Price Prediction:

Comparison between ARIMA Model and LSTM

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Abstract - This project report presents a comparative analysis of two time series forecasting models—ARIMA (Autoregressive Integrated Moving Average) and LSTM (Long Short-Term Memory)—applied to the stock prices of two companies: Nvidia Corporation (NVDA) and The Southern Company (SO). Nvidia is a leading technology firm, and has experienced significant market valuation changes in response to advancements in artificial intelligence (AI). Conversely, The Southern Company, a utility company, and its stock price are more stable and less influenced by AI innovations.

The study aims to reveal the strengths and weaknesses of each modeling approach when applied to different sectors, providing insights into the adaptability and efficiency of ARIMA and LSTM models in handling varying stock behaviors.

I. Introduction

NVIDIA's transition from a gaming graphic card supplier to a top-tier provider of AI hardware has positioned it as a leading company in AI and machine learning. Its stock has been a barometer for investor sentiment on AI, with its price reflecting the sector's rapid advancements.

Contrasting with Nvidia, The Southern Company operates in the utilities sector, known for its stability, making its stock less influenced by rapid technological advancements. Therefore, I have chosen the timeframe from November 30th, 2022, to December 15th, 2023, which aligns with the release of ChatGPT and recent global AI innovations, to analyze the AI influence on NVDA's stock compared to the stability of SO's stock.

Data was collected using Python's 'yfinance' library and no missing data was found. I extracted only the 'Close' price column from the datasets, as the closing prices are often considered the most significant in stock market analysis.

II. Exploratory Data Analysis

Trend Analysis. The adjusted closing price of NVDA and SO's stock prices shows distinct trends and volatility patterns, reflective of their respective sectors and market influences. NVDA's stock price demonstrates a pronounced upward trend and significant fluctuations, ranging between approximately $200 and $300.

In contrast, SO's stock price movement shows a different story, one of relative stability and narrower price range, primarily oscillating between $60 and $70. The stock starts relatively flat, with a notable mid-year dip followed by recovery, suggesting sensitivity to specific, possibly short-term, market factors.

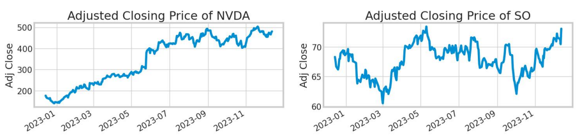


Figure 1. Adjusted Closing Price of NVDA & SO

Seasonality. NVDA's time series decomposition shows the presence of unpredictable swings, likely mirroring the sector's rapid technological evolution and market responsiveness.

SO, on the other hand, has an overall upward trend, with muted seasonality and less pronounced residual fluctuations. This pattern aligns with the expected behavior of stocks in the utilities sector, known for their resistance to rapid market changes.

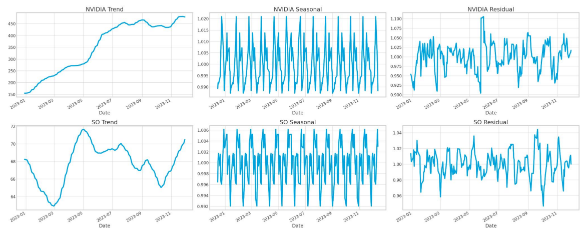


Figure 2. Seasonal Decomposition of NVDA & SO

Given the observation, NVDA's stock might require a more complex approach like LSTM to navigate its volatile price behavior, SO's stock can be effectively modeled with the more straightforward and traditional ARIMA model, reflecting its stable market nature.

III. Methodology

A. ARIMA

Stationarity Testing. ARIMA model began with a preliminary analysis to ensure the data's stationarity, which is a key requirement for ARIMA models. The Augmented Dickey-Fuller (ADF) test was employed for this purpose.

For NVDA The ADF test on the original NVDA stock prices failed to reject the null hypothesis of a unit root at a 99% confidence level, indicating that the data was non-stationary.

