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A Novel Semantic Approach for Intelligent Response Generation using Emotion Detection Incorporating NPMI Measure

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Abstract

Expressions and emotions are the most common way of communication in day-to-day life. In the age of Artificial Intelligence and technological advancements, the entire human race finds itself amidst many software driven voice-assistants. The only reason AI cannot excel and spread its limits is that humans can interpret, understand and express in the form of emotions and these AI-driven systems cannot. Hence, there is a need for a proper methodology for the interpretation of emotions based on both text and speech. In order to accomplish this task, a light weight computational linguistic semantic approach has been proposed for detecting emotions and generating response incorporating NPMI and NAVA words, bridging the gap between Semantics and Natural Language Processing. Experimentations are conducted for the real-word TDIL dataset for emotions such as joy, sorrow, anger, disgust, and fear. The proposed approach yields an accuracy of 96.155% for the emotion joy and 82.44 % for fear which definitely is the best-in-class accuracy for such systems.

Keywords: Chunking; Folksonomies; Role-based Ontology; Semantic Similarity; Knowledge Graph.

1. Introduction

A wide-study of emotions is being done currently in various sectors, as they form one of the most fundamental elements of humans. These structural behaviours of varied emotions have always attracted various scholars and researchers in the field of Computer Science. Human-computer Interaction is the area where these researchers concentrate on the study of various facial expressions and the depiction of emotions is carried out. With the massive growth of Artificial Intelligence and by the introduction of various intelligent computer assistants like Google's own Google-assistant, Microsoft's Cortana and Siri from Apple, it becomes very essential to devise a flexible and efficient method for the detection of emotions and to generate corresponding apt and intelligent responses. Google at its international event i.e., Google I/O 2018 has introduced a new feature called, Google Duplex that is built into their assistant. Interaction of the computer-driven assistant with the humans is enhanced by this feature in a huge way and indicates that there is a lot of room for research available in the sector. Therefore, in the computational linguistics, from an applicative point of view, it becomes increasingly important to devise an approach for the automatic detection of emotions. This paper tends to bridge this gap by proposing a novel and a hybridized model incorporating NPMI semantics to yield effective and efficient accuracies. This paper has been modelled on all the basic emotions like Happiness, Sorrow, Anger, Fear, and Disgust.

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There is a paradigm shift in business strategy specifically in online marketing avenues [1], where reviews on products are flooded which need to be semantically analysed [2] [3] [4] for the actual emotion conveyed. Emotion is a highly complicated characteristic [5], that is usually multifaceted. Inferring emotional states of various people is computationally complex as well as context-sensitive [6]. Owing to this, the scheme for detection emotions must be designed at several levels of cognition, keeping in mind various complexities that can arise. Words and their structure in Natural Language plays a central role in detecting emotions [7].

The reason for the extraction of NAVA (Noun Adjective Verb Adverb) is that these are the essential effect bearing words which form the most crucial part in influencing the emotion that is expressed by a person. These words express the effect more compared to all other words available in a sentence. For instance, in the sentence "Kevin got lots of new toys for his birthday" the words 'birthday' 'new' 'toys' together convey the emotion of happiness which may not be conveyed when the words are individually considered. These are called as the NAVA words. In the sentence "It feels Sad", the words 'sad' and 'feels', tagged as an adjective and verb respectively, are extracted. These words efficiently gauge the emotional affinity.

There is a dire need for the formulation of context-independent emotion detection model which incorporates both text and speech. Moreover, in the era of Semantic Web 3.0. there is a requisite to detect emotions in the text specifically the tweets and other social media. However, an alternative approach to sentiment analysis by combining both text and speech is a necessity so that confusing emotions like fear, disgust, and anger can be identified and differentiated. A reliable light weight approach for the detection of various emotions using both text and speech has been devised. The incorporation of semantics using NPMI techniques have yielded a much more intelligent and robust model with very promising accuracy which does not seem to be possible with the presently available models. The incorporation of NAVA words makes the proposed strategy a lexicon-driven approach and yields promising results. The proposed model bridges the formal gap between semantics and natural language processing and an intelligent context-independent approach that imbibes the semantics of NPMI has been proposed. The experimentations have been conducted for real-world TDIL dataset and the performance evaluation has been carried out.

