

# Stock Price Prediction Using Tensor Flow and Artificial Neural Networks

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## Abstract

**Stock prices are impacted by an array of different factors that can affect movement of prices daily. It is essential to investors and traders to understand the volatility of the nature of the stock, before investing in it. In today's markets, it is very common for different algorithms dictating the movement of prices, which are trained on variety of features or factors that can impact the price of the stock and/or the share. This project aims to use Tensor Flow's Artificial Neural Network to predict stock prices and compare it to the estimations done by conventional forecasting methods and see if there is a need to develop such networks which it comes to quantitative forecasting.**

## Keywords

**Artificial Neural Network. Tensor Flow. Simple Moving Average. Moving Average. Exponential Smoothing Via Trend Adjustment. Backpropagation. ReLu.**

## 1. Introduction:

Different forecasting methods like the simple moving average, weighted moving average and exponential smoothing via trend analysis are used for forecasting the stock price. But the idea of Artificial Neural Networks, which are usually used in more complex and subjective feature usage having any sort of relevancy to forecasting of stock prices is still an interesting domain area, because much of the past data that is used and/or the training data used is highly quantitative and one dimensional specifically when it comes to stock prices.

Since stock prices are impacted by an array of features like recent SEC public releases, quarterly reports, and macro-economic factors, can the set of features be

limited to just quantitative past data, and the performance of an Artificial Neural Network on data specifically meant for forecasting methods. This would give an idea of whether techniques employed in Artificial Intelligence might be irrelevant and/or not necessary for forecasting methods.

## 2. Background

One of the most momentous work done in a study [1], in the area of stock prices, specifically when it comes to volatility of different stock prices is using Tensor Flow's Long-Term Short-Term Memory method where funds are being considered for evaluation rather than individual securities. The funds being considered for evaluation are Exchange Traded Funds (ETFs), which have their own distinct personality in terms of quantitative traits, which are not dependent on their own elements present in the ETF, but rather the entire ETF itself. The study did focus on the impact of the Simple Moving Average and Moving Average Convergence Divergence. The study only focused on the nature of an ETF which is different from stock prices, even though it showed positive results for much of the predictions.

Another study [2] focused on using Artificial Neural Networks to decide which the equity fund would be better for an investor or a trader depending on the attributes of a fund relative to other funds, from other industries. There are many different features that are considered in the calculation of the equity funds, because the uniqueness of an industry, or a sector e.g. agriculture has its own distinct features that can be separated from let's say the healthcare sector. The black and white element of the industry existing in different sectors actually makes the ANN more intelligent in determining the output. That is why again, the equity fund performs differently, almost similarly like an ETF

as mentioned above and doesn't treat every stock differently from a large set. One of the most important work done [3] in terms of learning patterns is by using Genetic Algorithms search in the optimization of learning patterns of features before inputting them into ANN model. The study, however, focuses on a highly multi-dimensional problem, where many features can be tested but doesn't consider a simple feature like past data, and whether certain decision can be made on data that can just simply be forecasted.

## Methodology:

The data selected is stock data from NASDAQ, or the NYSE for the past 5 years for a set of companies. The data is extracted from the IEX Trading Platform, which provides attributes such as batch history, stock data, company information, dividends, security information and intra-day trading facts of different days. The specific attribute considered for the training data is the opening, closing and the average stock price for the day for a particular company.

It is very important to understand the nature of the opening prices. Opening prices vary for different stocks, specifically when it comes to premarket trading and the after-market trading hours. If there is a lot fluctuation in stock price when it opens relative to the old closing price for the previous day, that can be attributed to the volume of shares being traded in response to some big event which happened when market closed. This is why opening prices have an important impact on the how the stock price can and/or cannot behave. The problem with opening prices is that they aren't a good indicator of how the price might fluctuate throughout the open market hours because pre-market trading, after-market trading and regular market trading have huge differences in how the volumes of shares are traded when they hit certain lows or certain highs.

On the other hand, closing price has less to do with the market conditions prevailing upon the end of the previous regular, pre-market or after trading sessions, and more on the events that happen throughout the regular trading session. It is important for the closing price to reflect the actual sentiment of the regular market session.

Therefore, the average price during a regular session, is a good indicator of what seems to be the most appropriate

measure for knowing the fluctuations that happen throughout the regular trading session, however one of the biggest flaws of the average trading session is that it smooths any probability of extreme fluctuations. For example, if Apple stock went from \$192 to \$198 within 30 minutes, after news that shareholders are dumping much of their stocks, then the average price would not consider the \$6 jump, because there could be other highs and lows, but it didn't identify any of those highs or lows or give a more reasonable justification.

