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Are These Comments Triggering? Predicting Triggers of Toxicity in Online Discussions

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ABSTRACT

Understanding the causes or triggers of toxicity adds a new dimension to the prevention of toxic behavior in online discussions. In this research, we define *toxicity triggers* in online discussions as a non-toxic comment that lead to toxic replies. Then, we build a neural network-based prediction model for toxicity trigger. The prediction model incorporates text-based features and derived features from previous studies that pertain to shifts in sentiment, topic flow, and discussion context. Our findings show that triggers of toxicity contain identifiable features and that incorporating shift features with the discussion context can be detected with a ROC-AUC score of 0.87. We discuss implications for online communities and also possible further analysis of online toxicity and its root causes.

CCS CONCEPTS

• **Human-centered computing** → **Social media**; • **Computing methodologies** → **Supervised learning by classification**.

KEYWORDS

Reddit, toxicity, trigger detection, neural networks, online discussion

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1 INTRODUCTION

Social media has revolutionized how users communicate with each other, as it enables information exchange with great ease. Online platforms, such as Reddit, YouTube, and Facebook, allow users to discuss various topics by building communities around shared interests [29]. With the increase of user engagement in online

communities, moderating discussions for incivility becomes more challenging. These challenges stem from the difficulty in controlling toxic posts that target other users with various types of harassment and rudeness [29, 30]. The manifestation of toxic posts in online discussions discourages users from having healthy interactions, leading to conflicts and unpleasant user experiences [22].

There are multiple reasons why toxicity occurs, relating to motivations linked to cyberbullying, trolling, and socio-dynamic effects, such as group polarization [48, 50]. Various approaches have been suggested to combat online harassment, including counter-speech and creation of community guidelines [47]. One common approach is automatic detection and moderation of toxic comments [31, 44, 45]. Automation can be seen especially useful for active communities where users send thousands of messages daily, making manual moderation extremely challenging.

Despite the scholarly interest in detecting toxicity in online posts, studies that investigate the causes of such toxic posts within online discussions seem scarce [5]. To stop malicious posting from reoccurring or even prevent them from the beginning, detection of toxicity triggers is a novel and impactful research goal. To achieve this goal, understanding of the *initiation* of toxic discussions through the detection of toxicity triggers is required [5].

In this work, we identify toxicity triggers (i.e., the initiating actions), leading to toxicity in discussion threads. We define toxicity triggers as *non-toxic initiators* sparking following toxic interaction. We formulate our research questions for detecting toxicity triggers as follows: *Can we predict toxicity triggers that are likely to lead to toxic replies?* To address this research question, we analyze an extensive collection of more than 104 million Reddit comments during a period spanning nearly two years. We start with detecting toxic comments in our dataset and reconstructing discussion threads from the detected toxic comments. From the reconstructed discussion threads, we find toxicity triggers based on their definition that they are non-toxic, but their child (i.e., reply) comments are toxic.

To predict whether a given comment is a toxicity trigger, we incorporate its textual features and context feature. The context refers to the discussion that happened before that comment. Additionally, from a comprehensive review of previous literature, we extract two specific features from the context: topic shift [40] and emotional shift [33]. We then build a prediction model and find the toxicity triggers across multiple subreddits.

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The contribution of this work is as follows: We formulate a novel problem of predicting toxicity triggers and build a neural network-based prediction model based on previous literature of online communications. Our model achieves a high ROC-AUC of 0.87 across multiple subreddits, showing its generalizability.

2 RELATED WORK

2.1 Toxicity Detection

There is a high level of interest in investigating online hate and toxicity, as shown by the number of peer-reviewed publications on the subject (see [38] for a review). The problem of toxicity is prevalent in the wider society. For example, a 2016 report [6] states that 66% of the harassment that users report takes place on social media and that 21% of the harassment victims refrain from using all forms of social media. This report shows that toxicity can deter users from participating in online discussions and can negatively affect users' online social experience. Other studies focused on cyberbullying show similar findings [11, 18, 23], and individuals' freedom to participate in online discussions become *de facto* reduced by the presence of toxicity.

