Characterizing Partisan Political Narratives about COVID-19 on Twitter

A Preprint

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Abstract

The COVID-19 pandemic is a global crisis that has been testing every society and exposing the critical role of local politics in crisis response. In the United States, there has been a strong partisan divide which resulted in polarization of individual behaviors and divergent policy adoption across regions. Here, to better understand such divide, we characterize and compare the pandemic narratives of the Democratic and Republican politicians on social media using novel computational methods including computational framing analysis and semantic role analysis. By analyzing tweets from the politicians in the U.S., including the president, members of Congress, and state governors, we systematically uncover the contrasting narratives in terms of topics, frames, and agents that shape their narratives. We found that the Democrats' narrative tends to be more concerned with the pandemic as well as financial and social support, while the Republicans discuss more about other political entities such as China. By using contrasting framing and semantic roles, the Democrats emphasize the government's role in responding to the pandemic, and the Republicans emphasize the roles of individuals and support for small businesses. Both parties' narratives also include shout-outs to their followers and blaming of the other party. Our findings concretely expose the gaps in the "elusive consensus" between the two parties. Our methodologies may be applied to computationally study narratives in various domains.

1 Introduction

Human beings make sense of the reality around them by constructing narratives using what they see, hear, and encounter [1]. One of the areas where contrasting narratives fiercely collide and fight is politics. Political communication often happens through narratives and stories, rather than logical reasoning [2], [3]. These narratives have a tremendous power in shaping people's stances and behaviors on important social issues [4]. In the age of social media, narratives can be circulated, mutated, and amplified with incredible intensity and speed [5], [6]. For example, during the COVID-19 crisis, social media sites including Twitter and Facebook are used by the the anti-mask and anti-lockdown groups to organize multiple anti-mask protests [7]. The anti-mask narratives, accompanied by conspiracy theories, fake news, and unverified anecdotes, discouraged mask usage heavily, which might have led to the loss of hundreds of thousands more lives [8]. Furthermore, such narratives often lead to collisions between partisan beliefs that strengthens political polarization [9]. It is therefore urgent to understand political narratives on the pandemic and how they diverge.

Traditional studies of political narratives are often based on political discourse analysis (PDA). PDA studies the role of spoken and written language in politics [10], focusing on the rhetoric features, styles, logic, metaphors, and contents of the political language [11]. While traditional PDA often draws its material from formal political language such as public speeches from national leaders [12], legislative debates [13], and newspaper articles [14], social media has gained increasing attention as many politicians turn to social media sites as their main online platforms for public communication [15], where they respond to issues raised by the media and public and promote their own agendas [16].

Among social media sites, Twitter has been one of the most important platform for political discourse during the last decade [17]. Politicians use Twitter to not only broadcast to, but also interact with and attract their audience directly [18], [19]. Such direct communication often benefits politicians; for instance, the usage of Twitter may increase the amount of donation that a politician receives and benefit their campaigns [20], [21]. For these reasons, as well as the succinct, swift, and amplifying nature of the Twitter discourse, many politicians have been effectively using their tweets to spread their narratives [22]. While there have been studies on the hashtags [23], sentiments [24], and moral values [25] from the politicians' tweets, systematic studies of political narratives on Twitter are rare, although political science increasingly adopts text analysis methods [26].

While the scale of social media data provides great opportunities, it also poses many challenges. Traditional approaches to narrative studies through "close reading" [27] may allow deep understanding of narratives, but are labor-intensive and rely on subjective judgements. Such constraints may be addressed by computational methods, where we can automatically identify patterns in large datasets. For example, Shurafa, Darwish, and Zaghouani [28] studied hashtags and rhetoric devices used by U.S. Twitter users leaning towards the Democratic or Republican parties, and identified their framing preference regarding the COVID-19 crisis; Green, Edgerton, Naftel, *et al.* [29] identified key words from politicians' tweets, and showed that partisanship can be inferred by their word usage. However, these studies rely on word-level analysis and Twitter hashtags, while in-depth analysis of such narratives are rarely attempted. Here we examine the political narratives responding to the COVID-19 crisis from U.S. politicians by employing new approaches to detect frames from raw text data as well as analyzing semantic roles.

It has been recognized that the liberals and conservatives in the United States have different narratives that their followers adopt. For example, according to Haidt, Graham, and Joseph [30], the secular liberals have an internalized "liberal progress" narrative:

"The majority of people used to be oppressed, treated unequally and with unjust; however, the courageous fought against the powers and freed a lot of the oppressed people. We as successors must continue their errand and fight for more equality in the society."

Meanwhile, the conservatives have a different story of "community lost":

"People used to live in harmonious communities tied together by faith and tradition, however, this is broken by the modern lifestyle, science and the industrial revolutions. We must therefore hold to our values and resist these forces."

These narratives are not objective descriptions of history, but interpretations of the reality that fit with people's political beliefs. Additionally, even though the narratives are different and may be at conflict with each other, each of them achieve internal consistency and coherence [24], which makes them effective [31].

Here we characterize the political narratives in politicians' tweets from three perspectives: usage of terms, framing, and semantic agents. In doing so, we aim to provide more nuanced analysis beyond the common term-based approaches. First, we analyze the word frequencies in texts and identify the most characteristic words used by each party; this simple method allows us to see the most contrasting differences in each group's narratives at the level of "ingredients". Next, we ask how they are *framed*. Framing analysis is a central piece in political discourse analysis [32]. Framing is about selectively presenting some aspects of an issue and make them more salient, in order to promote certain values, interpretations, or solutions [33]. For example, on the undocumented immigration issue, the Democrats often focus on the human rights aspect, while the Republicans often focus on the legality. Similar divergence in framing across major political issues are widely recognized from the two parties. Hemphill, Culotta, and Heston [23] showed that using Twitter, a machine learning classifier can be trained to easily predict the partisanship of a politician from the frames that they use.

