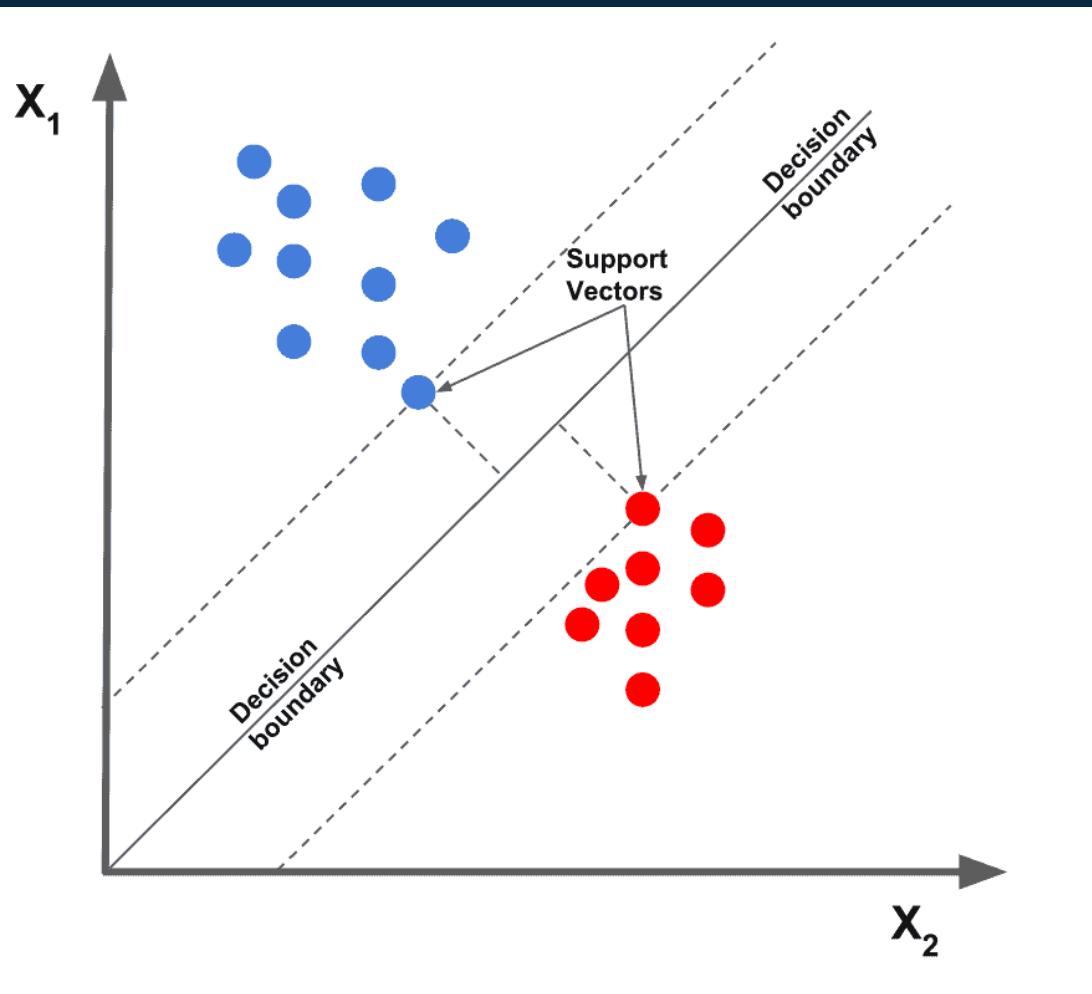


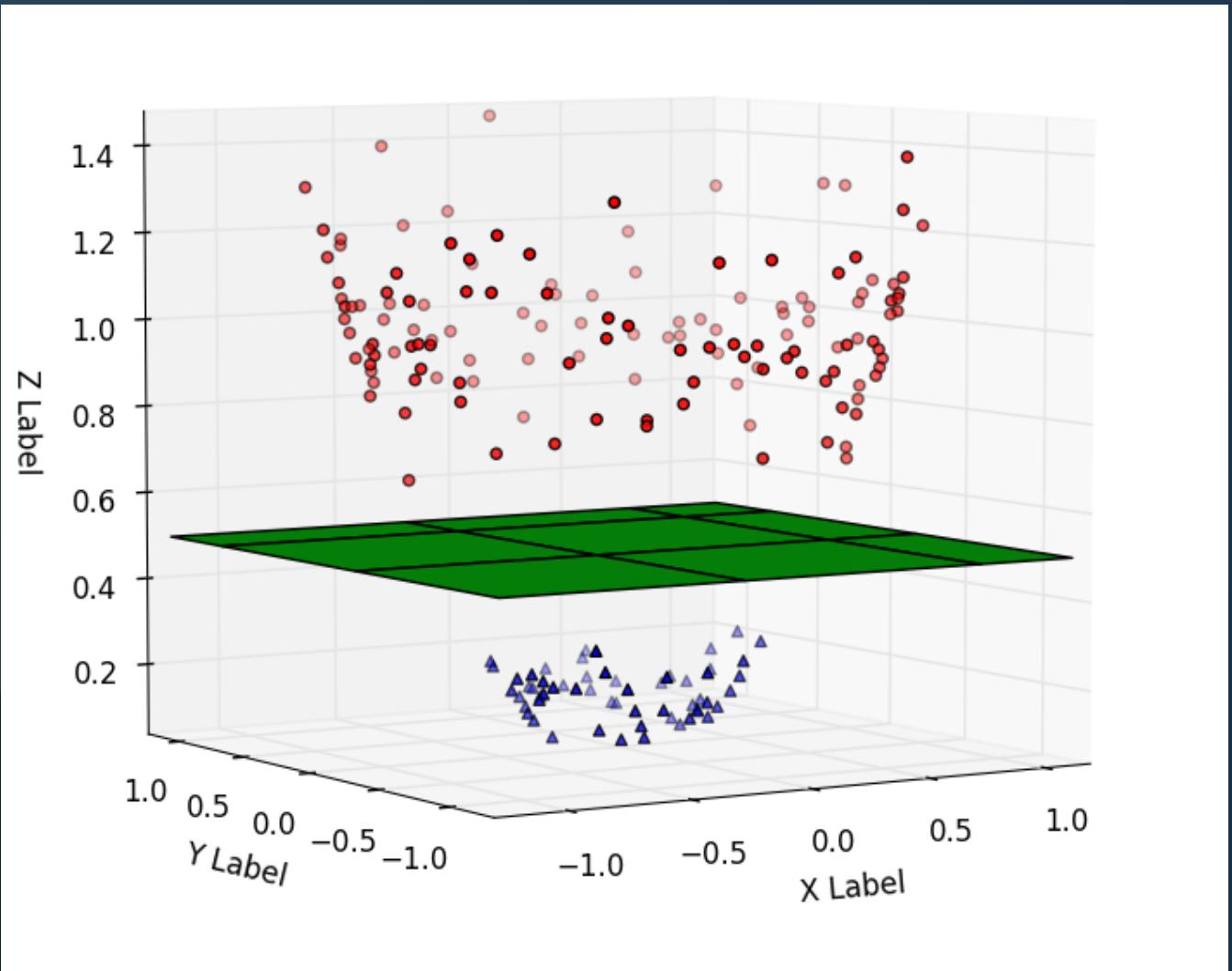
# SUPPORT VECTOR MACHINES

- Support Vector Machines (SVMs) are a type of supervised machine learning algorithm used for classification and regression analysis.
- The goal of SVMs is to find a hyperplane in a high-dimensional space that separates the different classes of data with the largest margin possible.



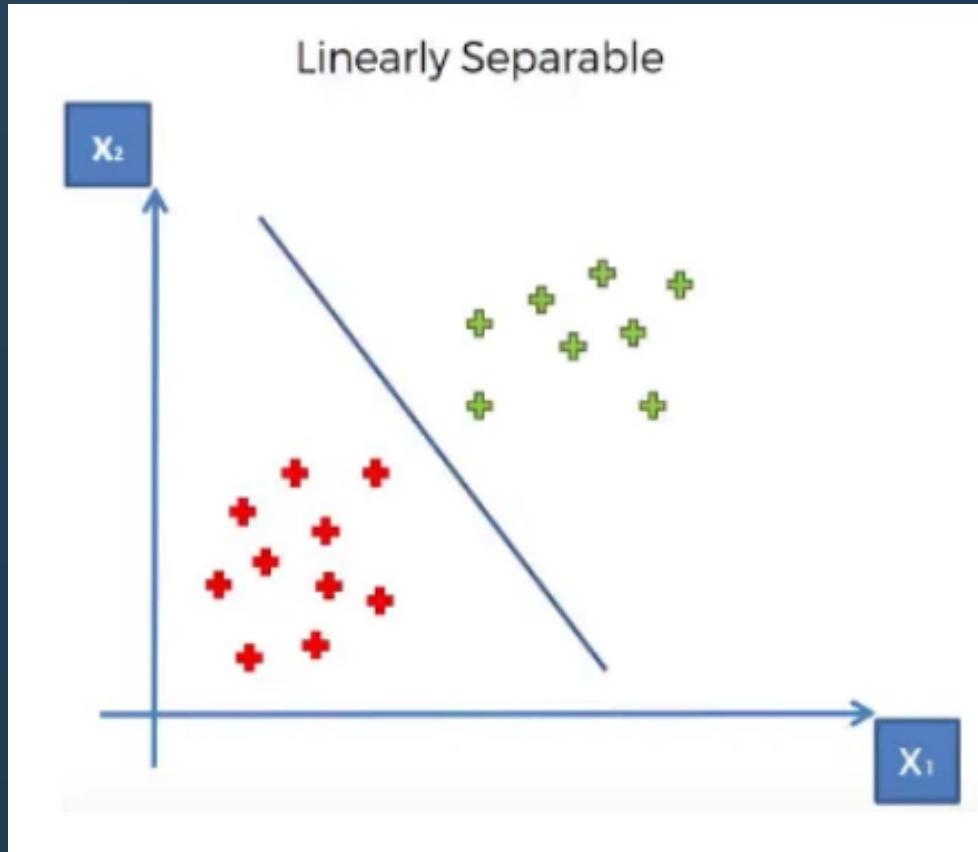
# What is Hyperplane?

- In math, a hyperplane is a flat surface that's one dimension less than the space it exists in. For example, in 3D space, a hyperplane is a flat 2D surface, like a piece of paper.
- A hyperplane can be defined by an equation that uses constants and variables. The variables represent coordinates on the hyperplane, and the constants determine its position and orientation in space.



