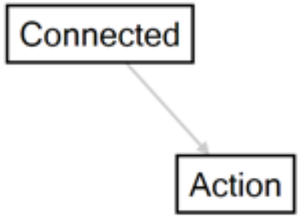
Phase 1: You get an audience



Phase 3: Audience becomes community

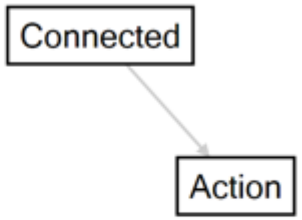


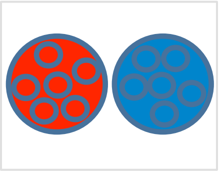
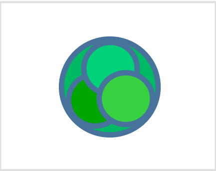
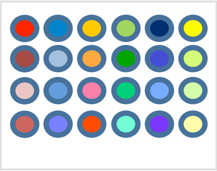
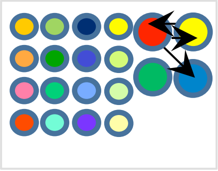
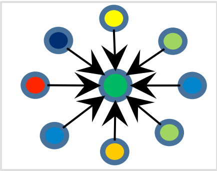
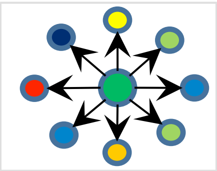
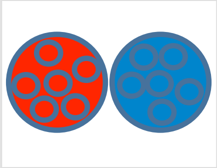
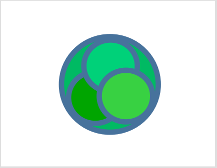
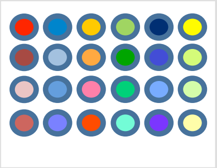
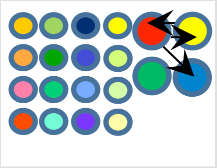
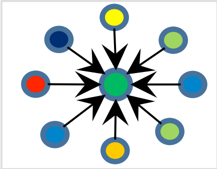
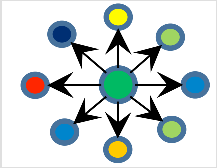
Phase 2b: Your audience gets an audience



Some shapes are better than others:

- The value of Broadcast versus community network!
- From community to brand!
- Support and why community can be a signal of failure!



	[Divided] *Polarized Crowds* 	[Unified] *Tight Crowd* 	[Fragmented] *Brand Clusters* 	*[Clustered] Communities* 	[In-Hub & Spoke] *Broadcast Network* 	[Out-Hub & Spoke] *Support Network* 
		[Low probability] Find bridge users. Encourage shared material.	[Low probability] Get message out to disconnected communities.	[Possible transition] Draw in new participants.	[Possible transition] Regularly create content.	[Possible transition] Reply to multiple users.
	[Undesirable transition] Remove bridges, highlight divisions.		[Low probability] Get message out to disconnected communities.	[High probability] Draw in new participants.	[Possible transition] Regularly create content.	[Possible transition] Reply to multiple users.
	[Undesirable transition] Increase density of connections in two groups.	[Low probability] Dramatically increase density of connections.		[High probability] Increase retention, build connections.	[Possible transition] Regularly create content.	[Possible transition] Reply to multiple users.
	[Undesirable transition] Increase density of connections in two groups.	[Low probability] Dramatically increase density of connections.	[Undesirable transition] Increase population, reduce connections.		[Possible transition] Regularly create content.	[Possible transition] Reply to multiple users.
	[Undesirable transition] Increase density of connections in two groups.	[Low probability] Dramatically increase density of connections.	[Low probability] Get message out to disconnected communities.	[Possible transition] Increase retention, build connections.		[High probability] Increase reply rate, reply to multiple users.
	[Undesirable transition] Increase density of connections in two groups.	[Low probability] Dramatically increase density of connections.	[Possible transition] Get message out to disconnected communities.	[High probability] Increase retention, build connections.	[High probability] Increase publication of new content and regularly create content.	

Request your own network map and report

http://connectedaction.net

socialmedia
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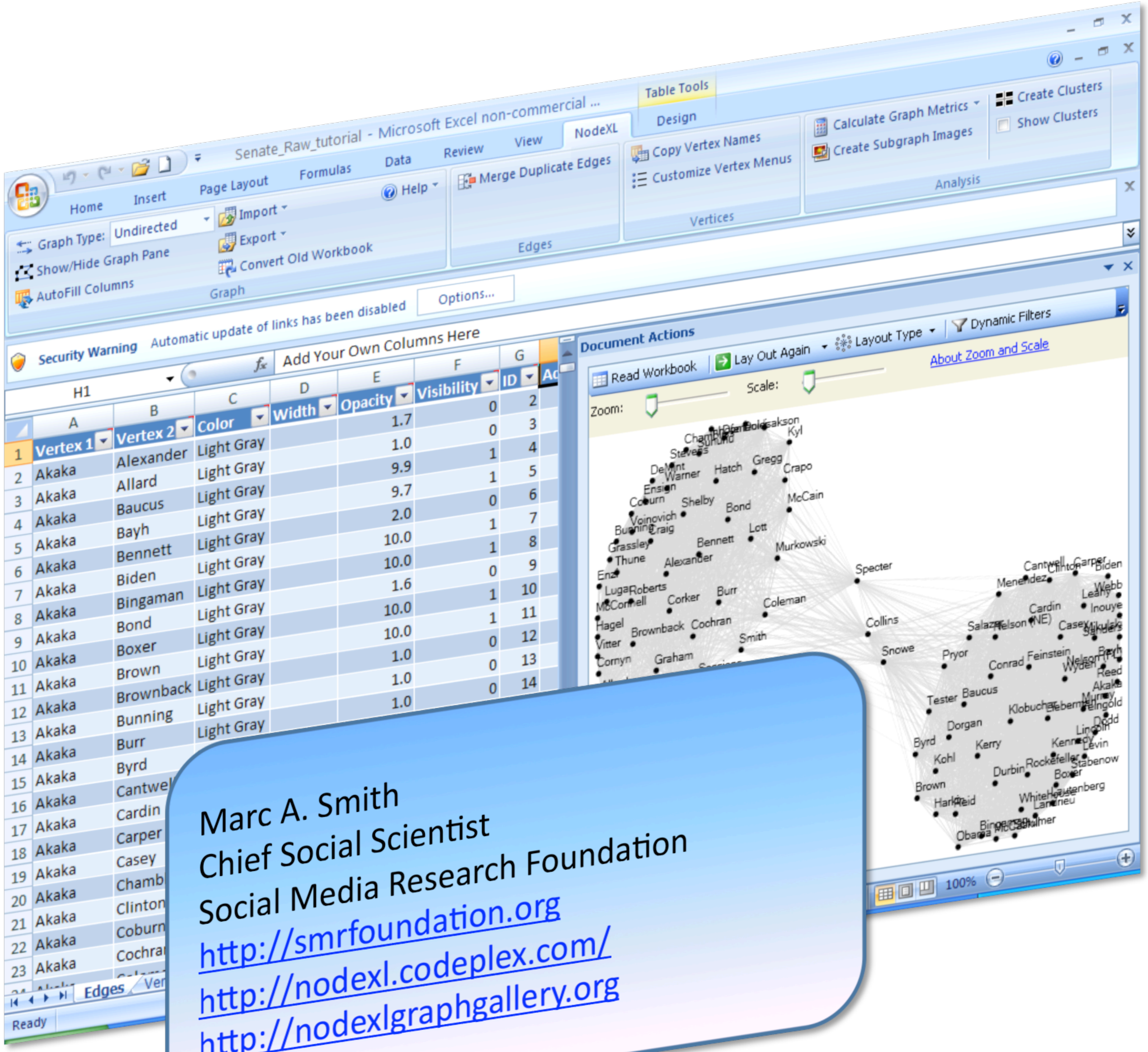
Contact Me

