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A Survey On Emotion Detection Techniques using Text in Blogposts

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Abstract

People express emotions as part of everyday communication. Emotions can be judged by facial expressions, prosodies, gestures, actions and written texts. Emotion is an important aspect in the interaction and communication between peoples. The communication of emotions through text messaging and personal blogs poses the informal style of writing is a challenge for researchers. Extraction of emotions from text can applied for deciding the human computer interaction which governs the communications. Emotions may be expressed by a persons speech, face expression and written text known as speech, facial and text based emotion respectively. This work is drawn from emotion theories in the fields of psychology and linguistics, and use natural language processing and machine learning techniques for automatic emotion detection. In this work, it is described that studies in manual and automatic recognition of expressions of the eight basic emotions Angry, Anticipate, Disgust, Fear, Joy, Sadness, Surprise, Trust in text form.

1 Introduction

Language is known to be a powerful tool to communicate and convey information and also a means to express emotion. Emotion identification is currently widely being studied in neuroscience, psychology and cognitive sciences, computer sciences and behavior sciences. Natural Language Processing (NLP) techniques have long been applied to automatically identify the information content in text. Integration of various interactive online diaries, journals and personal blogs into our daily lives contribute to fulfilment of important aspects of social interaction needs. People use blogs to share feelings, thoughts, opinions, insights, experiences and perspectives with each other[5]. Most of the attention of researchers is paid in the field of human computer interaction(HCI), especially in the field of emotion recognition.

In recent years, the research which is being inspired by Artificial Intelligence (AI) has focused increasing efforts on developing systems that incorporate emotion. Emotions are central to various natural processes that are modeled in AI systems. Emotion research is important for developing affective interfaces ones that can make sense of emotional inputs, provide appropriate emotional responses, and facilitate online communication through animated affective agents. Such interfaces can greatly help improve user experience in Computer-Mediated Communication (CMC) and Human-Computer Interaction (HCI). Emotion research is also vital for text-to-speech (TTS) synthesis systems. Emotion-aware TTS systems can identify emotional nuances in written text and accordingly provide more natural rendering of text in spoken form. Automatic emotion detection methods are also useful in many applications in psychological field. For example, it can be applied to learn user preferences and interests from users' personal writings and speeches.

This paper gives a general overview of the different approaches of detecting emotions. However, firstly we present the areas of application in which emotion detection techniques can be applied in Section 2 . Then we describe about different datasets which can be used to detect various emotions in Section 3. Then a survey of current methods and their related work is presented in Section 4. Further in Section 5 we describe various techniques that can be used in emotion detection, their limitations and some initial approaches to improve their capabilities. Then we conclude in Section 6.

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2 Areas of Application

The areas in which textual emotion detection can be used are manifold[24]:

2.1 Sentiment Analysis and Opinion Mining

Sentiment Analysis and Opinion Mining are the new and emerging area of research. It mainly focuses on knowledge discovery and information retrieval from text. The goal of Sentiment Analysis is to make computer able to detect and express emotions[29]. Opinion Mining is one of an important application of web data. It is used to collect user opinion and extract meaningful patterns from it. It can be positive or negative. During decision making process we can take good decision on the basis of opinion of others. This shows the growing importance and need of Opinion Mining.

2.2 Text-To-Speech Generation

Text is especially flat even though it has emotional content. In verbal communication, spokespersons effectively express emotions by modifying manner of speech or communication. Thus, in order to make Text–to–Speech combination, sound must be as usual and appealing as possible and it is also important that the emotional posture in the text is expressed. Use of this system implies the appropriate emotional meaning of the corresponding text passage.

2.3 Human Computer Interaction

Various kinds of the Human centered communication systems are there such as dialogue systems, automatic answering systems and human like robots etc. Emotion recognition techniques can be applied on them so that a user can feel that the system is more like human. A better response system, based on the users current mood / emotion, makes users and computer work in sync.

3 Datasets

Various datasets can be used in detecting emotions from text[25].

3.1 International Survey on Emotion Antecedents and Reactions (ISEAR)

The ISEAR dataset consists of 7,666 sentences (Scherer and Wallbott, 1994),annotated by 1,096 participants with different cultural background who completed questionnaires about experiences and reactions for seven emotions: anger, disgust, fear, sadness, shame and guilt. The ISEAR dataset contains the emotional statements that in turn contain the emotional sentences.