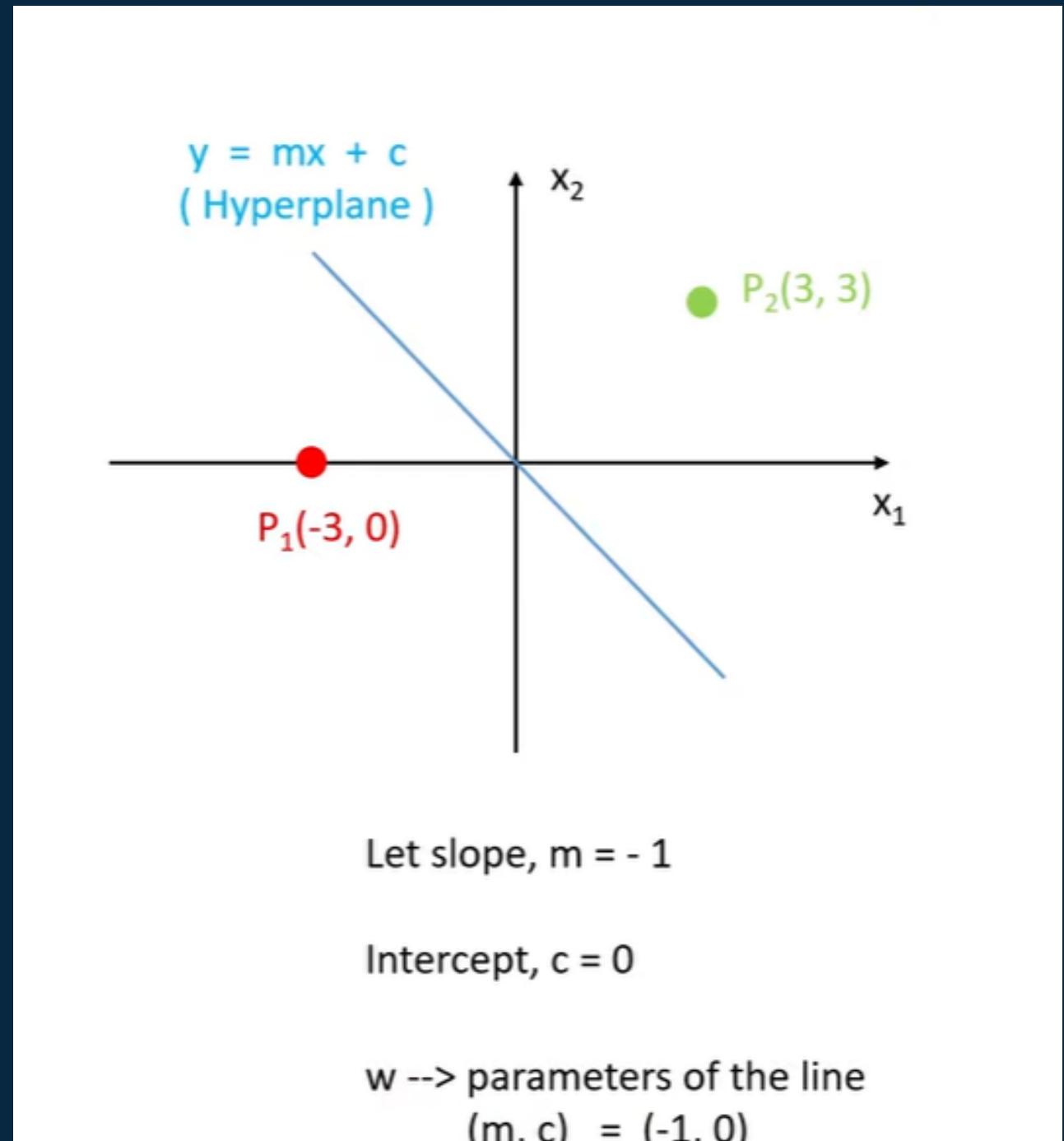
# What is Hyperplane?

- The hyperplane divides the space it exists in into two regions, with the points on one side of the hyperplane being different from the points on the other side.
- Think of it like a sheet of paper dividing a room into two parts - the points on one side are on one side of the paper, and the points on the other side are on the other side of the paper.



# The Math

- Let us take 2 points namely P1 and P2 as given in the figure.
- Let the equation of the hyperplane be  $y=m*x+c$ .
- Let us assume that the line passes through origin and has slope of -1.
- Since 'm' and 'c' affect the characteristics of the line let them be the parameters
- Thus let W be a 1d Vector containing the value of these parameters.



# The Math

●  $P_1(-3, 0)$

$$w^T x = \begin{bmatrix} -1 \\ 0 \end{bmatrix} \begin{bmatrix} -3 & 0 \end{bmatrix}$$

$$w^T x = 3$$

( Positive )

