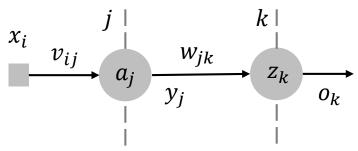




• Consider a multilayer perceptron whose **hidden units** use **x**³ and whose **output units** use **sin(3x)** as the transfer function, rather than the usual sigmoid or tanh. Using the chain rule, derive the formulas for the weight updates. Your final formulas should be purely algebraic, i.e., they should not contain partial derivatives.



$$a_{j} = x_{i}v_{ij}$$

$$y_{j} = (a_{j})^{3}$$

$$z_{k} = y_{j}w_{jk}$$

$$o_{k} = \sin(3z_{k})$$

$$e_k = \frac{1}{2}(o_k - t_k)^2$$

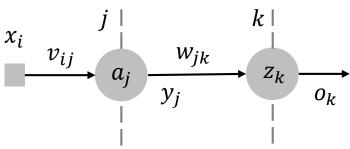
Feed forward











$$a_{j} = x_{i}v_{ij}$$

$$y_{j} = (a_{j})^{3}$$

$$z_{k} = y_{j}w_{jk}$$

$$o_{k} = \sin(3z_{k})$$

$$e_k = \frac{1}{2}(o_k - t_k)^2$$

Feed forward

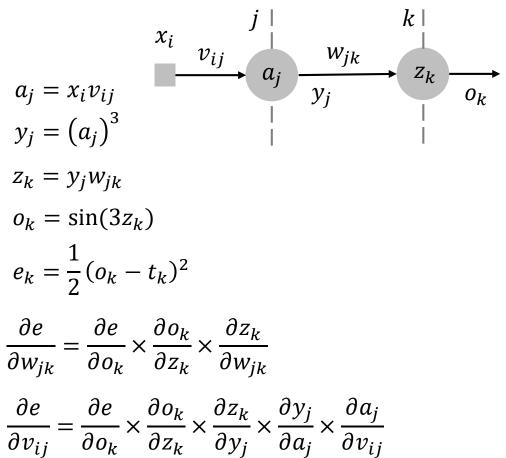
$$e_k = \frac{1}{2} \left(\sin(3(x_i v_{ij})^3 w_{jk}) - t_k \right)^2$$
 Given an input x_i and target out t_k

• The error function is variable in v_{ij} and w_{jk} . It's required to find set of weights to **minimize** the error function. Which is an **optimization problem**.







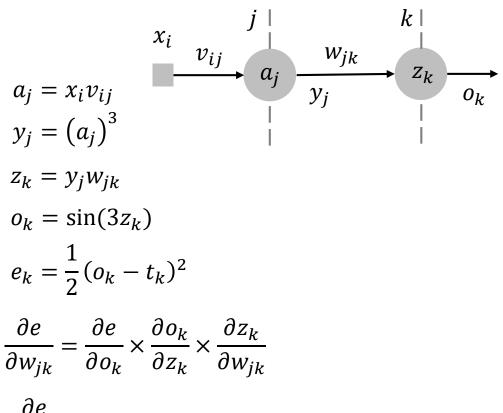


$$\begin{split} \frac{\partial e}{\partial w_{jk}} & \frac{\partial e}{\partial v_{ij}} \\ w_{jk}^{n+1} &= w_{jk}^n - \eta \frac{\partial e}{\partial w_{jk}} \\ v_{ij}^{n+1} &= v_{ij}^n - \eta \frac{\partial e}{\partial v_{ij}} \end{split}$$









$$\frac{\partial e}{\partial w_{jk}}$$

$$w_{jk}^{n+1} = w_{jk}^{n} - \eta \frac{\partial e}{\partial w_{jk}}$$

$$\frac{\partial e}{\partial o_{k}} = (o_{k} - t_{k})$$

$$\frac{\partial o_{k}}{\partial z_{k}} = 3\cos(3z_{k})$$

$$\frac{\partial z_{k}}{\partial w_{jk}} = y_{j}$$

$$\frac{\partial e}{\partial w_{jk}} = (o_k - t_k) \times 3\cos(3z_k) \times y_j$$

