

## Part I: Derivative of Tanh

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

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

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

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

$$f'(x) = \frac{d}{dx} (\tanh x) = \operatorname{sech}^2 x$$

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

$$\operatorname{sech}^2 x = 1 - \tanh^2 x$$

$$\Downarrow \operatorname{sech}^2 x + \tanh^2 x = 1$$

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

Hence proved

## → Part II Forward - backward Pass

$$1. h_1 = 0.7x - 0.3 + 0.5 \times 0.15 + 1 \times 0.9 = 0.765$$

$$- 2 \times 0.8 + 1 \times -0.14$$

$$h_2 = 0.5 \times 0.2 + 0.52 \\ = 0.52$$

$$\Rightarrow \hat{y} = 0.7 \times 0.265 + 0.52 \times 0.25 - 0.1 \\ = 0.5355 + 0.13 - 0.1 \\ = 0.5655 \\ \hat{y} = \text{predicted value} = 0.5655$$

$$2) \text{ MSE} = \frac{1}{2} (y - \hat{y})^2 \\ = \frac{1}{2} (0.5 - 0.5655)^2$$

MSE = 0.002145

3) Find the gradient using back-propagation

$$\nabla J_i = \left[ \begin{array}{c} \frac{\partial J_i}{\partial w_1} \\ \frac{\partial J_i}{\partial w_2} \\ \vdots \\ \frac{\partial J_i}{\partial w_q} \end{array} \right]$$

$$\rightarrow h_1 = i_1 w_1 + i_2 w_3 + w_5$$

$$h_2 = i_1 w_2 + i_2 w_4 + w_6$$

$$\hat{y} = (i_1 w_1 + i_2 w_3 + w_5) \times w_7 \\ + (i_1 w_2 + i_2 w_4 + w_6) \times w_8 \\ + w_9$$

$$\frac{\partial \text{Error}}{\partial w_9} = \frac{\partial \text{Error}}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial w_9}$$

$$= (y - \hat{y})(-1) \times 1$$

$$\frac{\partial \text{Error}}{\partial w_7} = -(y - \hat{y})$$

$$\frac{\partial \text{Error}}{\partial w_7} = (y - \hat{y})(-1) \times h_1$$

$$\frac{\partial \text{Error}}{\partial w_8} = \frac{\partial \text{Error}}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial w_8}$$

$$\frac{\partial \text{Error}}{\partial w_8} = (y - \hat{y})(-1) \times h_2$$

$$\frac{\partial \text{Error}}{\partial w_1} = \frac{\partial \text{Error}}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial h_2} \times \frac{\partial h_2}{\partial w_1}$$

$$\frac{\partial \text{error}}{\partial w_6} = (\hat{y} - \hat{y})(-1) = (\hat{y} - \hat{y})(-1) \times w_8$$

$$\times w_8 \times i_1$$

$$\boxed{\frac{\partial \text{error}}{\partial w_6} = (\hat{y} - \hat{y}) \times (-1) \times w_8}$$

$$\frac{\partial \text{error}}{\partial w_5} = \frac{\partial \text{error}}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial h_1} + \frac{\partial h_1}{\partial w_5}$$

$$= (\hat{y} - \hat{y}) \times (-1) \times w_7$$

$$\boxed{\frac{\partial \text{error}}{\partial w_5} = (\hat{y} - \hat{y})(-1) \times w_7}$$

$$\frac{\partial \text{error}}{\partial w_4} = \frac{\partial \text{error}}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial h_2} \times \frac{\partial h_2}{\partial w_4}$$

$$\frac{\partial \text{error}}{\partial w_4} = (\hat{y} - \hat{y}) \times (-1) \times w_8 \times i_2$$

$$\boxed{\frac{\partial \text{error}}{\partial w_4} = (\hat{y} - \hat{y}) \times (-1) \times w_8 \times i_2}$$

$$\frac{\partial \text{error}}{\partial w_3} = \frac{\partial \text{error}}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial h_1} \times \frac{\partial h_1}{\partial w_3}$$