However, since quantitative past data needs to be standardized in order to develop a metric more representative of the regular market trading session, it is essential to pick a price that can actually be forecasted using conventional methods.

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  "change": -1.67,
  "changePercent": -0.01158,
  "iexMarketPercent": 0.00948,
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Figure 1: IEX Stock Quote Time Stamp (AAPL)

As one might notice, the date at any given time can vary a lot from the closing and opening prices. This is because the volume of shares traded, specifically for companies with large market caps tends to show little volatility because any change percent values for the stocks are trivial, relative to companies with smaller market caps because their share price is highly likely to fluctuate

within regular trading hours. However, for the purposes of the project, companies with relatively larger market caps are preferred.

#### Key Stock Data

|                          |                       |                          |           |
|--------------------------|-----------------------|--------------------------|-----------|
| Best Bid / Ask           | N/A / N/A             | P/E Ratio                | 16.72     |
| 1 Year Target            | 220                   | Forward P/E (1y)         | 17.39     |
| Today's High / Low       | \$ 200.85 / \$ 198.15 | Earnings Per Share (EPS) | \$ 11.89  |
| Share Volume             | 47,800,589            | Annualized Dividend      | \$ 3.08   |
| 50 Day Avg. Daily Volume | 28,470,070            | Ex Dividend Date         | 5/10/2019 |
| Previous Close           | \$ 199.46             | Dividend Payment Date    | 5/16/2019 |
| 52 Week High / Low       | \$ 233.47 / \$ 142    | Current Yield            | 1.56 %    |
| Market Cap               | 914,601,688,500       | Beta                     | 1.02      |

*Figure 2: Market Cap and Dividend Data for AAPL (NASDAQ)*

As one might observe, the above data also gives the 52-week high and 52-week low price, which looks at the past year's return for investors to get a quick snapshot of their portfolio might be looking. Dividends issued have a huge impact on price as it is more likely to increase due to a board of directors' decision to appease shareholders. However, it is still a bad indicator for predicting stock performance for the coming days due to its dependency on multiple factors like payout ratio, the dividend rate, the dividend yield which would determine the actual fluctuation rate when that specific stock price is supposed to increase and/or decrease.

Some might believe that sentiment of recent news, specifically from the SEC has a huge impact on the stock price, however it is hard to assess the degree to which stock price at any given time can be attributed to a SEC Press Release. For example, if the sentiment on the SEC Press Release on January 3<sup>rd</sup> shows positive polarity, then it is hard to assess how the news can be linked or have a relationship with the stock price of the day of, or three days into the week, because reaction time for different traders is different, not to mention the difference of criteria of assessment when it comes to picking the right time to buy or sell, based on a fund's priorities.

#### Press Release

## SEC Charges Former Senior Attorney at Apple With Insider Trading

### FOR IMMEDIATE RELEASE 2019-10

*Washington D.C., Feb. 13, 2019* — The Securities and Exchange Commission today filed insider trading charges against a former senior attorney at Apple whose duties included executing the company's insider trading compliance efforts.

The SEC's complaint alleges that Gene Daniel Levoff, an attorney who previously served as Apple's global head of corporate law and corporate secretary, received confidential information about Apple's quarterly earnings announcements in his role on a committee of senior executives who reviewed the company's draft earnings materials prior to their public dissemination. Using this confidential information, Levoff traded Apple securities ahead of three quarterly earnings announcements in 2015 and 2016 and made approximately \$382,000 in combined profits and losses avoided. The SEC's complaint alleges that Levoff was responsible for securities laws compliance at Apple, including compliance with insider trading laws. As part of his responsibilities, Levoff reviewed and approved the company's insider trading policy and notified employees of their obligations under the insider trading policy around quarterly earnings announcements.

*Figure 3: SEC Press Release on Apple*

But one can assume that sentiment can be indicated by the trailing low or high price. For example, without assessing the sentiment of the news, one can just look at the downward plunge of a price between two different time stamps and assess the degree to which a negative press release might have had an impact.

To attribute for the sentiment, the project looks at past data's price fluctuation throughout the day, rather than the sentiment of the news as it is more accurate indicator of sentiment than the set of news that is published. However, it would be more convenient to get a sentiment on the news, it wouldn't have served the purpose since there is a lack of financial lexicons in financial training data for negative and/or positive news. For example, mergers and acquisitions have different connotations depending on who the trader is. If the trader believes a certain merger or acquisition can benefit a company, then it might have a positive impact, but if the trader believes otherwise, then it might have a negative impact.

