Online Partisan Polarization of COVID-19

blind submission

***Abstract*—In today's age of (mis)information, many people utilize various social media platforms in an attempt to shape public opinion on several important issues, including elections and the COVID-19 pandemic. These two topics have recently become intertwined given the importance of complying with public health measures related to COVID-19 and politicians' management of the pandemic. Motivated by this, we study the partisan polarization of COVID-19 discussions on social media. We propose and utilize a novel measure of partisan polarization to analyze more than 380 million posts from Twitter and Parler around the 2020 US presidential election. We find strong correlation between peaks in polarization and polarizing events, such as the January 6th Capitol Hill riot. We further classify each post into key COVID-19 issues of lockdown, masks, vaccines, as well as miscellaneous, to investigate both the volume and polarization on these topics and how they vary through time. Parler includes more negative discussions around lockdown and masks, as expected, but not much around vaccines. We also observe more balanced discussions on Twitter and a general disconnect between the discussions on Parler and Twitter.**

INTRODUCTION

On January 30th 2020, the World Health Organization director-general announced that COVID-19 represents a Public Health Emergency of International Concern and began encouraging countries to enforce preventative measures aimed at reducing further spread of the virus [1]. However, regulatory responses varied across different countries and even across regions within the same country, ranging from mandatory masks to complete lockdowns. These worldwide circumstances have brought many people to shape and express through social media platforms their views on how their government handles the situation [2]. Therefore, it is paramount to study and monitor online discussions around COVID-19 to enable policy makers to make more informed decisions.

Motivated by this and the known vulnerability of these platforms in spreading misinformation, many recent works have focused on detecting fake content related to COVID-19, e.g. [3], [4], [5], [6], [7], [8]. However, it has been recently shown that one of the primary psychological motivation behind sharing fake news is partisan polarization [9], [10]. Polarization also influences attitudes about the pandemic, and citizens' reactions to COVID-19 preventive measures [11]. There has been recent debate over whether social media platforms have an amplifying nature in regards to partisan polarization. The first step to investigate this hypothesis and to understand the role that social media played in this highly politicized pandemic is to measure partisan polarization on these platforms. This is the main objective of this paper.

More specifically, we focus on two main social media platforms, Twitter and Parler, to estimate partisan polarization of COVID-19 around the 2020 US presidential election. We collect over 287 million tweets from Twitter and 7 million posts from Parler, which span from before the election to days after the January 6th Capitol Hill riot. We next classify the users by their partisanship based on their profiles, with an average accuracy of 90%. We then investigate how polarized were their COVID-19-related posts—i.e., how divided were the discussions on COVID-19 between partisan groups. To measure the partisan polarization, we embed all the users based on their posts (on different issues) into a content space, using a language model, and then measure the dispersion of the two partisan groups in this embedded content space. In particular, we consider three main issues: [enforcing] lockdown, [wearing] masks, and vaccines, as well as anything else COVID-19 related. We show that the peaks in observed polarization are correlated with major political events, COVID-19-related announcements and/or viral misinformation campaigns. We further divide each topic/issue into three subcategories based on negative, positive and neutral sentiments. A negative sentiment indicates mostly sceptical views, for example advocating support for the mask off movement or claiming that COVID-19 is a hoax. This allows us to take a closer look into the overall discussion trends across these platforms. To summarize, the main contributions of this paper are threefold:

- Proposing a new methodology, including a novel measure, to study partisan polarization on social media based on the content of user posts.
- Introducing carefully curated datasets, including a labeled dataset for party prediction of users, and a comprehensive COVID-19 taxonomy for topic and sentiment classification of posts. These datasets will be released with the camera ready version of our analysis.
- Conducting a large scale longitudinal study which results in new findings around the partisan polarization of discussions related to COVID-19 on two main social media platforms around the 2020 US election. The two main highlights of our key findings are that **COVID-19 partisan polarization**:
  - **Peaks around major political events**: these include Election Day, when the election votes arrive in Congress and the Capitol Hill Riot.
  - **Peaks with a particular polarizing content**: the most polarizing moments on all three topics studied can be traced back to a viral polarizing post, often from now suspended users and containing misinformation.

These findings could help in improving the overall health of social media platforms, e.g. developing methods to detect and deamplify users (or posts) that tend to contribute significantly to partisan polarization.

RELATED WORKS

Below we briefly review the literature related to partisanship and online social media activities. This includes mainly studies on fake news detection and work focused on measuring polarization. We complete this section by elaborating on a few selected studies specific to COVID-19, misinformation, and its relationship with online polarization.

A large body of work focuses on detecting fake news [4], misinformation [3], [5], [6], [7], [8], or disinformation [12], [13] in social media platforms. These studies provide valuable tools to flag problematic content, while showing that this complex problem comes with many different approaches. In this work, we apply a classification tool, and show real-world settings have substantial challenges typical academic evaluations may not capture.

Closely related to this, several studies have investigated fake news around the *COVID-19 pandemic* on social media [14], [15]. For example, [16] investigates how Canadians and Americans users are exposed and engaged with COVID-19-related misleading information and confirm that exposure to US based fake news can be correlated with a higher propagation of misinformation. [17] also investigates misinformation on COVID-19. It demonstrates that fully false claims tends to be spread faster than partially false ones and that misinformation tends to manifest itself through the discrediting of other information on social media. Our work here is connected to misinformation, especially in the negative topics we analyze (where a significant part of the discussion is based on false information). But we examine discussion more broadly, such as anti-science narratives that are not outright linked to misinformation content, and positive and neutral narratives. We also go beyond measuring engagement with negative narratives and measure one of its products, partisan polarization.

Relatively fewer studies focus on analyzing the *overall health of online platforms*, e.g. how polarized are the discussions [18], [19], [20]. These studies generally adopt one of the three broad lines of models to analyze *partisan polarization* on social media platforms. The first type focuses on identifying partisan divisions by analyzing the text of online messages, either with dictionaries or word embedding [20], [21], [22]. The second approach studies online polarization from the network of users by looking at who follows who and their interactions on social media sites like Twitter [23], [24], [25]. Finally, a third type of model combines the text or network approach with a dynamic measure of polarization to investigate how polarization may have increased or decreased over time [26], [18], [20], [22].

