Detecting polarized structures in social media

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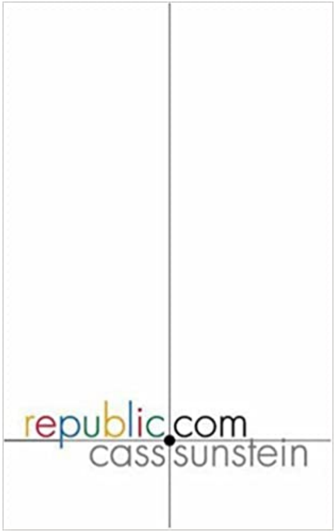
The dawn of Cyberbalkanization[1].

“It is some time in the future. Technology has greatly increased people’s ability to "filter" what they want to read, see, and hear. [...] With the aid of a television or computer screen, and the Internet, you are able to design your own newspapers and magazines. Having dispensed with broadcasters, you can choose your own video programming, with movies, game shows, sports, shopping, and news of your choice. You mix and match.”

Excerpt from Chapter 1: *“the daily me”*.

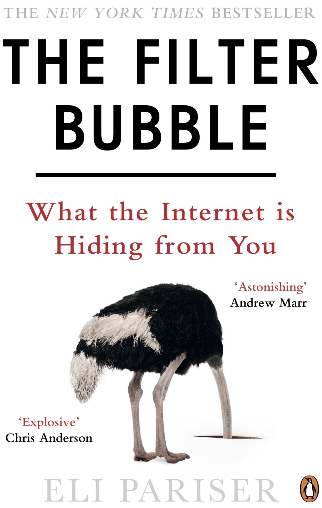


[1] Sunstein, Cass R. (2001). Republic.com. Princeton: Princeton University Press.

Polarized structures?

- Filter bubbles,
- Echo chambers,
- Extremism,
- Radicalization...

We will discuss algorithmic ideas to *detect* and *mitigate* these phenomena.

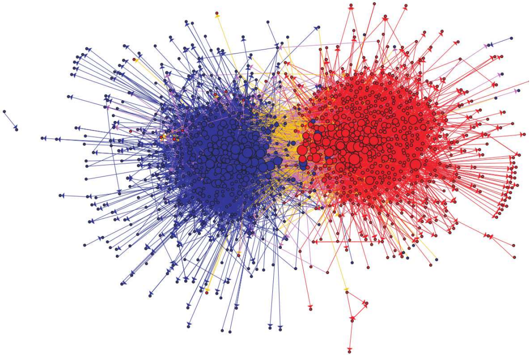


Pariser, Eli. The filter bubble: What the Internet is hiding from you. Penguin UK, 2011.

Detection

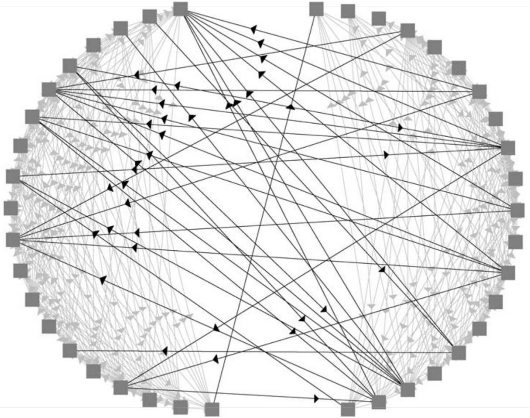
An early example of filter bubbles: link networks between political blogs prior to the 2004 US election (Adamic and Glance, 2005).

"In fact, 91% of the links originating within either the conservative or liberal communities stay within that community[2]"



[2] Adamic, Lada A., and Natalie Glance. "The political blogosphere and the 2004 US election: divided they blog." Proceedings of the 3rd international workshop on Link discovery. 2005.

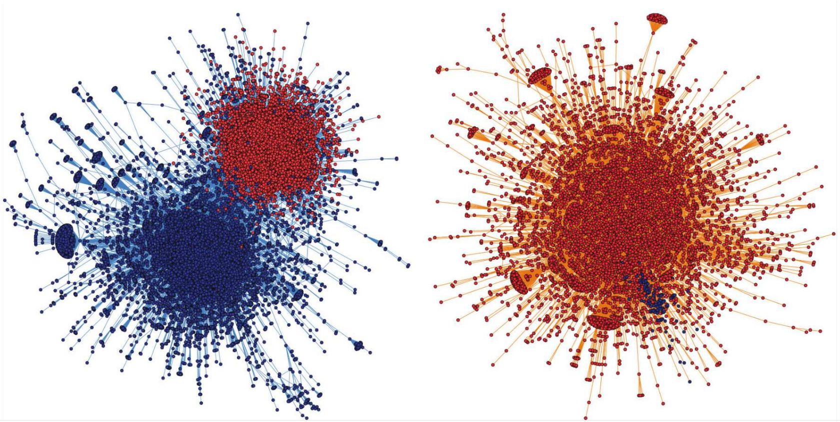
“..there is also some amount of linking to opposing points-of-view. [...] numerous links substantively engage others’ arguments[3]” (Hargittai et al., 2008)



[3] Hargittai, Eszter, Jason Gallo, and Matthew Kane. "Cross-ideological discussions among conservative and liberal bloggers." Public Choice 134.1-2 (2008): 67-86.

