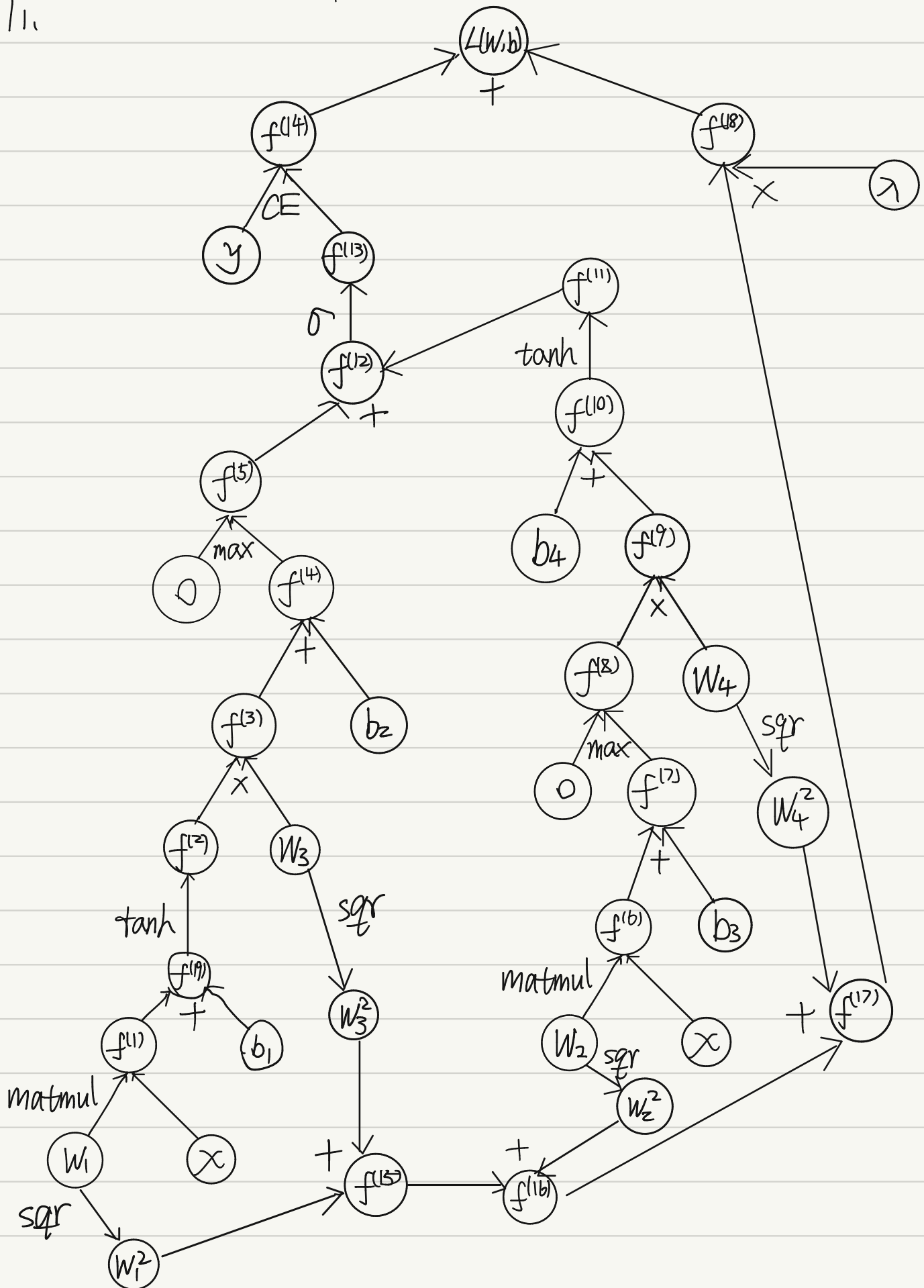


DDA 2020 Assignment 3

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T1.



