Predicting Different Types of Subtle Toxicity in Unhealthy Online Conversations

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Abstract

This paper investigates the use of machine learning models for the classification of unhealthy online conversations containing one or more forms of subtler abuse, such as hostility, sarcasm, and generalization. We leveraged a public dataset of 44K online comments containing healthy and unhealthy comments labeled with seven forms of subtle toxicity. We were able to distinguish between these comments with a top micro F1-score, macro F1-score, and ROC-AUC of 88.76%, 67.98%, and 0.71, respectively. Hostile comments were easier to detect than other types of unhealthy comments. We also conducted a sentiment analysis which revealed that most types of unhealthy comments were associated with a slight negative sentiment, with hostile comments being the most negative ones.

1 Introduction

Healthy online conversations occur when posts or comments are made in good faith, are not blatantly abusive or hostile, typically focus on substance and ideas, and generally invite engagement (Price et al., 2020). Conversely, toxic comments are a harmful type of conversation widely found online which are insulting and violent in nature (Price et al., 2020), such as “SHUT UP, YOU FAT POOP, OR I WILL KICK YOUR A**!!!”. This kind of toxic conversation has been the primary focus of several previous studies (Georgakopoulos et al., 2018; Srivastava et al., 2018). However, many comments that deter people from engaging in online conversations are not necessarily outright abusive, but contain subtle forms of abuse (e.g., “Because it drives you crazy, old lady. Toodoolo...”). These comments are written in a way to engage people, but to also hurt, antagonize, or humiliate others and are thus referred to as unhealthy conversations (Price et al., 2020). In other words, unhealthy comments are less negative, intense, and hostile than toxic ones. Detecting unhealthy conversations is more challenging and less explored in the literature than its toxic conversations counterpart (Price et al., 2020).

Many early signs of conversational failure are due to the subtlety in comments which deter people from engagement and create downward spirals in interactions. Behaviors such as condescension (e.g., “Utter drivel and undeserving of further response.”), “benevolent” stereotyping (e.g., “Women have motherly nurturing instincts.”), and microaggressions (e.g., racially-based such as “Why don’t you have an accent?”) are frequently experienced by members of minority social groups (Sue et al., 2007; Glick and Fiske, 2001). Nadal et al. (2014) indicated that such subtle abuse can be as emotionally harmful as outright toxic abuse to some individuals. Microaggressions (even unintended slights or social cues) have been linked to disagreements in intergroup relationships. Jurgens et al. (2019) also signify the importance of tackling more subtle and serious forms of online abuse by developing proactive technologies (e.g., intervention by bystanders [Markey, 2000], rephrasing parts of a message to adjust the level of politeness [Sennrich et al., 2016]) to counter abuse before it can cause harm.

In this paper, we sought to answer two research questions in the context of unhealthy conversations:

- **RQ1:** What is the general sentiment associated with unhealthy conversations compared to healthy conversations?

- **RQ2:** Can we differentiate unhealthy and healthy conversations? If so, which type of unhealthy conversation is the most detectable?

Towards this end, we analyzed a dataset comprised of 44K labeled comments of unhealthy conversations from Price et al. (2020). We submit-
ted this dataset first to sentiment analysis aimed at detecting the polarity (positive/negative/neutral) of the comments (RQ1), and then to a comprehensive machine learning analysis focused on distinguishing comments as healthy vs. unhealthy. (RQ2). Our experimental results revealed that: (i) although none of the types of comments had extremely polarizing sentiments, most forms of unhealthy online conversations were associated with a slight negative sentiment; and (ii) hostile comments were the most detectable form of unhealthy conversation. Findings from this work have the potential to inform and advance future research and development of online moderation tools, which pave the way for safer online environments.

This paper is organized as follows. Section 2 summarizes related work. Section 3 describes the dataset we leveraged for our experiments, as well as our preprocessing procedures. Section 4 details our study’s methodology. Section 5 analyzes our study’s results, and discusses our results by answering our proposed research questions. Section 6 analyzes our study’s limitations and proposes directions for future work. Section 7 concludes the paper.