3.2 Text Affect

This data consists of news headlines drawn from the most important newspapers, as well as from the Google News search engine [13] and it has two parts. The first one is developed for the training and it is composed of 250 annotated sentences. The second one is designed for testing and it consists of 1,000 annotated sentences. Six emotions (anger, disgust, fear, joy, sadness and surprise) were used to annotate sentences according to the degree of emotional load.

3.3 Neviarouskaya et al.'s Dataset

These authors produced two datasets that can be used in experiments [26]. In these datasets, ten labels were employed to annotate sentences by three annotators. These labels consist of the nine emotional categories defined by Izard (anger, disgust, fear, guilt, interest, joy, sadness, shame, and surprise) and a neutral category.

3.3.1 Dataset 1

This dataset includes 1000 sentences extracted from various stories in 13 diverse categories such as education, health, and wellness [26].

3.3.2 Dataset 2

This dataset includes 700 sentences from collection of diary-like blog posts [26].

3.4 Alm's Dataset

This data include annotated sentences from fairy tales [14]. Because of data sparsity and related semantics between anger and disgust, these two emotions were merged together by the author of the dataset, to represent one class.

3.5 Aman's Dataset

This dataset consists of emotion-rich sentences collected from blogs [27]. These sentences were labelled with emotions by four annotators. Ekmans basic emotions (happiness, sadness, anger, disgust, surprise, and fear), and also a neutral category were used for sentences annotation.

4 Related Work

Definitions about emotions, its categories, and influences have been an important research issue, so that the emotional state of a person may be inferred under different situations. Since Picard proposed the concept of affective computing in 1997 [1], the role of emotions in human-computer interactions has been gradually built [2]. Ensuing the trend, the computational research of emotion detection from texts emerged to determine human emotions from various point of view. In its most common formulation, the emotion detection from text problem is reduced to finding the relations between specific input texts and the actual emotions that drives the author to write in such styles. Once the relations can be determined, they can be generalized to predict other emotions from the responses of their articles[5].

In real life, different people tend to use similar phrases (i.e. 'Oh my god!') to express similar feelings (i.e. surprise) under similar circumstances (i.e. unexpected events occur)[22]. More specifically, the emotion detection from text problem can be formulated as follows: Let E be the set of emotions, A be the set of all authors, and let T be the set of all possible representations of emotion-expressing texts. Let r be a function to reflect emotion e of author a from text t that would be the answer to our problem., i.e., r: A+T→ E[28].

The central problem of emotion detection systems lies in that if E and T may be defined straightforward, the definitions of individual element or subsets in both sets of E and T would be rather confusing. Also for the set T, new elements may add in as the languages are constantly changing. Currently there are no standard classifications of all human emotions due to the complex nature of human minds[28]. As a result, before seeking the relation function r, all related research firstly define the classification system of emotions i.e. defining the number of emotions. Secondly, after finding the relation function r or equivalent mechanisms, they still need to be revised over time to adopt changes in the set T.

5 Techniques for Text Based Emotion Detection System

5.1 Keyword Based Techniques

The keyword pattern matching problem can be described as the problem of finding occurrences of keywords from a given set as substrings in a given string [3]. This problem has been studied in the past and algorithms have been suggested for solving it. In the context of emotion detection this method is based on certain predefined keywords. These words are classified into categories such as disgusted, sad, happy, angry, fearful, surprised etc.

Keyword spotting technique for emotion recognition consists of five steps shown in fig.1 where a text document is taken as input and output is generated as an emotion class. At the very first step text data is converted into tokens, from these tokens emotion words are identified and detected. Initially this technique will take some text as input and in next step we perform tokenization to the input text. Words related to emotions will be identified in the next step afterwards analysis of the intensity of emotion words will be performed. Sentence is checked whether negation is involved in it or not then finally an emotion class will be found as the required output[23].

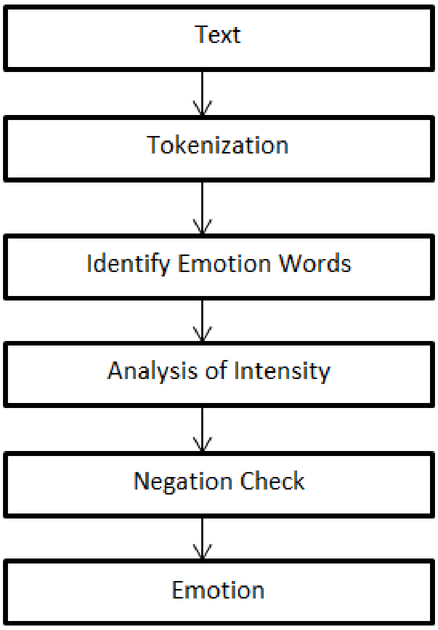

Figure 5.1: Keyword Spotting Technique

Kevin Hsin-Yih Lin et al. classified news into emotions using various combinations of feature sets and identifying the emotional influences of news articles on readers [4]. However, while detecting emotions based on related keywords is very straightforward and easy to use, the key to increase accuracy falls to two of the preprocessing methods, which are sentence parsing to extract keywords, and the construction of emotional keyword dictionary[6]. Parsers utilized in emotion detection are almost ready-made software packages, whereas their corresponding theories may differ from dependency grammar to theta role assignments.