In particular, [22] employs the text features of social media messages to build a dynamic measure of polarization over time. The authors trained a random forest machine learning algorithm to measure the level of elite polarization on Twitter during the 116$^{\text{th}}$ Congress. Their results confirm that there was a surge in the level of polarization on COVID-19 related tweets, with Republicans becoming more distinctive in their behavior than Democrats in the early months of 2020. Likewise, [27] found that Democrat politicians tended to frame the issue of COVID-19 as a public health problem, while Republicans focused more on the economic consequences of the lockdown measures. By using users' geolocations and hashtags clustering, [28] demonstrates that COVID-19 has polarized political attitudes along partisan lines on Twitter. Users from liberal states were more likely to be critical of their government, while users from conservative states used more supportive hashtags about President Trump. Most of the previous studies presented above analyzed polarization with a smaller size dataset than what we use here. Our goal is to advance this research area by examining the online behavior of both politician s and the general public, first by analyzing the general discussion on COVID-19, and second by zooming in on several topics considered to be key policy issues during the pandemic: lockdowns, masks, and vaccines.

METHODOLOGY

Here, we first explain our data collection process, then present our approach to classify posts by topics and sentiment as well as infer the partisan alignment of users. Finally, we explain how we represent the content posted by users, and how we measure the polarization from these representations.

TABLE I: Statistics on the three collected datasets.

Dataset	Source	Start	End	Posts	Users
Politicians	Twitter	2020-08-01	2021-01-17	359,811	995
Public	Twitter	2020-10-09	2021-01-04	387,090,097	23,758,112
Parler	Parler	2019-01-01	2021-01-08	7,683,252	566,486

Data Collection

We curated three separate datasets for this study, which are explained below.

Politicians: We collected all tweets, retweets and replies from 995 twitter accounts which are the public and personal Twitter accounts of US House Representatives (433), Senators (99), as well as Vice Presidential and Presidential candidates (8), using Twitter's Search API. This list of twitter handles was manually crafted by our political scientists and will be released.

Parler: We parsed all posts provided by the Distributed Denial of Secrets[1] and WayBack Machine.[2] We note that posts parsed have an estimated creation date since the data provided contain relative timestamps such as "1 day ago" or "1 week ago." This noise can be transferred to results we report on Parler, but we assume that it is not significant. There also exist many gaps in this data, which also appear as breaks in the subsequent plots.

Public: To sample political discussions, we collected around 1% of real-time tweets using Twitter's streaming API which included one of the following keywords related to the US election: 'JoeBiden,' 'DonaldTrump,' 'Biden,' 'Trump,' 'vote,' 'election,' '2020Elections,' 'Elections2020,' 'PresidentElectJoe,' 'MAGA,' 'BidenHaris2020,' 'Election2020.'

[1]https://ddosecrets.com/wiki/Parler

[2]https://web.archive.org/web/*/https://parler.com

TABLE II: Total Classified Posts for each Topic and Total Users in each Party. For topics, the percentage in the parentheses indicates proportion of the overall posts, e.g. 4,163 posts from classified users in our Politician datasets are about Vaccine, which corresponds to 1.16% of total posts from our Politicians. For party affiliation, the percentage corresponds to accuracy, e.g. we classified 1,174 users as Republicans in our Politicians dataset, with 97.7% accuracy.

Dataset	COVID-19 Content Classification					User Classification	
	Lockdown	Mask	Vaccine	Misc.	COVID (all)	Republican	Democrat
Politicians	1,473 (0.41%)	6,381 (1.77%)	4,163 (1.16%)	46,807 (13.01%)	58,824 (16.35%)	1,174 (97.7%)	1,068 (96.8%)
Public	116,574 (0.03%)	264,429 (0.07%)	403,066 (0.10%)	2,241,691 (0.58%)	3,025,760 (0.78%)	344,364 (87.0%)	369,509 (90.5%)
Parler	3,675 (0.05%)	5,248 (0.07%)	1,563 (0.02%)	13,709 (0.18%)	7,683,252 (0.31%)	31,966 (93.1%)	808 (82.9%)

Table I provides the time range and volume (number of users and posts) in each of these datasets. To analyze partisan polarization around COVID-19, we proceed to find the party affiliation of users and extract COVID-19-related posts from these political datasets. These two tasks are explained in the following sections.

Classifying Users: Partisan Alignment

We determine a user's party affiliation as *Republican* or *Democrat* based on their user profile description. First, we flag users as *Republican* when their profile description includes at least one the following keywords: 'conservative,' 'gop,' 'republican,' 'trump,' and *Democrat* with these keywords: 'liberal,' 'progressive,' 'democrat,' 'biden.' Users that do not explicitly use any of these keywords in their profile were considered to be *unknown*. Next, we randomly sampled 1000 flagged-*Republican* and 1000 flagged-*Democrat* users from the Public dataset and 200 flagged-*Republican* and 500 flagged-*Democrat* from the Parler dataset. Political scientists on our team hand labeled these sampled users as either *Republican* or *Democrat*. Using this hand-labeled data, we then fine-tuned a RoBERTa-large [29] model to predict the party each user is closest to from their profile description, using a 75-25 train-test split. For the Politicians dataset, we use the politician's party affiliation as their partisan alignment. Our predictions shown in Table II are highly accurate. Democrats on Parler are particularly challenging to properly classify because of the overwhelming amount of Republican users compared to the Democrat users, but even there we achieve a 82.9% accuracy.

Classifying Posts: Sentiment & Topic

We classify posts into four main topics: "Lockdown," "Mask," "Vaccine" and "Miscellaneous" (anything else), as well as three sentiments: neutral, negative and positive. Sentiments indicate if the post includes misinformation, e.g. anti-vaccine rhetoric is classified as negative. This results in a taxonomy with 12 categories (4 topics $\times$ 3 sentiments). For this classification, our political scientist experts manually classified 18k+ popular hashtags from our datasets as well as keywords previously classified from the related works. The full list of keywords is provided in Table IV.

More specifically, a post is positive if it has at least one positive keyword and no negative keywords. Negative posts contain at least one negative keyword. The rest are considered to be neutral. A post is classified as "Lockdown," "Mask," "Vaccine" or "Miscellaneous" if it contains the relevant keywords. We consider "Lockdown", "Mask", "Vaccine" to be subtopics of "COVID," and "Miscellaneous" stands for discussions around COVID-19 which are not related to the three key topics. Figure 1 illustrates a Venn diagram of topics and sentiments.

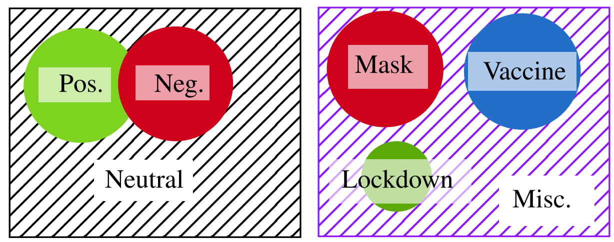


Fig. 1: COVID-19 Sentiment and Topic Classification.

