Dean&Francis

ISSN 2959-6157

A Citation Text Sentiment Recognition Method Based on Dynamic Weight Decay Mechanism

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Abstract:
This paper systematically investigates deep learning-based text sentiment recognition methods and their application in academic citation analysis. To address the limitations of traditional sentiment dictionaries, which rely on static weight allocation and exhibit insufficient domain adaptability, a dynamic weight decay mechanism is proposed. Building on the SO-PMI algorithm for constructing domain-specific dictionaries, this method incorporates decay factors based on word frequency distribution, sentiment concentration, and contextual position. These factors dynamically adjust sentiment word weights, effectively suppressing interference from high-frequency general terms while enhancing the representation of low-frequency, strongly affective words. Experimental results on citation sentiment classification tasks demonstrate that the proposed method significantly improves the recognition accuracy of neutral and weak sentiment citations. This approach offers a novel pathway for constructing more adaptive and accurate sentiment analysis systems in academic and other specialized domains. Furthermore, the study highlights the potential of integrating domain-specific knowledge and contextual features to refine sentiment analysis models, paving the way for future research on cross-domain and resource-efficient sentiment recognition techniques.

Keywords: Sentiment Recognition; Citation Analysis; Sentiment Dictionary; Weight Decay; Domain Adaptation

1. Introduction

This paper aims to systematically explore deep learning-based text sentiment recognition methods, focusing specifically on their application in academic citation analysis. The digital transformation of scholarly communication has led to an unprecedented accumulation and dissemination of academic resources, creating new opportunities for analyzing scientific discourse. Within this context, citations in academic literature serve not only their traditional function of knowledge association but also convey nuanced emotional attitudes and scholarly evaluations. The automatic identification of these embedded sentiment tendencies has emerged as a crucial capability for supporting scientific evaluation frameworks, tracking disciplinary evolution, assessing scholarly impact, and enabling dynamic research monitoring. Beyond these metric-oriented applications, citation sentiment analysis offers deeper insights into academic discourse by revealing the resonance, controversy, and reception of research findings within scholarly communities. This dual utility—supporting both evaluative and discursive analyses—has established citation sentiment analysis as an important interdisciplinary research domain bridging natural language processing and scientometrics, with significant theoretical implications and practical applications.

The methodological evolution of text sentiment recognition demonstrates a clear trajectory from rule-based to data-driven paradigms. Early approaches primarily depended on manually constructed sentiment dictionaries and linguistic rules, offering interpretability but suffering from limited coverage and domain adaptability. The advent of deep learning brought significant advancements, beginning with Convolutional Neural Networks (CNNs) that demonstrated exceptional capability in extracting local semantic features, particularly effective in short-text scenarios such as review analysis. Subsequent developments saw the widespread adoption of Long Short-Term Memory networks (LSTMs), which leveraged superior sequential modeling capacities to capture contextual dependencies across longer text spans, thereby expanding sentiment analysis to paragraph and document levels. The most recent breakthrough emerged with Transformer-based pretrained language models, notably BERT and its variants, which achieved remarkable performance across multiple sentiment analysis benchmarks by learning general linguistic representations from massive corpora through self-supervised learning objectives. Parallel to these architectural innovations, researchers have developed specialized strategies including domain adaptation training and dynamic word embedding adjustment to enhance model sensitivity to domain-specific terminology and contextual semantics, particularly addressing non-standard expressions in specialized domains like social media and technical reviews.Concurrently, emerging techniques such as data augmentation with ensemble learning and deep transfer learning frameworks have further pushed the boundaries of model robustness and domain adaptability[1,2] , opening new avenues for resource-efficient sentiment recognition.