Marc A. Smith
Chief Social Scientist / Director
Social Media Research Foundation
marc@smrfoundation.org

http://www.smrfoundation.org
http://www.twitter.com/marc_smith
http://www.linkedin.com/in/marcasmith
http://www.slideshare.net/Marc_A_Smith
http://www.flickr.com/photos/marc_smith
http://www.facebook.com/marc.smith.sociologist



Marc A. Smith
Chief Social Scientist
Social Media Research Foundation
http://smrfoundation.org
http://nodexl.codeplex.com/
http://nodexlgraphgallery.org

Map Social Media Connections with Excel & NodeXL

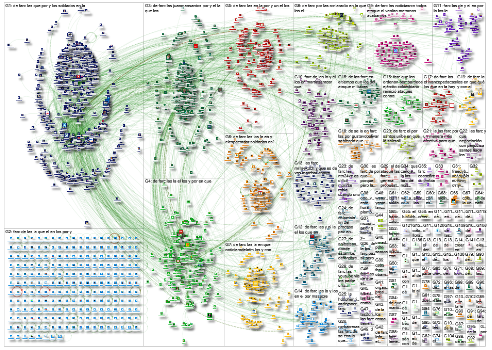
Mapping social media networks
to find
Influencers, Groups & Key Topics

socialmedia
RESEARCH FOUNDATION

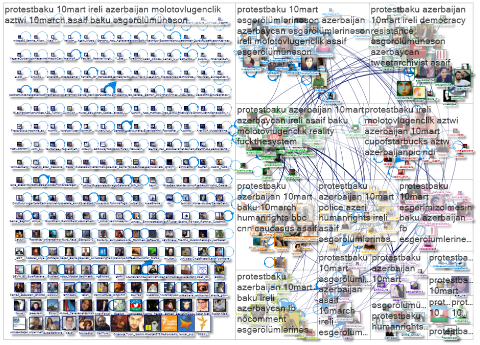
A project from the Social Media Research Foundation: http://www.smrfoundation.org

Examples of social network scholarship using NodeXL

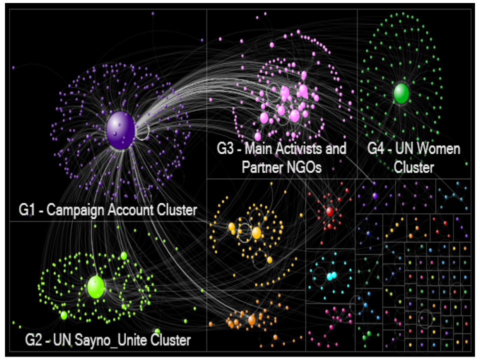
Margarita M. Orozco
Doctoral Student, School of Journalism & Mass Communication
University of Wisconsin- Madison



Katy Pearce (@katypearce)
Assistant Prof of Communication
Studies technology & inequality in Armenia & Azerbaijan.



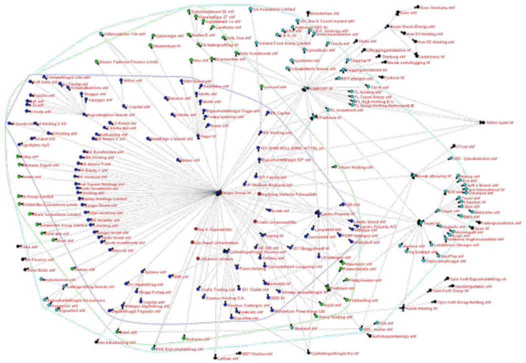
Elena Pavan, Ph.D.
Post Doctoral Research Fellow
Dipartimento di Sociologia e Ricerca Sociale
Università di Trento
via Verdi 26, 38122 Trento (Italy)



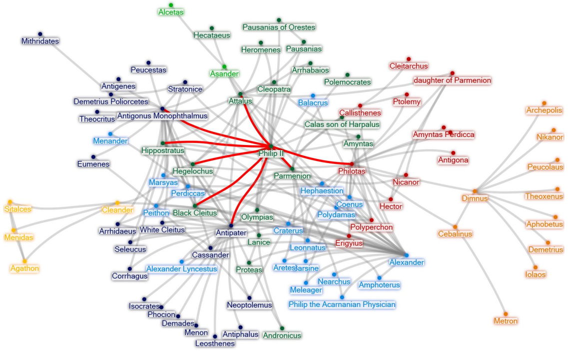
Created with NodeXL (http://nodexl.codeplex.com)

