Proceedings of the 13th Conference on Language Resources and Evaluation (LREC 2022), pages 2215–2225
Marseille, 20-25 June 2022
© European Language Resources Association (ELRA), licensed under CC-BY-NC-4.0

Large-Scale Hate Speech Detection with Cross-Domain Transfer

Cagri Toraman, Furkan Şahinuç, Eyup Halit Yilmaz
Aselsan Research Center, Ankara, Turkey
{ctoraman, fsahinuc, ehyilmaz}@aselsan.com.tr

Abstract

The performance of hate speech detection models relies on the datasets on which the models are trained. Existing datasets are mostly prepared with a limited number of instances or hate domains that define hate topics. This hinders large-scale analysis and transfer learning with respect to hate domains. In this study, we construct large-scale tweet datasets for hate speech detection in English and a low-resource language, Turkish, consisting of human-labeled 100k tweets per each. Our datasets are designed to have equal number of tweets distributed over five domains. The experimental results supported by statistical tests show that Transformer-based language models outperform conventional bag-of-words and neural models by at least 5% in English and 10% in Turkish for large-scale hate speech detection. The performance is also scalable to different training sizes, such that 98% of performance in English, and 97% in Turkish, are recovered when 20% of training instances are used. We further examine the generalization ability of cross-domain transfer among hate domains. We show that 96% of the performance of a target domain in average is recovered by other domains for English, and 92% for Turkish. Gender and religion are more successful to generalize to other domains, while sports fail most.

Keywords: cross-domain transfer, hate speech detection, low-resource language, offensive language, scalability

1. Introduction

With the growth of social media platforms, hate speech towards people who do not share the same identity or community becomes more visible (Twitter, 2021). Consequences of online hate speech can be real-life violence against other people and communities (Byman, 2021). The need to automatically detect hate speech text is thereby urging.

Existing solutions to detect hate speech mostly rely on supervised scheme, resulting in a strict dependency on the quality and quantity of labeled data. Most of the datasets labeled by experts for hate speech detection are not large in size due to the labor cost (Poletto et al., 2021), causing a lack of detailed experiments on model generalization and scalability. Indeed, most studies on hate speech detection report high performances on their test sets, while their generalization capabilities to other datasets can be limited (Arango et al., 2019). Moreover, existing datasets for hate speech detection are very limited for low-resource languages such as Turkic languages (Poletto et al., 2021). We thereby construct large-scale datasets for hate speech detection in English and Turkish, consisting of human-labeled 100k tweets per each and compare the performance of state-of-the-art models on these large-scale datasets.

Hateful language can be expressed in various topics (we refer to topics as *hate domains*). Hate domains vary depending on the target group. For instance, misogyny is an example of the domain of gender-based hatred. Existing studies mostly do not consider various domains explicitly. They also investigate hate speech in terms of an abstract notion including aggressive language, threats, slurs, and offenses (Poletto et al., 2021). We consider not only the hateful behavior in the definition of hate speech, but also five most frequently observed domains depending on target group; namely religion, gender, racism, politics, and sports.

Supervised models trained on a specific learning dataset can fail to generalize their performance on the original evaluation set to other evaluation sets. This phenomenon is studied in zero-shot cross-dataset[1] (Gröndahl et al., 2018; Karan and Šnajder, 2018), cross-lingual (Pamungkas and Patti, 2019), and cross-platform (Agrawal and Awekar, 2018) transfer for hate speech detection. However, transfer learning with respect to hate domains and low-resource languages are not well studied due to the lack of large-scale datasets. In this study, with the help of our datasets containing five hate domains, we analyze the generalization capability of hate speech detection in terms of cross-domain transfer among hate domains.

The **contributions** of this study are in three folds. (i) We construct large-scale human-labeled hate speech detection datasets for English and Turkish. (ii) We analyze the performance of various models for large-scale hate speech detection with a special focus on model scalability. (iii) We examine the generalization capability of hate speech detection in terms of zero-shot cross-domain transfer between hate domains.

In the next section, we provide a summary of related work. In Section 3, we explain our large-scale datasets[2]. In Section 4, we report our experiments. In Section 5, we provide discussions on error analysis and scalability. We conclude the study in the last section.

[1] In literature, the phrase "cross-domain" is mostly used for the transfer between two datasets that are published by different studies but not necessarily in different hate domains. We refer to them as cross-dataset.

[2] The paper contains some examples of language which may be offensive to some readers. They do not represent the views of the authors.

2. Related Work

We summarize related work on the methods, datasets, and transfer learning for hate speech detection.

2.1. Methods for Hate Speech Detection

Earlier studies on hate speech detection are based on matching hate keywords using lexicons (Sood et al., 2012). The disadvantage of such methods is strict dependency on lexicons. Supervised learning with a set of features extracted from a training set is a solution for the dependency issue. Text content is useful to extract bag-of-words features; such as linguistic and syntactical features, n-grams, and Part-of-Speech tags (Nobata et al., 2016; Waseem, 2016; Davidson et al., 2017). User-based features, including content history, meta-attributes, and user profile can be used to detect hate signals (Waseem, 2016; Chatzakou et al., 2017; Unsvåg and Gambäck, 2018).

To capture word semantics better than bag-of-words; word embeddings, such as GloVe (Pennington et al., 2014), are utilized to detect abusive and hatred language (Nobata et al., 2016; Mou et al., 2020). Character and phonetic-level embeddings are also studied for hate speech to resolve the issues related to noisy text of social media (Mou et al., 2020). Instead of extracting hand-crafted features; deep neural networks, such as CNN (Kim, 2014) and LSTM (Hochreiter and Schmidhuber, 1997), are applied to extract deep features to represent text semantics. Their application outperforms previous ones with lexicons and hand-crafted features (Zimmerman et al., 2018; Cao et al., 2020).

Recently, Transformer architecture (Vaswani et al., 2017) is studied for hate speech detection. Transformer employs self-attention for each token over all tokens, targeting to capture a rich contextual representation of whole text. Fine-tuning a Transformer-based model, BERT, (Devlin et al., 2019) for hate speech detection outperforms previous methods (Liu et al., 2019a; Caselli et al., 2021; Mathew et al., 2021). We examine the large-scale performance of not only BERT, but also various Transformer-based language models, as well as conventional bag-of-words and neural models.