**Inference:** For all the points which lie in the left side of the hyperplane,  $w^T x$  value will be **Positive**

●  $P_2(3, 3)$

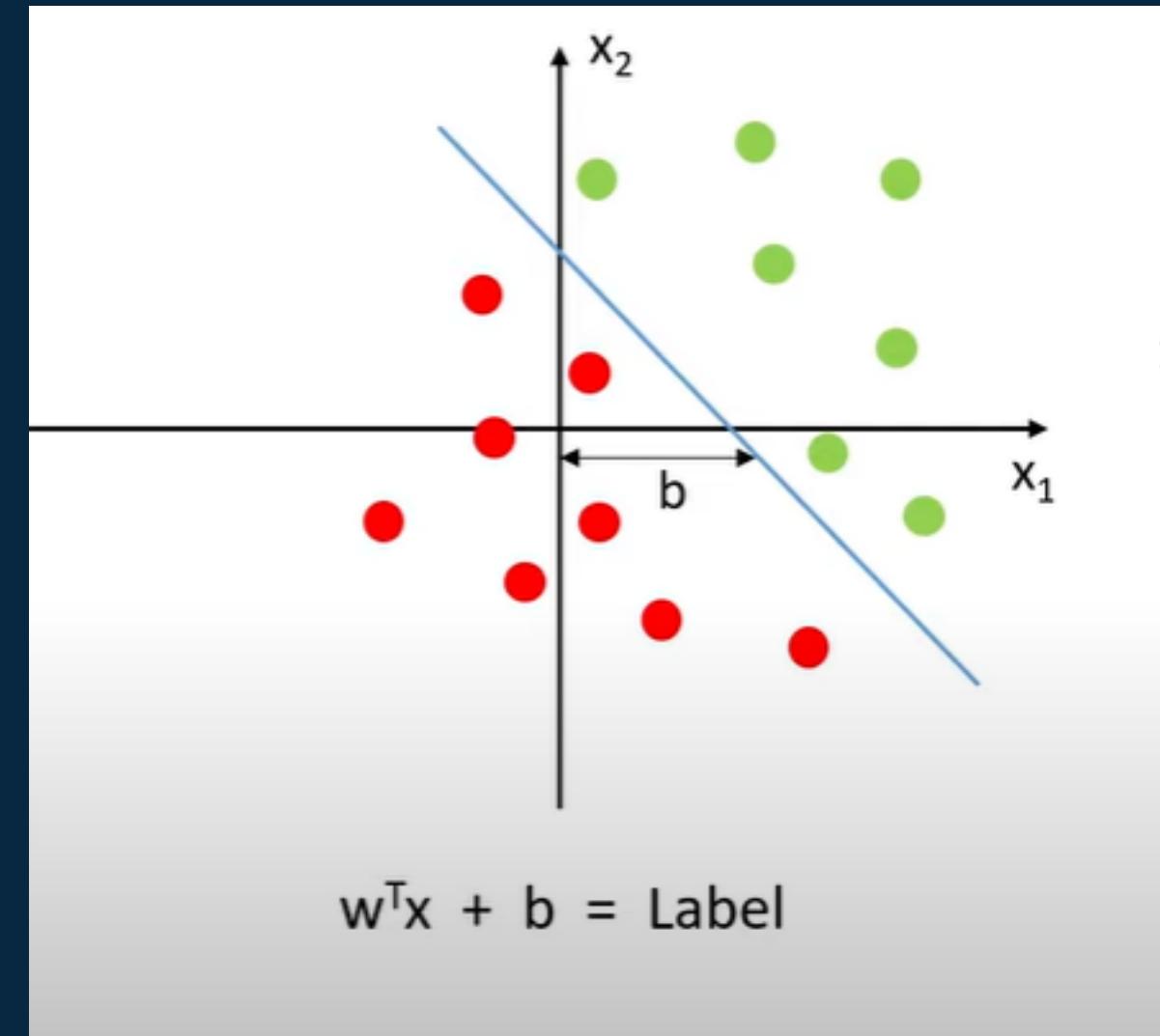
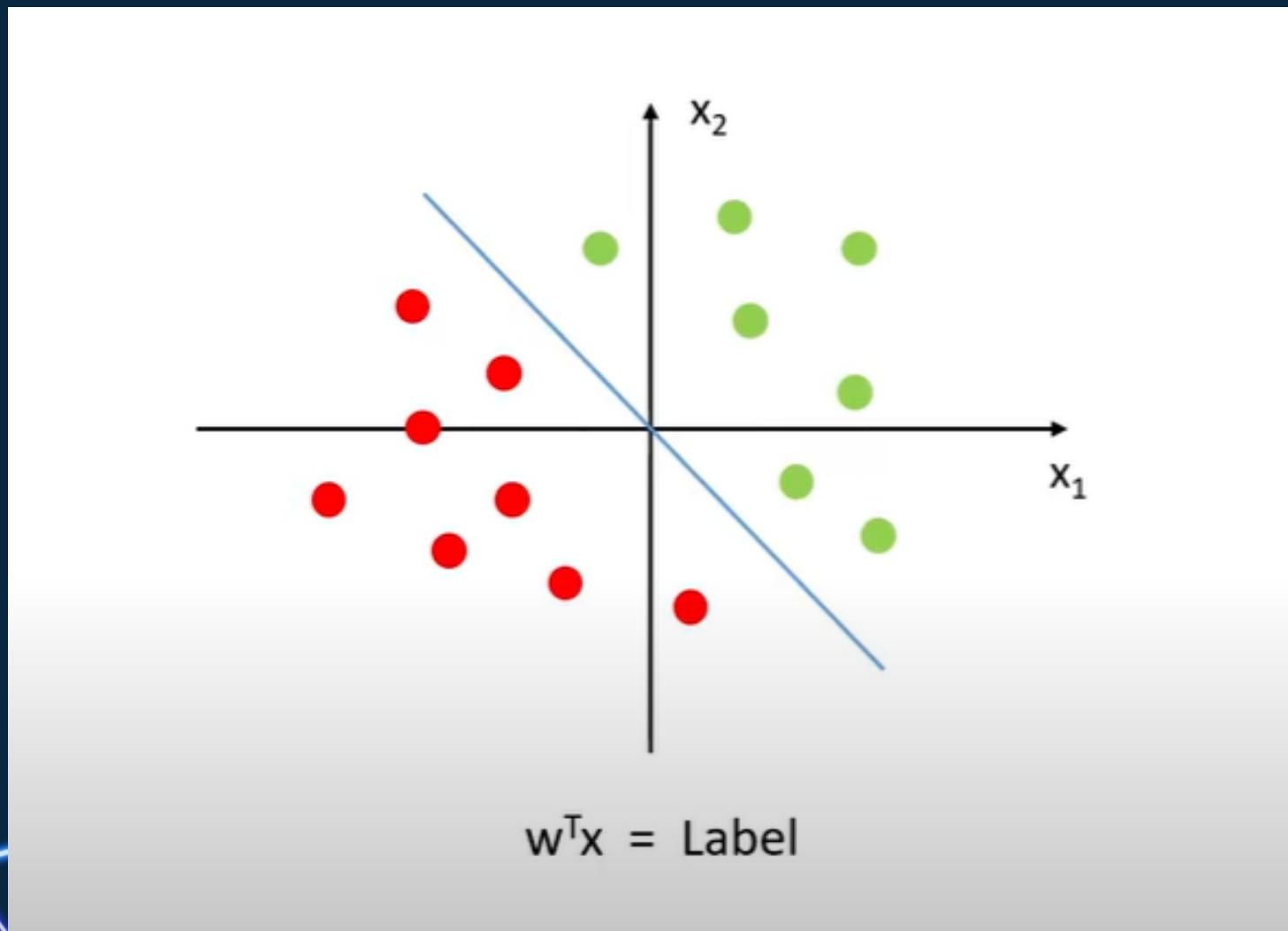
$$w^T x = \begin{bmatrix} -1 \\ 0 \end{bmatrix} \begin{bmatrix} 3 & 3 \end{bmatrix}$$

