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Sarcasm Detection on Social Network: A Review

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ABSTRACT

Sarcasm can be considered as a type of expression where people say or write the things that are entirely opposite than what they meant. Sarcasm is extremely difficult to detect due to its obscurity. An irony is a form of sarcasm. One of the most common uses of sarcasm is to express criticism. Sarcasm is commonly used to convey one's thoughts or emotions, especially on social networking media sites as Twitter and Facebook. The accuracy of sentiment analysis can be improved by a rigorous analysis and interpretation of sarcasm sentences. Sentiment analysis is the study of people's or society's feelings or thoughts regarding a specific occurrence or subject. We attempted to detail the general architecture of sarcasm detection in this article, as well as current techniques, ensemble learning methods, similar work performed by researchers in the context of sarcasm detection on Twitter and future scope.

KEYWORDS

Ensemble, Sentiment Analysis, Sarcasm, Feature, Machine Learning, Twitter.

Introduction

People may share their thoughts and viewpoints on a variety of subjects, including activities, people, and goods, through social networking websites. Social networking platforms have grown in popularity as a means of exchanging information and interacting with people all around the world. Facebook, for example, claims of having 1.59 billion monthly active users, each with 130 connections. Similarly, Twitter has over 500 million users, with 332 million of them currently utilising the site. Users send out over 340 millions messages and 1.6 billions search requests per day [19].

People begin tweeting, writing reviews, making comments, and other forms of social media activity when an incident or product is launched. People use social media sites to read product reviews from other customers before deciding whether or not to buy it. Organizations often depend on these platforms to gauge consumer reaction to their offerings and, as a result, use the reviews to develop them. Seeking and testing the validity of opinions or ratings, on the other hand, is a difficult challenge. It's impossible to manually go through all of the feedback to figure out which ones are sarcastic. Furthermore, the average human reader will struggle to recognise sarcasm in tweets or product reviews, which can contribute to them being misled.

Online promotion or messaging has grown in importance over the years, owing to the fact that social media is the only medium to reach out to young people and to express sentiment as a person's attitude toward a particular target. It can be time consuming to manually label sarcastic posts on social media. However, also with computer programmes, the most difficult part is identifying the existence of satire.

In a tweet or a summary, the user's exact inclination can be conveyed or not, i.e., it can be communicated in a sarcastic way. Sarcasm is a form of sentiment that can be used to alter the meaning of any message. ‘I like being missed #sarcasm,' for example. In this case, love reflects an optimistic emotion in an otherwise pessimistic situation. As a result, the tweet is considered ironic. Unlike pure negations, sarcastic tweets use encouraging or sometimes intensified positive words to express a cynical or conversely optimistic perspective. In order to predict their exact orientation, this necessitates the rapid study of large quantities of reviews, comments, or feedback messages. Furthermore, each tweet can be subjected to a series of algorithms in order to be classified correctly.

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Sarcasm

As per the dictionary of Cambridge English [20], the sarcasm is described as the usage of certain text which actually means the opposite of what is one saying, which is made in order to hurt anyone's feelings or to criticize something in a very humorous way.

Sarcasm is a kind of emotion in which a person uses optimistic or intensified positive terms in his writing to convey his negative feelings. To reflect sarcasm, people often use strong tonal tension and some gestural cues such as eye rolling, hand movement, and so on when speaking. These tonal and gestural hints are absent from the textual evidence, making sarcasm identification impossible for the ordinary person. Researchers are interested for identifying sarcasm in social media data, especially in the tweets, as a result of these challenges.

Sarcasm can take many different forms, including verbal and literary sarcasm. Spoken sarcasm is a term that refers to sarcasm that happens in conversation. Verbal sarcasm has characteristics such as pitch level and variety, speech time and speed, and acoustic characteristics (intensity, volume, and frequency). To demonstrate their ironic characteristics, this kind of sarcasm uses tones and movements such as eyes and hands expression. Printed sarcasm, on the other hand, is used in places like official letters, emails, product reviews and social medias. On the other hand, because of the inconsistencies between its subtle and formal meanings in a sentence, sarcasm is difficult to detect using data mining techniques as it is used in conversation.

