INTRODUCTION TO SEQUENCE CLASSIFICATION USING KERAS

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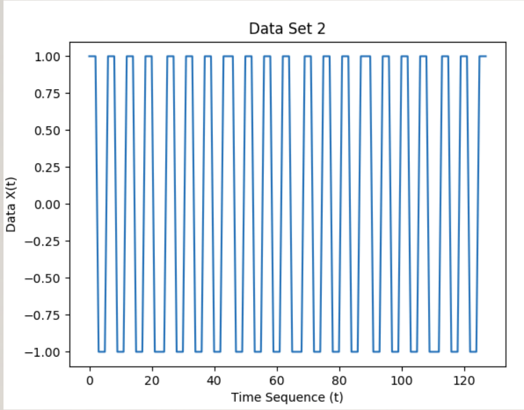
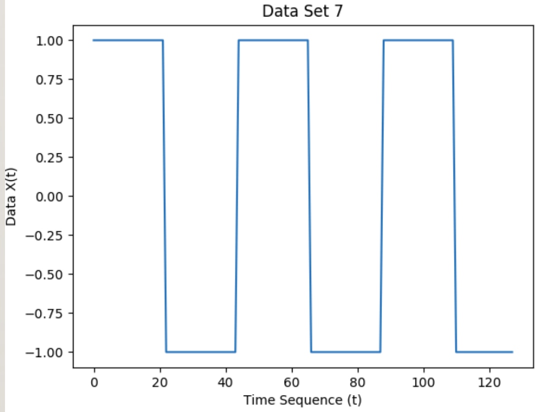
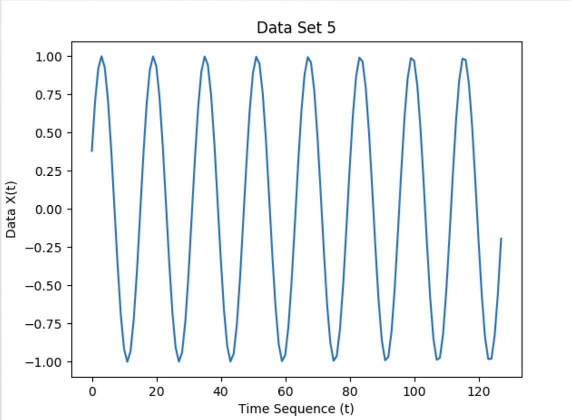
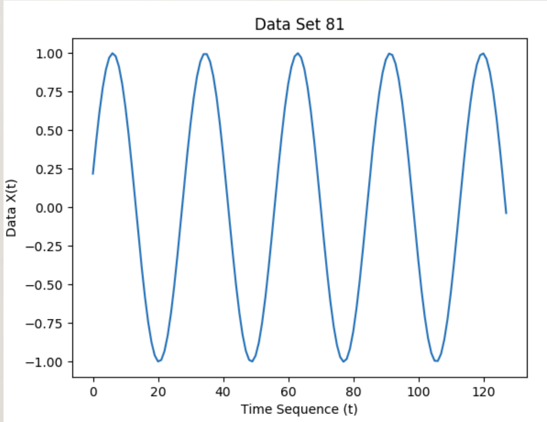
PROBLEM DEFINITION

- Consider a binary classification problem – where we have 2 classes – and we are asking the AI to examine time series data from two different types of time series:







