A Survey on Sarcasm detection and challenges

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***Abstract* – Sarcasm is a way of expressing feelings in which people says or write something, which is completely different of what they actually intended. Due to the obscurity nature of sarcasm, it is really hard to detect it. Sarcasm is a type of irony. Criticism is one of the main purpose to which sarcasm is being used. People generally use sarcasm to express their opinions or feelings especially in the social networking sites like Twitter and Facebook. Perfect analysis and understanding of the sarcasm sentences can improve the accuracy of sentiment analysis. Sentiment analysis means understanding the attitude or opinions of individuals or society about a particular event or topic. In this paper, we tried to detailing the general architecture of sarcasm detection, existing methods, and different types of sarcasm, issues, challenges and future scope.**

Index Terms – Sarcasm detection, Sentiment analysis, Machine learning, Social media.

I. INTRODUCTION

According to the definition of the Cambridge dictionary, sarcasm is the use of remarks that means the opposite of what they say, made to hurt someone's feelings or to criticize something humorously. For example, "You have been working hard!!!", "I love being ignored". Sarcasm is a way of expressing feelings in which people says or write something, which is completely different of what they actually intended. In the past few years, social networking sites like Twitter, Facebook etc., and e-commerce companies like Amazon, Flipkart etc., have achieved high acceptance and importance. Especially Twitter and Facebook becomes the favorite social networking sites for individuals to share their opinions, thoughts, feelings etc., about any topics or events. Due to this habit of people, the data of these sites increased exponentially. So we can call this twitter data or other social media data as an example for Big Data. Many organizations are interested in these data for studies and doing so to know the opinions of people in different areas like product popularity, political views etc. But it is a hard task to extract the opinions or sentiments from these online data, especially sites like Twitter and Facebook. Because users tend to use informal language in Twitter and Facebook and also presence of sarcasm in these data makes it more complicated to analyze. Effective analysis of sarcasm has greater influence to improve the effectiveness of sentiment analysis. Sarcasm and irony is related but not exactly the same. We can say that the sarcasm is a type of irony. Therefore it tends to be widely used in social networks, in particular, microblogging websites such as Twitter. Maynard et al [1] said that sentiment analysis performance might be highly enhanced when sarcasm within the sarcastic statements is identified. So, the need for an efficient way to detect sarcasm is increased. There are studies done on sarcasm in psychological and behavioral sciences and theories explaining when, why, and how sarcasm is expressed have been established. These theories can be extended and employed to detect sarcasm on data. For example, Rockwell et al [2] identified a positive correlation between cognitive complexity and the ability to produce sarcasm. Cognitive complexity is a psychological variable that indicates how complex or simple is the frame and perceptual skill of a person. In this paper, we are analyzing the sarcasm detection in various platforms. Also different types of sarcasm, the general architecture of sarcasm, and various approaches for sarcasm detection, issues, and challenges related to sarcasm detection.

II. LITERATURE SURVEY

Many researchers have studied and performed different methods for sarcasm detection. Most of the sarcasm detection works done on a textual data set. Relatively lesser works are done on the sarcasm detection on voice, images, and videos, etc., compared to the textual sarcasm detection. Joseph Tepperman et al [3] introduced a method to predict sarcasm detection from a spoken dialogue. They used contextual, spectral and prosodic cues to detect sarcasm from voice. They restricted their work to the expression “yeah right", due to the common use of "yeah right" with sarcastic sentences. They used laughter, question/answer, start, pause, end, gender as their feature set. They used Fisher and Switchboard corpora of spontaneous two-party telephone dialogues as their data set. They proposed that the addition of contextual and spectral feature to prosodic features is a key factor to improve the accuracy of sarcasm detection from text. Anupam khattri et al [4] proposed that the old tweets by an author can be very much useful for the prediction of sarcasm detection tweets. They used two types of prediction methods. A contrast-based prediction which anticipated the contrast of sentiment within tweet. Another one is the historical tweet-based prediction which analyzed the sentiments expressed by an author regarding an entity in the past. The main concept of their work is that the sentiments indicated by an author regarding an entity in the past can be significant to identify the sentiment of

