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3DText: Perceiving sentence-level text on 3-D model of emotions

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Abstract

Emotion is a psychological process which reveals the sentiments and feelings of a human being. Relating emotions detection process with psychological theory of emotions serves as the strong foundation for the system. In this paper, a model, 3DText, is proposed foe textual emotion detection. VAD (Pleasure, Arousal, and Dominance), a 3-D theory of emotion is used to extract features (P-A-D) from text. For this purpose, the dataset ANEW and WordNet are used. The objective of this paper is to determine VAD values at the sentence level of any size using word level VAD values for domain independent text. The proposed approach is evaluated on ISEAR and EMOBANK datasets. To the best of authors' knowledge, no such model exists till date.

Keywords: WordNet, Emotion, VAD values, ANEW dataset, Sentiment, Dimensional theory of emotions, RMSE, SME

1. Introduction

Emotion detection [1-3] is a field of affective computing in which emotions or sentiments of people are drawn from the text, speech, audio, videos etc. These days' social media is used as a platform by people to express their feelings. Hence, it has become a rich source of data that can play an important role in understanding, detecting and analyzing emotions. There are several applications of emotion detection in different domains such as in education sector, at hospitals, customer care, entertainment etc. Several models [4-10] are designed to detect the emotions from text. However, most of these models focus only on positive, negative and neutral emotion states. On the other hand, emotion is a psychological process, much more than only these three categories. So, there arises a need to move forward and work upon a set of emotions such as happiness, sad, fear, anger etc. Some researchers worked towards detecting discrete emotions. Still, the psychological aspect of emotion remained untouched. Incorporating psychological theory of emotions in emotion detection process serves as the strong foundation for the system.

Basically, 2 types of emotion models can be used for emotion mining from text: Categorical and Dimensional Emotion model. Categorical Emotion model are based the assumptions that there are fixed set of emotions. For instance, according to Ekman model [11], only six basic emotions (Fear, Disgust, Anger, Sadness, happiness and Surprise) exist. In case of Dimensional Emotion model [12], each emotion is represented by some VAD (3-Dimensions) values in the range of 1-9. VAD stands for Pleasure, Arousal, Dominance factors. Combination of VAD represents a number of emotions in a 3-D space. It is also known as 3-Dimension model of emotions. Pleasure (P) is the measure of pleasure or displeasure of a feeling. Arousal (A) is the degree of intensity of an emotion. Dominance (D) represents that whether an emotion is under control or not? For example, emotion HAPPY has more VAD value as compared to emotion SAD because HAPPY is more pleasant, and has more intensity and dominance compare to SAD. Figure 1 shows how the values of Valence (Pleasure- Displeasure), Arousal (Calmness-Excitement) and Dominance (being controlled-in control) are distributed on the 3-D plane [12]. Most of the datasets available work with the categorical theory of emotions [13]. Some dataset exists for VAD score only at word level [14-15].

In this paper, a model, 3DText, is proposed to obtain the VAD values of the sentence-level text while mapping it at 3-D model of emotion. To pursue this goal, two datasets ANEW [14] and WordNet [16] are used. ANEW dataset is a 3-Dimensional Emotion model which has 1030 words. Each word has word_id, Word frequency, Pleasure, Arousal and Dominance Mean and standard deviation (SD). WordNet dataset is a corpus of English words. It contains synonyms, antonyms and definitions of English words with 155327 words arranged in synsets of 175979 for an approximately of 207016 combinations of word sense pairs. First step is to clean the text by applying various preprocessing steps. Then, presence of word "not", if any, is managed using antonyms. At next, unknown words are handled using WordNet corpus. Here, unknown words are the words which are not in the ANEW dataset and hence their VAD values are unknown. Once VAD value is obtained for all words, finally, a

