Time Series Forecasting Using Deep Learning

This code is taken from https://de.mathworks.com/help/deeplearning/ug/time-series-forecasting-using-deep-learning.html

Notes are added to get full understanding of the code.

This example shows how to forecast time series data using a long short-term memory (LSTM) network.

An LSTM network is a recurrent neural network (RNN) that processes input data by looping over time steps and updating the RNN state. The RNN state contains information remembered over all previous time steps. You can use an LSTM neural network to forecast subsequent values of a time series or sequence using previous time steps as input. To train an LSTM neural network for time series forecasting, train a regression LSTM neural network with sequence output, where the responses (targets) are the training sequences with values shifted by one time step.

In other words, at each time step of the input sequence, the LSTM neural network learns to predict the value of the next time step.

Why LSTM?

LSTMs are designed to overcome the limitations of traditional RNNs, which struggle with long-term dependencies due to issues like vanishing gradients. LSTMs achieve this by incorporating memory cells and gates that control the flow of information:

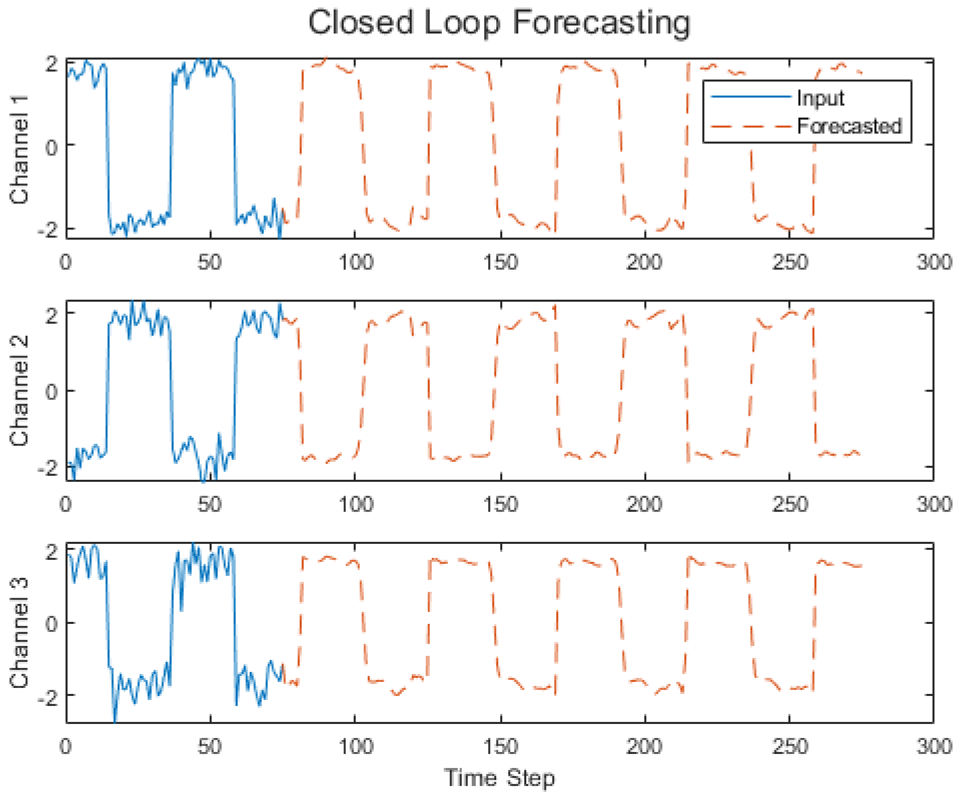
- Memory Cells: Store information over time.
- Input Gate: Controls how much new information is stored in the memory cell.
- Forget Gate: Decides what information to discard from the memory cell.
- Output Gate: Determines what information from the memory cell is used for output.

These mechanisms allow LSTMs to retain important information over long sequences, making them effective for time series forecasting.

There are two methods of forecasting: open loop and closed loop forecasting.

