Absract

Hateful and offensive language (also known as hate speech or cyber hate) posted and widely circulated via the World Wide Web can be considered as a key risk factor for individual and societal tension linked to regional instability. Automated Web-based hate speech detection is important for the observation and understanding trends of societal tension - especially in online social networks where hateful and antagonistic posts can be widely viewed and disseminated. Existing research has made significant in-roads into achieving this, albeit to levels of around 80% accuracy, leaving room for improvement. In this research, we improve on existing research by proposing different data mining feature extraction methods. While previous work has involved using lexicons, bags-of-words or probabilistic parsing approach (e.g. using Typed Dependencies), they all suffer from a similar issue which is that hate speech can often be subtle and indirect, and depending on individual words or phrases can lead to a significant number of false negatives. This problem motivated us to conduct new experiments to identify subtle language use, such as references to immigration or job prosperity in a hateful context. We propose a novel 'Othering Lexicon' to identify these subtleties and we incorporate our lexicon with embedding learning for feature extraction and subsequent classification using a neural network approach. Our method first explores the context around othering terms in a corpus, and identifies context patterns that are relevant to the othering context. These patterns are used along with the othering pronoun and hate speech terms to build our 'Othering Lexicon'. Embedding algorithm has the superior characteristic that the similar words have a closer distance, which is helpful to train our classifier on the negative and positive classes. captures the semantic meaning of the lexicon content jointly with a benign content, the negative content would be aligned in similar vectors with the othering pronoun and hateful content. For validation, several experiments were conducted on different types of hate speech, namely religion, disability, race and sexual orientation, with F-measure scores for classifying hateful instances obtained through applying our model of 0.93, 0.95, 0.97 and 0.92 respective

1. Introduction

The uptake of online social networks for social participation and social mobilisation is having a big impact on society. As people increasingly communicate through online applications, the need for high-quality, automated abusive language detection has become much more profound. While the benefits of online social media are enabling distributed societies to be connected, one unanticipated
disadvantage of the technology is the ability for hateful and antagonistic content or cyberhate to be published and propagated [5],[43]. Several studies have shown how individuals with biased or negative views towards a range of minority groups are taking to the Web to spread such hateful messages [23] [32]. Instances of cyberhate and racist tension on social media have also been shown to be triggered by antecedent events, such as terrorist acts [4] [44]. A hate crime or bias-motivated crime occurs when the perpetrator of the crime intentionally selects the victim because of his or her membership of a certain group [35].

Expressing hate speech or discriminative reactions implies different language uses. For example, to express emotions, hateful words might be used such as ‘hate them’; moreover, to encourage violence, an inflammatory verb could be used such as ‘kill’. While the previous example contains a directly offensive word (kill), some hate speech samples contain no single negative words (e.g. send them home). Although they do not contain hateful words, they setting a distance between different groups which promote the discriminative situations inside societies.

There have been a number of attempts to address online hate speech classification using different approaches (e.g. lexicons, syntax features and semantic features), yet the problem lies in classifying text that does not contain clearly hateful words and would have an impact on classification accuracy.

An example of a text that does not contain direct hate speech but imply hateful meaning is the tweets "send them home". While Previous studies highlight the use of embedding learning on different features sets (e.g BOW [10], POS, dependency, trained lexicon and n grams [28], they do not consider the previous example as hate and their results depended on the occurrence in the negative or positive context of the words "send", "them" and "home". To solve this problem, this study provides new insights into leveraging a specific hateful stereotype in the web content which is the othering terms as a pointer towards hate speech and discrimination. Our aim in this study is to add new feature that has not used before for advance the machine understanding of the negative text, specifically texts that do not contains explicit hateful expression.

Othering terms in different languages (e.g. English: You and Me), are used for pointing towards the side of the speaker, or tweets’ authors in our case. Our assumptions are based on studies that introduced the idea that some text content could contribute to detecting hateful speech, e.g. the othering terms [6]. In our study, English pronouns are considered the othering language, and we named two groups of English pronouns the ‘two-sided’ othering language. The first group of English pronouns comprises those that express the speaker/writer side (e.g. I, we, us, our, etc.), and the other group contains English pronouns that are used when the speaker/writer points towards different individuals or groups (e.g. you, she, he, them, those, these, etc.). The permutation of the pronouns is as follows: each pronoun from one side appears with a pronoun from the other side, as follows: You Our, You Us, She We, They I, etc) In addition, we refer to the content that frequently appears with the othering terms as a pattern of the othering use. For example, in ’send them all home’, the verb ’send’ appears with the pronoun ‘them’, which could be a pattern of the use of pronouns. The pronouns’ patterns could comprise verbs, nouns, etc.

We hypothesis that considering the sentence that contains two-sided othering language as hateful content improve the overall hate speech detection accuracy. Building on that, we propose a very effective frame work that captures the features that are expected to be seen with the two-sided othering language and extract their semantic meaning using paragraph2vec algorithm. From one side, This frame work adds a novel feature to be expected as negative meaning by building a lexicon which considers the two-sided othering terms, the two-sided othering patterns and the main negative components- the lexicon component were extracted from an external annotated data set. From another side, this framework improves the use of paragraph2vec algorithm that used in previous works as we consider our lexicon to improve the embedding learning. Differently from the previous works that include the syntactic features and semantic learning,
we add the two-sided pronouns as feature and we consider the (verbs, nouns and adjectives) which has no negative meaning but appear in a negative content as hateful content.

The paragraph2vec algorithm learn the semantic meaning of the lexicon component jointly with the main data sets. The lexicon component advance the semantic learning as following: the samples that contain two sided othering terms and patterns and negative content would be aligned in similar vectors.

For example, if we have the following sentence: (We want to hang them all) which contains clear hateful content "hang" and two-sided othering terms (we, them), from the embedding algorithm perspective, the previous sentence would aligned to similar vector of the following sentence: (We need to get them out).

