Text-Based Emotion Detection: A Literature Review

by

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Abstract

This literature review explores the complex and rapidly evolving field of emotion detection in the context of social media. With the rise of digital communication, understanding and interpreting emotions expressed in text data has become increasingly important. This paper delves into the theoretical underpinnings of emotion detection, discusses the process of dataset collection, touches on current emotion detection techniques and explores the challenges within text-based emotion detection.

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1 Introduction

Emotion detection and interpretation is a complex field due to the multidimensional factors of human language understanding. When recognising human emotion through speech, we rely on physical cues such as body language, tone of voice, and facial expression. With the rise of social media within the past decade, people rely heavily on self-expression through text and behind a screen, adding another layer of complexity to emotion recognition. Not only are these physical cues missing with text, but emotions also vary from person to person based on gender, location, ethnicity, culture, age, and other social and individual factors [24, 29]. The lack of these cues and understanding of other factors can lead to misinterpretations, which cause friction, disconnect, and even isolation [24, 30].

In our ever-increasing industrial world, people, companies, and societies are developing digitally more and more every day [2, 4, 24]. Social media platforms have become essential to our daily lives, playing a key role in communication across multiple sectors such as healthcare, education, and industry [24, 30]. For instance, the COVID-19 pandemic resulted in numerous people using social media platforms like Facebook, Twitter, and Instagram to express their concerns and frustrations [16, 24]. In the education stream, most institutions have learned to adapt to an online platform, which introduced increased isolation to many students, leading many to seek a virtual community [6]. Businesses use social media to gather feedback and reviews on their latest products, as well as the monetization of platforms [24]. Additionally, social media has created business opportunities for influencers [24]. Natural Language Processing (NLP) is a powerful field that analyses interactions and data that flood social media.

2 Background

NLP can detect, classify, and analyze emotion from social media text posts. The terms sentiment analysis and emotion detection, both fields of NLP, are often used interchangeably, but there is a difference between them, and it is important to understand the difference. Sentiment analysis focuses on the polarity of a text, classifying it as either positive, neutral, or negative [24, 29, 30]. Whereas emotion detection involves detecting (is the emotion present) and classifying (what is the emotion) a person's various feelings (for example, joy, sadness, anger) from the given text [25, 30, 31]. The two are confused due to their similar applications and shared techniques. Emotion detection is more dimensional than sentiment analysis, making it more challenging to accomplish successfully.

2.1 What is Emotion?

Emotion is a complex phenomenon that plays a significant role in human communication and interaction. The Merriam-Webster dictionary defines emotion as "a subjective response to a person, thing, or situation". Beyond its dictionary definition, emotion encompasses a wide range of psychological and physiological experiences that influence how individuals perceive and respond to their environment [5, 15, 28]. Psychologists have proposed various theories to understand the nature and mechanisms of emotion, each offering unique perspectives on the processes of underlying emotional experiences. These theories delve into the origins of emotions, their cognitive and behavioural manifestations, and the interplay between physiological responses and subjective feelings. By exploring these theories, we can better understand how emotions are expressed, interpreted, and detected, allowing us to decide which theory to use to train machine learning (ML) models.

2.2 Emotion Models

Psychological emotion models can be broadly put into one of two categories: *The Dimension Model* and *The Categorical Model* [12, 22]. The Dimensional Emotion model represents emotions based on three parameters: arousal, valence, and dominance, as seen in Figure 1 [12, 21, 22].

Arousal is how exciting a feeling is, valence describes the polarity (positive, neutral, or negative) of a feeling, and dominance is how powerful the feeling is [21]. The dimensional model used to be 2 dimensional (arousal on one axis and valence on the

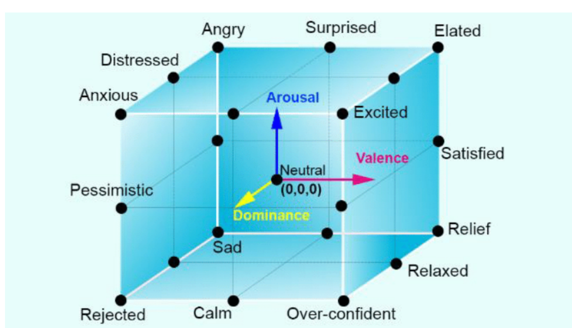

Figure 2.1: The Dimensional Model

other) [21]. By incorporating the dominance dimension, this model provides a more comprehensive framework for understanding emotions, especially in contexts where power dynamics play an important role.

