Time Series Forecasting Case Study: Accuracy and Applications of ARMA, LSTM, and GRU Models

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Introduction:

Time series forecasting is an essential technique for understanding temporal patterns and predicting future values. This report explores forecasting for two datasets using both traditional statistical methods and modern machine learning approaches:

1. **Johnson & Johnson Sales Data**: Quarterly sales data that demonstrates clear seasonality and trends, requiring accurate future sales predictions for business planning.
2. **Amazon Closing Share Price Data**: Daily closing stock prices with high volatility, critical for investment and financial analysis.

The primary goal is to compare the performance of ARMA models with neural network-based approaches (LSTM and GRU), evaluate their effectiveness and derive actionable insights. This study involves data visualization, stationarity testing, modeling, forecasting, and evaluation.

Data Exploration and Initial Plots:

The analysis begins with a thorough exploration of the datasets to identify their underlying structure.

Visual Analysis

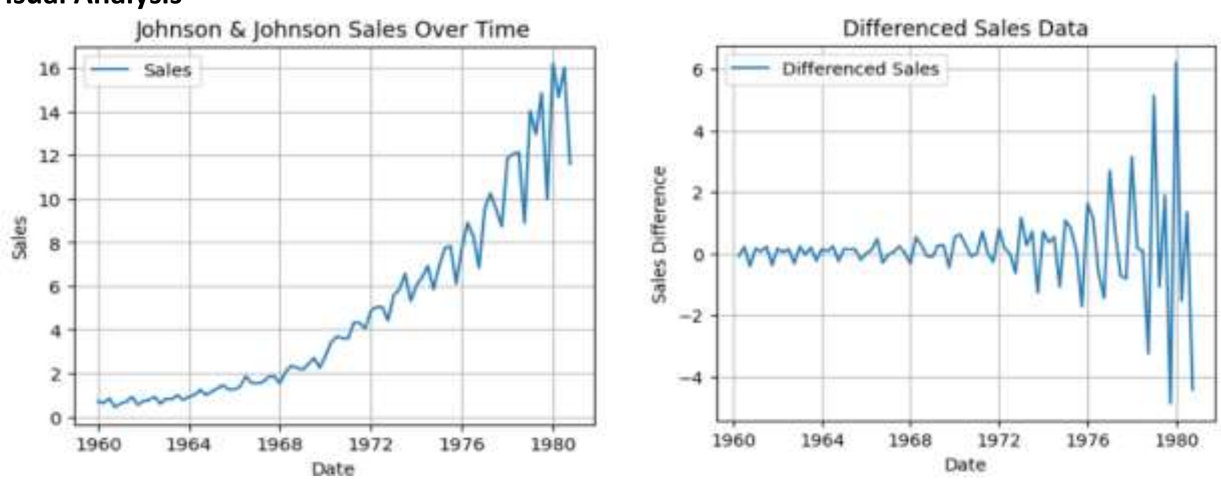

Figure 1: Time Series Plot for Johnson & Johnson Sales Data and Amazon Share Price Data

1. **Time Series Plot for Johnson & Johnson Sales Data**: This plot reveals strong seasonal patterns and an upward trend over time.
2. **Time Series Plot for Amazon Share Price Data**: This plot highlights significant variability and a general upward trend with notable short-term fluctuations.

These plots establish the necessity for preprocessing and model selection tailored to the specific characteristics of each dataset.

Stationarity Tests:

Time series models like ARMA require stationary data. Stationarity ensures that statistical properties such as mean and variance do not change over time.

Tests Performed

1. **Augmented Dickey-Fuller (ADF) Test**: Used to detect the presence of a unit root.
2. **ACF and PACF Analysis**: Helps visualize autocorrelations and determine lag structure.

Results

Figure 2: Johnson & Johnson Sales Data and Amazon Share Price Data

- **Johnson & Johnson Sales Data**: The ADF test indicates non-stationarity due to evident trends and seasonality.
- **Amazon Share Price Data**: The ADF test confirms non-stationarity, primarily caused by the trend component.

