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# SARCASM DETECTION WITH GLOVE AND WORD2VEC MODELS

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## ABSTRACT

In subtle communication, such as sarcasm, the speaker expresses the antithesis of what is indicated. The ambiguity of sarcasm is one of the biggest obstacles to its detection. Satirical language is not specifically defined. The increasing number of languages is a significant problem as well. On these websites, a large number of new slang phrases are developed each day. Therefore, it is possible that sarcasm cannot be accurately detected using the current corpus of positive and negative feelings. Additionally, users are now able to employ a variety of emoticons with text thanks to recent improvements in online social networks. The sentence could become sarcastic by using these emoticons, which can flip its polarity. Sentiment analysis' accuracy can be increased by carefully analysing and comprehending sarcastic statements. Sentiment analysis is the process of determining how people feel or what they think about a certain situation or issue and detection of sarcasm has become a part of it. A two-phase structure is used for the study article. Following the implementation of two models, GloVe and Word2Vec, we came to the conclusion as to which model is more effective at detecting sarcasm and may be used in real-time applications. The first step of the algorithm gathers features linked to moods and punctuation. In the first technique, the Word2Vec model achieves accuracy of 79.38%, and in the second way, the GloVe model achieves accuracy of 82.33%.

**Keywords:** sarcasm detection, machine learning, sentimental analysis, GloVe model, word2Vec model.

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## 1. INTRODUCTION

Data-driven society is a description that fits the world of today. A single networked device is now producing exponentially more data because to the development of mobile devices and networking technology. Over 3 billion devices worldwide are currently connected to the internet. [1] Sarcasm is defined by the Cambridge Dictionary as the use of remarks that mean the exact opposite of what they say and are intended to offend or mock something sarcastically. For example, "You have been working hard!!!"; "I love being ignored". Sarcasm is the expression of one's feelings when one says or writes something that has absolutely nothing to do with what one genuinely intends. Sarcasm is typically disregarded during social network analysis due to these challenges and its innately complex character. As a result, the outcomes of such analysis are negatively impacted. Therefore, one of the most important issues we must solve is sarcasm recognition. The ability to recognise sarcastic content is essential for many NLP-based systems, including sentiment analysis and text summarization. Slang and abbreviations like "LOL" (Laughing Out Loud) and "TTYL" (Talk To You Later), among others, have emerged in recent online culture. Emojis or emoticons can now be used to express any emotion. Traditional bag-of-words categorization algorithms are ineffective because social media data is frequently replete with slang, hashtags, and emoticons. It obviously qualifies, though, as a negative emotion that has been very sarcastically conveyed to the human brain. Data analytics and computer science now consider this to be a prominent subject of research. An alternative set of algorithms for sarcasm detection has been put out in numerous academic articles and publications. The study article is broken into two sections. It initially extracts elements associated with emotions and punctuation before creating model comparisons and displaying the findings.

## 2. RELATED WORKS

One of the most common ways to convey opinions and feelings on social media is through sarcasm. In the past 10 years, the amount of humorous content on well-known social networking sites like Twitter has multiplied many times over. Despite having a significant impact on sentiment analysis, it is typically ignored because of how difficult it is. Many studies have been conducted, and numerous models have been put out to identify sarcasm.

The majority of these models focus on contextualised sarcasm detection and are often concerned with two-person conversations. Practical and textual sarcasm detection has hardly received much research attention. A preset corpus of positive and negative words is often used by the few systems that have been suggested for these tasks. Although some effort has been done to distinguish between positive and negative sentiment, less has been done to extract sarcasm from that. There aren't many tools available for sarcasm detection. A French business claims to have created an analytical tool called "Sarcastic Invader" that can identify sarcasm up to 80% of the time in comments on websites like Facebook.

Sarcasm was examined by Rilof *et al.* as a contrast between pleasant sentiment and a bad scenario. They created corpuses for both positive and negative terms using a cutting-edge bootstrapping approach. They utilised Naive Bayes and SVM on tweets containing the hashtag "sarcasm" to develop machine learning-based classifiers [1].

