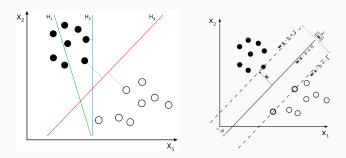
Support vector machines

Support vector machine (SVM)



 $\textbf{Figure 6:} \ \ \mathsf{Maximum \ margin \ idea} \ \ \mathsf{of \ SVMs \ http://en.wikipedia.org} \ .$

Principal idea

- The (two class) starting idea is that two point clouds are linearly separable
- The problem is to find the separating hyperplane that maximises the error margin
- A solution to the problem can be formulated as an inequality constrained quadratic optimisation problem

Linearly non-separable case

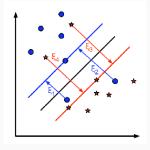


Figure 7: Linearly non-separable case http://http://docs.opencv.org.

- ullet We must allow errors ξ_i with respect to the margin inequalities
- We must penalise errors (C) in the optimisation procedure

Non-linear SVM

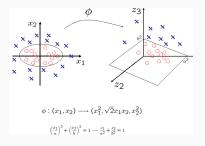


Figure 8: "Kernel trick" http://omega.albany.edu .

- Apply a transformation kernel to inputs to map them to a higher dimensional space
- The dual formulation of the quadratic optimisation problem allows efficient computation

State-of-the-art performance with many benchmarks

- Parameter 1: the error penalty C
- Parameter 2: the choice of the kernel $\phi(\vec{x})$ and optionally the kernel parameters (e.g., the degree of a polynomial)
- At the core are very efficient methods of quadratic optimisation and especially the dual formulation of the optimisation problem

Summary

Summary

- Idea of multi-layer perception (MLP) networks and their training
- MLP parameters (from underfitting to overfitting)
- Idea of support vector machines (SVMs)
- SVM parameters