Examples of social network scholarship

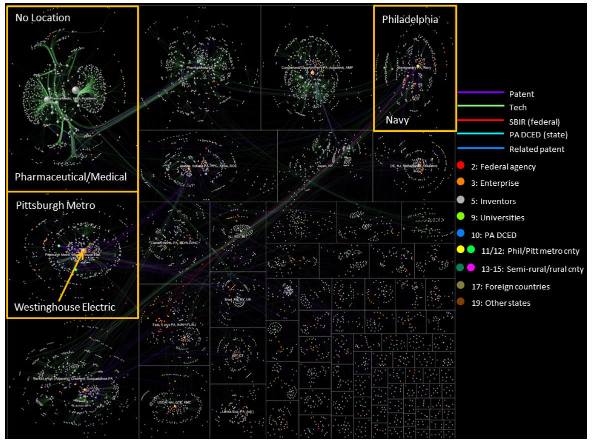
Margrét Vilborg Bjarnadóttir
Robert H. Smith School of Business |
University of Maryland
Data Scientist | Parliamentary
Special Investigation Commission



Prof. Diane Harris Cline
Associate Professor of History
George Washington University



C. Scott Dempwolf, PhD
Research Assistant Professor &
Director
UMD - Morgan State Center for
Economic Development



Margarita M. Orozco

Doctoral Student, School of Journalism & Mass Communication

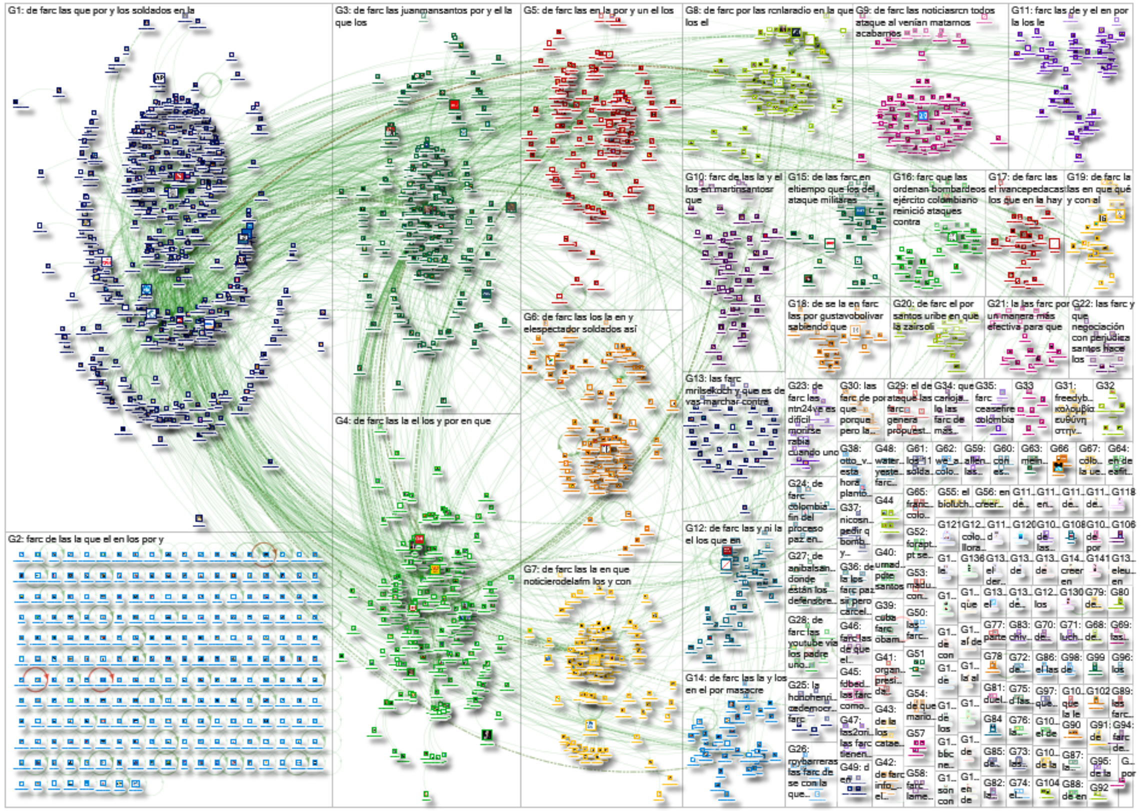
University of Wisconsin- Madison

WISCONSIN

UNIVERSITY OF WISCONSIN–MADISON

Studying the Colombian Peace Process in Twitter

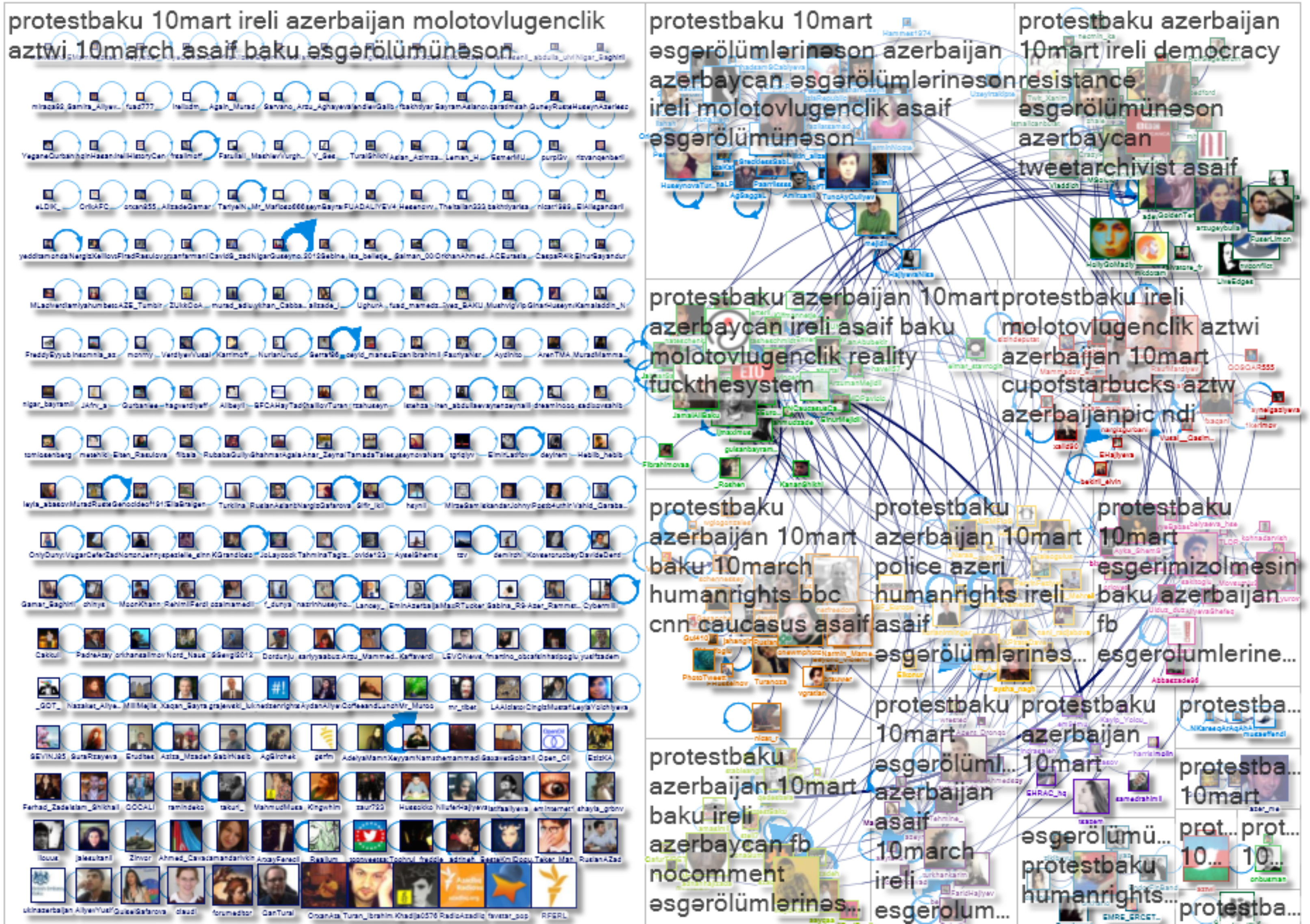
