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Comparative Study of Different Sarcasm Detection Algorithms Based On Behavioral Approach

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Abstract

Sarcasm changes the dichotomy of an apparently negative or positive utterance into its contrary. While a fair amount of work has been done on automatically detecting emotion in human speech, there has been little research on sarcasm detection. In this paper, we have applied 12 classification algorithms (Gradient Boosting, Gaussian Naive Bayes, Adaboost etc.) on 4 types of datasets (Set1, Set2, Set3, Set4) and varied the split ratio of the datasets to check for the accuracy of every algorithm in different situations. We have applied the behavioral approach to sarcasm detection on twitter dataset. In set 4 were, we found gradient boosting to give the best accuracy in all 3 cases of a split ratio-50:50, 25:75, 10:90 (85.14%, 85.71%, and 85.03%).

Keywords: Accuracy; Classification; Sarcasm; Sentiment; Twitter

1. Introduction

Social net-working platforms, like Twitter, have slowly but gradually now become one of the most exciting platforms for users to voice their ideas and opinions on miscellaneous events, products etc. A lot of companies have had a keen attraction towards this data, especially to analyze the thoughts and opinions of people concerning various genres like movies, songs, political events, reviews on products etc.

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One of the most important times when users open Twitter and other such social media sites is when they want to buy a product. People conduct a small survey by analyzing all the reviews and comments available online. Sentiment

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analysis is the opinion of the user for the particular things. Generally, there are two ways to express sentiment analysis: 1) Implicit sentiments: A sentence which entails any opinion, that sentence depicts the existence of implicit statements. 2) Explicit sentiments: A sentence that shows the expression (opinion) directly indicates the existence of explicit statements.

Sarcasm Detection is a particularly difficult task, even for humans. Sarcasm is an anti-thetic form of expression in which the meaning implied is opposite to literal message conveyed. Thus, the intentional ambiguity involved makes the aforementioned task an especially challenging one. An astounding relation between cognitive complexity and wit has been shown by [15]. Detection of wit automatically is still in its infancy. The non-existence of perfectly-annotated naturally manifesting expressions that can be used to edify machine learning systems could be one of the causes for the dearth of computational designs as shown by [4]. The messages in Twitter or tweets are generally labeled with hash tags like #angry, #driving, #joy etc. These hash tags have been used to construct a marked set of naturally transpiring negative, sarcastic and positive tweets. We utilized this corpus for our research. The major motivation behind this research was that not only is the problem tackled by it extremely interesting, but it also has seemingly endless real-world applications. Moreover, the methodology adopted and the features created are ingenious and intuitive at the same time. The systematic approach followed in modeling something as complex as the psychological behavior and cognitive ability of the user, using objective features, gives us an insight into how data mining transcends the boundaries of conventional statistical analysis to have applications a vast variety of disciplines. Research has also been done in languages like Czech as shown by [5].

The rest of the paper is organized as follows: Section 2 contains literature survey, Section 3 describes the overall architecture or the proposed model followed by the implementation in Section 4, Results are included in Section 5 and the paper is ended with a conclusion and future work in Section 6 and Section 7 respectively.

2. Literature Survey

In [1], authors proposed a neural network for detection of sarcasm and also reviewed semantic modeling using Support Vector Machine (SVM) that employed constituency parse trees fed and labeled with syntactic and semantic information and modeled serially using CNN, then LSTM and ended with a layer of DNN. In [3], the author recreated the experiments performed by Ghosh et al. (2015) using the algorithm described by them in the same publication ,i.e., re-framed the wit detection quest as a kind of problem having the sense either sarcastic or literal, called the Literal/Sarcastic Sense Disambiguation (LSSD) task. In [5], authors used two classifiers - SVM and MaxEnt having varied features on English and Czech tweets to detect sarcasm in both the languages. This was the first work of sentiment analysis in the Czech language. They also used the different preprocessing techniques such as Tokenizing, POS-tagging, no stemming and removing stop words for finding the issue of the Czech language. [6] presented a semi-supervised identification using their kNN-like classifiers with a 5-fold cross validation on the Twitter dataset and obtained an F score of 55 %. In [8], the researchers studied the properties of sarcasm on Twitter. They investigated not only by finding whether the tweets are sarcastic or not, but also took into account the duality of the messages. Researchers developed a hashtag tokenizer for “GATE” method so that wit and sentiment discovered inside the hashtag can be found with less difficulty. Hashtag tokenization method is very useful for detection of sarcasm and checks the polarity of the tweet i.e. positive or negative. Liebrecht et al. focused on the concept of hyperbole to identify sentiment in tweets. They used the “Balanced Winnow Algorithm” with an accuracy of 75% to categorize Dutch tweets as sarcastic or not. In [7], the importance of contextual information in the identification of wit was investigated. The authors used a sequential model for sarcasm detection.

