DL HW2

$$\frac{Ans4}{=}(a) \quad O(x) = \frac{1}{1+e^{-x}}$$

$$T_0 \text{ prove: } O(-x) = 1 - O(x)$$

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

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

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

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

$$(-x) = 1 - 5(x)$$

Hence provea.

(b)
$$\sigma'(x) = \underline{\partial \sigma}(x) = \sigma(x) ((-\sigma(x)) \forall x$$

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

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

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

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

$$= \frac{1}{e^{\pi(1+e^{-\pi})}} \cdot \frac{e^{\pi}}{(1+e^{\pi})}$$

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

$$=$$
 $O(\alpha)$. $O(-\alpha)$

Using egn in 4(a)

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

Heree proved!

Ans 2 (a)
$$f(x,y) = x^4 + xy + x^2$$

Since it's a polynomial func. the domain
of the func. is R
To be a PSD func. the Hessian of the
function should always be non-decreasing.

$$f(x,y) = x^{4} + xy + x^{2}$$

$$J(x,y) = \begin{bmatrix} 4x^{2} + y + 2x \\ x \end{bmatrix}$$

$$H(x,y) = \begin{bmatrix} 12x^{2} + 2 & 1 \\ 1 & 0 \end{bmatrix}$$

To check if H is convex, we'll find points (2) where $Z^THZ < 0$ Let $Z = [x,y]^T$ $[x y] [2x^2 + 2 1] [x] < 0$

$$\left[12x^3+2x+y \quad x\right]\left[\begin{array}{c}x\\y\end{array}\right]$$

$$\Rightarrow 12x^{4} + 2x^{2} + xy + xy$$

$$\Rightarrow 12x^{4} + 2x^{2} + 2xy < 0$$

$$\Rightarrow$$
 Let $z = (1, -10)$

$$= \begin{bmatrix} 1 & 7 & 7 & 14 & 1 \\ -10 & 7 & 7 & 14 & 16 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$$= \left[\begin{array}{cc} 2 & 1 \\ -10 \end{array} \right]$$

$$\Rightarrow$$
 f(x,y) is non convex as H of the func. is not a PSD.

$$f_{WE}(w) = \frac{1}{2n} (X^T w - y)^T (X^T w - y)$$

$$J(w) = \frac{1}{2n} \frac{\partial}{\partial w} \left[(x^T w - y)^T (x^T w - y) \right]$$

$$= \frac{1}{2n} \cdot x \cdot 2(x^T w - y)$$

$$= \frac{1}{2n} \cdot x (x^T w - y)$$

$$H(w) = \frac{\partial J(w)}{\partial w}$$

$$= \frac{1}{n} \frac{\partial}{\partial w} \left[(x \times x)^{T} w - xy \right]$$

$$= \frac{1}{n} (x \times x)^{T} \times x$$

$$= \frac{1}{n} (x \times x)^{T} \times x$$

=> Hessian doesn't depend on w

To prok:
$$V^THV > 0$$

$$\int_{\gamma} (V^T \chi^T \chi V) > 0$$

$$T.P. \Rightarrow V^T X^T X V > 0$$

$$v^{\tau} X^{\tau} X v = (X v)^{\top} (X v)$$

Let $\chi_{V} = z$ (a col. vector of size (9,1)

$$\Rightarrow \quad \sqrt{T} \chi^T \chi_{11} = z^T z$$

$$= Z_{1}^{2} + Z_{1}^{2} + ... + Z_{h}^{2}$$

$$= \sum_{i=1}^{9} Z_{i}^{2}$$

$$\sum_{i=1}^{q} z_i^2 > 0$$

for $z \in \mathbb{R}^{9\kappa^1}$

Hence fouse (w) is convex for a two layer linear regression model !