

# SVM

1 The linearly separable case

2 Non linearly separable case

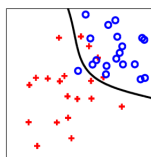
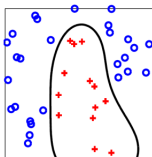
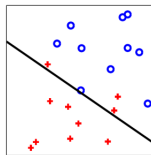
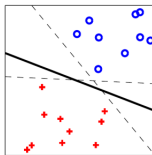
3 Non linear SVMs

# SVMs

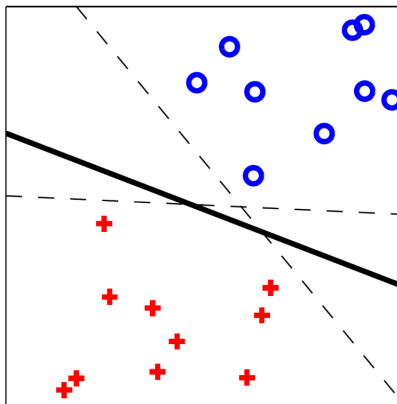
## Plan du cours

- The linearly separable case
- The linearly separable case
- The kernel trick
- Non linear SVMs

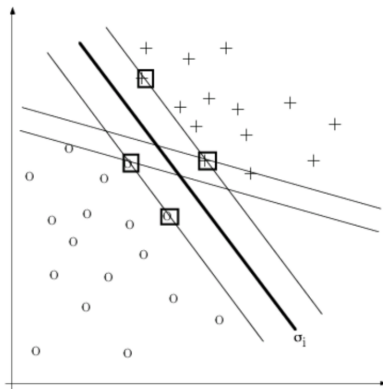
# Some examples of classification problems



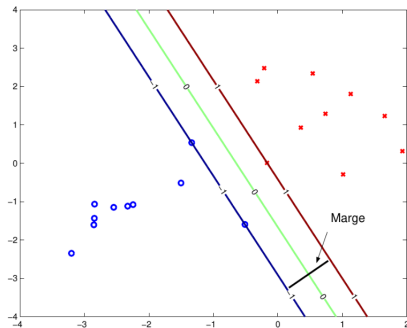
# Some examples of classification problems



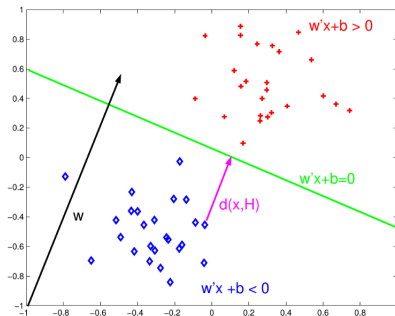
# Notion of margin



# Notion of margin



# Notion of margin





# Definitions

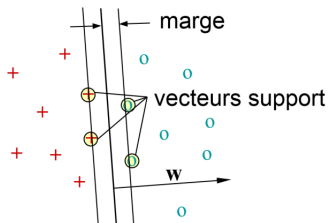
- Margin : Distance between the nearest example of the training set and the decision boundary.
- Dataset :  $\{(x_i, y_i), i = 1, \dots, n\}, x_i \in \mathbb{R}^d, y_i \in \{1, -1\}$
- Decision function :  $f(x) = w^T x + b = 0$ 
  - $f(x) = 0$  : separating hyperplane
  - $f(x) > 0$  : class 1 ( $y_i = 1$ )
  - $f(x) < 0$  : class 2 ( $y_i = -1$ )

# Formalization of the problem

- Decision function :  $h_w(x) = w^T x + b$ . Separating hyperplane  
 $h_w(x) = 0$
- Parameters :
  - $w$  is normal to the hyperplane
  - $b$  is the offset
- The parameters  $w$  and  $b$  are non unique. Indeed,  $kw$  and  $kb$  yield the same decision boundary

# Formalization of the problem

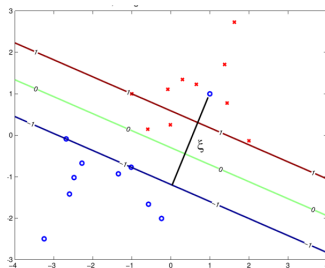
How should we choose  $h_w(x) = w^T x + b = 0$ ?



Solution : we maximize the margin!

# Non linearly separable case

What can we do if the data are not linearly separable?

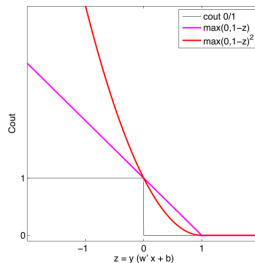
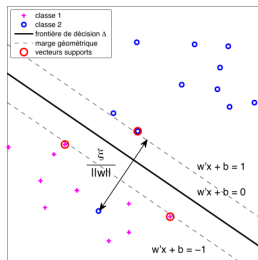


# Non linearly separable case

- Idea : model potential errors using slack positive variables  $\xi_i$  associated to the observations  $(x_i, y_i)$
- We have two situations :
  - No error :  $y_i(w^T x_i + b) \geq 1 \Rightarrow \xi_i = 0$
  - Error :  $y_i(w^T x_i + b) < 1 \Rightarrow \xi_i = 1 - y_i(w^T x_i + b) > 0$

# Non linearly separable case

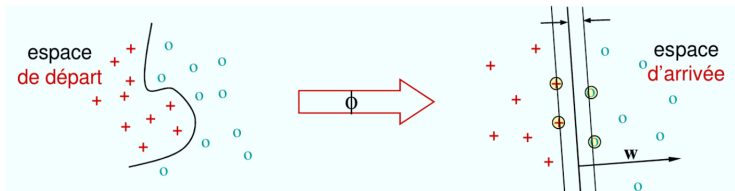
We associate to this situation a cost function :



In this example one single point is misclassified

# Non linear SVMs

- How can we extend this algorithm to the non linear case ?
- Principe : we transport the data into another space where the data are linearly separable using a transformation  $\varphi : x \rightarrow \varphi(x)$



# Non linear SVMs

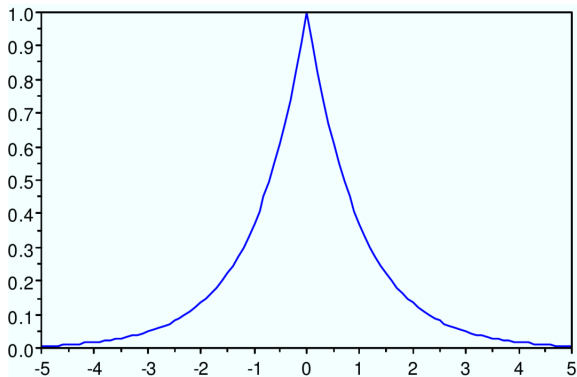
## The Kernel trick

- We observe that in the SVM algorithm, the only quantities involved are  $K(x, y) = \langle \phi(x), \phi(y) \rangle$
- We are given an explicit expression of  $K$  and forget  $\phi$



# Non linear SVMs

## Examples of kernels



# Non linear SVMs

## Examples of kernels

