



Linear Machines and SVM

– Part 2: The Concept of Margins

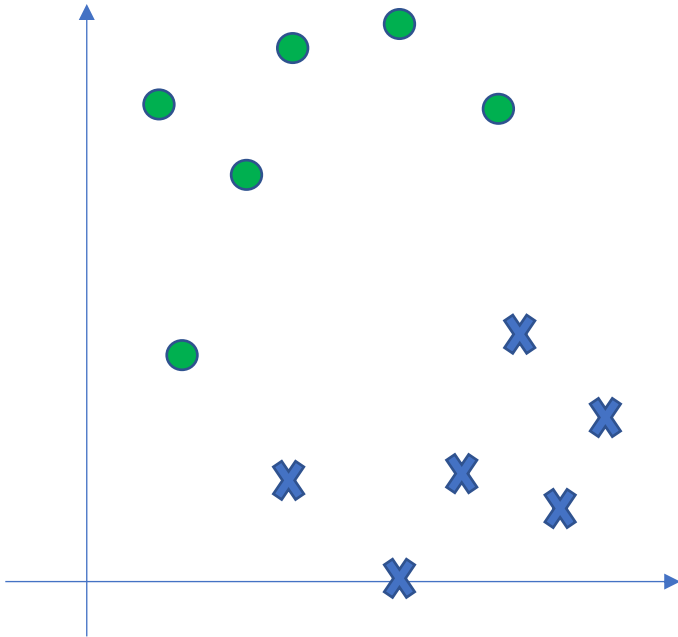
Objective



Objective

Illustrate Margins in
Classifier

Illustrating Linear Boundaries



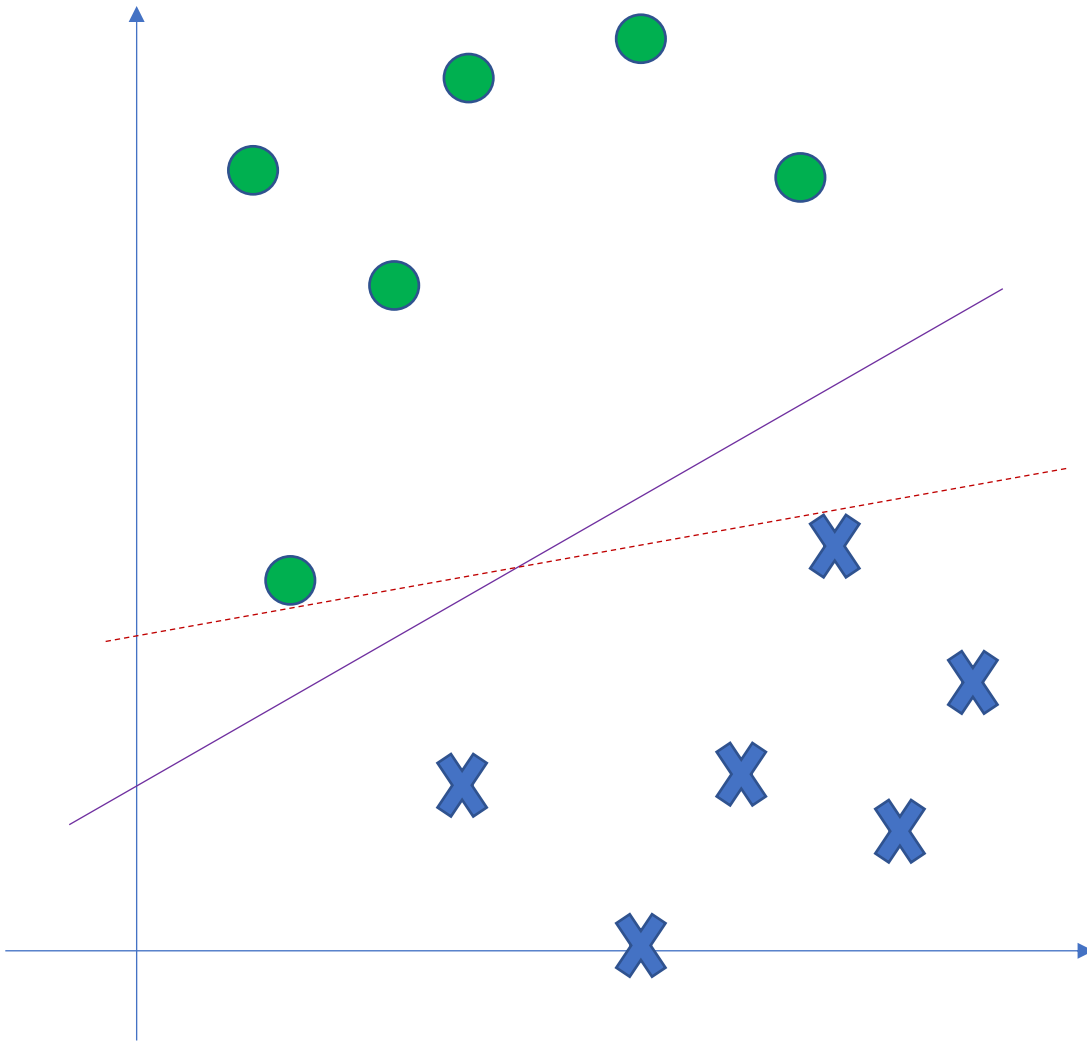
The decision boundaries is given by the line $g(\mathbf{x}) = 0$.

