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Pages 7 – 13
DOI: http://dx.doi.org/10.21700/ijcis.2018.xxx

Using a Generic Text-based Approach for Emotion Prediction

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Abstract: *Many researchers have addressed the need for automatic detection of users' emotions. To this end, various methods have been proposed. One of the most natural ways is to use text introduced by a user, for example in a blog or an online chat site, in order to predict his/her emotion. In this article, we adopt a supervised machine learning approach to recognize six basic emotions (anger, disgust, fear, happiness, sadness and surprise) using a heterogeneous emotion-annotated dataset which combines news headlines, fairy tales and blogs. For this purpose, different feature sets (lexical emotion features from WordNetAffect, bags of words, and N-grams) were used. The Support Vector Machines classifier (SVM) performed significantly better than other classifiers, and it generalized well on unseen examples. Three datasets with sentence-level emotion annotations of different types (news headlines, stories and diary-like blog posts) have been used for testing.*

Keywords: *Affective Computing, Emotion Analysis in Text, Natural Language Processing, Text Mining.*

Received: *May 01, 2016* | **Revised**: *August 10, 2016* | **Accepted**: *January 25, 2017*

1. Introduction

The interest in emotion analysis has grown notably in the 90s based on findings from neurophysiology and psychology that established a tenuous link between emotion, rationality and decision making. Damasio (1994) argued that human beings are not able to make even simple decisions without emotions. Therefore, automatic detection of emotions has attracted researchers' attention in different areas of computer science such as Natural Language Processing [7,8,22,32], Intelligent Tutoring Systems [9,10,13,28], intelligent agents [4,15,27], etc.

Recognizing emotional reactions in other people is a difficult, and sometimes an impossible task, even for humans. Generally, humans use sensors to identify a given emotion and to react accordingly. This emotion can be expressed in various forms: voice, facial expressions, physiological behaviour, etc. To process these various emotional channels, some researchers have used cameras, microphones, or physiological sensors for the automatic recognition of emotions. In general, using only one media to automatically detect emotions did not give good results. Therefore, some researchers proposed to combine different media in order to improve the automatic recognition of emotions [6]. However, there are two limitations to this method. On one hand, the use of sophisticated technologies can disturb the users. On the other hand, the cost and technical expertise required can represent a real burden. For computer applications, emotion recognition from text is more natural and familiar to users. In fact, some researchers in computational psycholinguistics have convincingly demonstrated that textual features can predict complex phenomena such as personality and deception [16,20]. Achievements in emotion recognition from text can be used in many applications, notably in Text-To-Speech (TTS) systems, ITS, etc. This is why in this research we are interested in detecting emotions from text.

The rest of the paper is organized as follows: Section 2 review some existing approaches for detecting emotions in text. Section 3 identifies datasets that have been used for emotion analysis in text. Section 4 describes the adopted methodology. Section 5 illustrates the experiments done for emotion analysis in text. Section 6 discusses the results. Finally, Section 7 concludes the paper and outlines the future directions.

2. Emotion Analysis in Text

Aiming to detect the writer's emotional state, researchers generally adopted one of the three approaches (lexical approach, rule-based linguistic approach and machine learning approach). The first approach uses a purely word-level analysis model based mostly on keyword-spotting techniques to recognize emotion in text (e.g., Strapparava et al., 2007). The main limitation with such an approach is that it cannot deal with complex sentence-level analyses, especially when a sentence expresses emotions indirectly through underlying meaning (e.g., "Thank you so much for everyone who came.").

The second approach consists of using rule-based models to classify emotional text. For instance, Boucouvalas (2003) developed an emotion extraction engine based on word tagging and analysis of sentences. The proposed system attempts to detect emotions from typed text and to display appropriate facial expression images in real time. However, the system uses a parser that generates emotional output only if an affective word refers to the person himself/herself and the sentence is in present continuous or present perfect continuous tense. In recent work, Neviarouskaya et al. (2011) used a rule-based linguistic approach to classify emotional text. Their affect recognition module is conceived to deal not only with grammatically and syntactically correct textual input, but also with informal messages written in an abbreviated or expressive manner. However, this module is strongly dependent on the resource of lexicon (affect database) and the commercially available syntactic parser; no disambiguation of word senses; and disregard of contextual information.

