Document Embedding Generation for Cyber-Aggressive Comment Detection using Supervised Machine Learning Approach

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Abstract

Cyber-bullying may be defined as the employment of technological means for the purpose of harassing, threatening, embarrassing, or targeting a particular person. It is also possible for Cyber-bullying to have occurred accidentally. One of the major challenges in identifying cyber-bullying or cyber-aggressive comments is to detect a sender's tone in a particular text message, email or comments on social media, since what a person may consider to be a joke, may act as a hurting insult to another. Nevertheless, cyber-bullying may prove to be non-accidental in specific cases where a repetition in the pattern of text in emails, messages, and online posts is existent. In order to curb such a social threat, this Paper proposes the usage of a combination of document embeddings along with different supervised machine learning algorithms to get optimized results in flagging cyber-aggressive comments. Extensive experimentation indicates that the SVM model with rbf kernel combined with document embeddings is capable of efficiently classifying unseen test comments with an accuracy score of 88.465 % and has surpassed other models in various evaluation metrics.

1 Introduction

Social media may be thought of as interactive media which let people read and write their views. Social media lets people present their talent as it gives the user freedom to build content and share it with ease, to large groups or to the society. Hence, social media is a platform where users not only generate data, but also consume it. Hence, any person having an access to internet holds the ability to produce media contents. As social media is popular among adolescents, cyber-bullying reports are increasing day by day. Smith et al (2008), defined cyber-bullying as an aggressive and intentional behavior of an individual or a particular group using electronic forms of contact that is carried out repeatedly and over time against an individual or a certain group who cannot easily defend themselves. Going by the definition of cyber-bullying by Smith et al (2008), any behaviour showing signs of bullying on social media is also considered cyber-bullying. Also, since it occurs online and is anonymous to a certain extent, tracing such behaviour to it's source can be challenging. Hence there is a need to have an effective cyber-bullying detection system to monitor comments posted in social media and efficiently flag comments as cyber aggressive or safe.

The first step in this objective is to obtain manually labelled data for training and testing purposes, in which comments have been collected from various social networking sites and have been labelled according to whether they are cyber aggressive or not. Such labelled comments have been taken from various sources in Kaggle and Github websites. After accumulating a large number of comments from various datasets containing manually labelled comments scraped from various social media sites, they were split into datasets containing 20645 training and 8817 testing comments. Corresponding to the comments contained in the datasets, vector representations or document embeddings are generated by Doc2Vec which are subsequently fed to the supervised machine learning algorithms for training and then predicting test labels.

The organization of the remaining part of the Paper is as follows. A summarized survey of various related research experiments and literatures has

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been elaborated in Section 2. The methodology proposed has been explained in Section 3. Section 4 includes the results obtained. The conclusions obtained from these results has been given in Section 5 along with a brief mention of the future work to be carried out.

2 Related Work

Despoina Chatzakou et al (2017), in an attempt to flag cyber-aggressive comments presented a method of classification by identifying behavioural aspects of cyber-bullies which differentiated their comments from others.They presented a principled and scalable approach for eliciting user, text, and network-based attributes of Twitter users, by extracting a total of 30 features and identifying the differentiating features. This paper has used word embeddings among their features.

In order to optimize detection of cyber aggressive comments, Vikas S Chavan and Shylaja S S (2015), proposed that using two additional features, simultaneously with conventional feature extraction techniques like TF-IDF and N-gram, increases the accuracy of the system up to 86% using logistic regression. This paper included two new features, which included pronoun capturing and the use of skip-grams.

Liew Choong Hon and Kasturi Dewi Varathan (2015), proposed a cyber-bullying detection system for tweets, with their focus on five types of words indicating cyber-bullying, which they deduced through their study. They used keyword matching for flagging cyber-bullying in tweets after capturing the keywords from tweets by various users.

Among other research activities carried out in the field include an effort by Kelly Reynolds and April Kontosthatis (2011), in which the data was accumulated from the Formspring.me website and labelled using Amazon's Mechanical Turk service. This labelled data was then employed to train a machine learning model to identify cyber-bullying comments through the usage of the weka toolkit.