How the network is built is crucial (Conover et al., 2011a):

*"Community structure is evident in the **retweet network**, but less so in the **mention network**.*[4] *"*



[4] Conover, Michael, et al. "Political polarization on twitter." AAAI WSM 2011.

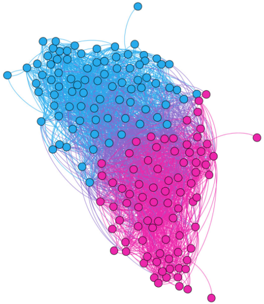
Direct application of known methods might fail: *"...not clear how much modularity is "enough" to state that a social network is polarized [...] on a non-polarized network, cross-group interactions should be at least as frequent as interactions with internal nodes on the community.[7]"*

(Guerra et al., 2013)

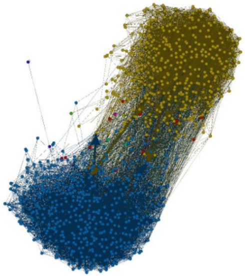
Definitions

Boundary: nodes interacting with the other community.

Polarization: a measure of how much boundary interactions stay within the community.



Facebook friends.
Graduates-undergraduates.
Modularity: 0.24. Polarization: -0.24.



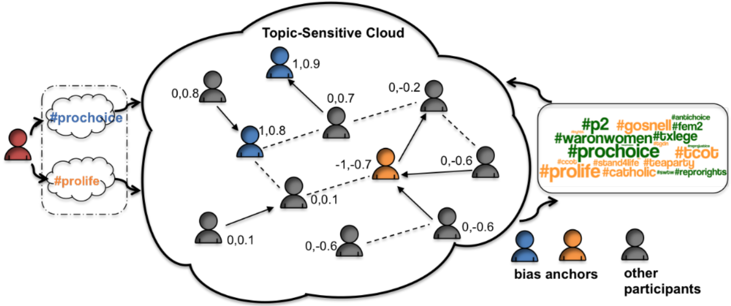
Political blogs.
Liberals-conservatives.
Modularity: 0.48. Polarization: 0.18.

[7] Guerra, Pedro, et al. "A measure of polarization on social media networks based on community boundaries." AAAI WSM 2013.

Biaswatch: a pipeline to detect opinion bias (Lu et al., 2015)

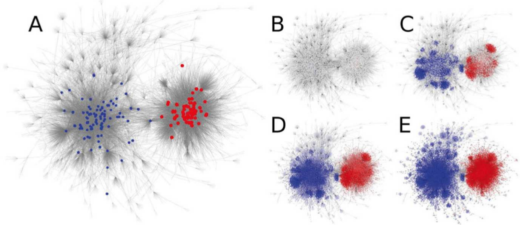
1. Find strongly biased users,
2. Propagate bias,
3. Optimize.

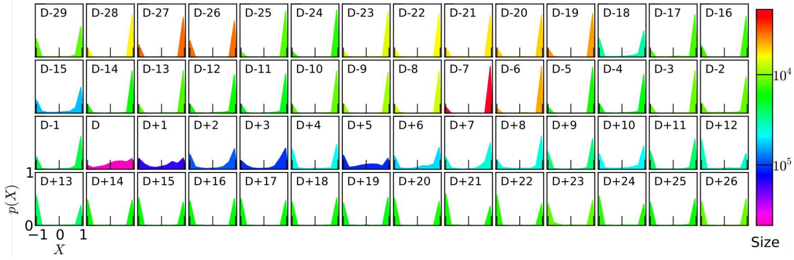
" Overall, we see a significant improvement of 20.0% in accuracy and 28.6% in AUC on average over the next-best method[8]."

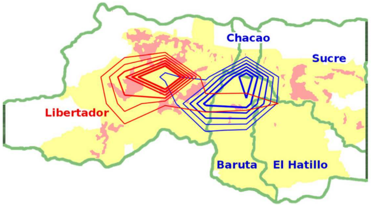


[8] Lu, Haokai, James Caverlee, and Wei Niu. "Biaswatch: A lightweight system for discovering and tracking topic-sensitive opinion bias in social media." CIKM 2015.

Polarization around death of Hugo Chávez (Morales et al., 2015).
Choice of influential users + DeGroot opinion formation model in retweet network.