$\partial w_3$  $y$  $\partial h_1$ 

$$\frac{\partial \text{error}}{\partial w_3} = (y - \hat{y}) \times (-1) \times w_7 \times i_2$$

$$\frac{\partial \text{error}}{\partial w_2} = \frac{\partial \text{error}}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial h_2} \times \frac{\partial h_2}{\partial w_2}$$

$$\frac{\partial \text{error}}{\partial w_1} = (y - \hat{y}) \times -1 \times w_8 \times i_1$$

$$\frac{\partial \text{error}}{\partial w_1} = (y - \hat{y}) \times -1 \times w_7 \times i_1$$

Gradients  
computed  
using back  
prop

$$\Rightarrow \nabla J_i =$$

$$\begin{cases} (y - \hat{y}) \times (-w_7) \times i_1 \\ (y - \hat{y}) \times (-w_8) \times i_1 \\ (y - \hat{y}) \times (-w_7) \times i_2 \\ (y - \hat{y}) \times (-w_8) \times i_2 \\ (y - \hat{y}) \times (-w_7) \\ (y - \hat{y}) \times (-w_8) \\ (y - \hat{y}) \times (-h_1) \\ \vdots \times (-h_2) \end{cases}$$

$$\left[ \begin{array}{c} (y - \hat{y}) \\ -(y - \hat{y}) \end{array} \right]$$

$$y - \hat{y} = 0.5 - 0.5655 = -0.0655$$

$$h_1, h_2 = 0.765, 0.52$$

$$w_1, w_2 = 0.7, 0.5$$

$$w_7, w_8 = 0.7, 0.25$$

$$\nabla J_i = 0.0655$$

$$\left[ \begin{array}{c} 0.7 \times 0.7 \\ 0.25 \times 0.7 \\ 0.7 \times 0.5 \\ 0.25 \times 0.5 \\ 0.7 \\ 0.25 \\ 0.765 \\ 0.52 \\ 1 \end{array} \right]$$

$$\Rightarrow 0.0655 \left[ \begin{array}{c} 0.49 \\ 0.175 \\ 0.35 \\ 0.125 \\ 0.7 \\ 0.25 \\ 0.765 \\ 0.52 \\ 1 \end{array} \right] = \left[ \begin{array}{c} 0.032095 \\ 0.0114 \\ 0.022 \\ 0.008 \\ 0.045 \\ 0.016 \\ 0.0501 \\ 0.0340 \\ 0.0655 \end{array} \right]$$

w<sub>1</sub>  
w<sub>2</sub>  
w<sub>3</sub>  
w<sub>4</sub>  
w<sub>5</sub>  
w<sub>6</sub>  
w<sub>7</sub>  
w<sub>8</sub>  
w<sub>9</sub>