For example, if 100 traders believe that a merger would have a positive impact on the stock price and 50 believe otherwise, there would still be a stock price increase but it wouldn't show the dip in price that would have happened due to the 50 traders believing otherwise because it would cancel out the 50 traders positivity over the 50 negative. Therefore, the fluctuation in price would show the cancellation effect, but it won't still be representative of the actual percentage of traders who believed there wouldn't be enough demand for a certain stock at any particular time.

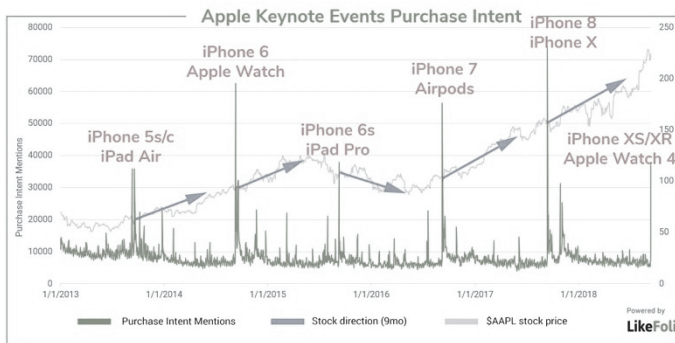


Figure 4: Apple Sentiment at Different Times of Product Launches (CNBC)

The above figure shows how certain trends can be adjusted for Apple's different product launches, which can also be observed in the stock price for those dates where their product launches. So, if there can be a trend that can be identified in a company's behavior, the probability of that trend being useful in forecasting can be essential in determining the direction of the stock price throughout the regular market, pre-market and after-market trading hours. To look deeply into the sentiment that can be assessed, one needs to assume that sentiment is correlated with historical price data.

### Simple Moving Average

Simple moving average is one of the most common methods used in operational research to forecast demand of products, commodities, and securities in the financial market. The adherence to the method can be found in its simple usage, but that also limits its forecasted variable to past data without any consideration to the importance of the past days.

$$SMA_t = \frac{1}{N} \sum_{i=1}^N P_{t_i}$$

(1)

$N$  is considered as the total number of past days under consideration, whereas  $t(i)$  can be thought of a very specific time in past data for which the price of a certain commodity or a stock can be considered.

SMA is the foundation for many other forecasting methods, and maybe not the most appropriate method for assessing the range of accuracy for a certain price. It can be used in benchmarking for comparative analysis on many forecasting

methods. The reason why SMA can't be used appropriately in assessing demand is because it does not give weightage to any days relative to the forecast. For example, let's assume the current stock under consideration is Tesla stock, and one applies the simple moving average to predict the stock price of the next day. Simple moving average will only consider the values in the most recent time period restricted by  $N$  and will not give any importance to each of those days. If the previous day, there was an SEC Press Release which put Tesla's stock at \$225, but the previous days showed a value of \$220, \$220.5, and \$221.9, the forecast will give equal weightages, even though the most recent news is more likely to make the most recent day more important. To solve this issue, weighted moving average is considered in order to adjust for the most recent time period, or any time period as more important than any other one.

### Weighted Moving Average

$$WMA_M = \frac{np_M + (n-1)p_{M-1} + \dots + 2p_{(M-n+2)} + p_{(M-n+1)}}{n + (n-1) + \dots + 2 + 1} \quad (2)$$

The denominator is the sum of the different weights assigned. For example, if the weights assigned to the past 5 days are 3, 2, 1, 0.5, 0.2, then it will be a sum of these weights, whereas the numerator will be the price of the days as a product of their respected weights. So, in the above example, where Tesla had a SEC Press release the previous day, the weight of 5 can be assigned to that day. So, the stock price of that day would be given more weightage, in order to adjust the forecasted value for that SEC Press Release.

The problem with weighted moving average, is the selection of weights, which has to be done in an arbitrary fashion, by using many assumptions, that hold for all prices. This makes the selection of weights a cumbersome process due to its reliance on the decision-making process behind the selection of the weights. Now, the decision vectors for the weights has to be true, which means that if the most previous day was given a weightage of 5, then there should be a justification. A possible justification in the Tesla example could be the stock price of the most recent day is more representative of the forecast because recent news has more impact on the current stock price and the older the news, the less the relevancy there is to that forecasted price.

