OPIM – 5671 – DATA MINING AND BUSINESS INTELLIGENCE

GOOGLE STOCK PRICE FORECASTING

Project White Paper

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TEAM DATA SQUAD

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INTRODUCTION

Stock price forecasting is a popular and important topic in the field of Finance because of its volatility. It attracts researchers to capture the unpredictability and predict its next moves. Stock brokers and market analysts continuously study the pattern of stocks to plan their buy or sell strategies. Internal to Google, it is important for them to know what triggers the stock price and what downfalls it. This influence various business decisions taken in Google. Stock market produces huge amount of data every day, so it's not an easy task to predict the future stock price considering all the current and past information. There are two main approaches to predict the stock prices, one being Technical analysis and other being Fundamental analysis. Technical analysis used the past prices and volume to predict the future trend whereas Fundamental analysis uses other financial and economic factors which influence the stock prices. In this paper, we have collected both technical and fundamental data from online sources for Google (Parent company ALPHABET) to forecast Google stock price. The popularity of Google and availability of heaps of information online for our research, motivated us to choose Google stock price forecasting.

PROBLEM STATMENT

Our project mainly aims to improve the predictive accuracy of Google stock prices and determine if Time series forecasting and LSTM models can be used to offer insights regarding the future stock prices and how other external events and factors are impacting the stock prices. On a broad perspective, we target to build models to predict the rise and fall of the stock price pattern and forecast the day-to-day stock price of Google that would help the company for a better planning. Thus, our problem can be categorized into two: Classification (to predict rise and fall pattern) and Regression (to predict the stock prices).

Our team decided to implement the same using Machine learning, Time series and Deep learning algorithms. Data sources used and the work corresponding to each of the data sources are mentioned below.

NEWS HEADLINES

Classification of whether the stock prices will have an upward/downward trend using news headline data (where previous day's news is used). Misclassification rate is the estimation metrics used.

HISTORICAL STOCK DATA

Stock price prediction based on historical stock data. RMSE is the estimation metrics. Another estimation metrics is the Misclassification rate (the number of times stock price trend - upward/downward is correctly predicted on the whole test dataset).

LITERATURE REVIEW

Stock price prediction is based on the implications of Efficient Market Hypothesis (EMH) that stock price reacts instantaneously to day-to-day news. Work has been done to predict the direction of stock price index movement using soft computing-based models such as Artificial Neural Networks (ANN) and Support Vector Machines. Other approaches like Fuzzy Logic, Genetic Algorithm, Machine Learning algorithms were also implemented. Hidden Markov Models (HMM) approach was used to forecast stock price for interrelated markets. This approach helped in pattern recognition and classification problems because of its ability for dynamic system modeling.

Econometric models that include methods such as Autoregressive method (AR), Moving average model (MA), Autoregressive Moving average (ARMA) model, Autoregressive Integrated moving average (ARIMA) models have been used for stock prediction and other time series analysis. Researchers have also experimented to enhance the basic ARIMA model for improved accuracy. These experiments helped the researchers understand that additional features should be brought into picture apart from the historical stock data. This resulted in gathering online news related to stock from various public media and textual information was processed further for news evaluation. One such work includes an automated text mining approach to gather news data from various sources, analyze using Natural Language Processing (NLP) techniques to determine the sentiment of news articles and its impact on the fluctuating energy demands. Work has also been done on Twitter feeds where keyword tagging was used to understand about the airline's customer satisfaction.

Our approach is to combine the traditional time series analysis with sentiment scores generated from the text mining process done on New York Times news headlines thereby incorporating additional features which will help in improving the stock price prediction accuracy.

DATA

Our data of historical stock is sourced from Yahoo Finance and New York Times data is pulled from official developer site. This data is recorded daily and made publicly available for further analysis.

Internal to Google, this data helps them take strategic decisions. External to Google, stock brokers and market analyst use this information to take buy/sell decisions. Lots of money revolves around this useful data. We have collected the stock price and New York times data for past 10.5 years -7th Jan 2008 to 29th June 2018. Our target variable is opening stock price. The different news sections included were National, Business, World, U.S. Politics, Opinion, Tech, Science, Health. For web scraping we have used Newsapi.articles library of python that allows to pull headlines from New York Times using Archive API from the URL - http://api.nytimes.com/svc/archive/v1/{}/{}.json?api-key={}

Once the web scraping is completed, SentimentIntensityAnalyzer from NLTK API was used to generate positive, negative, neutral and compound sentiments based on polarity-based and valence-based approach. Using both approaches helps us not only in classifying a news as positive, negative or neutral but also takes the intensity of the sentiment into account which is expressed in terms of Compound sentiment score.

INPUTS AND STATISTICS

The set of predictors includes company finance related predictors, socio – economic predictors and various events which were captured during this time frame. Sharp rise and falls in the time series were explored to find events and the duration of those events that had an impact on stock prices.

Statistics	Open Prices	Comp Sentiment	Negative Sentiment	Neu Sentiment	Positive Sentiment
Count	2735	2735	2735	2735	2735
Mean	495.58	-0.79	0.13	0.77	0.09
Std.Dev	270.72	0.52	0.03	0.05	0.02
Min	131	-0.99	0	0	0
25%	275	-0.99	0.11	0.75	0.07
50%	404	-0.99	0.13	0.77	0.09
75%	709	-0.96	0.15	0.8	0.1
Max	1188	0.99	0.27	1	0.23

Table 1: Summary statistics of dataset

Events captured

- Stock Market Crash- 2008
- Black Monday -2011
- Apple Impact-2012
- Hurricane Sandy -2012
- Google Internet Growth2013
- Pres- Election -2016
- EU Fine -2017
- Import Tariff -2018, Sep Low,
- Quarterly Impact

Feature engineering helped us pull socio economic predictors like Federal Fund Rate, Inflation, Gold, SP 500. Other company related features which we have included are Revenue, Assets and Liabilities. For each of the event, a dummy variable (new column) has been created and 1s were populated against the duration of the events. Thus, each of the events contributed to become a variable in our dataset and the duration of the event that actually influenced the stock price were captured.

EXPLORE

Exploratory Data Analysis (EDA) is the first step in the data analysis process. Statistical graphics is a collection of techniques--all graphically based and all focusing on one data characterization aspect. We have incorporated the graphical representations using R, Python and SAS tools.

ANALYSIS OF RAW DATA & ITS DISTRIBUTION

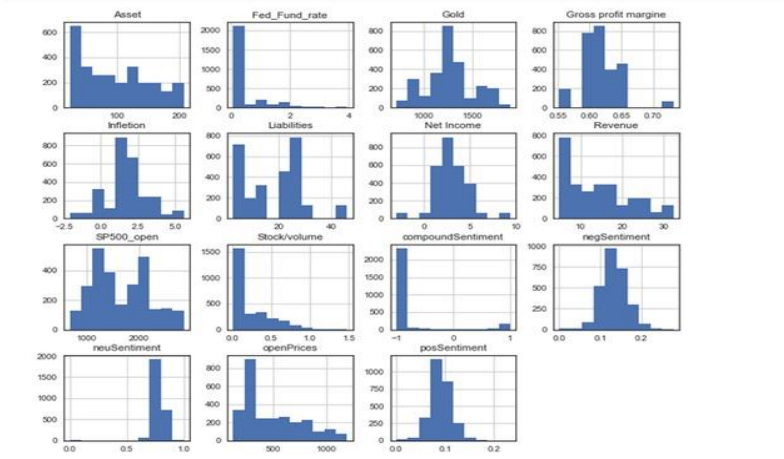


Figure 1: Data distribution

Plots were created to understand the distribution of each of the variables. Plot below shows that the variables Asset, liabilities, Federal Fund rate, negative Sentiment, stock volume, open Prices, neutral sentiment and compound sentiment had skewness issues and needs to be transformed.

CORRELATION

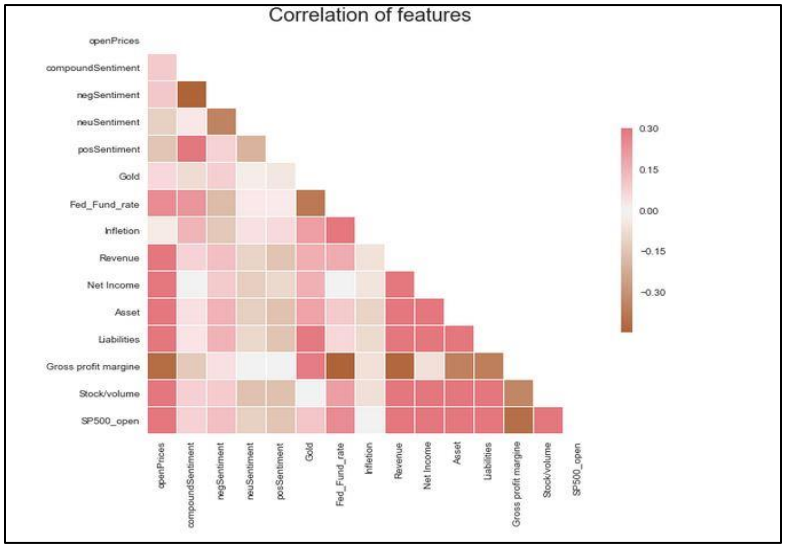


Figure 2: Correlation plot

How correlation & multi-collinearity were handled?

We observed that stock volume and SP 500 are highly correlated, so we choose to remove stock volume. Asset, Liabilities and Revenue seem to be multicollinear. So, we have removed these variables.

TIME SERIES DECOMPOSITION

For time series analysis, it is important that the data is stationary. For the data to be stationary, trend and seasonal components must be removed. We proceeded to decompose the time series using frequency of 100. From the graph below, we can see that there is an upward trend and seasonality in the time series data.

