Current Status and Future Prospects of Sentiment Analysis in Social Media Texts

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Abstract. With the flourishing of social media, its diversification, high interactivity, and richness of content are becoming increasingly significant, which has a profound impact on people's communication modes and information acquisition channels. Sentiment analysis of massive and diverse social media text data has become an important tool for grasping users' emotional tendencies and attitudes accurately. This paper aims to comprehensively analyze the current situation of social media text sentiment analysis. It focuses on three classic analysis paths, analyzes the strengths and weakness of each approach respectively, and on this basis sorts out the research methods and achievements of each researchers. In addition, this paper also analyzes the limitations of the current social media text sentiment analysis, discusses in detail the challenges and opportunities of the practical application of these analysis methods, and looks forward to the future development trend. This paper aims to provide a certain theoretical foundation and practical guidance for future related research and promote the further development and optimization of sentiment analysis techniques in the field of social media, to play a more active role in understanding public sentiment, guiding marketing strategies, and monitoring social opinions.

1 Introduction

With the rapid development and widespread popularization of network technology, social media, an emerging information exchange platform, has become an indispensable core stage for global information exchange because of its unique charm, powerful functions, and constantly innovative operation mode. It has not only significantly shortened the distance between people, enabling information to cross the boundaries of geography, culture, and language, and realizing fast and accurate transmission; it has also greatly accelerated the pace of interaction and information flow between users so that everyone can get the latest information and share their insights and feelings at any time and any place. The booming development of social media has brought people an unprecedented variety of communication methods and experiences. From text, and pictures to videos and live broadcasts, from personal sharing and social interaction to professional information and online learning, social media, with its diversified and instantaneous characteristics, meets people's diversified

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information needs and social needs, and further promotes the deepening of the global informatization process.

Therefore, in-depth sentiment analysis of social media texts can help to more accurately capture the public's emotional tendencies, opinion preferences, and the dynamics of online public opinion. This capacity can not only assist businesses in increasing brand influence, optimizing products and services, and better understanding consumer wants; it can also provide important public opinion references for governmental departments, and help policy formulation and implementation; at the same time, it is also valuable for academic research and social welfare. Sentiment analysis of social media texts plays a significant role in business decision-making, political trends, social dynamics, and other fields.

Textual sentiment analysis, alternatively referred to as trend analysis or opinion mining, is the act of evaluating subjective writings that have strong emotional undertones. Textual sentiment analysis aims to identify the emotional inclination indicated in the text, which can be further classified into positive, neutral, and negative categories, and the intensity or particular type of emotion can be examined. A significant quantity of user-generated text data includes incredibly rich sentiment information and subjective opinions due to the widespread usage of social media and online comments. Organizations like businesses and governments can make better judgments by better understanding public opinion through in-depth text sentiment analysis of these text data. Therefore, text sentiment analysis has extremely important application value and practical significance in today's information age.

A thorough overview of social media text sentiment analysis is given in this paper, along with an introduction to three conventional methods based on sentiment lexicon, machine learning, and deep learning. The research status is also summarized, combining and organizing the findings and research methodologies of various researchers. In addition, this paper analyzes their limitations in dealing with data noise problems, complex sentiment expressions, and cross-linguistic and cross-cultural problems, and looks forward to the future development prospects of social media sentiment analysis, such as emerging deep learning techniques, multimodal analysis, and personalized analysis, and other directions. The purpose of this paper is to provide a theoretical foundation and practical guidance for future research, to promote the further development and optimization of sentiment analysis techniques in the field of social media, and to play a more active role in understanding public sentiment, guiding marketing strategies, and monitoring social public opinion, to respond more effectively to the challenges of the information age.

2 Traditional sentiment analysis methods

2.1 Sentiment dictionary-based approach

Sentiment analysis of text based on sentiment dictionaries, that is, grading the sentiment of each word in the text using sentiment dictionaries in order to ascertain the general sentiment trend. To increase the accuracy of the ensuing analysis, the text is initially preprocessed before analysis, involving operations like denoising and eliminating undesirable letters. Next, a word-splitting operation is performed to split the text into independent words, and the words in the text are compared with the words in the sentiment dictionary to identify the sentiment words in the text. Based on the sentiment polarity values and weights of the sentiment words, the overall sentiment score of the text is calculated cumulatively to determine the sentiment tendency of the text, such as positive, negative, or neutral. In the absence of a large number of training datasets, sentiment analysis methods based on sentiment lexicons tend to show more excellent classification performance. Its advantages are mainly reflected in its intuitive and efficient nature, which does not require a complex training process and is easy to understand and implement. However, the completeness of the sentiment lexicon directly determines the accuracy of the analysis, and its comprehension is poor in the face of new vocabulary and polysemous words, which relies on artificial a priori knowledge and limits the analytical ability.

