



AirLine Tweets Sentiment Analysis using RNN and LSTM Techniques

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ABSTRACT

With the progression of web innovation and its development, there is an enormous volume of information present on the web for web clients, what's more, a great deal of information is created as well. The web has gotten a stage for internet picking up, trading thoughts, and sharing assessments. Lots of data generated from Facebook, WhatsApp, Twitter. All these data are in the form of text format. So, text processing plays a major role in decision making. In this paper, we applied RNN, LSTM models on airline tweets data. We applied sentiment analysis for airline customers and classified the reviews as positive or negative. The dataset is taken from a Kaggle repository and we performed airline sentiment analysis using a deep learning LSTM model. We applied various types of LSTM models to better classify the tweets. We achieved an accuracy of 90% with our proposed LSTM model.

Key words : Airline Tweets, RNN, LSTM, Kaggle repository, Python.

1. INTRODUCTION

In sentiment analysis, we collected datasets that contain emotions and feelings of customers regarding the products or services used by the customers.[1]. Twitter is a platform where the tweets pass on feelings and emotions. But attempting to acquire the general comprehension of this unstructured information (tweets) can be very tedious. This unstructured information (assessments) on a specific site is seen by the clients and consequently making a picture about the items or administrations and thus at long last producing a specific judgment. These feelings are then being summed up to accumulate criticisms for various purposes to give valuable assessments where we use assumption investigation. Twitter is one of the most generally utilized internet-based platforms that has monthly active users of 333 million and the number of tweets sent per day is over 500 million [2]. The reason for extracting information from tweets is that the success or

failure of the particular service or product is analyzed by the way how people responded to that service or product [3]. sentiment examination is also useful for customers. It is useful to decide whether to buy a product or not before they get it. Companies, advertisers, and firms utilize this examination information to comprehend their items so that it tends to be offered as per the user's prerequisites. Text information processing strategies principally center around handling, looking, or investigating the verifiable information present. Realities have a target part but, there is some other printed substance that expresses abstract attributes. These substances are primarily suppositions, estimations, evaluations, mentalities, feelings which structure the center of Sentiment Analysis (SA). It offers many provoking chances to grow new applications, chiefly due to the tremendous development of accessible data on online sources like websites and interpersonal organizations. In sentiment analysis, we need to make a binary decision like yes/no, like/dislike, or positive/negative based on the tweet or review. This process is also called as opinion mining or emotion mining. In the advertising field, organizations use it to build up their techniques, to get customers' emotions towards items or brand, how individuals react to item dispatches and why shoppers don't get a few items. In the political field, it is utilized to monitor political perspectives, to identify consistency and inconsistency among explanations and activities at the administration level, moreover to foresee political decision results too. In airline tweets data, sentiment analysis is useful for identifying user opinions and make changes to their services based on user responses. Text mining/classification is the procedure of consequently doling out at least one predefined classes to message records. In the current examination, the expressions "archives" also, "tweets" allude to a comparative idea. We can regard each tweet as an archive and use text-classification ideas, for example, tokenization, stemming, term-recurrence what's more, record recurrence to exemplify an adaptable portrayal of the issue.

