SVM / SVR

⇒ Svm / svr

⇒ Unsupervised ml algo

- → K-means
- → Heirarchial
- → DB SCAN
- → PCA

⇒ MLOPS + Projects

- → Git
- → End to end proj
- →
- → dB
- → File handling
- → API

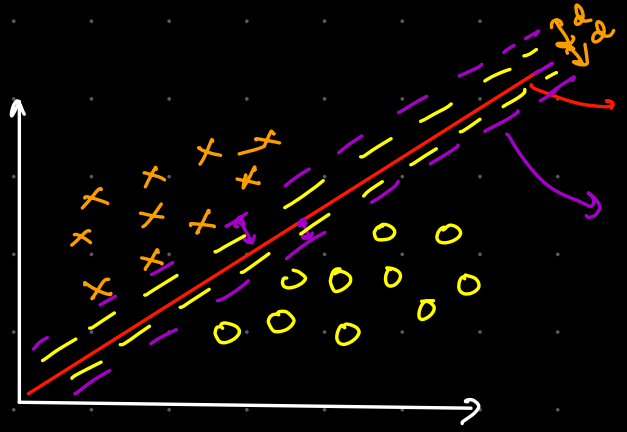
→ NLP / Deep learning / Time series.

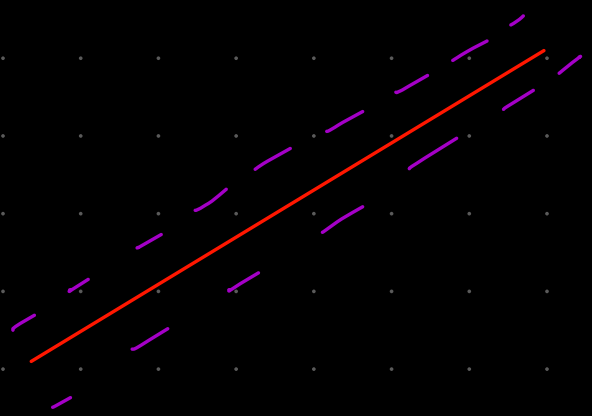
→ SQL

SVM & SVR algorithm

Useful for regression & classification algo.

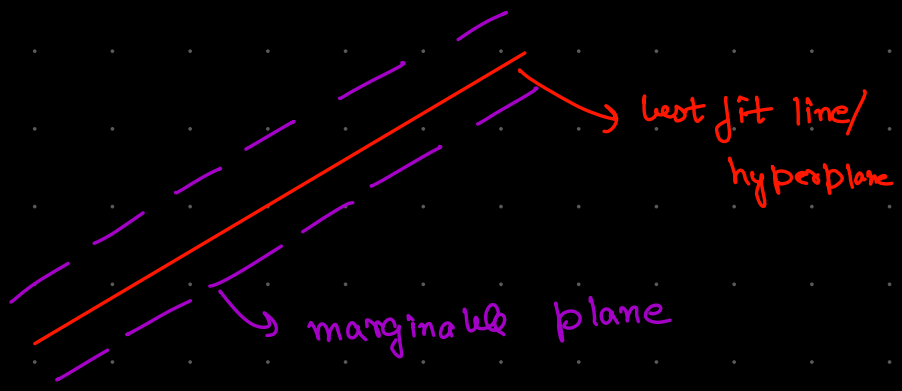
SVM ⇒ Support vector m/c
SVR ⇒ Support vector regression

