

Computational challenges in analyzing and moderating online social discussions

Aristides Gionis

Department of Computer Science Aalto University

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social media















- people use social media to
 - share information, express opinion, comment, interact, discuss, get personalized news feed
- 62% of adults in US get their news from social media

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social media: good and bad sides

advantages

- no information barriers
- citizen journalism
- social connectivity
- democratization
- . . .

disadvantages

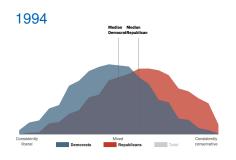
- harassment
- fake news
- echo chambers
- polarization
- ...

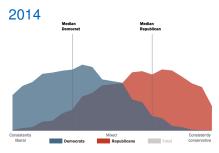
polarization

- political or social polarization
 the act of separating or making people separate into two groups with completely opposite opinions*
- related term: controversy
 public discussion and argument about something that many people strongly disagree about*

*oxford english dictionary

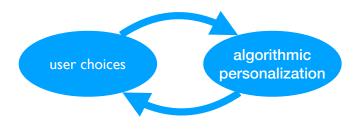
polarization in US politics





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the polarization cycle



related to the filter bubble and echo chamber

research questions

- can we identify polarized discussions in social media?
- has polarization increased over time?
- how does collective attention impact polarization?
- can we design algorithms to help reduce polarization?
- can we design algorithms to moderate online discussions?

research question

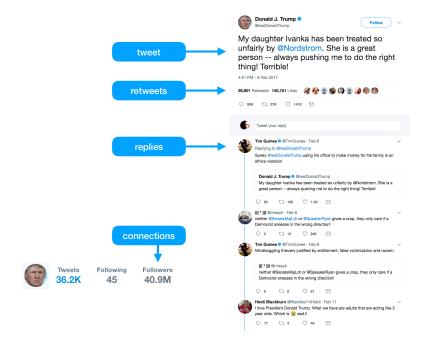
identify and quantify polarization

K. Garimella, G. De Francisci Morales, A. Gionis, M. Mathioudakis, "Quantifying controversy in social media", ACM WSDM 2016

focus on twitter

- microblogging platform
 launched in 2006
 300 million active users
- users post short messages tweets





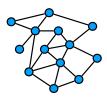
how can we identify polarization?

ideas

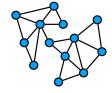
- content
 - do opposing sides say different things?
- sentiment
 - do polarized topics exhibit wider range of emotions?
- interactions
 - do people interact more with their own side?

method template

- build an interaction graph
 - try several types
 retweets, replies, connections
- is the interaction graph polarized?
- output polarization score

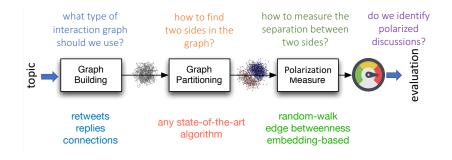


non polarized



polarized two sides well separated

pipeline



random-walk controversy score (RWC)

- assume graph is partitioned in two sides, A and B
- consider a random walk that started at a random node and finished in a hub in Y ∈ {A, B}
- probability that random walk started in $X \in \{A, B\}$

$$P_{XY} = Pr(r.w. started in X | r.w. finished in Y)$$

• random-walk controversy score (RWC)

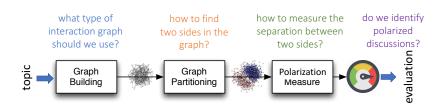
$$RWC = P_{AA}P_{BB} - P_{AB}P_{BA}$$

does not depend on cluster sizes and relative in-degrees

evaluation

- annotate polarized and non-polarized topics
- polarized
 - indian beefban, nemtsov protests, netanyahu US congress speech, baltimore riots, ukraine
- non-polarized
 - germanwings plane crash, sxsw, mother's day, jurassic world movie, national kissing day
- evaluate different settings on ground truth

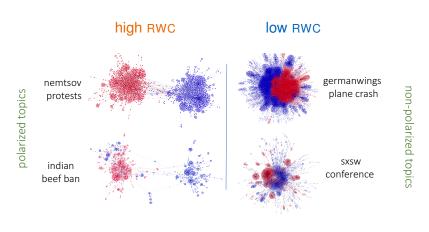
best performing setting



- retweet graph
- RWC

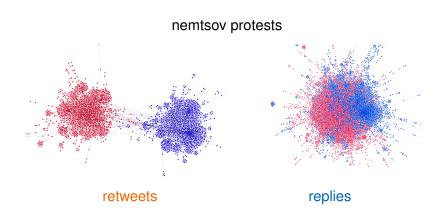
other good settings: edge betweenness score sentiment variance

example of results



using retweet graph

example of results



research questions

does polarization increase over time?

does polarization increase with spikes of activity?

