Proceedings of Machine Learning Research 1–5, 2024

Applying LSTM and SVR Models to Predict Stock Prices

Aknazar Janibek AJANIBEK@UNC.EDU
Bryan Reed FORSTERB@EMAIL.UNC.EDU
Grace Sun GTSUN@EMAIL.UNC.EDU
Amanda Xiao AMANDA64@EMAIL.UNC.EDU
University of North Carolina at Chapel Hill

Abstract

This study evaluates the effectiveness of Long Short-Term Memory (LSTM) networks and Support Vector Regression (SVR) models in predicting the stock prices of NVIDIA and Boeing, using historical S&P 500 data from 2010 to 2024. We aim to analyze and predict the diverging trends of these companies, focusing on how well each model captures their price movements. Our findings indicate that LSTM generally outperforms SVR, particularly in capturing the upward trend in NVIDIA's stock prices, suggesting that LSTM models may be more adept at handling stocks with volatile patterns.

Keywords: LSTM, SVR, Stock Prediction, Machine Learning

1. Introduction

The dynamic and often unpredictable nature of financial markets presents a compelling challenge for predictive analytics, particularly in the realm of stock price forecasting. This research paper focuses on the application of two advanced machine learning models, Long Short-Term Memory (LSTM) networks and Support Vector Regression (SVR), to predict the stock prices of NVIDIA and Boeing, which have recently exhibited significant and contrasting stock price movements. NVIDIA has seen an increase in its stock price, driven by substantial growth in demand for its products, while Boeing has experienced a decline in its stock price, influenced by recent airplane troubles. These divergent trends provide a unique opportunity to explore the effectiveness of machine learning models in predicting stock prices under varying market conditions. These models are able to handle time-series data and capture complex nonlinear relationships inherent in stock price movements in order to forecast the future stock prices of NVIDIA and Boeing.

2. Related Work

Recent studies have utilized machine learning techniques to enhance stock market predictions, reflecting the financial markets' complexity. Nelson et al. (2017) demonstrated a 55.9% accuracy with LSTM networks on Brazilian stock data, underscoring its superiority over traditional methods. Moghar and Hamiche (2020) used LSTM within Recurrent Neural Networks to effectively track stock prices for Google and Nike. Bathla (2020) found LSTM outperformed SVR in handling complex dependencies across major stock indexes. Additionally, Zheng et al. (2021) improved prediction accuracy in Chinese markets by integrating SVR with the Bat Optimization Algorithm, highlighting the potential of hybrid models. These studies confirm the growing impact of LSTM and hybrid approaches in global financial forecasting.

3. Data Collection and Model Development

For the development of our models, we utilized a dataset sourced from Kaggle, which comprises daily historical stock price data for S&P 500 companies from January 2010 to April 2024. We specifically extracted data for NVIDIA (NVDA) and Boeing (BA), focusing on 'Date', 'Symbol', and 'Close' prices.

3.1. LSTM

The first model that was developed in our research was a Long Short-Term Memory (LSTM) model, which is particularly suited for sequential data analysis due to its ability to remember long-term dependencies, a crucial feature for predicting stock price movements.

To prepare for the LSTM model, we partitioned the dataset into training and testing subsets with an 80/20 split—a common practice in time-series analysis that ensures models are evaluated on unseen data. We also applied a MinMaxScaler to the 'Close' prices, normalizing them to a range between 0 and 1. This normalization step is vital for optimizing neural network performance, as it accelerates the learning process and mitigates bias towards higher values.

In our study, we constructed a Sequential model utilizing Keras, which included an LSTM layer with 50 units followed by a Dense layer for output. The internal cell state of the LSTM model is represented by the equation:

$$s_i(t) = f_i(t) \cdot \left(s_i(t-1) + g_i(t) \cdot \sigma\left(b_{i_f} + \sum_j \left(U^f_{i,j} x_j(t) + W^f_{i,j} h_j(t-1)\right)\right)\right)$$

The external input gate is described as:

$$g_i(t) = \sigma\left(b_{i_g} + \sum_j U^g_{i,j} x_j(t) + W^g_{i,j} h_j(t-1)\right)$$

The output of the LSTM model at any time t is determined by the output gate equation:

$$h_i(t) = \tanh\left(s_i(t)\right) \cdot q_i(t)$$

The model was compiled using the Adam optimizer and a mean squared error loss function. This model was trained on normalized training data for 100 epochs before making predictions on the test dataset. Subsequently, both the predicted and actual stock values were transformed back to their original scale using the inverse function of the MinMaxScaler. This rescaling is essential as it enables a direct comparison of the predicted stock prices with their actual values.

