Detect Hate Speech in Unseen Domains using Multi-Task Learning: A Case Study of Political Public Figures

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ABSTRACT
Automatic identification of hateful and abusive content is vital in combating the spread of harmful online content and its damaging effects. Most existing works evaluate models by examining the generalization error on train-test splits on hate speech datasets. These datasets often differ in their definitions and labeling criteria, leading to poor model performance when predicting across new domains and datasets. In this work, we propose a new Multi-task Learning (MTL) pipeline that utilizes MTL to train simultaneously across multiple hate speech datasets to construct a more encompassing classification model. We simulate evaluation on new previously unseen datasets by adopting a leave-one-out scheme in which we omit a target dataset from training and jointly train on the other datasets. Our results consistently outperform a large sample of existing work. We show strong results when examining generalization error in train-test splits and substantial improvements when predicting on previously unseen datasets. Furthermore, we assemble a novel dataset, dubbed PubFigs, focusing on the problematic speech of American Public Political Figures. We automatically detect problematic speech in the 305,235 tweets in PubFigs, and we uncover insights into the posting behaviors of public figures.

1 INTRODUCTION
With the increasing importance of online media platforms in our day-to-day lives, detecting hateful and abusive content has become necessary to prevent the pollution of online platforms by problematic and malicious users. Automatic detection of hateful and abusive content has recently received significant attention from the research community. Currently, most existing works evaluate their models using a test train split, where the model is sequentially trained and then tested independently on each dataset. However, several recent works [4, 32] raise concerns over the poor generalization performance of such existing models when applied to a hate speech dataset gathered separately from the dataset used in training the model. This poor performance persists even for datasets gathered from the same platform.

A key challenge is the lack of a universally agreed-upon definition of hate speech specific enough to be operationalized. There are many facets to hateful and abusive speech, such as racism, sexism, ableism, bullying, harassment, incitement of violence, and extremism. Most prior work concerned with hate speech detection concentrate on specific facets, which translates to differences in the labeling criteria. Therefore, each dataset captures only a fraction of the hate speech domain, causing models trained on single datasets to generalize poorly on datasets concerned with other facets.

This work examines two open questions concerning hate speech detection. The first research question relates to constructing models that account for the various definitions of hate across different datasets. Most existing work adopt a narrow definition, construct labeled datasets, and measure the generalization error on train-test splits [6, 8, 9, 34]. Given the discussion in the previous paragraph, the results are overly optimistic and fail to generalize to new domains [4, 32]. The question is can we construct a model that can utilize multiple hate speech datasets to capture the differing definitions of hate across different datasets to improve a model’s classification performance? The second question relates to detecting hate speech in previously unseen domains and datasets. A limited number of works attempted to train on multiple models [35, 38], but they generally do not study the predictivity on previously unseen domains. Our approach differs from existing works in our pipeline architecture as well as our utilization of MTL across a significantly higher number of hate speech datasets. Can we construct a model that generalizes to an entirely new dataset in the hateful and abusive speech domain?

We address the first research question by introducing a novel transfer learning pipeline that trains a classification model using several hate speech datasets in parallel through Multi-Task Learning (MTL). We fine-tune a single BERT language model to which we attach as many classification heads as there are datasets to train on. Each classification head is adapted to detect the hate classes specific to its datasets; however, the gradients are back-propagated into a single language model. Intuitively, this constructs a single representation that captures a more generic definition of hate. We train on 8 publicly available datasets, to which we add a newly constructed dataset of American public political figures (described below). Our model produces strong predictive performances in train/test split scenarios; we compare MTL against 9 state-of-the-art hate speech detection architectures reported on several datasets. MTL outperforms the competing approaches (12 wins, 1 draw, 5 losses) on their reported performance measures.

We address the second open question in three steps. First, we simulate the hate speech detection on a new previously unseen target dataset using a leave-one-out scheme in which we jointly train on all but the target dataset. MTL consistently outperforms existing approaches, except for one dataset whose labeling is so specific that using a generalized model hurts performances. Second, we use MTL to study the generalization of classifiers trained on individual datasets to new unseen datasets. We find that specific pairs of datasets have high mutual generalization — typically those
This section discusses the definitions of hate speech, related works in hate speech classification, and transfer learning approaches.

**Defining Hate Speech.** Hate speech is not easily quantifiable as a concept [20, 22]. It lies on a continuum with offensive speech and other abusive content such as bullying and harassment. Some definitions given in literature are as follows: The United Nations [1] defines hate speech as "any kind of communication in speech, writing or behavior, that attacks or uses pejorative or discriminatory language concerning a person or a group based on who they are, in other words, based on their religion, ethnicity, nationality, race, color, descent, gender or other identity factor". Fortuna and Nunes [14] surveyed definitions of hate speech and produced their own: "Hate speech is language that attacks or diminishes, that incites violence or hate against groups, based on specific characteristics such as physical appearance, religion, descent, national or ethnic origin, sexual orientation, gender identity or other, and it can occur with different linguistic styles, even in subtle forms or when humor is used". Most of these definitions are enumerations of the facets of hate speech, which make it difficult to transform into detection.

**Hateful and Abusive Speech Classification.** Early approaches for hate speech classification utilized non-neural network-based classifiers, usually in conjunction with manual feature engineering. Examples of such works are Davidson et al. [8] and Waseem and Hovy [34] which used various engineered features in conjunction with a logistic regression classifier. More recently, MacAvaney et al. [22] utilized a Multi-view SVM with feature engineering, reporting results similar to modern neural network models.

Recent advances in deep learning have seen the state-of-the-art dominated by deep neural network-based models. Initial models utilized recurrent or convolutional neural networks [40] with textual features, often in conjunction with non-neural classifiers [5] and feature engineering [3, 36].

The introduction of large pre-trained transformer language models such as the "Bidirectional Encoder Representations from Transformers" (BERT) [10], and its variants have shown impressive performance in several NLP-related tasks, including hate speech detection [24, 26, 32]. Our work extends upon these works by exploring transfer learning and multi-task learning in conjunction with transformer-based models.

**Transfer and Multi-Task Learning.** Transfer learning is the exploitation of knowledge gained in one setting to improve the generalization performance in another setting [16]. Formally, given source domain $D_S$ and source task $T_S$, target domain $D_T$ and target task $T_T$ where $D_S \neq D_T$ or $T_S \neq T_T$, transfer learning seeks to make an improvement to the learning of the target predictive function $f_T(\cdot)$ in $D_T$ using knowledge in $D_S$ and $T_S$ [27].

