Workshop: Collecting and Analyzing Social Media Data

Pablo Barberá
University of Southern California
London School of Economics
www.pablobarbera.com

Workshop website:

pablobarbera,com/social-media-workshop

George Takei

March 28 at 10:10pm ·

Who's with me.

Like · Comment · Share

408,735 people like this.

66,990 shares

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Bon Alimagno
@karma_thief

Follow

I need a hug. I have never been so traumatized by a television show. #gameofthrones

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RETWEETS	FAVORITES
356	110

10:06 PM - 2 Jun 2013


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Who's with me.
HOW I PLAN ON SPENDING
MY FRIDAY NIGHT...
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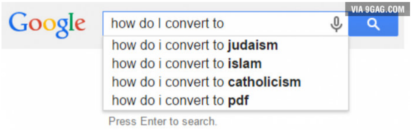
VIA 9GAG.COM
Google
how do I convert to
how do i convert to **judaism**
how do i convert to **islam**
how do i convert to **catholicism**
how do i convert to **pdf**
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how do i convert to **judaism**
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Press Enter to search.

Justin Bieber
@justinbieber

Follow

I make music. I love music.

Reply Retweet Favorite More

RETWEETS 54,213 FAVORITES 59,205

10:09 PM - 7 Apr 2014

dustin curtis
@dcurtis

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"At any moment, Justin Bieber uses 3% of our infrastructure. Racks of servers are dedicated to him. - A guy who works at Twitter

RETWEETS	FAVORITES
1,528	267

8:56 PM - 6 Sep 2010

Dmitry Medvedev
@MedvedevRussiaE

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The harmonious development of Crimea and Sevastopol as part of our state is one of the main objectives of the Russian Government

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10:39 AM - 21 Mar 2014

The New York Times
April 2

"Much of the foreign media coverage has distorted the reality of my country and the facts surrounding the events," writes Nicolás Maduro, the president of Venezuela, in Opinion: http://nyti.ms/1gP5o2I

Like · Comment · Share 57

262 people like this. Top Comments

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Elizabeth Warren shared a link.
January 16

I'm not giving up on our fight to extend unemployment benefits. Watch my interview with Now With Alex Wagner about why we need to keep fighting.

Warren: This is the moment to back on economy
www.msnbc.com

President Obama faces one huge problem with his effort to improve the economy: an opposition party

Like · Comment · Share 15,483 720 1,041

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www.msnbc.com

President Obama faces one huge problem with his effort to improve the economy: an opposition party

Like · Comment · Share 15,483 720 1,041

Jackie Walorski @RepWalorski

Follow

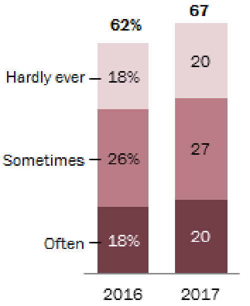
Today, a representative from my office will be meeting with constituents in Goshen. For more details, visit walorski.house.gov/services/upcom…

Reply Retweet Favorite More

11:22 AM - 8 Apr 2014

In 2017, two-thirds of U.S. adults get news from social media

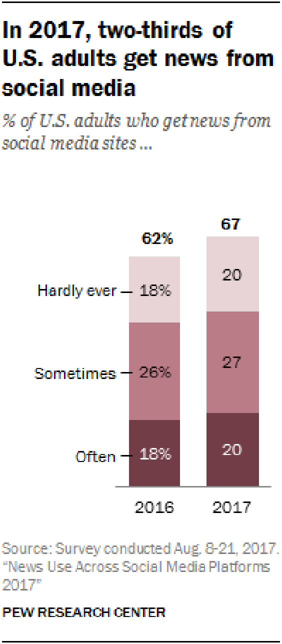
% of U.S. adults who get news from social media sites ...



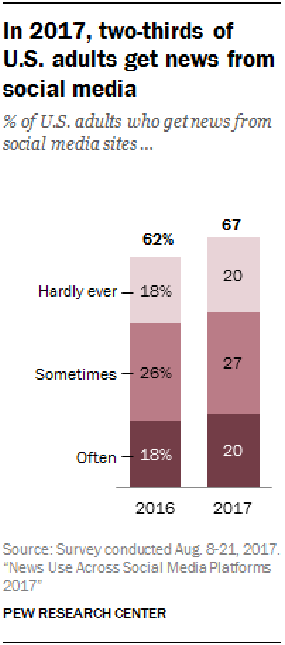
Source: Survey conducted Aug. 8-21, 2017.
"News Use Across Social Media Platforms 2017"

PEW RESEARCH CENTER

- 62% of Americans gets news on social media (Pew)



- 62% of Americans gets news on social media (Pew)
- 27% of online EU citizens use social media to get news on national political matters (Eurobarometer, Fall 2012)



- 62% of Americans gets news on social media (Pew)
- 27% of online EU citizens use social media to get news on national political matters (Eurobarometer, Fall 2012)
- Social media: top source of news for U.S. young adults (Pew)

Shift in communication patterns

Shift in communication patterns

Hello!