$$w^T x = -3$$

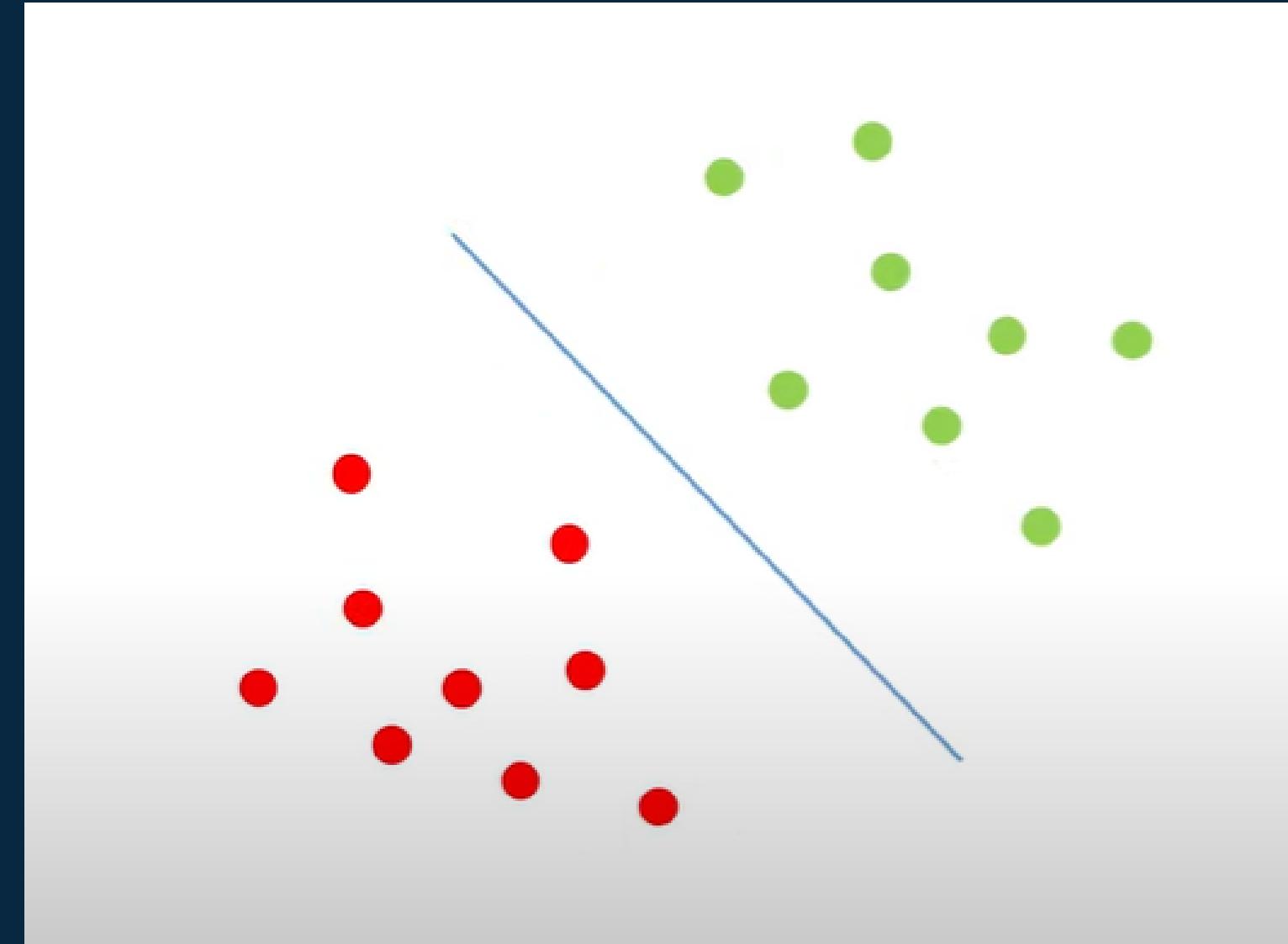
( Negative )