2.2. Resources for Hate Speech Detection

A recent survey summarizes the current state of datasets in hate speech detection by listing over 40 datasets, around half of which are tweets, and again around half of which are prepared in English language (Poletto et al., 2021). Benchmark datasets are also released as a shared task for hate speech detection (Basile et al., 2019; Zampieri et al., 2020).

There are efforts to create large-scale human-labeled datasets for hate speech detection. The dataset by (Davidson et al., 2017) has approximately 25k tweets each labeled by three or more annotators for three classes; offensive, hate, and neither. The dataset by (Golbeck et al., 2017) has 35k tweets labeled by at most three annotators per tweet for binary classification (harassing or not). The dataset by (Founta et al., 2018) has 80k tweets each labeled by five annotators for seven classes including offensive and hate. There also exist studies that construct datasets containing hateful content from various sources (e.g. Facebook and Reddit) in other low-resource languages; such as Arabic (Albadi et al., 2018), Greek (Pavlopoulos et al., 2017), Slovene (Fišer et al., 2017), and Swedish (Fernquist et al., 2019). However, our datasets differ in terms of the following aspects. We have 100k top-level tweets per two languages, English and Turkish. The datasets have three class labels (hate, offensive, and normal), and five annotators per each tweet. We focus on dataset cleaning, which will be explained in the next section. Lastly, we design to have 20k tweets for each of five hate domains, enabling us to analyze cross-domain transfer.

2.3. Transfer Learning for Hate Speech Detection

Generalization of a hate speech detection model trained on a specific dataset to other datasets with the same or similar class labels, i.e., zero-shot cross-dataset transfer, is widely studied (Karan and Šnajder, 2018; Swamy et al., 2019; Arango et al., 2019; Pamungkas et al., 2020; Markov and Daelemans, 2021). Using different datasets in different languages, cross-lingual transfer aims to overcome language dependency in hate speech detection (Pamungkas and Patti, 2019; Pamungkas et al., 2020; Markov et al., 2021; Nozza, 2021). There are also efforts to analyze platform-independent hate speech detection, i.e. cross-platform transfer (Agrawal and Awekar, 2018). In this study, we analyze whether hate speech detection can be generalized across several hate domains, regardless of the target and topic of hate speech.

3. Large-Scale Datasets for Hate Speech Detection

3.1. Dataset Construction

We used Full-Archive Search provided by Twitter Premium API to retrieve more than 200k tweets; filtered according to language, tweet type, publish time, and contents. We filter English and Turkish tweets published in 2020 and 2021, since old tweets are more likely to be deleted. The datasets[3] contain only top-level tweets, i.e., not a retweet, reply, or quote. Tweet contents are filtered based on a keyword list determined by the dataset curators. The list contains hashtags and keywords from five topics (i.e., hate domains); religion, gender, racism, politics, and sports. A tweet can only belong to a single topic. Samples from the complete keyword list with corresponding domains are given in Table 1. We design to keep the number of tweets belonging to each hate domain balanced. To this end,

[3]The datasets include publicly available tweet IDs, in compliance with Twitter's Terms and Conditions, and can be accessed from https://github.com/avaapm/hatespeech

Domain	Keywords
Religion	Christianity, Islam, Judaism, Hinduism, Atheist, belief, church, mosque, Jewish, Muslim, Bible
Gender	LGBTQ, bisexual, female, male, homophobia, gay, lesbian, homosexual, bisexual, transgender
Race	foreigner, refugee, immigrant, Syrian, African, Turk, American, Iranian, Russian, Arab, Greek
Politics	democratic party, republican party, government, white house, president, Trump, Biden, minister
Sports	football, baseball, volleyball, referee, barcelona, real madrid, chelsea, new york knicks, coach

Table 1: Samples from our keyword list. Turkish keywords are mostly translations of English keywords.

Domain	Tweet	Label
Gender	"I can't live in a world where gay marriage is legal." Okay, so die.	Hate
Race	Türklere iyi geceler, amerikalılar gebersin (Good night to the Turks, death to the Americans)	Hate
Religion	Self proclaim atheist doesn't make you cool kid bitch	Offensive
Sports	Bundan sonra 6sn kuralını saymayan Hakem de uygulamayan da Şerefsiz oğlu şerefsiztir (After that, the referee, who does not count and apply the 6-second rule, will be dishonest.)	Offensive
Politics	Biden your a lier and a cheat and a old idiot	Offensive

Table 2: Tweet examples (not edited) from the dataset. Translation for Turkish tweets are given in parentheses.

slightly more than 20k tweets are retrieved from Twitter for each domain. The exact amount of 20k tweets are then sampled for each domain to satisfy the balance.

For cleaning, we remove near-duplicate tweets by measuring higher than 80% text similarity among tweets using the Cosine similarity with TF-IDF weighting. We restrict the average number of tweets per user not exceeding 1% of all tweets to avoid user-dependent modeling (Geva et al., 2019). We remove tweets shorter than five words excluding hashtags, URLs, and emojis.

3.2. Dataset Annotation

Based on the definitions and categorization of hateful speech (Sharma et al., 2018), we label tweets as containing hate speech if they target, incite violence against, threaten, or call for physical damage for an individual or a group of people because of some identifying trait or characteristic. We label tweets as offensive if they humiliate, taunt, discriminate, or insult an individual or a group of people in any form, including textual. Other tweets are labeled as normal.

Each tweet is annotated by five annotators randomly selected from a set of 20 annotators, 75% of which are graduate students while the rest are undergraduate students. 65% of the annotators's gender of birth are female and 35% are male. Their ages fall within the range of 20-26. While annotating a tweet, if consensus is not achieved on ground-truth, a dataset curator outside the initial annotator set determines the label. The curator intervenes in only 8% of the total tweets (38% of tweets are labeled with the consensus of five, 26% with four, and 28% with three annotators). We provide a list of annotation guidelines to all annotators. The guidelines document includes the rules of annotations; the definitions of hate, offensive, and normal tweets; and the common mistakes observed during annotation. The annotations started on February 15th, and ended on May 10th, 2021 (i.e. a period of 84 days). We measure inter-annotator agreement with Krippendorff's alpha coefficient and get a nominal score of 0.395 for English and 0.417 for Turkish, which are higher than other similar hate speech datasets in the literature (0.38 in binary (Sanguinetti et al., 2018) and 0.153 in multi-class (Ousidhoum et al., 2019)). Sample hateful and offensive tweets from the datasets are given in Table 2.