The most common form of transfer learning is Sequential Transfer Learning (STL): the model is trained on related tasks one at a time, then fine-tuned to adapt the source knowledge to the target domain. Multi-Task Learning (MTL) is an alternative paradigm, also known as parallel transfer learning. MTL seeks to transfer knowledge between several target tasks simultaneously and jointly, rather than sequentially towards a single target task [7]. The tasks act as regularizers for each other in the joint model.

MTL has been previously applied to hateful and abusive speech detection. Waseem et al. [35] applied MTL to a Recurrent Neural Network classification model. Yuan et al. [38] leveraged two datasets in an MTL approach that creates generalized embeddings using a bi-directional LSTM model. Our work differs from the above by using a BERT architecture, adding significantly more datasets, and focusing on classification in previously unseen datasets.

**3 METHODOLOGY**

This section details our MTL pipeline (Section 3.1), its training (Section 3.2), and the classification on unseen datasets (Section 3.3).
3.1 Model

Fig. 2 shows the schema of our proposed BERT-based multi-task transfer learning pipeline. It consists of the following:

The Preprocessing Unit standardizes the text input by removing capitalization, repetitive punctuation, redundant white spaces, emojis, and URLs in text. It uses a single space character to separate all words and punctuation. We remove the Twitter-specific retweet flag “RT” and filter sequences that are empty after preprocessing.

The BERT Unit consists of the pretrained BERT tokenizer, the pretrained BERT language model, and a pooling layer. The BERT tokenizer creates a sequence of tokens to be used as input for the BERT model from the preprocessed text. The BERT model creates a representation for each token in the sequence. The pooling layer constructs a fixed-sized sentence embedding by pooling together the individual token representations. It consists of a fully connected layer and a tanh activation. It inputs from BERT the token outputs and the hidden state of the last BERT layer after processing the first token of the sequence. We use the original pretrained weights (bert-base-uncased) [10] to initialize the tokenizer, the BERT model, and the pooling layer. During pretraining, the Linear layer weights are trained using the next sentence prediction (classification) objective.

The Dataset-Specific Classifier Heads take the representation produced by the pooling layer and produce a classification for each task (corresponding to each dataset). Each head consists of a 3-layer neural network with a hidden size of 512 and softmax activation. Weights are not shared between classification heads.

3.2 Training Pipeline

Dataset Preprocessing. The training constructs a task-agnostic representation of hateful and abusive speech by jointly fine-tuning BERT’s parameters using several datasets. The datasets can have arbitrary numbers of classes (see Table 1). Hate speech datasets are known to have a heavy class imbalance [23, 38]; therefore, we use a stratified random split of 8:1:1 (training : validation : test set) to ensure that all subsets contain the same ratio of classes. We further use random oversampling of the minority classes during training.

Training and Loss Function. We train the MTL pipeline for 10 epochs. Each epoch consists of a pass over each of the $n$ datasets’ training sets. We use minibatching with a batch size of 512. Once all heads have completed the epoch, losses are accumulated and summed over all classification heads, then propagated using the Adam optimizer [19]. The total loss at each epoch is $L = \sum_{i=1}^{n} L_i$ where $L_i$ is the cross-entropy loss of the $i$-th classifier head.

Selecting Best Model. We evaluate using the holdout validation set at each epoch. We select the model weights with the highest validation macro-$F_1$ score over all epochs as the final model weights. We also explored the selection of final weights using the validation loss but found the performance worse than macro-$F_1$.

Single Dataset Baselines use the same architecture as MTL, but with only one input dataset and one classification head. Therefore, the BERT and classifier are tuned on a single task. We use this baseline in Section 5.1 to evaluate dataset pairwise generalization.

3.3 Classification on Unseen Datasets

Each classification head of the MTL pipeline independently predicts an arbitrary number of harmful classes, depending on each dataset’s labeling (see Table 1). As the number of classes in new, previously unseen datasets is unknown, we construct a binary classification of content as harmful/harmless. We build a binary mapping for each dataset by joining the classes shown in red italic font in Table 1 into a single harmful class (and the others into the harmless class).

We propose two schemes for classifying unseen datasets: New Classification Head (NCH) and Majority Vote (MV). NCH trains a new head on the binarized versions of the available datasets. First, we build a new training set that concatenates training instances from all datasets. Second, we build a validation set that concatenates all datasets’ validation and testing sets. Finally, we freeze the MTL tuned BERT and train a new binary classifier head for 10 epochs, selecting the final weights based on the best validation performance. MV leverages the trained dataset-specific classifier heads. Each classifier makes an individual prediction – binarized using its specific dataset mapping. For each instance in the unseen dataset, a majority vote is used to select the final classification label.

NCH and MV differ in the effect of dataset sizes on the final classification. In the NCH scheme, each dataset contributes proportionally to its size, as more training information originates from larger datasets than smaller ones. By contrast, the MV scheme gives smaller datasets equal weight to larger datasets in the majority vote. We investigate both schemes in Section 5. For single dataset baselines (see Section 3.2), we only binarize the output of the classification head – i.e., the MV scheme with a single voter.

4 DATASETS

In this section, we discuss the datasets used in this work. We split our discussion into two subsections. First, Section 4.1 discusses the publicly available hate speech datasets that we collated from existing works. Second, Section 4.2 discusses the novel datasets that we construct – dubbed PubFigs.

4.1 Datasets From Existing Works

We collect eight datasets from existing works that we use for training MTL. Table 1 shows for each dataset the number of instances and its classes – highlighting the ones that we deem as harmful. The datasets we use in this work are as follows:

**Davidson** [8] is a widely used dataset in hate speech classification as well as other related applications [5, 26, 40]. The dataset was collected from Twitter and labeled by crowdsourced workers from CrowdFlower. At least three workers labeled each data instance.
**Waseem** [34] is another Twitter dataset widely utilized in prior works. Several existing works have raised questions regarding the quality of the annotations in the dataset. Waseem [33] himself raised questions regarding the overall quality of the annotations associated with the data. Grönåhl et al. [17] highlight the skewed distribution of users who contribute to the racist and sexist classes, with 9 users accounting for all tweets labeled as racist.

**Reddit** [28]: Reddit is a well-known social media platform consisting of subreddits, where user-created communities discuss topics or themes. The Reddit dataset is collected from ten subreddits based on their tendency to contain toxicity and hate speech, such as r/DankMemes, r/MensRights, and r/TheDonald. The top 200 posts of each subreddit are annotated using Amazon Mechanical Turk. Each post was assigned to 3 different workers.

