

CS 541 - Deep Learning.

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Problem 1:-

$$\begin{aligned} J(w_1, w_2, b) &= \frac{1}{4} \sum (x^i{}^T w + b - y^i)^2 \\ &= \frac{1}{4} \left[(w_1 \times 0 + w_2 \times 0 + b - 0)^2 + (w_1 \times 1 + w_2 \times 0 + b - 1)^2 \right. \\ &\quad \left. + (w_1 \times 0 + w_2 \times 1 + b - 0)^2 + (w_1 \times 1 + w_2 \times 2 + b - 0)^2 \right] \end{aligned}$$

Taking Partial:-

$$\begin{aligned} \frac{\partial J}{\partial w_1} &= \frac{1}{2} (w_1 + b - 1 + w_1 + w_2 + b) \\ &= \frac{1}{2} (2w_1 + w_2 + 2b - 1) = 0 \quad \text{--- (1)} \end{aligned}$$

$$\begin{aligned} \frac{\partial J}{\partial w_2} &= \frac{1}{2} (w_2 + b - 1 + w_1 + w_2 + b) \\ &= \frac{1}{2} (w_1 + 2w_2 + 2b - 1) = 0 \quad \text{--- (2)} \end{aligned}$$

$$\begin{aligned} \frac{\partial J}{\partial b} &= \frac{1}{2} (b + w_1 + b - 1 + w_2 + b - 1 + w_1 + w_2 + b) \\ &= \frac{1}{2} (2w_1 + 2w_2 + 4b - 2) = 0 \quad \text{--- (3)} \end{aligned}$$

From (1) & (2) we get :-

$$2w_1 + w_2 + 2b - 1 = w_1 + 2w_2 + 2b - 1$$

$$\Rightarrow 2w_1 - w_1 = 2w_2 - w_2$$

$$\Rightarrow w_1 = w_2$$

(4)

Substituting (4) in (3)

$$2w_1 + 2w_2 + 4b - 2 = 0$$

$$\rightarrow 2w_1 + 2w_1 + 4b - 2 = 0$$

$$w_1 = \frac{1-2b}{2} \quad (5)$$

$$\text{Eqn (2)} \Rightarrow \frac{1}{2} (2w_2 + w_1 + 2b - 1) = 0$$

$$\text{Substituting (5)} \Rightarrow 3\left(\frac{1-2b}{2}\right) + 2b - 1 = 0$$

$$\Rightarrow (1-2b)\left(\frac{3}{2} - 1\right) = 0$$

$$b = \frac{1}{2}$$

$$\text{In equation (3)} \Rightarrow 2w_1 + 2w_2 + 4b - 2 = 0$$

$$2w_1 + 2\left(\frac{1}{2}\right) - 1 = 0$$

$$w_1 = 0 //$$

From (4) we can conclude that $w_1 = w_2 = 0$

Problem 3:-

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

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

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

$$= \frac{1+e^x + 1+e^{-x}}{1+e^x + 1+e^{-x}} = 1.$$

Hence Proved.

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

Applying the reciprocal rule:-

$$\sigma'(x) = -(1+e^{-x})^{-2} \frac{\partial}{\partial x} (1+e^{-x}) = -(1+e^{-x})^{-2} (-e^{-x})$$

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

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

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

$$\sigma'(x) = \sigma(x) (1 - \sigma(x))$$

Problem 4:-

$$\alpha \omega^T \omega = \alpha \omega^T S \omega$$

Here $\omega = \begin{bmatrix} \omega_1 \\ \omega_2 \end{bmatrix}$

considering $S = \begin{bmatrix} s_1 & s_2 \\ s_3 & s_4 \end{bmatrix}$

substituting

$$\alpha [\omega_1 \ \omega_2] \begin{bmatrix} s_1 & s_2 \\ s_3 & s_4 \end{bmatrix} \begin{bmatrix} \omega_1 \\ \omega_2 \end{bmatrix}$$

$$\alpha [\omega_1 s_1 + \omega_2 s_3 + \omega_1 s_2 + \omega_2 s_4] \begin{bmatrix} \omega_1 \\ \omega_2 \end{bmatrix}$$

$$\alpha \left[(\omega_1 s_1 + \omega_2 s_3) \omega_1 + \omega_2 (\omega_1 s_2 + \omega_2 s_4) \right]$$

$$\alpha \left[\omega_1^2 s_1 + \omega_2 \omega_1 s_3 + \omega_1 \omega_2 s_2 + \omega_2^2 s_4 \right]$$

$$\left[\omega_1^2 s_1 + \omega_1 \omega_2 (s_2 + s_3) + \omega_2^2 s_4 \right]$$

