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Review Article

A Review on the Emotion Detection from Text using Machine Learning Techniques

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Abstract

An emotion is a particular feeling that characterizes a state of mind, such as joy, anger, love, fear and so on. A great body of work exists in the field of emotion extraction. The work done in this area includes distinguishing subjective portions in text, finding sentiment orientation and, in few cases, determining fine-grained distinctions in sentiment, such as emotion and appraisal types. Work exclusively on emotion detection is comparatively rare and lacks empirical evaluation. This research paper tackles the problem of emotion recognition from text focusing on the implicit emotional statements – the descriptions of emotional events. Aim is to provide machines with the model for emotion reasoning allowing deeper understanding of causes of specific emotions. The ability to discern and understand human emotions is crucial for making interactive computer agents more human-like. So, there is the need of some machine learning approaches. In this paper, we are presenting a survey on the existing emotion detection techniques.

Keywords: *Emotions, Machine Learning, Text Processing, E-Learning*

Introduction

Emotion detection and analysis has been widely researched in neuroscience, psychology and behavior science, as they are an important element of human nature. In computer science, this task has also attracted the attention of many researchers, especially in the field of human computer interactions (Strapparava, C., & Mihalcea, R, 2008).

Recognizing user's emotions is a major challenge for both humans and machines. On one hand, people may not be able to recognize or state their own emotions at certain times. On the other hand, machines need to have accurate ground truth for emotion modeling, and also require advanced machine learning algorithms for developing the emotion models. Hard sensing methods and soft sensing methods have been traditionally used to recognize user's emotions. With hard sensing methods, sensors provide the data sources that may be relevant to emotion recognition such as audio, gestures, eye gazes and brain signals (Khalili, Z., & Moradi, M. H, 2009; Cohn, J. F., & Katz, G. S, 1998; De Silva, L. C., & Ng, P. C, 2000 ; Yanaru, T, 1995). Additional sensors may be attached to the user to provide personal physiological cues such as heart rate sensors. However these wearable sensors are not applicable in practical and natural settings since they can be obtrusive to the user. Soft sensing methods, on the other hand, extract information from software that already exists with the user (on her phone or PC) and analyzes it for the purpose of recognizing the user's emotions. Examples of software that can be analyzed to classify user's emotions include calendar, email, desktop activity, and social networking interactions. In this work, we focus on classifying emotions from text as text is not obstructive and is considered the main tool of communication between people and machines (Kao, E. C., Liu, C. C., Yang, T. H., Hsieh, C. T., & Soo, V. W, 2009, April).

Emotion recognition from text has many applications. Consider for example an employee sending a harsh email to his colleague or superior. A tool that can analyze the email for emotions and alert the employee about its harshness before sending it comes in very handy to protect the employee's state. Consider also an emotion-based search engine that ranks documents according to the emotion requested by the user. Such an engine could prove to be very beneficial to users in a certain emotional state and can improve the effectiveness of the information retrieval process. Other useful tools that can benefit from emotion recognition from text include recommender systems that aim to personalize recommendations based on the user's emotions.

In computational linguistics, the detection of emotion states of a person by analyzing a text

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document written by him/her can have many applications in different fields, such as in e-learning environment (Rodriguez, P., Ortigosa, A., & Carro, R. M, 2012, July) or suicide prevention (Desmet, B., & Hoste, V, 2013). For this reason, we decided to develop a survey about emotion detection systems from text using various machine learning approaches. In this paper, we are presenting a review on the existing emotion detection from text approaches using machine learning paradigm.

Rest of the paper is organized as follows: Section II gives the basic concepts of Machine learning techniques; Section III presents the literature survey for the emotion detection techniques; Section IV briefs comparative survey of the existing emotion detection from text using machine learning techniques and Section V concludes the paper with some future references.

Machine Learning

In the Machine Learning (ML) approach to sentiment analysis, the classifier automatically learns the properties of categories from the preclassified training documents. ML based classification is called as supervised learning because this process is guided by the labeled training set. There exists various machine learning approaches, some of these are explained as below:

A. Support Vector Machines

The fastest and most widely used algorithm among all the ML algorithms is the support vector machine (SVM). A binary SVM is a hyperplane separating the feature space of positive instances from the feature space of negative instances. During the training phase, the hyperplane that can separate the positive feature space from the negative feature space with a maximal margin is chosen. The margin is distance of the nearest point from the positive and negative sets to the hyperplane. Support vectors, the subset of the training instances, determine the hyperplane for a SVM. SVM classifiers perform extremely well irrespective of the dimensionality of the feature space.