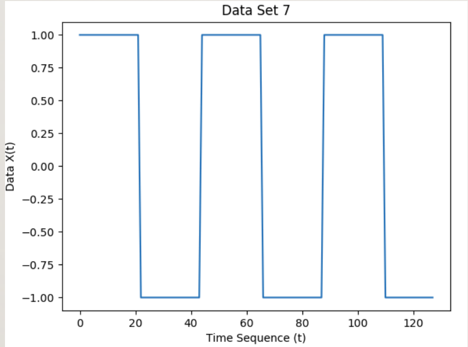


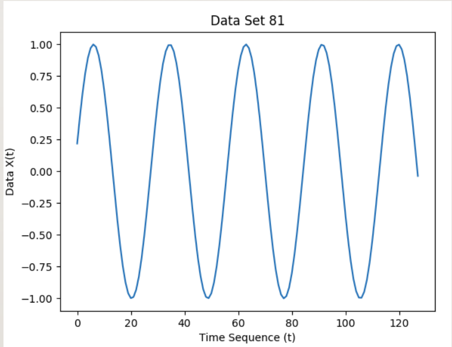
$$x(t) = square(0.1 + 0.3R_F)$$

$$x(t) = \sin(0.1 + 0.3R_F)$$

PROBLEM DEFINITION

- Can we create a machine learning tool which is able to load the sequence of data from a file and be able to distinguish between a sine or square wave for an arbitrary frequency?





- This is the goal of this tutorial – to achieve this goal, we will use Keras - a high end API which runs on top of Tensorflow.
- To train our neural network, we will need to create training data sets.

PROBLEM DEFINITION

- The data for each time series – or sequence – is separated into two folders:
  - A training folder (./Train) which contains a large number of files used for training.
  - A testing folder (./Test) which contains the data we will use to test our model.

    In each directly, we see X files (containing time series) and Y files (containing the classification, 1 or 0).

    All files are binary, double precision.

X_159.dat	X_2.dat	X_6.dat	Y_10.dat	Y_140.dat	Y_181.dat
X_16.dat	X_20.dat	X_60.dat	Y_100.dat	Y_141.dat	Y_182.dat
X_160.dat	X_200.dat	X_61.dat	Y_101.dat	Y_142.dat	Y_183.dat
X_161.dat	X_21.dat	X_62.dat	Y_102.dat	Y_143.dat	Y_184.dat
X_162.dat	X_22.dat	X_63.dat	Y_103.dat	Y_144.dat	Y_185.dat
X_163.dat	X_23.dat	X_64.dat	Y_104.dat	Y_145.dat	Y_186.dat
X_164.dat	X_24.dat	X_65.dat	Y_105.dat	Y_146.dat	Y_187.dat
X_165.dat	X_25.dat	X_66.dat	Y_106.dat	Y_147.dat	Y_188.dat
X_166.dat	X_26.dat	X_67.dat	Y_107.dat	Y_148.dat	Y_189.dat
X_167.dat	X_27.dat	X_68.dat	Y_108.dat	Y_149.dat	Y_19.dat
X_168.dat	X_28.dat	X_69.dat	Y_109.dat	Y_15.dat	Y_190.dat
X_169.dat	X_29.dat	X_7.dat	Y_11.dat	Y_150.dat	Y_191.dat
X_17.dat	X_3.dat	X_70.dat	Y_110.dat	Y_151.dat	Y_192.dat

PROBLEM DEFINITION

- For your reference, these files were generated using the MATLAB functions included in the Train and Test folders.
- From the MATLAB command prompt, call Generate_Data(N) where N is an integer. This will create N data files, numbered from 1 to N.
- You can see how these data files are generated – approximately half of them will be sine waves, the other have square waves.
- We could modify these MATLAB scripts for multi-class classification problems easily.

```
function [u] = Generate_Data(N)
% Dr. Matthew Smith, Swinburne University of Technology
% Generate N data files, each containing a time series
% (i.e. sequence) corresponding to one of two classes:
% Y = 0 : Sine Wave
% Y = 1 : Square wave
% Each file will employ a different phase and frequency
% so give the RNN some degree of challenge.

Sequence_size = 128; % 128 values in each time series

for i = 1:1:N

   filename_x = sprintf('X_%d.dat', i);
   filename_y = sprintf('Y_%d.dat', i);
   if (rand() < 0.5)
       % Make a sin wave
       freq = 0.1 + rand()*0.3;
       y = 0;
       x = 1:1:128;
       fx = sin(freq*x);
   else
       % Make a square wave
       freq = 0.1 + rand()*0.3;
       y = 1;
       x = 1:1:128;
       fx = square(freq*x);
   end
   % Now to save each
   fileID = fopen(filename_x,'w');
   fwrite(fileID, fx, 'double');
   fclose(fileID);
   fileID = fopen(filename_y,'w');
```

PROBLEM DEFINITION

- The mission, theoretically, is pretty straight forward:
  - Using Python (Python 2.7 to be exact), load both the training sets and testing sets of data.
  - Use Keras / Tensorflow to build a Recurring Neural Network (RNN) with numerous layers to create a model.
  - Use this model with our testing data to check its accuracy.
  - We will use python's matplotlib to perform some visualization of the accuracy obtained during the training process.

