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IMPLEMENTATION OF BACK PROPAGATION ALGORITHM USING MATLAB

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Abstract: Artificial Neural Network (ANN) are highly interconnected and highly parallel systems. Back Propagation is a common method of training artificial neural networks so as to minimize objective function. This paper describes the implementation of back propagation algorithm. The error generated at the output is fed back to the input and weights of the neurons are updated by supervised learning and it is a generalization of delta rule. The sigmoid function is used as a activation function. The design is simulated using MATLAB R2008a version. Maximum accuracy has been achieved.

Keywords: Artificial Neural Network, Back Propagation Algorithm, MATLAB.

1. INTRODUCTION

Back Propagation was created by generalising the Widrow-Hoff learning rule to multiple layer network and non linear differentiable transfer function. Input vectors and corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way. Networks with biases, a sigmoid layer and a linear output layer are capable of approximating any function with a finite number of discontinuities. Feed forward networks often have one or more hidden layers of sigmoid neurons followed by output layer of linear neurons. Multiple layers of neurons with non linear transfer functions allow the network to learn non linear and linear relationships between input and output vectors. The linear output layer lets the network produce values outside the range – 1 to +1.

2. SIGMOID ACTIVATION FUNCTION

If we want to constrain the outputs of network between 0 and 1, then the output layer should use a log-sigmoid transfer function. Before training a feed forward network, the weight and biases must be initialized. Once the network weights and biases have been initialized, the network is ready for training. We used random numbers around zero to initialize weights and biases in the network. The training process requires a set of proper inputs and targets as outputs. During training, the weights and biases of the network are iteratively adjusted to minimize the network performance function. The default performance function for feed forward networks is mean square errors, the average squared errors between the network outputs and the target output. Often the sigmoid function refers to the special case of the logistic function and defined by the formula:

$$f(x) = \frac{1}{1+e^{-x}}$$

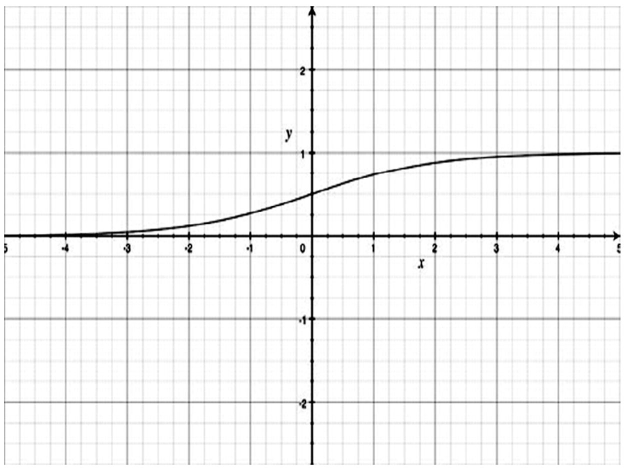

Figure 1: Sigmoid Function

3. IMPLEMENTATION USING MATLAB

The neural network explained here contains three layers. These are input, hidden, and output layers. During the training phase, the training data is fed into the input layer. The data is propagated to the hidden layer and then to the output layer. This is called the forward pass of the back propagation algorithm. In forward pass, each node in hidden layer gets input from all the nodes from input layer, which are multiplied with appropriate weights and then summed.

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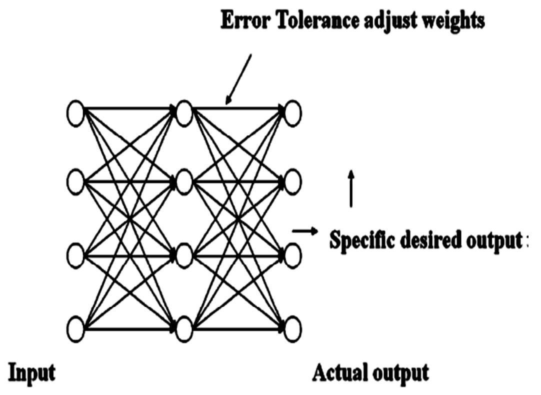


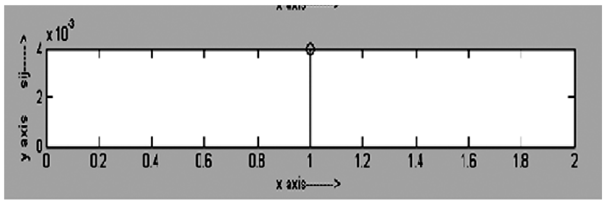
The output of the hidden node is the non-linear transformation of the this resulting sum. Similarly each node in output layer gets input from all the nodes from hidden layer, which are multiplied with appropriate weights and then summed. The output of this node is the non-linear transformation of the resulting sum. The output values of the output layers are compared with the target output values. The target output values are those that we attempt to teach our network. The error between actual output values and target output values is calculated and propagated back towards hidden layer. This is called the backward pass of the back propagation algorithm. The error is used to update the connection strengths between nodes, i.e. weight matrices between input-hidden layers and hidden-output layers are updated. During the testing phase, no learning takes place i.e., weight matrices are not changed. Each test vector is fed into the input layer. The feed forward of the testing data is similar to the feed forward of the training data.

