Map Social Media Connections with Excel & NodeXL

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

Marc A. Smith
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http://smrfoundation.org
http://nodexl.codeplex.com/
http://nodexlgraphgallery.org
About Me

Introductions

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http://www.linkedin.com/in/marcasmith
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http://www.flickr.com/photos/marc_smith
http://www.facebook.com/marc.smith.sociologist
Crowds matter
Crowds in social media matter
Crowds in social media have a hidden structure
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.
Kodak Brownie Snap-Shot Camera

The first easy to use point and shoot!
<table>
<thead>
<tr>
<th>Vertex</th>
<th>Betweenness Centrality</th>
<th>Eigenvector Centrality</th>
<th>Out-Degree</th>
<th>In-Degree</th>
<th>Metrics</th>
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</table>

**Description:**
- iubloomington: Indiana University of Bloomington
- indianaambmb: Indiana University of Bloomington
- skydiveindy: Skydive Indy, 14800 South Street, Indianapolis, IN 46217
- bus008811: Two Takes, 300 West Main Street, Bloomington, IN 47408
- collegeconfessx: College, 4740 W Fairbanks Ave, Bloomington, IN 47404
- auntbeavon: Aunt Beavon, 300 West Main Street, Bloomington, IN 47408
- aco_bloomington: 400 University of Bloomington
- martyr4sett: Marty 4sett, 300 West Main Street, Bloomington, IN 47408
- klangston27: Klangston, 300 West Main Street, Bloomington, IN 47408
- minerrealturns: Minerrealturns, 300 West Main Street, Bloomington, IN 47408
- jaypnye22: Jay Pnye, 300 West Main Street, Bloomington, IN 47408
- aloc01911: Alcock, 300 West Main Street, Bloomington, IN 47408
- kat24u: Katie, 300 West Main Street, Bloomington, IN 47408
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<td>32</td>
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</table>
"Indiana University" OR IUBloomington from Twitter Search Network

Counts of tweets over time.
NodeXL Ribbon in Excel
NodeXL in Excel
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.


Recent graphs:

Recent graphs:
### Top Influencers: Top 10 Vertices, Ranked by Betweenness Centrality

<table>
<thead>
<tr>
<th>Description</th>
<th>Author Description</th>
<th>Overall Metrics</th>
<th>Top Influencers</th>
<th>Top URLs</th>
<th>Top Domains</th>
<th>Top Hashtags</th>
<th>Top Words</th>
<th>Top Word Pairs</th>
<th>Top Replied-To</th>
<th>Top Mentioned</th>
<th>Top Tweeters</th>
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<tr>
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<td>Smart Tweet</td>
<td>@usaa_help</td>
<td>Follow 16.9K followers</td>
<td>Smart Tweet</td>
<td>@usaa_r</td>
<td>Follow 250 followers</td>
<td>Smart Tweet</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>@usaa_help</td>
<td>Follow 16.9K followers</td>
<td>Smart Tweet</td>
<td>@usaa_r</td>
<td>Follow 250 followers</td>
<td>Smart Tweet</td>
<td>@lindaquackenbus</td>
<td>Follow 341 followers</td>
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<tr>
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<td>Follow 250 followers</td>
<td>Smart Tweet</td>
<td>@usaa_jobs</td>
<td>Follow 2,523 followers</td>
<td>Smart Tweet</td>
<td>@33tobster</td>
<td>Follow 0 followers</td>
<td>Smart Tweet</td>
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<td>Follow 1,741 followers</td>
<td>Smart Tweet</td>
<td>@vlogpreneur</td>
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<td>Smart Tweet</td>
<td></td>
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<tr>
<td>@pepsi7965</td>
<td>Follow 1,741 followers</td>
<td>Smart Tweet</td>
<td>@vlogpreneur</td>
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<td>Follow 1,298 followers</td>
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![Twitter interface](image.png)
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<th>Description</th>
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Social Media (email, Facebook, Twitter, YouTube, & more) is all about connections from people to people.
Patterns are left behind.
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

Social media must contain one or more social networks

World Wide Web

twitter

facebook

VOSON

flickr

YouTube

WIKIPEDIA
“Think Link”

Nodes & Edges

A

Is related to

Is related to

B
“Think Link”

Nodes & Edges

A

Is related to

Is related to

B

Is related to
A network is born whenever two GUIDs are joined.

