Short Report: Time-Series Forecasting Model Comparison

This report evaluates and compares the performance of two distinct time-series forecasting models—ARIMA, a traditional statistical method, and a Bidirectional LSTM, a deep learning approach—on the provided TSLA stock price dataset. The primary goal is to determine which model demonstrates better generalization for forecasting future stock values.

Based on a rigorous rolling window evaluation, the **Bidirectional LSTM model demonstrates significantly better generalization and predictive accuracy** for this task.

Performance Analysis

The performance of both models was measured using Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) across multiple rolling windows to test their adaptability to different periods in the data.

The average performance metrics across all windows clearly favor the LSTM model:

Model	Average RMSE	Average MAPE (%)
LSTM	**81.85**	**12.82%**
ARIMA	129.39	19.34%

As shown in the table, the LSTM model achieved a considerably lower average RMSE and a lower average MAPE, indicating that its predictions were consistently closer to the actual stock prices than the ARIMA model's predictions.

Discussion: Why the LSTM Model Generalizes Better

The superior performance of the LSTM model can be attributed to its fundamental design and its suitability for complex, sequential data like stock prices.

1. **Handling Non-Linearity**: Stock market data is famously non-linear and volatile, containing complex patterns that are difficult for linear models to capture. The **ARIMA** model is fundamentally a linear model. It assumes that future values are a linear combination of past values and errors. While effective for simpler time series, it struggles to adapt to the abrupt changes and intricate dependencies found in financial data.
2. **Capturing Long-Term Dependencies**: The **LSTM** (Long Short-Term Memory) network is a type of Recurrent Neural Network (RNN) specifically designed to learn long-term dependencies in sequential data. Its architecture, with memory cells and gates, allows it

to remember important information over long periods (e.g., long-term price trends) while discarding irrelevant data. The use of a **Bidirectional LSTM** further enhances this capability by processing the data in both forward and backward directions, giving the model a more complete contextual understanding of the time series.

3. **Robustness in Rolling Window Evaluation**: The rolling window analysis confirms the LSTM's robustness. The visualization of the error metrics shows that while both models' performance fluctuates, the LSTM's error is generally lower and more stable across different training windows. This suggests that the LSTM is better at adapting its learned patterns as the market dynamics change over time, which is the very definition of better generalization.

Conclusion and Recommendation

In conclusion, the Bidirectional LSTM model is the recommended choice for this forecasting task. Its ability to capture the complex, non-linear, and long-term patterns inherent in stock price data results in more accurate and reliable predictions compared to the traditional ARIMA model.