Traditional studies on political framing mostly rely on manual content analysis and discourse analysis to detect frames from texts [34], and are therefore confined to a small set of frames because the process is labor-intensive. Here, we employ the FrameAxis model [35], which was developed to automate this process by using word embeddings and antonymous word pairs. With this method, the overall *bias* (the alignment with a frame) and *intensity* (the strength of a frame) of a document with respect to many "microframes", such as *illegal vs. legal* or *dead vs. live*, can be computed. Here, we apply the FrameAxis to identify important frames in the politicians' tweets.

Another key aspect of narrative is the events; as defined by the Oxford Dictionary of English, a narrative is essentially "A spoken or written account of connected events" [36]. From the semantic role labeling (SRL) approach's perspective, an event can be characterized by a verb and its corresponding semantic roles, in particular, the Agent (the one who

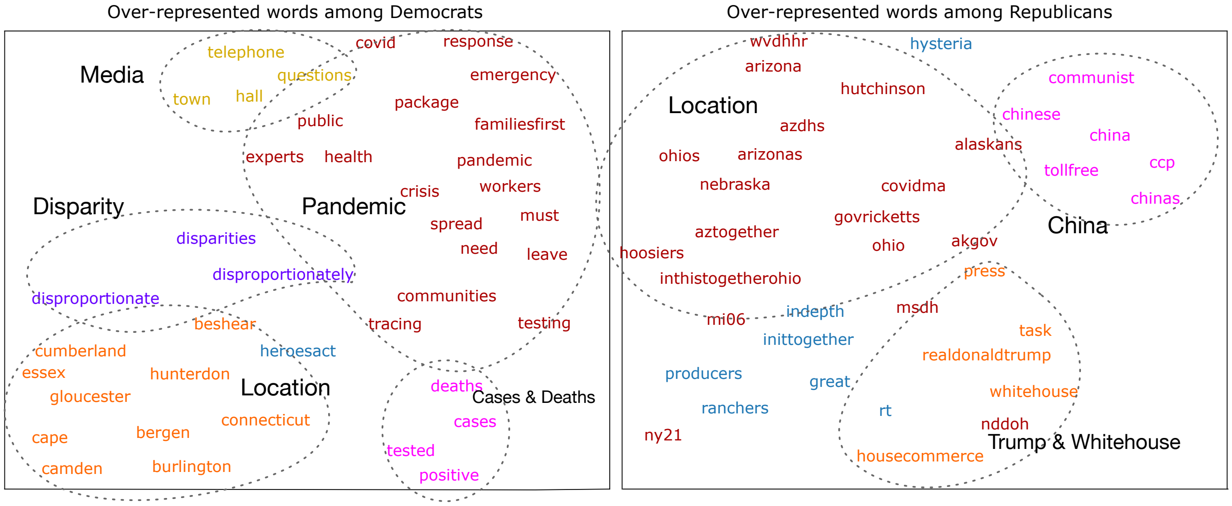

Figure 1: Characteristic words in each party's tweets related to COVID-19 in the GloVe word embedding space. We detect over-represented words by calculating the log odds ratio of each word (see Section 4) and obtain the GloVe embeddings for each word. We use UMAP to reduce dimensionality and plot each word. Colors indicate topic labels that we assigned. The Democratic party member's tweets features more words about the pandemic and about the pandemic and its disproportionate influences, while the Republican tweets features words about Trump and the White House as well as words about China.

initiates the action) and the Patient (the one being affected or the recipient of the action). For example, in the sentence *Tim Cook sold Apple*, *Tim Cook* is the Agent and *Apple* is the patient. The Agent–Patient–Action pattern appears to be universal in human cognition [37].

In this work, we use SRL models to automatically identify Agents, Patients, and verbs in our dataset. Originated in traditional linguistics [38], SRL has attracted much interest from Computational Linguistics, leading to the development of large annotated corpora such as FrameNet [39] and PropBank [40]. Trained on such corpora, modern NLP platforms such as SENNA and AllenNLP can perform the SRL task with very high accuracy [41], [42]. With the development of deep learning, SRL has been successfully applied to analyze events either as a stand-alone work or as part of an NLP pipeline [43]–[45]. In particular, Tangherlini, Shahsavari, Shahbazi, *et al.* [46] leverages semantic roles to create narrative networks for conspiracy theories.

We are especially interested in the Agents and Patients corresponding to actions related to the COVID-19 crisis. For example, when the Democrats use the word "help", *who are to be helped and who will help them?* Furthermore, how are these agents different in the Republican tweets? Our analysis shows the most prominent Agents and Patients in the Democratic/Republican narratives about the pandemic as well as the partisan differences. In particular, we identify a membership categorization process, namely the division between "us" and "them". As the most general membership categories, they help people to organize their everyday knowledge and actions [47]. For example, President Donald Trump frequently used this categorization in his campaign: "They hate me. They hate you. They hate rallies and it's all because they hate the idea of MAKING AMERICA GREAT AGAIN!" [48]. Our SRL analysis reveals a similar process where memberships are established by the semantic role usage.

Our study focuses on the differences between the two parties' narratives, showing the issues on which they diverge. Such divergence may be one of the "wedges" that exacerbate polarization in U.S. politics. The combination of methods we employed here to explore political narratives are not limited to politics. The code we develop and publish would allow similar automatic analysis in various domains.

