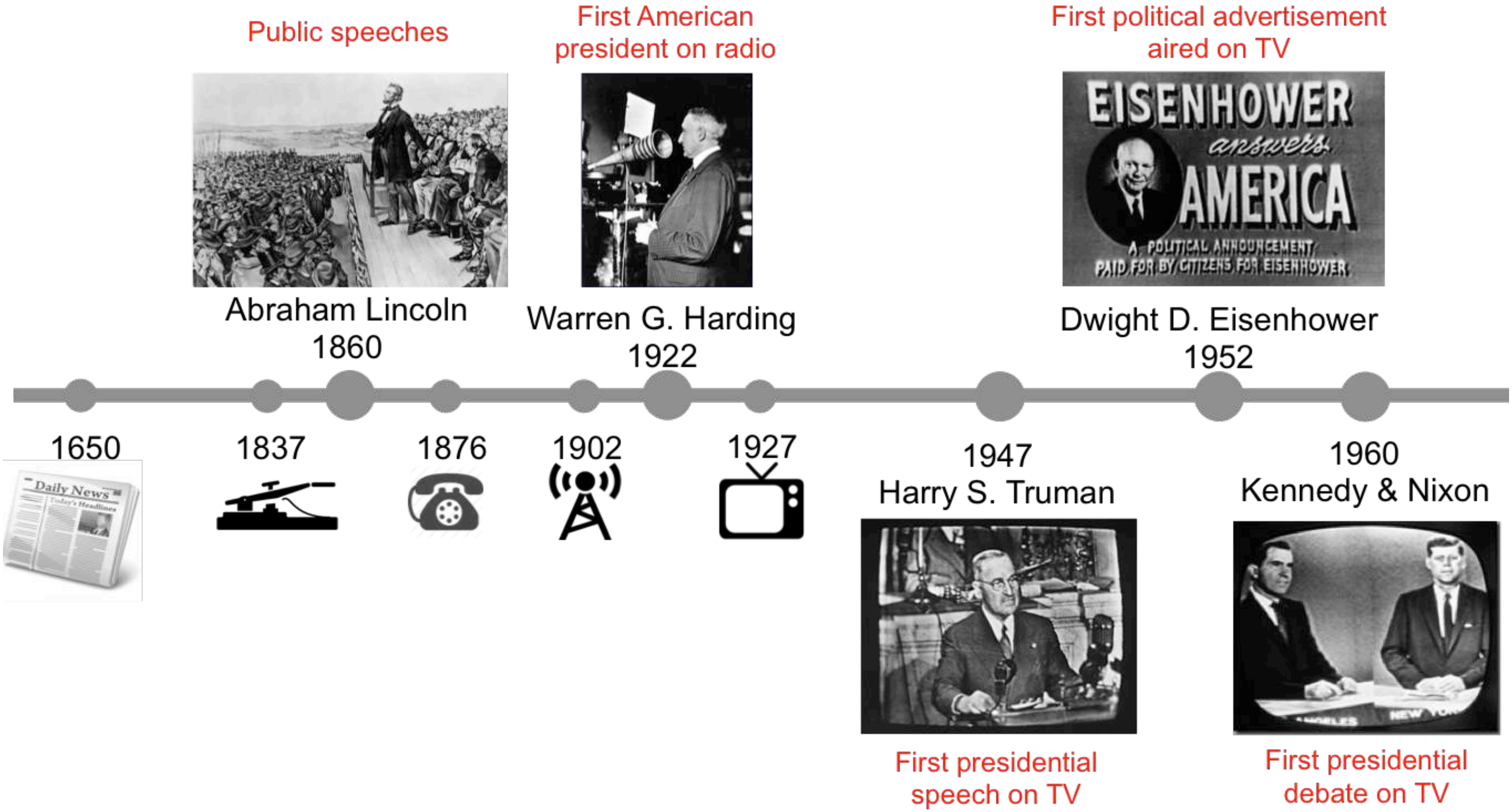
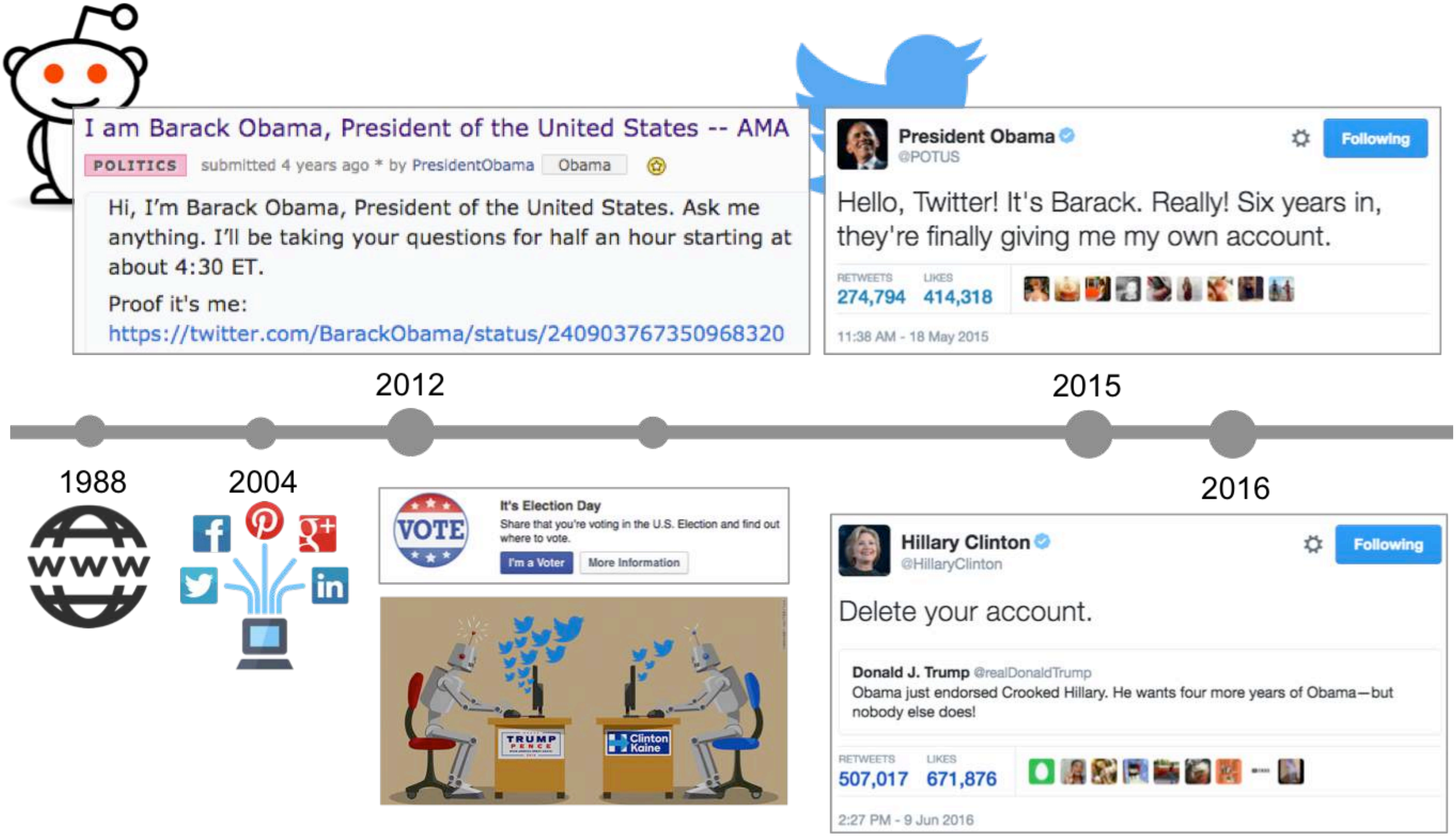
Analyzing Social Big Data to Study Online Discourse and its Manipulation

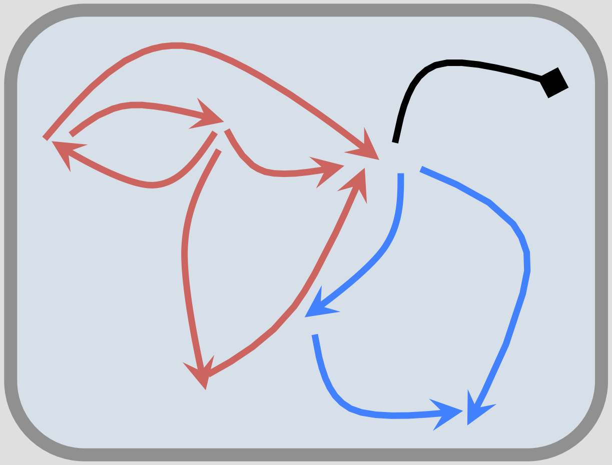
Onur Varol

Center of Complex Networks and Systems Research
School of Informatics and Computing
Indiana University
@onurvarol ⦿ onurvarol.com

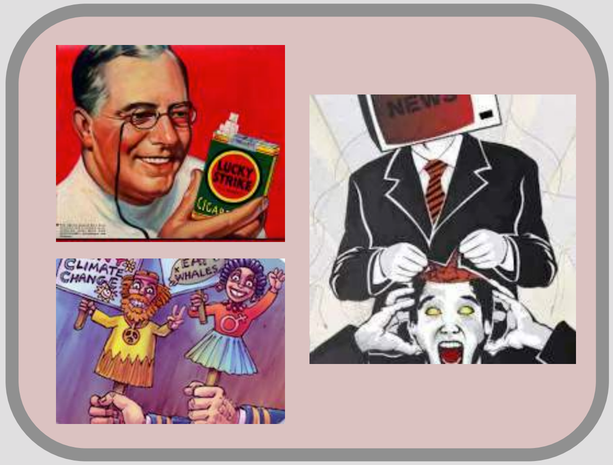

Public speeches
Abraham Lincoln
1860
First American president on radio
Warren G. Harding
1922
First political advertisement aired on TV
EISENHOWER
answers
AMERICA
A POLITICAL ANNOUNCEMENT
PAID FOR BY CITIZENS FOR EISENHOWER
Dwight D. Eisenhower
1952
1650
Daily News
1837
1876
1902
1927
1947
Harry S. Truman
First presidential speech on TV
1960
Kennedy & Nixon
First presidential debate on TV


I am Barack Obama, President of the United States -- AMA
POLITICS submitted 4 years ago * by PresidentObama Obama
Hi, I'm Barack Obama, President of the United States. Ask me anything. I'll be taking your questions for half an hour starting at about 4:30 ET.
Proof it's me:
https://twitter.com/BarackObama/status/240903767350968320
President Obama
@POTUS
Following
Hello, Twitter! It's Barack. Really! Six years in, they're finally giving me my own account.
RETWEETS 274,794
LIKES 414,318
11:38 AM - 18 May 2015
2012
2015
1988
2004
2016
It's Election Day
Share that you're voting in the U.S. Election and find out where to vote.
I'm a Voter
More Information
VOTE
TRUMP PENCE
Clinton Kaine
Hillary Clinton
@HillaryClinton
Following
Delete your account.
Donald J. Trump @realDonaldTrump
Obama just endorsed Crooked Hillary. He wants four more years of Obama—but nobody else does!
RETWEETS 507,017
LIKES 671,876
2:27 PM - 9 Jun 2016

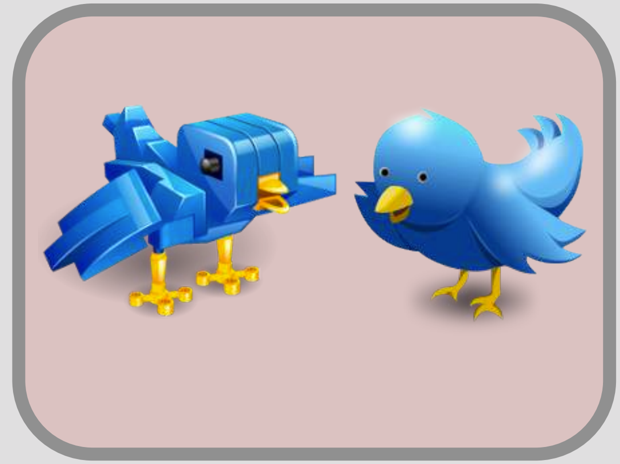
Part I
Online Discourse



Part II
Campaigns



Part III
Social bots

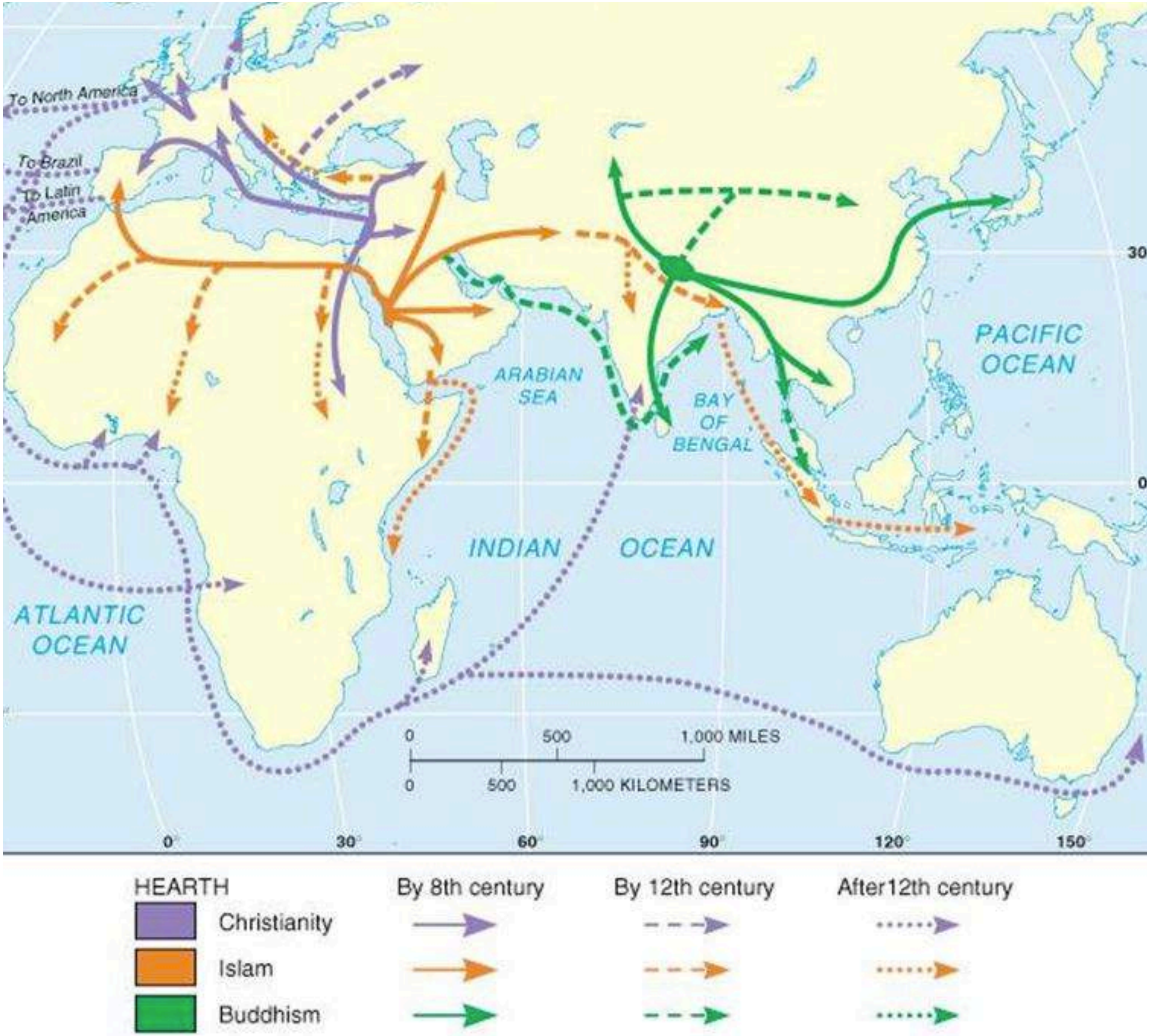


How does geography affect **information diffusion** and **user behavior**?