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the same author about the same entity in the present time. They downloaded the complete timeline of an author using Twitter API. Contrast-based prediction, Historical tweet-based prediction, and integrator are their main working modules. The role of the integrator is to combine the calculations from the contrast-based prediction and previous tweet based prediction. Floriam Kunneman et al [5] gathered a training data set, which consisted of 406 thousand Dutch tweets with the hashtags '#sarcasm', '#not', '#irony', and '#cynicism'. They proposed the significance of using hyperbole in sarcasm detection. For example, "I have told you to not disturb me like a million time!". Hyperbole helps to give more importance to the point in a sentence. Their data set consisted of Dutch versions of the selected hashtags '#sarcasm', '#not', '#irony', and '#cynicism'. They used Balanced Winnow algorithm for classification. Out of 353 sarcastic tweets, they were able to recognize 307 sarcastic tweets correctly.

Dmitry Davidov et al [6] introduced a semi-supervised sarcasm detection method. They used Twitter dataset and Amazon data set. Twitter data set consists of 5.9 million tweets and the Amazon data set consists of 66000 product reviews. Their main feature set is based on surface patterns. They used an algorithm, which is introduced by Davidov and Rapport, to extract such patterns. They used k-NN for classification purpose. They used recall, precision and F-score as evaluation metrics. Rachel Rakov and Andrew Rosenberg [7] introduced a model for automatic sarcasm detection from speech. They used sequential modeling to categorize pitch and intensity contours which acquired by using k-means clustering. They used a SimpleLogistic (LogitBoost) classifier. They got the accuracy of 81.57% to predict sarcasm. They created their data corpus from an animation series called Daria. They used acoustic and prosodic features of speech to predict sarcasm. They used snack, a toolkit of Python, for all acoustic analysis. Pitch was drawn out using the snack implementation of the ESPS algorithm. They performed a cross-validation method on the train set with the aim to understand extracted features and to decide which classifiers to use. They used SimpleLogistic classifier. They concluded from their work that, some intensity and pitch contours are indicators of sarcastic speech.

Dipto Das and Anthony J Clark [8] presented a supervised machine learning method. The main idea about their work is to consider the contents of a Facebook post and the user's activity or communication to that post. They suggested that the user's communication with a post can be significant to comprehend the context and will be vital to detect sarcasm. Their proposed supervised learning model showed 93% accuracy to detect sarcasm on Facebook. The collected posts from Facebook using Facebook Graph API. Within the collected posts, 98.26% of posts contained an image. They used SVM with linear kernel, AdaBoost, Multi-layer Perceptron (MLP), Random Forest and Gaussian Naïve Bayes algorithms for their work. J Kreuz and Gina M.Caucci [9] studied the influence of lexical factors to determine sarcasm. Their main aim was to find whether some particular lexical factors (For example, some specefic punctuation or use of some parts of speech) are useful to predict the reader's judgment of sarcasm. They included 101 undergraduates as participants of the experiment. These participants were informed to read extracts from long narratives and then to evaluate how likely it was that the speaker was being sarcastic. The researchers gave extracts along with a questionnaire to each participant. Based on the output from the participants, they proposed that the lexical factors are important to discover sarcasm. Christine Liebrecht et al [10] created a training corpus consisted of tweets with '# sarcasm' hashtag. They managed to collect 78 thousand Dutch tweets. They trained a machine learning classifier on the collected data corpus. Their test data consisted of 3.3 million Dutch tweets. From their work, they concluded that the sarcasm is usually expressed by the use of hyperbole words. They used the Balanced Winnow algorithm, TPR, FPR and AUC for their research.