Similarly, the ADF test on the original SO stock prices showed non-stationarity.

Differencing. To achieve stationarity, the first-order difference of the stock prices for both NVDA and SO was taken. The differenced data significantly improved the stationarity for both stocks, achieving p-values close to 0 in the ADF test. Based on these results, a differencing order (d) of 1 was chosen for the ARIMA model for both stocks.

Autocorrelation Analysis. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots were generated for both NVDA and SO to determine the appropriate lag values for the ARIMA model parameters (p and q).

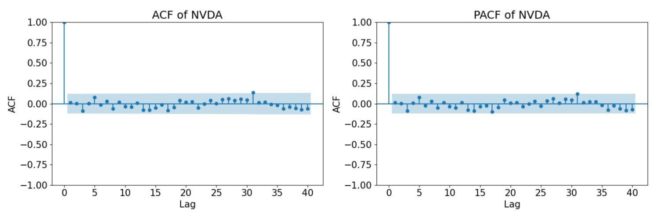


Figure 3. ACF & PACF of NVDA

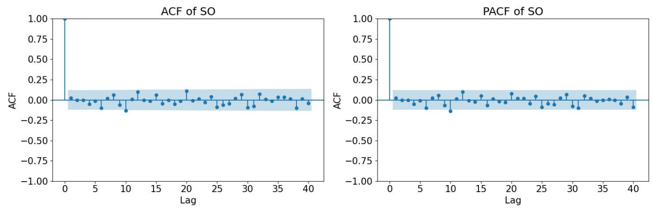


Figure 4. ACF & PACF of SO

Model Selection. Using a combination of ACF, PACF, and a custom search function (searchARMA from Lec 12), multiple ARIMA models were fitted with different orders. The root mean square error (RMSE) was calculated for each model to select the order that yields the lowest error.

Optimal Model Parameters. The selected orders for NVDA and SO were determined based on the smallest RMSE obtained from forecasting the differenced series. The best model orders and their corresponding RMSE values are:

NVDA: (p=0, d=1, q=0) with RMSE = 35.00745317511409

SO: (p=2, d=1, q=2) with RMSE = 1.8964533488240372

Model Fitting and Validation.

The diagnostic plots for the NVDA stock's residuals indicate that the model is performing reasonably well. The residuals are approximately normally distributed and show little to no autocorrelation.. However, the presence of outliers and deviations in the tails, as seen in both the histogram and the Q-Q plot, aligns with observations in EDA, suggesting that the ARIMA model may not fully account for extreme values or volatility in the data, and may not suitable for stock price data like NVDA.

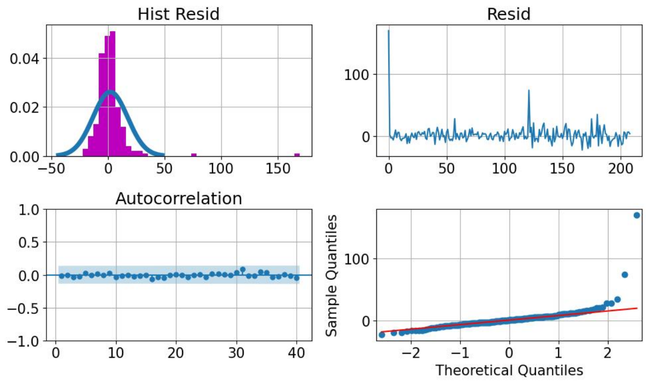


Figure 5. Diagnostic Plots for ARIMA(NVDA)

The diagnostic plots for SO stock show no significant autocorrelation in residuals, suggesting a good fit. However, the non-normal distribution of residuals, marked by a sharp peak and heavy tails, indicates potential for model improvement. Adjusting for the initial spike in residuals and considering alternative error distributions may enhance the model's performance.