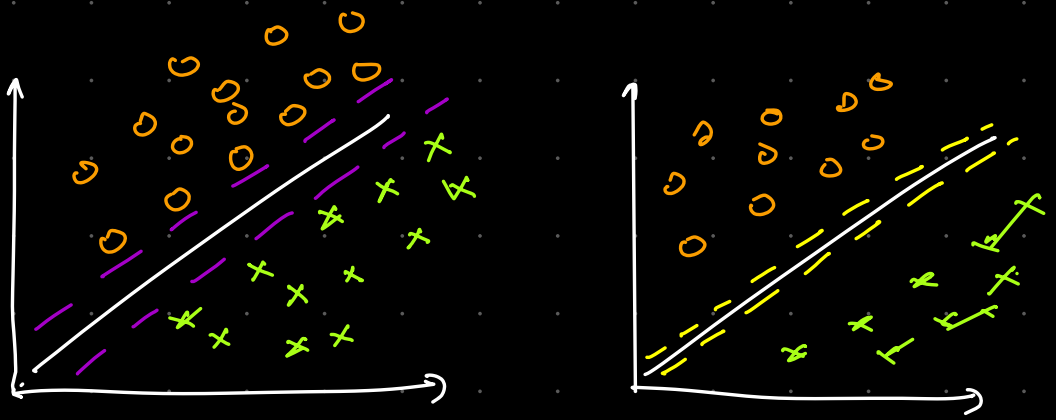


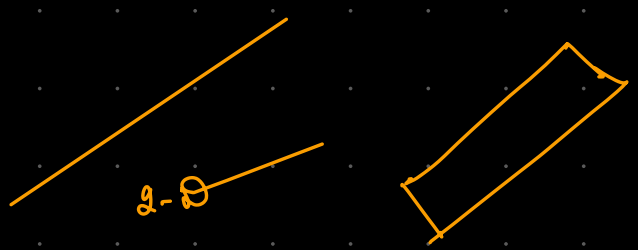


⇒ parallel to best fit line

⇒ make it farthest away from our best fit line.



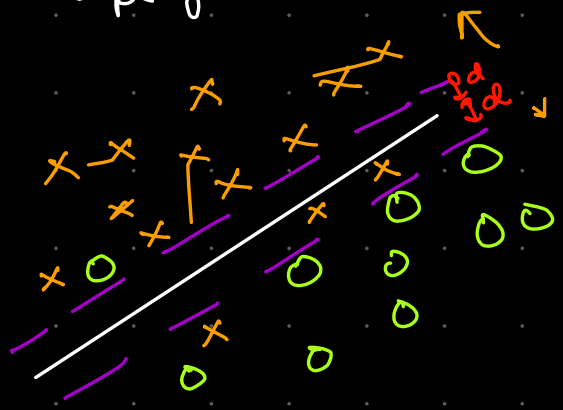




$\theta_0 + \theta_1 x = y$ — $\theta_0 + \theta_1 x_1 + \theta_2 x_2 = y$

hard marginal plane ⇒ perfect

Soft marginal errors →



$y = mx + c$

$= \theta_1 x_1 + \theta_2 x_2$

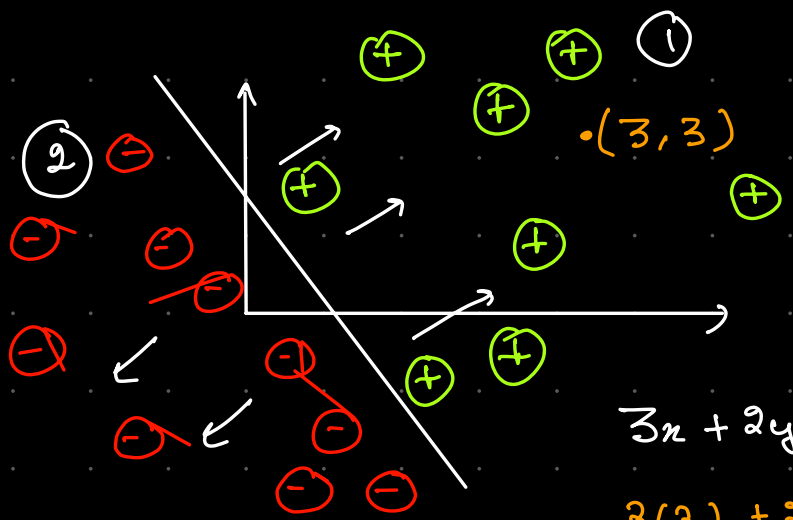
$ax + by + c = 0$

$y = -\frac{a}{b}x - \frac{c}{b}$

$y = w_1 x_1 + w_2 x_2 + w_3 x_3 + b$

$= w^T x + b \quad \approx m^T x + c$

$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} \begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix}$



