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Recent Trends in Sarcasm Detection on Online Social Networks

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Abstract— Online Social Networks become largest platform to express people feelings, opinions, views and real time events such as live tweets etc. Example Twitter has 315 million monthly active users, eighty two percent of active users on mobile and millions of tweets are being circulated through twitter every day. Various organizations as well as companies are interested in twitter data for finding the views of various people towards their products or events. Sarcasm refers to expressing negative feelings using positive words. To detect sarcasm among those tweets is comparatively more difficult. This paper discussed various approaches to find sarcasm on twitter. With the help of sarcasm detection, companies could analyze the feelings of user about their products. This is helpful for companies, as the companies could improve their quality of product.

Keywords—Sarcasm, Sarcasm detection, Twitter

I. INTRODUCTION

Macmillan English dictionary describes sarcasm is the activity of saying or writing the opposite of what one means or of saying in a way intended to make someone else feel stupid or show them that one is angry[1]. With sophistication of language, use of sarcasm in verbal and written text has become quite the norm. However, automatic detection of sarcasm is still in its infancy. The ambiguous nature of sarcasm makes it difficult even for humans to detect it in sentences [1].Sarcasm construct or exposure of contradictions between stated and intended meanings. It is the most typical form of verbal irony and often used to humorously convey thinly veiled disapproval, contempt, and scorn, as in the case of sarcastic criticisms. For instance, a boss catching his assistant surfing the Internet may state, ‘‘Pat, don’t work too hard!’’ to express disapproval [7]. Sarcasm may generate cognitive and behavioral benefits. Because sarcasm seems to exercise the brain more than the direct exchanges. Sarcasm often makes salient contradictory notions. As a result, both constructing and making sense of any type of sarcasm necessitate recognizing and reconciling disparate ideas, making sarcasm a potential facilitator of creativity for both sides of the exchange[7].

Twitter becomes platform for people express their feelings, opinions, views and real time events such as live tweets etc. With respect to previous years, the data of twitter has increased much and thus forming big data. Twitter using people around the world is 315 million monthly, eighty two percent of active users on mobile and millions of tweets are being circulated through twitter every day. Various organizations as well as companies are interested in twitter data for finding the views of various people towards their products or events. Twitter is also used to find out various views of people towards political events, movies etc [2].

Twitter uses 140 characters per tweet limit as well as the non formal language such as slang, emotions; hash tags etc. used in tweets, finding views of different people is very difficult. To detect sarcasm among those tweets is comparatively more difficult. Sarcasm refers to expressing negative feelings using positive words. Oxford dictionary explains sarcasm as “the use of irony to convey contempt”. Collins dictionary describes as “mocking or ironic language to convey insult or anger”. Sarcasm is also when people mean something else from what he speaks. Sarcasm is used not only to make jokes but also for criticizing other people, views, ideas etc. As reason of which sarcasm is very much used in twitter. For example-”I loved being ignored”. Here “love” expresses a positive sentiment in negative context. Therefore this tweet is referred as sarcastic. Thus analyzing sarcastic tweets is very difficult [2].Current research on sarcasm detection on Twitter has primarily focused on obtaining information from the text of the tweets. These techniques treat sarcasm as a linguistic phenomenon, with limited emphasis on the psychological aspects of sarcasm [3].

In this paper Section I contains the introduction of Sarcasm and sarcasm detection on twitter , Section II contain the related work of sarcasm detection, Section III contain the some methodologies of sarcasm detection on twitter, Section IV contain the conclusion.

