Right and left, partisanship predicts vulnerability to misinformation

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We analyze the relationship between partisanship, echo chambers, and vulnerability to online misinformation by studying news sharing behavior on Twitter. While our results confirm prior findings that online misinformation sharing is strongly correlated with right-leaning partisanship, we also uncover a similar, though weaker trend among left-leaning users. Because of the correlation between a user’s partisanship and their position within a partisan echo chamber, these types of influence are confounded. To disentangle their effects, we perform a regression analysis and find that vulnerability to misinformation is most strongly influenced by partisanship for both left- and right-leaning users.

Research questions

- Is exposure to more partisan news associated with increased vulnerability to misinformation?
- Are conservatives more vulnerable to misinformation than liberals?
- Are users in a structural echo chamber (highly clustered community within the online information diffusion network) more likely to share misinformation?
- Are users in a content echo chamber (where social connections are exposed to similar news) more likely to share misinformation?

Essay summary

- We investigated the relationship between political partisanship, echo chambers, and vulnerability to misinformation by analyzing news articles shared by over 15,000 Twitter accounts in June 2017.
- We quantified political partisanship based on the political valence of the news sources consumed by each user.
● We quantified the extent to which a user is in an echo chamber by two different methods: (1) the similarity of the content they shared to that of their friends, and (2) the level of clustering of users in their follower network.

● We quantified the vulnerability to misinformation based on the fraction of links a user shares from sites known to produce low-quality content.

● Our findings suggest that political partisanship, echo chambers, and vulnerability to misinformation are highly correlated. The effects of echo chambers and political partisanship on vulnerability to misinformation are confounded, but a stronger link can be established between partisanship and misinformation.

● The findings suggest that social media platforms can combat the spread of misinformation by prioritizing more diverse, less polarized content.

**Implications**

Two years since the call for a systematic “science of fake news” to study the vulnerabilities of individuals, institutions, and society to manipulation by malicious actors (Lazer et al., 2018), the response of the research community has been robust. However, the answers provided by the growing body of studies on misinformation are not simple. They paint a picture in which a complex system of ingredients — cognitive, social, and algorithmic biases, as well as abuse — interact to give rise to the patterns of misinformation spread, exposure, and impact that we observe in the information ecosystem.

Misinformation spreading is a process involving different classes of actors (information producers, consumers, and intermediaries) with different goals, incentives, capabilities, and biases (Ruths, 2019). Not only are individuals and organizations hard to model, but even if we could explain individual actions, we would not be able to easily predict collective behaviors, such as the impact of a disinformation campaign, due to the large, complex, and dynamic networks of interactions enabled by social media.

Despite the difficulties in modeling the spread of misinformation, several key findings have emerged. Regarding exposure, when one considers news articles that have been fact-checked, false reports spread more virally than real news (Vosoughi at al., 2018). Despite this, a relatively small portion of voters was exposed to misinformation during the 2016 US presidential election (Grinberg et al., 2019). This conclusion was based on the assumption that all posts by friends are equally likely to be seen. However, since social media platforms rank content based on popularity and personalization (Nikolov et al., 2018), highly-engaging false news would get higher exposure. The effect of algorithmic bias on exposure to low-quality content is a complex one (Ciampaglia et al., 2018).

Other vulnerabilities to misinformation stem from cognitive biases such as lack of reasoning (Pennycook & Rand, 2019) and preference for novel content (Vosoughi et al., 2018). Competition for our finite attention has also been shown to play a key role in content virality (Weng et al., 2012).

Misinformation spread can also be the result of manipulation. Social bots (Ferrara et al., 2016; Varol et al., 2017) can be designed to target vulnerable communities (Shao, Hui et al., 2018; Yan et al., 2020) and exploit human and algorithmic biases that favor engaging content (Ciampaglia et al., 2018; Avram et al., 2020), leading to an amplification of exposure (Shao, Ciampaglia et al., 2018).

Finally, the polarized and segregated structure of political communication in online social networks (Conover et al., 2011) implies that information spreads efficiently among people who are most vulnerable (Conover et al., 2012) and that users are shielded by diverse perspectives, including fact-checking sources (Shao, Hui et al., 2018). Models suggest that homogeneity and polarization are important factors in the spread of misinformation (Del Vicario et al., 2016).
While prior research highlighted a correlation between misinformation sharing and conservative political beliefs (Grinberg et al., 2019), we find that liberal partisans are also vulnerable. However, further work is necessary to understand the nature of the relationship between partisanship and vulnerability to misinformation. Are the two mutually reinforcing, or does one stem from the other? The answer to this question can inform how social media platforms prioritize interventions such as fact-checking of articles, reining in extremist groups spreading misinformation, and changing their algorithms to provide exposure to more diverse content on news feeds.

