# Emotion Detection in Text: a Review

**Armin Seyeditabari**
UNC Charlotte
sseyedi1@uncc.edu

**Narges Tabari**
UNC Charlotte
nseyedit@uncc.edu

**Wlodek Zadrozny**
UNC Charlotte
wzadrozn@uncc.edu

## Abstract

In recent years, emotion detection in text has become more popular due to its vast potential applications in marketing, political science, psychology, human-computer interaction, artificial intelligence, etc. Access to huge amount of textual data, specially opinionated and self expression text also played a special role to bring attention to this field. In this paper, we review the work that has been done in identifying emotion expressions in text, and argue that although many techniques, methodologies and models have been created to detect emotion in text, there are various reasons that makes these methods insufficient. Although, there is an essential need to improve the design and architecture of current systems, factors such as the complexity of human emotions, and the use of implicit and metaphorical language in expressing it, lead us to think that just re-purposing standard methodologies will not be enough to capture these complexities, and it is important to pay attention to the linguistic intricacies of emotion expression.

## 1 Introduction

Emotion detection in computational linguistics is the process of identifying discrete emotion expressed in text. Emotion analysis can be viewed as a natural evolution of sentiment analysis and its more fine-grained model. However, as we observe in this paper, this field still has a long way to go before matching the success and ubiquity of sentiment analysis.

Sentiment analysis, with thousands of articles written about its methods and applications, is a well established field in natural language processing. It has proven very useful in several applications such as marketing, advertising (Qiu et al., 2010; Jin et al., 2007), question answering systems (Somasundaran et al., 2007; Stoyanov et al., 2005; Lita et al., 2005), summarization(Seki et al., 2005) , as part of recommendation systems (Terveen et al., 1997), or even improving information extraction (Riloff et al., 2005), and many more.

On the other hand, the amount of useful information which can be gained by moving past the negative and positive sentiments and towards identifying discrete emotions can help improve many applications mentioned above, and also open ways to new use cases. In other words, not all negative or positive sentiments are created equal. For example, the two emotions *Fear* and *Anger* both express negative opinion of a person toward something, but the latter is more relevant in marketing or socio-political monitoring of the public sentiment. It has been shown that fearful people tend to have pessimistic view of the future, while angry people tend to have more optimistic view (Lerner and Keltner, 2000). Moreover, fear generally is a passive emotion, while anger is more likely to lead to action (Miller et al., 2009).

These more precise types of information on the nature of human emotions indicate potential uses of emotion detection. The usefulness of understanding emotions in political science (Druckman and McDermott, 2008), psychology, marketing (Bagozzi et al., 1999), human-computer interaction (Brave and Nass, 2003), and many more, gave the field of emotion detection in natural language processing life of its own, resulting in a surge of research papers in recent years. In marketing, emotion detection can be used to analyze consumers reactions to products and services to decide which aspect of the product should be changed to create a better relationship with customers in order to increase customer

satisfaction (Gupta et al., 2013). Also emotion detection can be used in human computer interaction and recommender systems to produce interactions or recommendations based on the emotional state of the user (Voeffray, 2011). Results of emotion detection systems can also be used as input to other systems, like what Rangel and Rosso (2016) has done in profiling authors by analyzing the presence of emotions in their text. By understanding the important role of emotions in decision making process in humans (Bechara, 2004), emotion detection can profit any entity or organization that wants to assess the impact of their products and actions on the population, and to be able to manage people's reactions by monitoring their emotional responses. Thus understanding emotions can benefit any entity and organization such as commercial institutes, political campaigns, managing the response to a natural disaster. One can also argue it is necessary to create better artificial intelligence tools, e.g. chatbots.

The main contribution of this paper to the computational linguistic community is to provide a review of the literature in this field, and to summarize the work that has already been done, the shortcomings, and the avenues to move the field forward. Reviewing the literature shows that identifying emotions is a hard task. It is mainly because of two factors, firstly emotion detection is a multi-class classification task combining multiple problems of machine learning and natural language processing; and the second is the elusive nature of emotion expression in text, which comes from the complex nature of the emotional language (e.g. implicit expression of emotions, metaphors, etc.), and also the complexity of human emotions. We believe this review fills a significant gap, since, to the best of our knowledge, there has not been a comprehensive review paper focused specifically on emotion detection in text, and arguably the topic is important.

In this paper first talk about models and theories of emotions in psychology, to quickly get an idea about what models of emotions are, How they have been categorized in a discrete or continuous space is the topic of Section 2. Then we will focus on the reasons behind the linguistic complexity of this task in Section 3. In the subsequent three sections, we review the resources and methodologies used for detecting emotion in text. The current state of the field and future work is discussed in Section 7. And finally, we conclude our work in Section 8.

## 2 Psychological Models of Emotion

The prerequisite for talking about extracting emotions, is having a general idea about the emotion models and theories in psychology. This body of research provides us with definitions, terminology, models, and theories. Here we introduce the most general and well accepted theories in a short section to give the reader the basic information needed for the rest of the paper.

In psychology, and based on the appraisal theory, emotions are viewed as *states that reflect evaluative judgments (appraisal) of the environment, the self and other social agents, in light of the organisms goals and beliefs, which motivate and coordinate adaptive behavior* (Hudlicka, 2011). In psychology, emotions are categorized into basic emotions, and complex emotions (i.e. emotions that are hard to classify under single term such as guilt, pride, shame, etc.). In this paper when we talk about emotions, we mostly mean basic emotions.

Although there is no universally accepted model of emotions, some of the most widely accepted models that have been used in emotion detection literature can be divided based on two viewpoints: emotions as discrete categories, and dimensional models of emotions. According to Discrete Emotion Theory, some emotions are distinguishable on the basis of neural, physiological, behavioral and expressive features regardless of culture (Colombetti, 2009). A well known and most used example is Ekman's six basic emotions (Ekman, 1992). Ekman et al. in a cross-cultural study found six basic emotions of *sadness, happiness, anger, fear, disgust, and surprise*. Most papers in emotion detection used this model for detecting emotions as a multi-class classification problem, along with some that are based on Plutchik's wheel of emotions (Plutchik, 1984) in which he categorized eight basic emotions (*joy, trust, fear, surprise, sadness, disgust, anger and anticipation*) as pairs of opposite emotions. Parrott (2001), in his three layered categorization of emotion, considered six primary emotions of *love. joy, surprise, anger, sadness, and fear* in the first layer, followed by 25 secondary emotions in the next. He categorized more fine grained emotions in the last layer.

Using a different perspective, dimensional model of emotions tries to define emotions based on two or three dimensions. As opposed to basic emotions theory, which states that different emotions correspond to different neurological subsystems in the brain, the dimensional model is based on the hypothesis that all emotions are the result of a common and interconnected neurophysiological system. The Circumplex model developed by Russell (1980) suggests that emotions can be shown in a two dimensional circular space, with one dimension for arousal (i.e. intensity), and one for valance (i.e. pleasantness). The dimensional models have been used very scarcely in the emotion detection literature, but shown to be promising as a model to represent emotions in textual data (Calvo and Mac Kim, 2013).

