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Emotion Detection and Analysis Techniques Based on NLP

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Abstract: Emotion, as one of the key bridges connecting human society, serves as a central hub for human communication. With the continuous advancement of computer science, the field of artificial intelligence has developed many innovative branches and subfields to help computers understand human language, analyze the emotions and sentiments embedded within it, and make decisions and judgments. This technology has been applied across various domains, playing practical and significant roles, greatly benefiting human daily life and scientific exploration. Over the past two decades, natural language processing (NLP) has achieved remarkable progress, demonstrated extensive potential and contributed significantly to numerous areas. Emotions hold profound significance and impact on human life and social relationships. As an essential subfield of NLP, sentiment analysis and emotion detection have found broad applications in multiple domains. Despite the rapid development of sentiment analysis technologies, their applications still face many challenges. This paper explores the practical value and future prospects of sentiment analysis and emotion detection, reviews their currently employed methods and technological advancements, and focuses on analyzing existing issues while discussing their causes and potential solutions.

Keywords: Natural Language Processing, Sentiment Analysis, Emotion Detection, Key Methods, Existing Issues.

1. Introduction

Emotions and moods are an integral and central part of human life and socialization, with far-reaching significance and impact on multiple levels. Emotions play the role of feedback and connecting links in various interpersonal relationships, which can promote mutual understanding and further depth of the relationship, as well as influence decision-making and judgment. Therefore, if emotions can be quantified and datamined, computers can apply them to many real-world tasks and projects.

In multimodal data, the current mainstream methods for sentiment to be detected and analyzed fall into three main categories: The first is the dictionary-based method, which relies on a pre-constructed sentiment dictionary and analyzes the matching relationship between the text and the sentiment vocabulary in the dictionary through a deep search, so as to determine the sentiment or emotional tendency of the text. This method has a simple structure and is easy to operate and run. Commonly used sentiment dictionaries include the Valence Aware Dictionary and Sentiment Reasoner (VADER), Affective Norms for English Words (ANEW), SentiWordNet, and National Research Council (NRC)

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Emotion Dictionary, etc. Each of these dictionaries has its own characteristics and limitations. Each of these dictionaries has its own features and limitations and is applicable to different domains.

The second is the machine learning-based approach. In natural language processing, machine learning methods for sentiment detection and analysis are usually divided into two categories: supervised learning and unsupervised learning, and supervised learning is mainly discussed here. This method uses well-labeled training datasets to learn sentiment features and analyze and judge them through algorithms. Commonly used machine learning methods include Simple Bayes, Support Vector Machine (SVM), Decision Tree, Random Forest, K Nearest Neighbor (KNN), Logistic Regression, etc., and each method is suitable for different data processing scenarios.

In addition, methods based on deep learning have become mainstream. Deep learning is capable of handling more complex features, relying on powerful models to automatically extract emotion-related information, and is especially prominent in processing large-scale text data. Common deep learning models include Convolutional Neural Networks (CNN), Long Short-Term Memory Networks (LSTM), and Self-Attention Mechanisms, etc., which have been widely used in sentiment analysis tasks.

Based on the above methods as well as different theories of emotion, emotion analysis and detection frameworks are divided into two main categories: discrete models and dimensional models. Discrete models, in the application of this model, often consider emotions as a set of finite categories, where emotions are regarded as mutually independent states rather than a continuous spectrum, and each emotion is usually represented by a specific label. The well-known Ekman model belongs to this category [1]. Alternatively, the dimensional model, in its application, often considers emotions as a continuous space consisting of multiple dimensions, with emotions being correlated and capable of varying in intensity. The dimensional model recognizes the complexity of emotions and is often adapted to models such as Plutchik's emotion wheel [2].

Despite significant advances in sentiment analysis techniques, the field still faces four major challenges: first, the lack of diversity in data resources; second, imperfect standardization of terminology; third, the lack of interdisciplinary perspectives; and fourth, the impact of demographic and cultural differences on the effectiveness of analysis. In addition, sentiment detection is also limited by the lack of data resources. Some common problems include the interference of Internet slang in model recognition and classification, and the use of sarcasm or irony by users to express anger or disappointment, adding to the complexity of sentiment detection [3]. Despite these challenges, sentiment analysis and emotion detection techniques have been widely used in several domains with remarkable results [4].