The present findings reinforce a view of the misinformation ecosystem as a complex network in which multiple types of actors have non-trivial cognitive biases and vulnerabilities. Online social interactions among them lead to emerging community and virality patterns that are hard to predict. And adversaries can effectively use frictionless automation to penetrate and manipulate the network while maintaining anonymity, creating a third layer of non-linear interactions. Funding agencies will have to support long-term research collaborations among cognitive, social, computer, and complex systems scientists if we are to overcome the challenges of online misinformation.

**Findings**

We want to test the hypothesis that partisanship, echo chambers, and the vulnerability to misinformation are related phenomena. We define a Twitter user’s vulnerability to misinformation by the fraction of their shared links that are from a list of low-quality sources. Consistent with past research (Grinberg et al., 2019), we observe that vulnerability to misinformation is strongly correlated with partisanship in right-leaning users. However, unlike past work, we find a similar effect for left-leaning users (Figure 1a). Overall, we observe that right-leaning users are slightly more likely to be partisan and to be vulnerable to misinformation. The great majority of users on both sides of the political spectrum have misinformation scores below 0.5, indicating that those who share misinformation also share a lot of other types of content. In addition, we observe a moderate relationship between vulnerability to misinformation and two measures that capture the extent to which a user is in an echo chamber: the similarity among sources of links shared by the user and their friends (Figure 1b) and the clustering in the user’s follower network (Figure 1c).

![Figure 1](image)

Figure 1: Relationship between misinformation and other variables. (a) Partisanship: the Pearson correlation is $r=0.65$ for left-leaning users and $r=0.69$ for right-leaning users. (b) Similarity: $r=0.33$. (c) Clustering: $r=0.31$.

In Figure 2 we show that the three independent variables we analyze (partisanship, similarity, and clustering) are actually correlated with each other. User similarity and clustering are moderately correlated, as we might expect given that they both aim to capture the notion of embeddedness within an online echo chamber. Partisanship is moderately correlated to both echo chamber quantities.
Figure 2: Relationship between independent variables. (a) Partisanship and similarity: Pearson correlation $r=0.45$ for left-leaning users and $r=0.42$ for right-leaning users. (b) Partisanship and clustering: $r=0.21$ for left-learning users and $r=0.19$ for right-leaning users. (c) Similarity and clustering: $r=0.40$.

Given these correlations, we wish to disentangle the effect of partisanship and echo chambers on vulnerability to misinformation. To this end, we conducted a regression analysis using vulnerability to misinformation as the dependent variable. The results are summarized in Table 1. We see that all independent variables except clustering for left-leaning users significantly affect the dependent variable ($p<0.01$). However, as shown by the coefficients and the adjusted increases in $R^2$, the effect is much stronger for partisanship.

| Variable | Left-leaning Users (Adjusted $R^2 = 0.43$) | Right-leaning Users (Adjusted $R^2 = 0.48$) |
|----------|------------------------------------------|-----------------------------------------------|
|          | Coefficient | $p$ | $Adj. R^2$ increase | Coefficient | $p$ | $Adj. R^2$ increase |
| Partisanship ($b_1$) | 0.451 | 0.001 | 0.3 | 0.640 | 0.001 | 0.4 |
| Similarity ($b_2$) | 0.046 | 0.001 | 0.003 | 0.031 | 0.004 | 0.001 |
| Clustering ($b_3$) | 0.032 | 0.05 | 0 | -0.095 | 0.001 | 0.002 |

Table 1: Regression coefficients, $p$-values, and adjusted $R^2$ increases quantifying the relationships between the three independent variables and vulnerability to online misinformation. Adjusted $R^2 = 0.43$.

Identifying the most vulnerable populations may help gauge the impact of misinformation on election outcomes. Grinberg et al. identified older individuals and conservatives as particularly likely to engage with fake news content, compared to both centrists and left-leaning users (Grinberg et al., 2019). These characteristics correlate with those of voters who decided the presidential election in 2016 (Pew Research Center, 2018), leaving open the possibility that misinformation may have affected the election results.