For toxic comment detection, the goal is generally to classify comments as either toxic or non-toxic for further actions such as deletion or analysis. Researchers have used machine learning models [31], such as deep neural networks [7] in a variety of ways to detect toxic comments. For instance, Nobata et al. (2016) used syntactic [2], linguistic [44], distributional semantics (embedding) [50], and n-gram [45] features to detect abusive and non-abusive comments. Their research showed that with variations of NLP features, the regression model outperforms a state-of-the-art deep learning model by not maintaining word embeddings in each iteration.

Similarly, Wulczyn et al. (2017) deploy machine learning models to detect toxicity at different levels, defined as targeted personal attacks. The features in this study were extracted from the comments text and did not exploit information associated with users or the communication network. Comparable to [31], the researchers extracted n-gram and semantic features to perform the detection. The study showed that the types of personal attacks on Wikipedia were not a result of a small number of malignant users, nor was it the outcome of anonymous commenters. Around 30% of the attacks came from registered users with more than 100 contributions per user [48]. Salminen et al. (2018) found that, in 137,098 comments from YouTube and Facebook videos in an online news media, most targets of hate were politicians and the media. Additionally, Spiros et al. (2018) used the same dataset as [48] to experiment with Convolutional Neural Networks (CNNs) for toxic comment classification. The outcomes of the study show that CNNs can outperform classic bag-of-words text classification techniques.

Finally, a prominent effort for toxic comment detection is the Perspective API [43] aimed at providing platform owners and researchers with a tool that scores comments based on their level of toxicity. The models used in the PerspectiveAPI were built using machine learning techniques from an extensive collection of comments labeled by respondents of online surveys. Each model returns a score between 0 and 1, indicating the toxicity of the comment. Some of the experimental models offered by the Perspective API classify severe toxicity, obscenity, spam, and attacks on people.

The experimental models of the Perspective API receive frequent revisions and updates that have improved its performance over time [43].

Overall, prior research focused on several aspects of toxic conversation using different angles and techniques to approach the problem and often focusing on the detection and classification of toxic comments. However, no prior work that we could locate has specifically focused on the detection of triggers of toxic online discussions. Our approach, therefore, addresses an open and vital research question with a diverse set of computational techniques and implications in a variety of domains.

2.2 Contagion of Toxicity

Apart from experimenting with online hate detection, prior research has established that contagion of toxicity is a considerable contamination risk for the health of online discussions [29]. Del Vicario et al. (2016) referred to this effect as emotional contagion. Kwon and Gruzd (2017) investigated how hatefulness formed a cascading effect and discovered that when parent comments in a discussion thread include swearing, the following child comments exhibit a higher degree of swearing as well.

The concept of topic shift is relevant to the problem of toxicity trigger analysis because the emotions of commentators [40] profoundly influence the tone of social media discussions. For example, Topal et al. (2016) provide indications that a topic shift could be an indicator of emotional shifts in online discussions. However, this premise was not explored in the context of toxicity. Moreover, the impact of tone shifts has not been studied using a large corpus of online discussions, such as the one in this research.

Therefore, our premise is that for toxicity to spread in conversations, there might be causes - *triggers* - that turn healthy conversations toxic. These triggers of toxicity may differ by the community and by topic due to different norms and uses of language [35, 46]. We could locate no prior research specifically on toxicity triggers in online discussion threads. However, in information behavior research, the concept of 'trigger' has been used to describe what causes users to initiate information-seeking activity [32]. Reddy and Jansen (2008) considered 'trigger' as a point for transitioning from individual to collaborative information-seeking behavior. This triggering behavior requires interaction, defined as a series of events that need at least two actions and two actors [42].

3 REDDIT DATA COLLECTION AND PREPROCESSING

Reddit is an online community with more than one million [37] communities, which are commonly known as "subreddits", denoted as "r/" in the platform. Overall, Reddit is considered a 'community of communities' where each subreddit is moderated independently; hence, it incorporates a mix of cultures [28].