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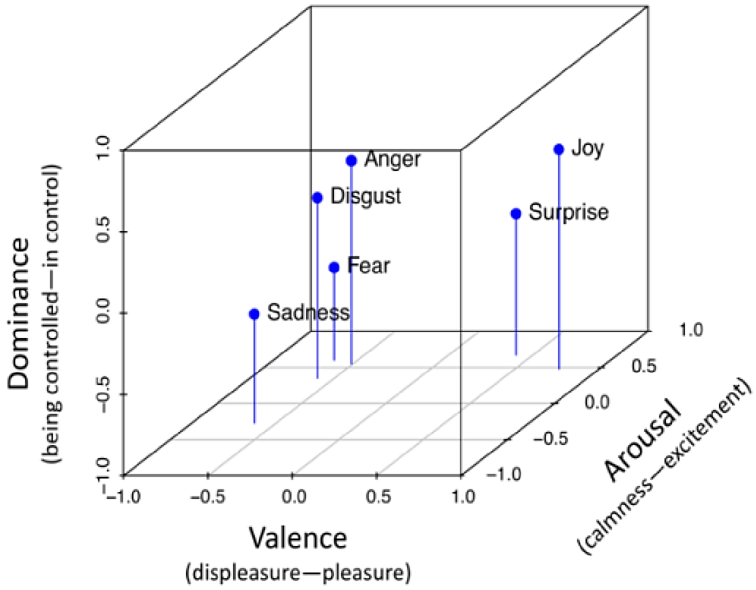

Figure 1 3-Dimension VAD values (Adapted from [12])

cumulative VAD value is obtained for the sentence-level text.

The main highlights of the paper are:

1. Proposes a mapping mechanism of sentence-level text to 3-D model (VAD model).
2. Unlike [5-7], a domain independent model is designed.
3. In contrast to other existing models, unknown words are handled instead of ignoring them.
4. Moreover, there is no limit on length of the sentence to be processed.
5. The proposed method has been evaluated on ISEAR and EMOBANK datasets.

The paper is organized as follows: Section II presents background study which includes detailing about dataset used and the state-of-art. Detailed implementation and results are discussed in Section III and Section IV respectively. The paper is concluded with future directions in Section V.

2. Background study

2.1 Dataset used

In the paper, 4 datasets: ANEW, WordNet for getting VAD values, EMOBANK and ISEAR datasets for testing are used. ANEW is used to get the VAD values of words. WordNet corpus is used to find the synonyms or similar words and antonyms. For testing

ANEW (Affective Norms for English Words) [14] dataset is a 3-Dimensional model which has 1030 instances in 3-D form (VAD value) in the range of 1-9. It has 8 attributes: Pleasure Mean, Arousal Mean, Dominance Mean, Arousal Standard Deviation (SD), Pleasure SD, Dominance SD, Word Number and Word Frequency. In the paper, VAD Mean values are used. For example, VAD values for word 'HAPPY' are (8.21, 6.49, 6.63) which shows that it is pleasant word with high intensity and dominance. Similarly, VAD values for SAD are (1.61, 4.13, and 3.45).

WordNet [16] is a lexical dataset of English Language which has synsets (synonyms), antonyms, and short definitions along with senses of English words. It contains synonyms, antonyms and definitions of English words with 155327 words arranged in synsets of 175979 words for an approximately of 207016 combinations of word sense pairs.

EMOBANK [17] dataset is a dimensional model where all 3D values i.e. Valence, Arousal and Dominance values has been given. It has 10063 instances but after preprocessing or cleaning it remains 9329 instances. Whereas ISEAR [13] dataset has 7667 instances which has emotion (7 emotions i.e. joy, anger, disgust, fear, guilt, sadness and shame) labels.

2.2 Literature review

Textual emotion detection is an important and interesting domain addressed by many researchers in different ways using different models such as categorical model or dimensional model. In categorical models, the text is directly mapped onto some discrete emotions [18-25] without understanding the underlying psychology. It is normally carried out using some machine learning classification algorithms which normally have a very high time complexity. Few researchers worked on textual emotion detection using dimensional theory of emotions. Here, we present the state of art of textual emotion detection using 3-D emotion theory.

Pambudi et al. [2] worked towards identifying the correct definition of each word in ANEW dataset using ISEAR dataset. Each word of ANEW is mapped to an emotion using a Thayer's model with four classes, i.e. JOY, ANGER, SADNESS, and CALM. After that, each word from ANEW dataset mapped with a sentence if it was in ISEAR dataset and identified its emotion label. This experiment achieved 66.44% accuracy on 149 words.

Rachman et al. [3] developed a corpus based model of emotions (CBE) using ANEW and WNA datasets. In this paper, the authors used 2 models to develop the CBE. Categorical models that used Ekman 6 emotion labels and Dimensional model which has a numeric score of Valence, Arousal and Dominance for each word. This experiment extracted the unknown word's (not present in ANEW dataset) emotions using WNA and Adapted Lesk Algorithm. Later, Latent Dirichlet Allocation (LDA) has been used to widen the CBE automatically. WNA with ANEW got 0.50 F-measure, whereas CBE using LDA got 0.61.

