



Introduction to Support Vector Machine

Formation continue
SII- Nov 2018

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Outline

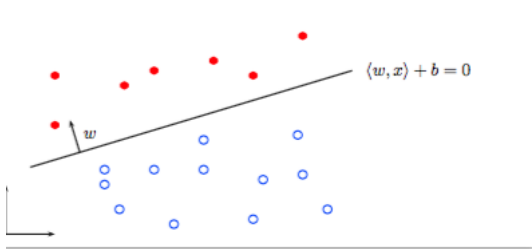
- Support Vector Machines.
 - Linear SVM in the separable case
 - Linear SVM in the non separable case
 - Non linear SVM and kernels
 - Conclusion

Linear Support Vector Machine

Definition

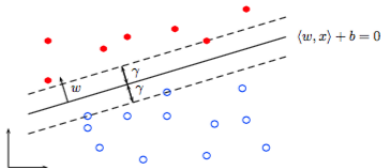
The training set $d_1^n = (x_1, y_1), \dots, (x_n, y_n)$ is called **linearly separable** if there exists (w, b) such that for all i ,
 $y_i = 1$ if $\langle w, x_i \rangle + b > 0$, $y_i = -1$ if $\langle w, x_i \rangle + b < 0$,
which means that $\forall i \ y_i (\langle w, x_i \rangle + b) > 0$.

The equation $\langle w, x \rangle + b = 0$ defines a separating hyperplane with orthogonal vector w .



- The function $f_{w,b}(x) = \mathbb{1}_{\langle w,x \rangle + b \geq 0} - \mathbb{1}_{\langle w,x \rangle + b < 0}$ defines a possible linear classification rule.
- The problem is that there exists an infinity of separating hyperplanes, and therefore an infinity of classification rules.
- Which one should we choose? The response is given by Vapnik (1999).

- The classification rule with the best generalization properties corresponds to the separating hyperplane maximizing the margin γ between the two classes on the training set.



- If we consider two entries of the training set, that are on the border defining the margin, and that we call x_1 and x_{-1} with respective outputs 1 and -1 , the separating hyperplane is located at the half-distance between x_1 and x_{-1} .

- The margin is therefore equal to the half of the distance between x_1 and x_{-1} projected onto the normal vector of the separating hyperplane :

$$\gamma = \frac{1}{2} \frac{\langle w, x_1 - x_{-1} \rangle}{\|w\|}.$$

Definition

The hyperplane $\langle w, x \rangle + b = 0$ is **canonical** with respect to the set of vectors x_1, \dots, x_k if

$$\min_{i=1\dots k} |\langle w, x_i \rangle + b| = 1.$$

- The separating hyperplane has the canonical form relatively to the vectors $\{x_1, x_{-1}\}$ if it is defined by (w, b) where $\langle w, x_1 \rangle + b = 1$ and $\langle w, x_{-1} \rangle + b = -1$. In this case, we have $\langle w, x_1 - x_{-1} \rangle = 2$, hence

$$\gamma = \frac{1}{\|w\|}.$$

- Finding the separating hyperplane with maximal margin consists in finding (w, b) such that

$$\begin{aligned} &\|w\|^2 \text{ or } \frac{1}{2}\|w\|^2 \text{ is minimal} \\ &\text{under the constraint} \\ &y_i (\langle w, x_i \rangle + b) \geq 1 \text{ for all } i. \end{aligned}$$

This leads to a convex optimization problem with linear constraints, hence there exists a unique global minimizer.