- For appreciating a geometric interpretation, we will write w_0 explicitly, i.e., we have

$$g(\mathbf{x}) = \mathbf{w}^t \mathbf{x} + w_0$$

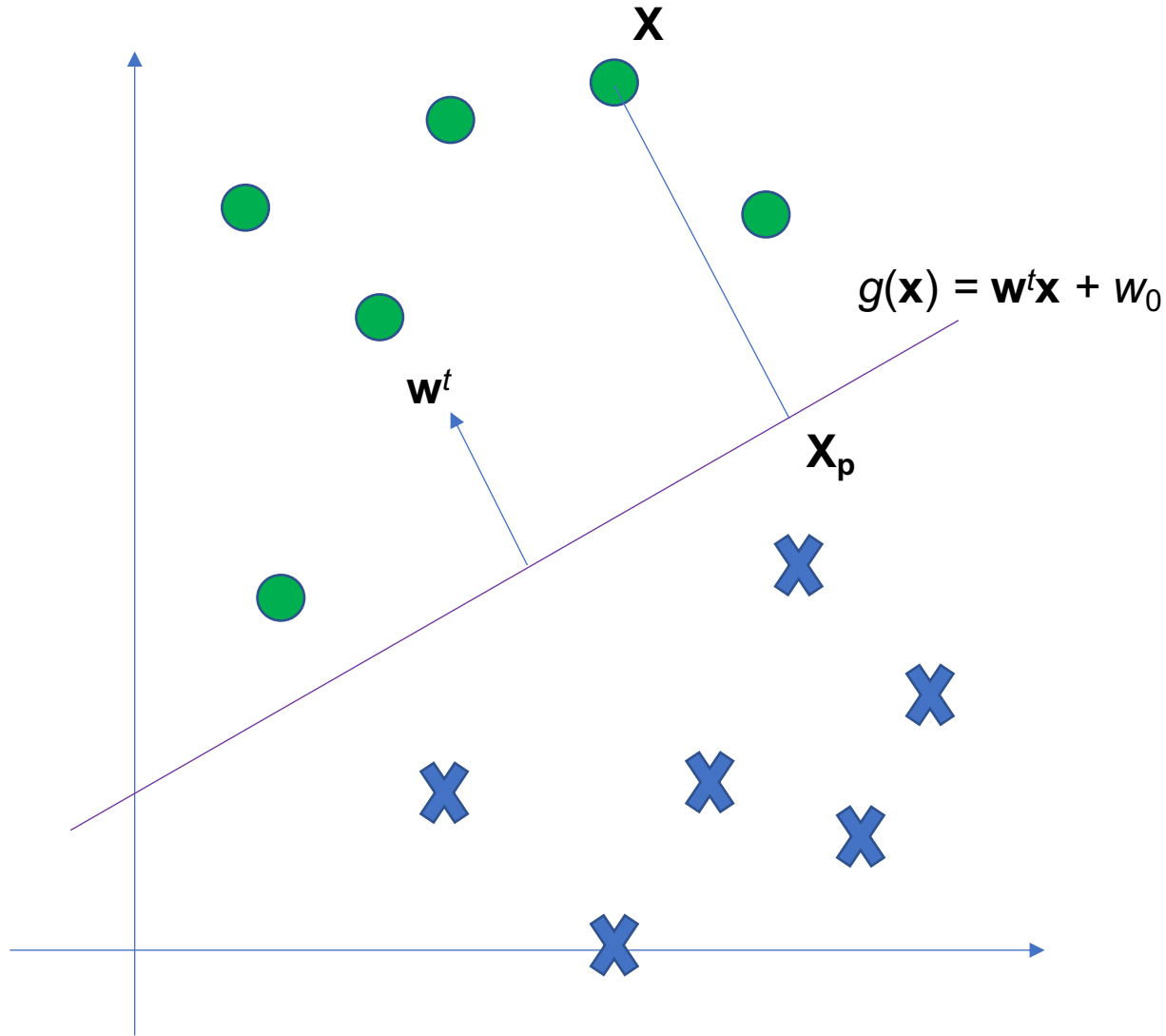
The normal vector of the decision line/plane is ____