2 Results

First, we look at the most characteristic words found in each party's tweets. We compute the log odds ratio with informative Dirichlet prior [49] of each word in the COVID-19 related tweets posted by the Democratic politicians or the Republican politicians, considering the non-COVID-19 related tweets in the same dataset as a prior. We determine whether a tweet is related to COVID-19 by checking if it contains the words "COVID" or "coronavirus" (see Methods). We consider the top 40 words by the z-score of the log odds ratio from each party as the most over-represented words.

To systematically obtain an overview of these words, we fine-tune a GloVe model [50] on our dataset and retrieve the word vector for each word (see Section 4.3). We plot these words using UMAP [51] for dimensionality reduction. With this visual aid, we identify and manually label six clusters for the Democratic tweets and three for the Republican tweets (see Figure 1).

We find that the Democratic tweets have over-represented words related to media, such as "telephone", "town hall", and "facebook", while a similar cluster for the Republican tweets appear to be related to the White House and its press conferences, such as "realdonaldtrump", "whitehouse", and "press". Additionally, each party has words related to states, cities, and public figures from these places in the US. Meanwhile, the largest category in the Democratic tweets appears to be about the pandemic, such as "health", "response", "covid", "emergency", etc. Another cluster including "disparities" and "disproportionately" also suggest that they discuss issues about social and racial inequalities more. In the Republican case, few words such as "inittogether" appears to be directly related to the pandemic. Only the phrases and hashtags for certain region such as "covidma" and "inthistogetherohio" are detected, indicating much less active narrative regarding the pandemic from the Republicans.

Lastly, both parties have some unique categories; the Democratic tweets has a cluster related to testing, specifically, including words such as "tested" and "positive". The Republican tweets has a particular cluster about China and the Chinese Communist Party, reflecting the president's narrative against China.

The overrepresented words give us a sense of the topics and issues that the two parties emphasize. Our analysis of the framing involved in each party's tweets bolster and provide more contexts to these differences. Using the FrameAxis model, we discover the top ten microframes from each party with the largest difference in intensity. For the Democratic party, we selected the microframes where the intensity in Democratic tweets is higher than the intensity in Republican tweets, and vice versa for the Republican party. The biases for each microframe are shown in Figure 2. For example, the Democratic tweets use the *public versus private* frame more often than the republican tweets, and at the same time they are more biased towards "public" rather than "private".

Since it is hard to interpret the pole words without context, we also show the tweets with the highest intensity for each microframe in Table 4. Combining the pole words and tweet texts, we show that the Democratic frames strongly feature the economic relief during the pandemic, discussing topics such as financial relief, increased funds for support, free testing, etc., which are picked up by the microframe pole words including *free*, *financial*, *increased*, and *paid*. Additionally, the *public versus private* microframe identifies the emphasis on the public aspect of the pandemic and its response. They also frequently tweet about live events and town hall meetings, invoking the *live* frame. Taken together, we interpret that they emphasize the roles that the government should play regarding the pandemic, contrasting to the Republican framing that we discuss below.

Republican microframes include aid for *small* business, the *eligibility* for financial aid, and *securing* the economy and nation. "*Slowing* the spread" appears to be the top slogan used in Republican tweets, emphasizing the roles that individuals play, which contrasts the Democratic discourse. Additionally, the top tweets about *declaring* national emergency, *important* information, and *full* statements also suggests that the Republicans tend to use Twitter as a channel for formal announcements. While some of the frames are aligned with the characteristic words, most are not found by the term analysis and are only identified by the FrameAxis.

Besides the topics and framing, it is also important to consider the people and groups in the pandemic: people who need healthcare, travelers, voters, etc. For insights into how these people are represented in the Democratic or Republican politicians' tweets, we explore the semantic roles in these tweets, in particular, the Agents and Patients. Figure 3 shows the most frequent Agents and Patients in both parties' tweets. While they overlap a lot, we notice some unique semantic roles, such as "the resources" and "lives" in Democratic tweets, and "COVID" and "relief" in Republican ones. Furthermore, the Republican tweets often use the Agent "Democrats", and the Democratic tweets often use "Trump" and "the president".

For a deeper analysis of the semantic roles, we consider the combinations of an Agent, a verb, and a Patient in each party's tweets. We use the frequency for each combination to identify the most characteristic combinations. We found 321,913 unique combinations in the Democratic tweets and 82,821 unique combinations in Republican tweets. Table 1 shows the top combinations whose frequency in Democratic tweets is higher than in Republican tweets, and vise versa.

