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PREDICTING CYBER BULLYING ON SOCIAL MEDIA IN THE BIG DATA ERA USING EXTREME LEARNING MACHINE

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Abstract

Cyber bullying disturbs harassment online, with alarming implications. It exists in different ways, and is in textual format in most social networks. There is no question that over 1.96 billion of them would have an inescapable social operation. However, the developing decade presents genuine difficulties and the online-conduct of clients have been put to address. Expanding instances of provocation and harassing alongside instances of casualty has been a difficult issue. Programmed discovery of such episodes requires smart frameworks. A large portion of the current studies have been moving towards this issue with standard machine learning models and most of the models produced in these studies are scalable at one time into a solitary social network. Deep learning-based models have discovered ways in the identification of digital harassing occurrences, asserting that they can beat the restrictions of the ordinary models, and improve the discovery execution using extreme machine learning techniques. However, numerous old-school models are accessible to control the incident, the need to successfully order the tormenting is as yet weak. To successfully screen the harassing in the virtual space and to stop the savage outcome with the execution of Machine learning and Language preparing. A system is proposed to give a double characterization of cyberbullying. Our technique utilizes an inventive idea of CNN for content examination anyway the current strategies utilize a guileless way to deal with furnish the arrangement with less precision. A current dataset is utilized for experimentation and our system is proposed with other existing methods and is found to give better precision and grouping.

Introduction

In this article, we propose a cyberbullying detection framework to generate features from Twitter content(tweets) by leveraging a pointwise mutual information technique. Based on these features, we have developed a supervised machine learning solution for cyberbullying detection and multi-class categorization of its severity in

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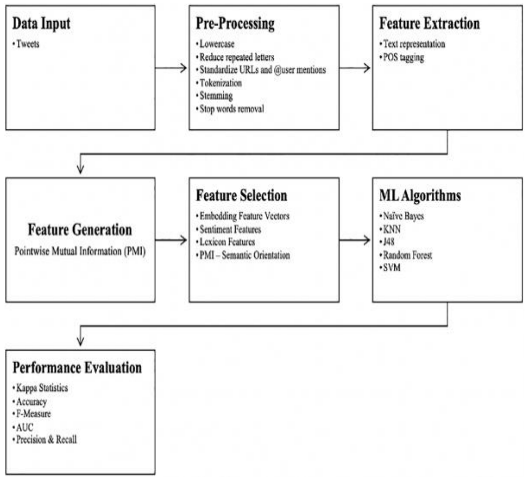
Twitter. We have applied Embedding, Sentiment, and Lexicon features along with PMI-semantic orientation. Extracted features were applied
with Naïve Bayes, KNN, Decision Tree, Random Forest, and Support Vector Machine algorithms. In this article we first briefly present background on key areas that our study focuses upon. In section 2, we outline related work in the state of the art related to classification of severity of cyberbullying. Section 3 provides the background for data usage for cyberbullying detection and its accessibility. Section 4 and 5 provide the research methodology framework used for cyberbullying detection and its severity. Proposed framework evaluation and results are presented in section 6 and comparison of baseline and proposed framework results are provided in section 7. Finally, the article provides some conclusions related to the significance of the proposed framework and suggests some future work.

System Architecture:



Literature Review:

Cyberbullying takes various forms, such as circulating filthy rumours on the bases of racism, gender, disability, religion and sexuality; humiliating a person; social exclusion; stalking; threatening someone online; and displaying personal information about an individual that was shared in confidence [1].According to the national advocacy group in US, the bullying can take several forms: racism and sexuality are two of these [2]. Based on a report at Pew Research Centre, two distinct categories of online harassment have been described among internet users. The first category includes less severe experiences: it involves swearing and humiliation, because those who see or experience it often claim they ignore it. The second category of harassment although targeting a smaller number of online users, includes more severe experiences such as physical threats, longterm harassment, trapping and sexual harassment [3].Assessing the severity level of a cyberbullying incident may be important in depicting the different correlations observed in cyberbullying victims, and principally, how these incidents impact victims' experience with cyberbullying [4]. Researchers, however, have not paid enough attention to the extent to which the different cyberbullying incidents could have more severe impact upon victims. Therefore, it is significant to develop a method to identify the severity of cyberbullying in OSNs.

Problem Definition:

This paperhighlights the limitation of existing techniques related to cyberbullying detection and its severity levels.

