CLASSIFICATION OF POETRY TEXT USING DEEP LEARNING.

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Abstract - The classification of emotional states from poetry or formal text has received less attention by the experts of computational intelligence in recent times as compared to informal textual content like SMS, email, chat, and online user reviews. In this study, an emotional state classification system for poetry text is proposed using the latest and cutting edge technology of Artificial Intelligence, called Deep Learning. For this purpose, an attention-based C-BiLSTM model is implemented on the poetry corpus. The proposed approach classifies the text of poetry into different emotional states, like love, joy, hope, sadness, anger, etc. Different experiments are conducted to evaluate the efficiency of the proposed system as compared to other state-of-art methods as well as machine learning and deep learning methods. Experimental results depict that the proposed model outperformed the baselines studies with 88% accuracy. Furthermore, the analysis of the statistical experiment also validates the performance of the proposed approach.

Keywords - Classification of emotional text, deep learning, Attention-based C-BiLSTM Model

I. INTRODUCTION

The classification of opinions, sentiments and emotional states has gained the attention of experts from different fields like natural language processing, computational linguistics and computational intelligence. There are two types of writings that can be analyzed by machine: formal and informal. The formal textual content pertains to poetry, novels, essays, novel, plays, and official/legal documentation, whereas the informal textual content is about SMS, chat, and social media posts.

Due to complex nature of the formal text (poetry), detection and classification of emotional states is a challenging task. For instance, the verse “And the sunlight clasps the earth, And the moonbeams kiss the sea:”, taken from the poem “Love Philosophy” (Shelley) conveys a love emotion. The manual strategy for detecting emotional states expressed by the poet in the poetry text is difficult and time-consuming.

In recent times, machine learning techniques have been applied successfully for extracting and analyzing emotional states and themes from poetic text. However, small datasets labeled with a limited number of emotional states are the major limitations of such studies. The existing studies on the detection of emotional states from poetry text have used traditional machine learning techniques with limited datasets tagged with a small number of emotion classes. One of the study conducted on emotion classification from poetry text has used one machine learning classifier, namely Support Vector Machine (SVM) and a BiLSTM classifier, for classifying poetry text into two emotion classes. This gap can be bridged by investigating Attention-based C-BiLSTM model, which can take advantage of both the Convolutional Neural Network (CNN), Bidirectional Long Short Term Memory (BiLSTM), as well as, we also exploited the Attention mechanism of deep learning. Furthermore, we exploit 13 emotion classes, which is an extension in baseline work, for a more accurate classification of emotional states from poetry text.

The emotion is an interdisciplinary field involving psychology, computer science and others. In psychology, emotions are expressed as psychological state differently connected with contemplations, sentiments, behavioural responses, and a level of delight or displeasure. In computer science, emotions can be identified in the form of audio records, video records and text documents. Analysing emotions from the text documents seems to be challenging due to the fact that textual expressions are not always directly use the emotion related words, but often outcome from the understanding of the meaning of concepts and interaction of concepts mentioned in the text document. Emotion expressions are the crucial form of communication in interpersonal relationship. It can be expressed into positive emotion, negative emotion or neutral. In general the positive emotions are expressed as happy, excited, joy, pride and negative emotions such as sad, disgust, fear, depressed and so on. In such a way, the emotions are expressed in various forms to communicate and the rich source of textual information is obtained from the social networking sites such as YouTube, Twitter, and Facebook etc., where people are spending most of their time in posting and expressing their emotions.

By considering the textual data available on the blogs, it is helpful to identify the intensity of emotion of an individual. For example “Really happy with this purchase” express the positive emotions from a customer about the purchase of product. The term “Really” intensifies the emotion expressed by the customer. In this case it implies it is more positive emotions. Another customer review on the same product expressed negative emotions on the purchase of the product such as “Really disappointed. Alexa has to be plug-in to wall socket all the time. My fault is for not checking”. Here the customer intensifies more negative comment about the purchase. By considering the intensity of emotion through the text, it helps to predict individual emotions. Also, it helps to know the state of emotions of the person that can assist friends and family to take preventive measures against accidents or self harm.

