Module: Machine Learning

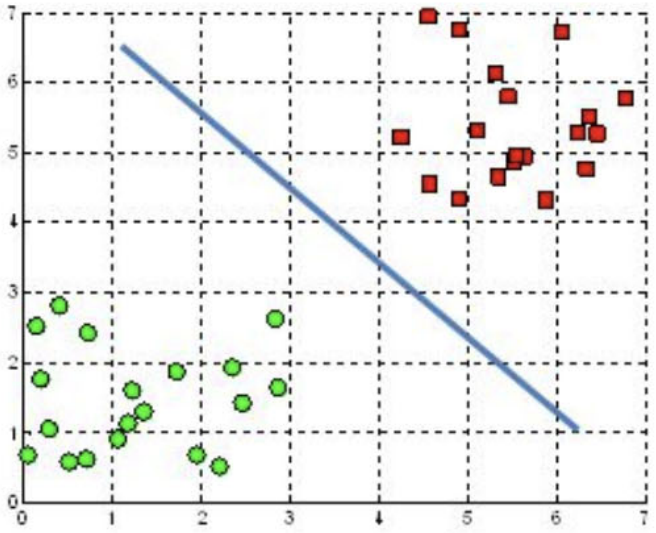
Live Session-5

Agenda:
Hard Margin SVM
Soft Margin SVM
Nonlinear SVM

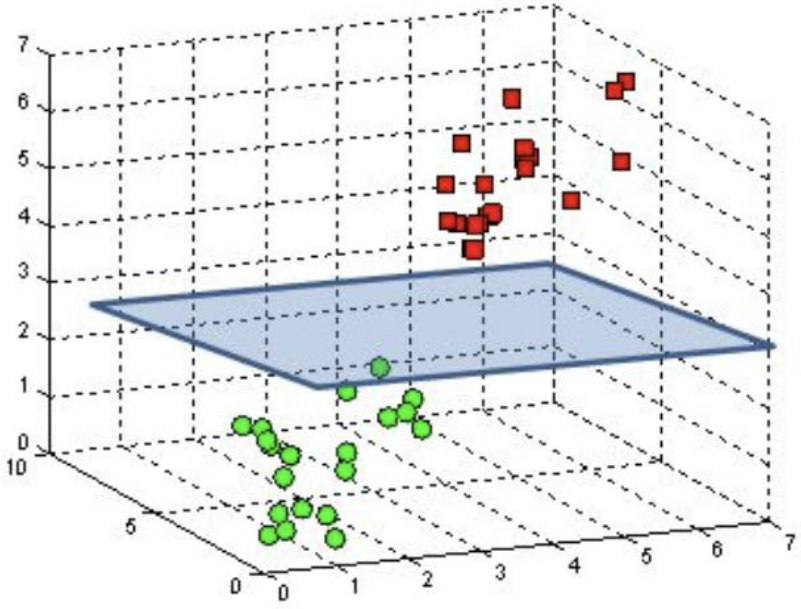
Hyperplane

In geometry, a **hyperplane** is a subspace whose dimension is one less than that of its ambient space. If a space is 3-dimensional then its **hyperplanes** are the 2-dimensional planes, while if the space is 2-dimensional, its **hyperplanes** are the 1-dimensional lines.

A hyperplane in $\mathbb{R}^2$ is a line



A hyperplane in $\mathbb{R}^3$ is a plane



Hyperplane: Mathematical representation

2D: $w_1 x_1 + w_2 x_2 + b = 0$ — 3 No.

$w^T x + b = 0$ ✓

3D: $w_1 x_1 + w_2 x_2 + w_3 x_3 + b = 0$ — 4 No.

$w^T x + b = 0$ ✓

nD: $w_1 x_1 + w_2 x_2 + \cdots + w_n x_n + b = 0$

$w^T x + b = 0$ ✓

n+1

$$\begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} \quad \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