We focused on the ten subreddits with the highest number of subscribers as of 2017 [4], as shown in stage (a) of Figure 1 and Table 1. Then, for each subreddit, we retrieved all the comments posted between January 2016 and August 2017 (stage (b) in Figure 1). Using Pushshift's public Reddit collection [3], we retrieved the comments and ensured that the comment objects included a)

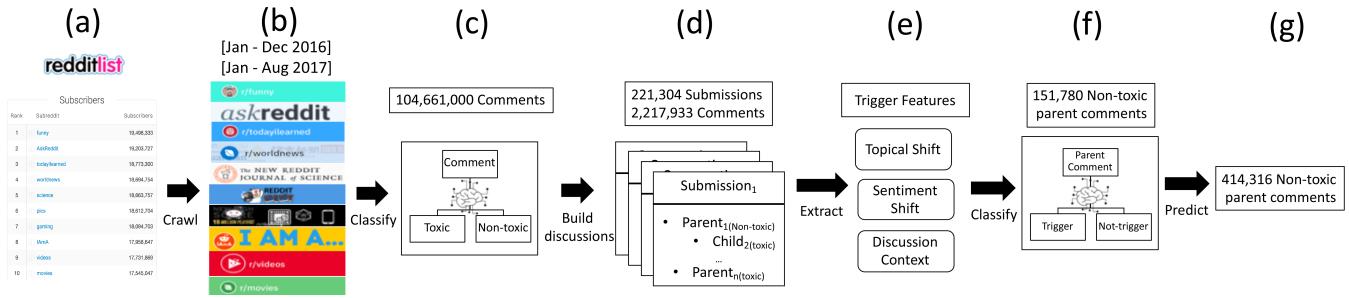


Figure 1: Pipeline for investigating toxicity triggers in Reddit discussions.

Table 1: Summary of our data collection. The Subreddits are sorted by the number of subscribers.

| Subreddit | Jan - Dec 2016 | Jan - Aug 2017 |
|-----------------|-------------------|-------------------|
| r/funny | 6,471,278 | 3,598,968 |
| r/AskReddit | 52,231,835 | 33,652,845 |
| r/todayilearned | 214,206 | 221,734 |
| r/science | 474,845 | 161,174 |
| r/worldnews | 1,986,401 | 876,046 |
| r/pics | 69,713 | 134,872 |
| r/IAmA | 140,637 | 57,468 |
| r/gaming | 65,496 | 68,037 |
| r/videos | 527,500 | 222,529 |
| r/movies | 3,292,659 | 192,757 |
| Total | 65,474,570 | 39,186,430 |

the time stamp, b) ID of the comment, c) ID of the comment’s parent, and d) the comment text. After collecting the comments, we removed the comments shown as deleted as well as comments that were removed by moderators. Then, we constructed discussion threads from the comments using the ID and parent ID of the corresponding comment. Following this procedure, we removed any comments that did not belong to a thread (i.e., parent comments with no children). We ended up with an extensive collection (i.e., corpus) of online discussions from the top 10 subreddits on Reddit, as shown by the statistics in Table 1.

4 TOXICITY DETECTION

To fully understand toxicity triggers in online discussions and build a statistical model to detect them, we propose an analysis framework as in Figure 1. In this section, we explain how to detect toxicity.

4.1 Building the Ground-Truth

To perform toxic comment detection, the first approach that we tried was scoring comments through Google’s Perspective API [2]. We scored 1,000 comments that we randomly sampled from our collection and examined the retrieved scores manually for their accuracy. Unfortunately, as the API was not stable at the time of our experiments in 2018, we could not rely on the scores obtained from the API. Also, as the Perspective API has a rate-limit of sending requests, it is infeasible to label each of 104 million comments

through the API. To overcome this limitation, we built our own toxic comment detection model based on comments sampled from our collection.

To build our model for toxic comment detection, we required a labeled collection of toxic and non-toxic comments to train the model. Since there is no Reddit-specific test collection for the task of toxic comment detection, we opted to create our own labeled collection. For this task, we used Figure Eight [1] to collect judgment labels for the 10,100 randomly sampled comments from r/AskReddit. The reason we choose r/AskReddit is that it is one of the largest and most popular question-answering communities on Reddit that deals with a wide range of types of topics [25]. Therefore, it is reasonable to assume that r/AskReddit captures various behaviors of Reddit users and minimizes the risk of dealing with subreddit-specific keywords. We verify this assumption by evaluating our model with sampled comments from multiple subreddits §4.3.

The designed labeling job required workers to label a given comment as either toxic or non-toxic. The designed labeling job required workers to label a given comment as either toxic or non-toxic. To help workers understand what toxicity means, we used the definition of the Perspective API, which states that a toxic comment is “a rude, disrespectful, or unreasonable comment that is likely to make you leave a discussion.”

