



Spreading of Misinformation online

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Introduction

- The massive diffusion of sociotechnical systems and micro-blogging platforms on Web creates a direct path from producers to consumers of content
 - Changes the way users become informed, debate, and form their opinions
 - This disintermediated environment can foster confusion about causation, and thus encourage speculation, rumors, and mistrust
- The authors study the determinants behind misinformation diffusion

Main Motivation/ Hypothesis

- This disintermediated social media environment can foster confusion about causation,
 - encouraging speculation, rumors, and mistrust.
- Examples of widespread misinformation:
 - In 2011 a blogger claimed that global warming was a fraud designed to diminish liberty and weaken democracy.
 - Misinformation about the Ebola epidemic has caused confusion among healthcare workers.
 - Jade Helm 15, a simple military exercise, was perceived on the Internet as the beginning of a new civil war in the United States.
- Hypothesis:
 - increasing the exposure of users to unsubstantiated rumors increases their tendency to be credulous.

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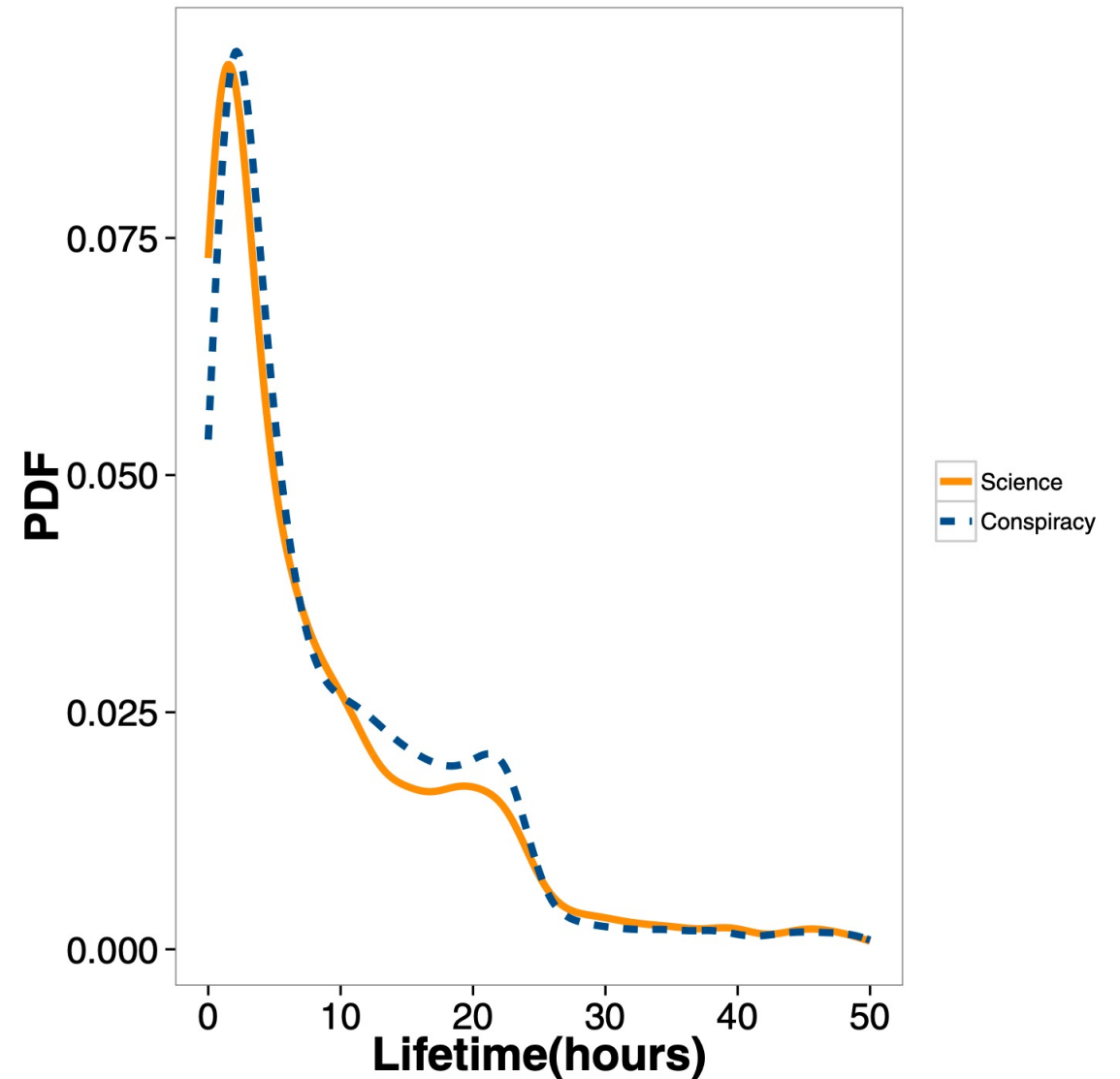
- Solutions and Discussion

Data

- Facebook dataset
 - Composed of 67 public pages
 - 32 about conspiracy theories and
 - 35 about science news.
 - A second set, composed of two troll pages, is used as a benchmark to fit our data-driven model.
 - **The first category (conspiracy theories)** includes the pages that disseminate alternative, controversial information, often lacking supporting evidence and frequently advancing conspiracy theories.
 - **The second category (science news)** includes the pages that disseminate scientific information.
 - **The third category (trolls)** includes those pages that intentionally disseminate sarcastic false information on the Web with the aim of mocking the collective credulity online.