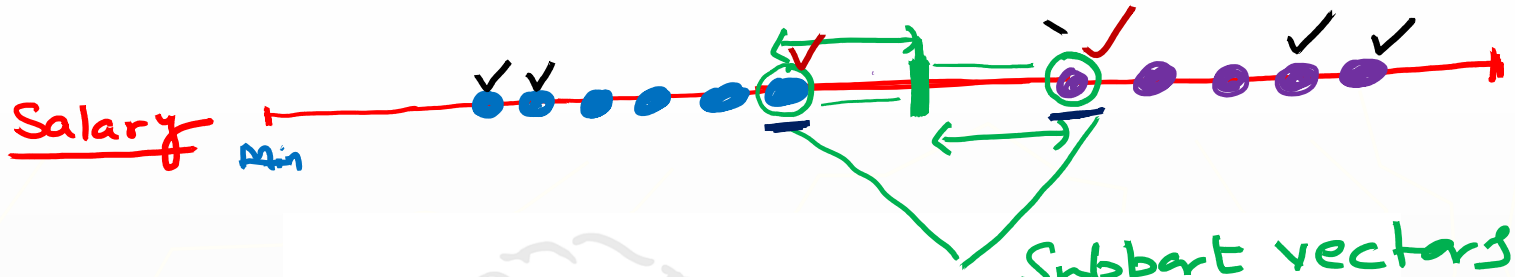
W X

SVM: Concept

A support vector machine (SVM) is a supervised machine learning classification algorithm. SVMs were introduced initially in 1960s and were later refined in 1990s.

To separate classes by finding a **hyperplane** which maximizes the distance between the closest boundary points (vectors) of each class.

SVM: Concept

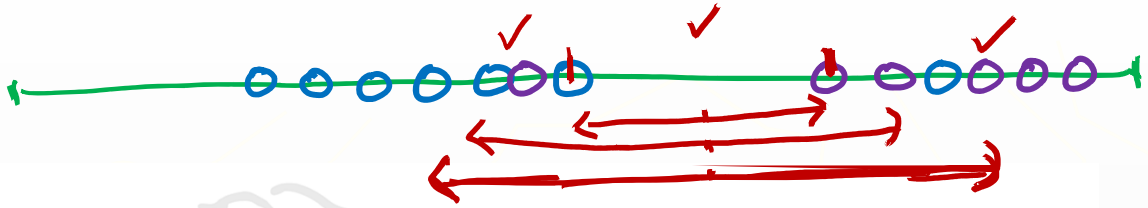


Objective: To find a hyperplane which maximize the margin from the closest boundary points of each class.

