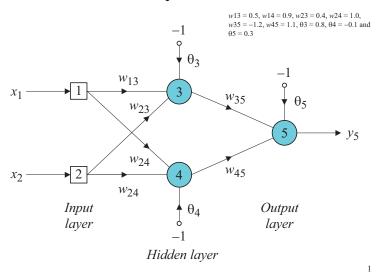
Three-layer network

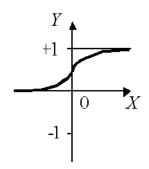


- The effect of the threshold applied to a neuron in the hidden or output layer is represented by its weight, θ , connected to a fixed input equal to -1.
- The initial weights and threshold levels are set randomly e.g., as follows:

$$w_{13} = 0.5$$
, $w_{14} = 0.9$, $w_{23} = 0.4$, $w_{24} = 1.0$, $w_{35} = -1.2$, $w_{45} = 1.1$, $\theta_3 = 0.8$, $\theta_4 = -0.1$ and $\theta_5 = 0.3$.

2

Assuming the sigmoid activation Function



$$Y^{sigmoid} = \frac{1}{1+e^{-X}}$$

Step 2: Activation

Activate the back-propagation neural network by applying inputs $x_1(p), x_2(p), ..., x_n(p)$ and desired outputs $y_{d,1}(p), y_{d,2}(p), ..., y_{d,n}(p)$.

(a) Calculate the actual outputs of the neurons in the hidden layer:

$$y_{j}(p) = sigmoid \left[\sum_{i=1}^{n} x_{i}(p) \cdot w_{ij}(p) - \theta_{j} \right]$$

where n is the number of inputs of neuron j in the hidden layer, and sigmoid is the sigmoid activation function.

Step 2: Activation (continued)

(b) Calculate the actual outputs of the neurons in the output layer:

$$y_k(p) = sigmoid \left[\sum_{j=1}^m x_{jk}(p) \cdot w_{jk}(p) - \theta_k \right]$$

where m is the number of inputs of neuron k in the output layer.

5

If the sigmoid activation function is used the output of the hidden layer is

$$y_3 = sigmoid (x_1w_{13} + x_2w_{23} - \theta_3) = 1/[1 + e^{-(1 \cdot 0.5 + 1 \cdot 0.4 - 1 \cdot 0.8)}] = 0.5250$$

$$y_4 = sigmoid (x_1w_{14} + x_2w_{24} - \theta_4) = 1/[1 + e^{-(1 \cdot 0.9 + 1 \cdot 1.0 + 1 \cdot 0.1)}] = 0.8808$$

And the actual output of neuron 5 in the output layer is

$$y_5 = sigmoid(y_3w_{35} + y_4w_{45} - \theta_5) = 1/[1 + e^{-(-0.52501.2 + 0.88081.1 - 1.0.3)}] = 0.5097$$

And the error is

$$e = y_{d,5} - y_5 = 0 - 0.5097 = -0.5097$$

6

What learning law applies in a multilayer neural network?

$$\Delta w_{jk}(p) = \alpha \cdot y_j(p) \cdot \delta_k(p)$$

Step 3: Weight training output layer

Update the weights in the back-propagation network propagating backward the errors associated with output neurons.

(a) Calculate the error $e_k(p) = y_{d,k}(p) - y_k(p)$

and then the error gradient for the neurons in the output layer: $\delta_k(p) = y_k(p) \cdot [1 - y_k(p)] \cdot e_k(p)$

 $O_k(p) - y_k(p) \cdot [1 - y_k(p)] \cdot e_k$

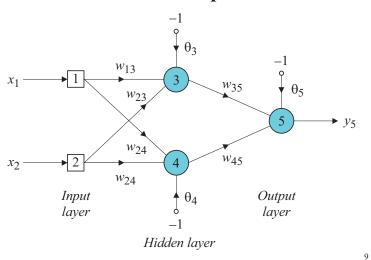
Then the weight corrections:

$$\Delta w_{ik}(p) = \alpha \cdot y_i(p) \cdot \delta_k(p)$$

Then the new weights at the output neurons:

$$w_{jk}(p+1) = w_{jk}(p) + \Delta w_{jk}(p)$$

Three-layer network for solving the Exclusive-OR operation



■ The error gradient for neuron 5 in the output layer:

$$\delta_5 = y_5 (1 - y_5) e = 0.5097 \cdot (1 - 0.5097) \cdot (-0.5097) = -0.1274$$

■ Determine the weight corrections assuming that the learning rate parameter, α , is equal to 0.1:

$$\Delta w_{35} = \alpha \cdot y_3 \cdot \delta_5 = 0.1 \cdot 0.5250 \cdot (-0.1274) = -0.0067$$

$$\Delta w_{45} = \alpha \cdot y_4 \cdot \delta_5 = 0.1 \cdot 0.8808 \cdot (-0.1274) = -0.0112$$

$$\Delta \theta_5 = \alpha \cdot (-1) \cdot \delta_5 = 0.1 \cdot (-1) \cdot (-0.1274) = -0.0127$$

