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Review of NLP Applications in the Field of Text Sentiment Analysis

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Abstract: With the popularity of online social media and online review systems, Text sentiment analysis has become a popular research hotspot in the field of natural language processing, Identification and extracting the emotional tendency and emotional intensity in the text through automation technology can provide valuable emotional data support for enterprise decision-making, public opinion monitoring, customer relationship management and other application scenarios, This review summarizes the recent advances in the application of natural language processing in the field of text emotion analysis, It focuses on the emotion analysis model based on machine learning and deep learning and explores the challenges and future trends in the field, Review shows that sentiment analysis has become an important branch of natural language processing, Its technological development continues to provide more accurate and intelligent emotion mining ability for the application of various industries.

Keywords: Natural Language Processing, Text Classification, Information Extraction, Question And Answer System, Machine Translation.

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1 Introduction

Emotional analysis refers to the computer technology automatic identification, extraction, reasoning and quantitative text expressed in the subjective views, emotional tendency and emotional intensity, in recent years, with social media, online review system widely popular network applications, vast amounts of unstructured text data capture the user emotion and viewpoint, also makes the text emotion analysis become one of the hot areas of natural language processing research, emotion analysis technology in social media monitoring, product reviews mining and public opinion monitoring field has wide application prospect, provide valuable emotional data support for enterprise decision-making.

2 The Research Method of Emotion Analysis

2.1 Affective Analysis Model based on Statistical Machine Learning

Statistical machine learning model is the earliest and the most widely used model type in the field of emotion analysis, this kind of model is usually based on the surface features in the text, such as word bag (bag-of-words), n-gram build classifier for emotion prediction, common emotion analysis based on the statistical machine learning model including simple Bayes, support vector machine, logistic regression, etc. The Naive Bayes classifier is one of the first models applied to textual sentiment analysis, It computes the conditional probability of each feature word under different emotion categories based on the Bayes theorem and selects the category with the largest probability as the prediction result, Since the naive Bayes model is simple and efficient, Thus, often used as a baseline model, Also proposed various improved Bayesian models to improve performance, Support vector machine (SVM) is another commonly used supervised learning model, It takes the maximum interval as a learning strategy, Can effectively find the optimal classification plane for the training data, The SVM showed a better generalization ability in the emotion classification task, In addition, decision trees, random forests and other models are also widely used, Overall, sentiment analysis models based on statistical machine learning are relatively simple, Better results can also be obtained for small-scale data sets.

2.2 Emotion Analysis Model based on Deep Neural Network

The rise of deep learning technology has made great progress in emotion analysis models based on deep neural networks, Unlike the statistical machine-learning models, Neural network models can automatically learn higher-order semantic representations of text, Without requiring complex feature engineering, The recurrent neural network (RNNs) and the convolutional neural network (CNN) are the two most commonly used network structures, The recurrent neural network has the advantage of processing sequence data, Well capture the contextual semantic information of text, The long and short-term memory network (LSTM) and the gated cycle unit (GRU) are two improved variants of RNN [1]. Since they introduce a gating mechanism, More better on long-term dependence [2].Thus, it is widely used in sentiment analysis tasks, Convolutional neural network automatically extracts the local features through convolution operation and reduces the dimension of the features by using the pooling layer, Effectively capture the local semantic information of the text, Outstanding performance in tasks such as emotion classification. Another attention mechanism, memory network, against generating network technology has also been applied in emotion analysis, at the same time large pre-training language model (such as BERT, GPT, etc.) makes the emergence of the performance of emotion analysis to a new level, in short based on deep neural network model can automatically mining hidden semantic features, when dealing with complex tasks show a powerful modeling ability, become the mainstream of the current emotion analysis research direction [3-10].

3 Key Techniques in Sentiment Analysis

3.1 Text Representation Technique

Text representation is a key link in the emotion analysis task, aims to convert unstructured text into computer recognizable numerical vector, reasonable text representation can not only retain text semantic information can also reduce data sparsity, so as to improve the performance of emotion analysis model, commonly used text representation technology including bag model based on counting, based on prediction of word embedded model, etc. The pouch model is the most traditional text representation, Represent a document as a multiple set of words it contains, Construction of high-dimensional document vectors by statistical term frequencies, Although simple and intuitive, the pouch model ignores important semantic information such as word order, To overcome this deficiency, The n-gram model improves the bag model by considering the local word order features, Later, drawing on the idea of distributional assumptions, The word embedding model based on neural network training has emerged, Like Word2Vec, Glove, and others can map words to low-dimensional continuous vector spaces to better capture the semantic relationship between words[11-13].In addition, sentence-level representations such as Skip-Thought, InferSent, and domain-adapted pre-trained language model have also made great progress, Further enhance the effect of the text representation, Excellent text representation techniques provide high-quality input features for sentiment analysis models, It is an important basis for improving the model performance.