$\{x_i, y_i\}_{i=1}^{n} \longrightarrow$ Hyperplane

HARD MARGIN CLASSIFIER

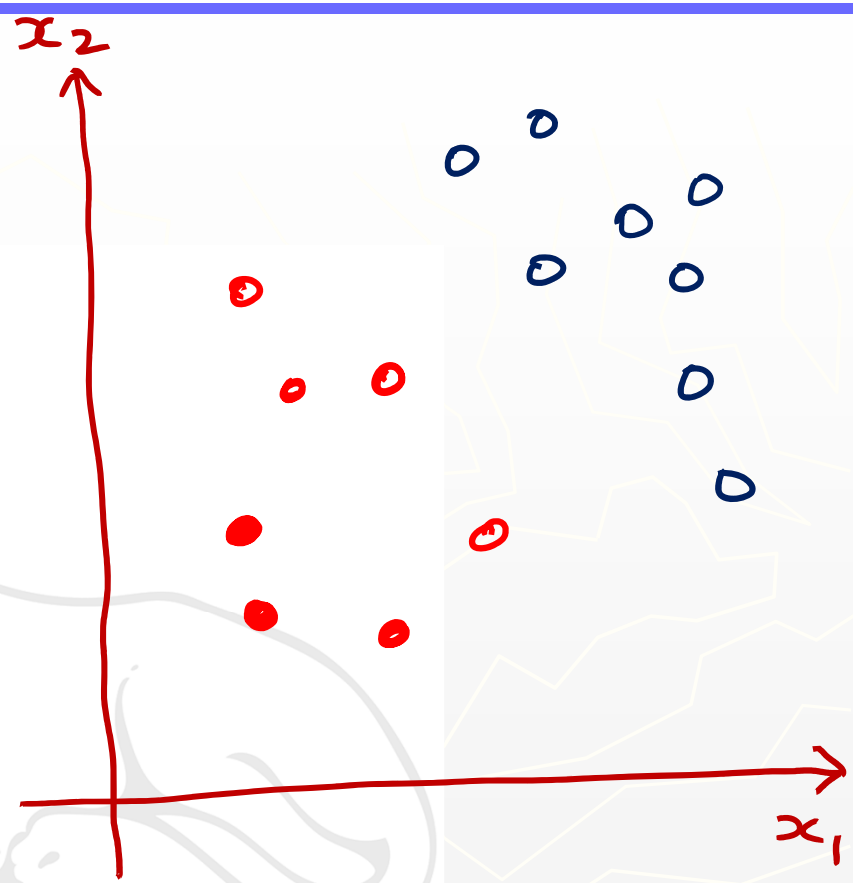
SVM: Concept



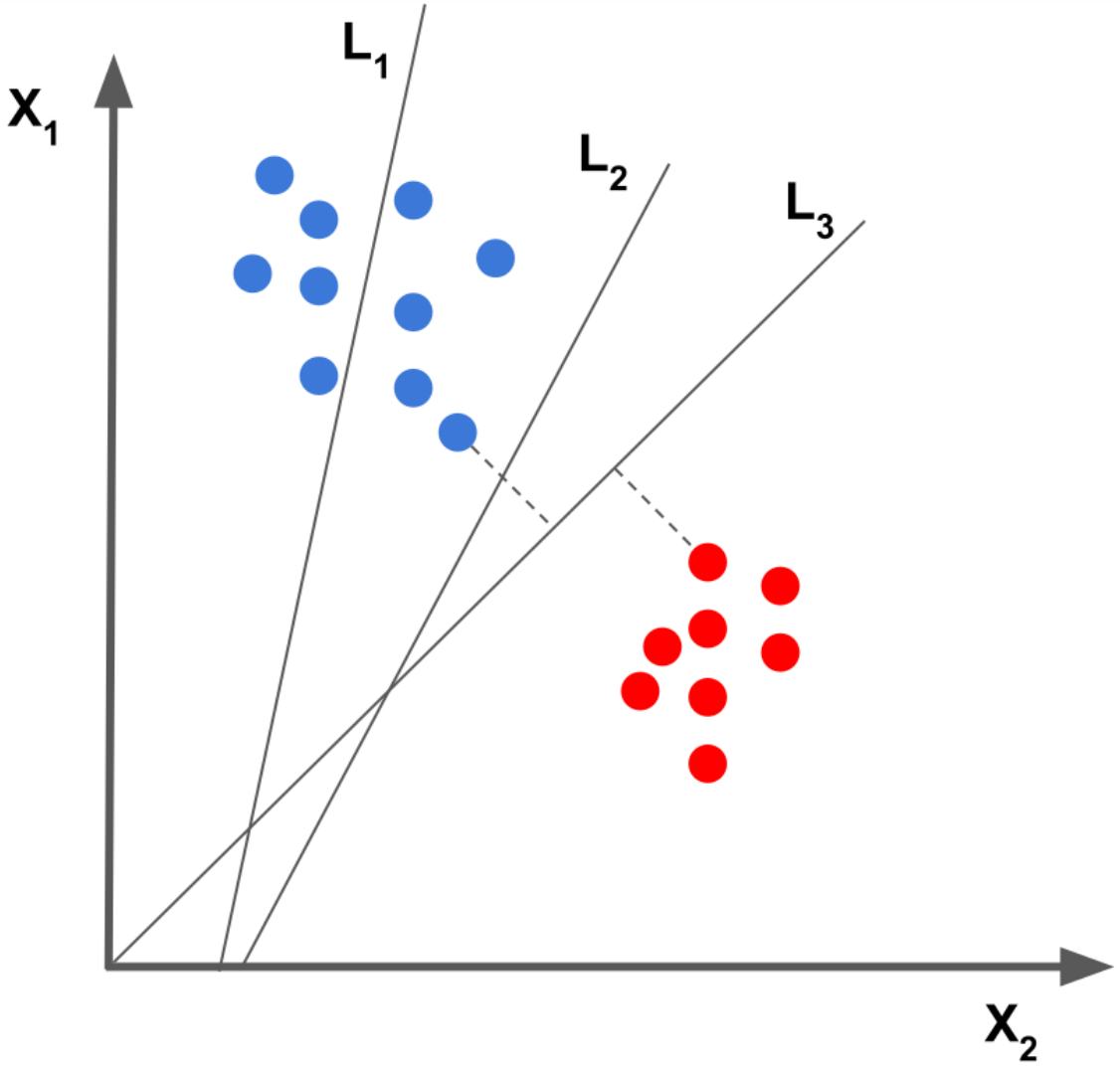
Add.-

