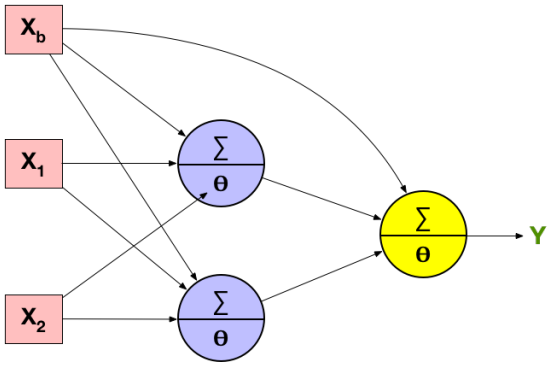
GALWAY-MAYO INSTITUTE OF TECHNOLOGY

Department of Computer Science & Applied Physics

Learning XOR with A Multilayer Perceptron

Overview

A single-layer perceptron is only capable of learning a linear-separable function. While logical OR and AND are linear-separable, the XOR operation requires an additional layer to represent the extra dimension needed for the computation. In this lab we will use the following design to create a Multilayer Perceptron (MLP) capable of learning the XOR rule. The 3-network consists of three input nodes, a hidden layer of two nodes and a single-node output layer.



While the MLP acronym is often used for the topology shown above, it is an inaccurate description of the network as the nodes use a sigmoidal activation function, as opposed to the step function of the Rosenblatt perceptron. Indeed, because of the sigmoidal activation function, the network above is more consistent with the original neurons described by McCulloch and Pitts. Note that it is not possible to simulate a perfect logical gate with a sigmoidal output neuron because the range is [0,1], but it can be approximated. Even a simple neural network (NN) like the one shown above will require a large number of epochs before the actual and expected outputs converge.

Exercises

- ***Create a new class called XORRunner***. Add a ***main()*** method and the following static Method to round the output to the nearest Boolean value:

```
public static long getRoundedValue(double[] vector){
  return Math.round(vector[0]);
}
```

- ***Specify the following elements as the training set*** (data and expected values):

```
double[][] data = {{0, 0}, {1, 0}, {0, 1}, {1, 1}};
double[][] expected = {{0}, {1}, {1}, {0}};
```

- ***Create an instance of the class NeuralNetwork with*** 2 input nodes, 2 hidden nodes, one output node and a sigmoidal activation function:

```
NeuralNetwork nn = new NeuralNetwork(Activator.ActivationFunction.Sigmoid, 2, 2, 1);
```

- ***Instantiate the back-propagation training algorithm*** and ask it to train the network with the training data, a learning rate of 0.01 and a maximum of 1,000,000 epochs.

```
BackpropagationTrainer trainer = new BackpropagationTrainer(nn);
trainer.train(data, expected, 0.01, 1000000);
```

  Note the large number of epochs specified. This is necessary as the sigmoidal activation function represents a continuum of values, as opposed to the discrete step function. If the neural network output converges with the training data before the maximum number of epochs is reached, then the training will terminate early.

- ***Create the following four data sets*** required to test if the network is fully trained. These correspond to the truth table permutations for the two operands of the XOR operator.

```
double[] test1 = {0.0, 0.0};
double[] test2 = {1.0, 0.0};
double[] test3 = {0.0, 1.0};
double[] test4 = {1.0, 1.0};
```

- Execute each test and round the result using the getRoundedValue() to convert the sigmoidal output to a binary value:

```
System.out.println("00=>" + getRoundedValue(nn.process(test1)));
```

  Execute the test data a number of times to see if the network is stable. A stable neural network consistently returns a result that is consistent with the training data.

- Progressively ***increase the learning rate*** to {0.05, 0.1, 0.2, 0.3, 0.4, 0.5} and examine the effect that this has on the output.

- Progressively ***reduce the number of epochs*** to {500,000, 100,000, 50,000, 10,000, 1000, 500, 100} and examine the effect that this has on the output.

- ***Change the activation function*** to a hyperbolic tangent function and examine the effect that this has on the output.