Measuring and Characterizing Hate Speech on News Websites

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Abstract

The Web has become the main source for news acquisition. At the same time, news discussion has become more social: users can post comments on news articles or discuss news articles on other platforms like Reddit. These features empower and enable discussions among the users; however, they also act as the medium for the dissemination of toxic discourse and hate speech. The research community lacks a general understanding on what type of content attracts hateful discourse and the possible effects of social networks on the commenting activity on news articles.

In this work, we perform a large-scale quantitative analysis of 125M comments posted on 412K news articles over the course of 19 months. We analyze the content of the collected articles and their comments using temporal analysis, user-based analysis, and linguistic analysis, to shed light on what elements attract hateful comments on news articles. We also investigate commenting activity when an article is posted on either 4chan’s Politically Incorrect board (/pol/) or six selected subreddits. We find statistically significant increases in hateful commenting activity around real-world divisive events like the “Unite the Right” rally in Charlottesville and political events like the second and third 2016 US presidential debates. Also, we find that articles that attract a substantial number of hateful comments have different linguistic characteristics when compared to articles that do not attract hateful comments. Furthermore, we observe that the post of a news article on either /pol/ or the six subreddits is correlated with an increase of (hateful) commenting activity on news articles.

1 Introduction

As the Web becomes more social, so becomes the discourse around news events. People share news articles on social media and discuss them with their friends [45] [83]. At the same time, news websites have become “social,” allowing users to post comments and discuss stories among themselves [23] [72]. While the ability to post comments empowers users to discuss news stories in a constructive fashion, discussion can also become toxic, leading to racist remarks and hate speech [27] [37] [41]. In particular, recent research showed that polarized Web communities such as 4chan’s Politically Incorrect Board (/pol/) and Reddit’s The_Donald board often organize coordinated campaigns in which users are instructed to “attack” a target by using hate speech [28] [39] [49]. In some cases, these “raids” can be directed towards news stories from sites that advocate policies that these users do not agree with. Despite the problem that hate speech in news comments poses to news platforms and users, comment moderation remains an open problem [61].

While hate speech and toxic discourse on social media has been the subject of study by a number of researchers [20] [22] [26] as a research community we still lack understanding on the characteristics and the dynamics of hateful comments on news articles. In this paper, we perform a large-scale quantitative study of hateful news comments. We analyze 125M comments from 412K news articles posted between July, 2016 and February, 2018. To select the articles, we use all the news articles that are posted by popular news sites and for which links to them appear on 4chan’s /pol/ and six selected subreddits from Reddit.

Research Questions. We aim to answer the following research questions: 1) Is hateful commenting activity correlated with real-world events? 2) Can we find important differences between the users that are posting on news sites according to their partisanship? 3) Can we find linguistic differences in articles that attract substantial numbers of hateful comments when compared to articles that do not? and 4) Do news articles attract more hate comments after they are posted on other Web communities like 4chan and Reddit?

To shed light on these research questions, we present a temporal and content analysis. We leverage changepoint analysis [43] to find significant changes in the time series of (hateful) commenting activity. We also use linguistic analysis that reveals the writing and linguistic peculiarities of news articles and whether articles that attract hate comments have differences to articles that do not attract hate. Overall, this paper provides an unprecedented view on hateful commenting activity on news websites and on the characteristics of news articles that attract significant hate from users.

Findings. Among others, we make the following findings:

- We find a substantial increase in (hate) comments in close temporal proximity with important real-world events; e.g., we find statistically significant changes in hateful comments in news articles in close temporal proximity with the “Unite the Right” rally in Charlottesville during August, 2017, as well as the second and third US Presi-
We find differences between the users that are commenting on news articles according to the site’s partisanship. Users that post on extreme-right sites tend to be more active overall by posting more comments and they tend to post more hateful content compared to users that are active on sites with other partisiances. Also, we find a higher percentage of hateful comments from users that choose to remain anonymous.

Our linguistic analysis reveals that there is a correlation between articles using the highest number of Clout words (probably for influencing the readers) and attracting more hate comments. We also find that the articles that had more than 10% hateful comments, use more social references and include negative emotions, such as, anxiety and anger emotions, compared to those articles that receive no hate comment.

We find a correlation between a link being posted on Reddit or /pol/, and receiving more (hateful) comments on that article. In particular, we find that the posting of news articles from domains with specific partisiances (i.e., Left, Center, Center-Right) to /pol/ or the six selected subreddits is correlated with an increase in hateful commenting activity in close temporal proximity with the posting of the news article on /pol/ or Reddit. We also discover that once a news article receives a substantial amount of hateful comments, it continues to receive a high fraction of such comments for a long period of time.

2 Related Work

Hate Speech Detection. A large body of work focuses on detecting hate speech. HateSonar is a classifier [22] that uses Logistic Regression to classify text into: offensive language, or hate speech. Recently, Google has released a state of the art hate speech detection tool, called Perspective API [63], that detects textual toxic content, including hate speech. This tool uses machine learning techniques and a manually curated dataset of texts, to identify the rudeness, disrespect, or toxicity of any comment. Most previous work [78] [76] [46] [33] [70] proposes the use of supervised machine learning approaches, such as Support Vector Machines, Naive Bayes, and Logistic Regression, as well as Natural Language Processing techniques. Others [24] [66] [29] [32] propose the use of neural network-based classifiers. Another work [43] uses a semi-supervised approach to detect different forms of hate speech like implicit and explicit hate content. Chandrasekharan et al. [19] propose Bag of Communities: an approach that uses data from 4chan, Voat, Reddit, and Metafilter, and aims to detect abusive content. Finally, Saleem et al. [55] focus on multiple networks like Reddit and Voat, and propose the use of a community-driven detection approach.

Hate Speech on the Web. Some recent work studies the prevalence and characteristics of hate speech on specific web communities, such as Gab [81], 4chan’s Politically Incorrect board (/pol/) [39], Twitter and Whisper [69]. Some works [53] study the effects of anonymity and forms of hate speech. Others [26] [25] perform an analysis on the personality of the targets and instigators of hate speech on Twitter. Another study by Zannettou et al. [84] shows the rise of racial slurs and in particular anti-semitism on 4chan and Gab. Chandrasekharan et al. [18] study the degree of hate speech on the platform after the bans of some prominent hateful subreddits like r/fatpeople and r/Con/Town, finding that these bans helped decrease the site’s hate speech usage. This is because a lot of accounts that were active on these subreddits stopped using the site and others that migrated to other subreddits did not post hateful content. Olteanu et al. [58] focus on understanding the effect that real-world extremist attacks, involving Arabs and Muslims, have on hateful speech on the Web. Among other things, they observe an increase in the use of hate speech after such attacks and in particular increase in posts that advocate violence. Jhaver et al. [42] study the effects of blocklists (i.e., blocking users) on online harassment, finding that users are not adequately protected online, while others feel that they are blocked unfairly. Finally, a recent work by Zannettou et al. [82] studies the dissemination of hateful memes across the Web.

