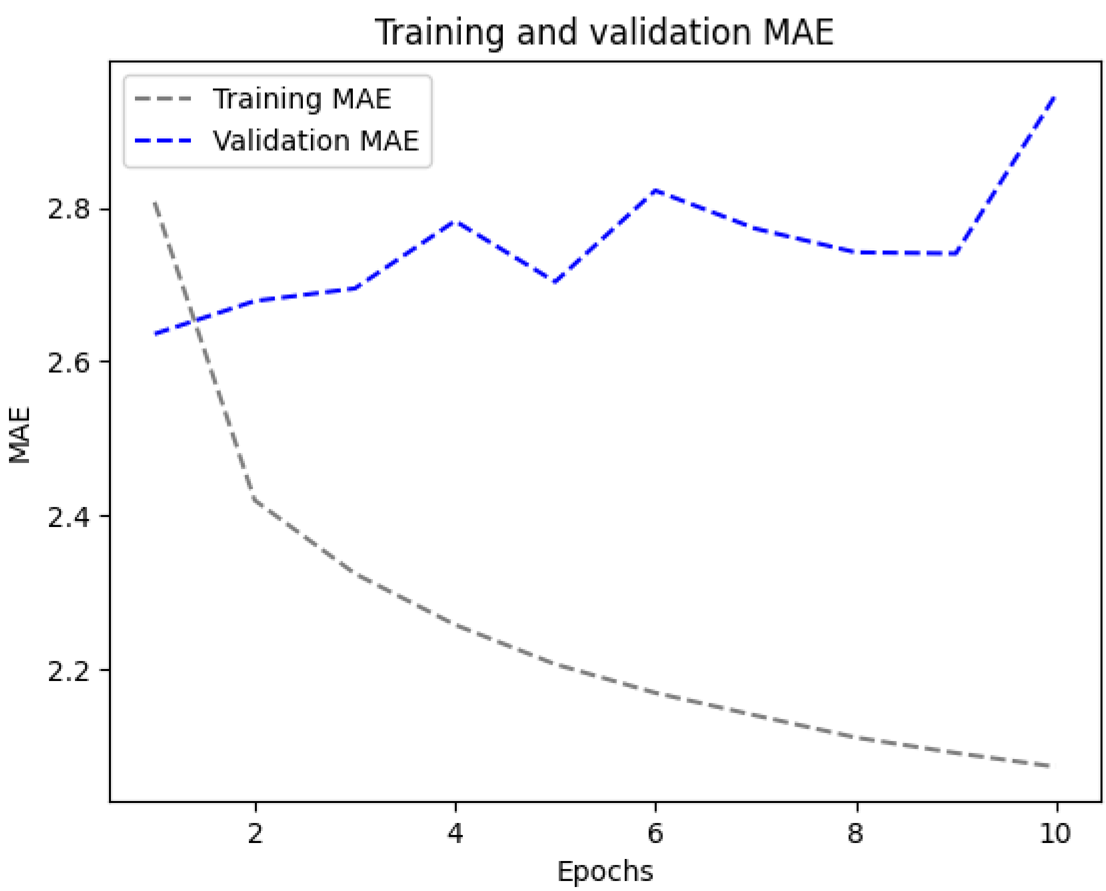
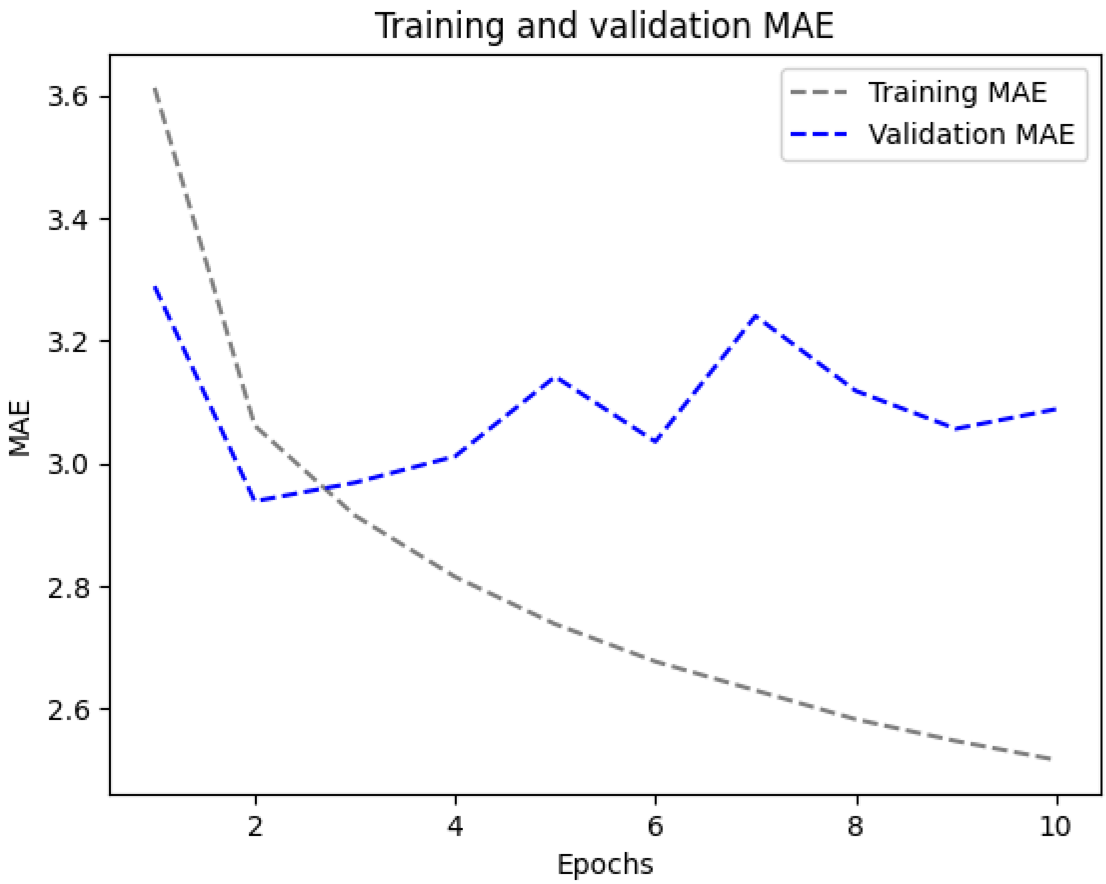
Weather Time Series Forecasting

