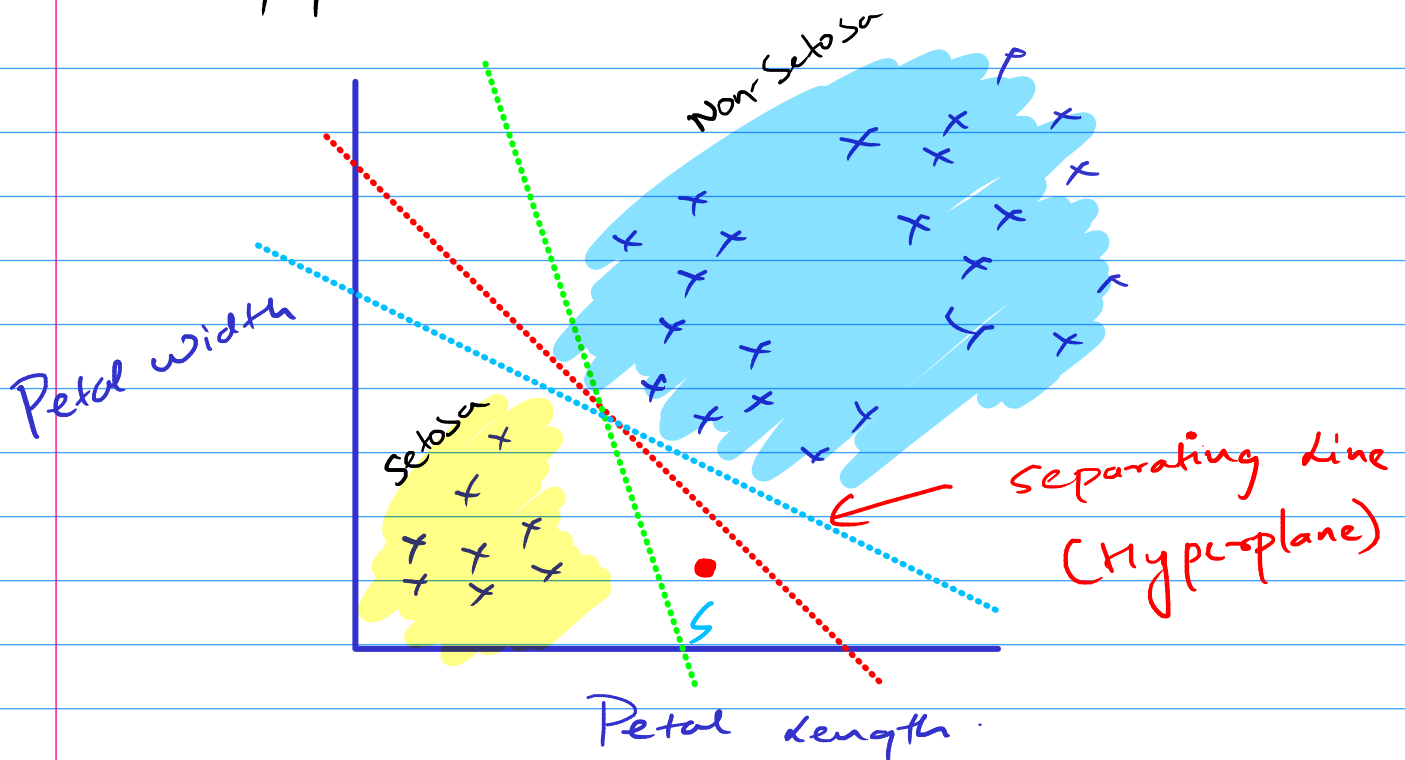
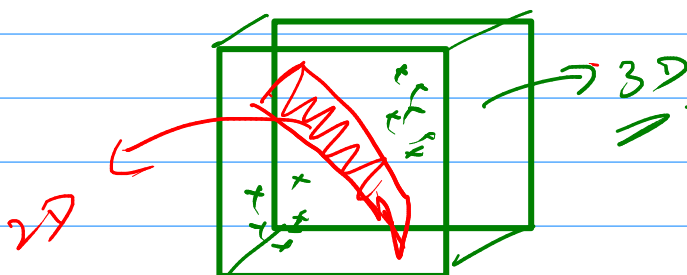
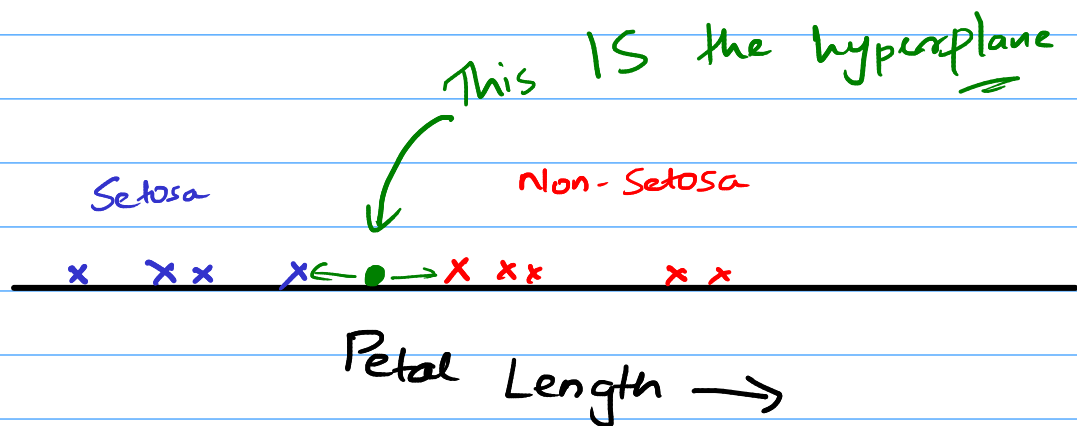


