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Introduction

Time-series forecasting is a crucial task in various fields, including finance, economics, and environmental science. Two popular deep learning models used for time-series forecasting are Long Short-Term Memory (LSTM) networks and Transformers. This report aims to compare the performance of Transformers and LSTMs for time-series forecasting, highlighting their strengths and weaknesses.

Background

LSTMs are a type of Recurrent Neural Network (RNN) designed to handle the vanishing gradient problem in traditional RNNs. They have been widely used for time-series forecasting due to their ability to capture long-term dependencies in data (Karim et al., 2017; Siami-Namini et al., 2018). On the other hand, Transformers are a type of neural network architecture introduced in 2017, which have revolutionized the field of natural language processing (Vaswani et al., 2017). Recently, Transformers have been applied to time-series forecasting, showing promising results (Liu et al., 2023; Wen et al., 2022).

Comparison of Transformers and LSTMs

Transformers and LSTMs have different strengths and weaknesses when it comes to time-series forecasting. LSTMs are suitable for modeling short-term dependencies and are computationally efficient, making them a good choice when computational resources are limited (Jiebo Song, 2024). However, LSTMs can struggle with long-term dependencies and may not perform well when the forecasting task requires modeling intricate relationships between variables.

Transformers, on the other hand, are well-suited for modeling long-term dependencies and can handle complex relationships between variables (Zhou et al., 2021; Ahmed et al., 2023). However, Transformers can be computationally expensive, especially when dealing with long input sequences. The quadratic complexity of Transformer self-attention can become dominant, making Transformers more computationally expensive than LSTMs for shorter input window widths (Jiebo Song, 2024).

Empirical Evaluation

Several studies have compared the performance of Transformers and LSTMs for time-series forecasting. A study by Jiebo Song (2024) evaluated the performance of six Transformer models and several LSTM models on two benchmark datasets, Traffic and Electricity. The results showed that Transformers can outperform LSTMs in certain scenarios, especially when the forecasting task requires modeling long-term dependencies.

Another study by Ailing Zeng et al. (2023) compared the performance of Transformers and LSTMs on several time-series forecasting datasets. The results showed that Transformers can be effective for time-series forecasting, especially when the data exhibits complex patterns and relationships.

Conclusion

In conclusion, the choice between Transformers and LSTMs for time-series forecasting depends on the specific characteristics of the data and the forecasting objectives. LSTMs are suitable for modeling short-term dependencies and are computationally efficient, making them a good choice when computational resources are limited. Transformers, on the other hand, are well-suited for modeling long-term dependencies and can handle complex relationships between variables, but can be computationally expensive.

Further research is needed to establish clear guidelines for selecting the optimal model based on the specific characteristics of the time series data and the forecasting objectives. Additionally, more extensive experiments are needed to validate the performance differences between Transformers and LSTMs.

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