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Twitter Visualization and Sentiment Analysis Using Deep Learning

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ABSTRACT

Sentiment analysis on social media like Twitter has become a really importantand challenging task. Due to the characteristics of such data tweet length,spelling errors, abbreviations, and special characters the sentiment analysistask in such an environment requires a non-traditional approach. Moreover,social media sentiment analysis is a fundamental problem with many interesting applications. Most current social media sentiment classification methodsjudge the sentiment polarity primarily consistent with textual content and neglectother information on these platforms. In this paper, we propose a neural network model that also incorporates user behavioural information within a givendocument (tweet). We utilize the Convolutional Neural Network in our project. The system is evaluated on two datasets provided bythe SemEval-2016 Workshop. The proposed model outperforms current baseline models (including Naive Bayes and Support Vector Machines), which showsthat going beyond the content of a document (tweet) is useful in sentimentclassification, because it provides the classifier with a deep understanding of the task.

Keywords : Twitter, Sentiment Analysis, CNN, LSTM, RNN

I. INTRODUCTION

The emergence of social media platforms has given web users a space for expressing and sharing their thoughts and opinions on all kinds of topics and events. One of the most popular social networking platforms is Twitter. It allows people to publish messages to express their interests, favourites, opinions, and sentiments towards various topics and issues they encountered in their daily life. The messages are called tweets, which are real-time and at most 140 characters.

Twitter gives us access to the unprompted views of a wide set of users on particular products or events. The opinions or expressions of sentiment about organizations, products, events, and people have proven extremely useful for marketing and social studies. Twitter has about 200 billion tweets per year, 500 million tweets per day, 350,000 tweets per minute, and 6,000 tweets per second. These are some reasons for choosing Twitter as a case study in this research.

In contrast to plain texts with many words that help gather sufficient statistics, the texts in social media, especially Twitter, only contains a limited number of characters. Moreover, when a user posts a message (tweet), it may have new abbreviations or acronyms that appear infrequently in conventional text documents. Therefore, applying traditional methods to such an environment won't yield acceptable performance.

To address this issue, we propose a neural network-based model that goes beyond the content of a given document (tweet). It takes into account, besides a given tweet, the behaviour of the user who wrote that tweet. It has been demonstrated by the experiments conducted in this paper that this approach increases the performance and the accuracy of sentiment classification tasks on social media.

The main motivation behind our approach is that the intuition that the association between the document (tweet) and therefore the behavioural information of the user who wrote that document can provide a model with useful indicators to spice up its performance.

However, most of these are related to emotion; they try to classify the users themselves from a psychological point of view. They develop a tool to classify users into positive and negative groups based on the network density and the degree of social activity. Their purpose is to know the connection between positive and negative users, also as, how emotion and mood can affect both a user's behaviour and their interaction with other users. They conclude that there's a robust relationship between the users' emotions and therefore the way users choose their friends. Accordingly, we believe that such a relationship also exists between users and their posts.

We propose a neural network-based model that classifies tweets into positive and negative categories based on a proposed set of features that enhance the classification performance. These features help the model to know a user's behaviour. The behaviour of a user can be identified by knowing two aspects of the user. The first aspect involves the personality traits, such as his/her general attitude; is it positive, negative or neutral? The second aspect regards the social activities of users, which can be revealed through the users' relationships and communication.

II. Literature Survey

With the ever growing quantity of information on the net, it's become vital to use this knowledge for understanding the audience on a selected application. What individuals trust a selected modification is very important for an organization to higher perceive its customers and develop product customized in keeping with their desires. one amongst the pioneers concerning this idea was explored in [18] wherever the author works on a learning algorithmic rule that may classify a review as either a thumbs-up or a thumbs-down in keeping with the sentiment of the review text. The usage of sentiment analysis in a very social media presence like Twitter is seen in [19].

In this, numerous avenues are mentioned wherever the strategy of sentiment analysis can be done. These previous techniques accustomed work on simply words instead of understanding the phrase as an entire. The construct of phrase-level analysis was worn out [20] wherever a complete expression is assessed as an entire instead of simply a mixture of scores for the individual words. The paper [21] talked concerning the introduction of lexicon-based analysis to sentiment analysis. This was the strategy within which each word was given a price in keeping with its positivity/negativity and this idea improved the generic sentiment detection compared to the opposite algorithms at that point. within the paper [22], the authors work on a method for detection of the tweets into 3 categories: positive, negative and neutral that was run on a stream of information from Twitter.