The third approach uses supervised machine learning algorithms to build models from annotated corpora. For instance, Katz et. al (2007) used a unigram model to annotate the emotional content of headlines. Machine learning techniques tend to obtain better results than knowledge-based techniques for sentiment analysis because they can adapt well to different domains [22], but this might not be the case for emotion classification (e.g. Strapparava and Mihalcea, 2008). Work in analysis of emotions in text can be done at different levels: words, phrases, sentences, or documents. At the document level, we generally seek to detect, for example, the writer's opinion on a given subject or his mood. The majority of existing work in this area is limited to classifying text into two classes (*positive* and *negative*). However, in order to adapt to users' need, it is important to detect specific emotions, such as *happiness*. Since the writer's emotional state may change several times in the document, it is more interesting to classify emotions on a lower level (words, phrases, sentences). Recently, a growing number of researchers were interested in emotion analysis on sentence level (e.g., Li et al., 2015; Neviarouskaya et al., 2011).

The experiments reported in the present paper were designed to analyse emotions in text on sentence level. Generally, two approaches were adopted for emotional sentences classification: a fine-grained and a coarse-grained one. The fine-grained approach aims at classifying sentences into specific emotions (e.g., *joy*, *sadness*, *fear*, etc.) and their intensities. However, the coarse-grained one is intended at classifying sentences into emotional valences (i.e., *positive* or *negative*) and their intensities. In this research work, we adopted the fine-grained approach since we aim to classify sentences into the six basic emotions specified by Ekman (1978). Most subsequent research and datasets developed in the field are based on these emotions (*anger*, *disgust*, *fear*, *joy*, *sadness* and *surprise*). The problem with existing developed datasets is that they are currently small and do not cover most of the words in a given language. For this reason, a large dataset is needed.

As we believe that emotion classification in text depends on the quality of the labelled datasets, we aim, in this paper, to test some classifiers' abilities to generalize on new emotional sentences (testing datasets) using different combinations of training datasets. We describe, in the next section, the datasets used for the experiments.

3. Datasets for Emotion Analysis

Five datasets have been used in the experiments reported in this paper. We describe each one below.

- **Text Affect**

This data consists of news headlines drawn from most important newspapers as well as from the Google News search engine [33] and it has two parts. The first one is developed for the training and it is composed of 250 annotated sentences. The second one is designed for testing and it consists of 1,000 annotated sentences. Six emotions (*anger*, *disgust*, *fear*, *joy*, *sadness* and *surprise*) were used to annotate sentences according to the degree of emotional load. Each emotion is indicated using a score in the interval [0, 100], where 0 means the emotion is not present in the headline and 100 represents the maximum amount of emotion found in the headline. For our experiments, we further use the most dominant emotion as the sentence label, instead of a vector of scores representing each emotion.

- **Neviarouskaya et al.'s Dataset**

Two datasets produced by these authors were used in our experiments [24, 25]. We briefly describe in the following the two datasets.

  - **Dataset 1**

This dataset includes 1000 sentences extracted from various stories in 13 diverse categories such as education, health, and wellness [24]. These sentences were annotated with 14 labels (9 emotions, 4 labels for judgements and appreciations, and a label for neutral sentences). The method of Neviarouskaya et al.'s (2010) can classify not only emotions but also ethical judgements and appreciations.

For our experiments, only sentences on which two annotators or more completely agreed on the emotion category were extracted from the whole dataset.

- **Dataset 2**

This dataset includes 700 sentences from collection of diary-like blog posts [25]. In these dataset, ten labels were employed to annotate sentences by three annotators. These labels consist of the nine emotional categories defined by Izard (1971) (*anger*, *disgust*, *fear*, *guilt*, *interest*, *joy*, *sadness*, *shame*, and *surprise*) and a *neutral* category. In our experiments, we considered only sentences on which two annotators or more completely agreed on the emotion category.