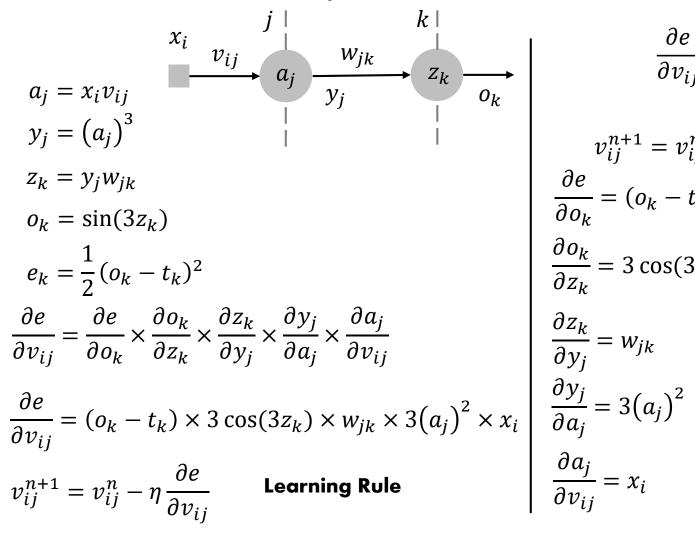
$$w_{jk}^{n+1} = w_{jk}^{n} - \eta((o_k - t_k) \times 3\cos(3z_k) \times y_j)$$

Learning Rule









$$\frac{\partial e}{\partial v_{ij}}$$

$$v_{ij}^{n+1} = v_{ij}^{n} - \eta \frac{\partial e}{\partial v_{ij}}$$

$$\frac{\partial e}{\partial o_{k}} = (o_{k} - t_{k})$$

$$\frac{\partial o_{k}}{\partial z_{k}} = 3\cos(3z_{k})$$

$$\frac{\partial z_{k}}{\partial y_{j}} = w_{jk}$$

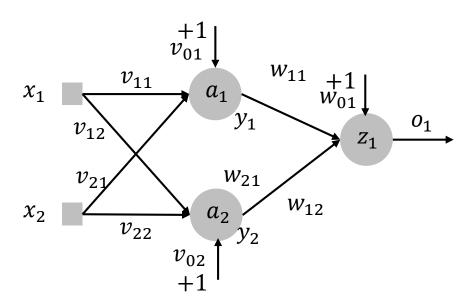
$$\frac{\partial y_{j}}{\partial a_{j}} = 3(a_{j})^{2}$$

$$\frac{\partial a_{j}}{\partial v_{ij}} = x_{i}$$





Consider a multilayer feedforward network, all the neurons of which operate in their linear regions. Justify the statement that such a network is equivalent to a single-layer feedforward network.









Feed forward

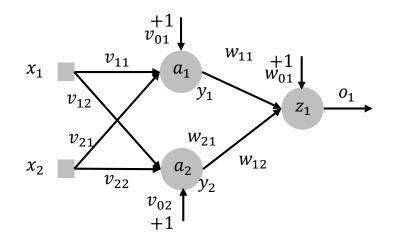
$$a_1 = x_1 v_{11} + x_2 v_{21} + v_{01}$$
 $y_1 = c_1(a_1)$

$$a_2 = x_1 v_{21} + x_2 v_{22} + v_{02}$$
 $y_2 = c_2(a_2)$

$$z_1 = y_1 w_{11} + y_2 w_{21} + w_{01}$$
 $o_1 = c_3(z_1)$

$$o_1 = c_3(y_1w_{11} + y_2w_{21} + w_{01})$$

$$o_1 = c_3(c_1w_{11}(a_1) + c_2w_{21}(a_2) + w_{01})$$



$$o_1 = c_3(c_1w_{11}(x_1v_{11} + x_2v_{21} + v_{01}) + c_2w_{21}(x_1v_{21} + x_2v_{22} + v_{02}) + w_{01})$$

$$o_1 = c_3((x_1c_1w_{11}v_{11} + x_2c_1w_{11}v_{21} + c_1w_{11}v_{01}) + (x_1c_2w_{21}v_{21} + x_2c_2w_{21}v_{22} + c_2w_{21}v_{02}) + w_{01})$$

$$o_1 = (x_1c_1c_3w_{11}v_{11} + x_2c_1c_3w_{11}v_{21} + c_1c_3w_{11}v_{01}) + (x_1c_2c_3w_{21}v_{21} + x_2c_2c_3w_{21}v_{22} + c_2c_3w_{21}v_{02}) + c_3w_{01}$$





