Engine Failure Prediction Challenge - Documentation

Model selection rationale

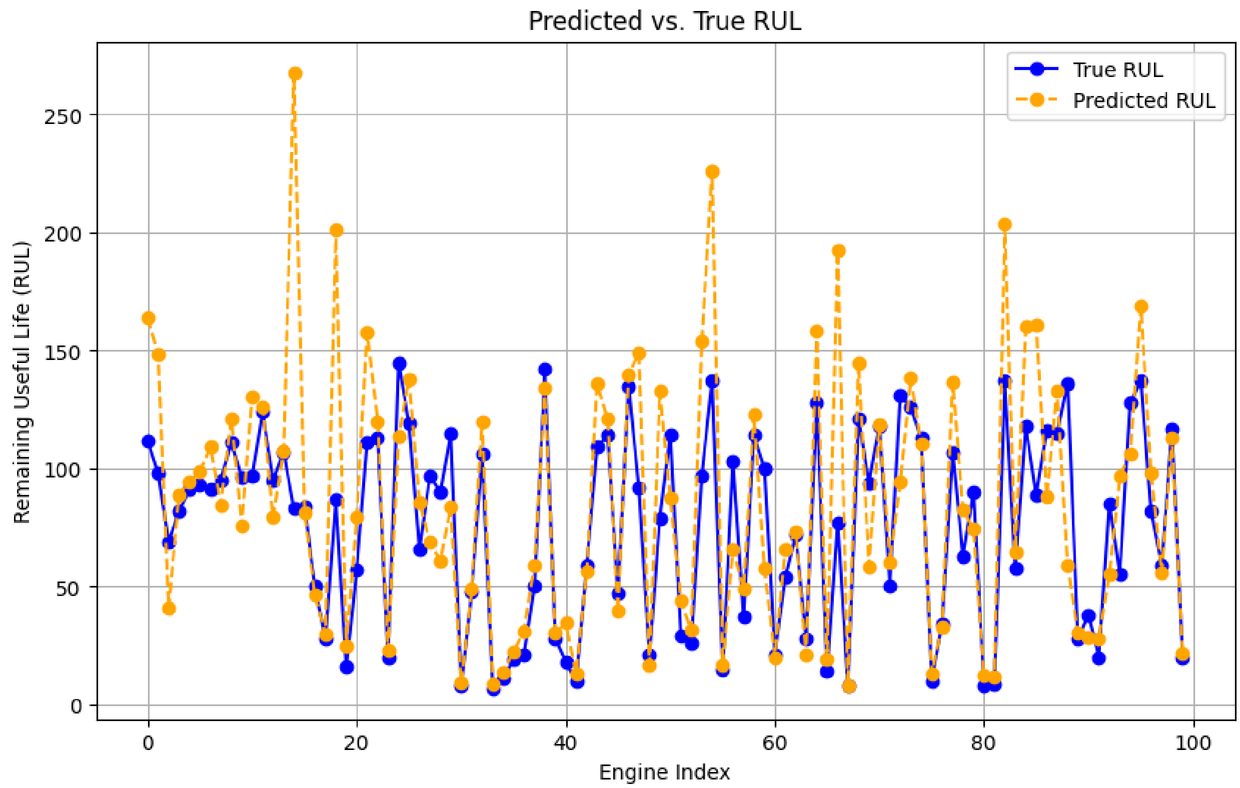
For this project, I ended up selecting a Long Short Term Model model to use for prediction. Since most of the engine data had a temporal feature and the timeline of the data mattered as we are trying to predict the failure state of an engine given its prior earlier states, I felt like using an LSTM model was appropriate for prediction since LSTMs are good at handling data with time features due to their memory cell feature. I ended up using an LSTM with an three LSTM layers with 128 hidden units and 3 fully connected layers to map the features to relu functions. (why?). I also included had a rather high dropout rate of 0.5 due to prior implementations constantly overfitting its predictions. I utilized mean square error (MSE) as my loss function to penalize big deviations, and also added a learning rate scheduler to reduce the learning rate to achieve better performance since my model was overfitting at first.

Feature Engineering Decisions

As part of the data pre-processing, I initially dropped the first two columns from the data set which were the unit identifiers and the current cycle number since they seemed like independent values from features that would help with the prediction and were mostly there for labeling rather than being features that could be indicators. I applied standard scaling to standarize all the feature values between 0 and 1 (why?) and since I was dealing with temporal data, I used the sliding window technique to maintain the temporal structure of the data since feeding the model a cycle of data does not help its prediction. The window size was set to 30, so every 30 cycles was squeezed into an array and for the training data, the final RUL value of the final cycle per sequence was calculated and added at the end. For testing data, I used only the last window per engine to predict RUL since i felt like the window prior to the last one did not matter too much.

Performance Metrics and Key Findings

My main performance metric was rmse root mean squared value, but i also used the predicted values compared to ground truth which was provided in the RUL.txt files. Graph is provided below. As you can see on my graph, my predicted RUL was decent but also seemed to really overfit on high RUL values and deviates really high. It was good in capturing overall degradation trends however, and definitely could be improved if i trained it longer or experimented more with the hyperparameters.



Limitations and Assumptions

There definitely could have been more feature engineering I could have done. I utilized all 24 sensor data for the prediction and only dropped the unit id and cycle number, but the dataset could have simplified and training could have been speed up if I eliminated other features. This implementation assumes all 24 feature readings are important for engine failure prediction but some key readings might have really low variance and not really play a large influence in final prediction. The model can struggle with really high RUL values and having the sliding windows is crucial for prediction. Removal of sliding windows and simply feeding in the training data would drastically lower its performance(from prior implementation experience). Some assumptions made from this particular implementation is that the sensor data is completely accurate as I did not eliminate any outliers from the dataset, and also since I only had to train it on the first dataset in the entire kaggle dataset, i did not need to worry about external factors like operational conditions such as weather.

Implementations Recommendations

This system could be used in maintenance planning where given the current state of an engine, the model could be used to predict whether or not the respective engine is close to engine failure or not. If the model predicts that the given RUL is low, then maintenance should be planned immediately that respective engine should be prioritized for repair. The system can also be used as part of an overall framework to help filter engine priority for maintenance as engineds with lower RUL could be scored higher for priority in maintenance.