

Prof. Dr. Rudolf Mathar, Dr. Gholamreza Alirezaei, Dr. Arash Behboodi

# Exercise 10

## - Proposed Solution -

Friday, January 27, 2017

### Solution of Problem 1

a)

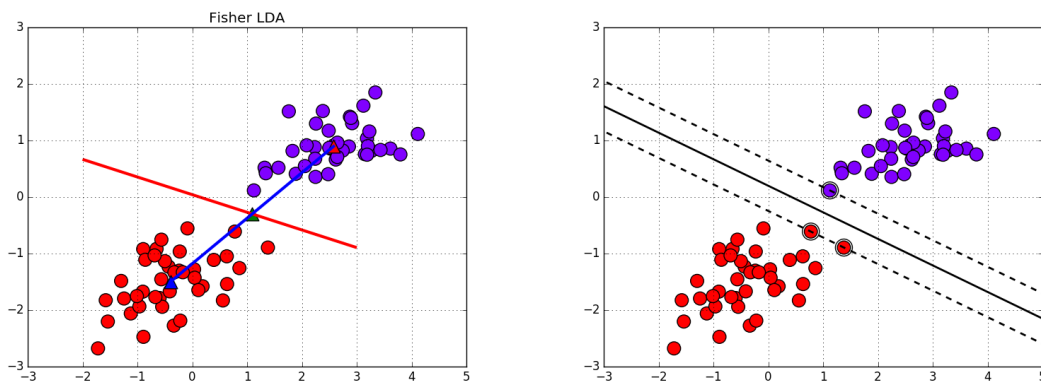


Figure 1: Two separable classes: SVM versus LDA

b) The constant  $C$  in the soft margin classifier has been chosen equal to 6.

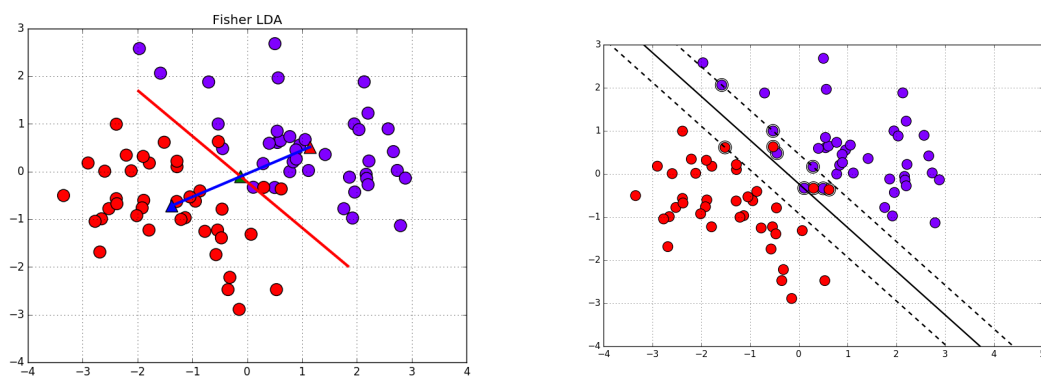


Figure 2: Two non-separable classes: SVM versus LDA

## Solution of Problem 2

The constant  $C$  in the soft margin classifier has been chosen equal to 6. Note that in this case, unlike ML-discriminant analysis, there is a region which cannot be attributed to a class.

a)

