Toxicity Detection can be Sensitive to the Conversational Context

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Abstract
User posts whose perceived toxicity depends on the conversational context are rare in current toxicity detection datasets. Hence, toxicity detectors trained on existing datasets will also tend to disregard context, making the detection of context-sensitive toxicity harder when it does occur. We construct and publicly release a dataset of 10,000 posts with two kinds of toxicity labels: (i) annotators considered each post with the previous one as context; and (ii) annotators had no additional context. Based on this, we introduce a new task, context sensitivity estimation, which aims to identify posts whose perceived toxicity changes if the context (previous post) is also considered. We then evaluate machine learning systems on this task, showing that classifiers of practical quality can be developed, and we show that data augmentation with knowledge distillation can improve the performance further. Such systems could be used to enhance toxicity detection datasets with more context-dependent posts, or to suggest when moderators should consider the parent posts, which often may be unnecessary and may otherwise introduce significant additional cost.

1 Introduction

Online fora are used to facilitate discussions, but can suffer from hateful, insulting, identity-attacking, profane, or otherwise abusive posts. Such posts are called toxic (Borkan et al., 2019), offensive (Sap et al., 2020) or abusive (Thylstrup and Waseem, 2020), and systems detecting them (Waseem and Hovy, 2016; Pavlopoulos et al., 2017b; Badjatiya et al., 2017) are called toxicity (or offensive or abusive language) detection systems. What most of these systems have in common, besides aiming to promote healthy discussions online (Zhang et al., 2018), is that they disregard much of the conversational context, making the detection of context-sensitive toxicity a lot harder.

We consider context to be information relevant to help understand the meaning and intention of a post; when context is missing, there is more ambiguity in the interpretation of a post. Context is very diverse in nature, because human communication is diverse; people may inhabit any number of roles in their relationships with others. A person on stage in a play about a murder might engage in dialog that would be illegal in other contexts. Far from being inappropriate, people may pay to see this behavior and applaud it. It is not always clear what social norms, jurisdictional mandates, and enforcement regimes apply. A comedian may deliberately engage in provocative language to entertain, inspire or critique society, but a disruptive heckler might still be removed by the venue’s bouncers.

In online discourse, context typically includes personal information about the authors (Pavlopoulos et al., 2017c), the interlocutors, metadata about the conversation or subtle references to specific subjects and topics. Within the scope of this work we presume some socially constructed context in the form of common notions about what constitutes appropriate communicative intent in a social media setting – at least enough that persons tasked with evaluating the communicative intent can sensually make judgements from the surface text alone. This concept, of common socially agreed norms, is obviously not a black and white concept, and while certainly worthy of deeper analysis, it is not the focus of our study here. Instead we follow the common practice of having these background social norms manifested through crowd-sourcing platforms and measured at a very abstract level by inter-annotator agreement metrics. Given this approach, we focus on the past conversational context, specifically the previous post in a discussion. For instance, a post “Keep the hell out” is likely to be
considered as toxic by a moderator who has not seen that the previous post was “What was the title of that ‘hell out’ movie?”.

Although toxicity datasets that include conversational context have recently started to appear, in previous work we showed that context-sensitive posts seem to be rare and this makes it hard for models to learn to detect context-dependent toxicity (Pavlopoulos et al., 2020). To study this problem, we construct and publicly release a context-aware dataset of 10,000 posts, each of which was annotated by raters who (i) considered the previous (parent) post as context, apart from the post being annotated (the target post), and by raters who (ii) were given only the target post, without any other previous conversational context.1

We limit the conversational context to the previous post of the thread, as in our previous work (Pavlopoulos et al., 2020), as a first step towards studying broader context-dependent toxicity. While this is still a very limited form of context, our previous work also highlighted the basic challenges of studying context: it is expensive and time consuming to consider on crowd-sourcing platforms, because of the challenges of ensuring that a person has in fact considered the context. The more context, and more subtle kinds of context, one attempts to include in a study, the harder it is to ensure annotators have accounted for it. Moreover context sensitive toxicity in posts is also rare; and thus it is reasonable to wonder if the impact of more indirect and subtle kinds of context is rarer still.

