Emotion Analysis of the Text Using Fuzzy Affect Typing over Emotions

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Abstract. This paper presents a novel approach of emotion estimation in the affective content of the textual messages or dialogues. The individual words in a sentence has been chopped and mapped onto the corresponding affective categories. An affective category is assigned to its membership value in the all basic 5 emotions viz. happy, surprise, neutral, anger and sad. To analyze the affective content effectively we use natural language processing for the lexical analysis and thereafter fuzzy affect typing over basic emotions with the membership modifier rules to handle various modifiers of affective contents. Machine learning based prediction approach has been suggested for new encountered words.

Keywords: Emotion prediction, Affective content, Hebbian learning, Natural language processing.

1 Introduction

In order to deal with the increasing demands of today's dialogue management systems introducing a human dimension into automatic text understanding and representation has become necessary. Recent work shows the importance of emotions in decision making, perception and learning [1]. Affect information thus becomes critical to Human Machine Interaction (HMI) for a quick identification and analysis of particular affect in the text and its intuitive presentation to the user.

The present work deals with the inherent ambiguities in the text due to the kind of emotions and words in the natural languages. Here we experiment with qualitative analysis of affect-related information in free textual dialogues. Affect-related information includes words describing primitive emotions in the following categories i.e. happy, surprise, neutral, anger and sad.

For any relevant word that appears in a textual dialogues, we include all of its possible meanings and connotations in our analysis by assigning it a corresponding weight of meta linguistic domain from 0 to 1 in all the 5 categories i.e. happy, surprise, neutral, anger and sad. We create a realistic picture of the textual dialogue's affective content by cumulative effect of all the related words in it.

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Fuzzy techniques provide an excellent framework for computational management of the ambiguity and imprecision those are pervasive in the words of the natural languages. The ambiguity due to the presence of certain modifiers in the text is addressed by constructing fuzzy modifier rules which improves on the whole affect estimation of the text.

The machine learning has been employed to predict the affect of the new encountered word in the text whenever the meta linguistic domain database becomes constraint. It trains the model using Hebbian learning rule for future affective context prediction based on past affective context. It not only improves our efficiency but at the same time also reduces the database dependency to a great extent.

2 Related Work

Achievements in this domain can be used in next generation intelligent robotics, artificial intelligence, psychology, blogs, product reviews, and finally development of emotion-ware applications. A variety of approaches, methodologies and techniques have been used by researchers in order to analyze affect communicated through text. Kamps and Marx [2] evaluated subjective aspects of meaning expressed in written texts, such as the attitude or value expressed in them. Kim and Hovy [3] developed a module for determining word sentiment and another for combining sentiments within a sentence by integrating various models of classifying and finally combining sentiment at word and sentence levels. Statistical language modeling techniques [4] have been applied by researchers to analyze moods conveyed through online diary posts. However, the main limitation of those “bag-of-words” approaches to textual affect classification is that they neglect the negation constructions and syntactical relations in sentences. Some researchers employed keyword-spotting technique [9]; they reported that textual recognition rate is lower than speech based recognition. According to their work, emotion recognition performance of multimodal system is better than performance of individual modalities. Liu et al. [5] employed a commonsense knowledgebase OMCS (Open Mind Common Sense) having 400,000 facts about everyday world to classify sentences created affect sensing engine into an affectively responsive email composer called Empathy Buddy. M. Shaikh, H. Prendinger, and M. Ishizuka [1] used semantic parsers to categorize the themes of the news using news fetched from different news sources. M. Shaikh, H. Prendinger, and M. Ishizuka [6], developed an ALICE chat-bot based on Artificial Intelligence markup language (AIML) script to improve interaction in a text based instant messaging system that uses emoticons or avatar that the sensed emotion to express the emotional state. The affective information present in the input sentences sensed using OCC model of cognitive theory. Emotion analysis of news headlines and blog posts produced on the data set developed for the Sem Eval 2007 task on “Affective Text”. For this purpose Strapparava and Mihalcea, [7] employ a range of techniques including keyword-spotting, Latent Semantic Analysis (LSA), Naïve Bayes, rule based analysis and Pointwise Mutual Information (PMI). A. C. Boucouvalas and X.Zhe, [8] described Emotion Extraction Engine that can analyze the input text in a chat dialogue, extract the emotion and displays the expressive image on the communicating users display. He focused on parsing technique that considers sentences in present continuous tense, sentences without starting auxiliary verbs positive sentences, etc. Taner Danisman and Adil Alpkocak Feeler [10] shown automatic classification of anger, disgust, fear, joy and sad emotions in news head- lines using Vector- Space Model.