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Today's workshop

Session 1, 3pm-4.30pm

- Social media research: opportunities and challenges

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- Social media research: opportunities and challenges
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Session 2, 5pm-6.30pm

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- Social media research: opportunities and challenges
- Guided coding session: collecting Twitter data from the Streaming API
- Challenge 1: interacting with Twitter's Streaming API

Session 2, 5pm-6.30pm

- Guided coding session: Collecting Twitter data from the REST API

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- Guided coding session: collecting Twitter data from the Streaming API
- Challenge 1: interacting with Twitter's Streaming API

Session 2, 5pm-6.30pm

- Guided coding session: Collecting Twitter data from the REST API
- Coding challenge 2: Twitter's REST API

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- Social media research: opportunities and challenges
- Guided coding session: collecting Twitter data from the Streaming API
- Challenge 1: interacting with Twitter's Streaming API

Session 2, 5pm-6.30pm

- Guided coding session: Collecting Twitter data from the REST API
- Coding challenge 2: Twitter's REST API
- Guided coding session: Collecting Facebook data from the Graph API

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- Application: Dictionary methods applied to social media text

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- Application: Dictionary methods applied to social media text
- Coding challenge 3: Facebook's Graph API

Social media research

Two different approaches in the growing field of social media research:

1. Social media as a new source of information
   - Behavior, opinions, and latent traits
   - Interpersonal networks
   - Elite behavior
   - Affordable field experiments

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Behavior, opinions, and latent traits

- Digital footprints: check-ins, conversations, geolocated pictures, likes, shares, retweets, ...

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$\rightarrow$ Non-intrusive measurement of behavior and public opinion

Toole et al (2015): "Tracking employment shocks using mobile phone data"

Behavior, opinions, and latent traits

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Toole et al (2015): "Tracking employment shocks using mobile phone data"
Beauchamp (2016): "Predicting and Interpolating State-level Polls using Twitter Textual Data"

Behavior, opinions, and latent traits

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$\rightarrow$ Non-intrusive measurement of behavior and public opinion

$\rightarrow$ Inference of latent traits: political knowledge, ideology, personal traits, socially undesirable behavior, ...

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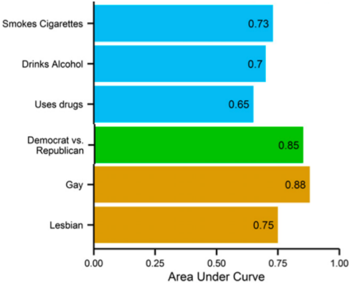

Fig. 2. Prediction accuracy of classification for dichotomous/dichotomized attributes expressed by the AUC.

Kosinki et al, 2013, “Private traits and attributes are predictable from digital records of human behavior”, *PNAS* (also personality, PNAS 2015)

Behavior, opinions, and latent traits

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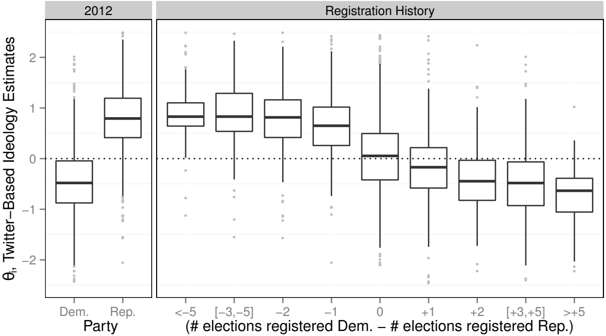
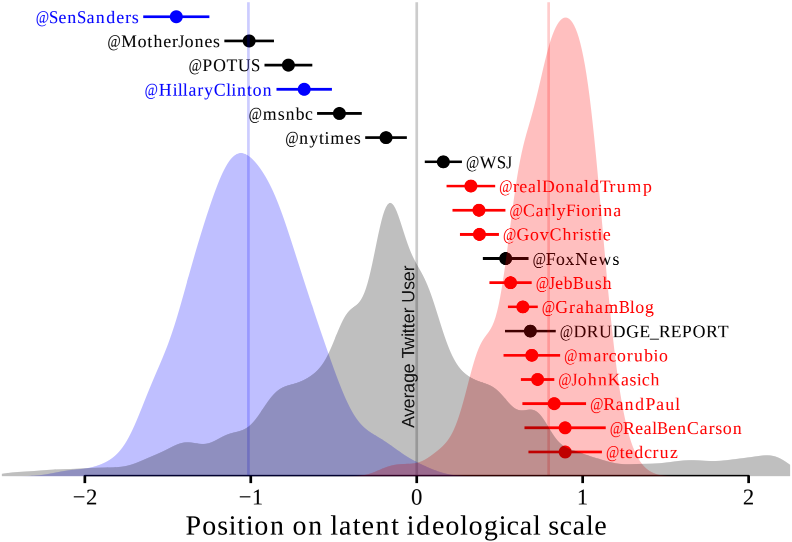


