

Political Partisanship and Anti-Science Attitudes in Online Discussions about Covid-19

A. Rao, F. Morstatter, M. Hu, E. Chen, K. Burghardt, E. Ferrara, K. Lerman

Information Sciences Institute
University of Southern California

Abstract

The novel coronavirus pandemic continues to ravage communities across the US. Opinion surveys identified importance of political ideology in shaping perceptions of the pandemic and compliance with preventive measures. Here, we use social media data to study complexity of polarization. We analyze a large dataset of tweets related to the pandemic collected between January and May of 2020, and develop methods to classify the ideological alignment of users along the moderacy (hardline vs moderate), political (liberal vs conservative) and science (anti-science vs pro-science) dimensions. While polarization along the science and political dimensions are correlated, politically moderate users are more likely to be aligned with the pro-science views, and politically hardline users with anti-science views. Contrary to expectations, we do not find that polarization grows over time; instead, we see increasing activity by moderate pro-science users. We also show that anti-science conservatives tend to tweet from the Southern US, while anti-science moderates from the Western states. Our findings shed light on the multi-dimensional nature of polarization, and the feasibility of tracking polarized opinions about the pandemic across time and space through social media data.

Introduction

Effective response to a health crisis requires society to forge a consensus on many levels: scientists and doctors have to learn about the disease and quickly and accurately communicate their research findings to others; public health professionals and policy experts have to translate the research into policies and regulations for the public to follow; and people have to follow guidelines to reduce infection threat. However, the fast-moving COVID-19 pandemic has brought into sharp relief our critical vulnerabilities at all these levels. Instead of orderly consensus-building, we have seen disagreement and controversy that exacerbated the disease. Research papers are rushed through the review, with results sometimes disputed or retracted¹; policy makers give conflicting advice; scientists and many in the public disagree on

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¹<https://retractionwatch.com/retracted-coronavirus-covid-19-papers/>

many issues—from the benefits of therapeutics to the need for lockdowns and face covering. The conflicting viewpoints create conditions for polarization to color perceptions of the pandemic.

Polarization is characterized by division of a group by sharply contrasting opinions. While diverse opinions are necessary in a healthy society, political scientists have observed a phenomenon called *pernicious polarization*, where one social or cultural ideology precludes the possibility of a rational public discussion on the topic (McCoy and Rahman 2016). Surveys have identified a partisan gulf in the attitudes about COVID-19 and the costs and benefits of mitigation strategies. According to a Pew Report (Pew 2020), partisanship significantly affects perceptions of public health measures. Polarization has colored the messages of US political leaders about the pandemic (Green et al. 2020), as well as discussions of ordinary social media users (Jiang et al. 2020). Coupled with a distrust of science and institutions, polarization can have a real human cost if it leads the public to minimize the benefits face coverings or reject a vaccine when it becomes available.

Current research measures polarization as divergence of opinions along the political dimension and its effect on other opinions, for example, discussion of scientific topics (Bessi et al. 2016). However, opinions on controversial issues are often correlated (Baumann et al. 2020b): for example, those who support transgender rights also believe in marriage equality, and those who oppose lockdowns also resist universal face covering. Inspired by this idea, we capture some of the complexity of polarization by projecting opinions in a multi-dimensional space, with different axes corresponding to different semantic dimensions. Once we identify the dimensions of polarization and define how to measure them, we can study dynamics of polarization and interactions between opinions.

Our work analyzes tweets related to the COVID-19 pandemic collected between January 21, 2020 and May 01, 2020 (Chen, Lerman, and Ferrara 2020). We study polarization along three dimensions— political (liberal vs conservative) and science (pro-science vs anti-science), and moderacy (hardline vs moderate). User alignments along the science axis identifies the polarization over scientific discus-

sions related to the pandemic. A user's political identity is defined in a two dimensional space. Working in tandem with the political axis, the moderacy dimension recognizes the intensity of political standing from hardline to moderate. For the hardliners identified along moderacy dimension we leverage the political axis to identify their partisanship as Liberal or Conservative.

Leveraging a set of media sources that have been classified by nonpartisan sites along these dimensions, we identify a *seed-set* that define the poles of each dimension. These media sources include mainstream news and a large variety of other sources, such as government agencies, non-governmental organizations, crowdsourced content, and alternative medicine news and health sites. We then describe network and content based inference methods to classify users along these multiple dimensions of polarization. Inferring the polarization of users discussing COVID-19 allows us to study the relationships between polarized ideologies and their temporal and geographic distributions. We show that political and science dimensions are highly correlated and that politically hardline users are more likely to be anti-science, while politically moderate users are more often pro-science. We also identify regions of the US and timepoints where the different ideological subgroups are comparably more active and their topics of conversation.

The contributions of this work are as follows:

- We describe a framework for quantifying multi-dimensional polarization.
- We describe two novel methods to infer multi-dimensional polarization from the text of online conversations and compare their performance to state-of-the-art methods.
- We provide empirical evidence for multi-dimensional polarization in Twitter conversations about COVID-19.
- We study the relationships between these dimensions, showing that political and science dimensions are highly correlated.
- We study the geographical distribution of users with polarized opinions and identify US states with larger proportion of Twitter users along each polarized axis.

As the amount of COVID-19 information explodes, we need the ability to proactively identify emerging areas of polarization and controversy. Early identification will lead to more effective interventions to reduce polarization and also improve the efficacy of disease mitigation strategies.

Related Work

Polarization is a well-recognized issue spanning the fields of psychology (Myers and Lamm 1976; Isenberg 1986), political science (McCoy and Rahman 2016), and even physics (Sasahara et al. 2020), as well as the present context of computer science (Conover et al. 2011). The foundation of polarization starts with initial studies in psychology on group polarization (Myers and Lamm 1976; Isenberg 1986), in which opinions of a group become more extreme than initial opinions of each individual. In the present

context, this could help explain why initially moderate individuals become more entrenched in the left, right, or anti-science domains. Polarization is also explored in political science in order to explain its potential effects on government efficiency and democracy (McCoy and Rahman 2016; Somer and McCoy 2019). These results show commonly negative effects of polarization on governments, thus motivating many explorations into this field. Moreover, they distinguish political polarization—the effect of polarization on elections—from societal polarization—its effect on social connections, with extreme polarization affecting both.