Using our curated taxonomy, we first analyze the frequency of keywords when used as hashtags, to examine the overall prevalent trends of harmful contents in the three datasets (discussed later in Figure 3). We then classify all posts by performing a case-insensitive text search to find all the matches beyond hashtags (through MongoDB's text index). This retrieves more COVID-19-related posts (compared to only considering hashtags) and is used for polarization experiments. Table II summarizes the number of classified posts per topic from users for which we have inferred their party affiliation.

Determining Partisan Polarization

To measure how divided the discussions were between users affiliated with the two parties, we first embed all users based on the content they have posted and then measure how well separated the two parties are in this content space. More specifically, we first embed the text of each post[3] into a 1024-dimensional vector space using a pre-trained RoBERTa-large language model [29], and then pool (mean aggregation) all of the post embeddings from each user to derive the user representations. We denote these by $\mathcal{U} = \{u^{(1)}, u^{(2)}, \ldots, u^{(n)}\}$, where $u^{(i)} \in \mathbb{R}^{1024}$ and n is the number of users.

Given $\mathcal{U}$, we measure daily polarization scores based on how dispersed *Republicans* ($\mathcal{R} \subset \mathcal{U}$) and *Democrats* ($\mathcal{D} \subset \mathcal{U}$) are in the content space. We adapt a clustering quality index, C-index [30], to compare the dispersion of $\mathcal{R}$ and $\mathcal{D}$ clusters

[3]As a preprocessing step, we replace all URLs with the keyword "URL."

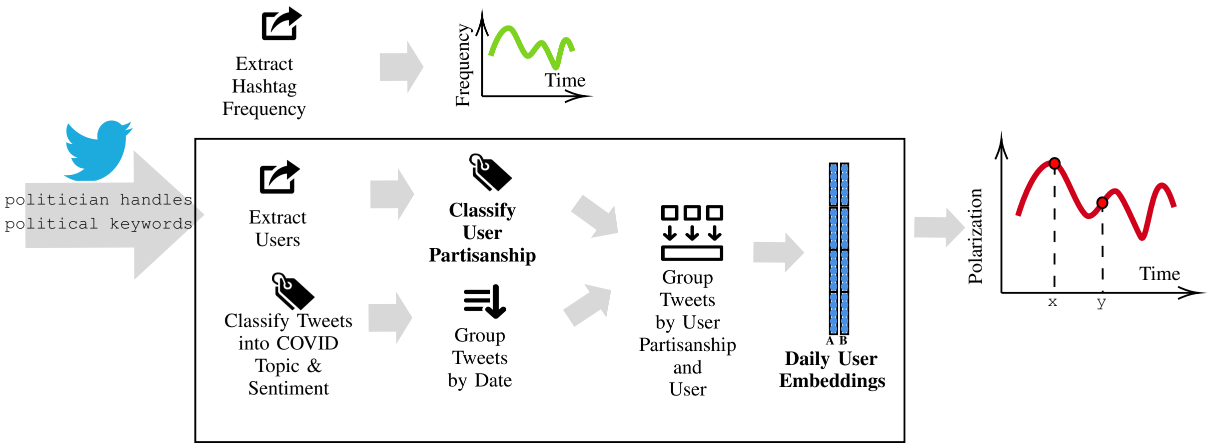


Fig. 2: Measuring Partisan Polarization of COVID-19 Discussions Over Time

relative to the total dispersion in $\mathcal{U}$. Specifically, we compute the sum of within-cluster distances as:

$$S_w = \sum_{u,v \in \mathcal{R}} ||u - v|| + \sum_{u,v \in \mathcal{D}} ||u - v||$$

This represents how dispersed the two parties are. This is then normalized by the minimum and maximum possible values for this sum, S_{min} and S_{max} respectively. These are computed as the sum of the m smallest (resp. largest) distances between points in $\mathcal{U}$; where $m = |\mathcal{R}|(|\mathcal{R}| - 1)/2 + |\mathcal{D}|(|\mathcal{D}| - 1)/2$. The polarization index, *poli*, is then derived as:

$$poli = \frac{S_{max} - S_w}{S_{max} - S_{min}} \tag{1}$$

This value ranges between zero and one, i.e. $poli \in [0, 1]$, with higher values indicating more polarization.

To get a measure of *polarization over time*, we compute *poli* based on the posts from each day independently and report the values per day.

To get the *overall partisan polarization on COVID-19*, we first measure *poli* on posts related to each of our four disjoint topics (see Fig. 1), to measure partisan polarization on each issue, and then average these to get the aggregated polarization score. This is more accurate than measuring *poli* on the combined posts, since talking about different issues by itself creates dispersion in the content space, which doesn't necessarily translates into polarization. However, talking about the same issue, but very differently, represents in our view a key manifestation of partisan polarization in our model.

An abstract overview of our methodology is given in Figure 2. The top row of the box represents the simple process to obtain Figure 3, the middle and bottom row explain the process to classify posts and users, embed users daily based on their discussions on different topics, and obtain the polarization trends over time and per topic.

Results

Topic & Sentiment Trends

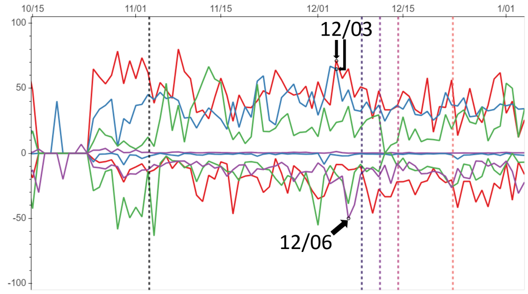
In the left column of Figure 3, we report the normalized hashtag frequencies, where peaks above the x-axis show the percentage of positive hashtags used compared to all hashtags for the corresponding topic in that day. On the other hand, the negative peaks below show the daily percentage of negative hashtags used. The right column displays the raw frequencies of the positive and negative hashtags, leaving out the neutral category.

Overall, we observe that the COVID-19 related discussions on Parler were mostly negative (Figure 3c), as suspected, except in the Vaccine topic. On Twitter, the public discussions were more balanced with equal volume of negative and positive content (Figure 3a), and with politicians rarely posting negative content (Figure 3e). Among the topics, Mask and Lockdown are the most divisive for the public in both Parler and Twitter, whereas Vaccine discussions seems to be generally positive on Twitter. The majority of the COVID-19 related posts are in one of our three categories (Figure 3b,3d) and most Miscellaneous posts are negative on Parler (Figure 3c). On the other hand, politicians tweet about masks much more compared to vaccines and lockdowns (Figure 3f), and their tweets overall are overwhelmingly supportive of masks (Figure 3e). However, politicians also seem to be occasionally divided on lockdown measures.

