

Collecting and Analyzing Social Media Data with R

Pablo Barberá
Politics – SMaPP Lab
New York University

slides and code:
github.com/pablobarbera/social-media-workshop

February 2nd, 2015



Why should we care about social media?

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1. Social media usage is widespread

Widespread use of social media sites

- ▶ One in every ten people in the world logged onto Facebook yesterday.



(Sources: Pew Research Center (2014), Twitter and Facebook official statistics)

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- ▶ Instagram has 300+ million active users (26% of online adults in the US)

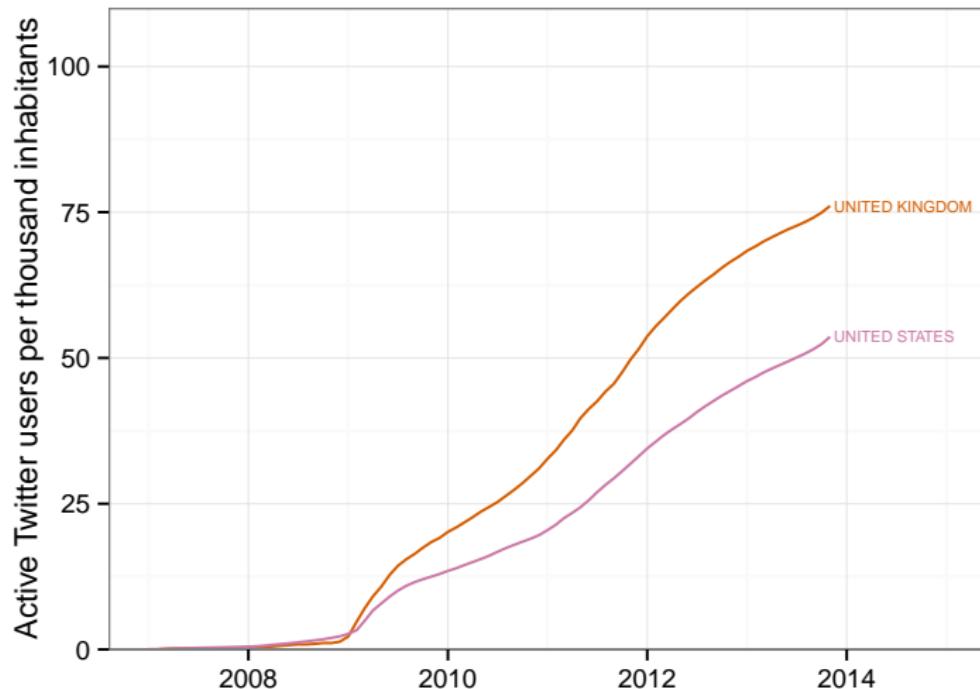


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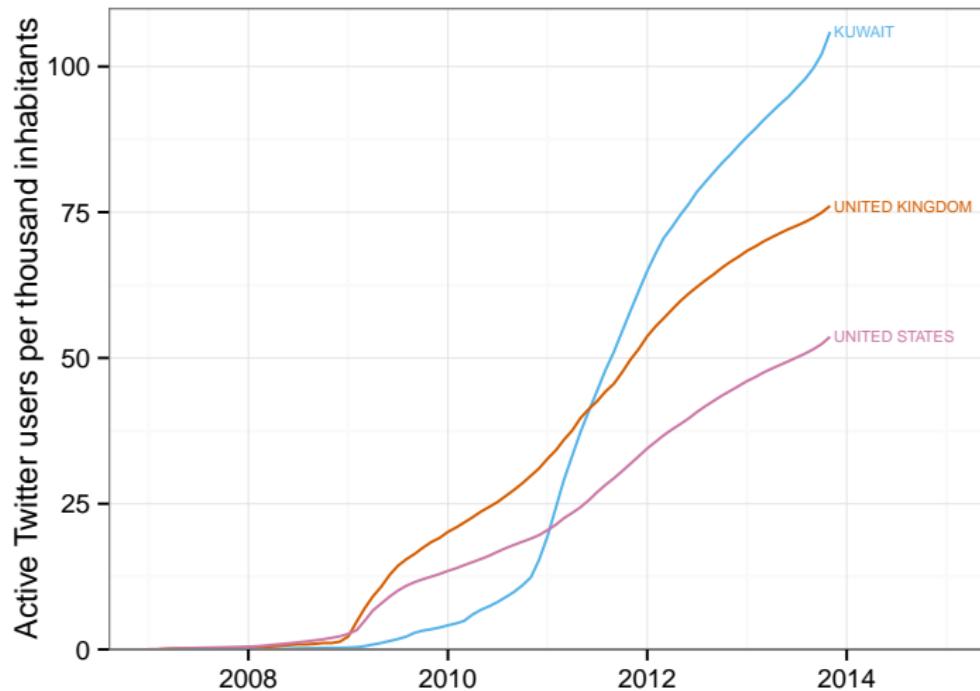
1. Social media usage is widespread
2. Social media usage is increasing