We then use our new dataset to study the nature of context sensitivity in toxicity detection, and we introduce a new task, context sensitivity estimation, which aims to identify posts whose perceived toxicity changes if the context (previous post) is also considered. Using the dataset, we also show that systems of practical quality can be developed for the new task. Such systems could be used to enhance toxicity detection datasets with more context-dependent posts, or to suggest when moderators should consider the parent posts, which may not always be necessary and may otherwise introduce significant additional cost. Finally, we show that data augmentation with teacher-student knowledge distillation can further improve the performance of context sensitivity estimators.

2 The New Dataset (CCC)

To build the dataset of this work, we used the publicly available Civil Comments (CC) dataset (Borkan et al., 2019). CC was originally annotated by ten annotators per post, but the parent post (the previous post in the thread) was not shown to the annotators. We randomly sampled 10,000 CC posts and gave both the target and the parent post to the annotators. We call this new dataset Civil Comments in Context (CCC). Each CCC post was rated either as NON-TOXIC, UNSURE, TOXIC, or VERY TOXIC, as in the original CC dataset. We unified the latter two labels in both CC and CCC to simplify the problem. To obtain the new in-context labels of CCC, we used the APPEN platform and five high accuracy annotators per post (annotators from zone 3, allowing adult and warned for explicit content),2 selected from 7 English speaking countries, namely: UK, Ireland, USA, Canada, New Zealand, South Africa, and Australia.3

The free-marginal kappa, a measure of inter-annotator agreement (Randolph, 2010), of the CCC annotations is 83.93 percent, while the average (mean pairwise) percentage agreement is 92 percent. In only 71 posts (0.07 percent) an annotator said UNSURE, meaning annotators were confident in their decisions most of the time. We exclude these 71 posts from our study, as there are too few to generalize about. The average length of target posts in CCC is only slightly lower than that of parent posts. Figure 1 shows this when counting the length in characters, but the same holds when counting words (56.5 vs. 68.8 words on average). To obtain a single toxicity score per post, we calculated the percentage of the annotators who found the post to be insulting, profane, identity-attack, hateful, or toxic in another way; all toxicity subtypes provided by the annotators were collapsed to a single toxicity label. This is similar to arrangements in the work of Wulczyn et al. (2017), who also found that training using the empirical distribution (over annotators) of the toxic labels (a continuous score per post) leads to better toxicity detection performance, compared to using labels reflecting the majority opinion of the raters (a binary label per post). See also Formaciari et al. (2021).

Combined with the original (out of context) annotations of the 10,000 posts from CC, the new

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1The dataset is released under a CC0 licence. It can be downloaded from https://github.com/ipavlopoulos/context_toxicity/tree/master/data.

2https://appen.com

3We chose populous majority English-speaking countries. The most common country of origin was USA.
Figure 1: Length of parent/target posts in characters.

Figure 2: Histogram (converted to curve) showing the distribution of toxicity scores according to annotators who were (IC) or were not (OC) given the parent posts.

The dataset (CCC) contains 10,000 posts for which both in-context (IC) and out-of-context (OC) labels are available. Figure 2 shows the number of posts (Y axis) per ground truth toxicity score (X axis). Orange (dashed) represents the ground truth obtained by annotators who were provided with the parent post when rating (IC), while blue (solid) is for annotators who rated the post without context (OC). The vast majority of the posts were unanimously perceived as NON-TOXIC (0.0 toxicity), both by the OC and the IC coders. However, IC coders found fewer posts with toxicity greater than 0.2, compared to OC coders. This is consistent with the findings of our previous work (Pavlopoulos et al., 2020), where we observed that when the parent post is provided, the majority of the annotators perceive fewer posts as toxic, compared to showing no context to the annotators. To study this further, in this work we compared the two annotation scores (IC, OC) per post, as discussed below.

For each post $p$, we define $s^{IC}(p)$ to be the toxicity score (fraction of coders who perceived the post as toxic) derived from the IC coders, and $s^{OC}(p)$ to be the toxicity derived from the OC coders. Then, their difference is $\delta(p) = s^{OC}(p) - s^{IC}(p)$. A positive $\delta$ means that raters who were not given the parent post perceived the target post as toxic more often than raters who were given the parent post. A negative $\delta$ means the opposite. Figure 3 shows that $\delta$ is most often 0, but when the toxicity score changes, $\delta$ is most often positive, i.e., showing the context to the annotators reduces the perceived toxicity in most cases. In numbers, in 66.1 percent of the posts the toxicity score remained unchanged while out of the remaining 33.9 percent, in 9.6 percent it increased (960 posts) and in 24.3 percent it decreased (2,408) when context was provided. If we binarize the ground truth (both for IC and OC) we get a similar trend, but with the toxicity of more posts remaining unchanged (i.e., 94.7 percent).