We compared our model with state of art that applied combination of different text features - probabilistic (e.g. typed dependency text) and vector space features (e.g. doc2vec) Our model improve on the state of art studies by decreasing the false negative and false positive prediction.

In this paper, we show our proposed method and how it leads to improving machine understanding of the 'othering' language, as follows:in Section 2 previous the data set and collection. In Section 3, we introduce the theoretical explanation of our model. In Section 4, we review related work that is relevant to our technical proposal. The othering terms used are defined in Section 5. We explain the experimental steps of the proposed framework in Section 6. The classification results are presented and compared in Section 7 with the baseline results from [6] through a deep discussion to clarify how the proposed approach leads to better performance of cyberhate classification than the main baseline one. In Section 8, we show the possibility of generalising our model and the limitations. Finally, in Section 8, the contributions of this paper are summarised and some further directions are suggested for advancing this research area further.

2. DATASETS

We used the dataset provided by [9] to extract the othering lexicon content. They used a crowdsourced hate speech lexicon to collect tweets containing different types of hate speech keywords. They used crowdsourcing to divide a sample of these tweets into three categories: those containing hate speech, those with only offensive language, and those with neither. Their dataset contains different samples of different hate speech types. We extracted the samples that contain hate speech or offensive language and then from the extracted samples we extracted those that only contain two-sided othering language, which resulted in 674 tweets. Those tweets are used for extracting the verbs, nouns and adjectives related to othering terms in hate speech for lexicon construction.

In addition to this sample, we extracted all nouns and adjectives that were mentioned in the whole hateful samples. For testing, to demonstrate an improvement on the state of the art, we used four datasets from previous work [6]. The datasets were collected from Twitter and annotated using the CrowdFlower human intelligence task service with a single question: ‘Is this text antagonistic or hateful based on a protected characteristic?’ The datasets comprise four different protected characteristics, as follows: sexual orientation 1803 tweets, with 183 instances of offensive or antagonistic content (10.15% of the annotated sample); race 1876 tweets, with 70 instances of offensive or antagonistic content (3.73% of the annotated sample); disability 1914 tweets, with 51 instances of offensive or antagonistic content (2.66% of the annotated sample); and religion 1901 tweets, with 222 instances of offensive or antagonistic content (11.68% of the annotated sample).

The authors conducted all of the necessary tests so as to ensure agreement between annotators for the gold-standard samples [6]. The amount of abusive or hate instances is small relative to the size of the sample. However, these are random instances of the full datasets for each event and they are considered representative of the overall levels of cyberhate within the corpus of tweets.

3. THEORETICAL FRAMEWORK

This study is based on leveraging the use of the othering pronouns in web-based content as features
for hate speech classification. [4] identified that the ‘othering’ language was a useful feature for classifying cyberhate based on religious beliefs, specifically for identifying anti-Muslim sentiment. Othering is an established construct in rhetorical narrative surrounding hate speech [25], and the ‘we-they’ dichotomy has always been identified in racist discourse [48]. [47], who focus on decoding racist discourse, argued that while the ‘self’ or the concept of ‘us’ is constructed as an in-group identity, the ‘other or the concept of ‘them’ is constructed as an out-group identity [39]. Therefore, polarisation and opposition are created by emphasising the differences between ‘us’ and ‘them’. Positive self-representation and negative representation of the ‘other’ mark are considered an out-group that is undesirable [46]. We assume that the text that appears with two-sided othering terms is more likely to represent negative speech, specifically in hate-related events.

Anti-Hispanic speech might make a reference to border crossing or legal identification, anti-African American speech often references unemployment or single parent upbringing, and anti-Semitic language often refers to money, banking, and the media. The use of stereotypes also means that some languages may be regarded as hateful even if no single word in the passage is hateful by itself [11].

Figure 1 presents an overview of textual features which are generated between different groups who discriminate themselves from others. The figure shows how the othering pronoun terms from one side (us, we, I, etc.) draw the boundary between the two different groups, e.g. people try to distinguish themselves from another group by using either ‘we’ or ‘they’. When they use two-sided pronouns in the same context, they define the boundary of the discriminative or negative text (whether it is directly or indirectly hateful). When the authors express their opinion or attitude using two-sided othering terms in related hateful web events, it is more likely that they will present the difference by drawing boundaries between the two different groups. The first boundary was drawn by expressing the first side of pronouns (e.g. we) and the second boundary was drawn by using the second side of pronouns (e.g. you). In the hate-related event, the text that appears with these pronouns expresses the tension in using two-sided pronouns, and we assume in our study that this is more likely a negative or discriminative perspective.

Our approach involves four main steps. The first step is to extract the othering term pattern, as well as all of the verbs, nouns and adjectives in the negative samples. The second step is to build the lexicon by adding the two previous results and the othering permutation. Thirdly, we learn the sentence embedding of the lexicon jointly with negative samples and benign samples. Finally, we feed our feature sets to MLP for training classifiers. Figure 9 explains the workflow of our method. To leverage the use of the two-sided othering terms as new features in hate speech classification, firstly, we investigate whether expressing two-sided othering terms would be more likely to elicit negative tension among short messages (e.g. tweets) and long messages (e.g. Wikipedia articles).
Secondly, depending on the previous findings, we begin to extract the othering pattern as features. The classification task is considered a validation one that aims at measuring the accuracy obtained by using our model.