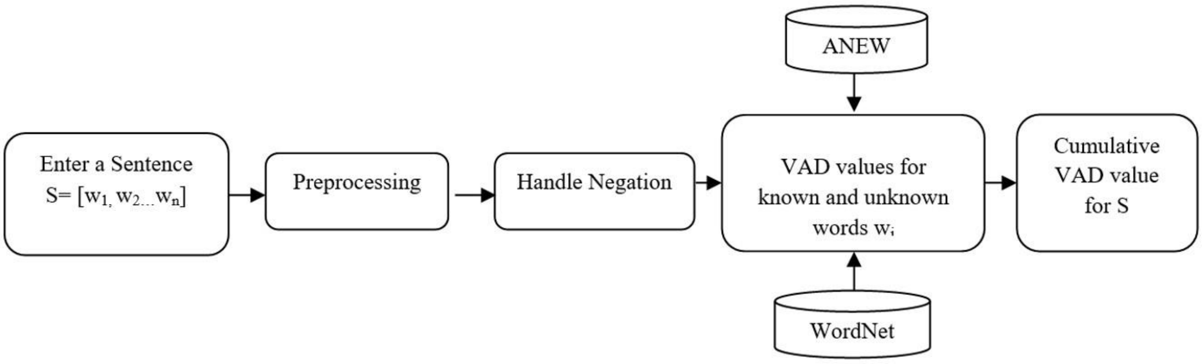

Figure 2 Proposed Model: 3DText

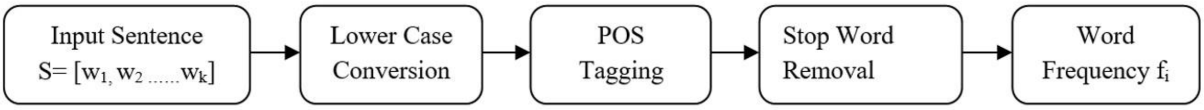

Figure 3 Steps of Preprocessing

Dodds and Danforth [4] measured the valence (happiness) factor of written songs, blogs and the States of Union addresses. Firstly, the overall balance of a text is calculated using the Valence score only. In this research, only the words present in ANEW dataset are considered while other words are ignored. It is found that happiness score of songs is decreased in 1960s to half 1990s and is stable after that, whereas, blog's happiness score is increased from year 2005 to 2009**.**

Islam and Zibran [5] used SEA (Software Engineering Arousal), SentiStrength-SE and ANEW dataset in their research work to measure emotions in software engineering domain. In this paper, the authors created a software tool known as DEVA (for software engineering text) and a dataset which has 1795 tagged comments. DEVA is constructed using two dictionaries, for Arousal and Valence both. It also defined 7 heuristics to further refine the results. SEA and ANEW dataset are used for creating Arousal dictionary and SentiStrenth-SE is dataset used in Valence dictionary. In this paper, both Arousal and Valence score are mapped from range [1, 9] to [-5, +5]. These researchers worked only on 2-Dimensions i.e. Arousal and Valence. DEVA is compared with TensiStrength and baseline and it is found to be better than others**.**

Islam et al. [6] developed a machine leaning tool known as Marvelous for emotion detection such as excitement, stress, and nervousness in the software engineering text. Later in this research this tool was compared with DEVA [5] and it is found that Marvelous has 19.04 % and 08.19% more precision and recall respectively as compared to DEVA**.**

After thorough literature survey it is observed that though, researchers are working towards emotion detection from text using dimensional theories, the work is limited to either word-level only or is restricted to a specific domain of software engineering or addressing only 1-D or 2-D models. To the best of the authors' knowledge, no domain independent, psychological theory based textual emotion detection model exist which works at sentence-level text for all 3 dimensions (namely V, A, D) and also handles unknown words.

3. Proposed work and implementation

In this paper, we propose a domain independent model, 3DText, to obtain the VAD values of the sentence-level text while mapping it at 3-D model of emotion. The whole process involves four steps (as shown in Figure 2): preprocessing, handling negation, obtaining VAD values for all words and finding cumulative VAD values. The task is carried out using two datasets: ANEW and WordNet.

3.1 Preprocessing

At first, input text is cleaned using different processes such as tokenization, stop word removal, all lower case conversion, and replacing slang language. The tokenization is the process that splits the whole sentence into tokens of words and makes the text or sentence easy to handle. Using Stop Word Removal process, all unnecessary words are removed from a sentence so that important words can be focused. Text is converted to lower case to have uniformity and Slangs are replaced with actual words s that they can be matched in standard corpus. Then, POS tagging is being done. It is used a very important part of preprocessing step in NLP to find the part of speech of each word in a sentence. After this, the occurrence (word frequency) of each word in a sentence is calculated and represented as f_i. For instance, if f_i=1, it means that occurrence of word (w_i) is 1 in that particular sentence .In the proposed work, it is used to find the best definition from WordNet dataset and to handle the "NOT" word in a sentence (fully described in subsequent step). Figure 3 shows the steps of preprocessing.

