Time Series Analysis on Financial Data from the NYSE

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Abstract

Predicting stock market trends is a popular statistical challenge that has baffled people for quite some time. Given advancement in technology, and the advent of machine learning, our project attempts to build a system that learns fluctuations in the share prices. After researching previous work, the team was motivated to analyze specific stock tickers to identify financial opportunities. The paper aims to summarize our project by explaining the classification approach taken, by segregating patterns through daily movement in the stock prices. Thereby, enabling us to conduct a time-series analysis on the data and better understand the overall scenario of the markets. A neural network, recurrent with a gated LSTM, was selected to solve our problem statement. The model's parameters were then tuned through experiments to optimize it for each specific stock. Finally, the performance was reported for various sectors (APPL for tech, BAC for banking, PFE for health care) to evaluate the feasibility of future work.

Introduction

The modeling of stocks traded on the NYSE into binary classes of gainers, shares that the model expects to appreciate, and losers, shares that the model predicts will lose value, over a time period is a challenge that can be extremely rewarding. The motivation behind this work is to help investors identify financial opportunities and, given a certain risk threshold (probability of price movement), be able to invest in the stock market with more confidence based both on fundamentals of a company as well as the share price history itself. Other desired benefits, apart from predicting price fluctuations for individual securities include the fact that the model should be able to aggregate data for all stocks, given it calculates the probability for each stock anyway, and provide insight into what the overall market should look like across various indexes and sectors (i.e. SP 500, the tech sector, etc), thus further aiding investors to park their money more intelligently through index/mutual funds if a more diversified portfolio is desired.

There are a plethora of existing solutions for the purpose of predicting share prices. Since at least the 1950s, companies have been building models to predict the future value of the stock market. Historically, those analysis could be categorized into fundamental analysis, which looks at the underlying company and its performance, and technical analysis, which focuses on patterns and trends of the past prices. The existing methodologies (Porshnev, Redkin, and Shevchenko 2013) mostly refrains from combining the two approaches. Further, the literature we found on the topic (Porshnev, Redkin, and Shevchenko 2013; Patel et al. 2015; Devi, Sundar, and Alli 2013) seems to solely focus on the prediction of share prices in the short term - intraday trading or at most daily charts. We believe there exists a gap in the literature of modelling a longer time frame.

We aim to build models that help classify stocks into two classes - gainers and losers. Although this itself is nothing new, the team will aim to predict these fluctuations daily - as opposed to intraday probabilities - thereby enabling a new approach to solve an existing challenge. We also plan to augment historical price trends with fundamentals of the company to achieve a more holistic view of the security. Given the project parameters, we believe this model will be useful for investors who want to invest for the longer term, rather than benefit from rapid, day-trading. Most current technologies use automation software to buy/sell at a faster pace, but in contrast, we aim to identify investment opportunities that will appreciate in the slightly longer term.

Related Works

Time Series Analysis for Financial Data :

An Effective Time Series Analysis for Stock Trend Prediction Using ARIMA Model for Nifty Midcap-50 (Devi, Sundar, and Alli 2013) article focuses on the Auto regressive integrated moving average(ARIMA) model proposed by the author to work on the time series analysis of Nifty Midcap-50 stock market index. Financial time series forecasting using support vector machines (Kim 2003) paper explains the time series analysis of the Korea composite stock price index (KOSPI) using ANNs and SVMs specifically. Twitter mood predicts the stock market (Bollen, Mao, and Zeng 2011) article points out that these models can have limitations in that learning patterns is difficult when there is a lot of noise and complex dimensionality.

Most of these previous works focus on using artificial neural networks (ANN) for the challenging task of finan-

cial time-series predictions. Our work is different from these works as we plan to apply Recurrent Neural Network with Long Short-Term Memory so that the model is better able to retain information from previous nodes.