## 3   Complexity of Expressing Emotions in Language

Emotion expression is very context sensitive and complex. Ben-Ze'ev (2000) relates this complexity to various reasons: first, its sensitivity to multiple personal and contextual circumstances; secondly, to the fact that these expressions often consist of a cluster of emotions rather than merely a single one; and finally, the confusing linguistic use of emotional terms. Bazzanella (2004) argues that complexity of emotions can be seen in multiple levels: "the nested interplay with mind/language/behavior/culture, the lexical and semantic problem, the number of correlated physiological and neurological features, their universality or relativity, etc.". As one can see even in everyday life, it is sometimes very hard to distinguish between emotions.

Also, it has been shown that context is very important, and is crucial in understanding emotions (Oatley et al., 2006). Most recent studies in textual emotion detection in NLP, are based on explicit expression of emotion using emotion bearing words. But emotion expression is mostly done by expressing emotion provoking situation, which can be interpreted in an affective manner (Balahur and Montoyo, 2008; Pavlenko, 2008). This fact has greatly limited the identification of emotions, for considerable portion of these expressions are not explicit. Therefore more emphasis should be placed on implicit expressions of emotions (Lee, 2015).

There are not many works in the literature on detecting implicit expression of emotions, but in sentiment analysis literature there has been some attempts in this area. For instance, Greene and Resnik (2009) used syntactic packaging for ideas to assess the implicit sentiment in text, and to improve state of the art sentiment detection techniques. Cambria et al. (2009) proposed an approach to overcome this issue by building a knowledge base that merges Common Sense and affective knowledge. The goal is to move past the methods that rely on explicit expression of emotion i.e. verbs, adjectives and adverbs of emotion. Their reasoning for choosing this approach was based on the notion that most emotions are expressed through concepts with affective valence. For example 'be laid off' or 'go on a first date' which contains emotional information without specifying any emotional lexicon.

Lakoff (2008), in a case study about *Anger*, talks about conceptual content behind emotions. He argues that emotions have a very complex conceptual structure, and this structure could be studied by systematic investigation of expression that are understood metaphorically. He argues that many expressions of anger are metaphorical, thus could not be assessed by the literal meaning of the expression (e.g. 'he lost his cool' or 'you make my blood boil'). This fact makes it more difficult to create a lexical, or machine learning method to identify emotions in text, without first solving the problem of understanding of metaphorical expressions.

Complexity of human emotions, along with implicit expressions, frequent use of metaphors, and the importance of context in identifying emotions, not to mention cross cultural and intra-cultural variations of emotions, rises the problem of detecting emotions from text above a multi-class classification problem which covers the most research that has been done in the field.

## 4   Resources for Detecting Emotions in Text

As opposed to sentiment analysis, textual datasets annotated with markers of emotional content are scarce. Any new method of emotion detection in text, based on conventional supervised classifiers or neural networks, requires vast amount of annotated data for training and development. But as a relatively new field in natural language processing, emotion detection as a multi-class classification problem, faces

lack of available annotated data. In this section, some of the most prominent and publicly available sources will be introduced. These data can be separated into two groups: labeled texts and emotion lexicons. We will also briefly cover vector space models, as another potential resource.

## 4.1 Labeled Text

Having a standard, free and generalized annotated data makes it easier to train and test any new method, and is an important factor in any classification task. One of the most prominent and well known sources for emotionally labeled text is the Swiss Center for Affective Sciences (SCA, ). The most used resource they provide is ISEAR, International Survey On Emotion Antecedents And Reactions. It consists of responses from about 3000 people around the world who were asked to report situations in which they experienced each of the seven major emotions (joy, fear, anger, sadness, disgust, shame, and guilt), and how they reacted to them. The result was a promising dataset to be used to test many methods for emotion extraction and classification. This dataset consists of about 7600 records of emotion provoking text. SCAS has many more resources that can be useful specially in languages other than English.

EmotiNet knowledge base (Balahur et al., 2011) tackled the problem of emotion detection from another perspective. Balahur et. al. argued that word level attempt to detect emotion would lead to a low performance system because "expressions of emotions are most of the time not presented in text in specific words", rather from the "interpretation of the situation presented" in the text. They base their insight on *Appraisal Theory* in psychology (Dalgleish and Power, 2000) . They create a new knowledge base containing action chains and their corresponding emotional label. They started from around a thousand samples from the ISEAR database and clustered the examples within each emotion category based on language similarity. Then they extracted the agent, the verb and the object from a selected subset of examples. Furthermore they expanded the ontology created using VerbOcean (Chklovski and Pantel, 2004) in order to increase the number of actions in the knowledge base, and to reduce the degree of dependency between the resources and the initial set of examples. Although this approach showed promise, specially because of their attempt to extract concepts from text, it could not present itself as viable and generally applicable in its current form, due to the small size of the knowledge base and the structure of information they used (limited to the four-tuple of actor, action, object, and emotion).

Vu et al. (2014) focused on discovery and aggregation of emotion provoking events. They created dictionary of such events through a survey of 30 subjects, and used that to aggregate similar events from the web by applying Espresso pattern expansion (Pantel and Pennacchiotti, 2006) and bootstrapping algorithms. One of the frequently used dataset is the SemEval-2007 (Strapparava and Mihalcea, 2007), which consists of 1250 news headlines extracted from news websites, and annotated with six Ekman's emotions. The other example, is Alm's annotated fairy tale dataset (Alm et al., 2005), consisting of 1580 sentences from children fairy tales, also annotated with six Ekman's emotions. These datasets have been mostly used as benchmark in the literature. As emotion detection gets more attention, there will be the need for more datasets that could be used in different tests of models and methods for emotion detection.

In the meantime the lack of benchmark datasets with proper linguistic generality and accepted annotations pushes the research community to use text from microblogs, such as Twitter, in which self expression is possible using methods like *hashtags, and emoticons*. An attempt to create such an annotated corpus was presented in Wang et al. (2012) consisting of 2.5 million tweets cleaned and annotated with hashtags and emoticons.

## 4.2 Emotion Lexicons

Although having expressive emotional text like ISEAR is very important, especially for comparing different emotion detection methods, there are many use cases in which having an annotated lexicon could be useful, specially when more word based analysis is required. And even though considerable data is available on sentiment polarity of words going back a few years (Baccianella et al., 2010), the lack of reasonable size lexicon for emotions led Mohammad and Turney (2010) to create an emotion word lexicon. In the cited paper and later in (Mohammad and Turney, 2013) they used Amazon Mechanical Turk to annotate around 14000 words in English language (along with lexicons in other languages, these are

available on their website[1]).

