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Mathematical Analysis of Different Learning Approaches on User Behavior and Contextual Evaluation for Sarcasm Prediction

L.K. Ahire[1], S. D. Babar[2], P. N. Mahalle[3]
[1]Dept of Computer Engineering,
Smt. Kashibai Navale College of Engineering, Savitribai Phule Pune University,
Pune, India
Email: lomesh.ahire@gmail.com
[2]Dept of Computer Engg., Sinhagad Institute of Technology, Lonavala, Pune
Email: sdbabar@sinhgad.edu
[3]Dept. of Artificial Intelligence and Data Science,
Vishwakarma Institute of Information Technology, Pune, India
aalborg.pnm@gmail.com

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Abstract:

A large number of people have been using social media platforms extensively to communicate their thoughts and feelings in the recent era of social networking. Both the user base and data volume on social networks are growing quickly every day. Any time an event or activity occurs nearby, nearby individuals express their thoughts and reactions on social media. When a new product is introduced, users on social media platforms also comment on it. Some people express their views or feelings using informal or complex language which makes it difficult to understand for another user. It is challenging to ascertain the true thoughts because different people express their opinions in complex ways. In this study, the various factors that affect these feelings are briefly discussed. In order to identify sarcasm on Twitter, a generic technique is also necessary in addition to the tweet's content. The proposed approach uses contents of tweet in association with important aspects like user behavior and context of tweet. By users' behavior we can identify its influence on other users and context is required to identify user behavior while detecting sarcasm. Proposed approach uses user behavior pattern and personality features along with contextual data. This all information and the already known sarcasm prediction mechanism will help us to set up the generic approach to detect sarcasm on Twitter.

Keywords: Social Networking, Sentiments, Context, Twitter, Sarcasm.

1. Introduction

Expressing ourselves on social media, especially Twitter, has become quite common. With around 340 million tweets sent daily, the brief structure limiting messages to 140 characters has led to widespread use of symbolic characters, emoticons, emojis, and abbreviations like "LOL." Recent studies note a significant rise in the insertion of interjections, particularly when expressing views, reflecting elements of human psychology and behavior. While psychological research has extensively investigated these behaviors, the design framework for identifying sarcasm on social platforms has not sufficiently incorporated this knowledge. This implies an opportunity for developing more effective sarcasm detection methods by combining insights from psychological studies into the algorithms designed for the nuances of social media interaction.

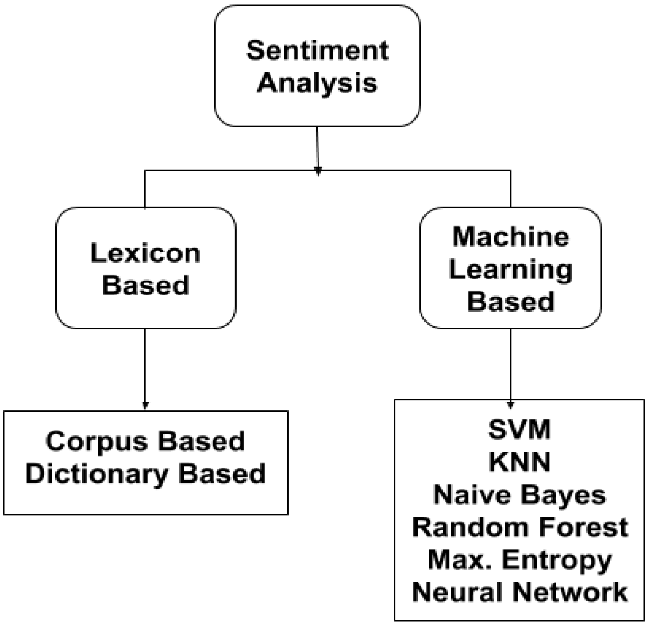

Figure 1 Sentiment Analysis Approaches

The importance of social media as a platform for information exchange has significantly increased due to people's tendency to seek [3] out opinions in order to make wise decisions. The amount of information on the Web has suddenly increased as a result of this trend. For the purpose of separating the pertinent knowledge, the enormous volume of this information must be processed technically. The widely used popular technique for this is sentiment analysis. It is described as a computational study that extracts opinions about the object of interest from the available content. Explicit and syntactically valid content can be captured using current techniques for sentiment analysis pretty successfully. When using informal data, sentiment analysis algorithms have, however, been discovered to have several limitations. The poor and ambiguous language used by internet users has made it necessary to focus on enhancing the present sentiment analysis algorithms.

