Towards Ethics by Design in Online Abusive Content Detection

Svetlana Kiritchenko  Isar Nejadgholi
National Research Council Canada
{svetlana.kiritchenko,isar.nejadgholi}@nrc-cnrc.gc.ca

Abstract

To support safety and inclusion in online communications, significant efforts in NLP research have been put towards addressing the problem of abusive content detection, commonly defined as a supervised classification task. The research effort has spread out across several closely related sub-areas, such as detection of hate speech, toxicity, cyberbullying, etc. There is a pressing need to consolidate the field under a common framework for task formulation, dataset design and performance evaluation. Further, despite current technologies achieving high classification accuracies, several ethical issues have been revealed. We bring ethical issues to forefront and propose a unified framework as a two-step process. First, online content is categorized around personal and identity-related subject matters. Second, severity of abuse is identified through comparative annotation within each category. The novel framework is guided by the Ethics by Design principle and is a step towards building more accurate and trusted models.

1 Introduction

With the increased use of social media, especially among young people, serious concerns about safety and inclusion in online communications have been raised. Up to 40% of users have reported being subjected to online harassment, cyberbullying, and other types of abuse (Duggan, 2017; Hinduja and Patchin, 2020). Often, the victims of online abuse are the most vulnerable parts of society: ethnic minorities, LGBTQ community, or people with disabilities. In response, many social media platforms strive to monitor online content and quickly remove abusive posts, but the sheer volume of posts poses significant problems. Automatic detection of abusive content can provide assistance and (partially) alleviate the burden of manual inspection.

Much NLP research has been devoted to the problem of automatic abusive content detection. It has been studied under a plethora of names, such as detection of flaming (Spertus, 1997), cyberbullying (Dadvar et al., 2013), online harassment (Golbeck et al., 2017), hate speech (Djuric et al., 2015; Davidson et al., 2017), toxicity (Dixon et al., 2018; Aroyo et al., 2019), and others. While these sub-areas of the general space of abusive language tackle similar problems, they differ in their focus and scope. Recent surveys by Schmidt and Wiegand (2017); Fortuna and Nunes (2018); Mishra et al. (2019); Vidgen et al. (2019); Vidgen and Derczynski (2020); Salawu et al. (2020) summarize the advancements in these areas focusing mostly on the technical issues and the variety of machine learning approaches proposed for the tasks.

In this paper, we examine the general area of abusive language detection from the ethical viewpoint. We bring together all the related sub-fields, and survey the past work focusing on the different formulations of the task and the common data collection and annotation techniques. We discuss challenges that the field faces from the ethical perspective, including fairness and mitigation of unintended biases, transparency and explainability, safety and security. In accordance with the Ethics by Design principle, we propose to bring the ethical issues to the early stages of system development: the task formulation and data collection and annotation.

Typically, the task has been defined as a binary classification problem (abusive vs. non-abusive). However, the social and ethical implications of the task call for more fine-grained labelling of abuse. A few attempts have been made to separate abusive language into sub-categories, such as hate speech, threats, aggressive, or offensive

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1 We use the term abusive broadly, covering the full range of inappropriate and disturbing content, from simple profanities and obscene expressions to threats and severe insults.
language, but the obscure boundaries between the sub-categories make the task challenging even for human annotators (Poletto et al., 2017; Founta et al., 2018). To overcome this challenge, we propose to annotate abusive texts for severity of abuse using comparative annotation techniques. We argue that severity is a simpler yet more practical dimension for abuse categorization. Further, employing comparative annotation would generate fine-grained (or continuous) severity scores while improving the overall reliability of annotations (Goffin and Olson, 2011; Kiritchenko and Mohammad, 2017).

Besides severity of abuse, the subject matter (or the target of abuse) is a crucial aspect of an abusive text (Waseem et al., 2017; Vidgen et al., 2019; Zampieri et al., 2019a). Knowing if the text (abusive or non-abusive) talks about an individual, a group of people, or an entity closely associated with a specific identity group (e.g., Muslims, gay people, etc.) can help in measuring and mitigating unintended biases in data and model outputs, and in transparency and explainability of the models.

