Support Vector Machines cheatsheet

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Kernels

The separator reads

$$h_{w,b}(x) = \sum_{i} w_i k(x_i, x) + b$$

Linear	k(x, x') = < x, x' >
RBF	$k_{\sigma}(x, x') = \exp(-\frac{\ x - x'\ ^2}{2\sigma^2})$
Polynomial	$k_{\gamma,c,d}(x,x') = (\gamma < x, x' > +c)^d$

Classification SVM : C-SVC

Primal optimization problem:

$$\underset{w,b\xi}{\operatorname{argmin}} \frac{1}{2} ||w||^2 + C \mathbf{1}^T \xi$$
subject to
$$\begin{cases} y_i h_{w,b}(x_i) \ge 1 - \xi_i &, \forall (x_i, y_i) \in S \\ \xi_i \ge 0 &, \forall i \end{cases}$$

Dual optimization problem:

$$\underset{\alpha}{\operatorname{argmin}} \frac{1}{2} \alpha^T Q \alpha - \mathbf{1}^T \alpha$$

$$\text{subject to } \begin{cases} y^T \alpha = 0 \\ 0 \le \alpha_i \le C, \forall i \end{cases}$$

$$Q_{i,j} = y_i y_j k(x_i, x_j)$$

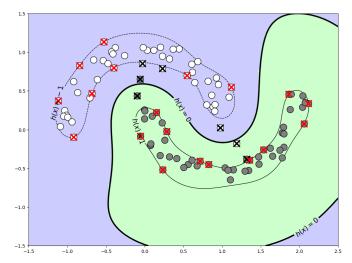
The optimal separator reads :

$$h(x) = \sum_{i} \alpha_{i} y_{i} k(x_{i}, x) + b$$

For the optimal separator, we have either:

- $\alpha_i = 0$ for **non support vector** x_i , the associated sample does not contribute to the definition of the separating hyperplane,
- $0 < \alpha_i < C$ for **support vectors** x_i just on the margin. These samples are associated with $\xi_i = 0$ and $y_i h_{w,b}(x_i) = 1$
- $\alpha_i = C$ for **support vectors** x_i which involve non null slack variables; they are "on the wrong side" of the margin. These samples are associated with $\xi_i > 0$ and $y_i h_{w,b}(x_i) = 1 \xi_i$

On the figure below, we see a bi-class problem solved with a C-SVC with C=1. The positive samples are drawn with a white dot; The negative samples with a gray dot.



The support vectors are the samples indicated with a cross. A red cross indicates the samples on the margin. A black cross indicates the samples with non null slack variables ξ . Only the support vectors (i.e. the samples indicated with a cross) contribute to the definition of the separator.

C-SVC examples