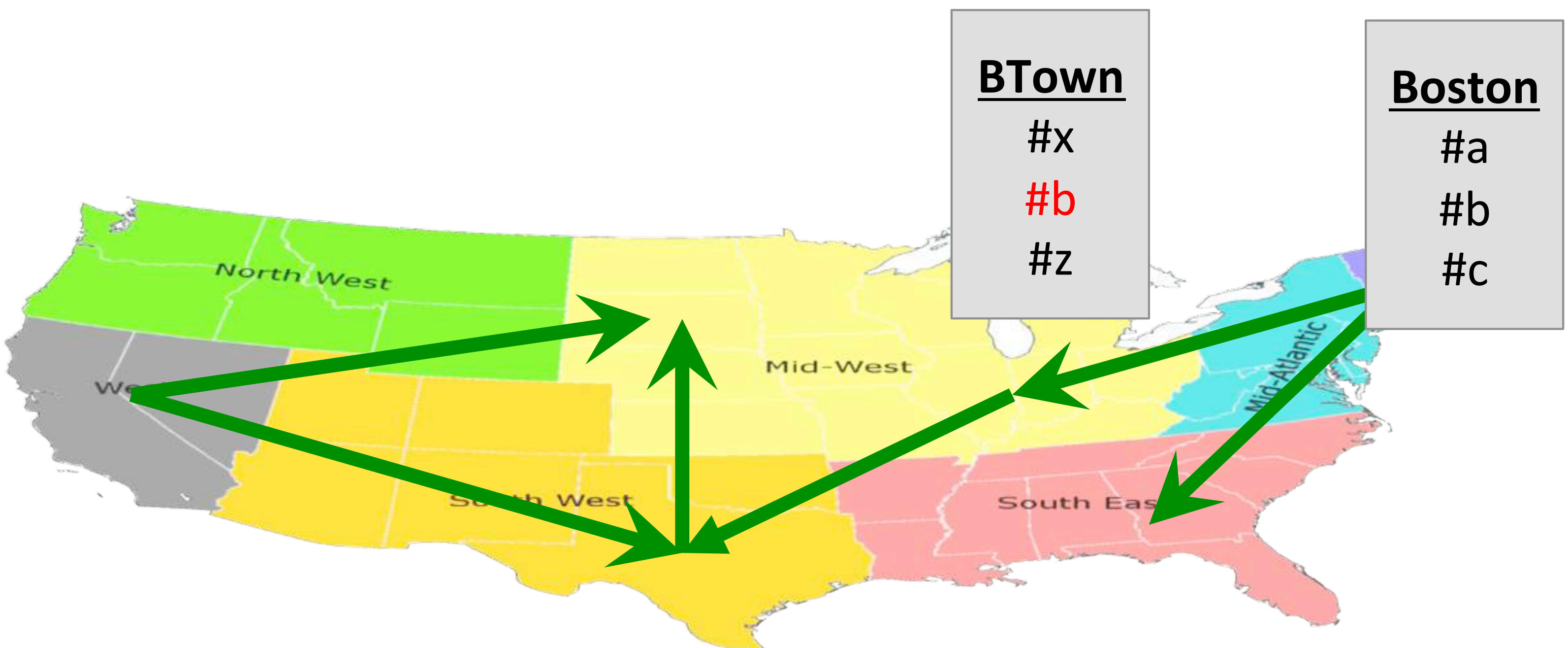
Can we build systems to detect **online campaigns** and **social bots**?

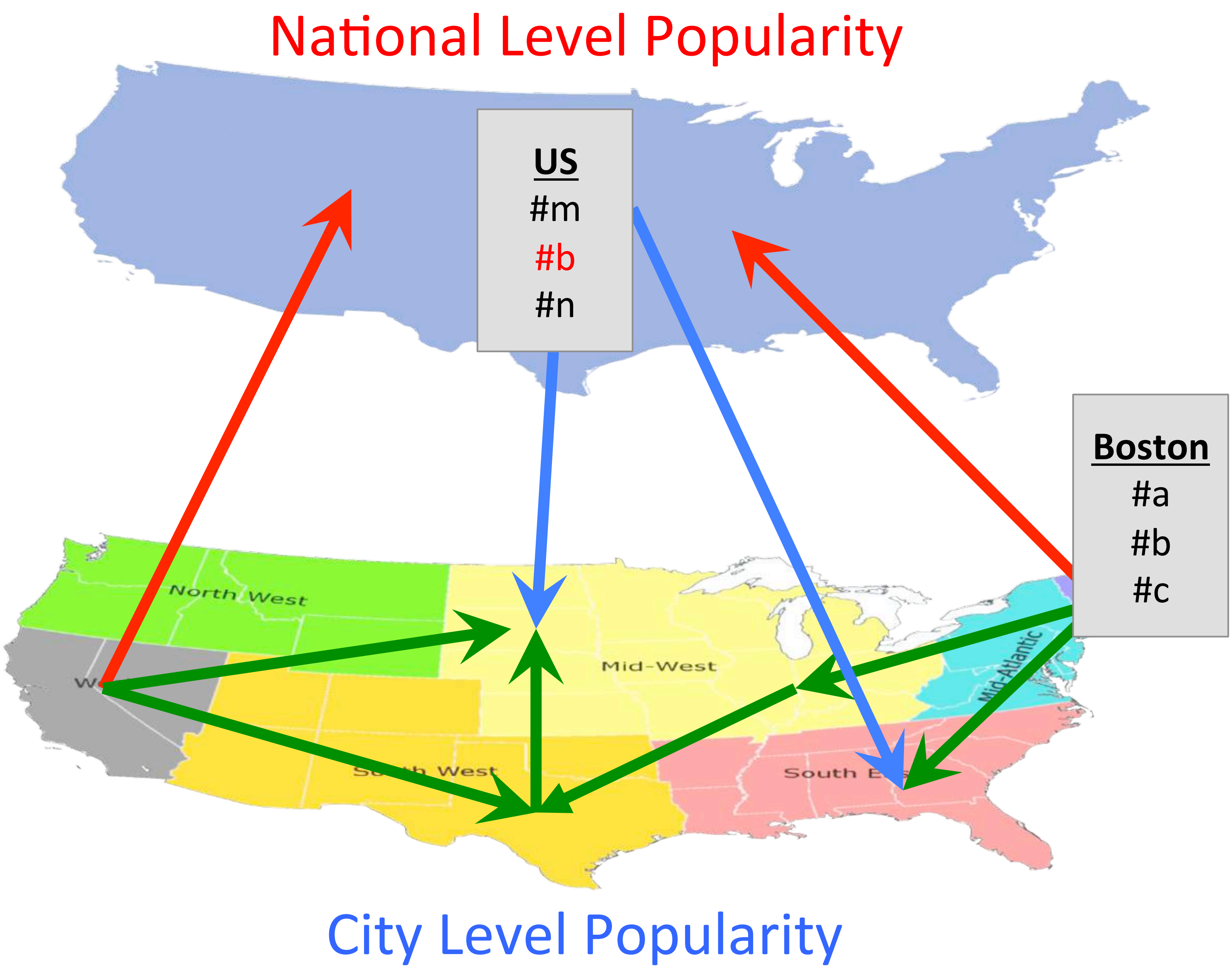
Analysis of Online Discourse

Part One


To North America
To Brazil
To Latin America
ARABIAN SEA
BAY OF BENGAL
PACIFIC OCEAN
INDIAN OCEAN
ATLANTIC OCEAN
0 500 1,000 MILES
0 500 1,000 KILOMETERS
30
0
0°
30°
60°
90°
120°
150°
HEARTH
Christianity
Islam
Buddhism
By 8th century
By 12th century
After12th century

Does geography still plays role in information diffusion?

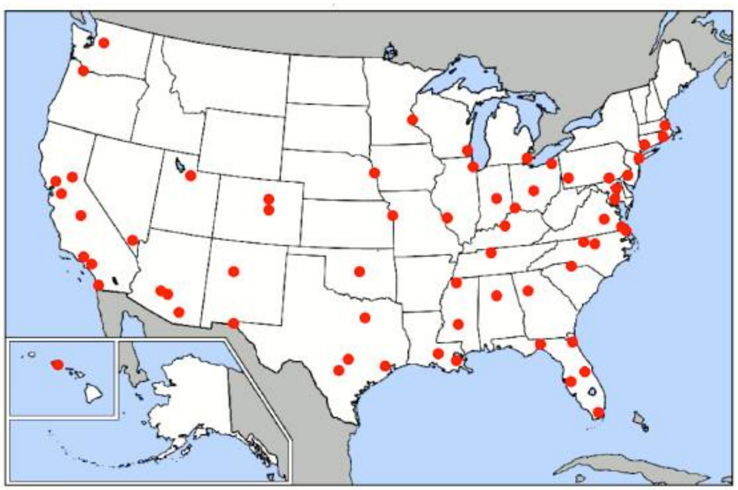

BTown
#x
#b
#z
Boston
#a
#b
#c
North West
Mid-West
Mid-Atlantic


National Level Popularity
US
#m
#b
#n
Boston
#a
#b
#c
North West
Mid-West
Mid-Atlantic
City Level Popularity

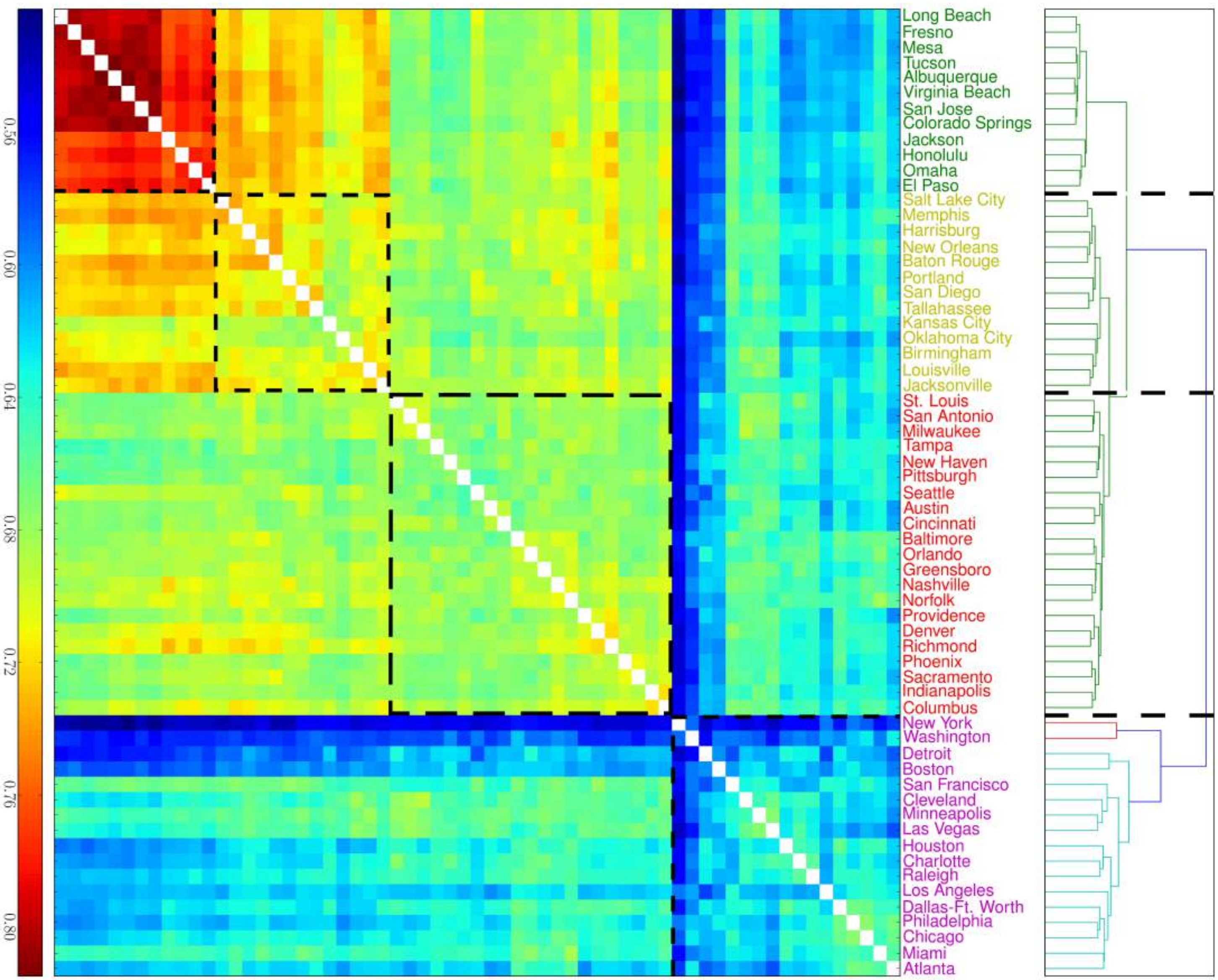
Twitter trends dataset

We collect 63 US cities and national trends between April-May 2013

In total 4,513 hashtags – 6,889 phrases trends



Spatial trend similarities



Southwest

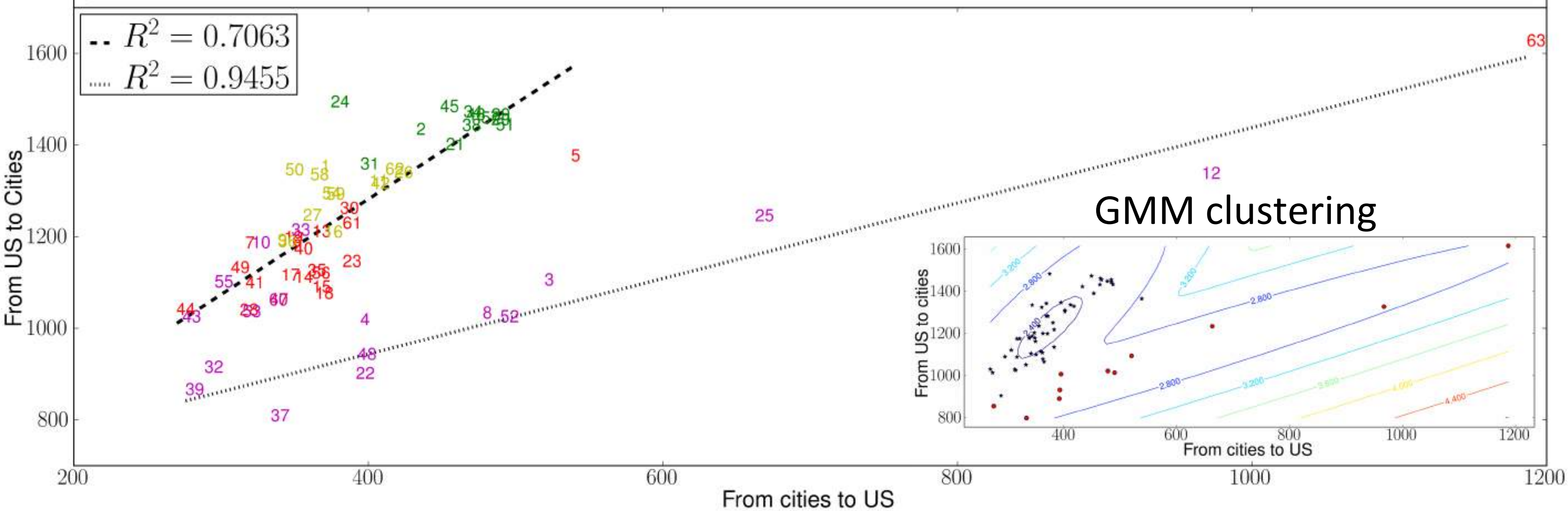
Midwest

East Coast

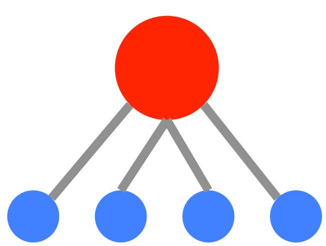
Metropolitan cities
(mostly traffic hubs)

National trendsetters and trend-followers

1) Baton Rouge	2) Jackson	3) Chicago	4) Philadelphia	5) Denver	6) Richmond	7) Providence
8) Dallas-Ft. Worth	9) Oklahoma City	10) San Francisco	11) Birmingham	12) Los Angeles	13) Columbus	14) Indianapolis
15) Phoenix	16) Harrisburg	17) Pittsburgh	18) Sacramento	19) Nashville	20) Albuquerque	21) El Paso
22) New York	23) Baltimore	24) Honolulu	25) Atlanta	26) Memphis	27) Jacksonville	28) Tampa
29) Colorado Springs	30) Norfolk	31) Omaha	32) Charlotte	33) Miami	34) San Jose	35) Orlando
36) Kansas City	37) Detroit	38) Tucson	39) Raleigh	40) Greensboro	41) Cincinnati	42) San Diego
43) Las Vegas	44) Austin	45) Mesa	46) Virginia Beach	47) St. Louis	48) Houston	49) New Haven
50) Tallahassee	51) Fresno	52) Boston	53) Washington	54) Louisville	55) Minneapolis	56) San Antonio
57) Long Beach	58) New Orleans	59) Salt Lake City	60) Cleveland	61) Milwaukee	62) Portland	63) Seattle



National to **city** level diffusion
(following trend)



City level to **national** diffusion
(setting national trends)

Social butterflies or frequent fliers?

16/17 **purple** cities are also top 20 air traffic hubs!

Some of the major traffic hubs are not major cities (Charlotte, Raleigh, Las Vegas, etc)

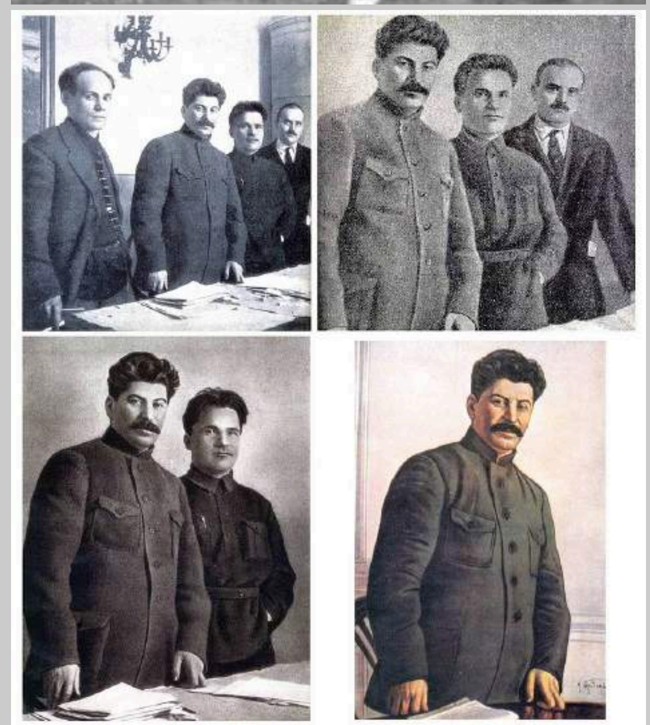
Does information travel faster by airplane than over the Internet?

