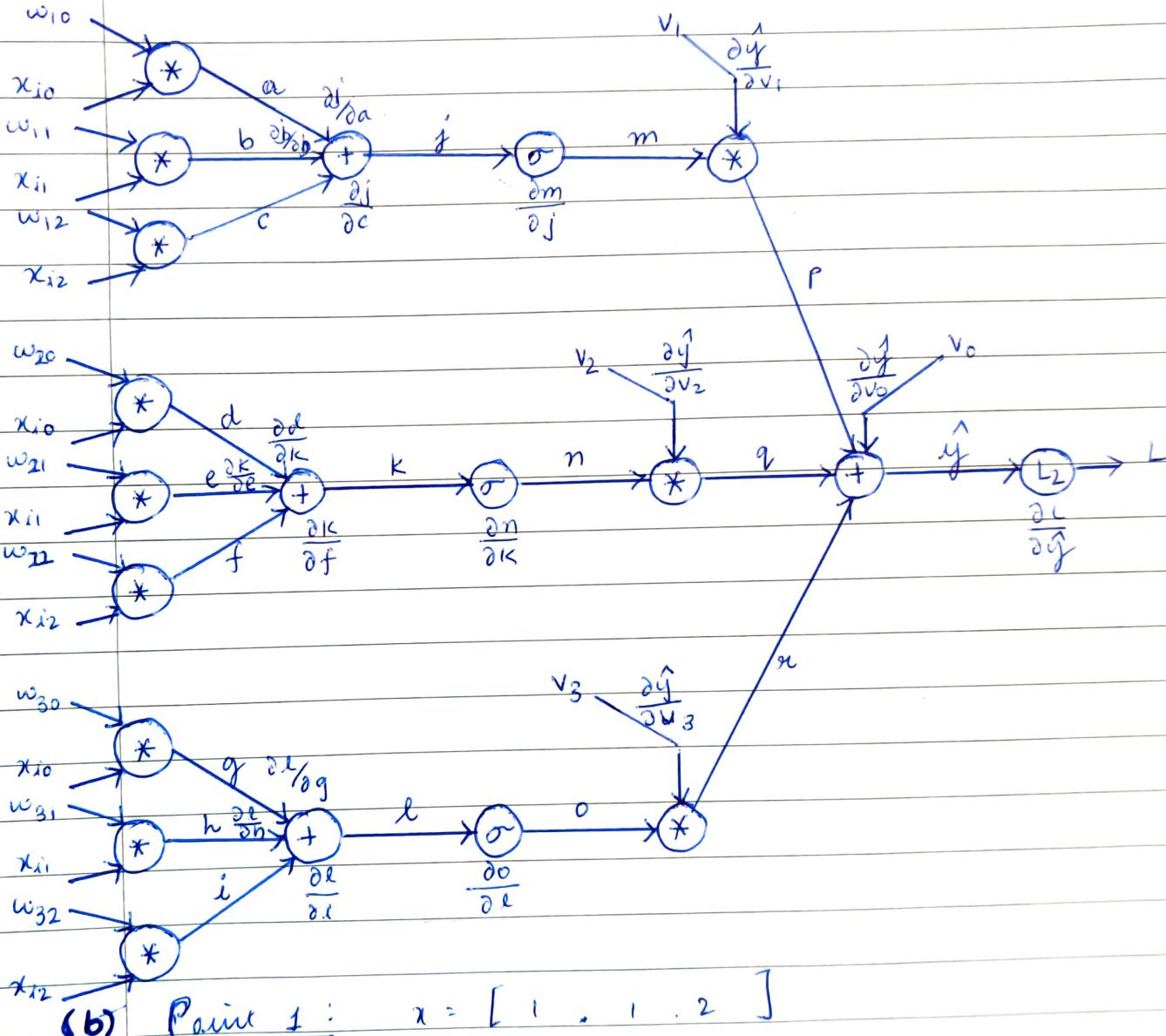


# Deep Learning Assignment 2 - A20442409.

1.