**Gar** [28]: Gab is a social media and microblogging platform with functionalities similar to Twitter, well known for its far-right user base [18]. The Gab dataset originates from the same work as the Reddit dataset and uses a similar methodology. Hateful keywords from [13] are used to identify potentially hateful posts, which are then labeled as hateful or non-hateful using Amazon Mechanical Turk. Each post was assigned to 3 different workers.

**Fox** [15] is a small binary hate speech dataset that contains user comments from ten news discussion threads on the Fox News website. Four of the ten threads were annotated by two native English-speaking, who discussed the labeling criteria before annotating. The other six threads were annotated by a single annotator.

**Mandl** [25] is a Twitter dataset released as a part of the HASOC track of the 2019 ACM Forum for Information Retrieval Evaluation (FIRE) conference. We only use the English dataset. Labeling was done in two steps. First, tweets were labeled as hateful or offensive or not hateful or offensive. Hateful and offensive tweets were then re-examined and further divided into 3 classes, resulting in a final set of 4 classes: Neutral, Hate, Offensive, and Profane. For this work, we consider only hate and offensive as harmful; according to most definitions of hate speech (see Section 2), profanities cannot be considered harmful content. “Several juniors” performed the annotations after being given rough guidelines and definitions.

**Stormfront** [9]: Stormfront is a neo-Nazi Internet forum and is considered one of the major racial hate sites. The Stormfront dataset contains 9,916 sentences from 500 posts posted across 22 sub-forums on the Stormfront website between 2002 and 2017. Three annotators first labeled 1,144 sentences as either hate, no hate, or skip/unclear. A relation label is used for posts hateful given the conversation chain’s full context, but not by themselves. Our work treats each sentence as an individual data instance. Hence, we consider the skip/unclear and relation classes as non-hate.

**HatEval** [6] is a Twitter dataset, containing tweets from July to September 2018. The hate speech class in this work is focused explicitly on hate against immigrants and women. The original work contributes a Spanish dataset in addition to the English one. Also, it contains additional labels for the target of hate as well as the aggressiveness of the content. These are not used in this work.

### 4.2 The PUBFigs Twitter Dataset

We present the PUBFigs dataset and its labeled subset PUBFigs-L.

**Dataset Construction.** We gather historical tweets from 15 American public figures across 16 Twitter accounts (one figure used two accounts). We select figures based on their perceived conservative (right-) vs. liberal (left-) political leaning and media presence to cover a range of personalities and social media behavioral patterns. Our dataset includes, among others, Alex Jones (far-right conspiracy theorist), Ann Coulter (conservative media pundit), Donald Trump and Barrack Obama (former US presidents, right- and left-leaning, respectively), and Alexandria Ocasio-Cortez and Ilhan Omar (democrat politicians perceived as very progressive). In total, we collected 305,235 tweets. Please see the online appendix [2] for the complete list of figures, their description, and tweet volumes.

**Data Selection for Annotation.** Labeling more than 300K postings is time and cost prohibitive. As such, we use an active sampling procedure to construct a subset for labeling - dubbed PUBFigs-L - using Amazon Mechanical Turk (procedure described below). Random sampling would yield very few hateful tweets - hate speech is rare, but public figure hate speech is even rarer. To build a more balanced set, we use the MTL-NCH classifier trained on all eight publicly available datasets (see Section 4.1) to label the tweets in PUBFigs. We add all tweets labeled as harmful to be human annotated via crowdsourcing. We build a likely negative tweet set by selecting an equal number of tweets labeled as harmless for each figure. This results in 20,327 tweets to be annotated.

**Amazon Mechanical Turk Labeling.** We first preprocess the tweets to remove links, identification data, and non-textual data such as videos and images. Next, we set to label the tweets as one of “Hate”, “Abuse”, or “Neutral”. We provided the workers with the definitions of each class and positive and negative examples. We further require workers to have a 98% approval rate and have completed at least 5000 MTurk HITs. In total, 456 workers contributed to the labeling process, and 8 workers labeled each tweet. The final annotations were determined based on a majority vote. As a tweet labeled by the workers as 3:2:5 (neutral : abuse : hate) is very likely not harmless, we devise a two stage tie-breaking procedure. We first choose between “Neutral” and non-“Neutral”, with ties breaking

| Dataset          | Classes       | # Neutral | # Harmful | # Total |
|------------------|---------------|-----------|-----------|---------|
| **Davidson** [8] | Neither       | 4,162     | 20,620    | 24,782  |
| **Waseem** [34]  | Offensive, Hate | 11,501    | 5,406     | 16,907  |
| **ReddIT** [28]  | Hate          | 10,053    | 3,130     | 13,183  |
| **Gar** [28]     | Hate          | 15,111    | 11,046    | 26,157  |
| **Fox** [15]     | Hate          | 919       | 332       | 1,251   |
| **Mandl** [25]   | Neutral, Hate, Offensive | 3,135 | 1,883 | 5,018 |
| **Stormfront** [9] | Non-Hate, Offensive | 9,330 | 1,089 | 10,419 |
| **HatEval** [6]  | Non-Hate, Hate | 6832      | 4,926     | 11,758  |
| **PubFigs-L**    | Neutral, Abuse, Hate | 17,963 | 2,364 | 20,327 |

# Table 1: The datasets used in this work with the number of labeled examples. The harmful are shown in red italics.
to non-neutral. If the latter, we then choose between "Abuse" and "Hate", with ties breaking to "Abuse". We determined this strategy by re-annotating a sample of 200 tweets from the DAVIDSON dataset, which has a similar class definition to our task. We examined several strategies and chose the one with the highest number of matching annotations to the ground truth DAVIDSON labels.

**Filtering Underperforming Workers.** Poor quality work are a concern for any Amazon MTurk labeling exercise, as randomly labeling minimizes the time spent on each HIT and maximizes worker gains. We found increasing worker payment to have no effect on work quality, and therefore resorted to blacklisting underperforming workers. We first identified suspect workers using metrics such as a worker’s Krippendorff’s Alpha [21], their mean consensus with the final instance label, and the distribution of assigned labels. Next, we manually inspected their annotations for behaviors such as random labeling or always picking one class. Finally, the underperforming workers were blacklisted, and their work was redone. This improved the mean consensus and the inter-worker Krippendorff’s Alpha (from 0.0634 to 0.1237). We fully detail the labeling process in the online appendix [2].

