

Support Vector Machines

- 1 Revisiting Linear Separation
 - High Dimensional Spaces
- 2 Structural Risk Minimization
 - Margins
 - Mathematical Formulation
- 3 Support Vector Machines

- 1 Revisiting Linear Separation
 - High Dimensional Spaces
- 2 Structural Risk Minimization
 - Margins
 - Mathematical Formulation
- 3 Support Vector Machines

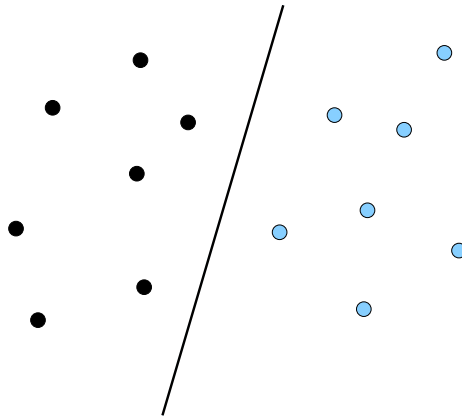
Observation
Almost everything becomes linearly separable when represented in high-dimensional spaces

"Ordinary" low-dimensional data can be "scattered" into a high-dimensional space.

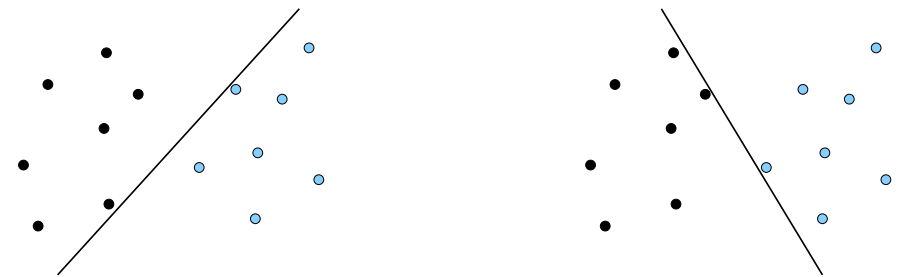
Two problems emerge

- 1 Many free parameters → bad generalization
- 2 Extensive computations

Linear Separation



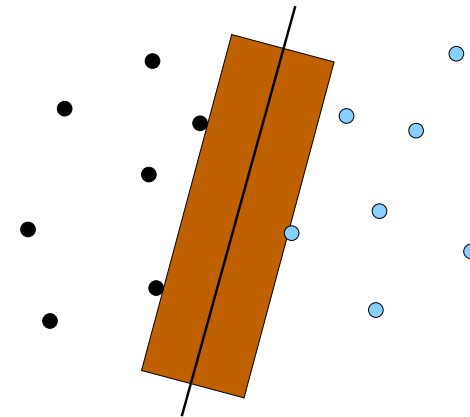
Many acceptable solutions \rightarrow bad generalization



• Structural Risk

- 1 Revisiting Linear Separation
 - High Dimensional Spaces
- 2 Structural Risk Minimization
 - Margins
 - Mathematical Formulation
- 3 Support Vector Machines

Hyperplane with margins



Less arbitrariness \rightarrow better generalization

- Wide margins restrict the possible weights to choose from
- Less risk to choose bad weights by accident
- Reduced risk for bad generalization

Minimization of the structural risk \equiv maximization of the margin

Out of all hyperplanes which solve the problem
the one with **widest margin** will **generalize best**

How wide is the margin?

- 1 Select two points, \vec{p} and \vec{q} , on the two margins:

$$\vec{w}^T \vec{p} + b = 1 \quad \vec{w}^T \vec{q} + b = -1$$

- 2 Distance between \vec{p} and \vec{q} along \vec{w} :

$$d = \vec{w}^T (\vec{p} - \vec{q}) \frac{1}{\|\vec{w}\|}$$

- 3 Simplify:

$$d = \frac{\vec{w}^T \vec{p} - \vec{w}^T \vec{q}}{\|\vec{w}\|} = \frac{(1 - b) - (-1 - b)}{\|\vec{w}\|} = \frac{2}{\|\vec{w}\|}$$

Maximal margin corresponds to minimal length of the weight vector

Mathematical Formulation

- Separating Hyperplane

$$\vec{w}^T \vec{x} + b = 0$$

- Hyperplane with a margin

$$\vec{w}^T \vec{x} + b \geq 1 \quad \text{when } t = 1$$

$$\vec{w}^T \vec{x} + b \leq -1 \quad \text{when } t = -1$$

- Combined

$$t(\vec{w}^T \vec{x} + b) \geq 1$$

Best Separating Hyperplane

Minimize

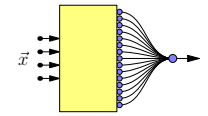
$$\vec{w}^T \vec{w}$$

Constraints

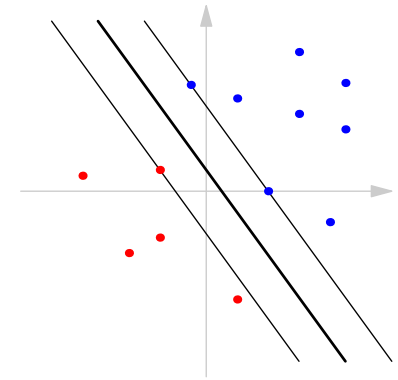
$$t_i(\vec{w}^T \vec{x}_i + b) \geq 1 \quad \forall i$$

- 1 Revisiting Linear Separation
 - High Dimensional Spaces
- 2 Structural Risk Minimization
 - Margins
 - Mathematical Formulation
- 3 Support Vector Machines

Support Vector Machines



- Transform the input to a suitable high-dimensional space
- Choose the separation that has maximal margins



Support Vector Machines

- Advantages
 - Very good generalization
 - Works well even with few training samples
 - Fast classification
- Disadvantages
 - Non-local weight calculation
 - Hard to implement efficiently