

Part-B

(1) (a) sigmoid

$$f(x) = \text{sigmoid}(x) = \frac{1}{1 + e^{-x}}$$

$$f'(x) = \frac{1}{(1 + e^{-x})^2} (0 - e^{-x})$$

$$f'(x) = \frac{e^{-x}}{(1 + e^{-x})(1 + e^{-x})}$$

$$f'(x) = [1 - f(x)] (f(x))$$

$$f'(x) = [1 - \text{sigmoid}(x)] [\text{sigmoid}(x)]$$

(b) hyperbolic tangent

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

$$f'(x) = \frac{(e^x + e^{-x})(e^x + e^{-x}) - (e^x - e^{-x})(e^x - e^{-x})}{(e^x + e^{-x})^2}$$

$$= 1 - \frac{(e^x - e^{-x})^2}{(e^x + e^{-x})^2}$$

$$f'(x) = 1 - (f(x))^2$$

$$f'(x) = 1 - [\tanh(x)]^2$$

$$(c) f(x) = \text{relu}(x) = \begin{cases} x & x > 0 \\ 0 & x \leq 0 \end{cases}$$

$$f'(x) = \begin{cases} 1 & x > 0 \\ 0 & x < 0 \\ 0 & x = 0 \end{cases}$$

Although derivative of relu does not exist at  $x=0$ , but we generally assume it to be 0

$$[(\text{softmax})'((x)_{\text{softmax}} - 1)] = (x)^{\prime}_{\text{softmax}}$$

Input-Softmax

$$\frac{x_3 - x_2}{x_3 + x_2} = (x)_{\text{softmax}} = (x)^{\prime}_{\text{softmax}}$$

$$(x_3 - x_2)(x_3 + x_2) - (x_3 + x_2)(x_3 - x_2) = (x)^{\prime \prime}_{\text{softmax}}$$

$$= \frac{(x_3 + x_2)}{(x_3 + x_2) - 1} =$$

$$((x)^{\prime \prime}_{\text{softmax}}) - 1 = (x)^{\prime \prime}_{\text{softmax}}$$

$$[(\text{softmax})' - 1] = (x)^{\prime \prime}_{\text{softmax}}$$

③

DATE \_\_\_\_\_  
PAGE \_\_\_\_\_

## # Cross-entropy loss

loss =  $\sum_{i=1}^n -y_i \log p_i$ , let 'n' be total no. of categories.

Now  $y_i = 1$  (where  $i$  is true label)  
else  $y_i = 0$

$$\text{loss} = -\log p_i ; p_i = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}}$$

$$\text{loss} = -\log \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}}$$

$$\text{loss} = -z_i + \log \sum_j e^{z_j}$$

$$\frac{\delta \text{loss}}{\delta z_i} = -1 + \frac{1}{\sum_j e^{z_j}} e^{z_i}$$

$$\boxed{\frac{\delta \text{loss}}{\delta z_i} = -1 + p_i}$$

$i$  corresponds to true label category.

$$\therefore \boxed{\frac{\delta \text{loss}}{\delta z_j} = \begin{cases} p_j - 1 & j \equiv \text{true label} \\ p_j & \text{otherwise} \end{cases}}$$

possible values of  $j = 1, 2, \dots, n$

# L<sub>2</sub> loss

let last layer has n-neurons

i.e. our prediction vector will be n-dimensional

let y be target vector of n-dimensions

$$L_2 = (a_i - y_i)^2 \quad \text{assuming reduction to be 'sum'}$$

$$\frac{\partial L_2}{\partial a_i} = 2 |a_i - y_i| \quad i \equiv \text{category index}$$

# L<sub>1</sub> loss

let last layer has n-neurons

i.e. prediction vector (a) will be n-dimensional

let y be target vector of n-dims.

$$L_1 = |a_i - y_i| = \begin{cases} a_i - y_i & a_i > y_i \\ y_i - a_i & y_i > a_i \end{cases}$$

$$\frac{\partial L_1}{\partial a_i} = \begin{cases} 1 & a_i > y_i \\ -1 & a_i < y_i \\ 0 & a_i = y_i \end{cases} = \begin{cases} 1 & a_i > y_i \\ -1 & a_i < y_i \\ 0 & a_i = y_i \end{cases} \quad \text{assuming reduction to be 'sum'}$$