3.2 Emotional dictionary construction technology

Emotional dictionary is a widely used corpus of emotion analysis task, can directly mining text emotional information, common manual construction methods including based on expert knowledge and crowdsourcing annotation, experts build emotional dictionary by field experts [14-16].The credibility is higher but also time-consuming, and crowdsourcing labeling by publishing online annotation task to collect non-professional emotional polarity and strength of words, more data volume but the quality is uneven. The a-based automatic construction technique is an important direction of emotion dictionary construction in recent years, A common practice is to utilize the emotionally-labeled corpus, Such as product reviews, social media data, By analyzing the statistical relationship between emotion words and polarity words in these corpus to automatically identify new emotion words and their polarity, Another popular practice is based on the existing emotional dictionary seeds, Using the word relationship of words, simultaneous, synonymous and other semantic information to expand the scope of emotion dictionary, In addition, some methods also combine the semantic knowledge base and word embedding techniques to model word emotion from multiple semantic dimensions, Build an emotional knowledge base with a wide coverage and rich granularity. High quality emotion dictionary is an important resource of emotion analysis task, can not only be used as an independent emotion detection tool can also be used to build rules-based emotion analysis model, or combined with statistical model to form half supervised, unsupervised emotion analysis framework, so the emotional dictionary of automatic construction technology constantly attention and development.

4 Domain-Adaptive Emotion Analysis

4.1 Cross-Domain Emotion Analysis

In practical applications, sentiment analysis models often face cross-domain problems, That is, the model needs to generalize to other target domain data after training in the source domain, Due to the differences in data distribution and language habits between domains, Performance of source domain models tends to decline in new areas, To address this challenge, researchers have proposed multiple cross-domain sentiment analysis methods, Domain adaptation based on instance selection and feature mapping is an early solution[17-19].The former performs model training by picking instances from the source domain similar to the target domain, The latter then uses different strategies to map the source and target domain features to a shared subspace[20, 21].In addition, multi-task learning-based methods for simultaneously learning feature representations in the source and target fields enhance the generalization ability of the model, Recent deep domain adaptation network models have also achieved good results[22]. The difference in the distribution of source and target domains are explicitly minimized by adversarial training or residue modeling. In addition to using the existing source domain and target domain corpus, some work also explores how to efficiently obtain domain adaptive emotion analysis model from unsupervised or a small amount of annotated emotion data. The unsupervised domain adaptation method usually assumes that there is shared data distribution between source and target fields and realizes knowledge migration by aligned the characteristic distribution of the two domains, while a small amount of supervised domain adaptation strategy combines a small amount of annotated target domain data to improve the domain specificity of the model.

4.2 A Domain-Specific-Oriented Emotion Analysis Model

For some specific application scenarios, researchers designed and optimized the emotion analysis model and related technologies, such as in the field of social media, user-generated text often mixed with a large number of informal language, abbreviations and emerging emoticons, to emotion analysis model based on formal text training brings new challenges, therefore some work focus on building social media emotion analysis model, combined with remote supervision annotation based on hash tags, expression annotation strategy from massive informal corpus mining effective emotional signals[23-27]. For specific products or services review analysis is also an important scene, comments often involves fine-grained emotional goals, such as mobile phone screen, camera and other specific attribute characteristics, based on the observation researchers put forward the fine-grained attributes of hierarchical emotion analysis framework, can identify the text of the emotional goal and its corresponding emotional polarity, provide the basis for product optimization and marketing decisions. In addition in other specific areas such as political public opinion analysis, financial view mining are developing customized emotion analysis solution demand, in general field adaptive emotion analysis technology is constantly to various application scenarios and penetration, for the actual needs of different areas to provide comprehensive and accurate emotional analysis services, industry specific emotional mining ability will also become one of the key direction of the field development in the future.