The sentiment lexicon approach is a well-established and extensively utilized technique in the field of text sentiment analysis. It has achieved notable advancements. Zhang et al. used the tf-idf algorithm to extract keywords and combined with lexical features to extract the keyword similarity evaluation object in the sentiment analysis of e-commerce text, and at the same time, established a reverse sentiment lexicon, which for the same sentiment word, in the case of different products, resulted in different [1]. The emotion polarity value makes the judgment of emotion tendency more accurate; By using word2vec technology, Jia et al. trained the emotion word vectors in the microblog content. He assessed in depth the extent to which negative words influence sentiment analysis by carefully selecting a benchmark word for each sentiment category as a reference. Then, he skillfully analyzed the sentiment word vectors for similarity with these benchmark word vectors and rationally combined the results to derive more accurate sentiment tendencies. This series of techniques skillfully blends sentiment vocabulary and semantic rules, thus enabling more accurate calculation of sentiment intensity. Eventually, these techniques were applied to microblogs to achieve a meticulous classification of various emotions and optimize the effect of sentiment expression. This enhanced both the original emotion lexicon and the emotion intensity of microblogs, which improves the calculation method of the original sentiment lexicon [2]. Bagherzadeh et al. used a unique bag-of-words weighting technique to do binary sentiment analysis on large amounts of TripAdvisor reviews from hotel customers. The approach makes sure that the process of creating, preparing, and evaluating lexicons is transparent and repeatable. Applying classification accuracy metrics to the weighted lexicon L1 and manually chosen lexicon L2 allowed for an efficient testing and validation process. The outcomes show that the method outperforms the public lexicon and machine learning-based approaches in terms of accuracy and versatility in predicting user sentiments [3].

2.2 Machine learning-based approach

Machine learning methods, i.e., automatic recognition of textual sentiment by training classifiers. Machine learning methods can be categorized into two broad groups: supervised and unsupervised learning techniques. Both rely on selecting and extracting appropriate sets of features, including N-grams, lexical features, sentiment word features, syntactic patterns, etc., which are usually generated by natural language processing techniques. In supervised learning, the model is trained using a labeled dataset, where each sample has a label that corresponds to a certain emotion, such as neutral, positive, or negative. Commonly used algorithms include Plain Bayes (NB), Support Vector Machine (SVM), Maximum Entropy, and so forth. The model learns the relationship between input characteristics and output labels in order to produce predictions. Unsupervised learning techniques, on the other hand, do not require labeled datasets for training. It mainly relies on the statistical laws and patterns of text content to discover similarities and differences between texts. Although unsupervised learning has relatively few applications in sentiment analysis, it still has a wide range of applications in areas such as text clustering and topic recognition. By combining these strategies and algorithms, machine learning techniques accomplish effective and precise information extraction and sentiment classification in text sentiment analysis, showcasing their broad applicability and enormous potential in the natural language processing domain. The machine learning-based sentiment analysis method utilizes machine learning algorithms to train sentiment classifiers by using a large amount of text data labeled with good sentiment polarity as a training dataset. The technique can well deal with problems such as polysemous words and sentences with complex grammatical structures, and it can automatically extract features from the text and obtain high classification accuracy when the training dataset is large enough. However, the machine learning model's effectiveness is heavily dependent on the quantity and quality of the labeled data; incomplete or inaccurate labeling may cause the model to produce less data.