(a)



(b)

$$\text{Point 1: } x = [1, 1, 2]$$

$$a = 0.01 \quad b = 0.02 \quad c = 0.06$$

$$j = 0.01 + 0.02 + 0.06 = 0.09$$

$$m = \text{sigmoid}(j) = 0.52248$$

$$d = 0.03 \quad e = 0.01 \quad f = 0.04$$

$$k = 0.03 + 0.01 + 0.04 = 0.08$$

$$n = \text{sigmoid}(k) = 0.51999$$

$$g = 0.03 \quad h = 0.02 \quad i = 0.02$$

$$l = 0.03 + 0.02 + 0.02 = 0.07$$

$$o = \text{sigmoid}(l) = 0.51799$$

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$$p = mv_1 = 0.01044$$

$$q = nv_2 = 0.015599$$

$$r = ov_3 = 0.02069$$

$$\hat{y}_1 = v_0 + p + q + r = \underline{0.05675}$$

Point 2:  $x = [1 \ 1 \ 3]$

$$a = 0.01 \quad b = 0.02 \quad c = 0.09$$

$$j = 0.01 + 0.02 + 0.09 = 0.12$$

$$m = \text{Sigmoid}(j) = 0.52996$$

$$d = 0.03 \quad e = 0.01 \quad f = 0.06$$

$$k = 0.03 + 0.01 + 0.06 = 0.1$$

$$n = \text{Sigmoid}(k) = 0.52498$$

$$g = 0.02 \quad h = 0.03 \quad i = 0.03$$

$$l = 0.02 + 0.03 + 0.03 = 0.08$$

$$o = \text{Sigmoid}(l) = 0.51999$$

$$p = mv_1 = 0.01059$$

$$q = nv_2 = 0.01574$$

$$r = ov_3 = 0.02079$$

$$\hat{y} = v_0 + p + q + r = \underline{0.057148}$$

Point 3:  $x = [1 \ 2 \ 2]$

$$a = 0.01 \quad b = 0.04 \quad c = 0.06$$

$$j = 0.01 + 0.04 + 0.06 = 0.11$$

$$m = \text{Sigmoid}(j) = 0.52747$$

$$d = 0.03 \quad e = 0.02 \quad f = 0.04$$

$$k = 0.03 + 0.02 + 0.04 = 0.09$$

$$n = \text{Sigmoid}(k) = 0.52248$$

$$g = 0.02 \quad h = 0.06 \quad i = 0.02$$

$$l = 0.02 + 0.06 + 0.02 = 0.10$$

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$$o = \text{sigmoid}(x) = 0.52498$$

$$p = mv_1 = 0.01054$$

$$q = nv_2 = 0.01567$$

$$\gamma = ov_3 = 0.02079$$

$$\hat{y} = v_o + p + q + \gamma = \underline{0.05722}$$

$$L_2 \text{ loss} = (\hat{y}_i - y_i)^2$$

$$\frac{\partial \hat{y}}{\partial v_o} - \frac{\partial \hat{y}}{\partial p} = \frac{\partial \hat{y}}{\partial q} = \frac{\partial \hat{y}}{\partial \gamma} = 1.$$

$$\frac{\partial p}{\partial v_1} = m \quad \frac{\partial q}{\partial v_2} = n \quad \frac{\partial \gamma}{\partial v_3} = 0$$

$$\frac{\partial m}{\partial j} = m(1-m) \quad \frac{\partial n}{\partial k} = n(1-n) \quad \frac{\partial o}{\partial l} = o(1-o)$$

$$\frac{\partial j}{\partial c} = \frac{\partial k}{\partial f} = \frac{\partial l}{\partial g} = \frac{\partial j}{\partial b} = \frac{\partial k}{\partial d} = \frac{\partial l}{\partial n} = \frac{\partial j}{\partial a} = \frac{\partial k}{\partial e} = \frac{\partial l}{\partial i}$$

$$\frac{\partial a}{\partial w_{10}} = \frac{\partial b}{\partial w_{20}} = \frac{\partial g}{\partial w_{30}} = 0.1.$$

$$\frac{\partial b}{\partial w_{11}} = x_{i1}, \quad \frac{\partial f}{\partial w_{12}} = x_{i2}, \quad \frac{\partial e}{\partial w_{21}} = x_{i1}, \quad \frac{\partial f}{\partial w_{22}} = x_{i2}$$