City	Rank	Traffic
New York	6,14,20	52.5 M
Atlanta	1	44.4 M
Chicago	2,25	41.0 M
Washington	22,23,26	31.1 M
Los Angeles	3	30.5 M
Miami	12,21	29.7 M
Dallas-Ft. Worth	4	27.5 M
Denver	5	25.7 M
San Francisco	7	20.0 M
Las Vegas	8	19.9 M

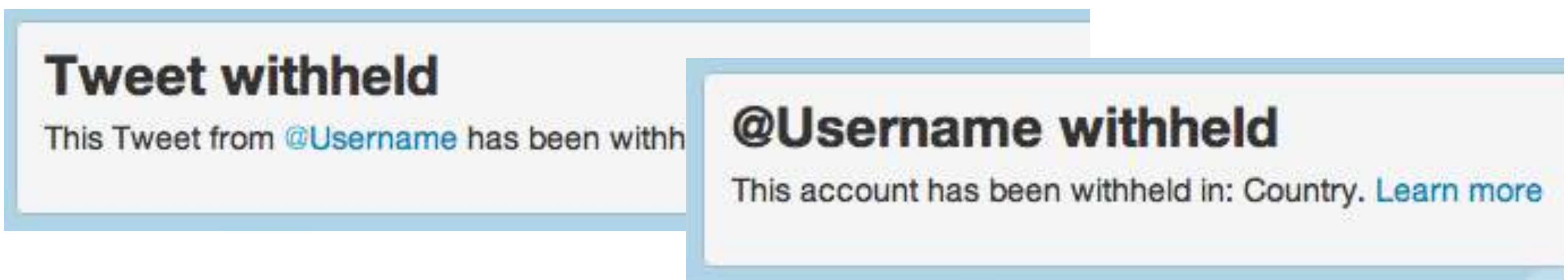
Two dynamics control trend dissemination

- local diffusion
- jumps through global hubs

Censorship



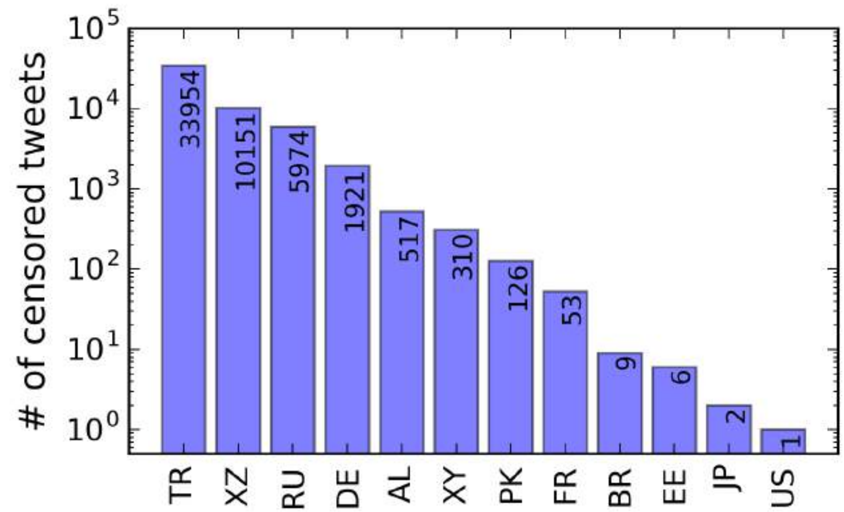
Twitter censorship



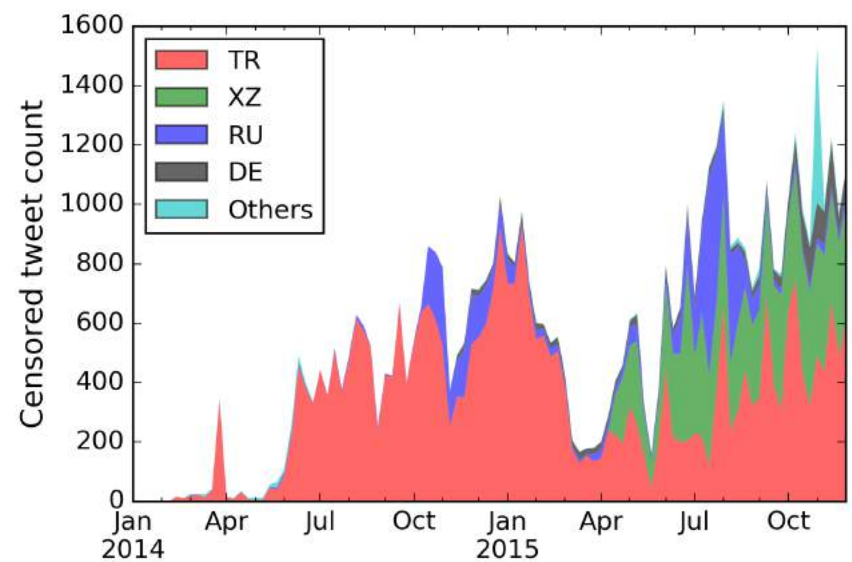
How does censorship affect information diffusion and user behavior?

Censorship dataset

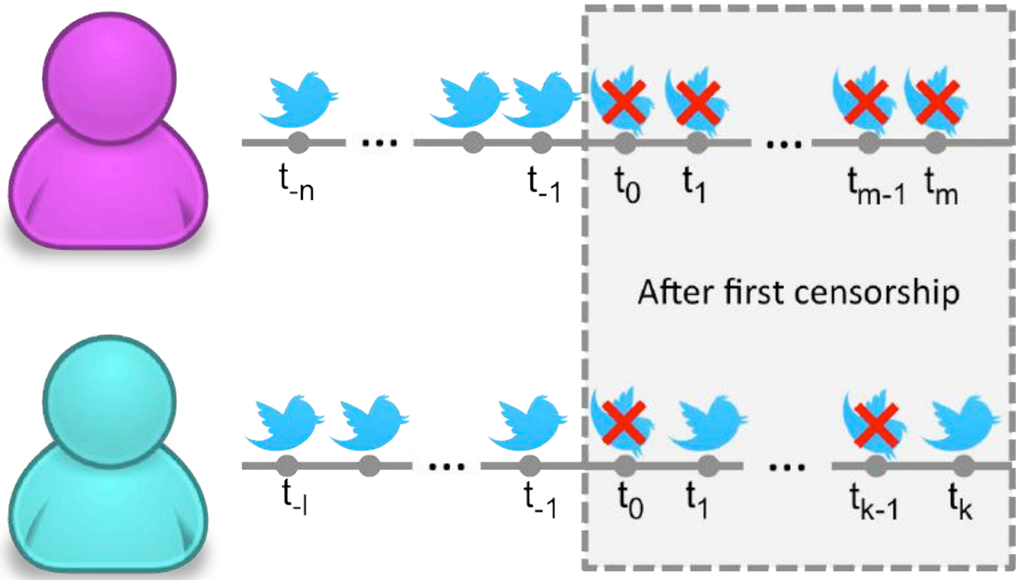
Over 50k censored tweet in two years period by more than 700 censored users.



Censorship volume correlates with political events (Russia, Ukraine, Turkey, etc.)



User behavior changes



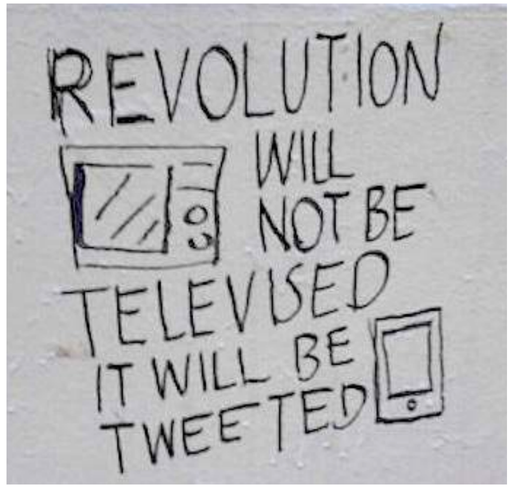
Property change	significance
Median censorship time	-0.14 (*)
Followers change	0.25 (***)
Friends change	-0.06 (NS)
Unique @user	0.21 (***)
Unique RTuser	0.31 (***)

Governments are blacklisting accounts

Twitter censorship favors dissemination of censored content


END SEGREGATED RULES IN PUBLIC SCHOOLS
WE DEMAND VOTING RIGHTS NOW!
JOBS FOR ALL NOW!


BLACK LIVES MATTER.

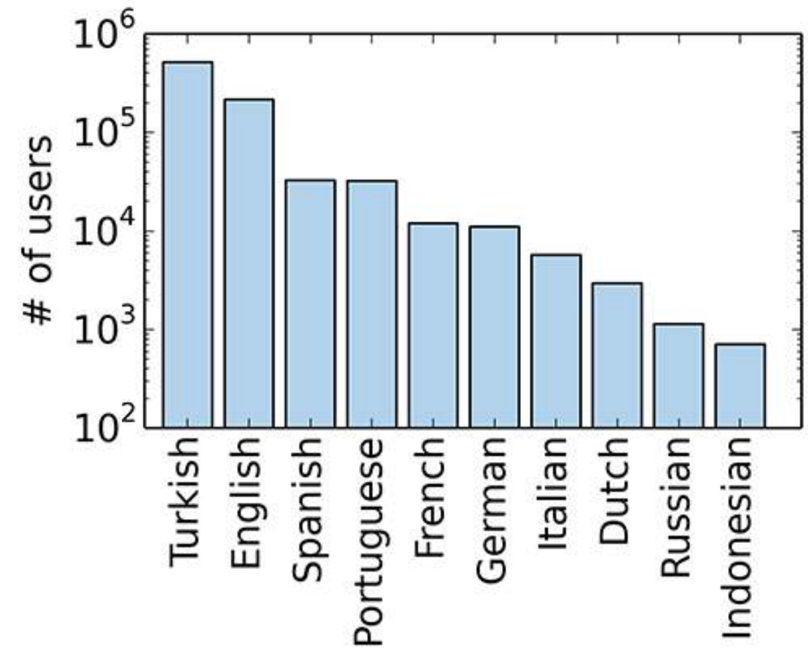

REVOLUTION WILL NOT BE TELEVISED
IT WILL BE TWEETED


REVOLUTION TOOLS
~~AK-47~~
~~MACHETE~~
TWITTER ✓
FACEBOOK ✓
t.sina.com.cn/she

Do users adopt different roles during the course of protests?

Gezi protest dataset

#direngezi, #resistgezi

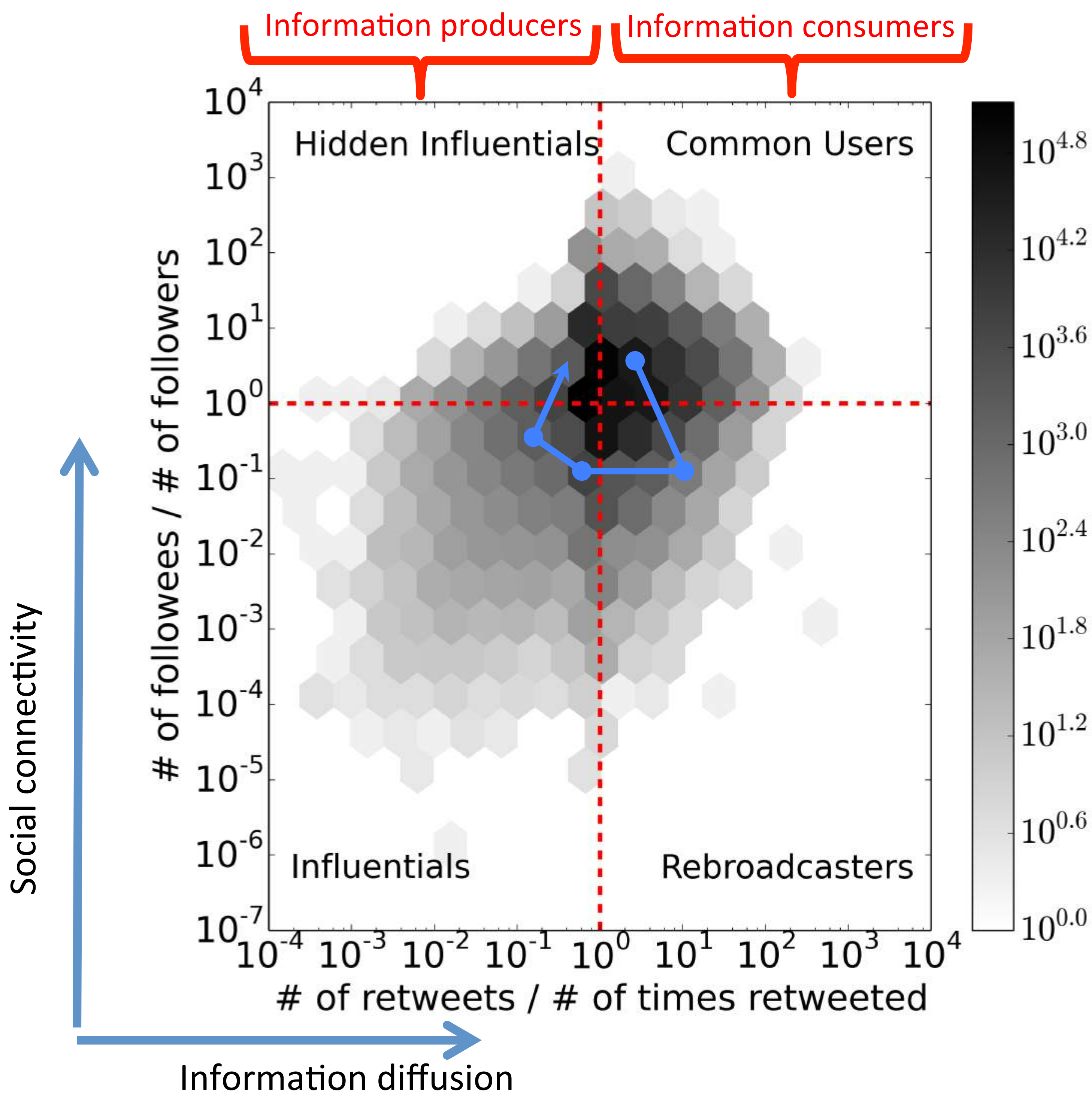


25 May – 20 June 2013

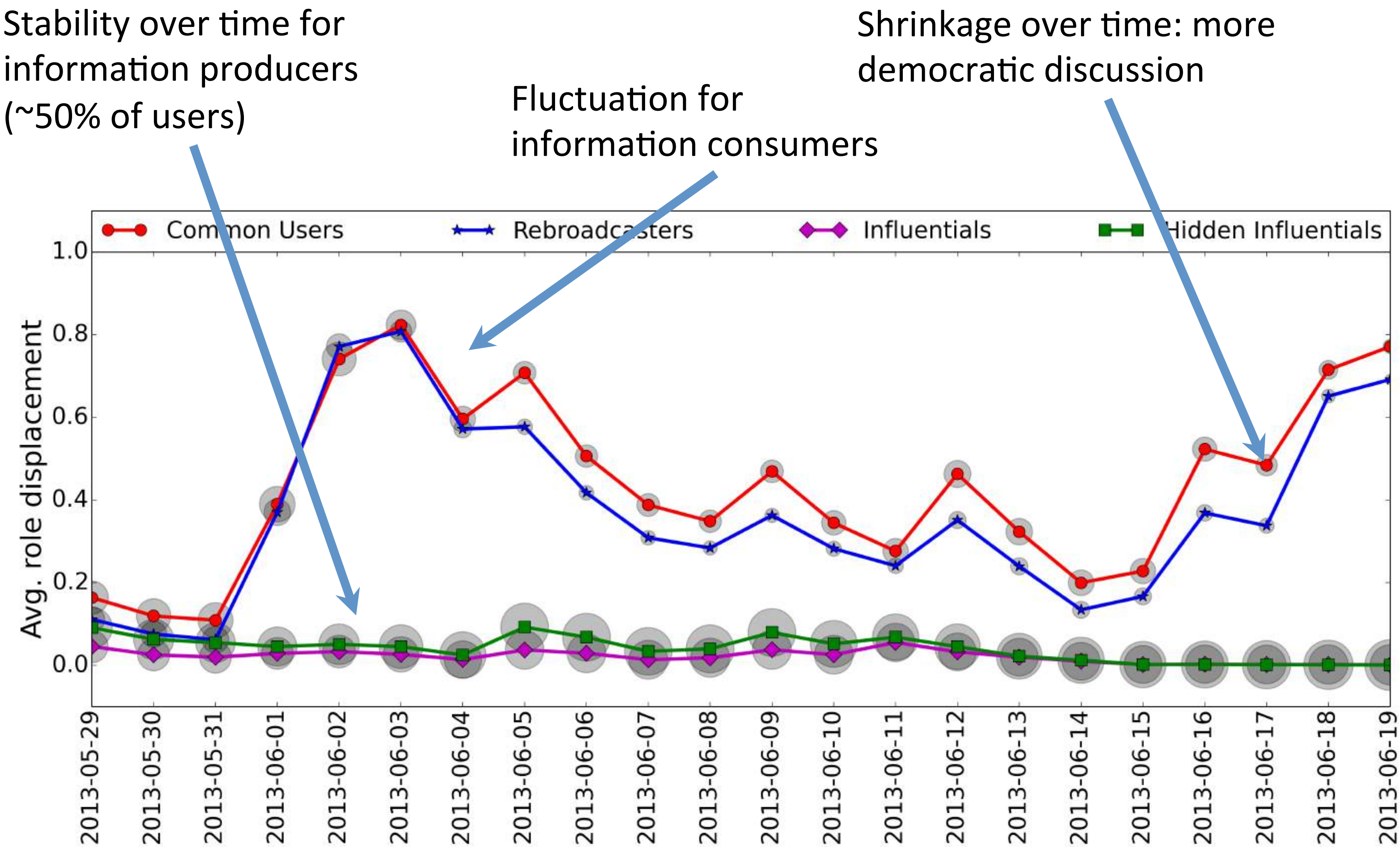
- ~855k participants
- ~2.3M tweets
- 75% retweet rate
- ~65k unique hashtags
- ~45k geolocated tweets