A model was put forth by Aditya et al. based on the explicit and implicit incongruity of attitudes revealed through tweets. The language of the tweet was broken down into many 2-grams and 3-grams, and the congruency of the grammatical units was evaluated using a corpus of positive and negative words that previously existed. This was done to identify sarcasm in the text. Support vector machine rules were created utilising the lexical and pragmatic characteristics of the tweet. Performance was 10% better than the previous systems, outperforming them [2].

By utilising the behavioural characteristics unique to users who express sarcasm, the system (SCUBA) sought to address the challenge of sarcasm identification on Twitter. They used the user's previous tweets to identify these characteristics, then they applied theories from behavioural and psychological studies to build a behavioural modelling framework that was specifically designed for sarcasm detection. Using already published psychological and behavioural findings, it first postulated the basic types of sarcasm. Using users' recent and prior tweets, it then created computational characteristics to capture these sarcastic expressions. Finally, it used these features to train a classifier using Naive Bayes and SVM [3].

Speaking sarcasm only when confident that it would be understood, according to the principle of infrability, is the foundation of the model for sarcasm detection that David et al. described. The likelihood of sarcasm increases when two people know one another. If a tweet has the hashtag "#sarcasm" and at least three words, it is classified as sarcastic. To serve as a training set, a subsample of these tweets was taken, including tweets in response to other tweets. Three categories of features- tweet, author, and audience are the foundation of it. The author yields were shown to be the most effective qualities [4], according to research.

It has been found that [4] [3] [2] recognise contextualised sarcasm, or sarcasm that occurs in dialogue between two persons. Additionally, [1] [2] [3] [4] [5] use machine learning algorithms like Support Vector Machine and Naive Bayes to complete this task. In order to recognise sarcasm, [1] [2] [3] [4] rely on an external corpus of sentences with positive and negative mood.

Anand Kumar *et al.* [22] discovered and described various supervised classification algorithms, primarily used for sarcasm detection. They focused their research mostly on the SVM and maximum entropy methods. According to their research, unigram performs better with TFIDF for sarcasm recognition from texts based on the Hindi language than bigram or n-gram based approaches. A innovative computer approach that can recognise sarcasm in tweets was introduced by Francesco Barbieri et al. in their study [23]. 60,000 tweets made up their data set. The tweets covered a variety of subjects, including irony and sarcasm, politics, and education. They also employed many lexical elements, such as synonyms and feelings.