II. PROPOSED SYSTEM

The proposed system is composed of multiple modules i) Data Acquisition, ii) Preprocessing,

iii) Feature representations, iv) Feature extraction v) Feature encoding, vi) Context information generation, and vi) classification layer.

1) DATA ACQUISITION To train a deep learning model one of the most important steps is to collect the data. For this purpose, we have used the dataset acquired from [1] which consists of 9142 posts.

2) PREPROCESSING To implement the deep learning model, the next step is to transform the words into numbers. So some of the basic preprocessing steps such as stop-words removal, conversion to lowercase, and tokenization, are performed.

3) FEATURE REPRESENTATION To enable the model to learn, each word is further transformed into an embedding vector by using the Keras embedding layer].

4) FEATURE EXTRACTION In this module, the proposed model extracts the n-gram features from the input received from the previous embedding layer .

5) FEATURE ENCODING A Bidirectional LSTM model is used in the proposed system to capture both the backward and forward dependencies of a word.

6) CONTEXT INFORMATION To make the system capable of retaining contextual information, we exploited the attention mechanism in the proposed model. Using this capability, the system can understand, which tokens are useful. The attention mechanism determines which words to focus on the most, by considering only the most relevant input feature and removing the unnecessary or irrelevant information from the input feature

7) CLASSIFICATION LAYER The final step is to apply the softmax function, implemented in CNN architecture so that the given input text is classified into one of the 13 emotion types.

The aim of our work is to design a computational model that is trained over a training dataset. It will help in classifying the emotional states of poetry text. We are using Attention- based C -BiLSTM model, which is an extended version of LSTM.

III. PROBLEM STATEMENT

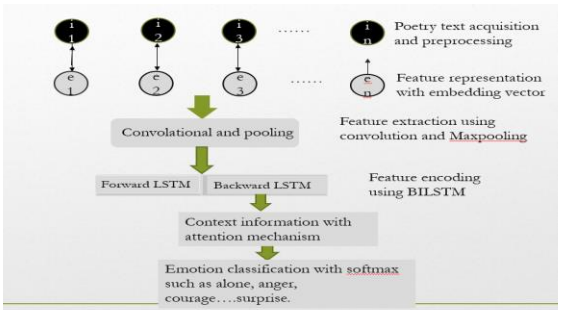
The detection and classification of emotional states from the formal text (poetry) faces different challenges, such as the small size of baseline datasets tagged with a limited set of emotional classes. Furthermore, classical machine learning classifiers are used to detect and classify emotional states expressed by the poet .However, recently deep learning-based neural network models for emotional state detection have shown promising results in different areas like multimedia sentiment and emotion analysis from images, audio, video, and text. We consider the task of emotional state detection from literary (poetry) text as a multi-mode classification issue. A training dataset Trd={trd1, trd2, trd3…trdn} is tagged with emotional-states ={love, hate, fear, joy, nature, suicides sad, surprise, sad, and alone}. Every poetry text is given an emotional-state. The aim of the work is to design a computational model, trained over a training dataset and which can classify a new poetry text according to the different emotional states.

Objectives

We propose an emotional state classification system from poems, with the following objectives.

- Classification of emotional states from poems by applying the attention-based C-BiLSTM neural network model.
- Evaluating the efficiency of the proposed approach with respect to multiple machines and deep learning techniques with an extension in emotional classes and dataset size.
- Comparing the efficiency of proposed technique with respect to similar works.

Flow Chart



Module Description

Classification of emotional states from poems by applying the attention-based C-BiLSTM neural network model. Attention-based C-BiLSTM model, which can take advantage of both the Convolutional Neural Network (CNN), Bidirectional Long Short Term Memory (BiLSTM), as well as, we also exploited the Attention mechanism of deep learning.