PROBLEM DEFINITION

- Questions we want to investigate at this stage are:
    - How do we use the Ozstar environment to perform this work?
    - How does the number of training data sets used influence the convergence and final accuracy?
    - How many epochs are required to see acceptable results?

PREPARATION – OZSTAR MODULES

- When using Ozstar to perform computation, only several very basic tools are loaded when you log in.
- To load functionality into our Ozstar environment, we use modules to load what we need.

```
module purge all
module load numpy/1.14.1-python-2.7.14
module load tensorflowgpu/1.6.0-python-2.7.14
module load scikit-learn/0.19.1-python-2.7.14
module load pandas/0.22.0-python-2.7.14
module load keras/2.1.4-python-2.7.14
```

- The modules we require are shown on the right – we could load them in one-by-one, but that would be a waste of time.
- Write them into a bash script (script.sh) using an editor you are comfortable with.
- Load the modules by typing ”. script.sh <enter>” (no quotation marks).

INTRODUCTION TO KERAS

- Today's tutorial includes several python files:

  - train.py – the main script which, when called, loads the training and test data sets, creates the Keras model and defines the neural network, performs the training and tests the model.
  - utilities.py – a script containing simple functions for loading data from files and plotting using matplotlib. This is not called directly; it contains functions called by train.py and view.py,
  - view.py – a stand-alone script which is used to inspect training data for your own verification purposes (i.e. sanity checking).

REVIEW OF TRAIN.PY

TRAIN.PY

- As with most python scripts, we start by loading modules.
- After loading modules, we define the number of training data sets to load (N_train) – here, we have 200 data sets.
- Each data set contains a time series with 128 elements (N_sequence).

```
# train.py
# Written by Dr. Matthew Smith, Swinburne University of Technology
# Prepared as training material for ADACS Machine Learning workshop
# This is an example of time series (sequence) classification
# for a binary classification problen.

# Import modules
import numpy as np
from keras.models import Sequential
from keras.layers import Dense
#from keras.layers import LSTM
from keras.layers import Activation
from keras.utils import plot_model
from utilities import *

# Create training arrays
# In this demonstration I create our numpy arrays and then
# load each time sequence in one-by-one.
N_train = 200          # Number of elements to train
N_sequence = 128       # Length of each piece of data
N_epochs = 300         # Number of epochs

# Create the training sequence data (X) and each set's classification (Y).
X_train = np.empty([N_train, N_sequence])
Y_train = np.empty(N_train)
```

TRAIN.PY

- We only load in the parts of Keras which we need.

- In this work, we are performing a neural network analysis on time series data - in keras, this form of analysis is known as a Sequential analysis – hence, we need to import Sequential.

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TRAIN.PY - SEQUENTIAL

- To employ Neural Networks for learning over time sequences of data, we use a Recurring Neural Network (RNN).
- A Recurrent neural networks is a deep neural neural network which has, as the name suggests, recurring inputs to the hidden layer i.e. the output from a hidden layer is fed back to itself.

