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Sentiment Analysis using Neural Network and LSTM

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1.

Abstract. People put their opinions or views on various events happening in the society or world. Twitter is one of the best social networking sites where a huge amount of data generates on the daily basis. These data can be used to classify their tweets based on various sentiments attached to them. Numerous technologies are applied to analyse the sentiments of users. Sentiment analysis needs a very efficient method to manage long arrangement data and their drawn-out dependencies. In this paper, we have applied a deep learning technique to perform Twitter sentiment analysis. Simple Neural Network, Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN) methods are applied for the sentiment analysis and their performances are evaluated. The LSTM is the best among all proposed techniques with the highest accuracy of 87%. We have collected a Twitter dataset from Kaggle to perform our experiment. The future improvement of the proposed research should include REST APIs and web crawling-based solutions to get live tweets to perform real-time analytics. We have analysed 1.6 million tweets in our research work.

2. Introduction

Sentimental analysis is the textual mining applied to extract useful subjective information to understand the social sentiments about the brand which help in business improvement or quality control. The opinion about the product utility varies from person to person. Customer feedbacks are very important in terms of brand monitoring and product reputation. It is used to find negative, positive, and neutral emotions about the subject. Twitter is an American social networking service on which users put their posts, retweet and read them. It is one of the most popular platforms to express our opinions or comment on ongoing issues from all sources.

These days social media, blogs and networks produce huge information. People share their thoughts on various events and issues. This bulk information is used for opinion and decision making in a business. Twitter generates massive short tweets and because of that, the tweet size is reduced to 140 characters. Opinion and Sentiment Mining are exceptionally helpful to get the opinion from the users or to analyse their sentiments. Our main objective is to classify sentiments into different categories.



Recurrent Neural Network (RNN) theoretically claimed to maintain the long-term dependencies but practically fall as addressed by Bengio et al. [2]. Information correlation over a long period needed distance calculation between nodes. The distance calculation is done based on multiple products of Jacobian Matrix. This prompts all the more normally vanishing gradient and less continuous exploding gradients. To overcome this issue Hochreiter et al. [1] presented Long Short-Term Memory networks typically called LSTMs. It has shown an unbelievable performance in NLP and Image Processing applications.

LSTM is a kind of RNN equipped for learning long term conditions. The RNN is the combination of repeating neural network modules. Figure 1 shows a single layer RNN that depicts how RNN collaborates to infer information from each module.

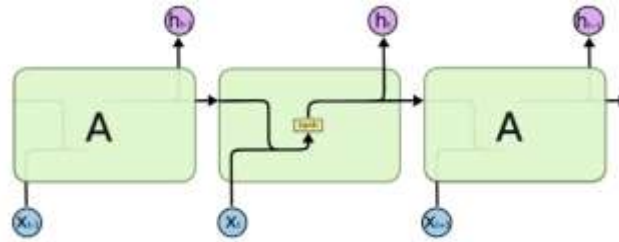


Figure 1: A single layer RNN

LSTM is a specialized RNN that has four network layers that interact uniquely. Equation (1) shows the outcome of the sigmoid function is.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

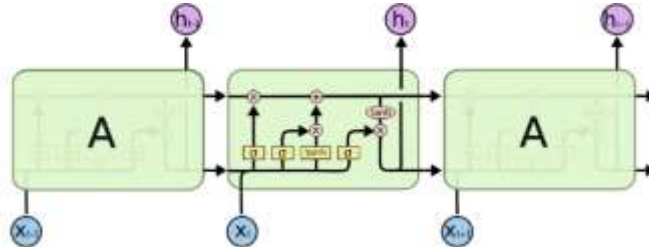


Figure 2: LSTM with interacting layers

Equation (2) represents the outcome of the cell state using the \tanh function.

$$C_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (2)$$

These parameters are updated in each training step and stored. Mike Schuster et al. [3] portrayed a Bidirectional RNN that utilizes distinctive hidden layers, feed-forward to a similar output layer. The LSTMs have shown significant performance improvement in speech recognition, synthesis and entity recognition. The deep learning-based techniques can be applied to sentiment analysis [13].

