

### Assignment - 3

## Data mining and machine learning

Q) (ii)

$$\frac{\partial E_d}{\partial \omega_{ii}^{(2)}}$$

The error function  $E_d$  can be given as:

$$E_d = \frac{1}{2} (y - oY_i)^2$$

Using the chain rule

$$\frac{\partial E_d}{\partial \omega_{ii}^{(2)}} = \frac{\partial E_d}{\partial oY_i} \cdot \frac{\partial oY_i}{\partial \text{net}Y_i} \cdot \frac{\partial \text{net}Y_i}{\partial \omega_{ii}^{(2)}}$$

where :

$$\frac{\partial E_d}{\partial oY_i} = -(y - oY_i)$$

$$\frac{\partial oY_i}{\partial \text{net}Y_i} = oY_i(1 - oY_i) \quad \text{= derivative of the sigmoid}$$

$$\frac{\partial \text{net}Y_i}{\partial \omega_{ii}^{(2)}} = oZ_i$$

∴ the full chain rule formula is:

$$\frac{\partial E_d}{\partial \omega_{ii}^{(2)}} = -(y - oY_i) \cdot oY_i(1 - oY_i) \cdot oZ_i$$

⑦ (iii) Computing  $\delta y_1$  as:

$$\delta y_1 = (y - o_{y_1}) \cdot o_{y_1} (1 - o_{y_1})$$

where:

$y$  is the target output ( $0$  in this case)

$o_{y_1}$  is the output ( $\approx 0.513122$ )

Substituting the values:

$$\delta y_1 = (0 - 0.513122) \cdot 0.513122 \cdot (1 - 0.513122)$$

Calculating  $\delta y_1$

$$\begin{aligned}\delta y_1 &= -0.513122 \times 0.513122 \times 0.486878 \\ &\approx -0.1294\end{aligned}$$

⑦ (iv)  $w_{ii}^{(2)}$

The weight update rule can be given as:

$$w_{ij}^{(\text{new})} = w_{ij}^{(\text{old})} + \eta \cdot \delta_j \cdot o_i$$

where:

$\eta$  is the learning rate ( $0.2$ )

$\delta_j$  is the error term for the neuron (in this case  $\delta y_1$ )

$o_i$  is the output from the previous layer (i.e.  $o_{x_1}$ )

Using

$$\omega_{11}^{(2)} = 0.1 \quad (\text{no } -) \text{ NO } \cdot (\text{NO } - \mu) \cdot \text{NO}$$

$$\delta y_1 \approx -0.1294$$

$$o_{z1} \approx 0.524979$$

Substituting into the update formula

$$\omega_{11}^{(2, \text{new})} = 0.1 + 0.2 \cdot (-0.1294) \cdot (0.524979)$$

$$\begin{aligned}\omega_{11}^{(2, \text{new})} &= 0.1 - 0.2 \cdot 0.0679 \approx 0.1 - 0.01358 \\ &\approx 0.08642\end{aligned}$$

⑦ (v)  $\omega_{21}^{(1)}$

$$\delta z_1 = \delta y_1 \cdot \omega_{11}^{(2)} \cdot o_{z1} (1 - o_{z1})$$

Using  $\omega_{11}^{(2)} = 0.1$

$$\delta y_1 \approx -0.1294$$

$$o_{z1} \approx 0.5249$$

$$\delta z_1 = -0.1294 \cdot 0.1 \cdot 0.524979 (1 - 0.524979)$$

$$\delta z_1 = -0.1294 \cdot 0.1 \cdot 0.524979 \cdot 0.475021 \approx -0.0031$$

Updating  $\omega_{21}^{(1)}$

$$\omega_{21}^{(1, \text{new})} = \omega_{21}^{(1, \text{old})} + \eta \cdot \delta z_1 \cdot x_2$$

