Free speech or Free Hate Speech?
Analyzing the Proliferation of Hate Speech in Parler

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Abstract
Social platforms such as Gab and Parler, branded as ‘free-speech’ networks, have seen a significant growth of their user base in recent years. This popularity is mainly attributed to the stricter moderation enforced by mainstream platforms such as Twitter, Facebook, and Reddit. In this work we provide the first large scale analysis of hate-speech on Parler. We experiment with an array of algorithms for hate-speech detection, demonstrating the limitations of transfer learning in that domain, given the illusive and ever changing nature of the ways hate-speech is delivered. In order to improve classification accuracy we annotated 10K Parler posts, which we use to fine-tune a BERT classifier. Classification of individual posts is then leveraged for the classification of millions of users via label propagation over the social network. Classifying users by their propensity to disseminate hate, we find that hate mongers make about 16% of Parler active users, and that they have distinct characteristics comparing to other user groups. We find that hate mongers are more active, more central, express distinct levels of sentiment, and convey a distinct array of emotions like anger and sadness. We further complement our analysis by comparing the trends observed in Parler to those found in Gab. To the best of our knowledge, this is among the first works to analyze hate speech in Parler in a quantitative manner and on the user level.

1 Introduction
Social platforms like Twitter, Facebook, and Reddit have become a central communication channel for billions of users. The immense popularity of social platforms resulted in a significant rise in the toxicity of the discourse, ranging from cyber-bullying to explicit hate speech and calls for violence against individuals and groups (Waseem and Hovy, 2016; Mondal et al., 2017; Laub, 2019; Ziems et al., 2020). Women, people of color, the LGBT community, Muslims, immigrants, and Jews are among the most targeted groups. Recent studies report on a surge in Islamophobia (Akbarzadeh, 2016; Sunar, 2017; Osman, 2017; Chandra et al., 2021), antisemitism (ADL, 2020; Zannettou et al., 2020), xenophobia (Iwama, 2018; Entorf and Lange, 2019), hate of Asians (An et al., 2021; Vidgen et al., 2020a) and hate crimes (Dodd and Marsh, 2017; Levin and Reitzel, 2018; Edwards and Rushin, 2018; Perry et al., 2020).

Facing an increased public and legislature scrutiny, mainstream social platforms (e.g., Facebook, Twitter, Reddit) committed to a stricter enforcement of community standards, curbing levels of hate on the platform.²

The stricter moderation of content drove many users into joining alternative social platforms such as Parler and Gab. Touting their commitment to ‘free speech’ and ‘no moderation’ policy, these platforms attract users that were suspended from mainstream platforms, conspiracy theorists, extremists, unhinged users, free-speech advocates, political activists as well as others.

User migration to Parler and Gab was not only grass-root. The platforms were promoted by prominent news anchors and political figures. For example, U.S. Senator Ted Cruz (R-TX) tweeted “I’m proud to join @parler_app – a platform gets what free speech is all about – and I’m excited to be a part of it. Let’s speak. Let’s speak freely. And let’s end the Silicon Valley censorship” (6/25/2020). Sean Hannity, a popular host and commentator on Fox news, informed the viewers of his daily show that “I saw that the president had joined it. At least there is a place, it’s like Twitter, it’s called Parler, I have an account there... good for you because the president joined, because they are censoring him and Dan Scavino and everybody else” (1/8/2021).

²E.g., Facebook 2021 report on hate-speech (Meta, 2021b), and the Time magazine cover of hate-speech in Twitter: (Time, 2021).
Hate, brewing online, often spills to the streets (Hankes and Amend, 2019; Munn, 2019; Malevich and Roberto, 2019; Thomas, 2019). Thus, defending ‘hate speech’ under the right for ‘free speech’ may result in very concrete actions in real life. The perpetrator of the Pittsburgh synagogue shooting was active on Gab, referring to “kike infestation” and “the children of satan”. His final post, minutes before opening fire in the synagogue, was “I can’t sit by and watch my people get slaughtered. Screw your optics, I’m going in.”. Similarly, the storming of the U.S. Capitol on January 6, 2021 was found by the U.S. Senate Investigation Committee to be encouraged and coordinated on Parler (Peters et al., 2021).

