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Comparison of Probabilistic Corpus Based Method and Vector Space Model for Emotion Recognition from Poems

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Abstract: This study discusses the automatic detection of emotions in English poems. Emotions are classified based on 'Navarasa' which is described in 'Natyasastra'. Navarasa consists of nine basic emotions such as Love, Sad, Anger, Hate, Fear, Surprise, Courage, Joy and Peace. We have manually created an emotions tagged corpus from poems. Using poems mined from the web, we applied corpus-based tagging method to recognize the emotion of a poem. For the emotion recognition, we have used the Vector Space model with a total of 348 poems of 165 poets mined from the web. We have approached this problem from four perspectives. Traditional Vector Space model Vector space model, eliminating stop words (emotionless words) and without stemming Vector Space model without eliminating stop words and without stemming. Corpus-Based emotion recognition system. The Traditional Vector Space model gives better performance than other methods.

Key words: Emotion Recognition, Emotion analysis, poem annotation, emotion corpus, Vector Space model, corpus-based analysis

INTRODUCTION

Humans by nature are emotionally affected by reading poems.Automatic recognition of emotions in the text is becoming important in human-computer interaction. Recent research into human-machine interaction has a vital role in emotional reactions. Automatic recognition of emotion is becoming important in opinion mining, market analysis, affective computing, etc. Emotion recognition in poems is an important task as poem databases or poem websites are growinga number. The retrieval of a poem or a lyric by emotion has various applications such as poem selection of poem websites. It can be applied in machine translation of poems, poetry therapy, etc.

The goal of poetry therapy is to achieve psychological well-being and healing through the uses of poetry or other spoken or written media. In poetry therapy, a poetry therapist reads to the client to elicit emotional responses. The choice of poetry or verse is directly influenced by the situational emotional state that the client is in. This method allows a client to explore intimate feelings that remain buried in their subconscious and identify how these feelings relate to their current life circumstances. Thousands of poems are available. As poem databases are growing, our proposed work will recommend a therapist to identify the poems for clients. To achieve this goal, we are identifying the emotion of the poem.

Emotion recognition in speech and facial expressions are a little bit easier than text. Emotion recognition in speech can be approached by the features such as pitch and modulation. By the modulation and pitch can recognize the emotion in the text only by the contextual meaning.

In this study, we propose an approach to recognize emotional states from English poems based on NAVARASAS described in NATYASHASTRA. Many research works have been done in the field of Emotion recognition in the text. In this paper, emotions are categorized into nine types such as love, sadness, joy, fear, hate, courage, anger, surprise and peace.

Natyashastra: The NatyaShastra is an ancient Indian text dated between 2nd century BC and 2nd century AD which analyzes all aspects of performing art. It is often called the fifth Veda because of its importance. Nava means nine and rasa means 'essence', but is used here in the sense of 'emotional state.' The nine races were the backbone of Indian aesthetics ever since they were codified in the Natyasastra and formed the premise from which traditions of dance, music, theatre, art and literature evolved. The nine rasas described in ancient Indian aesthetic philosophy can be seen as being indicative of prime human emotions. In it one finds a thorough exposition of the rasas or emotions that characterize Art as well as life more precisely.

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Shringara love: Shringara in Sanskrit means to love and beauty. This is the emotion used to represent that which appeals to the human mind, that which one finds beautiful that which evokes love. It can be used for the love between friends, the love between a mother and her child, the love for God or the love between a teacher and his disciples. But the Shringara or the love between a man and a woman is easily the most popular form of this race.

Hasya joy: Hasya in Sanskrit is the rasa used to express joy or mirth. It can be used to depict simple light heartedness or riotous laughter and everything in between. Teasing and laughing with a friend, being amused and carefree or simply feeling frivolous and naughty-these are all facets of hasya.

Bhibatsya hate: Bhibatsya is Hate. The emotion evoked by anything that nauseates us, that revolts or sickens us is B hibatsya. When something comes to our notice that is coarse and graceless, beneath human dignity, something that revolts or sickens us it is Bhibatsya that we feel.