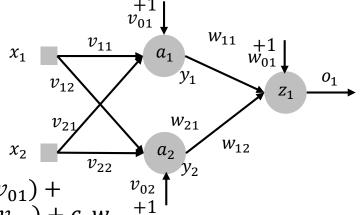


Feed forward

$$a_1 = x_1 v_{11} + x_2 v_{21} + v_{01}$$
 $y_1 = c_1(a_1)$

$$a_2 = x_1 v_{21} + x_2 v_{22} + v_{02}$$
 $y_2 = c_2(a_2)$

$$z_1 = y_1 w_{11} + y_2 w_{21} + w_{01}$$
 $o_1 = c_3(z_1)$



$$o_{1} = (x_{1}c_{1}c_{3}w_{11}v_{11} + x_{2}c_{1}c_{3}w_{11}v_{21} + c_{1}c_{3}w_{11}v_{01}) + v_{02}$$

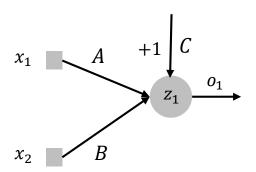
$$(x_{1}c_{2}c_{3}w_{21}v_{21} + x_{2}c_{2}c_{3}w_{21}v_{22} + c_{2}c_{3}w_{21}v_{02}) + c_{3}w_{01}$$

$$o_1 = (x_1A + x_2B + C)$$

$$A = c_1 c_3 w_{11} v_{11} + c_2 c_3 w_{21} v_{21}$$

$$B = c_1 c_3 w_{11} v_{21} + c_2 c_3 w_{21} v_{22}$$

$$C = c_1 c_3 w_{11} v_{01} + c_2 c_3 w_{21} v_{02} + c_3 w_{01}$$



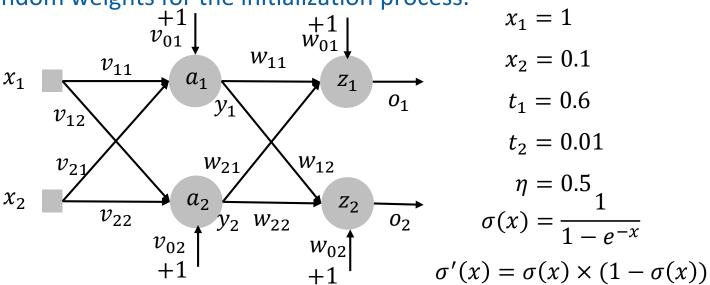
A multilayer network with only linear activation function is equivalent to a single-layer feedforward network.







Given the neural network shown below, carry out one iteration using the back-propagation algorithm using a learning rate of 0.5 and a sigmoid activation function. Your network is supposed to learn a pattern x1=1 and x2=0.1 with a desired output o1=0.6 and o2=0.01. Assume random weights for the initialization process.









Feed forward

$$a_1 = x_1 v_{11} + x_2 v_{21} + v_{01}$$
 $y_1 = \sigma(a_1)$

$$a_2 = x_1 v_{21} + x_2 v_{22} + v_{02}$$
 $y_2 = \sigma(a_2)$

$$z_1 = y_1 w_{11} + y_2 w_{21} + w_{01}$$
 $o_1 = \sigma(z_1)$

$$z_2 = y_1 w_{12} + y_2 w_{22} + w_{02}$$
 $o_2 = \sigma(z_2)$

$$e_1 = 0.5(o_1 - t_1)^2$$
 $e_2 = 0.5(o_2 - t_2)^2$

$$v_{12} = v_{21} = 1$$
 , $v_{11} = v_{22} = v_{01} = v_{02} = 0.5$

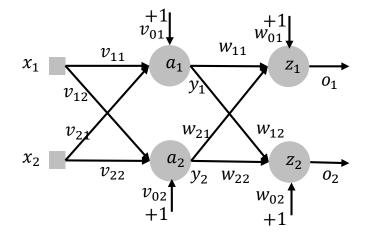
$$w_{12} = w_{21} = 1$$
 , $w_{11} = w_{22} = w_{01} = w_{02} = 0.5$

$$a_1 = 1.1$$
 $y_1 = 0.75026$ $z_1 = 1.7$ $o_1 = 0.84554$

$$a_2 = 1.55$$
 $y_2 = 0.82491$ $a_2 = 1.663$ $o_2 = 0.84060$

$$e_1 = 0.5(0.84554 - 0.6)^2 = 0.0301$$

$$e_2 = 0.5(0.84060 - 0.01)^2 = 0.34495$$



$$x_1 = 1$$
 $x_2 = 0.1$
 $t_1 = 0.6$ $t_2 = 0.01$







$$e_1 = 0.5(o_1 - t_1)^2$$
 $e_2 = 0.5(o_2 - t_2)^2$

$$\partial e_1/\partial o_1 = o_1 - t_1$$
 $\partial e_2/\partial o_2 = o_2 - t_2$

