Literature Survey : Multi-label Emotion Detection from Text

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Abstract

With increasing accessibility and availability to online data, it is very motivating and interesting to study huge data for sentiment and emotion analysis. Emotion Analysis is an extension of sentiment analysis. It is the process of analyzing text and classifying text into different emotion classes.In current scenario, emotion detection has become a trend because of its use in various domains like marketing, pervasive computing, recommendation systems, political science, etc. A lot of research work done so far deals with issues like context-dependency, word sense disambiguation and co-reference resolution and to resolve these issues and improve the design and implementation of systems is strictly needed. Treating emotion detection task as a single-label classification problem is not a good idea since a particular affective words can be mapped to multiple classes. In this paper, we review the approaches, methods and models that have been introduced and implemented. We also discuss the reasons why these models are insufficient.

1 Introduction

Emotion Analysis has been quite an interesting and trending topic in the area of Natural Language Processing . Initial Research work has been done in the area of Affective Computing where main focus was on the investigation of cognition, psychology and behaviours of humans. This mode of emotion analysis captured facial expressions, body postures, gestures and speech to detect the emotional state of human beings. Also, intonation and accentuation of speech has been of great importance for emotion detection. To detect emotions from online data is a different challenge since users use short forms of the words, emoticons, emojis', colloquial language, etc. Also, classifying text into multiple emotion classes surpasses single-label problem since a particular word like *excelled* can be mapped into categories *anticipation, joy* and *trust* while *guilt* can be mapped into *fear* and textitsadness. Most Recent research work involves various deep learning techniques like LSTM, Convolutional Neural Networks, Attention Models, etc. along with exploring semantics, syntactic, ontology, etc.

2 Traditional Approaches

The various traditional approaches discussed in (Tripathi et al., 2016) are as follows :

2.1 Keyword Spotting

The simplest approach to emotion analysis is spotting word which directly depict emotions. Text is categorised into different categories based on the presence of unambiguous emotion words like distressed, enraged and happy.

2.2 Lexical Affinity

It is slightly more sophisticated than keyword spotting. It assigns a probabilistic affinity for a particular word. For example, accident may be assigned a 70 percent probability of indicating a negative effect, as in bus accident". Linguistic corpora is used to train these probabilities. There are two problems with this approach:

- The approach works on word-level so it does not consider negations and different word senses.
- Lexical affinity probabilities are derived using linguistic corpora and are ,hence, biased towards text of a particular genere.

2.3 Statistical NLP

The statistical approach is the most common approach of emotion analysis. A large training corpus of annotated text is fed into a machine learning algorithm. The system not only learns the relationship between lexical entities and their valence but about pragmatic features like punctuation.

Other approaches involved the use of traditional machine learning algorithms like Naive Bayes and SVM. The use of Conditional Random Fields were also considered for emotion analysis. Another important approach introduces the concept of hierarchical classification to classify weblogs.

Prior results show that Support Vector Machines are better in the task of emotion analysis when compared to Naives bayes.

3 Hierarchical Classification Approach

The supervised hierarchical classification is the novel approach in the field of emotion analysis. The data mainly used for this approach is textual data from social media blogs like Twitter. The goal of such an approach is to develop relation between polarity and emotion content of text and arrange these categories and relation in hierarchical form and later, perform classification on such hierarchy. In this approach(Esmin et al., 2012), there are seven emotions classes. One is the non-emotional class for sentences which bear no emotion. Rest are Ekman's six classes: happiness, sadness, fear, anger, disgust and surprise.

3.1 Three Level Hierarchy

Hierarchical Classification Approach to Emotion Recognition in Twitter uses three-level classification. It works as follows :

1. The first step is to determine whether the text has emotional content or not. Thus, this step classifies the text into emotional and non-emotional.

2. The second step deals with finding the polarity of the emotional text, i.e., to classify the text into positive or negative emotional.