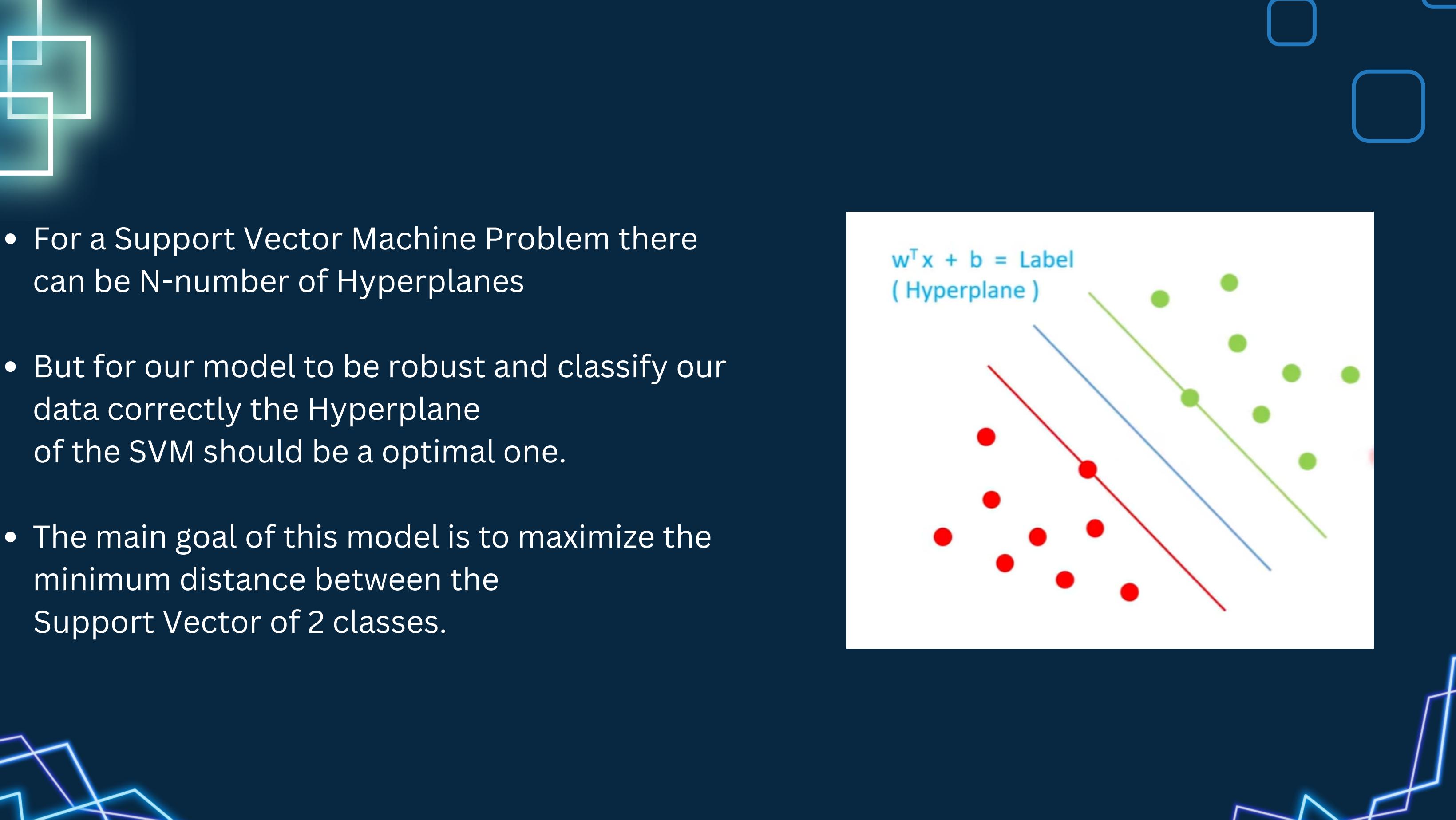
**Inference:** For all the points which lie in the right side of the hyperplane,  $w^T x$  value will be **Negative**

- Since all the hyperplanes doesn't pass through origin neither all the points can't be classified with origin as reference point we can add some bias(a constant) to our line for a better fit of our model.



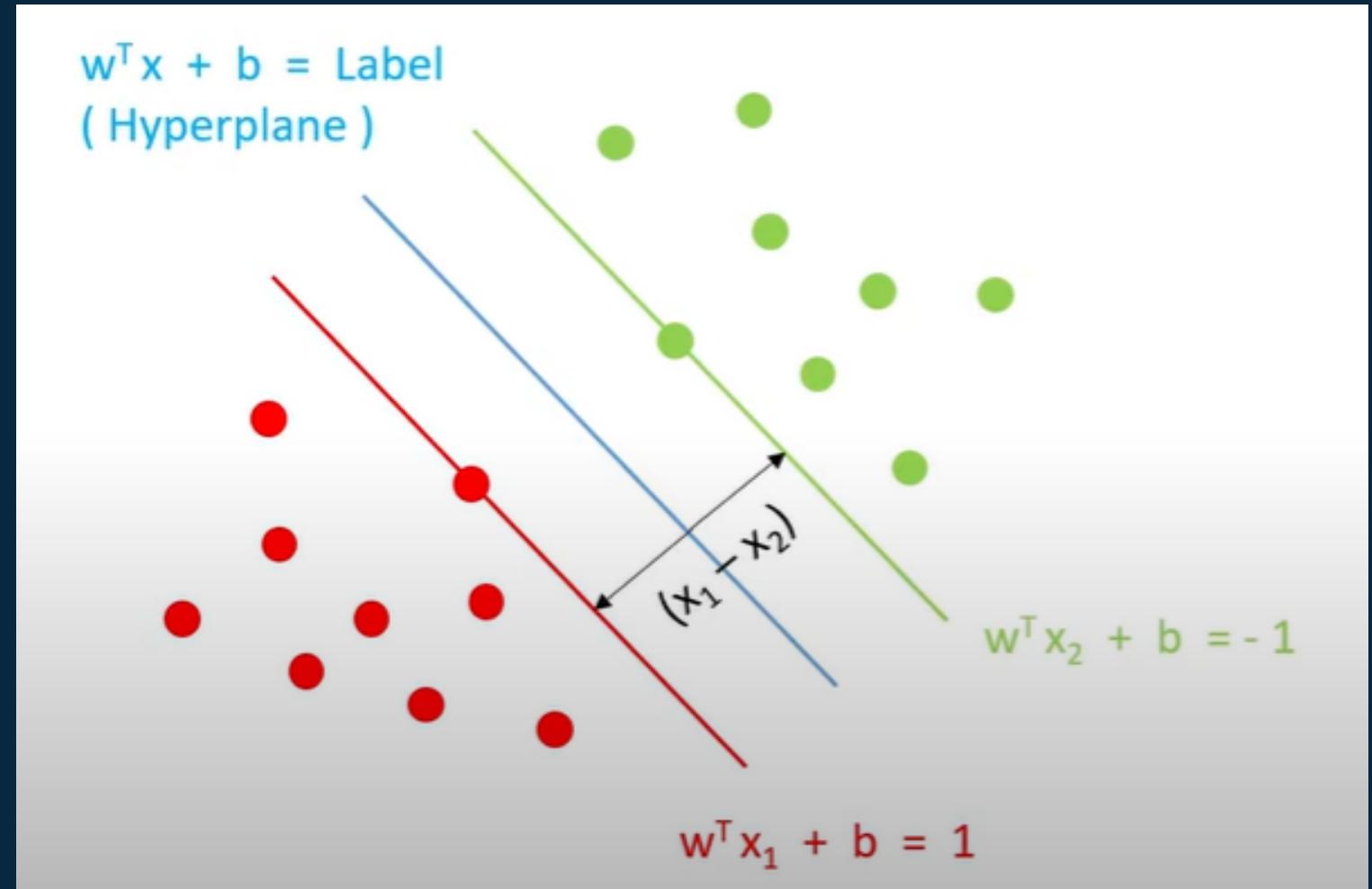
# How to find the best hyperplane?