5 The challenge of sentiment analysis in practical applications

5.1 Comment on quality issues

In practical applications, emotion analysis models need to process large amounts of unstructured text data derived from various scenarios, And the quality of these raw data is often uneven, Presence of many noise and low-quality samples, A serious impact on the performance of the model, Comment quality questions mainly include the following aspects[28-33].First of all, a large number of informal languages, typos, abbreviations often appear in online comments and social media texts, Leading to standard text preprocessing processes that are not handled well, In addition, some marketing exaggeration, derogatory abusive language and robot automatically generated disruptive content can challenge the accuracy of sentiment analysis, On the other hand, some comments have complex semantic structures such as extreme views or double negatives, Difficult to understand and classify correctly by the model. Researchers have proposed multiple solutions to critical quality issues, such as deep learning-based text normalization techniques to transform informal languages into standard text; enhanced semantic understanding models to better capture complex emotional tendencies; and combined rules-based and supervised learning methods to identify marketing reviews and robot content.

5.2 Context Understanding Questions

Many emotional classification tasks need to combine the context context to accurately judge the emotional tendency of the text, for example for contain 'good' the word sentence ',' phone life 'and' phone photo effect 'although contains the word' good ', but the former life positive evaluation, the latter positive photo effect, the semantic is very different, so emotional analysis model not only need to understand the literal meaning of the words also need to combine the context of the emotional reasoning. Traditional emotion analysis model based on statistical characteristics is usually difficult to effectively capture the long distance context dependence, and based on deep learning models such as short-term memory network (LSTM) sequence model through the gating and memory unit design in dealing with long range semantic dependence has achieved good effect, in addition to the introduction of attention mechanism makes the model can automatically learn the emotion of the target words of the words, further improve the context understanding ability. Besides some methods also try to introduce structured semantic information from the external knowledge base to auxiliary model of context reasoning, such as using the knowledge base, causal knowledge can better identify complex emotional quotation and metaphor expression, context understanding is a big problem of emotion analysis, need language model with deep semantic understanding and reasoning ability, there is still a lot of exploration space is worth further research and development.

5.3 Fine-Grained Emotion Recognition Problems

Most of the existing models of emotion analysis focus on overall emotion polarity judgments at the sentence or text level, The objects to be analyzed are divided into positive, negative or neutral categories, However, in practical applications, people tend to focus more on the fine-grained emotion of a specific target entity, For example, the attitude and evaluation of the screen, battery life and other attributes of a mobile phone brand, Fine-grained sentiment analysis arises in response to this need, Aned to simultaneously identify emotional targets and their corresponding emotional polarity, Fine-grained emotion classification requires not only the correlation between target words and emotional words in sentences, but also the aggregation of multiple emotions corresponding to the same target, There are larger challenges present, A common solution is to decompose the task into two serial sub-tasks, emotion goal retrieval and goal-level emotion classification, The former aims to extract all the emotional targets from the text, The latter then classifies the emotion for each extracted target. Other methods try to end-to-end both the target extraction and emotional classification, including the sequence annotation model based on conditional random airport and joint model based on transfer network, depth model on the task shows the excellent ability, such as the use of attention mechanism efficient mining target and emotional word dependence using graph neural network to capture structured semantic relationship between targets and modifiers, etc.

6 Future Trends of Sentiment Analysis Technology

6.1 Knowledge Enhancement and Emotion Analysis

Introduce external knowledge into sentiment analysis models is a research hotspot, Aiming to improve the models' comprehension of complex semantics and emotional expressions [34-38]. Knowledge enhancement emotion analysis mainly includes the following technical routes, First, some work tries to mine the rules and knowledge conducive to emotion analysis from the constructed emotion knowledge base or concept knowledge base, By injecting these explicit knowledge into the model can enhance its understanding of complex emotional expressions such as metaphor and irony, Secondly, some researchers take the pre-training language model as the knowledge enhancement module of the emotion analysis model, Semantic and common sense knowledge learned on large-scale unsupervised corpora using a pre-trained model, Enabling emotion analysis tasks. In addition, studies have integrated relationship knowledge from structured knowledge bases (e. g. ConceptNet, etc.) into sentiment analysis models, A common practice is to represent a triplet of a knowledge base as a low-dimensional vector and integrate it with the context vector of the text, Thus enabling the modeling of structured common-sense knowledge, Knowledge base-driven sentiment analysis models are able to mine the associations between entities, emotions, and causality, Enhanced understanding of complex emotional expressions, In the future, with the development of knowledge representation learning and multi-source knowledge integration, Knowledge-enhancing sentiment analysis will certainly become an important research direction, Give emotion analysis models more common sense reasoning and contextual understanding.

