An Early Look at the Parler Online Social Network

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Abstract

Parler is as an alternative social network promoting itself as a service that allows its users to "Speak freely and express yourself openly, without fear of being deplatformed for your views." Because of this promise, the platform become popular among users who were suspended on mainstream social networks for violating their terms of service, as well as those fearing censorship. In particular, the service was endorsed by several conservative public figures, encouraging people to migrate there from traditional social networks. In this paper, we provide the first data-driven characterization of Parler. We collected 120M posts from 2.1M users posted between 2018 and 2020 as well as metadata from 12M user profiles. We find that the platform has witnessed large influxes of new users after being endorsed by popular figures, as well as a reaction to the 2020 US Presidential Election. We also find that discussion on the platform is dominated by conservative topics, President Trump, as well as conspiracy theories like Qanon.

1 Introduction

Social media has proved incredibly relevant and impactful to nearly every aspect of our day-to-day lives. The nearly ubiquitous mechanism to reach potentially the entire world with a few taps on a touch screen has thrust social media platforms, especially with respect to moderation policies, into the political spotlight. For example, during the final few weeks of his presidency, Donald Trump vetoed the National Defense Authorization Act because (along with several other concerns) it did not include his demand to drastically alter Section 230 protection social media moderation policies work within.

Over the past five years or so, social media platforms that cater specifically to users disaffected by the policies of mainstream platforms have emerged. Typically, these platforms tend not to be terribly innovative in terms of features, but instead attract users based on their dedication to "free speech." In reality, these platforms have usually wound up as echo chambers, harboring dangerous conspiracies and violent extremist groups. For example, consider Gab, one of the earliest alternative homes for people banned from Twitter [40]. After the Tree of Life terrorist attack, Gab came under international scrutiny and was hit with multiple attempts to de-platform the service, essentially erasing it from the Web. Gab, however, has survived and even rolled out new features under the guise of free speech that are in reality tools used to further evade and circumvent moderation policies put in place by mainstream platforms [34].

Worryingly, Gab, and other more fringe platforms like Voat [29], and TheDonald.win [32] have shown that not only is it feasible in technical terms to create a new social media platform, but marketing the platform towards specific polarized communities is an extremely successful strategy to bootstrap a user base. I.e., there is a subset of users on Twitter, Facebook, Reddit, etc., that will happily migrate to a new platform, especially if it advertises moderation policies that do not restrict the growth and spread of political polarization, conspiracy theories, extremist ideology, hateful and violent speech, and mis- and dis-information.

In this paper, we present an early look at Parler, an emerging social media platform that has positioned itself as the new home of disaffected right wing social media users in the wake of active measures by mainstream platforms to excise themselves of dangerous communities and content. While Parler works approximately the same as Twitter and Gab, it additionally offers an extensive set of self-serve moderation tools. E.g., filters can be set to place replies to posted content into a moderation queue requiring manual approval, mark content as spam, and even automatically block all interactions with users that post content matching the filters.

2 Parler

Parler (generally pronounced "par-luh" as in the French word for "to speak") is a microblogging social network launched in August 2018. Parler markets itself as being "built upon a foundation of respect for privacy and personal data, free speech, free markets, and ethical, transparent corporate policy" [17]. Overall, Parler has been extensively covered in the news for fostering a substantial user-base of Donald Trump supporters, conservatives, conspiracy theorists, and right-wing extremists [1, 22].

Basics. At the time of writing, to create an account, users must provide an email address and phone number that can receive an activation SMS (Google Voice/VoIP numbers are not allowed).

Users interact on the social network by making posts of maximum 1,000 characters, called "parlays," which are broadcast to their followers. Users also have the ability to make comments on posts and on other comments.

Voting. Similar to Reddit and Gab, Parler also has a voting system designated for ranking content, following a simple upvote/downvote mechanism. On the platform, posts can only be upvoted, thus making upvotes functionally similar to likes on Facebook. Whereas, comments to posts can receive both upvotes and downvotes. Voting allows users to influence the order in which comments are displayed, akin to Reddit score.