Rajadesingan et al. tried to study the psychology that goes into sentiment analysis. They distinguished the types of sarcasm with their exhibition in Twitter and also depicted the value of history in the tweets. Joshi et al.[9] presented a perspective that predicted wit in a targeted tweet using the past tweets of the user and implemented four types of integrators with the purpose of combining the contrast-based predictor and the historical tweet-based predictor. In [10], authors made a slight improvement to traditional methods in sarcasm detection research. They showed the outcome of attributes based on word embeddings. In [11], authors showed the significance of detecting sarcastic statements to boost mining opinion. For this end, they initially presented a way for sentiment analysis by considering thirteen features to detect the polarity of the sentiment of the tweets and then considered the method put forth by Bouazizi et al. for detecting sarcasm. In [12], authors provide the polarity of tweets which include whether the tweet is positive, negative or neutral. Polarity confidence and subjectivity confidence were also found. The accuracy of tweets was found using Naïve Bayes and SVM classifiers. In [13], authors studied a new method of sarcasm detection which was based on patterns, by investigating the data of messages. Performance was measured using different classifiers like SVM, Maximum entropy etc. In [14], authors proved that by including a combined approach of contrast, lexical analysis, emoticons and hyperbole better accuracy can be achieved in comparison to the usage of only linguistic features.

3. Overall Architecture

Sarcasm can be expressed in 5 forms as suggested by [2]-Sarcasm as a constraint of sentiments: Multiple factors like mood, sentiment fall under this category. It uses contrasting connotations and comparison with the past. Sarcasm as a complex form of expression: Various perspectives are considered for sarcasm detection. This requires more effort as compared to the other categories. Sarcasm as a means of conveying emotion: Sarcasm is commonly used for expressing one's emotion. It is mostly used in negative situations or to display aggression.Sarcasm as a function of familiarity: Strangers find it difficult to detect sarcasm as compared to familiar people like friends and relatives. Familiarity of language also eases the task.Sarcasm as a written form of expression: Sarcasm is often used in written text also apart from oral communication especially in social media. Among these, we are considering the first, second and the fifth approaches.