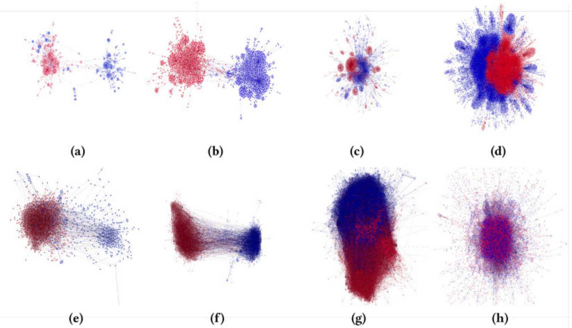


Morales, Alfredo Jose, et al. "Measuring political polarization: Twitter shows the two sides of Venezuela." Chaos: An Interdisciplinary Journal of Nonlinear Science (2015).

"Which topics spark the most heated debates on social media?" (Garimella et al., 2018)

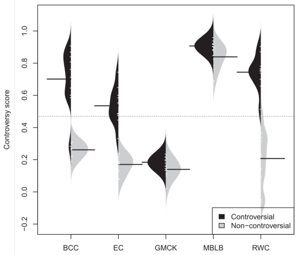
Random walk controversy

$$RWC = P_{XX}P_{YY} - P_{XY}P_{YX}.$$

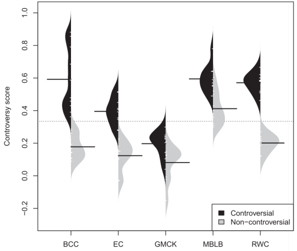


Controversial

Non-controversial



Retweet networks - controversy scores.

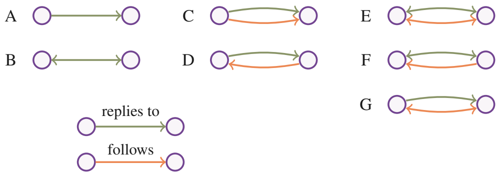


Follow networks - controversy scores.

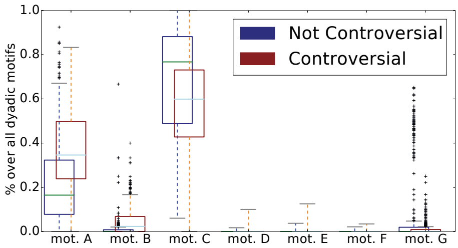
Garimella, Kiran, et al. "Quantifying controversy on social media." ACM Transactions on Social Computing (2018)

Motif-based controversy detection (Coletto et al., 2017).
Classifier with features from follow + reply graphs

Filtering	Accuracy	Precision	Recall	F-measure
Baseline				
>2 users	0.76	0.79	0.81	0.80
>3 users	0.77	0.80	0.82	0.81
>10 users	0.78	0.81	0.83	0.82
Baseline + dyadic motifs				
>2 users	0.82	0.84	0.86	0.85
>3 users	0.83	0.85	0.86	0.85
>10 users	**0.84**	**0.86**	**0.88**	**0.87**
Baseline + dyadic and triadic motifs				
>2 users	0.83	0.85	0.86	0.85
>3 users	0.84	0.86	0.85	0.86
>10 users	**0.85**	**0.87**	**0.88**	**0.87**
Dyadic motifs only				
>2 users	0.75	0.77	0.82	0.80
>3 users	0.75	0.77	0.82	0.80
>10 users	0.77	0.79	0.84	0.82



(a)



(b)

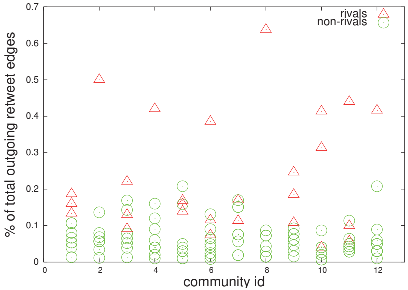
Coletto, Mauro, et al. "A motif-based approach for identifying controversy." AAAI WSM. 2017.

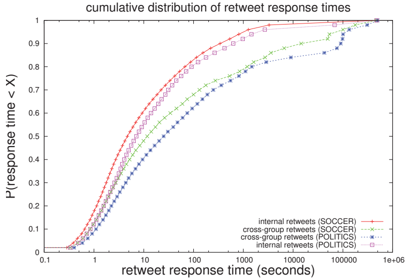
Check your assumptions!

"...we empirically demonstrate that groups holding antagonistic views can actually retweet each other more often than they retweet other groups[9]*."* (Guerra et al., 2017)

Table 2: Local rivalries in Brazilian Soccer.