The Categorical Emotion model defines emotions discretely, stating that there are a handful of widely recognized and physiologically defined basic emotions [12, 14]. Specific facial expressions and biological processes can identify these basic emotions [14]. These include happiness, sadness, anger, fear, disgust, and surprise [14].

Understanding and selecting the appropriate model for data creation and emotion detection Machine Learning (ML) models is crucial. The choice of model significantly influences how emotions are conceptualized and categorized, which affects the accuracy and reliability of emotion detection algorithms. For instance, a dimensional model allows for a nuanced representation of emotions, enabling finer-grained analysis of emotional states [7, 12, 21, 22, 28]. A categorical model simplifies emotions into discrete categories, which is beneficial for certain applications that require clear distinctions between specific emotional states [12, 19, 22]. Selecting the right model is essential for designing effective datasets that capture the diversity and complexity of human emotional experiences. A well-designed dataset ensures that the ML models trained on that data can accurately identify and classify emotions in textual content, leading to more robust and reliable emotion detection algorithms [2]. Therefore, understanding the different emotion models is critical for optimizing emotion text detection and creating high-quality datasets that reflect the richness of human emotions in social media.

3 Emotion Datasets

Selecting the appropriate model for emotion text detection and creating datasets is foundational for building robust and reliable ML models. Collecting raw data is often accomplished through methods such as web scraping, using APIs to extract data from social media platforms, or extracting dialogue to text from movies or TV shows [2, 17]. However, collecting data from online sources raises concerns about privacy, consent, ethics, and data quality [13]. Privacy concerns are paramount, given the potential risks of re-identification and the unclear anonymization processes in many studies [13, 26]. Consent is another critical aspect, as users may not have explicitly agreed to their posts being used for research or model training [20]. This raises ethical questions regarding the transparency of terms and conditions on social media platforms.

Furthermore, data quality can be compromised if not cleaned appropriately, considering the use of slang, acronyms, and biases in social media [1, 2, 5]. If not addressed adequately, biases in data lead to biased models that perpetuate prejudices. Therefore, the context of data collection is vital for accurate interpretation, as the same expressions may convey different emotions in various contexts [2]. Publicly available datasets offer a good starting point. The most commonly used datasets are SemEval, EmoBank, SST (Stanford Sentiment Treebank), and ISEAR (International Survey of Emotional Antecedent and Reactions) [24]. Understanding the context and domain of data collection is important to avoid misinterpreting the data when reusing emotion datasets.

4 Emotion Detection Models

Multiple methods have been used in sentiment analysis and emotion detection tasks, each offering unique advantages and capabilities. In this section, I'll explore different approaches to emotion detection, ranging from traditional lexicon-based and keyword-based methods to ML methods.

4.1 Lexicon-Based

Lexicon-based approaches rely heavily on predefined emotion lexicons and sentiment dictionaries [10, 24]. The lexicons in question encompass words or phrases that have been annotated with labels denoting emotions, such as joy or melancholy. The methodology encompasses the process of associating words or phrases inside textual material with corresponding entries in the lexicon to ascertain the corresponding emotions [24]. In their study, Bandhakavi et al. (2017) introduce an innovative method for extracting a comprehensive and accurate set of phrases that have been annotated with emotion scores. They illustrate the utilization of labelled emotion text and weakly labelled emotion text for the purpose of acquiring a word-emotion association lexicon [8]. Furthermore, they employ a generative unigram mixture model (UMM) to collectively represent the emotionality and polarity of words [8]. In contrast, the study conducted by Pajupuu et al. (2012) investigates the potential of automated emotion recognition in textual data by employing a limited lexicon consisting of 600 often-used emotion words. The primary emphasis is on the reader's perspective, specifically their expertise regarding the potential causes of the emotive impact [27].

There are various problems associated with lexicon-based techniques, including their significant dependence on pre-established emotion lexicons and dictionaries [2]. Despite the inclusion of emotion labels in these lexicons, the current lists frequently suffer from a limited lexicon and exhibit suboptimal performance in identifying certain emotions [2, 24]. An additional obstacle that arises pertains to managing contextual factors, instances of ridicule, phrases that communicate several emotions, web slang, and ambiguity [24].