$$\frac{\partial h}{\partial w_{31}} = x_{i1}, \quad \frac{\partial l}{\partial w_{32}} = x_{i2}, \quad \frac{\partial p}{\partial m} = v_1, \quad \frac{\partial q}{\partial n} = v_2$$

$$\frac{\partial k}{\partial o} = v_3.$$

Gradient descent of loss:

$$\frac{\partial \hat{y}}{\partial w_{10}} = \frac{\partial \hat{y}}{\partial p} \cdot \frac{\partial p}{\partial m} \cdot \frac{\partial m}{\partial j} \cdot \frac{\partial j}{\partial a} \cdot \frac{\partial a}{\partial w_{10}}$$

$$= v_1 \cdot m(1-m) \cdot 1 \cdot 1$$

$$\frac{\partial \hat{y}}{\partial w_{10}} = v_1 \cdot n(1-n).$$

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Similarly

$$\frac{\partial \hat{y}}{\partial w_{11}} = v_1 \cdot m(1-m) \cdot x_{i1}$$

$$\frac{\partial \hat{y}}{\partial w_{12}} = v_1 \cdot m(1-m) \cdot x_{i2}$$

$$\frac{\partial \hat{y}}{\partial w_{20}} = v_2 \cdot n(1-n) \cdot 1$$

$$\frac{\partial \hat{y}}{\partial w_{21}} = v_2 \cdot n(1-n) \cdot x_{i1}$$

$$\frac{\partial \hat{y}}{\partial w_{22}} = v_2 \cdot n(1-n) \cdot x_{i2}$$

$$\frac{\partial \hat{y}}{\partial w_{30}} = v_3 \cdot o(1-o) \cdot 1$$

$$\frac{\partial \hat{y}}{\partial w_{31}} = v_3 \cdot o(1-o) \cdot x_{i1}$$

$$\frac{\partial \hat{y}}{\partial w_{32}} = v_3 \cdot o(1-o) \cdot x_{i2}$$

c). Gradients of the function ~~with respect to~~ with respect to all weights are: for  $x = [1, 2]$

$$\begin{aligned} \frac{\partial L}{\partial \hat{y}} &= \frac{\partial}{\partial \hat{y}} (\hat{y} - y)^2 = 2(\hat{y} - y) \cdot 1 \\ &= 2(0.05675 - 8) \end{aligned}$$

$$= -15.8866$$

$$\frac{\partial y}{\partial v} = \left[ \frac{\partial \hat{y}}{\partial v_0} \quad \frac{\partial \hat{y}}{\partial v_1} \quad \frac{\partial \hat{y}}{\partial v_2} \quad \frac{\partial \hat{y}}{\partial v_3} \right]$$

$$= [1 \quad 0.52248 \quad 0.51999 \quad 0.51749]$$

$$\frac{\partial \hat{y}}{\partial w} = \begin{bmatrix} \frac{\partial \hat{y}}{\partial w_{10}} & \frac{\partial \hat{y}}{\partial w_{11}} & \frac{\partial \hat{y}}{\partial w_{12}} \\ \frac{\partial \hat{y}}{\partial w_{20}} & \frac{\partial \hat{y}}{\partial w_{21}} & \frac{\partial \hat{y}}{\partial w_{22}} \\ \frac{\partial \hat{y}}{\partial w_{30}} & \frac{\partial \hat{y}}{\partial w_{31}} & \frac{\partial \hat{y}}{\partial w_{32}} \end{bmatrix}.$$

$$= \begin{bmatrix} v_1 m(1-m) & v_1 m(1-m)x_{i1} & v_1 m(1-m)x_{i2} \\ v_2 n(1-n) & v_2 n(1-n)x_{i1} & v_2 n(1-n)x_{i2} \\ v_3 o(1-o) & v_3 o(1-o)x_{i1} & v_3 o(1-o)x_{i2} \end{bmatrix}$$

$$= \begin{bmatrix} 0.00499 & 0.00499 & 0.00996 \\ 0.00748 & 0.00748 & 0.0149 \\ 0.00998 & 0.00998 & 0.0199 \end{bmatrix}$$