Overall, the contributions of this work are as follows:

- We survey the existing works on abusive language detection (including various sub-areas, such as detection of hate speech, cyberbullying, online harassment, etc.) focusing on task formulation and data collection and annotation methods;
- We enumerate the main challenges of the task with regard to ethical issues, such as fairness, explainability, and safety;
- We propose a novel framework comprising two dimensions, severity of abuse and subject matter of an utterance, and outline the ways in which data collection and annotation can be adjusted to the framework. While identifying target groups subjected to abuse have been explored in previous work, annotating for severity of abuse using comparative annotation techniques has not been considered before. We further discuss how the proposed framework can help in addressing the technical and ethical issues.

We focus on abuse detection in online texts, though the framework can be applied to other media (images, video, speech) and multimodal contexts.

2 Overview of the Common Practices

We start with reviewing the common practices of formulating the task of online abuse detection and the methods for collecting and annotating datasets.

2.1 Task Formulation for Automated Abuse Detection

The abusive content detection task has typically been defined as a supervised classification problem across various definitions and aspects of abusive language. In addition to the main task of determining whether a text is abusive or not, several other dimensions have been explored, including expression of abuse, target of abuse, and legality of abuse (Waseem et al., 2017; Fišer et al., 2017; Poletto et al., 2017; Vidgen et al., 2019; Niemann et al., 2019; Zufall et al., 2020).

Expression of abuse: Online abuse can be expressed in different forms, such as hate speech, insults, physical threats, stereotyping, and more. Focusing on slightly different aspects of abuse, these categories have obscure boundaries, and are often challenging for humans and machines to split apart (Poletto et al., 2017; Founta et al., 2018).

Target of abuse: Abusive speech can be directed towards particular person(s) or entities, or contain undirected profanities and indecent language (Zampieri et al., 2019a). While obscene language, in general, can be disturbing to some audiences, abuse targeting specific individuals or groups is often perceived as potentially more harmful and more concerning for society at large. Therefore, majority
of research on abusive language detection has been devoted to targeted abuse. Waseem et al. (2017) distinguished two target types: an individual and a generalized group. They argued that the distinction between an attack directed towards an individual or a generalized group is important from both the sociological and the linguistic points of view. Thus, this distinction may call for different handling of the two types of abusive language when manually annotating abusive speech and when building automatic classification systems. For example, in research on cyberbullying, where abusive language is directed towards specific individuals, more consensus in task definition and annotation instructions can be found, and higher inter-annotator agreement rates are often observed (Dadvar et al., 2013).

A third target type—entity or concept—can also be considered (Zampieri et al., 2019a; Vidgen et al., 2019). Acceptable criticism of an entity (e.g., country), a concept (e.g., religion), an organization, or an event, can be semantically similar to abusive language. However, there is often a thin line between criticizing a concept and attacking people associated with the concept (e.g., an anti-Islamic propaganda can induce hatred towards Muslims).

**Legality of abuse:** Some types of abusive statements, such as hate speech and defamatory allegations, are not only morally unacceptable, but also illegal in several countries. To automatically determine if a statement is illegal, the corresponding laws need to be translated into manageable NLP tasks (Fišer et al., 2017; Zufall et al., 2020). However, the definitions of illegal online abuse vary across jurisdictions and typically cover only the most severe cases of abuse that can threaten the society at large. Therefore, the NLP research community should focus on a broader problem and design solutions that can be easily configurable for a specific set of requirements.

### 2.2 Data Collection

Several datasets manually annotated for abuse detection have been made available. Datasets can be collected from a single platform, such as Yahoo! (Djuric et al., 2015), Wikipedia (Wulczyn et al., 2017), Facebook (Kumar et al., 2018), Twitter (Waseem and Hovy, 2016; Davidson et al., 2017; Founta et al., 2018), or from multiple discussion forums (Van Brunaene et al., 2020).