3.3. Dataset Statistics

We report main statistics about our datasets in Table 3. Although we follow a similar construction approach for both languages, the number of tweets with hate speech that we can find in English is less than those in Turkish, which might indicate a stronger regularization of English content by Twitter. Normal tweets dominate as expected due to the nature of hate speech and the platform regulations. The statistics of tweet length imply that our task is similar to a short text classification for tweets, where the average number of words is ideal to be 25 to 30 (Şahinuç and Toraman, 2021).

The domain and class distributions of tweets are given in Table 4. In English, the number of hateful tweets is close in each domain; however, race has less number of offensive tweets than others. The number of hateful tweets in gender domain is less than those of other domains in Turkish dataset.

4. Experiments

We have two main experiments. First, we analyze the performance of various models for hate speech detection. In the second part, we examine cross-domain transfer for hate speech detection.

4.1. Hate Speech Detection

4.1.1. Experimental Design

We apply 10-fold cross-validation, where each fold has 90k train instances; and report the average score of weighted precision, recall, and F1 score. Since the dataset is unbalanced, we measure weighted metrics and avoid to report accuracy. The evaluation scores for each class are also examined in the scalability experiments in Section 5.3. We determine statistically

Definition	EN	TR
Number of tweets	100,000	100,000
Number of offensive tweets	27,140	30,747
Number of hate tweets	7,325	27,593
Number of users	85,396	69,524
First tweet date	26/02/20	17/01/20
Last tweet date	31/03/21	31/03/21
Average tweets per user	1.2	1.4
Average tweet length (words)	29.20	24.37
Shortest tweet length	5	5
Longest tweet length	72	121
Number of tweets with hashtag	12,751	17,390
Number of tweets with URL	73,439	71,434
Number of tweets with emoji	9,971	8,509

Table 3: Dataset statistics.

Lang.	Domain	Hate	Offens.	Normal	Total
EN	Religion	1,427	5,221	13,352	20k
	Gender	1,313	6,431	12,256	20k
	Race	1,541	3,846	14,613	20k
	Politics	1,610	6,018	12,372	20k
	Sports	1,434	5,624	12,942	20k
TR	Religion	5,688	7,435	6,877	20k
	Gender	2,780	6,521	10,699	20k
	Race	5,095	4,905	10,000	20k
	Politics	7,657	4,253	8,090	20k
	Sports	6,373	7,633	5,994	20k

Table 4: Distribution of tweets in our datasets.

significant differences between the means, which follow non-normal distributions, by using the two-sided Mann-Whitney U (MWU) test at %95 interval with Bonferroni correction. We compare the performances of three family of models.

- **BOW**: We encode tweets using the bag-of-words model (BOW) with TF-IDF term weightings, and train a multinomial Logistic Regression classifier for 1000 iterations, using default parameters with sklearn (Pedregosa et al., 2011). TF-IDF term weightings are extracted from the train and test sets separately.
- **Neural**: We employ two neural models, CNN (Kim, 2014) and LSTM (Hochreiter and Schmidhuber, 1997), using a dense classification layer on top with cross-entropy loss. For both models, we use Adam optimizer (Kingma and Ba, 2015) with a learning rate of 5e-5 for 10 epochs. FastText's English and Turkish word embeddings (Grave et al., 2018) are given as input with a dimension size of 300. For CNN, we use 100 kernels each having sizes between 3 and 5. We use PyTorch (Paszke et al., 2019) implementations for both.
- **Transformer LM**: We fine-tune Transformer-based language models that are pre-trained on English, Turkish, and multilingual text corpus. We use Huggingface (Wolf et al., 2020) implementation for Transformer-based language models.

We fine-tune the following models that are pre-trained by using English or Turkish text:

- **BERT** (Devlin et al., 2019): BERT uses bidirectional masked language modeling and next sentence prediction.
- **BERTweet** (Nguyen et al., 2020): BERTweet is trained based on the RoBERTa (Liu et al., 2019b) pre-training procedure by using only tweets.
- **ConvBERT** (Jiang et al., 2020): ConvBERT architecture replaces the quadratic time complexity of the self-attention mechanism of BERT with convolutional layers. The number of self-attention heads are reduced by a mixed attention mechanism of self-attention and convolutions that would model local dependencies.
- **Megatron** (Shoeybi et al., 2019): Megatron introduces an efficient parallel training approach for BERT-like models to increase parameter size.
- **RoBERTa** (Liu et al., 2019b): RoBERTa is built on the BERT architecture with modified hyperparameters and a diverse corpora in pre-training, and removes the task of next sentence prediction.
- **BERTurk** (Schweter, 2020): The model re-trains BERT architecture for Turkish data.
- **ConvBERTurk** (Schweter, 2020): Based on ConvBERT (Jiang et al., 2020), but using a modified training procedure and Turkish data.

To understand the generalization capability of multilingual models to both English and Turkish, we fine-tune the following multilingual models.

- **mBERT** (Devlin et al., 2019): mBERT is built on the BERT architecture, but using multilingual text covering 100 languages.
- **XLM-R** (Conneau et al., 2020): XLM-R is built on the RoBERTa architecture, but using multilingual text covering 100 languages. The model is trained on more data compared to mBERT, and removes the task of next sentence prediction.

We apply the same experimental settings to all models. Batch size is 32, learning rate is 1e-5, the number of epochs is 5, maximum input length is 128 tokens, using AdamW optimizer. Only exception is Megatron, due to its large size, we reduce batch size to 8. We use GeForce RTX 2080 Ti for fine-tuning.

4.1.2. Experimental Results

In Table 5, we report the performance of multi-class (hate, offensive, and normal) hate speech detection.

Transformer-based language models outperform conventional ones in large-scale hate speech detection. The highest performing models are Megatron with the highest number of model parameters in English, and ConvBERTurk in Turkish. BERTweet has higher performance than BERT, showing the importance of pre-training corpus. Conventional models (BOW, CNN, and LSTM) are not as successful as Transformer-based models in both languages.

