

# ML Sheet 6

1. (a) Convexity of the problem is clear since all linear functions and  $\|w\|^2$  are convex. Setting  $w \in \mathbb{R}^d$  arbitrary,  $\xi_1, \dots, \xi_N = 1$  and choosing  $g < 1 + \min_{i=1, \dots, N} \langle \phi(x_i), w \rangle$  we obtain a point  $(w, \xi_1, \dots, \xi_N, g) \in \mathbb{R}^{d+N+1} = \text{int}(\mathbb{R}^{d+N+1})$  so that the inequality constraints are fulfilled with strict inequality.

$$(b) \mathcal{L}(w, \xi, g, \mu, \eta) = \frac{1}{2} \|w\|^2 - g + \frac{1}{N} \sum_{i=1}^N \xi_i + \sum_{i=1}^N \mu_i (g - \xi_i - \langle \phi(x_i), w \rangle) - \sum_{i=1}^N \eta_i \xi_i$$

$$(c) \cdot \frac{\partial \mathcal{L}}{\partial w} = w - \sum_{i=1}^N \mu_i \phi(x_i) \stackrel{!}{=} 0$$

$$\cdot \frac{\partial \mathcal{L}}{\partial \xi_i} = \frac{1}{N} - \mu_i - \eta_i \stackrel{!}{=} 0 \quad (**)$$

$$\cdot \frac{\partial \mathcal{L}}{\partial g} = -1 + \sum_{i=1}^N \mu_i \stackrel{!}{=} 0 \quad (*)$$

Plugging into  $\mathcal{L}$  yields

$$\begin{aligned} \mathcal{L} &= \frac{1}{2} \left\| \sum_{i=1}^N \mu_i \phi(x_i) \right\|^2 - g + \sum_{i=1}^N (\mu_i + \eta_i) \xi_i \\ &\quad + g \cdot (-1) - \sum_{i=1}^N \mu_i \xi_i - \sum_{i=1}^N \eta_i \xi_i \\ &= -\frac{1}{2} \sum_{i,j=1}^N \mu_i \mu_j \underbrace{\langle \phi(x_i), \phi(x_j) \rangle}_{=k(x_i, x_j)} \end{aligned}$$

The dual is maximizing  $\bar{\mathcal{L}}$  over  $\mu_i, i=1, \dots, N$ , with constraints  $0 \leq \eta_i, 0 \leq \mu_i$ . From (\*)

we get  $1 = \sum_{i=1}^N \mu_i$  and from (\*\*) it follows

that  $0 \leq \eta_i = \frac{1}{N} - \mu_i$  i.e.,  $\mu_i \leq \frac{1}{N}$ .



~~$\inf_{\alpha \in \mathbb{R}^N} -\frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j k(x_i, x_j) =$~~

(d)

Let  $A = \left\{ \alpha \in \mathbb{R}^N \mid \sum_{i=1}^N \alpha_i = 1, \forall i=1, \dots, N: 0 \leq \alpha_i \leq \frac{1}{N} \right\}$ .

Since  $A$  is obviously compact, the continuous function  $F: A \rightarrow \mathbb{R}, \alpha \mapsto -\frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j k(x_i, x_j)$

$$= -\frac{1}{2} \alpha^T K \alpha$$

attains its maximum in a point  $\alpha^* \in A$ .

For any  $\alpha \in A$  it holds that

$$F(\alpha^*) \geq F(\alpha),$$

hence

$$-F(\alpha^*) \leq -F(\alpha).$$

This shows  $\max_{\alpha \in A} F(\alpha) = \min_{\alpha \in A} -F(\alpha)$ .

The condition  $\sum_{i=1}^N \alpha_i = 1$  is obviously equivalent to  $\mathbf{1}^T \alpha = 1$  and  $\forall i=1, \dots, N: 0 \leq \alpha_i \leq \frac{1}{N}$

is equivalent to

$$\begin{pmatrix} -I \\ I \end{pmatrix} \alpha = \begin{pmatrix} -\alpha_1 \\ \vdots \\ -\alpha_N \\ \alpha_1 \\ \vdots \\ \alpha_N \end{pmatrix} \preceq \begin{pmatrix} 0 \\ \vdots \\ 0 \\ 1/(N-1) \\ \vdots \\ 1/(N-1) \end{pmatrix} = \begin{pmatrix} 0 \\ \vdots \\ 0 \\ 1/(N-1) \end{pmatrix}.$$

(e)