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A Survey of Sarcasm Detection Techniques in Natural Language Processing

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***Abstract*. Sarcasm is a linguistic style that is often employed in regular conversation and that natural language processing (NLP) systems may find difficult to recognize. The use of sarcasm in social media, online reviews, and other digital communication has increased in recent years, making it essential for NLP systems to detect sarcasm accurately. In this survey, we provide an overview of the current state of the art in sarcasm detection using NLP techniques. We discuss the various approaches to detect sarcasm, including machine learning, deep learning, and lexicon-based methods. We also review recent research on sarcasm detection in various languages and contexts, such as social media, customer reviews, and online forums. We also identify opportunities for future study and address the difficulties and limits of the present sarcasm detection techniques. The overall goal of this survey is to further this field of study by providing a thorough grasp of sarcasm detection in NLP.**

Index Terms: Natural Language Processing, Sarcasm detection, Social media

I. Introduction

The language that uses sarcasm is frequently employed in daily speech. It is described as the use of irony to express scorn or mockery. Sarcasm frequently depends on context, tone, and other non-literal indicators, making it challenging to identify, especially in written material. Natural language processing (NLP) systems must be able to correctly identify sarcasm, given the rise in recent years in the usage of sarcasm in social media, online reviews, and other forms of digital communication. Due to its potential use in many areas, comprising sentiments assessment, opinion mine, and conversation systems, sarcasm recognition has drawn much attention in current years. Sarcasm detection can be used to improve the performance of these systems by providing a more accurate understanding of the underlying sentiment of the text [1]. It can also filter out inappropriate or offensive content on social media platforms or improve the accuracy of customer feedback analysis in e-commerce. *Figure 1* shows one such example from the social platform Twitter.

There are several approaches to sarcasm detection using NLP techniques, embracing machine learning, deep neural learning, and lexicon-based methods. Machine learning approaches use various features such as word n-grams, part-of-speech tags, and sentiment scores to train a classifier to detect sarcasm. Deep learning approaches, on the other hand, use neural networks to learn representations of the text that are useful for sarcasm detection. Lexicon-based methods rely on the use of a pre-existing lexicon of sarcasm-related words and phrases to detect sarcasm in the text.

Fig. 1. Example of sarcasm from Twitter

Recent research on sarcasm detection has also focused on different languages and contexts. For example, there has been research on sarcasm detection in various languages, such as English, Spanish, and Arabic. Additionally, there has been study on sarcasm recognition in different contexts, such as social media [2], customer reviews, and online forums.

In this survey paper, we provide an overview of the current state-of-the-art in sarcasm detection using NLP techniques. The significant contribution to the survey paper is as below:

- We discuss the various latest NLP approaches used to detect sarcasm, including machine learning, deep learning, and lexicon-based methods.
- We also review recent research on sarcasm detection in various languages and contexts, such as social media, customer reviews, and online forums.

We also identify opportunities for future study and address the difficulties and limits of the present sarcasm detection techniques.

II. Literature Review

Although the social language sciences have long studied sarcasm, automatic sarcasm detection in the text is a relatively recent field of research. Automated sentiment categorization has attracted the scientific community's attention in natural language processing [NLP]. Moores and Mago [38] did a survey but only on models based on Twitter. An NLP-based approach uses extensive linguistic collections and language properties to comprehend qualitative data. Machine Learning (ML) systems use supervised and unsupervised classification techniques based on identified or unmarked data to analyze sarcastic statements. We will further discuss the research under various techniques used in NLP, namely machine learning, deep learning, and lexicon-based methods.

A. *Machine Learning technique*

Sarcasm detection using machine learning involves training a classification model on a dataset of labelled sarcastic and non-sarcastic statements and then using that model to identify sarcasm in new, unseen statements. Commonly used machine learning techniques are n-grams, part-of-speech tags (POS), SVM, Naive Bayes and tree-based classifiers like Random forests.