Model	EN			TR		
	Prec.	Recall	F1	Prec.	Recall	F1
BOW	0.777	0.796	0.779	0.707	0.710	0.706
CNN	0.779	0.796	0.782	0.676	0.679	0.675
LSTM	0.787	0.798	0.790	0.689	0.688	0.686
BERT	0.815	0.817	0.816	-	-	-
BERTweet	0.825	0.829	0.826 ○	-	-	-
ConvBERT	0.823	0.825	0.823	-	-	-
Megatron	**0.831**	**0.830**	**0.830** •	-	-	-
RoBERTa	0.822	0.826	0.823	-	-	-
mBERT	0.817	0.818	0.818	0.757	0.752	0.753
XLM-R	0.823	0.826	0.824	0.770	0.767	0.768
BERTurk	-	-	-	0.778	0.777	0.777 ○
ConvBERTurk	-	-	-	**0.781**	**0.782**	**0.782** •

Table 5: **Multi-class hate speech detection**. Average of 10-fold cross-validation is reported. Highest score is given in bold. Models are divided into sub-groups in terms of BOW, Neural, and Transformer models (English, multilingual, and Turkish language models). The symbol "•" indicates statistical significant difference at a 95% interval (with Bonferroni correction $p < .006$ for English and $p < .008$ for Turkish) in pairwise comparisons between the highest performing method and others (except the ones with "○").

There are approximately 5% performance gap between the highest scores by conventional models and Transformer models in English, and 10% for Turkish.

Conventional BOW can be competitive. We observe that the bag-of-words model has surprisingly, competitive performance in both languages. We note that the tweets in all classes are obtained with the same keyword set. However, a possible reason could be the existence of expressions and keywords that are specific to offensive or hate classes, such as slurs and curse words.

Multilingual language models can be effective for trade-off between performance and language flexibility. Multilingual models, mBERT and XLM-R, have challenging performance with the models pre-trained using only English text. XLM-R has close results to BERTurk (pre-trained with Turkish text) as well. Multilingual models can thereby provide language flexibility (i.e., removing training dependency on new language) without sacrificing substantial task performance.

4.2. Cross-Domain Transfer

4.2.1. Experimental Design

We examine cross-domain transfer by fine-tuning the model on a source domain, and evaluating on a target domain. The performance can be measured by relative zero-shot transfer ability (Turc et al., 2021). We refer to it as *recovery ratio*, since it represents the ratio of how much performance is recovered by changing source domain, given as follows.

$$recovery(S,T) = \frac{M(S,T)}{M(T,T)} \tag{1}$$

where $M(S,T)$ is a model performance for the source domain S on the target domain T. For the recovery ratio, we set a hate domain as target, and remaining ones as source. When source and target domains are the same, recovery would be 1.0.

We also adapt the measurement used in cross-lingual transfer gap (Hu et al., 2020). We modify it to normalize, and refer to it as *decay ratio*, since it represents the ratio of how much performance is decayed by replacing target domain, given as follows.

$$decay(S,T) = \frac{M(S,T) - M(S,S)}{M(S,S)} \tag{2}$$

For the decay ratio, we set a hate domain as source, and remaining ones as target. In the case that source and target domains are the same, there would be no decay or performance drop, so decay would be zero. In the cross-domain experiments, we measure weighted F1; and use BERT for English, and BERTurk for Turkish with the same hyperparameters used in Section 4.1.1. We apply 10-fold cross-validation, where each fold has 18k train instances in a particular hate domain; and report the average score of recovery and decay in 2k test instances of the corresponding hate domain.

4.2.2. Experimental Results

The recovery and decay scores are given in Table 6. We note that recovery and decay represent independent measures for domain transfer performance. For instance, in English, the domain transfer from gender to politics has 99% recovery, and its decay ratio is 0%. The domain transfer from sports to politics has the same recovery ratio, but its decay is -6%, which shows that the same recovery values do not necessarily mean the same performance.

Hate domains can mostly recover each other's performance. Recovery performances between domains are quite effective, such that, on average, 96% of the performance of a target domain is recovered by others for English, and 92% for Turkish. The training dataset composed of only a single domain can be thereby employed to detect hate speech patterns of another domain. We argue that there can be overlapping hate patterns across multiple domains, which can be examined for hate speech in a more fundamental and social level. Moreover, common vocabulary across different topics can introduce domain transitivity such as women's sports or women in politics.

Recovering gender is more difficult than other domains. Gender-based hate tweets can not be easily predicted by other hate domains, as the average recover ratio for gender is lower than others, 91% in both English and Turkish. In addition to gender, politics has the average recover ratio of 90% in Turkish. One can deduce that hate speech patterns of these domains display different characteristics from general hate patterns.

Sports cannot generalize to other domains. While sports can be recovered by other domains, the average decay ratio of sports is poor (more than 10%) in both

	Source/Target	RE	GE	RA	PO	SP	RE	GE	RA	PO	SP	Avg.
	Religion	0.804	92%	96%	98%	97%	0.804	-9%	-1%	-2%	0%	-3%
	Gender	101%	0.799	98%	99%	99%	0%	0.799	0%	0%	0%	0%
EN	Racism	99%	93%	0.823	96%	94%	-3%	-10%	0.823	-6%	-2%	-5%
	Politics	97%	89%	95%	0.808	98%	-3%	-12%	-3%	0.808	0%	-5%
	Sports	95%	90%	93%	99%	0.853	-10%	-15%	-11%	-6%	0.853	-11%
	Avg.	98%	91%	96%	98%	97%						
	Religion	0.754	93%	96%	93%	95%	0.754	-5%	-1%	-6%	0%	-3%
	Gender	94%	0.772	95%	89%	94%	-8%	0.772	-4%	-12%	-3%	-7%
TR	Racism	97%	94%	0.779	92%	95%	-6%	-7%	0.779	-9%	-2%	-6%
	Politics	90%	89%	92%	0.765	90%	-11%	-10%	-6%	0.765	-6%	-8%
	Sports	92%	86%	91%	84%	0.799	-13%	-17%	-11%	-19%	0.799	-15%
	Avg.	93%	91%	94%	90%	94%						

Table 6: Cross-domain transfer for hate speech detection in terms of **column-wise recovery ratio** and **row-wise decay ratio**. Source domains are given in rows, targets in columns. The diagonal gray cells have the weighted F1 scores when source and target domains are the same. Recovery scores should be interpreted column-wise, e.g. 92% recovery from religion to gender in EN means that we recover 92% of 0.799 (gender to gender). As recovery increases, blue color gets darker. Decay scores should be interpreted row-wise, e.g. -9% decay from religion to gender in EN means that we lose 9% of 0.804 (religion to religion). If there is no loss in performance, decay is zero. As decay increases, red color gets darker.

languages, as observed in Table 6. A possible reason can be specific slang language used in sports.