We provide a systemic framework for identifying cyberbullying severity in online social networks, which is based on previous research from different disciplines. We build machine learning multi-classifier for classifying cyberbullying severity into different levels. Our cyberbullying detection model work with multi-class classification problem and as well as for binary class classification problem

Pre-processing step

The collected data was pre-processed before assigning severity levels. Tweets were converted to lower case to avoid any sparsity issue, reduced repeated letters, standardized URLs and @usermention to remove noise in the tweets. Tokenization was applied with Twitter-specific tokenizer based on the CMU TweetNLP library [8] and only words with minimum frequency of 10 were kept. Tokenization is the process of breaking a text corpus up into most commonly words, phrases, or other meaningful elements, which are then called tokens. Finally, stop-words and stemming procedures were performed before feature extraction. Stop words are defined as the insignificant words that appear in document which are not specific or discriminatory to the different classes. Stemming refers to the process of reducing words to their stems or roots. For instance, singular, plural and different tenses are consolidated into a single word. We applied stemming with an iterated version of the Lovins stemmer, it stems the word until it no further changes prior to extracting topic model features [9].

Feature extraction step

All tweets were represented with bag-of-words which is one of the most appropriate and quickest approaches. In this approach, text is represented by set of words and

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each word is treated as an independent feature. We applied part-of-speech (POS) tagging with Twitter-specific tagger based on the CMU TweetNLP library [6] for word sense disambiguation. The POS tagger assigns part-of-speech tag to each word of the given text in the form of tuples (*word*, *tag*), for instance, noun, verb, adjectives, etc.

Feature generation step

We applied document level classification and measured semantic orientation of each word in the corpus. In the document level classification, phrases were extracted using the POS tags. Once phrases have been extracted from the dataset, then their semantic orientation in terms of either cyberbullying or non-cyberbullying was determined. In order to achieve this goal, the concept of pointwise mutual information (PMI) [5] was used to calculate the semantic orientation for each word in a corpus of tweets. The PMI between two words, *word1* and *word2*, is defined as follows:

$$PMI(word_1, word_2) = \log_2\left[\frac{p(word_1 \& word_2)}{p(word_1)p(word_2)}\right]$$

The score was calculated by subtracting the PMI of the target word with a cyberbullying class from the PMI of the target word with a non-cyberbullying class. This method was clearly well suited for domain specific lexicon generation with PMI score, so we created our domain specific lexicon with PMI semantic orientation for each word and phrase by using Turney's technique [6]. Semantic Orientation of phrase, *phrase* is calculated as follows:

$$SO(phrase) = PMI(phrase, \text{"non} - \text{cyberbullying"}) - PMI(phrase, \text{"cyberbullying"})$$

Turney's method provides a representative lexicon-based technique consisting of three steps. First, phrases are extracted from the dataset. Second, sentiment polarity is estimated using PMI of each extracted phrase, which measures the statistical dependency between two terms. Lastly, polarity of all phrases in dataset is averaged out as its sentiment polarity. Turney's PMI technique does not depend on hard-coded semantic rules, so users may readily apply the technique into different contexts [5].

Feature engineering and selection step

Feature engineering is the process of generating or deriving features from raw data or corpus. Creation of additional features inferring from existing features is known as feature engineering [6]. It is not the number of features, but the quality of features that are fed into machine learning algorithm that directly affects the outcome of the model prediction [7].

One of the most common approaches to improve cyberbullying detection is to perform feature engineering, and most common features that improve quality of cyberbullying detection classifier performance are; textual, social, user, sentiment, word embeddings features [8]. Since social and user features were not available in the dataset provided by [12], we attempted to build features based on the textual context and their semantic orientation. As a consequence, we propose the following features to improve cyberbullying detection in multi-class classification setting for detecting cyberbullying predefined severity as well as same approach for the binary classification setting (whether or not cyberbullying behaviour exists in the tweets).

The following feature types were applied after pre-processing:

Embedding Feature Vector: In this study, tweet-level feature representation using pre-trained Word2Vec embeddings were applied. We used 400-dimension embeddings of 10 million tweets from the Edinburgh corpus [9].

Sentiment Feature Vector: SentiStrength [10] was used to calculate positive and negative score of each tweet.

Lexicon Feature Vector: Multiple phrase level lexicons were applied in this study that identify positive and negative contextual polarity of sentiment expression in our dataset. Lexicons includes: MPQA Subjectivity Lexicon [11], BingLiu [12], AFINN, Sentiment-140 , Expanded NRC-10, NRC Hashtag Sentiment lexicon , SentiWordnet , NRC-10 , and NRC Hashtag Emotion Association Lexwicon [19].

PMI-Semantic Orientation: In doing so, we processed previously generated domain specific lexicon (section 4.4) which contained mutual information of each word in the corpus. This PMI input approach assigns a PMI score to each word in the document. PMI-Semantic Orientation is then calculated for each document by subtracting the PMI of the target word.

Dealing with class imbalance data

Class imbalance refers to the scenario where the number of instances from one class is significantly greater than that of another class . Most machine learning algorithms work best when the number of instances of each of the classes are roughly equal. However, in many real-life applications and non-synthetic datasets, the data is imbalanced; that is, an important class (usually referred to as the minority class) may have many fewer samples than the other class (usually referred to as the majority class). In such cases, standard classifiers tend to be overwhelmed by the large class and ignore the small distributed instances. It usually produces a biased classifier that has higher predictive accuracy over majority classes, but poorer predictive accuracy over minority class. One way of solving the imbalanced class problem is to modify the class distributions in the training data by over-sampling the minority class or under sampling the majority class. SMOTE (Synthetic Minority Over-sampling Technique) [22] is specifically designed for learning from imbalanced datasets and is one of the most adopted approaches to deal with class imbalance due to its simplicity and effectiveness. It is a combination of oversampling and under sampling.

