

## Evaluation Criterion

$$\mathcal{E}(\beta) = - \sum_{n=1}^N \{ y_n \log [\sigma(\beta^T \mathbf{x}_n)] + (1 - y_n) \log [1 - \sigma(\beta^T \mathbf{x}_n)] \}$$

No closed-form solution that minimizes the function.

We use an approximate method, e.g. gradient descent, so we need to compute  $\nabla \mathcal{E}(\beta)$ .

Derivatives of sigmoid function  $\sigma(\eta)$ 

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

$$\frac{d\sigma(\eta)}{d\eta} = - \frac{-e^{-\eta}}{(1 + e^{-\eta})^2} = \frac{e^{-\eta}}{(1 + e^{-\eta})^2} = \frac{1}{1 + e^{-\eta}} \left( \frac{e^{-\eta}}{1 + e^{-\eta}} \right) = \frac{1}{1 + e^{-\eta}} \left( 1 - \frac{1}{1 + e^{-\eta}} \right) = \sigma(\eta) [1 - \sigma(\eta)]$$

$$\frac{d \log \sigma(\eta)}{d\eta} = \frac{1}{\sigma(\eta)} \cdot \frac{d\sigma(\eta)}{d\eta} = 1 - \sigma(\eta)$$

Derivation of  $\nabla \mathcal{E}(\beta) = \frac{\partial \mathcal{E}(\beta)}{\partial \beta}$ 

$$\begin{aligned} \nabla \mathcal{E}(\beta) &= - \sum_{n=1}^N \{ y_n [1 - \sigma(\beta^T \mathbf{x}_n)] \mathbf{x}_n - (1 - y_n) [1 - (1 - \sigma(\beta^T \mathbf{x}_n))] \mathbf{x}_n \} \\ &= - \sum_{n=1}^N \{ y_n [1 - \sigma(\beta^T \mathbf{x}_n)] \mathbf{x}_n + (1 - y_n) \sigma(\beta^T \mathbf{x}_n) \mathbf{x}_n \} \\ &= - \sum_{n=1}^N [y_n - y_n \sigma(\beta^T \mathbf{x}_n) - \sigma(\beta^T \mathbf{x}_n) + y_n \sigma(\beta^T \mathbf{x}_n)] \mathbf{x}_n \\ &= \sum_{n=1}^N \underbrace{(\sigma(\beta^T \mathbf{x}_n) - y_n)}_{\text{error}} \mathbf{x}_n \end{aligned}$$

Derivation of  $\mathbf{H} = \frac{\partial^2 \mathcal{E}(\beta)}{\partial \beta \partial \beta^T}$ 

$$\begin{aligned} \mathbf{H} &= \frac{\partial^2}{\partial \beta \partial \beta^T} \left[ \sum_{n=1}^N (\sigma(\beta^T \mathbf{x}_n) \cdot \mathbf{x}_n - y_n \mathbf{x}_n) \right] \\ &= \sum_{n=1}^N \underbrace{\sigma(\beta^T \mathbf{x}_n)}_{\in [0,1]} \cdot \underbrace{(1 - \sigma(\beta^T \mathbf{x}_n))}_{\in [0,1]} \cdot \underbrace{(\mathbf{x}_n \cdot \mathbf{x}_n^T)}_{\in \mathcal{R}^{D \times D}} \end{aligned}$$