Going Extreme: Comparative Analysis of Hate Speech in Parler and Gab

Abraham Israeli       Oren Tsur
Department of Software and Information System Engineering
Ben-Gurion University of the Negev
Beer-Sheva, Israel
isabrah@post.bgu.ac.il  orentsur@bgu.ac.il

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 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 16.1% of Parler active users, and that they have distinct characteristics comparing to other user groups.

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, and the first annotated dataset to be made available to the community.

1 Introduction
[Warning: Some of the readers may find the language in the examples provided in this manuscript offensive.]

Social platforms like Twitter, Facebook, and Reddit have become a central communication channel for billions of users1. However, 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, Silva, and Benevenuto [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]}, 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 platform2–3.

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 suspended from mainstream platforms, conspiracy theorists, extremists and other unhinged users, as well as ‘free-speech’ advocates.

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), and 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).

Hate, brewing online, often spills to the streets {Hankes and Amend 2019, Munn 2019, Malevich and Roberts 2019, Thomas 2019}. Thus, defending ‘hate speech’ under the right for ‘free speech’ may manifest itself through very concrete actions in “real life”. The perpetrator of the Pittsburgh synagogue shooting4 was active on Gab, referring to “the infestations of jews”. 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]}. Indeed, hate speech does plague Parler – a number of

1Facebook reported on 2.9 Billion monthly active users (retrieved 07/28/2021), see: https://tinyurl.com/2p8r4wd6
A growing body of research studies the magnitude and the different manifestations of hate speech in social media (Knuttila 2011; Chandrasekharan et al. 2017; Zannettou et al. 2018; Zampieri et al. 2020; Ranasinghe and Zampieri 2020), among others. Here, we present an overview of the current literature through 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. Keywords and sentence structure in Twitter and Whisper were used in (Mondal, Silva, and Benevenuto 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, Hanouna, and Tsur 2021). The detection of implicit forms of hate speech is addressed by (Magu, Joshi, and Luo 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 SVM classifier based on bag-of-words feature vectors. 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 API, 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 was Khow and Hovy (2016), and 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 and Hovy 2016; Nobata et al. 2016; Magu, Joshi, and Luo 2017), to neural

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Table 1: A sample of posts from Parler social platform.

| Post Content                                                                 | Target       |
|------------------------------------------------------------------------------|--------------|
| Raimondo can stick her mask mandate in her cunt .come tell me to my face it will be the last time we here from this bitch | Women        |
| Wdammit I hate kikes so much. Filthy, hooked nosed, baby penis sucking parasites | Jewish people |
| Muslim terrorists did this and obama brought them here to run our government. Gotta get rid of Obama, Omar and all these other fucking Muslims | Muslims      |
| Remember what (((they))) want to take from you                               | Jewish People |
| SMASH these radical freaks all over AMERICA !! Clean this mess up             | LGBTQ        |
| Now the blacks not only want welfare, free college, free healthcare, free housing, free food, free clothes, free transportation, free tampons, but they want the white man money. Wake up and smell the dog shit. | The Black Community |
| DemonKKKrats love rape and murder. Praying.                                 | Democrats     |

Examples is presented in Table 1. Notably, some posts are more explicit than others – using vulgar language (e.g., posts #1–#3), explicitly mentioning the targeted individual/group (e.g., #1,#3,#6,#7), while other posts are using nick-names, codes and implicit references (e.g., #2,#4,#5,#8).

Striking the right balance between contradicting values (e.g., the freedom of speech vs. public safety of members of protected groups) is a walk on a tightrope. We believe, however, that a data-oriented analysis may help individuals and policy maker alike at reaching an informed balance.

In this work we focus on Parler social platform, 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 (hate mongers, regular users and hate flirts) and show significant differences between them in terms of language, emotion, activity level and role in the network. We further compare our result to the hateful dynamics observed in the Gab platform.

Contribution Our contribution in this paper is fourfold: (i) We compare an array of state-of-the-art algorithms for hate detection, showing they all fail to accurately identify nuanced and novel manifestations of hate speech found on Parler, (ii) We share the first annotated Parler dataset, containing 10K Parler posts, each post labeled by the level of hate it conveys, (iii) We fine-tune a BERT-based classifier to achieve accurate classification, and modify DeGroot’s diffusion model (Colubub and Jackson 2010) in order to allow analysis on the platform level, and finally (iv) We provide the first large scale analysis of the proliferation of hate in Parler and compare it to the user dynamics in Gab.