- **Alm's Dataset**

This data include annotated sentences from fairy tales [1]. For our experiments, we used only sentences with high annotation agreement, in other words sentences with four identical emotion labels. Five emotions (*happy*, *fearful*, *sad*, *surprised* and *angry-disgusted*) from the Ekman's list of basic emotions were used for sentence annotations. Because of data sparsity and related semantics between *anger* and *disgust*, these two emotions were merged together by the author of the dataset, to represent one class.

- **Aman's Dataset**

This dataset consists of emotion-rich sentences collected from blogs [3]. These sentences were labelled with emotions by four annotators. We considered only sentences for which the annotators agreed on the emotion category. Ekman's basic emotions (*happiness*, *sadness*, *anger*, *disgust*, *surprise*, and *fear*), and also a *neutral* category were used for sentences annotation.

- **ISEAR Dataset**

The ISEAR (Intercultural Study on Emotional Antecedents and Reactions) dataset consists of 7666 sentences [30], annotated by 1,096 participants recruited from universities in 37 countries on five continents. These participants completed questionnaires about their emotional experiences and reactions for seven emotions: *anger*, *disgust*, *fear*, *joy*, *sadness*, *shame* and *guilt*. ISEAR is the largest cross-cultural dataset on emotions [31]. We used in our experiments only sentences annotated by the five emotion categories that overlap with the basic emotions of Eckman (that is, *anger*, *disgust*, *fear*, *joy*, *sadness*).

Table 1 bellow summarizes the major characteristics of the five datasets used in the experiments.

Table 1. Major characteristics of the five datasets used in the experiments.

	Text Affect	**Neviarouskaya et al. dataset**	**Alm dataset**	**Aman dataset**	**ISEAR**
Domain	*News headlines*	*Stories & diary-like blog posts*	*Fairy tales*	*Blogs*	*Emotional experiences*
Size for training set	250	0	1207	4090	7666
Size for test set	1000	595 656	0	0	0
# classes	6	10	5	7	5

4. Methodology

Emotional recognition of sentence involves the following process: a sentence is inspected, we extract features from it, we use the features and a model for emotion recognition learned from training data, in order to determine which emotional category it belongs to among a set of possible categories. Our emotional analysis problem is defined as a single-label multi-class classification problem since we used six emotional categories (*anger, disgust, fear, happiness, sadness, surprise*). In single-label multi-class classification, the purpose is to classify instances to one of k possible classes (k > 2).

To ensure proper emotional classification of text, it is essential to choose the relevant feature sets to be considered.

- **Feature Sets**

Many features can be used for classifying emotional sentences:

- **Bag-Of-Words (BOW)**: Each sentence in the dataset was represented by a feature vector composed of Boolean attributes for each word that occurs in the sentence. If a word occurs in a given sentence, its corresponding attribute is set to 1; otherwise it is set to 0. BOW considers words as independent entities and it does not take into consideration any semantic information from the text. However, it performs generally very well in text classification.
- **N-grams**: They are defined as sequences of words of length *n*. N-grams can be used for catching syntactic patterns in text and may include important text features such as negations, e.g., "not happy". Negation is an important feature for the analysis of emotion in text because it can totally change the expressed emotion of a sentence. For instance, the sentence "I'm not happy" should be classified into the *sadness* category and not into *hapiness*. For these reasons, some research studies in sentiment analysis claimed that N-grams features improve performance beyond the BOW approach [5].
- **Stems**: Stemming is the process for transforming words in the BOW representation into their stem, i.e., by removing terminations. For example, for

the word "sadness" is reduced to its stem "sad". With such a method, the features are generalized for classifying new sentences. However, reducing some words would result in incorrect feature, for example, transforming "fearless" to fear.

- **Lexical emotion features**: This kind of features represents the set of emotional words extracted from affective lexical repository such as, WordNetAffect [34]. We used in our experiments all the emotional words, from the WordNetAffect (WNA), associated with the six basic emotions.

- **Classification Algorithms**

For our experiments, we chose three modeling paradigms[1]: Decision Trees, Naïve Bayes and Support Vector Machines (SVM). We selected the Decision Trees because they are understandable for humans, the Naive Bayes classifiers because they are known to work well on text classification tasks [21], and SVM because they are known to achieve very good results on many classification tasks.