While polarization has traditionally been measured using surveys (Pew 2020), in recent years researchers have instead begun to measure polarization with social media discussions (Conover et al. 2011; Bessi et al. 2016; Schmidt et al. 2017; Bail et al. 2018). Three consistent effects in social media have been observed. First, there is strong polarization in what people consume, measured directly from content or indirectly from retweets (Conover et al. 2011; Smith et al. 2013; Schmidt et al. 2017). In other words, people seem to selectively confine what they watch due to, e.g., confirmation bias (Nickerson 1998), thus exacerbating polarization. Moreover, viewing information from the other ideological side does not necessarily affect ones opinion (Bail et al. 2018). Second, polarization is seen in different fields not directly related to left-right political polarization. This includes climate science (Tyagi, Uyheng, and Carley 2020) and even opinions about the COVID-19 epidemic (Pew 2020). Our goal in this paper is to combine these separate findings to better understand how some of these polarizations, such as pro- or anti-science and left and right polarization, relate to one another.

Finally, polarization has had real-world consequences outside of elections, by shaping people's perceptions of the pandemic (Chen, Lerman, and Ferrara 2020; Green et al. 2020; Jiang et al. 2020). Recent research finds, for example, that polarization has affected the language policy makers use (Green et al. 2020), which can drive policies in different directions due to a disunited front. Moreover, sentiment towards government measures (Jiang et al. 2020) or towards medical professionals (Pew 2020), has become more polarized, further reducing the efficacy of public health measures. Our work extends on these results by exploring how polarization is more generally impacting beliefs in science, and to what degree is this correlates with partisan polarization.

Sadly polarization is not altogether unexpected. Simple models of human behavior that were inspired by psychology have been created over several years. Under the simple assumptions of social influence and selectively cutting ties with ideological opposites, echo chambers form with large disparate groups of people (Durrett et al. 2012; Baumann et al. 2020b; Sasahara et al. 2020; Baumann et al. 2020a). This is also alike to homophily, in which users might form ties with people who are similar (McPherson, Smith-Lovin, and Cook 2001). Echo chambers could then drive group polarization, and therefore drive the current social media landscape.

Our model work uniquely applies both network and text analysis to infer the degree of polarization in the network.

For text analysis, we apply a number of candidate methods inspired by previous research, such as Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2003), and hashtag bag-of-words (BOW) (Conover et al. 2011). We, however, find the best results using text embedding. Text embedding was discovered in 2013 (Mikolov et al. 2013), and was rapidly extended due to its uniquely useful features associated with both words and text (Pennington, Socher, and Manning 2014; Joulin et al. 2016). The basic nature of these methods are to embed text into a vector space such that nearby vectors represent semantically similar text. Finally, to analyze networks, we apply a Label Propagation Algorithm (LPA) proposed by Raghavan et al., 2007. This algorithm, while first applied to community detection in networks, effectively assumes homophily drives how opinions form, and therefore its performance would test to some degree how homophily drives polarization.

Our work differs from these previous methods via systematic analysis of multiple polarized dimensions in social media. We also contrast with previous work via multi-dimensional polarization of COVID-19. This provides a test of some results predicted in polarization models (Baumann et al. 2020b; Baumann et al. 2020a).

Dataset and Methods

We describe the data and methods for measuring polarization and also inferring it from text and online interactions.

Data

In this study, we use a public dataset of COVID-19 tweets (Chen, Lerman, and Ferrara 2020). This dataset comprises of 115M tweets from users across the globe, collected over a period of 101 days from January 21, 2020 to May 01, 2020. These tweets contain at least one of a predetermined set of COVID-19-related keywords (e.g., coronavirus, pandemic, Wuhan, etc.). We specifically focus on tweets from users located in the US (at state-level granularity) based on information contained in their profile and tweets. This geo-referenced dataset consists of 27M tweets posted by 2.4M users over the 101 day period.

Measuring Polarization using Domain Scores

We characterize individual opinions along three polarization dimensions. The *political* dimension, standard dimension for characterizing partisan polarization, captures the difference between *Left/liberal* and *Right/conservative* political stances for users with Hardline opinions. The *science* dimension captures an individual’s acceptance of evidence-based *Pro-Science* views or the propensity to hold *Anti-Science* views. People believing and promoting conspiracies, especially health-related and pseudo-scientific conspiracies, are often grouped in the anti-science camp. Finally, the *moderacy* dimension describes the intensity of partisanship—from *Moderate* or neutral opinions to politically *Hardline* opinions.

We begin with a set of web domains of curated information sources that were labeled along these dimensions by non-partisan organizations, such as *Media Bias-Fact*

Check (<https://mediabiasfactcheck.com/>), *Allsides* (<https://www.allsides.com/>) and *Newsguard*, which tracks coronavirus misinformation. Table 1 lists exemplar domains in each category. Domains listed under “Conspiracy” and “Questionable Sources” are mapped to our Anti-Science category. For the Moderacy axis, we consider the union of Left and Right domains as a proxy for Hardline category, while union of “Least-Biased”, “Left-Moderate” and “Right-Moderate” domains form the proxy Moderate category.

