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SURVEY ARTICLE

AI-Based Learning Techniques for Sarcasm Detection of Social Media Tweets: State-of-the-Art Survey

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Abstract
Sarcasm, though difficult to define but plays a crucial role in one's life. Sarcasm as a jest is a matter of fun but when taken seriously can cause unwelcoming results. Sometimes, sarcasm is defined as "a sharp, bitter, or cutting expression or remark; a bitter jibe or taunt". These days' researchers are working towards the detection of sarcasm for the purpose of sentiment analysis. Emotion and sentiment-bearing information are carried by subjective sarcastic sentences. The objective of the paper is to highlight the different types of sarcastic tweets and their usage in sentiment analysis. The authors mainly emphasize several approaches which include sentiment analysis, machine and deep learning classifications. The paper focuses on the use of machine learning and deep learning for identifying sarcastic tweets. Numerous feature extraction techniques have been studied and machine and deep learning classifications have been taken into account. The comparative table shows the results obtained using the various evaluation metrics such as accuracy, precision, recall, and *f*-score.

Keywords Feature vector · N-gram · Sentiment analysis · Sarcasm detection · Machine learning · Deep learning

Introduction

Today's world is data driven, and the credit goes to technological advancements in the field of communication like mobile phones, social websites and many more. Such advancements have led to exponential increase in data generation. Recent years, we have witnessed tremendous usage in social websites such as Twitter, Facebook where people come together and share their thoughts, opinions, discoveries and also engage in various discussions. It is necessary to analyze this data for various purposes such as sentiment analysis, judging the tone of the writer, and many more. It is necessary to understand the mood of the writer who adds data to such social websites as these data have the capability to influence the mob.

The mood is polymorphic in nature, ranging from being puzzled to provoke or diverted to nauseate. It is a subject of research among psychologists to study different moods of people and their origin. Moods have an influential effect on one's behavior which can affect not only their lives but of others too. Moods are related to the feelings and concentrated mainly on opinion and attitude. That is why sentiments are considered to be subjective in nature. Some people refer to feelings as a natural way of replying to fascination, wish, discomfort, and repugnance. Whereas sentiment denotes an emotion, motivation by an opinion or observation.

There are various types of data available online, ranging from short character data like tweets to long character ones like debates. Twitter, a trending social website contains trillions of tweets and re-tweets provides a significant amount of data to understand the concept of sarcasm. Sarcasm plays a vital role in the process of sentiment analysis and researchers these days are employing this tone for their purpose of understanding the sentiments of a person. In this paper, we will walk through this tone and its usage, various contributions of researchers in this domain. We will gain an understanding of the technicalities involved to develop such a model.

This article is part of the topical collection "Computational Statistics" guest edited by Anish Gupta, Mike Hinchey, Vincenzo Puri, Zeev Zalevsky and Wan Abdul Rahim.

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Sentiment Analysis and Sarcasm Detection

Sentiment analysis is also called opinion mining. It is the process in which emotions are classified through text; emotion can be neutral, negative, or positive. With the growing rate [1] of social media, these days it has added a lot to Sentiment analysis and made this area more explored by the researchers. By applying sentiment analysis over social media, various useful information can be drained from it like it helps ad companies for calculating the success and failure rate, to expect user behavior, predict election result and many more (Fig. 1).

Sarcasm [2] is commonly called "taunt" which is used for expressing the context of another person. Due to the non-literal nature of comments these days, this has become a challenging NLP problem. These days sarcasm is being used frequently in social media, tweets, etc. Sentiment analysis and opinion mining applications have come on as the key solution for facing the battle against sarcasm.

Sarcasm is linked with various verbal phenomena like explicit gap among sentiments or discrepancy among the conveyed emotion. Sarcasm is compared between a positive and negative sentiment. Consider some of the examples [3]:

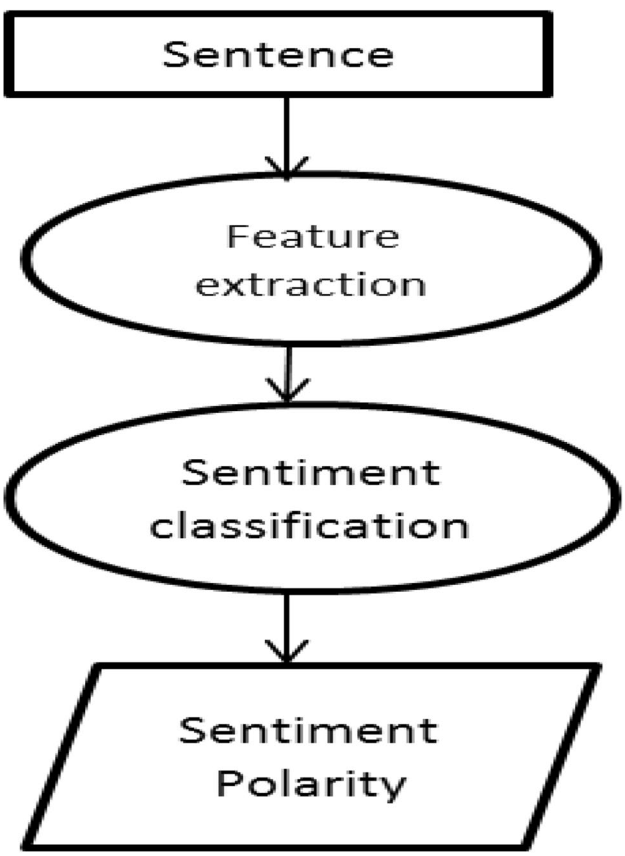


Fig. 1 Process of sentiment analysis

1. I absolutely love to be ignored!
2. Yay!!! The best thing to wake up to is my neighbor's drilling.
3. Perfect movie for people who can't fall asleep.

In the given examples, observation is to be made out in each statement. Sarcasm depends on the semantic association among individual words and phrases in a sentence. Like in these examples, movie, asleep, love, drilling, ignored highly describes the nature of sarcasm conveyed through them.

