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Article *in* IOSR Journal of Computer Engineering · September 2017

DOI: 10.9790/0661-1904053037

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IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 19, Issue 4, Ver. V. (Jul.-Aug. 2017), PP 30-37
www.iosrjournals.org

Emotion Detection from Text: Survey

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Abstract: *This paper discusses some relevant work of emotion detection from text which is a main field in affecting computing and artificial intelligence field. Artificial intelligence is not only the ability for a machine to think or interact with end user smartly but also to act humanly or rationally so emotion detection from text plays a key role in human-computer interaction. It has attracted the attention of many researchers due to the great revolution of emotional data available on social and web applications of computers and much more in mobile devices. This survey mainly collects history of unsupervised emotion detection from text.*

Keywords: *Emotion detection, Affecting computing, Machine learning, Human-computer interaction, text classification, Natural language*

Date of Submission: 14-07-2017 Date of acceptance: 05-08-2017

I. Introduction

"In psychology emotion is defined as strong feeling deriving from one's circumstances, mood, or relationships with others, they are a state of feeling that results in physical and psychological changes that influence our behaviour. "

Due to the aim of comprehensive account of applications and Internet community, textual data has proven to be one of the most important tool in communication also attracted the attention of many researchers in human machine interaction [1]. Emotion detection technology and effective computing [2] is an important component of artificial intelligence which offer a solution to computers recognize and express emotions. Recognizing the emotion in text plays a key role in the human-computer interaction. It is interesting to extract emotions through the web from large amount of textual information for multiple goals like those of deep emotional analysis of public data from tweets and blogs could reveal interesting insights into human political and social point of view, another meaningful applications such as business that have always been eager to find out the consumer's reviews and their reaction to a specific products, this enables the market moderators to develop better product designs and launches. Also online psychologists can better assist their patients by analysing their transcripts for affective content, even it could be used to detect symptoms of suicide risk through collecting and building an emotional profile to a user. Also online classes teachers can automatically identify their student's affective state. The remainder of the paper is organized as follows, in section II, describes the emotional models. Section III, outlines the labelled datasets that are being used in most of research papers of emotion detection from text. Section IV, presents the different computational approaches for emotion detection. In section V, analyses how to calculate Semantic relatedness similarity between two terms that appear frequently together, section VI summarizes the results of this work and research gaps of emotion models, the conclusion is reported in Section VII.

II. Emotion Models

It's important to mention and understand the different types of emotion models. According to some recent research in psychology, there are three emotional models, two of them most important and usually used [3].

2.1. Categories approaches

Categorical approaches are the most commonly used in emotion detection [4] as it models the emotions based on different emotion classes or labels. The simplest model of categorical one that classify the emotions into positive or negative only [5], happy or sad. Table I summarizes every author, its number of emotion, and the emotions cells. Shortcoming of categorical model that it detects only certain and limited number of emotion although there is a great variety of emotions within every categorical model could be detected where the dimensional model can do.

Table I. Categories of emotions [3].

Author	Count	Emotions
Ekman	6	anger, disgust, fear, joy, sadness, surprise
Parrot	6	anger, fear, joy, love, sadness, surprise
Frijda	6	desire, happiness, interest, surprise, wonder, sorrow
Plutchik	8	acceptance, anger, anticipation, disgust, joy, fear, sadness, surprise
Tomkins	9	desire, happiness, interest, surprise, wonder, sorrow
Izard	12	interest, joy, surprise, sadness, anger, disgust, contempt, self-hostility, fear, shame, shyness, guilt
Extended Ekman	18	anger, disgust, fear, joy, sadness, surprise, amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, and shame

2.2. Dimensional approaches

Dimensional approaches represent affects in a dimensional form. Each emotion occupies a location in a space, so there are no specific category for each emotion but to several variables. Experimental psychologists studying stimulus response phenomena have used dimensional models. Subjects receive a stimulus (e.g. a photo or a text), and then report on the affective experience using a dimensional representation. There are several types of dimensional model such as Rusell's Circumplex model that suggests emotions distributed in valence and arousal dimensions in two dimensional circular space as Figure 1 that valence dimension indicates how much this emotion corresponds to pleasant and unpleasant The arousal dimension indicates how much this emotion correspond to activation and deactivation states. Another model Mehrabian's model based of three dimensional space Pleasure, Arousal, and Dominance (PAD) representation. The dominance dimension indicates whether the subject in control of specific situation or not.