Report

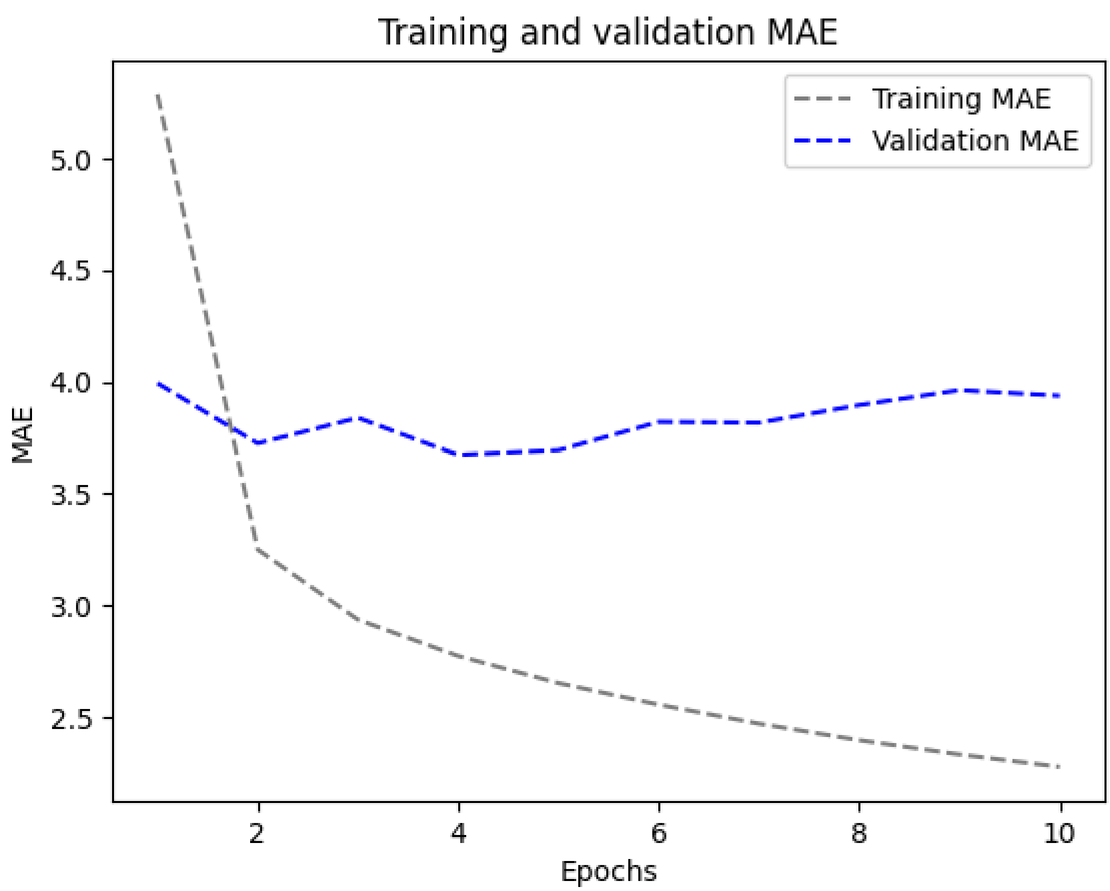
For time series data analysis, we developed an aggregate of 14 models. The first model served as a baseline, counting on common- sense styles, and yielding a Mean Absolute Error(MAE) of 2.62. Later, we created an introductory machine learning model with a thick layer, performing in a hardly advanced MAE of 2.70. The interpretation of the thick subcaste model was subpar due to the leveling of the time series data, removing the nonreligious environment. Also tried with a convolutional model which handled penurious effects as it treated all data parts slightly, indeed after pooling, which disintegrated the data's successional order.





