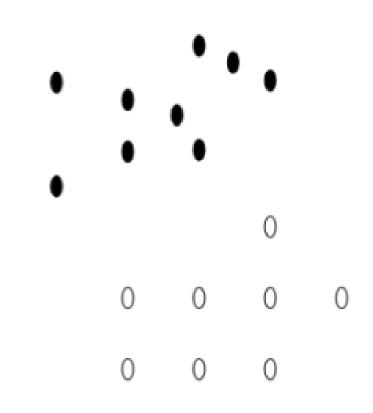
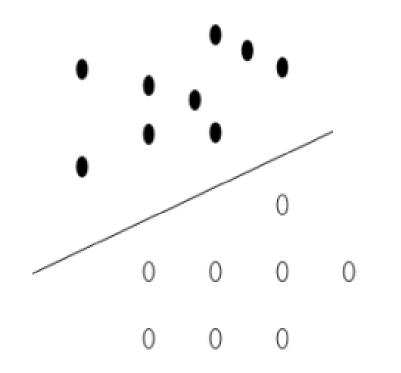


Support vector machine (SVM)

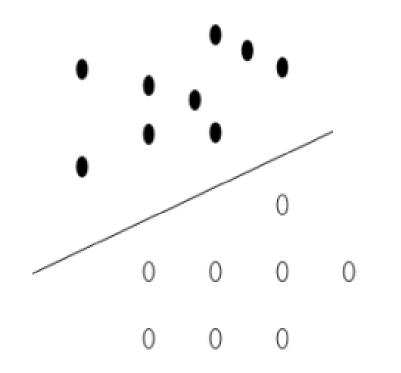
Support vector machine



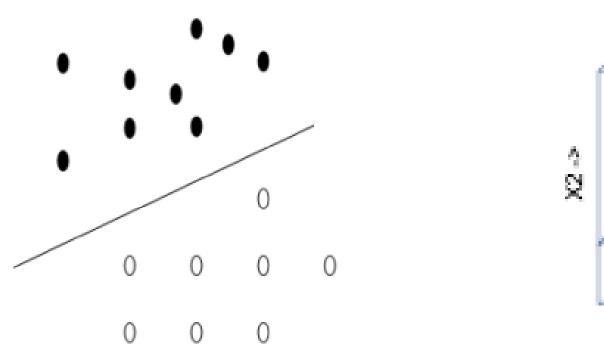
Support vector machine

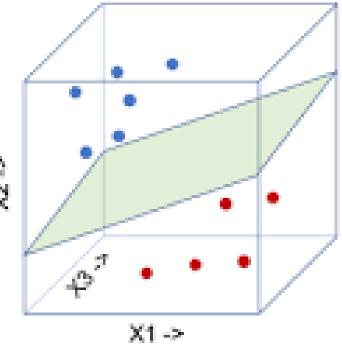


Support vector machine

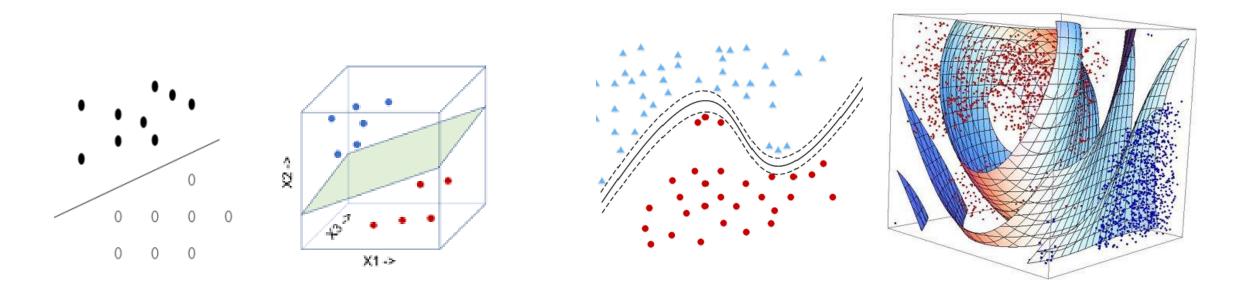


Support vector machine





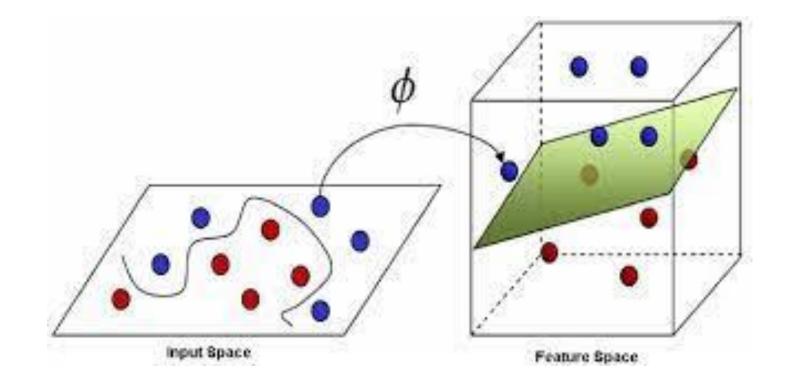
Support vector machine – Linear or Non-linear