$$\Delta v = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial v}$$

$$\Delta v = \begin{bmatrix} -15.8865 & -8.3 & -8.26 & -8.22 \end{bmatrix}$$

$$\Delta w = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w}$$

$$\Delta w = \begin{bmatrix} -0.07927 & -0.07927 & -0.15854 \\ -0.11896 & -0.11896 & -0.23793 \\ -0.15867 & -0.15867 & -0.31754 \end{bmatrix}.$$

$$\text{for } x = [1 \ 1 \ 3] \quad y = 11$$

$$\hat{y} = 0.057148$$

$$\frac{\partial L}{\partial \hat{y}} = 2(\hat{y} - y) = -21.8857$$

$$\frac{\partial \hat{y}}{\partial v} = \left[ \frac{\partial \hat{y}}{\partial v_0} \quad \frac{\partial \hat{y}}{\partial v_1} \quad \frac{\partial \hat{y}}{\partial v_2} \quad \frac{\partial \hat{y}}{\partial v_3} \right] = \begin{bmatrix} 1 & 0.52996 & 0.5 \\ & & 0.5 \end{bmatrix}$$

$$\Delta v = [-21.886 \quad -11.598 \quad -11.489 \quad -11.380]$$

$$\frac{\partial y}{\partial w} = \begin{bmatrix} 0.005 & 0.005 & 0.01 \\ 0.00712 & 0.00712 & 0.024 \\ 0.0099 & 0.0099 & 0.028 \end{bmatrix}$$

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$$\Delta w = \begin{bmatrix} -0.109 & -0.109 & -0.327 \\ -0.163 & -0.163 & -0.491 \\ -0.218 & -0.218 & -0.655 \end{bmatrix}$$

$\hat{y}_k = f$  for  $x = [1, 22]$ .

$$\frac{\partial L}{\partial \hat{y}} = 2(\hat{y} - y) = 2(0.05722 - 10) = -19.885$$

$$\frac{\partial \hat{y}}{\partial w} = [1 \quad 0.527474 \quad 0.52248 \quad 0.51999]$$

$$\Delta v = [-19.885 \quad -10.489 \quad -10.389 \quad -10.439]$$

$$\frac{\partial \hat{y}}{\partial w} = \begin{bmatrix} 0.00499 & 0.00998 & 0.00998 \\ 0.00748 & 0.0149 & 0.0149 \\ 0.00998 & 0.01996 & 0.01996 \end{bmatrix}$$

$$\Delta w = \begin{bmatrix} -0.099 & -0.198 & -0.198 \\ -0.198 & -0.297 & -0.297 \\ -0.198 & -0.396 & -0.396 \end{bmatrix}$$

$$(d) v_j \leftarrow v_j - \eta \sum_{i=1}^m (\hat{y}_j^{(i)} - y_j^{(i)}) z^{(i)}$$

$$\Delta v_j = \sum_{i=1}^m (\hat{y}_j^{(i)} - y_j^{(i)}) z^{(i)}$$

$$z^{(i)} = \text{sigmoid}(w_j^T x).$$

$$w \leftarrow w_j - \eta \sum_{i=1}^m \sum_{e=1}^K (\hat{y}_e^{(i)} - y_e^{(i)}) v_{kj} z_j (1 - z_j) x^{(i)}$$

$$Z = \begin{bmatrix} m & n & o \end{bmatrix}$$

for first datapoint  $[ (1, 2), 8 ]$ .

$$\Delta v_j = (\hat{y}_j^{\lambda} - y_j^{\lambda}) [ \text{imno} ].$$

$$\Delta v_j = [-15.8865 \quad -8.3 \quad -8.26 \quad -8.22]$$

$$\Delta w_1 = (-18.8865) (0.2) (0.52248)(1 - 0.52248) [1 \quad 1 \quad 2],$$

$$\Delta w_1 = \begin{bmatrix} -0.07927 & -0.07927 & -0.15854 \end{bmatrix} //$$

$$\Delta\omega_2 = (-15 - 88647(0.3)(0.51299)(1 - 0.51997)) [1 \ 1 \ 2]$$

$$= \begin{bmatrix} -0.11896 & -0.11896 & -0.23793 \end{bmatrix}$$

$$\Delta w_3 = [-15.8864] (0.4) (0.51749) (1 - 0.51749) [1, 1, 2]$$

$$= \begin{bmatrix} -0.15867 & -0.15867 & -0.31734 \end{bmatrix}$$

for the datapoint  $(1, 3), 11$ .