Dimension	Polarization along dimension	Domains
Science	Pro-Science (+1)	cdc.gov, who.int, the-lancet.com, mayoclinic.org, nature.com, newscientist.com ... (150+ domains)
	Anti-Science (−1)	911truth.org, althealth-works-.com, naturalcures.com, shoebat.com, prison-planet-.com ... (450+ domains)
Political	Liberal (−1)	democracynow.org, huffington-post.com, newyorker.com, occupy.com, rawstory.com, ... (300+ domains)
	Conservative (+1)	nationalreview.com, news-max.com, oann.com, theepochtimes.com, bluelifesmatter.blue ... (250+domains)
Moderacy	Moderate (+1)	ballotpedia.org, c-span.org, hbr.org, wikipedia.org, weforum.org, snopes.com, reuters.com ... (400+ domains)
	Hardline (−1)	gopusa.com, cnn.com, democracynow.org, huffington-post.com, oann.com, theepochtimes.com ... (500+ domains)

Table 1: Curated information and news domains with their polarization. Pro-Science domains are mapped to +1 along the science axis while, Anti-Science domains are mapped to −1. Along the political axis, Liberal domains are mapped to −1 while, Conservative ones are mapped to +1. On the moderacy axis, we map Hardline domains as −1 and Moderate domains as +1.

We quantify a user’s position along the dimensions of polarization by tracking the number of links to curated domains the user shares. Specifically, we extract domains shared by users in the 101 day period and filter for relevant domains present in our curated list of domains (Table 1). This gives us a set of 136K users who shared Science domains, 169K users who shared Political domains and 234K users who shared domains along the Moderacy dimension. After filtering out users who shared fewer than *three* relevant domains, this leaves us with 18.7K users who have shared domains across all three dimensions. For each user, we compute a *domain score* δ along each of the three dimensions, as the

average of mapped domain values of a dimension:

$$\delta_i = \frac{\sum D_{i,d}}{|D_{i,d}|}; \forall d \in \{\text{Science, Political, Moderacy}\}$$

where, δ_i is the domain score of $user_i$ and $D_{i,d}$ represents the set of domains shared by $user_i$ relevant to dimension d .

Figure 1 shows the distribution of domain scores across the three dimensions for users who post domains across all three dimensions of interest. The distribution are peaked at their extreme values, showing more users sharing information from Anti-Science than Pro-Science domains and more Conservative than Liberal domains.

For network level analysis, we then built a web scraper that maps domains to their respective Twitter handles. The scraper initiates a simple Google query of the form “*Domain Name Twitter Handle*”. This tool relies on the search engine to rank results based on relevance and picks out the title of the first result containing the sub-string “*|Twitter*”. This substring is of the form “*Account Name (@handle)| Twitter*” which is parsed to retrieve the domain’s corresponding handle. We manually verified the mapped domains.

The mapped Twitter handles form our seed sets for semi-supervised learning at the network level. Each dimension’s seed-set comprises key-value pairs of Twitter handles and their corresponding orientation along the dimension. Table 2 illustrates the number of seeds along each polarization axis.

Inferring Polarization

Using domain scores, we can quantify the polarization of just a small fraction (0.7%) of users in the dataset. In this section we describe how we leverage this data to infer the polarization of the remaining users in our dataset along multiple dimensions. In the results, we compare the performance of these inference methods.

We classify binned domain scores along each dimension because we find classifiers work better than regression in this dataset. In light of this fact, we bin the extreme ends of domain score distribution into two classes along each dimension as shown in Figure 1.

Label Propagation Label propagation was used in the past to label user ideology based on the ideology of accounts the user retweets (see, for example (Badawy, Ferrara, and Lerman 2018)). The idea behind label propagation is that people prefer to connect to—and retweet content posted by—others who share their opinions (Boyd, Golder, and Lotan 2010; Metaxas et al. 2015). This gives us an opportunity to leverage topological information from the retweet network to infer users propensity to orient themselves along ideological dimensions.

To this end, we build a network from 9.8M retweet interactions between 1.9M users from the geocoded Twitter dataset. In the retweet network, an edge runs from A to B if, user A retweets user B . Descriptive statistics of the retweet network are shown in Table 2. We then use a semi-supervised greedy learning algorithm to identify clusters in the retweet network.

Dim	Polarization	Seeds	Statistic	Value
Science	Pro-Science	81	Nodes	1,857,028
	Anti-Science	77	In-deg	39,149
Political	Liberal	96	Out-deg	1,450
	Conservative	99	RTs	9,788,251
Moderacy	Hardline	195	Uniq RTs	7,745,533
	Moderate	363	SCC	1,818,657

Table 2: Description of the retweet network. Number of seed handles along each polarization axis for initial node assignment in the LPA. Statistics of the network, including maximum in- and out-degree and size of the strongly connected component (SCC).

LPA proposed by (Raghavan, Albert, and Kumara 2007) is a widely-used near-linear time network community detection algorithm. This greedy learning approach starts off with an initial random label assignment and, iteratively re-assigns labels to nodes along a dimension. This reassignment eventually converges to a state of equilibrium where all nodes in the network are assigned labels which are shared by the majority of their corresponding neighbors. However, owing to arbitrary tie-breaking, a certain amount of randomness creeps into the results produced by this algorithm. Courtesy of this stochasticity, LPA tends to generate different cluster assignments (user polarization) for the same network.

Hashtag Bag of Words We extend the method used by (Conover et al. 2011) to measure user’s political ideology to additional dimensions of interest. First, we identify seed hashtags defining the extremes of each dimension of polarization and generate *vectors* of 100 hashtags that co-occur with these seeds. For the Science dimension, the two seed hashtags we picked are *#stayhome* and *#plandemic*. For the Political dimension, we identify hashtags that co-occur with the seeds *#trumpvirus* and *#chinavirus*; and for the Moderacy dimension, we find hashtags co-occurring with two moderate seeds - *#pandemic*, *#lockdown* and two hardline seeds - *#trumpvirus*, *#chinavirus*. We then, compute the dimension-wise TF-IDF transformations of corresponding vectors to generate feature vectors for each user, representative of each user’s content along a dimension over time.

However, this method suffers from a critical shortcoming: a significant number of users don’t use any of the hashtags in our seed sets. This results in empty feature vectors. Considering only users with non-zero feature vectors and domain scores along each dimension gives us 1.96K users along the Science dimension, 1.6K users along the Political dimension and 4.6K users along the Moderacy dimension.

To infer user polarization, we train a simple Logistic Regression model on the feature vector matrix with the domain scores as ground truth.