## 3. BASIC ARCHITECTURE OF SARCASM DETECTION

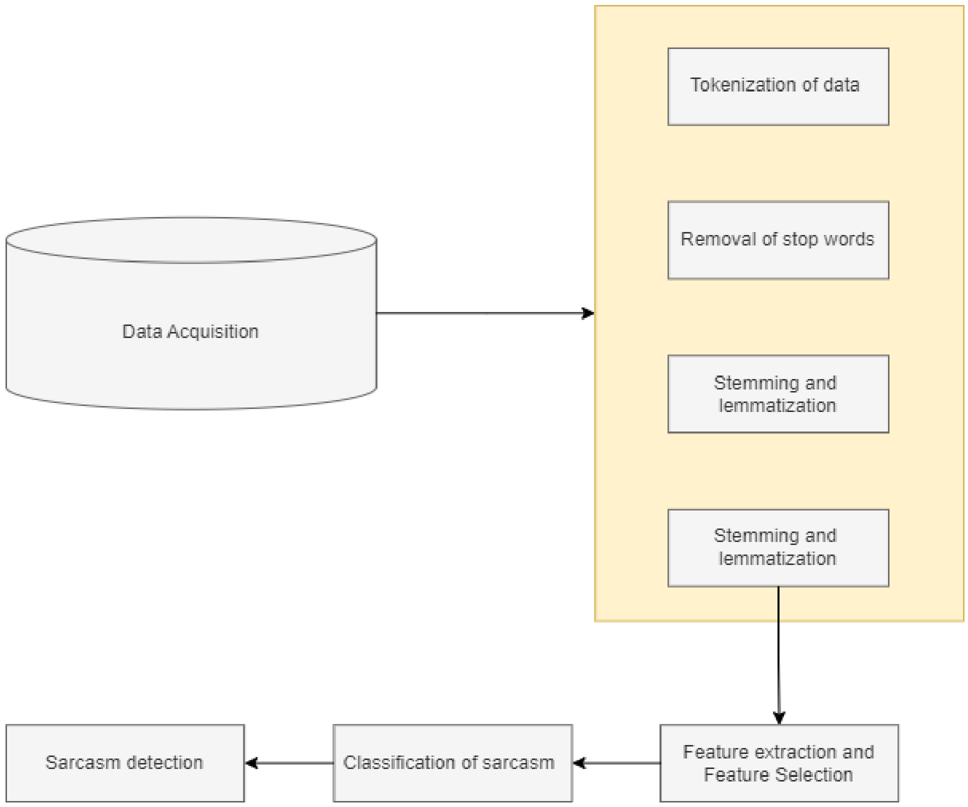


**Figure-1.** Sarcasm detection model architecture.

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## 4. PROCESS OF IMPLEMENTATION

### A. Data Collection / Data Acquisition

The majority of earlier research on sarcasm detection relied on Twitter datasets gathered under hashtag supervision, although these datasets are noisy in terms of labels and language. Additionally, a lot of tweets are answers to other tweets, thus having access to contextual tweets is necessary to detect sarcasm in them. To overcome the limitations imposed by noise in Twitter datasets, this News Headlines dataset for Sarcasm Detection was compiled from two news websites. Because The Onion tries to provide humorous perspectives of current events, we have gathered all the titles for the categories Brief News and News in Pictures (with irony). We use genuine (not ironic) headlines from HuffPost. The dataset consists of about 28,000 text data points, and each category of this data is divided into 4,444 satirical or non-sarcastic groups.

Three qualities make up each record:

| | |
|---|---|
| is sarcastic: | 1 if the record contains irony, 0 else the news article's heading |
| article link: | the URL of the original news story. useful for gathering additional info |

### B. Data Pre-Processing

The information acquired from websites like Amazon, Twitter, Facebook, and others is scarce and poorly formatted. Therefore, one of the key procedures in sarcasm detection is data pre-processing. Data pre-processing can be defined as the process of eliminating sounds from a data set. Pre-processing of data typically involves techniques like tokenization of data, removing stop words, stemming, and lemmatization. Tokenizing data entails breaking down phrases into words. The words are changed into their stem form or root form throughout the stemming and lemmatization processes. The stop words will be eliminated during the stop word removal procedure. Take articles as an example. The part-of-speech (POS) tagging method is another illustration of a data pre-processing technique and is crucial for sarcasm identification. The words are separated into several parts of speech using POS tagging, such as nouns, adjectives, and so on. Parsing and the elimination of URLs are additional crucial data pre-processing procedures.

### C. Concept of Word Embedding

We represent documents and words by using word embedding or word vector. It is described as a type of numeric vector input that enables words with related meanings to share a single representation. It can represent a word in a smaller-dimensional space and roughly convey meaning. Compared to manually created models that employ graph embeddings like WordNet, these can be trained significantly more quickly.

### D. Tokenization vs Word Embedding

Tokenization is the process of breaking up input data into understandable chunks that can be inserted in a vector space, whereas Tokens are converted into word vectors, also known as word embeddings, using embedding layers. In tokenization, text and the image have been divided into tokens, but in word embedding, Similar token-vector mappings are frequently shared between the input and output embeddings layers.

### E. Word2Vec for Sarcasm Detection

Word2Vec builds word vectors, which are distributed numerical representations of word features. These word features may include words that indicate the context of the specific vocabulary words that are present individually Word embeddings help establish the association between a word and another word with a comparable meaning by using the created vectors. Words with comparable semantic meanings are closer together in space, as can be seen in the graphic below when word embeddings are plotted. For Instance, Take the phrases "You can scale your business" and "You can grow your business" as examples. The meaning of these two phrases is the same. These words would make up the vocabulary we would use to discuss these two sentences: "You can scale up and build your business." These words might be encoded in one go, yielding a vector of length 6. Each of the words would have the following encodings:

You: [1,0,0,0,0,0], Can: [0,1,0,0,0,0], Scale: [0,0,1,0,0,0], Grow: [0,0,0,1,0,0],
Your: [0,0,0,0,1,0], Business: [0,0,0,0,0,1]

Each phrase would occupy one of the six dimensions in a six-dimensional space, therefore regardless of their literal meanings; none of these words are identical to one another.

