MACHINE LEARNING

Linear Classifier: The Perceptron

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Summary

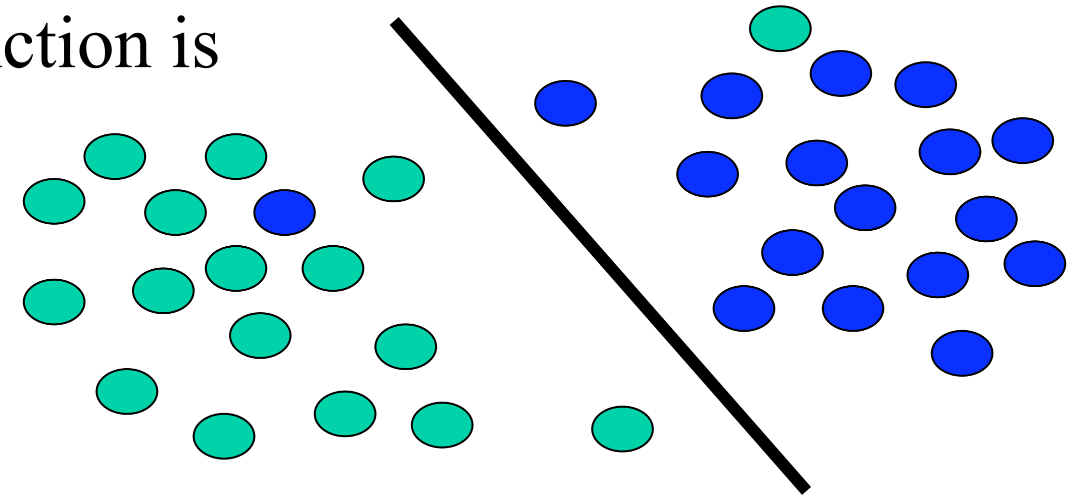
- Computational Learning theory
  - Perceptron Learning
  - Margins

Linear Classifier (1)

- The equation of a hyperplane is

$$f(\vec{x}) = \vec{x} \cdot \vec{w} + b = 0, \quad \vec{x}, \vec{w} \in \Re^n, b \in \Re$$

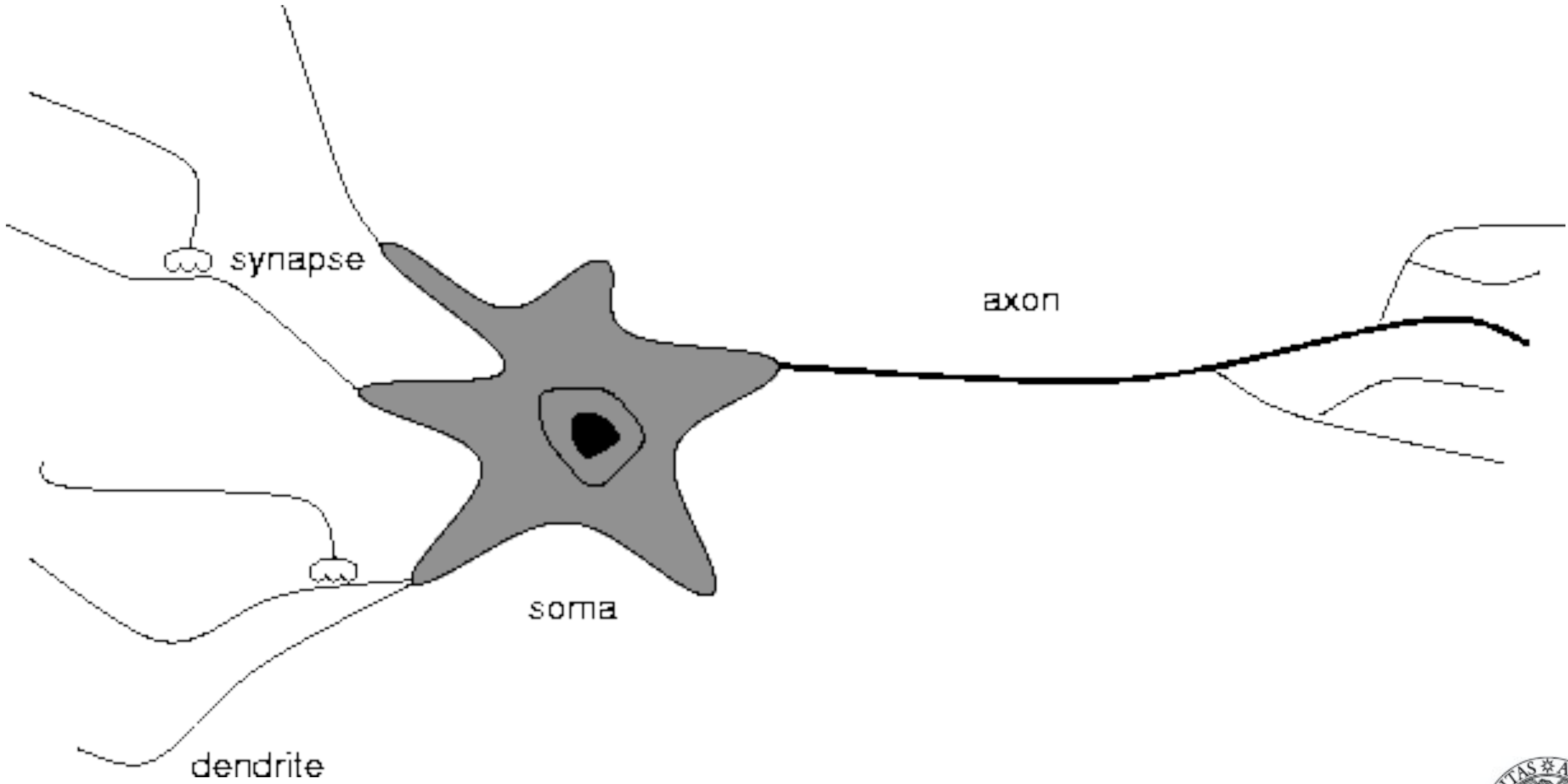
- $\vec{x}$ is the vector representing the classifying example
- $\vec{w}$ is the gradient to the hyperplane
- The classification function is
  $h(x) = \text{sign}(f(x))$



