ECHO CHAMBERS

How to detect and mitigate them within our network

What are echo chambers?

Definition

Echo chambers are situations where one is exposed only to opinions that agree with their own. An echo chamber exists if the political leaning of the content that users receive from the network agrees with that of the content they share or generate.

Context

- An issue of concern in the political discourse of democratic countries.
- As citizens become more polarized about political issues, they do not hear the arguments of the opposite side, but are rather surrounded by people and news sources who express only opinions they agree with.
- Reinforces biases, leads to partisan perspective.
- Also helps in spreading fake news faster.

Political Discourse on Social Media: Echo Chambers, Gatekeepers, and the Price of Bipartisanship

Kiran Garimella, Gianmarco De Francisci Morales, Aristides Gionis, and Michael Mathioudakis, The 2018 Web Conference

This paper studies echo chambers that exist within political discourse on Twitter. We study it in terms of two components: the **opinion** (content items) that is shared by a user, and the "**chamber**", i.e., the social network around the user, which allows the opinion to propagate or "echo" back to the user as it is also shared by others.

Content consumption is studied at three levels:
(i) potential exposure, which includes all content shared by the friends of a user
(ii) exposure, which includes all content appearing in the feed of a a user
(iii) engagement, which includes all content that a user clicks.

Here, we study content consumption at the level of **potential exposure**, as a study at the remaining two levels requires access to data that is not publicly available.

Analysis of different kinds users within a network:

- **Partisan Users**
  - produce content with predominantly one-sided leaning
  - partisan users enjoy a higher “appreciation” as measured by both network and content features
- **Bipartisan Users**
  - produce content with both leanings
  - “price of bipartisanship,” required to be paid by users who try to bridge echo chambers
  - producing content that expresses opinions aligned with both sides of the political divide, has a cost in terms of centrality in the network and content engagement rate.
- **Gatekeeper Users**
  - consume content of both leanings, but produce content of a single-sided leaning i.e. *filter* information from a side
  - These users are border spanners in terms of location in the social network, who remain aware of the positions of both sides, but align their content with one side.
  - enjoy higher than average network centrality, while not being very embedded in their community

Implementation

Table 1: Description of the datasets.

Topic	#Tweets	#Users	Event
guncontrol	19M	7506	Democrat filibuster for gun-control reforms (June 12–18, 2016)[6]
obamacare	39M	8773	Obamacare subsidies preserved in U.S. supreme court ruling (June 22–29, 2015)[7]
abortion	34M	3995	Supreme court strikes down Texas abortion restrictions (June 27–July 3, 2016)[8]
combined	19M	6391	2016 US election result night (Nov 6–12, 2016)
large	2.6B	676 996	Tweets from users retweeting a U.S. presidential/vice presidential candidate (from [19], 2009–2016)
ff	4M	3204	filtering for these hashtags
gameofthrones	5M	2159	
love	3M	2940	
tbt	28M	12 778	
foodporn	8M	3904	

Using the Archive Twitter Stream grab, select tweets that contain keywords pertaining to each topic that were posted in a time period of one week around the event (3 days before and 3 days after the event). We identify the subset of users who have at least 5 tweets about the topic during this time window.

Data includes:

- Tweets
- User details
- Full follower network
- Domains ideology score
- User polarity score

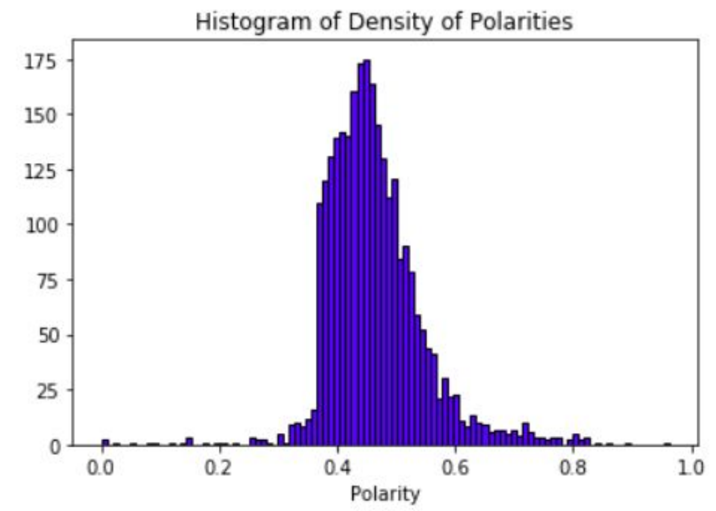
1. To quantify the political leaning of content posted on Twitter, we consider only messages that contain a link to an online news organization with a known and independently derived political leaning, corresponding to our ground truth values.
2. **Production polarity** - For each user u in a given dataset, we consider the set of tweets Pu posted by u that contain links to news organizations of known political leaning Ln. We then associate each tweet t ∈ Pu with leaning ℓ(t) = Ln. The production polarity p(u) of user u is then defined as the average political leaning over Pu , i.e.,

$$p(u) = \frac{\sum_{t \in P_u} \ell(t)}{|P_u|}.$$

3. The value of production polarity ranges between 0 and 1. For users who regularly share content from liberal sources, production polarity is closer to 0, while for the ones who share content from conservative sources it is closer to 1.
4. Also compute variance in political leaning over the same set of tweets.