For instance, let the input is '**I am Sad and nervousness'**

Then after preprocessing step this sentence become: **[('sad', 'JJ',1), ('nervousness', 'JJ',1)]**

3.2 Handling negation

After preprocessing, next step is to handle negation due to occurrence of word "NOT". Based upon the common observation, most of the times, word "NOT" precedes either adjective (JJ) or verbs (RB). So, here, after preprocessing, we check if not word is present in the sentence or not. If it is present, then the immediate next word of "NOT" word is checked in the sentence. If the successor word is either 'Adjective (JJ)' or 'Verb (VB)', its antonym is obtained from WordNet. Finally, the antonym is substituted in place of

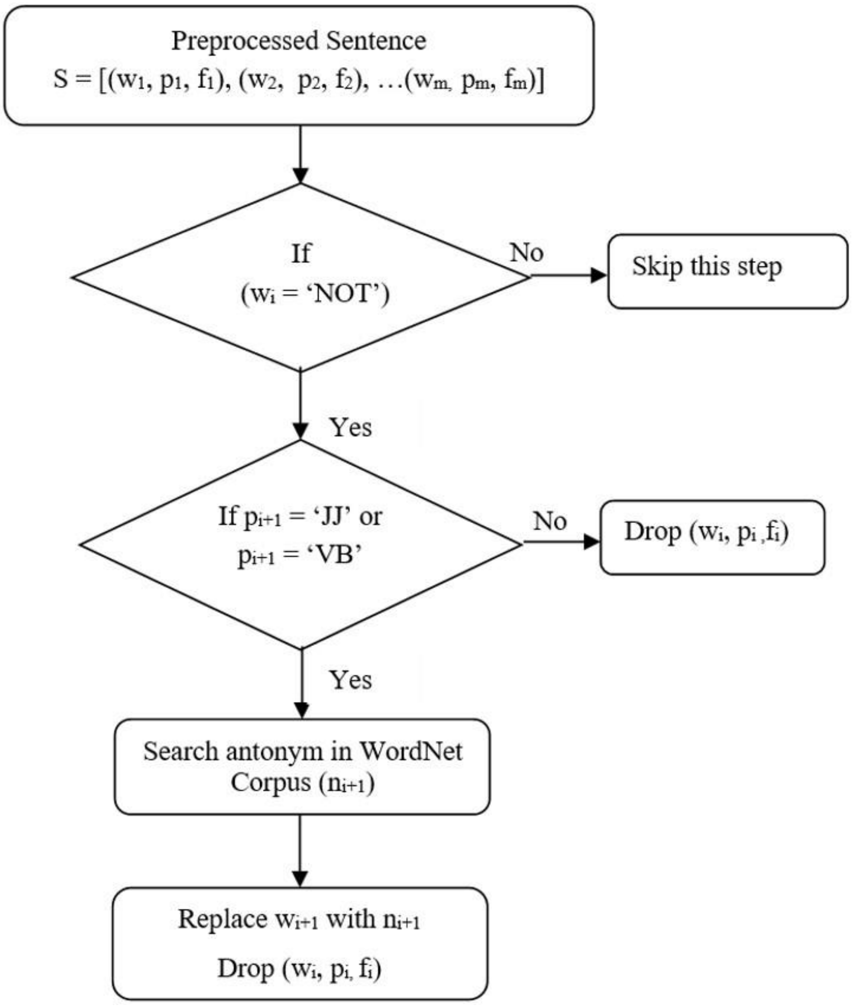

Figure 4 Steps to handle negation

"NOT" and the immediate successor word in the sentence. Now, this new sentence will be the input sentence for the next step.

Figure 4 shows the set of steps followed to handle the 'NOT' word in a sentence. WordNet corpus is used to find antonym of the word. In the figure, w_i represents the i^{th} word of the preprocessed sentence and p_i is its POS tag. 'JJ' means adjective 'VB' means verb. n_{i+1} is the antonym of w_{i+1} word.