$$\frac{\partial \mathcal{L}(w, b)}{\partial f^{(14)}} = \frac{d\mathcal{L}(w, b)}{d\mathcal{L}} \cdot \frac{\partial \mathcal{L}}{\partial f^{(14)}} = \frac{\partial \mathcal{L}}{\partial f^{(14)}}$$

$$\frac{\partial \mathcal{L}(w, b)}{\partial f^{(13)}} = \frac{\partial \mathcal{L}}{\partial f^{(14)}} \cdot \frac{\partial f^{(14)}}{\partial f^{(13)}}$$

$$\frac{\partial \mathcal{L}(w, b)}{\partial f^{(12)}} = \frac{\partial \mathcal{L}}{\partial f^{(13)}} \cdot \frac{\partial f^{(13)}}{\partial f^{(12)}}$$

$$\frac{\partial \mathcal{L}(w, b)}{\partial f^{(5)}} = \frac{\partial \mathcal{L}}{\partial f^{(12)}} \cdot \frac{\partial f^{(12)}}{\partial f^{(5)}}$$

$$\frac{\partial \mathcal{L}}{\partial f^{(4)}} = \frac{\partial \mathcal{L}}{\partial f^{(5)}} \cdot \frac{\partial f^{(5)}}{\partial f^{(4)}}, \quad \frac{\partial \mathcal{L}}{\partial b_2} = \frac{\partial \mathcal{L}}{\partial f^{(4)}} \cdot \frac{\partial f^{(4)}}{\partial b_2}$$

$$\frac{\partial \mathcal{L}}{\partial f^{(3)}} = \frac{\partial \mathcal{L}}{\partial f^{(4)}} \cdot \frac{\partial f^{(4)}}{\partial f^{(3)}}, \quad \frac{\partial \mathcal{L}}{\partial f^{(12)}} = \frac{\partial \mathcal{L}}{\partial f^{(3)}} \cdot \frac{\partial f^{(3)}}{\partial f^{(12)}}$$

$$\frac{\partial \mathcal{L}}{\partial f^{(19)}} = \frac{\partial \mathcal{L}}{\partial f^{(12)}} \cdot \frac{\partial f^{(12)}}{\partial f^{(19)}}, \quad \frac{\partial \mathcal{L}}{\partial f^{(11)}} = \frac{\partial \mathcal{L}}{\partial f^{(19)}} \cdot \frac{\partial f^{(19)}}{\partial f^{(11)}}$$

$$\frac{\partial \mathcal{L}}{\partial b_1} = \frac{\partial \mathcal{L}}{\partial f^{(19)}} \cdot \frac{\partial f^{(19)}}{\partial b_1}, \quad \frac{\partial \mathcal{L}}{\partial f^{(11)}} = \frac{\partial \mathcal{L}}{\partial f^{(12)}} \cdot \frac{\partial f^{(12)}}{\partial f^{(11)}}$$

$$\frac{\partial \mathcal{L}}{\partial f^{(10)}} = \frac{\partial \mathcal{L}}{\partial f^{(11)}} \cdot \frac{\partial f^{(11)}}{\partial f^{(10)}}, \quad \frac{\partial \mathcal{L}}{\partial b_4} = \frac{\partial \mathcal{L}}{\partial f^{(10)}} \cdot \frac{\partial f^{(10)}}{\partial b_4}$$

$$\frac{\partial \mathcal{L}}{\partial f^{(9)}} = \frac{\partial \mathcal{L}}{\partial f^{(10)}} \cdot \frac{\partial f^{(10)}}{\partial f^{(9)}}, \quad \frac{\partial \mathcal{L}}{\partial f^{(8)}} = \frac{\partial \mathcal{L}}{\partial f^{(9)}} \cdot \frac{\partial f^{(9)}}{\partial f^{(8)}}$$

$$\frac{\partial \mathcal{L}}{\partial f^{(7)}} = \frac{\partial \mathcal{L}}{\partial f^{(8)}} \cdot \frac{\partial f^{(8)}}{\partial f^{(7)}}, \quad \frac{\partial \mathcal{L}}{\partial b_3} = \frac{\partial \mathcal{L}}{\partial f^{(7)}} \cdot \frac{\partial f^{(7)}}{\partial b_3}$$

$$\frac{\partial \mathcal{L}}{\partial f^{(6)}} = \frac{\partial \mathcal{L}}{\partial f^{(7)}} \cdot \frac{\partial f^{(7)}}{\partial f^{(6)}}, \quad \frac{\partial \mathcal{L}}{\partial f^{(18)}} = \frac{d\mathcal{L}(w, b)}{d\mathcal{L}} \cdot \frac{\partial \mathcal{L}}{\partial f^{(18)}} = \frac{\partial \mathcal{L}}{\partial f^{(18)}}$$