Rowdra anger: Rowdra is anger and all its forms. The self-righteous wrath of kings, outrage over the audacious behavior and disobedience, the fury caused by an offense, the rage evoked by disrespect and anger over injustice are just someof its forms. Rowdracan probablybe considered.

Shanta peace: Peace andserenity can be described in one word as Shantha. It represents the state of calm and unruffled repose. It can be marked simply as by the lack of all other rasas. It is the position where complete harmony between mind, body and universe is laid and this state is regarded as the key to eternity.

Veera courage: Veera is simple heroism. It represents bravery and self-confidence. Courage and intrepidity in the face of daunting odds are heroism.

Bhaya Fear: Bhaya represents fear. Bhaya is fear. The subtle and nameless anxiety caused by a presentiment of evil, the feelings of helplessness evoked by a mighty and cruel ruler and the terror felt while facing certain death are all aspects of Bhaya.

Karuna sad: Karuna is grief and compassion. It is the feeling of unspeakable tragedy and despair, utter hopelessness and heartbreak and sorrow.

Adbhuta surprise: Emotions like wonder, amazement and curiosity are portrayed through this rasa.

Literature review: This is one of the first works in emotion detection in the text that used a simple natural language parser for keyword spotting, phrase length measurement and emoticon identification (Oleveres *et al*., 1998). Emotion Recognition from text has been done using Semantic Labels and Separable Mixture models (Wu *et al*., 2006).

They used Emotion Generation Rules (EGRs) are manually deduced from psychology to represent the conditions for generating emotion. Based on the EGRs, the sequence of Semantic Labels (SLs) and Attributes (ATTs) are represented. The Emotion Association Rules (EARs) represented by SLs and ATTs for each emotion are automatically derived from the sentences in emotional text corpus using the a priori algorithm. A Separable Mixture Model (SMM) is adopted to estimate the similarity between an input sentence and the EARs of each emotional state.

The construction of a large dataset annotated for six basic emotions such as Anger, Disgust, Fear, Joy, Sadness and Surprise are described by Straparava and Michalcea (2008). They proposed and evaluated several knowledge-based methods for the automatic identification of these emotions in the text.

Minato *et al*. (2008) have done an analysis ofthe Japanese Emotion Corpus to identify the Automatic Emotion Word. The most straightforward approach is to construct an emotion dictionary and then identify words as emotions if they are present in the dictionary. This approach should yield a high precision, but it is impossible to identify words, not in the dictionary. Another approach is to treat the identification as a binary classification problem and use machine learning. The advantage of this approach is that it should be possible to classify words that have not been seen before. However, there will probably be a lose in precision due to rise in false positives for non-emotion carrying words.

An automatic classifier applied for recognizing six basic emotion types for different words in a sentence is done by Das and Bandyopadhyay (2009). Hierarchical versus flat classification of emotions in text is done by Ghazi *et al*. (2010). They explored the task of automatic classification of texts by the emotions expressed. Their novel method arranges neutrality, polarity and emotions hierarchically. According to Ghazi *et al*. (2010) hierarchical classification is a new approach to emotional analysis which considers the relation between neutrality, polarity and emotion of a text. The main idea is to arrange these categories and their interconnections into a hierarchy and leverage it in the classification process.

Emotion analysis based on latent semantic analysis has been done by Bellegarda (2010) and it still relies on some measure of expert knowledge to isolate the emotional keywords or Keysets necessary to construct affective categories. According to Jerome R. Bellegarda, Data-driven approaches based on LSA purport to "individuate" such indirect affective words via inference mechanisms automatically derived in an unsupervised way from a large corpus of texts.

An empirical study of the text-based emotion prediction problem in the domain of children's fairy tales discussed by Am *et al.* (2005) with child-directed expressive text-to-speech synthesis.

Automatic classification of anger, disgust, fear, joy, sad emotions in the text has been studied on the ISEAR (International Survey on Emotion Antecedents and Reactions) dataset. The classification task employs Vector Space Model with a total of 801 News Headlines provided by "Affective Task" in SemEval 2007 workshop[4] that focused on the classification of emotions and valences in the text. Danisman and Alpkocak (2008) have compared[5] the results with ConceptNet and powerful text-based classifiers including Naive Bayes and Support Vector[6] Machines. Their experiments showed that Vector Space Model classification gives better performance than ConceptNet, Naive Bayes and SVM based classifiers.

