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A Survey of Sarcasm Detection in Social Media

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Abstract*: Sentiment is the feeling or attitude towards something and sentiment analysis is analyzing or studying about various reviews and comments given by people. The process of Sentiment Analysis tends to understand these opinions and categorize them into positive, negative and neutral. The main challenge in Sentimental Analysis is the presence of sarcasm. Sarcasm is a sophisticated form of language use that acknowledges a gap between the intended meaning and the literal meaning of the words. With this ambiguity, sarcasm detection is a difficult task even for humans. People regularly express it verbally using heavy tonal stress and certain gestural intimations like rolling of the eyes. This tonal and gestural information is clearly not available for communicating sarcasm in content, making its detection dependent upon different variables. This paper presents a survey on various approaches used for detecting sarcasm and different approaches for classifying the sarcastic text and findings of each algorithm are discussed. The study proves that Deep learning approach is a better approach for Sarcasm detection.

Keyword: Naïve Bayes, Maximum Entropy, Sarcasm, Neural Network, Decision Tree

I. INTRODUCTION

Sentiment Analysis is a Natural Language Processing (NLP) and data extraction process that helps to acquire user's sentiments written in positive, negative, neutral remarks, questions and demands by doing research on large quantities of documents. As a rule, sentiment analysis expects to decide the perception of a speaker or an author as for some point or the general tonality of a report. Sentiments of people can be analyzed as Positive, Negative and Neutral. The sentiment analysis is vital to the business fields. By analyzing, the negative sentiment from the twitter can be used to improve the business and can benefit to the customers. Sarcasm is a kind of sentiment derived from the French word "Sarkasmos" which means "tear flesh" or "grind the teeth. The meaning is different than what the speaker intends to say through sarcasm. Sarcasm can also be defined as a "contrast between a positive sentiment and negative situation" [1] and vice versa. It is very important to identify the sarcasm in opinion mining and sentiment analysis. Sarcasm is a very important aspect in social media data analysis because of the absence of face-to-face contact. As social media is gaining more popularity, the problem of sarcasm detection will become even more challenging. This style of expressions were featured in Microblogs and social media which made it very difficult for the annotators to manually analyze each sentence, hence came the use for developing a tool to determine Sarcasm Detection. Sarcasm Detection is a part of NLP, which deals with humor detection, which is in the form of text. The various ways to detect sarcasm and the identifiers present in the comments are shown in the figure 1.

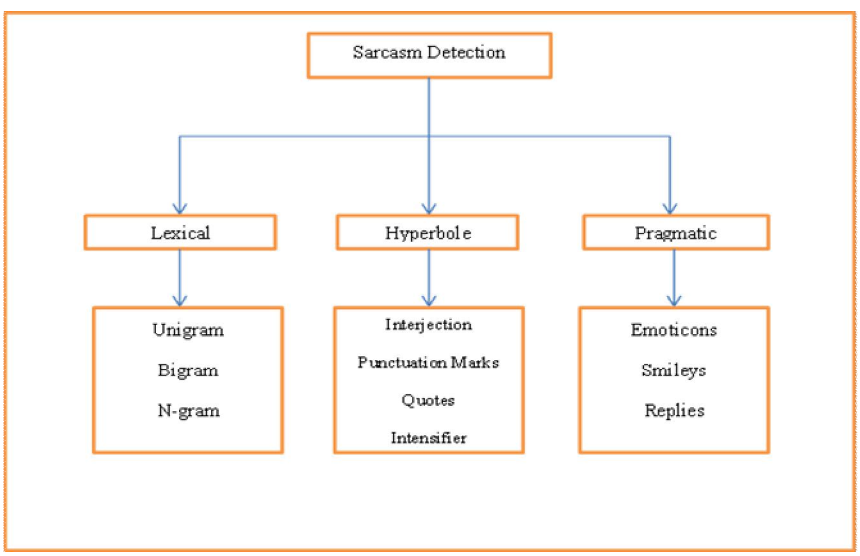

Figure [1] Approaches and Components used in the Sarcasm Detection

II. APPROACHES FOR SARCASM DETECTION

Sentiment classification can be done in two ways namely machine learning approach and lexicon-based approaches. Machine learning results in maximum accuracy and semantic orientation gives better generality.