Ashwin Rajadesingan et al [11] introduced a method for sarcasm detection from tweet messages by using characteristics of users. They tried to find users those who expressing sarcasm. To find such characteristics or traits, they used the past tweets of users. They introduced SCUBA (Sarcasm Classification Using a Behavioral modeling Approach). To evaluate the performance of SCUBA, they used AUC and accuracy as evaluation metrics. Aditya Joshi et al [12] studied the influence of different cultures of annotators on the standard of sarcasm annotation. They considered the scenario of American text and Indian annotators. Both Indian annotators and American annotators were given a labeled dataset of American tweets and discussion forum posts, and they annotated it. The Indian annotators concur with one another more than American annotators. Indian annotators also faced difficulties in case of unknown studies and name entities. Due to these problems in sarcasm annotation, an analytically insignificant degradation happened in the case of sarcasm classification. Edwin et al [13] introduced two more feature which helps to identify sarcasm after a sentiment analysis is carried out. The features they used were the number of interjection words and the negatively information. They used SentiWordNet and Machine learning algorithms for their work. They found out that the use of the above mentioned additional features increased the accuracy of sarcasm detection by 6%. Adity Joshy et al [14] proposed a computational system that using context incongruity as the main criteria for sarcasm detection. The statistical sarcasm classifier introduced by the researchers consisted of two different types of incongruity characteristics. Explicit characteristic and implicit characteristic. Incongruity can defined as the situation where things don't seem as they should be. They used a dataset of 18,141 sarcastic tweets. They trained their classifiers for different feature combinations. They used LibSVM with RBF kernel and 5-fold cross-validation method. They conclude from their work that, the use of incongruity features improved precision by 21.6%.

D. K. Tayal et al [15] introduced an approach to detect sarcastic tweets and to find the polarity detection on political tweets. They carried out work to analyze and predict the Indian government election in 2014 based on tweets. Their entire work includes steps like collecting the twitter data set, data pre-processing, identification of sarcasm etc. They used a supervised approach to identify the polarity of the sarcastic sentence. From analyzing the result, they found that the use of sarcastic tweets is helpful to predict the election result up to an efficient level. Aniruddha and Tony [16] suggested that the important steps to do accurate processing of sentence meaning are, the precise semantic representation of a sentence and definitive information extraction. And this approach can be very much useful for sarcasm detection. Their work is based on a neural network semantic model for doing sarcasm detection. They constructed the model using support vector machine. Their model surpassed existed sarcasm detection model with an F-score of 0.92.

Mondham et al [17] used different components of the tweets to predict sarcasm in tweets. They collected tweets by using Twitter streaming API. Then they extracted sentiment features, syntactic features, and pattern features. They evaluated their model based on accuracy, precision, recall and f-score. For their proposed method, they got an accuracy of 83.1%, precision 91.1 %, recall of 73.4% and f-score of 81.3%. Lohita et al [18] published a paper that focused on the challenges in sarcasm detection and general types of sarcasm detection methods. They classified sarcasm detection algorithms based on semi-supervised approach, supervised approach, and hybrid approaches etc. They classified semi-supervised and supervised approach under machine learning approach. They concluded that the majority of the works was done using machine learning approach only. David Bannan et al [19] suggested that inclusion of extra-linguistic information can increase the accuracy of sarcasm detection of tweets. Some examples for extra-linguistic information are the author details, the audience and the immediate communicative environment. They used binary logistic regression. They used different classes of features in their model. Those are the tweet, author, audience and response features. From their work, they found that the including more features together can produce a better performance.

Mary Jane et al [20] collected Tagalog and English tweets from Twitter and created a data set. Their data set consisted of total 12000 tweets. By using the help of linguistic professionals, they annotated the tweets. For Classification purpose they used SVM, Naïve Bayesian, and Maximum entropy algorithms and developed a model. They mainly focused on sentence level sarcasm detection. Also, they used a framework called WEKA. Roberto Gonzalez et al [21] used a data set of sarcastic twitter messages in which the author of each tweet determined the sarcasm of their tweets .Then they compared this data set with tweets which shows either positive or negative attitude without using sarcasm. They studied the machine learning method performance to identify the sarcastic messages based on some factors like lexical and pragmatic. They compared the performance of human judges and machine learning approaches on this task. They concluded from their result that neither the human judges nor the machine learning techniques performed well.