- **Open loop forecasting** — Predict the next time step in a sequence using only the input data. When making predictions for subsequent time steps, you collect the true values from your data source and use those as input. For example, say you want to predict the value for time step t of a sequence using data collected in time steps 1 through $t-1$. To make predictions for time step $t+1$, wait until you record the true value for time step t and use that as input to make the next prediction. Use open loop forecasting when you have true values to provide to the RNN before making the next prediction.
- **Closed loop forecasting** — Predict subsequent time steps in a sequence by using the previous predictions as input. In this case, the model does not require the true values to make the prediction. For example, say you want to predict the values for time steps t through $t+k$ of the sequence using data collected in time steps 1 through $t-1$ only. To make predictions for time step i, use the predicted value for time step $i-1$ as input. Use closed loop forecasting to forecast multiple subsequent time steps or when you do not have the true values to provide to the RNN before making the next prediction.

This figure shows an example sequence with forecasted values using closed loop prediction.



This example uses the Waveform data set, which contains 1000 synthetically generated waveforms of varying lengths with three channels. The example trains an LSTM neural network to forecast future values of the waveforms given the values from previous time steps using both closed loop and open loop forecasting.

Load Data

Load the example data from `WaveformData.mat`. The data is a `numObservations`-by-1 cell array of sequences, where `numObservations` is the number of sequences. Each sequence is a `numTimeSteps`-by-`numChannels` numeric array, where `numTimeSteps` is the number of time steps of the sequence and `numChannels` is the number of channels of the sequence.

```
load WaveformData
%If error is there for path,add the folder in matlab path
%Loads the dataset WaveformData, which contains sequences of varying lengths
with multiple channels.
```

View the sizes of the first few sequences.

```
data(1:4)
```

```
ans = 4x1 cell
```

	1
1	103×3 double
2	136×3 double
3	140×3 double
4	124×3 double

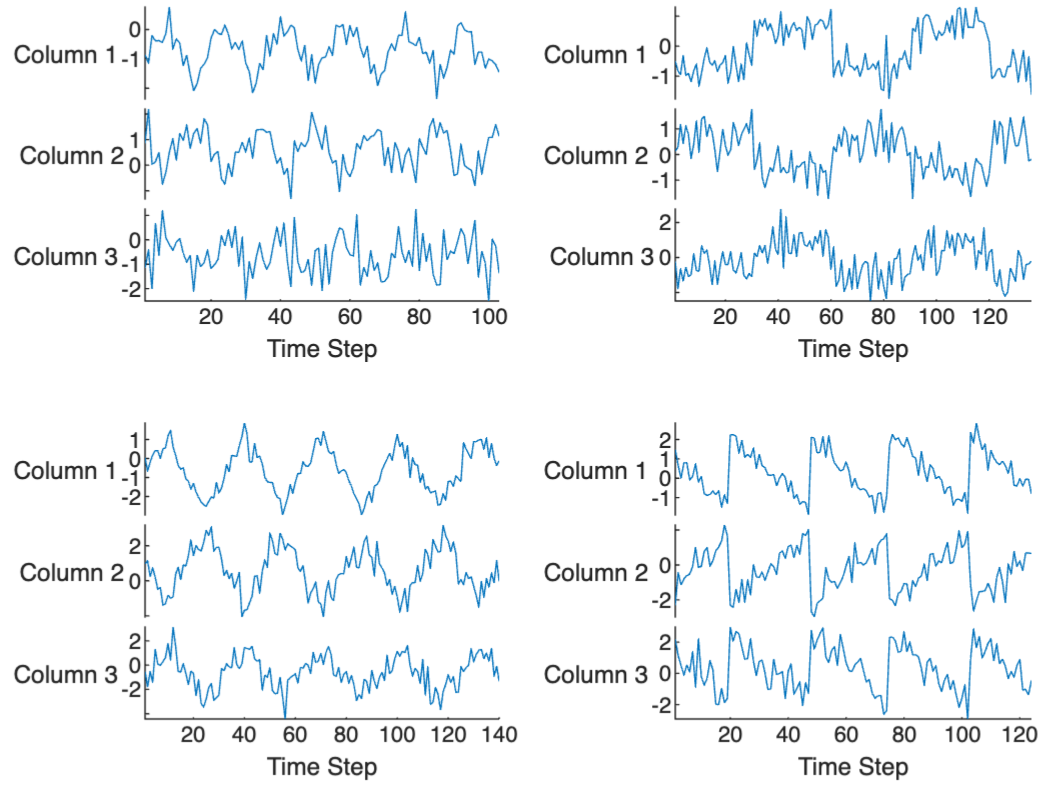
View the number of channels. To train the LSTM neural network, each sequence must have the same number of channels.

```
numChannels = size(data{1},2) %Determines the number of channels in the
first sequence, which is crucial for defining the input size for the LSTM
network
```

```
numChannels =
3
```