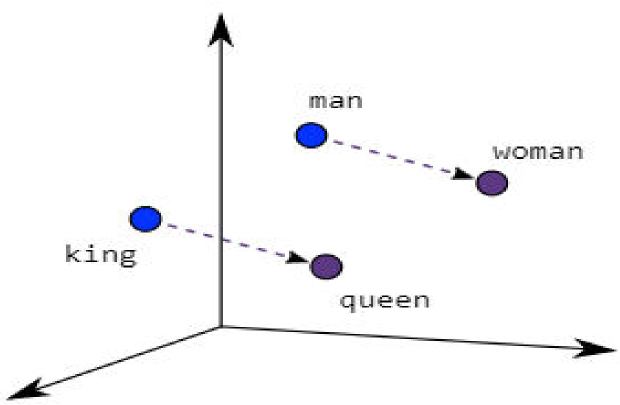


**Figure-2.** Word2Vec sample representation.

### F. GloVe Method for Sarcasm Detection

The foundation of the GloVe technique is the notion that it is possible to infer semantic connections between words using the co-occurrence matrix. If a corpus contains V words, the co-occurrence matrix X will be a V x V matrix, with the ith row and jth column of X, X ij, designating the number of times word I has co-occurred with word j. The following is an illustration of a co-occurrence matrix.

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| | the | cat | sat | on | mat |
|---|---|---|---|---|---|
| the | 0 | 1 | 0 | 1 | 1 |
| cat | 1 | 0 | 1 | 0 | 0 |
| sat | 0 | 1 | 0 | 1 | 0 |
| on | 1 | 0 | 1 | 0 | 0 |
| mat | 1 | 0 | 0 | 0 | 0 |

**Figure-3.** GloVe Co-occurrence matrix.

In order to reduce the difference between the vectors of two words' dot products and the logarithm of the number of times they occur together, GloVe employs a weighted least squares objective J:

$$J = \sum_{i,j=1}^{V} f(X_{ij})(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij})^2$$

## 5. RESULTS AND ANALYSIS

Accuracy refers to a classification's correctness. It provides us with the percentage of all correctly classified samples among all samples. As a result, it served as a benchmark for comparing the effectiveness of various classifiers on the set of attributes that each strategy employed. Table-1 gives us the accuracy values of two models implemented in here.

**Table-1.** Comparing Model Accuracies.

| S. No | Model Name | Training Data Accuracy | Testing Data Accuracy |
|---|---|---|---|
| 1 | Word2Vec | 99.76% | 79.38% |
| 2 | GloVe Model | 95.54% | 82.33% |

As we have implemented Word2Vec model initially, we will have its visualisation analysis between accuracy and epochs as shown below, which depicts that the model is overfitting and its working is not suitable for test data where the accuracy got decreased drastically.

