

Derivation of the Backpropagation Learning for network with one hidden layer.

• Notation:

- I = the number of input units
- J = the number of hidden units
- K = the number of output units
- v_{ji} is the weight of the connection from input unit $i = 1, 2, \dots, I$ to hidden unit $j = 1, 2, \dots, J$.
- w_{kj} is the weight of the connection from hidden unit $j = 1, 2, \dots, J$ to output unit $k = 1, 2, \dots, K$
- \mathbf{z} is the input vector with components z_1, z_2, \dots, z_I .
- \mathbf{d} is the output vector with components d_1, d_2, \dots, d_K .

• Activation at the hidden unit j :

$$y_j = f(net_j) \quad (1)$$

$$net_j = \sum_{i=1}^I v_{ji} z_i \quad (2)$$

• Activation at the output unit k :

$$o_k = f(net_k) \quad (3)$$

$$net_k = \sum_{j=1}^J w_{kj} y_j \quad (4)$$

• Total error at the output units:

$$E = \frac{1}{2} \sum_{k=1}^K (d_k - o_k)^2$$

• Computation of w_{kj} adjustment:

- Weight adjustment:

$$\Delta w_{kj} = -\eta \frac{\partial E}{\partial w_{kj}} \quad (5)$$

- Take the partial derivative of E with respect to w_{kj} :

$$\frac{\partial E}{\partial w_{kj}} = \frac{\partial \frac{1}{2} \sum_{k=1}^K (d_k - o_k)^2}{\partial w_{kj}} \quad (6)$$

$$= \frac{\partial \frac{1}{2} (d_k - o_k)^2}{\partial w_{kj}} \quad (7)$$

$$= -(d_k - o_k) \times \frac{\partial o_k}{\partial w_{kj}} \quad (8)$$

$$= -(d_k - o_k) \times \frac{\partial f(net_k)}{\partial w_{kj}} \quad (9)$$

$$= -(d_k - o_k) \times \frac{\partial f(\sum_{j=1}^J w_{kj} y_j)}{\partial w_{kj}} \quad (10)$$

$$= -(d_k - o_k) \times f'(\sum_{j=1}^J w_{kj} y_j) \times \frac{\partial(\sum_{j=1}^J w_{kj} y_j)}{\partial w_{kj}} \quad (11)$$

$$= -(d_k - o_k) \times f'(\sum_{j=1}^J w_{kj} y_j) \times y_j \quad (12)$$

• Let

$$\delta_{ok} = (d_k - o_k) \times f'(\sum_{j=1}^J w_{kj} y_j) \quad (13)$$

$$= (d_k - o_k) \times f'(net_k) \quad (14)$$

$$= (d_k - o_k) \times o'_k \quad (15)$$

then

$$\frac{\partial E}{\partial w_{kj}} = \frac{\partial \frac{1}{2} \sum_{k=1}^K (d_k - o_k)^2}{\partial w_{kj}} \quad (16)$$

$$= -(d_k - o_k) \times f'(\sum_{j=1}^J w_{kj} y_j) \times y_j \quad (17)$$

$$= -\delta_{ok} \times y_j \quad (18)$$

and

$$\Delta w_{kj} = -\eta \frac{\partial E}{\partial w_{kj}} \quad (19)$$

$$= \eta \delta_{ok} y_j \quad (20)$$

• **Computation of v_{ji} adjustment:**

– Weight adjustment:

$$\Delta v_{ji} = -\eta \frac{\partial E}{\partial v_{ji}} \quad (21)$$

– Take the partial derivative of E with respect to v_{ji} :

$$\frac{\partial E}{\partial v_{ji}} = \frac{\partial \frac{1}{2} \sum_{k=1}^K (d_k - o_k)^2}{\partial v_{ji}} \quad (22)$$

$$= -\sum_{k=1}^K (d_k - o_k) \frac{\partial o_k}{\partial v_{ji}} \quad (23)$$

$$= -\sum_{k=1}^K (d_k - o_k) \frac{\partial f(net_k)}{\partial v_{ji}} \quad (24)$$

$$= - \sum_{k=1}^K (d_k - o_k) f'(net_k) \frac{\partial(net_k)}{\partial v_{ji}} \quad (25)$$

$$= - \sum_{k=1}^K (d_k - o_k) f'(net_k) \frac{\partial \sum_{j=1}^J w_{kj} y_j}{\partial v_{ji}} \quad (26)$$

$$= - \sum_{k=1}^K (d_k - o_k) f'(net_k) \frac{\partial w_{kj} y_j}{\partial v_{ji}} \quad (27)$$

$$= - \sum_{k=1}^K (d_k - o_k) f'(net_k) \frac{\partial w_{kj} f(net_j)}{\partial v_{ji}} \quad (28)$$

$$= - \sum_{k=1}^K (d_k - o_k) f'(net_k) w_{kj} f'(net_j) \frac{\partial \sum_{i=1}^I net_j}{\partial v_{ji}} \quad (29)$$

$$= - \sum_{k=1}^K (d_k - o_k) f'(net_k) w_{kj} f'(net_j) \frac{\partial \sum_{i=1}^I v_{ji} z_i}{\partial v_{ji}} \quad (30)$$

$$= - \sum_{k=1}^K (d_k - o_k) f'(net_k) w_{kj} f'(net_j) z_i \quad (31)$$

$$= - \sum_{k=1}^K \delta_{ok} w_{kj} f'(net_j) z_i \quad (32)$$

• Let

$$\delta_{yj} = \sum_{k=1}^K \delta_{ok} w_{kj} f'(net_j) \quad (33)$$

$$= \sum_{k=1}^K \delta_{ok} \times w_{kj} \times y'_j \quad (34)$$

then

$$\frac{\partial E}{\partial v_{ji}} = \frac{\partial \frac{1}{2} \sum_{k=1}^K (d_k - o_k)^2}{\partial v_{ji}} \quad (35)$$

$$= - \sum_{k=1}^K \delta_{ok} w_{kj} f'(net_j) z_i \quad (36)$$

$$= - \delta_{yj} z_i \quad (37)$$

and

$$\Delta v_{ji} = -\eta \frac{\partial E}{\partial v_{ji}} \quad (38)$$

$$= \eta \delta_{yj} z_i \quad (39)$$