For instance, let the input sentence is: **'I am not Happy'**

After preprocessing (Step 1): **[('not', 'RB',1), ('happy', 'JJ',1)]**

After handling negation (Step 2): **[('unhappy', 'JJ',1)]**

Obtaining VAD values for each word

This step is to find the VAD values for each word of the given sentence. For this task algorithm is adapted from [3] as illustrated in Figure 5 and 6. If the word is available in ANEW dataset, then the word is called as known words and its value is directly fetched from ANEW. Else, the word is called unknown word.

First, synonym of the unknown word is searched in ANEW, if present values are fetched. Otherwise Adaptive Lesk algorithm [26] along with Euclidean distance formula and Gauss-Jordan Elimination method are used to obtain the values for the unknown word. This process is called as Automatic Tagging Procedure and explained in Figure 6. For more details, readers are advised to refer [3]. This way VAD values of each word of the sentence is obtained and represented as

$S=[(x_1, V_1, A_1, D_1, f_1), (x_2, V_2, A_2, D_2, f_2), \ldots, (x_n, V_n, A_n, D_n, f_n)]$

where $(x_i, V_i, A_i, D_i, f_i)$ represents i^{th} word of the sentence with its valence, arousal and dominance values and frequency of occurrence as f_i.

3.3 VAD value at sentence-level

Once VAD value of each word is obtained in the sentence, next step is to calculate the cumulative VAD value for the whole sentence. 3DText views the previous stage output as

$S= [(x_1, V_1, A_1, D_1, f_1), (x_2, V_2, A_2, D_2, f_2), \ldots, (x_n, V_n, A_n, D_n, f_n)]$

Now, overall VAD value of the sentence is computed as follows using Equation 1, 2, 3.

$$V_s = \sqrt{\frac{\sum_{i=1}^{n} (V_i f_i)^2}{\sum_{i=1}^{n} (f_i)}} \qquad (1)$$

$$A_s = \sqrt{\frac{\sum_{i=1}^{n} (A_i f_i)^2}{\sum_{i=1}^{n} (f_i)}} \qquad (2)$$

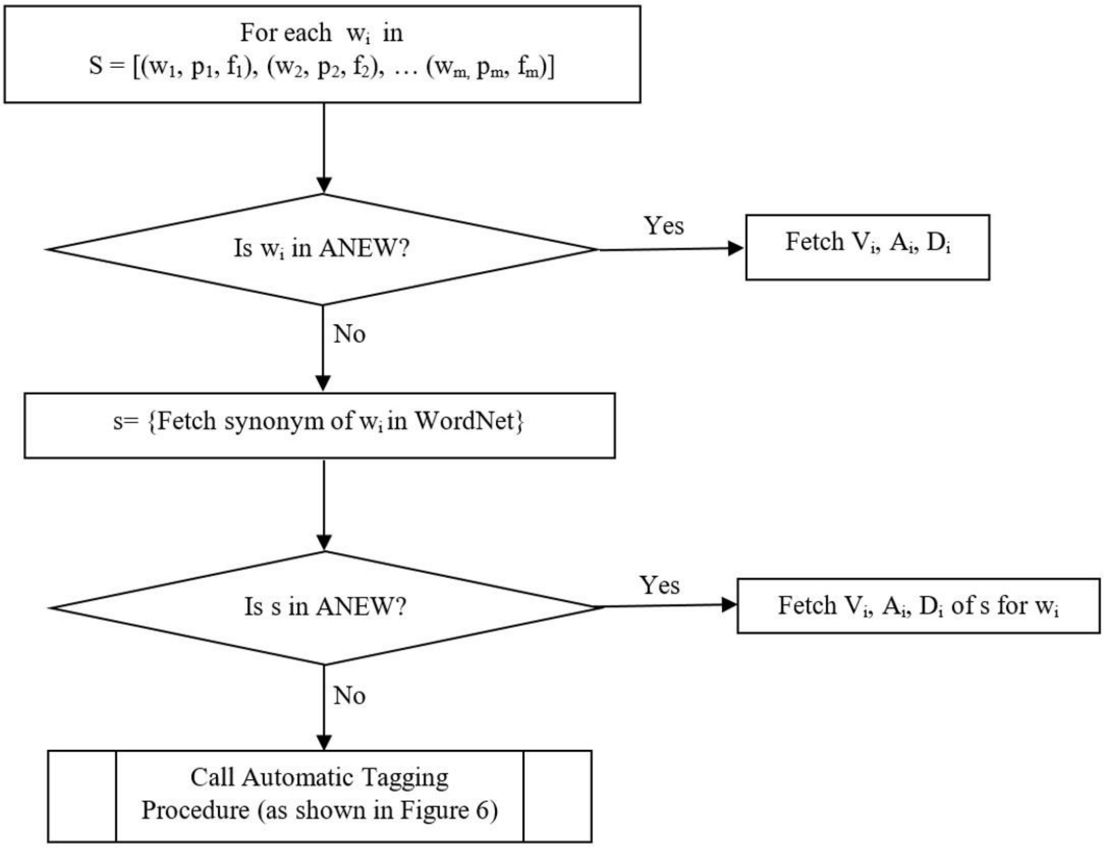

Figure 5 Steps to obtain word level VAD values [3]

