

# E0 270: Machine Learning (Jan-April 2025)

## Problem Sheet #2

Indian Institute of Science

### Problem 1

Suppose we are given a dataset  $D = \{(x_n, y_n)\}_{n=1}^N$ . For solving the SVM problem on this dataset, suppose the four support vectors  $x_{n_1}, x_{n_2}, x_{n_3}, x_{n_4}$  are given a priori. Is it possible to directly solve the SVM problem using these support vectors without needing to use the whole dataset? Justify.

### Problem 2

Let  $Z(\cdot)$  denote the vector of monomials up to degree  $d$ , i.e.,

$$Z(x) = \begin{bmatrix} 1 \\ x \\ x^2 \\ \vdots \\ x^d \end{bmatrix}. \quad (1)$$

Let  $Q$  be a symmetric positive definite matrix. Is the following function a valid kernel? Justify.

$$k(x, y) = Z(x - y)^T Q Z(x - y). \quad (2)$$

### Problem 3

Let  $X = [0, \pi/2]^2$ . Is the following function defined on  $X \times X$  a kernel? Justify.

$$k(x, y) = \cos(x_1 - y_1) \cos(x_2 - y_2), \quad \forall x = (x_1, x_2), y = (y_1, y_2) \in X. \quad (3)$$

### Problem 4

$\ell_2$  norm soft margin SVM:

When introducing slack variables to soft margin SVM, instead of adding  $\xi_n$  to the objective function, we can also add  $\xi_n^2$ , giving rise to the following optimization problem:

$$\min_{w, b, \xi} \quad \frac{1}{2} \|w\|^2 + c \sum_{n=1}^N \xi_n^2 \quad (4)$$

subject to

$$y_n(w^T x_n + b) \geq 1 - \xi_n, \quad n \in [N]. \quad (5)$$

- (a) Compared to the standard soft margin SVM formulation, we have dropped the extra set of constraints  $\xi_n \geq 0$ . Show that these non-negativity constraints can be removed without affecting the optimal solution.
- (b) Write the Lagrangian for the above optimization problem.

### Problem 5

Consider the logistic regression model with a target variable  $t \in \{-1, 1\}$ . If we define  $p(t = 1|y) = \sigma(y)$  where  $y(x)$  is given by  $y(x) = w^T \phi(x) + b$ , show that the negative log-likelihood, with the addition of a quadratic regularization term, takes the form:

$$\sum_{n=1}^N \text{E}_{LR}(y_n t_n) + \lambda \|w\|^2$$

where

$$\text{E}_{LR}(y_t) = \ln(1 + \exp(-y_t)).$$