$$\Delta V_j = [-21.886 \quad -11.598 \quad -11.489 \quad -11.380].$$

$$\Delta\omega_1 = -21.886 \times (0.2) \times (0.522996) \times (1 - 0.522996)$$

$$\Delta w_1 = \begin{bmatrix} -0.109 & -0.109 & -0.327 \end{bmatrix}$$

$$\Delta w_2 = (-21.886)(0.3)(0.52498)(1 - 0.52498) [1 \quad 1]$$

$$\Delta w_2 = \begin{bmatrix} -0.163 & -0.163 & -0.491 \end{bmatrix}$$

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$$\Delta w_3 = (-21.886)(0.4)(0.51999)(1 - 0.51999) \begin{bmatrix} 1 & 1 & 3 \end{bmatrix}$$

$$\Delta w_3 = \begin{bmatrix} -0.218 & -0.218 & -0.655 \end{bmatrix},$$

for the datapoint  $[ (2, 2), 10 ]$ .

$$\Delta v = \begin{bmatrix} -19.885 & -10.489 & -10.389 & -10.439 \end{bmatrix}.$$

$$\Delta w_1 = (-19.885)(0.2)(0.527474)(1 - 0.527474) \begin{bmatrix} 1 & 2 & 2 \end{bmatrix}$$

$$\Delta w_1 = \begin{bmatrix} -0.099 & -0.099 & -0.198 \end{bmatrix}$$

$$\Delta w_2 = (-19.885)(0.3)(0.52248)(1 - 0.52248) \begin{bmatrix} 1 & 1 & 3 \end{bmatrix}$$

$$\Delta w_2 = \begin{bmatrix} -0.148 & -0.297 & -0.297 \end{bmatrix}$$

$$\Delta w_3 = (-19.885)(0.4)(0.51999)(1 - 0.51999) \begin{bmatrix} 1 & 1 & 3 \end{bmatrix}$$

$$\Delta w_3 = \begin{bmatrix} -0.498 & -0.398 & -0.398 \end{bmatrix}$$

It is seen that the weights obtained in part d is almost the same as obtained in part c. Hence the values are matching.

⑨

2.

a)  $f(x, y) = (2x + 3y)^2$

$$\nabla f(x, y) = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

$$\frac{\partial f}{\partial x} = 2(2x + 3y)2 = 8x + 12y$$

$$\frac{\partial f}{\partial y} = 2(2x + 3y)3 = 12x + 18y$$

$$\nabla f(x, y) = \begin{bmatrix} 8x + 12y \\ 12x + 18y \end{bmatrix}$$

b)  $F(x, y) = \begin{bmatrix} x^2 + 2y \\ 3x + 4y^2 \end{bmatrix}$

$$DF(x, y) = \begin{bmatrix} f_1(x, y) \\ f_2(x, y) \end{bmatrix} = \begin{bmatrix} f_1(x^2 + 2y) \\ f_2(3x + 4y^2) \end{bmatrix}$$

$$= \begin{bmatrix} \frac{\partial f_1}{\partial x} & \frac{\partial f_1}{\partial y} \\ \frac{\partial f_2}{\partial x} & \frac{\partial f_2}{\partial y} \end{bmatrix}$$

$$DF(x, y) = \begin{bmatrix} 2x & 2 \\ 3 & 8y \end{bmatrix}$$

$$DF(1, 2) = \begin{bmatrix} 2 & 2 \\ 3 & 16 \end{bmatrix}$$

$$c) \quad G(x) = \begin{bmatrix} x \\ x^2 \end{bmatrix} \quad f(x, y) = \begin{bmatrix} x^2 + 2y \\ 3x + 4y^2 \end{bmatrix}$$

$D(F \circ G)(x)$  using chain rule

$$D(F \circ G)(x) = Df(G(x)) Dg(x) = \begin{bmatrix} 2x & 2 \\ 3 & 8x^2 \end{bmatrix} \begin{bmatrix} 1 \\ 2x \end{bmatrix} = \begin{bmatrix} 6x \\ 3 + 16x^3 \end{bmatrix}$$