Linear classifiers (2)

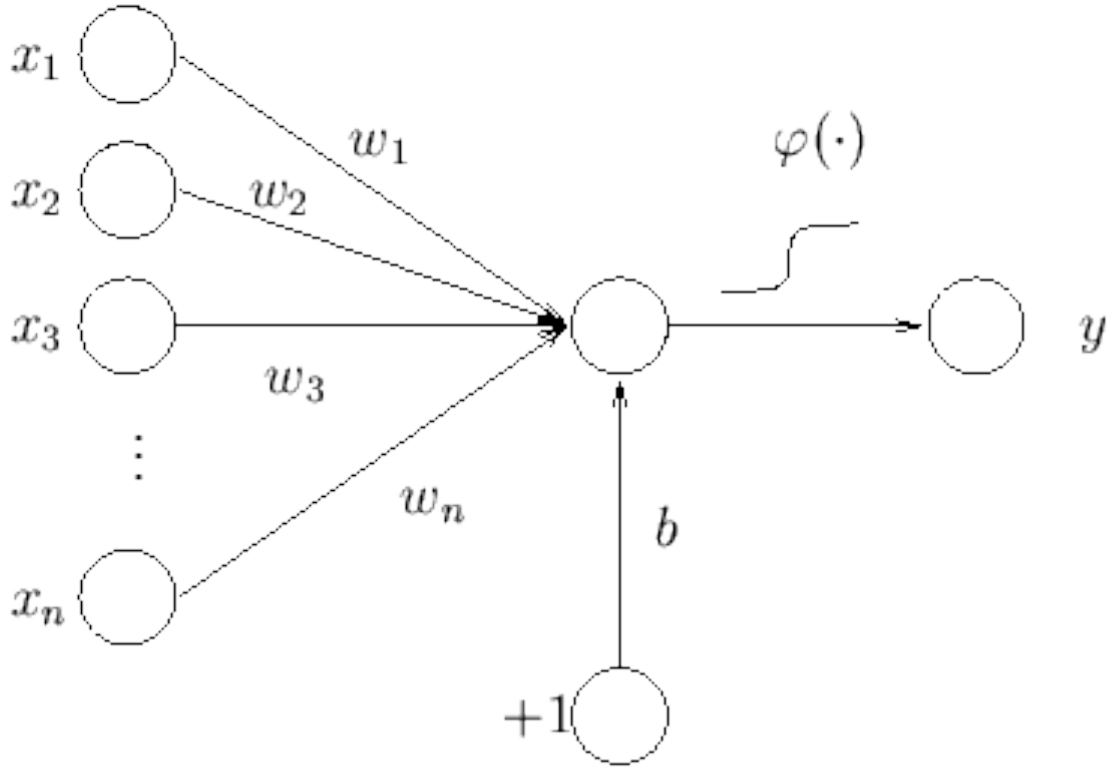
- Linear Functions are the simplest ones from an analytical point of view.
- The basic idea is to select a hypothesis with null error on the training-set.
- To learn a linear function a simple neural network of only one neuron is enough (Perceptron)

An animal neuron



The Perceptron

$$\varphi(\vec{x}) = \operatorname{sgn}\left(\sum_{i=1..n} w_i \times x_i + b\right)$$



Useful Concepts

- ***Functional Margin*** of an example with respect to a hyperplane: $\gamma_i = y_i(\vec{w} \cdot \vec{x}_i + b)$
- ***The distribution of functional margins*** of a hyperplane with respect to a training set *S* is the distribution of the margins of the examples in *S* *wrt* the hyperplane $(\vec{w}, b)$.
- ***The functional margin of a hyperplane*** is the minimum margin of the distribution

Notations (con'td)

- If we normalize the hyperplane equation, i.e.

$$\left(\frac{\vec{w}}{\|\vec{w}\|}, \frac{b}{\|\vec{w}\|}\right)$$, we obtain the ***geometric margin***

- The ***geometric margin*** measure the Euclidean distance between the target point and the hyperplane.
- ***The training set Margin*** is the maximum geometric (functional) margin among all hyperplanes which separates the examples in S.
- The hyperplane associated with the above quantity is called ***maximal margin hyperplane***

