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A Cross-platform Analysis

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5 Fringe players on political Twitter

Source-sharing dynamics, partisanship and problematic actors

Maarten Groen and Marloes Geboers

Abstract

Focusing on the (early) run-up to and aftermath of the 2020 U.S. presidential elections, this study examines the extent of problematic information in the most engaged-with content and with the most active users in "political Twitter." It was found that mainstream sources are shared more often than problematic ones, but their percentage was much higher prior to the Capitol riots of January 2021. Significantly, (hyper) partisan sources are close to half of all sources shared, implying a robust presence. By March 2021, though, both the share of problematic and of (hyper)partisan sources decreased significantly, suggesting the impact of Twitter's deplatforming actions. Additionally, active, problematic users (fake profiles, etc.) were found across the political spectrum, albeit more abundantly on the conservative side.

Keywords: hyperpartisanship, misinformation, U.S. elections, deplatforming, Capitol riots, digital methods

Research questions

To what extent are problematic sources present in the most engaged-with content in political and social issue spaces on Twitter in the run-up to and aftermath of the 2020 U.S. elections? Has Twitter's deplatforming affected the quality of sources shared? Are there problematic users among the most active, and are they typically of a particular political leaning?

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Essay summary

To probe the extent to which problematic sources are present on political Twitter, the study queries political keywords and investigates the most shared news sources and their credibility as well as the most active users, their authenticity and partisanship. Problematic sources refer to Jack's characterization as containing information that is "inaccurate, misleading, inappropriately attributed, or altogether fabricated" (2017, p. 1). Most engaged-with content on Twitter refers to the most retweeted tweets and/or most frequently shared sources within the given time periods. Most active users or accounts are those with the highest tweeting activity, and problematic ones are fake accounts, bots or locked/suspended users. Political and issue spaces on Twitter (or "political Twitter") refer to the result sets from keyword and hashtags queries for presidential candidates, political parties and social issues.

In March 2020 the amount of problematic news sources shared on Twitter was 16% of all shared news sources. By December 2020 the share of problematic news sources almost had doubled to 30%. In March 2021 we found a sharp decline in those shared, at just over 10%. While it may have to do with the decline in source sharing during that time frame, it also could reflect the significant purge of user accounts by Twitter in the days after the Capitol riots of January 6. The purge likely affected users who were involved in sharing problematic sources.

In the first two time spans under study (March 2020 and December 2020/January 2021), close to half of the non-problematic sources circulating the news were classified as (hyper)partisan,[1] suggesting that Twitter, like Facebook before it, is a platform where such sources perform well (Silverman, 2016). In March 2021, the third timeframe, we saw a drop to 34% in that category. The first two periods set themselves apart from the third in that they witnessed the dominance of conservative (hyper)partisan sources which were no longer as strongly in evidence in the third period of time (after the deplatforming).

In terms of the users, in 2016 it was mostly pro-Republican fake and bot accounts that shared problematic information on Twitter (Bovet and Makse, 2019). We noticed, however, that there are also pro-Democrat fake and bot

1 (Hyper)partisan is used with the parentheses not only to indicate an amalgamation of the hyperpartisan and partisan source types, but also to signal the difficulty in consistently disentangling them. Below we use (hyper)partisan when discussing sources that were labeled as such in the study.

accounts actively circulating such information. In addition, instead of using their own hashtags, both Democrat and Republican supporters tend to use each other's hashtags to draw attention from their opposition.

Implications

Ever since its tagline changed from *What are you doing?* to *What's happening?* (2009) Twitter has become regarded less as an ambient friend-following medium than as a "reporting machine" at least in the Western social media realm (Rogers, 2014; Tate, 2009). In the past decade, Twitter also has been regarded as a space for doing politics, exemplified by Donald Trump's usage of the platform as a political tool in his campaigning for the presidency in 2015–2016 and later by its integration into his administration. Trump's tweeting changed the nature of the presidency and allowed him to leverage a relatively novel form of media power (Enli, 2017), at least up until the banning of his account on January 8, 2021, as a response to the Capitol building riots and violence two days before, given the role that Trump played in fueling and "glorifying" them.

Given the dominant presence of Trump on Twitter, but also of other candidates and their supporters and observers, it arguably became the key social media platform where the politics of the 2020 U.S. presidential elections played out. Trump's "populist anger" (Wahl-Jorgensen, 2019, p. 117) was not only on display on Twitter but connected to a hybrid media system in which mainstream media co-mingle with "fringe" players (Chadwick, 2017; Wahl-Jorgensen, 2019). It is the extent of this co-mingling that one is able to study on Twitter.

In this regard, it is important to note how social media posting not only "folds into" (Niederer, 2019, pp. 119–120) the content of mainstream media (within which we distinguish more or less partisan sources) but also impacts their "affective styles" (Wahl-Jorgensen, 2019, p. 116). A broad set of transformations have accompanied these new media, enabling a media regime to emerge in which there is a "normalization of a new set of 'emotion rules' that allow a president to consistently make statements that are verifiably false, be called out on these falsehoods and pay no political price for them" (Delli Carpini, 2018, pp. 18–20).

Twitter is a space that is vulnerable to problematic information and the presence of potentially problematic users such as fake accounts and bots (Boyd et al., 2018). We identified such problematic activity during the periods under study, each of which with distinctive user activity. The initial time span is the period around "Super Tuesday" on March 3, 2020, when the greatest number of states hold their primaries or caucuses. We then repeated our analyses in the final days of 2020 from late December up until January 4, 2021, which covers the post-election time span and the significant U.S. Senate run-off elections in Georgia on January 5 which would result in a Senate majority for the Democrats. In retrospect, these days were also close to the Capitol riots of January 6 that were spurred by ongoing speculations about election fraud. This time frame represents a Twitter discourse centering on speculations concerning the balance of power after the Senate run-offs as well as allegations of election fraud and subsequent calls for protesting the "vote steal." The final time span under study covers March 10 to 22, 2021 and can be characterized as not only post-election but also post-purge after Twitter deplatformed over 70,000 accounts (many linked to QAnon conspiracies) between January 9 and 12, in response to the aforementioned riots (Conger, 2021).