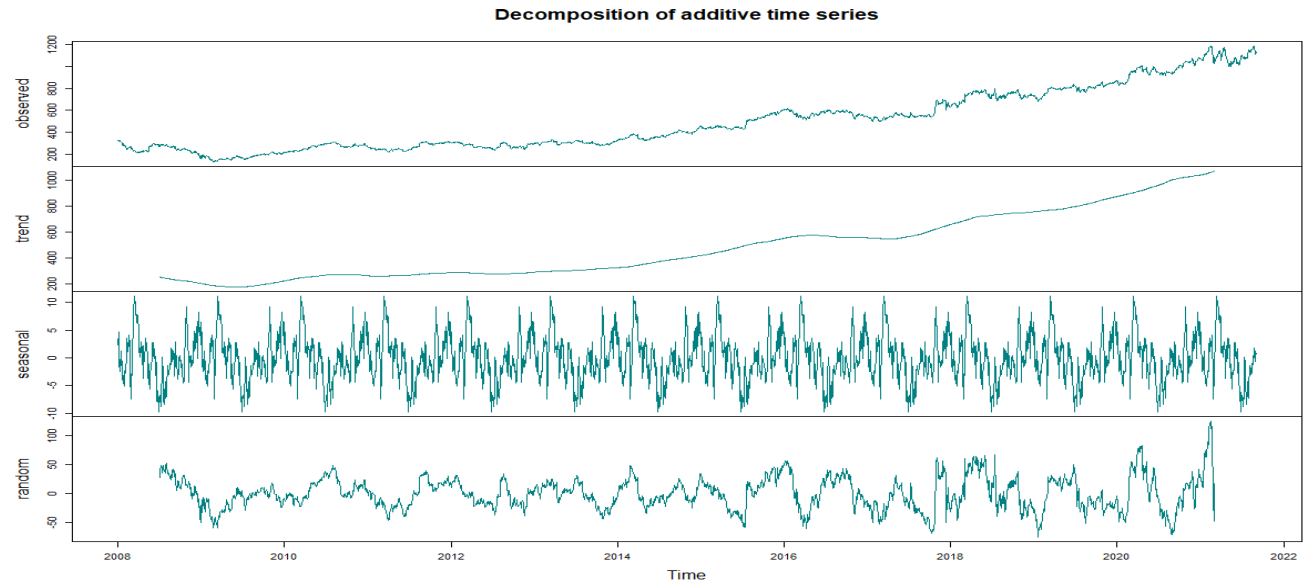


Figure 3: Time series decomposition

STATIONARITY TESTS

To further confirm the presence of trend and seasonality, Unit root test and seasonal root test were performed. As per the unit root test of Dickey -Fuller, we observed that series is not stationary. This is because p value is significantly high, so we reject null hypothesis that series is stationary, which implies that trend exists.

As per the seasonal root test of Ljung- Box test, we observed that seasonality exists in the time series. This is because p- value is significantly high, so we reject the null hypothesis that series is stationary, which also implies that seasonality exists in the series. Having confirmed both trend, trend and seasonlity would be handled during time series modeling.

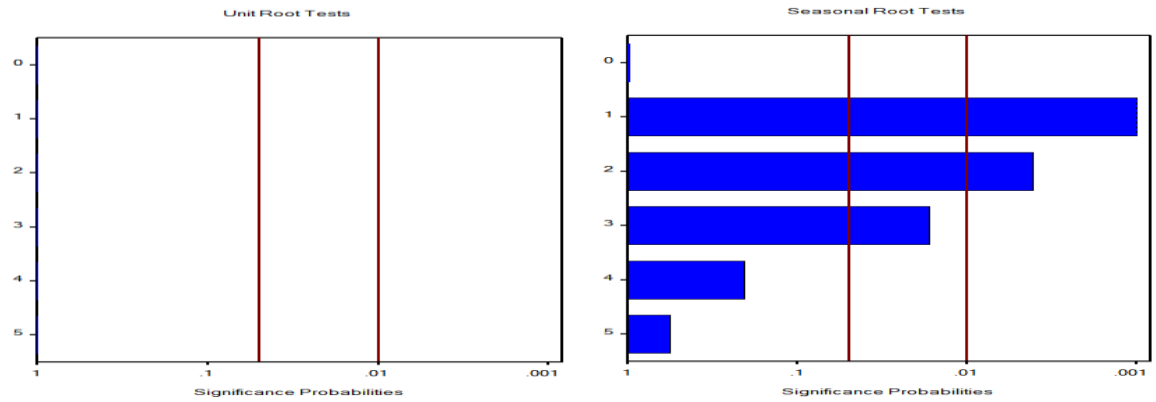


Figure 4: Test for stationarity

DATA PRE-PROCESSING

Our dataset went through a series of steps during preprocessing phase. The sub steps under this are mentioned below in two sections

1. DATA CLEANING

Our data of stock prices is present in frequency of 5 days. Weekday's stock price is provided, however the stock prices on holidays was missing. Every year there were around 12 days of missing stock prices. So, we choose LOCF (Last observation carry forward technique) to impute the missing values. The previous observation's stock price is considered on the holiday. This makes our data uniform and useful for further predictions.

2. DATA TRANSFORMATION

Below graph shows the data distribution of each variable. Data looks highly skewed and modeling wouldn't be efficient if these variables are used. Transformations are usually applied so that the data appear to more closely meet the assumptions of a statistical inference procedure that is to be applied, or to improve the interpretability or appearance of graphs.

We have tried different transformation techniques like log, square root, cube root, auto box- cox. We further varied lambda value and observed data was looking nearly normalized with auto box-cox transformation.

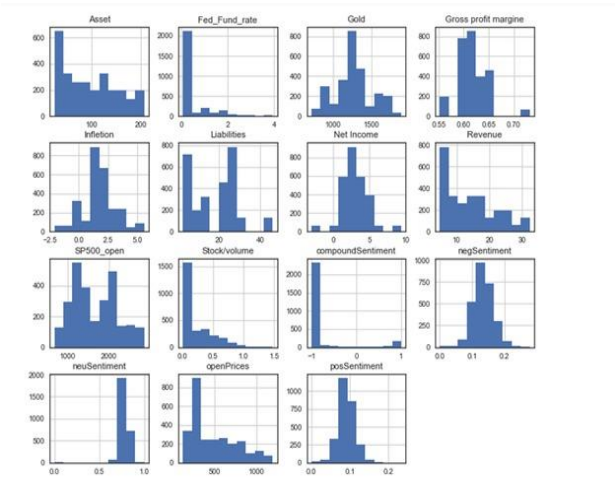


Figure 5: Distribution before transformation

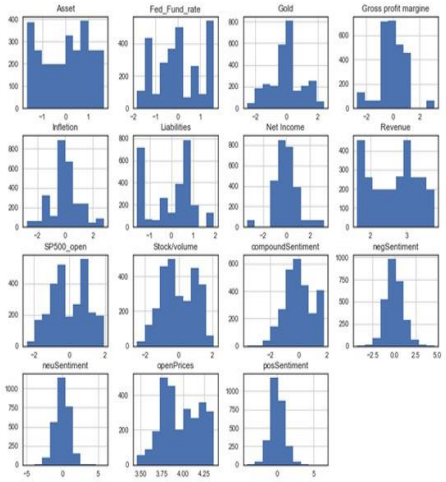


Figure 6: Distribution after transformation

3. DATA PARTITIONING

We have 10.5 years of data with 2735 rows. Last 1 year of data from 29-June-2017 to 29-June-2018 is taken as test set (262 rows). We also decided that we would forecast for one month from 30th June 2018 to 29th July 2018.

MACHINE LEARNING

MULTIPLE LINEAR REGRESSION

Since multiple linear regression has the ability to capture the trend we began modeling with multiple linear regression. With all variables included, the model resulted in a very high RSME. So, we decided to proceed with variable selection. Forward, backward and mixed stepwise algorithms were used to select significant variables. Inflation, positive sentiment, negative sentiment, compound sentiment, gold, Federal fund rate, Net income, Gross profit margin, SP500_open and events like Black Monday, Presidential election, EU Fine, import tariff, Sept low were also selected as significant variables. Interactions were also added and the resulting model ended up in a RMSE of 120. Above graph is plotted for Actual open prices(blue) versus predicted stock prices(red) for test data. Though the model was able to capture the increasing trend, the predicted values showed vast variances when compared to the actual values.

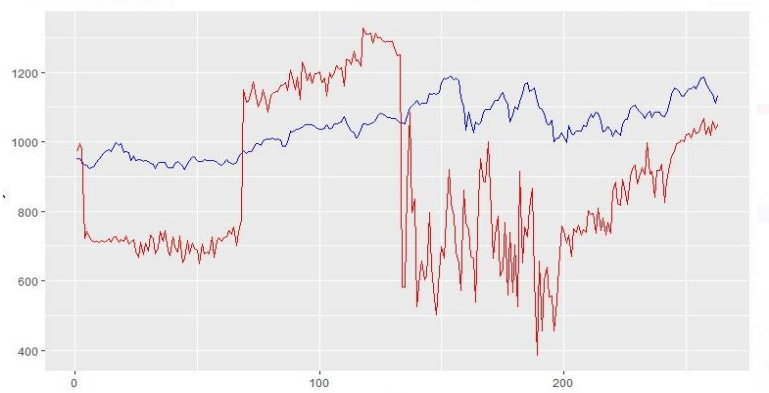


Figure 7: Actual(blue) vs predicted(red) stock price using Linear regression

TIME SERIES MODELING

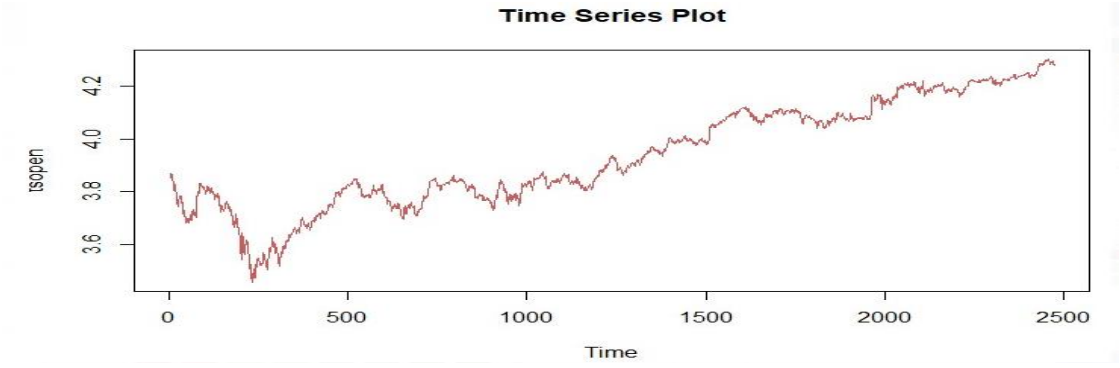


Figure 8: Time series plot

Time series was implemented to do the forecasting process. We first proceeded with decomposing the time series to find trend, seasonality and then worked to make the data stationary after which

different time series models like Holt winters, Exponential Smoothing, ARIMA models were implemented. We also incorporated the sentiment scores and other regressors, and finally added different events identified for improving the model accuracy.

AUTO CORRELATION

The ACF plots show significant autocorrelation is present in the data.

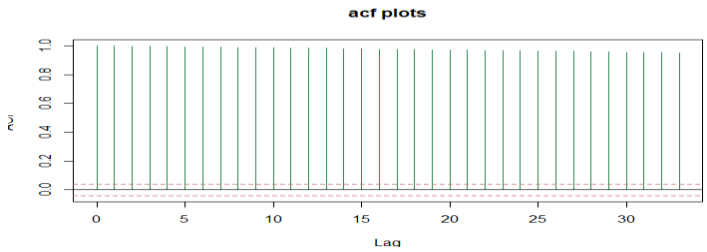


Figure 9: ACF plot on time series data

From ACF plot, we can see that the time series of open prices is not random, but rather has a high degree of autocorrelation between adjacent values.