Latent Dirichlet Allocation To reduce the dimensionality of hashtag feature vectors, we use LDA (Blei, Ng, and Jordan 2003) to identify topics, or groups of hashtags, and represent users as vectors in this topic space. In contrast to

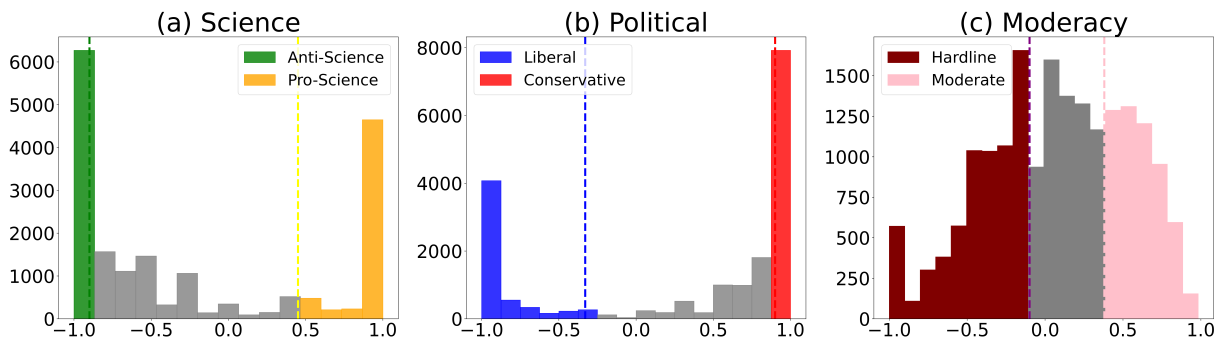


Figure 1: The distribution of domain scores along Science, Political and Moderacy dimensions. The vertical lines at 0.42 and -1 in (a), marks the top and bottom 30% cutoffs of distribution along the Science dimension which are binned as *Pro-Science*(+1) and *Anti-Science*(-1), respectively. The vertical lines at 1 and -0.33 in (b), marks the top and bottom 30% cutoffs of distribution along the Political dimension which are binned as *Conservative*(+1) and *Liberal*(-1), respectively. The vertical lines in (c) at 0.38 and -0.18 indicates the top and bottom 30% cutoffs of distribution along Moderacy dimension which are binned as *Moderate*(+1) and *Hardline*(-1), respectively.

Method	Dimension	Dataset Size	Accuracy	Precision	Recall	F1-Score
LPA	Science	158	92.6%	100%	80%	88.9%
	Political	195	92.3%	86.9%	100%	93.0%
	Moderacy	1205	20.1%	72%	1.4%	2.74%
Hashtag BOW	Science	1960	88.2%	88.9%	98.8%	93.6%
	Political	1610	72.9%	75.4%	61.1%	67.4%
	Moderacy	4684	75.1%	77.7%	90.6%	83.6%
LDA	Science	9983	92.2%	91.6%	92.4%	91.9%
	Political	11020	93.5%	95.1%	93.3%	94.2%
	Moderacy	9565	86.4%	85.6%	85.0%	85.4%
fastText	Science	11202	93.8%	93.9%	93.7%	93.8%
	Political	12425	95.1%	96.5%	94.6%	95.5%
	Moderacy	11197	90.2%	90.1%	90.5%	90.2%

Table 3: Performance of Polarization Classification. Results compare classification performance of LPA and content-based methods including Hashtag BOW, topic modeling (LDA) and full text embedding (fastText). Results are averages of 5-fold cross validation.

the hashtag BOW method, we consider *all* hashtags generated by a user as a document representing that user (after ignoring hashtags used by fewer than 10 users or more than 75% of the users)—leaving us with 25.2K hashtags. We use 20 topics, as that gives the higher coherence score.

We use the document-topic affinity matrix generated by LDA to represent users. An *affinity vector* is comprised of 20 likelihood scores, adding up to 1, with each score indicating the probability of corresponding topic being a suitable representation for the set of hashtags generated by the user. Using these affinity vectors, we generate feature vector matrices for each of the three dimensions of interest. In doing so, we can represent over 900K users who use some hashtag in their tweets with a dense vector of length 20.

Text Embedding Previous methods (see (Conover et al. 2011)) classified user’s political polarization based on the text of their tweets by generating TF-IDF weighted unigram vectors for each user. However, the advent of more powerful text-embedding techniques (Mikolov et al. 2013;

Pennington, Socher, and Manning 2014; Joulin et al. 2016) allows us to generate sentence embedding vectors to better represent content.

We group the tweets generated by each of the 2.4M users over a 101-day period from January to May 2020. More specifically, we collect all tweets generated by a user in this time period and concatenate them to form a text document for each user. After preprocessing the 2.4M documents to remove hashtags, URLs, mentions, handles and stopwords, we use fastText sentence embedding model pretrained on Twitter data, to generate tweet embeddings for each user. The *Sent2vec* Python package (Gupta, Pagliardini, and Jaggi 2019) provides us with a Python interface to quickly leverage the pretrained model and generate 700-dimension feature vectors representing each user’s discourse.

Results

First, we visualize the domain scores of the 18.7K user, showing the relationship between the Science, Moderacy