Deep Learning Techniques for Financial Models :

A deep learning framework for financial time series using stacked auto-encoders and long-short term memory (Bao, Yue, and Rao 2017) explained the process of predicting stock market prices using wavelet transforms (WT), stacked auto encoders (SAEs) and long-short term memory (LSTM). Stock prediction using deep learning (Singh and Srivastava 2017) focuses on NASDAQ to predict stock prices using Artificial Neural Network (ANN), Deep Neural Network (DNN) and Radial Basis Function Neural Network (RBFNN). A new hybrid constructive neural network method for impacting and its application on tungsten price prediction (Muzhou et al. 2017) introduces a new hybrid constructive neural network method (HCNNM) which repairs the impacting value in the original data similar to jumping points of a function with regards to fluctuation in tungsten prices. A review of unsupervised feature learning and deep learning for time-series modeling (Längkvist, Karlsson, and Loutfi 2014) compares different unsupervised methods and deep learning methods with respect to time series domain. Stock price prediction using LSTM, RNN and CNN-sliding window model (Selvin et al. 2017) elaborates the prediction of stock prices in the NSE (National Stock Exchange) using LSTMs and CNNs.

Apart from the techniques mentioned in the above articles, we might also be using recurrent neural network to view the result outcome. Also apart from the mentioned convolution methods we aim to change the pooling layer size to observe Since later found out that our model would have the best optimal solution using neural networks we decided to combine the techniques of time series analysis with deep learning methods.

Methods

The procedure aims at extracting data from the database and building a machine learning model that involves four major steps:

Loading :

The data from the CSV file is loaded into the database using Python. The data is loaded using the python package pandas in the form of a Data-frame. The packages required for the analyses are imported in the beginning. The values of hyper parameters were defined prior to the analyses. Data exploration was performed to get a better grasp of the data set.

Filtering :

The Data-frame was then filtered to remove unused columns(volume and stock symbol) which wont be used in the analyses. The value of train, validation and test sets were defined. The sets were then scaled and normalized to be used later while fitting the model.

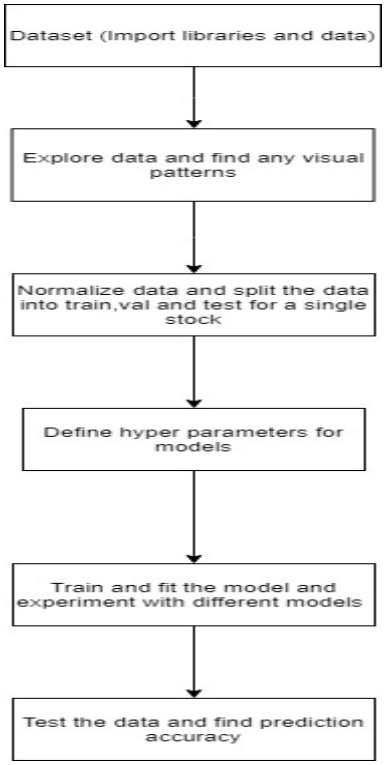


Figure 1: Work flow representing the entire process of the experiment

Visual Analysis :

Plots of volume v/s time and price v/s time were drawn to find any visual patterns and relations within the data. For this purpose one specific stock was chosen manually and the analyses involved this particular stock. The model was built on the entire data but the analyses was carried out just to depict the relation with respect to a single stock.

Build Machine Learning Model :

First the model was trained using the training RNN data set. Then the model was fitted using the validation data set. Finally it was tested for accuracy using the test data set. The model was optimized using different hyper-parameters using the test classifications predictions as further experiments to determine a final model. The features used in the model are the open, close, low and high.

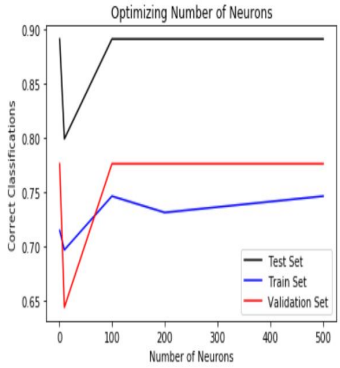
Experimental Design

The main purpose of the experiments was to determine which of the hyper-parameters yield the highest prediction accuracy for the RNN model. The motive is to find the best possible combination that yield the best predictive performance without over fitting the data. The data set used is from the New York Stock Exchange from 2010 to 2016. The data was sourced from the site kaggle.com. The data set contains the open, close, high and low prices of different stock prices during each day for each of the seven years. We conducted

our experiments on the same data set each time. We conducted the following experiments on our model:

Optimal Number of Neurons :

The objective of this experiment was to test the model's predictive power on various values of number of neurons to determine one that would yield the best test classification rate. Initially, the model RNN with LSTM was chosen with 200 neurons but the team wanted to further optimize the neural network. This hyper parameter will be chosen based on the evaluation metric of correct classification which we have denoted in our model as the open price of a stock minus the close price from the previous day.

