A Comprehensive Review of Text Sentiment Analysis: A Survey of Traditional Methods and Deep Learning Approaches

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Abstract:

Text sentiment analysis is a crucial aspect within the realm of natural language processing. This paper, incorporating the latest research advancements, systematically reviews and summarizes mainstream methods in text sentiment analysis. It covers a spectrum of traditional text analysis techniques, including rule-based and dictionary-based methods, as well as machine learning approaches. The paper further delves into an in-depth discussion of text sentiment analysis methods based on deep learning. This encompasses Recurrent Neural Networks and their enhanced structures, Convolutional Neural Networks and their extended techniques, along with applications involving pre-trained models and transfer learning.

Keywords: Text Sentiment Analysis, Deep Learning, Machine Learning, Transfer Learning, Natural Language Processing.

1. Introduction

1.1 *Background*

In the current era of big data, the generation of data is exceedingly rapid. As of June 2023, reports indicate that China has a staggering 1.079 billion internet users, with an internet penetration rate of 76.4%. Simultaneously, with the widespread use of digital communication, social media, and online comments, a substantial amount of textual data continues to emerge every second, containing rich emotional information. Analyzing the emotional changes within this textual data holds significant implications for businesses, governments, and social science research. Therefore, text sentiment analysis, a critical task in the field of natural language processing, has garnered widespread research interest.

Traditional sentiment analysis studies have largely relied on machine learning methods such as SVM, decision trees, and others. In recent years, with the development of deep learning, neural network models, particularly LSTM and Transformer, have begun to demonstrate superior performance in sentiment analysis tasks.

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1.2 *Research Methodology and Objectives*

This paper conducted searches on mainstream academic paper platforms, including Google Scholar, Web of Science, and CNKI, utilizing the search query "Topic=("Sentiment Analysis" OR "Emotion Classification" OR "Sentiment Polarity Analysis")" to ensure the identification of literature highly relevant to text sentiment analysis. The paper provides a brief introduction and analysis that combines traditional text analysis techniques with deep learning methods and the latest research findings. The aim is to offer readers an understanding of the field of text sentiment analysis, assist researchers in selecting the most suitable methods for addressing sentiment analysis issues, and inspire future research directions. The goal is to further propel the development of the text sentiment analysis field.

2. Traditional Text Analysis Methods

and Techniques

2.1 *Rule-Based and Dictionary-Based Methods*

In the early stages of sentiment analysis, researchers predominantly relied on rule-based and dictionary-based methods. These approaches are founded on the construction of linguistic and sentiment dictionaries, determining the emotional polarity of text based on rules or sentiment words within the dictionary. For sentiment analysis, researchers initially need to construct a sentiment dictionary, which involves annotating vocabulary to distinguish its positive, negative, or neutral emotional tendencies. Currently, mainstream sentiment dictionaries include SentiWordNet, GI (General Inquirer), NTUSD from National Taiwan University, and the emotional vocabulary ontology library from Dalian University of Technology. Common models can be classified into three main types: unsupervised models based on the quantity of positive and negative words, unsupervised models based on text sentiment scores, and supervised models extracting features based on sentiment dictionaries[2]. These methods were widely employed in the early stages of sentiment analysis tasks, particularly in situations with limited resources or insufficient annotated data, demonstrating a certain degree of effectiveness for rule-based and dictionary-based methods. With the increase in data volume and the emergence of deep learning methods, researchers have gradually shifted towards more sophisticated models to enhance the performance of sentiment analysis.

2.2 *Machine Learning Methods*

2.2.1 *Support Vector Machine (SVM)*

When dealing with large-scale feedback data, Support Vector Machines have proven effective in achieving automatic sentiment classification. By utilizing large feature vectors and combining them with feature reduction, linear SVM training achieves high classification accuracy[3]. Gupta et al. proposed three classification models for the effective prediction of iris flower varieties. Their models involved exploratory data analysis, analysis, and preprocessing of the dataset, employing classification models such as logistic regression and SVM for prediction[4]. Liu et al. conducted text mining on tourist reviews, studying the perception and attention dimensions of tourists to Fuzhou using topic modeling and sentiment analysis methods like LDA and SVM[5]. Kim et al. introduced a novel approach to predict basic interest rate voting results, achieving 83.7% performance in sentence sentiment prediction using Support Vector Machines[6].

