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The Technological Development and Application Frontiers of Social Media Sentiment Analysis: A Ten Year Review (2016-2026)

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Abstract

Social media sentiment analysis technology has been rapidly iterative in the past decade, but the existing research lacks a systematic review of its technology evolution and application context. This paper reviews the relevant literature from 2016 to 2026 from two dimensions of technology paradigm and application scenarios. The technical level has experienced four paradigm iterations from the explicit emotion classification of SVM and TextCNN, to the implicit emotion detection led by BiLSTM+Attention and BERT, to the multimodal fusion model, and to the generative reasoning of the big language model. The application level has been deeply embedded in public opinion governance, brand insight, financial forecasting and public health monitoring. The research points out that the lack of cross domain generalization, short text noise interference and model bias are the core bottlenecks. In the future, people should build a cross language unified model and a lightweight multimodal framework, and establish a fairness evaluation system.

Keywords

social media, emotional analysis, deep learning, large language model, multimodal fusion

1. Introduction

In recent years, the popularity of the Internet has boosted the number of UGC and user comments, and social media has become the core of comment contributions. By 2023, the global Internet users will reach 5.07 billion, including 4.95 billion social media users; By 2026, Reddit platform will generate about 9.7 million comments on a daily basis, and Twitter will generate about 500 million comments on a daily basis. Driven by massive data, social media sentiment analysis technology has rapidly iterated in the past decade, and its applications cover finance, health, marketing, politics and other fields.

At present, there have been a number of relevant reviews. For example, AISH ALBLADI and others divided the emotion analysis architecture into three categories: traditional machine learning, deep learning and transformer, compared the performance of BERT, GPT, RoBERta and other models, and provided precise guidance at the algorithm level [1]; Margarita Rodríguez-Ibanez and others combed academic research and industrial applications, pointing out that research focuses on marketing, politics, economy and health, and dictionary, SVM and other classic methods still dominate [2].

This paper will compare the evolution of technology and the evolution of task themes, and describe the development of social media sentiment analysis in the past decade from two aspects, technical methods and application scenarios, in order to make up for the gap of overview materials that may arise due to the rapid development of the field, and present a clear development context for readers. At the same time, this review will evaluate mainstream technologies and predict future application scenarios, hoping to provide inspiration for relevant researchers.

2. Social Media Sentiment Analysis Task and Technology Evolution in the Past Decade

2.1 Explicit Emotional Expression Stage (2016-2018)

At this stage, emotion analysis focused on the dichotomy of positive and negative polarity of Twitter comments and began to focus on emoticons and slang, which was consistent with the Sentiment Analysis in Twitter, ABSA, Effect in Tweets, Iron Detection and other tasks set up by SemEval at the same time. The technical paradigm is dominated by SVM+word bag/TF-IDF, and CNN and LSTM are exploring. For example, at least 20 teams in SemEval-2017 Task 4 use neural networks [3].

TextCNN uses convolution kernels with heights of 3, 4, and 5 to extract n-gram features. After maximum pooling and full connection Softmax classification, it is fast in training and suitable for short tweets. It can efficiently capture local signals such as slang, but lacks the ability to model in sequence. LSTM regulates information through forgetting gate, input gate and output gate, and alleviates gradient problems by linear transmission of cell state, effectively modeling negative, turning and other word order sensitive semantics; The bi-directional hiding state of BilSTM splicing further improves performance.

2.2 Implicit Emotion and Social Semantic Stage (2019 to 2021)

This stage turned to implicit emotion and social semantic detection. Satire, hatred, position and other contents increased, which was consistent with SemEval's tasks of OffensEval and hate speech detection at the same time. The technical paradigm is dominated by BiLSTM+Attention and BERT. For example, Li et al. used BERT variants plus supervised comparative learning [4], Wei et al. proposed bipolar orthogonal attention BiLSTM [5].