Overall, our findings show that mainstream sources outperform (or are shared more often than) problematic sources on political Twitter. Though the circulation of problematic sources was higher just after the election, they never outperformed mainstream sources as was the case on Facebook in the run-up to the 2016 elections (Silverman, 2016). We do see a significant drop in March 2021 in the circulation of problematic sources after the Twitter purge.

In both March 2020 and December 2020/January 2021 nearly half of the sources shared were coming from sources that we sub-categorized as (hyper)partisan progressive or (hyper)partisan conservative. We also witnessed a noticeable uptick in problematic sources shared in the aftermath of the elections which spans the weeks in which the Twitter discourse was dominated by allegations of electoral fraud. While (hyper)partisan sources do not share conspiracy or pseudo-science and are not problematic in that sense, the findings point to a particular kind of hybrid media landscape. It provides plenty of space for (hyper)partisanship and problematic information to co-mingle with mainstream sources. Put differently, mainstream news is increasingly confronted with more partisan players in the field, at least on Twitter in the run-up to and aftermath of the U.S. elections.

Though beyond the scope of this study, our findings imply that more problematic information is engaged with on social media than in other online media spaces such as the web, where the top-ranked media properties (by traffic) are rather mainstream and include NBC, CBS, Disney and Turner (ComScore, 2019), though a separate measure should be taken of the "political web." This disparity between Twitter and the web aligns with what Barnidge and Peacock (2019) point out concerning the reliance on social media for the dissemination of hyperpartisan (and problematic) sources.

In the run-up to the presidential elections in 2016, multiple studies indicated that suspect accounts were mostly spreading problematic, pro-Republican information on Twitter (Bovet and Makse, 2019). During the campaigning and in the (immediate) aftermath of the 2020 elections, however, we also identified problematic, pro-Democrat accounts actively spreading problematic information across Twitter, though they do not outnumber those on the other side of the political spectrum. That is, compared to the findings of previous studies concerning the type of problematic accounts, to date there are indications of a shift from mainly conservative to a mix of conservative as well as progressive problematic accounts. Additionally, among the datasets of most active users we found more problematic accounts than authentic ones, implying that highly active accounts during election campaigning deserve scrutiny.

With respect to the most engaged-with tweets, the vast majority is posted by influential users, and they do not circulate many problematic sources. The finding indicates that most retweeted content (rather than most tweeted content only) is a quality indicator, at least in this brief study. The role of follower counts is thus important as there is a direct relationship between follower and retweet counts. If problematic users would attain influential masses of followers, such analyses might look different.

In light of the societal consequences of disseminating problematic or hyperpartisan sources, it is important to stipulate that the link between sharing and the actual visibility of such sources is not clear cut, given how visibility is algorithmically determined. We can assume a higher probability of exposure, however, when tweets are retweeted (Kwak et al., 2010). Meier et al. (2014) found that retweeting and liking could be regarded as audience engagement in a conversation and attention to the messages, which facilitates information transmission.

Situating the findings: Diversification and polarization on Twitter

We situate our findings around the sharing of problematic and non-problematic sources in the affordances of a platform that, to a certain extent, democratized news sharing in the sense of opening the gates for non-mainstream sources to circulate and be amplified. In order for sources to be successful on Twitter, we need to understand both how people are exposed to news sources and what makes (news) content prone to amplification in that realm. The rise of social platforms has posed challenges to theorizing selective exposure to news. Barnidge and Peacock (2019) distinguish two ways in which social media have restructured selective exposure to news. Both ways provide a means to assess the implications of our findings that social media diversify social connections and facilitate the rise of hyperpartisan news.

The diversification aligns with Bruns's reflections (2019) on the existence of filter bubbles and echo chambers (Pariser, 2011; Sunstein, 2001). Such structures of isolated communities are based on a belief that social media inevitably promote echo chambers and filter bubbles as they personalize content to the extent that individuals consume news in isolated ways. Empirical research into the existence of such structures have not found evidence to support this belief (O'Hara and Stevens, 2015; Barnidge, 2017). Bruns (2019) modified these concepts through introducing degrees of "bubbleness" or "chamberness": scholars can quantify the extent to which people connect or communicate *within* and beyond ideological groups. This modification does justice to the fact that by far most people use multiple sources for their news consumption (Dubois and Blank, 2018) and that people befriend others not just on the basis of their political leanings. Bruns (2019) backs the latter argument by stating how people are not primarily on social media (or at least on Facebook) to talk politics. We would like to note that Twitter's use culture is more geared toward talking politics than is Facebook's, for example, which might lead to different ways of curating one's social network.

Though Twitter users may have diverse social networks and the information that people are exposed to is varied, the findings from our study underscore how sharing sources seems to largely follow one's own political leaning: in the datasets where Republican leaning users were most active, the (hyper)partisan sources were mainly conservative in kind and vice versa. Note, too, how the Republicans are overrepresented in the data demarcated by keywords pertaining to the Democrats, which is related to how Twitter users are calling out or attacking their opponents in their tweets.

Within all datasets we found a pattern whereby users employ the opposition's keywords and hashtags, in order to target each other. It occurs in political spaces organized around both political parties and candidates. Within these supporter spaces, there appear to be more sources shared that attack the opponent rather than support the candidate. (See also Starbird (2017) as well as Groshek and Koc-Michalska (2017) for investigations into strategies of attack and trolling of mainstream media, especially apparent on Twitter.) Our findings thus reiterate how the relentless targeting of people through hyperpartisan viewpoints continues and is a phenomenon practiced on both sides of the political spectrum. One methodological implication is that one cannot neatly demarcate a supporter space through hashtag and/or keyword queries only.

Barnidge and Peacock (2019) point out that alongside the diversification of information described above, social media also allow hyperpartisan voices to reach a wider audience that is now able to share messages independently of mainstream media. Hyperpartisan news could be described as having a slanted political agenda and making scant effort to balance opposing views. It could be said to push anti-system messages that are critical of mainstream media and established politicians, relying on dubious information or misinformation to do so. It also depends heavily on social media for its dissemination (Barnidge and Peacock, 2019).

