Stock Prediction and Analysis based on Airline Reviews

Prajakta Gaydhani
Department of Computer Science
Golisano College of Computing and Information Sciences
Rochester Institute of Technology
Rochester, NY 14586
pag3862@cs.rit.edu

***Abstract*—Sentimental analysis of online customer feedbacks on different airlines plays a important role in understanding the behavior and traveling adventures of people and can assist different airlines companies to boost their performances and improve their customer services. This paper proposes a novel technique of correlating sentiments in customer reviews with the stock behavior of different airline companies in the United States. Application of Gradient Descent Regressor, Random Forest Regressor, AdaBoost Regressor, and LSTM deep learning model to forecast stock prices of airline companies using user sentiments and historical stock market data are discussed in this paper. Experiments conducted in this paper showed that users sentiments are positively correlated with the stock market behavior of 5 different airlines. LSTM deep learning model outperformed all the conventional machine learning models for predicting stock prices and achieved a Mean Squared Error (MSE) of 0.0236. In this paper, both positive and negative were analyzed using word cloud for helping airline companies to improve their customer services.**

I. Introduction

Nowadays, millions of people all around the world share and expresses their thoughts, experiences, views, and emotions in the form of tweets or reviews on different social media platforms. Sentimental analysis and Natural language processing of these online reviews give insights into the mood patterns of different users on several subjects. Analyzing the data on social media can also help companies to increase their sales and productivity by targeting its valuable customers. It can also guide companies to improve their services and facilities and attract more people and increase customer satisfaction [1]. Although the stock market always plays a critical role in the progress of a company, the success of a company also depends on its customers. A company can make continuous progress only if its customers are happy and satisfied and continuously provide positive reviews on the services offered by the company. Hence, it is essential to understand the impact of customers moods and feedbacks on the performance and stock market of a company [2].

People are using air travel as their primary mode of traveling from one place to another. With the increase in the popularity of several online forums, people have started sharing their views and traveling adventures on different airlines in the form of reviews and feedbacks[3]. Analyzing these reviews can not only encourage companies to improve their services but can also assist them to improve the traveling satisfaction of its customers[3]. According to a report released by the International Air Transport Association (IATA) in 2016, different airlines companies contributed to 2.7 percent of the total Gross Domestic Product (GDP) growth of the United States [4]. As the stock market indirectly influences the economic growth (GDP) of a nation, it is extremely important to understand the impact of those customer reviews on the stock market behavior of various airlines companies.

This paper performs sentimental analysis of millions of customer's reviews on major airlines in the USA for learning their traveling experiences. User sentiments and stock market data was aggregated to find a correlation between the user emotions and stock market behavior of different airline companies. Stock market prices were also forecasted using the user sentiments and historical stock market data of several airline companies.

The entire paper is divided into different sections. Section II discusses background information on the research topic. Section III-A and section III-B outlines various data sources and data preprocessing techniques for cleaning customer reviews and stock market data. Section III-C classifies the customer reviews using sentimental analysis. Section III-D talks about the actual reasons for positive and negative reviews using word cloud visualization technique. Section III-E and section III-F analyzes the effect of user sentiments on the stock market of different airlines. Section III-G discusses several machine learning and deep learning techniques for forecasting stock market prices using user sentiment and stock market data. Section IV compares the results and performances of different models built in section III-G. Section V talk about future work and conclusion.

II. Background

Natural Language Processing (NLP) plays a vital role in analyzing the moods patterns and sentiments of millions of people using online reviews. It can help different companies to find the most potential customers and can further guide them to improve their services for increasing the customer satisfaction[1].Different NLP techniques such as Stemming, POS tagging, Word Sense disambiguation improves the performance of different sentimental analysis algorithms by resolving semantic as well as lexical ambiguity in the text data[1]. This paper [1] uses different NLP techniques and ensemble classifiers for determining public sentiments. The ensemble technique discussed in this paper [1] outperformed the traditional bag-of-words and TF-IDF feature extraction approach.

With the popularity of online reviews, this paper [3] examined the characteristics of several airline reviews on Skytrax website [5] for increasing the traveling satisfaction of its customers. After extensive analysis using C4.5 and CART models, [3] concluded that cabin staff and seat comfort highly correlated to the customer's traveling satisfaction and achieved a correlation score of 0.96. Yaket et al. [6] also analyzed online reviews on different airlines using K-means clustering and Multivariate Regression analysis for increasing the customer satisfaction and improving the services offered by the airlines. This paper [6] also concluded that value for money and seat comfort are related with the customer traveling satisfaction and the airline companies should work to improve these services.