$$\frac{\partial \mathcal{L}}{\partial f^{(17)}} = \frac{\partial \mathcal{L}}{\partial f^{(18)}} \cdot \frac{\partial f^{(18)}}{\partial f^{(17)}}, \quad \frac{\partial \mathcal{L}}{\partial (w_4^2)} = \frac{\partial \mathcal{L}}{\partial f^{(17)}} \cdot \frac{\partial f^{(17)}}{\partial (w_4^2)}$$

$$\frac{\partial \mathcal{L}}{\partial w_4} = \frac{\partial \mathcal{L}}{\partial f^{(9)}} \cdot \frac{\partial f^{(9)}}{\partial w_4} + \frac{\partial \mathcal{L}}{\partial (w_4^2)} \cdot 2w_4, \quad \frac{\partial \mathcal{L}}{\partial f^{(16)}} = \frac{\partial \mathcal{L}}{\partial f^{(17)}} \cdot \frac{\partial f^{(17)}}{\partial f^{(16)}}$$

$$\frac{\partial \mathcal{L}}{\partial (w_2^2)} = \frac{\partial \mathcal{L}}{\partial f^{(16)}} \cdot \frac{\partial f^{(16)}}{\partial (w_2^2)}, \quad \frac{\partial \mathcal{L}}{\partial w_2} = \frac{\partial \mathcal{L}}{\partial f^{(16)}} \cdot \frac{\partial f^{(16)}}{\partial w_2} + \frac{\partial \mathcal{L}}{\partial (w_2^2)} \cdot 2w_2$$

$$\frac{\partial \mathcal{L}}{\partial f^{(15)}} = \frac{\partial \mathcal{L}}{\partial f^{(16)}} \cdot \frac{\partial f^{(16)}}{\partial f^{(15)}}, \quad \frac{\partial \mathcal{L}}{\partial (w_3^2)} = \frac{\partial \mathcal{L}}{\partial f^{(15)}} \cdot \frac{\partial f^{(15)}}{\partial (w_3^2)}$$

$$\frac{\partial \mathcal{L}}{\partial W_3} = \frac{\partial \mathcal{L}}{\partial f^{(3)}} \cdot \frac{\partial f^{(3)}}{\partial W_3} + \frac{\partial \mathcal{L}}{\partial (W_3^2)} \cdot 2W_3$$

$$\frac{\partial \mathcal{L}}{\partial (W_1^2)} = \frac{\partial \mathcal{L}}{\partial f^{(15)}} \cdot \frac{\partial f^{(15)}}{\partial (W_1^2)} \quad , \quad \frac{\partial \mathcal{L}}{\partial W_1} = \frac{\partial \mathcal{L}}{\partial f^{(1)}} \cdot \frac{\partial f^{(1)}}{\partial W_1} + \frac{\partial \mathcal{L}}{\partial (W_1^2)} \cdot 2W_1$$

$$\therefore W_1 = W_1 - \alpha \frac{\partial \mathcal{L}}{\partial W_1} \quad , \quad W_2 = W_2 - \alpha \frac{\partial \mathcal{L}}{\partial W_2}$$

$$W_3 = W_3 - \alpha \frac{\partial \mathcal{L}}{\partial W_3} \quad , \quad W_4 = W_4 - \alpha \frac{\partial \mathcal{L}}{\partial W_4}$$

$$b_1 = b_1 - \alpha \frac{\partial \mathcal{L}}{\partial b_1} \quad , \quad b_2 = b_2 - \alpha \frac{\partial \mathcal{L}}{\partial b_2}$$

$$b_3 = b_3 - \alpha \frac{\partial \mathcal{L}}{\partial b_3} \quad , \quad b_4 = b_4 - \alpha \frac{\partial \mathcal{L}}{\partial b_4}$$

T₂

$$\text{Conv}_1 : (63 + 2 \times 2 - 5) / 2 + 1 = 32$$

\therefore the shape of activation map : $32 \times 32 \times 1$

the number of parameters : $(5 \times 5 \times 3 + 1) \times 10 = 760$

the computational cost : $[5 \times 5 \times 3 + (5 \times 5 \times 3 - 1) + 1] \times 32 \times 32 \times 10 = 1536000$

$$\text{Maxpool}_1 : (32 - 2) / 3 + 1 = 11$$

\therefore the shape of activation map : $11 \times 11 \times 1$

the number of parameters : 0

the computational cost : $2 \times 2 \times 11 \times 11 \times 10 = 4840$

$$\text{Conv}_2 : (11 + 2 \times 1 - 3) / 2 + 1 = 6$$

\therefore the shape of activation map : $6 \times 6 \times 1$

the number of parameters : $(3 \times 3 \times 10 + 1) \times 20 = 1820$

the computational cost : $[3 \times 3 \times 10 + (3 \times 3 \times 10 - 1) + 1] \times 6 \times 6 \times 20 = 129600$

