Remaining Useful Life Estimation Using Convolutional Neural Network

This example shows how to predict the remaining useful life (RUL) of engines by using deep convolutional neural networks (CNNs) [1]. The advantage of a deep learning approach is that you do not need manual feature extraction or feature selection for your model to predict RUL. Furthermore,you do not need prior knowledge of machine health prognostics or signal processing to develop a deep learning based RUL prediction model.

This example uses:

Predictive Maintenance Toolbox

Deep Learning Toolbox

Copy Command

Download Data set

This example uses the Turbofan Engine Degradation Simulation data set [1]. The data set is in ZIP file format, and contains run-to-failure time-series data for four different sets (namely FD001, FD002, FD003, and FD004) simulated under different combinations of operational conditions and fault modes.

This example uses only the FD001 data set, which is further divided into training and test subsets. The training subset contains simulated time series data for 100 engines. Each engine has several sensors whose values are recorded at a given instance in a continuous process. Hence, the sequence of recorded data varies in length and corresponds to a full run-to-failure (RTF) instance. The test subset contains 100 partial sequences and corresponding values of the remaining useful life at the end of each sequence.

Create a directory to store the Turbofan Engine Degradation Simulation data set.

```
dataFolder = "data";
if ~exist(dataFolder,'dir')
    mkdir(dataFolder);
end
```

Download and extract the Turbofan Engine Degradation Simulation data set.

```
filename = matlab.internal.examples.downloadSupportFile("nnet","data/TurbofanEngineDegradationSimulationData.zip");
unzip(filename,dataFolder)
```

The data folder now contains text files with 26 columns of numbers, separated by spaces. Each row is a snapshot of data taken during a single operational cycle, and each column represents a different variable:

- Column 1 — Unit number
- Column 2 — Timestamp
- Columns 3–5 — Operational settings
- Columns 6–26 — Sensor measurements 1–21

Preprocess Training Data

Load the data using the function `localLoadData`. The function extracts the data from a data file and returns a table which contains the training predictors and corresponding response (i.e., RUL) sequences. Each row represents a different engine.

```
filenameTrainPredictors = fullfile(dataFolder,"train_FD001.txt");
rawTrain = localLoadData(filenameTrainPredictors);
```

Examine the run-to-failure data for one of the engines.

```
head(rawTrain.X{1},8)
```

```
ans=8×26 table
    id    timeStamp    op_setting_1    op_setting_2    op_setting_3    sensor_1    sensor_2    sensor_3    sensor_4    sensor_5    sensor_6    se
    __    _________    ____________    ____________    ____________    ________    ________    ________    ________    ________    ________    __

    1         1          -0.0007         -0.0004           100          518.67      641.82      1589.7      1400.6      14.62       21.61       5
    1         2           0.0019         -0.0003           100          518.67      642.15      1591.8      1403.1      14.62       21.61       5
    1         3          -0.0043          0.0003           100          518.67      642.35        1588      1404.2      14.62       21.61       5
    1         4           0.0007               0           100          518.67      642.35      1582.8      1401.9      14.62       21.61       5
    1         5          -0.0019         -0.0002           100          518.67      642.37      1582.8      1406.2      14.62       21.61
    1         6          -0.0043         -0.0001           100          518.67       642.1      1584.5      1398.4      14.62       21.61       5
    1         7            0.001          0.0001           100          518.67      642.48      1592.3      1397.8      14.62       21.61       5
    1         8          -0.0034          0.0003           100          518.67      642.56        1583        1401      14.62       21.61       5
```

Examine the response data for one of the engines.

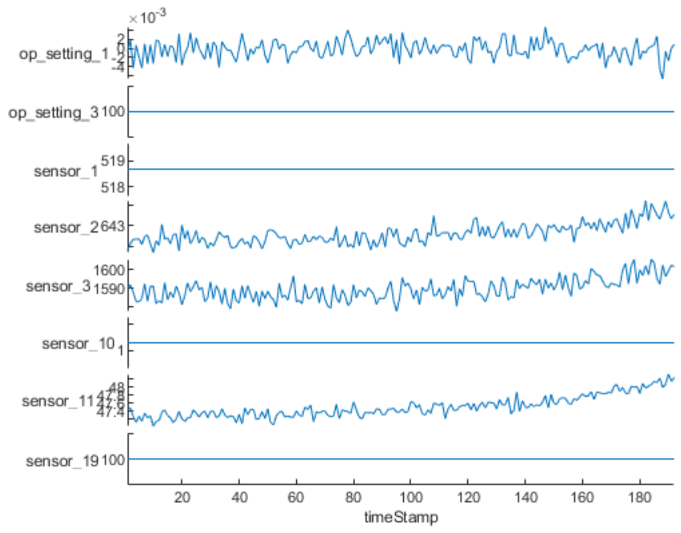
```
rawTrain.Y{1}(1:8)
```

```
ans = 8×1

   191
   190
   189
   188
   187
   186
   185
   184
```