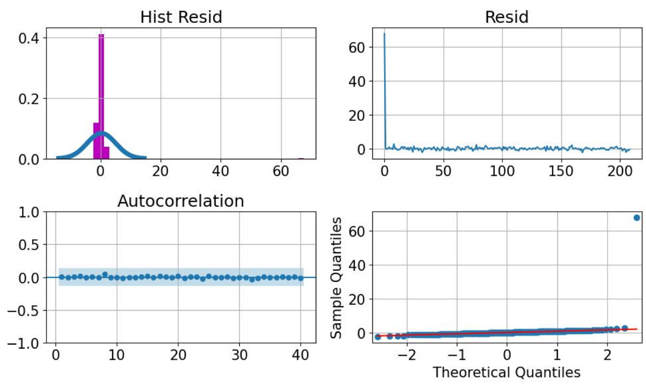


Figure 6. Diagnostic Plots for ARIMA(SO)

Out-of-Sample Prediction. The NVDA model exhibits a Mean Absolute Error (MAE) of approximately 30.38, a Mean Squared Error (MSE) of around 1228.97, and a Root Mean Squared Error (RMSE) of about 35.06. The Mean Absolute Percentage Error (MAPE) stands at 6.49%, indicating the average percentage deviation between the model's predictions and the actual stock prices.

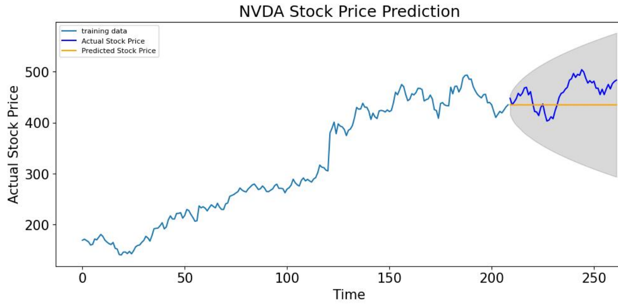
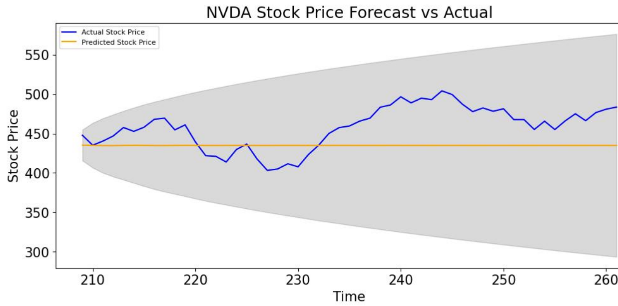


Figure 7. ARIMA Prediction - NVDA



The NVDA results demonstrate a reasonable predictive capability, with errors that suggest moderate accuracy in the context of stock price movements. The relatively low MAPE indicates that the model's predictions are, on average, within 6.49% of the actual stock prices, which can be considered a decent level of accuracy in the volatile environment of stock trading. However, the RMSE indicates that there are instances where the model's predictions deviate from the actual values more significantly.

The SO model exhibits a MAE of around 1.52, a MSE of around 3.60, and a RMSE of nearly 1.90, The MAPE stands at about 2.19%.

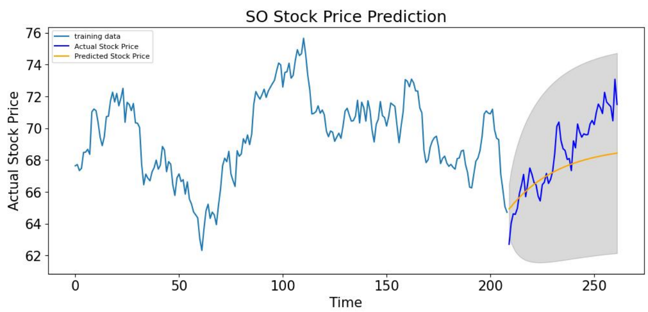
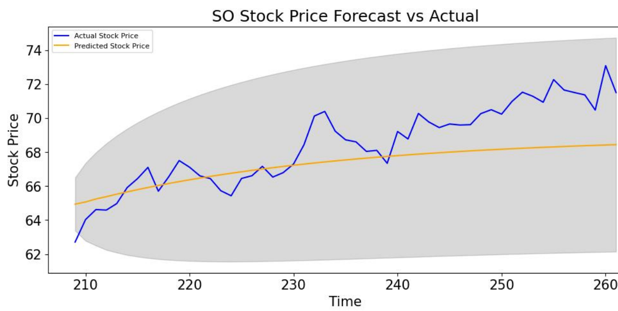