A system for the Semeval 2012 Sentence Textual Similarity task combined few simple vector space-based methods for word meaning similarity. This included a basic bag-of-words model and a slightly simplified variant of the contextualization model of Dinu and Theare (2012) and two different methods to compute similarity scores. They are one "compositional" method that computes vectors for sentences by summing over the vectors of the constituent words and one alignment-based method that uses vector based similarity scores for word pairs to compute an alignment between the words in the two sentences.

Many of the related works mentioned above have labelled of emotions under six or five categories such as (love, sad, fear, disgust, anger and surprise). Emotion categorization is different for different domains. Emotions in education domain can be classifiedinto boredom and interesting. Here, emotions such as sad, fear, laughter, courage, anger, etc. are not usually found. Whereas for News domain different emotions such as sad, fear, hate, anger, joy, surprise, etc. Since, our domain focus on poems, we thought to categorize our corpus into nine emotions such as (love, sad, hate, anger, joy, fear, courage, surprise and peace) based on Natyasastra (Sreeja and Mahalaksmi, 2015).

MATERIALS AND METHODS

Emotion recognition system in poems

Corpus-Based emotion recognition

Corpus construction: As the study of emotion recognition combined with natural language processing is rather new, it is still difficult to obtain such a vast linguistic resource. Different sets of emotions are required for different domains. All keyword-based systems have encountered problems such as:

- Ambiguity in defining all emotional keywords
- Recognizing emotion from sentences with no emotional keywords
- Lack of semantic and syntactic information for emotion recognition
- Recognizing emotion from poems with no emotional keywords
- Creative writing such as figurative language, rhyme, poetic form
- Emotion Intensity

As there is no tagged dataset for English poem, we created our own by mining public websites. The poem database is made up poems extracted from a few websites. We collected 348 poems by 165 poets. The corpus is having 348 poems and 28384 poetic words.

Table 1 depicts the details of poem corpus and statistics of poems. The training is done in a supervised setting and 8609 unique words after removing the stop words. The corpus was consisting of 2020 emotional words among these unique words.

Emotion tagged poem corpus construction: This emotion corpus is built offline with words collected from the database of English poetry created. This corpus has

Table 1: Corpus details

Emotion	No. of poems	No. of emotion words
Anger	42	225
Courage	61	100
Fear	29	155
Hate	21	115
Joy	57	310
Love	59	700
Peace	29	75
Sad	41	300
Surprise	9	40
Total poems	348	2020

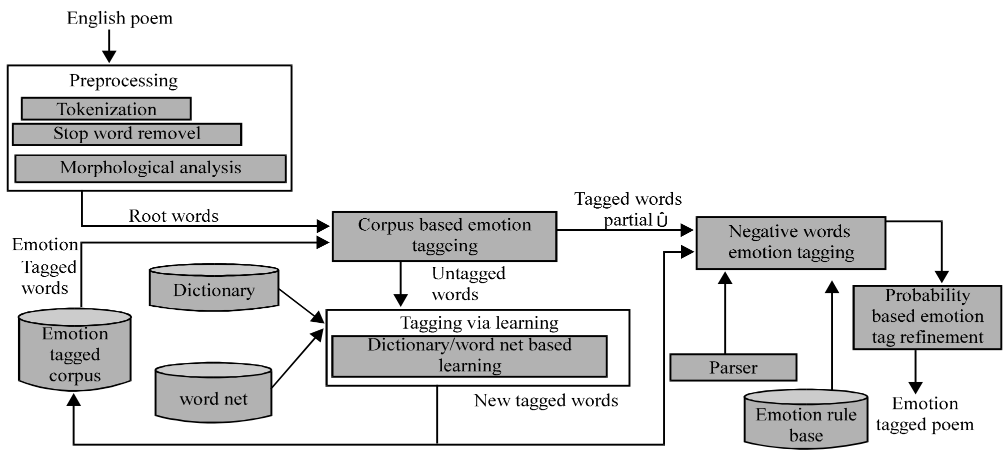

Fig. 1: Automatic emotion recognization for poem system architecture

manually tagged poetic words. Poems of different emotions are collected. These words are then tagged manually using emotion tags such as "love", "sad", "joy", "anger", "surprise", "hate", "peace", "fear", "courage". The words such as "doesn't", "shouldn't", "won't" are converted into "does not", "should not" and "will not" respectively. These 'not' words are tagged as <neg> which indicates negative emotion.