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Optimal Number of Neurons: 1.000000
Highest correct classifiation of close - open price for test set: 0.890804597701149
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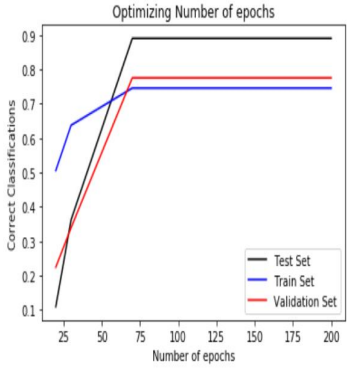
Figure 2: Optimizing Number of Neurons in the Neural Network

Optimal Number of Epochs :

The objective of this experiment was to test the model's predictive power on various values of batch size to determine one that would yield the best test classification rate. Initially, the model RNN with LSTM was chosen with a batch size of 50 layers but the team wanted to further optimize the neural network. This hyper-parameter will be chosen based on the evaluation metric of correct classification which we have denoted in our model as the open price of a stock minus the close price from the previous day.

Optimal Learning Rate :

The objective of this experiment was to test the model's predictive power on various values of batch size to determine one that would yield the best test classification rate. Initially, the model RNN with LSTM was chosen with a batch size of 50 layers but the team wanted to further optimize the neural network. This hyper-parameter will be chosen based on the evaluation metric of correct classification which we have denoted in our model as the open price of a stock minus the close price from the previous day.

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Optimal Number of Epochs: 70.000000
Highest correct classifiation of close - open price for test set: 0.890804597701149
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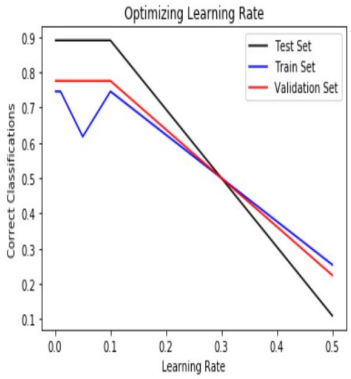
Figure 3: Optimizing Number of Epochs in the Neural Network

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Optimal Learning Rate: 0.001000
Highest correct classifiation of close - open price for test set: 0.890804597701149
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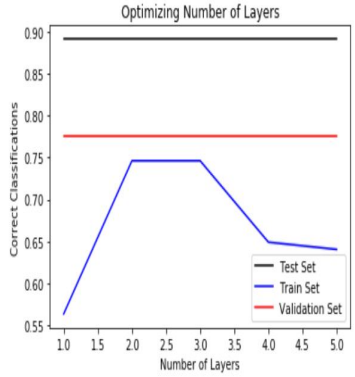
Figure 4: Optimizing Learning Rate in the Neural Network

Optimal Number of Layers :

The objective of this experiment was to test the model's predictive power on various values of number of layers to determine one that would yield the best test classification rate. Initially, the model RNN with LSTM was chosen with two layers but the team wanted to further optimize the neural network. This hyper-parameter will be chosen based on the evaluation metric of correct classification which we have denoted in our model as the open price of a stock minus the close price from the previous day.

Optimal Batch Size :

The objective of this experiment was to test the model's predictive power on various values of batch size to determine one that would yield the best test classification rate. Initially, the model RNN with LSTM was chosen with a batch size of 50 layers but the team wanted to further optimize the neural network. This hyper-parameter will be chosen based on the evaluation metric of correct classification which we have denoted in our model as the open price of a stock minus the

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Optimal Number of Layers: 1.000000
Highest correct classifiation of close - open price for test set: 0.890804597701149
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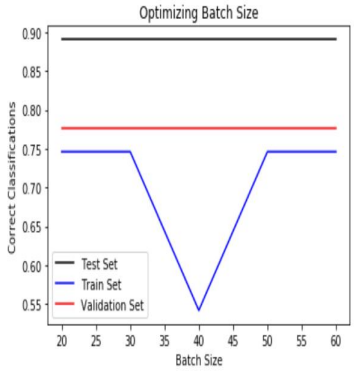
Figure 5: Optimizing Number of Layers in the Neural Network

close price from the previous day.