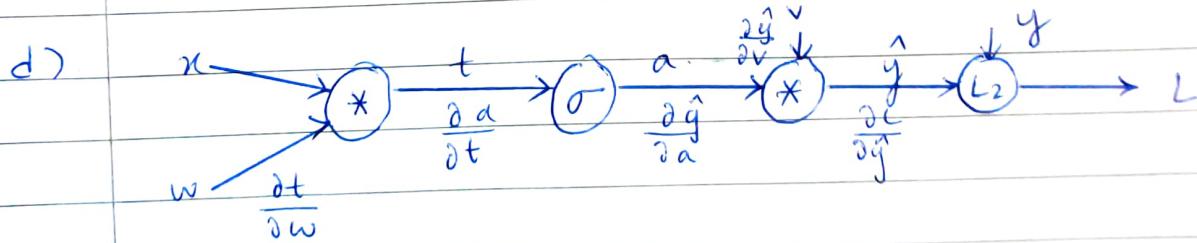
$$D(F \circ G)(2) = \begin{bmatrix} 12 \\ 3 + (16 \times 8) \end{bmatrix} = \begin{bmatrix} 12 \\ 131 \end{bmatrix}$$

$D(F \circ G)(x)$  without using chain rule

$$F(G(x)) = \begin{bmatrix} 3x^2 \\ 3x + 4x^4 \end{bmatrix}$$

$$D[F(G(x))] = \begin{bmatrix} 6x \\ 3 + 16x^3 \end{bmatrix}$$

$$D[F(G(2))] = \begin{bmatrix} 12 \\ 3 + (16 \times 8) \end{bmatrix} = \begin{bmatrix} 12 \\ 131 \end{bmatrix}$$



Point (1)  $x^T = [1 \ 1 \ 2]$

$$w = \begin{bmatrix} 0.01 & 0.02 & 0.03 \\ 0.03 & 0.01 & 0.02 \\ 0.02 & 0.03 & 0.01 \end{bmatrix}$$

$$v = [0.01 \quad 0.02 \quad 0.03 \quad 0.04]$$

$$y = 8$$

Forward Propagation for  $x = [1 \quad 1 \quad 2]$

$$a = \text{sigmoid}(wx) = \text{sigmoid} \begin{bmatrix} 0.09 \\ 0.08 \\ 0.07 \end{bmatrix} = \begin{bmatrix} 0.52248 \\ 0.51999 \\ 0.51749 \end{bmatrix}$$

$$a' = \begin{bmatrix} 1 \\ 0.52248 \\ 0.51999 \\ 0.51749 \end{bmatrix}$$

$$\hat{y} = va' = [0.01 \quad 0.02 \quad 0.03 \quad 0.04] \begin{bmatrix} 1 \\ 0.52248 \\ 0.51999 \\ 0.51749 \end{bmatrix}$$

$$\hat{y} =$$

$$\hat{y} = 0.05675$$

$$L = 2(\hat{y} - y)^2 = 2(0.05675 - 8)^2 = 63.095$$

Forward propagation for  $x = [1 \quad 1 \quad 3]$ .

$$y = 11$$

$$a = \text{sigmoid}(wx) = \text{sigmoid} \begin{bmatrix} 6.12 \\ 0.1 \\ 0.08 \end{bmatrix} = \begin{bmatrix} 0.52996 \\ 0.52498 \\ 0.51999 \end{bmatrix}$$

$$a^1 = \begin{bmatrix} 1 \\ 0.52996 \\ 0.52498 \\ 0.51999 \end{bmatrix}$$

$$\hat{y} = Va^1 = 6.057148$$

$$L = \frac{1}{2}(\hat{y} - y)^2 = (6.057148 - 11)^2 = 119.748$$

Forward propagation for  $x = [1 \ 2 \ 2]$

$$H = \text{sigmoid}(w \cdot x) = \text{sigmoid} \begin{bmatrix} 0.11 \\ 0.09 \\ 0.10 \end{bmatrix} = \begin{bmatrix} 0.52747 \\ 0.52248 \\ 0.51999 \end{bmatrix}$$

