Week 2 Assignment Report
Time Series Forecasting Using ARIMA and LSTM

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1 Introduction

Time series forecasting is a vital tool for predicting stock prices and understanding trends. In this report, we explore two widely used approaches: ARIMA, a statistical model, and LSTM, a deep learning model. We discuss their differences, implementation, challenges, and insights gained from forecasting Tesla stock prices.

2 Understanding the Models

2.1 ARIMA Model

ARIMA (AutoRegressive Integrated Moving Average) is a classical statistical method for time series forecasting. It models the data using three components: autoregression (AR), differencing (I), and moving average (MA).

2.1.1 Key Concepts

- **Stationarity**: A stationary time series has constant mean, variance, and autocorrelation over time. Non-stationary data must be differenced to make it stationary.
- **Differencing**: Subtracting previous values from current ones to remove trends and stabilize the mean.
- **ACF and PACF plots**: Used to select the AR and MA parameters by analyzing correlations at different lags.

2.2 LSTM Model

LSTM (Long Short-Term Memory) is a type of recurrent neural network capable of learning long-term dependencies in sequential data. Unlike ARIMA, LSTM can capture non-linear patterns and complex temporal relationships.

2.2.1 Key Concepts

- **Sliding Window Technique**: Input sequences of fixed length are used to predict future values, enabling the model to learn temporal dependencies.
- **Data Normalization**: Scaling data (e.g., Min-Max normalization) is crucial for neural networks to ensure faster convergence and prevent dominance of large values.

3 Insights and Observations

3.1 ARIMA and LSTM Forecast Comparison

- In our analysis, the ARIMA model produced a nearly straight-line forecast, effectively predicting a constant value. This indicates that ARIMA could not capture the complex, non-linear patterns present in the Tesla stock data, likely due to the high volatility and insufficient linear structure in the series.
- In contrast, the LSTM model closely followed the actual test data, accurately capturing trends, fluctuations, and short-term variations. This demonstrates the strength of LSTM in modeling non-linear dependencies and long-term temporal relationships that ARIMA cannot capture.

3.2 LSTM Learning Curves (Training vs. Validation Loss)

- The LSTM learning curves plot the training and validation loss over each epoch of training. The training loss steadily decreases, indicating that the model is learning patterns from the input sequences effectively.
- The validation loss closely follows the training loss and does not diverge significantly, suggesting that the model is not overfitting and is generalizing well to unseen data. Minor fluctuations in the validation loss are expected due to the inherent volatility in stock prices.

4 Conclusion

Both ARIMA and LSTM models are effective for time series forecasting, but their strengths differ:

- ARIMA is limited to modeling linear patterns and may revert to mean predictions when the series is highly volatile or non-stationary.
- LSTM can leverage sequential dependencies and non-linear patterns, providing forecasts that are much closer to actual observed values.
- The comparison highlights that deep learning models like LSTM are better suited for complex, noisy, and non-linear time series data, while ARIMA may perform adequately for simpler, more linear trends.