Our analysis of the correlation between misinformation sharing, political partisanship, and echo chambers paints a more nuanced picture. While right-leaning users are indeed the most likely to share
misinformation, left-leaning users are also significantly more vulnerable than moderates. In comparing these findings, one must keep in mind that the populations are different --- voters in the study by Grinberg et al. versus Twitter users in the present analysis. Causal links between political bias, motivated reasoning, exposure, sharing, and voting are yet to be fully explored.

Methods

Dataset

We collected tweets from a 10% random sample of public posts in June 2017, through the Twitter API. Since we are interested in studying the population of active online news consumers, we selected all accounts that shared at least ten links from a set of news sources with known political valence (see “Partisanship” below). To focus on users who are vulnerable to misinformation, we further selected those who shared at least one link from a source labeled as low-quality. This second condition excludes 5% of active right-leaning users and 30% of active left-leaning users. We then used the Twitter Friends API to build the follower network among the resulting set of users. Those with no friends in the network were further excluded, guaranteeing that we can compute partisanship and misinformation scores for each user and their friends.

Finally, to ensure that we are analyzing human users and not social bots, we used the BotometerLite classifier (Yang et al., 2020) to remove likely bot accounts. This resulted in the removal of a little less than 1% of the accounts in the network. The user selection process resulted in 15,070 accounts that we analyzed.

Partisanship

To define partisanship, we track the sharing of links from web domains (e.g., cnn.com) associated with news sources of known political valence. For a source of political valence, we use a dataset compiled by Facebook (Bakshy et al., 2015), which consists of 500 news organizations. By examining the Facebook page of each news organization, the political valence score was computed based on the political self-identification of the users who liked the page. The valence ranges from −1, indicating a left-leaning audience, to +1, indicating a right-leaning audience.

We define the partisanship of each user \( u \) as

\[
P_u = p(s|u)v_s,
\]

where \( p(s|u) \) is the fraction of links from source \( s \) that \( u \) shares, derived from the Twitter data, and \( v_s \) is the political valence of source \( s \). In correlation and regression calculations, we take the absolute value \(|P_u|\) for left-leaning users.

Misinformation

To define misinformation, we considered a list of low-quality sources labeled by human judges (OpenSources). Although this list is no longer maintained, it was current at the time when our data was collected. While the list provides granular labels such as “fake news,” “conspiracy,” “junk science,” and so on, the number of shared links in our dataset including labeled sources was not sufficient to capture such granularity. Therefore, we combined all labeled sources into a single misinformation category.
We extracted all links shared by each user, irrespective of whether they were from legitimate news, misinformation, or any other source. Each user $u$’s misinformation score $M_u$ is the fraction of all links they shared that were from sources labeled as misinformation.

**User Similarity**

To measure similarity between users, we construct the matrix of TF-IDF values for the user-domain matrix, with users analogous to documents (rows), and domains analogous to terms (columns). Thus, each user is represented by a vector of TF-IDF values indicating how strongly they are associated to each domain:

$$TFIDF(u, dom) = TF(u, dom) \times IDF(dom),$$

where $u$ is a user, $dom$ is a domain, $TF(u, dom)$ is the frequency with which $u$ visits $dom$, and

$$IDF(dom) = \log \frac{|\{v\}|}{|V(dom)|}$$

with $V(dom)$ being the subset of users who have visited domain $dom$, out of the set of users $U$.

To compute the similarity between two users, we take the dot product between their TF-IDF vectors. Finally, we take $S_u$ to be the average similarity between user $u$ and all of their friends. This measure quantifies how embedded a user is in their social network based on the content they and their friends share. A higher value indicates a homogeneous social network, which is one way to quantify an echo chamber.

**User Clustering**

To capture user clustering based on the followers network, we compute the clustering coefficient for each user as:

$$C_u = \frac{T(u)}{d_{in}(u)(d_{out}(u) - 1) - 2d_{out}(u)},$$

where $T(u)$ is the number of directed triangles through the user node $u$, $d_{in}(u)$ is the sum of in-degree and out-degree for $u$, and $d_{out}(u)$ is the reciprocal degree of $u$ (Fagiolo, 2007). This measure quantifies how densely interconnected a user’s social network is. A dense follower network is another way to quantify an echo chamber.

**Regression Analysis**

To compare the different factors that may contribute to a user’s misinformation score, we used multiple linear regression. Since the regression was performed for right- and left-leaning users separately, we took the absolute values of the partisanship scores. In addition, we took the z-score transform of each variable. The resulting regression equation is:

$$z_M = b_0 + b_1 z_P + b_2 z_S + b_3 z_C.$$

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