Inmost of the text mining process tokens will be undergoing stemming to obtain root words. This is done to reduce the size of the corpus, obtain entities, etc. But this is not done here as words in different forms or tenses have different emotions. Consider Example:

- I love him
- I loved him

Both the sentence has different emotions. The first sentence states that the person is still in love with him. The emotion represented here is love. But the second sentence tells that the person was once in love with him, but the emotion at present is not known. Which means we have to find using contextual information. Hence we make an assumption to tag 'love' as "love" and "loved" as "hate" and "anger".

Selective stopword removal: Stop words are usually articles, auxiliary verbs, prepositions, conjunctions, etc. There are publicly available stop-word lists consisting of most frequent words in a given language. However, Stopword list consisting of negative verbs such as not, is not, does not, do not, should not, etc. cannot be removed. As mentioned before, we are not stemming here. Consider Example:

- I love you
- I do not love you

Sentence and have two different emotions. Sentence 1 represents the emotion of love and) represents the emotion of hate or anger depends on the context. Hence, in this stage a selected set of stopwords, that do not contribute to emotions are removed.

Corpus based emotion tagging: The words are then subjected to emotion tagging guided by emotion corpus. This might result in partial tagging of emotion words. Sometimes the words can have more than one tag. At this stage, we used probabilistic based classification is used for tagging that word (Fig. 1).

$$P(\text{Emotion}|\text{word}) = \frac{\#\text{timesword}_i \text{ occurs in a emotion file}}{\#\text{timesword}_i \text{ occurs in a emotion file}} \quad (1)$$

Tagging via learning: Untagged words would be subjected toWordnet based tagging via machine learning. Here, the untagged words are searched for alternate synonyms across the Wordnet and every synonym thus identified would be subjected to corpus-based emotion tagging. The emotion recommended by the majority of synonyms would be assumed as the emotion of the word under consideration and the corpus would be made to learn the new emotion entry. Thus, by tagging the individual words for their emotions and embedding them inline with the poem would result in a poem tagged for emotion words.

Negative words emotion tagging: When <neg> tags are observed in the tag set of a given poem, bigram model is used to handling negation. <neg> tagged word and its immediate successor words are observed. If the immediate successor word represents an emotion, then its opposite emotion is swapped. Example:

- Not hate = love

Vector space model system

Traditional vector space model: Vector Space Model or term vector model is an algebraic model for representing text documents as vectors. In Vector Space model, each word is a dimension. Hence, in text mining, we may deal with a few hundred thousand dimensions. If we have M different words, then, we have an M-dimensional vector space. Each document is regarded as a point in this vector space as D= $\{w_1, w_2, \ldots w_m\}$, Where $w_1, w_2, \ldots\ldots w_m$ are unique words in the entire corpus.

Regarding geometry, w_i is the coordinate of dimension i in d. Yet, conceptually,w_i denotes the importance of word i in d. The VSM system has nine documents with each document represents only one emotion where $D_j = E_j$. Using a weighting schema(tf-idfschema), we can normalize the document into unit length (5).

$$\text{Weight}(\text{word}_i) = \text{TF}(\text{word}_i) \times \text{IDF}(\text{word}_i) \quad (2)$$

Where:

$$\text{TF}((\text{word}_i) = \text{Number of timesword}_i \text{ appears} \quad (3)$$

$$\text{IDF}(\text{word}_i) = \frac{\text{Logtotaldocuments}}{\text{Document frequency}} \quad (4)$$

$$\text{Normalised weight} = \frac{W(\text{word}_i)}{\sqrt{W^2(\text{word}_1) + \ldots + W^2(\text{word}_n)}} \quad (5)$$