DIFFERENCING

To make the data stationary, we proceeded with first differencing of the data. On first differencing we see that the series plot appears to be stationary. On doing the dickey fuller test, the null hypothesis is less than 0.01, which means that the series is stationary.

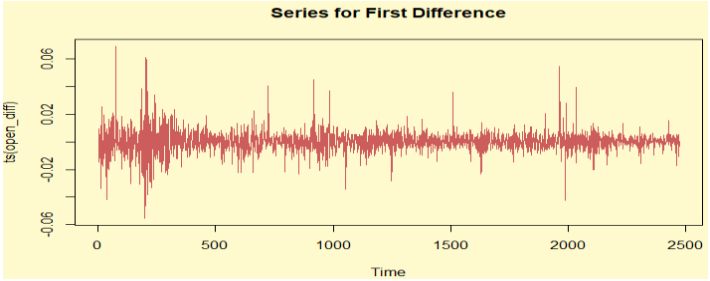


Figure 10: After First difference

The ACF plot below shows the absence of any significant autocorrelation in the first difference. The PACF plot shows random significant lags.

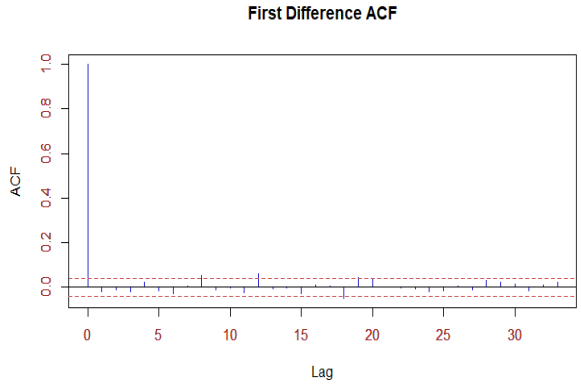


Figure 11: ACF plot after first difference

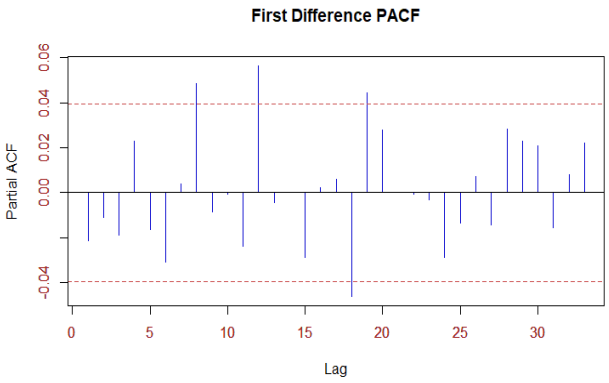
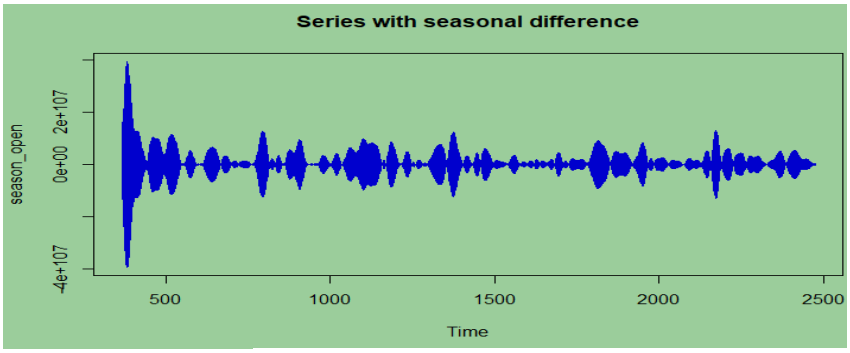


Figure 12: PACF plot after first difference

SEASONAL DIFFERENCING

We proceeded with seasonal differencing using a frequency of 365, since we have daily data for 10.5 years. On plotting the series, and doing a Dickey Fuller test, the series proves to be stationary. The ACF plot shows slow decay of the autocorrelation function suggests the data follow a long-memory process. A higher order autoregressive term in the data. The PACF plot shows a significant lag till 4



The series plot shows that it is s tationary, and doing a Dickey F uller test the p value is 0.01, wh ich means that we can reject th e null hypothesis and say that the series is stationary.

Figure 13: Series with seasonal difference

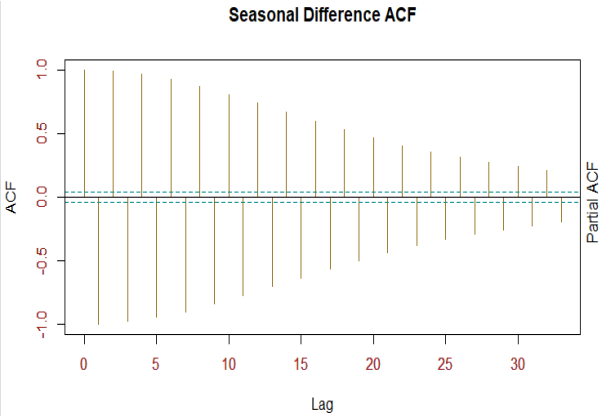


Figure 14: Seasonal difference ACF plot

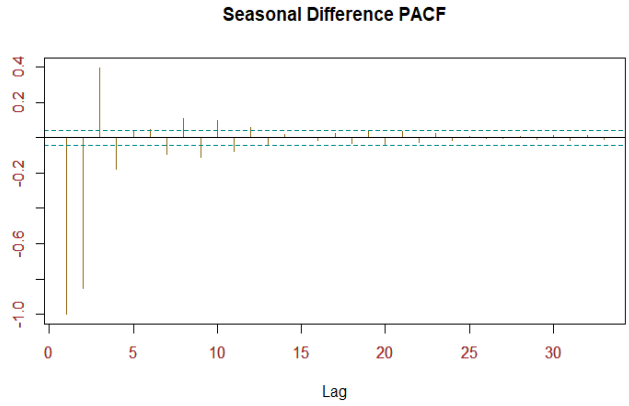


Figure 15: Seasonal difference PACF plot

Once the differencing is applied, we proceeded with time series modeling.

HOLT WINTERS MODEL

Winters is a way to model three aspects of the time series: an average value, trend and seasonality. This method uses exponential smoothing to encode lots of values from the past and predict typical values for the future. Initially we used the Holt-winters exponential and holt winters trend models, but they did not perform well on the test data, giving very high RMSE. Since there is presence of both trend and seasonality in the data, we proceeded with the Holts seasonal model.

HOLTS SEASONAL MODEL

Hol

t-Winters seasonal uses an exponential smoothing with trend and additive seasonal component.

The additive model is used when the seasonal variation remains constant through time.

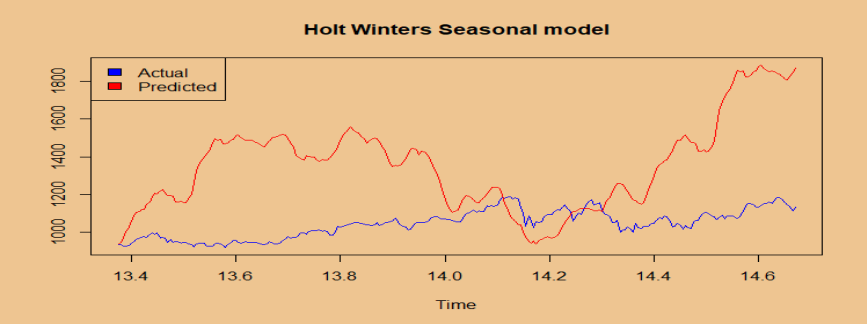


Figure 16: Actual(blue) vs predicted(red) stock price on test data using Holts Seasonal

SMOOTHING PARAMETERS
alpha: 0.7212766 beta: 0 gamma: 1 RMSE: 292.4075

Table 2: Results from Holts seasonal model

The model resulted with a hig

h alpha value and the gamma value as 1, which shows that the data highly depends on recent trend and seasonality. Applying the Holts seasonal model on the test data, we get a very high RMSE of 292.4075. We see that the Holtwinters seasonal model is not fitting the test data well. Hence, we proceeded with ARIMA.

ARIMA

Advantages of ARIMA model is that it takes into consideration previous values in the time series (AR terms) and the errors made by previous predictions (MA terms). This allows the model to rapidly adjust for sudden changes in trend, resulting in more accurate forecasts. Since the first difference data was stationary, we did an ARIMA model using first difference and on using auto.arima, it selected the same ARIMA model as the best model, i.e., ARIMA(0,1,0) . The ACF and PACF plots from figure 11 and figure 12 shows that there is no significant autocorrelation in the data. The model gave an RMSE of 123.73 on the test data

sigma^2 estimated as 6.031e-05: log likelihood=8508.43 AIC=-17014.87 AICc=-17014.86 BIC=-17009.05 RMSE: 123.73

Table 3: Results of ARIMA(0,1,0)

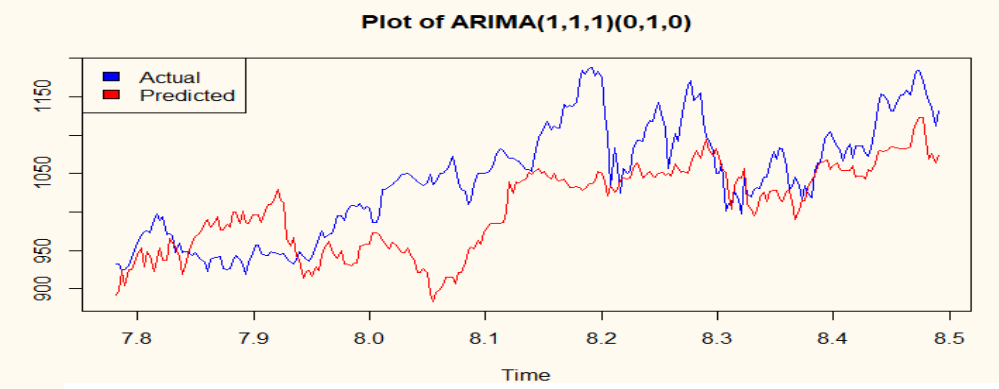
ARIMA SEASONAL

Since there is seasonality present in the data, we tried ARIMA seasonal models. Taking a frequency of 365, we checked the ACF and PACF plots. The PACF plots indicate an AR model of P value 4. However, trying to implement a seasonal P value of 4, the model fitting failed for a frequency of 365 with seasonal

differencing. Hence, we applied an auto ARIMA with seasonal difference of 1, and the best model that came was ARIMA(1,1,1)(0,1,0). The auto ARIMA function returns the best ARIMA model according to either AIC, AICC or BIC value. The function conducts a search over all possible models within the order constraints provided. The RMSE on the test set is 65.755. Best time series model that resulted in lowest RMSE is ARIMA(1,1,1)(0,1,0).

sigma^2 estimated as 0.0001042: log likelihood=6674.37 AIC=-13342.75 AICc=-13342.74 BIC=-13325.79 RMSE: 65.75556

Table 4: Model Results for ARIMA(1,1,1)(0,1,0)[365]



The plot shows th e difference betw een actual and pre dicted open prices for test dataset.