Generally, it is laborious and costly to build an abuse detection corpus that is balanced with respect to hateful and harmless comments (Schmidt and Wiegand, 2017). Since abusive behaviour is relatively infrequent, random sampling results in datasets extremely skewed towards benign samples (Founta et al., 2018). Existing sampling strategies rely on known abusive/profane words, words describing the target populations, or monitoring users known for abusive behavior. A combination of random sampling and targeted search have also been used (Chatzakou et al., 2017; Wulczyn et al., 2017; Founta et al., 2018).

Sometimes, specific data collection procedures are defined based on the task at hand. For example, Hosseinmardi et al. (2015) used a snowball sampling method starting from a small number of users who posted offensive content on Instagram. Waseem and Hovy (2016) focused on sexism and racism, and collected tweets matching query words that are likely to occur in these cases. Davidson et al. (2017) used a lexicon of words and phrases identified by users as related to hate speech.

### 2.3 Data annotation

Tversky and Kahneman (1974) were the first psychologists that showed how humans employ heuristics to make judgements under uncertainty. These heuristics are formed based on complex factors and lead to systematic personal biases. On top of the general issue of subjectivity, in the case of abuse detection, a different understanding of what to consider abusive language resulted in sometimes contradictory annotation guidelines, and incompatible and erroneous datasets. For example, van Aken et al. (2018) questioned 10–15% of manually obtained labels on two widely used datasets, Kaggle Toxicity by Jigsaw and Google² and the one by Davidson et al. (2017). Waseem et al. (2017) and Nobata et al. (2016) observed that expert annotators reach higher inter-rater agreements and produce better quality annotations compared to crowd-sourced workers.

To minimize the effect of subjectivity, some of the datasets are annotated by multiple annotators. The proportion of majority votes per instance represents the level of agreement, and can serve as a rough estimate for severity of abuse. However, most often the votes are aggregated into a single label. Wiegand et al. (2019) and Davidson et al. (2017) used majority voting whereas Gao

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²https://www.kaggle.com/c/jigsaw-toxic-comment-classification-challenge
and Huang (2017) annotated a statement as hate speech if at least one annotator labeled it as hateful. Golbeck et al. (2017) collected judgments from two trained annotators, and a third annotator was employed only if the first two disagreed.

3 Current Technical and Ethical Challenges

In this section, we highlight common technical and ethical issues related to the currently employed task definition and the available datasets, regardless of applied machine learning techniques.

Task Formulation: In practical applications, the definitions of abusive language heavily rely on community norms and context and, therefore, are imprecise, application-dependent, and constantly evolving (Chandrasekharan et al., 2018). To make the task more tractable and focused, previous research has mostly concentrated on specific types of online abuse (e.g., hate speech, sexism, personal attacks). However, it has been shown that defining and annotating types of abuse are challenging tasks and often result in inconsistent definitions across studies, highly overlapping categories, and low inter-annotator agreements (Waseem et al., 2017; Poletto et al., 2017; Founta et al., 2018).

Recently, the complexity of the task formulation has been brought to the attention of the community, and several studies have proposed multi-level frameworks to address the task. Waseem et al. (2017) mapped the different types of abuse to two-dimension: identity- versus person-directed abuse and explicit versus implicit abuse. They argued that inter-annotator agreement is high when the abuse is directed to a person and explicit and low when the abuse is generalized and implicit. Founta et al. (2020) demonstrated that many different definitions are being used for equivalent concepts, which makes most of the publicly available datasets incompatible. They suggested that hierarchical multi-class annotation schemas should be deployed to formulate the online abuse detection task. Sap et al. (2020) formulated offensive language detection as a hierarchical task that combines structured classification with reasoning on social implications. They trained a model that translates an offensive statement to the implied stereotype that is hurtful to the target demographic. Assimakopoulos et al. (2020) formulated hate speech as hierarchical and multi-layer inferences on sentiment, target, expression of abuse and violence.

Because of the complexities of task formulation, most of the studies focus on one specific dataset, and combining existing datasets is not a trivial task. Moreover, the scope of studied abusive behaviors has been limited (Jurgens et al., 2019).

