Conspiracy and Polarization Around the COVID-19 Pandemic on Social Media

blind submission

Abstract

On January 30th, the World Health Organization (WHO) General-director announced that COVID-19 represents a Public Health Emergency of International Concern (PHEIC) and encouraged countries to enforce measures in reducing further spread of the virus. In today's age of information, many people utilize various social media platforms which shape their views around many different topics including sanitary measures and political events. We analyze microblogging data from Twitter and Parler to answer: how polarized was the discussion around COVID-19 pandemic? How has polarization fluctuated over time? Did fake accounts on Twitter have an effect on the support of the government's response (e.g. wearing masks) to the COVID-19 pandemic? In this project, we aim to investigate how unified was the message sent from the politicians to the public on COVID-19, how polarized was the overall discussion on social media and what roles social bots played on users' public opinion.

Introduction and Related Works

Since the beginning of COVID-19 pandemic, regulatory responses varied across states, ranging from mandatory masks to complete lockdowns with WHO encouraging preventive measures (Zhang et al. 2020). These worldwide circumstances have brought many users to shape and express their views on how the US government handles the situation through social media platforms (Lits et al. 2020). However, because anyone has the ability to voice their opinion, those perceptions may generate or shape online polarization. Furthermore, the rise of social bots calls into question the reliability of online information, as they may rattle the digital sphere by spreading fake news (Keller and Klinger 2019). This project aims to investigate how unified were the politicians' messages to the public around COVID-19, and to answer questions including: how polarized was the online discussion around the implementation of face mask, which became mandatory in some American states? What was the impact of social bots on COVID-19 discourses in the US? Were these social bots more active during the US Election and the widespread implementation of mask mandates? And finally, if social bots play a role in shaping users' opinion, do some users engage more with fake news and social bots' content relative to masks?

Here we first briefly review the line of work related to this research, mainly general studies on Bot and Troll detection, fake news detection, and measuring polarization; as well as few recent studies specific to COVID-19 polarization.

There are many existing studies that focus on **user classification**, often to detect fake and non-genuine accounts, e.g. bots (Rheault and Musulan 2020; Davis et al. 2016; Cornelissen et al. 2018), trolls (Zannettou et al. 2019; Fornacciari et al. 2018), or sock puppets (Zhou et al. 2019). The goal here is often to measure the extent of their engagement and influence in the general discussions. There are fewer studies that also try to classify users based on their political affiliation (Xiao et al. 2020), or rank the polarity of users (Barberá 2015).

Another large body of relevant work focuses on **classifying content** posted on social media platforms as misinformation (Micallef et al. 2020; Allcott, Gentzkow, and Yu 2019), fake news (Kaliyar, Goswami, and Narang 2021; Sahoo and Gupta 2021; Pérez-Rosas et al. 2017; Baruah et al. 2020), or disinformation (Ferrara et al. 2020; Faris et al. 2017). These studies provide valuable tools to flag problematic content. These analyses also often focus on the influence and reach of the content on the general public.

Relatively fewer studies focus on studying the **overall health of the online platforms** over time, e.g. how polarized are the discussions (Garimella and Weber 2017; Howard et al. 2018; Garimella and Weber 2017; Guerra et al. 2017). The methods discussed above could be used to derive aggregated indices over time, e.g. the ratio of bots to all users. There are few recent analyses that look at measuring polarization over time (Badawy, Ferrara, and Lerman 2018).

There are a few studies on the **COVID-19** outbreak and online polarization. At the mass level, (Jiang et al. 2020) examine geographic and temporal differences in online discussions by associating tweets with the level of state partisanship. At the elite level, (Panda, Siddarth, and Pal 2020) found that Democrats tend to frame the issue as a public health problem, while Republicans focus more on small business and the economy.

In this project, we are studying the polarization and conspiracy around COVID-19 and how it intersected with the political events over the last year.