When counting the number of posts for which $|\delta|$ exceeds a threshold $t$, called context-sensitive posts in Figure 4, we observe that as $t$ increases, the number of context sensitive posts decreases. This means that clearly context sensitive posts (e.g., in an edge case, ones that all OC coders found as toxic while all IC coders found as non toxic) are rare. Some examples of target posts, along with their parent posts and $\delta$, are shown in Table 1.

Figure 3: Histogram of context sensitivity. Negative (positive) sensitivity means the toxicity increased (decreased) when context was shown to the annotators.

Figure 4: Number of context-sensitive posts ($|\delta| \geq t$), when varying the context-sensitivity threshold $t$. 

| Context-Sensitive Posts | 0 | 2000 | 4000 | 6000 | 8000 | 10000 |
|-------------------------|---|------|------|------|------|-------|
| Context-Sensitivity Threshold | 0 | 0.2 | 0.4 | 0.6 | 0.8 | 1.0 |

For an example of target posts, along with their parent posts and $\delta$, see Table 1.
3 Experimental Study

Initially, we used our dataset to experiment with existing toxicity detection systems, aiming to investigate if context-sensitive posts are more difficult to automatically classify correctly as toxic or non-toxic. Then, we trained new systems to solve a different task, that of estimating how sensitive the toxicity score of each post is to its parent post, i.e., to estimate the context sensitivity of a target post.

3.1 Toxicity Detection

We employed the Perspective API toxicity detection system, as is and with no further fine-tuning, to classify CCC posts as toxic or not.\(^4\) We either concatenate the parent post to the target one to allow the model to “see” the parent, or not.\(^5\) Figure 5 shows the Mean Absolute Error (MAE) of Perspective, with and without the parent post concatenated, when evaluating on all the CCC posts \((t = 0)\) and when evaluating on smaller subsets with increasingly context-sensitive posts \((|\delta| \geq t, t > 0)\). In all cases, we use the in-context (IC) gold labels as the ground truth. The greater the sensitivity threshold \(t\), the smaller the sample (Figure 4).

![Figure 5: Mean Absolute Error (Y-axis) when predicting toxicity for different context-sensitivity thresholds \((t; X-axis)\). We applied Perspective to target posts alone (w/o) or concatenating the parent posts (w).](image)

Figure 5: Mean Absolute Error (Y-axis) when predicting toxicity for different context-sensitivity thresholds \((t; X-axis)\). We applied Perspective to target posts alone (w/o) or concatenating the parent posts (w).

By contrast, if no context-sensitivity threshold is imposed \((t = 0)\) when constructing a dataset, the non-context sensitive posts \((|\delta| = 0)\) dominate (Figure 4), hence adding context mechanisms to toxicity detectors has no visible effect in test scores. This explains related observations in our previous work (Pavlopoulos et al., 2020), where we found that context-sensitive posts are too rare and, thus, context-aware models do not perform better on existing toxicity datasets.

Notice that the more we move to the right of Figure 5, the higher the error for both Perspective variants (with, without context). This is probably due to the fact that Perspective is trained on posts that have been rated by annotators who were not provided with the parent post (out of context; OC), whereas here we use the in-context (IC) annotations as ground truth. The greater the \(t\) in Figure 5, the larger the difference between the toxicity scores of OC and IC annotators, hence the larger the difference between the (OC) ground truth that Perspective saw during its training and the ground truth that we use here (IC). Experimenting with artificial parent posts (long or short, toxic or not) confirmed that the error increases for context-sensitive posts.

The solution to the problem of increasing error as context sensitivity increases (Figure 5) would be to train toxicity detectors on datasets that are richer in context-sensitive posts. However, as such posts are rare (Figure 4) they are hard to collect and annotate. This observation motivated the experiments of the next section, where we train context-sensitivity detectors, which allow us to collect posts that are likely to be context-sensitive. These posts can then be used to train toxicity detectors on datasets richer in context-sensitive posts.

