

تکلیف شماره ۵ درس شبکه های عصبی
آرین ششدر - ۴۰۰۲۳۴۹۴

E 11.2. we will use the nominal values presented in the example below

Figure 11.4, and modify them slightly to fine tune the network response to

our desired shape.
$$\left[\begin{array}{l} w_{1,1}^1 = 10, w_{2,1}^1 = 10, b_1^1 = -10, b_2^1 = 10, \\ w_{1,1}^2 = 1, w_{1,2}^2 = 1, b^2 = 0 \end{array} \right]$$

i. The response looks like the nominal response except the entire diagram is displaced by $-2 \Rightarrow$ we set $b^2 = -2$

ii. $w_{1,2}^2$ controls the step direction of the left most sigmoid, by

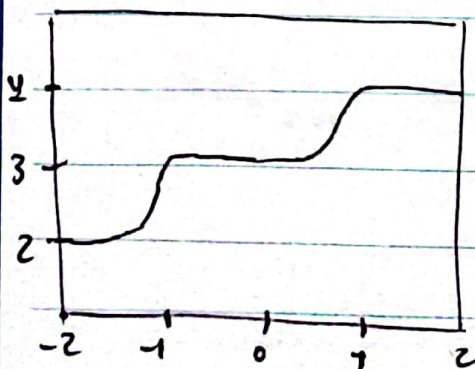
setting $w_{1,2}^2 = -1$ we will flip the first sigmoid while the second one

stays the same.

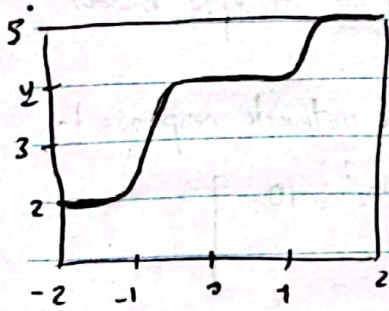
iii. This response looks like (ii) but it is flipped w.r.t. $y=0$.

In order to obtain this response this time we will use $w_{1,1}^2$ that controls the step direction of the rightmost sigmoid. If we set $w_{1,1}^2 = -1$, the second sigmoid is flipped but the first one stays the same.

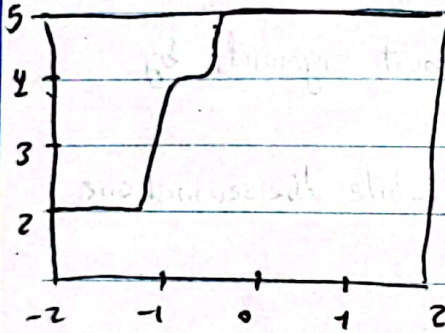
iv. we will use a step by step transformation from the nominal response to get the desired output. First we set $b^2 = 2$ to move the response higher:



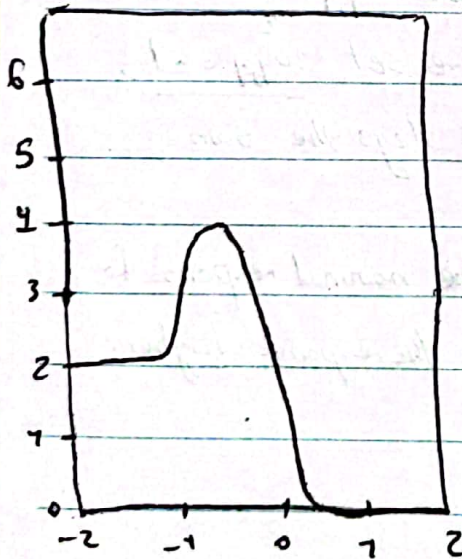
next, we set $w_{1,2}^2 = 2$ so that the left sigmoid has a higher peak:



then we bring the step of the next sigmoid close to the first one, specifically we want the step to occur at $-0.5 \rightarrow -b_{1,1}^1 / w_{1,1} = -0.5 \Rightarrow b_{1,1}^1 = 5$



now, all that is left to do is to flip the second sigmoid so that it touches $y=0$. To that end we set $w_{1,1}^2 = -4$