Most of the work on sentimentanalysis focuses on the English language. there's but a lexical resource that has been used extensively, that is is aware of for its express divisiveness to support sentiment analysis and opinion mining, SentiWordNet three [23]. SentiWordNet is Associate in Nursing ex- tension to its forerunner referred to as WordNet wherever every set is related to 3 scores describing the positive,negative and objective nature of the terms within the set. The paper [24] talks regarding the likelihood of exploitation emotions by emoticons within the tweet to permit sentiment analysis over multi-lingual tweets. instead of simply exploitation the tweet contents, the paper [25] mentioned a couple of technique that used the hashtags related to the tweet to see sentiment analysis for a selected topic. The paper [17] uses a hybrid approach in their algorithmic program to classify the twitter feed. The framework of the paper is predicated on three totally different classifiers, associate facial gesture classifier, associate improved polarity classifier and a SentiWordNet classifier.

The paper [10] presses on the difficulty of the inconsistency of sentiment analysis which might be improved by exploitation totally different types of meta-data of the tweet which might embrace knowledge like location, time and a lot of. the results of emoji on sentiment analysis has been talked regarding within the paper [13]. that they had complete that the usage of emoji will facilitate improve the score of the sentiment values for a tweet. The authors of [9] have manually mapped emoticons from Unicode 8 to 9 emotional classes then have had a sentiment analysis performed exploitation the emoticons and bag-of-words as options. Another progressive performing artist within the field of emojis is DeepMoji [6]. DeepMoji may be a model trained on 1.2 billion tweets with emojis to grasp however text will be expressed as emojis.

III. Background

Sentiment analysis tasks can be performed efficiently byimplementing different models such as deep learning models,which have been extended recently. These models includeCNN (convolutional neural networks), RNN (recursive neuralnetwork), DNN (deep neural networks), RNN (recurrent neuralnetworks) and DBN (deep belief networks). This section describes the efforts of different researchers toward implementingdeep learning models for performing the sentiment analysis.

Convolutional Neural Networks (CNN)

The CNN (convolutional neural network) [24] includes pooling layers and class because it gives a typical architecture to map the sentences of variable length into sentences of fixed size scattered vectors. This study has proposed a completely unique convolutional neural network (CNN) framework for visual sentiment analysis to predict sentiments of visual content. CNN has been implemented using Caffe and Python on a Linux machine. Transfer learning approach and hyper-parameter has been utilized in biases and weights are utilized from pre-trained Google Net. As CNN enhance its performance by increasing its size and depth, so a really deep CNN model, inspired by Google Net is proposed with 22 layers for sentiment analysis. it's optimized by using SGD (Stochastic gradient descent) algorithm. The strategy with 60 epochs has been performed for training the network as Google Net has performed 250 epochs.

The proposed model was evaluated on this dataset and purchased better performance than existing systems. Results shows that proposed system achieve high performance without fine-tuning on Flickr dataset. However,Alex Net was utilized in previous works and Google Net provided almost 9% performance progress than Alex Net. By converting Google Net in to visual sentiment analysis framework, the higher feature extraction was achieved. Stable and reliable state were achieved by using hyper parameters.

The authors have proposed the system of deep learning for sentiment analysis of twitter. the most focus of this work was to initialize the load of parameters of convolutional neural network and it's critical to coach the model accurately while avoiding the need of adding new feature. A neural language is employed to initialize the word embedding and is trained by big unsupervised group of tweets.

Deep Neural Networks (DNN)

In this study, author has proposed a model for sentiment analysis considering both visual and textual contents of social networks. This new scheme used deep neural network model like Denoising auto encoders and skip gram. the bottom of the scheme was CBOW (Continuous Bag-Of-Words) model. The proposed model consisted of two parts CBOW-LR (logistic regression) for textual contents and was expanded because the CBOW-DA-LR. The classification was done consistent with the polarity of visual and textual information.

In this study, deep neural specification has been proposed to gauge the similarity of documents. Thearchitecture was trained by using several market news to supply vectors foe articles. The T&C news are used as dataset. The cosine similarity was calculated among labelled articles and therefore the polarity of documents was considered but contents weren't considered. The proposed method accomplished superior performance in terms of similarity estimation of articles consistent with polarity.