2 Related Work

Sentiment classification of social media posts with regards to toxicity has been researched extensively over the past years (Chen and Qian, 2019; Saeed et al., 2018; Saif et al., 2018; Srivastava et al., 2018). The primary focus of most of the related work has been on algorithmic moderation of toxic comments, which are derogatory and threatening. The importance of community norms in detection and classification of these subtler forms of abuse have been noted elsewhere (Blackwell et al., 2017; Guberman and Hemphill, 2017; Liu et al., 2018; Salminen et al., 2018), but have not received the same attention in the NLP community.

Although recognized in the larger NLP abuse typology (Waseem et al., 2017), there have been only a few attempts at solving the problems associated with subtle abuse detection, such as a study on classification of ambivalent sexism using Twitter data (Jha and Mamidi, 2017). There is a need for development of new methods to identify the implicit signals of conversational cues. Detecting subtler forms of toxicity requires idiosyncratic knowledge, familiarity with the conversation context, or familiarity with the cultural tropes (van Aken et al., 2018; Parekh and Patel, 2017). It also requires reasoning about the implications of the propositions. Dinakar et al. (2012) extract implicit assumptions in statements and use common sense reasoning to identify social norm violations that would be considered an insult.

Identification of subtle indicators of unhealthy conversations in online comments is a challenging task due to three main reasons (Price et al., 2020): (i) comments are less extreme and thus have lesser explicit vocabulary; (ii) a remark may be perceived differently based on context or expectations of the reader; and (iii) greater risk of false positives or false negatives. Cultural diversity also plays an important role on how a comment/remark may be perceived differently (Qiufen, 2014), thus making identification of subtle toxicity online more challenging.

From a machine learning perspective, abusive comments classification research initially began with the application of combining TF-IDF (Term Frequency–Inverse Document Frequency) with sentiment and contextual features by Yin et al. (2009). They compared the performance of this model with a simple TF-IDF model and reported a 6% increase in the F1-score of the classifier on chat-style datasets. Since then, there have been many advances in the field of toxicity classification. Davidson et al. (2017) detected hate speech on Twitter using a three-way classifier: hate speech, offensive but not hate speech, and none. They implemented Logistic Regression and SVM classifiers using several different features including TF-IDF n-grams, Part-of-Speech (POS) n-grams, Flesch Reading Ease scores, and sentiment scores using an existing sentiment lexicon. Using a similar set of features, Safi Samghabadi et al. (2017) applied a linear SVM to detect “invective” posts on Ask.fm, a social networking site for asking questions. They also utilized additional features such as Linguistic Inquiry and Word Count (LIWC; Pennebaker et al., 2001), word2vec (Mikolov et al., 2013), paragraph2vec (Le and Mikolov, 2014), and topic modeling. The authors reported an F1-score of 59% and AUC-ROC (area under the ROC curve) of 0.785 using a specific subset of features. Yu et al. (2017) proposed a word vector refinement model that could be applied to pre-trained word vectors (e.g., Word2Vec [Mikolov et al., 2013] and Glove [Pennington et al., 2014a]) to improve the efficiency of sentiment analysis. Chu et al. (2016)
compared the performance of various deep learning approaches to toxicity classification, using both word and character embeddings. They analyzed the performance of neural networks with LSTM (Long Short-Term Memory) and word embeddings, a CNN (Convolution Neural Network) with word embeddings, and another CNN with character embeddings; the latter achieved top accuracy of 93%.

This paper aims to tackle the issue of recognizing unhealthy online conversations. Existing research usually focuses on classifying the most hateful/vile comments; we, on the other hand, aimed to identify the subtle toxicity indicators in online conversations.

## 3 Data Preparation

In this section, we describe the dataset of 44K labeled comments of unhealthy conversations from Price et al. (2020), and detail the preprocessing steps taken to prepare the dataset for our machine learning analyses.

