# computational social media

# **lecture 3: tweeting** part 3

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#### announcements

reading #3 will be presented today

Z. Tufekci, Big Questions for Social Media Big Data: Representativeness, Validity and Other Methodological Pitfalls, in Proc. AAAI ICWSM 2014

projects

please contact me about your HREC submission if you haven't done it yet

#### this lecture



a human-centric view of twitter

- 1. introduction
- 2. twitter users & uses
- 3. understanding large-scale human behavior
- 4. inferring real-world events & trends
- 5. spreading information in the real world

## spreading information in the real world

### 1. who talks to whom on twitter

- 2. cascading behavior in networks
- 3. structural virality of online diffusion
- 4. twitter and the news

#### 1. who talks to whom on Twitter

S. Wu, J. M. Hofman, W. Mason, and D. Watts, "Who Says What to Whom on Twitter," in Proc. WWW 2011. Thanks to A. Olteanu for some of the slides.

#### the goal of media communication research

Harold Lasswell (1948): "who says what to whom in what channel with what effect"

"difficult to examine information flow in large populations"

"communication channels may have different effects"

H. Lasswell, "The structure and function of communication in society," in L. Bryson (ed.), The Communication of ideas, U. Illinois Press, 1949 credit: photo by John Schnobrich on Unsplash https://unsplash.com/photos/2FPjlAyMQTA

#### three models of communication

#### mass communication:

"one-way message transmission from one source to a large, relatively undifferentiated and anonymous audience" interpersonal communication: "two-way message exchange between two or more individuals"

#### two-step flow of communication:

"mass media influence the public only indirectly" "the critical intermediate layer are media-savvy individuals – the opinion leaders"

J. B. Walther, C. T. Carr, S. S. W. Choi, D. C. DeAndrea, J. Kim, S. T. Tong, and B. Van Der Heide. Interaction of interpersonal, peer, and media influence sources online. In Z. Papacharissi, (ed.) A Networked Self: Identity, Community, and Culture on Social Network Sites, Routledge, 2010.

#### who is on twitter?

Communication Туре

User Category Examples

Mass media

Media, Organizations

User Examples



Mass-personal

Celebrities, Bloggers



Personal

Others (the rest of us)



WWF

#### questions



# who talks on Twitter? user categories who listens to whom? information flow & consumption



credit: photo by Marten Bjork on Unsplash: https://unsplash.com/photos/FVtG38Cjc\_k

#### quick detour: what is the "full" dataset of users?

Q1. all people living in a given country? Q2. all Twitter user accounts?

A1: exact number unknown A2: exact number known only to Twitter

estimates for each case might exist (with varying levels of uncertainty)

more often than not, we work with partial data a.k.a. <u>samples</u>



#### sampling

assume that X is a random variable with distribution p(X)

Monte Carlo: sampling p(X) provides a finite number of samples that can be used to approximate functions of X (e.g. expected value)



a random sample of X:  $(X_1, ..., X_N)$  is representative in this sense

Image source: https://www.slideshare.net/kohta/particle-filter-tracking-in-python

#### sampling in the social sciences

access to full populations is impossible or impractical

X is a vector of individual attributes: age group, zip code, etc.

how to obtain representative population samples has been studied in depth in the social sciences

non-probabilistic sampling techniques exist, e.g. convenience sampling, known to be non-representative of the population

**bias**: systematic error arising from many factors, including but not limited to the lack of representativeness of the sample



#### **Twitter data samples for research (up to 2021)**

<b>Y</b>	Developer	Use cases	Products	Docs	More	Labs
STANDARD Our free, standard APIs are great for getting started, testing an integration, or validating a concept.		<b>PREMIUM</b> Our premium APIs offer scalable access to Twitter data for those looking to grow, experiment, and			ENTERPRISE Our enterprise APIs offer the highest level of access and reliability to those who depend on Twitter data.	
<b>Feat</b> Four Basic Foru	<b>uring:</b> ndational, free APIs c query complexity m access	innovate Featurii Scalable increase Free sar flexible contract Forum a	e. <b>ng:</b> e access to ed data ndbox and month-to-mo is access	onth	Featuring Enterprise Tailored pa annual con Dedicated managers support	: -grade APIs ackages and ntracts account and technical

**fully random sampling**: impossible unless you were Twitter or paid for data: Twitter API - Enterprise category **convenience sample**: Twitter API - Standard category

https://developer.twitter.com/en/pricing (link no longer active)

# Twitter data samples for academic research (since Nov 2021)

## Enhance your academic research with global, realtime and historical data

Get more precise, complete, and unbiased data from the public conversation for free. This specialized access includes access to all Twitter API v2 endpoints, a higher monthly **Tweet <u>cap</u>**, and enhanced features designed to support research.

#### Who it's for

Academic researchers with specific research objectives are encouraged to apply. This includes graduate students working on a thesis, PhD candidates working on a dissertation, or research scholars affiliated with or employed by an academic institution.

#### Use cases

Find global data for your thesis or dissertation, gather historical or realtime data for your research lab, and study the public conversation with the API v2.