2. LITERATURE SURVEY

Machine Learning is a term coined in 1950s. But its impact is very high after several years of its introduction. Deep learning is a subset of machine learning. The difference between machine learning and deep learning is that, Deep learning has the capability of automatic feature extraction. Analyzing text data is not a new trend in machine learning. Several researchers applied various machine learning and deep learning techniques for analyzing text information. Generally, machine learning techniques work with mathematical approaches. But, if we need to analyze text data, first we need to convert text information into the numerical format and then we will apply machine learning techniques. A. Lakshmanarao [4] *et al.* applied various machine learning technique for analyzing fake news data. Bac Le [5] *et al.* applied various machine learning algorithms for twitter sentiment analysis. They applied two machine learning techniques naïve Bayes and support vector machines. They extracted features using Bigram, Information Gain, Object-oriented extraction methods. Neethu M.S [6] *et al.* applied shallow learning techniques for sentiment analysis and achieved good results. Hanaa Aldahawi [7] *et al.* applied several machine learning classifiers on tweets dataset taken from the oil business. For classification the used concepts instead of words. They applied the n-gram model and achieved good accuracy rates. Sachin Kumar [8] *et al.* applied machine learning techniques on airline tweets for analyzing customer satisfaction. They applied the n-gram method to extract features and later they applied feed-forward neural networks on the dataset. They also applied Convolutional Neural Networks on preprocessed data and get good results. They suggested an association analysis of tweets data to get more accuracy. Brinda Hegde [9] *et al.* applied machine learning models on demonetization tweets. They applied three classification models SVM, Naive Bayes, Logistic Regression. Geetika Gautam [10] *et al.* applied various machine learning methods on twitter data. They applied semantic analysis techniques and later they applied Support Vector Machines and Naïve Bayes classifier and achieved a maximum accuracy of 89.9%. Duyu Tang [11] *et al.* applied a deep learning model for tweet sentiment analysis. They used a technique called Cooll. It is a supervised learning framework that combines word embedding technique with feature extraction method Imane El Alaoui [12] *et al.* applied an adaptable approach for sentiment analysis on big social data. They implemented a method in which first they build a word dictionary polarity based on subject, then they classified the tweets into different classes. Alec Go [13] *et al.* used Naïve Bayes and SVM models for sentiment classification and achieved good results. Swati Powar [14] *et al.* applied various machine learning techniques on tweets data and achieved the best accuracy with the Naïve Bayes machine learning model. Oduwa Edo-Osagie [15] *et al.* proposed a semi-supervised

learning model for twitter data analysis and achieved good results. Soumya S [16] *et al.* proposed machine learning techniques for sentiment analysis of Malayalam tweets and achieved good results. Abdullah Alsaedi [17] *et al.* reviewed various techniques of sentiment analysis. They exposed various machine learning models, ensemble approaches, dictionary-based methods, hybrid methods.

3. RESEARCH METHODOLOGY

The dataset used for our experiments is collected from the Kaggle repository. The dataset contains 14640 tweets with 15 columns. The features are tweet-id, airline sentiment, airline_sentiment_confidence, negative-reason, negative reason-confidence, airline name, airline_sentiment_gold, name, negativereason_gold, retweet_count, text, tweet_coord, tweet_created tweet_location, user_timezone.

In these features, “text” is a feature that contains reviews of customers. The feature “airline-sentiment” has two labels namely positive and negative. This feature is dependent feature. The remaining features are not relevant. So, we ignored all the remaining features. The data is in text format. So, it is not possible to apply machine learning or deep learning algorithms directly to this data. First, we applied various Natural Language Processing techniques to preprocess this text data. Python provides NLTK (Natural Language Processing Toolkit) for applying various NLP techniques. With the NLTK tool, we can able to perform various operations on text information.

3.1 Recurrent Neural Networks/LSTM

RNN is a deep learning model designed for time series data and text data. RNN is a special type of deep learning technique where it has some memory to remember previous data. But there is a problem in RNN called a vanishing gradient problem. This problem states that the gradient value does not affect weight update values. To solve this problem, LSTMs are designed. LSTM has forgot the gate which can keep discard data depending on the situation. It also has input and output gates. Generally, LSTM performs well than the Simple RNN model.

Before applying RNN or LSTM, we applied various text preprocessing techniques on our dataset.

3.2 Text Preprocessing

In the text preprocessing, we need to remove punctuations. Later, we normalize all words to lowercase and remove the stop words. Stop Words are the words that are not useful for deciding a review as positive or negative. Examples of stop words are is, was, an, etc. To reduce the complexity of the machine learning model, we removed all the stop words. All these tasks can be implemented through python NLTK library. After that, we applied the word-stemming technique.

Stemming is the normalization of words. For example, a word playing can be normalized as play. We implemented the removal of stopwords and stemming techniques by using regular expression notations in python language.

3.3 Extract the word-to-integer mapping

After removing all unnecessary text and symbols from the dataset, we extracted the word-to-integer transformations of all the words in the dataset. The frequency of all the words in the dataset is extracted.