The primal problem to solve is :

$$\text{Minimizing } \frac{1}{2} \|w\|^2 \text{ s. t. } y_i (\langle w, x_i \rangle + b) \geq 1 \quad \forall i.$$

Lagrangian $L(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^n \alpha_i (y_i (\langle w, x_i \rangle + b) - 1).$

Dual Function :

$$\frac{\partial L}{\partial w}(w, b, \alpha) = w - \sum_{i=1}^n \alpha_i y_i x_i = 0 \Leftrightarrow w = \sum_{i=1}^n \alpha_i y_i x_i$$

$$\frac{\partial L}{\partial b}(w, b, \alpha) = -\sum_{i=1}^n \alpha_i y_i = 0 \Leftrightarrow \sum_{i=1}^n \alpha_i y_i = 0$$

$$\begin{aligned}\theta(\alpha) &= \frac{1}{2} \sum_{i,j=1}^n \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle + \sum_{i=1}^n \alpha_i - \sum_{i,j=1}^n \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle \\ &= \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j=1}^n \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle.\end{aligned}$$

The corresponding **dual problem** is :

Maximizing

$$\theta(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j=1}^n \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle$$

under the constraint $\sum_{i=1}^n \alpha_i y_i = 0$ and $\alpha_i \geq 0 \forall i$.

The solution α^* of the dual problem can be obtained with classical optimization softwares.

Remark : The solution does not depend on the dimension d , but depends on the sample size n , hence it is interesting to notice that when \mathcal{X} is high dimensional, linear SVM do not suffer from the curse of dimensionality.

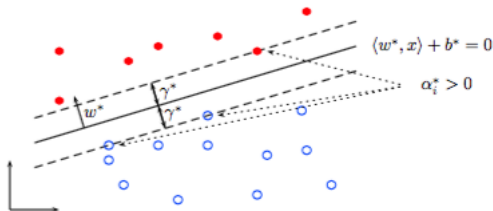
For big data sets, n is very large, it is preferable to solve the primal problem.

Supports Vectors

- For our optimization problem, the **Karush-Kuhn-Tucker conditions** are
 - $\alpha_i^* \geq 0 \quad \forall i = 1 \dots n.$
 - $y_i (\langle w^*, x_i \rangle + b^*) \geq 1 \quad \forall i = 1 \dots n.$
 - $\alpha_i^* (y_i (\langle w^*, x_i \rangle + b^*) - 1) = 0 \quad \forall i = 1 \dots n.$
(complementary condition)
- Only the $\alpha_i^* > 0$ are involved in the resolution of the optimization problem.
- If the number of values $\alpha_i^* > 0$ is small, the solution of the dual problem is called **sparse**.

Definition

The x_i such that $\alpha_i^* > 0$ are called the **support vectors**. They are located on the border defining the maximal margin namely $y_i (\langle w^*, x_i \rangle + b^*) = 1$ (c.f. complementary KKT condition).



We finally obtain the following classification rule :

$$\hat{f}(x) = \mathbb{1}_{\langle w^*, x \rangle + b^* \geq 0} - \mathbb{1}_{\langle w^*, x \rangle + b^* < 0},$$

with

- $w^* = \sum_{i=1}^n \alpha_i^* x_i y_i,$
- $b^* = -\frac{1}{2} \{ \min_{y_i=1} \langle w^*, x_i \rangle + \min_{y_i=-1} \langle w^*, x_i \rangle \}.$

The maximal margin equals $\gamma^* = \frac{1}{\|w^*\|} = (\sum_{i=1}^n (\alpha_i^*)^2)^{-1/2}.$

The α_i^* that do not correspond to support vectors (sv) are equal to 0, and therefore

$$\hat{f}(x) = \mathbb{1}_{\sum_{x_i \text{ sv}} y_i \alpha_i^* \langle x_i, x \rangle + b^* \geq 0} - \mathbb{1}_{\sum_{x_i \text{ sv}} y_i \alpha_i^* \langle x_i, x \rangle + b^* < 0}.$$

Linear SVM in the non separable case

- The previous method cannot be applied when the training set is not linearly separable. Moreover, the method is very sensitive to outliers.
- In the general case, we allow some points to be in the margin and even on the wrong side of the margin.
- We introduce the slack variable $\xi = (\xi_1, \dots, \xi_n)$ and the constraint $y_i(\langle w, x_i \rangle + b) \geq 1$ becomes

$$y_i(\langle w, x_i \rangle + b) \geq 1 - \xi_i, \text{ with } \xi_i \geq 0.$$

- If $\xi_i \in [0, 1]$ the point is well classified but in the region defined by the margin.
 - If $\xi_i > 1$ the point is misclassified.
- The margin is called **flexible margin**.