In the research work we have used a LSTM and neural network-based approach to Tweeter sentiment analysis. We have taken Tweeter dataset for our experimental analysis.

3. Related work

This section deals with the related methods used for sentiment analysis. We have mainly concentrated on deep learning-based approach. Patel et. al. [4], have described a model using Recursive RNN to classify the movie reviews. The proposed system does sentiment analysis based on the review text.

Jan Deriu et. al. [6] have developed a Twitter sentiment classification using deep learning. In the proposed model they have used a Two-layer convolutional neural network. The main task is divided into 3 subtasks.

Anand et.al. [5] have posed a system to do the same task with CNN. In this approach, sentiment analysis is done using Natural Language Processing (NLP) as most text present on Twitter is in the form of emotions or opinions. The proposed model gives a comprehensive view of the emotions in terms of positive, negative, or neutral.

Fenna Miedema et al. [7] have proposed a system that used LSTM networks to develop a model that has to turn out to be most efficient among other approaches. Zainuddinet al. [8] have posed a sentiment classification approach using Support Vector Machines. This model lack accuracy in the case of long sentences obtained from a variety of resources.

Mathieu Cliché [9] has implemented a CNN and LSTM based approach that is trained on SemEval-2017 twitter dataset. This approach uses a large set of unlabelled dataset and pre-trained word embedding. This hybrid approach has shown better improvement in the accuracy level of the classification. The proposed approach included 5 steps – Reading CSV file (Twitter data), Pre-processing, Feature extraction, and classification. In the paper, the tasks are accomplished in two ways in the first approach. ML- based approach is applied to the dataset whereas in the second approach deep neural network-based methods are used.

The mode which is incorporating the LSTM approach shows improved performance as compared to other approaches. In the previous few years, the deep learning approaches have demonstrated critical improvement in the performance of NLP mechanisms. [10, 11-14].

4. Proposed system

In the present research we have used LSTM based approach to analyze the Twitter post. Our deep learning model is built using Keras Python libraries.

5. Methodology

4.1. Data Collection

Twitter sentiment dataset is collected from a Kaggle repository and analyzed for negative and positive sentiments. Figure 3 shows the negative sentiment in the red color bar whereas positive sentiments using a green color bar. Dataset is read using the panda library.

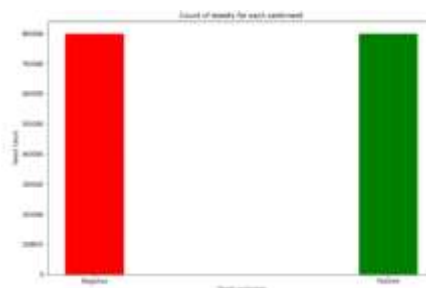


Figure 3: Sentiment classification

5.2. Data Pre-processing

The data preprocessing includes a set of operations to be performed on the dataset to extract sentiments. It cleans the tweets by removing stop words, spacing, or any special symbols. The step also lemmatizes and stems words. The processed data is further used for the model training and testing.

5.3. Training and testing with LSTM

The read dataset after cleaning is classified into training (80%) and test dataset (20%). The *Train_and_Test()* function is used to split the dataset. The trained model is tested further to check model efficiency.

6. Experimental results

6.1. Dataset Description

We have used 1.6 million tweets to form training and testing dataset. These datasets are cleaned for the further processing.

7. Experimental setup

The RNN based LSTM model is built using Keras and Tensorflow. Table 1 represents the network configuration parameters of the RNN-LSTM model.

Table 1: LSTM parameters

| Parameters | Value |
|----------------------------------|----------------------|
| Batch-size | 10 |
| Epochs | 128 |
| Hidden layer-activation function | Relu |
| Output layer-activation function | Sigmoid |
| Optimizer learning-rate | Adam 0.001 |
| Dropout | 0.5 |
| Loss-function | Binary cross-entropy |

8. Performance evaluation

In this subsection, we are going to assess the performance of the applied approach and other related methods. Figure 4 shows the set of positive sentiments obtained from Twitter data.