B. Decision Tree Classifiers

A Decision Tree (DT) classifier resembles a tree in which the features are represented by nodes and the edges leaving a node are labeled by the feature weight and leaves represent the categories. The tree is constructed based on a recursive procedure. At each step a feature ‘F’ is picked and the training collection is divided into two groups, one containing ‘F’ and another not containing ‘F’. This procedure is carried out until only documents of a single category remain. A leaf is generated at the end of this procedure. Information gain or entropy is used to choose a feature at each step. Generally the DT classifiers are used as baseline classifiers.

C. Fuzzy Logic

Fuzzy logic based systems are handy in real life situations where the decision to be taken are based on multiple criteria with complex interlink among them. It is very true for a sentiment analysis process in which the system must be able to understand the sentiment expressed by a customer in a review based on the statements about various features of the product or service. For example, in a movie review, the reviewer may praise the director for the usage of technology and blame on the acting and story. Deciding on the overall sentiment as positive or negative depends on the opinion words or phrases used by the reviewer for each of the features. When the number of features is more, the complexity in the decision making gets added and hence the decision making becomes tough. In such situations, fuzzy logic can be effectively used (Bhansali, K., Doshi, A., & Kurup, L, 2014).

D. Probabilistic Classifier - Naïve Bayes Algorithm

Probabilistic classifiers use the Bayes’ theorem to calculate the probability P (c|d), that a document belongs to a category c.

$$P(c|d) = P(d|c)\, P(c) / P(d)$$

In order to determine the probability P (d|c), it is assumed that the coordinates representing the document as a feature vector are independent. These classifiers are called as Naïve Bayes (NB) classifiers. Some justification about the robustness of these classifiers can be found in Domingos and Pazzani (1997) (Domingos, P., & Pazzani, M, 1997).

E. Neural Networks

Neural network (NN) can be designed to carry out the task of opinion mining. The features of a document are the input nodes, the output nodes deliver the category. The dependence relations are taken care by the link weights (Lam, M, 2004). Generally the NN are trained by back propagation, i.e. the training documents are fed into the input nodes and if a wrong classification occurs, the error is propagated back in the network to minimize the error by adjusting the link weights. Perceptron is the simplest kind of a NN, which has only two layers viz. input layer and output layer. A multi layer perceptron contains one or more hidden layers between the input and output layers.

F. Regression Method

A real-valued function can be approximated using the knowledge of its values on a set of points. This is the crux of regression techniques. The regression techniques can be used for Text Categorization (TC) and opinion mining problems if the assignment function is a member of a family of continuous real valued functions (Li, H., & Yamanishi, K., 2002).

Literature Survey

Obdal and Wang (2014) proposed a novel approach for emotion detection from Chinese language. The proposed algorithm was segment based fine grained emotion detection model which is a supervised learning approach. In this method, the emotion label of each dependency subtree of a subjective sentence or short text is represented by a hidden variable. The values of the hidden variables are calculated in consideration of interactions between variables whose nodes have head-modifier relation in the dependency tree (Wang, Z, 2014).

Kaur and Gupta (2013) have given a survey on sentiment analysis and opinion mining. Beside English, there is also existence of algorithms that have successfully applied on emotion detection and sentiment analysis to detect the public opinion. In India, scarcity of resources has become the biggest issue for Indian languages. This paper shows that SentiWordNet has successfully implemented for Hindi, Telgu, Bengali and others, a sum of 57 languages for detection of sentiments (Kaur, A., & Gupta, V, 2013).

Ho & Cao (2012) exploited the idea that emotions are related to human mental states which are caused by some emotional events. This means that the human mind starts with initial mental state and moves to another state upon the occurrence of a certain event. They implemented this idea using Hidden Markov Model (HMM) where each sentence consists of multiple sub-ideas and each idea is considered an event that causes a transition to a certain state. By following the sequence of events in the sentence, the system determines the most probable emotion of the text. The system achieved an F-score of 35% when tested on the ISEAR dataset (International Survey on Emotion Antecedents and Reactions), where the best precision achieved was 47%. The low accuracy was mainly due to the fact that the system ignored the semantic and syntactic analysis of the sentence, which made it non-context sensitive (Ho, D. T., & Cao, T. H, 2012).