The remainder of the paper is organized as follows: Section 2 provides a brief review of the relevant literature. A detailed description of the datasets and the annotation procedure are given in Section 3. In Section 4 we present the computational methods we use for the post and user level classification, and results follow in Section 5. A detailed analysis of hate levels and user propensity for hate speech in Parler and Gab is provided in Section 6. Finally, Section 7 offers some discussion regarding some of the observations, including ethical considerations.

2 Related Work

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, Hanouna, and Tsur 2021). The detection of implicit forms of hate speech is addressed by (Magu, Joshi, and Luo 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 SVM classifier based on bag-of-words feature vectors. 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 API, and different variants of BERT (Devlin et al. 2018).

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3https://www.perspectiveapi.com
architectures such as RNNs and CNNs (Zhang, Robinson, and Tepper 2016; Gambück and Sickar 2017; Del Vigna et al. 2017; Park and Fung 2017). Transformer-based architectures achieved significant improvements, see (Moza-far, Farahbakhsh, and Crespi 2019; Aluru et al. 2020; Samghabadi et al. 2020; Salmanen et al. 2020; Qian et al. 2021; Kennedy et al. 2022; Arviv, Hanouna, and Tsur 2021), among others. In an effort to mitigate the need for extensive annotation some works use transformers to generate more samples, e.g., (Vidgen et al. 2020; Wullach, Adler, and Minkov 2020; Zhou et al. 2021) integrate features from external resources to support the model performance.

In order to account for the sometimes elusive and coded language and the unfortunate variety of targeted groups (Schmidt and Wiegand 2017; Ross et al. 2017), a set of functional test was suggested by Köttger 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 and violence is gaining interest from the research community and industry alike, whether in order to better understand the 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), Arviv, Hanouna, and Tsur (2021), among others. An annotated dataset of a few hundreds of 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. An annotated dataset of Twitter users using the ambiguous (((())))) (‘echo’) symbol was released by Arviv, Hanouna, and Tsur (2021).

Hate speech on Parler and Gab  While most prior work focus on the manifestations of hate in the 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 the platform 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. Galagher 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 spread of hate speech and the diffusion dynamics of the content posted by hateful and non-hateful Gab users is modeled by Mathew et al. (2019) and Mathew et al. (2020).

Parler, launched in August 2018 and experiencing its impressive expansion of user base from late in 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, Hannák, and Urman 2021), COVID-19 vaccine (Baines, Ittefaq, and Ab-

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 speek’, 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 “deplatforme” for your views.”

Parler users post texts (called parlays) of up to 1,000 characters. Users can reply to parlays and to previous replies. Parler supports a reposting mechanism similar to Twitter’s retweets (referred to as ‘echos’). Throughout this paper we refer to echo posts as reposts, not to confuse with the (((()))) (echo) hate symbol.

Parler’s official guidelines explicitly allow “trolling” and “not-safe-for-work” 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.” and spamming.

By January 2021, 13.25M users have joined Parler and its mobile 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 the @realDonaldTrump account from Twitter and Facebook.

Gab  Gab, launched on August 2016, was created as an alternative to Twitter and it positioning itself as putting “people and free speech first” and welcoming users suspended

6Parler branding on its landing page (accessed: 1/10/2022).
7parler.com/documents/guidelines.pdf (accessed: 1/15/2022)
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 pornographic and obscene content, as long as it is labeled NSFW (Not-Safe-For-Work). Previous research finds that Gab is a politically oriented system – while many users who use the platform are extremists, the majority of users are Caucasians-conservatives-males (Lima et al. 2018). For more details about gab usage, users and manifestations of hate see references at Section 3.

### 3.2 Parler and Gab Corpora

We use the Parler and Gab datasets published by Aliapoulios 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 and total number of likes. Each of the datasets is composed of millions of posts and replies, see Table 2. 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. We discuss this point and its impact on the analysis and comparison in Section 4.

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, Hanouna, and Tsur (2021). In total, we collect a corpus of 42.1K annotated Gab posts. 7.7K (18.4%) of the posts are tagged as hateful.

| | 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 |

Table 2: Datasets Statistics. Replies are comments to main posts. Reposts are equivalent to reweets in Twitter.

