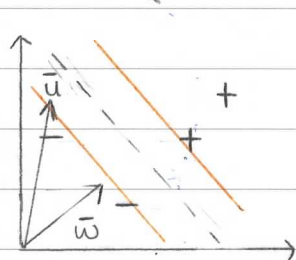


SVM \rightarrow 監督式學習，以統計風險最小化的原則來估測一個分類的超平面。



$\bar{w} \cdot \bar{u} \geq C$ \rightarrow 常數

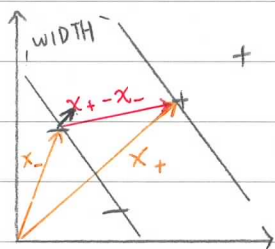
① $\bar{w} \cdot \bar{u} + b \geq 0$ + 樣本

$C = -b$

\Rightarrow "+" : $\bar{w} + \bar{x}_+ + b \geq 1 \rightarrow y_i(x_i \bar{w} + b) \geq 1 \rightarrow y_i(x_i \bar{w} + b) - 1 \geq 0$

"-" : $\bar{w} + \bar{x}_- + b \leq -1 \rightarrow y_i(x_i \bar{w} + b) \leq -1 \rightarrow y_i(x_i \bar{w} + b) - 1 \leq -2$

\rightarrow for x_i in gutter



$WIDTH = (\bar{x}_+ - \bar{x}_-) \cdot \frac{\bar{w}}{\|\bar{w}\|} = \frac{2}{\|\bar{w}\|}$

$\Rightarrow \bar{x}_+ = 1 - b, \bar{x}_- = 1 + b$

$\text{MAX } \frac{2}{\|\bar{w}\|} \Rightarrow \text{MAX } \frac{1}{\|\bar{w}\|} \Rightarrow \text{min } \|\bar{w}\| \Rightarrow \text{min } \frac{1}{2} \|\bar{w}\|^2$

$L = \frac{1}{2} \|\bar{w}\|^2 - \sum \alpha_i [y_i(\bar{w} \cdot \bar{x}_i + b) - 1]$

$\frac{\partial L}{\partial \bar{w}} = \bar{w} - \sum \alpha_i y_i x_i = 0 \rightarrow \bar{w} = \sum \alpha_i y_i x_i$ ③

$\frac{\partial L}{\partial b} = -\sum \alpha_i y_i = 0 \rightarrow \sum \alpha_i y_i = 0$

$L = \frac{1}{2} (\sum \alpha_i y_i \bar{x}_i) (\sum \alpha_j y_j \bar{x}_j) - \sum \alpha_i y_i x_i (\sum \alpha_j y_j x_j) - \sum \alpha_i y_i b + \sum \alpha_i$
 $= \sum \alpha_i - \frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j y_i y_j x_i x_j$ ④ 求最大值

$\sum \alpha_i y_i \bar{x}_i \cdot \bar{u} + b \geq 0 \rightarrow$ "+"

不可線性分離: $\phi(\bar{x}_i) \cdot \phi(\bar{x}_j)$ to MAX $K(x_i, x_j) = \phi(\bar{x}_i) \cdot \phi(\bar{x}_j)$
 $\phi(x_i) \cdot \phi(x_u)$

$\Rightarrow \phi(\bar{u} \cdot \bar{v} + 1)^n \quad \phi = e^{-\frac{\|x_i - y_i\|^2}{2\sigma^2}}$