Verification. Verification on Parler is opt-in; i.e., users can willingly make a verification request by submitting a photograph of themselves and a photo-id card. According to the website, verification, in addition to giving users a red badge, evidently "unlocks additional features and privileges." They also declare that personal information required for verification is never shared with third parties, and deleted upon completion, except for "encrypted selfie data." At the time of writing, only 240,666 (2%) users on Parler are verified.

Moderation. The Parler platform has the capability to perform content moderation and user banning through administrators. We explore these functionalities, from a quantitative perspective, in Section 4. Note that there are several moderation attributes put in place per account, which are visible in an account's settings. More specifically, there are fields for whether the account is "aiEnabled" or "pending." It appears that new accounts show up as "pending" until they are approved by automated moderation.

Each account has a "moderation" panel allowing users to view comments on their own content and perform moderation actions on them. A comment can fall into any of five moderation categories: *review*, *approved*, *denied*, *spam*, or *muted*. Users can also apply keyword filters, which will enact a choice of several automated actions based on a filter match: *default* (prevent the comment), *approve* (require user approval), *pending*, *ban member notification*, *deny*, *deny with notification*, *deny detailed*, *mute comment*, *mute member*, *none*, *review*, and *temporary ban*. These actions are enforced at the level of the user configuring the filters, i.e., if a filter is matched for temporary ban, then the user making the comment matching the filter is banned from commenting on the original user's content.

There are several additional comment moderation settings available to users. For example, they can only allow verified users to comment on their content, handle spam, etc. Overall, Parler allows for more individual content moderation compared to other social networks; however, recent reports have highlighted how global moderation is arguably weaker, as large amounts of illegal content has been allowed on the platform [9]. We posit this may be due to global *manual* moderation performed by a few accounts.

Monetization. Parler supports "tipping," allowing users to tip one another for content they produce. This behavior is turned off by default, both with respect to accepting and being able to give out tips. An additional monetization layer is incorporated within Parler, which is called "Ad Network" or "Influence Network." Users with access to this feature are able to pay for or earn money for hosting ad campaigns. Users set their rate per thousand views in a Parler specified currency called "Parler Influence Credit."

	Count	**#Users**	**Min. Date**	**Max. Date**
Posts	58,661,396	776,952	2018-08-01	2020-12-30
Comments	61,489,973	1,610,745	2018-08-24	2020-12-30
Total	120,151,369	2,141,708	2018-08-01	2020-12-30

Table 1: Parler Dataset.

3 Dataset

In this section, we present our dataset. We collect data from Parler using a custom-built crawler that accesses the (undocumented) Parler API.

Crawling. The crawler works as follows. First, we populate users via an API request that maps a monotonically increasing integer ID (modulo a few exceptions) to a UUID that serves as the user's ID in the rest of the API. Next, for each user ID we discover, we query for its profile information, which includes metadata such as badges, whether or not they are banned, bio, posts, comments, follower and following counts, when they joined, their name, their username, whether or not they are private, whether or not they are verified, etc. Note that, to retrieve posts and comments, we use an API endpoint that allows for time-bounded queries; i.e., for each user, we retrieve the set of post/comments since the most recent post/comment we have already collected for that user.

Data. Overall, we collect all user profile information for the 12,031,849 Parler accounts created between August 2018 and December 2020. Additionally, we collect 58.6M posts and 61.4M comments from a random set of 2.1M users; see Table Table 1. Our dataset will be made available to other researchers upon request.

Limitations of Sampling. As mentioned above, posts and comments in our dataset are from a sample of users; more precisely, 777k and 1.6M users, respectively. Although, numerically, this should in theory provide us with a good representation of the activities of Parler's user base, we acknowledge that our sampling might *not* necessarily be representative in a strict statistical sense. In fact, using a two-sample KS test, we reject the null hypothesis that the distribution of comments reported in the profile data from all users is the same as the distribution of those we actually collect from 1.1M users ($p < 0.01$). Moreover, we have posts from much fewer users than we have comments for; this is due to users' tendency to make more posts than comments, which increases the wall clock time it takes to collect posts.

