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A Review on Detecting Content Feelings Emotion from Text

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ABSTRACT: Many different text-based documents are produced as the internet community grows. This paper provides an overview of the emerging field of emotion detection from text, as well as a description of the current generation of emotion detection methods. Emotion recognition in text is just one of many aspects of the task of teaching computers to understand emotions. On the basis of a review of important recent techniques, the main research focus of this study will be on suggestions for designing more efficient and adaptive Natural Language Processing Systems for the detection of various emotions (sentiment analysis).

KEYWORDS: Sentiment, sentiment score, polarity

I. INTRODUCTION

Emotions play a crucial role in human life and decision-making. People's understanding and expression of emotional feelings form a complex web. This complicated interactional phenomenon is a hot research topic. "Emotion" is a broad topic with a wide range of terminology and numerous concepts, theories, and models. In the human-computer interaction (HCI) field, the terms "emotion extraction/emotion computing/affective computing/Sentiment Analysis" are now commonly used to refer to systems that address human emotion in some way, and this has become a major topic of interest in the community over the last fifteen years. Emotion Detection in Text Documents is a content-based classification problem that incorporates concepts from Natural Language Processing and Machine Learning.

The techniques for emotion detection and emotion recognition based on textual data are discussed in this paper. Joy, sadness, anger, surprise, hate, fear, and other emotions are all examples of emotion. W. Gerrod Parrot [1] published "Emotions in Social Psychology" in 2001, in which he explained the emotion system and formally classified human emotions into six classes at the primary level, which are Love, Joy, Anger, Sadness, Fear, and Surprise (see fig. 1). Other words can also be found in the secondary and tertiary levels. Because they understand the meaning of the words and phrases, people are able to distinguish the expressed emotions perfectly. They also are able to generate expressions and sentences for different emotions. However, developing a computer system to analyze and interpret different emotions in a given text is a difficult task.

II. RELATED WORK

In the field of emotion extraction, there is a large body of work. Work in this area includes identifying subjective parts of text, determining sentiment orientation, and, in a few cases, determining fine-grained sentiment distinctions like emotion and appraisal types. Work devoted solely to emotion detection is uncommon and has yet to be empirically validated. Emotions are mental states that are accompanied by bodily changes. Happiness, sadness, anger, fear, disgust, and surprise are the six basic emotions identified by Ekman [2].

In [3,] it was proposed to characterise emotional interactions in social networks and then use these characteristics to distinguish friends from acquaintances. The goal was to extract emotional content from online social network texts. The question is whether or not the text is an expression of the author's emotions. Text mining techniques are used on comments retrieved from a social network for this purpose.

[4] Proposed a model for statistical analysis of collective emotions in product reviews. The scope of this study is limited to the extraction of emotional variables such as helpfulness, unhelpfulness, and rating. This work was done to give manufacturers guidelines on how to improve customer satisfaction.

The most common approach to sentiment classification is based on the idea that a document's overall sentiment is the sum of the sentiments of the words that make it up. As a result, these techniques search for appropriate affect words in text. Some words are unmistakably affective, while others convey affect to varying degrees. This method either relies on some existing affect lexicons or uses a corpus-driven approach to assign affective orientation or scores to words.

As more people become aware of the scientific challenges posed by the processing of subjective language, and the scope of new applications enabled by it, many researchers have become interested in sentiment analysis. The papers examined in [5] are a representative sample of early research in the field.

On the basis of a deep syntactic-semantic approach, a lexicon model for subjectivity description of Dutch verbs [6,7] was presented, which provides a framework for the development of sentiment analysis and opinion mining applications. The model aims to express multiple attitudes for each verb sense by describing the detailed subjectivity relations that exist between the participants of the verbs.

