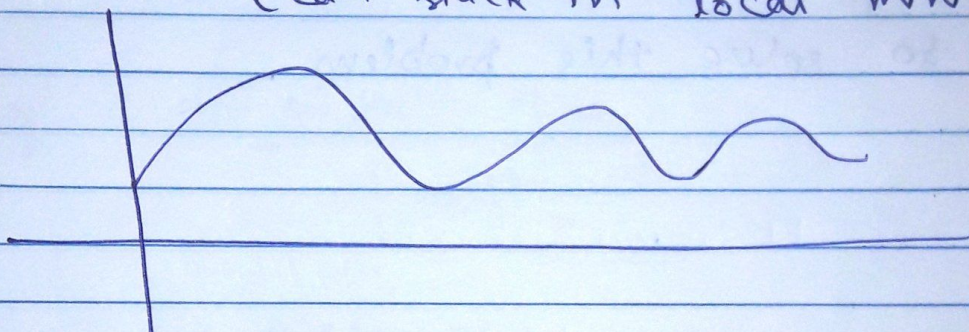


③ SVM - Objective as Constrained Convex Optimization :

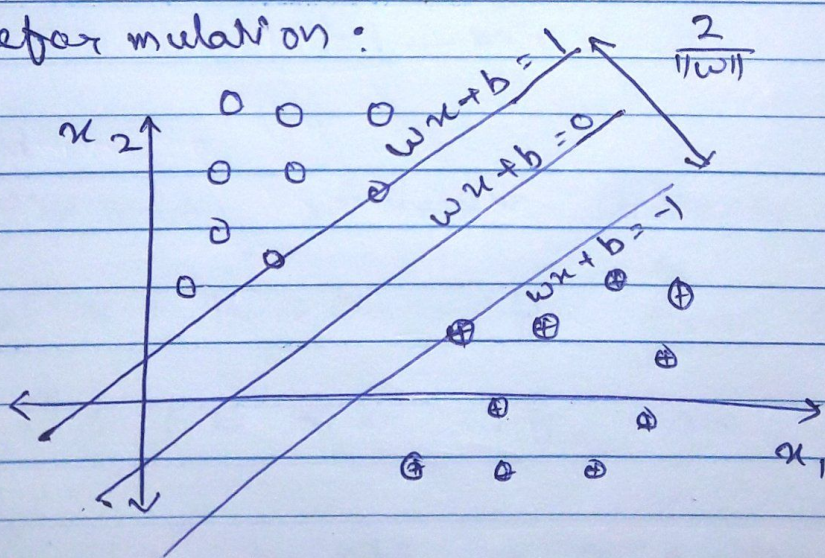
$$\gamma = \min_{i=1 \dots m} \frac{w^T x^{(i)} + b}{\|w\|}$$

The function is Nonconvex.
(Can stuck in local minima)



Reform our problem :