Visualize the time-series data for some of the predictors.

```
stackedplot(rawTrain.X{1},[3,5,6,7,8,15,16,24],XVariable='timeStamp')
```



Remove Features with Less Variability

Features that remain constant for all time steps can negatively impact the training. Use the `prognosability` function to measure the variability of features at failure.

```
prog = prognosability(rawTrain.X,"timeStamp");
```

For some features, prognosability is equal to zero or NaN. Discard these features.

```
idxToRemove = prog.Variables==0 | isnan(prog.Variables);
featToRetain = prog.Properties.VariableNames(~idxToRemove);
for i = 1:height(rawTrain)
    rawTrain.X{i} = rawTrain.X{i}{:,featToRetain};
end
```

Normalize Training Predictors

Normalize the training predictors to have zero mean and unit variance.

```
[~,Xmu,Xsigma] = zscore(vertcat(rawTrain.X{:}));
preTrain = table();
for i = 1:numel(rawTrain.X)
    preTrain.X{i} = (rawTrain.X{i} - Xmu) ./ Xsigma;
end
```

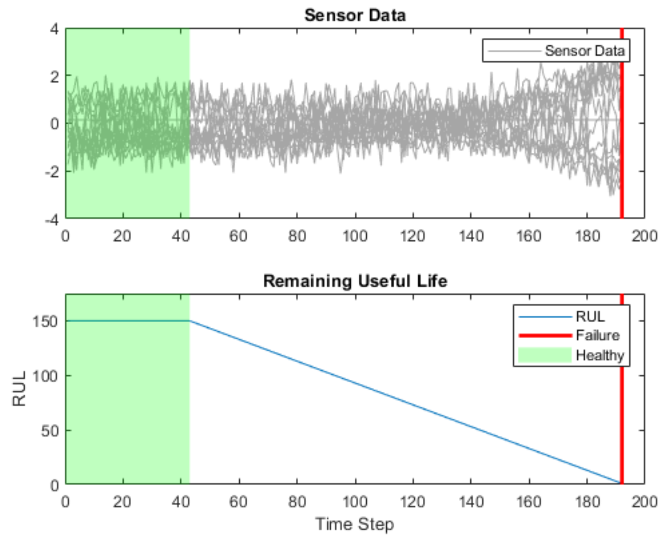
Clip Responses

The response data represents the RUL value over life for each engine and is based individual engine lifetime. The sequence assumes a linear degradation from the time of the initial measurement to the time of engine failure.

In order for network to focus on the part of the data where engines are more likely to fail (end of the engine's life), clip the responses at the threshold of 150. Clipping the responses causes the network to treat instances with higher RUL values as equal.

```
rulThreshold = 150;
for i = 1:numel(rawTrain.Y)
    preTrain.Y{i} = min(rawTrain.Y{i},rulThreshold);
end
```

This figure shows the first observation and the corresponding response (RUL), which is clipped at the threshold. The green overlay defines the clipping region on both sensor amd RUL plots.



Prepare Data for Padding

This network supports input data with varying sequence lengths. When passing data through the network, the software pads, truncates, or splits sequences so that all the sequences in each mini-batch have the specified length.

To minimize the amount of padding added to the mini-batches, sort the training data by sequence length. Then, choose a mini-batch size which divides the training data evenly and reduces the amount of padding in the mini-batches.