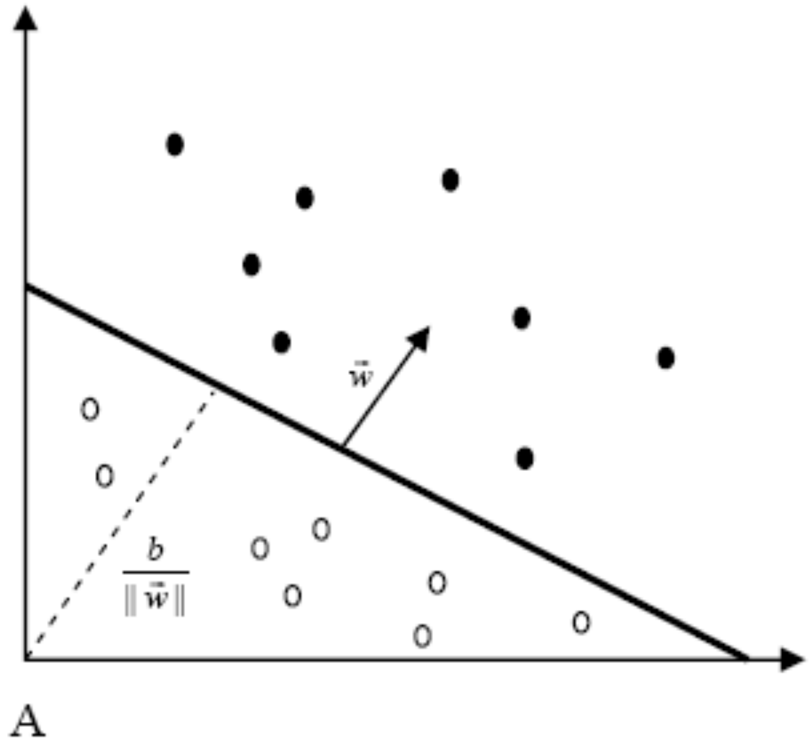
Basic Concepts

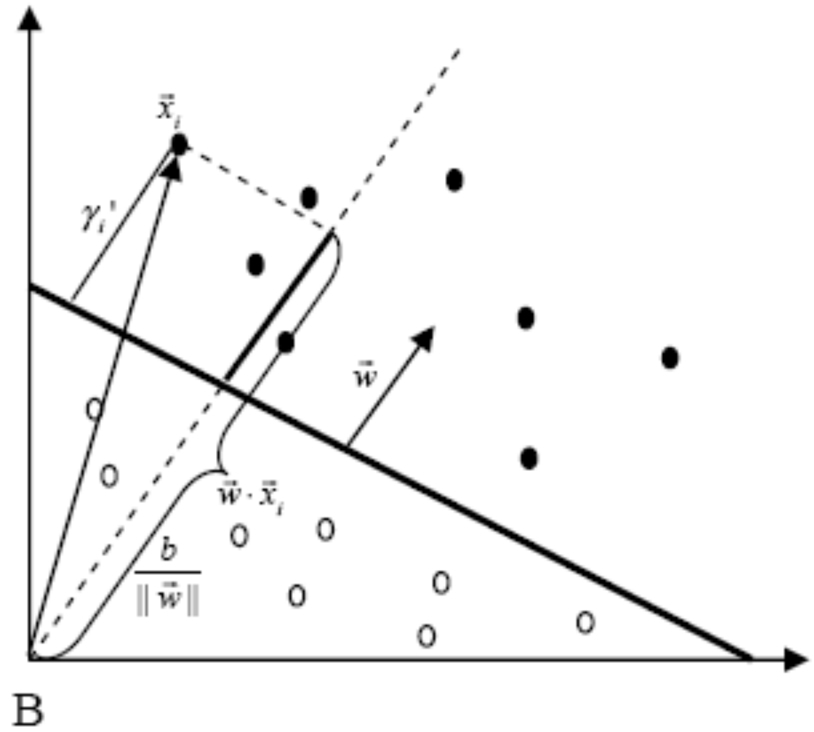
- From $\cos(\vec{x},\vec{w}) = \dfrac{\vec{x}\cdot\vec{w}}{\|\vec{x}\|\cdot\|\vec{w}\|}$
- It follows that

$$\|\vec{x}\|\cos(\vec{x},\vec{w}) = \frac{\vec{x}\cdot\vec{w}}{\|\vec{w}\|} = \vec{x}\cdot\frac{\vec{w}}{\|\vec{w}\|}$$

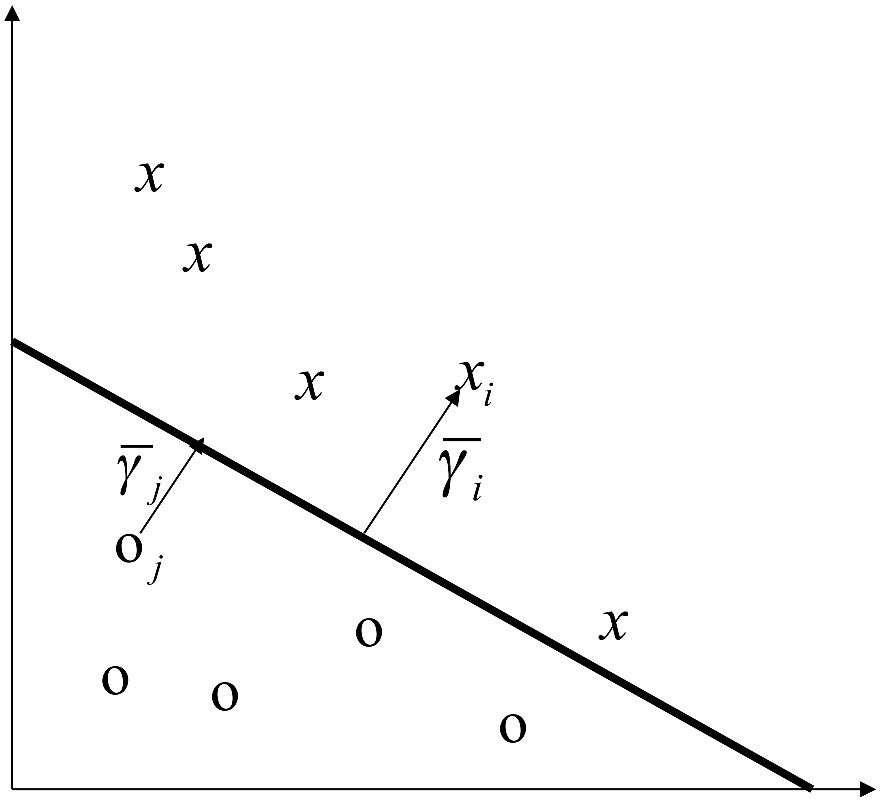
- Norm of $\vec{x}$ times the cosine between $\vec{x}$ and $\vec{w}$, i.e. the projection of $\vec{x}$ on $\vec{w}$