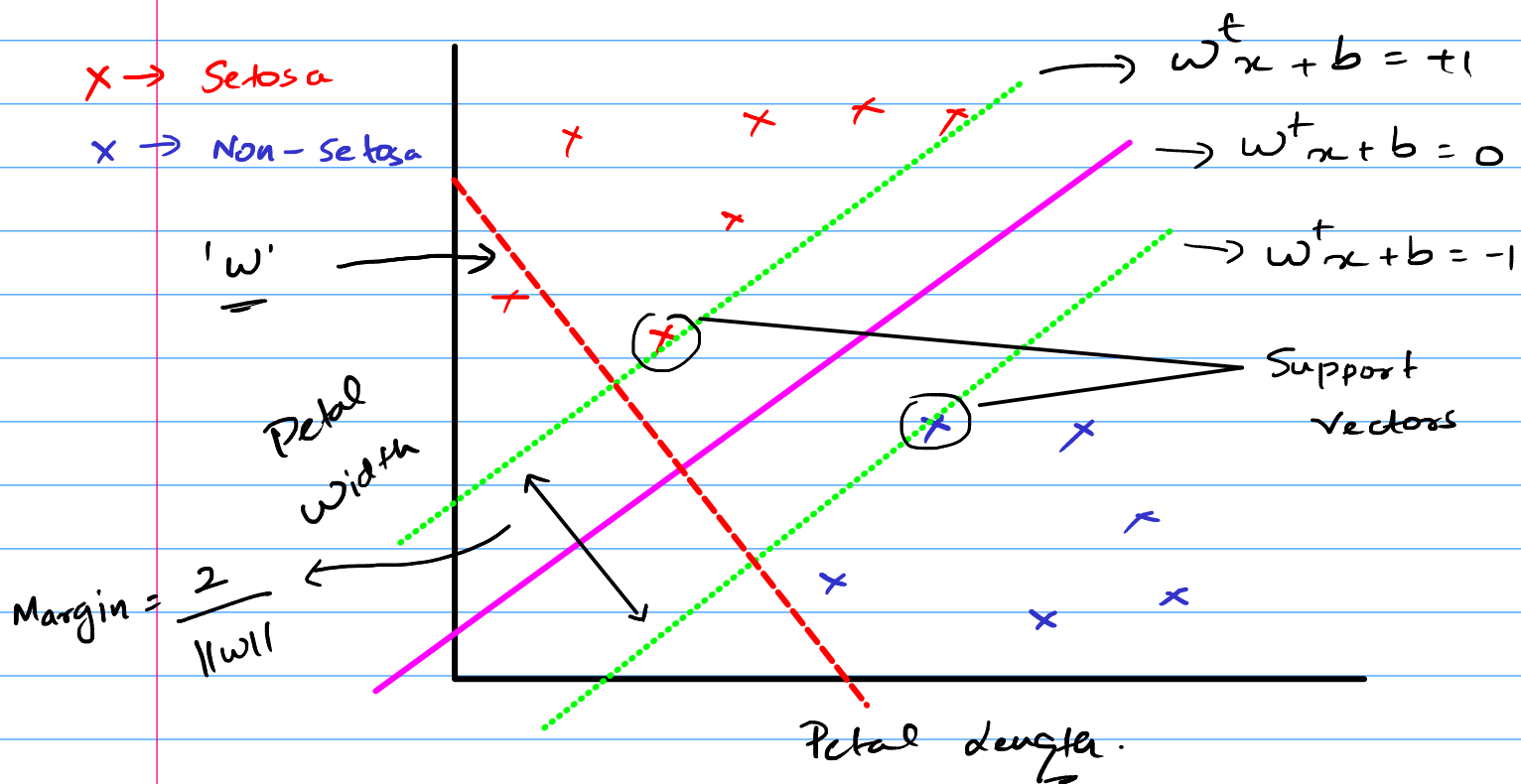
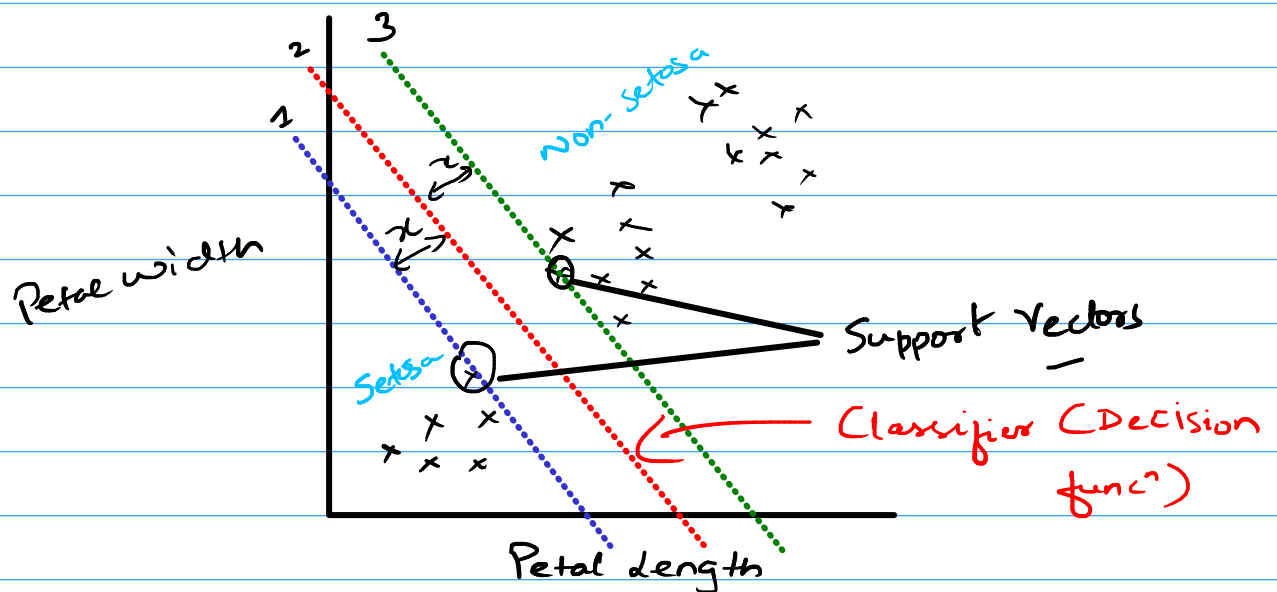
Support Vector Machines.