Challenges for Sentiment Analysis Stages

Some challenges for sentiment analysis stages are discussed as under (Fig. 2):

1. Language problem [4]: for English language availability for dictionaries, corpora and lexicons can be made easily but researchers are in search of OP language and building the dictionaries, corpora, and lexicons for this language which is the main challenge faced by researchers.
2. Natural language processing (NLP): using the OP process with NLP has attracted various researchers for this field. NLP helps in providing better results for the OP process. More attention should be given to domain-dependent corpus rather than domain-independent corpus because domain-dependent provides better results for OP than domain-independent corpus.
3. Fake opinion: termed as fake review [5] or may refer to fake blogs that misguide the users by providing them with false opinion related to any object. This is done to lower the object's reputation. Such type of spam creates sentiment opinion impractical in various application areas.

Different Types of Tweets

Various types of tweets have been used these days but five main types of tweets used these days are discussed below in Table 1:

Different Opinions or Common-Sense Knowledge

Common sense and concept level knowledge [6] are the way for understanding and recognizing the things which are united through the common knowledge and facts that can be rationally realized. Research is done on semantic analysis of tweets with the help of a semantic network which consists of various concepts of words for obtaining more sentimental information.

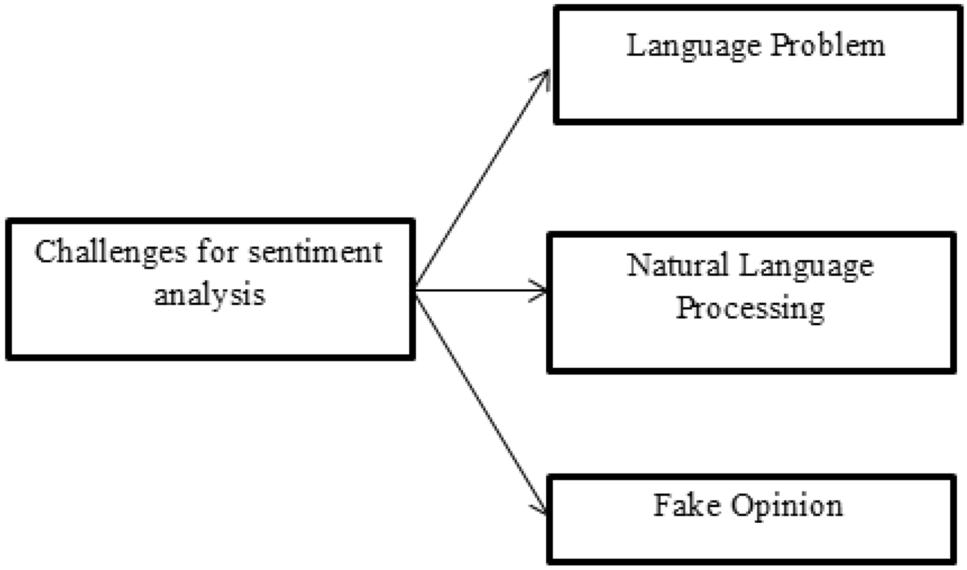


Fig. 2 Challenges for sentiment analysis

Table 1 Different types of tweets

S.no	Tweet	Description
1	Shares	This is the most common tweet these days. It is sharing a tweet link with a piece of content or resource which is valuable and feels it should be shared with others also. Sharing can be of any text, value, image, pdf or can website. Sharing can be done within some limited characters. By sharing such valuable things that followers like help in gaining respect and tweet love thus helps in increasing your followers
2	Content	Do not get confused in share tweets and this tweet. In a tweet a link of content is shared, but in content, the valuable "CONTENT" is being shared with the followers. Content tweets can be tricky sometimes. So be particular what content you are sharing with the followers. Do not go beyond the topic. It should be related to the twitter profile. Avoid religious, ethical, or political statements if you're tweeting for a brand
3	Crowdsourcing	In this type of twitter users directly ask answers to the problems from their followers. Problems can be any, related to personal life, business problems, etc. followers give their positive response which helps in finding the better solution to the user
4	Marketing	This type of tweet is related to sales or marketing like "get a free apple phone in 2 h when you register in our conference". Such types of tweets are not so effective. Twitter users are looking for valid information. Any false information will give a negative effect of yours to your followers. Sharing interesting and informative sources related to marketing is the best way of building reliability, which attracts potential customers to make interest in them. Another method for supporting your services is to tweet about projects or new technology you are working on and ask the followers to rate your project and tell what the drawbacks of it are so that you can remove that drawback before finally submitting it to the market
5	Conversations	In this type of tweet, you are replying back to some previous tweet or sending any public message to the other user like wishing someone their birthday on their wall. This type of tweet plays an important role in making personal connections with followers

Let us take an example for some sarcastic comment "honesty is the best policy, where there is money in it" the system will miss-understood in a random sentence because of a lack of sentiment information. In this particular phrase, honesty represents some good source of knowledge. But when we include common sense and concept level knowledge, we will know the meaning of other words like "money" with it and we can sense what exactly the sentence is delivering the meaning. A contradiction of the polarity [7] in this sentence could be found by classifying the words either positive or negative. Hence, the given sentence can be classified as sarcastic.

Background Work

This section contains the framework for the sentiment analysis for the detection of sarcasm detection including preprocessing techniques, different optimization techniques, and classification methods for the detections of sarcasm tweets.

Framework for Sentiment Analysis

Framework for sentiment analysis for detecting the sarcasm is discussed below (Fig. 3).

Preprocessing Steps

The preprocessing step for sarcasm detection in sentiment analysis is carried out with two kinds of preprocessing step over the tweet dataset. The first one is "lemmatization" [8] and another one is "usernames, URLs and hash-tags removal".

The Stanford Lemmatizer is being used for lemmatization steps and for URLs, hash-tags, and usernames which are detached from tweets as they do not deliver any information about the concepts and can be uproar for the classification process [9].

- Feature extraction

To cite the features [10] out of a given sentence is the first main step. Types of features are:

1. Part of speech: may include adjectives that are very important for making opinion or thought.
2. Presence of terms and their frequencies: these may include individual word or N-gram words and count the frequency of words that is repeated again and again. This is known as frequency count.
3. Words and phrases for opinion: some words and phrases which are mostly delivered for citing the opinions related to love or hate and many more.
4. Negation: these are the negative words which are introduced before any word that might change the meaning of that word and also opinion is changed.