Figure 17: Actual(blue) vs predicted(red) stock price on test data using ARIMA (1,1,1)(0,1,0)

ARIMA WITH REGRESSORS

We then added all regressors (Compound Sentiment, Negative Sentiment, Neutral Sentiment, Positive Sentiment, Gold, Federal Fund rate, Inflation, Net Income, Gross profit margin, Stock Volume, SP500_open) on the best model ARIMA (1,1,1)(0,1,0).We observed that the RMSE is increasing to 78.98. This shows that all the regressors might not be significant for the model.

Proceeded to remove insignificant regressors, and tried adding certain events, we found that the model RMSE decreased to 62.7. This shows that events greatly influence the stock prediction.

Figure 18: ARIMA with regressors

Several combinations of regressor and events were tried to arrive at the best model ARIMA(1,1,1)(0,1,0) with regressors compoundSentiment, negSentiment, posSentiment, Inflation. The events important to the model are HurricaneSandy_12, Quarterly Impact, BlackMonday_11,PresElection_16.

The RMSE on the test set using this model is 44.5, which is the lowest obtained so far. The below graph shows that the predicted series shows good signs of predicting when there might be a rise or fall in the stock prices.

Figure 19: ARIMA model with regressors and events

RESIDUAL ANALYSIS

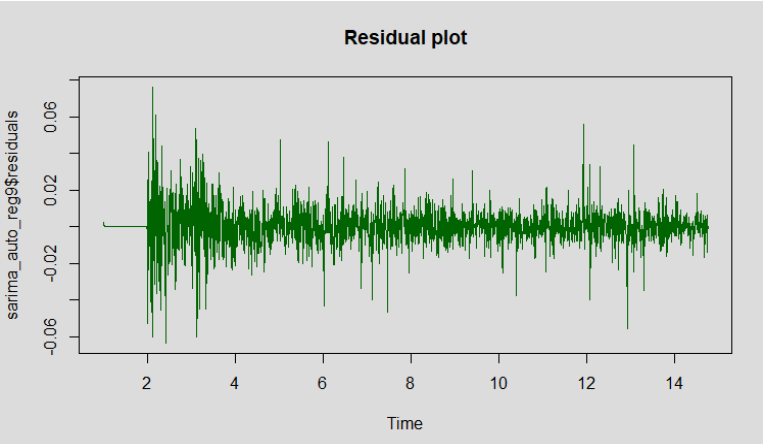


Figure 20: Residual analysis of best model ARIMA(1,1,1)(0,1,0) with regressors & events

The Residual plots of the best model arima(1,1,1)(0,1,0) with events and regressors show stationarity. The Dickey Fuller test has a p value of 0.01, which shows that the residuals are stationary. On doing the Ljung Box test, the p value is less than 0.01, which shows that the residuals are following white noise.

PROPHET MODEL

We also implemented the Prophet model (a forecasting tool by Facebook) using R. This model uses a Bayesian based curve fitting method to forecast the time series data. It is advantageous as it doesn't require much prior knowledge or experience of forecasting time series data since it automatically finds seasonal trends in data and provides easily understandable parameters.

The plot of the model is shown below. The forecasted confidence interval was plotted and the forecast clearly shows an increasing trend. However, when we check the RMSE on test data using the mean (yhat) value, the RMSE is 87.06718, which shows that this model is not predicting well for exact data (single point data). This suggests that Prophet model is good for forecasting confidence intervals, but might not be well suited for predicting exact data.

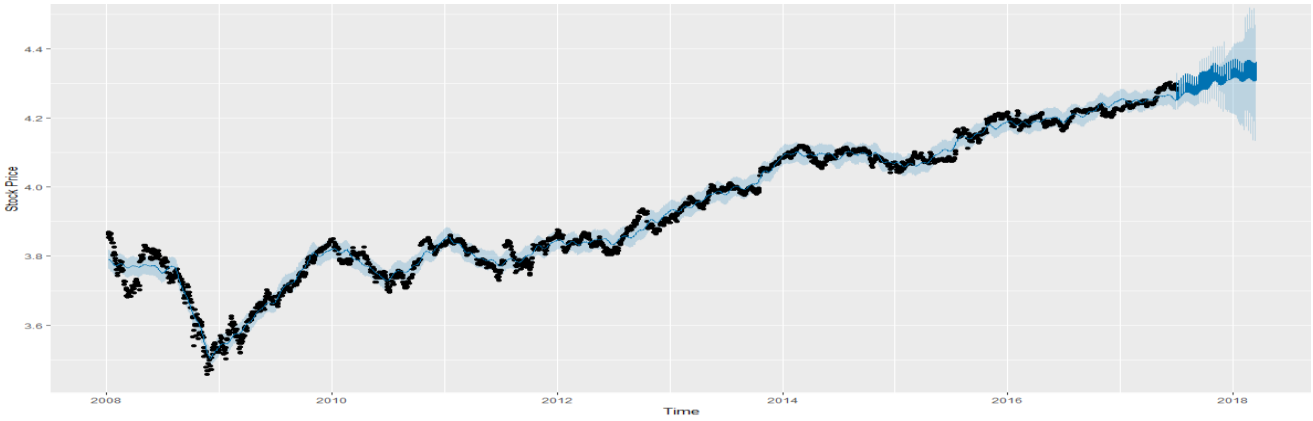


Figure 21: Actual(blue) vs predicted(red) stock price on test data using PROPHET

Best model from ARIMA shows that Positive, Negative, Compound Sentiments and Inflation variables ar e significant for stock price prediction. Events like Hurricane Sandy, Quarterly Impact, Black Monday, Pre sidential election helps in improving the accuracy of the model.

DEEP LEARNING ALGORITHM

FEATURE EXTRACTION FROM NEWS HEADLINES FOR DEEP LEARNING

SP500_open, Net Income, Gold, Federal fund rate, Gross profit margin, Inflation, StockMarketCrash_08, posSentiment, negSentiment, compoundSentiment are the variables used for Deep learning algorithms.

Headlines from “Business & Technology” section of New York Times is extracted resulting in 600 words for each day stock prediction.

	0	1	2	3	4	5	6	7	8	9	...	590	591	592	593	594	595	596	597	598	599
0	1615	3869	1070	381	1030	2151	566	85	33	683	...	7843	4809	533	4012	375	177	84	296	1236	21531
1	7847	1836	292	292	11516	2602	15793	2527	4983	56	...	918	2839	9325	7843	4012	375	1144	296	1916	21544
2	1966	124	17191	2690	3486	3194	4901	8094	12155	82	...	159	263	4412	8645	157	2839	31476	375	296	13644
3	3114	496	11524	526	109	21559	2039	315	1135	29	...	978	7032	9699	157	2839	5342	2088	12815	84	14647
....																					
2730	2252	25	104	297	4	4511	22700	13200	12481	7376	...	0	0	0	0	0	0	0	0	0	0
2731	16895	25	4698	4	2482	238	309	3916	409	439	...	0	0	0	0	0	0	0	0	0	0
2732	1634	1115	48928	25	1286	9696	21527	1973	48929	345	...	0	0	0	0	0	0	0	0	0	0
2733	345	297	206	587	6823	1314	4	23831	572	2740	...	1803	215	469	7734	263	139	177	2822	5366	84
2734	26121	2950	25	3193	104	2558	297	206	1314	14751	...	8757	263	1092	139	1287	5898	157	375	1144	84

2735 rows × 600 columns

Figure 22: Data set with features from news headlines

WORD EMBEDDING DICTIONARY

A dictionary is then created for the words extracted and features for each of the words is created to generate embedded matrix using GloVe vector introduced by Stanford.

	0	1	2	3	4	5	6	7	8	9	...	290	291	292	293	294	295	296	297	298	299
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	0.04656	0.21318	-0.00744	-0.45854	-0.03564	0.23643	-0.28836	0.21521	-0.13486	-1.6413	...	-0.01306	-0.29686	-0.07991	0.195	0.031549	0.28506	-0.08746	0.009061	-0.20989	0.053913
2	-0.44399	0.12817	-0.25247	-0.18582	-0.16614	0.25909	-0.22678	-0.06923	-0.0772	-1.5814	...	-0.2745	-0.03724	0.10104	0.10798	0.37727	0.87977	0.33583	-0.20043	-0.08219	-0.06255
3	-0.62333	-0.42434	-0.03532	-0.02669	0.2312	0.17631	0.28722	-0.24921	0.22212	-1.678	...	-0.36521	-0.90286	-0.42851	0.10705	0.038003	0.68034	-0.0401	-0.13613	0.09868	0.609
4	-0.29712	0.094049	-0.09666	-0.344	-0.18483	-0.12329	-0.11656	-0.09969	0.17265	-1.6386	...	0.075972	-0.42426	-0.3967	0.32683	0.62049	0.34719	0.26952	0.059717	-0.22853	0.29602
5	-0.0776	0.20635	0.12249	0.09923	0.038728	-0.53596	-0.1892	-0.37368	0.072637	-1.8313	...	-0.1919	-0.20638	0.10474	0.13918	-0.13912	-0.01349	-0.24372	0.25485	-0.25126	0.4511
.....																					
48968	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
48969	0.051716	0.42022	-0.21343	0.53152	0.097709	-0.05417	0.16817	-0.11129	-0.31371	0.50621	...	0.19112	-0.6125	-0.42155	-0.19326	-0.20231	-0.72849	-0.05113	0.2667	0.2004	0.20037
48970	-0.10429	-0.8626	-0.19244	0.1387	-0.26248	-0.11136	0.21312	-0.14763	0.26376	-0.26989	...	0.22237	0.17908	-0.06613	-0.20855	-0.3812	0.50681	0.23118	-0.25264	0.10568	-0.21511
48971	-0.34161	-0.27296	-0.43022	-0.61088	0.25762	0.14928	0.2196	0.37686	-0.14627	-0.11448	...	-0.1424	0.41448	-0.44141	-0.23488	0.074307	-0.27457	0.11875	0.028054	-0.25622	0.26626
48972	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
48973	-0.10791	-0.00699	0.025826	0.57931	0.021725	-0.19264	0.60894	0.41559	-0.05171	0.68508	...	0.22362	-0.6078	0.1186	-0.23505	-0.51686	-0.16199	-0.04971	0.24597	-0.28552	-0.00443

48974 rows × 300 columns

Figure 23: Embedded matrix

Since each word has 300 features associated to it, a single day headlines which has 600 words results in 600*300 = 1,80,000 features. Since the number of features is more, CNN algorithm is used for feature reduction. This data feature is primarily used for the classification part of the problem statement for identifying the rise and fall for today, next day and day after tomorrow from which the misclassification rate can be calculated.