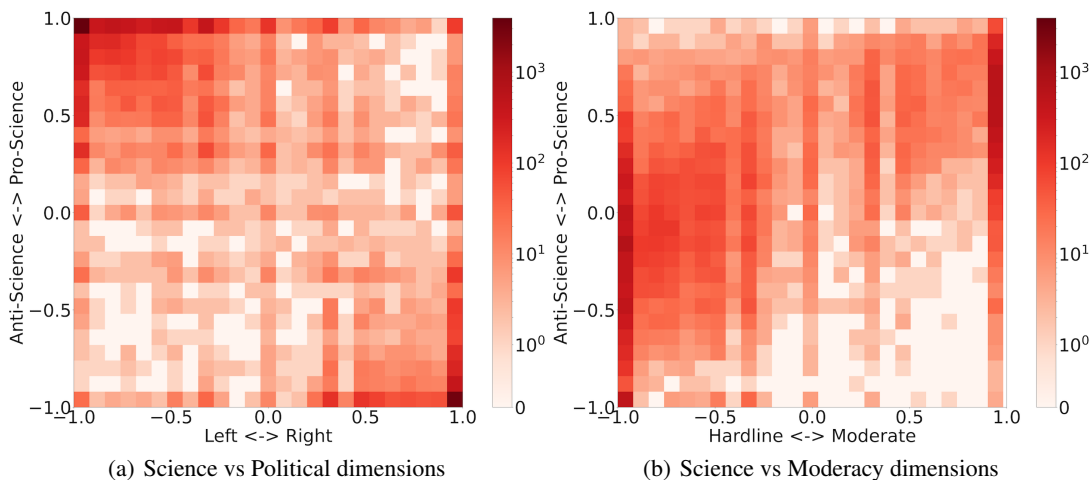


Figure 2: Polarization of COVID-19 tweets. (a) Heatmap of polarization (domain scores) along the Science–Partisanship dimensions. Each bin within the heatmap represents the number of users with domain scores falling within that bin. (b) Heatmap of polarization along the Science–Moderacy dimensions.

and Political dimensions. Then we compare the performance of algorithms for classifying users along the three dimensions of polarization, using domain scores as ground truth data. We used the inferred scores to study the dynamics and spatial distribution of polarized opinions of users engaged in online discussions about COVID-19.

Visualizing Polarization

Figure 2 shows the relationship between dimensions of polarization, leveraging domain scores of 18.7K users who shared information from curated domains. The heatmap shows the density of users with specific domain scores. Large numbers of users are aligned with Pro-Science-Left (top-left corner) or Anti-Science-Right (bottom-right corner) extremes, with lower densities along the diagonal between these extremes (Fig. 2(a)). This illustrates the strong correlation between political partisanship and scientific polarization, thereby highlighting the influence of pernicious political divisions on evidence-based discourse during the pandemic, with Conservatives being more likely to share Anti-Science information than Pro-Science sources. Figure 2(b), highlights the interplay between the Science and Moderacy axes. The white region in the bottom right corner shows there are few Anti-Science users who are politically moderate. The shading also highlights a higher density of Pro-Science users identifying as politically moderate.

Classifying Polarization

To run the LPA, we start from a set of labeled seeds—Twitter handles corresponding to domains categorized along the dimensions of interest (Tables 1 & 2). We reserve some of the seeds along each dimension for testing LPA predictions and report accuracy of 5-fold cross validation.

For content-based approaches, we used binned domain scores of 18.7K users as ground truth data to train Logistic Regression models to classify user polarization along the

three dimensions. We represented each user as a vector of features generated by different content-based approaches: hashtag frequencies for the BOW approach, topic vectors for LDA and sentence embeddings for the fastText approach. We reserved a subset of users for testing performance.

Table 3 compares the performance of polarization classification methods. LPA works best when it tries to identify user alignment along the Political and Science dimensions. However, it fails to capture the subtler distinctions along the Moderacy axis. Training is further hampered by the low number of retweet interactions with Moderate domains in comparison to Hardline ones. Of the 1.8M retweet interactions, only 250K involve some Moderate seed nodes, whereas over 1M interactions involve some Hardline seed nodes. Moreover, poor classification performance with LPA reveals an important pattern: that moderates surround themselves with diverse opinion and thus a clear distinction cannot be made by observing who they retweet.

Hashtag BOW describes users as vectors of weighted frequencies of hashtags they use. This method critically suffers from the curse of dimensionality and the lack of uniformity of usage among users. Since the dimensionality of hashtag vectors is the entire vocabulary, each vector describing a user is sparse, resulting in non-competitive performance.

LDA modeling on hashtags allows us to generate reduced-dimension, dense feature vectors for over 900K users who use hashtags in their tweets. This representation allows us to design better learning models that significantly outperform the Hashtag BOW and LPA models.

A Logistic Regression model trained on user-text embeddings and domain scores (fastText) outperforms all other models described in this study. Coupled with fastText’s ability to better handle out-of-vocabulary terms, the model’s access to finer levels of detail at tweet text, culminates in it better predicting dimensions of polarization. Given the model’s superior performance across all three dimensions, we lever-

Dimension	$\bar{\Delta}_{2,1}$	$\bar{\Delta}_{3,2}$	$\bar{\Delta}_{4,3}$	$\bar{\Delta}_{5,4}$	$\bar{\Delta}_{6,5}$	$\bar{\Delta}_{7,6}$
Political	0.09	0.05	0.03	0.02	0.03	0.02
Science	0.13	0.07	0.04	0.02	0.02	0.02
Moderacy	0.21	0.11	0.07	0.04	0.04	0.03

Table 4: Average absolute change in domain score along consecutive biweekly intervals.

age its predictions in subsequent analyses.

We classify users along the three polarization dimensions. However, since the definition of the Hardline extreme of the Moderacy dimension overlaps with the Political dimension, we need to report only six ideological groups, rather than all eight combinations.

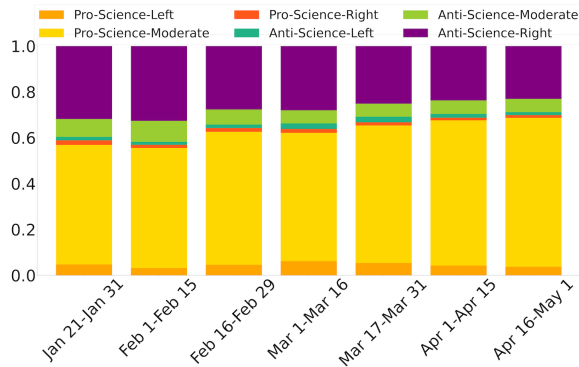


Figure 3: Fraction of active users per ideological group in bi-weekly periods.