Visualize the first few sequences in a plot.

```
figure
tiledlayout(2,2)
for i = 1:4
    nexttile
    stackedplot(data{i})

    xlabel("Time Step")
end
```



Partition the data into training and test sets. Use 90% of the observations for training and the remainder for testing.

```
numObservations = numel(data); %Counts the total number of sequences.
idxTrain = 1:floor(0.9*numObservations);
idxTest = floor(0.9*numObservations)+1:numObservations;
dataTrain = data(idxTrain);
dataTest = data(idxTest);
%The data is split into training (90%) and test (10%) sets using indices
```

Prepare Data for Training

To forecast the values of future time steps of a sequence, specify the targets as the training sequences with values shifted by one time step. Do not include the final time step in the training sequences. In other words, at each time step of the input sequence, the LSTM neural network learns to predict the value of the next time step. The predictors are the training sequences without the final time step.

```
numObservationsTrain = numel(dataTrain);
%Creates cell arrays to store input (XTrain) and target (TTrain) sequences
XTrain = cell(numObservationsTrain,1); % 1 column and #Noobs rows
TTrain = cell(numObservationsTrain,1);
for n = 1:numObservationsTrain
    X = dataTrain{n};
    XTrain{n} = X(1:end-1,:);
```

```
    TTrain{n} = X(2:end,:);
end

%For each sequence, the input is all but the last time step (X(1:end-1,:)),
and the target is shifted by one time step (X(2:end,:))
```

For a better fit and to prevent the training from diverging, normalize the predictors and targets so that the channels have zero mean and unit variance. When you make predictions, you must also normalize the test data using the same statistics as the training data.

Calculate the per-channel mean and standard deviation values for the sequences. To easily calculate the mean and standard deviation for the training data, create numeric arrays that contains the concatenated sequences using the `cell2mat` function.

```
muX = mean(cell2mat(XTrain));
sigmaX = std(cell2mat(XTrain),0);

muT = mean(cell2mat(TTrain));
sigmaT = std(cell2mat(TTrain),0);

%Converts cell arrays to matrices for easy computation of mean and standard
deviation.
```

Normalize the sequences using the calculated mean and standard deviation values.

```
for n = 1:numel(XTrain)
%numel returns the the number of elements
    XTrain{n} = (XTrain{n} - muX) ./ sigmaX;
    TTrain{n} = (TTrain{n} - muT) ./ sigmaT;
end
%Normalizes each sequence to have zero mean and unit variance, which
stabilizes training
```

Define LSTM Neural Network Architecture

Create an LSTM regression neural network.

- Use a sequence input layer with an input size that matches the number of channels of the input data.
- Use an LSTM layer with 128 hidden units. **The number of hidden units determines how much information is learned by the layer. Using more hidden units can yield more accurate results but can be more likely to lead to overfitting to the training data.**
- To output sequences with the same number of channels as the input data, include a fully connected layer with an output size that matches the number of channels of the input data.

```
layers = [
    sequenceInputLayer(numChannels) %Specifies input size matching the
number of channels
    lstmLayer(128) % Adds an LSTM layer with 128 hidden units, balancing
complexity and risk of overfitting.
```

```
    fullyConnectedLayer(numChannels)]; %Outputs sequences with the same
number of channels as inputs
```

Specify Training Options

(Setting Hyperparameter)

Specify the training options.

- Train using Adam optimization.

What is adam optimizer

- Adam optimizer is a popular algorithm used for training deep learning models, including LSTMs. In simple terms, it's a method that helps the neural network learn more efficiently by adjusting the learning rate for each parameter individually

Key features of Adam optimizer:

1. Adaptive learning rates: It adjusts the learning rate for each parameter based on past gradients, allowing faster learning for infrequent parameters and slower learning for frequent ones.
2. Momentum: It uses an average of past gradients to determine the direction of updates, helping to overcome local minima and saddle points.
3. Bias correction: It corrects for the bias in the early stages of training when there's limited historical data.