The results from the labeling task showed that 81.57% of the 10,100 comments are non-toxic, while the remaining 18.43% are toxic. As this is the dataset of highly imbalanced, we measure the agreement between annotators by using Gwet’s gamma, which takes the average-distribution approach that outperforms the Kappa statistic measurements in handling class imbalance [15]. Gwet’s gamma score was 0.70, which is considered high.

4.2 Training the Model

Then, we build models that can classify comments into toxic or non-toxic, as shown in stage (c) of Figure 1. For this task, we employed a variety of features that capture the semantic and syntactic properties of the comments. First, we looked at n-gram features at different configurations [19]; then, we incorporated an advanced set of features based on word embeddings such as word2vec [21] and sentence2vec [27]. We also extracted 13 content-based features used in [38], such as the number of emoticons, capital letters, and misspellings.

The toxic comment classification experiment takes into account several issues that persisted in the collection, such as the skewness

of the classes. To solve the problem of class imbalance, we used a technique that combines Synthetic Minority Over-sampling TEchnique (SMOTE) and Tomek Links (an under-sampling method) [8]. This technique performs over-sampling using SMOTE and cleaning with Tomek links; then, we performed feature transformation by scaling each feature to a range between 0 and 1.

The next step in the classification pipeline was to perform feature selection. For this purpose, we used the Random Forest algorithm to perform the classification, ranking, and selection of features. Feature selection is essential in reducing the dimensionality of the large feature vectors, such as the highly dimensional N-gram features, and it can be useful in many algorithmic approaches. The last step in the classification experiment was to perform the classification using 10-fold cross-validation and grid search for parameter tuning. As a result, we extracted 8,623 features.

We tested a variety of classifiers to choose the best performing model, including Decision Tree, Random Forest, Adaboost, and Logistic Regression. Moreover, we experimented with two neural network models: Bidirectional Encoder Representations from Transformers (BERT) in its vanilla form with fine tuning [13], and Long Short Term Memory (LSTM) pre-trained word embeddings from GloVe (840B tokens, 2.2M vocabulary terms, cased, 300d) [34]. For BERT, we used the uncased version of the vocabulary model to train the neural network on the relationship between sentences. For the fine-tuning step, we adjusted the maximum sequence length to 128 characters, used a batch size of 32, a learning rate of 0.00003, and a total of 4 epochs. For LSTM, we used 'Nadam' as our optimizer. The training task ran in batches of size 64 on a total of 3 epochs. The maximum features for the GloVe embeddings were 30,000, and the maximum length of each comment was 400 words. Table 2 shows the max performance of the models we tested. As the LSTM-based model outperforms other models, we chose the LSTM-based model to perform the toxicity prediction for the following experiments.

Table 2: Max Performance of each model

| Model | F_1 |
|---------------------|-------------|
| Decision Tree | 0.85 |
| Random Forest | 0.86 |
| Logistic Regression | 0.74 |
| Adaboost | 0.91 |
| BERT-based | 0.81 |
| LSTM-based | 0.94 |

4.3 Additional Model Evaluation with Other Subreddits

While we assume that comments from r/AskReddit are general enough to study toxicity in Reddit, that assumption should be tested with the actual data. Therefore, we design an additional evaluation with comments that are randomly sampled from other subreddits. To evaluate the predictive accuracy of the model, we computed a simple agreement score on 1,000 random comments from the other nine subreddits (excluding r/AskReddit). We used crowdsourcing (Figure Eight) to label the comments, then we computed the

Table 3: Percentage of toxic and non-toxic comments in each subreddit.

| Subreddit | 2016 | | 2017 | |
|--------------------|---------------|---------------|---------------|---------------|
| | %Toxic | %Non-toxic | %Toxic | %Non-toxic |
| r/funny | 13.32% | 86.69% | 12.62% | 87.38% |
| r/AskReddit | 13.33% | 86.67% | 12.86% | 87.14% |
| r/todayilearned | 12.41% | 87.59% | 11.81% | 88.19 |
| r/science | 2.84% | 97.16% | 2.74% | 97.26% |
| r/worldnews | 13.45% | 86.55% | 13.01% | 86.99% |
| r/pics | 11.23% | 88.77% | 12.27% | 87.73% |
| r/lAmA | 8.73% | 91.27% | 8.71% | 91.29% |
| r/gaming | 10.28% | 89.72% | 10.82% | 89.18% |
| r/videos | 15.44% | 84.56% | 12.87% | 87.13% |
| r/movies | 11.18% | 88.82% | 9.82% | 90.18% |

agreement between the crowd worker labels the labels of the prediction model. The achieved agreement score is 0.95, which further supports our choice r/AskReddit to obtain labeled comments for training the model.