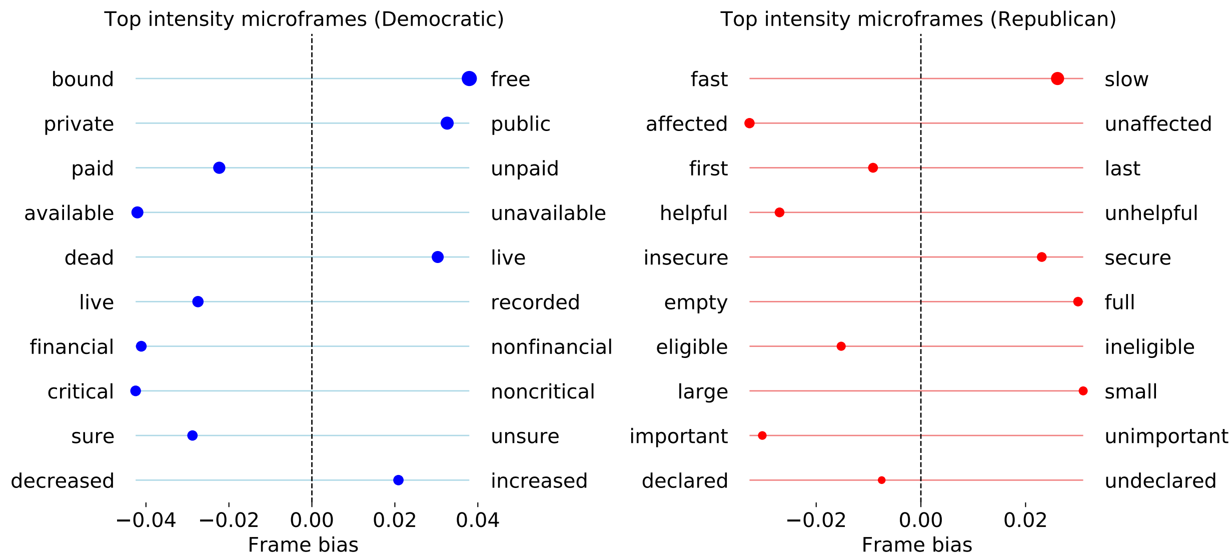

Figure 2: Top 10 microframes with the largest intensity differences between parties, as well as their frame bias. The position of points indicate the values of bias, and the size of points indicate the values of difference in intensity. The tick labels are the poles of the microframes.

Top Democratic combinations	Top Republican combinations
they, need, the resources	we, combat, covid
we, can, everything	I, holding, a news conference
we, do, more	covid, impacted, small businesses
they, need, the support	we, fight, covid
we, do, everything we can	governor hutchinson, provides, update
we, save, lives	we, moving, tax day
I, joined, my colleagues	I, provide, a covid update
we, do, what	I, holding, a press conference
those who, need, it	socialism, destroys, nations
we, recommit, ourselves	covid, affected, those

Table 1: Top Agent, verb, and Patient combinations in Democratic and Republican tweets extracted by semantic role labeling with largest differences in frequency. The left column shows the combinations where the frequencies in Democratic tweets are larger than the frequencies in Republican tweets, and vice versa. Most combinations in Democratic tweets focus on resources and support, while combinations in Republican tweets discuss combating COVID, news updates, support for small businesses, and the threat of socialism.

We find that most of the top combinations from Democratic tweets convey a message of "they" need support and "we" do everything we can to provide the resources, save lives, etc, further confirming the emphasize on the public response to the pandemic that we found in our framing analysis. Meanwhile, the combinations from Republicans feature combating COVID, holding press conference, and aiding small businesses which we also found in our framing analysis. Additionally, one combination discusses the threat of socialism.

With a general understanding of the semantic roles in both parties' tweets, we focus on specific verbs for a more detailed investigation. Here we choose three verbs from the verbs with highest frequency, "help", "want", and "stop", to reflect different themes of discussion. We select the Agents and Patients with the highest frequency for each verb.

From Figure 3, we also notice that the Agents often contains personal pronouns such as "I", "we", "they", and both parties frequently discuss the opposite party, such as the Agent "Trump" from Democratic tweets, and "Democrats" from Republican tweets, evoking a membership categorization. Inspired by Tangherlini, Shahsavari, Shahbazi, *et al.* [46], we divide the Agents into two categories—*us*, including the personal pronouns "I", "we", "us", "our", and "ours", and *them*, including the word "they", "their", and "them". Additionally, we compile two lists of words associated with