Through challenging mainstream narratives, hyperpartisan media also overlap with notions of alternative media. Strengthening Bruns's argument about the absence of isolated bubbles, Peacock et al.'s empirical investigation (2019) found that strong partisans on social media are exposed to both left- as well as right-leaning news. In order to proffer an "alternative perspective" to mainstream news, hyperpartisan media and users have to monitor mainstream sources to know how these outlets talk about issues. They attach commentary to the narratives of mainstream media. As O'Hara and Stevens point out: "engaging with the enemy does not necessarily make a group less partisan" (2015, p. 418). Bruns (2019) expands on this point and situates exposure to diversified information as intensifying polarization through in-group identification and providing an outside "other" that serves as an embodiment of the political enemy. We might not live in isolated bubbles; rather, it is the diversification of information on platforms that seems to spur polarization because of an increased exposure to opposing views. This observation would involve a much-needed research focus into *how* people perceive and recontextualize news on social media to fit it into their existing beliefs.

Expanding on Bruns' argument about "porous" filter bubbles and echo chambers, we found that many tweets were formatted to call out or attack opponents, e.g., from the dataset that queried GOP: "If we 'move on', the GOP will refuse to concede future elections, then judge-shop until they steal one. There must be a price paid for sedition or we will lose our democracy. This is critically important work in the next couple of years" (Alter, 2021). This strategy of attacking opponents was apparent in the fact that the tweet data collected through (for example) words that relate to Democrats contained largely Republican-leaning users who were calling out or attacking Democrats and vice versa. Note for example that in the March 2020 Republican-oriented dataset, a tweet from a Democrat reads: "Real quick: How are Republicans like Donald ok with 2% of people dying from coronavirus as if 2% is not a very high number. But when you discuss a 2-cent wealth tax on people making over 50 million they freak out like it's the worst thing that could ever happen to them" (Salenger, 2020).

Mainstream media attempts to contextualize and balance the narratives injected by hyperpartisan sources. When terms like "junk news" and "conspiracy theory" are invoked, they seem to trigger political backlash (Rogers, 2020a) and increase distrust in mainstream media. This dynamic can only be further understood if affective and intuitive tactics of people who are consuming and sharing news on social media are taken into account. As Swart and Broersma (2021) found in their analyses of young people's assessments of the trustworthiness of news, it is prior knowledge, lived experiences, and endorsements of sources by people within their own social networks that guide how people assess sources, which in turn plays a vital role in the choice to share particular sources over others.

When it comes to sharing news, the existing literature also steers attention toward the emotive underpinnings of hyperpartisan news and its effects when disseminated in the realm of social media. Twitter's business model is based on an attention economy, which places emotion at the forefront of journalistic practices. While emotion and information are not mutually exclusive, hyperpartisan media tend to exploit anger and a culture of outrage (Barnidge and Peacock, 2019; Berry and Sobieraj, 2014). Berry and Sobieraj (2014) move away from conventional wisdom that the rise of outrage media is the result of increased political polarization and argue for considering the economic underpinnings of what they dub an "outrage industry." They situate this industry in the context of structural changes to the media landscape that have fostered its exponential growth.

Twitter as part of this new media landscape is market-driven and dependent on the stickiness of content circulating on its platform. What makes users stick around (and share)? In the context of problematic and hyperpartisan news media, Berger and Milkman's study into viral news content (2012) is instructive for it examines what animates users to share content by assessing the emotive components of more and less shared content. They found that the virality of the content depends on evoking high-arousal positive (awe) or high-arousal negative (anger or anxiety) emotions. Content that evokes low-arousal, or deactivating, emotions (e.g., sadness) is less viral.[2] Thus outrage is seen as viral, which sheds light on the rise of hyperpartisan news on Twitter, as this kind of news is "meant to cause outrage, cue partisan emotions, and get clicks (i.e., make money). Hyperpartisan news … provides low-quality news with the goal of making money from people's—in many cases misguided—anger and outrage" (Barnidge and Peacock, 2019, p. 6). Note, however, that a binary opposition between quality journalism that is "informing" and less emotive and a sensationalized form that is merely emotive is false, as Wahl-Jorgensen (2019) also stipulates, in reference to Boltanski (1999). The creation of empathy is a prerequisite for political action. We want to stipulate that our distinction between problematic and non-problematic sources is not based on considerations regarding a distinction between factual and emotive news sources; rather, we point to the role of exploiting outrage through a socio-technical synergy between (hyper)partisan news outlets and a market-driven platform.

Notwithstanding the fact that all journalistic items hold some emotion, the affordances of Twitter facilitate a discursive climate which is more extreme, divisive and polarized than most mainstream news spaces (Shepherd et al., 2015). Trump but also hyperpartisan (and problematic) news outlets have benefitted from this affective shift by crafting messages in such a way that they spill over to mainstream media (Karpf, 2017) that in turn, and perhaps unwantedly, amplify fringe players on the platform. So, although the majority of shared sources is still comprised of mainstream news organizations, problematic and hyperpartisan sources are pushing for more space and might have spillover effects in the form of steering mainstream content and affective styles of communication on the platform.

Though investigating such spillover effects into content and style of legacy media is beyond the scope of our analyses, we did find that in political issue spaces such as that of DACA, mainstream media either followed uptakes in problematic source-sharing (see third time span, Figure 5.4) or seemed to veer upwards after such flares in problematic source-sharing (second time span, Figure 5.4), suggesting that problematic sources can be at the forefront of constructing a particular narrative about an issue at hand that is then taken up by mainstream sources. The latter dynamic can be the result of an algorithmically maintained power disparity between mainstream and fringe sources due to the intensification of majority (already popular)

2 These results hold even when the authors controlled for how surprising, interesting, or practically useful content is (all of which are positively linked to virality), as well as external drivers of attention, e.g., how prominently content was featured.

voices, a dynamic also hypothesized by among others Bruns (2019) as well as Bozdag and Van den Hoven (2015). This observation opens a relevant future direction for misinformation research which is more sensitive to detecting the adoption, or the "folding in," of fringe and at times problematic sources in the coverage and affective styles of mainstream media.

Findings

Finding 1: On Twitter the number of mainstream sources attached to political tweets or retweets is greater than problematic sources, however much the high share of (hyper)partisan sources within mainstream sources points to a rather polarized platform. After the Twitter purge of problematic accounts in January 2021, the share of (hyper)partisan sources within mainstream sources decreased significantly.