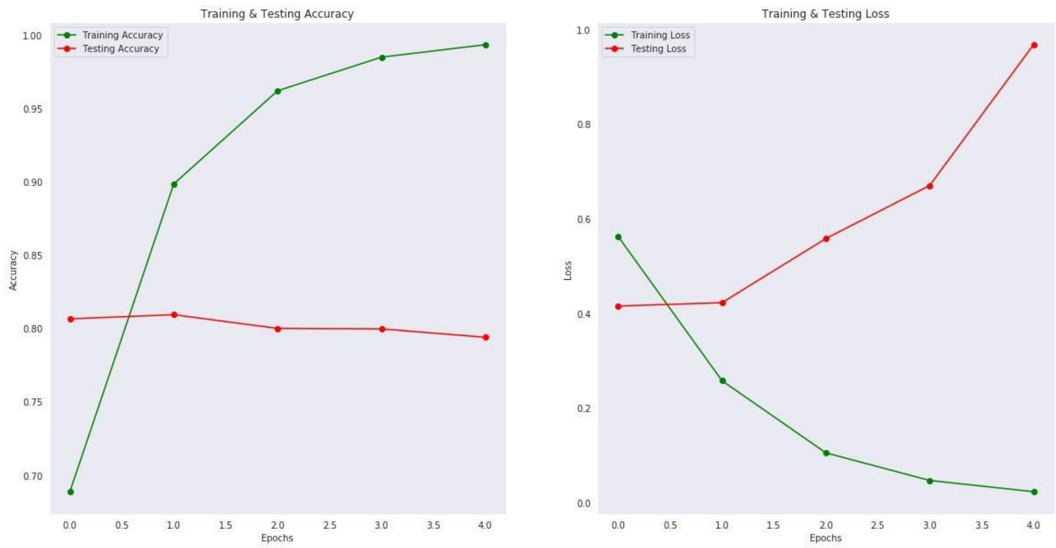


**Figure-4.** Word2Vec visualisation between Accuracy vs Epochs.

For the GloVe model as mentioned in Table-1, the accuracy is best for test data when compared with Word2Vec model which went around 82.33% as its accuracy. When comparing the first and second methods, it is clear that accuracy rises as the number of TF-IDF features rises.

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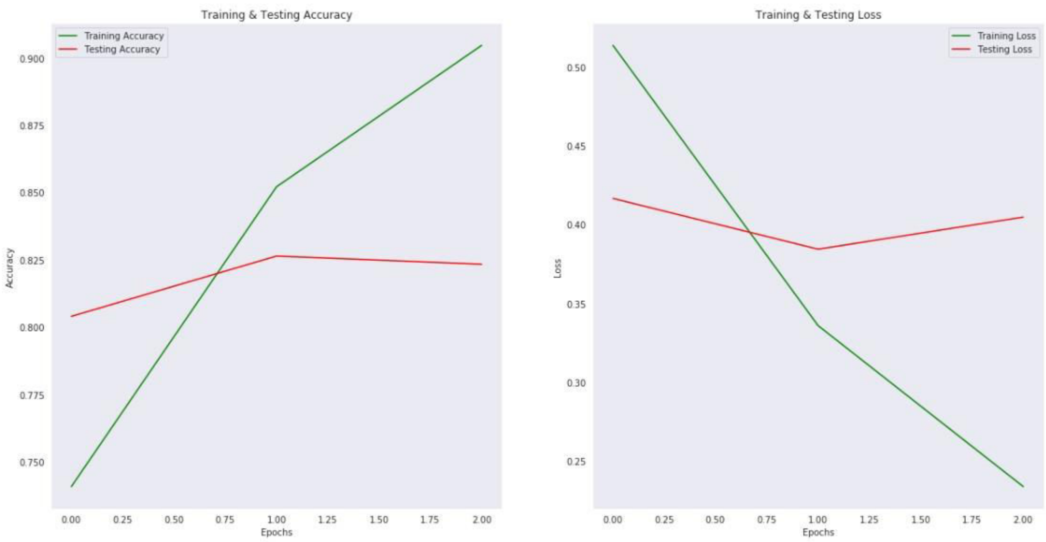


**Figure-5.** GloVe visualisation between Accuracy vs Epochs.

## 6. CONCLUSION AND FUTURE SCOPE

Sarcasm recognition is one of the primary difficulties in sentiment analysis, as we highlighted in this work. In recent years, the significance of sarcasm detection has significantly increased. In this study, we attempted to provide an overview of the various sarcasm detection efforts made in the past, as well as a general architecture of sarcasm detection, several types of sarcasm, various methods for sarcasm identification, and some difficulties with sarcasm detection. The complexity of sarcasm increases its difficulty and raises expectations for potential future work. The majority of sarcasm detection research is conducted in English. Future works include

Two methods are applied in this paper. In the first method, Word2Vec provides test data accuracy of 79.38%, which is lower than GloVe Model's accuracy of 82.33%. Using text mining techniques like emoji and slang detection, this research presents a method for enhancing the sarcasm detection algorithms already in use. There are several methods used to categorise tweets as sardonic or non sarcastic; these are briefly discussed in section 2.

There are many other kinds of communication, including text, images, audio clips, and memes, as social media usage increases daily. While sarcasm in texts is frequently identified, very little research has been done on the topic of sarcasm in memes. It is a field that is expanding, and the amount of data that can be utilised to identify sarcasm is growing every day. Detecting sarcasm in audio clips is another wide area that has to be studied.

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