Assuming  $\omega_{21}^{(1)} = 0.1$  and  $a_2 = 0$

$$\omega_{21}^{(1, \text{new})} = 0.1 + 0.2 \cdot (-0.0031) \cdot 0 = 0.1$$

Therefore

$$dy_1 \approx -0.1294$$

$$\text{Updated } \omega_{11}^{(2)} \approx 0.08642$$

$$\text{Updated } \omega_{21}^{(1)} = 0.1$$

Q. (i) Given image

2 4 5 9 7 8 6 3 1 4 6

6 3 1 4 6 (18,0) - High

4 2 7 7 2

6 5 9 9 8

8 4 3 6 5

Given filter

2 3 1  
1 0 4

4 8 4

Taking the red region from top left corner

$$\begin{matrix} 2 & 4 & 5 \\ 6 & 3 & 1 \\ 4 & 2 & 7 \end{matrix}$$

So calculating each element of the filter with corresponding element of image region

$$(2 \cdot 2) + (3 \cdot 4) + (1 \cdot 5) + (1 \cdot 6) + (0 \cdot 3) + (4 \cdot 1) + (4 \cdot 4) \\ + (8 \cdot 2) + (4 \cdot 7)$$

$$= 4 + 12 + 5 + 6 + 0 + 4 + 16 + 16 + 28$$

$$= 91$$

Applying the ReLU activation function as

$$\text{output} = \max(0, 91) = 91$$

Since the output is positive ReLU does not alter it.

⑧ (ii) Given stride = 2, no padding

the size of the feature map can be calculated

$$\text{as output size} = \left\lceil \frac{(\omega - f + 2p)}{s} \right\rceil + 1$$

Ans: Not got mark higher bcoz soft proof

where  $W$  = width of the input image

$F$  = width of the filter

$P$  = padding

$S$  = stride

$$W = 5$$

$$F = 3$$

$$P = 0$$

$$S = 2$$

$$\text{Output width} = \left\lfloor \frac{(5-3+2 \cdot 0)}{2} \right\rfloor + 1 = \left\lfloor \frac{2}{2} \right\rfloor + 1$$

$$= 1 + 1 = 2$$

Since the image is also  $5 \times 5$  the height will be the same

$$\text{Output height} = 2$$

∴ the size of the feature map is  $2 \times 2$

(8)(iii) total number of parameters when there are 10 feature maps can be given as:

$$\text{Total parameters} = (F \cdot F \cdot \text{input channels} + 1) \cdot \text{no. of feature maps}$$

Assuming the input image has 1 channel i.e.  
grayscale:

filter size  $F = 3$

no. of feature maps = 10

$$\text{Parameters per feature map} = (3 \cdot 3 \cdot 1 + 1) = 9 + 1 = 10$$

so for 10 feature maps the total parameters  
can be given as  $10 \cdot 10 = 100$

∴ therefore output of feature map node = 91

Size of feature map =  $2 \times 2$

Total no. of parameters for 10 feature maps = 100

Q(i) Example of  $1 \times 1$  convolution filter

$$\text{filter} = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \\ \omega_4 \end{bmatrix}$$

where  $\omega_1, \omega_2, \omega_3, \omega_4$  are the weights for  
each channel

$$\text{So, filter} = \begin{bmatrix} 0.5 \\ 1.0 \\ -0.5 \\ 2.0 \end{bmatrix}$$

Q(iii) Assuming the multi channel data at the upper left corner as:

channel 1	channel 2	channel 3	channel 4
1	2	3	4
5	6	7	8
9	10	11	12

Given values of the upper top left corner are

2 1 5 4

the values at the upper left corner are:

channel 1:1

channel 2:2

channel 3:3

channel 4:4

Using the  $1 \times 1$  filter

$$\begin{aligned}
 \text{Output} &= (\omega_1 \cdot 1) + (\omega_2 \cdot 2) + (\omega_3 \cdot 3) + (\omega_4 \cdot 4) \\
 &= (0.5 \cdot 2) + (1.0 \cdot 1) + (-1.5 \cdot 5) + (2.0 \cdot 4) \\
 &= (1) + (1) + (-7.5) + (8) \\
 &= 2 - 7.5 + 8 \\
 &= 10 - 7.5 \\
 &= 2.5
 \end{aligned}$$