Khedr et al. [7] proposed an approach for predicting stock market behavior using machine learning and sentimental analysis of financial news articles. Naive Bayes machine learning algorithm along with N-gram and TF-IDF approach was used for classifying news articles into positive (1) and negative (0). Different machine learning models such as KNN, SVM, and Naive Bayes algorithms were developed for predicting the stock market behavior using news articles. Among all the three classifiers, Naive Bayes model when trained using both the sentiment and stock market data achieved an accuracy of approximately 89% [7]. The approach developed in [7] outperformed all the previous approaches of predicting stock market behavior using user's sentiment data. Another approach proposed by Chakraborty et al. [8] analyzed the effect of tweets on the stock market behavior. Tweets related to stock market were collected from Twitter and Stocktwits website. DJIA (Dow Jones Industrial Average) was used for extracting closing prices for various companies. All the stock market tweets were labeled as positive and negative using SVM, Logistic Regression, and Decision Trees machine learning models. Both user sentiments and stock market data were correlated using Boosted Regression Tree with a Root Mean Squared Error (RMSE) of 1.73[8].

Mittal [9] discuss a novel approach using Self Organizing Fuzzy Neural Networks, which correlated public moods on twitter and stock DJIA (Dow Jones Industrial Average) stock prices with an accuracy of 75%. Vegras et al. [10] proposed an approach by combining Convolution neural networks (CNN) and Long Short Term Memory (LSTM) neural networks with word2vec embeddings for predicting stock market prices using user sentiment data and achieved an accuracy of 89%.

III. Proposed Methodology

Figure 1 describes a detailed architecture and the overall flow of different methods and techniques proposed in this paper.

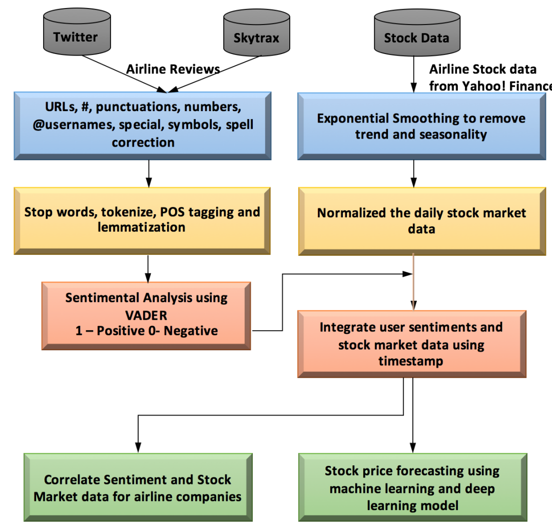

Fig. 1. Proposed System

A. Data Collection

The data collection process was divided into two parts. The first part included the scrapping of customer reviews/feedbacks on different airlines from the Twitter and Syktrax.com [5]. The second part involved extracting stock market data from Yahoo! Finance. Around 2 million reviews were collected from January 2010 to October 2018 for 5 major airlines in the United States like American, United, Delta, JetBlue, and Alaska Airlines.

1) Collecting the data from Twitter: All the customer reviews from Twitter were scrapped using Twitter's Tweepy Search API [11] for Python. Different keywords and @usernames related to American, United, Delta, JetBlue, and Alaska Airlines were used for extracting the data from Twitter. Some of the major keywords and @usernames used for extracting the reviews on different airlines are list in the Table I. Timestamps and user's tweets were extracted using Tweepy API.

TABLE I
List of #hashtags and @usernames for extracting customer reviews from Twitter

Keywords	Usernames
#AmericanAirlines #AASucks	@AmericanAir
#unitedAIRLINES #BoycottUnited #Dontflyunited	@United
#DeltaAirlines #neverflydelta	@Delta @DeltaNewsHub
#JetBlueAirlines #JetBlueSUCKS #jetBlueForever	@JetBlue
#AlaskaAirlines #iFlyAlaska #alaskaairsucks	@Alaskaair

2) Scrapping the data from Skytrax.com: Skytrax [5] is a website containing reviews on different airlines, airports and customer's traveling experiences with these airlines. All the reviews and customers traveling experiences from Skytrax were extracted using web scraping tool called Selenium [12] and a Web Driver for chrome browser. Selenium is known for dynamically scraping data from web pages that contain large JavaScript code[12]. It takes charge of the web browser and automates the process of loading and scanning the HTML page content for extracting the data from a given website. Web driver program helps Selenium to interact with the web browser. Selenium API for Python was installed using PIP command and the web driver code for Chrome was downloaded from [13]. Only timestamps and customer reviews were extracted from the Skytrax website.