3 Affect Lexicon and Fuzzy Affect Typing over Emotions

The affect lexicon is a compendium of lexical entries for words having affectual connotation, with their corresponding parts of speech, affect category. An affect lexicon, which characterizes a large vocabulary of affectual words in terms of a small set of basic categories, such as love, hate, happiness, ecstatic, burdened, anxious, each to some numerical fuzzy membership value in the basic 5 emotions: happy, surprise, neutral, sad and anger.

Assigning category labels to a lexicon entries and emotion membership degrees to an affect category is a very subjective process. During the present proof-of concept phase, the assignments have been made by a single linguist. They are obviously influenced by the linguist's own experience, reading background, and (since affects are in question) personal/emotional background and prejudices. Though subjective, the process is not completely arbitrary—the assignments are general enough to yield useful results. The different fuzzy membership values assigned to each categories for each emotion is given below in the table1.

The 2000 words having affectual connotation have been mapped onto one of the 40 emotion oriented affect categories, as listed below.

> *angry, sad, happy, ecstatic, irresistible, powerless, out_of_control, apathetic, adequate, alone, independent, attached, codependent, hatred, love, belittled, embarrassed, average, esteemed, cheated, singled_out, justified, entitled, trapped, burdened, free, derailed, lost, focused, obsessed, demoralized, bored, attracted, lustful, fearful, anxious, fearless, safe, surprise and unsorted.*

Entries in the affect lexicons and its probable emotional content are represented in the form:

(lexical entry) (POS_tag) (affect category)(Centrality Score) (Intensity Score)
(lexical entry) (affect category) (Happy membership) (Surprise membership) (Neutral membership) (Sad membership) (Anger membership)

Eg: 'annoyed' 'vb' 'angry' '0.6' '0.5' and 'annoyed' 'vb' 'hatred' '0.8' '0.6'

'annoyed' 'hatred' '0.1' '0.2' '0.3' '0.8' '0.5

In a sentence affectual connotations usually are represented by a verb and an adjective. The POS tagger has been used to tag the Verbs and Adjectives. As of natural constraint all words cannot be completely classified into different categories, so few words were listed under the 'Unsorted' Category. Each word is associated with centrality and intensity score [11] which could help in selecting the best affect category, in case it is listed in more than one affect categories.

Table 1. Different fuzzy membership values assigned to affect category into basic five Emotions

Affect Category	Happy	Surprise	Neutral	Sad	Anger
angry	0.1	0.2	0.5	0.3	1.0
sad	0.1	0.1	0.3	1.0	0.4
happy	1.0	0.7	0.3	0.1	0.1
ecstatic	1.0	0.7	0.3	0.1	0.2
irresistible	0.1	0.2	0.4	0.5	0.9
powerless	0.1	0.2	0.4	0.9	0.5
out_of_control	0.2	0.3	0.4	0.7	0.5
adequate	0.8	0.3	0.6	0.1	0.2
alone	0.1	0.2	0.4	0.9	0.3
attached	0.7	0.4	0.5	0.2	0.3
hatred	0.1	0.2	0.3	0.8	0.5
love	0.8	0.3	0.4	0.2	0.1
belittled	0.1	0.2	0.3	0.9	0.5
Embarrassed	0.1	0.2	0.3	0.9	0.5
Average	0.2	0.1	0.9	0.3	0.4
Esteemed	0.8	0.6	0.4	0.1	0.2
Cheated	0.2	0.6	0.3	0.7	0.9
Justified	0.7	0.1	0.5	0.3	0.2
Trapped	0.2	0.1	0.3	0.7	0.4
Burdened	0.2	0.1	0.3	0.7	0.4
Free	0.7	0.5	0.4	0.2	0.3
Lost	0.2	0.1	0.3	0.7	0.4
Focused	0.5	0.3	0.7	0.1	0.2
Demoralized	0.1	0.3	0.2	1.0	0.4
Bored	0.3	0.2	0.3	0.8	0.5
Attracted	0.7	0.6	0.5	0.1	0.2
Fearful	0.1	0.2	0.3	0.8	0.5
Anxious	0.1	0.2	0.3	0.8	0.5
Fearless	0.8	0.6	0.5	0.2	0.4
Safe	0.7	0.4	0.5	0.2	0.3
Surprise	0.7	1.0	0.3	0.5	0.4
Unsorted	0.3	0.4	0.8	0.6	0.5

