

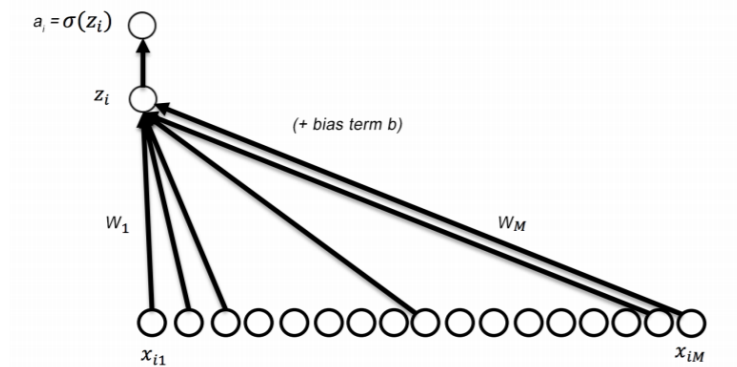
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# CEE690/ECE590: Homework 1 Solutions

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## 1 Problem 1

### 1.1 Part A



#### 3 Model set-up:

4 Pre-activation:  $z = \sum_{j=1}^M w_j x_j + b$

5 Activation:  $a = \sigma(z) = \frac{1}{1+e^{-z}}$

6 Loss:  $\mathcal{L} = -\left(y \log(a) + (1 - y) \log(1 - a)\right)$

#### 8 Gradients:

9 Weights:  $\frac{\partial \mathcal{L}}{\partial w_j} = \frac{\partial \mathcal{L}}{\partial a} \frac{\partial a}{\partial z} \frac{\partial z}{\partial w_j}$

10 Biases:  $\frac{\partial \mathcal{L}}{\partial b} = \frac{\partial \mathcal{L}}{\partial a} \frac{\partial a}{\partial z} \frac{\partial z}{\partial b}$

11 with  $\frac{\partial \mathcal{L}}{\partial a}$ ,  $\frac{\partial a}{\partial z}$ ,  $\frac{\partial z}{\partial w_j}$ ,  $\frac{\partial z}{\partial b}$  defined as the following:

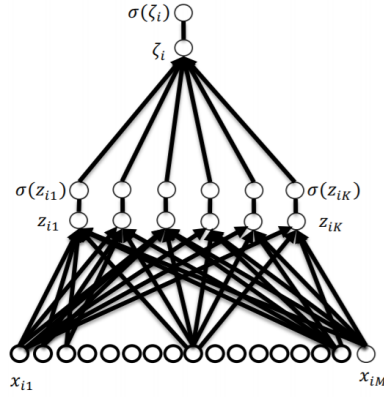
12  $\frac{\partial \mathcal{L}}{\partial a} = -\frac{y}{a} + \frac{1-y}{1-a}$

13  $\frac{\partial a}{\partial z} = \frac{e^{-z}}{(1+e^{-z})^2} = a(1-a)$

14  $\frac{\partial z}{\partial w_j} = x_j$

15  $\frac{\partial z}{\partial b} = 1$

16 **1.2 Part B**



17 **Model set-up:**

18 Layer 1:

19 Pre-activation:  $z_k^{(1)} = \sum_{j=1}^M w_{kj}^{(1)} x_j + b^{(1)}$

20 Activation:  $a_k^{(1)} = \sigma(z_k^{(1)}) = \frac{1}{1+e^{-z_k^{(1)}}}$

21 Layer 2:

22 Pre-activation:  $z^{(2)} = \sum_{k=1}^M w_k^{(2)} a_k + b^{(2)}$

23 Activation:  $a^{(2)} = \sigma(z^{(2)}) = \frac{1}{1+e^{-z^{(2)}}}$

24

25 Loss:  $\mathcal{L} = -\left(y \log(a^{(2)}) + (1 - y) \log(1 - a^{(2)})\right)$

26

27 **Gradients:**

28 **Weights:**

29  $\frac{\partial \mathcal{L}}{\partial w_k^{(2)}} = \frac{\partial \mathcal{L}}{\partial a^{(2)}} \frac{\partial a^{(2)}}{\partial z^{(2)}} \frac{\partial z^{(2)}}{\partial w_k^{(2)}}$

30  $\frac{\partial \mathcal{L}}{\partial w_{kj}^{(1)}} = \frac{\partial \mathcal{L}}{\partial a^{(2)}} \frac{\partial a^{(2)}}{\partial z^{(2)}} \frac{\partial z^{(2)}}{\partial a_k^{(1)}} \frac{\partial a_k^{(1)}}{\partial z_k^{(1)}} \frac{\partial z_k^{(1)}}{\partial w_{kj}^{(1)}}$

31

32 **Biases:**

33  $\frac{\partial \mathcal{L}}{\partial b^{(2)}} = \frac{\partial \mathcal{L}}{\partial a^{(2)}} \frac{\partial a^{(2)}}{\partial z^{(2)}} \frac{\partial z^{(2)}}{\partial b^{(2)}}$

34  $\frac{\partial \mathcal{L}}{\partial b^{(1)}} = \frac{\partial \mathcal{L}}{\partial a^{(2)}} \frac{\partial a^{(2)}}{\partial z^{(2)}} \frac{\partial z^{(2)}}{\partial a_k^{(1)}} \frac{\partial a_k^{(1)}}{\partial z_k^{(1)}} \frac{\partial z_k^{(1)}}{\partial b^{(1)}}$

35

36 Terms in chain rule defined similarly as in 1a)

37 **1.3 Part C**

38 To change 1a) to multi-class, we replace the vector dot product with a matrix multiply and replace the  
39 binary cross entropy with a softmax cross entropy:

40 **Model set-up:**

41 Pre-activation:  $z_k = \sum_{j=1}^M w_{kj} x_j + b$

42 Activation:  $a_k = \frac{e^{z_k}}{\sum_{\kappa} e^{z_{\kappa}}}$

43 Loss:  $\mathcal{L} = - \sum_k y_k \log(a_k)$

44 Similar changes are made to the top layer 1b).

45 The gradients for 1a) and 1b) remain the same, with the gradients of the new layers being:

46 **Gradients:**

47  $\frac{\partial \mathcal{L}}{\partial a_k} = - \sum_k \frac{y_k}{a_k}$

48

49  $\frac{\partial a_k}{\partial z_j} = \begin{cases} a_k(1 - a_k), & \text{if } k = j \\ -a_j a_k, & \text{otherwise} \end{cases}$