This paper will systematically organize the current mainstream methods commonly used in the field of sentiment analysis and emotion detection, and provide an in-depth analysis and summary with examples. In addition, relevant sentiment theories supporting sentiment classification will be explored through the practical application of dimensional and discrete models.

2. Methods for Sentiment Analysis and Sentiment Detection

Sentiment analysis and sentiment detection are both very important areas in natural language processing, involving extracting sentiment polarity and categorizing sentiment in text, and commonly used methods can be categorized into the following categories: sentiment lexicons, machine learning, and deep learning.

2.1. Dictionary-based approach

The dictionary-based approach is a classic technique in sentiment analysis and emotion detection in natural language processing. This method mainly relies on a pre-constructed sentiment lexicon, and

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by analyzing the matching relationship between the words in the text and the sentiment words in the lexicon, it can then determine the sentiment or emotional tendency of the text. Its structure is simple and intuitive, especially suitable for some basic sentiment analysis tasks. The lexicon-based approach works on the principle that the sentiment lexicon is first constructed and then the sentiment is analyzed.

The sentiment lexicon, which is the core component of the lexicon-based approach, contains a large number of words, each labeled with the corresponding sentiment category or sentiment intensity. The method performs emotion detection by extracting emotion keywords from the text and combining them with predefined emotion information in the dictionary. Matching of emotion keywords usually employs techniques such as recursive search (e.g., depth-first search) to identify emotion expressions in the text. Sentiment dictionaries provide a standardized set of vocabularies that can help automated systems classify the sentiment of text and thus enable sentiment analysis and detection. Commonly used emotion dictionaries are the Valence Aware Dictionary and Sentiment Reasoner (VADER), Affective Norms for English Words (AFINN), SentiWordNet, National Research Council (NRC) Sentiment Dictionary, etc. VADER, a rule-based sentiment analysis tool designed specifically for use with social media texts and short texts, was developed by Hutto et al. in 2014 and contains about 7,500 English words, each labeled with a sentiment intensity score. For example, the Arora team used the lexicon to analyze public opinions on social media to study the impact of sentiment on topic discussions and ultimately found that VADER excelled in handling short text and social media informal language (e.g., abbreviations, slang, emoticons, etc.) [5]. The Pano team, in analyzing the sentiment fluctuations in tweets about Bitcoin during the COVID-19 period through VADER, the team investigated the impact of sentiment changes on the market price and ultimately found that tweet sentiment was found to serve as an important indicator of market volatility [6]. AFINN is a lexical method for sentiment analysis, published in 2011 by Finn Årup Nielsen, that contains approximately 2,500 English words and phrases, each assigned a sentiment score. In the Biswas team's use of AFINN for sentiment labeling, automatically categorized as positive, negative, or neutral, it was found that the proportion of assigned sentiment labels varied across methods [7].

The basic process of sentiment analysis is to compare the keywords in the text with the entries in the sentiment lexicon and count the matched sentiment words and the corresponding sentiment scores, based on which the sentiment distribution or sentiment tendency of the whole text can be calculated. It helps to identify the overall sentiment direction of the text, such as positive, negative, or neutral sentiment. This analysis method can effectively capture the sentiment trends in the text to support further market forecasting or sentiment-driven decision making.

2.2. Machine Learning Based Approaches

In natural language processing, machine learning methods for sentiment detection and sentiment analysis are usually divided into two categories: supervised learning and unsupervised learning. Supervised learning is mainly discussed here. The method uses labeled training datasets, learns sentiment features through algorithms, and makes analyses and judgments. Commonly used machine learning methods are methods such as Plain Bayes, Support Vector Machines (SVMs), Decision Trees and Random Forests, KNNs, and Logistic Regression. The plain Bayesian algorithm is based on Bayes' theorem assuming conditional independence between text features, i.e., the contribution of each word to the sentiment category is independent of each other. It calculates the probability of each sentiment category and selects the category with the highest probability as the prediction. Support Vector Machine separates texts with different sentiment categories by finding an optimal hyperplane. This method is more suitable for small samples and high dimensional data. Random Forest makes predictions by integrating multiple decision trees, which are suitable for dealing with nonlinear relationships, have a better tolerance for noise and high-dimensional data, and are suitable for unstructured text common in sentiment analysis. Logistic regression is used for binary classification

