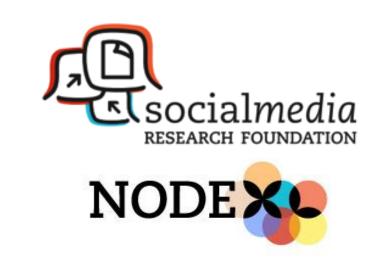


Can social accounting improve the social media "marketplace of ideas"?



Creating social network maps and measures with NodeXL

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

### About me

### **Introductions**

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

marc@smrfoundation.org

http://www.smrfoundation.org

http://nodexlgraphgallery.org

http://www.twitter.com/marc smith

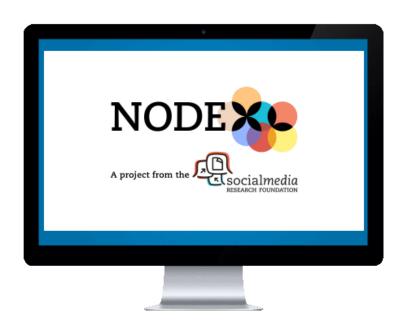
http://www.linkedin.com/in/marcasmith

http://www.slideshare.net/Marc A Smith

http://www.flickr.com/photos/marc smith

http://www.facebook.com/marc.smith.sociologist





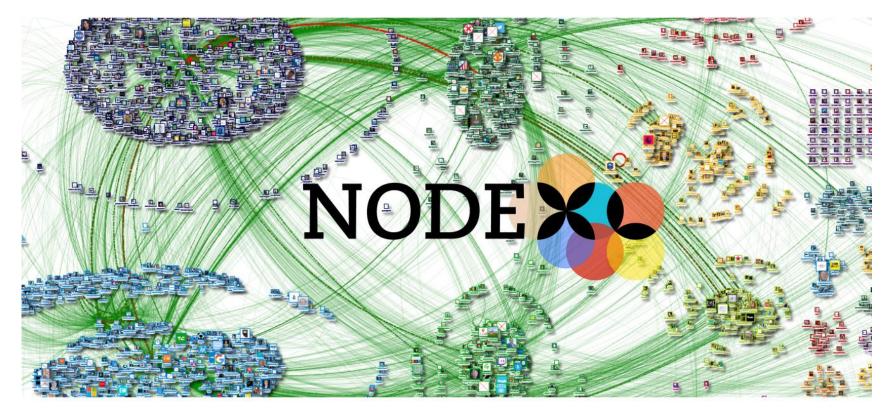


## **About Us**





Home NodeXL Licenses Networks Blog Newsletter 💆 f



### Welcome to the Social Media Research Foundation

The Social Media Research Foundation is the home of NodeXL – Network Overview Discovery and Exploration for Excel (2010, 2013 and 2016) – extending the familiar spreadsheet so you can collect, analyze and visualize complex social networks from Twitter, Facebook, Youtube and Flickr.

## **About Us**











### Marc A. Smith

Marc A. Smith is a sociologist specializing in the social organization of online communities and computermediated interaction. Smith leads



### Ben Shneiderman

Ben Shneiderman (www.cs.umd.edu/~ben) is a professor in the Department of Computer Science and founding director (1983-2000) of the



#### Itai Himmelboim

Itai Himelboim from the Grady College of Journalism and Mass Communication at the University of Georgia where he studies the role social media plays in news,

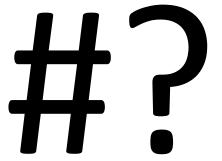


### Wasim Ahmed

Wasim Ahmed is a Doctoral Candidate at the Information School at the University of Sheffield. He regularly posts to his social media blog and

# What does a hashtag look like?

What is an adequate visualization of social media?





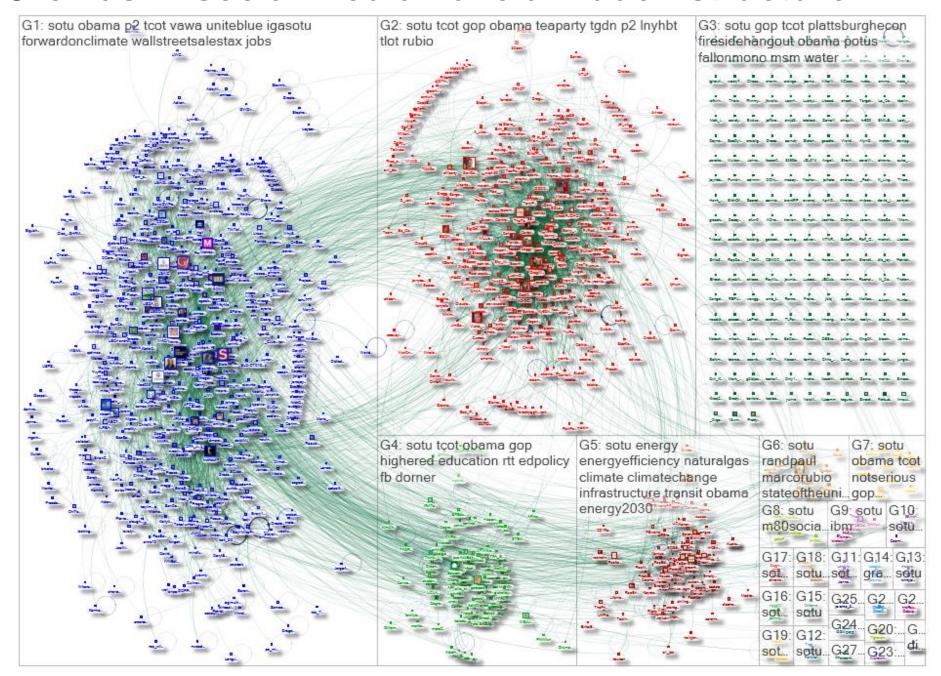




### Crowds in social media matter



### Crowds in social media have a hidden structure







### Just how social is social media?

- Not very.
- Low density
- Low reciprocity
- More like broadcast than peer communication.



# How much community is in online community?

• Not much.



# Social Media makes one promise, but *people hear two*!

- Social media promises:
  - "All may speak."

- Social media does *not* promise:
  - "All may be heard."



# Social media are "Marketplaces for Ideas"

- But they lack accounting systems for those markets.
- Markets without accounting systems tend towards rampant fraud.
- Accounting softeware for the marketplace of ideas is a necessary but not sufficient condition to cultivating high quality information markets.





https://en.wikipedia.org/wiki/Luca\_Pacioli

### https://en.wikipedia.org/wiki/Accounting



# Information systems =/= High quality information systems



Information quality =/= Information validity



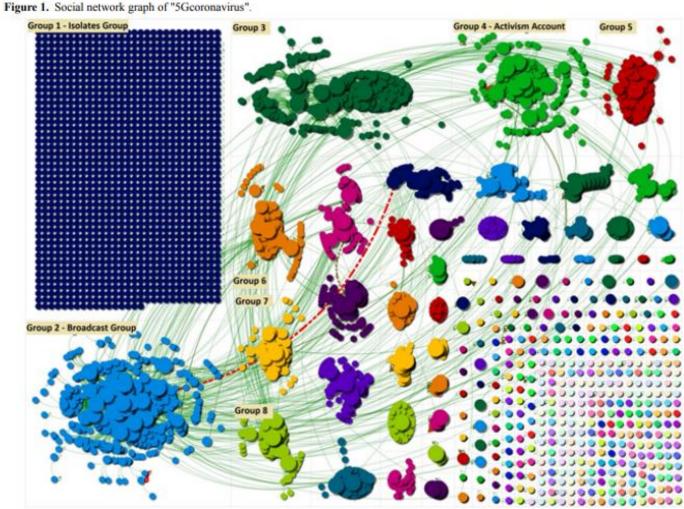
## 5G and COVID-19 Conspiracy Theory on Twitter

Advertisement



Ahmed W, Vidal-Alaball J, Downing J, López Seguí F: **COVID-19 and the 5G Conspiracy Theory: Social Network Analysis of Twitter Data** J Med Internet Res 2020;22(5):e19458 URL: <a href="https://www.jmir.org/2020/5/e19458">https://www.jmir.org/2020/5/e19458</a> DOI: 10.2196/19458

## 5G and COVID-19 Conspiracy Theory on Twitter



Ahmed W, Vidal-Alaball J, Downing J, López Seguí F COVID-19 and the 5G Conspiracy Theory: Social Network Analysis of Twitter Data J Med Internet Res 2020;22(5):e19458 URL: <a href="https://www.jmir.org/2020/5/e19458">https://www.jmir.org/2020/5/e19458</a> DOI: 10.2196/19458 PMID: 32352383 PMCID: 7205032

### 5G and COVID-19 Conspiracy Theory on Twitter

**Table 1.** Influential users ranked by their betweenness centrality score.

Rank	Account description	Betweenness centrality score	Followers, n	Network group in Figure 1
1	Citizen	3,059,934.33	432	7
2	Citizen	3,042,916.47	12	2
3	Citizen	2,926,695.58	546	3
4	Writer	2,655,235.44	1874	2
5	5G and coronavirus dedicated activism account	2,637,433.23	383	4
6	Citizen	2,577,072.58	14	6
7	Citizen	2,354,744.84	175	2
8	Citizen	2,066,430.77	51	2
9	YouTuber	2,003,753.23	130	5
10	Donald Trump	1,380,314.74	75,916,289	4

Ahmed W, Vidal-Alaball J, Downing J, López Seguí F COVID-19 and the 5G Conspiracy Theory: Social Network Analysis of Twitter Data J Med Internet Res 2020;22(5):e19458 URL: <a href="https://www.jmir.org/2020/5/e19458">https://www.jmir.org/2020/5/e19458</a> DOI: 10.2196/19458 PMID: 32352383 PMCID: 7205032

## Challenge: Truth is like beauty

- It's in the eye of the beholder('s tribe)
- Everyone is entitled to his own opinion, but not his own facts.
- No way to "fact check"
- Facts are not persuasive
- Truth is a property of bounded populations within social networks
- Things are "true" for some people at some times
- Repetition makes things true
- Exposure to "fake" ideas and images have impact even when disputed
- Cultural awe for "science" eroded

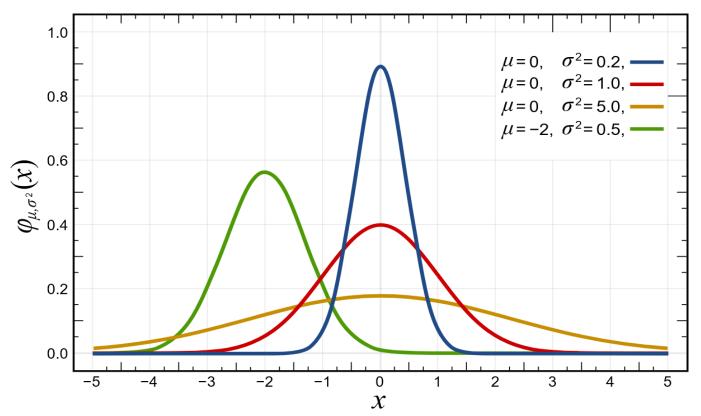
# Challenge: Weaponization of Social Media

- Propaganda
- Misinformation
- Disinformation

• Pollution of cultural space erodes ability to create universal truths.



# There is nothing Normal



About the Normal curve

RESEARCH FOUNDATION

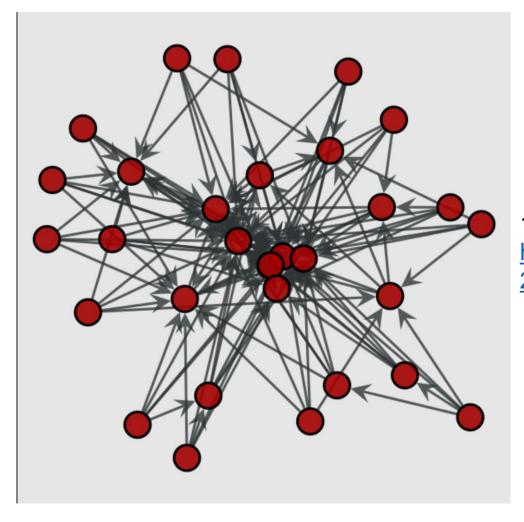
## Networks are often

Power law distributions



https://en.wikipedia.org/wiki/Matthew\_effect

https://en.wikipedia.org/wiki/Preferential\_attachment



1-9-90

https://en.wikipedia.org/wiki/1% 25\_rule\_(Internet\_culture)

A power law distribution is often created when some people gain an early advantage that builds over time. Prominent people become more prominent, rich people become richer.



"The Journalistic Question"

The 5 "W"s

Who?

Did What?

With Whom?

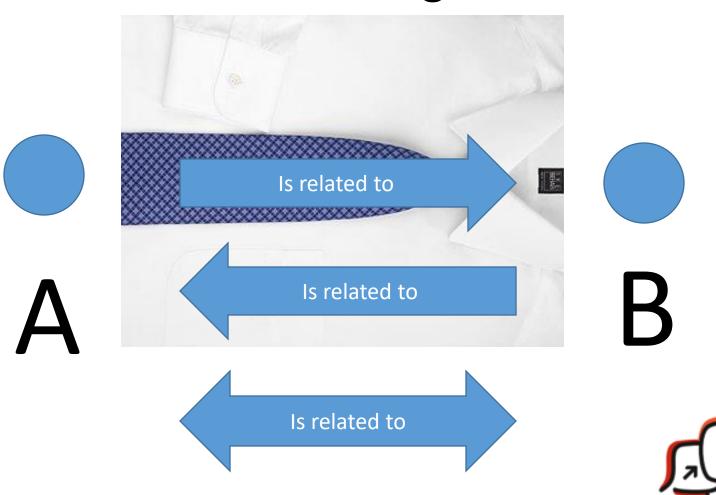
When?