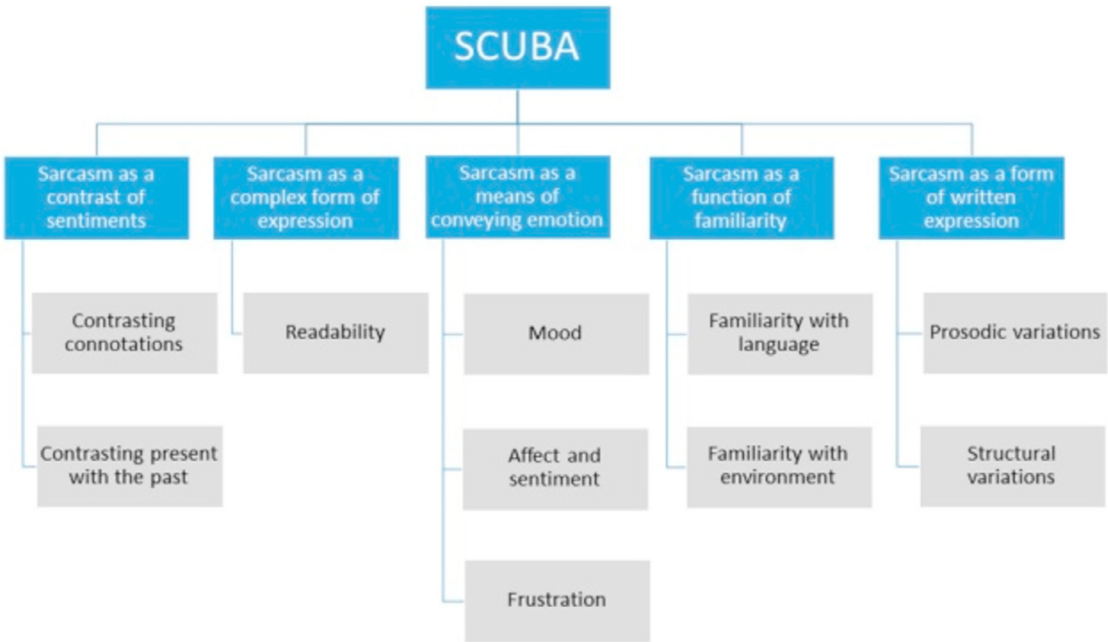

Fig 1: Types of Sarcasm [2]

In general, we will be using 12 different classification algorithms on the feature sets generated and will be comparing their results. These are Gaussian Naive Bayes, Extra Trees, Decision Tree, Random Forest, Adaboost, L1 regularized Logistic Regression, L2 regularized Logistic Regression, Gradient Boosting, Bagging Model, SVM (rbf kernel), K-neighbors hybrid and K neighbors. The process begins with the extraction of three distinct feature sets from the dataset. The first feature set is generated using n-grams (bigrams and trigrams) along with pre-processing of the tweets which include lemmatization, removal of punctuation marks, hashtags etc. from the tweets. The second feature set is generated using word-length-distribution and syllables. And, the third feature set is generated using POS tagging. Finally, these feature sets are subjected to 12 different classification algorithms and compared on the basis of their accuracy in sarcasm detection.

4. Implementation

We used a Twitter API for assembling tweets that contain hashtags which showcase direct positive sentiment (e.g., #cheerful, #happy, #delighted), sarcasm (#sarcasm, #sarcastic), and direct negative sentiment (e.g., #sorrow, #angry, #grief), respectively. We implemented necessary filtering to remove quotes, re-tweets, spam, tweets in other languages, and tweets with URLs. The initial dataset consisted of Tweet IDs (unique IDs assigned to tweets by Twitter) and their respective classification tags i.e. Sarcastic or Non-Sarcastic. The dataset was further elaborated using Tweepy- a python library built as a wrapper on the Twitter API easy use of the same in python. Tweet details- namely text, date-time and the author name were extracted from twitter servers using Tweepy. Another dataset was used which consists of 16 lacs tweets with a tag for 'positive', 'negative' or 'neutral' (http://thinknook.com/twitter-sentiment-analysis-training-corpus-dataset-2012-09-22/).