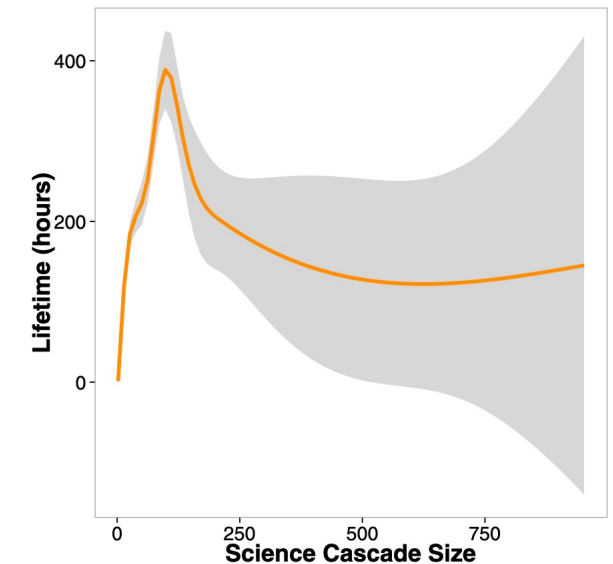
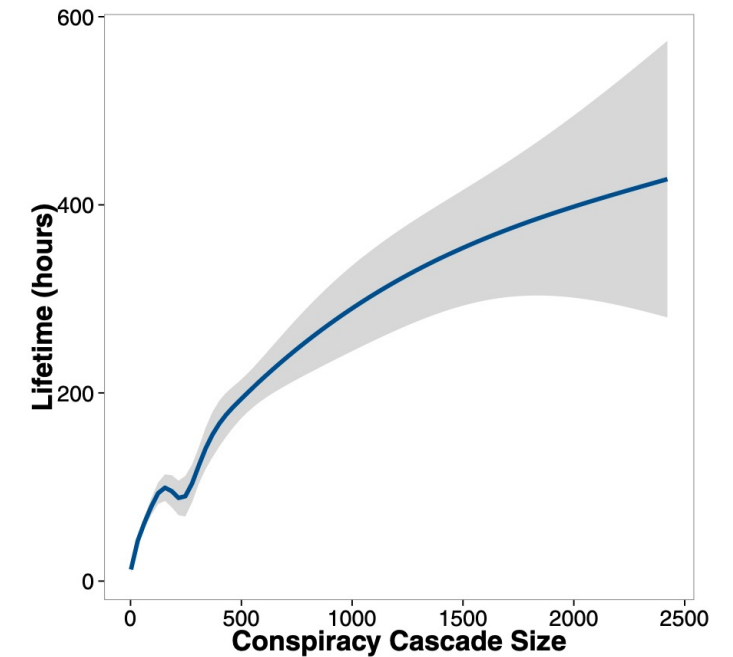
Methods (Anatomy of Cascades)

- Probability density function (PDF) of the cascade lifetime.
 - lifetime is the length of time between the first user and the last user sharing a post. In both categories:
 - a first peak at ~1–2 h and a second at ~20 h, indicating that the temporal sharing patterns are similar
 - A significant percentage of the information diffuses rapidly
 - 24.42% of the science news and 20.76% of the conspiracy rumors diffuse in less than 2 h,
 - 39.45% of science news and 40.78% of conspiracy theories in less than 5 h.
 - Only 26.82% of the diffusion of science news and 17.79% of conspiracy lasts more than 1 d



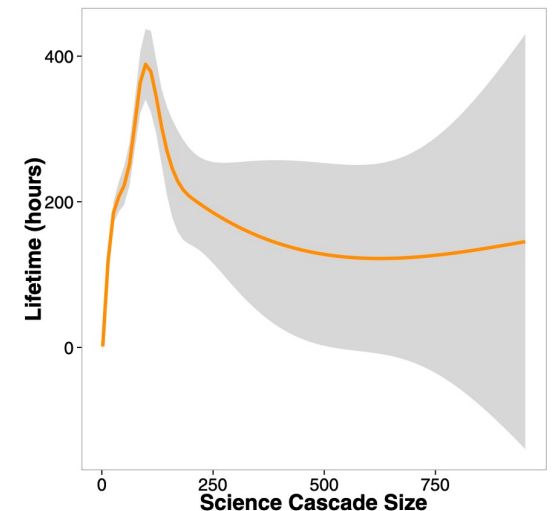
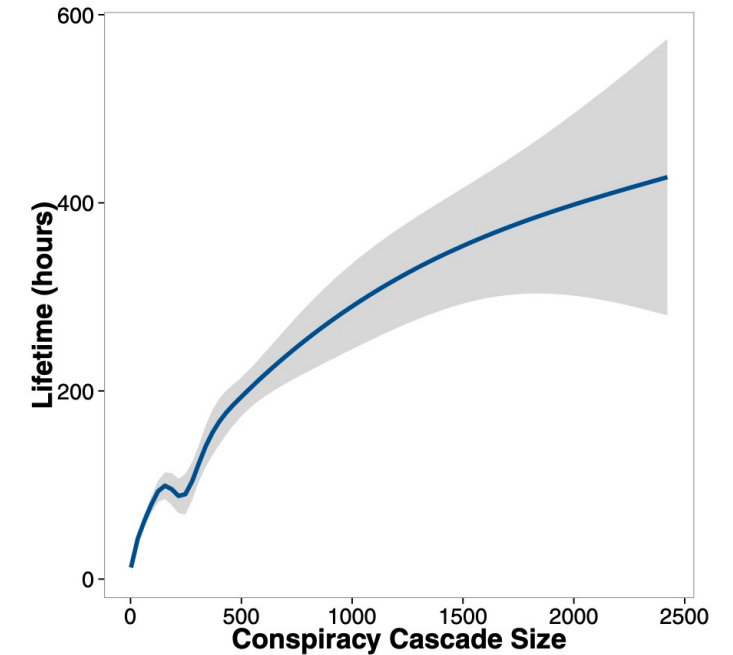
Methods (Anatomy of Cascades)

