Sentence Level News Emotion Analysis in Fuzzy Multi-label Classification Framework

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Abstract. Multiple emotions are evoked with different intensities in readers' minds in response to text stimuli. In this work, we perform reader perspective emotion analysis in sentence level considering each sentence to be associated with the emotion classes with fuzzy belongingness. As news articles present emotionally charged stories and facts, a corpus of 1305 news sentences are considered in this study. Experiments have been performed in Fuzzy k Nearest Neighbor (FkNN) classification framework with four different feature groups. Word feature based classification model is considered as baseline. In addition to that, we have proposed three features namely, polarity, semantic frame and emotion eliciting context (EEC) based features. Different measures applicable to multi-label classification problem have been used to evaluate the system performance. Comparisons between different feature groups revealed that EEC based feature is the most suitable one in reader perspective emotion classification task.

1 Introduction

With the recent thrust in Human-Computer Interaction (HCI) and Human Centered Computing (HCC), researchers are concerned about modeling human behavior in order to provide truly intelligent interfaces. Emotion is one of the distinguishing features of human character and plays an important role in shaping human behavior. Current efforts in HCI area are exploring the possibilities of developing emotionally intelligent interfaces. *Emotional intelligence* refers to one's ability to understand and manage the emotion of one's self or of others. Apart from other modes like speech and facial expression, language is one of the most common modes for expressing emotion whether it is day-to-day speech communications (spoken language) or published communications (written language). Recent works in natural language processing area look into different behavioral aspects of human like personality trait, sentiment and emotion. Emotion can be studied from two perspectives.

- From the writer/speaker perspective, where we need to understand the emotion that the writer/speaker intended to communicate and

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- from the reader's perspective, where we try to identify the emotion that is triggered in a reader in response to a language stimulus.

In this work, we intend to perform sentence level emotion classification from reader's perspective. The issues that are needed to be addressed in this kind of task are as follows:

- Fuzzy and multi-label characteristics: In response to a text stimuli, a blend of emotions may be evoked in reader's mind with different degrees of intensity. Thus, from a classification point of view, a text segment may have multiple memberships in different emotion categories.
- Identification of suitable features: As reader perspective emotion analysis is in its infancy, the exploration on the identification of suitable features has to be performed.
- Feature sparseness: While emotion elicitation from a discourse or paragraph may provide larger number of cues as features, the number of features available from a single sentence is less and hence the feature space becomes sparse.

The earlier works towards reader perspective emotion classification have used word feature [1, 2] and word co-occurrence statistics [3]. In this work, we have introduced three new features, namely the polarity feature, semantic frame feature and emotion elicitation context (EEC) feature towards the same objective. As fuzziness is involved in subjective entity like emotion, Fuzzy k Nearest Neighbor (FkNN) framework has been used for developing emotion classification models with proposed features.

2 Related Works

As stated earlier, emotion analysis can be performed in two different perspectives. There are a number of efforts towards writer perspective emotion analysis [4–8]. As we focus on performing reader perspective emotion analysis, we provide an overview of the works addressing the related task.

Affective text analysis was the task set in *SemEval-2007 Task 14* [9]. A corpus of news headlines extracted from Google news and CNN was provided. Two types of tasks were to classify headlines into positive/negative emotion category as well as distinct emotion categories like anger, disgust, fear, happiness, sadness and surprise.

The system UA-ZBSA [3] gathers statistics from three different search engines (MyWay, AllWeb and Yahoo) to attach emotion lables to the news headlines. The work computes the PMI score of each content word of a headline with respect to each emotion by querying the search engines with the headline and the emotion. The accuracy, precision and recall of the system is reported to be 85.72%, 17.83% and 11.27%.

UPAR7 [10] is a linguistic rule-based approach towards emotion classification. The system performs emotion analysis on news headline data provided in

SemEval-2007 Task 14. In the preprocessing step, the common words are decapitalized with the help of parts of speech tagger and Wordnet. Each word first is rated with respect to emotion classes. The main theme word is detected by parsing a headline and it is given a higher weight than the other words in the headline. The emotion score boosting to the nouns are performed based on their belongingness to some general categories in Wordnet. The word scoring also considers some other factors like human will, negation and modals, high-tech names, celebrities etc. The average accuracy, precision and recall of the system is 89.43%, 27.56% and 5.69%.