Consumption polarity - Similarly to production polarity, we define consumption polarity based on the set of tweets C(u) that a user receives on their feed from users they follow. We again focus on tweets that contain a link to a news article from a domain with known source polarity. The consumption polarity c(u) of user u is defined as the average political leaning of received tweets C(u).

$$c(u) = \frac{\sum_{t \in C_u} \ell(t)}{|C_u|}$$



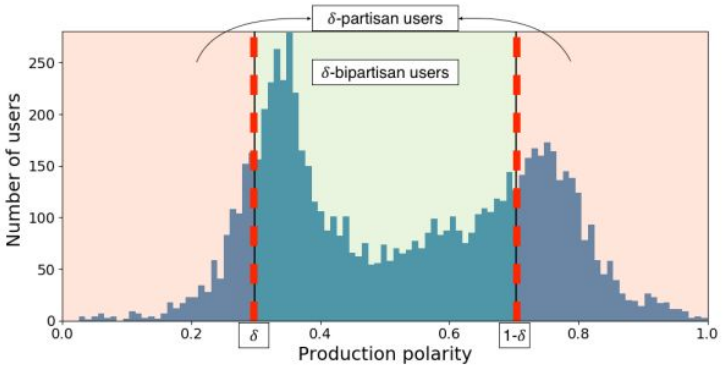


Figure 1: Example showing the definition of δ-partisan users. The dotted red lines are drawn at δ and 1-δ. Users on the left of the leftmost dashed red line or right of the rightmost one are δ-partisan.

Within the network, we adopt the following measures:
User polarity - This score is based on the assumption that Twitter users prefer to follow politicians whose
position on the latent ideological dimension is similar to theirs.
Network centrality - We employ the PageRank measure to characterize the centrality of a node in a network. PageRank reflects the importance of a node in the follow network, and a higher PageRank can be interpreted as a higher chance of the user to spread its content to its community.
Clustering coefficient - In an undirected graph, the clustering coefficient cc(u) of a node u is defined as the fraction of closed triangles in its immediate neighborhood. Specifically, let d be the degree of node u, and T be the number of closed triangles involving u and two of its neighbors. The clustering coefficient is then defined as $cc(u) = d(2dT-1)$. A high clustering coefficient for a node indicates that the ego network of the corresponding user is tightly knit, i.e., the node is embedded in a well-connected community.
Retweet/Favorite rate - For a given dataset, the retweet rate (favorite rate) of a user is the fraction of the tweets of that user that have received at least one retweet (favorite).
Retweet/Favorite volume - For a given dataset, the retweet volume (favorite volume) of a user is defined as the median number of retweets (favorites) received by their tweets.

RESULTS AND OBSERVATIONS

- Production and consumption polarities are highly correlated for Political datasets, so users do tend to consume content with political leaning aligned to their own.
- Production and consumption polarities for the Political datasets exhibit clearly separated and bi-modal distributions, while the distributions coincide for the Non-Political datasets.
- The production/consumption polarities are more concentrated towards the middle of the spectrum (i.e., there are few very extreme users).
- Bipartisan users follow news sources with a wider spread of political leaning, rather than just picking from the center.
- Partisan users are significantly more polarized than bipartisan ones and enjoy a more central position in the network, indicated by higher PageRank.
- Gatekeepers also occupy positions with high centrality in the network. However, they show a lower clustering coefficient, they are not completely embedded in a single community.