3.2. SVR

The second model that was developed to predict stock prices is a type of Support Vector Machine (SVM) known as Support Vector Regression (SVR), which is used for regression tasks. The model is a supervised learning algorithm that predicts continuous values.

For the SVR model, we applied a similar data preparation process as with the LSTM model. Like the LSTM model, we divided the data using an 80/20 split and employed a MinMaxScaler to normalize the 'Close' prices. This normalization is critical because SVR models are particularly sensitive to the scale of input data. This focused approach not only facilitated direct comparisons between the two models but also reduced the computational load during training and evaluation.

The SVR model uses a Radial Basis Function (RBF) kernel, which can be defined as the following equation:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)$$

where $\|x_i - x_j\|^2$ represents the squared Euclidean distance between the two vectors x_i and x_j.

This kernel function, denoted as K, transforms the input data into a higher-dimensional space, enabling the model to perform non-linear regression. In this model, the regularization parameter C is set to 100 to balance overfitting and underfitting; a high C value can lead to overfitting by imposing high penalties on data points that fall outside of a certain error threshold, while a low C value might cause underfitting by oversimplifying the regression line, increasing the number of support vectors and complicating the pattern recognition process. Additionally, the gamma parameter is set at 0.1, affecting the influence of individual training samples, and the epsilon parameter is also set at 0.1, defining a margin of tolerance within which no penalty is given for errors in the training loss function. The training data, X_{train} and y_{train}, are utilized to fine-tune the model weights, minimizing the discrepancy between predicted and actual stock prices.

4. Evaluating Model Results

4.1. Performance Indicator

To evaluate the performance of our two models, we utilized the Mean Absolute Error (MAE) as the accuracy metric. MAE is highly effective in regression models, providing a clear measure of the average deviation between the predictions and the actual values. The MAE is calculated using the formula:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

where y_i represents the actual values, $\hat{y}_i$ represents the predicted values, and n is the number of observations.

We also visually assessed the both models' performance by plotting both the actual and predicted stock prices (Fig.1, 2, 3, 4). This graphical representation not only facilitates a quick evaluation of how well the model captures data trends but also emphasizes any significant discrepancies between the predicted and actual values.

4.2. Model Performance Results

Analyzing the Mean Absolute Error (MAE) values for both the LSTM and SVR models reveals distinct performance characteristics across the two stocks examined. For Boeing, the LSTM model achieved an MAE of 8.39, while the SVR model performed slightly better with an MAE of 5.14. This suggests that the SVR model is marginally more effective at capturing the price dynamics of Boeing stocks. Conversely, for NVIDIA, the LSTM model demonstrated a substantially lower MAE of 34.78 compared to the SVR's 96.45. This indicates that LSTM is significantly more adept at handling the upward price trend of NVIDIA stocks, despite both models showing less accuracy in this scenario than with Boeing stocks.

These results suggest that while both models are fairly proficient at predicting Boeing stocks, there is a notable divergence in their ability to predict NVIDIA stock prices effectively. The substantially higher MAE for NVIDIA in the SVR model might also hint at potential issues such as overfitting or inadequate model tuning for this particular stock's volatility and trend behaviors.

The high error rates for NVIDIA suggest potential overfitting, where the model captures noise rather than the underlying pattern, performing well on training data but poorly on unseen testing data. Considering NVIDIA's complex price fluctuations, it's crucial to address whether the models are overfit to the training data. To mitigate this, future model iterations could incorporate regularization techniques, robust validation methods, and additional datasets reflecting broader market conditions. These adjustments aim to enhance the models' precision and generalizability.

5. Future Work

For future research, our primary goal is to enhance the accuracy of our predictive models. We plan to integrate real-time data sources, such as financial news and market sentiment, using advanced natural language processing techniques to better capture market dynamics. This integration aims to improve our models' responsiveness to sudden market changes.

Future work should also be done to develop robust ensemble methods by combining different predictive models, including LSTM, SVR, and possibly others like Random Forests or Gradient Boosting Machines. This approach will help reduce variance and bias, enhancing the overall prediction accuracy.

6. Conclusion and Impact

This study demonstrated the effectiveness of LSTM and SVR models in predicting stock prices for companies like NVIDIA and Boeing, with LSTM particularly excelling in handling volatile stocks such as NVIDIA, as evidenced by lower Mean Absolute Error. These findings are crucial for financial analysts leveraging advanced, data-driven models to enhance investment strategies and risk management. The research also opens avenues for future exploration into integrating real-time data, potentially enhancing predictive accuracy and responsiveness to market dynamics. This integration could lead to more sophisticated trading algorithms and advance financial technology, highlighting the practical applications of machine learning in financial decision-making and market stability. This work not only contributes to the field by improving investment strategies but also by encouraging further technological integration in financial markets.

