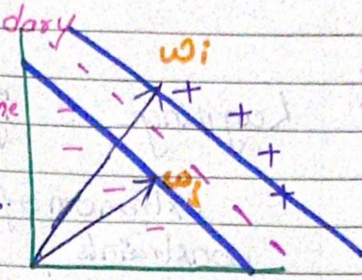
GOAL :- Linear ~~Sepra~~ classifies two classes.

DATE

SVM

Hyperplane :- Decision boundary

Support Vectors :- Data points nearest to Hyperplane



① Divide the negative and positive samples.

② Draw a vector ⊥ar to the median

+ve Sample

$\vec{\omega}\cdot\vec{u} \geq C$ ω = weight

u = unknown sample

3 c = constant (b)

Decision RULE 1. $\vec{\omega}\cdot x_+ + b \geq 0$

$\vec{\omega}\cdot x_+ + b > 1$ (+ve sample)

$\vec{\omega}\cdot x_- + b \leq -1$ (-ve sample)

$y_i(\omega_i x_i + b) > 1$ y_i = Variable

$y_i(\omega x_i + b) \geq 1$

we multiplied -ve sample by -1 so the both the resultant equations are same.

2. $y_i(x_i \cdot \omega + b) - 1 \geq 0$

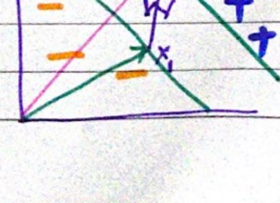
③ Maximum Margin

Width of the street

$$W = (x_+ - x_-) \times \frac{\omega}{\|\omega\|}$$

$(1-b)$ $(1+b)$

$$= \frac{2}{\|W\|}$$ +ve sample



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$$\text{Max} = \approx \text{MIN} = \frac{1}{2}\|W\|^2$$

KKT

Lagrange :- if we are finding a extremem of functions with constraints, our new expression without thinking of constraints.

$$L = \frac{1}{2}\|W\|^2 - \sum \alpha_i \left[y_i (\omega x_i + b) - 1 \right]$$

= To find maximum, we find derivatives and set them to Zero

w.r.t ω

$$\frac{dL}{d\omega} = W - \sum \alpha_i y_i x_i = 0$$

$$\Rightarrow \omega = \sum \alpha_i y_i x_i$$

w.r.t b

$$\frac{dL}{db} = \sum \alpha_i y_i = 0$$

Substitute for ω

$$L = \frac{1}{2}\left(\sum \alpha_i y_i x_i\right)\left(\sum \alpha_j y_j x_j\right)$$

$$- \sum \alpha_i y_i x_i \left(\sum \alpha_j y_j x_j\right)$$

$$- \sum \alpha_i y_i b$$

→ if constraint is Zero.

$$\boxed{L = \sum \alpha_i - \frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j y_i y_j x_i x_j}$$

HARD MARGIN : Linear Seprate, 100% classificatio
SOFT MARGIN : only Support Vector not outlier

To project data in higher dimension

$$Z = x^2 + y^2$$

mapping Z using x & y → Kernel Transformatio