We provide annotators only with the textual content of the post. Each of the 10K posts was annotated by three annotators. Annotators presented a satisfying agreement level of 72% and a Cohen’s Kappa of 0.44. Labels of posts with a low agreement level8 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 in the project’s repository9 – 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 all social network, and 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 4.

#### 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 performance of

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8We define low agreement as posts labeled with less than three unique values or if the difference between annotations was higher than 2.

9https://github.com/NasLabBgu/parler-hate-speech
the models on the respective datasets against four competitive models:

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

2. **deHateBERT** (Aluru et al. 2020): An adaptation of the BERT Transformer for hate-speech detection – the pre-trained 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 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 on 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 mainly selected from HateBase’s English lexicon and is composed only of explicit hate terms like “kike” (slur targeting Jews, see post #2 in Table 1), ‘paki’ (slur against Muslims, especially with Pakistani roots), and ‘cunt’ (see post #1 in Table 1).

### 4.2 User Level Classification

Ideally, an account should be classified as a hate account based on the content it posts (or likes). However, this seemingly straightforward approach is severely limited by ambiguity, vagueness, dog-whistling, and emerging idioms and racial slurs. For example, defining a threshold of $k$ hateful posts is still not well defined. How explicit these $k$ posts should be? would 2$k$ less explicit posts make the cut? is one post enough to declare a user a hate-monger? Moreover, defining a threshold does not account for networked aspect of the data and the fact that “birds of a feather flock together” (Himelboim, McCreery, and Smith 2013).

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 directed edge $(A, B)$ with a weight of 6 indicates that user $A$ reposted 6 posts originally posted by user $B$.

We build on the diffusion-based approach for the detection of hate mongers, proposed by Mathew et al. (2019), modifying it in order to achieve a more accurate classification. The basic diffusion-based classification is achieved in two stages: (a) Identifying a seed group of hate mongers; (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.

**Modified Diffusion Model** We modified the diffusion model used by Ribeiro et al. (2018) and Mathew et al. (2019) in two ways: (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 belief (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 these 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 Section 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.
As described in Section 4.2, in order to classify accounts we use a diffusion model. Unlike the other four methods, this approach cannot be controlled by a threshold parameter, hence only a single PR value is available.

The precision-recall curves of the Parler and Gab models are presented in Figure 2. Our fine-tuned models significantly outperform the other models in both datasets. We wish to point out that while the popular keyword base approach (HateBase) achieves a high precision and a moderate recall on the Gab data, it collapses in both measures on the newer Parler dataset. These results validate the limitations of lexical approaches, and of neural methods that are not fine-tuned for the specific dataset (even though they were fine-tuned for a similar task – hate speech detection in another microblogging platform).

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. 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; normal users (denoted N) 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 joining the network in the last 60 days) were not considered.

The distribution of active users by type is presented in Figure 3.

### 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 and our modified models (see Section 4.2). We find our modified model to outperform the standard models, 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 Hate Analysis

In this section we provide a comprehensive analysis of the propensity for hate speech on Parler and Gab.

#### 6.1 Hate on the Post Level

Taking our conservative approach, we find that hate posts are more frequent in Parler (3.29%) than in Gab (2.13%). However, we find that 13.95% of Parler users share at least one hateful post – 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 over-representation of replies compared with full corpus distribution (46.3% of posts are replies, see Table 2). Similarly, 38.9% of the hate content on Gab are replies.

#### 6.2 Hate on the User Level

We provide an analysis of the characteristics of the HM, HM and N 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 4). We find that the HM users have similar characteristics in both platforms – they share less content than the HM users, repost more content than the N group, and their tendency to reply is lower compared to the N 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).

Figure 4: Activity measures per user group. Numbers are averaged per measure and group. We use a log-scale over the y-axis.

Social Structure We further analyze the differences between Parler and Gab platforms over the different user groups from a social network analysis (SNA) perspective, based on the reposts network. Table 4 provides an overview of a number of centrality measures. The $HM$ users have a significantly higher values in all measures in both platforms. Interestingly, the full order between the different user groups is kept only for the ‘betweenness’ centrality, while other centrality measures a less stable comparing the $HM$ and $N$ groups.