Yang *et al*. (2012) proposed a hybrid model for emotion classification that includes lexicon-keyword spotting, CRFbased (conditional random field) emotion cue identification, and machine-learning-based emotion classification using SVM, Naïve Bayesian and Max Entropy. The results generated from the aforementioned techniques are integrated using a vote-based system. They tested the system on a dataset of suicide notes where it achieved an F-score of 61% with precision 58% and recall 64%. This method achieved relatively good results; however, both the classifier and the dataset are not available (Yang, H., Willis, A., De Roeck, A., & Nuseibeh, B, 2012).

Burget R. *et al*. (2011) proposed a framework that depends heavily on the pre-processing of the input data (Czech Newspaper Headlines) and labeling it using a classifier. The pre-processing was done at the word and sentence levels, by applying POS tagging, lemmatization and removing stop words. Term Frequency – Inverse Document Frequency (TFIDF) was used to calculate the relevance between each term and each emotion class. They achieved an average accuracy of 80% for 1000 Czech news headlines using SVM with 10- fold cross validation. However their method was not tested on English dataset. Also it is not context sensitive as it only considers emotional keywords as features (Burget, R., Karasek, J., & Smekal, Z, 2011).

Cheng-Yu Lu *et al*. (2010) presented vent-level textual emotion sensing by building a mutual action histogram between two entities where each column in the histogram represented how common an action (verb) existed between the two entities. They achieved an F-score of 75% when tested on four emotions. However, their method does not consider the meaning of the sentence and is highly dependent on the structure of the training data, i.e. the grammatical type of sentences in the training data and the frequency of the emotions for a certain subject. Moreover, only four of the six Ekman emotions are used in the classification (Lu, C. Y., Lin, S. H., Liu, J. C., Cruz-Lara, S., & Hong, J. S, 2010).

Ghazi *et al*. (2010) tried hierarchical classification to classify the six Ekman emotions. They used multiple levels of hierarchy while classifying emotions by first classifying whether a sentence holds an emotion or not, then classifying the emotion as either positive or negative and finally classifying the emotion on a fine-grained level. For each stage of classification they used different features for the classifier, and they achieved a better accuracy (+7%) over the flat classification where flat classification is classifying the emotions on a fine-grained level directly. The main drawback of this approach is that it is not context sensitive (Ghazi, D., Inkpen, D., & Szpakowicz, S. ,2010).

Strapparava *et al*. (2008) developed a system that used several variations of Latent Semantic Analysis to identify emotions in text when no affective words exist. However their approach achieved a low accuracy because it is not context sensitive and lacks the semantic analysis of the sentence (Strapparava, C., & Mihalcea, R, 2008).

Hancock *et al*. (2007) used content analysis Linguistic Inquiry and Word Count (LIWC) to classify emotions as positive or negative. They found that positive emotions are expressed in text by using more exclamation marks and words, while negative emotions are expressed using more affective words. However, this method is limited to positive/negative emotions (happy vs. sad) (Hancock, J. T., Landrigan, C., & Silver, C, 2007).

Emotion Detection from Text using Machine Learning Paradigms

Machine learning is a scientific discipline that deals with the construction and study of algorithms that can learn from data (Kohavi, R., & Provost, F, 1998). Such algorithms operate by building a model based on inputs and using these inputs to make predictions or decisions, rather than following only explicitly programmed instructions (Bishop, C. M, 2006). Specifically in emotion detection, Machine learning algorithms are used to learn how detect emotions. These approaches can be divided into *supervised* and *unsupervised learning*.

A. Supervised Learning

Supervised learning approaches rely on a labelled training data, a set of training examples. The supervised learning algorithm analyses the training data and infers a function, which we use for mapping new examples.

