Towards generalisable hate speech detection: a review on obstacles and solutions

Wenjie Yin, Arkaitz Zubiaga
Queen Mary University of London, London, UK

Abstract
Hate speech is one type of harmful online content which directly attacks or promotes hate towards a group or an individual member based on their actual or perceived aspects of identity, such as ethnicity, religion, and sexual orientation. With online hate speech on the rise, its automatic detection as a natural language processing task is gaining increasing interest. However, it is only recently that it has been shown that existing models generalise poorly to unseen data. This survey paper attempts to summarise how generalisable existing hate speech detection models are, reason why hate speech models struggle to generalise, sums up existing attempts at addressing the main obstacles, and then proposes directions of future research to improve generalisation in hate speech detection.

Introduction
The Internet saw a growing body of user-generated content as social media platforms flourished (Schmidt & Wiegand, 2017; Chung, Kuzmenko, Tekiroglu, & Guerini, 2019). While social media provides a platform for all users to freely express themselves, offensive and harmful content are not rare and can severely impact user experience and even the civility of a community (Nobata, Tetreault, Thomas, Mehdad, & Chang, 2016). One type of such harmful content is hate speech, which is speech that directly attacks or promotes hate towards a group or an individual member based on their actual or perceived aspects of identity, such as ethnicity, religion, and sexual orientation (Waseem & Hovy, 2016; Davidson, Warmsley, Macy, & Weber, 2017; Founta et al., 2018; Sharma, Agrawal, & Shrivastava, 2018).

Major social media companies are aware of the harmful nature of hate speech and have policies regarding the moderation of such posts. However, the most commonly used mechanisms are very limited. For example, keyword filters can deal with profanity, but not the nuance in the expression of hate (Gao, Kuppersmith, & Huang, 2017). Crowd-sourcing methods (e.g. human moderators, user reporting), on the other hand, do not scale up. This means that by the time that a hateful post gets detected and taken down, it has already made negative impacts (Chen, McKeever, & Delany, 2019).

The automatic detection of hate speech is thus an urgent and important task. Since the automatic detection of hate speech was formulated as a task in the early 2010s (Warner & Hirschberg, 2012), the field has been constantly growing along the perceived importance of the task.
Hate speech, offensive language, and abusive language

Although different types of abusive and offensive language are closely related, there are important distinctions to note. Offensive language and abusive language are both used as umbrella terms for harmful content in the context of automatic detection studies. However, while “strongly impolite, rude” and possible use of profanity are seen in the definitions of both (Fortuna & Nunes, 2018), abusive language has a strong component of intentionality (Caselli, Basile, Mitrović, Karttoziya, & Granitzer, 2020). Thus, offensive language has a broader scope, and hate speech falls in both categories.

Because of its definition mentioned above, hate speech is also different from other sub-types of offensive language. For example, personal attacks (Wulczyn, Thain, & Dixon, 2017) are characterised by being directed at an individual, which is not necessarily motivated by the target’s identity. Hate speech is also different from cyberbullying (Zhao, Zhou, & Mao, 2016), which is carried out repeatedly and over time against vulnerable victims that cannot defend themselves. This paper focuses on hate speech and generalisation across hate speech datasets, although studies that cover both hate speech and other offensive language are also mentioned.

Generalisation

Most if not all proposed hate speech detection models rely on supervised machine learning methods, where the ultimate purpose is for the model to learn the real relationship between features and predictions through training data, which generalises to previously unobserved inputs (Goodfellow, Bengio, & Courville, 2016). The generalisation performance of a model measures how well it fulfils this purpose.

To approximate a model’s generalisation performance, it is usually evaluated on a set-aside test set, assuming that the training and test data, and future possible cases come from the same distribution. This is also the main way of evaluating a model’s ability to generalise in the field of hate speech detection.

Generalisability in hate speech detection

The ultimate purpose of studying automatic hate speech detection is to facilitate the alleviation of the harms brought by online hate speech. To fulfil this purpose, hate speech detection models need to be able to deal with the constant growth and evolution of hate speech, regardless of its form, target, and speaker.

Recent research has raised concerns on the generalisability of existing models (Swamy, Jamatia, & Gambäck, 2019). Despite their impressive performance on their respective test sets, the performance significantly dropped when the models are applied to a different hate speech dataset. This means that the assumption that test data of existing datasets represent the distribution of future cases is not true, and that the generalisation performance of existing models have been severely overestimated (Arango, Pérrez, & Poblete, 2020). This lack of generalisability undermines the practical value of these hate speech detection models.

So far, existing research has mainly focused on demonstrating the lack of generalisability (Gründahl, Pajola, Juuti, Conti, & Asokan, 2018; Swamy et al., 2019; Wiegand, Ruppenhofer,
& Kleinbauer, 2019), apart from a handful of studies that made individual attempts at addressing aspects of it (Waseem, Thorne, & Bingel, 2018; Arango et al., 2020). Recent survey papers on hate speech and abusive language detection (Schmidt & Wiegand, 2017; Fortuna & Nunes, 2018; Al-Hassan & Al-Dossari, 2019; P. Mishra, Yannakoudakis, & Shutova, 2019; Vidgen et al., 2019; Poletto, Basile, Sanguinetti, Bosco, & Patti, 2020; Vidgen & Derczynski, 2020) have focused on the general trends in this field, mainly by comparing features, algorithms and datasets. Among these, Fortuna and Nunes (2018) provided an in-depth review of definitions, Vidgen et al. (2019) concisely summarised various challenges for the detection of abusive language in general, Poletto et al. (2020) and Vidgen and Derczynski (2020) created extensive lists of dataset and corpora resources, while Al-Hassan and Al-Dossari (2019) focused on the special case of the Arabic language.

This survey paper thus contributes to the literature by providing (1) a comparative summary of existing research that demonstrated the lack of generalisability in hate speech detection models, (2) a systematic analysis of the main obstacles to generalisable hate speech detection and existing attempts to address them, and (3) suggestions for future research to address these obstacles.

Survey Methodology

For each of the three aims of this paper mentioned above, literature search was divided into stages.

Sources of search

Across different stages, Google Scholar was the main search engine, and two main sets of keywords were used. References and citations were checked back-and-forth, with the number of iterations depending on how coarse or fine-grained the search of that stage was.

- General keywords: “hate speech”, “offensive”, “abusive”, “toxic”, “detection”, “classification”.

- Generalisation-related keywords: “generalisation” (“generalization”), “generalisability” (“generalizability”), “cross-dataset”, “cross-domain”, “bias”.

We started with a pre-defined set of keywords. Then, titles of proceedings of the most relevant recent conferences and workshops (Workshop on Abusive Language Online, Workshop on Online Abuse and Harms) were skimmed, to refine the set of keywords. We also modified the keywords during the search stages as we encountered new phrasing of the terms. The above keywords shown are the final keywords.

Main literature search stages

Before starting to address the aims of this paper, an initial coarse literature search involved searching for the general keywords, skimming the titles and abstracts. During this stage, peer-reviewed papers with high number of citations, published in high-impact venues were prioritised. Existing survey papers on hate speech and abusive language detection (Schmidt & Wiegand, 2017; Fortuna & Nunes, 2018; Al-Hassan & Al-Dossari, 2019; P. Mishra et al., 2019; Vidgen et al., 2019; Poletto et al., 2020; Vidgen & Derczynski, 2020) were also used as seed papers. The purpose of this stage was to establish a comprehensive high-level view of the current state of hate speech detection and closely related fields.
For the first aim of this paper – building a comparative summary of existing research on 
generalisability in hate speech detection – the search mainly involved different combinations of the 
general and generalisation-related keywords. As research on this topic is sparse, during this stage, 
all papers found and deemed relevant were included.

Building upon the first two stages, the main obstacles towards generalisable hate speech 
detection were then summarised, as appeared in the section headings of the body of this paper. This 
was done through extracting and analysing the error analysis of experimental studies found in the 
first stage, and comparing the results and discussions of the studies found in the second stage. Then, 
for each category of obstacles identified, another search was carried out, involving combinations of 
the description and paraphrases of the challenges and the general keywords. The search in this stage 
is the most fine-grained, in order to ensure coverage of both the obstacles and existing attempts to 
address them.

After the main search stages, the structure of the main findings in the literature was laid 
out. During writing, for each type of findings, the most representative studies were included in 
the writing up. We defined the relative representativeness within studies we have found, based on 
novelty, experiment design and error analysis, publishing venues, and influence. We also prioritised 
studies that addressed problems specific to hate speech, compared to better-known problems that 
are shared with other offensive language and social media tasks.

**Generalisation Studies in Hate Speech Detection**

Testing a model on a different dataset from the one which it was trained on is one way to 
more realistically estimate models’ generalisability (Wiegand et al., 2019). This evaluation method 
is called cross-dataset testing (Swamy et al., 2019) or cross-application (Gröndahl et al., 2018), and 
sometimes cross-domain classification (Wiegand et al., 2019) or detection (Karan & Šnajder, 2018) 
if datasets of other forms of offensive language are also included.

As more hate speech and offensive language datasets emerged, a number of studies have 
touched upon cross-dataset generalisation since 2018, either studying generalisability per se, or as 
part of their model or dataset validation. These studies are compared in Table 1. Most of them 
carried out cross-dataset testing. Genres and publications of the datasets used are summarised in 
Table 2. As different datasets and models were investigated, instead of specific performance metrics, 
the remainder of this section will discuss the general findings of these studies.

Firstly, **existing “state-of-the-art” models had been severely over-estimated** (Arango et 
al., 2020).

Gröndahl et al. (2018) trained a range of models, and cross-applied them on four datasets 
(Walczyn, Davidson, Waseem, Zhang). The models included LSTM, which is one of the most pop-
ular neural network types in text classification, and CNN-GRU (Zhang et al., 2018), which outper-
formed previous models on six datasets. On a different testing dataset, both models’ performance 
dropped by more than 30 points in macro-averaged F1 across the Twitter hate speech datasets.