3.2 Context Sensitivity Estimation

We trained and assessed four regressors on the new CCC dataset, to predict the context-sensitivity \(\delta\). We used Linear Regression, Support Vector Regression, a Random Forest regressor, and a BERT-based (Devlin et al., 2019) regression model (BERTr).\(^6\) The first three regressors use TF-IDF features. In the case of BERTr, we add a feed-forward neural network (FFNN) on top of the top-level embedding of the [CLS] token. The FFNN consists of a dense layer (128 neurons) and a \texttt{tanh} activation function, followed by another dense layer. The last dense layer has a single output neuron, with no activation function, that produces the context sensitivity

\(^4\)https://www.perspectiveapi.com

\(^5\)We are investigating better context-aware models.
**Table 1**: Examples of context-sensitive posts in CCC. Here $s^{OC}(p)$ and $s^{IC}(p)$ are the fractions of out-of-context or in-context annotators, respectively, who found the target post $p$ to be toxic; and $\delta = s^{OC}(p) - s^{IC}(p)$.

| PARENT OF POST $p$ | POST $p$ | $s^{OC}(p)$ | $s^{IC}(p)$ | $\delta$ |
|-------------------|----------|-------------|-------------|----------|
| Oh Don..... you are soooo predictable. | oh Chuckie you are such a tall tale. | 36.6% | 80% | -43.4% |
| Oh Why would you wish them well? They’ve destroyed the environment in their country and now they are coming here to do the same. | “They”? Who is they? Do all Chinese look alike to you? Or are you just revealing your innate bigotry and racism? | 70% | 0% | 70% |

Table 2: Mean Squared Error (MSE), Mean Absolute Error (MAE), Area Under Precision-Recall curve (AUPR), and ROC AUC of all context sensitivity estimation models. An average (B1) and a random (B2) baseline have been included. All results averaged over three random splits, standard error of mean in brackets.

|     | MSE ↓ | MAE ↓ | AUPR ↑ | AUC ↑ |
|-----|-------|-------|--------|-------|
| B1  | 2.3 (0.1) | 11.56 (0.2) | 12.69 (0.7) | 50.00 (0.0) |
| B2  | 4.6 (0.0) | 13.22 (0.1) | 13.39 (0.8) | 50.01 (1.6) |
| LR  | 2.1 (0.1) | 11.00 (0.3) | 30.11 (1.2) | 71.67 (0.8) |
| SVR | 2.3 (0.1) | 12.8 (0.1) | 28.66 (1.7) | 71.56 (1.0) |
| RFS | 2.2 (0.1) | 11.2 (0.2) | 21.37 (1.0) | 59.67 (0.3) |
| BERTr | **1.8 (0.1)** | **9.2 (0.3)** | **42.01 (1.3)** | **80.46 (1.3)** |

**4 Collecting Context Sensitive Posts**

In Section 2 we saw that context sensitive posts can be very rare in toxicity datasets (Figure 4). In Section 3 we showed that adding a simple context aware mechanism (concatenating the parent post) to an existing toxicity detection system can reduce the system’s error on context sensitive posts (Figure 5). However, the error of the toxicity detector remains high for context-sensitive posts. This problem can potentially be addressed by augmenting the current datasets with more context-sensitive posts. As shown in Section 3, a regressor trained to predict the context sensitivity of a post can achieve low error (Table 2). Hence, we assessed the scenario where a context sensitivity regressor is employed to obtain a dataset richer in context-sensitive posts.

We used our best context-sensitivity regressor (BERTr) to retrieve the 250 most likely context-sensitive posts from the 2M CC posts, excluding the 10,000 CCC posts. We then crowd-annotated the 250 posts in context (IC) as with CCC posts, keeping also the original out-of-context (OC) annotations. Table 3 shows examples of the 250 target posts obtained, along with their parent posts and $\delta$. We then repeated the same experiment, this time using 250 randomly selected posts from the 2M CC posts, excluding the 10,000 CCC posts and the 250 posts that were selected using BERTr. Figure 6 is the same as Figure 4, but we now consider the 250 randomly selected posts (dashed line) and the 250 posts that were selected using BERTr (solid line). As in Figure 4, we vary the context-sensitivity threshold $t$ on the horizontal axis. The 250 posts that were sampled using BERTr clearly
Figure 6: Number of context-sensitive posts ($|\delta| \geq t$), for different context-sensitivity thresholds ($t$), using 250 likely context-sensitive posts sampled with BERT (solid) or 250 randomly selected posts (dashed line).