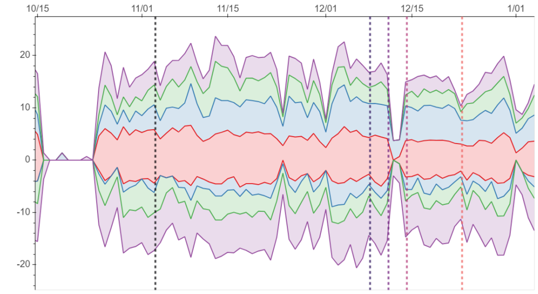
We further investigate COVID-19 and political events that happened during the observed peaks. In Figure 3a, we can see a peak on December 3rd with positive hashtags for the Mask and Vaccine topics. On this day, Biden called all Americans to wear masks during his first 100 days in office [31], and Facebook announced that it would remove all posts containing misleading claims regarding vaccines [32]. The highest negative peak in the Miscellaneous topic happens on December 6th, which is correlated with the announcement of Rudy Giuliani's hospitalization after contracting COVID-19.

On Misinformation Detection

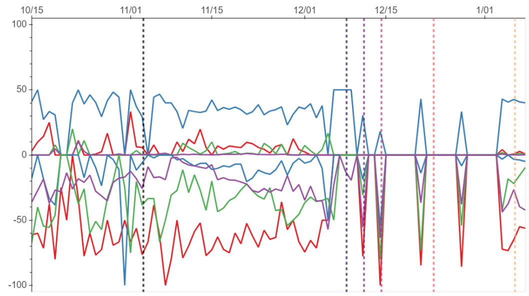
We also examine the percentage of misinformation in our datasets by training a classifier to detect it. For this, we use two COVID-19 misinformation datasets, CoAID [3] and Mediaeval 2020 COVID-19 and 5G conspiracy [4]. The former is general, while the latter focuses on the conspiracy that 5G causes



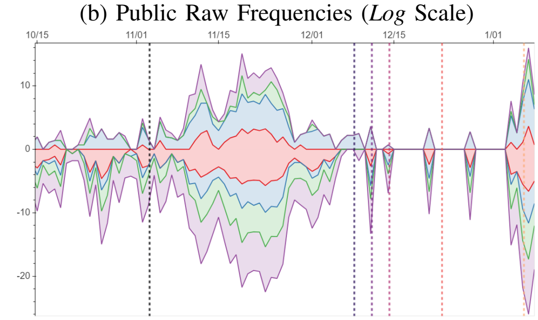
(a) Public Normalized Frequencies



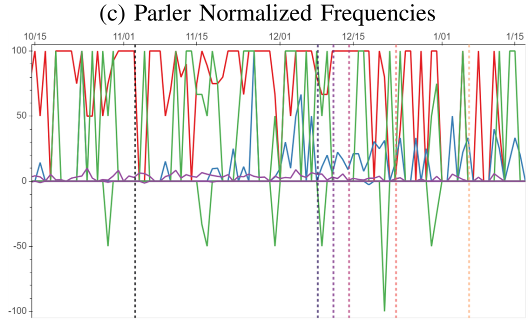
(b) Public Raw Frequencies (*Log* Scale)



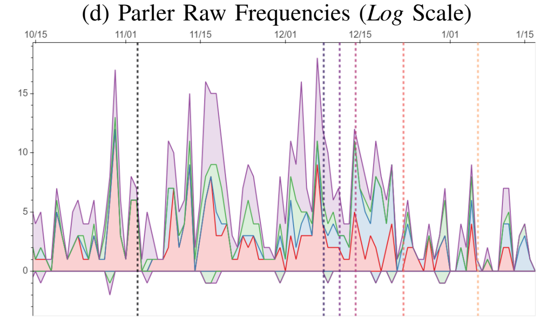
(c) Parler Normalized Frequencies



(d) Parler Raw Frequencies (*Log* Scale)



(e) Politicians Normalized Frequencies



(f) Politicians Raw Frequencies

Mask
Vaccine
Lockdown
Misc.

Election Day (11/03/2020)
States Resolve Controversies (12/08/2020)
FDA Approved Vaccine (12/11/2020)
State Electoral Votes (12/23/2020)
Election Votes Arrive (12/23/2020)
Capitol Riot Day (01/06/2021)

Fig. 3: Hashtag Usage of the Mass (Public), the Elite (Politicians) and the Extreme (Parler). Positive sentiments are above the x-axis and negative ones are below. Neutral sentiments are not included in the plots and only used for the normalization by topic (left column). We can see a much higher usage of negative hashtags in the Parler dataset compared with Public.

COVID-19, but contains other COVID-19 misinformation as well. We fine-tune a BERT-Tiny [33] model on the combination of these datasets. With an 80-20 train-test split and no hyperparameter tuning, this achieves 98.5% macro F1 score on the test data. However, we observe poor performance when we apply this model to our own datasets.

More specifically, we manually evaluated 101 random tweets that were classified as misinformation. The results, shown in Table III, indicate that only 6.93% of these were actually misinformation, while 63.37% was not related to misinformation, and 15.84% were even counter-misinformation (trying to refute the false claims). The remaining 13.86% could not be verified one way or another. This shows that misinformation detection in this domain is a challenging task. Detection methods similar to what we applied here can give excellent performance on existing academic datasets –

TABLE III: Despite very good performance (98.5% F1) on the academic test set, most of the tweets the classifier flags as misinformation are false positives.