Govindan and Balakrishnan [3] utilized features such as intensifier, capital letters, interjections, lengthened words, and punctuation marks from every tweet in the dataset. This feature set was fed to machine learning algorithms such as SVM and Random Forest for classification. The issue was that the dataset had only negative sentiment tweets. Sarcastic tweets can be marked as positive sentiments also. Chia et al. [4] classified irony and sarcasm to identify cyberbullying. They employed ML algorithms like Naïve Bayes, K-nearest neighbor (KNN), JRip, J48, and SVM for classification. The observation was that hashtags and positive words like 'love' & 'great' led to misclassifications. Deep et al. [5] used multi-classification within the sarcastic comments. They utilized Logistic Regression, Naiive Bayes and SVM ML models. Their binary classification had good accuracy but not with multi-class classification. Vinoth & Prabhavathy [6] employed "Intelligent ML-based sarcasm detection and classification" [IMLB-SDC]. They employed multiple feature engineering like Information Gain (IG) & Chi-square besides TF-IDF. The results were impressive due to additional feature engineering. Rao & Sindhu [7] employed ML for sentiment analysis over Amazon product reviews and identified sarcastic reviews. They employed KNN, SVM & RF models. Sarcasm was detected using an ML classification model by Pawar and Bhingarkar [8]. Data on recurrent topics, interjections, punctuation, and emotions were gathered. SVM and RF were used to train each of these feature sets for classification. Gupta et al. [9] utilized a two-part model. The chi-square test was used to narrow down the most beneficial qualities after extracting features related to feelings and punctuation in the first step. The second phase involves extracting the top tf-idf characteristics and combining them with sentiment- and punctuation-related data to detect sarcastic material in the tweets. Godra et al. [41] employed various machine learning models for detect sarcastic material and train their healthcare practitioner. These health-care practitioners decide sentiments based on the patient's feelings, medical experts. Kumar and Sarin [42] used word embeddings techniques for sarcasm detection. In this study, context-aware linguistic model and word embeddings, which are used to extract features, are integrated to offer autonomous feature technical capability and considerably better performance than baseline methods.

B. *Deep Learning technique*

Deep learning employs various methods such as neural networks, convolutional neural network (CNNs) & recurrent neural network (RNNs). These methods can effectively learn the nuances of sarcasm, such as irony and tone, from the training data and apply them to new examples. Additionally, these models can also be fine-tuned using transfer learning for better performance.

Goel et al.[10] employed "Long short term memory" [LSTM], Gated Recurrent Unit [GRU] and CNN in ensemble frmaework for sarcasm detection. Various word embedding algorithms like GloVe, Word2Vec and fastText were employed. The proposed model worked very well on news headlines but had lower accuracy than the social media dataset. Nayak and Bolla [11] also worked on a headlines dataset to detect sarcastic headlines. They employed the LSTM model and used a pre-trained transformer-based word embedding method. Razali et al. [12] employed a hybrid method of combining deep learning and a hand-crafted feature set. They extracted the feature set of sarcasm using the CNN model but later fused it with a hand-crafted feature set from lexicons and used Logistic Regression as a classifier. Kumar et al. [13] employed multihead attentionbased bidirectional longshort memory (MHA-BiLSTM) system to identify sarcastic comment in the corpus. On the other hand, Eke et al. [14] first tried detecting sarcastic comments using the GloVe technique. The results were not that promising. Later on, the same author's Eke et al. [15], fused BERT and LSTM to get improved results for sarcasm detection over the internet dataset. The accuracy was excellent over the datasets as LSTM understood the context within the sentence, and BERT understood the context between the sentences. However, for pre-processing step, they used GloVe and passed the word embedding to the fused proposed algorithm. Jamil et al. [16] employed LSTM with CNN for sarcasm detection. They verified their proposed model over multiple domain datasets. They validated on Twitter, New headlines, Sarcasm corpus and Reddit, an aggregator over multiple social media platforms. Pradhan, Agarwal and Singh [17] employed LSTM-RNN fused model for detecting sentiment in Tweets. Elkamchouchi et al. [18] used an evolutionary model hybrid. A hosted Cuckoo Optimization Algorithm and stacked auto-encoders from machine learning models are used to detect sarcasm. They checked their results using the Kaggle dataset. The architecture was built on steps. Word embeddings were produced using TF-IDF following basic pre-processing. The hosted cuckoo optimization algorithm received the embeddings next for parameter tweaking. Stacked auto-encoders were used for the classification process. Mohan et al. [35] employed BERT and Graph Convolutional Network (GCN) based framework. These GCN quickly learnt complex structural and semantic patterns and helped predict the sarcasm over the large dataset. Bharti et al [39] research put out a fresh method for identifying sarcasm in conversation data that combines textual and auditory elements. The input for this hybrid technique is a vector that combines the retrieved audio and text characteristics from their respective models. The limitations of only the text features will be made up for by the combined characteristics, and contrariwise. Ding, Tian and Yu [40] also used multi-modal framework. For accurate sarcasm detection, it's important to take into account all of the text's information, tone shifts in the audio stream, face gestures, and body position. Their study suggests two model versions based on various experimental circumstances, a multilevel latefusion learning framework with residual connections, and a more logical experimental data-set split. Chen et al [46] used in their study, a multitask self-learning model that models context inconsistency, integrates semantic features, and adds sentiment hints via soft sentiment descriptions. Zhang et al [47] focused on the stances within the sentences. As per them the fact, a book's true sarcastic orientation is heavily influenced by the author's attitude/stances, whether they are for, against, or neutral toward the concept or subject discussed in the text. Zahra et al [49] employed attention mechanism for classifying sarcastic tweet with others. They understood that it is predicated on the notion that, in deciphering a sarcastic message, the incoherence between a good phrase and a bad scenario plays a crucial part, necessitating greater attention to certain phrases in the text in order to interpret it correctly.