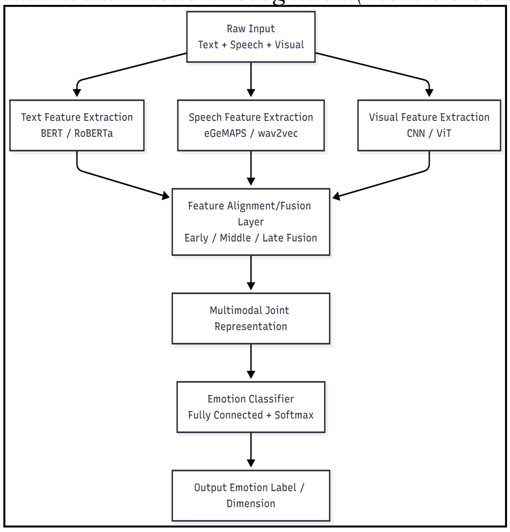
Based on self-attention, Transformer overcomes the bottleneck of RNN serial and long-distance dependence. It is stacked by multi-head self-attention and feedforward network, supplemented by residual connection and layer normalization. It captures global semantics in parallel by scaling point product attention, and injects sequence information into position coding. Its advantage is that it is efficient in parallel, but its limitation is that square complexity is not suitable for very long text, which lays the foundation of BERT. BERT uses deep bidirectional transformer to obtain dynamic context representation to solve polysemy through mask language model and next sentence prediction pre training. Input is added by word element, segment and position embedding. Emotional classification only needs to add classifier fine-tuning on [CLS] tag.

2.3 Multimodal and Contextual Integration Stage (2022 to 2023)

With the increasing diversity of social media content, non-text elements such as images, short videos, and expression packs can more accurately express emotions. Their integration with text can effectively detect irony and humour, and adapt to the compound environment of “text+image+context”. For example, Ye et al. fused text, image and emotional context modeling, whose accuracy rate on text+image data set is significantly better than that of single mode and ordinary multimodal models, and confirmed the effectiveness of multimodal methods [6]. This is in line with SemEval's multi-modal emotional analysis Video QA, Satire, structured emotion and other tasks have the same theme, and the technology paradigm has shifted to Transformer extension classes (such as VisualBert) and multimodal models.

Multi modal emotion analysis integrates complementary information such as text, voice and vision to overcome pure text ambiguity and improve accuracy and robustness. The process includes feature extraction, cross modal fusion and emotion classification. In feature extraction, text uses BERT/RoBERTa, voice uses eGeMAPS, MFCC or wav2vec2.0, and vision uses CNN or ViT to extract facial expressions and attitudes. In cross modal fusion, early fusion is directly spliced, and late fusion is decision integration. Intermediate fusion uses Transformer's cross modal attention to align text word elements, voice frames, and image regions to capture fine-grained semantic associations. Mainstream methods such as MulT and MMBT map multimodality to the same semantic space for joint coding. The final fusion indicates that emotional labels or dimensional emotions are output through full connection and Softmax, and the process is shown in Figure 1.

Figure 1: Multimodal Emotion Recognition.(Picture credit: Original)

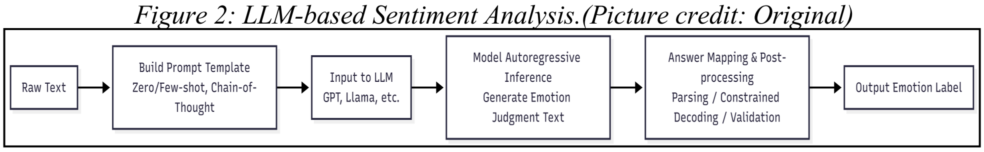


2.4 Big Model and Cognitive Emotional Stage (2024 to Now)

SemEval competition questions in recent three years (such as emotional cause analysis of multimodal dialogue, emotional discovery and reasoning flip, etc.) show that emotional analysis is combining multidimensional information such as images in dynamic dialogue to give continuous psychological assessment changes such as valence and arousal to specific aspects. The pre training model (RoBERTA/XLM - R, etc.) is still the first choice for landing, but the generative fine-tuning of big language models is becoming a new paradigm of complex emotional reasoning. For example, EmoLLMs perform emotional command fine-tuning on LLaMA2, OPT, etc., and outperform ChatGPT and GPT - 4, fully confirming the advantages of this path [7].