Anand Kumar et al [22] identified and listed different supervised classification techniques mainly using for sarcasm detection. They mainly studied on SVM and maximum entropy method algorithms. From their work, they concluded that for sarcasm detection from the messages based on the Hindi language, unigram gives greater performance with TFIDF than bigram or n-gram based approach. Francesco Barbieri et al [23] presented a novel computational model in their paper which is capable of to detect sarcasm in Twitter. Their data set consisted of 60,000 tweets. The tweets consisted of different topics like education, politics, irony and sarcasm. They also used different sets of lexical features like, synonyms, sentiments etc. Spubhodip Saha et al [24] used Twitter Archiver to collect data containing #sarcasm hashtag from Twitter. Then they tried to classify collected tweets as positive, negative and neutral. They classified the tweets using SVM and Naïve Bayes classifiers. They used Weka and they found that the accuracy of Naïve Bayes is 65.2% and SVM is 60.1%. Nabeela Altrabsheh et al [25] proposed a work to identify sarcasm from student's feedback collected fromTwitter. They collected 1522 tweets with corresponding emotion and polarity labels to use as a dataset. They used Naïve Bayes, Maximum entropy, Complement Naïve Bayes, Multinomial Naïve Bayes, SVM and Random forest. They concluded from their work that the better performance shown by the best classifiers to detect sarcasm are Naïve Bayes and its modified versions like Complement Naïve Bayes.

Mansa Khokhlova et al [26] tried to find the linguistic distinctions among the irony and sarcasm based on the examining of tweets. They collected tweets from Twitter, which contains #irony and # sarcasm hashtags. They concluded from their work that some tweets tagged by #irony or #sarcasm are difficult to interpret as ironic or sarcastic. So the hashtags are the only indication of figurative meaning. Santhosh Kumar Bharati et al [27] proposed a context-based method to identify sarcasm from Hindi tweets. They collected news from Twitter Hindi news sources such as ABP News, Aaj-Tak News Hindi, etc. Then they spoted the sentiment of a tweet and the context of related news. If both contradict, then the tweet is classified as sarcastic. Satoshi Hiai et al [28]

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proposed an extraction method for sarcastic sentences in product reviews.

Diana Maynard and Mark Greenwood [29] performed a study on the effect of sarcasm on the polarity of tweets. They proposed certain rules to improve the sentiment analysis performance when sarcasm is present in a sentence. Ratahn and Suchithra [30] studied the sarcasm detection works. From their work they ended upon a conclusion that the integrate approach of emoticons, lexical analysis and hyperbole can give better performance when compared to the sarcasm detection based only on linguistic features. Tananya Jain et al [32] studied sarcasm detection problems. They used an ensemble-based approach, pragmatic classifier and a seeding algorithm in their work.

III. GENERAL ARCHITECTURE OF SARCASM DETECTION

Fig.1 shows the general architecture of a sarcasm detection approach. The main steps are, (a) Data acquisition or data collection (b) Data pre-processing, (c) Feature extraction and feature selection, (d) Classification of sarcasm and, (e) Sarcasm detection.

A) Data collection

Twitter data sets are, one of the main sources which using for sarcasm detection works. Twitter API is using to collect tweets from Twitter, especially using # sarcasm hashtag. Other famous data sets using for sarcasm detection are Amazon product data set and Facebook data set. But we cannot say that there is one most accurate or a gold standard data set is available for sarcasm detection. It is one of the challenges in sarcasm detection. Some researchers had created annotated data corpus by using the help of human support to use in sarcasm detection.

B) Data pre-processing

The data gathered from online platforms like Amazon, Twitter, Facebook, etc., are unstructured and sparse. So data pre-processing is one of the major processes in sarcasm detection. We can define data pre-processing is the removal of noises which present in the data set. Pre-processing of data mainly done using methods like tokenization of data, removal of stop words, stemming and lemmatization. Tokenization of data means to convert the sentences into words. In the stemming and lemmatization, the words are converted into its stem form or root form. The stop words will be removed in the stop word removal process. For example, Articles. Another example of data pre-processing technique is POS (part-of-speech) tagging which is very important in sarcasm detection. POS tagging divides the words into different parts of speech like noun and adjectives, etc. Another important data pre-processing steps are, Parsing and removal of URLs etc.

