

# Derivation

let 'x' be one of the vectors in the dataset.

let 'H' be a hyperplane defined through 2 parameters 'w' and 'b'.

Then,

$H = \text{set of points which lie on hyperplane } \{w, b\}$

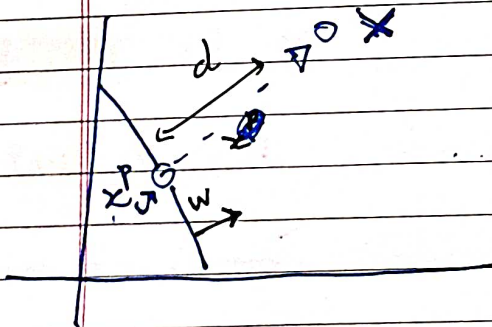
$$= \{x \mid w^T x + b = 0\}$$

Assuming binary classification right now, let margin 'γ' be the distance from hyperplane to closest point across both classes.

Calculating distance of 'x' to hyperplane 'H'

$x = \text{sample point}$

$d = \text{vector from } H \text{ to } x \text{ of minimum length.}$



$$x^p = x - d \quad \text{--- (1)}$$

Since  $d$  is parallel to  $w$  by defn,  
let  $d = \lambda w$  for some  $\lambda \in \text{Real}$ .

$$\text{Since } x_p \in H \Rightarrow w^T x^p + b = 0 \quad \text{--- (2)}$$

$|w| = \text{length of } w$

111

Date \_\_\_/\_\_\_/\_\_\_

Saathi

putting (1) in (2), we get

$$w^T(x-d) + b = w^T(x-dw) + b = 0$$

$$\Rightarrow d = \frac{w^T x + b}{w^T w} \quad \text{--- (3)}$$

Now, length of 'd' is

$$\|d\| = \sqrt{d^T d} = \sqrt{d^T w} \quad \text{using (3)}$$

$$= \frac{|w^T x + b|}{\sqrt{\|w\|^2}} = \frac{|w^T x + b|}{\|w\|}$$

(4)

By defn of margin

margin of  $H$  for a dataset  $D$

$$\gamma(w, b) = \min_{x \in D} \left( \frac{|w^T x + b|}{\|w\|} \right)$$

~~Now, by defn, margin~~

~~for  $y'$  to be~~

Also,  $y'$  must be distance  $H$  to closest point within both classes.

If not, then we could always move the hyperplane towards the data points of the class that is further away and increase  $\gamma$  which is a contradiction to fact that  $\gamma$  was maximized.



## Search for optimal hyperplane

Finding max margin separating hyperplane can be modelled as a constrained optimization problem.  
 The objective is to MAXIMIZE margin.  
 Constraint = all points must lie on correct side of hyperplane

$$y_i = \text{label} = \pm 1 \text{ or } -1$$

$$\therefore \max_{w, b} \gamma(w, b) \text{ such that } \forall i \rightarrow y_i (w^T x_i + b) \geq 0$$

As

$$\text{for } y_i = -1, w^T x_i + b \leq 0$$

$$\text{for } y_i = 1, w^T x_i + b \geq 0$$

combine



$$\max_{w, b} \frac{1}{|w|} \left[ \min_{i \in D} |w^T x_i + b| \right] \text{ such that } \quad (4)$$

$$\forall i \rightarrow y_i (w^T x_i + b) \geq 0$$

Since hyperplane is scale invariant i.e.,

$$(\text{B.2.1}) \gamma(\pm w, \pm b) = \gamma(w, b) \text{ where } t \in \mathbb{R}, t \neq 0$$

(Note direction for  $(\pm w, \pm b)$  is same as  $(w, b)$ )



Proof of 5,

We can say that if the optimal hyperplane  $(w, b)$  exists such that

$$\min_{x_i \in D} \left( \frac{|w^T x_i + b|}{\|w\|} \right) = c \quad \text{with constraints satisfied,}$$

then hyperplane  $\{ \frac{w}{c}, \frac{b}{c} \}$  where  $c > 0$  will also be optimal

$$\gamma\left(\frac{w}{c}, \frac{b}{c}\right) = \gamma(w, b)$$

and since  $y_i (w x_i + b) \geq 0$  would also mean

$$y_i \frac{(w x_i + b)}{c} \geq 0$$

(for  $c > 0$ )

$$\left\{ \begin{array}{l} \text{with} \\ \min_{x_i \in D} \left| \frac{w^T x_i + b}{c} \right| = 1 \end{array} \right.$$

(6)

Due to (6), without loss of generality, let

$$\min_{x_i \in D} (w^T x_i + b) = 1$$

margin now is

$$\gamma(w, b) = \frac{\min_{x_i \in D} |w^T x_i + b|}{\|w\|} = \frac{1}{\|w\|}$$

$\Rightarrow$  we need to ~~minimize~~ <sup>maximize</sup>  $\frac{1}{\|w\|}$  while satisfying constraints

$\Rightarrow$  ~~minimize~~ <sup>minimize</sup>  $\|w\|^2$  while satisfy constraints



Problem reformulated as

Find  $(w, b)$  such that

minimize  $w^T w$  Such that  $\left\{ \begin{array}{l} \forall i, (w^T x_i + b) y_i \geq 0 \\ \text{AND} \\ \min(|w^T x_i + b|) = 1 \end{array} \right.$

Now,

$\left\{ \begin{array}{l} \forall i, (w^T x_i + b) y_i \geq 0 \\ \text{AND} \\ \min(|w^T x_i + b|) = 1 \end{array} \right.$  is same as  $\left\{ \begin{array}{l} \forall i, y_i (w^T x_i + b) \geq 1 \end{array} \right.$

Final formulation

minimize  $w^T w \rightarrow \text{quadratic}$

such that  $y_i (w^T x_i + b) \geq 1 \quad \forall i$

constraint  $\rightarrow$  linear in nature

$\therefore$  objective = quadratic  
 $\therefore$  constraint = linear

$\Rightarrow$  can be solved using QPQP.

Also  $y_i (w^T x_i + b) = 1$  would hold for atleast one vector of each class. (called support vector).

211  
Date \_\_\_\_/\_\_\_\_/\_\_\_\_

HS

Saathi

∴ Problem now reduced to

Find the simplest hyperplane (ie, one with minimum  $w^T w$ )

such that all input samples lie at least 1 unit away from hyperplane on correct side.

Hence, proved.