Which one is better?

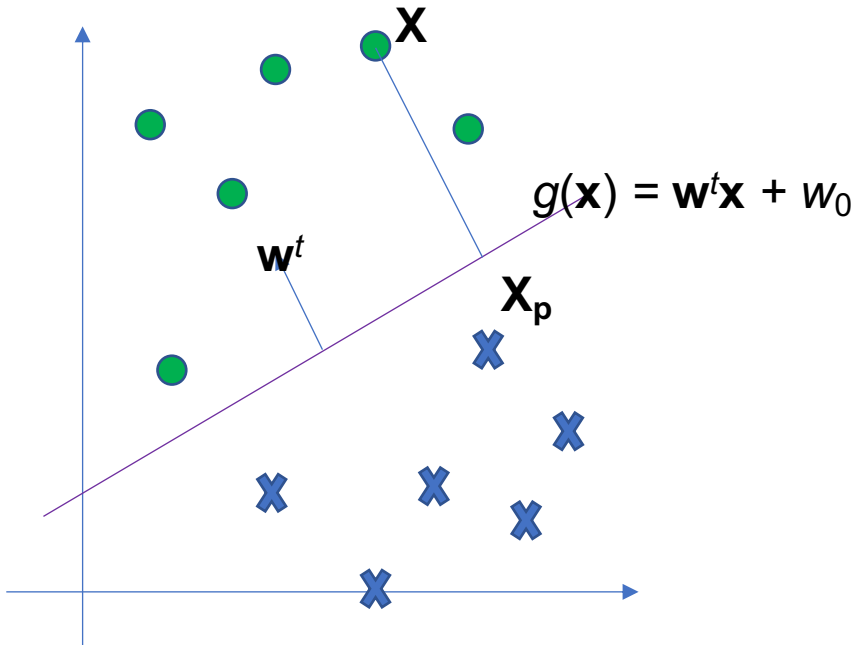


→ Consider the distances of the samples to the decision plane.

Distance to the Decision Plane



Distance to the Decision Plane



$g(\mathbf{x})$ gives an algebraic measure of the distance from \mathbf{x} to the decision plane.

