## Practice Set 3

- 1. Consider a one-dimensional two-category classification problem with equal priors. Three i.i.d training observations were collected:  $D_1 = \{1, 2, 6\}$  and  $D_2 = \{4, 5, 7\}$  for  $\omega_1$  and  $\omega_2$ , respectively. It is desired to classify a test pattern using the Parzen Window technique. Recall that in this approach, the estimate for  $\mathbf{x}$  over the set of training samples  $\{\mathbf{x}_i\}_{i=1}^n$  is given by  $p_n(\mathbf{x}) = \frac{1}{n} \sum_{i=1}^n \phi(\mathbf{x} \mathbf{x}_i)$ .
  - (i) Using the window function  $\phi(x) = \frac{1}{2} \exp^{-|x|}$ , classify the pattern x = 4.5. You may assume the scenario of zero-loss loss function.
  - (ii) Verify whether the function  $\phi(x)$  is a probability density function.
- 2. You are given 2 training examples (comprising 2 dimensions) for classes  $\omega_1$  and  $\omega_2$ .

$$\omega_1: \left[ egin{array}{c} 1 \\ 1 \end{array} 
ight], \left[ egin{array}{c} 3 \\ 2 \end{array} 
ight] \qquad \qquad \omega_2: \left[ egin{array}{c} 1 \\ 2 \end{array} 
ight], \left[ egin{array}{c} 0 \\ 3 \end{array} 
ight]$$

Compute the optimal weight vector  $\mathbf{w}$  (projection line in a reduced dimension) using the Fisher's criterion.

The inverse of 
$$2 \times 2$$
 matrix: 
$$\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}.$$

3. You are given a data set  $\{\mathbf{x}_i, y_i\}_{i=1}^N$  of size N. Each input  $\mathbf{x}_i$  is d-dimensional and its corresponding target  $y_i$  takes one of the 2 values (+1 or -1). A modified version of the SVM classifier is obtained by reformulating the minimization problem of the traditional problem as:

$$\min_{\mathbf{w},b,\xi,\rho} \qquad \frac{1}{2}\mathbf{w}^T\mathbf{w} + \frac{1}{N}\sum_{i=1}^N \xi_i - \rho$$

subject to the constraints:

$$y_i(\mathbf{w}^T \mathbf{x}_i + b] \ge \rho - \xi_i \qquad i = 1, 2, 3, \dots, N$$
  
$$\xi_i \ge 0 \qquad i = 1, 2, 3, \dots, N$$
  
$$\rho > 0$$

- (a) Write down the Lagrangian Function  $L(\mathbf{w}, b, \boldsymbol{\xi}, \rho)$  corresponding to this optimization problem. Here  $\boldsymbol{\xi} = \{\xi_1, \xi_2, .... \xi_N\}$ .
- (b) State the KKT conditions to the primal problem, that are to be satisfied at optimality.

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4. Consider a data set  $\{\mathbf{x}_i, y_i\}_{i=1}^N$ , where each input  $\mathbf{x}_i$  is d-dimensional and its corresponding target  $y_i$  is an integer valued scalar, taking values +1 or -1. Additionally, assume that each data pair  $(\mathbf{x}_i, y_i)$  is associated with a **known** weight  $r_i$ , (where  $r_i > 0$ ). Accordingly, the sum of squares error function can be written as  $E(\mathbf{w}) = \sum_{i=1}^N r_i (y_i - \mathbf{w}^T \mathbf{x}_i)^2$ . An iterative approach to this minimization/learning problem is the method of gradient descent. Using this technique, write an equation that updates the weight vector  $\mathbf{w}(j-1)$  in the  $j^{th}$  iteration. You may assume the 'batch-mode' learning paradigm for updating the weights.