More recently, Arango et al. (2020) also found performance drops of around 30 points in 
macro-averaged F1 with BiLSTM (Agrawal & Awekar, 2018) and GBDT over LSTM-extracted 
embeddings (Badjatiya, Gupta, Gupta, & Varma, 2017) models when applied on Basile. These two 
models were both considered state-of-the-art when trained and evaluated on Waseem. They demon-
strated methodological flaws in each: overfitting induced by extracting features on the combination 
of training and test set; oversampling before cross-validation boosted F1 scores mathematically. 
Gröndahl et al. (2018) also reported that they failed to reproduce Badjatiya et al. (2017)’s results.
The most recent popular approach of fine-tuning BERT (Devlin, Chang, Lee, & Toutanova, 2019) is no exception, although the drop is slightly smaller. In a cross-dataset evaluation with four datasets (Waseem, Davidson, Founta, Zampieri), performance drop ranged from 2 to 30 points in macro-averaged F1 (Swamy et al., 2019).

Similar results were also shown in traditional machine learning models, including character n-gram Logistic Regression (Gröndahl et al., 2018), character n-gram Multi-Layer Perceptron (MLP) (Gröndahl et al., 2018; Waseem et al., 2018), linear Support Vector Machines (Karan & Šnajder, 2018). The same was true for shallow networks with pre-trained embeddings, such as MLP with Byte-Pair Encoding (BPE)-based subword embeddings (Heinzerling & Strube, 2018; Waseem et al., 2018) and FastText (Joulin, Grave, Bojanowski, & Mikolov, 2017; Wiegand et al., 2019).

**Generalisation also depends on the datasets that the model was trained and tested on.**

The lack of generalisation highlights the differences in the distribution of posts between datasets (Karan & Šnajder, 2018). While the size of the difference varies, some general patterns can be found. Some datasets are more similar than others, as there are groups of datasets that produce models that generalise much better on each other. For example, in Wiegand et al. (2019)’s study, FastText models (Joulin et al., 2017) trained on three datasets (Kaggle, Founta, Razavi) achieved F1

### Table 1

| Dataset name | Type   | Study                  |
|--------------|--------|------------------------|
|              |        | Waseem (2019)          |
|              |        | Gröndahl et al. (2018) |
|              |        | Waseem et al. (2018)   |
|              |        | Swamy et al. (2019)    |
|              |        | Arango et al. (2020)   |
|              |        | Fortuna et al. (2020)  |
|              |        | Caselli et al. (2020)  |

**Comparison of studies that looked at cross-dataset generalisation, by datasets and models used.**

Dataset types: H: hate speech, O: other offensive language, *: contains subtypes. Fortuna et al. (2020) compared datasets through class vector representations, the rest of the studies carried out cross-dataset testing. Gröndahl et al. (2018) didn’t control model type across testing conditions.

| Dataset name | Type   | SVM | FastText | Mixed | MLP  | BERT | Mixed | N/A | BERT |
|--------------|--------|-----|----------|-------|------|------|-------|-----|------|
| Waseem       | H*     | ✓   | ✓        | ✓     | ✓    | ✓    | ✓     | ✓   | ✓    |
| Davidson     | H,O    | ✓   | ✓        | ✓     | ✓    | ✓    | ✓     | ✓   | ✓    |
| Founta       | H,O    | ✓   | ✓        | ✓     | ✓    | ✓    | ✓     | ✓   | ✓    |
| Basile       | H*     | ✓   | ✓        |       | ✓    | ✓    | ✓     | ✓   | ✓    |
| Kaggle       | H,O*   | ✓   | ✓        |       | ✓    | ✓    | ✓     | ✓   | ✓    |
| Gao          | H      | ✓   |          |       | ✓    | ✓    | ✓     | ✓   | ✓    |
| Fersini      | H*     |     |          |       | ✓    | ✓    | ✓     | ✓   | ✓    |
| Warner       | H      | ✓   |          |       |     | ✓    | ✓     | ✓   | ✓    |
| Zhang        | H      |     |          |       |     |     | ✓     | ✓   | ✓    |
| Kumar        | O      | ✓   | ✓        |       |     |     |       |     | ✓    |
| Wulczyn      | O      | ✓   | ✓        |       |     |     |       |     | ✓    |
| Zampieri     | O      | ✓   |          |       |     | ✓    | ✓     | ✓   | ✓    |
| Caselli      | O*     |     |          |       |     |     |       |     | ✓    |
| Kolhatkar    | O      | ✓   |          |       |     |     |       |     | ✓    |
| Razavi       | O      |     |          |       |     |     |       |     | ✓    |
| Model        | SVM    | FastText | Mixed | MLP  | BERT | Mixed | N/A | BERT |

The lack of generalisation highlights the differences in the distribution of posts between datasets (Karan & Šnajder, 2018). While the size of the difference varies, some general patterns can be found. Some datasets are more similar than others, as there are groups of datasets that produce models that generalise much better on each other. For example, in Wiegand et al. (2019)’s study, FastText models (Joulin et al., 2017) trained on three datasets (Kaggle, Founta, Razavi) achieved F1
| Dataset name | Publication | Source | Positive labels | Annotator type |
|--------------|-------------|--------|----------------|----------------|
| Waseem      | Waseem and Hovy (2016) | Twitter | Racism, Sexism | Expert |
| Davidson    | Davidson et al. (2017) | Twitter | Hate speech, Offensive | Crowdsourcing |
| Founta      | Founta et al. (2018) | Twitter | Hate speech, Offensive | Crowdsourcing |
| Basile      | Basile et al. (2019) | Twitter | Hateful | Crowdsourcing |
| Kaggle      | Jigsaw (2018) | Wikipedia | Toxic, Severe toxic, Obscene, Threat, Insult, Identity hate | Crowdsourcing |
| Gao         | Gao and Huang (2017) | Fox News | Hateful | ? (Native speakers) |
| Fersini     | Fersini et al. (2019) | Twitter | Misogynous | Expert |
| Warner      | Warner and Hirschberg (2012) | Yahoo! American Jewish Congress | Anti-semitic, Anti-black, Anti-asian, Anti-woman, Anti-muslim, Anti-immigrant, Other-hate | ? (Volunteer) |
| Zhang       | Zhang et al. (2018) | Twitter | Hate | Expert |
| Kumar       | Kumar, Reganti, et al. (2018) | Facebook, Twitter | Overtly aggressive, Covertly aggressive | Expert |
| Wulczyn     | Wulczyn et al. (2017) | Wikipedia | Attacking | Crowdsourcing |
| Zampieri    | Zampieri et al. (2019a) | Twitter | Offensive | Crowdsourcing |
| Caselli     | Caselli et al. (2020) | Twitter | Explicit (abuse), Implicit (abuse) | Expert |
| Kolhatkar   | Kolhatkar et al. (2019) | The Globe and Mail | Very toxic, Toxic, Mildly toxic | Crowdsourcing |
| Razavi      | Razavi et al. (2010) | Natural Semantic Module, Usenet | Flame | Expert |

Table 2
Datasets used in cross-dataset generalisation studies. Positive labels are listed with their original wording. Expert annotation type include authors and experts in social science and related fields. ?: Type of annotations not available in original paper, the found descriptions are thus included. Note that only datasets used in generalisation studies are listed – for comprehensive lists of hate speech datasets, see Vidgen and Derczynski (2020) and Poletto et al. (2020).
scores above 70 when tested on one another, while models trained or tested on datasets outside this group achieved around 60 or less. The authors (Wiegand et al., 2019) attributed this to the higher percentage of explicit abuse in the samples and less biased sampling procedures. In Swamy et al. (2019)’s study with fine-tuned BERT models (Devlin et al., 2019), Founta and Zampieri produced models that performed well on each other, which was considered an effect of the similar characteristics shared between these two datasets, given that similar search terms were used for building the datasets.

So far, there has been only one study that attempted to quantify the similarity between datasets. Fortuna et al. (2020) used averaged word embeddings (Bojanowski, Grave, Joulin, & Mikolov, 2017; Mikolov, Grave, Bojanowski, Puhrsch, & Joulin, 2018) to compute the representations of classes from different datasets, and compared classes across datasets. One of their observations is that Davidson’s “hate speech” is very different from Waseem’s “hate speech”, “racism”, “sexism”, while being relatively close to Basile’s “hate speech” and Kaggle’s “identity hate”. This echoes with experiments that showed poor generalisation of models from Waseem to Basile (Arango et al., 2020) and between Davidson and Waseem (Waseem et al., 2018; Gröndahl et al., 2018).

Training on some datasets might produce more generalisable models, but in terms of which datasets or what properties of a dataset lead to more generalisable models, there is not enough consistency. Swamy et al. (2019) holds that a larger proportion of abusive posts (including hateful and offensive) leads to better generalisation to dissimilar datasets, such as Davidson. This is in line with Karan and Šnajder (2018)’s study where Kumar and Kolhatkar generalised best, and Waseem et al. (2018)’s study where models trained on Davidson generalised better to Waseem than the other way round. In contrast, Wiegand et al. (2019) concluded that the proportion of explicit posts and less biased sampling played the most important roles: Kaggle and Founta generalised best, despite being the datasets with the least abusive posts. Caselli et al. (2020) found that, on Basile, a BERT (Devlin et al., 2019) model trained on the dataset they proposed (Caselli) outperformed the one trained on Basile end-to-end. They attributed this to their quality of annotation as well as to a bigger data size. This is encouraging, yet more synthesis across different studies is needed surrounding this very recent dataset.

Obstacles to Generalisable Hate Speech Detection

Demonstrating the lack of generalisability is only the first step in understanding this problem. This section delves into three key factors that may have contributed to it: (1) presence of non-standard grammar and vocabulary, (2) paucity of and biases in datasets, and (3) implicit expressions of hate.

Non-standard Grammar and Vocabulary on Social Media

On social media, non-standard English is widely used. This is sometimes shown in a more casual use of syntax, such as the omission of punctuation (Blodgett & O’Connor, 2017). Alternative spelling and expressions are also used in dialects (Blodgett & O’Connor, 2017), to save space, and to provide emotional emphasis (Baziotis, Pelekis, & Doulkeridis, 2017).

Hate speech detection, which is largely focused on social media, shares the above challenges and has its specific ones. Commonly seen in hate speech, the offender adopts various approaches
to evade content moderation. For example, the spelling of offensive words or phrases can be obfuscated (Nobata et al., 2016; Serrà et al., 2017), and common words such as “Skype”, “Google”, and “banana” may have a hateful meaning – sometimes known as euphemism or code words (Taylor, Peignon, & Chen, 2017; Magu & Luo, 2018).