- Sentiment features

For both negative and positive phrases [11], sentiment scores are being provided. Three classes are being used i.e. low, high and medium. Classes are being included for indicating the degree of positive and negative polarity of the tweets in the phrase. First, preliminary experiment is to be done then three positive sentiment features can be defined like:

Positive	Negative
low-activated if sum_pos_score < = − 1	low-activated if sum_neg_score < = − 1
medium-activated if 0 < = sum_pos_score < = 1	medium-activated if 0 < = sum_neg_score < = 1
high-activated if sum_pos_score > = 2	high-activated if sum_neg_score > = 2

- Creation of feature vector

How classifier is being trained for detecting sarcasm in some tweet is being explained below [12]:

1. N-grams feature

   The sequence of words in a particular tweet is referred to as N-gram. In N-grams feature, N represents the size of the sequence. Mainly used N-grams are uni-gram, bi-

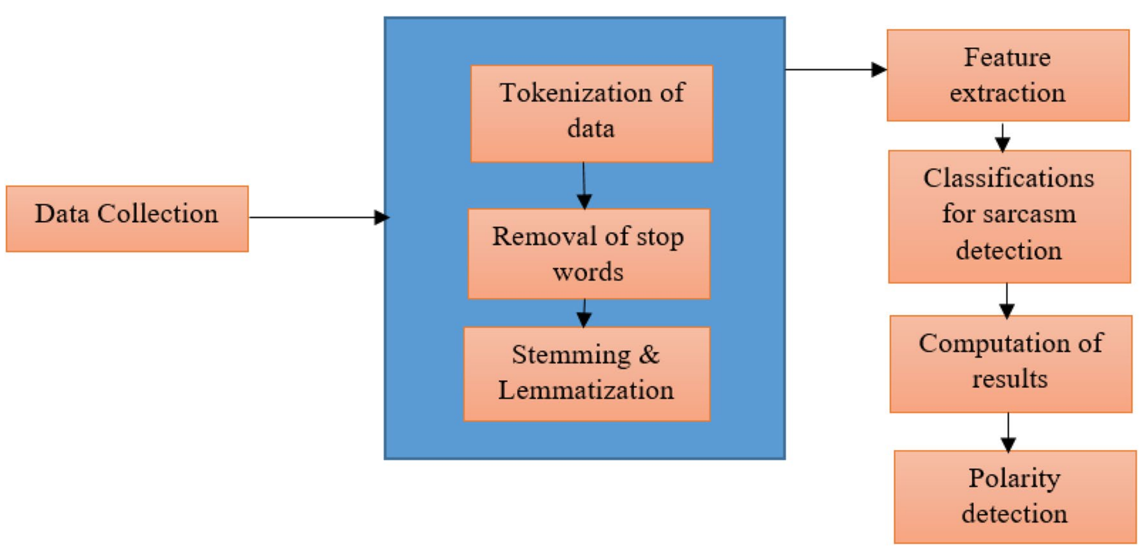


Fig. 3 Workflow of sarcasm detection in sentiment analysis

gram, and trigram. First, each tweet is divided into sets of sequences of single words, in sequence of two words and in sequence of three words. These will be used as features. Weights of N-gram can be either 1, if present or 0, if absent.

2. Contradiction feature

   For sarcasm identification, ambiguity [13] and coherent, score is very useful. Therefore, for this reason, two binary features i.e. “contra and contra + coher” are activated for sarcasm identification. “Contra” is stimulated only when the tweet consists of one sentence and “contra + coher” is activated only when the tweet consists of two or more sentences.

3. Punctuation and special symbols feature

Punctuation plays a very important role in feature [14] vectors. Many researches have shown that punctuation has a lot of effect over classification of the text, mainly in the field of SA. Some researchers have listed seven indicators for introducing punctuation features [15]:

A1. No. of capitalized word.
A2. No. of exclamation marks.
A3. No. of idioms.
A4. No. of emoticons.
A5. No. of slang and booster words4.
A6. No. of repetitive sequence of punctuations.
A7. No. of repetitive sequence of characters.

Optimizations Techniques for Sarcasm Detection

The design objective of optimization [16] is to improve efficiency of production by minimizing the cost. In optimization algorithms iteratively various solutions are compared with each other till we find the best solution which satisfies our needs.

Optimization Algorithms

Design problem formulation [8] is different from problem to problem. Some of them are:

i. Linear terms.
ii. Nonlinear terms.

The optimization algorithms are categorized into a various group, which are discussed briefly:

1. Single variable optimization algorithms

   Single variable optimization algorithms are broadly classified into two categories, i.e. direct method and Gradient-based method.

   In direct method no derivative information is being used for getting objective function, for the search process only objective function values are taken. Whereas in gradient-based method, derivative information is used for the search process.

   Mostly in optimization problems, we use more than one variable i.e. single variable optimization algorithm is only used in case of unidirectional search methods.

2. Multi-variable optimization algorithms

   This type of algorithm helps in guiding how the search for the optimum point progresses is done in multiple dimensions. This algorithm is further divided into two techniques which totally depend on gradient information.

3. Constrained optimization algorithms

   In this type of algorithm, the single variable and multivariable optimization algorithms are used frequently and at the same time for maintaining the search effort. Such algorithms are used for engineering optimization problems.

4. Specialized optimization algorithms

   The specialized optimization algorithm is classified into two [17]: geometric programming and integer programming. Geometric programming solves the optimization problems through objective functions, whereas integer programming methods solve optimization problems through integer design variables.

5. Nontraditional optimization algorithms

   For nontraditional, there are two algorithms, genetic algorithms and simulated annealing.

