Data Science and Artificial Intelligence

Machine Learning

Support Vector Machine

Lecture No. 2

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Recap of Previous Lecture

Topic — Generative & Discriminative

Topic — Naive Bayes Advantage & Disadvantage

Topic — Svm

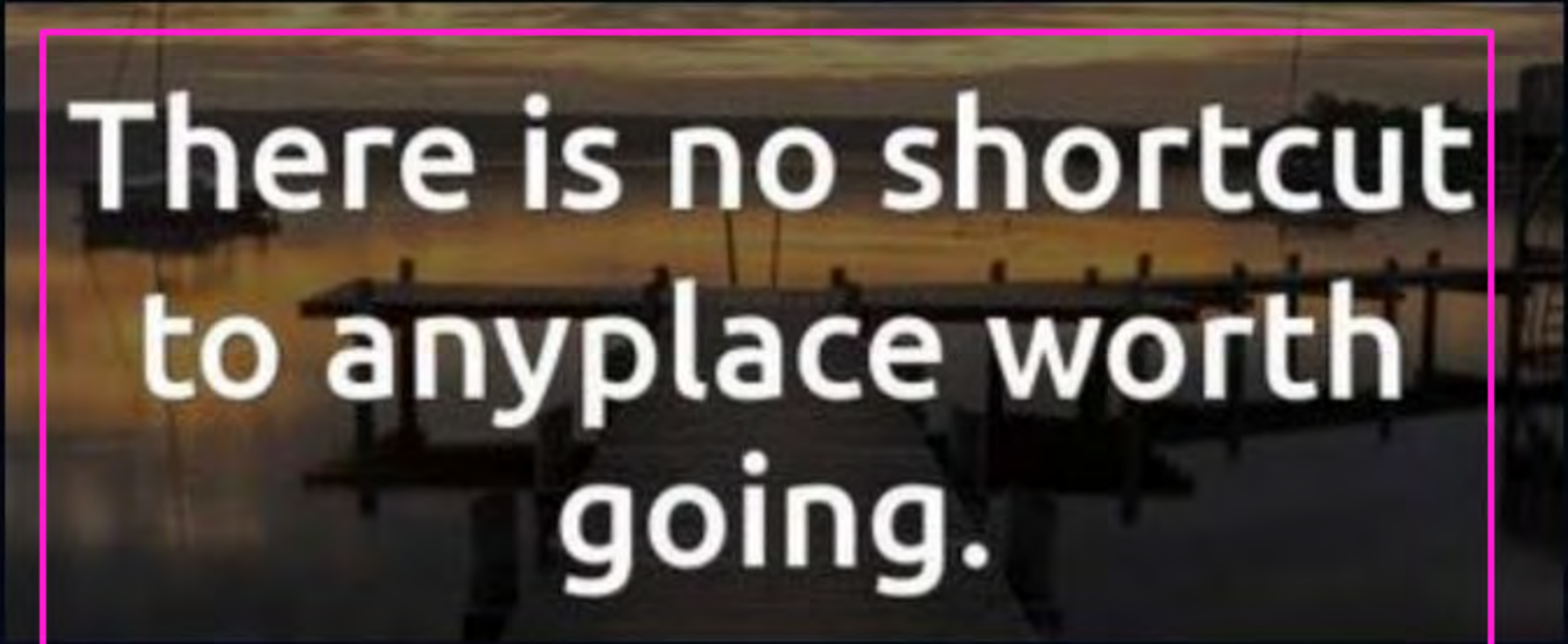
Topic

Topic