4. Update the weights and the bias

$$\dots \rightarrow -0.1 - 0.03 \times 0.0655$$

$$w_9 = w_9 - \alpha \times 0.0655 \rightarrow -0.101$$

$$w_8 = w_8 - \alpha \times 0.0340 \rightarrow 0.24898$$

$$w_7 = w_7 - \alpha \times 0.0501 \rightarrow 0.698497$$

$$w_6 = w_6 - \alpha \times 0.016 \rightarrow -0.14048$$

$$w_5 = w_5 - \alpha \times 0.045 \rightarrow 0.89865$$

$$w_4 = w_4 - \alpha \times 0.008 \rightarrow 0.19976$$

$$w_3 = w_3 - \alpha \times 0.022 \rightarrow 0.14934$$

$$w_2 = w_2 - \alpha \times 0.014 \rightarrow 0.299658$$

$$w_1 = w_1 - \alpha \times 0.032095 \rightarrow -0.30096285$$

$$w_9 = -0.101$$

$$w_5 = 0.89865$$

$$w_8 = 0.24898$$

$$w_4 = 0.19976$$

$$w_7 = 0.698497$$

$$w_3 = 0.14934$$

$$w_6 = -0.14048$$

$$w_2 = 0.299658$$

$$w_1 = -0.30096285$$

$$6. \quad h_1 = w_1 \times 0.7 + w_3 \times 0.5 + w_5 \times 1$$

$$h_2 = w_2 \times 0.7 + w_4 \times 0.5 + w_6 \times 1$$

$$h_1 = 0.7626$$

$$h_2 = 0.519$$

$$\text{output} = h_1 \times w_7 + h_2 \times w_8 + w_9$$

$$= 0.56089 \Rightarrow \hat{y} = 0.5608$$

$$MSE = \frac{1}{2} (0.56089 - 0.5)^2$$

~~$\star$~~   $= 0.001854$

~~Task-2 0.5 is written after part 3~~

### Part III

$$i) \quad w_1 = 32 \quad K = 10 \quad P = 0$$

$$H_1 = 28 \quad F = 5$$

$$D_1 = 3 \quad S = 1$$

$$w_2 = (32 - 5 + 2 \times 0) / 1 + 1 = 28$$

$$H_2 = (28 - 5 + 2 \times 0) / 1 + 1 = 24$$

$$D_2 = 10$$

$$28 \times 24 \times 10$$

② output size after the  
first layer =

2) No. of parameters in the layer

↓

$5 \times 5 \times 3 + 1 = 26$  params (+1 for bias)

↓

$26 \times 10 = 260$  parameters

No. of parameters = 260

3) Output size  $\Rightarrow$  pad = 1

$$W_2 = \left\lceil \frac{(32 - 5 + 2 \times 1)}{1} + 1 \right\rceil$$

$$H_2 = \left\lceil \frac{(28 - 5 + 2 \times 1)}{1} + 1 \right\rceil$$

$$W_2, H_2 = 20, 26$$

$$W_2, H_2, D_2 = 20 \times 26 \times 10$$

4) grayscale = 1

↓

$5 \times 5 \times 1 + 1 = 26 \text{ params}$

$= 26 \times 10 = 260 \text{ parameters}$

5) Since it is multi-class classification problem, the most suitable activation function for the output layer would be softmax function

6) Softmax is invariant to constant shifts  
total =  $e^{x_1} + e^{x_2} + e^{x_3}$

↓

$x_1, x_2, x_3$  are the inputs

probabilities  
are  
calculated  
using

$$\frac{e^{x_1}}{\text{total}}, \frac{e^{x_2}}{\text{total}}, \frac{e^{x_3}}{\text{total}}$$

on adding a constant, we get  
 $\text{new} = e^{(x_1+c)} + e^{(x_2+c)} + e^{(x_3+c)}$

$$\Rightarrow \frac{e^{(x_1+c)}}{\text{new}}, \frac{e^{(x_2+c)}}{\text{new}}, \frac{e^{(x_3+c)}}{\text{new}}$$

new

$$\Rightarrow \frac{e^{x_1} \times e^{c_1}}{e^{c_1}(e^{x_1} + e^{x_2} + e^{x_3})}, \frac{e^{x_2} + e^{c_2}}{e^c(e^{x_1} + e^{x_2} + e^{x_3})}, \frac{e^{x_3} + e^{c_3}}{e^{c_3}(e^{x_1} + e^{x_2} + e^{x_3})}$$

$\Rightarrow$

From the above, we can see that  
 the softmax activation function  
 is invariant to constant shifts  
 in the input values

Task 2

(Q5)