Figure 7: Percentage of the 250 target posts, sampled with BERT (solid) or random (dashed line), for which the majority of annotators found the parent post useful when assessing the toxicity of the target post.

include more context-sensitive posts than the 250 random ones, with the threshold ($t$) in the range $0.1 \leq t < 0.7$, indicating that BERT can be successfully used to obtain datasets richer in context-sensitive posts. As in Figure 4, there are very few context-sensitive posts for $t \geq 0.7$.

In this experiment, we also asked the crowd-annotators to indicate whether the parent post was helpful or not, when assessing the toxicity of each target post. Figure 7 shows for how many of the 250 target posts (sampled using BERT or random) the majority of the annotators responded that the parent post was useful. We vary the sensitivity threshold ($t$) on the horizontal axis up to $t = 0.7$, since no posts are context-sensitive for $t > 0.7$ (Fig. 6). The perceived utility of the parent posts is clearly higher for the 250 posts sampled with BERT, compared to the 250 random ones, for all sensitivity thresholds. This again indicates that BERT can be used to obtain datasets richer in context-sensitive posts.

To verify the statistical significance of the finding that the annotators find the parent post useful more frequently in posts sampled with BERT than in random posts, we performed a paired bootstrap resampling, following the experimental setting of Koehn (2004). We sampled 100 posts from the 250 random posts, and 100 posts from the 250 posts obtained by using BERT, and we computed the percentage of posts where the majority of annotators found the parent post helpful, for random posts and BERT posts. By resampling 1,000 times, we find that this percentage is greater for BERT posts than for random posts, with a $P$-value of 0.05.

Finally, by turning the ground truth toxicity probabilities (for IC and OC annotation) into binary labels as in Section 3, we estimated a context sensitivity class ratio (fraction of context-sensitive posts out of all 250 posts), for the BERT-sampled and the randomly sampled posts. By using this class ratio, we found that 99 out of the 250 BERT-sampled posts (39.6 percent) were context sensitive, while only 43 out of the 250 randomly sampled posts (17.2 percent) were context-sensitive (22 percent points lower; i.e., 57 percent decrease). We verified the statistical significance of this finding (lower fraction) by using bootstrapping with a $P$-value of 0.05, as in the previous paragraph. We conclude that sampling with BERT leads to a higher context-sensitivity class ratio than random sampling.

5 Improving the Context-Sensitivity Regressor with Data Augmentation

We showed in the previous section that by employing a context sensitivity regressor (BERT was our best one) one can sample new sets of posts (e.g., from the 2M CC posts) that are richer in context-sensitive posts (by 22 percent points in our previous experiments) compared to random samples. By adding such richer (in context-sensitive posts) sets to an existing context sensitivity dataset (e.g., our CCC dataset), one can gradually increase the ratio of context-sensitive posts (which is low in CCC, see Fig. 4). A natural question then is whether one could improve the context-sensitivity regressor by re-training it on the augmented dataset, which is less dominated by context-insensitive posts (more balanced in terms of context-sensitivity). Ideally the newly sampled (and overall more context-sensitive) posts would
Table 3: Examples of context-sensitive posts in the sampled dataset. Here $s^{OC}(p)$ and $s^{IC}(p)$ are the fractions of out-of-context or in-context annotators, respectively, who found the target post $p$ to be toxic; and $\delta = s^{OC}(p) - s^{IC}(p)$.