Dataset	Source	Start	End	Total Posts	COVID Posts	% COVID	Users	Cons.	Lib.	Cons. Acc.	Lib. Acc.
Politicians	Twitter	10/25/2020	1/17/2021	156,562	13,717	8.761%	19, 423	1,174	1,068	99.00%	98.00%
Parler	Parler	10/25/2020	1/8/2021	6,546,658	110,673	1.691%	566,486	29,166	1,870	97.33%	7.33%
Public	Twitter	10/25/2020	1/4/2021	348,671,076	6,310,723	1.810%	20,533,41	205,162	134,860	68.67%	78.00%

Table 1: Dataset Descriptions. Here we have two datasets from Twitter and one from Parler. The biggest dataset contains about 350 million tweets, among which 6 million are COVID related (around 1.8%). In this dataset we have around 20 million users who posted or were mentioned/retweeted/replied to in these tweets. We were able to find 200 thousands conservative and 134 thousands liberals given the method explained in weak labelling. We have verified the accuracy of this to be 68% for labeled conservatives and 78% for liberals.

Preliminary Results

In this work we have curated three datasets, summarized in Table 1. Here we explain how each of these datasets were collected:

Politicians: We collected all tweets, retweets and replies from 995 twitter accounts linked to the public and personal Twitter accounts of the US representatives (433), senators (99), as well as vice presidential and presidential candidates (8) using Twitter's Search API.

Parler: We parsed all posts provided by the Distributed Denial of Secrets[1] and WayBack Machine[2]. Posts parsed[3] have an estimated creation date since the data provided contain relative timestamps such as "1 day ago" or "1 week ago".

Public: Using Twitter's streaming API, we collected around 1% of real-time tweets that included one of the following US election related keywords: [JoeBiden, DonaldTrump, Biden, Trump, vote, election, 2020Elections, Elections2020, PresidentElectJoe, MAGA, BidenHaris2020, Election2020].

For all datasets, we consider **all the users** that are posting the tweets as well as those that are mentioned, retweeted, or replied to in those tweets. We further filter COVID related posts/tweets by first creating a text index on the tweet / post text and use MongoDB to perform a text search for the following keywords: [mask, mandatorymask, facemask, COVID, corona, socialdistancing, flattenthecurve, stopthespread, coronavirus, COVIDwise, coronavirusmask, stayhomestaysafe]. MongoDB automatically performs tokenization, stemming and the removal of stop-words. The search is also case insensitive.[4]

Creating Weak Labels: For each dataset, we weakly label users as "conservative", "liberal" or "unknown" based on the user description found in their respective social media platform. The following are "conservative" identifiers: [conservative, gop, republican, trump]. For "liberal," we use: [liberal, progressive, democrat, biden]. We label users as "conservative" ("liberals") if their user description contains at least one of the conservative (liberal) identifiers and does not include any of the liberal (conservative) identifiers. The rest of the users remain as "unknown."

For some sense of accuracy, we randomly sampled 150 weakly labeled users (conservative & liberal) and had human experts determine if they were accurately labeled as conservative/liberal. Results are reported in Table 1. We find that users in the Politicians dataset are generally more politically involved and hence the simple keyword search is very accurate. Upon using the same rules on the general public in the Public and Parler datasets, the accuracy drops as some of the words used in the description are non-political in nature or include different variations of negative keywords, such as "*anti*-Trump" or "*not* liberal". As expected, the users on the Parler platform are much more conservative; we identified only a very limited number of liberal users, resulting in the low accuracy of the weakly labeled liberal category. We plan to improve this with a classifier later on and here only report the preliminary results that depends on labelling on the Twitter datasets which are more accurate.

Hashtag Usage Frequency

The graphs in Figure 1 are produced by finding the number of tweets / posts that use specific hashtags that we classified into one of the following categories: *Conspiracy*, *Mask* and *COVID*. The number is then normalized to show the percentage of the tweets / posts correctly identified as belonging to each category. Given domain experts' input, *Conspiracy* includes the following hashtags: [maskdontwork, masksdontwork, scamdemic, nomask, maskoff, antimasker, nomaskmandate, COVIDiots, unmask, electioninfection, endthelockdown, endtheshutdown, ConstitutionOverCoronavirus, talesoftheunmaskedpatriot, chinabiden, COVIDhoax]. *Mask* includes the following: [masque, mask, mask, mandatorymask, facemask, maskssavelives, n95, ppe, wearamask, maskup]. *COVID* contains: [corona, coronavirus, COVIDWise, stayhome, socialdistancing, coronavirusmask, stayhomestaysafe, coronaviruspandemic, flattenthecurve, stopthespread, sars-cov-2, CDCgov, Vaccines, FDA]. The graphs then show the percentage of the filtered tweets surrounding the discussion of masks, COVID conspiracy, and COVID itself [5].