Social media usage is increasing



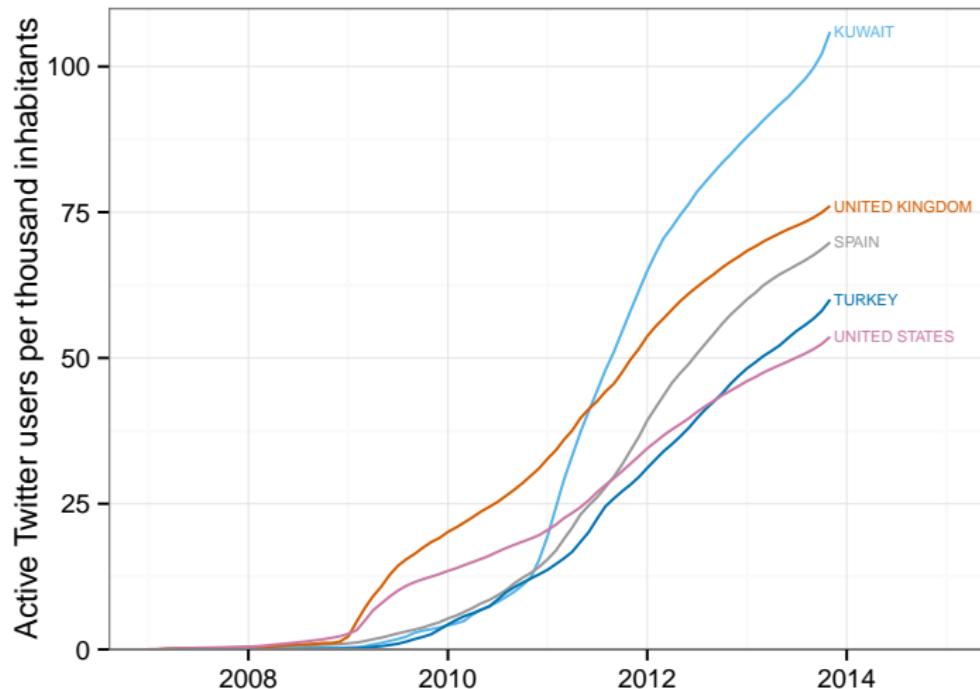
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Why should we care about social media?

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3. Political content on social media



Dmitry Medvedev @MedvedevRussiaE

Follow

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

Reply Retweet Favorite More

RETWEETS
144

FAVORITES
57



10:39 AM - 21 Mar 2014



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10:39 AM - 21 Mar 2014



Justin Amash

December 10, 2014 ·

Sec. 309 of the new Intelligence Authorization Act permits the U.S. government to acquire, retain, and disseminate nonpublic telephone or electronic communications to or from a U.S. person. I demanded a roll call vote on the bill, and I will be voting NO.

[Like](#) · [Comment](#) · [Share](#) · 2,534 120 673



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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.

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RETWEETS 144 FAVORITES 57



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262 people like this.

Top Comments ▾



Donald J. Trump

@realDonaldTrump

Follow

This very expensive GLOBAL WARMING bullshit has got to stop. Our planet is freezing, record low temps, and our GW scientists are stuck in ice

Reply Retweet Favorite More

RETWEETS 2,007 FAVORITES 1,145



7:39 PM - 1 Jan 2014

Social media and politics

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(Sources: Electionista; Zeitzoff and Barberá, MPSA 2014; Pew Research Center)

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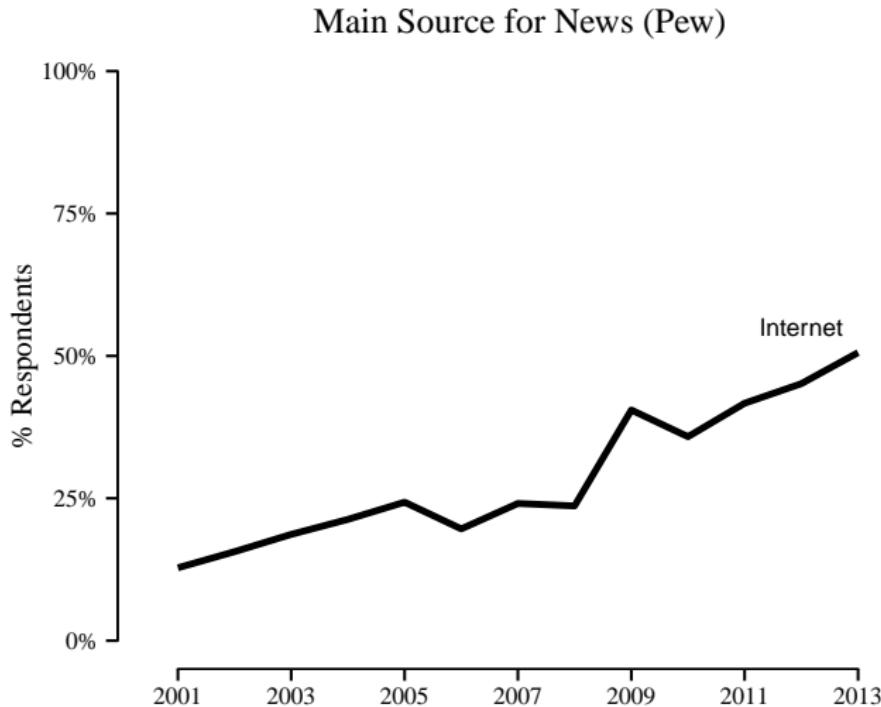
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- ▶ 46% have discussed a news issue or event on social media