As was observed in [8], keyword-based emotion detection methods have three limitations described below.

5.1.1 Ambiguous Definition of Keywords

Though using emotion keywords is a straightforward way to detect associated emotions, the meanings of keywords could be multiple and vague. Except those words standing for emotion labels themselves, most words could change their meanings according to different usages and contexts, and it is just not feasible to include all possible combinations into the set of Emotion Labels. Moreover, even the minimum set of emotion labels (without all their synonyms) could have different emotions in some extreme cases such as ironic or cynical sentences.

5.1.2 Incapability of Recognizing Sentences without Keywords

Keyword-based approach is totally based on the set of emotion keywords. Therefore, sentences without any keywords would imply they do not contain any emotions at all, which is obviously wrong. For example, “I passed my qualify exam today” and “Hooray! I passed my qualify exam today” should imply the same emotion (joy), but the former without hooray could remain undetected if hooray is the only keyword to detect this emotion.

5.1.3 Lack of Linguistic Information

Syntax structures and semantics also have influences on expressed emotions. For example, “I laughed at him” and “He laughed at me” would suggest different emotions from the first persons perspective. As a result, ignoring linguistic information also poses a problem to keyword-based methods.

5.2 Learning Based Methods

Researchers using learning-based methods attempt to formulate the problem differently. The original problem that determining emotions from input texts has become how to classify the input texts into different emotions. Unlike keyword-based detection methods, learning-based methods try to detect emotions based on a previously trained classifier, which apply various theories of machine learning such as support vector machines [9] and conditional random fields [10], to determine which emotion category should the input text belongs. Learning-based methods are being used to formulate the problem differently. Originally the problem was to determine emotions from input texts but now the problem is to classify the input texts into different emotions. Unlike keyword-based detection methods, learning-based methods try to detect emotions based on a previously trained classifier, which apply various theories of machine learning such as support vector machines and conditional random fields, to determine which emotion category should the input text belongs[21].

XU Lin hong et al computed semantic similarity of the vocabulary and tagged vocabulary in HowNet, adopted the derogatory or commendatory terms as features of classification, utilized Support Vector Machine classifier to identify the text orientation, and dealt with the negative sentence via matching negative rules [11]. Prem Melville et al developed a unified framework in which one can use background lexical information in terms of word-class associations, and refine this information for specific domains using any available training examples [12].

Carlo Strapparava et al [13] provide unsupervised learning experimenting with the automatic analysis of emotions in text. They proposed and evaluated several knowledge based and corpus based methods for the automatic identification of emotions in text. They developed dataset for emotion analysis using news headlines that are drawn from major newspaper such as New York Times, CNN, and BBC news as well as from Google News search engine for the experiment. Two data set with 250 annotated headlines and other is the test data set with 1000 annotated headlines. This task was carried out in an unsupervised setting. They have implemented five different systems for emotions analysis using the knowledge based and corpus based approaches. They compared their overall average results obtained by the five proposed system with three SemEval System. Through comparative evaluation of several knowledge based and corpus based methods they tried to identify the methods that work best for the annotation of emotions.

Cecila Ovesdotter Alm et al. [14] provides experiments and empirical study on text based emotion prediction problem, using supervised machine learning with SNoW (Sparse Network of Windows) learning architecture. SNoW is a multiclass classifier that is specifically tailored for large scale learning tasks. They focused on the basic task of recognizing emotional passages and on determine their valence. They predict finer emotional meaning distinctions according to emotional categories in the speech. They work on data set of 22 fairy tales that show encouraging results over a naive baseline and BOW approach for classification of emotional versus non-emotional contents, with some dependency on parameter tuning.