With the help of powerful context understanding and generation ability, the big model replaces the traditional annotation fine-tuning with prompt learning or parameter efficient fine-tuning. The process is divided into prompt building, model reasoning and answer mapping (Figure 2). When constructing prompts, people often use zero sample and few sample prompts, and introduce the thought chain to gradually infer complex situations such as irony and metaphor; In the model reasoning phase, you will be prompted to enter GPT - 4, Llama, ChatGLM, etc. and freeze the autoregression generation of parameters; Answer mapping is transformed into predefined emotional tags through limited decoding, rule parsing or verifier. In the professional field, it can be combined with LoRA, Adapter and other parameters to effectively fine tune, quickly adapt on a small number of samples, and take into account flexibility and accuracy.

Figure 2: LLM-based Sentiment Analysis.(Picture credit: Original)



3. Typical Application Scenarios of Social Media Emotional Analysis

3.1 Social Public Opinion Analysis and Government Governance

Real-time monitoring of speech emotions in specific events with social media sentiment analysis can help the government effectively grasp the trend of public opinion, prevent social unrest caused by negative emotions, and assist in reasonable decision-making based on public opinion and mass feedback. Empirical research in Kazakhstan from 2020 to 2024 shows that sentiment analysis has become an important digital tool for public opinion research and judgment and governance modernization. Its frequency of use is strongly positively correlated with the speed of policy response ($r=0.68$, $p<0.01$), which has reduced the average policy lag from 37 days to 18 days, significantly improving decision-making efficiency [8]. In combination with the analysis of population characteristics, it can accurately identify the emotions and attitudes of different age groups, improve the applicability of policy groups, provide emotional voice channels for marginal groups, and monitor the dynamics of social thoughts.

3.2 Brand Public Opinion Analysis and Demand Retrieval

The emotional analysis of social media users' product sharing and evaluation can help enterprises optimize product and market strategies by mining emotional tendencies. Fine grained emotion mining can grasp consumers' preferences for various dimensions of products, locate the main problems of negative emotion concentration and clarify the direction of improvement through matching demand and emotion detection. For example, Boumhidi et al. built a multilingual dynamic reputation generation system based on Twitter, which guarantees data quality through multilingual unification, noise filtering and emotion calibration, and realizes fine-grained emotion analysis, industry weight matching, dynamic reputation calculation and visualization, providing platform support for enterprise public opinion and demand analysis [9].

3.3 Analysis of Financial Market Sentiment

Social media sentiment analysis is widely used and has significant value in financial market sentiment analysis, empowering financial forecasting and trading. Zhang et al. conducted empirical analysis on stocks in the four major industries of technology, healthcare, finance, and energy based on Twitter data, using NLP sentiment analysis combined with graph neural network (GNN) influence weighting and integrating traditional financial indicators [10]. Research has confirmed that this method can accurately quantify market sentiment, effectively improve stock price prediction accuracy, and generate actionable trading strategies, creating excess returns. From a practical perspective, it confirms that social media sentiment analysis has been deeply integrated into financial market analysis, with wide application coverage and outstanding practical value.

3.4 Public Health Public Opinion Analysis

Social media sentiment analysis is widely used in public health public opinion analysis and has significant value. Although Zhang et al.'s research focuses on financial scenarios, its core methods - relying on NLP to analyse social media texts, combining graph neural network (GNN) to quantify user influence and emotional weight, and efficiently processing massive unstructured data - have strong scenario versatility, providing a mature technical paradigm for public health public opinion analysis [11]. This technology can be used in key scenarios such as public sentiment monitoring, public opinion risk early warning, rumor identification and guidance, and policy feedback analysis to quickly capture public attitudes, mine public opinion laws, help public health departments make accurate judgments and scientific decisions, and reflect its important application value and popularity in public health public opinion governance.