Data: 2,360 Twitter accounts, matched with Ohio voter file.

Barberá, 2015, "Birds of the Same Feather Tweet Together. Bayesian Ideal Point Estimation Using Twitter Data", *Political Analysis*

Estimating political ideology using Twitter networks



Barberá "Who is the most conservative Republican candidate for president?" *The Monkey Cage / The Washington Post*, June 16 2015

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Interpersonal networks

- Political behavior is social, strongly influenced by peers

Bond et al, 2012, "A 61-million-person experiment in social influence and political mobilization", *Nature*

Interpersonal networks

- Political behavior is social, strongly influenced by peers
- Costly to measure network structure

Interpersonal networks

- Political behavior is social, strongly influenced by peers
- Costly to measure network structure
- High overlap across online and offline social networks

OPEN ACCESS Freely available online

PLOS ONE

Inferring Tie Strength from Online Directed Behavior

Jason J. Jones[1,2]*, Jaime E. Settle[2], Robert M. Bond[2], Christopher J. Fariss[2], Cameron Marlow[3], James H. Fowler[1,2]

1 Medical Genetics Division, University of California, San Diego, La Jolla, California, United States of America, **2** Political Science Department, University of California, San Diego, La Jolla, California, United States of America, **3** Data Science, Facebook, Inc., Menlo Park, California, United States of America

Abstract

Some social connections are stronger than others. People have not only friends, but also *best* friends. Social scientists have long recognized this characteristic of social connections and researchers frequently use the term *tie strength* to refer to this concept. We used online interaction data (specifically, Facebook interactions) to successfully identify real-world strong ties. Ground truth was established by asking users themselves to name their closest friends in real life. We found the frequency of online interaction was diagnostic of strong ties, and interaction frequency was much more useful diagnostically than were attributes of the user or the user's friends. More private communications (messages) were not necessarily more informative than public communications (comments, wall posts, and other interactions).

Jones et al, 2013, "Inferring Tie Strength from Online Directed Behavior", *PLOS One*

Interpersonal networks

- Political behavior is social, strongly influenced by peers
- Costly to measure network structure
- High overlap across online and offline social networks
- Online and offline ties are similar in nature

American Political Science Review

Article Supplementary materials Metrics

Volume 111, Issue 3 August 2017 , pp. 502-521

Testing Social Science Network Theories with Online Network Data: An Evaluation of External Validity

JAMES BISBEE [a1] and JENNIFER M. LARSON [a1]

https://doi.org/10.1017/S0003055417000120 Published online: 13 June 2017

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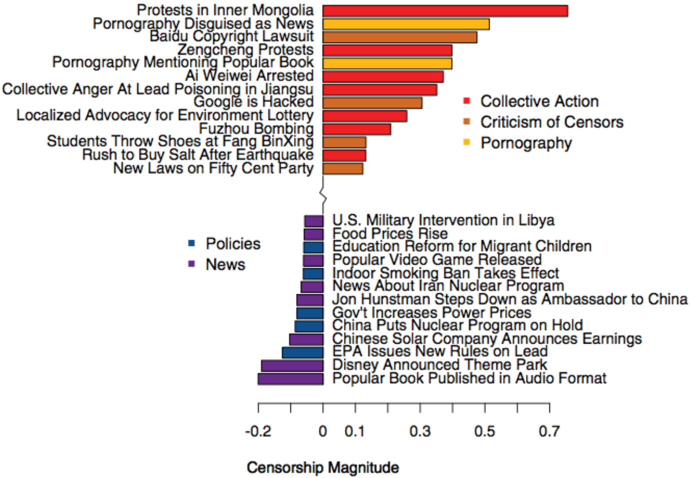
Elite behavior

- Authoritarian governments' response to threat of collective action



King et al, 2013, "How Censorship in China Allows Government Criticism but Silences Collective Expression", *APSR*

Elite behavior

- Authoritarian governments' response to threat of collective action
- Estimation of conflict intensity in real time