In this work we focus on Parler, investigating the proliferation of hate speech on the platform, both on the post level and on the user level. We identify three distinct groups of users, denoted as hate mongers, standard users and hate flirts. We show significant differences between the groups in terms of language, emotion, activity level and role in the network. We further compare our results to the hateful dynamics reported for Gab.

2 Related Work

A growing body of work studies the magnitude and the different manifestations of hate speech in social media (Chandrasekharan et al., 2017; Zannettou et al., 2018; Zampieri et al., 2020; Ransinghe and Zampieri, 2020), among others. Here, we present an overview of the current literature in three different perspectives: (i) The detection of hate speech on the post level, (ii) The detection of hate-promoting users, and (iii) The characterization of hate speech on the platform level.

Post-level classification Most previous works address the detection of hate in textual form. Key-words and sentence structure in Twitter and Whisper were used in (Mondal et al., 2017; Saleem et al., 2017), demonstrating the limitations of a lexical approach. The use of code words, ambiguity and dog-whistling, and the challenges they introduce to text-based models were studied by (Davidson et al., 2017; Ribeiro et al., 2017; Arviv et al., 2021). The detection of implicit forms of hate speech is addressed by Magu et al. (2017) which detects the use of hate code words (e.g., google, skype, bing and skittle to refer to Black people, Jews, Chinese, and Muslims, respectively) using an SVM classifier based on bag-of-words. ElSherief et al. (2021) introduced a benchmark corpus of 22.5K tweets to study implicit hate speech. The authors presented baseline results over this dataset using Jigsaw Perspective, SVM, and different variants of BERT (Devlin et al., 2018).

The use of demographic features such as gender and location in the detection of hate speech is explored by Waseem and Hovy (2016). User meta features, e.g., account age, posts per day, number of followers/friends, are used by Ribeiro et al. (2017).

Computational methods for the detection of hate speech and abusive language range from SVM and logistic regression (Davidson et al., 2017; Waseem et al., 2016; Nobata et al., 2016; Magu et al., 2017), to neural architectures. Recently, Transformer-based architectures (Mozafari et al., 2019; Aluru et al., 2020; Samghabadi et al., 2020; Salminen et al., 2020; Qian et al., 2021; Kennedy et al., 2020; Arviv et al., 2021) achieved significant improvements over RNN and CNN models (Zhang et al., 2016; Gambäck and Sikdar, 2017; Del Vigna et al., 2017; Park and Fung, 2017). In an effort to mitigate the need for extensive annotation some works use transformers to generate more samples, e.g., (Vidgen et al., 2020b; Wullach et al., 2020, 2021). Zhou et al. (2021) integrate features from external resources to support the model performance.

In order to account for the often elusive and coded language and for the unfortunate variety of targeted groups (Schmidt and Wiegand, 2017; Ross et al., 2017), a set of functional test was suggested by Röttger et al. (2020), allowing an quick evaluation of hate-detection models.

Classification of hate users Characterizing accounts that are instrumental in the propagation of hate is gaining interest from the research community and industry alike, whether in order to better understand the social phenomena or in order to suspend major perpetrators instead of removing sporadic content. Detection and characterization of hateful Twitter and Gab users was tackled by Ribeiro et al. (2018); Mathew et al. (2018, 2019) and Arviv et al. (2021), among others. An annotated dataset of a few hundreds Twitter users was released as part of a shared task in CLEF 2021, see (Bevendorff et al., 2021) for an overview of the data and the submissions. Das et al. (2021) intro-
duced a user-level annotated dataset of 798 Gab users which we use for evaluation and comparison.

Hate speech on Parler and Gab While most prior work focus on the manifestations of hate in mainstream platforms, a number of works do address alternative platforms such as Gab and Parler. Two annotated Gab datasets were introduced by Kennedy et al. (2018) and by Qian et al. (2019). We use these datasets in this work as we compare Parler to Gab.

Focusing on users, rather than posts, Das et al. (2021) experiment with an array of models for hate users classification. Lima et al. (2018) aims to understand what users join Gab and what kind of content they share, while Jasser et al. (2021) conduct a qualitative analysis studying Gab’s platform norms, given the lack of moderation. Gallacher and Bright (2021) explore whether users seek out Gab in order to express hate, or that the toxic attitude is adopted after joining the platform. The diffusion dynamics of the content posted by hateful and non-hateful Gab users is modeled by Mathew et al. (2019) and by Mathew et al. (2020).