- Now we'll calculate the distance between those support vectors  $X_1$  and  $X_2$ .
- The Equation  $W^T X_1 + b = 1$  and  $W^T X_2 + b = -1$  be the hypothesis equations which classifies the data points into 2 different classes



$$w^T x_1 + b = 1$$

$$(-) w^T x_2 + b = 1$$

$$w^T (x_1 - x_2) = 2$$

- We'll subtract these 2 equations from each other.

- Then we divide the Entire equation with the magnitude of W vector which is  $\|W\|$ .

- Since  $Wt/\|W\|$  is a unit vector it's magnitude becomes 1.

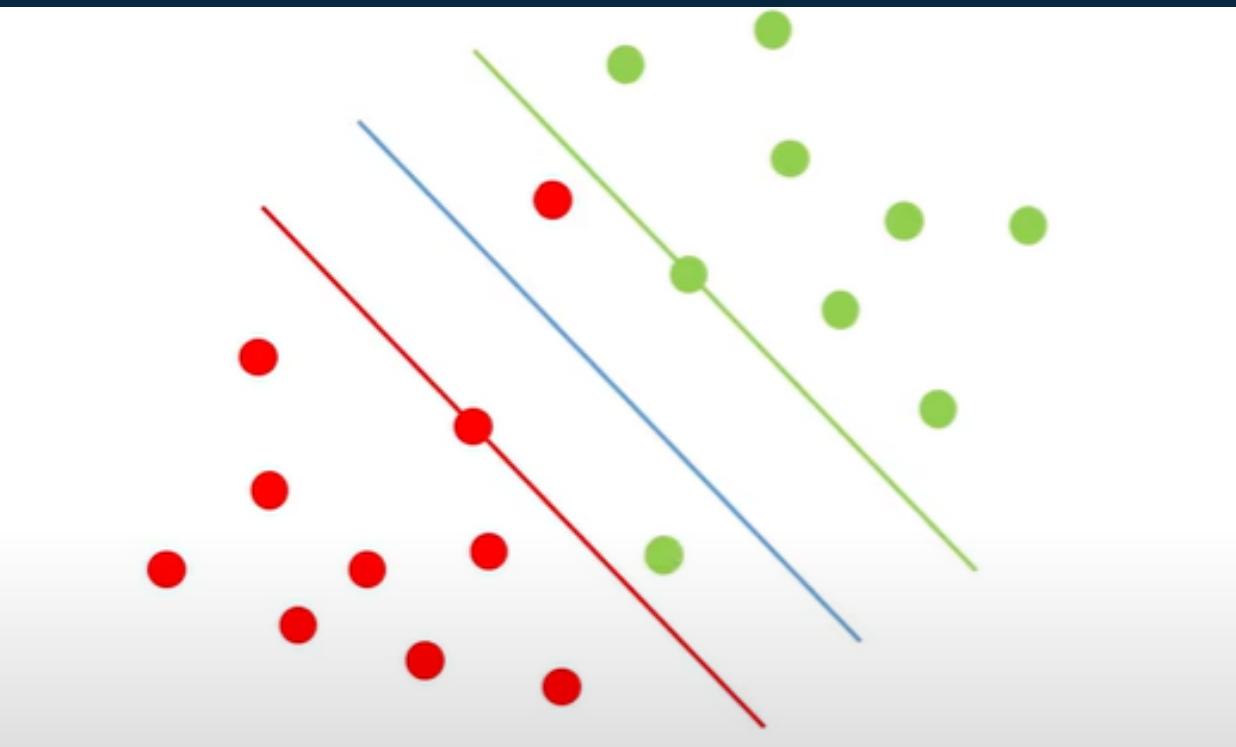
$$\frac{w^T (x_1 - x_2)}{\|w\|} = \frac{2}{\|w\|}$$

$$(x_1 - x_2) = \frac{2}{\|w\|} \quad (\text{margin})$$

- Now, our goal is to maximize this  $2/\|W\|$  this means in turn we have to minimize the  $\|w\|$ .
- So Now we've defined our own hypothesis function inorder to label the datapoint for our classification.

$$y_i = \begin{cases} -1, & w^T x_i + b \leq -1 \\ 1, & w^T x_i + b \geq 1 \end{cases}$$

- Now that we've defined our hypothesis function, so for the following image to your right side , Do you think that could we able to classfiy the red and green points correctly?