The remaining paper organization is given as follows. Section 2 provides the insights of related literature of research. Section 3 illustrates the architecture of the proposed model. Section 4 describes the implementation in detail. Result and performance analysis are discussed in Section 5 and in Section 6, the paper is concluded.

2. Related works

Tang et al., [8] proposed a topic-emotion transition model considering multi-level social emotions. The modelling of emotions and topics in the successive statements is done by encompassing Markov chain. Ashutosh et al., [9] have proposed a method for the detection of facial expressions. The computational cost was tried to be kept minimal. The model incorporated Distance Metric Learning (DML) for improving the results. Kanjo et al., [10] have modelled a method of emotion detection from multiple modalities. Various physiological signals are being incorporated. The model is being employed by the usage of a series of algorithms like that of Convolutional Neural Networks and Long Short-term Memory Recurrent Neural Networks. Hasan et al., [11] have devised a model for emotion detection in the form of text streams. Analysis of Twitter data is done for the implementation of the model and a soft classification approach is proposed. Pandey et al., [12] have proposed a model for the detection of emotions. The devised model is independent of the subject given. For the detection, various EEG signals from humans have been studied and the model is implemented. DEAP benchmark database has been incorporated. Lotfian et al., [13] have proposed a model for emotion detection. The proposed model is lexical Dependent and is achieved by using Synthetic Speech Reference. Various voices and Text-to-Speech approaches have been considered. Luz et al., [14] have devised a model for emotion detection based on the usage of Convolutional Neural Networks. The entire implementation has been done on a physiological signals dataset, called (AMIGOS). For the process of emotion recognition, various classic Machine Learning methods have been used. Zamil et al., [15] have proposed a model for the detection of emotions. Various Speech signals have been used for the model and a Voting Mechanism was formulated on Classified Frames. Castillo et al., [16] have proposed a strategy for emotion detection in a smart environment. The model is regulated from a personal robot, that works as an assistant. A full description is given for all the features of the proposed personal assistant robot.

Srinivasan et al., [17] have proposed a method for emotion detection by using text data. Latent Dirichlet Allocation (LDA) topic modeling has been incorporated for the proposed model. Tafreshi et al., [18] have put-forward a model for emotion detection and annotation at sentence and clause level. The model is encompassed by the incorporation of a multi-genre corpus. Majumder et al., [19] devised a model for emotion detection which is mainly used to detect the emotions in conversations. An attentive RNN strategy is incorporated for the proposed model. Jayakrishnan et al., [20] have proposed a model for multi-class emotion detection. The implementation is done for Malayalam novels. Ghosh et al., [21] have devised a model for emotion detection based on typing on smartphones. Deep Neural Networks have been incorporated. Antonio et al., [22] have modelled an architecture for emotion detection and also regulation. A smart environment was encompassed. Laperdon et al., [23] have proposed a model for real-time emotion detection. Various audio interactions have been studied for the implementation of the model. Bandhakavi et al., [24] have devised a model for emotion detection from text. The process was achieved by the Lexicon generation. Patwardhan et al., [25] have devised a model for the detection of various emotions. The process is achieved by incorporating multiple mixed modes of data. The semantic approaches discussed in [26-32] can be a part of this work and would definitely have a huge impact on emotion detection and response generation. However, the semantic approaches alone have to be incorporated as [26-32] employs semantic strategies for various other domains as well as motives. From this, it is clearly inferable that semantics plays a vital role and creates a huge impact in applications involving the web or natural language computing.