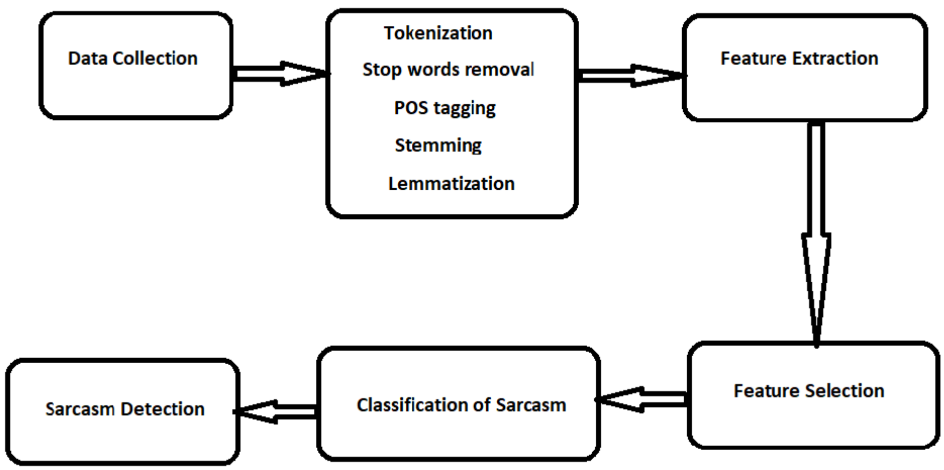

Fig. 1. Phases of Sarcasm detection

Phases of Sarcasm Detection

The general design for sarcasm detection method can be seen in Figure 1. Data discovery or data analysis, data preprocessing, extraction of features and feature selection, sarcasm classification, and sarcasm identification are the key stages.

- **Data Collection**

One of the most popular outlets for sarcasm identification is Twitter data sets. The Twitter APIs are being used for collecting Twitter tweets, specially those with the hashtag # sarcasm. Amazon products data set and Facebook data sets are two other well-known data sets for sarcasm identification. However, there is no single most accurate or standard data collection method for detecting sarcasm. It's one of the most difficult aspects of sarcasm detection. Any researchers used human assistance to construct an annotated data corpus to be used during sarcasm identification.

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- **Data Preprocessing**

The information obtained from different websites such as Twitter, Amazon and Facebook are scattered and unstructured. As a result, one of the most critical stages in identifying sarcasm is data preprocessing. Data preprocessing can be described as the method of removing noise from a data collection. Tokenization of data, elimination of stop terms, lemmatization and stemming are some of the more popular techniques for pre-processing data. The term "tokenization" refers to the process of converting sentences into terms. The terms are translated into their stem or root form during stemming and lemmatization. In the stop word replacement procedure, the stop words would be deleted. Articles, for example. POS (part-of-speech) identifying is another data pre-processing technique that is essential in identifying sarcasm. The terms are divided into various sections of vocabulary, such as nouns and adjectives, using POS marking. Parsing and removing URLs are two other critical data preprocessing stages.

- **Feature Extraction, Feature Selection**

There are various methods for extracting functionality from a textual data collection. TF-IDF, Bag of words and N-Grams are several instances of procedures. Due to the complexities and challenges of detecting sarcasm, researchers are constantly attempting to enhance sarcasm identification by using more suitable features. Emoticons, hyperboles, negation and exclamation marks, among other things, are used to detect the existence of sarcasm. The following are few examples of function selection methods:

- **Term Frequency (TF)**

TF describes amount or count of times a particular word occurs in single document. Two well-known techniques for retrieving information are term existance and term frequency.

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

Text mining is where TF-IDF is most often used. The TF-IDF specifies to what degree a word is capable of providing details for the classification of a text. TF-IDF may determine if a word appears often in all records or is rare. The TF-IDF is used to measure a term’s frequency in a document.