The system SWAT [11] adopts a supervised approach towards emotion classification in news headlines. A word-emotion map constructed by querying the Roget's New Millennium Thesaurus is used to score each word in the headline and the average score of the headline words are taken into account while labeling it with a particular emotion. The reported classification accuracy, precision and recall are 88.58%, 19.46% and 8.62%.

The work by Lin and Chen [1, 2] provides the method for ranking reader's emotions in Chinese news articles. Eight emotional classes are considered in this work. Chinese character bigram, Chinese words, news metadata, affix similarity and word emotion have been used as features. The best reported system accuracy is 76.88%.

3 Emotion Data

The emotion text data collected by us consists of 1305 sentences extracted from *Times of India* news paper archive[1]. The sentences were collected from headlines as well as from the bodies of articles belonging to political, social, sports and entertainment domain. The annotation scheme considers the following points:

- *Choice of emotion classes*: The annotation scheme considers four basic emotions, namely, *Disgust, Fear, Happiness, Sadness.*
- *Fuzzy and Multi-label annotation*: A sentence may trigger multiple emotions simultaneously. So, one annotator may classify a sentence to more than one emotion category. Fuzzy annotation is considered in this work, i.e., for a sentence, the annotators provide a value from the range [0,1] against each emotion category.

The distribution of sentences across emotion categories is as follows: Disgust = 307, Fear = 371, Happiness = 282 and Sadness = 735.

4 Features for Emotion Classification

Following features were considered in the experiments on emotion analysis on the data set described above.

[1] http://timesofindia.indiatimes.com/archive.cms

4.1 Word Feature

Words are sometimes indicative of the emotion class of a text segment. For example, the word 'bomb' may be highly co-associated with fear emotion. Thus, words present in the sentences may be considered to be potential features. Now, if we consider all the words in a text corpus, only a subset of these will be present in a particular sentence. The presence of these words is used to form a binary feature vector. Before creating the word feature vectors, following preprocessing steps are adopted.

- Stop words are removed.
- Named Entities may introduce noise in emotion classification. So, named entities are removed using the Stanford named entity recognizer[2].
- The remaining content words are stemmed using Porter's stemmer algorithm.

4.2 Polarity based Feature

Polarity of the subject, object and verb of a sentence may be good indicators of whether the sentence evokes positive or negative emotions. For example, let us consider the following sentence.

`Relief work improves the poor conditions of flood affected people.`

Here, the subject, *Relief work*, is of positive polarity; the verb, *improves*, is of positive polarity; and the object phrase, *poor conditions of flood affected people*, is of negative polarity. Intuitively, a positive subject performs a positive action on a negative object and this pattern evokes a positive emotion.

The polarity values of each word in the corpus are tagged manually. Existing resources like SentiWordnet may have been employed in word level polarity tagging. However, as this resource is developed using machine learning techniques, the error introduced in the polarity learning may affect the performance of emotion classification. The polarity of a word may have values like POSITIVE (P), NEGATIVE (Ne) or NEUTRAL (N).

The problem of finding polarity of verb and its corresponding subject and object in a sentence can be broken down into following sub-problems:

- Finding out the main verb and head words of the corresponding subject and object phrase
- Finding the modifier words for verb, subject and object head words
- Finding polarities of subject, object and verb phrases

The Stanford Parser[3] is used to parse the sentences and the dependency relations (nsubj, dobj, etc.) obtained as parser output are used to extract the subject, verb and object phrases. A dependency relation from the output of the parser is of the following form.

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[2] http://nlp.stanford.edu/software/CRF-NER.shtml

[3] http://nlp.stanford.edu/software/lex-parser.shtml

```
relation(arg1, arg2)
```

The main verb, subject and object head words in a sentence is detected using the dependency relations obtained from the parser output. Some of these relations are given in Table 1.

