

Error Function:-

$$E = \frac{1}{2} \sum_{i=1}^M (y^{(i)} - \hat{y}^{(i)})^2$$

Applying sigmoid function to both the layers

$$\hat{y} = \text{Sigmoid}(V^T z)$$

$$z_j = \text{Sigmoid}(w_j^T x)$$

Taking Partial Derivative of Error function using chain rule

$$\frac{\partial E}{\partial V} = \frac{\partial E}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial V} \quad \& \quad \frac{\partial E}{\partial w_j} = \frac{\partial E}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial z_j} \cdot \frac{\partial z_j}{\partial w_j}$$

So,

$$\frac{\partial E}{\partial V} = \frac{\partial E}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial V}$$

$$= \frac{1}{2} \times 2 \sum_{i=1}^M (y^{(i)} - \hat{y}^{(i)}) \hat{y}^{(i)} (1 - \hat{y}^{(i)}) z_j^{(i)}$$

$$\therefore \frac{\partial E}{\partial V} = \sum_{i=1}^M (y^{(i)} - \hat{y}^{(i)}) \hat{y}^{(i)} (1 - \hat{y}^{(i)}) z_j^{(i)}$$

Update Equation for output layer,

$$V_j \leftarrow V_j - \eta \sum_{i=1}^M (y^{(i)} - \hat{y}^{(i)}) \hat{y}^{(i)} (1 - \hat{y}^{(i)}) z_j^{(i)}$$

And,

$$\frac{\partial E}{\partial w_j} = \frac{\partial E}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial z_j} \cdot \frac{\partial z_j}{\partial w_j}$$

$$= \frac{1}{2} \times 2 \sum_{i=1}^M (y^{(i)} - \hat{y}^{(i)}) \hat{y}^{(i)} (1 - \hat{y}^{(i)}) V_j z_j^{(i)} (1 - z_j^{(i)}) x^{(i)}$$

$$w_j \leftarrow w_j - \eta \sum_{i=1}^M (y^{(i)} - \hat{y}^{(i)}) \hat{y}^{(i)} (1 - \hat{y}^{(i)}) V_j z_j^{(i)} (1 - z_j^{(i)}) x^{(i)}$$

Comparison:-

Loglikelihood

$$v_j \leftarrow v_j - \eta \sum_{i=1}^m (\hat{y}^{(i)} - y^{(i)}) z_j^{(i)}$$

$$w_j \leftarrow w_j - \eta \sum_{i=1}^m (\hat{y}^{(i)} - y^{(i)}) v_j z_j^{(i)} (1 - \hat{z}_j^{(i)}) x_j^{(i)}$$

The term for \hat{y} uses sigmoid function for activation but it cancels out in loglikelihood whereas it remains in error method using mean square