Within the specialized subfield of citation sentiment analysis, research remains in developing stages, confronting several persistent challenges including limited domain adaptability, predominance of neutral samples, and the characteristically implicit nature of academic sentiment expression. Zuo Renxian et al. made significant contributions by employing the SO-PMI algorithm to construct a domain-specific sentiment dictionary [3], empirically validating the feasibility of dictionary-based approaches for citation contexts. However, their methodology maintained a static weight allocation strategy that insufficiently accounted for the actual distributional characteristics of vocabulary in real-world citation corpora and contextual variations. Complementary research by Wang Lanxin et al. adopted a multimodal perspective, proposing a Bi-LSTM-CNN hybrid architecture that integrated textual and acoustic features to enhance recognition performance through cross-modal semantic complementarity [4], thereby demonstrating the distinctive advantages of multimodal integration for complex sentiment recognition tasks. Hu Tingting et al. further elucidated the significant complementary relationships between acoustic and textual features across different emotion categories, providing theoretical foundations for heterogeneous information fusion in affect recognition [5]. Meanwhile, Lu Wenxing and Wang Yanfei conducted a systematic review of Chinese sentiment analysis research, establishing comprehensive task classification frameworks and technical systems while clearly identifying fundamental constraints such as corpus scarcity [6], context dependency, and colloquial expression handling that particularly challenge Chinese language sentiment analysis.

Despite these foundational contributions, static dictionary approaches exhibit pronounced limitations, most notably inadequate discrimination capability for high-frequency words possessing weak sentiment intensity, which consequently generates elevated misclassification rates for neutral and weakly-sentimented citation instances. To address this fundamental limitation, this paper proposes an enhanced sentiment dictionary construction methodology incorporating a dynamic weight decay mechanism. Building upon the foundation of SO-PMI expanded domain dictionaries, our approach introduces multidimensional features—including word frequency distribution patterns, sentiment consistency metrics, and contextual positioning information—to construct sophisticated decay factors for dynamic sentiment weight modulation. This mechanism effectively suppresses the disproportionate influence of high-frequency, low-discriminatory sentiment words while strategically amplifying the classification contribution of low-frequency, strongly-affective domain-specific terms, thereby holistically improving the domain adaptation capacity and discriminative accuracy of the sentiment

ISSN 2959-6157

dictionary for academic texts.

The subsequent organization of this paper proceeds as follows: Section 2 systematically reviews mainstream technical approaches and related work in text sentiment recognition; Section 3 elaborates the design rationale and implementation framework of the dynamic weight decay mechanism; Section 4 summarizes the principal theoretical contributions and practical implications of this research while outlining promising future directions. Through innovative sentiment dictionary construction strategies, this research aims to advance the perception and recognition capabilities for implicit emotions in academic texts, thereby pioneering refined pathways for developing more granular, accurate, and reliable citation sentiment analysis systems.

2. Mainstream Techniques Overview

2.1 Domain-Specific Sentiment Dictionary Construction Based on SO-PMI

In the field of text sentiment recognition research, scholars have achieved valuable experimental results using different methods. The research by Zuo Renxian et al. focuses on the sentiment recognition task of academic citation texts. Based on the Opinion Finder English sentiment dictionary, this research used the SO-PMI algorithm to calculate the pointwise mutual information values of words in citation texts, thereby judging the semantic similarity between words and constructing an optimized sentiment dictionary for the citation domain. The study collected 65,976 citations from 1,045 papers in the information retrieval field from the PLOS ONE journal database for empirical analysis. The results showed that neutral citations accounted for up to 84.02%, positive citations for 13.11%, and negative citations for only 2.87%. This research provides an important reference for the construction of sentiment dictionaries in other citation domains and their application in larger-scale citation data [3].

2.2 Bi-LSTM-CNN Multimodal Fusion Model

Another study completed by scholar Wang Lanxin et al. in 2022 aimed to solve the problem of low accuracy in single-modal sentiment recognition and proposed a speech-text bimodal sentiment recognition model algorithm based on Bi-LSTM-CNN. This algorithm uses a Bidirectional Long Short-Term Memory network (Bi-LSTM) with word embedding and a Convolutional Neural Network (CNN) to form a Bi-LSTM-CNN model for text feature extraction, and uses the fusion result of text features and acoustic features as the input of a joint CNN model for speech emotion calculation. Test results based on the IEMOCAP multimodal emotion detection data showed that the emotion recognition accuracy of this model reached 69.51%, which is at least 6 percentage points higher than that of single-modal models, effectively verifying the superiority of multimodal fusion [4].