3.1 Measuring the Othering Language

Most existing efforts to measure hate speech require knowing the hateful words or targets [21]. The key idea is as follows: if some users post their hateful emotions, they are likely to use pronouns that express their feelings (e.g. we like), but if another pronoun that points towards the other side is expressed in the same message, the post might be more likely a discriminative or negative post. This idea could not be applied in all instances for hate speech detection but it could boost the assumption of hate existence in a specific post, specifically within text that contains no directly hateful words. This step of the investigation does not aim to predict all hateful instances, yet points towards the usage of two-sided otherness in hateful instances, so we examine the instances that contain othering terms only. Hateful and neutral instances were collected from six types of hate speech characteristics: anti-Muslim, anti-Semitism, homosexuality, disability, racism and sexism. We investigate 9400 benign and 1329 negative instances. We found that two-sided otherness expression is considered a hate-related feature of hate speech classification, as otherness usage is 0.9% and 17.6% for benign and negative instances respectively in short messages such as tweets. Comparing the two-sided otherness appearance in benign and negative samples illustrates that negative hate clearly involves this language for expressing a hateful attitude, whereas it was used
in a non-observable manner in the benign instances. We should notice that the percentage of 0.9% is considerably tiny for the benign sample. However, it contains 28% of the negative articles but produces a higher percentage of positive articles (46%), which means that two different sides of othering terms in long text (e.g. articles) are used frequently in both benign and negative text and could not be considered hateful features. Clearly, this strategy does not identify all existing hate speech in social media, which is fine when considering the purpose of the analysis presented in this study. Overall, despite the volume of hateful instances in comparison with the volume of benign samples, it is clear in Figure 3 that two-sided othering term existence in the hateful sample exceeds the occurrence of othering terms in the benign samples. In 4, we implemented a comparative experiment measure the frequent occurrence of two-sided othering terms in both hateful samples and non-hateful samples among different types of hate speech datasets.

It is obvious in Figure 4 that the anti-Muslim dataset contains the most frequent usage of the two-sided othering language, followed by anti-Semitism, which means that as [4] identified, 'othering' language was a useful feature for classifying cyberhate based on religious beliefs, specifically for identifying anti-Muslim sentiment. The difference in this investigation from previous study [6] is that we investigate the use of two sides of othering terms (English pronouns in our case) as a pointer towards negative or discriminative attitudes in different types of hate speech events. The third hate speech characteristic that uses the othering term is the Racism dataset. In contrast, we noticed that in the Disability dataset, the use of the two-sided othering term was more frequent in the neutral language than in the negative one. This means that the othering terms are more likely to be benign in the disability event, an example extracted from the same Disability dataset (e.g. we

Figure 2: Our model workflow using ten-fold cross-validation. Our dataset comprises the four datasets of religion, race, disability, and sexual orientation and non-hateful samples among different types of hate speech datasets.
are proud of you), which means that two-sided othering terms are used to explain the situation of the achievement more than discrimination in the disability-related event. Ending with the Sexism and Bisexual hate speech characteristics, we found that the othering terms are frequented in a similar percentage for both hateful and neutral samples (higher in the negative sample), which indicates that the two-sided othering contributes intermediately to discriminating genders and sexual orientations. The size of the hateful samples is still a limitation.

Figure 3: The graph shows the overall amount of two-sided othering term use in both hateful and non-hateful samples.

Figure 4: The graph shows the use of two-sided othering for each hate speech type in both hateful and non-hateful samples.
In summary, we found that the use of the two-sided othering language in short messages might be more likely to be that of hate speech, whereas the use of two-sided othering language in the articles tends to be neutral.

In addition, we found that the othering language contributes significantly to expressing religious and racist attitudes and intermediate to expressing gender and sexual orientation discrimination. For both the former and latter we consider the othering terms to be effective features for hate speech detection. Clearly, this strategy does not identify all existing hate speech in social media, which is fine when considering the purpose of the analysis presented in this study. This investigation leads us to produce a novel feature that uses two-sided pronouns and their pattern usage as pointers of hate speech.

3.2 Features Analysis

This study discovers the effectiveness of a text portion which somehow could be considered a hate pointer, which is using two-sided othering pronouns. To leverage the use of the two-sided othering terms as a new feature in hate speech classification, two core steps were implemented to build our model: (a) building the othering lexicon and (b) learning the vector space embedding of the lexicon jointly with the negative and benign samples. The othering lexicon contains the othering terms and their patterns extracted by a dependency parser, as well as the verbs, nouns and adjectives that appear in all of the negative samples extracted by the POS tagger and all of the two-sided pronoun permutations. The dataset was provided by [9]. An example of the previous method for the tweet 'we want to send them all home' contains two-sided pronouns and the verb 'send', which grammatically relates to the pronoun 'them' as a subjective clause. Even though the verb 'send' is not offensive, we include it in the lexicon. This verb was extracted from the dependency parser of the sample tweets that contain two-sided othering terms, which is considered a pattern verb of the othering terms (pronouns). The reason for pronoun permutation was to increase the possibility of the pronouns appearing with each hateful content, as it was expected that people might use any combination of two pronouns from different sides so as to express discriminative attitudes using different hateful content. Algorithm 1 shows the steps of building our lexicon. All pronoun combinations will appear with each row that contains the othering pattern and the POS results (verbs, nouns and adjectives). Figure 5 illustrates a focused part of the entire workflow which is presented in Figure 9. In Figure 5 we show how a specific negative sample contributes to building our lexicon.
The authors will now turn to the second phase of the model, which is paragraph embedding learning. The two-sided pronouns, which appear frequently in the negative and discriminative attitudes, change the process of assigning the vectors of the negative content to similar vector space by using the paragraph2vec embedding algorithm. In this case, all of the two-sided combinations of the pronouns appear with all of the negative content. To show the othering effectiveness on the context, which would be learned by the embedding algorithm, assume that we have the following rows in our lexicon:

* we them nsubj send all ni**as home
* we you nsubj getout wogs country

Figure 10 shows how the pronouns would be predicted by the paragraph2vec algorithm during the training phase of the dataset for producing vectors. This prediction scheme could be applied so as to predict unseen data instances that contain similar content.