Manually annotated dataset (135 users, ~5100 tweet)

- **Info-share:** Type of information shared in tweets.
- **Purpose:** Main motivation of user to share the tweet.
- **Position:** Opinion of user about protests or particular event

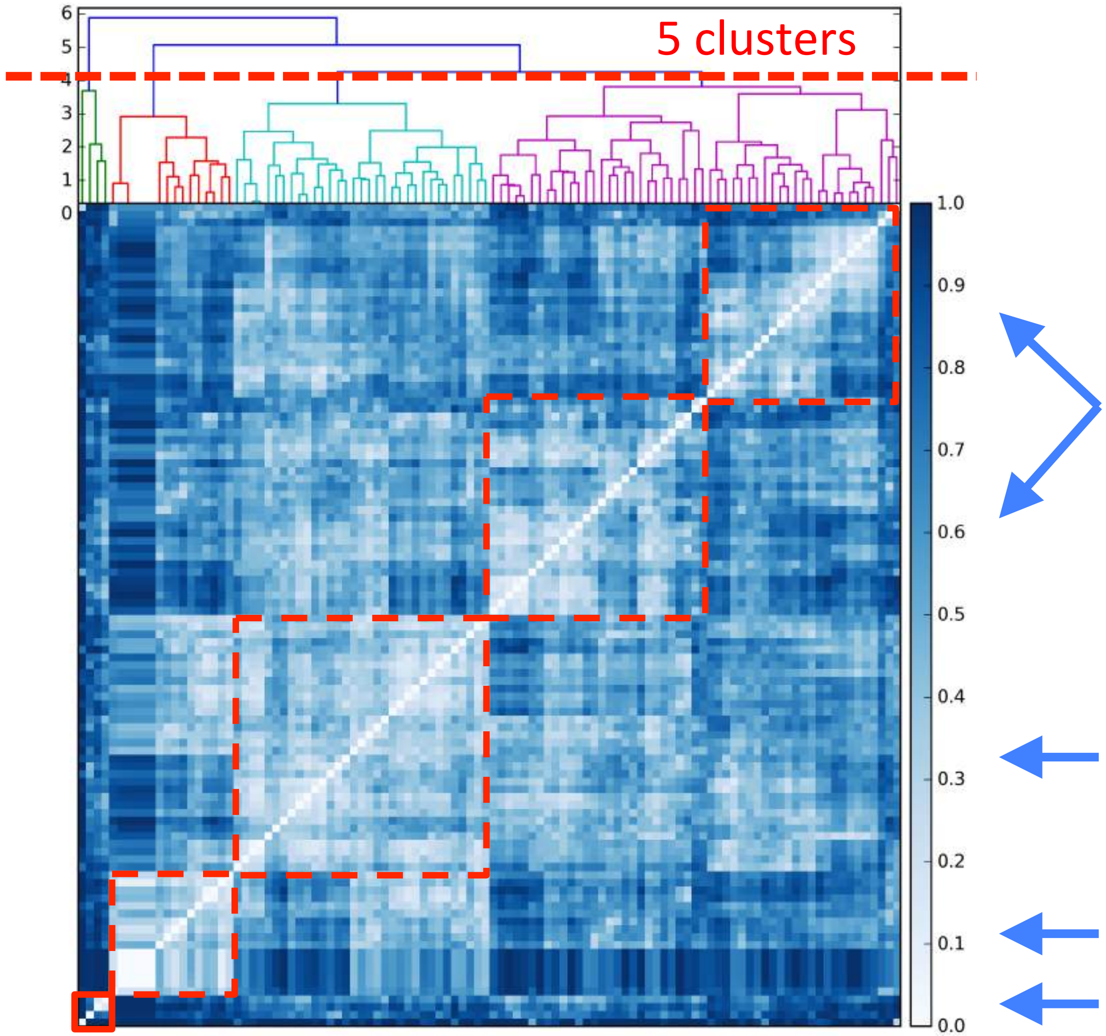


Information producers
Information consumers
Hidden Influentials
Common Users
Influentials
Rebroadcasters
# of followees / # of followers
# of retweets / # of times retweeted
Social connectivity
Information diffusion
10^{4}
10^{3}
10^{2}
10^{1}
10^{0}
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}
$10^{4.8}$
$10^{4.2}$
$10^{3.6}$
$10^{3.0}$
$10^{2.4}$
$10^{1.8}$
$10^{1.2}$
$10^{0.6}$
$10^{0.0}$



Stability over time for information producers (~50% of users)
Fluctuation for information consumers
Shrinkage over time: more democratic discussion
Common Users
Rebroadcasters
Influentials
Hidden Influentials
Avg. role displacement
1.0
0.8
0.6
0.4
0.2
0.0
2013-05-29
2013-05-30
2013-05-31
2013-06-01
2013-06-02
2013-06-03
2013-06-04
2013-06-05
2013-06-06
2013-06-07
2013-06-08
2013-06-09
2013-06-10
2013-06-11
2013-06-12
2013-06-13
2013-06-14
2013-06-15
2013-06-16
2013-06-17
2013-06-18
2013-06-19

User clustering by annotated activity



Participating in production of generic information.

Sharing specific information about news, network availability, and events.

Mostly broadcasting 3rd party information

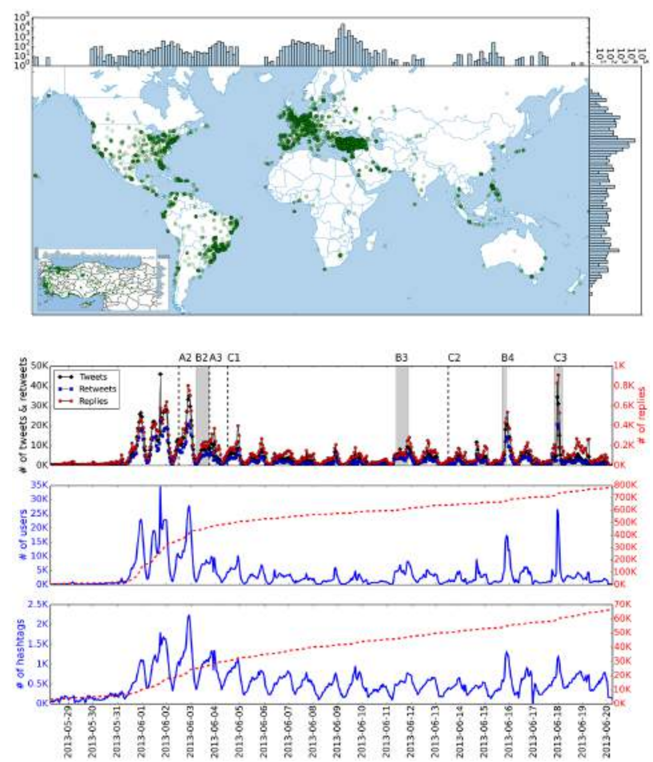
Active, on-the-ground protesters

Individual behaviors change in response to events

Different groups of users based on their content

Spatiotemporal analysis of Twitter discussion about event

Collective behaviors emerge in response to exogenous events



Varol, O., Ferrara, E., Ogan, C. L., Menczer, F., & Flammini, A. (2014, June). **Evolution of online user behavior during a social upheaval**. In Proceedings of the 2014 ACM conference on Web science (pp. 81-90). ACM.

Ogan, C., & Varol, O. (2016). **What is gained and what is left to be done when content analysis is added to network analysis in the study of a social movement: Twitter use during Gezi Park**. Information, Communication & Society, 1-19.

Varol, O. (2016, May). **Spatiotemporal analysis of censored content on Twitter**. In Proceedings of the 8th ACM Conference on Web Science (pp. 372-373). ACM.

Ferrara, E., Varol, O., Menczer, F., & Flammini, A. (2013, October). **Traveling trends: social butterflies or frequent fliers?.** In Proceedings of the first ACM conference on Online social networks (pp. 213-222). ACM.

Detection of Campaigns

Part Two

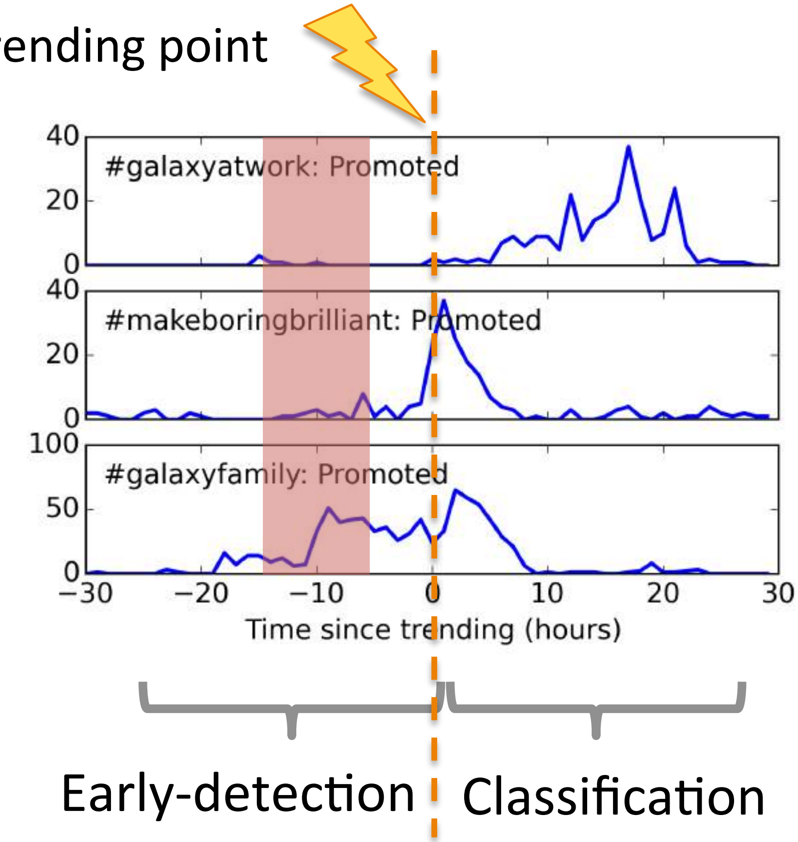
Campaigns

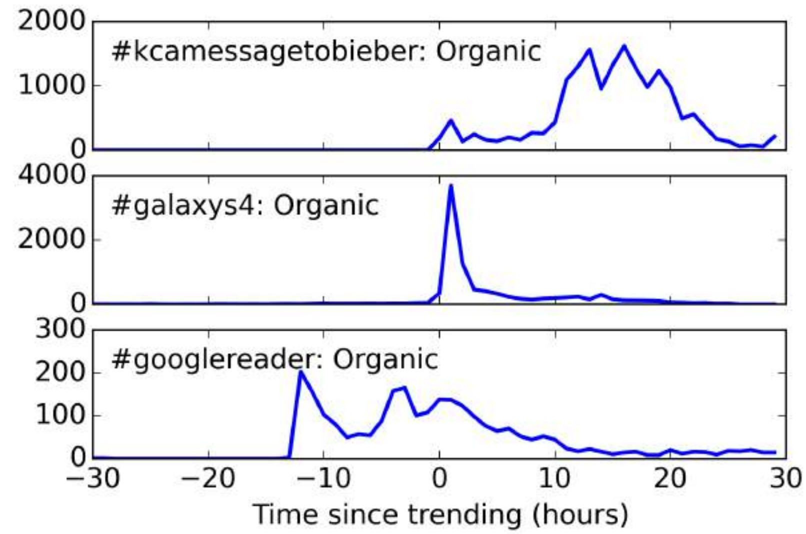
Crystallizing Public Opinion - Edward L. Beynays

Can we build tools to detect online campaigns?