3.4 Mapping of word to word

Next, we mapped each word in a sentence to the corresponding word associated with it in the dataset. In this step, we converted the review into a list of lists where each list constitutes the ID of words contained in a sentence.

3.5 Padding

As the length of all sentences in the dataset is not the same. But Recurrent Neural Network expects the number of time steps for each input to be the same. For achieving this requirement, We normalized all sentences to the same length. For this, first, we find the length of the sentence with maximum length. Later, we applied padding (pad with 0) to the sentences which are having less than maximum length word. After this step, all the sentences length becomes the same, which means all the inputs have similar length.

3.6 Make Training and testing sets

In machine learning, we divide the total dataset into two parts. After getting a preprocessed dataset, we divide it into training and testing sets. There is no rule of thumb in machine learning for this split ration. But the general assumption is that it is better to have a large split for training data so that the model can learn patterns more efficiently. The train, test ratio split is 70%,30%.

3.7 Label Encoding

The dependant variable(airline-sentiment) is a categorical feature with two features namely positive, negative. But machine learning deals with numerical data. So, we converted these two labels into 0 and 1. We applied the encoding technique to this feature For this task, we used Keras_to_categorical. We can also perform label encoding with Label Encoder class in the python sklearn package.

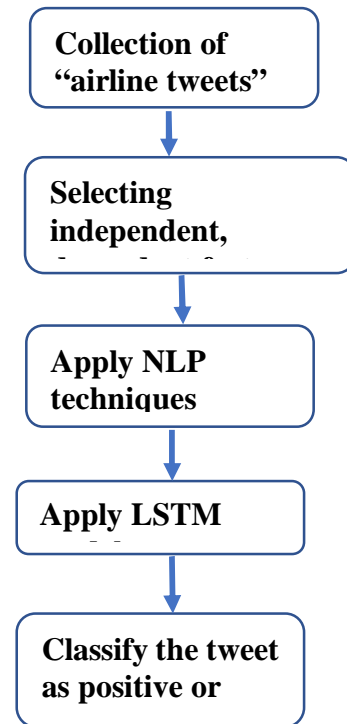


Figure 1:Proposed Model

3.8 Prepare Word Embeddings

Word embedding is created to make a dense representation of words. It takes several different words as input and generates a vector for each word. It is an important layer that lies between input and RNN/LSTM layer. Its performance is generally better than the traditional method “bag-of-words”. Embedding layer weights can be random values or they can be generated from other methods such as wrod2vec or Glove. For the Embedding layer, we need to give input dimensions, output dimensions, and input length. Here, output dimensions indicate the number of dimensions in each word. The input dimensions represent the total number of different words in the total dataset. Input_length represents the number of words in each sentence.

3.9 Apply RNN/LSTM Model

Now, the dataset is ready for applying RNN/LSTM. We applied RNN and various LSTM techniques on the preprocessed dataset. First, we applied the SimpleRNN model. Next, we applied vanilla LSTM (Long Short-Term Memory). After applying these three models, we compared these models.

4. EXPERIMENTATION AND RESULTS

The dataset contains 14,640 tweets. It contains other features also. But we consider only text tweets for our analysis. Based on the given tweet, we need to classify it as a positive or

negative review First, we preprocessed the dataset using various natural language processing techniques. Later we divided the dataset into training and testing sets. Next, we prepared word embedding and applied three different deep learning models RNN, LSTM, Stacked LSTM and compared the results. We used python for all implementations, as python provides various packages for deep learning.

4.1 SimpleRNN model:

We applied SimpleRNN on the training set and applied the model on testing data. We added one embedding layer, one SimpleRNN layer, and the output layer. The error function used in the model is “binary_crossentropy”. As this problem is a binary classification problem, we applied “sigmoid” as an output function. The number of epochs is set to 120. We used “adam” as an optimizer. The average accuracy of all epochs is 86%.