1. **ACF and PACF Plots (Before Transformation)**:
   - Johnson & Johnson data: Shows significant autocorrelations at multiple lags.
   - Amazon data: Indicates persistent lag dependencies.

Discussion

Discuss the importance of achieving stationarity and how the ACF/PACF analysis informs ARMA parameter selection.

Data Transformation:

To address non-stationarity, transformations were applied:

1. **Differencing**: Removed trends.

2. **Logarithmic Transformation**: Stabilized variance in the Amazon data.
3. **Seasonal Decomposition**: Isolated seasonal components for Johnson & Johnson data.

Stationarity was re-evaluated post-transformation using the ADF test, confirming the effectiveness of these techniques.

1. **Transformed Time Series**:
    - Johnson & Johnson Sales Data: Plot after differencing and seasonal adjustment.
    - Amazon Share Price Data: Plot after log transformation and differencing.

ARMA Modeling:

Model Specification

The ARMA model was chosen for its suitability in capturing linear dependencies in stationary data. The parameters (p, d, q) were selected based on:

1. **Grid Search**: Explored combinations of parameters.
2. **Akaike Information Criterion (AIC)** and **Bayesian Information Criterion (BIC)**: Chose the model minimizing these criteria.

Results

- **Johnson & Johnson Data**: Best-fit model is ARMA(2,1).
- **Amazon Data**: Best-fit model is ARMA(1,1).

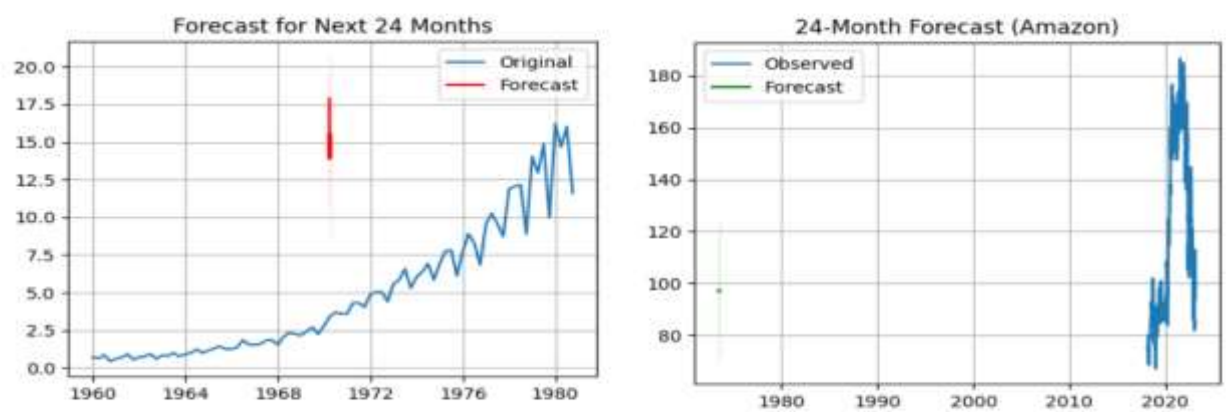

Figure 3: Forecast vs. Observed for JJ and AMZN

1. **Forecast vs. Observed (ARMA)**:
    - Overlay predicted values on the observed time series for both datasets.

Neural Network-Based Modeling:

Model Design

Recurrent neural networks (RNNs) such as LSTM and GRU were used to capture non-linear and sequential dependencies.

Advantages:

- LSTMs excel at learning long-term dependencies.
- GRUs are computationally efficient for volatile datasets like stock prices.