$$a^1 = \begin{bmatrix} 1 \\ 0.52747 \\ 0.52248 \\ 0.52498 \end{bmatrix}$$

$$\hat{y} = Va^1 = [0.01 \ 0.02 \ 0.03 \ 0.04] \begin{bmatrix} 1 \\ 0.52747 \\ 0.52248 \\ 0.52498 \end{bmatrix}$$

$$\hat{y} = 0.05722$$

$$L = (\hat{y} - y)^2$$

$$L = (0.05722 - 10)^2$$

$$L = 98.858$$

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Backward propagation for  $x = [1, 1, 2]$

$$\frac{\partial L}{\partial v} = \frac{\partial L}{\partial g} \frac{\partial g}{\partial a} \frac{\partial a}{\partial v} = 2a^T (\hat{y} - y) = 2 \begin{bmatrix} 1 \\ 0.52248 \\ 0.51999 \\ 0.51749 \end{bmatrix} (0.05675 - 8) = \begin{bmatrix} -15.8865 \\ -8.3 \\ -8.26 \\ -8.22 \end{bmatrix}^T$$

$$\begin{aligned} \frac{\partial L}{\partial w} &= \frac{\partial L}{\partial g} \frac{\partial g}{\partial a} \frac{\partial a}{\partial w} \\ &= x \times [a^T (1 - a^T) v^T 2(\hat{y} - y)] \\ &= \begin{bmatrix} 1 \\ 1 \\ 2 \end{bmatrix} \times \begin{bmatrix} 0.52996 \\ 0.52498 \\ 0.51999 \end{bmatrix} \times \begin{bmatrix} 1 - 0.52996 \\ 1 - 0.52498 \\ 1 - 0.51999 \end{bmatrix} \times \begin{bmatrix} 0.02 \\ 0.03 \\ 0.04 \end{bmatrix} \\ &= \begin{bmatrix} 1 \\ 1 \\ 2 \end{bmatrix} \times \begin{bmatrix} 0.52248 \\ 0.51999 \\ 0.51749 \end{bmatrix} \times \begin{bmatrix} 1 - 0.52248 \\ 1 - 0.51999 \\ 1 - 0.51749 \end{bmatrix} \times \begin{bmatrix} 0.02 \\ 0.03 \\ 0.04 \end{bmatrix}^T \times 2(0.05675 - 8) \\ &= \begin{bmatrix} 1 \\ 1 \\ 2 \end{bmatrix} \times [-0.07927 \quad -0.11896 \quad -0.15867]^T \\ &= \begin{bmatrix} -0.07927 & -0.07927 & -0.15854 \\ -0.11896 & -0.11896 & -0.23793 \\ -0.15867 & -0.15867 & -0.31734 \end{bmatrix} \end{aligned}$$

Backward propagation of  $x = [1, 1, 3]$ .

$$y = 11$$

$$\frac{\partial L}{\partial v} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial v} = a' \cdot 2 \cdot (\hat{y} - y) = \begin{bmatrix} 1 \\ 0.52996 \\ 0.52498 \\ 0.51999 \end{bmatrix}^T \cdot 2 \cdot (6.0514 - 11)$$

$$= [-21.886 \quad -11.598 \quad -11.489 \quad -11.380]^T$$

$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial a} \frac{\partial a}{\partial w} = \pi x \left[ a'(1-a') v^T 2(\hat{y} - y) \right]$$

$$= \begin{bmatrix} 1 \\ 1 \\ 3 \end{bmatrix} \times \begin{bmatrix} (0.52996) \\ (0.52498) \\ (0.51999) \end{bmatrix} \left( 1 - 0.52996 \right) \begin{bmatrix} 0.02 \\ 0.03 \\ 0.04 \end{bmatrix}^T \cdot 2 \cdot (0.05714 - 11)$$

$$= \begin{bmatrix} 1 \\ 1 \\ 3 \end{bmatrix} \begin{bmatrix} -0.109 & -0.163 & -0.218 \end{bmatrix}$$

$$= \begin{bmatrix} -0.109 & -0.109 & -0.327 \\ -0.163 & -0.163 & -0.491 \\ -0.218 & -0.218 & -0.655 \end{bmatrix}.$$

Backward propagation of  $x = [1, 2, 2]$ .