- **Parts of Speech Tagging**

Part of Speech tagging, as the name implies, is the practise of tagging or associating each term in a category with a part of speech based on meaning clues. The main benefit of POS is that it specifies the contextual importance of the terms in the text. For instance, verb, noun, adjective, and so on.

- **N-gram**

In statistical linguistics and chance, N-gram is a continuous set of tokens. The unigram, bigram, trigram, and other n-grams are examples. Unigrams are made up of just one common phrase, whereas bigrams are made up of two common words, and so on.

When it comes to function collection, there are mostly two methods. There are two types of approaches: statistical-based and lexicon-based. The importance of features selection is equal to that of feature extraction. In function selection, a text is viewed as a list of terms. The semantics of terms was used in a lexicon-based approach. It uses semantics to determine the sentiment of a word. Various methods make up the mathematical system. A mathematical approach such as pointwise reciprocal knowledge is an example. Mutual knowledge between features and groups is formed using pointwise mutual information. Another way to choose features is to use the Chi-square rule.

Sarcasm Classification Techniques

Different classifiers and rule-based approaches are used for identifying sarcasm. Most studies use the following classification techniques:

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- **Support Vector Machine (SVM)**

Support vector machine is one of the supervised machine learning algorithms. SVM can be considered for the purpose of classification and regression. In the SVM, each of the text entity is defined in the n-dimensional space where n represents functions. Coordinates in n-dimensional space are used to represent the definition of a function. The most challenging task for the SVM is searching for the hyper plane that perfectly divides two groups.

- **Naïve Bayes**

Nave Bayes can be used for performing binary classification and multi-class classifications. In supervised machine learning systems, the Nave Bayes classifiers are commonly used as Naive Bayes classifiers have been shown to work in a multitude of real-world situations. Two common examples are text labelling and spam filtering. They do not require a lot of training data for predicting the necessary parameters. Three common Nave Bayes classifiers considered are Gaussian Naive Bayes, Multinomial Naive Bayes, and Bernoulli Naive Bayes.

- **Random Forest**

An ensemble algorithm is a category of algorithm which can combine different algorithms to classify objects. Random forest algorithms are a well-known ensemble algorithm. It uses a randomly selected subset of the required training set for creating a series of the decision trees.

- **Decision Tree**

A supervised-machine learning algorithm is the decision tree algorithm. It is primarily used to address various classification problems and variety of regression problems. The decision tree generates a tree like representation to solve a specified class mark query. The class attributes are shown in the internal nodes of a given tree.

Various Approaches to Identify Sarcasm

In the literature, there are lexicon-based, rule-based, machine learning-based approaches for automated sarcasm detection.

Lexicon based Approach

In this approach, a lexicon bag consisting of unigrams, bigrams, trigrams, etc. and phrases explains the sarcasm in the tweets. Two bags-of-lexicon comprising unigram, bigram, and trigram terms were created using a bootstrapping strategy. Furthermore, these terms were used to detect sarcasm in tweets that used an optimistic tone in a gloomy situation. Good attitude, pessimistic emotion, positive case, and negative scenario are the four lexicon bags formed in contrast. Sarcasm is described as negative sentiment in the positive environment and a positive sentiment in the negative environment using these terms.

Rule based Approach

Detection of sarcasm using a rule-based method is actually a problem solving strategy that uses an object based on a particular definition or guideline. The rule based methodology detects sarcasm in every language by analysing syntactic, textual, and textural attributes of the sentence, such as lexical structure and phrase pattern. This approach is often used in experiments to equate their performance to the classifier they're using. The semantic-based system is similar to the rule based methods that considers nature of terms, their design, hierarchical relationships, and relational language usage.

Machine Learning Approach

Researchers use this as one of the most popular techniques for identifying sarcasm. This is attributed to its willingness to observe itself according to a dataset and a series of parameters, as well as its stability. Machine

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learning models work by constructing a statistical model using an intelligent approach. It was examined how aspects of pragmatic, lexical nature affects the machine learning algorithms. Machine learning includes unsupervised learning, directed learning, structural-learning, semi-supervised learning, and mixed learning. Here's a quick rundown of the techniques.