BiasWatch: A Lightweight System for Discovering and Tracking Topic-Sensitive Opinion Bias in Social Media

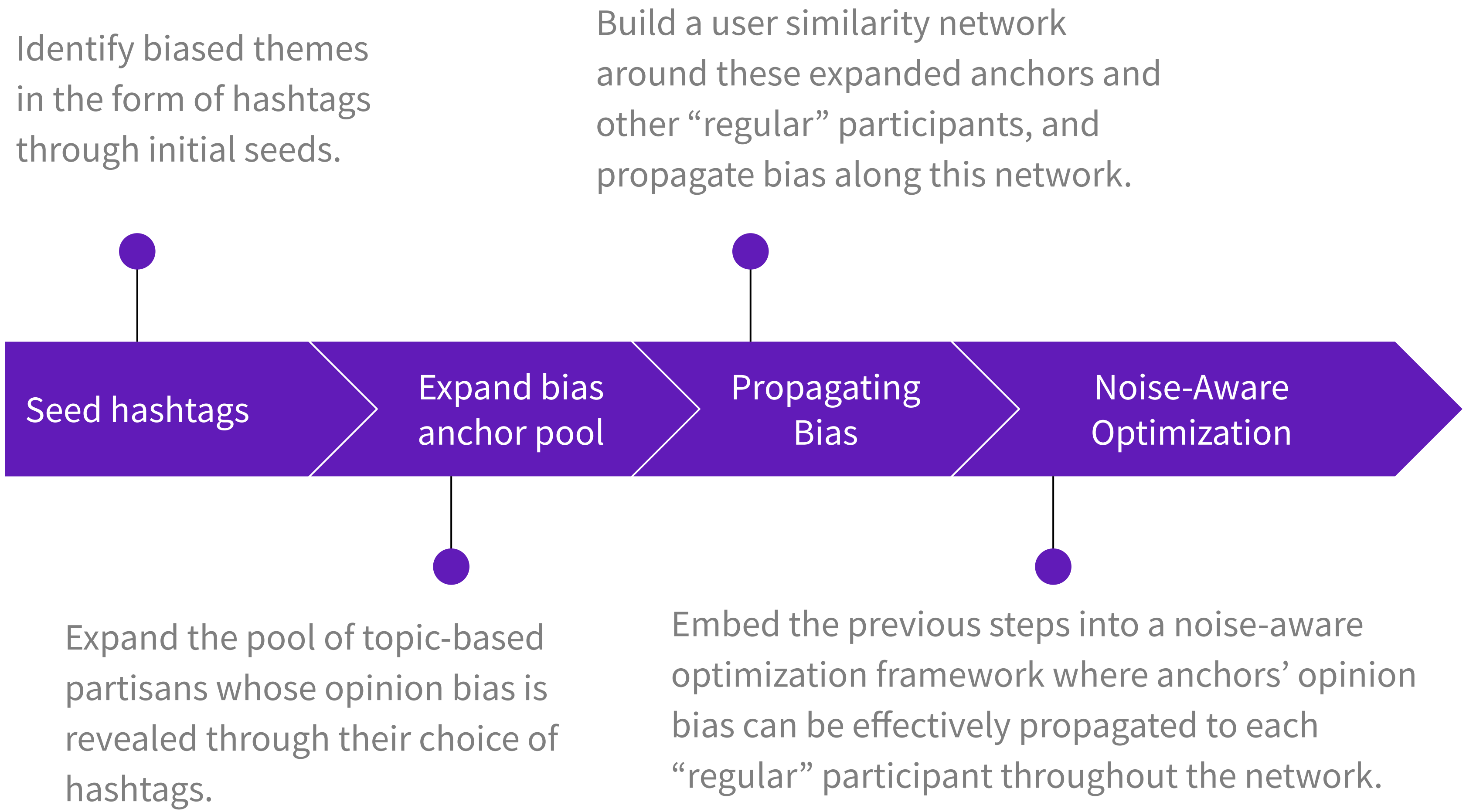
Haokai Lu, James Caverlee, Wei Niu;
CIKM 2015

This paper proposes a lightweight system for :

(i) semi-automatically discovering and tracking bias themes associated with opposing sides of a topic

(ii) identifying strong partisans who drive the online discussion

(iii) inferring the opinion bias of "regular" participants.


Identify biased themes in the form of hashtags through initial seeds.
Build a user similarity network around these expanded anchors and other “regular” participants, and propagate bias along this network.
Seed hashtags
Expand bias anchor pool
Propagating Bias
Noise-Aware Optimization
Expand the pool of topic-based partisans whose opinion bias is revealed through their choice of hashtags.
Embed the previous steps into a noise-aware optimization framework where anchors’ opinion bias can be effectively propagated to each “regular” participant throughout the network.