$$y = 10$$

$$\frac{\partial L}{\partial v} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial v} = a' \cdot 2 \cdot (\hat{y} - y) = \begin{bmatrix} 1 \\ 0.52747 \\ 0.52248 \\ 0.51999 \end{bmatrix}^T \cdot 2 \cdot (6.0572 - 10)$$

$$= [-19.885 \quad -10.489 \quad -10.389 \quad -10.439]^T$$

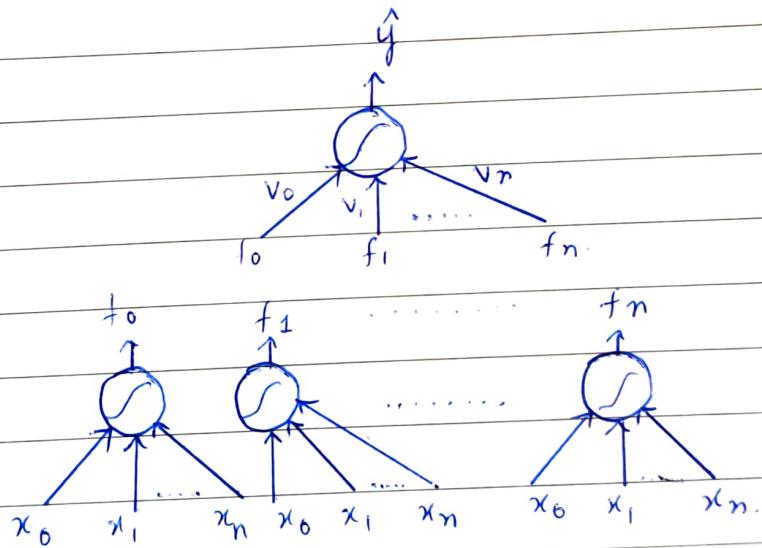
$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial a} \frac{\partial a}{\partial w} = \pi x \left[ a'(1-a') v^T 2(\hat{y} - y) \right]$$

$$= \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} \begin{bmatrix} 0.52747 \\ 6.52248 \\ 0.51999 \end{bmatrix} \begin{bmatrix} 1 - 0.52747 \\ 1 - 0.52248 \\ 1 - 0.51999 \end{bmatrix} \cdot \begin{bmatrix} 0.02 \\ 0.03 \\ 0.04 \end{bmatrix} \cdot 2 \cdot (0.05722 - 10)$$

$$= \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} \begin{bmatrix} -0.099 \\ -0.148 \\ -0.198 \end{bmatrix}$$

$$= \begin{bmatrix} -0.099 & -0.198 & -0.198 \\ -0.148 & -0.297 & -0.297 \\ -0.198 & -0.396 & -0.396 \end{bmatrix}$$

3.



given training set  $\{x^{(i)}, y^{(i)}\}_{i=1}^m$

$$E = \frac{1}{2} \left( \sum_{i=1}^m (y^{(i)} - \hat{y}^{(i)})^2 \right)$$

we have

$$\frac{\partial E}{\partial v} = \frac{\partial E}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial v} = \left[ 2 \cdot \frac{1}{2} \cdot \sum_{i=1}^m (\hat{y}^{(i)} - y^{(i)}) \right] f'^{(i)}$$

$$= \left[ \sum_{i=1}^m \hat{y}^{(i)} - y^{(i)} \right] [\hat{y}^{(i)}(1 - \hat{y}^{(i)})]$$

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$$v \leftarrow v - \eta \sum_{i=1}^m (\hat{y}^{(i)} - y^{(i)}) \hat{y}^{(i)} (1 - \hat{y}^{(i)}) f^{(i)}$$

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial f_i} \frac{\partial f_i}{\partial w_j}$$

$$\frac{\partial E}{\partial w} = \left[ \sum_{i=1}^m (\hat{y}^{(i)} - y^{(i)}) \right] v_j \left[ f_j^{(i)} (1 - f_j^{(i)}) \cdot x^{(i)} \right].$$

$$w \leftarrow w - \eta \left[ \sum_{i=1}^m (\hat{y}^{(i)} - y^{(i)}) \right] v_j \left[ f_j^{(i)} \cdot (1 - f_j^{(i)}) \cdot x^{(i)} \right].$$