This paper's primary contributions are

1. To identify the motivations behind sarcasm utilized by users on social media platforms.
2. The user's behavior and how it affects sarcasm detection precision.
3. To research contextual cues that aid in the recognition of sarcasm.

2. Related Work

The study of sarcasm detection in sentiment analysis has grown to be fascinating. The majority of the research has focused on pragmatic, hyperbolic, and lexicon-based methods. According to academics, the following is the fundamental model for sarcasm detection on Twitter. The whole procedure consists of the subsequent steps [2]. Bharti, S. K., Vachha, B., Pradhan, R. K., Babu, K. S., & Jena, S. K. [7] a framework based on Hadoop that effectively detects sarcastic sentiment in real-time tweets by processing them using a series of algorithms was proposed. Authors exploited syntactic elements, n-grams, and bi-grams found in speech to detect sarcasm effectively. Authors employed Hadoop and the Map-Reduce function, a sarcasm detection engine, POS tagging, and parsing for implementation. This method [4] uses the Apache Flume and Hive frameworks to collect and process real-time tweets. This method has a 96% tweeter sarcasm detection accuracy.

3. Issue in Current System

Finding the precise sentiment, attitude, or opinion underlying a tweet is the focus of sentiment analysis. Humans are able to [5] understand a sentence's actual meaning quite readily. However, a machine cannot determine the precise orientation [6] of a contradictory statement. The concerns listed below were discovered during a literature review.

1. Language fluidity: English is one of the most widely spoken languages today. Social media now supports more user local languages like hindi, marathi, and kannada, among others, and has become incredibly technologically advanced [8]. In order to make these intelligent systems more effective, these languages should be included.
2. Overuse of emoticons and emojis: Since emojis were accessible in chat platforms, their use has significantly increased. It [9] is frequently used by people to communicate their feelings instead of typing lengthy sentences. Because there may be some confusion among some users as to the precise meaning of a specific emoticon or emoji. The majority of current frameworks for detecting sarcasm concentrate on deciphering the meaning of a text [10]. These emoticons' feature is not integrated into modern platforms. These emoticons have a strong tendency to change a sentence's overall polarity. [11, 12].

4. Proposed Approach

To evaluate whether a particular comment is sarcastic or not, the proposed solution primarily employs user behavior, personality factors, and contextual features. This information is then employed with any established sarcasm detection algorithm. Our goal is to correctly identify sarcasm in a tweet given a tweet (t) for user (u). We'll try to take a step further and try to extract certain features from a tweet that may be used to train patterns [13], [14]. Additionally, we'll concentrate on examining specific user behavior patterns and psychological characteristics that are frequently observed in users who publish thoughts on social media [15, 16]. When sarcasm is being detected on Twitter, there are two types of tweets that are observed. The first kind of tweet is only a single line with the hashtag "#sarcasm," and the second kind is just tweets that are separated by conjunctions (such as "and," "or," "but," "if," and "while").

1. U are too glorious!!!! #sarcasm

2. You look too smart and what a brain you have ;)

Since the user in the first example used the #sarcasm hashtag to indicate sarcasm directly, this sort of sarcasm is simple to identify and does not require the extraction of any special patterns or features. #sarcasm is sufficient to recognize the irony in this tweet.