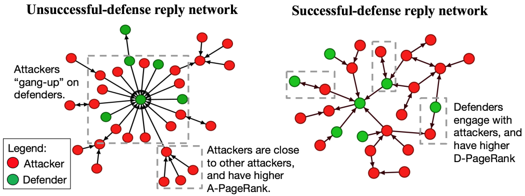
Brazilian state	local rivalries
M. Gerais	Cruzeiro, Atlético
S. Paulo	SPFC, Santos, Corint., Palmeiras
R. G. do Sul	Grêmio, Internacional
R. de Janeiro	Flamengo, Flumin., Vasco, Botafogo



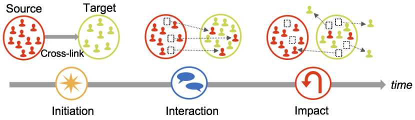


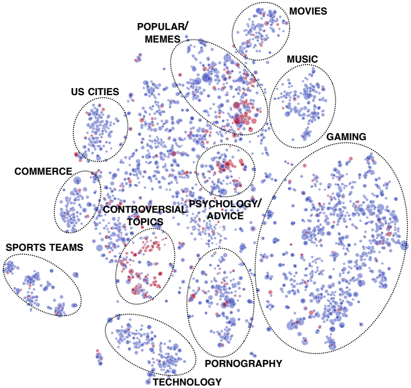
[9] Guerra, Pedro, et al. "Antagonism also flows through retweets: The impact of out-of-context quotes in opinion polarization analysis." Proceedings of the International AAAI WSM 2017.

A look at conflict between Reddit communities. (Kumar et al., 2018)



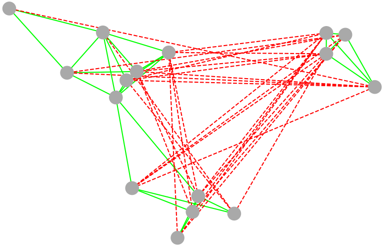
- *"74% of negative mobilizations are initiated by 1% of source communities[10]."*
- *"...a more fierce defense may be a more effective mitigation strategy, compared to ignoring or isolating the attacking users."*





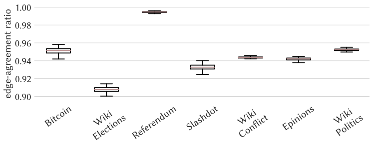
[10] Kumar, Srijan, et al. "Community interaction and conflict on the web." WWW 2018.

Methods based on signed networks
(+ and - edges).

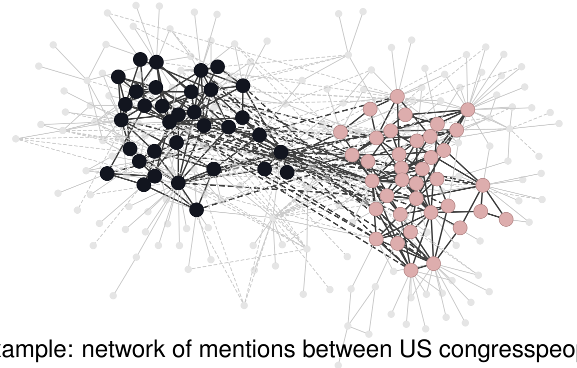


Highland tribes data set.

Community detection + partitioning based on the “first” eigenvector of the signed adjacency matrix (limited to 2 groups). (Bonchi et al., 2019)



Detected communities are highly polarized



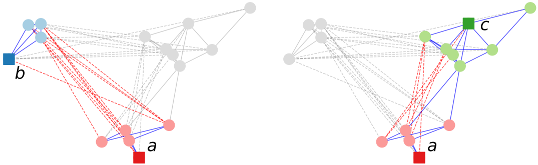
Example: network of mentions between US congresspeople

Later extended to *k* groups by (Tzeng et al., 2020).

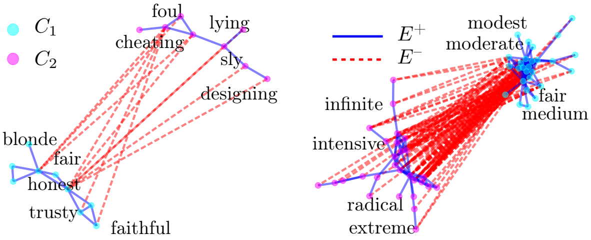
Bonchi, Francesco, et al. "Discovering polarized communities in signed networks." CIKM 2019.

Tzeng, Ruo-Chun, Bruno Ordozgoiti, and Aristides Gionis. "Discovering conflicting groups in signed networks." NeurIPS 2020.

Finding polarized groups with queries (Xiao et al., 2020)



(a) query $S_1 = \{a\}$ and $S_2 = \{b\}$ (b) query $S_1 = \{a\}$ and $S_2 = \{c\}$

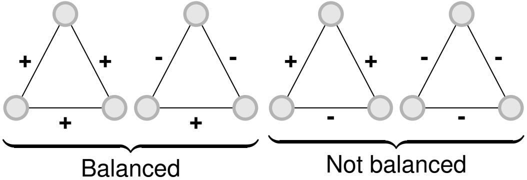


(a) *fair* as *without cheating* e.g., a *fair* game (b) *fair* as *not excessive* e.g., *fair* amount of time

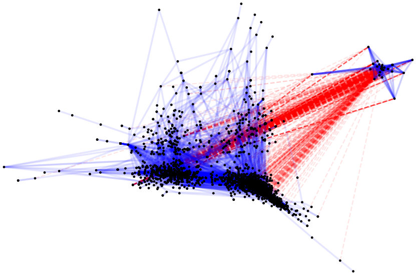
Applications beyond polarization: synonym/antonym network.