All the reviews collected from Twitter and Skytrax websites were merged together and were sorted by timestamps value for analysis.

3) Collecting Stock data from Yahoo! Finance: Yahoo! Finance [14] is a website that provides daily as well as historical financial news, reports, and stock prices for larger number of companies. Stock market data including High, Low, Open, Close prices for different airline companies were collected from the Yahoo! Finance Website [14]. Ticker symbols like AAL, UAL, DAL, JBL, and ALK for American, United, Delta, JetBlue, and Alaska airlines respectively. were used for extracting the historical stock market data.

B. Data Preprocessing

This section is divided into three parts. The first two parts includes data cleaning and natural language processing of customer reviews. The third part includes cleaning and smoothing the stock market data of various airline companies.

1) Cleaning Customer Reviews:
Python's regular expression were used for cleaning customer reviews.

- All the customer reviews collected were into the standard UTF-8 encoding format [15].
- Customer reviews extracted from twitter contained @usernames and # symbols. All the @usernames mentions and # symbols were removed. Since #hashtags signify user sentiments only # symbols were removed from customer reviews[15].
- All the punctuations, numbers, and special symbols were removed from the user reviews. Since "!" and different emoticons symbols add to user emotions, they were not eliminated from the reviews[15].
- All the URLs beginning with "http:", "www." and ending with the ".pic" were also removed from the customer reviews[15].
- Some of the reviews scrapped from twitter contained words with repetitive letters. For example words like "helloooo" , "woowww", etc., in the reviews were replaced with words "hello" and "wow".
- All the contractions in the reviews such as "don't", "should've", etc., were replaced with their original expanded versions such as "do not" and "should have"[15].
- All the extra leading and trailing white spaces were eliminated. All the extra spaces between different words was replaced with a single space[15].

2) Natural Language Processing (NLP) on Customer Reviews:
Natural Language TookKit (NLTK) [16] and TextBlob [17] package for python was utilized for performuing different NLP tasks.

- **Removing Stopwords** : All the stop words were removed from the the user reviews[15] .
- **Tokenization**: All the reviews were tokenized into individual words[15].
- **Spelling Correction** : All the misspelled words in different reviews were corrected using TextBlob package[18] for Python.
- **Parts of Speech (POS) Tagging** : Parts of Speech Tagging was performed, for understanding the role of every word in the reviews. It was implemented using Penn TreeBank POS Tagger [19] from NLTK package.
- **Lemmatization** : Lemmatization converts all the words to their base format for resolving the ambiguity. For example, words like "fell", "fall", "falling" were all converted to the root "fall". This was implemented using WordNet lexical database [20] from NLTK package.

3) Cleaning Stock Market Data:
Stock market data collected from Yahoo! Finance [14] included upward trend along with some seasonal variations. Machine learning and deep learning models, when applied on a dataset containing spikes and seasonality, may produce unusual or unpredictable results. Therefore, it was necessary to smooth out the data by making time series as stationarity (with no trend and seasonality) as possible.

For this purpose, Exponential smoothing was implemented using StatsModel [21] package for python. For smoothing the stock market data, the exponential smoothing assigns greater weights to all the latest observations and the weights decrease exponentially for all the older observations.

C. Sentimental Analysis

All the customer reviews were classified either as positive or negative reviews. The customer reviews dataset was not labeled, therefore, a dictionary and rule-based approach called Valence Aware Dictionary and sEntiment Reasoner (VADER) [22] was used to classify the customer reviews. VADER is known to perform well on real-time social media data. It also takes into consideration the punctuation marks (e.g., "!"), emoticon symbols, acronyms revealing sentiments (e.g., lol, ugh), capitalized words, intensifiers (e.g., very, so, extremely), negative connections (e.g., but, although, whereas) and slangs during sentimental analysis[22]. Hence, it performs better and even faster than many supervised machine learning algorithms for sentimental analysis. VADER reveals both the polarity of the sentiment as well as its intensity [22]. VADER calculates a compound score by adding the valence scores of all the words in a given sentence[22]. The compound score is normalized where -1 shows extreme negativity and +1 shows extreme positivity. Along with the compound score, a positive, negative and a neutral score is also computed for sentiment analysis. VADER classifies the tweet as positive if compound score ≥ 0.5, negative if compound score ≤ -0.5 and neutral if $-0.5 <$ compound score < 0.5 [22]. All the customer reviews were classified as positive or negative (neutral sentiments were excluded) using VADER sentiment package for python. The compound score computed was used to classify the reviews as negative (indicated by 0) or positive (indicated by 1).