Classification of tweets	Percentage
Not misinformation	63.37 %
Misinformation	6.93 %
Counter-misinformation	15.84 %
Unverifiable	13.86 %

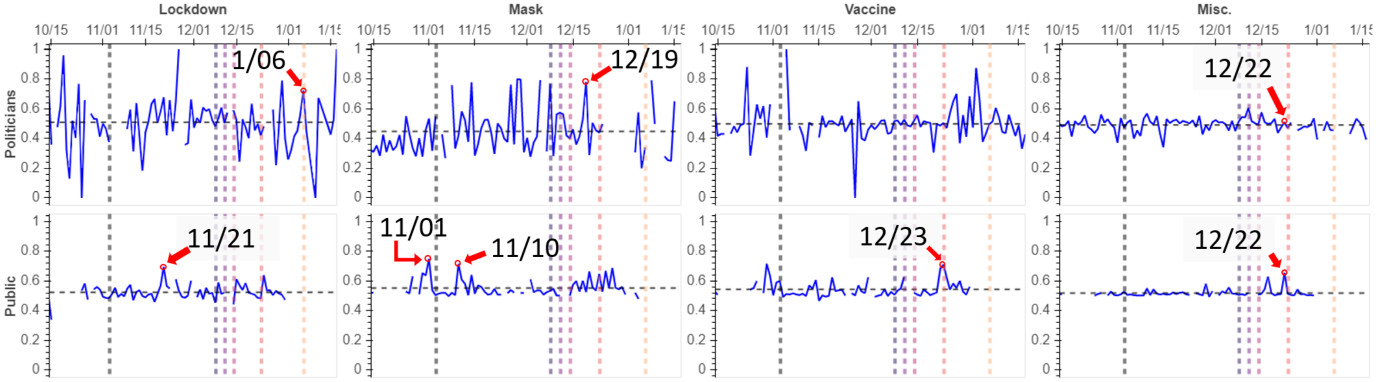
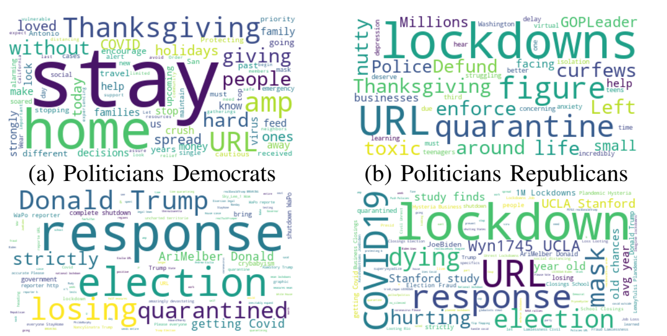


Fig. 4: Partisan Polarization of Mass (Public) and Elite (Politicians) on each COVID-19 issue. Base polarization on Lockdown, Mask, Vaccine, and Misc. are respectively 0.508, 0.447, 0.498 and 0.491 on the elite and 0.523, 0.552, 0.543 and 0.518 on the mass. These are marked by the dashed horizontal lines in the plots. Vertical dashed lines are the same as Figure 3b.

the primary approach for evaluating misinformation detection algorithms [34] – but may not generalize well in the real world. More sophisticated methods or carefully constructed data are needed, as well as more extensive validation to verify real-world performance. Our neutral, positive, and negative keyword analysis is a practical alternative.

Partisan Polarization Trends

Figure 4 shows the discovered polarization trends of political and COVID-19 discourse in each dataset. Due to the imbalance of Democrat and Republican users in Parler, there were not many data points to effectively investigate the trends there directly. Instead, in Figure 7, we compare how polarized the Parler discussions are against the general public on Twitter. Below, we investigate the peaks in polarization per topic and the overall trend.



(a) Politicians Democrats (b) Politicians Republicans

(c) Public Democrats (d) Public Republicans

Fig. 5: Summarized Discussions on Nov. 21st - the Highest Polarized Point on the Public Discussions Around **Lockdown**.

Lockdown topic: The highest peak found in the Public dataset (Figure 4 bottom) is on November 21st, which also correlates with a peak in the Politicians dataset (top). In Figure 5, we show the word clouds on lockdown related discussions on this specific day. These wordclouds correspond to two viral polarizing tweets, one from each side. The Twitter handles responsible for the viral tweets are also present in the corresponding wordcloud, which is interesting and can potentially help in detecting such users. Here, Democrats are mocking Trump for strictly quarantining in response to losing the election (Figure 5c), and Republicans are misrepresenting [35] a UCLA and Stanford study [36], suggesting the chances of dying from COVID-19 are 1 in 19.1M and lockdowns are only hurting the economy (Figure 5d). The user who posted this tweet is now suspended from Twitter. The messages from politicians are also divided: Democrat politicians (Figure 5a) echo the recommendations made by the CDC, ahead of Thanksgiving, to avoid travel and gatherings [37], showing keywords such as "stay," "home," "thanksgiving," whereas the Republican politicians (Figure 5b) are more concerned with "lockdowns" and "curfew." We also observe other peaks, e.g. a peak on January 6th in the Politicians dataset that correlates with the Capitol Hill riot.

(a) Public Democrats (b) Public Republicans

(c) Debunked fake-news that Biden did not wear a mask on a plane

Fig. 6: Summarized Discussions on Nov. 1st - The Most Polarized Point on the Public Discussions Around **Mask**.

Mask topic: In the Public dataset, the highest peak is on November 1st. On this date, the Republicans accuse Joe Biden of using masks politically [38]. Figure 6b mainly refers to fake news (Figure 6c) being retweeted. Here too the retweeted user name shows up in the word cloud. We also see another major peak on Nov. 10th, when the FDA announced that on November 12th they will host a virtual seminar providing

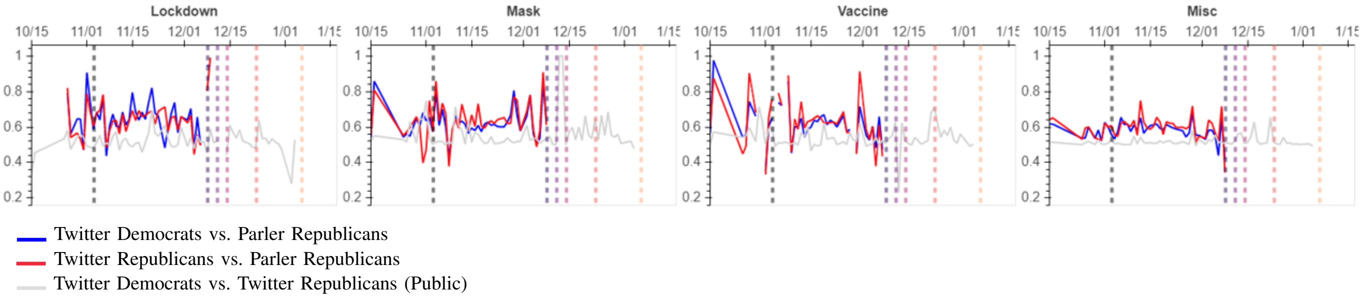


Fig. 7: Cross-Platform Partisan Polarization Around Specific COVID-19 topics. Vertical dashed lines are same as Figure 3b.

insights on the FDA's research about the efficiency of masks [39]. One other major peak is observed on December 19th, during which several representatives of the House and the Senate received their first dose of vaccine [40].