Parler, launched in August 2018 and experiencing its impressive expansion of user base from late 2020, is only beginning to draw the attention of the research community. Early works analysed the language in Parler in several aspects such as QAnon content (Sipka et al., 2021), COVID-19 vaccines (Baines et al., 2021), and the 2021 Capitol riots (Esser, 2021). The first dataset of Parler messages was introduced by Aliapoulios et al. (2021), along with a basic statistical analysis of the data, e.g., the number of posts and the number of registered users per month, along with the most popular tokens, bigrams, and hashtags. We use this dataset in the current work to analyze hate speech on Parler. Ward (2021) used a list of predefined keywords (hate terms), assessing the level of hate-speech on the platform.

Our work differs from these works in a number of fundamental aspects. First, we combine textual and social (network) signals in order to detect both hateful posts and hate-promoting accounts. Second, we suggest models that rely on state-of-the-art neural architectures and computational methods, while previous work detects hate speech by matching a fixed set of keywords from a predefined list of hate terms. Furthermore, we provide a thorough analysis of the applicability of different algorithms, trained and fine-tuned on various datasets and tasks.

Third, we provide a broader context to our analysis of the proliferation of hate in Parler, as we compare and contrast it to trends observed on Gab.

3 Data

In this section we describe the datasets used for this work – starting with a general overview of the platforms, then providing a detailed description of the datasets and the annotation procedure.

3.1 Parler and Gab Social Platforms

Parler Alluding to the french verb ‘to speak’, Parler was launched on August 2018. The platform brands itself as “The World’s Town Square” a place in which users can “Speak freely and express yourself openly, without fear of being “deplatformed” for your views.”

Parler users post texts (called parleys) of up to 1000 characters. Users can reply to parleys and to previous replies. Parler supports a reposting mechanism similar to Twitter’s retweets (called ‘echos’). Throughout this paper we refer to echo posts as reposts, not to confuse with the (((()))) (echo) hate symbol (Arviv et al., 2021).

Parler’s official guidelines explicitly allow “trolling” and “not-safe-for-work” (NSFW) content, include only two “principles” prohibiting “unlawful acts”, citing “Obvious examples include: child sexual abuse material, content posted by or on behalf of terrorist organizations, intellectual property theft”.

By January 2021, 13.25M users have joined Parler and its application was the most downloaded app in Apple’s App Store. This growth is attributed to celebrities and political figures promoting the platform (see Section 1) and the stricter moderation enforced by Facebook and Twitter, culminating with the suspension of Donald Trump (@realDonaldTrump), the 45th President of the United States, from Twitter and Facebook.

Gab Gab, launched on August 2016, was created as an alternative to Twitter, positioning itself as putting “people and free speech first”, welcoming users suspended from other social networks (Zannettou et al., 2018). Gab posts (called gabs) are limited to 300-characters, and users can repost, quote or reply to previously created gabs. Gab permits
Table 1: Datasets Statistics. Replies are responses to main posts. Reposts are equivalent to Twitter retweets.

|          | Parler | Gab   |
|----------|--------|-------|
| Users    | 4.08M  | 144.3K|
| Posts    | 20.59M | 7.95M |
| Replies  | 84.55M | 5.92M |
| Reposts  | 77.93M | 8.24M |
| Time-Span| 08/2018-01/2021| 08/2016-01/2018|

3.2 Parler and Gab Corpora

We use the Parler and Gab datasets published by Aliapoullos et al. (2021) and Zannettou et al. (2018), respectively. The Parler dataset is unlabeled, therefore annotation is required. We describe the annotation procedure and label statistics in Section 3.3.

Both datasets include posts and users’ meta data, though the Parler dataset is richer, containing more attributes such as registration time. Each of the datasets is composed of millions of posts and replies, see Table 1. The Parler dataset is bigger, containing more posts and more users, however, on average, Gab users post more content per user. We note that there is no temporal overlap between the two datasets. In Section 7 we discuss this point and its possible impacts on our analysis.

We use three Gab annotated datasets which are all sampled from the unlabeled Gab corpus we use: (i) The Gab Hate Corpus – 27.5K Gab posts published by Kennedy et al. (2018), (ii) 9.5K Gab posts published by Qian et al. (2019), and (iii) 5K posts published by Arviv et al. (2021). In total, we collect a corpus of 42.1K annotated Gab posts. 7.7K (18.4%) of the posts are tagged as hateful.