4.2 Keyword-Based

Keyword-based approaches involve identifying keywords or phrases associated with different emotions and using them as indicators to classify the emotional content of text data [29]. Unlike the lexicon-based approach, this approach focuses on identifying contextually relevant keywords indicative of emotional states [29, 10].

Bharti et al. (2022) present a hybrid model that integrates keyword-based, deep learning (DL), and ML methodologies for the purpose of emotion detection. They primarily concentrate on phrasal verbs and construct their database by identifying these verbs and terms synonymous with different emotions [9]. The researchers opted for a hybrid methodology to address the difficulties associated with keyword-based techniques, which primarily emphasize semantic relationships [9]. The ML technique employed is a Support Vector Machine (SVM), whereas the DL techniques utilized are a Convolutional Neural Network (CNN) and Bi-Gru. The researchers employed a blend of three datasets, namely phrases, Tweets, and dialogues, to assess the efficacy of their model, yielding an accuracy rate of 80.11% [9].

One significant obstacle inherent in this methodology is the lack of alignment between the emotion keyword and the conveyed emotion [24]. As an illustration, the statements "Does that bring you joy?" and "I am not content." Please incorporate the emotion keyword "happy" without explicitly expressing said emotion. Keyword-based approaches, like the lexicon-based approach, face challenges in handling ambiguity, phrases that express many emotions, and web slang [24].

4.3 Machine Learning

ML methodologies utilize algorithms and statistical models to acquire knowledge about patterns and characteristics from annotated data, hence facilitating the classification of textual content into distinct emotional classifications [4, 17, 19]. In contrast to lexicon and keyword-based methodologies that depend on predetermined lists, ML algorithms can autonomously extract pertinent features and associations from textual data. This attribute renders them exceptionally versatile and efficacious in capturing intricate emotional expressions [11, 18, 24, 29, 30]. ML has recently been widely utilized and has emerged as the predominant method for detecting emotions in textual data. The ML methodology is a widely accepted procedure, encompassing many stages such as data collection, preprocessing, feature extraction, model training, model testing, and emotion categorization [2, 9, 19].

For instance, a study by Al-Omari et al. (2020) aimed to recognize emotion and sentiment in text and classify it into four categories: happy, sad, angry, and other.

They used the SemEval (2019) dataset and applied their preprocessing techniques to balance the data, correct spelling errors, and transform emojis into textual data [3]. They then extracted features in two steps. First, they used the word2vec embedding model to extract a 300-dimensional vector (Al-Omari et al., 2020). Second, they used the AffectiveTweets Weka package to extract semantic features [3]. Lastly, they built their EmoDet2 model by assembling four sub-models after several experiments were conducted to determine the best architecture for their model [3].

Emotion detection methods have evolved significantly over the years, with advancements in both computational power and algorithmic design. Traditional methods, lexicon-based and keyword-based, provided a foundation for the field. However, the advent of ML has revolutionized emotion detection, enabling a more accurate and nuanced understanding of human emotions from text. Despite these advancements, challenges remain, particularly in handling the complexity and variability of emotions.

5 Emotion Detection Challenges

Despite its potential, text-based emotion detection faces several challenges. One primary issue is the lack of resources, such as annotated datasets, which are crucial for training and evaluating ML models [13, 17]. The use of web slang or non-standard language can pose significant challenges in detecting and classifying lexicon-based, keyword-based, and ML models. Another challenge is dealing with sentences that convey multiple emotions, which adds additional complexity to the emotion detection task. Sarcasm and irony further complicate matters, as they often involve saying one thing but meaning another, which is difficult for models to interpret correctly

[23]. Lastly, ambiguous sentences that could be interpreted in multiple ways pose a significant challenge for text-based emotion detection, as the models would require an extensive dataset to be trained on to even be able to identify these sentences [23].

6 Conclusion

Finally, emotion detection is a difficult and quickly expanding field, especially in social media. Text-based communication and human emotions' complexity provide distinct obstacles. However, advances in NLP and AI have made text data emotion detection and classification possible. While commonly confused, sentiment analysis and emotion detection serve different objectives and require separate methodologies. The former emphasizes text polarity, whereas the latter explores specific emotions. Significant progress has been made despite problems such as text data's lack of physical indicators, demographic differences in emotions, and ambiguity. This literature study covered emotion detection's theoretical foundations, datasets, methods, and problems. As we use more digital communication, detecting and understanding emotions in text data will become increasingly important. Future research will improve these methods and overcome the obstacles, enabling more accurate and sophisticated emotion recognition systems.

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