Accordingly, we honored that intermittent Neural Networks(RNNs) are more suited for time series data. An essential point of intermittent Neural Networks(RNNs) is their capacity to integrate information from once way into their present-day resolution- making process. This enables the network to discover dependences and patterns within successional data. The RNN's internal country effectively acts as a mind, retaining information from once inputs, therefore allowing it to model sequences of varying lengths. Still, the introductory Simple RNN is frequently too simplistic to be authentically ultrapractical. especially, Simple RNN has a significant debit as substantiated by the vivid representation, it constantly performs the desolate among all models. While in proposition, Simple RNN should be able to retain information from all former time, it tends to struggle virtually, especially in deep networks, due to the opprobrious" evaporating grade case ”. This case renders the network nearly untrainable. In reaction to this challenge, more improved RNN variants, similar as Long Short- tenure Mind(LSTM) and Reopened intermittent Unit(GRU), were developed and are integrated into Keras. Our trial with the simple GRU model demonstrated stylish results among all the models, primarily because of its capability to capture long- range dependencies in successional data while being more computationally effective assimilated to LSTMs.

The notorious armature for effectively handling time series data is LSTMs and we ran six nonidentical LSTM models with varying units in mounding intermittent layers(8, 16, and 32), and the model with 8 units demonstrated the stylish interpretation. Also, we assumed intermittent powerhouse to help overfitting and experimented with bidirectional data donation to enhance delicacy and manipulate the forgetting case. These LSTM models all displayed analogous MAE valuations, which were constantly lesser than the common or garden - sense model.



In the end, we tried to combine a 1D complication model with an RNN. Still, this mongrel model yielded an advanced MAE of 3.75, probably due to the complication's terminations in maintaining the order of information. Grounded on my compliances, it's passed to shake simple RNNs for time series dissection, as they struggle with the evaporating grade case and can not effectively prisoner long- tenure dependencies . rather, call for more improved RNN infrastructures, similar as LSTM and GRU, which are aimed to beat these expostulations. While LSTM is a popular liberty for handling time series data, our trials suggest that GRU may extend more effective effects. To optimize GRU models, call tuning hyperparameters similar to the number of units in piled intermittent layers, intermittent powerhouse classes, and the use of bidirectional data donation. Likewise, it's judicious to concentrate on RNN infrastructures acclimatized for successional data, as the combination of 1D complication and RNN didn't yield optimal effects. Convolutional approaches tend to disrupt the order of information, making them less able for time series data dissection.