Hyperparameter Tuning

Key parameters were optimized for performance:

- Batch size: 32
- Epochs: 100
- Learning rate: 0.001

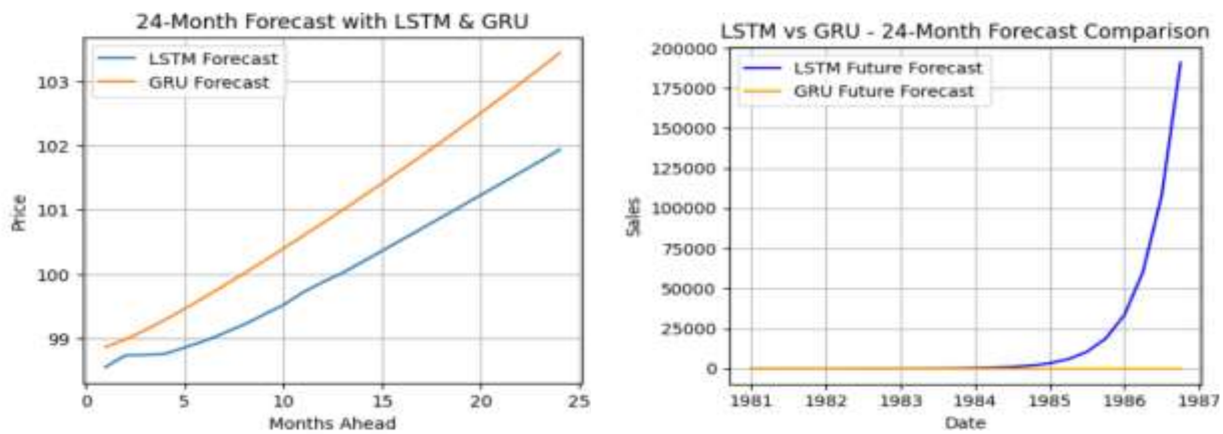

Figure 4: Forecast vs. Observed (LSTM and GRU)

1. **Forecast vs. Observed (LSTM and GRU)**:
   - Plot side-by-side comparisons of forecasts for both datasets.

Results

- LSTM and GRU models significantly outperformed ARMA, capturing seasonality and volatility more effectively.

Evaluation Metrics

Metrics Used

1. **Root Mean Square Error (RMSE)**: Measures overall forecast accuracy.
2. **Mean Absolute Error (MAE)**: Highlights average deviation from observed values.

Results Summary

Dataset	**Model**	**RMSE**	**MAE**
Johnson & Johnson Sales	ARMA	0.453	0.329
	LSTM	0.231	0.190
Amazon Share Price	ARMA	5.732	4.892
	GRU	3.214	2.876