- Analyzing perceptions of the peace process in Colombian public opinion in Twitter.
- It is important to know what are citizens thinking, perceptions, and concerns.
- Q: who are the main actors in Twitter in favor and against the peace process who are leading sources of information about it?
- Colombians are the world's 15th top Twitter users. For this reason this social media constitutes an important source of information about public opinion.

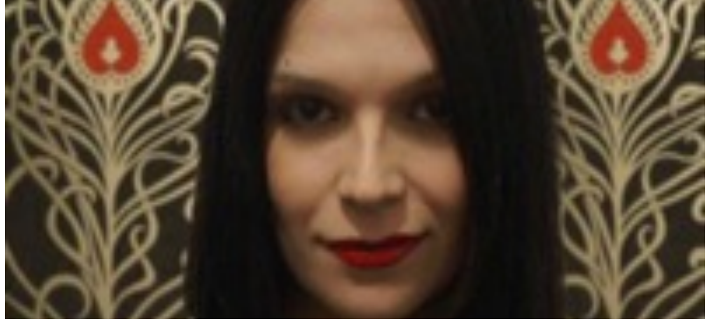


Katy Pearce (@katypearce)
Assistant Prof of Communication
Studies technology & inequality in Armenia & Azerbaijan.

UNIVERSITY of WASHINGTON

#ProtestBaku Azerbaijan





Elena Pavan, Ph.D.
Post Doctoral Research Fellow
Dipartimento di Sociologia e Ricerca Sociale
Università di Trento
via Verdi 26, 38122 Trento (Italy)