Table 1. Example dependency relations for identification of verb, subject and object head words.

Relation	Argument	Example Sentence	Example Relation
		Example dependency relations for identification of verb	
Agent: *agent*	arg1	The man has been killed by the police	agent(*killed*, police)
Passive auxiliary: *auxpass*	arg1	The president was killed	auxpass(*killed*, was)
Clausal subject: *csubj*	arg1	What he has done made me proud	csubj(*made*, done)
Direct object: *dobj*	arg1	He gave me a book	dobj(*gave*, book)
Nominal subject: *nsubj*	arg1	Millitants destroyed the bridge	nsubj(*destroyed*, millitants)
Passive nominal subject: *nsubjpass*	arg1	The bridge was destroyed by millitants	nsubjpass(*destroyed*, bridge)
		Example dependency relations for identification of subject head word	
Agent: *agent*	arg2	The man has been killed by the police	agent(killed, *police*)
Clausal subject: *csubj*	arg2	What he has done made me proud	csubj(made, *done*)
Clausal passive subject: *csubjpass*	arg2	That he will excel was predicted	csubjpass(predicted, *excel*)
Nominal subject: *nsubj*	arg2	Millitants destroyed the bridge	nsubj(destroyed, *millitants*)
Controlling subject: *xsubj*	arg2	Tom likes to eat fish	xsubj(eat, *Tom*)
		Example dependency relations for identification of object head word	
Direct object: *dobj*	arg2	He gave me a book	dobj(gave, *book*)

The second step is to find out the modifiers of the subject and object and verb head words. The example relations that were used for extracting the modifiers are given in Table 2. The polarity assignment to a phrase is performed with

Table 2. Example dependency relations for identification of modifier words

Relation	Argument	Example Phrase	Example Relation
Adverbial modifier: *advmod*	arg2	Genetically modified food	advmod(modified, *genetically*)
Adjectival modifier: *amod*	arg2	Genetically modified food	amod(food, *modified*)
Negation modifier: *neg*	arg2	He was not killed	negkilled, *love*

two different sets of phrase polarity assignment rules one for verb phrase (see Table 3)and another for subject and object phrase (see Table 4).

4.3 Semantic Frame Feature

Every word in lexicon refers to some ground truth conceptual meaning that helps in clustering the words based on their conceptual similarity. In frame semantics [12], a word evokes a frame of semantic knowledge relating to the specific concept it refers to.

Table 3. Example rules for verb polarity assignment (P = Positive, Ne = Negative, N = Neutral, NULL = absent, X = independent of relation)

Rule#	Head	Modifier	Relation	Phrase	Example
V1	Ne	Ne	advmod	Ne	[brutally]/Ne [killed]/Ne ⟶ [brutally killed]/Ne
V2	P	P	advmod	P	[heartily]/P [welcomed]/P ⟶ [heartily welcomed]/P
V3	Ne	P	advmod	Ne	[artistically]/P [murdered]/Ne ⟶ [artistically murdered]/Ne
V4	P	Ne	advmod	Ne	[ghastly]/Ne [welcomed]/P ⟶ [ghastly welcomed]/Ne
V5	N	P|Ne	advmod	Modifier polarity	[beautifully]/P [taken]/N ⟶ [beautifully taken]/P

Table 4. Example rules for subject and object polarity assignment

Rule#	Head	Modifier	Phrase	Example
N1	P	P	P	[great]/P [win]/P ⟶ [great win]/P
N2	Ne	P|Ne|N	Ne	[airplane]/N [hijack]/Ne ⟶ [airplane hijack]/Ne
N3	N	P|Ne	Modifier polarity	[excellent]/P [performance]/N ⟶ [excellent performance]/P
N4	N	N	N	[Minor]/N [girl]/N ⟶ [Minor girl]/N
N5	P|Ne	NULL	Head polarity	[bomb]/Ne ⟶ [bomb]/Ne

The Berkeley FrameNet project[4] is a well-known resource of frame-semantic lexicon for English. Apart from storing the predicate-argument structure, the frames group the lexical units. For example, the frame **Apply_heat** is evoked by the lexical units such as *bake, blanch, boil, simmer, steam,* etc. So, assignment of appropriate frames to the words may be used as a generalization technique.