And Where?



# "Think Link"

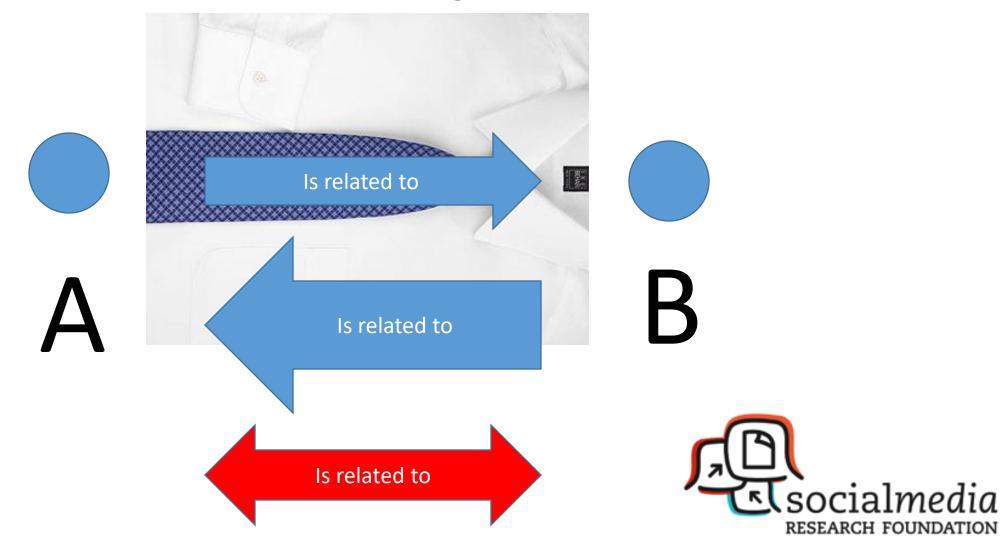
Nodes & Edges



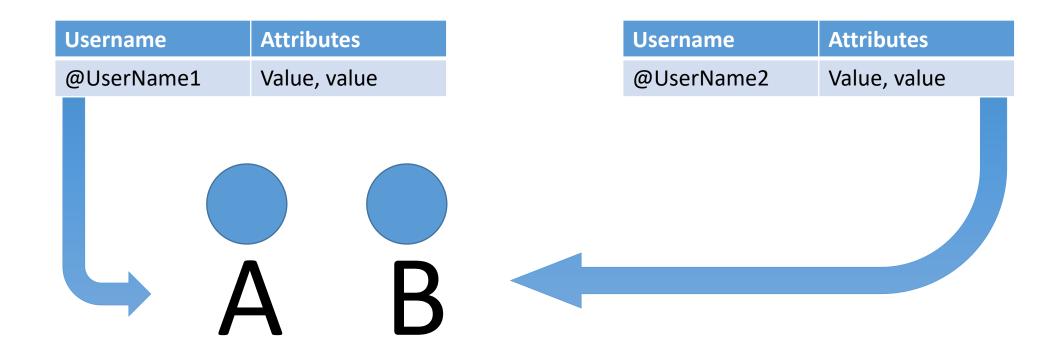


# "Think Link"

Nodes & Edges

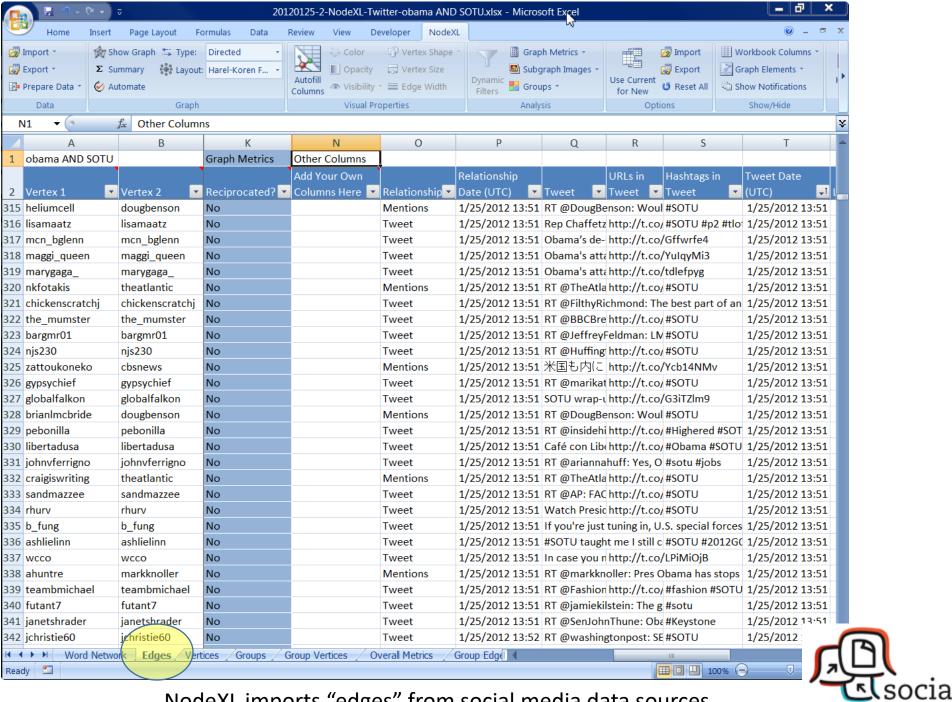


### A network is born whenever two GUIDs are joined.



Vertex1		"Edge" Attribute	"Vertex1" Attribute	"Vertex2" Attribute
@UserName1	@UserName2	value	value	value





NodeXL imports "edges" from social media data sources

RESEARCH FOUNDATION

"The Journalistic Question"

The 5 "W"s

Who?

Did What?

With Whom?

When?

And Where?



"The Journalistic Question"

The 5 "W"s

Who?

Did What?

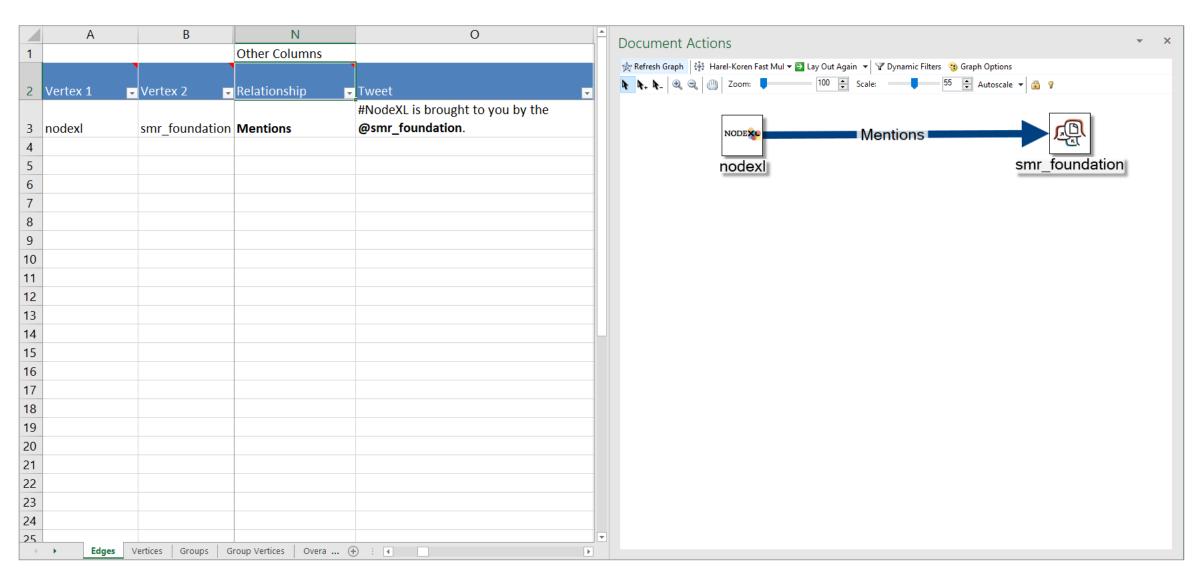
With Whom?

When?

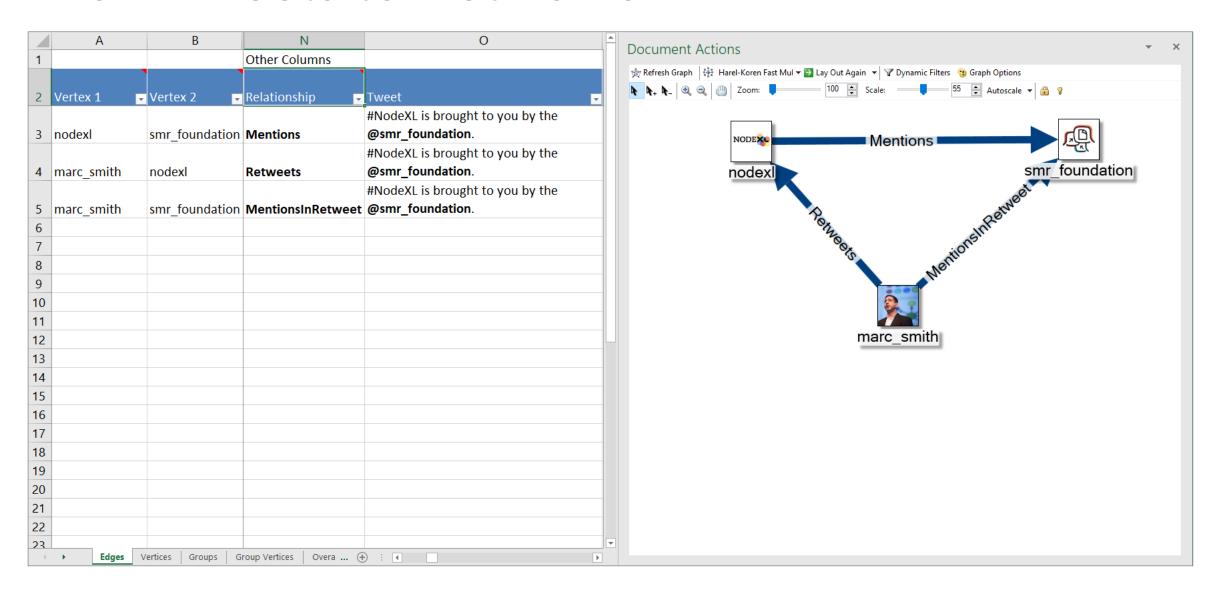
And Where?

Vertex1		"Edge" Attribute		"Vertex2" Attribute
@UserName1	@UserName2	value	value	value

