Document-Based Sentiment Analysis Employing BERT-Deep Learning Method

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ABSTRACT

In this work an integrated deep learning approach is presented for document-based sentiment analysis. To categorize the polarity of the sentiments into positive, negative, and neutral, deep learning method is integrated with document-based sentiment analysis. The Convolutional Neural Network (CNN) considers the customers' review as a document and classifies them based on sentiments. Transfer learning-based deep learning model has been implemented in this work for natural language processing. Transfer learning-based Bidirectional Encoder Representations from Transformer (BERT) model has given better results than the other methods. This work applied a Bidirectional Encoder Representations from Transformer – Convolutional Neural Network (BERT-CNN) for sentiment classification. BERT is used to capture feature representation and deep learning layers for extraction, followed by softmax classification. The proposed approach achieved 95% accuracy on IMDB and Amazon reviews, demonstrating practical effectiveness.

INTRODUCTION

Users' opinions from comments are identified by the sentiment analysis task. It operates on three levels: document-level, which examines overall document sentiment; sentence-level, which assesses each sentence; and aspect-level, which focuses on specific aspects within a document. Document-level sentiment analysis (DSA) provides a comprehensive view of user sentiment by capturing the document's overall structure. Document-level analysis enhances sentiment analysis (SA) by accounting for individual user differences.

Document-level sentiment analysis (SA) plays an important role in areas such as social media, healthcare, education, and finance. It focuses on determining users' sentiments towards products based on detailed reviews, where each sentiment is represented by a rating score. This process recognizes that individual user characteristics and behaviours result in varying sentiments about the same product. As

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such, SA also accounts for factors like user and product attributes. A major challenge in SA is handling discrepancies between the text of a review and its associated sentiment rating. For example, different users might provide reviews for the same product but assign different ratings, such as one user giving a 3-star rating while another gives 5 stars. Moreover, reviews with positive language may have low ratings, while reviews with negative language could receive unexpectedly high ratings. Different deep learning techniques have been developed to solve these issues. Tang et al. (2015) proposed UPNN, a CNN-based model that captures both user and product features. Dou et al. (2017) introduced UPDMN, a model with a Memory Network for semantic understanding. Chen et al. (2016) developed NSC+UPA using LSTM. Other models, such as HUAPA (Wu, 2018) and CHIM (Amplayo, 2019), utilize BiLSTM, while Yuan et al. (2019) integrated Memory Network, CNN, and BiLSTM in RRP-UPM. Seyler et al. (2020) created P-CNNLSTM to extract user language features, and Zhang et al. (2021) proposed MA-BERT, which uses bidirectional transformers.

Electronic commerce platforms provide a wide range of products, allowing convenient shopping from anywhere (Liang and Wang, 2019). However, challenges like mismatched product descriptions, low-quality items, and lack of support exist (Ji et al., 2019). The vast amount of online product reviews makes it difficult to extract useful information, emphasizing the need for sentiment analysis to organize opinions (Atandoh et al., 2021). This can assess customer emotions by analysing the language used in reviews (Zeng et al., 2019). Deep learning techniques have gained popularity due to their effectiveness in extracting text features (Zhao et al., 2020). However, the growing number of reviews presents challenges in processing and classifying them. Approaches that integrate sentiment features with word embeddings have shown improvements in classification performance (Liu and Lee, 2021). Convolutional neural networks (CNNs) are particularly effective at identifying local patterns that are invariant to position.

This work investigated the use of convolutional neural networks (CNNs) for text classification, although CNNs face challenges in capturing global features (Amin and Nadeem, 2018). To overcome this, Hameed and Garcia-Zapirain (2020) provided a pooling mechanism and a BiLSTM layer. Wu et al. (2021) developed a users' sentiment classification method for microblog text using BiLSTM and attention mechanisms. LSTMs, however, are prone to overfitting, prompting Zulqarnain et al. (2021) to propose an enhanced Gated Recurrent Unit (GRU), which is less prone to overfitting and better suited for long sequences. While CNNs extract n-gram features from sentences, BiGRU captures contextual meaning. The CNN-BiGRU model was further improved with a single-head attention mechanism (Yan et al., 2021). Van Dinter et al. (2021) used parallel CNNs with GloVe embeddings and utilized BERT to address polysemy issues, enhancing word representation. This model, processed through a multi-layer CNN, classifies e-commerce reviews, benefiting from BERT's advanced contextual word representation (Devlin et al., 2019). Several researchers have suggested deep learning-based sentiment analysis, which differs in features and performances. In the latest works, deep-learning models like Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Deep Convolutional Neural Networks (DCNN) have been implemented to solve sentiment analysis problems like sentiment polarity.

In the last decade, several researchers have suggested deep-learning-based sentiment analyses, which have better performance. In the recent works deep learning techniques like deep neural networks, recurrent neural networks and convolutional neural networks have been used to solve sentiment analysis problem. We used deep learning techniques with TF-IDF and word embedding for twitter data. Despite the availability of various methods, a comprehensive overview of sentiment analysis (SA) is still lacking, hindering a full understanding of the field. Although several surveys on SA (F. Hemmatian & M.K. Sohrabi, 2019; S. Behdenna et al., 2018) have been conducted, they mainly focus on comment

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