3.3 Annotation of Parler Data

Hate speech takes different forms in different social platforms (Wiegand et al., 2019) and across time (Florio et al., 2020). It is often implicit (ElSherief et al., 2021), targeting a variety of groups. Consequently, transfer learning remains a challenge for hate-speech detection, and an annotated Parler dataset is needed in order to achieve accurate classification. These challenges and the significant improvements in performance achieved by proper fine-tuning are demonstrated through extensive experimentation in Section 4.1. In the remainder of this section we describe the annotation procedure.

The annotation task was designed as follows: 10K posts were sampled from the Parler corpus. All posts are: (i) in English; (ii) at least 10 characters long; (iii) neither a repost nor a comment; and (iv) do not contain a URL.

The 10K annotated posts were not randomly selected from the Parler corpus. A random selection of posts would have led to an extremely imbalanced dataset as most of the posts are not expected to express hate. Hence, we opt to stratified sampling. This sampling process relies on an approximation of the likelihood of each post to include hateful content. We used a pretrained hate speech prediction model to approximate this likelihood.

Annotation was done by 112 student (more than half of them are graduate students), who were provided detailed guidelines and training involving the various types of hate speech, the elusiveness of hate expressions using coded language, how to detect it, and a number of examples of different types. Each of the annotators was prompted with a list of 300 expressions using coded language, and a number of examples of different types. Each of the annotators was prompted with a list of 300 expressions using coded language, and a number of examples of different types. Each of the annotators was prompted with a list of 300 expressions using coded language, and a number of examples of different types.

Annotators presented a satisfying agreement level of 72% and a Cohen’s Kappa of 0.44. Labels of posts with a low agreement level were ignored (~7% of the annotated posts). We define a post as hateful (non-hateful) if its average score is higher (lower) than three. We omit posts with an average score of exactly three. Accordingly, 3224 of the 10K posts (32.8%) were labeled as hateful and 6053 (59.8%) as non-hateful.

We make this annotated corpus available under our public GitHub repository – the first public annotated corpus of Parler.

4 Methods

In this work we are interested in the detection of hate, both on the post level and the account...
level. Our interest in the post level classification is twofold. Given an accurate classifier, we can:
(a) Approximate the hate degree in different aggregation levels – e.g., over the full network or per user, and (b) Use the post-level predictions to support training a user level classifier. A review of the various post level classifiers is provided in Section 4.1 and our modifications to a diffusion-based model for user classification are presented in Section 4.2. Ethical considerations related to user classification are discussed at the end of Section 7.

4.1 Post Level Classification Models

We fine-tune the DistilBERT (Sanh et al., 2019) transformer on each of the datasets, obtaining two fine-tuned models (referred to as Our-FT BERT). We compare the models performance on the respective datasets against four competitive models:

1. Jigsaw Perspective: A widely used commercial model geared toward detection of hateful and toxic content, developed by Google. Jigsaw was found to perform well in an array of tasks related to hate-speech detection (Rötger et al., 2020). Jigsaw implementation is not public and the service is provided as a black-box through an online API.10

2. deHateBERT (Aluru et al., 2020): An adaptation of the BERT Transformer for hate-speech detection – the pretrained transformer was fine-tuned on a corpus of 96.3K text snippets from Twitter and from the white supremacist forum Stormfront.org. The authors indicate that 15.01K (15.6%) training samples were labeled as hate-speech.

3. Twitter-roBERTa (Barbieri et al., 2020): This model uses the RoBERTa (Liu et al., 2019) architecture, specifically fine-tuned on the task of hate-speech detection of micro-messages. The authors used a corpus of 13K tweets, 5.2K (40%) of them are labeled as hate speech.

4. HateBase (Tuckwood, 2017): HateBase is a multilanguage vocabulary of hate terms that is maintained in order to assist in content moderation and research. We use 68 explicit hate terms that were used in prior works (Mathew et al., 2018, 2019). These terms were manually selected from HateBase’s English lexicon. All the terms in the list are explicit, e.g., ‘kike’ (slur targeting Jews), ‘paki’ (slur against Muslims, especially with Pakistani roots), and ‘cunt’. Text is labeled as hate if it contains at least a single hate term.