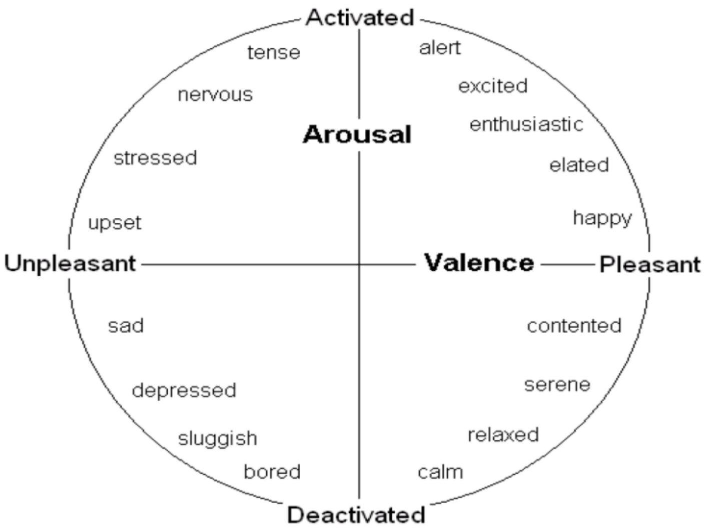

Figure 1. Dimensional model with highlighted important emotions.

2.3. Extended Approach

There are more additional models considered in emotion detection from text such as five factors model and Ortony, Clore and Collins (OCC) model [6] which mainly assume that emotions develop as a consequence of certain cognitions and interpretations. In paper [7] authors used OCC features tree to determine emotion, by building the relation between the feeling and the situation. This approach their central assumption, represent valance reactions to these perceptions of the world. One can be pleased about the consequences of an event or not (pleased/displeased); one can endorse or reject the actions of an agent (approve/disapprove) or one can like or not like aspects of an object (like/dislike). In summary, emotional categories are the most commonly used in emotion detection systems as the emotions are discrete well known simple to detect and more familiar. The advantage of dimensional model that it's able to detect emotions concepts that it differs from one another slightly, not subjected to a specific emotion. It's clear that there are not specific model better than other, it depends on your system its usage and what do you want the system to perform.

III. Labelled Emotion Datasets

It's very expensive and time consuming to label dataset manually so annotated emotional dataset are established and widely used throughout emotion detection, it is used for training, testing and validating the accuracy and efficiency of an algorithm with the previous work. From the widely used datasets are:

3.1. SemEval2007-Task [8]

This dataset is commonly used in many emotion detection research in training or testing, Affective text dataset focuses on the classification of emotions in news headlines and web sites such as CNN, which have multiple emotion tags for the same sentence [9] Using the Ekman's six basic emotions for annotation with addition to the neutral category. The dataset consist of 250 training set headlines and 1,000 test set headlines.

3.2. International Survey on Emotion Antecedents and Reactions (ISEAR)

A large group of psychologists all over the world collected data in the ISEAR project which is composed of 7.666 sentences provided by 1,096 participants with different cultures and from different countries. They were asked to report situations in which they had experienced all of 7 major emotions (joy, fear, anger, sadness, disgust, shame, and guilt), in each case they reported the way they are reacted to the situation.

3.3. Fairy Tales

This database is collected form stories and fairy tales as it is well known that stories and fairy tales are full of emotions these stories are labelled at sentence level.

IV. Emotion Detection Approaches

There are several approaches for emotion detection from text such as Lexicon-based approaches that mainly rely on bag of words, lexicon database or ontology, on the other hand learning detection based on machine learning (ML) approaches that apply ML techniques allows computers to find hidden insights without being explicitly programmed and hybrid approach that can combine one or more approaches together for better detection.

1. Lexicon-based approaches
2. Machine Learning-based detection
3. Hybrid approach

4.1. Lexicon-based approaches

Emotional lexicon is a predefined list of emotions and its corresponding words that can express this emotion [10] this approach is based on using several lexicon resources such as datasets for emotion detection. From these approaches there are

4.1.1. Keyword-based detection approach

Classifying is based on searching for emotional keywords that describe a specific feeling of the input sentence [11]. Strapparava developed a linguistic resource for lexical representation of affective knowledge named WordNet Affect [12]. WordNet Affect contains a subset of synonyms that represent affective concepts corresponding to affective words. Emotion Classification is then done by mapping emotional keywords that exist in the input sentence to their corresponding WordNet-Affect concepts. However, there are a lot of drawbacks of emotion detection based only on keywords [13].