II. RELATED WORK:

Sarcasm was ideally studied by psychologists, behavioral scientists and linguists for many years. Theories describing the cognitive processes behind sarcasm usage such as the echoic reminder theory, allusion pretense theory, and implicit display theory were extensively researched. However, sarcasm detection is a unexplored research topic and a challenging problem. While a study on automatic detection of sarcasm in speech utilizes prosodic, spectral and contextual features, sarcasm detection in text has relied on identifying text patterns and lexical features. A semi-supervised model to detect sarcasm in Amazon product feedback tweets. They used interesting pattern-based (high frequency words and content words) and punctuation-based features to build a weighted k-nearest neighbor classification model to perform sarcasm detection. Classifiers duty to identify verbal irony based on ambiguity, polarity, unexpectedness and emotional cues derived from text. A sarcasm detection technique using numerous lexical features and pragmatic features such as emoticons and replies. Unigrams, bigrams and trigrams as features to detect sarcastic Dutch tweets using a balanced winnow classifier. More recently, well-constructed lexicon based approach to detect sarcasm based on an assumption that sarcastic tweets are a contrast between a positive sentiment and a negative situation.
As explained, past studies on automatic detection of sarcasm had focused on linguistic features of sarcasm and used only the text of the tweet. We introduce all approaches for effective sarcasm detection by not only analyzing the content of the tweets but by also exploiting the behavioral traits of users derived from their past activities.

III. TRENDS IN DETETION OF SARCASM

A. The Behavioral Model

In the social media people were posted sarcasm tweets. They may decide to use sarcasm as a behavioral response to a certain situation, observation or emotion. These situations, observations or emotions may be observed and analyzed on twitter.

SCUBA considers the user's perception by analyzing the past tweets. By that SCUBA find that sarcasm generation can be characterized as one of the following

- Sarcasm as a contrast of Sentiment
- Sarcasm as a Complex form of expression
- Sarcasm as a mean of Conveying emotions
- Sarcasm as a possible Function of familiarity
- Sarcasm as a Form of written Expression

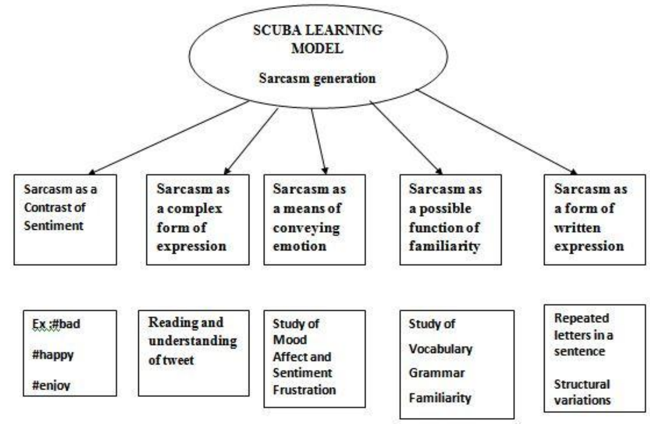

Figure 1: SCUBA Model

B. The CLSA Model

The CLSA approach work towards sentiment analysis which brings eight NLP modules that are probably necessary for the suitable interpretation of expressed text, namely [4]:

- Micro text analysis, for normalizing informal and irregular text
- Semantic parsing, for constructing natural language text into concepts
- Subjectivity detection, for filtering non-opinionated or neutral text
- Anaphora resolution, for resolving references in the discourse
- Sarcasm detection, for detecting sarcastic opinions and flip their polarity
- Topic spotting, for contextualizing opinions to a specific topic
- Aspect extraction, for constructing text into different opinion targets
- Polarity detection, for detecting a polarity value for each opinion target

C. Naive Bayes And Fuzzy Clustering

In this model feature extraction methodology is main concept. Because Feature Extraction is a method amount of resources required to describe a dataset [1]. In this methodology we used a absolute list of features for the purpose of classification [11, 12]. By using multiple features we can compare different accuracies. The features were

- Content words
- Function words
- Parts of speech tags
- Parts of speech N-grams
- Content words + Function words
- Function words + Parts of speech N-grams
- Content words + Function words + Parts of speech N-grams

1) Using Naive Bayes

Let's consider a tweet with some features of our interest T = (F1, F2 ….Fn). Here F be the features to classify the tweets (content words, n-gram part of speech tags, function words etc.). Given the tweet "T" we would like to predict whether it belongs to a particular category viz. sarcastic or non-sarcastic.

Using Bayes' theorem we can write,

$$p(C/F1, \ldots. fn) = (p(c)p(F1, \ldots\ldots, Fn/C))/p(F1, \ldots\ldots \quad \text{— (1)}$$

Where, C = {sarcastic, non-sarcastic}. Fi represents the features selected as inputs.

