

FOUTE
TAPE
JORDAN
M1 IA.

TD 4 Support Vector Machine.

3. Cas non linéairement séparable

$$y(x) = w^T \phi(x) + b; \text{ (PRIMAL): } \min \frac{1}{2} \|w\|^2$$

$$\text{s.t. } t^i (w^T \phi(x^i) + b) \geq 1 \quad i=1, \dots, N.$$

$$w \in \mathbb{R}^n, b \in \mathbb{R}$$

$$\text{(DUAL): } \max e^T \lambda - \frac{1}{2} \lambda^T Q \lambda$$

$$\text{s.t. } \lambda^T t = 0$$

$$\lambda \geq 0$$

3) Conditions d'optimalité de K-K-T sur le primal.

posons $q(w) = \frac{1}{2} \|w\|^2$ et $g_i(w) = 1 - t^i (w^T \phi(x^i) + b)$.

$$1) \nabla_w q(w) + \sum_{i=1}^N \lambda_i \nabla_w g_i(w) = 0$$

$$\text{on a: } \nabla_w q(w) = \frac{\partial q(w)}{\partial w_k} = \frac{1}{2} \frac{\partial w_k^2}{\partial w_k} = w_k, \quad k=1, \dots, N.$$

$$\nabla_w g_i(w) = \frac{\partial (1 - t^i (w^T \phi(x^i) + b))}{\partial w_k} \quad \text{or} \quad w^T \phi(x^i) = \sum_{j=1}^n w_j \phi(x_j)$$

$$\frac{\partial w^T \phi(x^i)}{\partial w_k} = \phi(x_k)$$

$$\nabla_w g_i(w) = -t^i \phi(x^i)$$

$$\text{donc } w_k - \sum_{i=1}^N \lambda_i t^i \phi(x^i) = 0, \quad k=1, \dots, N.$$

$$w - \sum_{i=1}^N \lambda_i t^i \phi(x^i) = 0$$

$$2^o) \nabla_b f(w) + \sum_{i=1}^M \lambda_i \nabla_b g_i(w) = 0$$

$$\nabla_b f(w) = 0, \quad \nabla_b g_i(w) = \frac{\partial (1 - t^i (w^T \phi(x^i) + b))}{\partial b} = -t^i$$

$$\text{donc } - \sum_{i=1}^M \lambda_i t^i = 0$$

$$3^o) \lambda_i g_i(w) = 0$$

$$4) \text{ Montrons que si } \lambda \text{ solution du DUAL alors } w = \sum_{i=1}^M \lambda_i t^i \phi(x^i)$$

d'après la question précédente, on a :

$$w - \sum_{i=1}^M \lambda_i t^i \phi(x^i) = 0 \Rightarrow w = \sum_{i=1}^M \lambda_i t^i \phi(x^i).$$

$$5) \text{ Montrons que } y(x) = \sum_{i=1}^M \lambda_i t^i k(x, x^i) + b.$$

$$\begin{aligned} y(x) &= w^T \phi(x) + b \\ &= \left[\sum_{i=1}^M \lambda_i t^i \phi(x^i) \right]^T \phi(x_j) + b \\ &= \sum_{i=1}^M \lambda_i t^i \phi^T(x^i) \phi(x_j) + b \quad \text{on } k(x_i, x_j) = \phi^T(x^i) \phi(x_j) \end{aligned}$$

$$y(x) = \sum_{i=1}^M \lambda_i t^i k(x^i, x^j) + b.$$

$$6) \text{ Montrons que si } \lambda_i > 0 \text{ alors } t^i y(x^i) = 1.$$

$$\text{on a : } \lambda_i g_i(w) = 0, \quad \text{si } \lambda_i > 0 \Rightarrow g_i(w) = 0$$

$$g_i(w) = 0 \Rightarrow 1 - t^i (w^T \phi(x^i) + b) = 0$$

$$\Rightarrow 1 - t^i y(x^i) = 0$$

$$\Rightarrow t^i y(x^i) = 1.$$

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7) Deducisons que si $\lambda_i > 0$ alors $y(x^i) = t^i$

si $\lambda_i > 0$, $t^i y(x^i) = 1$.

si $t^i = 1 \Rightarrow y(x^i) = 1$

si $t^i = -1 \Rightarrow y(x^i) = -1$

done $y(x^i) = t^i$

8) Deducisons que si λ est solution optimale du DUAL, alors b optimal est $b = \frac{1}{|S|} \sum_{i \in S} (t^i - \sum_{d \in S} \lambda_d t^d k(x^i, x^d))$.

$$y(x^i) = \sum_{d=1}^M \lambda_d t^d k(x^i, x^d) + b = t^i$$

$$\Rightarrow b = t^i - \sum_{d=1}^M \lambda_d t^d k(x^i, x^d)$$

$$\sum_{i \in S} b = \sum_{i \in S} (t^i - \sum_{d=1}^M \lambda_d t^d k(x^i, x^d))$$

$$b = \frac{1}{|S|} \sum_{i \in S} (t^i - \sum_{d \in S} \lambda_d t^d k(x^i, x^d))$$