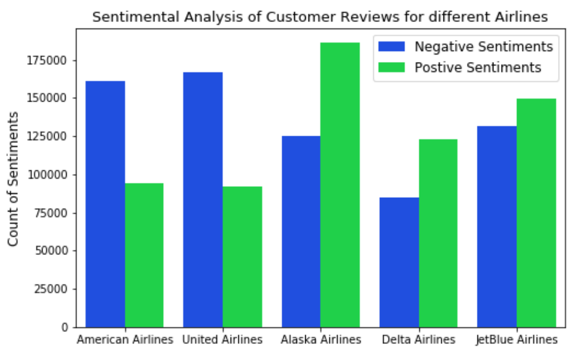

Fig. 2. Sentimental Analysis of Customer Reviews for different Airlines

Figure 2 shows comparison between the number of positive and negative user sentiments for different airlines. American and United Airlines had the maximum number of negative reviews. It revealed that the customers were not very happy with the services offered by American and United Airlines. On the other hand, Alaska, Delta, and JetBlue Airlines had more number of positive reviews than the negative. It showed that the customers were more satisfied with the services offered by Alaska, Delta, and JetBlue airlines.

D. Word Clouds for Positive and Negative Customer Reviews

After classifying the airline reviews using sentimental analysis, word cloud helped in understanding various reasons behind different opinions of the customers. World Cloud is an excellent tool for analyzing the textual data extracted from different social media platforms. In a word cloud, all the frequently occurring words in the textual data are more highlighted and have larger font sizes than all the words that are less frequent in the textual data [23].

For this project, word cloud was implemented for understanding the customer's experiences when traveling with different airlines. Both positive as well as negative traveling experiences of different customer were analyzed for helping airline companies to improve their services and facilities[24].

Figure 3 shows a word cloud of all the positively classified customer reviews on different airlines. Words like "travel", "love", "flying", "airport", "great", "best", "service", and "help" which are highlighted in the word cloud were the most frequently occurring words in the positive reviews. These words signified the actual reasons for the customer to be happy and satisfied with the services offered by different airlines.

Fig. 3. Wordcloud for positive reviews on different airlines

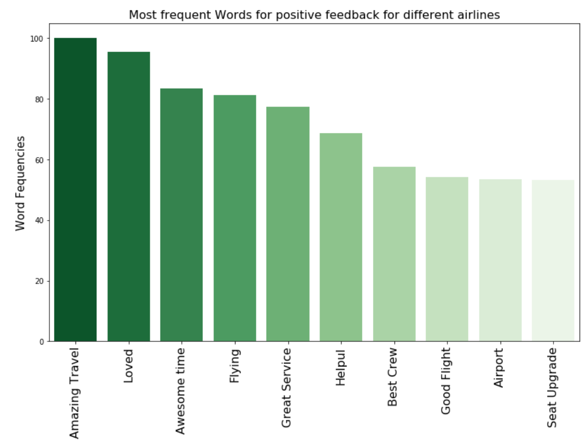

Fig. 4. Histogram of the most frequent words in positive reviews

Figure 4 depicts the first 10 frequently occurring words in the positive reviews. Among all the positive reviews, the customers were most happy about the amazing travel experience, awesome time spent while traveling, good flight, great services, best crew, and seat upgrade facilities offered by the airlines.

Fig. 5. Word Cloud for negative reviews on different airlines

Figure 5 shows a word cloud of all the negatively classified customer reviews on different airlines. Words like "delay", "flight attendant", "customer service", "fail", "suck", "flying", "worst", and "bad" were the most frequently occurring words in the negative reviews. These words signified the actual reasons for the customers to be unsatisfied with the airlines.

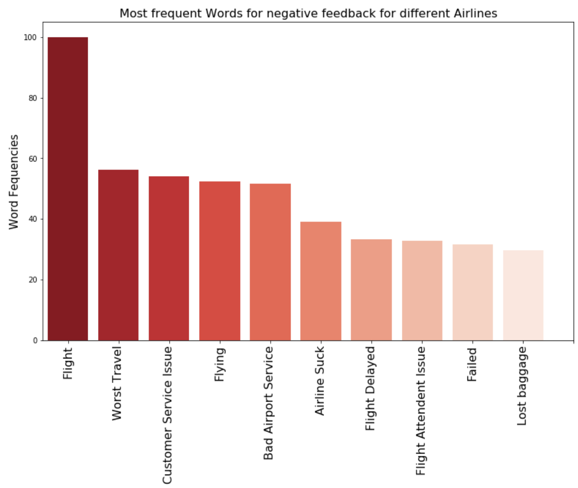

Fig. 6. Histogram of the most frequent words in negative reviews

Figure 6 depicts the first 10 frequently occurring words in the negative reviews. Among all the negative reviews, the customers were not satisfied with the delayed flight, airline, lost baggage, customer service, and flight attendant services offered by the airlines.