Classical Optimization Techniques

Various classification techniques [12, 13] are listed as below:

a. Classical optimization techniques

- The classical optimization techniques involve analytical approaches and use differential calculus for tracing the optimum solution.
- The classical method uses inadequate scope in practical applications as some of them include objective functions which are neither continuous nor differentiable.
- These classical methods undertake that the function is differentiable double time with respect to the design variables and the derivatives are continuous.
- The classical optimization techniques handle three main problems: single variable functions, multivariable functions with no constraints and multivariable functions with both equality and inequality constraints.

b. Numerical methods

- Nonlinear program design: where the objective function, constraints or both contain nonlinear parts.
- Stochastic program design: where few constraints are determined by random variables.
- Dynamic program design: where the optimization policy is constructed by dividing the problem into smaller subproblems.
- Combinatorial optimization: is alarmed with problems where the set of possible results is discrete or can be compact to a discrete one.
- Infinite dimensional optimization: where the set of possible clarifications is a subset of an infinite dimensional space.
- Constraint satisfaction: where the objective function f is constant and is mainly used in artificial intelligence.

Advanced Optimization Techniques

Some of the advanced optimization techniques [6] are discussed as below:

Hill Climbing

- It is a graph search algorithm where the current path is elongated with a successor node that is quicker in finding the solution.
- The first node is selected whereas in steepest ascent hill climbing all successors are associated and nearer to the answer is chosen.

Simulated Annealing

- In such a type of technique, heating and cooling of solids are done for increasing the dimensions of its crystals and decreasing flaws present in them.

Genetic Algorithms

- A genetic algorithm [18] is one of the local searching techniques which are used for finding estimated solutions.
- GA is evolutionary algorithms that take the help from biology evolutions like inheritance, mutation, selection and crossover.
- GA is implemented as a computer simulation; in which the population represents the chromosomes which indeed help in getting the better solution.
- The starting of evolution is from random individuals that occur over generations.
- For each generation, evaluation for fitness of the whole population is generated. Multiple individuals are selected from the population and modified according to the formation of a new population.

Ant Colony Optimization

- In the real world, what ants do? When they find some food and return back with it, it lay down some pheromone trails. They lay this trail for some purpose so that other ants can easily find the food following that trail and can get the food easily by following that trail.
- But after sometime, this trail starts to evaporate, thus the attraction becomes less. Thus, more time is to be taken by the ant to travel and find the food.
- Thus, pheromone density remains high when ants start marching quickly.
- There are various advantages of pheromone evaporation for getting optimal solutions. If no evaporation process will be followed then the paths selected by the first ants would lean towards to be extremely attractive to the other ones.
- Thus, once the ant finds the good path, i.e. the shortest path for getting the food source, the ants will follow that path and will surely lead in finding the best path in getting the best solution.
- The idea for having an ant colony algorithm is to impersonator the behavior like "simulated ants" walking about the search space on behalf of the problem to be solved.
- Ant colony optimization algorithms help in producing the solutions to the traveling salesman problem.
- Ant colony optimization algorithms have much advantage over approaches like simulated annealing and genetic algorithms.

Classifications Approaches Used for Sarcasm Detection

Approaches [6] used for sarcasm detection are classified as under (Fig. 4):

1. Rule-based approaches

Through specific evidence, rule-based approaches [6] find sarcasm. These evidences are some rules that help in identifying the sarcasm. Various researchers have done different research over getting the rules. Some authors have worked over a given smile and worked on whether the given smile is intended to be sarcastic or not. Author has used Google search for determining how likely a simile is. They have used nine different steps to validate the given smile. At each step, a smile is validated using a number of rules. The benefit of using this approach is that it presents an error analysis corresponding to multiple rules. Many authors have identified hash-tags as an indicator of sarcasm. Such hash-tags are being used by authors for highlighting the sarcasm. Let us take a case, if any statement contains some hash tag and does not fit with the rest of the

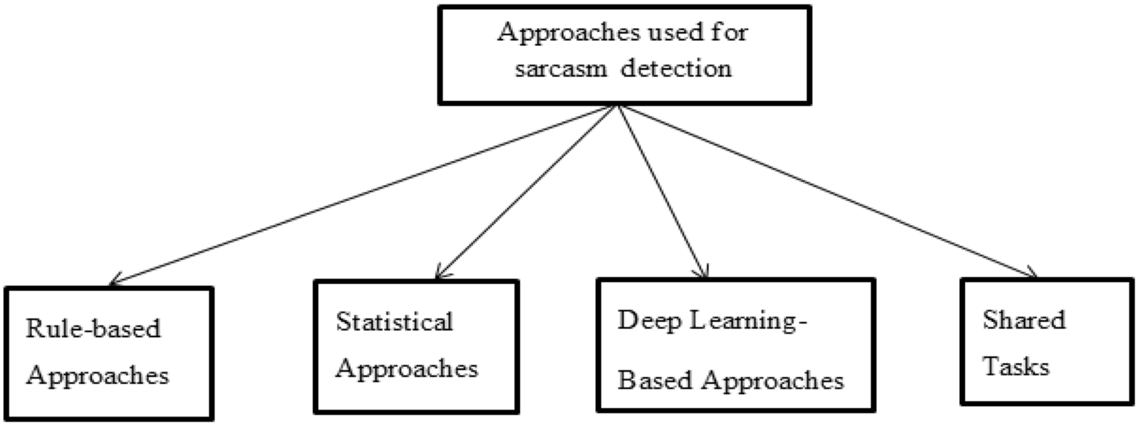


Fig. 4 Approaches used for sarcasm detection

tweet then that statement is classified to be sarcastic. There are two rule-based classifiers. One classifier is used for making the parse tree and recognizing them in the phrase while as other classifier captures hyperboles using interjection and intensifiers together [8].

2. Statistical approaches

Statistical approaches [1] to sarcasm detection are different in terms of features and learning algorithms. These further are of two types which are discussed as under (Fig. 5):

a) Features used

Various features are being categorized for sarcasm detection. This approach uses a bag of words as one of the features. In addition to these various other features have also been introduced with it for getting to know whether the given statement is sarcastic or not.