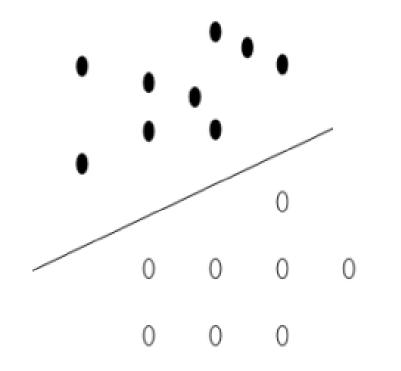


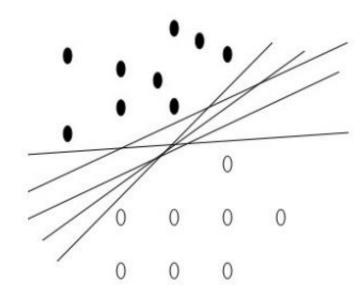
Linear SVM

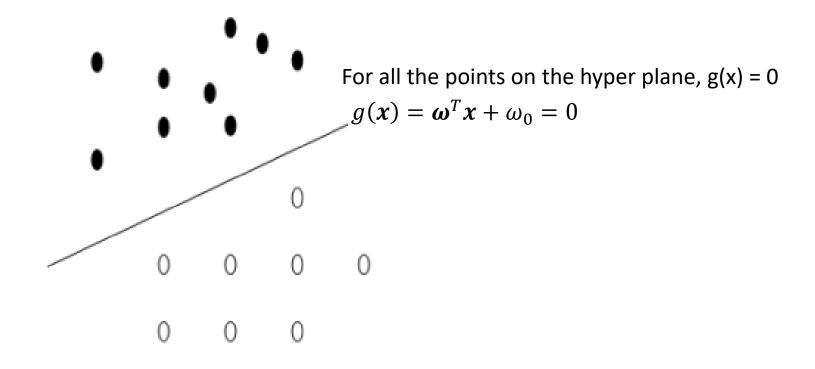
Non-Linear SVM

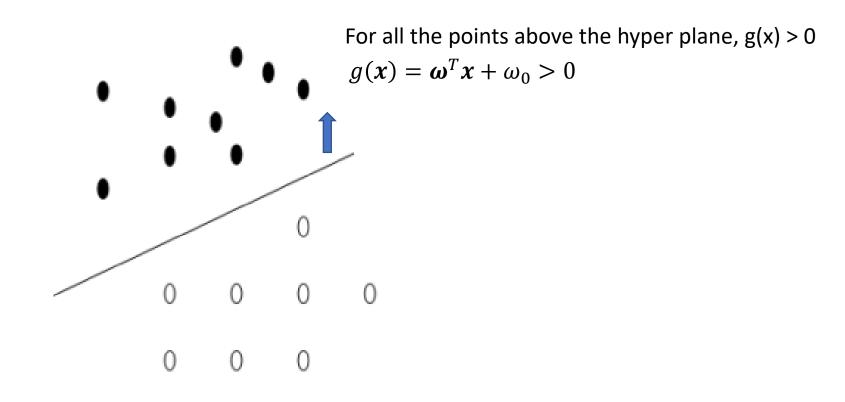
Non-Linear to Linear

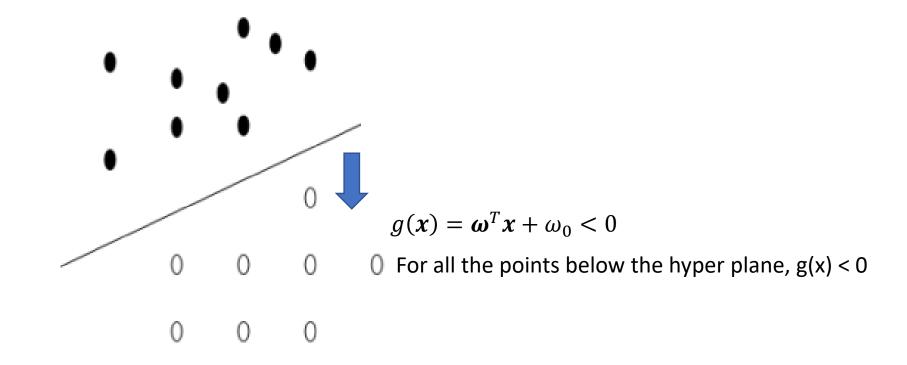


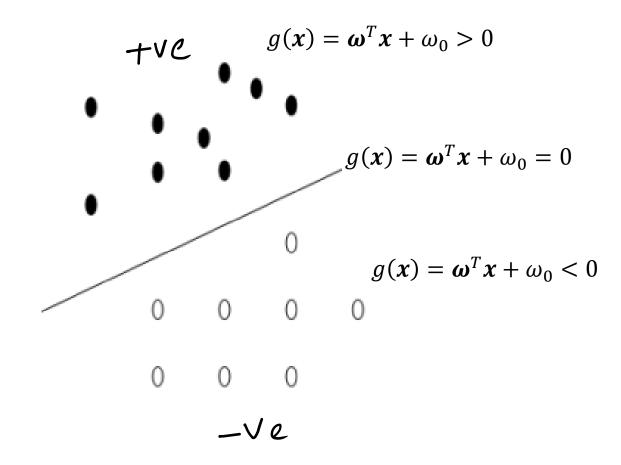






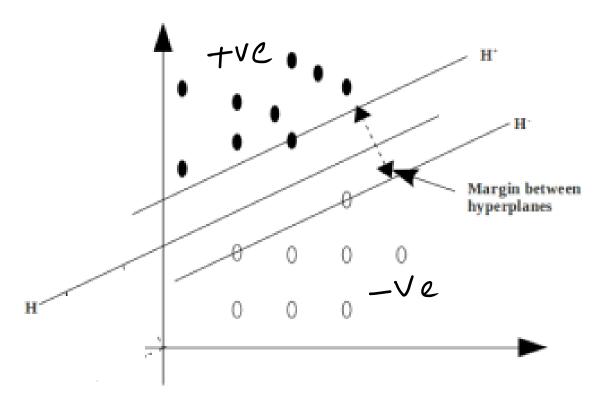






We choose the hyperplane that has the maximum separating margin