Journal of Conflict Resolution
55(6) 938-969

DOI: 10.1177/0022002711408014
http://jcr.sagepub.com
SAGE

Using Social Media to Measure Conflict Dynamics: An Application to the 2008–2009 Gaza Conflict

Thomas Zeitzoff[1]

Elite behavior

- Authoritarian governments' response to threat of collective action
- Estimation of conflict intensity in real time
- How elected officials communicate with constituents

FEBRUARY 23, 2017

For members of 114th Congress, partisan criticism ruled on Facebook

Facebook posts from members of the 114th Congress attracted more attention when they contained disagreement with the opposing party than when they expressed bipartisanship, according to a Pew Research Center analysis of over 100,000 posts.

Social media research

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Affordable field experiments

Political Behavior
September 2017, Volume 39, Issue 3, pp 629–649 | Cite as

Tweetment Effects on the Tweeted: Experimentally Reducing Racist Harassment

Authors | Authors and affiliations

Kevin Munger

Original Paper
First Online: 11 November 2016

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MY BODY
NOT YOURS
LOVE
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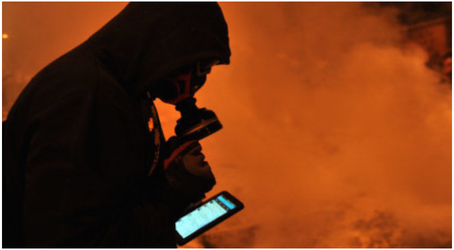
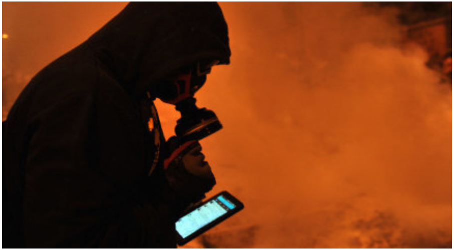


#OccupyGezi

#Euromaidan



#OccupyGezi

#OccupyWallStreet

#Euromaidan

#Indignados

slacktivism?

Why the revolution will not be tweeted

When the sit-in movement spread from Greensboro throughout the South, it did not spread indiscriminately. It spread to those cities which had preexisting "movement centers" – a core of dedicated and trained activists ready to turn the "fever" into action.

The kind of activism associated with social media isn't like this at all. [. . .] Social networks are effective at increasing participation – by lessening the level of motivation that participation requires.

***Gladwell**, Small Change (New Yorker)*

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You can't simply join a revolution any time you want, contribute a comma to a random revolutionary decree, rephrase the guillotine manual, and then slack off for months. Revolutions prize centralization and require fully committed leaders, strict discipline, absolute dedication, and strong relationships.

When every node on the network can send a message to all other nodes, confusion is the new default equilibrium.

***Morozov**, The Net Delusion: The Dark Side of Internet Freedom*

The critical periphery

PLOS | ONE

RESEARCH ARTICLE

The Critical Periphery in the Growth of Social Protests

Pablo Barberá[1]*, Ning Wang[2], Richard Bonneau[3,4], John T. Jost[1,5,6], Jonathan Nagler[6], Joshua Tucker[6], Sandra González-Bailón[7]*

- Structure of online protest networks:

The critical periphery

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  1. Increase reach of protest messages (positional effect)

