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Emotion Analysis: A Survey

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***Abstract*—Emotions form a very important and basic aspect of our lives. Whatever we do, whatever we say, somehow does reflect some of our emotions, though may not be directly. To understand the very fundamental behavior of a human, we need to analyze these emotions through some emotional data, also called, the affect data. This data can be text, voice, facial expressions etc. Using this emotional data for analyzing the emotions also forms an interdisciplinary field, called Affective Computing. Computation of emotions is a very challenging task, much work has been done but many more increments are also possible. With the advent of social networking sites, many people tend to get attracted towards analyzing this very text available on these various sites. Analyzing this data over the Internet means we are spanning across the whole continent, going through all the cultures and communities across. This paper summarizes the previous works done in the field of textual emotion analysis based on various emotional models and computational approaches used.**

Keywords*—emotion analysis, sentiment analysis, machine learning, bootstrapping, distant supervision.

I. INTRODUCTION

The emotional analysis forms a fundamental part of the affective computing. “Affect” means emotion and “computing” means to calculate or measure. Affective computing is all that takes us to design the devices or systems that process, recognize, interpret and simulate the human affects[1][2], thus making it possible for us to analyze the human and machine interactions. This data can be the text, voice, facial expressions etc. Analyzing the emotions and sentiments of various textual data over the Internet has its own significance, for example, we can measure the well being of a community, we can prevent suicides [3], and also it can be very helpful for organizations to measure the degree of satisfaction of their customers by analyzing the comments or the feedback they provide The emotion and the sentiment analysis also provide a way for opinion mining for the business organizations: in other words, we can explore the text extracted from e-learning environment and can use that for emotion analysis [4].

This survey paper is based on prior works done in the field of emotion analysis through text which is an emerging field with many applications in real world [5]. There has been a lot work done in the field from past and the researches are still on, particularly, using the Tweet data [6] [7] [8][9][10][11]. However, text emotion analysis also introduces some challenges in our work in the sense that emotions and the ways to express these emotions are all subjective.

The emotion analysis uses the natural language processing, text analysis and various computational techniques to determine the emotions hidden in a particular text. This analysis can be done at various levels: document level [12][13], sentence level [14], word level [15], and aspect level [16]. The emotion analysis of some input data consists of the following steps as shown in the figure1 below;

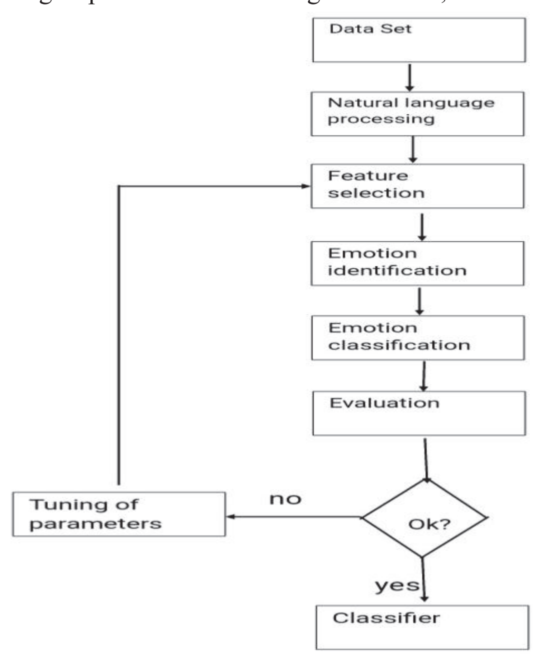

Figure1: steps in emotion analysis

This paper has been divided into the following sections; Section II: Related work, describing:

A) Expression of emotions

B) The various emotional models.

C) Data sets

D)The various computational approaches in emotion detection.

Section III: Conclusion.

II. RELATED WORK

The field of emotion analysis has been of much interest, much work has been done but before describing that we need to discuss the very fundamental aspect of the emotion analysis which is, the expression of emotions;

A. Expression of emotions;

The emotions can be expressed in two modes, one being the vocabulary of the emotional words and the other some affective items. The vocabulary mode simply consists of choosing an emotional word from the vocabulary of emotion terms, like sad, love, hate etc.The other mode uses some interjections like ugh, eww, yuhuu, to dictate ones emotions. In addition to this, the emotional words have some properties associated with them that help to define the emotions more accurately.

B. Emotion models;

These models describe the basic ways of classifying the emotions. They are represented in various ways but the two important approaches in sentiment analysis are: emotional categories and emotional dimensions.

The emotional categories follow the approach of dividing the emotions into discrete emotion labels, one of its notable works being [17]. The Ekman's basic emotion model [18] and the Plutchik's bipolar emotion model [19] fall in this category. Ekman in his model has divided emotions into six discrete classes of ANGER, DISGUST, FEAR, HAPPINESS, SADNESS and SURPRISE. Plutchik's model, on the other hand, is a super set of Ekman's model with two additional classes: TRUST and ANTICIPATION.