SOFT MARGIN

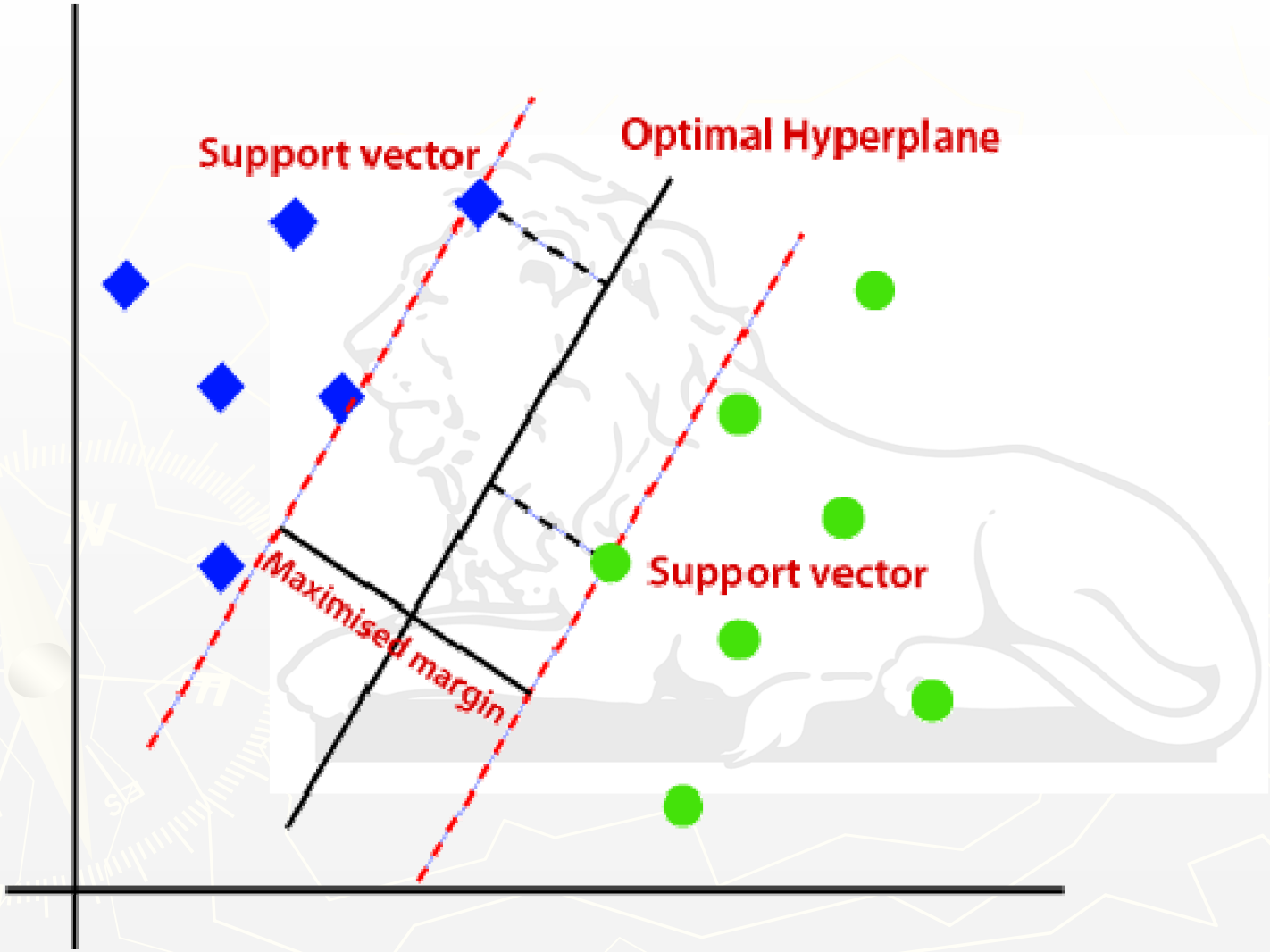
SVM: Concept



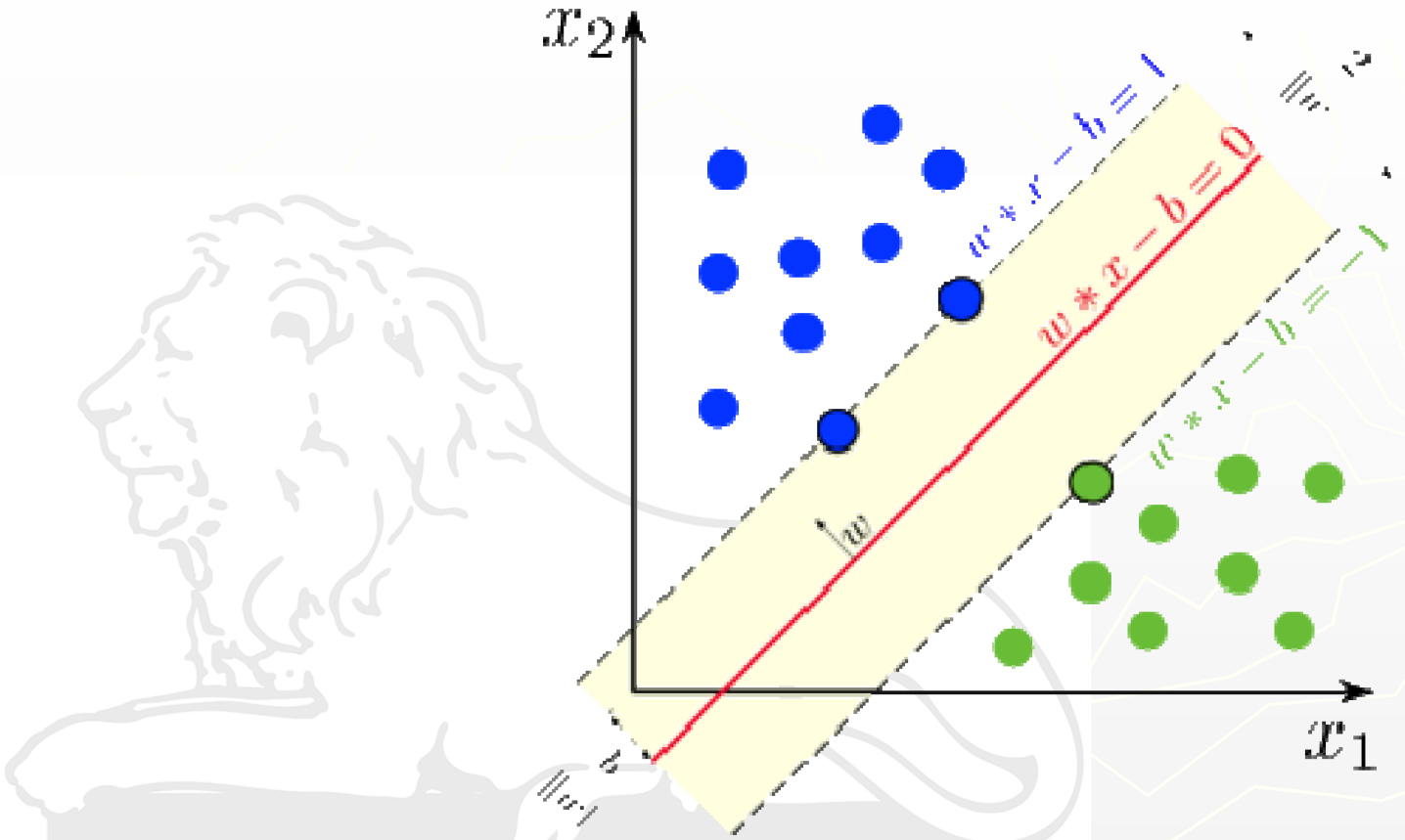
SVM: Concept 2D case



SVM: Concept 2D case



SVM: Concept