To compensate for the shortcomings of the weighted moving average, one has to rely on smoothing and automated trend

adjustment in the forecast. This can be done through a forecast method commonly used in forecasting prices, where trend has an importance.

### Exponential Smoothing with Trend Adjustment

ESTA is most appropriate for the adjustment of trend within a smoothing equation to attribute some weightage to the trend in the value being forecasted while applying a smoothing constant.

In basic exponential smoothing, there is an assumption that there is no trend and/or no sort of increase and decrease for the trend adjusted. So, in every interval, new forecasts or estimates are done.

$$F_t = \alpha * D_{t-1} + (1 - \alpha) * F_{t-1}. \quad (3)$$

New Estimate =  $\alpha \cdot$  New information +  $(1 - \alpha) \cdot$  Old Estimate.

One of the most important things to consider in the new forecast is the trend, which isn't attributed for. So, to do that one needs to understand there is a linear relationship between the output and the input, or the independent and dependent variables. For this, Linear Regression is considered.

$$Y(t) = a + bt. \quad (4)$$

The period t, one gets a straight-line forecast for the demand of the particular period. To adjust for the trend within a smoothing forecast, can be done by getting the estimate during that particular time, the estimate of the trend.

$$\begin{array}{l} S_t \quad \text{our estimate of the level at time } t \text{ (kind of like an intercept, but not exactly).} \\ T_t \quad \text{our estimate of the trend in period } t, \text{ or the slope.} \\ TAF_{t+1} = S_t + T_t. \end{array} \quad (5)$$

**S**t can be thought of the estimate without the necessary trend adjustment considered. **T**t is the actual trend that considered for the period. For example, snowmobiles are more likely to be sold in the winter, so for all the days that lie in November, December and January are likely to be adjusted in this trend for a snowmobile company.

1. At the end of a period, compute a new intercept:

$$S_t = TAF_t + \alpha(A_t - TAF_t).$$

We can also write this as:

$$S_t = (1 - \alpha) * TAF_t + \alpha A_t \quad (6)$$

The alpha value is the smoothing constant which can determine by which degree, to smooth the data. The alpha value determination is based on the type of the security or stock. For example, Tesla Stock is likely to be smoothed for any data before their Model X launch, to consider the forecasted values only after the launch of the Model X.

2. Compute a new, smoothed estimate of the trend

$$T_t = T_{t-1} + \beta(TAF_t - TAF_{t-1} - T_{t-1}). \quad (7)$$

The smoothing constant Beta can be considered the trend adjustment factor in the entire process to attribute for how much of the trend one wants to associate with the forecasted value for a particular time.

3. Use these two new terms to predict the demand for period t + 1:

$$TAF_{t+1} = S_t + T_t. \quad (8)$$

Now once we have the forecasted and the adjusted trend terms, we can move on to adjusting the equations together to attribute for trend adjustment in the earlier forecast, where the trend wasn't given weightage.

ESTA is a highly reliable method where one needs to revise trend for the initial forecasts upon consideration and consider the error rate, and while using that error rate, revise the trend for which a certain price was forecasted.

In this case, we use the Mean Squared Error method to compute the error, so that we can easily understand the error rates for which a trend adjustment forecasted a stock price for a given time period. Even though the error rate recommended along with the ESTA method can be different, depending on the type of data one deals with. For the purposes of the project, we used the MSE for its simplicity and its adherence to basic error identification processes in stock price prediction tools.

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2. \quad (9)$$

Now, it is important to understand that an initial value is required for the ETSA method to accept. Many studies suggest the back-casting method where one forecasts into the past to attain that certain value, but we chose the initial value randomly by a difference of -1 +1 on the actual initial value during  $t = 0$ . There shouldn't be much of a difference by not using the back-casting method, but one can only cross validate when the output is produced.

### Tensor Flow and Artificial Neural Network

Preparation and pre-processing of the data was essential before one got to the feature selection process. As stated above the feature selection was done on the basis of all the forecasted methods, by using the opening and closing prices for some experiments and the average price for others, where standardization of regular market trading hours was not an issue.

The data extracted from the IEX platform was in a JSON object format, where the training and test data were divided using an 70-30% split. One of the crucial elements in the entire process was the data scaling process where the ANN architecture depends on the activation function such as sigmoid being between  $[-1,1]$  etc. But for this, one can use the MinMaxScaler method using the SkLearn library. The problem again with the data scaling process is that it is hard to assess when the scaling should be done, and to what degree on the training data.