Therefore, we need to take these possible limitations into account when analyzing user content (see Section 5); nonetheless, we believe that our sample does ultimately capture the general trends of measured from profile data, and thus we are confident our sample provides at least a reasonable approximation of content posted to Parler.

Ethical Considerations. We only collect and analyze publicly available data. We also follow standard ethical guidelines [33],

Word	(%)	Bigram	(%)
conservative	1.31%	trump supporter	0.27%
god	1.05%	husband father	0.26%
trump	1.00%	wife mother	0.21%
love	0.93%	god family	0.18%
christian	0.83%	trump 2020	0.18%
patriot	0.79%	proud american	0.18%
wife	0.79%	wife mom	0.17%
american	0.74%	pro life	0.15%
country	0.69%	christian conservative	0.15%
family	0.66%	love country	0.14%
life	0.61%	love god	0.14%
proud	0.60%	family country	0.13%
maga	0.58%	president trump	0.13%
mom	0.58%	god bless	0.13%
father	0.57%	business owner	0.12%
husband	0.56%	jesus christ	0.11%
jesus	0.47%	conservative christian	0.11%
freedom	0.44%	american patriot	0.10%
retired	0.44%	maga kag	0.10%
america	0.43%	god country	0.09%

Table 2: Top 20 words and bigrams found in Parler users bios.

not making any attempts to track users across sites or de-anonymize them.

4 User account analysis

This section outlines several analyses of the 12M Parler users collected between November 25th 2020 to December 30th 2020.

4.1 User bios

Next, we analyze the user bios of all the Parler users in our dataset. Specifically, we extract the most popular words and bigrams and we report them in Table 2. We observe several popular words that indicate that a substantial number of users on Parler self identify as conservatives (1.3% of all users include the word "conservative" it in their bios), Trump supporters (1% include the word "trump" and 0.27% the bigram "trump supporter"), patriots (0.79% of all users include the word "patriot"), and religious individuals (1.05% of all users include the word "god" in their bios). Overall, these results indicate that Parler attract similar user base as the one that exists on Gab [40].

4.2 Bans

Parler profile data includes a flag about whether or not a user was banned, and we find this flag set for 252,209 (2.09%) of users. Almost all of these banned accounts, 252,076 (99.95%) are also set to private, but for those that are not, we can observe their username, name and bio attributes, and even retrieve comments/posts they might have made. While not a thorough analysis of the ban system, when exploring the hundred 130 or so non-private banned accounts we noticed some interesting things. In general, there appear to be two general classes of bans on these users. The first are accounts baned for impersonating notable figures, e.g., the name "Donal J Trump" and a bio that describes the user as the "45th President of the United States of America," or a "ParlerCEO" username with "John Matza" as the user's display name These type of bans fall within 5th Parler guideline around "Fraud, IP Thefy, Impersonation, Doxxing" suggesting Parler does in fact enforce at least some of their moderation policies.

The other type of account we observed were harder to determine the guideline violation that led to the ban. For example, an account named "ConservativesAreRetarded" whose profile picture was a hammer and sickle made a comment (the account's only comment) in response to a post by the "Matthew Matze" account with a bio describing the user as "Parler Quality Assurance Lead"). The comment,"You look like garbage, at least take a decent photo of the shirt," was made in reply to a post that included an image of Matthew Matze wearing a Parler t-shirt. While the comment by "ConservativesAreRetarded" is certainly not nice, it was not clear to us which of the Parler guidelines it violated. We do not believe this would be considered violent, threatening, or sexual content, which are explicitly noted in the guidelines. Although outside the scope of this paper, it does call into question how consistently Parler's moderation guidelines are followed.

4.3 Badges

There are several badges awarded to a Parler user profile. These badges correspond to different types of account behavior. Users are able to select which badges they opt to appear on their user profile. There are a variety badges and each type is detailed in 3. A user can have no badges or multiple badges. The crawler returnes a badge number and we then looked up users with specific badges in the Parler UI in order to see the badge tag and description which are displayed visually.