CNN Layer

The convolutional layer involves a convolutional operation ``_'', between a poetry text matrix *S* 2 R*dxn* and a _ltermatrix *F* 2 R*m*xk [24], which results in an output matrix *O*, known as feature map, where the bias vector is the b, the weight matrix is W and f represents the nonlinear activation function of the convolutional operation.We used Relu (Recti_ed nonlinear activation function) as a non-linear activation function because it speeds up the training and produces signi_cantly better results.

$$O_{uv} = (S * F) = f(W \circ s_{u:u+k-1,v+d-1} + b) \qquad (1)$$

BiLSTM Layer

To achieve exact predictions, it is necessary that the model should learn the long term dependency in text data. The convolutional layer lacks this capability [26] Therefore, to include this functionality to the proposed model, we applied BiLSTM. BiLSTM allows the model to learn data from both right to left and left to right directions. Hence BiLSTM improves the classi_cation accuracy.

$$\overleftrightarrow{h} = \vec{h} \oplus \overleftarrow{h} \qquad (3)$$

The BiLSTM cell is implemented using the following Equations [27].

Forward LSTM:

$$\mathrm{X} = \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix}$$

$$\sigma f_t = (W_f.X + b_f) \qquad (4)$$

$$\sigma i_t = (W_i.X + b_i) \qquad (5)$$

$$\sigma o_t = (W_o.X + b_o) \qquad (6)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c.X + b_c) \qquad (7)$$

$$h_t = o_t \odot \tau\,(c_t) \qquad (8)$$

Backward LSTM:

$$\mathrm{X} = \begin{bmatrix} h_{t+1} \\ x_t \end{bmatrix}$$

$$\sigma f_t = (W_f.X + b_f) \qquad (9)$$

$$\sigma i_t = (W_i.X + b_i) \qquad (10)$$

$$\sigma o_t = (W_o.X + b_o) \qquad (11)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c.X + b_c) \qquad (12)$$

$$h_t = o_t \odot \tau\,(c_t) \qquad (13)$$

Attention Layer

Inside a sentence, there are some words, which are irrelevant, while others are decisive. To attend such informative words, the attention mechanism is introduced. Therefore, we added this layer to automatically mine the significant words. The word importance vector *ut* is computed,in which the attention mechanism takes the whole BiLSTM hidden states h as input. W is the weight and b is the bias and tanh is the activation function

$$u_t = tanh(W_h h_t + b_h) \qquad (14)$$

After that, the normalized word weight *at* is obtained through the softmax function using Eq. 15.

$$a_t = softmax(u_t) \qquad (15)$$

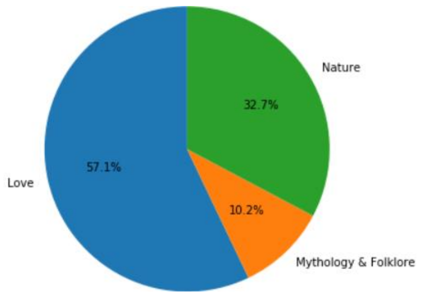
Finally, to generate the attention mechanism output. A weighted summation is computed using Eq.16.

$$c_t = \sum_{t=1}^{n} a_t h_t \qquad (16)$$

The output of Attention layer i.e c D [c1; _ _ _ ; cT] is made input to the Flatten layer.

Data Set

An Automatic poetry classifier takes a poem as an input and identifies its category as an output. For experimentation, a benchmark dataset is used with an extension into the emotion classes: Alone, Hope, Nature, and Surprise along with their respective poems. Then this dataset is passed through the following modules, i) Data Acquisition, ii) Pre-Processing, iii) Feature representation, iv) Feature extraction v) Feature encoding, vi) Context information generation, and vii) classification. As India is having a rich literature, this poetry classification system is having an application in classifying literature pieces, poetry, according to the theme of poetry.



	author	content	poem name	age
type				
Love	326	326	326	326
Mythology & Folklore	58	58	58	58
Nature	187	187	187	187

IV. RESULT AND CONCLUSION

To categorize English poetry text within multiple emotion classes, we have exploited a deep learning technique namely, Attention-based C-BiLSTM model. Results depict that the proposed approach attained highest performance in terms of better (0.88%) precision, and (88%) accuracy, as compared to the state of the art studies.

The limitations of this work include: (i) limited size of the poetry dataset, which is needs to be increased to get the model trained with improved accuracy, (ii) the system predicts only one emotion category from 13 classes, which needs to extended to predict multiple emotions with proper ranking mechanism.

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