$$D_s = \sqrt{\frac{\sum_{i=1}^{n}(D_i f_i)^2}{\sum_{i=1}^{n}(f_i)}} \tag{3}$$

where V_s is the valence value, A_s is the arousal value and D_s is the dominance value of the sentence.

A schematic example for measuring the cumulative VAD values of the input sentence: “The quick brown fox jumps over the lazy dog.”

KNOWN (ANEW)	**Valence (V_s)**	**Arousal (A_s)**	**Dominance (D_s)**	**f_i**	Using eq (1), eq (2), eq (3)
1. quick	6.64	6.57	6.57	1	
2. lazy	4.38	2.65	4.07	1	**V_s** = 5.65579314
3. dog	7.57	5.76	6.25	1	
UNKOWN					**A_s** = 4.4548208
4. brown	4.7510494	3.5290542	3.42495112	1	**D_s** = 4.89983215
5. fox	6.01115459	2.25363669	4.99429571	1	
6. jumps	3.55564714	4.26315242	2.92994035	1	

4. Results and discussion

For the comparison of the proposed model, we selected two closely related models: DEVA: Sensing Emotions in the Valence Arousal Space in Software Engineering text [5] (Model_1) and Measuring the Happiness of Large-Scale Written Expression: Songs, blogs, presidents [4] (Model_2). Table 1 illustrates the comparison of the proposed model (3DText) with Model_1 and Model_2.

It can be observed from the Table 1 that 3DText, the proposed model is a domain independent, psychological theory based textual emotion detection model which works

