

1a)

$$\frac{\partial C^n(w)}{\partial w^i} = \frac{\partial C^n(w)}{\partial \hat{y}^n} \times \frac{\partial \hat{y}^n}{\partial f(x^n)} \times \frac{\partial f(x^n)}{\partial w^i}$$

$$\text{As } \hat{y}^n = f(x^n), \quad \frac{\partial \hat{y}^n}{\partial f(x^n)} = 1$$

$$\therefore \frac{\partial C^n(w)}{\partial w^i} = \frac{\partial C^n(w)}{\partial \hat{y}^n} \times \frac{\partial f(x^n)}{\partial w^i}$$

$$\begin{aligned} \frac{\partial C^n(w)}{\partial \hat{y}^n} &= - \left(y^n \times \frac{1}{\hat{y}^n} + (1 - y^n) \left(\frac{1}{1 - \hat{y}^n} \right) (-1) \right) \\ &= \frac{1 - y^n}{1 - \hat{y}^n} - \frac{y^n}{\hat{y}^n} \\ &= \frac{\hat{y}^n(1 - y^n) - y^n(1 - \hat{y}^n)}{(\hat{y}^n)(1 - \hat{y}^n)} \\ &= \frac{\hat{y}^n - \hat{y}^n y^n - y^n + y^n \hat{y}^n}{(\hat{y}^n)(1 - \hat{y}^n)} \end{aligned}$$

$$= \frac{\hat{y}^n - y^n}{(\hat{y}^n)(1 - \hat{y}^n)}$$

We know $\frac{\partial f(x^n)}{\partial w}$ from the question, Hence,

$$\frac{\partial C^n(w)}{\partial w_i} = \frac{\hat{y}^n - y^n}{(\hat{y}^n)(1 - \hat{y}^n)} x_i^n f(x^n)(1 - f(x^n))$$

As $\hat{y}^n = f(x^n)$,

$$\begin{aligned} \frac{\partial C^n(w)}{\partial w_i} &= x_i^n \frac{\hat{y}^n - y^n}{(\hat{y}^n)(1 - \hat{y}^n)} \times (\hat{y}^n)(1 - \hat{y}^n) \\ &= -(y^n - \hat{y}^n) x_i^n \quad (\text{Shown}) \end{aligned}$$

$$(b) \quad C^n(w) = - \sum_{k=1}^K y_k^n \ln(y_k^n) \quad \hat{y}_k^n = \frac{e^{z_k}}{\sum_{k'=1}^K e^{z_{k'}}} \quad z_k = \sum_i^I w_{k,i} \cdot x_i$$

$$\frac{\partial C^n(w)}{\partial w_{kj}} = \frac{\partial C^n(w)}{\partial \hat{y}_k^n} \times \frac{\partial \hat{y}_k^n}{\partial z_k} \times \frac{\partial z_k}{\partial w_{kj}}$$

$$\frac{\partial z_k}{\partial w_{kj}} = x_j \text{ as all other } w \text{ in matrix treated as const.}$$

$$\frac{\partial \hat{y}_k^n}{\partial z_{k'}} = \frac{\partial}{\partial z_{k'}} \frac{e^{z_k}}{\sum_{k'=1}^K e^{z_{k'}}}$$

$$\frac{\partial \hat{y}_k^n}{\partial z_{k'}} = \frac{(\sum e^{z_{k'}}) \frac{\partial}{\partial z_{k'}} e^{z_k} - e^{z_k} \frac{\partial}{\partial z_{k'}} \sum_{k'=1}^K e^{z_{k'}}}{(\sum e^{z_{k'}})^2}$$

when $k = k'$,

$$\frac{\partial \hat{y}_k^n}{\partial z_{k'}} = \frac{(\sum e^{z_{k'}}) e^{z_{k'}} - e^{z_{k'}} \cdot e^{z_{k'}}}{(\sum e^{z_{k'}})^2} = \frac{e^{z_{k'}} - \left(\frac{e^{z_{k'}}}{\sum e^{z_{k'}}} \right)^2}{\sum e^{z_{k'}}$$

$$= \frac{1}{\sum_k e^{z_k}} (z_k)$$

$$= \hat{y}_{k'} - (\hat{y}_{k'})^2 = \hat{y}_{k'} (1 - \hat{y}_{k'})$$

When $k \neq k'$

$$\frac{\partial \hat{y}_k}{\partial z_{k'}} = \frac{\sum_k e^{z_k} \times 0 - e^{z_k} \cdot e^{z_{k'}}}{\left[\sum_k e^{z_k} \right]^2}$$

