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Approaches of Emotion Detection from Text

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Abstract: **Emotion detection from text is a relatively new classification task. This research paper tackles the problem of emotion recognition from text focusing on the implicit emotional statements – the descriptions of emotional events. Aim is to provide machines with the model for emotion reasoning allowing deeper understanding of causes of specific emotions. The ability to discern and understand human emotions is crucial for making interactive computer agents more human-like. This research paper focuses on prior approaches to this problem explaining their assumptions, employed sources of affective information, ways of event representation, and proposed classification algorithms.**

Keywords: **Emotion Recognition, Event Detection, Text Processing, Affective Interface.**

I. INTRODUCTION

Emotion technology is an important component of artificial intelligence, especially for human-computer communication. For emotion recognition by an artificial intelligent system we must take into account different contexts. Many kinds of physiological characteristics are used to extract emotions, such as voice, facial expressions, hand gestures, body movements, heartbeat, blood pressure and textual information. The face and the verbal language can reflect the outside deepest emotions: a trembling voice, a tone altered, a sunny smile, the face corrugated. This paper focuses on textual emotion recognition.

Nowadays in the web there is a large amount of textual information. It is interesting to extract emotions for different goals like those of business. For example, in luxury goods, the emotional aspects as brand, uniqueness and prestige for purchasing decisions, are more important than rational aspects such as technical, functional or price. In this case customer is happy to buy a product even with high prices. Emotional Marketing aims to stimulate emotions in customer for tying him to brand and so increase the sell of product/service. Nowadays it isn't the product to be sold, since for each category there is a wide choice, but the focus is the relationship that the consumer establishes with the brand and with the emotions which the product communicates.

An emotion is a particular feeling that characterizes a state of mind, such as joy, anger, love, fear and so on. Automatic emotion detection from text has attracted growing attention due to its potentially useful applications. For examples, psychologists can better assist their patients by analyzing their session transcripts for any subtle emotions; reliable emotion detection can help develop powerful human-computer interaction devices; and deep emotional analysis of public data such as tweets and blogs could reveal interesting insights into human nature and behavior.

II. LITERATURE SURVEY

A great body of work exists in the field of emotion extraction. The work done in this area includes distinguishing subjective portions in text, finding sentiment orientation and, in few cases, determining fine-grained distinctions in sentiment, such as emotion and appraisal types. Work exclusively on emotion detection is comparatively rare and lacks empirical evaluation.

Emotions are mental states accompanied by physiological changes. Ekman identified six basic emotions: happiness, sadness, anger, fear, disgust and surprise [1].

To characterize emotional interactions in social networks, and then using these characteristics to distinguish friends from acquaintances was proposed. The goal was to extract the emotional content of texts in online social networks. The interest is in whether the text is an expression of the writer's emotions or not. For this purpose, text mining techniques are performed on comments retrieved from a social network [2].

A model for statistical analysis of collective emotions for product reviews was proposed. This research work is limited to the extraction of emotional parameters like helpfulness, unhelpfulness and rating. This work was for providing the guidelines to manufacturers on how to increase customer satisfaction [3].

The prevalent approach to sentiment classification is based on the premise that the overall sentiment of a document is the aggregate of the sentiment of the words comprising it. These techniques therefore look for the presence of appropriate affect words in text. Some words are quite unambiguously affect words, while others convey affect to some degree. This method either uses a corpus-driven approach to assign affective orientation or scores to words, or it relies on some existing affect lexicons.

Many researchers have become interested in sentiment analysis, as more people learn of the scientific challenges posed, and the scope of new applications enabled, by the processing of subjective language. The papers studied in [4] are a relatively early representative sample of research in the area.

In general, automatic sentiment classification can focus on words, sentences, or documents. There are two approaches of sentiment classification methods for documents: lexicon-based and corpus-based.

Lexicon-based methods compute a sentiment score for texts, according to the scores of the words in the texts that are also in a sentiment lexicon. The sentiment orientation of customer reviews using the semantic orientation scores of the constituent adjectives was estimated. The orientation of the adjectives was measured by their co-occurrence frequency on the Web with several positive or negative seed adjectives [5].

A lexicon model for subjectivity description of Dutch verbs that offers a framework for the development of sentiment analysis and opinion mining applications based on a deep syntactic-semantic approach was presented. The model aims to describe the detailed subjectivity relations that exist between the participants of the verbs, expressing multiple attitudes for each verb sense. Validation is provided by an annotation study that shows that these subtle subjectivity relations are reliably identifiable by human annotators [6].

III. EMOTION DETECTION METHODS

Emotion detection approaches use or modify concepts and general algorithms created for subjectivity and sentiment analysis. There are many approaches that are being explored. However, there are a few similarities that appear in a majority of the approaches. Majority of the methods available are described here.