In the data collected during all three time frames (March 2–22, 2020, December 24, 2020–January 4, 2021 and March 10–21, 2021) around a million links to media articles were shared. Of these, overall, mainstream news sources outperformed problematic sources on Twitter. In March 2020, the share of problematic news sources shared on Twitter was 16% of all shared news sources. In December, the share of problematic news sources almost doubled to 30%. In March 2021, the share of problematic sources dropped significantly to 11%. The source classifications are based on source labeling platforms and contain two main categories indicating whether a source is mainstream or problematic and sub-labels for mainstream sources indicating (hyper)partisanship conservative or (hyper)partisanship progressive. The percentage of mainstream sources shared from sources subcategorized as (hyper)partisan decreased slightly from 48% in March 2020 to 43% in December and further dropped to 33% in March 2021. This drop mostly owes to conservative (hyper)partisan sources being less circulated. Overall, mainstream sources are shared more often than problematic news websites, though closely after the election, there was a significant rise in the share of problematic sources which decreased again in March 2021.

Finding 2: Conservative sources are shared more often when discussing Democrat keywords, and in most cases progressive sources are shared more often when discussing Republican ones. In Twitter we queried for specific keywords and hashtags (see Table 5.1) that represent each party and political candidate and found that in both March periods of 2020 and 2021 conservative sources were shared more than progressive ones when discussing Democrat keywords, and vice versa (Figures 5.2 and 5.3). Only in the December/January

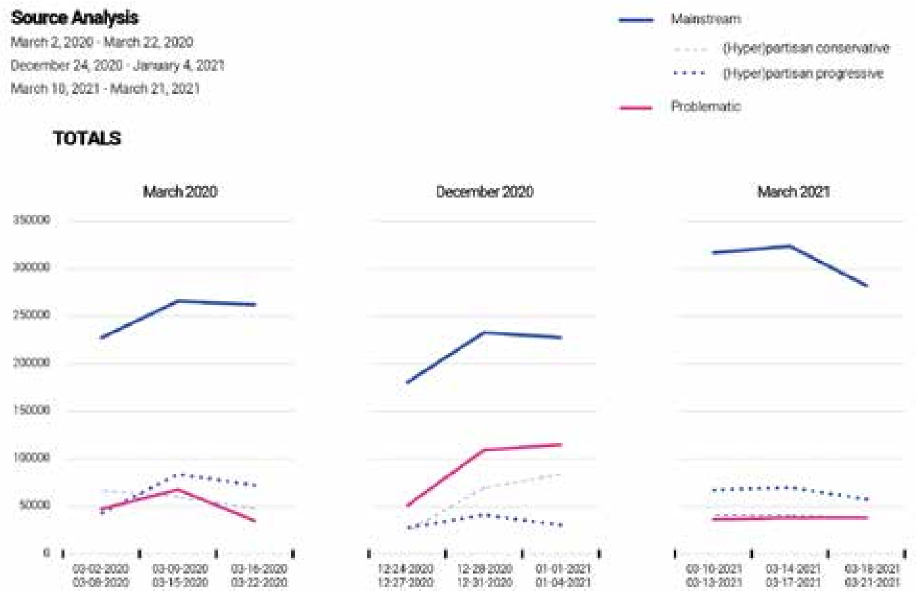
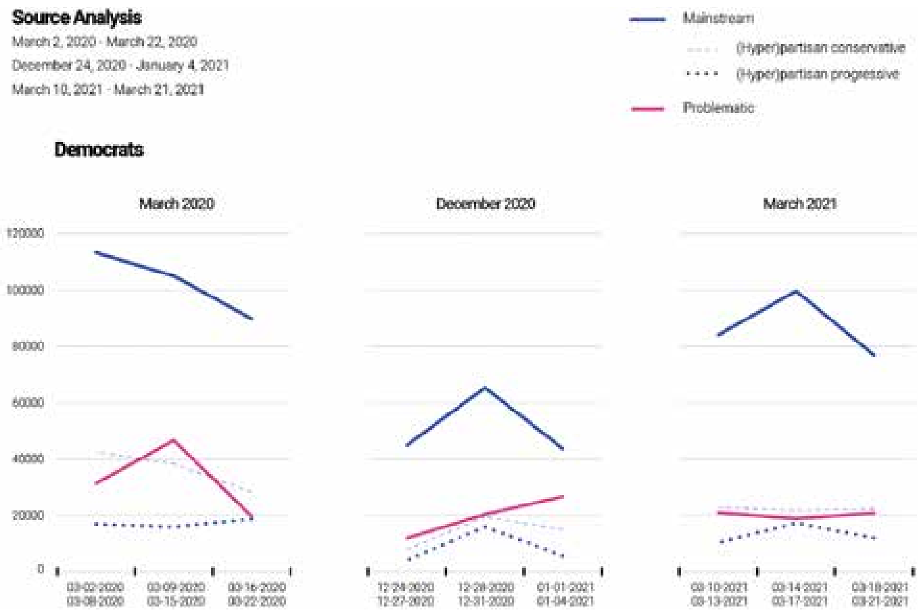


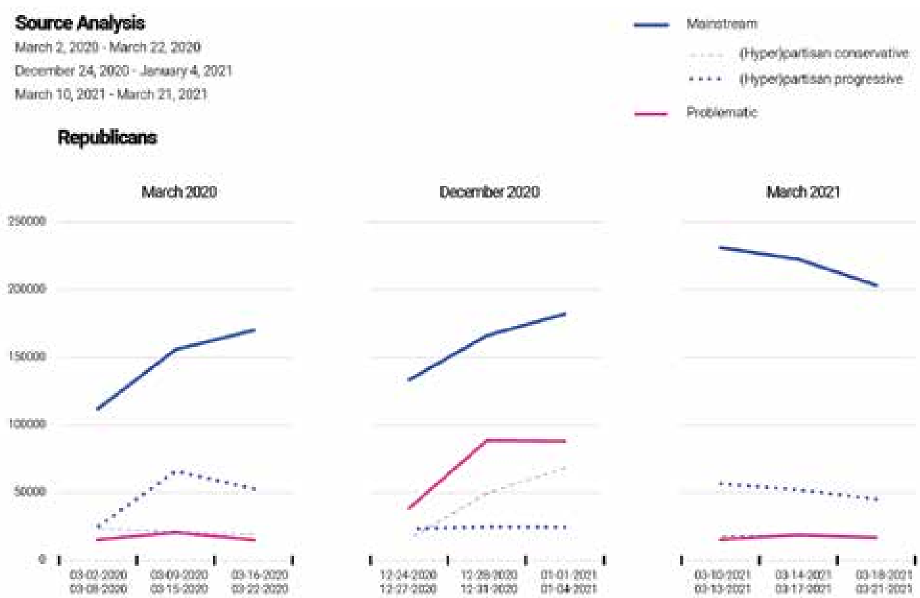
Figure 5.1 Cumulative total of mainstream and problematic hosts shared on political Twitter over three time spans: March 2–22, 2020, December 24, 2020–January 4, 2021 and March 10–21, 2021. Line graphs by Carlo De Gaetano and Federica Bardelli.

period the share of progressive sources in the Republican dataset was lower than that of conservative sources. We also found that in both March periods there were fewer problematic sources shared when discussing Republican keywords than Democrat ones. In December the proportion of problematic sources was much higher which is a trend we see across all datasets. The (hyper)partisan conservative sources in December are shared more often across both Republican and Democrat political spaces.