The Naïve Bayes assumption for a classification task is as shown below:

$$p(F1, \ldots\ldots Fn|C) = (p(F1 \mid c)p(F2 \mid c), \ldots\ldots., p(Fn|(\quad \text{—— (2)}$$

The assumption of independence between or amongst the features is considered in the above expression. In the case of tweets it will mean that the two words (a feature) in a tweet occur independent of each other. Although the assumption is simplistic it has been shown to work well

in earlier research (Yan and Yan, 2006).

This equation could now be written as,

$$p(C/T) = (p(F1 \mid c)p(F2 \mid c), \ldots\ldots., p(Fn|C))/p(T) \quad \text{\_ (3)}$$

We then compute the ratios of the posterior probabilities $p(c = sarcastic|T)\ and\ P(C = non - sarcastic|T)$ of the two classes for a given document. This is done by calculating the prior probabilities $p(C)$ and the conditional probabilities of $P(Fi|T)$. The tweet is then classified to the class that yields the higher probability.

2) Fuzzy Clustering

Cluster analysis is one of the major techniques in pattern recognition. It is an approach to unsupervised learning [9]. The conventional clustering methods restrict that each point of the data set belongs to exactly one cluster. Fuzzy set theory developed by Zadeh in 1965 gave an idea of uncertainty of belonging which was described by a membership function. The use of fuzzy sets provides imprecise class membership information.

Fuzzy C-means (FCM) algorithm, one of the most popular fuzzy clustering techniques. FCM is able to determine and iteratively update the membership values of a data point with predefined number of clusters [10]. Thus, a data point can be the member of all clusters with the corresponding membership values.

D. SVM Classifier And Naïve Bayes Classifiers

This method differentiates between SVM Classifier and Naïve baye's Classifier. These methods categorize sarcastic sentiment into three parts.

- Lexical feature based classification- Lexical feature based classification involves text properties such as unigram, bigram and n-grams. Various authors have provided different paper for detecting sarcasm based on lexical feature based classification. In viewed that bigram based features provide more betters result for detecting sarcasm in tweets. In explained various lexical features for detection of sarcasm. In used bigram and trigram for generation of bag of lexicons to detect sentiment in tweets [2,13].
- Pragmatic features based classification- Pragmatic feature based classification involves figurative and symbolic texts such as similes, emoticons. Various authors have used pragmatic features for sarcasm detection [2][14].
- Hyperbole features based classification- Hyperbolic features based classification contains interjection, intensifiers, quotes and punctuation marks. Various authors have used hyperbolic features based classification to detect sarcasm. In provided detection of sarcasm using interjection and punctuation marks. In viewed that phrase level and sentence level does not provide good accuracy and showed that text in document could improve accuracy. In viewed that tweets having interjection words such as yay, wow etc. have more chance of being sarcastic. In found concept level knowledge by using hyperbolic words in sentences. In viewed the tweets that start with interjection words for detection of sarcasm [2][15].

The twitter data is collected using Twitter Archiver and the aim is to classify the sarcastic tweets as positive, negative and neutral. The aim is also to classify the tweets using Naïve Bayes classifier and SVM classifier and to differentiate between the accuracy, precision, recall and F-score of Naïve Bayes classifier and SVM classifier. A package named TextBlob that is installed in Natural Language Toolkit is used for preprocessing of the twitter data. The preprocessing steps involve tokenization, part of speech tagging and parsing. The stop words are removed using python programming. The stop words corpus which consist of 2400 stop words and which is distributed with NLTK have been used. RapidMiner, a tool have been used for finding the polarity and subjectivity of the data. TextBlob is used to find the polarity and subjectivity confidence of the data. Weka has been used to find the accuracy, precision, recall and F-score using Naïve Bayes classifier and SVM classifier[2].

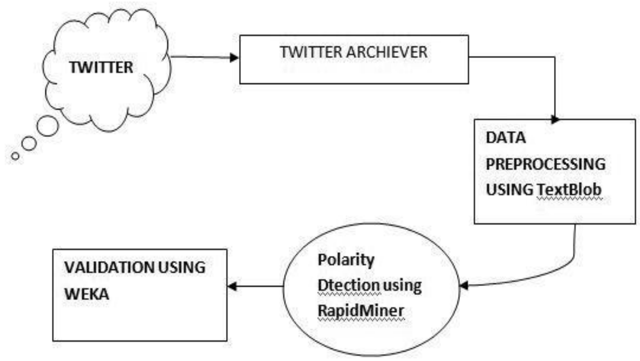

Figure 2: Steps involved in the sarcasm detection using WEKA Tool

A. Using EMOJIS

In today's world social media main source for the communication. The communication can be done by using Text, Emojis. Emojis are plays main role for expressing the human emotions. Emojis were a proxy for the emotional content of the text in this method we have three steps.