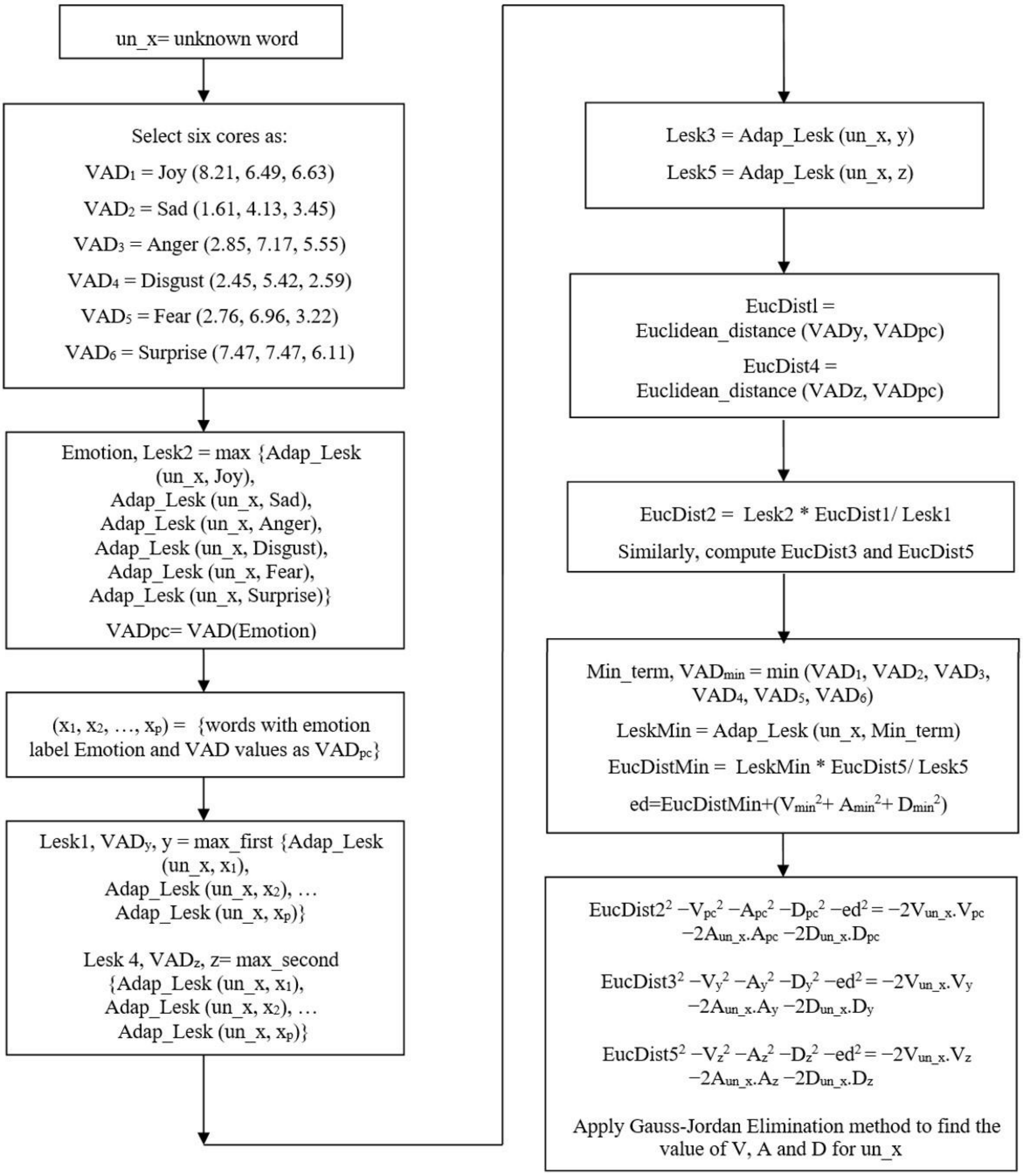

Figure 6 Steps of Automatic Tagging Procedure [3]

Table 1 Comparison of 3DText with existing Models

	(Model_1) [5]	**(Model_2) [4]**	**3DText: Proposed Model**
Dataset Used	ANEW, SEA and SentiStrength	ANEW	ANEW and WordNet
Dimensions Model Used	2-D (Valence and Arousal)	1-D (Valence)	3-D (Valence, Arousal and Dominance)
Cumulative Value Approach	MIN-MAX	Absolute Mean	Root Mean Square
Does Model Handle unknown words?	No, ignore unknown words in sentence	No, ignore unknown words in sentence	Yes
Handle Negation	Assume and reverse the Arousal of the word	No	Yes
Range of VAD values considered	[-5 +5]	[1-9]	[1-9]
Set of Emotions Considered	Excitement, stress, depression, relaxation and Neutral	Happiness	Worked on 3-D space, so any emotion can be detected
Domain used	Software Engineering	Domain Independent	Domain Independent

Table 2 Excerpts of ISEAR dataset [13]

S.No	Sentence	Emotion Label	VAD values [12]
1.	During the period of falling in love	Joy	8.21, 6.49, 6.63
2.	When I failed an exam	Sadness	3.71679588,4.2060114, 2.8269206
3.	When I was the first to arrive at the scene after an accident	Fear	2.76, 6.96, 3.22
4.	Several good friends made me a surprise visit and this made me happy They are my closest friends and we had not seen each other for a long time	Joy	8.21, 6.49, 6.63
5.	I felt happy when I received the letter telling me that I had been admitted to the university	Joy	8.21, 6.49, 6.63
6.	Being treated unfairly	Anger	2.85, 7.17, 5.55
7.	At the underground station	Disgust	2.45, 5.42, 2.59
8.	When I was cycling to school	Fear	
9.	Breaking up with a girl	Sadness	3.71679588,4.2060114, 2.8269206
10.	When I saw a person I had not seen for a long time	Joy	8.21, 6.49, 6.63
11.	Our tutorial group was soon to be divided	Fear	2.76, 6.96, 3.22
12.	Can not think of any situation	Disgust	2.45, 5.42, 2.59
13.	The inability to read a book at college	Sadness	3.71679588,4.2060114, 2.8269206
14.	When I am accused of something I have not done	Anger	2.85, 7.17, 5.55
15.	When I was finally qualified for my profession	Joy	8.21, 6.49, 6.63
16.	Quarrel in the family	Anger	2.85, 7.17, 5.55
17.	When I get a hug from someone I love	Joy	8.21, 6.49, 6.63
18.	When I began to read a thick book	Sadness	3.71679588,4.2060114, 2.8269206
19.	When my son has a pain in his leg for no apparent reason	Fear	2.76, 6.96, 3.22
20.	When I argue with my boyfriend	Anger	2.85, 7.17, 5.55

