

$$2) f(w) = \frac{1}{2n} \|y - Xw\|_2^2 + \frac{\lambda}{2} \|w\|_2^2 = \frac{1}{n} \sum_{i=1}^n f_i(w) \quad \text{ou } f_i(w) = \frac{1}{2} [(y_i - x_i^T w)^2 + \lambda \|w\|^2]$$

$$\nabla f_i(w) = (y_i - x_i^T w) x_i + \lambda w.$$

$$\nabla f(w) = \frac{1}{n} \sum_{i=1}^n \underbrace{x_i (y_i - x_i^T w)}_{\text{red. scalaire.}} + \lambda w = \left[ \frac{1}{n} \sum_{i=1}^n x_i x_i^T + \lambda I \right] w + \text{cte } \% w.$$

$$\|\nabla f(w) - \nabla f(w')\| \leq \left\| \frac{1}{n} \sum_{i=1}^n x_i x_i^T + \lambda I \right\| \|w - w'\|$$

si  $\Pi$  : symétrique nulle,  $\Pi = U^T D U$   $U^T U = I$ .

$$\|L = \Pi\| = \sup_u \frac{\| \Pi u \|}{\|u\|} = \sqrt{\sup_u \frac{u^T \Pi^T \Pi u}{u^T u}} = \sup_{\lambda \in \text{Spec}(\Pi)} |\lambda| = \sup_u \frac{|u^T \Pi u|}{u^T u}$$

↑  
Norme spectrale

si  $x_i \in \mathbb{R}^d$ ,  $\|x_i x_i^T\| = \sup \lambda ; \lambda \in \text{Spec}(\Pi_i)$

si  $\Pi_i \in \{x_i x_i^T\}$ ,  $(x_i x_i^T)_{\text{v}} = 0$  donc : 0 vp. d'ordre  $d-1$ .

$(x_i x_i^T) x_i = \|x_i\|^2 x_i \rightarrow \|x_i\|^2$  vp d'ordre 1.

Donc  $\|x_i x_i^T\| = \|x_i\|^2 \Rightarrow \|x_i x_i^T + \lambda I\| = \|x_i\|^2 + \lambda$ .

$$L = \left\| \frac{1}{n} \sum x_i x_i^T + \lambda I \right\| = \left\| \frac{1}{n} \sum x_i x_i^T \right\| + \lambda$$

$$L_{\max} = \max [L_{\nabla f_1}, \dots, L_{\nabla f_n}] = \max \left[ \underbrace{\|x_1 x_1^T + \lambda I\|, \dots, \|x_n x_n^T + \lambda I\|}_{(\|x_1\|^2 + \lambda, \dots, \|x_n\|^2 + \lambda)} \right]$$

$(L_1, \dots, L_d) :$   $\frac{\partial f}{\partial w_j} = \frac{1}{n} \sum_{i=1}^n -x_i [j] (y_i - x_i^T w) + \lambda w [j]$

$$\frac{\partial^2 f}{\partial w_j^2} = \frac{1}{n} \sum_{i=1}^n x_i^2 [j] + \lambda = L_j$$

Régression Logistique :

Loss:  $f(w) = -\frac{1}{n} \sum_{i=1}^n \log \ell(y_i | x_i) + \frac{\lambda}{2} \|w\|^2$

$$\ell(y_i | x_i) = \begin{cases} \frac{e^{x_i^T w}}{1 + e^{x_i^T w}} = \frac{1}{1 + e^{-x_i^T w}} & \text{si } y_i = 1 \\ \frac{1}{1 + e^{x_i^T w}} & \text{si } y_i = -1 \end{cases} = \frac{1}{1 + e^{-y_i x_i^T w}}$$

$$f(w) = \frac{1}{n} \sum_{i=1}^n \underbrace{\log(1 + e^{-y_i x_i^T w})}_{\psi(y_i x_i^T w)} + \frac{\lambda}{2} \|w\|^2$$

ou  $\psi(t) = \log(1 + e^{-t})$

$$\psi'(t) = \frac{-e^{-t}}{1 + e^{-t}} = \frac{-1}{1 + e^t}$$

$$\nabla f(w) = \frac{1}{n} \sum_{i=1}^n \psi'(y_i x_i^T w) y_i x_i + \lambda w$$

$$\psi''(t) = \frac{e^t}{(1 + e^t)^2}$$

$$\text{smc: } \nabla f(w) = \frac{1}{n} \sum_{i=1}^n \frac{1}{1+e^{y_i X_i^T w}} y_i X_i + \lambda w. \quad ; \quad X = \begin{bmatrix} X_1^T \\ \vdots \\ X_n^T \end{bmatrix}$$

$$= \frac{1}{n} [X_1, \dots, X_n] \left\{ \begin{bmatrix} -y_1 \\ \vdots \\ -y_n \end{bmatrix} \odot \begin{bmatrix} -\frac{1}{1+e^{y_1 X_1^T w}} \\ \vdots \\ -\frac{1}{1+e^{y_n X_n^T w}} \end{bmatrix} \right\} + \lambda w.$$

↑  
multip. term  
à term.

$$\nabla^2 f(w) = \frac{1}{n} \sum_{i=1}^n \frac{e^{y_i X_i^T w}}{(1+e^{y_i X_i^T w})^2} \frac{y_i^2}{4} X_i X_i^T + \lambda I.$$

$$\frac{u}{(1+u)^2} = \binom{p}{1+u} \binom{1-p}{1+u} \leq \frac{1}{4}.$$

$$\|\nabla^2 f(w)\| = \sup_{\|u\|=1} u^T \nabla^2 f u = \sup_{\|u\|=1} \frac{1}{n} \sum_{i=1}^n \varphi(y_i X_i^T w) u^T X_i X_i u + \lambda \frac{u^T u}{4}.$$

$$\leq \frac{1}{4} \sup_{\|u\|=1} u^T \left[ \frac{1}{n} \sum_{i=1}^n X_i X_i^T \right] u + \lambda.$$

$$= \frac{1}{4} \left\| \frac{1}{n} \sum_{i=1}^n X_i X_i^T \right\| + \lambda.$$

$$L = \left\| \frac{1}{4} \left( \frac{1}{n} \sum_{i=1}^n X_i X_i^T \right) \right\| + \lambda.$$

$$L_{\max} = \max \left( \frac{1}{4} \|X_1\|^2 + \lambda, \dots, \frac{1}{4} \|X_n\|^2 + \lambda \right)$$

$$(L_1, \dots, L_d) = \left( \frac{1}{4} \frac{1}{n} \sum_{i=1}^n X_i^2 [1] + \lambda, \dots, \frac{1}{4} \frac{1}{n} \sum_{i=1}^n X_i^2 [d] + \lambda \right)$$