Turn on Slide map

Topics to be Covered

- Topic — Svm
- Topic
- Topic
- Topic
- Topic

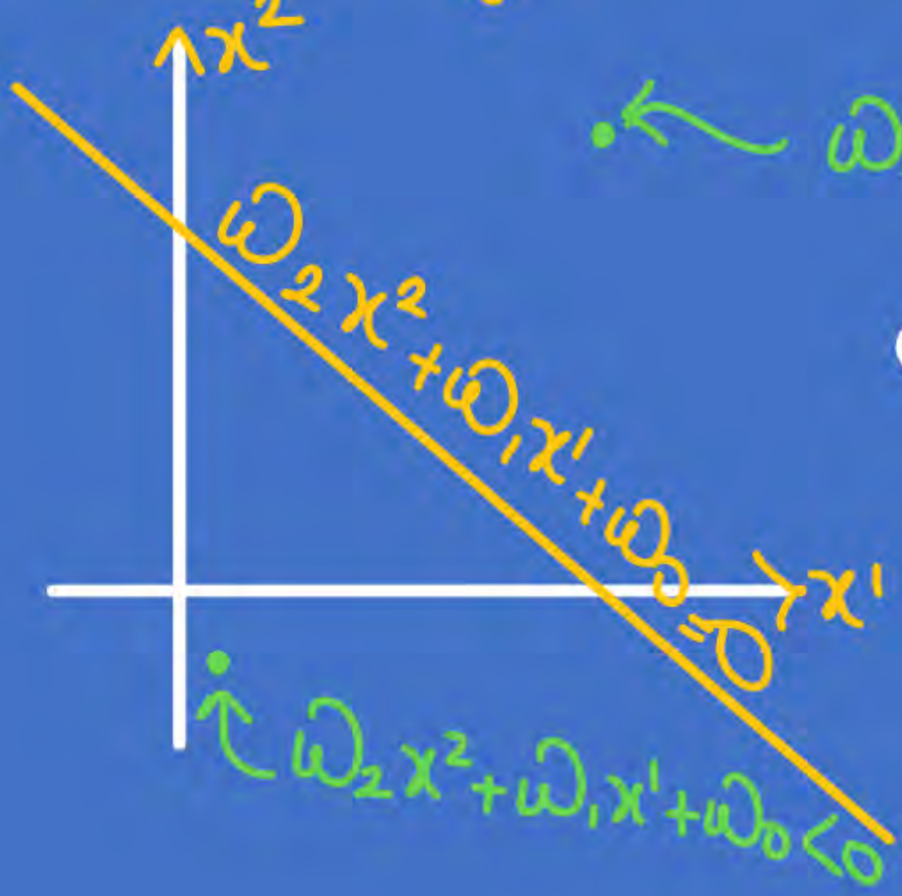

There is no shortcut
to anyplace worth
going.

Naïve Bayes $\Rrightarrow$ done

REVISION

SVMs $\Rightarrow$

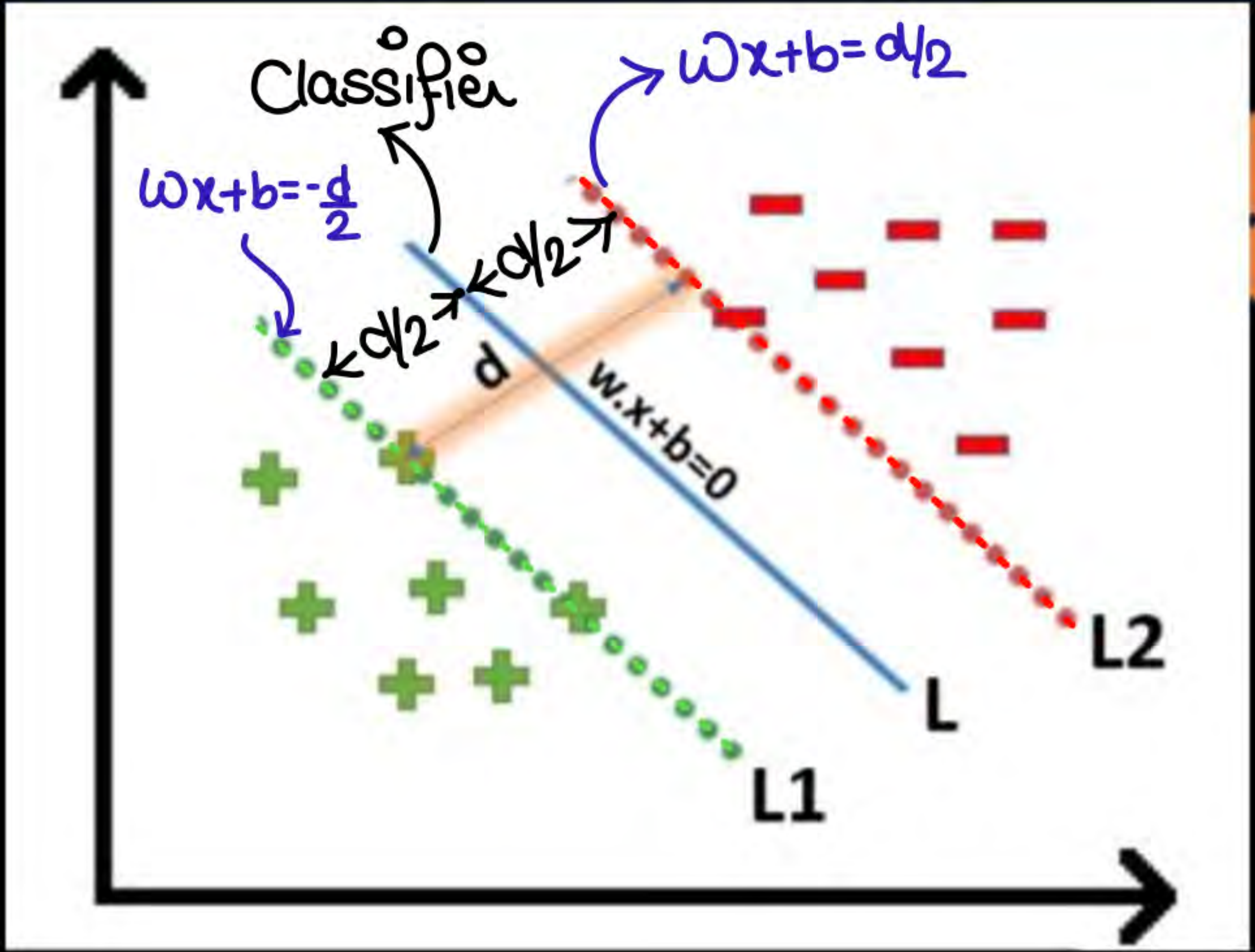
- The algorithm that try to give best classifier