In related text classification problems such as sentiment analysis of comments, the incorporation of paragraph vectors or document embeddings has been found to be efficient for the purpose of generating dense and low dimensional feature vectors for semantically representing entire comments or paragraphs unlike the feature matrices obtained from standard feature extraction techniques like n-grams or it's special case bag-of-words. An expedition was carried out by Parinya Sanguansat (2016) in which the employment of an unsupervised deep learning technique for numerically representing text comments in the form of document embeddings or paragraph vectors with machine learning algorithms proved to be more effective than standard methods for the task of sentiment analysis of comments on social media. Since the detection of cyber-aggressive comments is also a binary text classification task, this Paper proposes the incorporation of paragraph vectors as features to be learnt for classification by machine learning algorithms. Various classifiers are subsequently tested and evaluated to come up with an effective model for identification of cyber-aggressive comments.

3 Proposed Method

The preliminary step involved in our proposed methodology is to generate a vector sequence for each of the comments in the dataset, that represents the semantic meaning of the document or the comment, which can then be processed by machine learning algorithms to associate test data with labels. We perform extensive experimentation and evaluation on several machine learning algorithms and compare the results based on these parameters to find a suitable model which can efficiently perform the task involved.

3.1 Pre-Processing

The inability of machine learning algorithms to process raw text directly is a keen issue in the field of natural language processing. This brings out the necessity for numerical representations of linguistic units, for the purpose of which several standard feature extraction techniques such as Bag-of-Words, n-grams, etc. Though these models have been shown to be considerably effective and are the state-of-the-art models for generating vector representations for text, yet these models do not take into account the order of words in a sentence, which is an important parameter upon which the detection of cyber-aggressive comments is dependent. Also, there is a necessity for dense feature vectors of suitable dimensions unlike those provided by the bag-of-words or n-gram models which are sparse and high dimensional feature matrices. Such dense feature matrices are also ob-

tained from other models such as word2vec, which may be incorporated as well, but are more preferred in problems involving identification of analogous words or classification of topics in a sentence. In order to tackle this issue of obtaining a favourable feature matrix for the task, this Paper proposes the incorporation of document embeddings or paragraph vectors generated through Doc2Vec which is an unsupervised learning algorithm to effectively generate semantic vector representation of comments and paragraphs which fits our purpose, as we deal with multiple line comments as well. Though Doc2Vec consists of two architectures for generating paragraph vectors, namely the Distributed Bag of Words (PV-DBOW) and the Distributed Memory (PV-DM) models, the PV-DM architecture has been incorporated in our pre-processing step, not only due to the fact that it outperforms the PV-DBOW model as per the report by T Mikolov (2014) but also because it takes into account word order, leading to better results in flagging cyber-aggressive comments.

Further details include a brief summarization of the distributed memory model of Doc2Vec as used in our pre-processing step.

In the distributed memory framework, every comment or set of comments and all of the words are associated with a corresponding unique vector representation for each depicted by separate column matrices for comments and words. The model is trained such that the vector representations play a role in predicting succeeding words, taking into account various contexts which are sampled from the comments. Typically, this prediction task is performed by softmax or other multi-class classifiers. The framework performs concatenation operation for aggregating the vector representations. Generally using stochastic gradient descent, where the gradients are obtained through the back-propagation algorithm, the vectors are then trained. Therefore, since the error may be calculated at each step and be employed to upgrade the parameters of the model, the framework is capable of capturing semantics even though the vectors were initialized randomly. Using gradient descent while performing an inference step , we retrieve the vectors corresponding to a new comment or multiple lines of comments. Thus, once the weights and vectors for seen comments are obtained, the inference step helps in retrieving vectors for unseen comments as well.

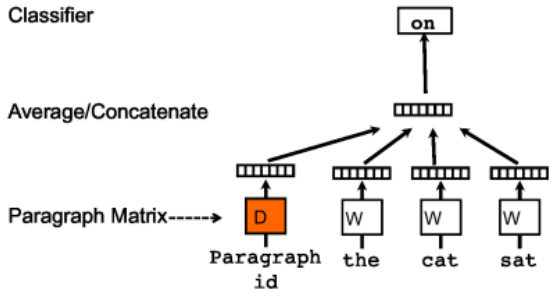


Figure 1: The above figure portrays framework for the purpose of learning paragraph vectors.This framework includes the addition of paragraph token that is mapped to a vector via matrix D. In order to predict the fourth, word the average or concatenation of this vector with a context of three words is used in this model. The paragraph vector not only represents the missing information from the current context but can also act as a memory of the topic of the paragraph. Figure adapted from the report in T Mikolov(2014)

