

# Home Work 2

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1.

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

then to show:  $\sigma'(x) = \sigma(x)[1 - \sigma(x)]$

$$\begin{aligned}\sigma'(x) &= \frac{d}{dx}\left(\frac{1}{1+e^{-x}}\right) = \frac{d}{dx}\left((1+e^{-x})^{-1}\right) \\ &= e^{-x}(1+e^{-x})^{-1} = \left(\frac{1}{1+e^{-x}}\right)\left(\frac{e^{-x}}{1+e^{-x}}\right) = \sigma(x)\left(\frac{1+e^{-x}-1}{1+e^{-x}}\right) \\ &= \sigma(x)\left(1 - \frac{1}{1+e^{-x}}\right) = \sigma(x)[1 - \sigma(x)]\end{aligned}$$

b.

negative log likelihood equation for logistic regression =  $nll(\theta)$

$$nll(\theta) = -\sum_i y_i \log \sigma(\theta^T x_i) + (1 - y_i) \log(1 - \sigma(\theta^T x_i))$$

Taking the gradients wrt  $\theta$ , we get:

$$\nabla_{\theta} nll(\theta) = -\sum_i y_i \frac{1}{\sigma(\theta^T x_i)} \sigma'(\theta^T x_i) + (1 - y_i) \frac{1}{1 - \sigma(\theta^T x_i)} (-\sigma'(\theta^T x_i))$$

this can be further simplified to yield

$$\begin{aligned}\nabla_{\theta} nll(\theta) &= \sum_i (\sigma(\theta^T x_i) - y_i) x_i \\ &= \sum_i (\mu_i - y_i) x_i = X^T (\mu - y)\end{aligned}$$

where  $\mu_i = (\sigma'(\theta^T x_i))$  and  $x_i$  is the  $i$ th column of  $X^T$

c.

Thus, from (b) we can find the Hessian Matrix:

$$\begin{aligned} \text{So } H_\theta &= \nabla_\theta (\nabla_\theta \text{nl}l(\theta))^T = \nabla_\theta [X^T(\mu - y)]^T = \nabla_\theta (\mu^T X - y^T X) \\ &= \nabla_\theta \mu^T X = \nabla_\theta \sigma(X\theta)^T X = X^T \text{diag}(\mu(1 - \mu))X = X^T S X \end{aligned}$$

where  $S$  is  $\mu(1 - \mu)$ . Therefore we can see that  $H_\theta$  is positive and semi-definite and from the equivalence above and assuming eigenvalues of  $S \geq 0$ , we can also say that  $S$  is positive and semi-definite. Since  $S$  is a diagonal matrix, its eigenvalues are the entries on the diagonal, Hence:

$\mu_i(1 - \mu_i) = \sigma(\theta^T x_i)(1 - \sigma(\theta^T x_i)) \geq 0$  and since  $0 \leq \sigma(\cdot) \leq 1$ , we need  $\sigma(\cdot)(1 - \sigma(\cdot)) \geq 0$  and thus we can show that the hessian matrix  $H$  is positive semi definite

2.

$$\int_{\mathbb{R}} \frac{1}{Z} \exp\left(\frac{-x^2}{2\sigma^2}\right) dx = 1$$

$$\int_{\mathbb{R}} \exp\left(\frac{-x^2}{2\sigma^2}\right) dx = Z$$

$$Z^2 = \int_{\mathbb{R}} \exp\left(\frac{-x^2}{2\sigma^2}\right) dx \int_{\mathbb{R}} \exp\left(\frac{-y^2}{2\sigma^2}\right) dy = \iint_{\mathbb{R}^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) dx dy$$

$$= \int_0^\infty \int_0^{2\pi} \exp\left(\frac{-r^2}{2\sigma^2}\right) r d\theta dr = 2\pi(\sigma^2) \int_0^\infty \exp\left(\frac{-r^2}{2\sigma^2}\right) \left(\frac{-2}{\sigma^2}\right) dr$$

on solving, we get  $= -2\pi\sigma^2(0 - 1) = 2\pi\sigma^2$

Hence, we get  $Z^2 = 2\pi\sigma^2 \Rightarrow Z = \sqrt{(2\pi\sigma^2)} = \sqrt{(2\pi)}\sigma$

3. refer to pdf