distance of a point from a line

$$\Rightarrow \left\{ \frac{\omega_2 x^2 + \omega_1 x^1 + \omega_0}{\sqrt{\omega_2^2 + \omega_1^2}} \right\}$$

Support Vector Machine

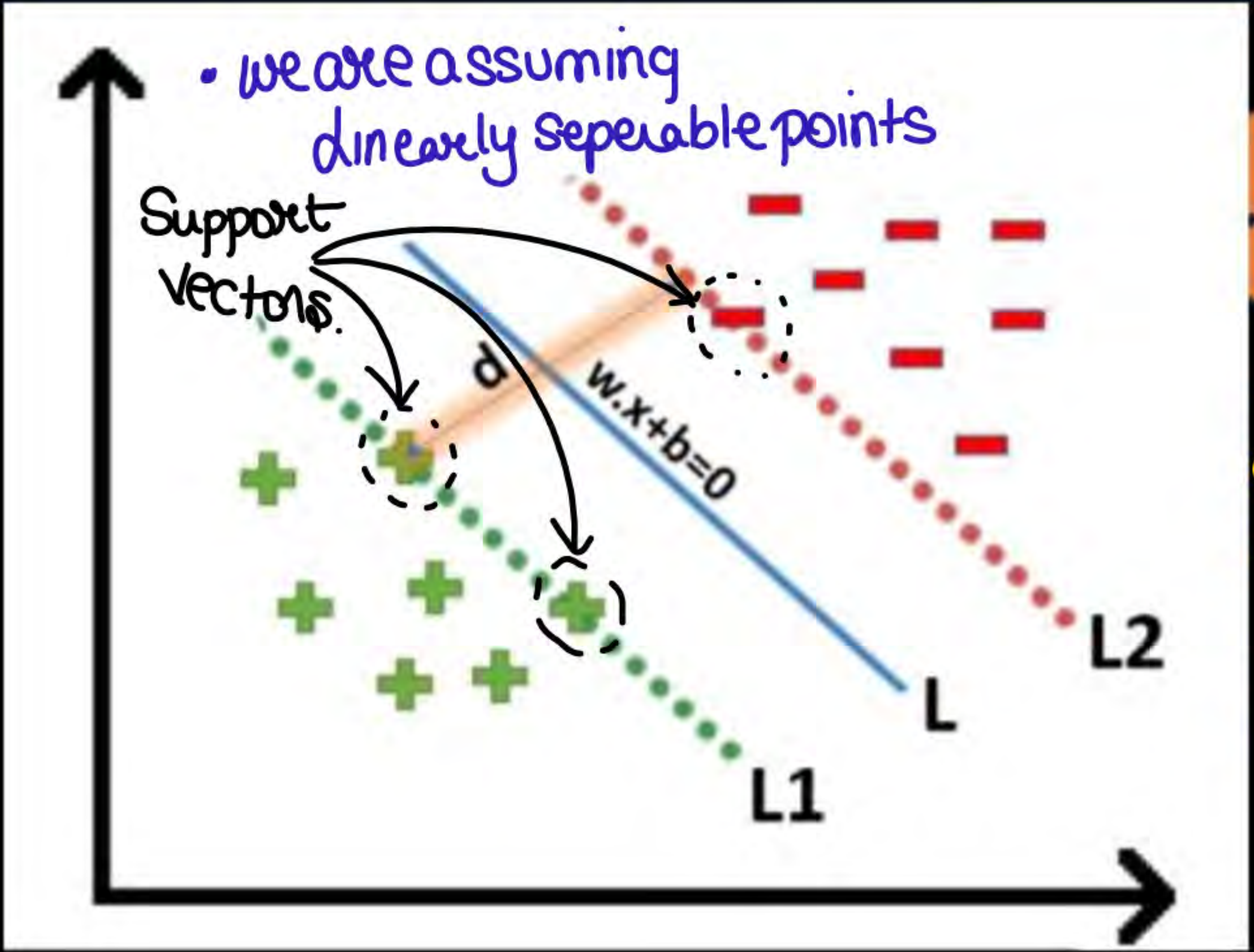


So in SVM we want the classifier which has max separation from both the classes..