Recursive Neural Network (RNN)

The recursive neural network (RNN) lies in supervised learning. It contains a tree structure which is settled before training and therefore the nodes can have different matrices. there's no need of reconstruction of input in RNN.

The proposed work builds a Treebank for chines sentiments of social data to beat the deficiency of labelled and enormous corpus in existing models. To predict the labels at sentence level i.e., positive or negative, the Recursive Neural Deep Model (RNDM) was proposed and achieved high performance than SVM, Nave Bayes and Maximum Entropy. 2200 movie reviews were collected from the web site and Chinese word segmentation tool ICTCLAS was wont to segment these reviews.

The proposed model improved the prediction of sentiment labels of sentences by concluding 13500 chines sentences and 14900 words. ME and NB performs higher with contrastive conjunction structure than baselines with great margin. during this study, a model comprising RNTN (Recursive Neural Tensor Network) and Sentiment Treebank has been proposed to properly clarify the compositional effects at different levels of phrases, i.e., positive and negative phrases. The proposed model was compared with all the prevailing models. In existing models, the meaning of long phrases can't be expressed effectively by semantic word spaces, so for sentiment detection, more rich and supervised evaluation and training resources are needed because it requires more influential composition models. The RNTN achieved 80% accuracy in sentiment prediction by performing fine-grained labelling over all the phrases and outperformed previous models.

Deep Belief Networks (DBN)

Deep belief networks (DBNs) include several hidden layers, composed by RBM (restricted Boltzmann machines). DBN has been proved efficient for feature representation. It utilizes the unlabelled data and fulfils the deficiencies of labelled analysis issues. during this paper, a replacement deep neural network structure has been presented termed as WSDNNs (Weakly Shared Deep Neural Networks). the aim of WSDNNs is to facilitate two languages to share sentiment labels. The features of language specific and inter language are presented through building multiple weakly shared layers of features.

As compared with existing studies the proposed work addresses the challenge of shortening overlap among feature spaces of both source and target language data through cross lingual information transfer process using backpropagation. DNNs used for transformation of data from source to focus on language. The experiments are conducted for sentiment classification tasks of cross multilingual product reviews of Amazon. results concluded that the proposed approach is simpler and powerful in terms of cross lingual sentiment classification than the previous studies.

IV. Methodology

Deep Learning Architecture

Our proposed model for sentiment analysis consists of a convolutional neural network. The system architecture is presented in Fig. The model is implemented using the Weka4 library.

The main components of the network are the input, convolution, pooling, activation, and SoftMax layers. The input layer consists of word embeddings and an inventory of features. The word embedding could also be randomly initialized or pre-trained. For the aim of this work, we utilize the publicly available word2vec embeddings [5]. We pre-train the 200-dimensional word embeddings on each dataset. For that purpose, each tweet is tokenized and every generated token is mapped to a distributional feature representation referred to as the word embedding. Moreover, the features that describe the author of the tweet are appended to the generated vector then fed into subsequent layer. that's the convolutional layer; its main goal is to extract patterns.

In order to permit the training of non-linear decision boundaries, a non-linearactivation function is found at the activation layer. There are variety ofcommon choices of activation functions used with neural networks; for instance,sigmoid (or logistic), hyperbolic tangent (tanh), and rectified linear (ReLU)functions.

In our model, we use ReLU because it's acknowledged by several studies, suchas in [2], that ReLUaccelerates the training and produces more accurate results than other activation functions.The SoftMax layer is an activation function whose output is that the probabilitydistribution over labels. during this 2-classes task, given an input representationvector v, a SoftMax operation is computed as follows:

$$softmax(v, L) = \frac{\exp(v)}{\sum_{l=1}^{L} \exp(\widehat{v})} \qquad (i)$$

where L is the number of sentiment classes and ˆv is the predicted probability of sentiment class l. The reason for adding the dropout layer before the SoftMax layer is to prevent overfitting.

Sentiment Analysis Application

Number of a User's Tweets. This feature represents the amount of a user's tweets retrieved from his or her timeline via the Twitter API. Twitter allows to return a set of the foremost recent tweets posted by the user. It can only return up to three ,200 tweets of the user.