Identifying Bias Anchors

Anchors are strong topic-based partisans who serve as basis for propagation.

a) One reasonable method for identifying anchors is to manually label a number of users. However, it is potentially expensive and time-consuming; and random.
b) Start with seed set of hashtags that weakly label the polarity of a tweet with respect to a controversial topic.
c) **Seed Expansion via Signed Information Gain -**
   i) Training with pro-seed and anti-seed. First, we aggregate a user's tweets and use a bag-of-words model to compute TFIDF for each user. From these users, we treat users with only pro-seed as positive class $c+$, users with only anti-seed as negative class $c-$, and the rest for prediction. Finally, an SVM classifier is learned on the training data and used to predict the polarity of users which are left. We now have an expanded set of users who are positive, and an expanded set of users who are negative.

ii) Selecting hashtags - From the expanded sets of users, we use signed information gain (SIG) as the measure to select hashtags for pro-seed and anti-seed.

$$SIG(h_i, c) = sign(AD - BC) \cdot \sum_{c \in \{c_+, c_-\}} \sum_{h \in \{h_i, \bar{h}_i\}} p(h, c) \cdot log \frac{p(h, c)}{p(h) \cdot p(c)}$$

where A is the number of users with hi and in class c+,
B is the number of users with hi and in class c−,
C is the number of users without hi and in class c+,
D is the number of users without hi and in class c−.
h¯i represents hashtags other than hi.
Here, the probability p is obtained by maximum likelihood estimation. We select m hashtags with the largest SIG as the finalized hashtag set P for pro-seed, and m hashtags with the smallest SIG as the finalized hashtag set N for anti-seed.

Given the expanded set of hashtags, we identify as **bias anchors** those who consistently adopt hashtags from only one opinion standpoint and assign a bias score.

Bias Propagation Network

We want to build a propagation network where two users are only connected if their similarity (both content and link features) passes a threshold.

a) Content-Based Propagation - we aggregate each user's topic-related tweets and treat each user as a document. Thus, content similarity of two users can be computed with document similarity. Here, we adopt cosine similarity of the TFIDF of the two documents with a standard bi-gram model. To reduce the propagation complexity, we construct a sparse network by only considering k-nearest neighbors for each user.

b) Link-Based Propagation - Retweeting can be considered a form of endorsement for users in Twitter. So if a user retweets another user on a topic, both users tend to share similar opinion bias.

$$w_{ij}^{content} = \begin{cases} C_{ij}, & \text{if } u_j \in \mathcal{N}^c(u_i) \\ 0, & \text{if } u_j \notin \mathcal{N}^c(u_i) \end{cases} \qquad w_{ij}^{link} = \begin{cases} 1, & \text{if } u_j \in \mathcal{N}^l(u_i) \\ 0, & \text{if } u_j \notin \mathcal{N}^l(u_i) \end{cases}$$

And combined, $w_{ij} = w_{ij}^{content} + \lambda w_{ij}^{link}$ where lambda is a weighting param.

Optimization Framework - User-guided Opinion Propagation [UOP]

We embed the discovered anchors and bias propagation network into an optimization setting to propagate the opinion-bias score of all users more effectively.

By allowing each user's true opinion bias bi to change as an optimization variable:

(i) for bias anchors, bi should be as close to the bias indicated by adopting biased hashtags

(ii) for other participants, bi and bj should be close to the degree indicated by their content and link similarity.

Their opinion bias is initialized randomly between [−1; 1] and can now be iteratively propagated through optimization.

$$\min_{b_i \in B} \quad f = \sum_{u_i \in U_{anchor}} (b_i - \tilde{b_i})^2 + \mu_1 \sum_{i=1}^{n} \sum_{j=i+1}^{n} w_{ij}(b_i - b_j)^2$$

$$\text{subject to} \qquad -1 \leq b_i \leq 1 \qquad \forall i \in \{1, ..., n\}$$

We introduce another variable yi for ui as the ideal opinion bias to handle noisy bias anchors.

RESULTS

Table 4: Comparison of performance with alternative opinion bias estimators. Boldface: the best result for each topic among all methods. '$*$' marks statistically significant difference against the best of alternative opinion bias estimators (with two sample t-test for $p \leq 0.05$).

Method	Accuracy				AUC			
	gun control	abortion	obamacare	average	gun control	abortion	obamacare	average
SWN	0.560	0.527	0.465	0.517	0.570	0.531	0.541	0.547
uCC	0.534	0.537	0.516	0.529	0.533	0.527	0.522	0.527
uCCL	0.586	0.530	0.520	0.545	0.584	0.531	0.546	0.554
wSVM+IS	0.696	0.825	0.786	0.769	0.745	0.790	0.594	0.710
wSVM+SIG	0.860	0.884	0.727	0.824	0.844	0.874	0.800	0.839
UOP*	0.851	0.847	0.826	0.841	0.853	0.843	0.842	0.846
LCGC+SIG	0.858	0.900	0.811	0.856	0.857	0.900	0.864	0.874
UOP†	0.881	0.906	0.894	0.894	0.861	0.903	0.915	0.893
UOP	**0.908***	**0.915**	**0.945***	**0.923***	**0.883***	**0.910**	**0.945***	**0.913***

Thank you!