$\Rightarrow$ we want that classifier must have equal distance from both classes

SVMs

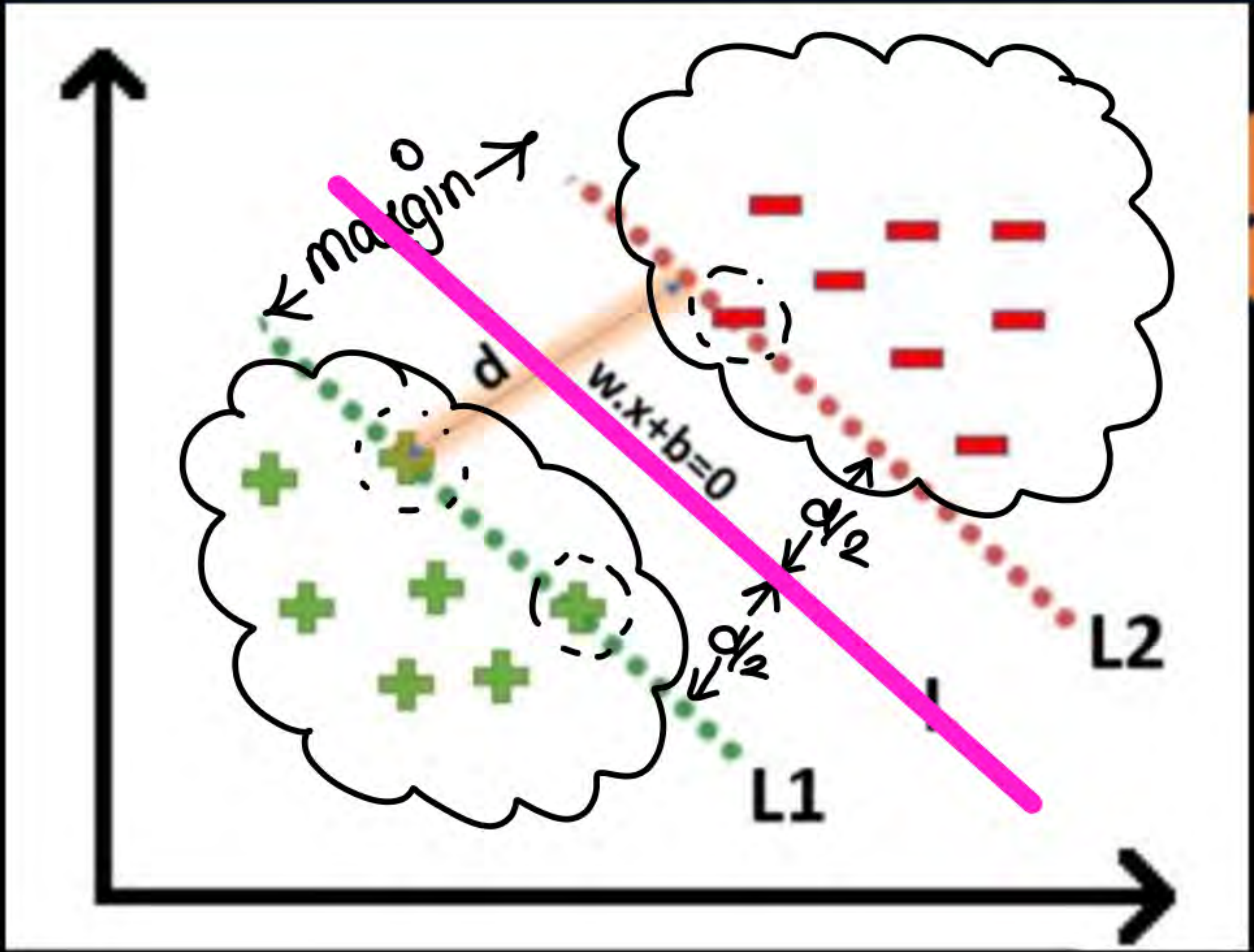
Support Vector Machine



The points above the line have .....
And below the line have ....

⇒ So here we can see that the Classifier eq depend mainly on the Support Vectors only.

Support Vector Machine



The equation of Line L, L1 and L2 will be ….

done

Support Vector Machine

So the algorithm ⇒

* The best classifier is that which seperate the class 1 and Class 2 Such that the gap b/w them ⇔ margin is maximized

The equation of Line L, L1 and L2 will be ....

Support Vector Machine

This becomes the min max problem…

So our task it to maximise the margin …

So the classifier is $(\omega x+b)$ Parameters are ω, b

So we find the distance of all points from classifier

So $d/2$ is min distance.

