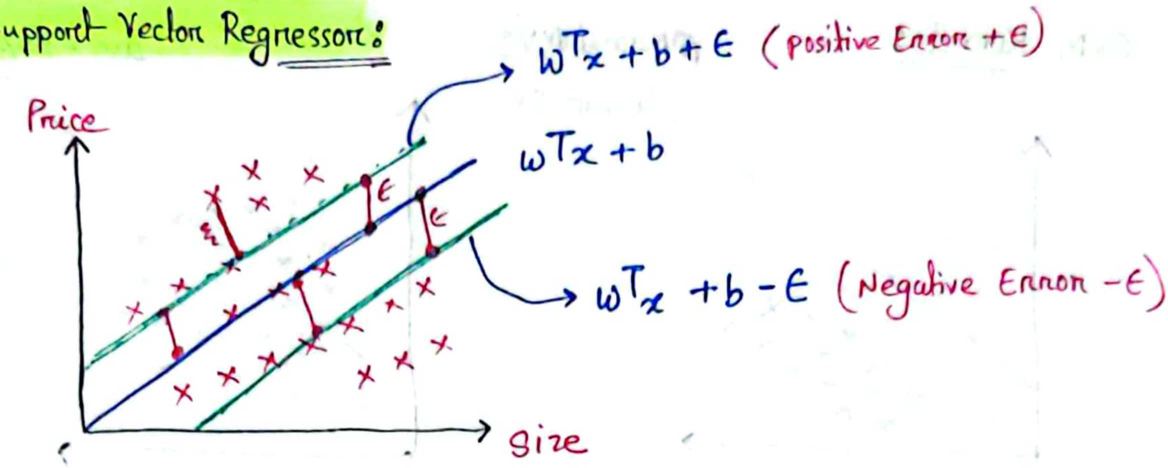
Support Vector Regressor:



Cost Function:

$$\min_{w,b} \frac{\|W\|}{2} + \boxed{C \sum_{i=1}^{n} \xi_i} \rightarrow \text{Hinge loss}$$

Constraint $\rightarrow$ $|y_i - w^T x_i| \leq \epsilon + \xi_i$

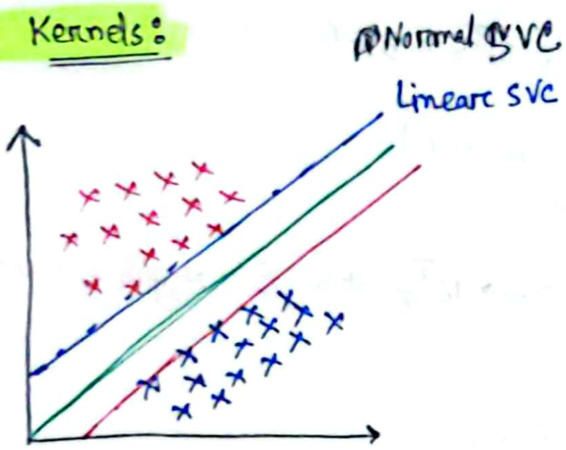
Means data points should be under marginal planes
But in real world scenario data points can be outside of marginal points.

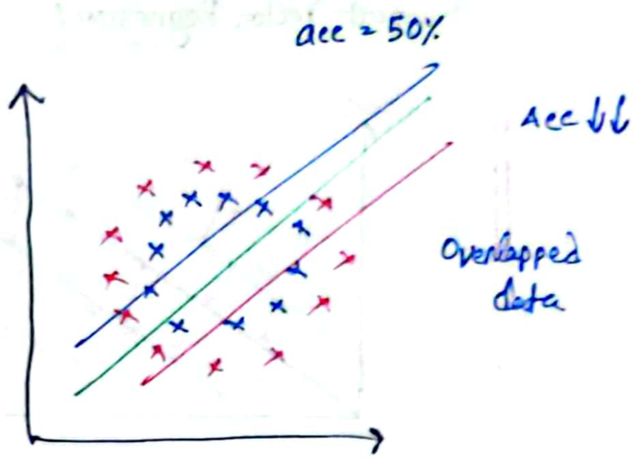
$\epsilon \rightarrow$ distance of marginal ~~point~~ plane and bFT

~~$\xi \rightarrow$ Distnce of~~

$\xi \rightarrow$ Sum of the distance of the data points with the marginal plane.

SVM Kernels:

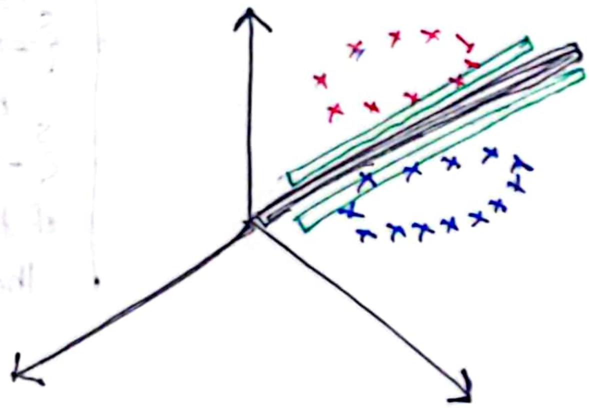




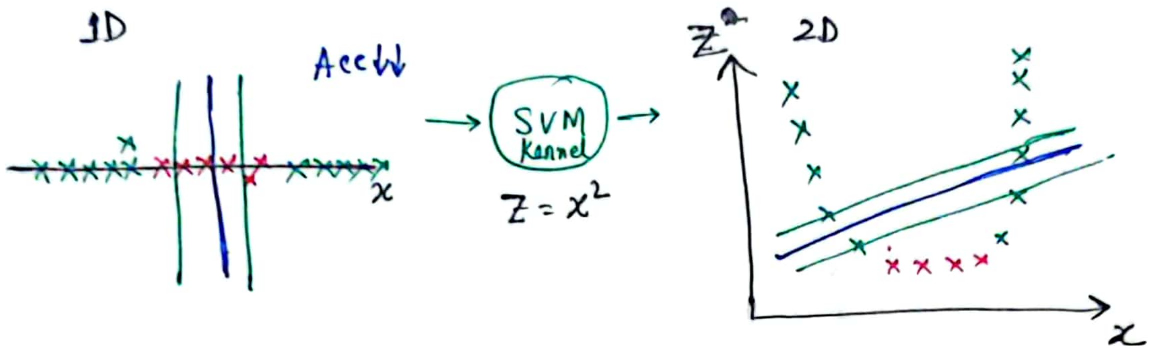
If data orientation is like right chart, the linear SVC won't be able make the best fit model. It would create low accuracy model. So we have to use 'SVM Kernels' to solve this problem

What SVM Kernel do?

→ SVM Kernel take the 2D Data, and by applying mathematical formulas it changes the 2D features into 3D features where we can actually seperate the overlapped data by marginal hyperplane



Another example: Suppose Data overlapped in a single axis



So, we can see that SVM Kernels help data to seperate from each other by creating new dimensions.

There are three types of SVM Kernels:

1. Polynomial Kernel
2. RBF Kernel
3. Sigmoid Kernel