Supervised Learning

The most commonly used machine learning algorithm in sarcasm detection is supervised learning, which creates the model by using a labelled data-set as input and generate the output data. This is mostly that the training datasets are already having the result which the model will process.

Semi Supervised Learning

With a limited number of the data with annotations and a huge volume of data without annotations, this kind of machine learning algorithm mixes supervised learning and unsupervised learning techniques. Supervised learning differs from semi-supervised learning in that it includes unlabelled datasets and allows unlimited access to them. Using Amazon product analysis datasets, the author used this form of learning methodology for automatic sarcasm identification.

Ensemble Learning

A classifier ensemble is just a series of classifiers where individual decisions will be combined for producing a majority decision. The ultimate aim of the approach is combining the decision of various models, referred as base classifiers, into an aggregated outcome which is exceeding all of the individual baseline classifiers. The very first step in constructing a classifier ensemble is to generate a series of base classifiers. One alternative is to use N separate learning methods with single training data-set to accomplish N-different classification models. Another method is to split the training data set into N parts and add a single learning algorithm to each of them. It's important to use an approach which allows for creating a number of classifiers throughout the learning phase. It has also been shown that, rather than simply combining all of the base classifiers into a single ensemble, proper base classifier selection will affect overall classification accuracy. The base classifier can be selected in static manner or in the dynamic manner. Both research samples are exposed to the same subset of base classifiers in the static process. In the dynamic strategy, each new instance is selected separately.

The next step is to integrate the outputs of the baseline classifiers to arrive at a final output decision. What types of knowledge will be combined and the blending method will be used are the most important topics to resolve during this phase. Both base classifiers make decisions regarding an undefined pattern that are then fed back to a combination function. Different ways of blending, such as class mark or class probability distribution, utilise different types of base classifier outputs. Another approach for meta-learning is to train a mix feature using forecasts as a list of attributes. A procedure that integrates both an acceptable mixture scheme and a detailed list of the base classifiers is used to construct the most successful ensemble solution.

When analysing supervised learning algorithms, the expression "bias, noise and variance decomposition of error" is widely used. According to the review, a classifier's learning algorithm error can be divided into three dimensions: bias, noise and variance. When a model's performance is conditioned with different training data, these characteristics are derived. Data noise is a measurement of an error that happens independent of the learning algorithm. Bias against a particular input is described as calculating the average error of a learner prepared with different sets of training data. Variance is considered as an indicator of how much a learner's forecasts differ as presented to different learning data.

Ensemble Generation

The first step in creating of the classifier ensemble is to generate a list of different baseline classifiers. A selection of

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N separate learning techniques could be used as one approach. In the approach, every baseline classifier is generated with the same set of training data but with a variety of learning algorithm. So, there are N-different classification models from where to select. The next step is combining their findings for making a final output decision.

The second choice is to use a single learning scheme with several training sets in the course of creating a sequence of baseline classifiers. The major issue in this approach is turning the original data-set into a sequence of different training data sets in a timely manner. Several methods were used to subdivide the actual data-set into N-subsets, like random sorting or clustering. The other choice is to tamper with the data distribution process. After the subsets have been developed, each of the baseline classifier is builded using the same learning algorithm and the different subsets. The sections that follow describes and evaluates the popular methods investigated for the system.

The sections that follow describe and evaluate the most popular methods investigated for this system.

Partitioning of training data set: Most common technique for removing several training sets from a single data source is called bagging. It is a process in which the training sets are chosen at random, k times from the original data selection using bootstrap techniques. Certain instances are likely to be appearing more than once in certain training datasets using this form, whilst others may never appear. Thus, K-training datasets (k different types of classifiers) are created, each of same size as the original data. The most significant benefit of bagging is that different band sets may be practised independently in combination, thus reducing the preparation time.