MODEL ARCHITECTURE OF HYBRID RNN & CNN MODEL

CLASSIFICATION to detect rise/fall pattern prediction using 2D data for 1 day

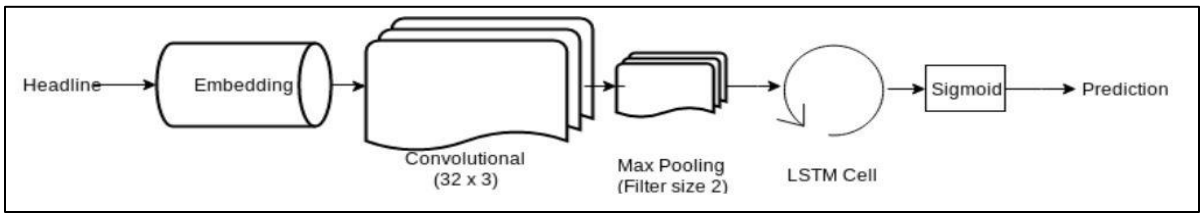


Figure 24: Classification model architecture

News headlines is preprocessed and passed to Convolutional neural network. During pre-processing vector representation of these words (Word Embeddings) are calculated. Each word has various features associated to it. Thus, our input to neural network will be an Embedded matrix representation of words (600 words * 300 features each). Convolution layers are applied on Embedded matrix. They are a set of filters that have their weights updated as and when the algorithm learns and have a smaller dimension than the input matrix. Thus, when they slide over the height and width of the input vector, a dot product is calculated resulting in dimension reduction. Max Pooling is a part of Convolution where layers are introduced between successive convolution layers helping to reduce the parameters to controlling overfitting. Output from Max pool layer is then passed on to LSTM cell that has 3 hyper parameters to set– Activation function, recurrent activation and number of units identified using cross validation. For the predicted probability to be in the range of 0 to 1, sigmoid function is used.

REGRESSION for stock price prediction using 1D data on sliding window

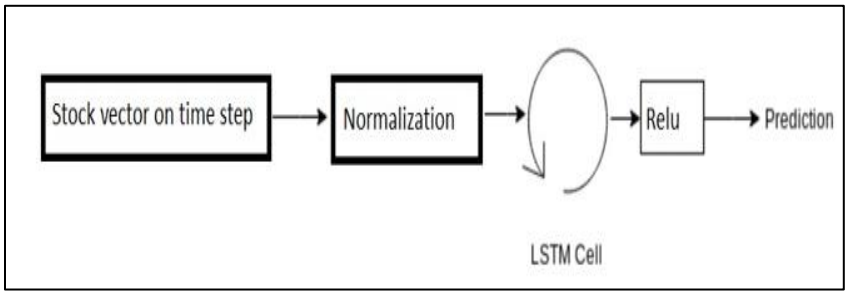


Figure 25: Regression model architecture

Data vector is created by shifting the stock price for 60 days back. We use the 60 days stock price to predict next day stock price. We tried by shifting for different number of days (30, 60 and 90), but we got better result on 60 days sliding window and proceeded with that. Below table shows the data vector that has 60 features generated from the past 60 days. Then it is normalized and passed to the RNN LSTM cells and for the predicted stock price to be zero or positive number, Relu activation function is used.

	0	1	2	3	4	5	6	7	8	9	...	50	51	52	53	54	55	56	57	58	59
0	0.169219	0.168813	0.158887	0.165359	0.16436	0.168009	0.165744	0.158425	0.154875	0.149515	...	0.071539	0.071967	0.077211	0.071249	0.071249	0.076052	0.084279	0.082174	0.079325	0.079956
1	0.168813	0.158887	0.165359	0.16436	0.168009	0.165744	0.158425	0.154875	0.149515	0.149515	...	0.071967	0.077211	0.071249	0.071249	0.076052	0.084279	0.082174	0.079325	0.079956	0.074846
2	0.158887	0.165359	0.16436	0.168009	0.165744	0.158425	0.154875	0.149515	0.149515	0.129486	...	0.077211	0.071249	0.071249	0.076052	0.084279	0.082174	0.079325	0.079956	0.074846	0.080077
....																					
2703	0.820632	0.807279	0.818507	0.827836	0.810734	0.825331	0.825029	0.825029	0.815916	0.81374	...	0.981049	1	0.961934	0.950412	0.956804	0.939002	0.962047	0.958963	0.967946	0.972014
2704	0.807279	0.818507	0.827836	0.810734	0.825331	0.825029	0.825029	0.815916	0.81374	0.821099	...	1	0.961934	0.950412	0.956804	0.939002	0.962047	0.958963	0.967946	0.972014	0.977205
2705	0.818507	0.827836	0.810734	0.825331	0.825029	0.825029	0.815916	0.81374	0.821099	0.847763	...	0.961934	0.950412	0.956804	0.939002	0.962047	0.958963	0.967946	0.972014	0.977205	0.974139
2706	0.827836	0.810734	0.825331	0.825029	0.825029	0.815916	0.81374	0.821099	0.847763	0.869901	...	0.950412	0.956804	0.939002	0.962047	0.958963	0.967946	0.972014	0.977205	0.974139	0.967246

2707 rows × 60 columns

Figure 26: 60 features from past 60 days stock price

RECURRENT NEURAL NETWORK

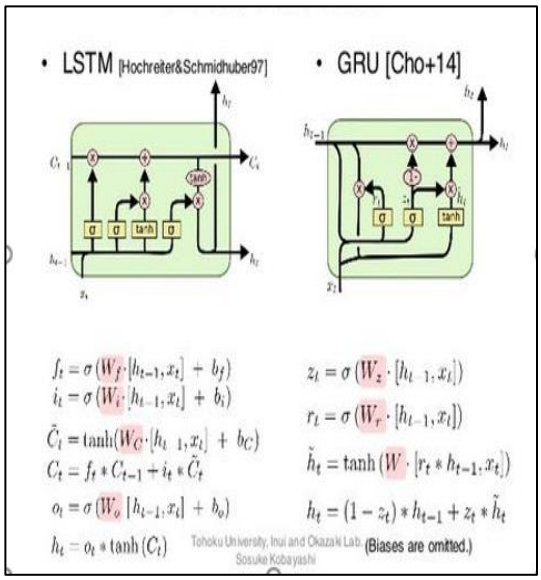


Figure 27: LSTM and GRU architecture

In order to capture the long-term dependencies of stock prices on features from the past 60 days (Different number of days were used as a tuning parameter and the variability was best captured when the sliding window is 60) Long short-term memory modeling is used. LSTM architecture is composed of

- Memory cell
- Input gate
- Forget gate
- Output gate

GRU on the other hand is a simplified version of LSTM (with three gates excluding the Forget gate). Stock price predictions are done using both LSTM and GRU on test data. Below graph shows the plotted Actual test data Open prices and the predicted Open price.

Test RMSE using LSTM: 21.533

Figure 29: Actual(blue) vs predicted(red) stock price on test data using LSTM

Test RMSE using GRU - 112.639

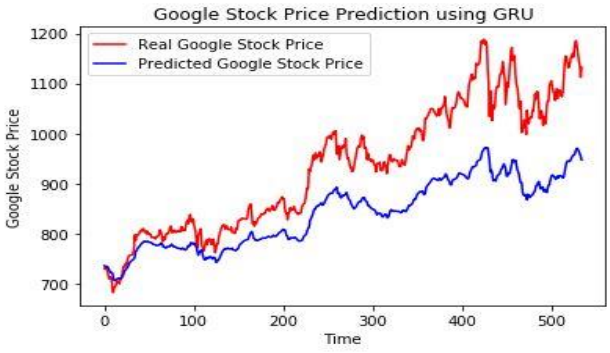


Figure 28: Actual(blue) vs predicted(red) stock price on test data using GRU

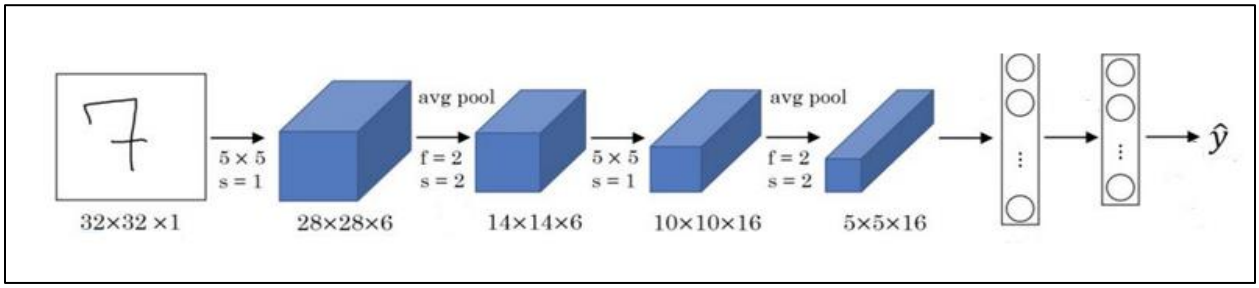
We can see that GRU is failing to capture the trend accurately. But on the other hand, LSTM captured long range dependency well so we used LSTM in our Model.

CONVOLUTIONAL NEURAL NETWORK

Three architectures are experimented here which will be covered in the following sections.