The semantic frame feature extraction was performed by considering the semantic parse of each sentence through SHALMANESER[5]. In the example sentence given below, the words 'arrest', 'man', 'abducting', 'assaulting' and 'girl' are assigned with *Arrest, People, Kidnapping, Rape* and *People* frames. These frames are considered as semantic frame features.

```
Villivakkam police arrested a 26-year old married man for
abducting and sexually assaulting a 16-year-old girl
```

4.4 Emotion Elicitation Context (EEC) Feature

Emotion is evoked in reader based on the situation described in the text. The surface level features like words are not adequate to encode these situations. In order to represent these situations, we need to capture the context in which they occur. In order to capture these contexts, we develop a knowledge base of emotion eliciting contexts.

Representing EEC Knowledge An EEC involves an action and entities related to the action. One context is described by a semantic graph that contains a special node called the *pivot* representing the action part of EEC. The *pivot* node

[4] http://framenet.icsi.berkeley.edu/

[5] http://www.coli.uni-saarland.de/projects/salsa/shal/

is reference to a semantic frame like *Cause_harm* of Framenet. The entity nodes in the semantic graph are related to the *pivot* node with semantic relations. The entity nodes are reference to the semantic groups (SG). An SG is a collection of similar semantic frames or concepts or both. The g^{th} SG is represented as follows.

$$SG_g : SF_1, SF_2, \ldots, SF_s; C_1, C_2, \ldots, C_c \tag{1}$$

where SG_g contains s number of semantic frames and c number of concepts. The s^{th} semantic frame SF_s is reference to a frame in FrameNet. There are some terms which cannot be mapped to any frame in the FrameNet. Those terms have been accommodated in the knowledge base by defining some concepts. Thus, a concept is represented as a collection of terms. For example, there is no entry for 'tiger' in FrameNet and it has been represented through the concept *fearful_animal*. The semantic group *Fearful_Entity* is given in Table 5. In

Table 5. Example of Fearful_Entity semantic group

Fearful_Entity
Terrorist
fearful_animal
Weapon
Catastrophe

this example, the SG *Fearful_Entity* contains three Frames (*Terrorist, Weapon, Catastrophe*) and one concept *fearful_animal*.

An example semantic graph for the EEC describing the killing of people in disease (Killing_by_Disease) is presented in Figure 1.

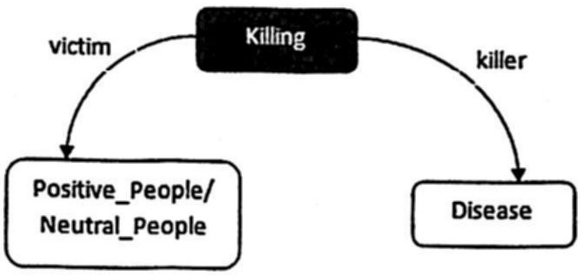

Fig. 1. An example EEC describing the context of killing by disease.

Identifying EEC in Sentence We analyze a sentence to identify the EECs present in it. The semantic parse of the sentence is obtained by means of a semantic parser like SALMANESER. The EEC identification method takes the EEC graphs and the semantic parse graph of a sentence as input and outputs the matched EECs for that particular sentence.

The identification method starts with taking each EEC graph from the EEC knowledge base and tries to fit it into the semantic parse graph. Based on the extent of match, a match score is assigned to the current EEC. The matching process for an EEC graph and a semantic parse graph is depicted in Figure 2. The matching process starts with finding the *pivot* node of the EEC in the