Geometric Margin

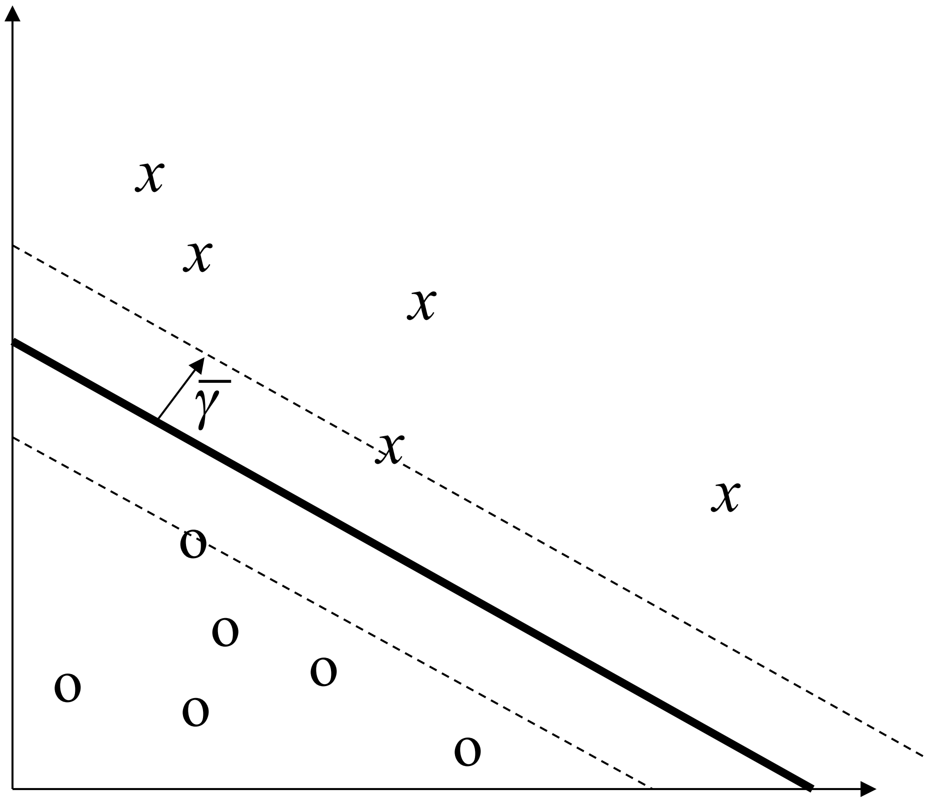




Geometric margins of 2 points and hyperplane margin

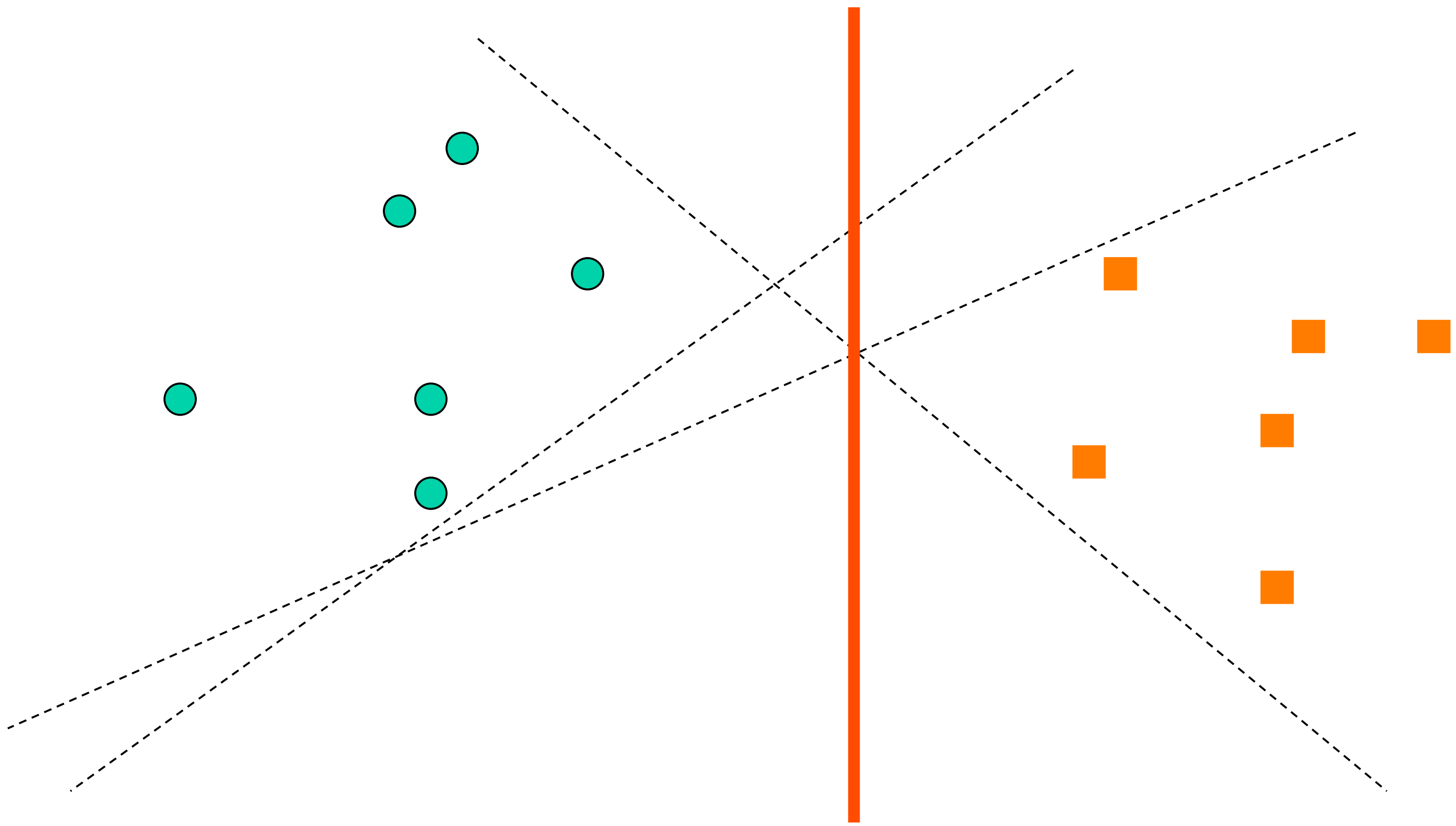


Geometric Margin



Hyperplane Margin

Maximal margin vs other margins



Perceptron training on a data set (on-line algorthm)

$\vec{w}_0 \leftarrow \vec{0}; b_0 \leftarrow 0; k \leftarrow 0; R \leftarrow \max_{1 \le i \le l} \|\vec{x}_i\|$