K. Garimella, G. De Francisci Morales, A. Gionis, M. Mathioudakis, "The effect of collective attention on controversial debates on social media", ACM Web Science 2017

polarization over time

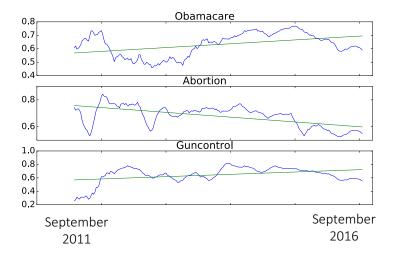
data

1% sample of all tweets September 2011 to September 2016

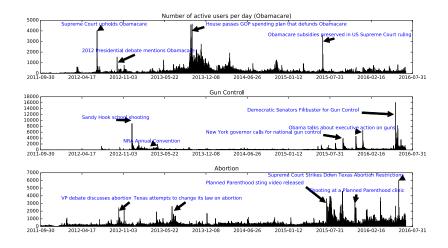
method

for a given topic (e.g., obamacare) build retweet graph for each day measure RWC score

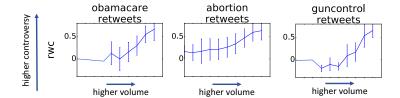
RWC over time



activity spikes at major events



RWC vs. activity volume



other measures vs. activity volume

clustering coefficient, core density, core-periphery edges, bi-directional links, content distribution, etc.

findings

- polarization increases with volume
- most retweeting activity occurs within a side
- retweet network becomes more hierarchical
- more discussion on the reply network
- content becomes more similar between the two sides

research questions

design algorithms to help reduce polarization design algorithms to moderate online discussions

- K. Garimella, G. De Francisci Morales, A. Gionis, M. Mathioudakis, "Reducing controversy by connecting opposing views", ACM WSDM 2017
- K. Garimella, A. Gionis, N. Parotsidis, N. Tatti, "Balancing information exposure in social networks", NIPS 2017

reducing polarization how can we bridge the divide?

- assuming
 - polarization score measured by RWC we want to reduce RWC
- problem
 - add k edges that maximally reduce RWC

reducing polarization

- greedy algorithm
 - find the single best edge to reduce RWC
 - repeat k times
- inefficient
 - computing RWC requires $\mathcal{O}(\texttt{MMULT}(n))$ faster in practice with iterative computation
 - still, greedy requires $\mathcal{O}(n^2 \cdot k \cdot \text{MMULT}(n))$
- improvements
 - consider adding edges only between hubs
 - incremental RWC computation using Sherman-Morrison formula

reducing polarization

- what does it mean "add k edges"?
- answer: recommendations
- but many recommendations are unlikely to be materialized no point recommending D. Trump to retweet H. Clinton
- incorporate probability of accepting a recommendation
 - compute user polarity, and
 - acceptance probability as a function of user polarity

reducing polarization: real example



Christopher Waterson @adizzle03

Animal lover. Second Amendment Originalist. Dad. Husband. Christian. Unapologetic @POTUS Trump Supporter. Snowflake hater. #MAGA

- New Jersey, USA
- iii Joined March 2010





(((ImpeachTheCon))) @arquitetinha

Architecture | Innovation | Futurist | Fight apocalypse, lies & Idiocracy | Punch Nazis, Block Rt-Wng Nut-jobs & Drumpf zombie-cult-puppets | 2-state | ENFP

- New York, USA [also IL | BR]
- iii Joined September 2015

polarity=.95

reducing polarization: real example





polarity=-.99

polarity=.15

reducing polarization: results

	obamacare		guncontrol	
	node1	node2	node1	node2
ROV	mittromney	barackobama	ghostpanther	barackobama
	realdonaldtrump	truthteam2012	mmflint	robdelaney
	barackobama	drudge_report	miafarrow	chuckwoolery
	barackobama	paulryanvp	realalexjones	barackobama
	michelebachmann	barackobama	goldiehawn	jedediahbila
ROV-AP	kksheld	ezraklein	chuckwoolery	csgv
	lolgop	romneyresponse	liamkfisher	miafarrow
	irritatedwoman	motherjones	csgv	dloesch
	hcan	romneyresponse	jonlovett	spreadbutter
	klsouth	dennisdmz	drmartyfox	huffpostpol

balancing information exposure

- the standard viral-marking setting [Kempe et al. 2003]
 - a social network
 - a model of information propagation
 e.g., the independent-cascade model
 - an action (e.g., meme) propagates in the network
- the influence-maximization problem
 - find k seed nodes to maximize spread
- the standard solution
 - spread is non-decreasing and submodular
 - greedy given $(1 \frac{1}{e})$ approximation

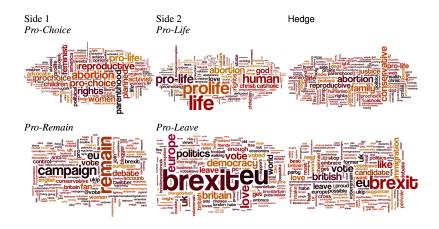
balancing information exposure

- proposed setting
 - a social network and two campaigns
 - seed nodes l_1 and l_2 for the two campaigns
 - a model of information propagation
- the problem of balancing information exposure
 - find additional seeds S_1 and S_2 , with $|S_1| + |S_2| \le k$
 - s.t. minimize # of users who see only one campaign or maximize # of users who see both or none

balancing information exposure : our results

- optimization problem is NP-hard
- objective function non monotone and non submodular
- different models of how the two campaigns propagate
- approximation guarantee $\frac{1}{2}(1 \frac{1}{e})$ maximization version

balancing information exposure : example



discussion, limitations, future work

- models use mostly network structure
 - language-independent, but
 - incorporating language can help
- simple models
 - two-sided controversies
 - external influence is ignored
 - random walk and independent cascade too simple
- evaluation is challenging, done on few topics
- go beyond twitter

references

- K. Garimella, A. Gionis, N. Parotsidis, N. Tatti, "Balancing information exposure in social networks", NIPS 2017
- K. Garimella, G. De Francisci Morales, A. Gionis, M. Mathioudakis, "The effect of collective attention on controversial debates on social media", International ACM Web Science 2017
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thank you Q&A