(5)

DATE \_\_\_\_\_  
PAGE \_\_\_\_\_~~Classification Loss~~~~Classification Loss~~

## Hinge loss → Let 'n' be no. of neurons in last layer  
 i.e. 'n' categories we want to output.

$$\text{loss} = \max(0, 1 - y \cdot a)$$

$$\text{loss} = \begin{cases} 0 & y \cdot a \geq 1 \\ 1 - y \cdot a & y \cdot a < 1 \end{cases}$$

vector properties = 1

$$\frac{\text{loss}}{sa_i} = \begin{cases} 0 & y \cdot a > 1 \\ 0 - y_i & y \cdot a < 1 \end{cases}$$

$$\boxed{\frac{\text{loss}}{sa_{id(i)}} = \begin{cases} 0 & y \cdot a \geq 1 \\ -y_i & y \cdot a < 1 \end{cases}}$$

assuming reduction to be 'sum'

$i = \text{category}$  [possible values  $\rightarrow 1, 2, \dots, n$ ]

# Huber loss

$$L_x(a, y) = \frac{1}{n} \sum_{i=1}^n \begin{cases} \frac{1}{2} (y_i - a)^2 & |y_i - a| \leq x \\ x |y_i - a| - \frac{1}{2} x^2 & \text{otherwise} \end{cases}$$

$$\therefore \frac{\partial L_x(a, y)}{\partial a} = \frac{1}{n} \sum_{i=1}^n \begin{cases} -(y_i - a) & |y_i - a| \leq x \\ -\text{sign}(y_i - a) & \text{otherwise} \end{cases}$$

## ## Cosine similarity loss

$$\cos(a, y) = \frac{a \cdot y}{|a||y|}$$

let  $a, y$  be  
n-dimensional  
vector

$$\cos(a + da, y) = \frac{(a + da) \cdot y}{|a + da||y|}$$

$a \rightarrow$  prediction  
 $y \rightarrow$  one-hot  
vector with  
actual  
label

$$|a + da| = \sqrt{(a + da) \cdot (a + da)}$$

$$= \sqrt{|a|^2 + |da|^2 + 2a \cdot da}$$

approximate as small  $da$

$$= |a| \sqrt{1 + \frac{|da|^2}{|a|^2} + \frac{2a \cdot da}{|a|^2}}$$

$$\approx |a| \left(1 + \frac{2a \cdot da}{|a|^2}\right)$$

Binomial expansion

$$\approx |a| \left(1 + \frac{a \cdot da}{|a|^2}\right)$$

$$\cos(a + da, y) \approx \frac{a \cdot y + da \cdot y}{|a| \left(1 + \frac{a \cdot da}{|a|^2}\right) |y|}$$

$$\approx \frac{a \cdot y + da \cdot y}{|a||y|} \left(1 + \frac{a \cdot da}{|a|^2}\right)^{-1}$$

Binomial expansion

$$\approx \frac{a \cdot y + da \cdot y}{|a||y|} \left(1 - \frac{a \cdot da}{|a|^2}\right)$$

$$\approx \frac{a \cdot y + da \cdot y}{|a||y|} - \frac{a \cdot y}{|a||y|} \frac{a \cdot da}{|a|^2} - \frac{(a \cdot da)(da \cdot y)}{|a||y||a|^2}$$

$$\approx \frac{a \cdot y}{|a||y|} + \left(\frac{y - a \cdot y}{|a||y||a|^2}\right) \cdot da$$

(7)

DATE \_\_\_\_\_  
PAGE \_\_\_\_\_

$$\cos(a + da, y) = \cos(a, y) + \left( \frac{y}{|a||y|} - \cos(a, y) \frac{a}{|a|^2} \right) \cdot da$$

