

so  $\eta$  is also expressed in terms of  $\lambda, \mu$ .

The condition  $\nu > (p_f + q_f)/(p + q)$  cannot be satisfied if  $p_f + q_f = p + q$ , but in this case all points fail the margin, which indicates that  $\delta$  is too big, so we reduce  $\nu$  and try again.

**Remark:** The equation

$$\sum_{i=1}^p \lambda_i + \sum_{j=1}^q \mu_j = \nu$$

implies that either there is some  $i_0$  such that  $\lambda_{i_0} > 0$  or there is some  $j_0$  such that  $\mu_{j_0} > 0$ , which implies that  $p_m + q_m \geq 1$ .

Another way to compute  $\eta$  is to assume the Standard Margin Hypothesis for  $(\text{SVM}_{s3})$ . Under the **Standard Margin Hypothesis** for  $(\text{SVM}_{s3})$ , either there is some  $i_0$  such that  $0 < \lambda_{i_0} < K_s$  or there is some  $j_0$  such that  $0 < \mu_{j_0} < K_s$ , in other words, there is some support vector of type 1. By the complementary slackness conditions  $\epsilon_{i_0} = 0$  or  $\xi_{j_0} = 0$ , so we have

$$w^\top u_{i_0} - b = \eta, \quad \text{or} \quad -w^\top v_{j_0} + b = \eta,$$

and we can solve for  $\eta$ .

Due to numerical instability, when writing a computer program it is preferable to compute the lists of indices  $I_\lambda$  and  $I_\mu$  given by

$$\begin{aligned} I_\lambda &= \{i \in \{1, \dots, p\} \mid 0 < \lambda_i < K_s\} \\ I_\mu &= \{j \in \{1, \dots, q\} \mid 0 < \mu_j < K_s\}. \end{aligned}$$

Then it is easy to see that we can compute  $\eta$  using the following averaging formulae: If  $I_\lambda \neq \emptyset$ , then

$$\eta = w^\top \left( \sum_{i \in I_\lambda} u_i \right) / |I_\lambda| - b,$$

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

$$\eta = b - w^\top \left( \sum_{j \in I_\mu} v_j \right) / |I_\mu|.$$

Theoretically the condition  $\nu > (p_f + q_f)/(p + q)$  is less restrictive than the **Standard Margin Hypothesis** but in practice we have never observed an example for which  $\nu > (p_f + q_f)/(p + q)$  and yet the **Standard Margin Hypothesis** fails.

The “kernelized” version of Problem  $(\text{SVM}_{s3})$  is the following:

**Soft margin kernel SVM**  $(\text{SVM}_{s3})$ :

$$\begin{aligned} &\text{minimize} \quad \frac{1}{2} \langle w, w \rangle + \frac{1}{2} b^2 - \nu \eta + K_s \begin{pmatrix} \epsilon^\top & \xi^\top \end{pmatrix} \mathbf{1}_{p+q} \\ &\text{subject to} \\ &\quad \langle w, \varphi(u_i) \rangle - b \geq \eta - \epsilon_i, \quad \epsilon_i \geq 0 \quad i = 1, \dots, p \\ &\quad -\langle w, \varphi(v_j) \rangle + b \geq \eta - \xi_j, \quad \xi_j \geq 0 \quad j = 1, \dots, q, \end{aligned}$$