Xiao, Han, Bruno Ordozgoiti, and Aristides Gionis. "Searching for polarization in signed graphs: a local spectral approach." WWW 2020.

Finding balanced subgraphs (Ordozgoiti et al., 2020).



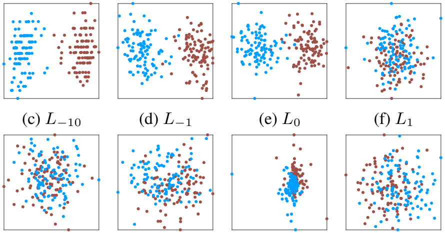
The four possible non-isomorphic signed triangles.



A perfectly polarized subgraph in the Bitcoin trust network.

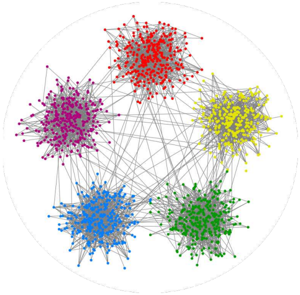
Ordozgoiti, Bruno, Antonis Matakos, and Aristides Gionis. "Finding large balanced subgraphs in signed networks." WWW 2020.

Recovering signed stochastic block model using power mean Laplacians (Mercado et al., 2019).

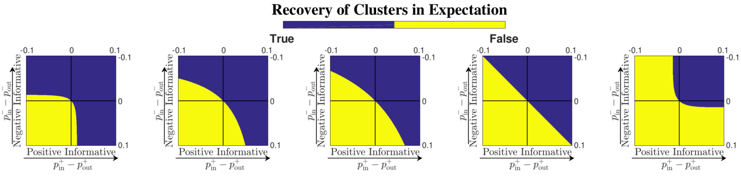


(c) L_{-10} (d) L_{-1} (e) L_0 (f) L_1

(g) L_{10} (h) L_{SN} (i) L_{BN} (j) H



(Abbe, 2017)



(a) $\mathcal{L}_{-10}$ (b) $\mathcal{L}_{-1}$ (c) $\mathcal{L}_0$ (d) $\mathcal{L}_1$ (e) $\mathcal{L}_{10}$

Mercado, Pedro, Francesco Tudisco, and Matthias Hein. "Spectral clustering of signed graphs via matrix power means." ICML 2019.

Mitigation

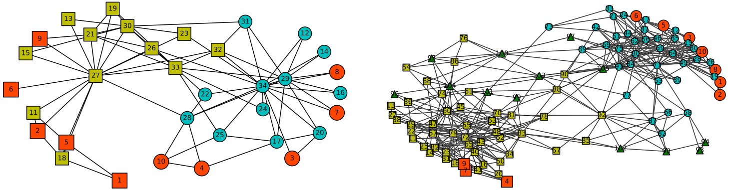
Problem definition (Matakos et al., 2017)

Given a Friedkin-Johnsen opinion network, find the best k moderators.

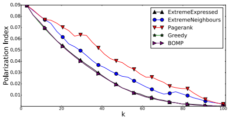
Opinion $\in [-1, 1]$.

A node's opinion is a function of its neighbours'.

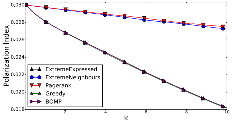
Moderator's opinion $= 0$.



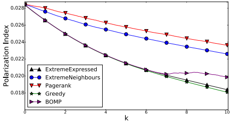
(a) (b)



(a)



(c)



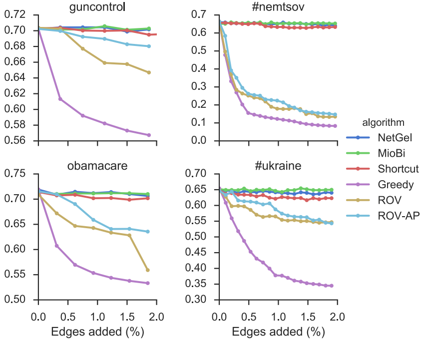
(e)

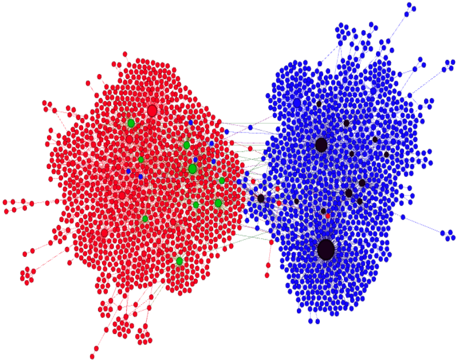
Matakos, Antonis, Evimaria Terzi, and Panayiotis Tsaparas. "Measuring and moderating opinion polarization in social networks." DAMI 2017.