3. Proposed System Architecture

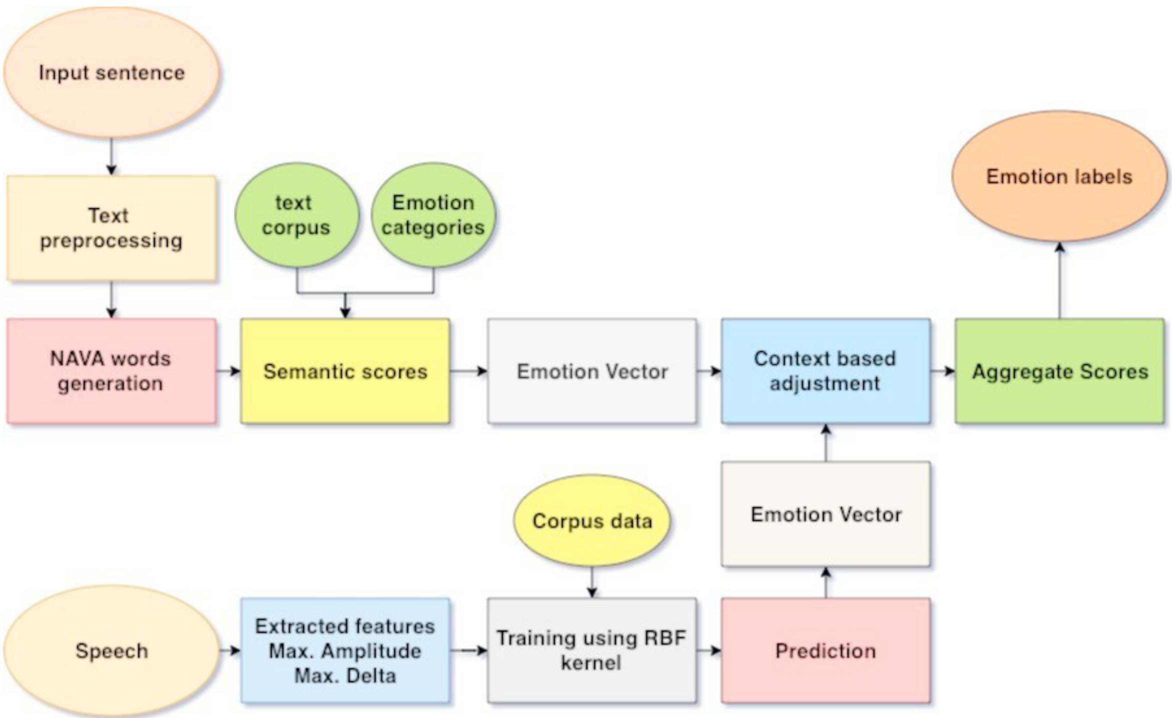

Figure 1: Proposed Architecture

3.1 Dual tunnel processing

The earlier models carried out, detect emotions based on text alone. These kinds of methods pave-way to a lot of limitations. These methods are incapable of detecting emotions of the phrases like “I got the first mark!!”, where there is no indication of any happiness-associated word. These models are also not capable of detecting sentences like “the performers were greeted with joyless cheer”. This sentence is detected as a neutral emotion by these models. In order to fill this gap, the proposed system architecture uses both sound and text input to efficiently determine the emotion of the sentence. As shown in figure 1, an extra tunnel is added which processes speech as a sound wave rather than a text. Based on this text an emotion vector is obtained by training the data. This emotion vector is compared with the result obtained from processing the speech using text and the final emotion is recognized.

3.2 Pre-processing

Initially, the sentence is input into the system for the detection of emotion. This text is then tokenized into sentences, and the sentences obtained are further tokenized into words. These words then are tagged using parts of speech tagging and NAVA (Noun Adjective Verb Adverb).

3.3 Semantic Module

A text corpus is input in this module and emotion categories are incorporated. Semantic scores are then calculated to obtain an Emotion Vector. This obtained vector is obtained from text processing purely and is kept aside for future use.

3.4 Speech processing

In this step speech is input and by processing, features are extracted based on maximum amplitude and maximum delta. These features are then added with the input corpus data and are trained using RBF kernel to obtained prediction. Using this prediction another emotion vector is generated.

3.5 Syntactic module

The obtained emotion vectors are passed through the Syntactic module in which Context based Adjustment is done, followed by sentence level analysis to which aggregate scores are calculated. Finally, the appropriate emotion labels are assigned, and the emotion is predicted. In this way using both speech and text parallelly, the emotion is predicted effectively.