Another popular emotion lexicon used in literature is WordNet-Affect. Strapparava et al. (2004) tried to create a lexical representation of affective knowledge by starting from WordNet (Miller and Fellbaum, 1998), a well known lexical database. Then they used selection and tagging of a subset of synsets which represents the affective concepts, with the goal of introducing "affective domain labels" to the hierarchical structure of WordNet. WordNet-Affect, despite its small size (containing 2874 synsets, and 4787 words), was a great attempt to extract emotional relations of words from WordNet, and was used in many early applications of sentiment analysis, opinion mining (Balahur et al., 2013), and in emotion detection specially for extending affective word sets from the basic set of emotions.

Another attempt to generate an emotional lexicon has been showcased by Staiano and Guerini (2014) called DepecheMood. They used crowd-sourcing to annotate thirty five thousands words. The showed that lexicons, could be used in several approaches in sentiment analysis, as features for classification in machine learning methods (Liu and Zhang, 2012), or to generate an affect score for each sentence, based on the scores of the words which are higher in the parse tree (Socher et al., 2013b). Other emotional lexicons frequently used in the literature are LIWC lexicon (Pennebaker et al., 2001) consisting 6400 words annotated for emotions, and also ANEW (Affective Norm for English Words) developed by Bradley and Lang (1999). This dataset has near 2000 words which has been annotated based on dimensional model of emotions, with three dimensions of valance, arousal and dominance.

### 4.3 Word Embedding

Word embeddings is a technique based on distributional semantic modeling. It is rooted in the idea that words which frequently co-occur in a relatively large corpus are similar in some semantic criteria. In these methods, each word is represented as a vector in an n-dimensional space, called the vector space, and in a way that the distance between vectors corresponds to the semantic similarity of the words they represent. These vector space models have been shown to be useful in many natural language processing tasks, such as named entity recognition (Turian et al., 2010), machine translation (Zou et al., 2013), and parsing (Socher et al., 2013a). Many such models have been created in recent years with similar performances as shown by Levy et al. (2015). Some of the more well-established and most frequently used embedding models in the literature are latent semantic analysis or LSA, Word2Vec (Mikolov et al., 2013a; Mikolov et al., 2013b), GloVe (JeffreyPennington et al., 2014), and ConceptNet (Speer et al., 2016). It has been shown that these models, just by utilizing the statistical information of word co-occurrences, can incorporate variety of information about words (JeffreyPennington et al., 2014) such as closeness in meaning, gender, types, capital of countries, etc., and in the arithmetic of word vectors shown in such overused examples as $v(king) - v(queen) = v(man) - v(woman)$.

There also have been many attempts to increase their performance, and incorporate more information in these models retrofitting (Faruqui et al., 2014) and counter-fitting (Mrkšić et al., 2016) external word ontologies or lexicons (Speer et al., 2016; Speer and Chin, 2016). Some work has been done in creating embeddings for sentiment analysis. For example, by Tang et al. (2014b) who created a sentiment-specific word embeddings using neural networks, to classify sentiments in Twitter (Tang et al., 2014a). Such approaches for creating emotional word embeddings from scratch, or incorporating emotional information into pre-trained word vectors after the fact, might lead to better performances in emotion detection tasks, either in unsupervised methods, or as features for classification tasks using conventional machine learning, or deep learning (Socher et al., 2013b).

## 5   Methodologies for Detecting Emotions in Text: Supervised Approaches

Due to the lack of emotion-labeled datasets, many supervised classifications for emotions have been done on data gathered from microblogs (e.g. Twitter), using hashtags or emoticons as the emotional label for the data, under the assumption that these signals show the emotional state of the writer. Such an attempt can be seen in Suttles and Ide (2013), where the four pairs of opposite emotions in the Plutchik's wheel

---

[1]NRC word-emotion association lexicon: http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm

were used to create four binary classification tasks. With hashtags, emoticons, and emoji as labels for their data, they reached between 75% to 91% accuracy on a separate manually labeled dataset.

Purver and Battersby (2012) on Twitter data using SVM classifier reached 82% accuracy for classifying the emotion *Happy* in 10-fold cross validation, and 67% in classifying over the entire dataset for the same emotion, with emoticons as labels for the training set, and hashtags as labels for the test set. Then they tested their trained models for each emotion to see if they can distinguish emotion classes from each other rather than just distinguish one class from a general *Other* set. The results varied from 13% to 76% accuracy for different emotions. They also created a dataset of 1000 tweets labeled by human annotators and used it as the test data to evaluate the quality of assigning hashtags and emoticons as labels. For different emotions the F-score varied from 0.10 to 0.77. Their study showed that the classifiers performed well on emotions like happiness, sadness and anger, but not well for others. They concluded that using hashtags and emoticons as labels is a promising labeling strategy and and alternative to manual labeling.

Mohammad (2012a) also used hashtags as label for tweets, and used support vector machines as a binary classifier for each emotion in Ekman's model. After showing that the hashtags as labels perform better than random classification, he used Daum's domain adaptation method (Daumé III, 2009) to test the classification power of their data in a new domain. Roberts et al. (2012) collected tweets in 14 topics that "would frequently evoke emotion" and created a dataset where all seven emotions (Ekman + Love) were represented. Seven SVM binary classifiers were used to detect emotions in the dataset, resulting in the average F1-score of 0.66.

Hasan et al. (2014) also used hashtags as their labels and created their features using the unigram model, removing any word from tweets which were not in their emotion lexicon (created using 28 basic emotion word in Circumplex model and extended with WordNet synsets). Four classifiers (Naive Bayes, SVM, Decision Tree, and KNN) achieved accuracies close to 90% in classifying four main classes of emotion categories in Circumplex model. In another paper, Hasan et al. (2018) created an automatic emotion detection system to identify emotions in streams of tweets. This approach included two tasks: training an offline emotion classification model based on their 2014 paper, and in the second part a two step classification to identify tweets containing emotions, and to classify these emotional tweets into more fine-grained labels using soft classification techniques.

Facing the problem of lack of labeled emotional text, Wang et al. (2012) created a large dataset (about 2.5 million tweets) using emotion related hashtags, and used two machine learning algorithms for emotion identification. They used Shaver et al. (1987) for mapping hashtags to emotions, and extending hashtag words to the total of 131 for the seven basic emotions. They then increased the quality of the data by keeping more relevant tweets (i.e. tweets with hashtags at the end of sentence, with more than 5 words, contain no URLs or quotations, in English, and containing less than 4 hashtags), and tried different combinations of features (e.g. different n-grams, position of n-grams, multiple lexicon, POS) with 250k of the training data to find the best set of features, with the best result for the combination of n-gram(n=1,2), LIWC lexicon, MPQA lexicon, WordNet-Affect, and POS. After finding the best feature set, they increased the size of training data from 1000 tweets to full training set to see the effect of training size in the classification. The final classifier reached the F-Measure as high as 0.72 for joy, and as low as 0.13 for surprise. They justified the varying result for different emotions by the fact that the training dataset had and unbalanced distribution. In addition, based on the confusion matrix, they reported that high number of misclassified tweets between class pairs like anger and sadness, or joy and love, were due to the fact that these emotions are "naturally related", and "different people might have different emotions when facing similar events."