The emotional dimensions follow the approach of representing the emotion classes in a dimensional form: either 2D or 3D, with each emotion occupying a distinct position in space. These emotions can be described in 3 dimensions of: pleasurable or unpleasurable, arousing or subduing and strain or relaxation. The three dimensions could also be defined as: pleasant vs. unpleasant, attention vs. rejection and level of activation. Some research have been done using both the models of emotion representation [20]

Most dimensional models have valence and arousal or intensity dimensions: valence dimension indicates how much pleasant or unpleasant an emotion is, arousal dimension differentiates between activation and deactivation states. The most prominent ones being as defined under:

<u>2D models</u>:

- *Circumplex model:* [21] defined this model where the vertical axis represent the arousal and horizontal axis represent the valence, while the origin represents neutral valence and a medium level of arousal.
- *Vector model*: [22] consist of two vectors pointing in two directions assuming the presence of an underlying arousal dimension with valence dimension vector determining the direction in which a particular emotion lies.
- *PANA(positive activation-negative activation) model:* [23] it divides the system into positive and negative effect, with vertical axis representing the low to high positive affect and the horizontal axis representing the low to high negative effect.

<u>3D models</u>

- *Plutchik' model*: [19]Plutchik gave a hybrid model arranging the emotions into concentric circles with inner being the basic and the outer more complex emotions.
- *PAD (pleasure, arousal and dominance) model*: [24] In addition to arousal and valence, it describes a third dimension of the dominance, which indicates whether the subject feels in control of the situation or not.
- *Lovheim cube model*: [25] presents signal substances forming the axis of the coordination system and the eight basic emotions are placed at the eight corners of the cube.

C. Datasets

After choosing one of the emotion models, the next important thing under consideration is the data sets employed for computational studies in emotional analysis. These data sets can be broadly categorized into two classes: short text and long text. Most of the initial works in emotion analysis and classification, use short text primarily because they are easy to handle compared to long texts where emotions may be difficult to detect. The most common short texts used include: news headlines, microblogs. Few works in emotional classification have also used long texts, the most notable being [26], news headlines [27], blogs [28][29], children's tales [30], combination of datasets (heterogeneous datasets) [31]. Few researchers like [32] have tried to explore data sets in languages other than English.

D. Computational approaches

The computational approaches include all the techniques that are employed to design and implement an emotional classifier. They can be broadly classified into two main categories: lexicon based approach and the machine learning approach as shown in figure2 below. An emotion lexicon is a knowledge repository containing textual units annotated with emotional labels. They rely on the lexical resources like lexicons, bags of words or ontology. On the other hand machine learning approaches use machine learning algorithms to train the system and map a function for future classification of emotions. It is based on linguistic features that we choose for training the machine.

