SARCASM DETECTION USING TWITTER ANALYSIS

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ABSTRACT

Sarcasm is a sophisticated form of irony widely used in social networks and microblogging websites. It is usually conveys implicit information within the message a person transmits. Sarcasm might be used for various purposes, for example criticism or mockery. However, it's hard even for humans to recognize. Therefore, recognizing sarcastic statements can be very useful to improve automatic sentiment analysis of data which is collected from microblogging websites or social networks. Sentiment Analysis refers to the identification and aggregation of attitudes and opinions expressed by internet users towards a particular topic. In this paper, we have proposed a pattern-based approach to detect sarcasm on Twitter. We propose four sets of features that covers all the different types of sarcasm we defined. We use those to classify tweets as sarcastic and non-sarcastic. Our proposed approach reaches an accuracy of 82%. We also study the importance of each of the proposed sets of features and evaluate its added value to the classification. In particular, we emphasize the importance of pattern-based features for the detection of sarcastic statements.

Keyword- *Twitter, Sentiment Analysis, Sarcasm Detection, Machine Learning.*

1. INTRODUCTION

Twitter became one of the biggest web destination for people to express their opinion, share their thoughts and report real-time events and so on. Throughout the previous years, Twitter content continued to increase, thus constituting a typical example of the so-called big data. Today, according to its official website, Twitter has more than 288 million active users, and more than 500 million tweets are sent everyday. Many companies and organizations have been interested in these data for the purpose of studying the opinion of people towards political events , popular products or movies . However, due to the informal language used in Twitter and the limitation in terms of characters (i.e., 140 characters per tweet), understanding the opinions of users and performing such analysis is quite difficult. Furthermore, the presence of sarcasm makes the task even more challenging: sarcasm is when a person says something different from what he means. Liebrecht et al. discussed how sarcasm can be a polarity switcher, and Maynard and Greenwood proposed a set of rules to decide on the polarity of the tweet (i.e., whether it is positive or negative) when sarcasm is detected.

1.1 MOTIVATION

As mentioned above, the identification of sarcasm helps us enhance sentiment analysis tasks when performed on microblogging websites such as Twitter. Sentiment analysis and opinion mining rely on emotional words in the text to detect its polarity (i.e., whether it deals ‘‘positively’’ or ‘‘negatively’’ with it's theme).

However, the appearance of the text form might be misleading. A typical example of that is when the text is sarcastic. On Twitter, such sarcastic texts are very common. ‘‘All your products are incredibly amazing!!!’’ might be considered as a compliment. However, considering the following tweet ‘‘Did I say incredibly??? Well, it’s true, nobody will believe that. They break the second day you buy them -_-’’, here the user explicitly explains that he did not mean what he said. Although some users indicate they are being sarcastic, most of them do not. Therefore, it might be indispensable to find a way to automatically detect any sarcastic messages.

Through their work, Rajadesingan et al. highlighted the limitations of some state of the art tools that are used to perform sentiment analysis, when more sophisticated forms of speech such as sarcasm are present. They explained why sarcasm is hard to detect even by humans, and demonstrated how the nature of tweets makes it even more complicated. Hence, arise the importance of detection of sarcastic utterances in Twitter.

However, several challenges arise and make the task complicated. Joshi et al. highlighted 3 main challenges which are i) the identification of common knowledge, ii) the intent to ridicule, and iii) the speaker-listener (or reader in the case of written text) context. In a related context, even though Brown stated that a sarcasm ‘‘is not a discrete logical or linguistic phenomenon’’, works such as and were proposed to identify sarcastically written patterns to decide on whether or not an utterance is sarcastic. During our experiments as well as while manually annotating tweets, we also noticed that such pattern do exist, in particular among non-native speakers of English. Therefore, we focus on detecting and collecting such patterns from a manually annotated dataset, and we quantify them so that we can judge whether or not a given tweet is sarcastic by comparing patterns which are extracted from it to them. Throughout this work, we present a pattern-based framework that performs the task of sarcasm detection, a framework relatively easy to implement, and that presents performances competitive to those of more complex ones.

1.2 RELATED WORK

In the last few years, more attention has been given to Twitter sentiment analysis by researchers, and a number of recent papers have been addressed to the classification of tweets. However, the nature of the classification and the features used vary depending on the aim. Sriram et al. used non-context related features such as the presence of slangs, time-event phrases, opinionated words, and the Twitter user information to classify tweets into predefined set of generic classes including events, opinions, deals, and private messages. Akcora et al. proposed a method to identify the emotional pattern and the word pattern in Twitter data to determine the changes in public opinion over the time. They implemented a dynamic scoring function based on Jaccard’s similarity of two successive intervals of words and used it to identify the news that led to breakpoints in public opinion. However, most of the work focused on the content of tweets and were conducted to classify tweets based on the sentiment polarity of the users towards specific topics. A variety of features was proposed. Not only they include the frequency and presence of unigrams, bigrams, adjectives, etc. , but they also include non-textual features such as emoticons (i.e., facial expressions such as smile or frown that are formed by typing a sequence of keyboard symbols, and that are usually used to convey the writer’s sentiment, emotion or intended tone) and slangs . Dong et al. proposed a target-dependent classification framework which learns to propagate the sentiments of words towards the target depending on context and syntactic structure.