Hate Speech on News Comments. Some studies analyze aspects of hate speech on comments posted on news articles. Erjavéc and Kovacic [27] undertake interviews with posters of hate speech on news sites to uncover their motives and strategies to share hateful content, finding that posters are driven by thrill and fun, while others are organized. Hughey and Daniels [41] analyze the methodological pitfalls for studying racist comments posted on news articles. Specifically, they analyze various strategies employed by news platforms, such as extreme moderation policies, not storing comments or disabling comments, and their implications on the Web. Harlow [37] analyzes comments posted on US news sites to understand racist discourse. They find that the comments included racial slurs despite the fact that the article did not; Latinos were the most targeted ethnicity.

3 Methodology

In this section, we describe our dataset collection process and our analysis methodology. In a nutshell, we create a list of news sites, based on their popularity on 4chan’s /pol/ and six selected subreddits, then we assess their partisanship, collect comments posted on their news articles whose links appear on /pol/ and the six subreddits, and finally, analyze their hate activity.

Dataset. Our dataset includes news articles and the comments posted on them between July 2016 and February 2018, on 4chan’s Politically Incorrect board (/pol/) and six subreddits from Reddit, namely AskReddit, politics, conspiracy, The_Donald, news, and worldnews. We select these subreddits because they are among the most important subreddits when it comes to sharing news articles on Reddit [83]. These subreddits attract both a general audience (i.e., news, politics,
Donald, and /pol/). Due to this diversity in the Web technology they used, six (9.3%) sites use Disqus, Spot.IM, and Facebook. For each of these, we built a crawler that uses the platform’s API to get all the comments on articles posted on /pol/ or the six subreddits. For news sites that use custom solutions as their commenting platforms, we had to implement a separate crawler for each domain, which is not efficient. Therefore, we focused on the domains for which we have the most articles; we implemented custom crawlers for dailymail.co.uk, theguardian.com, and nytimes.com. Note that we initially aimed to also implement a crawler for washingtonpost.com but we were unable due to implementation issues. Table 1 summarizes the number of the collected articles and comments for each news site that supports comments as of June 2018. Note that since we collect the data well after their publication date (collection period between June and November 2018), there is a small percentage of articles that are not available either because they were removed or because the URL was not available. In total, we obtained 125M comments posted on 412K news articles. Finally, for each article, we collected its content and associated article metadata using Newspaper3k.

Identifying partisanship. To identify the partisanship of news sites, we use information about news media listed on the Media Bias/Fact Check (MBFC) website [6], which contains annotations and analysis of the factual reporting and/or bias for news sites. MBFC has been used to annotate data in prior work for analyzing the factuality of reports and bias of news media [11]. Table 2 shows the partisanship/bias of each news site in our dataset.

Identifying hate comments. To identify comments that are hateful, we explore the use of two popular hate speech classifiers: Hatesonar [22] and the Perspective API [63]. The former is a classifier that uses Logistic Regression to classify comments as hateful, offensive, or neither. The classifier is trained on a corpus of 24K tweets annotated as either “Hate Speech,” “Offensive Language,” or “Neither” by workers on CrowdFlower. Similarly, the Perspective API leverages crowdsourced annotations of text to train machine learning models that predict the degree of rudeness, disrespect, or unreasonableness of a comment. In particular it offers two distinct models: the “Toxicity” and “Severe Toxicity” models. The difference between the two models is that the latter is more robust to the use of swear words. To assess the performance of these classifiers in our dataset, we extract a set of 100 random comments. Then, three of the authors of this study independently marked each comment as hateful or not, and we treat the majority agreement of these annotations as groundtruth. Then, all comments in our random sample were evaluated both with HateSonar and the Perspective API. We find that HateSonar performs poorly with respect to identifying toxic and severe toxic comments, but is more accurate in identifying non-hateful comments.

Table 1: Top news sources that support comments as of June, 2018, that appear on /pol/ and the six selected subreddits.

| News site               | # of articles on /pol/ | # articles on 6 subreddits | # collected articles | # collected comments |
|-------------------------|------------------------|----------------------------|----------------------|----------------------|
| dailymail.co.uk         | 14,124                 | 31,861                     | 38,463               | 14,287,096           |
| theguardian.com         | 10,430                 | 49,318                     | 42,137               | 11,090,592           |
| nytimes.com             | 9,288                  | 89,359                     | 54,107               | 4,959,119            |
| washingtonpost.com      | 9,212                  | 136,120                    | 41,918               | 46,684,682           |
| breitbart.co.uk         | 7,698                  | 39,793                     | 41,918               | 46,684,682           |
| independent.co.uk       | 6,232                  | 28,971                     | -                    | -                    |
| rt.com                  | 5,980                  | 13,913                     | 17,075               | 2,707,512            |
| thehill.com             | 3,610                  | 46,957                     | 47,226               | 28,862,389           |
| almadarenews.com        | OneAll                 | 3,589                      | 477                  | -                    |
| express.co.uk           | Spot.IM                | 3,344                      | 6,351                | 8,609                |
| huffingtonpost.com      | Facebook               | 3,009                      | 34,999               | 27,092               |
| cbc.ca                  | Custom                 | 2,745                      | 11,127               | -                    |
| dailyCall.com           | Disqus                 | 2,727                      | 18,516               | 19,457               |
| politico.com            | Facebook               | 2,684                      | 26,247               | 19,916               |
| latimes.com             | Custom                 | 2,991                      | 15,902               | -                    |
| thesun.com              | Custom                 | 1,848                      | 3,822                | -                    |
| washingtontimes.com     | Spot.IM                | 1,793                      | 12,531               | 13,236               |
| mirror.co.uk            | Custom                 | 1,734                      | 5,001                | -                    |
| infowars.com            | Disqus                 | 1,533                      | 8,682                | 8,789                |
| newswowk.com            | Facebook               | 1,481                      | 11,110               | 9,336                |
| spunkinnews.com         | Facebook+Custom        | 1,380                      | 3,808                | 4,343                |
| timesofisrael.com       | Facebook               | 1,381                      | 4,367                | 4,588                |
| dailycite.com           | Disqus                 | 1,173                      | 6,892                | 7,343                |
| welt.de                 | Custom                 | 1,139                      | 504                  | -                    |
| jpost.com               | Spot.IM                | 1,080                      | 4,037                | 4,707                |
| slate.co.uk             | Custom                 | 916                        | 9,049                | -                    |
| salon.com               | Spot.IM                | 794                        | 9,675                | 9,792                |
| huffpost.com            | Facebook               | 583                        | 7,106                | 5,996                |
| townhall.com            | Disqus                 | 548                        | 7,015                | 7,235                |
| fiancito.com            | Facebook               | 76                         | 23,310               | 20,759               |