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problems (e.g., positive vs. negative sentiment) and predicts sentiment by training a linear model to learn the relationship between text features and sentiment categories. KNNs determine the sentiment category based on the position of the text features in the feature space by calculating the similarity between the new text and the annotated text and finding the nearest-neighbor text. Mishra's team used the plain Bayesian algorithm for Twitter data for sentiment categorization [8]. The study successfully classified the tweets in the sentiment classification task into positive and negative sentiments through a series of preprocessing steps, such as deactivation and stemming, as well as feature extraction. Most findings show that the plain Bayesian algorithm is able to efficiently differentiate between positive and negative sentiments, and demonstrates high efficiency and reliability when dealing with the task of analyzing the sentiments of short texts. Zainuddin's team trained the sentiment classifier using support vector machines (SVMs) on a benchmark dataset and emphasized that SVMs are also effective for complex, non-linear data [9]. Zheng's team also used Random Forest based on the IMDB movie review dataset for sentiment analysis on the IMDB movie review dataset, comparing the effectiveness of different machine learning algorithms [10]. The final experiments show that Random Forest performs well in terms of classification accuracy and robustness, especially when dealing with large-scale text data. Aliman's team applies a logistic regression algorithm to analyze the sentiment in the text and compares it with multiple machine learning methods [11]. The final experimental results show that logistic regression has a better performance in terms of accuracy and performance. Isnain team applied the KNN algorithm to analyze the sentiment of Twitter users on government policy issues related to online learning affected because of the epidemic [12]. The KNN classifier performs well in the sentiment classification task with an accuracy rate of 84.65%, and the results show that the KNN algorithm is very effective in large-scale sentiment analysis tasks is very effective, especially for those social media platforms where public opinions are expressed more informally. In addition, Nandwani et al. proposed that transfer learning is also a way of machine learning [13]. Models trained on large datasets to solve one problem can be applied to other related problems. Reusing pre-trained models as a starting point on related domains can save time and produce more efficient results.

2.3. Deep learning-based methods

The application of deep learning-based methods in sentiment analysis and emotion detection has gradually become mainstream. Compared with traditional machine learning methods, deep learning is able to handle more complex features and automatically extract emotion-related features through more powerful models, especially when the amount of text data is huge. Common models in deep learning include convolutional neural networks (CNNs), long and short-term memory networks (LSTMs), and self-attention mechanisms, which have been widely used in sentiment analysis tasks. Convolutional neural networks are able to efficiently extract local features from text and capture the spatial structure of words through their unique convolutional and pooling layers and are good at extracting local features in text and processing short texts. In addition, because of its relatively simple model, it is faster to train and does not rely on long-distance textual relationships. Nandwani's team explored the application of CNNs in sentiment analysis of short texts, especially in social media data (e.g., tweets and microblogs) [13]. It is proposed that CNNs can effectively extract sentiment-related local features and outperform traditional machine learning methods in sentiment classification tasks, especially when dealing with short texts. LSTM is a special type of recurrent neural network, which is particularly suitable for processing and predicting time-series-based data. LSTM solves the problem of traditional RNNs by introducing the “memory units”. This solves the problem of gradient vanishing that traditional RNNs are prone to encounter when processing long sequence data, and thus it shows strong capabilities in sentiment analysis and emotion detection tasks, excelling in capturing long-range dependencies in text, understanding the context of sentiment changes, and dealing with