Optimization problem with relaxed constraints

- In order to avoid too large margins, we penalize large values for the slack variable ξ_i .
- The **primal optimization problem** is formalized as follows :

Minimize with respect to (w, b, ξ) $\frac{1}{2}\|w\|^2 + C \sum_{i=1}^n \xi_i$
such that

$$y_i (\langle w, x_i \rangle + b) \geq 1 - \xi_i \quad \forall i$$
$$\xi_i \geq 0$$

Remarks :

- $C > 0$ is a tuning parameter of the SVM algorithm. It will determine the tolerance to misclassifications.
- If C increases, the number of misclassified points decreases, and if C decreases, the number of misclassified points increases. C is generally calibrated by cross-validation.
- One can also minimize $\frac{1}{2}\|w\|^2 + C \sum_{i=1}^n \xi_i^k$, $k = 2, 3, \dots$, we still have a **convex optimization problem**.
The choice $\sum_{i=1}^n \mathbb{1}_{\xi_i > 1}$ (number of errors) instead of $\sum_{i=1}^n \xi_i^k$ would lead to a non convex optimization problem.

The **Lagrangian** of this problem is :

$$\begin{aligned} L(w, b, \xi, \alpha, \beta) = & \frac{1}{2} \|w\|^2 + \sum_{i=1}^n \xi_i (C - \alpha_i - \beta_i) \\ & + \sum_{i=1}^n \alpha_i - \sum_{i=1}^n \alpha_i y_i (\langle w, x_i \rangle + b), \end{aligned}$$

with $\alpha_i \geq 0$ and $\beta_i \geq 0$.

The cancellation of the partial derivatives $\frac{\partial L}{\partial w}(w, b, \xi, \alpha, \beta)$, $\frac{\partial L}{\partial b}(w, b, \xi, \alpha, \beta)$ and $\frac{\partial L}{\partial \xi_i}(w, b, \xi, \alpha, \beta)$ leads to the following dual problem.

Dual problem :

Maximizing $\theta(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j=1}^n \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle$

s. t. $\sum_{i=1}^n \alpha_i y_i = 0$ and $0 \leq \alpha_i \leq C \forall i$.

Karush-Kuhn-Tucker conditions :

- $0 \leq \alpha_i^* \leq C \forall i = 1 \dots n$.
- $y_i (\langle w^*, x_i \rangle + b^*) \geq 1 - \xi_i^* \forall i = 1 \dots n$.
- $\alpha_i^* (y_i (\langle w^*, x_i \rangle + b^*) + \xi_i^* - 1) = 0 \forall i = 1 \dots n$.
- $\xi_i^* (\alpha_i^* - C) = 0$.

Supports vectors

We have the complementary Karush-Kuhn-Tucker conditions :

$$\begin{aligned}\alpha_i^* (y_i (\langle w^*, x_i \rangle + b^*) + \xi_i^* - 1) &= 0 \quad \forall i = 1 \dots n, \\ \xi_i^* (\alpha_i^* - C) &= 0\end{aligned}$$

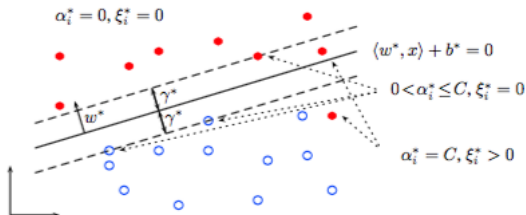
Definition

The points x_i such that $\alpha_i^* > 0$ are the **support vectors**.

We have two types of support vectors :

- The support vectors for which the slack variables are equal to 0.
They are located on the border of the region defining the margin.
- The support vectors for which the slack variables are not equal to 0 :
 $\xi_i^* > 0$ and in this case $\alpha_i^* = C$.