2. PROPOSED APPROACH

Given a set of tweets, we aim to classify each one of them depending on whether it is sarcastic or not. Therefore, from each tweet, we extract a set of features, refer to a training set and use machine learning algorithms to perform the classification. The features are extracted in a way that makes use of different components of the tweet, and covers different types of sarcasm. The set of tweets on which we run our experiments is checked and annotated manually.

2.1 DATA

Throughout the period ranging from December 2018 to November 2020. To collect sarcastic tweets, we queried the API for tweets containing the hashtag ‘‘#sarcasm’’. Although Liebrecht et al. concluded in their work that this hashtag is not the best way to collect sarcastic tweets, other works such as highlighted the fact that this hashtag can be used for this purpose. However, they also concluded that the hashtag cannot be reliable and is used mainly for 3 purposes:

- To serve as a search anchor,
- To serve as a sarcasm marker in case of a very subtle sarcasm where it is very hard to get the sarcasm without an explicit marker, as in ‘‘Today was fun. The first time since weeks! #Sarcasm’’,
- To clarify the presence of sarcasm in a previous tweet, as in ‘‘I forgot to add #sarcasm so people like you get it!’’. In total, we collected 58609 tweets with the hashtag ‘‘#sarcasm’’, which we cleaned up by removing the noisy and irrelevant ones, as well as ones where the use of the hashtag does fall into one of the two first uses of the three described above.

As for non-sarcastic tweets, we collected tweets dealing with different topics and made sure they have some emotional content.

2.2 FEATURES EXTRACTION

Being a sophisticated form of speech, sarcasm is used for various purposes. While annotating the data, the annotators concluded that these purpose fall mostly, but not totally, in three categories: sarcasm as wit, sarcasm as whimper and sarcasm as avoidance.

Sarcasm as wit: when used as a wit, sarcasm is used with the purpose of being funny; the person employs some special forms of speeches, tends to exaggerate, or uses a tone that is different from that when he talks usually to make it easy to recognize. In social networks, voice tones are converted into special forms of writing: use of capital letter words, exclamation and question marks, as well as some sarcasm-related emoticons.

Sarcasm as whimper: when used as whimper, sarcasm is employed to show how annoyed or angry the person is. Therefore, it tempts to show how bad the situation is by using exaggeration or by employing very positive expressions to describe a negative situation.

Sarcasm as evasion: it refers to the situation when the person wants to avoid giving a clear answer, thus, makes use of sarcasm. In this case, the person employs com- plicated sentences, uncommon words and some unusual expressions.

Four families of features are extracted: sentiment-related features, punctuation-related features, syntactic and semantic features, and pattern features.

I. SENTIMENT-RELATED FEATURES

A very popular type of sarcasm that is widely used in both regular conversation as well as short messages such as tweets, is when an emotionally positive expression is used in a negative context. A similar way to express sarcasm is to use expressions having contradictory sentiments. This type of sarcasm we qualified as ‘‘whimper’’ is very common in social networks and microblogging websites. This type of sarcasm can be identified and detected when a positive statement, usually a verb or a phrasal verbs, are collocated with a negative situation (e.g., ‘‘I love being ignored all the time’’). They built a lexicon-based approach that learns the possible positive expression and negative situations and used it to detect such contrast in unknown tweets. However, learning all possible negative situations requires a big and rich source and might be infeasible because negative situations are unpredictable.

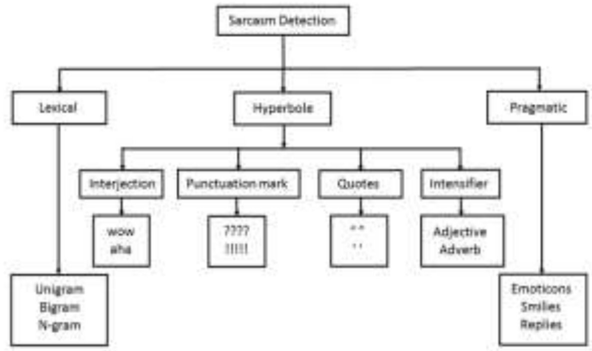

Chart-1: Tags for words considered as highly emotional

II. PUNCTUATION-RELATED FEATURES

Sentiment-related features are not enough to detect all kinds of sarcasm that might be present. In addition, they do not make use of all the components of the tweet. Therefore, more features are to be extracted. As mentioned before, sarcasm is a sophisticated form of speech: not only it plays with words and meanings, but also it employs behavioral aspects such as low tones,facial gestures or exaggeration. These aspects are translated into a certain use of punctuation or repetition of vowels when the message is written. To detect such aspects, we extract a set of features that we qualify as punctuation-related features. For each tweet, we calculate the following values:

- Number of exclamation marks.
- Number of question marks.
- Number of dots.
- Number of all-capital words.
- Number of quotes.