With the built prediction model, we performed the prediction on all the comments in the years 2016 and 2017. We then computed the percentage of toxic and non-toxic comments in each subreddit, as shown in Table 3. The outcomes of this experiment show that the subreddit r/videos was the most toxic in the year 2016 (and still quite high in 2017), while the subreddit r/worldnews was the most toxic in the year 2017 (and was quite high in 2016). Furthermore, the subreddit r/science exhibits the lowest percentage of toxicity across both years 2016 and 2017. Our findings indicate that toxicity is prevalent in Reddit communities; therefore, the problem of detecting toxicity triggers is important in online communities. Furthermore, our results show that subreddits vary in their toxic nature.

5 TOXICITY TRIGGER DETECTION

5.1 Feature Modeling for Trigger Prediction

Changes in the topic of a discussion, the context of the discussion, or the overall emotion could tell us something about the comments that might trigger toxicity [40]. This insight motivated us to introduce topical and emotional shifts along with the discussion context as features to predict toxicity triggers.

The features were extracted from discussion threads that we show in stage (d) from Figure 1 to capture the occurrence of changes that might lead to toxicity triggers. Hence, in the following, we explain the proposed features that include topical shift, sentiment shift, and the discussion context, as in stage (e) in Figure 1.

5.1.1 Topical Shift. By using pre-trained word embeddings to represent the comments in the discussion, we can measure the topical similarity of the comments using the cosine similarity measure [26], as in Equation (1). This measure captures the topical similarity between the non-toxic parent comment and all preceding comments that came before it within the discussion thread. For any given parent comment p and a preceding comment c that came before p within a discussion, we calculate the similarity between p and c as:

$$\cos(\vec{v}_p, \vec{v}_c) = \frac{\vec{v}_p \cdot \vec{v}_c}{|\vec{v}_p| \cdot |\vec{v}_c|} = \frac{\sum_{t=1}^n v_p(t)v_c(t)}{\sqrt{\sum_{t=1}^n v_p(t)^2} \sqrt{\sum_{t=1}^n v_c(t)^2}} \quad (1)$$

where v_p and v_c correspond to the vector space representations of both p and c , while n corresponds to the total number of terms.

To build the word embedding representations in comments, we used the GloVe pre-trained model on 5 billion tokens to generate vectors of 100 dimensions for each comment. Next, we computed the cosine similarity between the parent comment and all preceding comments. Then, we used a threshold to determine if the comments were on-topic or off-topic. To compute this threshold, we relied on the k-means clustering algorithm [17] to construct two clusters that denote on-topic and off-topic comments. Then, we considered the smallest cluster to be an indicator of comments that exhibit topical shift [40]. As a threshold, we used the centroid, which is the arithmetic mean of all the data points that belong to a cluster. So, if the cosine similarity of a comment \leq the threshold, then a topic shift had occurred in the discussion thread.

5.1.2 Sentiment Shift. To study the sentiment of each comment within the discussion thread [49], we used AFINN’s lexicon [16] to score each comment based on the sentiment’s polarity. The lexicon contains 2,477 words and phrases labeled for their valence in the range [-5,5], where minus represents negative polarity, and the plus represents positive polarity. To compute the lexicon score, we mapped terms in comments with words or phrases in the lexicon. Then, we aggregated the score of all the terms in the comment to end up with a single score that represents the sentiment of each comment. The final score of each comment is used to cast judgment on the overall sentiment present in the comment. To capture the sentiment shift, we followed the same approach that we used in the topic similarity shift analysis, where we clustered the obtained scores into two classes that correspond to comments with sentiment change and comments without sentiment change. The smallest centroid value was also used as a threshold to determine if comments had any sentiment shift [40].

5.1.3 Discussion Context. When users initiate online discussions, the topics and events discussed earlier usually dictate the flow of the upcoming responses in the discussion thread [10]. This premise motivated us to introduce the discussion context as a feature to detect toxicity triggers. To compute the discussion context, we collected all the comments that came before the toxicity trigger, granted that these comments fall between the post or comment that the trigger replies to and the trigger itself (i.e., creating a sense of a context). Then, we generated the word embedding representation of these comments, as we mentioned previously.