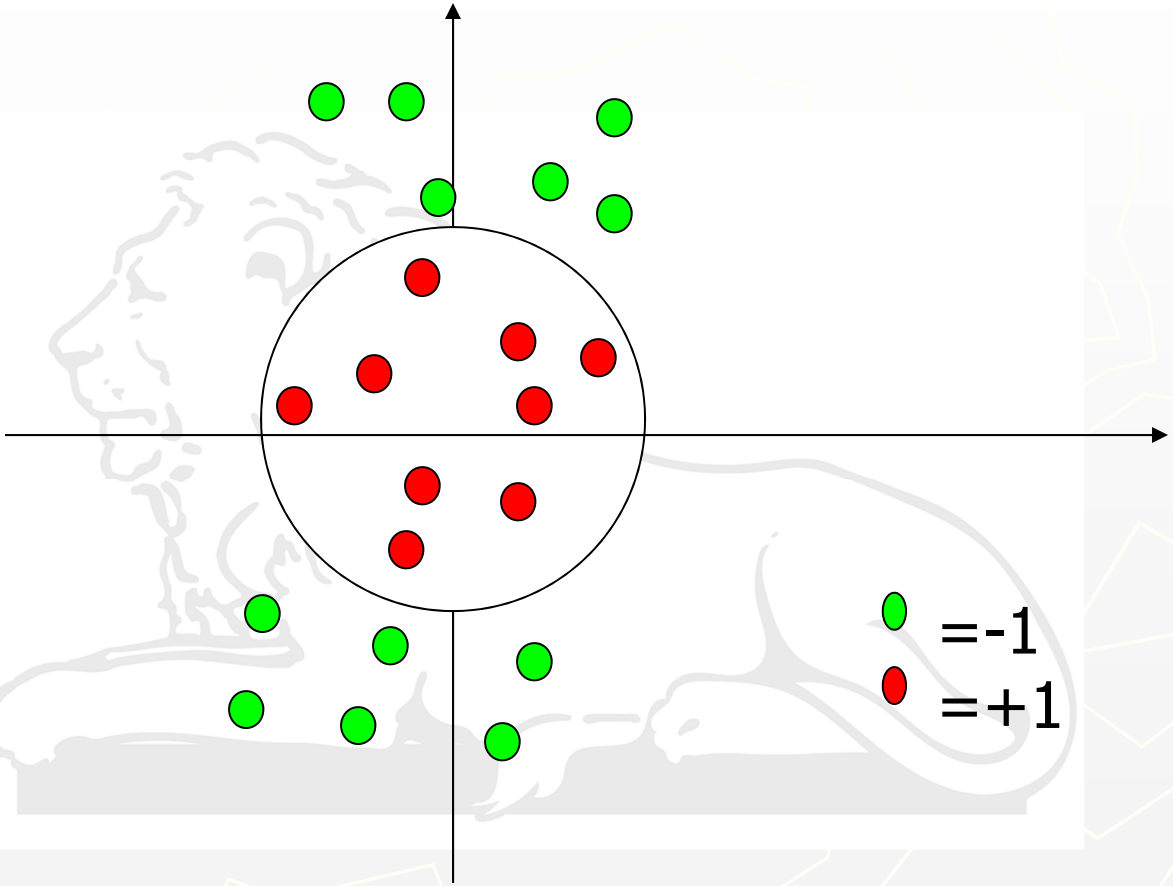


SVM: Formulation

SVM: Formulation

SVM: Formulation

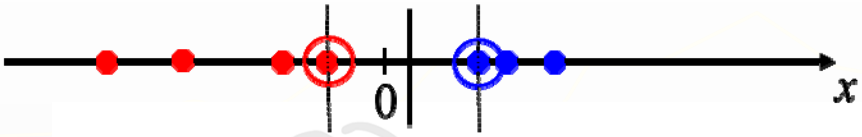
Problem with Linear SVM



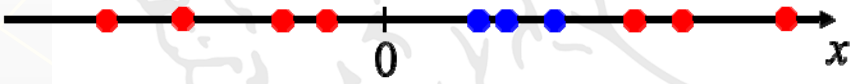