Number of Positive, Negative and Neutral Tweets Posted by a User. These features aim to live the overall attitude of a user. consistent with [8],one among the ways in which one can predict a user personality is thru his or her words. Therefore, in our experiments we use the frequency of tweets supported three aspects, positive, negative, and neutral.

To achieve this, we'd like to gather tweets from each user who appear within the dataset, which successively provides us with an enormous number of unlabelled tweets. In some datasets, we got about 600,000 tweets posted by quite 3,400 users. However, labelling of these tweets manually isn't a simple task and can be very time consuming and dear. one among the solutions adopted by researchers is that the SentiStrength algorithm, which is taken into account a state-of-the-art sentiment analysis system. it had been developed.[5], and uses a scoringrange from 5 (very negative) to +5 (very positive). to elucidate in additional detail, for every text, SentiStrength outputs two integers: 1 to five for positive sentimentstrength and a separate score of 1 to five for negative sentiment strength. Forexample, a text with a score of three, 5 would contain moderate positive sentimentand strong negative sentiment. A neutral text would be coded as 1, 1.

Accordingly, we create an application that receives SentiStrength's output and is interpreted as follows. A tweet is taken into account positive if its positive sentiment strength is above both 1 and its negative sentiment strength; otherwise, it's considered a negative tweet. just in case a tweet gets 1 as a score for its positive and negative sentiment strength, it's considered a neutral tweet. A tweet might be neutral if it's an equivalent score in positive and negative sentiment strength, as an example, a tweet with scores 3 for positive and three for negativestrength. This can be formulated as:

$$SS(t_i) = \begin{cases} positive \quad if\ SS(t_i)pos\ > 1\ and\ SS(t_i)pos > SS(t_i)neg \\ negative \quad if\ SS(t_i)neg\ > 1\ and\ SS(t_i)neg > SS(t_i)pos \\ neutral \quad if\ SS(t_i)neg = SS(t_i)pos \end{cases} \quad (ii)$$

For each user u ∈ U = {u1, u2, ..., un} where U is a user set and n is the number of users extracted from the dataset, the application calculates SS (ti).

Here SS (ti) is a function that takes as input a tweet ti∈ Tu (where Tu has all tweets retrieved from user u’s timeline), and returns its label based on the SentiStrength algorithm. SS (ti)pos and SS (ti)neg are scores of the positive and negative sentiment strengths, respectively.

$$SS(t_i) = \begin{cases} positive \quad if\ SS(t_i)pos\ > 1\ and\ SS(t_i)pos > SS(t_i)neg \\ negative \quad if\ SS(t_i)neg\ > 1\ and\ SS(t_i)neg > SS(t_i)pos \\ Both \quad if\ SS(t_i)neg = SS(t_i)pos\ \neq 1 \\ Neutral \quad Otherwise \end{cases} \quad (iii)$$

The change implies that, in case of having a tweet scored with equal values of positive and negative sentiment strengths that are greater than 1, then the tweet will be counted twice, one for each label.

Convolutional Neural Network (CNN)

CNNs belong to the category of neural networks and have shown significant success and innovation in computer vision and image processing. the elemental architecture of CNN is displayed in Fig. As evident from the figure, CNN consists of varied layers, like the input layer, convolutional layer, pooling layer, and fully connected layer. The task of the input layer is to require the pixel value of the image as an input. Next, convolution layer (CONV) has the responsibility to supply output supported its kernel or filter values. The output obtained through a convolution operation, and Pooling Layer (POOL) is employed to scale back the dimensions of representation (dimensionality) and to hurry up computation.

The most popular sort of pooling is max pooling, during which maximum value from each window is taken. The Fully connected layer (FC) connects every neuron during this layer to all or any the activations of previous layer, as seen in ordinary neural networks. More and more researchers are actively using CNNs within the field of sentiment analysis. the foremost popular CNN model for sentence-level sentiment classification is that the work done by Kim (2014). The author conducted an experiment with CNN built on top of pre-trained word2vec. The experimental results show that pre-trained vectors can function a superb feature extractor for tasks associated with NLP using deep learning. Motivated by these results, Zhang and Wallace (2015) discussed an architecture for sentence classification using one-layer CNN. They explored how the performance of a model are often suffering from changing its configuration (hyperparameters, filter size, regularization parameters, etc.). Figure illustrates the architecture proposed by Zhang and Wallace (2015). The tokenized sentence of length sis given as an input to the network, and it's converted into a sentence matrix by following the work of Colbert and Weston (2008) which applies a look-up table concept to get the sentence matrix. The dimensionality of the matrix is s ∗ d, where d represents dimensionality of word vectors. Hence, sentence matrix can now be treated as an input image on which convolution is performed using linearfilters to get the feature maps. the peak of the filter is referred as region size of thefilter. For pooling operation, 1-max pooling is performed on each feature map.