Early detection & classification tasks

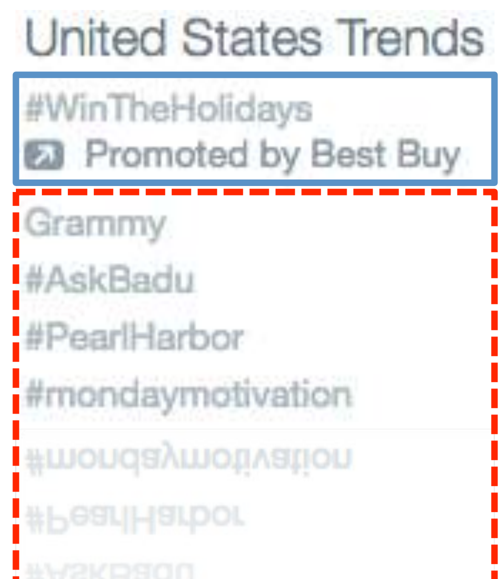
Trending point





Promoted

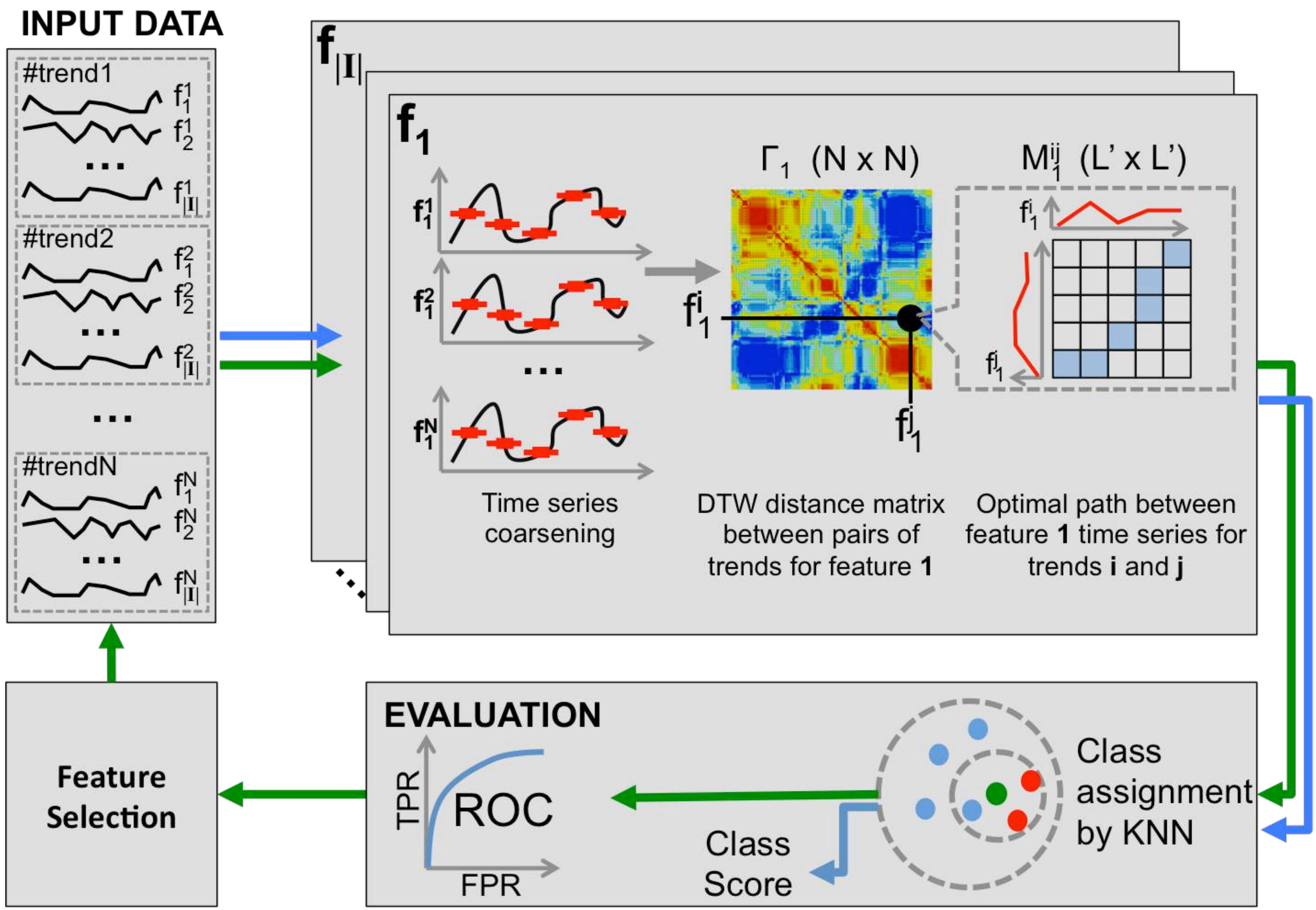
Organic



420+ dimension of time series

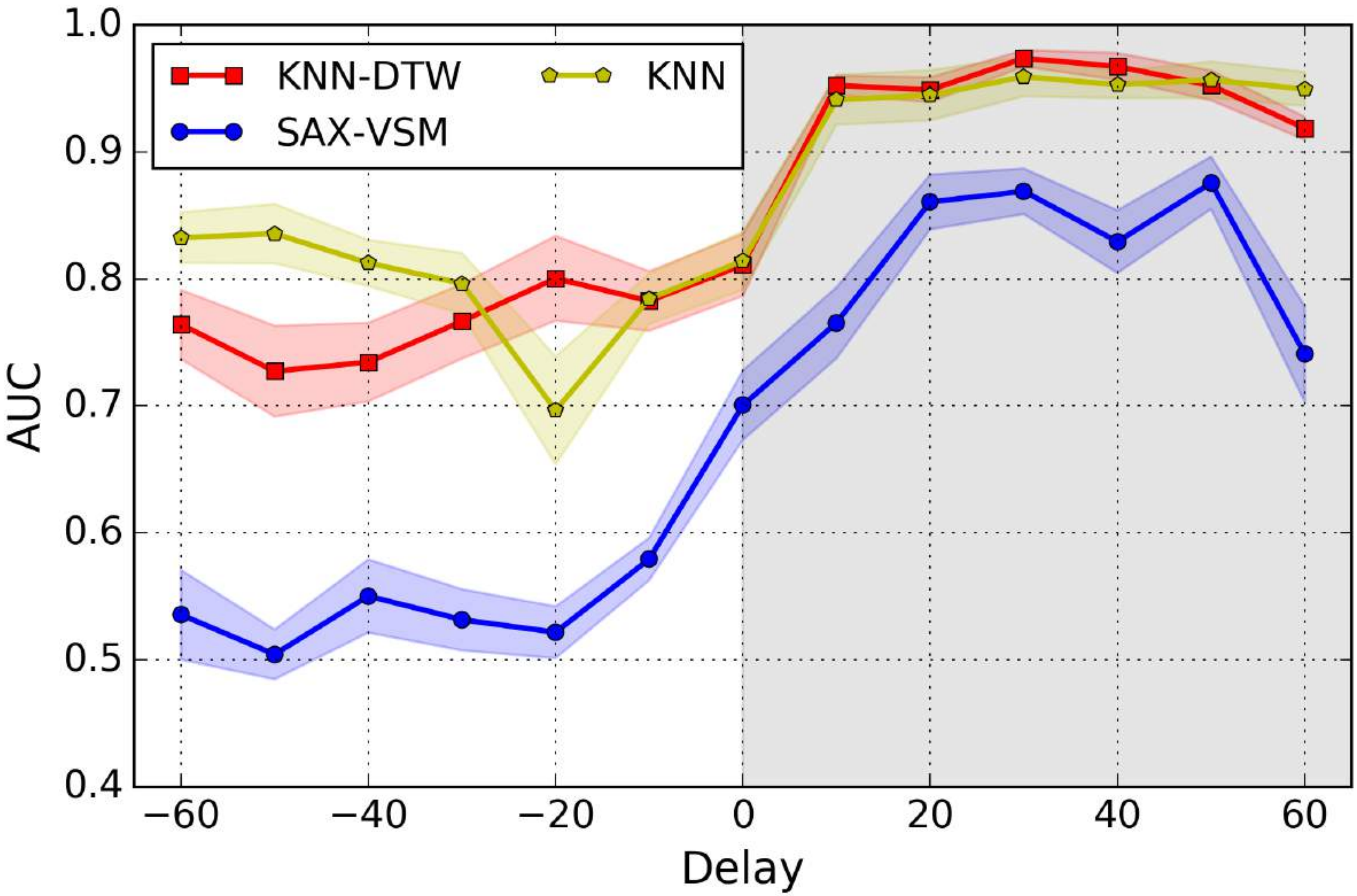
Features generated

- 20 min interval
- 6h sliding window
- 7 days before trending time 3 days after

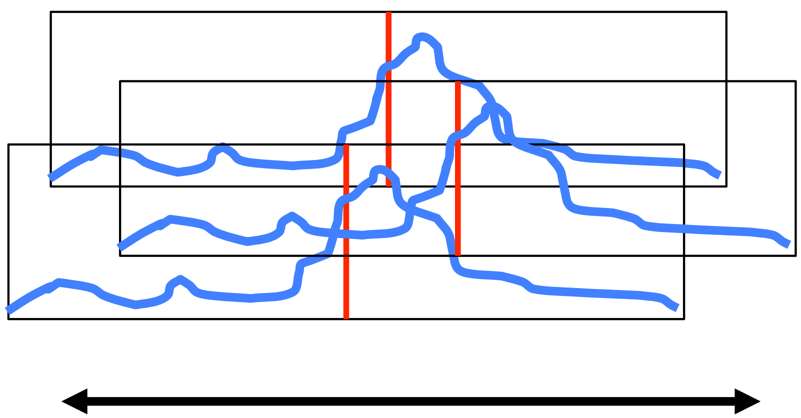


INPUT DATA
#trend1
#trend2
#trendN
$f_{|I|}$
f_1
Γ_1 (N x N)
M_1^{ij} (L' x L')
Time series coarsening
DTW distance matrix between pairs of trends for feature **1**
Optimal path between feature **1** time series for trends **i** and **j**
EVALUATION
TPR
ROC
FPR
Class Score
Class assignment by KNN
Feature Selection

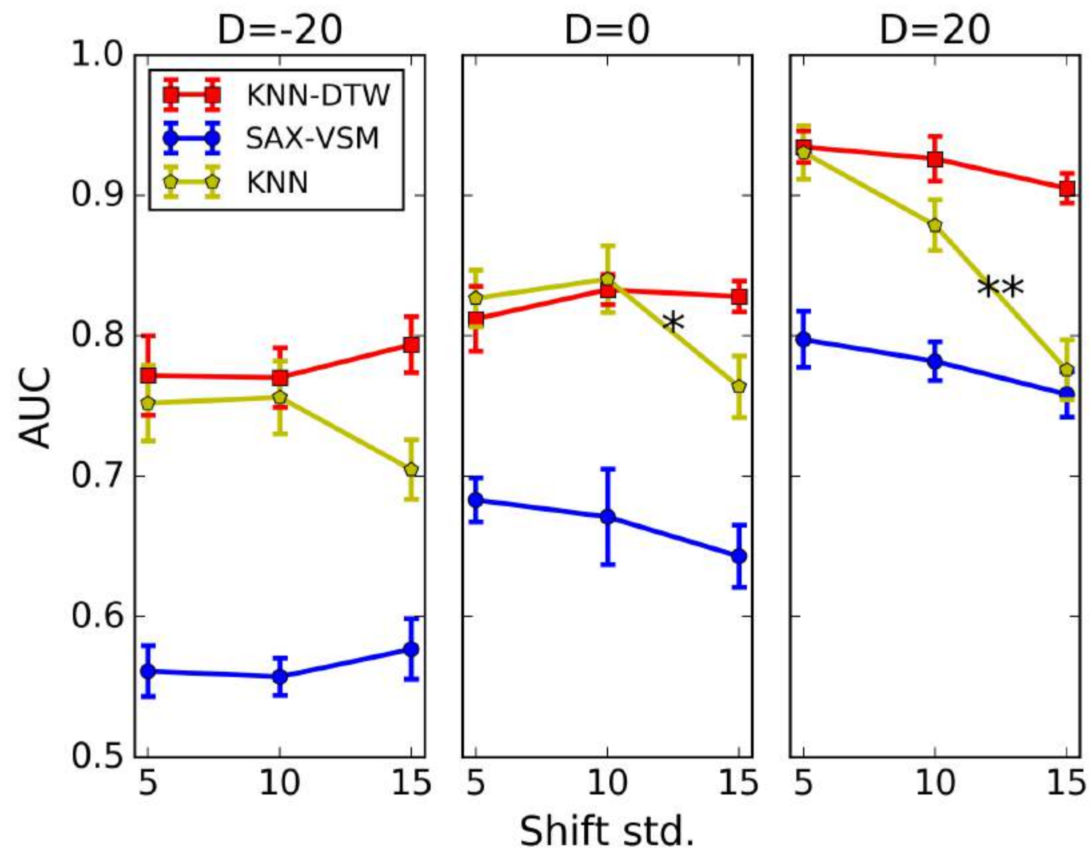
Accuracy


KNN-DTW
KNN
SAX-VSM
AUC
1.0
0.9
0.8
0.7
0.6
0.5
0.4
−60
−40
−20
0
20
40
60
Delay

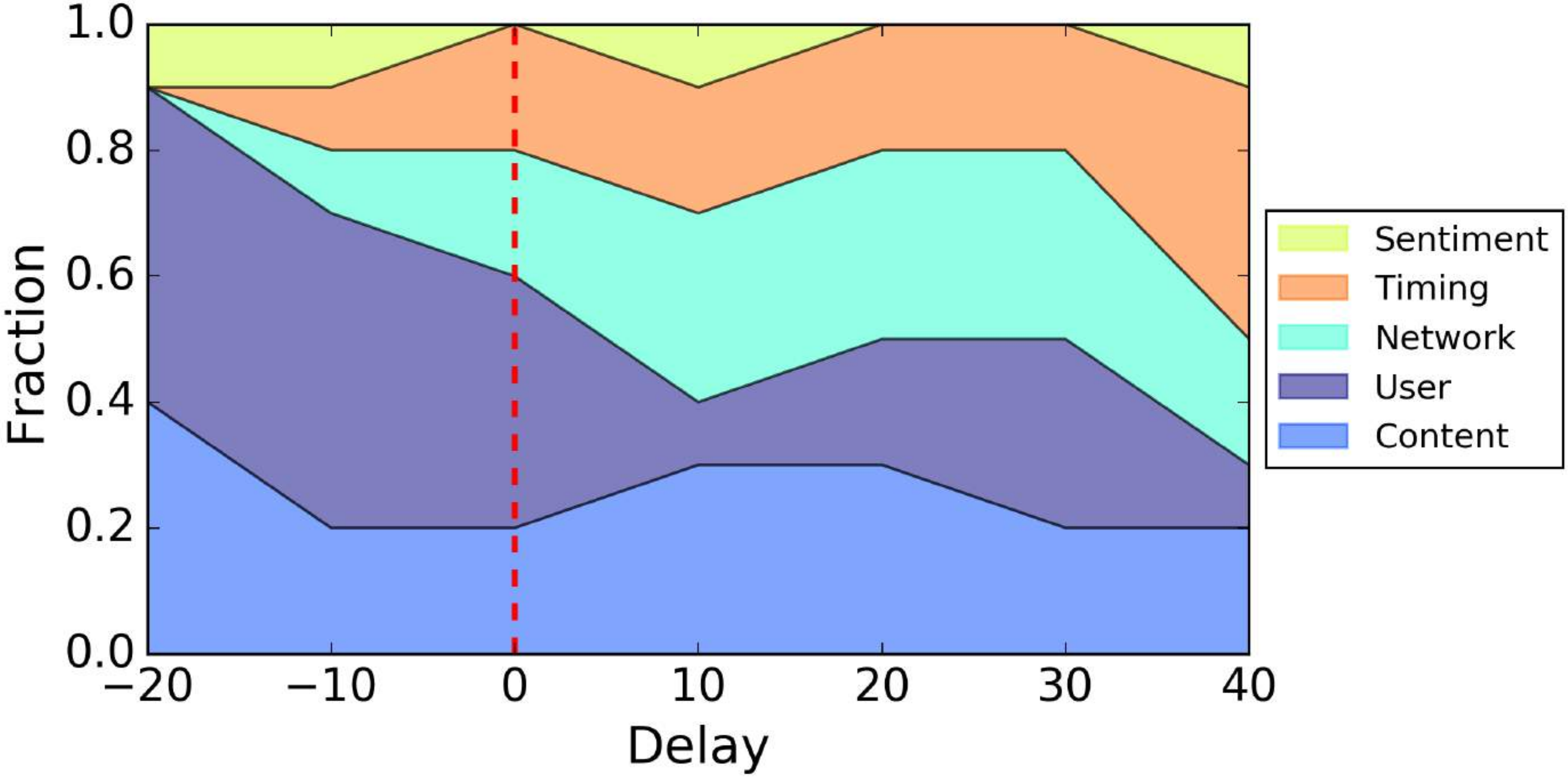
Robustness



Random shifts sampled from Normal distribution



Feature importance



We can distinguish organic and promoted trends

Temporal information is important

Features from different classes helpful in different stages

Varol, O., Ferrara, E., Menczer, F., & Flammini, A. (2017). **Early Detection of Promoted Campaigns on Social Media**. arXiv preprint arXiv:1703.07518. (*EPJ Data Science, Under review*)

Ferrara, E., Varol, O., Menczer, F., & Flammini, A. (2016, March). **Detection of promoted social media campaigns**. In Tenth International AAAI Conference on Web and Social Media.

Analysis of Social Bots

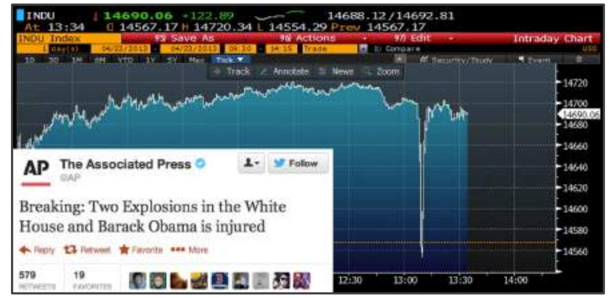
Part Three

Real social bots can …

Manipulate stock market

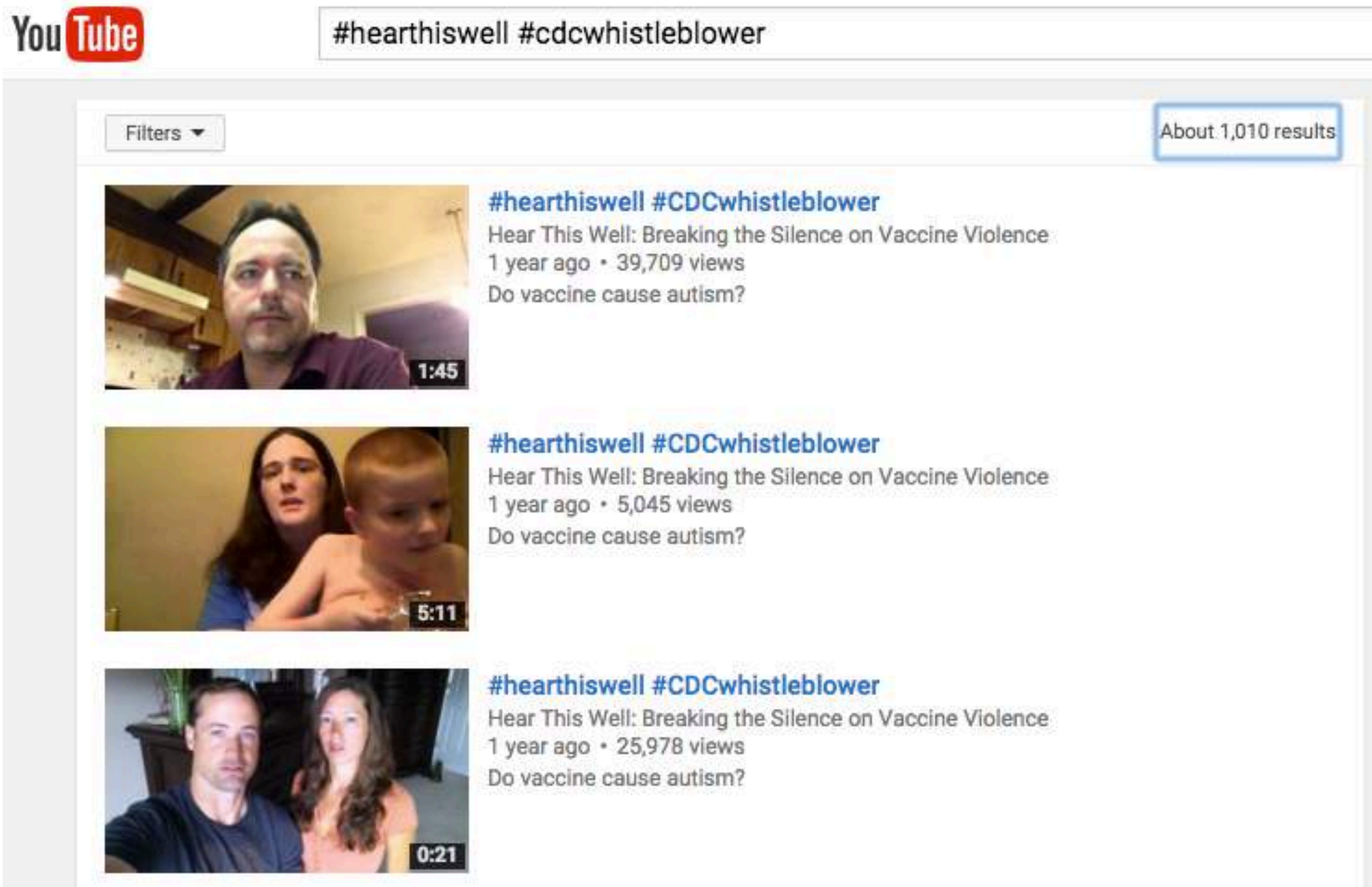
Political smearing, astroturf, fake followers