1. LeNet ARCHITECTURE

Figure 30: LeNet architecture



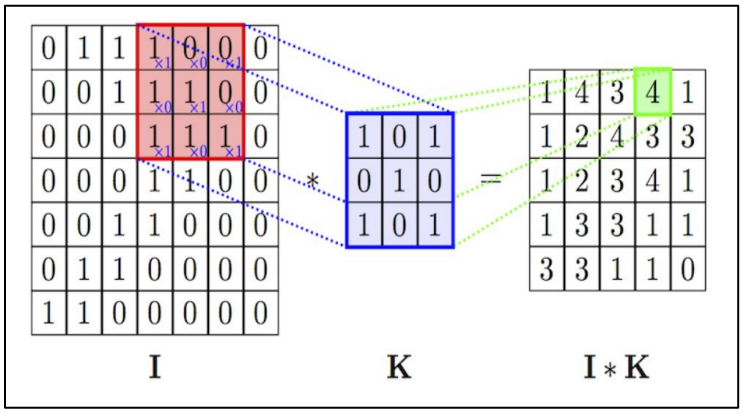


Figure 31: Dimension reduction in CNN

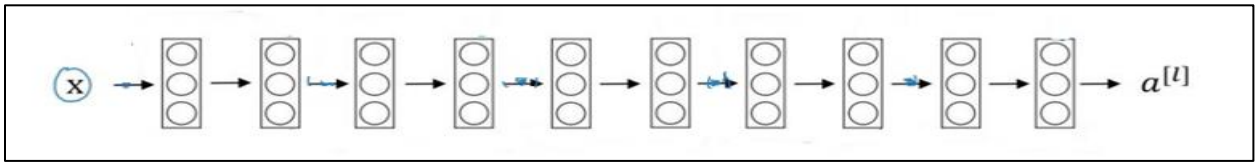
DIMENSION REDUCTION IN CNN

Word embedded matrix is passed through LeNet5 architecture for dimension reduction. A filter with reduced dimension is applied on data matrix with stride 1 or 2, and a dot product is calculated. The resulting matrix will have reduced dimension.

2. RESIDUAL NETWORK ARCHITECTURE

Residual network architecture is used where-in the weight of a node will also depend on the weight of the previous node.

Figure 32: Residual network architecture



PLAIN NEURAL

With increased number of layers, Plain neural is expected to overfit reducing the training error. But in reality, the training error starts to increase after some layer because of exploding gradient or vanishing gradient. To fix this problem we update the previous weight to the later part of layer, this way it helps to retain the information learned by the previous nodes in the algorithm.

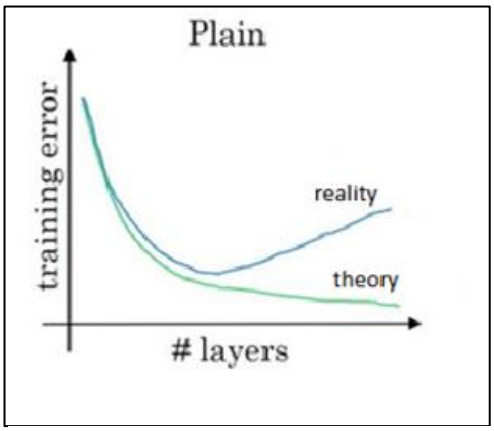


Figure 33: Layers vs training error in Plain Neural

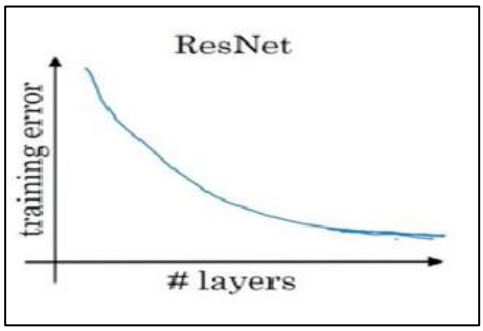


Figure 34: Layers vs training error in Residual network

RESIDUAL NETWORK

We can see that the training error is reducing in case of Residual network and is behaving as expected.

3. INCEPTION MODEL ARCHITECTURE

As shown in the picture below, different dimensional filters are used in this model for capturing the variation in the data. As the name "Inception" suggests, number of mini models using different dimensional filters are built within a bigger model.

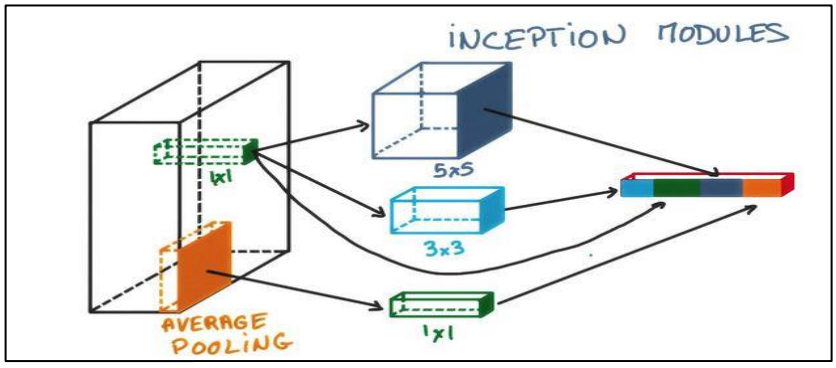


Figure 35: Inception model architecture (single layer)

The diagram shows the Inception operation on a single layer where multiple filters have used to fetch different information from the different part of the dataset. This helps to retrieve features better than the other network because of the multiple filters like 5*5, 3*3, 1*1, max pooling, average pooling and so on. Below is the complete Inception network for all layers where we perform similar operation throughout the network.

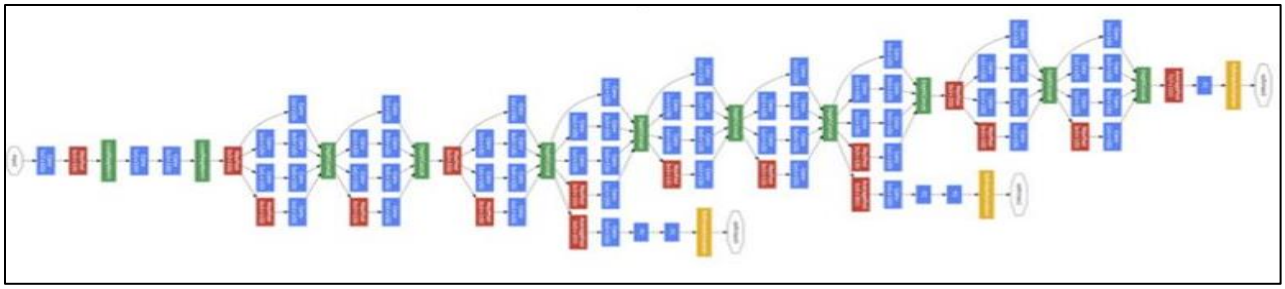


Figure 36:Figure 35: Inception model architecture (entire network)

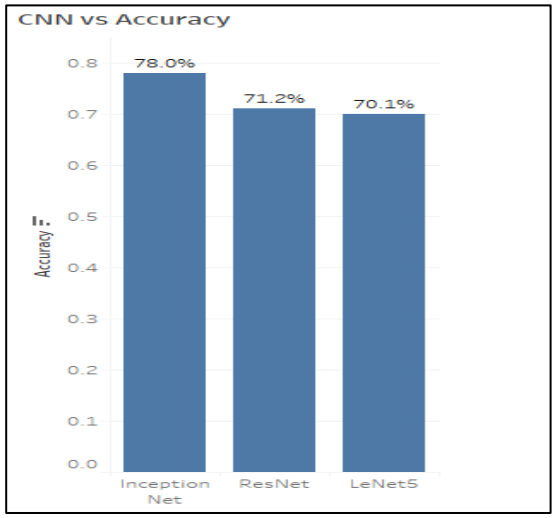


Figure 38: Model comparison between 3 CNN architecture

Model comparison

Graph shows the model comparison between the three architectures.

We can see that Inception Network captures better information the other CNN architectures and gives highest accuracy.

OPTIMIZATION TECHNIQUE

Adam optimization algorithm is the combination of RMS Prop and Momentum. It does the exponential smoothing of gradient in both horizontal and vertical direction in order to avoid divergence which helps to converge gradient descent to global minimum very fast.

Drop out is used to avoid overfitting. It randomly selects nodes to drop in each layer with a given probability in every cycle of iteration. This forces algorithm to distributes the weight evenly on all the nodes of network which cause to reduce overfitting. It also has L2 regularization effect.

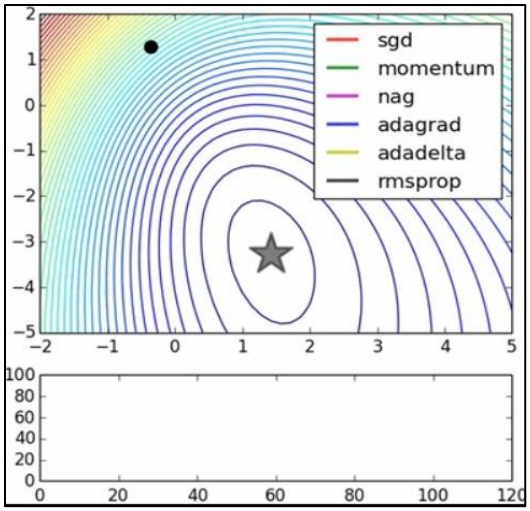


Figure 39: ADAM optimization

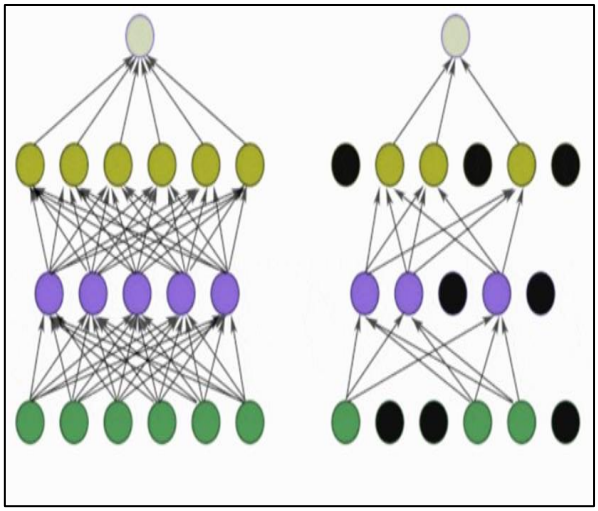


Figure 40: Drop out optimization technique

CLASSIFICATION MODEL COMPARISON

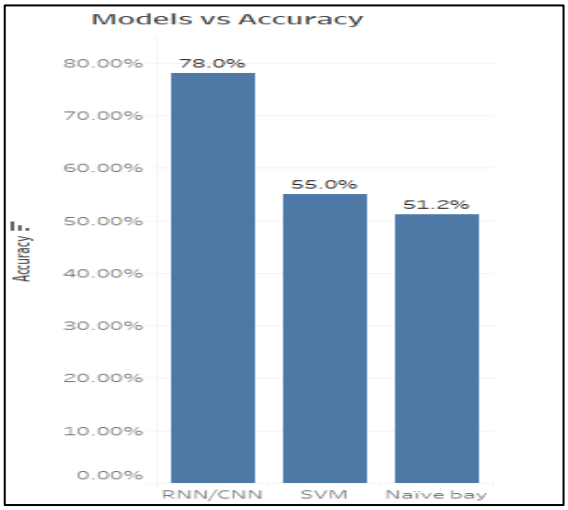


Figure 41: Classification model comparison

Different models were tried to classify the positive/negative trend based on news data the next day and the results are shown in the graph.