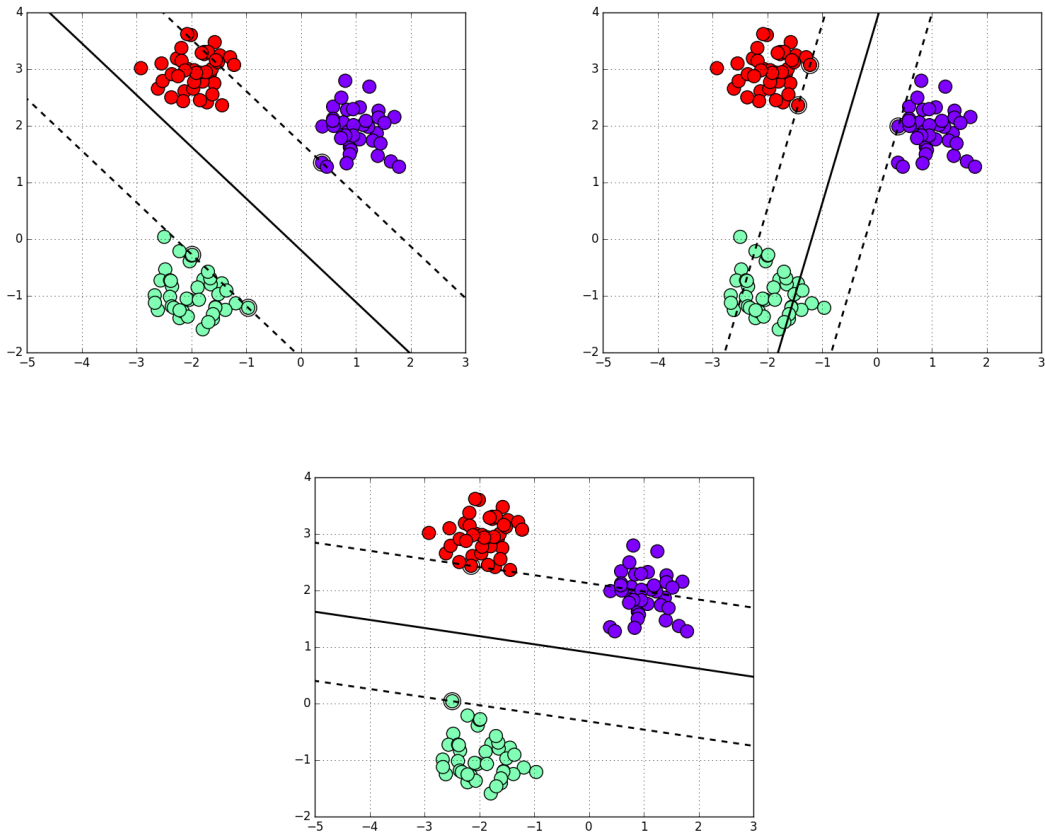


Figure 3: SVM applied to each pair of classes

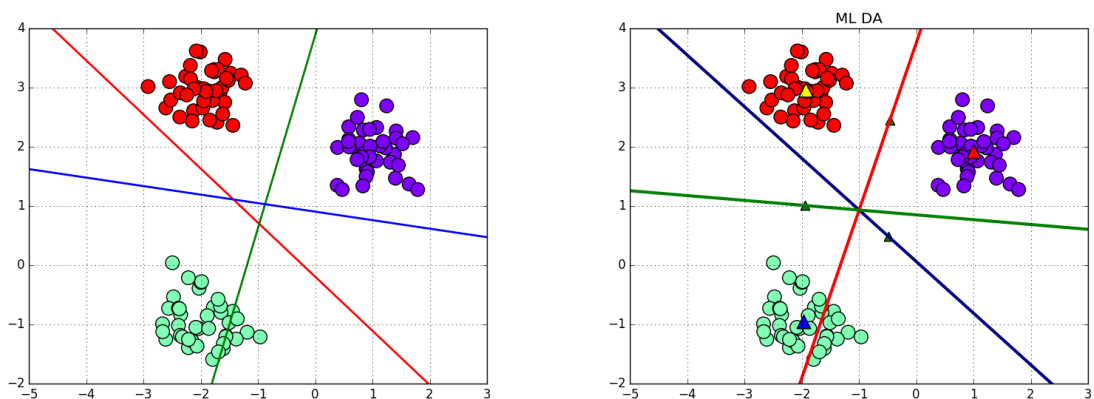


Figure 4: Three separable classes: SVM versus ML

b)

