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Multi Label Sentiment Analysis of Covid Handling of Government through Tweets

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Abstract

Determining someone's emotional state from a written text might be challenging, but it's crucial because textual expressions often transcend the use of emotion terminology. They emerge from the way concepts are seen and relate to one another inside the text. Text sentiment recognition is a critical skill for human-computer interaction. Text-based emotion recognition still requires further research, despite significant progress in speech and facial expression emotion detection. expressions and movements. In essence, emotion detection in text texts is a content-based classification task that incorporates ideas from machine learning and natural language processing. The methods for emotion detection and recognition based on textual data are covered in this study.

Keywords: Textual emotion detection, emotion word ontology, human-computer interaction, tweet

INTRODUCTION

Determining someone's emotional state from a written text might be challenging, but it's crucial because textual expressions often transcend the use of emotion terminology. They emerge from the way concepts are seen and relate to one another inside the text. Text sentiment recognition is a critical skill for human-computer interaction. Text-based emotion recognition still requires further research, despite significant progress in speech and facial expression emotion detection. The recognition of human emotions in text has become more important in practical applications within the field of computational linguistics.

People frequently display a wide range of emotions, including fear, hate, rage, surprise, joy, and sadness. There isn't a single hierarchy of emotion words that is widely acknowledged, thus the cognitive psychology literature now in publication is a useful resource. A thorough explanation of the emotion system and a systematic classification of human emotions into six main classes—Love, Joy, Anger, Sadness, Fear, and Surprise—can be found in W. Gerrod Parrot's 2001 book "Emotions in Social Psychology". There are secondary and tertiary levels for other terms. In an effort to promote more developments in the field of text-based emotion detection, this study suggests ways to improve the capabilities of existing techniques [1–8].

RELATED WORK

Since Picard first proposed the idea of affective computing in 1997 [3], it has focused on the part that emotions play in human-computer interaction. Researchers from a variety of disciplines, including computer science, biotechnology, psychology, and cognitive science, have shown interest in this interdisciplinary topic. Consequently, studies in the field of textual data emotion detection have arose, providing a distinct

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viewpoint on comprehending human emotions. The following is a definition of the challenge of text-based emotion recognition: The objective is to identify the function r: A x T → E, which reflects the emotion e of author a from text t, given the sets E representing all emotions, A representing all authors, and T spanning multiple representations of emotion-expressing texts [4]. The main difficulty with emotion detection algorithms is that it can be difficult to define specific elements and subsets within sets E and T [9–14]. On the one hand, as new languages are developed, the set T is always changing. Conversely, the complexity of the human mind is the reason why "all human emotions" lack regular categorization. Any current categorization of emotions are only labels or comments made after the fact for certain uses. Text-based emotion recognition systems [4, 5] use the following techniques:

Keyword Spotting Technique

Finding instances of keywords from a given set within a given string and treating them as substrings is the goal of the keyword pattern matching issue [4]. Numerous algorithms have been developed to handle this problem as a result of much research into it. Regarding emotion recognition, this method is based on preset keywords that are classified into feelings like disgust, despair, joy, rage, fear, surprise, and so on. Figure 1 shows how the keyword detecting method works.

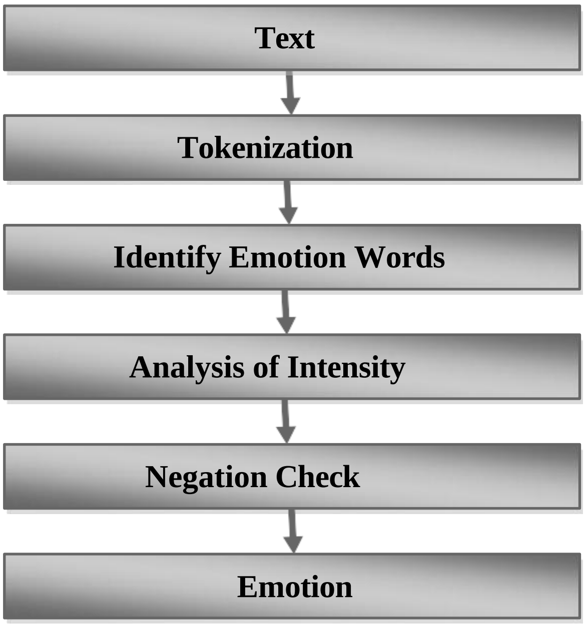

Figure 1. Keyword spotting technique.

As shown in Figure 1, the keyword spotting technique for emotion recognition consists of five consecutive steps. Tokenization, the process of breaking up a text document into discrete tokens, is what happens in the first phase. The method then finds and recognizes emotion words inside these tokens. The intensity of the emotion words that were identified is then examined. The next step is to determine whether the sentence contains negation [15]. Ultimately, the method chooses the right emotion class as the output depending on these steps.