6.2 Multimodal Emotion Analysis

Most of the current sentiment analysis efforts are still limited to a single textual modality, Unable to capture the rich emotional information contained in other modes, such as speech and vision, While in real-world scenarios, human perception and expression of information is multimodal, It is difficult to fully understand complex emotions by relying solely on a single modality, Therefore, multimodal emotion analysis arises, Aned to incorporate information from multiple modalities for a more comprehensive understanding of emotions.Su et al. executed a comprehensive study on large language models for forecasting and anomaly detection, and VR as a certain kinds of time series data could be beneficial from LLMs at a certain level from forcasting aspect [39].At present, multimodal emotion analysis focuses on the fusion of text and vision, A common technical route is the use of visual modalities to identify emotional objects or scenes in an image, And then associated with text information to improve the accuracy of emotional judgment, There are also attempts to cascading visual features directly with textual features, Input into the deep multimodal model for joint training, These models usually use strategies such as attention fusion or external product fusion to automatically mine the correlation and complementarity between different modes. Voice signal also contains the rich emotional information, so the modal emotion analysis also gradually expand to voice modal, some work will integrate speech features and text features to identify the speech and text expression, facial expression and body movements video modal has also been included in the research category of modal emotion analysis, to sum up the multimodal emotion analysis technology is developing rapidly, is expected to promote emotional understanding model toward a more natural and comprehensive direction [40-43]. Yi and Qiao (2024) explore GPU-based parallel computing for medical image reconstruction, which could be leveraged for efficient processing in multimodal emotion analysis [44].

6.3 Interpretative Emotion Analysis

As deep learning models achieve increasingly superior performance on sentiment analysis tasks, An urgent question is how to understand the decision-making process of the model, To increase their interpretability and credibility, The interpretable emotion analysis model can not only "explain the reasons" for the final emotion prediction result, but also give a reasonable explanation for the semantic behavior expressed within the model, Thus to improve the ability of human-machine collaboration[9]. At present, the interpretability research for emotion analysis models mainly has the following technical lines, The first one implements the model local interpretability based on the attention mechanism, By analyzing the attention weights assigned by the model at the different locations of the text to visually observe the words or phrases that the model concerns when making predictions, The second idea is to design intermediate representations with semantic interpretability, Make the internal computational path of the model correspond to the human cognitive process and visualize it. The third scheme is to explicitly introduce prior knowledge, Ening global interpretability to the emotion analysis model, For example, using the emotional knowledge base to build rule-based models or inject interpretable external knowledge into a deep learning model, In addition, new technologies such as interpretability analysis framework based on causal reasoning and explanatory analysis against samples are also emerging, Overall, interpretable sentiment analysis remains a challenging and emerging field, In the future, as the issues of AI security, robustness and reliability become increasingly prominent, The interpretability of sentiment analysis models will surely receive increasing attention, Assist in the transparency and standardization of model decisions.

Table 1: Table of the application parameters of natural language processing in the field of text emotion analysis

Parameters / models	naive bayes	support vector machine (SVM)	long short-term memory network (LSTM)	convolutional neural network (CNN)	BERT
precision (%)	78	85	91	89	94
The F1 fraction, (%)	76	84	90	88	93
Training time (seconds)	30	200	600	450	1200
Test Time (milliseconds / sample)	0.5	1.2	2.5	2.1	3.4
Model size (MB)	15	50	100	80	430
Dataset size (one thousand comments)	10	10	100	100	1000

7 Conclusion

Natural language processing in the field of text emotion analysis application research is developing rapidly, based on machine learning and deep learning emotion analysis model constantly breakthrough, the future emotion analysis technology will continue to the direction of the multidimensional, high precision and interpretability, for intelligent information processing, decision support to provide more powerful technical support, for emotion analysis algorithm and application of continuous innovation is beneficial to the natural language processing research theory will also bring great industry application scenarios of practical value.

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Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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