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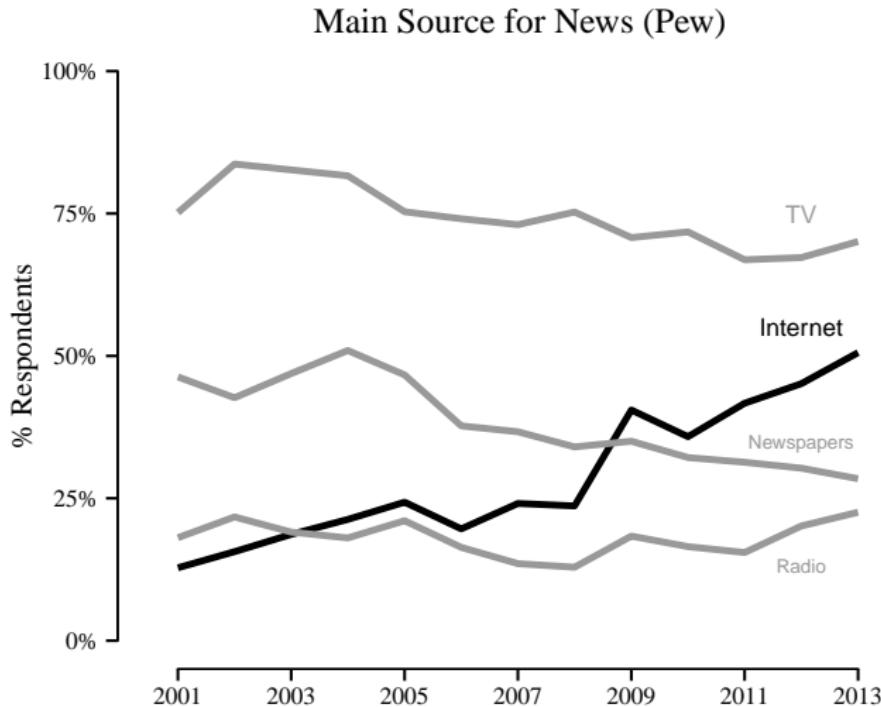
1. Social media usage is widespread
2. Social media usage is increasing
3. Political content on social media
4. Social media is a primary source of political information

- ▶ Large changes in citizens' news consumption habits



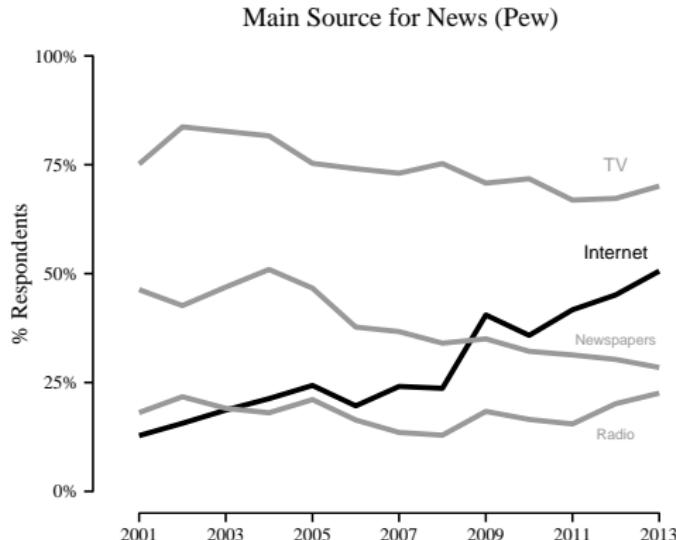
Data: Pew Research Center. Respondents were allowed to name up to two sources.

