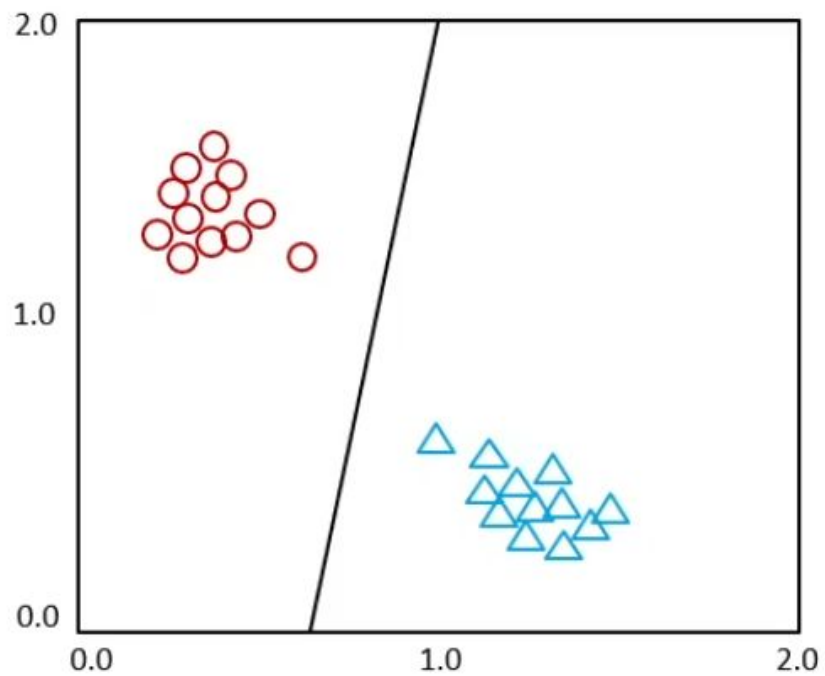


# Support Vector Machine

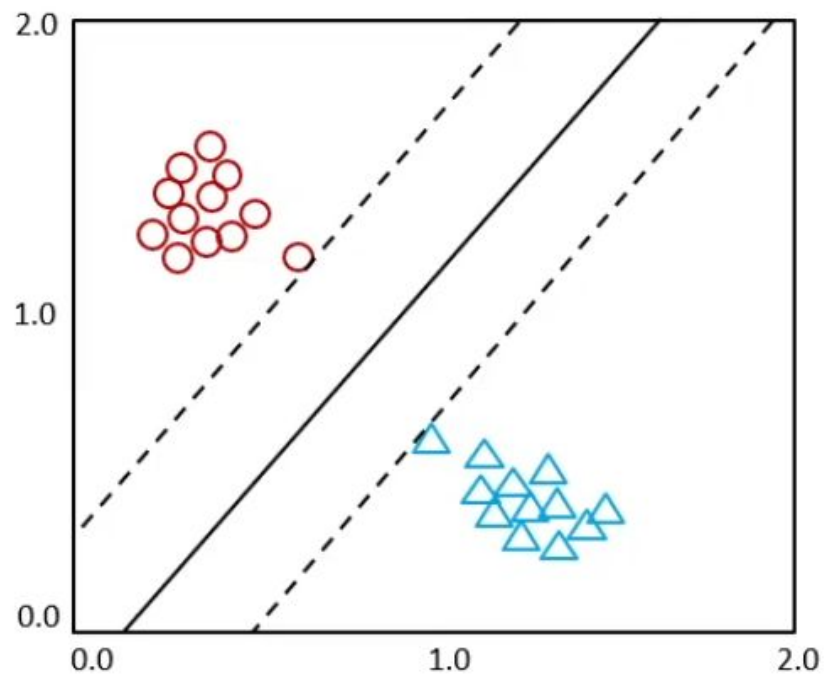
---

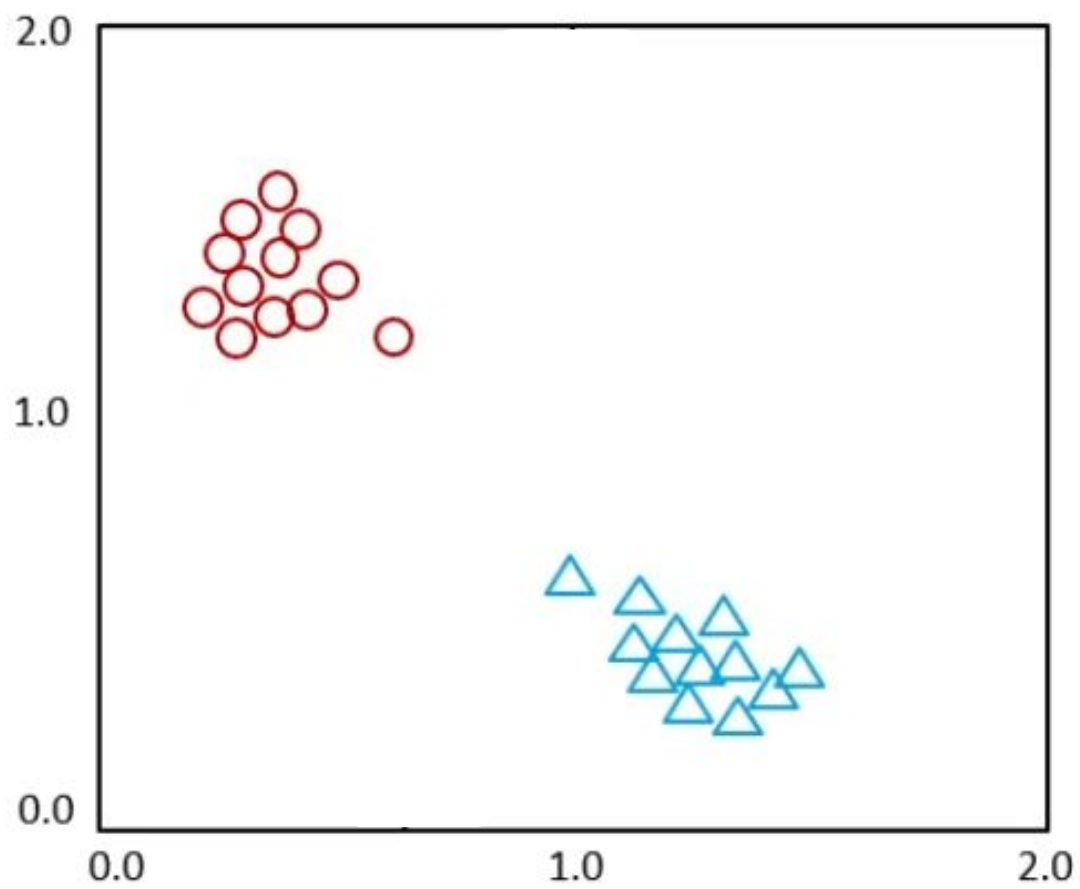
- outliers, Noise يتعامل مع
- Curse of dimensionality
- Non linear data