Dynamics of Polarization

Research shows that opinions of Twitter users about controversial topics do not change over time (Smith et al. 2013). To investigate whether user alignments along the three polarization dimensions change over time, we group tweets by time into seven biweekly intervals: January 21–31, 2020; February 1–15, 2020; February 16–29, 2020; March 1–16, 2020; March 17–31, 2020; April 1–15, 2020; April 16–May 1, 2020. There are 3.0K users who tweet consistently in all the 7 biweekly intervals. For each of the N users, we compute cumulative domain scores along Science, Political and Moderacy dimensions for all time intervals t and compute the average absolute change $\bar{\Delta}_{t,t-1}$ in domain score from biweekly period $t-1$ along each dimension given by,

$$\bar{\Delta}_{t,t-1} = \frac{\sum_{i=1}^N |\delta_{i,t} - \delta_{i,t-1}|}{N}$$

where, $\delta_{i,t}$ represents the domain score for a user i in bi-weekly period t . The small values of $\bar{\Delta}_{t,t-1}$ in Table 4 confirm that user alignments do not change significantly over time.

Although individual’s alignments do not change, the number of users within each ideological group does change over time. User alignments do not change, therefore we leverage

polarization classification results to show biweekly fractions of active users per ideological category. Figure 3 shows the composition of active users in all categories. As time progresses, we can clearly see the growth in the Pro-Science-Moderate category accompanied by a corresponding decline in Anti-Science-Right users.

Topics of Polarization

To better understand what each of the six groups tweets about, we collect the 50 most frequent hashtags used by each group, after removing hashtags common to all six groups. Figure 4 shows the wordclouds of the most common hashtags within each group, sized by the frequency of their occurrence. Most striking is the use of topics related to conspiracy theories, such as *#qanon*, *#wwg1wga*, by the Anti-Science-Right group, along with politically charged references to the *#ccpvirus* and *#chinavirus*. This group also uses hashtags related to President Trump’s re-election campaign, showing the hyper-partisan nature of COVID-19 discussions. Another partisan issue appears to be *#hydroxychloroquine*, a drug promoted by President Trump. It shows up in both Pro-Science-Right and Anti-Science-Right groups, but is not discussed by other groups.

The polarized nature of the discussions can be seen in the user of the hashtags *#trumppandemic* and *#trumpvirus* by the Left and Pro-Science groups. However, in contrast to Anti-Science groups, Pro-Science groups talk about COVID-19 mitigation strategies, using hashtags such as *#stayhomesavelives*, *#staysafe* and *#flattenthecurve*.

Geography of Polarization

Responses to the coronavirus pandemic in the US have varied greatly by state. While governors of New York, California, Ohio and Washington reacted early by ordering lockdowns, governors of Florida and Mississippi have downplayed the gravity of the situation for a longer time. To explore the geographical variation in ideological alignments, we group users by the state from which they tweet and compute the fraction of their respective state’s Twitter users belonging to an ideological group. We then generate geo-plots, shown in Figure 5, to highlight the ideological composition of each state.

We see a higher composition of Pro-Science-Moderates (Figure 5(b)) in Washington, Oregon, DC, Vermont. As expected, these states have a lower fraction of Anti-Science users as can be seen from Figures 5 (d),(e) and (f). Governors of these states were quick to enforce lockdowns and spread pandemic awareness amongst the general public.

Over the course of the pandemic, we have seen the strong opposition to masking mandates and closing down of businesses in California, Nevada, Hawaii, Georgia and Texas. These anti-science sentiments are reflective in Figure 5 (e), which shows that these states have a comparatively higher proportion of their Twitter users in the Anti-Science-Moderate ideology group.

States such as South Carolina, Mississippi, Louisiana, Wyoming, Texas and Arizona have had chequered responses to the pandemic with political and religious leaders consistently downplaying the pandemic. The geo-plot is reflective

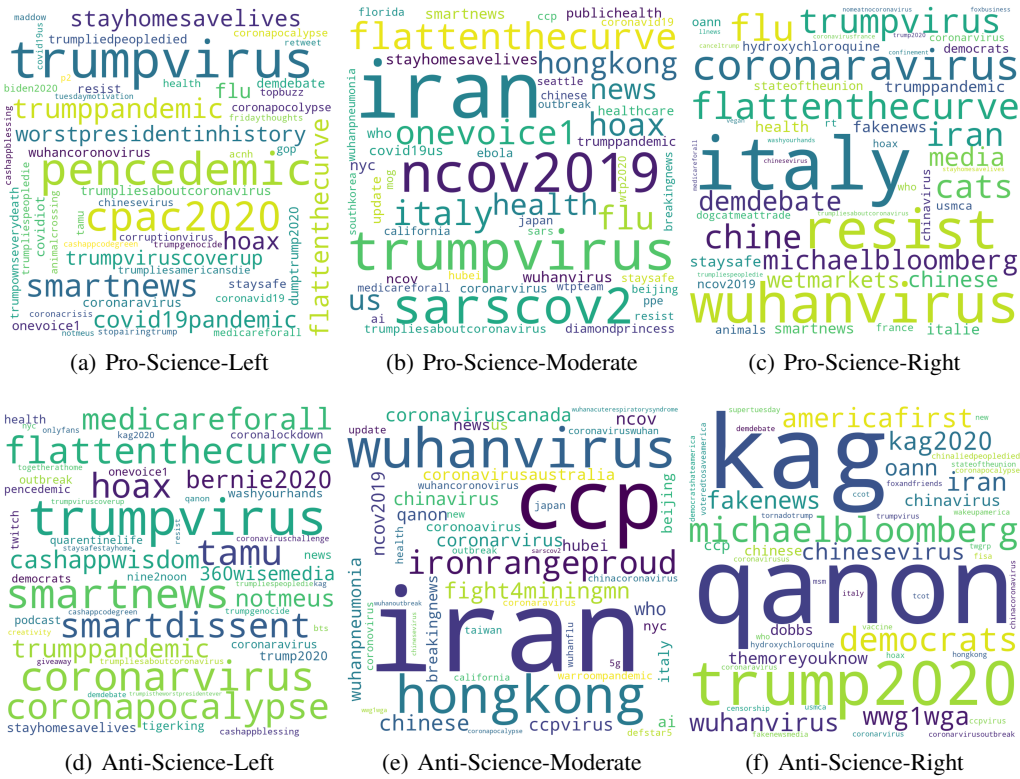


Figure 4: Topics of discussion within the six ideological groups.