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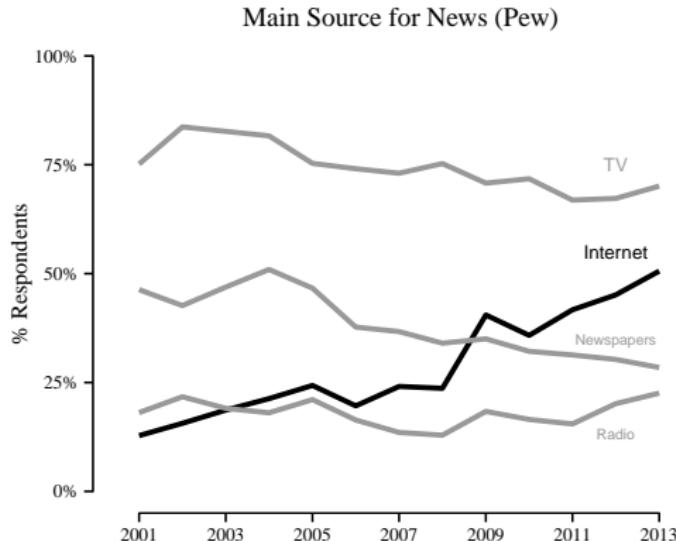
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- ▶ 41% of Americans see news on social media every day (Pew)

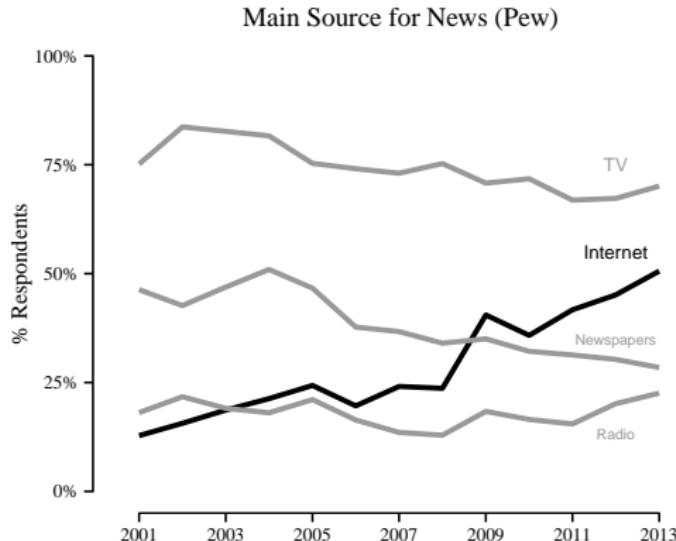
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- ▶ Social media: top source of news for U.S. young adults (Pew)

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2. Overview of social media research
3. Social media APIs
4. Tools and applications:
 - 4.1 Twitter
 - 4.2 Facebook
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Two different approaches to the study of social media and politics:

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1. Social media as data

- ▶ Behavior, opinion, and latent traits
- ▶ Interpersonal networks
- ▶ Elite behavior

2. Social media as a variable

- ▶ Mass protests
- ▶ Political persuasion
- ▶ Social capital
- ▶ Political polarization

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Today is Election Day

What's this? • close

 Find your polling place on the U.S. Politics Page and click the "I Voted" button to tell your friends you voted.

I Voted

  Jaime Settle, Jason Jones, and 18 other friends have voted.

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

Behavior, opinions, and latent traits

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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 Pfeffer²

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 research" (researchers who have special relationships with providers that give them access to platform-specific data, algorithms, and resources) is creating a diverse media research community. Such researchers, for example, can see a platform's workings and make accommodations that may not be able to reveal their own identities or the data used to generate their findings.

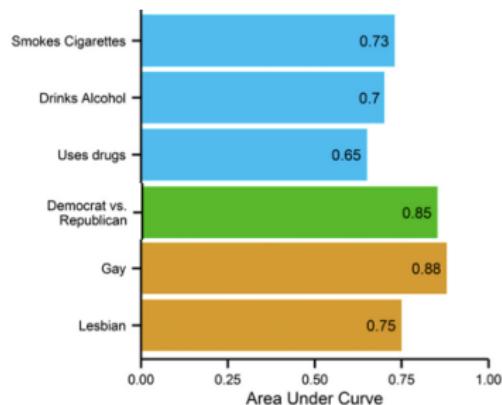
Ruths and Pfeffer, 2015, "Social media for large studies of behavior", *Science*