**Logistic Regression**



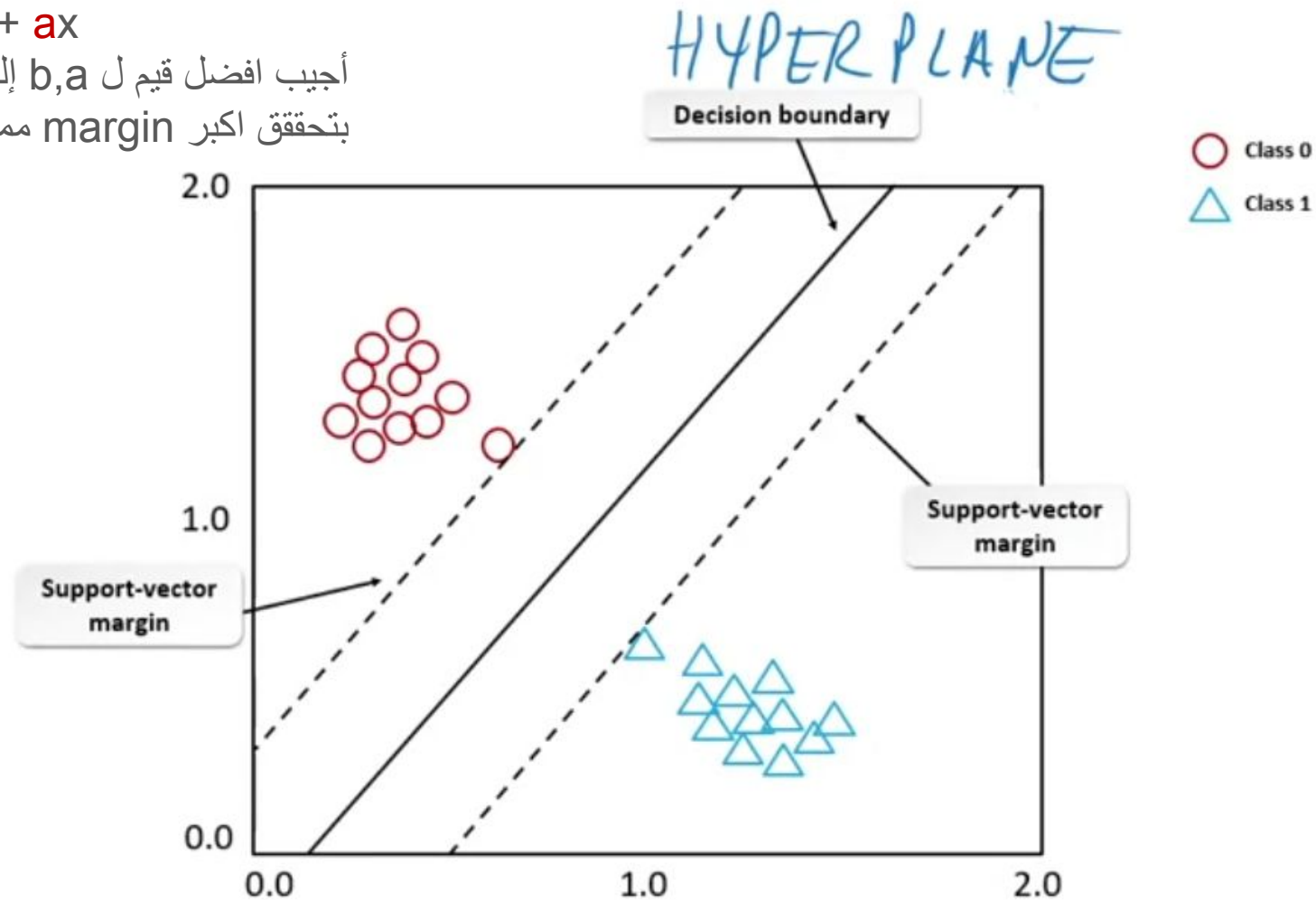
**Linear Classification with SVMs**



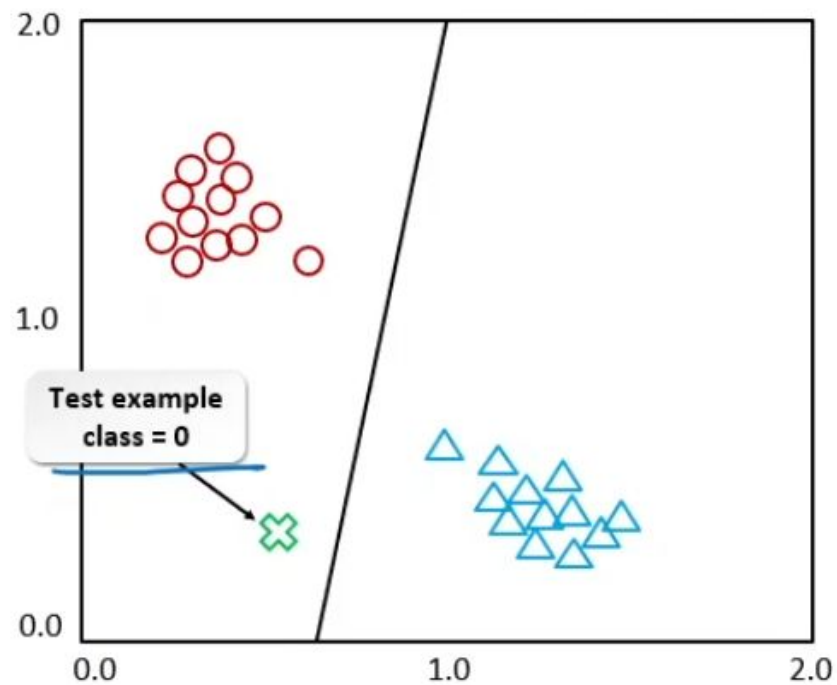


$$Y = b + ax$$

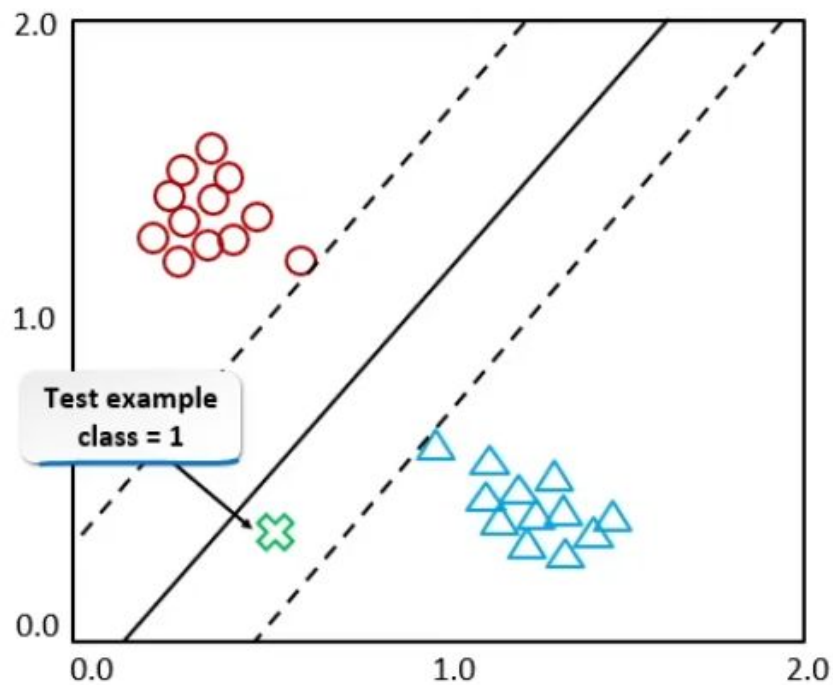
أجيب افضل قيم ل  $b, a$  إلي  
بتحقق اكبر margin ممكن



**Logistic Regression**



**Linear Classification with SVMs**



## What Is the Margin Exactly?

The **margin** is the distance between the hyperplane and the closest data points from each class — those are your support vectors.

Mathematically, the margin is:

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

So, if we want a larger margin, we need a **smaller weight magnitude** ( $||w||$ ).