To find the best classification algorithm for emotion analysis in text, we compared the three classification algorithms from the *Weka* software [35] with the BOW representation: J48 for Decision Trees, Naïve Bayes for the Bayesian classifier and the SMO implementation of SVM.

5. Results

For an exploratory purpose, we conducted several experiments using the labelled datasets for classifying emotional sentences. As mentioned, six categories of emotions were used for the classification: *anger*, *disgust*, *fear*, *happiness*, *sadness*, *surprise*. First, in the development stage we trained the different supervised machine learning algorithms using several datasets. Then, we tried to find the most efficient feature sets to be considered in the classification of emotional sentences. Finally, we compared two approaches of binary classification algorithms for the multiclass classification problem.

- **Development Stage**

First of all, it is important to prepare the data for proper emotional sentence classification. Stop-words represent a list of common words that are generally considered to be useless for classification, because they tend to occur in sentences from all the classes. For classifying text into emotion categories, some words such as "I" and "the" are clearly useless and should be removed. In these experiments, we used a Bag-of-Words (BOW) representation of sentences excluding stop-words, since we obtained better results than when we included them. Moreover, in order to reduce the number of words in the BOW representation we used the *LovinsStemmer* stemming technique from the *Weka* tool [35]. As we described earlier, the stemming technique replaces a word by its stem. Bringing words together as if they were occurrences of one word would sometimes give a good indication of sentences' emotions, while each word individually might not. For instance, when we tested the SMO classifier on Neviarouskaya et al.'s first dataset, we obtained 46.61% without stemming and 56.77% with stemming. Thus, for all subsequent experiments we used stems for training and testing the classifier.

Another important way for reducing the number of words in the BOW representation is to replace negative short forms by negative long forms, e.g., "don't" is replaced by "do not", "shouldn't" is replaced by "should not", and so on. Applying this method of standardizing negative forms gave us better results for BOW representation and can consider effectively negative expressions in N-grams representation.

We applied the same data reducing techniques (removing stop-words, stemming words and replacing negative short form by long form ones) for both emotional words from WordNetAffect and N-grams representation. In this later, the features include words, bigrams and trigrams.

In the spirit of exploration, we used five datasets to train supervised machine learning algorithms: Text Affect, Alm's dataset, Aman's dataset, Global dataset, and ISEAR (see Table 2). The global dataset includes the three first datasets, since ISEAR deals only with five categories (*anger*, *disgust*, *fear*, *joy*, *sadness*) of the basic emotions of Ekman (1978). We also used the ZeroR classifier from Weka as a baseline; it classifies data into the most frequent class in the training set.

Table 2. Results for the training datasets, using the accuracy rate (%).

	Baseline	*Naive Bayes*	*J48*	*SMO*
Text Affect	31.6	**39.6**	32.8	**39.6**
Alm's Dataset	36.86	54.92	47.47	**61.88**
Aman's Dataset	68.47	73.02	71.43	**81.16**
ISEAR	19.90	56.87	56.83	**62.40**
Global Dataset	50.47	59.72	64.70	**71.69**

The results presented in Table 2 show that in general the SMO algorithm has the highest accuracy rate for each dataset. Moreover we can see from the table that the use of Aman's dataset gave good results (81.16 %), but it remains a homogenous data collected from blogs (with a high baseline of 68.47%); therefore the improvement to our method is 12.69 percentage points. The use of the global dataset for the training is much better, because, on one hand it contains heterogeneous data collected from blogs, fairly tales and news headlines, and on the other hand the difference between accuracy rates for the SMO algorithm and the baseline is higher compared to

[1] The type of data requires us to restrict the set of classifiers to consider as we work only with discrete values.

Aman's dataset. The improvement is from a baseline of 50.47% to an accuracy of 71.69%, that is, 21.22 percentage points. With the global dataset, SMO is statistically better than the next-best classifier (J48) with a confidence level of 95% based on the accuracy rate (according to a paired t-test). Thus, for all subsequent experiments we use the SMO algorithm trained on the global dataset.