E. Integration of customer reviews and stock market data

A new dataset was created by aggregating the customer reviews and stock market data. The number of all the positive, negative and total reviews for each day from January 2010 to October 2018 were recorded and was sorted by date in ascending order. In table II, the columns "PosCnt", "NegCnt" and "TotalCnt" indicates the the count of positive, negative, and total reviews for a particular day. An inner join was implemented based on the Date value, for merging the sentiment data mentioned above with the stock data containing Open, High, Low, and Close values[25]. Table II shows the snapshot of the final integrated sentiment and stock market data.

TABLE II
SNAPSHOT OF INTEGRATED SENTIMENT AND STOCK MARKET DATA

Date	PosCnt	NegCnt	TotalCnt	Open	High	Low	Close
6/20/17	50	107	157	49.22	49.36	48.01	48.03
6/21/17	54	96	150	48.33	48.64	48.13	48.43
6/22/17	53	89	142	50.5	50.56	48.79	48.97

F. Correlate Sentiments and Stock Market Movement

This section shows the impact of sentiments both positive and negative on the stock market movement of different airline companies [25].

A new column "Close_Rise_Fall" was added to the dataset mentioned in the table II. This column recorded the rise and fall in the closing stock prices of airline companies. If the previous day's closing price $\succ$ today's closing price, then Close_Rise_Fall for that day was set to -1. If today's closing price $\succ$ the previous day's closing price, then Close_Rise_Fall for that day was set to +1. If the todays closing prices was same as previous day's closing price , then Close_Rise_Fall for that day was set as 0 [25].

Similarly, another column "Sentiment" was also added to the dataset mentioned in the table II. This column marked the overall sentiment for that particular day. From table II, if for a particular day, the NegCnt $\succ$ PosCnt then the Sentiment was set to -1. If for a particular day, the NegCnt $\prec$ PosCnt then the Sentiment was set to +1. If the NegCnt was same as PosCnt, then Sentiment was set as 0 [25].

A correlation between "Close_Rise_Fall" and "Sentiment" columns was calculated using the "corr()" correlation function from Pandas package for Python. corr() function returns a value in range [-1,+1] where -1 indicates that "Close_Rise_Fall" and "Sentiment" columns are negatively related to each other whereas +1 indicates that these columns are positively related to each other. Correlation of 0 shows that the two columns are not at all related to each other.

TABLE III
IMPACT OF SENTIMENTS ON THE STOCK MARKET MOVEMENT FOR DIFFERENT AIRLINE COMPANIES

American	United	Delta	JetBlue	Alaska
0.94	0.93	0.92	0.90	0.89

Table III shows the correlation between sentiments and stock market movement [25] of American, United, Delta, JetBlue and Alaska airlines. A positive value of correlation (closer to +1) indicated that both "Close_Rise_Fall" and "Sentiment" columns are highly correlated with each other. Therefore, it can be concluded that if the overall sentiment for a particular day is positive (indicated by +1), there is a rise in the closing price (also indicated by +1). Whereas, if the overall sentiment for a particular day is negative (indicated by -1), there is a fall in the closing price (also indicated by -1) [25]. Among all the 5 airlines, American Airlines had the highest correlation of 0.94 whereas Alaska Airlines had the lowest correlation of 0.89 with sentiment and stock market.

G. Implementation

Previous section showed that sentiments and stock prices are correlated with each other. This section experiments with forecasting closing prices for various airline companies with the help of user sentiments and historical stock market data from table II. This section is divided into two subsections. In the first section, different machine learning models were built for forecasting the closing stock prices. In the second section, deep learning model (LSTM) was built for forecasting stock prices. In both the sections, closing prices were foretasted using user sentiments as well as historical stock market data.

Before building any models, the data was divided into training and testing datasets. Around 80 % of the data from January 2010 to December 2016 was used for training various machine learning and deep learning models. 20 % of the data from January 2017 to October 2018 was utilized for evaluating different models. The entire dataset mentioned in the table II was normalized to the scale [0,1]. This normalized dataset was used for training and testing the models. Later, the forecasted closing prices were de-normalized for determining actual closing prices.