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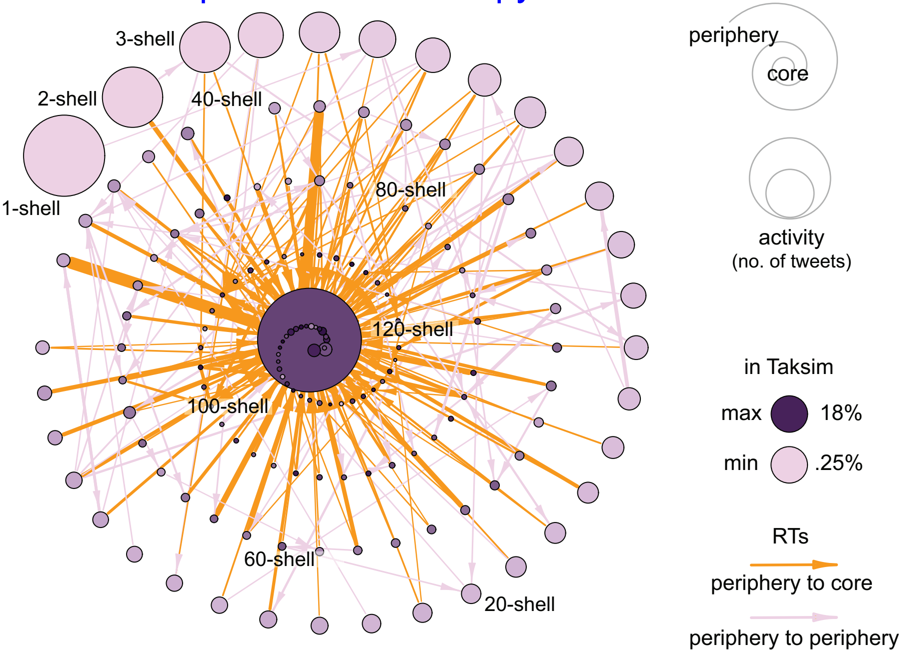
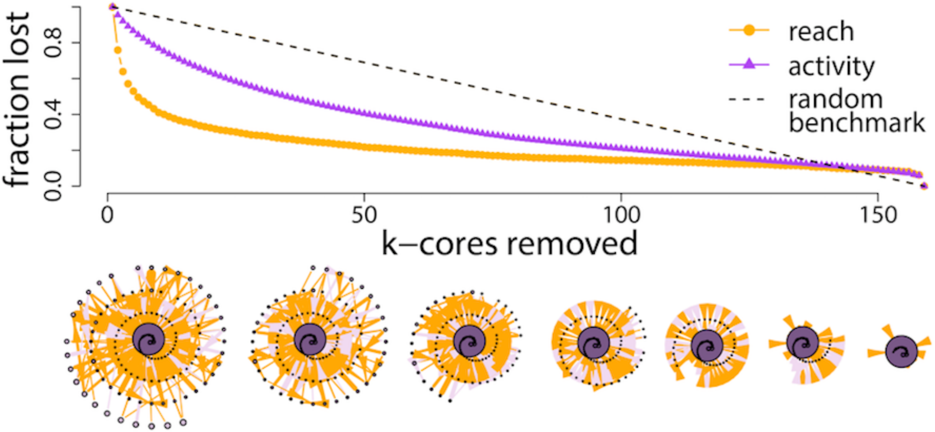
  2. Large contribution to overall activity (size effect)

k-core decomposition of #OccupyGezi network



Relative importance of core and periphery



reach: aggregate size of participants' audience

activity: total number of protest messages published (not only RTs)

Social media research

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Barack Obama
@BarackObama

Follow

Four more years.

RETWEETS	FAVORITES
756,411	288,867

11:16 PM - 6 Nov 2012

Post Politics

By the end of the 2012 campaign, every Mitt Romney tweet had to be approved by 22 people

Political persuasion

Social media as a new campaign tool:

> *“Let me tell you about Twitter. I think that maybe I wouldn’t be here if it wasn’t for Twitter. [...] Twitter is a wonderful thing for me, because I get the word out... I might not be here talking to you right now as president if I didn’t have an honest way of getting the word out.”*
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  - Affects how campaigns perceive voters (Hersh, 2015), but unclear if effective in mobilizing or persuading voters

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Social capital

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American Politics Research
1–31

DOI: 10.1177/1532673X14557942
apr.sagepub.com
SAGE

Tweeting Alone? An Analysis of Bridging and Bonding Social Capital in Online Networks

Javier Sajuria[1], Jennifer vanHeerde-Hudson[1], David Hudson[1], Niheer Dasandi[1], and Yannis Theocharis[2]

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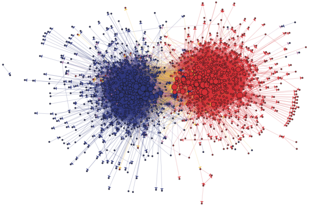
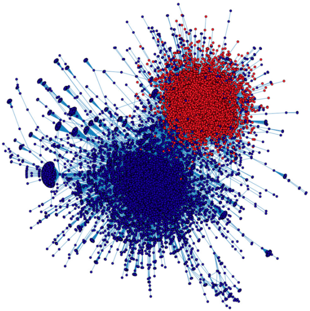
Social media as echo chambers?

- communities of like-minded individuals (homophily, influence)



Adamic and Glance (2005)



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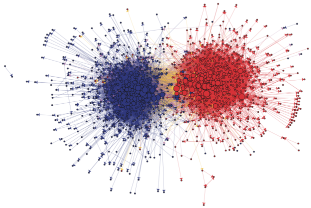

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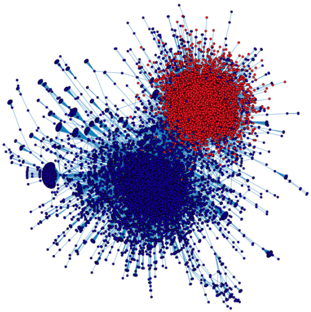

Conover et al (2012)