Our data set turned out to have an imbalanced class distribution (as shown in Table 3), that is, cyberbullying tweets with high severity class distribution were 4%, Medium 6%, Low 3%, and non-cyberbullying class distribution having 87%. Accordingly, we employed the SMOTE over sampling technique for our study. The next section presents the comparative results before and after using each machine learning approach.

Machine learning algorithms selection step

Choosing the best classifier is the most significant phase of the text classification pipeline. We cannot efficiently determine the most effective model for a text classification implementation without a full conceptual comprehension of each algorithm. The features (given in 4.E section) obtained from the tweets have been used to build a model to detect cyberbullying behaviours and its severity. In order to select the best classifier, we tested several machine learning algorithms namely: Naïve Bayes, Support Vector Machine (SVM), Decision Tree, Random Forest, and K-Nearest Neighbours (KNN).

Naïve bayes

In the field of machine learning, Naïve Bayes [21] is regarded as one of the most efficient and effective inductive learning algorithms and has been used as an effective classifier in several social media studies [38]. Since 1950s, Naïve Bayes classification for text has been commonly used in document categorization assignments and has ability to classify any type of data from text, network features, phrases, and so on. This technique is a generative model, it refers to how dataset

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is generated based on probabilistic model. By sampling from this model, it can generate new data similar to the data on which the model is being trained [22]. In our study, we used the most basic version of Naïve Bayes classifier for textual features and word embeddings.

K-Nearest Neighbours (KNN)

The K-Nearest Neighbours (KNN) is a supervised learning algorithm and one of the simplest instance-based learning algorithms suitable for multi-class problems [23]. In this algorithm, distance is used to classify a new sample from its neighbour. Thus, finds the K-nearest neighbours among the training set and places an object into the class that is most frequent among its k nearest neighbours. KNN is considered as non-parametric lazy learning algorithm that does not make any assumptions on the underlying data distribution.

Decision trees (J48)

In machine learning, decision tree is one of the well-known classification algorithms and one of the most widely used inductive learning method. It can handle training data with missing values and can handle both continuous and discrete attributes. Decision trees are built from labelled training data using the concept of information entropy [16]. Their robustness to noisy data and their capability to learn disjunctive expressions seem suitable for text classification [18].

Random forest

Random forest (RF) is an ensemble algorithm which is used for the classification and regression problem. RF creates several decision trees classifiers on a random subset of data samples and features. The classification of new sample is done by majority voting of decision trees. The main advantage of RF is that it runs efficiently on large datasets, it is an effective method for estimating missing data, and offers good accuracy even if a large portion of the data is missing [19].

Support Vector Machine (SVM)

SVM is a pattern recognition supervised learning algorithm to classify both linear and non-linear data. The primary concept of SVM is to determine separators that can best distinguish the distinct classes in the search space. The data points that separate one or more hyperplane using essential training tuples are called support vectors.

In a few cases, nonlinear SVM classifier is used when all the data points cannot be separated by a straight line. Nonlinear function generally uses the kernel function namely; linear kernels, polynomial kernel, RBF kernel, and sigmoid kernel are the popular kernels. Normally, Radial basis function (RBF) kernel performs better than others when the number of features is much lower than the number of observations and Polynomial kernels works better when the data is normalized [20]. In order to achieve high classification performance, it is necessary to properly select kernel parameters. In this study, we selected RBF and Polynomial kernel. SVM is traditionally used for binary classification and it needs to be modified to work with multi-class classification since we have considered four classes for cyberbullying severity detection. There are two different types of techniques to tackle this problem; i) One-against-one: In this technique, SVM combines several binary classifiers, ii) one-against-all: In this technique, SVM considers all data at once [29].

By training our SVM model, each of the four classes high, medium, low and non-cyberbullying were applied as target variables using one-against-all approach. This strategy consists of fitting one classifier per class. For each classifier, the class is fitted against all the other classes

Conclusion

The use of internet and social media has clear advantages for societies, but their frequent use may also have significant adverse consequences. This involves unwanted sexual exposure, cybercrime and cyberbullying. We developed a model for detecting cyberbullying behaviour and its severity in Twitter. Feature generation with PMI at pre-processing stage has proven to be the efficient technique to handle class imbalance in binary and multi-class classification where misclassification for minority class (es) has higher cost in terms of its impact on reliability of detection model. The developed model is a feature-based model that uses features from tweets contents to develop a machine learning classifier for classifying the tweets as cyberbullying or non-cyberbullying and its severity as low, medium, high or none

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