We found the relation of the input poem with all the poems under each emotion using cosine similarity. Each document is represented as a vector of weights D = <x>. Cosine similarity (dot product) is the most widely used similarity measure between two documents. The similarity between the particular emotionis calculated by using Eq. 6. The emotion with the highest score is considered as the emotion of that particular poem.

$$\text{Sim}(\text{Inputpoem}, D_i) = \frac{\sum_i x_{1i} x_{2i}}{\sqrt{\sum_j x_j^2}\sqrt{\sum_k x_k^2}} \quad (6)$$

Table 2: Examples of emotions before and after stemming

Words	Actual emotion	After pre-processing	Emotion
Loved	Anger or hatred or sad	Love	Love
Loving	Love	Love	Love
No fear	Courageous	Fear	Fear
Fearless	Courageous	Fear	Fear

Modified vsm-I: In the traditional vector space model, stemming of words and stopwords are carried out. In our model, we skip these steps to preserve the emotion of words in the context. Some example of the effects of stopwords and non-stemmed word in determining the emotion is shown in Table 2.

The word ‘loved’ and ‘loving’ are not different, but here in this context they convey different meaning because of the impact of other words associated with them. Hence, the words ‘loved’ and ‘loving’ have different emotions. Similarly, the word “fearless” subjected to stemming will give an output as the fearthat is opposite to courage, emotion and it represents the emotion of fear.“No Fear“ with stopword removed will give an output as the fearthat is opposite to the expected emotional Courage. To avoid these difficulties our algorithm we continued without performing the two basic techniques.

Some of the stop words such as (why, what, where) like question words are also preserved as theyused to represent anger emotion. The emotion,“anger“ in a few instances as Example: Why is this happening to me?

Modified VSM-II: Our modified VSM-I is found to be tedious as some stop words are also considered. So, we decided to eliminate only those stopwordsthat would not contribute any emotions, i.e., stopwords such as functional words like prepositions, pronouns, etc. We created one emotionless-words list that contains articles (a, an, the), auxiliary verbs (be, am, is, are), prepositions (in, on, of, at), pronouns and few conjunction words such (as and, or, because) are not included. The conjunction words such as (nor, while, when) as it provides emotional values. The word "nor" is a negative word. The word "when" can be a question word that will invoke anger emotion. The negative words such as not and neither also not included in the emotionless word list. The words like (don’t, won’t),etc.are converted as (do not, will not), etc. These emotionless words will be eliminated as considering it as stopwords. Therefore, this method has the same number of steps as modified VSM-I and one additional step for the elimination of emotionless-words.

RESULTS AND DISCUSSION

We have created a corpus of 348 poems. We have used 10cross folding validation for a better result. So that, the training set won’t be biased. Details of Most frequently observed words of each emotion are indicated

Table 3: Most frequently used words in each emotion

Rank	Anger	Courage	Fear	Hate	Joy	Love	Peace	Sad	Surprise
1	Anger	Dreams	Eyes	Sorry	laughter	Love	Peace	Grief	Surprise
2	Love	Believe	Fear	Hate	Day	Heart	World	House	Morning
3	Day	Love	Stay	Love	Idiot	Loving	Human	Words	Words
4	Pain	Courage	Running	Hear	Box	Honey	Energy	Brought	Death
5	Mad	Yourself	Strong	Thou	Love	Hold	Violence	Love	Inside

Table 4: Result of corpus-based system

			Wrongly identified poems								
Emotion	Actual	Correctly identified poems	Anger	Courage	Fear	Hate	Joy	Love	Peace	Sad	Surprise
Anger	42	13	13	11	1	0	10	1	2	4	0
Courage	61	43	1	43	1	0	5	5	2	4	0
Fear	29	0	3	11	0	0	4	8	0	3	0
Hate	21	0	4	5	1	0	6	3	1	1	0
Joy	57	37	2	10	1	0	37	7	1	0	0
Love	59	31	1	9	0	0	9	31	6	3	0
Peace	29	17	0	3	0	0	3	5	17	1	0
Sad	41	11	4	10	1	0	13	2	0	11	0
Surprise	9	0	0	2	0	0	4	2	0	1	0
	348	152									