~~derivative~~

$$\cos(a + da, y) - \cos(a, y) = \frac{y \cdot da}{|a||y|} - \frac{\cos(a, y) a \cdot da}{|a|^2}$$

$$\frac{\delta \cos(a, y)}{\delta a_i} = \frac{y_i}{|a||y|} - \frac{\cos(a, y) a_i}{|a|^2}$$

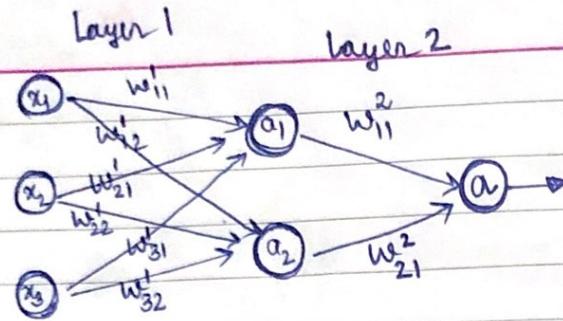
assuming  $a = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$  i.e. last layer is having  $n$ -neurons.

$$y = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \\ 0 \end{bmatrix} \quad \begin{array}{l} 1 \text{ is in position} \\ \text{which corresponds to} \\ \text{label } \end{array}$$

general term:

$$\frac{\delta \cos(a, y)}{\delta a_i} = \frac{y_i}{|a||y|} - \frac{\cos(a, y) a_i}{|a|^2}$$

 $i \equiv$  category index.



$$L_2 \equiv \text{loss} = (a - y)^2$$

$$\frac{\delta L_2}{\delta w_{11}^2} = 2(a-y) \frac{\delta a}{\delta w_{11}^2}$$

$$= 2(a-y) \frac{\delta a}{\delta z} \frac{\delta z}{\delta w_{11}^2}$$

$$\frac{\delta L_2}{\delta w_{11}^2} = 2(a-y) a (1-a) a_1$$

Forward propagation

$$\begin{cases} z_1 = w_{11}x_1 + w_{21}x_2 + w_{31}x_3 \\ a_1 = \text{sigmoid}(z_1) \end{cases}$$

$$\begin{cases} z_2 = w_{12}x_1 + w_{22}x_2 + w_{32}x_3 \\ a_2 = \text{sigmoid}(z_2) \end{cases}$$

$$\begin{cases} z = w_{11}^2 a_1 + w_{21}^2 a_2 + b \\ a = \text{sigmoid}(z) \end{cases}$$

similarly

$$\frac{\delta L_2}{\delta w_{21}^2} = 2(a-y) a (1-a) a_2$$

$$\frac{\delta L_2}{\delta w_{11}} = 2(a-y) \frac{\delta a}{\delta w_{11}}$$

$$= 2(a-y) \left( \frac{\delta a}{\delta z} \right) \left( \frac{\delta z}{\delta w_{11}} \right)$$

$$= 2(a-y) (a)(1-a) \left( \frac{\delta z}{\delta a_1} \right) \left( \frac{\delta a_1}{\delta w_{11}} \right)$$

$$= 2(a-y) [a(1-a)] w_{11}^2 \left( \frac{\delta a_1}{\delta z_1} \right) \left( \frac{\delta z_1}{\delta w_{11}} \right)$$

$$\boxed{\frac{\delta L_2}{\delta w_{11}} = 2(a-y)[a(1-a)] w_{11}^2 a_1 (1-a_1) x_1}$$

(9)

$$(w_j z + x_j) \cdot = (w+x) \cdot$$

$$(w) \cdot (x) \cdot = (wx) \cdot$$

DATE \_\_\_\_\_

PAGE \_\_\_\_\_

Backward propagation

$$\frac{\delta L_2}{\delta w_{ii}^1} = \left[ \left( \frac{\delta L_2}{\delta a} \right) \left( \frac{\delta a}{\delta z} \right) \left( \frac{\delta z}{\delta a_i} \right) \left( \frac{\delta a_i}{\delta z_i} \right) \left( \frac{\delta z_i}{\delta w_{ii}^1} \right) \right]$$

