Detecting Echo Chambers in social media; a graph-based approach

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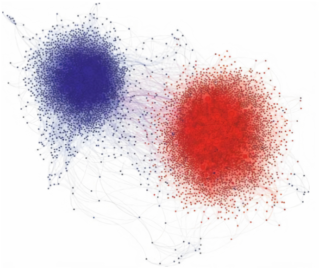
Social media and Echo Chambers

- Social media are more and more diffused
- On these platforms we experience every day phenomenons like polarization and **Echo Chambers**
- Echo chambers correspond to groups of users with the same ideas who, after interacting, reinforce their initial opinions



Data model: Contents and Threads

Our definition of Echo Chamber is based on the concepts of **Contents** and **Threads**

- **Content**: the resource which is discussed. We can generally think of it as an online newspaper article. It is identified by a URL, e.g.

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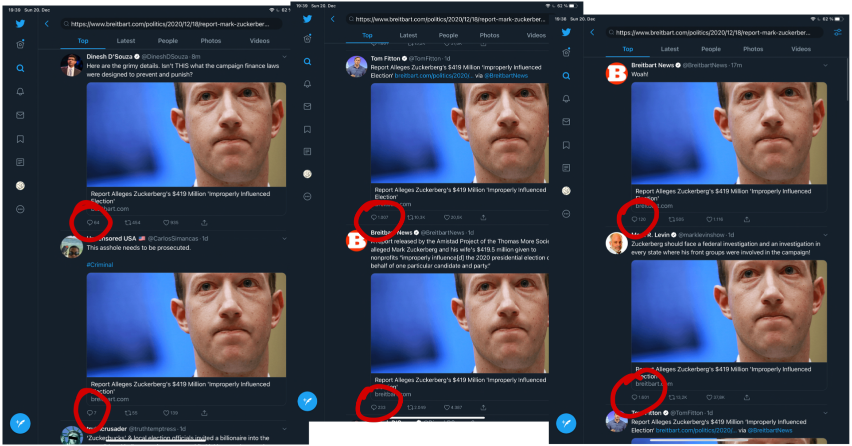
- **Thread**: the social media *locality* discussing a content. Identified by its URL, e.g.

  `https://twitter.com/DineshDSouza/status/1340726209446113280`

Content and threads: an example



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We can now give an initial informal definition of Echo Chambers.

- **Echo Chambers**: users discussing controversial contents with mostly friendly interactions

Some graph concepts

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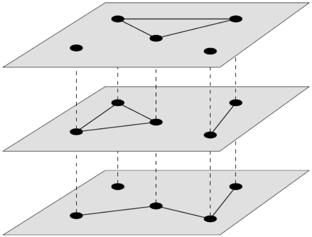
- **Signed graphs**: graph with positive and negative edges
- **Multiplex graph**: graph with multiple layers. Each layer has the same set of vertices but its own set of edges



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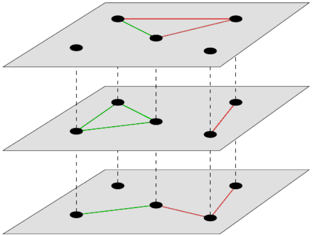

Data model: Echo Chambers (2)

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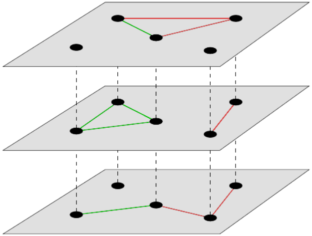
- Consider only *non-controversial* threads associated to *controversial* contents
  - *Controversial*: more than α percent of edges is negative

Data model: $\mathcal{S}_C$

- $\mathcal{S}_C(U)$ contains threads which are *locally* non-controversial but it is defined only for contents that are *globally* controversial.



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$$\xi(U) = \sum_{C \in \hat{\mathcal{C}}} \sum_{T[U] \in S_C(U)} (|T^+[U]| - |T^-[U]|)$$

  - $T[U]$ is the subgraph induced by U in T
  - $|T^+[U]|$ is the number of positive edges in $T[U]$

Echo Chamber Problem: find vertices U maximizing $\xi(U)$.

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We will not show the proofs of our results.

The Echo Chamber Problem: our results (2)

The Echo Chamber Problem cannot be approximated in polynomial time for a non-trivial factor.

Theorem

The ECP has no $n^{1-\epsilon}$-approximation algorithm for any $\epsilon > 0$ unless $\mathcal{P} = \mathcal{NP}$.