4.2 User Level Classification

In order to leverage the network structure, we view each platform as a social network with users as nodes and reposts as directed edges. Edges are weighted to reflect levels of engagement, as illustrated in Figure 1(a): a directed edge \((A, B)\) with a weight of 6 indicates that user \(A\) reposted 6 posts originally posted by user \(B\).

We modify the diffusion-based approach for the detection of hate mongers proposed by Ribeiro et al. (2018) in order to achieve a more accurate classification. The basic diffusion-based classification is performed in two stages: (a) Identifying a \textit{seed} group of hate mongers; and (b) Applying a diffusion model over the social network. We use the DeGroot’s hate diffusion model (Golub and Jackson, 2010) which outputs an estimated belief value (i.e., “hate”) per user, over the \([0,1]\) range. A toy example of the diffusion process is illustrated in Figure 1. In our experiments we set the number of diffusion iterations to three. One clear advantage of this approach over fully supervised methods is that it does not require a large dataset annotated on the user level.

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10https://www.perspectiveapi.com
**Modified Diffusion Model** We introduced two modifications to the diffusion model used by Ribeiro et al. (2018) and Mathew et al. (2019): (i) **Seed definition**: Instead of taking a lexical approach in order to identify users posting more than \( k \) hateful posts, we use our fine-tuned Transformers. We argue that fine-tuning the classifiers for each social network significantly improves the classification on the post level (as demonstrated in Section 5.1), and ultimately, improves the performance of the diffusion model; and (ii) **Hateful users definition**: In the original diffusion process, hate (as well as “not-hate”) labels are diffused through the network. This way, seed hate mongers may end with a low hate score, which in turn propagates to their neighbours. However, seed users were chosen due to the fact that they post a significant number of undoubtedly hateful posts. Fixing the hate score of seed users results in a more accurate labeling of the accounts in the network.

5 Classification Results

5.1 Post Level Results

We use the annotated corpora (see Sections 3.2 and 3.3) to fine-tune the pretrained Transformer on each social platform, splitting the labeled data to train (60%), validation (20%), and test (20%) sets.

The precision-recall curves of the Parler and Gab models are presented in Figure 2. Our fine-tuned models significantly outperforms the other models in both datasets. We wish to point out that while the popular keywords base approach (Hate-Base) achieves a high precision and a moderate recall on the Gab data, outperforming all Transformer models except the platform fine-tuned ones, it collapses in both measures on the Parler dataset. These results revalidate the limitations of lexical approaches, and of neural methods that are not fine-tuned for the specific dataset.

5.2 User Level Results

As described in Section 4.2, in order to classify accounts we use a diffusion model. The diffusion process is seeded with a set of hateful accounts. The choice of seed accounts involves the following steps: (i) After establishing the accuracy of the fine-tuned models (Section 5.1) we use these models to label all the posts in the respective datasets; (ii) Opting for a conservative assignment of seed users, we consider only posts with hate score (likelihood) over 0.95 (0.9) in the Parler (Gab) dataset to be hateful. This threshold setting yields a precision of 0.801 (0.902) and a recall of 0.811 (0.903) over the Parler (Gab) dataset.\(^{11}\); Finally, (iii) Users posting 10 or more hateful posts are labeled as seed accounts. We take the conservative approach in steps (ii) and (iii) in order to control the often noisy diffusion process.

Simulating the modified diffusion process described in Section 4.2 we obtain a hate score per user. For analysis purposes we divide users to three distinct groups – hate mongers (denoted \( HM \)), composed of the users making the top quartile of hate scores; Standard users (denoted \( S \)) making the bottom quartile; the rest of the users (denoted \( HM \)) suspected as “flirting” with hate mongers and hate dissemination. Users with a low level of activity (less than five posts or users who joined the network less than 60 days prior to data collection) were not considered.\(^{12}\) The distribution of active users by type in Parler is 16.1%/42.4%/41.5% per \( HM/HM/S \) populations, and 10%/41.7%/48.3% in Gab.