3.6 PMI and NPMI for each NAVA words

Pointwise Mutual Information (PMI) [33] of the formulated NAVA words is calculated by using Equation (1). PMI computes the degree of association between words and serves as the key indicator for response generation by aligning with and identifying the emotions. However, it is a relative measure and needs normalization. The NPMI (Normalized Point-wise Mutual Information) [34] is a normalized PMI value and is depicted in Equation (2) which is the core strategy that has been employed in the proposed approach. If two words co-occur more frequently, then they tend to be semantically related. The method chosen here is PMI (Point-wise Mutual Information) followed by NPMI. Equation (1) depicts the theoretical formula for the calculation of PMI for two words. Equation (2) and (4) are used for the calculation of PMI and NPMI respectively for the NAVA words formulated. Depending on the obtained NPMI scores the sentences are arranged properly into various sets. Now, these sets are classified based on various emotions. The emotions considered are e = {happiness, sorrow, anger, surprise, fear and disgust}. It becomes difficult to compute an emotion vector for a word without context. One method is to use the NPMI score between the word and another word representing an emotion. This method is not always desirable because more than one word can express the same meaning. For example, ‘joy’ and ‘glad’ both express ‘happiness’. Hence using just one generic word is not useful always. It is recommended to use different words for this process. Equation (3) depicts the calculation of NMPI scores for the words without a proper context with the generic words that represent emotion and the emotion vectors are calculated using the Equation (4).

PMI between two words x and y

$$\mathrm{PMI}(\mathrm{x},\mathrm{y}) = \frac{\mathrm{co-occurrence}\ (\mathrm{x},\mathrm{y})}{\mathrm{occurrence}(\mathrm{x}) * \mathrm{occurrence}(\mathrm{y})} \quad (1)$$

The NPMI of two words x and y is calculated as

$$NPMI(m_i; x_j) = \frac{PMI(m_i; x_j)}{h(m_i, x_j)} \quad (2)$$

$$NPMI(x,y) = \sqrt[r]{\prod_{g=1}^{r} NPMI(m_i, K_j^g)}. \quad (3)$$

Emotion vector is calculated as

$$\sigma_{wi} =< NPMI(w_i, e_1), NPMI(w_i, e_2), \ldots \ldots NPMI(w_i, e_m) > \quad (4)$$

4. Implementation

The experiment was set up in a Python 3.6 environment. The system used had RAM specification of 8GB and the operating system used was Ubuntu. The TDIL standard dataset was considered and experimentation was conducted. The Language Text Corpus is unannotated, which makes the process of emotion detection quite cumbersome. The NLTK toolkit was encompassed to carry out the NLP subtasks that are required specifically for pre-processing. Since, the corpus used in experimentation is an unannotated, text linguistic corpus, the dataset comprises of a large amount of unstructured data, which was subject to pre-processing using NLP Techniques and was further structured based on the structure of sentences as well as the emotion of the speech. A recent version of the standard SQLite database was encompassed into the proposed strategy. However, the choice of database has no impact on the results as the proposed algorithm is dependent only on the techniques imbibed and the corpus used.

4.1 Extracting emotion from text

Table 1: Algorithm for the proposed architecture.

Input: Converted text C_T, Speech S_T.
Output: Prediction of the emotion.

begin
    W= [], N_w= [], A_w= [], V_w= [], A_D= []
    for each words W_D in C_T
    begin
        POS_TAG $P_T(W_D)$
        W.add($P_T(W_D)$)
        for each word T in W
        begin
            if(POS_TAG(T) is noun)
                N_w.add(W_D)
            if(POS_TAG(T) is adjective)
            A_W.add(W_D)
            if(POS_TAG(T) is verb)
            V_W.add(W_D)
            if(POS_TAG(T) is adverb)
            A_D.add(W_D)
            Print N_W, A_W, V_W, A_D
            Calculate PMI as NPMI (m_i,x_j)= $\sqrt[r]{\prod_{g=1}^{r} NPMI(m_i, K_j^g)}$
            Calculate NPMI as $NPMI(mi; xi) = \frac{PMI(mi;xi)}{h(mi,xi)}$
            Emotion vector is calculated as σ_{wu}
            σ_{wu}=< NPMI (m_i, x_1), NPMI (m_i, x_2) …., NPMI (m_i, x_m)
        end
    end
end

Table 1 depicts the proposed NPMI based hybrid algorithm for emotion detection. Initially, the text corpus is input into the system. This corpus consists of various sentences with different types of emotions. Now the sentence to which the emotion is to be detected is input into the system. The sentence is then tokenized into words. The words thus obtained are tagged based on the Parts Of Speech. Then NAVA words are gathered from all the tagged words. PMI is calculated for the obtained NAVA words, followed by NPMI. Emotion vector is then calculated for the formulated words and the context is understood and finally, the emotion label is assigned. This is the implementation of the sentence in the form of text. This text is then converted into speech and then the features are extracted, based on these features prediction of emotion is done by considering the tone of the sentence. The emotion vector for the speech is calculated and an emotion label is assigned correspondingly. Both emotion labels are compared and finally, the detected emotion is output.