Manipulation of data distribution: Boosting is a technique that employs several training data sets when using the same learning methodology. Boosting is a type of iterative process in which the training range's distribution is dynamically changed according to the accuracy of the classifier. Both instances which are classified correctly or incorrectly categorised as gain or loose weight are reweighted until a base classifier has been created and applied to the ensemble. The final prediction is focused on each base classifier's prediction being given a weighted vote. The weights are relative to each classifier's accuracy rather than its training results. AdaBoost is a common and highly effective booster.

Partitioning of the attribute space: The other alternative is creating a list of the baseline classifiers using various feature subspaces and the original training data set. Random Forest is a well-known method for creating ensemble members from random subspaces. A Random Forest is a classification system comprised of several separate trees. Each individual tree is made in the same way as individual bags are rendered. The ensemble's size and number of the variables used to calculate the break at a tree node are the input parameters. A single bootstrap sample is used to construct each tree. The variables used to make choices for each node are chosen at random. Following the creation of a tree body, the final decision is made by a voting process. The Random Forest can be called a variation of the bagging strategy to some degree.

Majority Voting: A selection of base classifiers is generated as the consequence of bagging, boosting or other method of developing ensemble. The effects of all of the different classification models are combined during the construction of a classifier ensemble.

The MV method is the most straightforward way to merge base level classifiers. This protocol collects all classifiers' votes and selects the class with the most votes as the final judgement.

When we use probabilistic classifiers, we assume that every model votes for the class with the highest likelihood. Weighted majority voting is a more advanced variant of this method (WMV). Various different weights are allocated to the base classifiers in this process. The weight of each classifier indicates how relevant it is to the final judgement.

Cross-validation (CV)

CV is a mathematical approach for evaluating the output of a model or algorithm in which data is divided into two subsets: preparation and testing. A subset of learning is used to train a model or algorithm, which is then verified by a

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subset validation. Furthermore, CV forms may be chosen depending on the scale of the dataset. A K-fold CV is often used since it can minimise processing time while maintaining estimation precision. The K-fold used in this analysis is 10-fold, which divides data into 10 nearly equal bits, giving us 10 data subsets to test the classifier model's output. As seen in Fig.2, the CV would use 9 fold (90 percent) for preparation and 1 fold (10 percent) for checking for each of the 10 data subsets. The dark shaded area is a section of the dataset used as evaluation results, whereas the light shaded area is used for data practise.

	10 Cross Validation									
	1	2	3	4	5	6	7	8	9	10
1										
2										
3										
4										
5										
6										
7										
8										
9										
10										

Fig. 2. Cross Validation

Classification Evaluation

A confusion matrix is a method of summarising a classification algorithm's results as shown in Fig 3.

	Actual Instance	
	YES	NO
Predicted Instance		
YES	True Positive	False Positive
NO	False Positive	True Negative

Fig. 3. Confusion matrix

- The instance that was correctly labelled are called true positive (TP).
- Instances wrongly placed in different class are true negative (TN).
- Instances that does not belongs to the class but they are wrongly placed in the class are false positive (FP).
- Instances that neither belongs to a particular class nor classified in the class are the false negative (FN).

The confusion matrix for binary classification is described by these four participants, as seen in Fig 3. The model's efficiency was evaluated using a variety of performance parameters. Accuracy, F-measure, precisions, and recalls are the most widely applied text classification metrics.

Accuracy

The proportion correctly identified instances in the comparison to overall number of instances.

$$\text{Accuracy} = \frac{\text{TruePositive} + \text{TrueNegative}}{} \quad (1)$$

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TruePositive + TrueNegative+FalsePositve+FalseNegative

Recall

The proportion of real positives that are expected positive is known as recall.

$$\text{Recall} = \frac{\text{TruePositive}}{\text{TruePositive + FalseNegative}} \quad (2)$$

Precision

Precision is described as ratio of the true positive over positive result in a computation.

$$\text{Precision} = \frac{\text{TruePositive}}{\text{TruePositive + FalsePositve}} \quad (3)$$

F measure

F-measure is represented by harmonic mean of accuracy and recall.

$$\text{F-measure (F-m)} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} * \text{Recall}} \quad (4)$$

Literature Review

Eduardo R. Hruschka an et al. [1] suggested a classifier ensemble using lexicons, emoticons, a bag of terms, and attribute hashing. Random Forest, Multinomial Naive Bayes, logistic regression and Support Vector Machine were chosen as baseline classifiers with recorded precision is 81.08 percent.