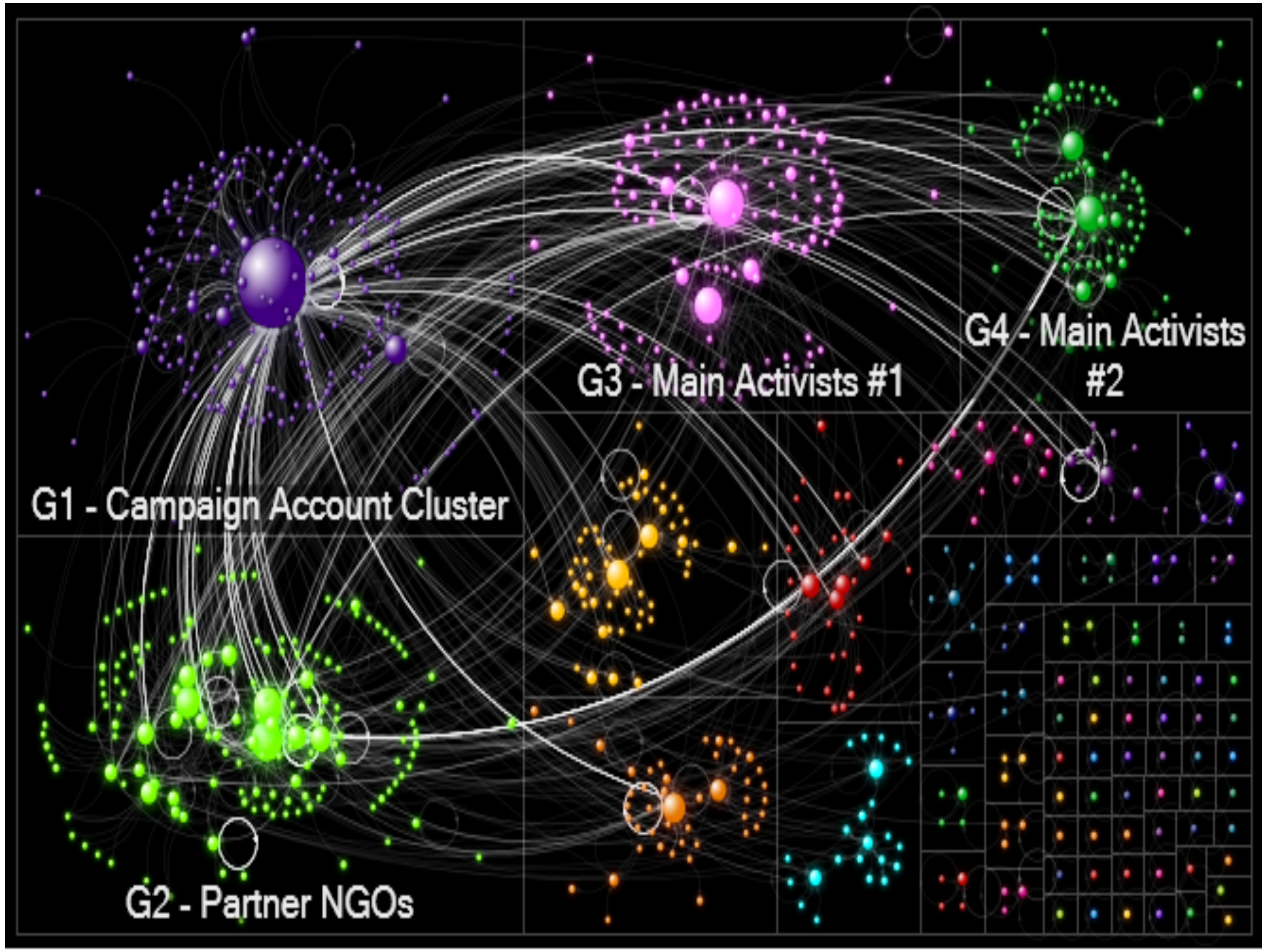
UNIVERSITÀ DI TRENTO

Take Back The Tech!
Reclaiming ICTs against Violence Against Women

- Launched in 2006 by the Association for Progressive Communications Women Rights Program (APC WRP)
- Runs yearly during the 16 days against Violence Against Women (VAW)
- Website http://www.takebackthetech.net
- "16 daily actions" to reclaim ICTs against VAW and a Tweetathon
- Explored in the context of the project REACtION (http://www.reactionproject.info) in relation to the interplay between the "offline" advocacy strategy and the "online" Twitter networks over time
- Findings: shifts in the advocacy strategy shift the network structure – moving from the outside to the online of the institutions (lobbying at the Commission on the Status of Women) led to a centralized Twitter network where organizational and institutional accounts play most central roles

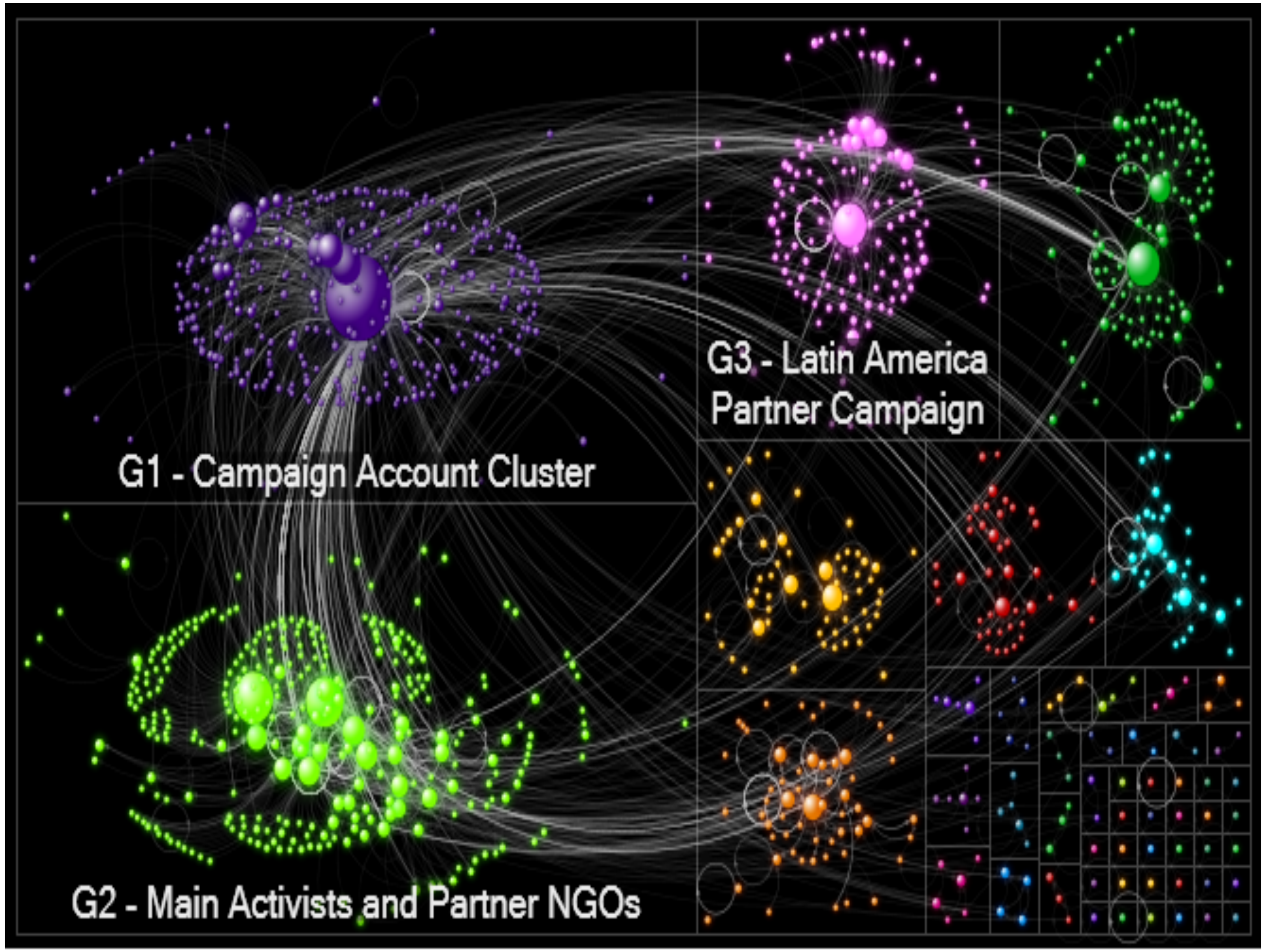
REACtION - Collective Action Networks between Online and Offline Interactions - http://www.reactionproject.info.
Grant post-doc 2011 by the Provincia Autonoma di Trento (Italy)