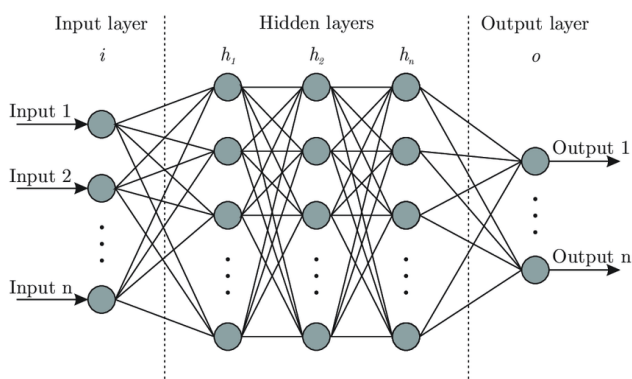


Figure 5: ANN Architecture

Tensor Flow operates in a graphical representational form where the different layers represent different feature decision points and certain attributes with every hidden layer contributing a set of answers for the next layer. Usually, placeholders are defined and certain initiation values for integers are set. Placeholders can be the stock prices, or the

past data calculated, with the output being the forecasted price. Then, there are variables which are used to assist in the entire training process, with weights and assumptions being the foundation of these variables. Usually the hidden layers are smaller than the input layer because of the decrease in the number of neuros as the information is narrowed down like a funnel.

The type of network being used is the Multi-Layer perceptron. With every weight or assumption of the previous layer where a decision was made, being transferred to the next layer and so forth. One of the most commonly used activation functions, used for this project is called the ReLU or the Rectified Linear Unit activation function. The architecture under consideration, therefore, is the feedforward network. With the above MSE technique used for the cost function to assess the prediction of the neural network and the actual values. There are different kind of ReLus like the Noisy ReLus, the Leaky ReLus and the Parametric ReLus, where the difference is primarily in the noise factor, the gradient factor and sometime integration of the coefficient leakage during the learning patterns process.

$$f(x) = x^+ = \max(0, x) \tag{10}$$

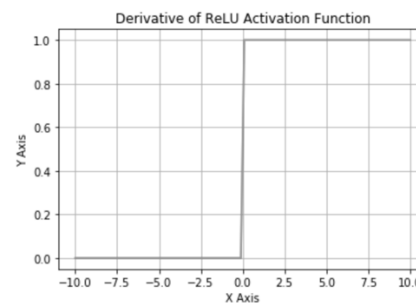


Figure 6 RELU Derivative (LearnOpenCV)

ReLU helps the network converge much faster, making the backpropagation of the entire 0s when  $x$  is below 0, minimal.

The optimizer is useful for using the MSE in the training process by the calculation of the gradients that is kind of a guide to where the weights and the assumptions have to be modified to minimize the entire cost function. Optimization is a difficult process since there can be different factors influence the way the gradient can guide the assumptions for a neural network.

The whole process then starts with the batch training for the training data, which in this case would be the entire stock price data for different companies stretching weeks. The training of this specific data will halt once the max number of epochs are reached, which is defined by the user initially if applicable.

The experiment is done on Tesla's historical price data. Again, the training data for these companies will be sparsely populated due to their higher market cap, so more accurate data concerning closing price is chosen because of its higher relevancy to the regular market trading hours. This will make the standardization of all the companies' stock data more easy to do since opening and average prices aren't really representative of the entire regular market trading hours period, as the above discussion stated.

One neuron in the entire process might look something like this:

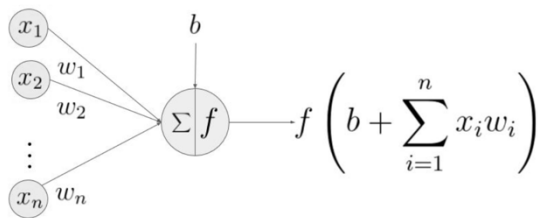


Figure 7: Sample Neuron (LearnOpenCV)

In the above figure, the input  $x_1$  or  $x_2$  where the closing price of a time period  $t$ , is considered with the SMA, WMA and the ESTA forecasted prices being used as the other features for the  $x$  values. Weights are assigned to the  $x$  variables which act as a signal vector in totality, in relation to the bias  $b$ .

In the entire learning process, the weights are updated through backpropagation, a core fundamental of ANN. The error is sent back in the network by using the derivatives in a loop, till the derivative becomes 0.

For the initiation of values, the number of neurons is set to 2000, the batch-size to 1, the number of iterations to 200 and the learning rate to 0.001.