What is Separating Margin?

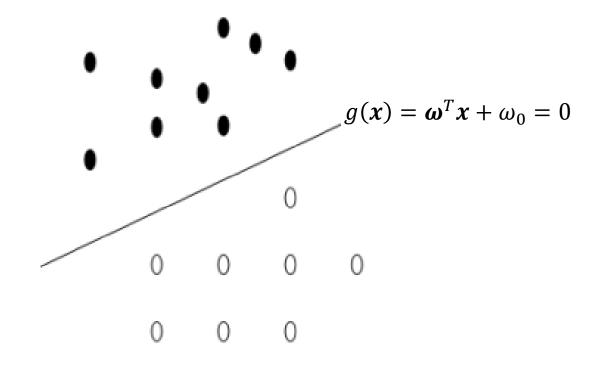


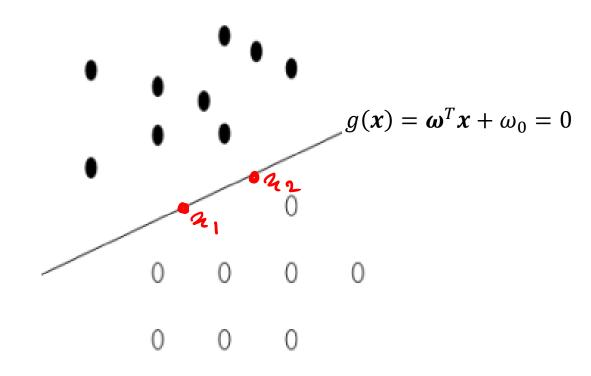
H is the separating hyperplane

H⁺ is the plane parallel to H and passing through the nearest +ve points to H

H⁻ is the plane parallel to H and passing through the nearest -ve points to H

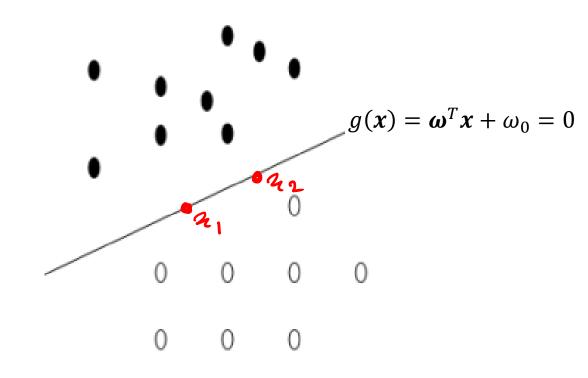
Separating margin is the distance between H⁺ and H⁻ We choose H that has the maximum margin.