In our experimentation, the sentences are tok-

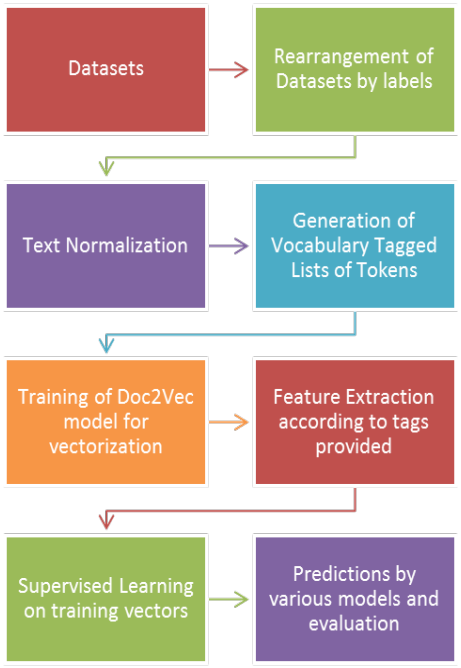


Figure 2: Methodology involved in our proposed method

enized and each set of tokens is associated with a paragraph id or tag before training, indicating the document type the sentence comes from. For convenience in our experimentation, we generate

the document ids with respect to the files the comments come from, because of which the training and testing data is split into a pair of files each containing cyber-aggressive and non cyber-aggressive comments. The tags are then conveniently generated with a prefix indicating whether the data is from training or testing dataset and whether it is cyber-aggressive or non cyber-aggressive. This prefix is coupled with a unique index for each comment for uniqueness and to facilitate retrieval of vectors after training. This aggregation of tagged tokenized comments from training and testing pairs of datasets are shuffled randomly for better training and eliminating any dependency on the order of feeding the input, are then fed to the Doc2Vec model for training. The training has been performed for 10 epochs in order to obtain better results. Though the number of epochs here improves the training and model performance, yet it is not a fixed parameter as such and is to be tuned according to the purpose. Typically 10 epochs is found to be sufficiently suitable for generating favourable features and therefore our experimentation includes this parameter as such. After training is performed, we extract the feature vectors for training and testing data into separate arrays with their corresponding labels in separate arrays, for being fed to machine learning algorithms for classification. The number of dimensions of the dense feature vectors has been chosen to be 100, found to be optimum, neither being too high or too low a value for being learnt by machine learning algorithms. Since the training arrays are arranged such that the cyber-aggressive and non cyber-aggressive comments are grouped together, we shuffle the arrays randomly to ensure that the models remain independent of the feeding order of the input vectors.

3.2 Classification

Following are the various Machine Learning Classification algorithms which have been trained using the document embeddings and tested for generating the predicted labels of test data :

3.2.1 Support Vector Machines (SVM)

Support vector machine, commonly referred as SVM, is one of the most common machine learning algorithm used for performing binary classification on data.It has always proved itself worthy in the field of supervised machine learning.They are motivated by the principle of optimal separation, the idea that a good classifier finds the largest gap possible between data points of different classes.Ideally, the classification boundary will be a curve or a hyper-plane that goes right down the middle of the gap between classes, because this would be the classification boundary which will have the maximum distance from the nearest data points (referred to as support vectors). This algorithm being based on the principle of optimum separation, is aimed at finding the largest distance between data points of separate classes. Ideally, the decision boundary for this classifier is a curve or a hyper-plane such that it possesses the maximum distance to the nearest data points known as support vectors. After training for classification task, an SVM is capable of efficiently predicting the class in which other data points fall, since there is only a necessity of few support vectors, due to which other data points may be neglected. We use the following three kernels for the SVM model for flagging cyber-aggressive comments.

linear kernel

$$K(X, Y) = X^T Y \tag{1}$$

polynomial kernel

$$K(X, Y) = (\gamma X^T Y + r)^d, \gamma > 0 \tag{2}$$

rbf (radial bias function) kernel

$$K(X, Y) = exp(-\gamma \parallel X - Y \parallel^2 / 2\sigma^2), \gamma > 0 \tag{3}$$

Where r,d and gamma refer to the kernel parameters and K(X,Y) corresponds to the dot product of input points mapped into the feature space Y by the transformation function. However, only the results for rbf kernel have been portrayed in Section 4 since it is found to have maximum accuracy among the three kernels and it also has surpassed other kernels in various other evaluation metrics.