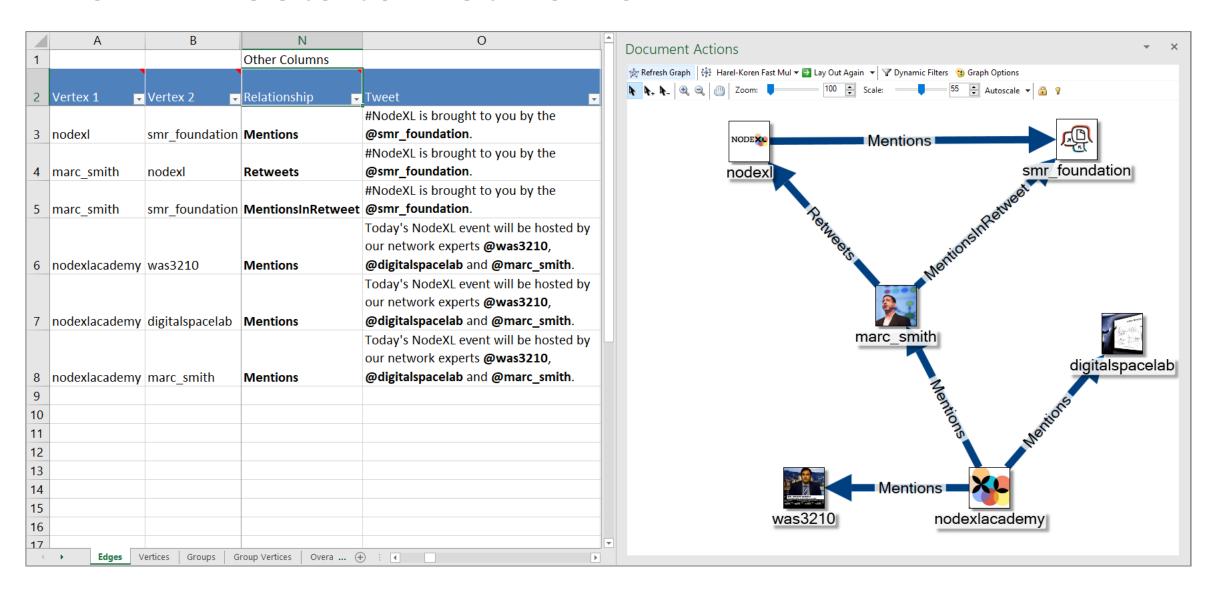
### From Tweets to Networks



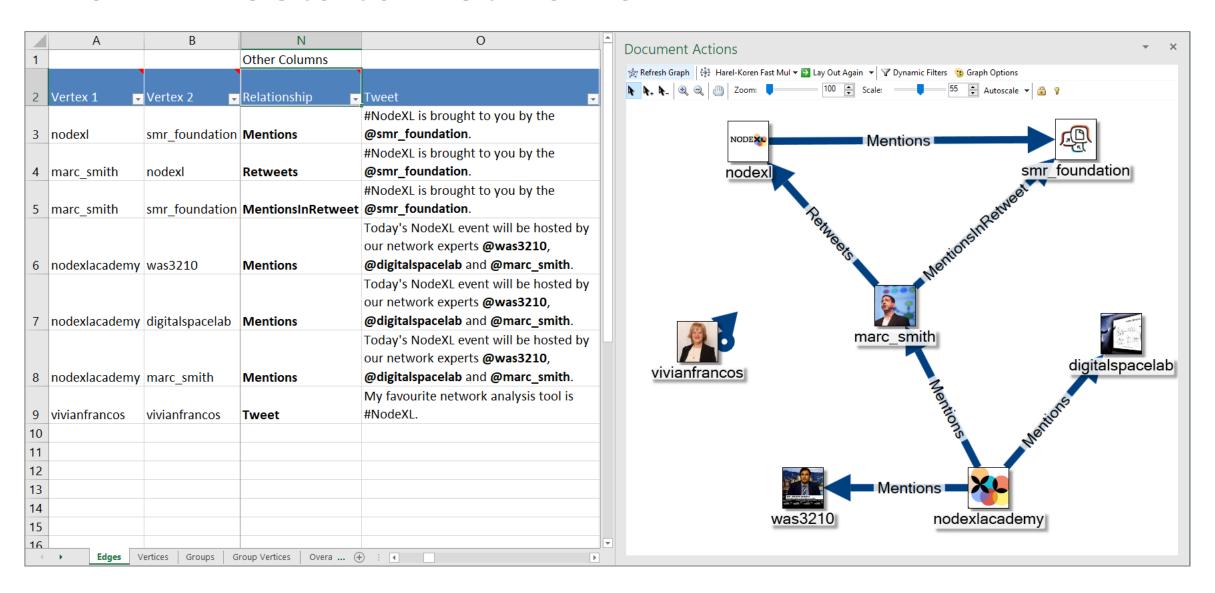
### From Tweets to Networks



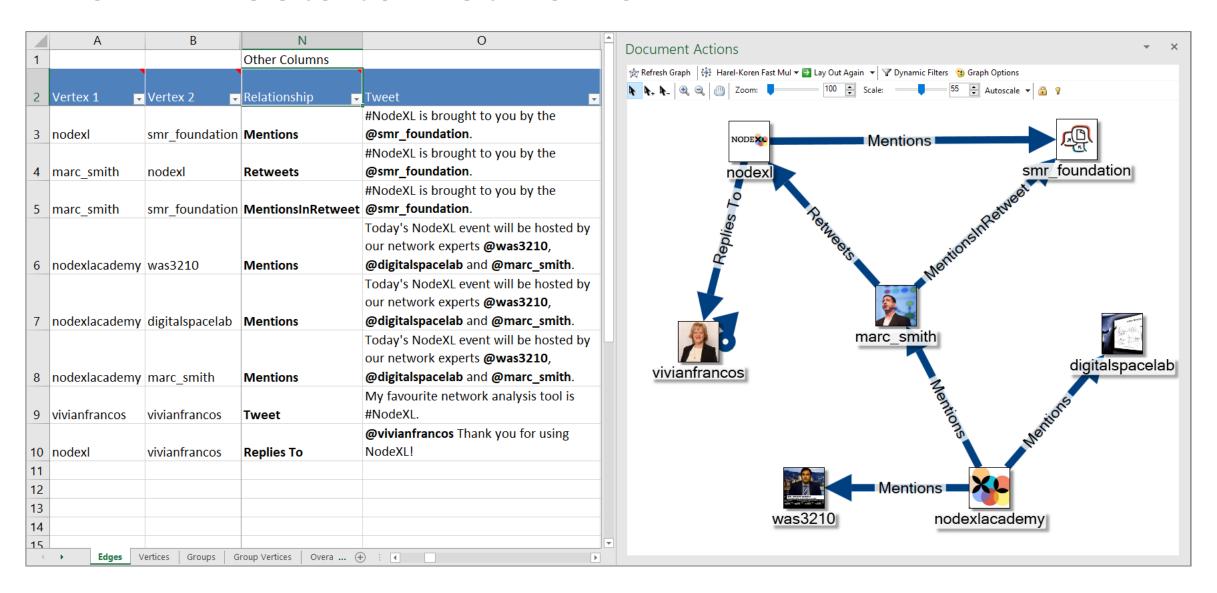
### From Tweets to Networks



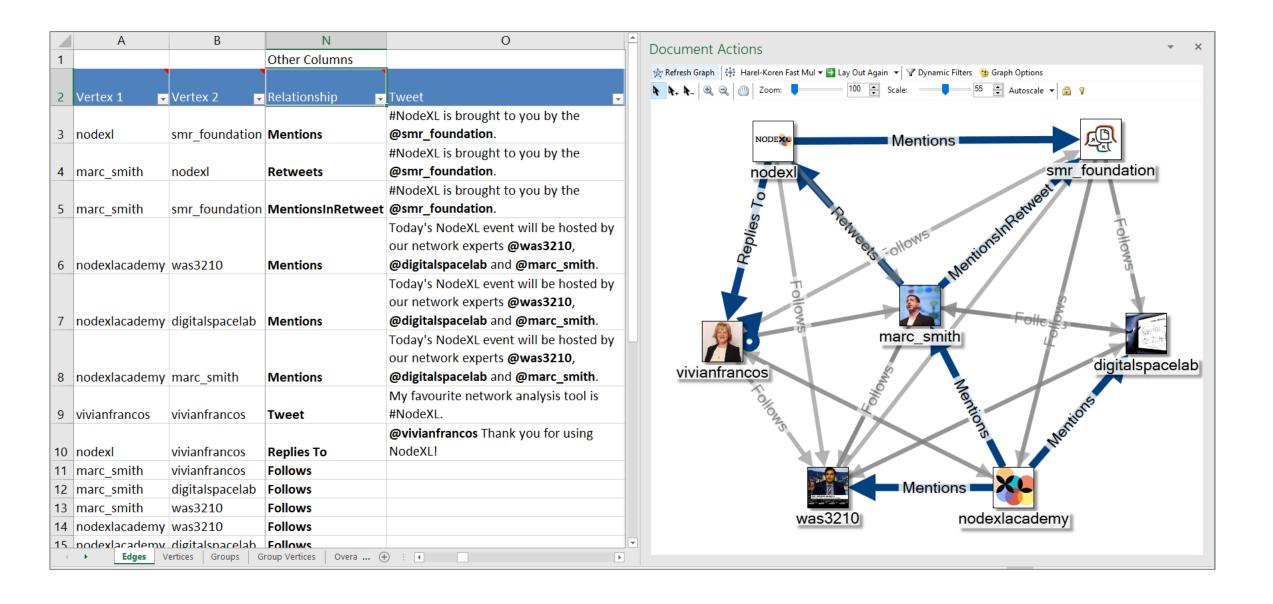
# From Tweets to Networks



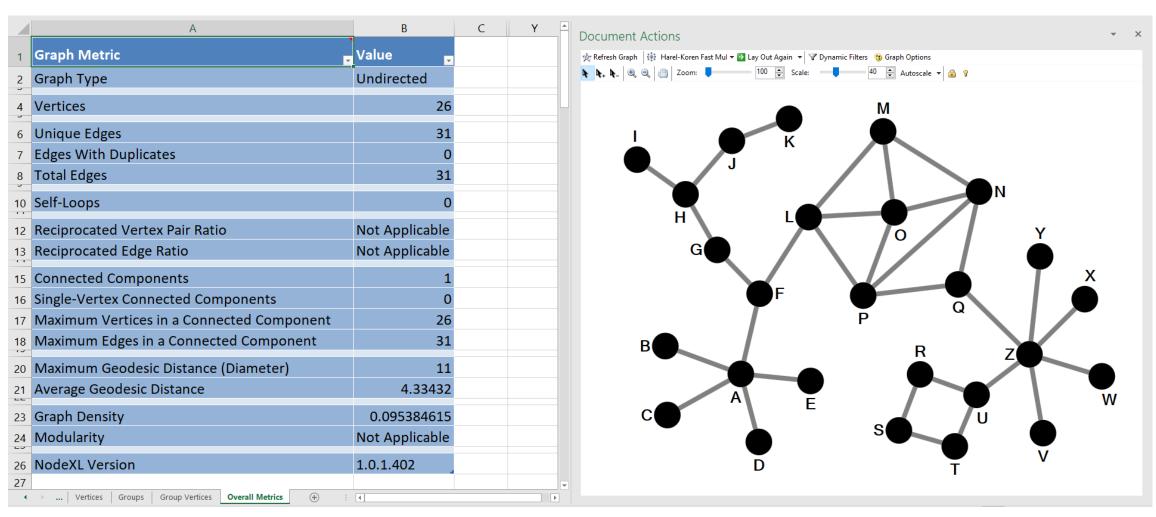
# From Tweets to Networks



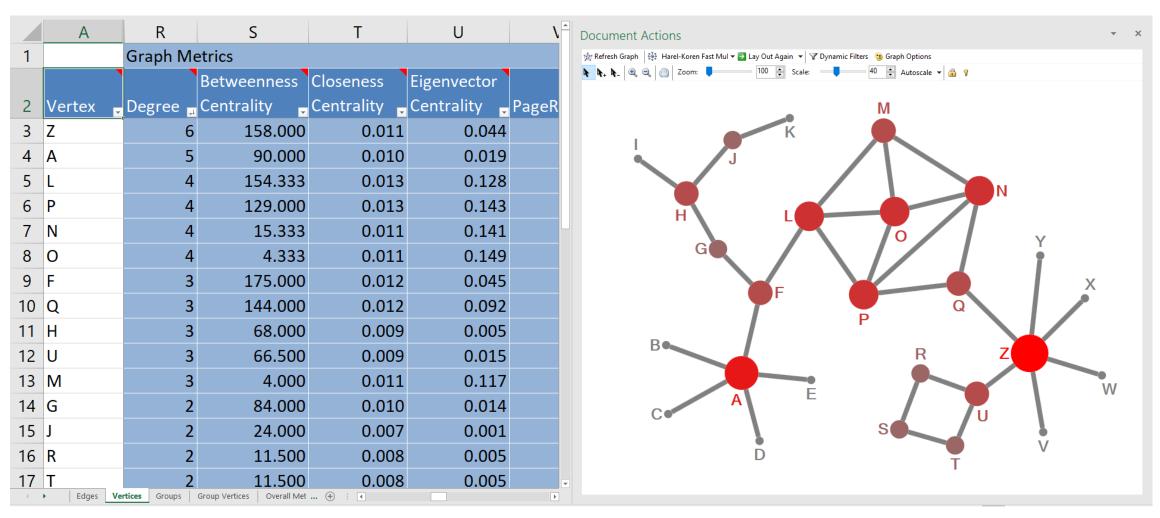
# From Tweets to Networks



# The Alphabet Network



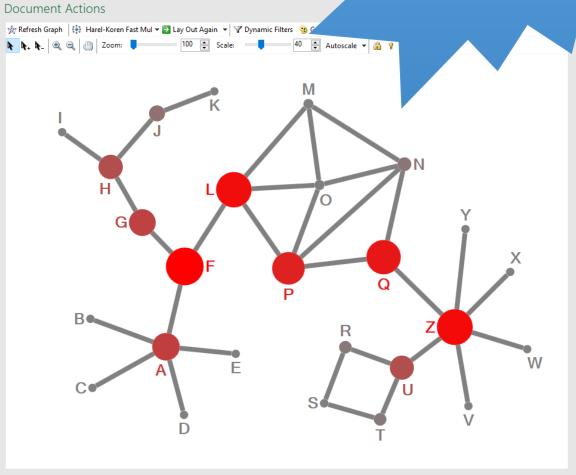
# Degree



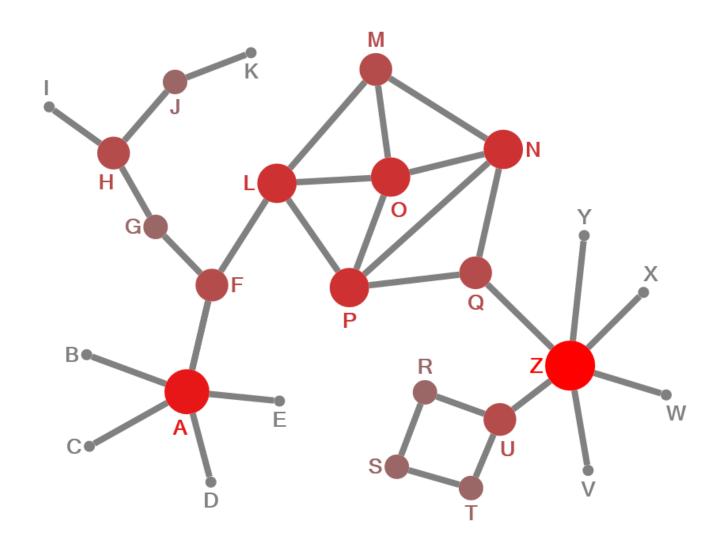
# Betweenness Centrality

Network metrics of social media can be useful for identifying people in strategic locations. The strongest indicator of an individual's wide connection across the graph is "betweenness centrality".