Analysing the degree distribution of users provides an interesting difference between the platforms. In line with the numbers in Table 4 $HM$ users have the most distinctive distribution in both Parler and Gab. However, while the $HM$ and the $N$ group distributions are inseparable in Gab, the Parler user groups have distinct distributions (see Figure 6). These distributions highlight the distinctiveness of the location of $HM$ users in the network, as well the role of the $HM$ compared to $N$ users.

Linguistic features We compare the sentiment expressed and the emotions conveyed by different user groups. We use pretrained BERT models for both the sentiment\textsuperscript{12} and emotion\textsuperscript{13} predictions. Results are presented in Table 4.

\textsuperscript{12}https://huggingface.co/nlptown/bert-base-multilingual-uncased-sentiment

\textsuperscript{13}https://huggingface.co/bhadresh-savani/distilbert-base-uncased-emotion
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 \( HM \) is closer to the sentiment of the \( HM \) users, rather than that of the \( N \) users. Aggregating the emotion predictions, we find that \( HM \) users tend to convey more \textit{Anger} and \textit{Sadness} than the other groups. This observation holds for both Parler and Gab, although \textit{Anger} is more prominent.

Table 4: 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). We omit \textit{Love} and \textit{Surprise} emotions since their proportion in all groups is negligible.

|      | \textit{Anger} | \textit{Joy} | \textit{Sad} | \textit{Fear} | Sentiment |
|------|----------------|-------------|-------------|-------------|----------|
| \( HM \) | 48%            | 37.9%       | 7.4%        | 5.1%        | 2.63     |
| \( HM \) | 41.9%          | 44.3%       | 6.7%        | 5.3%        | 2.84     |
| \( N \)  | 33.6%          | 55.7%       | 5%          | 4.3%        | 2.84     |
| \( \tilde{HM} \) | 40.0%          | 44.5%       | 7.2%        | 6.3%        | 2.55     |
| \( \tilde{HM} \) | 35.9%          | 49.7%       | 5.9%        | 7.1%        | 2.56     |
| \( N \)  | 35.5%          | 51.1%       | 6.0%        | 5.7%        | 2.67     |

Table 3: Structural features. Values are averaged over all users in each user group. ‘ID’ and ‘OD’ are the in-degree and out-degree respectively.

|      | \( ID \) Centrality | \( OD \) Centrality | Betweenness | PageRank |
|------|---------------------|----------------------|-------------|----------|
| \( HM \) | 3.26 \times 10⁻³   | 4.01 \times 10⁻⁵   | 3.43 \times 10⁻⁶ | 1.11 \times 10⁻⁶ |
| \( \tilde{HM} \) | 1.43 \times 10⁻⁵   | 1.97 \times 10⁻⁶   | 1.61 \times 10⁻⁷ | 2.47 \times 10⁻⁷ |
| \( N \)  | 3.64 \times 10⁻⁶   | 2.31 \times 10⁻⁶   | 1.1 \times 10⁻⁷ | 4.74 \times 10⁻⁷ |

Table 3: Structural features. Values are averaged over all users in each user group. ‘ID’ and ‘OD’ are the in-degree and out-degree respectively.

|      | \( ID \) Centrality | \( OD \) Centrality | Betweenness | PageRank |
|------|---------------------|----------------------|-------------|----------|
| \( HM \) | 3.35 \times 10⁻³   | 1.18 \times 10⁻⁴   | 1.43 \times 10⁻⁴ | 8.85 \times 10⁻⁵ |
| | 3.5 \times 10⁻⁴ | 4.06 \times 10⁻⁴ | 6.11 \times 10⁻⁶ | 7.17 \times 10⁻⁶ |

Table 3: Structural features. Values are averaged over all users in each user group. ‘ID’ and ‘OD’ are the in-degree and out-degree respectively.

Figure 6: Social networks degree distribution. We present the in-degree distributions. Network is based on reposts. p(k) (y-axis) is the probability value per a each node’s degree (x-axis). We use a log-scale over both the axis.

8 Conclusion

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 annotate and share a the first 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.
Gab respectively. However, they create 41.23% of the content in Parler and 71.38% of the content in Gab. We find that HM are show higher engagement and they have significantly more followers and followees. Other differences are manifested through the sentiment level expressed and the emotions conveyed.

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