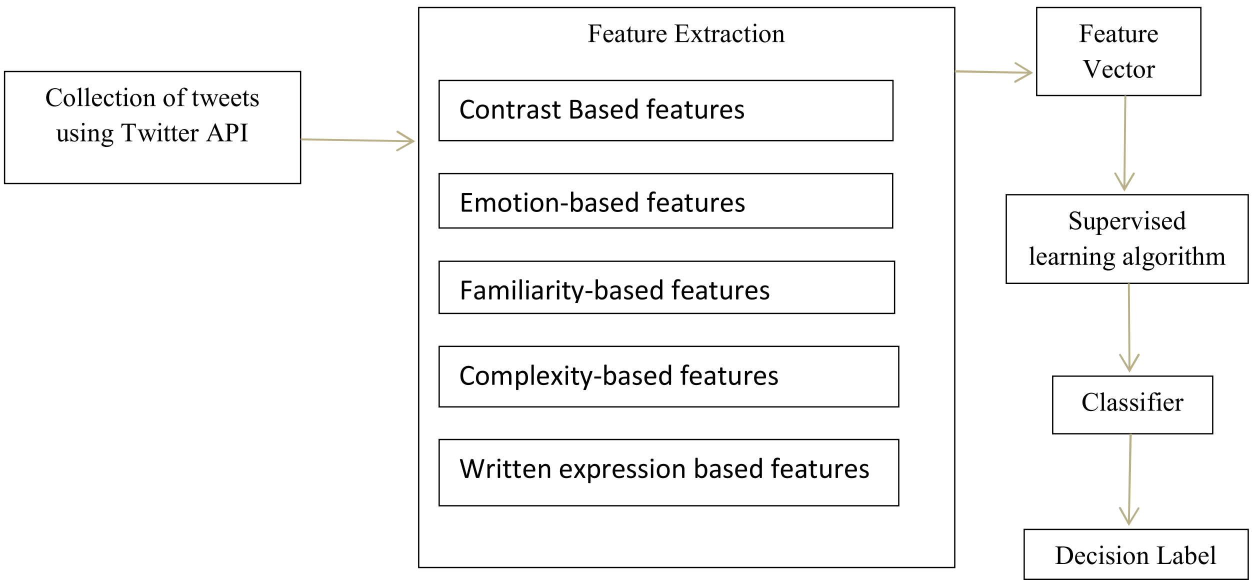

Fig 2: Proposed Process of sarcasm detection

5. Results

We divided our features into four feature sets namely: 1. Sarcasm as a contrast of Sentiments (Set 1). 2. Sarcasm as a complex form of expression (Set 2). 3. Sarcasm as a written form of expression (Set 3). 4. All of these features combine (BigFeautreSet).

12 algorithms were applied to these feature sets to measure which feature set contributed towards the prediction to what extent. We also employed the idea of varying training-testing split on the dataset to get a vague idea of the location of optimum results. We used accuracy as our performance parameter which just represents the closeness of the result to the actual result that has been calculated by many researchers. The idea of percent error was proposed for accurate measurement.

% error = (accepted - experimental) / accepted *100%

Set 1 Analysis: The performance of all algorithms is more or less stable, the algorithms, when compared to one another, give varied results. While some algorithms like SVM (rbf kernel) perform as poor as 54%, some robust algorithms like Gradient Descent Ensemble perform extremely well at an accuracy of about 79%. Hence we can safely conclude that Set 1 is a moderate predictor. Also, it must be noted that this dataset is pathological to multi-layered perceptron model.

