

Application of Recurrent Neural Networks for Time-Series Data

AML Assignment 3



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# Summary

The Jena Climate 2009-2016 dataset is a time series dataset containing weather-related information between 2009 and 2016. It includes 210,225 training samples, 105,112 validation samples, and 105114 test samples. This analysis aims to assess the effectiveness of Recurrent Neural Networks (RNNs) in analyzing time series data. Various recurrent models with stacked layers and varying units, as well as a hybrid model that combines 1D Convolutional networks with RNN, were built to understand the performance of the models. The models' performance is evaluated based on the Mean Absolute Error (MAE), and the best-performing model with the lowest MAE value is chosen.

*Keywords: Time Series Data, Forecasting, Recurrent Neural Networks (RNNs), Temporal Dependencies, Mean Absolute Error (MAE), Naive Method, Densely Connected Network Model, 1D Convolutional Model, Simple LSTM-Based Model, Stacked LSTM Model with 64 Units*

# Introduction

Time series data is collected through regular interval measurements and is used in various applications, from predicting stock prices and weather patterns to classifying user activity or detecting specific events in data streams. Forecasting involves predicting future values in a series, such as forecasting electricity consumption. However, time series analysis offers more than just prediction. It includes classification, event detection, and anomaly identification. It helps to understand the dynamics of systems by capturing periodic cycles, trends, regular patterns, and abrupt deviations. Recurrent Neural Networks (RNNs) are a type of artificial neural network designed to process sequential data, making them highly effective for tasks involving a time order, like text, speech, or time series data. What sets RNNs apart is their ability to maintain an internal memory or context of previous data points in the sequence. This memory allows them to capture dependencies and patterns over time, making RNNs exceptionally well-suited for tasks like natural language processing, speech recognition, and time series forecasting. We will explore using Recurrent Neural Networks (RNNs) to model and predict time series data.

# Observations and Analysis

This analysis includes exploring the effective application of RNNs to time-series data, exploring the effective application of RNNs to time-series data, and utilizing their inherent capability to capture temporal dependencies aiming to improve the performance of our neural network models, especially when dealing with time-series data. Additionally experimenting with change in the number of units within each recurrent layer in a stacked configuration, fine-tuning the number of class units, and combining 1D convolutional networks with RNNs to achieve better results.

**Table: Different models built with their test MAE values**

|  |  |
| --- | --- |
| **Models** | **Test MAE** |
| Navie method | 2.62 |
| Densely connected Network model | 2.63 |
| 1D convolutional Model | 3.21 |
| simple LSTM-based Model | 2.61 |
| RNN Model with the sequence of any length | 9.93 |
| Stacking RNN model | 9.91 |
| Dropout-regularized LSTM Model | 2.59 |
| Simple LSTM-based Model with 32 units | 2.58 |
| Stacked LSTM Model with 16 units | 2.63 |
| Stacked LSTM Model with 32 units | 2.63 |
| Stacked LSTM Model with 64 units | 2.57 |
| Stacked LSTM Model with 8 units | 2.78 |
| Combined 1D convolutional with RNN Model | 3.27 |

In this analysis of various predictive models, each model was evaluated based on the Mean Absolute Error (MAE) values on their test set. The Naive Method served as a fundamental baseline, demonstrating an MAE of 2.62, while the Densely Connected Network Model closely mirrored this performance with an MAE of 2.63. The simplicity of the Naive Method offers a reference point for other models to compare with.

The 1D Convolutional Model exhibits a slightly higher MAE of 3.21, indicating the need for further optimization to enhance its predictive accuracy. On the other hand, the Simple LSTM-Based Model, with an MAE of 2.61, outperforms the Naive Method, presenting a straightforward yet effective approach for predictions.

In contrast, both the RNN Model with a sequence of any length and the Stacking RNN Model display the highest MAEs of 9.93 and 9.91, respectively, signifying substantial inaccuracy in their predictions. These models require extensive refinement to become practically viable.

The Dropout-Regularized LSTM Model delivers competitive accuracy with an MAE of 2.59. The Simple LSTM-Based Model with increased of units with 32 Units gives an MAE of 2.58.

The stacked LSTM models changing the number of units at each recurrent layer, including those with 16 units, 32 units, and 8 Units, obtained the MAE of 2.63, 2.63, and 2.78 respectively showing they exhibit MAEs closely aligned with the baseline models.

Meanwhile, the Stacked LSTM Model with 64 Units achieves the lowest MAE among all models, standing with the MAE of 2.57, making it the recommended best-performing model when compared to other models. Finally, the Combined 1D Convolutional with RNN Model yields an MAE of 3.27, indicating comparatively less accuracy compared to simpler models.

# Conclusion:

In conclusion, after analysing different predictive models using Mean Absolute Error (MAE) values on the test dataset, we have gathered valuable insights into their performance. The Naive Method and the Densely Connected Network Model are baseline models with MAEs of 2.62 and 2.63, respectively. The 1D Convolutional Model has a slightly higher MAE of 3.21 and the RNN Model with a sequence of any length and the Stacking RNN Model show significantly higher MAEs of 9.93 and 9.91, respectively, indicating a need for optimization to improve accuracy. The Simple LSTM-Based Model, The Dropout-Regularized LSTM Model, and the various Stacked LSTM models with different units at each recurrent layer show the close alignment of MAE. The Combined 1D Convolutional with RNN Model has an MAE of 3.27, which is less accurate compared to simpler models.

The best-performing model among all the models is the Stacked LSTM Model with 64 Units, with the lowest MAE of 2.57. The performance of stacked layers can vary depending on the specific problem and dataset. In this case, the Stacked LSTM Model with 64 Units has proven to be the most accurate choice.

The following is a visual representation that shows the Mean Absolute Error (MAE) values for each model.