Forward pass

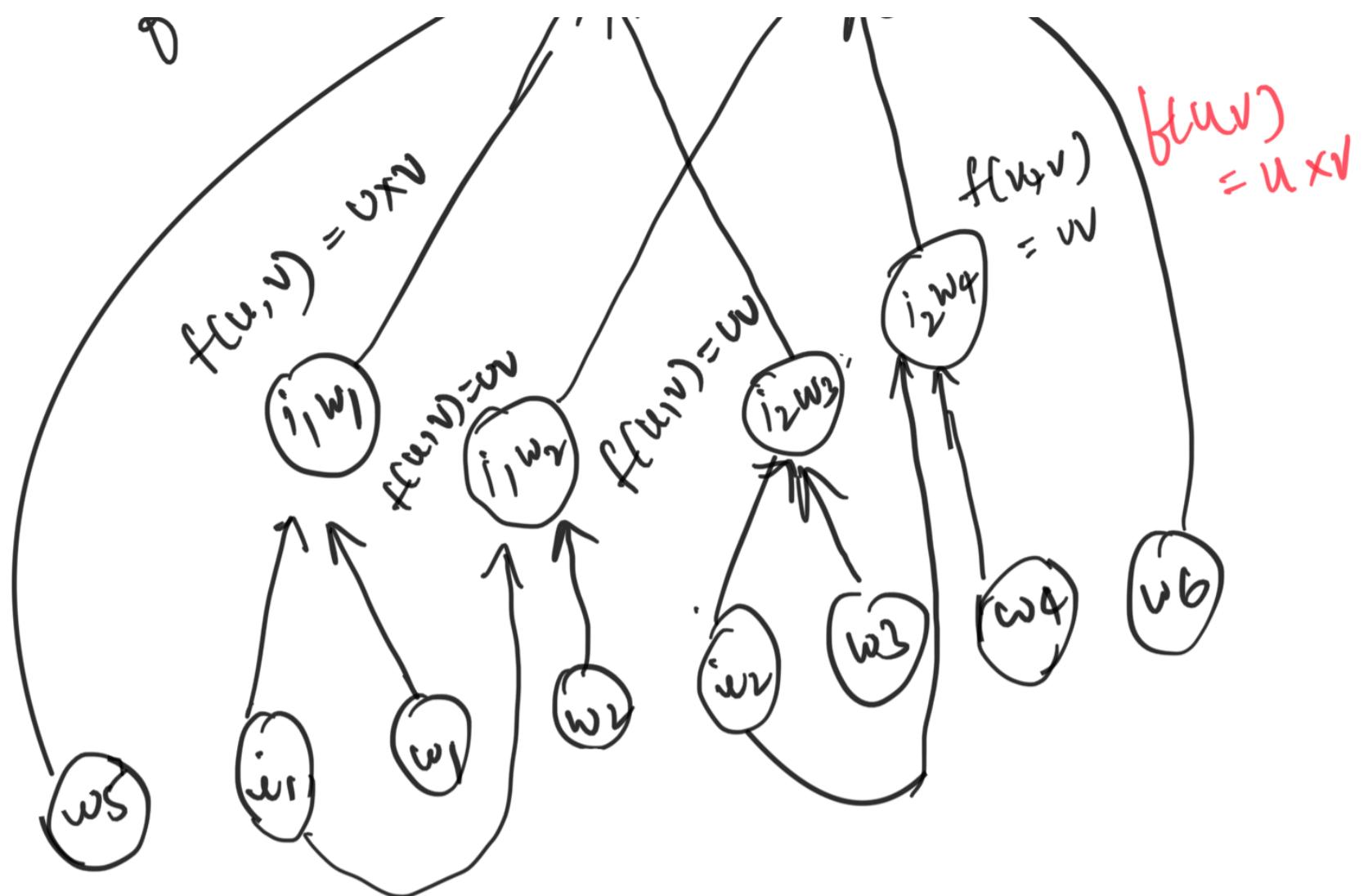
$$i_1 = 0.2 \quad i_2 = 0.5 \quad b = 1$$