Pointing out limitations of previous research

• Ambiguity in Keyword Definitions A keyword could have multiple meaning and definition. A words meaning could change according to different usages and contexts.

• In capability of Recognizing Sentences without keywords Sentence without keyword will not output the correct emotion as it is completely based on keywords only.

• Lack of Linguistic Information The system should also detect the linguistic information to detect emotions more accurately, not only the existence of the word in the sentence.

4.1.2. Linguistic Rules-based

Computational linguists use various rules to define a language structure.

• Rule based with affect Lexicons Chau martin [8] manually added seed words to emotion lists and created a few rules in their system which identifies what is being said about the main subject and boosts its emotion rating by exploiting dependency graphs.

• Rule-based without affect lexicon using statistical approach for analysing the relationships between a set of documents and the terms mentioned in these documents in order to produce a set of meaningful patterns related to the documents and terms [15].

In paper [16] they introduced an approach for understanding the underlying semantics of language using Latent Semantic Analysis (LSA), or you can use any dimension reduction method to Reduce the computation time and noise in the data by dissipating the unimportant data and making the underlying semantic text to become more patent.

4.1.3. Ontology based detection

This method depends on extraction of ontology from input sentences and match it with ontology base which consists of the ontology relation between classes or objects and its related emotion. Used ontology extraction method from the input sentence [20] by using a triplet extraction algorithm by the OpenNLP parser. Authors in [21] employed an ontology engineering approach to the problem of fine grained emotion detection in sparse messages. Authors in paper [22] presented an approach towards automatically detecting emotions from contexts in which no clues of sentiment appear, based on common sense knowledge. The resource they built towards this aim EmotiNet is a knowledge base of concepts with associated affective value.

4.2. Machine Learning-based detection

This method relies on scientific algorithms which give the machine the ability to learn from data to deal with the constructions of algorithms [23]. This approach trying to use the input data to predict and take decisions instead of following the programmed instructions [24]. It can be divided into supervised and unsupervised learning.

4.2.1. Supervised learning approach

This approach rely on set of labelled training data. The supervised learning algorithm analyses the training data and deduce a function, which we use for mapping new examples [25]. Training phase for labelling data is considered from the weakest points in supervised learning approach as it becomes exhausting and time consuming task. However, there are some recent works that find a solution for this issue using methods automatic labelled from implicit emotions or hashtags [26-29]. We can find both categorical and the dimensional approaches applied on supervised learning algorithms. It’s obvious that categorical model is commonly used in supervised emotion detection [5].

• Supervised learning using Categorical model Roth [30] explored the text-based emotion prediction problem experimental, using supervised machine learning with the SNoW learning architecture. Authors in [12] introduced methods for automatic 6 basic emotion "anger, disgust, fear, joy, sadness and surprise” detection from a set of a large data. Authors [31] build an emotion classifier that determine the emotion class of the person writing e.g. twitter.

Their emotion classifier is based on multi-class SVM kernels. Roberts [28] Added Love emotion to the six basic Ekaman’s emotions. Classifying emotions to eight basic emotion categories defined by Plutchick [29] allows them to deal with multi-class problem for opposing emotion pairs of emotion classification by applying distant supervision [32].

• Supervised learning using Dimensional model Authors proposed[26] a new approach to conclude emotional states by classifying text messages of individuals automatically to model emotional states, we utilize the well-established Circumplex model that characterizes affective experience along two dimensions: valence and arousal.

4.2.2. Unsupervised learning approach

A set of inputs without any need for labelled training examples that deduce a function to describe hidden structure from unlabelled data [25], such as clustering. Like also supervised learning, you can find two types of systems based on categorical and dimensional emotion models using unsupervised learning approach.

