

Gradient descent:

$$E(w) = \sum_{i=1}^N \log(1 + e^{-w^T x_i y_i}) + \frac{\lambda}{2} \|w\|^2$$

$$w_{j+1} = w_j - \alpha \frac{\partial E(w)}{\partial w_j} \quad \alpha_j < \epsilon$$

$\frac{\partial E(w)}{\partial w}$  can be

written in matrix form as  $\frac{\partial E(w)}{\partial w} = \sum_{i=1}^N (\sigma(w^T x_i) - y_i) x_i + \lambda w$

as

$$\frac{\partial E(w)}{\partial w} = \sum_{i=1}^N (\sigma(w^T x_i) - y_i) x_i + \lambda w$$

$$\Rightarrow w_{j+1} = w_j - \alpha \sum_{i=1}^N (\sigma(w^T x_i) - y_i) x_i + \lambda w$$

To be used for programming

$$\begin{cases} \text{for } j = 0 \\ w_0 = \alpha \sum_{i=1}^N (\sigma(w^T x_i) - y_i) x_i \\ \text{for } j = 1 \text{ to } n \\ w_{j+1}^* = w_j - \alpha \sum_{i=1}^N (\sigma(w^T x_i) - y_i) x_i + \lambda \|w\| \end{cases}$$