Project Proposal: TimeWizard: Forecasting Trends with Powerful LSTM Models

Instructor: Narendra Kumar, Senior Machine Learning Engineer

Tuesday 14th May, 2024

1 Introduction

Time series forecasting plays a critical role in various industries, enabling organizations to make informed decisions based on future predictions. In this project, we propose to explore various Long Short-Term Memory (LSTM) models for time series forecasting.

2 Methodology

2.1 Univariate LSTM Models

- **Data Preparation:** Preprocess the univariate time series data, including handling missing values, scaling, and splitting into training and testing sets.
- **Vanilla LSTM:** Implement a basic LSTM model architecture for univariate time series forecasting.
- **Stacked LSTM:** Explore the use of multiple LSTM layers stacked on top of each other to capture more complex patterns in the data.
- **Bidirectional LSTM:** Implement LSTM models with bidirectional processing to incorporate future context into predictions.
- **CNN LSTM:** Combine Convolutional Neural Networks (CNNs) with LSTM layers to learn spatial and temporal patterns in the data simultaneously.
- **ConvLSTM:** Implement Convolutional LSTM models, which have convolutional operations within the LSTM architecture, to capture both spatial and temporal dependencies in the data.

2.2 Multivariate LSTM Models

- **Multiple Input Series:** Preprocess and model time series data with multiple input variables.
- **Multiple Parallel Series:** Handle and forecast multiple time series simultaneously.

2.3 Multi-Step LSTM Models

- **Data Preparation:** Prepare the data for multi-step forecasting by splitting into input-output pairs.
- **Vector Output Model:** Design LSTM models to directly predict multiple future time steps at once.
- **Encoder-Decoder Model:** Implement LSTM architectures with encoder-decoder structures for multi-step forecasting.

2.4 Multivariate Multi-Step LSTM Models

- **Multiple Input Multi-Step Output:** Handle scenarios where multiple input variables are used to forecast multiple future time steps.

- **Multiple Parallel Input and Multi-Step Output:** Forecast multiple future time steps using multiple parallel input time series.

3 Architecture Diagram

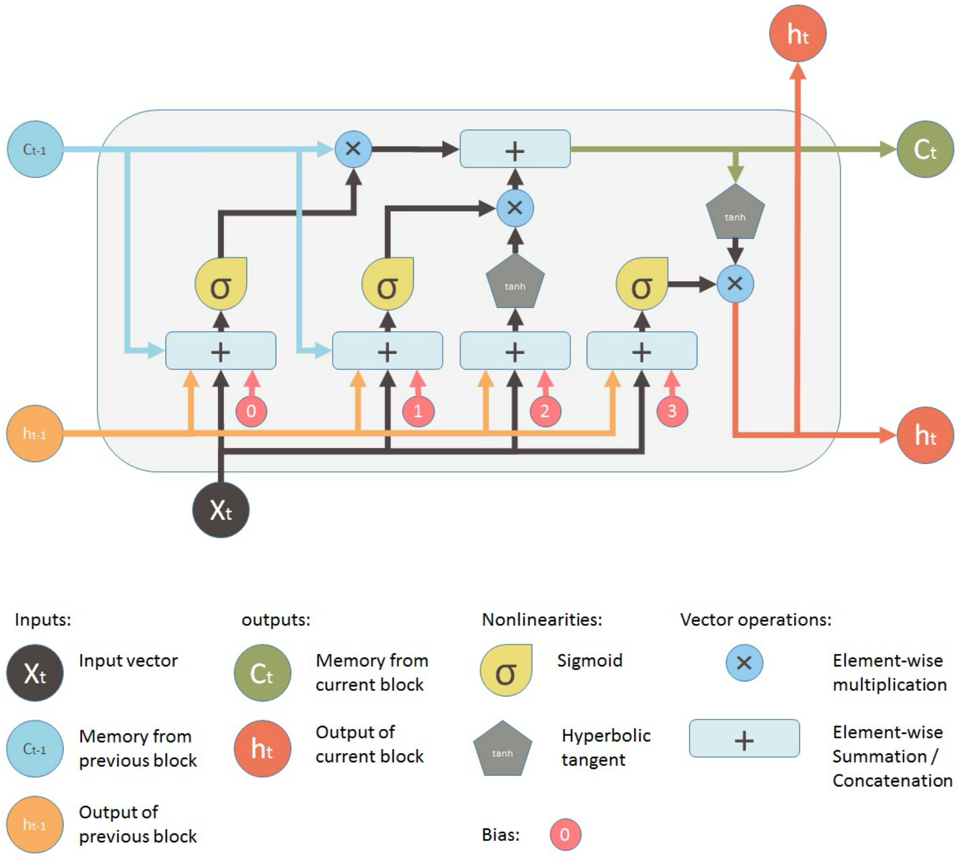

Figure 1: Architecture diagram illustrating the structure of various LSTM models

4 Expected Deliverables

- Trained LSTM models for various time series forecasting scenarios.
- Evaluation reports comparing the performance of different LSTM models.
- Visualizations of forecasted values and model diagnostics.
- Documentation detailing the methodology, implementation details, and findings of the project.

5 Project Timeline (8 weeks)

- **Week 1-2:** Data loading and preprocessing
- **Week 3-4:** Implementation and training of univariate LSTM models
- **Week 5-6:** Implementation and training of multivariate LSTM models

- **Week 7-8:** Implementation and training of multi-step LSTM models, final evaluation and documentation

6 Conclusion

The proposed project aims to explore and implement various LSTM models for time series forecasting, ranging from univariate to multivariate, single-step to multi-step. By evaluating and comparing these models, we aim to provide insights into their effectiveness in different forecasting scenarios. We believe that the successful implementation of these LSTM models will contribute significantly to the field of time series forecasting and offer valuable insights for decision-making in diverse industries.