$$= - \frac{e^{z_k}}{\sum_k e^{z_k}} \times \frac{e^{z_{k'}}}{\sum_k e^{z_k}}$$

$$= - \hat{y}_k \times \hat{y}_{k'}$$

$$\frac{\partial C^n(w)}{\partial \hat{y}_k} = - \sum_{k'=1}^K \frac{\partial}{\partial \hat{y}_{k'}} (y_{k'}) \ln(\hat{y}_k)$$

$$= - \sum_{k'=1}^K \frac{y_{k'}}{\hat{y}_{k'}}$$

$$\frac{\partial C^n(w)}{\partial w_{kj}} = - \sum_{k'=1}^K \frac{y_{k'}}{\hat{y}_{k'}} \times \frac{\partial \hat{y}_k}{\partial z_{k'}} \times x_j$$

$$= - x_j \sum_{k'=1}^K \frac{y_{k'}}{\hat{y}_{k'}} \times \frac{\partial \hat{y}_k}{\partial z_{k'}} \quad \left. \vphantom{\sum_{k'=1}^K} \right\} \begin{array}{l} \text{Only 1 instance when} \\ k=k', \text{ rest } k \neq k' \end{array}$$

$$= - x_j \left[\frac{y_{k'}}{\hat{y}_{k'}} \times \hat{y}_{k'} (1 - \hat{y}_{k'}) + \sum_{k'=1, k' \neq k}^K \frac{y_{k'}}{\hat{y}_{k'}} (-\hat{y}_k \times \hat{y}_{k'}) \right]$$

$$= -x_j \left[\hat{y}_k^{\sim} (1 - \hat{y}_k^{\sim}) + \sum_{k'=1, k' \neq k}^K (-\hat{y}_k^{\sim} \hat{y}_k^{\sim}) \right]$$

$$= x_j \left[\hat{y}_k^{\sim} \hat{y}_k^{\sim} - \hat{y}_k^{\sim} + \sum_{k'=1, k' \neq k}^K \hat{y}_k^{\sim} \hat{y}_k^{\sim} \right]$$

$$= x_j \left[-\hat{y}_k^{\sim} + \hat{y}_k^{\sim} \hat{y}_k^{\sim} + \sum_{k'=1, k' \neq k}^K \hat{y}_k^{\sim} \hat{y}_k^{\sim} \right], \quad \text{as in } \hat{y}_k^{\sim} \hat{y}_k^{\sim}, \quad k=k', \therefore \hat{y}_k^{\sim} = \hat{y}_k^{\sim}$$

$$= x_j \left[-\hat{y}_k^{\sim} + \hat{y}_k^{\sim} \left[\hat{y}_k^{\sim} + \sum_{k'=1, k' \neq k}^K \hat{y}_k^{\sim} \right] \right]$$

$$= x_j \left[-\hat{y}_k^{\sim} + \hat{y}_k^{\sim} \left(\sum_{k'=1}^K \hat{y}_k^{\sim} \right) \right]$$

$$= -x_j \left[\hat{y}_k^{\sim} - \hat{y}_k^{\sim} (1) \right]$$

$$= -x_j \left[\hat{y}_k^{\sim} - \hat{y}_k^{\sim} \right] \quad (\text{Shown})$$

as $\sum_{k'=1}^K \hat{y}_k^{\sim} = 1$ in that instance and $k=k'$

4a)

$$J(w) = C(w) + \lambda R(w)$$

$$\frac{\partial J(w)}{\partial w} = \frac{\partial C(w)}{\partial w} + \lambda \frac{\partial R(w)}{\partial w}$$

$$\frac{\partial R(w)}{\partial w} = \frac{\partial}{\partial w} \frac{1}{2} \sum_{i,j} w_{ij}^2$$

Derivative will only be non-zero when $i'=i$ and $j'=j$
Hence at each matrix cell, the derivative is:

$$\frac{1}{2} \times \frac{\partial}{\partial w} w_{ij}^2 = w_{ij}$$

Hence $\frac{\partial R(w)}{\partial w} = w$, where w is the weight matrix.

$$\therefore \lambda \cdot \frac{\partial R(w)}{\partial w} = \lambda w \quad \leftarrow \text{Update due to L2}$$

$$\text{We know } C(w) = \frac{1}{N} \sum_{n=1}^N C^n(w)$$

$$\therefore \frac{\partial C(w)}{\partial w} = \frac{1}{N} \sum_{n=1}^N \frac{\partial C^n(w)}{\partial w}$$

As earlier computed, we know $\frac{\partial C^n(w)}{\partial w}$ for softmax regression.

hence we have our update term for softmax regression with L2 regularization, $\frac{\partial J(w)}{\partial w}$.

$$\frac{\partial J(w)}{\partial w} = \frac{1}{N} \sum_{n=1}^N \left[-x_j^n (y_k^n - \hat{y}_k^n) \right] + \lambda w$$