# Sentiment Analysis of US Airlines Tweets using LSTM/RNN

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***Abstract*—Nowadays, a million users use social networking services such as Twitter to tweet their products and services by placing the reviews based on their opinions. Sentiment analysis has emerged to analyze the twitter data automatically. Sentiment classification techniques used to classify US airline tweets based on sentiment polarity due to flight services as positive, negative and neutral connotations done on six different US airlines. To detect sentiment polarity, we explored word embedding models (Word2Vec, Glove) in tweets using deep learning methods. Here, we investigated sentiment analysis using the Recurrent Neural Network (RNN) model along with Long-Short Term Memory networks (LSTMs) units can deal with long term dependencies by introducing memory in a network model for prediction and visualization. The results showed better significant classification accuracy trained 80% for training set and 20% for testing set which shows that our models are reliable for future prediction. To improve this performance, the Bidirectional LSTM Model (Bi-LSTM) is used for further investigation studies.**

***Keywords—Twitter, Sentiment, Recurrent neural networks, LSTM, Word embeddings***

## I. Introduction

Social media such as Twitter created since 2006 is increasing day by day with a wide-spread of customers expressing their feedbacks about goods and services. Many organizations attract customers with the use of social media [14]. Hence, it is more important for the companies for an automatic finding of each customer reviews is identified by opinion mining. It acts as a major key challenge in research areas in social media. Sentiment analysis introduced on Twitter in 2009 to classify the sentiment tweets. It is easier to collect tweets from twitter which is a reliable one and is used for data analysis [10].

Twitter has a basic length of the tweets as 140 characters. Tweets have positive, negative, neutral (neither positive nor negative) which helps customers to choose better service airlines [15].

The Airline industry is critical in customer reviews. Traditional methods provide inconsistent information about data to the airline industry.

The Neural network model builds artificially intelligent machines to solve most of the complex computational problems. Artificial neural nets described in Mc Culloch and Pitt's work in 1943. It uses machine learning which has several layers involving various mathematical operations. Earlier deep learning features use Lexicon based techniques for supervised, unsupervised and semi-supervised approaches. Recently, Deep structured learning (DL) emanates as a powerful machine learning algorithm in various domains from Text and Speech recognition, Natural Language Processing (NLP), and Computer vision, etc. [13] based on artificial neural networks with multi-layer perceptrons. Popular research performed in deep learning by employing sentiment analysis [7]. Recurrent Neural Networks along with Long Short Term Memory classify airline tweets using Keras and word embeddings. LSTM is a powerful classifier for sentiment analysis that uses LSTM units called memory cells in the network learning long term dependencies from a sequence of words. Tweets gathered from Twitter are pre-processed [1].

In this work, 14640 tweets of six different US airlines such as Virgin America, United, US Airways, Delta and Southwest dataset taken from Kaggle released by CrowdFlower in CSV form. The percentage of tweets is higher in the negative of 91.78 %.

This paper comprises six sections: Section I shows an introduction. Section II covers the literature related to the proposed work. Section III explains the sentiment analysis. The model of network architecture is described in Section IV. Section V discusses about evaluation of experimental data whereas, Section VI concludes the overall work.

## II. Related Work

Autoencoders is the process to encode huge features into smaller in unsupervised pre-training models (Yoshua Bengio and Yann LeCun, 2007) [22]. Recurrent neural networks that have an issue in long sequences of data (Tomas Mikolov et al., 2010). LSTM network addresses to solve these problems.

Go and L.Huang (2009) [23] proposed automated sentiment analysis of twitter data which classifies tweets as positive and negative with feature classifiers using the Support vector machine (SVM).

[1] proposed airline tweets using the Naïve Bayes classifier algorithm that explored in AYLIEN which results in better improvement of analysis in the future by interpreting a large number of tweets data.

[2] proposed sentiment analysis of US airline service using word embedding models (Doc2Vec) of six airlines with seven different features classifiers of KNN (K-Nearest Neighbour), AdaBoost, Support Vector Machine(SVM), Decision Tree, Random Forest, Logistic regression, and Naïve Bayes classifier algorithm.

[3] proposed sentiment classification for short term from social media posts with word embedding models

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using LSTM approaches which show better improvement than Extreme Learning Machines (ELM) and Naïve Bayes classifier.

[4] Proposed sentiment classification in Machine Learning (ML) in Indian railways data using four different classifiers as C4.5, Support Vector Machine (SVM), Naïve Bayes, and Random Forest which classifies accuracy, F-measure, recall, and precision for model evaluation. It estimates better accuracy in SVM than C4.5.

[5] Proposed sentiment analysis in financial news in a deep learning approach which predicts the change in price earlier based on the polarity of data. It uses LSTM/RNN and CNN methodologies for better improvement.