We can see that the hybrid model of RNN/CNN on embedded words gives better accuracy in predicting on the test data compare to SVM and Naïve bay.

TUNING REGRESSION MODEL FOR STOCK PRICE PREDICTION

We have experimented with three hyper-parameters on RNN LSTM regression model.

1. Training parameters by changing Epoch number and batch size.

Model 1: a one layer LSTM cell of cell state size 100, followed by a dense layer; and the time step during BPTT is 50.

Model 2: a one layer LSTM cell of cell state size 100, followed by a dense layer; and the time step during BPTT is 10

Model 3: two-layer-stacked LSTM cells of cell state size 50 and 100, followed by a dense layer; and the time step during BPTT is 50

Model 4: two-layer-stacked LSTM cells of cell state size 50 and 100, followed by a dense layer; and the time step during BPTT is 10

Model comparison for the 4 models are shown below.

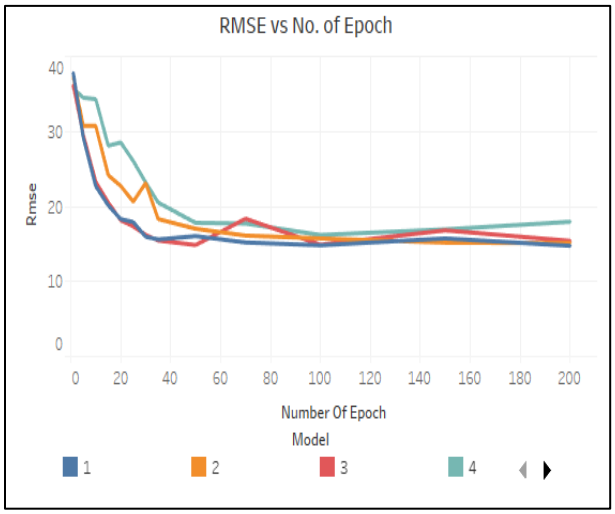


Figure 42: RMSE vc no. of Epoch in LSTM

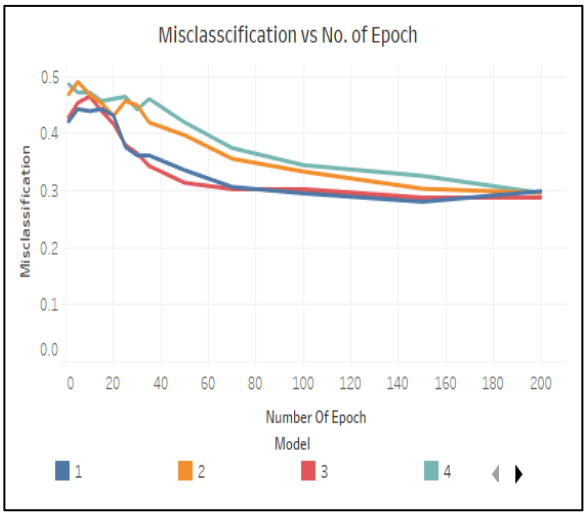


Figure 43: Misclassification vs no. of Epoch in LSTM

From the above graph we can see that as the epoch number increases, misclassification decreases all the way down to around 0.2. In addition, the final RMSE for each of the four models are all 20. This means all the tested four models doesn't pick up any hidden rule about the input data. Instead, they are trying to echo back the input of the current time as the prediction of the price of next time step.

In terms of RMSE, compared with the two models of time step 10, the two models with time steps of 50 get stable faster. This means, a more complex model needs more epochs to get trained. But from this result, we find out that around 70 epochs are enough.

2. LSTM cell hyper-parameter: Varying the number of nodes in hidden layers

Prediction performance of two layers stacked LSTM cells with the time step during BPTT is 50 with different hidden nodes.

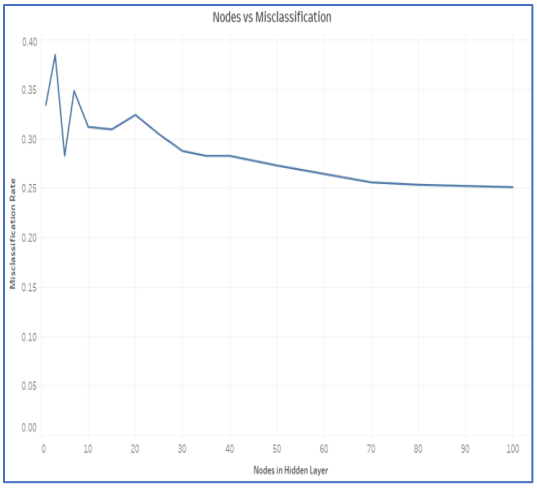


Figure 44: Misclassification vs no. of nodes in in hidden layers in LSTM

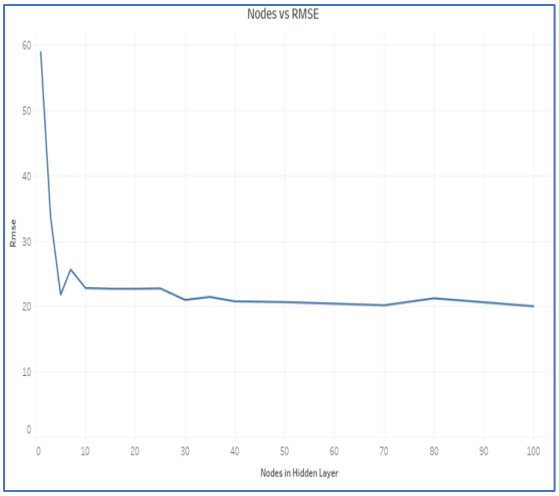


Figure 45: RMSE vs no. of nodes hidden layers in LSTM

From the above graph we can see that as the number of hidden nodes increases, misclassification decreases all the way down to around 0.2. In addition, the final RMSE for each of the four models are all 20. This means above model doesn't pick up any hidden rule about the input data. Instead, they are trying to echo back the input of the current time as the prediction of the price of next time step.In terms of RMSE and misclassification, we find out that around 60 hidden nodes are enough.

3. Network hyper parameters: with different number of layers

Model 1: one-layer LSTM cell of cell state size 60, followed by a dense layer; and the time step during BPTT is 50

Model 2: two-layer-stacked LSTM cells both of cell state size 30, followed by a dense layer; and the time step during BPTT is 50

Model 3: three-layer-stacked LSTM cells all of cell state size 20, followed by a dense layer; and the time step during BPTT is 50

One layer - RMSE **17.97**

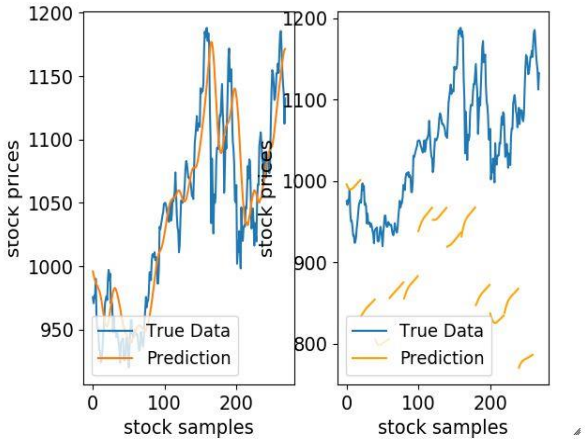


Figure 46: One-layered LSTM performance

Two layer -RMSE **16.2**

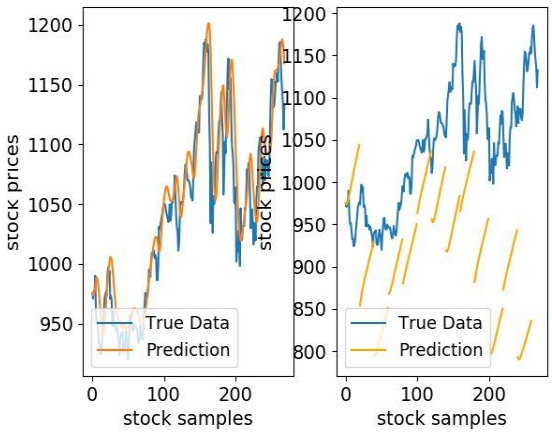


Figure 47: Two-layered LSTM performance

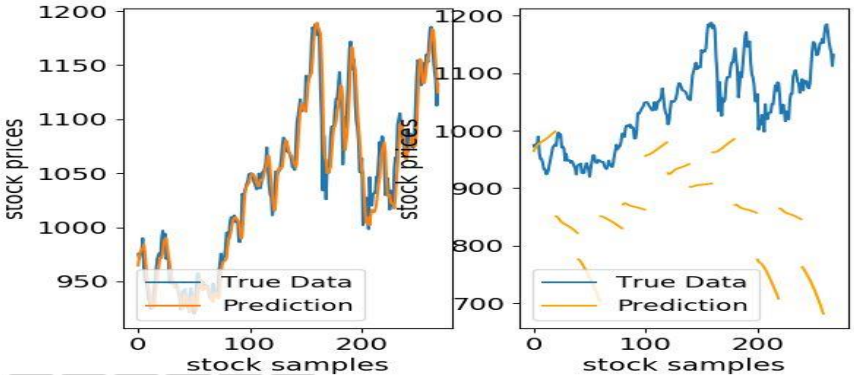


Figure 48: Three-layered LSTM performance

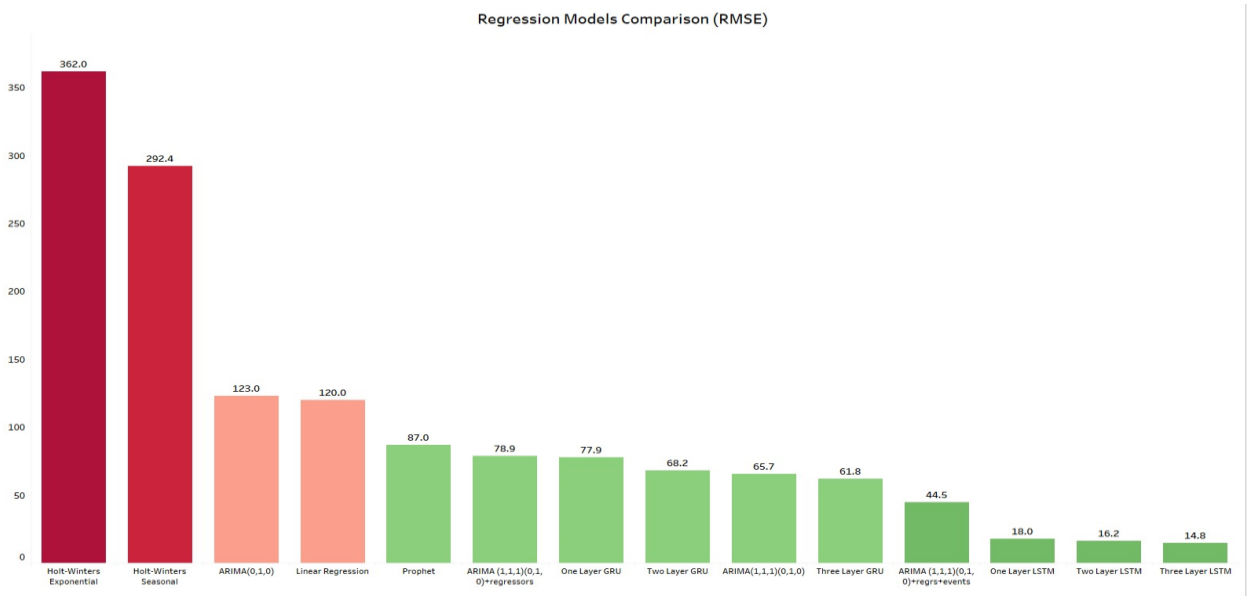
Three layer- RMSE **14.87**

Above graph shows that as the number of hidden layers increases, the algorithm captures more trend and seasonality (left plot) and rise and fall trend (right plot) precisely. In terms of predicting the stock price fluctuations and next day rise/fall pattern, 3 hidden layers are sufficient for accurate prediction.