Let us take two points x_1 and x_2 lying on g(x)

$$g(x_1) = g(x_2) = 0$$

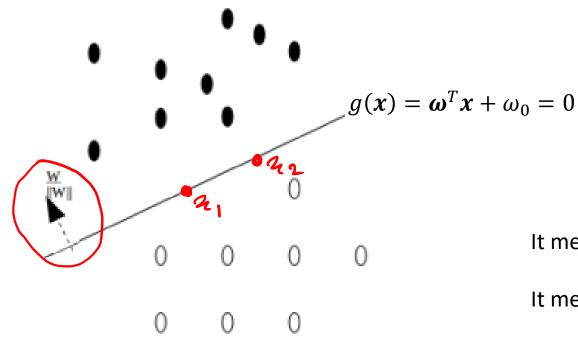


Let us take two points x_1 and x_2 lying on g(x)

$$g(x_1) = g(x_2) = 0$$

$$\Rightarrow \boldsymbol{\omega}^T \boldsymbol{x}_1 + \boldsymbol{\omega}_0 = \boldsymbol{\omega}^T \boldsymbol{x}_1 + \boldsymbol{\omega}_0$$

$$\Rightarrow \boldsymbol{\omega}^T (\boldsymbol{x}_1 - \boldsymbol{x}_1) = 0$$



Let us take two points x_1 and x_2 lying on g(x)

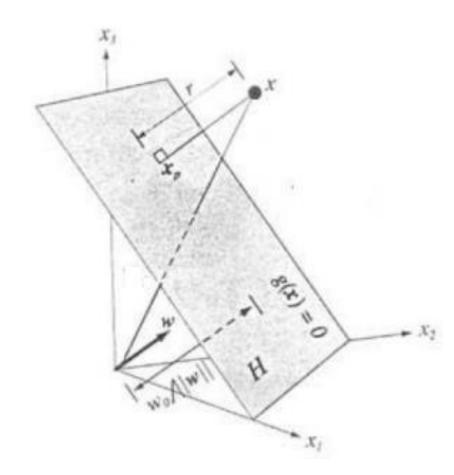
$$g(x_1) = g(x_2) = 0$$

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It means $\boldsymbol{\omega}$ is orthogonal (90°/perpendicular) the vector $(\boldsymbol{x_1} - \boldsymbol{x_2})$.

It means $\boldsymbol{\omega}$ is orthogonal (90°/perpendicular) to $\boldsymbol{g(x)}$.

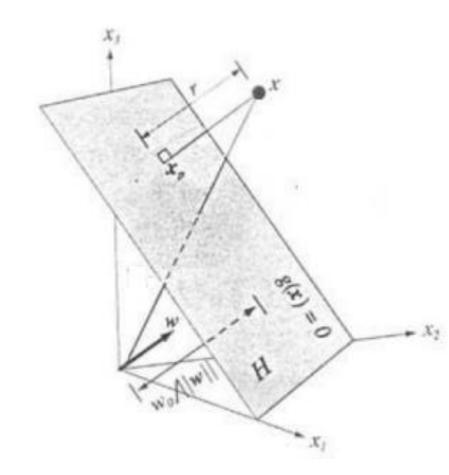


Let x be a point in space.

Let r be the distance of the point x from the hyperplane g(x), and x_p be the corresponding projection point of x on g(x).

Now, vector x can be defined by the sum of the vector x_p and vector r.

$$x = x_p + r$$
$$\Rightarrow x = x_p + r \frac{\omega}{\|\omega\|}$$



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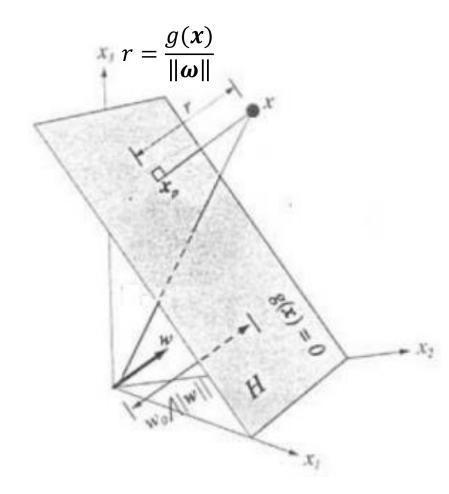
Now, vector x can be defined by the sum of the vector x_p and vector r.

$$x = x_p + r$$
$$\Rightarrow x = x_p + r \frac{\omega}{\|\omega\|}$$

If you substitute x in g(x).