Rahman presented a multi-layer classification model and investigated preprocessing methods and machine learning models for sentiment multi-class classification in order to obtain fine-grained classification and enhance classification performance. According to experimental findings, the multilayer model has a higher recall and produces better categorization than the single-layer model [4]. Cam et al. applied sentiment analysis to financial tweets in Turkish and implemented six different supervised learning classifiers to achieve sentiment classification, and findings indicate that the accuracy of SVM and multilayer perceptual classifiers are higher than other classifiers [5]. Biradar et al. used Apache Hadoop and Hive tools and efficiently handled a large amount of twitter data by designing algorithms that incorporate preprocessing, unsupervised clustering, n-gram and TF-IDF feature extraction, synonym integration, and sentiment categorization, which outperforms the traditional method by 1.5 times, the accuracy rate is nearly 80%, which provides a strong support for in-depth user interaction and feedback [6]. Using cosine similarity as a basis, Pavitha et al. developed a movie recommendation system that improves user experience by using machine learning to analyze the sentiment of user reviews in addition to suggesting comparable films. They examined two machine learning supervised algorithms, SVM and NB, and found that SVM performed better in sentiment analysis than NB, with an accuracy of 98.63% compared to 97.33% for NB. Based on these results, SVM is the better choice for this task [7].

2.3 Deep learning-based approach

Deep learning methods are used in deep learning techniques to identify sentiment in text. Deep learning dramatically increases the accuracy and efficiency of sentiment analysis by automatically learning data characteristics, whereas traditional sentiment analysis approaches rely on manual feature extraction and rule-based models with limited efficacy. Deep learning-based sentiment analysis is progressively gaining traction as a result of the growth of social media, big data, and cloud computing. The convolutional neural network (CNN), recurrent neural network (RNN), long short-term memory network (LSTM), gated recurrent unit (GRU), and other models are currently widely employed in deep learning.

CNN is suitable for processing local features and is good at capturing keywords or phrases in text sentiment analysis, but it is often ineffective in scenarios that need to be used before and after information as a reference. However, CNNs are often ineffective in scenarios that require before and after information to be used as a reference, while RNNs are equipped with cyclic connectivity, which can handle sequential data and better capture contextual information. LSTM is an improved version of RNN, which solves the problem of disappearing or exploding gradient of RNNs in practical applications. GRU is a simplified version of LSTM, which has fewer parameters and faster computation speed. Computational speed. It controls the flow of information through update gates and reset gates, thus effectively capturing long and short-term dependencies while reducing model complexity. Deep learning-based sentiment analysis further improves the accuracy and complexity of sentiment analysis. It utilizes neural networks to automatically extract deep features in text and can capture more subtle changes in sentiment. This method performs well when dealing with large-scale text data and does not require human-set features, which improves the accuracy and efficiency of data processing and is especially suitable for sentiment analysis of large-scale text data. Sentiment analysis is made even more complicated and accurate by deep learning-based methods. It can detect more subtle changes in sentiment and automatically extract deep features from text using neural networks. However, deep learning models require a lot of computational resources and time for training, and may not be suitable for small data sets.

Basiri et al. suggested the attention-based bi-directional CNN-RNN depth model (ABCDM), which takes into account the temporal information flow in both directions and extracts rich contextual information using two separate bi-directional LSTM and GRU layers. The model also applies an attention mechanism to the output of the ABCDM bi-directional layer, so as to regulate the weights of different words and emphasize or diminish the information according to the important degree to emphasize or diminish the information, while the convolution and pooling mechanism is used to provide strong support for subsequent sentiment polarity judgments by extracting local features and reducing the feature dimensions [8]. Assiri proposes the DeBERTa-GRU sentiment classification model, a hybrid deep learning model that combines DeBERT and GRU with the use of pre-trained of DeBERT weights to more efficiently convert text tokens into semantically rich embedding representations, and subsequently feeds these DeBERT elaborated word embeddings into the GRU network in order to further refine and capture the most critical semantic information in the text, which achieves an F1 score of 97% on Twitter's large language modeling dataset, significantly outperforming the existing techniques [9]. Rhanoui suggested using CNN and the Bidirectional Long Short 1-Term Memory (BiLSTM) model with embedded Doc2vec to analyze long texts from the perspective of the reader. By first using CNN's convolutional layer to extract a significant amount of textual data, which then serves as the input for BiLSTM, the model 16 effectively combines the benefits of both techniques: CNN's spatial feature extraction capabilities and BiLSTM's time series modeling capabilities. Multiple models with Word2vec/Doc2vec embeddings are compared, and the results show that Doc2vec with CNN-BiLSTM model achieves 90.66% accuracy, which outperforms the others [10]. Liao et al. propose a RoBERTa-based multi-task model, which first extracts text and aspect-tagged features by RoBERTa. Subsequently, the cross-attention mechanism is utilized to generate a feature representation r that is closely related to the given aspect. Next, the three key elements s, p, and rare spliced to form the final feature vector. This feature vector is ultimately processed by the fully connected layer and the softmax 26 function to offer the emotion polarity prediction of texts in the designated aspect category. Experimental results show that the model outperforms other models in aspect category sentiment analysis [11].