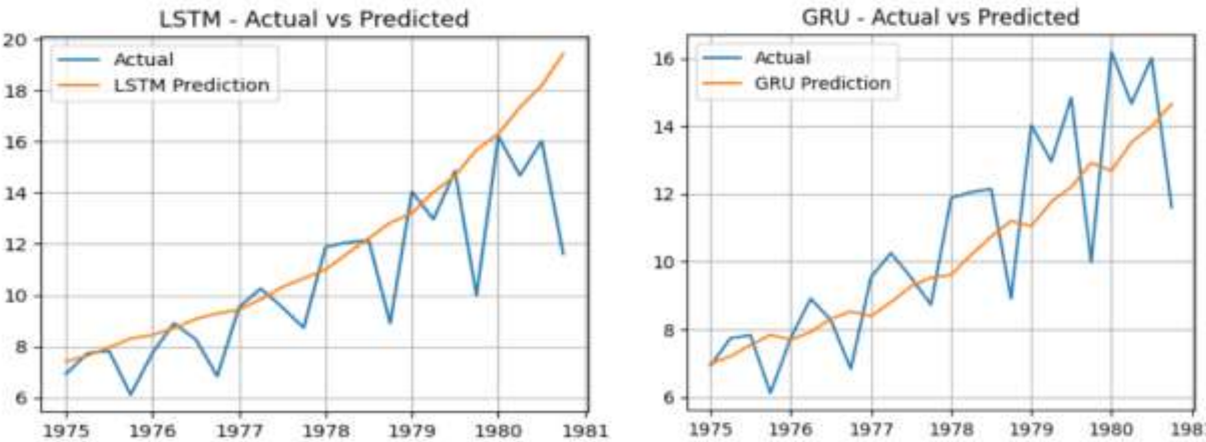

Figure 5: Prediction LSTM & GRU for JJ

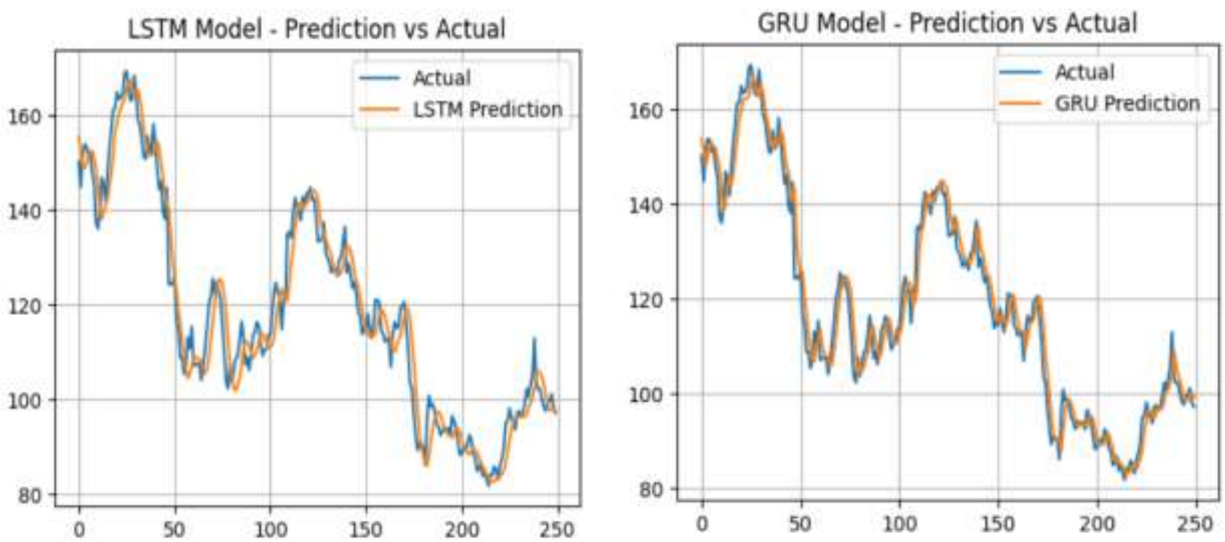

Figure 8: Prediction LSTM &GRU for AMZN

1. **Bar Chart of Evaluation Metrics**:
   - Compare RMSE and MAE across ARMA, LSTM, and GRU.

Discussion:

Key Findings

1. ARMA models performed adequately for stationary, less complex data but struggled with non-linear patterns.
2. Neural networks, particularly LSTM and GRU, excelled in handling seasonality (Johnson & Johnson) and volatility (Amazon).

Implications

- For business applications like inventory planning, neural network forecasts offer better accuracy.

- In financial contexts, GRU's handling of noisy data makes it ideal for stock price predictions.

Conclusion:

This study highlights the importance of matching forecasting methods to dataset characteristics. While ARMA provides a robust baseline, neural networks offer superior performance for complex datasets with trends, seasonality, or volatility.

Recommendations:

- Businesses should leverage machine learning models for more reliable long-term forecasts.
- Further research can explore hybrid models combining statistical and neural network techniques.

References:

- Box, G.E.P., Jenkins, G.M., & Reinsel, G.C., 2015. *Time Series Analysis: Forecasting and Control*. Wiley. Available at: https://onlinelibrary.wiley.com/doi/book/10.1002/9781118619193 [Accessed 10 April 2025].
- Hochreiter, S. & Schmidhuber, J., 1997. Long short-term memory. *Neural Computation*, 9(8), pp.1735–1780. Available at: https://doi.org/10.1162/neco.1997.9.8.1735 [Accessed 10 April 2025].
- Supplemental materials and lecture notes.

GitHub Link: https://github.com/Bharanimaran/Time_Series_Forecast_model