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Optimal Number of Layers: 20.000000
Highest correct classifiation of close - open price for test set: 0.890804597701149
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Figure 6: Optimizing Batch Size in the Neural Network

All selected hyper-parameters were chosen via the test rate because it gives us the best performing model. Although, we could have chosen to pick through an indirect method, this seemed impractical as we had the true values of the predicted dates.

Experimental Results

Our main findings from the results were that a recurrent neural network (RNN) was the best at modeling time series for financial data. Further, a gated RNN with Long Short-Term Memory (LSTM) provides significant predictive power gain to the model. Although the hyper-parameters number of neurons, number of layers, and batch size were optimized, we do not expect any significant difference as the initial runs were set with fairly standard parameters. The optimal number of epochs was 70. The optimal learning rate was 0.001. The optimal number of neurons for our model was 1. The

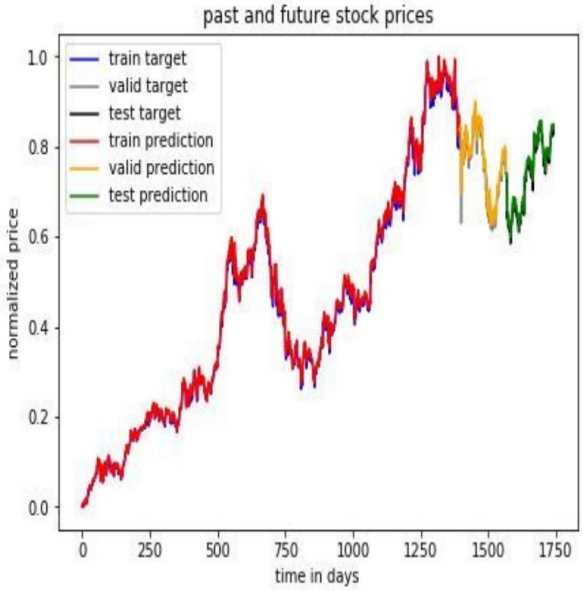

Figure 7: Normalized Price Predictions for Training/Validation/Test sets

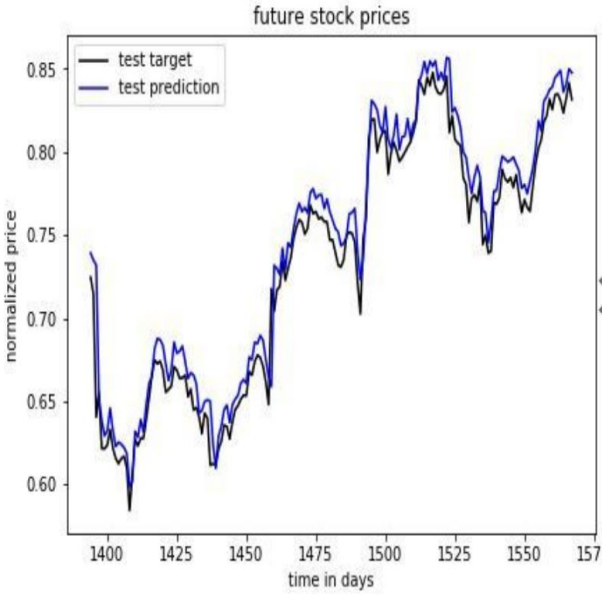

Figure 8: Normalized Price Predictions for Test Set vs True Values

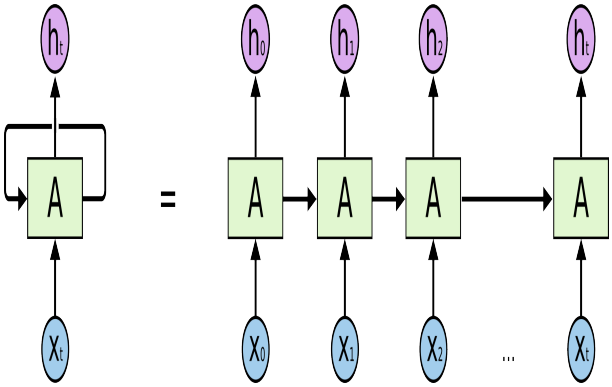

Figure 9: Final Model Architecture

optimal number of layers was 1. Finally, the best batch size to train on was 20.

