Sarcasm and Irony Detection in Social Media

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Sarcasm and irony represent intricate linguistic forms in social media communication, demanding nuanced comprehension of context and tone.

sarcasm irony social media deep learning attention mechanism

1. Introduction

Recently, the rapid expansion of social media platforms has revolutionized human communication, enabling people to interact and share their thoughts globally [1]. While this digital revolution has brought unprecedented connectivity, it has also introduced unique challenges to understanding the true intent and emotions underlying the concise and often informal online messages [2]. These challenges are significantly pronounced when deciphering the intricate emotional nuances and subtle intentions woven into text-based content.

At the heart of this complex dynamic lies the enigmatic interplay of two pervasive linguistic phenomena—sarcasm and irony. These forms of expression involve the skillful deployment of language to convey meanings that often diverge from the surface interpretation [3]. The contextual cues that help unravel such linguistic intricacies are more easily accessible in face-to-face interactions, where visual cues like facial expressions and vocal modulations aid in grasping the intended message [4]. However, digital communication hinges entirely on the written word, necessitating a highly sophisticated approach to unraveling the multifaceted layers of meaning concealed within written expressions of sarcasm and irony on social media platforms [5].

2. Understanding Sarcasm and Irony in Social Media

Sarcasm and irony, intricate linguistic constructs where the intended meaning contradicts the literal interpretation, are commonly encountered in social media; hoaxes and manipulations, involving the dissemination and distortion of false information, can blur the lines between genuine expression and deliberate misrepresentation, posing a challenge in discerning their true intent [6].

This interconnectedness of sarcasm, irony, and manipulation in molding narratives and influencing public perception online emphasizes the significance of critical thinking and contextual comprehension, underlining the need for thorough fact-checking and media literacy when engaging with social media content [7].

Their reliance on context and tone, coupled with the absence of non-verbal cues, further complicates the task of deciphering the underlying message, necessitating the exploration of innovative approaches in identifying and understanding these linguistic phenomena within digital communication [8].

Early studies such as [9] focused on linguistic patterns and syntactic inconsistencies, with some employing lexical and sentiment-based features for differentiation [10]. However, these approaches faced challenges in capturing the dynamic contextual dependencies and evolving language trends of digital communication. More recent research has introduced novel approaches, combining rule-based approaches and employing machine learning algorithms that classify unforeseen data by measuring the neighbor points for accurate classification and categorization of different types of sarcasm based on their severity [11][12][13]. Additionally, various methodologies for irony detection within sentiment analysis have been explored, emphasizing pre-processing techniques and evaluating different machine learning classifiers [14][15].

Overall, these studies have significantly contributed to the advancement of sentiment analysis methodologies, highlighting the importance of innovative strategies in uncovering the intricate emotional nuances embedded in social media text.

3. Deep Learning Paradigm in Natural Language Processing

The advent of deep learning techniques has significantly impacted natural language processing. According to [16], recurrent neural networks (RNNs) also gained traction for their ability to model sequential data, with a proposed bidirectional LSTM-based approach for sentiment analysis. Ref. [17] analyzed conventional methods like logistic regression that fall short in capturing word groupings, which led to the design of a deep neural network merging CNN and LSTM. Trained on 21,709 word vector encodings, this CNN-LSTM architecture achieves an 86.16% accuracy in classifying sarcastic and genuine news headlines. Ref. [18] highlighted the complexity of identifying sarcasm in sentiment analysis due to contextual nuances. It introduced a context-feature technique using BERT and conventional machine learning, attaining high precision rates of 98.5% and 98.0% on benchmark datasets. Ref. [19] tackled sarcasm detection in the context of social media's rapid data-based generation. Its proposed deep learning framework, integrating RNN and LSTM with GloVe word vectors, achieved an accuracy of 92% by utilizing simple sentence patterns for sarcasm identification. Ref. [20] focuses on the prevalence of media manipulation in the digital landscape and individuals' false sense of immunity, emphasizing the importance of media literacy and critical thinking, particularly in Slovak educational initiatives. Ref. [21] discusses the potential role of credible social media in mitigating the negative impacts of the COVID-19 pandemic on online education, highlighting the perspectives of teachers and students and offering recommendations for integrating social media into the online learning environment. Ref. [22] examines the post-COVID-19 internet consumption patterns of the Slovak Generation Z, highlighting the changes in online behavior compared to pre-pandemic and peak pandemic times, with implications for marketing and mass media communication.

4. Contextualized Embeddings for Enhanced Understanding

Contextualized word embeddings, a breakthrough in NLP, have demonstrated the capacity to capture intricate linguistic nuances. Ref. [23] introduced Bidirectional Encoder Representations from Transformers (BERT), a contextual embedding model that achieved state-of-the-art performance across various NLP tasks, including sentiment analysis. Similarly, Ref. [24] presented a generative pre-trained transformer (GPT), showcasing the power of transfer learning in understanding context and semantics. Ref. [25] addresses the absence of tonal and gestural cues in identifying sarcasm in social media posts. It introduces T-DICE, a transformer-based contextual embedding approach combined with attention-based BiLSTM, demonstrating enhanced irony and sarcasm classification performance. Ref. [26] tackles the challenge of detecting sarcasm without vocal and facial cues. Its novel ACE 1 and ACE 2 models extend BERT architecture to incorporate both affective and contextual features, significantly outperforming existing models in sarcasm detection across multiple datasets. Ref. [27] proposes a BERT-LSTM model for identifying sarcasm in code-mixed language. Its approach combines pre-trained BERT embeddings with an LSTM network, improving sarcasm detection accuracy on code-mixed datasets.

5. Multimodal Fusion for Holistic Interpretation

Researchers have ventured into multimodal analysis to address the challenges of sarcasm and irony detection. Ref. [28] incorporated visual features from images shared alongside textual content to improve irony detection accuracy. Researchers like the authors of [29] explored self-supervised techniques to alleviate the need for extensive labeled data. Utilizing emojis as an additional modality, [30] demonstrated their significance in enhancing sentiment analysis. The intricate interplay of cultural references, context shifts, and evolving language trends in social media text has posed ongoing challenges. Ref. [31] introduced a transfer learning framework to enhance cross-lingual sarcasm detection, acknowledging the global nature of online communication. Ref. [32] tackles the challenge of fusing different feature modalities by introducing a quantum-inspired framework. Drawing from quantum theory, it models interactions within and across modalities using superposition and entanglement. Its complex-valued neural network implementation achieves competitive results on video sentiment analysis datasets, enabling direct interpretation of sentiment decisions. Ref. [33] addresses the issue of missing modal information in sentiment analysis. It proposes the Integrating Consistency and Difference Networks (ICDN) approach, incorporating a cross-modal transformer for mapping and generalization. Unimodal sentiment labels obtained through self-supervision guide sentiment analysis, resulting in improved classification performance on benchmark datasets.

The literature underscores the evolving landscape of understanding sarcasm and irony in capturing intricate social cues, contextual intricacies, and sentiment shifts inherent in media text. Early rule-based approaches have paved the way for deep learning methodologies, which offer the potential to capture context, sentiment, and linguistic nuances more effectively. Contextualized embeddings have revolutionized sentiment analysis, and multimodal fusion approaches have shown promise in accounting for the diverse signals embedded in digital communication. As challenges persist, such as cross-cultural understanding and context sensitivity, ongoing research aims to refine and broaden the applicability of these methods to comprehend the intricate world of language on social media platforms. Effectively deciphering sarcasm and irony within social media text necessitates advanced NLP techniques.

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