We further investigated on COVID-related events that happened during the observed peaks. The graphs in Figure 1 show a high frequency of tweets with conspiracy hashtags only for the Public and Parler data on November 22nd. On this day, the US reached 12 millions COVID-19 cases since

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

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

[3]https://github.com/RSTZZZ/parler_parser

[4]https://docs.mongodb.com/manual/core/index-text/#index-feature-text

[5]To investigate COVID-19 conspiracy keywords, we look at trending hashtags on Twitter that tend to be against mask measures. Some of these conspiracy keywords have been used by (Ahmed et al. 2020) and neutral keywords by (Kouzy et al. 2020)

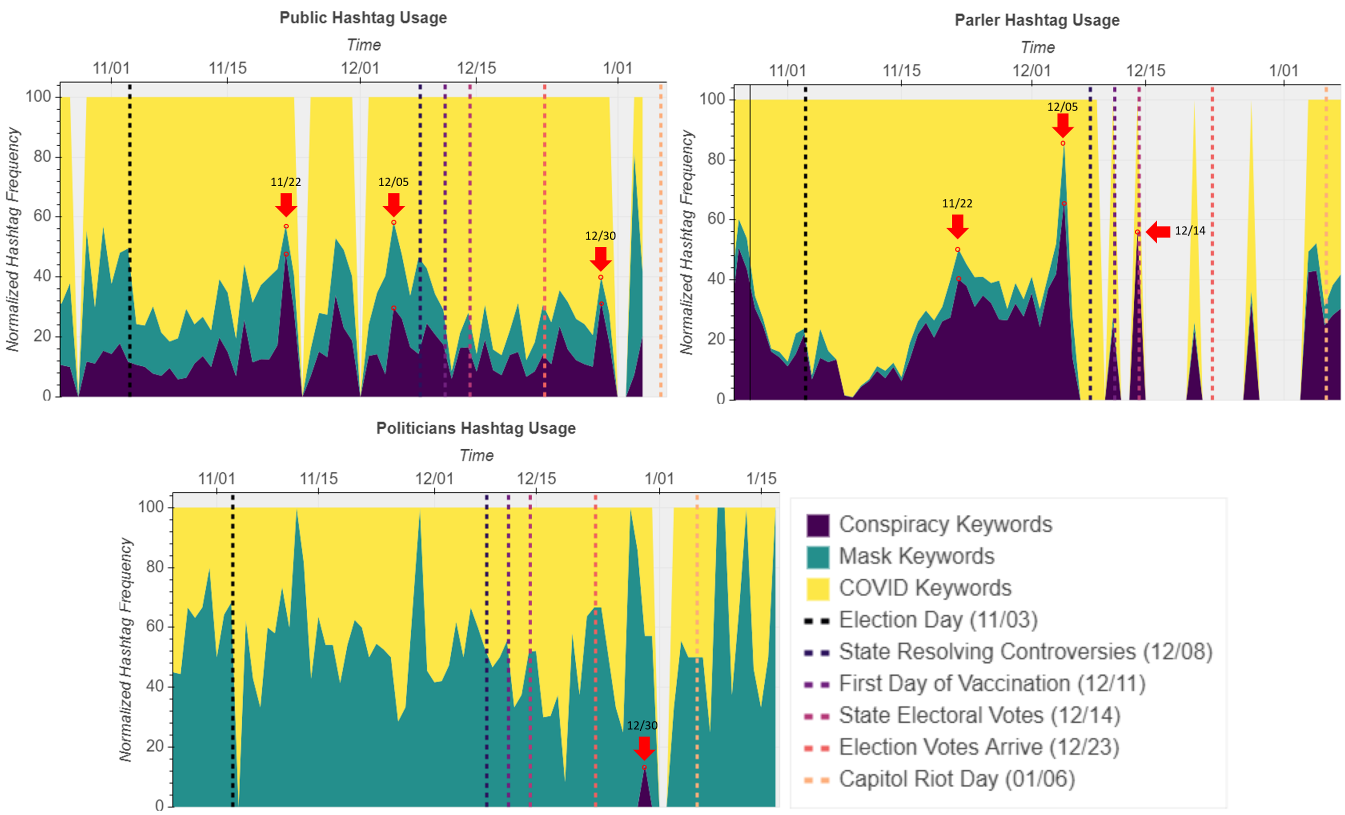

Figure 1: Hashtag Usage of the Mass, the Elite and the Extreme. We can see higher rate of conspiracy related keywords in the Parler discussions.

the beginning of pandemic (Crump 2020). Furthermore, analyzing tweets collected on November 22nd shows that many were falsely claiming that Biden held a mask-less birthday party two days prior to this date. Pfizer and BioNTech also sought the approval for their COVID-19 vaccines from the Food and Drug Administration (FDA) (Pfizer 2020) a few days before.

On December 5th, a higher percentage of conspiracy hashtags are used in Parler dataset compared to the Public one. COVID-19 news such as 25,068 additional cases being reported in California (Higgins-Dunn 2020) and 12,884 additional cases in Pennsylvania (Chinchilla 2020) could have increased the number of discussions, especially conspiracies ones. Furthermore, the President elect Biden also encouraged everyone to wear masks (Albert and Watson 2020) just a day prior.

On December 14th, a peak happens on the Parler dataset but not in the other two. Few days after the approval of Pfizer and BioNTech vaccine (Food and Administration 2020), the US had counted more than 300,000 new deaths in a single day (Harmon 2020).

