

Lagrange dual function (面状问题)

$$g(\lambda, \nu) = \inf_{x \in D} L(x, \lambda, \nu) = \inf_{x \in D} \left(f_0(x) + \sum_{i=1}^m \lambda_i f_i(x) + \sum_{i=1}^p \nu_i h_i(x) \right)$$

SVM - Lagrange Multiplier:

Goal: find hyperplane with maximal margin ($\frac{1}{\|w\|}$)

$$\begin{cases} w^T x_n + b \geq 1 & \text{for } t_n = +1 \\ w^T x_n + b \leq -1 & \text{for } t_n = -1 \end{cases}$$

choose w, b such that $d = \frac{1}{\|w\|}$

\Rightarrow minimizing $\|w\|^2$

argmin $\frac{1}{2} \|w\|^2$ under constraints $t_n (w^T x_n + b) \geq 1 \quad \forall n$

$$L(w, b, a) = \frac{1}{2} \|w\|^2 - \sum_{n=1}^N a_n \{ t_n (w^T x_n + b) - 1 \}$$

Lagrange multiplier

$$\frac{\partial L}{\partial b} = 0 \Rightarrow \sum_{n=1}^N a_n t_n = 0$$

$$\frac{\partial L}{\partial w} = 0 \Rightarrow w = \sum_{n=1}^N a_n t_n x_n$$

if $t_n (w^T x_n + b) > 1$ then consider KKT (Karush-Kuhn-Tucker condition)

$$\begin{aligned} L &= \|w\|^2 + \lambda \cdot f(x) \\ \lambda &\geq 0 \\ f(x) &\geq 0 \end{aligned} \Rightarrow \begin{aligned} \lambda f(x) &= 0 \\ \text{if } \lambda > 0 \quad f(x) &= 0 \end{aligned}$$

$$a_n \geq 0$$

$$t_n y(x_n) \geq 1 \Rightarrow \geq 0$$

\downarrow

$$a_n \{ t_n y(x_n) - 1 \} = 0$$

$$w^T x_n + b$$

Lagrange multiplier

if $a_n \neq 0$

$$t_n y(x_n) - 1 = 0$$

$$a_n = 0$$

$t_n y(x_n) - 1 \neq 0 \Leftarrow$ not lay on the boundary.

$$\begin{array}{cccc} x & & x & \\ - & 0 & - & \dots \\ \hline - & - & 0 & - \\ 0 & & x & \end{array}$$

$$t_n y(x_n) = t_n \left(\sum_{m \in S} a_m t_m x_m^T \cdot x_n + b \right) \geq 1, \quad t_n^2 = 1$$

$$b = t_n - \sum_{m \in S} a_m t_m x_m^T \cdot x_n$$



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$$L_P = \frac{1}{2} \|w\|^2 - \sum_{n=1}^N \alpha_n \left[t_n (w x_n^T + b) - 1 \right] \quad \text{primal}$$

→ re-written as dual from

$$w = \sum_{n=1}^N \alpha_n t_n x_n^T$$

$$\sum_{n=1}^N \alpha_n t_n = 0$$

$$L_{P_{\text{re-written}}} = \frac{1}{2} \|w\|^2 - \sum_{n=1}^N \alpha_n t_n w x_n^T - b \sum_{n=1}^N \alpha_n t_n + \sum_{n=1}^N \alpha_n$$

$$= \frac{1}{2} \|w\|^2 - \sum_{n=1}^N \alpha_n t_n \left(\sum_{m=1}^N \alpha_m t_m x_m^T \right) x_n^T + \sum_{n=1}^N \alpha_n$$

$$\Rightarrow L_{\text{dual}} = -\frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N \alpha_n \alpha_m t_n t_m (x_m^T x_n) + \sum_{n=1}^N \alpha_n \quad (\text{no } w, b \text{ anymore})$$

maximize L_{dual} under constraint $\alpha_n \geq 0 \quad \forall n, \sum_{n=1}^N \alpha_n t_n = 0$

$$w = \sum_{n=1}^{N_{\text{support vector}}} \alpha_n t_n x_n$$

$$\hookrightarrow N_{\text{support vector}} \quad O(N^2)$$

of data points for support vectors
not rely on # of dimensions.