These unique linguistic phenomena pose extra challenge on training generalisable models, mainly by making it difficult to utilise common NLP pre-training approaches. When the spelling is obfuscated, a word is considered out-of-vocabulary and thus no useful information can be given by the pre-trained models. In the case of code words, pre-trained embeddings will not reflect its context-dependent hateful meaning. At the same time, simply using identified code words for a lexicon-based detection approach will result in low precision (Davidson et al., 2017). As there are infinite ways of combining the above alternative rules of spelling, code words, and syntax, hate speech detection models struggle with these rare expressions even with the aid of pre-trained word embeddings.

In practice, this difficulty is manifested in false negatives. Qian, ElSherief, Belding, and Wang (2018) found that rare words and implicit expressions are the two main causes of false negatives; Aken, Risch, Krestel, and Löser (2018) compared several models that used pre-trained word embeddings, and found that rare and unknown words were present in 30% of the false negatives of Wikipedia data and 43% of Twitter data. Others have also identified rare and unknown words as a challenge for hate speech detection (Nobata et al., 2016; Zhang & Luo, 2019).

Existing solutions

From a domain-specific perspective, Taylor et al. (2017) and Magu and Luo (2018) attempted to identify code words for slurs used in hate communities. Both of them used keyword search as part of their sourcing of Twitter data and word embedding models to model word relationships. Taylor et al. (2017) identified hate communities through Twitter connections of the authors of extremist articles and hate speech keyword searches. They trained their own dependency2vec (Levy & Goldberg, 2014) and FastText (Bojanowski et al., 2017) embeddings on the hate community tweets and randomly sampled “clean” tweets, and used weighted graphs to measure similarity and relatedness of words. Strong and weak links were thus drawn from unknown words to hate speech words. In contrast, Magu and Luo (2018) collected potentially hateful tweets using a set of known code words. They then computed the cosine similarity between all words based on word2vec (Mikolov, Sutskever, Chen, Corrado, & Dean, 2013) pre-trained on news data. Code words, which have a neutral meaning in news context, were further apart from other words which fit in the hate speech context. Both studies focused on the discovery of such code words and expanding relevant lexicons, but their methods could potentially complement existing hate lexicons as classifier features or for data collection.

Recently, a lot more studies approached the problem by adapting well-known embedding methods to hate speech detection models.

The benefit of character-level features has not been consistently observed. Three studies compared character-level, word-level, and hybrid (both character and word-level) CNNs, but drew completely different conclusions. Park (2018) and Meyer and Gambäck (2019) found hybrid and character CNN to perform best respectively. Probably most surprisingly, Lee, Yoon, and Jung (2018) observed that word and hybrid CNNs outperformed character CNN to similar extents, with all CNNs worse than character n-gram logistic regression. Small differences between these studies could have contributed to this inconsistency. More importantly, unlike the word components of the models, which were initialised with pre-trained word embeddings, the character embeddings were trained
end-to-end on the very limited respective training datasets. It is thus likely that these character embeddings severely overfit on the training data.

In contrast, simple character n-gram logistic regression has shown results as good as sophisticated neural network models, including the above CNNs (Aken et al., 2018; Gao & Huang, 2017; Lee et al., 2018). Indeed, models with fewer parameters are less likely to overfit. This suggests that character-level features themselves are very useful, when used appropriately. A few studies used word embeddings that were additionally enriched with subword information as part of the pre-training. For example, FastText (Bojanowski et al., 2017) models were consistently better than hybrid CNNs (Bodapati, Gella, Bhattacharjee, & Al-Onaizan, 2019). MIMICK (Pinter, Guthrie, & Eisenstein, 2017)-based model displayed similar performances (P. Mishra, Yannakoudakis, & Shutova, 2018).

The use of sentence embeddings partially solves the out-of-vocabulary problem by using the information of the whole post instead of individual words. Universal Sentence Encoder (Cer et al., 2018), combined with shallow classifiers, helped one team (Indurthi et al., 2019) achieve first place at HatEval 2019 (Basile et al., 2019). Sentence embeddings, especially those trained with multiple tasks, also consistently outperformed traditional word embeddings (Chen et al., 2019).

Large language models with sub-word information have the benefits of both subword-level word embeddings and sentence embeddings. They produce the embedding of each word with its context and word form. Indeed, BERT (Devlin et al., 2019) and its variants, have demonstrated top performances at hate or abusive speech challenges recently (Liu, Li, & Zou, 2019; S. Mishra & Mishra, 2019).

Nonetheless, these relatively good solutions to out-of-vocabulary words (subword- and context-enriched embeddings) all face the same short-coming: they have only seen the standard English in BookCorpus and Wikipedia. NLP tools perform best when trained and applied in specific domains (Duarte, Llanso, & Loup, 2018). In hate speech detection, word embeddings trained on relevant data (social media or news sites) had a clear advantage (Chen, McKeever, & Delany, 2018; Vidgen & Yasseri, 2020). The domain mismatch could have similarly impaired the subword- and context-enrich models’ performances.

Limited, Biased Labelled Data

Small data size. It is particularly challenging to acquire labelled data for hate speech detection as knowledge or relevant training is required of the annotators. As a high-level and abstract concept, the judgement of “hate speech” is subjective, needing extra care when processing annotations. Hence, datasets are usually not big in size.

When using machine learning models, especially deep learning models with millions of parameters, small dataset size can lead to overfitting and harm generalisability (Goodfellow et al., 2016).

Existing solutions

The use of pre-trained embeddings (discussed earlier) and parameter dropout (Srivastava, Hinton, Krizhevsky, Sutskever, & Salakhutdinov, 2014) have been accepted as standard practice in the field of NLP to prevent over-fitting, and are common in hate speech detection as well. Nonetheless, the effectiveness of domain-general embedding models is questionable, and there has been only a limited number of studies that looked into the relative suitability of different pre-trained embeddings on hate speech detection tasks (Chen et al., 2018; P. Mishra et al., 2018; Bodapati et al., 2019).
In Swamy et al. (2019)’s study of model generalisability, **abusive language-specific pre-trained embeddings** were suggested as a possible solution to limited dataset sizes. Alatawi, Al-bothali, and Moria (2020) proposed White Supremacy Word2Vec (WSW2V), which was trained on one million tweets sourced through white supremacy-related hashtags and users. Compared to general word2vec (Mikolov et al., 2013) and GloVe (Pennington, Socher, & Manning, 2014) models trained on news, Wikipedia, and Twitter data, WSW2V captured meaning more suitable in the hate speech context – e.g. ambiguous words like “race” and “black” have higher similarity to words related to ethnicity rather than sports or colours. Nonetheless, their WSW2V-based LSTM model did not consistently outperform Twitter GloVe-based LSTM model or BERT (Devlin et al., 2019).

Research on **transfer learning from other tasks**, such as sentiment analysis, also lacks consistency. Uban and Dinu (2019) pre-trained a classification model on a large sentiment dataset\(^2\), and performed transfer learning on the Zampieri and Kumar datasets. They took pre-training further than the embedding layer, comparing word2vec (Mikolov et al., 2013) to sentiment embeddings and entire-model transfer learning. Entire-model transfer learning was always better than using the baseline word2vec (Mikolov et al., 2013) model, but the transfer learning performances with only the sentiment embeddings were not consistent.

More recently, Cao, Lee, and Hoang (2020) also trained sentiment embeddings through classification as part of their proposed model. The main differences are: the training data was much smaller, containing only Davidson and Founta datasets; the sentiment labels were produced by VADER (Gilbert & Hutto, 2014); their model was deeper and used general word embeddings (Mikolov et al., 2013; Pennington et al., 2014; Wieting, Bansal, Gimpel, & Livescu, 2015) and topic representation computed through Latent Dirichlet Allocation (LDA) (Blei, Ng, & Jordan, 2003) in parallel. Through ablation studies, they showed that sentiment embeddings were beneficial for both Davidson and Founta datasets.

Use of existing knowledge from a more mature research field like that of sentiment analysis has the potential to be used to jumpstart relatively newer fields, but more investigation into the conditions in which transfer learning works best has to be done.

**Sampling bias.** Non-random sampling makes datasets prone to bias. Hate speech and, more generally, offensive language generally represent less than 3% of social media content (Zampieri et al., 2019b; Founta et al., 2018). To alleviate the effect of scarce positive cases on model training, all existing social media hate speech or offensive content datasets used boosted (or focused) sampling with simple heuristics.

Table 3 compares the **sampling methods** of hate speech datasets studied the most in cross-dataset generalisation. Consistently, keyword search and identifying potential hateful users are the most common methods. However, what is used as the keywords (slurs, neutral words, profanity, hashtags), which users to include (any user from keyword search, identified haters), and the use of other sampling methods (identifying victims, sentiment classification) all vary a lot.

Moreover, different studies are based on varying definitions of “hate speech”, as seen in different **annotation guidelines** (Table 4). Despite all covering the same two main aspects (directly attack or promote hate towards), datasets vary by their wording, what they consider a target (any

\(^2\)https://help.sentiment140.com/
\(^1\)https://www.hatebase.org/
\(^2\)https://www.noswearing.com/dictionary/
\(^3\)https://www.hatebase.org/
\(^4\)https://www.noswearing.com/dictionary/
Towards Generalisable Hate Speech Detection

| Dataset | Keywords | Haters | Other |
|---------|----------|--------|-------|
| Waseem | “Common slurs and terms used pertaining to religious, sexual, gender, and ethnic minorities” | “A small number of prolific users” | N/A |
| Davidson | HateBase³ | “Each user from lexicon search” | N/A |
| Founta | HateBase, NoSwearing⁴ | N/A | Negative sentiment |
| Basile | “Neutral keywords and derogatory words against the targets, highly polarized hashtags” | “Identified haters” | “Potential victims of hate accounts” |

Table 3
Boosted sampling methods of the most commonly studied hate speech datasets (Waseem & Hovy, 2016; Davidson et al., 2017; Founta et al., 2018; Basile et al., 2019). Description as appeared in the publications. N/A: no relevant descriptions found.