Table 2: News sites in our dataset and their partisanship.

| Partisanship | News sites               |
|-------------|--------------------------|
| Left        | salon.com, huffPost.com, huffingtonpost.com, newsweek.com, firstPost.com |
| Center-Left | nytimes.com, theguardian.com, thehill.com, timesofisrael.com |
| Center      | jpost.com, politico.com  |
| Center-Right| rt.com, washingtontimes.com, spunkinnews.com |
| Right       | dailymail.co.uk, express.co.uk, dailyCall.com, dailycite.com, townhall.com |
| Extreme-Right| breitbart.com, infowars.com |
on our random sample (precision 0.5 and recall 0.31), while the Severe Toxicity model of Perspective API performs substantially better (precision 0.71 and recall 0.52). Interestingly, the Toxicity model of Perspective API performs better with respect to recall but is subpar in terms of precision (precision 0.53 and recall 0.84). Based on these results, we elect to use the Severe Toxicity model available from Perspective API, mainly because we favor precision over recall and we aim to be more robust to the use of swear words (i.e., not everything that includes a swear word is hateful).

Note that hate speech detection is an open research problem and, to the best of our knowledge, there is no classifier that can detect all kinds and forms of hate speech. This task is even difficult for humans as there are no clear definitions of what constitutes hate speech. For instance, in our random sample the three human annotators had a Fleiss Inter-Annotator agreement score of 0.39 that can be regarded as “fair agreement” [3]. Due to this, in this work, we follow a best effort approach to study the prevalence and spread of hate speech using Perspective API that outperforms other readily available alternatives, such as the HateSonar classifier.

4 Results

In this section, we first provide a general characterization of the collected data with a focus on hateful content. Next, we provide a user-based analysis to understand user activity on news articles and then we investigate whether news articles with specific linguistic features attract more hateful content. Finally, we examine whether there is any correlation between posting an article on 4chan’s /pol/ and six subreddits and receiving hateful comments on those articles.

4.1 General Characterization

Prevalence of Hate Comments. We present statistics of the comments that are posted for news articles and the prevalence of hate speech in these comments. Fig. 1 shows the cumulative distribution function (CDF) of the number of comments and the fraction of hate comments over all comments per news article, grouped by the partisanship of the news sites (see Table 2). Note that for readability purposes we only show the distributions for articles that have at least one comment. When looking at the distribution of all the comments (Fig. 1(a)), we observe that extreme-right sites attract more comments, while left and center sites have a substantially lower commenting activity. To assess whether these results are affected by the different size of audiences for each news site, we use SimilarWeb [8] to obtain the number of monthly views per news site (as of December 2018). The full list of these views are publicly available via [5]. Interestingly, we find that the most visited partisanship of news sites in our dataset is center-left (669M visits), followed by right (491M visits), center-right (286M visits), left (251M visits), extreme-right (77M visits), and last center (65M visits). These findings indicate that the audience of left and extreme-right news sites are more active in posting comments despite the fact that center-left, right, and center-right news sites have a larger number of visits.

For hate comments (Fig. 1(b)), we plot the fraction of hate comments over all comments per news article. We find that center and left-leaning sites attract more hate speech, while center-left sites have the lowest rate of hate comments. To assess whether the distributions shown in Fig. 1 have statistically significant differences, we perform a two-sample Kolmogorov-Smirnoff (KS) test for each pair of distributions; in all cases we find statistically significant differences with \( p < 0.01 \).

Fig. 2 shows the percentage of hate comments over all the comments posted in news articles, grouped by news site. We find that infowars.com, a popular alt-right conspiracy-oriented news site, and timesofisrael.com are the sites with the highest percentage of hate comments (15.3%), followed by sputniknews.com (12.9%), jpost.com (12.5%), and politico.com (12.5%). When looking at the news sites with the least hateful commenting activity we find nytimes.com (0.9%), followed by express.co.uk (1.9%), and theguardian.com (3.9%). These results highlight the audience and comment moderation for each site: i.e., Infowars.com is likely to attract users that post hate comments and the site might not apply strict moderation policies, while nytimes.com might not attract hate comments or it might enforce strict moderation policies.
Temporal Analysis. Here, we examine the temporal aspect of the collected comments to understand how (hateful) commenting activity changes over time. This is a particularly interesting and important analysis since it will allow us to understand whether hateful commenting activity is correlated with real-world events and whether hateful commenting activity is increasing or decreasing over time. Fig. 3 shows the weekly percentage of comments and hateful comments for the whole dataset. We focus on the time period after July, 2016, as the vast majority of the collected comments are within the depicted time period. We find that the overall commenting activity started increasing during the months leading to the 2016 US election (between September and November 2016), decreased after the election, while again started increasing after Trump’s Inauguration (January 2017). Furthermore, we note that the biggest peak in commenting activity coincides with the “Unite the Right” rally in Charlottesville [71], during August 2017, which lead to the death of one woman [16]. When looking at the hate comments (Fig. 3(b)), we find a somewhat similar activity with all the comments (Fig. 3(a)). Some peaks in hateful commenting activity coincide with the 2016 US election period, with Trump’s Inauguration in January 2017, with the Charlottesville rally in August 2017. Since our dataset is based on articles posted on 4chan’s/pol/ and the six subreddits, these...
findings indicate that their users are particularly interested in discussing these political events and that they likely comment on them both on their platform as well as in the comments section of each article.