2.2.2 *Decision Trees and Random Forests*

Within machine learning methods, decision trees and random forests are important classification tools. Decision trees classify samples by recursively splitting data and constructing a tree-like structure. Random forests improve classification accuracy by integrating predictions from multiple decision trees. Hitesh et al. aimed to perform sentiment analysis on real-time 2019 election Twitter data using a feature selection model. Compared to traditional methods like BOW and TF-IDF, word2vec with random forests significantly improved sentiment analysis accuracy[7]. Jadhav et al. trained a random forest (RF) machine learning algorithm combining demographic information, and the feature importance analysis of the RF model showed[8].

2.2.3 *Clustering Methods*

In text sentiment analysis research, clustering methods are introduced to further analyze and understand the structure of data. Clustering, an unsupervised learning method, aims to group similar data points together, forming clusters to reveal inherent patterns and structures in the data. Ravi et al. applied various word embedding techniques on tweets from popular news channels and used the K-means algorithm to cluster the generated vectors[9]. Gogula et al. proposed a four-tier strategy for commenter clustering to enhance the user's book recommendation experience[10]. Somani et al. analyzed discussions on statin drugs on social media using dimensionality reduction techniques and clustering algorithms, providing assistance to readers in understanding knowledge about statin drugs[11].

Traditional sentiment analysis studies mostly relied on machine learning methods. With the development of an information society, traditional machine learning methods, more suitable for relatively simple tasks, gradually fail to meet algorithmic requirements. Emerging deep learning methods are showing advantages in handling complex, large-scale datasets.

3. Deep Learning Approaches for Text Sentiment Analysis

3.1 *Recurrent Neural Networks (RNN) and Their Enhanced Architectures*

In the field of deep learning, Recurrent Neural Networks (RNN) and their enhanced architectures have garnered significant attention for their powerful modeling capabilities on sequential data. RNN is specifically designed to handle sequence data, allowing information to be passed through the network, enabling it to capture temporal relationships in the data. However, it faces challenges such as the vanishing and exploding gradient problems when dealing with long sequences. To address these issues, researchers introduced improved structures like Long Short-Term Memory networks (LSTM) and Gated Recurrent Units (GRU). Habbat et al. proposed a multi-model combination strategy, integrating different RNN models such as LSTM, Bidirectional LSTM, and GRU, using various word embedding techniques. This approach achieved significant performance on unstructured tweet data[12]. Ainapure et al. employed Bi-LSTM and GRU techniques for sentiment analysis of comments posted on the Twitter platform, achieving accuracies of 92.70% and 91.24%, respectively, on a COVID-19 dataset[13]. Guesbaya et al. introduced a soft transfer of Long Short-Term Memory Recurrent Neural Network (LSTM-R) sensor, estimating the ventilation opening based on measurements of indoor and outdoor climate variables[14].

Table 1. Common RNN and Their Enhanced Architectures in Deep Learning

Structure	Description	Features
RNN	Recurrent Neural Network	Used for processing sequential data but faces issues of vanishing and exploding gradients.
LSTM	Long Short-Term Memory Network	Introduces gating mechanisms to address the vanishing gradient problem, better capturing long-term dependencies.
GRU	Gated Recurrent Unit	Simplifies the LSTM structure by merging input and forget gates, reducing the number of parameters; comparable performance to LSTM with lower computational cost.
Bidirectional RNN	Bidirectional Recurrent Neural Network	Considers both forward and backward sequences simultaneously, providing a more comprehensive context for capturing patterns and dependencies in the sequence.

3.2 CNN and Its Extended Techniques

Convolutional Neural Networks (CNNs) are also widely applied models in text sentiment analysis. Unlike RNNs, CNNs primarily focus on capturing local features in input data through convolution operations. This local sensitivity enables CNNs to effectively capture keyword combinations and phrase structures in text data. Introducing strategies such as multi-scale convolution and attention mechanisms allows the model to simultaneously capture information at different ranges in the text. This enables selective attention to key parts of the text, enhancing the model's understanding of hierarchical features in the text. Jinfeng Zhou et al. investigated a new CNN model based on position-gated res2net convolutional networks, incorporating selective fusion features for sentiment analysis using residual network technology and attention mechanisms [15]. Xiangang Cao et al. proposed a Multi-Scale Concatenation CNN (MSCCNN) method with mixed features and an improved CNN for recognizing the health status of rotating machinery, aiming to improve the model's superiority and generalization capability [16]. Hanyun Li et al. introduced a dual-channel algorithm that integrates CNN and Bidirectional Long Short-Term Memory (BiLSTM) with an attention mechanism (DC-CBLA) [17].