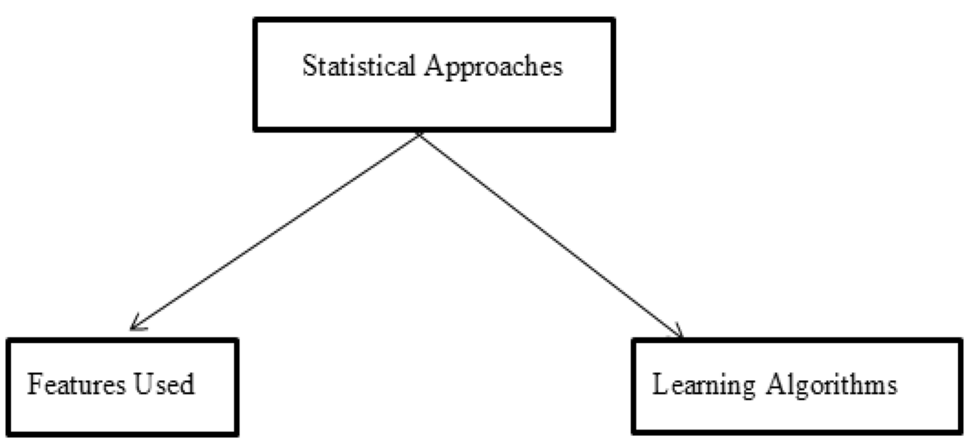
b) Learning algorithms

For sarcasm detection, various classifiers have been identified. Most work with the help of SVM. Chi-squared test is also used to identify sarcasm features. Naive Bayes is also used for sarcasm detection. Some authors have done the comparison between rule-based and SVM based classifiers. Other authors have used balanced winnow algorithm [9, 17] for controlling high ranking features, some used SVM HMM and some have done comparison among several classification approaches like bagging, boosting, etc.

3. Deep learning-based approaches

Deep learning techniques are gaining importance in day today life. Very few techniques are listed for finding out the automatic sarcasm and deep learning is one of them. For sarcasm detection, use of similarity among word embedding's act as one of the features. Congruent and incongruent word pairs are reported for improving the performance. The key basis used for this is augmentation. A novel on convolutional network based was written which has insight for user embedding's in addition to utterance-based embedding. This novel

Fig. 5 Types of statistical approaches



further helps in learning of user specific context. Various authors have used the combination of convolutional neural networks and DNN and have compared their results against SVM. Deep learning has shown far better results from other all techniques [19].

4. Shared tasks

The name shared task [4] itself indicates its significance. In shared tasks some common datasets are to be shared across various teams for relative estimation. Two different tasks are shared for detecting sarcasm. Example of the shared task is from "SemEval" that takes sentiment analysis for metaphorical languages. Data sets of sarcastic and figurative statements are provided by the coordinators which help in getting the positive, neutral and negative labels from the statements. The users are probably asked to rightly identify the polarity of sentiment in case of sarcastic detection [20]. The teams that have taken part in shared task castoff affective resources, etc. The team which is winning uses four lexica. One lexicon is automatically generated and others are crafted manually.

Role of Deep Learning Neural Network for the Identification of Sarcasm

The target of attention for these days is semantic modeling that uses neural networks [10] for social media. Architectures of neural networks like DNN, CNN and RNN have shown a variety of capabilities for figuring out complex word composition in a sentence. A sarcastic text is called to be an element of sequence for text or combination of words. RNN is used for modeling temporal text signals. These temporal text signals include temporal memory components. These components help in storing the temporal information directly. This also helps in aggregating the whole sequence into temporal context which itself is free of size constraints. There are many implementations of RNN, but among all LSTM is very easy to use and train also. They do not undergo any vanishing or exploding gradients while developing back propagation over time. LSTM has one advantage of recognizing long distance temporal dependencies. Furthermore, as they achieve temporal text modeling in excess of input features, advanced level of modeling can differentiate the aspects of semantic deviation within the input.

With the help of convolutional filters, CNN's help in capturing temporal text. CNN's help in decreasing the frequency variation. A convolutional filter is connected with subsets of features that help in sharing the input across all the members. Research has also shown that CNN [6] can directly access temporal text patterns for shorter texts. For longer texts, text patterns may span across 15–20 words.

Limitation of CNN is static convolutional filter width. CNN is not appropriate for diverse lengths of temporal text designs and is not constant resolution for dependencies correctly. In CNN, gaining size of optimal filter is very costly and is corpus dependent. While in LSTM, it works free of any window size. By providing better features LSTM performance can be improved. CNN's abilities can be improved for decreasing the frequency variation and map input features.

DNN is preferable for mapping features into a further divisible cosmos. At the top of LSTM network, fully DNN is connected which helps in getting best taxonomy by mapping among hidden and output variables through renovating features into an output space. Some detail [15] for given work is discussed as under.

1. Input layer

Firstly, the tweet that is taken as an input consists of n words. Then that input tweet is changed into a vector by swapping each word with its index related to its dictionary $s \in < 1 \times n$. For solving different inputs of different lengths, the tweet vector is amplified. Amplified tweet is then converted into matrix $s \in < 1 \times 1$, where 1 is the maximum length of tweets in the given amount. The input vector is served with an inserting layer that translates each word of the input into a distributional vector of dimension D. Therefore, till the end input tweet matrix is renewed to $s \in < 1 \times D$.

2. Convolutional network

The goal of a convolution network is to decrease frequency discrepancy over and done with convolutional filters and take out perceptive word series as a compound article map for the LSTM layer. Each component is calculated as keep an eye on this formula:

$$c_i = (s * k)_i = \sum_{k,j} (S_{:,i-m+1:i} \otimes F)_{kj} \tag{1}$$

Convolution filter, that is having the identical dimension D of the input matrix, that slips along the column element of the input matrix, executing an section wise creation among a column shares and a filter matrix k constructing a vector module ci and summed for generating a feature map $c \in$ R1(|s|m + 1).

3. LSTM

RNN has established the authority in semantic modeling which is capable of joining response cycles in the network structural design. RNN networks comprises a temporal memory module that permits the model for supplying the temporal contextual info straightly in the model [12].

- Deep neural network layer

The amount produced by the LSTM layer is voted for by the completely associated DNN layer that yields an advanced order feature regular based on the LSTM output, which is simply independent from anticipated number of programs. Lastly, a softmax layer is included on top of the DNN layer. Preparation of the network is achieved by reducing the binary cross-entropy fault. For parameter optimization, ADAM is to be used with a 0.001 learning rate set.