4.4 Gold badge users

The user profile objects returned by the Parler API contain a "verified" field that corresponds to a boolean value. All users with this value set to "True" have a gold badge and vice versa. We assume that these users are actually the small set of truly "verified" users in the more widely adopted sense of the word, akin to "blue check" users on Twitter. There are only 596 gold badge users on Parler, which is less than 1% of the entire user count. Users are "verified" through an identity check process but this only gets you a "Verified" tag. This is separate from the rarer "Gold" badge users.

From rudimentary exploratory analysis of the "Gold badge" verified users it appears to mostly be a mixture of right wing celebrities, conservative politicians, conservative alternative media blogs, and conspiracy outlets. Some notable accounts are Rudy Giuliani and Enrique Tarrio who is the recently arrested head of the Proud Boys [18]. Of the 596 accounts we found with the gold badge, 51 of them had either "Trump" or "maga" in their bios.

For the remainder of the analysis we analyze by gold badge users, users who are verified and not gold badge, and users who are not verified and not gold badge (other). For example, Figs. 3 and 4 show post and comment activity respectively split by these categorizations. We see that both gold badge and

Badge #	#Unique Users	Badge Tag	Description
0	240,666	Verified	Users who have gone through verification.
1	596	Gold	Users whom Parler claims may attract targeting, impersonation, or phishing campaigns.
2	81	Integration Partner	Used by publishers to import all their articles, content, and comments from their website.
3	111	Affiliate (RSS Feed)	Shown as affiliates in the website but known as RSS feed to Parler mobile apps. Integrated directly into an existing off-platform feed. Share content on update to an RSS feed.
4	844,812	Private	Users with private accounts.
5	4,587	Verified Comments	User is verified (badge 0) and is restricting comments only to other verified users.
6	48	Parody	Users with “approved” parody. Despite guidelines against impersonation, some are allowed if approved as parody.
7	31	Employee	Parler employee.
8	2	Real Name	Using real name as their display name. Not clear how/if this information is verified.
9	957	Early Parley-er	Joined Parler, and was active, early on (on or before December 30th, 2018).

Table 3: Badges assigned to user profiles. Users are given an array of badges to choose from based on their profile parameters.

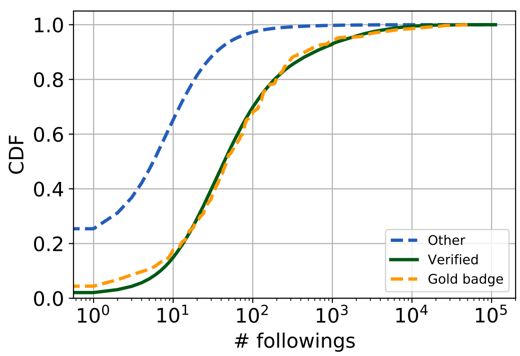


Figure 1: CDF of the number of following of gold badge, verified, and other users. (Note log scale on x-axis).

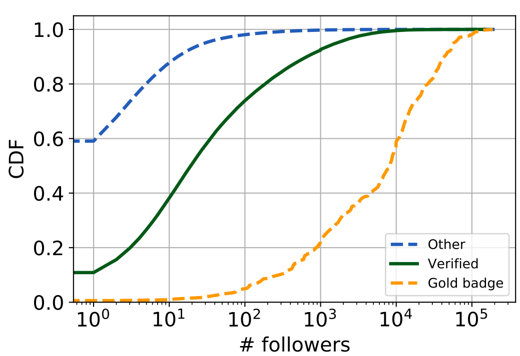


Figure 2: CDF of the number of followers of gold badge, verified, and other users. (Note log scale on x-axis).

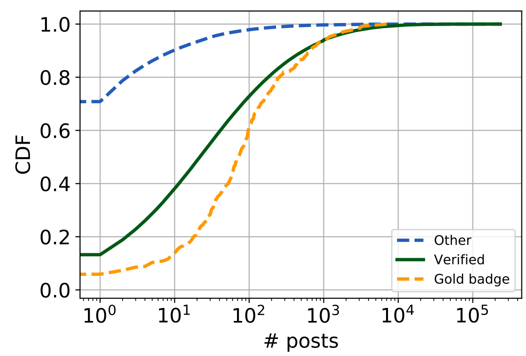


Figure 3: CDF of the number of posts of verified, gold badge, and other users. (Note log scale on x-axis).