4. Research Hotspots, Core Challenges and Future Trends

4.1 Cross Domain and Cross Language Emotional Analysis

At present, with cross domain transfer learning and multilingual pre training models (BERT, XLM-R) as the core, focusing on field adaptation and code-mixed text, low resource languages (such as Arabic, Chinese) are increasingly valued [1,12,13]. The main problem is that the strong domain dependence of emotional words is prone to a sudden decline in cross domain performance, low resource language tagging is scarce, and cross language semantic gap and code mixed ambiguity are difficult to resolve [14,15]. The future trend is to build multi domain and multi language benchmark data sets, develop unsupervised cross domain adaptive and cross language unified models, and integrate common sense knowledge to enhance semantic alignment capabilities [1,13].

4.2 Multimodal and Complex Emotion Analysis

Multimodal analysis integrating text, image and audio has become the core direction of identifying complex implicit emotions such as irony and sarcasm. Aspect level emotion analysis and context aware modelling have attracted much attention [1,12]. The challenge lies in the difficulty of integration caused by modal heterogeneity, the high cost of multimodal tagging, and the strong cultural dependence of complex emotions such as irony, semantic concealment, and fuzzy boundary of mixed emotions [12,14,15]. In the future, people will focus on building multimodal complex emotional data sets, promoting the cross modal joint reasoning framework, and developing lightweight fusion models to support short video, live broadcast and other real-time analysis scenarios [14,15].

4.3 Short Text Noise and Implicit Emotion Modelling

Research focuses on the standardization of slang, abbreviations, emoticons and other noises in social media short texts, as well as implicit emotional reasoning [1,12,14] using prompt learning, causal reasoning and other methods. The core problem is that short text information is extremely sparse, noise types are complex and lack of unified cleaning standards, implicit emotions have no explicit clues and are highly dependent on context, and labels are highly subjective and costly [14]. In the future, people will build an end-to-end noise cleaning pipeline and an implicit emotion knowledge base, and combine data enhancement and comparative learning strategies to significantly improve the robustness of implicit emotion recognition in noisy environments [14].

4.4 Model Bias and Model Efficiency

Model bias detection and data equalization began to receive attention [1,14]. At the same time, the realization of large model lightweight through knowledge distillation, model quantification and sparsity to improve reasoning efficiency has become a hot spot [1,12,15]. The main problem is that systematic bias such as gender and region in the training data will be directly transmitted to the model output. Large model parameters have large scale, high computational cost, and the lightweight process is often accompanied by a significant decline in accuracy. In the future, a fairness evaluation system will be established and a diversified data set will be built. At the same time, distillation and quantification technologies will be deepened to balance accuracy and low resource consumption.

5. Conclusion

This overview combs the technological evolution and application prospect of social media emotion analysis from 2016 to 2026. At the technical level, it has gone through four paradigm iterations: from the explicit emotion classification of SVM and TextCNN, to the implicit emotion detection driven by BiLSTM+Attention and BERT, to the multimodal integration of dealing with mixed content of images and texts, until the current big language model generative reasoning realizes dynamic and multi-dimensional psychological emotion assessment; The internal logic is that the content moves from pure text to multimodality, the emotional expression moves from direct to implicit satire, and the driving technology moves from “shallow pattern recognition” to “deep cognitive reasoning”. The application level has been deeply embedded in social public opinion governance, brand insight, financial forecasting and public health monitoring, resulting in quantifiable effects such as shortening policy lag, improving the accuracy of stock price forecasting, and forming the paradigm of “pre training basic model + specific scenario adaptation”. However, insufficient cross domain generalization, short text noise and model bias are still the main bottlenecks. The limitations of this study lie in the fact that the literature is mainly in English, the lack of systematic discussion of low resource language, the lack of unified quantitative benchmarks and ethical discussion to be deepened; In the future, multilingual literature will be expanded, standardized evaluation will be added, and ethical governance topics will be included to enhance empirical guidance and integrity.

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