| PARENT OF POST $p$ | POST $p$ | $s^{OC}(p)$ | $s^{IC}(p)$ | $\delta$ |
|-------------------|----------|-------------|-------------|----------|
| And since Thomas Aquinas never observed animals having gay sex in the wild, homosexuality never made it into the annals of natural law theory. | Animals having gay sex? You mean there are gay animals? So, when they're not "doing it" do they do other things like go to Madonna concerts? | 60% | 60% | 0% |
| Making a cake is a masterful art. Different states have different rules about doing it. Making the cake is a form of artistry and requires the cake maker to artistically express him/herself which means the cake maker is actively participating. Owning a gas station where random people pump their own gas does not require active participation. | Oh, ok. So like if you gas station had to pump gas for that gay man he should be able to refuse that, right? | 60% | 60% | 0% |
| And SCOTUS will slap Watson & Chump down yet again...those Oldmanny Sock-Puppets never learn. That threesome they shared back in the day must have been amazing. | Is the post implying that the judge is gay? I don’t understand the comment, please explain? Are gays involved in this and not Muslims and their relatives? * | 83.3% | 20% | 63.3% |
| The appeal court have one thing to do to it is legal or not, then it, that is what appeals judges do, and they did, they coward away cause they knew then could not rule it illegal sorry for your ignorance | The case has not yet been adjudicated on its merits (whether the Executive Order is illegal or not). Both the trial decision and the appeal decision were about staying the EO *until the trial on its merits* - i.e., an injection. I’d think about finding out some facts before calling someone else ignorant. Rex. | 80% | 20% | 60% |
| ...marriage, by definition, meant one man, one woman | The definitive dictionary of the English language, the OED, does not contain a single instance in which “modern” civilized society has included gay marriage. It does mention instances of “group” marriage in small, primitive societies, where all the men in a village are married to all the women. But those, as you know, are by far the exception. Actually, your argument bolsters my point. It was so universally understood at the foundation of the Nation that marriage meant man-woman that marriage did not need to be defined. Indeed, in most States, marriage could not have been defined so as to allow gay marriage, because until 1961, ALL 50 STATES outlawed sodomy. Do you begin to get at least part of the point? | 0% | 60% | -60% |
| And since Thomas Aquinas never observed animals having gay sex in the wild, homosexuality never made it into the annals of natural law theory. | What has this got to do with the rape and abuse of boys and girls in residential schools? | 83.3% | 20% | -63.3% |

be crowd-annotated for context-sensitivity (by IC and OC raters) to obtain ground truth (gold context-sensitivity scores). To avoid this additional annotation cost, however, in this section we explore a teacher-student approach (Hinton et al., 2015). The teacher is the initial BERTr context-sensitivity regressor (Section 3.2), which provides silver context-sensitivity scores for the newly sampled posts. The student is another BERTr instance, which is trained on the augmented dataset (the data with gold sensitivity scores the teacher was trained on, plus the newly sampled posts with silver sensitivity scores).

These steps can be repeated in cycles, by using the student as the new teacher to sample and silver-score additional posts in each cycle. Similar teacher-student approaches have recently been used in several NLP and computer vision tasks (Xie et al., 2020a; Yu et al., 2018; Xie et al., 2020b), often using teacher and student models with different capacities. In our case, the teacher and student are the same model, but the student is trained on additional data silver-scored by the teacher, which is very similar to classical semi-supervised learning with Expectation Maximization (Bishop, 2006).

Following this teacher-student approach, we experimented with data augmentation to improve the context-sensitivity estimator, using two different settings. In both settings, the teacher silver-scores the newly sampled additional training posts. In the setting discussed first, the teacher is also used to sample the new training posts. By contrast, in the second setting the new posts are randomly sampled, and the teacher is only used to silver-score them.

**Teacher-student with teacher sampling:** In this setting, we randomly sampled 20,000 posts from the Civil Comments (CC) dataset and used them as a pool to select (and silver-score) new training instances from, as follows:

1. Train a BERTr teacher on the gold-scored (by crowd- annotators) training instances of our CCC dataset (Section 2).
2. Use the BERTr teacher to silver-score for context-sensitivity all the posts of the pool (initially 20,000).
3. Select from the pool the 1,000 posts with the highest silver sensitivity scores, remove them from the pool, and add them (with their silver sensitivity scores) to the training set.
4. Train a BERTr student on the new training set (augmented by 1,000 silver-scored posts).
5. Evaluate the student using exactly the same splits as in Section 3.2.
6. (Optional) Go back to step 2, using the student as a new teacher in a new cycle.
We repeated this process for five cycles and ended up with a training set augmented by 5,000 likely context-sensitive posts. Experimental results (Fig. 8, blue solid line) show performance gains in MSE even from the first cycle. We also compared against using a single cycle with 5,000 new posts added at once (blue dashed line), instead of adding only 1,000 posts per cycle and re-training the teacher. Performing cycles and re-training the teacher clearly leads to lower MSE, but with diminishing returns after cycle 4.

Figure 8: Data augmentation with knowledge distillation to improve BERT context-sensitivity regressor. Blue solid line: the teacher model is used both to silver-score the new training instances and to sample them. Orange solid line: the teacher model is used only to silver-score the new training instances, which are randomly selected. Dashed lines: same as the solid ones, but only one cycle is performed, which adds 5,000 silver-scored new training instances at once.