To make it the least asymmetric the difference between $(\omega_1 - \omega_2)^2$ should be the smallest

$$\Rightarrow \omega_1^2 - 2\omega_1\omega_2 + \omega_2^2$$

By comparing,

Here

$$S_1 = S_4 = 1$$

$$S_2 + S_3 = -2$$
$$S_2 = S_3 = -1$$

$$S = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$$

Problem 5:-

$$p(y|x, w, \sigma^2) = N(\mu = x^T w, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y - x^T w)^2}{2\sigma^2}}$$

$$p(\mathcal{D}|w, \sigma^2) = \prod_{i=1}^n p(y^{(i)} | x^{(i)}, w, \sigma^2)$$

$$\begin{aligned} \log p(\mathcal{D}|w, \sigma^2) &= \log \prod_{i=1}^n p(y^{(i)} | x^{(i)}, w, \sigma^2) \\ &= \sum_{i=1}^n \log p(y^{(i)} | x^{(i)}, w, \sigma^2) \\ &= \sum_{i=1}^n \log \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y^{(i)} - x^{(i)T} w)^2}{2\sigma^2}} \\ &= \sum_{i=1}^n \left(-\frac{(y^{(i)} - x^{(i)T} w)^2}{2\sigma^2} - \log \sigma \right) + C \\ &= -\frac{1}{2\sigma^2} \sum_{i=1}^n (y^{(i)} - x^{(i)T} w)^2 - n \log \sigma + C \end{aligned}$$

Differentiating wrt w and σ and setting derivative

to 0 to find the MLE

$$\nabla_w \left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (y^{(i)} - x^{(i)T} w)^2 - n \log \sigma + C \right) = 0$$

$$\sum_{i=1}^n x^{(i)} (y^{(i)} - x^{(i)T} w) = 0$$

$$\sum_{i=1}^n x^{(i)} y^{(i)} - \sum_{i=1}^n x^{(i)} x^{(i)T} w = 0$$

$$\Rightarrow w = \left(\sum_{i=1}^n x^{(i)} x^{(i)T} \right)^{-1} \left(\sum_{i=1}^n x^{(i)} y^{(i)} \right)$$

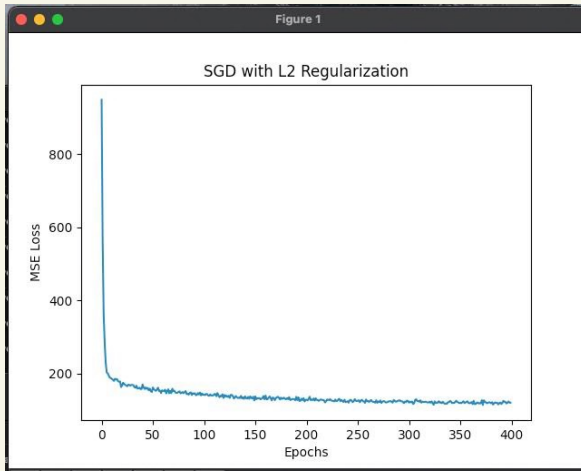
$$\nabla_{\sigma} \log P(\mathcal{D} | w, \sigma^2) = \nabla_{\sigma} \left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (y^{(i)} - x^{(i)T} w)^2 - n \log \sigma + c \right) = 0$$

$$\frac{1}{\sigma^3} \sum_{i=1}^n (y^{(i)} - x^{(i)T} w)^2 - \frac{n}{\sigma} = 0$$

$$\sigma^2 = \frac{1}{n} \sum_{i=1}^n (y^{(i)} - x^{(i)T} w)^2 //$$

Hence Proved.

Problem 2:-



Tuned Hyperparameters:-

Learning Rate :- 0.005

Epochs :- 400

Batchsize :- 2048

Alpha :- 0.002 .