A labelled corpus is a large and structured set of text that it is necessary annotated with emotional tags. In this case, the annotation process is considered as one of their most important disadvantages as it becomes a tedious and time-consuming task. However, there are recent works related with emotion detection in Twitter messages, where the training examples are automatically labelled through hashtags and emoticons contained. (Maryam Hasan, Emmanuel Agu, and Elke Rundensteiner. 2014; Wang, W., Chen, L., Thirunarayan, K., & Sheth, A. P, 2012; Roberts, K., Roach, M. A., Johnson, J., Guthrie, J., & Harabagiu, S. M, 2012; Suttles, J., & Ide, N ,2013) among others, are proposals that use this method for labeling training data automatically. Moreover, (Hasan, M., Agu, E., & Rundensteiner, E) confirms that hashtags are indeed good emotion labels. Concerning works that apply supervised learning algorithms, we can find both the categorical and the dimensional approaches to base their emotional models. Categorical approaches are the most commonly used in emotion detection (Calvo, R. A., & Mac Kim, S, 2013). One of the first works based in this model is (Alm, C. O., Roth, D., & Sproat, R, 2005). This proposal presented an empirical study of applying supervised machine learning with the SNoW learning architecture. They used an annotated corpus with an extended set of Ekman basic emotions. (Strapparava, C., & Mihalcea, R, 2008), in one of the experiment presented in their work, applied Naïve Bayes classifier trained on the blog entries from LiveJournal.com 3. They used a collection of blogposts annotated with Ekman's emotions. More recently, (Balabantaray, R. C., Mohammad, M., & Sharma, N, 2012)) presents an Emotion classifier that is able to determinate the emotion class of the person writing. Their emotion classifier is based on multi-class SVM kernels and takes decisions according to the basic emotions identified by Ekman. (Roberts, K., Roach, M. A., Johnson, J., Guthrie, J., & Harabagiu, S. M, 2012). also use the Ekman's six basic emotions and include LOVE emotion. Their system uses a series of binary SVM classifiers to detect each of the seven emotions. Other related work with categorical emotion models, (Suttles, J., & Ide, N, 2013) classify emotions according to a set of eight basic bipolar emotions defined by Plutchick. This allows them to treat the multi-class problem of emotion classification as a binary problem for opposing emotion pairs. Their approach applies *Distant Supervision (*Mintz, M., Bills, S., Snow, R., & Jurafsky, D, 2009, August).

About works that apply supervised learning approach and use dimensional emotion model, we can find the work of (Hasan, M., Agu, E., & Rundensteiner, E.), where they propose an approach for automatically classifying text messages of individual to infer their emotional states. They use the Rusell's Circumplex Model of Affect as emotion model and train supervised classifiers to detect multiple emotion. Specifically, they have compared the accuracy of SVM, KNN, Decision Tree and Naïve Bayes for classifying Twitter messages.

B. Unsupervised Learning

Regarding *unsupervised learning* approaches, these algorithms try to find hidden structure in unlabeled data in order to build models for emotion classification (Strapparava, C., & Mihalcea, R, 2008, March). As occurs in supervised learning, among unsupervised learning proposals also it can be found systems based on categorical and dimensional emotion models.

With respect to works based in categorical emotion model, (Strapparava, C., & Valitutti, A, 2004, May) apply unsupervised techniques combining LSA with WordNet Affect (Agrawal, A., & An, A, 2012, December). This proposal used the Ekman's basic emotions. (Calvo, R. A., & Mac Kim, S, 2013) proposes a novel unsupervised context-based approach based on a methodology that does not depend on any existing affect lexicon, thereby their model is flexible enough to classify sentences beyond Ekman's model of six basic emotions. (Bradley, M. M., & Lang, P. J, 1999) presents different categorical approaches based on Vector Space Model (VSM) with three dimensionality reduction techniques: Latent Semantic Analysis (LSA), Probabilistic Latent Semantic Analysis (PLSA) and Non-negative Matrix Factorization (NMF). This work concludes that NMF-based categorical classification performs the best among categorical approaches to classification.

About unsupervised approach with dimensional emotion model, we find (Calvo, R. A., & Mac Kim, S, 2013). This work used a normative database ANEW (Bradley, M. M., & Lang, P. J, 1999). to produce tree-dimensional vectors (valence, arousal, dominance) for each pseudo-document.

Conclusion

As for *Machine Learning approaches*, the supervised learning approach is more used in emotion detection because it usually leads to better results than unsupervised learning [Kim 2011]. Although, these approaches need labelling training examples and annotating of examples, which is a time-consuming task. For this reason, several researches have analyzed as realize this task automatically and when our system process Twitter messages, the messages can be annotated through hashtags or emotions that it contains.

Although unsupervised learning approach leads worse results than supervised learning, it can be a good election for the emotion detection task because the emotional interpretations of a text can be highly subjective and the annotation task is an error prone task (Kim 2011).

In conclusion, Machine Learning approaches are better option for detection emotion task since we obtain a model is also able to detect emotions in texts that have only an indirect reference to an emotions. Although, it is important use a good lexical resource as features in Machine Learning algorithms to obtain good results.

Moreover, in emotional detection systems based on machine learning approach, we have detected that most of these systems use features based on a shallow analysis on the text as: n-grams, punctuation, emoticons or Part-Of-Speech. Hence, we propose a new direction focuses on deep analysis, since we consider that if we use features based on a deep analysis on the text we could improve the emotional detection systems.

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