Support Vector Machine

This becomes the min max problem… with a constraint…

So our task it to maximise the margin …

So we want to

$\Rightarrow$ maximize $d/2$

Support Vector Machine

So algorithm is

$$\left\{ \left[\max \min (\text{distance}) \right] \right.$$

Such that $y_i(\omega x_i + b) > 0$

⇒ So if class 1 $(\omega x_i + b) > 0$ i.e point shd be above classifier

" " " -1 $(\omega x_i + b) < 0$ " " " " below classifier

this constraint ensure that classifier does no error.

For generalising this we convert the lines L1 and L2 into...

Support Vector Machine

This maxmin contraint problem will be used to solve for best w and b.

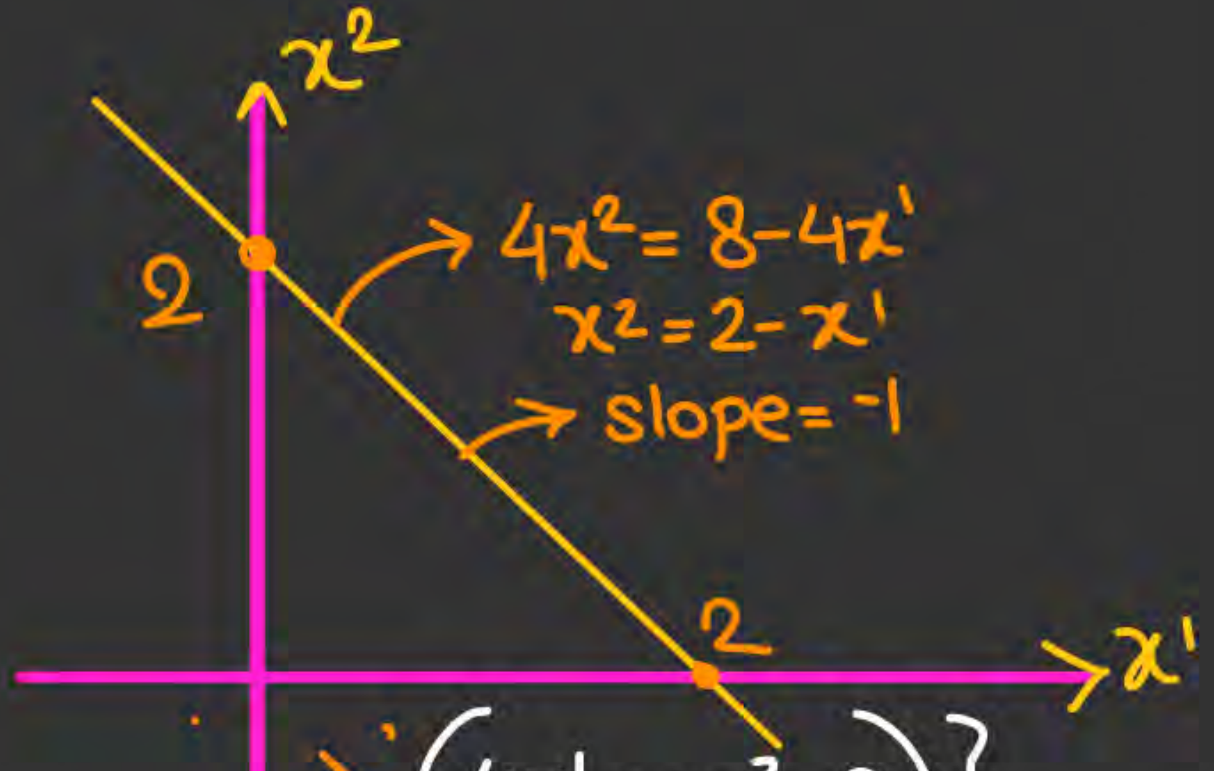
For generalising this we convert the lines L1 and L2 into…