The peak on December 30th in the Public and Politicians dataset is also pretty interesting. It is also the first time in Politicians that conspiracy keywords were used. Some events that happened include Governor Gavin Newsom announcing that a new COVID-19 variant has been identified in South California (News 2020), another variant was also suspected in Colorado (Mandavilli 2020), and Ohio Governor Mike DeWine announcing students in class did not need to isolate anymore (Bamforth 2020).

Polarization in Political and COVID Discourse

Next, we use a pre-trained RoBERTa language model (Liu et al. 2019) to generate embeddings for tweets. Our implementation uses the roberta-large version available through the Huggingface Transformers library (Wolf et al. 2019). We preprocess the tweet text by replacing URLs with the keyword "URL." We use the classification (CLS) token to get a single 1024-dimensional vector representing the tweet.

Given these tweet embeddings, we measure the polarization in the discussions using silhouette score between our weakly labeled users' tweet embeddings. We then compare the overall polarization and COVID-related only discussions in both the Politicians and Public dataset. The following steps describe the process of measuring polarization over time:

1. order tweets by their post time on a daily basis.
2. group tweets based on their labels. For the Politicians dataset, this is their *political party* (either Republican or Democrat) while for the Public dataset, it is their assigned *weak label* (either Conservative or Liberal).
3. group tweets by their user.

4. embed the tweet using RoBERTa.
5. calculate the mean tweet embedding for tweets from each user (on a daily basis).
6. calculate the silhouette score from the label and each user's mean tweet embedding.