Gender can generalize to other domains in English, but not in Turkish. Gender can maintain its in-domain success to other domains in English, as its average decay ratio is zero. Although average decay ratio is not too high in Turkish, it is still higher than English. One possible reason could be that Turkish has a gender neutral grammar with gender-free pronouns. The success of gender in English can be important for data scarcity in hate speech detection, since one can use the model trained with gender instances to infer a target domain.

5. Discussion

5.1. Error Analysis

We provide an error analysis on the model predictions in Table 7. We select a representative model from each model family that we compare in the previous section; namely BERT/BERTurk, XLM-R, CNN, and BOW.

There are eight tweet examples divided into three groups. The first group with the tweets numbered 1 to 4 is given to represent the examples of both success and failure of Transformer-based language models. BERT and XLM-R incorrectly predict the first tweet, possibly due to giving more attention to "I hate my life" that is not actually a hateful phrase but describes dislike for the current situation. CNN's prediction is also incorrect possibly due to convolution on the same phrase. BOW's prediction is correct by using a sparse vector with many non-hate words. The second tweet is a similar example given for Turkish that BERT and XLM-R probably give more attention to "almamız gereken bir intikam var" (translated as "there is a revenge we need to take"). On the other hand, BERT and XLM-R succeed in the third and fourth tweets due to "I'll kill them" and "bir kaç erkek ölsün istiyorum" (translated as "I want a few men to die"). The difference from the first two examples is that the third and fourth tweets include true-hate phrases.

The second group is given to show the model performance on offensive tweets. All models except XLM-R incorrectly label the fifth tweet as offensive, possibly due to the existence of "f**g". On the other hand, BERT and XLM-R correctly predict the sixth tweet. There are no clear offensive words in this tweet. CNN and BOW therefore fail in this tweet, while BERT and XLM-R could capture the semantics.

The last group is given to show hard examples that all models fail. The seventh tweet is difficult to detect, since the positive word "nice" can be confusing in this short tweet. The models fail to understand the semantics in the last Turkish tweet.

5.2. Existing Models

We evaluate the generalization capability of existing hate speech detection models to our dataset. Since there is no publicly available Turkish-specific models, we only examine it in English. We use the following fine-tuned models for zero-shot inference, as well as

#	Label	Tweet	Predictions BERT	XLM-R	CNN	BOW
1	Normal	Was on an absolute heater, then I lose 500 dollars on Korean baseball and Costa Rican soccer. I hate my life	Hate	Hate	Hate	**Normal**
2	Normal	Kazanmamız gereken bir maç, almamız gereken bir intikam var. Allah büyük. (We have a game to win, a revenge to take. God is great.)	Hate	Hate	**Normal**	**Normal**
3	Hate	...I'm that fast. Hitting someone going full speed. Over 20 mph 190 lbs. I'll kill them	**Hate**	**Hate**	Normal	Normal
4	Hate	Feminist değilim de, tanıdığıma pişman olduğum bir kaç erkek ölsün istiyorum (I am not a feminist, but I want a few men to die that I regret knowing)	**Hate**	**Hate**	Normal	Normal
5	Normal	I'm gay but I've got the biggest fucking crush on @katyperry I have for years!	Offensive	**Normal**	Offensive	Offensive
6	Offensive	The three different ways to become a brain dead zombie are, a virus, radiation and Christianity.	**Offensive**	**Offensive**	Normal	Normal
7	Hate	A gay killing another gay nice	Normal	Normal	Normal	Normal
8	Hate	Yahudiler cinayet Araplar hiyanet kavmidir (Jews are a people of murder, Arabs of treason)	Normal	Normal	Normal	Normal

Table 7: Error analysis using model predictions. Correct predictions are given in bold. For Turkish tweet examples, BERT refers to BERTurk. Translations for Turkish tweets are given in parentheses.

fine-tuning them further with our data.

- **HateXplain** (Mathew et al., 2021): HateXplain fine-tunes BERT, using a novel dataset with 20k instances, 9k of which are tweets. The model can be used for zero-shot inference on multi-class (hate, offensive, and normal) detection.
- **HateBERT** (Caselli et al., 2021): HateBERT pre-trains BERT architecture by using approximately 1.5m Reddit messages by suspended communities due to promoting hateful content. The model can be used for zero-shot inference on binary classification (hate or not). To adapt our dataset to binary classification, we merge offensive and hate tweets.

We apply 10-fold cross-validation, as in previous experiments. The results of existing models are given Table 8. We compare their performances on our dataset with BERT's performance. In multi-class scheme, HateXplain cannot outperform BERT in both zero-shot inference and further fine-tune scheme. In binary scheme, zero-shot inference fails more compared to HateXplain despite having less number of classes. The poor performance of zero-shot HateBERT is probably due to Reddit messages used in pre-training, while our dataset consists of tweets. Fine-tuning the model further provides similar performance with BERT. Overall, we show that existing models have limited generalization capability to new data. A possible reason for existing models failing to generalize can be that our dataset consists of tweets from various topics.