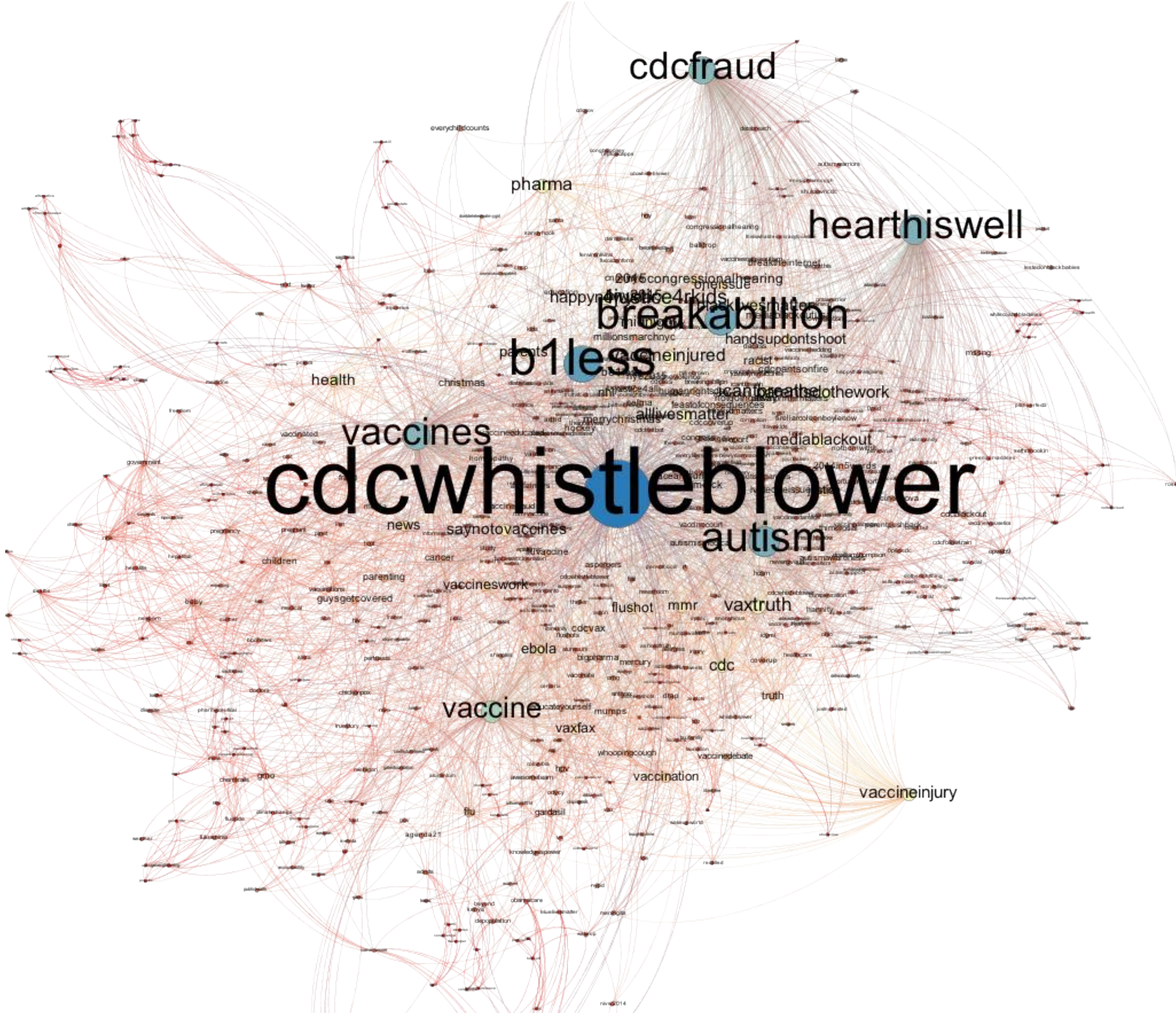
Marketing, spamming and social pollution



Can we build tools to detect and study social bots?

Do vaccines cause autism?




cdcwhistleblower
cdcfraud
hearthiswell
breakabillion
b1less
vaccines
autism
vaccine
pharma
health
christmas
everychildcounts
2015congressionalhearing
handsupdontshoot
millionsmarchnyc
racist
cdcpantsonfire
alllivesmatter
merrychristmas
mediablackout
news
saynotovaccines
vaccineswork
guysgetcovered
parenting
children
cancer
flushot
mmr
vaxtruth
cdcvax
ebola
cdc
truth
vaxfax
vaccination
vaccineinjury
whoopingcough
vaccinedebate
mumps
flu
gardasil
agenda21

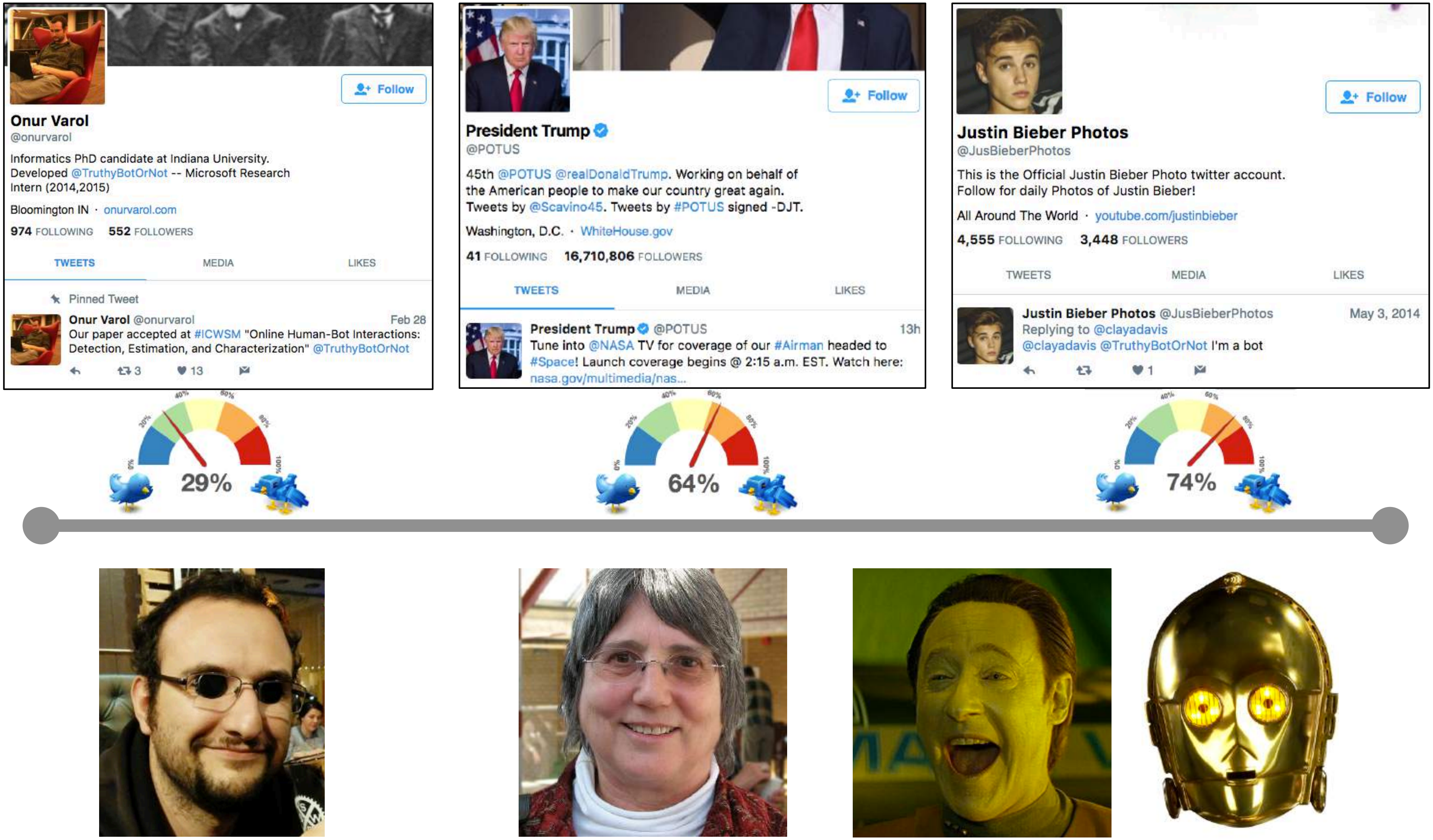
Strategies on bot detection challenge

Fake images from Wikipedia

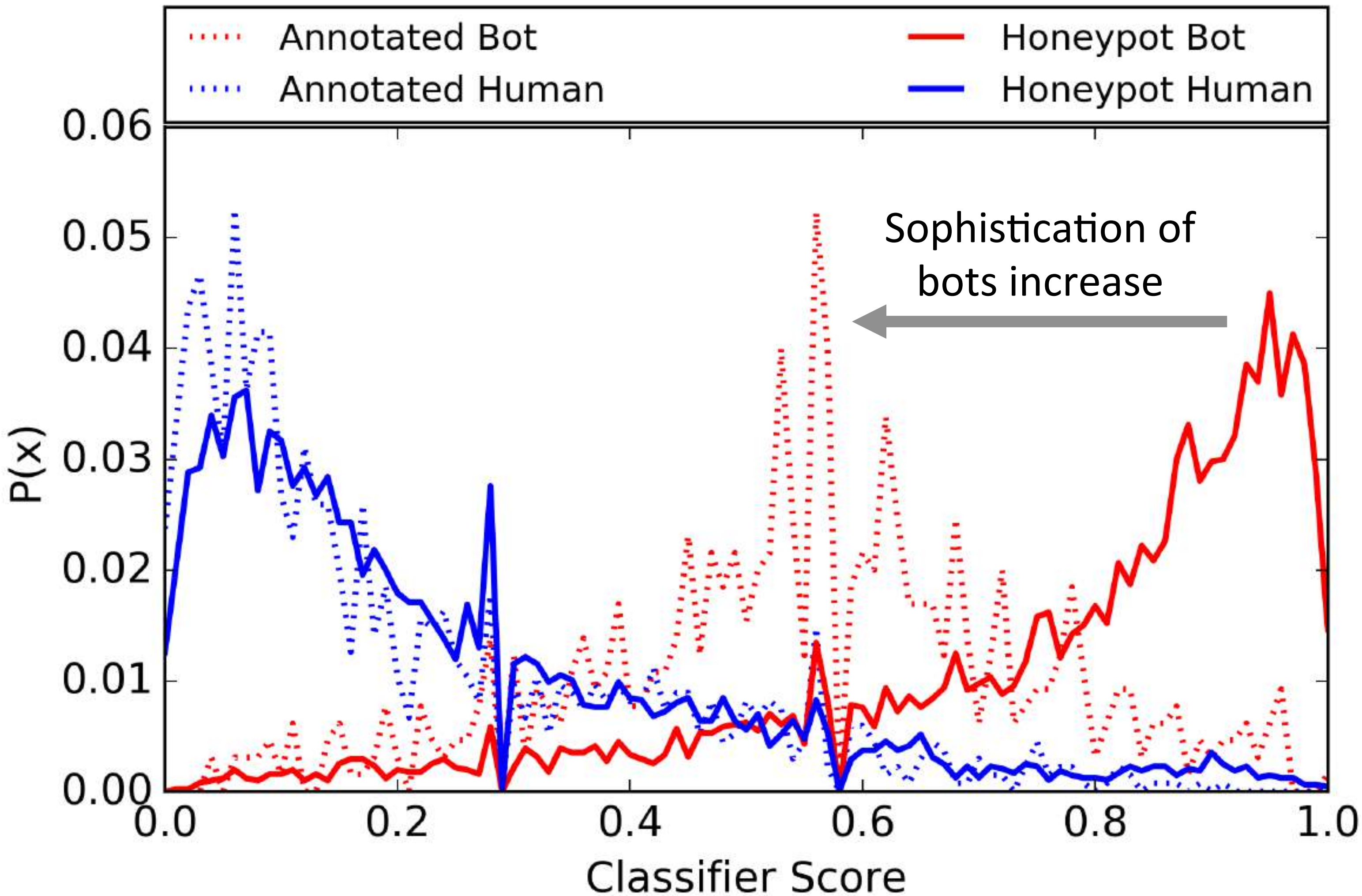
Persuasive description

Suspicious temporal activity

Simple and repetitive content


Onur Varol
@onurvarol
Informatics PhD candidate at Indiana University. Developed @TruthyBotOrNot -- Microsoft Research Intern (2014,2015)
Bloomington IN · onurvarol.com
974 FOLLOWING 552 FOLLOWERS
TWEETS MEDIA LIKES
Pinned Tweet
Onur Varol @onurvarol Feb 28
Our paper accepted at #ICWSM "Online Human-Bot Interactions: Detection, Estimation, and Characterization" @TruthyBotOrNot
Follow
President Trump
@POTUS
45th @POTUS @realDonaldTrump. Working on behalf of the American people to make our country great again. Tweets by @Scavino45. Tweets by #POTUS signed -DJT.
Washington, D.C. · WhiteHouse.gov
41 FOLLOWING 16,710,806 FOLLOWERS
TWEETS MEDIA LIKES
President Trump @POTUS 13h
Tune into @NASA TV for coverage of our #Airman headed to #Space! Launch coverage begins @ 2:15 a.m. EST. Watch here: nasa.gov/multimedia/nas...
Follow
Justin Bieber Photos
@JusBieberPhotos
This is the Official Justin Bieber Photo twitter account. Follow for daily Photos of Justin Bieber!
All Around The World · youtube.com/justinbieber
4,555 FOLLOWING 3,448 FOLLOWERS
TWEETS MEDIA LIKES
Justin Bieber Photos @JusBieberPhotos May 3, 2014
Replying to @clayadavis
@clayadavis @TruthyBotOrNot I'm a bot
Follow
29%
64%
74%