- Calculates the lifetime of news as a function of the cascade size.
 - For science news we have a peak in the lifetime corresponding to a cascade size value of ≈ 200 , and higher cascade size values correspond to high lifetime variability.
 - For conspiracy-related content the lifetime increases with cascade size



Discussion of Anatomy of Cascades

- News assimilation differs according to the categories.
 - Science news is usually assimilated, i.e., it reaches a higher level of diffusion quickly,
 - a longer lifetime does not correspond to a higher level of interest.
 - Conversely, conspiracy rumors are assimilated more slowly and show a positive relation between lifetime and size



Methods (Homogeneous Clusters)

- PDF of the mean-edge homogeneity, computed for all cascades of science news and conspiracy theories.
 - Majority of links between consecutively sharing users is homogeneous.
 - The average edge homogeneity value of the entire sharing cascade is always greater than or equal to zero,
 - either the information transmission occurs inside homogeneous clusters in which all links are homogeneous
 - or it occurs inside mixed neighborhoods in which the balance between homogeneous and nonhomogeneous links is favorable toward the homogeneous.
 - Contents tend to circulate only inside the echo chamber

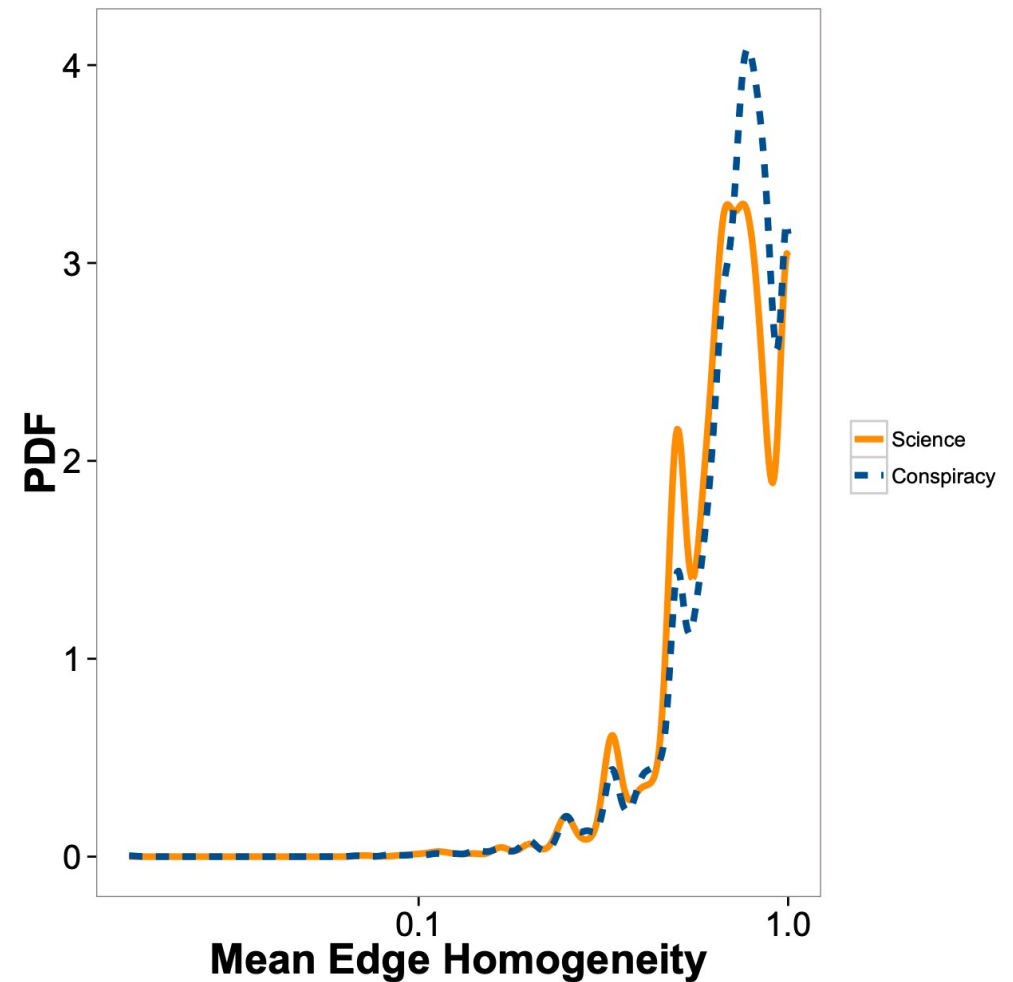


Fig. 3. PDF of edge homogeneity for science (orange) and conspiracy (blue) news. Homogeneity paths are dominant on the whole cascades for both scientific and conspiracy news.