Machine learning can be divided into supervised and unsupervised approaches. Supervised approaches require two sets of annotated data, one set is for training and the other is for testing. The various types of classifiers used for supervised learning are Decision Tree (DT), Support Vector Machine, Neural Network (NN), Naive Bayes and Maximum Entropy (ME). The other approach called lexicon based contains two approaches namely dictionary based or corpus based approach. Dictionary based approach makes use of existing dictionary, which is a collection of opinion words along with their positive (+ve) or negative (-ve) sentiment. Dictionaries can be created with/without using ontology. An ontology is defined as an ''explicit, machine-readable specification of a shared conceptualization''[2]. Ontology can be used for new words which are not found in named corpus. Corpus based approach relies on the probability of occurrence of a sentiment word in conjunction with positive or negative set of words by performing search on very huge amount of texts like Google search, AltaVista search etc.

A. Supervised Approaches

Supervised techniques can be implemented by building a classifier. This classifier is trained by examples, which can be manually labeled. Most commonly used supervised algorithms are Support Vector Machines (SVM), Naive Bayes classifier and Maximum Entropy [3].

1) *Support Vector Machine:* Support vector machines (SVM) is a Supervised machine learning algorithm basically used for both classification and Regression. it is mostly used in classification problems. Each data item is plotted as a point in n-dimensional area, where 'n' is number of features, with the value of every feature being the value of a specific coordinate.
2) *Naïve Bayes*: Naïve Bayes (NB) is mainly used for text categorization and it is based on Bayes'theorem with the Naive assumption of independence between every pair of features. Naive Bayes is often used to predict the probability of sentiments in the text.
3) *Maximum Entropy*: It is a Probabilistic classifier model based on the class of exponential model. And it supports various natural language tasks, such as language modeling, part-of-speech tagging, and text categorization.
4) *Artificial Neural Networks*: It is a Computational model. Artificial neural network works as the way human brains processes information. To process the data ANN incorporates a huge amount of associated processing units and produce meaningful results.

Pang and Lee [4] used various supervised techniques such as Naïve Bayes, Maximum Entropy (ME) and Support Vector Machine for binary sentiment classification for movie reviews. For experiments, authors have collected movie reviews from IMDb.com. Authors have done experiment with different feature engineering, where SVM provided the highest accuracy of 82.9 percentage with unigrams features. Dang et al. [5] classified sentiments using SVM by using different feature selection methods. They have done the experiments by using two corpora one with 305 positive reviews and 307 negative reviews on digital camera and the other corpora was the multi-domain dataset from Blitzer et al. [6]. SVM was trained on three collections of feature set based on domain free, domain dependent and sentiment features. Information Gain (IG) was applied to reduce the number of features from different combination of features. The reduced feature set performed better on multi-domain dataset than digital camera dataset and obtained an accuracy of 84.15 percentage. Zhang et al. [7] classified sentiment using machine learning (NB and SVM) for restaurant reviews written in Cantonese. Authors have studied the effects of feature representations and feature size on the classification performance. Authors have performed an experiment on 1500 '+ve' and 1500 '-ve' reviews and used different feature representations like unigram, unigram_freq, bigram, bigram_freq, trigram and trigram_freq and other features in the range of 50 to 1,600 features. The highest accuracy reported was 95.67 percentage using Naïve Bayes algorithm for 900–1100 features. The Dynamic Artificial Neural Network (DAN2) and Support Vector Machine were employed as multi-class classifiers. DAN2 was designed in such a way to contain multiple hidden layers with four hidden nodes per layer. DAN2 outperformed SVM with an accuracy of 71.3 percentage for strongly positive, 66.7 percentage for mildly positive, 89.9 percentage for mildly negative and 95.1 percentage for strongly negative.

B. Unsupervised Approaches

Unsupervised approach concerns the analysis of unclassified examples. This system is not provided with any training examples. Unsupervised learning is a method for finding patterns in data without any information about the outcome of the data. The strength of unsupervised learning lies within finding associations in data and show how it is arranged by Michie et al. [8].

1) *Lexicon based approaches:* The Lexicon-based Approach depends on a sentiment lexicon, a collection of known and precompiled sentiment terms. For extracting two-word, phrases from comments. Turney[9] used a collection of patterns of tags.