Support Vector Machine

SVM primal equation

dets modify the algo ⇒

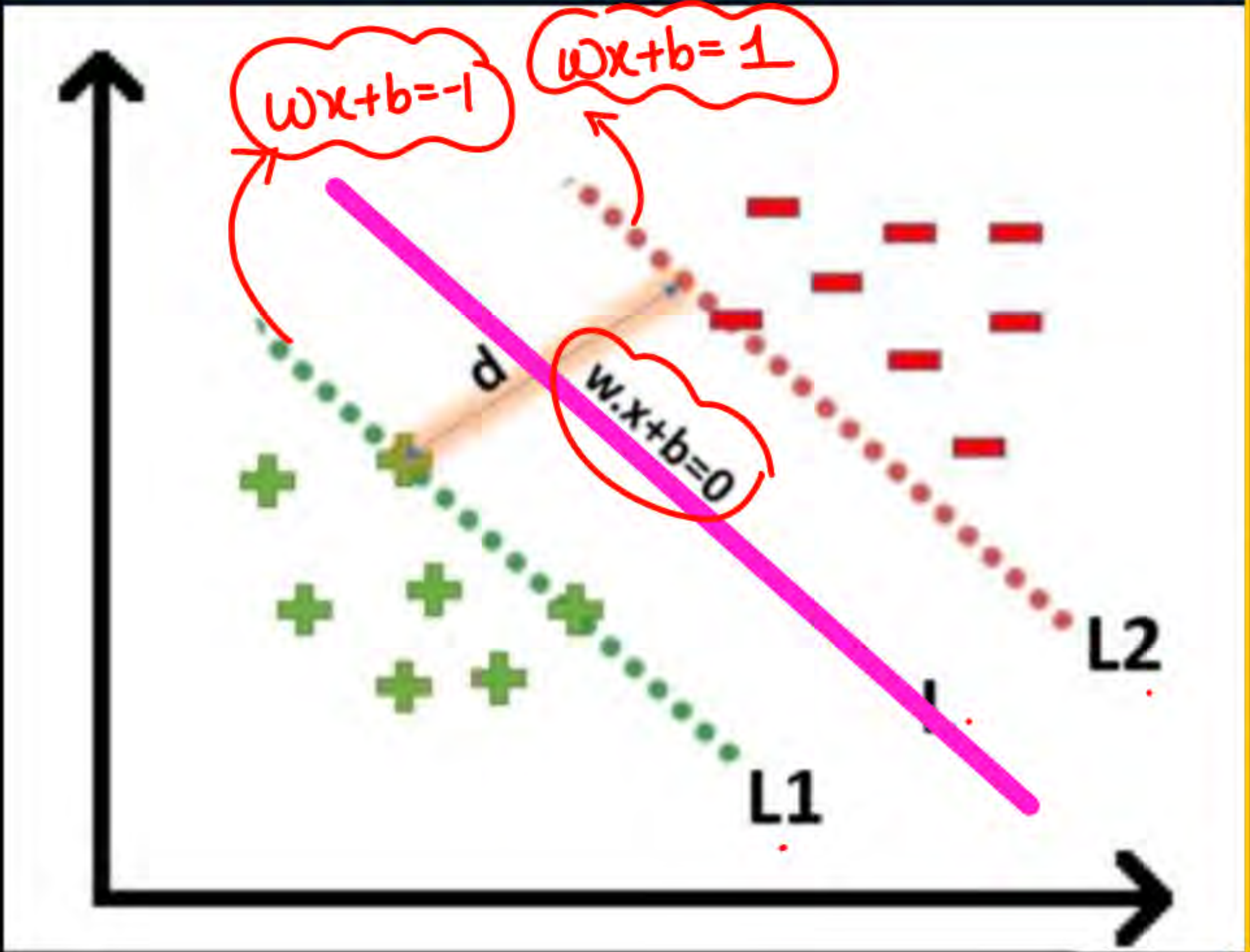
$$\underbrace{(\omega x + b)}_{C} = 0 \quad , \underbrace{\omega x + b}_{C} = \underbrace{d/2}_{C} \quad , \underbrace{\omega x + b}_{C} = -\underbrace{d/2}_{C}$$



$$\left.\begin{aligned} &\Rightarrow (4x^1 + 4x^2 = 8) \\ &x^1 + x^2 = 2 \\ &\tfrac{1}{2}x^1 + \tfrac{1}{2}x^2 = 1 \end{aligned}\right\} \text{All 3 are same eq.}$$

SVMs

Support Vector Machine



- So we see that if we scale the straight line eq, the eq and their plot remain same