### 3.1 Dataset Description

The dataset used in this study was made publicly available\(^1\) by Price et al. (2020) in October 2020. It contains 44,355 unique comments of 250 characters or less from the Globe and Mail\(^2\) opinion articles sampled from the Simon Fraser University Opinion and Comments Corpus dataset by Kolhatkar et al. (2020). Each comment was coded by at least three annotators with at least one of the following class labels: antagonize, condescending, dismissive, generalization, generalization unfair, healthy, hostile, and sarcastic. A maximum of five annotators were used per comment until sufficient consensus—measured by a confidence score \(\geq 75\%\)—was reached. Each annotator was asked to identify for each comment whether it was healthy and if any of the types of unhealthy discourse (i.e., condescending, generalization, etc.) were present or not. The comments were presented in isolation to annotators, without the surrounding context of the news article and other comments (i.e., the annotators had no additional context about where the comment was posted or about the engagement of the comment with the users), thus possibly reducing bias. Since the comments were sourced from the SFU Opinion and Comments Corpus dataset, the prevalence of each attribute is unavoidably low.

The following are a few examples of every class label:

1. **Antagonize**: “An idiot criticizing another idiot, seems about right.”
2. **Condescending**: “So, everyone who disagrees with her - and YOU - are fascists? You’re just another pouting SJW\(^3\), angry that you didn’t get a ‘Participant’ trophy...”
3. **Dismissive**: “You are certifiably a nut job with that comment.”
4. **Generalization**: “This is all on the Greeks. Period. They are the ones who have been overspending for decades and lying about it.”
5. **Generalization Unfair**: “Progressives ALWAYS go over the top. They cannot help it. It’s part of their MO.”
6. **Healthy**: “We are seeing fascist tendencies and behaviours in our government, but its [sic] so hard to believe that it is happening to us, to Canada, that we will just continue to be in denial.”
7. **Hostile**: “Crazy religious f**kers are the cause of overpopulating the planet with inbred, uneeducated people with poor prospects of earning a satisfying life. An endless pool of desperate terrorists in waiting.”
8. **Sarcastic**: “You should write another comment, [user] - there are a few right-wing buzzwords you didn’t use yet. Not many, but some.”

Price et al. (2020) used Krippendorff’s \(\alpha\) as the inter-rater reliability metric for the crowd-sourced annotators (note, however, that they did not report the \(\alpha\) for two labels: healthy and generalization unfair). Opposite to most inter-rater reliability metrics which address agreement, Krippendorff’s \(\alpha\) measures the disagreement among coders, ranging from 0 (perfect disagreement) to 1 (perfect agreement). Table 1 lists the Krippendorff’s \(\alpha\) for each attribute (reproduced from Price et al., 2020), along with the final distribution of our preprocessed dataset (detailed below).

### 3.2 Preprocessing

First, we removed one comment from the dataset that was empty and 1,106 other comments which were not assigned to any class label. This decreased the total number of comments to 43,248. All comments were then preprocessed for the feature ex-

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1. https://github.com/conversationai/unhealthy-conversations
2. https://www.theglobeandmail.com/
3. Social Justice Warrior; a pejorative term typically aimed at someone who espouses socially liberal movements.
Table 1: Distribution of comments per category along with the respective Krippendorff’s $\alpha$ reported by Price et al. (2020). Note that some comments (10.6\%) were attributed to multiple labels.

| Class label                  | Count   | K-alpha |
|------------------------------|---------|---------|
| Antagonize                   | 2,066   | 0.39    |
| Condescending                | 2,434   | 0.36    |
| Dismissive                   | 1,364   | 0.31    |
| Generalization               | 944     | 0.35    |
| Generalization Unfair        | 890     | Not reported |
| Healthy                      | 41,040  | Not reported |
| Hostile                      | 1,130   | 0.36    |
| Sarcastic                    | 1,897   | 0.34    |

traction step. We converted all characters to lowercase, then removed HTML tags, non-alphabetic characters, newline, tab characters, and punctuation from the comments. We also converted accented characters to their standardized representations to avoid our classifier ambiguity words such as “latte” and “latté.” We then expanded contractions (e.g., “don’t” is replaced with “do not”). The final step was lemmatization, which consists of reducing words to their root forms (e.g., “playing” becomes “play”). After preprocessing the data, three comments were deleted because they contained just numbers or special characters. Thus, the total number of comments was 43,245 with an average length of 19.8 words. The final distribution of the preprocessed dataset is shown in Table 1. Most of the comments were assigned to a single class label ($N = 38,661, 89.4\%$), while 10.6\% of the comments ($N = 4,584$) were associated with two or more labels.