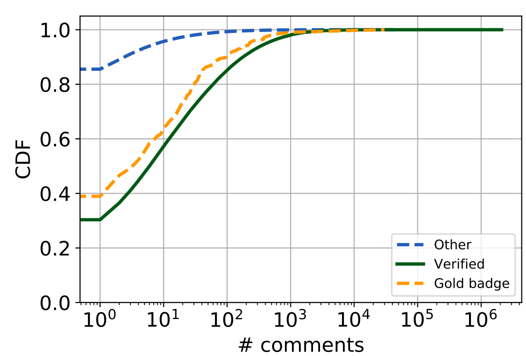


Figure 4: CDF of the number of comments of verified, gold badge, and other users. (Note log scale on x-axis).

verified users are overall more active than the “other” users.

There are only 4 users who are both gold badge and private. These users are “ScottMason”, “userfeedback”, “AFPhq” (Americans for Prosperity), and “govgaryjohnson” (Governor Gary Johnson).

4.5 Followers/Followings

There are two numbers related to the underlying social network available in the user profile objects. A users followers corresponds to how many individuals are currently following someone whereas their followings corresponds to how many useres they follow. Fig. 1 shows a CDF plot of the following per user split by badge type and Fig. 2. First we note that standard users are less popular, as we see in 2 they have less followers. Gold badge users on the other hand have a much larger amount of followers We see that about 40% of the typical users have more than a single follower where as about 40% of gold badge users have more than 10,000 followers, and 40% of verified users fall somewhere in the middle. As seen in Fig. 1 have a small amount of users they are following compared to typical users.

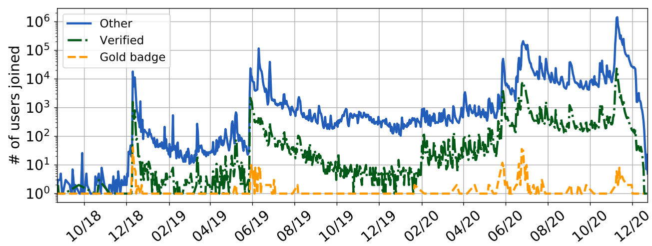


Figure 5: Number of users joining daily split by gold badge, verified, and other users. (Note log scale on y-axis.)

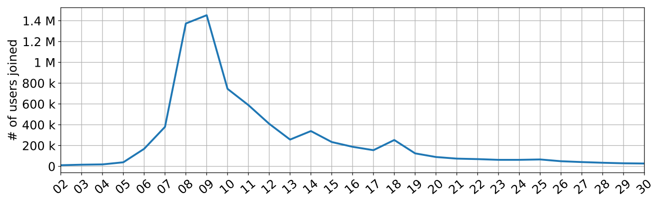


Figure 6: Number of users joining per day in November 2020.

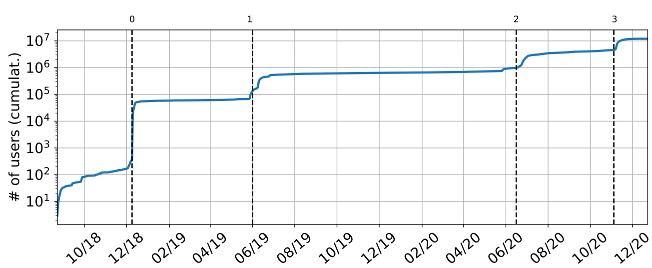


Figure 7: Cumulative number of users joining daily. (Note log scale on y-axis). Table 4 reports the events annotated in the figure.