- So initially the equations were

  $wx+b=0$, $wx+b=d/2$, $wx+b=-\frac{d}{2}$

$\Rightarrow \frac{wx+b}{d/2}=0$, $\frac{wx+b}{d/2}=1$, $\frac{wx+b}{d/2}=-1$

$\Rightarrow$

Support Vector Machine

SVM primal equation

So

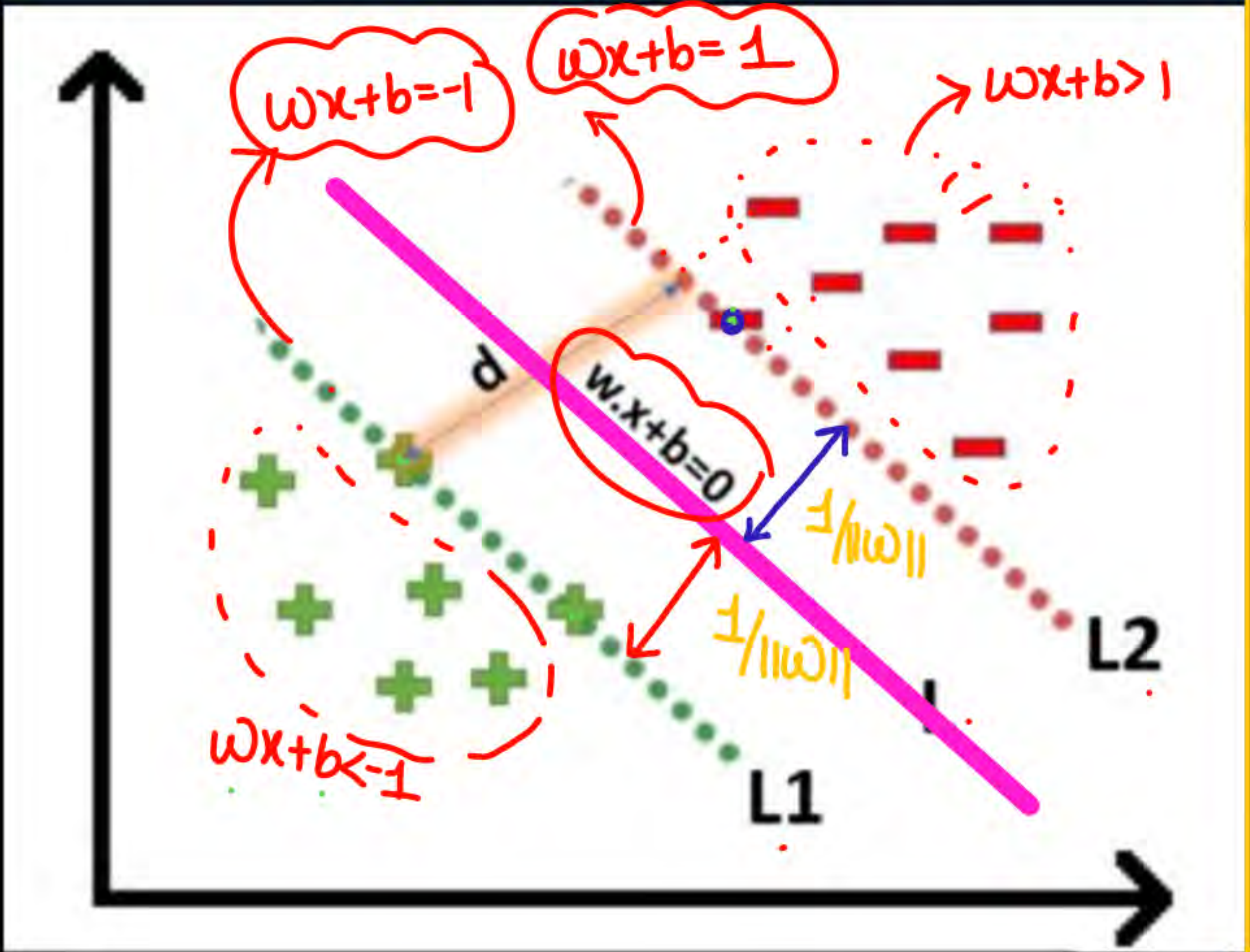
$$wx+b=0$$
$$wx+b=1$$
$$wx+b=-1$$

- So we can assume that $wx+b=\pm 1$ are the lines from support vectors.

SVMs

$\left(\|\omega\| = \sqrt{\omega_1^2 + \omega_2^2 - - - -} \right)$

Support Vector Machine



So by removing 'd' algo. become much clear

⇒ distance of SV = $\dfrac{\omega x_i + b}{\sqrt{\omega_1^2 + \omega_2^2 + \ldots}}$