We further investigate whether the peaks in overall and hate commenting activity are statistically significant with respect to the time series of the comments. We run changepoint analysis that provides points in time where statistically significant changes occur on a time series. Specifically, we run the Pruned Exact Linear Time (PELT) algorithm on the weekly time series of both all comments and hate comments. This algorithm maximizes the log-likelihood of the means and variances of the time series with a penalty function that enables us to rank the changepoint according to their statistical significance. Fig. 3 is annotated with the obtained changepoints for both all comments and hate comments, while Tables 3 and 4 report each changepoint and real-world events that coincide with each changepoint. For the overall commenting activity we find statistically significant changepoints that coincide with the Presidential Inauguration of Donald Trump (changepoint 1 in Table 3), Brexit protests (changepoint 2 in Table 3), and developments on the USA-North Korea relations (changepoint 3 in Table 3). For hateful commenting activity we find statistically significant changepoints that coincide with Brexit developments (changepoint 1 in Table 4), the Las Vegas shooting during October 2017 (changepoint 4 in Table 4), developments in US politics (changepoint 2 in Table 4), and the presidential debates during the 2016 US election (changepoints 6 and 7 in Table 4). Finally, we find a changepoint coinciding with the Charlottesville protest (changepoint 3 in Table 4).

### 4.2 User Analysis

In this section, we analyze the users that comment on news articles. We are particularly interested in understanding how these users interact in the comments of news articles, how persistent users are in disseminating hateful comments, and whether users that post on news sites with specific partisan-ship are more hateful. Furthermore, since some commenting platforms (e.g., Disqus) allow users to post comments anonymously, we investigate the effect of anonymity with respect to the dissemination of hateful comments on news articles. Note that due to ethical reasons, we do not make any attempt to link users across the multiple commenting platforms we study, while at the same time we make no attempt to de-anonymize users.

**Effect of anonymity.** We investigate the prevalence of posting comments anonymously. We find that in our dataset 6.5M (5.2%) comments are posted by anonymous users, while the rest of the comments are posted by users that have accounts on the various commenting platforms we study. Next, we look into the prevalence of hateful comments in each of these subsets: we find that in the anonymous subset there are relatively more hateful comments (10.7% of them), while for the subset where users had accounts we find a lower percent-
Overall User Activity. Since we want to analyze the dataset in the granularity of specific users, we therefore next focus on the subset of the dataset where users posted comments by creating accounts on the commenting platforms. Overall, we find 3.1M accounts across all the commenting platforms. To get a better understanding of how users interact with news comments, we plot the CDF of the number of comments per user in our dataset in Fig. 4. Since a substantial percentage of users had only posted one comment, we show the results for users that posted at least ten comments through all the articles in Fig. 4(b). Specifically, we find that from the users that are active on extreme-right news articles comments, 31% of them posted only once across all news articles, while the same percentage increases for other partisanships: 36% for right, 44% for center-left, 60% for left, and 63% for center and center-right. Furthermore, we note that users that post on extreme-right news articles comments are more active (mean number of comments 134.32), followed by users on center-left (mean number of comments 38.6) and right (mean 29.9).

Fig. 5 shows the fraction of hateful comments over all the comments that a user made per partisanship. We make several observations. First, a large percentage of users across all partisanships post only non-hateful comments: e.g., for extreme-right 56% of the users post only non-hateful comments, while for other partisanships like center-right and center-left the percentage is much higher reaching 84%. When we look at the results for the users with at least ten comments (see Fig. 5(b)), however, we note that these percentages are substantially lower compared to all users. This indicates that “power-users” are more likely to share hateful comments, while users that are posting only a few times are less likely to post hateful comments. Second, we note that users that post on extreme-right and right news articles are more likely to post hateful comments compared to users active on center- or left- leaning news articles.

User Activity per Article. Finally, we analyze the user commenting activity in the granularity of specific articles. This analysis allows us to understand the discussion on specific news articles and whether users that post hateful comments are persistent (i.e., posting multiple hateful comments) or whether they are “one-off.” We plot the CDF of the number of comments per user for each article by distinguishing between hateful and non-hateful comments in Fig. 6. We observe that for both hateful and non-hateful comments, a large percentage
users post only once on the news article. This happens for 79% for non-hateful comments and 89% for hateful comments, while by only considering users that posted over ten times (see Fig. 6(b)) the percentages decline to 66% for non-hateful and 86% for hateful comments. Also, we run a KS test on the distributions in Fig. 6 finding that the distributions exhibits statistically significant differences \( p < 0.01 \). These results indicate that it is more likely that users that post non-hateful comments to hold a lengthy discussion on news articles, while users that post hateful comments are more likely to just post a single hateful comment once and then do not post other hateful comments. Note that we performed the same analysis by dividing the users according to their activity in news articles per partisanship finding no substantial differences between the results across partisanship (we omit these results from the manuscript).

4.3 Content Linguistic Analysis

In Journalism, extensive research have studied news article construction for better reader engagement [17, 50, 57, 44, 80, 52, 14]. In this section, we assess whether specific linguistics used in news articles have any correlation with hate intensity. This analysis is important as it sheds light into the linguistics that drive hateful activity in news article comments. These cues can later be used to predict whether an article is likely to attract hate based on linguistics.

In our analysis, we divide the collection of news articles into four types of articles based on their comment engagement and hate intensity in their associated comments: first, those that do not receive any engagement in terms of number of comments (ZERO_Eng); second, those that receive no hate comments (ZERO_HATE); third, those for which the number of hateful comments exceeds a pre-defined threshold \( k \) (HATE); and finally, the rest of the articles, which are the ones that receive at least one hate comment but less than the pre-defined threshold \( k \) (MED_HATE). By checking the CDF of the hate fraction in different articles (see Fig. 6(a)), we observe that a threshold of 10% over all comments represents a substantial number of articles; hence we set \( k = 10\% \). Using this threshold, we find that 52.4% of the articles are ZERO_Eng, 7.3% are ZERO_HATE, 33.2% are MED_HATE, 7.1% are HATE articles.