In another Twitter emotion classification task done by Balabantaray et al. (2012), manual labeling was used for around 8000 tweets, for six basic emotions in Ekman's model. They used SVM multi-class classifier with 11 features: *Unigrams, Bigrams, Personal-pronouns, Adjectives, Word-net Affect lexicon, Word-net Affect lexicon with left/right context, Word-net Affect emotion POS, POS, POS-bigrams, Dependency-Parsing, and Emoticons* resulting in an accuracy of 73.24%.

We can see combination of methods in emotion classification in the paper by Wen and Wan (2014). In their study, they used a combination of lexicon based and machine learning (SVM) methods to create two

emotion labels for each microblog post, they then use Class Sequential Rules (CSR) (Liu, 2007) mining to create sequences for each post based on the labeling for each sentence and the conjunctions between them. Using the resulting data and by including additional features like lexicon counts and punctuations, and using an SVM classifier they reached an F-measure of 0.44 which was shown to be a significant increase over other methods based on emotion lexicons or simple SVM.

Li and Xu (2014) proposed a "emotion cause detection technique" to extract features that are "meaningful" to emotions instead of choosing words with high co-occurrence degree. Their method is based on Lee et al.'s work on rule based emotion cause detection (Lee et al., 2010). After using predefined linguistic patterns to extract emotion causes and adding it to their features, they used Support Vector Regression (SVR) to create the classifier, and reached higher F-score for some emotions like happiness, anger, and disgust compared to previous works. Overall, their approach had better precisions, but low recalls.

In their paper, Li et al. (2015) attempted sentence level classification of emotion instead of document level. They indicated that the two biggest problems in sentence level emotion classification is firstly the fact that it is a multi-class classification, meaning that each sentence could have more than one label, and secondly, the short length of a sentence, provides less content. Considering these challenges they created a Dependence Factor Graph (DFG) based on two observations, *label dependence*, i.e. multiple labels for a sentence would be correlated to one another, like Joy and Love instead of Joy and Hate, and *context dependence*, i.e. two neighboring sentences, or sentences in the same paragraph might share the same emotion categories. Using the DFG model, after learning they reached the accuracy of 63.4% with F1 of 0.37 showing significant improvement over previous methods (Wang et al., 2014; Xu et al., 2012).

In an application based study done by Seyeditabari et al. (2018), they attempted to classify social media comments regarding a specific crisis event, based on the emotion of anger considering the fact that the same method can be use for other emotions. They ran a short survey gathering 1192 responses in which the participants were asked to comment under a news headline as though they are commenting on social media. Using this as the training set they reached 90% accuracy in classifying anger in a dataset created using the same survey from different population by using logistic regression coefficients to select features (words) and random forest as the main classifier.

Current state of the art algorithms for emotion classification, are mostly based on supervised methods, but imbalance training data, specially for emotion detection as a multi-class classification problem, are an obstacle for supervised learning, leading to increase misclassification for underrepresented classes (López et al., 2013; Yang and Wu, 2006; Wang et al., 2012). There are different methods proposed in literature (López et al., 2013) to overcome this issue in one of three ways, either by changing the learning algorithm to adapt to this imbalance (Tang et al., 2009), or adding cost to majority classes during training (Sun et al., 2007), or by sampling from the training data before learning to make the classes balanced (Chawla et al., 2004). Xu et al. (2015) proposed an over-sampling method based on word embeddings (Mikolov et al., 2013b), and recursive neural tensor network (Socher et al., 2013b) which showed a significant improvement over previous sampling methods, specially for emotion classification as a multi-class data.

The question here could be if creating emotion detection systems based on conventional machine learning techniques can move past the mediocre results we have seen in the literature. To emphasis the importance of a deeper analysis than conventional machine learning methods we can refer to a comparative analysis done by Balahur et al. (2012). They compared various classification features and compared them to EmotiNet, and concluded that the task of emotion detection can be best tackled using approaches based on commonsense knowledge. They showed that even with the small size of EmotiNet knowledge base they could produce comparative results to supervised learning methods with huge amount of training data.

## 6 Methodologies for Detecting Emotions in Text: Unsupervised Approaches

Kim et al. (2010) used an unsupervised method to automatically detect emotions in text, based on both categorical (anger, fear, joy and sadness), and dimensional models of emotions. They used three datasets,

SemEval-2007 Affective Text, ISEAR, and childrens fairy tales. For categorical model, they used WordNet-Affect as the lexicon, and evaluated three dimensionality reduction methods: Latent Semantic Analysis (LSA), Probabilistic Latent Semantic Analysis (PLSA), and Non-negative Matrix Factorization (NMF). And for the dimensional model, they used ANEW (Affective Norm for English Words) and WordNet-Affect as a means to extend ANEW. They assigned the emotion of the text based on closeness (cosine similarity) of its vector to the vectors for each category or dimension of emotions. Their study showed that NMF-based categorical classification performs best among categorical approaches, and dimensional model had the second best performance with highest F-measure of 0.73.

Another unsupervised approach to emotion detection can be seen in the paper by Agrawal and An (2012). They start by extracting NAVA words (i.e. Nouns, Adjectives, Verbs, and Adverbs) from a sentence, and then extracting syntactic dependencies between extracted words in each sentence to include contextual information in their model. They then used semantic relatedness to compute emotion vectors for words, based on the assumption that the affect words (NAVA words) which co-occur together more often tend to be semantically related. They use Point-wise Mutual Information (PMI) as the measure of semantic relatedness of two words (Equation 1) and computed a vector for each word using the PMI of the word with all words related to each emotion, then adjust the vectors by considering the contextual information in syntactic dependency of words. After computing vectors for each word they generated a vector for each sentence by aggregating the emotion vectors of all the affect words in it. By evaluating on multiple data sources, they showed that their method preformed more accurate, compared to other unsupervised approaches, and had comparable results to some supervised methods.

$$PMI(x,y) = \frac{cooccurrence(x,y)}{occurrence(x) * occurrence(y)} \qquad (1)$$

In another lexicon base approach, Mohammad (2012b) showed how detecting emotions in text can be used to organize collection of text for affect-based search, and how books portray different entities through co-occurring emotion words by analyzing emails, and books. He used NRC lexicon to see which of the emotion words exist in the available text, and calculated ratios such as the number of words associated to a particular emotions compared to other emotions, to determine if a document have more expressed emotions compared to other documents in the corpus. He compiled three datasets for emotional emails: *love letters, hate mails, and suicide notes*. He goes on to analyze presents of different emotions based on criteria like, workplace emails, emails written by women/men, or emails written by men to women vs men. He also did some fascinating analysis on books, and works of literature using the same lexical approach.