Sampling Bias: Sampling techniques deployed to boost the number of abusive examples may result in a skewed distribution of concepts and entities related to targeted identity groups. These unintended entity misrepresentations often translate into biased abuse detection systems. Dixon et al. (2018) and Davidson et al. (2019) focused on the skewed representation of vocabulary related to racial demographics in the abusive part of the dataset, and showed that adding counter-examples (benign sentences with the same vocabulary) would mitigate the bias to some extent. Park et al. (2018) measured gender bias in models trained on different abusive language datasets and suggested various mitigation techniques, such as debiasing an embedding model, proper augmentation of training datasets, and fine-tuning with additional data. Nejadgholi and Kiritchenko (2020) explored multiple types of selection bias and demonstrated that the ratio of offensive versus normal examples leads to a trade-off between False Positive and False Negative error rates. They concluded that this ratio is more important than the size of the training dataset for training effective classifiers. They also showed that the source of the data and the collection method can lead to topic bias and suggested that this bias can be mitigated through topic modeling.

Annotation Bias: Besides skewed data representations resulting from data sampling, annotator bias is another barrier for building fair and robust systems. Wilhelm and Joeckel (2019) studied the influence of social media users’ personal characteristics on the evaluation of hate comments, focusing on abuse aimed towards women and sexual minorities. Their results indicate that moral judgments can be gendered. Breitfeller et al. (2019) used the degree of discrepancies in annotations between male and female annotators to surface nuanced microaggressions. Also, it has been shown that annotators’ knowledge of different aspects of hateful behaviour can have a significant impact on the performance of trained classification models (Waseem, 2016). Similarly, annotators’ insensitivity or unawareness of dialect can lead to biased annotations and amplify harms against racial minorities (Waseem et al., 2018; Sap et al., 2019).
Quantifying Bias: Even though the developers of datasets and models are cognizant of the risk of various biases, quantifying the extent of this risk is challenging. Dixon et al. (2018) proposed a way of measuring bias in trained models by building a synthetic dataset and using an evaluation metric that computes error disparity across identity groups. Kaggle competition on the Unintended Bias in Toxicity Classification, introduced a set of metrics that measure unintended bias for identity references across multiple dimensions. Also, different definitions and frameworks of fairness have been used for the evaluation of automatic abuse detection systems to encourage the development of systems that are optimized not only for the overall performance but also for fair outputs across different target groups (Borkan et al., 2019; Garg et al., 2019). Dinan et al. (2020) decomposed gender bias in text along several pragmatic and semantic dimensions and proposed classifiers for controlling gender bias.

Embedding models are one of the important sources of bias in natural language processing systems. There has been an active line of work that aims to quantify bias and stereotypes in language models that generate text representations. Early works focused on gender and racial bias and introduced association tests for measuring bias in word embeddings (Bolukbasi et al., 2016; Caliskan et al., 2017; Manzini et al., 2019). For contextualized word embeddings, May et al. (2019) and Kurita et al. (2019) used pre-defined sentence templates, and Nadeem et al. (2020) and Nangia et al. (2020) collected crowd-sourced sentences to measure stereotypical biases hidden in language models. Not only do pre-trained neural language models reflect social biases, they are also prone to generating racist, sexist, or otherwise toxic language which hinders their safe deployment (Gehman et al., 2020). However, it is still unclear how the bias and toxicity present in language models impact the output of the trained classifiers.

Generalizability: Wiegand et al. (2019) showed that sampling bias can limit the generalizability of trained models. Depending on the sampling method and the platform that the dataset is collected from, some datasets are mostly comprised of explicitly abusive texts while others mainly contain sub-types of implicit abusive language such as stereotypes. The study demonstrated that models trained on datasets with explicit abuse and less biased sampling perform well on other datasets with similar characteristics, whereas datasets with implicit abuse and biased sampling contain specific features usually not generalizable to other datasets. Nejadgholi and Kiritchenko (2020) demonstrated that platform-specific topics can negatively impact the generalizability of the trained classifiers. They showed that removing over-represented benign topics can improve the generalization across datasets.