4 Methodology and Analysis

This section describes our feature engineering process followed by a detailed description of our machine learning analysis targeting the recognition of unhealthy comments through a diverse set of classification models, including traditional and deep architectures. We also describe the process of sentiment analysis of the comments.

4.1 Feature Engineering

We vectorized the comments using the Term Frequency-Inverse Document Frequency (TF-IDF) statistic, which is commonly used to evaluate how important a word is to a text in relation to a collection of texts (Manning et al., 2008). This measure considers not only the frequency of words or character $n$-grams in the text but also the relevancy of those tokens across the dataset as a whole. We also included other features that we considered useful in recognizing unhealthy comments, including length of comments, percentage of characters which are capitalized in each comment, and percentage of punctuation characters in each comment.

4.2 Machine Learning Analysis

In our machine learning experiments of multi-label classification, we considered the following well-known models:

Logistic regression. We used the Logistic Regression model with TF-IDF vectorized comment texts using only words for tokens (limited to 10K features).

Support Vector Machine (SVM). Essentially, SVM focuses on a small subset of examples that are critical to differentiating between class members and non-class members, throwing out the remaining examples (Vapnik, 1998). This is a crucial property when analyzing large data sets containing many ambiguous patterns. We used linear kernel since it is robust to overfitting.

LightGBM. LightGBM is a tree-based ensemble model that is trained with gradient boosting (Ke et al., 2017; Barbier et al., 2016; Zhang et al., 2017). The unique attribute of LightGBM versus other boosted tree algorithms is that it grows leaf-wise rather than level-wise, meaning that it prioritizes width over depth. There is an important distinction between boosted tree models and random forest models. While forest models like Scikit-Learn’s (Pedregosa et al., 2011) RandomForest use an ensemble of fully developed decision trees, boosted tree algorithms use an ensemble of weak learners that may be trained faster and can possibly generalize better on a dataset like this one where there are a very large number of features but only a select few might have an influence on any given comment. Given the huge disparity between healthy and unhealthy comments, we used a tree-based model with the top 50 words and the engineered features.

Convolutional Neural Network Long Short Term Memory (CNN-LSTM) with pre-trained
word embeddings. We used Global Vectors for Word Representation (GloVe; Pennington et al., 2014b) to create an index of words mapped to known embeddings by parsing the data dump of pre-trained embeddings. Since the comments had variable length (range: [3, 250] characters), we fixed the comment length at 250 characters, adding zeros at the end of the sequence vector for shorter sentences. Next, the embedding layer was used to load the pre-trained word embedding model. The LSTM layer effectively preserved the characteristics of historical information in long texts, and the following CNN layer extracted the local features from the text. After the CNN, we made use of `globalmaxpooling` function to reduce the dimensionality of the feature maps output by the preceding convolutional layer. The pooling layer was followed by a dense layer (regular deeply connected neural network); there was also a dropout layer placed between the two dense layers to help regularize the learning and reduce overfitting of the dataset. We used Tensorflow (Abadi et al., 2016) to implement our CNN-LSTM deep model, whose architecture is illustrated in Fig. 1. We used binary cross entropy as loss function because it handles each class as an independent vector (instead of an 8-dimensional vector). The input to the model was a random number of samples (represented as “?” in Fig. 1), all having a fixed length of 250 characters.

