

Derivation of Dual

of soft-margin SVM with arbitrary kernel k .

Let gram-matrix of training points with k be $K_{n \times n}$. Let Y be the diagonal matrix with entries as labels of training pts. and y be the vector with entries as labels of training pts. Let $Q = YKY$. Let $\mathbf{1}$ be the vector of ones of appropriate size. Let \mathcal{H} be the RKHS for which kernel is k . Let $\langle \cdot, \cdot \rangle_{\mathcal{H}}$ & $\|\cdot\|_{\mathcal{H}}$ be the inner-product & induced norm in \mathcal{H} .

SVM:

$$\min_{w, b, \xi} \frac{1}{2} \|w\|_{\mathcal{H}}^2 + C \sum_{i=1}^n \xi_i$$

$$\text{s.t. } y_i (\langle w, \phi x_i \rangle - b) \geq 1 - \xi_i, \xi_i \geq 0.$$

Using representer theorem we have this equivalent formulation:

$$\min_{\alpha, b, \xi} \frac{1}{2} \alpha^T Q \alpha + C \mathbf{1}^T \xi$$

$$\text{s.t. } Q\alpha - b y \geq \mathbf{1} - \xi, \xi \geq 0$$

$$\mathcal{L} = \frac{1}{2} \alpha^T Q \alpha + C \mathbf{1}^T \xi + \lambda^T (Q\alpha - b y - \mathbf{1} + \xi) - \beta^T \xi$$

(Here λ, β are Lagrange multipliers; both are vectors)

$$\nabla_{\alpha} \mathcal{L} = 0 \Rightarrow Q\alpha = Q\lambda$$

(Note: Q is symmetric, may not be invertible)

$$\nabla_{\xi} \mathcal{L} = 0 \Rightarrow C \mathbf{1} = \lambda + \beta$$

$$\frac{\partial \mathcal{L}}{\partial b} = 0 \Rightarrow \lambda^T y = 0$$

eliminating α we get:

$$L = -\frac{1}{2} \lambda^T Q \lambda + 1^T \lambda \quad \left(\because \frac{1}{2} x^T Q x = \frac{1}{2} x^T Q \lambda = \frac{1}{2} \lambda^T Q x \right)$$

Hence dual is:

$$\max_{\lambda} \quad 1^T \lambda - \frac{1}{2} \lambda^T Q \lambda$$

$$\text{s.t.} \quad 0 \leq \lambda \leq C \mathbf{1}, \quad y^T \lambda = 0$$

\downarrow
vector of zeros

This is usually expressed in the following form where λ is replaced by α :

$$\min_{\alpha_i} \quad \frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j y_i y_j k(x_i, x_j) - \sum_{i=1}^m \alpha_i$$

$$\text{s.t.} \quad 0 \leq \alpha_i \leq C, \quad \sum_{i=1}^m y_i \alpha_i = 0$$