3.2.2 Logistic Regression

Logistic regression refers to the fitting of a linear model to the data which gives a real number. Since this number does not directly contribute to classification, it is fed into the logistic function which is :

$$\sigma = \frac{1}{1 + e^{-}x} \tag{4}$$

The sigmoid function enables the normalization of the numbers fed to be in the range 0 and 1, which facilitates the interpretation of the number obtained as a probability, which in this case is the probability of comments being cyber-aggressive.

3.2.3 Bernoulli Naive Bayes Algorithm

The Bernoulli Naive Bayes classifier uses the implementation of Naive Bayes training along with it's outstanding classification algorithms for the given data, assuming the data distribution to be a multivariate Bernoulli distribution, wherein multiple features may be included, however individual features are assumed to possess binary values. Hence it is necessary for samples to be represented as feature vectors with binary values. It is therefore necessary for the classifier implementation to binarize data before learning if the data handled is already not in the required form. Bernoulli naive Bayes's decision rule is build on :

$$P(x_i \mid y) = P(i \mid y)x_i + (1 - P(i \mid y))(1 - x_i) \tag{5}$$

3.2.4 Decision Trees

Decision Trees work on a sequence of test queries and answers with conditions which have been structured as a tree. In such trees, the root node and internal nodes consist of characteristic test conditions for the purpose of segregating data with different attributes. The terminal nodes of such trees possesses an assigned label which is typically a 0 or a 1. For the purpose of classification using a decision tree, the process begins at the root node where the test condition is applied to a data instance. Depending on the result of this step, the relevant branch is chosen and followed subsequently, thereby leading to either another internal node where a different test case is to be applied to decide the further path or to a terminal leaf node, where the data instance is associated with a class label.

3.2.5 Random Forest Classifier

Random Forest Classifiers are composed of set of diverse decision trees with the incorporation of randomness in their construction. The predictions of the individual classifiers are averaged to generate the prediction of the ensemble. The individual trees of such an ensemble are sampled from the training set with replacement. In these trees, when a particular node is split, the split is performed only after discovering the best way of splitting among a subset of features which are chosen randomly instead of the set of all features. Therefore, random forest classifiers possess greater bias than a single tree without randomness. However this is compensated, often in excess by the lower variance of random forests due to which an overall good model is created.

4 Results

Extensive experimentation is performed by testing and evaluating the models using the test dataset consisting of 8817 comments in all.A detailed comparison has been made by applying various evaluation metrics on the different models.

4.1 Evaluation Metrics on various Models

The various evaluation parameters that we have applied to compare the models when applied to the test dataset are as follows :

4.1.1 Accuracy score

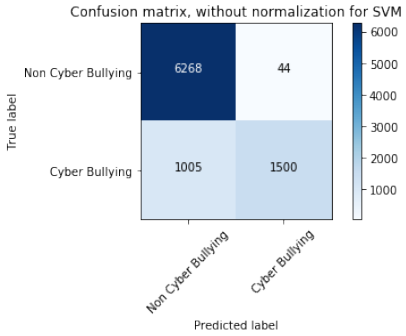
The accuracy score is a metric used in multi-label classification tasks, which corresponds to a measure of the number of data samples which have been accurately labelled according to the set of test labels provided.

4.1.2 K-Fold Cross Validation

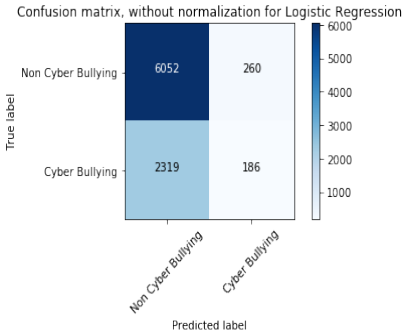
For evaluating a model using the K-fold cross-validation technique, we take the original sample and then randomly split it into equal sized k sub-samples , of which only a single sub-sample is assigned for testing purpose, which is known as the validation set. The remaining sub-samples are used for the purpose of training of the models to be evaluated. We repeat the process of cross-validation k times , taking care that each of these k sub-samples is involved in the process of testing or validation only once. In order to obtain a single value to evaluate the models, the arithmetic mean of all of the k results thus obtained is taken. The value of k has been taken as 20 in our experimentation, but in general k remains an unfixed parameter as such.