Table 5: Emotion recognition results of traditional VSM

			Wrongly Identified Poems								
Emotion	Actual	Correctly Identified	Anger	Courage	Fear	Hate	Joy	Love	Peace	Sad	Surprise
Anger	42	41	41	0	0	1	0	0	0	0	0
Courage	61	60	0	60	0	0	0	0	0	1	0
Fear	29	28	0	1	28	0	0	0	0	0	0
Hate	21	21	0	0	0	21	0	0	0	0	0
Joy	57	57	0	0	0	0	57	0	0	0	0
Love	59	56	0	1	1	0	0	56	1	0	0
Peace	29	14	0	14	0	0	0	1	14	0	0
Sad	41	40	0	0	1	0	0	0	0	40	0
Surprise	9	9	0	0	0	0	0	0	0	0	9
	348	326									

Table 6: Emotion recognition results of modified VSM-I

			Wrongly Identified poems								
Emotion	Actual	Correctly Identified poems	Anger	Courage	Fear	Hate	Joy	Love	Peace	Sad	Surprise
Anger	42	21	21	5	1	4	1	0	1	9	0
Courage	61	44	1	44	4	0	2	3	0	7	0
Fear	29	2	4	10	2	6	2	2	0	3	0
Hate	21	2	5	6	2	2	1	1	0	2	2
Joy	57	33	2	1	5	2	33	6	0	7	1
Love	59	32	2	10	4	1	1	32	6	2	1
Peace	29	20	0	0	0	1	1	5	20	2	0
Sad	41	13	10	9	1	1	3	2	1	13	1
Surprise	9	9	0	0	0	0	0	0	0	0	9
	348	176									

in Table 3 and 4 describes the result obtained in Corpus-based System. We have collected 348 poems in nine categories from the above-stated websites. About 2020 emotion words are tagged under nine categories. Among 348 poems 152 poems are correctly identified the emotion by the proposed system developed by us. Seventy words among 2020 words had the emotional ambiguity. Love poems are misinterpreted to joy classification. Sad poems are classified into the Joy classification because the poems were sad love poems. Surprise and Hate poems are not identified correctly due to the ambiguity of emotion words. Anger poems are misinterpreted to Joy and Courage poems. Hate poems are misinterpreted to love, sadness, anger and courage. Peace poems are interpreted to love and joy. The misinterpretations are due to the ambiguity of emotion words and the small size of emotion corpus. Untagged words are searched through the word net and sometimes it is possible to tag pronouns, or it will search continuously in Wordnet. Corpus should be very

Table 7: Emotion recognition results of VSM-II

			Wrongly identified poems								
Emotion	Actual	Correctly Identified poems	Anger	Courage	Fear	Hate	Joy	Love	Peace	Sad	Surprise
Anger	42	20	20	5	1	4	1	0	1	9	1
Courage	61	42	1	42	4	0	2	4	0	7	0
Fear	29	2	4	8	2	7	2	3	0	3	0
Hate	21	2	6	5	2	2	1	1	0	2	2
Joy	57	30	3	2	4	4	30	5	0	8	1
Love	59	30	2	12	4	1	1	30	6	2	1
Peace	29	20	0	0	0	1	1	5	20	2	0
Sad	41	13	10	11	2	1	2	1	0	13	1
Surprise	9	9	0	0	0	0	0	0	0	0	9
	348	168									

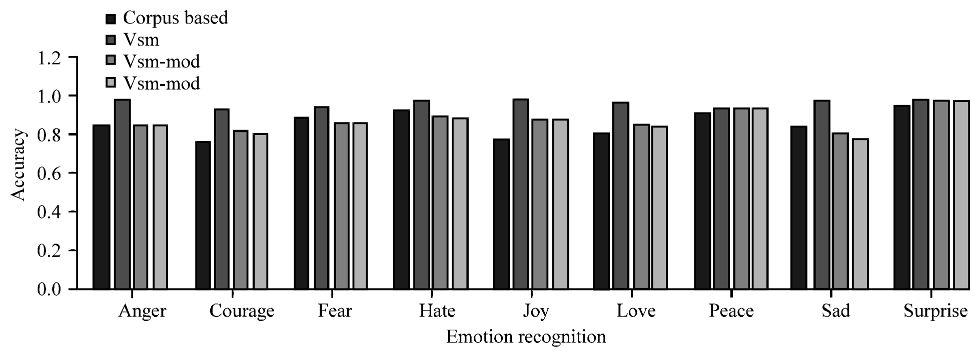

Fig. 2: Emotional recognization

large.Stop words cannot be removed. Untagged words contain named entities and stop words. Named Entity Recognizer has tobe implemented.