$3x + 2y + 4 = 0$

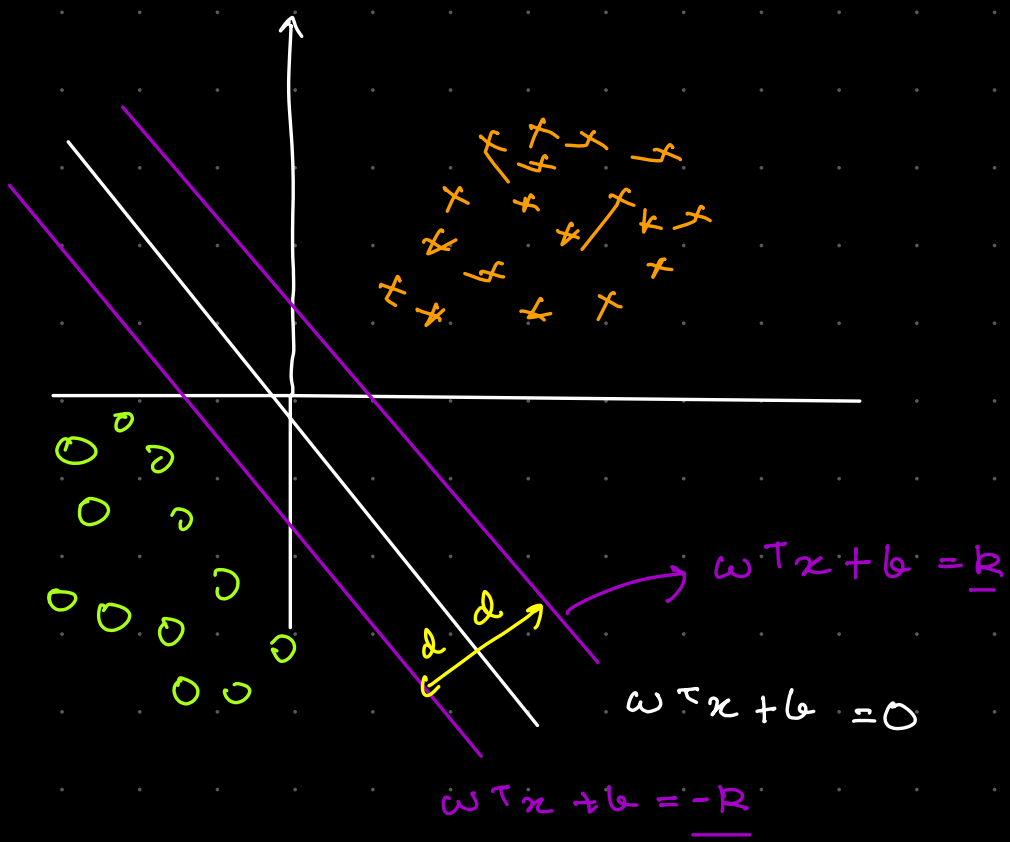
$3(3) + 2(3) + 4 \quad (3,3)$

$\Rightarrow +ve \quad > 0$

$(-5, 0)$

$3(-5) + 4(0) + 4$

$-11 \quad < 0$



$$w^T x + b = +1 \qquad w^T x + b = -1$$

$$w^T x_1 + b = 1$$

$$w^T x_2 + b = -1 \quad (+)$$

$$w^T (x_1 - x_2) = 2$$

$w \Rightarrow$ coeff.