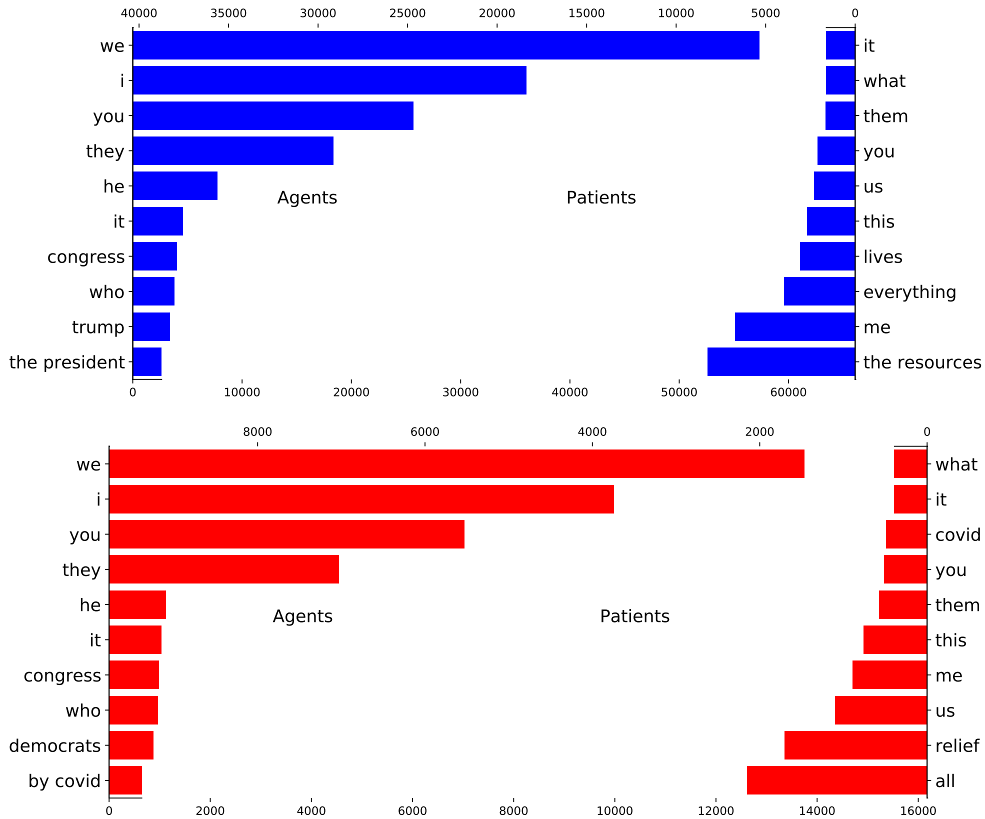

Figure 3: Ten most frequent Agents and Patients in Democratic and Republican tweets, with their frequencies. Top figure shows the Democratic Agents and Patients, and bottom figure shows the Republican ones.

"Democrats" for Republicans, and vice versa (see Section 4.3). The top Agents and Patients for each verb are shown in Figure 4.

Considering the verb "help", in the "us" category, we found that both parties have shared Patients such as "#flattenthecurve" and "save lives", and a universal theme about protecting people and curbing the pandemic. In the "them" category, the landscape is a little more complicated; when the Democrat tweets use the Agent "they", they may refer to people and entities such as health care workers, Democratic politicians, and New York state, i.e. entities that they side with. However, when they use the Agent "Republicans", they talk about "himself" and "his campaign", likely referring to President Trump. The Republican tweets, on the other hand, do not discuss Democrats with this verb much.

In the case of the verb "want", we found that the Patients are rather distinctive for both categories. In the "us" category, the Democrats emphasizes "answers", "change", "a healthy earth", and calling for the Equal Rights Amendment. Meanwhile, the Republicans do not have such strong callings, potentially due to the ruling/opposition party dynamics. In the "them" category, we see strong partisan messages about the opposite party, such as the Republican tweets discussing the Democrats' "blue masks" and "to remove president".

Despite common expressions such as "stop fighting" and "stop the spread", we observe the most inter-partisan exchanges with the verb "stop" for both categories. For example, the Democrats discuss stop "misinformation" and "whitewashing white supremacy", seemingly referring to the other party, and the Republicans discuss "stop the partisanship". In the "them" category, the Democrats indicate that the Republicans are stopping Fauci and "wasting time", and the Republicans calls for the other party to stop "attacking our allies" and "herself", potentially referring to Speaker Pelosi.

3 Discussion

In this work, we characterize the political narratives about the COVID-19 crisis from politicians in two major U.S. parties using their tweets. We examine the narrative from three aspects: topics/keywords, framing, and semantic