**PubFigs-L Dataset Profiling.** The crowdsourced annotation yielded 17, 963 neutral instances, 1, 422 abusive instances, and 942 hate instances. We find that all figures had consistently more neutral than problematic (abuse, hate) labeled tweets – highlighting the class imbalance. The vast majority of problematic tweets (96.62%) belong to right-leaning figures: 915 (out of 942) hateful tweets and 1369 (1422) abusive tweets. Ann Coulter, a controversial right-leaning political commentator, accounts for just under half of all hate-labeled instances (464 out of 942). Comparatively, the left-leaning figure with the most hate tweets was Ilhan Omar (23). Beto O’Rourke, Taylor Swift, Barrack Obama, and Michelle Obama had no tweets assigned as hate.

**Hate speech annotation – a difficult problem.** We quantify the difficulty of the labeling task by examining inter-annotator agreement. We assume that a difficult task makes a choice less evident for the workers, leading to lower consensus. We use the mean consensus over all tweets as opposed to the more commonly used Krippendorff’s Alpha – many workers perform few annotations, which would mechanically skew the Krippendorff’s Alpha to low values due to little overlap of annotated instances between workers. Fig. 3 shows the average consensus on the final label for each of the labels. In the binary problem, we find that consensus is significantly higher in the harmless class compared to harmful classes. Most harmful tweets achieved a consensus of only 4/8 and were assigned due to tie-breaking. This indicates that the language used by the public figures is not overtly abusive or hateful and that even the binary problem is difficult. In the 3 class problem, we notice that a 3:5 tie break is the second most likely outcome for the assignment of a tweet as either abuse or hate. This indicates that identifying explicit facets of problematic content is difficult even when there is strong agreement that the overall tweet is problematic.

5 EXPERIMENTS AND RESULTS

This section discusses the evaluation of our MTL approach. First, in Section 5.1, we present the hate speech detection on unseen datasets and the improvements in train-test splits. Next, in Section 5.3, we apply the MTL model on the PubFigs-L dataset and analyze the inappropriate speech patterns of a sample of American public figures. Unless stated otherwise, we use macro averaged F1 as the evaluation metric due to the known tendency for hate speech datasets to be highly imbalanced with few positive examples [23, 38]. All reported results are mean averages over 10 experimental runs.

### 5.1 Unseen Data Set Classification.

Here, we examine whether the MTL pipeline can train models that detect hateful and abusive speech in previously unseen datasets.

**Setup.** We use a leave-one-out setup: given n datasets, we train the shared BERT representation using n − 1 datasets, leaving out the dataset di. We use the MTL trained BERT – either in the NCH or MV classification scheme (see Section 3.3) – to evaluate di. Note that no portion of di is observed during training; thus, di is an entirely new dataset. We rotate the left-out dataset di until we have evaluated all datasets. We evaluate transferability between datasets by training single dataset baselines (see Section 3.2). We train on one dataset and test on another for each possible pair of datasets (81 unique pairs). Datasets with more than one harmful class are binarized as harmful/harmless using the mapping in Table 1.

**Predicting on Unseen Datasets.** Table 2 shows the classification performance of MTL and the single dataset baselines. We make two observations. First, we observe that the MTL flavors consistently outperform the single dataset baselines, achieving the best results on seven of nine datasets. This demonstrates that our MTL approach successfully improves the prediction power on unseen datasets. On the remaining two datasets (WASEEM and MANDL), the best performances are produced by the single dataset baseline trained on PubFigs-L. Second, we find that MTL-NCH outperforms MTL-MV in seven of the nine datasets while being within 2% of the MTL-MV performance on the other two (WASEEM and PubFigs-L). As such, we only discuss the MTL-NCH flavor from hereafter.

Fig. 1 visualizes the results in Table 2 as violin plots. There is one violin per target dataset; the left half of each violin shows the performance distribution of all single datasets baselines and the right half shows the results for MTL-NCH. In addition to a higher mean prediction performance, we observe that MTL-NCH shows less variance than the single baselines. Moreover, the single
Table 2: Macro-F1 prediction performances on a target dataset, unseen during training (shown by column headers). (above horizontal ruler) Our two MTL flavors (NCH and MV) trained on all datasets except the target dataset. (below horizontal ruler) Transferability between pairs of datasets. A single dataset baseline (see Section 3.2) is trained on the source dataset (rows) and tested on the target dataset (columns). The best results are in bold.

| Testing Dataset | Model | Waseem | Reddit | Gab | Fox | Stormfront | Mandl | HatEval | PubFigs-L | # Wins |
|-----------------|-------|--------|--------|-----|-----|------------|-------|---------|-----------|--------|
| MTL-NCH         |       | 0.6822 | 0.3801 | 0.8456 | 0.8738 | 0.6150 | 0.6826 | 0.5312 | 0.6449 | 0.6175 | 6 |
| MTL-MV          |       | 0.6435 | 0.4048 | 0.8263 | 0.8660 | 0.6030 | 0.6771 | 0.4834 | 0.6315 | 0.6231 | 1 |
| Differential    |       | 0.0387 | 0.0247 | 0.0193 | 0.0071 | 0.0080 | 0.0055 | 0.0078 | 0.0034 | 0.0016 | 5 |
|     |       | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 1 |

Table 3: Unseen dataset performance of existing works and our MTL pipeline. MTL is trained on all datasets except the testing dataset. The best results are in bold; we report the same number of decimals as the original work. For MTL we show ±1 std. dev. We could not obtain the Founta and OLID datasets, and we do not include them in our work. The number of wins in parentheses.

| Works | Model | Train Dataset | Test Dataset | Metric | Reported (3/8) | MTL-NCH (5/8) |
|-------|-------|---------------|--------------|--------|----------------|---------------|
| Arango et al. [4] | Badjatiya et al. [5] | LSTM + GBDT baseline (binary) | Waseem + Davidson | HatEval | Macro F1 | 0.516 | 0.645 ±0.006 |
| Arango et al. [4] | Agrawal and Awekar [3] | Bi-LSTM baseline (binary) | Waseem + Davidson | HatEval | Macro F1 | 0.541 | 0.645 ±0.006 |
| Swamy et al. [32] | BERT binary | Waseem | Davidson | Macro F1 | 0.5296 | 0.6822 ±0.0197 |
| Swamy et al. [32] | BERT binary | Founta | Davidson | Macro F1 | 0.5824 | 0.6822 ±0.0197 |
| Swamy et al. [32] | BERT binary | OLID | Davidson | Macro F1 | 0.5982 | 0.6822 ±0.0197 |
| Swamy et al. [32] | BERT binary | Founta | Waseem | Macro F1 | 0.6094 | 0.4995 ±0.0085 |
| Swamy et al. [32] | BERT binary | OLID | Waseem | Macro F1 | 0.6269 | 0.4995 ±0.0085 |

Outperforming the State-of-the-Art. We compare, in Table 3, MTL to existing state-of-the-art that examined unseen hate speech dataset classification on datasets used in our work. Our model outperforms existing works in 5 of 8 comparisons — by almost 10% on HatEval and Waseem. We underperform solely on the Waseem dataset; this dataset’s labeling is known to be very specific and to contain many false positives [33, 38]. This dataset was not even constructed for hate speech classification but to assess the performance for a known target dataset (in a train-test split), by transferring knowledge from the other datasets.