Behavior, opinions, and latent traits

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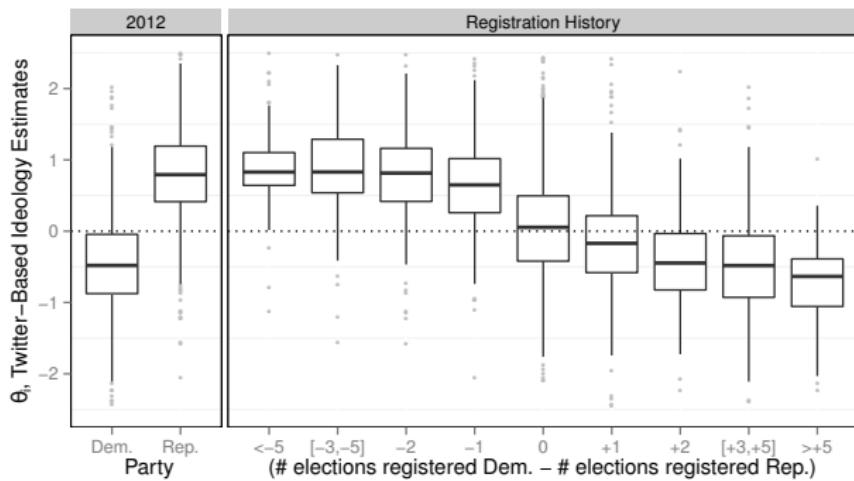


Kosinski et al, 2013, “Private traits and attributes are predictable from digital records of human behavior”, PNAS (also personality, PNAS 2015)

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

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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*

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Interpersonal networks

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OPEN  ACCESS Freely available online



Inferring Tie Strength from Online Directed Behavior

Jason J. Jones^{1,2*}, Jaime E. Settle², Robert M. Bond², Christopher J. Fariss², Cameron Marlow³, 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*

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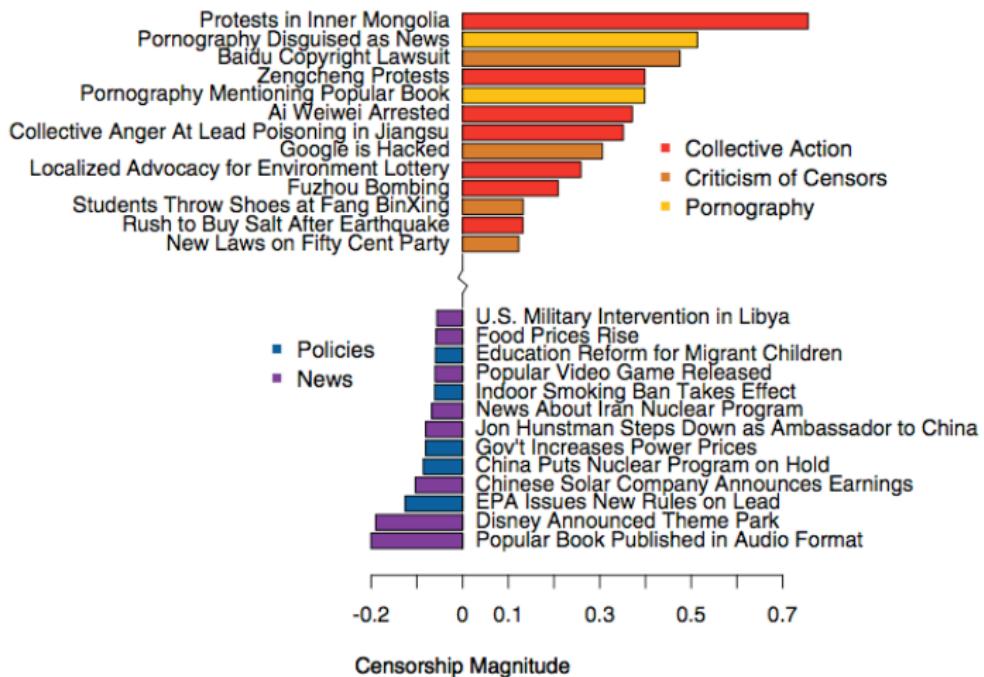
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Elite behavior

- ▶ Authoritarian governments' response to threat of collective action

Elite behavior

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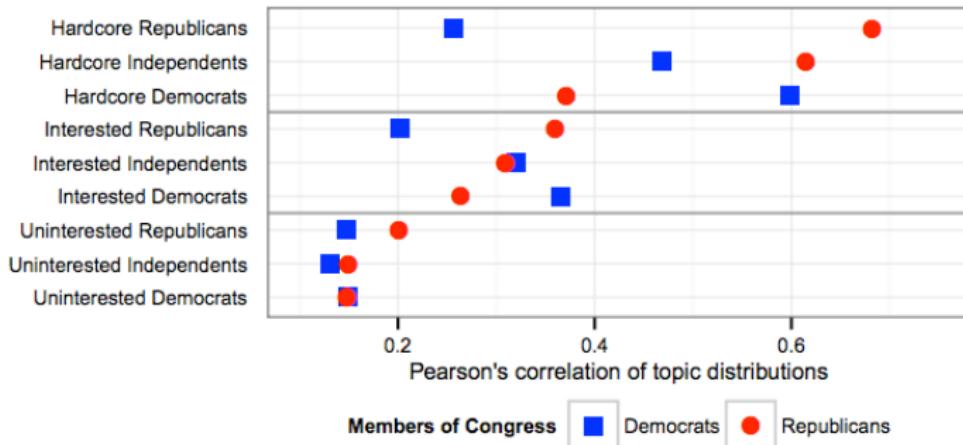
King et al, 2013, "How Censorship in China Allows Government Criticism but Silences Collective Expression", *APSR*