Figure 8. ARIMA Prediction - SO



The ARIMA model for SO stock has a decent degree of predictive accuracy, indicated by the low MAPE value, suggesting the model's forecasts are closely aligned with the actual stock prices. The RMSE value, being under 2, implies that the forecasted prices are generally close to the true values, making this model a potentially reliable tool for predicting short-term movements in SO's stock price.

B. LSTM

Normalization. To ensure efiicient training of the LSTM model, I normalized the data using the MinMaxScaler, scaling the closing prices to a range between 0 and 1. This normalization helps in accelerating the learning process and improves model convergence.

Window Size. Nvidia's stock is more reactive to market trends, especially those related to technological advancements and AI innovations. This reactivity suggests a need for a shorter window size to capture more immediate market responses. Therefore, a window size of 30 was chosen for NVDA.

The SO stock in the utility sector often experiences changes based on regulatory decisions and broader economic cycles. A larger window size would help in capturing such influences. Therefore, a window size of 30 was chosen for SO.

First, Second Layer and Dense Layer. For NVDA, a more complex and volatile stock due to its position in the rapidly changing technology sector, a robust model architecture was required. Therefore I chose 128 units for the first layer, 64 for the second layer and 25 for the dense layer.

For SO, a utility stock with more stable and predictable behavior, a less complex model was deemed sufiicient. Therefore I have chosen 64 units for the first layer, 32 for the second, 15 for the dense layer.

Evidence of Convergence. Evidence of convergence in the context of training a machine learning model like an LSTM refers to the indication that the model's learning process is stabilizing and that it is effectively minimizing the loss function over time.

Based on the plots of two stocks' loss function, evidence of convergence can be deduced from the following observations:

Sharp decrease in loss, low final loss value and no rebound or increase in loss.

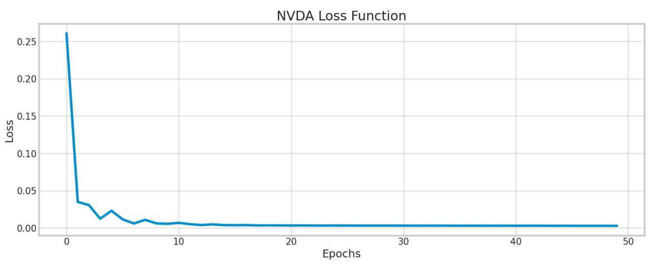
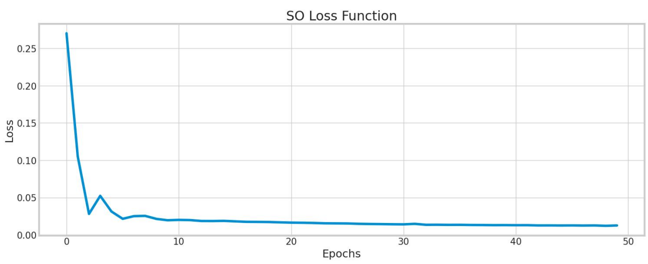


Figure 9. Loss Function - NVDA & SO



Out-of-Sample Prediction. The evaluation of LSTM performance on two stocks are:

NVDA: RMSE: 22.7424, MAE: 19.2069, MSE: 517.2145, MAPE: 4.2168%.