→ which looks like what we want

$$E11.3. \quad a^1 = w^1 p + b^1$$

$$a^2 = w^2 a^1 + b^2 = w^2 (w^1 p) + [w^2 b^1 + b^2]$$

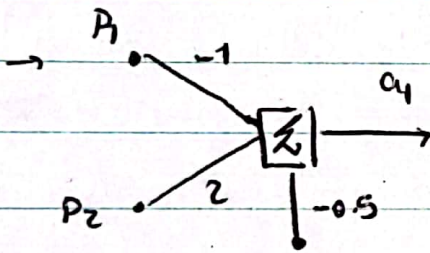
$$\rightarrow \text{output} = w p + B, \quad w = w^2 w^1, \quad B = w^2 b^1 + b^2$$

$$\rightarrow w^1 = \begin{bmatrix} -2 & -1 \\ 1 & 3 \end{bmatrix}, \quad w^2 = \begin{bmatrix} 1 & 1 \end{bmatrix} \Rightarrow w = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} -2 & -1 \\ 1 & 3 \end{bmatrix}$$

$$= \begin{bmatrix} -1 & 2 \end{bmatrix}$$

$$b^1 = \begin{bmatrix} -0.5 \\ -0.5 \end{bmatrix}, \quad b^2 = 0.5 \Rightarrow B = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} -0.5 \\ -0.5 \end{bmatrix} + 0.5$$

$$= -0.5$$



→ This network is equivalent to the original two layer network.

E11.7.

$$i. \quad a_1 = w^1 p + b^1 = \begin{bmatrix} 1 \\ -1 \end{bmatrix} \times 1 + \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 3 \\ 0 \end{bmatrix}$$

$$a_2 = w^2 a^1 + b^2 = \begin{bmatrix} -1 & 1 \end{bmatrix} \begin{bmatrix} 3 \\ 0 \end{bmatrix} + \begin{bmatrix} 3 \end{bmatrix} = 0$$

$$e = t - a = 2 - 0 = 2$$

$$ii. \quad S^2 = -2 f'(n^2) (t - a) = -2 \begin{bmatrix} 1 \end{bmatrix} \begin{bmatrix} 2 \end{bmatrix} = -4$$

$$f'(n^2) = \frac{d}{dn^2} (n^2) = 1$$

$$S^1 = \dot{F}(n^1)(w^2)^T S^2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \end{bmatrix} [-4] = \begin{bmatrix} 4 \\ -4 \end{bmatrix}$$

$$\dot{F}(n^1) = 1 \rightarrow \dot{F}(n^1) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\text{iii. } \frac{\partial \text{loss}}{\partial w_{1,1}} = s_1^1 \frac{\partial \text{loss}}{\partial a_1} = 4 \times 1 = 4$$

\downarrow
 P_1

E11.10.

Forward pass:

$$n_1 = w^1 p + b^1 = \begin{bmatrix} 1 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$a_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \odot \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$n_2 = a_2 = w^2 a_1 + b^2 = \begin{bmatrix} 2 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \begin{bmatrix} -1 \end{bmatrix} = 1$$

$$e = t - a = 2 - 1 = 1$$

Backward Pass:

$$S^2 = -2 \dot{F}(n^2)(t - a) = -2 \left[\dot{F}(n^2) \right] (t - a) = -2 [1] [1] = -2$$

$$\dot{F}(n^2) = \frac{d}{dn^2}(n^2) = 1$$

$$S^1 = \dot{F}(n^1)(w^2)^T S^2 = \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix} [-2] = \begin{bmatrix} -8 \\ 0 \end{bmatrix}$$

$$\dot{F}(n^1) = \begin{bmatrix} \dot{F}(n_1^1) & 0 \\ 0 & \dot{F}(n_2^1) \end{bmatrix} = \begin{bmatrix} 2n_1^1 & 0 \\ 0 & 2n_2^1 \end{bmatrix} = \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix}$$

$$\text{update: } w^2(1) = w^2(0) - 0.5 S^2 (a^1)^T$$

$$= \begin{bmatrix} 2 & 1 \end{bmatrix} - 0.5 (-2) \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 3 & 1 \end{bmatrix}$$

$$b^2(1) = b^2(0) - 0.5 S^2 = \begin{bmatrix} -1 \end{bmatrix} - 0.5 [-2] = \begin{bmatrix} 0 \end{bmatrix}$$

$$\begin{aligned} w^1(1) &= w^1(0) - 0.5 s^1 (a^0)^T \\ &= \begin{bmatrix} 1 & -1 \\ 1 & 0 \end{bmatrix} - 0.5 \begin{bmatrix} -8 \\ 0 \end{bmatrix} \begin{bmatrix} 1 & 1 \end{bmatrix} = \begin{bmatrix} 5 & 3 \\ 1 & 0 \end{bmatrix} \end{aligned}$$