3. The third step finds exactly to which emotion class a text belongs. Since, in Ekman's six classes of emotions, only happiness has positive polarity and rest five emotions are of negative polarity. So, third step classifies the negative instances into five negative emotion classes.

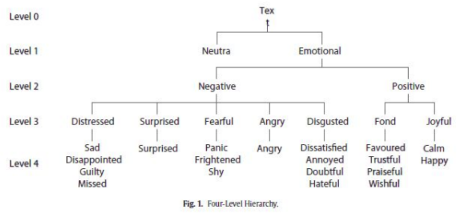

Figure 1: Four-Level Hierarchy.(Xu et al., 2015)

The experiment was performed on a dataset which contains 2809 annotated tweets, annotated by three judges by tagging each tweet with a dominant emotion in the sentence. 901 non-emotional tweets were removed. Experiment was performed with two machine learning approaches: multiclass SVM and Naives Bayes. SVM gives better results with accuracy of 80.35 percent as a result of emotion classification experiments and settling for "10 fold cross-validation" as a testing option.

When results of a three-level hierarchical approach are compared with flat classification approach, the observations were that the F-measure of almost all the emotional classes in the three-level experiment is higher than the F-measure of of the emotional classes in flat classification, with the exception of the "anger" class. In anger class, the F-measure of both the approaches is same but the precision of three level approach is higher.

In addition to the three level hierarchical classification, an experiment conducted on hierarchical emotion classification on Chinese micro-blog posts suggests the addition of fourth level which further classifies basic emotions into finer-grained emotion classes.

The four-level hierarchy (Xu et al., 2015) is presented in the figure . The hierarchy contains 19 fine grained emotion classes at the bottom with 20 leaf nodes if neutral is also considered. Neutral denotes the non- emotional class.

4 Word- Emotion Association

The NRC word-emotion association lexicon (NRC-10)(Mohammad and Turney, 2013) is well-known lexical resource for emotion analysis created by crowdsourcing via Mechanical Turk.

NRC-10 is built by compiling a large English termemotion association lexicon by manual annotation through Amazons Mechanical Turk service. This dataset, which we call EmoLex, is an order of magnitude larger than the WordNet Affect Lexicon.

The lexicon contains 14,182 distinct English words which are manually annotated in accordance to 10 non-exclusive binary categories. The categories include eight emotions from Plutichik's wheel of emotion - joy, sadness, anger, surprise,fear, disgust, trust and anticipation; and two sentiment classes : positive and negative. The drawback of this lexicon is that it does not cover informal aspects of the language used on social platforms like hashtags, slang words and misspelled words and thus, suffers from limitations.

(Mohammad and Turney, 2013) studies how to automatically expand a lexicon by using words found in a corpus of unlabelled tweets. The words are represented as words expressed as feature vector and the expansion is performed using multi-label emotion classification. The two approaches discussed are as follows -

1. **Word-Centroid Model** creates word vectors from tweet-level attributes (e.g. unigrams and Brown clusters) by taking the average of all the tweets in which the word appears.

2. **Word embeddings**, which are low-dimensional continuous dense word vectors trained from document corpora.

Two models are used for extracting features - word centroid model and skip-gram model. The three multi-label classification techniques used are as follows -

1. **Binary relevance (BR)** - in which one binary classifier for each label is trained independently. So, when given a test dataset, the combined model, then predicts all labels for this sample for which the respective classifier returns a positive result.

2. **Classifier Chains (CC)** - It transforms multi-label classification problem into one or more single label classification problem

3. **Bayesian Classifier Chains (BCC)** - A Bayesian network which represents the dependency relations between class variables is learned from data. Several chain classifiers are built so that the order of class variables in the chain is consistent with the class.

