so

$$b = \frac{1}{2}\left(\sum_{i=1}^{p} \lambda_i(\kappa(u_i, u_{i_0}) + \kappa(u_i, v_{j_0})) - \sum_{j=1}^{q} \mu_j(\kappa(v_j, u_{i_0}) + \kappa(v_j, v_{j_0}))\right),$$

and the classification function

$$f(x) = \mathrm{sgn}(\langle w, \varphi(x)\rangle - b)$$

is given by

$$\begin{aligned} f(x) = \mathrm{sgn}\Bigg(&\sum_{i=1}^{p} \lambda_i(2\kappa(u_i, x) - \kappa(u_i, u_{i_0}) - \kappa(u_i, v_{j_0})) \\ &- \sum_{j=1}^{q} \mu_j(2\kappa(v_j, x) - \kappa(v_j, u_{i_0}) - \kappa(v_j, v_{j_0}))\Bigg). \end{aligned}$$

54.6 Classification of the Data Points in Terms of ν (SVM$_{s2'}$)

For a finer classification of the points it turns out to be convenient to consider the ratio

$$\nu = \frac{K_m}{(p+q)K_s}.$$

First note that in order for the constraints to be satisfied, some relationship between K_s and K_m must hold. In addition to the constraints

$$0 \leq \lambda_i \leq K_s, \quad 0 \leq \mu_j \leq K_s,$$

we also have the constraints

$$\begin{aligned} \sum_{i=1}^{p} \lambda_i &= \sum_{j=1}^{q} \mu_j \\ \sum_{i=1}^{p} \lambda_i + \sum_{j=1}^{q} \mu_j &\geq K_m \end{aligned}$$

which imply that

$$\sum_{i=1}^{p} \lambda_i \geq \frac{K_m}{2} \quad \text{and} \quad \sum_{j=1}^{q} \mu_j \geq \frac{K_m}{2}. \tag{$\dagger$}$$

Since λ, μ are all nonnegative, if $\lambda_i = K_s$ for all i and if $\mu_j = K_s$ for all j, then

$$\frac{K_m}{2} \leq \sum_{i=1}^{p} \lambda_i \leq pK_s \quad \text{and} \quad \frac{K_m}{2} \leq \sum_{j=1}^{q} \mu_j \leq qK_s,$$