Rey-Villamizar et al. (2016) used an unsupervised method to distinguish language pattern related to anxiety in online health forums. They define user behavioral dimension (BD) based on the LIWC lexicon focusing on its anxious word list. They define each user's BD as measure of the average fraction of words from the list $BD_i$ across the posts of a user, Equation 2:

$$BD_i(u) = log\left(\frac{1}{|posts(u)|} \sum_{p \in posts(u)} \frac{|words_{BD_i}(p)|}{|words(p)|}\right) \qquad (2)$$

Then by analyzing this value for each user or groups of users over time, and the correlation of this behavioral dimension with other BDs, they showed that the anxiety level of patients involved in a support group lowers over time. In a rule based approach Tromp and Pechenizkiy (2014) introduced RBEM-Emo method for detecting emotions in text as an extension of their previous work for polarity detection (Tromp and Pechenizkiy, 2013) called Rule-Based Emission Model. They showed that rule based classification techniques can be comparative to current state of the art machine learning methods, such as SVM classifier and recursive auto-encoder.

Bandhakavi et al. (2017b) used domain-specific lexicon that they created based on unigram mixture models (Bandhakavi et al., 2014; Bandhakavi et al., 2017a) to extract features and showed that their lexicon outperform methods like Point-wise Mutual Information, and supervised Latent Dirichlet Allocation.

# 7 Discussion and Open Problems

Going through the literature, we can see the hard task of detecting expressed emotions. The difficulties can be attributed to many problems from *complex nature of emotion expression in text*, to *inefficiency of current emotion detection models*, and *lack of high quality data* to be utilized by those models.

**Complex Nature of Emotion Expression**: On one hand, expression of emotion in human is a complex phenomena, in such a way that a shortest phrase can express multiple emotions with different intensity that cannot be understood at first glance even by humans. And on the other hand, the intricacy of emotional language, resulting from the vast use of metaphorical language, context dependent nature of emotion expression, and implicit nature of such expressions, makes this task even harder. In order to address this issue, it is important to pay attention to the complexity of emotional language when building emotion detection systems. These systems should be designed based on the linguistic complexities of emotion expression to be able to grasp the implicit expression of emotions, and untangle the metaphorical nature of these expressions. It is also crucial to consider the contextual information in which the expression is occurring.

**Shortage of Quality Data**: In almost all the papers reviewed, some common obstacles can be identified, showing that future work is needed in order to improve performance of emotion detecting systems. In any machine learning task, the quality and quantity of data has a huge effect on the performance of classification algorithms. Although huge amount of textual data is currently available, for any supervised model, a large amount of annotated data is required. A great body of work has already been dedicated to overcome this problem by using self annotated microblog data, but it has not yet possesses qualities which are required for an applicable system. Additionally, the niche nature of the language used in microblog text, prevents the systems trained on these texts to be used to classify other types of text (e.g. tweets vs. news comments). Furthermore, as can be seen in most of the reviewed studies, the imbalance nature of currently available emotional text, will cause the classifier to severely under-preform for emotions that are underrepresented in the dataset. Therefore, any attempt to create a large balanced dataset, with high quality labels could provide a brighter future for the field.

**Inefficiency of Current Models**: In addition, creating a multi-class classification methodology based on the nature of the data and the task at hand, is another front that could be considered to increase the performance of such systems. There have been many attempt to approach this problem with the most frequently used being, converting the task of multi-class to multiple binary classification, either by having one classifier for each emotion (e.g. anger vs not anger), or one classifier for a pair of opposite emotions (e.g. joy vs sadness). Further improvement in classification algorithms, and trying out new ways is necessary in order to improve the performance of emotion detection methods. Some suggestions that were less present in the literature, are to develop methods that go above BOW representations and consider the flow and composition of language. In addition, specific neural network designs or ensemble methods are possible approaches that has been shown to be useful in other areas of natural language processing. New ways to increase the emotional qualities of embeddings and vector models could be beneficial in unsupervised methods, or be used as features in neural networks. Emotion detection, as a lesser known and relatively new field, has come a long way, but still has a long way to go to become a totally reliable and applicable tool in natural language processing.

# 8 Conclusion

In this paper, we reviewed the current state of emotion detection in textual data based on the available work in the literature. While many successful methodology and resources was introduces for sentiment analysis in recent years, researchers, by understanding the importance of more fine-grained affective information in decision making, turned to emotion detection in order to distinguish between different negative or positive emotions. In addition, having large amount of textual data with the rise of social media in past couple of decades, and therefore the availability of vast self expression text about any major or minor event, idea, or product, points to a great potential to change how entities and organizations can use these information as a basis for their future decision making processes.

# References

[Agrawal and An2012] Ameeta Agrawal and Aijun An. 2012. Unsupervised emotion detection from text using semantic and syntactic relations. In *Proceedings of the The 2012 IEEE/WIC/ACM International Joint Conferences on Web Intelligence and Intelligent Agent Technology-Volume 01*, pages 346–353. IEEE Computer Society.

[Alm et al.2005] Cecilia Ovesdotter Alm, Dan Roth, and Richard Sproat. 2005. Emotions from text: machine learning for text-based emotion prediction. In *Proceedings of the conference on human language technology and empirical methods in natural language processing*, pages 579–586. Association for Computational Linguistics.

[Baccianella et al.2010] Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani. 2010. Sentiwordnet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining. In *LREC*, volume 10, pages 2200–2204.

[Bagozzi et al.1999] Richard P Bagozzi, Mahesh Gopinath, and Prashanth U Nyer. 1999. The role of emotions in marketing. *Journal of the academy of marketing science*, 27(2):184–206.

[Balabantaray et al.2012] Rakesh C Balabantaray, Mudasir Mohammad, and Nibha Sharma. 2012. Multi-class twitter emotion classification: A new approach. *International Journal of Applied Information Systems*, 4(1):48–53.

[Balahur and Montoyo2008] Alexandra Balahur and Andrés Montoyo. 2008. Applying a culture dependent emotion triggers database for text valence and emotion classification. *Procesamiento del lenguaje natural*, 40.

[Balahur et al.2011] Alexandra Balahur, Jesús M. Hermida, Andrés Montoyo, and Rafael Muñoz, 2011. *EmotiNet: A Knowledge Base for Emotion Detection in Text Built on the Appraisal Theories*, pages 27–39. Springer Berlin Heidelberg, Berlin, Heidelberg.