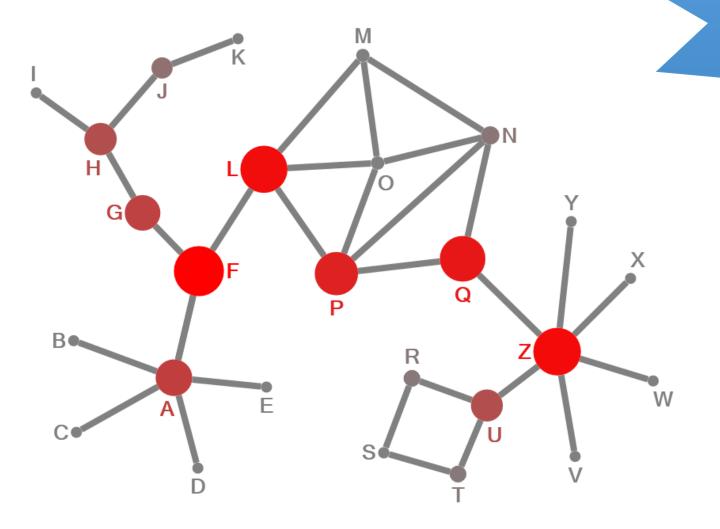
	Α	R	S	Т	U	\
1		Graph Me	etrics			
			Betweenness	Eigenvector		
2	Vertex 🕌	Degree 💂	Centrality 💂	Centrality 🗸	Centrality 🔻	PageR
3	F	3	175.000	0.012	0.045	
4	Z	6	158.000	0.011	0.044	
5	L	4	154.333	0.013	0.128	
6	Q	3	144.000	0.012	0.092	
7	P	4	129.000	0.013	0.143	
8	Α	5	90.000	0.010	0.019	
9	G	2	84.000	0.010	0.014	
10	Н	3	68.000	0.009	0.005	
11	U	3	66.500	0.009	0.015	
12	J	2	24.000	0.007	0.001	
13	N	4	15.333	0.011	0.141	
14	R	2	11.500	0.008	0.005	
15	Т	2	11.500	0.008	0.005	
16	0	4	4.333	0.011	0.149	
17	M	3	4.000	0.011	0.117	<b>•</b>
17		rtices Groups	Group Vertices Overall Met		0.117	



# Degree



# Betweenness Centrality



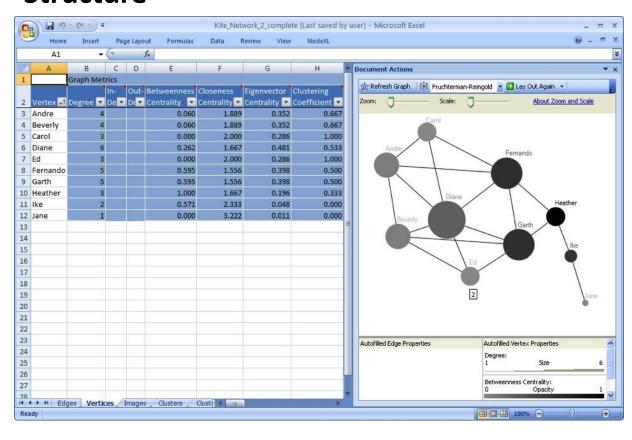
Network metrics of social media can be useful for identifying people in strategic locations. The strongest indicator of an individual's wide connection across the graph is "betweenness centrality".

# What is different in a network view?

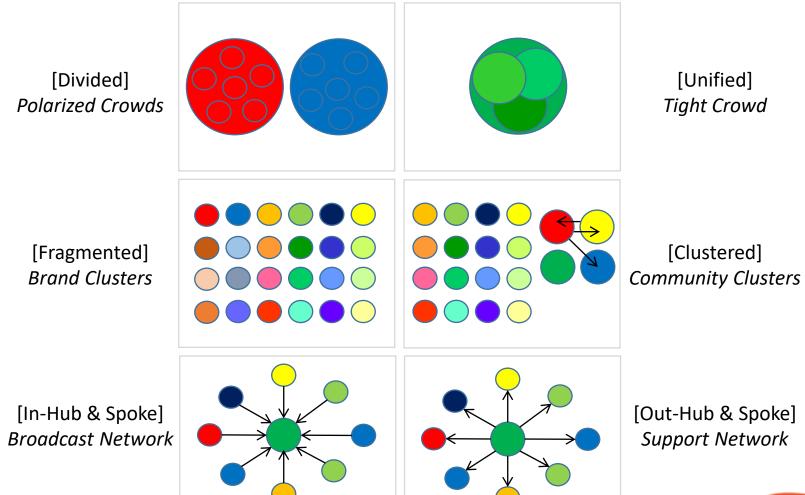
## Volume

10

## **Structure**



## 6 kinds of Twitter social media networks







REPORT

FEBRUARY 20, 2014



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

## **Summary of Findings**

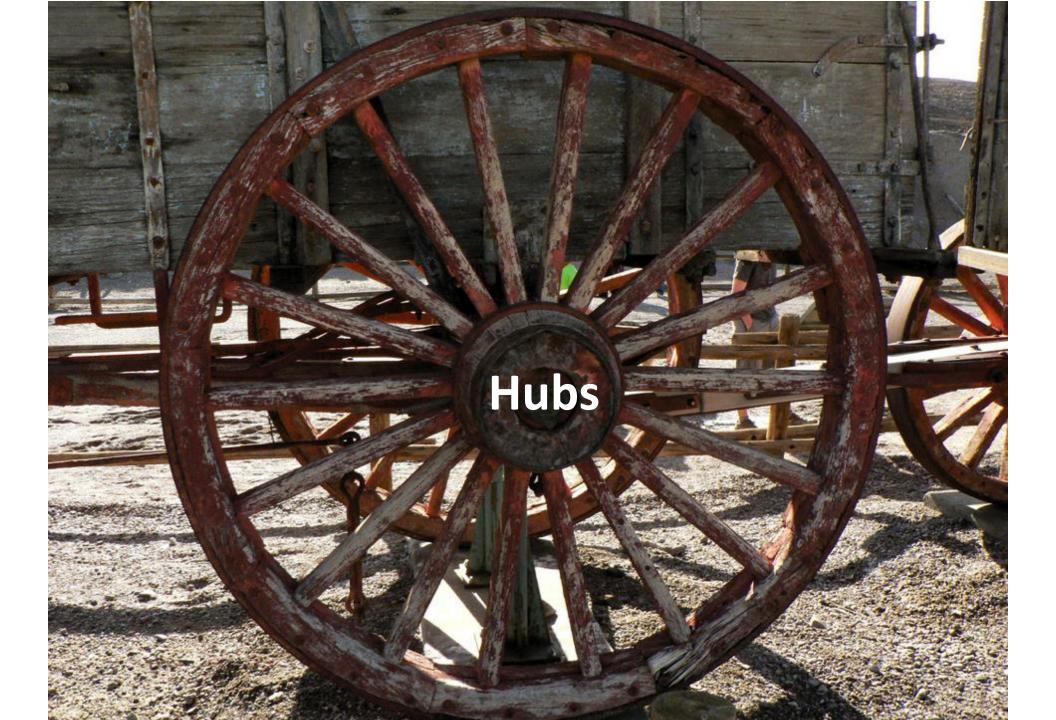
### Polarized Crowds: Political conversations on Twitter

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.

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

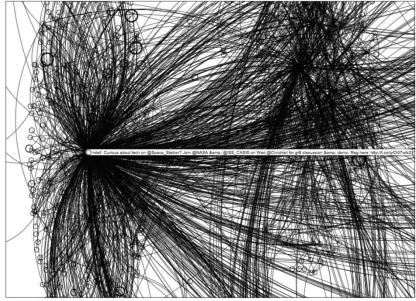




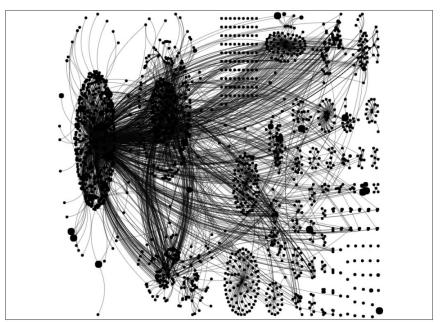


## https://flic.kr/p/4Z6GHv





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



#pdf15 OR #wegov OR pdmteam OR <code>@techpresident</code> OR <code>%22personal</code> democracy<code>%22</code> OR <code>MlsifTwitter NodeXL SN</code> (experimental version)



https://flic.kr/p/etEmeR



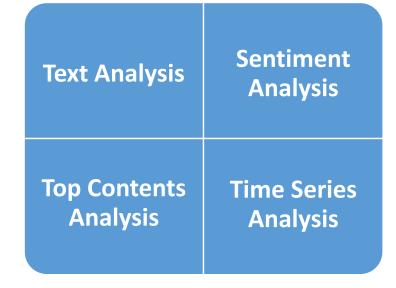


# Key Features of a network approach

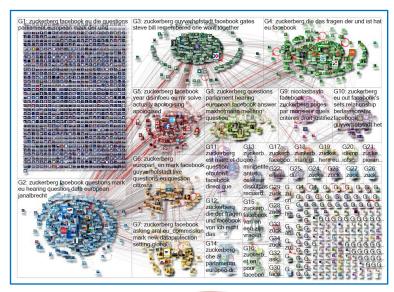
## **Network Analysis**

# Network Group Metrics Vertex Metrics

## **Content Analysis**



## **Visualisation**





# Key Features of NodeXL Pro

**Data Import** 

**Network Analysis** 

**Content Analysis** 

Visualization

**Data Export** 

**Data formats** 

Excel/UCINET/GraphML/ Pajek/GEFX/GDF

Social media data







**3rd Party importers** 

**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/ Page Rank

**Path 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/...

**Customize** 

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

**Autofill Columns** 

**Graph Layout** 

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

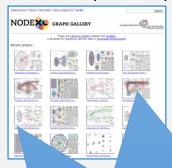
**Group-In-a-Box Layout** 

Treemap Force-directed Packed rectangles **Data formats** 

Excel/UCINET/GraphML/ Pajek/GEFX/GDF

Publish to the web

**NodeXL Graph Gallery** 

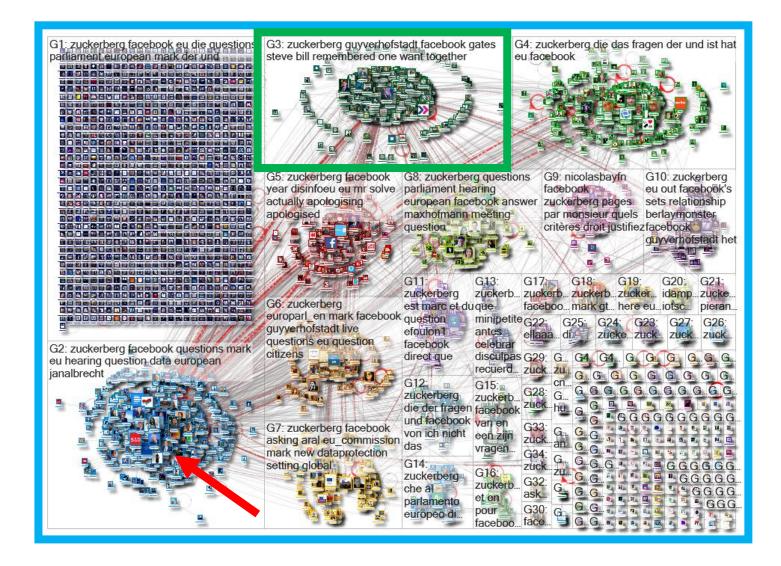


Expo

New!
Discovery and
Presentation!