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<td>Value, value</td>
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<table>
<thead>
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<th>Attributes</th>
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<tbody>
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<table>
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<th>“Vertex1” Attribute</th>
<th>“Vertex2” Attribute</th>
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<td>@UserName2</td>
<td>value</td>
<td>value</td>
<td>value</td>
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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
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.

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 recognizable 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
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
### Top Influencers: Top 10 Vertices, Ranked by Betweenness Centrality

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<th>Smart &gt;</th>
<th>Tweet</th>
</tr>
</thead>
<tbody>
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<td>Follow: 8,807 followers</td>
<td>Smart &gt;</td>
<td>Tweet</td>
</tr>
<tr>
<td>@jose_garde</td>
<td>Follow: 23.6K followers</td>
<td>Smart &gt;</td>
<td>Tweet</td>
</tr>
<tr>
<td>@hipmediakits</td>
<td>Follow: 2.024 followers</td>
<td>Smart &gt;</td>
<td>Tweet</td>
</tr>
<tr>
<td>@socialmktgsitns</td>
<td>Follow: 32.2K followers</td>
<td>Smart &gt;</td>
<td>Tweet</td>
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<tr>
<td>@tapinfluence</td>
<td>Follow: 10.4K followers</td>
<td>Smart &gt;</td>
<td>Tweet</td>
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<td>@kesbutters</td>
<td>Follow: 227K followers</td>
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<td>Tweet</td>
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<td>@juntaedelane</td>
<td>Follow: 275K followers</td>
<td>Smart &gt;</td>
<td>Tweet</td>
</tr>
<tr>
<td>@socialmedia2day</td>
<td>Follow: 588K followers</td>
<td>Smart &gt;</td>
<td>Tweet</td>
</tr>
<tr>
<td>@adifresco_media</td>
<td>Follow: 1,163 followers</td>
<td>Smart &gt;</td>
<td>Tweet</td>
</tr>
</tbody>
</table>
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
Beyond 'Bitter Twitter': Crowd-Photography for the Cyber-Tahrir Square


Visualizing the War on Women Debate

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

Mapping Twitter Topic Networks: From Polarized Crowds to Community Clusters

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.
### The Six Structures of Twitter Conversation Networks

<table>
<thead>
<tr>
<th>NETWORK TYPE</th>
<th>GROUPS</th>
<th>COMPLEX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Divided</td>
<td>2 large</td>
<td>Politics or divisive topics that display separate “echo chamber” structures.</td>
</tr>
<tr>
<td>Unified</td>
<td>2–6 medium</td>
<td>Hobbies, professional topics, conferences. No outsiders, all participants are members.</td>
</tr>
<tr>
<td>Fragmented</td>
<td>Many small</td>
<td>Brands, public events, popular subjects.</td>
</tr>
<tr>
<td>Clusters</td>
<td>Many small and medium</td>
<td>Global news events.</td>
</tr>
<tr>
<td>In-Hub &amp; Spoke</td>
<td>1 large, some secondary</td>
<td>News pundits and media outlets, famous individuals.</td>
</tr>
<tr>
<td>Out-Hub &amp; Spoke</td>
<td>1 large, some secondary</td>
<td>Companies and services with customer support.</td>
</tr>
</tbody>
</table>

**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.

**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.

**Brand Clusters**
- This type is framed around products and celebrities. These popular topics attract large fragmented Twitter populations, generating mass interest, but little connectivity.

**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.

**Broadcast Network**
- This type is often triggered by news media outlets and punchlines who have loyal followers who retweet them. These communities are often star-shaped, so little interaction exists among members of the audience.