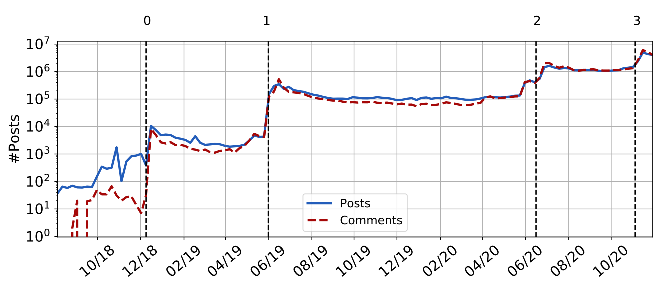


Figure 8: Number of posts per week. (Note log scale on y-axis). Table 4 reports the events annotated in the figure.

4.6 User account creation

Users grew regularly throughout the course of Parler's lifetime. Several key events have been reported throughout in terms of user growth. Parler originally launched in August 2018. Fig. 7 plots cumulative users growth since Parler went live. Parler saw the first major user growth in December 2018, reportedly because conservative activist Candace Owens tweeted about it [28]. The second large new user event occurred in June 2019 when Parler reported that a large amount of accounts from Saudi Arabia joined [10]. In 2020 there were two large events of new users. The first occurred in June 2020, where on June 16th 2020 conservative commentator Dan Bongino announced he had purchased an ownership stake [36]. Parler also received a second endorsement from Brad Parscale, the social media campaign manager for Trump's 2016 campaign. The last major user growth event in 2020 occurred around the time of the United States 2020 election and some cite [11] this growth as a result of Twitter's continuous fact-checking on Donald Trump's tweets. As we show in Fig. 6 new account creation while the outcome of the US 2020 Presidential Election was determined.

Fig. 5 shows a longitudinal plot of users joined per day. The chart is split by users which have a "gold" badge, "verified" badge and users which do not have either, or "other."

Event ID	Description	Date
0	Candance Owens tweets about Parler [28].	2018-12-09
1	Large amount of users from Saudi Arabia join Parler [10].	2019-06-01
2	Dan Bongino announces purchase of ownership stake on Parler [36].	2020-06-16
3	2020 US Presidential Election [11].	2020-11-04

Table 4: Events depicted in Figs. 7 and 8.

5 Content Analysis

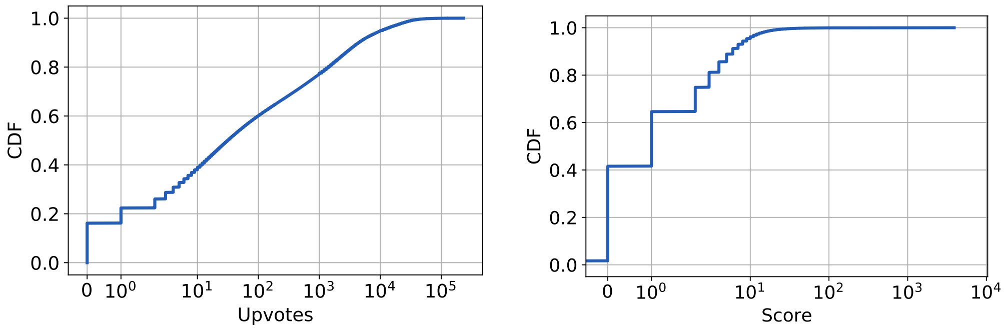
We now analyze the content posted by Parler users across several axes; specifically, we focus on the activity volume, voting, as well as hashtags and URLs shared on the platform.

5.1 Activity Volume

We begin our analysis by looking at the volume of posts and comments over time. Fig. 8 plots the weekly number of posts and comments in our dataset. We observe that the shape of curves is similar to that in Fig. 7, i.e., there are spikes in post/comment activity at the same dates where there is an influx of new users due to external events. Parler was a relatively small platform between August 2018 and June 2019, with less than 10K posts and comments per week. Then, by June 2019, there is a substantial increase in the volume of posts and comments, with approximately 100K posts and comments per week. This coincides with a large-scale migration of Twitter users originating from Saudi Arabia, who joined Parler due to Twitter's "censorship" [10]. The volume of posts and comments remain relatively stable between June 2019 and June 2020, while, in mid-2020, there is another large increase in posts and comments, with 1M posts/comments per week. This coincides with when Twitter started flagging President's Trump tweets related to the George Floyd Protests, which prompted Parler to launch a campaign called "Twexit," nudging users to quit Twitter and join Parler [23]. Finally, by the end of our dataset in late 2020, another substantial increase in posts/comments coincides with a sudden interest in the platform after Donald Trump's defeat in the 2020 US Presidential Election.