Adam combines the benefits of two other optimization techniques: AdaGrad (which works well with sparse gradients) and RMSProp (which works well in online settings). This makes Adam particularly effective for a wide range of deep learning tasks, including time series forecasting with LSTMs

- Train for 200 epochs. For larger data sets, you might not need to train for as many epochs for a good fit.
- In each mini-batch, left-pad the sequences so they have the same length. Left-padding prevents the RNN from predicting padding values at the ends of sequences.
- Shuffle the data every epoch.
- Display the training progress in a plot.
- Disable the verbose output.

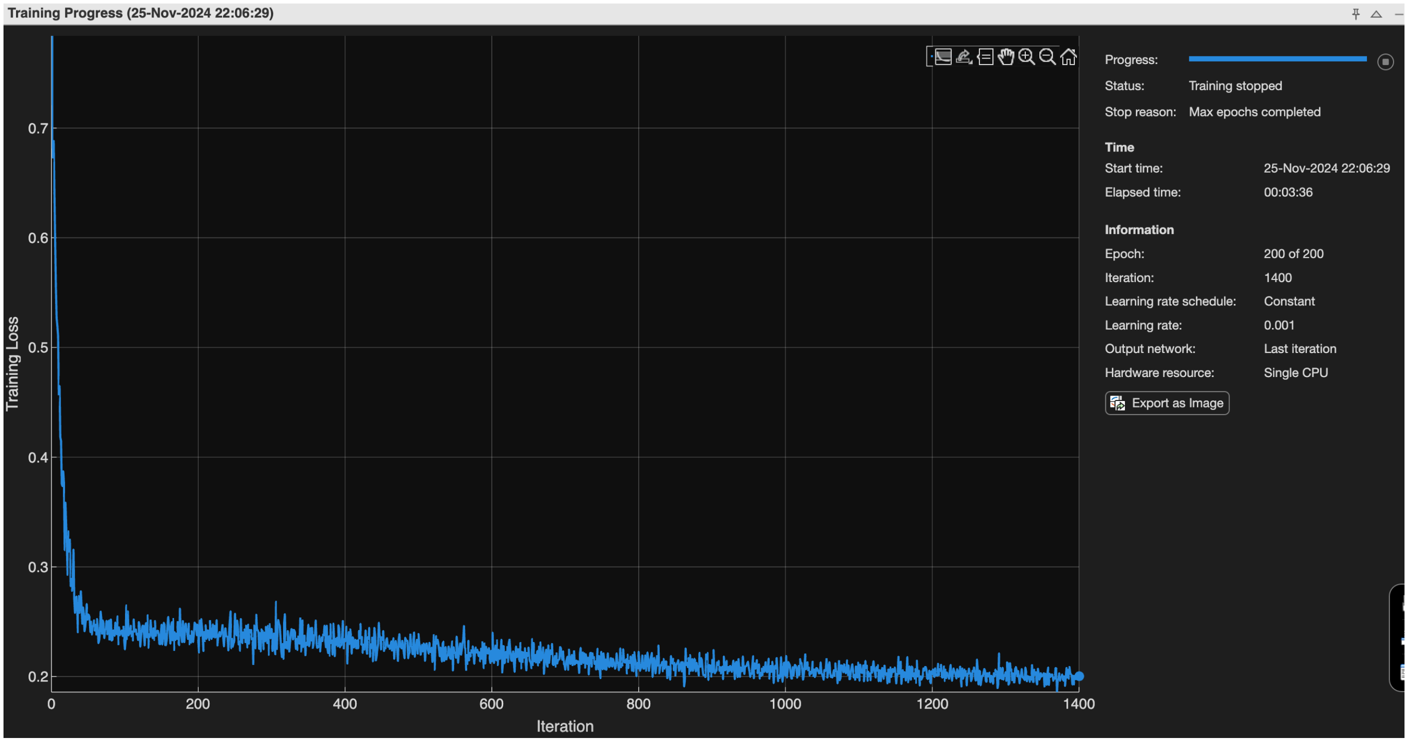
```
options = trainingOptions("adam", ...
    MaxEpochs=200, ...
    SequencePaddingDirection="left", ...
    Shuffle="every-epoch", ...  %Shuffles data each epoch to improve
generalization
    Plots="training-progress", ...
    Verbose=false);
```

Train Recurrent Neural Network

Train the LSTM neural network using the `trainnet` function. For regression, use mean squared error loss. By default, the `trainnet` function uses a GPU if one is available. Using a GPU requires a Parallel

Computing Toolbox™ license and a supported GPU device. For information on supported devices, see GPU Computing Requirements. Otherwise, the function uses the CPU. To specify the execution environment, use the `ExecutionEnvironment` training option.

```
net = trainnet(XTrain,TTrain,layers,"mse",options);
```



Test Recurrent Neural Network

Prepare the test data for prediction using the same steps as for the training data.