5.3. Scalability

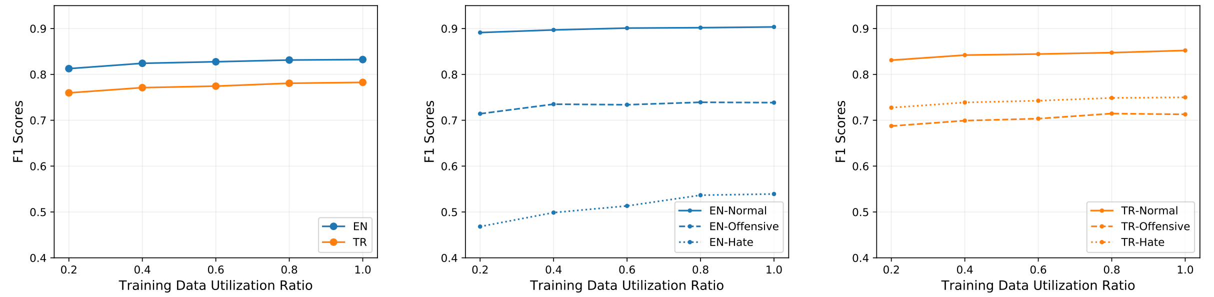
We examine scalability as the effect of increasing training size on model performance. Since labeling hate speech data is costly, the data size of hate speech detection becomes important. Our large-scale datasets are available to analyze scalability. To do so, we split 10% of data for testing, 10% for validation, and remaining 80% for training. From the training split, we set five scale values starting from 20% to 100%. To obtain reliable results, we repeat this process five times, and report the average scores. At each iteration, training and validation datasets are randomly sampled. We use BERT for English, and BERTurk for Turkish with the same hyperparameters used in Section 4.1.1.

We train the models for five epochs, but report the highest performance during training to have a fair comparison by neglecting the positive effect of having more training data, since more number of instances means more number of train steps. We observe that using smaller number of instances (e.g. 20% of data size) needs more epochs to converge, compared to larger data. The highest performances are obtained for 20-60% scales at 2.5 epochs in English and 3.5 epochs in Turkish, whereas for 80-100% at 2 epochs in English and 2.5 epochs in Turkish.

The results for overall detection performance are given in Figure 1a. We observe that the performance slightly improves as training data increases in both English and Turkish. Moreover, 98% of full-sized data performance can be obtained when 20% of training instances are used in English. This ratio is 97% in Turkish. In order to reveal the reason of this result, we also investi-

Model	Mutliclass F1	Type	Binary F1	Type
BERT	0.816	Fine-tune	0.862	Fine-tune
HateXplain	0.796	Fine-tune	-	-
HateXplain	0.769	Zero-shot	-	-
HateBERT	-	-	0.865	Fine-tune
HateBERT	-	-	0.485	Zero-shot

Table 8: Zero-shot and further fine-tuning results for existing hate speech detection models.



(a) Weighted F1 scores for multi-class hate speech detection for different scales of training data. There is a slight performance increase in both languages.

(b) Weighted F1 scores for different classes in EN. The performance of normal class saturates early, and hate class benefits the most.

(c) Weighted F1 scores for different classes in TR. There is a slight performance increase in all classes.

Figure 1: Scalability analysis for hate speech detection.

gate the scalability performance of individual classes in Figure 1b for English, and Figure 1c for Turkish.

The model for English has the highest performance in the normal class, and worst in the hate class. Interestingly, the performance of hate class improves significantly as training data increases whereas normal and offensive tweets exhibit a slightly increasing pattern. One can observe the impact of class imbalance on performance improvements. The normal class with more number of instances is not affected much by different scales. The performance improvement is more prominent in the hate class, which has a smaller number of data instances than the normal class. This result emphasizes the importance of the data size, especially number of hate instances, for hate speech detection. Given that the main bottleneck in hate speech detection is misprediction of hate tweets rather than normal ones, using a higher number of data instances with hate content can improve the performance.

The performance of all classes slightly increase in Turkish. The performance of predicting hate tweets is higher than offensive ones (vice versa in English). The reason could be the different speech patterns in different languages. Moreover, the hate performance of English is still worse than Turkish when similar number of training instances are considered, e.g., hate score of ratio 100% in Figure 1b (7,325 hate tweets) is still worse than the score of 20% in Figure 1c (5,519 hate tweets). When greater class imbalance in English is considered in this case, we argue that class imbalance is also an important factor besides the number of hate tweets.

5.4. Ablation Study

To assess the effect of tweet-specific components on the performance of hate speech detection, we remove each component from tweets, and re-run BERT for English, and BERTurk for Turkish. Tweet-specific components that we examine in the ablation study are URLs, hashtags, and emoji symbols. Table 9 reports the experimental results of the ablation study. The results show that removing tweet-specific components has almost no effect on the performances for both languages. The reason could be that the numbers of hashtags and emojis are low in the dataset, as observed in Table 3. On the other hand, there are many tweets with URLs, yet there is no significant difference when URLs are removed. We argue that BERT-like models can be robust to noise in text caused by URLs.

Data	Model	Prec.	Recall	F1
EN	Raw text	0.815	0.817	0.816
	w/o URL	0.816	0.819	0.817
	w/o Hashtag	0.816	0.818	0.817
	w/o Emoji	0.815	0.818	0.816
	w/o Any	0.817	0.818	0.817
TR	Raw text	0.778	0.777	0.777
	w/o URL	0.779	0.778	0.778
	w/o Hashtag	0.777	0.776	0.776
	w/o Emoji	0.779	0.778	0.778
	w/o Any	0.777	0.777	0.777

Table 9: Effect of removing tweet-specific components in terms of the average of 10-fold cross-validation.

6. Conclusion

We construct large-scale datasets for hate speech detection in English and Turkish to analyze the performances of state-of-the-art models, along with scalability. We design our datasets to have equal size of instances for each of five hate domains and two languages; so that we can report zero-shot cross-domain results. We find that Transformer-based language models outperform conventional models, and their performances can be scalable to different training sizes. We also show that the vast majority of the performance of a target domain can be recovered by other domains. In future work, the generalization capability of domains can be examined in other languages and platforms. One can further analyze model scalability beyond Transformer-based language models.

7. Bibliographical References

Agrawal, S. and Awekar, A. (2018). Deep learning for detecting cyberbullying across multiple social media platforms. In *Advances in Information Retrieval*, pages 141–153, Cham. Springer International Publishing.

Albadi, N., Kurdi, M., and Mishra, S. (2018). Are they our brothers? Analysis and detection of religious hate speech in the Arabic Twittersphere. In *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, pages 69–76.

Arango, A., Pérez, J., and Poblete, B. (2019). Hate speech detection is not as easy as you may think: A closer look at model validation. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR'19, pages 45–54, New York, NY, USA. Association for Computing Machinery.

Basile, V., Bosco, C., Fersini, E., Nozza, D., Patti, V., Rangel Pardo, F. M., Rosso, P., and Sanguinetti, M. (2019). SemEval-2019 Task 5: Multilingual detection of hate speech against immigrants and women in Twitter. In *Proceedings of the 13th International Workshop on Semantic Evaluation*, pages 54–63, Minneapolis, Minnesota, USA. Association for Computational Linguistics.