Automate all steps with NodeXL Data Recipes

# Social Network Analysis

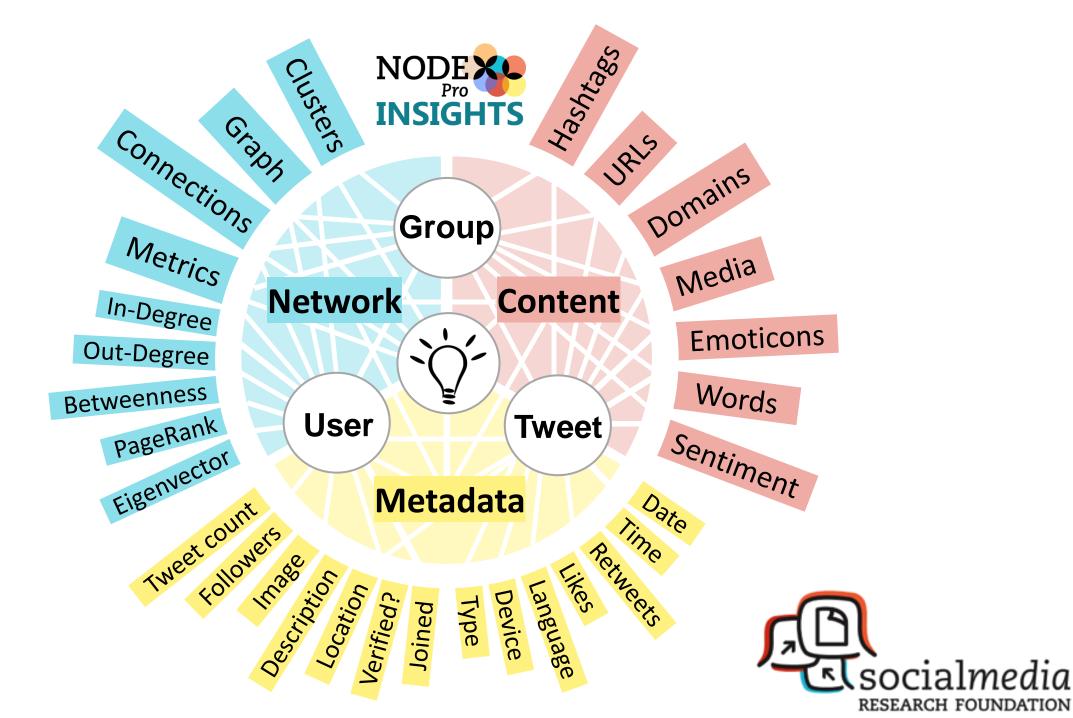


**Network metrics** 

**Group metrics** 

**Vertex metrics** 





















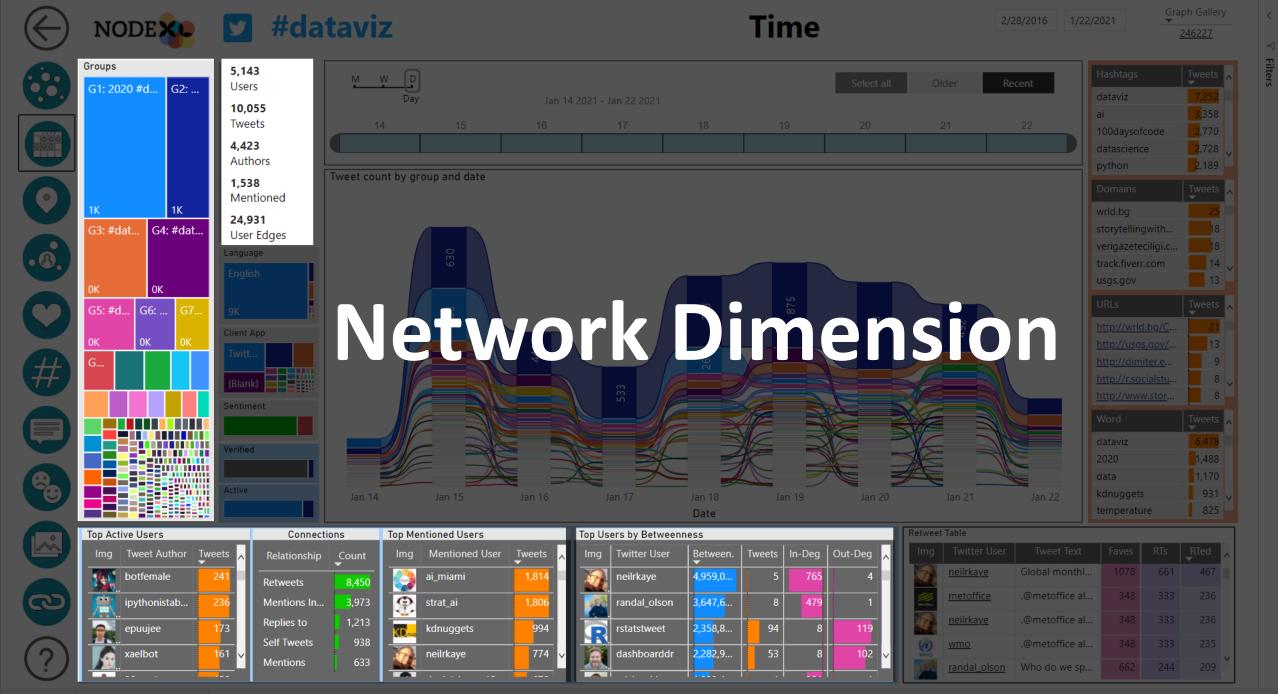










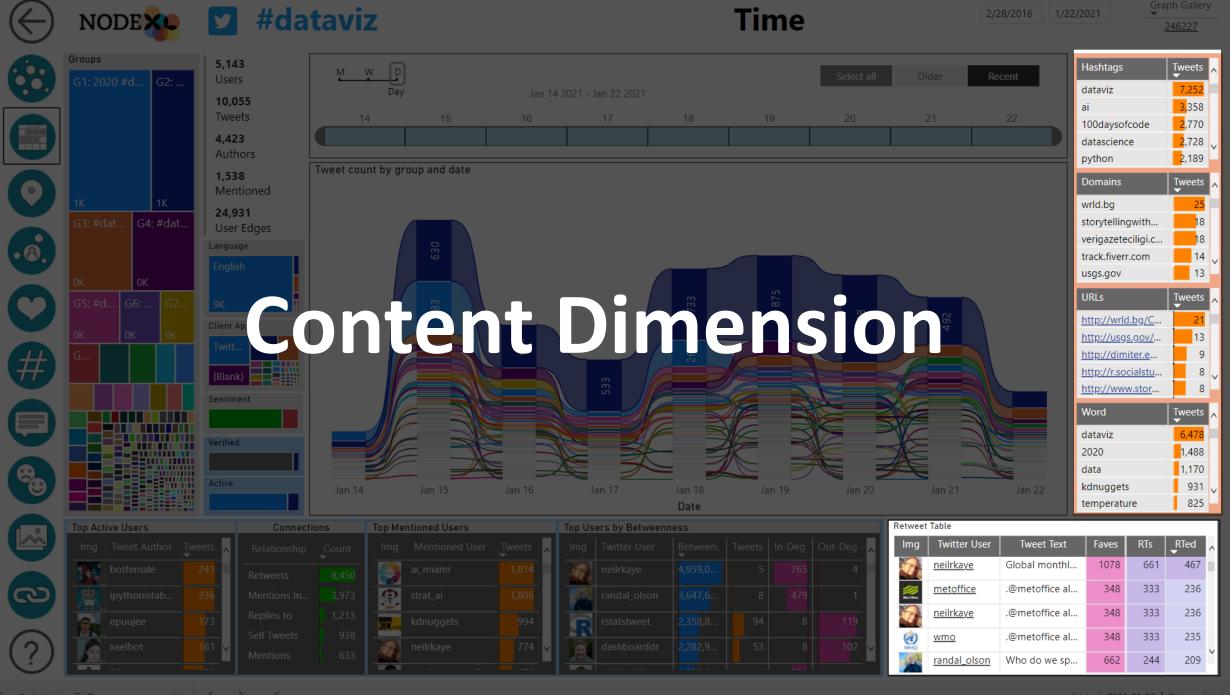


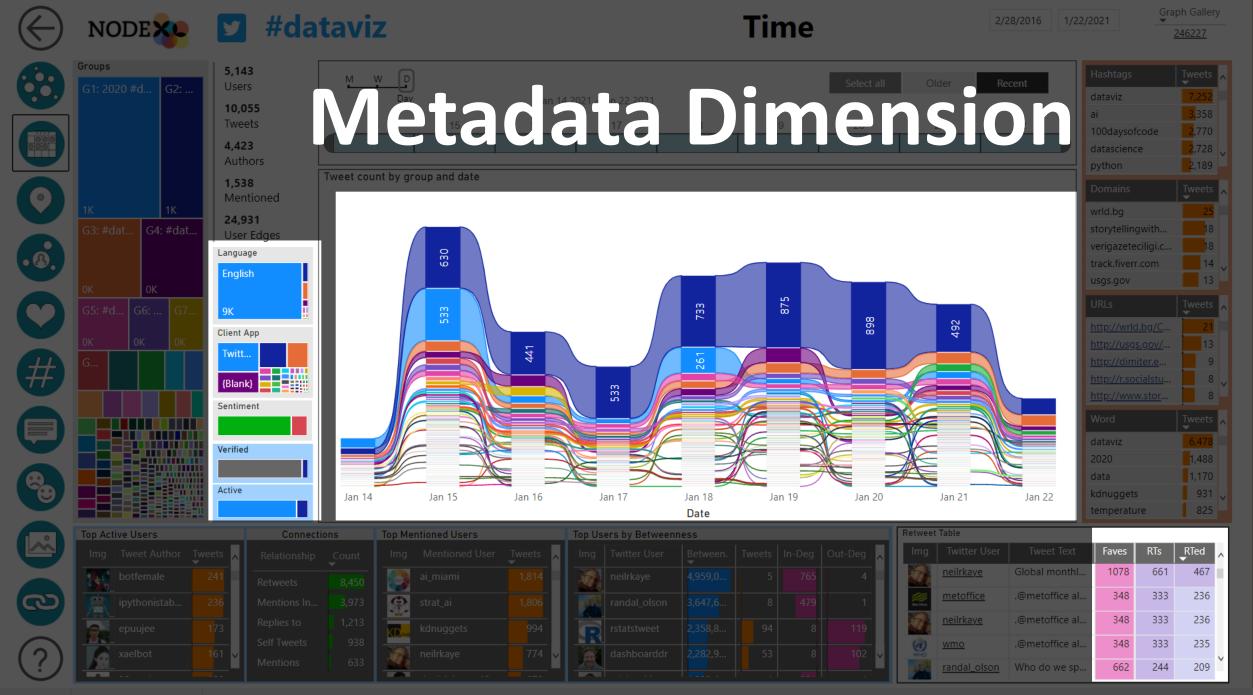














Groups

G3: tune b...

G5: #wp...

G6: musi...

G4: mu..

1K

G7: ..

## NODEX WPU Twitter List

## **Network**

8/3/2017

3/15/2022

Graph Gallery

273123





















1,364

Users

9,841 Tweets 465

**Authors** 

1,360 Mentioned

13,015 Connections

Language

**English** 

Client App

Sentiment

Verified

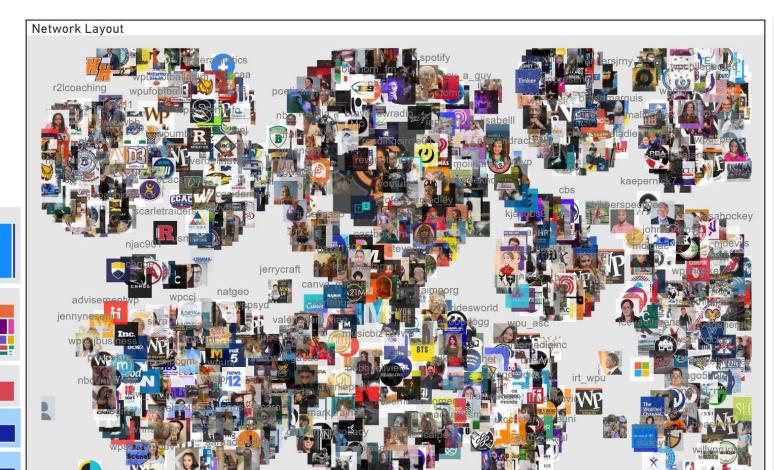
Active

Twitter for iP.

Twitter Web ..





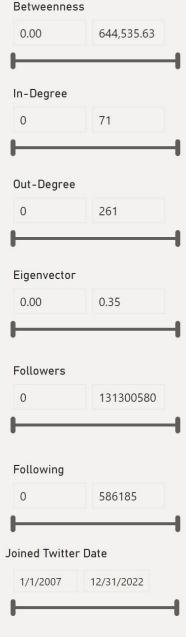


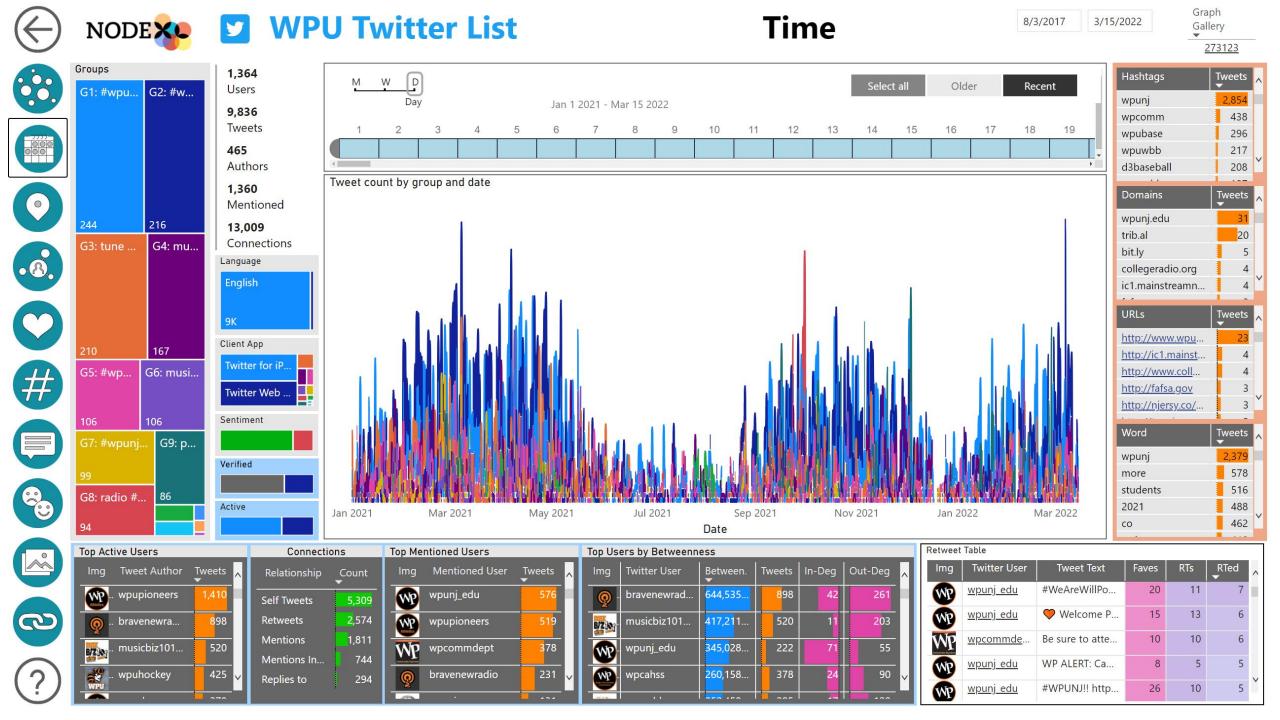


Hashtags	Tweets	^
wpunj	2,858	h
wpcomm	438	
wpubase	296	
wpuwbb	217	
d3baseball	208	ı
wpumbb	187	
wpuws	160	V
d3hoops	158	h

261

203







G1: #wpunj co nja..