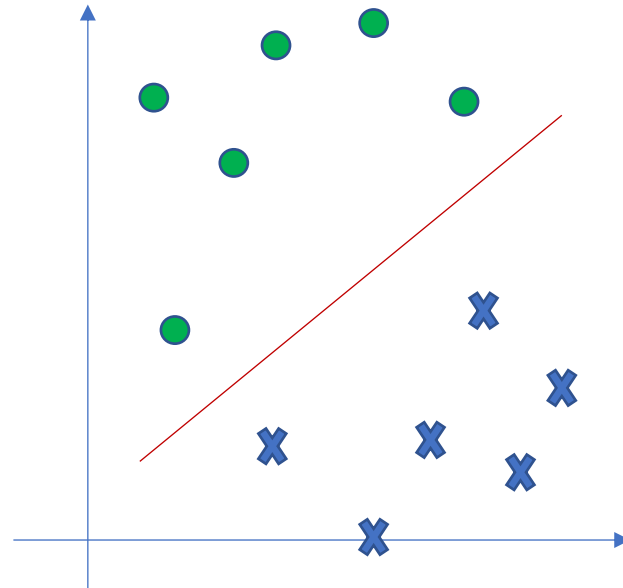
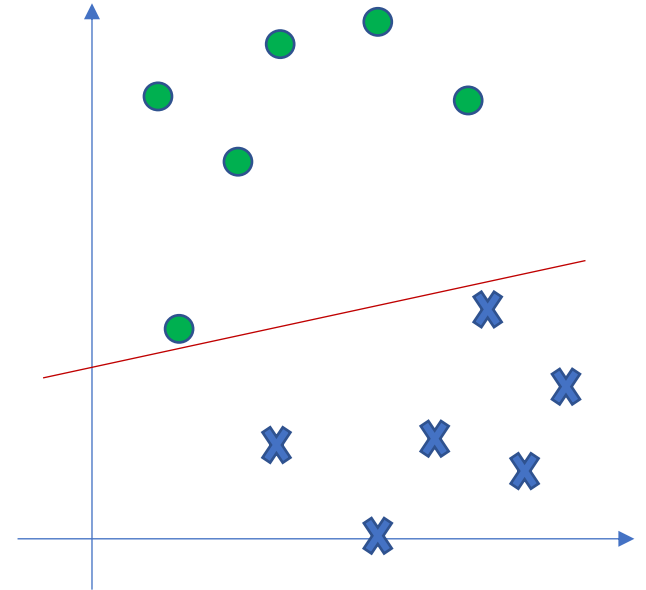
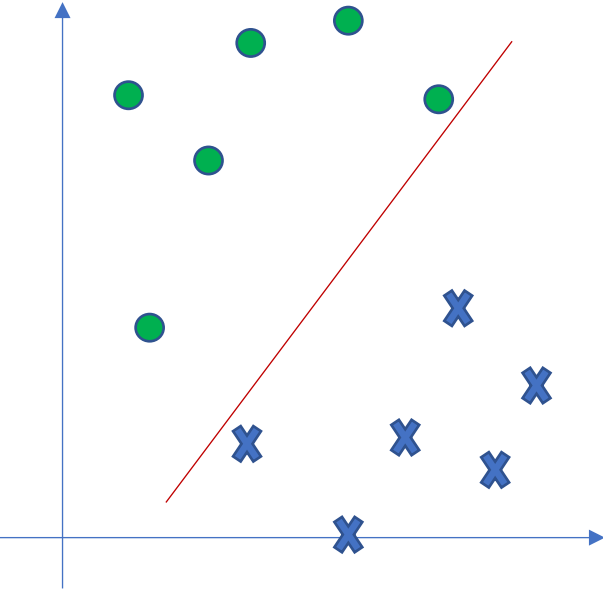
The Concept of Margins

| Let $g(\mathbf{x}) = 0$ be a decision plane

- The **margin** of a sample \mathbf{x} (w.r.t. the decision plane) is the distance from \mathbf{x} to the plane.
- For a given set of samples S , the margin (w.r.t a decision plane) is the smallest margin over all \mathbf{x} in S .

| For a given set, a classifier that gives rise to a larger margin will be better.

Use Margins to Compare Solutions



➔ Max margin

➔ SVM