Elite behavior

- ▶ Authoritarian governments' response to threat of collective action
- ▶ How legislators in democracies are responsive to their constituents in how they communicate publicly

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Barberá et al, 2014, “Leaders or Followers? Measuring Political Responsiveness in the U.S. Congress Using Social Media Data”, APSA

Elite behavior

- ▶ Authoritarian governments' response to threat of collective action
- ▶ How legislators in democracies are responsive to their constituents in how they communicate publicly
- ▶ Estimation of conflict intensity in real time

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

Thomas Zeitzoff¹

Journal of Conflict Resolution
55(6) 938-969
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DOI: [10.1177/0022002711408014](https://doi.org/10.1177/0022002711408014)
<http://jcr.sagepub.com>



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THE NEW YORKER

ANNALS OF INNOVATION

SMALL CHANGE

Why the revolution will not be tweeted.

by Malcolm Gladwell

OCTOBER 4, 2010



Social media can't provide what social change has always required.

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Barack Obama

@BarackObama



Follow

Four more years.



RETWEETS

756,411

FAVORITES

288,867



11:16 PM - 6 Nov 2012

Sections ≡

The Washington Post

Search



Sign In

Post Politics

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

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

American Politics Research

1–31

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DOI: [10.1177/1532673X14557942](https://doi.org/10.1177/1532673X14557942)

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**Javier Sajuria¹, Jennifer vanHeerde-Hudson¹,
David Hudson¹, Niheer Dasandi¹, and Yannis
Theocharis²**

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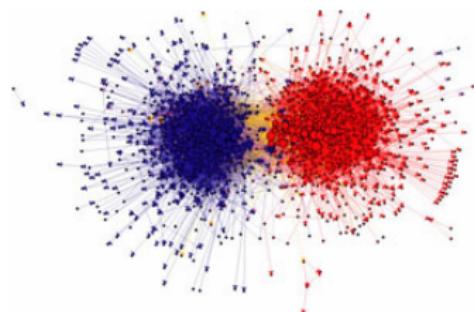
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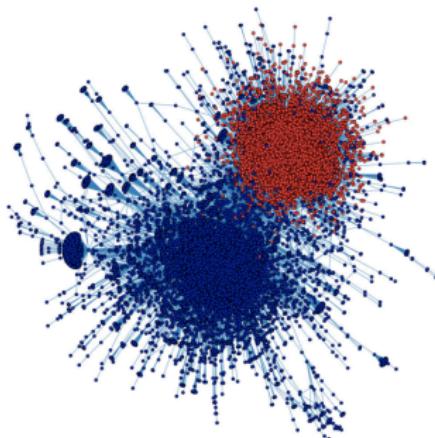
Political polarization

Social media as *echo chambers* or *filter bubbles*:

- ▶ communities of like-minded individuals (homophily)



Adamic and Glance (2005)

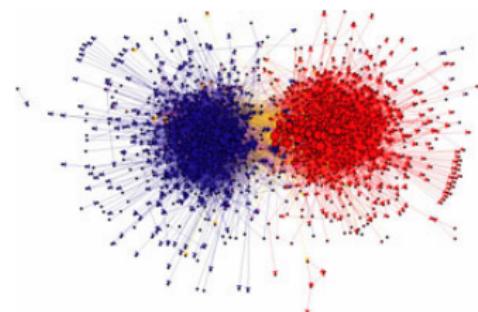


Conover et al (2012)

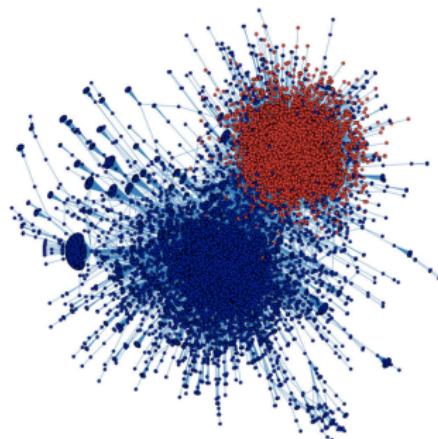
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Social media as *echo chambers* or *filter bubbles*:

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Adamic and Glance (2005)



Conover et al (2012)

- ▶ ...generates selective exposure to congenial information
- ▶ ...increases political polarization (Sunstein, Prior)

Political polarization

Social media usage induces political moderation (Barberá, 2015)

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...increases exposure to dissonant views

...and therefore mass political polarization decreases.