• Unsupervised using categorical model the task was carried out in an unsupervised approach, so no training was provided, they [12] combined Latent Semantic Analysis with WordNet Affect. Authors [33] have proposed unsupervised context-based approach for emotion detection from text at the sentence level. There is no need any existing manually affect lexicons, the methodology is based on computing an emotion vector for each potential word based on semantic relatedness between words. Rafael and Sunghwan [5] have worked in Vector space model with the three dimension reduction techniques: Latent Semantic Analysis, Probabilistic Latent Semantic Analysis and Non-negative Matrix Factorization. They concluded from the comparison of the three reduction techniques that NMF-based categorical classification performs the best among categorical approaches to classification

• Unsupervised approach with dimensional model ANEW [34] is a set of normative emotional ratings for a collection of English words (N=1,035), where after reading the words, subjects report their emotions in a three dimensional representation [5]. The occurrences of these words in a text can be used, in a naive way, to weight the sentence in this emotional plane.

4.3. Hybrid approach

The hybrid approach is a combination of multiple approaches together which help to improve accuracy and refine the categories. This approach is used by Wu, Lin and Chuang [13], which utilizes a rule-based approach to extract semantics related to specific emotions, and Chinese lexicon ontology to extract attributes.

Authors described [35] an emotion annotation task of identifying emotion category, emotion intensity and the words/phrases that indicate emotion in text. Authors in paper [36] presented a hybrid based architecture comprising of keyword based component and learning system component.
All mentioned methods with authors' papers are summarized in table 3.

Table III Emotion detection approaches.

Papers	Categories	Emotion Model	Approaches
(Morinaga, et al.,2002)	Positive , Negative	Categorical	Rule-based
(Alm et al 2005)	Anger, Disgust, Fear, Happiness, Sadness, Positively Surprise, Negatively Surprise	Categorical	Supervised Learning based
(Neviarouskaya, etal., 2007)	Anger, Disgust, Fear, Guilt, Interest, Joy, Sadness, Shame, Surprise, Intensity	Hybrid	Rule-based
(S. Aman and S.Szpakowicz ,2007)	anger, disgust, fear, joy, sadness, surprise	Categorical	Hybrid
(Strapparava and Mihalcea 2008)	Anger, Disgust, Fear, Joy, Sadness, Surprise	Categorical	Lexical based
(Gill et al 2008)	Anger, Fear, Surprise, Joy, Anticipation, Acceptance, Sadness, Disgust	Categorical	Lexical based
(Strapparava and Mihalcea, 2008)	Anger, Disgust, Fear, Joy, Sadness, Surprise	Categorical	Unsupervised Learning based
(Strapparava and Mihalcea 2008)	Anger, Disgust, Fear, Joy, Sadness, Surprise	Categorical	Supervised Learning based
(Balahur et al 2011)	Anger, Disgust, Fear, Guilt, Joy, Sadness, Shame	Categorical	Lexical based
(Balabantaray et al 2012)	Anger, Disgust, Fear, Happiness, Sadness, Surprise	Categorical	Supervised Learning-based
(Roberts et al., 2012)	Anger, Disgust, Fear, Joy, Sadness, Surprise, Love	Categorical	Supervised Learning based
(Agrawal and An, 2012)	Anger, Disgust, Fear, Happiness, Sadness, Surprise	Categorical	Unsupervised Learning based
(Sykora et al., 2013)	Anger, Confusion, Disgust, Fear, Happiness, Sadness, Shame, Surprise	Categorical	Lexical based
(Wang and Zheng, 2013)	Anger, Disgust, Fear, Guilt, Joy, Sadness, Shame	Categorical	Lexical based
(Suttles and Ide, 2013)	Anger, Disgust, Fear, Happiness, Sadness, Surprise, Trust, Anticipation	Categorical	Supervised Learning based
(Calvo and Kim, 2013)	Anger-Disgust, Fear, Joy, Sadness	Categorical	Unsupervised Learning based
(Calvo and Kim, 2013)	Anger-Disgust, Fear, Joy, Sadness	Dimensional	Unsupervised Learning based
(Hasan et al, 2014b)	Happy-Active, Happy-Inactive, Unhappy-Active, Unhappy-Inactive	Dimensional	Supervised Learning based

V. Semantic Relatedness Similarity between Two Terms

Words that appear frequently together then they tend to be semantically related, as per [38] adjectives with the same polarity tend to appear together.

5.1. Pointwise Mutual Information (PMI)

Church and Hanks [39] they were the first to introduce the concept of measuring the semantic relatedness between two terms by using probability of co-occurrence mathematically.
PMI between two words x and y is calculated as follows:

$$PMI\ (x, y) = co\text{-}occurrence\ (x, y) / (occurrence\ (x) * occurrence\ (y)).$$

They found [40] from the advantages of PMI as a measure of semantic relatedness that it is scalable, incremental and simple in measurements.