$$\Rightarrow \boldsymbol{g}(\boldsymbol{x}) = \boldsymbol{\omega}^T \boldsymbol{x}_p + r \frac{\boldsymbol{\omega}^T \boldsymbol{\omega}}{\|\boldsymbol{\omega}\|} + \boldsymbol{\omega}_0$$

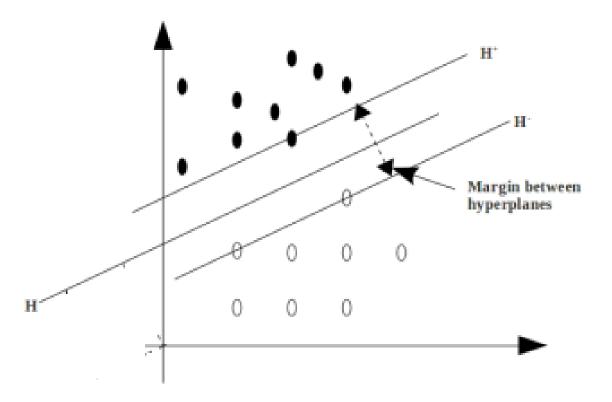
$$\Rightarrow g(x) = \omega^T x_p + \omega_0 + r \frac{\omega^T \omega}{\|\omega\|} \Rightarrow g(x) = r \frac{\omega^T \omega}{\|\omega\|} \Rightarrow r = \frac{g(x)}{\|\omega\|}$$



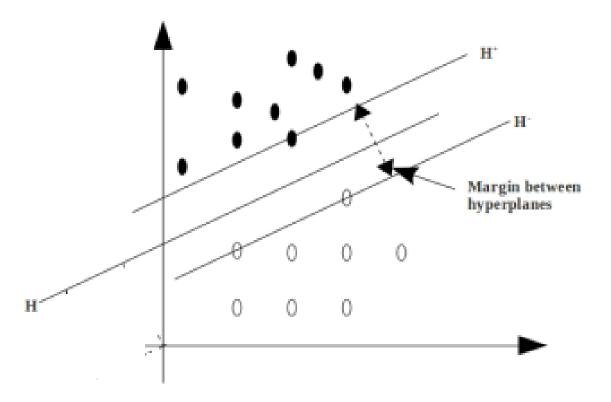
Distance of
$$x_p$$
 from g(x)=0 is $r = \frac{g(x)}{\|\omega\|}$

So, the distance of origin from g(x)=0 is

$$\Rightarrow r_{\mathbf{0}} = \frac{\boldsymbol{\omega}^{T} \mathbf{0} + \boldsymbol{\omega}_{0}}{\|\boldsymbol{\omega}\|}$$
$$\Rightarrow r_{\mathbf{0}} = \frac{\boldsymbol{\omega}_{0}}{\|\boldsymbol{\omega}\|}$$



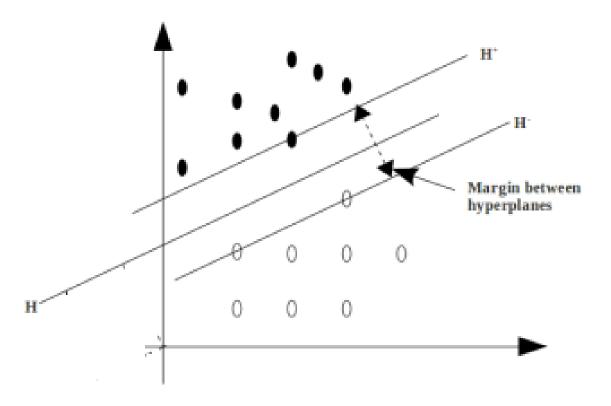
What is the Margin between H+ and H-?



To define the expression for H+ and H-, let us make the following assumptions.

Given a datapoint $\langle x_i, y_i \rangle$ where $y_i \in \{+ve, -ve\}$ is the class label of x_i ,

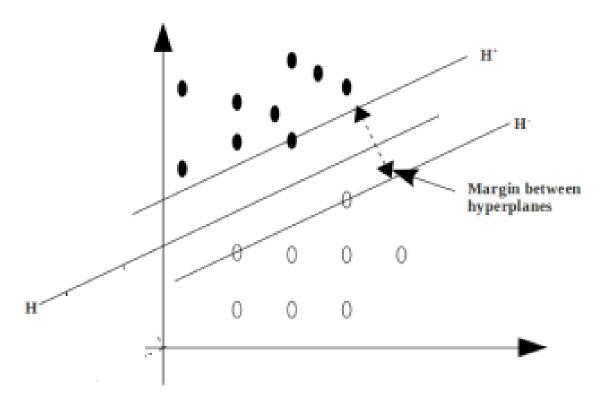
• let us replace -ve by +1, and -ve by -1.