TABLE I: MOST FREQUENT EMOTION INDICATORS IN DATA

Happiness	**Sadness**	**Anger**	**Disgust**	**Surprise**	**Fear**
love	Hurt	fucking	Hate	Surprise	afraid
lol	Miss	Angry	Dislike	amazing	scared
fun	Sorry	Bitch	Dislike	amazing	nervous
good	Bad	furious	Shit	wonder	worry
happy	Sad	annoyed	Stupid	unexpected	security
nice	Lost	possed	Fucking	can't belive	fear
awesome	Cry	yelling	Disgusting	weird	what if
funny	Stress	upset	Crap	suddenly	threat
great	Wept	mad	Bitch	odd	freak
excited	Longing	shut up	Sick	strange	dangerous

3.1. Keyword-based Methods

Keyword based approaches use synonyms and antonyms in WordNet to determine word sentiments based on a set of seed opinion words.

In [7] a bootstrapping approach is proposed, which uses a small set of given seed opinion words to find their synonyms and antonyms in WordNet (wordnet.princeton.edu) to predict the semantic orientation of adjectives. In WordNet, adjectives are organized into bipolar clusters and share the same orientation of their synonyms and opposite orientation of their antonyms. To assign orientation of an adjective, the synset of the given adjective and the antonym set are searched. If a synonym/antonym has known orientation, then the orientation of the given adjective could be set correspondingly. As the synset of an adjective always contains a sense that links it to the head synset, the search range is rather large. Given enough seed adjectives with known orientations, the orientations of all the adjective words can be predicted [8].

As was observed in [9] keyword-based emotion detection methods have three limitations described below.

1) Ambiguity in Keyword Definitions

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. 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.

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.

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 person’s perspective. As a result, ignoring linguistic information also poses a problem to keyword-based methods. In summary, keyword-based methods should also detect not only the existence of keywords, but also their linguistic information to detect emotions more accurately.

3.2 Vector Space Model

Vector Space Model (VSM) is an approach that utilizes categorical classification. The process begins by representing the dataset dimensionally through a matrix of co-occurrence frequency vectors. The rows represent words and the columns can represent sentences, paragraphs, or documents. (Kim, Valitutti, et al. 2010) did their study with the columns representing documents. Therefore, the row vectors represent a term and its relation to each document, and the column vectors represent a document and its relation to each term. VSM weighs these frequencies using the tf-idf weighting schema.

The tf-idf score is the weight of each word in terms of its importance within the dataset of documents. The score is broken down into tf and idf. The tf stands for term frequency and is the frequency of a term within a document. The equation for calculating tf is as follows:

$$tf = n_{t,d} / k_d$$

In this equation, $n_{t,d}$ is the number of times the term, t, appears in the document, d, and k_d is the total number of words in the document, d.

The second part of the score is idf, which stands for inverse document frequency and is the importance of the term based on its rarity. This value tells if a word is common or rare in the corpus. The equation for calculating idf is as follows:

$$idf = \log_{10*} |D| / |D_t|$$

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In this equation, D is the total number of documents in the corpus and the D_t represents all the documents in which the term, t appears. Once the tf and idf values have been calculated, the tf-idf score is calculated by multiplying the two values together: tf-idf = tf * idf.

The tf-idf score is important because it prevents bias towards a large corpus and provides the importance of each word. If a term appears in more documents, then the ratio inside the idf's log calculation becomes closer to 1 while the actual idf value and td-idf score becomes closer to 0.

3.3. Pointwise Mutual Information

Adjectives with same polarity tend to appear together [10]. The affect words (adjectives, nouns, verbs and adverbs) that frequently co-occur together have the same emotional tendency. If two words co-occur more frequently, they tend to be semantically related. There are various models for measuring semantic relatedness and although they use different algorithms, they are all fundamentally based on the principle that a word's meaning can be induced by observing its statistical usage across a large sample of language.

Pointwise Mutual Information (PMI) is a simple information-theoretic measure of semantic relatedness that measures the similarity between two terms by using the probability of co-occurrence [11]. Mathematically, the PMI between two words x and y is calculated as follows:

PMI (x, y) = co-occurrence (x, y) / (occurrence (x) * occurrence (y))

where occurrence (x) is the number of times that x appears in a corpus, and co-occurrence (x, y) is the number of times that x and y co-occur within a specified window1 in the corpus. The corpus can be domain-dependent or general depending on the task at hand.

Being a measure of the degree of statistical dependence between two words, the purpose of PMI is to determine how closely two words are related. The motivation for using PMI instead of other measures of semantic relatedness stems from the statistical results found in the study [12] which found that PMI, which is a scalable and incremental method greatly benefits from training on large corpus of data and can outperform a commonly used version of LSA. For five out of six tests, the model built on Wikipedia using PMI was the second highest performing measure, outperformed solely by the model built using WordNet similarity vector measure. PMI was the highest performing measure on the remaining test.