Long-Short term Memory (LSTM)

Long Short Term Memory network (LSTM) may be a special type of RNN, which is capable of learning long-term dependencies.All RNNs have the shape of a sequence of repeating modules. In standard RNNs, this repeating module normally features a simple structure. However, the repeating module for LSTM is more complicated.Instead of having a single neural network layer, there are four layers interacting in a special way. Besides, it's two states: hidden state and cell state.

Figure shows an example of LSTM. At time step t, LSTM first decides what information to dump from the cell state. This decision is formed by a sigmoid function/layer σ, called the "forget gate". The function takes h!!! (output from the previous hidden layer) and xt (current input), and outputs variety in [0, 1], where 1 means "completely keep" and 0 means "completely dump" in Equation.

$$f_t = \sigma\left(W^f x_t + U^f h_{t-1}\right) \qquad (iv)$$

Then LSTM decides what new information to store within the cell state. This has two steps. First, a sigmoid function/layer, called the "input gate" as Equation, decides which values LSTM will update. Next, a tanh function/layer creates a vector of latest candidate values , which can be added to the cell state. LSTM combines these two to make an update to the state.

$$i_t = \sigma\left(W^i x_t + U^i h_{t-1}\right) \qquad (v)$$

$$\tilde{c}_t = \tanh(W^n x_t + U^n h_{t-1}) \qquad (vi)$$

It is now time to update the old cell state C_{t-1} into new cell state as Equation. Note thatforget gate f_t can control the gradient passes through it and allow for explicit "memory" deletes andupdates, which helps alleviate vanishing gradient or exploding gradient problem in standard RNN.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \qquad (vii)$$

LSTM is commonly applied to sequential data but can also be used for tree-structured data. Tai et al.introduced a generalization of the standard LSTM to Tree-structured LSTM (Tree-LSTM) and showed better performances for representing sentence meaning than a sequential LSTM.

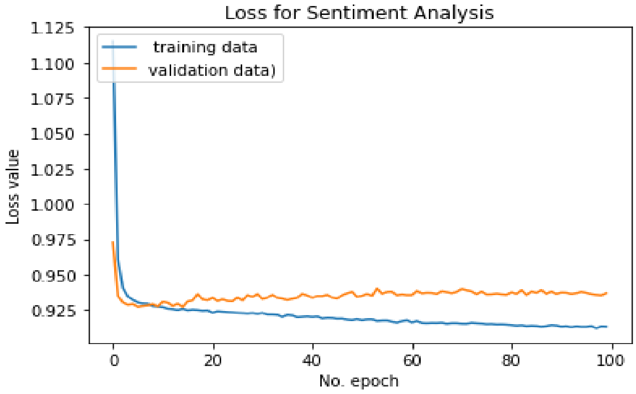
A slight variation of LSTM is the Gated Recurrent Unit (GRU) [15,13]. It combines the "forget" and "input" gates into a single update gate. It also merges the cell state and hidden state, and makes some other changes. The resulting model is simpler than the standard LSTM model, and has been growing in popularity.