C. *Cognitive/behavior techniques*

Besides learning the manual hand-crafted feature sets using machine learning or self-extracted feature sets from deep learning, other approaches taken by researchers were using the behavioral and cognitive feature sets.

Examining the context is essential for sarcasm identification, according to Du et al. [19]. The participant's preferred modes of expression and the attitudes expressed in remarks made in response to the specific linguistic content should be considered in this context. They suggested two-stream CNN, which analyzes the target language's semantics and emotional content of the text. SenticNet extends the notion of "long short-term memory" (LSTM) with common sense. Then, the attention system considers the user's expressive activities. A strategy for capturing user behavioural patterns, personality attributes, and contextual information for sarcasm recognition was reported by Malave and Dhage [20]. The hashtag approach is based on social network applications and was proposed by Sykora, Elayan, and Jackson [21]. It looked at the features of the hashtags and picked out sarcastic remarks. Yao et al. [22] approach were incredibly novel. They identified sarcasm using text and Twitter images based on four different content settings. They used tweets with photos, text over images, picture captions, and tweets with images. These multi-modalities are taught using a multi-channel interaction technique with a gated and directed attention module. Other studies employed various modalities to detect sarcasm, including consumer behaviours, hashtags, personal characteristics, and emotions. Hazarika et al. [23] introduced context- and content-based embedding techniques for classifying sarcasm on social platforms. The model uses user attributes, including personality and stylometric traits of users. Fernandes et al. [33] studied psychopathy and social cognition for sarcasm detection. *Table 1* compares the results on similar datasets using various techniques. Chauhan et al [44] employed emojis for their sarcasm detection. They suggest the SEEmoji in the work as an addition to the multi-modal MUStARD dataset. Each phrase is annotated with the appropriate emoji, emojis meaning, and emojis emotions. For sarcasm identification, they suggested an emoji-aware multi-modal multi-task deep learning neural network architecture. Gracia et al. [45] also employed emoji as the linguistic characteristic for focusing on the sarcastic comments. They found that winking emojis face is more common in the sarcastic statements. Jhonson, and Kreuz [50] studied the pattern of three variables to examine sarcasm production patterns in the United States by age, geographic location and gender. Findings showed that only self-reported usage varied by geographic area, whereas older people and women used less sarcasm while speaking.

TABLE I. RESULTS COMPARISON AMONG VARIOUS TECHNIQUES (ACCURACY)

Author	Technique	Twitter [30]	Sarcasm [31]	SARC [32]
Chia et al. [4]	Machine Learning	-	85.2%	-
Gupta et al. [9]	Machine Learning	-	83.53 %	-
Razali et al. [12]	Deep Learning	94%	-	-
Kumar et al. [13]	Deep Learning	-	-	72.63%
Eke et al. [15]	Deep Learning	-	98.21%	-
Jamil et al. [16]	Deep Learning	92%	-	-
Sharma et al. [2]	Deep Learning	-	92.80%	83.92%
Du et al. [19]	Cognitive Learning	-	-	72%

D. Other Languages

Majorly, all research is conducted in the English language. This is due to its universality and the availability of datasets. English language datasets and social media platforms are available. But, multiple languages are also supported on the same platforms as Twitter and Facebook. Detecting sarcasm in other languages is more complex due to the grammar and context of the language. But studies on sarcasm detection have been done in other languages.

