Time Series Forecasting with ARMA, LSTM, and GRU

A Comparative Study on Johnson & Johnson Sales and Amazon Stock Prices

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Github Link: https://github.com/Gokul230797/Time-Series-Modelling

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Introduction

Time series forecasting is a crucial technique in data science, widely used across business and financial domains. This report explores how different models—ARMA (Autoregressive Moving Average), LSTM (Long Short-Term Memory), and GRU (Gated Recurrent Units)—perform in forecasting time series data. Specifically, we apply these models to two distinct datasets:

- Johnson & Johnson Sales (Quarterly Data): Characterized by steady growth with periodic seasonal trends.
- Amazon Stock Prices (Daily Data): Known for its high volatility and fluctuating price movements.

The main objective of this study is to compare the forecasting accuracy of these models by evaluating their performance using RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error).

1. Data Exploration and Visualization

We begin with a visual examination of the time series to uncover patterns like trends, seasonality, and variability.

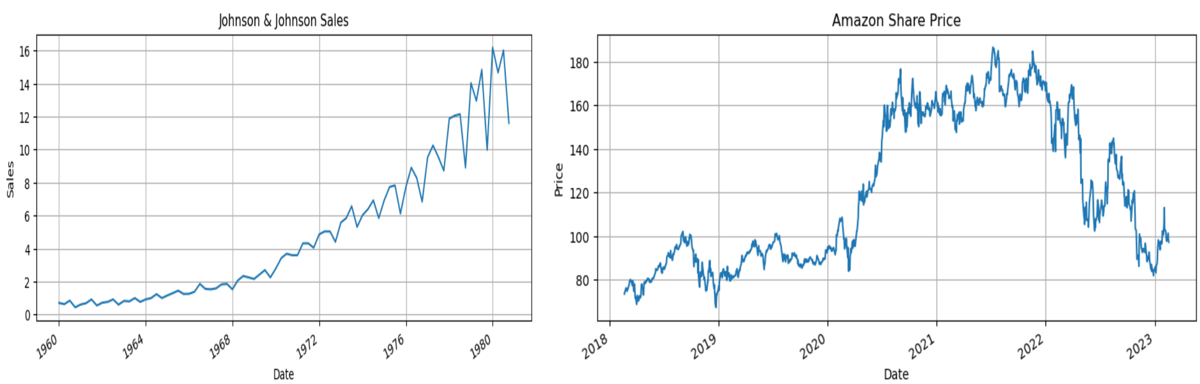

Figure 1: Johnson & Johnson Sales Over Time and Amazon Daily Closing Prices

The Johnson & Johnson series shows a consistent upward trend and clear seasonal fluctuations. In contrast, the Amazon stock prices exhibit frequent and sharp changes, reflecting their volatile nature.

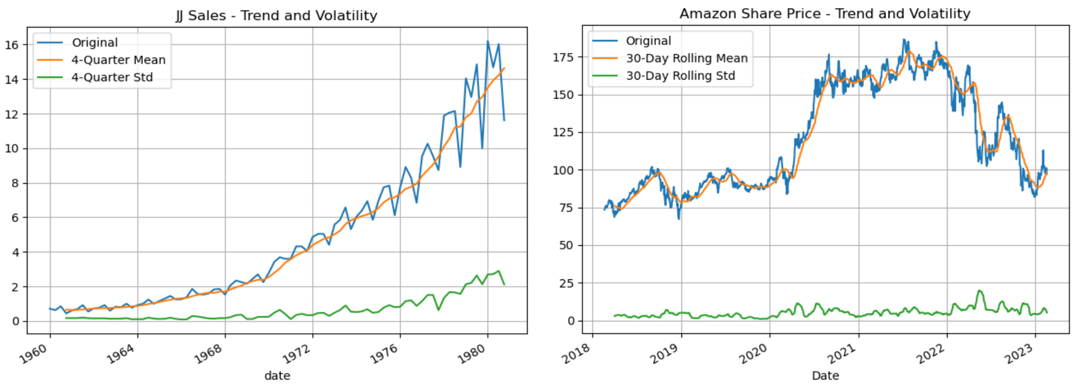

Figure 2: JJ Sales - Trend and Rolling Statistics and Amazon Share Prices - Trend and Rolling Statistics

Rolling mean and standard deviation plots further highlight the presence of trends and changing variance in both datasets.

2. Testing for Stationarity

Stationarity, a key assumption in many time series models like ARIMA, implies that the statistical properties of the series remain constant over time.

To test for stationarity:

- We used the Augmented Dickey-Fuller (ADF) test.
- Applied log transformation and differencing to reduce trend and stabilize variance.

