Predicting S&P 500 Price Movement Using Historical Macroeconomic Factors: A Comparison of RNN and MLP Models

Junlong Zhang
Department of Computer Science
University of Toronto
junlong.zhang@mail.utoronto.ca

Kevin Sun
Deparment of Computer Science
University of Toronto
kevinuoft.sun@mail.utoronto.ca

Yixiao Zhang
Deparment of Computer Science
University of Toronto
yixiao.zhang@mail.utoronto.ca

Abstract

Investing in traditional stocks comes with inherent risks, as investors are exposed to both firm-only and market risks. However, exchange-traded funds (ETFs), such as the S&P500, have become an increasingly popular investment option due to their ability to diversify firm-only risks, leaving only market risks. Market risks are influenced by several macroeconomic factors such as GDP, interest rate, inflation, and unemployment rate. In this study, we aim to use these factors along with the closed price and traded volume of the S&P ETF as inputs to an RNN and MLP respectively to predict the price movement of S&P500 in the following month.

1 Introduction

Stock performance prediction has been an attractive topic in finance, as investors aim to gain an edge in the market by predicting future price movements. Traditional finance approaches have attempted to explain uncertainties in stock performance through various factors such as macroeconomic conditions, earnings/price ratio, and the Capital Asset Pricing Model (CAPM). However, investing in traditional stocks can be challenging due to the existence of firm-only risks, which suggests that the factors that influence stock performance differ by stock. For instance, stocks in the online-tool industry, such as Netflix, show a completely inverse relationship to stocks in the in-person entertainment industry when vaccines were introduced during the Covid-19 pandemic. To address this, an exchange-traded fund (ETF) like the S&P 500 has been considered a more stable security that successfully diversifies the firm-only risks for each stock, leaving only the market risks. Since market risks are mostly affected by factors that can be measured, such as GDP, interest rates, inflation rate, and unemployment rate, along with historical data of S&P 500 closed price and traded volume, it is possible to predict the direction of the S&P 500 price movement. In this research, we aim to compare the performance of a recurrent neural network (RNN) and a multi-layer perceptron (MLP) model given the task to predict the price movement of the S&P 500 ETF, taking into account the factors affecting market risk in the most recent 5 months, and predicting whether the price will increase or decrease in the following month. This research will contribute to the field of finance by exploring the potential of machine learning techniques to predict market risk and provide insights into the performance of the S&P 500 ETF.

37th Conference on Neural Information Processing Systems (NeurIPS 2023).

2 Relation to existing works

The incorporation of machine learning techniques for stock prediction has become popular in recent years. In particular, neural network has shown promise in this area due to their ability to model complex non-linear relationships. The work by Kamalov, F., Smail, L., amp; Gurrib, I. [1] proposed a convolution-based neural network model for predicting the future value of the S&P 500 index. The model utilized the closing and trading volume from the previous 14 days as input, and 2 hidden layers to predict the direction of the index the next day. The group also used 7 benchmark models to evaluate the performance of their model. The result shows that their model outperforms the benchmark model with a prediction accuracy of 55%. As the stock market tends to fluctuate more frequently and with greater volatility on a daily basis compared to a monthly basis, we believe that by computing the monthly average of closed price and traded volumes, the prediction accuracy would increase, and this is also what we did in this study.

Another paper by Patel [2] focuses on predicting the direction of movement of stock and stock price index for Indian stock markets using four prediction models, Artificial Neural Network (ANN), Support Vector Machine (SVM), random forest and naive-Bayes. The results of the experiment have shown that the performance of all the prediction models improves when technical parameters are represented as trend deterministic data. To use trend data in this study, we decided to predict the S&P price movement in the following month given the data of the most recent five months. As price movements are not only based on the most recent data but are more likely based on a trend of the recent data, this should increase the prediction accuracy of our model.