3 Existing limitations and prospects

Even if social media sentiment analysis has advanced significantly in the cutting-edge field of natural language processing, practical use of the technology will unavoidably encounter several difficult obstacles and constraints. Due to the diversity and arbitrariness of social media platform users, the problem of data noise often results in text filled with a large number of spelling errors, a variety of special characters, and symbols that have no practical meaning. The presence of these unstructured data not only significantly raises the difficulty and unpredictability of the sentiment classification task, but also substantially impedes the machine learning model's capacity to capture and learn useful information. In addition to this, social media texts are also known for their complex and varied sentiment expressions, which is undoubtedly another major test for sentiment analysis techniques. For example, the extensive use of rhetorical devices such as sarcasm, irony, and metaphor makes sentiment analysis even more difficult. These sentiment expressions often go beyond the simple sentiment vocabulary matching that traditional methods rely on, and instead require deeper semantic understanding and contextual analysis capabilities. However, current models are often overwhelmed when dealing with these types of sentiment expressions that contain polysemous words and are highly context-sensitive, leading to a significant decrease in the accuracy of sentiment categorization.

Although social media text sentiment analysis faces many limitations and challenges at the current stage, its future development prospects are undoubtedly full of unlimited potential. In today's fast-changing technological era, emerging deep learning technologies and a series of advanced models have significantly improved the accuracy and efficiency of sentiment recognition, injecting a powerful new impetus for social media sentiment analysis. Sentiment analysis in the future will no longer be limited to the analysis of text content but will move towards a more diversified and comprehensive development stage. By comprehensively applying and analyzing multi-dimensional information such as users' text expressions, emoticons, body language, and action behaviors, the research can understand users' real emotional states in a more comprehensive and in-depth way, to provide users with more intimate and personalized services. In this field, some scholars have already made positive explorations and attempts. For example, the MSSA-SC method proposed by Hu et al. [12] is a highly innovative multimodal sentiment analysis strategy. The method first determines whether the graphic content is relevant or not, and then decides whether to use multimodal analysis or unimodal analysis according to the judgment result. The experimental findings demonstrate that this technique successfully mitigates the detrimental effects of textual and graphic irrelevance on sentiment analysis accuracy and provides a fresh perspective on how to raise sentiment analysis accuracy.

With the continuous maturity of deep learning technology and the increasing improvement of multimodal data fusion technology, social media sentiment analysis will become more accurate, comprehensive, and personalized. At the same time, personalized sentiment analysis and real-time dynamic processing technology will become more mature, capable of real-time updating and optimization, and providing accurate personalized recommendations and feedback based on users' historical behavioral data. This will enable social media sentiment analysis to achieve a qualitative leap in user experience, bringing users a more accurate, intimate, and personalized service experience.

4 Conclusions

Sentiment analysis of social media text is crucial, it helps to understand public opinion, optimize user experience, guide marketing and crisis management, and is an indispensable analysis tool. An overview of social media text sentiment analysis is given in this work, which also methodically separates the three conventional analysis techniques based on sentiment lexicon, machine learning, and deep learning, and on this basis, this paper organizes the research methods and achievements of different researchers and summarizes the challenges and problems as well as the future development trend. Currently, despite many advances, sentiment analysis still faces many challenges and problems. Data noise, complex expressions of emotions, and cross-linguistic and cross-cultural issues are the main difficulties in the current field of sentiment analysis. The diversity, informality, and dynamics of social media texts make data preprocessing particularly difficult, while the complexity and diversity of sentiment require higher intelligence and adaptability of the analytic models. In addition, cross-language and cross-cultural issues add to the difficulty of sentiment analysis, as sentiment expressions and meanings may differ significantly across languages and cultures. In the face of these challenges, future sentiment analysis will pay more attention to the directions of multimodal sentiment analysis, personalized real-time analysis, and emerging deep learning technologies, which will promote the precision and effectiveness of algorithms for sentiment analysis and capture and interpret emotions more comprehensively, and in the future, more accurate, comprehensive, and real-time sentiment analysis is expected to be achieved, which will promote the continuous development and prosperity of the field of social media sentiment analysis.

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