MODEL COMPARISON AND MODEL SELECTION

To identify the best model, RMSE of Regression models and Misclassification rate for classification models tried from Machine Learning, Time series and Deep learning are plotted and shown below.

Figure 49: Regression model comparison



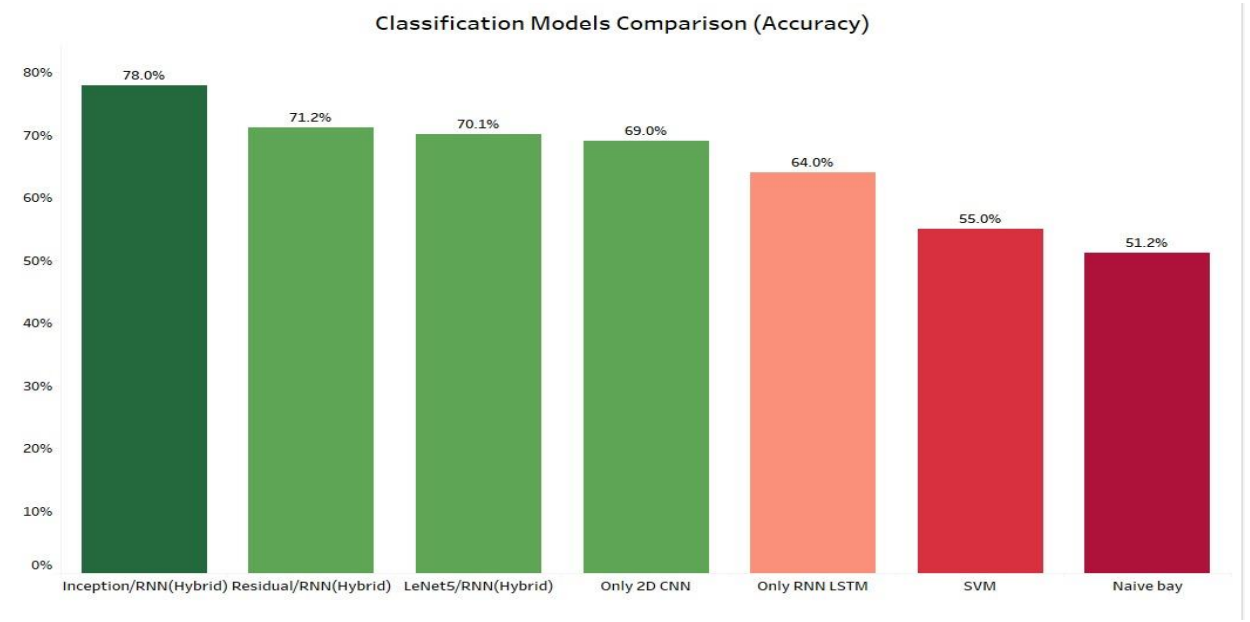


Figure 50: Classification model comparison

Our final best model is having 3 hidden -layer, LSTM cells all of cell state size 20, followed by a dense layer; and the time step during BPTT is 50.

GOOGLE STOCK PRICE FORECASTING FOR JULY 2018

With the selected model, we have forecasted the stock price for July 2018 month (our data set is

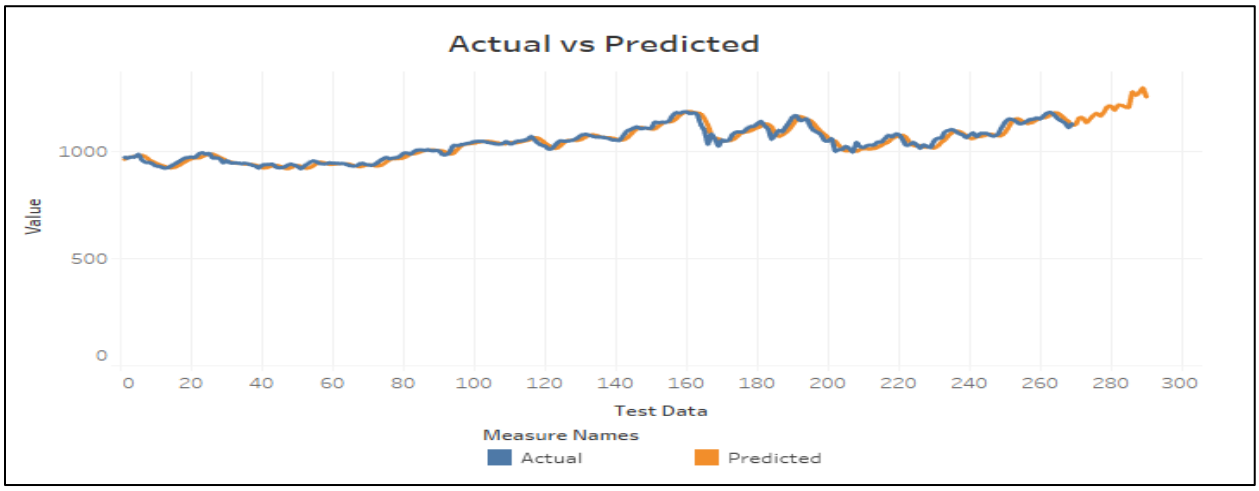


Figure 51: Google stock price forecasted for July 2018

available only until June 2018). As per our prediction, the stock price in July shows an upward trend and the price hits $1200. This forecast also matches with last month (July 2018) Google's stock price which was around $1200 showing the accuracy of our model.

LEARNING CURVE FOR THE BEST MODEL

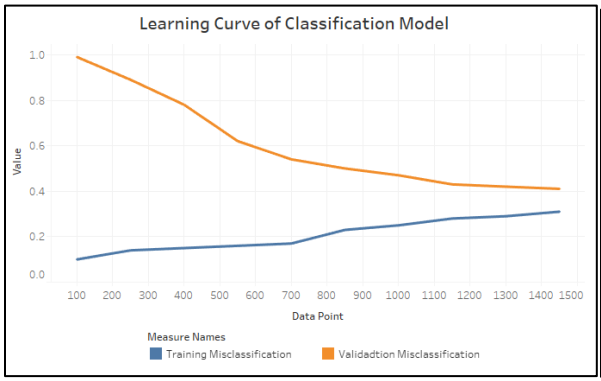


Figure 52: Learning curve for Regression model

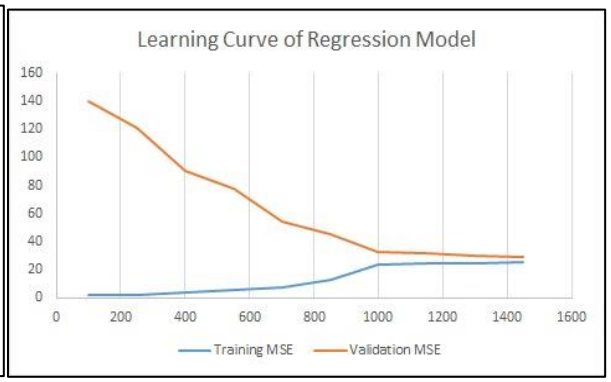


Figure 53: Learning curve for classification model

For the learning curve, we have trained our best model on different sizes of training sets starting from 100, 250, 400, 600, 800, 1000, 1200, and 1450. We can see that model which is trained on lower training size has lowest RMSE and Misclassification rate, whereas the same model performs worst on test data set because as we trained on less data our model is not generalizing well when we are testing on new data set. As we are increasing the training set size, training

errors are increasing and it start performing better on test data set. Finally, the model is trained on highest size of training set, have almost similar error on test dataset which proves that our best model is working as expected.

BUSINESS INSIGHTS

- From the table, we can see that when we use the news headlines to do the rise/ fall pattern classification on same day, the accuracy is lesser compared to predicting next day stock price and next-to-next day stock price. This shows that news headlines have more impact on next day stock price compared to today's stock price and 2 days later stock price.

News	Same day	1 day later	2 day later
Tech News	61.34%	75.98%	71.49%
Business News + Technology	66.36%	78.44%	70.91%

Figure 54: Business insights from news data

- Google and stock investors will be able to identify rise and fall pattern of its stock prices for better planning.
- Past 60 days of stock prices helps in accurate prediction of next day stock price.
- Every Quarter end, Google can expect a fall in stock price.
- Impact of Business & Technology headlines is more on the next day stock price.

CHALLENGES FACED

To retrieve every day's news headlines from NY Times from multiple huge Json files ranging from 20mb to 100mb. We wrote an algorithm to scan all files of a folder and parse the Json document and retrieve the texts from headlines for each day of last 10 and half years using Python from various sections. The Google Stock price data had missing data for holidays and weekends. So, we choose LOCF (Last observation carry forward technique) to impute the missing values Stock price data and other features included were skewed implying that data was not normally distributed. Used Auto Box-cox transformations on the data to get an approximate normal distribution. During model Selection, based on different cost functions, different models were available. Final model was selected considering different metrics.

FUTURE WORK

- Using sliding window on news headlines, i.e., work with 3D data matrix for improved accuracy. Lack of infrastructure limited this implementation for the project.
- Increase the size of historical stock price data used.
- RNN Model - Using all feature engineered variables to do predictions on sliding windows.\

APPENDIX 1 - REFERENCES

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APPENDIX 2 – FIGURES

APPENDIX 3 – TABLES