C) Feature extraction and feature selection

There are different procedures to extract features from textual data set. Some examples of procedures are Bag of words, N-Grams and TF-IDF etc. Due to the complexity and difficulties in sarcasm detection, researchers are always trying to use more appropriate features to improve sarcasm detection. The presence of emoticons, hyperboles, negation and exclamation mark, etc., are some features using to identify the presence of sarcasm. Some feature selection methods are as follows:

a) Term- Frequency (TF)

TF shows the frequency or number of appearance of a word in a particular document. Term Frequency and term presence are among the famous approaches for information retrieval

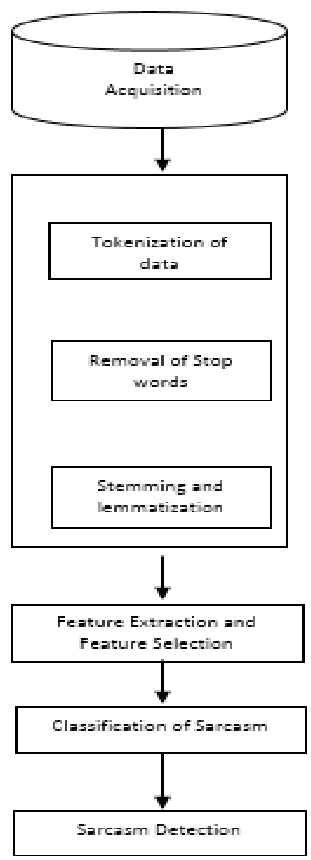

Fig.1 Flow diagram of Sarcasm detection

b) Term Frequency- Inverse Document Frequency (TF-IDF)

TF-IDF is mainly used in text mining. TF-IDF defines up to what extent, a term able to give the information for the purpose of classification of the document. Means, TF-IDF can imply whether a term is an often occurring one or uncommon in all documents. TF-IDF is used as frequency measures of feature. Weighted Term Frequency- Inverse Document Frequency, Delta Term Frequency- Inverse Document Frequency are the different types of TF-IDF.

c) Part of Speech (POS) tagging

Like the word itself indicating, Part of Speech tagging is the process in which each word in a group is tagged or attached with a part of speech by analyzing the context clues. Main advantage of POS is to state the semantic importance of the words which present in the document. For example like, verb, noun, adjective etc.

d) N-gram

N-gram is an uninterrupted sequence of tokens in computational linguistics and probability. Different types of n-grams are the unigram, bigram, trigram etc. Unigram consist of only one common word and bigram consist of two common word and so on.

There are mainly two approaches to feature selection. They are lexicon-based and the statistical-based approaches. Feature selection is as important as feature extraction. A document is considered as a collection of words in feature selection. Lexicon-based approach is based on the semantics of words. It finds the sentiment of a term based on the semantics. The statistical method consists of different techniques. Pointwise mutual information is an example of a statistical method. Pointwise mutual information helps to form a mutual information between the features and the classes. Chi-square is another method to do feature selection.

D) Sarcasm classification techniques

Sarcasm detection done by using different classifiers and rule-based methods. The main classification techniques are used by many researchers are:

a) Support vector machine (SVM)

A support vector machine comes under the supervised machine learning algorithm. SVM can be used for both classification and regression methods. In SVM, every data item can be represented using an n-dimensional space. N is the number of features. Co-ordinates in the n-dimensional space represents the value of a particular feature. The main challenge in the SVM is to find the hyper plane which separate the two classes perfectly.

b) Naïve Bayes

Naïve Bayes is using for binary and multi-class classifications. The Naïve Bayes classifiers are very common in the applications of supervised machine learning. This is because the Naive Bayes classifiers have performed well in many real-world scenarios. Very well-known examples are document classification and spam filtering. They don't need huge amount of training data to estimate the needed parameters. Some well-known Naïve Bayes classifiers are Gaussian Naïve Bayes, Multinomial Naïve Bayes, and Bernoulli Naïve Bayes.