G2: #wpunj #wpc...

G3: tune...

G5: #...

G...

0K

G4: m...

0K

Groups

## NODEX WPU Twitter List

## **Time Grid**



Graph Gallery

Hashtags

wpcomm

wpubase

wpuwbb

d3baseball

**Domains** 

wpunj.edu

trib.al

wpunj

273123

Tweets

2,858

438

296

217

208

Tweets

20

٦



















1,364

Users

9,841

465

**Tweets** 

Authors

Mentioned

Connections

1,360

13,015

Language

English

Client App

Sentiment

Verified

Active

Self T Retwe

Twitter for

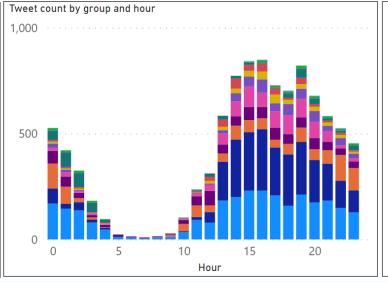
Twitter We..

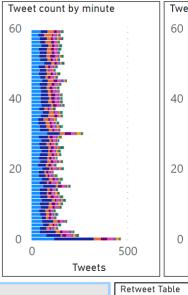


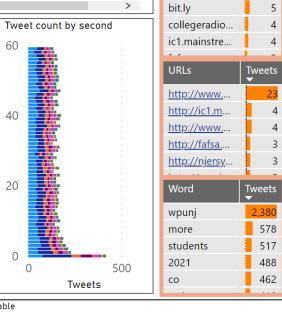
_																			-	
	Tweet cou	nt by da	ay and	hour																
	Day	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
	Sun	96	82	56	42	20	5	1		2	2	9	23	19	24	32	41	51	34	2
	Mon	60	41	18	12	9	3	2	2	1	3	18	48	52	104	151	145	151	135	14

Day	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Sun	96	82	56	42	20	5	1		2	2	9	23	19	24	32	41	51	34	29	45	44	28	33	56
Mon	60	41	18	12	9	3	2	2	1	3	18	48	52	104	151	145	151	135	141	134	131	79	79	64
Tue	43	46	46	11	8	3		1	2	4	16	32	39	91	140	163	153	137	104	119	114	97	67	48
Wed	64	44	30	19	8	4		4	4	1	11	36	56	91	119	160	147	139	159	167	115	119	96	71
Thu	70	54	57	30	19	4	1	1	3	3	9	29	48	91	152	155	145	112	108	119	100	81	70	80
Fri	101	52	48	18	14	1	6	1	3	3	21	34	63	115	119	113	160	122	95	149	95	89	88	47
Sat	93	102	70	51	18	5	4	1		13	19	34	35	68	60	66	42	50	67	88	80	90	93	89
Total	527	421	325	183	96	25	14	10	15	29	103	236	312	584	773	843	849	729	703	821	679	583	526	455
<																								>

1	Tweet count b	y date	
	Date	Tweets	^
	2022-03-15	11	
	2022-03-14	20	
	2022-03-13	9	
	2022-03-12	6	
	2022-03-11	38	
	2022-03-10	33	
	2022-03-09	40	
	2022-03-08	22	
	2022-03-07	73	
	2022-03-06	23	
	2022-03-05	16	
	2022-03-04	39	
1	2022-03-03	45	~
	2022-03-02	21	

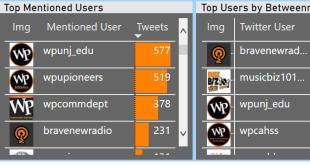






M	Top Act	ive Users	
	lmg	Tweet Author	Tweets ∧
	WP	wpupioneers	1,410
	<b>@</b>	bravenewra	898
	B/ZJe <sub>1</sub>	musicbiz101	520
	SN	wpuhockey	425 🗸

Connectio	ns	ľ
tionship	Count ▼	
Tweets	5,313	
eets	<b>2</b> ,574	
tions	1,812	
tions In	744	
ies to	294	
		ľ



	Top Use	ers by Betweenn	ess				
^	lmg	Twitter User	Between. ▼	Tweets	In-Deg	Out-Deg	^
1	<b>@</b>	bravenewrad	644,535	<mark>8</mark> 98	42	261	H
ı	B/Z log	musicbiz101	417,211	520	11	203	П
ı	WP	wpunj_edu	<mark>345,0</mark> 28	225	71	55	П
Y	WP	wpcahss	<mark>260</mark> ,158	378	24	90	~
	77 A W.	11	150	205		100	

Retweet	Table					
Img	Mentioned	Tweet Text	Faves	RTs	RTed	,
WP	<u>wpunj</u> edu	#WeAreWillPo	20	11	7	
WP	<u>wpunj</u> edu	Welcome P	15	13	6	
WP	wpcommde	Be sure to atte	10	10	6	
WP	<u>wpunj</u> edu	WP ALERT: Ca	8	5	5	,
WP	<u>wpunj</u> edu	#WPUNJ!! http	26	10	5	

Groups

G1: #wpunj co njac w.

G2: #wpunj #wpcom...

G5: #w...

G9:...

OK

G3: tune b...



1,055

Users

9,265

**Tweets** 

**Authors** 

1.312

12,223

Language

English

Client App

Sentiment

Verified

Active

Twitter Web

Twitter for iP...

Mentioned

Connections

375

## NODEX WPU Twitter List

User Location by Tweet Count

## Location

ASIA

Indian

**ANTARCTICA** 

Arctic

Ocean

Pacific

Ocean

8/3/2017

3/15/2022

Graph Gallery









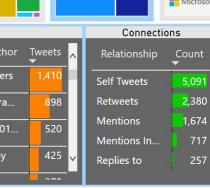


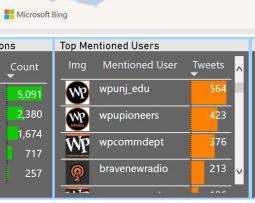












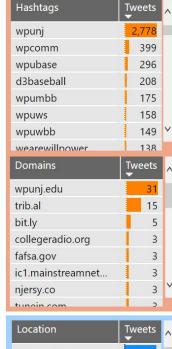
	Top Use	ers by Betweenn	ess			
^	lmg	Twitter User	Between. ▼	Tweets	In-Deg	Out-Deg ^
H	<u>@</u>	bravenewrad	644,535	898	42	261
П	BIZIO	musicbiz101	417,211	520	11	203
П	WP	wpunj_edu	<mark>345,0</mark> 28	225	71	55
~	WP	wpcahss	<mark>260</mark> ,158	378	24	90
				440		

**AFRICA** 

Atlantic

SOUTH AMERICA

Ocean



Location	Tweets ▼	^
Wayne, NJ	3,597	h
Wayne, N.J.	1,479	l
Wayne, NJ.	898	
William Paterson U	868	
Wayne, New Jersey	425	
Wayne, NJ 07470	225	V
Will. Power. TV.	154	ľ
	1	

Retweet Table								
Img	Mentioned	Tweet Text	Faves	RTs	RTed	/		
WP	wpunj edu	#WeAreWillPo	20	11	7			
WP	<u>wpunj</u> edu	Welcome P	15	13	6			
WP	wpcommde	Be sure to atte	10	10	6			
WP	<u>wpunj</u> edu	WP ALERT: Ca	8	5	5	,		
WP	wpunj edu	#WPUNJ!! http	26	10	5			

596

© 2022 Microsoft Corporation Terms

Location(s)



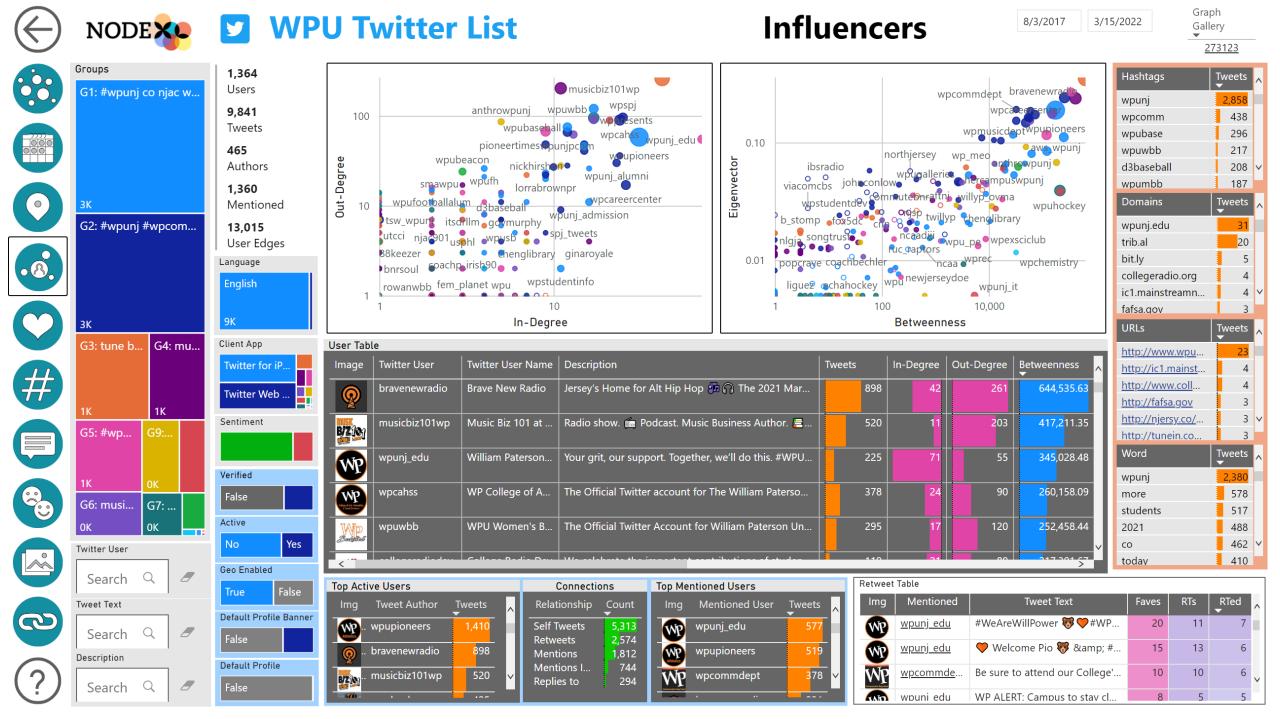


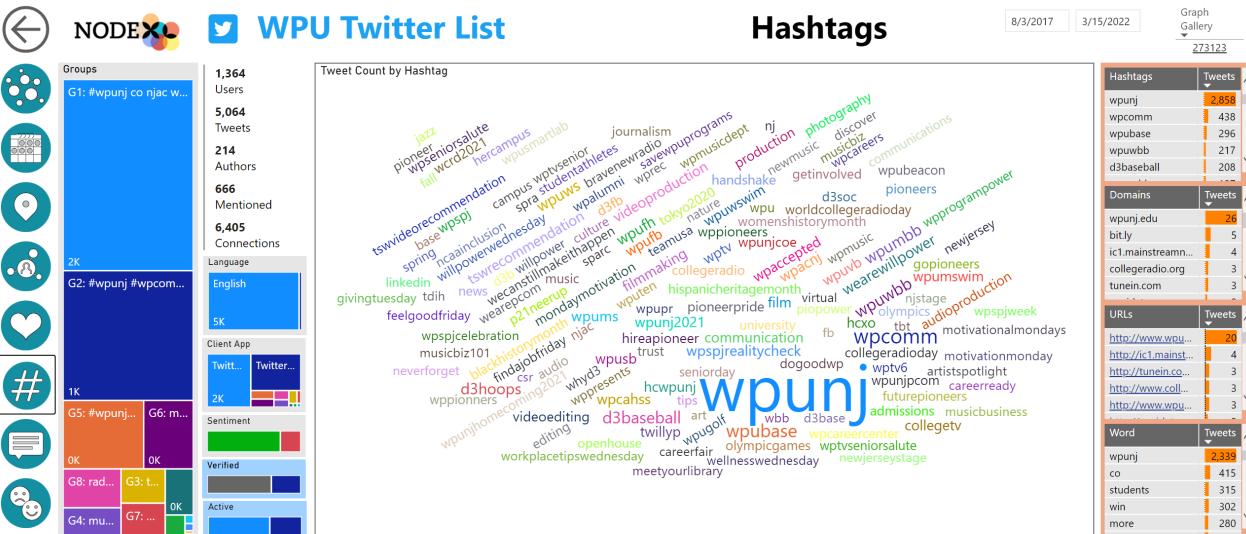










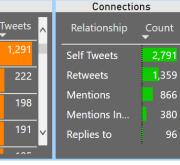


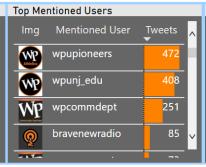












	Top Users by Betweenness							
^	lmg	Twitter User	Between. ▼	Tweets	In-Deg	Out-Deg ^		
н	<b>@</b>	bravenewrad	644,535	114	42	261		
Ш	BJZJOJ	musicbiz101	417,211	102	11	203		
Ш	WP	wpunj_edu	<mark>345,0</mark> 28	185	71	55		
~	WP.	wpcahss	<mark>260</mark> ,158	222	24	90 🗸		
	77 A W				,	100		

Retweet Table									
Img	Mentioned	Tweet Text	Faves	RTs	RTed	^			
WP	<u>wpunj</u> edu	#WeAreWillPo	20	11	7				
WP	<u>wpunj edu</u>	Welcome P	15	13	6				
M	<u>wpcommde</u>	Be sure to atte	10	10	6				
WP	<u>wpunj edu</u>	#WPUNJ!! http	26	10	5	_			
WP	<u>wpunj</u> edu	#WPUNJ's 202	5	6	5	_			