Explainability: As the impact of AI becomes more significant in our daily lives, developers of automatic systems are expected to earn the trust of users by providing explanations for automatically made decisions. Traditional lexicon and feature-based models are interpretable to some extent as they use features understandable by humans. Several lexicons of abusive expressions have been built manually, automatically, and semi-automatically (Razavi et al., 2010; Gitari et al., 2015; Wiegand et al., 2018). In feature-based systems, bag-of-words and character n-grams have been most frequently used, but some other explainable features, such as the ones derived from sentiment analysis, tone analysis, subjectivity, and topic modelling, have also been employed (Fortuna and Nunes, 2018). However, the accuracy of lexicon and feature-based systems is often significantly lower than the accuracy of deep learning models (Dixon et al., 2018; Gunasekara and Nejadgholi, 2018; Founta et al., 2019).

Neural networks, on the other hand, are effectively black boxes. Recent research has leveraged the LIME (locally interpretable model-agnostic explanations) algorithm in an attempt to interpret a model’s representation of abusive statements (Srivastava and Khurana, 2019; Mahajan et al., 2020). LIME’s explanations consist of words highly weighted by the model, but no further information is provided on why a text is classified as abusive (Ribeiro et al., 2016). Similarly, attention mechanisms embedded in deep learning architectures were used to identify the abusive parts of a text (Chakrabarty et al., 2019). However, it is not clear if such mechanisms provide meaningful explanations of a model’s decisions (Jain and Wallace, 2019; Wiegreffe and Pinter, 2019).

Output probability (or confidence) scores produced by classifiers have been used to explain the severity of abuse (Hosseini et al., 2017; Gröndahl et al., 2018). However, it is not clear how well these probabilities correspond to the human perception
of severity and in what ways they might be affected by sampling methods.

Another approach to explainability is through more comprehensive data annotation so that more particulars can be learned directly from training data. For example, models trained on the Kaggle Toxicity dataset labelled for five sub-categories of toxicity provide more information than the previous versions of this dataset annotated with binary labels (Wulczyn et al., 2017). Another example is the OffensEval dataset that includes annotations for the target of abuse (individual, group, or other) (Zampieri et al., 2019b). Sap et al. (2020) employed modern large-scale language models in an attempt to automatically generate explanations as social bias inferences for abusive social media posts that target members of identity groups. They asked human annotators to provide free-text statements that describe the targeted identity group and the implied meaning of the post in the form of simple patterns (e.g., “women are ADJ”, “gay men VBP”). They showed that while the current models are capable of accurately predicting whether the online post is offensive or not, they struggle to effectively reproduce human-written statements for implied meaning.

Transparency: Mitchell et al. (2019) introduced the concept of model cards as a means to address transparency of deep learning models. They urged the developers of models to report the details of data on which the models were trained and clarify the scope of use, including the applications where the employment of the model is not recommended. As an example, they presented a model card for an automatic abuse detection system, Perspective API (Jigsaw, Perspective API, 2017). Similar concepts, data statements (Bender and Friedman, 2018) and datasheets for datasets (Gebru et al., 2018), were proposed to standardize the process of documenting datasets. Bender (2019) explained how transparent documentation can help in mitigating the ethical risks.

Safety and Security: Several studies have shown that trained abuse detection systems can be deceived or attacked by malicious users. Hosseini et al. (2017) demonstrated that an adversary can query the system multiple times and find a way to subtly modify an abusive phrase resulting in significantly lowering confidence that the phrase is abusive. Gröndahl et al. (2018) showed that adding a positive word such as ‘love’ to an abusive comment can flip the model’s predictions. They studied seven models trained for hate speech detection and concluded that although character-based models are more resistant to attacks, model variety is less important than the type of training data and labelling criteria. Further, Kurita et al. (2020) observed that in spite of rich sub-word representations, a BERT-based classifier can be deceived by inserting a specific rare word to an abusive sentence. Kalin et al. (2020) proposed a structured approach for securing a toxicity detection classifier in a production setting.