Articles’ Linguistic Styles and Hate Comments. The interplay of language use and journalism, media and society has been the focus of political science and journalism research [75, 47]. In particular, many principles of journalism are grounded in psycho-linguistic research, the study of how language is acquired, represented, and used [51]. To better understand the characteristics of the articles and their relation to receiving hate comments, we perform a psycho-linguistic analysis on the news articles. For a full psycho-linguistic analysis, we use a tool called Linguistic Inquiry and Word Count (LIWC) [62]. LIWC is a text analysis program that calculates the degree to which various categories of words are used in a text. LIWC has been widely adopted by researchers to study emotional, cognitive, and structural components present in individuals’ verbal and written speech samples. We focus on the following dimensions provided by the tool: summary scores, psychological processes, and linguistic dimensions. Summary scores include general attributes derived from the text, like the authenticity of the text, and basic statistics, like words per sentence. Psychological processes describe the emotions that the text exposes, and linguistic attributes describe the linguistic style of the text. We perform the analysis on each article. Fig. 7 shows the mean scores for our key LIWC attributes. To assess the statistical significance of our results, we perform unpaired (two sample) \( t \)-tests with a 95% confidence interval for the difference between the means. Our analysis yields the following observations:

HATE articles include content with the highest clout scores and the least tone scores in comparison to all other articles. Fig. 7(a) shows the language values obtained from LIWC averaged over all content for ZERO_Eng, ZERO_HATE, MED_HATE, and HATE articles. We show that HATE articles have the highest mean \( \mu = 74.67, p < 0.05 \) for clout (influence and power) values and the lowest mean \( \mu = 28.06, p < 0.05 \) for tone. The high clout score suggests that the linguistic style of HATE articles is associated with high expertise and confident cues, which can be used to influence an audience. Also, the low tone scores suggest that the linguistic style of HATE articles is associated with the highest negative tone.

HATE articles include content with the highest social, religion, and affect references in comparison to all other ar-
Figure 7: Mean scores for LIWC categories across articles with different level of hate comment.
ticles. Fig. [7(b)] shows that HATE articles have the highest mean for the social (µ = 9.94, p < 0.05), religion (µ = 0.57, p < 0.05), and affect (µ = 0.56, p < 0.05). Social processes include family, friends, female and male references. For example, an excerpt from a news article, belonging to the HATE category, that evokes the social category is “Hillary Clinton has an explanation for why women white women in particular voted against her last November they caved in to pressure from their husbands fathers boyfriends and male bosses.” Our analysis also reveals that HATE articles reference religion-related entities and are on average more emotional than other types of articles.

On average, HATE articles include the highest first (I) and third person (she/he) singular pronouns in comparison to all other types of articles. Fig. [7(c)] shows that HATE articles have the highest mean for scores associated with first (µ = 0.68, p < 0.05) and third singular pronouns (µ = 1.92 p < 0.05). These findings show that articles which are about individual people, or include and cite their opinions receive hate comments with higher probability.

HATE articles include the highest anger and anxiety references. Fig. [7(d)] shows that anger is the most prevalent negative emotion for all three types of articles. In particular, HATE articles on average have the highest level of anger (µ = 1.15, p < 0.05). Also, we find that HATE articles on average have the highest level of anxiety (µ = 0.39, p < 0.05).

Emotion and journalism have already been well studied [77, 13, 60, 55, 59]. Mostly, the focus is on how to use emotion to have quality reporting and editing, and to articulate the news more effectively. The use of emotion for manipulation has also been studied [74, 64, 73]. Moreover, findings in political psychology suggest that specific emotions may play an important role in political mobilization. Our finding in particular is aligned with others who also identified anger, more than anxiety or enthusiasm, to mobilize [73].

HATE articles include the least number of words that suggest causation, discrepancy, tentative, and differentiation. Fig. [7(e)] shows that HATE articles tend to have the lowest scores for causation (µ = 1.39, p < 0.05), discrepancy (words like “would” and “should,” µ = 0.95, p < 0.05), tentative (words like “maybe” and “perhaps,” µ = 1.53, p < 0.05), and differentiation (words like “hasn’t,” “but,” and “else,” µ = 2.1, p < 0.05). This can indicate that HATE articles tend to have less justification of arguments in terms of causes or effects.

HATE articles include the highest references related to affiliation and the lowest references to achievement. Fig. [7(f)] shows that HATE articles have the highest mean for words suggesting affiliation (µ = 2.23, p < 0.05) and the lowest achievement references (µ = 1.38, p < 0.05). This likely suggests that HATE articles are motivated by the need to be affiliated to certain groups and because of their negative nature they might not mention achievements.

We also perform the linguistics analysis on the articles grouped by partisanship to understand if news sites with different partisanship have differences in terms of linguistic dimensions. In general, we find minor differences in the linguistic dimensions across partisanship with some exceptions: articles that have a center partisanship have the least affect and the least focus on the past in comparison with articles from other partisanship.

4.4 Activity after Social Network Posts

In this section, we study the commenting activity on news articles after they appear on social networks. We aim to provide answers to the following questions: 1) Is the appearance of news articles on social networks like 4chan and Reddit correlated with the (hateful) commenting activity on news articles? 2) How does the (hateful) commenting activity decay after the posting of news articles on 4chan and Reddit? 3) What portion of news articles receive increased hateful activity shortly after appearing in other social networks? This analysis is important since it sheds light into the external factors (i.e., appearance of news articles on other social networks) that possibly affect the commenting activity on news sites.

To provide answers to the above questions, we find the first occurrence of each news article on the six subreddits and on /pol/. Then, we normalize the occurrence of each comment in the news article, with respect to the first occurrence of the article in each platform, hence obtaining a view of whether com-
ments, and in particular hate comments, increase after the appearance of articles on Reddit and 4chan. To do this, we subtract the timestamp of each comment in news articles with the timestamp of the first occurrence of the article on the six subreddits and /pol/, hence obtaining a normalized time for the comments. Fig. 8 shows the average percentage of comments that were posted in close proximity with the first occurrence of each article on the six subreddits and /pol/. Time zero corresponds to the first occurrence of the article on /pol/ or the six subreddits, while each bar corresponds to a time period of two hours. For instance, the bars that have the number zero correspond to the time interval between the first occurrence of the article and the next two hours. We report the results using three ways: Fig. 8(a) shows the occurrence of all comments per normalized time slot, Fig. 8(b) shows the occurrence of hateful comments per normalized time slot, while Fig. 8(c) shows the fraction of hateful comments over all comments per normalized time slot. The latter is useful as it captures the correlation between the hateful commenting activity and the overall activity.