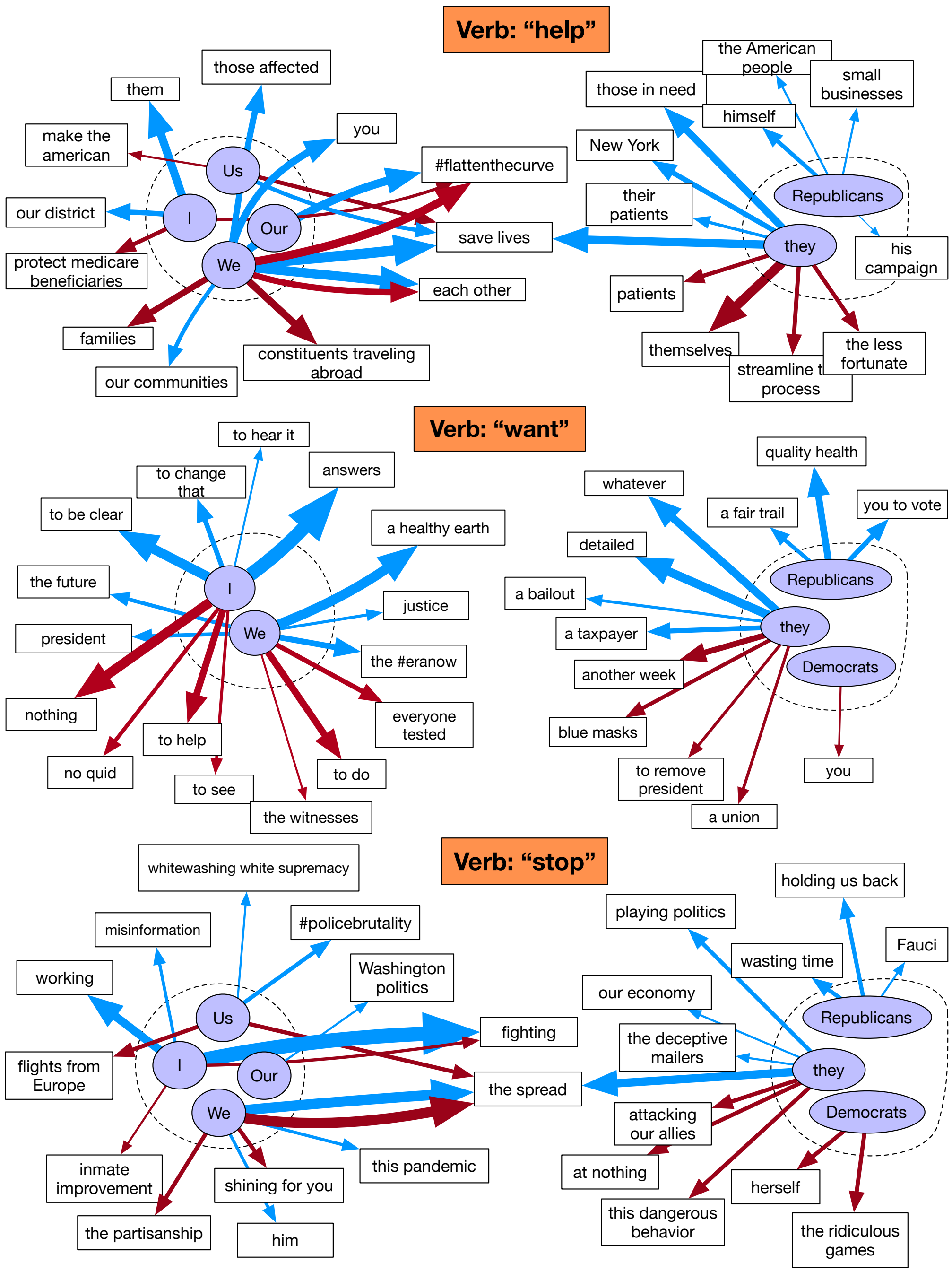

Figure 4: Agents and Patients for selected verbs with the highest frequency. Blue arrows represent relationships found in Democratic tweets, and red in Republican tweets.

agents. We notice that the Democratic narrative is more concerned about the pandemic overall, whereas the Republican narrative includes more mentioning of other political entities. In terms of framing, the Democratic narrative focuses on the financial relief and public health service during the COVID-19 crisis, whereas the Republican narrative emphasizes small business and policy announcements. When we consider the semantic agents, these different foci are further exposed, and we also found that while both parties emphasize battling the pandemic, they also send out messages to their followers about their political goals and to criticize the other party.

Our study has several key limitations. One limitation of our frame detection model is not being able to distinguish word senses; for example, it is not able to separate "live" as the antonym of "dead", and "live" as the antonym of "recorded". This may lead to confusion when both word senses are widely used in the corpora. Tweets with very different topics may also be identified under the same microframe, such as in the case of *available versus unavailable*, where the availability of COVID testing and availability for comment are put together. Such limitations may be partially addressed by using contextualized word embeddings such as ELMO or BERT, and will be an interesting future work.

The methods we use also naturally highlight the differences between the two parties' narratives and overlook the commonalities. For example, while we present the most characteristic microframes from each party's tweets, it is worth noting that the most common microframes from each party overlaps greatly.

Our semantic agent analysis use modern SRL tools to automatically identify semantic roles, but the interpretation of such roles remain a difficult task. For example, in Figure 4, manual examination is required to select the Agents and verbs, as well as inferring their context. We are also limited to showing a small set of verbs and their semantic roles. More automatic ways of analyzing and exploring the SRL data is therefore one direction of future work.

We analyze the political narratives on a party level by combining all tweets posted by the Democratic or Republican politicians, and do not consider individual politicians. As opinions within a party often diverge, our overarching analysis may miss such dissents. Our study also does not distinguish original tweets and retweets by the politicians.

Even with these limitations, we believe that our study provides useful insights into the political narratives on Twitter with novel approaches. Our methods can be easily transferred to other topics and domains. During the development of the pandemic and with the U.S. presidential election, the temporal changes of the political narratives may be substantial and revealing of specific political strategies. This temporal evolution can be studied in future work.

4 Data and Methods

	Number of tweets	Average number of tweets per politician
Senate (Republican)	34,329	635.7
Senate (Democratic)	38,539	**820.0**
House (Republican)	108,095	420.6
House (Democratic)	205,746	**635.2**
Governor (Republican)	23,397	899.9
Governor (Democratic)	30,398	**1085.6**
POTUS	1,196	1,196
Total (Republican)	167,017	494.1
Total (Democratic)	274,683	**704.3**

Table 2: The number of tweets posted by each group of politicians and the average number of tweets posted per person.

We collect data from major U.S. politicians on Twitter. Using the Twitter lists created by `cspan`[1], we retrieve screen names of politicians including: U.S. Senators, House Representatives, state governors, and President of the United States. These Twitter accounts may be managed by the politicians or their staff, but in either case, they convey the messages from these politicians and are integral part of their public images. We collect tweets from these accounts monthly starting in April 2020. In this study, we use tweets timestamped between February 1, 2020—one week after Wuhan's lockdown started—to July 22, 2020. We use the full texts of tweets and only keep the English tweets.

The number of politicians' tweets from each group is summarized in Table 2. We found that the Democratic politicians tend to post more compared to their Republican peers. Figure 5 shows the distribution of politicians' posting frequencies and the length distribution of the tweets. We found a highly skewed distribution, where a few politicians tweet a lot while most only tweet occasionally. The majority of tweets are between 100–120 words for both groups.