Methods (Homogeneous Clusters)

- Compute cascade size as a function of mean-edge homogeneity for both science and conspiracy news
 - In science news, higher levels of mean-edge homogeneity in the interval (0.5, 0.8) correspond to larger cascades, but in conspiracy theories lower levels of mean-edge homogeneity (~ 0.25) correspond to larger cascades.
 - Homogeneity is clearly the driver of information diffusion. meaning, different contents generate different echo chambers, characterized by a high level of homogeneity inside them.

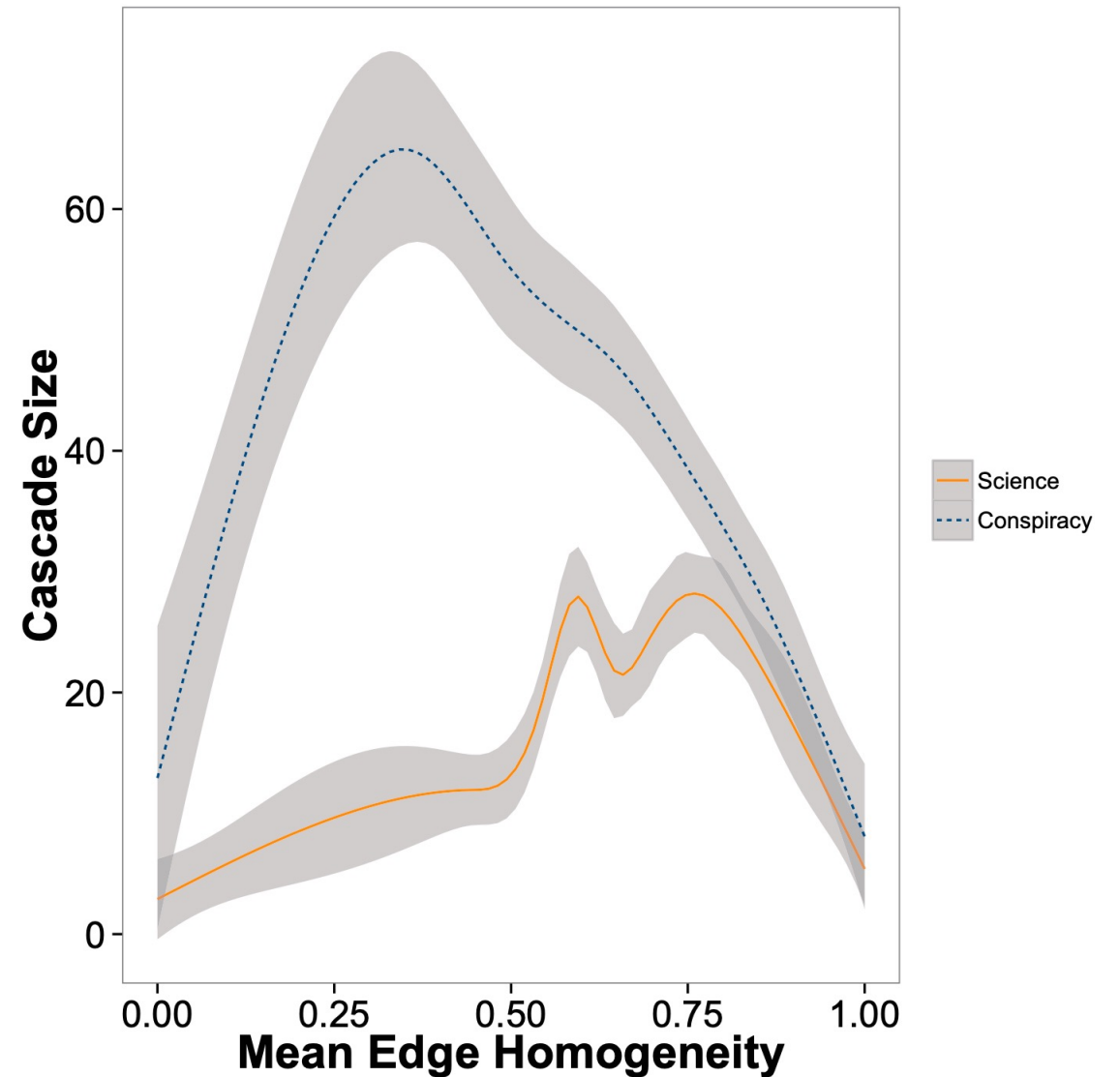


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Socio-Political effects

Echo Chamber

Political Polarization

Radicalization

Socio-Political effects

Echo Chamber

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Radicalization

Echo Chamber

- An **echo chamber** refers to situations in which beliefs are amplified or reinforced by communication and repetition inside a closed system and insulated from rebuttal.
 - People can seek out information that reinforces their existing views without encountering opposing views, potentially resulting in an unintended exercise in confirmation bias.
 - Echo chambers may increase social and political polarization and extremism