Now it is important to understand that most of the values initiated are basic in terms of network architecture, with not

much being done for a sensitivity analysis of different values for the learning rate, which might have an unexpected impact on the output generated by the neural network. The reason behind this is because of further work being done necessary in order to set the learning rate in an appropriate way.

## Results and Conclusion

| Date       | Actual Closing | Forecasted Closing |
|------------|----------------|--------------------|
| 2017-06-29 | 360.75         | 375.43             |
| 2017-06-30 | 361.61         | 371.06             |
| 2017-07-03 | 352.62         | 366.69             |
| 2017-07-05 | 327.09         | 361.72             |
| 2017-07-06 | 308.83         | 354.66             |
| 2017-07-07 | 313.22         | 342.18             |
| 2017-07-10 | 316.05         | 332.67             |
| 2017-07-11 | 327.22         | 323.56             |
| 2017-07-12 | 329.52         | 318.48             |
| 2017-07-13 | 323.41         | 318.97             |
| 2017-07-14 | 327.78         | 321.88             |

Figure 8 SMA (TSLA - Tesla Stock) Forecast

The SMA was taken of the 5 most recent days, with 11 days of forecasted values. As seen in the data from 2017, the actual closing price of the data changes dramatically in intervals of average of 5 per day. That signifies the change one might see in the regular market trading hours. However, this should not be narrowed down as a common attribute since the average can and would change with different stocks. Secondly, since the data is basically a snapshot of a particular time period, it is isn't indicative of many other elements like seasonal trends or weightage given to the days. Note that the weights would be irrelevant in a scenario where the average might be consistent throughout the days.

| ABS Errors & %Error |         |           |
|---------------------|---------|-----------|
| 2017-06-29          | : 14.68 | 4.0693 %  |
| 2017-06-30          | : 9.45  | 2.6133 %  |
| 2017-07-03          | : 14.07 | 3.9901 %  |
| 2017-07-05          | : 34.63 | 10.5873 % |
| 2017-07-06          | : 45.83 | 14.8399 % |
| 2017-07-07          | : 28.96 | 9.2459 %  |
| 2017-07-10          | : 16.62 | 5.2587 %  |
| 2017-07-11          | : 3.66  | 1.1185 %  |
| 2017-07-12          | : 11.04 | 3.3503 %  |
| 2017-07-13          | : 4.44  | 1.3729 %  |
| 2017-07-14          | : 5.9   | 1.8 %     |

Figure 9: SMA Error Identification (TSLA - Tesla Stock)

The difference in the closing prices can be noted for the same dates. It is important to know that the error rate shows high variation for Tesla stock. The reason might be the unpredictability of the time period which isn't accounted for. Secondly, there seems to be an anomaly of 10% for one forecast where the stock price difference is of \$34, which is

too high to be even considered as an actual forecast. Average error rates that can be considered appropriate should be minimized within a range of 2% to 5% depending on the type of forecasting technique use. An inference can be made that even though the price change from closing market hours to the next day's closing market hours can be seen by the consistency of changes seen in the prices, but a large variance when it comes to error rate of the forecast.

| 5 Days Weighted Moving Average |                |                    |
|--------------------------------|----------------|--------------------|
| Date                           | Actual Closing | Forecasted Closing |
| 2017-06-29                     | 360.75         | 372.67             |
| 2017-06-30                     | 361.61         | 367.34             |
| 2017-07-03                     | 352.62         | 364.23             |
| 2017-07-05                     | 327.09         | 359.77             |
| 2017-07-06                     | 308.83         | 347.63             |
| 2017-07-07                     | 313.22         | 332.67             |
| 2017-07-10                     | 316.05         | 323.23             |
| 2017-07-11                     | 327.22         | 317.38             |
| 2017-07-12                     | 329.52         | 318.86             |
| 2017-07-13                     | 323.41         | 322.77             |
| 2017-07-14                     | 327.78         | 324.09             |

Figure 10: WMA Forecast TSLA

In WMA, different weights were assigned based on initial assumptions that recent stock price is more indicative of sentiment due to the most recent news from the SEC Press releases impacting the stock price by a higher margin than old news, of **0.5, 1.5, 2, 2.5, 3.5**. The weightages have an issue. The first issue is that it is hard to assess how important a particular day was for the company, just based on assumptions regarding recent sentiment. Secondly, it is hard to come up with a standardized technique for deciding weights.