That's why the optimization goal is to **minimize**  $||w||$  while still classifying all points correctly.

## The Optimization Problem

The SVM problem is formulated as an **optimization task**:

Minimize:

$$\frac{1}{2} ||w||^2$$

Subject to:

$$y_i(w \cdot x_i + b) \geq 1$$

Where:

- $y_i$  is the true class label (+1 or -1)
- $x_i$  is the data point

The constraint ensures that every point lies on the correct side of the boundary.

So basically:

👉 We're searching for the **smallest w** (largest margin) that still classifies every point correctly.

The algorithm doesn't just "draw lines and guess".

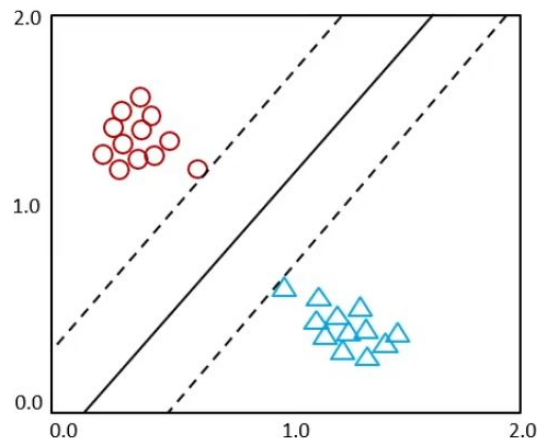
It uses mathematical optimization techniques like:

- **Quadratic Programming**
- **Lagrange Multipliers**

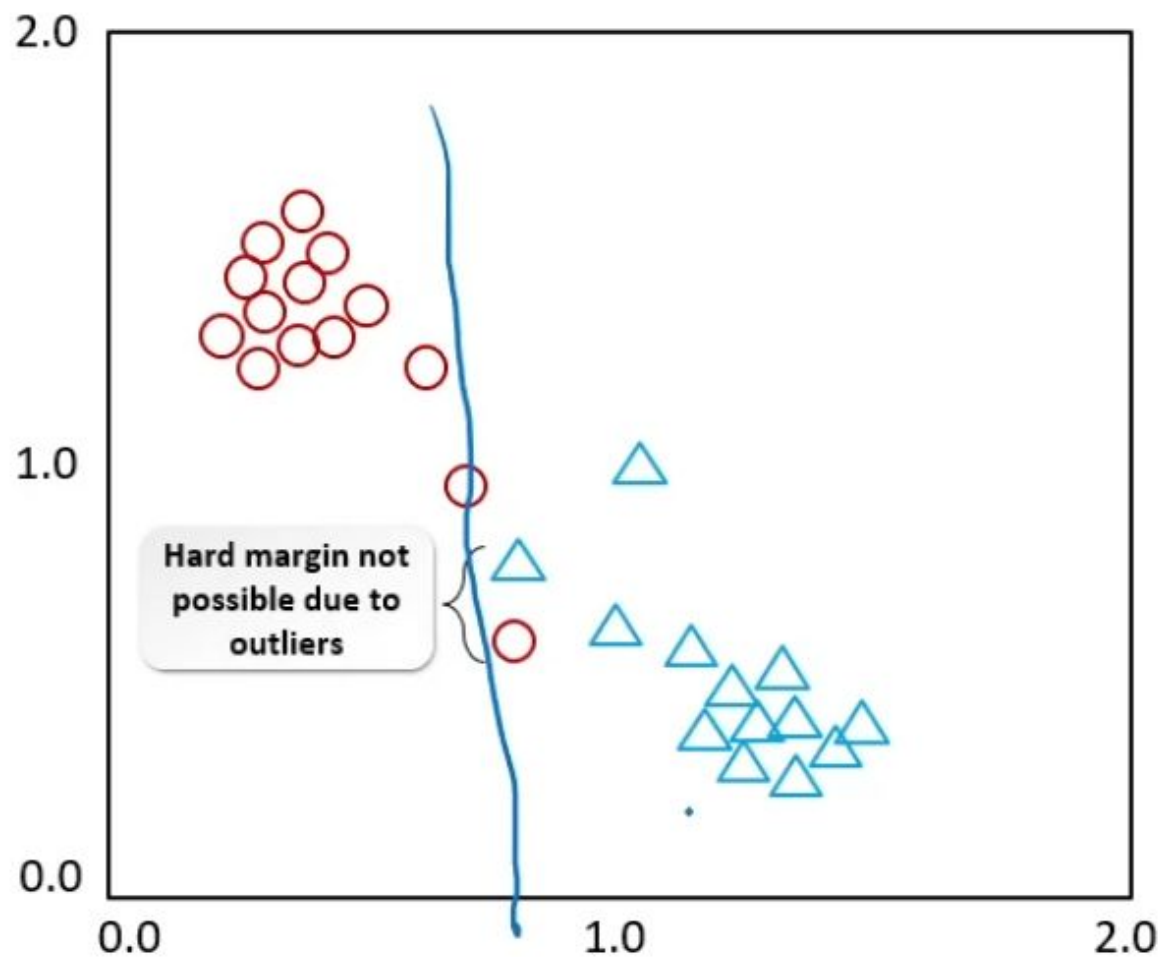
>>> to find the precise values of **w** and **b** that maximize the margin.

So, it keeps adjusting these parameters — testing margins, calculating distances — until it finds the line that perfectly balances both sides.