Sort the training data by sequence length.

```
for i = 1:size(preTrain,1)
    preTrain.X{i} = preTrain.X{i}';    %Transpose training data to have features in the first dimension
    preTrain.Y{i} = preTrain.Y{i}';    %Transpose responses corresponding to the training data
    sequence = preTrain.X{i};
    sequenceLengths(i) = size(sequence,2);
end

[sequenceLengths,idx] = sort(sequenceLengths,'descend');
XTrain = preTrain.X(idx);
YTrain = preTrain.Y(idx);
```

Network Architecture

The deep convolutional neural network architecture used for RUL estimation is described in [1].

Here, you process and sort the data in a sequence format, with the first dimension representing the number of selected features and the second dimension representing the length of the time sequence. You bundle convolutional layers with batch normalization layer followed by an activation layer (relu in this case) and then stack the layers together for feature extraction. The fully connected layers and regression layer are used at the end to get the final RUL value as output .

The selected network architecture applies a 1-D convolution along the time sequence direction only. Therefore, the order of features do not impact the training and only trends in one feature at a time are considered.

Define the network architecture. Create a CNN that consists of five consecutive sets of a convolution 1-d, batch normalization and, a relu layer, with increasing `filterSize` and `numFilters` as the first two input arguments to `convolution1dLayer`, followed by a fully connected layer of size `numHiddenUnits` and a dropout layer with a dropout probability of 0.5. Since the network predicts the remaining useful life (RUL) of the turbofan engine, set `numResponses` to 1 in the second fully connected layer and a regression layer as the last layer of the network.

To compensate for the varying time-sequences in the training data, use `Padding="causal"` as the Name-value pair input argument in `convolution1dLayer`.

```
numFeatures = size(XTrain{1},1);
numHiddenUnits = 100;
numResponses = 1;

layers = [
    sequenceInputLayer(numFeatures)
    convolution1dLayer(5,32,Padding="causal")
    batchNormalizationLayer()
    reluLayer()
    convolution1dLayer(7,64,Padding="causal")
    batchNormalizationLayer
    reluLayer()
    convolution1dLayer(11,128,Padding="causal")
    batchNormalizationLayer
    reluLayer()
    convolution1dLayer(13,256,Padding="causal")
    batchNormalizationLayer
    reluLayer()
    convolution1dLayer(15,512,Padding="causal")
    batchNormalizationLayer
    reluLayer()
    fullyConnectedLayer(numHiddenUnits)
    reluLayer()
    dropoutLayer(0.5)
    fullyConnectedLayer(numResponses)
    regressionLayer()];
```

Train Network

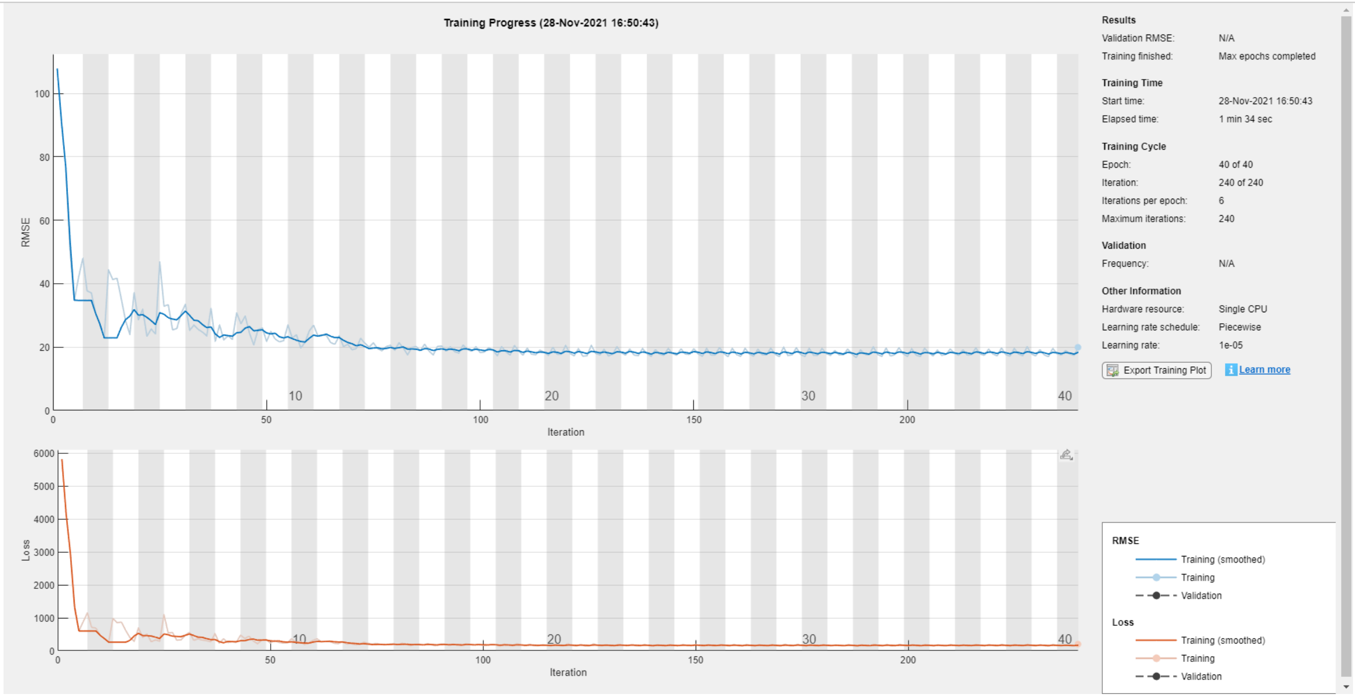
Specify `trainingOptions` (Deep Learning Toolbox). Train for 40 epochs with minibatches of size 16 using the Adam optimizer. Set `LearnRateSchedule` to `piecewise`. Specify the learning rate as 0.01. To prevent the gradients from exploding, set the gradient threshold to 1. To keep the sequences sorted by length, set `'Shuffle'` to `'never'`. Turn on the training progress plot, and turn off the command window output (`Verbose`).

```
maxEpochs = 40;
miniBatchSize = 16;

options = trainingOptions('adam',...
    LearnRateSchedule='piecewise',...
    MaxEpochs=maxEpochs,...
    MiniBatchSize=miniBatchSize,...
    InitialLearnRate=0.01,...
    GradientThreshold=1,...
    Shuffle='never',...
    Plots='training-progress',...
    Verbose=0);
```