Problem definition (Garimella et al., 2017a)

Given a network, add k edges to reduce Random Walk Controversy as much as possible.

- Efficient algorithm[11], faster than $\mathcal{O}(n^2)$.
- Possibility of rejection taken into account.





Nodes chosen in the #russia_march retweet graph.

Garimella, Kiran, et al. "Reducing controversy by connecting opposing views." WSDM 2017.

[11] Demo: `https://users.ics.aalto.fi/kiran/reducingControversy/homepage/`

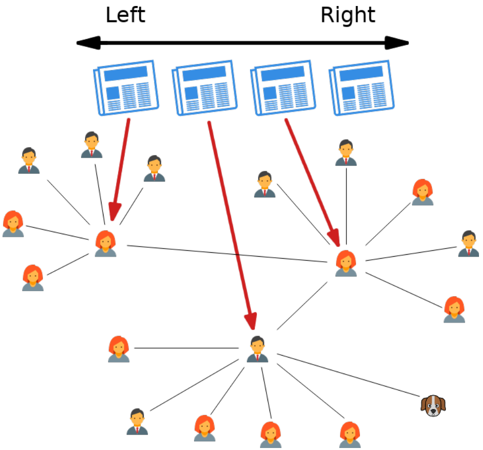
Problem definition (Matakos et al., 2020a)

Given a network of users and a set of items, all with ideological leanings, recommend *k* items to a set of users so as to maximize exposure diversity across the network.

Assumptions:

- Propagation is an independent cascade.
- Users unlikely to spread ideologically-far items.
- Monotone submodular obj. s.t. matroid constraint.
- Efficient alg. with modified reverse-reachable sets.

Related work: (Matakos et al., 2020b; Garimella et al., 2017b; Becker et al., 2020)



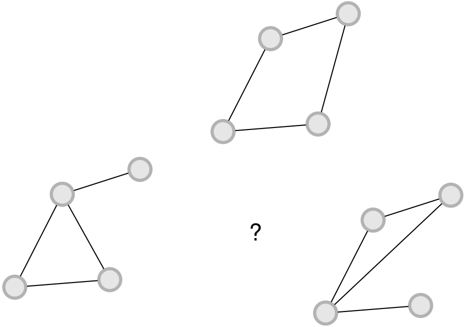
Aslay, Cigdem, et al. "Maximizing the diversity of exposure in a social network." ICDM 2018.

Icons: draw.io, Loïc Poivet via Wikimedia Commons

Problem definition (Musco et al., 2018)

Given n agents and an opinion dynamics model, what is the network structure with given weight that minimizes polarization and disagreement simultaneously?

$$\begin{aligned} \min_{L} \quad & z^T z + z^T L z \\ \text{s.t.} \quad & L \in \mathcal{L} \\ & Tr(L) = 2m \end{aligned}$$



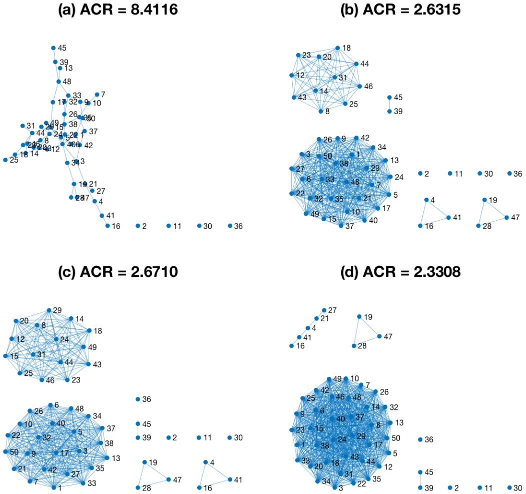
"Should a recommender system prefer a link suggestion between two users with similar mindsets to keep disagreement low, or two users with different opinions in order to expose each to the others viewpoint of the world?"

Result

There is always a graph with $\mathcal{O}(n/\epsilon^2)$ edges that achieves a $(1+\epsilon)$-approximation.

Musco, Cameron, Christopher Musco, and Charalampos E. Tsourakakis. "Minimizing polarization and disagreement in social networks." WWW 2018.

Conflict **risk** minimization in a Friedkin-Johnsen model (each user i has an internal s_i and and expressed opinion z_i) (Chen et al., 2018).



Measures of conflict :

- Internal conflict: $\sum_i (z_i - s_i)^2$.
- External conflict: $\sum_{(i,j)\in E} w_{ij}(z_i - z_j)^2$.
- Controversy: $\sum_i z_i^2$.
- Resistance: $r = z^T s$.

Conservation law of conflict

IC+2×EC+C= $s^T s = \sum_i s_i^2$.