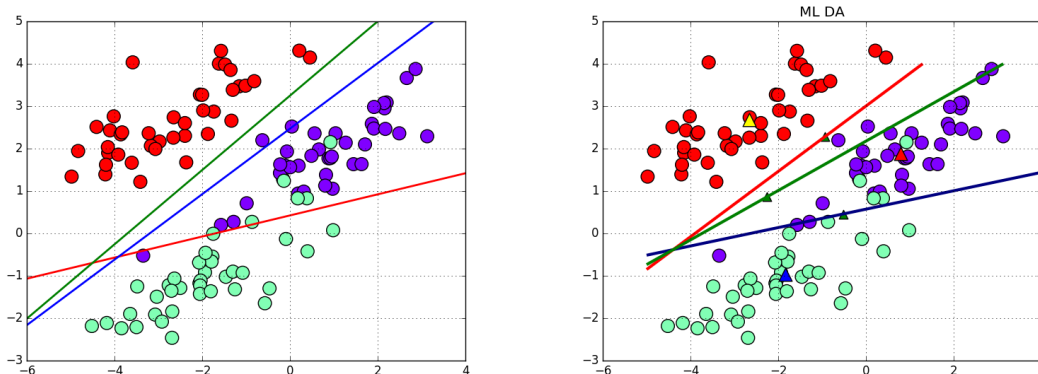


Figure 5: Three non-separable classes: SVM versus ML

### Solution of Problem 3

a) The first step is to formulate the Lagrangian function:

$$\Lambda(\mathbf{a}, b, \boldsymbol{\xi}, \boldsymbol{\alpha}, \boldsymbol{\lambda}) = \frac{1}{2} \|\mathbf{a}\|^2 + c \sum_{i=1}^n \xi_i - \sum_{i=1}^n \lambda_i [y_i (\mathbf{a}^T \mathbf{x}_i + b) - 1 + \xi_i] - \sum_{i=1}^n \alpha_i \xi_i,$$

where  $\lambda_i, \alpha_i \geq 0$  and we know that  $y_i = 1$  or  $-1$ .

Next step is to find Lagrange dual function:

$$g(\boldsymbol{\lambda}, \boldsymbol{\alpha}) = \inf_{\boldsymbol{\xi}, \mathbf{a} \in \mathbb{R}^n, b \in \mathbb{R}} \Lambda(\mathbf{a}, b, \boldsymbol{\xi}, \boldsymbol{\alpha}, \boldsymbol{\lambda})$$

Taking the derivation with respect to these parameters lead to:

$$\frac{\partial}{\partial \mathbf{a}} \Lambda(\mathbf{a}, b, \boldsymbol{\xi}, \boldsymbol{\alpha}, \boldsymbol{\lambda}) = 0 \implies \mathbf{a} = \sum_{i=1}^n \lambda_i y_i \mathbf{x}_i$$

$$\frac{\partial}{\partial b} \Lambda(\mathbf{a}, b, \boldsymbol{\xi}, \boldsymbol{\alpha}, \boldsymbol{\lambda}) = 0 \implies 0 = \sum_{i=1}^n \lambda_i y_i$$

$$\frac{\partial}{\partial \boldsymbol{\xi}} \Lambda(\mathbf{a}, b, \boldsymbol{\xi}, \boldsymbol{\alpha}, \boldsymbol{\lambda}) = 0 \implies c = \lambda_i + \alpha_i \quad i = 1, \dots, n$$

Using these assumptions, the dual problem can be written as:

$$\begin{aligned} \max \quad & \sum_{i=1}^n \lambda_i - \frac{1}{2} \sum_{i,j} y_i y_j \lambda_i \lambda_j \mathbf{x}_i^T \mathbf{x}_j \\ \text{s.t.} \quad & 0 \leq \lambda_i \leq c \\ & \sum_{i=1}^n \lambda_i y_i = 0. \end{aligned}$$

b) Take two support vector  $\mathbf{x}_k$  and  $\mathbf{x}_l$  with  $y_k = 1$  and  $y_l = -1$ . Those support vectors are those with  $0 < \lambda < c$ . Then since for support vectors we have  $y_i (\mathbf{a}^T \mathbf{x}_i + b) = 1$ , we have:

$$(\mathbf{a}^{*T} \mathbf{x}_k + b^*) = -(\mathbf{a}^{*T} \mathbf{x}_l + b^*) \implies b^* = \frac{-1}{2} \mathbf{a}^{*T} (\mathbf{x}_k + \mathbf{x}_l) \quad (1)$$

In literature, sometimes an average is calculated over all support vectors for better robustness.