(a) Public Democrats (b) Public Republicans

Fig. 8: Summarized Discussions on Dec. 23rd - the Highest Polarized Point on the Public Discussions Around **Vaccine**.

Vaccine topic: The Public is most polarised on December 23rd, with the summary of these Vaccine topic discussions shown in Figure 8. This is also one of the two highest peaks in the overall polarization of COVID-19 related discussions shown in Figure 9. On this day the CDC Director, Robert R. Redfield, announced that more than one million Americans had received their first dose of the vaccine, and indicated that there was a limited supply of COVID-19 vaccine [41]. On that same day, Pfizer and BioNtech announced a new agreement with the US government to provide the country with additional vaccine doses [42]. On the other hand, Republicans were retweeting that they were *"NOT going to comply with @JoeBiden's 100 day mask mandate."* The originating user for this message is now suspended from Twitter, and his handle is also represented in the wordcloud (Figure 8b).

Cross-platform: In Figure 7, we compare the discussions on Twitter versus the discussions on Parler (which consists mostly of Republicans). We observe that Parler users reflect a similar degree of polarization relative to both Twitter Democrat and Twitter Republican users, i.e. the red and blue curves closely match.

This implies that *COVID-19 discussions on Parler are very different from COVID-19 discussions on Twitter,* to the extent that the differences between the platforms, even considering only people from the same party, dominate the differences between opposing parties on Twitter. While this does not show causality – whether users only select a platform based on their existing partisan beliefs, or whether interactions induced by participation on the platform shapes them – it shows that they form coherent partisan bubbles, with very different narratives and discussion.

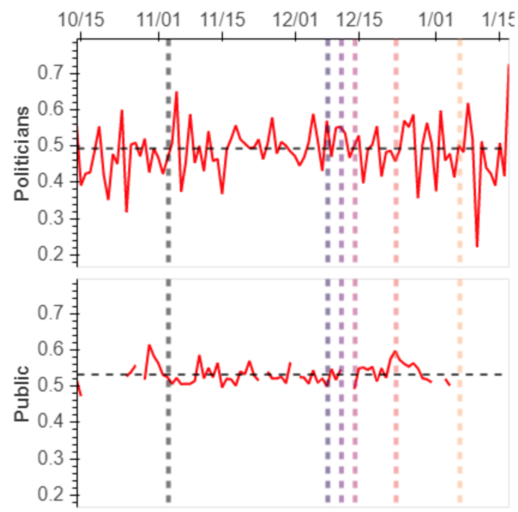


Fig. 9: Aggregated Partisan Polarization of COVID-19 discussions. Base polarization for the elite and the mass are 0.493 and 0.532, respectively. These are marked by the dashed horizontal lines in the plots. Vertical dashed lines correspond to major events and are same as Figure 3b.

Aggregated Polarization: In Figure 9, we report the aggregated partisan polarization which is the average *poli* scores for all of the four topics on a daily basis. From this, we observe a significant peak in polarization in the Politicians dataset right after the Capitol Hill Riot, which has been one of the most divisive moments in the recent history of the US. There seems to be a general pattern that politician's COVID-19 discourses on Twitter become increasingly polarized as major events unfold. This was notably seen around Election day, when the Electoral College votes arrived, and when the Election results were officially validated by Congress. The two most polarizing points for the Public are before the Election on 10/30/2020, and when the Electoral College votes arrived in Washington (12/23/2020). Figure 10 shows the per topic discussions on this date. Vaccine keywords are more frequently used by Democrats on December 23rd, when it was announced that more than one million Americans received their first doses of the vaccine [41].

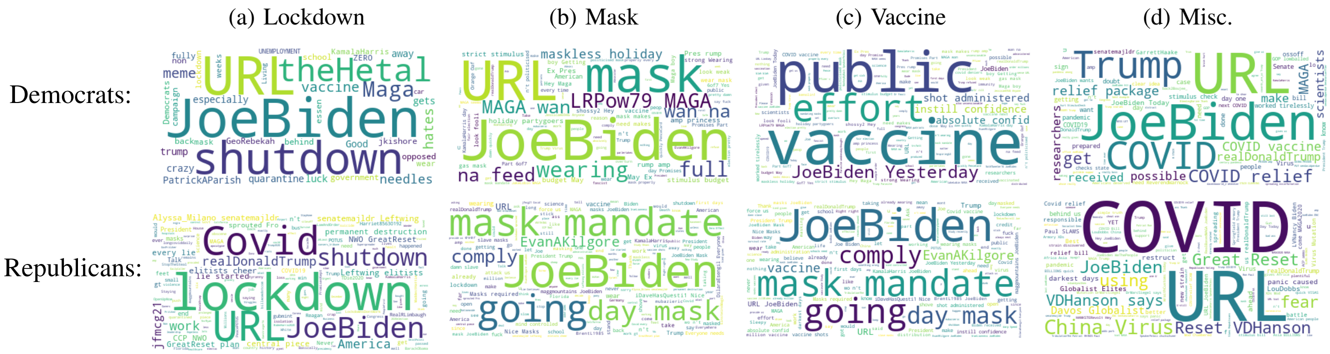


Fig. 10: Summarized Discussions on Dec. 23rd - the Highest Polarized Point overall on the Public's COVID-19 Discussions. Top row and bottom rows correspond to the Democrats and Republicans, respectively.

On this day, Republican users were retweeting a conspiracy theory that has been on the rise in online COVID-19 discussions: *The Great Reset (TGR)*.[4] The 'Great Reset' also appears on the Misc. word cloud for Republicans (Figure 10d bottom). Here, we see that the peak in polarization, among other things, is clearly linked to a conspiracy theory that is being shared/amplified on the platform.

Discussions

From Figure 3, users in Parler employ a higher number of negative hashtags related to COVID-19 events when compared to Politician and Public users. Unsurprisingly, we find that Politicians use fewer negative hashtags when they are tweeting about this issue. The highest frequency of negative hashtags is related to the general topic of COVID for the Public and Parler datasets. The Lockdown topic is the most negative topic discussed on the Politicians dataset. However, the Mask topic is the least used in combination with negative hashtags in our data. This last finding suggests that masks were generally discussed positively during the period studied.

From Figure 4, we investigate changes in polarization over time by looking at the correlations between peaks and other relevant political and COVID-19 related events. The overall picture indicates that some topics become more polarized over time. Indeed, the mask topic appears to be a more divisive issue in the Politicians dataset. On the other hand, in the public dataset, the mask topic only becomes a polarizing issue on December 23rd when the Electoral College votes arrive. From the public dataset, there appears to be a reduction in the polarization level on December 13th when the first doses of vaccines have been delivered. In fact, COVID topics seem to be the least polarized in the Public and Politicians datasets.