Train the network using `trainNetwork`. It should take about 1-2 minutes.

```
net = trainNetwork(XTrain,YTrain,layers,options);
```



Results
Validation RMSE: N/A
Training finished: Max epochs completed

Training Time
Start time: 28-Nov-2021 16:50:43
Elapsed time: 1 min 34 sec

Training Cycle
Epoch: 40 of 40
Iteration: 240 of 240
Iterations per epoch: 6
Maximum iterations: 240

Validation
Frequency: N/A

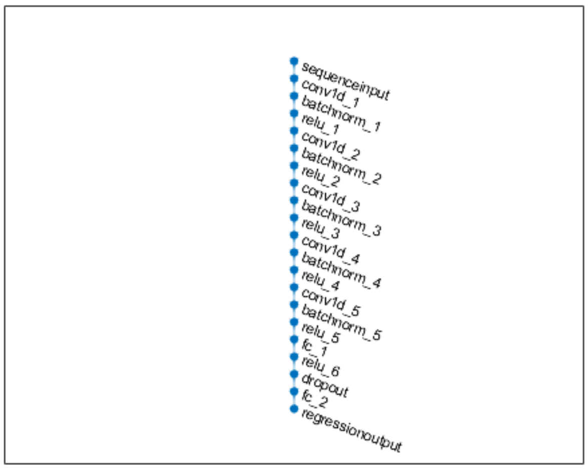
Other Information
Hardware resource: Single CPU
Learning rate schedule: Piecewise
Learning rate: 1e-05

RMSE
Training (smoothed)
Training
Validation

Loss
Training (smoothed)
Training
Validation

Plot the layer graph of the network to visualize the underlying network architecture.

```
figure;
lgraph = layerGraph(net.Layers);
plot(lgraph)
```



Test Network

The test data contains 100 partial sequences and corresponding values of the remaining useful life at the end of each sequence.

```
filenameTestPredictors = fullfile(dataFolder,'test_FD001.txt');
filenameTestResponses = fullfile(dataFolder,'RUL_FD001.txt');
dataTest = localLoadData(filenameTestPredictors,filenameTestResponses);
```

Prepare the test data set for predictions by performing the same preprocessing steps you use to prepare the training data set.

```
for i = 1:numel(dataTest.X)
    dataTest.X{i} = dataTest.X{i}{:,featToRetain};
    dataTest.X{i} = (dataTest.X{i} - Xmu) ./ Xsigma;
    dataTest.Y{i} = min(dataTest.Y{i},rulThreshold);
end
```