$\Downarrow$

magnitude & vector

$$\frac{w^T}{\|w\|} (x_1 - x_2) = \left(\frac{2}{\|w\|} \right)$$

$$\arg\max_{(w,b)} = \boxed{\frac{2}{\|w\|}}$$

$\Rightarrow$ overall

Maximize $_{(w,b)}$ $\left(\frac{2}{\|w\|} \right) \Rightarrow$ marginal plane

$$\frac{2}{\|w\|} \Rightarrow \text{maximize}$$

Such that

$$y_i = \begin{cases} +1 & w^T x_i + b \geq 1 \\ -1 & w^T x_i + b \leq -1 \end{cases}$$

y_i ⟸ real output

Above is my constraint

For all the correctly labeled

$$y_i * (w^T x_i + b) \geq 1$$

Our main aim :

$$\underset{(w,b)}{\text{maximize}} \ \frac{2}{\|w\|} \iff \underset{(w,b)}{\text{Min}} \ \frac{\|w\|}{2}$$

$$\frac{1}{x} \iff x$$

max $\frac{2}{x}$

min $\frac{x}{2}$

$x = 2$	1
$x = 1$	2
$x = 0.5$	4
$x = 0.1$	20
$x = 0.05$	40

Soft margin :-

we will have some error.

$$\underset{(w,b)}{\text{argmin}} \quad \frac{|w|}{2} + C \sum_{i=1} \xi_i$$

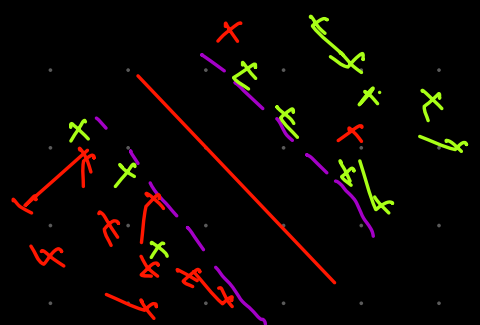
C: 1000/1000

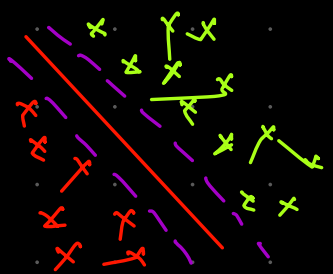
$\sum_{i=1} \xi_i$: classification error