1) Machine Learning Models: Different machine learning models listed below were implemented for forecasting closing prices for various airline companies with the help of user sentiments and historical stock market data. All the models were built using Sklearn [26] machine learning library in Python. Grid search technique with 5 fold cross validation was used for tuning various hyper parameters of all the models. All the machine learning models were evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 Error metrics. Performance of different machine learning models is illustrated in the section IV.

- Support Vector Regressor (SVR)
- K-Nearest Neighbor Regressor
- Random Forest Regressor
- AdaBoost Regressor
- Gradient Descent Regressor

2) Deep Learning Models: Closing prices for various airline companies were also forecasted using Long Short-Term Memory (LSTM) model which are a type of Recurrent Neural Networks. LSTM deep learning model was implemented using Keras [27] deep learning library in Python.

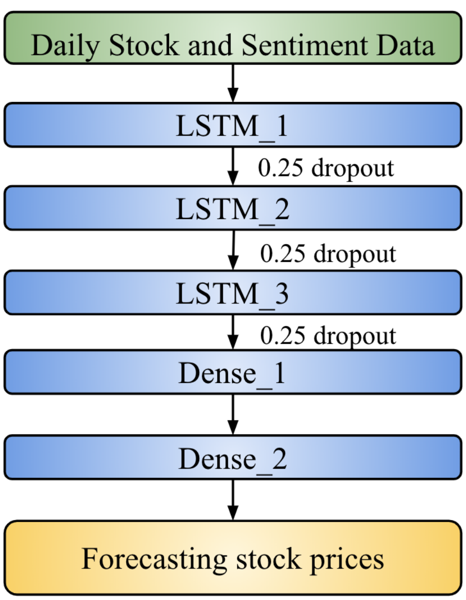

Fig. 7. LSTM architecture for forecasting stock prices

Figure 7 shows the architecture that achieved the best performance for forecasting stock market prices using user sentiments and historical stock market data. The architecture consisted of 1 input layer (LSTM_1), 3 hidden layers (LSTM_2, LSTM_3, and Dense_1), and 1 output layer (Dense_2) all stacked together in a consecutive series. Between every LSTM layer, a dropout of 25% was added to improve the regularization and to decrease the over-fitting while training the deep learning model [28]. All the dense layers in the figure 7 were fully connected layers. Before training the deep learning model, both user sentiments and historical stock market data were normalized to scale [0,1]. The stock market prices forecasted by the output layer (Dense_2) were de-normalized to show the original stock prices.

Table IV shows the best set of hyper-parameters used for training the deep learning model. Around 80% of the data was used for training the model and remaining 20% of the data was used for testing and validating the model. Relu activation function was used since the stock market data was continuous in nature. Relu helped to train the deep learning model at a faster rate without much decay in the learning rate. The model was trained for 100 epochs with a learning rate of 0.0005 and a batch size of 64. Adam Optimizer was used for reducing the over-fitting. The train and test performance of the model was evaluated using a mean squared error metric. Section IV shows in detail the performance of the LSTM model.

TABLE IV
BEST HYPER-PARAMETERS FOR LSTM DEEP LEARNING MODEL

Hyper-parameters	**Values**
Train/Test/Valid	80/10/10
Batch size	64
Epochs	100
Learning rate	0.0005
Optimizer	Adam
Activation Function	Relu
Regularization	Dropout
Loss Function	Mean Squared Error

IV. RESULTS

This section compares the performances of different machine learning as well as the deep learning model developed for forecasting stock market prices of various airline companies using user sentiment and historical stock market data. The performance of all the models was assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 error evaluation metric. Lower error indicates that the performance of the model was better and that model would accurately predict the future stock prices.

TABLE V
PERFORMANCE OF VARIOUS MACHINE LEARNING MODELS

Model	MSE	RMSE	R^2
Support Vector Regressor	11.82	3.43	0.5137
K-Nearest Neighbor Regressor	7.56	2.74	0.6889
Random Forest Regressor	0.47	0.63	0.9832
AdaBoost Regressor	0.62	0.78	0.9745
Gradient Descent Regressor	0.34	0.58	0.9856

Table V compares the performances of Support Vector Regressor, K-Nearest Neighbor Regressor, Random Forest Regressor, AdaBoost Regressor, and Gradient Descent Regressor machine learning models using MSE, RMSE, and R^2 error. Among the 5 machine learning models, Gradient Descent Regressor model performed the best and achieved an MSE of 0.34 and R^2 error of 0.9856. Support Vector Regressor model and K-Nearest Neighbor model performed worst on the given stock market and sentiment dataset and achieved an MSE of 11.82 and 7.56 respectively. This indicated that the stock prices predicted by Gradient Boosting Regressor were more correlated with the user sentiments than all other machine learning models.