Echo Chamber Effect On Social Media

- Social media may limit the exposure to diverse perspectives and favor the formation of groups of like-minded users framing and reinforcing a shared narrative.
 - The interaction paradigms among users and feed algorithms greatly vary across social media platforms.
- This paper explores the key differences between the main social media platforms and how they are likely to influence information spreading and echo chambers' formation.
- The authors perform a comparative analysis of more than 100 million pieces of content concerning several controversial topics.
- They quantify echo chambers over social media by
 - homophily in the interaction networks and
 - bias in the information diffusion toward like-minded peers.
- Their results show that the aggregation of users in homophilic clusters dominate online interactions on Facebook and Twitter..

Echo Chamber Effect On Social Media

- Data
 - Twitter
 - Tweets posted by user i that contain links to news outlets of known political leaning.
 - Facebook
 - Users considering endorsements in the form of likes to posts.
 - Reddit
 - links to news organizations in the content produced by the users, submissions, and comments
 - Gab
 - Similar to Reddit and Twitter

- Methods
 - The network's topology can reveal echo chambers.
 - Users are surrounded by peers with similar leanings, and thus they get exposed, with a higher probability, to similar contents.

Results and Discussion

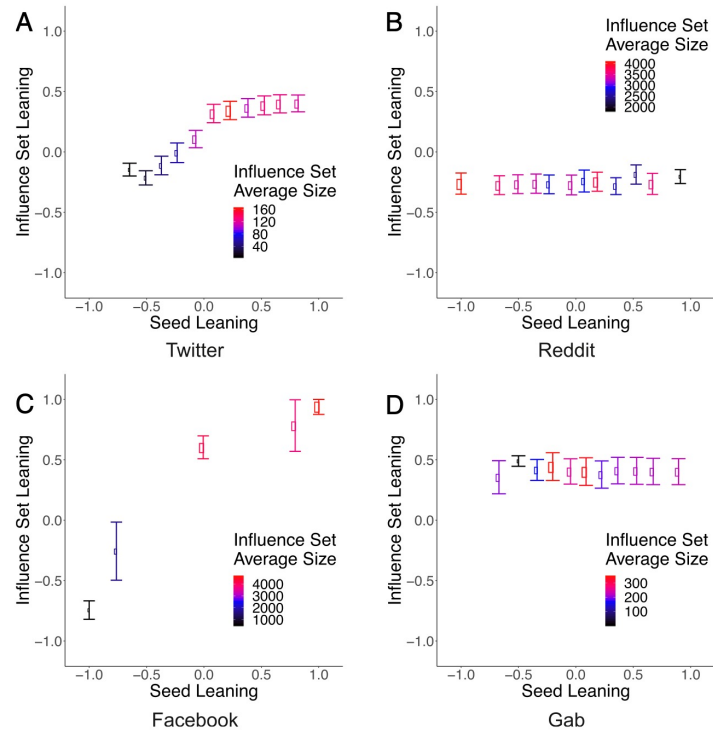


Fig. 3. Average leaning $\langle \mu(x) \rangle$ of the influence sets reached by users with leaning x , for different datasets under consideration. Size and color of each point represent the average size of the influence sets. The parameters of the SIR dynamics are set to (A) $\beta = 0.10\langle k \rangle^{-1}$, (B) $\beta = 0.01\langle k \rangle^{-1}$, (C) $\beta = 0.05\langle k \rangle^{-1}$, and (D) $\beta = 0.05\langle k \rangle^{-1}$, while ν is fixed at 0.2 for all simulations.

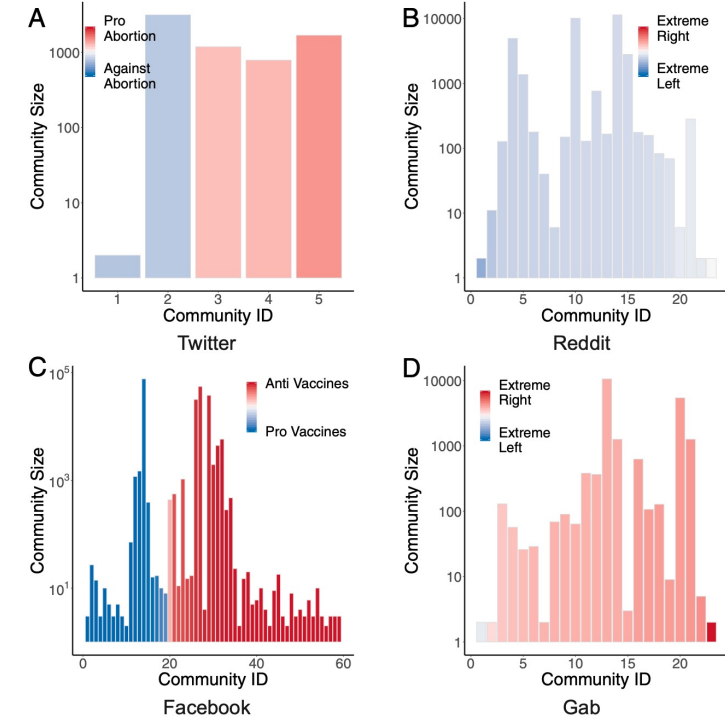


Fig. 2. Size and average leaning of communities detected in different datasets. A and C show the full spectrum of leanings related to the topics of abortions and vaccines with regard to communities in B and D, where the political leaning is less sparse.

