Scikit-learn

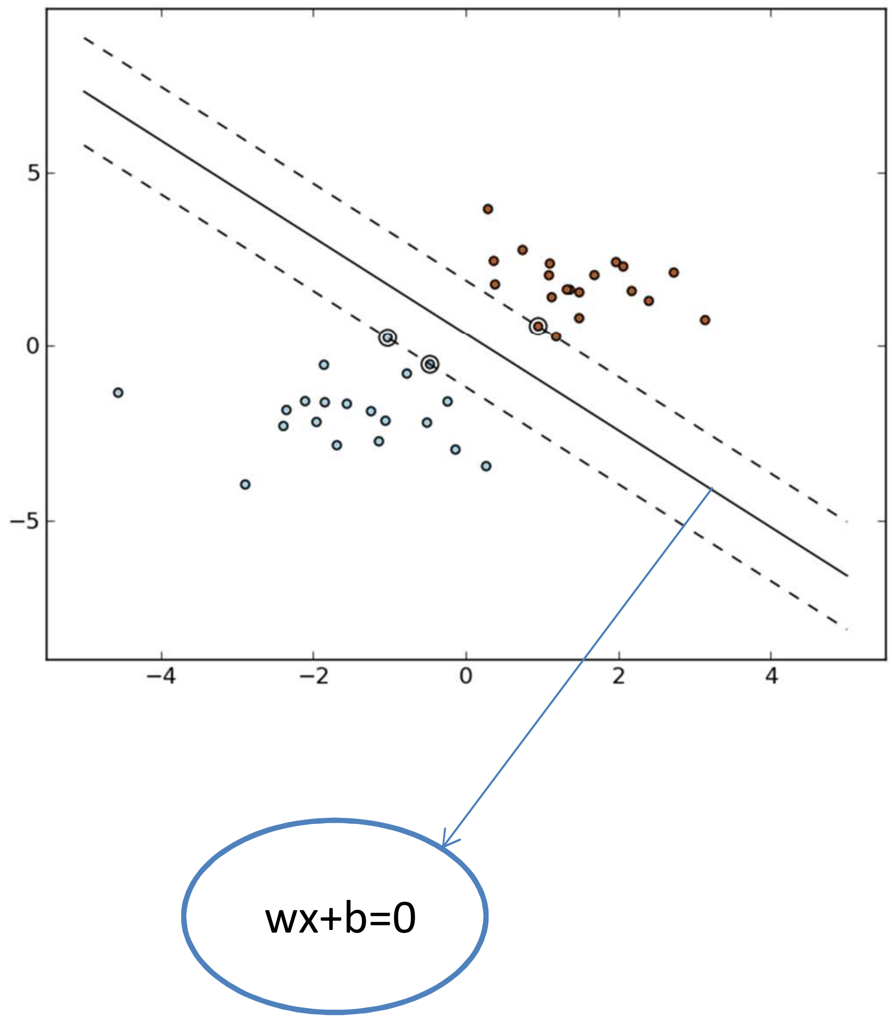
1.2.7. Mathematical

1.2.7.1.SVC

1.2.7.2. NuSVC

1.2.7 Mathematical formulation

A support vector machine constructs a hyper-plane or set of hyper-planes in a high or infinite dimensional space, which can be used for classification, regression or other tasks. Intuitively, a good separation is achieved by the hyper-plane that has the largest distance to the nearest training data points of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.



1.2.7.1 SVC

- Given training vectors , i=1,..., n, in two classes, and a vector such that , SVC solves the following primal problem:

$$\min_{w,b,\zeta} \frac{1}{2} w^T w + C \sum_{i=1,n} \zeta_i$$

$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1 - \zeta_i,$$
$$\zeta_i \geq 0, i = 1, ..., n$$

Its dual is

$$\min_{\alpha} \frac{1}{2} \alpha^T Q \alpha - e^T \alpha$$
$$\text{subject to } y^T \alpha = 0$$
$$0 \leq \alpha_i \leq C, i = 1, ..., l$$

Where e is the vector of all ones, C>0 is the upper bound, Q is an *n* by *n* positive semidefinite matrix, Qij=K(xi,yi) and $\phi(xi)^T\phi(x)$ is the kernel. Here training vectors are mapped into a higher (maybe infinite) dimensional space by the function ϕ.

1.2.7.2. NuSVC

- We introduce a new parameter ν which controls the number of support vectors and training errors. The parameter $\nu \in (0,1]$ is an upper bound on the fraction of training errors and a lower bound of the fraction of support vectors.
- It can be shown that the *nu*-SVC formulation is a reparametrization of the *C*-SVC and therefore mathematically equivalent.