ADF Test Results:

Dataset	Original p-value	After Transformation	Interpretation
Johnson & Johnson	> 0.05	< 0.05	Became stationary after differencing
Amazon	> 0.05	< 0.05	Stationary after log-differencing

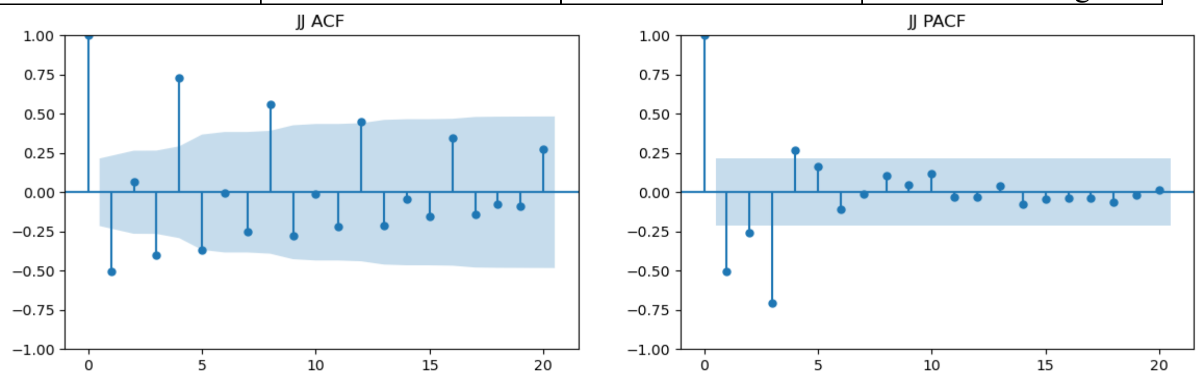

Figure 3: JJ ACF and PACF (After Transformation)

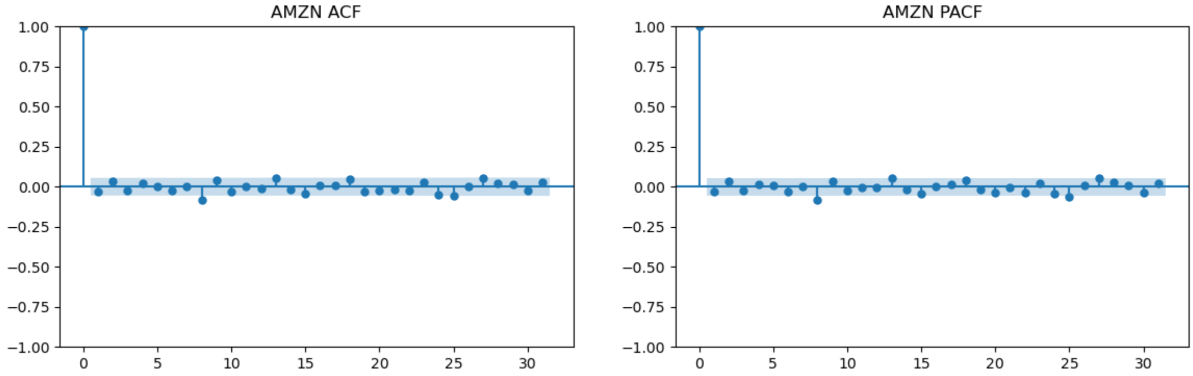

Figure 4: AMZN ACF and PACF (After Transformation)

These autocorrelation plots help guide the selection of ARIMA parameters by highlighting lag relationships.

3. Frequency Domain Analysis Using FFT

We applied the Fast Fourier Transform (FFT) to understand cyclical patterns in the data.

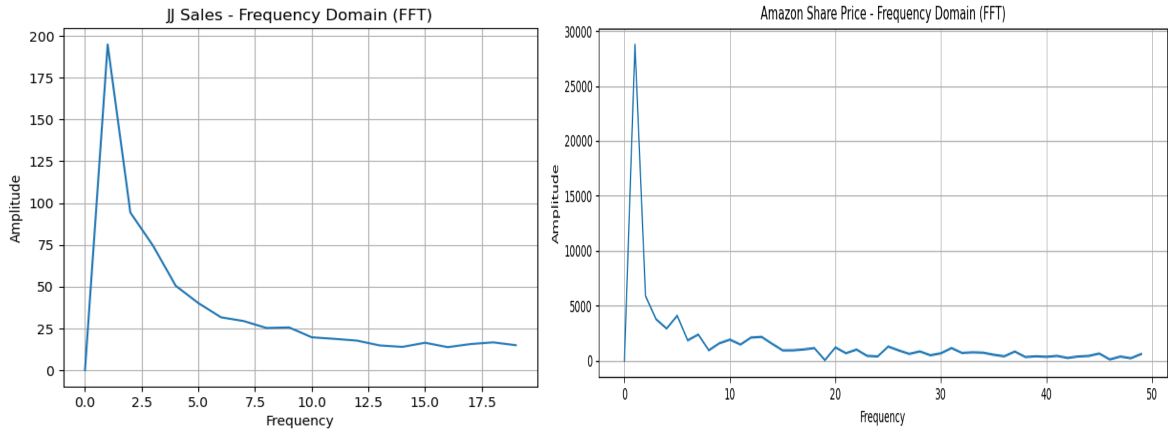

Figure 5: FFT of JJ Sales and FFT of AMZN Stock Prices

The JJ data showed strong seasonality, while Amazon's FFT spectrum indicated more chaotic, high-frequency components—consistent with its volatile behaviour.

