Hybrid Incremental Learning: A Novel Approach to Time Series Forecasting

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With extreme heat events becoming more frequent and severe due to climate change, accurate temperature prediction is critical for preparedness and risk mitigation. Traditional offline models, such as TCN-LSTM (temporal convolutional network-long short-term memory), perform well when historical data is abundant. However, offline models are not optimal when data is limited or arrives sequentially in real time. This project explores an alternative approach using incremental learning (IL) to improve temperature forecasting under these constraints. To evaluate IL's effectiveness, I developed two IL models, TCN-LSTM-Inc-Fixed and TCN-LSTM-Inc-Replay, and compared them to the TCN-LSTM. A key component of IL design is the selection of the buffer type, which determines how data is stored for retraining. A fixed-size buffer retains only the most recent data, while a replay buffer strategically selects past events to improve learning. Using Python, I built and tested all three models, assessing their predictive performance using squared error (? = (Predictions - True Values)^2). Results showed that both IL models outperformed the hybrid offline model, with TCN-LSTM-Inc-Replay achieving the highest accuracy by effectively learning from seasonal patterns. These findings suggest that incremental learning can significantly improve real-time temperature prediction, making it a valuable tool for extreme heat event forecasting and management.

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