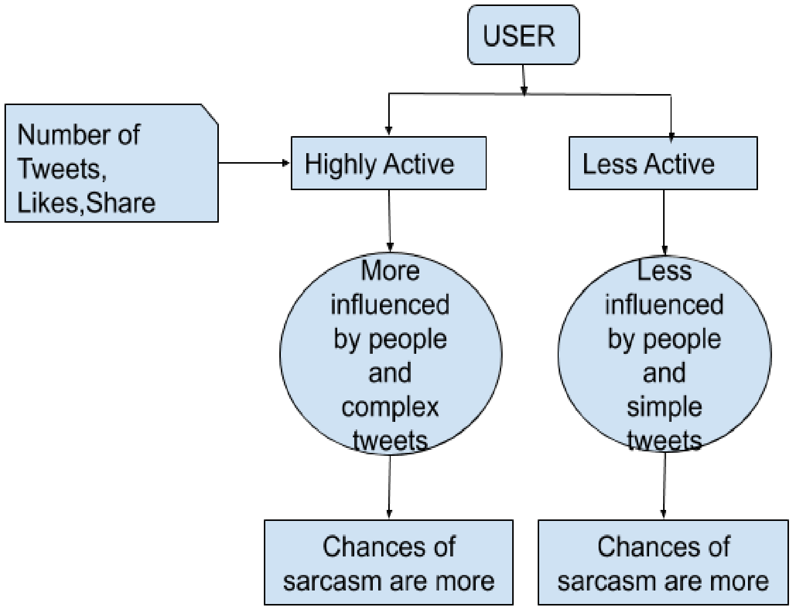

Figure 2 Sarcasm Detection User Behavior features

4.1 *User Behavior Pattern*

The proposed method will concentrate on identifying user behavior and personality features by examining user tweet patterns and grouping these individuals according to their behavior. This classification will enable us to anticipate a person's future behavior in light of the relevant circumstances. As seen in Figure 2, an individual's behavior on a social media network typically varies with their experience with that platform. People who are less familiar with a particular social platform tend to communicate their ideas in a direct and plain manner rather than using sarcasm in a sentence, according to a survey on platform familiarity.

Algorithm for User Behavior and Sarcasm Prediction:

Step 1: Define Notation and Data: Input Data from Dataset

Step 2: RNN Model:

- Initialization:
  - Set hyperparameters: Learning rate η, number of hidden units H, number of layers L, etc.
  - Initialize RNN parameters: Wih, Whh, bh, Who, bo.
- Forward Pass:

  For each time step t:

$$ht \; = tanh\, tanh\, (Wihxt \; + \; Whhht - 1 \; + \; bh) \qquad (1)$$

$$ot \; = \; sigmoid(Whoht \; + \; bo) \qquad (2)$$

- Loss Calculation:
- Compute the binary cross-entropy loss:

$$L = -\frac{1}{N}\Sigma i = 1N\ \Sigma t = 1T\ [yi, t\ log\ log\ (oi, t)\ + (1 - yi, t)\ log\ log\ (1 - oi, t)\ ] \quad (3)$$

- Backward Pass (Gradient Descent):
- Compute gradients using back propagation.
- Update parameters using gradient descent:

$$\theta \leftarrow \theta - \eta\frac{\partial\theta}{\partial L} \quad (4)$$

Step 3: Gradient Boosting:

- Initialize Ensemble:
- Set the number of boosting rounds M.

$$Initialize\ F0(x) = mean(Y) \quad (5)$$

For m = 1 to M:

Compute the residuals:

$$rim = yi - Fm - 1(xi) \quad (6)$$

Fit a weak learner (e.g., decision tree) to the residuals:

$$hm(x) = argminh\ \Sigma i = \frac{1}{N}L\big(yi, Fm - 1(xi) + h(xi)\big) \quad (7)$$

Step 4: Update the ensemble model:

$$Fm(x) = Fm - 1(x) + \alpha mhm(x) \quad (8)$$

Where,

- αm is the learning rate.

Step 5: Final Prediction:

- The final prediction is given by $FM(x)$.

4.2 *Contextual Features*

Lack of context knowledge is a major obstacle in sarcastic tweet detection. Knowing the context in which sarcasm is employed is essential for understanding it. Thus, context is essential to sentiment analysis and cannot be disregarded when creating an effective sarcasm-detection engine. This strategy has only been used by a small number of scholars, hence one of the main goals of this publication is to shed some light on it. Here are some instances of contexts from Twitter:

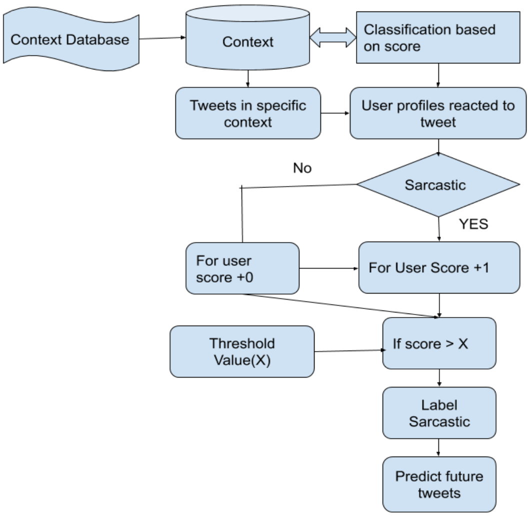

Figure 3 Sarcasm Detection using Contextual Evaluation

5. Result and Discussion

The figure 3 shows the results obtained when applied the different learning approaches using user behavior features and figure 4 shows the Evaluation of results when applied the different learning approaches using user contextual features.