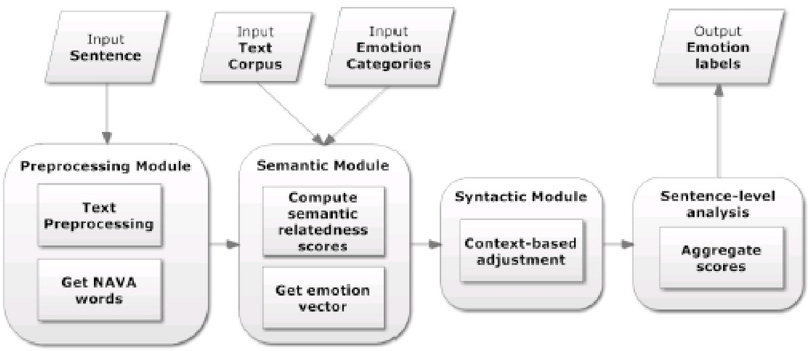

Figure 5.2: Framework for Learning Based Emotion Analysis

However, comparing the satisfactory results in multimodal emotion detection [13], the results of detection from texts drop considerably. The reasons are addressed below:

5.2.1 Difficulties in Determining Emotion Indicators

The first problem is, though learning-based methods can automatically determine the probabilities between features and emotions, learning-based methods still need keywords, but just in the form of features. The most intuitive features may be emoticons, which can be seen as authors emotion annotations in the texts. The cascading problems would be the same as those in keyword-based methods.

5.2.2 Over-simplified Emotion Categories

Nevertheless, lacking of efficient features other than emotion keywords, most learning-based methods can only classify sentences into two categories, which are positive and negative. Although the number of emotion labels depends on the emotion model applied, we would expect to refine more categories in practical systems.

5.3 Lexical Affinity Method

Detecting emotions based on related keywords is an easy to use and straightforward method. Lexical Affinity approach is an extension of keyword spotting technique; it assigns a probabilistic affinity for a particular emotion to arbitrary words apart from picking up emotional keywords.

Previous approaches to spot affect in text include the use of models simulating human reactions according to their needs and desires [15], fuzzy logic [16], lexical affinity based on similarity of contextsthe basis for the construction of WordNet Affect [17] or SentiWordNet [18], detection of affective keywords [19] and machine learning using term frequency [20]. The two latter approaches are the most widely used in emotion detection systems implemented for NLP, because they are easily adaptable across domains and languages.

5.4 Hybrid Methods

Since keyword-based methods with thesaurus and naive learning-based methods could not acquire satisfactory results, some systems use hybrid approach by combining both keyword spotting technique and learning based method, which help to improve accuracy. This feature detection is based on the combination of keyword based and learning based approach, and other supplementary information.

The main advantages of this approach is that it can give up higher accuracy results from training and adding knowledge-rich linguistic information from dictionaries and thesauri. It will balance the high cost involved for information retrieval tasks and minimize difficulties encountered while adding different lexical resources [9].

The most significant hybrid system so far is the work of Wu, Chuang and Lin [8], which utilizes a rule-based approach to extract semantics related to specific emotions, and Chinese lexicon ontology to extract attributes. These semantics and attributes are then associated with emotions in the form of emotion association rules. As a result, these emotion association rules, replacing original emotion keywords, serve as the training features of their learning module based on separable mixture models. Their method outperforms previous approaches, but categories of emotions are still limited.

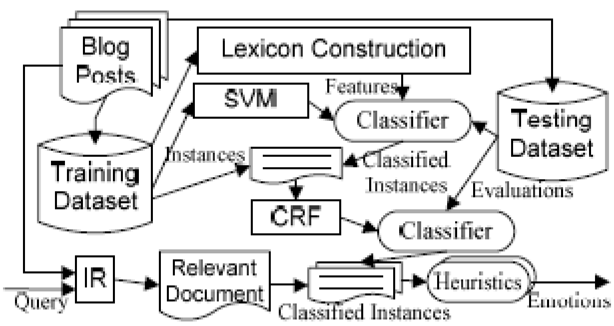

Figure 5.3: Overview of Hybrid Emotion Detection Framework

6 Conclusion

This paper addresses a very important and less examined area of sentiment research, that is, emotion detection from text. The major contribution is to show that it is practical to apply computational methods to identify and distinguish various types of emotions in text. The goal of the emotion identification experiment is to manually add emotion information to each sentence in a dataset of blogs collected from the web or standard dataset. This manually annotated data can be used to train computer based systems to automatically identify emotion information on a large-scale. This paper is mainly focused on various emotion detection techniques and also suggested that to achieve good performance, it is beneficial to test a wide variety of words that go away from the conventional emotion words.

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