Anatomy of news Consumption on Facebook

- Explore the anatomy of the information space on Facebook
 - The news consumption patterns of 376 million users over a time span of 6 y (January 2010 to December 2015).
- They find that users tend to focus on a limited set of pages
 - producing a sharp community structure among news outlets.
- They also find that the preferences of users and news providers differ.
 - By tracking how Facebook pages “like” each other and examining their geolocation,
 - They discover that news providers are more geographically confined than users.
- They devise a simple model of selective exposure that reproduces the observed connectivity patterns

Anatomy of news Consumption on Facebook

- Data
 - The European Media Monitor provides a list of all news sources. We limit our collection to all those pages reporting in English. The downloaded data from each page includes:
 - Posts made from January 1, 2010, to December 31, 2015,
 - the likes and comments on those posts.
 - The European Media Monitor list includes the country and the region of each news source.
 - the geographical location—latitude and longitude—of each page
- Methods
 - **Community Detection Algorithm.**
 - A community detection algorithm is used to identify groups of nodes in a network.
 - **Backbone Detection Algorithm.**
 - We use this algorithm to determine the connections that form the backbones of our networks and to produce clear visualizations.

Results and Discussion

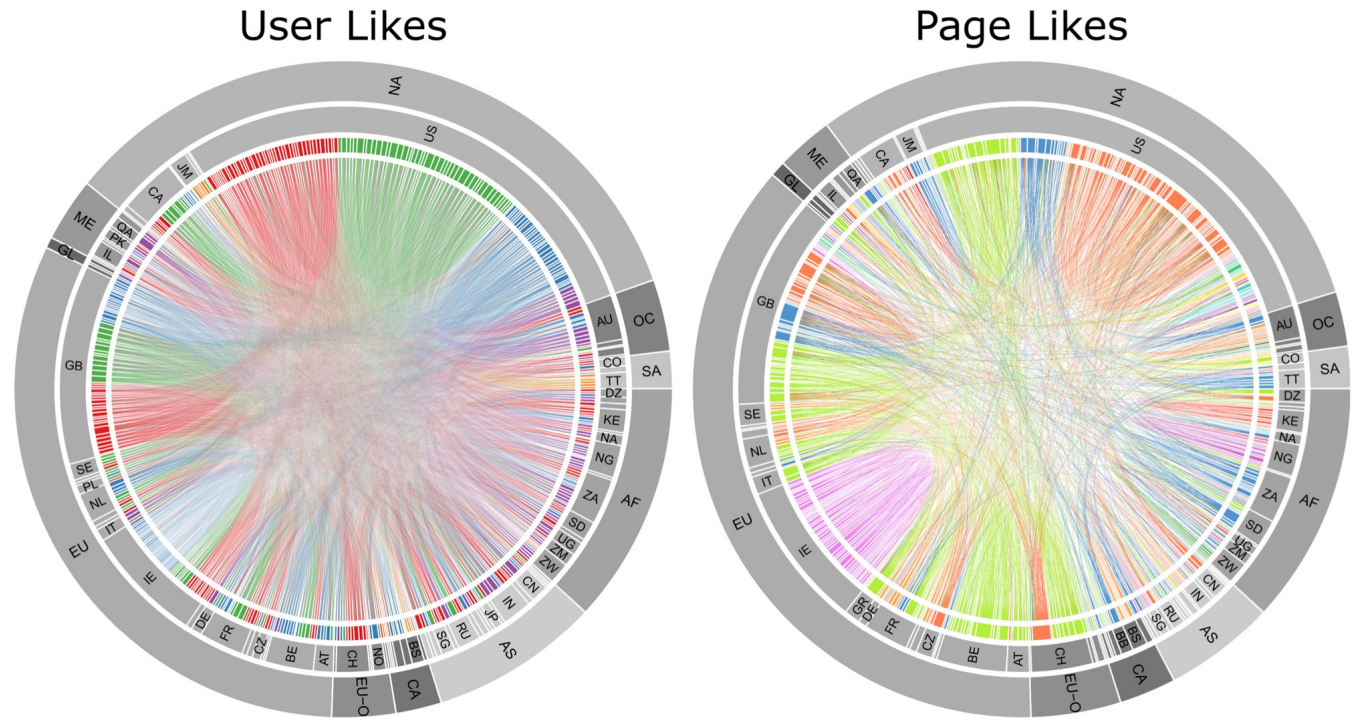


Fig. 4. Pages and users' communities and locations. Backbone of the projections on pages of the user likes reduced to the pages that appear in N_p (Left) and the network of pages liking each other (Right). Inner nodes represent the pages and their color indicates the Fast Greedy community, middle track marks the country, and outer track the region as established by the European Media Monitor. Order of the inner nodes in both plots is done by region, country, and community, in that order. AF, Africa; AS, Asia; CA, Central America; EU, European Union; EU-C, EU Candidate; EU-O, EU Other; GL, Global; ME, Middle East; NA, North America; OC, Oceania; SA, South America.