- **Final Evaluation**

Given the performance on the training datasets, one important issue that we need to consider in emotion analysis in text is the ability to generalize on unseen examples, since it depends on sentences' context and the vocabulary used. Thus, we tested our models (trained on ISEAR and on the global dataset separately) on three test datasets: Text Affect, and Neviarouskaya et al.'s dataset 1 and 2. With the global dataset, the SMO algorithm performs significantly better than with ISEAR on the three test sets. For instance, with the BOW representation of the global dataset, the accuracy rate of the SMO classifier tested on Text Affect was 38.9%; however, with ISEAR, it was only 25%. In addition, when we tested on the BOW representation of the Neviarouskaya et al.'s dataset 1, the accuracy rate of the SMO classifier trained on the global dataset was about 57%, but the one trained on ISEAR dataset was around 35%. So, for the rest of the experiments, we used only the trained global dataset.

We tested our model (trained on the global dataset) on the three testing datasets using three kinds of feature sets (BOW, N-grams, emotional words from WordNetAffect) and combinations. The results are presented in Table 3 below.

Table 3. SMO results using different feature sets, for a classifier trained on the global dataset.

Test sets	**Feature sets**	**Accuracy rate (%)**	
		baseline	***SMO***
Text Affect	*WNA*	36.20	36.55
	BOW		38.90
	BOW +WNA		36.55
	N-grams		**40.30**
Neviarouskaya et al.'s dataset 1	*WNA*	24.73	44.76
	BOW		**57.81**
	BOW +WNA		56.28
	N-grams		49.47
Neviarouskaya et al.'s dataset 2	*WNA*	35.89	48.91
	BOW		**53.45**
	BOW +WNA		52.56
	N-grams		50.69

As shown in Table 3, using the N-grams representation for Text Affect gives better results than the BOW representation, but the difference is not statistically significant. However, the use of N-grams representation for Neviarouskaya et al.'s datasets decreased the accuracy rate compared to the BOW representation. As we notice from the table, using feature sets from WordNetAffect did not help in improving the accuracy rates of the SMO classifier.

6. Discussion

We noted that SMO algorithm used in the development stage achieved the best results using BOW representation of various datasets. Specifically, for Aman's dataset we achieved an accuracy rate of 81.16% which is better than those reported in [2]. In their work they used emotion words from lexical resources (e.g., WordNetAffect) as features for automatic recognition of emotion. The highest accuracy rate that they achieved is of 73.89%. Compared to their work, we used not only emotional words, but also non-emotional ones as we believe that some sentences can express emotions through underlying meaning and depending on the context, i.e., "Thank you so much for everyone who came". From the context, we can understand that this sentence expresses *happiness*, but it does not include any emotional word.

In addition, for ISEAR, our results are almost similar to the ones reported in [12]. They studied the effect of stemmers on emotion classification in text using 10-fold cross-validation on the ISEAR dataset. Their results showed that the use of the stemming technique gives additional increase in classification accuracy.

Due to the limitation of the vocabulary collected from the global dataset, errors may occur in emotion detection from text. Moreover, the analysis of errors reveals that some sentences are very difficult to classify like "When I'm feeling really anxious, walking really helps to reduce my anxiety". This sentence is annotated with the *happiness* label in the Neviarouskaya's et al.'s dataset 1, however it can be classified as *fear*. The more examples like this (false negatives), the more the recall is reduced.

The SMO classifier was developed and integrated in the AGET System (see figure 1).

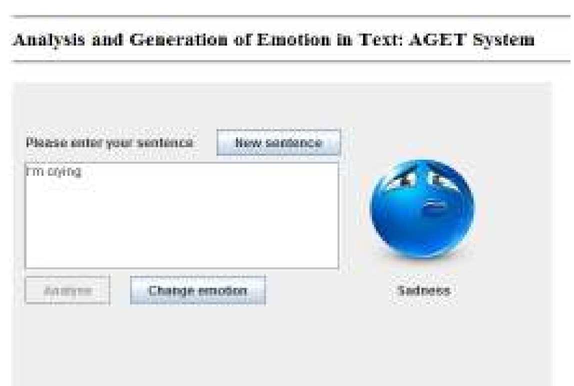

Figure 1. Analysis and Generation of Emotion in Text (AGET) system

7. Conclusion

Nowadays the emotional aspects attract the attention of many research areas not only in computer science, but also in psychology, healthcare, communication, etc. For instance, in healthcare some researchers are interested in how acquired diseases of the brain (e.g., Parkinson) affect the ability to communicate emotions [26]. Otherwise, with the emergence of Affective Computing in the late nineties [29], several researchers in different computer science areas, e.g., Natural Language Processing (NLP), Human Computer Interaction (HCI), etc. are interested more and more in emotions. Their aim is to develop machines that can detect users' emotions and express different kinds of emotion. The most natural way for a computer to automatic emotion recognition of the user is to detect his emotional state from the text that he entered in a blog, an online chat site, or in another form of text.