5.2 Voting

As mentioned in Section 2, posts on Parler can be upvoted, while comments can be upvoted and downvoted, thus yielding



(a) Posts (b) Comments

Figure 9: CDFs of the number of upvotes on posts and scores (upvotes minus downvotes) on comments. (Note log scale on x-axis).

a score (sum of upvotes minus the sum of downvotes). Fig. 9 plots the Cumulative Distribution Functions (CDFs) of the upvotes and score for posts and comments. We find that 16% of the posts do not receive any upvotes, and 62% of them at least 10 upvotes. Looking at the score in comments (see Fig. 9(b)), we observe that comments rarely have a negative score (only 1.6%), while 39% of them have a score equal to zero, and the rest of the comments have positive scores. Overall, our results indicate that a substantial amount of content posted on Parler is viewed positively by its users, as it usually has a positive score or upvotes.

5.3 Hashtags

Next, we focus on the prevalence and popularity of hashtags on Parler. We find that only a small percentage of posts/comments include hashtags: 2.8% and 3.6% of all posts and comments, respectively. We then analyze the most popular hashtags, as they can provide an indication of the users' interests. Table 5 reports the top 20 hashtags in posts and comments. Among the most popular hashtags in posts (left side of the table), we find #trump2020, #maga, and #trump, which suggests that a lot of Parler's users are Trump supporters and discuss the 2020 US elections. We also find hashtags referring to conspiracy theories, such as #wwg1wga, #qanon, and #thegreatawakening, which refer to the QAnon conspiracy theory [2, 29].[1] Furthermore, we find several hashtags that are related to the alleged election frauds that Trump and his supporters claimed happened during the 2020 US Elections (e.g., #stopthesteal, #voterfraud, and #electionfraud).

In comments (see right side of Table 5), we observe that the most popular hashtag is #parlerconcierge. A manual examination of a sample of the posts suggests that this hashtag is used by Parler users to welcome new users (e.g., when a new user makes their first post, another user replies with a comment including this hashtag). Similar to posts, we find thematic use of hashtags showing support for Donald Trump and conspiracy theories like QAnon.

5.4 URLs

Finally, we focus on URLs shared by Parler users: 15.6% and 7.7% of all posts and comments, respectively, include at least one URL. Table 6 reports the top 20 domains. Among the most popular ones, we find Parler itself, YouTube, image hosting sites like Imgur, links to mainstream social media platforms like Twitter, Facebook, and Instagram, as well as news sources like Breitbart and New York Post.

Hashtag	#Posts	Hashtag	#Comments
trump2020	207,939	parlerconcierge	611,296
maga	162,446	trump2020	161,789
wwg1wga	113,222	maga	135,968
stopthesteal	112,076	stopthesteal	74,875
parler	110,852	wwg1wga	45,601
trump	97,009	parler	42,207
qanon	76,271	kag	40,388
kag	74,742	trump	33,697
parlerksa	58,387	maga2020	27,857
usa	56,327	usa	25,282
maga2020	53,540	obamagate	23,686
freedom	51,806	1	18,335
americafirst	51,634	wethepeople	18,291
obamagate	48,132	fightback	17,867
voterfraud	46,682	america	17,352
newuser	46,102	trump2020landslide	17,154
electionfraud	45,490	blm	16,969
trumptrain	45,394	qanon	16,932
meme	44,973	americafirst	16,694
thegreatawakening	43,086	2a	16,142

Table 5: Top 20 hashtags in posts and comments.

Overall, our URL analysis suggests that Parler users are sharing a mixture of both the mainstream and alternative spectrum of the Web. For instance, they are sharing YouTube URLs and Bitchute URLs, a "free speech" oriented YouTube alternative [38]. Same applies with news sources; Parler users are sharing both alternative news sources (e.g., Breitbart) and mainstream ones (New York Post, a conservative-leaning outlet), with the alternative news sources being more popular in general.