IV. KEY APPLICATIONS

Opinions are so important that whenever one needs to make a decision, one wants to hear others' opinions. This is true for both individuals and organizations. The technology of opinion mining thus has a tremendous scope for practical applications.

Individual consumers: If an individual wants to purchase a product, it is useful to see a summary of opinions of existing users so that he/she can make an informed decision. This is better than reading a large number of reviews to form a mental picture of the strengths and weaknesses of the product. He/she can also compare the summaries of opinions of competing products, which is even more useful.

Organizations and businesses: Opinion mining is equally, if not even more, important to businesses and organizations. For example, it is critical for a product manufacturer to know how consumers perceive its products and those of its competitors. This information is not only useful for marketing and product benchmarking but also useful for product design and product developments.

Sentiment detection has a wide variety of applications in information systems, including classifying reviews, summarizing review and other real time applications. There are likely to be many other applications that is not discussed. It is found that sentiment classifiers are severely dependent on domains or topics. From the above work it is evident that neither classification model consistently outperforms the other, different types of features have distinct distributions. It is also found that different types of features and classification algorithms are combined in an efficient way in order to overcome their individual drawbacks and benefit from each other merits, and finally enhance the sentiment classification performance. In future, more work is needed on further improving the performance measures. Sentiment analysis can be applied for new applications.

Although the techniques and algorithms used for sentiment analysis are advancing fast, however, a lot of problems in this field of study remain unsolved. The main challenging aspects exist in use of other languages, dealing with negation expressions; produce a summary of opinions based on product features/attributes, complexity of sentence/ document, handling of implicit product features, etc. More future research could be dedicated to these challenges.

V. CHALLLENGES

Following are the major issues where intensive research is required.

1. *Keyword Selection*

Topic based classification usually uses a set of keywords to classify texts in different classes. In sentiment analysis, text is classified into two classes (positive and negative) which are so different from each other. But coming up with a right set of keyword is not a petty task. This is because sentiment can often be expressed in a delicate manner making it tricky to be identified when a term in a sentence or document is considered in isolation.

2. *Sentiment is Domain Specific*

Sentiment is domain specific and the meaning of words changes depending on the context they are used in.

3. *Multiple Opinions in a Sentence*

Single sentence can contain multiple opinions along with subjective and factual portions. It is helpful to isolate such clauses. It is also important to estimate the strength of opinions in these clauses so that we can find the overall sentiment in the sentence.

4. *Negation Handling*

Handling negation can be tricky in sentiment analysis. For example, _I like this dress and _I don't like this dress different from each other by only one token but consequently are to be assigned to different and opposite classes. Negation words are called polarity reversers.

5. *Sarcasm*

Sarcasm and irony are very quiet difficult to identify. Sarcasm is a very often used in social media.eg "thank you Janet Jackson for yet another year of Super Bowl classic rock!"

6. *Comparative Sentences*

A comparative sentence expresses a relation based on similarities or differences of more than one object. Research on classifying a comparative sentence as opinionated or not is limited. Also the order of words in comparative sentences manifests differences in the determination of the opinion orientation. E.g. The sentence, Camera A is better than Camera B communicates a completely opposite opinion from _Camera B is better than Camera A.

7. *Opinion Spam*

Opinion spam refers to fake or bogus reviews that try to deliberately mislead potential readers or automated systems by giving undeserving positive opinions to some target objects in order to promote the objects and/or by giving malicious negative opinions to some other objects in order to damage their reputations [19]. Many review aggregation sites try to recognize opinion spam by procuring the helpfulness or utility score of each review from the reader by asking them to provide helpfulness feedbacks to each review.

VI. CONCLUSIONS AND FUTURE WORK

Emotion detection has a promising future. Major approaches towards Emotion Extraction from text have been discussed in this paper. Although not enough time has passed to have established standards in the field, there is some consistency between the approaches, and the algorithms are continuing to increase in accuracy. A glaring issue with this field is the inability to compare a majority of the algorithms. Few studies have taken the time to compare different algorithms on multiple datasets and start defining standards to steer this field away from its current free reign. Many of the studies hope, in the future, to adjust their algorithms so they apply to a more general textual dataset.

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There are many advantages in being able to detect emotion in text. Some of the proposed applications include: the ability to search based on emotions; the ability to study how emotional expression changes over time, between genders, or between ethnic groups; and the capability to gather the overall emotion of a specific text. In addition to being able to create some applications, the ability to detect emotion in text can increase human-computer interaction. If the computer could tell a person's mood or emotional state, it would be able to switch to an accommodating form of interaction.

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