Trends in Sarcasm Detection

Two of these trends [21] for sarcasm detection have been gaining its importance widely. These trends are discussed below in detail (Fig. 6).

1. Pattern discovery

Learning sarcastic patterns [19] is considered as an initial fashion in discovery of sarcasm. Numerous tactics were shared for digging out configurations that are analytical for sarcasm. Such patterns might be recycled as countryside for either statistical classifiers or as procedures in a rule-based classifier. Amongst these words, classify an enormous set of applicant patterns. The patterns that happen discriminatively in either class are nominated. Some researchers have postulated that sarcasm happens because of divergence among positive and negative circumstances of the phrases. For determining a reference book for such verbs and phrases, they suggest an iterative procedure.

The procedure adds to the gradient of known verbs and phrases. Many researchers have modified this procedure by eradicating subsumption and confirm that it has added a lot of value. First, the set of meanness and sarcasm patterns are generated via Amazon Mechanical Turk. They train a high accurate sarcastic post-classifier which is monitored by an extraordinary exactness non-sarcastic post-classifier. These two classifiers are then recycled for generating a huge categorized dataset from a bootstrapped set of forms.

2. Requirement of context for detecting sarcasm

Use of context [22] is the recent trend for detecting sarcasm. The term "context" denotes any related information that is out there in the text which is to be projected and that too is far from some one's common knowledge. Textual unit is also called as target text. The context can be merged in different ways. Either it can be used as complementary data or can be used as complementary info for the source policy of the data. Researchers have described a mark study for first highlighting the need of context for detecting sarcasm. Sarcasm labels are being used for such studies. The researchers have also presented a transition matrix which helps in telling how many times users have changed their labels after the context is presented to them.

Using this context for detecting sarcasm, many approaches have been looked forward to incorporating the things. Three types have been reported for this context in detecting sarcasm [20] (Fig. 7).

a) Author-specific context brings up the literal footmark of the researcher to the target text. According to researchers, a tweet can be sarcastic if it has words of divergent emotions in it or because there can be sentiment that compares with the user's Chronological sentiment. Chronological tweets are also considered as the context. These historical sentiments can be used for detecting whether the user is probable to be sarcastic or not in the given tweet. Various features of such classifiers are used in context. These features deal with numerous dimen-

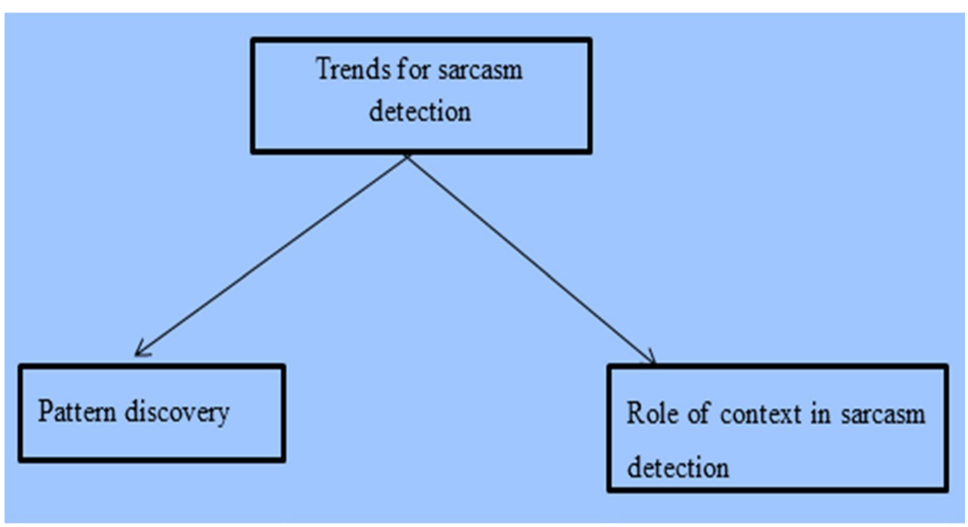


Fig. 6 Trends for sarcasm detection

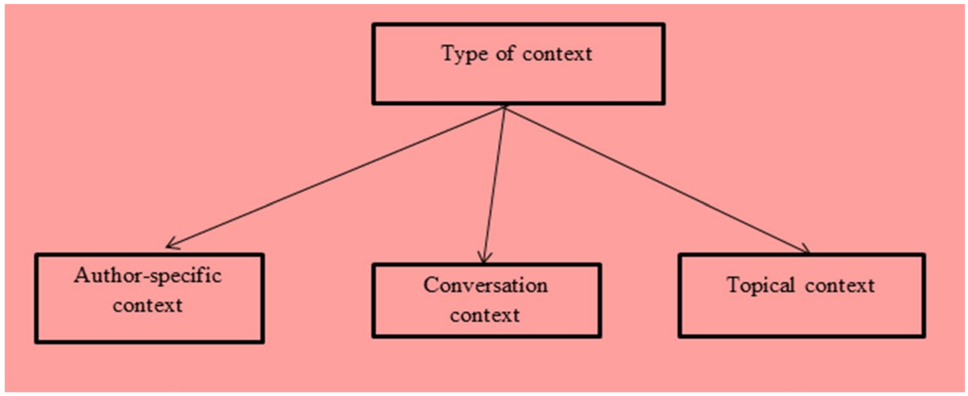


Fig. 7 Type of context

sions. Some features that they use are user's awareness with twitter, awareness with language and awareness with sarcasm.

b) Conversation context states to text in the exchange of which the objective text is a part of it. This unites the dissertation erection of a conversation. Some researchers have seized conversational context by means of pairwise features, among the target and previous tweet. It also customized the spectator's features.

c) The topical context monitors the perception that several themes are probable for suggesting sarcasm more frequently than others. Some researchers use topical context and find it better as compared with others. For forecasting sarcasm in a tweet, downloading of tweets is to be done, which contain a hash tag.

Sarcasm Detection: Issues

Current scenarios in various techniques are using detection for sarcasm upshot in recurring problems which are controlled in different ways by different former works. There are three main issues [23].