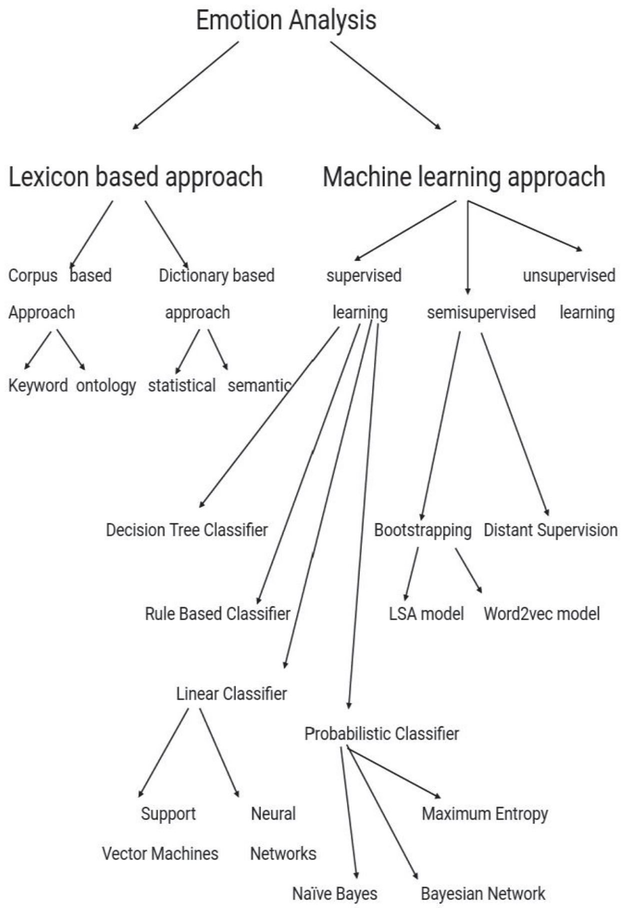

Figure2: computational approaches

1. Lexicon based approach: The lexicon based approaches using lexical features [33] are divided into two sub types: dictionary based and corpus based. The dictionary based approaches begin with some predefined dictionary of emotional words and then use various measures like term frequency, word count(called statistics) or word synonyms(called semantics) etc to label the sentences in the data. Most statistical approaches use Latent Semantic Analysis (LSA) and even their variation have been employed [33] for analyzing relationship between set of documents and the terms in these documents in order to produce meaningful patterns related to documents and terms. The dictionary approach has a low cost but at the same time validating a dictionary can be difficult. The corpus based approach utilizes any general data for emotion analysis. Here the corpus (data) is first annotated by following a set of abstract rules, from a text, for governing a natural language emotion analysis. Keyword based approaches define a set of predefined terms to classify the text into emotional classes. Strapparava used WordNet-Affect [34] also for checking emotion words in the headlines. Ontology based approach uses the relationship between the terms and the EmotiNet [35] and model situation as a chain of actions and their corresponding emotional affect. This approach is also followed by [36] for fine-grained emotion detection.

2. Machine learning approach: The machine learning approach relies on machine learning algorithms that can learn from data [37] by making use of linguistic features of text. They are further divided into following:

a) Supervised machine learning: These algorithms form a function (model) based on the input data and using this function take decisions of how to map the future data to appropriate output [38][39]. The SVM is a tradition approach in this regard. Few researchers [40] [41] have moved beyond these traditional approaches to more efficient and reliable methods like CRF [42] The supervised learning models are further of following; *Decision tree classifiers*: use the hierarchical recursive decomposition of training data based on the bases of the value of the attributes; until some leaf nodes are reached that contain values for the classification purpose [43]; *Rule based classifier*: here the classification is modeled on the basis of some set of rules. The conditions in disjunctive normal form on the features are represented by the left hand side while the class labels are represented by right hand side of the rule [44]; *Linear Classifiers*: it classifies the emotions by making a decision based on the value of linear combination of characteristics of the input text. These characteristics are also known as feature values and are represented in a vector form called feature vectors. It consists of many proposed models, among them is the support vector machines [45] and Neural Networks [46]; *Probabilistic Classifier:* assumes each class to be a component of the mixture which provides the probability of sampling a particular term for that component. It further consists of following classifiers; Naïve Bayes classifier, which computes posterior probability based on distribution of words in a document [47]: Bayesian network, is an acyclic graph whose nodes represent random variable and edges represent conditional dependencies; Maximum entropy, uses encoding to convert labeled feature sets to vectors. This vector then calculates weights for each feature which are combined to determine the class for each feature set [48].[49] shows a comparison between hierarchical verses flat classification of emotions.

b) Unsupervised machine learning: these algorithms try to find the hidden structures in the input data and using those structures map the unlabelled data to emotion classes [50].

c) Semi-supervised machine learning: There are many works developed where labeling is done automatically through hashtags etc [51]. Semisupervised algorithms use this idea of automatic labeling and follow the following two approaches: Bootstrapping [52] and distant supervision [53][54].

Table1 given below summarizes some of the prior work done in the field;