**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.

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PEW RESEARCH CENTER in association with Social Media Research Foundation
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
#CMgrChat

In-group / Community
Lumia

Brand / Public Topic
#FLOTUS

G1: happybirthday flotus michelleobama tsbreakingnews twitter news wild nikes flotus flotus efficia

G2: happybirthday obama ft nikday twitterversary forwardcomunicación política rrs foreverflotus

G3: happybirthday ft flotus letuscreate 1stworldinternational olympic inauguration nikday 1stworld transformationolympic fierce armeny

G4: happybirthday madmestyle flotus

G5: bangsfriday kallyandmichael juffy happybirthday omginsider stylecrush hairstyle ft hair beauty

G6: flotus bangs michelleobama happybirthday hot hair how nails justsayin stylenest

G7: flotus happybirthday nunca febflotus haute zebra copicart approvalhisstyle statement indoo cronstrikes

G8: flotus bangs michelleobama happybirthday hot hair how nails justsayin stylenest

G9: flotus bangs michelleobama happybirthday hot hair how nails justsayin stylenest

G10: ft twitternews elonmagroup moni flotus obama banana sceauen, socialmedia davos service hilththetiff

G11: twitter

G12: happy covem

G13: g35 g37 g38 g39 g40 g42 g48

G14: g22 g36 g3 g32 g28 g29

G15: g20

G16: g18

G17: g14

G18: g10 g16 g15

G19: g19
New Book in Progress!

Analyzing Social Media Networks with NodeXL
Insights from a Connected World
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**
Applying the insights of social networks to social media:

Your social media audience is smaller...

...than the audiences of ten influential voices.
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 user's most salient:
  – Words
  – Word pairs
  – URLs
  – #Hashtags

• Mix the language of the Mayors with your brand’s messages.
Speak the language of the mayors

➢ The “perfect” tweet:

.@Theirname #Theirhashtag News about your brand using their words http://your.site #Yourhashtag
Speak the language of the mayors

- Identify users to follow
- 20-30% of time the user follows you back
- Monitor User Tweet Stream for Content worth Retweeting
- Retweet selected content
- Prominent users are now able to hear your content and may retweet you!
- Regularly tweet (or re-tweet) high relevance content
- Identify topics of interest to stakeholders
- Create social network maps of connections among the people who tweet a keyword or hashtag that matters to your business.
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 1: You get an audience

Phase 2a: People mention you

Phase 2b: Your audience gets an audience

Phase 3: Audience becomes community
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!
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<td>Support Network</td>
</tr>
</tbody>
</table>

**Low probability**
- Find bridge users.
- Encourage shared material.

**Low probability**
- Draw in new participants.
- Get message out to disconnected communities.

**Possible transition**
- Regularly create content.
- Reply to multiple users.

**High probability**
- Increase retention, build connections.
- Increase response rate, reply to multiple users.

**Possible transition**
- Increase retention, build connections.
- Increase publication of new content and regularly create content.

**Undesirable transition**
- Remove bridges, highlight divisions.
- Increase density of connections in two groups.
- Increase density of connections, dramatically increase density of connections.
- Increase population, reduce connections.
Request your own network map and report

http://connectedaction.net
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
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

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
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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
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.

#ProtestBaku Azerbaijan
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

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

Grant post-doc 2011 by the Provincia Autonoma di Trento (Italy)
2012: Outside institutions, a grassroots conversation

Grant post-doc 2011 by the Provincia Autonoma di Trento (Italy)
2013: Accessing institutions, a more structured conversation

G1 - Campaign Account Cluster

G2 - Main Activists and Partner NGOs

G3 - Latin America Partner Campaign

Grant post-doc 2011 by the Provincia Autonoma di Trento (Italy)

http://www.reactionproject.info
2014: Inside institutions, a centralized conversation

G1 - Campaign Account Cluster

G2 - UN Sayno_Unite Cluster

G3 - Main Activists and Partner NGOs

G4 - UN Women Cluster

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

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