2.3 Speech and Text Feature Complementary Analysis Method

Furthermore, the research by Hu Tingting et al. focused on the problem of confusion between anger and happiness in speech emotion recognition. This research distinguished these two emotions by incorporating textual information to improve the recognition rate. The study used speech data from the IEMOCAP and SAVEE databases to extract acoustic features, and employed Convolutional Neural Networks and Support Vector Machines respectively as classifier models to recognize four types of emotions: neutral, angry, happy, and sad. Experiments verified the conclusion that channel information from speech is prone to misjudgment between anger and happiness, and effectively solved this problem by adding textual information. The study found that acoustic features had higher accuracy in recognizing anger and sadness, while text features performed better in recognizing neutral and happy states, showing obvious complementarity between the two [5].

2.4 Systematic Review of Chinese Text Sentiment Analysis

Lu Wenxing and Wang Yanfei conducted a systematic review of research on Chinese text sentiment analysis, dividing sentiment analysis tasks into two major categories: information extraction (such as topic extraction, opinion holder identification, evaluation word extraction) and sentiment recognition (word, sentence, and document level). The article summarized methods based on dictionaries, corpora, and machine learning, and pointed out the challenges faced by Chinese sentiment analysis, such as lack of corpora, context dependency, and handling of internet language. This review provides a theoretical framework and methodological reference for subsequent Chinese sentiment analysis research, emphasizing the importance of multi-level and multi-feature fusion [6].

2.5 Recent Advances in Cross-domain and Multimodal Emotion Recognition

Building upon the foundation of established techniques, recent research has continued to expand the frontiers of emotion recognition into specialized domains and multimodal contexts. In the medical field, Gan et al. demonstrated the enhanced capability of audio and text emotion recognition [7], combined with large language model fine-tuning, to extract valuable insights from the unstructured data of depression patients, highlighting the practical impact of sentiment analysis in healthcare informatics. Similarly, exploring linguistic diversity, Skowroński et al. developed a multimodal system for Polish speech and text emotion recognition [8], addressing the unique challenges posed by non-English languages.

For textual emotion recognition itself, significant efforts have been directed towards optimizing model architectures and improving accessibility. Alshahrani et al. proposed an optimal self-attention deep learning model specifically designed for recognizing textual emotions [9], showcasing superior performance for specialized applications. On the other hand, Xu provided an early yet foundational exploration into sentiment computing based on semantic resources [10], which conceptually underpins many subsequent dictionary and resource-based methods, including the approach taken in this work. These studies collectively underscore the ongoing evolution towards more efficient, adaptable, and inclusive emotion recognition systems.

These research results demonstrate the experimental effects of text sentiment recognition technology in different application scenarios. Dictionary-based methods show good applicability in processing texts from specific domains, while deep learning models show potential in feature extraction. These experimental results provide useful references for subsequent research and also indicate the possibilities and limitations of text sentiment recognition technology in practical applications. Future research should further explore cross-lingual and cross-domain sentiment recognition models, strengthen contextual semantic understanding, and promote the construction and sharing of high-quality annotated corpora to facilitate the implementation and promotion of sentiment analysis in practical applications.

3. Proposed Optimization Method

Within the framework of the citation sentiment recognition method based on sentiment dictionaries proposed by Zuo Renxian et al., this paper introduces a key improvement: on the basis of building a domain-specific sentiment dictionary using the SO-PMI algorithm, a dynamic weight decay mechanism is designed and implemented to enhance the domain adaptability and contextual awareness of sentiment words in the weight allocation process [3].

