

**Problem 56.4.** Prove that the matrices

$$A = \begin{pmatrix} \mathbf{1}_m^\top & -\mathbf{1}_m^\top & 0_m^\top & 0_m^\top & 0 \\ \mathbf{1}_m^\top & \mathbf{1}_m^\top & 0_m^\top & 0_m^\top & 1 \\ I_m & 0_{m,m} & I_m & 0_{m,m} & 0_m \\ 0_{m,m} & I_m & 0_{m,m} & I_m & 0_m \end{pmatrix}, \quad A_2 = \begin{pmatrix} \mathbf{1}_m^\top & -\mathbf{1}_m^\top & 0_m^\top & 0_m^\top \\ \mathbf{1}_m^\top & \mathbf{1}_m^\top & 0_m^\top & 0_m^\top \\ I_m & 0_{m,m} & I_m & 0_{m,m} \\ 0_{m,m} & I_m & 0_{m,m} & I_m \end{pmatrix}$$

have rank  $2m + 2$ .

**Problem 56.5.** Derive the version of  $\nu$ -SV regression in which the linear penalty function  $\sum_{i=1}^m (\xi_i + \xi'_i)$  is replaced by the quadratic penalty function  $\sum_{i=1}^m (\xi_i^2 + \xi_i'^2)$ . Derive the dual program.

**Problem 56.6.** The linear penalty function  $\sum_{i=1}^m (\xi_i + \xi'_i)$  can be replaced by the quadratic penalty function  $\sum_{i=1}^m (\xi_i^2 + \xi_i'^2)$ . Prove that for an optimal solution we must have  $\xi_i \geq 0$  and  $\xi'_i \geq 0$ , so we may omit the constraints  $\xi_i \geq 0$  and  $\xi'_i \geq 0$ . We must also have  $\gamma = 0$  so we may omit the variable  $\gamma$  as well. Prove that  $\xi = (m/2C)\lambda$  and  $\xi' = (m/2C)\mu$ . This problem is very similar to the Soft Margin SVM (SVM<sub>s4</sub>) discussed in Section 54.13.

**Problem 56.7.** Consider the version of  $\nu$ -SV regression in Section 56.5. Prove that for any optimal solution with  $w \neq 0$  and  $\epsilon > 0$ , if the inequalities  $(p_f + q_f)/m < \nu < 1$  hold, then some point  $x_i$  is a support vector.

**Problem 56.8.** Prove that the matrix

$$A_3 = \begin{pmatrix} \mathbf{1}_m^\top & \mathbf{1}_m^\top & 0_m^\top & 0_m^\top \\ I_m & 0_{m,m} & I_m & 0_{m,m} \\ 0_{m,m} & I_m & 0_{m,m} & I_m \end{pmatrix}$$

has rank  $2m + 1$ .

**Problem 56.9.** Consider the version of  $\nu$ -SV regression in Section 56.5. Prove the following formulae: If  $I_\lambda \neq \emptyset$ , then

$$\epsilon = w^\top \left( \sum_{i \in I_\lambda} x_i \right) / |I_\lambda| + b - \left( \sum_{i \in I_\lambda} y_i \right) / |I_\lambda|,$$

and if  $I_\mu \neq \emptyset$ , then

$$\epsilon = -w^\top \left( \sum_{j \in I_\mu} x_j \right) / |I_\mu| - b + \left( \sum_{i \in I_\mu} y_i \right) / |I_\mu|.$$

**Problem 56.10.** Implement  $\nu$ -Regression Version 2 described in Section 56.5. Run examples using both the original version and version 2 and compare the results.