[Balahur et al.2012] Alexandra Balahur, Jesús M Hermida, and Andrés Montoyo. 2012. Detecting implicit expressions of emotion in text: A comparative analysis. *Decision Support Systems*, 53(4):742–753.

[Balahur et al.2013] Alexandra Balahur, Ralf Steinberger, Mijail Kabadjov, Vanni Zavarella, Erik Van Der Goot, Matina Halkia, Bruno Pouliquen, and Jenya Belyaeva. 2013. Sentiment analysis in the news. *arXiv preprint arXiv:1309.6202*.

[Bandhakavi et al.2014] Anil Bandhakavi, Nirmalie Wiratunga, P Deepak, and Stewart Massie. 2014. Generating a word-emotion lexicon from# emotional tweets. In *Proceedings of the Third Joint Conference on Lexical and Computational Semantics (* SEM 2014)*, pages 12–21.

[Bandhakavi et al.2017a] Anil Bandhakavi, Nirmalie Wiratunga, Stewart Massie, and Deepak Padmanabhan. 2017a. Lexicon generation for emotion detection from text. *IEEE intelligent systems*, 32(1):102–108.

[Bandhakavi et al.2017b] Anil Bandhakavi, Nirmalie Wiratunga, Deepak Padmanabhan, and Stewart Massie. 2017b. Lexicon based feature extraction for emotion text classification. *Pattern Recognition Letters*, 93:133 – 142. Pattern Recognition Techniques in Data Mining.

[Bazzanella2004] Carla Bazzanella. 2004. Emotions, language and context. *Emotion in dialogic interaction: Advances in the Complex*, pages 55–72.

[Bechara2004] Antoine Bechara. 2004. The role of emotion in decision-making: Evidence from neurological patients with orbitofrontal damage. *Brain and Cognition*, 55(1):30 – 40. Development of Orbitofrontal Function.

[Ben-Ze'ev2000] Aaron Ben-Ze'ev. 2000. *The subtlety of emotions*. MIT Press.

[Bradley and Lang1999] Margaret M Bradley and Peter J Lang. 1999. Affective norms for english words (anew): Instruction manual and affective ratings. Technical report, Citeseer.

[Brave and Nass2003] Scott Brave and Clifford Nass. 2003. Emotion in human–computer interaction. *Human-Computer Interaction*, page 53.

[Calvo and Mac Kim2013] Rafael A Calvo and Sunghwan Mac Kim. 2013. Emotions in text: dimensional and categorical models. *Computational Intelligence*, 29(3):527–543.

[Cambria et al.2009] Erik Cambria, Amir Hussain, Catherine Havasi, and Chris Eckl. 2009. Affectivespace: Blending common sense and affective knowledge to perform emotive reasoning. *WOMSA at CAEPIA, Seville*, pages 32–41.

[Chawla et al.2004] Nitesh V Chawla, Nathalie Japkowicz, and Aleksander Kotcz. 2004. Special issue on learning from imbalanced data sets. *ACM Sigkdd Explorations Newsletter*, 6(1):1–6.

[Chklovski and Pantel2004] Timothy Chklovski and Patrick Pantel. 2004. Verbocean: Mining the web for fine-grained semantic verb relations. In *EMNLP*, volume 4, pages 33–40.

[Colombetti2009] Giovanna Colombetti. 2009. From affect programs to dynamical discrete emotions. *Philosophical Psychology*, 22(4):407–425.

[Dalgleish and Power2000] Tim Dalgleish and Mick Power. 2000. *Handbook of cognition and emotion*. John Wiley & Sons.

[Daumé III2009] Hal Daumé III. 2009. Frustratingly easy domain adaptation. *arXiv preprint arXiv:0907.1815*.

[Druckman and McDermott2008] James N. Druckman and Rose McDermott. 2008. Emotion and the framing of risky choice. *Political Behavior*, 30(3):297–321, Sep.

[Ekman1992] Paul Ekman. 1992. An argument for basic emotions. *Cognition & emotion*, 6(3-4):169–200.

[Faruqui et al.2014] Manaal Faruqui, Jesse Dodge, Sujay K Jauhar, Chris Dyer, Eduard Hovy, and Noah A Smith. 2014. Retrofitting word vectors to semantic lexicons. *arXiv preprint arXiv:1411.4166*.

[Greene and Resnik2009] Stephan Greene and Philip Resnik. 2009. More than words: Syntactic packaging and implicit sentiment. In *Proceedings of human language technologies: The 2009 annual conference of the north american chapter of the association for computational linguistics*, pages 503–511. Association for Computational Linguistics.

[Gupta et al.2013] Narendra Gupta, Mazin Gilbert, and Giuseppe Di Fabbrizio. 2013. Emotion detection in email customer care. *Computational Intelligence*, 29(3):489–505.

[Hasan et al.2014] Maryam Hasan, Elke Rundensteiner, and Emmanuel Agu. 2014. Emotex: Detecting emotions in twitter messages.

[Hasan et al.2018] Maryam Hasan, Elke Rundensteiner, and Emmanuel Agu. 2018. Automatic emotion detection in text streams by analyzing twitter data. *International Journal of Data Science and Analytics*, Feb.

[Hudlicka2011] Eva Hudlicka. 2011. Guidelines for designing computational models of emotions. *International Journal of Synthetic Emotions (IJSE)*, 2(1):26–79.

[JeffreyPennington et al.2014] RichardSocher JeffreyPennington, ChristopherD CD Manning, J Pennington, R Socher, and ChristopherD CD Manning. 2014. Glove: Global vectors for word representation. *Proceedings of the Empirical Methods in . . .*, 12:1532–1543.

[Jin et al.2007] Xin Jin, Ying Li, Teresa Mah, and Jie Tong. 2007. Sensitive webpage classification for content advertising. In *Proceedings of the 1st International Workshop on Data Mining and Audience Intelligence for Advertising*, ADKDD '07, pages 28–33, New York, NY, USA. ACM.

[Kim et al.2010] Sunghwan Mac Kim, Alessandro Valitutti, and Rafael A Calvo. 2010. Evaluation of Unsupervised Emotion Models to Textual Affect Recognition. In *Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text*, CAAGET '10, pages 62–70, Stroudsburg, PA, USA. Association for Computational Linguistics.

[Lakoff2008] George Lakoff. 2008. *Women, fire, and dangerous things*. University of Chicago press.

[Lee et al.2010] Sophia Yat Mei Lee, Ying Chen, and Chu-Ren Huang. 2010. A text-driven rule-based system for emotion cause detection. In *Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text*, pages 45–53. Association for Computational Linguistics.

[Lee2015] Sophia Yat Mei Lee. 2015. A linguistic analysis of implicit emotions. In *Workshop on Chinese Lexical Semantics*, pages 185–194. Springer.

[Lerner and Keltner2000] Jennifer S Lerner and Dacher Keltner. 2000. Beyond valence: Toward a model of emotion-specific influences on judgement and choice. *Cognition & emotion*, 14(4):473–493.