4.1.3 Confusion matrices

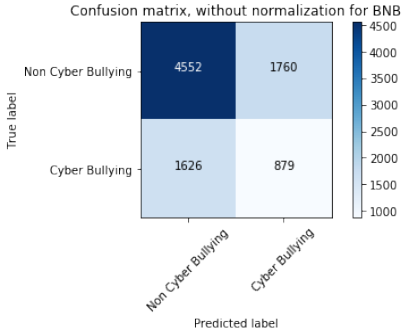
A confusion matrix is an evaluation metric which summarizes the prediction results obtained for a classification problem. It provides exact counts of the number of accurate and inaccurate predictions made by a classifier for each class. For a binary classifier, the information provided by such matrices include all four possible ways by which data may has been classified as follows :



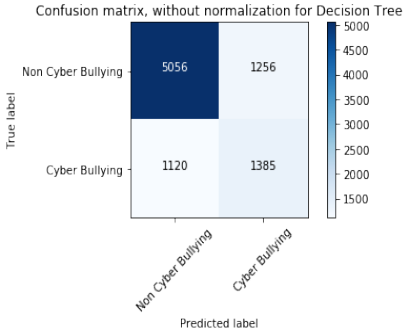
(a) SVM with rbf kernel



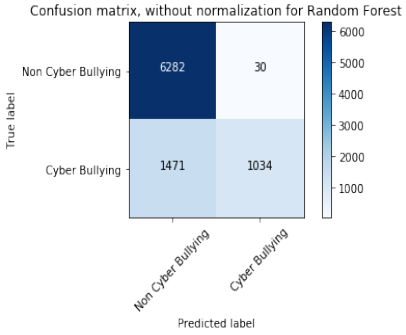
(b) Logistic Regression



(c) Bernoulli Naive Bayes



(d) Decision Tree



(e) Random Forest

Figure 3: Confusion Matrices for the various mod-

- Frequency of accurate predictions stating an instance to be negative.
- Frequency of inaccurate predictions stating an instance to be positive.
- Frequency of inaccurate predictions stating an instance to be negative.
- Frequency of accurate predictions stating an instance to be positive.

4.1.4 Precision

Precision corresponds to a measure of relevance of the results obtained from a model. It is given by.

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

where TP refers to the frequency count of true positives, whereas FP is the frequency count of false positives.

4.1.5 Recall

Recall value is an evaluation metric which corresponds to a measure of how many of the results obtained from a model are actually relevant. Recall may be written as :

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

where TP corresponds to the frequency of true positive predictions while the term FNP corresponds to frequency of false negative predictions.

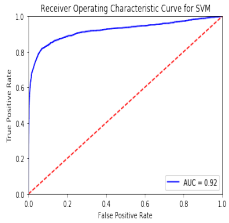
4.1.6 F-Beta-score

This metric corresponds to the weighted mean of precision and recall . The best value of this metric when evaluating a model is 1, the worst being 0. The value of beta acts as the factor which determines the weight of precision final score. A beta value less than 1 signifies that precision is weighed more whereas a beta value greater than 1 indicates recall is favoured. A beta value equal to one as used in our evaluation indicates both are weighed equally.

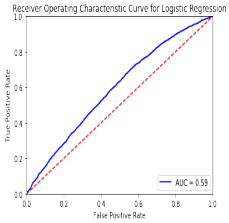
4.1.7 Area under ROC Curve

A receiver operating characteristic curve or ROC curve refers to the plot of the true positive rate or TPR values obtained against the false positive rate or FPR values obtained for the models tested at several threshold settings. The area under this

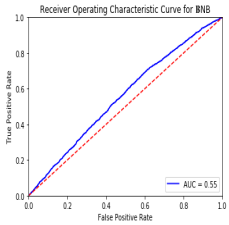
curve acts as an evaluation metric to obtain an optimum model. The best value of this score for an ideal model is 1.0.