2012: Outside institutions, a grassroots conversation



Created with NodeXL (http://nodexl.codeplex.com)

2013: Accessing institutions, a more structured conversation



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REACtION - Collective Action Networks between Online and Offline Interactions - http://www.reactionproject.info.
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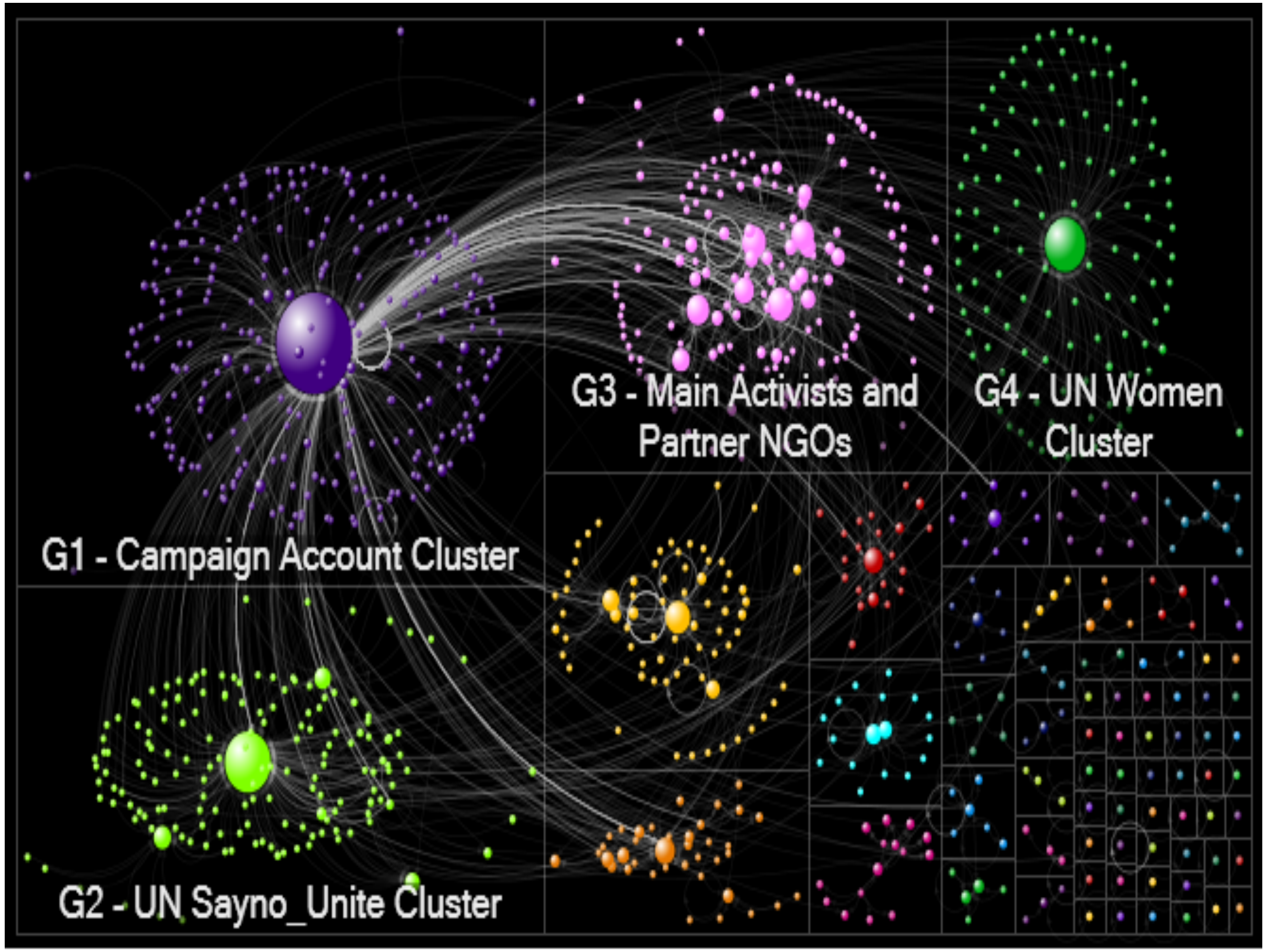
2014: Inside institutions, a centralized conversation



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REACtION - Collective Action Networks between Online and Offline Interactions - http://www.reactionproject.info.
Grant post-doc 2011 by the Provincia Autonoma di Trento (Italy)