Pairwise Dataset Generalization. The multi-modality in Fig. 1 can be explained by some datasets generalizing better to specific others. This may be due to the datasets addressing similar facets of hate speech and/or being annotated similarly or by the same team. Table 2 shows the single dataset baseline performance for each pair of datasets; higher unseen prediction performance is interpreted as better dataset generalization. GAB and REDDIT generalize well to each other, with more than 80% macro-F1 performance in both directions. Unsurprisingly, both data sets were proposed in the same work. Other dataset pairs generalize only one way, e.g., Davidson to GAB, PubFigs-L to Davidson, PubFigs-L to Gab, and Waseem to Reddit. This may occur when one dataset covers more hate speech facets than the other. We also analyze dataset similarity based on their vocabulary usage. We measure the Ruzicka similarity [31] (also known as the weighted Jaccard similarity) for the terms in the harmful and harmless classes. We find that Gab and Reddit have similar language use for both classes; however, GAB and PubFigs-L are similar only for the harmless class (Ruzicka= 0.37 for harmless, 0.08 for harmful), which still translates to moderate dataset generalization (macro-F1= 0.66). See the detailed Ruzicka similarities in the online appendix [2].

5.2 Improving Targeted Classification with MTL

Here, we examine MTL’s ability to improve the classification performance for a known target dataset (in a train-test split), by transferring knowledge from the other datasets.
We find that MTL consistently outperforms the baselines against these works using the same performance metrics they reported on the same datasets as us. Table 4 compares the performances of MTL against the works (column “Reported”) and our MTL (column “MTL”) on the same number of decimals as reported in the original papers (column “Metric”). ± standard deviation. The number of wins is shown in parentheses. Arango et al. [4] use a binary hate/non-hate label mapping that we replicate for the corresponding MTL comparisons. Waseem et al. [35] do not specify the averaging method; hence we assume micro-F1.

| Work                  | Model in related work | Dataset     | Metric   | Reported (5/18) | MTL (12/18) |
|-----------------------|-----------------------|-------------|----------|-----------------|-------------|
| Moazafari et al. [26] | BERT+CNN              | WASEEM      | Micro F1 | 0.88            | 0.83 ± 0.01 |
| Moazafari et al. [26] | BERT+CNN              | DAVIDSON    | Weighted F1 | 0.92        | 0.90 ± 0.01 |
| MacAvaney et al. [22] | BERT finetune         | HATEVAL     | Macro F1 | 0.7452 ± 0.0154 | 0.7526 ± 0.0154 |
| MacAvaney et al. [22] | mSVM                  | HATEVAL     | Macro F1 | 0.7481 ± 0.0154 | 0.7526 ± 0.0154 |
| Zhang and Luo [40]    | CNN+scNN              | WASEEM      | Micro F1 | 0.83            | 0.83 ± 0.01 |
| Zhang and Luo [40]    | CNN+scNN              | WASEEM      | Macro F1 | 0.77            | 0.78 ± 0.01 |
| Zhang and Luo [40]    | CNN+scNN              | DAVIDSON    | Micro F1 | 0.94            | 0.90 ± 0.01 |
| Zhang and Luo [40]    | CNN+scCNN             | DAVIDSON    | Micro F1 | 0.64            | 0.74 ± 0.01 |
| Arango et al. [4]     | Badjatiya et al. [5]  | WASEEM      | Micro F1 | 0.807           | 0.828 ± 0.008 |
| Arango et al. [4]     | Badjatiya et al. [5]  | WASEEM      | Micro F1 | 0.731           | 0.802 ± 0.010 |
| Arango et al. [4]     | Agrawal and Awekar [3] | WASEEM     | Micro F1 | 0.843           | 0.828 ± 0.008 |
| Arango et al. [4]     | Agrawal and Awekar [3] | WASEEM     | Micro F1 | 0.796           | 0.802 ± 0.010 |
| Madukwe et al. [24]   | GA (BERT+CNN+LSTM)    | DAVIDSON    | Weighted F1 | 0.87        | 0.90 ± 0.01 |
| Madukwe et al. [24]   | GA (BERT+CNN+LSTM)    | DAVIDSON    | Macro F1 | 0.73            | 0.74 ± 0.01 |
| Waseem et al. [35]    | BOW                   | WASEEM      | Micro F1 | 0.87            | 0.83 ± 0.01 |
| Waseem et al. [35]    | BOW                   | DAVIDSON    | Micro F1 | 0.89            | 0.90 ± 0.01 |
| Yuan et al. [38]      | Bi-LSTM               | WASEEM      | Macro F1 | 0.7809 ± 0.0133 | 0.7823 ± 0.0133 |
| Yuan et al. [38]      | Bi-LSTM               | DAVIDSON    | Macro F1 | 0.7264 ± 0.0052 | 0.7450 ± 0.0052 |

Figure 4: Diminishing returns for increasing the datasets used in the MTL targeted training. Shaded areas are the 95% confidence intervals over 10 runs.

Setup. Given the set of all datasets $D := \{d_i | i \in 1..n\}$, we designate a target dataset $d_i \in D$. Each $d_i \in D$ is split in a 8:1:1 (train:validation:test) setup; we train MTL as described in Section 3.2. We report the final testing results on $d_i$.

Outperforming the Baselines. We performed an extensive literature search and found seven prior works that report predictions on the same datasets as us. Table 4 compares the performances of MTL against these works using the same performance metrics they report. The Reported column copies the results reported in the said works. We find that MTL consistently outperforms the baselines (12 wins, 1 draw, 5 losses). Even when losing, MTL still achieves comparable performances. As an aside (and intuitively), the targeted classification obtains significantly better results than the unseen. For example, the unseen macro-F1 for HATEVAL is 0.6449 (see Table 2) whereas the targeted macro-F1 is 0.7526 (see Table 4).