c) Random forest

If an algorithm is capable to join different algorithms for the purpose of classifying objects, it is known as ensemble algorithm. Random forest classifiers is a famous ensemble algorithm. Random forest classifier uses any arbitrarily chosen subset from the given training set to create a set of decision trees.

d) Decision tree

Decision tree algorithm is an example of supervised learning. The main use of a decision tree algorithm to solve classification problems and regression problems. To solve a given class label problem, the decision tree creates a tree representation. The internal nodes of a particular tree shows the class attributes.

e) Cross-validation

The idea behind the cross-validation is to divide the data sample in to k-sequel sub-samples of data. This sub-samples of data will be used for training and testing. 10-fold cross-validation, 5-fold cross-validation are some of the examples for cross-validation.

f) Lexicon based approach

The words with opinions are playing important role in this method. These words are using to find the sentiments in a sentence. Dictionary-based approach and the corpus-based approach are the examples of lexicon based method.. In a corpus-based approach, the finding of a context is based on the opinion words. In a dictionary-based approach, the group

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opinion words is collected manually from a base knowledge. For example, using a repository like WordNet.

IV. Classification of sarcasm

We can generally classify sarcasm into following categories;

a) Sarcasm as a contradistinction of sentiments.

We can represent sarcasm as contradistinction of sentiments. In a sentence, if the literal meaning of the sentence is found opposite to the present context of that sentence, we can say that the text is showing sarcasm.

b) Sarcasm as a complex form of expression

There are several things to consider for the well acceptance of sarcastic statements or sentences. Some examples are, form an adequate phrase of sarcasm, a suitable environment, and appropriate audience with the capability of understanding the sarcasm correctly. These so many required conditions makes sarcasm a complex form of expression.

c) Sarcasm as a means of showing emotion

The main use of sarcasm is to show the emotion of a person. Different emotions can be represented by using sarcasm. People use sarcastic sentences to show self-pity, sadness, whine, loneliness etc.

d) Sarcasm as a form of written expression

Nowadays, the use of sarcasm in written text is increasing due to the use of online social networking sites like Twitter, Facebook etc. Using hyperboles, emoticons, etc. are the different ways to show sarcasm in written text.

V. Challenges in Sarcasm detection

Sarcasm detection is known as the 'Achilles heel of sentiment analysis. It is the most difficult area in sentiment analysis. Some researchers are proved that correctly detecting sarcasm in a sentence can increase the sentiment analysis of that particular sentence. The main challenges in sarcasm detection are followed:

a) It is an easier task to detect sarcasm from speech when it is compared to the sarcasm detection from text. Because, the use of a certain tone of speech, body language, and facial expression can be useful while identifying sarcasm from speech.
b) The quality of the data set also a crucial factor in sarcasm detection. The general nature of sarcastic sentences are ambiguous and doubtful. The presence of hashtags which indicates the sarcasm solves this ambiguity. But without hashtags, sarcastic sentences are complicated to understand.

c) Feature selection is another important task in sarcasm detection. So, introducing new features and using them with already existing features can increase the accuracy of sarcasm detection. Selecting an appropriate new feature should involve deeper study abut semantic, punctuation-based and hyperbole features, etc.

d) Selection of appropriate classification techniques is also significant. Data sets may be balanced or imbalanced. So the correct classification techniques should be used on the dataset for precise categorization of sentences into non-sarcastic and sarcastic.

e) The sarcasm detection from a noisy text is very challenging. Because generally short and noisy texts would not reveal much about context and provides lesser features.

f) Generally, a sarcastic sentence delivers a negative sentiment by using only positive words. So sarcastic detection needs more additional features like semantic features, features related to text author, etc.