For the lockdown topic, higher polarization can be found in the Politicians dataset compared to the Public one.

[4]*The Great Reset* is the name given to the structural reforms discussed during the World Economic Forum (WEF) meeting that took place in May 2020 [43]. Many political leaders and economics met to discuss the actual COVID-19 crisis, its aftermath and ways to build a sustainable economy. However, conspiracy theorists have manipulated the narrative detaching *The Great Reset* from its true WEF meaning. As a result, many conspiracy theorists indicate that TGR is one of the final step by the elites to control the economy and the social life [43]

Conclusion

In this paper, we proposed a new methodology to investigate partisan polarization on social media and applied it to study the COVID-19-related discussions on two main social media platform during the 2020 US Election.

Overall, the analysis found that there was a marked increase in partisan polarization on several different topics: Lockdown / Mask / Vaccine / Miscellaneous. We also found that the surges in partisan conflict were strongly correlated with major political and COVID-19-related events, including the Capitol Hill riot. We further provided detailed discussions on the observed peaks in partisan polarization on each issue and in our broader datasets. In most cases, these peaks were linked to suspended accounts and viral posts circulating among users affiliated with the Democratic and Republican parties, which we confirmed are polarizing, misinformation, fake news or conspiracy theories. On the other hand, for detecting such misinformation directly, we found that while some current algorithms showed promise in an academic setting, they performed very poorly on our real world data. We believe the methodology proposed in this paper is better suited for analyzing highly evolving public policy crises similar to the COVID-19 pandemic. We hope that this work will motivate a new class of methods for detecting and de-amplifying polarizing content on social media.

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Appendix Timeline of major politically and COVID-19 related events

November 1st, 2020:

Politically related events: The Texas Supreme Court rejected a push to throw out nearly 127,000 votes cast in Harris County [44].

November 2nd, 2020:

COVID-19 related events: Deborah Birx, a White House coronavirus adviser, warned in a report that the Trump administration should take much "aggressive actions" to contain the coronavirus spreading [45]

November 7th, 2020:

Politically related events: Major news outlets such as ABC, CNN, NBC, MSNBC and Fox News officially declare the election in favor of Joe Biden (D).

November 20th, 2020:

COVID-19 related events: Pfizer applied for FDA emergency use authorization of COVID-19 vaccine [46].

The Centers for Disease control and Prevention (CDC) warns against Thanksgiving travel as U.S. Coronavirus Cases Hit Another Record High [37].

November 22nd, 2020:

COVID-19 related events: The US reached 12 millions COVID-19 cases since the beginning of pandemic [47].

December 3rd, 2020:

COVID-19 related events: Biden called all Americans to wear masks during his first 100 days [31].

Facebook announced removing all posts containing misleading claims regarding vaccines[32].

December 4th, 2020:

COVID-19 related events: The CDC urged Americans to wear masks indoors when they’re not in their homes in order to fight the coronavirus crisis [48].

December 6th, 2020:

COVID-19 related events: Rudy Giuliani is hospitalized after contracting the coronavirus [49].

December 11th, 2020:

COVID-19 related events: The Food and Drug Administration approved Pfizer and BioNtech vaccine for emergency use and to be distributed across US [50].

December 22nd, 2020:

COVID-19 related events: Trump criticizes and disapproves the 900 billion coronavirus relief bill just passed by Congress indicating that he would not sign the legislation unless it is changed [51].

Biden warns public that pandemic's 'darkest days' are frontwards and urged American to remain cautious [52].

The CDC urged Americans to wear masks indoors when they're not in their homes in order to fight the coronavirus crisis [48].

Pfizer and Moderna test their vaccines against the new coronavirus variant across the United Kingdom. [53]

December 23rd, 2020:

COVID-19 related events: the CDC Director, Robert R. Redfield, announced that more than one millions Americans have received their first dose of vaccine and indicated that they are currently have a limited supply of COVID-19 vaccine [41].

Pfizer and BioNtech announced a new agreement with the U.S. to provide the country with additional vaccine doses [42].

December 30th, 2020:

COVID-19 related events: Governor Gavin Newsom announcing that a new COVID-19 variant has been identified in South California [54].

Another variant was also suspected in Colorado [55].

Ohio Governor Mike DeWine announcing students in class do not need to isolate anymore [56].

January 3rd, 2021:

COVID-19 related events: Fauci Adams disputes Donald Trump's claims that federal authorities COVID data were inflated [57].

January 6th, 2021:

Politically related events: Capitol Hill Riot.

January 20th, 2021:

Politically related events: Presidential inauguration of Joe Biden (D).

TABLE IV: Keywords used to classify posts into their respective topic and sentiment. When querying for hashtag usage, only keywords without spaces were used. When classifying posts, all keywords as well as phrases derived from the keywords were used. For example, the keyword "secondlockdown" can be further broken down to "second lockdown". Keywords gathered were manually found, from our own dataset or selected from related works of [58], [59], [60], [61], [62], [63] and [64]. Keywords were used in both positive and negative context.