Teacher-student with random sampling: This setting is the same as the previous one, but in step 3 we randomly select 1,000 posts from the pool, instead of selecting the 1,000 posts with the highest silver sensitivity scores. Again, we used five cycles (Fig. 8, orange solid line) and we also compared to a single cycle that adds 5,000 silver-scored training instances at once (orange dashed line). Sampling with the teacher’s scores (blue solid line) is clearly better than random sampling (orange lines).

6 Related Work

We describe related work along three dimensions. First, we describe work regarding toxicity detection. Second, we focus on context-aware natural language processing approaches. Third, we describe work that tackles classification tasks with regression-based approaches.

Toxicity detection

Abusive language detection is a difficult task due to its subjective nature. Cyberbullies attack victims on different topics such as race, religion, and gender across multiple social media platforms (Agrawal and Awekar, 2018). Thus, the vocabulary used and the perceived meaning of words may vary when abusive language occurs in a different context. Several approaches have been examined in order to tackle the problem of abusive language detection. Researchers initially experimented with machine learning techniques using hand crafted features, such as lexical features, syntactic features, etc. (Davidson et al., 2017; Waseem and Hovy, 2016; Djuric et al., 2015). Then, deep learning techniques were employed, operating on word embeddings (Park and Fung, 2017; Pavlopoulos et al., 2017b,c; Chakrabarty et al., 2019; Badjatiya et al., 2017; Haddad et al., 2020; Ozler et al., 2020). These techniques seem to work better for this task than the traditional machine learning methods based on handcrafted features (Badjatiya et al., 2017).

To facilitate research in this field, researchers have published several datasets containing different types of toxicity. Nobata et al. (2016) developed a corpus of user comments posted on Yahoo Finance and News annotated for abusive language, the first of its kind. Wulczyn et al. (2017) created and experimented with three new datasets; the “Personal Attack” dataset where 115k comments from Wikipedia Talk pages were annotated as containing personal attack or not, the “Aggression” dataset where the same comments were annotated as being aggressive or not, and the “Toxicity” dataset that includes 159k comments again from Wikipedia Talk pages that were annotated as being toxic or not. Waseem and Hovy (2016) experimented on hate speech detection using a corpus of more than 16k tweets containing sexist, racist and non-toxic posts that they annotated by themselves. Most of the published toxicity datasets contain posts in English, but datasets in other languages also exist, such as Greek (Pavlopoulos et al., 2017a), Arabic (Mubarak et al., 2017), French (Chiril et al., 2020), Indonesian (Ibrohim and Budi, 2018) and German (Ross et al., 2016; Wiegand et al., 2018).

Context-aware NLP

Incorporating context into human language technology has been successfully applied to various applications and domains. In text/word represen-
tation, context has a central role (Mikolov et al., 2013; Pennington et al., 2014; Melamud et al., 2016; Peters et al., 2018; Devlin et al., 2019). Integrating context is crucial in the sentiment analysis task too, where the semantic orientation of a word changes according to the domain or the context in which that word is being used (Agarwal et al., 2015). Vanzo et al. (2014) explored the role of contextual information in supervised sentiment analysis over Twitter. They proposed two different types of contexts, a conversation-based context and a topic-based context, which includes several tweets in the history stream that contain overlapping hashtags. They modeled each tweet and its context as a sequence of tweets and used a sequence labeling model, SVM\textsuperscript{HMM}, to predict their sentiment labels jointly. They found that the kind of context they considered leads to specific consistent benefits in sentiment classification. Ren et al. (2016) proposed a context-based neural network model for Twitter sentiment analysis, incorporating contextualized features from relevant tweets into the model in the form of word embedding vectors. They experimented with three types of context, a conversation-based context, an author-based context, and a topic-based context. They found that integrating contextual information about the target tweet in their neural model offers improved performance compared with the state-of-the-art discrete and continuous word representation models. They also reported that topic-based context features were the most effective for this task.

Despite the wide use of context in other Natural Language Processing (NLP) tasks, such as dialogue systems (Lowe et al., 2015; Dušek and Jurčiček, 2016) and informational bias detection (van den Berg and Markert, 2020), very few researchers have focused on context-aware toxic language detection. Gao and Huang (2017) provided a corpus of speech labeled by annotators as hateful, obtained from full threads of online discussion posts under Fox News articles. They proposed two types of hate speech detection models that incorporate context information, a logistic regression model with context features and a neural network model with learning components for context. They reported performance gains in F1 score when incorporating context and that combining the two types of models they considered further improved performance by another 7 percent in F1 score. Mubarak et al. (2017) provided the title of the respective news article to the annotators during the annotation process, but they ignored parent comments since they did not have the entire thread. As Pavlopoulos et al. (2020) already noticed, this presents the following problem: new comments may change the topic of the conversation and replies may require the previous posts to be assessed correctly. Pavlopoulos et al. (2017a) provided the annotators with the whole conversation thread for each target comment as context during the annotation process. The plain text of the comments is not available, however, which makes further analysis difficult.