VI. CONCLUSION AND FUTURE WORK

Like we discussed in this paper, sarcasm detection is one of the main challenges in sentiment analysis. The importance of sarcasm detection has increased notably in the past years. In our paper we have tried to give a survey about different sarcasm detection works done in past, a general architecture of sarcasm detection, different types of sarcasm, different approaches for sarcasm detection and some challenges in sarcasm detection. The complexity of sarcasm makes it a more challenging task and give more hope of future work. Most of the sarcasm detection works done in the English language. As a future work, to detect sarcasm in other languages is a considerable area. Including new data sets, new feature sets, considering different types of sarcasm, etc., can be considered as a future work. For our future work, we will try to use different deep learning methods and inspect more conceptual based feature. Our main aim will be to increase the performance of the sarcasm detection model based on f-score, accuracy, recall, and precision. Also, we will try to give more focus on hyperbole feature and will try to explore more on syntactic dependencies in text.

References

[1] Maynard, D.G. and Greenwood, M.A., 2014, March. Who cares about sarcastic tweets? investigating the impact of sarcasm on sentiment analysis. In *LREC 2014 Proceedings*. ELRA.

[2] Rockwell, P., 2003. Empathy and the expression and recognition of sarcasm by close relations or strangers. *Perceptual and motor skills*, *97*(1), pp.251-256.

[3] Tepperman, J., Traum, D. and Narayanan, S., 2006. " Yeah Right": Sarcasm Recognition for Spoken Dialogue Systems. In *Ninth International Conference on Spoken Language Processing*

[4] Khattri, A., Joshi, A., Bhattacharyya, P. and Carman, M., 2015, September. Your sentiment precedes you: Using an author's historical tweets to predict sarcasm. In *Proceedings of the 6th workshop on computational approaches to subjectivity, sentiment and social media analysis* (pp. 25-30).

[5] Kunneman, F., Liebrecht, C., Van Mulken, M. and Van den Bosch, A., 2015. Signaling sarcasm: From hyperbole to hashtag. *Information Processing & Management*, *51*(4), pp.500-509.

[6] Davidov, D., Tsur, O. and Rappoport, A., 2010, July. Semi-supervised recognition of sarcastic sentences in twitter and amazon. In *Proceedings of the fourteenth conference on computational natural language learning* (pp. 107-116). Association for Computational Linguistics.

[7] Rakov, R. and Rosenberg, A., 2013, August. " sure, i did the right thing": a system for sarcasm detection in speech. In *Interspeech* (pp. 842-846).

[8] Das, D. and Clark, A.J., 2018, October. Sarcasm detection on facebook: A supervised learning approach. In *Proceedings of the 20th International Conference on Multimodal Interaction: Adjunct* (pp. 1-5).

[9] Kreuz, R.J. and Caucci, G.M., 2007, April. Lexical influences on the perception of sarcasm. In *Proceedings of the Workshop on computational approaches to Figurative Language* (pp. 1-4). Association for Computational Linguistics.

[10] Liebrecht, C.C., Kunneman, F.A. and van Den Bosch, A.P.J., 2013. The perfect solution for detecting sarcasm in tweets# not.

[11] Rajadesingan, A., Zafarani, R. and Liu, H., 2015, February. Sarcasm detection on twitter: A behavioral modeling approach. In *Proceedings of the Eighth ACM International Conference on Web Search and Data Mining* (pp. 97-106). ACM.

[12] Joshi, A., Bhattacharyya, P., Carman, M., Saraswati, J. and Shukla, R., 2016, August. How do cultural differences impact the quality of sarcasm annotation?: A case study of indian annotators and american text. In *Proceedings of the 10th SIGHUM Workshop on Language Technology for Cultural Heritage, Social Sciences, and Humanities* (pp. 95-99).

[13] Lunando, E. and Purwarianti, A., 2013, September. Indonesian social media sentiment analysis with sarcasm detection. In *2013 International Conference on Advanced Computer Science and Information Systems (ICACSIS)* (pp. 195-198). IEEE.

[14] Joshi, A., Sharma, V. and Bhattacharyya, P., 2015, July. Harnessing context incongruity for sarcasm detection. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)* (pp. 757-762).