From an embedding learning perspective, two-sided othering words and dependency modifiers decrease the distance between the directly/indirectly hateful content and align them in similar vectors. The similarity increment advanced the classification accuracy as the negative vectors.
Algorithm 1 Othering Lexicon

1: O1 = o1, o2, ..., o1
2: S = s1, s2, ..., s1 [parsed sentences rows]
3: M = m1, m2, ..., m1 [list of four dependency modifiers nsubj, obj, det, and compound]
4: PoS = p1, p2, ..., p1 [list of three POS tagged modifiers VB, NN, and JJ]
5: Pattern = null [empty list for save the othering terms related patterns]
6: Terms = null [empty list for save the hateful terms]
7: Lex = null [empty list for lexicon]
8: for each S, ∈ S do
9: for o1, o2, ∈ O1 and O2 do
10: if o1, and o2, ∈ s, then
11: addS to P
12: end if
13: for line ∈ Pattern do
14: dependency parser
15: if m ∈ line then
16: keep line
17: else
18: discard line
19: end if
20: save Pattern
21: end for
22: end for
23: for s, ∈ S do
24: POS tagging
25: if m ∈ line then
26: keep line
27: else
28: discard line
29: end if
30: save Terms
31: end for
32: end for
33: for o1, o2, ∈ O1 and O2 do
34: permutation(o1, o2)
35: end for
36: write to first column → Lex
37: write Pattern to second column → Lex
38: write Terms to third column → Lex
39: delete POS modifiers (VB, NN, JJ)
40: save Lex

Figure 7: The steps of building the two-sided othering lexicon

Figure 8: Concatenation or average of a paragraph ID vector with a lexicon context of five words is used to predict the sixth word.
4. LITERATURE REVIEW

4.1 Lexicon-based Hate Speech Detection

A number of previous works have attempted to generate sentiment words representing negative and positive orientation [8] [30] [36]. Furthermore, several works begin by first creating prior-polarity lexicons [50] [19] [17]; in contrast, we build an othering lexicon that assumes that a portion of the hate text contains the othering language, which could be a useful feature for boosting hate speech prediction. However, while the dictionary-based approaches generally suffer from the inability to find offensive words with domain and context-specific orientations, Corpus-based approaches use a domain corpus to capture opinion words with preferred syntactic or co-occurrence patterns. Focusing on a theme-related lexicon, [15] generate a lexicon of sentiment expressions using semantic and subjectivity features with an orientation towards hate speech, and then use these features to create a classifier for hate speech detection. This is similar to our work somehow, in that they depend on extracting useful expressions related to their main themes of race, nationality and religion that can be used as a lexicon in hate speech detection. However, we are trying to extract the theme of the use of the othering terms in the antagonistic samples; in addition, we are learning the vector embeddings. In relation to the context pattern, [34] detect hate speech using sentence structure by assuming specific patterns starting with the word 'I'. They assume that the word 'I' means that the user is talking about the emotions that he or she is feeling. Meanwhile, our work assumes that if 'I' and 'you' exist in the same context, the context is more likely to be discriminative.

Phrase-level sentiment analysis is different from lexicon-based analysis in that the former focuses on the polarity of the contextual content (e.g. whether there is negation in the sentence or not), whereas the latter predicts the polarity depending on the occurrence of the words that exist in the dictionary. A work conducted by [45] proposed a method for automatic hate detection using two steps: firstly, they concentrated on whether sample instances are neutral or polar in context (where polar in context refers to having a contextual polarity that is positive, negative or both). They used word features (tokens), sentence/structure features (dependency relations) and document features (document topic). They used Negated, which is a binary feature that captures whether the word is being locally negated. Its value is true if a negation word or phrase is found within the four proceeding words or in any of the word’s children in the dependency tree, and if the negation word is not in a phrase that intensifies rather than negates. They combined sentence-level features and dictionary-based levels and achieved significant improvement in hate speech polarity prediction. While their experiments classified individual words and phrases, we focused on the tension of the author in respect of the othering terms. In addition, they focused on content used in the negative sentiment (e.g. negation), whereas we clarify the effectiveness of content that is not related yet is used in a specific form in hate speech.

4.2 Linguistic Features

One of the most basic forms of natural language processing is the Bag of Words (BoW) feature extraction approach. BoW has been successfully applied as a feature extraction method for the automated detection of hate speech, relying largely on keywords relating to offence and antagonism [5, 29, 42]. However, the method also suffers from a high rate of false positives, since the presence of hateful words can lead to the misclassification of tweets being hateful when they are used in a different context (e.g. 'black') [16]. Similar to BoW, n-grams consecutive words of varying
sizes (from1...n) have been used to improve the accuracy of hate speech classification [14] [?] by capturing context within a sentence that is lost in the BoW model [3,7,28,41]. [41] found that character n-grams have been shown to be appropriate for abusive language tasks due to their ability to capture variations of words associated with hate. In general, while previous studies addressed the difficulty of the definition of hateful language, their experiments led to better results when combined with a large set of features such as BoW. They showed that BoW, n-grams, part-of-speech tagging, and data preprocessing (stop word/punctuation removal) provided a significant improvement in sentiment classification among different datasets (blogs and movies) when applied as a sophisticated combination of feature sets. They speculated that engineering features based on deeper linguistic representations (e.g. dependencies and parse tree) may work for content on social media. In general, lexical and syntactic features are useful when they are applied directly for automatic categorisation of annoying behaviours or topic detection [40], whereas in cyberhate detection we need a deep understanding of the posted text, which will be the focus of the current work. According to [49], while part-of-speech tagging does not significantly improve classifier performance, we apply POS tagging for extracting specific content (verbs, nouns and adjectives) for lexicon building. [9] prepared their data by stemming and then creating unigram, bigram and trigram features, each of which was weighted by its TF-IDF metric. Then they demonstrated how non-hateful content might be misclassified due to the fact that it contains words used in racist text. In contrast, there were hateful instances misclassified because they did not contain any of the terms most strongly associated with cyberhate. We aim to overcome this limitation by moving away from dependencies on specific keywords. Typed dependencies have been widely used for extracting the functional role of context words for sentiment classification [17,18] and document polarity [37]. [5,6] demonstrated the effectiveness of applying typed dependencies for classifying cyberhate. Their study showed that typed dependencies consistently improved the performance of machine classification for different types of cyberhate by reducing the false negatives by 7%, beyond the use of BoW and known hateful terms.