Proposal: minimize **expected** and **worst-case** conflict risk over s, w.r.t. edge editions.

Chen, Xi, Jefrey Lijffijt, and Tijl De Bie. "Quantifying and minimizing risk of conflict in social networks." KDD 2018.

RePBubLik (Haddadan et al., 2021) (WSDM '21).

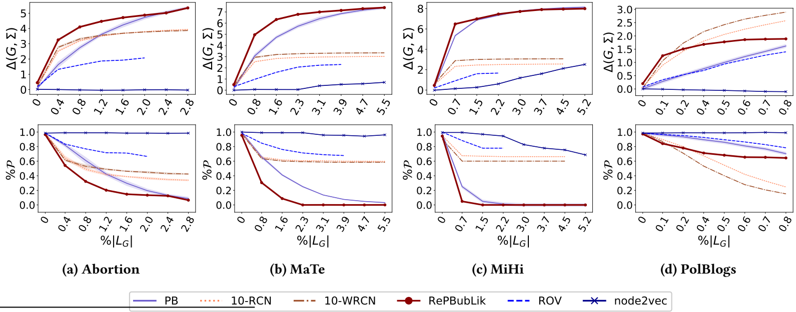
Definitions

Consider a graph with vertices of 2 colours.

- Bubble radius of v: hitting time of a vertex of a different colour from v.
- Parochials: nodes with high BR.
- Cosmopolitans: nodes with low BR.

Problem: add k edges to maximally reduce n. of parochials.

Results: monotone submodular objective. Approx. guarantees.



(a) Abortion (b) MaTe (c) MiHi (d) PolBlogs

Haddadan, Shahrzad, et al. "RePBubLik: Reducing the Polarized Bubble Radius with Link Insertions." WSDM 2021.

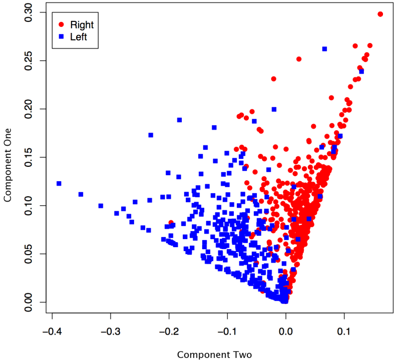
Annotation

Predicting political alignment on Twitter (Conover et al., 2011b)

SVM trained on different feature vectors:

- Tweet text
- Hashtags
- Network structure

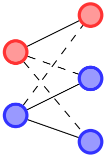
Features	Conf. matrix	Accuracy	Section
Full-Text	$\begin{bmatrix} 266 & 107 \\ 75 & 431 \end{bmatrix}$	79.2%	§ IV-A1
Hashtags	$\begin{bmatrix} 331 & 42 \\ 41 & 465 \end{bmatrix}$	90.8%	§ IV-A2
Clusters	$\begin{bmatrix} 367 & 6 \\ 38 & 468 \end{bmatrix}$	94.9%	§ IV-B
Clusters + Tags	$\begin{bmatrix} 366 & 7 \\ 38 & 468 \end{bmatrix}$	94.9%	§ IV-B

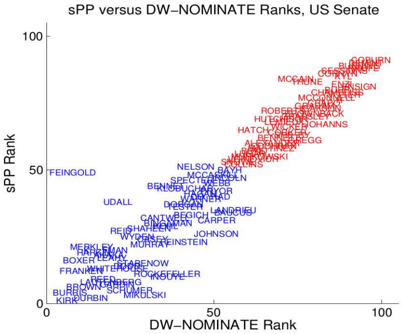


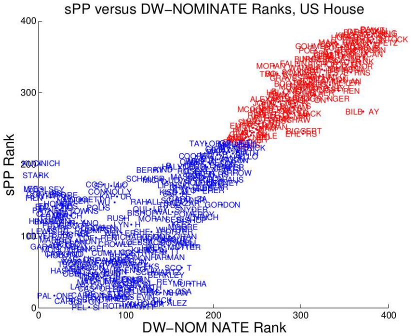
First two LSA factors of the hashtag-user matrix.

Conover, Michael D., et al. "Predicting the political alignment of twitter users." 2011 IEEE third international conference on privacy, security, risk and trust and 2011 IEEE third international conference on social computing.

