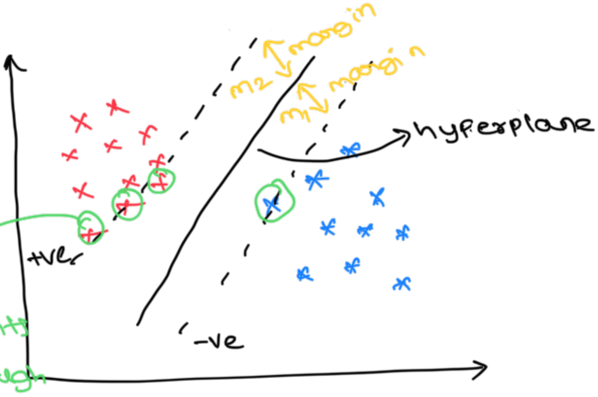
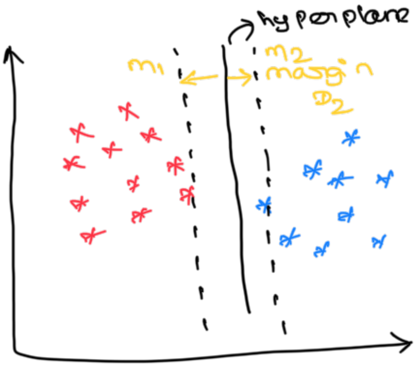
SVM can be used for both classification & Regression Problem.



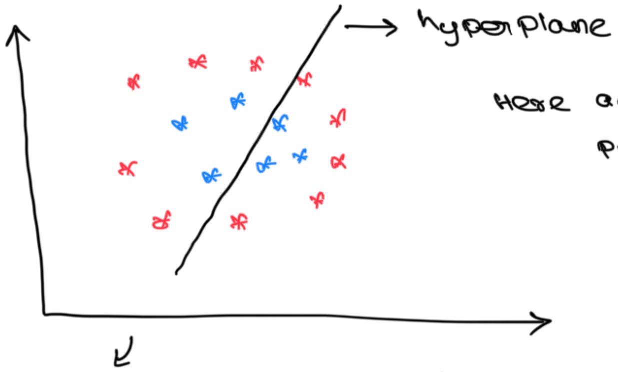
support vector refers to one cor)
more data points which passes through marginal plane which is parallel to hyperplane.

Fig(1) → linearly separable



Fig(2)

marginal distance $d_1 > d_2$, hence Fig(1) will be preferred
where $d_1 = |m_1 - m_2|$



Here accuracy will be poor.

Example for non linearly separable points.

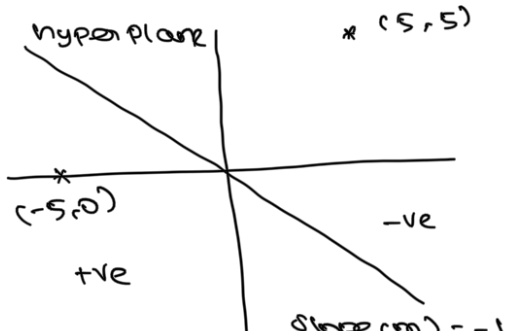
SVM kernel → convert lower dimension data into higher dimension so that even for non-linearly separable dataset we could have a hyperplane.

SVM (vs) logistic Regression
↳ SVM accounts marginal distance to choose the best hyperplane among available hyperplanes.

From linear Regression
$y = w^T x + b$

$b =$ 'y' Intercept

Equation of hyperplane
$w^T x + b = 0$



For points on the left side of hyperplane

$$w^T x + b > 0$$

For points on right side of hyperplane

$$w^T x + b < 0$$

let's generalize

left side $\quad w^T x_2 + b = +1$

Right side $\quad w^T x_1 + b = -1$

$\quad (-) \quad (-) \quad (-)$

$$w^T [x_2 - x_1] = 2$$

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

svg optimization Function $\rightarrow \max \left\{ \frac{2}{\|w\|} \right\}$

(or)

$$\min \left\{ \frac{\|w\|}{2} \right\} + c_i \sum_{i=1}^{n} \varepsilon_i$$

where

c_i = Error tolerance

ε_i = value of Error.

we know that

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

sum

$$\boxed{y_i * w^T x_i + b_i \geq 1}$$