- ...generates selective exposure to congenial information
- ...reinforced by ranking algorithms – “filter bubble” (Parisier)

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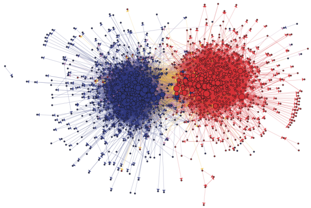

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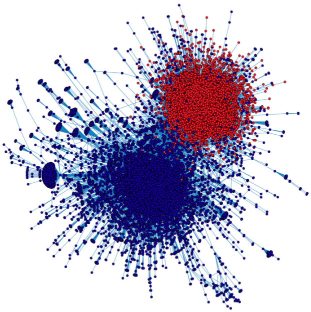

Conover et al (2012)

- ...generates selective exposure to congenial information
- ...reinforced by ranking algorithms – “filter bubble” (Parisier)
- ...increases political polarization (Sunstein, Prior)

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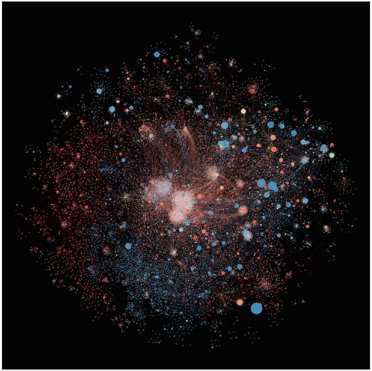
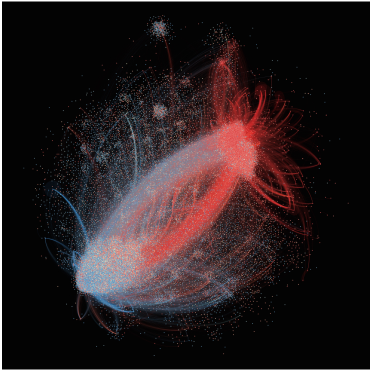


2013 SuperBowl

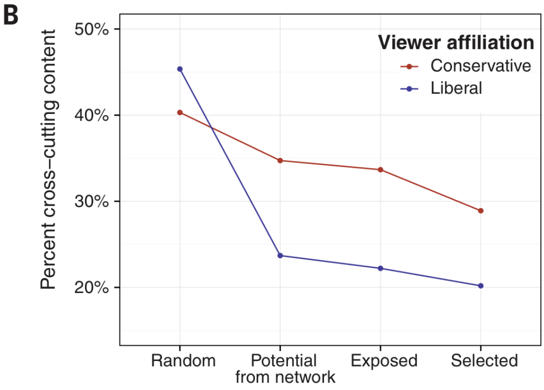


2012 Election

Barberá et al (2015) “Tweeting From Left to Right: Is Online Political Communication More Than an Echo Chamber?” *Psychological Science*

Social media as echo chambers?

Fig. 3. Cross-cutting content at each stage in the diffusion process. (**A**) Illustration of how algorithmic ranking and individual choice affect the proportion of ideologically cross-cutting content that individuals encounter. Gray circles illustrate the content present at each stage in the media exposure process. Red circles indicate conservatives, and blue circles indicate liberals. (**B**) Average ideological diversity of content (i) shared by random others (random), (ii) shared by friends (potential from network), (iii) actually appeared in users' News Feeds (exposed), and (iv) users clicked on (selected).



Bakshy, Messing, & Adamic (2015) "Exposure to ideologically diverse news and opinion on Facebook". *Science.*

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What are the most important challenges when working with social media data?

Social media data and social science: challenges

1. Big data, big bias?

Social media data and social science: challenges

1. Big data, big bias?
2. The end of theory?

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5. Generalizing from online to offline behavior
6. Ethical concerns

1. Big data, big bias?

SOCIAL SCIENCES

Social media for large studies of behavior

Large-scale studies of human behavior in social media need to be held to higher methodological standards

By **Derek Ruths**[1]* *and* **Jürgen Pfeffer**[2]

On 3 November 1948, the day after Harry Truman won the United States presidential elections, the *Chicago Tribune* published one of the most famous erroneous headlines in newspaper history: "Dewey Defeats Truman" (*1*, *2*). The headline was informed by telephone surveys, which had inadver-

different social media platforms (*8*). For instance, Instagram is "especially appealing to adults aged 18 to 29, African-American, Latinos, women, urban residents" (*9*) whereas Pinterest is dominated by females, aged 25 to 34, with an average annual household income of $100,000 (*10*). These sampling biases are rarely corrected for (if even acknowledged).