This finding is in contrast with the results in the other two periods that indicate a crossover of information where (hyper)partisan conservative sources were shared in the Democrat issue space and (hyper)partisan progressive sources were shared in the Republican. The change in December indicates that in the aftermath of the elections, Democrats continue to attack Donald Trump and the Republican party while some problematic and conservative (hyper)partisan sources seem to make a shift and even attack Republicans in the December/January time period when the alleged election fraud was a major topic. One example of this shift is an article[3]

3 https://www.thegatewaypundit.com/2020/12/raffensperger-gets-caught-georgia-ballots-printed-differently-gop-counties-vs-dem-counties-election-rigged/





Figures 5.2 and 5.3 Cumulative total of mainstream and problematic hosts shared on political Twitter when querying Republican or Democrat terms for three time spans: March 2–22, 2020, December 24, 2020–January 4, 2021 and March 10–21, 2021. Line graphs by Carlo De Gaetano and Federica Bardelli.

by the Gateway Pundit which made up 25% (23,000 shares) of the total of problematic content shared in that 4-day period, attacking a Republican in Georgia (who had not followed Trump's wishes). In terms of hashtag use, users who support the Democrats would use Republican keywords or hashtags such as #gop and #republicans to tweet against or at them. The same holds for the Republican supporters using the Democrat terms.

Finding 3: Mainstream sources are shared more often than problematic sources concerning social issues related to health care and climate change but not DACA (Deferred Action for Childhood Arrivals) where problematic sources outperformed mainstream sources in certain periods during March and December 2020 as well as in March 2021. In the third time span DACA has fewer partisan sources than in the first two time spans. That is, of those under study, the one issue where problematic sources are shared more often than mainstream sources (only during the first week of March and December 2020) is DACA (Figure 5.4), though the high engagement is largely attributed to a few articles. In the second and third weeks of March 2020, the number of problematic sources in the DACA issue space significantly decreased. Indeed, across the three social issues, with the exception of DACA, few problematic sources were shared.

We note a similar pattern of shared problematic sources across the issues when comparing all time frames. In general, all issue spaces show less engagement in the time periods after the election. For example, there was almost no activity in the Medicare issue space in March 2021, indicating its election relevance rather than a broader societal concern. Note that the sample sizes in these issue spaces are small, so one article can quickly spike engagement.

Finding 4: There were more problematic accounts (fake accounts, bots or locked/suspended) than real accounts on Twitter among selected keyword and hashtag datasets (Democrat, Republican, Trump) except for Biden's dataset in the first time frame. The latter data did contain problematic accounts in the second time span, covering the immediate aftermath of the elections.

We now move to the top 20 users with the highest number of tweets and retweets during two, three-day time frames in March (one during and one after "Super Tuesday," March 3, 2020) and a third time frame (January 1–4, 2021). In the Republican and Democrat keyword and hashtag datasets we noticed that, in total, there were more problematic accounts than real accounts (Figure 5.7) for these time frames. For the Democrat dataset we found only four real accounts in March and one account that clearly labeled itself as a bot that retweets all tweets by Trump. The rest was a combination

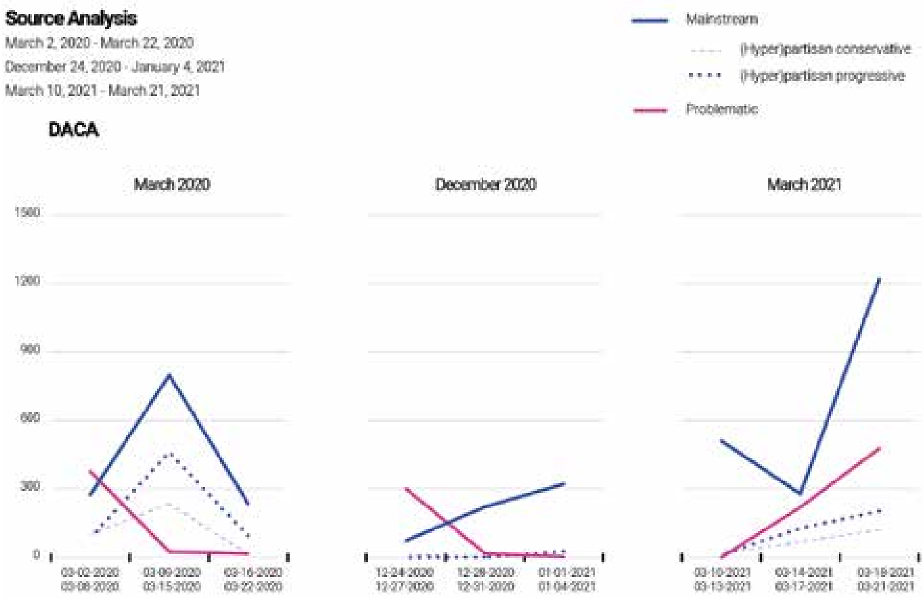


Figure 5.4 Cumulative total of mainstream and problematic hosts shared on political Twitter concerning DACA, during the time spans: March 2–22, 2020, December 24, 2020–January 4, 2021 and March 10–21, 2021. Line graphs by Carlo De Gaetano and Federica Bardelli.