Group, minority groups, specific minority groups), and their clarifications on edge cases. Davidson and Basile both distinguished “hate speech” from “offensive language”, while “uses a sexist or racist slur” is in Waseem’s guidelines to mark a case positive of hate, blurring the boundary of offensive and hateful. Additionally, as both Basile and Waseem specified the types of hate (towards women and immigrants; racism and sexism), hate speech that fell outside of these specific types were not included in the positive classes, while Founta and Davidson included any type of hate speech. Guidelines also differ in how detailed they are: Apart from Founta, all other datasets started the annotation process with sets of labels pre-defined by the authors, among which Waseem gave the most specific description of actions. In contrast, Founta only provided annotators with short conceptual definitions of a range of possible labels, allowing more freedom for a first exploratory round of annotation. After that, labels were finalised, and another round of annotation was carried out. As a result, the labelling reflects how the general public, without much domain knowledge, would classify offensive language. For example, the “abusive” class and “offensive” class were so similar that they were merged in the second stage. However, as discussed above, they differ by whether intentionality is present (Caselli et al., 2020).

Such different annotation and labelling criteria result in essentially different tasks and different training objectives, despite their data having a lot in common.

As a result of the varying and sampling methods, definitions, and annotation schemes, what current models can learn on one dataset is specific to the examples in that dataset and the task defined by the dataset, limiting the models’ ability to generalise to new data.

One type of possible resulting bias is author bias. For example, 65% of the hate speech in the Waseem dataset was produced by merely two users, and their tweets exist in both the training and the test set. Models trained on such data thus overfit to these users’ language styles. This overfitting to authors was proven in two state-of-the-art models (Badjatiya et al., 2017; Agrawal & Awekar, 2018) (Arango et al., 2020). Topic bias is another concern. With words such as “football” and “announcer” among the ones with the highest Pointwise Mutual Information (PMI) with hate speech posts, a topic bias towards sports was demonstrated in the Waseem dataset (Wiegand et al., 2019).

Existing solutions
| Dataset  | Action                                                                 | Target                     | Clarifications                                                                                                                                 |
|----------|------------------------------------------------------------------------|----------------------------|------------------------------------------------------------------------------------------------------------------------------------------------|
| Waseem  | Attacks, seeks to silence, criticises, negatively stereotypes, promotes hate speech or violent crime, blatantly misrepresents truth or seeks to distort views on, uses a sexist or racial slur, defends xenophobia or sexism | A minority                 | (Inclusion) Contains a screen name that is offensive, as per the previous criteria, the tweet is ambiguous (at best), and the tweet is on a topic that satisfies any of the above criteria |
| Davidson | Express hatred towards, humiliate, insult*                             | A group or members of the group | (Exclusion) Think not just about the words appearing in a given tweet but about the context in which they were used; the presence of a particular word, however offensive, did not necessarily indicate a tweet is hate speech |
| Founta  | Express hatred towards, humiliate, insult                              | Individual or group, on the basis of attributes such as race, religion, ethnic origin, sexual orientation, disability, or gender | N/A                                                                                                                                     |
| Basile  | Spread, incite, promote, justify hatred or violence towards, dehumanizing, hurting or intimidating**       | Women or immigrants         | (Exclusion) Hate speech against other targets, offensive language, blasphemy, historical denial, overt incitement to terrorism, offense towards public servants and police officers, defamation |

Table 4
Annotation guidelines of the most commonly studied hate speech datasets. Original wording from the publications or supplementary materials; action verbs grouped for easier comparison: underlined: directly attack or attempt to hurt, italic: promote hate towards. N/A: no relevant descriptions found. *Davidson et al. (2017) also gave annotators “a paragraph explaining it (the definition) in further detail”, which was not provided in their publication. **Basile et al. (2019) also gave annotators some examples in their introduction of the task (rather than the main guidelines, thus not included).
A few recent studies have attempted to go beyond one dataset when training a model. Waseem et al. (2018) used multitask training (Caruana, 1997) with hard parameter sharing up to the final classification components, which were each tuned to one hate speech dataset. The shared shallower layers, intuitively, extract features useful for both datasets, with the two classification tasks as regularisation against overfitting to either one. Their multitask-trained models matched the performances of models trained end-to-end to single datasets and had clear advantage over simple dataset concatenation, whilst allowing generalisation to another dataset. Karan and Šnajder (2018) presented a similar study. Frustratingly Easy Domain Adaptation (Daumé III, 2007), had similar beneficial effects but was much simpler and more efficient. These two studies showed the potential of combining datasets to increase generalisability, but further investigation into this approach is lacking.

**Representation bias.** Natural language is a proxy of human behaviour, thus the biases of our society are reflected in the datasets and models we build. With increasing real-life applications of NLP systems, these biases can be translated into wider social impacts (Hovy & Spruit, 2016). Minority groups are underrepresented in available data and/or data annotators, thus causing biases against them when models are trained from this data. This phenomenon is also seen in audio transcribing (Tatman, 2017), sentiment analysis (Kiritchenko & Mohammad, 2018), etc.

Hate speech detection models not only have higher tendency to classify African-American English posts as offensive or hate than “white” English (Davidson, Bhattacharya, & Weber, 2019), but also more often predict false negatives on “white” than African-American English (Sap, Gabriel, et al., 2019). Certain words and phrases, including neutral identity terms such as “gay” (Dixon, Li, Sorensen, Thain, & Vasserman, 2018) and “woman” (Park, Shin, & Fung, 2018) can also easily lead to a false positive judgement. Moreover, just like biases in real life, racial, gender, and party identification biases in hate speech datasets were found to be intersectional (Kim, Ortiz, Nam, Santiago, & Datta, 2020). Unlike the other types of biases mentioned above, rather than performance metrics such as the overall F1 score, they do more harm to the practical value of the automatic hate speech detection models. These biases may cause automatic models to amplify the harm against minority groups instead of mitigating such harm as intended (Davidson et al., 2019). For example, with higher false positive rates for minority groups, their already under-represented voice will be more often falsely censored.

**Existing solutions**

Systematic studies of representation biases and their mitigation are relatively recent. Since Dixon et al. (2018) first quantified unintended biases in abusive language detection on the Wulczyn dataset using a synthetic test set, an increasing number of studies have been carried out on hate speech and other offensive language. These attempts to address biases against minority social groups differ by how they measure biases and their approaches to mitigate them.

Similar to Dixon et al. (2018), a number of studies measured bias as certain words and phrases being associated with the hateful or offensive class, which were mostly identity phrases. Attempts to mitigate biases identified this way focus on decoupling this association between features and classes. Model performance on a synthetic test set with classes and identity terms balanced, compared to the original test data, were used a measure for model bias. Well-known identity terms and synonyms are usually used as starting points (Dixon et al., 2018; Park et al., 2018; Nozza, Volpetti, & Fersini, 2019). Alternatively, bias-prone terms could be identified through looking at skewed distributions within a specific dataset (Badjatiya, Gupta, & Varma, 2019; Mozafari, Farahbakhsh, & Crespi, 2020b).
A few studies measured biases across directly predicted language styles or demographic attributes of authors. Davidson et al. (2019) and Kim et al. (2020) both tested their hate speech detection models on Blodgett, Green, and O’Connor (2016)’s distantly supervised dataset of African-American vs white-aligned English tweets, revealing higher tendencies of labelling an African-American-aligned tweet offensive or hateful. Kim et al. (2020) further extended this observation to gender and party identification. As the testing datasets do not have hateful or offensive ground truth labels, one caveat is that, using this as a metric of model bias assumes that all language styles have equal chances of being hateful or offensive, which might not be true.

Huang, Xing, Demoncourt, and Paul (2020) approached author demographics from a different angle, and instead predicted author demographics on available hate speech datasets using user profile descriptions, names, and photos. They built and released a multilingual corpus for model bias evaluation. Although now with ground truth hate speech labels, this introduces additional possible bias existing in the tools they used into the bias evaluation process. For example, they used a computer vision API on the profile pictures to predict race, age, and gender, which displayed racial and gender biases (Buolamwini & Gebru, 2018).

One mitigation approach that stemmed from the first approach of measuring biases is “debiasing” training data through data augmentation. Dixon et al. (2018) retrieved non-toxic examples containing a range of identity terms following a template, which were added to Wulczyn. Following a similar logic, Park et al. (2018) created examples containing the counterpart of gendered terms found in the data to address gender bias in the Waseem and Founta datasets. Badjatiya et al. (2019) extended this word replacement method by experimenting with various strategies including named entity tags, part of speech tags, hypernyms, and similar words from word embeddings, which were then applied on the Wulczyn and Davidson datasets.

Less biased external corpora and pre-trained models could also be used. To reduce gender bias, Park et al. (2018) also compared pre-trained debiased word embeddings (Bolukbasi, Chang, Zou, Saligrama, & Kalai, 2016) and transfer learning from a larger, less biased corpus. Similarly, Nozza et al. (2019) added samples from the Waseem dataset to their training dataset (Fersini), to keep classes and gender identity terms balanced.

From the perspective of model training, “debiasing” could also be integrated into the model training objective. Based on 2-grams’ Local Mutual Information with a label, Mozafari et al. (2020b) gave each training example in the Davidson and Waseem datasets a positive weight, producing a new weighted loss function to optimise. Kennedy, Jin, Davani, Dehghani, and Ren (2020) built upon a recent study of post-hoc BERT feature importance (Jin, Du, Wei, Xue, & Ren, 2019). A regularisation term to encourage the importance of a set of identity terms to be close to zero was added to the loss function. This changed the ranks of importance beyond the curated set of identity terms in the final model trained on two datasets (de Gibert, Perez, García-Pablos, & Cuadros, 2018; Kennedy et al., 2018), with that of most identity terms decreasing, and some aggressive words increasing, such as “destroys”, “poisoned”. Vaidya, Mai, and Ning (2020) used a similar multitask learning framework to Waseem et al. (2018) on Kaggle, but with the classification of author’s identity as the auxiliary task to mitigate the confusion between identity keywords and hateful reference.

There is little consensus in how bias and the effect of bias mitigation should be measured, with different studies adopting varying “debiased” metrics, including Error Rate Equality Difference (Dixon et al., 2018; Park et al., 2018; Nozza et al., 2019), pinned AUC Equality Difference (Dixon et al., 2018; Badjatiya et al., 2019), Pinned Bias (Badjatiya et al., 2019), synthetic test set AUC (Park et al., 2018), and weighted average of subgroup AUCs (Nozza et al., 2019; Vaidya et al., 2020). More
importantly, such metrics are all defined based on how the subgroups are defined – which datasets are used, which social groups are compared, which keywords or predictive models are chosen to categorise those groups. As a consequence, although such metrics provide quantitative comparison between different mitigation strategies within a study, the results are hard to compare horizontally. Nonetheless, a common pattern is found across the studies: the standard metric, such as raw F1 or AUC, and the “debiased” metrics seldom improve at the same time. This raises the question on the relative importance that should be put on “debiased” metrics and widely accepted raw metrics: How much practical value do such debiased metrics have if they contradict raw metrics? Or do we need to rethink the widely accepted AUC and F1 scores on benchmark datasets because they do not reflect the toll on minority groups?