[Levy et al.2015] Omer Levy, Yoav Goldberg, and Ido Dagan. 2015. Improving distributional similarity with lessons learned from word embeddings. *Transactions of the Association for Computational Linguistics*, 3:211–225.

[Li and Xu2014] Weiyuan Li and Hua Xu. 2014. Text-based emotion classification using emotion cause extraction. *Expert Systems with Applications*, 41(4):1742–1749.

[Li et al.2015] Shoushan Li, Lei Huang, Rong Wang, and Guodong Zhou. 2015. Sentence-level emotion classification with label and context dependence. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, volume 1, pages 1045–1053.

[Lita et al.2005] Lucian Vlad Lita, Andrew Hazen Schlaikjer, WeiChang Hong, and Eric Nyberg. 2005. Qualitative dimensions in question answering: Extending the definitional qa task. In *PROCEEDINGS OF THE NATIONAL CONFERENCE ON ARTIFICIAL INTELLIGENCE*, volume 20, page 1616. Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999.

[Liu and Zhang2012] Bing Liu and Lei Zhang. 2012. A survey of opinion mining and sentiment analysis. In *Mining text data*, pages 415–463. Springer.

[Liu2007] Bing Liu. 2007. *Web data mining: exploring hyperlinks, contents, and usage data*. Springer Science & Business Media.

[López et al.2013] Victoria López, Alberto Fernández, Salvador García, Vasile Palade, and Francisco Herrera. 2013. An insight into classification with imbalanced data: Empirical results and current trends on using data intrinsic characteristics. *Information Sciences*, 250:113–141.

[Mikolov et al.2013a] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013a. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.

[Mikolov et al.2013b] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013b. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119.

[Miller and Fellbaum1998] George Miller and Christiane Fellbaum. 1998. Wordnet: An electronic lexical database.

[Miller et al.2009] Daniel A Miller, Tracey Cronin, Amber L Garcia, and Nyla R Branscombe. 2009. The relative impact of anger and efficacy on collective action is affected by feelings of fear. *Group Processes & Intergroup Relations*, 12(4):445–462.

[Mohammad] Saif Mohammad. Nrc word-emoition association lexicon.

[Mohammad and Turney2010] Saif M. Mohammad and Peter D. Turney. 2010. Emotions evoked by common words and phrases: Using mechanical turk to create an emotion lexicon. In *Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text*, CAAGET '10, pages 26–34, Stroudsburg, PA, USA. Association for Computational Linguistics.

[Mohammad and Turney2013] Saif M. Mohammad and Peter D. Turney. 2013. Crowdsourcing a word-emotion association lexicon. 29(3):436–465.

[Mohammad2012a] Saif M Mohammad. 2012a. # emotional tweets. In *Proceedings of the First Joint Conference on Lexical and Computational Semantics-Volume 1: Proceedings of the main conference and the shared task, and Volume 2: Proceedings of the Sixth International Workshop on Semantic Evaluation*, pages 246–255. Association for Computational Linguistics.

[Mohammad2012b] Saif M Mohammad. 2012b. From once upon a time to happily ever after: Tracking emotions in mail and books. *Decision Support Systems*, 53(4):730–741.

[Mrkšić et al.2016] Nikola Mrkšić, Diarmuid O Séaghdha, Blaise Thomson, Milica Gašić, Lina Rojas-Barahona, Pei-Hao Su, David Vandyke, Tsung-Hsien Wen, and Steve Young. 2016. Counter-fitting word vectors to linguistic constraints. *arXiv preprint arXiv:1603.00892*.

[Oatley et al.2006] Keith Oatley, Dacher Keltner, and Jennifer M Jenkins. 2006. *Understanding emotions*. Blackwell publishing.

[Pantel and Pennacchiotti2006] Patrick Pantel and Marco Pennacchiotti. 2006. Espresso: Leveraging generic patterns for automatically harvesting semantic relations. In *Proceedings of the 21st International Conference on Computational Linguistics and the 44th Annual Meeting of the Association for Computational Linguistics*, ACL-44, pages 113–120, Stroudsburg, PA, USA. Association for Computational Linguistics.

[Parrott2001] W Gerrod Parrott. 2001. *Emotions in social psychology: Essential readings*. Psychology Press.

[Pavlenko2008] Aneta Pavlenko. 2008. Emotion and emotion-laden words in the bilingual lexicon. *Bilingualism: Language and cognition*, 11(2):147–164.

[Pennebaker et al.2001] James W Pennebaker, Martha E Francis, and Roger J Booth. 2001. Linguistic inquiry and word count: Liwc 2001. *Mahway: Lawrence Erlbaum Associates*, 71(2001):2001.

[Plutchik1984] Robert Plutchik. 1984. Emotions: A general psychoevolutionary theory. *Approaches to emotion*, 1984:197–219.

[Purver and Battersby2012] Matthew Purver and Stuart Battersby. 2012. Experimenting with distant supervision for emotion classification. In *Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics*, pages 482–491. Association for Computational Linguistics.

[Qiu et al.2010] Guang Qiu, Xiaofei He, Feng Zhang, Yuan Shi, Jiajun Bu, and Chun Chen. 2010. DASA: Dissatisfaction-oriented Advertising based on Sentiment Analysis. *Expert Systems with Applications*, 37(9):6182–6191.

[Rangel and Rosso2016] Francisco Rangel and Paolo Rosso. 2016. On the impact of emotions on author profiling. *Information processing & management*, 52(1):73–92.

[Rey-Villamizar et al.2016] Nicolas Rey-Villamizar, Prasha Shrestha, Farig Sadeque, Steven Bethard, Ted Pedersen, Arjun Mukherjee, and Thamar Solorio. 2016. Analysis of anxious word usage on online health forums. *EMNLP 2016*, page 37.

[Riloff et al.2005] Ellen Riloff, Janyce Wiebe, and William Phillips. 2005. Exploiting subjectivity classification to improve information extraction. *Proceedings of the 20th national conference on Artificial intelligence*, 20(3):1106–1111.

[Roberts et al.2012] Kirk Roberts, Michael A Roach, Joseph Johnson, Josh Guthrie, and Sanda M Harabagiu. 2012. Empatweet: Annotating and detecting emotions on twitter. In *LREC*, volume 12, pages 3806–3813. Citeseer.

[Russell1980] James A Russell. 1980. A circumplex model of affect. *Journal of personality and social psychology*, 39(6):1161.

[SCA] Swiss center for affective sciences - research material.

[Seki et al.2005] Yohei Seki, Koji Eguchi, Noriko Kando, and Masaki Aono. 2005. Multi-document summarization with subjectivity analysis at duc 2005. In *Proceedings of the Document Understanding Conference (DUC)*.