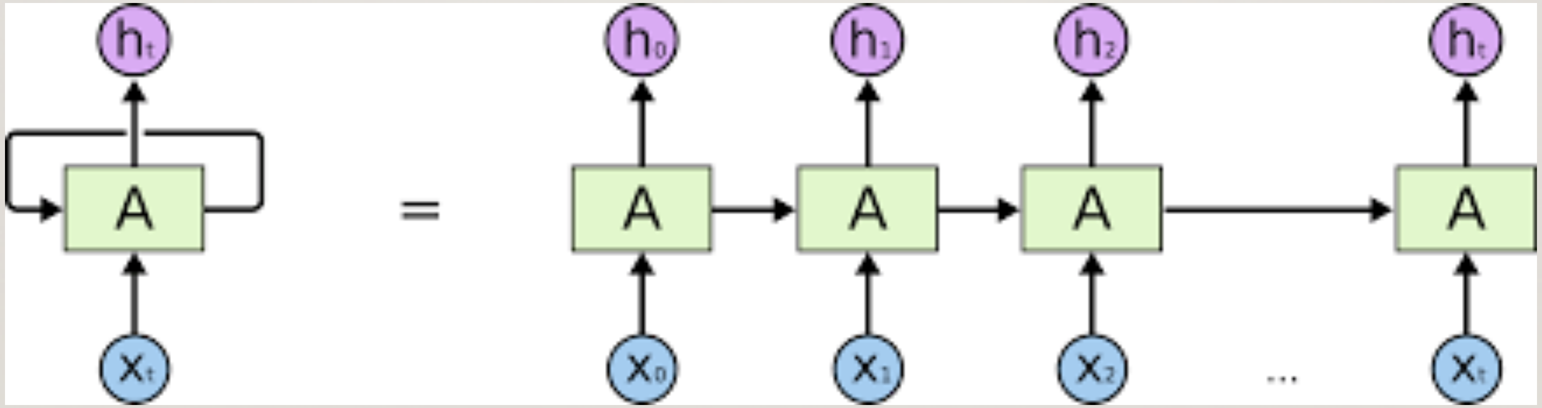

Image: https://medium.com/themlblog/time-series-analysis-using-recurrent-neural-networks-in-tensorflow-2a0478b00be7

TRAIN.PY - SEQUENTIAL

- Here, A – our neural network – may contain numerous layers - is repeatedly fed consecutive data from our time series. This is to ensure that the history of our time data is taken into account – that we have what we might describe as a Neural Memory.
- Neural memory is the ability imparted to a model to retain the input from previous time steps when the input is sequential.

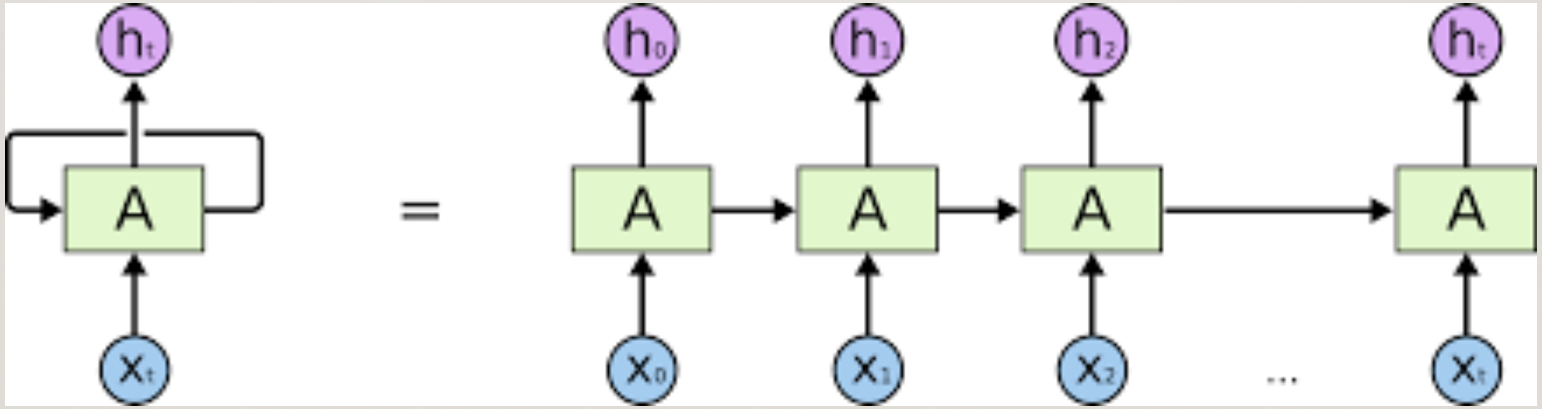

Image: https://medium.com/themlblog/time-series-analysis-using-recurrent-neural-networks-in-tensorflow-2a0478b00be7

TRAIN.PY - SEQUENTIAL

- One potential problem with very large data sets is that information – which might tend to be very important on a small time scale in the the large time sequence – tends to disappear into the background when the process is repeated over very large time steps.
- We can use an approach called Long-short Term Memory networks(LSTM) to solve this problem.
- In this case, we won't – our sequences are quite short, and periodic – but modification of this script to perform this improvement over conventional RNN is quite simple.