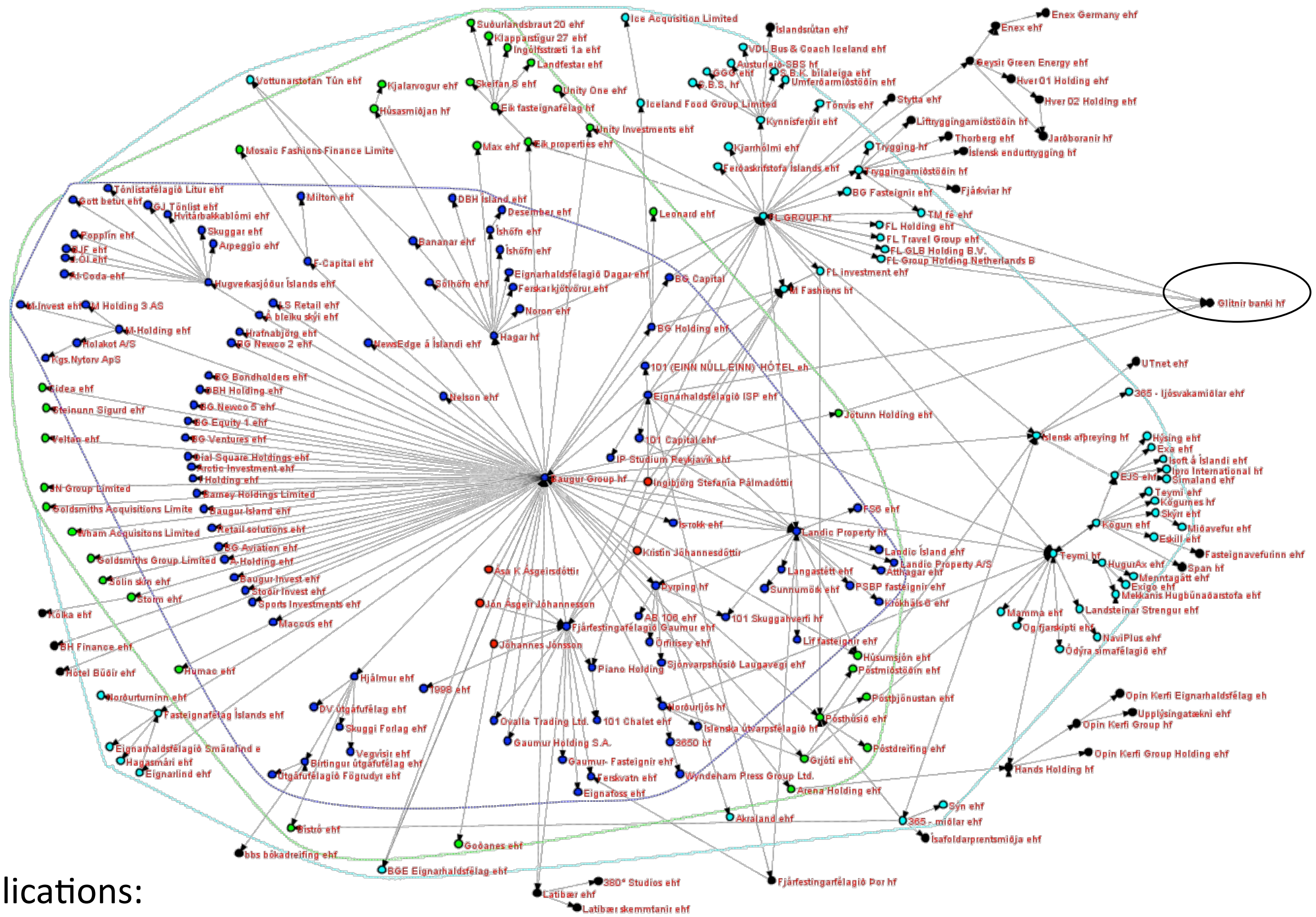
Data Driven Large Exposure Estimation: A Case Study of a Failed Banking System

Margrét Vilborg Bjarnadóttir

Robert H. Smith School of Business | University of Maryland

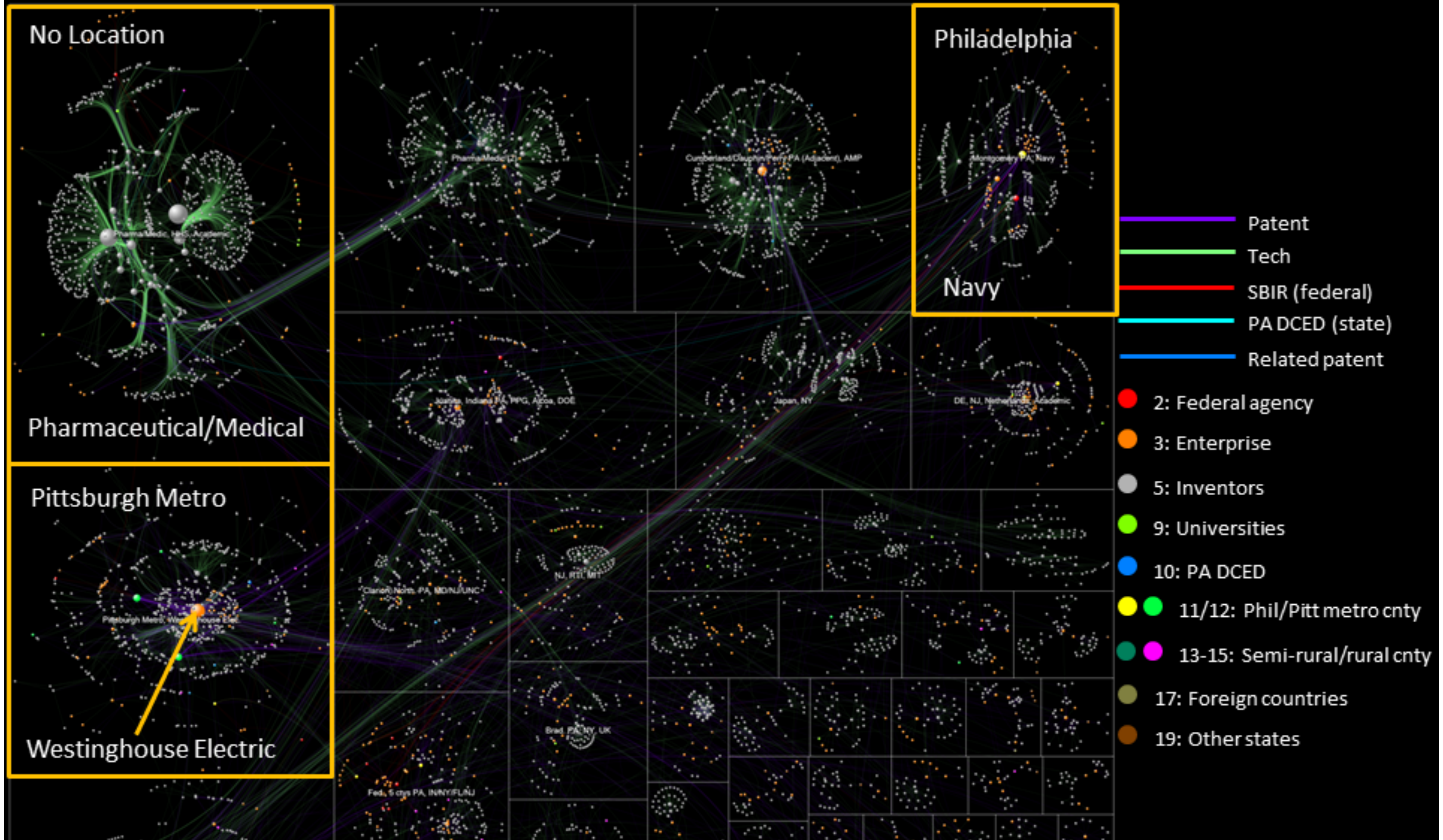
Data Scientist | Parliamentary Special Investigation Commission