## III. Sentiment Analysis

The study of sentiment states by Natural Language Processing (NLP), computational linguistics, text analysis, and biometrics refers to text mining or opinion mining [11]. It extracts tweets and classifies them as positive, negative, and neutral based on various reasons of the customers due to the delayed flight or by rude service.

Sentiment categories of six different US airline tweets are shown in Fig.1.

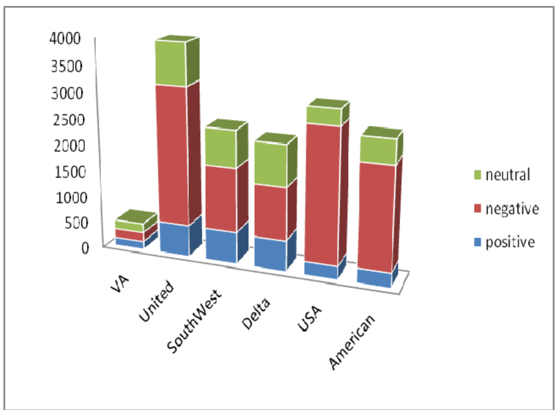


Fig. 1. Sentiment Categories of Airline Tweets

It identifies and extracts the tweets contain a set of words that are grouped from pre-trained GloVe (Average/Sum). The GloVe is a representation of words in vectors that has several pre-built words embedding files (Jeffrey Pennington et.al, 2014) from the standard NLP group.

Table I illustrates the tweet dataset for airline industry service.

TABLE I. TWEETS DATASET IN SOCIAL MEDIA

| Airline Tweets | | | | |
|---|---|---|---|---|
| ***Tweet id*** | ***Sentiment*** | ***Negative reason*** | ***Name*** | ***Text*** |
| 5.68E+17 | Negative | Flight Booking Problems | Portugrad | @Southwest Air tried to rebook online but it says that I have to pay $200 for the difference in price. |
| 5.70E+17 | Positive | 0 | YupitsTate | @Virgin America it was amazing, and arrived an hour early. You're too good to me. |
| 5.68E+17 | Neutral | 0 | DubCook | @Southwest Air Guys, we've got to do something about the inability to check-in online for an international flight that has…(1/2) |

Comparing with Word2Vec, word vectors are in the form of shallow neural network which tries to predict word but in the GloVe model is an object matrix calculates by using co-occurrence matrix and dimensionality reduction to get vectors [19, 20, and 21]. Distributed representation of word embedding models in the GloVe map into hot encoding vector space in the lower dimension (word_to_vec_map). GloVe embedding models mostly used with the Keras library which has high accuracy. A collected tweet consists of tweet id, location, time zone, airline sentiment, negative reason, and text.

## IV. Models

The overall architecture for sentiment analysis of tweets is shown in Fig.2.

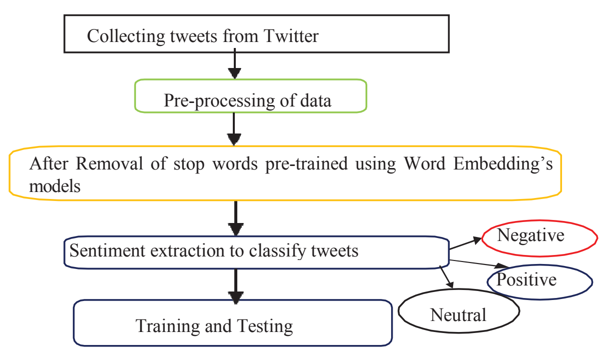


Fig. 2. Flow diagram of data

Text collected from social media is pre-processed and cleaned, word embedding's model learns word representations as vectors and by using LSTM is applied for sequence prediction of words in sentences [12].

### *A. Recurrent Neural Networks (RNN)*

RNN is a class of neural nets that remember its inputs due to an internal memory that involves sequences of data, such as, text, genomes, or numerical time series data [17, 19]. Remembering of previous words to predict the next word of the sequence is quite difficult in a traditional neural network but in RNN's solve this issue with the help of hidden layers remember sequence information through time to produce the output [16, 18].

Each hidden layer has its weights and sigmoid activation function. Recurrent neural networks deal only with short-term dependencies, whereas it cannot handle long dependencies by vanishing gradient problems during back propagation through time [9].

$$h_t = f_0\,(W'_{hh}h_{t-1} + W'_{xh}X_t) \qquad (1)$$

In Equation (1), $f_0$ is the tanh function for ReLu (Rectified Linear Unit) function. $h_{t-1}$ is the preceding state of the word. The input for the current state at a time (t) is $X_t$.

### *B. Long Short-Term Memory Units (LSTMs)*

LSTM algorithm learns long dependencies were introduced by Sepp Hochreiter and Jurgen Schmidhuber analysis a solution to solve the gradient problem over multiple time steps [6]. It has three gatings and multiplicative units ($i_0$), ($f_0$), and ($O_0$).