6 Related Work

In this section, we review relevant related work.

Fringe Communities. Over the past few years, a number of research papers have provided data-driven analyses of fringe, alt- and far-right online communities, such as 4chan [3, 19, 31,

[1] Where We Go One We Go All (WWG1WGA) is a popular QAnon motto.

Domain	#Posts	Domain	#Comments
parler.com	2,902,300	parler.com	2,003,228
youtu.be	794,606	giphy.com	1,242,213
youtube.com	475,161	youtu.be	244,763
twitter.com	459,094	youtube.com	177,635
thegatewaypundit.com	296,283	imgur.com	153,719
facebook.com	276,872	par.pw	48,293
imgur.com	233,057	twitter.com	30,444
breitbart.com	223,383	tenor.com	30,060
foxnews.com	210,199	bitchute.com	28,056
theepochtimes.com	130,991	facebook.com	23,299
giphy.com	105,642	rumble.com	15,485
instagram.com	92,114	thegatewaypundit.com	11,158
rumble.com	72,031	google.com	10,854
westernjournal.com	63,453	whitehouse.gov	10,661
nypost.com	53,051	blogspot.com	10,646
t.co	52,114	wordpress.com	8,573
par.pw	48,790	amazon.com	8,439
townhall.com	44,256	foxnews.com	7,238
bitchute.com	43,561	gmail.com	7,122
ept.ms	42,058	t.co	6,882

Table 6: Top domains on Parler.

39], Gab [40], Voat [29], The_Donald and other hateful subreddits [13, 26], etc. Prior work has also analyzed their impact on the wider web, e.g., with respect to disinformation [42], hateful memes [41], and doxing [37].

Toxicity and Migration. Researchers have extensively studied online abuse, such as toxic behavior [5], harassment [4, 20], trolling [8], cyberbullying [21], etc. In particular, movements and ideologies that engage in harassment campaigns and real-world violence, or espouse hateful views towards minorities [24, 25], have also been analyzed. For instance, Grover and Mark [16] study text-based signals to identify ideological radicalization on Reddit. Moreover, previous research has examined the efficacy of community-level moderation within platforms like Reddit [7, 35] and analyzed the resulting cross-platform migrations [27, 32].

Datasets. Brena et al. [6] present a data collection pipeline and a dataset with news articles along with their associated sharing activity on Twitter. Fair and Wesslen [12] release a dataset of 37M posts, 24.5M comments, and 819K user profiles collected from Gab. Papasavva et al. [30] present an annotated dataset with 3.3M threads and 134.5M posts from the Politically Incorrect board (/pol/) of the imageboard forum 4chan, posted over a period of almost 3.5 years (June 2016–November 2019). Garimella and Tyson [15] present a methodology for collecting large-scale data from WhatsApp public groups and release an anonymized version of the collected data. They scrape data from 200 public groups and obtain 454K messages from 45K users. Finally, Founta et al. [14] use crowdsourcing to label a dataset of 80K tweets as normal, spam, abusive, or hateful. More specifically, they release the tweet IDs (not the actual tweet) along with the majority label received from the crowdworkers.

7 Conclusion

In this work, we performed a large-scale characterization of the Parler social network. We collected user information for 12M users that joined the platform between 2018 and 2020 finding that Parler attracts the interest of conservatives, Trump supporters, religious, and patriot individuals. Also, we find that Parler experienced large influxes of new users in close temporal proximity with real-world events related to online censorship on mainstream platforms like Twitter, as well as events related to US politics.

Additionally, by collecting a random sample of 120M posts by 2.1M users, we shed light into the content that is disseminated on Parler. We find that Parler users share content related to US politics, content that show support to Donald Trump and his efforts during the 2020 US elections, and content related to conspiracy theories like the QAnon conspiracy theory.

Overall, our findings indicate that Parler is an emerging alternative platform that needs to be considered by the research community that focuses on understanding emerging socio-technical issues (e.g., online radicalization, conspiracy theories, or extremist content) that exist on the Web and are related to US politics.

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