Swami et al. [24] generated and published a pattern for sarcasm identification across Hindi-English tweet in a manner that is similar. . In 2020, Farha and Magdy [25] conducted research on Arabic sarcasm recognition. Nezhad & Deihimi [26] studied the Persian language. They employed hand-crafted feature sets like part of speech, deep polarity, sentiments, and punctuation features from the Persian tweets and employed machine learning models for classification. Abdelaal et al. [27] took a similar approach for the Arabic language. They employed six supervised machine learning models: Logistic Regression, Multinomial Naïve Bayes, Decision Tree, SVM, RF and KNN. Israeli et al. [28] further used meta-features over and above the hand-crafted features and employed multiple machine-learning models for sarcasm recognition in the Arabic language. Khan et al. [34] researched sarcasm detection in the Urdu language. Frenda et al. [36] worked on the Italian language. The dataset they had comprises of tweets from Italian users discussing hot-button societal problems including migration, political, and more generic hot topics. Each tweet has an annotation indicating whether it is ironic or not, as well as if it is sarcastic or not. Wen et al [43] employed Sememe learning and auxiliary data for detecting sarcasm on Chinese language. The Chinese language is very complex and has many variations for the same word based on the context of the communication between two people. So, they employed sememe which is the smallest unit of meaning, a detailed representation of a word. Jain, Kumar and Sangwan [48] worked on Hindi language. The framework, which combines an LSTM with the loss function of an SVM to detect sarcasm, is trained using two embeddings:- word and emoji embeddings. They made use of the Sarc-H datasets, that was created by manual annotating Hindi-language tweets centered on hashtags.

From the *Table 1* results, deep learning neural network techniques are more accurate in predicting the sarcasm of the various domains. Deep learning models can predict sarcasm better than traditional machine learning models because they can capture and model more complex relationships between the inputs and outputs. Moreover, because deep learning models are able to learn different levels of abstraction, they can simulate higher-level traits like sarcasm. However, it is essential to note that deep learning models are not perfect at detecting sarcasm and still make mistakes. Issues with various techniques are described in the below section.

III. Challenges in Sarcasm Detection

However, despite the recent progress in sarcasm detection, several challenges and limitations remain to be addressed. One of the main challenges is the lack of large, labelled datasets for training and evaluating sarcasm detection models. Another is the context and sentiment. To illustrate, sarcasm frequently employs good language, but the context causes it to express negative emotions. Other challenges are tabulated below.

- Identifying sarcasm in the text as it often relies on tone and context, which can be challenging to discern in written text.
- Handling sarcasm in tweets (social media), as the limited characters can make it challenging to understand the context.
- Handling sarcasm in informal language, as it often includes slang, misspellings, and grammar errors.
- Dealing with sarcasm in multiple languages, as idiomatic expressions and cultural references may vary.
- Handling sarcasm in social media, users often use emoticons, hashtags and mentions, which can be challenging to interpret.
- Distinguishing between sarcasm and irony, as they are often used interchangeably but have different meanings.
- Tough to generalize NLP techniques across all domains of sarcasm
- Identifying sarcasm with images is more complex than simple sarcastic text. Figure 2 shows one such example.

Fig. 2. Sarcasm in the context of an image

Table 2 describes the issues with each technique in particular. The accuracy of sarcasm detection depends on the training data's quality and the model's design. Sarcasm has ambiguity, context dependence, cultural differences in slang words and a complex relationship between the words and sarcasm, making it difficult to detect. But each technique has its advantages and issues, as described below.

TABLE II. ISSUES WITH VARIOUS TECHNIQUES

Machine Learning	- Manual feature extraction - Limited feature knowledge - Data imbalance - Overfitting
Deep Learning	- Automated feature extraction - Black box model - Need huge datasets
Cognitive Learning	- Manual features - Subjective features - Cognitive bias

Yet, it is getting easier to create models that can accurately identify sarcasm due to the continuing development of deep learning methods and the accessibility of big, annotated dataset. Though Misra. R [37] has a new dataset from news headlines. News Headlines Dataset is compiled from: HuffPost covers actual news and TheOnion attempts to produce satirical takes on current events. There are around twenty-eight thousand headlines in the dataset, thirteen thousand of which are ironic. He added links to the news stories' sources to increase their usefulness and allow for the future extraction of further information.

IV. CONCLUSION

The survey paper on sarcasm detection highlights the challenges and recent progress in the field. The survey paper covers definitions and the need for sarcasm detection. We then explain the methodologies adopted using NLP techniques like machine learning, deep learning, and cognitive feature sets. We concluded that deep learning techniques performed better in detecting sarcasm over social media platforms. We also explained the current challenges in detecting sarcasm over various domains in detail. The research shows that while there have been advancements in detecting sarcasm in text, there are still limitations and difficulties, such as dealing with informal language and understanding the context. Sarcasm over fake images should also be accounted for [29]. Future research should focus on developing more advanced methods to improve the accuracy of sarcasm detection.

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