Diminishing Prediction Returns. The above results show that MTL successfully improves prediction performance for single datasets by transferring knowledge from the other datasets. In Fig. 4, we explore how the prediction performance on a target dataset $d_i$ varies with $i$, the number of additional datasets used in MTL. For each increment of $i$, we iterate 10 times: sample without replacement $i$ datasets (non-identical to $d_i$), train MTL on $d_i$ and the $i$ datasets, and report performance on the testing subset of $d_i$.

We find that performances improve with $i$ in terms of both mean and variance of macro-F1. However, most datasets observe a diminishing returns effect, with less improvement when $i > 5$. We posit this happens due to two phenomena. First, some datasets transfer significantly better to others (see Table 2) and, as $i$ increases, so does the chance of having them in the MTL training. Second, there is likely significant overlap in the transferable knowledge between the datasets; this makes newly added datasets increasingly redundant compared to datasets already used.

5.3 PubFigs-L Twitter Dataset Analysis.

Here, we analyze the posting of inappropriate tweets by 15 American public figures. We train a MTL classifier targeted to PubFigs-L (see Section 5.2) and use it to label all 305, 235 tweets in PubFigs.

More Inappropriate Speech by Right-Leaning Figures. Fig. 5a shows the monthly volumes of problematic tweets for each figure. We find that right-leaning figures (like Anne Coulter) post significantly more content classified as hateful than the left-leaning
We investigate whether this behavior is a reaction to external events. We compare the number of problematic tweets posted during the three months before and the three months after select events for each figure in the PUBFigs dataset.

**Online Hate Speech and Socio-political Events.** Fig. 5a shows the volume of problematic tweets to spike and drop for most figures. We investigate whether this behavior is a reaction to external events. We compile a list of 10 major social and political events in the United States, having occurred between Donald Trump’s election win (Nov 2016) to the 2021 Capitol Attacks (Jan 2021). For each figure, we compare the number of problematic tweets posted during the three months before and after each event. Fig. 5b highlights two behaviors. First, problematic tweets noticeably peak for right-leaning figures before the elections in 2016 and 2020 – followed by a sharp decrease afterward. This may indicate that right-leaning figures customized their narratives for a more far-right audience during the electoral campaign [11, 12]. The notable exception is Alex Jones, whose problematic tweets slightly increased three months after the 2016 elections. This makes sense, as Alex Jones is a known pundit whose permanent audience is far-right groups. Second, Donald Trump’s response to events about him appears to evolve. In the first half of his presidency, Trump decreases his problematic posting in response to events such as the confirmation of Russian interference and the release of the Muller report. In contrast, Trump’s problematic postings increase in response to events during the later half of his presidency, such as his impeachment.

**Granger Causality Between Figures.** Here we explore links between the problematic posting behaviors of the different figures. We calculate Pearson correlation and Granger Causality between all pairs of figures over the time when both figures were active on Twitter. We find statistically significant ($p < 0.05$) Granger Causality between several right-leaning political pundits and commentators – such as, from Candice Owens to Ann Coulter (lags 1, 2, and 3), from Ben Shapiro to Ann Coulter (lags 2 and 3), and from Amy Kremer to Ben Shapiro (lags 2 and 3). We find that Granger Causality relations are exclusively one-way. We also find a moderate positive correlation between Donald Trump and Donald Trump Jr, likely due to their family and political ties during Trump’s presidency.

6 **FUTURE WORKS**

We identify three directions for future works listed as follows:

Currently when classifying on new domains, label mapping is used to binarize the dataset class labels for unseen classification. Increasing specificity beyond a harmful vs harmless binary problem can yield much more informative results. Another direction is to add additional context into the MTL framework. Currently, we process only textual data from a single posting and discard accompanying media such as images or videos. Adding this additional context into the learning framework could improve predictive power.

Finally, while our unseen classification results outperforms the baselines and existing works, the raw F1 value is still relatively low. The exact definition of hate learnt by the MTL and single dataset baselines is still unknown due to the black box nature of the model.
As such, examining dataset characteristics and exploring explainability methods could provide insight into the learnt definitions and what characteristics makes text hateful.

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This document accompanies the submission Detect Hate Speech in Unseen Domains using Multi-Task Learning: A Case Study of Political Public Figures. The information in this document complements the submission and is presented here for completeness reasons. It is not required to understand the main paper or reproduce the results.

A DATASET LABELLING METHODOLOGY

A.1 Dataset Building Process

The collection process of the tweets was conducted as follows: First, we scraped raw JSON tweets [37] from polititweet.com to obtain tweet IDs for each figure. Polititweet is a website that archives the twitter postings of many public figures. The archived tweets are obtained using the Twitter API from Twitter itself. However, an issue with these archived tweets is that many longer tweets are truncated due to the API settings used where the “extended_text” flag was not set. As such, we used the tweet IDs obtained from polititweet to scrape the full non-truncated text using the twitter API for each of the most of the figures. There were several exceptions to this: The tweets of Donald Trump which was collected from www.thetrumparchive.com, an archive of all of Donald Trump’s tweets due to it being a more complete source without truncation. The tweets of Alex Jones were collected from deleted-tweets-archive hosted at github.com/travisbrown/deleted-tweets-archive due to polititweet not monitoring his tweets. Finally the archived tweets from polititweet of Beto O’Rourke and Marjorie Taylor Greene were used instead of recollecting from the twitter API due to a significant number of their tweets being unable to be retrieved using the API.

A.2 Data Selection

Due to the large amount of data collected, it was unfeasible to label the entirety of dataset due to cost constraints. As such, we utilised a classifier trained using the MTL pipeline to aid us in selecting potentially relevant data points to annotate. The classifier was trained on all 8 datasets that were used in this work sans the public figure dataset using the MTL pipeline. The NCH unseen classification method was then used to classify on the entirety of tweets for each of the public figures. The data points labeled problematic were added to the set of instances to be labeled by the MTurkers. For each figure, an equal amount of tweets which were not labelled as problematic by the MTL trained classifier was undersampled and added to the final set of all instances to annotate.

A.3 Preprocessing

As preprocessing, we removed all images, videos, URL links, and other media from the twitter posts. This was done with two main considerations in mind. The first was to ensure that only the textual data in each tweet was being used to inform the annotation decision. This was important as the classifier utilises only the textual in a given post to make its classification. The second consideration was to ensure that the mechanical Turk was not exposed to harm while annotating the tweets. As the tweets of each figure was scraped using the twitter API, all media in the tweets was automatically converted into a URL link to where the media is hosted. As such, all URLs were replaced with a replacement URL token (denoted “[URL]”) indicating that a URL existed at that point in the text. A replacement token was added to prevent confusion over incomplete or non-sensical sentences which may result from removal without replacement. While URLs may contain some textual information which maybe useful for classification, leaving the full URL in text encouraged workers to follow links which biases the annotations with information outside what is strictly in the post text. This also assisted in preventing annotators from following potentially harmful hyperlinks present in the tweets.