- The first issue is related to supervision of hashtags, data imbalance and inter-annotator settlements.
- The second issue is related to the precise kind of features that is best suited for classification.
- The third issue is related to the context of classification techniques.
- Some other issues include (Fig. 8):

1. Issues with data

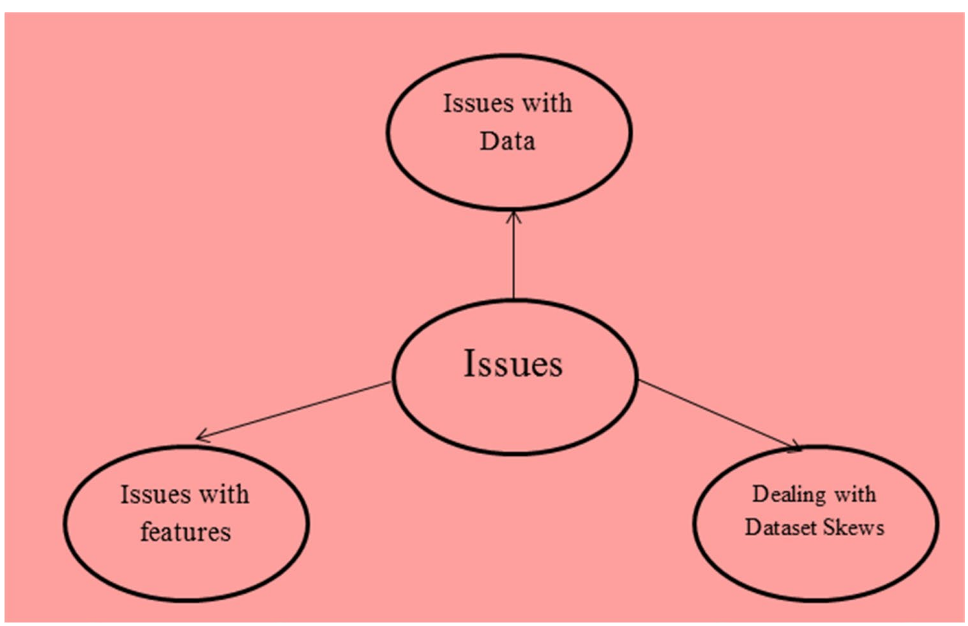


Fig. 8 Issues for sarcasm detection

While this hash tag-based classification provides large-scale supervision, the value of the data set has turned into the doubtful state. This is chiefly correct in situation of use of #not for indicating two-faced emotion.

2. Issues with features

Many researchers have this question whether the sentiment should be used as a feature for sarcasm detection or not. The inspiration ahead for detecting sarcasm is repeatedly keen as sarcastic judgments confusing a sentiment classifier. Moreover, various approaches use sentiment as an input for sarcasm classifiers in detecting sarcasm. These approaches use surface polarity.

Reported Work

This section of the article deals with the introduction to the work of various researchers to analyze sentiments through various machine learning and deep learning algorithms.

Prasad et al. [24] in their work encountered the problems associated with data from social media. Their aim was to overcome hurdles like short text nature, usage of short forms, continuous streaming, slangs and ever growing sarcasm in posts and messages. Data mining can be easily misled by the sarcastic tone which leads to wrong classification, hence reducing the performance. They used various algorithms like Gradient Boosting, Decision Trees, Random Forest, Logistic Regression and Naive Bayes to detect sarcasm in tweets using Twitter Streaming API. They introduced an emoji and slang dictionary in their work which is novel. They employed various preprocessing techniques and divided their preprocessing procedure into three steps: Identification of Hashtag and its replacement, mapping of Slang dictionary and mapping of emoji dictionary. The dataset considered contained 2000 tweets. Among the feature set 22 features were selected for the purpose of classification. Gradient Boosting gave the best results among all the classifiers used. It gave an accuracy of 81.82%. Their study proved that use of emoji and slang dictionary helped to improve the performance of the model, even by 8%.

Dharmavarapu et al. [25] in their work changed a traditional usage of logistic regression to Naive Bayes and AdaBoost algorithms for the purpose of classification. Logistic regression based models have the incapability of detecting continuous variables. That is why they came up with the new method which combined Naive Bayes with AdaBoost. AdaBoost was helpful in making weak statements strong by considering the subset iteratively. In their work, they achieved an accuracy of approximately 80%.

Yunitasari et al. [26] designed a model for sentiment analysis via sarcasm in Indonesian tweets. They used global stream data of twitter using geolocation filters and some hashtag keywords. A data of 3000 tweets was considered. They considered unigram and 4 Boazizi for the purpose of feature selection. They employed Random Forest for the purpose of classification of sarcasm. For sentiment analysis, they used TF-IDF as a feature selector and Naive Bayes as a classifier. Their method helped to improve accuracy by 5.49%, hence proving that it is necessary to remove sarcasm for sentiment analysis. They achieved an accuracy of 80.4%, precision as 83.2%, and recall as 91.3%.

A revisit to the notion of modeling contrast, was implemented by Tay et al. [27], in respect with sarcasm. They proposed a neural network based on attention. The novelty of the proposed work lies in the fact that the model checked in-between rather than across which enabled it to model contrast explicitly. In their study they used six benchmark datasets which were gathered from sources like Reddit, Twitter and Internet Argument Corpus, two from each source. They compared the performance of their model with the following algorithms: NBOW, CNN, LSTM, ATT-LSTM, GRNN and CNN-LSTM-DNN. They proposed two models, namely, MIARN and SIARN for the purpose of multidimensional and single-dimensional intra-attention, respectively. The results obtained showed that the proposed models outperformed for all the six benchmarks datasets. Their models showed an improvement of 2–5% on datasets with shorter texts like tweets and reddits as compared to the best baselines. In fact, datasets of debates showed an improvement of 8–10% over the baseline. Also, it can be inferred from the results that MIARN showed better results as compared to SIARN.

Two methodologies for political sarcasm detection were adopted, by Wandra et al. [28], namely: Machine Learning Approach—they used two supervised learning classifiers like Logistic Regression and Support Vector Machines and Lexicon-based approach. Three feature selectors were used: lexical features, hyperbole, pragmatic features. They did manual scraping of the tweets. They used a data of 7000 words. They obtained presentable results: precision as 0.866 for logistic regression and 0.928 for support vector machine.