In later work Pavlopoulos et al. (2020) published two new toxicity datasets containing posts from the Wikipedia Talk pages, where during the annotation process, annotators were provided with the previous post in the thread and the discussion title. The authors found that providing annotators with context can result both in amplification or mitigation of the perceived toxicity of posts. Moreover, they found no evidence that context actually improves the performance of toxicity classifiers. In a similar work that was conducted by Menini et al. (2021), the authors investigated the role of textual context in abusive language detection on Twitter. They first re-annotated the tweets in the dataset of Founta et al. (2018) in two settings, with and without context. After comparing the two datasets (with and without context-aware annotations) they found that context is sometimes necessary to understand the real intent of the user, and that it is more likely to mitigate the abusiveness of a tweet even if it contains profanity. Finally, they experimented with several classifiers, using both context-aware and context-unaware architectures. Their experimental results showed that when classifiers are given context and are evaluated on context-aware datasets, their performance drops dramatically compared to a setting where classifiers are not given context and are evaluated on context-unaware datasets.

### Regression as classification in NLP

Approaching a text classification problem as a regression-based problem has been tested by researchers in various NLP tasks, such as sentiment analysis (Wang et al., 2016), emotional analysis (Buechel and Hahn, 2016), metaphor detection (Parde and Nielsen, 2018), toxicity detection. A work similar to ours in that respect is the work of Wulczyn et al. (2017), who noticed that estimating the likelihood of a post to be personal attack or not,
using the empirical distribution of human-ratings, rather than the majority vote, produces a better classifier, even in terms of the ROC AUC metric. D’Sa et al. (2020) experimented on the English Wikipedia Detox corpus by designing both binary classification and regression-based approaches aiming to predict whether a comment is toxic or not. They compared different unsupervised word representations and different deep learning based classifiers. In most of their experiments, the regression-based approach showed slightly better performance than the classification setting, which is consistent with the findings of Wulczyn et al. (2017).

7 Limitations and Considerations

- We limited our study to the parent post of the conversational context, but we note that more posts or even the entire thread could be used. Also, other possible sources of context exist and could be examined along the thread’s posts. For instance, the discussion title could provide the annotators with more information when they annotate each post of the discussion. We consider this study as the first of a series of steps that need to be taken to investigate the relation of context in toxicity detection.

- Online discussions are currently moderated by human raters and machine learning models. Both may carry bias introduced by the annotators (e.g., if all the annotators originate from the same cultural background). The same limitation applies to this study, for which we employed crowd annotators, but without trying to control for possibly different social norms.

- We focused on English posts and we employed English-speaking annotators. The English-centric nature of the Internet is a widely acknowledged problem. The ways that the communicative intent is mixed into culture, and the notions of what is appropriate in a given context are problems that are sometimes simpler for a language like English that does not mark gender and has lost its formal/casual distinctions. This is also related to the difficulty of doing work with social norms, which is challenging in well resourced languages and virtually impossible in languages that lack modeling resources.

The above mentioned limitations only highlight the challenges of the work that remains to be done.

8 Conclusions and Future Work

We introduced the task of estimating the context-sensitivity of posts in toxicity detection, i.e., estimating the extent to which the perceived toxicity of a post depends on the conversational context. We constructed, presented, and released a new dataset that can be used to train and evaluate systems for the new task, where context is the previous post. We also showed that context-sensitivity estimation systems can be used to collect larger samples of context-sensitive posts, which is a prerequisite to train toxicity detectors to better handle context-sensitive posts. Furthermore, we showed that the performance or our best context sensitivity estimator is further improved by augmenting the training dataset with teacher-student knowledge distillation. Context-sensitivity estimators can also be used to suggest when moderators should consider the context of a post, which is more costly and may not always be necessary. In future work, we hope to incorporate context mechanisms in toxicity detectors and train (and evaluate) them on datasets sufficiently rich in context-sensitive posts.

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