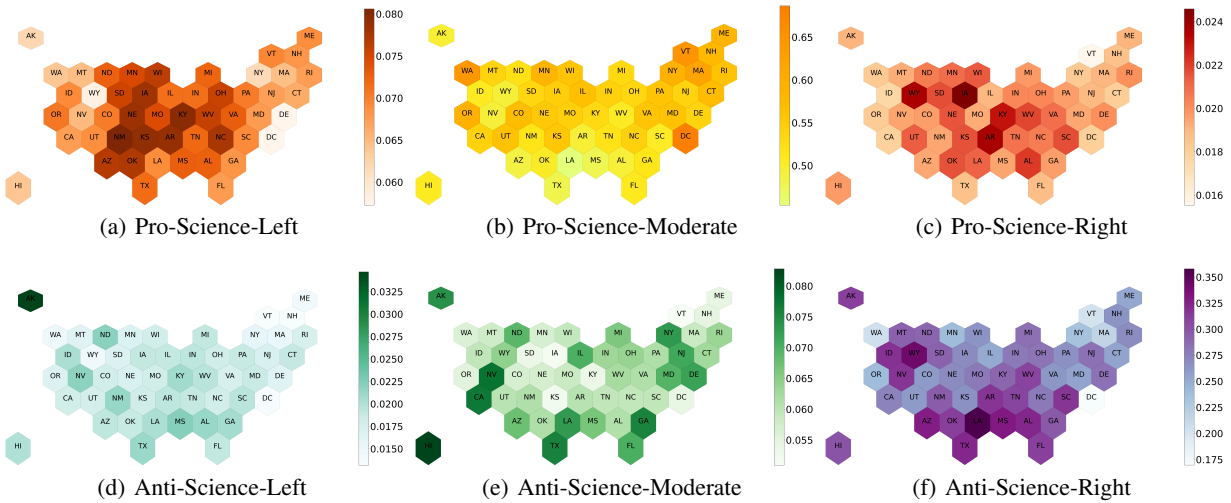


Figure 5: Fraction of state's Twitter users per ideological category. Figures (a)-(c) show the fraction of states' Twitter users who are classified as Pro-Science Left, Pro-Science Moderate and Pro-Science Right, respectively. Figures (d)-(f) show the fraction of states' Twitter users who are classified as Anti-Science Left, Anti-Science Moderate and Anti-Science Right, respectively.

of the same with these states have a higher fraction of Anti-Science hardline-right users.

Conclusion

Our analysis of a large corpus of online discussions about COVID-19 confirm the findings of opinion polls and surveys (Pew 2020): opinions about COVID-19 are strongly polarized along partisan lines. Political polarization strongly

interacts with attitudes toward science: conservatives are more likely to share conspiracy and anti-science information, while liberals and moderates are more likely to share information from pro-science sources. On the positive side, we find that the number of pro-science, politically moderate users dwarfs other ideological groups, especially anti-science groups. This is reassuring from the public health point of view, suggesting that a plurality of people are ready to accept scientific evidence and trust scientists to lead the way out of the pandemic. The geographical analysis of polarization identifies regions of the country, particularly in the South and the West where anti-science attitudes are more common. Messaging strategies should be tailored in these regions to communicate with science skeptics.

A larger issue of polarization is that it creates societal-scale vulnerabilities by amplifying distrust of authorities and making it easier for malicious actors to influence public opinion through concentrated digital misinformation campaigns (Thorp 2020; Ferrara 2020). Amplifying the negative opinions about face coverings or vaccines within even a fraction of the population could create a cascade of adverse effects. Once polarization gets a life of its own it can lead to political instability, paralysis, and at worst democratic erosion (Conover et al. 2011; McCoy and Rahman 2016). If societal trust is weakened, cynicism towards politics intensifies and confidence in public institutions wanes (McCoy and Rahman 2016). Because we find a slow-but-steady increase in moderate users, we believe that ongoing efforts to inform the public could be benefiting user behavior online.

Although we show good performance on classifying polarized opinions, additional work is required to infer finer-grained opinions. Namely, by predicting fine-grain polarization among users, we could better infer, for example, network effects such as whether users prefer to interact with more polarized neighbors. Moreover, longer-term trends need to be explored in order to better understand how opinions change dynamically. This will better test whether social influence or selective formations of ties are the drivers of echo chambers and polarization. Finally, we want to explore polarization across countries to understand how different societies and governments are able to address polarization and how these polarized dimensions relate to one another across the world.