Create a table for storing the predicted response (YPred) along with the true response (Y). Make predictions on the test data using `predict`. To prevent the function from adding padding to the test data, specify the mini-batch size 1.

```
predictions = table(Size=[height(dataTest) 2],VariableTypes=["cell","cell"],VariableNames=["Y","YPred"]);

for i=1:height(dataTest)
    unit = dataTest.X{i}';
    predictions.Y{i} = dataTest.Y{i}';
    predictions.YPred{i} = predict(net,unit,MiniBatchSize=1);
end
```

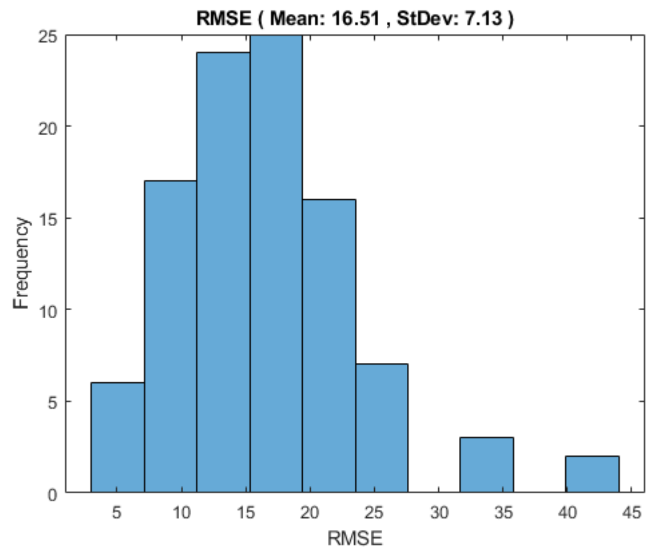
Performance Metrics

Compute the root mean squared error (RMSE) across all time cycles of the test sequences to analyze how well the network performs on the test data.

```
for i = 1:size(predictions,1)
    predictions.RMSE(i) = sqrt(mean((predictions.Y{i} - predictions.YPred{i}).^2));
end
```

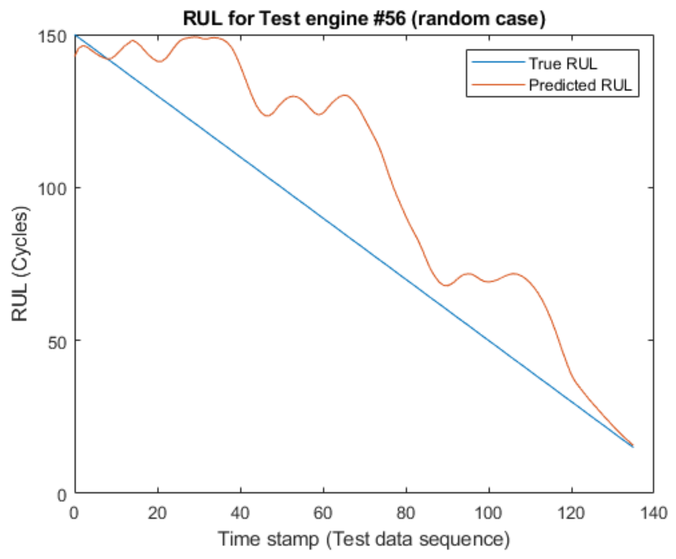
Create a histogram to visualize the distribution of RMSE values across all test engines.

```
figure;
histogram(predictions.RMSE,NumBins=10);
title("RMSE ( Mean: " + round(mean(predictions.RMSE),2) + " , StDev: " + round(std(predictions.RMSE),2) + " )");
ylabel('Frequency');
xlabel('RMSE');
```



Additionally, to see how the network predictor performs throughout the given sequence of data in the test engines, use the `localLambdaPlot` function to plot the predicted RUL against the true RUL of a random test engine.

```
figure;
localLambdaPlot(predictions,"random");
```



The result shows that the CNN deep learning architecture for estimating RUL of the turbo engine data is a viable approach to predict RUL. The RMSE values at all timestamps indicates that the network can perform well towards the end of the given test sequence data. Therefore, having a brief history of the sensor data is important when trying to predict RUL.