The formula for entity synapse $s1$ is:

$$m_{ij} = i * w_{ij}$$

$$s_j = m_{ij} \times 4$$

s_j is the sum of neurons, m_{ij} are the intermediate weights, i is the input to neurons. The waveform for this equation is shown below:



Formula for entity neuron $n1$:

$$O_j = \frac{1}{1 + e^{-sj}}$$

$$\text{der}_{j=O_j} * (1 - o_j)$$

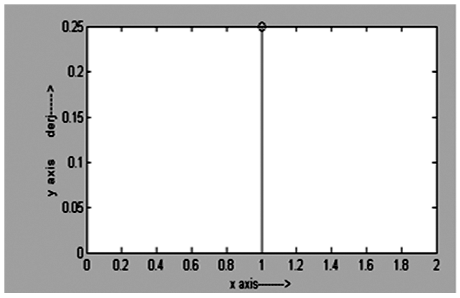


Figure 3: Waveform for Entity Neuron n1

The formula for entity error generated at output-$e1$:

$$\text{delta}_{j=(tO-O_j)} * \text{der}_j$$

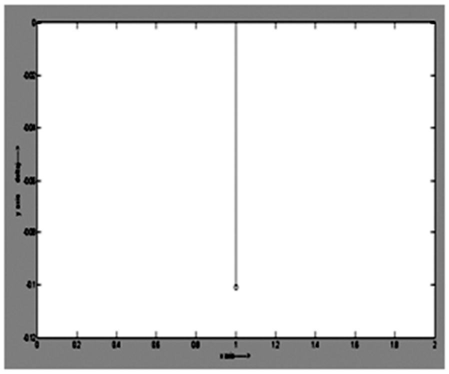


Figure 4: Waveform for Entity e1

Formula for weight update for entity $w1$:

$$\text{delta}_{wij} = w_{ij} - (\text{delta}_{\downarrow} j * O_j)$$

The figure shows the value for the weight update i.e. now the value of weight w_{ij} replaced with this value.

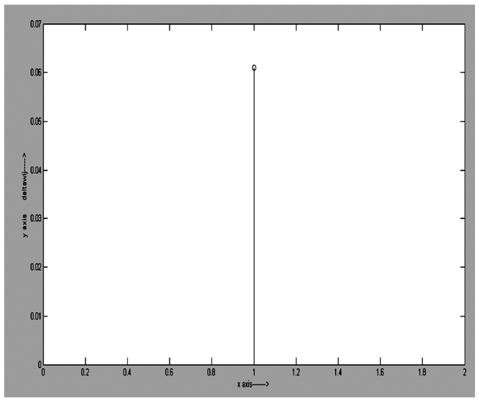


Figure 5: Waveform for Entity w1

Formula for weight transfer is given below i.e. now the value of weight w_{ij} replaced with the value shown in the waveform.

$$w_{ij} = \text{delta } w_{ij}$$

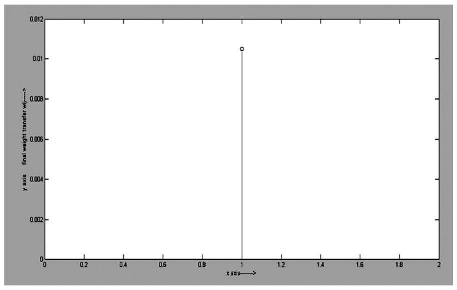
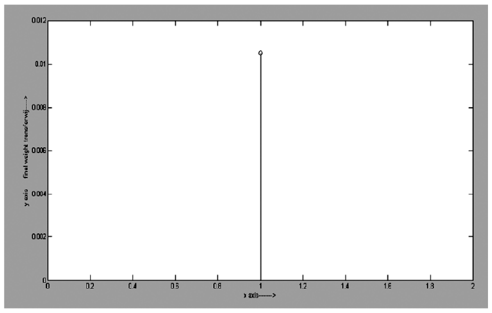


Figure 6: Waveform for Weight Transfer

Formula for final weight transfer is:

$$w_{ij} = \text{delta2 } w_{ij}$$



4. RESULT AND CONCLUSION:

The algorithm is the Error Back propagation learning algorithm for a layered feed forward network and this algorithm has many successful applications for training multilayer neural networks. In this paper the last waveform shows that the weight value becomes constant to minimize the error at the ouitput. So the output remains constant which is the objective of this paper.

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