Byman, D. L. (2021). How hateful rhetoric connects to real-world violence. https://www.brookings.edu/blog/order-from-chaos/2021/04/09/how-hateful-rhetoric-connects-to-real-world-violence/. Accessed: 2022-01-11.

Cao, R., Lee, R. K.-W., and Hoang, T.-A. (2020). DeepHate: Hate speech detection via multi-faceted text representations. In *12th ACM Conference on Web Science*, WebSci '20, pages 11–20, New York, NY, USA. Association for Computing Machinery.

Caselli, T., Basile, V., Mitrović, J., and Granitzer, M. (2021). HateBERT: Retraining BERT for abusive language detection in English. In *Proceedings of the 5th Workshop on Online Abuse and Harms (WOAH 2021)*, pages 17–25, Online. Association for Computational Linguistics.

Chatzakou, D., Kourtellis, N., Blackburn, J., De Cristofaro, E., Stringhini, G., and Vakali, A. (2017). Mean birds: Detecting aggression and bullying on Twitter. In *Proceedings of the 2017 ACM on Web Science Conference*, WebSci '17, pages 13–22, New York, NY, USA. Association for Computing Machinery.

Conneau, A., Khandelwal, K., Goyal, N., Chaudhary, V., Wenzek, G., Guzmán, F., Grave, E., Ott, M., Zettlemoyer, L., and Stoyanov, V. (2020). Unsupervised cross-lingual representation learning at scale. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8440–8451. Association for Computational Linguistics.

Davidson, T., Warmsley, D., Macy, M., and Weber, I. (2017). Automated hate speech detection and the problem of offensive language. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 11, pages 512–515.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Fernquist, J., Lindholm, O., Kaati, L., and Akrami, N. (2019). A study on the feasibility to detect hate speech in Swedish. In *2019 IEEE International Conference on Big Data*, pages 4724–4729.

Fišer, D., Erjavec, T., and Ljubešić, N. (2017). Legal framework, dataset and annotation schema for socially unacceptable online discourse practices in Slovene. In *Proceedings of the First Workshop on Abusive Language Online*, pages 46–51, Vancouver, BC, Canada. Association for Computational Linguistics.

Founta, A., Djouvas, C., Chatzakou, D., Leontiadis, I., Blackburn, J., Stringhini, G., Vakali, A., Sirivianos, M., and Kourtellis, N. (2018). Large scale crowdsourcing and characterization of Twitter abusive behavior. In *International AAAI Conference on Web and Social Media*, volume 12, pages 491–500.

Geva, M., Goldberg, Y., and Berant, J. (2019). Are we modeling the task or the annotator? An investigation of annotator bias in natural language understanding datasets. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 1161–1166, Hong Kong, China. Association for Computational Linguistics.

Golbeck, J., Ashktorab, Z., Banjo, R. O., Berlinger, A., Bhagwan, S., Buntain, C., Cheakalos, P., Geller, A. A., Gergory, Q., Gnanasekaran, R. K., Gunasekaran, R. R., Hoffman, K. M., Hottle, J., Jienjitlert, V., Khare, S., Lau, R., Martindale, M. J., Naik, S., Nixon, H. L., Ramachandran, P., Rogers, K. M., Rogers, L., Sarin, M. S., Shahane, G., Thanki, J., Vengataraman, P., Wan, Z., and Wu, D. M. (2017). A large labeled corpus for online harassment research. In *Proceedings of the 2017 ACM on Web Science Conference*, WebSci '17, pages 229–233, New York, NY, USA. Association for Computing Machinery.

Grave, E., Bojanowski, P., Gupta, P., Joulin, A., and Mikolov, T. (2018). Learning word vectors for 157 languages. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*, pages 3483–3487, Miyazaki, Japan. European Language Resources Association

(ELRA).

Gröndahl, T., Pajola, L., Juuti, M., Conti, M., and Asokan, N. (2018). All you need is “Love”: Evading hate speech detection. In *Proceedings of the 11th ACM Workshop on Artificial Intelligence and Security*, AISec ’18, pages 2–12, New York, NY, USA. Association for Computing Machinery.

Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9(8):1735–1780.

Hu, J., Ruder, S., Siddhant, A., Neubig, G., Firat, O., and Johnson, M. (2020). XTREME: A massively multilingual multi-task benchmark for evaluating cross-lingual generalization. In *Proceedings of the 37th International Conference on Machine Learning*, volume 119, pages 4411–4421. PMLR.

Jiang, Z., Yu, W., Zhou, D., Chen, Y., Feng, J., and Yan, S. (2020). ConvBERT: Improving BERT with span-based dynamic convolution. In *Advances in Neural Information Processing*, volume 33, pages 12837–12848. Curran Associates, Inc.

Karan, M. and Šnajder, J. (2018). Cross-domain detection of abusive language online. In *Proceedings of the 2nd Workshop on Abusive Language Online (ALW2)*, pages 132–137, Brussels, Belgium. Association for Computational Linguistics.

Kim, Y. (2014). Convolutional neural networks for sentence classification. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1746–1751, Doha, Qatar. Association for Computational Linguistics.

Kingma, D. P. and Ba, J. (2015). Adam: A method for stochastic optimization. In *3rd International Conference on Learning Representations, ICLR 2015*, San Diego, CA, USA.

Liu, P., Li, W., and Zou, L. (2019a). NULI at SemEval-2019 Task 6: Transfer learning for offensive language detection using bidirectional transformers. In *Proceedings of the 13th International Workshop on Semantic Evaluation*, pages 87–91, Minneapolis, Minnesota, USA. Association for Computational Linguistics.

Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., and Stoyanov, V. (2019b). RoBERTa: A robustly optimized BERT pretraining approach. *arXiv preprint arXiv:1907.11692*.

Markov, I. and Daelemans, W. (2021). Improving cross-domain hate speech detection by reducing the false positive rate. In *Proceedings of the Fourth Workshop on NLP for Internet Freedom: Censorship, Disinformation, and Propaganda*, pages 17–22, Online. Association for Computational Linguistics.