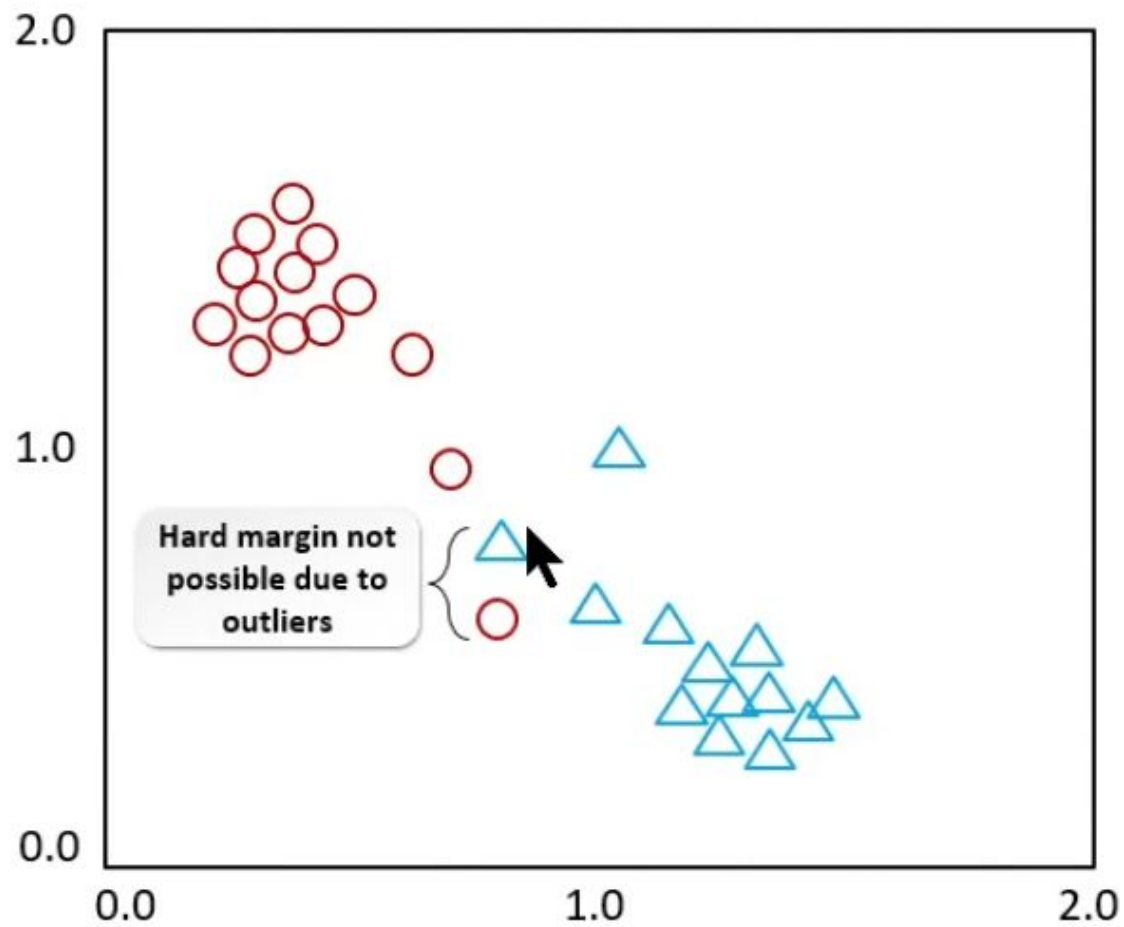
Linear Classification with SVMs



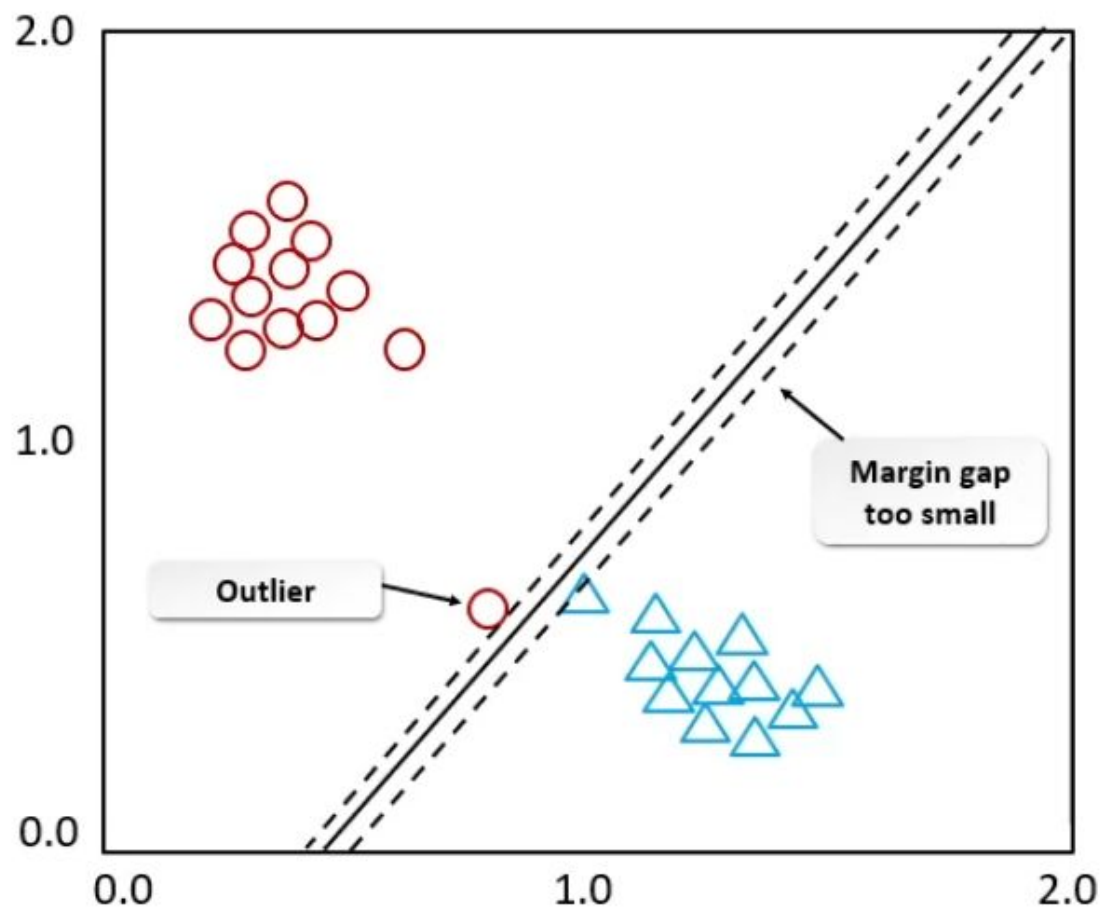
## hard Margins



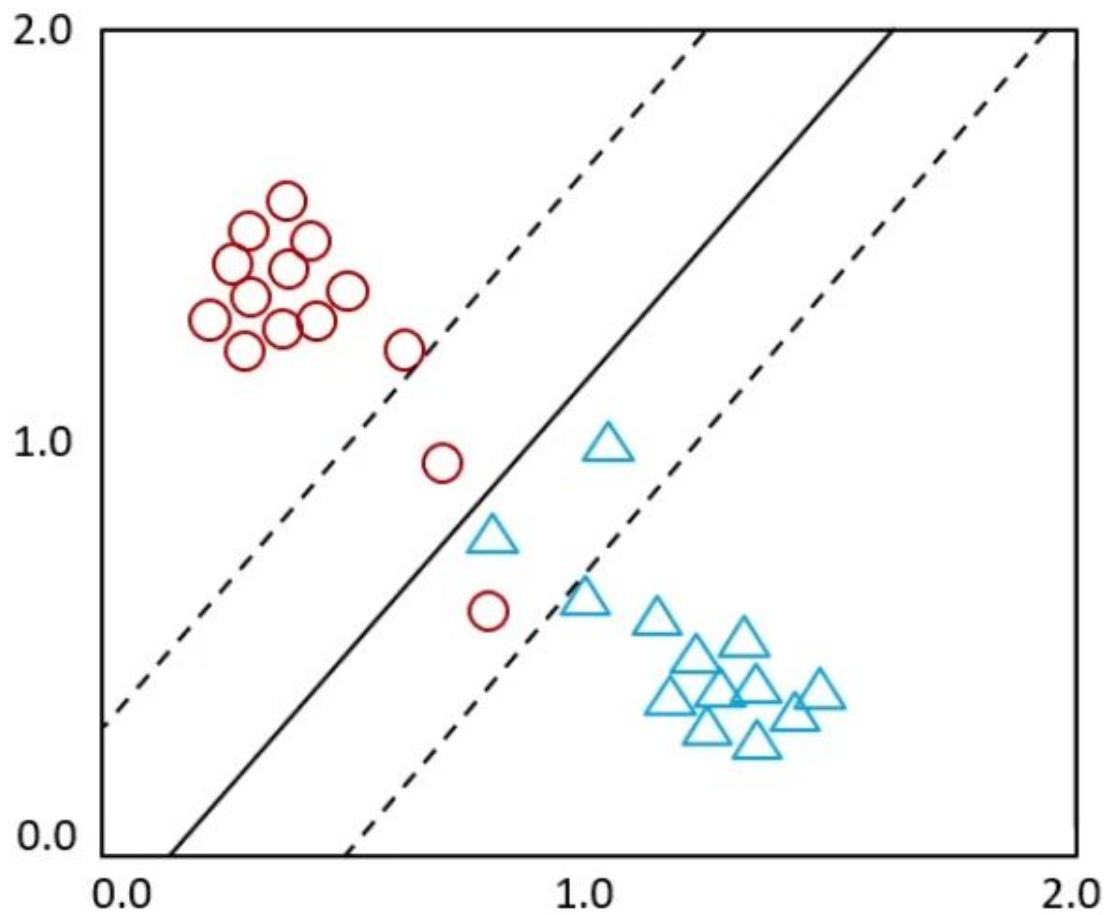