Figure 4: Positive sentiments

Figure 5 shows the set of negative sentiments obtained from tweets.



Figure 5: Negative sentiments

The LSTM model classifies the sentiments with an accuracy of 85.04%. Figure 6 represents the accuracy and loss of our model in each iteration for 5 epochs.

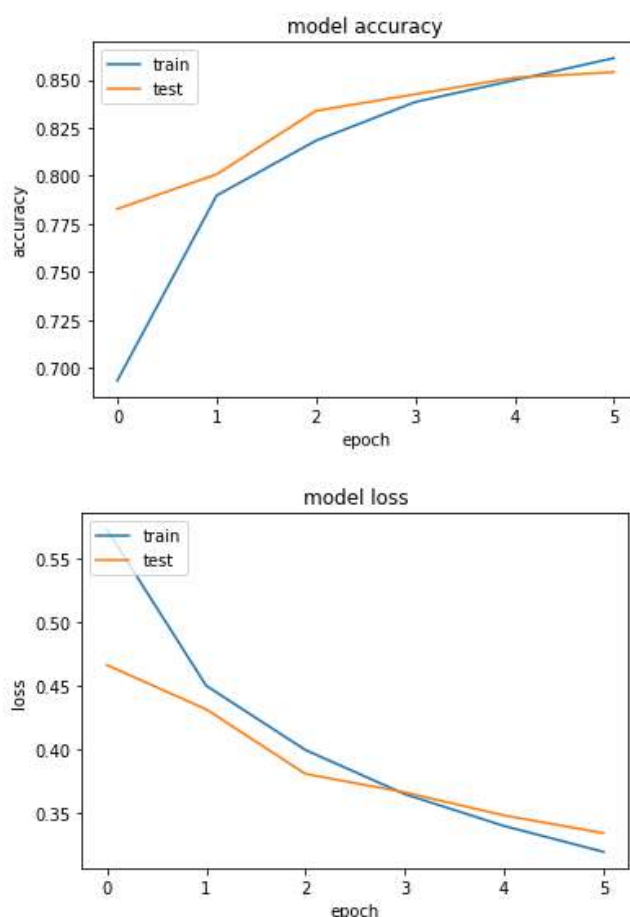


Figure 6. Model performance

The LSTM approach shows improved result compare to Convolutional Neural Network (CNN) and a simple neural network. Table 2 shows the performance comparison of the algorithms for 1.6 million tweets.

Table 2. Performance Matrix-I

| Algorithm name | Training accuracy | Testing accuracy |
|-----------------------|-------------------|------------------|
| LSTM | 87.4 | 87.01 |
| CNN | 92 | 82 |
| Simple Neural Network | 85.3 | 74.7 |

Table 3 indicates the performance of the three different methods based on four parameters.

Table 3. Performance matrix-II

| Methods | Accuracy | Precision | Recall | F-measure |
|-----------------------|----------|-----------|--------|-----------|
| LSTM | 87 | 81 | 80 | 80 |
| CNN | 82 | 77 | 76 | 76 |
| Simple Neural Network | 81 | 76 | 75 | 74 |

9. Conclusion and future work

Our proposed research work addressed the need for RNN and LSTM for improved performance in Sentiment classification. In the paper, we have also addressed the different AI-based approaches and their performances. We have calculated the performance of the LSTM-RNN model. We have analysed 1.6 million tweets for our research to categorize them into Positive or negative sentiments.

The proposed approach has an 87% accuracy level which is best among all the approaches used in the current study. To conduct the experiment, we have collected a Twitter dataset from the Kaggle repository.

Although the proposed LSTM based approach is the best but to analyse real-time data and classify them into different emotions, we can use the REST API based web service approach. To solve scalability issues a big data platform can be chosen to analyse the huge number of tweets.

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