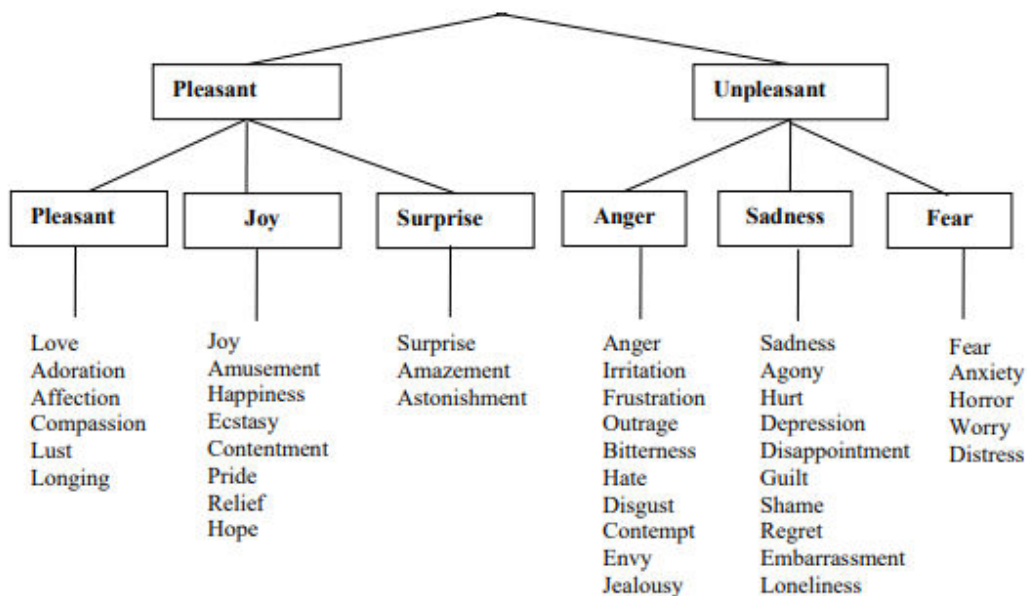


Fig. 1 Hierarchical Structure of Emotions

Polarity scores to a large list of words, based on their WordNet distance from positive and negative seed words was assigned in [8]. Deep language analysis techniques for machine translation to extract sentiment scores for words in documents were used in [9].

Customer reviews were analysed for sentiment by counting positive and negative terms, as well as contextual valence shifters like negations and intensifiers [10, 11]. In [12], a metric for determining positive or negative polarity in financial news text was proposed.

The goal of this study is to see if the opinions expressed in a conditional sentence are positive, negative, or neutral. One of the most commonly used language constructs in text is conditional sentences. Around 8% of sentences in a typical document are like this. This study examines the linguistics of such sentences before developing supervised learning models to determine whether the sentiments expressed in a conditional sentence are positive, negative, or neutral. The effectiveness of the proposed approach is demonstrated by experimental results on conditional sentences from five different domains [13].

As opinion mining and sentiment analysis applications increasingly rely on the value and properties of the verbs expressed by their dependency trees, there is a need for specialised lexicons where this information can be found. The identification of the attitude holder and topic is critical for the analysis of more complex opinionated text such as news, political documents, and (online) debates. Applications that take advantage of the connections between a verb's

meaning and its arguments can better determine sentiment at the sentence level and track emotions and opinions back to their source. [14]

To train a sentiment classifier, corpus-based methods use a corpus of documents that have been labelled with polarity. To improve classification performance, various classification models and linguistic features were introduced. The Structured Model was investigated for classifying text sentiment at various levels of granularity. The effect of negativity on sentiment analysis and retrieval effectiveness has been studied [15, 16, 17].

III. METHODOLOGY

Even though texting is one of the most common ways to communicate, your tone may be misunderstood by others. Because the other person won't be able to read your body language, it's critical to state your feelings clearly so they don't get lost in translation. In both healthcare and manufacturing, gathering feedback on products and services helps companies generate significant revenue, but doing so by hand is more complex and inaccurate.

The process of recognising human emotion is known as emotion recognition. People's ability to recognise other people's emotions varies greatly. The use of technology to assist people in recognising emotions is a relatively new research area. In general, technology works best when multiple modalities are used in conjunction. The rule-based method and the machine-learning (ML) method are the two main methods for emotion recognition. The first explains how to detect emotions from documents using grammatical and logical rules. It may be simple to create rules for a small number of documents; however, with a large number of documents, complexities may arise. ML method applies kinds of classification algorithms to associate text data to different emotion labels. In this paper, we used the ML methods and compared their effect. Process: Analyse the impact of effective words on the sentence. Used supervised learning models to classify the emotion classes on given sentence.

Further work includes Emotional analysis on a given sentence/paragraph and find the relation.

IV. CONCLUSION

This paper proposes ways to improve the capabilities of current text-based emotion detection methods. In addition to the informative and/or explanatory content, text documents contain attitude or emotional information. Document classification based on this piece of information can be useful in a variety of applications. However, emotional classification differs from simple topic classification in that it does not simply compare document content to a set of 'keywords' or 'keyphrases.' This study provides an overview of the fields of opinion analysis and emotion extraction, which employ a variety of sentiment analysis techniques such as machine learning.

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