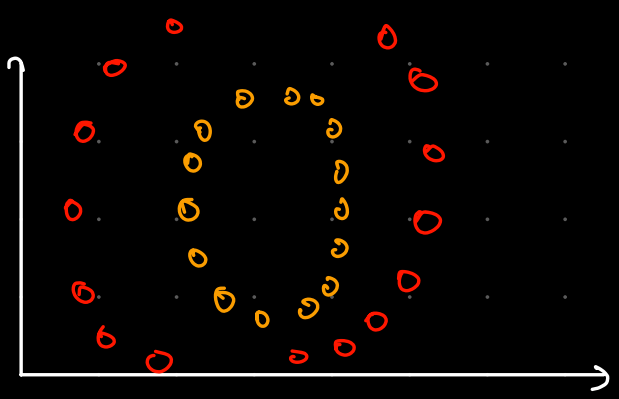
$\xi_i = 0$ for correctly classified

SVM ⇒ 2 things minimized

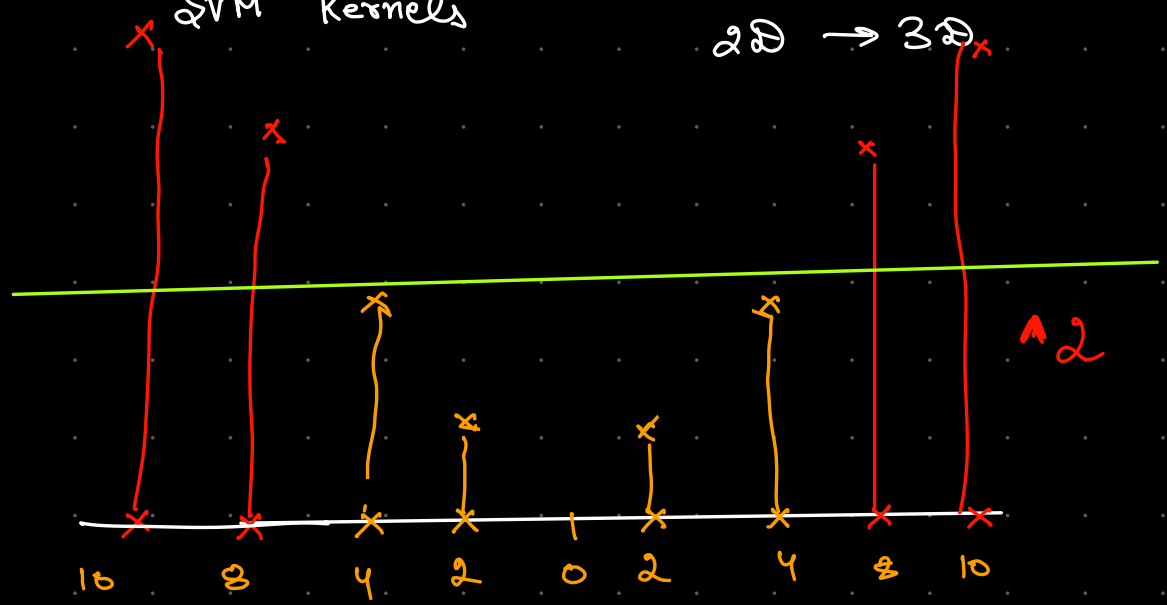
1. margin error
2. classification error.



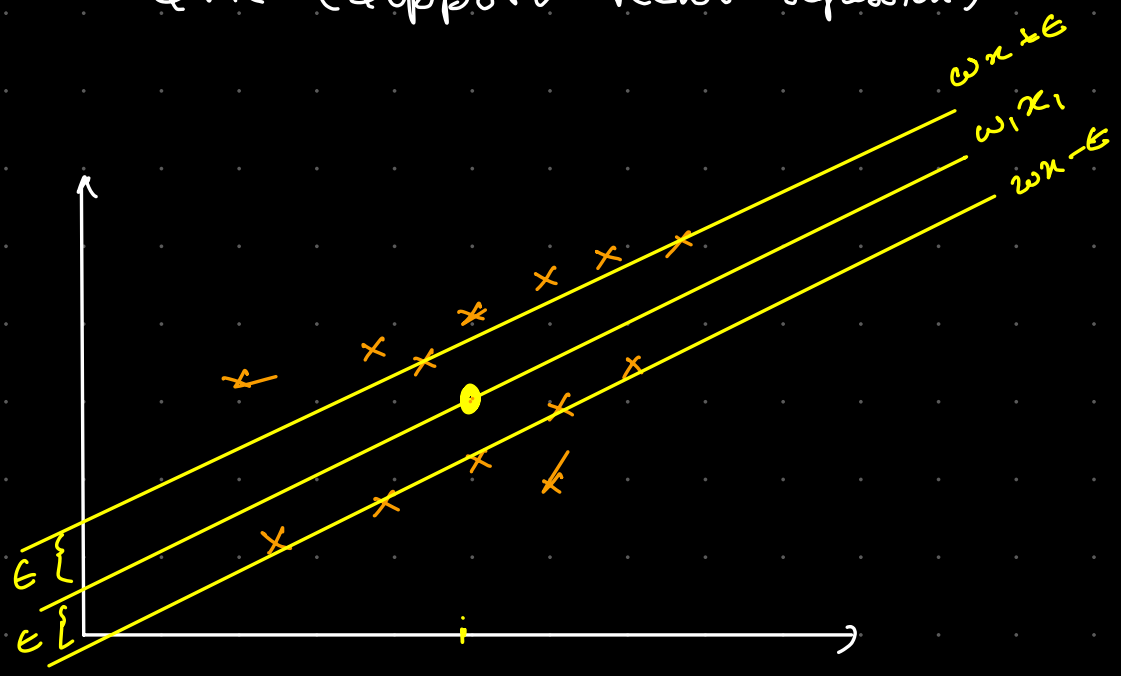




SVM Kernels



SVR (Support vector regression)