For the vectors that are not support vectors, we have $\alpha_i^* = 0$ and $\xi_i^* = 0$.



The classification rule is defined by

$$\begin{aligned}\hat{f}(x) &= \mathbb{1}_{\langle w^*, x \rangle + b^* \geq 0} - \mathbb{1}_{\langle w^*, x \rangle + b^* < 0}, \\ &= \text{sign}(\langle w^*, x \rangle + b^*)\end{aligned}$$

with

- $w^* = \sum_{i=1}^n \alpha_i^* x_i y_i$,
- b^* such that $y_i (\langle w^*, x_i \rangle + b^*) = 1 \ \forall x_i, \ 0 < \alpha_i^* < C$.

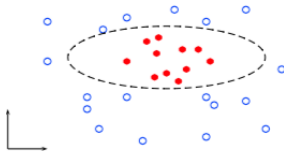
The maximal margin equals $\gamma^* = \frac{1}{\|w^*\|} = (\sum_{i=1}^n (\alpha_i^*)^2)^{-1/2}$.

The α_i^* that do not correspond to support vectors are equal to 0, hence

$$\hat{f}(x) = \mathbb{1}_{\sum_{x_i \text{ sv}} y_i \alpha_i^* \langle x_i, x \rangle + b^* \geq 0} - \mathbb{1}_{\sum_{x_i \text{ sc}} y_i \alpha_i^* \langle x_i, x \rangle + b^* < 0}.$$

Non linear SVM and kernels

A training set is rarely linearly separable and linear SVM are not appropriate in this case.



- The solution is to enlarge the feature space and send the entries in an Hilbert space \mathcal{H} , with high or possibly infinite dimension, via a function ϕ , and to apply a linear SVM procedure on the new training set $\{(\phi(x_i), y_i), i = 1 \dots n\}$. The space \mathcal{H} is called the **feature space**. This idea is due to Boser, Guyon, Vapnik (1992).
- In the previous example, setting $\phi(x) = (x_1^2, x_2^2, x_1, x_2)$, the training set becomes linearly separable in \mathbb{R}^4 .

The kernel trick

- A natural question arises : how can we choose \mathcal{H} and ϕ ? In fact, we do not choose \mathcal{H} and ϕ but a *kernel* .
- The classification rule is

$$\hat{f}(x) = \mathbb{1}_{\sum y_i \alpha_i^* \langle \phi(x_i), \phi(x) \rangle + b^* \geq 0} - \mathbb{1}_{\sum y_i \alpha_i^* \langle \phi(x_i), \phi(x) \rangle + b^* < 0},$$

where the α_i^* 's are the solutions of the dual problem in the feature space \mathcal{H} :

- Maximizing $\theta(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j=1}^n \alpha_i \alpha_j y_i y_j \langle \phi(x_i), \phi(x_j) \rangle$
s. t. $\sum_{i=1}^n \alpha_i y_i = 0$ and $0 \leq \alpha_i \leq C \ \forall i$.
- It is important to notice that the final classification rule in the feature space depends on ϕ only through scalar products of the form $\langle \phi(x_i), \phi(x) \rangle$ or $\langle \phi(x_i), \phi(x_j) \rangle$.

- The only knowledge of the function k defined by $k(x, x') = \langle \phi(x), \phi(x') \rangle$ allows to define the SVM in the feature space \mathcal{H} and to derive a classification rule in the space \mathcal{X} . The explicit computation of ϕ is not required.

Definition

A function $k : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ such that $k(x, x') = \langle \phi(x), \phi(x') \rangle$ for a given function $\phi : \mathcal{X} \rightarrow \mathcal{H}$ is called a **kernel**.

- A kernel is generally more easy to compute than the function ϕ that returns values in a high dimensional space. For example, for $x = (x_1, x_2) \in \mathbb{R}^2$, $\phi(x) = (x_1^2, \sqrt{2}x_1x_2, x_2^2)$, and $k(x, x') = \langle x, x' \rangle^2$.
- Let us now give a property to ensure that a function $k : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ defines a kernel.