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Collecting Social Media Data

Two different methods:

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Types of APIs:

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2. Streaming APIs: changes in users' data in real time (e.g. new messages, deletions, etc.)

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Potential issues

1. Rate limits: restrictions on number of API calls by user and period of time (APIs are expensive!)
2. Ongoing debate on replication of social science research using social media data

Connecting with an API

Constructing a REST API call

- ▶ Baseline URL: <http://graph.facebook.com/>
- ▶ Parameters: ?ids=barackobama,johnmccain

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Authentication

- ▶ Most common is an open standard called OAuth
- ▶ Connections without sharing username and password, only temporary tokens that can be refreshed
- ▶ httr package in R implements most cases (examples)

Interacting with social media APIs

R packages

- ▶ Twitter: twitteR for REST, streamR for Streaming
- ▶ Facebook: Rfacebook
- ▶ Instagram: instaR (not on CRAN)

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Other APIs: CRAN Task View for Web Technologies and Services

Equivalent libraries for python, java, ruby... whatever works for you!

Collecting and Analyzing Social Media Data with R

1. Motivation
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4. Tools and applications:
 - 4.1 Twitter
 - 4.2 Facebook
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Fork my repo! github.com/pablobarbera/social-media-workshop

Code:

- ▶ Twitter
 - ▶ 01-twitter-data-collection.r
 - ▶ 02-twitter-data-analysis.r
- ▶ Facebook
 - ▶ 03-facebook-data-collection.r
 - ▶ 04-facebook-data-analysis.r
- ▶ Instagram
 - ▶ 05-instagram-data.r

Slides: [slides/social-media-workshop.pdf](#)

Data: [backup/](#)

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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

Four more years.

◀ ▶ ★ ...