With a 93 percent accuracy rate, Anthony J. Clark [2] has proposed a supervised-machine learning method for detection of sarcasm in Facebook messages. To determine whether or not a post is satirical, a combination of numeric, text, and picture is used. Support vector machine along linear kernel, two ensemble algorithms – Adaboost with decision tree classifier and Random forest with Multi-layer perceptron and Gaussian Nave Bayes – and five machine learning algorithms were included. Both ensemble learning approaches have a high level of precision (>90%).

By using pragmatic particles and POS marks in the function sets, Fersini.et.al used an ensemble technique to spot sarcasm and cynicism in the document. Ensemble models include Support Vector Machines, Decision Trees, Naive Bayes and Bayesian Networks. Pragmatic particles were found to be better at identifying sarcasm, whereas POS tags were better at identifying irony [3].

Author [4] applied the feature reduction approach – Principal Component Analysis to a twitter dataset of product feedback and tested it with Support Vector Machine and Nave Bayes in this article. The use of PCA resulted in an improvement in precision.

In the article [5,17], author proposes a modified solution for K-means clustering system by reducing number of features using Principal Component Analysis, and finds that the modified algorithm takes significantly less time than the K-mean algorithm when applied to a large number of data sets.

Jotheeswaran. et.al [6] suggested a way for improving the performance of the classifier on tweets by utilising a feature reduction method called Principal Component Analysis, and discovered that the proposed random forest tree-based feature reduction method increased the classifier's accuracy, recall and precision.

SK Bharti. et. al. [7] introduced Hadoop-based architecture for recording tweets in the real time and manipulating

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them using a series of algorithms to efficiently recognise satirical sentiments. TCUF, LDC, IWS, PBLGA, TCTDF and PSWAP are six algorithms suggested in this paper for detecting sarcasm in the tweets received from Twitter. Then three algorithms were tested using the Hadoop system and without it. Processing time was found to be decreased by up to 66 percent using the Hadoop system.

Ankita et al. [8] suggested an ensemble classification scheme to improve sentiment analysis accuracy for tweets. Nave Bayes classifiers, Random Forest classifiers, Support Vector Machines, Logistic Regression are most popular classification techniques used. Twitter datasets on a variety of topics: Stanford – Sentiment 140 corpus, Health Care Changes, First GOP Discussion Twitter Sentiment Dataset, and Twitter Sentiment Analysis Dataset. The suggested ensemble classifier outperforms stand-alone classifiers and plurality voting ensemble classifiers, according to the results. The analysis of neutral tweets can be recommended for future research. The job may also be expanded to include other social media sites.

Vinodhini et al. [9] suggested a method for sentiment analysis that categorises text emotions as positive or negative. Principal component analysis was used as a feature reduction tool, and a back propagation neural network classifier is used for the classification of data. In digital camera reviews, the datasets were downloaded from www. amazonreviews.com. Cross validation was done ten times. Results were tested using the receiver operating characteristics (ROC) curve. When the performance of BPN and PCA+BPN is contrasted, it was discovered that the ROC curve for PCA + BPN was closer to perfect point (0,1) compared to BPN-based model.

One of the most difficult tasks of emotion analysis is detecting sarcasm. Ashima. Et.al. [10] investigated emotion analysis sarcasm in tweets about a single subject utilising features such as interjection and unigram features in this article. They used a Support Vector Machine with polynomial kernels to detect sarcastic sentences and compare them. It was discovered that using the interjection and unigram functionality on tweets with SVM increased sentiment analysis accuracy by 91%.

