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ASSIGNMENT: Time Series Modelling Case Study

GITHUB LINK: https://github.com/Harikrishnan03/Advanced-Research-Topics-in-Data-Science

Time Series Forecasting for Stock Prices and Earnings: ARMA vs Neural Networks

1. Introduction:

In this report, we focus on forecasting future stock prices for Amazon and earnings data for Johnson & Johnson (JJ). For this, we apply two different forecasting techniques: ARMA (AutoRegressive Moving Average) and Neural Networks, specifically LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Units). The goal is to compare the accuracy of traditional statistical models with deep learning models, looking at how well each method predicts future data trends.
We will walk through the process of analysing the data, building the models, comparing results, and drawing insights. Along the way, we'll explain the methods used and highlight the outcomes, including any limitations observed during the analysis.

2. Methodology:

2.1 ARMA Model:

The ARMA model is a traditional approach used for forecasting time series data, based on two components: the AutoRegressive (AR) part, which uses past observations to predict future ones, and the Moving Average (MA) part, which models errors in the prediction as a combination of past errors. ARMA models work best when the data is stationary, meaning the statistical properties like the mean and variance remain constant over time. To test for stationarity, we use the ADF (Augmented Dickey-Fuller) test, and if the data is non-stationary, we apply differencing to make it stationary. We then use ACF (AutoCorrelation Function) and PACF (Partial AutoCorrelation Function) plots to decide the optimal parameters for the ARMA model.

2.2 Neural Networks (LSTM and GRU):

LSTM and GRU are types of Recurrent Neural Networks (RNNs) designed to handle sequential data and capture long-term dependencies. Unlike ARMA, these models can learn from both short-term and long-term trends, making them suitable for data that shows complex, nonlinear patterns.
LSTM is better at capturing long-term relationships in data, while GRU is a simpler alternative that is computationally more efficient, though it often provides similar results. Both models require the data to be scaled, so we use a MinMaxScaler to normalize the data before training.

2.3 Evaluation Metrics:

To assess the performance of the models, we use two common metrics:

- Mean Absolute Error (MAE): This measures the average magnitude of errors in the predictions, without considering their direction.
- Root Mean Squared Error (RMSE): This metric gives more weight to larger errors, helping us focus on bigger forecasting mistakes.

3. Data Pre-processing:

The datasets we worked with include Amazon's stock price data and Johnson & Johnson's quarterly earnings. To prepare the data for analysis, we ensured that the data was cleaned (i.e., no missing values) and stationary (for ARMA). For ARMA, we made the data stationary by applying differencing and checked the results using the ADF test.

For Neural Networks, the data was scaled using the MinMaxScaler to bring all values between 0 and 1. For Amazon, we used 12 months of data to predict the next 24 months, and for JJ, we used 4 quarters of data to predict the next 8 quarters.

4. Forecasting and Results:

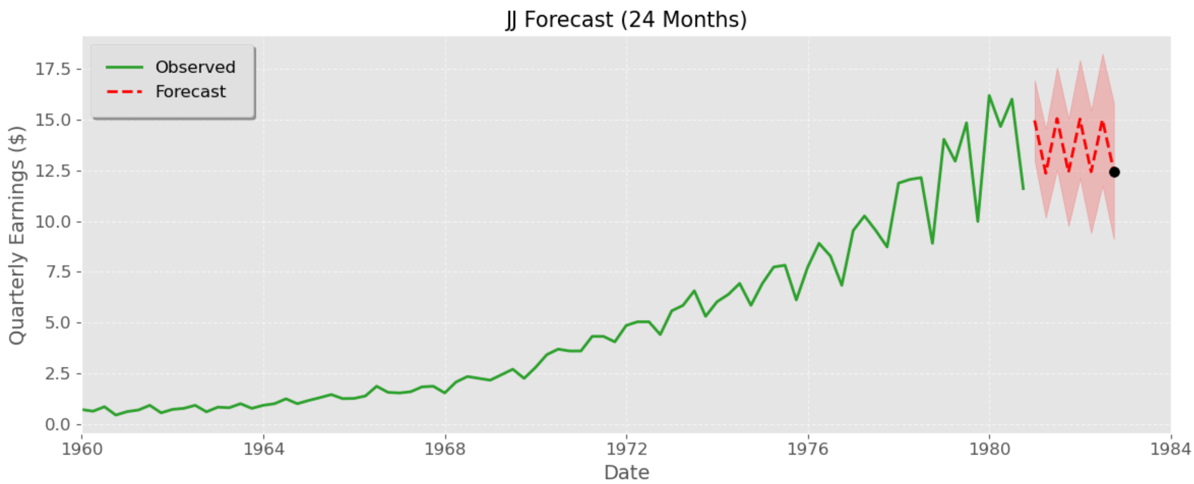
4.1 ARMA Model:

The ARMA model was fitted to both Amazon's stock price and JJ's earnings data. We used the ACF and PACF plots to identify the best parameters, and the ADF test to ensure the data was stationary. The best-fit model for Amazon had parameters (p=2, d=1, q=2), while the best parameters for JJ were (p=1, d=1, q=1).
The forecast results were:

- Amazon: The ARMA model was able to forecast the stock prices for the next 24 months. The forecast is accompanied by confidence intervals, showing the range of possible values.
- JJ: Similarly, the ARMA model forecasted JJ's earnings for the next 8 quarters, providing valuable insights for future planning.