Table 2. Common CNN and Its Extended Techniques

Structure	Description	Features
LeNet-5	Used for handwritten digit recognition, includes convolutional and pooling layers, simple structure.	Early representative, successfully applied to handwritten digit recognition, relatively simple.
AlexNet	Used for ImageNet image classification, introduces ReLU activation and Dropout techniques.	A significant milestone in deep learning, introduces the concept of deep convolutional networks.

Structure	Description	Features
VGGNet	Uses a simple and regular structure, stacking deep and narrow convolutional layers.	Structurally simple and regular, easy to understand and implement, suitable for various tasks.
ResNet	Introduces residual blocks, uses global average pooling layers, common versions include ResNet-50 and ResNet-101.	Addresses the vanishing gradient problem, allows training very deep networks, subsequent networks borrow its skip connection idea.

3.3 Sentiment Analysis Based on Pretrained Models

Methods for sentiment analysis using pretrained models typically involve pretraining on large-scale text corpora and fine-tuning for specific sentiment classification tasks. During the pretraining phase, the model learns abstract representations of language automatically, enhancing its generalization capabilities. Researchers have successfully applied pretrained models to sentiment analysis tasks. Hanyun Li et al. studied sentiment analysis methods for Chinese online travel-related comments, utilizing pretrained BERT to extract dynamic vector representations for each word corresponding to the current context [18]. Raychawdhary trained the modern pretrained language model AfriBERTa on the AfriSenti-SemEval shared task 12 Twitter dataset for sentiment classification [19]. Scherrmann introduced German FinBERT, a novel pretrained German model tailored for financial text data [20].

3.4 *Application of Transfer Learning in Deep Learning*

Transfer learning methods enhance model performance in target domains by leveraging knowledge learned in the source domain. Researchers employ techniques such as pretrained model transfer, domain adaptation, multitask learning, and knowledge transfer to help models better understand sentiment expressions, adapt to different language styles and characteristics in various domains, thereby improving the generalization capability and practical application effectiveness of sentiment analysis models. Xiaogang Huang et al. proposed a method that converts audio data into spectrograms and performs sentiment classification using a transfer learning-based visual transformer model [21]. For efficient multimodal transfer learning, Yanan Wang et al. introduced VideoAdviser, which transfers multimodal knowledge from multimodal base models to specific modal base models for enhancing video prompt-based video understanding [22].

4. Conclusion

4.1 *Analysis and Summary*

Traditional text analysis methods have limitations in sentiment analysis tasks. Rule-based and dictionary-based methods rely on manually constructed sentiment lexicons, which may not cover all contexts and domains, leading to poor generalization. Machine learning methods like SVM and decision trees have shown good performance in certain contexts but have limitations in modeling long texts and semantic understanding. Clustering methods perform well in unsupervised learning but may have difficulty accurately capturing complex sentiment changes. In contrast, deep learning methods have demonstrated superior performance in sentiment analysis tasks. Models such as RNN and CNN, with hierarchical structures and learned feature representations, better capture sequential relationships and local features in text, improving model generalization. Particularly, the introduction of pretrained models enables models to learn richer and more abstract language representations, providing powerful semantic understanding capabilities for sentiment analysis tasks. Moreover, the application of transfer learning further strengthens the effectiveness of deep learning methods in sentiment analysis. By leveraging knowledge learned in the source domain, models exhibit better performance in the target domain.

4.2 *Future Research Directions*

In recent years, there are still unresolved issues in deep learning in the field of text sentiment analysis. With increasing real-time application demands, researchers have begun to focus on designing lightweight deep learning models for efficient sentiment analysis in resource-constrained environments. Efforts are directed towards improving the generalization performance of sentiment analysis models in different domains and languages to adapt to a wider range of application scenarios. Additionally, adversarial learning, a method that focuses on model resistance to adversarial attacks, is crucial. In-depth research on how to enhance the robustness of sentiment analysis models through techniques like adversarial training holds significant importance.

In conclusion, with the rise of deep learning, the field of text sentiment analysis has achieved significant advancements, making substantial progress in accuracy and generalization performance. However, challenges persist, and there is vast potential for further development.

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