Evaluation of the diffusion model A user-level annotated dataset of 798 Gab users was shared by Das et al. (2021). We use this dataset to validate the performance of the diffusion models – both the standard model and our modified model (see Section 4.2). We find our modified model to outperform the standard model, achieving precision/recall/F1-scores of 0.9/0.54/0.678, comparing to 0.95/0.34/0.5. Therefore, results and analysis in the remainder of the paper are based on the modified diffusion model.

6 Analysis: The Propensity of Hate

6.1 Hate on the Post Level

Taking our conservative approach, we find that the frequency of hate posting is higher in Parler (3.29%), compared in Gab (2.13%). However, we find that 13.95% of Parler users share at least one hateful post – a significantly lower number compared to Gab (18.58%). We find that 65.5% of the hate content in Parler is posted as a reply to other parleys. This reflects a significant overrepresentation of replies compared with full corpus distribution (46.2% of posts are replies, see Table 1). Similarly, 38.9% of the hate content on Gab are replies.

\(^{11}\)These measures are the weighted average precision/recall over both hate/non-hate classes.

\(^{12}\)87.1% (63.4%) of the users in Parler (Gab).
6.2 Hate on the User Level

We provide an analysis of the characteristics of the $HM$, $\tilde{H}M$ and $S$ accounts on an array of attributes, ranging from activity levels to centrality, sentiment and the emotions they convey.

**Activity Level**  Activity levels are compared via four features – number of posts, replies, reposts, and users’ age (measured in days).

$HM$ are the most active user group in both platforms across all activity types (see Figure 3). We find that the $\tilde{H}M$ users have similar characteristics in both platforms – overall, they post less content than the $HM$ users, repost more content than the $S$ group, and their tendency to reply is lower compared to the $S$ users.

Interestingly, although the $HM$ make only 16.1% (10%) of the active users in Parler (Gab) – they generate a disproportional number of posts: 30.6% (59.45%) of the posts in Parler (Gab). The same holds for replies – the $HM$ users post 36.68% (75.57%) of the replies in Parler (Gab). When aggregating all activity types (post/reply/repost) – the $HM$ users generate 41.23% (71.38%) of the content in Parler (Gab).

User Age (days from account creation to the most recent post in the data), is an exceptional feature. We observe only insignificant differences between the three user groups. This observation holds for both platforms. However, collapsing the groups – we do find a significant difference between the two platforms. Gab users are “older” with an average age of 323.9 compared to 189.6 of the Parler users. We hypothesize that the difference is a result of the way both platform evolve over time, given the unfolding of events driving users to these platforms (see Sections 1 and 3.1).

**Popularity and Engagement**  We quantify the popularity level of users based on the number of followers they have. Figure 4 presents numbers for both platforms. On both platforms hate mongers ($HM$) are significantly more popular compared to users in other user groups. In Parler, the median number of followers is 121 compared to 15 and 12 of $\tilde{H}M$ and $S$, respectively. The same holds for Gab – a median value of 160 for $HM$ users compared to 43 and 41 of the other two user groups. Interestingly, although Parler is a much larger social platform (mainly in terms of registered users, see Section 3 and Table 1) we do not see a significantly higher number of followers in Parler. Moreover, when calculating the number of followers over the
whole population, the median in Gab is three times higher – 48 vs. 16.

Engagement level is measured by the number of followees each account has (the number of accounts a user follows). We find that HM are highly engaged in both platforms, compared to other user groups. In Parler, the median number of followees of HM users is 106 – significantly higher than 46 and 36 median values of the \( \tilde{HM} \) and S users, respectively.

**Account’s Self Description**  Analogous to the account’s description in Twitter, Parler users can provide a short descriptive/biographical text to appear next to the user’s avatar. For example, the biography that is associated with a specific Parler user is: “Conservative banned by mainstream social media outlets for calling the leftists out for what they really are! Been awake for YEARS! #trump2020”.

We use this content to further assess users’ commitment to the Parler platform, assuming more engaged users are the more likely they add the description to their profile. We find that while only 35.8% of the S users use the biography field, 59.6% of the HM users provide the description in their profile. We also find that the average (median) biographical text length of HM users is 128.6 (134). This is considerably longer, compared to HM and S users who included the description in their profile, with an average (median) of 99.4 (90) and 94.6 (84) text length, respectively.