III. SYNTACTIC AND SEMANTIC FEATURES

Along with the punctuation-related features, some common expressions are used usually in a sarcastic context. It is possible to correlate these expressions with the punctuation to decide whether what is said is sarcastic or not. Besides, in other cases, people tend to make complicated sentences or use uncommon words to make it ambiguous to the listener/reader to get a clear answer. This is common when sarcasm is used as ‘‘evasion’’, where the person's purpose is to hide his real feeling or opinion by using sarcasm. Hence, we extract the following features that reflects these aspects:

- Use of uncommon words
- Number of uncommon words
- Existence of common sarcastic expressions
- Number of interjections
- Number of laughing expressions.

IV. PATTERN-RELATED FEATURES

The patterns selected in the previous subsection, and qualified of ‘‘common sarcastic expression’’ are very common, even in spoken language. However, their number is small, they are not unique and most of the tweets in both our training and test sets do not contain them. That being the case, we dig further and extract another set of features. The idea of our pattern related features is inspired from the work of Davidov et al.. In his approach, the author classified words into two categories: high-frequency words and content words based on their frequency of appearance in his data set and defined a pattern as an ‘‘ordered sequence of high frequency words and slots for content words’’.

We ran a first simulation in our training set (6000 tweets) and optimization set (2256 tweets), for each pattern length. The results presents the accuracy of the classification of tweets as sarcastic and non-sarcastic. The obtained results show that the patterns having a length from 4 to 10 give the highest accuracy (i.e., more than 75% accuracy during 10-folds cross validation). Pattern length 3 gives the highest accuracy on our optimization set. Given that the average number of words per tweet is equal to 11.48, we set the parameters LMin and LMax respectively to 3 and 10. Afterwards, we set MinLength and MaxLength as mentioned, keeping the values of $\beta 1, \ldots, \beta NL$ as they are . We tried different values of α. We ran different simulations on the same data sets using pattern features, for different values of α.

3. EXPERIMENTAL RESULTS

Once the features are extracted, we proceed to our experi- ments. The Key Performance Indicators (KPIs) used to eval- uate the approach are:
Accuracy: it represents the overall correctness of clas- sification. In other words, it measures the fraction of all correctly classified instances over the total number of instances.
Precision: it represents the fraction of retrieved sar- castic tweets that are relevant. In other words, it mea- sures the number of tweets that have successfully been classified as sarcastic over the total number of tweets classified as sarcastic.
Recall: it represents the fraction of relevant sarcastic tweets that are retrieved. In other words, it measures the number of tweets that have successfully been classified as sarcastic over the total number of sarcastic tweets.
We ran the classification using the classifiers ‘‘Support Vector Machine’’ (SVM), ‘Neural Networks’’. The overall accuracy obtained reaches 66.1% using the classifier “Neural Networks”. This accuracy is obtained when setting the parameters of the classifier as follows:
Number of Sarcastic sentences: 25273
Number of Regular sentences: 117825
Batch size = 30
Number of epochs = 80

SVM, on the other hand, presents a precision equal to 80.1% . This means that most of the tweets that were classified as sarcastic are indeed sarcastic. However, a very few percentage of the sarcastic tweets were detected (almost 20%). In other words, SVM is capable of detecting sarcasm with a high precision and the output can indeed be used to refine sentiment analysis, however, it does not cover all the sarcastic tweets. In a real stream of tweets, the number of sarcastic tweets is quite lower than that in the dataset used; therefore, the results obtained mean that only one out of five sarcastic tweets will be detected. Classifiers such as Neural Networks and SVM present a high accuracy and F1-scores, however, the performances of SVM are the highest. During the preliminary experiments (i.e., parameters optimization) as well as for the rest of our analysis, the results used are those returned by the classifier SVM.

3.1 CONFLICT OF INTEREST

Sarcasm detection research has grown significantly necessitating a look back at the general representation that these individual works have led to. In this paper we have tried to review various techniques for detecting sarcasm in short text and long text .We have identified pattern extraction, hashtag based and contextual approach.

4. CONCLUSIONS

In this work, we proposed a new method to detect sarcasm on Twitter. The proposed method makes use of the different components of the tweet. Our approach makes use of Part-of-Speech tags to extract patterns characterizing the level of sarcasm of tweets. The approach has shown good results, though might have even better results if we use a bigger training set since the patterns we extracted from the current one might not cover all possible sarcastic patterns. We also proposed an efficient way to enrich our set with more sarcastic patterns using an initial training set of 6000 Tweets, and the hashtag ‘‘#sarcasm’’. In a future work, we will study how to use the output of the current one to enhance the performances of sentiment analysis and opinion mining.

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