For Logistic Regression, SVM, and LightGBM, we used the implementations available in Scikit-Learn (Pedregosa et al., 2011) with slight modifications to the default parameters. These models were evaluated using \( k \)-fold cross-validation for \( k = 10 \). Importantly, in multi-label classification tasks (our case), a given comment may be associated with more than one label, so we did not use traditional stratified \( k \)-fold sampling which preserves the distribution of all classes. Instead, we opted to use iterative stratification (Sechidis et al., 2011; Szymański and Kajdanowicz, 2017), via the `IterativeStratification` method from Scikit-Multilearn (Szymański and Kajdanowicz, 2017), which gives a well-balanced distribution of evidence of label relations up to a given order. Owing to the high computational costs of training a deep neural network, the CNN-LSTM neural network was evaluated with 5-fold cross-validation instead of 10 folds.

The evaluation metrics used in our experiments were micro and macro F1-scores, and AUC-ROC (i.e., area under the ROC curve). F1-score is defined as the harmonic mean of precision, a measure of exactness, and recall, a measure of completeness. It is well-suited to handle imbalanced datasets (as in our case; Han et al., 2011). A macro-average F1-score will compute the F1-score independently for each class and then take the average (hence treating all classes equally), whereas a micro-average F1-score will aggregate the contributions of all classes to compute the average F1-score (Zheng, 2015). AUC-ROC curve is a performance measurement for the classification problems at various threshold settings. ROC is a probability curve and AUC represents the degree or measure of separability, indicating how much the model is capable of distinguishing between classes (wherein higher values indicate better discernment; Zheng, 2015).

We ran multiple experiments with different values of hyper-parameters for every model. For the logistic regression model, we tested different values of \( n \)-grams (words and characters), and max features (words and characters). We achieved the
best results with 10,000 word max-features and word n-grams range between [1, 3]. For the SVM model, we chose a linear kernel and tested distinct values of the regularization parameter \( C \); we observed that a value of \( C = 0.7 \) gave us better results than the default value of \( C = 1.0 \). During our experiments with LightGBM, we modified some baseline parameters to better suit the problem at hand: \( num_leaves = 128 \), \( n_estimators = 700 \) and \( max_depth = 32 \).

4.3 Sentiment Analysis

We used NLTK VADER (Valence Aware Dictionary for sEntiment Reasoning; Hutto and Gilbert, 2015) to analyze the polarity of comments. VADER is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media. We used the \textit{compound} value from the result for analyzing the polarity of the sentiments. For every input text, VADER normalizes the overall sentiment score to fall within \(-1\) (very negative) and \(+1\) (very positive), where scores between \((-0.05, 0.05)\) are labeled as neutral polarity.

5 Results & Discussion

In this paper, we analyzed the granularities of subtle toxic online comments. This section presents our experimental results in detecting the general sentiments associated with healthy and unhealthy online comments (RQ1) as well as recognizing such comments via machine learning classifiers (RQ2). Lastly, we summarize our main takeaways.

5.1 Results

Table 2 shows the mean values of the sentiment polarity for each category of comment. All types of unhealthy comments except sarcastic and condescending resulted in slight negative scores. The most negative result was observed for the class hostile, while the most positive result was obtained from the class sarcastic. The classes condescending and healthy produced the most neutral sentiment scores.

Table 3 exhibits the average micro F1-score, macro F1-score, and ROC-AUC obtained with all tested classifiers. As can be observed, the best classification results were achieved with the CNN-LSTM model, followed by SVM and LightGBM. Table 4 presents the ROC-AUC values resulted from CNN-LSTM (our best-performing classifier) for all analyzed types of comments. The best result was observed for the class healthy \((AUC = 0.9524)\), followed by the classes hostile \((AUC = 0.8141)\) and antagonize \((AUC = 0.7362)\). The class sarcasm yielded the poorest result \((AUC = 0.5707)\).

5.2 Take-Aways

RQ1: What is the general sentiment associated with unhealthy conversations compared to healthy conversations?

Our sentiment analysis revealed that none of the types of comments (i.e., classes) have extremely polarizing sentiment values (Table 2). However, all the classes except healthy, sarcastic, and condescending have an overall slightly negative sentiment associated with them, as expected for unhealthy types of conversations. Hostile comments were the most negative, likely due to the use of blatantly vulgar and vile language. This could possibly indicate that hostile comments were less subtle in their hateful content, and thus easier for sentiment tools and machine learning algorithms to detect.