5.2. Vector Space Model (VSM)

VSM space model considered from information retrieval fundamentals which terms and textual documents are represented through a weighted frequency matrix, the rows represent words where columns can represent sentences, paragraphs, or documents. Both terms and documents are encoded as vectors in k-dimensional space. Where the K choice is done based on number of unique terms, topics or categories related to the text corpus. Frequencies are weighted with respect to log entropy using frequency inverse document frequency (tf-idf) weighting schema [41]. Where each vector is used in order to reflect the significance of the corresponding term, topic, or categories in representing the semantics of a document. VSM is reduced through the dimension reduction methods.

5.2.1 Latent Semantic Analysis (LSA).

Its technique for analysing the relationships between documents or sentences and terms by applying set of concepts related to each other. Which considered from the earliest techniques successfully applied to various text processing areas [17]. LSA use Singular Value Decomposition to map terms or documents into a vector space of reduced dimensionality.

5.2.2 Probabilistic LSA (PLSA).

PLSA [18] it is statistical technique that uses LSA with some more probabilistic theories such as Bayes rule for the analysis of two-mode and co-occurrence data, the reduced matrix only contains positive values.

5.2.3 Non-Negative Matrix Factorization (NMF).

NMF is another reduction technique[19] usually used in semantic analysis where a matrix V is factored into two matrices W and H, where the three matrices have no negative elements. This non-negativity makes the resulting matrices easier to inspect.

VI. Results And Research Gaps Of Unsupervised Emotion Models

In table II displays the results of five different approaches categorical model using VSM with dimensionally reduction methods (LSA, PLSA and NMF), dimensional model and Majority Class Baseline (MCB) where it is based on baseline algorithm that always heads to predict the majority category. Using the cosine angle for similarity measure in categorical model while using nearest neighbours in dimensional model. The following five approaches evaluated using different datasets such as SemEval dataset that consists of news headlines, ISEAR dataset that consists of answers to specific questions and Fairy tales' sentences. Macro average calculations are used for classification performance as it prevent incorrect results due to unequal data distribution. We can see from previous results that CPLSA has the lowest performance across all datasets. While CNMF is better than other methods in SemEval and Fairy tales datasets and DIM beat the others in ISEAR. Also precision, recall and F-measure of fairy tales stories have higher results than other datasets as it contains more emotional terms and sentences.

Here are the acronyms used in table II:
- MCB: Majority Class Baseline.
- CLSA: Categorical classification of LSA.
- CPLSA: Categorical classification of PLSA.
- CNMF: Categorical classification of NMF.
- DIM: Dimension-based estimation.

Table II. Overall average results [42].

Dataset	**SemEval**			**ISEAR**			**Fairy tales**		
MCB	0.077	0.250	0.118	0.100	0.250	0.143	0.102	0.250	0.145
CLSA	0.363	0.348	0.340	0.484	0.282	0.228	0.662	0.640	0.630
CPLSA	0.189	0.282	0.219	0.260	0.317	0.270	0.282	0.307	0.280
CNMF	**0.523**	**0.506**	**0.505**	0.461	0.258	0.166	**0.747**	**0.731**	**0.733**
DIM	0.446	0.422	0.386	**0.528**	**0.528**	**0.372**	0.530	0.404	0.419

From key limitations of datasets that SemEval 2007 deals only with the words of headlines (lexical approach) also the imbalance of datasets with emotion in space. We aim to
identify more effective strategies that can deal with generic dataset.

VII. Conclusion

From the research that has been carried out, it is possible to conclude that emotion detection is a challenging and complex task, that there are many advantages, benefits and applications of being able to detect emotion in text which can increase the human-computer interaction where the computer would be able to switch to an conciliate form of interaction. This study has shown that the categorical model is used more in emotion detection approaches for their simplicity and specific well defined output, while dimensional models more flexible to detect emotions where there are no specific labels but it need more calculation. Extended models try to provide a better assignment of emotions based on personal typology. This paper describes the different text based emotion recognition methods with different datasets and their limitations. Also we covered in this survey different emotion detection approaches lexicon-based, Machine-learning detection, and hybrid approach which can be used with categorical or dimensional models. The results show that the NMF performs best classification among categorical and dimensional approaches. Also we summarized the semantic relatedness between two terms methods and different types of dimensionally reduction methods.

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