SO: RMSE: 1.1955, MAE: 0.8847, MSE: 1.4291, MAPE: 1.3037%

The LSTM model showed remarkable accuracy on the SO stock, with all error metrics significantly lower than those for NVDA. The lower MAPE value for SO suggests that the predictions were very close to the actual stock prices. Despite exhibiting a relatively high MSE for NVDA, the LSTM model showed significant improvement over the ARIMA model.

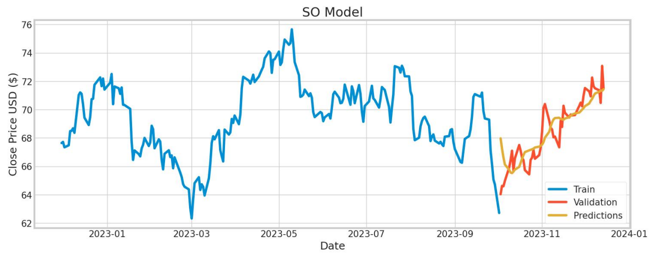


Figure 10. LSTM Prediction

IV. Conclusion

In conclusion, we can summarize the Pros and Cons of two models when facing significant market fluctuation:

ARIMA Pros. ARIMA showed good performance with SO's stock, which has a more stable and linear trend. This demonstrates ARIMA's suitability for datasets with less volatility and clearer trends. Compared to LSTM, ARIMA is simpler to implement and requires less computational resources, making it a practical option for less complex datasets.

ARIMA Cons. ARIMA struggled with NVDA's stock, which exhibits non-linear behavior and higher volatility. This underscores its limitation in capturing complex patterns and abrupt market changes.

ARIMA are limited to which the data must be stationary, often requiring transformations like differencing, which can complicate the model setup and interpretation.

LSTM Pros. LSTM excelled in modeling NVDA's stock, adeptly capturing its non-linear and volatile trends. This highlights LSTM's strength in dealing with complex, erratic data often seen in technology stocks.

Furthermore, given its deep learning foundation, LSTM can adjust to new information and patterns, making it ideal for sectors like technology where rapid changes are common.

LSTM Cons. Higher Computational Cost: LSTM requires more computational power and resources, making it more expensive and less accessible for smaller firms or individual analysts.

Secondly, Due to its complexity, LSTM can overfit the training data, especially if not properly regularized or if trained on insufiicient data.

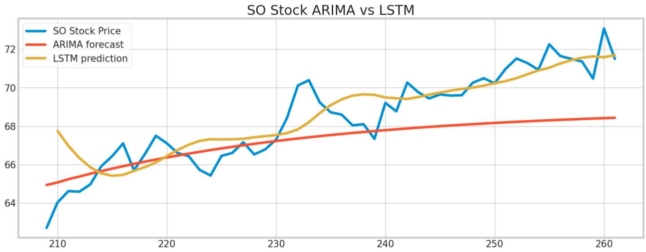


Figure 11. Out-of-Sample Prediction Comparison

V. Financial Insight

Nvidia Corporation (NVDA). As a leading player in the technology sector, is characterized by high volatility and rapid growth potential. The LSTM model's effectiveness in capturing this volatility suggests that it can be a valuable tool for identifying short-term trading opportunities. Investors might use these predictions to capitalize on quick market movements, aligning with a more aggressive trading strategy.

The LSTM model's ability to process complex patterns makes it particularly useful in anticipating stock price reactions to specific events like product launches, technological breakthroughs, or significant market announcements. Investors could leverage these insights for strategic entry and exit points, enhancing their potential for high returns.

Southern Company (SO). As a utility company, it generally offers more stability and consistent dividend yields. The ARIMA model's effectiveness in capturing SO's stock trends suggests its utility in long-term investment strategies focused on steady returns. Investors looking for stable income or wanting to hedge against market volatility could find these predictions particularly valuable.