References

- [Badawy, Ferrara, and Lerman 2018] Badawy, A.; Ferrara, E.; and Lerman, K. 2018. Analyzing the digital traces of political manipulation: The 2016 russian interference twitter campaign. In *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, 258–265. IEEE.
- [Bail et al. 2018] Bail, C. A.; Argyle, L. P.; Brown, T. W.; Bumpus, J. P.; Chen, H.; Hunzaker, M. B. F.; Lee, J.; Mann, M.; Merhout, F.; and Volfovsky, A. 2018. Exposure to opposing views on social media can increase political polarization. *Proceedings of the National Academy of Sciences* 115(37):9216–9221.
- [Baumann et al. 2020a] Baumann, F.; Lorenz-Spreen, P.; Sokolov, I. M.; and Starnini, M. 2020a. Emergence of polarized ideological opinions in multidimensional topic spaces. *arXiv preprint arXiv:2007.00601*.
- [Baumann et al. 2020b] Baumann, F.; Lorenz-Spreen, P.; Sokolov, I. M.; and Starnini, M. 2020b. Modeling echo chambers and polarization dynamics in social networks. *Physical Review Letters* 124(4):048301.
- [Bessi et al. 2016] Bessi, A.; Zollo, F.; Del Vicario, M.; Puliga, M.; Scala, A.; Caldarelli, G.; Uzzi, B.; and Quattrociocchi, W. 2016. Users polarization on facebook and youtube. *PloS one* 11(8):e0159641.
- [Blei, Ng, and Jordan 2003] Blei, D. M.; Ng, A. Y.; and Jordan, M. I. 2003. Latent dirichlet allocation. *Journal of machine Learning research* 3(Jan):993–1022.
- [Boyd, Golder, and Lotan 2010] Boyd, D.; Golder, S.; and Lotan, G. 2010. Tweet, tweet, retweet: Conversational aspects of retweeting on twitter. In *2010 43rd Hawaii international conference on system sciences*, 1–10. IEEE.
- [Chen, Lerman, and Ferrara 2020] Chen, E.; Lerman, K.; and Ferrara, E. 2020. Tracking social media discourse about the covid-19 pandemic: Development of a public coronavirus twitter data set. *JMIR Public Health and Surveillance* 6(2):e19273.
- [Conover et al. 2011] Conover, M. D.; Ratkiewicz, J.; Francisco, M.; Gonçalves, B.; Menczer, F.; and Flammini, A. 2011. Political polarization on twitter. In *Fifth international AAAI conference on weblogs and social media*.
- [Durrett et al. 2012] Durrett, R.; Gleeson, J. P.; Lloyd, A. L.; Mucha, P. J.; Shi, F.; Sivakoff, D.; Socolar, J. E. S.; and Varghese, C. 2012. Graph fission in an evolving voter model. *Proceedings of the National Academy of Sciences* 109(10):3682–3687.
- [Ferrara 2020] Ferrara, E. 2020. What types of covid-19 conspiracies are populated by twitter bots? *First Monday* 25(6).
- [Green et al. 2020] Green, J.; Edgerton, J.; Naftel, D.; Shoub, K.; and Cranmer, S. J. 2020. Elusive consensus: Polarization in elite communication on the covid-19 pandemic. *Science Advances* 6(28):eabc2717.
- [Gupta, Pagliardini, and Jaggi 2019] Gupta, P.; Pagliardini, M.; and Jaggi, M. 2019. Better word embeddings by disentangling contextual n-gram information. In *NAACL-HLT (1)*, 933–939. Association for Computational Linguistics.
- [Isenberg 1986] Isenberg, D. J. 1986. Group polarization: A critical review and meta-analysis. *Journal of personality and social psychology* 50(1141).
- [Jiang et al. 2020] Jiang, J.; Chen, E.; Lerman, K.; and Ferrara, E. 2020. Political polarization drives online conversations about covid-19 in the united states. *Human Behavior and Emerging Technologies*.
- [Joulin et al. 2016] Joulin, A.; Grave, E.; Bojanowski, P.; and Mikolov, T. 2016. Bag of tricks for efficient text classification. *arXiv preprint arXiv:1607.01759*.
- [McCoy and Rahman 2016] McCoy, J., and Rahman, T. 2016. Polarized democracies in comparative perspective:

- Toward a conceptual framework. In *International Political Science Association Conference, Poznan, Poland, July*, volume 26.
- [McPherson, Smith-Lovin, and Cook 2001] McPherson, M.; Smith-Lovin, L.; and Cook, J. M. 2001. Birds of a feather: Homophily in social networks. *Annual Review of Sociology* 27(1):415–444.
- [Metaxas et al. 2015] Metaxas, P. T.; Mustafaraj, E.; Wong, K.; Zeng, L.; O’Keefe, M.; and Finn, S. 2015. What do retweets indicate? results from user survey and meta-review of research. In *ICWSM*, 658–661. Citeseer.
- [Mikolov et al. 2013] Mikolov, T.; Chen, K.; Corrado, G.; and Dean, J. 2013. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.
- [Myers and Lamm 1976] Myers, D. G., and Lamm, H. 1976. The group polarization phenomenon. *Psychological bulletin* 83(6):602–627.
- [Nickerson 1998] Nickerson, R. S. 1998. Confirmation bias: A ubiquitous phenomenon in many guises. *Review of General Psychology* 2:175–220.
- [Pennington, Socher, and Manning 2014] Pennington, J.; Socher, R.; and Manning, C. D. 2014. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, 1532–1543.
- [Pew 2020] Pew. 2020. Partisan differences over the pandemic response are growing.
- [Raghavan, Albert, and Kumara 2007] Raghavan, U. N.; Albert, R.; and Kumara, S. 2007. Near linear time algorithm to detect community structures in large-scale networks. *Phys. Rev. E* 76:036106.
- [Sasahara et al. 2020] Sasahara, K.; Chen, W.; Peng, H.; Ciampaglia, G. L.; Flammini, A.; and Menczer, F. 2020. Social influence and unfollowing accelerate the emergence of echo chambers. *Journal of Computational Social Science*.
- [Schmidt et al. 2017] Schmidt, A. L.; Zollo, F.; Del Vicario, M.; Bessi, A.; Scala, A.; Caldarelli, G.; Stanley, H. E.; and Quattrociocchi, W. 2017. Anatomy of news consumption on facebook. *Proceedings of the National Academy of Sciences* 114(12):3035–3039.
- [Smith et al. 2013] Smith, L. M.; Zhu, L.; Lerman, K.; and Kozareva, Z. 2013. The role of social media in the discussion of controversial topics. In *2013 International Conference on Social Computing*, 236–243. IEEE.
- [Somer and McCoy 2019] Somer, M., and McCoy, J. 2019. Transformations through polarizations and global threats to democracy.
- [Thorp 2020] Thorp, H. H. 2020. Persuasive words are not enough. *Science* 368(6498):1405–1405.
- [Tyagi, Uyheng, and Carley 2020] Tyagi, A.; Uyheng, J.; and Carley, K. M. 2020. Affective polarization in on-line climate change discourse on twitter. *arXiv preprint arXiv:2008.13051*.