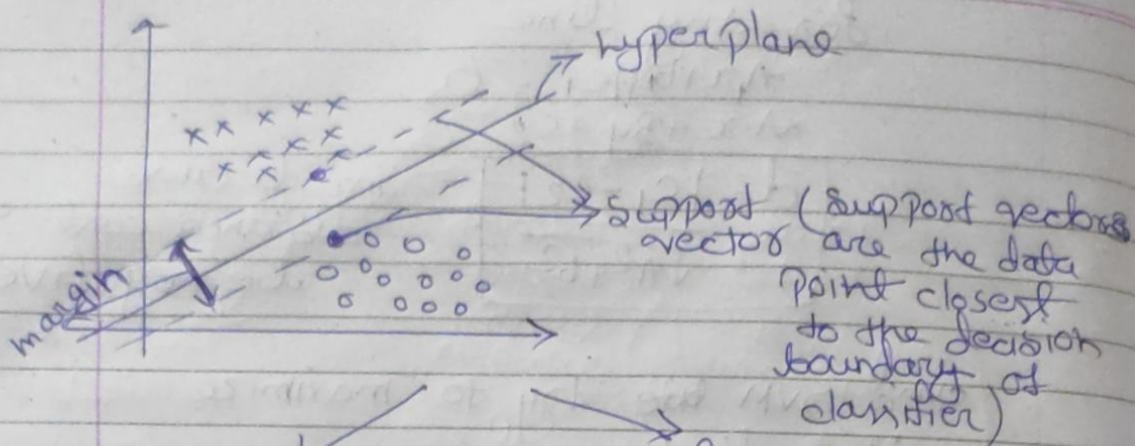


Support vector machine.

↳ for classification

No.

Date: / /



Hard margin

scenario where decision boundary strictly separates classes without allowing any misclassification.

Soft margin

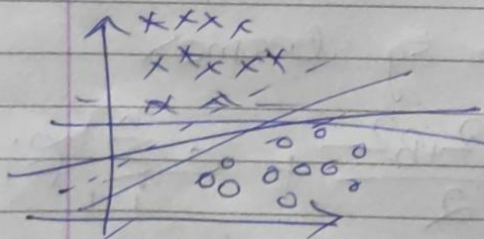
here a margin of tolerance is allowed for misclassification.

for two points:-

line $y = mx + c \rightarrow ax + by + c = 0$
or $w_1x_1 + b$

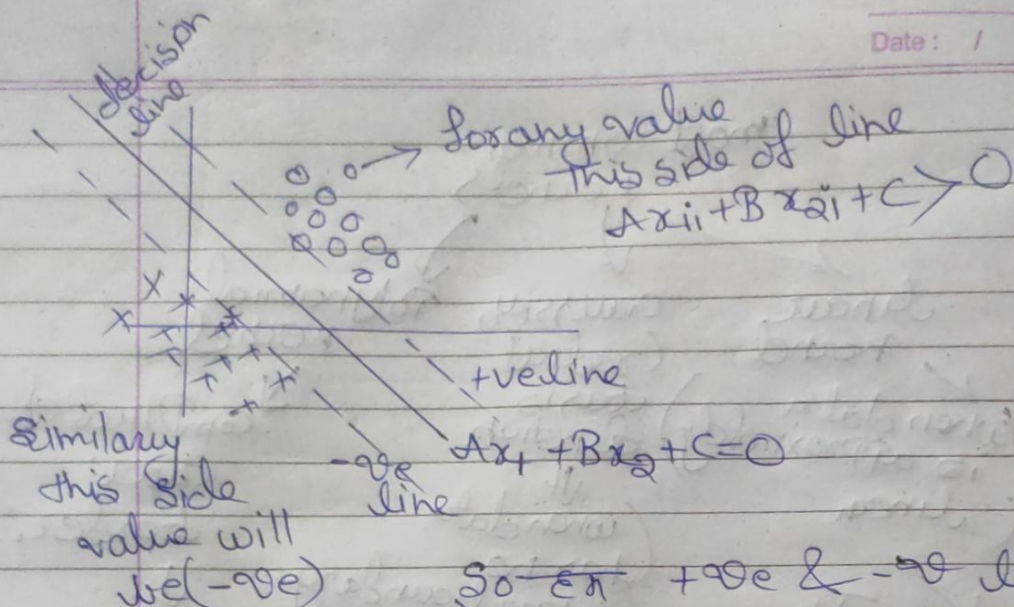
for hyper plane

$$y = w^T x + b$$



In these three which line is best fit because all three classifies well. In SVM

we choose line for which distance of margin is maximum.



So $+ve$ & $-ve$ line
 $Ax_1 + Bx_2 + C < 0$ define $ax_1 + bx_2 + c = 1$

by $Ax_1 + Bx_2 + C \geq k$ (we assume $k=1$)

then $Ax_1 + Bx_2 + C \geq 1$ — (1)

Similarly for negative line

by $Ax_1 + Bx_2 + C \leq -1$ — (2)

can we combine this both eq.
~~Yes~~ because y_i also +ve for
 line of side +ve & -ve side
 line side -ve.

$$y_i (Ax_1 + Bx_2 + C) \geq 1$$

condition

How to find distance:

by line equation

$$d = \frac{|C - 1 - (C + 1)|}{\sqrt{A^2 + B^2}} = \frac{2}{\sqrt{A^2 + B^2}}$$

For any line

$$Ax + By + C_1 = 0$$

$$Ax + By + C_2 = 0$$

$$d = \frac{|C_1 - C_2|}{\sqrt{A^2 + B^2}} \rightarrow \text{not because distance can't be negative}$$

and SVM we try to maximize this distance

$$\Rightarrow \arg \max_{A, B, C} \frac{2}{\sqrt{A^2 + B^2}} \text{ for } \forall i (Ax_i + By_i + C) \geq 1$$

↳ That is the eq for hard margin SVM, here we can not misclassify any single point.

To overcome this problem we add a parameter ξ (misclassification score).

For soft margin eq becomes

$$\arg \min_{(A, B, C)} \frac{\sqrt{A^2 + B^2}}{2} + C \sum_{i=1}^n \xi_i$$

Here C is a hyperparameter known as regularization parameter.

⇒ C controls the tradeoff between maximizing the margin & minimizing the classification errors.

⇒ A large value of C , narrower the margin & few misclassification, which may lead to overfitting.

⇒ A small value of C wider margin & may tolerate more misclassification prevents overfitting.

What is kernel trick?

↳ The "kernel trick" is a method in support vector machines (SVMs) which is used to convert data (that is not linearly separable) into a higher dimensional feature space where it may be linearly separated.

This technique enables the SVM to identify a hyperplane that separates the data with the maximum margin. Even when the data is not linearly separable in its original space.

most common kernels

linear kernel

(when data is approximately linear)

$$k(x, y) = x^T y$$

Gaussian (radial basis function)

(when data has no clear boundary & has many complicated areas)

$$k(x, y) = \exp(-\gamma \|x - y\|^2)$$

Polynomial kernel

↓ complicated case border.

$$k(x, y) = (x^T y + c)^d$$