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unstructured textual data. Miedema et al. built a short-term model to classify the movie review sentiment for classification [14]. The model correctly classified 86.74% of the reviews in the validation, indicating that the model performs well when dealing with tasks such as sentiment classification. The self-attention mechanism is particularly suitable for long text data in sentiment analysis and emotion detection, as it is able to establish relationships between multiple words and focus on more distant dependencies. For example, when analyzing long comments that contain emotional transitions, the self-attention mechanism is able to effectively capture changes in sentiment and understand emotional nuances. Frequently used self-attention mechanism models are the Transformer model, BERT model, GPT, etc. Vaswani's team proposes the Transformer architecture, which is very good at processing long text data, thus improving the accuracy of sentiment classification and enhancing the model's ability to understand sentiment changes and emotional transitions [15]. Naseem's team proposed an approach called Deep Intelligent Contextual Embedding Transformer (DICET) [16]. DICET uses the Transformer model to generate contextual embeddings, which enhances the ability to represent the sentiment of the text while improving the quality of the tweets through noise reduction methods, taking into account word sentiment, polysemy, syntax, and semantic relationships. Kenton's team proposed the Bert model, which utilizes the Transformer architecture and understands the context through the bi-directional self-attention mechanism[17]. In sentiment analysis tasks, BERT obtains strong sentiment understanding by pre-training on a large number of texts. BERT is widely used in a variety of sentiment analysis tasks, including sentiment classification, emotional tendency analysis, and so on. Test results on multiple datasets show that BERT can better capture the contextual information in sentiment expressions compared to traditional deep learning methods, and achieve significant results.

3. Categorization of emotions in emotion theory

Based on different approaches, many models have emerged to categorize and explain emotions, which are mainly divided into two categories: discrete models and dimensional models. Because these two categories of models are based on different emotion theories, they have different characteristics and functions. The sentiment framework provides a standardized method to classify emotions, which provides an important theoretical basis for sentiment analysis, thus making the classification of emotions more scientific and reasonable. Discrete Model Affect theory based on the discrete model treats emotions as a finite set of categories. In this model, emotions are regarded as mutually independent states rather than a continuous spectrum, and each emotion is usually represented as a specific label, such as the Ekman model, the Plutchik roulette wheel model, and so on. Dimensional modeling Affect theory based on dimensional modeling supports the idea that affect is a continuous space defined by multiple dimensions. The dimensional model views emotions as interrelated rather than separate wholes. This model recognizes that emotions can vary in intensity and can be represented along different dimensions, consisting of multiple dimensions. There is a wide variety of emotion frameworks, and the main focus here is on the common Ekman model, Plutchik's Roulette wheel model, and Russell's Circle of Emotion model.

The Ekman model, proposed by psychologist Paul Ekman, identifies six basic emotions that he argued are universally recognized across cultures, and can be recognized and understood in almost all cultural contexts [1]. These six emotions include: anger, fear, disgust, happiness, sadness, and surprise. The Plutchik Roulette Model is Robert Plutchik's emotional roulette wheel model that emphasizes the composite nature of emotions, their intensity hierarchy, and their evolutionary function [2]. The model diagrams emotions in a structure of hierarchy, intensity, and interactions through the form of an emotion wheel. As such, Plutchik proposes eight basic emotions that are believed to underlie all other emotions. These eight emotions include: joy, trust, fear, surprise, sadness, disgust, anger, and anticipation.

Russell's Emotional Circle Model was proposed by psychologist Russell in 1980 to explain and describe the structure of emotions [18]. The model represents emotions in a two-dimensional spatial form, distributing complex emotional states in a circular diagram that is used to capture the continuity and interrelationships of emotions. The core of Russell's emotion circle model describes emotions through two key dimensions, pleasure and arousal.

4. Conclusion

With the continuous and profound development of artificial intelligence, the technology that allows computers to quantify and understand human emotions is also progressing and developing. This paper has explored the mainstream methods currently used for sentiment detection and sentiment analysis in natural language processing and the sentiment framework and sentiment theory that underpin the methods, and briefly outlined the main problems they face. Even though some problems and challenges are faced, it just proves that the development space and prospect of the two major fields of sentiment detection and sentiment analysis in the field of natural language processing are broad, and it is believed that with the deepening of learning and development, these problems will be overcome one by one, and natural language processing will be more maturely and more widely applied in other fields.

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