- Pre training
- LSTM model
- Transfer learning

1) Pre Training: The set of emojis were used for the pre training on the classification task of predictions which emoji were initially part of text can improve performance on the target task. Tweets contain repetitions of emojis. We addressed for each unique emoji type. We save them for the pre training. By this type of data preprocessing get multiple types of emotional content are associated with that tweet.

2) LSTM *Model:* Long Short-Term Memory model decide importance of each word for the prediction task by weighting then when constructing the representation of text.

3) Transfer learning: simple transfer learning approach, 'chain-thaw' that sequentially unfreezes and fine-tunes a single layer at a time. This approach increases accuracy on the target task at the expense of extra computational power needed for the fine-tuning. By training each layer separately the model is able to adjust the individual patterns across the network with a reduced risk of over fitting. The sequential fine-tuning seems to have a regularizing effect similar to what has been examined with layer-wise training in the context of unsupervised learning [5]

IV. ISSUES IN THE SARCASM DETECTION

Issues that appear in different sarcasm detection. First deals with the quality of the annotation. Second issue deals with using sentiment as a feature for classification. Finally, the third issue lies in the context of handling unbalanced datasets [8].

A. Issues with Annotation

Hash tag-based labelling can provide large-scale supervision; the quality of the dataset may be dubious. This is particularly true in the case of using #not to indicate insincere sentiment. Show that #not is often used to express sarcasm - while the rest of the sentence is not sufficient for identifying the sarcasm. For example, 'Looking forward to going back to school tomorrow #not'. Speaker expresses sarcasm through #not. In most reported works that use hash tag-based supervision, the hash tag is removed in the pre-processing step. .is reduces the sentence above to 'Looking forward to going back to school tomorrow' - which may not have a sarcastic interpretation, unless the author's context is incorporated, hash tag-based supervision may cause ambiguities (or be incorrect) in some cases. To mitigate this problem, a new trend is to validate on multiple datasets - some annotated manually while others annotated through hash tags. Train their deep learning-based model using a large dataset of hash tag-annotated tweets, but use a test set of manually annotated tweets [8].

B. Issues with sentiment as a feature

Several approaches use lexical sentiment as a feature to the sarcasm classifier. It must, however, be noted that these approaches require 'surface polarity': the apparent polarity of a sentence, defines a rule-based approach to predicts a sentence as sarcastic if a negative phrase occurs in a positive sentence. As described earlier, use sentiment of a past tweet by the author to predict sarcasm. In a statistical classifier, surface polarity may be used directly as a feature. Capture polarity in terms of two emotion dimensions: activation and pleasantness. Use a sentiment imbalance feature that is represented by star rating of a review disagreeing with the surface polarity [8].

C. Dealing with Skewed Datasets

Sarcasm is an infrequent phenomenon of sentiment expression. .is skew also reflects in datasets. Uses a dataset with a small set of sentences are marked as sarcastic. 12.5% of tweets in the Italian dataset given by are sarcastic. On the other hand, present a balanced dataset of 15k tweets. In some papers, specialized techniques are used to deal with the dataset imbalances. For example, present a multi-strategy ensemble learning approach. Use SVM-perf that performs F-score optimization [8].

V. CONCLUSION AND FUTURE SCOPE

Sarcasm detection researches growing rapidly in past few years, so we had knowledge of various techniques to find sarcasm. This paper presents different techniques overview to sarcasm detection like learning models (SVM Classifier, Naïve Baye's Classification, and Fuzzy Clustering), Deep learning models (The Behavioral Model (SCUBA), The CLSA Model) and sarcasm detection using Emojis .This paper will help for knowing the technologies about sarcasm detection in social websites. In future we want continue the research on effective automatic sarcasm detection on stream data which can find in real time.

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