**Social Structure**  Analysing the degree distribution of users provides an interesting difference between the platforms. As observed in Figure 5, HM users have the most distinctive distribution in both Parler and Gab. However, while the HM and the S group distributions are inseparable in Gab, the Parler user groups have distinct distributions. These distributions highlight the distinctiveness of the position of HM users in the network, as well the role of the \( \tilde{HM} \) compared to S users.

**Emotional Features**  We compare the sentiment expressed and the emotions conveyed by different user groups. We use pretrained BERT models for both the sentiment\(^{14}\) and emotion\(^{15}\) predictions. Results are presented in Table 2. Looking at the Parler users, we find a small though significant (p-value < \( 10^{-3} \)) tendency of HM to express a more negative sentiment. The same holds for Gab, although the sentiment expressed by \( \tilde{HM} \) is closer to the sentiment of the HM users, rather to that of the S users. Aggregating the emotion predictions, we find that HM users tend to convey more Anger and Sadness than the other groups. This observation holds for both Parler and Gab, although Anger is more prominent.

7 Discussion

**Time span**  Given that we provide a comparison between trends in Parler and Gab, it is im-

\(^{13}\)In this part, we do not compare Parler to Gab since account’s self description is not available for the Gab corpus.

\(^{14}\)https://huggingface.co/nlptown/bert-base-multilingual-uncased-sentiment

\(^{15}\)https://huggingface.co/bhadresh-savani/distilbert-base-uncased-emotion
Figure 5: Social networks degree distribution. We present the in-degree distributions. Network is based on reposts. \( p(k) \) (y-axis) is the probability value per each node’s degree (x-axis). We use a log-scale over both axis.

![Graphs showing the degree distribution for Parler and Gab.](image)

Table 2: Emotions and sentiment analysis. The four leftmost columns are the distribution of emotions per user group while the rightmost column is the median sentiment score. The sentiment spans over \([1,5]\) (i.e., 5 is the highest score).

|        | Anger | Joy | Sad | Fear | Sentiment |
|--------|-------|-----|-----|------|-----------|
| Parler |       |     |     |      |           |
| HM     | 48%   | 37.9% | 7.4% | 5.1% | 2.63      |
| S      | 33.6% | 55.7% | 5%   | 4.3% | 2.84      |
| Gab    |       |     |     |      |           |
| HM     | 40.0% | 44.5% | 7.2% | 6.3% | 2.55      |
| S      | 35.5% | 51.1% | 6.0% | 5.7% | 2.56      |

Table 2: Emotions and sentiment analysis. The four leftmost columns are the distribution of emotions per user group while the rightmost column is the median sentiment score. The sentiment spans over \([1,5]\) (i.e., 5 is the highest score).

It is important to note the datasets span different and non-overlapping time-frames (see Table 1). Therefore, the comparison we provide should be read cautiously. We do note, however, that each of the datasets was crawled from the early days of the social platform and spans over a similar time range (17 months). Moreover, the temporal disparity between the dataset could be considered as an advantage – allowing us to examine the generalization performance of hate speech models, as we report in Section 5.1.

**Ethical Considerations** Analyzing and modeling hate speech in a new social platform such as Parler is of great importance. However, classifying users as hate mongers, based on the output of an algorithm, may result in marking users falsely (which may result in suspension or other measures taken against them). While we always opted for a conservative approach, as well as focusing on aggregated measures characterizing the trends of a platform, we note that user labeling should be carefully used, ideally involving a ‘man-in-the-loop’.

8 Conclusion and Future Work

To the best of our knowledge, we present the first large-scale computational analysis of hate speech on Parler, and provide a comparison to trends observed in the Gab platform.

We tag and share the first annotated Parler dataset, containing 10K posts labeled by the level of hate they convey. We used this dataset to fine-tune a transformer model to be used to mark a seed set of users in a diffusion model, resulting in user-level classification. We find significant differences between hate mongers (HM) and other user groups: HM represent only 16.1% and 10% of the active users in Parler and Gab respectively. However, they generate 41.23% of the content in Parler and 71.38% of the content in Gab. We find that HM show higher engagement levels and they have significantly more followers and followees. Other differences are manifested through the sentiment level expressed and the emotions conveyed.

Future work takes two trajectories: (i) Comparison of the current results with a more traditional social platform (e.g., Twitter); and (ii) An early detection of hate mongers – building a classifier to detect hate mongers based on their very first steps in the social platform.
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