$$\frac{\delta L_2}{\delta w_{ii}^2} = \left[ \left( \frac{\delta L_2}{\delta a} \right) \left( \frac{\delta a}{\delta z} \right) \left( \frac{\delta z}{\delta w_{ii}^2} \right) \right]$$

general expression for weights gradient in Layer-1

$$\frac{\delta L_2}{\delta w_{ij}^1} = \frac{\delta L_2}{\delta a} \frac{\delta a}{\delta z} \frac{\delta z}{\delta a_j} \frac{\delta a_j}{\delta z_j} \frac{\delta z_j}{\delta w_{ij}^1}$$

$$= 2(a-y) a (1-a) w_{ji}^1 a_j (1-a_j) x_i$$

general expression for weights gradient in Layer-2

$$\frac{\delta L_2}{\delta w_{ij}^2} = \frac{\delta L_2}{\delta a} \frac{\delta a}{\delta z} \frac{\delta z}{\delta w_{ij}^2}$$

$$\frac{\delta L_2}{\delta w_{ij}^2} = 2(a-y) a (1-a) a_i$$

10

DATE \_\_\_\_\_  
PAGE \_\_\_\_\_

$$\begin{aligned}\frac{\delta L_2}{\delta b_1^2} &= 2(a-y) \frac{\delta a}{\delta b_1^2} \\ &= 2(a-y) \frac{\delta a}{\delta z} \frac{\delta z}{\delta b_1^2} \\ &= 2(a-y) a(1-a) (1)\end{aligned}$$

$$\boxed{\frac{\delta L_2}{\delta b_1^2} = 2(a-y) a(1-a)} \quad ①$$

$$\begin{aligned}\frac{\delta L_2}{\delta b_1^1} &= 2(a-y) \frac{\delta a}{\delta b_1^1} = 2(a-y) \frac{\delta a}{\delta z} \frac{\delta z}{\delta b_1^1} \\ &= 2(a-y) a(1-a) \frac{\delta z}{\delta a_1} \frac{\delta a_1}{\delta z_1} \frac{\delta z_1}{\delta b_1^1} \\ &= 2(a-y) a(1-a) w_{11}^2 a_1(1-a_1) (1)\end{aligned}$$

$$\boxed{\frac{\delta L_2}{\delta b_1^1} = [2(a-y)] [a(1-a)] [w_{11}^2] [a_1(1-a_1)]} \quad ②$$

$$\boxed{\frac{\delta L_2}{\delta b_2^1} = 2(a-y) a(1-a) w_{21}^2 a_2(1-a_2)} \quad ③$$

$$\begin{aligned}(a-y)(w_{11}-0)(w_{21}-0) \times 1108 \cdot 0 &= (a-y) \cdot 0 \cdot 1108 \cdot 0 \\ &= 0 \cdot 0 \cdot 0 \cdot 0 = 0\end{aligned}$$

11

DATE \_\_\_\_\_  
PAGE \_\_\_\_\_parameters

$$\begin{array}{l} x_1 = -0.06 \\ x_2 = -1.38 \\ x_3 = -0.32 \\ y = -1.43 \end{array} \quad \left. \begin{array}{l} w_{11}^1 = -0.06 \\ w_{21}^1 = -0.14 \\ w_{31}^1 = -0.43 \\ w_{12}^1 = 0.29 \\ w_{22}^1 = 0 \\ w_{32}^1 = -0.12 \end{array} \right\} \quad \left. \begin{array}{l} b_1^1 = 0.05 \\ b_2^1 = -0.22 \\ w_{11}^2 = -0.59 \\ w_{21}^2 = -0.14 \\ b_1^2 = -0.23 \end{array} \right\}$$

forward propagation

$$\begin{aligned} z_1 &= w_{11}^1 x_1 + w_{21}^1 x_2 + w_{31}^1 x_3 + b_1^1 \\ z_1 &= (-0.06)(-0.06) + (-0.14)(-1.38) + (-0.43)(-0.32) + 0.05 \\ z_1 &= 0.3844 \end{aligned}$$