4.3 Text Embedding

Embedding learning is aimed at training a model that can automatically transform a sentence/word into a vector that encodes its semantic meaning. It has been shown that embedding representation is very capable of semantic learning when word vectors are mapped into a vector space, such that distributed representations of sentences and documents with semantically similar words have similar vector representations [26] [27]. Based on the distributional representation of the text, many methods of deriving word representations that are related to cyberhate and offensive language detection are explored in the following works. In general, neural network applications were shown to be capable of capturing specific semantic features from complex natural language (e.g. location [31], entity [33] and images feature [1]). For hate speech detection purposes, [10] solved the problem of high dimensionality and sparsity by applying sentence embedding (paragraph2vec) directly in the context. In their study, paragraph2vec, which is an extended version of word2vec for sentences, has been shown to outperform the BoW representation for cyberhate classification. However, they limited their study by comparing the classification results with TF-BoW and TF-IDF-BoW for the same comments. Similarly, [2] compared the classification accuracy of the combination of different baselines and classifiers (Char n-gram, TF-IDF, BoW and LSTM) and found that learning embedding with gradient-boosted decision trees led to the best classification performance. Word vector extraction was also applied to tweets for cyberhate classification by [12], who built four feature sets: character 4-grams, word vectors based on semantic information built using word2vec, randomly generated word vectors, and word vectors combined with character n-grams. They showed that the second feature set (word2vec alone) outperformed the other ones, which clarified that n-grams might affect classifier performance negatively. Several works have merged typed
dependencies with embedding learning and clarified the different levels of embedding learning when using the dependency context rather than the raw or linear text. [20] showed that dependency-based embeddings are less topical and exhibit more functional similarity than linear embeddings, and [24] showed that dependency context embeddings can provide valuable syntactic information for sentence classification tasks, which is a motivation for implementing classification tasks in respect of dependency embedding text. In addition, [51] defined the differences between flat text, which they called neighbour words, and the dependency context, and clarified through examples the drawbacks of learning embedding of flat text. While these studies introduced the effectiveness of the word distances of the dependency context, which capture the semantic relations, their works targeted other areas of research, not cyberhate; therefore, we are yet to see much evidence that the complex and nuanced 'us and them' narrative emerging on social media can be captured using a combination of typed dependencies and embeddings. One study that has combined typed dependencies with embedding learning in the context of cyberhate was reported by [28]. They developed a machine learning approach to cyberhate based on different syntactic features as well as different types of embedding features, and reported its effectiveness when combined with the standard NLP features (n-gram, linguistics feature, dependency context) in detecting hate speech in online user comments. They showed how applying each feature set alone resulted in different classification performance, and found that character n-grams alone are useful in noisy datasets. While using n-grams boosted training performance, n-grams result in high dimensionality and render the models susceptible to overfitting. This study is arguably closest to ours, but differs insomuch as they used the dependency context to capture long-range dependencies between words, whereas we focused on employing the dependency modifiers as a connection between the pronouns and offensive language in order to capture distances between social groups. To determine the effectiveness of our novel approach, we have compared our method with [28]. Our work is therefore distinct from the above literature in that we utilise the dependency modifiers for embedding learning in the context of cyberhate classification. Furthermore, we validate our model by training in an unseen dataset for hate speech classification so as to provide evidence that the model itself is applicable for training using various web-based sources of information and testing using short, informal posts from Twitter.

5. EXPERIMENTAL SETUP

5.1 Othering Lexicon

Based on the previous findings in Section 3.1, we evaluate the effectiveness of the othering language as features in hate speech detection by implementing a classification based on training in a negative lexicon. As the othering language might appear in the benign and negative language, we construct the following basic expression in order to build a lexicon, with each row of the lexicon being as follows. The lexicon assumes that two-sided pronouns appear with a specific pattern and offensive words in each row. This row is then converted to vector space using the paragraph2vec algorithm:

\[\text{<Othering Terms Permutation><Othering Pattern><Hateful Words>}\]

Each part was extracted as following:

\[\text{<All two-sided Pronouns><dependency(nsubj,dobj,det,compound)>}
\text{<POS (VB, NN, JJ)>}\]

Our lexicon content was extracted from negative samples of an annotated dataset [9]. From each instance in the negative dataset we constitute one row in the lexicon, with each row in the lexicon containing three columns: (1) all combinations of two-sided English pronouns, (2) the othering pronoun-related patterns which were extracted using typed dependency parser, and (3) the negative words which were extracted by POS 3 tagging [9]. The pronoun patterns extracted from the samples that contain two-sided pronouns and the hateful words were extracted from all of the samples. A typed dependency parser provides subjective relations between the
othering terms and nouns, verbs and adjectives (see Figure 7). We identify these relations by using four types of dependency relations: nsubj, dobj, det and compound. All of the dependency identifiers and their relations were discarded from the context and we kept the nsubj, dobj and compound identifiers without discarding. The reason for preserving these identifiers is as follows: nsubj presents the grammatical relations between the othering and the verb in a tweet, and dobj concerns the direct object of a VP. It is the noun phrase, which is the (accusative) object of the verb which presents the grammatical relation between the verb and the noun that occur in the same tweet. The compound modifier compounds any noun that serves to modify the head noun, which exist in the same tweet. We apply the dependency parser to all of the 674 samples and start extracting all of the othering terms, verbs, nouns and adjectives related to the othering terms through a dependency relationship for building a lexicon.