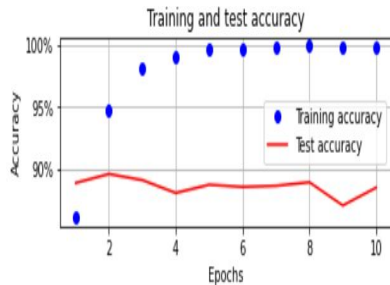


Figure 2: Accuracy of training, testing sets

4.2 LSTM model

Next, we applied the LSTM model on the same dataset. We applied a simple Vanilla LSTM model, which is a basic LSTM model. We used one embedded layer, one lstm layer, and one output layer. The error function is “binary_crossentropy”. The optimizer used is “adam”. The output function is “sigmoid”. The number of epochs is set to 125. The average accuracy of all epochs is 89.4%. This accuracy is higher than accuracy of SimpleRNN.

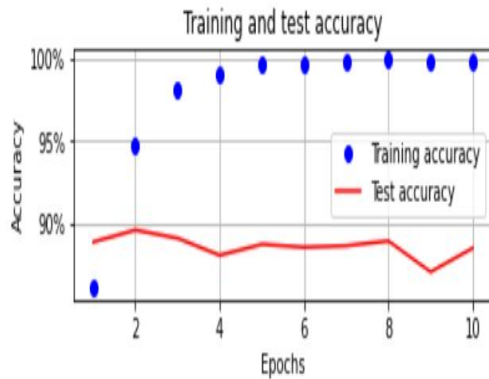


Figure 3: Accuracy of training, testing sets

4.3 Stacked LSTM model

Next, we applied a stacked LSTM model on the same dataset. We used one embedded layer, two lstm layers and one output layer. The error function is “binary_crossentropy”. The optimizer used is “adam”. The output function is “sigmoid”. The number of epochs is set to 100.

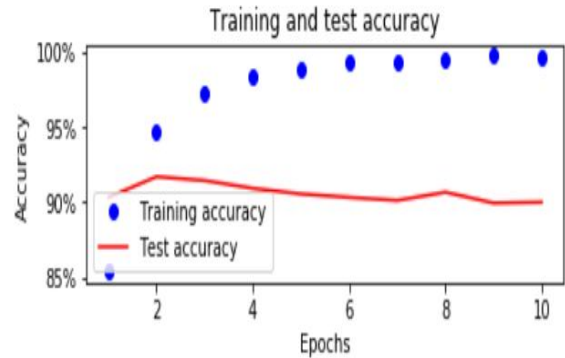


Figure 4: Accuracy of training, testing sets

After applying three different models, we compared accuracy of all three models. The results are tabulated.

DL model	Accuracy	Loss
Simple RNN	86%	0.86
LSTM	89.4%	0.52
Stacked LSTM	91%	1.206

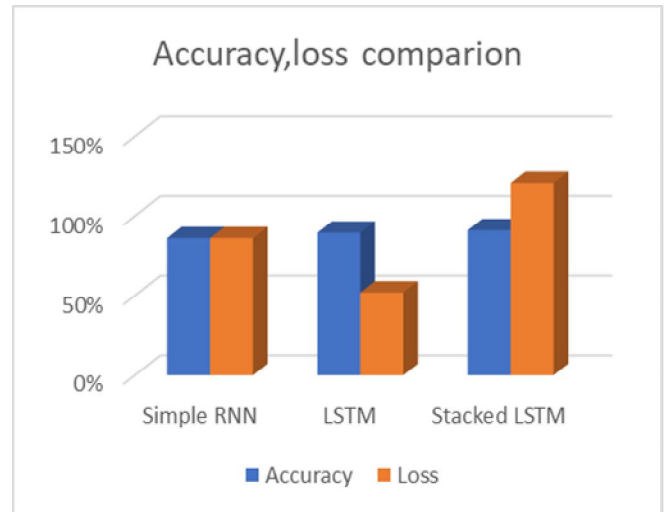


Figure 5: Comparison of Regression Models

5. CONCLUSION

In this paper, we applied deep learning methods for airline tweets classification. As the dataset contains text data, first we applied various natural language processing methods and prepared a preprocessed data. Later we applied three models

namely Simple RNN, LSTM, and Stacked LSTM. After applying all three models, we observed that LSTM has given better accuracy than Simple RNN, and Stacked LSTM has given slightly better accuracy than Vanilla LSTM. We achieved an accuracy of 91% with stacked LSTM.