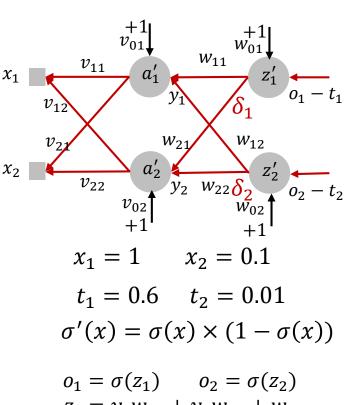
$$\delta_1 = (o_1 - t_1) \times (\partial o_1 / \partial z_1)$$

$$\delta_1 = (o_1 - t_1) \times o_1 \times (1 - o_1)$$

$$\delta_2 = (o_2 - t_2) \times o_2 \times (1 - o_2)$$

$$\frac{\partial e_1}{\partial w_{11}} = \delta_1 \times y_1 \quad \frac{\partial e_1}{\partial w_{21}} = \delta_1 \times y_2 \quad \frac{\partial e_1}{\partial w_{01}} = \delta_1 \times 1$$

$$\frac{\partial e_2}{\partial w_{12}} = \delta_2 \times y_1 \quad \frac{\partial e_2}{\partial w_{22}} = \delta_2 \times y_2 \quad \frac{\partial e_2}{\partial w_{02}} = \delta_2 \times 1$$



$$o_{1} = \sigma(z_{1}) \qquad o_{2} = \sigma(z_{2})$$

$$z_{1} = y_{1}w_{11} + y_{2}w_{21} + w_{01}$$

$$z_{2} = y_{1}w_{12} + y_{2}w_{22} + w_{02}$$

$$y_{1} = \sigma(a_{1}) \qquad y_{2} = \sigma(a_{2})$$

$$a_{1} = x_{1}v_{11} + x_{2}v_{21} + v_{01}$$

$$a_{2} = x_{1}v_{21} + x_{2}v_{22} + v_{02}$$





$$\frac{\partial e_1}{\partial w_{11}} = \delta_1 \times y_1 \quad \frac{\partial e_1}{\partial w_{21}} = \delta_1 \times y_2 \quad \frac{\partial e_1}{\partial w_{01}} = \delta_1 \times 1$$

$$\frac{\partial e_2}{\partial w_{12}} = \delta_2 \times y_1 \quad \frac{\partial e_2}{\partial w_{22}} = \delta_2 \times y_2 \quad \frac{\partial e_2}{\partial w_{02}} = \delta_2 \times 1$$

$$\delta_1 = 0.0321 \quad y_1 = 0.75026$$

$$\delta_2 = 0.1113 \quad y_2 = 0.82491$$

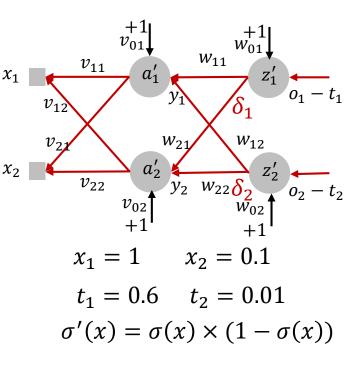
$$w_{11}^2 = w_{11}^1 - 0.5 \frac{\partial e_1}{\partial w_{11}}$$

$$w_{11}^2 = 0.5 - 0.5(0.0241) = 0.488$$

$$w_{21}^2 = 1 - 0.5(0.0265) = 0.9868$$

$$w_{01}^2 = 0.5 - 0.5(0.0321) = 0.484$$

$$w_{12}^2 = 0.958$$
 $w_{22}^2 = 0.4541$ $w_{02}^2 = 0.4443$



$$o_{1} = \sigma(z_{1}) \qquad o_{2} = \sigma(z_{2})$$

$$z_{1} = y_{1}w_{11} + y_{2}w_{21} + w_{01}$$

$$z_{2} = y_{1}w_{12} + y_{2}w_{22} + w_{02}$$

$$y_{1} = \sigma(a_{1}) \qquad y_{2} = \sigma(a_{2})$$

$$a_{1} = x_{1}v_{11} + x_{2}v_{21} + v_{01}$$

$$a_{2} = x_{1}v_{21} + x_{2}v_{22} + v_{02}$$





$$\delta_{1} = 0.0321 \quad y_{1} = 0.75026$$

$$\delta_{2} = 0.1113 \quad y_{2} = 0.82491$$

$$\frac{\partial e}{\partial y_{1}} = \delta_{1} \times w_{11} + \delta_{2} \times w_{12} = 0.1273$$