Co-authors: Sigríður Benediktsdóttir and Guðmundur Axel Hansen



Supporting Publications:

Margrét V. Bjarnadóttir and Gudmundur A. Hanssen. 2010. Cross-Ownership and Large Exposures; Analysis and Policy Recommendations. Report of the Special Investigation Commission, Volume 9. Sigridur Benediksdottir and Margrét V. Bjarnadóttir. "Large Exposure Estimation through Automatic Business Group Identification". Proceedings to DSMM 2014.



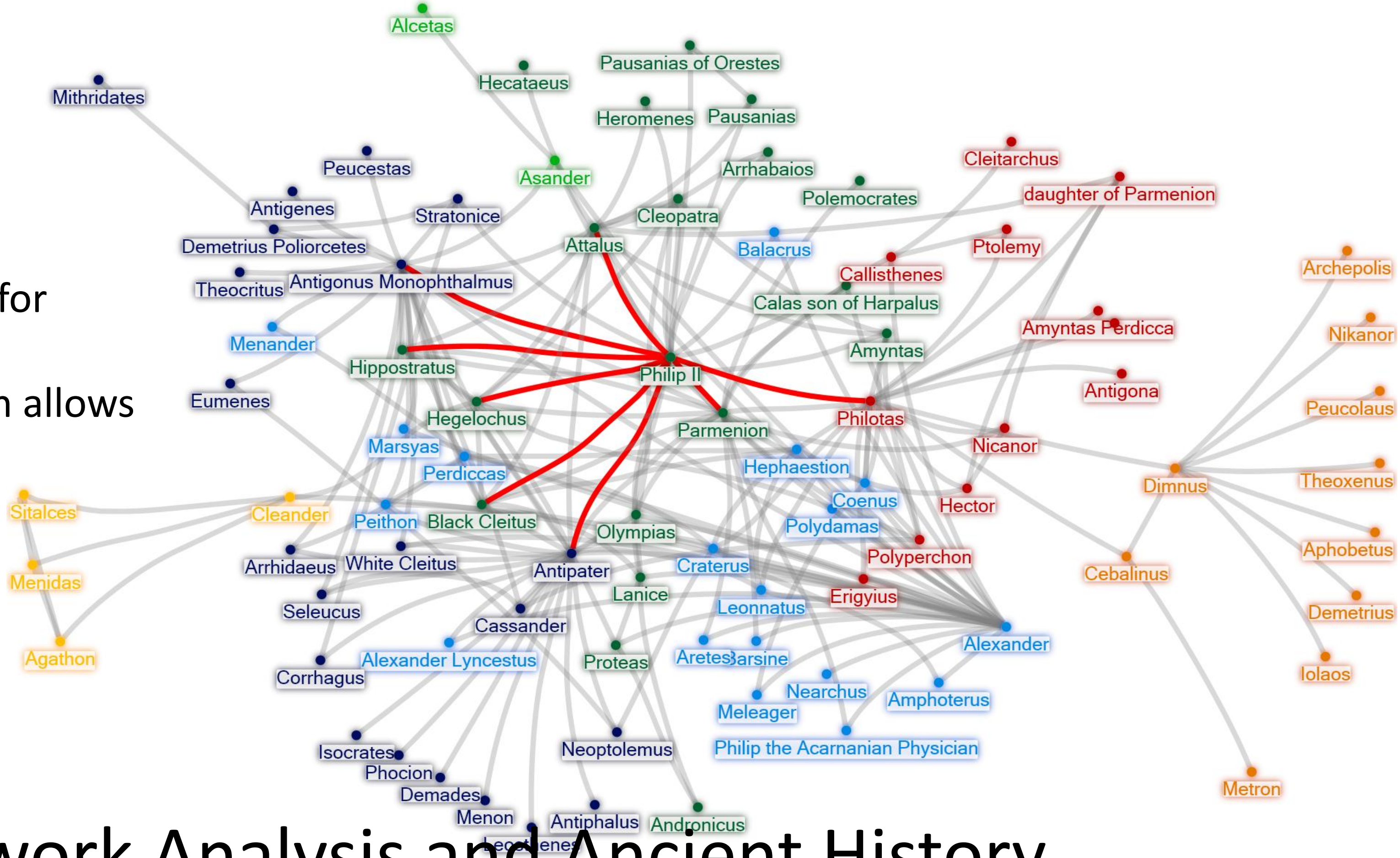
http://www.terpconnect.umd.edu/~dempy/

C. Scott Dempwolf, PhD
Research Assistant Professor & Director
UMD - Morgan State Center for Economic Development

Prof. Diane Harris Cline
Associate Professor of History; Affiliated faculty member in Classical and Near Eastern Literatures and Civilizations.
George Washington University

Social Network Analysis for the humanities?

1. New framework for analysis
2. Data visualization allows new perspectives – less linear, more comprehensive



Social Network Analysis and Ancient History

Many papers of interest created using NodeXL can be found at
http://www.pinterest.com/nodexl/pins/