Socio-Political effects

Echo Chamber

Political Polarization

Radicalization

Radical Content Consumption on YouTube

- YouTube is arguably the largest and most engaging online media consumption platform in the world
 - concerns that YouTube users are being radicalized via a combination of biased recommendations and ostensibly apolitical “anti-woke” channels,
 - Direct attention to radical political content.
 - Here we test this hypothesis using a representative panel of more than 300,000 Americans and their individual-level browsing behavior, on and off YouTube, from January 2016 through December 2019.
- They find that news consumption on YouTube is dominated by mainstream and largely centrist sources.
 - Consumers of far-right content, while more engaged than average, represent a small and stable percentage of news consumers.
- Consumption of “anti-woke” content, defined in terms of its opposition to progressive intellectual and political agendas, grew steadily in popularity and is correlated with consumption of far-right content off-platform.
- They find no evidence that engagement with far-right content is caused by YouTube recommendations systematically, nor do we find clear evidence that anti-woke channels serve as a gateway to the far right.
 - Rather, consumption of political content on YouTube appears to reflect individual preferences that extend across the web.

Radical Content Consumption on youtube

- Data
 - Nielsen's nationally representative desktop web panel,
 - January 2016 through December 2019
 - The authors quantify the user's attention by the duration of in-focus visit to each video in total minutes .

- Methods
 - **Community Detection Algorithm.**
 - To check for any overall trends in category preferences, the authors examine changes in total consumption associated with each of the six communities over the 4-year period of their data,
 - **User Clustering.**
 - An individual is considered a news consumer if, over the course of 1 month, they spend a minimum of 1 minute watch time on any of the political channels in our labeled set

Results and Discussion

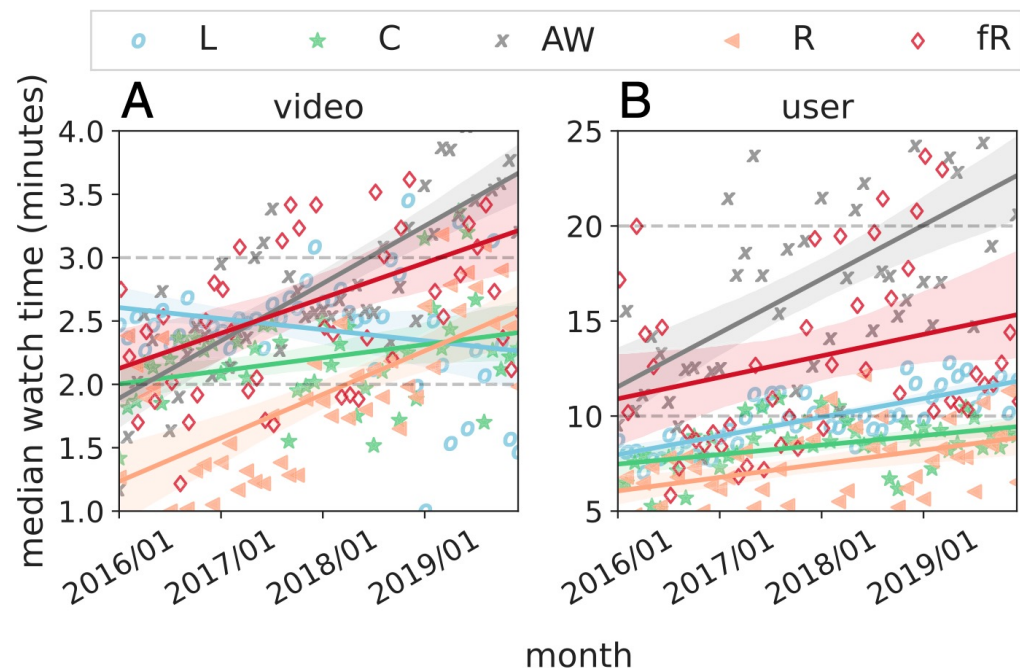


Fig. 3. (A) Median monthly video consumption (minutes) across different channel categories, and (B) median user consumption (minutes) within each community. Solid lines show the fitted linear models and the shading shows the 95% confidence intervals.