Lexical Affinity Method

A simple and approachable technique for emotion identification is the usage of related terms. Building on the keyword detection technique, an enhanced method termed Lexical Affinity identifies emotional keywords as well as assigns a probabilistic "affinity" to random words. A common source of these probability is linguistic corpora. There are certain disadvantages to this strategy, though. First of all, bias is introduced into the assigned probability as a result of the particular genre of texts in the corpus. Second, it is unable to convey emotional information that is outside the scope of this technique's word-level examination. For example, although the word "accident" is likely to convey a negative sentiment, it might not be a good indicator of the mood behind statements like "I met my girlfriend by accident" or "I avoided an accident."

Learning-based Methods

The issue of emotion recognition has been approached differently thanks to learning-based techniques. At first, the goal was to extract emotions straight from input sentences. But now that learning-based methods have been developed, the challenge is to categorize input texts according to many emotional categories. Learning-based approaches, in contrast to keyword-based detection methods, make use of learned classifiers that apply machine learning theories, like conditional random fields [9] and support vector machines [8]. These classifiers identify which emotion category the incoming text should be placed in.

Hybrid Methods

Owing to the drawbacks and poor performance of keyword-based and naïve learning-based approaches, several systems have opted for a hybrid strategy that blends the two approaches in order to improve accuracy. Wu, Chuang, and Lin's work [11] is particularly noteworthy as a noteworthy example of a hybrid system. Their methodology combines an ontology of Chinese lexicons for attribute extraction with a rule-based method for emotion-related semantics extraction. Emotion association rules are then used to link these semantics and properties to emotions. These emotion association rules are employed as training features in their separable mixture model-based learning module, as opposed to depending only on the original emotion keywords. Though the number of emotion categories is still restricted, this strategy has proven to function better than earlier ones.

Limitations

From above discussion there are few limitations [7]:

1. *Ambiguity in Keyword Definitions:* Although using emotion keywords to detect emotions is a straightforward method, it has drawbacks because these terms might have numerous meanings and be ambiguous. Various words can have distinct meanings based on how they are used and the context in which they are used. Moreover, in some extreme situations, like words including irony or cynicism, even a limited collection of emotion labels (without taking into account their counterparts) might produce diverse emotions [16].
2. *Incapability of Recognizing Sentences without Keywords:* A predetermined list of emotion keywords is the only source of support for the keyword-based strategy. As a result, statements without any of these keywords may misimply that there are no feelings present. Examples that highlight this constraint are "Hooray! I passed my qualifying exam today" and "I passed my qualifying exam today." The same emotion (joy) is expressed in both sentences, but since "hooray" is the only keyword used to identify this particular emotion, its absence in the first sentence may cause it to go unnoticed.
3. *Lack of Linguistic Information:* Expressions of emotions are also influenced by semantics and syntax. For instance, from the first person's point of view, "I laughed at him" and "He laughed at me" would imply quite different feelings. Thus, neglecting language data also presents an issue for keyword-based approaches.
4. *Difficulties in Determining Emotion Indicators:* The probability between characteristics and emotions can be automatically determined by emotion detection techniques based on learning. These techniques do, however, still need the use of keywords—just as features. One of the simplest features is emojis, which are basically the author's comments of emotions in texts. Nevertheless, in terms of cascading problems, this strategy encounters the same difficulties as keyword-based approaches [10].

PROPOSED ARCHITECTURE

In order to expand the capabilities and enhance performance, the methods outlined in Section II are adjusted and merged; as a result, a straightforward model is created and presented in Figure 2.

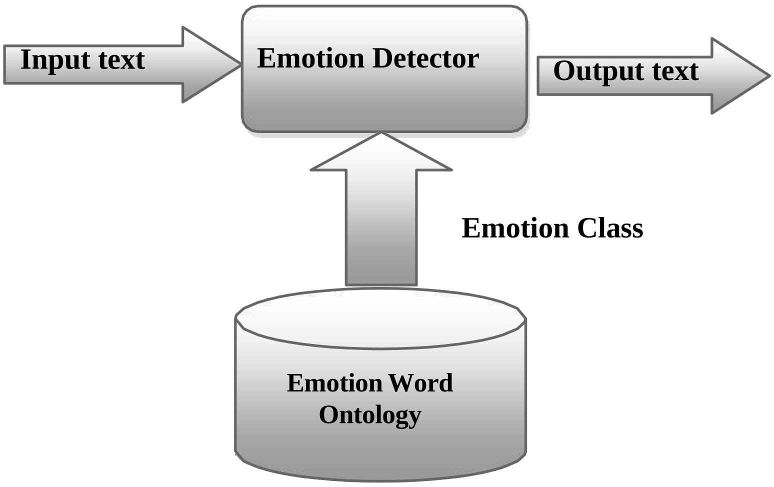

Figure 2. Proposed architecture.