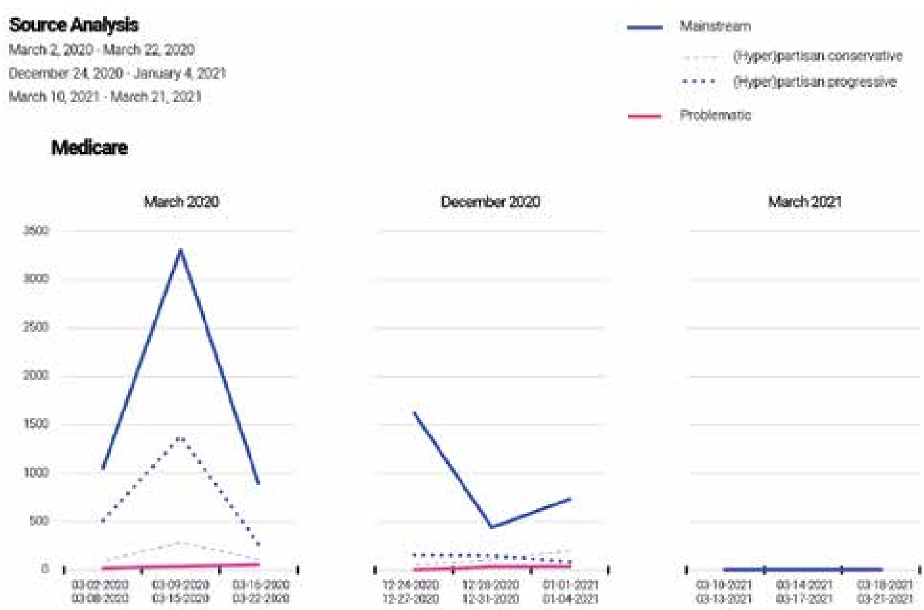


Figure 5.5 Cumulative total of mainstream and problematic hosts shared on political Twitter concerning Medicare, during the time spans: March 2–22, 2020, December 24, 2020–January 4, 2021 and March 10–21, 2021. Line graphs by Carlo De Gaetano and Federica Bardelli.

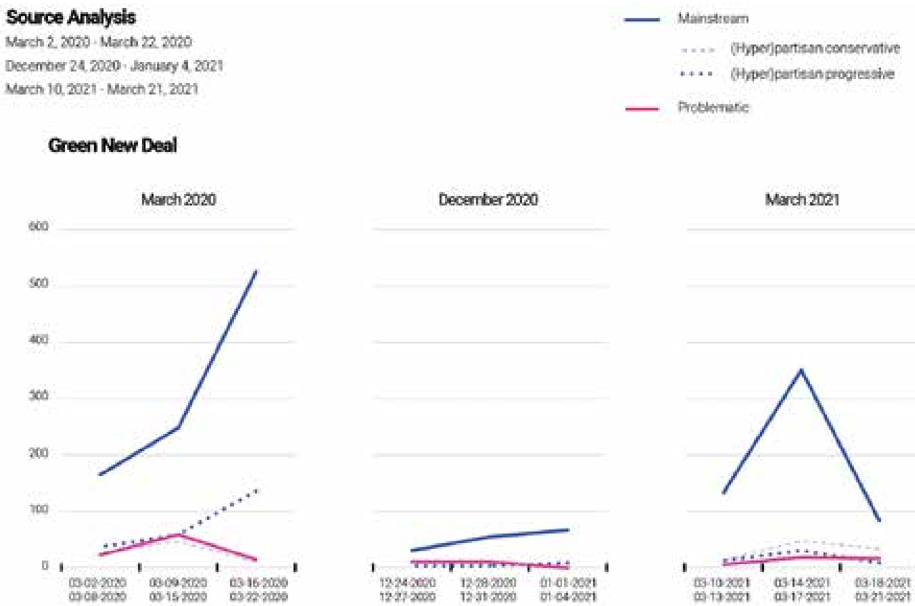


Figure 5.6 Cumulative total of mainstream and problematic hosts shared on political Twitter concerning Green New Deal, during the time spans: March 2–22, 2020, December 24, 2020–January 4, 2021 and March 10–21, 2021. Line graphs by Carlo De Gaetano and Federica Bardelli.

of fake accounts and locked/suspended accounts that had been banned by Twitter. In the Democrat keyword and hashtag dataset, most accounts, whether real or fake, were mostly pro-Republican, indicating again how users are employing the opposing political party's terms. The same applies to the Republican keyword and hashtag dataset, where most users are pro-Democrat as opposed to Republican, though a smaller proportion is fake. Interestingly, in January 2021, the share of fake and bot accounts shifts between these two issue spaces. The number of fake accounts in the Republican hashtag space is now larger than the Democratic space. In our datasets in total, problematic accounts in January make up about 60% of all accounts which is roughly the same as in March.

In 2016 it was found that suspect accounts were mostly Pro-Republican, and these were responsible for spreading most of the problematic information (Bovet and Maske, 2019). In March we found that there was already a rise in problematic accounts associated with pro-Democrats. In January, we found that there are more problematic pro-Democrat accounts compared to March. Thus, it can be argued that Democrats are employing problematic accounts within Republican political spaces to attack the Republican party.