TABLE VI
PERFORMANCE OF THE DEEP LEARNING MODEL ON TRAIN AND TEST DATASETS

	Train	Test
MSE	0.00826	0.00236
RMSE	0.09	0.05

Table VI shows the performance of the LSTM model on the train and test datasets. On the training dataset, LSTM obtained an MSE of 0.00826 and RMSE of 0.09. Whereas on the testing dataset LSTM achieved an MSE of 0.00236 and RMSE of 0.05. Higher value of error on train data than the test data indicated that the model did not suffer from over-fitting. LSTM deep learning model performed the best and achieved a least mean squared error (MSE) of 0.00236 on the test dataset when compared with the MSE of the different machine learning models in the table V.

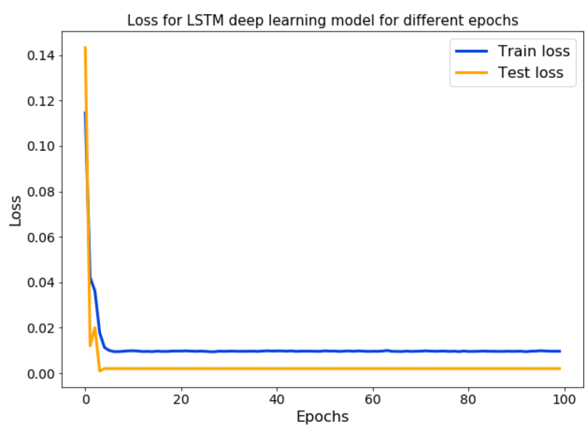

Fig. 8. Train and Test loss of the LSTM model for 100 epochs

Figure 8 shows the performance (loss) of LSTM model on train and test datasets for 100 epochs. For initial epochs, the loss on the test data was much greater than the loss on the train data (over-fitting). As the number of epochs increased, both train and test losses gradually decreased. Test loss was much lower than the training loss (no over-fitting) after the 3^{th} epoch. Figure 8 also shows that the train and test losses remained constant after 5^{th} epoch. This shows that training the deep learning model for many iterations helps to improve the prediction results by reducing the over-fitting

Figure 9 depicts the stock market prediction result using Support Vector Regressor (SVR). The plot reveals that SVR

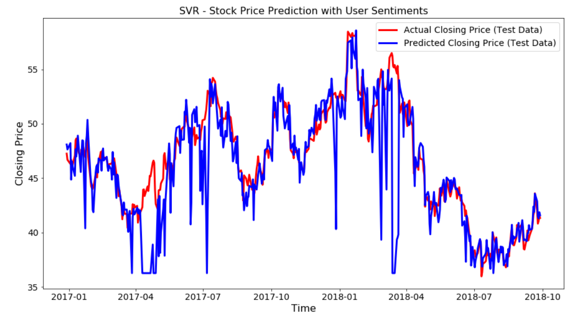

Fig. 9. Stock price prediction results using Support Vector Regressor

did not produce accurate predictions of the stock prices. Table V showed the prediction error for SVR was around 11.82.

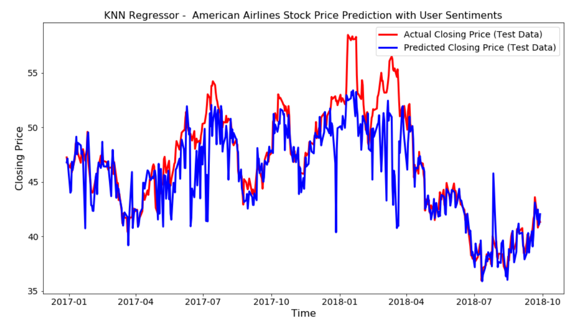

Fig. 10. Stock price prediction results using K-Nearest Neighbor Regressor

Figure 10 shows the stock market prediction result using K-Nearest Neighbor Regressor. This plot also reveals that the K-Nearest Neighbor Regressor did not produce accurate predictions of the stock prices. Table V showed the K-Nearest Neighbor Regressor performed little better than SVR with a prediction error of 7.56.