For each toxicity trigger, we averaged the word embeddings of all the comments that came before it to create the discussion context. The averaging of word embeddings was necessary to generate a single context for each toxicity trigger in the collection.

5.2 Training a Statistical Model

For the prediction experiment that we show in stage (f) of Figure 1, we used the LSTM-based neural network. As for the training data, we randomly sampled 151,780 non-toxic parent comments (50% for

training and 50% for testing). We checked the toxicity of their child comments and marked whether they are τ -toxicity triggers (i.e., it belonged to the class Trigger) or not. In our analysis, we ensured that the training data from the class Trigger and Non-trigger were evenly split (balanced). Then, we evaluated the performance of the prediction model and used it to predict the occurrence of toxicity triggers in the remaining 414,316 non-toxic parent comments, as in stage (g) of Figure 1. We formally define a τ -toxicity trigger as non-toxic comment having equal or more than τ toxic child comments. Intuitively, higher τ leads to clear but lower coverage of toxicity triggers. To determine the appropriate threshold for further analysis, we tested varying values of τ , the threshold of the number of toxic child comments, from one toxic child ($\tau=1$) to five toxic children ($\tau=5$). We experimented with the value of τ by running small prediction experiments at each threshold and manually evaluated the prediction performance. Starting with $\tau=1$, when we set the training set size to 57,760, the prediction accuracy on the 6,418 test set was 0.63. Then, we increased the value of τ to 2, where the training set size was 6,476, and the prediction accuracy on 720 comments was 0.46. Increasing τ to 3 reduced the training set size to 1,288, and the prediction accuracy on 144 comments also dropped to 0.40. As for $\tau=4$, the training set size became 394, and the prediction accuracy of 44 comments dropped to 0.10. Lastly, by setting τ to 5, the training set size became 182, and the prediction accuracy on 20 comments was 0.10. Our findings show that having two or more toxic children is enough to detect toxicity triggers as long as the training set size is large.

5.3 Performance Evaluation

The results of the classification experiment are presented in Table 4. As a baseline model, we trained the LSTM model using GloVe word embeddings only. Then, we added sentiment shift features to the model by concatenating the shift scores with the embedding feature vector. The results of including topical shift features did not show a significant improvement over the baseline. Similarly, we added topical shift features to the word embedding feature vector. The improvement over the baseline was slightly better than sentiment shift features. Then, we added the discussion context feature, which provided another slight improvement over the topical shift features. Lastly, we combined topical shift, sentiment shift, and discussion context features with GloVe embeddings. The achieved average accuracy of the model was 78.2%, which shows a 6% improvement over the baseline model. This result indicates that topical and sentiment shift features, along with the discussion context, improve the detection of toxicity triggers. As for the predictive model’s agreement score, we manually labeled 100 comments from our collection and computed the agreement between the labels and the prediction of the model. The agreement that we got was 84%, which is good enough for us to consider the model for performing toxicity trigger detection.

6 ERROR ANALYSIS

Lastly, we tie-in our findings from the prediction experiments by examining some of the online discussions in which toxicity triggers might have occurred. The discussion depicted in Figure 2 shows an example of a correctly and incorrectly classified toxicity trigger.

Table 4: Performance of the neural network models in terms of accuracy, macro F_1 , and ROC-AUC score. BL:Baseline, sent:sentiment, cont:context. (The results are obtained by taking the average of 5 random runs.)

| Features | ROC-AUC | Accuracy | Macro F_1 |
|--------------|-------------|--------------|-------------|
| GloVe(BL) | 0.81 | 72.8% | 0.73 |
| GloVe+sent. | 0.81 | 72.9% | 0.72 |
| GloVe+topic | 0.82 | 73.8% | 0.73 |
| GloVe+cont. | 0.83 | 74% | 0.78 |
| All features | 0.87 | 78.2% | 0.78 |

The correctly identified toxicity trigger in Figure 2 shows some form of disagreement in opinion, which leads to toxicity.