Topic	Sentiment	Keywords
Lockdown	Neutral	quarantine, secondlockdown, lockdownDC, californialockdown, 2ndLockdown, Lockdown3, lockdowns, coronavirusshutdown, covidlockdown, covidshutdown, shutdowns, coronaviruslockdown, lock down, Wuhanlockdown, lockdownextension, home-quarantine, lockdownTrump
	Positive	Stayhome, StayHomeStaySafe, lockdownlife,StayHomeSaveLives,nationallockdown, TogetherAtHome, Prolockdown, Proshut-down, LockdownWorks, AvoidGatherings, stay home challenge, safe at home, stay at home, stay home, sheltering in place, quarantine life, 14DayQuarantine, inmyquarantinesurvivalkit, quarantine shelter, shelteringinplace, stay home challenge, stayathome, stay_home_safe, stayhometosavelives, workfromhome, stayhome!, saferathome, safe at home
	Negative	endthelockdown, endlockdowns, NoShutdown, NoMoreLockdown, NoMoreShutdown, ReopenAmerica, OpenAmericaNow , Antilockdown, LockdownsKill, Breakthelockdown, LockdownsAreNotACure, nolockdown2, BreakTheLockdowns, Lockdown-Chaos, LockdownsDontWork, StopThelockdowns, LockdownFraud, Bidenlockdown, NoMoreLockdowns, CancelTheLock-down, freetheUSA2020, NoLockdowns, NoLockdown, Antishutdown, Anti shutdown, endtheshutdown
Mask	Neutral	mask, masks, facemask, facemasks, ppe, n95, kn95, CoronavirusMask, surgicalmasks, clothmasks, n95facemask, kn95facemask, facecover, cloth mask, ffp2mask, ffp3mask, ffp3, ffp1, ffp2, kn95 mask, n95 mask, surgical mask, faceshield
	Positive	masksSaveLives, wearamask, maskup, wearadamnmask, MaskYourKids, MaskMandates, WearMaskProtectLife, Wear a mask protect a life, WearAMaskSaveALife, maskon, Doublemasking, Doublemask, MaskOnAmerica, MaskSelfie, MasksWork, MaskWorks, mandatorymask, GetMePPE, masks4all, wear face mask, CoronavirusCoverup
	Negative	maskdontWork, Nomasks, Nomask, MasksOff, MaskOff, antimasker, antimaskers, NoMaskMandate, Nomoremasks, Un-MaskAmerica, Maskless, IWillNotWearAMask, SheepNoMore, unmask, MaskOffAmerica, Talesoftheunmaskedpatriot, take-offthemask, maskburning, Burnyourmask, Burnyourmaskchallenge, nomaskonme, nomaskselfie, maskhoax, nomaskEVER, facefreedom, masksmakemesweaty, MasksAreDangerous, TakeMaskOff, Stopforcingmaskonme, takeoffyourmask, refusemask, NeverMasker, StopWearingMask, StopWearingtheDamnMasks, MasksdontMatter, stopmasking, stopthestupidmask, mask-ingchildrenischildabuse, MomsAgainstMasks, MasksRUnhealthy, SheepWearMasks, MasksAreForSheep, RefuseToWearMasks, MasksAreMurderingMe, maskshoax, TakeOffTheMask
Vaccine	Neutral	vaccination, vaccines, CovidVaccine, Covid19Vaccine, Covid19Vaccination, Astrazeneca, Moderna, Modernavaccine, Pfizer, Pfizervaccine, PfizerBionTech, BioNTech, Covaxin, Coronavaccine, SputnikV,CoronaVac, PfizerBioNTech, Operationwarp-speed, Warpspeed, CovidVaccination, Vaccinating, CoronavirusVaccines, Covisdhield, Astrazenecavaccine, Janssen, Janssen-vaccine, JohnsonandJohnson, JohnsonandJohnsonvaccine, immunization, SputnikVVaccine, CoronavacVaccine, SinovacVaccine, Sinovac , Herdimmunity
	Positive	VaccinesSaveLives, ThisIsOurShot, Vaccinated, getvaccinated, BidenVaccine, Trumpvaccine, VaccinesWork, VaccinationWorks, TakeYourShot, BestShot, vaccinationdone, CovidVaccineFacts, SecondDose, GetYourShot, VaxUp, VaccineSelfie, CrushCOVID, MyCOVIDVax, IGotTheShot, VaccinesAreSafe, vaccine against coronavirus
	Negative	NoVaccine, MedicalFreedom, Medical freedom, AstrazenecaKills, Astrazeneca kills, AntiVaccine, AntiVacc, AntiVaxx, KnowtheRisk, BewaretheNeedle, FuckAstrazeneca, FuckPfizer, PfizerKills, FuckModerna, ModernaKills, FuckJohnsonandJohn-son, JohnsonandJohnsonkills, Deathbyvaccine, VaccinesKill, NeverVaccine, SayNoToVaccines, hydroxycloroquine, saynobill-gatesvaccine
Misc.	Neutral	SARSCoV2, Pandemic, COVID19, Covid_19, COVID, COVIDSecondWave, CovidCases, Covid19usa, Covidusa, COVID20, CovidReliefBill, COVIDReliefBill, COVIDRelief, COVID Relief, StimulusChecks, COVIDReliefPackage, 2000StimulusCheck, Virus, Regeneron, DrFauci, Secondwave, longcovid, covid19pandemic, CDCgov, FDA, GlobalPandemic, CovidVariants, coronaviruspandemic, Sars-cov-2, corona, coronavirusoutbreak, 2019ncov, COVID-19, coronavirus, CoronavirusUpdate, CoronaOutbreak, CDC, Epidemic, corona virus, covd, coronavirusimpact, covid19 epidemic, covid19 pandemic, covid19update, covidlife, covidresearch, koronavirus, outbreak, pandemic2020, sars-cov-2 virus, centre for disease control, covidiot, covidiots
	Positive	FlattentheCurve, StopTheSpread, crushthevirus, BidenWillCrushCovid, StopCOVID19, FauciHero, COVIDWise, Protectyour-self, Protectothers, GetTested, BreakTheChain, washyourhands, fightagainstcorona, Socialdistancing, Social Distancing, Social Distancing Now, Dont be a spreader, don't touch your face, fightagainstcorona, fightagainstcoronavirus,fightcoronatogether, fightcovid19, fighttogether, slow the spread of covid19, standtogether, treat coronavirus, wehealasone, uniteagainstcovid19, togetherwecan, togetherwecandoit
	Negative	Scamdemic, Scamdemic2020, ScamdemicIsOver, Shamdemic, electioninfection, Covidhoax, ConstitutionOverCoronavirus, chinesevirus, chinavirus, Plandemic, Fakepandemic, TrumpPandemic, TrumpCovid, TrumpCovid19, Controlavirus, Covid1984, TrumpCovidHoax, GreatReset, TheGreatReset, CCPVIRUS, TrumpVirus, TrumpVirus2020, wuhanvirus, WuhanFlu, corona-hoax, AmyCovidBarrett, TrumpVirusCatastrophe, SuperSpreaderEvents, TyphoidTrump, WhatCOVID, TrumpPlague, Omnibus-CovidReliefBill, WHOHoax, FakeCovid19, KongFlu, Kungflu, Wuhancoronavirus, Trump pandemic, coronapocalypse, china virus, coronials, dr. fraud fauci

Confucius Matrix for Topic Stance Keyword Labelling

TABLE V: Lockdown Confucius Matrix

		Predicted		
		Positive	Negative	Neutral
True	Positive	148	5	32
	Negative	24	625	107
	Neutral	3	5	70

TABLE VI: Mask Confucius Matrix

		Predicted		
		Positive	Negative	Neutral
True	Positive	265	36	62
	Negative	38	628	23
	Neutral	8	5	26

TABLE VII: Vaccine Confucius Matrix

		Predicted		
		Positive	Negative	Neutral
True	Positive	171	24	88
	Negative	6	43	41
	Neutral	6	45	308