Proprietary algorithms for public data. Platform-specific sampling problems, for example, the highest-volume source of pub-

The rise of "embedded researc
searchers who have special rela
with providers that give them ele
cess to platform-specific data, al
and resources) is creating a divic
media research community. Such
ers, for example, can see a platfor
workings and make accommodat
may not be able to reveal their c
or the data used to generate their f

Ruths and Pfeffer, 2015, "Social media for large studies of behavior", *Science*

Big data, big bias?

Sources of bias (Ruths and Pfeffer, 2015; Lazer et al, 2017)

- Population bias

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- Human behavior and online platform design
  - e.g. *Google Flu* (Lazer et al, 2014)

1. Big data, big bias?

Reducing biases and flaws in social media data

DATA COLLECTION

- 1. Quantifies platform-specific biases (platform design, user base, platform-specific behavior, platform storage policies)
- 2. Quantifies biases of available data (access constraints, platform-side filtering)
- 3. Quantifies proxy population biases/mismatches

METHODS

- 4. Applies filters/corrects for nonhuman accounts in data
- 5. Accounts for platform and proxy population biases
  a. Corrects for platform-specific and proxy population biases
  OR
  b. Tests robustness of findings
- 6. Accounts for platform-specific algorithms
  a. Shows results for more than one platform
  OR
  b. Shows results for time-separated data sets from the same platform
- 7. For new methods: compares results to existing methods on the same data
- 8. For new social phenomena or methods or classifiers: reports performance on two or more distinct data sets (one of which was not used during classifier development or design)

Issues in evaluating data from social media. Large-scale social media studies of human behavior should i address issues listed and discussed herein (further discussion in supplementary materials).

Ruths and Pfeffer, 2015, "Social media for large studies of behavior", *Science*

2. The end of theory?

Petabytes allow us to say: "Correlation is enough." We can stop looking for models. We can analyze the data without hypotheses about what it might show. We can throw the numbers into the biggest computing clusters the world has ever seen and let statistical algorithms find patterns where science cannot.

***Chris Anderson**, Wired, June 2008*

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> ***Chris Anderson**, Wired, June 2008*

> *Correlations are a way of catching a scientist's attention, but the models and mechanisms that explain them are how we make the predictions that not only advance science, but generate practical applications.*
>
> ***John Timmer**, Ars Technica, June 2008*

(Big) social media data as a complement - not a substitute - for theoretical work and careful causal inference.

3. Spam and bots

"Follow your coordinators. We need to start tweeting, all at the same time, using the hashtag #ItsTimeForMexico. . . and don't forget to retweet tweets from the candidate's account..."

Unidentified PRI campaign manager

minutes before the May 8, 2012 Mexican Presidential debate

3. Spam and bots

Ferrara et al, 2016, *Communications of the ACM*

4. The privacy paradox

Online data present a paradox in the protection of privacy: Data are at once too revealing in terms of privacy protection, yet also not revealing enough in terms of providing the demographic background information needed by social scientists.

***Golder & Macy**, Digital footprints, 2014*

5. Generalizing from online to offline behavior

What makes online behavior different:

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- Anonymity encourages vitriol

6. Ethical concerns

1. Shifting notion of *informed consent*

PNAS

Experimental evidence of massive-scale emotional contagion through social networks

Adam D. I. Kramer[a,1], Jamie E. Guillory[b,2], and Jeffrey T. Hancock[b,c]

[a]Core Data Science Team, Facebook, Inc., Menlo Park, CA 94025; and Departments of [b]Communication and [c]Information Science, Cornell University, Ithaca, NY 14853

Edited by Susan T. Fiske, Princeton University, Princeton, NJ, and approved March 25, 2014 (received for review October 23, 2013)

Emotional states can be transferred to others via emotional contagion, leading people to experience the same emotions without their awareness. Emotional contagion is well established in laboratory experiments, with people transferring positive and negative emotions to others. Data from a large real-world social network, collected over a 20-y period suggests that longer-lasting moods (e.g., depression, happiness) can be transferred through networks [Fowler JH, Christakis NA (2008) *BMJ* 337:a2338], although the results are controversial. In an experiment with people who use Facebook, we test whether emotional contagion occurs

demonstrated that (*i*) emotional contagion occurs via text-based computer-mediated communication (7); (*ii*) contagion of psychological and physiological qualities has been suggested based on correlational data for social networks generally (7, 8); and (*iii*) people's emotional expressions on Facebook predict friends' emotional expressions, even days later (7) (although some shared experiences may in fact last several days). To date, however, there is no experimental evidence that emotions or moods are contagious in the absence of direct interaction between experiencer and target.