To determine semantic orientation of comments authors used a mechanism called PMI-Information retrieval (Pointwise Mutual Information) by giving queries to a search engine by considering two boundary values as “excellent” and “poor” for positive and negative respectively. For experiments 410 reviews on various domains have been carried out from a site called Epinions.com. As a result, the highest accuracy of 84 percentage achieved on smallest dataset, which contains only 75 reviews on automobiles, and for the movie reviews, the lowest accuracy level of 65.83 percentage was achieved. Subject Favorability determination was done by Yi [10] by developing sentiment lexicons of 3513 sentiment words. Two factors were considered such as syntactic dependencies among the phrases and subject term modifiers. Authors have done experiments in two sets the first one is a multi-domain corpus contains 175 cases of subject terms within the context and the second one is camera reviews of 2000 cases. The proposed work has been evaluated on web pages and news articles of 552586 and 230079 reviews respectively to extract sentiments by defining 13 subject terms, which acquired the precision rate of 86 percentage and 88 percentage respectively. The accuracy of 91 percentage was achieved when the sentiment extraction conducted on 476126 web pages of pharmaceutical domain.

2) *Corpus and Dictionary Based:* Dictionary based approach works as normal dictionary concept, first the given words of opinions are searched and then it looks for their synonyms and antonyms. Some of the opinion words are listed manually. The list is then expanded by searching into popular or well-known corpora like WordNet. The strength of polarity for each word is also listed in the dictionary. The Corpus Based approach is used to find opinion words with context-specific orientations, which depend on syntactic patterns.

C. Other Machine Learning Approaches

1) *Hybrid approach:* This approach combines various machine learning approaches to get better results. Ortigosa et al.[11] Performed sentiment classification and sentiment change detection on Facebook remarks using lexicon and machine learning based approach. Poria et al. in [12] have introduced a novel paradigm for concept-level sentiment analysis by combining linguistics, common-sense computing, and machine learning for improving the polarity detection task. A sentiment lexicon was developed based on Spanish Linguistic Inquiry and Word Count (LIWC) and slang found in the reviews. So as to assess the proposed lexicon, authors used C4.5, NB, and SVM to characterize 3000 status messages and each 1000 for positive, negative and neutral comments and yielded an accuracy of 83.17 percentage, 83.135 percentage, and 83.27 percentage respectively. A hybrid machine learning approach has been developed in [13] for extracting the information from unstructured documents by combining Maximum Entropy Modeling (MEM) and a classifier based on Data-Oriented Parsing (DOP) and the experiments were done in the corpora of German newspaper articles about company turnover and obtained a result of 85.2 percentage. Md Shad et al.[14] proposed a novel hybrid deep learning architecture for sentiment analysis in resource-poor languages. Convolution Neural Network(CNN) and Support Vector Machine approaches have been used and authors evaluated the proposed approach on different datasets such as Twitter (generic as well as sarcastic) and online product reviews (sentence-level and aspect-level), across two different languages viz. Hindi and English and obtained an accuracy of 62.52 percentage for Twitter_H(Twitter-Hindi). For aspect-level Hindi review dataset Review_{AH} obtained an accuracy of 65.96 percentage and 57.34 percentage for Sentence-level Hindi review. The proposed method for Twitter_E(English) dataset has obtained an accuracy of 58.62 percentage for generic twitter and 61.67 percentage for the sarcastic tweets. The Review $_{AE}$(Aspect-level English) for laptop and restaurants have acquired the accuracy of 68.04 percentage and 77.16 percentage respectively.

2) *Deep learning:* It is a part of Machine learning algorithms. For feature extraction and transformation it uses many different layers of non-linear processing units. Meizhan et al.in [15] used a bi-directional gated recurrent neural network for capturing the syntactic and semantic information and to extract contextual features automatically from the tweets and used a pooling neural network. By using local tweet features, an accuracy of 78.55% achieved with the neural model whereas the accuracy of the neural model goes up to 90.74% .These results states that there is large benefits for the neural models on the sarcasm detection task. A pre-trained convolution neural network model has been developed by Soujanya et al.[16] for extracting the sentiments and emotions for Sarcasm detection. Three different Datasets were used for the implementation and obtained the result of F1-score: 87.00 percentage for the sentiment model. F1 score or F-measure is mainly used in Natural language processing to measure the test’s accuracy. Authors could obtain an accuracy level of F1-score: 90.70 percentage when sentiment, emotion and personality features were combined. For the dataset2 Baseline features have given better performance than all other features with an accuracy of F1-score:92.32 percentage. In the third Dataset the highest performance of F1-score was 93.30 percentage obtained by combining baseline features with sentiment, emotion and personality features.