V. Experimental Result

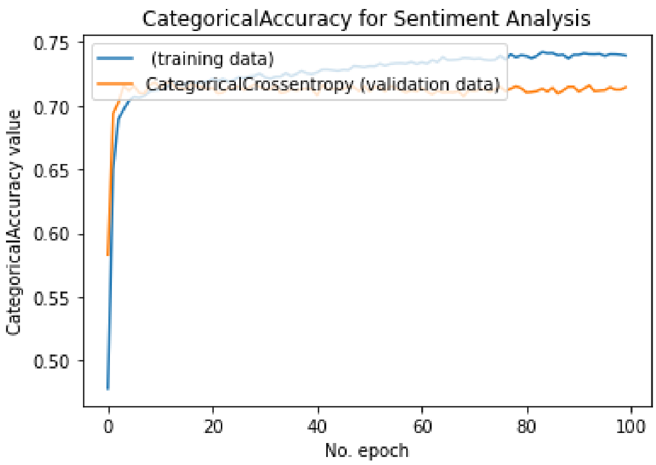
We take the Kaggle dataset, which contains 26750 emotions tweets collected using twitter API. The dataset contains user identification (id) number, sentiment, and tweet text columns. The target variable is about to 0 = negative, 1 = neutral and 2 = positive. The negative, neutral, and positive mean negative, neutral, and positive impressions in tweets, respectively. Tweets contain raw text which must be refined before getting used for prediction purposes. The pre-processing steps are wont to convert these tweets into useful features without noisy data. Tweets are mostly not an equal number of words, and there's no proper rule that restricts users to a limited number of words and no grammar rule while posting tweets. We faced two problems within the training phase. First, the category imbalance problem among minority classes and secondly high correlation among weighing features. These two problems must be solved so as to urge better classification accuracy.

The experimental investigations of the proposed CNN-LSTMbased sentiment analysis scheme are conducted using 10-fold cross validation over the labelled tweets. The proposed CNN-LSTMbased sentiment analysis scheme was executed using Keras, which considers Tensor flow at the rear end within the Python package over a desktop PC with a GTX-configured 1080 TI GPU. The investigations of the proposed CNN-LSTMbased sentiment analysis scheme are conducted using the evaluation metrics of classification accuracy, precision, recall and F-Measure.

The deep learning algorithm with TensorFlow framework is applied. The acc, val_acc, val_loss denote accuracy, validated the accuracy, and validatedloss, respectively. The accuracy and loss metrics with 100 epochs are shown with and without fineconfiguration, i.e., (a) and (b). The blue color presents train data and loss value curves in figures. Similarly,orangecolor shows the validation loss value and validation data. First, we performed theexperiment without fine-tuning configuration and got 76.7% accuracy, i.e., (a). The loss and validatedcurves show during a range of 0.96 to 0.92. Initially, the loss is sort of high but gradually decreases up to 0.60.Similarly, accuracy and validated calculated during a range of 0.5 to 0.75. While on the hand with fine-tuneconfiguration, we got an accuracy of 78.4%. The loss curves start at 0.72 but soon decrease to 0.6.Similarly, the accuracy curve starts from 0.5 but soon increases to 0.75 on 100 epoch. Fine-tune configurationsolved the overfitting problem and improved the prediction accuracy as proved from both subgraphs.



(i) Loss Value for Sentiment Analysis



(ii) Accuracy Graph for Training data and Validation data

	precision	recall	f1-score	support
positive	0.75	0.76	0.76	1075
negative	0.71	0.67	0.69	983
neutral	0.67	0.69	0.68	1376
accuracy			0.71	3434
macro avg	0.71	0.71	0.71	3434
weighted avg	0.71	0.71	0.71	3434

(iii) Evaluation Metrics

Model: "sequential"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 40, 64)	1280064
conv1d (Conv1D)	(None, 38, 128)	24704
global_max_pooling1d (Global	(None, 128)	0
dropout (Dropout)	(None, 128)	0
dense (Dense)	(None, 3)	387

Total params: 1,305,155
Trainable params: 1,305,155
Non-trainable params: 0

(iv) Structure of CNN model

VI. Conclusion

In this paper, we tend to gift a sentiment analysis model developed by combining an inventory of options. We tend to propose the design of a Convolutional Neural Network (CNN) that takes into consideration not solely the text (user tweets) however additionally user behaviour. Our analysis results demonstrate the potency of the model in a very social media setting.

Our model outperforms the baseline ways in accuracy, recall, precision, and F1. Additionally, the planned model is affected less by unbalanced dataset problems. Moreover, the approach overcomes the problem of needing an oversized dataset to coach deep learning models like CNN and LSTM.

This work suggests fascinating directions for future work. for instance, it'd be fascinating to research the contributions of the created list offeatures for non-binary sentiment classification tasks. In future work, we tend to additionally attempt to explore alternative neural network primarily based learning models, like continual Neural Networks (RNN) and gated feedback RNN for sentiment analysis.

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