

SVM part-1

↳ It is generally used in -

- classification (binary, multiclass)

- Regression

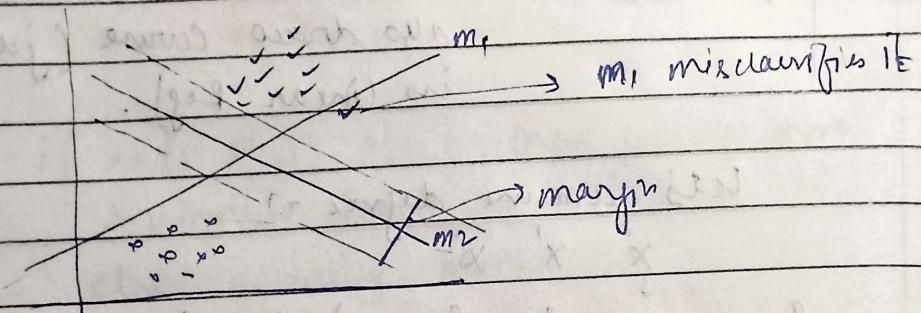
- Image processing

→ It can also be used on Non-linear Data set

Maximal Margin Classifier - (Hard Margin SVM)

cptp is place.

✗ → Not placed
✓ → placed



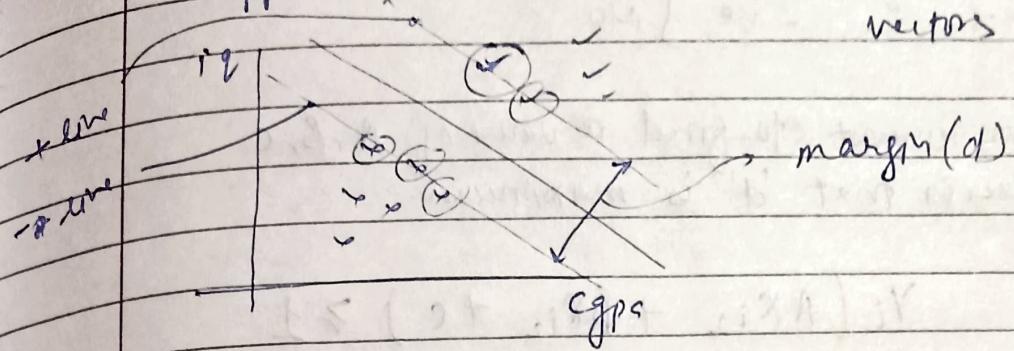
→ m_1, m_2 both can classify the classes but here m_2 is better model than m_1 , because m_2 is creating a margin whereas m_1 is passing very close to pts. So it's possible for new pts. that m_1 can misclassify

So SVM has more margin.

- The basic requirement is classes should be linearly separable

Support Vectors

These pts. are support vectors



- The points which lie on the margin are support vectors

Mathematical Formulation -

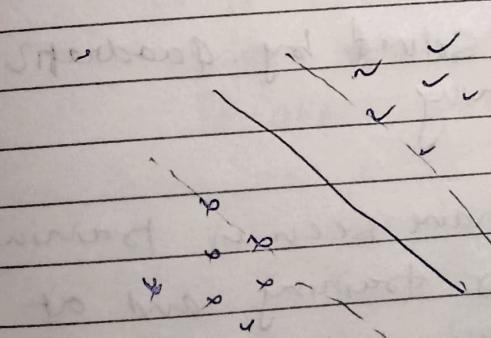
↳ We want a line segment which maximizes 'd' such that no points lie inside the margin.

$$\text{Eqn of line : } Ax + By + C = 0$$

$$+ \text{ve line : } Ax + By + C = 1$$

$$- \text{ve line : } Ax + By + C = -1$$

Now we want to write Eqn for the condit'



$$\left\{ \begin{array}{l} \text{+ve line : } -Ax -By -C \geq 1 \\ \text{-ve line : } -Ax -By -C \leq -1 \end{array} \right.$$

By using if we can ensure any pt which come will either lie in the region of +ve line or -ve line.