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Table 1 : The Summary of Best Systems for Sarcasm Detection

Author Name	Approach Used	Dataset	Results or Accuracy
Erik Forslid, Niklas Wikén.[17]	Support Vector Machine, Decision tree, Naïve Bayse	Amazon & twitter	Amazon -87% and Twitter data - 71%
Meishan Zhang,Yue Zhang and Guohong Fu[18]	Deep learning	Twitter	90.74%
Raghavan V M, Mohana Kumar P , Sundara Raman R and Rajeswari Sridhar[19]	Hybrid Approach	Facebook	82%
Chun-Che Peng, Mohammad Lakis, Jan Wei Pan[20]	Naive Bayes , One class Support vector machine	Twitter	Naïve Bayes-62.02%. One Class SVM-50%
Peter Clews, Dr. Joanne Kuzma[21]	Lexicon Based	Twitter(#sarcasm, #trump)	#sarcasm-36.7%, #trump-30.9%
Aditya Joshi Vinita Sharma Pushpak Bhattacharyya[22]	Lexicon Based	Twitter & Discussion Forums	F1-score:0.8876
Shubhadeep Mukherjee Pradip Kumar Bala[23]	Naïve Bayes, Maximum Entropy Classifier	Twitter	70%
Toma´s Ptacek, Ivan Habernal and Jun Hong[24]	Maximum Entropy (MaxEnt) and Support Vector Machine	Twitter	F1-score:0.947
Lakshya Kumar, Arpan Somani, Pushpak	Support vector Machine Rule	Twitter	F1-score:0.93

Bhattacharyya[25]	Based, Deep learning		
Pulkit Mehndiratta, Shelly Sachdeva, Devpriya Soni[26]	Deep Convolutional Neural Networks	Twitter	89.9%

III. FINDINGS OF THE STUDY AND DISCUSSION

1) *Support Vector Machine Technique:* Existing SVM techniques applied in various works lack transparency in results. If the dimensions of datasets are very high, SVM might not be able to show the accurate result. Hinge loss in SVM is often scattered that affects the accuracy of the results. A loss function which is used to train the classifiers is called Hinge loss.
2) *Decision Trees:* Decision Tree is easy and simple to use yet it has inherent drawbacks such as it works with only known groups. Even little changes in the input data can make huge changes on the decision tree and many times leads to redrawing the tree.
3) *Deep learning :* This gives better results for large dataset with the pre trained data. Deep learning learns itself without grouping from the data by assigning statistic probabilities.
4) *Random Forest:* It can work with less data and more attributes and does not work efficiently with extrapolation. Deep learning works with limited attributes with large data, which in turn results in better accuracy.
5) *Naive Bayes:* A subtle issue with Naive Bayes is that it works with small amount of training data whereas Deep learning works efficiently with large data sets. Rule Based algorithm is very labor intensive as the Rule base is very large. Hence, decision-making is very complex. When a new knowledge is added, new rules have to be framed.
6) *Lexicon Based:* This approach gives better results if it works with small dictionary and does not focus on large database. From the above findings, this study has come to a conclusion that most of the existing approaches work on small datasets and small dictionaries. As Sarcasm, detection can be efficient only if the detection is made on large set of data and existing approaches cannot determine Sarcasm efficient as data is collected in a large amount from social media like Twitter and Facebook. Thereby this study concludes that Deep learning is a better approach for Sarcasm Detection.

IV. CONCLUSION

Sarcasm detection in writing is a trivial challenging task due to lack of articulation and facial expressions. Many approaches are there to do Sentiment analysis for sarcasm detection. The number of Twitter users are increasing day by day, the comments shared by the people are very large, and large data set is generated. There are many techniques developed to do sentiment analysis but the problem of sarcasm detection is still not solved. This paper gives a survey on various methodologies used to detect sarcasm in Twitter social media data and have done the analysis of various classifiers such as Support Vector Machine, Naïve Bayes, Lexicon based with accuracy rate. Sarcasm can be determined efficiently only if the existing approaches can deal with large data set but most of the existing approaches can deal with only small datasets. So deep learning approach is considered as an efficient approach to detect Sarcasm in case of large datasets.