For all of the extracted content, we implemented a permutation between all of the othering terms of two groups. Then for each row in the lexicon, we added all of the combination permutations, the process of which resulted in 51,753 rows. The goal behind implementing a permutation between the othering terms is to advance the possibility of pronoun occurrence in each lexicon row. It seems to assume that each negative sample might contain any combination of two-sided pronouns. The dependency modifiers were included in the lexicon. In the discussion section, we will clarify the role of the dependency modifiers in embedding learning. To develop the lexicon content, POS tagging was applied in all of the negative samples (whether containing two-sided othering language or not). Then we filtered the POS tagged dataset in order to obtain only three types of text content: verbs, nouns and adjectives. After the nouns, adjectives, verbs and adverbs were extracted, the POS tagged modifiers were removed and then the content was added to the lexicon. The POS modifiers were removed from the lexicon because the embedding algorithm takes any content into consideration in the learning vector stage.

5.2 Embedding Learning
We learned the Distributed Memory (PV-DM) vectors using Gensim 4 implementation of distributed representations of the sentence [22]. In paragraph2vec, every sentence is mapped to a unique vector, and every word included in the sentence is also mapped to a unique vector.

\[
\text{Max} \sum \forall (\text{tar,con,doc}) \log P(\text{targetword} | \text{contextword,documentcontext}) (1)
\]

The paragraph vectors and word vectors are averaged or concatenated so as to predict the next word in a context. In the Distributed Memory component (PV-DM), the paragraph (the tweet) acts as a memory that remembers the missed word in the current context of the paragraph or tweet.
According to [27], the distributed memory model is consistently better than PV-DBOW. To find the best implementation for our data, we experimented with both and found that distributed memory performed better in learning our dataset vectors. We used small window sizes because, according to [24], a window of size 5 is commonly used to capture broad topical content, whereas smaller windows (e.g. k=2 windows) contain more focused information regarding the target word. For further explanation, using a window of size k around the target word \( w \), 2k the contexts which are produced by using k Windows size as k words before and the k words after \( w \). For example, for k=2, the contexts of the target word comprise \( w-2, w-1, w+1, w+2 \). In fact, we cannot assign a meaning to any particular dimension. We observed the different results being captured by the model by examining which dimension behaved better in which dataset. We report results for 600 dimension embeddings and windows = 2, though similar trends were also observed with 100, 300, 800 and 1000 dimensions and windows = 3, 5, 6 and 10. We recorded the best performance for 600 dimensions and windows = 2 parameters. The final output is a vectorised dataset that is used as a feature set for developing a machine classification approach.  

5.3 Machine Classification

Ten-fold cross-validation was used due to the volume of positive and negative instances for supervised classification. This method has previously been used for building machine classifiers for short text [37]. In addition to that, we implemented semi-supervised classification by training in the positive samples of the [9] dataset and training in only the lexicon as negative samples. The model was evaluated by testing it on the four datasets: religion, disability, racism and sexual-orientation. Two classifiers were applied: Multilayer Perception (MLP) and Logistic Regression (LR). Multilayer Perceptron (MLP) is a feed-forward artificial neural network model which maps input datasets on an appropriate set of outputs. MLP consists of multiple layers of nodes in a directed graph, with each layer being fully connected to the next layer [13]. Non-linear MLP classifiers work better with our vectorised features. Two-layer MLP achieved better performance for our vectors with 200 iterations.

An LR model is a simplified model on which MLP is based. We also implemented this model to test the potential for a much less computationally intensive approach to classification, possibly something that could be utilised in real time to classify content in streamed data. For ten-fold cross-validation, we learned the vector space of the negative samples and the othering lexicon (as a negative feature set) jointly with positive samples for supervised learning (see Figure 5). For semi-supervised learning, when we tested our lexicon on unseen datasets, we trained the embedding algorithm in our othering lexicon as negative and the positive samples of the [9] dataset (see Figure 9). Then we labelled each instance individually, assigning the positive and negative labels as 0 and 1 respectively.

![Multilayer Perception (MLP) classifier with two hidden layers.](image-url)
6. RESULTS AND DISCUSSION
The main baselines in this work are the results produced in [6], [10] and [28]. The previous studies use different feature sets for hate speech classification, part of which we applied in our study. [6] apply lexicon, BoW, n-grams and dependency, [10] used paragraph2vec for joint modeling of comments and words, and [28] add to [6] paragraph2vec and word2vec. We validate our model (a) by using ten-fold cross-validation and (b) by training our classifier in the lexicon for negative training and in the benign samples of davidson2017automated for positive training, testing the four datasets as unseen data. Table 1 shows machine classification performance for cyberhate based on disability, race, sexual orientation and religion datasets. The table shows the effectiveness of including the othering language terms as features in embedding learning for classification of cyberhate, which leads to reducing the false positive rate in two out of three types of hate speech classification - race and sexual orientation - when compared with using a BoW model and/or hateful terms as features. In our work, we show how our model led to reducing the false negative and false positive rates in comparison with the baselines. The previous results for [6] were provided using the F-measure metric, with 0.77 for religion, 0.75 for disability, 0.75 for race, and 0.47 for sexual orientation. Table 1 shows that we have improved considerably on these results. The key finding from previous research was that the inclusion of othering language in the classification of religious cyberhate reduced the false negative rate by 7% when compared to using hateful terms alone. In addition, there was no significant improvement in using typed dependencies for disability over a standard BoW approach [6]. In our study, the lowest false negative rate was achieved when using the n-gram feature set for all of the datasets. For religious cyberhate, the classification task achieved a 56% reduction in false negatives through using an n-gram feature set, which was the lowest false negative rate in [6]. In addition, the classifier predicted effectively the majority of the positive instances, with an overall false positive rate of 0.3%. For the religion dataset, the classifier correctly predicted 89.5% of the cyberhate and around 98% of non-hateful instances. This resulted in a 38% reduction in the false negative rate when compared with the lowest rate achieved when applying typed dependency with hateful terms. For disability, we improved on the result in [6] with a 16% reduction in false negatives. However, our model produced no improvement in the false positive rate when compared with the best rate reported by [6].

