

# Numerical Methods and Optimization: introduction

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Numerical Methods and Optimization  
Master in Computer Science – University of Pisa

## Course Organization

- ▶ 1 course (12 cfu/ects)
- ▶ 1 program
- ▶ 1 exam
- ▶ 2 lecturers

## Federico Poloni (Numerical methods)

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## Information

### Course Schedule

- ▶ Tuesday 9:00-11:00 room L1
- ▶ Tuesday 16:00-18:00 room H-lab
- ▶ Wednesday 11:00-13:00 room C (except September 21: room C1)
- ▶ Thursday 11:00-13:00 room C

### Web page

<https://elearning.di.unipi.it/course/view.php?id=77>

### Exam

Written and oral exam

## Bibliography

- ▶ S. Boyd, L. Vandenberghe, Convex optimization, Cambridge University Press, 2004 (available on <http://web.stanford.edu/~boyd/cvxbook/>)
- ▶ M.S. Bazaraa, H.D. Sherali, C.M. Shetty, Nonlinear programming: theory and algorithms, Wiley & Sons, 2006 (Chapters 1-6, 8-9)
- ▶ J. Nocedal, S. Wright, Numerical Optimization, Springer Series in Operations Research and Financial Engineering, 2006 (Chapters 1-3, 5, 12, 16, 17)
- ▶ A.R. Conn, K. Scheinberg, L.N. Vicente, Introduction to Derivative-Free Optimization, SIAM series on Optimization, 2009 (Chapters 1, 7)
  
- ▶ J. Demmel, Applied Numerical Linear Algebra, SIAM press, 1996
- ▶ L. N. Trefethen, D. Bau, Numerical Linear Algebra, SIAM press, 1997

## Syllabus

- ▶ Linear algebra and calculus background
- ▶ Unconstrained optimization and systems of equations
- ▶ Direct and iterative methods for linear systems
- ▶ Iterative methods for nonlinear systems
- ▶ Numerical methods for unconstrained optimization
- ▶ The linear least-squares problem
- ▶ Iterative methods for computing eigenvalues
- ▶ Constrained optimization and systems of equations
- ▶ Lagrangian duality
- ▶ Numerical methods for constrained optimization
- ▶ The fast Fourier transform
- ▶ Applications: regression, parameter estimation, approximation and data fitting, support vector machines, image and signal reconstruction
- ▶ Software tools for numerical and optimization problems (Matlab).

## Support Vector Machines for Data Classification

Given training data in different classes (labels **known**)

Predict test data (labels **unknown**)

Examples:

- ▶ handwritten digits recognition
- ▶ spam filtering
- ▶ credit card fraud detection
- ▶ marketing
- ▶ medical diagnosis
- ▶ image processing
- ▶ ...

## Support Vector Machines for Data Classification

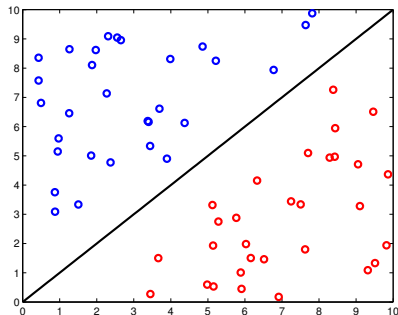
Given two sets  $A, B \subset \mathbb{R}^n$  (training set).

Assume that  $A$  and  $B$  are linearly separable, i.e., there is an hyperplane

$H = \{x \in \mathbb{R}^n : w^T x + b = 0\}$  such that

$$w^T x^i + b > 0 \quad \forall x^i \in A$$

$$w^T x^j + b < 0 \quad \forall x^j \in B$$

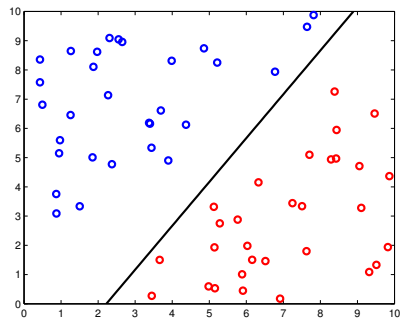
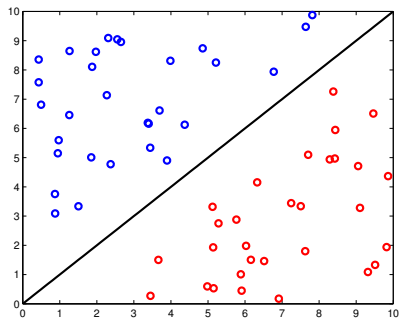