We observe that for all comments (see Fig. 8(a)), the commenting activity increases after the first occurrence of the news articles in the six subreddits and /pol/ (normalized time 0) with a peak of activity at normalized time 3 and 4 for /pol/ and the six subreddits, respectively. Also, we find that the commenting activity close to the first occurrence (between 0 and 2 normalized time) is greater for /pol/ when compared to the six subreddits, while later on (after normalized time 2) the percentage activity is larger for the six subreddits. This is likely due to Reddit bots that post news articles without user interaction and likely because of 4chan’s ephemeral nature: 4chan users are more likely to interact with the article closer to the article’s post on the platform, as threads are short-lived. By only considering the hateful commenting activity (see Fig. 8(b)), we observe a similar pattern with the important difference that the peak in hateful activity is closer to the appearance of the articles on the six subreddits and /pol/, namely during normalized time 1. This indicates that hateful commenting activity increases substantially right after the appearance of news articles on the six subreddits and /pol/, in a far quicker pace when compared to the overall commenting activity.

To further study the interplay between the overall commenting activity and the hateful commenting activity, we plot the fraction of hate comments over all comments per normalized time in Fig. 8(c). We observe that despite the fact that the overall commenting activity and hateful activity decreases sub-
nomenon and its prevalence on the Web, we filter the articles so that we select the ones that had the maximum (hateful) commenting activity during the normalized time zero: we find 39K articles for hateful commenting activity and 17K for all commenting activity. Fig. 10 reports the percentage of articles over all articles (with at least one comment) that have an increase in commenting activity, and in particular hate commenting activity, shortly after the first occurrence of the news articles on /pol/ or the six subreddits. We find that domains that are center-right have the most articles with commenting activity increase, while extreme-right domains have the least (see Fig. 10(a)). When considering only hateful activity (see Fig. 10(b)), we find something similar: again, center-right domains have the most articles with activity increase and in this case it is hateful. A possible explanation is that users from the six subreddits or /pol/ disagree or have a different ideology with articles from center-right news sites, hence posting hateful comments in the comments section right after their appearance on their platform. Finally, we note that for hateful commenting activity the percentages are higher for Reddit across all partisanship with the exception of center-right, possibly indicating that Reddit users are more likely to post hateful comments on these news articles in close temporal proximity after their appearance on the six subreddits.

Next, we make the same analysis focusing on hate comments, by grouping the articles according to each news site’s partisanship (see Table 2). Fig. 9 shows the fraction of hateful comments over all comments per normalized time period for each partisanship (we omit the figures for the overall commenting activity and overall hateful commenting activity due to space constraints). We find that extreme-right news sites are more persistent in hateful commenting activity as the fraction of hateful comments over all comments decays substantially slower compared to the other partisanship. On the other hand, news sites that are more on the center (i.e., center, center-left, center-right) have the fastest decay of hateful comments over all comments. These findings indicate that extreme news sites (i.e., extreme-right) are more likely to maintain a substantial percentage of hateful commenting activity after the appearance of news articles on the six subreddits and /pol/ when compared to other partisanship on the center.

These results are based on all the articles in our dataset that have at least one comment. However, not all articles receive hate comments after their first occurrence in other platforms like /pol/ and the six subreddits. To understand this phenomenon and its prevalence on the Web, we filter the articles so that we select the ones that had the maximum (hateful) commenting activity during the normalized time zero: we find 39K articles for hateful commenting activity and 17K for all commenting activity. Fig. 10 reports the percentage of articles over all articles (with at least one comment) that have an increase in commenting activity, and in particular hate commenting activity, shortly after the first occurrence of the news articles on /pol/ or the six subreddits. We find that domains that are center-right have the most articles with commenting activity increase, while extreme-right domains have the least (see Fig. 10(a)). When considering only hateful activity (see Fig. 10(b)), we find something similar: again, center-right domains have the most articles with activity increase and in this case it is hateful. A possible explanation is that users from the six subreddits or /pol/ disagree or have a different ideology with articles from center-right news sites, hence posting hateful comments in the comments section right after their appearance on their platform. Finally, we note that for hateful commenting activity the percentages are higher for Reddit across all partisanship with the exception of center-right, possibly indicating that Reddit users are more likely to post hateful comments on these news articles in close temporal proximity after their appearance on the six subreddits.

5 Conclusion

In this paper, we presented a large-scale quantitative analysis of the news commenting ecosystem. We analyzed 125M comments and 412K news articles across several axes: we performed a general characterization of hateful content in news comments, a temporal analysis, as well as a linguistics characterization. Overall, among other things, we found that (hateful) commenting activity increases with notable events that have a strong political nature, articles that attract varying hateful activity have significant linguistic differences, while our user-based analysis reveals that users that post comments in extreme-right sites tend to be more active and post more hateful comments compared to users that post on sites with other partisanship. Furthermore, we found a correlation between the posting of news articles on either /pol/ or the six selected subreddits and increased (hateful) commenting activity on the article.

Naturally our work has some limitations. First, our dataset was collected well after the publication of the articles and their comments, hence it is likely that some of the hateful content was moderated/deleted. Second, we relied on the Perspective API for detecting hate speech, which is expected to miss some hateful content (as mentioned in Section 3). This is because hate speech detection is an open research problem and available classifiers are unable to detect all possible types of hateful content.

To conclude, for our future work, we plan to work on proactively detecting organized campaigns, mainly from users of fringe Web communities, that aim to “raid” news articles with hate comments. Also, we aim to assess the effect that other
mainstream social networks (e.g., Twitter) have on the commenting activity of news articles. Finally, we plan to build a classifier that will be able to detect whether news articles are likely to attract hateful comments.