| ABS Errors & %Error |         |           |
|---------------------|---------|-----------|
| 2017-06-29          | : 11.92 | 3.3042 %  |
| 2017-06-30          | : 5.73  | 1.5846 %  |
| 2017-07-03          | : 11.61 | 3.2925 %  |
| 2017-07-05          | : 32.68 | 9.9911 %  |
| 2017-07-06          | : 38.8  | 12.5635 % |
| 2017-07-07          | : 19.45 | 6.2097 %  |
| 2017-07-10          | : 7.18  | 2.2718 %  |
| 2017-07-11          | : 9.84  | 3.0072 %  |
| 2017-07-12          | : 10.66 | 3.235 %   |
| 2017-07-13          | : 0.64  | 0.1979 %  |
| 2017-07-14          | : 3.69  | 1.1258 %  |

Figure 11: WMA Error Identification (TSLA - Tesla Stock)

One might note that the error rate put side by side with SMA one would show a large difference. With the values ranging from 3% to 12% in terms of range, and also exhibiting smaller forecast errors when it comes to normalized prices. For example, the error rate for 6<sup>th</sup> July seems to be 12% whereas for the SMA approach, it was at 14%. This shows that the forecast error, even with the weightages seems to remain consistent, even when weights are given importance

in the forecast. The most recent day's closing price does not have an impact when it comes to limiting the error rate, which can be seen by the consistency of the forecast errors. But it does show a reduction of the errors, which shows that WMA might be a better approach than the SMA, if not the most appropriate one. Even though for this specific experiment, Tesla is considered, an observation was made for some other companies that there wasn't much fluctuation in regular market trading hour prices, but Tesla showed huge fluctuation in prices, so the reason for the picking Tesla for the experiment was to truly assess the importance of historical data and stretch it' capacity to forecast future prices.

| Trend Adjusted Exponential Smoothing |                |        |         |        |
|--------------------------------------|----------------|--------|---------|--------|
| Value change from initial: -0.11     |                |        |         |        |
| Value of Alpha: 0.7                  |                |        |         |        |
| Value of Beta: 0.3                   |                |        |         |        |
| Actual Closing: 382.61               |                |        |         |        |
| Forecasted Closing (FIT): 382.5      |                |        |         |        |
| Date                                 | Actual Closing | F(T)   | T(T)    | FI(T)  |
| 2017-06-22                           | 382.61         | ---    | 0.0     | 382.5  |
| 2017-06-23                           | 383.45         | 382.58 | 0.024   | 382.6  |
| 2017-06-26                           | 377.49         | 383.19 | 0.201   | 383.39 |
| 2017-06-27                           | 362.37         | 379.26 | -1.038  | 378.22 |
| 2017-06-28                           | 371.24         | 367.12 | -4.368  | 362.75 |
| 2017-06-29                           | 360.75         | 368.69 | -2.586  | 366.1  |
| 2017-06-30                           | 361.61         | 362.36 | -3.708  | 358.65 |
| 2017-07-03                           | 352.62         | 360.72 | -3.087  | 357.63 |
| 2017-07-05                           | 327.09         | 354.12 | -4.14   | 349.98 |
| 2017-07-06                           | 308.83         | 333.96 | -8.946  | 325.01 |
| 2017-07-07                           | 313.22         | 313.68 | -12.345 | 301.33 |
| 2017-07-10                           | 316.05         | 309.65 | -9.849  | 299.8  |
| 2017-07-11                           | 327.22         | 311.18 | -6.435  | 304.75 |
| 2017-07-12                           | 329.52         | 320.48 | -1.716  | 318.76 |
| 2017-07-13                           | 323.41         | 326.29 | 0.543   | 326.83 |
| 2017-07-14                           | 327.78         | 324.44 | -0.174  | 324.27 |

Figure 12: ESTA (TSLA - Tesla Stock)

For the ESTA Method, the alpha value was selected at 0.7, even though it was observed that the forecast error reduction was higher at 1, but 1 is not a suitable value since it does not consider the range of sensitivity of historical data. Secondly, the Beta value was set at 0.3. Different dates were selected for the exponential smoothing via trend analysis method because of testing dates before the market days, on which WMA and SMA were calculated. Note that the closing price on 11<sup>th</sup> of July was at \$316.05, whereas the forecasted value stands at \$309, and the trend is not optimized at a value of -9.849. This means that the trend did not pick up for a variety of dates. The alpha and the beta values have a momentous impact on the range of forecasts, and it is a highly debated area of research for the methodology to set them.