Test data  $x$ :

decision function  $f(x) = \text{sign}(w^T x + b)$

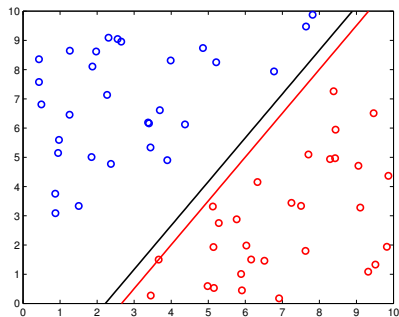
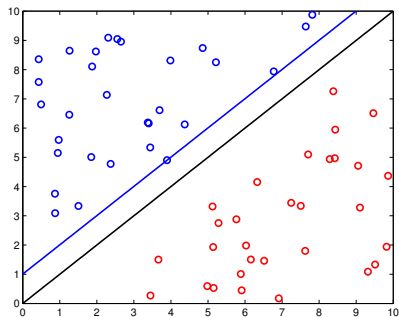
## Support Vector Machines for Data Classification

Many possible choices of  $w$  and  $b$ . Which hyperplane do we choose?





## Support Vector Machines for Data Classification



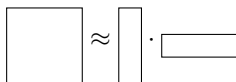
We look for the separating hyperplane with the **maximum margin** of separation. This problem can be modeled as

$$\begin{cases} \min \|w\|^2 \\ w^T x^i + b \geq 1 & \forall x^i \in A \\ w^T x^j + b \leq -1 & \forall x^j \in B \end{cases}$$

## Low-rank approximation with the Singular Value Decomposition

### Problem

Given a matrix  $M \in \mathbb{R}^{n \times m}$ , approximate it with the product of a 'tall thin'  $A \in \mathbb{R}^{n \times k}$  and a 'fat large'  $B \in \mathbb{R}^{k \times m}$  ( $k \ll n, m$ ):



$$\min_{A,B} \|M - AB\|$$

Why?

- ▶ Reduce data dimension
- ▶ Reveal features

Applications:

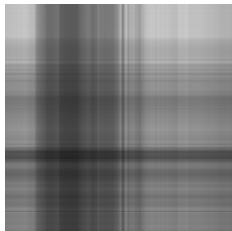
- ▶ Text and data mining
- ▶ Neural networks
- ▶ Web search
- ▶ Graph / community analysis. . .

## An example

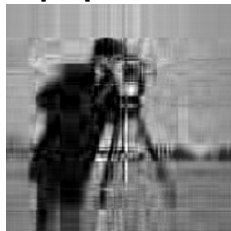
An example easy to visualize: image compression by approximation.  
Black/white image: matrix with color intensities  $\in [0, 1]$ .



Original ( $512 \times 512$ )



$k = 1$



$k = 10$



$k = 25$



$k = 50$



$k = 100$

## Eigenvalue problems

### Problem

Given a matrix  $M \in \mathbb{R}^{n \times m}$ , approximate it with the product of a 'tall thin'  $A \in \mathbb{R}^{n \times k}$  and a 'fat large'  $B \in \mathbb{R}^{k \times m}$  ( $k \ll n$ ):  $\min_{A,B} \|M - AB\|$ .

Optimal  $A, B$  can be obtained from **eigenvectors** of  $M^T M$  and  $MM^T$ .

- ▶ How can we solve this problem?
- ▶ What if  $M$  is very large and sparse?
- ▶ What if  $M$  has some special structure?
- ▶ Can we avoid forming  $M^T M$  and  $MM^T$ ?
- ▶ Is the solution numerically stable, or should we expect large errors?