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Given a datapoint $\langle x_i, y_i \rangle$ where $y_i \in \{+ve, -ve\}$ is the class label of x_i ,

- Let us replace –ve by +1, and –ve by -1.
- Now, each data point will satisfy the following $\boldsymbol{\omega}^T \boldsymbol{x_i} + \boldsymbol{\omega_0} \ge 1, \forall y_i = +1$ $\boldsymbol{\omega}^T \boldsymbol{x_i} + \boldsymbol{\omega_0} \le -1, \forall y_i = -1$



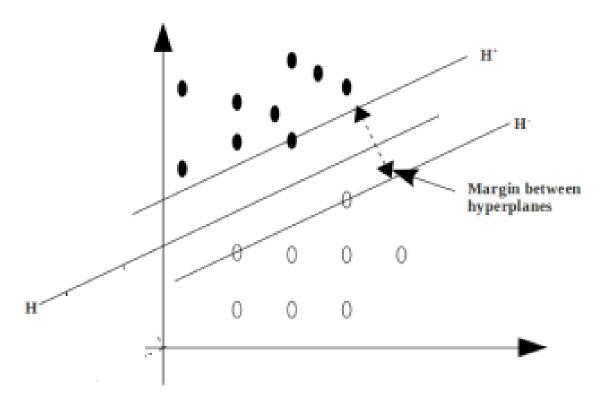
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- let us replace -ve by +1, and -ve by -1.
- Now, each data point will satisfy the following $\boldsymbol{\omega}^T \boldsymbol{x_i} + \boldsymbol{\omega_0} \ge 1, \forall \boldsymbol{y_i} = +1$ $\boldsymbol{\omega}^T \boldsymbol{x_i} + \boldsymbol{\omega_0} \le -1, \forall \boldsymbol{y_i} = -1$

The above two expression can be merged to form a single expression

$$y_i(\boldsymbol{\omega}^T \boldsymbol{x_i} + \omega_0) \ge 1, \forall \boldsymbol{x_i}$$



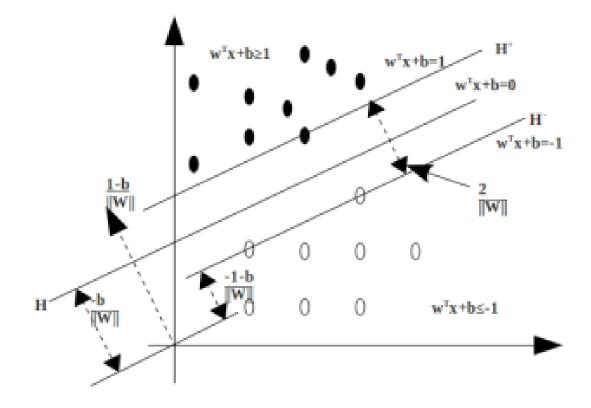
To define the expression for H+ and H-, let us make the following assumptions.

Given a datapoint < x_i , y_i > where $y_i \in \{+ve, -ve\}$ is the class label of x_i ,

- let us replace -ve by +1, and -ve by -1.
- Now, each data point will satisfy the following $\boldsymbol{\omega}^T \boldsymbol{x_i} + \boldsymbol{\omega_0} \ge 1, \forall \boldsymbol{y_i} = +1$ $\boldsymbol{\omega}^T \boldsymbol{x_i} + \boldsymbol{\omega_0} \le -1, \forall \boldsymbol{y_i} = -1$

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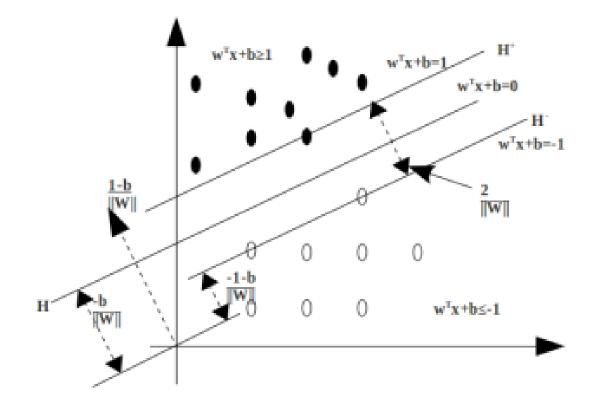
$$y_i(\boldsymbol{\omega}^T \boldsymbol{x}_i + \omega_0) \ge 1, \forall \boldsymbol{x}_i$$
$$y_i(\boldsymbol{\omega}^T \boldsymbol{x}_i + \omega_0) - 1 \ge 0, \forall \boldsymbol{x}_i$$