$$\begin{aligned} z_2 &= w_{12}^1 x_1 + w_{22}^1 x_2 + w_{32}^1 x_3 + b_2^1 \\ z_2 &= (0.29)(-0.06) + (0)(-1.38) + (-0.12)(-0.32) - 0.22 \\ z_2 &= -0.199 \end{aligned}$$

$$a_1 = \frac{1}{1 + e^{-z_1}}$$

$$a_2 = \frac{1}{1 + e^{-z_2}}$$

$$a_1 = \frac{1}{1 + e^{-0.3844}}$$

$$a_2 = \frac{1}{1 + e^{-0.199}}$$

$$a_1 = 0.5949$$

$$a_2 = 0.4504$$

$$z = w_{11}^2 a_1 + w_{21}^2 a_2 + b_1^2$$

$$z = (-0.59)(0.5949) + (-0.14)(0.4504) - 0.23$$

$$z = -0.644$$

$$a = \frac{1}{1 + e^{-z}} = \frac{1}{1 + e^{0.644}} = 0.3443$$

$$\hat{y} = 0.3443$$

$$\text{loss} = (\hat{y} - y)^2 = 3.148$$

(12)

DATE  
PAGEsimilarly

$$\frac{\delta L_2}{\delta w_{21}'} = 2(a-y)(a(1-a)) w_{11}^2 a_1 (1-a_1) x_2 \quad (5)$$

$$\frac{\delta L_2}{\delta w_{31}'} = 2(a-y)(a(1-a)) w_{11}^2 a_1 (1-a_1) x_3 \quad (6)$$

$$\frac{\delta L_2}{\delta w_{12}'} = 2(a-y)(a(1-a)) w_{21}^2 a_2 (1-a_2) x_1 \quad (7)$$

$$\frac{\delta L_2}{\delta w_{22}'} = 2(a-y)(a(1-a)) w_{21}^2 a_2 (1-a_2) x_2 \quad (8)$$

$$\frac{\delta L_2}{\delta w_{32}'} = 2(a-y)(a(1-a)) w_{21}^2 a_2 (1-a_2) x_3 \quad (9)$$

Calculating

$$2(a-y)(a(1-a)) = 2(0.3443 + 1.43)(0.3443)(1 - 0.3443)$$

$$2(a-y)a(1-a)w_{11}^2 a_1 (1-a_1) = 0.8011 (-0.59)(0.5949)(1-0.5949) \\ = -0.01139$$

$$2(a-y)(a(1-a))w_{21}^2 a_2 (1-a_2) = 0.8011 \times (-0.14)(0.4504)(1-0.4504) \\ = -0.02776$$

(12)

DATE

PAGE

back propagation

Putting values from forward propagation in ①, ②, ③, ④, ⑤,  
 ⑥, ⑦, ⑧, ⑨, ⑩, ⑪

$$\frac{\delta L_2}{\delta b_1^2} = 2(0.3443 + 1.43)(0.3443)(1 - 0.3443)$$

$$\boxed{\Delta b_1^2 = 0.8011}$$

$$\begin{aligned}\frac{\delta L_2}{\delta b_1^1} &= 2(0.3443 + 1.43)(0.3443)(1 - 0.3443) (-0.59)(0.5949) \\ &\quad \downarrow \\ &= (0.8011)(-0.59)(0.5949)(1 - 0.5949) \\ &= -0.1139\end{aligned}$$

$$\boxed{\Delta b_1^1 = -0.1139}$$

$$\begin{aligned}\frac{\delta L_2}{\delta b_2^1} &= 2(0.3443 + 1.43)(0.3443)(1 - 0.3443)(-0.14)(0.4504)(1 - 0.4504) \\ &\quad \downarrow \\ &= (0.8011)(-0.14)(0.4504)(1 - 0.4504) \\ &= -0.0278\end{aligned}$$

$$\boxed{\Delta b_2^1 = -0.0278}$$

(14)