4 Architecture of Fuzzy Affect Typing over Emotions

The process for tagging a dialogue with an emotion is shown in figure1. It includes the following processes:

1. Parts of speech tagging
2. Checking for emotion membership value modifier rule applicability.
3. Retrieving fuzzy membership values of each lexical word.
4. Training the model of emotion prediction.

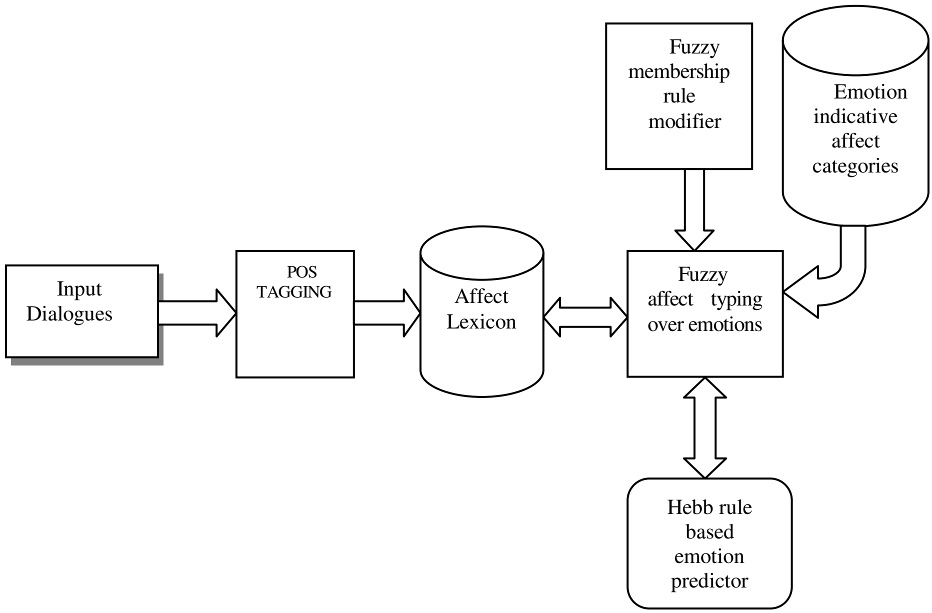

Fig. 1. Architecture for Emotion Prediction

The fuzzy membership values for a lexical entry are retrieved from the database using the table 1 shown above. It may be possible that one word can be listed in two categories. In that case the context sensitive information indicated by centrality score and intensity score [11] are used to assign the best match. Centrality and intensity score of an affect lexicon within an emotion oriented affect category addresses the key issues - *To what extent an affect word X related to category C? To what extent can affect word X be replaced with category C in the text, without changing the meaning?* For example as shown in table 2, the word "Discouraged" is found in categories "*Sad*", "*Demoralized*" and "*Powerless*". But the meaning is different in these three categories, which makes the emotion membership values assigned to this word different depending on the contextual relationship of the word in the affect categories.

5 Hebbian Learning for Emotion Prediction

Hebbian learning which states that with each input value, the model vector will tend to get updated towards the goal value with a constant learning rate, not too high and not too low. The fuzzy membership values assigned to a lexicon have been used to train a neural network model. The hebb rule is used to find weights for each emotion 'i' and updates itself after each iteration 'j' as follows-

$$\mathbf{W[i][j+1] = w[i][j] + alpha*(p[i]-w[i][j])} \quad (1)$$

where:

'**w[j]**' is the previous weight of the 'i'th emotion
'**w[i][j+1]**' is the updated weight of the (j+1)th iteration for 'i'th emotion
'**alpha**' is the learning rate
'**p[i]**' is the input value for 'i'th emotion
'i' is one emotion belongs to the set of all basic five emotions.