What if the decision function is not a linear?

Non-linear SVMs

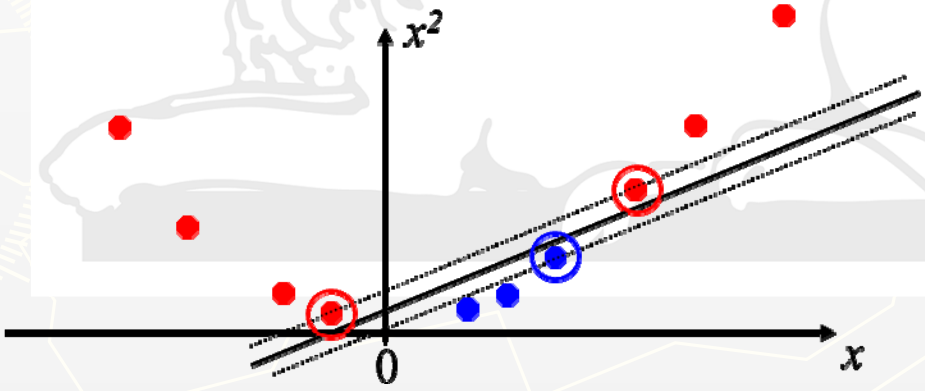
- Datasets that are linearly separable with some noise work out great:



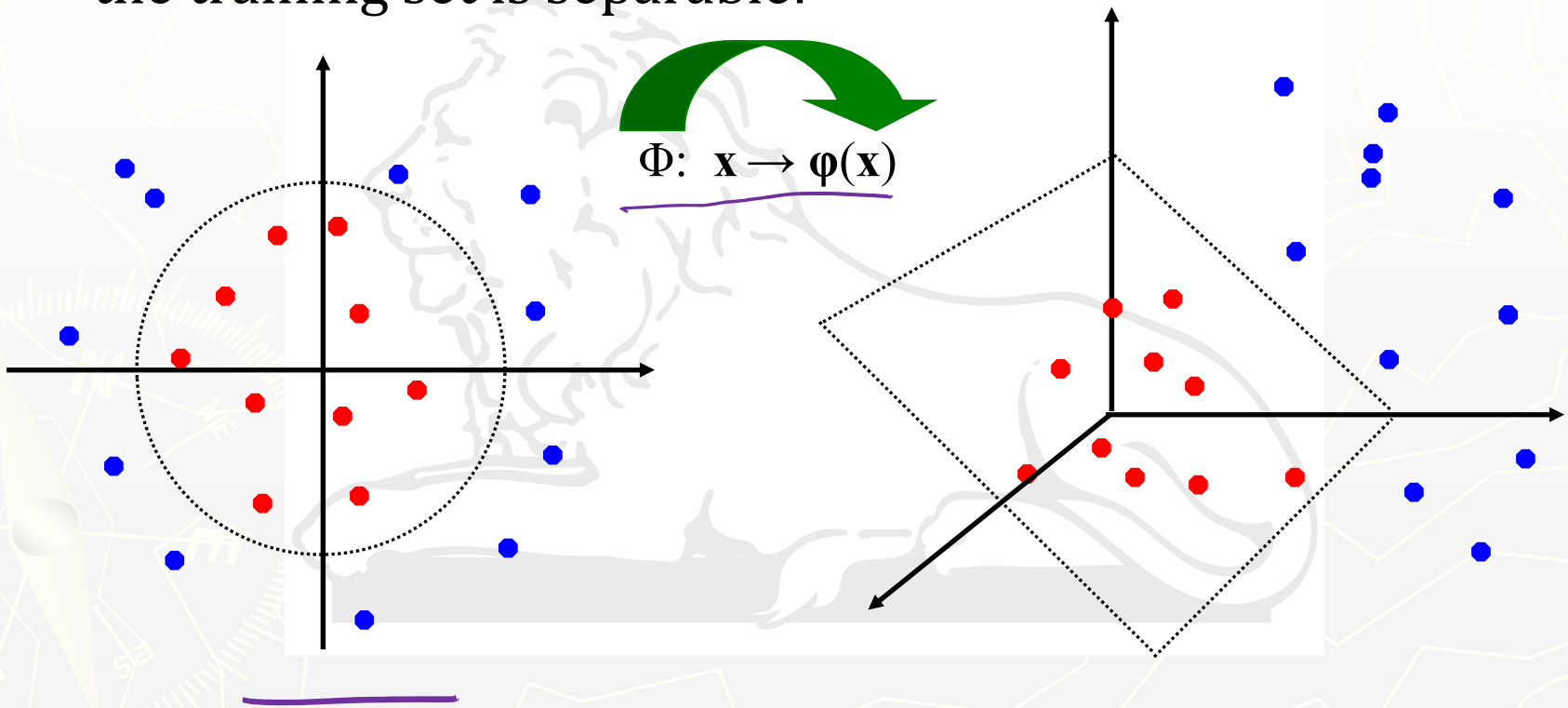
- But what are we going to do if the dataset is just too hard?



- How about… mapping data to a higher-dimensional space:

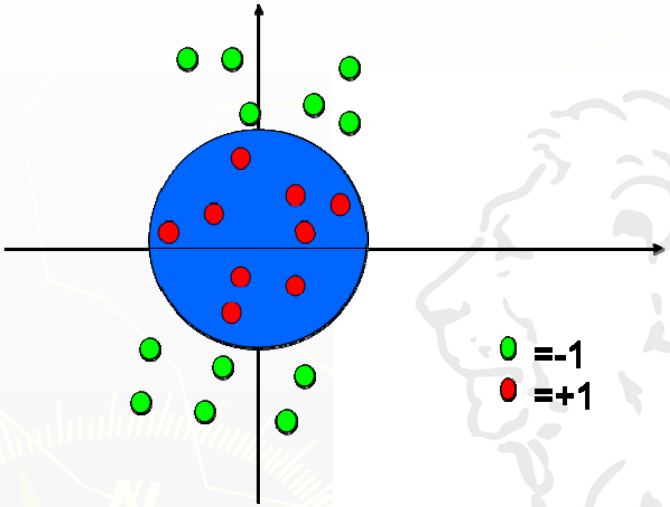


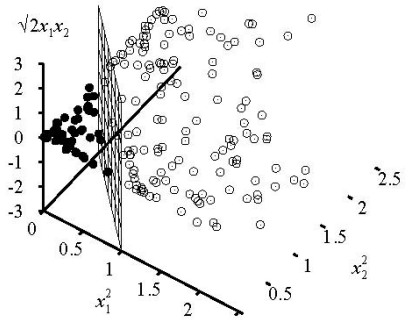
- General idea: the original feature space can always be mapped to some higher-dimensional feature space where the training set is separable:



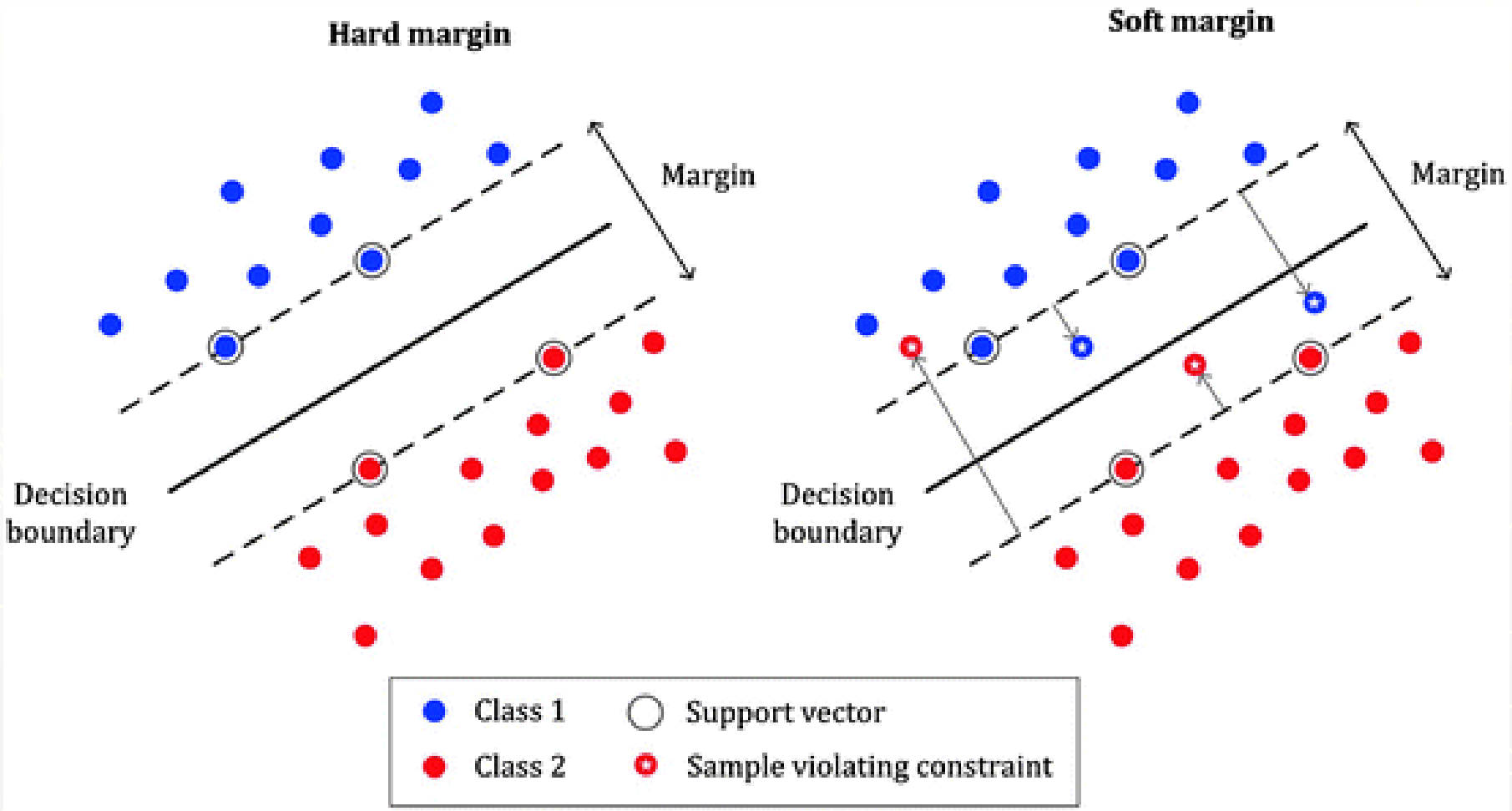
Kernel-SVM

Data points are linearly separable in the space $(x_1^2, x_2^2, \sqrt{2}x_1x_2)$





SVM: Concept 2D case



SVM and Logistic Regression

- The risk of overfitting is less in SVM, while Logistic regression is vulnerable to overfitting.
- SVM works well with unstructured and semi-structured data like text and images while logistic regression works with already identified independent variables.
- SVM is based on geometrical properties of the data while logistic regression is based on statistical approaches.

THANK YOU