[1]https://twitter.com/cspan

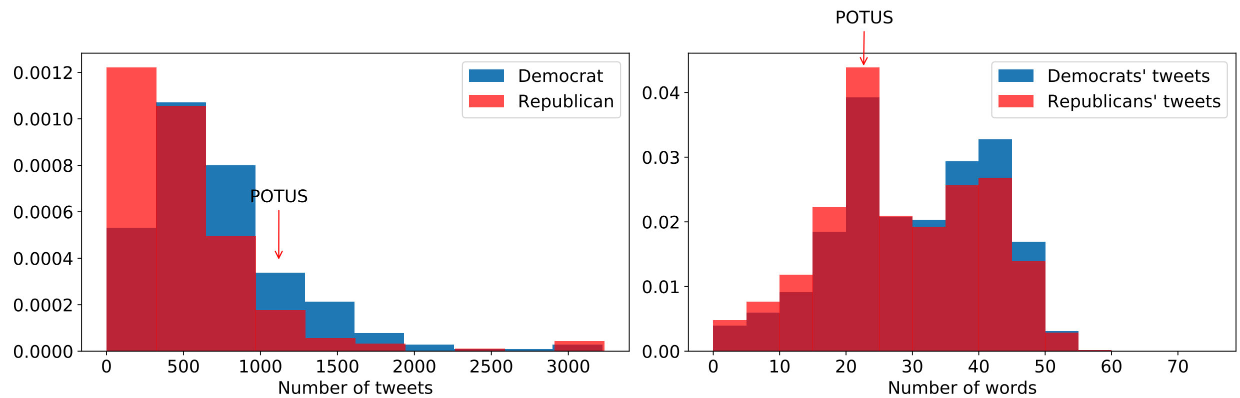

Figure 5: The distribution of the amounts of tweets that politicians post (left) and the length distribution of tweets (right).

4.1 Filtering COVID-19 related tweets

Because we are most interested in the COVID-19 related political discourse, we identify COVID-19 related tweets by checking if “COVID” or “coronavirus” is present in a tweet (case insensitive). This may omit some tweets that are about the pandemic but do not mention the name, but it ensures that all tweets we consider are related to COVID-19. The number of COVID-19 related versus non-related tweets are show in Table 3.

	Number of COVID-19 related tweets	Number of non-related tweets
Republican	37,854	127,275
Democratic	61,944	212,050

Table 3: The number of COVID-19 related tweets and non-related tweets for each party

4.2 Computing characteristic words

Our method for calculating log-odds ratio is derived from Monroe, Colaresi, and Quinn [49]. The log odds ratio for each word is computed as:

$$z_w = \frac{\log_{f_i+f_{bg}} - \log_{n_i+n_{bg}-(f_i+f_{bg})} - \log_{f_j+f_{bg}} + \log_{n_j+n_{bg}-(f_j+f_{bg})}}{\frac{1}{f_i+f_{bg}} + \frac{1}{f_j+f_{bg}}} \quad (1)$$

where f_i is the frequency of the word in the target corpus; for example, words in the COVID-19 related Democratic tweets. f_{bg} is the frequency of the word in the background corpus. In this case, it is the combination of the Democratic and Republican tweets that are not related to COVID-19. n_i is the size of the target corpus, and n_{bg} is the size of the background corpus. f_j is the frequency of the word in the *other* corpus, in this case, the COVID-19 related Republican tweets; and n_j is the size of this corpus.

4.3 Using GloVe embeddings

To obtain GloVe embeddings for words that are specific to the COVID-19 crisis, we fine-tune a GloVe model on our tweet corpus, training the model for 500 epochs[2] and obtain word vectors with 300 dimensions. Furthermore, for a consistent representation for terms related to “COVID”, we compile a list of all tokens including “COVID” or “coronavirus” and replace them with “COVID” in texts. To produce Figure 1, we then use the Python package `umap` to reduce the dimensionality to 2 and plot them against each other. To obtain a list of people and entities related to the Democratic and the Republican party, we produce lists of words most similar to the words “Democrat”, “Democratic”, and “Republican”, and obtain the relevant names and terms. The terms most similar to “Democrat” and “Democratic” include “dems”, “housedemocrats”, “reddemocrats”, “democraticled”, “pelosi”, “speakerpelosi”, “nancy

[2]Training for less epochs result in less distinct clustering of the embeddings, but does not change the overall result.

pelosi", "chuck schumer", "ralph northam", "ayanna pressley", "gwen moore", and "senatedems". The terms most similar to "Republican" include "gop", "republicans", "president", "trump", "donald trump", 'patrick mchenry", "larry hogan", "mitch mcconnell", and "mcconnell' (case insensitive).

4.4 Frame detection

We use the code accompanying Kwak, An, Jing, *et al.* [35] to perform frame detection. We compute the *bias* and *intensity* for each COVID19-related tweet, using a background of non-COVID-19 related tweets, for each microframe. Microframes are pairs of antonym word pairs each consisting two pole words, where we compute the bias based on proximity to each pole word, and the intensity based on how many words in the tweet is associated with the microframe (see [35] for details).

4.5 Semantic Role Analysis

We use the Python package `Allennlp` [42] to perform semantic role labeling on our corpus. We then extract each verb, and all Arg0s and Arg1s for each verb that consist of three or less tokens, corresponding to the Agents and Patients. We consider the top 50 verbs with highest frequency in our corpus and manually select a few as examples in Figure 4.

5 Data & Code Availability

Our dataset and code will be made available at `github.com/yzjing/covid19-politics`.

6 Acknowledgements

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Democratic Microframe	Republican Microframe
bound—free	fast—slow)
"Free COVID testing is available near you. " "Today's free COVID testing sites" "Testing, testing, testing. the bill makes sure that COVID testing is free for all Americans. "	'Do your part to slow the spread of the Wuhan COVID: " "We all need to do our part to slow the spread of the COVID. here's what you can do to help: " "rt @housegop: are you doing your part to slow the spread of the COVID?"
decreased—increased	declared—undeclared
"Check to see if you qualify for paid sick leave because of the COVID here" " Stand with @pattymurray and @sengillibrand and support the paid leave act to provide additional support to workers & businesses for paid family and sick leave during the COVID outbreak. " "Today, the house will vote on our next COVID response legislation to provide Americans wpaid family and medical leave, increased federal medicaid funds to support our state public health partners, free testing, & emergency sick leave for those impacted by the virus"	"My statement after president @realdonaldtrump declared a #nationalemergency to respond to COVID." "The first public health emergency was declared on March 6 and allows the state to increase coordination across all levels of government in the state's response to COVID." "President @realdonaldtrump has declared today as national day of prayer. Please join me in praying for our country as we continue to respond to the COVID pandemic."
sure—unsure	important—unimportant