For the race classifier, we detected 95% of the cyberhate instances, which is considered an improvement of 22% in detecting hateful instances when compared to. For the false positive rate, we achieved an improvement of 1.6% when compared to [6]. For sexual orientation, there is a large reduction in the false negative rate achieved by our model. There is a 57% improvement on [6]. While [6] produced no false positives when applying the n-grams feature and hateful terms to the sexual orientation dataset, we achieved 98% of correctly classified hateful instances. We recorded a 0.99 F-measurement, whereas [6] reported a 0.18 F-measurement. Our results were compared with using only the paragraph2vec algorithm which introduced in [10], We noticed that our frame work improve the paragraph2vec learning by decreasing the false negative by 3%, 47%, 7% and 4% for the Religion, Disability, race and sexual orientation respectively. In addition to that, We notice the high reduction of the false positive measurements by 43%, 50%, 99% and 24% for the Religion,
Disability, race and sexual orientation respectively, which mean that our framework provides better understanding for semantic learning as take into consideration the effectiveness of the othering language use. Moreover, we compare our model with [28], because they used a combination of several NLP methods (one of them are typed dependency and POS) with paragraph2vec and word2vec and found them to be very powerful when combined with each other. For religion data set, our framework outperforms [28] features by reducing the FP from 14 to 4 and decreasing the FN by 45%. For Disability, the FP instances were reduced from 30 to just one and the FN from 36 incorrectly classified to 4 and same thing for the Race data set when the former was 8 and the later were 10. For Sexual-Orientation, we could notice the reduction of the FP and FN by approximately the half, from 8 to 4 and from 22 to 10 incorrectly classified instances for both FP and FN respectively.

In our study, different features have an effect on the results: The othering terms, the othering patterns which extracted by typed dependency, and the negative content which extracted by POS.

| Features | classifier | Religion | Disability | Race | Sexual-Orientation |
|----------|------------|----------|------------|------|--------------------|
| n-Gram words 1 to 5 with 2000 features | SVM | 0.89 | 0.74 | 0.72 | 0.62 |
| n-Gram hateful terms[6] | SVM | 0.89 | 0.76 | 0.93 | 0.67 |
| n-Gram words (1-5) with 2000 features + hateful terms[6] | SVM | 0.74 | 0.76 | 0.79 | 0.57 |
| n-Gram typed dependencies[6] | SVM | 0.53 | 0.77 | 0.87 | 0.72 |
| n-Gram typed dependencies + hateful terms[6] | SVM | 0.89 | 0.77 | 0.91 | 0.71 |
| n-Gram words (1-5) with 2000 features + n-Gram typed dependencies + hateful terms | SVM | 0.89 | 0.77 | 0.87 | 0.72 |
| The othering lexicon | MLP | 0.99 | 0.90 | 0.97 | 0.79 |
| Comment Embedding | MLP | 0.89 | 0.84 | 0.92 | 0.79 |
| N-grams+linguistic+dependencies+word and comment Embedding | MLP | 0.86 | 0.83 | 0.92 | 0.89 |
| The lexicon without othering terms + Paragraph2vec Embedding | MLP | 0.90 | 0.86 | 0.92 | 0.89 |
| The othering lexicon + Paragraph2vec Embedding | MLP | 0.98 | 0.93 | 0.99 | 0.96 |

Table 1: Machine classification performance for cyber hate based on Religion, disability, race and sexual orientation.
tagging, the semantic meaning of the previous features which extracted jointly with the main data set by Paragraph2vec algorithm. Despite that the Disability has not been affected by the othering terms, we could notice the reduction of the FP and FN results when using our framework. This means that the semantic meaning of the othering patterns (which extracted by dependency parser) and the negative content (which extracted by POS tagging) have an effect on results even if the Disability data set does not contain that much use of the two-sided othering terms. This means that our framework improved in understanding the negative content in general.

To clarify the effectiveness of the othering terms in hate speech detection, we implemented the same experiments yet we discarded the othering terms from the lexicon (see the ninth row in Table 1). The results illustrate that there are increases in false negatives and false positives in only extracting the two-sided othering terms from the lexicon. This means that the two-sided othering terms (pronouns in our study) advance the paragraph embedding training, which has an effect on the classifier results. Our results are affected by these factors: (a) lexicon content, (b) embedding learning, and (c) MLP classifier. Changing any factors of the previous ones produces low-accuracy results. For example, we implemented a classification using a Logistic Regression (LR) classifier but we found that MLP behaves better with our feature sets. The F-measure of LR were 0.79, 0.73, 0.76 and 0.86. The lexicon provides a pattern of the two-sided othering language and the related words (verb, noun, adjectives) which were extracted from human-annotated tweets. The othering terms, the othering patterns and the hateful related verbs, nouns and adjectives, which are not necessarily offensive, play an important role in boosting the accuracy of the results. Paragraph2vec learns the embedding algorithm and produces two matrices: vocabulary vector matrix and paragraph vector matrix. Paragraph2vec aligns the combination of two-sided othering language and the hateful content in similar vectors (in the vocabulary matrix). This increases the probability that using two-sided othering language in the same sentence increases the possibility that the entire sentence is negative. As paragraph2vec aligns the lexicon content with similar vectors, the verb ‘send’ would be negative if it appeared with two-sided pronouns, as the paragraph2vec algorithm would predict them if they had ‘them’ and ‘we’ OR any combination of two-sided othering. The novelty of our lexicon is that it not only provides negative words but also provides a pattern or stereotype of negative speech. However, our lexicon does not provide an enhanced result when it is used for training the classifier without paragraph embedding learning, and vice versa. This means that the combination of the lexicon and paragraph2vec provides the best results. To be specific, the othering terms and dependency modifiers in our lexicon play an important role in aligning the negative in similar vectors in the embedding learning phase.