In comparison, Sap, Card, Gabriel, Choi, and Smith (2019) proposed to address the biases of human annotators during dataset building, rather than debiasing already annotated data or regularising models. By including each tweet’s dialect and providing extra annotation instructions to think of tweet dialect as a proxy of the author’s ethnic identity, they managed to significantly reduce the likelihood of the largely white annotator group (75%) to rate an African-American English tweet offensive to anyone or to themselves. This approach bears similarity to Vaidya et al. (2020)’s, which also sought to distinguish identity judgement from offensiveness spotting, although in automatic models. Although on a small scale, this study demonstrated that more care can be put into annotator instructions than existing datasets have.

Hate Expression Can Be Implicit

Slurs and profanity are common in hate speech. This is partly why keywords are widely used as a proxy to identify hate speech in existing datasets. However, hate can also be expressed through stereotypes (Sap, Gabriel, et al., 2019), sarcasm, irony, humour, and metaphor (P. Mishra et al., 2019; Vidgen et al., 2019). For example, a post that reads “Hey Brianne - get in the kitchen and make me a samich. Chop Chop” (Gao & Huang, 2017) directly attacks a woman based on her female identity using stereotypes, and thus certainly fulfills the definition of hate speech, without any distinctive keyword.

Implicit hate speech conveys the same desire to distance such social groups as explicit hate speech (Alorainy, Burnap, Liu, & Williams, 2019) and are no less harmful (Breitfeller, Ahn, Jurgens, & Tsvetkov, 2019). Implicit expressions are the most commonly mentioned cause of false negatives in error analysis (Zhang & Luo, 2019; Qian et al., 2018; Basile et al., 2019; Mozafari, Farahbakhsh, & Crespi, 2020a). Inability to detect nuanced, implicit expressions of hate means the models do not go beyond lexical features and cannot capture the underlying hateful intent, let alone generalise to hate speech cases where there are no recurring hate-related words and phrases. Because of the reliance on lexical features, automatic detection models fall far short of human’s ability to detect hate and are thus far from being applicable in the real world as a moderation tool (Duarte et al., 2018).

It has been proposed that abusive language should be systematically classified into explicit and implicit, as well as generalised and directed (Waseem, Davidson, Warmsley, & Weber, 2017). Several subsequent studies have also identified nuanced, implicit expression as a particularly important challenge in hate speech detection for future research to address (Aken et al., 2018; Duarte et al., 2018; Swamy et al., 2019). It is especially necessary for explainability (P. Mishra et al., 2019). Despite the wide recognition of the problem, there has been much fewer attempts at addressing it.

Existing solutions
Implicit cases of hate speech are hard to identify because they can be understood only within their specific context or with the help of relevant real-world knowledge such as stereotypes. Some have thus included context in datasets. For example, Gao and Huang (2017) included the original news articles as the context of the comments. de Gibert et al. (2018)’s hate speech forum dataset organised sentences in the same post together, and has a “relation” label separate from “hate”/“no hate” to set apart cases which can only be correctly understood with its neighbours.

Offensive or abusive language datasets that include implicitness in annotation schemes have appeared only recently. The Caselli dataset (Caselli et al., 2020) is so far the only dataset with a standalone “implicit” label. They re-annotated the Zampieri dataset (Zampieri et al., 2019a), splitting the offensive class into implicitly abusive, explicitly abusive, and non-abusive. Their dataset thus offered a clearer distinction between abusiveness and offensiveness, and between implicit and explicit abuse. Sap, Gabriel, et al. (2019) asked annotators to explicitly paraphrase the implied statements of intentionally offensive posts. The task defined by this dataset is thus very different from previously existing ones – it is a sequence-to-sequence task to generate implied statements on top of the classification task to identify hateful intent.

Both of their experiments reveal that predicting implicit abuse or biases remains a major challenge. Sap, Gabriel, et al. (2019)’s model tended to output the most generic bias of each social group, rather than the implied bias in each post. Caselli et al. (2020)’s best model achieved only a precision of around .234 and a recall of 0.098 for the implicit class, in contrast to .864 and .936 for non-abusive and .640 and .509 for explicit.

To the best of our knowledge, so far there has only been one attempt at annotating the implicitness of hate speech specifically. Alatawi et al. (2020) crowd-sourced annotation on a small set of tweets collected through white supremacist hashtags and user names, dividing them into implicit white supremacist, explicit white supremacist, other hate, and neutral. Unfortunately, the inter-annotator agreement was so low (0.11 Cohen’s kappa (Cohen, 1960)) that they reduced the labels into binary (hateful vs non-hateful) in the end. The main disagreements are between neutral and implicit labels. Compared to Sap, Gabriel, et al. (2019) and Caselli et al. (2020)’s studies, their result highlights the difficulty of annotating implicit hate speech and, more fundamentally, the perception of hate speech largely depends on the reader, as posited by Waseem (2016).

Fewer studies proposed model design motivated by implicit hate speech. Gao et al. (2017) designed a novel two-path model, aiming to capture both explicit hate speech with a “slur learner” path and implicit hate speech with an LSTM path. However, it is doubtful whether the LSTM path really learns to identify implicit hate speech, as it is also trained on hate speech cases acquired through initial slur-matching and the slur learner.

Targeting specific types of implicit hate speech seems more effective. Alorainy et al. (2019) developed a feature set using dependency trees, part-of-speech tags, and pronouns, to capture the us vs them sentiment in implicit hate speech. This improved classification performance on a range of classifiers including CNN-GRU and LSTM. The main shortcoming is that the performance gain was relative to unprocessed training data, so it is not clear how effective this feature set is compared to common pre-processing methods.

Discussion

While cross-dataset testing highlights the low generalisability of existing models, it is important to not reduce the study of generalisability in hate speech detection to cross-dataset performance.
or “debiased” metrics. Ultimately, we want generalisability to the real world. Why we are developing these models and datasets, how we intend to use them, and what potential impacts they may have on the users and the wider society are all worth keeping in mind. While mathematical metrics offer quantification, our focus should always be on what we plan to address and its context. Furthermore, hate speech datasets and models should be representative of what hate speech is with no prioritising of any facets of it (Swamy et al., 2019), and shouldn’t discriminate against minority groups that they are intended to protect (Davidson et al., 2019).

Hate speech detection as a sub-field of NLP is rather new. Despite the help of established NLP methods, achieving consensus in the formulation of the problem is still ongoing work – whether it is binary, multi-class, hierarchical, how to source representative data, what metadata should be included, and where we draw the line between offensive and hateful content. Thus, no existing dataset qualifies as a “benchmark dataset” yet (Swamy et al., 2019). In the near future, it is likely that new datasets will continue to emerge and shape our understanding of how to study hate speech computationally. Thus, while it is important to try to solve the problems defined by existing datasets, more emphasis should be put on generalisability.

Future research

More work can be done from the perspectives of both models and datasets to make automatic hate speech detection generalisable and thus practical. Here, we lay out critical things to keep in mind for any researcher working on hate speech detection as well as research directions to evaluate and improve generalisability.

Datasets. Clear label definitions

A prerequisite is to have clear label definitions, separating hate speech from other types of offensive language (Davidson et al., 2017; Founta et al., 2018), and abusive language from offensive language (Caselli et al., 2020). In addition to this, to address the ambiguity between types of abusive language, future datasets can cover a wider spectrum of abusive language such as personal attacks, trolling, and cyberbullying. This could be done either in a hierarchical manner like what Basile et al. (2019) and Kumar, Reganti, et al. (2018) did with subtypes of hate speech and aggression respectively, or in a multi-label manner, as there might be cases where more than one can apply, as seen in Waseem and Hovy (2016)’s racism and sexism labels. At the same time, the definitions of labels should have as little overlap as possible.

Annotation quality

Poletto et al. (2020) found that only about two thirds of the existing datasets report inter-annotator agreement. Guidelines also range from brief descriptions of each class to long paragraphs of definitions and examples. To ensure a high inter-annotator agreement, extensive instructions and the use of expert annotators is required. There exists a trade-off between having a larger dataset and having annotations with a high inter-annotator agreement that reflect an understanding of the concepts. At the same time, extra guidelines were shown to be effective in addressing some of the biases in crowd-sourced annotations (Sap, Card, et al., 2019). Future research can look into what type of and how much training or instruction is required to match the annotations of crowdworkers and experts.

Understanding perception

The perception of hate speech depends on the background of the person reading it (Waseem, 2016). Existing datasets mostly reported the number of annotators and whether they are crowdworkers, but seldom the demographics of annotators. Furthermore, within the range of “expert”
annotators, there are also many possibilities, such as the authors themselves (de Gibert et al., 2018; Mandl et al., 2019), experts in linguistics (Kumar, Ojha, Malmasi, & Zampieri, 2018), activists (Waseem, 2016; Waseem & Hovy, 2016), experts in politics (Vidgen & Yasseri, 2020). Future studies can investigate what factors contribute to the disagreement between annotators, quantitatively or qualitatively. Datasets with extensive annotator attributes and their judgements could be built. Annotating implicit hate speech is especially challenging (Alatawi et al., 2020). Through improved understanding of hate speech perception, an implicit hate speech dataset could be made possible.

Drawing representative samples
As discussed above, before the annotation process, how the initial pool of posts is collected and how the proportion of positive cases is boosted could introduce bias into the dataset. It is a better approach to start with an initial random sample and then apply boosting techniques, compared to drawing a filtered sample (Wiegand et al., 2019). Boosting techniques can also be improved, by shifting away from keywords towards other less lexical proxies of possible hate. Future datasets should also actively address different types of possible biases, such as regularising each user’s contribution to one dataset, analysis of the topics present in the dataset, limiting the association between certain terms or language styles and a label.