## hard Margins







## Soft Margins

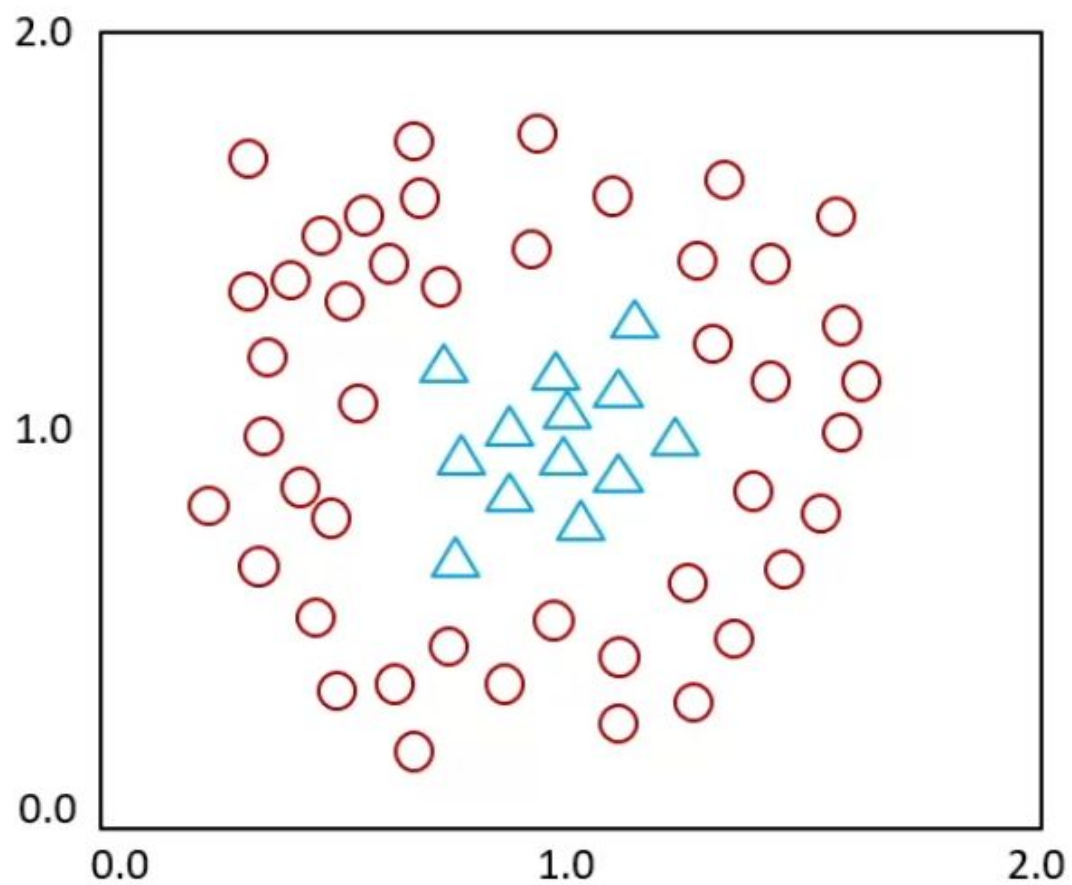


## Regularization Penalty in SVM

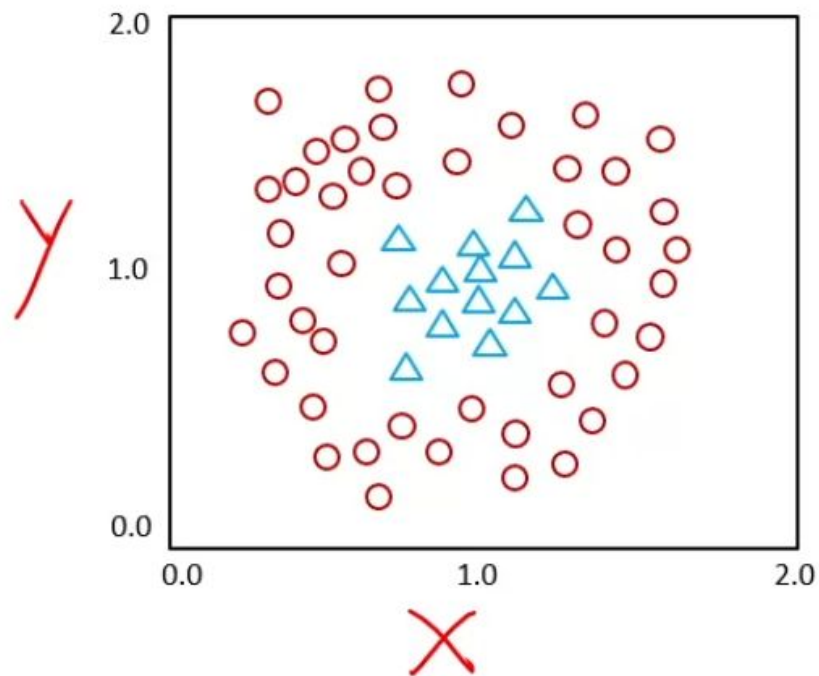