4.2 Extracting Emotion from voice

As the process of generation of emotion vector from text is finished and an emotion label is assigned. The next step is the detection of emotion from the speech, followed by assigning the emotion label. Initially, the text is converted into speech by text-converters. This speech is fed in the format of ".wav" to the system. Depending on the amplitude of the input signals features are calculated for the given speech file. These features are then worked upon and prediction of emotion vector is done. The similarity is calculated between this prediction and the emotion vector that is obtained by processing the obtained features. Finally, emotion vector is found out and the respective emotion label is assigned to the speech file. By incorporating both text and speech final assignment of emotion label for a given text file is assigned and this emotion label is given as output by the formulated model.

5. Results and Performance Evaluation

The devised model for emotion detection yielded positive results and was able to detect emotions of various words from the input text corpus. The obtained efficiencies of the formulated model for various emotions are shown in table 2. The Performance was evaluated by considering Precision, Recall, and Accuracy as the standard metrics.

Table 2: Precision, Recall, and Accuracy for the devised model.

Emotion	Precision (%)	Recall (%)	Accuracy (%)
Joy	95.16	97.15	96.155
Sorrow	91.16	93.54	92.35
Anger	88.17	91.75	89.96
Disgust	82.16	86.78	84.47
Fear	80.21	84.67	82.44

Table 2 depicts the Precision, Recall and Accuracy Analysis for the emotions detected by the proposed model. As shown clearly for Joy, Precision was found out to be 95.16 (%) and the recall was 97.15, both yielding an Accuracy of 96.155 %. The difference in the Precision for Joy and Sorrow was found out to be 2.99 % and the corresponding difference in the Accuracy was 3.805 %. Figure 2 depicts the Accuracy of various emotions that are detected by the formulated model. The proposed model was able to detect various emotions and generate apt, intelligent and appropriate responses for the same. The model formulated was able to predict the emotions for the sentences with no context or (emotion-associated words) like that of "No one is helping me". The model correctly predicted the emotion as sorrow by analysing the sound wave characteristics. Unlike other models, the proposed model is not heavily dependent on the data set and is made flexible to yield better results. "the performers were greeted with joyless cheer" this particular sentence is detected as joy sentence by other available models, owing to the words "greeted" and "cheer". This happens because the models are heavily depending on the context. The proposed model clearly distinguishes these kinds of sentences and was able to provide apt results. Figure 3 represents the percentage of Precision, Recall, and Accuracy for the detected emotions. Figure 4 shows the Comparison of Accuracy that is obtained in the proposed model by varying the strategies in the proposed hybridized model. Percentage of 96.155 is achieved by incorporating NPMI and NAVA words. Without the inclusion of NAVA words, the model obtained an accuracy of 89.67 %. While considering PMI and NAVA words the model yielded 88.45 % and the model yielded an accuracy of 80.3 % when only PMI was used for the computation of the proposed strategy.