While the othering terms as a feature have an effect on the previous hate speech types, it is noticeable that adding the othering language to the lexicon does not produce a significant change for the results prediction in the disability dataset and the improvement of the results due to the other content of the lexicon. It could be justified that disability hate speech is more related to hate terms than the othering terms (which are the pronouns in our study). In other words, people tend to describe the situation of the disabled rather than discriminate themselves from them, as the boundary between the two groups (disabled and non-disabled) is clear. In contrast, people in the religion, racism and sexual orientation events tend to use the two-sided othering language because they tend to clarify the ambiguity of their tension in respect of others (e.g. ‘my religion is different from yours’, ‘my ethnicity is different from yours’, etc.). With globalisation, people cannot clarify religious identity, racial identity and sexual orientation, so in their speaking or writing they tend to clarify their identity and their attitude towards other identities, which leads them to use two pronouns: the first points towards the speaker/writer and the second points towards others. Our framework composed to three main components, The lexicon, the embedding learning and the classification algorithm. At this paragraph, We discover the effectiveness of our classifier on our data embedding. We compare MLP classifier with different classifiers which used in previous studies for hate speech detection without embedding (e.g. SVM, DT, NB and RF [4]) and with
embedding (e.g. LR [10]). Table 2 shows the results of F-score measurements of applying six different classifiers.

|          | Religion | Disability | Race      | Sexual-Orientation |
|----------|----------|------------|-----------|--------------------|
| **Our framework** |          |            |           |                    |
| SVM      | 0.72     | 0.85       | 0.81      | 0.51               |
|          | FP=0, FN=96 | FP=0, FN=13 | FP=0, FN=22 | FP=5, FN=121      |
| NB       | 0.86     | 0.85       | 0.81      | 0.90               |
|          | FP=58, FN=10 | FP=6, FN=9  | FP=24, FN=6 | FP=21, FN=15     |
| LR       | 0.91     | 0.88       | 0.91      | 0.95               |
|          | FP=6, FN=30 | FP=0, FN=11 | FP=0, FN=12 | FP=2, FN=16      |
| DT       | 0.90     | 0.87       | 0.93      | 0.88               |
|          | FP=23, FN=22 | FP=8, FN=6  | FP=3, FN=6  | FP=33, FN=15     |
| RF       | 0.92     | 0.92       | 0.96      | 0.95               |
|          | FP=13, FN=19 | FP=6, FN=2  | FP=0, FN=5  | FP=5, FN=12      |
| MLP      | 0.93     | 0.92       | 0.97      | 0.96               |
|          | FP=4, FN=19 | FP=1, FP=4  | FP=1, FN=4  | FP=9, FN=6       |

Table 2: F-score measurements of Different Classifiers Performance on our Framework

Table 2 shows the results of F-score measurements of applying six different classifiers. Multiple Layer Perception classifier produced the best results for both false benign and false negative detection.

Turning to true hate speech classified as offensive it appears that our framework success in increasing the true negative and true positive tweets. As we consider the the othering language and the embedding learning. To show how our lexicon improved the detection results, using only our lexicon resulted in decreasing the false negative than the previous word which use m-gram, BoW and hateful terms. Looking at the tweets misclassified as hate speech, despite that our framework successfully advance the machine understanding of hateful content, the misclassified means that the there are tweets contains content which considered benign yet the machine consider them as negative. For Religion data set, this data set collected after Woolwich event, which contains language about Muslim and African man (religion and race), according to [9] Twitter users use this type of language in their everyday communications which could be contained in the benign tweets.

7. STUDY LIMITATIONS
As our study assume that the tweet which contains two-sided othering language is more likely to be hateful, this do not mean that all tweet that contain two-sided pronoun are considered as hateful tweet. At this sort of studies, different factors have an effect on the results. For example, similar tweet that related to different event might imply different meaning (e.g. "send them"). The previous text if belong to races hash-tags show different meaning when it belong to a transportation hash-tags.

8. CONCLUSION
To conclude, two-sided othering language could be considered an effective feature for hate speech classification in events related to Religious (anti-Muslim, anti-Semitism), racism and sexual orientation hate speech. We investigate the use of two-sided othering terms in negative samples and conclude that a combination of two-sided pronoun terms is used frequently in negative tweets, whereas they are rarely used in the benign tweets. We leverage this finding to produce a new feature for hate speech detection, i.e. two-sided pronoun terms and their patterns. This leads
us to build our own lexicon, learn the vector space of the lexicon and the datasets jointly, and validate the features using ten-fold cross-validation. We found that our framework decrease the incorrectly classified instances for both benign and negative samples for the four data sets including the disability data set which does not contain a noticeable use of two-sided othering terms. which mean that our framework provide better understanding for the hate speech. We examined the case of removing the othering terms from the lexicon in our framework and found how those terms have an effect on the results. Our work is different from the previous work as following: (a) using the two-sided othering terms as features, (b) use the two-sided othering patterns as features extracted by typed dependency, (c) using just the verbs, nouns and adjectives of an annotated negative samples which extracted by POS tagging and (d) applying paragraph embedding on the previous feature jointly with the main data set to extract the vector space features. differently, we did not apply the dependency learning on the examined data set yet for extracting the othering patterns also we use the POS for extracting the negative content from an annotate data set. In addition, the semantic learning was implemented to extract the vector space of the lexicon content jointly with the data set, this step guarantee that the negative instances would be aligned in similar vector of the lexicon if the content of both is similar, which boost the classifier prediction accuracy.
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