| ABS Errors & %Error |       |          |
|---------------------|-------|----------|
| 2017-06-23          | 0.85  | 0.2217 % |
| 2017-06-26          | 5.9   | 1.563 %  |
| 2017-06-27          | 15.85 | 4.374 %  |
| 2017-06-28          | 8.49  | 2.2869 % |
| 2017-06-29          | 5.35  | 1.483 %  |
| 2017-06-30          | 2.96  | 0.8186 % |
| 2017-07-03          | 5.01  | 1.4208 % |
| 2017-07-05          | 22.89 | 6.9981 % |
| 2017-07-06          | 16.18 | 5.2391 % |
| 2017-07-07          | 11.89 | 3.7961 % |
| 2017-07-10          | 16.25 | 5.1416 % |
| 2017-07-11          | 22.47 | 6.8669 % |
| 2017-07-12          | 10.76 | 3.2654 % |
| 2017-07-13          | 3.42  | 1.0575 % |
| 2017-07-14          | 3.51  | 1.0708 % |

Figure 13 ESTA Error Identification (TSLA Stock)

The error rate was significantly reduced for the forecast, as seen. The 12% value from the WMA method was reduced to the 5% and shows that past error in the trend forecast does impact the new forecasts. This is why ESTA is the most widely known method for forecasting prices in operational research.

| close | Prediction_1 | Prediction_2 | Prediction_3 | Prediction_4 |        |
|-------|--------------|--------------|--------------|--------------|--------|
| 380   | 326.09       | 312.610533   | 323.80       | 322.24       | 312.67 |
| 381   | 316.13       | 315.359194   | 318.66       | 315.10       | 313.38 |
| 382   | 333.87       | 317.908452   | 318.97       | 314.92       | 330.31 |
| 383   | 332.80       | 320.220403   | 319.19       | 319.89       | 335.16 |
| 384   | 310.12       | 322.282724   | 319.70       | 325.21       | 315.48 |
| 385   | 300.36       | 324.103182   | 325.38       | 331.99       | 299.58 |
| 386   | 317.69       | 325.699341   | 334.30       | 338.57       | 310.74 |
| 387   | 334.96       | 327.094432   | 340.21       | 342.54       | 331.26 |
| 388   | 335.35       | 328.312478   | 340.10       | 340.40       | 338.55 |
| 389   | 338.53       | 329.377342   | 341.92       | 342.27       | 342.96 |
| 390   | 344.97       | 330.311607   | 343.42       | 343.44       | 349.22 |
| 391   | 347.26       | 331.131314   | 343.89       | 344.48       | 352.28 |
| 392   | 334.40       | 331.850647   | 334.89       | 330.21       | 340.44 |
| 393   | 344.43       | 332.481763   | 327.79       | 318.78       | 344.75 |
| 394   | 346.05       | 333.036368   | 316.43       | 305.24       | 347.45 |
| 395   | 347.31       | 333.523549   | 305.52       | 296.41       | 349.11 |
| 396   | 302.26       | 333.951408   | 295.46       | 294.31       | 308.23 |

Figure 14: Tensor Flow ANN Forecast

Tensor Flow's neural network displayed a wide array of qualities. Prediction 1 encompasses the original price as a feature. Prediction 2 has SMA. Prediction 3 encompasses SMA, WMA as core features for the model and Prediction 4 uses ESTA along with the others. The forecasts of the different models are used to come up with an intelligent. Forecast. However, an observation can be made that when ESTA was incorporated into the Prediction 4 feature selection, the forecasts improved dramatically for some closing prices, coming within a range of 1% error rate while performing bad for others.

There were no consistent results when it came to assess the impact ESTA had on the neural network.

Finally, there were many flaws with the methodology adopted. The first flaw was that data wasn't standardized for experimentation among the same time period. The reason behind this is to identify more fluctuations with different methods. The second flaw was that there wasn't improvement or work done to improve the values of alpha and beta in the calculation of the ESTA forecasts. Moreover, only assumptions were taken for the WMA approach. Thirdly, the division of data for the ANN method seemed almost random as displayed for the array of values predicted. Fifthly, sentiment analysis of news should have been incorporated as an important feature, specifically in the domain of macro-economic news, since the macro-economic news has a huge impact on sector-wise market performance. Finally, there wasn't any importance given to the competitor's stock price variation in the to give some momentum to the automobile industry as a whole. Plus, forecasting TSLA's prices is also really specific, and does not stretch to stocks belonging to different companies in other sectors.

More work needs to be done in coming up with better features, for neural network to perform better in stock price prediction, specifically in the error range of 1%, since an automatic trading algorithm can't be forged together with a 5% error rate which for many institutional investors might be too high. Then again, it is really subjective.

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