TABLE1: SUMMERIZATION OF PRIOR WORK

Paper by	Year	Emotion labels used	Dataset used	Approach used	Features/Lexicon used
Liu et al.	2003	Happy,Sad,Anger, Fear,Disgust & Surprise	OMCS(Open Mind Common Sense)	Common Sense Affect based approach (Real-world knowledge concept models)	Ortony's Affective Lexicon, Affect keyword Spotting, adjective, nouns & verbs
Alm et al.	2005	Angry, Disgust, Fear, Happy, Sad, positively & negatively surprised	Children Fairy Tales	Supervised Learning (SNoW learning Architecture)	WordNet Affect, conjunction of features, special punctuations
Strapparava and Mihalcea	2007	Anger, Disgust, Fear, Joy, Sad, Surprise &/or valence (positive, negative, neutral)	News headlines	Unsupervised knowledge based, rule based, supervised corpus based and Naïve Bayes	WordNet Affect and SentiWordNet
Yang et al.	2007	Positive(happy, joy) and Negative (sad, angry)	Web-blogs	Supervised Learning , SVM and CRF(Conditional Random field)	Custom made lexicon, Emotion Words & emoticon features
Aman and Szpakowicz	2007	Happy, Sad, Angry, Disgust, Surprise, Fear, mixed & no emotions	Blogs-posts	Supervised Learning (NB, SVM)	WordNet Affect, General Inquires
Alm	2008	Angry, Disgust, Fear, Happy, Sad, Neutral, +vely & -vely surprised	Tales	Supervised Learning	Bags of words, Roget's Thesaurus
Strapparava & Mihalcea	2008	Anger, Disgust, Fear, Joy, Sad, Surprise	News headlines	Supervised(NB) & unsupervised (variation of LSA) learning	Lexical features & WordNet Affect
Gill et al.	2008	Surprise, Joy, Sadness Anticipation, Acceptance, Disgust, Anger, Fear	Blog texts	LSA & HAL (Hyperspace Analogue to Language)	Rogets II: The New Thesaurus
Bellegarda	2010	Joy, Sad, Surprise, Anger, Disgust, Fear	News Headlines	Supervised (NB, SVM and decision trees), Latent Semantic Mapping (LSM)	WordNet Affect, WordNet synset, Bag of words
Ghazi et al.	2010	Joy, Sad, Surprise, Anger, Disgust, Fear, Neutral	Web-blogs, children Stories	Hierarchical classifier, SVM	Prior Polarity Lexicon, Bag of words, Polarity Feature Set
Balahur et al.	2011	Surprise-anticipation, Disgust-trust, anger-fear, sad-joy, shame, guilt	ISEAR, Documents	Common Sense Knowledge	EmotiNet
Chaffar and Inkpen	2011	Anger, Disgust, Fear, Happiness, Sad, Surprise	News, blogs, Fairy tales, diary like blog posts	Supervised learning (NB, SVM and decision trees)	WordNet Affect, n-grams and bag of words
Balabantaray et al.	2012	Anger, Disgust, Fear, Joy, Sad, Surprise, neutral	blog	Supervised learning (multi class SVM)	n-grams, pos, WordNet Affect, emoticons, dependency parsing
Roberts et al.	2012	Anger, Disgust, Fear, Joy, Sad, Surprise, love	blog	Supervised (SVM)	WordNet synset & hypernyms, n-grams, punctuations, topic scores
Agrawal and An	2012	Anger, Disgust, Fear, Joy, Sad, Surprise	____	Unsupervised Learning(context based)	Emotion Vector, Wikipedia Gulenberg corpus
Wang et al.	2012	Joy, Sad, Anger, Love, Fear Thankfulness, Surprise	blog	LIBLINEAR, Multi Nomial Naïve Bayes (MNB)	LIWC, MPQA lexicon, n-grams, POS, Affect words
Purver & Battersby	2012	Joy, Sad, Surprise, Anger, Disgust, Fear	Blog texts	SVM (LIBSVM)	Words, hashtags, emoticons
Sykora et al.	2013	Anger, Disgust, Fear, Joy, Sad, Surprise, confusion, shame	blog	Ontology Engineering approach, Custom NLP pipeline	Emotive ontology Lexicon, feature intensifiers, negators
Wang and Zheng	2013	Anger, Disgust, Fear, Joy, Sad, Surprise, guilt, shame	ISEAR	Improved LSA Algorithm	Scientific Library
Suttles and Ide	2013	Anger, Disgust, Fear, Happy, Sad, Surprise, Trust, Anticipation	blog	Supervised Learning (NB, ME), Natural language toolkit	Hashtags, Emoticons, Emojis
Calvo and Kim	2013	Anger, Disgust, Fear, Joy, Sadness	Headlines, ISEAR, Fairy tales, USE	Unsupervised(LSA,PLSA), NMF(Non negative Matrix Factorization)	Emotional Thesaurus, Bag of words

Hasan et al.	2014	Happy active, happy inactive, unhappy active, unhappy inactive	Blog	Supervised learning	ANEW lexicon, LIWC dictionary, AFINN, emoticons, punctuations
Kang & Ren	2016	Joy, Love, Expect, Surprise Anxiety, Sorrow, Anger, Hate	Chinese Blogs	Hierarchical Bayesian Model	Latent Factors
Rosa Meo & Emilio Sulis	2017	Anger, Disgust, Fear, Joy, Sad, Surprise, Anticipation, Trust	Blog	NB, SVM, Random Forest, Logistic Regression	Emotion lexicon, polarity lexicon, latent factor, 5 dictionaries

III. CONCLUSION

Upon reviewing the previous works in the domain of the emotion analysis, we conclude that much of the work has been done in the field especially in the domain of textual datasets. The experimentation result of some of the works for various computational models with their overall system accuracy has been shown in table2 below. We note that there has been a significant improvement in the system accuracies over the time with the improvement or modification of traditional computational approaches, the lexical resources and the features generated.

TABLE2: EXPERIMENTATION RESULTS

Paper	Model	Overall system Accuracy with All Features On
Alm et al.,2005	SNoW	63.31%
Yang et al.,2007	SVM	48.83%
	CRF	56.00%
Aman & Szpakowicz,2007	NB	72%
	SVM	73.89%
Chaffar & Inkpen, 2011	NB	59.72%
	DT	64.70%
	SVM	71.69%
Balabantaray et al., 2012	SVM	73.24%

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