## NODEX WPU Twitter List

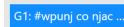
## **Top Tweets**

8/3/2017

3/15/2022

Graph Gallery 273123





Groups



0	







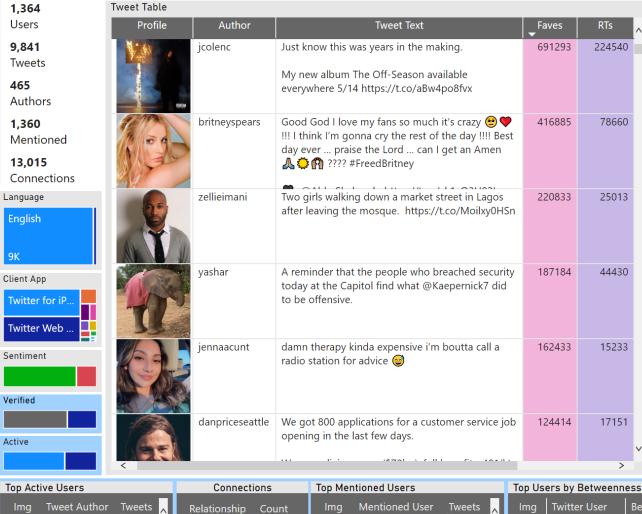


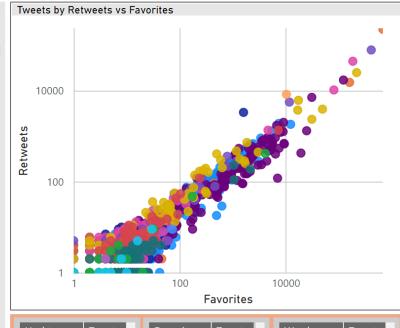












Hashtags	Tweets ^	Domains	Tweets	Word	Tweets ^
wpunj	2,858	wpunj.edu	31	wpunj	2,380
wpcomm	438	trib.al	20	more	578
wpubase	296	bit.ly	5	students	517
wpuwbb	217	collegera	4	2021	488
d3baseball	208	ic1.mains	4	со	462
wpumbb	187	fafsa.gov	3	today	410
wpuws	160	njersy.co	3	12	394



G3: tune ..

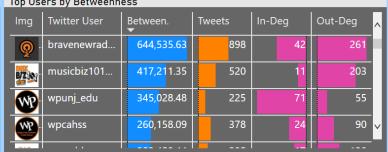
1K	0K
G9: period	G7: #
ОК	OK

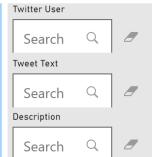
G1...

G8: radio #...

Top Act	ive Users	Conne	
Img	Tweet Author	Tweets ∧	Relationship
WP .	wpupioneers	1,410	Self Tweets
<b>@</b>	bravenewra	898	Retweets
BYZJej	musicbiz101	520	Mentions Mentions I
WPU	wpuhockey	425 🗸	Replies to

	Top Mentioned Users				
unt	lmg	Mentioned User	Tweets	^	
313	WP	wpunj_edu	577	ı	
574	WP	wpupioneers	519	ı	
812 744	WP	wpcommdept	378	ı	
294	<b>@</b>	bravenewradio	231	~	
	A1110.00				





Groups



## Words

8/3/2017

3/15/2022

Graph Gallery

273123







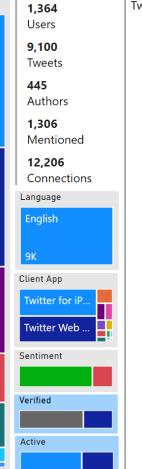


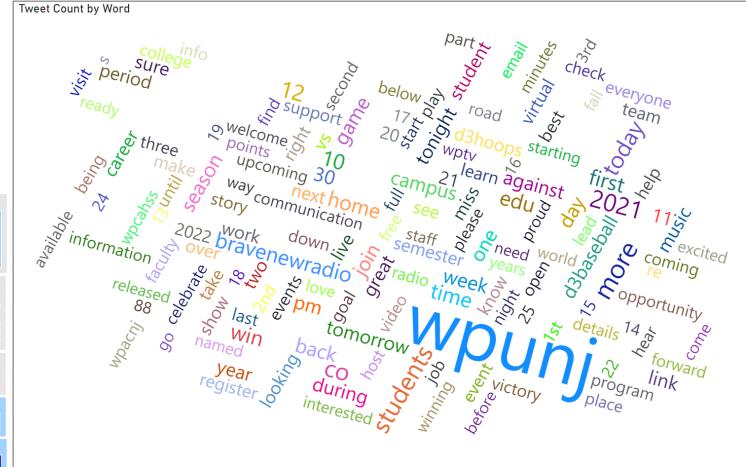










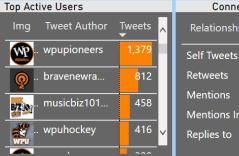


Hashtags	Tv	Tweets ▼	
wpunj	2	2,830	
wpcomm	ı	430	П
wpubase	ı	296	П
wpuwbb	L	217	L
d3baseball	ı	208	_
	4		
Domains	Tv •	veets	^
wpunj.edu		31	
trib.al		14	
bit.ly	ı	5	
collegeradio.org	1	4	
ic1.mainstreamn	1	4	_
	1	_^	
URLs	Tv ▼	veets	^
http://www.wpu		23	
http://ic1.mainst		4	
http://www.coll		4	
http://fafsa.gov		3	
http://njersy.co/		3	~
1	å		
Word	Tv	veets	^
wpunj		2,380	
more		578	
students		517	П
students	-		
2021	i	488	
	İ	488 462	~
2021	İ		~







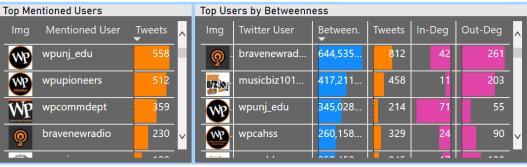


G8: .

G7: ..

G1.





Retweet Table								
Mentioned	Tweet Text	Faves	RTs	RTed	^			
<u>wpunj</u> edu	#WeAreWillPo	20	11	7				
<u>wpunj</u> edu	Welcome P	15	13	6				
wpcommde	Be sure to atte	10	10	6				
<u>wpunj</u> edu	WP ALERT: Ca	8	5	5	_			
<u>wpunj</u> edu	Undecided on	3	6	5	ľ			
	Mentioned  wpunj edu  wpunj edu  wpcommde  wpunj edu	Mentioned     Tweet Text       wpunj edu     #WeAreWillPo       wpunj edu     ❤ Welcome P       wpcommde     Be sure to atte       wpunj edu     WP ALERT: Ca	MentionedTweet TextFaveswpunj edu#WeAreWillPo20wpunj edu❤ Welcome P15wpcommdeBe sure to atte10wpunj eduWP ALERT: Ca8	MentionedTweet TextFavesRTswpunj edu#WeAreWillPo2011wpunj edu❤ Welcome P1513wpcommdeBe sure to atte1010wpunj eduWP ALERT: Ca85	MentionedTweet TextFavesRTsRTedwpunj edu#WeAreWillPo20117wpunj edu❤ Welcome P15136wpcommdeBe sure to atte10106wpunj eduWP ALERT: Ca855			



G1: #wpunj co njac w.

G2: #wpunj #wpcom...

G4: mu..

1K

G7: .

Tweets

1.410

898

520

Relationship

**Self Tweets** 

Retweets

Mentions

Mentions I..

Replies to

Count

5,313

2,574

1,812

744

294

G3: tune b...

G5: #wp...

G6: musi...

## NODEX WPU Twitter List

## Sentiment





273123



















Mentioned Tweets

378

231

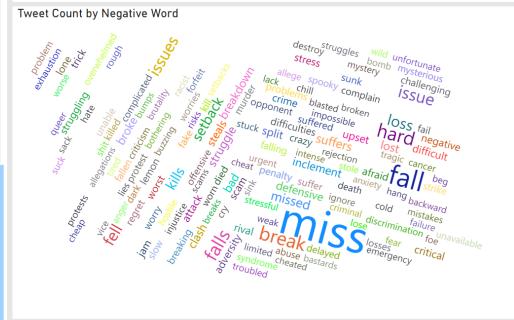
wpunj\_edu

wpupion...

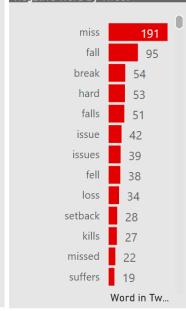
wpcomm..

bravene...









NODEX

Groups

## **WPU Twitter List**

## **Web Links**

3/15/2022 8/3/2017

Graph Gallery

Hashtags

wpunj

wpacnj

wppresents

blackhistorymo.

collegeradio.org

ic1.mainstreamn.

http://www.wpu...

http://ic1.mainst.

http://www.coll. http://fafsa.gov

http://njersy.co/..

wcrd2021

Domains

wpunj.edu

trib.al

bit.ly

URLs

Word

wpunj

more

visit

please

information

273123

Tweets

33

14

11

Tweets

Tweets

Tweets

26

18

15

15

31

20









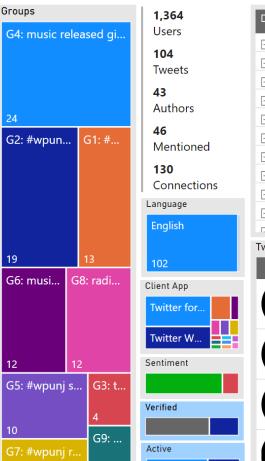


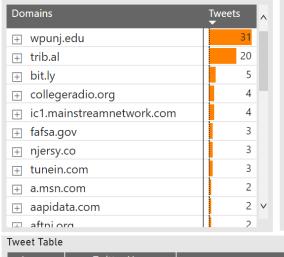












URLs	Tweets	^
http://www.wpunj.edu/wppresents/	23	
http://ic1.mainstreamnetwork.com/wpsc-fm	4	
http://www.collegeradio.org/	4	
http://fafsa.gov	3	
http://njersy.co/3vSd3rA	3	
http://tunein.com/topic/?TopicId=165581837	3	
http://www.wpunj.edu/articles/news/2020-12-23/coming-together-in-hard-times-community-shows-extra-generosity-in-2020-with-donations-to-wp/	3	
http://a.msn.com/0B/en-us/BB1cEjQA?ocid=st	2	
http://aapidata.com/blog/tip-iceberg-march2021-survey/	2	
http://aftnj.org/topics/news/higher-education/2021/william-paterson-professors-speak-at-bot-meeting-in-support-of-saving-jobs-programs/	2	<b>V</b>

, |

Image	Twitter User	Tweet Text	Faves	RTs	First URL in Tweet	^
billiboard	billboard	Lana Del Rey is saying goodbye to social media. https://t.co/ebFQPrfDcx	3521	236	http://trib.al/9Dje0Kr	
billboard	billboard	The 1975 cancel all 2021 dates: "these are incredibly difficult times for a lot of people." https://t.co/Ju13Sit50q	1221	106	http://trib.al/EYFPXXS	
billboard	billboard	For its first-ever listening party, Roblox is teaming with Poppy and her label Sumerian Records to stream her brand-new album Flux.	698	81	http://trib.al/eqDZ1Sd	
	pitchfork	A perfect album https://t.co/6BBuFzBqOg	512	59	http://trib.al/k1F2yAA	<b>~</b>

	<b>*</b>			
Top Active Users	Connections	Top Mentioned Users	Top Users by Betweenness	
Img Tweet Author Tweets	Relationship Count	Img Mentioned User Tweets	Img Twitter User Between. Tweets	In-Deg Out-Deg ^
musicbiz101 12	Self Tweets 45	wpunj_edu 13	<b>o</b> bravenewrad 644,535	3 42 261
wp wpacnj 10	Retweets 42	billboard 5	musicbiz101 417,211 12	2 11 203
wp wppresents 8	Mentions 16  Mentions In 11	wpacnj 5	wpunj_edu 345,028 !	5 71 55
collegeradio 6	Replies to 3	biz billboardbiz 4	wpcahss 260,158	3 24 90 🗸

F	Retweet Table						
	lmg	Mentioned	Tweet Text	Faves	RTs	RTed	^
	STUDENT INFO	<u>wpstudenti</u>	Happy Friday!	1	2	3	
		<u>northjersey</u>	Very proud of	17	7	3	
	WP	<u>wpunj</u> edu	The spirit of gi	6	1	2	
	VET2VET	<u>njvet2vet</u>	New Jersey Vet	0	1	2	~
	:AIMP	<u>aimporg</u>	Beyonce, Adel	2	4	2	~





## 

## **Compare 4**



Graph Gallery

273123





G6: music #..

G1: #wpunj ..