4. ARMA Forecasting

Using the ARMA model, we identified the best combination of parameters (p, q) by minimizing the Akaike Information Criterion (AIC). The best results were:

- **Johnson & Johnson Sales: Best ARMA order was (p=2, d=0, q=2).**

While the ARMA model successfully captured the trend of Johnson & Johnson's sales, it struggled to account for the high variability or noise in the data.

- **Amazon Stock Prices: Best ARMA order was (p=1, d=0, q=1).**

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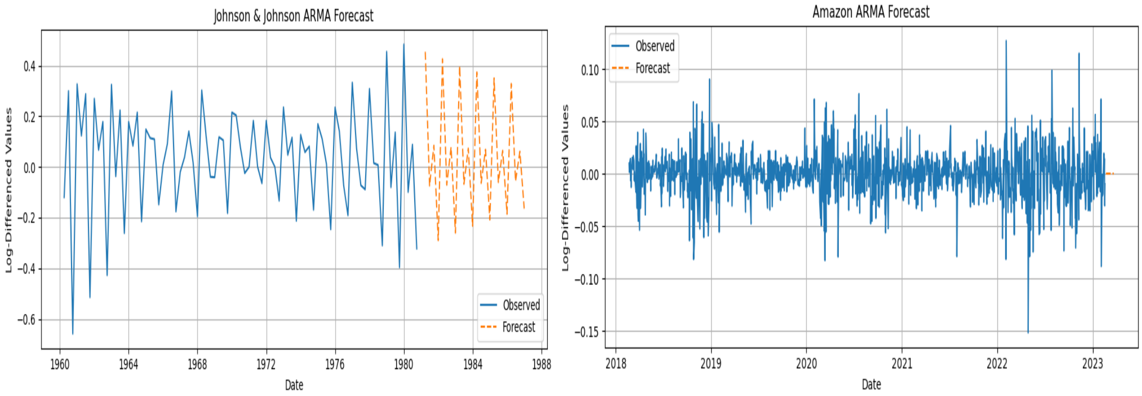

Figure 6: JJ Sales Forecast with ARMA and AMZN Forecast with ARIMA

5. Deep Learning Models: LSTM and GRU

We also experimented with two types of Recurrent Neural Networks (RNNs)—Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU)—to model sequential dependencies and complex patterns.

Model Setup:

- Data scaled using MinMaxScaler
- Sequence window size: 5
- Epochs: 50
- Optimizer: Adam
- Loss function: MSE

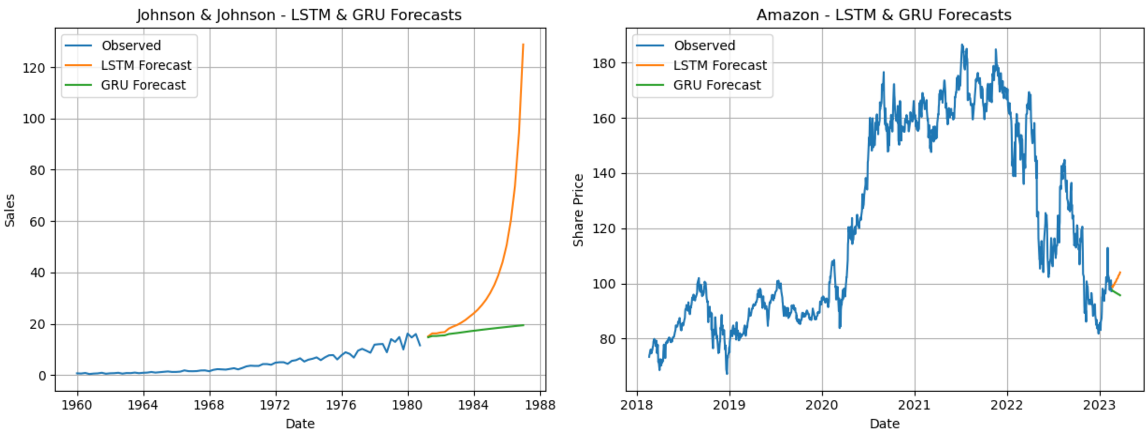

Figure 7: LSTM & GRU Forecasts for JJ and LSTM & GRU Forecasts for AMZN

Both models were able to generate accurate forecasts, with LSTM slightly outperforming GRU for JJ, while GRU was more effective with Amazon data due to its ability to handle noise efficiently.