Normalize the test data using the statistics calculated from the training data. Specify the targets as the test sequences with values shifted by one time step and the predictors as the test sequences without the final time step.

```
numObservationsTest = numel(dataTest);
XTest = cell(numObservationsTest,1);
TTest = cell(numObservationsTest,1);
for n = 1:numObservationsTest
    X = dataTest{n};
    XTest{n} = (X(1:end-1,:) - muX) ./ sigmaX;
    TTest{n} = (X(2:end,:) - muT) ./ sigmaT;
end
```

Make predictions using the `minibatchpredict` function. By default, the `minibatchpredict` function uses a GPU if one is available. Pad the sequences using the same padding options as for training. For sequence-to-sequence tasks with sequences of varying lengths, return the predictions as a cell array by setting the `UniformOutput` option to `false`.

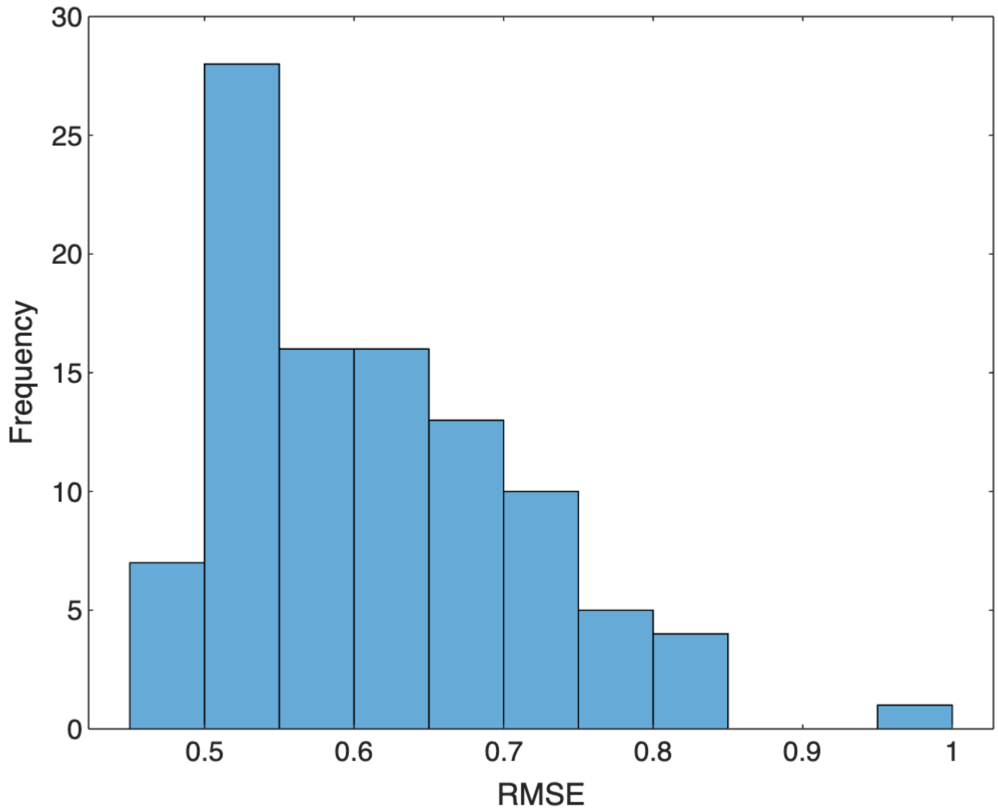
```
YTest = minibatchpredict(net,XTest, ...
    SequencePaddingDirection="left", ...
    UniformOutput=false);

%Makes predictions on test data, handling varying sequence lengths by
padding.
```

For each test sequence, calculate the root mean squared error (RMSE) between the predictions and targets. Ignore any padding values in the predicted sequences using the lengths of the target sequences for reference.

```
for n = 1:numObservationsTest
    T = TTest{n};

    sequenceLength = size(T,1);

    Y = YTest{n}(end-sequenceLength+1:end,:);

    err(n) = rmse(Y,T,"all");
end
%Computes root mean squared error (RMSE) between predictions and actual
targets, ignoring padding
```