Since there is no static form for sarcasm in the data stream. As a result, utilising Machine Intelligence to forecast sarcasm in Twitter (or every other semi-structured knowledge format) is challenging. As opposed to other heuristics that use pattern match or context dependent, this is a more challenging yet thorough assignment. In the paper, Asthwith et al. [11] demonstrated how various digital technologies can be utilized to combat societal issues and constructs which impede free speech. It is shown by the usage of the classification schemes for description and the tweets classification. It was accomplished using a hyperbolic feature set. The project's potential analysis will involve resolving semantic uncertainty utilising a radical Recurrent Neural Network paradigm. Feed the network with the functionality and metadata created by the current model to accomplish this. Bidirectional LSTMs can be considered for the context identification and the VADER library can be used to perform a comprehensive emotion search.

In paper [12], a method for detecting sarcasm in bilingual texts that uses a variety of feature extraction categories and NLP is presented. The method extracts functionality from bilingual or interpreted corpora. Pragmatic, lexical, syntactic, idiosyncratic, prosodic NLP characteristics were all listed. To test the feature groups, a non linear SVM was used for classification purpose for the sarcasm detection (used on their own and in combination). The proposed model outperformed the others as compared to a baseline function.

Ilavarasan.et.al [13] have provided a review of previous sarcasm detection work, an architecture for detecting sarcasm, various types of sarcasm, various sarcasm detection techniques, and certain sarcasm detection challenges. The complexity present in sarcasm renders things a more difficult task and raises the chances of finding jobs. The bulk of study into sarcasm detection is done in English. Future analysis should focus on detecting sarcasm in other languages. New datasets, features sets, and consideration of different types of sarcasm, among other aspects, were proposed for future research.

Kumar et al. [14] proposed a feature-rich SVM model for detecting sarcasm that includes hand-crafted textual, sentiment, and punctuation features. They contrasted the SVM model to four prior studies and found that their feature-rich model outperformed the others in terms of F-score. At the sentence stage, the proposed neural network has two major layers: a word encoder and multi-head orientation. Encoder layer provides a new symbol for every word by adding semantic information from both the directions in a paragraph. In the sentence stage, the multi head fixation layer focuses on multiple parts of the expression at the same time to perceive different aspects of the grammar of the argument. The BiLSTM model's utility is enhanced much further by the inclusion of manually created auxiliary functions to the network.

Bouazizi. et al. [15] proposed classification scheme which had a consistency and the precision score of 83.1% and 91.1 % respectively. The importance of each proposed feature sets was investigated in the study. This research has assessed its added importance to the classification.

Jurek.et.al. [16] conducted a review of the most significant literature on ensemble methodology to date. The three most well-known methods have been discussed: bagging, boosting, and stacking. Present classifier ensemble selection methods were also explored, utilising both static and dynamic techniques.

According to an analysis of the literature, ensemble classification methods have been extensively used to address classification problems in a variety of fields. However, no research into the usage of ensemble classifiers in tweet sentiment analysis has been conducted. In the majority of the articles, an ensemble classification system is proposed, which is expected to increase tweet sentiments classification accuracy in comparison with other traditional sentiment analysis methods.

Conclusion

One of the most challenging facets of emotion research, as we discussed earlier in this article, is recognising sarcasm. In recent years, recognising sarcasm has become exceedingly necessary. We attempted to provide a survey of previous sarcasm detection work, a general architecture for detecting sarcasm, various types of sarcasm, different sarcasm detection techniques in our article. The complexity in sarcasm renders things a more difficult task and raises the chances of finding jobs. This article also includes an analysis of numerous ensemble classification systems, which are seen to improve tweet sentiment classification performance.

Future Directions

The majority of study into sarcasm detection is done in English. Sarcasm detection in different languages is a significant direction for future study. New datasets, function sets, and consideration of different ways of sarcasm, among other aspects, may be used in future research. In future, we would like to try out different deep learning methods and look at more conceptually oriented functionality. The f-score, awareness, memory, and accuracy of the sarcasm detection model will all be improved. We'll also try to place more focus on the hyperbole function and go further into the document's syntactic dependencies. The analysis of neutral tweets would also be a potential priority since certain tweets have neither optimistic nor negative opinion.