	<b>1,364</b> Users
ı	<b>9,841</b> Tweets
ı	<b>465</b> Authors
	<b>1,360</b> Mentioned

Top Us	Top Users by Betweenness					
lmg	Twitter User	Tweets	Betweenness	In-Deg	Out-Deg	^
<b>@</b>	bravenewradio	898	644,535.63	42	261	Н
Bizio	musicbiz101wp	520	417,211.35	11	203	П
WP	wpunj_edu	225	345,028.48	71	55	П
WP	wpcahss	378	<mark>260</mark> ,158.09	24	90	~
WAFF	hh	יסב	3E3 4E0 44	17	120	

Hashtag	Tweets ▼
wpunj	2,858
wpcomm	438
wpubase	296
wpuwbb	217
d3baseball	208
wpumbb	187
wpuws	160

Domains	Tweets ▼	^
wpunj.edu	31	
trib.al	20	Г
bit.ly	5	
collegeradio.org	4	
ic1.mainstreamnet	4	
fafsa.gov	3	ļ
njersy.co	3	h

Word	Tweets	^
wpunj	2,380	H
more	578	П
students	517	П
2021	488	П
со	462	П
today	410	V
12	394	







,364	Top Use
Jsers	Img
<b>),841</b> weets	<b>@</b>
165	BYZJOJ
uthors	WP
,360 Mentioned	WP
remandica	TAF

Top Use	op Users by Betweenness					
lmg	Twitter User	Tweets	Betweenness ▼	In-Deg	Out-Deg	^
<b>@</b>	bravenewradio	898	644,535.63	42	261	H
BYZJOJ	musicbiz101wp	520	417,211.35	11	203	П
WP	wpunj_edu	225	345,028.48	71	55	H
WP	wpcahss	378	<mark>260</mark> ,158.09	24	90	~
TIAN TO	wniwhh	205	252 458 44	17	120	

ı	Hashtag	Tweets	^
П	wpunj	2,858	۱
П	wpcomm	438	1
П	wpubase	296	1
П	wpuwbb	217	1
П	d3baseball	208	1
П	wpumbb	187	И
П	wpuws	160	

Domains	Tweet:	S	,
wpunj.edu		31	ı
trib.al	20		ľ
bit.ly		5	l
collegeradio.org		4	l
ic1.mainstreamnet		4	l
fafsa.gov		3	ŀ
njersy.co		3	ŀ

Word	Tweets
wpunj	2,380
more	578
students	517
2021	488
со	462
today	410
12	394

	Group	Users
	G1: #wpunj	244
	G2: #wpunj	216
	G3: tune br	210
	G4: music r	<mark>1</mark> 67
9	G5: #wpunj	106
	G6: music #	106

1,364
Users
9,841
Tweets
465
Authors
1,360
Mentioned

Top Us	ers by Betweenness	5			
Img	Twitter User	Tweets	Betweenness •	In-Deg	Out-Deg ^
<b>@</b>	bravenewradio	898	644,535.63	42	261
BYZJO	musicbiz101wp	520	417,211.35	11	203
WP	wpunj_edu	225	345,028.48	71	55
WP	wpcahss	378	<mark>26</mark> 0,158.09	24	90
CAVAIL	wnuwhh	205	252 458 44	17	120

Hashtag	Tweets ▼	^
wpunj	2,858	H
wpcomm	438	П
wpubase	296	П
wpuwbb	217	П
d3baseball	208	П
wpumbb	187	V
wpuws	160	
	wpunj wpcomm wpubase wpuwbb d3baseball wpumbb	wpunj     2,858       wpcomm     438       wpubase     296       wpuwbb     217       d3baseball     208       wpumbb     187

Domains	Tweets	/
wpunj.edu	31	l
trib.al	20	
bit.ly	5	
collegeradio.org	4	
ic1.mainstreamnet	4	
fafsa.gov	3	V
njersy.co	3	b

Word	Tweets	^
wpunj	2,380	н
more	578	П
students	517	П
2021	488	П
со	462	П
today	410	V
12	394	Н

	. 0
V	

	▼
G1: #wpunj	244
G2: #wpunj	216
G3: tune br	210
G4: music r	167
G5: #wpunj	106

364
ers
841
reets
55
thors
260
360
entioned

Top Us	ers by Betweennes	s				
lmg	Twitter User	Tweets	Betweenness ▼	In-Deg	Out-Deg	^
<b>@</b>	bravenewradio	898	644,535.63	42	261	H
Bizio	musicbiz101wp	520	417,211.35	11	203	П
WP	wpunj_edu	225	345,028.48	71	55	П
WP	wpcahss	378	<mark>26</mark> 0,158.09	24	90	\ <u></u>
VAF	warmh	יסנ	253 450 44	17	120	

	Hashtag	Tweets ▼	$\lceil \cdot \rceil$
П	wpunj	2,858	Н
П	wpcomm	438	П
П	wpubase	296	П
П	wpuwbb	217	Н
П	d3baseball	208	П
П	wpumbb	187	М
	wpuws	160	Н

Domains	Tweets	/
wpunj.edu	31	ı
trib.al	20	ľ
bit.ly	5	
collegeradio.org	4	
ic1.mainstreamnet	4	
fafsa.gov	3	ļ
njersy.co	3	

Tweets ▼
2,380
578
517
488
462
410
394





## Help & Info

























**Start your NodeXL Pro INSIGHTS subscription now** 

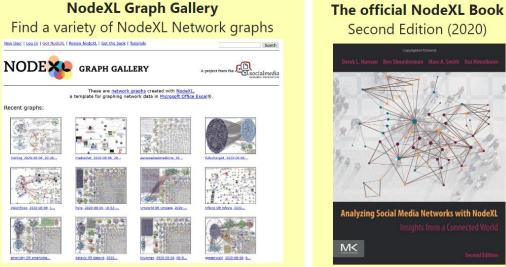
Request your own custom NodeXL Pro INSIGHTS sample report

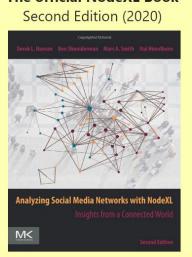


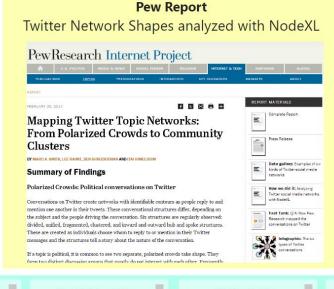


NodeXL Pro Insights Version: 1.4

## Learn more about NodeXL









**Questions?** 

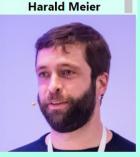
Social Media Research Foundation: info@smrfoundation.org

Contact Team NodeXL at the

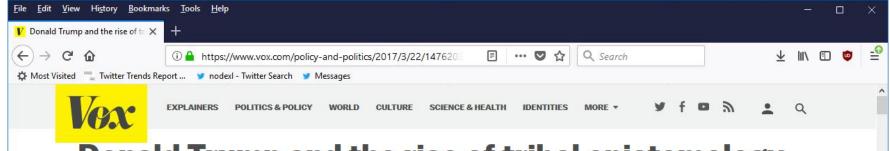












## Donald Trump and the rise of tribal epistemology

Journalism cannot be neutral toward a threat to the conditions that make it possible.

By David Roberts | @drvox | david@vox.com | Updated May 19, 2017, 9:58am EDT





(Javier Zarracina)

Back in November 2009, as the Obama backlash was just gathering steam, Rush Limbaugh devoted a segment of his radio program to "Climategate."

That was the enjoyde in which a climate research institute was hacked and the private

### Most Read



8 winners and 2 losers from the 2018 Oscars



It's not just Russia — Mueller is digging into Trump associates' potentially corrupt foreign ties

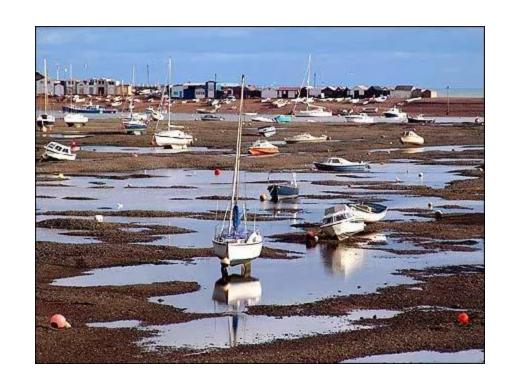


attacks minority voices

**Censoring of critical voices** 

Problem:
Only
information
amplifiers
are available



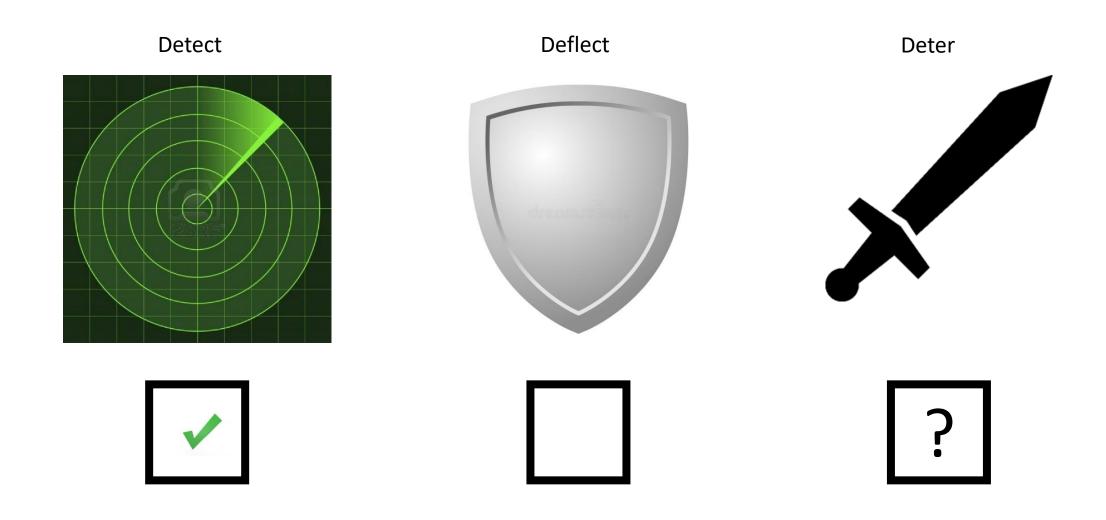








# Needed



## Nodexl Pro Tutorials

## **How to Automate NodeXL Pro**

This tutorial shows you how to use the most powerful feature of NodeXL Pro: Automation. The automation feature allows you to run all steps of a social network and content analysis with a single click: Data preparation, cluster analysis, metrics calculation, time series analysis, top content analysis, visualization and data export. <u>Visit this URL</u>, <u>Download as pdf file</u> or <u>watch this video</u>.

## Social network and content analysis with Twitter network data – step by step

This tutorial shows you how you can run a full social network and content analysis with NodeXL Pro. While we will use Twitter network data as an example, this approach can be applied to any network dataset of your choice (content analysis depends on the available metadata). Download as pdf file.

## **Working with Twitter User lists**

Twitter User lists are a very helpful tool to manage the diverse information streams on Twitter. This tutorial shows you how to work with Twitter User lists using the **NodeXL Pro Users Network Importer** and the **NodeXL Pro Users Network Importer**. Click here.

## **Semantic Networks – Create networks with words, hashtags or video tags**

This tutorial shows you how to create a <u>semantic network</u> by using the **text analysis** feature of NodeXL Pro which can be applied to any column that contains text in the edges or vertices spreadsheets of a NodeXL workbook. <u>Click here</u>.

## **Exploring YouTube Video Recommendation Networks**

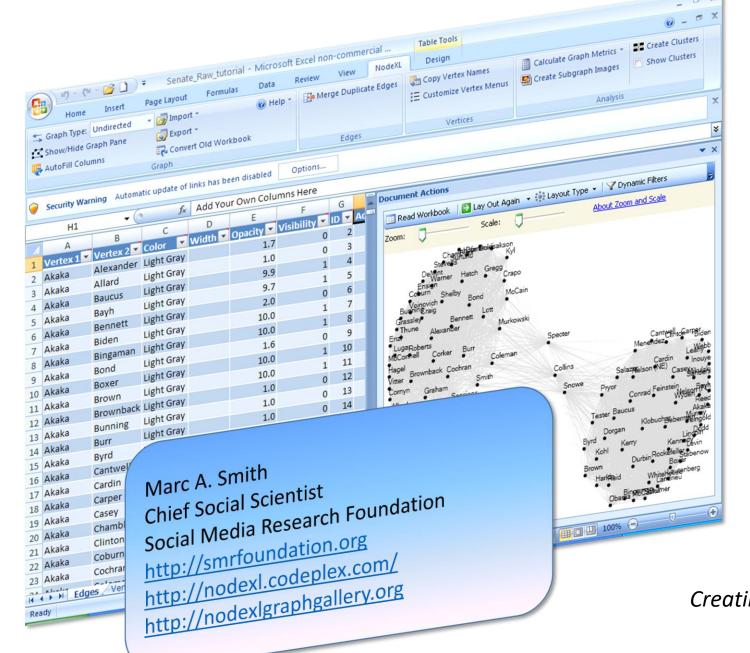
NodeXL Pro offers several ways to access the official YouTube API (v3). This tutorial shows you how to create YouTube Video-to-Video Recommendation Networks with the NodeXL Pro YouTube Video Network importer. Click here.

# LINKS / LITERATURE

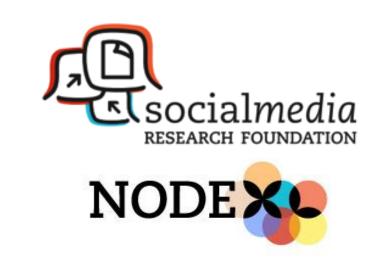
- Social Media Research Foundation: <a href="http://www.smrfoundation.org/">http://www.smrfoundation.org/</a>
- NodeXL Graph Gallery: <a href="https://nodexlgraphgallery.org/">https://nodexlgraphgallery.org/</a>
- Marc Smith | Network Mapping the Ecosystem: https://www.youtube.com/watch?v=kDiGl-2m868
- How to Automate NodeXL Pro: <a href="https://www.youtube.com/watch?v=mjAq8eA7uOM">https://www.youtube.com/watch?v=mjAq8eA7uOM</a>
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Can social accounting improve the social media "marketplace of ideas"?



Creating social network maps and measures with NodeXL

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