Sophisticated vs. simple bots

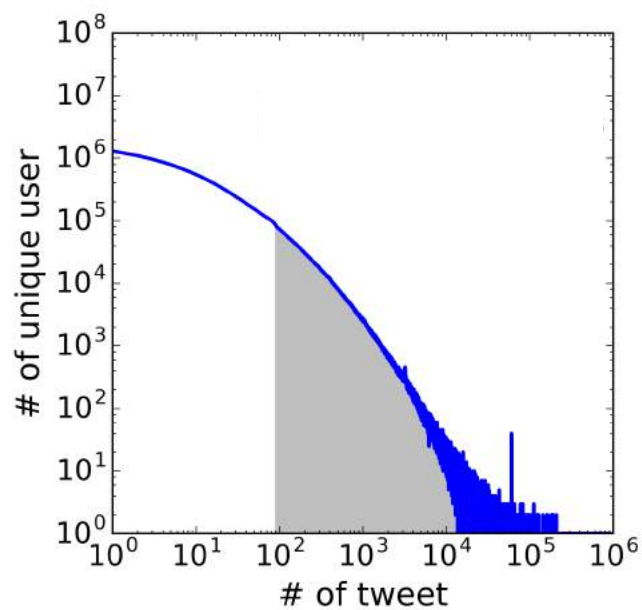


Dataset

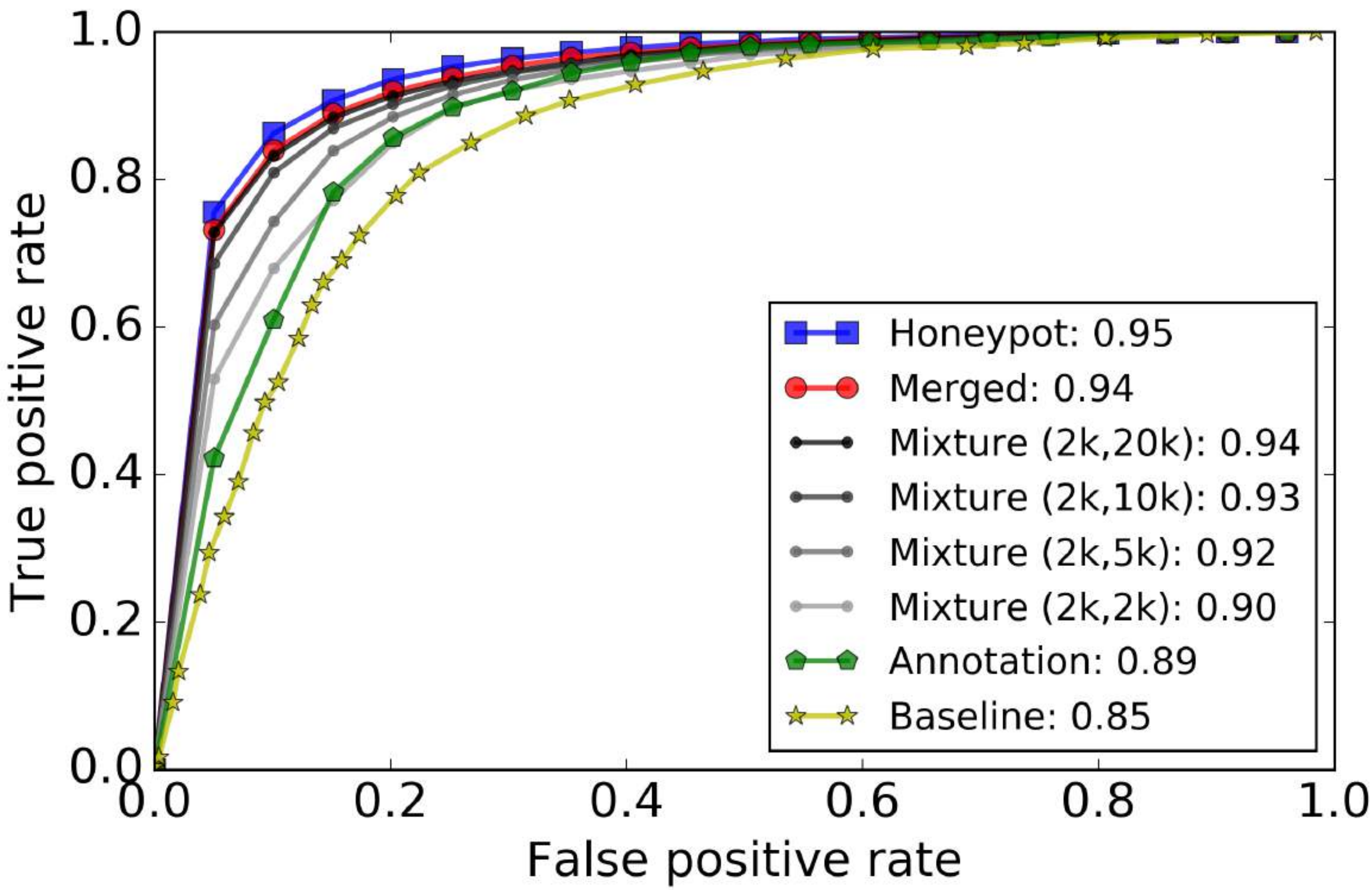
Collection of 14M users:

– Active (200 tweets at least, 90 tweets in 3 month observation period)

– English speaking (as indicated in profile)

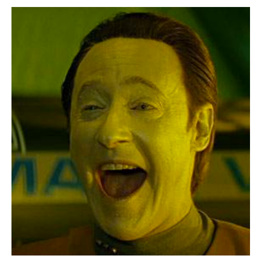


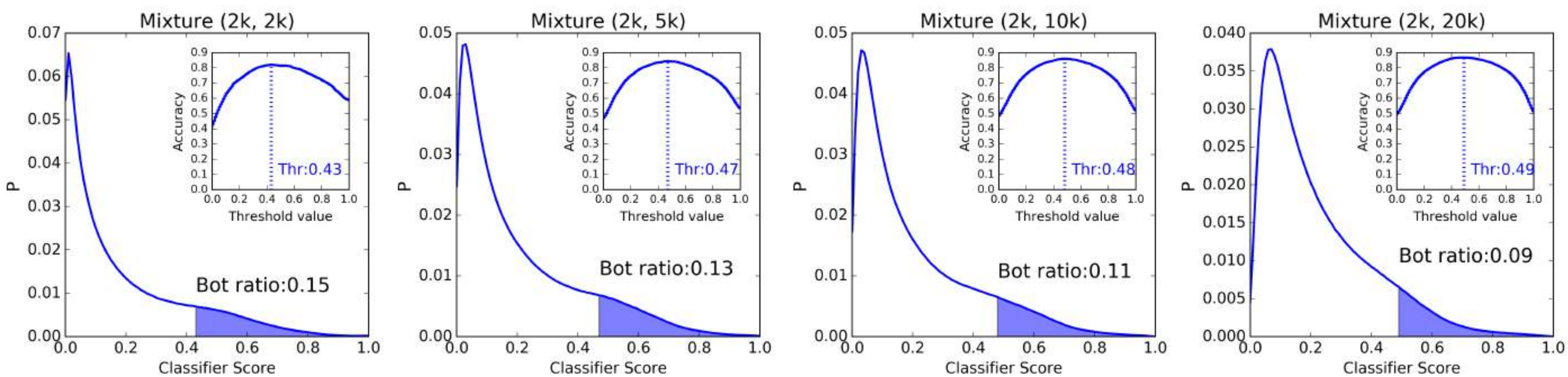
Dataset effect on model accuracy



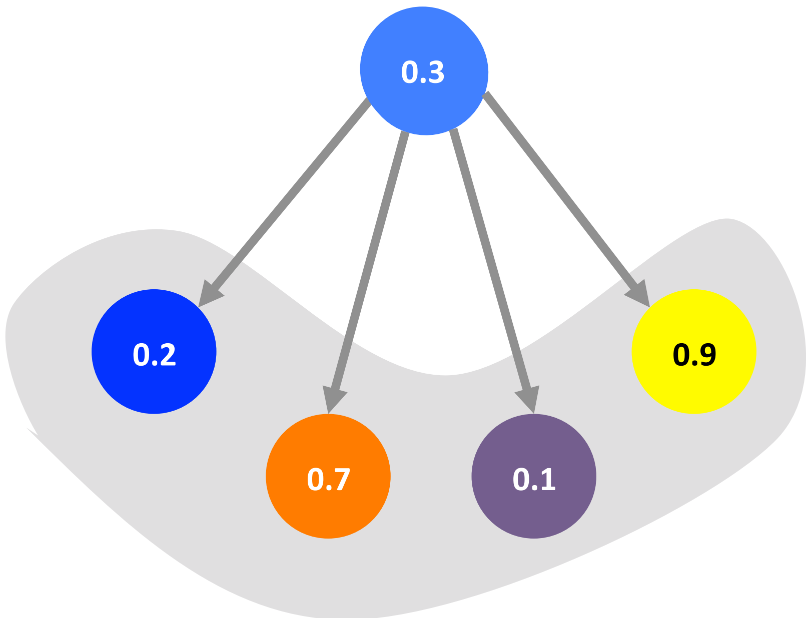
Estimating bot population

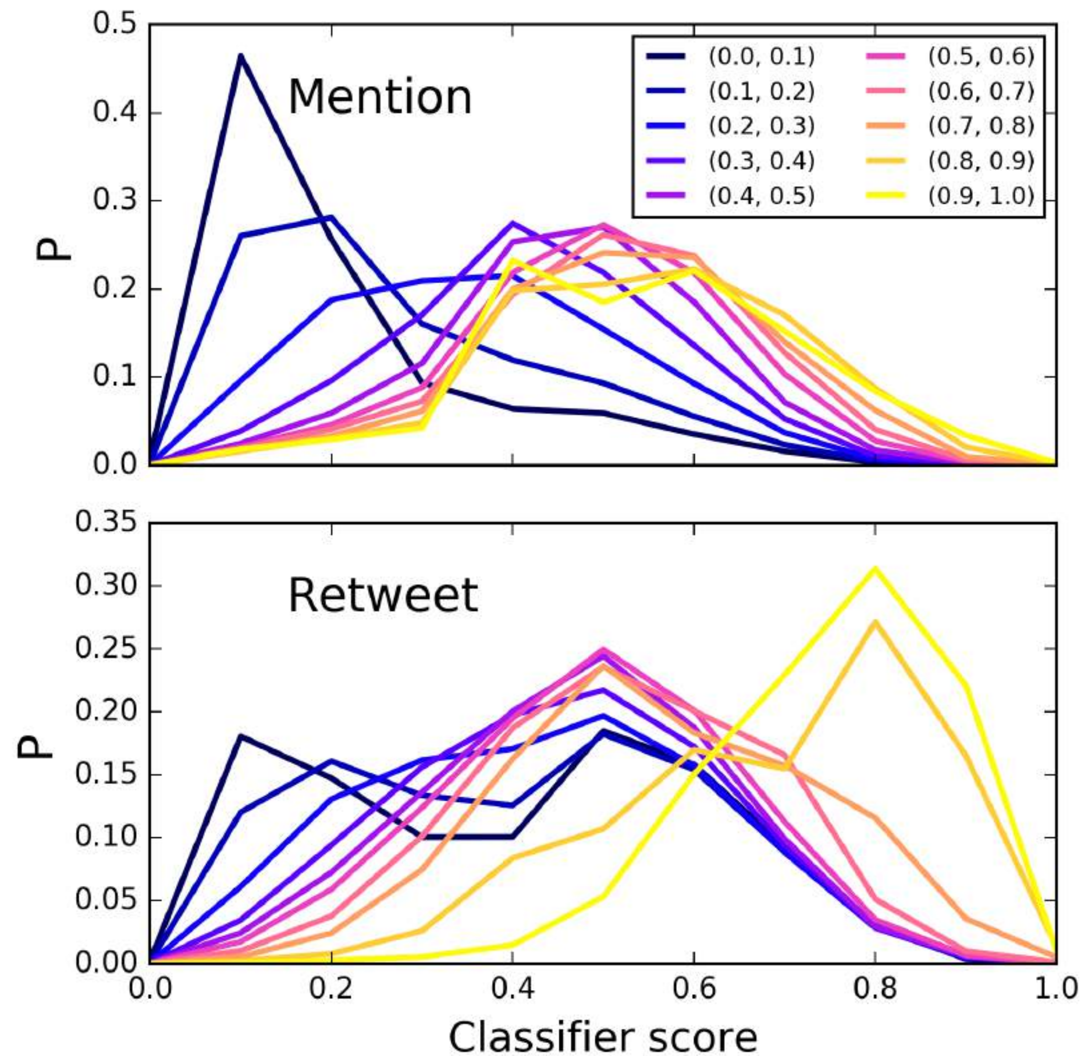
Adjusting sensitivity of detection system for sophisticated bots



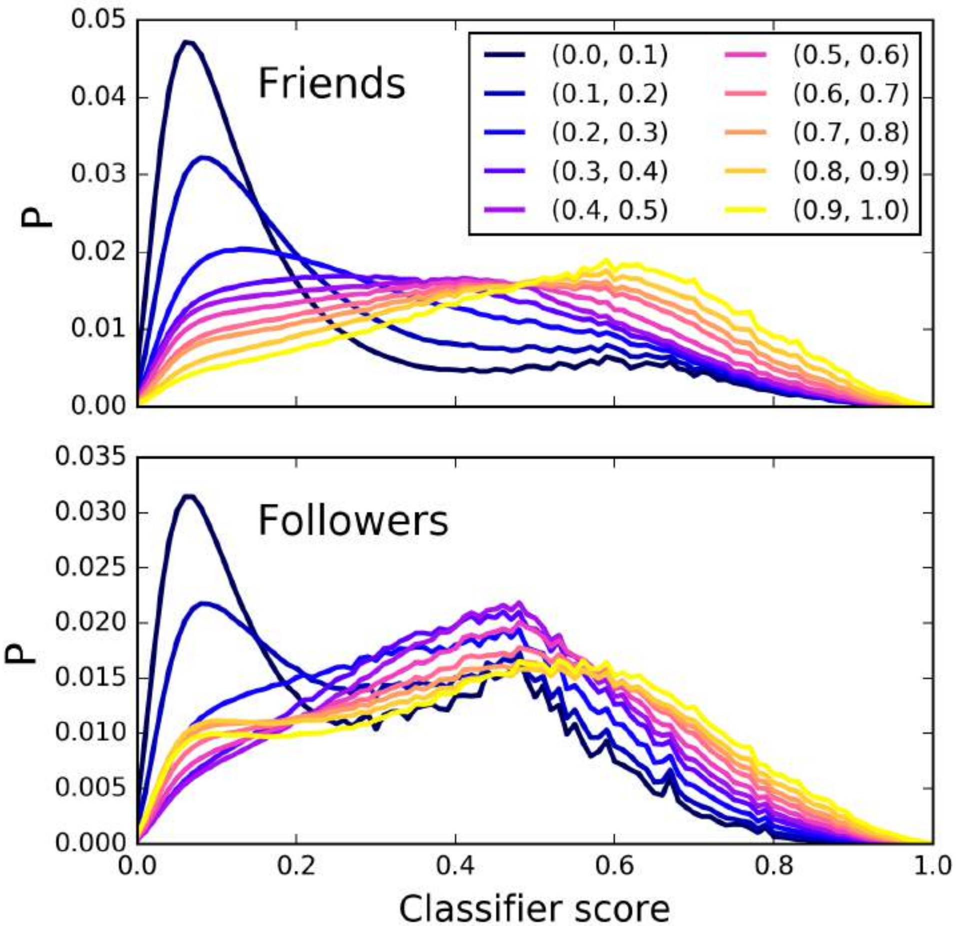


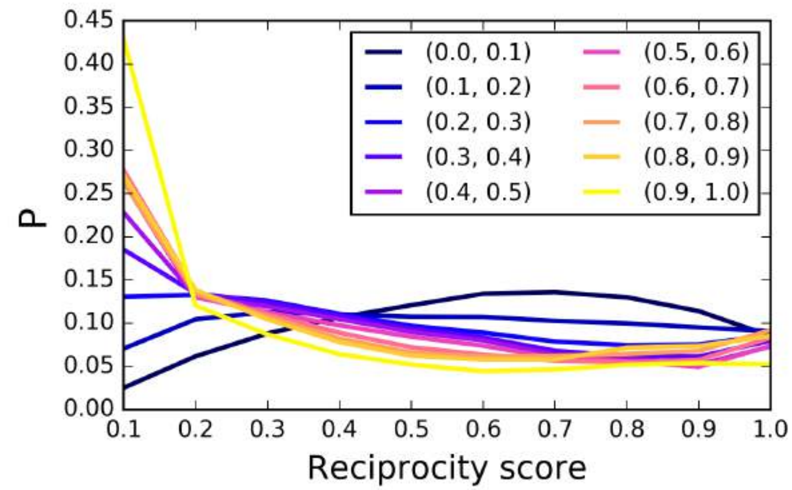
Information flow





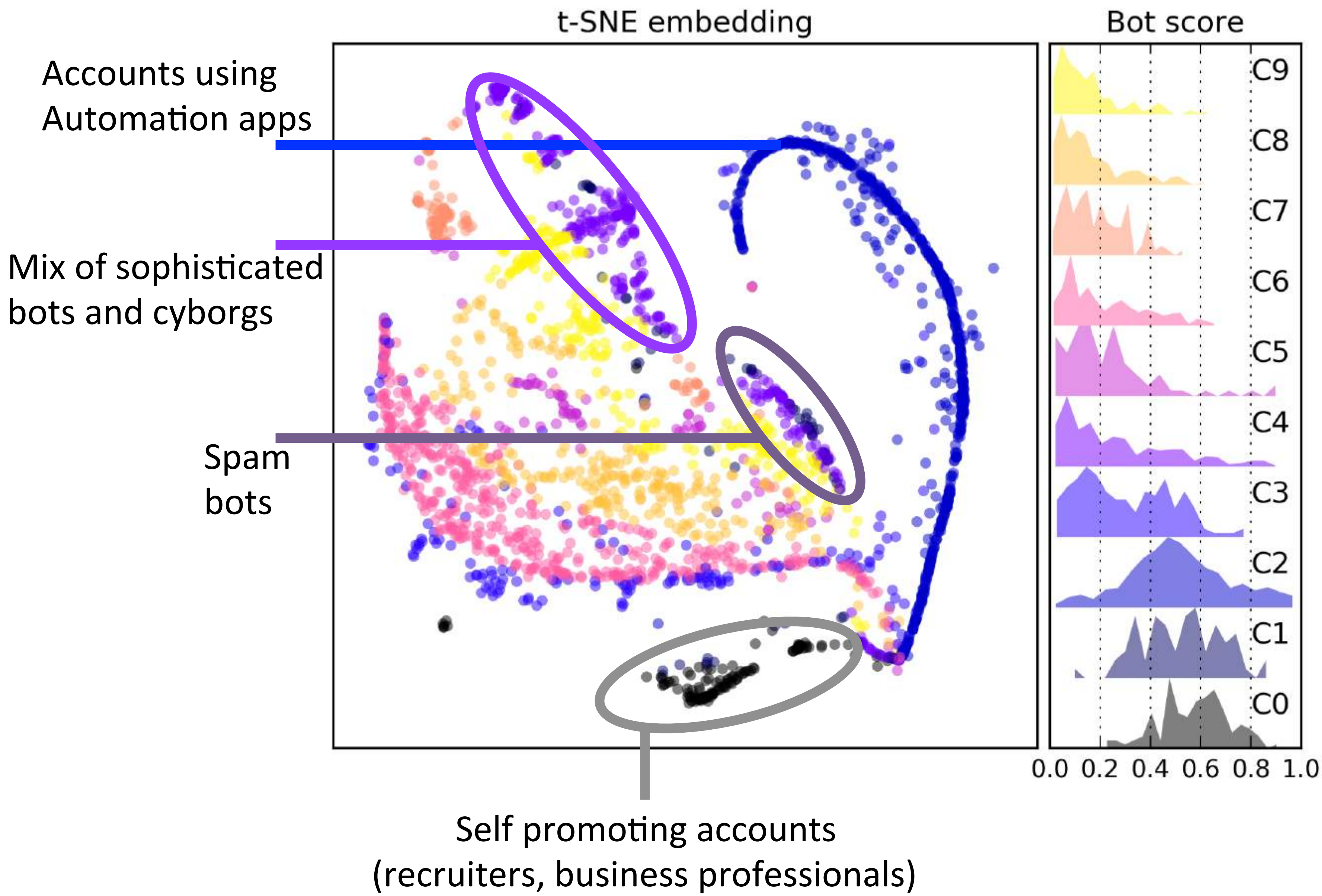
Social connectivity





$$R_u = \frac{|S_{friends} \cap S_{followers}|}{|S_{friends}|}$$

Account behavior embedding



We built an accurate bot detector

We found humans and bots have different behaviors. Bots tend to interact with other bots, but humans can do both