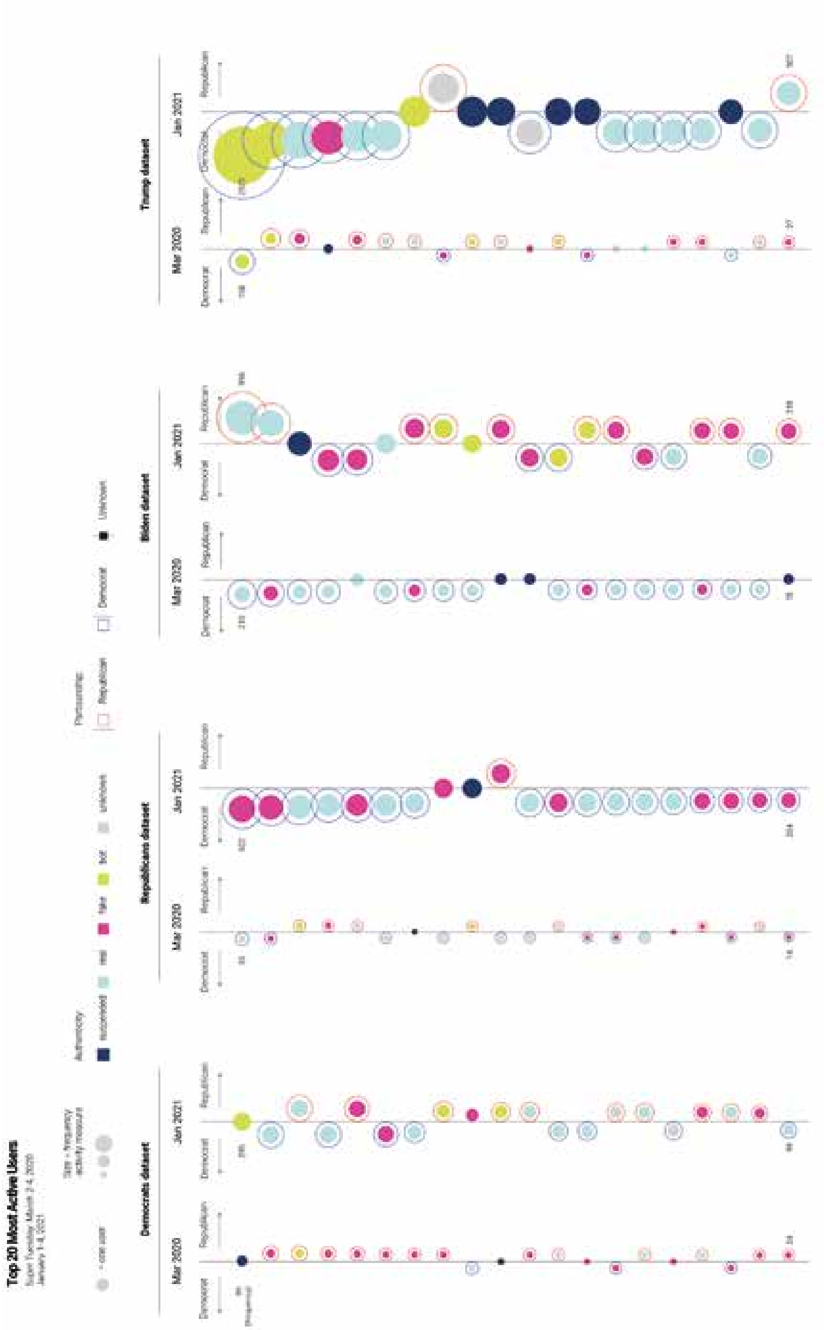


Figure 5.7 The top 20 users with the highest activity measure on Twitter within the Democrat, Republican, Biden and Trump hashtag/keyword datasets, collected March 2–4, 2020 and January 1–4, 2021. Bubble diagrams by Carlo De Gaetano and Federica Bardelli.

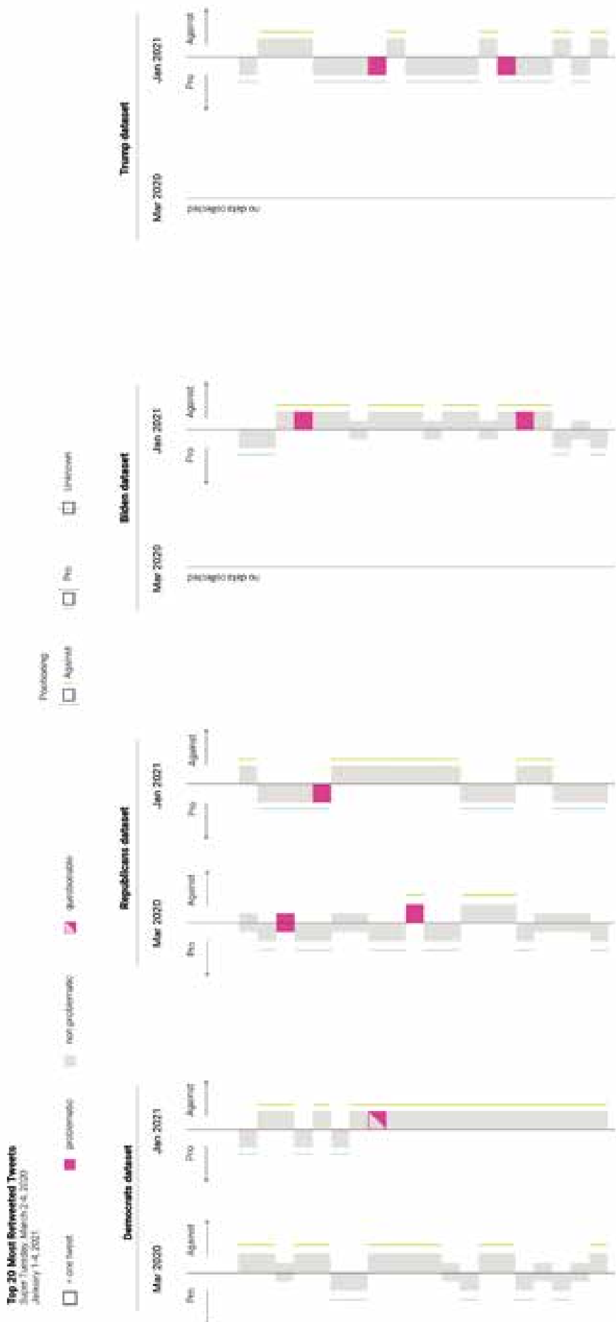


Figure 5.8 The top 20 users with the highest activity measure on Twitter within the Democrat and Republican hashtags/keywords datasets, collected during the time spans: March 2–4, 2020 and January 1–4, 2021. Diagrams by Carlo De Gaetano and Federica Bardelli.

Figure 5.9 The top 20 users with the highest activity measure on Twitter within the hashtag/keyword datasets for the three political issues, collected during the time spans: March 2–4, 2020 and January 1–4, 2021. Diagrams by Carlo De Gaetano and Federica Bardelli.

For the candidates' datasets (Biden and Trump) the same process was followed, but we filtered the top 20 users (by tweeting activity) that @mention each candidate (Figure 5.7). Interestingly, a similar shift can be seen in the Democrat and Republican datasets when comparing the two time frames. In March, the Biden dataset had the highest number of real accounts, with a few fake and locked/suspended accounts. The majority of users that @ mention Biden is not problematic, and they are supporters of his political campaign. The opposite holds for users mentioning Trump where results are equally distributed between bots, fake, and real accounts. In terms of partisanship, the majority is pro-Republican, which indicates that in contrast to the political party spaces, the most active users are supportive. In January, however, the most active users are those who are attacking either candidate. There are more pro-Democrat bots attacking Trump and more real pro-Republican accounts attacking Biden. Overall, the debate seems (even) more polarized in January compared to March.