Antagonizing, dismissive, and generalizing comments all had similar negative sentiment scores in the range of \([-0.1045, -0.0814]\). Though it is likely clear to most readers that such comments (examples given in Sec. 3) demonstrate negative sentiment, both NLTK’s VADER and CNN-LSTM demonstrated poor results for these classes, which highlights how sentiment tools and machine learning models may struggle to detect subtle forms of unhealthy language.

Interestingly, condescending comments scored neutral sentiment \((-0.03513)\). Detecting patronizing and condescending language is still an open

Table 2: Sentiment Analysis using VADER’s compound score; values range from \(-1\) (extremely negative) to \(+1\) (extremely positive).

| Class label    | Mean score |
|----------------|------------|
| Antagonize     | -0.104498  |
| Condescending  | -0.035128  |
| Dismissive     | -0.081356  |
| Generalization | -0.085851  |
| Generalization Unfair | -0.091320 |
| Healthy        | 0.035745   |
| Hostile        | -0.175975  |
| Sarcastic      | 0.101285   |
Table 3: Classification results.

| Model                  | Average Micro F1 | Average Macro F1 | AUC-ROC |
|------------------------|------------------|------------------|---------|
| Logistic Regression    | 57.54%           | 48.31%           | 0.51    |
| SVM                    | 69.15%           | 61.29%           | 0.62    |
| LightGBM               | 64.83%           | 52.11%           | 0.57    |
| CNN LSTM Network       | **88.76%**       | **67.98%**       | **0.71**|

Table 4: AUC-ROC results from the CNN-LSTM model.

| Class label             | ROC-AUC |
|-------------------------|---------|
| Antagonize              | 0.7362  |
| Condescending           | 0.6702  |
| Dismissive              | 0.6311  |
| Generalization          | 0.6633  |
| Generalization Unfair   | 0.6590  |
| Healthy                 | 0.9524  |
| Hostile                 | 0.8141  |
| Sarcastic               | 0.5707  |
| Mean                    | **0.7121**|

Research problem because, amongst many reasons, condescension is often shrouded under “flowery words” and can itself fall into seven different categories (Pérez-Almendros et al., 2020). Meanwhile, sarcastic comments were notably labeled as positive sentiment (0.1013), even higher than healthy comments (0.0357); this may have been because sarcasm tends to be an ironic remark, often veiled in a potentially distracting positive tone.

Unhealthy comments were mostly related with a low polarizing negative sentiment, with hostile comments labeled as the most negative and sarcastic as the most positive. Healthy comments were associated with neutral sentiment.

RQ2: Can we differentiate unhealthy and healthy conversations? If so, which type of unhealthy conversation is the most detectable one?

From Table 3, we can see that it was possible to differentiate between unhealthy comments with a maximum micro F1-score, macro F1-score, and ROC-AUC of 88.76%, 67.98%, and 0.7121, respectively, using the CNN-LSTM model. The remaining models tested (Logistic Regression, SVM, and LightGBM) reached poorer performances. All tested models reported a lower average macro F1-score compared to the micro F1-score results, which is intuitive given the highly imbalanced dataset—note that macro F1-score gives the same importance to each class, i.e., this value is low for models that perform poorly on rare classes, which was the case for CNN-LSTM when analyzing unhealthy conversation classes. Therefore, it is possible to speculate that the other models also performed better when recognizing healthy comments compared to unhealthy ones.

Additionally, Table 4 shows that healthy comments can be differentiated from the remaining classes relatively well with generally high predictive accuracy ($AUC_{healthy} = 0.9524$), likely due to the high number of healthy samples in the dataset. In contrast, despite only 1,130 samples associated with the hostile class, $AUC_{hostile} = 0.8141$, which was the second-highest AUC achieved by our top performer classifier. Most of the hostile comments have explicit language, which might make it easier for the classifier to properly recognize this type of conversation. The AUC for antagonizing comments was the third-highest achieved, at 0.7362, potentially because $n_{antagonize} = 2,066$ was the second largest sample size out of the remaining unhealthy conversations categories; antagonize also achieved the second most negative mean sentiment score ($-0.1045$), further indicating that there may be characteristics of this class that facilitate detection from machine learning algorithms.