$$\frac{\delta L_2}{\delta w_{11}^1} = (-0.1139)(-0.06)$$

$$\boxed{\Delta w_{11}^1 = 0.0068}$$

$$\frac{\delta L_2}{\delta w_{21}^1} = (-0.1139)(-1.38)$$

$$\boxed{\Delta w_{21}^1 = 0.15718}$$

$$\frac{\delta L_2}{\delta w_{31}^1} = (-0.1139)(-0.32)$$

$$\boxed{\Delta w_{31}^1 = 0.036448}$$

$$\frac{\delta L_2}{\delta w_{12}^1} = (-0.02776)(-0.06)$$

$$\boxed{\Delta w_{12}^1 = 0.0016656}$$

$$\frac{\delta L_2}{\delta w_{22}^1} = (-0.02776)(-1.38)$$

$$\boxed{\Delta w_{22}^1 = 0.038308}$$

$$\frac{\delta L_2}{\delta w_{32}^1} = (-0.02776)(-0.32)$$

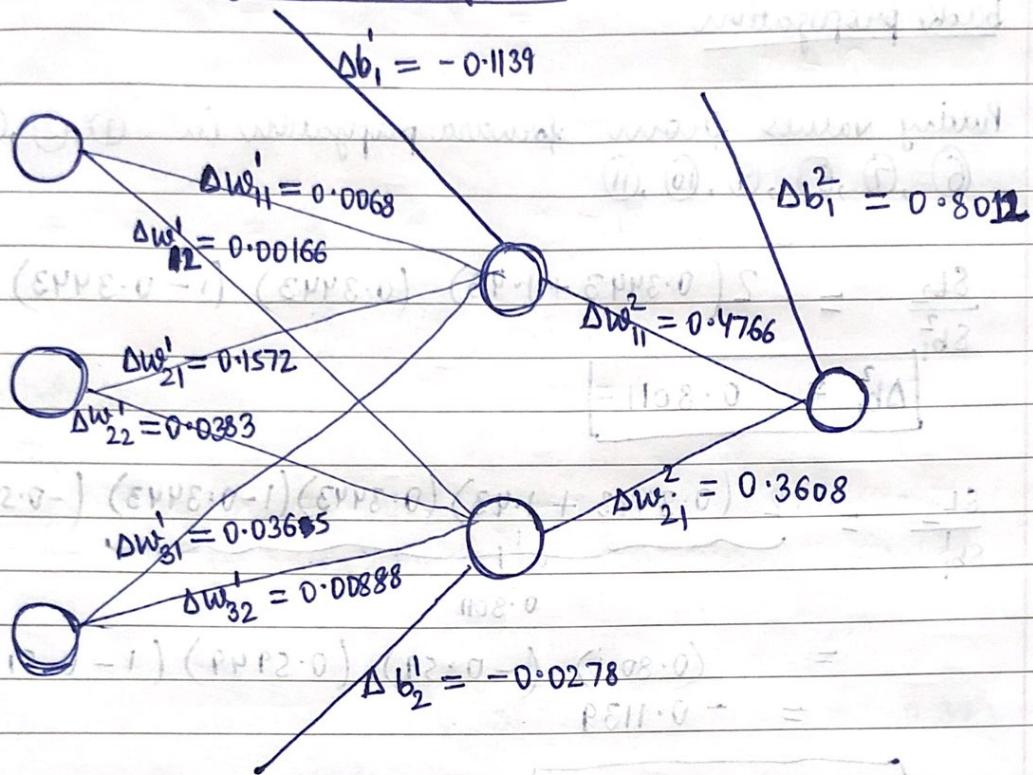
$$\boxed{\Delta w_{32}^1 = 0.00888}$$

$$\frac{\delta L_2}{\delta w_{11}^2} = (0.8011)(0.5949)$$

$$\boxed{\Delta w_{11}^2 = 0.47657}$$

$$\frac{\delta L_2}{\delta w_{21}^2} = (0.8011)(0.4504)$$

$$\boxed{\Delta w_{21}^2 = 0.360815}$$

back propagation graph

[ PEII-0- = 1d Δ ]  
Submitted by,

(TU3H-0) (H-0-1) (EHNE-0-1) (EHNC-0) (EH-1) + Nasudev Gupta ME18B182

(H02H-0-1) (H02H-0) (H-0-1) (H08-0) = 8FSU-0- =

[ 8FSU-0- = 1d Δ ]