In a different paper by Hasselmo, Schnell, and Barkai [3], the team presented several approaches to predict stock price on a weekly forecast horizon. They used convolutional Neural Network models with univariate/multivariate and varied input data size and network configurations. They concluded that the performance of the convolutional neural network based models had a far superior result. There have been several studies that have successfully applied neural networks to predict the trend of the S&P 500 ETF. Our proposed project aims to build on previous works to possibly achieve a higher accuracy in predicting the price movement of the S&P 500 in a monthly horizon.

3 Model

3.1 Multi-Layer perceptron (MLP)

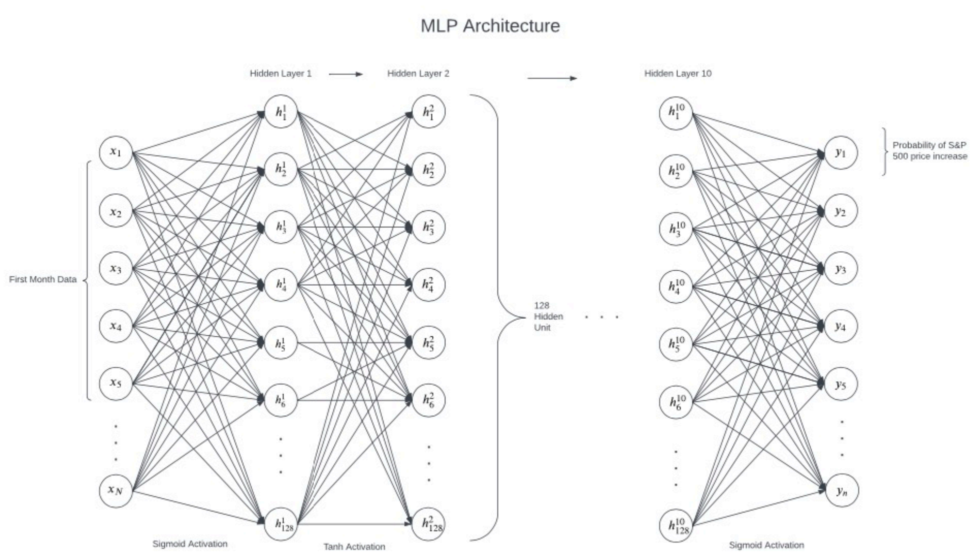

Figure 1: MLP Architecture

Using the four macroeconomic indicators (percent growth of GDP, inflation rate, interest rate, unemployment rate) along with monthly average closed price & traded volume of the S&P ETF in the most recent five months as input and the price movement of the S&P ETF in the following months (0 if decreases, 1 if increases), we train and test the MLP model. We randomly split the data into a training set, a validation set, and a testing set, with a ratio of 70:15:15. During training, We used the Adam optimizer with a learning rate of 0.001 to train our MLP model. Our MLP model consists of 10 hidden layers each with a dimension of 128. We then used the trained MLP model to predict the monthly price movement of the S&P 500 for the test data set.

3.2 Recurrent Neural Network (RNN)

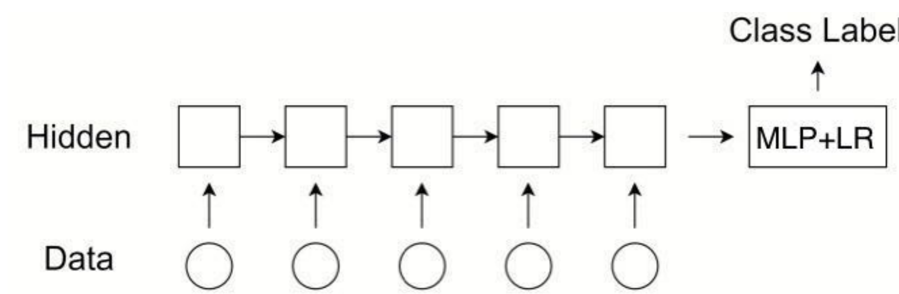

Figure 2: RNN Architecture

We applied RNN to this sequence classification task. In sequence classification tasks, we are given an observed sequence and asked to assign a class label to the sequence. The observed sequence in this case is data of the most recent five months and we try to assign a label to represent the price movement of the S&P ETF in the following month (1 if increases, 0 if decreases). We first encode the observed data sequence into a hidden representation. The last hidden state is used as the representation of the entire sequence. MLP and Logistic Regression are then used to map from the last hidden state to class labels. Figure 2 illustrates the design of the RNN model in this study. Similar to the MLP model, we used the Adam optimizer and a learning rate of 0.01 in our training process. We then used the trained RNN model to predict the monthly price movement of the S&P 500 for the test data set.