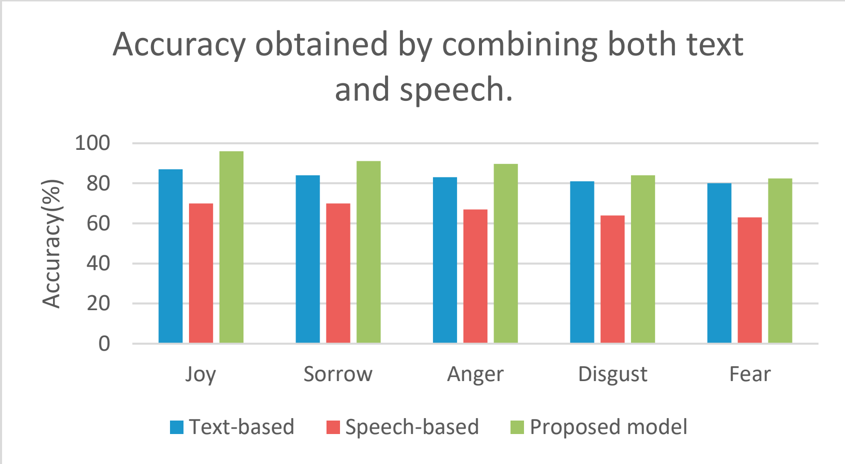

Figure 2: Accuracy analysis

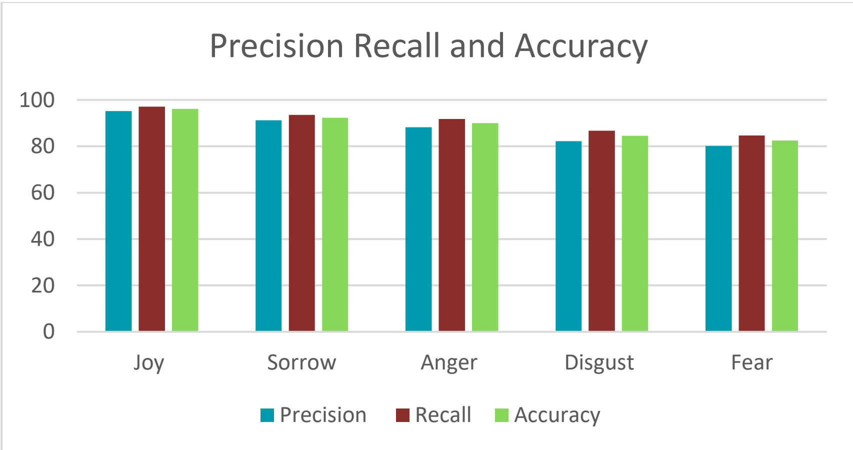

Figure 3: Precision, Recall, and Accuracy Comparison

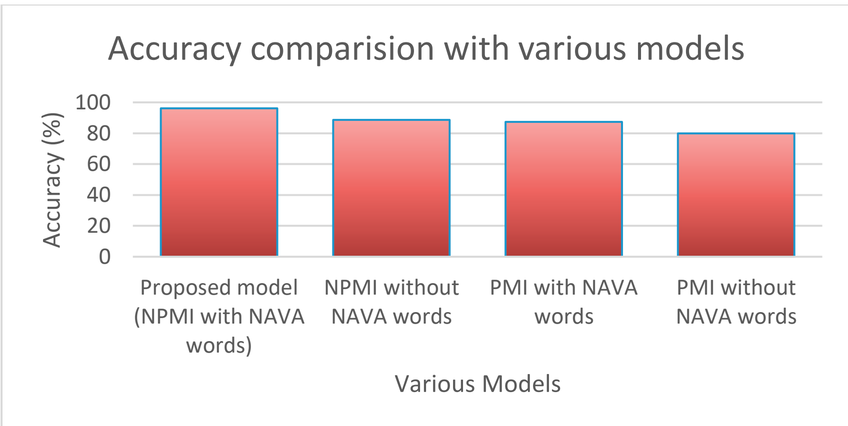

Figure 4: Comparison of Accuracy with other models

6. Conclusions

A novel semantic strategy for Emotion Detection using NPMI techniques hybridizing both text and speech has been proposed. Experimentations were carried out for TDIL dataset and a promising average accuracy percentage of 96.15 for Joy, 92.35 for sorrow, 89.86 for anger, 84.47 for disgust and 82.44 for fear has been achieved for the proposed strategy. The proposed approach clearly takes into account both the NPMI measure and the presence of NAVA words which makes it quite efficient. The proposed approach also realizes the context-independent detection of emotions and definitely outperforms the other existing strategies. Since the NPMI measure has been used, the emotions are detected with at most accuracy and response is triggered. Moreover, since semantic and statistical models are used, the proposed approach is both lightweight and dynamic. The future enhancements could be imbibing co-occurrence based models or heterogonous semantic strategies for detecting emotions.

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