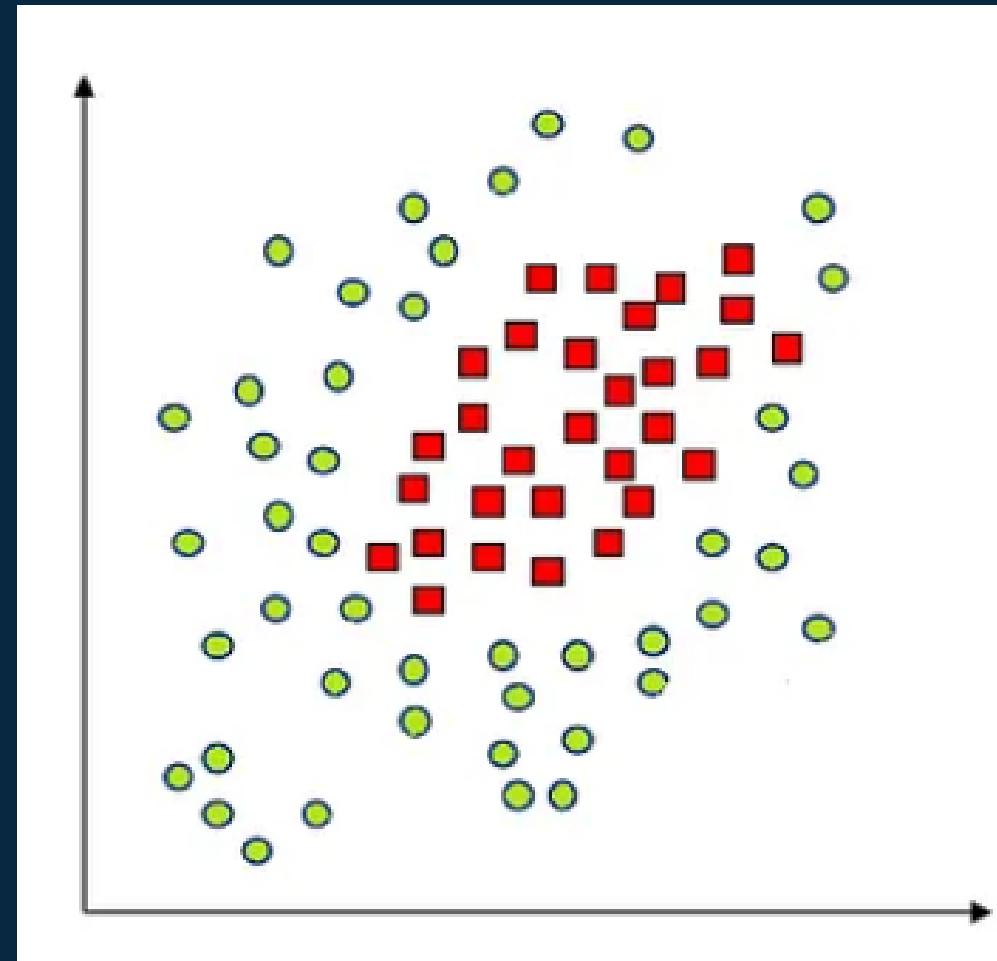
- These are the outliers in the data which affects our model's performance .

$$\min \left( \frac{\|w\|}{2} \right) + c * \sum \varepsilon_i$$

c --> Number of errors

$\varepsilon_i$  --> Error magnitude

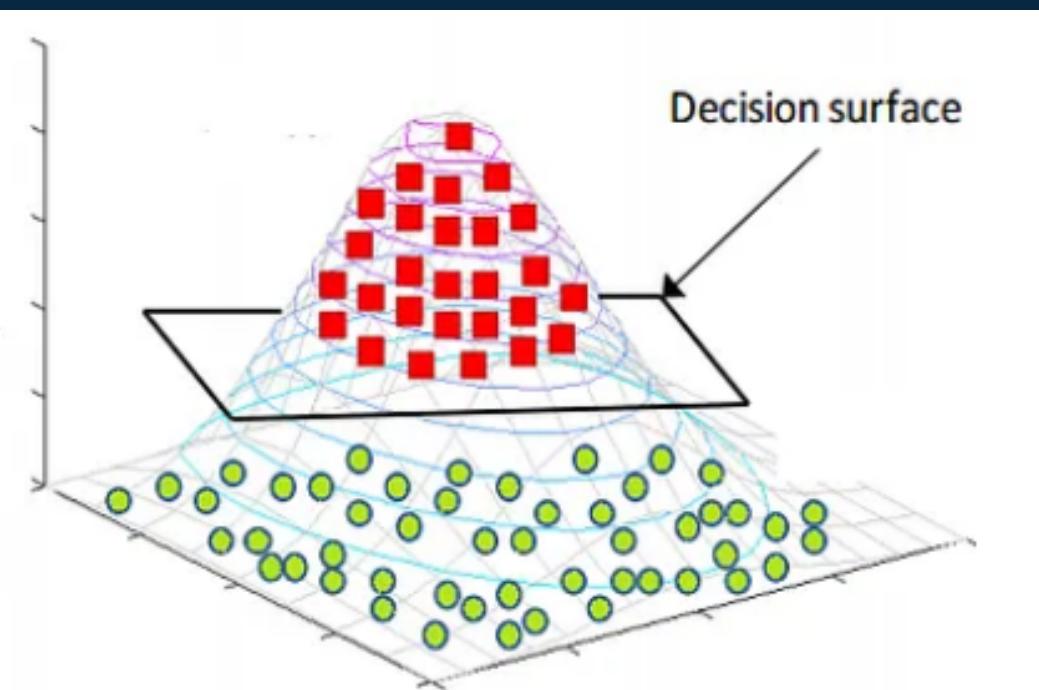
# How do you separate this data?



**Hint: Always look for a different angle!!**

# What is kernel trick?

- Kernel Trick is widely used in Support Vector Machines (SVM) model to bridge linearity and non-linearity.
- It converts non-linear lower dimension space to a higher dimension space thereby we can get a linear classification.
- So, we are projecting the data with some extra features so that it can convert to a higher dimension space.



# Types of kernel in SVM?

- **Linear Kernel**
- **Polynomial Kernel**
- **Gaussian Kernel**
- **Exponential Kernel**
- **Hyperbolic or the Sigmoid Kernel**

## Kernel Definition

- A function that takes as its inputs vectors in the original space and returns the dot product of the vectors in the feature space is called a *kernel function*
- More formally, if we have data  $\mathbf{x}, \mathbf{z} \in X$  and a map  $\phi: X \rightarrow \Re^N$  then

$$k(\mathbf{x}, \mathbf{z}) = \langle \phi(\mathbf{x}), \phi(\mathbf{z}) \rangle$$

is a kernel function