7. Tables and Figures

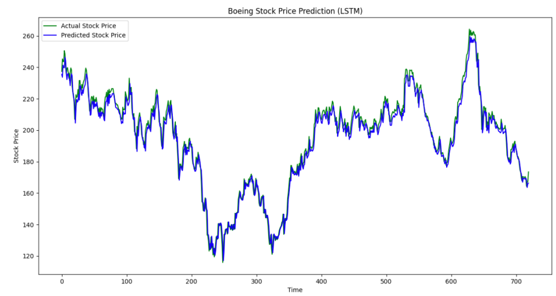

Figure 1: LSTM Boeing Stock Prediction

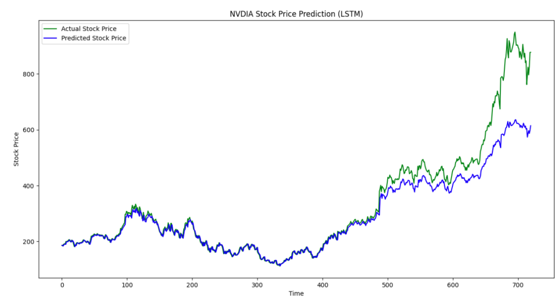

Figure 2: LSTM NVIDIA Stock Prediction

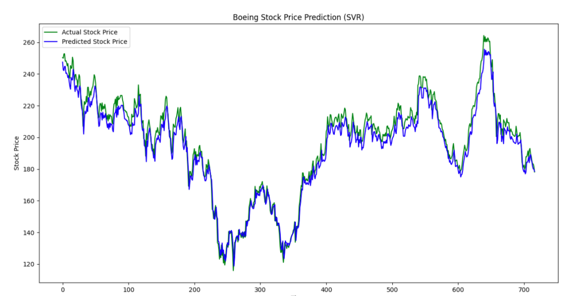

Figure 3: SVR Boeing Stock Prediction

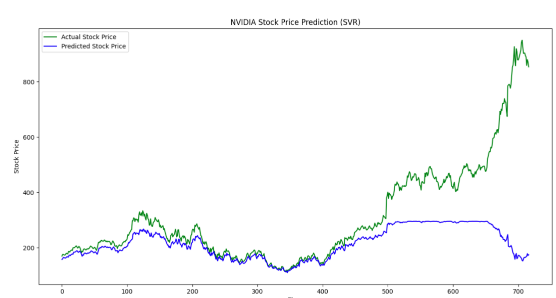

Figure 4: SVR NVIDIA Stock Prediction

References

Sp 500 stocks (daily updated). URL https://www.kaggle.com/datasets/andrewmvd/sp-500-stocks?select=sp500_companies.csv.

Gourav Bathla. Stock price prediction using lstm and svr, 11 2020. URL https://ieeexplore.ieee.org/document/9315800.

Aakarsha Chugh. Deep learning — introduction to long short term memory, 01 2019. URL https://www.geeksforgeeks.org/deep-learning-introduction-to-long-short-term-memory/.

Sepp Hochreiter and Jürgen Schmidhuber. *Long short term memory*. München Inst. Für Informatik, 1995.

Adil Moghar and Mhamed Hamiche. Stock market prediction using lstm recurrent neural network. *Procedia Computer Science*, 170:1168–1173, 2020. doi: 10.1016/j.procs.2020.03.049.

David M. Q. Nelson, Adriano C. M. Pereira, and Renato A. de Oliveira. Stock market's price movement prediction with lstm neural networks. *2017 International Joint Conference on Neural Networks (IJCNN)*, 05 2017. doi: 10.1109/ijcnn.2017.7966019.

Ashwin Raj. Unlocking the true power of support vector regression, 10 2020. URL https://towardsdatascience.com/unlocking-the-true-power-of-support-vector-regression-847fd123a4a0.

Sushanth Sreenivasa. Radial basis function (rbf) kernel: The go-to kernel, 10 2020. URL https://towardsdatascience.com/radial-basis-function-rbf-kernel-the-go-to-kernel-acf0d22c798a.

Jianguo Zheng, Yilin Wang, Shihan Li, and Hancong Chen. The stock index prediction based on svr model with bat optimization algorithm. *Algorithms*, 14:299, 10 2021. doi: 10.3390/a14100299.