4 Results

We trained our MLP model with 100 epochs, and plotted the training and validation loss curves (Figure 3). However, we observed that the training and validation losses were very unstable, indicating that the model was overfitting to the training data and was not generalizing well to new data.

After training our RNN model for 100 epochs, we plotted the training and validation loss curves (Figure 3). We observed that the loss quickly converged around 5 epochs and remained stable thereafter, which indicates that the RNN model outperformed the MLP model as the model actually learned as the number of epochs increases. The stability in the loss curves suggests that the RNN model is not overfitting to the training data and is able to generalize well to new data. Therefore, we conclude that the RNN model is better suited for our task compared to the MLP model.

We then evaluated our model by calculating the test accuracy. We used the trained MLP and RNN model to predict the monthly price movement of the S&P 500 for the test data set, and the results are stated in Table 1, where RNN has a higher test accuracy and outperformed both the model in the previous study (which has an accuracy of 55%) and the MLP model in this study.

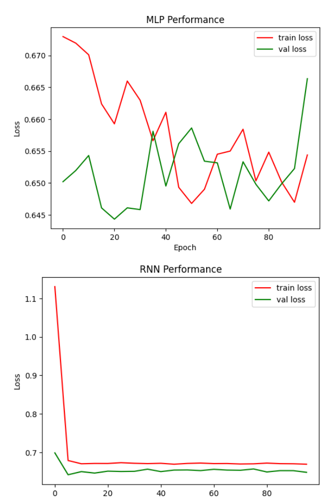

Figure 3: Model Loss Plot

Table 1: Test Accuracy

MLP	RNN
0.5327	0.5981

5 Discussion

The results of our study show that the RNN model outperformed both the MLP model in this study and the model in the previous study [1] in predicting the monthly price movement of the S&P 500 using historical macroeconomic factors along with the monthly average of S&P closed price and traded volumes. The instability in the training and validation losses of the MLP model suggests that the model was overfitting to the training data and was not generalizing well to new data. On the other hand, the RNN model quickly converged and remained stable, indicating that it was able to learn and generalize well to new data.

The test accuracy results showed that the RNN model achieved higher accuracy than the MLP model and outperformed both the model in the previous study and the MLP model in our study. This indicates that the RNN model is better suited for predicting the S&P 500 price movement using historical macroeconomic factors along with closed price/traded volume of the S&P ETF.

The better performance of the RNN model may be due to its ability to capture temporal dependencies in the data, which is essential for time-series prediction tasks such as the one studied in this research. The MLP model, on the other hand, may not have been able to capture these temporal dependencies effectively, which could explain its poor performance.

Overall, our study highlights the importance of selecting the appropriate machine-learning model for time-series prediction tasks. Our results show that the RNN model is a better choice than the MLP model for predicting the S&P 500 price movement using historical macroeconomic factors. Future studies can explore other deep learning models and additional macroeconomic factors to further improve the performance of the prediction task.

References

[1] Alexander, J.A. & Mozer, M.C. (1995) Template-based algorithms for connectionist rule extraction. In G. Tesauro, D.S. Touretzky and T.K. Leen (eds.), *Advances in Neural Information Processing Systems 7*, pp. 609–616. Cambridge, MA: MIT Press.

[2] Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. Expert Systems with Applications, 42(1), 259–268. https://doi.org/10.1016/j.eswa.2014.07.040

[3] Hasselmo, M.E., Schnell, E. & Barkai, E. (1995) Dynamics of learning and recall at excitatory recurrent synapses and cholinergic modulation in rat hippocampal region CA3. *Journal of Neuroscience* **15**(7):5249-5262.