TRAIN.PY

- Since – in this case – our data is small, we can load it all at once into memory.
- We create two numpy arrays (X_train and Y_train) to hold our training data – initially empty.
- We then load each file (one by one) using the read_training_data function contained in utilities.py
- We repeat the process for the testing data set.

```python
# Create the training sequence data (X) and each set's classification (Y).
X_train = np.empty([N_train, N_sequence])
Y_train = np.empty(N_train)

# Load the data from file
for x in range(N_train):
        # This will create x = 0, 1, 2...to N_train-1
        X_train[x,], Y_train[x] = read_training_data(x+1, N_sequence)

# Also create the numpy arrays for the testing data set
N_test = 50
X_test = np.empty([N_test, N_sequence])
Y_test = np.empty(N_test)
for x in range(N_test):
        X_test[x,], Y_test[x] = read_test_data(x+1, N_sequence)
```

We might have used only one variable (X_train) for both testing and training using splitting in Keras – you can google this if you are interested.

Keras has numerous strategies for managing data which is too large to fit into memory in a single instance, using data generators.

TRAIN.PY

- We start by creating a Keras Sequential model:

```
# Create our Keras model - an RNN (in Keras this is a Sequence)
model = Sequential()

# Configure our RNN by adding neural layers with activation functions
model.add(Dense(16, activation='relu',input_dim=N_sequence))
model.add(Dense(8, activation='tanh'))
model.add(Dense(1, activation='sigmoid'))
```

- The model variable holds our neural network, weights and all parameters.
- The Sequential class also has a large number of class functions, some of which we will see later on in this tutorial.

TRAIN.PY

- We add hidden Neural layers to the model using the add() function.

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```

- The first layer we are adding is a densely connected neural layer with an input of N_sequence – we are inputting each piece of time series data as an input - and an intermediate output of 16 neurons.
- Each layer has an associated activation function – in this case, it is ‘relu’ - Rectified Linear Unit.

TRAIN.PY

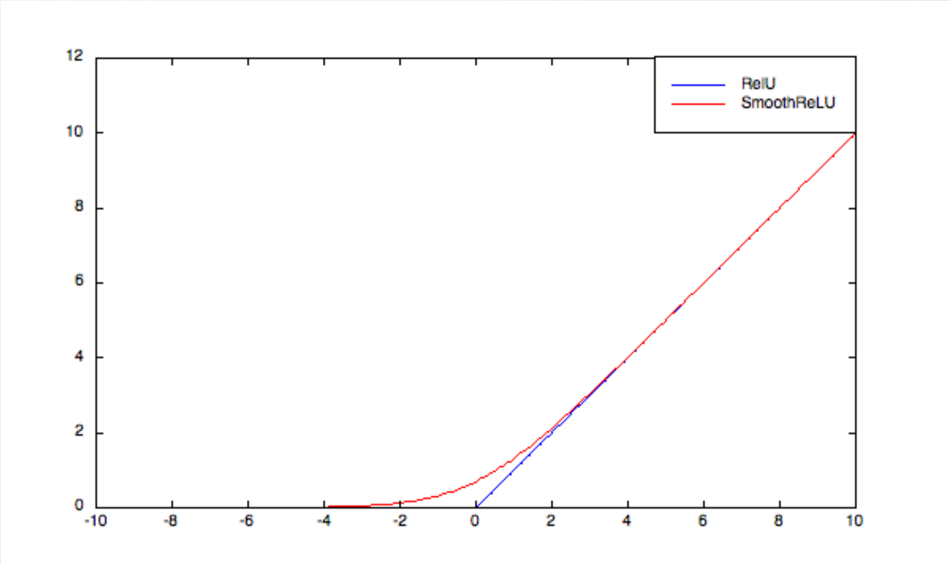
- The relu function is defined as the maximum positive part of its argument tensor:

$$f(x) = \max(0, x)$$

- It has found popular use in deep learning networks in recent years, but is discontinuous. A smooth option is SmoothReLU:

$$f(x) = \log(1 + \exp(x))$$

- We use relu due to its ability to pass gradient information between subsequent iterations – allowing us to avoid the use of LSTM for now.



TRAIN.PY

- We then add another layer, using a different activation function (which you might comment out)

```
# Create our Keras model - an RNN (in Keras this is a Sequence)
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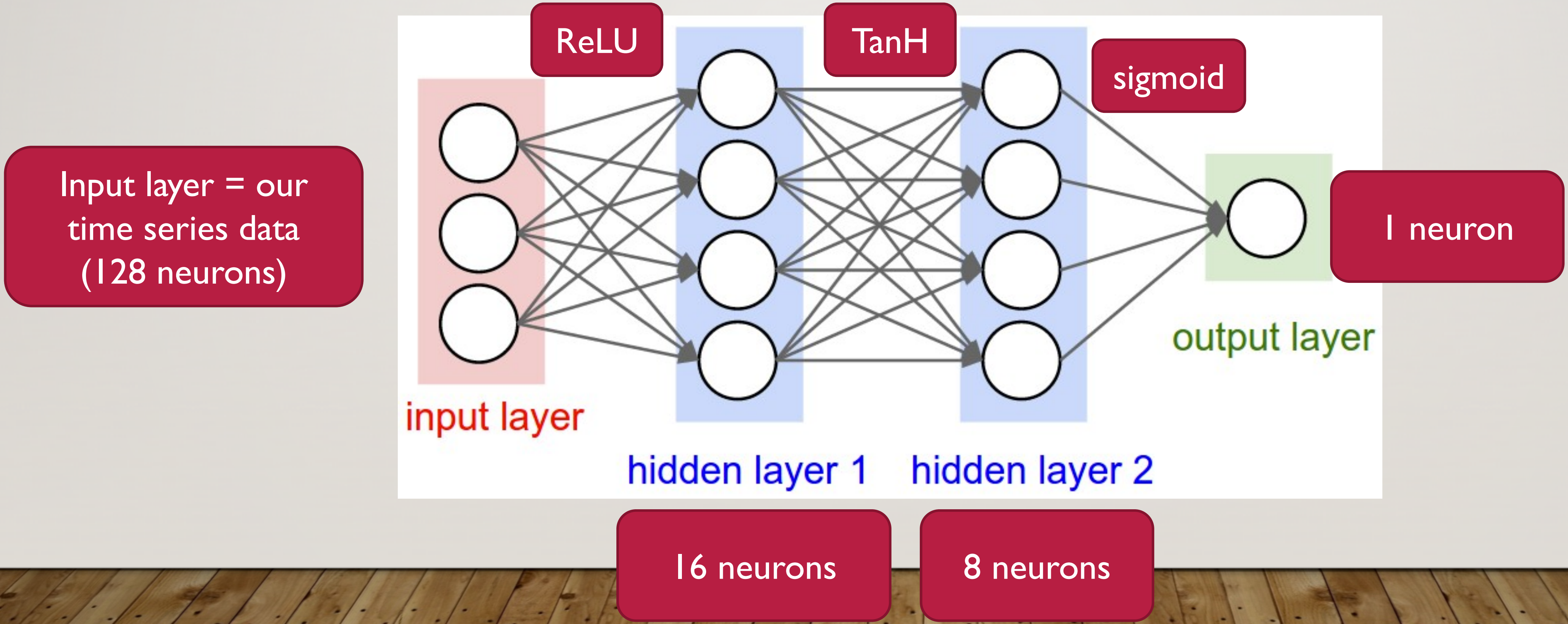
model.add(Dense(16, activation='relu',input_dim=N_sequence))
model.add(Dense(8, activation='tanh'))
model.add(Dense(1, activation='sigmoid'))
```

- This time we use the tanh function – this is a non-linear function, which allows us to introduce non-linear dependences into our neural network.
- We've also changed the number of neurons in the layer to 8 – all of which are fully connected (dense).