RETWEETS FAVORITES
756,411 **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"
}
```

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- ▶ Collect a random sample of tweets
- ▶ Download all tweets sent by a given user

Streaming API

- ▶ Recommended method to collect tweets
- ▶ Potential issues:
 - ▶ Filter streams have same rate limit as spritzer (1% of all tweets)
 - ▶ Stream connections tend to die spontaneously. Restart regularly.
 - ▶ Lots of invalid content in stream. If it can't be parsed, drop it.
- ▶ My workflow:
 - ▶ Amazon EC2 Ubuntu micro instance (free tier)
 - ▶ Cron jobs to restart R scripts every hour.
 - ▶ Save tweets in .json files or in MongoDB.
 - ▶ For large .json files, preprocess with python (see:
github.com/pablobarbera/pytwools)

Analyzing Twitter Data

The R script 02-twitter-data-analysis.r shows:

1. How to work with geolocated tweets

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Analyzing Twitter Data

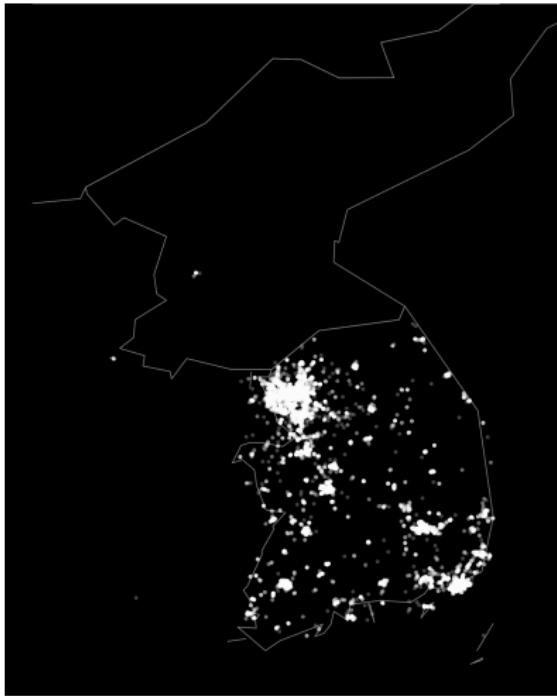
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2. How to measure opinions on Twitter
 - ▶ Supervised sentiment analysis using a dictionary of positive and negative words



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

Who is tweeting from North Korea?



North Korea English
@uriminzok_engl
An English translation of @uriminzok - the official North Korea Twitter feed
uriminzokkiri.com

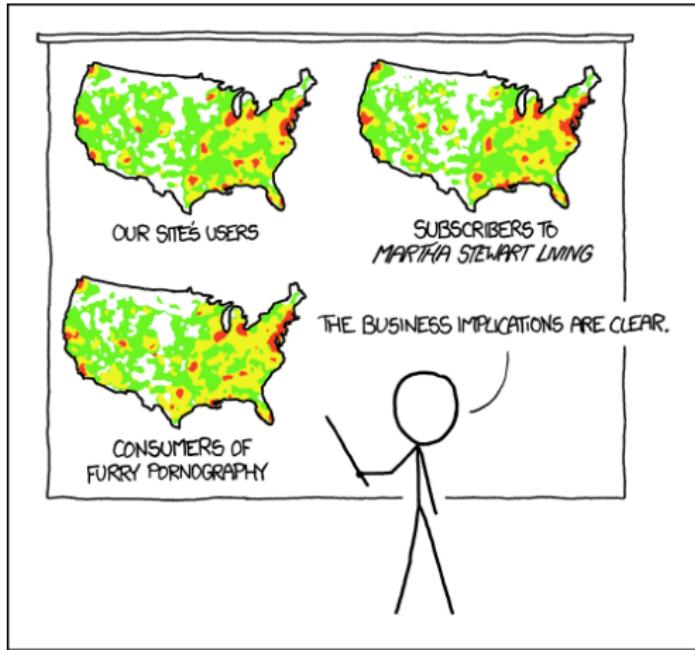
671 TWEETS	940 FOLLOWING	129 FOLLOWERS	Profile Follow
---------------	------------------	------------------	--

Tweets

 **North Korea English** @uriminzok_engl 13h
Beloved Comrade Kim Jong-un to stay in the national light industry competition attended by Code speeches do was goo.gl/eJWsJ
[Expand](#)

Twitter user: @uriminzok_engl

But remember...



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

Sentiment analysis

Sentiment, tone, valence, affective score... = % positive messages about a subject

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In practice, accuracy over 80% is impossible (and that's ok)

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Facebook allows access to two different types of data through the public API:

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- ▶ Capture data from a Facebook page

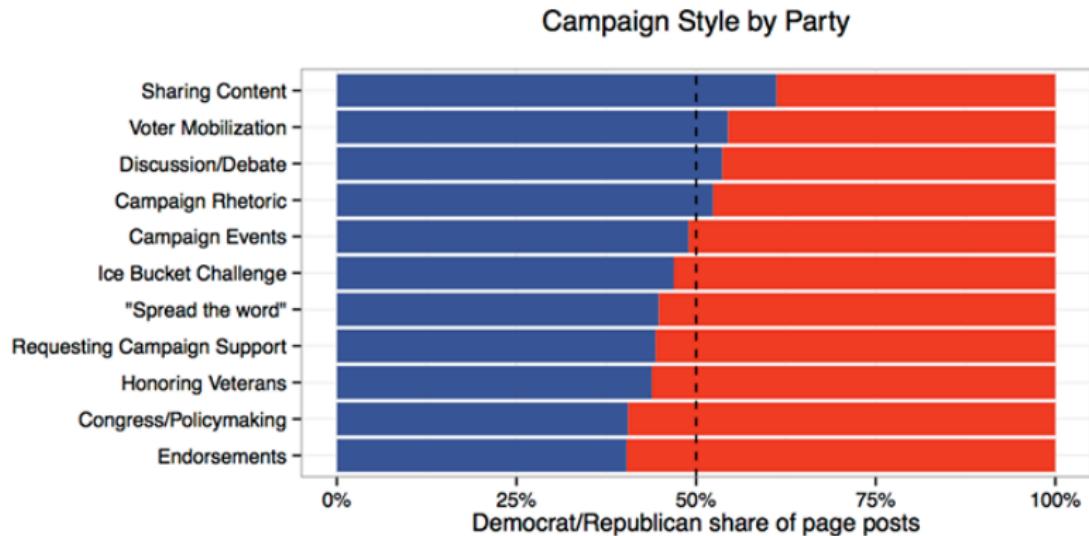
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- ▶ Capture data from a Facebook page
- ▶ Collect likes and comments data from a public post

Facebook data analysis

What issues do Members of the U.S. Congress discuss on Facebook?



Messing et al, 2014, "Campaign Rhetoric and Style on Facebook in the 2014 U.S. Midterms" (Facebook Data Science Blog)

Analyzing Facebook Data

The R script 04-facebook-data-analysis.r shows how to:

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- ▶ Interpret the results of this model

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Instagram data

What is available through Instagram API:

- ▶ Search and download pictures that mention a given hashtag on its caption, or that were sent from a specific location
- ▶ Collect information about these pictures (creation date, caption, author, filter, hashtags ...)
- ▶ Download pictures sent by a given user
- ▶ Count number of photos that mention a specific hashtag

Examples: 05-instagram-data.r

Thanks! Questions?

materials: github.com/pablobarbera/social-media-workshop

website: pablobarbera.com

twitter: [@p_barbera](https://twitter.com/@p_barbera)