⇒ distance of SV = $\dfrac{1}{\sqrt{\omega_1^2 + \omega_2^2 + \ldots}}$

⇒ total margin = $2/\|\omega\|$

SVMs

Support Vector Machine

SVM primal equation

$\max \frac{2}{||\omega||}$

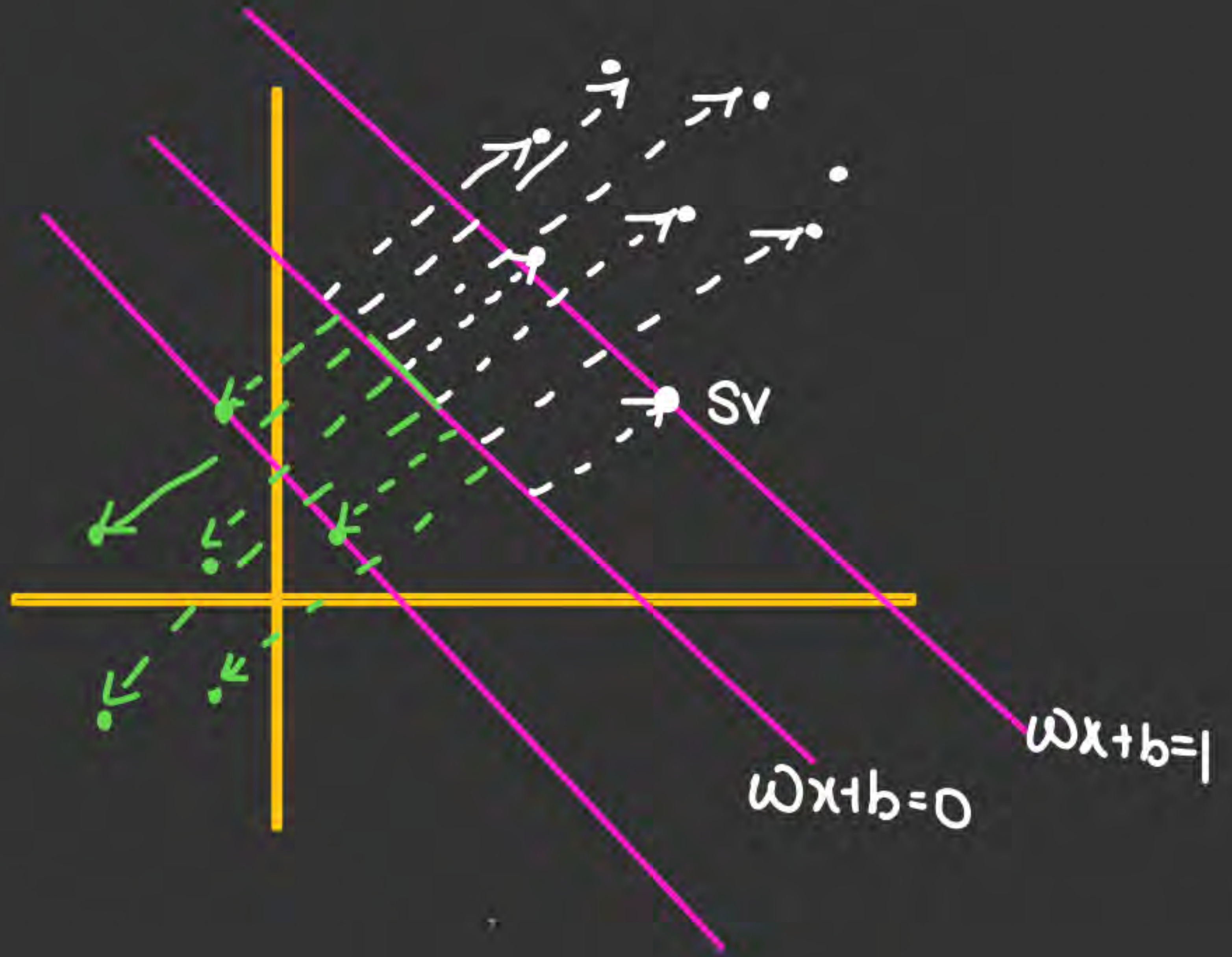
Such that $y_i(\omega x_i + b) \geq 1$

→ equal to 1 for SV

→ greater than 1 for non SV.

$\min ||\omega||$

St. $y_i(\omega x_i + b) \geq 1$


SV
ωx+b=1
ωx+b=0

SVMs

Support Vector Machine

$(\omega_1^2 + \omega_2^2 + \omega_3^2 - - -)$

final algo $\min \frac{1}{2}||\omega||^2$

St. $y_i(\omega x_i + b) \geq 1$

$\Downarrow$

This is Constraint optimization

SVM primal equation

SVMs

Steps in Support Vector Machine

Lets see the lagrangian...

Just a brief ⇒

ex

$$\min f(x) \quad \text{st. } g(x) \leq 0$$

Constraint Problem

lagrangian

$$\min_{x} \max_{\lambda} f(x) + \lambda g(x)$$

Condition $\lambda \geq 0$

How

Steps in Support Vector Machine

Lets see the lagrangian...

$$\left[\min_{x}\left[\underbrace{\max_{\lambda}\ f(x)+\lambda g(x)}\right]\right]$$

when we solve this then this eq will Convert to $\min_{x} f(x)$.

$\lambda \geq 0,\ g(x) \leq 0$

if $g(x)<0$
$\lambda = 0$

So that term in Bracket is maximized

if $g(x)=0$
λ Can take any value

Steps in Support Vector Machine

How lagrangian equation and our problems equate...

$\min f(x)$

$g_1(x) \leq 0$

$g_2(x) \leq 0$

$g_3(x) \leq 0$

$$\min_{x} \left[\max_{\lambda_1, \lambda_2, \lambda_3} f(x) + \lambda_1 g_1(x) + \lambda_2 g_2(x) + \lambda_3 g_3(x) \right]$$

Condition $\lambda_1, \lambda_2, \lambda_3 \geq 0$.

The Lagrangian

The primal formulation

The Lagrangian

How the primal form is same as the original minimization equation

The Lagrangian

What is the dual formulation...

The Lagrangian

The solution of primal is also the solution of the dual

THANK - YOU