TRAIN.PY

- The result is something like this – only don't pay attention to the number of neurons in each layer.



TRAIN.PY

- We need to compile our Keras model before we start:

```
# Compile model and print summary
model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['accuracy'])
print(model.summary())

# Fit the model using the training set
history = model.fit(X_train, Y_train, epochs=N_epochs, batch_size=32)

# Plot the history
plot_history(history)
```

- An optimizer is a function designed to increase learning speed – we can specify these separately if we wish to alter the learning rate etc – find more info here: https://keras.io/optimizers/
- Our loss function is the function used to measure the effectiveness of the learning (for the optimizer) – the binary cross entropy function has found favour recently for binary classification.

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TRAIN.PY

- Finally we can perform our fit:

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print(model.summary())

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plot_history(history)
```
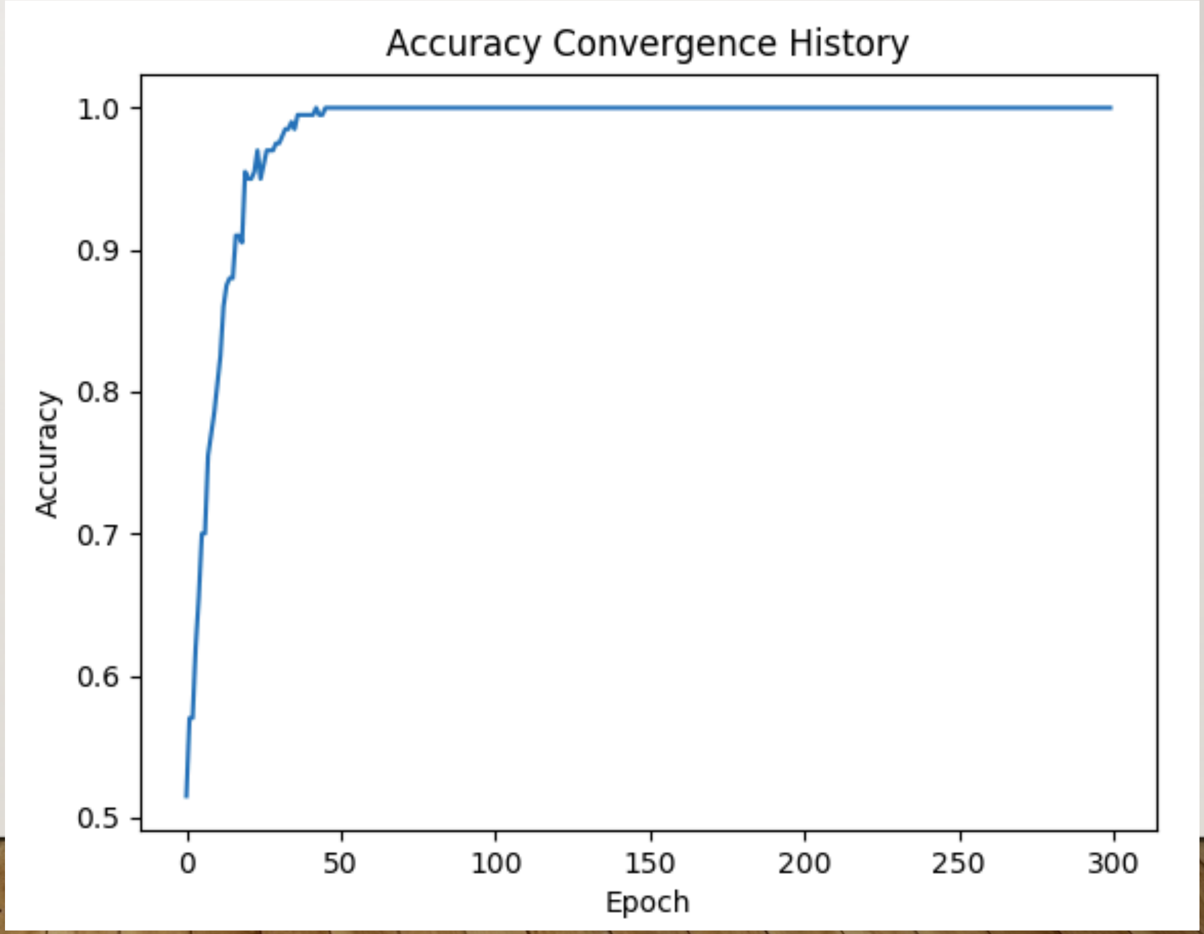

