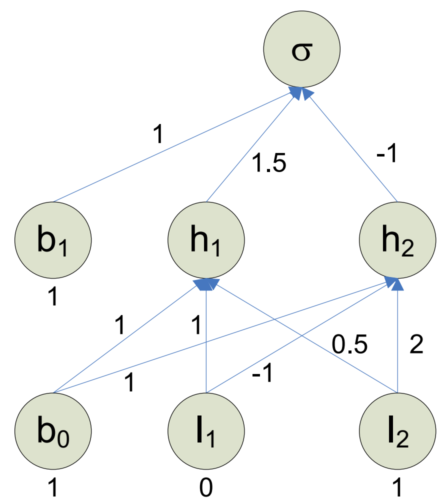
Multi-layer Perceptron Learning: one sample

Below is a snapshot of a neural network during training. There are two input units, two hidden layer perceptrons, and a single output unit. Input I_1 has a value of 0; input I_2 has a value of 1; all bias have value 1. Edges are labeled with their corresponding weights. Learning factor η = 0.5. Target value is 1.



Step 1: Feed the inputs forward

Use the formula, output = $\dfrac{1}{1+e^{-\sigma}}$ where $\sigma = \sum_i w_i x_i + bias$

h_1 = (1 • 0) + (0.5 • 1) + (1 • 1) = 1.5 ⇨ 1/(1+$e^{-1.5}$) = 0.818

h_2 = (-1 • 0) + (2 • 1) + (1 • 1) = 3 ⇨ 1/(1+e^{-3}) = 0.953

y = (1.5 • 0.818) + (-1 • 0.953) + (1 • 1) = 1.274 ⇨ 1/(1+$e^{-1.274}$) = 0.781

Calculate total error in network, $E = \frac{1}{2}(t-y)^2$

E = ½ (1 – 0.781)^2 = 0.024

Step 2: <u>Backpropagate the errors</u>

a) Calculate the error for the output unit y,
Use the formula, $E_y = y(1-y)(t-y)$

E_y = (0.781)(1 – 0.781)(1 – 0.781) = 0.037

b) Calculate the error for each hidden unit h_i
Use the formula, $E_{h_i} = h_i(1-h_i)(w_{h_i,y} \cdot E_y)$

E_{h1} = (0.818)(1 – 0.818)(1.5 • 0.037) = 0.008
E_{h2} = (0.953)(1 – 0.953)(-1 • 0.037) = -0.002

Step 3: <u>Learn</u>

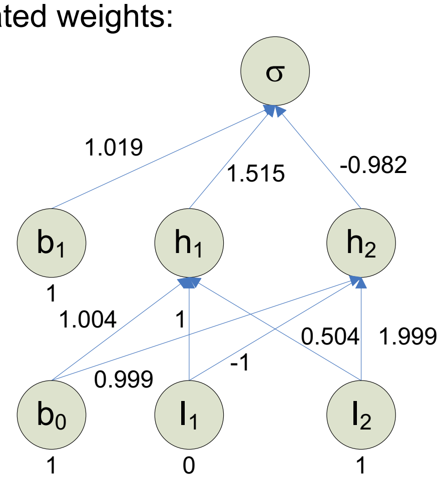
a) Update network weights proportionately
Use the formula, $w_{i,j} = w_{i,j} + \eta E_j z_i$ where z_i is value of i

$w_{h1,y}$ = 1.5 + (0.5)(0.037)(0.818) = 1.515
$w_{h2,y}$ = -1 + (0.5)(0.037)(0.953) = -0.982
$w_{b1,y}$ = 1 + (0.5)(0.037)(1) = 1.019

$w_{I1,h1}$ = 1 + (0.5)(0.008)(0) = 1
$w_{I2,h1}$ = 0.5 + (0.5)(0.008)(1) = 0.504
$w_{b0,h1}$ = 1 + (0.5)(0.008)(1) = 1.004

$w_{I1,h2}$ = -1 + (0.5)(-0.002)(0) = -1
$w_{I2,h2}$ = 2 + (0.5)(-0.002)(1) = 1.999
$w_{b0,h2}$ = 1 + (0.5)(-0.002)(1) = 0.999

Label network with updated weights:



Repeat for all training samples ⇨ one epoch.