Visualize the errors in a histogram. Lower values indicate greater accuracy.

```
figure
histogram(err)
xlabel("RMSE")
ylabel("Frequency")
```



Calculate the mean RMSE over all test observations.

```
mean(err,"all")
```

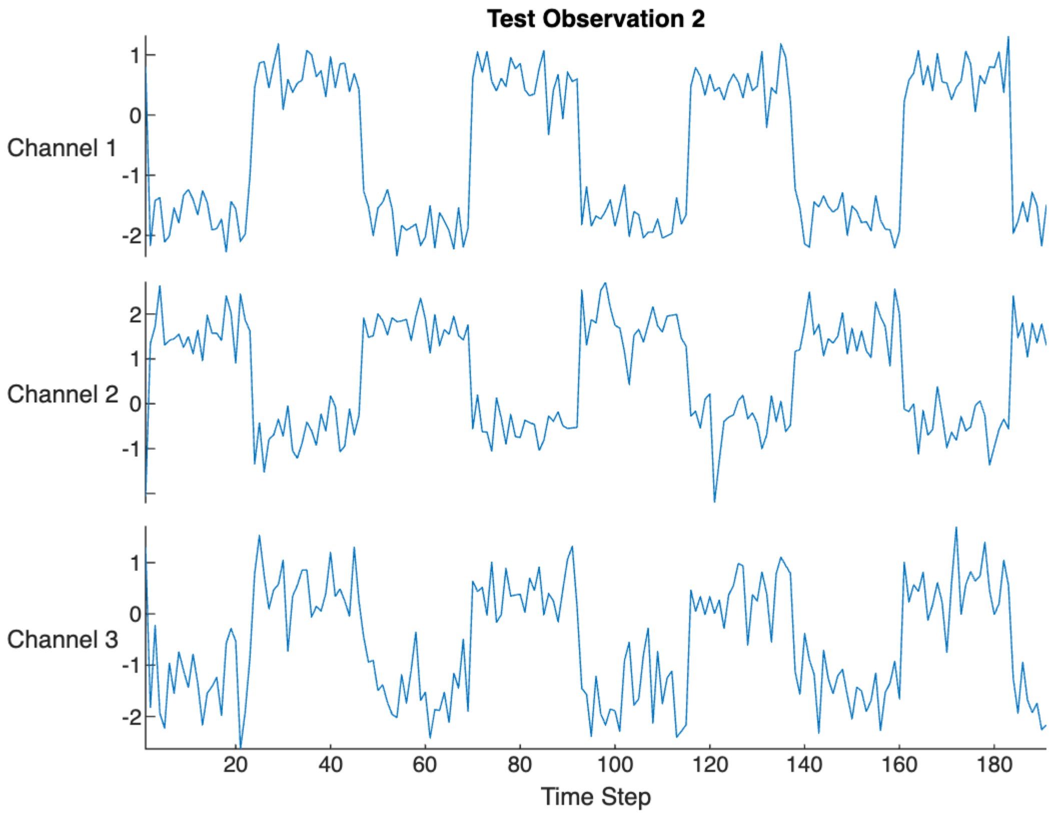
```
ans = single

0.6161
```

Forecast Future Time Steps

Given an input time series or sequence, to forecast the values of multiple future time steps, use the `predict` function to predict time steps one at a time and update the RNN state at each prediction. For each prediction, use the previous prediction as the input to the function.

Visualize one of the test sequences in a plot.

```
idx = 2;
X = XTest{idx};
T = TTest{idx};

figure
stackedplot(X,DisplayLabels="Channel " + (1:numChannels))
xlabel("Time Step")
title("Test Observation " + idx)
```



Open Loop Forecasting

Open loop forecasting predicts the next time step in a sequence using only the input data. When making predictions for subsequent time steps, you collect the true values from your data source and use those as input. For example, say you want to predict the value for time step t of a sequence using data collected in time steps 1 through $t-1$. To make predictions for time step $t+1$, wait until you record the true value for time step t and use that as input to make the next prediction. Use open loop forecasting when you have true values to provide to the RNN before making the next prediction.

Initialize the RNN state by first resetting the state using the `resetState` function, then make an initial prediction using the first few time steps of the input data. Update the RNN state using the first 75 time steps of the input data.