H: $\boldsymbol{g}(\boldsymbol{x}) = \boldsymbol{\omega}^T \boldsymbol{x} + \omega_{\mathbf{0}} = \mathbf{0}$

H+:
$$\boldsymbol{g}(\boldsymbol{x}) = \boldsymbol{\omega}^T \boldsymbol{x} + \omega_{\boldsymbol{0}} = 1$$

H-:
$$g(x) = \omega^T x + \omega_0 = -1$$

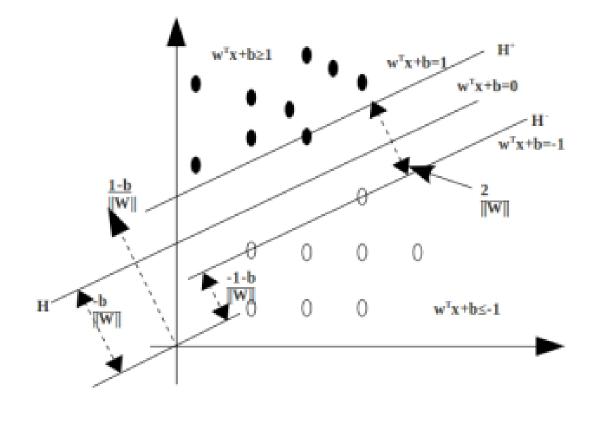


H: $\boldsymbol{g}(\boldsymbol{x}) = \boldsymbol{\omega}^T \boldsymbol{x} + \omega_{\mathbf{0}} = \mathbf{0}$

$$H_{+:} \boldsymbol{g}(\boldsymbol{x}) = \boldsymbol{\omega}^T \boldsymbol{x} + \boldsymbol{\omega}_{\mathbf{0}} = 1$$

H-:
$$g(x) = \omega^T x + \omega_0 = -1$$

 $Margin = r_{H^{+}} - r_{H^{-}}$ $= \frac{\omega_0 - 1}{\|\boldsymbol{\omega}\|} - \frac{\omega_0 + 1}{\|\boldsymbol{\omega}\|}$ $= \frac{\omega_0 - 1 - \omega_0 - 1}{\|\boldsymbol{\omega}\|}$ $\Rightarrow Margin = \frac{-2}{\|\boldsymbol{\omega}\|}$



H: $\boldsymbol{g}(\boldsymbol{x}) = \boldsymbol{\omega}^T \boldsymbol{x} + \omega_{\mathbf{0}} = \mathbf{0}$

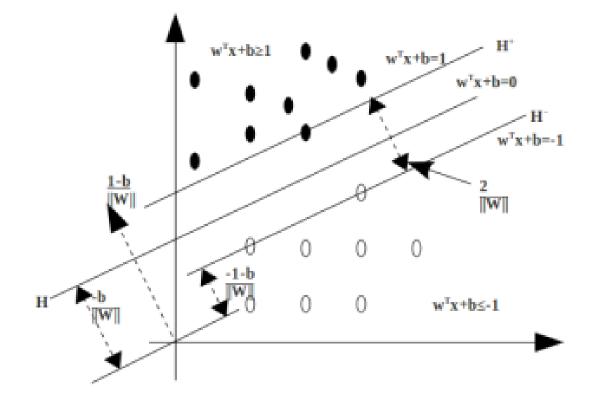
H+:
$$\boldsymbol{g}(\boldsymbol{x}) = \boldsymbol{\omega}^T \boldsymbol{x} + \omega_{\boldsymbol{0}} = 1$$

H-:
$$g(x) = \omega^T x + \omega_0 = -1$$

 $Margin = r_{H^+} - r_{H^-}$

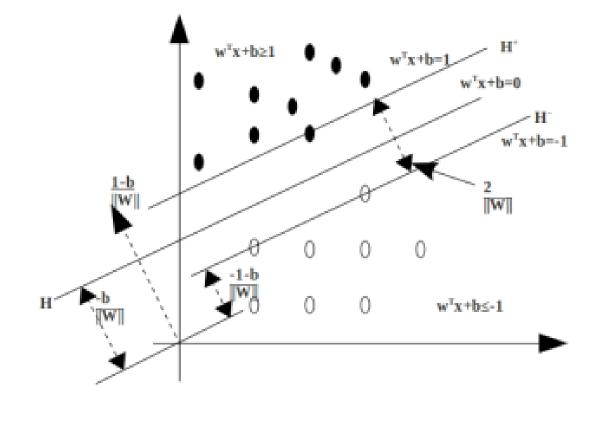
$$= \frac{\omega_0 - 1}{\|\boldsymbol{\omega}\|} - \frac{\omega_0 + 1}{\|\boldsymbol{\omega}\|}$$
$$= \frac{\omega_0 - 1 - \omega_0 - 1}{\|\boldsymbol{\omega}\|}$$
$$\Rightarrow Margin = \frac{-2}{\|\boldsymbol{\omega}\|}$$