Repeat

for i = 1 to m

if $y_i(\vec{w}_k \cdot \vec{x}_i + b_k) \le 0$ then

$\vec{w}_{k+1} = \vec{w}_k + \eta y_i \vec{x}_i$

$b_{k+1} = b_k + \eta y_i R^2$

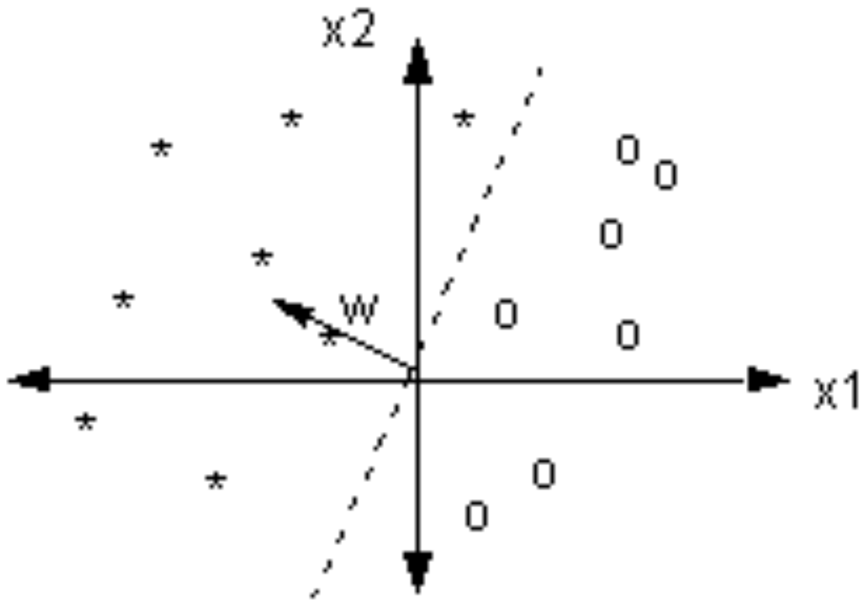
k = k + 1

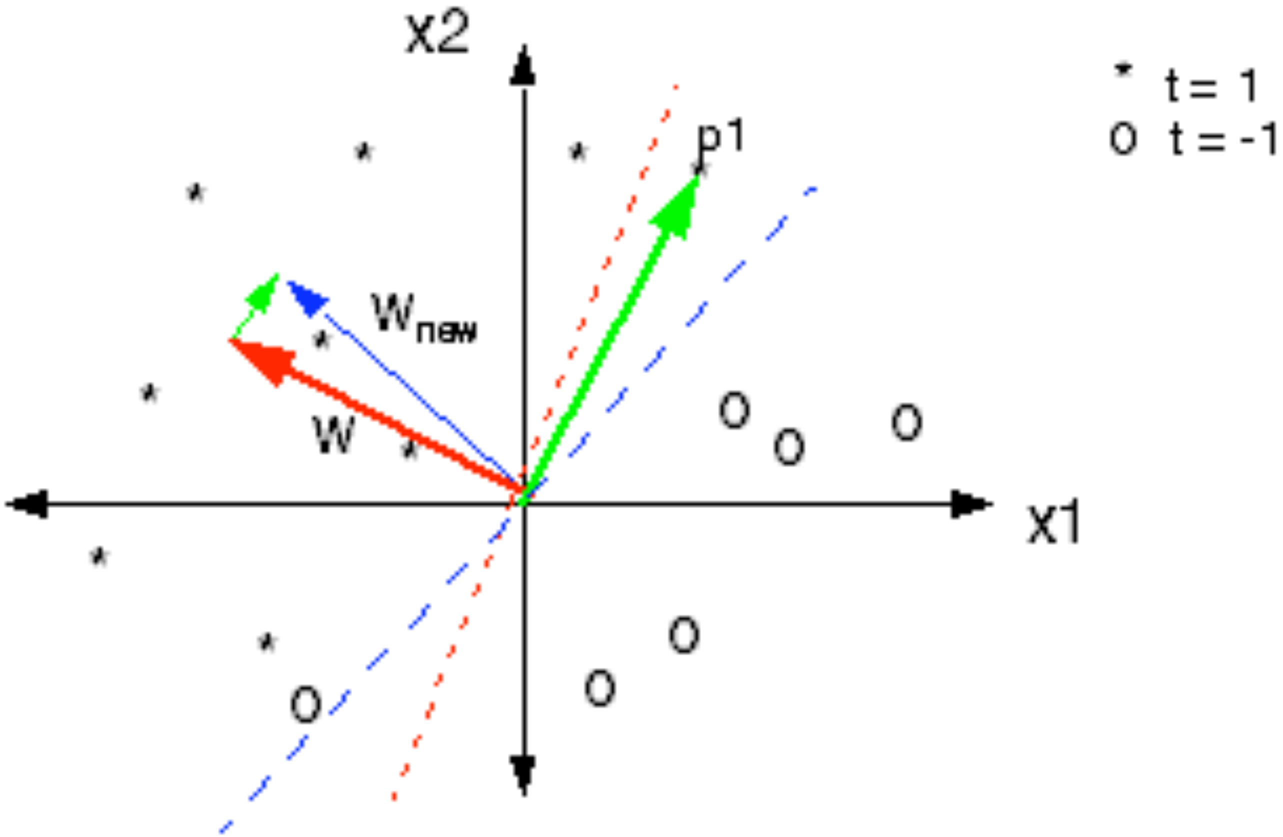
endif

endfor

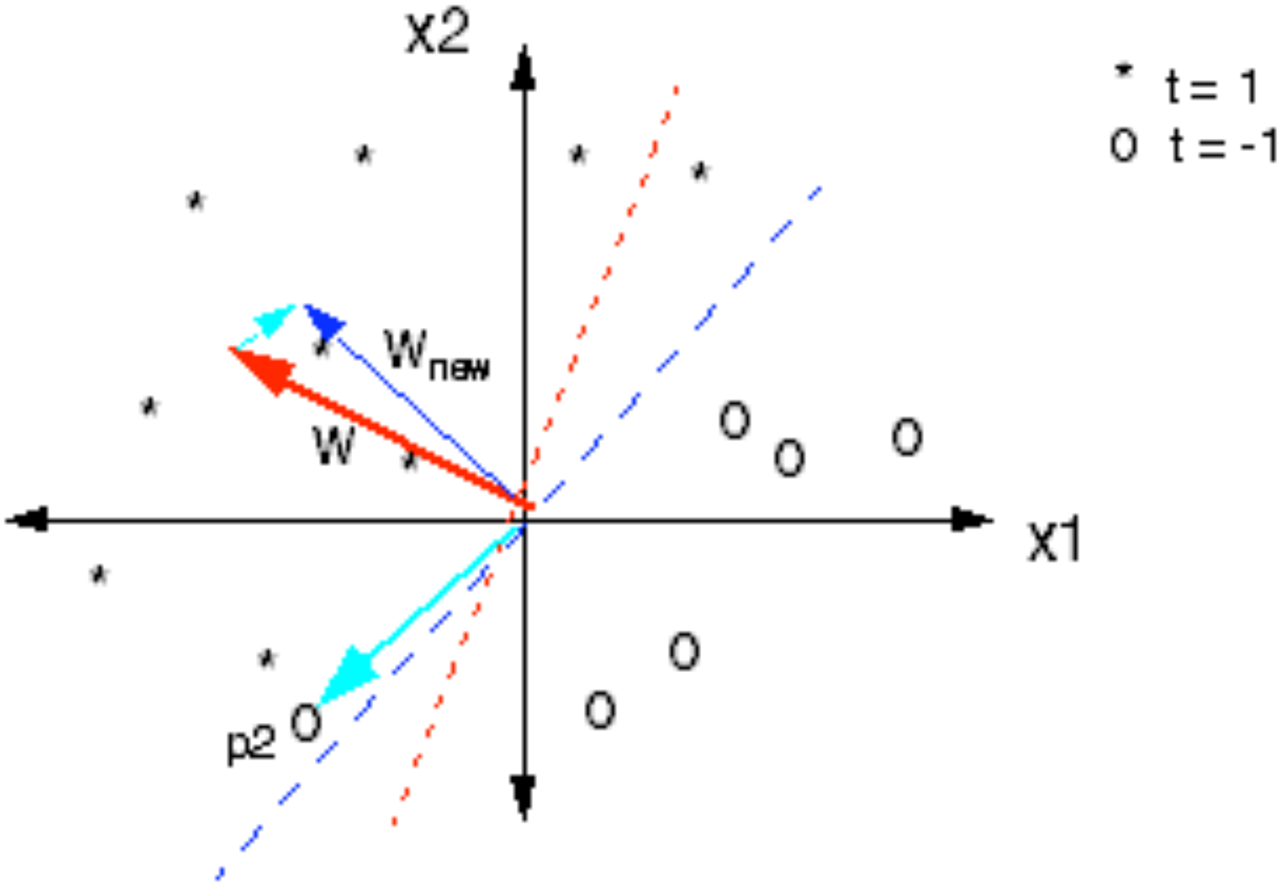
until no error is found

return k,$(\vec{w}_k, b_k)$

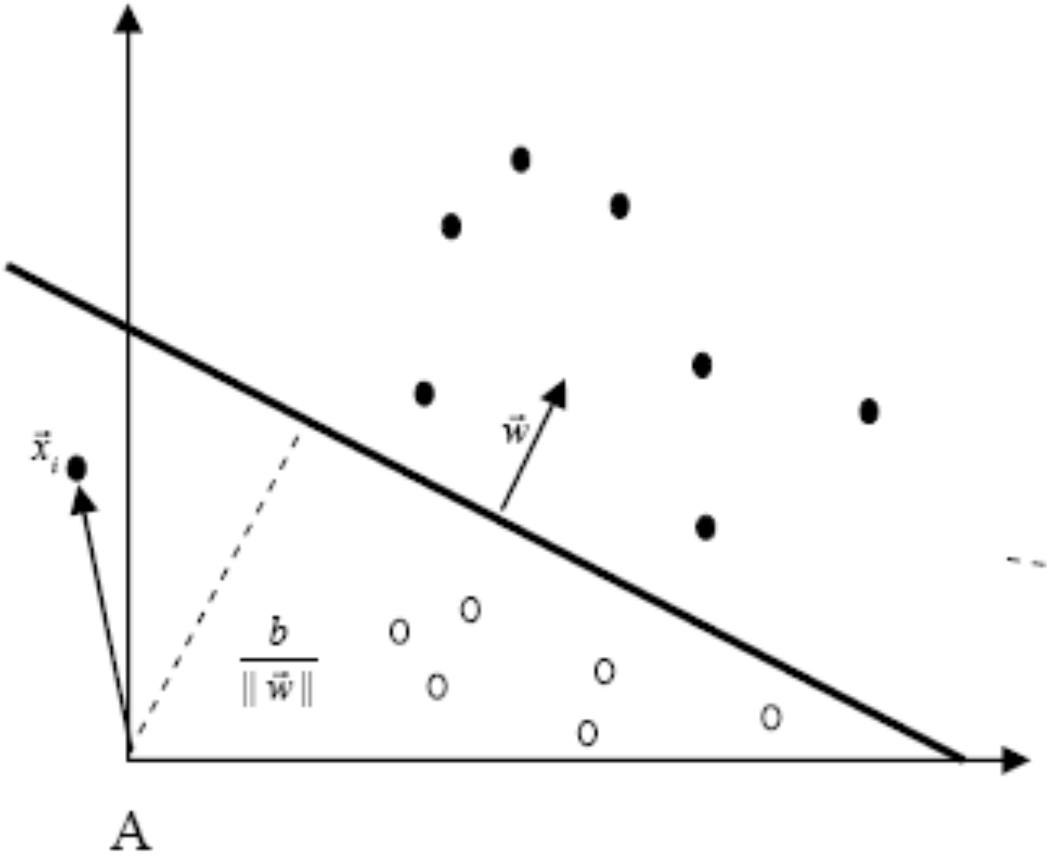

x2
w
x1



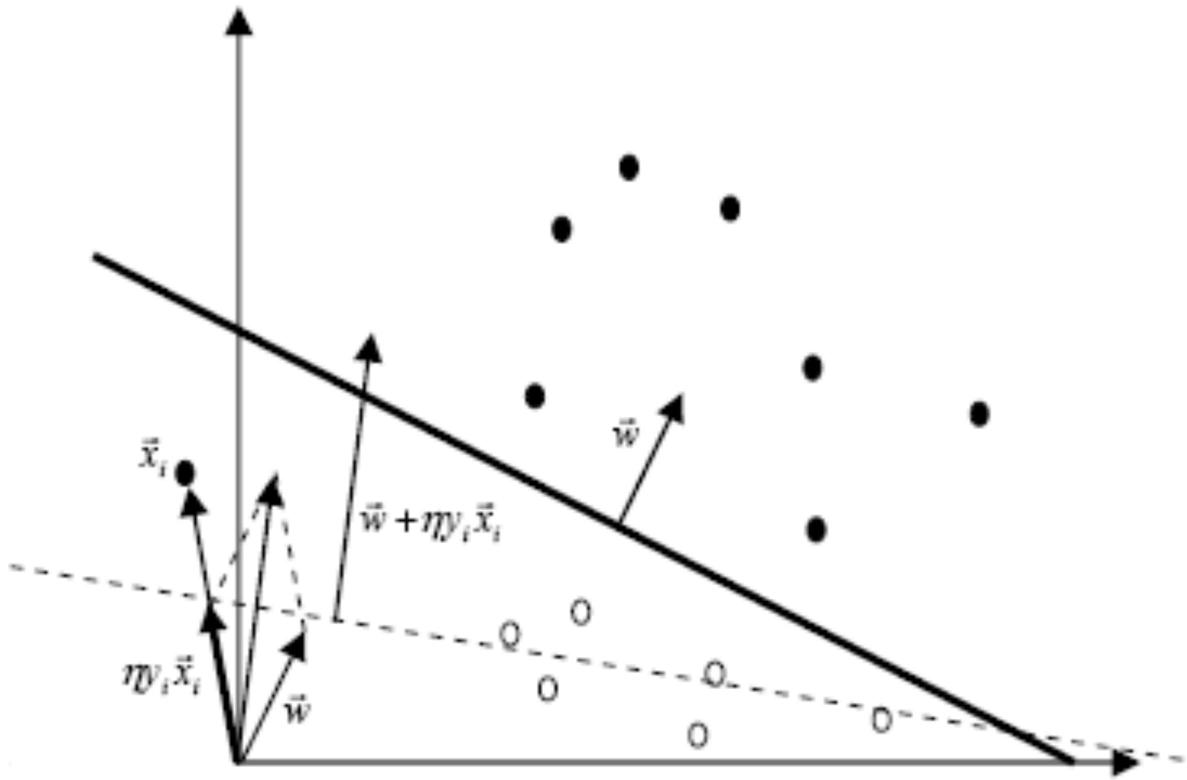
x2
x1
p1
W_{new}
W
* t = 1
o t = -1



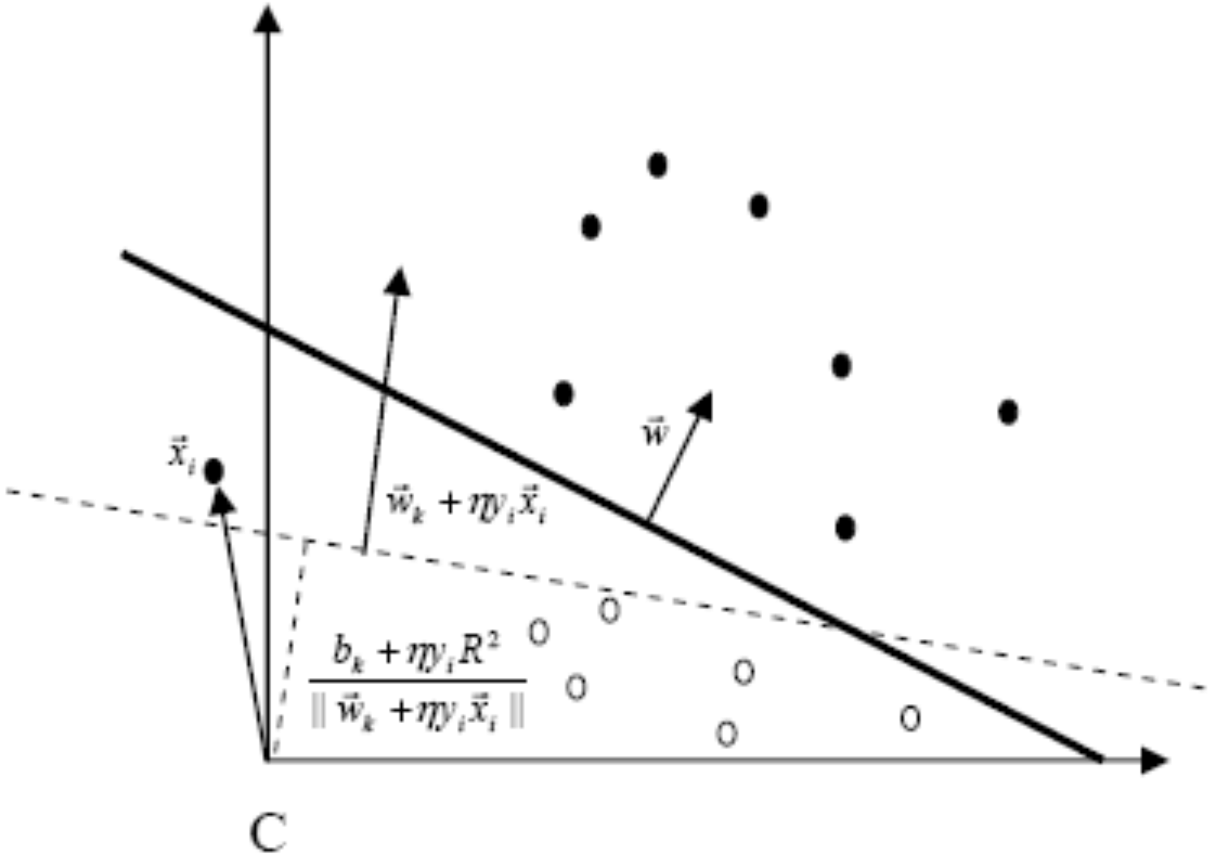
x2
x1
* t = 1
o t = -1
W
W_new
p2



$\vec{x}_i$
$\vec{w}$
$\frac{b}{\|\vec{w}\|}$
A



B


$\vec{x}_i$
$\vec{w}$
$\vec{w}_k + \eta y_i \vec{x}_i$
$\dfrac{b_k + \eta y_i R^2}{\|\vec{w}_k + \eta y_i \vec{x}_i\|}$
