

# Exercise Sheet 1

Machine Learning 2, SS16

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Sascha Huk, 321249; Viktor Jeney, 348969; Mario Tambos, ??????; Jan Tinapp, 0380549

## Exercise 2

(i) We have to prove  $w^\top Cw \stackrel{?}{=} \epsilon \stackrel{(3)}{=} |x - \sum_j w_j \eta_j|^2$ .

$$\begin{aligned} & w^\top Cw \\ &= w^\top (\mathbf{1}_k x^\top - \eta) (\mathbf{1}_k x^\top - \eta)^\top w \\ &= w^\top (\mathbf{1}_k x^\top - \eta) (x \mathbf{1}_k^\top - \eta^\top) w \\ &= w^\top \mathbf{1}_k x^\top x \mathbf{1}_k^\top w - w^\top \mathbf{1}_k x^\top \eta^\top w - w^\top \eta x \mathbf{1}_k^\top w + w^\top \eta \eta^\top w \\ &= (w^\top \mathbf{1}_k x^\top) (x \mathbf{1}_k^\top w) - 2(w^\top \mathbf{1}_k x^\top) (\eta^\top w) + (w^\top \eta) (\eta^\top w) \\ &= |(w^\top \mathbf{1}_k x^\top) - (w^\top \eta)|^2 \\ &= |w^\top (\mathbf{1}_k x^\top - \eta)|^2 \\ &= \left| \sum_j w_j (x - \eta_j) \right|^2 \end{aligned}$$

Since  $\sum_i w_i = 1$  we find  $\sum_i w_i x = x$ , which leads to the desired result.  $\square$

We now perform Lagrange optimization:

$$\begin{aligned} \Lambda(w, \lambda) &= w^\top Cw - \lambda(w^\top \mathbf{1}_k - 1) \\ \frac{\partial \Lambda}{\partial w} &= 2Cw - \lambda \mathbf{1}_k \stackrel{!}{=} 0 \implies 2Cw = \lambda \mathbf{1}_k \implies w = \frac{\lambda}{2} C^{-1} \mathbf{1}_k \\ \frac{\partial \Lambda}{\partial \lambda} &= w^\top \mathbf{1}_k - 1 \stackrel{!}{=} 0 \implies w^\top \mathbf{1}_k = 1 \end{aligned}$$

We now replace  $w$  in the constraint  $w^\top \mathbf{1}_k = 1$ . Since  $C = C^\top$  we find

$$\frac{\lambda}{2} = \frac{1}{\mathbf{1}_k^\top C^{-1} \mathbf{1}_k}$$

(ii) Replacing  $\lambda/2$  in the deduced definition of  $w$  leads to the desired result. The candidate  $w$  is indeed a minimum since  $\frac{\partial^2 \Lambda}{\partial w^2} = 2C$  (invertible covariance matrices have positive definite quadratic forms).  $\square$

(iii) Multiplying by  $C$  from the left in the deduced definition of  $w$  leads to  $Cw = \frac{\lambda}{2} \mathbf{1}_k$  (resp.  $Cw' = \mathbf{1}_k$  for  $w' = \frac{2}{\lambda} w$ ). Both,  $w'$  and  $w$ , point to the same direction. Therefore, by rescaling  $w'$  such that  $w'^\top \mathbf{1}_k = 1 = w^\top \mathbf{1}_k$  the desired  $w$  is identified.  $\square$