ARIMA's suitability for SO reflects the stock's lower volatility and more predictable patterns, typical of the utility sector. This can be crucial for conservative investors, like retirement funds or risk-averse individuals, who prioritize capital preservation over high growth.

While the utility sector is less volatile, it is sensitive to regulatory changes and economic conditions. ARIMA's predictions can help in anticipating how such external factors might impact SO's stock, aiding in making more informed decisions regarding the timing and size of investments.

Portfolio Diversification. By integrating the insights from both models, we can design diversified strategies that balance high-growth opportunities with stability. For example, a portion of the portfolio can be allocated to NVDA for growth, leveraging LSTM predictions, while another portion can be invested in SO for stability, guided by ARIMA forecasts.

VI. Sector Analysis (Extra)

In this section I will compare the performance of NVDA and SO with other companies in their respective sectors. This could offer insights into how sector-specific trends impact stock prices and whether my models are effective across the sector or unique to these companies. The two extra stocks I have chosen are MSFT and DUK.

Next we can plot a correlation heatmap understanding the correlations between stock returns, which is vital for portfolio diversification. From the heatmap we can observe that there's a moderate positive correlation between the returns of MSFT and NVDA, which might reflect market-wide tech sector movements or broader economic conditions affecting these stocks similarly.

DUK shows a strong positive correlation with SO, which is expected as they both belong to the utility sector and are likely influenced by similar factors.

The correlations between the tech and utility stocks are near zero or very weak, indicating that there is no strong relationship between the returns of these two sectors.

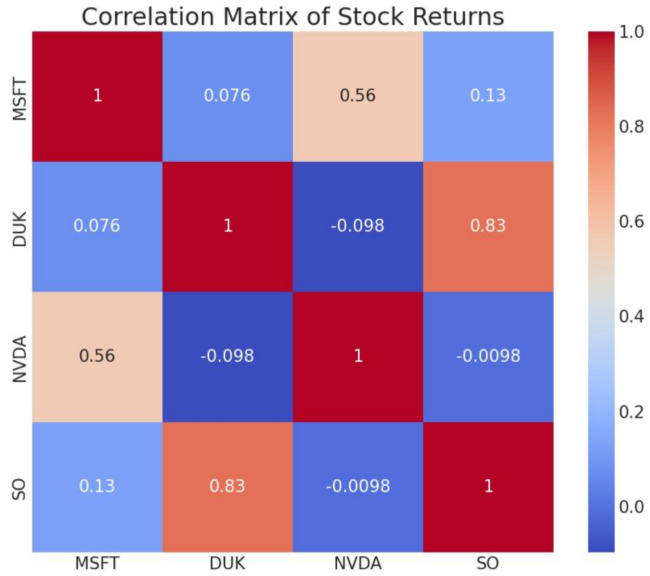


Figure 12. Correlation Heatmap

We can observe the growth trajectory and volatility of stocks within the technology sector by looking at the Time Series Closing Price plot. Similarly, the plots for DUK and SO provide a visual representation of the typically less volatile utility sector.

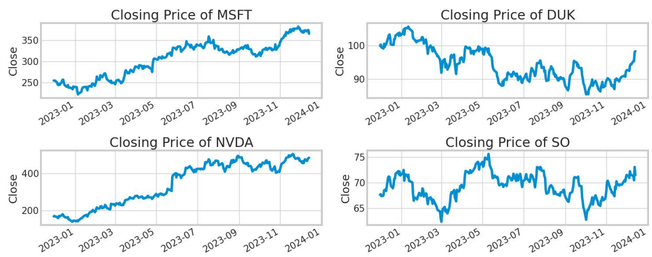


Figure 13. Closing Price Comparison

In conclusion, AI innovations have a positive correlation with the performance of the technology sector. This could be due to increased investor optimism, the potential for higher future earnings.

Reference

1.) Faressayah. (2023, January 3📊 Stock Market Analysis 📈 + Prediction using LSTM Kaggle