The topic of the discussion (i.e., the submission post) aims at provoking reactions from readers. As the context of the parent-comment was in agreement with the submission post, the first child-comment was aggravated by the parent-comment, which led it to be toxic. It was triggered by the parent comment, which itself was not toxic.

```

Post-submission: Went to buy evolve. Saw this. HAHAAHHAHHAHHAHHA no — Not-toxic
Parent-comment: This is my exact reaction.. I laughed at their greedy nature. Noperino. Even if it was free.
Nope. Don't support this type of conduct. — Trigger
Child-comment 1: Greedy my ass. Explain how. Because I can think of a handful of reasons why not and
why you're plain wrong. — Toxic
    
```

Figure 2: An example discussion with trigger parent comment that was correctly predicted as “trigger” by the model.

As for incorrectly-classified toxicity triggers, Figure 3 shows an example of a non-toxicity trigger classified as a trigger by the prediction model. The submission post talks about a racial issue that happened in Britain. While the parent comment made an assuring claim without any proof, the subsequent child comments did not respond to the claim in an aggressive manner then proceeded to provide evidence to their counter-argument. Cases where child comments behave in an unaggressive manner (like producing high-quality arguments [9]) can lead to incorrect classification.

On the other hand, one might argue that the parent comment triggers toxicity if a subsequent child comment was toxic. In this case, the classification mistake was due to the lack of information about the end of the discussion thread [20]. With this example, we demonstrate some of the challenges associated with the problem of detecting toxicity triggers in discussion threads, which mainly stem from unpredictable child comment toxicity and lack of knowledge about the discussion termination.

```

Post-submission: British cops use a Taser on a black man they thought was a robber. He was their race-relations
adviser — Not-toxic
Parent-comment: I'm pretty sure it is, though I live in Hungary, but when asked for identification (and they
don't usually ask for it for kicks) we are required to show them. I'm pretty sure this is
the case in Britain too.. — Trigger
Child-comment 1: I'm pretty sure it is You are [pretty wrong] (http://content.met.police.uk/Article/
Frequently-Asked-Questions/1400009364853/1400009364853) — Not-toxic
    
```

Figure 3: An example discussion with not-trigger parent comment that was incorrectly classified as “trigger” by the model.

Also, the outcomes of the examination showed that when the model correctly identifies toxicity triggers, it usually relies on specific trigger-terms that contain provocative words like *argument* and shift ques from the conversation thread. However, when the model incorrectly classifies a toxicity trigger, this is usually attributed to: a) the lack of features that detect the end of the discussion thread, and b) incorrect toxic-comment classification results, making it difficult to detect if the parent comment triggers toxicity or not.

Other incorrect classification examples shed light on some of the challenges associated with toxicity trigger detection and open areas for future work. Such as incorporating additional features into the toxicity trigger detection model that detect sarcasm or trolling [41], discussion end-points [20], and introducing semantic shift features [40] that track the stylistic writing style of comments.

7 CONCLUSION

By utilizing a large-scale dataset and multiple techniques to detect toxic comments and toxicity triggers in online discussions, this research contributes to the stream of ongoing literature on online toxicity. Our approach shows novelty by being, to our knowledge, the first study to examine online toxicity triggers by using an extensive collection of online discussions and incorporating two shift features and a discussion context feature to detect toxicity triggers.

In this study, we detect toxicity in online communities and build discussion threads to use along with toxicity predictions to detect toxicity triggers. In the context of a discussion thread, we defined toxicity trigger as a non-toxic parent comment that has at least one toxic comment as its child. Based on this definition, we built an LSTM neural network model that combines topical and sentiment shift features along with discussion context features to detect toxicity triggers.

The findings from this research pave the way toward many interesting directions. For example, we show preliminary evidence that some communities are more robust against toxicity than others - it then becomes a crucial question to isolate the “resistance tactics” that more healthy communities employ to tackle the toxicity problem. Moreover, with our large-scale dataset, we can perform a multitude of analyses, including temporal studies on the emergence of toxicity within online communities and thus create research that can impact the health of those communities positively by identifying toxicity triggers.

Regarding the practical implications of our work, we note that by studying toxicity triggers, social media platforms, community moderators, and decision-makers can deploy automatic or semi-automatic techniques to prevent toxicity from spreading in online discussions. Such attempts could shield users from the adverse effects of toxicity and encourage them to participate in meaningful discussions without disseminating toxic content in online communities.

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