The original research method assigned a fixed sentiment weight to each sentiment word through the SO-PMI algorithm and used it as the basic contribution indicator in sentiment classification. However, emotional expression in academic texts has strong context dependence. The same sentiment word in different contextual environments—for example, modified by degree adverbs, interfered with by negation structures, or distributed in different academic functional paragraphs (such as method description, result discussion, conclusion evaluation, etc.)—may experience significant fluctuations in sentiment intensity. Although the original model introduced local modification operators (such as degree adverbs and negation words) at the sentence level to adjust sentiment intensity, its underlying sentiment dictionary remained a static structure, unable to reflect the distribution differences of words in actual corpora and their usage characteristics in specific domains.

To address this limitation, this paper constructs a dynamic weight decay mechanism aimed at creating a sentiment dictionary system with a richer structural hierarchy and more sensitive contextual response. Specifically, after obtaining the basic polarity and weight of each sentiment word through SO-PMI calculation, the system further introduces a multi-factor integrated decay coefficient. This coefficient synthesizes the following three types of features: First, word frequency features, i.e., the frequency of occurrence of the target sentiment word in the entire citation corpus; Second, sentiment distribution concentration, used to evaluate the consistency level of the word's sentiment tendency across different documents; Third, contextual position information, including the academic paragraph types where the word frequently appears (e.g., method statement, result analysis, conclusion summary) and the emotional expression intensity of the corresponding paragraphs.

In this mechanism, if a sentiment word appears with excessively high frequency in the corpus (such as general evaluation words like "important" or "useful"), or its sentiment distribution is highly consistent lacking contextual diversity, or it often appears in paragraphs with weaker emotional color (such as the method description section), its sentiment weight will be subjected to decay. Such words, due to their widespread appearance in various contexts, often have weak emotional discriminative power, and over-reliance on them can interfere with the classification performance for neutral and weak sentiment citations. Conversely, for those low-frequency words that show strong sentiment tendencies only in specific contexts—especially those often appearing in conclusion sections or critical discussions—their weights will be preserved or appropriately enhanced, thereby more accurately capturing their true emotional contribution.

The core innovation of this research lies in transforming the traditional static sentiment dictionary into a dynamic model capable of perceiving domain-specific language usage habits by embedding a dynamic decay mechanism.

ISSN 2959-6157

This model not only contains the inherent emotional attributes of words but also incorporates their distribution characteristics and contextual effects in actual academic communication, thereby significantly alleviating the problem of insufficient adaptability of general sentiment dictionaries in academic texts. It is expected that this improvement can provide a more reliable foundation for sentiment calculation at the sentence and document levels, improve overall performance in citation sentiment classification tasks, and particularly help improve the recognition effect for neutral citations and citations with implied weak sentiment.

4. Conclusion

In citation sentiment recognition research, this paper proposes a dictionary optimization method based on a dynamic weight decay mechanism to address the insufficient domain adaptability of traditional sentiment dictionaries in academic texts. Existing research often relies on static weight allocation strategies, ignoring the distribution differences and semantic dynamics of sentiment words in academic contexts, leading to limited discriminative performance for neutral and weak sentiment texts.

On the basis of constructing a basic sentiment dictionary using the SO-PMI algorithm, this research introduces multi-dimensional decay factors to dynamically adjust the weights of sentiment words from three aspects: word frequency distribution, sentiment consistency, and contextual position. This method effectively suppresses the weight contribution of high-frequency but weakly discriminative general evaluation words while enhancing the representational capacity of low-frequency words with domain-specific emotional expressions, thereby improving the semantic sensitivity of the sentiment dictionary to academic texts. This research provides an interpretable dictionary optimization path for academic text sentiment calculation, enhancing the model's ability to capture implicit emotional semantics.

Future research can advance from the following aspects: On one hand, academic knowledge graphs and terminology databases can be introduced to enhance the semantic modeling of domain-specific expressions; On the other hand, it is necessary to explore adaptive mechanisms in cross-lingual and low-resource scenarios, combining prompt learning and lightweight network structures to improve model generalization ability and actual deployment efficiency. Furthermore, the deep integration of sentiment calculation models with scientometrics and academic evaluation is also a direction worth exploring.

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