4 A Novel Framework for Abusive Language Detection

To address some of the issues outlined in the previous section, we propose a novel framework for categorizing online abusive language. We identify two primary dimensions of interest, designed to cover the full range of the spectrum, from most genial, non-abusive to extremely abusive texts:

1. subject matter of utterance
2. severity of abuse

Subject Matter: As previous research demonstrated, it is essential from both legal and linguistic points of view to identify the target of abuse—who (or what) the abuse is directed towards. We extend this idea to cover both abusive and non-abusive texts, and propose to specify the subject matter of an utterance. We define subject matter as the topic of a factual statement or the target of an opinion. Having all types of texts, positive, negative, and neutral opinions as well as factual statements, annotated for subject matter can help in balancing the distribution of abusive and non-abusive instances for different types of targets and broadening the range of instances related to the same subject matter. However, we consider only subject matters that can potentially be targets of abuse, namely people (individuals and groups) and entities related to identity groups. All other subject matters are grouped under the category ‘other’. Identity groups are sections of population with significant membership that are usually defined by ethnicity, religion, gender, or sexual orientation, but can also be defined by other characteristics, such as physical appearance, occupation, political affiliation, etc. Entities related to identity groups include concepts (e.g., Islam is related to Muslims), events (e.g., Pride Parade is related to the LGBTQ community), ideas, etc. While negative remarks towards entities would normally
constitute an acceptable form of criticism, having such instances in the training datasets would ensure the systems’ exposure to examples of non-abusive texts linguistically similar to abusive instances.

When the subject matter is people, we distinguish personal and identity group related reference. If the subject matter (whether a single person or a group) is referred to by identity terms associated with an identity group, we call it ‘related to identity group’; otherwise, we classify it as ‘personal’. Notice that unlike previous research, we do not distinguish subject matters at the level of individuals and groups as similar legal considerations and linguistic patterns are observed for both types. Identity group related subject matters can be further characterized by the basis on which the identity group is defined (e.g., race) as well as by the specific identity (e.g., African-Americans).

Figure 1 shows the full multi-level hierarchical taxonomy for subject matters. Since an utterance can refer to more than one identity group, multiple categories can be assigned to an instance.

Severity of Abuse: Online abusive content embodies a spectrum of practices that differ in motivation, expression, and consequences (Shepherd et al., 2015; Pohjonen and Udupa, 2017). While separating different forms of online abuse (e.g., threats, insults, hate speech) proved problematic, a more attainable, yet valuable objective can be determining the level of severity of abuse—a point on the scale from non-abusive, friendly instances to extremely abusive, violent messages. Ordering textual instances by the severity of abuse can help human moderators to prioritize messages for manual inspection and to promptly respond to potentially dangerous ones.

The common technique for annotating items on a fine-grained ordinal scale is rating scales. However, traditional rating scales suffer from a number of shortcomings, including inconsistencies in annotations by different annotators and by the same annotator over time, scale region bias, and fixed granularity (Baumgartner and Steenkamp, 2001; Presser and Schuman, 1996). To overcome these problems, human annotators can be asked to provide comparative judgements instead (Goffin and Olson, 2011; Aroyo et al., 2019).

An efficient comparative technique, widely used in marketing research, is Best–Worst Scaling (Louviere and Woodworth, 1990; Louviere et al., 2015). In Best–Worst Scaling (BWS), an annotator is presented with $n$ items (where $n$ is typically 4 or 5) and asked to select the best item (the most abusive) and the worst item (the least abusive). All the items to be annotated are organized in $m \times n$-tuples in such a way that ensures each item is annotated multiple times and compared with a diverse set of other items. After annotating around $1.5 \times N$ to $2 \times N$ such $n$-tuples (where $N$ is the total number of textual instances to be annotated), a real-valued score of severity can be calculated for each textual instance, and a ranked list of instances by severity can be obtained (Flynn and Marley, 2014; Kiritchenko and Mohammad, 2016).

Since BWS tuples are formed randomly (though, ensuring the diversity of comparisons for each item), for some tuples the choice of the most abusive and/or least abusive texts might be apparent for most annotators. Extremely abusive texts would be often selected as the most abusive and get a high severity score while genial and friendly texts would mostly be selected as the least abusive and get low scores. Yet, in some tuples two or more texts might express similar levels of severity. In such cases, since annotators are forced to make a decision for each tuple, the answer by each annotator would be selected randomly between these similarly abusive items. This means that the items would be chosen (on average) by the same number of annotators, and, therefore, the aggregated scores for these items would be close to each other.