The Echo Chamber Problem: our results (3)

An exact solution for the problem can be found through the following Mixed Integer Programming (MIP) Model

$$
\begin{aligned}
\text{maximize} \quad & \sum_{T_k \in \mathcal{T}_C,\ C \in \hat{\mathcal{C}}} \Big(\sum_{ij \in E_k^+} x_{ij}^k - \sum_{ij \in E_k^-} x_{ij}^k \Big) && (1) \\
\text{subject to} \quad & x_{ij}^k \leq y_i \quad \forall ij \in E_k && (2) \\
& x_{ij}^k \leq y_j \quad \forall ij \in E_k && (3) \\
& x_{ij}^k \leq z_k \quad \forall ij \in E_k && (4) \\
& x_{ij}^k \geq -2 + y_i + y_j + z_k \quad \forall ij \in E_k && (5) \\
& \sum_{ij \in E_k^-} x_{ij}^k - \alpha \sum_{ij \in E_k} x_{ij}^k \leq 0 \quad \forall T_k \in \mathcal{T}_C, C \in \hat{\mathcal{C}} && (6) \\
& y_i \in \{0, 1\} \quad \forall i \in V && (7) \\
& 0 \leq x_{ij}^k \leq 1 \quad \forall ij \in E_k && (8) \\
& 0 \leq z_k \leq 1 \quad \forall T_k \in \mathcal{T}_C, C \in \hat{\mathcal{C}} && (9)
\end{aligned}
$$

An heuristic for the Echo Chamber Problem

We propose a heuristic for solving the Echo Chamber Problem

- It is based on the relaxation of the MIP (integrality constraints are removed)
- Each edges is assigned a value in the MIP. This heuristic considers the vertices associated to edges with the highest value as possible solutions

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Clustering problem

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- Graphs are built from Reddit or Twitter
- Similar data collection process:
  - Retrieve contents from posts of a *subreddit* or of a Twitter account
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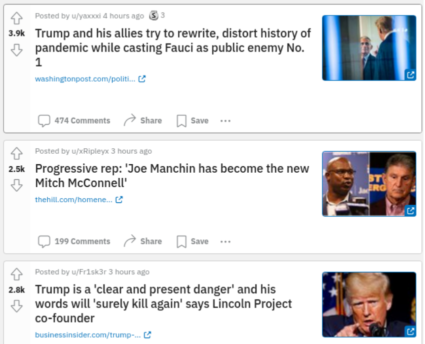

Data collection

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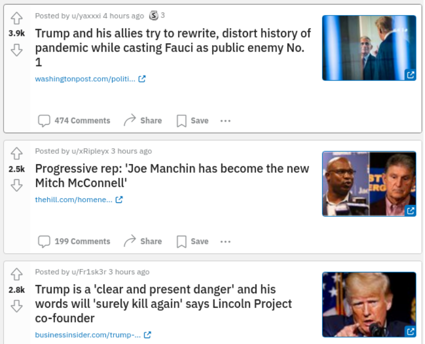
- Edge labels are obtained through a *sentiment analyzer*



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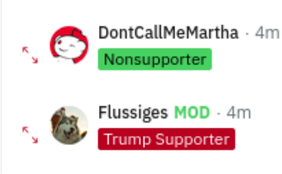
- r/asktrumpsupporters asks users to choose a flair among *Trump Supporter*, *Non Supporter* and *Undecided*
- Twitter users are labeled according to the politicians they follow (if they are mostly *democrat* or *republican*). This dataset is built on @nytimes.



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Observations on the results

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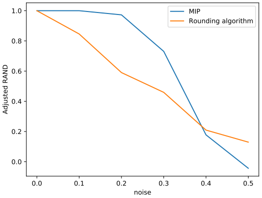

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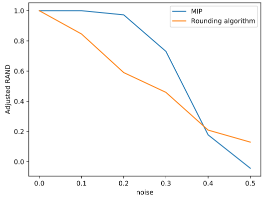

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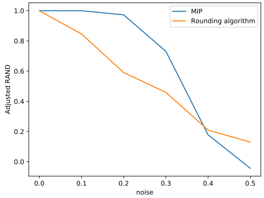

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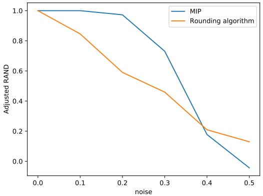

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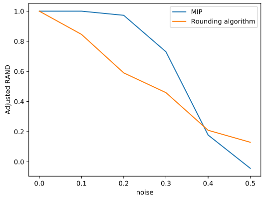

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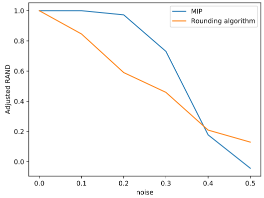

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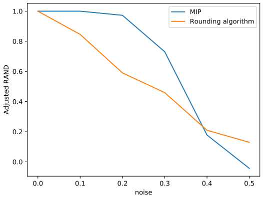

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- Formulation can be extended with *follow graph*