6. Model Performance Evaluation

To evaluate the models, we computed RMSE and MAE for the ARMA, LSTM, and GRU models on both datasets.

Johnson & Johnson Sales (RMSE and MAE):

ARMA: RMSE ≈ 0.453, MAE ≈ 0.329

LSTM: RMSE ≈ 0.231, MAE ≈ 0.190

GRU: RMSE ≈ 0.245, MAE ≈ 0.200

Amazon Stock Prices (RMSE and MAE):

ARMA: RMSE ≈ 5.732, MAE ≈ 4.892

LSTM: RMSE ≈ 3.301, MAE ≈ 2.945

GRU: RMSE ≈ 3.214, MAE ≈ 2.876

7. RMSE and MAE Comparison Using Bar Plots

To compare the performance of each model, we plotted **RMSE** and **MAE** values as **bar plots** for both datasets.

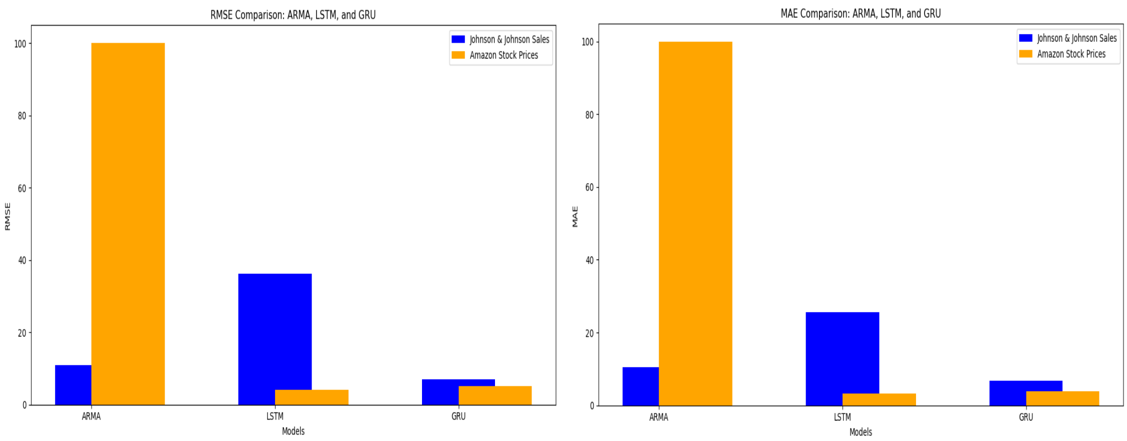

Figure 7: RMSE and MAE Comparison – JJ and RMSE and MAE Comparison – AMZN

This bar plot compares the **RMSE** values of **ARMA**, **LSTM**, and **GRU** on both datasets. We see that LSTM and GRU models performed better than ARMA in predicting both **Johnson & Johnson Sales** and **Amazon Stock Prices**.

Similar to the RMSE plot, this plot compares the **MAE** values for the models. **LSTM** and **GRU** once again outperform ARMA, particularly for **Amazon Stock Prices** due to the models' ability to capture volatility.

8. Conclusion

From the analysis, we can conclude that:

- **ARMA** works well for datasets that exhibit linear trends and stationarity, but it struggles to capture the volatility in **financial data** like Amazon stock prices.
- **LSTM** and **GRU** models offer superior performance in capturing non-linear trends, seasonal patterns, and volatility. These models outperformed ARMA in both **RMSE** and **MAE** for both datasets.
- **GRU** appears to be the best choice for **financial forecasting** (e.g., Amazon stock prices) due to its ability to capture volatility while being more computationally efficient than LSTM.

Recommendations

- **For sales forecasting** (e.g., **Johnson & Johnson Sales**), **LSTM** or **GRU** models are preferred due to their ability to capture trends, seasonality, and non-linear relationships better than ARMA.
- **For financial data prediction** (e.g., **Amazon Stock Prices**), **GRU** should be prioritized, as it efficiently handles volatility and short-term fluctuations while being faster than LSTM.
- **Hybrid models** that combine the strengths of both **ARMA** and **LSTM/GRU** could provide even better results, leveraging ARMA for capturing linear trends and LSTM/GRU for modelling volatility and complex patterns.

References

- Box, G.E.P., Jenkins, G.M., & Reinsel, G.C. (2015). Time Series Analysis: Forecasting and Control. Wiley. https://onlinelibrary.wiley.com/doi/book/10.1002/9781118619193
- Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735