B MECHANICAL TURK ANNOTATIONS

Amazon Mechanical Turk operates in HITs (Human Intelligence Tasks). A HIT represents the a self contained task that can be completed by worker to obtain a reward. In the context of our annotation task, each hit consisted assigning 10 labels to 10 independent tweets from public figures. Each HIT was annotated by 8 unique workers and workers were paid $0.1 USD per HIT completed. Workers in Amazon Mechanical Turk are allowed to do as many and as few HITs as they so choose.

The annotation process for is as follows: In each HIT, workers are asked to view the tweet text and assign one of either “neutral”, “abusive”, or “hate” as the label for each of the 10 tweets. The definitions for each of the labels are given at the start of the page with examples of correct annotations for each label. Screenshots of the web interface are shown in Fig. 6.

Workers could only submit the HIT if they have completed all 10 of the tweets in the HIT. Several conditions were set on the workers in order to improve the quality of the completed work. We wanted workers whom were competent in the English language and were knowledgeable of social and political contexts in the tweets. As such, only workers with more than 5000 completed and accepted HITs, an overall approval rating of over 98%, and residing in either the UK, the United States, Canada, or Australia were allowed to work on our task. HITs were run in batches each consisting of 50 to 100 HITs at a time over the period from April to May 2022.

B.1 Dealing With Bad Workers

Due to the loosely regulated nature of Amazon Mechanical Turk, the quality of annotations from some workers was of poor quality. The most common examples of such poor quality work being workers selecting randomly and arbitrarily selecting only 1 or 2 classes. This was due to the nature of Amazon Mechanical Turk paying workers by the amount of work they complete which incentives for workers to complete work as quickly as possible. To address this issue, bad workers were blacklisted and their work redone. For each batch, the top 25 workers with the most completed work were manually examined and blacklisted if found to produce noticeably bad work or exhibit malicious behaviours. The examination involved two stages. First, the overall distribution of labels for a worker was examined. From existing works, we know that the problem of hate speech labelling is typically extremely imbalanced with hate speech being a minority class. As such, the work of workers who exhibited unusual behaviour such as having a labelling distribution close to random labelling, labelling only in 1 or 2 classes, or deviating significantly from the expected distribution were manually examined and blacklisted if found to be of poor quality. In particular we examined the posts which were labeled as hate and abusive for the presence of overtly benign content which would indicate a lack
of quality. In the second stage, we examined the worker’s overall agreement with the majority on each of the posts they labeled. This assumes that the majority of workers are in fact doing work of quality, and therefore a worker who routinely or systematically disagrees with the majority of the other workers on each hit they work on is likely to be doing work of a poor quality. The work of these workers were manually examined and the workers blacklisted if the work was found to be bad. We found the majority of workers with a low overall agreement were also usually picked up in the first stage of filtering.

Finally, HITs with bad workers were then redone if more than 2 bad workers worked on the HITs. This was done after annotating all of the dataset to improve the quality of the annotations by maximizing the number of bad workers removed. To analyze the effects of this filtering and reannotation process, we examined the mean agreement with the majority vote across all instances for both the 3 class problem and the binary problem.

Table 5: Table showing comparison of mean consensus with majority vote of MTurk worker annotations on tweets before removing bad workers, and after removing bad workers then redoing HITs. Mean consensus for between 3 different labels ("neutral", "abusive", "hate") and between neutral and problematic labels ("abusive" and "hate") shown. Results have been rounded to 4 DP.

|                  | 3 Class Mean Consensus | Binary Mean Consensus |
|------------------|------------------------|-----------------------|
| With bad workers | 0.6490                 | 0.7010                |
| bad work Redone  | 0.8026                 | 0.8125                |

B.2 Tie Breaking
As we were interested both in the 3 classes annotation as well as whether instances are problematic (abusive or hateful) or neutral, it was to implement a tie breaking strategy that can account for both problems. The main consideration is when the number of neutral annotations is the same as that for either abusive or hateful annotations, but less than abusive and hateful annotations combined. Breaking naïvely would give a tie between neutral and one of either abusive or hateful despite there being more votes for the instance being problematic. As such, we broke ties in two ways, first between problematic and non-problematic, then between hateful and abusive. We examined breaking towards the more hateful class, and towards the less hateful class for both stages.

Overall, we explored the following tie breaking strategies: breaking naïvely between 3 classes, breaking to the more hateful class for both stages (HH), breaking to the less hateful class for both stages (LL), breaking first to the more hateful class between neutral and problematic then to the less hateful class between abusive and hate (HL), and breaking first to the less hateful class between neutral and problematic then to the more hateful class between abusive and hate (LH).

To evaluate each tie breaking strategy, we conducted experiments using the DAVIDSON dataset. We took a small sample of 200 instances from the DAVIDSON dataset and relabelled this sample using Amazon Mechanical Turk following the same methodology as for our dataset. The DAVIDSON dataset was chosen over other datasets used in this work due to its closeness to our labelling task. Both the DAVIDSON and our labelling tasks utilised tweets from twitter, both tasks utilised 3 classes: neutral, offensive, hate for DAVIDSON and neutral, abusive, hate for our task. The offensive class was mapped to the abusive class in the labelling process as both classes followed roughly the same definition.
Table 6: Table showing comparison of tie breaking strategies applied to a sample of the Davidson dataset for the 3 class problem ("neutral", "abusive", "hate") and the binary problem (neutral vs "abusive" and "hate"). The 3 class problem uses Macro averaged F1. Results have been rounded to 4 DP.

| Strategy | 3 Class F1 | Binary F1 |
|----------|------------|-----------|
| HH       | 0.4681     | 0.7093    |
| HL       | 0.4806     | 0.7093    |
| LH       | 0.4531     | 0.6147    |
| LL       | 0.4223     | 0.6147    |

Using the already assigned labels from the Davidson dataset as the ground truth, we selected the best tie breaking method which produced the most similar results from the MTurk labelling and the pre-labelled ground truth. The results are shown in Appendix B.2 from which we can see that the highest macro F1 for both the binary and 3 class problem is obtained when breaking first to the more hateful class between neutral and problematic, then to the less hateful class between abusive and hate. Based on these results, we adopted the aforementioned tie breaking strategy for use on collected labels.