- The training process is repeated for all training sets N_epochs time – this value should be large enough that we demonstrate convergence on the accuracy computed during training.
- To inspect this, we plot the history using the plot_history function inside utilities.py

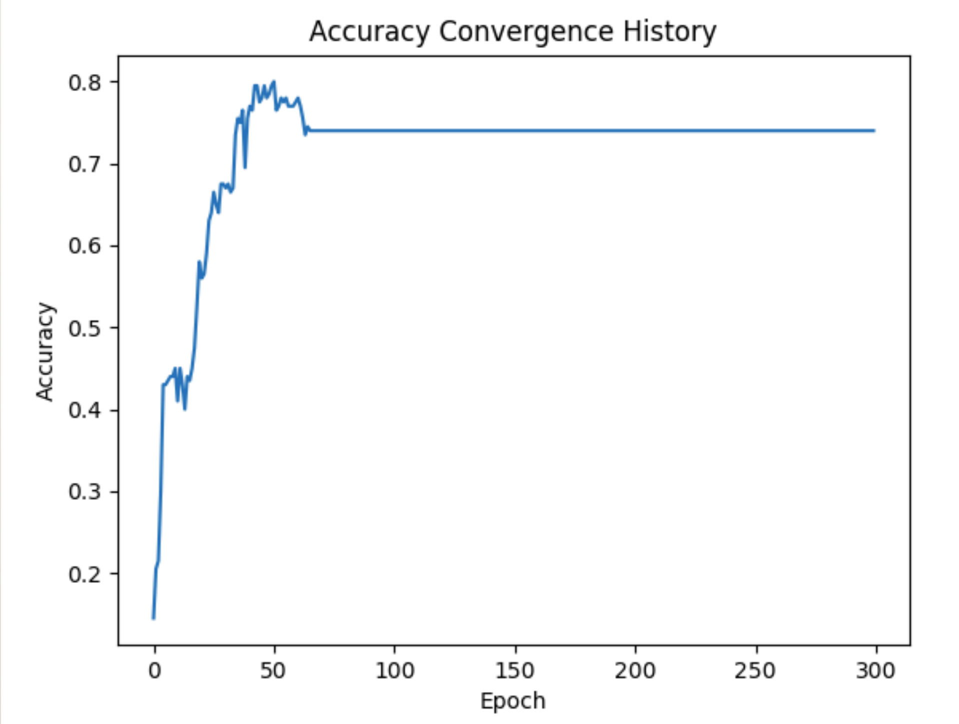
RESULTS

- After running the script with N_epochs = 300 with 200 training sets, you should see convergence look like this.
- This was with 2 layers of neurons – you should experiment by adding various numbers (and sizes) of neuron layers; it will influence the accuracy convergence.



DISCUSSION - ACTIVATORS

- Consider the case where we have a single neural layer and no activation functions.
- Hence, the relationship between input and output is strictly linear.
- We can see that the machine is incapable of learning – indicating to us that some manner of non-linearity exists.



https://towardsdatascience.com/exploring-activation-functions-for-neural-networks-73498da59b02

NEXT STEPS

- There are several improvements we might build into this example.

- Use the time you have now to experiment with different numbers of layers, different numbers of neurons in each layer, and different activation functions, and inspect the influence these changes have on the learning speed.