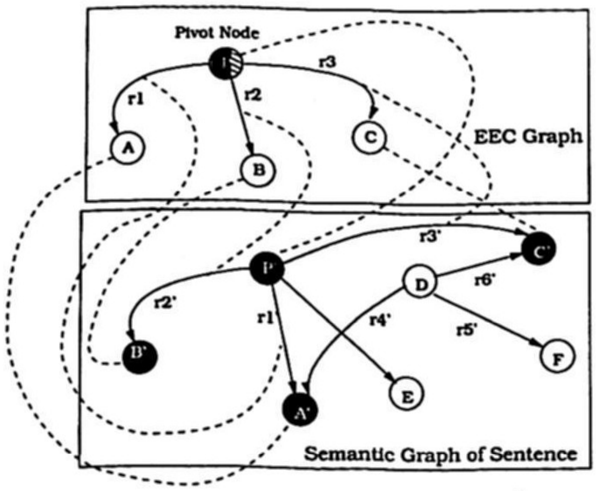

Fig. 2. Illustration of match procedure of an EEC graph and a semantic parse graph

semantic parse graph. Then the relations (an edge and node pair) are probed for matching in semantic parse graph. The match score (m) for an EEC is computed as follows.

$$m = \frac{Number\,of\,relations\,that\,are\,matched}{Total\,number\,of\,relations\,in\,EEC} \tag{2}$$

In the example shown in Figure 2, pivot node P is matched with P' of semantic parse graph. The relations $P - r1 - A$, $P - r2 - B$ and $P - r3 - C$ are matched with $P' - r1' - A'$, $P' - r2' - B'$ and $P' - r3' - C'$ respectively. So, the match score m for this EEC is $\frac{3}{3} = 1$. After computing match scores, the EECs with match scores greater than zero are selected to be the emotion elicitation contexts for the concerned sentence.

By analyzing the corpus, we have defined 62 EECs, some of which are presented in Table 6.

Table 6. Examples of EECs

EEC names		
Reduction_in_Harmful_Entity	Killing_by_Mass_Destruction_Entity	Death_by_Accident
Growth_of_Positive_Entity	Punishing_for_Illegal_Act	Death_by_Catastrophe
Appreciation_of_Entity	Killing_by_Relatives	Performing_Illegal Act
Outbreak_of_Disease	Suffering_from_Disease	Death_by_Suicide

5 Experiments

As we are dealing with fuzzy annotated data, a fuzzy classification framework has been used for developing the emotion classification models. In this section, we present results pertaining to experiments with different feature combinations in FkNN framework.

5.1 Fuzzy k Nearest Neighbor (FkNN) for Emotion Classification

FkNN [13] is a fuzzy extension of popular k nearest neighbor algorithm and it assigns class memberships against a test instance. Let $S = \{s_1, s_2, \ldots s_n\}$ be n labeled training instances and μ_{ij} be the membership of the training instance s_j in i^{th} class. In order to assign membership of a test instance s_t in the i^{th} class, k nearest neighbors of s_t in the training data set are found with a distance measure. The membership of s_t in i^{th} class is determined using equation 3.

$$\mu_i(s_t) = \frac{\sum_{j=1}^{k} \mu_{ij}(1/\|s_t - s_j\|^{\frac{2}{(f-1)}})}{\sum_{j=1}^{k}(1/\|s_t - s_j\|^{\frac{2}{(f-1)}})} \tag{3}$$

The variable f controls the extent to which the distance is weighted while computing a neighbor's contribution to the membership value. Number of nearest neighbors (k) is another parameter in FkNN algorithm.

5.2 Evaluation Measures

As mentioned earlier, the reader perspective emotion analysis is a fuzzy and multi-label classification task. The classification model outputs a membership vector for each test instance where the i^{th} entry μ_i $(0 \leq \mu_i \leq 1)$ is the predicted membership value in the i^{th} class. The evaluation of the fuzzy membership value prediction is performed by measuring Euclidean distance between the predicted and actual membership vector. The evaluation measures those are applicable to multi-label classification task can also be applied here by converting the real valued prediction vector into a binary prediction vector. This kind for conversion is performed by applying α-cut with $\alpha = 0.4$. The evaluation measures used in this study are presented in Table 7.

5.3 Experimental Results

Experiments have been performed with different feature combinations. All the experiments have been performed with $f = 1.5$ and $k = 5$. Results have been reported based on 5-fold cross validation setting for each experiments. Table 8 summarizes the results of emotion classification with different features and their combinations with best results presented in bold face.