$$\text{Maxpool}_2 : (6 + 2 \times 1 - 2) / 2 + 1 = 4$$

\therefore the shape of activation map : $4 \times 4 \times 1$

the number of parameters : 0

the computational cost : $2 \times 2 \times 4 \times 4 \times 20 = 1280$

total number of parameters : 2580

total computational cost : 1671720

T₃,

Gini index:

$$G_A = 1 - \left[\left(\frac{5}{18} \right)^2 + \left(\frac{5}{18} \right)^2 + \left(\frac{8}{18} \right)^2 \right] = 0.648$$

$$G_{B_1} = 1 - \left[\left(\frac{1}{8} \right)^2 + \left(\frac{2}{8} \right)^2 + \left(\frac{5}{8} \right)^2 \right] = 0.531$$

$$G_{B_2} = 1 - \left[\left(\frac{4}{10} \right)^2 + \left(\frac{6}{10} \right)^2 \right] = 0.48$$

$$G_{C_1} = 1 - \left[\left(\frac{1}{6} \right)^2 + \left(\frac{5}{6} \right)^2 \right] = 0.278$$

$$G_{C_2} = 1 - 1^2 = 0$$

Entropy:

$$E_A = -\frac{5}{18} \log_2 \frac{5}{18} - \frac{5}{18} \log_2 \frac{5}{18} - \frac{8}{18} \log_2 \frac{8}{18} = 1.547$$

$$E_{B_1} = -\frac{1}{8} \log_2 \frac{1}{8} - \frac{2}{8} \log_2 \frac{2}{8} - \frac{5}{8} \log_2 \frac{5}{8} = 1.299$$

$$E_{B_2} = -\frac{4}{10} \log_2 \frac{4}{10} - \frac{6}{10} \log_2 \frac{6}{10} = 0.971$$

$$E_{C_1} = -\frac{1}{6} \log_2 \frac{1}{6} - \frac{5}{6} \log_2 \frac{5}{6} = 0.65$$

$$E_{C_2} = -1 \cdot \log_2(1) = 0$$

Misclassification error:

$$M_A = 1 - \frac{8}{18} = \frac{5}{9}$$

$$M_{B_1} = 1 - \frac{5}{8} = \frac{3}{8}$$

$$M_{B_2} = 1 - \frac{6}{10} = \frac{2}{5}$$

$$M_{C_1} = 1 - \frac{5}{6} = \frac{1}{6}$$

$$M_{C_2} = 1 - 1 = 0$$

T₄

(a) empirical MSE:

$$\widehat{MSE} = \frac{1}{10} \times [(6-7)^2 + (8-7)^2 + (9-7)^2 + (5-7)^2 + (10-7)^2 + (5-7)^2 + (4-7)^2 + (8-7)^2 + (9-7)^2 + (3-7)^2] = 5.3$$

$$\bar{h}_D(X=3) = \frac{1}{10} \times (6+8+9+5+10+5+4+8+9+3) = 6.7$$

$$\text{Bias}^2 = [\bar{h}_D(X=3) - t(X=3)]^2 = (6.7 - 6.7)^2 = 0$$

$$\text{Variance} = \frac{1}{10} \sum_i (h_D(X=3) - \bar{h}_D(X=3))^2$$

$$= \frac{1}{10} \times [(6-6.7)^2 + (8-6.7)^2 + (9-6.7)^2 + (5-6.7)^2 + (10-6.7)^2 + (5-6.7)^2 + (4-6.7)^2 + (8-6.7)^2 + (9-6.7)^2 + (3-6.7)^2] = 5.21$$

(b) reason ①:

in fact, the theoretical equation is:

$$E_{(x,y),D}[(h_D(x) - y)^2] = E_{(x,y),D}[(h_D(x) - \bar{h}(x))^2] + E_{(x,y),D}[(\bar{h}(x) - t(x))^2] + E_{x,y}[(t(x) - y)^2]$$

and we need to use integral and the probability distribution to compute each expectation term. But in reality, we don't know the distribution and our sample is limited within finite data point.