REFERENCES

1. R. Feldman, "Techniques and Applications for Sentiment Analysis," *Communications of the ACM*, Vol. 56 No. 4, pp. 82-89, 2013.
2. Online, <https://www.omnicoreagency.com/twitter-statistics/>
3. Ch Chauhan, S Sehgal "Sentiment Analysis on Product Reviews," *International Conference on Computing, Communication and Automation, 2017, International Conference on Computing, Communication and Automation (ICCCA)*.
4. A. Lakshmanarao, Y. Swathi, T. Srinivasa Ravi Kiran, "Sentiment Analysis on Product Reviews", *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, Volume-8 Issue-10, August 2019, Page No.: 3125-3129.
5. Bac Le, Huy Nguyen, "Twitter Sentiment Analysis Using Machine Learning Techniques", *Advanced Computational Methods for Knowledge Engineering, Springer International Publishing Switzerland 2015*.
6. Neethu M. S, R. Rajasree, "Sentiment Analysis in Twitter using Machine Learning Techniques", *4th ICCNT 2013, July 4 - 6, 2013, Tiruchengode, India, IEEE-31661*.
7. Hanaa Aldahawi and Stuart Allen, "An Approach to Tweets Categorization by Using Machine Learning Classifiers in Oil Business", *Springer International Publishing Switzerland 2015, A. Gelbukh (Ed.): CICLing 2015, Part II, LNCS 9042, pp. 535-546, 2015*.
8. Sachin Kumar, Mikhail Zymbler, "A machine learning approach to analyze customer satisfaction from airline tweets", *Journal of Bigdata, Springer Open, 2019*.
9. Brinda Hegde, Nagashree H S, Madhura Prakash, "Sentiment analysis of Twitter data: A machine learning approach to analyze demonetization tweets", *International Research Journal of Engineering and Technology, Volume: 05 Issue: 06 June-2018*.
10. Geetika Gautam, "Sentiment Analysis of Twitter Data Using Machine Learning Approaches and Semantic Analysis", 978-1-4799-5173-4/14/\$31.00 ©2014 IEEE.
11. Duyu Tang, Furu Wei, Bing Qin, Ting Liu, Ming Zhou, "Coooolll: A Deep Learning System for Twitter Sentiment Classification", *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014), pages 208-212, Dublin, Ireland, August 23-24, 2014*.
12. Imane El Alaoui, Youssef Gahi, Rochdi Messoussi, Youness Chaabi, Alexis Todoskoff and Abdessamad Kobi, "A novel adaptable approach for sentiment analysis on big social data", *Journal of Bigdata, Springer Open, <https://doi.org/10.1186/s40537-018-0120-0>, 2018*.
13. Alec Go, Richa Bhayani, Lei Huang "Twitter Sentiment Classification using Distant Supervision", CA 94305 alecmgo@stanford.edu, 2009.
14. Swati Powar, Unmesh Kadam, Tanmay Salvi, "Twitter Sentiment Analysis for Classifying Hate Tweets and Normal Tweets Using Logistic Regression and Naive Bayes Algorithm", *2018 JETIR October 2018, Volume 5, Issue 10*.
15. Oduwa Edo-Osagie, Gillian Smith, Iain Lake, Obaghe Edeghere, Beatriz De La Iglesia, "Twitter mining using semi-supervised classification for relevance filtering in syndromic surveillance", *PLOS ONE | <https://doi.org/10.1371/journal.pone.0210689> July 18, 2019*.
16. Soumya S., Pramod K.V, "Sentiment analysis of malayalam tweets using machine learning techniques", *Science Direct, 2020 The Korean Institute of Communications and Information Sciences (KICS)*.
17. Abdullah Alsaedi, Mohammad Zubair Khan, "A Study on Sentiment Analysis Techniques of Twitter Data", *(IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 10, No. 2, 2019*