Models. Reducing overfitting
Overfitting can be reduced through training on more than one dataset (Waseem et al., 2018; Karan & Šnajder, 2018) or transfer learning from a larger dataset (Uban & Dinu, 2019; Alatawi et al., 2020) and/or a closely related task, such as sentiment analysis (Uban & Dinu, 2019; Cao et al., 2020), yet synthesis in the literature is lacking. More work can be done on comparing different training approaches, and what characteristics of the datasets interact with the effectiveness. For example, when performing transfer learning, the trade-off between domain-specificity and dataset size and representativeness is worth investigating.

Reducing the reliance on lexical features can also help alleviate overfitting to the training dataset. Domain knowledge such as linguistic patterns and underlying sentiment of hate speech can inform model design, feature extraction or preprocessing (Alorainy et al., 2019). Future studies can look into how features of different nature can be effectively combined.

Debiasing models
A range of approaches could be used to make the model less biased against certain terms or language styles, from the perspectives of training data or objective. Each study shows that their approach takes some effect, yet comparison across studies is still difficult. More systematic comparisons between debiasing approaches is favourable. This can be done by applying a range of existing approaches on a number of datasets, with a set of consistent definitions of attributes. There could also be an interaction between debiasing approaches and the types of biases. When experimenting with “debiasing”, it is important to always stay critical of any metrics used.

Model application and impact
When evaluating models, dataset-wise mathematical metrics like F1/AUC should not be the only measurement. It is also important to evaluate models also on datasets not seen during training (Wiegand et al., 2019), and carry out in-depth error analysis relevant to any specific challenge that the model claims to address.

Machine learning models should be considered as part of a sociotechnical system, instead of an algorithm which only exists in relation to the input and outcomes (Selbst, Boyd, Friedler, Venkatasubramanian, & Vertesi, 2019). Thus, more future work can be put into studying hate speech detection models in a wider context of application. For example, can automatic models
practically aid human moderators in content moderation? In that case, how can human moderators make use of the outputs or post-hoc feature analysis most effectively? Would that introduce more bias or reduce bias in content moderation? What would the impact be on the users of the platform? To answer these questions, interdisciplinary collaboration is needed.

**Conclusion**

Existing hate speech detection models generalise poorly on new, unseen datasets. Reasons why generalisable hate speech detection is hard come from limits of existing NLP methods, dataset building, and the nature of online hate speech, and are often intertwined. The behaviour of social media users and especially haters poses extra challenge to established NLP methods. Small datasets make deep learning models prone to overfitting, and biases in datasets transfer to models. While some biases come from different sampling methods or definitions, others merely reflect longstanding biases in our society. Hate speech evolves with time and context, and thus has a lot of variation in expression. Existing attempts to address these challenges span across adapting state-of-the-art in other NLP tasks, refining data collection and annotation, and drawing inspirations from domain knowledge of hate speech. More work can be done in these directions to increase generalisability. At the same time, the task shouldn’t be framed entirely as an algorithmic one. Instead, wider context and impact should also be considered.

**References**

Agrawal, S., & Awekar, A. (2018). Deep learning for detecting cyberbullying across multiple social media platforms. In *European conference on information retrieval* (pp. 141–153).

Aken, B. v., Risch, J., Krestel, R., & Löser, A. (2018). Challenges for Toxic Comment Classification: An In-Depth Error Analysis. In *ALW* (pp. 33–42). doi: 10.18653/v1/w18-5105

Alatawi, H. S., Alhothali, A. M., & Moria, K. M. (2020, October). Detecting White Supremacist Hate Speech using Domain Specific Word Embedding with Deep Learning and BERT. *arXiv:2010.00357 [cs].* Retrieved 2020-10-02, from http://arxiv.org/abs/2010.00357 (arXiv: 2010.00357)

Al-Hassan, A., & Al-Dossari, H. (2019, February). Detection of Hate Speech in Social Networks: a Survey on Multilingual Corpus. In *Computer Science & Information Technology* (CS & IT) (pp. 83–100). AIRCC Publishing Corporation. Retrieved 2020-06-18, from https://airccj.org/CSCP/vo19/csit90208.pdf doi: 10.5121/csit.2019.90208

Alorainy, W., Burnap, P., Liu, H., & Williams, M. L. (2019, July). “The Enemy Among Us”: Detecting Cyber Hate Speech with Threats-based Othering Language Embeddings. *ACM Transactions on the Web, 13*(3), 1–26. Retrieved 2020-01-21, from http://dl.acm.org/citation.cfm?doid=3352383.3324997 doi: 10.1145/3324997

Arago, A., Pérez, J., & Poblete, B. (2020, June). Hate speech detection is not as easy as you may think: A closer look at model validation (extended version). *Information Systems*, 101584. Retrieved 2020-10-19, from http://www.sciencedirect.com/science/article/pii/S0306437920300715 doi: 10.1016/j.is.2020.101584

Bajdriya, P., Gupta, M., & Varma, V. (2019, May). Stereotypical Bias Removal for Hate Speech Detection Task using Knowledge-based Generalizations. In *The World Wide Web Conference* (pp. 49–59). New York, NY, USA: Association for Computing Machinery. Retrieved 2020-10-26, from https://doi.org/10.1145/3308558.3313504 doi: 10.1145/3308558.3313504

Bajdriya, P., Gupta, S., Gupta, M., & Varma, V. (2017). Deep learning for hate speech detection in tweets. In *Proceedings of the 26th international conference on world wide web companion* (pp. 759–760).

Basile, V., Bosco, C., Fersini, E., Nozza, D., Patti, V., Rangel Pardo, F. M., … Sanguinetti, M. (2019, June). *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 (pp. 54–63). Minneapolis, Minnesota, USA: Association for Computational Linguistics. doi: 10.18653/v1/S19-2007

Baziotis, C., Pelekis, N., & Doulkeridis, C. (2017, August). DataStories at SemEval-2017 Task 4: Deep LSTM with Attention for Message-level and Topic-based Sentiment Analysis. In Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017) (pp. 747–754). Vancouver, Canada: Association for Computational Linguistics. Retrieved 2020-02-14, from https://www.aclweb.org/anthology/S17-2126 doi: 10.18653/v1/S17-2126

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. Journal of machine Learning research, 3(Jan), 993–1022.

Blodgett, S. L., Green, L., & O’Connor, B. (2016). Demographic dialectal variation in social media: A case study of african-american english. In Proceedings of the 2016 conference on empirical methods in natural language processing (pp. 1119–1130).

Blodgett, S. L., & O’Connor, B. (2017, June). Racial Disparity in Natural Language Processing: A Case Study of Social Media African-American English. arXiv:1707.00061 [cs]. Retrieved 2020-02-10, from http://arxiv.org/abs/1707.00061 (arXiv: 1707.00061)

Bodapati, S., Gella, S., Bhattacharjee, K., & Al-Onaizan, Y. (2019). Neural word decomposition models for abusive language detection. In Proceedings of the third workshop on abusive language online (pp. 135–145).

Bojanowski, P., Grave, E., Joulin, A., & Mikolov, T. (2017). Enriching word vectors with subword information. Transactions of the Association for Computational Linguistics, 5, 135–146.

Bolukbasi, T., Chang, K.-W., Zou, J. Y., Saligrama, V., & Kalai, A. T. (2016). Man is to computer programmer as woman is to homemaker? debiasing word embeddings. In Advances in neural information processing systems (pp. 4349–4357).

Breitfeller, L., Ahn, E., Jurgens, D., & Tsvetkov, Y. (2019, November). Finding Microaggressions in the Wild: A Case for Locating Elusive Phenomena in Social Media Posts. 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) (pp. 1664–1674). Hong Kong, China: Association for Computational Linguistics. Retrieved 2020-01-20, from https://www.aclweb.org/anthology/D19-1176 doi: 10.18653/v1/D19-1176

Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. In Conference on fairness, accountability and transparency (pp. 77–91).

Cao, R., Lee, R. K.-W., & Hoang, T.-A. (2020, July). DeepHate: Hate Speech Detection via Multi-Faceted Text Representations. In 12th ACM Conference on Web Science (pp. 11–20). New York, NY, USA: Association for Computing Machinery. Retrieved 2020-09-21, from https://doi.org/10.1145/3394231.3397890 doi: 10.1145/3394231.3397890

Cer, D., Yang, Y., Kong, S.-y., Hua, N., Limtiaco, N., John, R. S., ... others (2018). Universal sentence encoder for english. In Proceedings of the 2018 conference on empirical methods in natural language processing: System demonstrations (pp. 169–174).

Caselli, T., Basile, V., Mitrović, J., Kartozija, I., & Granitzer, M. (2020, May). I Feel Offended, Don’t Be Abusive! Implicit/Explicit Messages in Offensive and Abusive Language. In Proceedings of The 12th Language Resources and Evaluation Conference (pp. 6193–6202). Marseille, France: European Language Resources Association. Retrieved 2020-06-25, from https://www.aclweb.org/anthology/2020.lrec-1.760

Cer, D., Yang, Y., Kong, S.-y., Hua, N., Limtiaco, N., John, R. S., ... others (2018). Universal sentence encoder for english. In Proceedings of the 2018 conference on empirical methods in natural language processing: System demonstrations (pp. 169–174).

Chen, H., McKeever, S., & Delany, S. J. (2018). A Comparison of Classical Versus Deep Learning Techniques for Abusive Content Detection on Social Media Sites. In S. Staab, O. Koltsouva, & D. I. Ignatov (Eds.), Social Informatics (pp. 117–133). Cham: Springer International Publishing. doi: 10.1007/978-3-030-01129-1_8

Chen, H., McKeever, S., & Delany, S. J. (2019, July). The Use of Deep Learning Distributed Representations in the Identification of Abusive Text. Proceedings of the International AAAI Conference on Web
TOWARDS GENERALISABLE HATE SPEECH DETECTION

Chung, Y.-L., Kuzmenko, E., Tekiroglu, S. S., & Guerini, M. (2019, July). CONAN - COunter NAarratives through Nichesourcing: a Multilingual Dataset of Responses to Fight Online Hate Speech. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (pp. 2819–2829). Florence, Italy: Association for Computational Linguistics. Retrieved 2020-01-20, from https://www.aclweb.org/anthology/P19-1271

doi: 10.18653/v1/P19-1271

Daumé III, H. (2007). Frustratingly easy domain adaptation. In Proceedings of the 45th annual meeting of the association of computational linguistics (pp. 256–263).