This trained model is used to predict the overall emotional content of a dialogue as well it also helps to predict emotional values of words whose corresponding affect category is not in the affect category database. Thus, it helps in overcoming the dependency on the affect category database.

6 Rules for Modifying Membership Value

Following modifier rules have been proposed to modify the membership value assigned to a word to get the impact of the fuzzified affective word at sentence level.

A. Non-Arousal Modifiers -- {shall, can, will, could, would}
All of these words depict a permission seeking quality (politeness) contributing to Non-Arousal quality. Hence, we reduce the overall membership value of the word by a small factor.

B. Dominance Modifiers -- {shouldn't, can't, won't, don't}
All of these words depict a dominating characteristic thus not asking for a favour but giving an order. Therefore we increase the angriness membership value of the word by a small factor.

C. Quantifier Modifiers -- {very, little}
Both these words act as quantifiers. Thus enhancing or attenuating the emotion respectively.

- 'Very' modifier rule: increases the overall membership value of the word significantly.
- 'Little' modifier rule: decreases the overall membership value of the word significantly.

D. Negation Modifiers -- {not}
'Not' changes the emotion to the opposite affect content. Thus, overall membership value of the word should be complemented.

E. Tense Modifiers -- {was, is}

- 'Is' modifier rule: 'Is' represents the present emotion of the speaker and thus increases the overall membership value of the word because of present tense.
- 'Was' modifier rule: 'Was' represents the event has happened in the past, hence emotion has attenuated in the present by some amount. Therefore we decrease the overall membership value of the word because of past tense.

After applying these rules, the final values of different emotions for this word are used to update the prediction model.

These calculated values as well as the predicted values are plotted on a graph by GNU Plot and the dialogue's context based prediction by Hebbian learning is compared with the mean value approach.

7 Results and Conclusion

As an example, let us consider the following paragraph:

I was feeling astonished and ecstatic after seeing such a bright, sunny and cheerful festive season all around. Everyone was so excited and sparkling looking really enthusiastic and high-spirited which made me feel delighted and overjoyed. I was also welcomed and loved. At the same time I was shocked at the people's response. But as soon as I remembered what happened the previous day I was grief-stricken and started feeling guilty. I was depressed to be a part of the act and felt awkward to face them. I started feeling hopeless but suddenly I was outraged and decided to face it how bitter it may be.

The result for the overall emotion prediction of the speaker based on the above example shown in table2.

Table 2. Emotion Prediction

Method	Happy (%)	Surprise (%)	Neutral (%)	Sad (%)	Anger (%)
Our Prediction	5.58	9.50	22.08	21.75	41.09
Mean	31.06	23.05	15.51	17.18	13.20

The mean method result gives very different results from what was expected and on the other hand the prediction approach understands the mood swing of the speaker very efficiently and provides realistic results. Few other samples were collected from movie reviews and analyzed for emotional content to form a summarization of common emotions used in a particular type of movies: Romance, Action, Sci-Fi, Family and Comedies, with 10-15 reviews in each group.

The common categories of emotional words and their relative frequency found in the above reviews are shown in the table 3. These results conforms the nature of dominant emotional content present in them.

Table 3. Affect categories observed in various kinds reviews

	High (0.7-1.0)	Medium (0.4-0.7)	Low (0.1 – 0.4)
Movies – Romance	love, attached, happy, ecstatic, free	Justified, Average, irresistible, lost, out_of_control	adequate, sad, alone, trapped, embarrassed, burdened, unsorted
Movies – Action	Angry, Hatred, cheated, out-of-control, trapped, fearless	fearful, safe, Powerless, lost, belittled, irresistible	justified, lost, anxious, unsorted
Movies – Sci-Fi	irresistible, focused, out_of_control	trapped, justified, free, lost	happy, love, average, adequate, unsorted
Movies – Family	attached, love, esteemed, safe, happy, ecstatic	adequate, burdened, average, sad, free, cheated	alone, embarrassed, justified, unsorted
Movies – Comedy	happy, ecstatic, surprise, free, out_of_control	average, adequate, Justified, focused	Belittled, sad, embarrassed, Lost, unsorted

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