As we are interested in the absolute value, we consider the margin as $\frac{2}{\|\omega\|}$



Task is to find the hyperplane (g(x)=0) that maximizes the margin $\frac{2}{\|\omega\|}$

$$Margin = \frac{2}{\|\boldsymbol{\omega}\|}$$
$$\Rightarrow Margin = \frac{1}{\frac{\|\boldsymbol{\omega}\|}{2}}$$



Task is to find the hyperplane (g(x)=0) that maximizes the margin $\frac{2}{\|\omega\|}$

$$Margin = \frac{2}{\|\boldsymbol{\omega}\|}$$
$$\Rightarrow Margin = \frac{1}{\frac{\|\boldsymbol{\omega}\|}{2}}$$

Maximizing $\frac{2}{\|\omega\|}$ is equivalent to minimizing $\frac{\|\omega\|}{2}$

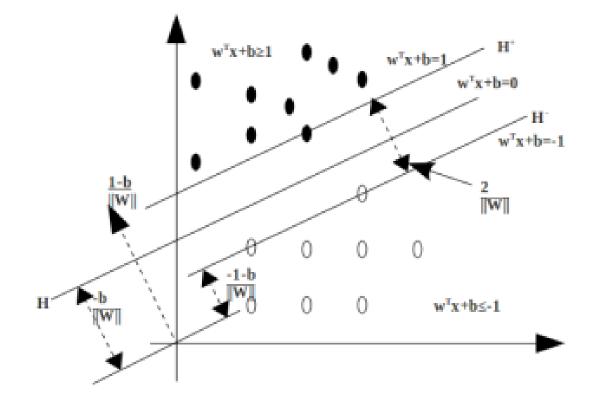
Minimizing $\frac{\|\omega\|}{2}$ is equivalent to minimizing $\frac{\omega^T \omega}{2}$

w^xx+b≥i w^Tx+b=1 $w^{T}x+b=0$ ·H $w^T x + b = -1$ <u>1-b</u> JW| W 0 0 0 0 $w^T x + b \le -1$

Now, we need to solve the following optimization

Minimize objective function $\frac{\omega^T \omega}{2}$

Subject to the constraint $y_i(\boldsymbol{\omega}^T \boldsymbol{x_i} + \boldsymbol{\omega_0}) \ge 1, \forall \boldsymbol{x_i}$



Objective function is to minimize $\frac{\omega^T \omega}{2}$

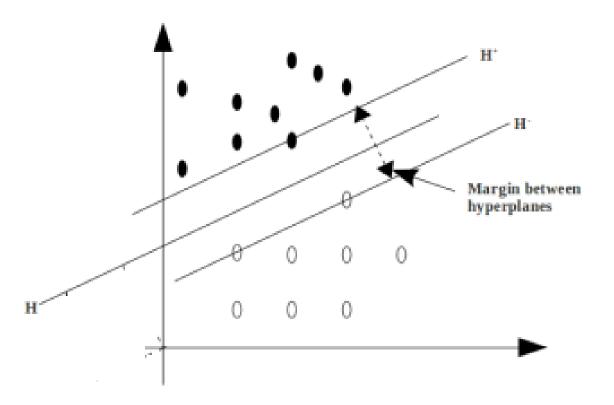
Subject to $y_i(\boldsymbol{\omega}^T \boldsymbol{x_i} + \boldsymbol{\omega_0}) \ge 1, \forall \boldsymbol{x_i}$

To find the parameters $\boldsymbol{\omega}$ and where $\boldsymbol{\omega}_0$, solve the following optimization function

$$L_p = \frac{\boldsymbol{\omega}^T \boldsymbol{\omega}}{2} - \sum_{i=1}^n \lambda_i (y_i (\boldsymbol{\omega}^T \boldsymbol{x}_i + \boldsymbol{\omega}_0) - 1)$$

where λ_i are Lagrange multipliers

What are the support vectors?



$$L_p = \frac{\boldsymbol{\omega}^T \boldsymbol{\omega}}{2} - \sum_{i=1}^n \lambda_i (y_i (\boldsymbol{\omega}^T \boldsymbol{x}_i + \boldsymbol{\omega}_0) - 1)$$

In order to find the parameters, we need to solve this objective function.

Summary

- What is separating hyperplane?
- How to define separating hyperplane?
- What are Support Vector Machine?
- How to classify a new example using SVM