A set of gates is used for data control, flow from the network in the cell by the form of the sigmoid (btw [0, 1]). Input gate ($i_0$), passes input information through the interchangeable block. Forget gate ($f_0$), control information away from the cell. Output gate ($O_0$), passed to the next time step [8]. LSTM cell recognizes the input, stores to determine the removed information.

$$Y = \text{Softmax}\,(V_{st}) \qquad (2)$$

In Equation (2), Vst is the hidden state information.

```
Layer (type)                 Output Shape              Param #
=================================================================
input_3 (InputLayer)         (None, 26)                0
_________________________________________________________________
embedding_3 (Embedding)      (None, 26, 200)           80000200
_________________________________________________________________
lstm_5 (LSTM)                (None, 26, 128)           168448
_________________________________________________________________
dropout_5 (Dropout)          (None, 26, 128)           0
_________________________________________________________________
lstm_6 (LSTM)                (None, 128)               131584
_________________________________________________________________
dropout_6 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_3 (Dense)              (None, 3)                 387
_________________________________________________________________
activation_3 (Activation)    (None, 3)                 0
=================================================================
Total params: 80,300,619
Trainable params: 300,419
Non-trainable params: 80,000,200
_________________________________________________________________
```

Fig. 3. Parameters using LSTM model

Fig.3 shows the parameters using the LSTM model. Fig.4 show the model of long short-term memory unit with dropout regularization (dropping the weights) and softmax.

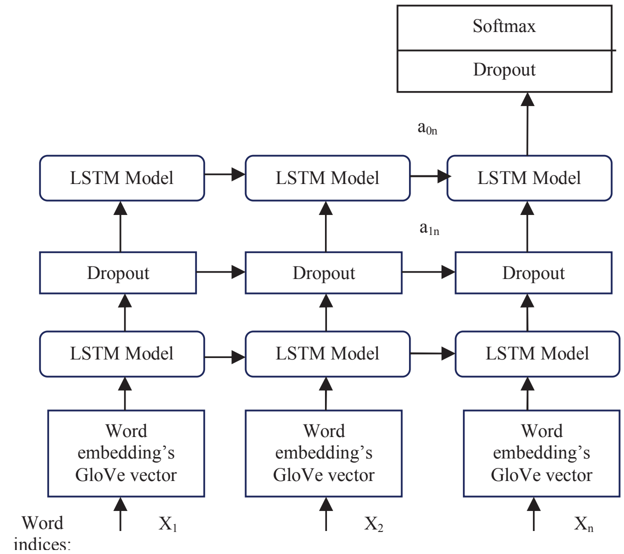


Fig. 4. LSTM model

## V. Evaluation

For this work, we used Pandas, Keras library in Jupyter notebook experimented using 200-dimensional GloVe vectors. Pandas is an open-source library provides high performance to load dataset and analysis tools for python. Jupyter notebook creates and shares documents that contain equations and visualization on a web-based application. The Softmax loss function helps to optimize the error. The Model trained with 300,419 parameters. It is helpful to predict the best airlines evaluated from the sentiment analysis. Fig.5 and Fig.6 shows the model loss and accuracy of the training and validation dataset estimated in the LSTM network unit.

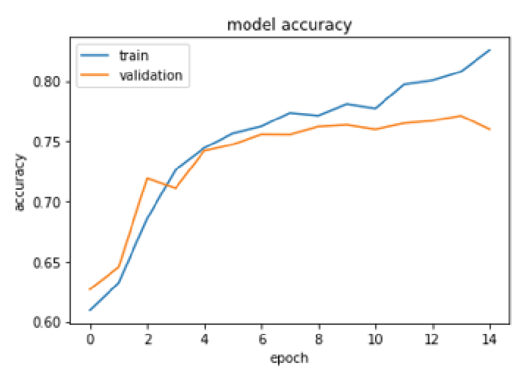


Fig. 5. Model accuracy of training and validation set using the LSTM network

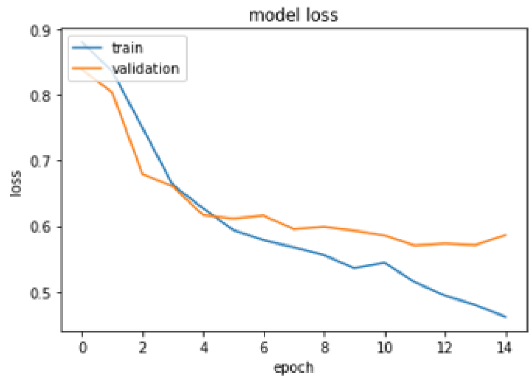


Fig. 6. Model loss of training and validation set using the LSTM network.

## VI. Conclusion

This paper proposed a sentiment analysis using deep learning techniques by the LSTM network model. We analyze tweets data for the airline industry in social media which shows better performance in the training set. Furthermore, accuracy can be enhanced using the Bidirectional LSTM network (Bi-LSTM) [24].

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