It has been shown that Best–Worst Scaling produces more reliable annotations as compared to the traditional rating scales, especially on linguistically more complex items (Kiritchenko and Mohammad, 2017). Figure 2 demonstrates an example of a hypothetical BWS annotation for severity of abuse. Table 1 shows examples of texts annotated according to the entire framework.
Claiming to be transgender is a sign of mental illness. The military has no place for people with mental disabilities.

Transgender people have a gender identity or gender expression that differs from their sex assigned at birth.

Shove it up your f*cking *ss and burn in hell.

This movie was a f*cking piece of sh*t.

I personally believe that Islam requires a Reformation or an Enlightenment.

Table 1: Examples of texts with hypothetical annotations. Severity scores are on the scale from 0 (least abusive) to 1 (most abusive). The absolute values of severity scores are not meaningful but the relative values distinguish between facts, criticism, obscene sentences, and highly abusive contents. Some of the texts are taken from the Kaggle Unintended Bias in Toxicity dataset by Jigsaw and Google.

| Text                                                                 | Subject matter       | Severity score |
|----------------------------------------------------------------------|----------------------|----------------|
| Claiming to be transgender is a sign of mental illness. The military has no place for people with mental disabilities. | People, Transgender  | 0.8            |
| Transgender people have a gender identity or gender expression that differs from their sex assigned at birth. | People, Transgender  | 0.0            |
| Shove it up your f*cking *ss and burn in hell.                     | People, Personal     | 0.0            |
| This movie was a f*cking piece of sh*t.                            | Entities, Other      | 0.9            |
| I personally believe that Islam requires a Reformation or an Enlightenment. | Entities, Islam      | 0.2            |

Table 1: Examples of texts with hypothetical annotations. Severity scores are on the scale from 0 (least abusive) to 1 (most abusive). The absolute values of severity scores are not meaningful but the relative values distinguish between facts, criticism, obscene sentences, and highly abusive contents. Some of the texts are taken from the Kaggle Unintended Bias in Toxicity dataset by Jigsaw and Google.

5 Advantages of the Novel Framework

The proposed framework addresses some of the problems outlined earlier.

Task Formulation: The framework focuses on a general class of abusive behavior and aims to extend the scope of studied online abuse without the painful process of enumerating and precisely defining a myriad of types. Instead, many types can be roughly defined as regions in the proposed two-dimensional space of subject matter and severity of abuse. For example, ‘physical threat’ can be mapped to (subject matter: people, severity: high), and ‘personal attack’ can be mapped to (subject matter: personal, severity: moderate to high). In this way, separate research efforts are expected to produce more compatible and more applicable outputs. Still, listing different types of abuse with their coarse-grained definitions and examples can be extremely helpful in guiding data collection and annotation.

Data Collection and Sampling Bias: To ensure adequate representation for different identity groups, data can be collected for each group using abusive and benign query terms that refer to members of that group or to entities associated with the group. The sets of terms can be acquired manually or semi-automatically using unsupervised techniques, such as topic modeling, clustering, etc. Textual messages collected in this way would include abusive as well as neutral and friendly utterances about an identity group or closely related concepts, cover a variety of topics, and contain explicit and implicit language. However, this method of data collection does not specifically target the ‘personal’ category. It can also result in low proportions of abusive texts and introduce unintended biases, such as topic bias (Wiegand et al., 2019). Therefore, the data collection should be spread out over a period of time (to diversify the set of covered topics) and supplemented with other techniques, such as sampling based on lexicons of common abusive words and expressions, sampling of messages written by users known for abusive behavior, and random sampling. Further, data from existing abusive language datasets as well as abusive examples reported by users on dedicated websites, such as HeartMob and Microaggressions, are valuable data sources.

Collecting data with a specific focus on identity groups allows to account for fairness in representation at the beginning of the development cycle.