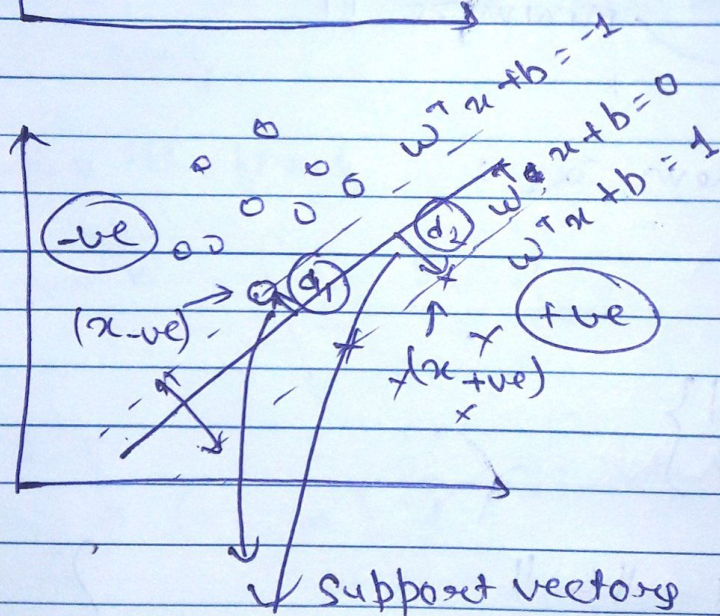
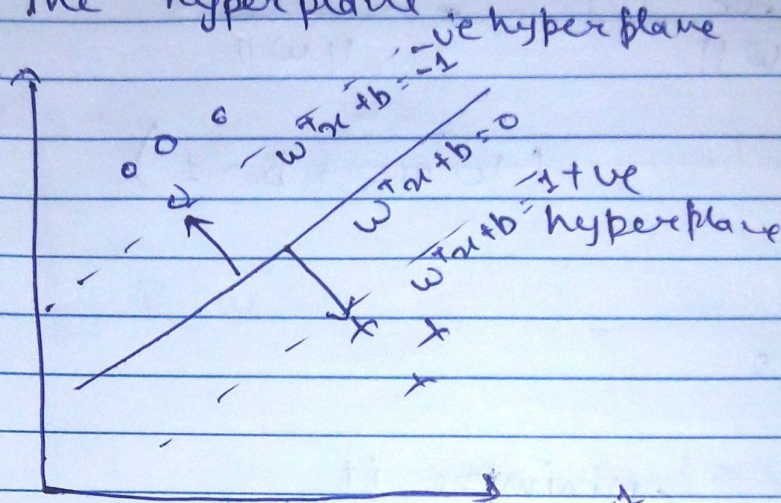
Reformulation :



$$\left. \begin{aligned} w^T x + b &= 1 \\ w^T x + b &= -1 \end{aligned} \right\} \text{Hyperplanes}$$

Support vector : (Nearest points)

- we renormalize our dataset such that support vectors should always lie on the hyperplane



Equidistant support vectors.

Goal:

Maximize d such that

$$y_i (w^T x_i + b) \geq \gamma$$

$$d_1 = \frac{|w^T x_p + b|}{\|w\|} \quad \text{positive} = \frac{1}{\|w\|}$$

$$d_2 = \frac{|w^T x_{-ve} + b|}{\|w\|} = \frac{1}{\|w\|}$$

$$(w^T x_p + b = 1)$$

↙ Maximize

$$d = d_1 + d_2$$

$$d = \frac{2}{\|w\|}$$

↘ Minimize it

Rewrite our problem as:

SVM Objective:

$$\text{minimize } \left\{ \frac{\|w\|}{2} \right\}$$

$$= \min \left\{ \begin{array}{l} \frac{1}{2} \|w\| \\ y_i \left(\frac{w^T x^{(i)} + b}{\|w\|} \right) \geq \frac{1}{\|w\|} \end{array} \right\}$$

SVM Objective 2:

Final objective:

$$\text{minimize } \frac{\|w\|}{2} \quad (\text{L2 norm of } w)$$

such that

Such that

$$\forall_i \in (1 \dots m)$$

$$\{y_i (\omega^T x^{(i)} + b) \geq 1\}$$

Now

$$\begin{bmatrix} \|\omega\|_2^2 & = & \omega^T \omega \\ \nabla_{\omega} \omega^T \omega & = & \omega \end{bmatrix}$$