The goal of SVM can be defined as to find an optimal hyperplane that separates the data into classes.

Hyperplane: is a subspace of one dimension less than its ambient space.





Decision Boundary Expression:

$$f(x) = \sum_{i=1}^n w_i^T x_i + b \quad \text{where } i = 1 - n \text{ data points}$$

$x = \text{training or test patterns}$

$w =$ is a ^{weight} vector Normal to the hyperplane (red dashed line)

$b =$ bias

The result of this funcⁿ \rightarrow $\begin{matrix} \rightarrow +ve \\ \rightarrow -ve \end{matrix}$ based on the

predicted class of the test data point.

Expression of the Hyperplanes!

Decision hyperplanes divides the two classes of data $\rightarrow +ve$
 $\rightarrow -ve$

All the data points that fall on the hyperplane has a value 0, when substituted by

the expression " $w_i^T x_i + b$ ".

if you move on the +ve side \Rightarrow its value \uparrow from 0.
if you move on the -ve side \Rightarrow its value \downarrow from 0.

Understanding the weight Vector " w ".

$$w = \sum_{i=1}^n a_i y_i x_i,$$

$$y_i = (-1, +1)$$

where a_i value is close to 0 for most points
except support vectors.

Let "u" represent the new test data point.

Then $w = \sum a_i y_i u$

$$y_i = (-1, +1)$$

" y_i " is -1 for data points that fall on the -ve side of the hyperplane

" y_i " is +1 " " " " " "
+ve side " " "

$\therefore, y_i (w_i^T x_i + b)$ is always positive.

Margin width:

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

where $\|w\|$ = length of the vector
 $= \sqrt{w^T w}$

Maximum Margin:

is achieved by finding " w " & " b ":

$\frac{2}{\|w\|}$ is maximized $\forall \{ (x_i, y_i) \}$,
 $y_i (w_i^T x_i + b) \geq 1$

In case of 2 features, the discriminant

funcⁿ is

$$f(x) = w_1 x_1 + w_2 x_2 + b$$

When evaluating this equation, the resulting sign divides the 2D space into 2 regions. After training, the SVM provides us with the estimates for w_1 , w_2 , and b .

The decision function can thus be constructed as the line, which crosses the discriminant function at the point where $f(x) = 0$.

The dotted (green) lines can be constructed as the lines crossing the discriminant function at the points where it evaluates to "-1" and "+1" respectively.