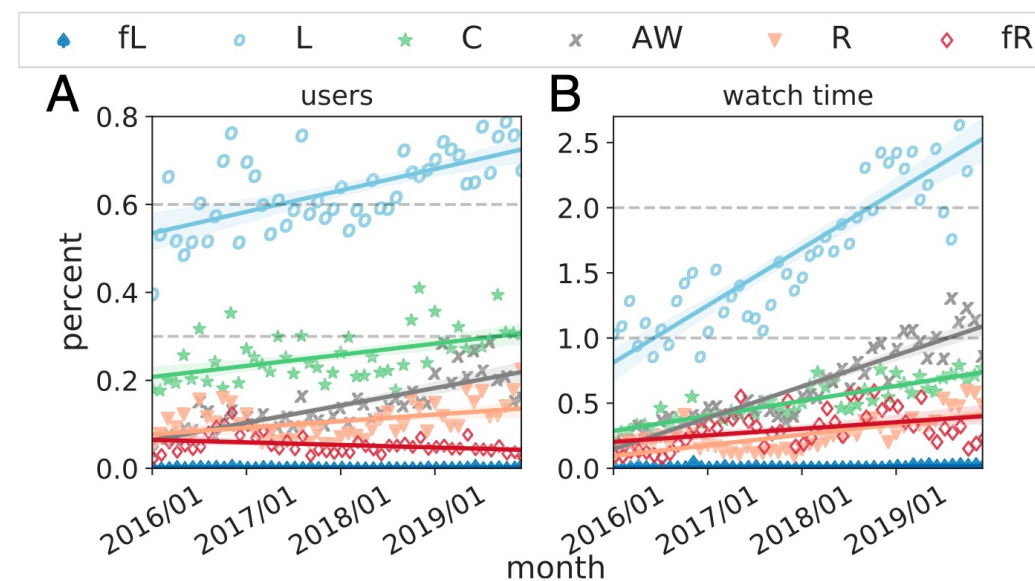


Fig. 2. Breakdown of percent of (A) users and (B) consumption falling into the six political channel categories, per month, January 2016 to December 2019. A is the percent of users falling into each community, and B presents the percentage of viewership duration from each channel category. Solid lines show the fitted linear models and the shading shows the 95% confidence intervals.

Results and Discussion

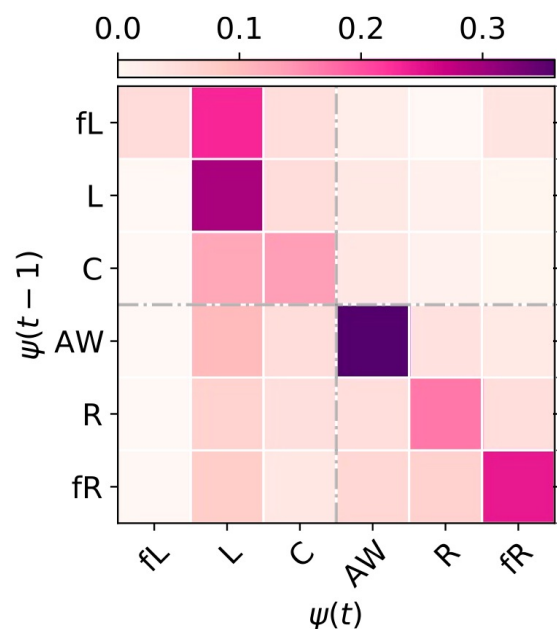


Fig. 4. A heatmap showing the probability that an individual from cluster $\psi(t-1)$ at month $t-1$ will move to cluster $\psi(t)$ at month t . Each month, users may not fall into any of these communities, if they are not among “news consumers” in that particular month.

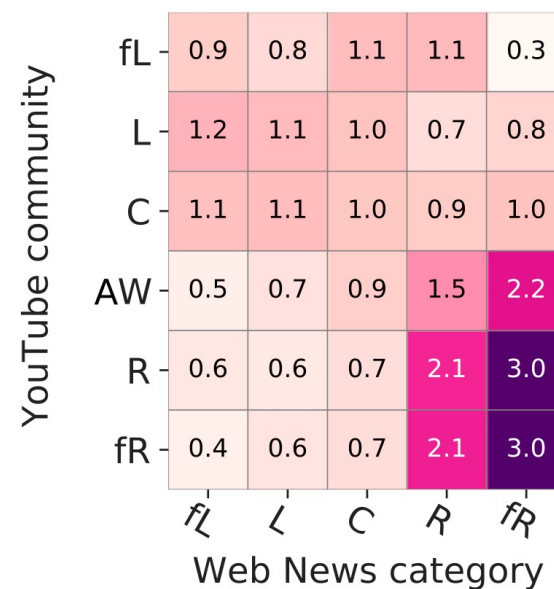


Fig. 6. Risk ratio of consumption from category j on the web ($j \in \{fL, L, C, R, fR\}$) for users inside each community $i \in \{fL, L, C, AW, R, fR\}$ on YouTube. Users of far right, right, and AW are more likely than random YouTube users to consume right and far-right content on web.

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Overall Conclusion

- Digital misinformation has become so pervasive in online social media that it has been listed by the WEF as one of the main threats to human society.
- Whether a news item, either substantiated or not, is accepted as true by a user may be strongly affected by social norms or by how much it coheres with the user's system of beliefs
- The authors provide important insights toward the understanding of the mechanism behind rumor spreading

Solutions and Discussions

Users tend to aggregate in communities of interest, which causes reinforcement and fosters confirmation bias, segregation, and polarization.

- Exploration Vs Exploitation: Requiring social media sites to show different news stories at regular intervals, so users have information outside their clusters

This comes at the expense of the quality of the information and leads to proliferation of biased narratives fomented by unsubstantiated rumors, mistrust, and paranoia.

- Accountability of new sources allowed to create and share news, and easy access to fact checking of news stories shared on social media



Thank you

Questions?

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