“#MD02 constituents, unsure where to turn for local COVID resources? check out the below graphic for the hotline for your county. ” “The least the president can do is make sure they have the equipment they need. COVID 3/3” “The response to COVID needs to help all Americans. i’m working with my colleagues to make sure that it does.”	“Important information for you and your family about the COVID ” “Important information from @cdcgov regarding COVID ” “Important COVID update from the @deptofdefense in the thread below.”
critical—noncritical	large—small
“rt @frankpallone: @WHO is critical in the fight against the COVID pandemic. Trump must work with the world?s premier public health... ” “rt @uazmedphx: to address the critical needs of the Navajo nation during the COVID outbreak, #uazmedphx, @repgregstanton, as well as?” “It is critical that we ensure those who have access to any COVID vaccine are not the privileged few, but the many who actually need it most.”	“If you own or work for a small business affected by the COVID pandemic, visit my website for information on support for small businesses” “Visit learn about the EPCC’s grant program for small businesses impacted by the COVID find more helpful EPCC small business resources” “Welcomed news for Georgia small business owners. @sbagov emergency loans are now available to impacted businesses in all 159 counties. COVID”
financial—nonfinancial	eligible—ineligible
“Thank you, @abigaildisney, for looking out for the most vulnerable affected by the financial repercussions of COVID. ” “rt @repmalinowski: "the COVID will prey not just on the health of Americans but their financial wellbeing. In its next bill responding...” “May 1 is quickly approaching, and I know that many marylanders are experiencing severe financial hardship because of the COVID. In this thread you’ll find information about financial assistance available in MD.”	“Alabamians laid off or unpaid due to COVID are eligible for unemployment compensation ” “rt @oronline: if you work in Pennsylvania and the novel COVID has affected your job, you may be eligible for benefits. ” “Small businesses: you may be eligible for up to $2 million in @sbagov low-interest loans if your business has been affected by the COVID. These loans can help fill your working capital needs. Non-profits may also be eligible. Apply online here: ”
live—recorded	empty—full
“Tune in now: I’m hosting a Facebook live town hall with @repbillfoster and @repcasten. We will be answering your questions on COVID. Watch live here: ” “tune in now for my Facebook live COVID town hall with @stevelockhartmd of @sutterhealth:” “I am #live now on Facebook addressing your questions and concerns about the COVID. Tune in here: ”	“Read here: my full statement in support of the COVID relief legislation the House just passed. ” “My full statement on presumptive COVID cases in South Dakota ” “See my full statement on president @realdonaldtrump’s new actions to fight COVID here”
dead—live	insecure—secure
“Tune in now: I’m hosting a Facebook live town hall with @repbillfoster and @repcasten. We will be answering your questions on COVID. Watch live here: ” “I am #live now on Facebook addressing your questions and concerns about the COVID. tune in here: ” “As of 2pm today 1,700 people in my state new jersey are tragically dead from COVID and 16,642 Americans are dead across the country.”	“rt @waysandmeansgop: in the phase three package to secure our economy as we fight against COVID, @ustreasury secretary @stevenmnuchi? ” “I also thank our brave frontline @tsa officers for the risks they face on our behalf, continuing to keep our nation safe & secure in the COVID pandemic.” “rt @waysandmeansgop: Dems voted against the phase three package to secure our economy as we fight against COVID. This package include?”
available—unavailable	helpful—unhelpful

“More information is available from @cdcgov here: COVIDupdates COVIDUS” “Free COVID testing is available near you.” “rt @sfpelosi: 77,000 Americans killed by COVID unavailable for comment.”	"This is a helpful resource for hoosiers to stay updated on COVID " “Here’s some helpful information on COVID for pregnant women and parents from the @cdcgov. You can find these and other resources on my website at ” “Continue to follow @cdcgov for the latest updates on the COVID and helpful information. #MI06 ”
paid—unpaid	first—last
“Check to see if you qualify for paid sick leave because of the COVID here ” “rt @facttank: new: as COVID spreads, which U.S. workers have paid sick leave ? and which don’t? ” “I stand with @pattymurray and @sengillibrand and support the paid leave act to provide additional support to workers & businesses for paid family and sick leave during the COVID outbreak.”	“Love this. @starbucks is fueling our first responders on the frontlines of the COVID crisis! #inittogether ” “’rt @chadsabadie: @repabraham: the first responders, you bring calm to chaos COVID” “rt @woodtv: @rephuizenga pitches COVID aid bill for doctors, nurses and other first responders:”
private—public	affected—unaffected
“rt @indivisibleteam: medicines, like the COVID vaccine, that are developed with public money should benefit public health, not create?” “@unitedwaydenver @cohealth coloradans can call the cohelp line for the latest public health information on the COVID at 1-877-462-2911. ” “rt @bryan_pietsch: healthcare workers battling the COVID would have their public and private student loans forgiven under a new bill?”	“If you own or work for a small business affected by the COVID pandemic, visit my website for information on support for small businesses” “If you own a small business and your operations are being affected by COVID you may be able to get assistance from @sbagov. More info here: ” “Appeared on @foxbusiness to discuss congressional action being taken to help Americans affected by COVID”

Table 4: Three top tweets from each microframe with the largest difference in intensity between two parties. URLs, emojis, and some special characters are omitted.

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