As hyperparameter  $C$

**low  $C \gg$  soft margins**

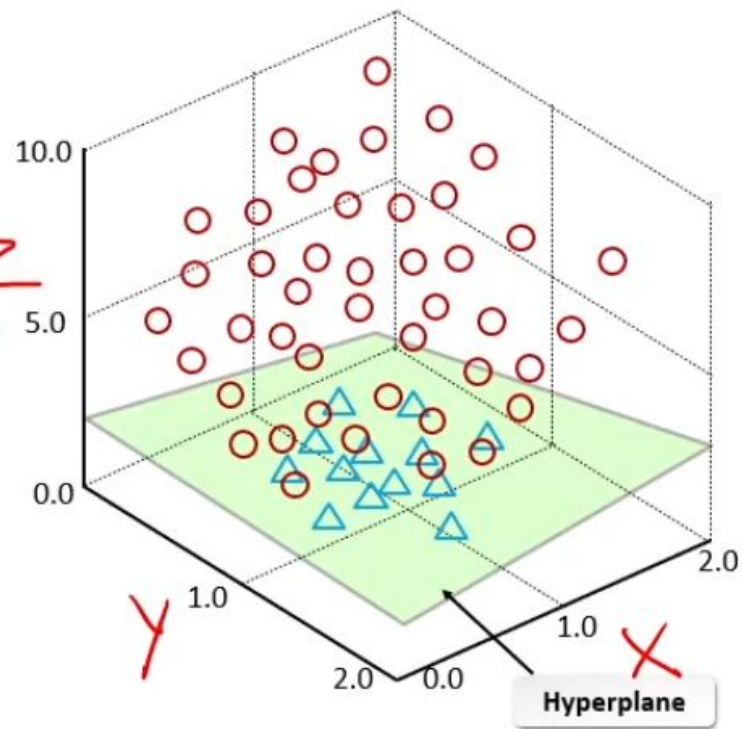
**High  $C \gg$  Hard margins  $\gg$  overfitting**