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References
[1] Disqus API. https://disqus.com/api/docs/, 2019.
[2] Facebook Graph API. https://developers.facebook.com/docs/graph-api/, 2019.
[3] Fleiss’ Kappa. https://en.wikipedia.org/wiki/Fleiss_kappa, 2019.
[4] Full list of sites we use. https://bit.ly/2XZtwvA, 2019.
[5] List of monthly views. https://bit.ly/3bb9vzl, 2019.
[6] Media Bias/Fact Check Site. https://mediabiasfactcheck.com/, 2019.
[7] Newspaper3k. https://newspaper.readthedocs.io/en/latest/, 2019.
[8] SimilarWeb Site. https://www.similarweb.com/, 2019.
[9] Spot.Im API. https://developers.spot.im/, 2019.
[10] Virus Total API. https://www.virustotal.com/, 2019.
[11] R. Baly, G. Karadzhov, D. Alexandrov, J. Glass, and P. Nakov. Predicting factuality of reporting and bias of news media sources. In EMNLP, 2018.
[12] J. Baumgartner, S. Zannettou, B. Keegan, M. Squire, and J. Blackburn. The Pushshift Reddit Dataset. In ICWSM, 2020.
[13] C. Beckett and M. Deuze. On the role of emotion in the future of journalism. Social Media+ Society, 2016.
[14] A. Bell. The language of news media. Blackwell Oxford, 1991.
[15] D. Byers. Trump picks Sean Spicer as White House press secretary. http://cnnmon.ie/2hZdXuE, 2016.
[16] C. Caron. Heather Heyer, Charlottesville Victim, Is Recalled as “a Strong Woman”. https://nyti.ms/2vuxF2X, 2017.
[17] P. Catenaccio, C. Cotter, M. De Smedt, G. Garzone, G. Jacobs, F. Macgilchrist, L. Lams, D. Perrin, J. E. Richardson, T. Van Hout, et al. Towards a linguistics of news production. Journal of Pragmatics, 2011.
[18] E. Chandrasekharan, U. Pavalanathan, A. Srinivasan, A. Glynn, J. Eisenstein, and E. Gilbert. You can’t stay here: The efficacy of reddit’s 2015 ban examined through hate speech. CSCW, 2017.
[19] E. Chandrasekharan, M. Samory, A. Srinivasan, and E. Gilbert. The bag of communities: Identifying abusive behavior online with preexisting internet data. In CHI, 2017.
[20] D. Chatzakou, N. Kourtellis, J. Blackburn, E. De Cristo-faro, G. Stringhini, and A. Vakali. Mean birds: Detecting aggression and bullying on twitter. In WebSci, 2017.
[21] S. Collinson. It’s official: Trump is Republican nominee. http://cnn.it/2a6ytZN, 2016.
[22] T. Davidson, D. Warmsley, M. Macy, and I. Weber. Automated Hate Speech Detection and the Problem of Offensive Language. In ICWSM, 2017.
[23] N. Diakopoulos and M. Naaman. Towards quality discourse in online news comments. In CSCW, 2011.
[24] N. Djuric, J. Zhou, R. Morris, M. Grbovic, V. Radosavljevic, and N. Bhamipati. Hate Speech Detection with Comment Embeddings. In WWW, 2015.
[25] M. ElSherief, V. Kulkarni, D. Nguyen, W. Y. Wang, and E. M. Belding-Royer. Hate Lingo: A Target-based Linguistic Analysis of Hate Speech in Social Media. In ICWSM, 2018.
[26] M. ElSherief, S. Nilizadeh, D. Nguyen, G. Vigna, and E. M. Belding-Royer. Peer to Peer Hate: Hate Speech Instigators and Their Targets. In ICWSM, 2018.
[27] K. Erjavec and M. P. Kovačić. “You Don’t Understand, This is a New War!” Analysis of Hate Speech in News Web Sites’ Comments. Mass Communication and Society, 2012.
[28] C. Flores-Saviaga, B. C. Keegan, and S. Savage. Mobilizing the Trump Train: Understanding Collective Action in a Political Trolling Community. In ICWSM, 2018.
[29] A.-M. Founta, D. Chatzakou, N. Kourtellis, J. Blackburn, A. Vakali, and I. Leontiadis. A Unified Deep Learning Architecture for Abuse Detection. 2019.
[30] Fox News. Congress passes bill letting 9/11 victims sue Saudi Arabia, in face of veto threat. http://fxn.ws/2zRQFuW, 2016.
[31] Fox News. Intel report says Putin ordered campaign to influence US election. http://fxn.ws/2jHnt0, 2018.
[32] B. Gambäck and U. K. Sikdar. Using Convolutional Neural Networks to Classify Hate-Speech. In Workshop on Abusive Language Online, 2017.

[33] L. Gao and R. Huang. Detecting Online Hate Speech Using Context Aware Models. In RANLP, 2017.

[34] L. Gao, A. Kuppersmith, and R. Huang. Recognizing Explicit and Implicit Hate Speech Using a Weakly Supervised Two-path Bootstrapping Approach. In IJCNLP, 2017.

[35] E. Gringberg and E. Levenson. At least 17 dead in Florida school shooting, law enforcement says. https://edition.cnn.com/2018/02/14/us/florida-high-school-shooting/index.html 2018.

[36] L. Ha, Y. Xu, C. Yang, F. Wang, L. Yang, M. Abuljadail, X. Hu, W. Jiang, and I. Gabay. Decline in news content engagement or news medium engagement? a longitudinal analysis of news engagement since the rise of social and mobile media 2009–2012. Journalism, 2018.

[37] S. Harlow. Story-chatterers stirring up hate: Racist discourse in reader comments on us newspaper websites. Howard Journal of Communications, 2015.

[38] B. Henderson. Donald Trump and Hillary Clinton to clash in Las Vegas “Fight Night” debate: US election briefing and polls. https://bit.ly/3cDVKQu, 2016.

[39] G. E. Hine, J. Onuolapo, E. De Cristofaro, N. Kourtellis, I. Leontiadis, R. Samaras, G. Stringhini, and J. Blackburn. Kek, Cucks, and God Emperor Trump: A Measurement Study of 4chan’s Politically Incorrect Forum and its Effects on the Web. 2017.

[40] S. Holland and E. Stephenson. Trump, now president, pledges to put “America First” in nationalist speech. http://reut.rs/2iQMMmK, 2017.

[41] M. W. Hughey and J. Daniels. Racist comments at online news sites: a methodological dilemma for discourse analysis. Media, Culture & Society, 2013.

[42] S. Jhaver, S. Ghoshal, A. Bruckman, and E. Gilbert. Online harassment and content moderation: The case of blocklists. TOCHI, 2018.

[43] R. Killick, P. Fearnhead, and I. A. Eckley. Optimal detection of changepoints with a linear computational cost. Journal of the American Statistical Association, 2012.

[44] Y. Kim, H.-T. Chen, and H. G. De Zúñiga. Stumbling upon news on the internet: Effects of incidental news exposure and relative entertainment use on political engagement. Computers in human behavior, 2013.

[45] H. Kwak, C. Lee, H. Park, and S. Moon. What is twitter, a social network or a news media? In WWW, 2010.

[46] I. Kwok and Y. Wang. Locate the Hate: Detecting Tweets against Blacks. In AAAI, 2013.