#### Non-commercial use

Reserving this access for only noncommercial use makes it possible to provide long-term support for researchers who rely on the Twitter API to do their work.

https://developer.twitter.com/en/products/twitter-api/academic-research

### back to the main topic: datasets

- 1. follower graph [Kwak et al, WWW 2010] collected in Jul 2009, 42M users, 1.5B edges
- 2. twitter firehose (full stream)
  223 days (Jul 2009 Mar 2010)
  5B tweets
  260M tweets with <u>bit.ly</u> URL links
  URLs are easier to track content
  & give access to rich content



### lists: feature to groups users

lists allow to organize users into sets

list names are meaningful labels to describe listed users → user categorization

celebrity List members A public list by Mashabl KANYE WEST 📀 @kanyewest Celebrities on Twitter. + Follow SUBSCRIBERS MEMBERS 2.705 92 Conan O'Brien 📀 @ConanOBrien + Follow The voice of the people. Sorry, people. Subscribe Tracy Morgan 🕗 @RealTracyMorgan ж. ..... List members **BreakingNews** E A public list by Patrick LaForge, N The latest headlines from top online news Vox 📀 @voxdotcom Ö + Follow Understand the news. sources. MEMBERS SUBSCRIBERS 3,084 64 NYT Now @NYTNow + Follow An app from @Nytimes. We work around the clock to bring you the day's most important stories. Named Subscribe one of Apple's best apps. Download: bit.ly/1hU6llw . . . **Public-Companies** List members public list by Dominic Jones TwitterIR 📀 @TwitterIR The most-followed list of exchange-traded + Follow companies on Twitter. Follow @irwebreport to Official Account of Twitter Investor Relations TWTR be added. MEMBERS SUBSCRIBERS McEwen Mining @McEwenMining + Follow 375 324 The goal of McEwen Mining is to qualify for inclusion in the S&P 500 by creating a high growth gold producer focused in the Americas. (NYSE & TSX: Subscribe MUX) Best Blogs 2011 List members public list by TIME.com The Verge 🥝 @verge Our annual blog extravaganza features 25 fresh + Follow picks, from politics, pop culture, travel & tech, theverge.com covers the future of technology, science, art, and culture. SUBSCRIBERS MEMBERS 28 174 The Hairpin @thehairpin **Follow** Witch museum. Subscribe Everyday Carry @everydaycarry m l + Follow

https://help.twitter.com/en/using-twitter/twitter-lists

#### snowball user sample: using lists of popular users

uo: manual **seed users** (4 categories)

check all lists that seed users belong to & manually select keywords

lo: crawl all lists where seed users appear in

prune lists to keep those lists that contain keywords

u1: crawl all users In pruned lists

repeat



Media (news, news-media), Celebrities (stars, celebs) Organizations (company, ngo, brand), Blogs (blog, blogger)



### the concept of elite users: top 5000 users (ranked by how frequently they are listed in each category)

statistics of the snowball sample

top 5 users per category (ranked by #lists in that category)

counts of URLs initiated by each category composed of 5000 elite users

		Snowball Sample				
category	#	# of users % of		users		
celeb	82,770		15.8%			
media	media 2		216,010 4			
org		97,853 1		8.7%		
blog		127,483	24.3%			
total		$524,\!116$		100%		
Celebrity		Media		Org		Blog
aplusk		cnnbrk		google		mashable
ladygaga		nytimes		Starbucks		problogger
TheEllenShow		asahi		twitter		kibeloco
tay lors wift 13		BreakingNews		joinred		naosalvo
Oprah		TIME		ollehkt		dooce

		# of URLs
category	# of URLs	per-capita
celeb	$139,\!058$	27.81
media	$5,\!119,\!739$	1023.94
org	$523,\!698$	104.74
blog	$1,\!360,\!131$	272.03
ordinary	$244,\!228,\!364$	6.10

#### elite users: how do they relate to ordinary users?

start with 100K ordinary (non-elite) users

**celebrities** dominate: users get 25% of their tweets from the top 1000 celebrities



average fraction of tweets for an ordinary user that are accounted for by the top K elite users that the ordinary user follows

#### who listens to whom?

"Ordinary users receive their information from thousands of distinct sources, many of which are not the media."

"Audiences are increasingly fragmented."

"Only ~15% of tweets received by ordinary users are received directly from the media"

"20K elite users attract ~50% of all attention" → add values for k=5000 for 4 categories



#### who listens to whom among the 4 categories?



### two-step flow of information

media has an indirect influence over the public via an **intermediate** layer of opinion leaders (Katz 1955)



information on Twitter passes through intermediaries via

(1) retweets(2) tweets of URLs

### two-step flow of information (2)



for 1M random **ordinary** users, **46%** of **received URLs** generated by **top 5000 media** users were received via **intermediaries** 

intermediaries: pass along content to at least one other user

- \* 99% are ordinary users, not elite
- \* exposed to more media than ordinary users (9100 vs.1300 URLs)
- \* more active (543 vs. 34 followers; 180 vs. 7 tweets)

#### what to remember

#### sampling

critical issue for computational social science

#### who talks to whom on Twitter

fragmented audiences: no longer dominated by classical media concentrated attention: 20K elite users get half the attention homophily: celebrities follow celebrities; media follows media information flow: half of media URLs pass via intermediaries

# questions?

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