[15] Tayal, D.K., Yadav, S., Gupta, K., Rajput, B. and Kumari, K., 2014, March. Polarity detection of sarcastic political tweets. In *2014 International conference on computing for sustainable global development (INDIACom)* (pp. 625-628). IEEE.

[16] Ghosh, A. and Veale, T., 2016, June. Fracking sarcasm using neural network. In *Proceedings of the 7th workshop on computational approaches to subjectivity, sentiment and social media analysis* (pp. 161-169).

[17] Bouazizi, M. and Ohtsuki, T., 2015, December. Sarcasm Detection in Twitter:" All Your Products Are Incredibly Amazing!!!"-Are They Really?. In *2015 IEEE Global Communications Conference (GLOBECOM)* (pp. 1-6). IEEE.

[18] Sivaprakasam, L. and Jayaprakash, A., 2017. A Study on Sarcasm Detection Algorithms. *International Journal of Engineering Technology Science and Research*, *4*(9).

[19] Bamman, D. and Smith, N.A., 2015, April. Contextualized sarcasm detection on twitter. In *Ninth International AAAI Conference on Web and Social Media*.

[20] Samonte, M.J.C., Dollete, C.J.T., Capanas, P.M.M., Flores, M.L.C. and Soriano, C.B., 2018, October. Sentence-Level Sarcasm Detection in English and Filipino Tweets. In *Proceedings of the 4th International Conference on Industrial and Business Engineering* (pp. 181-186). ACM.

[21] González-Ibánez, R., Muresan, S. and Wacholder, N., 2011, June. Identifying sarcasm in Twitter: a closer look. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies: Short Papers-Volume 2* (pp. 581-586). Association for Computational Linguistics.

[22] Dave, A.D. and Desai, N.P., 2016, March. A comprehensive study of classification techniques for sarcasm detection on textual data. In *2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)* (pp. 1985-1991). IEEE.

[23] Barbieri, F., Saggion, H. and Ronzano, F., 2014, June. Modelling sarcasm in twitter, a novel approach. In *Proceedings of the 5th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis* (pp. 50-58).

[24] Saha, S., Yadav, J. and Ranjan, P., 2017. Proposed approach for sarcasm detection in twitter. *Indian J. Sci. Technol*, *10*, p.25.

[25] Altrabsheh, N., Cocea, M. and Fallahkhair, S., 2015. Detecting sarcasm from students' feedback in Twitter. In *Design for teaching and learning in a networked world* (pp. 551-555). Springer, Cham.

[26] Khokhlova, M., Patti, V. and Rosso, P., 2016. Distinguishing between irony and sarcasm in social media texts: Linguistic observations. In *2016 International FRUCT Conference on Intelligence, Social Media and Web (ISMW FRUCT)* (pp. 1-6). IEEE.

[27] Bharti, S.K., Babu, K.S. and Raman, R., 2017, December. Context-based Sarcasm Detection in Hindi Tweets. In *2017 Ninth International Conference on Advances in Pattern Recognition (ICAPR)* (pp. 1-6). IEEE.

[28] Hiai, S. and Shimada, K., 2016, July. A sarcasm extraction method based on patterns of evaluation expressions. In *2016 5th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI)* (pp. 31-36). IEEE.

[29] Maynard, D.G. and Greenwood, M.A., 2014, March. Who cares about sarcastic tweets? investigating the impact of sarcasm on sentiment analysis. In *LREC 2014 Proceedings*. ELRA.

[30] Rathan, K. and Suchithra, R., 2017. Sarcasm detection using combinational Logic and Naïve Bayes Algorithm. *Imperial Journal of Interdisciplinary Research (IJIR) Vol-3, Issue-5*, pp.546-551.

[31] Jain, T., Agrawal, N., Goyal, G. and Aggrawal, N., 2017, August. Sarcasm detection of tweets: A comparative study. In *2017 Tenth International Conference on Contemporary Computing (IC3)* (pp. 1-6). IEEE.

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