Node classification and ranking based on signed bipartite network[12].
Markov random field MLE with loopy belief propagation.
(Akoglu, 2014)





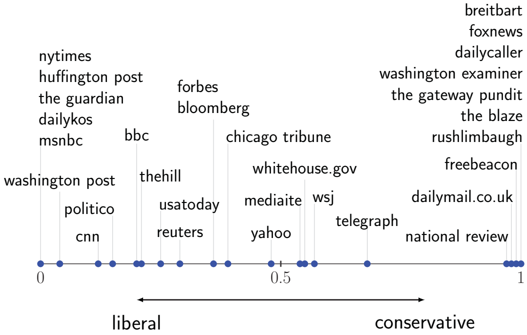


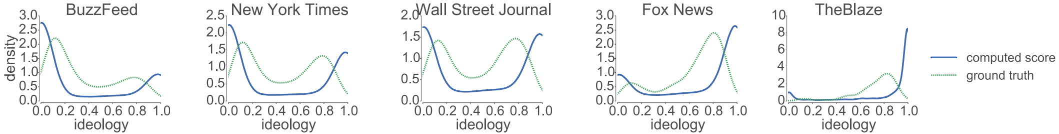
[12] Akoglu, Leman. "Quantifying political polarity based on bipartite opinion networks." Proceedings of the International AAAI Conference on Web and Social Media, 2014.

User and source ideology with joint NMF (Lahoti et al., 2018).

Setting

- User-user matrix $A \approx U H_u U^T$.
- User-source matrix $C \approx U H_s V^T$.





Lahoti, Preethi, Kiran Garimella, and Aristides Gionis. "Joint non-negative matrix factorization for learning ideological leaning on twitter." WSDM 2018.

"...reported accuracies have been systemically over-optimistic due to the way in which validation datasets have been collected[13]*.(Cohen and Ruths, 2013)"*

Previous works focus on highly-political accounts (politicians or self-declared users). This work:

- US politicians,
- users with self-reported political orientation,
- modest users who do not declare their political views, but make sufficient mention of politics.

Result

- Performance drops from $\geq$ 90% to 65%.
- *"We found that classifiers based on politicians, while achieving 91% labeling accuracy on other politicians, only achieved 11% accuracy on politically modest users."*

[13] Cohen, Raviv, and Derek Ruths. "Classifying political orientation on Twitter: It's not easy!." AAAI WSM.

Finding early signs of Trump support on Reddit (Massachs et al., 2020).

"We find that homophily-based and social feedback-based features are the most predictive signals."

	Precision	Recall	F1	AUC
Participation	0.25	0.56	0.34	0.68
Score	0.24	0.60	0.33	0.67
Interaction	0.18	0.52	0.26	0.55
Part. + Score	0.27	0.56	0.35	0.70

Trump supporters		**Trump non-supporters**	
Subreddit	β	Subreddit	β
r/Conservative	0.3815	r/raspberry_pi	-0.2847
r/Libertarian	0.3740	r/TrueAtheism	-0.2577
r/conspiracy	0.3733	r/AskCulinary	-0.2355
r/4chan	0.3341	r/comics	-0.2249
r/circlejerk	0.3107	r/rpg	-0.2186
r/NoFap	0.2918	r/ireland	-0.2034
r/Entrepreneur	0.2539	r/Fantasy	-0.1983
r/ImGoingToHellForThis	0.2510	r/explainlikeimfive	-0.1944
r/trees	0.2482	r/environment	-0.1892
r/MensRights	0.2482	r/doctorwho	-0.1878
r/guns	0.2293	r/polyamory	-0.1806
r/blackops2	0.2110	r/scifi	-0.1777
r/runescape	0.2031	r/books	-0.1772
r/Anarcho_Capitalism	0.1937	r/askscience	-0.1738
r/Catholicism	0.1931	r/london	-0.1691
r/leagueoflegends	0.1920	r/britishproblems	-0.1687
r/nfl	0.1843	r/Homebrewing	-0.1632
r/starcraft	0.1714	r/programming	-0.1521
r/CCW	0.1638	r/gadgets	-0.1501
r/breakingbad	0.1631	r/AndroidQuestions	-0.1463
r/investing	0.1624	r/listentothis	-0.1462
r/AdviceAnimals	0.1589	r/hiphopheads	-0.1397
r/DeadBedrooms	0.1577	r/boardgames	-0.1336
r/Firearms	0.1551	r/asoiaf	-0.1292
r/Advice	0.1537	r/whatisthisthing	-0.1244
r/seduction	0.1518	r/lgbt	-0.1187
r/Christianity	0.1455	r/cringepics	-0.1175
r/golf	0.1453	r/ukpolitics	-0.1136
r/mylittlepony	0.1437	r/Python	-0.1089
r/POLITIC	0.1423	r/baseball	-0.1080

Massachs, Joan, et al. "Roots of Trumpism: Homophily and Social Feedbackin Donald Trump Support on Reddit." Web Science. 2020.

A word on signed networks:

- There is a shortage of signed networks! E.g. check:
  - `https://snap.stanford.edu/data/` 9 out of about 120 are signed.
  - `http://konect.cc/` 8 out of 1,326 are signed.
- Annotating user interactions with signs is challenging. Ideas are welcome!

To conclude, a personal note: we won't solve this with algorithms alone.

Thanks for listening, and thanks to all researchers working in the field, especially present and past members of the group led by Aris Gionis at Aalto/KTH.

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