Helper Functions

Load Data Function

This function loads run-to-failure data from the provided text file and groups time-series data and its corresponding RUL values in a table as predictors and responses.

```
function data = localLoadData(filenamePredictors,varargin)

if isempty(varargin)
    filenameResponses = [];
```

```
else
    filenameResponses = varargin{:};
end

%% Load the text file as a table
rawData = readtable(filenamePredictors);

% Add variable names to the table
VarNames = {...
    'id', 'timeStamp', 'op_setting_1', 'op_setting_2', 'op_setting_3', ...
    'sensor_1', 'sensor_2', 'sensor_3', 'sensor_4', 'sensor_5', ...
    'sensor_6', 'sensor_7', 'sensor_8', 'sensor_9', 'sensor_10', ...
    'sensor_11', 'sensor_12', 'sensor_13', 'sensor_14', 'sensor_15', ...
    'sensor_16', 'sensor_17', 'sensor_18', 'sensor_19', 'sensor_20', ...
    'sensor_21'};
rawData.Properties.VariableNames = VarNames;

if ~isempty(filenameResponses)
    RULTest = readmatrix(filenameResponses);
end

% Split the signals for each unit ID
IDs = rawData{:,1};
nID = unique(IDs);
numObservations = numel(nID);

% Initialize a table for storing data
data = table(Size=[numObservations 2],...
    VariableTypes={'cell','cell'},...
    VariableNames={'X','Y'});

for i=1:numObservations
    idx = IDs == nID(i);
    data.X{i} = rawData(idx,:);
    if isempty(filenameResponses)
        % Calculate RUL from time column for train data
        data.Y{i} = flipud(rawData.timeStamp(idx))-1;
    else
        % Use RUL values from filenameResponses for test data
        sequenceLength = sum(idx);
        endRUL = RULTest(i);
        data.Y{i} = [endRUL+sequenceLength-1:-1:endRUL]'; %#ok<NBRAK>
    end
end
end
```

Lambda Plot function

This helper function accepts the `predictions` table and a `lambdaCase` argument, and plots the predicted RUL against the true RUL throughout its sequence (at every timestamp) for a visualization of how the prediction changes with every timestamp. The second argument, `lambdaCase`, can be the test engine number or one of a set of valid strings to find an engine number : "random", "best", "worst", or "average".

```
function localLambdaPlot(predictions,lambdaCase)

if isnumeric(lambdaCase)
    idx = lambdaCase;
else
    switch lambdaCase
        case {"Random","random","r"}
            idx = randperm(height(predictions),1); % Randomly choose a test case to plot
        case {"Best","best","b"}
            idx = find(predictions.RMSE == min(predictions.RMSE)); % Best case
        case {"Worst","worst","w"}
            idx = find(predictions.RMSE == max(predictions.RMSE)); % Worst case
        case {"Average","average","a"}
            err = abs(predictions.RMSE-mean(predictions.RMSE));
            idx = find(err==min(err),1);
    end
end
y = predictions.Y{idx};
yPred = predictions.YPred{idx};
x = 0:numel(y)-1;
plot(x,y,x,yPred)
legend("True RUL","Predicted RUL")
xlabel("Time stamp (Test data sequence)")
ylabel("RUL (Cycles)")

title("RUL for Test engine #"+idx+ " ("+lambdaCase+" case)")
end
```

References

1. Li, Xiang, Qian Ding, and Jian-Qiao Sun. “Remaining Useful Life Estimation in Prognostics Using Deep Convolution Neural Networks.” Reliability Engineering & System Safety 172 (April 2018): 1–11. https://doi.org/10.1016/j.ress.2017.11.021.

See Also

`imageInputLayer` (Deep Learning Toolbox) | `prognosability` | `trainingOptions` (Deep Learning Toolbox)

Related Topics

- Learn About Convolutional Neural Networks (Deep Learning Toolbox)
- Sequence-to-Sequence Regression Using Deep Learning (Deep Learning Toolbox)
- Similarity-Based Remaining Useful Life Estimation
- Battery Cycle Life Prediction Using Deep Learning

External Websites

- Predictive Maintenance, Part 3: Remaining Useful Life Estimation
- Convolutional Neural Network - 3 things you need to know