Fersini, E., Gasparini, F., & Corchs, S. (2019, September). Detecting Sexist MEME On The Web: A Study on Textual and Visual Cues. In 2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW) (pp. 226–231). doi: 10.1109/ACIIW.2019.8925199

Fortuna, P., & Nunes, S. (2018, July). A Survey on Automatic Detection of Hate Speech in Text. ACM Computing Surveys, 51(4), 1–30. Retrieved 2020-01-09, from http://dl.acm.org/citation.cfm?doid=3236632.3232676 doi: 10.1145/3232676

Fortuna, P., Soler, J., & Wanner, L. (2020, May). Toxic, Hateful, Offensive or Abusive? What Are We Really Classifying? An Empirical Analysis of Hate Speech Datasets. In Proceedings of the 12th Language Resources and Evaluation Conference (pp. 6786–6794). Marseille, France: European Language Resources Association. Retrieved 2020-10-16, from https://www.aclweb.org/anthology/2020.lrec-1.838

Founta, A.-M., Djouvas, C., Chatzakou, D., Leontiadis, I., Blackburn, J., Stringhini, G., ... Kourtellis, N. (2018). Large scale crowdsourcing and characterization of twitter abusive behavior. In Proceedings of icwsm. AAAI Press.

Gao, L., & Huang, R. (2017). Detecting online hate speech using context aware models. In Proceedings of the international conference recent advances in natural language processing, ranlp 2017 (pp. 260–266).

Gao, L., Kuppersmith, A., & Huang, R. (2017). Recognizing explicit and implicit hate speech using a weakly supervised two-path bootstrapping approach. In Proceedings of the eighth international joint conference on natural language processing (volume 1: Long papers) (pp. 774–782).
Gilbert, C., & Hutto, E. (2014). VADER: A parsimonious rule-based model for sentiment analysis of social media text. In Eighth international conference on weblogs and social media (ICWSM-14), available at (20/04/16) http://comp.social.gatech.edu/papers/icwsm14.vader.hutto.pdf (Vol. 81, p. 82).

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press. (http://www.deeplearningbook.org)

Grøndahl, T., Pajola, L., Juuti, M., Conti, M., & Asokan, N. (2018). All you need is "love" evading hate speech detection. In Proceedings of the 11th ACM workshop on artificial intelligence and security (pp. 2–12).

Heinzerling, B., & Strube, M. (2018). BPEmb: Tokenization-free pre-trained subword embeddings in 275 languages. In Proceedings of the eleventh international conference on language resources and evaluation (LREC 2018) (pp. 2989–2993).

Hovy, D., & Spruit, S. L. (2016, August). The Social Impact of Natural Language Processing. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers) (pp. 591–598). Berlin, Germany: Association for Computational Linguistics. Retrieved 2020-10-28, from https://www.aclweb.org/anthology/P16-2096 doi: 10.18653/v1/P16-2096

Huang, X., Xing, L., Dernoncourt, F., & Paul, M. (2020). Multilingual twitter corpus and baselines for evaluating demographic bias in hate speech recognition. In Proceedings of the 12th language resources and evaluation conference (pp. 1440–1448).

Indurthi, V., Syed, B., Chakravartula, N., Gupta, M., & Varma, V. (2019, June). FERMI at SemEval-2019 Task 5: Using Sentence embeddings to Identify Hate Speech Against Immigrants and Women in Twitter. In Proceedings of the 13th International Workshop on Semantic Evaluation (pp. 70–74). Minneapolis, Minnesota, USA: Association for Computational Linguistics. doi: 10.18653/v1/S19-2009

Jigsaw. (2018). Toxic comment classification challenge. (https://www.kaggle.com/c/jigsaw-toxic-comment-classification-challenge)

Jin, X., Du, J., Wei, Z., Xue, X., & Ren, X. (2019). Towards hierarchical importance attribution: Explaining compositional semantics for neural sequence models. arXiv preprint arXiv:1911.06194.

Joulin, A., Grave, É., Bojanowski, P., & Mikolov, T. (2017). Bag of tricks for efficient text classification. In Proceedings of the 15th conference of the european chapter of the association for computational linguistics: Volume 2, short papers (pp. 427–431).

Karan, M., & Šnajder, J. (2018). Cross-domain detection of abusive language online. In Proceedings of the 2nd workshop on abusive language online (ALW2) (pp. 132–137).

Kennedy, B., Atari, M., Davani, A. M., Yeh, L., Omrani, A., Kim, Y., . . . Dehghani, M. (2018, July). The Gab Hate Corpus: A collection of 27k posts annotated for hate speech (Tech. Rep.). PsyArXiv. Retrieved 2020-10-29, from https://psyarxiv.com/hqjxn/ doi: 10.31234/osf.io/hqjxn

Kennedy, B., Jin, X., Davani, A. M., Dehghani, M., & Ren, X. (2020, July). Contextualizing Hate Speech Classifiers with Post-hoc Explanation. arXiv:2005.02439 [cs]. Retrieved 2020-10-26, from http://arxiv.org/abs/2005.02439 (arXiv: 2005.02439)

Kim, J. Y., Ortiz, C., Nam, S., Santiago, S., & Datta, V. (2020, May). Intersectional Bias in Hate Speech and Abusive Language Datasets. arXiv:2005.05921 [cs]. Retrieved 2020-05-13, from http://arxiv.org/abs/2005.05921 (arXiv: 2005.05921)

Kiritchenko, S., & Mohammad, S. M. (2018). Examining gender and race bias in two hundred sentiment analysis systems. In Proceedings of *sem (pp. 43–53).

Kolhatkar, V., Wu, H., Cavasso, L., Francis, E., Shukla, K., & Taboada, M. (2019, November). The SFU Opinion and Comments Corpus: A Corpus for the Analysis of Online News Comments. Corpus Pragmatics, 4(2), 155–190. Retrieved 2020-06-21, from http://link.springer.com/10.1007/s41701-019-00065-w doi: 10.1007/s41701-019-00065-w

Kumar, R., Ojha, A. K., Malmasi, S., & Zampieri, M. (2018, August). Benchmarking Aggression Identification in Social Media. In Proceedings of the First Workshop on Trolling, Aggression and Cyberbullying (TRAC-2018) (pp. 1–11). Santa Fe, New Mexico, USA: Association for Computational Linguistics. Retrieved 2020-04-09, from https://www.aclweb.org/anthology/W18-4401
Kumar, R., Reganti, A. N., Bhatia, A., & Maheshwari, T. (2018, May). Aggression-annotated Corpus of Hindi-English Code-mixed Data. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018). Miyazaki, Japan: European Language Resources Association (ELRA). Retrieved 2020-10-22, from https://www.aclweb.org/anthology/L18-1226

Lee, Y., Yoon, S., & Jung, K. (2018). Comparative studies of detecting abusive language on twitter. In Proceedings of the 2nd workshop on abusive language online (alw2) (pp. 101–106).

Levy, O., & Goldberg, Y. (2014). Dependency-based word embeddings. In Proceedings of the 52nd annual meeting of the association for computational linguistics (volume 2: Short papers) (pp. 302–308).

Liu, P., Li, W., & Zou, L. (2019, June). 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 (pp. 87–91). Minneapolis, Minnesota, USA: Association for Computational Linguistics. Retrieved 2020-01-27, from https://www.aclweb.org/anthology/S19-2011 doi: 10.18653/v1/S19-2011

Magu, R., & Luo, J. (2018, October). Determining Code Words in Euphemistic Hate Speech Using Word Embedding Networks. In Proceedings of the 2nd Workshop on Abusive Language Online (ALW2) (pp. 93–100). Brussels, Belgium: Association for Computational Linguistics. Retrieved 2020-04-14, from https://www.aclweb.org/anthology/W18-5112 doi: 10.18653/v1/W18-5112

Mandl, T., Modha, S., Majumder, P., Patel, D., Dave, M., Mandlia, C., & Patel, A. (2019, December). Overview of the HASOC track at FIRE 2019: Hate Speech and Offensive Content Identification in Indo-European Languages. In Proceedings of the 11th Forum for Information Retrieval Evaluation (pp. 14–17). Kolkata, India: Association for Computing Machinery. Retrieved 2020-02-03, from https://doi.org/10.1145/3368567.3368584

Meyer, J. S., & Gambäck, B. (2019, August). A Platform Agnostic Dual-Strand Hate Speech Detector. In Proceedings of the Third Workshop on Abusive Language Online (pp. 146–156). Florence, Italy: Association for Computational Linguistics. Retrieved 2020-10-19, from https://www.aclweb.org/anthology/W19-3516 doi: 10.18653/v1/W19-3516

Mikolov, T., Grave, É., Bojanowski, P., Puhrsch, C., & Joulin, A. (2018). Advances in pre-training distributed word representations. In Proceedings of the eleventh international conference on language resources and evaluation (lrec 2018) (pp. 52–55).

Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems (pp. 3111–3119).

Mishra, P., Yannakoudakis, H., & Shutova, E. (2018, October). Neural Character-based Composition Models for Abuse Detection. In Proceedings of the 2nd Workshop on Abusive Language Online (ALW2) (pp. 1–10). Brussels, Belgium: Association for Computational Linguistics. Retrieved 2020-01-14, from https://www.aclweb.org/anthology/W18-5101 doi: 10.18653/v1/W18-5101

Mishra, P., Yannakoudakis, H., & Shutova, E. (2019, August). Tackling Online Abuse: A Survey of Automated Abuse Detection Methods. arXiv:1908.06024 [cs]. Retrieved 2020-02-04, from http://arxiv.org/abs/1908.06024 (arXiv: 1908.06024)

Mishra, S., & Mishra, S. (2019). 3Idiots at HASOC 2019: Fine-tuning Transformer Neural Networks for Hate Speech Identification in Indo-European Languages. FIRE, 6.