On Facebook, people frequently express emotions, which are

6. Ethical concerns

1. Shifting notion of *informed consent*
2. Most personal data can be de-anonymized

Ethics and Information Technology
December 2010, Volume 12, Issue 4, pp 313–325

“But the data is already public”: on the ethics of research in Facebook

Authors | Authors and affiliations

Michael Zimmer

Article

First Online: 04 June 2010

DOI: 10.1007/s10676-010-9227-5

Cite this article as:
Zimmer, M. Ethics Inf Technol (2010) 12: 313. doi:10.1007/s10676-010-9227-5

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3. Rise of “embedded researchers”

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“Ethical concerns must be weighed against the value of social research with appropriate steps taken to protest individual privacy” (Shah et al, 2015)

Twitter data

Twitter APIs

Two different methods to collect Twitter data:

1. REST API:

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    - Queries for specific information about users and tweets

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     - 2.3 Sample stream: 1% random sample of tweets

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   - R library: streamR

Important limitation: tweets can only be downloaded in real time (exception: user timelines, $\sim$ 3,200 most recent tweets are available)

Anatomy of a tweet

Barack Obama
@BarackObama

Follow

Four more years.

RETWEETS 756,411 FAVORITES 288,867

11:16 PM - 6 Nov 2012

Anatomy of a tweet

Tweets are stored in JSON format:


```
{ "created_at": "Wed Nov 07 04:16:18 +0000 2012",
  "id": 266031293945503744,
  "text": "Four more years. http://t.co/bAJE6Vom",
  "source": "web",
  "user": {
    "id": 813286,
    "name": "Barack Obama",
    "screen_name": "BarackObama",
    "location": "Washington, DC",
    "description": "This account is run by Organizing for Action staff.
        Tweets from the President are signed -bo.",
    "url": "http://t.co/8aJ56Jcemr",
    "protected": false,
    "followers_count": 54873124,
    "friends_count": 654580,
    "listed_count": 202495,
    "created_at": "Mon Mar 05 22:08:25 +0000 2007",
    "time_zone": "Eastern Time (US & Canada)",
    "statuses_count": 10687,
    "lang": "en" },
  "coordinates": null,
  "retweet_count": 756411,
  "favorite_count": 288867,
  "lang": "en"
}
```

Streaming API

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  - For large .json files, preprocess with python (see: github.com/pablobarbera/pytwools)

Sampling bias?

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- 1% random sample from Streaming API is not truly random
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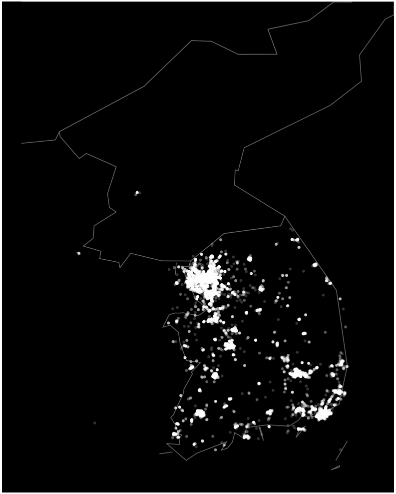
González-Bailón et al, 2014, *Social Networks*, “Assessing the bias in samples of large online networks”:

- Small samples collected by filtering with a subset of relevant hashtags can be biased
- Central, most active users are more likely to be sampled
- Data collected via search (REST) API more biased than those collected with Streaming API

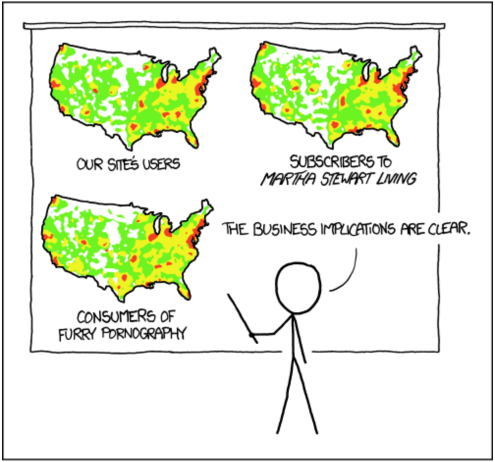


Tweets from Korea: 40k tweets collected in 2014 (left)
Korean peninsula at night, 2003 (right). Source: NASA.

Who is tweeting from North Korea?

Twitter user: @uriminzok_engl

But remember...



PET PEEVE #208:
GEOGRAPHIC PROFILE MAPS WHICH ARE BASICALLY JUST POPULATION MAPS

Facebook data

Collecting Facebook data

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R library: Rfacebook

Login details: RStudio Server

RStudio Server URL:

`rstudio.pablobarbera.com`

user = userXX and password = passwordXX

where XX is your assigned number