Table 5-7 describes the output of Corpus-based emotion recognition system, Traditional VSM, Modified VSM-I and Modified VSM-II. Traditional VSM shows the better result than other programs. Table 7 contains a sample poem and its results obtained by three methods. Fig. 2.

CONCLUSION

We have explored a technique to analyze automatically a poem and recognize the emotion of a given poem in four methods. We have developed the system of the automatic emotion recognition system by a corpus tagging method in bigram model. Negative emotion handled better in bi-gram model. Some natural language understanding should be attempted to handle the emotion of individual words via phrase level up to sentence level. This would result in phrases/ sentences tagged with emotions for the given input poetry. Disambiguation of emotions should be resolved by semantic analysis.

We have also explored VSM for the of automatic emotion recognition using a unigram model. We approached VSM in three ways. Among that Modified, VSM-I give better results. The main issue of VSM is large dimensionality. Searching keywords must match poetic words. Otherwise, it will lead to 'false positive' match. The poems with similar context, but different vocabulary would not be matched as it would result in 'false negative' match. These difficulties can be overcome by mathematical techniques such as singular value decomposition. Some natural language understanding should be attempted to handle the emotion of individual words via phrase level up to sentence level. This would result in phrases/ sentences tagged with emotions for the given input poetry. Negative emotion can be handled better. To overcome, some semantic analysis can be followed.

REFERENCES

Am, C.O., D. Roth and R. Sproat, 2005. Emotions from text: Machine learning for text-based emotion prediction. Proceedings of the Conference on Human Language Technology and Empirical Methods in Natural Language Processing, October 2005, Vancouver, pp: 579-586.

Bellegarda, J.R., 2010. Emotion analysis using latent affective folding and embedding. Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text, June 2010, Los Angeles, CA., pp: 1-9.

Danisman, T. and A. Alpkocak, 2008. Feeler: Emotion classification of text using vector space model. Proceedings of AISB 2008 Convention, Communication, Interaction and Social Intelligence, April 1-4, 2008, Aberdeen, Scotland, pp: 53-59.

Das, D. and S. Bandyopadhyay, 2009. Word to sentence level emotion tagging for Bengali blogs. Proceedings of the ACL-IJCNLP 2009 Conference Short Papers, August 2009, Singapore, pp: 149-152.

Dinu, G. and S. Thater, 2012. Saarland: Vector-based models of semantic textual similarity. Proceedings of the 1st Joint Conference on Lexical and Computational Semantics, June 2012, Stroudsburg, PA, USA., pp: 603-607.

Ghazi, D., D. Inkpen and S. Szpakowicz, 2010. Hierarchical versus flat classification of emotions in text. Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text, June 2010, Stroudsburg, PA, USA., pp: 140-146.

Minato, J., D.B. Bracewell, F. Ren and S. Kuroiwa, 2008. Japanese emotion corpus analysis and its use for automatic emotion word identification. Eng. Lett., 16: 172-177.

Olveres, J., M. Billinghurst, J. Savage and A. Holden, 1998. Intelligent, expressive avatars. Proceedings of the 1st Workshop on Embodied Conversational Characters, October 12-15, 1998, Lake Tahoe, California, pp: 47-55.

Sreeja, P.S. and G.S. Mahalaksmi, 2015. Applying vector space model for poetic emotion recognition. Adv. Nat. Applied Sci., 9: 486-491.

Straparava, C. and R. Michalcea, 2008. Learning to identify emotions in text. Proceedings of the ACM Symposium on Applied Computing, March 16-20, 2008, Fortaleza, Ceara, Brazil, pp: 1556-1560.

Wu, C.H., Z.J. Chuang and Y.C. Lin, 2006. Emotion recognition from text using semantic labels and separable mixture models. ACM Trans. Asian Language Inform. Process., 5: 165-183.