Mozafari, M., Farahbakhsh, R., & Crespi, N. (2020a). A BERT-Based Transfer Learning Approach for Hate Speech Detection in Online Social Media. In H. Cherifi, S. Gaito, J. F. Mendes, E. Moro, & L. M. Rocha (Eds.), Complex Networks and Their Applications VIII (pp. 928–940). Cham: Springer International Publishing. doi: 10.1007/978-3-030-36687-2_77

Mozafari, M., Farahbakhsh, R., & Crespi, N. (2020b, August). Hate speech detection and racial bias mitigation in social media based on BERT model. PLOS ONE, 15(8), e0237861. Retrieved 2020-10-26, from https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0237861 (Publisher: Public Library of Science) doi: 10.1371/journal.pone.0237861

Nobata, C., Tetreault, J., Thomas, A., Mehdad, Y., & Chang, Y. (2016, April). Abusive Language Detection
TOWARDS GENERALISABLE HATE SPEECH DETECTION

in Online User Content. In *Proceedings of the 25th International Conference on World Wide Web* (pp. 145–153). Republic and Canton of Geneva, CHE: International World Wide Web Conferences Steering Committee. Retrieved 2020-10-19, from https://doi.org/10.1145/2872427.2883062 doi: 10.1145/2872427.2883062

Nozza, D., Volpetti, C., & Fersini, E. (2019, October). Unintended Bias in Misogyny Detection. In *IEEE/WIC/ACM International Conference on Web Intelligence* (pp. 149–155). New York, NY, USA: Association for Computing Machinery. Retrieved 2020-10-26, from https://doi.org/10.1145/3350546.3352512 doi: 10.1145/3350546.3352512

Park, J. H. (2018, August). Finding Good Representations of Emotions for Text Classification. *arXiv:1808.07235* [cs]. Retrieved 2020-01-20, from http://arxiv.org/abs/1808.07235 (arXiv: 1808.07235)

Park, J. H., Shin, J., & Fung, P. (2018). Reducing gender bias in abusive language detection. In *Proceedings of the 2018 conference on empirical methods in natural language processing* (pp. 2799–2804).

Pennington, J., Socher, R., & Manning, C. (2014). Glove: Global Vectors for Word Representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)* (pp. 1532–1543). Doha, Qatar: Association for Computational Linguistics. Retrieved 2020-10-21, from http://aclweb.org/anthology/D14-1162 doi: 10.3115/v1/D14-1162

Pinter, Y., Guthrie, R., & Eisenstein, J. (2017). Mimicking word embeddings using subword rnns. In *Proceedings of the 2017 conference on empirical methods in natural language processing* (pp. 102–112).

Poletto, F., Basile, V., Sanguinetti, M., Bosco, C., & Patti, V. (2020). Resources and benchmark corpora for hate speech detection: a systematic review. *Language Resources and Evaluation*, 1–47.

Qian, J., ElSherief, M., Belding, E., & Wang, W. Y. (2018). Leveraging intra-user and inter-user representation learning for automated hate speech detection. In *Proceedings of the 2018 conference of the north american chapter of the association for computational linguistics: Human language technologies, volume 2 (short papers)* (pp. 118–123).

Razavi, A. H., Inkpen, D., Uritsky, S., & Matwin, S. (2010). Offensive Language Detection Using Multi-level Classification. In D. Hutchison et al. (Eds.), *Advances in Artificial Intelligence* (Vol. 6085, pp. 16–27). Berlin, Heidelberg: Springer Berlin Heidelberg. Retrieved 2020-06-20, from http://link.springer.com/10.1007/978-3-642-13059-5_5 (Series Title: Lecture Notes in Computer Science) doi: 10.1007/978-3-642-13059-5_5

Sap, M., Card, D., Gabriel, S., Choi, Y., & Smith, N. A. (2019, July). The Risk of Racial Bias in Hate Speech Detection. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics* (pp. 1668–1678). Florence, Italy: Association for Computational Linguistics. Retrieved 2020-01-21, from https://www.aclweb.org/anthology/P19-1163 doi: 10.18653/v1/P19-1163

Sap, M., Gabriel, S., Qin, L., Jurafsky, D., Smith, N. A., & Choi, Y. (2019, November). Social Bias Frames: Reasoning about Social and Power Implications of Language. *arXiv:1911.03891* [cs]. Retrieved 2020-01-17, from http://arxiv.org/abs/1911.03891 (arXiv: 1911.03891)

Schmidt, A., & Wiegand, M. (2017, April). A Survey on Hate Speech Detection using Natural Language Processing. In *Proceedings of the Fifth International Workshop on Natural Language Processing for Social Media* (pp. 1–10). Valencia, Spain: Association for Computational Linguistics. doi: 10.18653/v1/W17-1101

Selbst, A. D., Boyd, D., Friedler, S. A., Venkatasubramanian, S., & Vertesi, J. (2019, January). Fairness and Abstraction in Sociotechnical Systems. In *Proceedings of the Conference on Fairness, Accountability, and Transparency* (pp. 59–68). New York, NY, USA: Association for Computing Machinery. Retrieved 2020-10-29, from https://doi.org/10.1145/3287560.3287598 doi: 10.1145/3287560.3287598

Serrà, J., Leontiadis, I., Spathis, D., Stringhini, G., Blackburn, J., & Vakali, A. (2017). Class-based Prediction Errors to Detect Hate Speech with Out-of-vocabulary Words. In *Proceedings of the First Workshop on Abusive Language Online* (pp. 36–40). Vancouver, BC, Canada: Association for Computational Linguistics. Retrieved 2020-02-11, from http://aclweb.org/anthology/W17-3005 doi:
Sharma, S., Agrawal, S., & 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) (pp. 106–112).

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: a simple way to prevent neural networks from overfitting. The journal of machine learning research, 15(1), 1929–1958.

Swamy, S. D., Jamatia, A., & Gambäck, B. (2019, November). Studying Generalisability across Abusive Language Detection Datasets. In Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL) (pp. 688–700). Hong Kong, China: Association for Computational Linguistics. Retrieved 2020-02-11, from https://www.aclweb.org/anthology/K19-1088

Vaidya, A., Mai, F., & Ning, Y. (2020). Empirical analysis of multi-task learning for reducing identity bias in toxic comment detection. In Proceedings of the international aaai conference on web and social media (Vol. 14, pp. 683–693).

Vidgen, B., Harris, A., Nguyen, D., Tromble, R., Hale, S., & Margetts, H. (2019). Challenges and frontiers in abusive content detection. In Proceedings of the Third Workshop on Abusive Language Online (pp. 80–93). Florence, Italy: Association for Computational Linguistics. Retrieved 2020-09-22, from https://www.aclweb.org/anthology/W19-3509 doi: 10.18653/v1/W19-3509

Vidgen, B., & Derczynski, L. (2020, April). Directions in Abusive Language Training Data: Garbage In, Garbage Out. arXiv:2004.01670 [cs]. Retrieved 2020-08-06, from http://arxiv.org/abs/2004.01670 (arXiv:2004.01670)

Warner, W., & Hirschberg, J. (2012, June). Detecting Hate Speech on the World Wide Web. In Proceedings of the Second Workshop on Language in Social Media (pp. 19–26). Montréal, Canada: Association for Computational Linguistics. Retrieved 2020-06-22, from https://www.aclweb.org/anthology/W12-2103

Waseem, Z. (2016, November). 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 (pp. 138–142). Austin, Texas: Association for Computational Linguistics. Retrieved 2020-10-16, from https://www.aclweb.org/anthology/W16-5618 doi: 10.18653/v1/W16-5618

Waseem, Z., Davidson, T., Warmsley, D., & Weber, I. (2017). Understanding abuse: A typology of abusive language detection subtasks. In Proceedings of the first workshop on abusive language online (pp. 78–84).

Waseem, Z., & Hovy, D. (2016, June). Hateful Symbols or Hateful People? Predictive Features for Hate Speech Detection on Twitter. In Proceedings of the NAACL Student Research Workshop (pp. 88–93). San Diego, California: Association for Computational Linguistics. Retrieved 2020-01-27, from https://www.aclweb.org/anthology/N16-2013 doi: 10.18653/v1/N16-2013

Waseem, Z., Thorne, J., & Bingel, J. (2018). Bridging the Gaps: Multi Task Learning for Domain Transfer of Hate Speech Detection. In J. Golbeck (Ed.), Online Harassment (pp. 29–55). Cham:
TOWARDS GENERALISABLE HATE SPEECH DETECTION

Springer International Publishing. Retrieved 2020-01-08, from https://doi.org/10.1007/978-3-319-78583-7_3 doi: 10.1007/978-3-319-78583-7_3

Wiegand, M., Ruppenhofer, J., & Kleinbauer, T. (2019, June). Detection of Abusive Language: the Problem of Biased Datasets. 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) (pp. 602–608). Minneapolis, Minnesota: Association for Computational Linguistics. Retrieved 2020-01-08, from https://www.aclweb.org/anthology/N19-1060 doi: 10.18653/v1/N19-1060

Wieting, J., Bansal, M., Gimpel, K., & Livescu, K. (2015). From paraphrase database to compositional paraphrase model and back. Transactions of the Association for Computational Linguistics, 3, 345–358.

Wulczyn, E., Thain, N., & Dixon, L. (2017). Ex machina: Personal attacks seen at scale. In Proceedings of the 26th international conference on world wide web (pp. 1391–1399).

Zampieri, M., Malmasi, S., Nakov, P., Rosenthal, S., Farra, N., & Kumar, R. (2019a). Predicting the type and target of offensive posts in social media. 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) (pp. 1415–1420).

Zampieri, M., Malmasi, S., Nakov, P., Rosenthal, S., Farra, N., & Kumar, R. (2019b, June). SemEval-2019 Task 6: Identifying and Categorizing Offensive Language in Social Media (OffensEval). In Proceedings of the 13th International Workshop on Semantic Evaluation (pp. 75–86). Minneapolis, Minnesota, USA: Association for Computational Linguistics. Retrieved 2019-11-02, from https://www.aclweb.org/anthology/S19-2010 doi: 10.18653/v1/S19-2010

Zhang, Z., & Luo, L. (2019). Hate speech detection: A solved problem? the challenging case of long tail on twitter. Semantic Web, 10(5), 925–945.

Zhang, Z., Robinson, D., & Tepper, J. (2018). Detecting Hate Speech on Twitter Using a Convolution-GRU Based Deep Neural Network. In A. Gangemi et al. (Eds.), The Semantic Web (pp. 745–760). Cham: Springer International Publishing. doi: 10.1007/978-3-319-93417-4_48

Zhao, R., Zhou, A., & Mao, K. (2016). Automatic detection of cyberbullying on social networks based on bullying features. In Proceedings of the 17th international conference on distributed computing and networking (pp. 1–6).