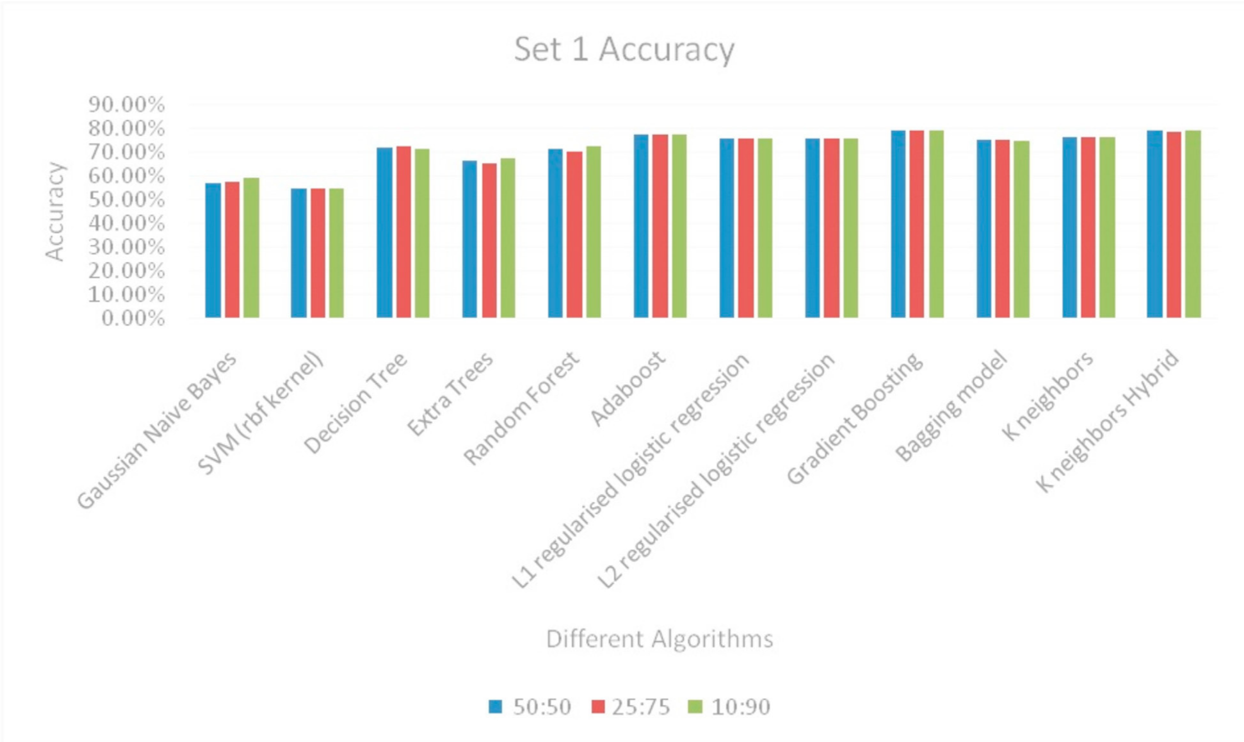

Fig. 3: Set 1 Accuracy

Set 2 Analysis: All the 12 classification algorithms that we applied performed poorly on the features of Set. Hence, we may infer that Set 2 as a whole is a poor predictor. The best performance is obtained by using the Gradient Boosting, at an accuracy of 65.95%.