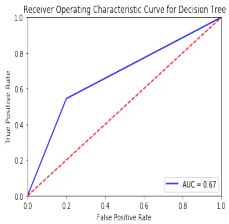
(a) SVM with rbf kernel



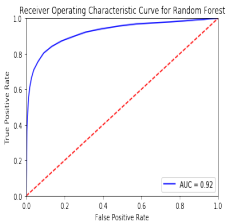
(b) Logistic Regression



(c) Bernoulli Naive Bayes



(d) Decision Tree



(e) Random Forest

Figure 4: Receiver Operating Characteristic Curves for the various modes tested

RESULTS			
Algorithm	**Accuracy Score**	**20-Fold Cross Validation Score**	**Time consumed for training and prediction (in seconds)**
SVM (rbf kernel)	88.465 %	82.179 %	1619.232
Logistic Regression	70.749 %	73.979 %	0.943
Bernoulli Naive Bayes	61.506 %	68.951 %	0.243
Random Forest	83.033 %	78.759 %	17.489
Decision Tree	72.734 %	70.666 %	13.303

Table 1: EVALUATION METRICS

RESULTS				
Algorithm	**AUROC Score**	**Precision**	**Recall**	**F-score**
SVM (rbf kernel)	0.92	0.89	0.88	0.88
Logistic Regression	0.59	0.63	0.71	0.62
Bernoulli Naive Bayes	0.55	0.62	0.62	0.62
Random Forest	0.92	0.86	0.83	0.80
Decision Tree	0.67	0.73	0.73	0.73

Table 2: EVALUATION METRICS

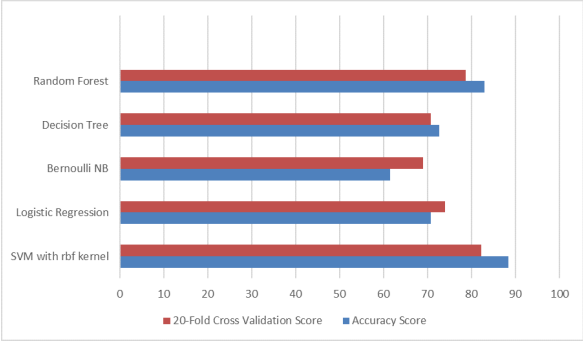


Figure 5: Comparison of the various models based on Accuracy Score and 20-Fold Cross Validation

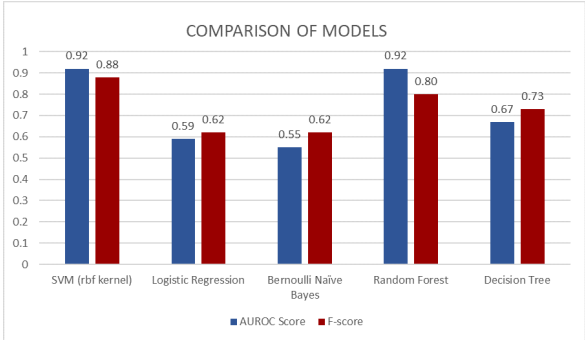


Figure 6: Comparison of the various models based on AUROC Score and F1-Score

4.2 Inference

Based on our experiments with the tested models , in labelling the test comments as cyber aggressive/non cyber aggressive, we have made a detailed summarization of various models. The metrics results have been specified in Table 1, Table 2 and in figures 3-6. Table 1 reflects the contrast between the models with respect to accuracy score, 20-fold cross validation score and time consumed for training and prediction, whereas in Table 2, we have evaluated the models based on AUROC-Score, precision, recall and f-score. Our evaluation of the tested models indicate that the highest accuracy achieved is that of the SVM model using rbf kernel, which is approximately 88.465% with an AUROC score of 0.92. Having surpassed other tested models in effectively labelling the unseen test dataset, such a model may effectively be used to flag cyber-aggressive comments which may later be used to estimate the performance of a manual based flagging system over automated approaches.

5 Conclusion and Future Work

In this Paper, we have proposed the usage of Doc2Vec to generate paragraph vectors or document embeddings as features for supervised machine learning for flagging cyber-aggressive comments. Document embeddings have been generated using Doc2Vec. We built a range of models by learning the vector representations of various comments by few supervised machine learning algorithms, and applied various evaluation metrics on the models to obtain a good efficiency in classifying comments. As a consequence of such an experiment, we found that the Doc2Vec approach coupled with SVM classifier using rbf kernel, gives an increased accuracy of approximately 88.465% in labelling test comments as cyber aggressive/non cyber- aggressive.

Further future work may be directed towards further optimization of the results obtained by applying deep learning techniques to the existing model. Further work may also be directed towards incorporating an application programming interface for real time identification of cyber-aggressive comments on social media using a model efficient in terms of both accuracy in classification as well as time taken.

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a. For training dataset :. http://www.github.com.

b. For testing dataset :. http://www.kaggle.com.