The set of identity groups represented in a dataset is decided apriori based on a research focus, a data source, and available resources. A preliminary round of exploratory annotations can be beneficial to expand the list of commonly addressed groups (e.g., women, African-Americans, immigrants) to other identities. Further exploratory rounds can be run periodically to include new, previously non-existent or missed, categories.

Annotation Bias: Manually annotating for sever-

![Image](image_url)
ity of abuse is a particularly subjective task, and often requires specific expertise obtained through training or life experiences. We recommend having data annotated for subject matter first, and then the severity annotations can be done independently for different identity groups and involve corresponding annotator pools. Most often, online abuse is directed towards minorities and marginalized communities, therefore it is vital to involve and consult the members of these communities to adequately represent their values and to reduce data annotation bias (Blackwell et al., 2017). In cases where community involvement in annotation is infeasible, professionals specializing in related issues or trained annotators can be employed.

**Quantifying Bias:** Although the new framework does not guarantee the fairness of trained models, it allows measuring and mitigating bias through comparability of the overall automatic detection error or the False Positive and False Negative error rates for different identity groups.

**Generalizability:** The conceptions of target groups based on specific identities are expected to be applicable across online platforms and domains. The generalizability of trained models will be improved by increasing the proportion of texts with implicit meaning and texts that provide acceptable criticism of entities and concepts. Further, the proposed framework will improve the generalizability by allowing data annotators to use the full spectrum of the severity dimension without forcing them to decide where the boundary between abusive and benign languages lies. That decision is application and domain specific and can be left to human moderators, making trained systems suitable to a greater variety of applications.

**Explainability:** Within the framework, the systems are trained to predict and output the detailed information on the target of abuse and the level of severity that can serve as basic explanations for human and machine decisions. More comprehensive explanations can sometimes be derived when the targeted group is coupled with the words and expressions in the message that are considered particularly insulting for that group. Similarly, knowing the target of abuse is imperative in recognizing and explaining implicit abuse and stereotypical references. Further, these explanations can serve educational purposes when employed in a system that assists users at the time of message creation.

**Transparency:** The framework provides a means to measure the class imbalances in a dataset across target groups. Reporting the limitations of a dataset is essential for transparency and helps practitioners to better identify the scope of use of trained models.

**Safety and Security:** The vulnerability of classification systems due to their high sensitivity to specific words suggests that those words are over-represented in the training datasets. The proposed framework can improve the safety of such systems by including more training examples with implicit meaning and training systems to learn fine-grained information which is not directly correlated with explicitly abusive words.

## 6 Limitations and Ethical Considerations

Delineating target categories based on identity groups, selecting search terms associated with the groups, and annotating for fine-grained target categories can propagate harmful stereotypes and reinforce social iniquity (Beukeboom and Burgers, 2019). NLP researchers should ground their work in the relevant literature from other disciplines, such as sociology, sociolinguistics, and social psychology, and engage with the lived experiences of members of affected communities in order to minimize such adverse effects (Blodgett et al., 2020).

Viewing and annotating abusive content for prolonged periods of time can cause significant distress to human annotators (Roberts, 2016; Vidgen et al., 2019). This concern is even more critical for members of marginalized groups annotating abusive texts directed towards their community. To reduce the possible harmful effects on mental health of the annotators, special procedures can be put in place, including the right consent process, comprehensive instructions, limited exposure time, fair compensation, and mental health support. Annotators should be made aware of why they are labeling such contents and how their work contributes to the safety of online platforms for their communities.

## 7 Conclusion and Future Directions

A new framework structured around the dimensions of **subject matter** and **severity of abuse** is proposed as a step towards building less biased, more accurate and generally more trustable automatic abuse detection systems. Comprehensive data collection and annotation proposed within the framework allow for better control and transparency on data characteristics and model performance with regard to unintended biases, generalizability, ex-
plainability, and safety. As the next step, the usability and efficacy of the proposed framework need to be tested. Thus, future work will include building an extensive list of identity groups subjected to online abuse, assembling lexicons of terms associated with the groups for targeted sampling, and writing detailed annotation guidelines for both annotation steps. Then, empirical datasets in multiple languages can be collected, annotated, and released to the research community for experimenting and building trustable machine learning models.

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