10

Apportioning error in the hidden layer

- Error is apportioned in proportion to the weights of the connecting arcs.
- Higher weight indicates higher error responsibility

Step 3: Weight training hidden layer

(b) Calculate the error gradient for the neurons in the hidden layer:

$$\delta_j(p) = y_j(p) \cdot [1 - y_j(p)] \cdot \sum_{k=1}^l \delta_k(p) w_{jk}(p)$$

Calculate the weight corrections:

$$\Delta w_{ij}(p) = \alpha \cdot x_i(p) \cdot \delta_j(p)$$

Update the weights at the hidden neurons:

$$w_{ij}(p+1) = w_{ij}(p) + \Delta w_{ij}(p)$$

■ The error gradients for neurons 3 and 4 in the hidden layer:

$$\begin{split} \delta_3 &= y_3(1-y_3) \cdot \delta_5 \cdot w_{35} = 0.5250 \cdot (1-0.5250) \cdot (-0.1274) \cdot (-1.2) = 0.0381 \\ \delta_4 &= y_4(1-y_4) \cdot \delta_5 \cdot w_{45} = 0.8808 \cdot (1-0.8808) \cdot (-0.1274) \cdot 1.1 = -0.0147 \end{split}$$

■ Determine the weight corrections:

$$\Delta w_{13} = \alpha \cdot x_1 \cdot \delta_3 = 0.1 \cdot 1 \cdot 0.0381 = 0.0038$$

$$\Delta w_{23} = \alpha \cdot x_2 \cdot \delta_3 = 0.1 \cdot 1 \cdot 0.0381 = 0.0038$$

$$\Delta \theta_3 = \alpha \cdot (-1) \cdot \delta_3 = 0.1 \cdot (-1) \cdot 0.0381 = -0.0038$$

$$\Delta w_{14} = \alpha \cdot x_1 \cdot \delta_4 = 0.1 \cdot 1 \cdot (-0.0147) = -0.0015$$

$$\Delta w_{24} = \alpha \cdot x_2 \cdot \delta_4 = 0.1 \cdot 1 \cdot (-0.0147) = -0.0015$$

$$\Delta \theta_4 = \alpha \cdot (-1) \cdot \delta_4 = 0.1 \cdot (-1) \cdot (-0.0147) = 0.0015$$

■ At last, we update all weights and threshold:

$$\begin{aligned} w_{13} &= w_{13} + \Delta w_{13} = 0.5 + 0.0038 = 0.5038 \\ w_{14} &= w_{14} + \Delta w_{14} = 0.9 - 0.0015 = 0.8985 \\ w_{23} &= w_{23} + \Delta w_{23} = 0.4 + 0.0038 = 0.4038 \\ w_{24} &= w_{24} + \Delta w_{24} = 1.0 - 0.0015 = 0.9985 \\ w_{35} &= w_{35} + \Delta w_{35} = -1.2 - 0.0067 = -1.2067 \\ w_{45} &= w_{45} + \Delta w_{45} = 1.1 - 0.0112 = 1.0888 \\ \theta_{3} &= \theta_{3} + \Delta \theta_{3} = 0.8 - 0.0038 = 0.7962 \\ \theta_{4} &= \theta_{4} + \Delta \theta_{4} = -0.1 + 0.0015 = -0.0985 \\ \theta_{5} &= \theta_{5} + \Delta \theta_{5} = 0.3 + 0.0127 = 0.3127 \end{aligned}$$

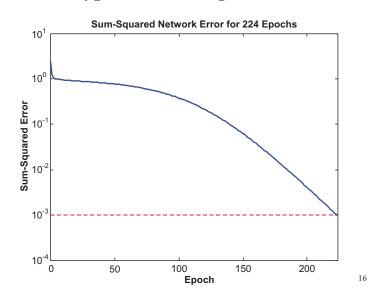
■ The training process is repeated until the sum of squared errors is less than 0.001.

Step 4: Iteration

Increase iteration p by one, go back to Step 2 and repeat the process until the selected error criterion is satisfied.

As an example, we may consider the three-layer back-propagation network. Suppose that the network is required to perform logical operation *Exclusive-OR*. Recall that a single-layer perceptron could not do this operation. Now we will apply the three-layer net.

Typical Learning Curve



14

Final results of three-layer network learning

Inputs		Desired output	Actual output	Error	Sum of squared
x_1	x_2	y_d	<i>y</i> ₅	e	errors
1	1	0	0.0155	-0.0155	0.0010
0	1	1	0.9849	0.0151	
1	0	1	0.9849	0.0151	
0	0	0	0.0175	-0.0175	

Network represented by McCulloch-Pitts model for solving the Exclusive-OR operation