When the different features are considered separately, the performance of the emotion classifier with polarity feature (**P**) deteriorated as compared to the

Table 7. Evaluation measures (↑ = Higher the value better the performance, ↓ = lower the value better the performance).

Evaluation Measure Group	Evaluation Measure	Convention
Example based measures [14]	Hamming Loss (HL)	↓
	Partial Match Accuracy (P-Acc)	↑
	Subset Accuracy (S-Acc)	↑
	F1 Measure (F1)	↑
Ranking based measures [15]	One Error (OE)	↓
	Coverage (COV)	↓
	Ranking Loss (RL)	↓
	Average Precision (AVP)	↑
Label based measures [14]	Micro Average F1 (Micro-F1)	↑
	Macro Average F1 (Macro-F1)	↑
Fuzzy membership measure	Euclidean distance (ED)	↓

Table 8. Comparison of features (W = word feature, P = polarity feature, SF = Semantic frame feature, EEC = Emotion elicitation context)

Measure	W	P	SF	EEC	W+P	P+SF	W+SF	W+P+SF	P+EEC
HL	0.136	0.186	0.092	0.063	0.121	0.080	0.099	0.109	**0.051**
P-Acc	0.645	0.562	0.781	0.864	0.705	0.823	0.757	0.728	**0.894**
S-Acc	0.574	0.514	0.692	0.791	0.612	0.740	0.668	0.644	**0.832**
F1	0.679	0.628	0.803	0.899	0.750	0.862	0.800	0.769	**0.925**
OE	0.180	0.213	0.116	**0.059**	0.167	0.090	0.129	0.158	0.061
COV	0.931	1.105	0.719	0.547	0.868	0.656	0.767	0.795	**0.484**
RL	0.163	0.194	0.081	0.053	0.136	0.061	0.104	0.092	**0.041**
AVP	0.850	0.796	0.884	0.925	0.864	0.922	0.889	0.874	**0.957**
Micro-F1	0.688	0.641	0.781	0.827	0.729	0.816	0.750	0.737	**0.877**
Macro-F1	0.615	0.613	0.743	0.818	0.652	0.771	0.681	0.665	**0.857**
ED	0.282	0.302	0.253	0.185	0.284	0.218	0.250	0.260	**0.151**

baseline classifier (using word feature (**W**)) for all the evaluation metrics. This explains how important the terms present in the text are for emotion classification. The use of semantic frames (**SF**) as features improves the performance of emotion classification significantly. This improvement may be attributed to two different transformations over the word feature set.

- *Dimensionality Reduction*: There is a significant reduction in the dimension of semantic frame feature set as compared to word feature set (semantic frame feature dimension = 279 and word feature dimension = 2345).
- *Feature Generalization*: Semantic frame assignment to the terms in the sentences is one generalization technique where conceptually similar terms are grouped into a semantic frame.

On the other hand, a notable improvement have been observed with the use of EEC features. As the contextual information is encoded in EEC feature, it is more powerful than the semantic frame features. Reduction in dimension with respect to semantic frame feature is also observed in case of EEC feature.

General observations over the feature comparison experiment are as follows.

- The **P+EEC** feature combination performs best in emotion classification with Fuzzy kNN. The **EEC** feature performs closer to **P+EEC** as compared to other feature combinations.
- The polarity feature (**P**) is inefficient than other combinations but whenever coupled with other feature combinations (i.e., **W** vs. **W+P**, **SF** vs. **SF+P**, **W+SF** vs. **W+SF+P** and **EEC** Vs. **P+EEC**), the performance improves. This improvement can be explained with the fact that the polarity feature may help the word or semantic frame based models by classifying the data set into positive and negative category.

6 Conclusions

In this paper, we have presented a fuzzy classification model based on different proposed features in order to perform reader perspective emotion analysis. The problem of reader perspective emotion recognition has been posed as a fuzzy classification problem. We have introduced three new features, namely, polarity, semantic frame and emotion eliciting context based features. Extensive experiments with different feature combinations have been performed and the best performance was achieved with EEC and polarity feature combination.

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