reason ②:

here we suppose the error $\varepsilon \in N(0, \sigma^2)$ and $\sigma^2 = 0.5$ but in fact, the error may not satisfy the normal distribution we have supposed.

reason ③:

even in the discrete case, we have:

$$\begin{aligned}
\widehat{MSE}(x, y) &= \frac{1}{10} \sum_{i=1}^{10} (h_{D_i}(x) - y)^2 \\
&= \frac{1}{10} \sum_{i=1}^{10} (h_{D_i}(x) - \bar{h}(x) + \bar{h}(x) - y)^2 \\
&= \frac{1}{10} \sum_{i=1}^{10} [2(h_{D_i}(x) - \bar{h}(x))(\bar{h}(x) - y)] + \frac{1}{10} \sum_{i=1}^{10} [h_{D_i}(x) - \bar{h}(x)]^2 \\
&\quad + \frac{1}{10} \sum_{i=1}^{10} [\bar{h}(x) - y]^2 = \frac{1}{10} \sum_{i=1}^{10} [h_{D_i}(x) - \bar{h}(x)]^2 + \frac{1}{10} \sum_{i=1}^{10} [\bar{h}(x) - y]^2 \\
&= \frac{1}{10} \sum_{i=1}^{10} [h_{D_i}(x) - \bar{h}(x)]^2 + \frac{1}{10} \sum_{i=1}^{10} [\bar{h}(x) - t(x) + t(x) - y]^2 \\
&= \frac{1}{10} \sum_{i=1}^{10} [h_{D_i}(x) - \bar{h}(x)]^2 + \frac{1}{10} \sum_{i=1}^{10} (h(x) - t(x))^2 + \frac{1}{10} \sum_{i=1}^{10} [t(x) - y]^2 \\
&\quad + \frac{1}{10} \sum_{i=1}^{10} [2(\bar{h}(x) - t(x))(t(x) - y)] \\
&= \frac{1}{10} \sum_{i=1}^{10} [h_{D_i}(x) - \bar{h}(x)]^2 + \frac{1}{10} \sum_{i=1}^{10} (h(x) - t(x))^2 + \frac{1}{10} \sum_{i=1}^{10} [t(x) - y]^2 \\
&= \text{bias}^2 + \text{Variance} + \frac{1}{10} \sum_{i=1}^{10} [t(x) - y]^2 \\
&\quad \text{and } \sigma^2 \neq \frac{1}{10} \sum_{i=1}^{10} [t(x) - y]^2
\end{aligned}$$

in fact, it is similar to limited sample reason

T5.

$$\sigma(a) = \frac{1}{1+e^{-a}}$$

$$\tanh(a) = \frac{e^a - e^{-a}}{e^a + e^{-a}}$$

$$\therefore \tanh(a) = 2\sigma(2a) - 1$$

$$y_k(x, w) = \sigma\left(\sum_{j=1}^M w_{kj}^{(2)} \sigma\left(\sum_{i=1}^D w_{ji}^{(1)} x_i + w_{j0}^{(1)}\right) + w_{k0}^{(2)}\right)$$

$$\begin{aligned} \hat{y}_k(x, \hat{w}) &= \sigma\left(\sum_{j=1}^M \hat{w}_{kj}^{(2)} \left[2\sigma\left(2\left(\sum_{i=1}^D \hat{w}_{ji}^{(1)} x_i + \hat{w}_{j0}^{(1)}\right)\right) - 1\right] + \hat{w}_{k0}^{(2)}\right) \\ &= \sigma\left(\sum_{j=1}^M 2\hat{w}_{kj}^{(2)} \sigma\left(\sum_{i=1}^D 2\hat{w}_{ji}^{(1)} x_i + 2\hat{w}_{j0}^{(1)}\right) - \sum_{j=1}^M \hat{w}_{kj}^{(2)} + \hat{w}_{k0}^{(2)}\right) \end{aligned}$$

$$\text{we let } 2\hat{w}_{kj}^{(2)} = w_{kj}^{(2)}$$

$$2\hat{w}_{ji}^{(1)} = w_{ji}^{(1)}$$

$$2\hat{w}_{j0}^{(1)} = w_{j0}^{(1)}$$

$$\hat{w}_{k0}^{(2)} - \sum_{j=1}^M \hat{w}_{kj}^{(2)} = w_{k0}^{(2)}$$

then $y_k(x, w) = \hat{y}_k(x, \hat{w})$, and the above is linear transformation between w and \hat{w} .

\therefore Q.E.D.