C WHEN MTL GENERALIZATION HURTS PERFORMANCES

Table 2 shows that MTL-MV and MTL-NCH underperform on the Mandl and Waseem datasets, compared to the single dataset baselines. The poor performance is especially significant on the Waseem dataset, with macro-F1 below all of the single dataset baselines. We posit that this underperformance is due to differences in the labeling criteria of the Waseem and Mandl datasets. The Waseem data set differs from the other datasets used in this work as it was not constructed with the goal of hate speech classification in mind, but rather to quantify the agreement between amateur and expert annotators. The problematic classes in the Waseem dataset also differ from the other datasets. The other datasets focus more broadly on hateful and offensive language while Waseem’s “Racism” and “Sexism” instead focus on very specific facets of problematic speech. Due to this, we posit that the poor performance can be attributed to the representation constructed by the MTL models being too generalized for the specific labeling criteria used in the Waseem dataset. Another potential factor is the high number of false positives, which Waseem [33] acknowledges. Yuan et al. [38] also uncovers biases in the data set, such as a cluster of tweets that start with “I’m not sexist, but...” being labeled as sexist regardless of the continuation, creating many false positives. Underperformance on the Mandl dataset is not as significant, with only the Davidson, PubFigs-L, and HATEval baselines outperforming MTL-NCH. The performance difference between the HATEval baseline and MTL-NCH is relatively insignificant (less than 0.01) while a larger difference exists between MTL-NCH to the Davidson and PubFigs-L baselines. These two datasets have similar labeling criteria to Mandl in that they explicitly differentiate between hateful speech and offensive/abusive speech. As the majority of datasets do not explicitly make this differentiation between the facets, the definition learnt by MTL may therefore be less vivid about the separation between hateful speech and offensive/abusive speech, causing MTL-NCH to underperform compared to the Davidson and PubFigs-L baselines.
Table 7: Ruzicka [31] similarity between unigrams of problematic (Red) and non-problematic (green) instances in each dataset. Results rounded to 4 d.p.

|            | Davidson | Waseem | Reddit | Gab | Fox | Mandl | Stormfront | HatEval | PubFigs-L |
|------------|----------|--------|--------|-----|-----|-------|------------|---------|-----------|
| Davidson   | 0.2078   | 0.0531 | 0.0817 | 0.1941 | 0.2214 | 0.2082 | 0.1972 | 0.1083 |
| Waseem     | 0.1472   | 0.1557 | 0.2265 | 0.0982 | 0.1837 | 0.3464 | 0.3169 | 0.2564 |
| Reddit     | 0.3052   | 0.2152 | 0.4546 | 0.0297 | 0.0647 | 0.1593 | 0.1540 | 0.2273 |
| Gab        | 0.3123   | 0.1456 | 0.4731 | 0.0474 | 0.1023 | 0.2469 | 0.2415 | 0.3729 |
| Fox        | 0.0224   | 0.0879 | 0.0407 | 0.0258 | 0.1766 | 0.1233 | 0.1153 | 0.0589 |
| Mandl      | 0.0729   | 0.2165 | 0.1205 | 0.0840 | 0.1379 | 0.2050 | 0.2343 | 0.1327 |
| Stormfront | 0.0481   | 0.1590 | 0.0764 | 0.0528 | 0.2642 | 0.2247 | 0.3605 | 0.2576 |
| HatEval    | 0.2052   | 0.2784 | 0.2694 | 0.2096 | 0.0723 | 0.2087 | 0.1296 | 0.2828 |
| PubFigs-L  | 0.0662   | 0.2322 | 0.1059 | 0.0774 | 0.1833 | 0.2900 | 0.2647 | 0.2030 |

Table 8: Table showing the Twitter public figures in the PubFigs-L dataset.

| Figure                  | Twitter Handle  | Perceived Political Leaning | # Neutral | # Abuse | # Hate | # Total | Description                                                                                                                                                                                                 |
|-------------------------|-----------------|-----------------------------|-----------|---------|--------|---------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Alex Jones              | @RealAlexJones  | Right                       | 1666      | 182     | 173    | 2021    | Far right show host and prominent conspiracy theorist.                                                                                                                                                    |
| Marjorie Taylor Greene | @mtgreenee      | Right                       | 486       | 45      | 27     | 558     | American Republican politician. Georgia Congress representative.                                                                                                                                         |
| Candace Owens           | @RealCandaceO   | Right                       | 261       | 38      | 21     | 320     | American conservative influencer and political commentator.                                                                                                                                             |
| Amy Kremer              | @AmyKremer      | Right                       | 1086      | 61      | 23     | 1170    | Right winged American political activist.                                                                                                                                                                 |
| Ann Coulter             | @AnnCoulter     | Right                       | 5143      | 523     | 464    | 6130    | American conservative media pundit and author.                                                                                                                                                             |
| Laura Ingraham          | @IngrahamAngle  | Right                       | 1474      | 28      | 10     | 1512    | American conservative television host.                                                                                                                                                                   |
| Ben Shapiro             | @benshapiro     | Right                       | 1753      | 129     | 56     | 1938    | American conservative political commentator.                                                                                                                                                              |
| Donald Trump            | @realDonaldTrump| Right                       | 1972      | 197     | 85     | 2254    | 45th president of the US. Republican.                                                                                                                                                                    |
| Donald Trump Jr         | @DonaldjTrumpJr | Right                       | 1862      | 166     | 56     | 2084    | Son of Donald Trump.                                                                                                                                                                                     |
| Taylor Swift            | @taylorswift13  | Left                        | 247       | 1       | 0      | 248     | American singer-songwriter.                                                                                                                                                                               |
| Beto O’Rourke           | @BetoORourke     | Left                        | 282       | 2       | 0      | 284     | American Democrat politician. Former Texas Congress representative.                                                                                                                                     |
| Barack Obama            | @BarackObama    | Left                        | 76        | 0       | 0      | 76      | 44th president of the US. Democrat.                                                                                                                                                                      |
| Michelle Obama          | @MichelleObama  | Left                        | 34        | 0       | 0      | 34      | Wife of Barack Obama                                                                                                                                                                                    |
| Alexandria Ocasio Cortez| @AOC            | Left                        | 354       | 4       | 4      | 362     | American Democrat politician. New York Congress representative.                                                                                                                                         |
| Ilhan Omar              | @Ilhan & @IlhanMN| Left                        | 1267      | 46      | 23     | 1336    | American Democrat politician. Minnesota Congress representative.                                                                                                                                       |
Figure 7: Comparison of the number of problematically classified tweets in the three months leading up to, and the three months after an event for each figure in the PubFigs dataset for all events.