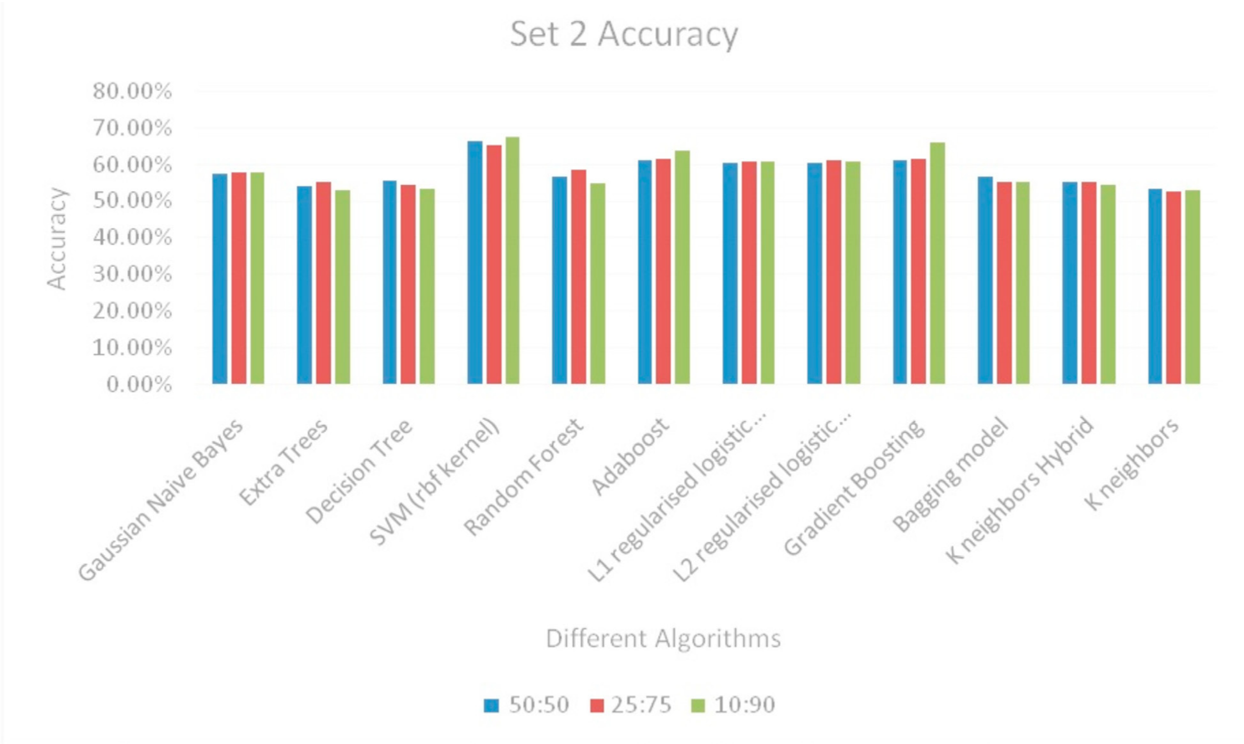

Fig 4: Set 2 Accuracy

Set 3 Analysis: This feature set is by far the best predictor giving an accuracy of as high as 85%. Even relatively primitive algorithms such as Gaussian Naive Bayes give a pretty satisfactory result of about 75%.

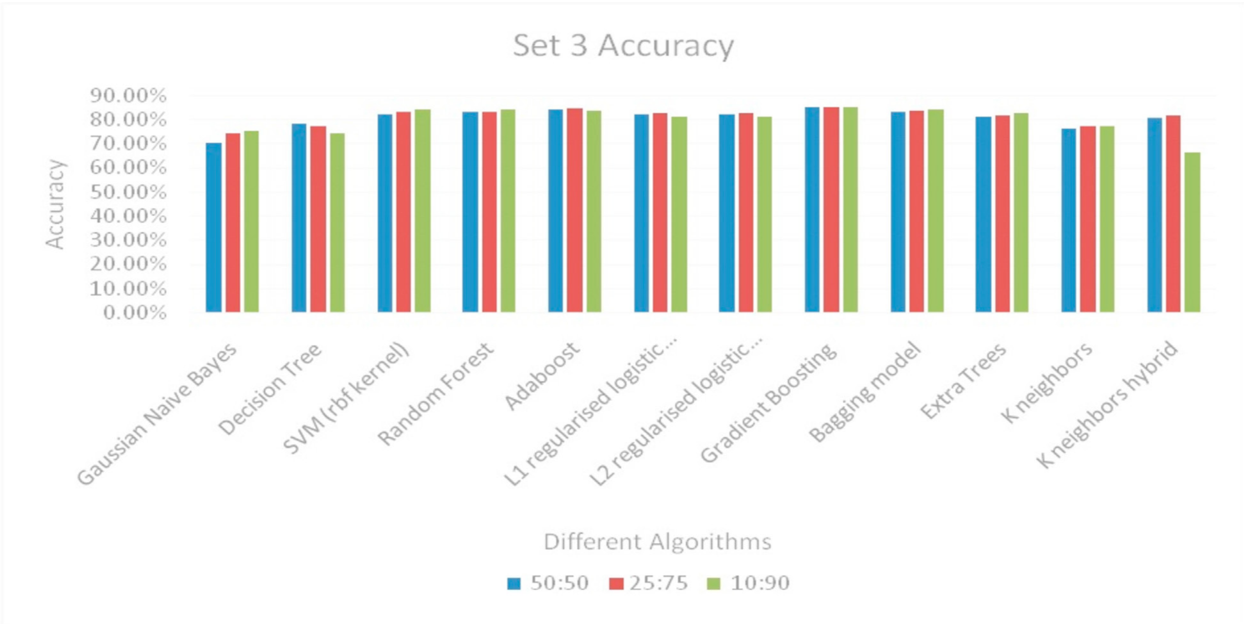

Fig. 5 Set 3 Accuracy

Full Feature set Analysis: By running classification algorithms on different features sets individually, and then running them on the BigFeatureSet, we drew certain conclusions. Gradient boosting gives the best accuracy of 85.71% on a train-test split of 75:25. K-neighbors and SVM (rbf kernel) give a below-par accuracy of about 55%. All the other ensemble classifiers give a satisfactory performance.