In this paper, we adopted a corpus-based approach for automatic emotion recognition from text. For this purpose, we used a heterogeneous dataset collected from blogs, fairly tales and news headlines. We showed in the development stage that the SMO made a statistically significant improvement over other approaches and that it generalizes well on unseen examples. Moreover, different feature sets (lexical emotion features from WordNetAffect, BOW and N-grams) used to train the SMO classifier and were tested on different datasets. The BOW representation gives relatively good results; however, there are many features correlated together, e.g, synonyms. For better classification results, it is important to choose discriminating and independent features. Thus, for future work, we aim to reduce dependencies between words in the BOW feature set by replacing synonyms with one common synonym.

Another direction of future work is a multi-label classification, that is, to allow more than one emotion class in a sentence. This is possible for the Text Affect dataset, but not for the other datasets labelled with only one emotion. Therefore, this direction can be explored when more multi-labels annotated datasets will become available.

References

[1] C. O. Alm, *Affect in Text and Speech*. PhD Dissertation, University of Illinois at Urbana-Champaign, 2008.

[2] S. Aman, and S. Szpakowicz, Identifying Expressions of Emotion in Text, *Lecture Notes in Computer Science*, 4629: 196-205, 2007.

[3] S. Aman, Identifying Expressions of Emotion in Text, Master's thesis, University of Ottawa, Ottawa, Canada, 2007.

[4] E. André and M. Mueller, Learning affective behavior, *Proceedings of the 10th Intl. Conf. on Human-Computer Interaction,* pp. 512-516, 2003.

[5] S. Arora, E. Mayfield, C. Penstein-Ros and E. Nyberg, Sentiment Classification using Automatically Extracted Subgraph Features. *Proceedings of the NAACL-HLT, Workshop on Computational Approaches to Analysis and Generation of Emotion in Text*, 2010.

[6] N. Bianchi and C. L. Lisetti, Modeling Multimodal Expression of User's Affective Subjective Experience. *User Modeling and User Adapted Interaction,* 12**,** pp. 49-84, 2002.

[7] A. C. Boucouvalas, Real time text-to-emotion engine for expressive Internet communications. In Being There: Concepts, Effects and Measurement of User Presence in Synthetic Environments, Ios Press, pp. 306-318, 2003.

[8] S. Chaffar and D. Inkpen, Using a Heterogeneous Dataset for Emotion Analysis in Text. Proceedings of the 24th Canadian Conference on Artificial Intelligence. St-John's, NFL, Canada, 2011.

[9] S. Chaffar and C. Frasson, Predicting Learner's Emotional Response in Intelligent Distance Learning Systems. *19th International FLAIRS Conference.* Melbourne, FL, USA, AAAI Press, 2006.

[10] C. Conati and H. Mclaren, Data-driven refinement of a probabilistic model of user affect. In *Proceedings of the 10th Intl. Conf. on User Modeling,* pp. 40-49, 2005.

[11] A. R. Damasio, *Descartes' Error: Emotion, Reason and the Human Brain,* New York, Gosset/Putnam Press, 1994.

[12] T. Danisman and A. Alpkocak, Feeler: Emotion classification of text using vector space model, in *AISB 2008 Convention Communication, Interaction and Social Intelligence*, Aberdeen, UK, 2008.

[13] S. D'Mello and A. C. Graesser, Multimodal semi-automated affect detection from conversational cues, gross body language, and facial features. *User Modeling and User-adapted Interaction*. 20 (2), pp 147-187, 2010.

[14] P. Ekman and W. V. Friesen, *Facial action coding system: Investigator's guide,* Palo Alto, Consulting Psychologists Press, 1978.