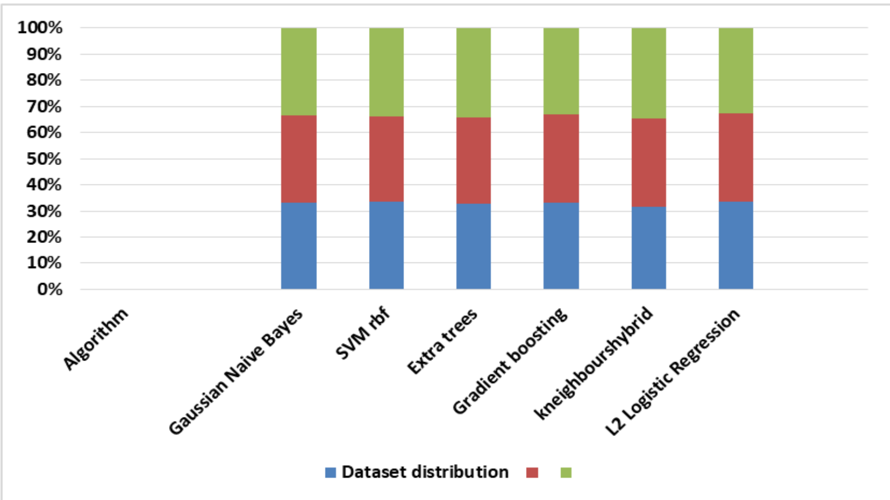

Figure 3 User behavior approach evaluation using different learning approaches

This figure demonstrates the assessment of various user behavior methods through different learning techniques. A comparative examination of these approaches, such as machine learning and deep learning models, offers understandings into their proficiency in capturing and anticipating user behavior patterns. This visual helps in choosing premier strategies for analyzing and improving user behavior.

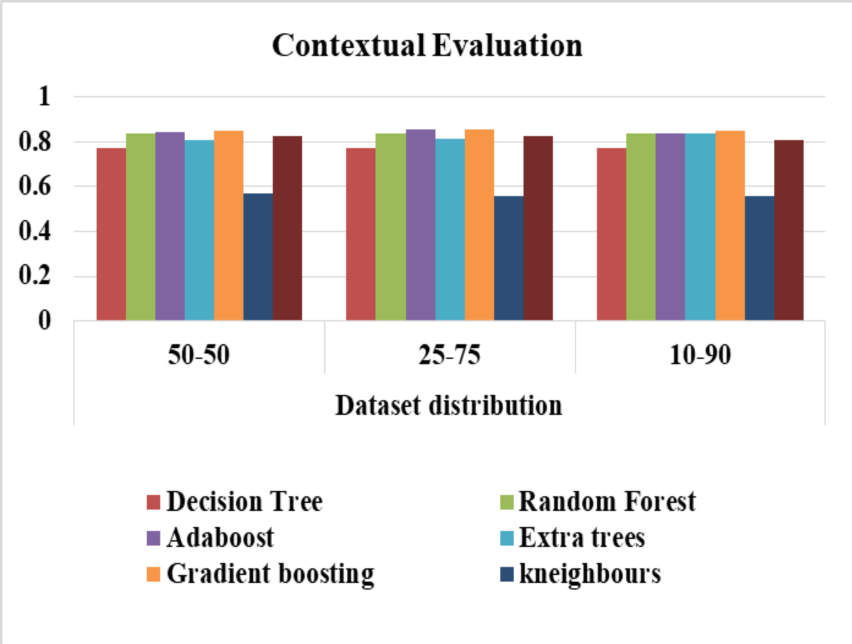

Figure 4 Contextual Evaluation using different learning Approaches

6. Conclusion

In the area of sentiment analysis, there is still a lot of study being done. Language patterns have so far been used to identify sarcasm, but we still need to take into account the underlying cause. Researchers are working on a variety of solutions, but we need to develop a general strategy that would depend on the domain. As a result, we have developed a user behavioral method that will aid in obtaining results that are broadly applicable to Twitter. We can forecast future behaviors of users once we have identified their personality types and patterns of conduct. Research using a variety of behavior modeling techniques that consider the user's mood and examine their previous tweets to determine the likelihood that sarcasm will be used in the present message. Our suggested system would simplify existing methods and contribute to a reduction in the stress placed on domain-based frameworks. To improve the precision of sarcasm recognition in tweets, user behavioral approaches can be added to currently available sarcasm-detection technology.

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