The Framework is divided into two main components: Emotion Ontology, Emotion Detector.

Emotion Ontology

An formal statement of conceptualization that includes particular items and characteristics as well as high-level concepts is referred to as ontology [16]. It provides a thorough understanding of a specific domain by representing the relationships between items and the domain vocabulary. Ontologies help people, organizations, and application systems communicate inside the domain. W.G. Parrot's emotion word hierarchy is converted into an ontology when applied to emotions. This project makes use of a variety of electronic components, including sensors and microcontrollers, to create a communication medium using motions and sensors. The project aims to create a portable electronic automated healthcare system for patients with paralysis [13], as well as an ontology development tool. The suggested ontology is organized according to a class and subclass connection structure, with the tertiary level emotion classes located at the bottom of the ontology and the primary level emotion classes in the emotion hierarchy occupying the top positions. Giving the higher-level emotion classes more weight and the lower-level emotion classes less weight is the main focus.

Emotion Detector Algorithm

The algorithm for emotion recognition facilitates the identification of emotions found in textual material. It functions by averaging the weights assigned at each level of the emotion hierarchy to determine the weights for a given emotion. Weights are also computed for the opposite feeling. Subsequently, the computer evaluates these scores and designates as the detected emotion the emotion with the highest score.

Parameters Used

The method seeks to ascertain the proper weights to be applied to various emotion terms so that they can be sorted according to these weights. It is necessary to compute certain parameters in order to achieve this. First, these parameters need to be calculated, and the Jena library makes this process easier. The ontology may be efficiently traversed and parsed thanks to this module. The following method is used to compute various parameters:

Parent-Child Relationship

A text document that is the property of a child also alludes, albeit subtly, to the parent of the child. Therefore, the parent score must also be adjusted if a particular value is added to the child's score. This is accomplished by using the Jena API to traverse the ontology model in a breadth first fashion. Every node that is found has all of its offspring recovered. Then each child receives the identical instruction.

Depth in Ontology

This is necessary because it provides insight into the term's level of specificity with respect to the associated ontology structure. Age should be given greater weight the more detailed it is. The computation of this value occurs concurrently with the ontology tree traversal.

Frequency in Text Document

This is a crucial element as well because a term's relevance increases with its frequency. By parsing the text document and looking for word occurrences, this value is determined.

Algorithm

The suggested method uses the parameters that were determined in the earlier rounds to determine a score for every word related to emotion. The term's depth in the ontology and frequency are taken into account while calculating this score. To prove this relationship, a formula created especially for the mth language is used. A score matching to each primary level emotion class is calculated. The emotion state of the associated text document is ultimately determined by tallying the scores of all the emotion classes, with the class with the greatest score emerging as the victor. This is the algorithm's paraphrased version:

for *j* 🡐1 to No. of Nodes [*Ontology*]
do parent [*j*] 🡐 parent of node j
child [*j*] 🡐 child of node j
for *m* 🡐1 to No. of Nodes [Ontology]
do freq [m] 🡐 frequency of occurrence of m^{th}
depth [m] 🡐 depth of m^{th} node in ontology

Calculate (x):
for m 🡐 1 to No. of Nodes [Ontology]
score (*x*) 🡐 *freq* [*root*] / *depth* [*root*]
for *m* 🡐 1 to No. of parent nodes [Ontology]
score (parent) = score (parent) + score (child) return score (parent)
for *m* 🡐 1 to No. of parent nodes [*ontology*]
emotion class 🡐 *High score* [*parent*] return emotion class

The suggested technique uses the ontology's nodes to represent classes, parent [j] to indicate parent classes, and child [j] to indicate child classes. The depth denotes the class's place in the ontology, while Freq[m] indicates how frequently the mth class occurs in the text. In the ontology, the parents' scores are represented by the score [parent]. The suggested algorithm can be used to calculate the primary emotion classes' scores. The ultimate emotion class for the blog will be determined by tallying the scores of all the emotion classes.

CONCLUSION

In the topic of human-computer interaction, sentiment analysis is important and has attracted a lot of study interest. Although significant advancements have been made in the identification of emotions from audio and face data, the identification of emotions from textual data is still a relatively new and active field of study. This work offers a thorough analysis of the current techniques used to extract emotions from text while emphasizing their drawbacks. Furthermore, a unique system design is put forth with the intention of resolving these issues and improving the overall effectiveness of text-based emotion recognition.

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