CS/ECE 528: Embedded Systems and Machine Learning
Fall 2023

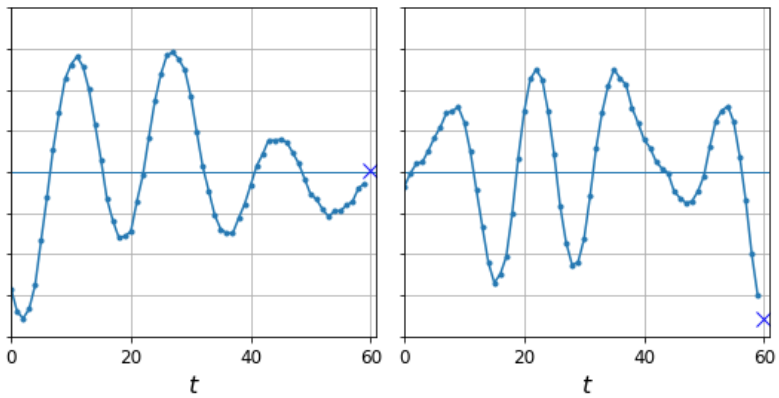
Homework/Lab 4: Time Series Prediction and Classification

Assigned: 12 October 2023
Due: 19 October 2023

Instructions:

- Submit your solutions via Canvas.
- Submissions should include your jupyter notebooks in a zip file, with notebooks names q1.ipynb, q2.ipynb, etc. in a single folder. You can include comments in your notebooks to explain your design choices.
- **"Save and checkpoint" your notebook after running your notebook, so that cell outputs are preserved.** If you are using Colab, make sure to 'Save' your notebook after running it, before downloading it and submitting.

Q1. (50 points) Consider the problem of forecasting a time series (e.g., stock price, temperature readings). We will consider the case of a time series with a single value per time step, which is called a univariate time series. A typical task is to predict future values, which is called forecasting. In this question you will forecast a single value for time series data. The ***notebook univariate-time-series-1-step.ipynb*** contains code that loads a time series dataset with 12,000 time series, each with 60 steps, and the goal here is to forecast the value at the next time step for each of them. The figure below shows two of the time series, with X representing the forecasted value at the 61st time step.



The 12,000 time series are split up into 9000 training, 2000 validation, and 1000 test time series. The notebook contains a simple linear regression model that achieves a mean square error (MSE) of 0.00142 on the test set. Design an RNN-based model with the lowest possible MSE for the test dataset that outperforms this model. Your score will depend on the MSE value achieved by your model.

Q2. (50 points) In this question you will forecast multiple values for time series data. The notebook ***univariate-time-series-multi-step.ipynb*** contains code that is similar to that in Q1 except that now the time series must be predicted for 10 steps instead of just 1 step in the future. The notebook contains a simple linear regression model that achieves a mean square error (MSE) of 0.0454 on the test set. Design an RNN-based model with the lowest possible MSE for the test dataset that outperforms this model. Your score will depend on the MSE value achieved by your model.

Q3. (50 points) Instead of training the model to forecast the next 10 values only at the very last time step as we did in Q2, we can train it to forecast the next 10 values at each and every time step. In other words, we can turn this sequence-to-vector RNN into a sequence-to-sequence RNN. The advantage of this technique is that the loss will contain a term for the output of the RNN at each and every time step, not just the output at the last time step. This means there will

be many more error gradients flowing through the model, and they will also flow from the output of each time step. This will both stabilize and speed up training. To be clear, at time step 0 the model will output a vector containing the forecasts for time steps 1 to 10, then at time step 1 the model will forecast time steps 2 to 11, and so on. So each target must be a sequence of the same length as the input sequence, containing a 10-dimensional vector at each step.

To turn the model into a sequence-to-sequence model, we must set return_sequences=True in all recurrent layers (even the last one), and we must apply the output Dense layer at every time step. Keras offers a TimeDistributed layer for this very purpose: it wraps any layer (e.g., a Dense layer) and applies it at every time step of its input sequence. It does this efficiently, by reshaping the inputs so that each time step is treated as a separate instance (i.e., it reshapes the inputs from [batch size, time steps, input dimensions] to [batch size × time steps, input dimensions]; then it runs the Dense layer, and finally it reshapes the outputs back to sequences (i.e., it reshapes the outputs from [batch size × time steps, output dimensions] to [batch size, time steps, output dimensions]. Another change that needs to be made is related to the loss metric. While all outputs are needed during training, only the output at the last time step is useful for predictions and for evaluation. So although we will rely on the MSE over all the outputs for training, we will use a custom metric for evaluation, to only compute the MSE over the output at the last time step

The notebook ***univariate-time-series-multi-step-enhanced.ipynb*** contains code that is similar to that in Q2 except for the variations discussed in this question. The notebook contains a simple linear regression model that achieves a last time step mean square error (MSE) of 0.096 on the test set. Note the use of the TimeDistributed layer in the model and the calculation of the last step MSE. Design a RNN-based model with the lowest possible last step MSE for the test dataset that outperforms this model. Your score will depend on the MSE value achieved by your model.

Q4. (100 points) In this question we will explore classification on timeseries data. The dataset consists of a set of timeseries corresponding to a measurement of engine noise captured by a vehicle sensor. The goal is to classify each timeseries as ‘normal’ or ‘faulty’ (i.e., binary classification). The notebook ***timeseries_noise_classification.ipynb*** contains code that performs basic classification on this time series data. Your goal is to design a model that can achieve at least 75% accuracy on the test dataset. You can consider exploring 1D convolutional, dense, and other layer types in your model; as well as suitable values for training hyperparameters.