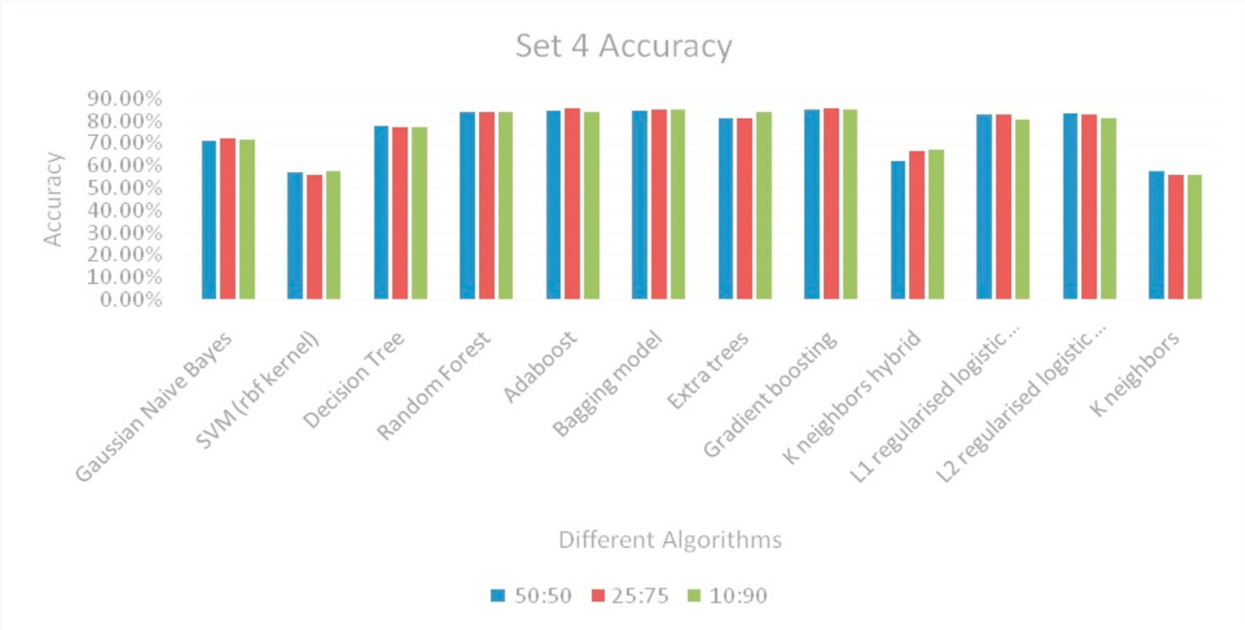

Fig 6: Total Feature Set Accuracy

6. Conclusion

Sarcasm detection analysis has become big considerably over the last few years, entailing that we glance behind and evaluate the image that these independent accomplishments have proposed. The paper conferred illustrations containing the methods, datasets and performance values. As is evident from the results described above, even the partial implementation of the SCUBA framework gives pretty robust results. This clearly indicates that incorporating features that describe the psychological and behavioural aspects of the user goes a long way in helping the process of automatic identification of sarcasm. In general, ensemble methods always outperform singleton classifier algorithms, showcasing consistency with the theoretical expectation. Gradient Boosting works the best, for all feature sets individually, as well as on the BigFeatureSet. Multi-Layered Perceptron model gives the most absurd, inaccurate and inconsistent results. In general, the 10:90 train-test split gives the best accuracy results. L1 and L2 regularized logistic regression gives a result almost at par with Gradient Boosting. The comparatively better performance of primitive algorithms on Feature Set 3 as compared to other feature sets is probably because of the sparse nature of the data produced by the feature set 3.

7. Future Work

Because of the encouraging results obtained, future work could definitely be pursued in the direction of expanding the feature set in order to include more features that are expressive of the user's behavior. Moreover, the detection of sarcasm in tweets is limited, in the sense that the sentences are of limited sizes. The same approach could be expanded to detect sarcasm on other social media platforms (To classify posts as sarcastic on face book for example). This could go a long way in restricting the spread of fake news on account of people not recognizing the posts as sarcastic. On an ending note, the current approach works on a static dataset. The possibility of adding incremental classification capabilities could also be attempted in the future.

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