

The Derivative of Cost function:-

$$h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}}$$

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

$$\frac{d(\sigma(x))}{dx} = \frac{1}{1 + e^{-x}} \times \left(1 - \frac{1}{1 + e^{-x}}\right) = \sigma(x)(1 - \sigma(x))$$

Apply chain rule and ~~rule~~ in terms of partial Derivative

$$\begin{aligned} \frac{\partial(J(\theta))}{\partial(\theta_j)} &= -\frac{1}{m} \times \sum_{i=1}^m \left[y^{(i)} \times \frac{1}{h_{\theta}(x^{(i)})} \times \frac{\partial(h_{\theta}(x^{(i)}))}{\partial(\theta_j)} \right] \\ &\quad + \sum_{i=1}^m \left[(1 - y^{(i)}) \times \frac{1}{(1 - h_{\theta}(x^{(i)}))} \times \frac{\partial(1 - h_{\theta}(x^{(i)}))}{\partial(\theta_j)} \right] \end{aligned}$$

$$\begin{aligned} \frac{\partial(J(\theta))}{\partial(\theta_j)} &= -\frac{1}{m} \times \left(\sum_{i=1}^m \left[y^{(i)} \times \frac{1}{h_{\theta}(x^{(i)})} \times \sigma(z) (1 - \sigma(z)) \times \frac{\partial(\theta^T x)}{\partial(\theta_j)} \right] \right. \\ &\quad \left. + \sum_{i=1}^m \left[(1 - y^{(i)}) \times \frac{1}{(1 - h_{\theta}(x^{(i)}))} \times (-\sigma(z)(1 - \sigma(z))) \times \frac{\partial(\theta^T x)}{\partial(\theta_j)} \right] \right) \end{aligned}$$

Evaluate partial Derivative as a derivative of sigmoid function.

$$\begin{aligned} \frac{\partial(J(\theta))}{\partial(\theta_j)} &= -\frac{1}{m} \times \left(\sum_{i=1}^m \left[y^{(i)} \times \frac{1}{h_{\theta}(x^{(i)})} \times \sigma(z) (1 - \sigma(z)) \times \frac{\partial(\theta^T x)}{\partial(\theta_j)} \right] \right. \\ &\quad \left. + \sum_{i=1}^m \left[(1 - y^{(i)}) \times \frac{1}{(1 - h_{\theta}(x^{(i)}))} \times (-\sigma(z)(1 - \sigma(z))) \times \frac{\partial(\theta^T x)}{\partial(\theta_j)} \right] \right) \end{aligned}$$

$$\frac{\partial(J(\theta))}{\partial(\theta_j)} = -\frac{1}{m} \times \left(\sum_{i=1}^m \left[y^{(i)} \frac{1}{h_\theta(x^{(i)})} \cdot h_\theta(x^{(i)}) (1 - h_\theta(x^{(i)})) \times x_j^{(i)} \right] \right. \\ \left. + \sum_{i=1}^m \left[(1 - y^{(i)}) \times \frac{1}{(1 - h_\theta(x^{(i)}))} \times (-h_\theta(x^{(i)}) (1 - h_\theta(x^{(i)}))) \times x_j^{(i)} \right] \right)$$

Simplify :-

$$\frac{\partial(J(\theta))}{\partial(\theta_j)} = -\frac{1}{m} \times \left(\sum_{i=1}^m \left[y^{(i)} \times (1 - h_\theta(x^{(i)})) \times x_j^{(i)} - (1 - y^{(i)}) \times \right. \right. \\ \left. \left. h_\theta(x^{(i)}) \times x_j^{(i)} \right] \right)$$

$$\frac{\partial(J(\theta))}{\partial(\theta_j)} = -\frac{1}{m} \left(\sum_{i=1}^m \left[y^{(i)} - y^{(i)} \times h_\theta(x^{(i)}) - h_\theta(x^{(i)}) + \right. \right. \\ \left. \left. y^{(i)} \times h_\theta(x^{(i)}) \right] \times x_j^{(i)} \right)$$

$$\frac{\partial(J(\theta))}{\partial(\theta_j)} = -\frac{1}{m} \times \left(\sum_{i=1}^m \left[y^{(i)} - h_\theta(x^{(i)}) \right] \times x_j^{(i)} \right)$$

Convert this into matrix form for the gradient w.r.t. all the weights include the bias term.

$$\frac{\partial(J(\theta))}{\partial(\theta)} = \frac{1}{m} X^T [h_\theta(x) - y]$$