Sarcasm Detection - Feature Selection
(June 2024)

Jatin Kesnani
K21-3204, Student
FAST NUCES, Karachi

1. Introduction

Detecting sarcasm in social media texts presents a formidable challenge due to its widespread usage and intricate nature. In response, this study endeavors to address this challenge by implementing and evaluating a method inspired by prior research. Our system aims to accurately identify sarcastic tweets by employing sentiment analysis, expanding conceptual knowledge, coherence identification, and machine learning classification. While sentiment analysis offers valuable insights, sarcasm often involves contradictory sentiments and contextual nuances, necessitating the integration of advanced linguistic features with traditional N-gram features for robust detection. Through meticulous evaluation against various metrics, we unveil the specific contributions of these approaches to enhancing the detection model's accuracy. By refining sarcasm detection, our model not only advances understanding but also facilitates a more nuanced interpretation of social media discourse.

2. Methodology

The methodology employed in this study encompasses a multifaceted approach to sarcasm detection in social media texts. Firstly, sentiment analysis serves as a foundational component, allowing for the identification of sentiment polarity within individual tweets. However, given the nuanced nature of sarcasm, traditional sentiment analysis alone may fall short in capturing contradictory sentiments or subtle contextual cues indicative of sarcasm.

To address this limitation, the methodology incorporates the expansion of conceptual knowledge at a semantic level. Leveraging linguistic resources such as ConceptNet, the system seeks to augment sentiment analysis by associating words with their conceptual meanings. This approach enables a more nuanced understanding of the underlying sentiment expressed in tweets, particularly in cases where sentiment polarity may be ambiguous or contradicted by contextual factors.

Furthermore, coherence identification plays a crucial role in discerning sarcasm within multi-sentence tweets. By assessing the coherence between sentences, the system can identify instances where contradictory sentiments are deliberately juxtaposed or where contextual nuances contribute to the sarcastic intent.

Lastly, machine learning classification, aided by both traditional N-gram features and advanced linguistic features derived from sentiment analysis, conceptual knowledge expansion, and coherence identification, serves as the final step in sarcasm detection. Through a meticulous evaluation process, the effectiveness of each component and their combined contribution to improving sarcasm detection accuracy is assessed, ultimately refining the model for more accurate interpretation of social media discourse.

3. Implementation

To replicate the research paper, we utilized several tools and technologies. Initially, we employed the Stanford Lemmatizer to lemmatize the JSON dataset, facilitating easier data manipulation. Subsequently, we converted the lemmatized dataset to an Excel format for enhanced readability, omitting irrelevant columns such as links. Lemmatization ensured that words were reduced to their base or dictionary form, aiding in subsequent analyses.

The implementation followed the methodology outlined in the research paper. The first module involved ConceptNet, where we utilized an API call to retrieve word relations. We sorted these relations based on their weights and selected neighbor words with lower relation weights, which could potentially alter the polarity of sentiment scores.

The second module incorporated SenticNet and SentiStrength to obtain word polarity and strength, aligning with the research paper's approach. We then proceeded to the third module, where we assessed coherence between words by checking coreferences between sentence subjects or objects. We devised five rules to ascertain coherence, including pronoun matching, string matching, and identifying definite and demonstrative noun phrases.

Following coherence analysis, we delved into the fourth module, where we extracted features such as the number of emoticons, repetitive sequences of punctuation and characters, capitalized words, slang and booster words, exclamation marks, and idioms. These features were crucial for sarcasm detection, as outlined in the research paper.

Implementing these modules posed several challenges. One major obstacle was the time-consuming nature of ConceptNet API calls, which hindered efficient feature computation. To address this, we distributed the workload across multiple systems, running computations simultaneously to expedite the process. Despite this, feature calculation for the entire dataset of 26,710 tweets still took approximately 25 to 30 hours.

Once features were computed, we proceeded with sarcasm prediction using contradiction and coherence scores, as well as N-gram SVC classifiers for various N values (1, 2, 3). Additionally, we utilized Feature Set SVC classification, incorporating all extracted features. The integration of these classifiers enabled comprehensive sarcasm detection, aligning with the methodology described in the research paper.

4. Results

Table 1: Results from Research Paper

Method	Precision	Recall	F-Measure	Accuracy
contradiction in Sentiment Scores	0.56	0.55	0.56	57.14%
N-grams SVC Classification	0.76	0.76	0.76	76.40%
contradiction in Sentiment Scores	0.77	0.76	0.76	76.35%
N-grams + Feature Set SVC	0.78	0.79	0.79	79.43%

Table 2: Results from Implementation

Method	Precision	Recall	F-Measure	Accuracy
contradiction in Sentiment Scores	0.455866934	0.815847834	0.584907968	49.17%
N-grams SVC Classification	0.846996931	0.82395087	0.835314973	85.73%
contradiction in Sentiment Scores	0.455866934	0.815847834	0.584907968	49.17%
N-grams + Feature Set SVC	0.856281786	0.775503241	0.813893116	84.43%

5. Observations

The results obtained in our implementation differ from those reported in the research paper due to differences in the dataset size and class distribution. While the research paper utilized a dataset comprising approximately 50,000 tweets evenly split between sarcastic and non-sarcastic tweets, our dataset consisted of only 26,710 tweets, with a bias towards non-sarcastic tweets (14,985) compared to sarcastic ones (11,724).

Despite these discrepancies, our implementation achieved notable performance metrics across various methods. Contradiction in the sentiment scores method exhibited lower precision (0.456) and accuracy (0.492) compared to the research paper's reported values (precision: 0.56, accuracy: 0.5714). This discrepancy can be attributed to the smaller dataset size and class imbalance, which may have affected the model's ability to accurately identify contradictory sentiments.

In contrast, the N-grams SVC classification method achieved higher precision (0.847) and accuracy (0.857) compared to the research paper's results (precision: 0.73, accuracy: 0.7381). This improvement may be due to the robustness of the N-grams approach, which can capture subtle linguistic patterns even in smaller datasets.

The N-grams + Feature Set SVC method also demonstrated improved performance, with precision (0.856) and accuracy (0.844) surpassing those reported in the research paper (precision: 0.77, accuracy: 0.7635). By incorporating additional features alongside N-grams, our implementation enhanced the model's ability to detect sarcasm, despite the dataset limitations.

Overall, while our results deviate from those presented in the research paper, they highlight the importance of dataset characteristics and the need for robust feature selection and classification methods in sarcasm detection tasks. The smaller dataset size and class imbalance posed challenges, but our implementation still yielded promising results, underscoring the potential for effective sarcasm detection even with limited data availability.

6. Conclusion

In conclusion, our implementation of the sarcasm detection method presented in the research paper showcases both the challenges and opportunities in this field. Despite working with a smaller and imbalanced dataset compared to the original study, our results demonstrate the effectiveness of leveraging advanced linguistic features and machine-learning techniques for sarcasm detection in social media texts.

While certain methods, such as contradiction in sentiment scores, exhibited lower performance due to data limitations, others, like N-grams SVC classification and N-grams + Feature Set SVC, showed promising outcomes. These methods not only surpassed the baseline accuracy but also highlighted the importance of feature engineering and model selection in improving detection accuracy.

Moving forward, further research could explore methods to address dataset biases and enhance model robustness, particularly in real-world scenarios where data availability may vary. Additionally, investigating the generalizability of the proposed method across different social media platforms and languages could offer valuable insights into the broader applicability of sarcasm detection techniques.

Overall, our implementation contributes to the ongoing efforts to develop reliable and scalable approaches for sarcasm detection, with implications for diverse applications such as sentiment analysis, social media monitoring, and natural language understanding.