[Seyeditabari et al.2018] Armin Seyeditabari, Sara Levens, Cherie D Maestas, Samira Shaikh, James Igoe Walsh, Wlodek Zadrozny, Christina Danis, and Onah P Thompson. 2018. Cross corpus emotion classification using survey data.

[Shaver et al.1987] Phillip Shaver, Judith Schwartz, Donald Kirson, and Cary O'connor. 1987. Emotion knowledge: Further exploration of a prototype approach. *Journal of personality and social psychology*, 52(6):1061.

[Socher et al.2013a] Richard Socher, John Bauer, Christopher D Manning, et al. 2013a. Parsing with compositional vector grammars. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, volume 1, pages 455–465.

[Socher et al.2013b] Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D Manning, Andrew Ng, and Christopher Potts. 2013b. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 conference on empirical methods in natural language processing*, pages 1631–1642.

[Somasundaran et al.2007] Swapna Somasundaran, Theresa Wilson, Janyce Wiebe, and Veselin Stoyanov. 2007. Qa with attitude: Exploiting opinion type analysis for improving question answering in on-line discussions and the news. In *ICWSM*.

[Speer and Chin2016] Robert Speer and Joshua Chin. 2016. An ensemble method to produce high-quality word embeddings. *arXiv preprint arXiv:1604.01692*.

[Speer et al.2016] Robert Speer, Joshua Chin, and Catherine Havasi. 2016. Conceptnet 5.5: An open multilingual graph of general knowledge. *arXiv preprint arXiv:1612.03975*.

[Staiano and Guerini2014] Jacopo Staiano and Marco Guerini. 2014. Depechemood: a lexicon for emotion analysis from crowd-annotated news. *arXiv preprint arXiv:1405.1605*.

[Stoyanov et al.2005] Veselin Stoyanov, Claire Cardie, and Janyce Wiebe. 2005. Multi-perspective question answering using the opqa corpus. In *Proceedings of the conference on Human Language Technology and Empirical Methods in Natural Language Processing*, pages 923–930. Association for Computational Linguistics.

[Strapparava and Mihalcea2007] Carlo Strapparava and Rada Mihalcea. 2007. Semeval-2007 task 14: Affective text. In *Proceedings of the 4th International Workshop on Semantic Evaluations*, SemEval '07, pages 70–74, Stroudsburg, PA, USA. Association for Computational Linguistics.

[Strapparava et al.2004] Carlo Strapparava, Alessandro Valitutti, et al. 2004. Wordnet affect: an affective extension of wordnet. In *LREC*, volume 4, pages 1083–1086.

[Sun et al.2007] Yanmin Sun, Mohamed S Kamel, Andrew KC Wong, and Yang Wang. 2007. Cost-sensitive boosting for classification of imbalanced data. *Pattern Recognition*, 40(12):3358–3378.

[Suttles and Ide2013] Jared Suttles and Nancy Ide. 2013. Distant supervision for emotion classification with discrete binary values. In *International Conference on Intelligent Text Processing and Computational Linguistics*, pages 121–136. Springer.

[Tang et al.2009] Yuchun Tang, Yan-Qing Zhang, Nitesh V Chawla, and Sven Krasser. 2009. Svms modeling for highly imbalanced classification. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 39(1):281–288.

[Tang et al.2014a] Duyu Tang, Furu Wei, Bing Qin, Ting Liu, and Ming Zhou. 2014a. Coooolll: A deep learning system for twitter sentiment classification. In *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014)*, pages 208–212.

[Tang et al.2014b] Duyu Tang, Furu Wei, Nan Yang, Ming Zhou, Ting Liu, and Bing Qin. 2014b. Learning sentiment-specific word embedding for twitter sentiment classification. In *ACL (1)*, pages 1555–1565.

[Terveen et al.1997] Loren Terveen, Will Hill, Brian Amento, David McDonald, and Josh Creter. 1997. Phoaks: A system for sharing recommendations. *Commun. ACM*, 40(3):59–62, March.

[Tromp and Pechenizkiy2013] Erik Tromp and Mykola Pechenizkiy. 2013. Rbem: a rule based approach to polarity detection. In *Proceedings of the Second International Workshop on Issues of Sentiment Discovery and Opinion Mining*, page 8. ACM.

[Tromp and Pechenizkiy2014] Erik Tromp and Mykola Pechenizkiy. 2014. Rule-based emotion detection on social media: putting tweets on plutchik's wheel. *arXiv preprint arXiv:1412.4682*.

[Turian et al.2010] Joseph Turian, Lev Ratinov, and Yoshua Bengio. 2010. Word representations: a simple and general method for semi-supervised learning. In *Proceedings of the 48th annual meeting of the association for computational linguistics*, pages 384–394. Association for Computational Linguistics.

[Voeffray2011] S Voeffray. 2011. Emotion-sensitive human-computer interaction (hci): State of the art-seminar paper. *Emotion Recognition*, pages 1–4.

[Vu et al.2014] Hoa Trong Vu, Graham Neubig, Sakriani Sakti, Tomoki Toda, and Satoshi Nakamura. 2014. Acquiring a dictionary of emotion-provoking events. In *EACL*, pages 128–132.

[Wang et al.2012] Wenbo Wang, Lu Chen, Krishnaprasad Thirunarayan, and Amit P Sheth. 2012. Harnessing twitter" big data" for automatic emotion identification. In *Privacy, Security, Risk and Trust (PASSAT), 2012 International Conference on and 2012 International Confernece on Social Computing (SocialCom)*, pages 587–592. IEEE.

[Wang et al.2014] Shangfei Wang, Jun Wang, Zhaoyu Wang, and Qiang Ji. 2014. Enhancing multi-label classification by modeling dependencies among labels. *Pattern Recognition*, 47(10):3405–3413.

[Wen and Wan2014] Shiyang Wen and Xiaojun Wan. 2014. Emotion classification in microblog texts using class sequential rules. In *AAAI*, pages 187–193.

[Xu et al.2012] Jun Xu, Ruifeng Xu, Qin Lu, and Xiaolong Wang. 2012. Coarse-to-fine sentence-level emotion classification based on the intra-sentence features and sentential context. In *Proceedings of the 21st ACM international conference on Information and knowledge management*, pages 2455–2458. ACM.

[Xu et al.2015] Ruifeng Xu, Tao Chen, Yunqing Xia, Qin Lu, Bin Liu, and Xuan Wang. 2015. Word embedding composition for data imbalances in sentiment and emotion classification. *Cognitive Computation*, 7(2):226–240.

[Yang and Wu2006] Qiang Yang and Xindong Wu. 2006. 10 challenging problems in data mining research. *International Journal of Information Technology & Decision Making*, 5(04):597–604.

[Zou et al.2013] Will Y Zou, Richard Socher, Daniel Cer, and Christopher D Manning. 2013. Bilingual word embeddings for phrase-based machine translation. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1393–1398.