→ $x=1$ means +ve } y_i
 $x=-1$ " -ve } NO

→ we want to find the value of A, B, C
 such that 'd' is maximum

$$y_i (Ax_{i1} + Bx_{i2} + C) \geq 1$$

here $y_i = 1$ means +ve or True
 $y_i = -1$ " -ve or False

↳ we know that the distance b/w two parallel line is $\frac{|C_1 - C_2|}{\sqrt{A^2 + B^2}}$

$$\text{So } \frac{|C_1 - C_2|}{\sqrt{A^2 + B^2}} = \frac{2}{\sqrt{A^2 + B^2}}$$

→ $\underset{A, B, C}{\text{argmax}} \frac{2}{\sqrt{A^2 + B^2}}$ given $\{y_i (Ax_{i1} + Bx_{i2} + C) \geq 1\}$

↳ It will be solved by Quadratic Programming

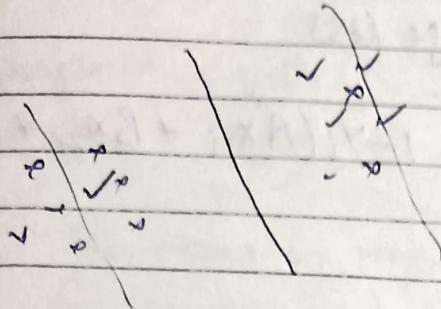
→ All the above we have seen is training.
 we need margin for training and at time of prediction we only need model.

for prediction: $Ax + Bx + C = 0$

$$(8, 30) = Ax_1 + Bx_2 + C > 0 \quad \checkmark$$

$\leq 0 \quad \times \quad (\text{NO placed})$

- Problem with hard margin sum



→ can't apply here.

• Session - 2

- in hard margin sum

$$\underset{ABC}{\text{argmax}} \quad \frac{2}{\sqrt{A^2+B^2}} \quad \text{such that} \quad \underbrace{Y_i(Ax_{1i} + Bx_{2i} + C) \geq 1}_{\text{,}}$$

due to this constraint no red pt (x) can go in region of green ~~or~~ point (\checkmark) area.
So we have to make this constraint flexible i.e softens it.

• Slack variable -

↳ It is used to handle the cases where data are not linearly separable.

It allows some degree of error in classification.

↳ for each data pt. i we calculate $\epsilon_i \geq 0$ introduced

ϵ_i measures degree of misclassification for data point x_i

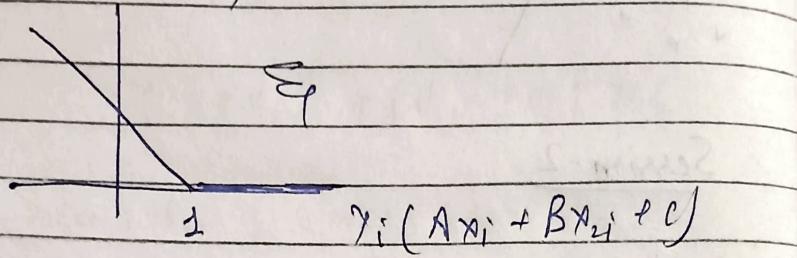
→ $\epsilon_i = 0$ x_i is on correct side of margin

→ $0 < \epsilon_i < 1$ x_i is on correct side but on wrong side of margin

→ $\epsilon_i \geq 1$ x_i is on wrong side

$\epsilon_i \rightarrow$ misclassified score
↳ also called hinge loss

$$\text{Hinge loss} = \max(0, 1 - y_i(Ax_{1i} + Bx_{2i} + c))$$



→ Soft margin Sum -

$$\underset{\text{Sum}}{\arg\min} \frac{1}{2} \underset{A, B, c}{\sqrt{A^2 + B^2}}$$

$$\underset{A, B, c}{\arg\min} \frac{\sqrt{A^2 + B^2}}{2} \text{ such that } y_i(Ax_{1i} + Bx_{2i} + c) \geq 1 - \epsilon_i$$

for all x_i such that
 $\epsilon_i > 0$

Here we have now introduced ϵ_i

→ After introducing the slack variable

There pts also starts following
the constraints

i.e. the constraint is followed
by all the pts
means it is no more a constraint

This is not good so,

we update it

$$\underset{A, B, C}{\operatorname{argmin}} \left(\frac{\sqrt{A^2 + B^2}}{2} + C \sum_{i=1}^n \xi_i \right) \text{ such that} \quad \text{Soft margin SVM}$$

This term is responsible for maximizing 'd'

it tells us total misclassification, so we want to minimize it

Due to this we will choose an optimum pt -

→ we can introduce a ^{hyper} parameter 'C'

$$\underset{A, B, C}{\operatorname{argmin}} \left(\frac{\sqrt{A^2 + B^2}}{2} + C \sum_{i=1}^n \xi_i \right) \text{ such that}$$

If 'C' is more then our focus will be more on minimizing $\sum \xi_i$

& if 'C' is less our focus will be more on minimizing $\frac{\sqrt{A^2 + B^2}}{2}$

→ Bias Variance tradeoff :-

if C value is high then overfitting (low bias high variance)

if C value is low then underfitting (high bias & low variance)