C

Novikoff's Theorem

Let S be a non-trivial training-set and let

$$R = \max_{i=1,..,m} \| x_i \|.$$

Let us suppose there is a vector $\mathbf{w}^*, \| \mathbf{w}^* \| = 1$ and

$$y_i(\langle \mathbf{w}^*, \mathbf{x}_i \rangle + b^*) \geq \gamma, \quad i = 1,..,m,$$

with $\gamma > 0$. Then the maximum number of errors of the perceptron is:

$$t^* = \left(\frac{2R}{\gamma} \right)^2,$$

Observations

- The theorem states that independently of the margin size, if data is linearly separable the perceptron algorithm finds the solution in a finite amount of steps.
- This number is inversely proportional to the square of the margin.
- The bound is invariant with respect to the scale of the *patterns* (i.e. only the relative distances count).
- The learning rate is not essential for the convergence.

Dual Representation

- The decision function can be rewritten as:

$$h(x) = \mathrm{sgn}(\vec{w} \cdot \vec{x} + b) = \mathrm{sgn}(\sum_{j=1..m} \alpha_j y_j \vec{x}_j \cdot \vec{x} + b) =$$

$$\mathrm{sgn}(\sum_{i=1..m} \alpha_j y_j \vec{x}_j \cdot \vec{x} + b)$$

- as well as the updating function

$$\text{if } y_i(\sum_{j=1..m} \alpha_j y_j \vec{x}_j \cdot \vec{x}_i + b) \leq 0 \text{ then } \alpha_i = \alpha_i + \eta$$

- The learning rate η only affects the re-scaling of the hyperplane, it does not affect the algorithm, so we can fix $\eta = 1$.

First properties of SVMs

- DUALITY is the first feature of Support Vector Machines
- SVMs are learning machines using the following function:

$$f(x) = \mathrm{sgn}(\vec{w} \cdot \vec{x} + b) = \mathrm{sgn}\Big(\sum_{j=1..m} \alpha_j y_j \vec{x}_j \cdot \vec{x} + b \Big)$$

- Note that data appears only as scalar product (for both testing and learning phases)
- The Matrix $G = \left(\vec{x}_i \cdot \vec{x}_j\right)_{i,j=1}^{m}$ is called Gram matrix

Limits of Linear Classifiers

- Data must be linearly separable
- Noise (almost all classifier types)
- Data must be in vectorial format

Solutions

- Multi-Layers Neural Network: back-propagation learning algorithm.
- SVMs: kernel methods.

  The learning algorithm is decoupled by the application domain which is encoded by a kernel function