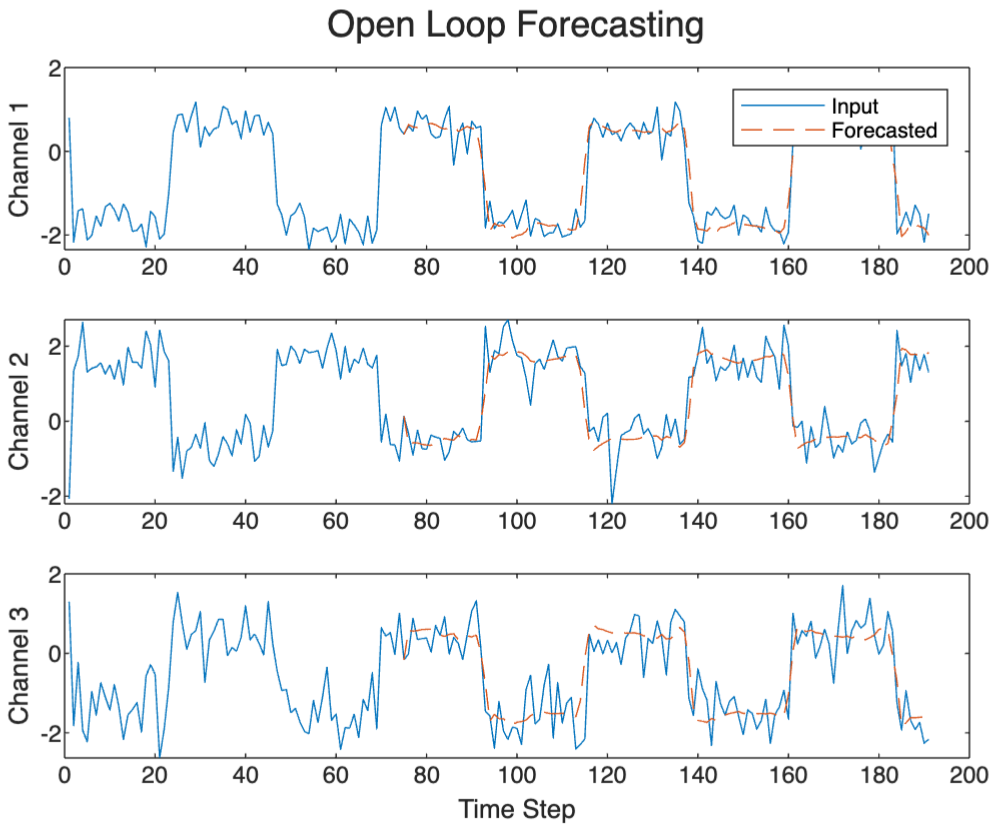
```
net = resetState(net);
%Resets network state before prediction
offset = 75;
[Z,state] = predict(net,X(1:offset,:));
net.State = state;
```

To forecast further predictions, loop over time steps and make predictions using the `predict` function. After each prediction, update the RNN state. Forecast values for the remaining time steps of the test observation by looping over the time steps of the input data and using them as input to the RNN. The last time step of the initial prediction is the first forecasted time step.

```
numTimeSteps = size(X,1);
numPredictionTimeSteps = numTimeSteps - offset;
Y = zeros(numPredictionTimeSteps,numChannels);
Y(1,:) = Z(end,:);

for t = 1:numPredictionTimeSteps-1
    Xt = X(offset+t,:);
    [Y(t+1,:),state] = predict(net,Xt);
    net.State = state;
end
```

Compare the predictions with the input values.

```
figure
t = tiledlayout(numChannels,1);
title(t,"Open Loop Forecasting")

for i = 1:numChannels
    nexttile
    plot(X(:,i))
    hold on
    plot(offset:numTimeSteps,[X(offset,i) Y(:,i)'],"--")
    ylabel("Channel " + i)
end

xlabel("Time Step")
nexttile(1)
legend(["Input" "Forecasted"])
```



Closed Loop Forecasting

Closed loop forecasting predicts subsequent time steps in a sequence by using the previous predictions as input. In this case, the model does not require the true values to make the prediction. For example, say you want to predict the value for time steps t through $t+k$ of the sequence using data collected in time steps 1 through $t-1$ only. To make predictions for time step i, use the predicted value for time step $i-1$ as input. Use closed loop forecasting to forecast multiple subsequent time steps or when you do not have true values to provide to the RNN before making the next prediction.