[47] A. Lukin. Journalism, ideology and linguistics: The paradox of chomsky’s linguistic legacy and his ‘propaganda model’. Journalism, 2013.

[48] E. Ly and A. Dewan. Thousands say “No” to Brexit in colorful protest. http://cnn.it/29drqiT, 2016.

[49] E. Mariconti, G. Suarez-Tangil, J. Blackburn, E. De Cristofaro, N. Kourtellis, I. Leontiadis, J. L. Serrano, and G. Stringhini. “You Know What to Do”: Proactive Detection of YouTube Videos Targeted by Coordinated Hate Attacks. In CSCW, 2019.

[50] J. Martin and A. Chozick. Hillary Clinton’s Doctor Says Pneumonia Led to Abrupt Exit From 9/11 Event. https://nyti.ms/2cFiCkr, 2016.

[51] K. C. McAdams. Psycholingustics explains many journalism caveats. The Journalism Educator, 1984.

[52] R. D. Mersey, E. C. Malthouse, and B. J. Calder. Focusing on the reader: Engagement trumps satisfaction. Journalism & Mass Communication Quarterly, 2012.

[53] M. Mondal, L. A. Silva, and F. Benevenuto. A Measurement Study of Hate Speech in Social Media. In HT, 2017.

[54] M. Mondal, L. A. Silva, and F. Benevenuto. A measurement study of hate speech in social media. In HT, 2017.

[55] J. E. Newhagen and B. Reeves. The evening’s bad news: Effects of compelling negative television news images on memory. Journal of Communication, 1992.

[56] Nytimes. Multiple Weapons Found in Las Vegas Gunman’s Hotel Room. https://nyti.ms/2fKkQ8p, 2017.

[57] H. L. O’Brien. Exploring user engagement in online news interactions. Proceedings of the American society for information science and technology, 2011.

[58] A. Olteanu, C. Castillo, J. Boy, and K. R. Varshney. The effect of extremist violence on hateful speech online. In ICWSM, 2018.

[59] K. E. Palazzolo and A. J. Roberto. Media representations of intimate partner violence and punishment preferences: Exploring the role of attributions and emotions. Journal of Applied Communication Research, 2011.

[60] M. Pantti. The value of emotion: An examination of television journalists’ notions on emotionality. European Journal of Communication, 2010.

[61] J. Pavlopoulos, P. Malakasiotis, and I. Androutsopoulos. Deep learning for user comment moderation. In ACL, 2017.
[62] J. W. Pennebaker, R. L. Boyd, K. Jordan, and K. Blackburn. The Development and Psychometric Properties of LIWC2015, 2015.

[63] Perspective API. https://www.perspectiveapi.com/ 2018.

[64] B. Richards. Emotional Governance: Politics, media and terror. 2007.

[65] H. M. Saleem, K. P. Dillon, S. Benesch, and D. Ruths. A Web of Hate: Tackling Hateful Speech in Online Social Spaces. CoRR, 2017.

[66] J. Serra, I. Leontiadis, D. Spathis, G. Stringhini, J. Blackburn, and A. Vakali. Class-based Prediction Errors to Detect Hate Speech with Out-of-vocabulary Words. 2017.

[67] R. Shabad. Second presidential debate 2016: What time, how to watch and live stream online. https://cbsn.ws/2S0a4eh 2016.

[68] D. Sherfinski. Kellyanne Conway selected as Donald Trump’s counselor. https://go.shr.lc/2TOpkcv 2016.

[69] L. A. Silva, M. Mondal, D. Correa, F. Benevenuto, and I. Weber. Analyzing the Targets of Hate in Online Social Media. In ICWSM, 2016.

[70] T. D. Smedt, G. D. Pauw, and P. V. Ostaeyen. Automatic Detection of Online Jihadist Hate Speech. CoRR, 2018.

[71] H. Spencer. A Far-Right Gathering Bursts Into Brawls. https://nyti.ms/2uTmIgV 2017.

[72] M. Tsagkias, W. Weerkamp, and M. De Rijke. News comments: Exploring, modeling, and online prediction. In ECIR, 2010.

[73] N. A. Valentino, T. Brader, E. W. Groenendyk, K. Gregorowicz, and V. L. Hutchings. Election night’s alright for fighting: The role of emotions in political participation. The Journal of Politics, 2011.

[74] N. A. Valentino, V. L. Hutchings, A. J. Banks, and A. K. Davis. Is a worried citizen a good citizen? emotions, political information seeking, and learning via the internet. Political Psychology, 2008.

[75] T. Van Hout. Between text and social practice: Balancing linguistics and ethnography in journalism studies. In Linguistic Ethnography. 2015.

[76] F. D. Vigna, A. Cimino, F. Dell’Orletta, M. Petrocchi, and M. Tesconi. Hate Me, Hate Me Not: Hate Speech Detection on Facebook. In ITASEC, 2017.

[77] K. Wahl-Jorgensen. Emotion and journalism. The SAGE handbook of digital journalism, 2016.

[78] W. Warner and J. Hirschberg. Detecting Hate Speech on the World Wide Web. In Workshop on Language in Social Media, 2012.

[79] E. Watkins. Trump taunts North Korea: My nuclear button is “much bigger,” “more powerful”. http://cnn.it/2A7Q4e5 2018.

[80] R. A. Yaros. Is it the medium or the message? structuring complex news to enhance engagement and situational understanding by nonexperts. Communication Research, 2006.

[81] S. Zannettou, B. Bradlyn, E. De Cristofaro, H. Kwak, M. Sirivianos, G. Stringini, and J. Blackburn. What is Gab: A Bastion of Free Speech or an Alt-Right Echo Chamber. In WWW Companion, 2018.

[82] S. Zannettou, T. Caulfield, J. Blackburn, E. De Cristofaro, M. Sirivianos, G. Stringhini, and G. Suarez-Tangil. On the Origins of Memes by Means of Fringe Web Communities. In IMC, 2018.

[83] S. Zannettou, T. Caulfield, E. De Cristofaro, N. Kourtellis, I. Leontiadis, M. Sirivianos, G. Stringhini, and J. Blackburn. The Web Centipede: Understanding How Web Communities Influence Each Other Through the Lens of Mainstream and Alternative News Sources. In IMC, 2017.

[84] S. Zannettou, J. Finkelstein, B. Bradlyn, and J. Blackburn. A quantitative approach to understanding online antisemitism. 2020.