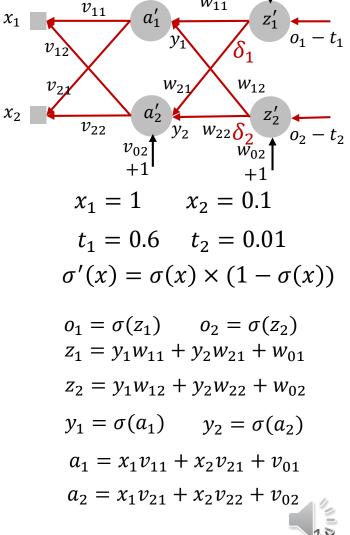
$$\frac{\partial e}{\partial y_{2}} = \delta_{1} \times w_{21} + \delta_{2} \times w_{22} = 0.0877$$

$$\frac{\partial e}{\partial a_{1}} = \frac{\partial e}{\partial y_{1}} \times y_{1} \times (1 - y_{1}) = 0.02385$$

$$\frac{\partial e}{\partial a_{2}} = \frac{\partial e}{\partial y_{2}} \times y_{2} \times (1 - y_{2}) = 0.01267$$

$$\frac{\partial e}{\partial v_{11}} = \frac{\partial e}{\partial a_{1}} \times x_{1} \quad \frac{\partial e}{\partial v_{21}} = \frac{\partial e}{\partial a_{1}} \times x_{2} \quad \frac{\partial e}{\partial v_{01}} = \frac{\partial e}{\partial a_{1}} \times 1$$

$$\frac{\partial e}{\partial v_{12}} = \frac{\partial e}{\partial a_{2}} \times x_{1} \quad \frac{\partial e}{\partial v_{22}} = \frac{\partial e}{\partial a_{2}} \times x_{2} \quad \frac{\partial e}{\partial v_{02}} = \frac{\partial e}{\partial a_{2}} \times 1$$







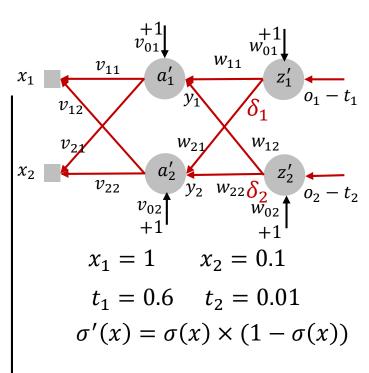
$$\frac{\partial e}{\partial v_{11}} = \frac{\partial e}{\partial a_1} \times x_1 \quad \frac{\partial e}{\partial v_{21}} = \frac{\partial e}{\partial a_1} \times x_2 \quad \frac{\partial e}{\partial v_{01}} = \frac{\partial e}{\partial a_1} \times 1$$

$$\frac{\partial e}{\partial v_{12}} = \frac{\partial e}{\partial a_2} \times x_1 \quad \frac{\partial e}{\partial v_{22}} = \frac{\partial e}{\partial a_2} \times x_2 \quad \frac{\partial e}{\partial v_{02}} = \frac{\partial e}{\partial a_2} \times 1$$

$$v_{11}^2 = v_{11}^1 - \eta \frac{\partial e}{\partial v_{11}}$$

$$v_{11}^2 = 0.4881$$
 $v_{12}^2 = 0.9937$ $v_{10}^2 = 0.4881$

$$v_{21}^2 = 0.9988$$
 $v_{22}^2 = 0.4994$ $v_{20}^2 = 0.4973$



$$o_{1} = \sigma(z_{1}) \qquad o_{2} = \sigma(z_{2})$$

$$z_{1} = y_{1}w_{11} + y_{2}w_{21} + w_{01}$$

$$z_{2} = y_{1}w_{12} + y_{2}w_{22} + w_{02}$$

$$y_{1} = \sigma(a_{1}) \qquad y_{2} = \sigma(a_{2})$$

$$a_{1} = x_{1}v_{11} + x_{2}v_{21} + v_{01}$$

$$a_{2} = x_{1}v_{21} + x_{2}v_{22} + v_{02}$$





4- Derive the learning rule for the network of problem 3 but using a tanh activation function.