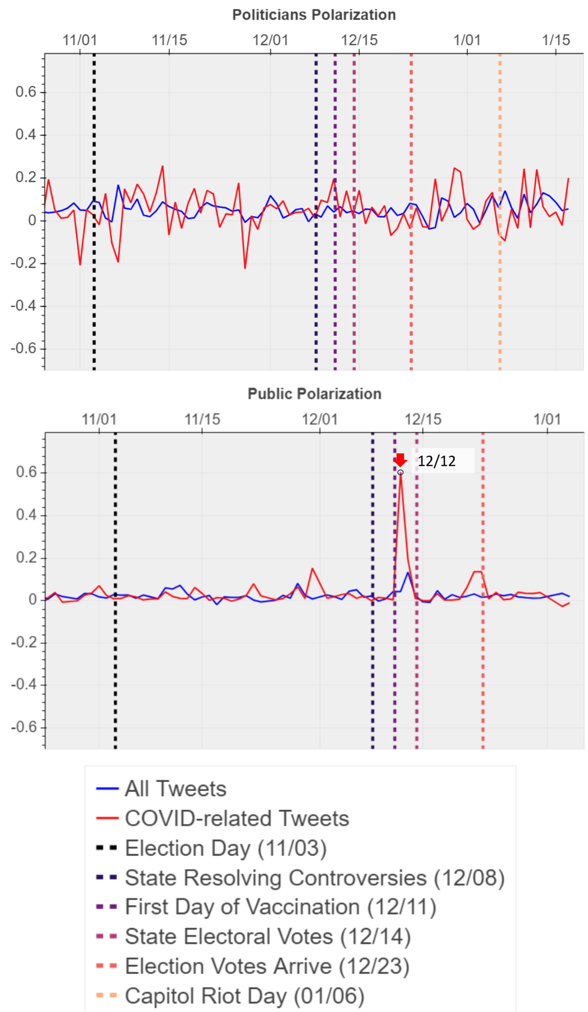

Figure 2: Political and COVID-related Polarization of the Mass and the Elite.

Silhouette score is a commonly used clustering index which reflects how well clustered the data is. This translates into how polarized are the discussions in our embedding space. Silhouette score is defined in terms of the "mean intra-cluster (a) and the mean nearest-cluster distance (b)" for each user. In this case, b is the distance between a user and its weak label. Here we are using the scikit-learn implementation. [6]

The peak presented in the Public dataset in Figure 2 shows a growing peak from December 11th through December 12th. One major political event that could explain such polarization on the Public dataset is the FDA's approval of Pfizer and BioNtech vaccine for emergency use on December 11th (Food and Administration 2020).

[6]https://scikit-learn.org/stable/modules/generated/sklearn.metrics.silhouette_score.html

COVID Misinformation

We 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 (Cui and Lee 2020) and Mediaeval 2020 COVID and 5G conspiracy (Pogorelov et al. 2020). We fine-tune a BERT-Tiny (Turc et al. 2019) model on the combination of these datasets, using HuggingFace Transformers (Wolf et al. 2019) and AllenNLP (Gardner et al. 2017). With an 80-20 split and no hyperparameter tuning, this achieves 98.5% test accuracy. We then apply this model to our own datasets.

Dataset	Misinformation Posts
Politicians	0.6%
Parler	5.6%
Public	4.6%

Table 2: Misinformation Detection Results

As shown in Table 2, the percentage of politician tweets flagged by our model is low. There are significantly more flagged posts among the general public: four percentage points more on twitter, and five more on Parler. We plan to further validate and analyze these results and investigate the changes over time.

Conclusion and Future Work

In this short paper, we explained our ongoing project on understanding the polarization around COVID related discussions on social media platforms. We showed interesting insights from simple hashtag frequency plots where the peaks in increased used of conspiracy related hashtags are correlated with major event. Further, we explained a procedure to monitor how polarized are the overall discussions over time, and observed a significant increase in the polarization which also seems to be correlated with meaningful real life events. Our plan is to investigate these further.

As peaks in specific hashtags' usage can be explained by some salient political events, we can further investigate how people are discussing topics such as masks and vaccine with our approach. We can also study how misinformation campaigns is spread and how much of it is organized by human and bot users, as well as the extent to which people are sucked into the echo chamber of twitter.

Our goal is also to scrutinize online speeches and echo chambers around facial masks through incorporating sentiment analysis. By identifying whether a tweet is from a human vs. a bot and the positive, negative or neutral emotion expressed in a tweet, we could then investigate how people react to different types of news spreaders (Saleh et al. 2020). To combat the rise of (automated) misinformation, we plan to provide a starting point to study their impact on public opinion. With regards to polarization scores, we can also analyze the relations between plots to find the correlation between the time plots in order to determine whether one social media platform influences another or if there are delays in response from one social media platform to the next. We welcome any suggestions for future works from the readers.

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