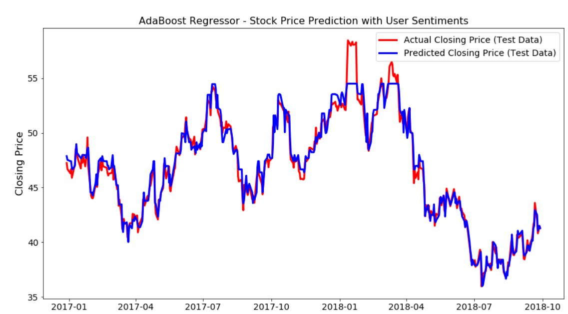

Fig. 11. Stock price prediction results using AdaBoost Regressor

Figure 11 depicts the stock market prediction result using AdaBoost Regressor. The plot shows that AdaBoost Regressor accurately predicted the stock prices than SVR and K-Nearest Neighbor Regressor models.

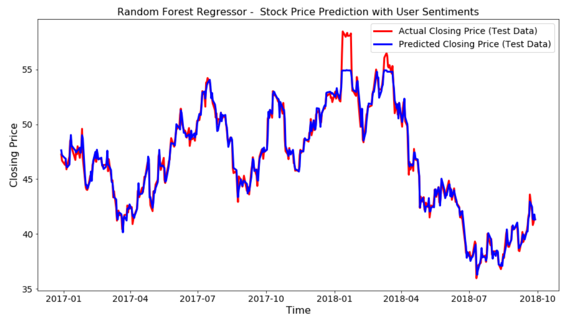

Fig. 12. Stock price prediction results using Random Forest Regressor

Figure 12 depicts the stock market prediction result using Random Forest Regressor. The plot reveals that both Random forest Regressor and AdaBoost Regressor performed equally well on the test datasets.

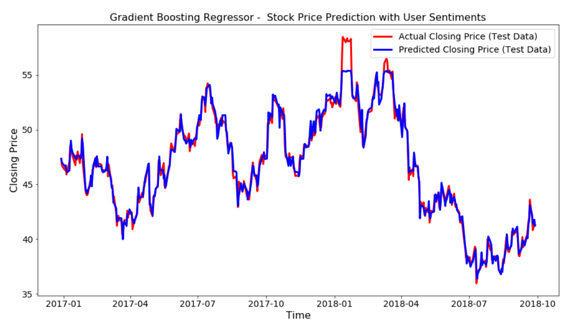

Fig. 13. Stock price prediction results using Gradient Descent Regressor

Figure 13 depicts the stock market prediction result using Gradient Descent Regressor. The plot shows that the stock prices were predicted more accurately by the Gradient Descent Regressor than all other machine learning models.

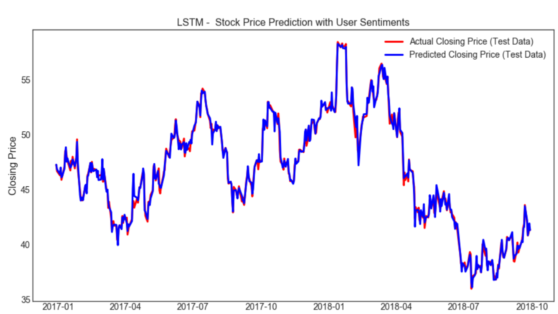

Fig. 14. Stock price prediction results using LSTM deep learning model

Figure 14 shows the stock market prediction result using LSTM model. The plots shows that among all the models, the stock prices forecasted by the LSTM model were more accurate and closer to the original stock values.

V. Conclusion and Future Scope

In this paper, millions of reviews from Twitter and Skytrax website were analyzed using VADER sentimental analysis tool and word cloud for understanding customers traveling experiences with different airlines. Later, it concluded that the user sentiments are positively correlated with the stock movement of American, JetBlue, Delta, Alaska, and United airlines. Different machine learning and deep learning techniques were utilized to predict stock prices using the sentiment data. Comparative analysis of the results of different models showed that the stock prices forecasted using LSTM deep learning method were closely related to the actual stock prices. In this paper, LSTM model achieved a MSE of 0.00236 and outperformed all other conventional machine learning models.

In future different time series models can be built for analyzing the impact of user sentiments on the stock market of different airline companies. The results can be compared with the existing results, to see if the time series models performs better than existing models. Also, more unstructured data such as news articles on different airlines can be collected and analyzed to see the impact of several news articles on stock market prices of several airline companies. An online application can be created that will be used by different airline companies to foresee their stock prices and interpret their overall performance.

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