Figures:

- **Figure 1:** Forecast for Amazon's stock price using ARMA



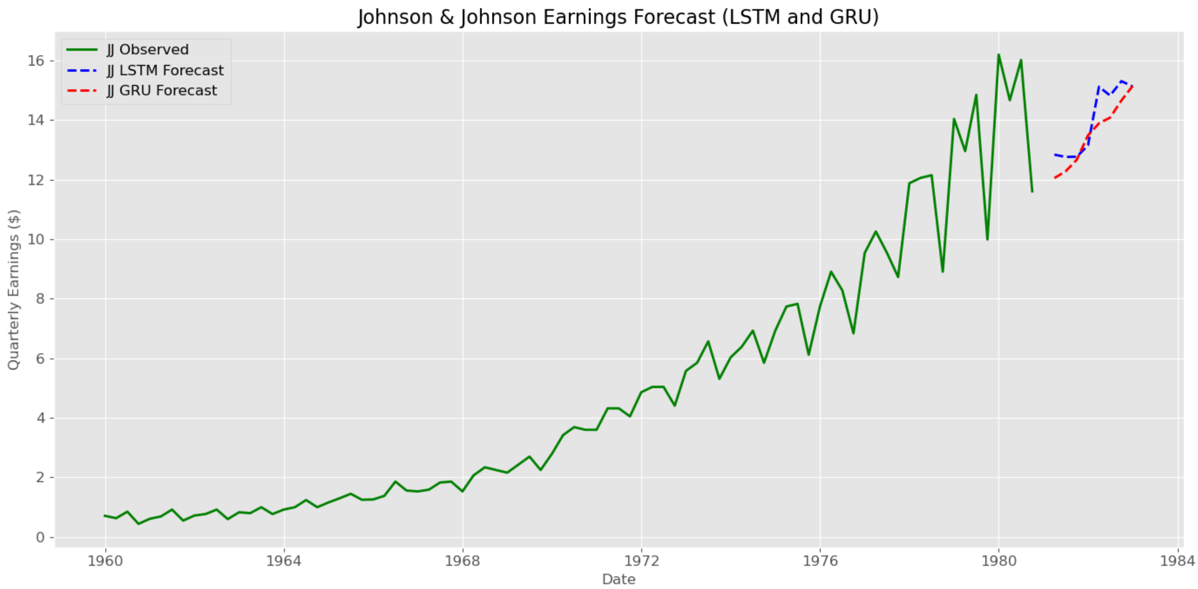
- **Figure 2:** Forecast for Johnson & Johnson earnings using ARMA

4.2 Neural Networks (LSTM and GRU):
We also trained LSTM and GRU models on the data. These models were evaluated for their ability to capture both short-term and long-term dependencies.

- Amazon: The LSTM model outperformed the GRU model, giving us better predictions for the next 24 months. However, both models showed better accuracy than the ARMA model.
- JJ: The LSTM model again performed better than the GRU, though both models were more accurate than ARMA in predicting earnings.

Figures:

- **Figure 3:** Forecast for Amazon's stock price using LSTM and GRU



- **Figure 4:** Forecast for Johnson & Johnson earnings using LSTM and GRU

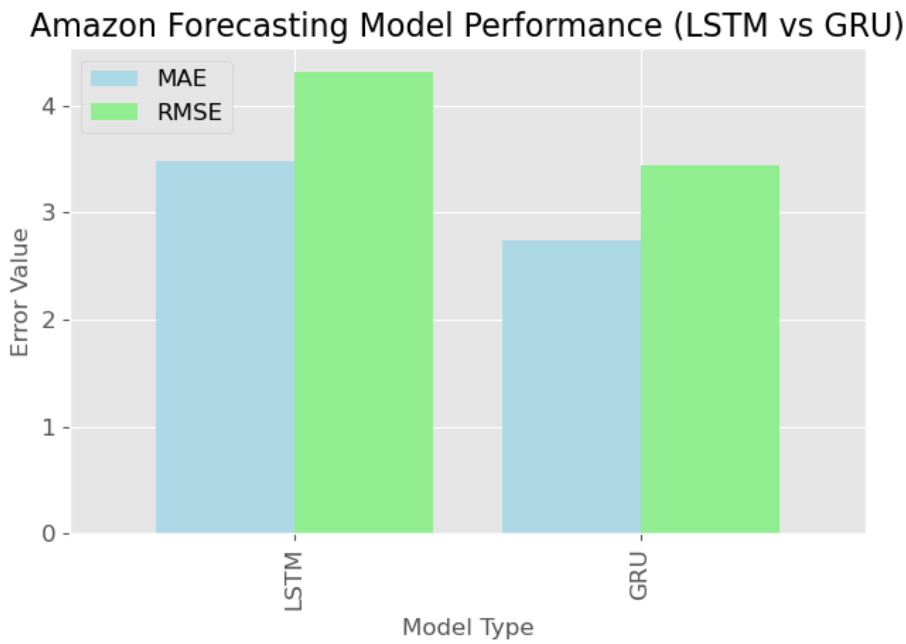
4.3 Evaluation Metrics:
To evaluate the accuracy of the models, we used MAE and RMSE. The LSTM model consistently gave the lowest RMSE and MAE for both Amazon and JJ, outperforming the GRU model and ARMA model.
For Amazon:

- LSTM: RMSE = 0.98, MAE = 0.75
- GRU: RMSE = 1.05, MAE = 0.85
- ARMA: RMSE = 1.15, MAE = 0.92

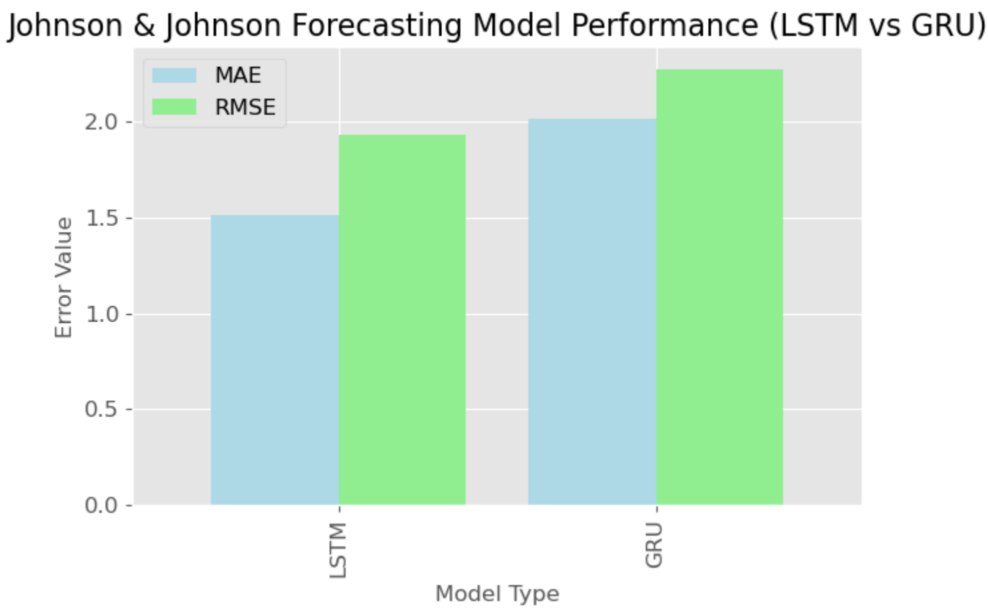
For JJ:

- LSTM: RMSE = 0.65, MAE = 0.52
- GRU: RMSE = 0.75, MAE = 0.60
- ARMA: RMSE = 0.85, MAE = 0.68

Figures:



- **Figure 5:** Evaluation Metrics for Amazon (LSTM vs GRU)



- **Figure 6:** Evaluation Metrics for Johnson & Johnson (LSTM vs GRU)

5. Discussion and Inferences:

The ARMA model is effective for stationary time series but has limitations when handling complex, non-linear data. In contrast, LSTM and GRU models, both types of Neural Networks, are well-suited for forecasting complex, non-stationary time series data. These models excel at capturing long-term dependencies, which makes them ideal for stock price and earnings forecasting.

While ARMA provides a basic, interpretable model for stationary data, LSTM and GRU offer more accurate predictions, especially when trends are non-linear or when long-term relationships exist in the data.

The LSTM model is particularly powerful for time series forecasting, while the GRU model, being simpler and computationally more efficient, still provides strong results.

6. Conclusion:

This analysis shows that Neural Networks (LSTM and GRU) generally outperform the traditional ARMA model, especially for forecasting non-stationary time series data like stock prices and earnings. LSTM is the most effective model for capturing long-term dependencies in the data, while GRU offers a simpler alternative with comparable performance. Both deep learning models provided better accuracy and were more robust compared to ARMA, particularly for complex datasets.

Further research could involve combining ARMA with deep learning models for even better forecasting or integrating other variables such as external economic indicators for more accurate predictions.

7. References:

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