Finding 5: The most retweeted tweets among all datasets in both March 2020 and December–January 2021 were made mostly by influential accounts like the presidential candidates, members of Congress, organizations, and journalists and largely do not contain any problematic sources. Few problematic sources were found among the top 20 most retweeted tweets in the Democrat and Republican keyword and hashtag datasets in the two time frames (Figure 5.8). For example, the two tweets flagged as problematic in the Republican space in March are linked to the website run by Dan Bongino, a conservative talk show host. A large majority of the retweets are by less controversial, influential people, including presidential candidates, members of Congress and journalists. The results are largely similar for the January 2021 dataset, where one highly resonating retweet opposing Democrats was labeled as questionable. It relates to a news item around electoral fraud from the OAN (One America News), which is a problematic source as per our classification based on Media Bias/Fact Check (see also methods section). Another resonating retweet referred to Breitbart News covering calls for investigating electoral fraud.

Methods

Before initiating our Twitter data collection, we curated a list of queries for political candidates, political parties and social issues, incorporating politician-specific, party-specific and issue-specific keywords and hashtags (Table 5.1). Three social issues (likely to animate both sides of the political spectrum) were selected from a longer issue list made by triangulating issue lists on voter aid sites: Politico, VoteSmart, On the Issues and Gallup. These keywords and hashtags were captured using DMI-TCAT (Borra and Rieder, 2014) from the 2nd until the 23rd of March 2020 and from December 24, 2020 until January 4, 2021. 4CAT[4] was used in the period from March 10 to 22, 2021, when problematic users were not analyzed. In these time spans, close to 3 million tweets were captured that contain a link to a news article. These tweet sets we term "political Twitter."

Table 5.1 Curated list of political keywords and hashtags queried in Twitter.

Topic	Query
Democrat	#democrats, 2020Democrats, BackTheBlueWave, CountryOverParty, DemocraticParty, Democrats2020, Dems, NotMeUs, TowardsADemocraticPartyICanTrust, VoteBlue, VoteBlueNoMatterWho, VoteBlueNoMatterWho2020, VoteBlueToSaveAmerica, WelcomeToNotMeUs, democrats, thedemocrats
Republican	#gop, gop, republicans, #republicans, VoteRed, VoteRed2020, VoteRedToSaveAmerica, VoteRedToSaveAmerica2020
Biden	#biden, #joebiden, "joe biden," Biden2020, BidenBounceBack, BidenForPresident, BidenHarris, BidenHarris2020, BidenBeatsTrump, JoeBiden2020, JoeMentum, Mojoe, QuidProJoe, RidinWithBiden, TeamBiden, TeamJoe, WeKnowJoe, biden, joebiden
Trump	#trump, "donald trump," BlackVoicesForTrump, CubansForTrump, DonaldTrumpjr, KAG, KAG2020, KAG2020LandslideVictory, KeepAmericaGreat, MAGA, MAGA2020, MAGA2020Landslide, PresidentTrump, PresidentTrump2020, ReElectPresidentTrump2020, TWGRP, Trump2020, Trump2020Landslide, Trump2020LandslideVictory, trump
DACA	Daca
Green New Deal	Greennewdeal
Medicare	medicareforall, medicare4all

The three types of data we collected were most shared links, the top users (in terms of the number of tweets made), and the most retweeted tweets. To study the most shared links, an expert list of sources was created. Each source was labeled into two main categories, mainstream or problematic. Mainstream sources could be sub-categorized as (hyper)partisan conservative, (hyper)partisan progressive or neither. The expert list was created using existing labeling sites such as Allsides.com, Media Bias/Fact Check, "the Chart," and NewsGuard. We consider the categorization as rough. By calculating the total number of times problematic sources were shared

4 https://github.com/digitalmethodsinitiative/4cat

during our duration of study and comparing it with the mainstream sources we were able to show the magnitude of the matter at hand. Are problematic sources present and shared by the users on Twitter who make use of specific political hashtags and keywords? We limited the scope of the top users and hashtags under study to three days in the first two time frames, starting from the 2nd of March 2020 and from the 1st of January 2021. The reason for choosing the specific March period was that it encompassed "Super Tuesday," a day when the largest number of U.S. states hold primary elections, and it would be a reasonable assumption that the Twitter engagement on this day, the day prior, and the day after would be higher than the other days in our date range. The January time frame was just before the deciding Georgia run-off elections for the U.S. Senate on January 5, which would give the Democrats a slim majority and in hindsight, with that time frame, we also captured the days before the Capitol riots of January 6, 2021.

With the dataset of most active users, we investigated the extent to which problematic users/accounts (fake profiles, bots, or locked/suspended users) were present. We examined the top 20 users with the greatest number of tweets on political Twitter. These users were then coded or categorized on two scales: "authenticity" and "partisanship." For the authenticity label, the top 20 users were classified into four types based on their Twitter profiles, where the idea is to gain a sense of the genuineness and legitimacy of the top users: real, fake, bot, and locked/suspended. The categories are adopted from the audience intelligence website, SparkToro, which ranks Twitter users based on their attributes (Fishkin, 2018). For bots, the website categorizes accounts by determining whether they have Twitter's default profile image, if an account has an unusual ratio of followers/following, or posts an abnormal number of tweets per day, among other signals. Fake/real profiles, too, are judged according to (usual/unusual) tweeting habits and behavior. The second categorization is "partisanship," where all the top users' political leanings were labeled independently by two authors by looking at their Twitter profiles and classifying them into one of three categories: Democrat-leaning, Republican-leaning, or unknown. Any disagreements between the authors resulted in labeling the one in question as unknown.

With regards to the most retweeted tweets, the top 20 tweets were extracted from the political spaces, and from the three issue-specific hashtags, DACA, Green New Deal, and Medicare. The most retweeted or the most popular tweets were further categorized into two categories of partisanship and the categories problematic or non-problematic information provider. Similar to the problematic users' segment, the partisanship of the tweets was manually labeled by looking at the language of the tweet and further details about the person who tweeted. To decide if a tweet contains problematic information, we checked whether any news sources linked in the tweets were classified as such in the labeled source list.

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Data availability

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