Initialize the RNN state by first resetting the state using the `resetState` function, then make an initial prediction Z using the first few time steps of the input data. Update the RNN state using all time steps of the input data.

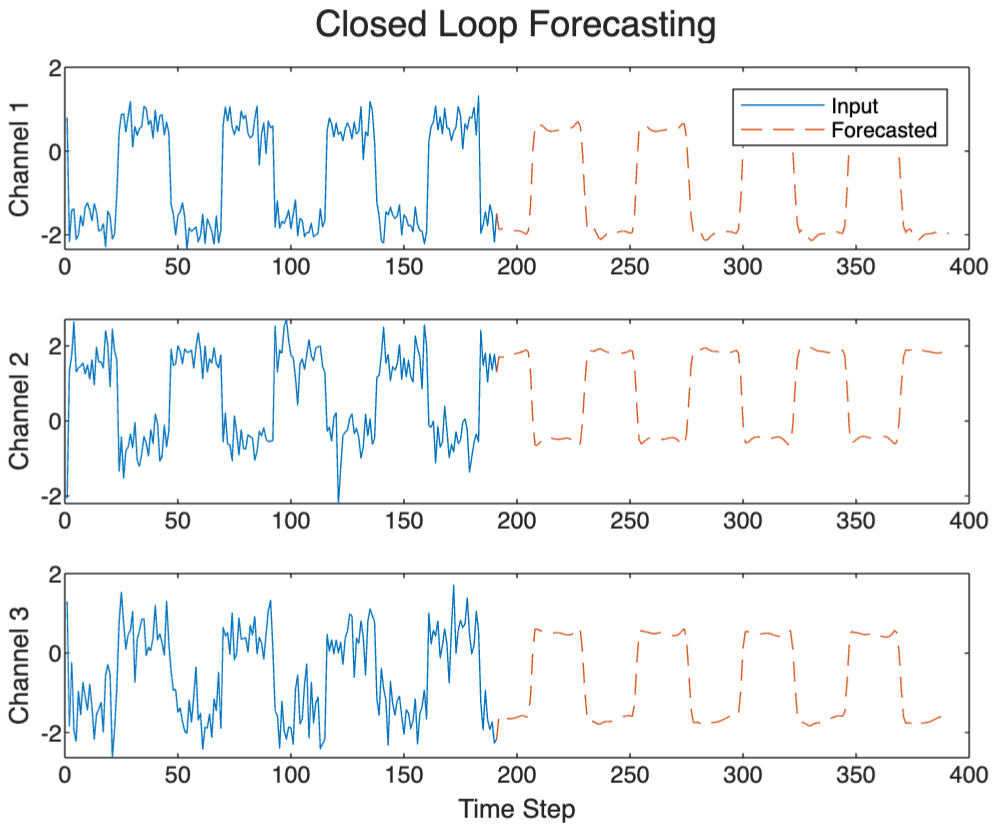
```
net = resetState(net);
offset = size(X,1);
[Z,state] = predict(net,X(1:offset,:));
net.State = state;
```

To forecast further predictions, loop over time steps and make predictions using the `predict` function. After each prediction, update the RNN state. Forecast the next 200 time steps by iteratively passing the previous predicted value to the RNN. Because the RNN does not require the input data to make any further predictions, you can specify any number of time steps to forecast. The last time step of the initial prediction is the first forecasted time step.

```
numPredictionTimeSteps = 200;
Y = zeros(numPredictionTimeSteps,numChannels);
Y(1,:) = Z(end,:);

for t = 2:numPredictionTimeSteps
    [Y(t,:),state] = predict(net,Y(t-1,:));
    net.State = state;
end
```

Visualize the forecasted values in a plot.

```
numTimeSteps = offset + numPredictionTimeSteps;

figure
t = tiledlayout(numChannels,1);
title(t,"Closed Loop Forecasting")

for i = 1:numChannels
    nexttile
    plot(X(1:offset,i))
    hold on
    plot(offset:numTimeSteps,[X(offset,i) Y(:,i)'],"--")
    ylabel("Channel " + i)
end

xlabel("Time Step")
nexttile(1)
legend(["Input" "Forecasted"])
```



Closed loop forecasting allows you to forecast an arbitrary number of time steps, but can be less accurate when compared to open loop forecasting because the RNN does not have access to the true values during the forecasting process.