ASSIGNMENT_3
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TIME-SERIES DATA

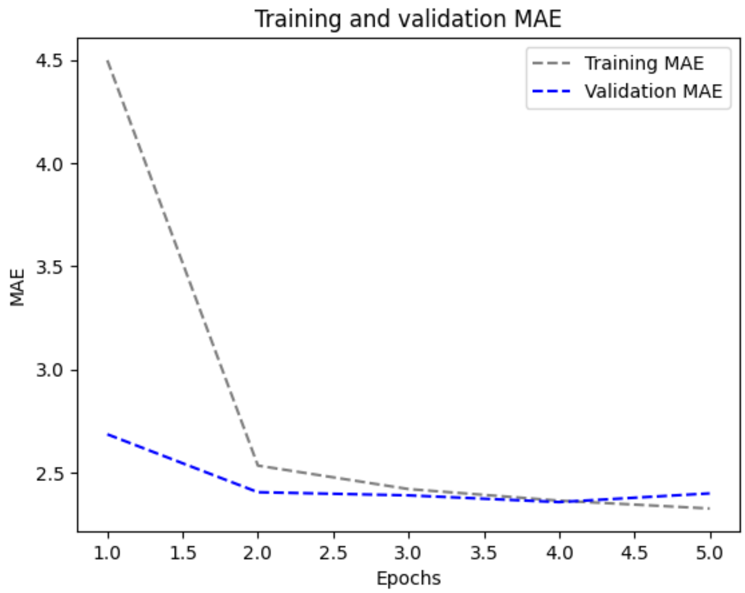
Exploring Time Series Forecasting: A Journey through 14 models

Introduction:
Fourteen time-series forecasting models were created and evaluated to predict if a certain stock will rise or fall over the course of the next week. This journey began with an initial level model which didn't involve machine learning. Next, convolutional models and foundational machine learning were created. However, in these first attempts, it was challenging to maintain the temporal component of the data.

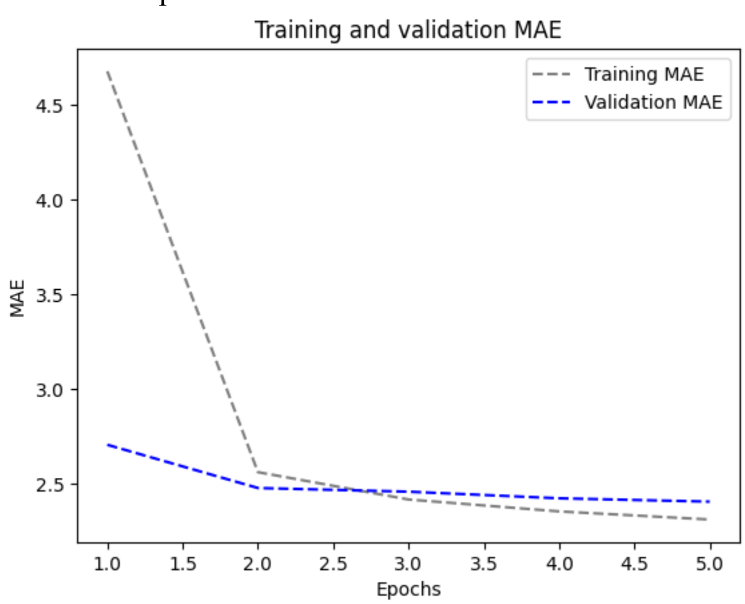
Searching for Temporal Perception:
Recurrent Neural Networks (RNNs), that are well-known to process sequential input, have been implemented because of the early models' limitations. Because RNNs are so good at identifying complex patterns and connections in time-series data, decision-makers may utilize past data to inform their current choices.

Dealing with Complexity of RNNs:
The fundamental RNN model could theoretically conserve knowledge from all previous eras, but its applicability in deep networks was limited by the issue of vanishing gradients and other practical concerns. This conclusion was corroborated by graphical analysis, which demonstrated that the basic RNN was the least successful model overall.

The GRU's Emergence:
A reaction to the shortcomings of the basic RNNs was the development of Gated Recurrent Unit (GRU) models. The best-performing models was found to be an RNN version known as GRUs, with an MAE of 2.47. GRUs use less processing power for effectively recording long-term dependencies in sequential data than LSTM (Long Short-Term Memory) models.



Optimizing LSTM:
In parallel, studies were conducted on Long Short-Term Memory (LSTM) models, which are well-known for their efficiency in handling time-series data. There were six different LSTM models developed, with varying numbers of units in stacking recurrent layers. With an MAE of 2.55, the eight-unit layout proved to be the most effective.
LSTM - Simple



Enhancements for Improvement:
To further enhance the model's performance, techniques including recurrent dropout and bidirectional data consumption were employed. Following these enhancements, the MAE values of the sensible baseline model were consistently higher.

Challenges of Combining Models:
The inability of the attempts to combine RNN and 1D convolution models to function well (MAE of 3.81) was attributed to convolutional challenges in preserving information order.

Conclusion:
In conclusion, LSTM and GRU designs were successfully investigated, with GRU emerging as the most effective choice. Important hyperparameters including the total amount of units in stacking recurrent layers, the recurrent dropout rate, and the utilization of bidirectional data should be appropriately set to maximize GRU performanc

MODEL	Validation MAE	Test MAE
DENSE MODEL	2.80	2.62
1D convolutional Model	3.08	3.2
Simple RNN	9.84	9.90
Stacked Simple RNN	9.82	9.91
GRU	2.3	2.46
LSTM Simple	2.40	2.54
LSTM STACKED 16 Units	2.45	2.65
LSTM STACKED 32 Units	2.82	2.70
LSTM STACKED 8 Units	2.40	2.61
LSTM – Dropout Regularization- stacked model	2.42	2.60
1D convolutional And LSTM	3.9	3.80