Detection of sarcasm was the most difficult for the CNN-LSTM model ($AUC_{sarcasm} = 0.5707$). There have been numerous studies which have faced similar issues with detection of sarcasm given the difficulty of understanding the nuances and context surrounding sarcastic texts (Poria et al., 2016; Zhang et al., 2016). The AUC scores for condescending, dismissive, and generalizing comments were only slightly better (range: [0.6590, 0.6702]), again highlighting the difficulty in detecting such nuanced and subtle language.
Healthy online comments were accurately distinguished from unhealthy ones. Hostile comments were easier to detect than other forms of unhealthy conversations.

6 Limitations & Future Work

This section discusses the limitations of our study, and suggests possible future work.

We leveraged the Price et al. (2020) dataset, which sampled comments from the opinions section of the Canadian Globe and Mail news website. Though our results are promising (with top average micro and macro F1-scores of 88.76% and 67.98%, respectively), this dataset is nonetheless contained in a highly specific context (data was collected from a single Canadian newspaper website), which likely decreases the generalizability of our results. The dataset was also notably imbalanced, where most of the labels were attributed to healthy comments. Another limitation of the dataset is the low inter-reliability among the coders (Table 1). The low values of the metric reduce the confidence in the dataset, but also suggests that identification of different types of unhealthy conversations is challenging even for humans. Also, Krippendorff’s $\alpha$ was not reported for two out of eight classes (generalization unfair and healthy). In future work, we thus aim to expand our experiments on a more diverse dataset by replicating Prince et al.’s coding process using a variety of comments from different news websites.

One limitation of our machine learning analysis is that we trained a deep learning architecture (CNN-LSTM) using a relatively small dataset, mainly in terms of unhealthy categories of conversations. In future work, we plan to increase the number of unhealthy comments of our analysis by using data augmentation techniques such as Generative Adversarial Networks (GAN), which can synthetically generate new comments. NLP data augmentation techniques could also be used to increase the dataset without requiring significant human supervision, such as simulating keyboard distance error, substituting words according to their synonyms/antonyms, replacing words with their common spelling mistakes, etc. (Şahin and Steedman, 2019). This may help increase the performance of machine learning classifiers in general.

Another limitation is that we included only four classifiers in our analysis, which may restrict the generalizability of our findings. Future work is therefore advised to include other models successfully used by previous studies in classifying conversations with unhealthy and toxic elements, such as RandomForest, Bi-LSTM networks, Stacked Bi-LSTM (Bagga, 2020), capsule networks (Srivastava et al., 2018) and transformer models including BERT (Price et al., 2020). Future work is also advised to test feature selection methods, which usually help increase classification accuracy by focusing on the most discriminating features while discarding redundant and irrelevant information. Lastly, given the challenging nature of unhealthy comments classification tasks, future work should look at specialized corpora (e.g., Wang and Potts, 2019; Oraby et al., 2017) and machine learning models trained at differentiating particular types of conversations, for example, solely sarcastic comments from non-sarcastic ones (e.g., Dadu and Pant, 2020; Hazarika et al., 2018).

7 Conclusion

This paper analyzed the granularities of subtle toxic online conversations. The study goal was to systematically investigate the general sentiment associated with healthy and unhealthy online comments, as well as the accuracy of machine learning classifiers in recognizing these comments. Towards this end, we leveraged a public dataset containing healthy and unhealthy comments labeled with seven forms of subtle toxicity. We were able to distinguish between these comments with a maximum micro F1-score, macro F1-score, and AUC-ROC of 88.76%, 67.98%, and 0.71, respectively, using a CNN-LSTM network with pre-trained word embeddings. Our conclusions are two-fold: (i) hostile comments are the most negative (i.e., less subtle toxic) and detectable form of unhealthy online conversation; (ii) most types of unhealthy comments are associated with a slight negative sentiment. Findings from this work have the potential to inform and advance future research and development of online moderation tools, which pave the way for safer online environments.
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