Table 3 RMSE on EMOBANK dataset

	Valence RMSE	Arousal RMSE	Dominance RMSE
RMS Approach	1.9745781709999997	0.48433076500000016	1.0311140749999996
Absolute Mean Approach	1.9156598089999997	0.5575680799999998	0.9586054429999997
MIN-MAX Approach	2.7	2.0	2.2

Table 4 SME (Square Mean Error) on EMOBANK dataset

	Valence SME	Arousal SME	Dominance SME
RMS Approach	3.898958953389704	0.23457628992548538	1.0631962356631048
Absolute Mean Approach	3.6697525038179153	0.31088216383488615	0.9189243953492258
MIN-MAX Approach	7.290000000000001	4.0	4.840000000000001

at sentence-level text for all 3 dimensions (namely V, A, D). Moreover, it can handle unknown words. Mapping of text to 3-D space makes the model capable of handling all emotion states.

Further, to test the model, we used ISEAR dataset [13]. We evaluated our proposed model on ISEAR and EMOBANK dataset and get VAD value and then calculate RMSE and SME error. ISEAR dataset contains 7666 sentences tagged with appropriate emotions. We analyzed the VAD values of 20 sentences randomly picked from ISEAR dataset shown in Table 2. The analysis is carried out for three different cumulative value approaches: Min-Max, Absolute Mean and Root Mean Square for both known words only and all words.

It is observed that when unknown words are not handled, irrespective of the cumulative value approach, 50% sentences are assigned VAD value as (0,0,0). The reason is that each word of that sentence is either stop word or a unknown word and hence ignored. For example: Sentence *"When I failed an exam"* actually represents emotion sadness but when these three approaches are applied, the values comes out to be 0(zero) which represents no emotions. This leads to the understanding that the unknown words cannot be ignored simply. These words are unknown because they are not present in ANEW dataset. However, they do carry some emotions. Hence, in next set of experiment we applied handling of unknown word algorithm and then applied, these three cumulative value approaches. RMS (proposed model) is handling the negation and gives VAD value accordingly. For example: "Several good friends made me a surprise visit and this made me happy They are my closest friends and we had not seen each other for a long time" according ISEAR dataset, it represented "joy" emotion but our proposed model (RMS) gives its VAD value which are near to "Surprise" emotion and it looks like SURPRISE also.

To evaluate the proposed approaches (MIN-MAX, Absolute Mean and RMS) RMSE (Root Mean Square Error) and SME (Square Mean Error) for all 3-D (Valence, Arousal and Dominance) values have been used. The Root Mean Square and Squared Mean Error of MIN-MAX approach is higher than Absolute Mean and RMS models when evaluated on both datasets. It is shown that RMS method is performing better than other methods. Table 3-6 represented that RMSE and SME value of all three proposed methods for both EMOBANK and ISEAR datasets.

Table 5 RMSE on ISEAR dataset

	Valence RMSE	Arousal RMSE	Dominance RMSE
RMS Approach	1.5358815080000001	1.6072013429999998	0.40858749500000036
Absolute Mean Approach	1.8805210310000007	3.960510158	0.38093201200000015
MIN-MAX Approach	4.63	4.96	5.09

Table 6 SME on ISEAR dataset

	Valence SME	Arousal SME	Dominance SME
RMS Approach	2.3589320066163544	2.583096156941003	0.16694374107037532
Absolute Mean Approach	3.5363593480333053	15.685640711621184	0.14510919776636827
MIN-MAX Approach	21.436899999999998	24.6016	25.908099999999997

5. Conclusion and future directions

The paper presents a domain independent, psychological theory based textual emotion detection model, 3DText, which works at sentence-level text for all 3 dimensions (namely V, A, D). Since the model works on textual data, it can easily be applied to live speech also simply after converting the speech to text. Moreover, it handles unknown words and negation both. ANEW t dataset is used for obtaining VAD values. WordNet is used to obtain the similar words in case give word is not present in ANEW. The proposed model is compared with two existing models on the basis of several parameters. In addition to this, model is implemented for three different cumulative value approaches: Min-Max, Absolute Mean and Root Mean Square for both known words only and all words. RMS method is performing better than other methods. In this approach, there is no limitation on the text size and it is applicable only for written text. The VAD value which has been obtained has no fluctuation within the text. In future, a better approach can be developed to handle negation in the sentence. Moreover, VAD values can be mapped to emotions using 3-D model. Moreover, the model can be extended to handle the conversation data on person basis in the given time scale

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