Exercise of Supervised Learning: SVM Part 1

Yawei Li

yawei.li@stat.uni-muenchen.de

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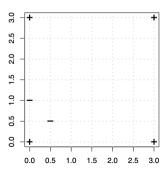
Exercise 1: Soft Margin Classifier

The primal optimization problem for the two-class soft margin SVM classification is given by

$$\min_{\boldsymbol{\theta}, \theta_0, \zeta^{(i)}} \frac{1}{2} ||\boldsymbol{\theta}||^2 + \sum_{i=1}^n \zeta^{(i)}$$
s.t.: $y^{(i)}(\boldsymbol{\theta}^T \mathbf{x}^{(i)} + \theta_0) \ge 1 - \zeta^{(i)},$

$$\zeta^{(i)} \ge 0, \quad \forall i = 1, \dots, n.$$

(a) Add the decision boundary to the figure for $\hat{\theta} = (1, 1)^T$, $\hat{\theta}_0 = -2$. (NB: This is the approximate optimum for C = 10).



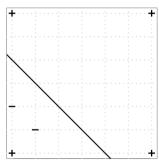
Solution to Exercise 1 (a)

The hyperplane is given by:

$$\theta_1 x_1^{(i)} + \theta_2 x_2^{(i)} + \theta_0 = 0$$

Plugging in the values for the θ s and solving for x_2 , we get the decision boundary:

$$x_2 = -x_1 + 2$$



Draw this figure on whiteboard.

Exercise 1 (b)

(b) Identify the coordinates of the support vector(s) and compute the values of their slack variable $\zeta^{(i)}$.

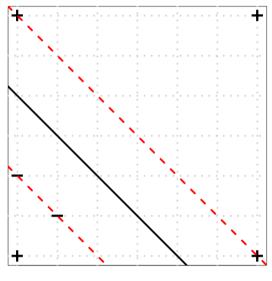
Solution to Exercise 1 (b)

To determine which points are support vectors, we will use the constraint:

$$y^{(i)}(\mathbf{x}^{(i)}\hat{\boldsymbol{\theta}}+\hat{\theta}_0)\geq 1-\zeta^{(i)}$$

- ▶ (0,0): $1(0+0-2) = -2 \ge 1 \zeta^{(1)} \to \zeta^{(1)} \ge 3$, \leadsto Support vector with slack variable $\zeta^{(i)} = 3$.
- ▶ (0.5, 0.5): $-1(0.5 + 0.5 2) = 1 \ge 1 \zeta^{(2)} \to \zeta^{(2)} \ge 0$, \leadsto Support vector with slack variable $\zeta^{(i)} = 0$.
- ▶ (0,1): $-1(0+1-2) = 1 \ge 1 \zeta^{(3)} \to \zeta^{(3)} \ge 0$, \leadsto Support vector with slack variable $\zeta^{(i)} = 0$.
- ▶ (0,3): $1(0+3-2) = 1 \ge 1 \zeta^{(4)} \to \zeta^{(4)} \ge 0$, \leadsto Support vector with slack variable $\zeta^{(i)} = 0$.
- ▶ (3,0): $1(3+0-2) = 1 \ge 1 \zeta^{(5)} \to \zeta^{(5)} \ge 0$, \leadsto Support vector with slack variable $\zeta^{(i)} = 0$.
- (3,3): $1(3+3-2) = 4 \ge 1 \zeta^{(6)} \to \zeta^{(6)} \ge -3$, \leadsto **Not** a support vector.

Solution to Exercise 1 (b): Continued



Exercise 1 (c)

(c) Compute the Euclidean distance of the non-margin-violating support vector(s) to the decision boundary.

Solution to Exercise 1 (c)

We can use $\mathbf{x}^{(i)} = (0.5, 0.5)^T$:

$$d(f, \mathbf{x}^{(i)}) = \frac{y^{(i)}f(\mathbf{x}^{(i)})}{||\boldsymbol{\theta}||_2} = \frac{-1(0.5 + 0.5 - 2)}{\sqrt{2}} = \frac{1}{\sqrt{2}}$$

The distance is the same for all non-margin-violating support vectors.

Exercise 1 (d)

(d) What needs to be changed in the plot such that a hard margin SVM results into the same decision boundary?

Solution to Exercise 1 (d)

Some alternatives are:

- ► Convert the $(0,0)^T$ into a negative class.
- ► Move the $(0,0)^T$ to $(2,2)^T$.
- ightharpoonup Delete $(0,0)^T$.

Exercise 2: Optimization

Write your own stochastic subgradient descent routine to solve the soft-margin SVM in the primal formulation.

Hints:

- ► Use the regularized-empirical-risk-minimization formulation, i.e., an optimization criterion without constraints.
- No kernels, just a linear SVM.
- Compare your implementation with an existing implementation (e.g. kernallab in R. Are your results similar? Note that you might have to switch off the automatic data scaling in the already existing implementation.

Solution: show the standard solution.