$$h_1 = i_1 w_1 + i_2 w_3 + w_b$$

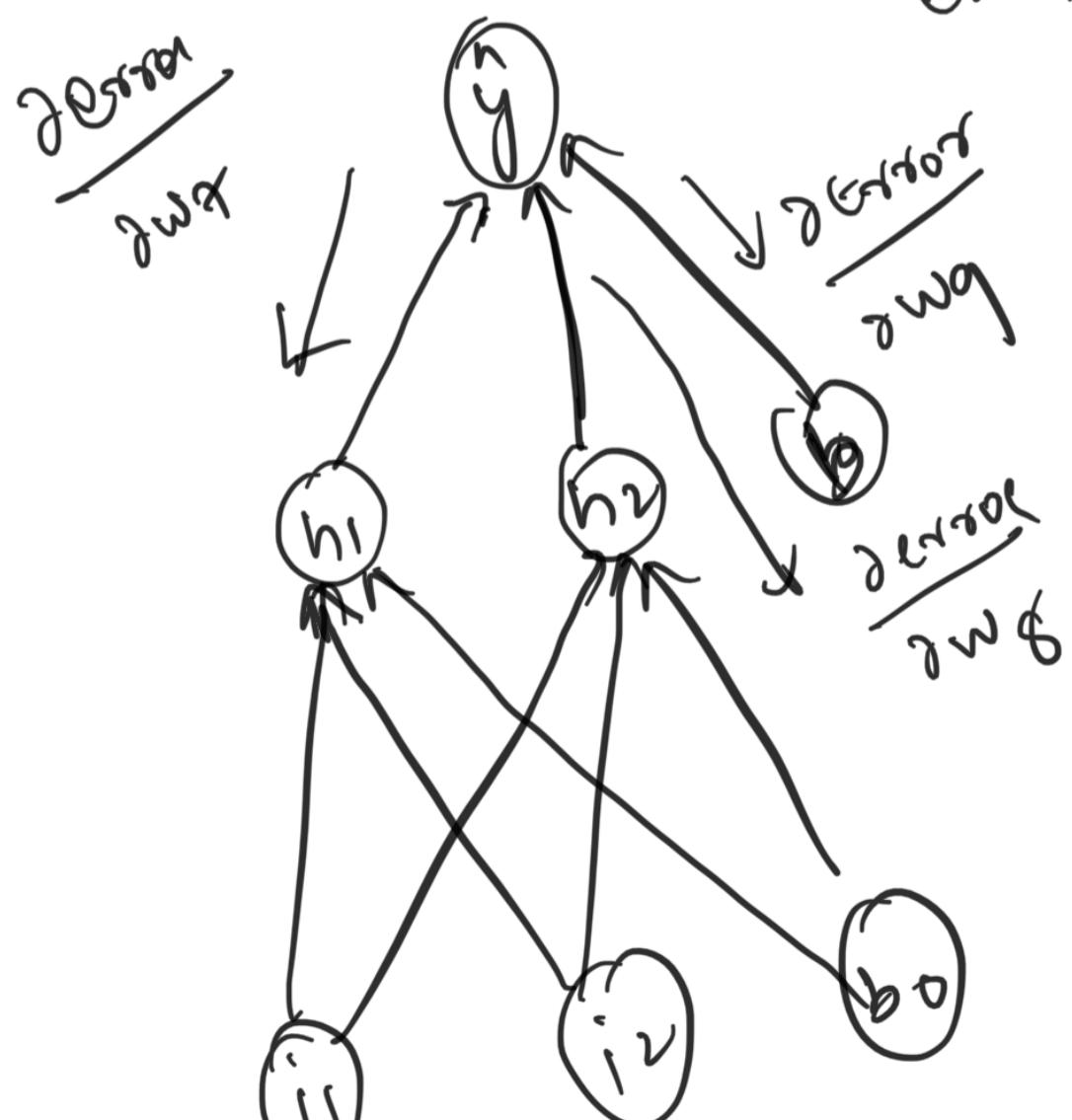
$$h_2 = i_1 w_2 + i_2 w_4 + w_b$$

$$(w_1, w_2, w_3) \in \mathbb{R}^3$$





⇒ Backward passes:





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