5 Deep Learning based Approaches

Multi-Label Emotions Detection in Conversation Transcripts(Phan et al., 2016) is similar to detection of emotions expressed by a paragraph where the context information of the conversation and what is said in the previous utterance should be taken into consideration. proposes three step method for emotion detection -

1. Building Emotion Lexicon from WordNet.

2. Using simple Neural Network to adapt the Lexicon to the training data.

3. Using Deep Neural Network with features extracted from adapted lexicon and classify the multi-label corpus.

The raw input is pre-processed and features are extracted and fed to the network as input layer. The network comprises of two hidden layers and an output layer. The output layer is the sigmoid layer.

(Yu et al., 2018) uses both sentiment classification and emotion classification techniques. This new architecture involves transfer learning which produces representations of sentences by dividing the sentences into two different features spaces which captures both sentiment and emotion using a dual attention network.

The dataset used is the dataset available for SemEval2018 Task 1C (Mohammad et al., 2018). The goal of the model is that it should predict multiple emotions given a sentence. The input sentence consists of words and each word is mapped into a d- dimensional vector space. In order to represent the sentences, Bidirectional Long Short Term Memory (Bi- LSTM) is used to process each word. For the final layer, the MultiLayer Perceptron (MLP) is applied followed by a hidden layer which is normalised using Softmax layer to obtain probabilistic values for all emotion classes.

For transfer learning scenario, a shared attention-based Bi-LSTM layer to transform the input sentences in sentiment classification task and emotion clasification task into a shared hidden representation and also employ another task-specific Bi-LSTM layer to get the hidden representation. Next, softmax activation function is employed in the last layer to map the hidden representations to the sentiment label and the emotion label .

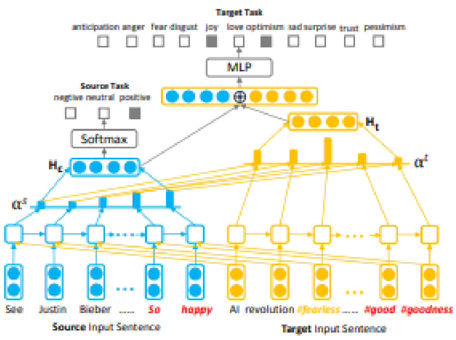

Figure 2: Dual Attention Network.(Yu et al., 2018)

(Kim et al., 2018) proposes an attention-based classifier for multi-label emotion classification. The system comprises of a self attention module and multiple CNNs which enables it to imitate humans two-step procedure of analyzing sentences: comprehend and classify. Furthermore, to improve model performance on given dataset, emoji-to-meaning pre-processing and extra lexicon utilization is performed.

The model comprises of two parts. Firstly, self-attention module and multiple independent CNNs as depicted in Figure . The self-attention structure try to read the sentence and comprehend as humans do.The second part uses independent CNNs since humans categorize sentences to each emotion separately.

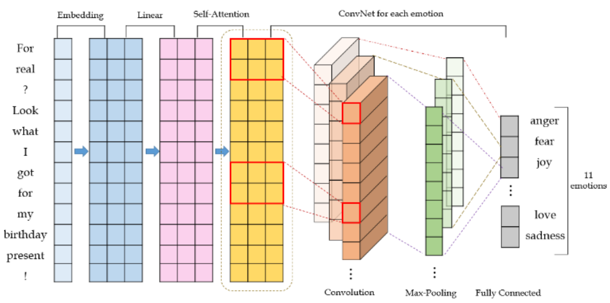

Figure 3: Self-Attention model.(Kim et al., 2018)

6 Conclusion and Future Work

The survey report concludes that varied approaches have been introduced and implemented, starting from traditional approaches like SVM and Naive Bayes to the latest approaches which uses deep learning models. The datasets are also explored along with the usage of word embeddings like Word2Vec (Mikolov and Dean, 2013), GloVe (Pennington et al., 2014) and emoji embeddings.Emoji and emoticons can be mapped into 300 dimensional vector using emoji2vec (Wijeratne et al., 2017b) and EmojiNet (Wijeratne et al., 2017a). However, there still have been a lot of improvement in the performance of systems required because of shortage of quality data, complexity of emotions and various other components of NLP such as word-sense disambiguation and co-reference resolution.

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