[15] J. Gratch and S. Marsella, A domain-independent framework for modeling emotion. *Journal of Cognitive Systems Research, 5*(4), pp. 269–306, 2004.

[16] J. T. Hancock, L. E. Curry, S. Goorha and M. Woodworth, On lying and being lied to: A linguistic analysis of deception in computer-mediated communication. *Discourse Processes,* vol. 45, pp. 1-23, 2008.

[17] C. E. Izard, The Face of Emotion. Appleton-Century-Crofts, New York, 1971.

[18] P. Katz, M. Singleton and R. Wicentowski, Swat-mp: the SemEval-2007 systems for task 5 and task 14. Proceedings of SemEval-2007, Prague, Czech Republic, 2007.

[19] H. Li, A. Mukherjee, J. Si, and B. Liu, Extracting Verb Expressions Implying Negative Opinions. *Proceedings of Twenty-Ninth AAAI Conference on Artificial Intelligence (AAAI-15)*. 2015.

[20] F. Mairesse, M. A. Walker, M. R. Mehl, and R. K. Moore, Using linguistic cues for the automatic recognition of personality in conversation and text, *Journal of Artificial Intelligence Research,* vol. 30, pp. 457-500, 2007.

[21] A. McCallum, and K. Nigam, A comparison of event models for naive Bayes text classification. *AAAI-98 Workshop on Learning for Text Categorization*, AAAI Press, 1998.

[22] P. Melville, W. Gryc and R. Lawrence, Sentiment Analysis of Blogs by Combining Lexical Knowledge with Text Classification, *Proceedings of KDD*, pp. 1275–1284, 2009.

[23] A. Neviarouskaya, H. Prendinger and M. Ishizuka, Affect Analysis Model: novel rule-based approach to affect sensing from text. International Journal of Natural Language Engineering 17(1): pp. 95-135, 2011.

[24] A. Neviarouskaya, H. Prendinger and M. Ishizuka, @AM: Textual Attitude Analysis Model. *Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text*, Los Angeles, USA, 2010.

[25] A. Neviarouskaya, H. Prendinger and M. Ishizuka, Compositionality Principle in Recognition of Fine-Grained Emotions from Text. *Proceedings of the International Conference on Weblogs and Social Media*, AAAI, San Jose, US, pp. 278-281, 2009.

[26] S. Paulmann and M. D. Pell, Dynamic emotion processing in Parkinson's disease as a function of channel availability. *Journal of Clinical and Experimental Neuropsychology, 32* (8), 822-835, 2010.

[27] C. Pelachaud, Modelling Multimodal Expression of Emotion in a Virtual Agent, *Philosophical Transactions of Royal Society B Biological Science*, 364, pp. 3539-3548, 2009.

[28] S. Petrovica, Adaptation of Tutoring to Students' Emotions in Emotionally Intelligent Tutoring Systems, Proceedings of Second International Conference on e-Learning and eTechnologies in Education, pp. 131-136, 2013.

[29] R. W. Picard, *Affective Computing*, Cambridge, MA: MIT Press, 1997.

[30] K. R. Scherer and H.G. Wallbott, Evidence for universality and cultural variation of differential emotion response patterning. *Journal of Personality and Social Psychology*, 66, pp.310-328, 1994.

[31] K. R. Scherer, The role of culture in emotion-antecedent appraisal. Journal of Personality and Social Psychology, 73, pp. 902-922, 1997.

[32] C. Strapparava and R. Mihalcea, Learning to Identify Emotions in Text. Proceedings of ACM Symposium on Applied computing, Fortaleza, Brazil, pp. 1556-1560, 2008.

[33] C. Strapparava and R. Mihalcea, Semeval-2007 task 14: Affective text. Proceedings of the 4th International Workshop on the Semantic Evaluations , Prague, Czech Republic, 2007.

[34] C. Strapparava, A. Valitutti and O. Stock, The affective weight of lexicon. Proceedings of the Fifth International Conference on Language Resources and Evaluation, Genoa, Italy, 2006.

[35] I. H. Witten and E. Frank, Data Mining: Practical machine learning tools and techniques. 2nd Edition, Morgan Kaufmann, San Francisco, 2005.

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