In practice: $O(N) \sim O(N^2)$

summary: Dual problem is good for high dimension problem

↓
can apply kernel Trick.



Lagrangean multiplier

$$L_p = \frac{1}{2} \|w\|^2 - \sum_{n=1}^N a_n \{ t_n (w^T \overset{\text{then S.V.}}{\overbrace{x_n}^{\text{then S.V.}}} + b) - 1 \} = 0 \quad \left(\begin{array}{l} \text{suit for} \\ \text{low dimension data} \end{array} \right)$$

only if $\neq 0$

$$L_d = -\frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N a_n a_m t_n t_m \underbrace{(x_m^T x_n)} + \sum_{n=1}^N a_n \quad O(N^3) : O(N) \sim O(N^2)$$

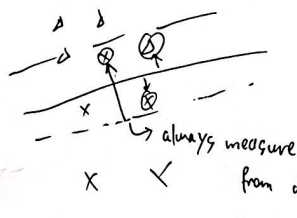
in practice
b/c it only use it

If we use kernel trick, we need L_d (dual form)

$$L_p(w, b, a)$$

$$L_d(a)$$

slack variable



$$w^T x_n + b \geq 1 - \zeta_n \quad \text{for } t_n = +1$$

$$w^T x_n + b \leq -1 - \zeta_n \quad \text{for } t_n = -1$$

$$\boxed{\zeta_n \geq 0}$$

goal: non-separable data, minimize $\frac{1}{2} \|w\|^2 + C \sum_{n=1}^N \zeta_n$

Trade-off parameter

new sum relaxation (primal)

$$\text{optimize } L_p = \frac{1}{2} \|w\|^2 + C \sum_{n=1}^N \zeta_n - \sum_{n=1}^N a_n (t_n y(x_n) - 1 + \zeta_n)$$

$$- \sum_{n=1}^N a_n \zeta_n$$

apply KKT:

$$\textcircled{1} a_n \geq 0$$

$$t_n y(x_n) - 1 + \zeta_n \geq 0$$

$$a_n (t_n y(x_n) - 1 + \zeta_n) = 0$$

$$\textcircled{2} \mu_n \geq 0$$

$$\zeta_n \geq 0$$

$$\mu_n \zeta_n = 0$$

$$\frac{\partial L}{\partial \zeta_n} \stackrel{!}{=} 0 \Rightarrow$$

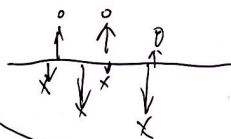
$$C - a_n - \mu_n = 0$$

$$C - \mu_n = a_n$$

$$\boxed{C \geq a_n \geq 0}$$

trade-off b/w slack & margin

$C \rightarrow \infty \Rightarrow$ linear discriminant (will measure every noise)



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we can determine whether the data work with SVM using lagrange multiplier.

i) $a_n = 0$, it is not S.V.
it is clearly classified

ii) ~~0 < a_n < C~~ $0 < a_n < C \rightarrow \mu_n \neq 0 \rightarrow \xi_n = 0$, it's SV.

it doesn't have slack (it is on the decision boundary)

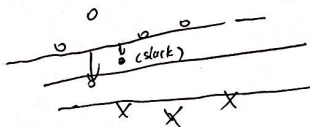
iii) $a_n = C$

$$C - a_n - \mu_n = 0$$

$$\mu_n = 0$$

$\mu_n \xi_n = 0$, ~~it~~ It has slack variable (slack loss)

$$\begin{matrix} \downarrow & \downarrow \\ 0 & \neq 0 \end{matrix}$$



so we can know where data located according to $\boxed{a_n}$.