We estimate 9-15% of active accounts are bots of different types

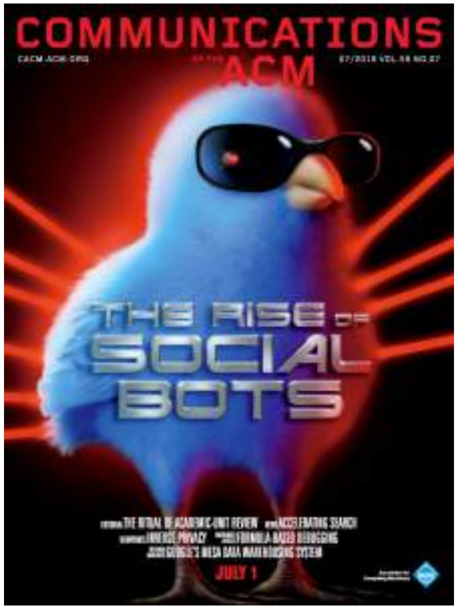
Varol, O., Ferrara, E., Davis, C. A., Flammini, A., & Menczer, F. **Online Human-Bot Interaction: Detection, Estimation, and Characterization,** ICWSM’17

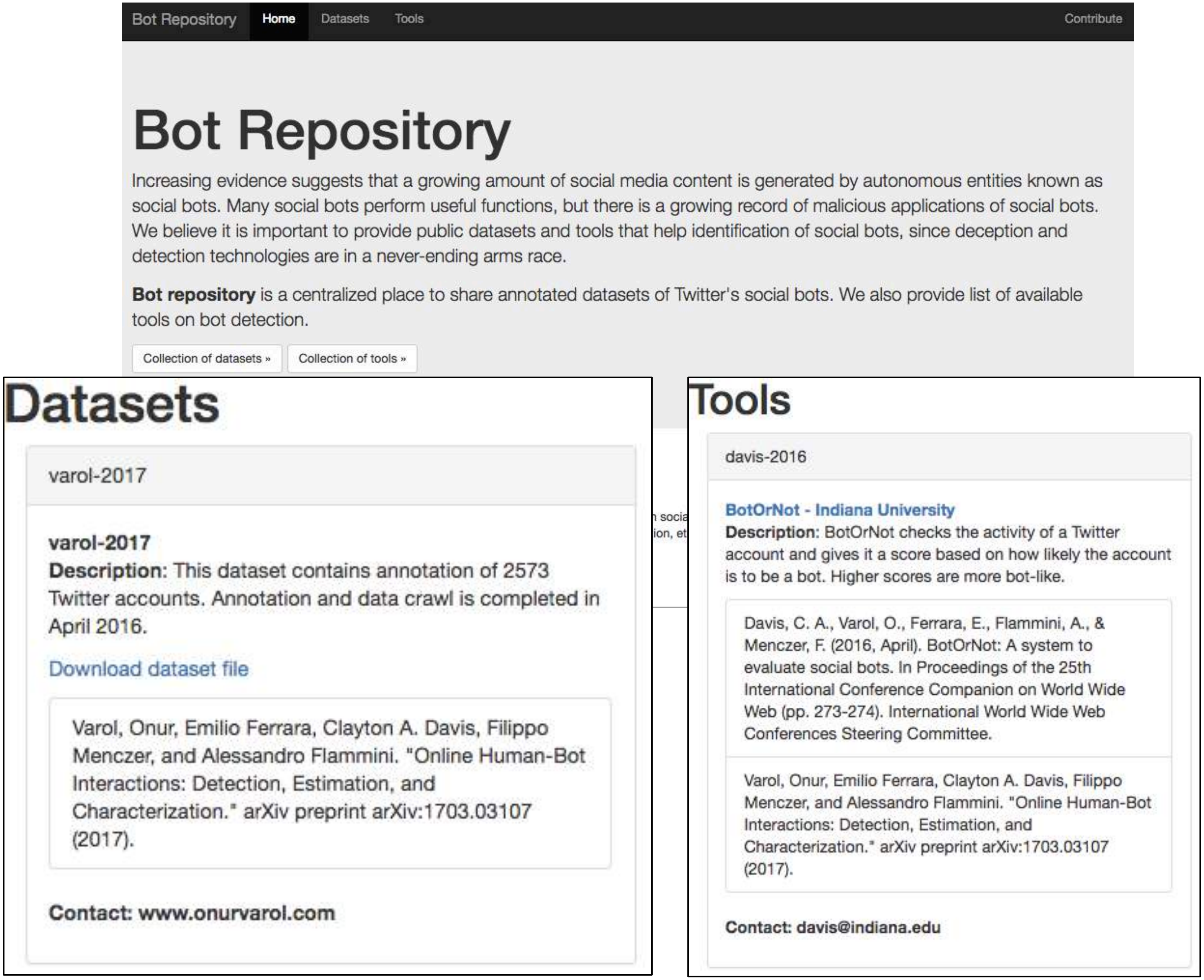
Ferrara, E., Varol, O., Davis, C., Menczer, F., & Flammini, A. (2014). **The rise of social bots**. Communications of the ACM 59 (7), 96-104

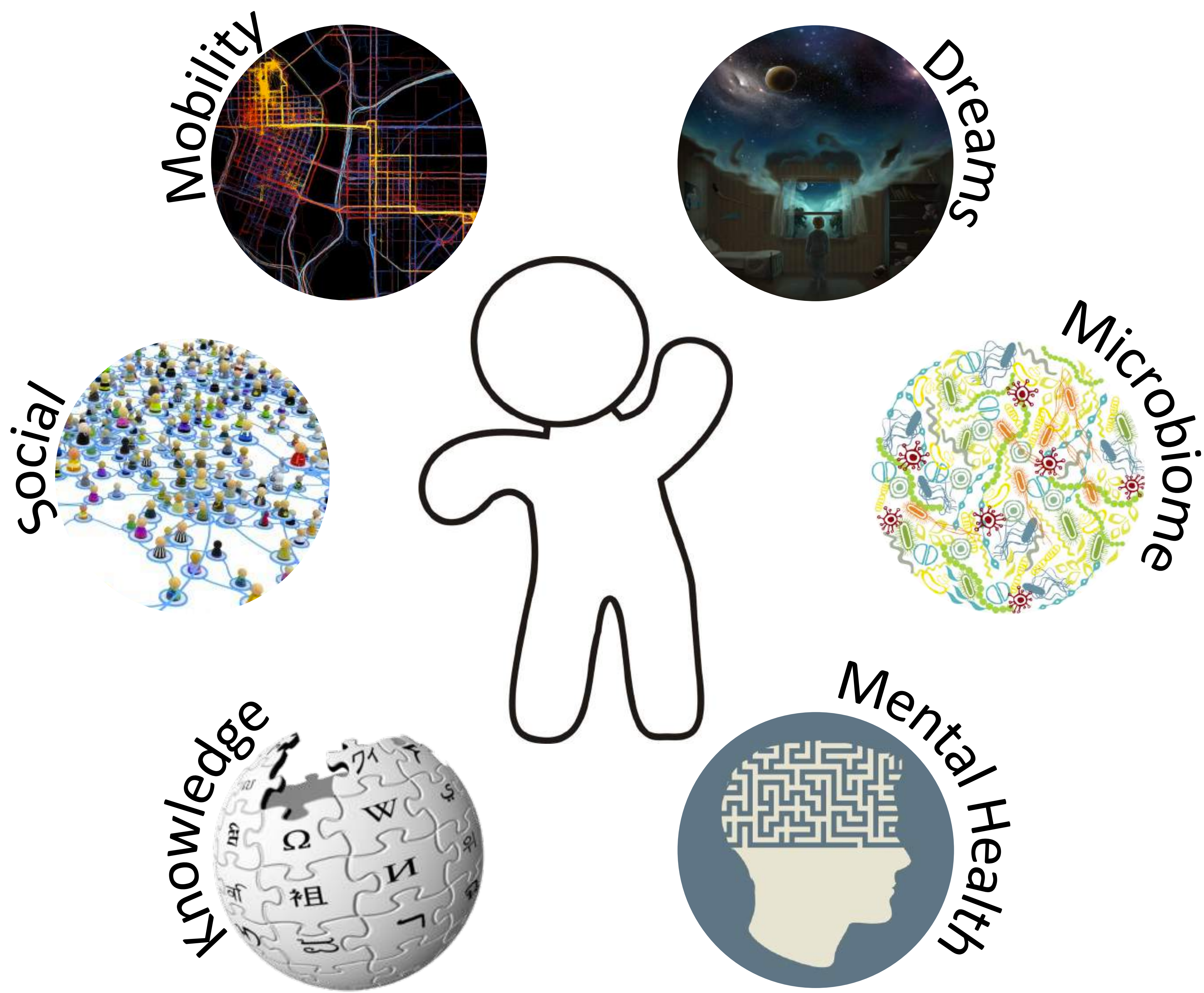
Davis, C. A.[†], Varol, O.[†], Ferrara, E., Flammini, A., & Menczer, F. (2016, April). **BotOrNot: A system to evaluate social bots**. In Proceedings of the 25th International Conference Companion on World Wide Web (pp. 273-274).

Subrahmanian, V. S., Azaria, A., Durst, S., Kagan, V., Galstyan, A., Lerman, K., ... & Waltzman, R. (2016). **The DARPA Twitter Bot Challenge**. Computer 49 (6), 38-46

Varol, O., Menczer, F., & Flammini, A. **Feature Generation for Social Bot Detection.** (In preparation for invited book chapter)




Bot Repository
Home
Datasets
Tools
Contribute
Bot Repository
Increasing evidence suggests that a growing amount of social media content is generated by autonomous entities known as social bots. Many social bots perform useful functions, but there is a growing record of malicious applications of social bots. We believe it is important to provide public datasets and tools that help identification of social bots, since deception and detection technologies are in a never-ending arms race.
Bot repository is a centralized place to share annotated datasets of Twitter's social bots. We also provide list of available tools on bot detection.
Collection of datasets »
Collection of tools »
Datasets
varol-2017
varol-2017
Description: This dataset contains annotation of 2573 Twitter accounts. Annotation and data crawl is completed in April 2016.
Download dataset file
Varol, Onur, Emilio Ferrara, Clayton A. Davis, Filippo Menczer, and Alessandro Flammini. "Online Human-Bot Interactions: Detection, Estimation, and Characterization." arXiv preprint arXiv:1703.03107 (2017).
Contact: www.onurvarol.com
Tools
davis-2016
BotOrNot - Indiana University
Description: BotOrNot checks the activity of a Twitter account and gives it a score based on how likely the account is to be a bot. Higher scores are more bot-like.
Davis, C. A., Varol, O., Ferrara, E., Flammini, A., & Menczer, F. (2016, April). BotOrNot: A system to evaluate social bots. In Proceedings of the 25th International Conference Companion on World Wide Web (pp. 273-274). International World Wide Web Conferences Steering Committee.
Varol, Onur, Emilio Ferrara, Clayton A. Davis, Filippo Menczer, and Alessandro Flammini. "Online Human-Bot Interactions: Detection, Estimation, and Characterization." arXiv preprint arXiv:1703.03107 (2017).
Contact: davis@indiana.edu


Mobility
Dreams
Social
Microbiome
Knowledge
Mental Health

Works outside of the thesis focus

Varol, O., & Menczer, F. (2014, April). **Connecting dream networks across cultures**. In Proceedings of the 23rd International Conference on World Wide Web (pp. 1267-1272). ACM.

Ferrara, E., JafariAsbagh, M., Varol, O., Qazvinian, V., Menczer, F., & Flammini, A. (2013, August). **Clustering memes in social media**. In Advances in Social Networks Analysis and Mining (ASONAM), 2013 IEEE/ACM International Conference on (pp. 548-555). IEEE.

JafariAsbagh, M., Ferrara, E., Varol, O., Menczer, F., & Flammini, A. (2014). **Clustering memes in social media streams.** Social Network Analysis and Mining, 4(1), 1-13.

Das, A., Gollapudi, S., Kıcıman, E., & Varol, O. (2016, May). **Information dissemination in heterogeneous-intent networks**. In Proceedings of the 8th ACM Conference on Web Science (pp. 259-268). ACM.

Olteanu, A., Varol, O., & Kıcıman, E. (2016, March). **Towards an Open-Domain Framework for Distilling the Outcomes of Personal Experiences from Social Media Timelines**. In Tenth International AAAI Conference on Web and Social Media.

Olteanu, A., Varol, O., & Kıcıman, E. (2017). **Distilling the Outcomes of Personal Experiences: A Propensity-scored Analysis of Social Media**. In Proc. of The 20th ACM Conference on Computer-Supported Cooperative Work and Social Computing.

Acknowledgements








and all of the present and past members of **NaN** group and **Cnets**

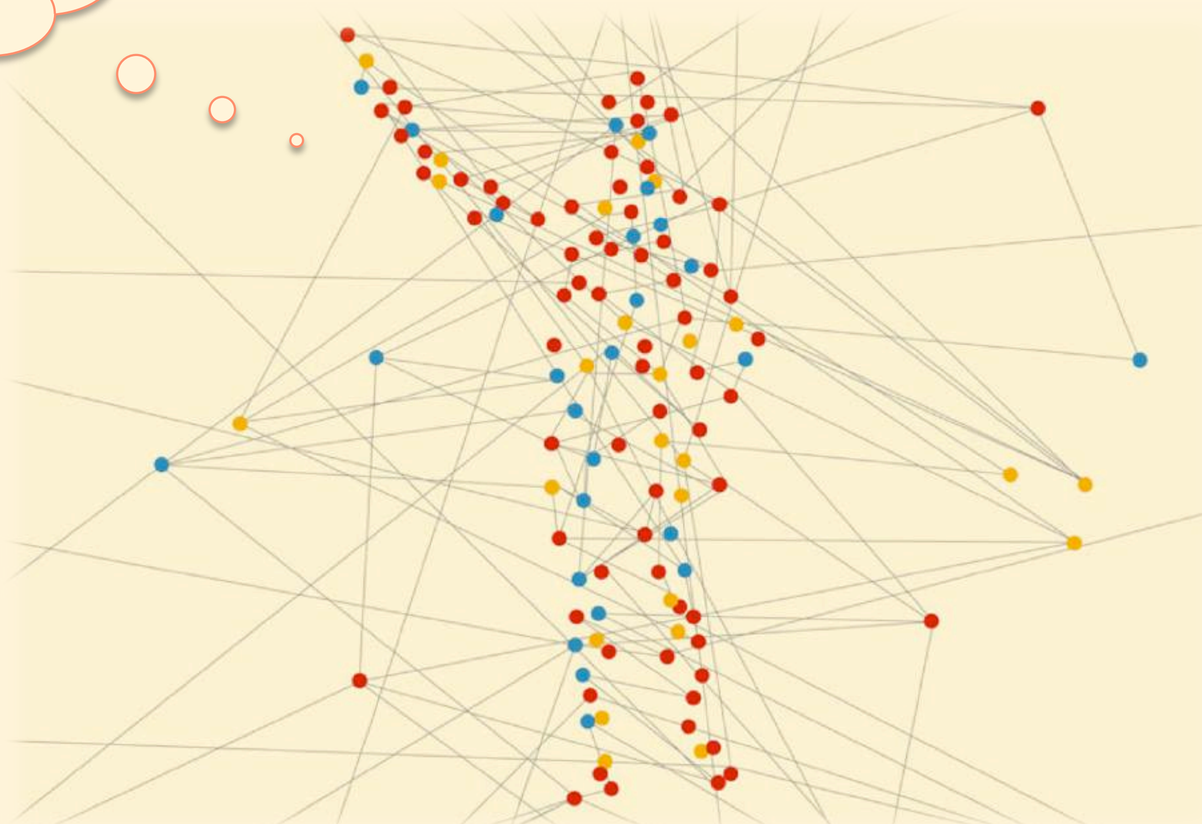
James S. McDonnell Foundation

DARPA

NSF

Questions?

Thank you!



Onur Varol
@onurvarol
ovarol@indiana.edu