Rajeshwar et al. [29] employed Multinomial Naive Bayes for sarcasm detection in tweets whereas, detected sarcasm types with the help of Support Vector Machines. They effectively handled the noise present in the tweet data. They used data available on twitter. They used Count-Vectorizer for feature selection and TF-IDF to calculate the importance of each word. They used SVM for classification of tweets into four classes: Brooding, Depression, Polite and Maniac. They achieved the following results: true positive rate as 0.92 and false positive as 0.9.

An exploration of the characteristics of Chinese and English sarcastic tweets was done by Liu et al. [30]. They also introduced a feature set for detection of sarcasm present in social media data. They also proposed a multi-strategy ensemble learning approach (MSELA) to address the problem of imbalance. For English language, three features were selected-punctuation symbols, lexical features, and syntactic features. For Chinese language, they used the described three features in addition to the following: rhetorical features, construction, semantic imbalance rate, recurring sequences, and homophony. For English, they gathered Amazon dataset, twitter dataset and News articles, whereas Chinese data was collected from Tencent Weibo, Sina Weibo, and Netease BBS. Mallet Tool6 was used to implement Maximum Entropy and Naive Bayes, while SVM was implemented by SVM-light tool7. They compared results of various multi-strategy algorithms. Among all, MSELA outperformed for all the datasets considered.

Multi-Rule Based Ensemble Feature Selection was used by Sundararajan et al. [31] for detection of type of sarcasm. The novelty of the work is based on the fact they were diverted towards detecting the harshness in the tone. They identified optimal features using ensemble learning. After the detection of sarcastic features, a rule based approach was used to determine the type of sarcasm. They divided the sarcasm into four classes: rude, raging, polite, and deadpan. They experimented using Twitter dataset and obtained following results: for ensemble feature selection algorithm accuracy was 92.7% and for rule-based approach where sarcasm type was detected following accuracies were obtained:

- polite: 95.98%
- rude: 96.20%
- raging: 99.79%
- deadpan: 86.61%

Comparative Analysis among Various Machine Learning Techniques for Sarcasm Detection

Various machine learning classification [32] has been used in the area of sarcasm detection for social media tweets. The following table shows the few of the classification techniques that have been used for the detection and outcomes in the form accuracy, precision, recall and *f*-score (Table 2).

Conclusion

In this paper, new schemes for recognition of sarcasm in tweets are being studied. The schemes are constructed on a multiple method, comprising concept level knowledge expansion, sentiment analysis and using various machine learning algorithms for classification. For the classification process, sentiment scores for each word are assigned. The concept of using common sense for finding the unknown sentiments is also being accessible in this paper. Various trends on sarcasm detection are discussed in this paper. N-gram is being used by the SVM classifier. However, in this paper, classification algorithms and various suggested improvements, which directly contribute to the improvement of accuracy, are explained in detail. In fact for humans also, it is a tedious task to identify sarcasm in tweets. The credit for this inability of humans to detect sarcasm, because sarcasm depends on common sense knowledge associated with the context of tweets. It makes automatic identification of sarcasm difficult. About 80% accuracy could be considered for satisfying results. Sarcasm is a kind of sentiment where people express their negative feelings using positive or strengthened positive arguments in the manuscript. While talking, people frequently use substantial tonal stress and confident gestural signs like continuing of the eyes, hand movement, etc. to disclose irony. There is a lot of work that has been done in the field of sarcasm detection for social media databases especially for twitter tweets. But still, there is scope to improve accuracy for sarcasm detection using different learning techniques including machine learning and deep learning. Also, the datasets are available in different languages. From the related work and comparative analysis section, it is clear that advanced machine learning and deep learning techniques have led to great results. It can also be inferred from the results discussed that sarcasm detection leads to great improvement in sentiment analysis model performance.

Table 2 Different ML techniques for sarcasm detection

Name of authors	Task	Dataset	Feature extraction	Classification used	Results
A. Ghosh et al. [33]	To find the effectiveness of the model	Retrieved from twitter api	Sarcasm as a wit, sarcasm as a whimper, sarcasm as an avoidance	Sentiment related features, punctuation related features, lexical and syntactic features, and pattern related features	Accuracy—90.5%, precision—89.6%, recall—76.4%, *f*-score—81.7%
S. M. Mohammad [7]	To find the accuracy of proposed model	Online review sites, media sites, and micro blogging sites	Term presence, term frequency, term frequency—inverse document frequency	Naive Bayes classifier, maximum entropy, SVM, 10 cross validation	Accuracy—50%
M. Zhang et al. [34]	Identify sarcasm	Sarcasm labeled corpus and features based on punctuations such as “!” And “?	Bag-of-words	N-gram, boosting rules and rejection rules	*F*-score baseline—0.012, *f*-score their method—0.053
A. C. Georgios [2]	Relate comments with ratings	Twitter and amazon	Emoticons, heavy punctuation marks, quotation marks, positive interjections	Semi-automatic procedure	Presence of irony does not affect readers
A. Cambero [22]	To find the better classifier among the used	Twitter streaming api	Word tokenization, pos tagging, stemming, lemmatization	Random forest, decision tree, logistic regression, naïve Bayes, gradient boost	Gradient boost provides highest accuracy percent
O. Bark et al. [8]	To find, the better classifier	News article dataset	Emotion, sentiment, bag of sorted emotion, sentinet,	Regression, SVM, Naïve Bayes, Bagging, Adaboost, random forest, extratree, gradient boosting	*F*-score = 0.724
Y. Tay et al. [15]	Find feature that gives a better result	Original bilingual corpus	Lexical, pragmatic, prosodic, syntactic, idiosyncratic	N—grams, SVM	Syntactic category *f*-measure = 0.847
Yessi Yunitasari et al. [35]	sarcasm detection on sentiment analysis for Indonesian languages	Indonesian Language Tweets	1. The feature extraction of sarcasm detection uses unigram 2. lexical and syntactic features	Naïve Bayes	Accuracy = 80.4% Precision = 83.2% Recall = 91.3%

Compliance with Ethical Standards

Conflict of Interest The authors declare that they do not have any conflict of interests that influence the work reported in this paper.

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