Markov, I., Ljubešić, N., Fišer, D., and Daelemans, W. (2021). Exploring stylometric and emotion-based features for multilingual cross-domain hate speech detection. In *Proceedings of the Eleventh Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, pages 149–159, Online. Association for Computational Linguistics.

Mathew, B., Saha, P., Yimam, S. M., Biemann, C., Goyal, P., and Mukherjee, A. (2021). HateXplain: A benchmark dataset for explainable hate speech detection. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 14867–14875.

Mou, G., Ye, P., and Lee, K. (2020). Swe2: Subword enriched and significant word emphasized framework for hate speech detection. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, CIKM ’20, pages 1145–1154, New York, NY, USA. Association for Computing Machinery.

Nguyen, D. Q., Vu, T., and Nguyen, A. T. (2020). BERTweet: A pre-trained language model for English tweets. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 9–14. Association for Computational Linguistics.

Nobata, C., Tetreault, J., Thomas, A., Mehdad, Y., and Chang, Y. (2016). Abusive language detection in online user content. In *Proceedings of the 25th International Conference on World Wide Web*, pages 145–153.

Nozza, D. (2021). Exposing the limits of zero-shot cross-lingual hate speech detection. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pages 907–914, Online. Association for Computational Linguistics.

Ousidhoum, N., Lin, Z., Zhang, H., Song, Y., and Yeung, D.-Y. (2019). Multilingual and multi-aspect hate speech analysis. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 4675–4684, Hong Kong, China. Association for Computational Linguistics.

Pamungkas, E. W. and Patti, V. (2019). Cross-domain and cross-lingual abusive language detection: A hybrid approach with deep learning and a multilingual lexicon. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop*, pages 363–370, Florence, Italy. Association for Computational Linguistics.

Pamungkas, E. W., Basile, V., and Patti, V. (2020). Misogyny detection in Twitter: A multilingual and cross-domain study. *Information Processing & Management*, 57(6):102360.

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Kopf, A., Yang, E., De-

Vito, Z., Raison, M., Tejani, A., Chilamkurthy, S., Steiner, B., Fang, L., Bai, J., and Chintala, S. (2019). PyTorch: An imperative style, high-performance deep learning library. In *Advances in Neural Information Processing Systems*, volume 32, pages 8024–8035, Vancouver, BC, Canada. Curran Associates, Inc.

Pavlopoulos, J., Malakasiotis, P., Bakagianni, J., and Androutsopoulos, I. (2017). Improved abusive comment moderation with user embeddings. In *Proceedings of the 2017 EMNLP Workshop: Natural Language Processing meets Journalism*, pages 51–55, Copenhagen, Denmark. Association for Computational Linguistics.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830.

Pennington, J., Socher, R., and Manning, C. D. (2014). GloVe: Global vectors for word representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1532–1543, Doha, Qatar. Association for Computational Linguistics.

Poletto, F., Basile, V., Sanguinetti, M., Bosco, C., and Patti, V. (2021). Resources and benchmark corpora for hate speech detection: A systematic review. *Language Resources and Evaluation*, 55(2):477–523.

Şahinuç, F. and Toraman, C. (2021). Tweet length matters: A comparative analysis on topic detection in microblogs. In *Advances in Information Retrieval*, pages 471–478, Cham. Springer International Publishing.

Sanguinetti, M., Poletto, F., Bosco, C., Patti, V., and Stranisci, M. (2018). An Italian Twitter corpus of hate speech against immigrants. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*, pages 2798–2805, Miyazaki, Japan. European Language Resources Association (ELRA).

Schweter, S. (2020). BERTurk - BERT models for Turkish. https://doi.org/10.5281/zenodo.3770924. Accessed: 2021-10-15.

Sharma, S., Agrawal, S., and Shrivastava, M. (2018). Degree based classification of harmful speech using Twitter data. In *Proceedings of the First Workshop on Trolling, Aggression and Cyberbullying (TRAC-2018)*, pages 106–112, Santa Fe, New Mexico, USA. Association for Computational Linguistics.

Shoeybi, M., Patwary, M., Puri, R., LeGresley, P., Casper, J., and Catanzaro, B. (2019). Megatron-LM: Training multi-billion parameter language models using model parallelism. *arXiv preprint arXiv:1909.08053*.

Sood, S., Antin, J., and Churchill, E. (2012). Profanity use in online communities. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 1481–1490.

Swamy, S. D., Jamatia, A., and Gambäck, B. (2019). Studying generalisability across abusive language detection datasets. In *Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL)*, pages 940–950, Hong Kong, China. Association for Computational Linguistics.

Turc, I., Lee, K., Eisenstein, J., Chang, M.-W., and Toutanova, K. (2021). Revisiting the primacy of English in zero-shot cross-lingual transfer. *arXiv preprint arXiv:2106.16171*.

Twitter. (2021). Twitter Transparency Report. https://transparency.twitter.com/en/reports/rules-enforcement.html#2020-jul-dec. Accessed: 2021-10-15.

Unsvåg, E. F. and Gambäck, B. (2018). The effects of user features on Twitter hate speech detection. In *Proceedings of the 2nd Workshop on Abusive Language Online (ALW2)*, pages 75–85.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. (2017). Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 30, pages 5998–6008. Curran Associates, Inc.

Waseem, Z. (2016). Are you a racist or am I seeing things? Annotator influence on hate speech detection on Twitter. In *Proceedings of the First Workshop on NLP and Computational Social Science*, pages 138–142.

Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., Davison, J., Shleifer, S., von Platen, P., Ma, C., Jernite, Y., Plu, J., Xu, C., Le Scao, T., Gugger, S., Drame, M., Lhoest, Q., and Rush, A. (2020). Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

Zampieri, M., Nakov, P., Rosenthal, S., Atanasova, P., Karadzhov, G., Mubarak, H., Derczynski, L., Pitenis, Z., and Çöltekin, Ç. (2020). SemEval-2020 Task 12: Multilingual offensive language identification in social media (OffensEval 2020). In *Proceedings of the Fourteenth Workshop on Semantic Evaluation*, pages 1425–1447, Barcelona (Online). International Committee for Computational Linguistics.

Zimmerman, S., Kruschwitz, U., and Fox, C. (2018). Improving hate speech detection with deep learning ensembles. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*, pages 2546–2553, Miyazaki, Japan. European Language Resources Association (ELRA).