Conclusion

Our analysis show that a recurrent neural network work strikingly well for time series analysis. We were able to gain a relatively high percentage of correct classifications of gainers and losers for each share daily. Adding a gate to our RNN, via LSTM, was tremendously useful. The team believes this aids the model weights to remember history and learn not just from neighboring neurons but more similar to a biological brain, in the sense that it is learning through experience.

Further, it was interesting to find that some hyperparameters of our system seem to have a significant impact on the classification rate but others seemed not to. Our experiments should that the number of neurons in the architecture, the number of epochs spent learning, and the learning rate of the algorithm itself were variables that determined the accuracy of our analysis. The number of layers and batch size did not seem to affect the model significantly. This makes sense to us: movement in prices should only require short-term memory and therefore not many layers of information processing was needed.

Our system performs very well when predicting companies in the tech sector, but does not provide as high an accuracy when modeling other securities. When predicting banking, the model only provided a 60 percent rate of correct classification. The health care sector was similarly low. Given more time and computational resources, we request to evaluate our system further and increase the adaptability of our neural network.

Future Scope

A few lines of research that would be interesting to follow this analysis up would be the addition of ensemble learning. During the team's literature review, ensemble learning (in relation to Random Forests) were highly recommended. It would be interesting to see the results when our RNN model could be improved upon by combining several network or by adding convolution layers. Another area our experiments fail to cover is the inclusion of the volume feature. We would expect the network to learn the impact of volume levels on share prices but we were not able to consider this path due to time constraints.

Regression Techniques in Financial Models :

Machine learning in prediction of stock market indicators based on historical data and data from Twitter sentiment analysis (Porshnev, Redkin, and Shevchenko 2013) compared the prediction accuracy of stock market using machine learning menthods and twitter sentimental analysis. Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques (Patel et al. 2015) focussed on Support Vector Machines (SVMs) for their prediction. Predicting stock market index using fusion of machine learning techniques (Patel et al. 2015) elaborated the process of fusing three machine learning models for prediction. Evolving Least Squares Support Vector Machines for Stock Market Trend Mining (Yu et al. 2009) focusses on Support Vector Machines and Least Sqaures Support Vector Machines (SVMs and LSSVMs)

All the above mentioned literary articles had SVM as the common regression technique to predict stock prices. The articles didn't focus or display information regarding other methods such as Decision tree and KNN - even though it was just vaguely mentioned in the second reference. We propose to use all the regression techniques and display accuracy metrics to select the best possible technique. None of the articles worked on enhancing techniques such as dimension reduction or subset applications to reduce the variance and thus keeping minimal bias. We propose to work on smaller data sets that keep only the essential subsets of the data. Also the articles focused more on prediction of stock market prices and none of the papers classified the data into groups to predict the possibility of the market opening up or down for a given day. We propose to work on classification of data so as to predict the open price to be below or above the close price at the end of the previous day.

Ensemble Learning in Financial Modeling :

Chinese Stock Index Futures Price Fluctuation Analysis and Prediction Based on Complementary Ensemble Empirical Mode Decomposition (Chen and Pan 2016) elaborates the Empirical Mode Decomposition (EMD) method, the Ensemble EMD method, and Complementary Empirical Mode Decomposition (CEEMD). Comparison of individual, ensemble and integrated ensemble machine learning methods to predict Chinas SME credit risk in supply chain finance (Zhu et al. 2017) compares individual models with fusion of different Machine Learning models while dealing with China's financial statistics. Stock market prediction with multiple classifiers (Qian and Rasheed 2007) focusses on Artificial neural network (ANN), k-nearest neighbor (kNN), and Decision tree (DT). The paper also elaborates the process of ensembles of the mentioned three methods.

Ensemble learning is a popular technique to gain prediction accuracy. These works discuss model architecture that have been applied and some strengths and weaknesses that were found. These analyses have used a combination of ar-

tificial neural networks, decision trees, and k-nearest neighbors and through appropriate collaboration achieved 65 percent correct results. From the first reference, it is also important to note that we must consider the type of market when selecting the modelling tools - markets in an emergent state, such as China, will use different analysis than mature ones such as the NYSE. That being said, some learnings from these works can be transferred over to our project: random subspace boosting seemed to provide a substantial increase in accuracy. Our work is different from these works because we plan on building various models, creating ensembles from them over various combinations, and then optimizing our model to select optimal parameters. None of these papers discuss building the ensembles and the effect of different inputs on the results.

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