References

[1] Da Silva, N.F., Hruschka, E.R., & Hruschka Jr, E.R. (2014). Tweet sentiment analysis with classifier ensembles. *Decision Support Systems*, *66*, 170-179.

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

[3] Fersini, E., Pozzi, F.A., & Messina, E. (2015, October). Detecting irony and sarcasm in microblogs: The role of expressive signals and ensemble classifiers. In *2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA)* (pp. 1-8). IEEE.

[4] Vinodhini, G., & Chandrasekaran, R.M. (2013). Effect of feature reduction in sentiment analysis of online reviews. *International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)*, *2*(6), 2165-2172.

[5] Dash, B., Mishra, D., Rath, A., & Acharya, M. (2010). A hybridized K-means clustering approach for high dimensional dataset. *International Journal of Engineering, Science and Technology*, *2*(2), 59-66.

[6] Jotheeswaran, J., & Koteeswaran, S. (2016). Feature selection using random forest method for sentiment

analysis. *Indian Journal of Science and Technology*, *9*(3), 1-7.

[7] Bharti, S.K., Vachha, B., Pradhan, R.K., Babu, K.S., & Jena, S.K. (2016). Sarcastic sentiment detection in tweets streamed in real time: a big data approach. *Digital Communications and Networks*, *2*(3), 108-121.

[8] Saleena, N. (2018). An ensemble classification system for twitter sentiment analysis. *Procedia computer science*, *132*, 937-946.

[9] Vinodhini, G., & Chandrasekaran, R.M. (2014). Sentiment classification using principal component analysis based neural network model. In *International Conference on Information Communication and Embedded Systems (ICICES2014)* (pp. 1-6). IEEE.

[10] Garg, A., & Duhan, N. (2020). Sarcasm Detection on Twitter Data Using Support Vector Machine. *ICTACT Journal of soft computing*, *10*(4), 2165-2170.

[11] Ashwitha, A., Shruthi, G., Shruthi, H.R., Upadhyaya, M., Ray, A.P., & Manjunath, T.C. (2021). Sarcasm detection in natural language processing. *Materials Today: Proceedings*, *37*, 3324-3331.

[12] Suhaimin, M.S.M., Hijazi, M.H.A., Alfred, R., & Coenen, F. (2017). Natural language processing based features for sarcasm detection: An investigation using bilingual social media texts. In *2017 8th International conference on information technology (ICIT)* (pp. 703-709). IEEE.

[13] Ilavarasan, E. (2020, March). A Survey on Sarcasm detection and challenges. In *2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS)* (pp. 1234-1240). IEEE.

[14] Kumar, A., Narapareddy, V.T., Srikanth, V.A., Malapati, A., & Neti, L.B.M. (2020). Sarcasm detection using multi-head attention based bidirectional LSTM. *Ieee Access*, *8*, 6388-6397.

[15] Bouazizi, M., & Ohtsuki, T.O. (2016). A pattern-based approach for sarcasm detection on twitter. *IEEE Access*, *4*, 5477-5488.

[16] Jurek, A., Bi, Y., Wu, S., & Nugent, C. (2014). A survey of commonly used ensemble-based classification techniques. *The Knowledge Engineering Review*, *29*(5), 551.

[17] Malli, S., Nagesh, H.R., & Rao, B.D. Approximation to the K-Means Clustering Algorithm using PCA. *International Journal of Computer Applications*, *975*, 8887.

[18] Eke, C.I., Norman, A.A., Shuib, L., & Nweke, H.F. (2020). Sarcasm identification in textual data: systematic review, research challenges and open directions. *Artificial Intelligence Review*, *53*(6), 4215-4258.

[19] D. Chaffey, Global social media research summary 2016. URL:http://www.smartinsights.com/social-media-marketing/social-media-strategy/ new-global-social-media-research/

[20] Dictionary, C. (2008). Cambridge advanced learner's dictionary. *Recuperado de: https://dictionary. cambridge.org/es/diccionario/ingles/blended-learning*.