$$b^1(1) = b^1(0) - 0.5 s^1 = \begin{bmatrix} 1 \\ -1 \end{bmatrix} - 0.5 \begin{bmatrix} -8 \\ 0 \end{bmatrix} = \begin{bmatrix} 5 \\ -1 \end{bmatrix}$$

$$E11.13. \quad a^0 = p, \quad a^{m+1} = f^{m+1}(\beta^{m+1} [w^{m+1} a^m + b^{m+1}]), \quad m=0, 1, \dots, M-1$$

$$a = a^M$$

Sensitivities are derivatives w.r.t. net input and is therefore invariant w.r.t. changes in the formulation of the net inputs. (Only the performance Index affects sensitivities)

$$\Rightarrow S^m = -2 \dot{f}(n^m) (1-a), \quad s^m = \dot{f}(n^m) (w^{m+1})^T s^{m+1}, \quad m=0, 1, \dots, M-1$$

However the update rules will change because net inputs have changed.

$$\text{we have: } n^m = \beta^m [w^m a^{m-1} + b^m]$$

$$\Rightarrow \frac{\partial n^m}{\partial w^m} = \beta^m a^{m-1}, \quad \frac{\partial n^m}{\partial b^m} = \beta^m, \quad \frac{\partial n^m}{\partial \beta^m} = [w^m a^{m-1} + b^m]$$

$$\Rightarrow \left\{ \begin{aligned} w^m(k+1) &= w^m(k) - \alpha s^m (\beta^m a^{m-1})^T \\ b^m(k+1) &= b^m(k) - \alpha s^m (\beta^m) \\ \beta^m(k+1) &= \beta^m(k) - \alpha s^m (w^m a^{m-1} + b^m)^T \end{aligned} \right.$$

$$b^m(k+1) = b^m(k) - \alpha s^m (\beta^m)$$

$$\beta^m(k+1) = \beta^m(k) - \alpha s^m (w^m a^{m-1} + b^m)^T$$

E11.16. For the same reason as the previous problem, the equations for sensitivities do not change because F_{ex} (the performance index) has stayed the same.

Moreover, the gradients w.r.t. w^1, w^2 and b^1, b^2 are unchanged. The only additional term w.r.t. which we need to backpropagate is $w^{2,1}$.

$$\frac{\partial F}{\partial w_{i,j}^{2,1}} = \frac{\partial F}{\partial n_i^2} \times \frac{\partial n_i^2}{\partial w_{i,j}^{2,1}} = s_i^2 \times \frac{\partial n_i^2}{\partial w_{i,j}^{2,1}}$$

$$n_i^2 = n_1^2 = n^2 = w_{1,1}^{2,1} \cdot p + w_{1,1}^2 a_1 + b^2 \rightarrow \frac{\partial n^2}{\partial w_{1,1}^{2,1}} = p$$

$$\Rightarrow w_{1,1}^{2,1}(k+1) = w_{1,1}^{2,1}(k) - \alpha S^m(p)^T$$

E11.23. We need the gradient $\frac{\partial}{\partial y(0)} F(y(0)) = \frac{\partial}{\partial y(0)} e^2(K)$.

We define $q(k) = \frac{\partial}{\partial y(k)} e^2(K)$, then we would need to calculate $q(0)$

as we have: $\frac{\partial}{\partial y(0)} F(y(0)) = \frac{\partial}{\partial y(0)} e^2(K) = q(0)$.

We can derive a recurrence relation for $q(k)$ as follows:

$$q(k-1) = \frac{\partial}{\partial y(k-1)} e^2(K) = \frac{\partial e^2(K)}{\partial y(k)} \times \frac{\partial y(k)}{\partial y(k-1)} = q(k) \cdot \frac{\partial (f(y(k-1)))}{\partial y(k-1)}$$

$$= q(k) \cdot f'(y(k-1)). \text{ Also at } k=K \text{ we have, } q(K) = \frac{\partial e^2(K)}{\partial y(K)}$$

$$= \frac{\partial}{\partial y(K)} (t - y(K))^2 = -2y(K)(t - y(K))^2$$

$$\rightarrow \left\{ \begin{aligned} q(K) &= -2y(K)(t - y(K))^2, \quad q(k-1) = q(k) \cdot f'(y(k-1)), \quad \forall k = K-1, \dots, 1 \\ \rightarrow \frac{\partial F(y(0))}{\partial y(0)} &= q(0) \end{aligned} \right.$$