2-D Space



3-D Space



## Feature Expansion / Feature Mapping / Basis Expansion

- Explicitly transform input into higher-dimensional features

$$K(x, y) = \langle f(x), f(y) \rangle$$

**Assume:**

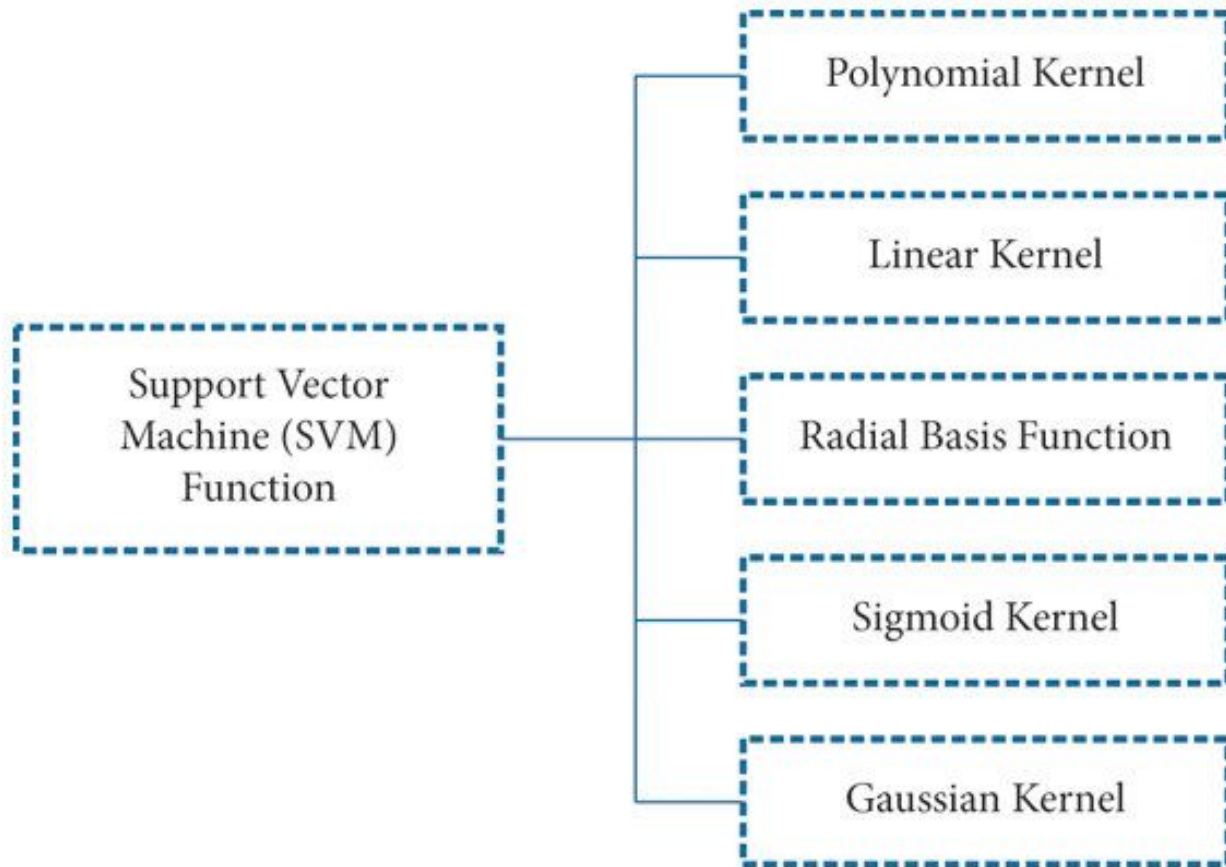
- $x = (x_1, x_2, x_3)$
- $y = (y_1, y_2, y_3)$

$$(x_1x_1, x_1x_2, x_1x_3, x_2x_1, x_2x_2, x_2x_3, x_3x_1, x_3x_2, x_3x_3)$$

# Kernel Trick

$$x = (0, 1, 2)$$
$$y = (3, 4, 5)$$

$$K(x, y) = (\underline{0} + \underline{4} + \underline{10})^2 = 196$$



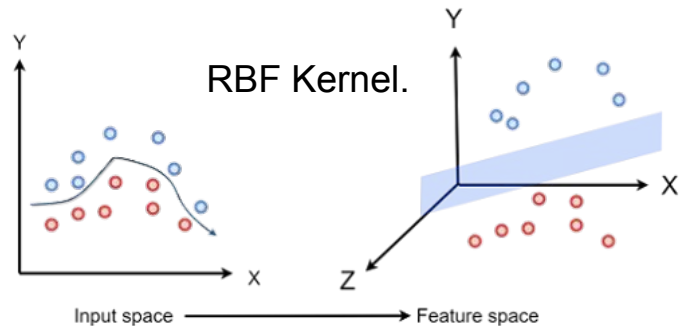
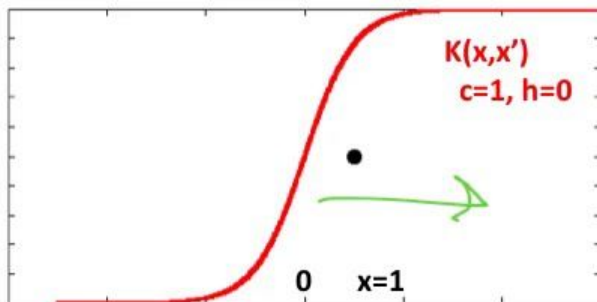
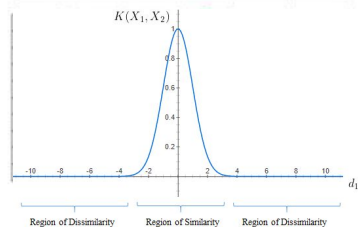
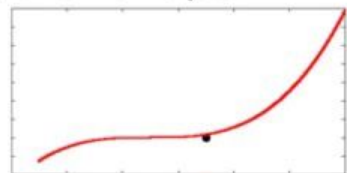


# Common kernel functions

- Some commonly used kernel functions & their shape:

- Polynomial  $K(a, b) = (1 + \sum_j a_j b_j)^d$
- Radial Basis Functions & Gaussian  
 $K(a, b) = \exp(-(a - b)^2 / 2\sigma^2)$
- Saturating, sigmoid-like:

$$K(a, b) = \tanh(ca^T b + h)$$



# Guidelines for Building SVM Models for Classification

- Consider using an SVM model when the problem you are trying to solve is sensitive to outliers.
- Consider using an SVM model when working with a high-dimensional dataset.
- In classification, recognize that the goal of an SVM model is to widen the margins as much as is feasible, while at the same time keeping data examples outside of the margins.
- Tune the (c)regularization hyperparameter to adjust the size of the margins.

# Guidelines for Building SVM Models for Classification

- Consider that narrowing the margins too much to keep all examples outside of those margins may lead to complications (e.g., overfitting). Consider softening the margins to avoid hard-margin overfitting issues.
- Recognize that softening the margins will likely place some examples within those margins, which is often a necessary tradeoff.
- Apply a kernel trick method to SVM models whose training data is not linearly separable.
- Consider the different types of kernel methods and how one might be more applicable to your current problem.
- قد يش المودل مركز على الجيران القريبين ولا مبسط اكثر؟  $\gamma >$