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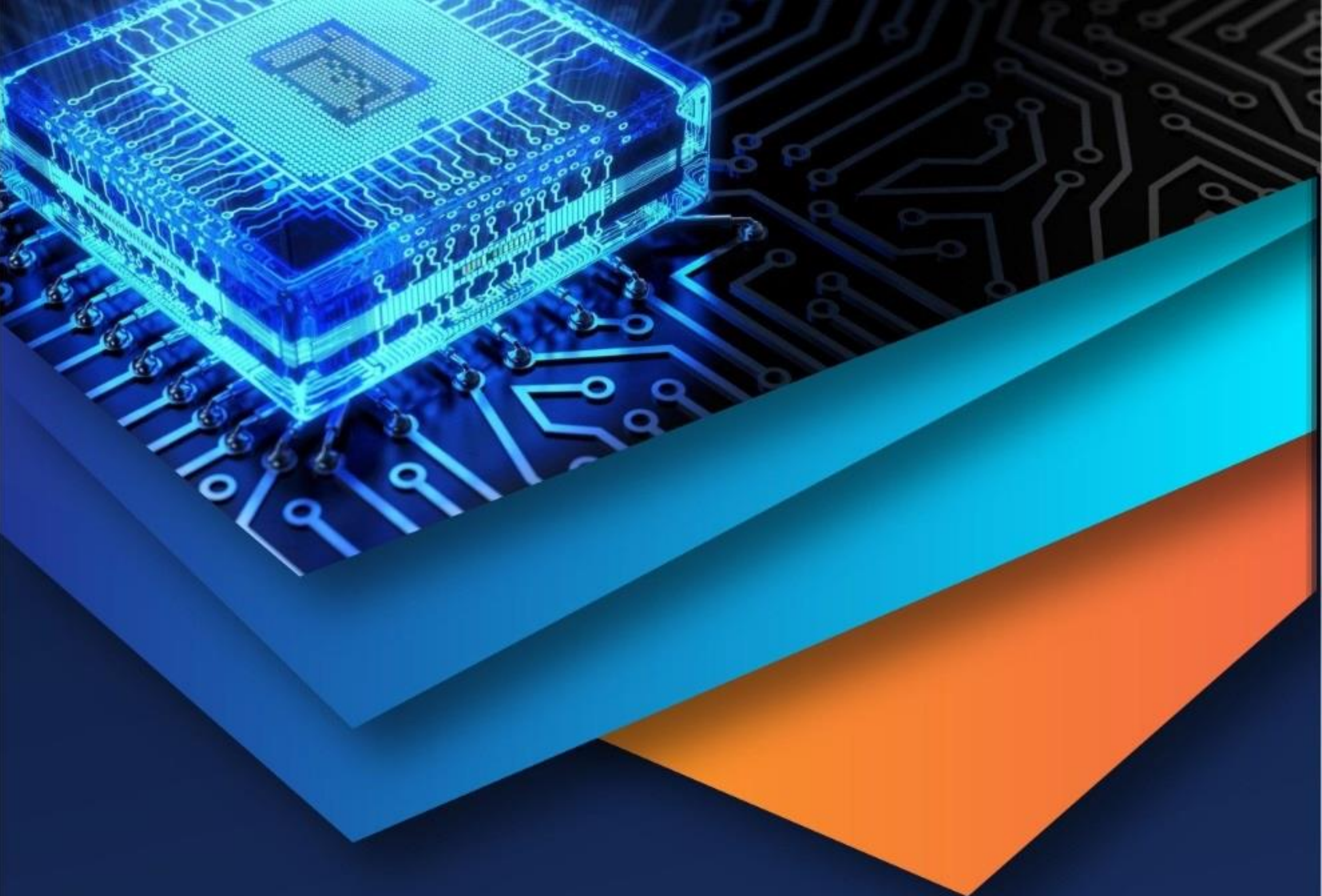

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