\therefore for making derivative calculation easy

we will find

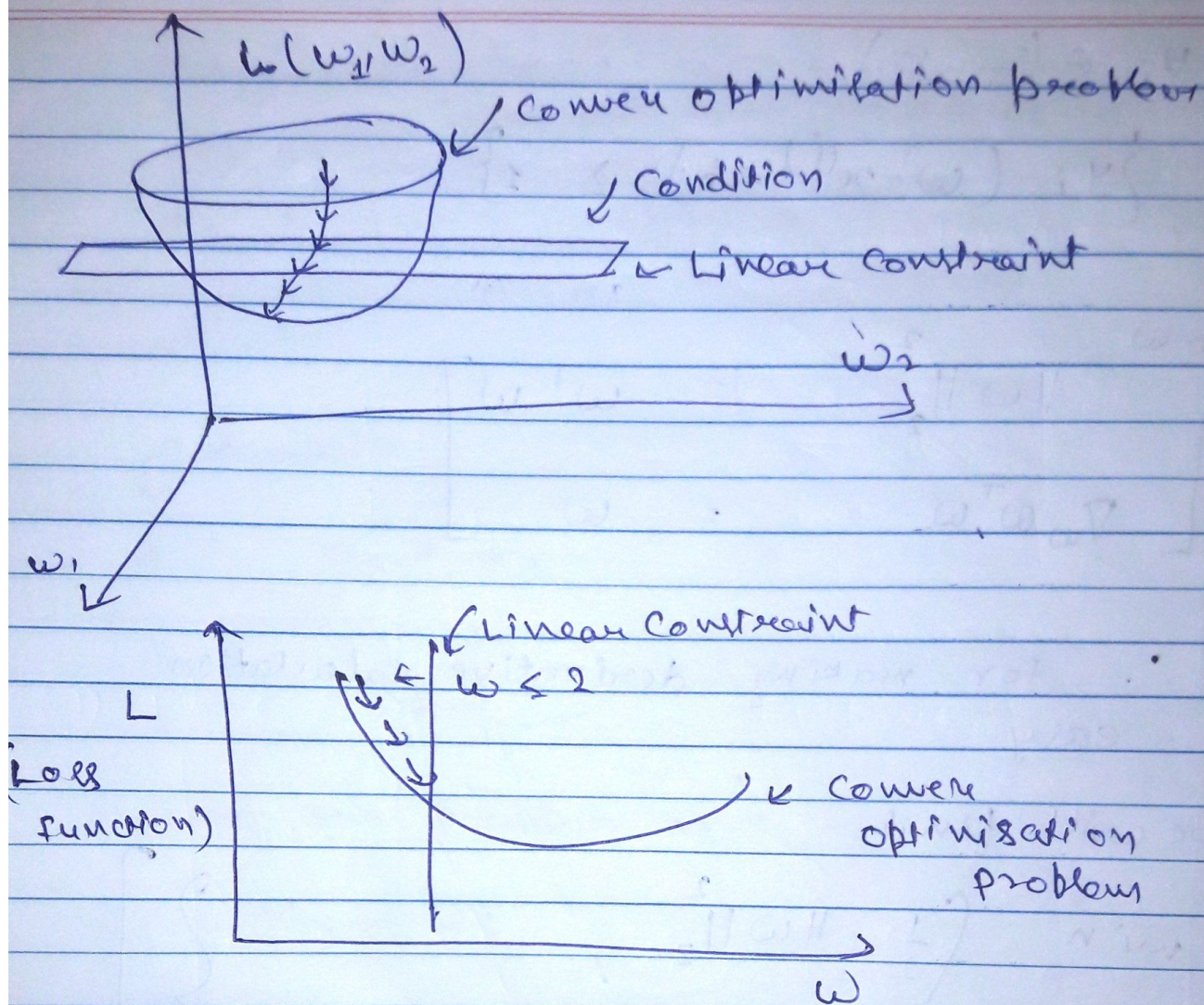
$$\left[\begin{array}{l} \min \left(\frac{1}{2} \|\omega\|_2^2 \right) \\ \text{s.t.} \\ \forall_i \in (1 \dots m) \end{array} \right\} \left\{ y_i (\omega^T x^{(i)} + b) \geq 1 \right\}$$

Final SVM Objective (convex optimisation problem)

This is convex with linear constraint,
can be solved using:

(a) Quadratic solver

(b) Lagrangian duality



Reference :

CS 229 : Andrew NG

Machine Learning

We will solve it using a modern approach

- Proxos
and also
one method

- Convex Optimisation without
constraint

or unconstrained convex optimisation
problem (then gradient descent)