PROPOSITION

—**Mercer condition** If the function $k : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ is continuous, symmetric, and if for all finite subset $\{x_1, \dots, x_n\}$ in \mathcal{X} , the matrix $(k(x_i, x_j))_{1 \leq i, j \leq n}$ is positive definite :

$$\forall c_1, \dots, c_n \in \mathbb{R}, \sum_{i,j=1}^n c_i c_j k(x_i, x_j) \geq 0,$$

then, there exists an Hilbert space \mathcal{H} and a function $\phi : \mathcal{X} \rightarrow \mathcal{H}$ such that $k(x, x') = \langle \phi(x), \phi(x') \rangle_{\mathcal{H}}$. The space \mathcal{H} is called the **Reproducing kernel Hilbert Space (RKHS)** associated to k .

We have :

- ➊ For all $x \in \mathcal{X}$, $k(x, \cdot) \in \mathcal{H}$ where $k(x, \cdot) : y \mapsto k(x, y)$.
- ➋ **Reproducing property** :

$$h(x) = \langle h, k(x, \cdot) \rangle_{\mathcal{H}} \text{ for all } x \in \mathcal{X} \text{ and } h \in \mathcal{H}.$$

- Let us give some examples. The Mercer condition is often hard to verify but we know some classical examples of kernels that can be used.
- We assume that $\mathcal{X} = \mathbb{R}^d$.
 - **p degree polynomial kernel** : $k(x, x') = (1 + \langle x, x' \rangle)^p$
 - **Gaussian kernel (RBF)** : $k(x, x') = e^{-\frac{\|x-x'\|^2}{2\sigma^2}}$
 ϕ returns values in a infinite dimensional space.
 - **Laplacian kernel** : $k(x, x') = e^{-\frac{\|x-x'\|}{\sigma}}$.
 - **Sigmoid kernel** : $k(x, x') = \tanh(\kappa \langle x, x' \rangle + \theta)$ (this kernel is not positive definite).

- We have seen some examples of kernels. One can construct new kernels by aggregating several kernels.
- For example let k_1 and k_2 be two kernels and f a function $\mathbb{R}^d \rightarrow \mathbb{R}$, $\phi : \mathbb{R}^d \rightarrow \mathbb{R}^{d'}$, B a positive definite matrix, P a polynomial with positive coefficients and $\lambda > 0$.
The functions defined by $k(x, x') = k_1(x, x') + k_2(x, x')$, $\lambda k_1(x, x')$, $k_1(x, x')k_2(x, x')$, $f(x)f(x')$, $k_1(\phi(x), \phi(x'))$, $x^T B x'$, $P(k_1(x, x'))$, or $e^{k_1(x, x')}$ are still kernels.
- We have presented examples of kernels for the case where $\mathcal{X} = \mathbb{R}^d$ but a very interesting property is that kernels can be defined for very general input spaces, such as **sets, trees, graphs, texts, DNA sequences ...**

Conclusion

- Using kernels allows to delinearize classification algorithms by mapping \mathcal{X} in the RKHS \mathcal{H} with the map $x \mapsto k(x, \cdot)$. It provides nonlinear algorithms with almost the same computational properties as linear ones.
- SVM have nice theoretical properties, cf. Vapnik's theory for empirical risk minimization.
- The use of RKHS allows to apply to any set \mathcal{X} (such as set of graphs, texts, DNA sequences ..) algorithms that are defined for vectors as soon as we can define a kernel $k(x, y)$ corresponding to some measure of similarity between two objects of \mathcal{X} .

Conclusion

- Important issues concern the choice of the kernel, and of the tuning parameters to define the SVM procedure.
- Note that SVM can also be used for multi-class classification problems for example, one can build a SVM classifier for each pair of classes and predict the class for a new point by a majority vote.
- Kernels are also used for regression as mentioned above or for non supervised classification (kernel PCA).

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