$$\min_{w,b} \quad \frac{|w|}{2}$$

Constraint $\quad |y_i - w_i x_i| \leq \epsilon$

y_i ↓ actual $\qquad$ $w_i x_i$ ↓ pred

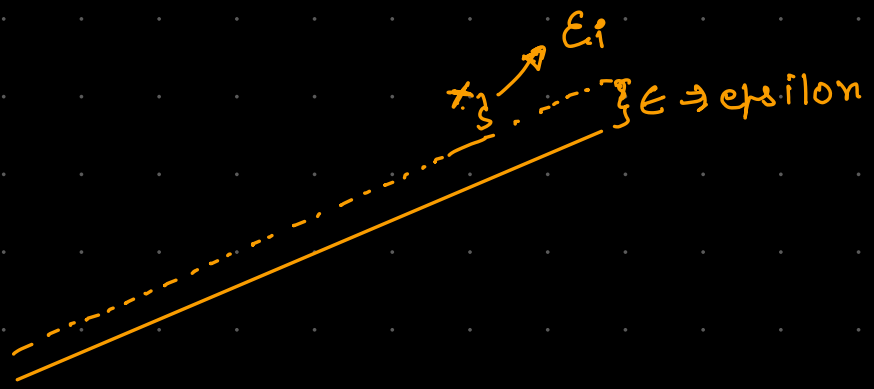
$w_i x_i + \epsilon$ & $w_i x_i - \epsilon$

giving some range below & above

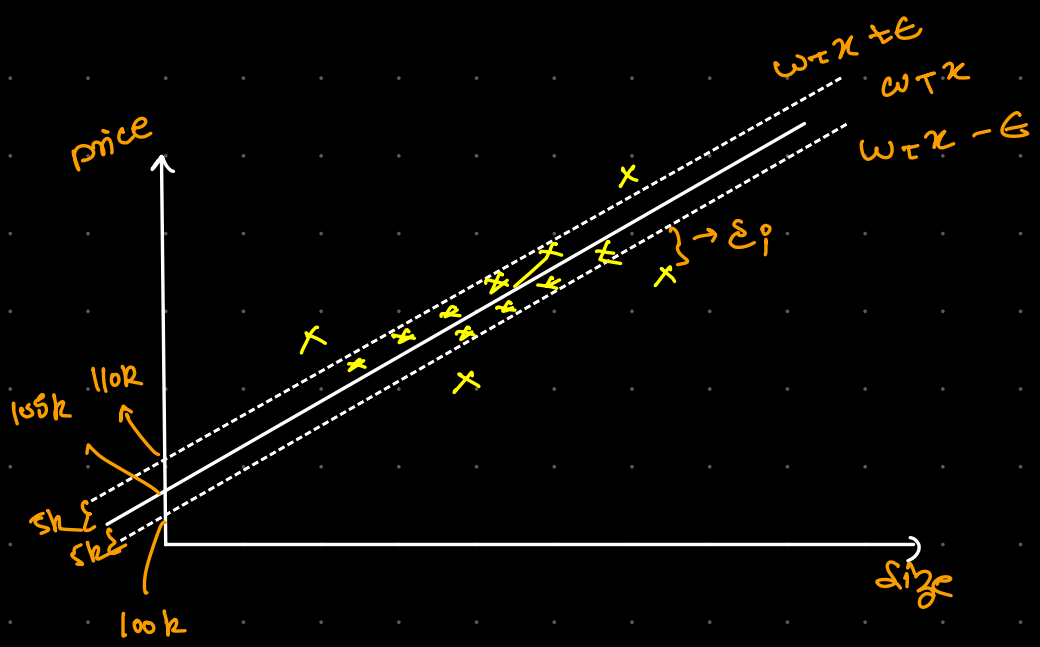
$+1$ -1 SVD

ϵ in SVR

$$y_i - \hat{y} \leq \epsilon$$



$$|y_i - w_i x_i| \leq \epsilon + |\xi_i|$$



$$\min \frac{|w|}{2} + C \sum \xi_i$$

$$(y - \hat{y}) \leq \epsilon + \xi_i$$

$$| y_i - w^T x_i | \leq \epsilon + |\xi_i|$$

$$\downarrow\!\uparrow$$

$$\hat{y}_{pred}$$

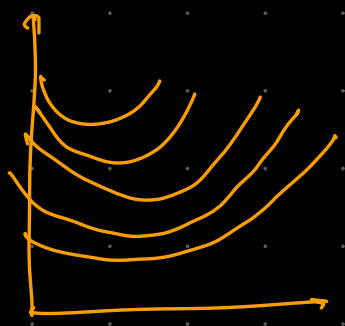
$$\min_{(w,b)} \underbrace{\frac{|w|}{2}}_{\text{margin}} + \underbrace{C_i \leq \xi_i}_{\text{loss}} \rightarrow \text{Hingeloss.}$$

$$\text{( )} + \lambda \text{( )}$$

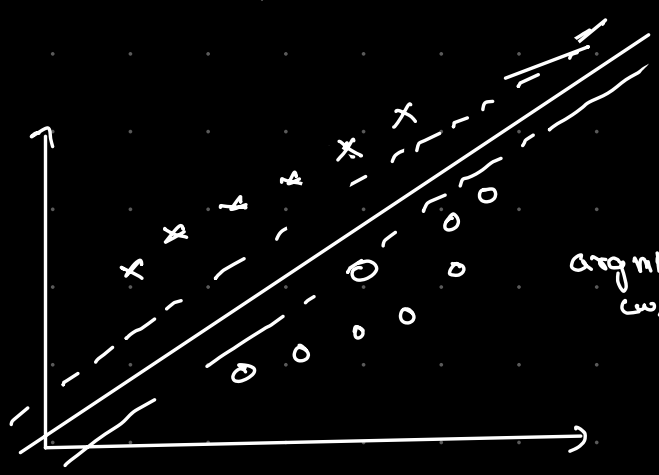
$$\lambda \propto \frac{1}{m}$$

$$C \propto \frac{1}{\lambda}$$

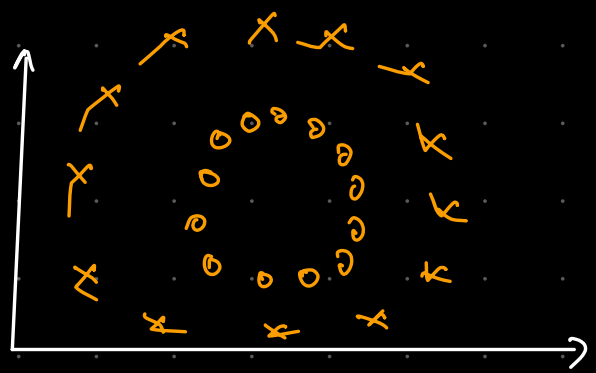
$$\boxed{C \propto \frac{1}{\frac{1}{\lambda}} \propto m}$$



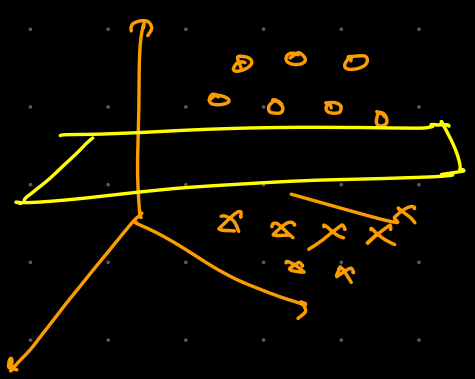
SVM · Kernels



$$\underset{(w,b)}{\operatorname{argmin}} \frac{|w|}{2} + C \sum \varepsilon_i$$



linear ⇒ line ⟹



$X = \{x_1, x_2\}$ x_1 x_2 y.

Polynomial Kernel

$$= (x^T x + c)^d$$

$d = 2$

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \begin{bmatrix} x_1 & x_2 \end{bmatrix} = \begin{bmatrix} x_1^2 & x_1 x_2 \\ x_1 x_2 & x_2^2 \end{bmatrix}$$

3 unique terms.

RBF

$$\exp\left(-\frac{(x - x')^2}{2\sigma^2}\right)$$