



# Theory of Machine Learning

## Exercise sheet 4 — Session 4

**Exercise I (A bit of coding)** . The goal of this exercise is to reproduce the figure of slide 79. Consider vector-valued inputs and real-valued outputs ( $\mathcal{X} = \mathbb{R}^d$  and  $\mathcal{Y} = \mathbb{R}$ ) with  $X := (X_1, \dots, X_n)^\top \in \mathbb{R}^{n \times d}$  the input vector and  $Y := (Y_1, \dots, Y_n)^\top \in \mathbb{R}^n$  the response vector. Let  $\phi(x) = (x_1, \dots, x_d)^\top$  and  $\Phi \in \mathbb{R}^{n \times d}$  the matrix of inputs with row  $i$  defined as  $\Phi_{i,:} := \phi(X_i)^\top$ . We work in the fixed design setting where for a fixed input  $X \in \mathbb{R}^{n \times d}$ , the output is  $Y = \Phi\theta^* + \varepsilon$  ( $\varepsilon$  i.i.d.  $\mathcal{N}(0, \sigma^2)$ ) and  $\theta^* \in \mathbb{R}^d$ .

- Generate the data for fixed  $d = 2$ ,  $\theta^* = (1, \dots, 1)^\top \in \mathbb{R}^d$  and noise  $\sigma = 1$ :
  - Sample the input data  $X_{i,j} \sim \mathcal{U}([-1, 1])$ , where  $X \in \mathbb{R}^{n \times d}$ . (Hint: use `numpy.random.uniform()`)
  - Compute the design matrix  $\Phi \in \mathbb{R}^{n \times d}$ .
  - Compute the output  $Y = \Phi\theta^* + \varepsilon$  on the fixed input data  $X$ . (Hint: use `numpy.random.normal()`)
- Estimation of the expected excess risk  $\mathbb{E}[\mathcal{R}(\hat{\theta})] - \mathcal{R}^* := \mathbb{E}_Y \left[ \left\| \hat{\theta} - \theta^* \right\|_{\hat{\Sigma}}^2 \right]$ , where  $\left\| \hat{\theta} - \theta^* \right\|_{\hat{\Sigma}}^2 := (\hat{\theta} - \theta^*)^\top \hat{\Sigma} (\hat{\theta} - \theta^*)$  and  $\hat{\Sigma} := \frac{1}{n} \Phi^\top \Phi$ :
  - For the fixed input  $X$  from Question 1.a, generate  $N = 100$  samples of  $Y$  as described in Question 1.c.
  - Compute the OLS estimators  $\hat{\theta}_i := (\Phi^\top \Phi)^{-1} \Phi^\top Y$  for each sampled  $Y_i$  ( $i \in \llbracket N \rrbracket$ ).
  - Compute the estimate of  $\mathbb{E}[\mathcal{R}(\hat{\theta})] - \mathcal{R}^*$  as  $\frac{1}{N} \sum_{i=1}^N \left\| \hat{\theta}_i - \theta^* \right\|_{\hat{\Sigma}}^2$ .
- By reusing the previous code that computes the (estimated) excess risk for a fixed  $n$ , plot the (estimated) excess risk as a function of  $n \in \llbracket 10, 100 \rrbracket$ .
- (Bonus) For each  $n$ , repeat the experiment several times and plot error bars.


**Exercise II (Mahalanobis distance)** . Let  $A \in \mathbb{R}^{d \times d}$  be a positive definite matrix and set  $\|u\|_A^2 := u^\top A u$  for all  $u \in \mathbb{R}^d$ . As in the lecture, define  $d_A(x, y) := \|x - y\|_A$ . Let us prove that  $d_A$  is indeed a distance.

- Write  $u^\top A u$  when  $d = 2$  as a function of the coefficients of  $u$  and  $A$ .
- Prove that  $d_A$  is symmetric;
- Prove that  $d_A(x, y)$  is always greater than 0;
- Prove that  $d_A(x, y) = 0$  only if  $x = y$ ;
- Prove that  $d_A$  satisfies the triangle inequality

$$\forall x, y, z \in \mathbb{R}^d, \quad d_A(x, y) \leq d_A(x, z) + d_A(z, y).$$

Hint: prove that  $(x^\top A y)^2 \leq x^\top A x \cdot y^\top A y$ .

- Is  $d_A$  a distance when  $A$  is only assumed to be positive semi-definite?

**Exercise III (Expected empirical risk)** . Assume that  $Y = \Phi\theta^* + \varepsilon$  where  $\varepsilon$  is centered and the  $\varepsilon_i$ s are independent, and have common variance  $\sigma^2$  (assumptions I and II in the lecture).

- Show that


$$\widehat{R}(\hat{\theta}) = \frac{1}{n} \|\Pi \varepsilon\|^2,$$

where  $\Pi := \mathbf{I} - \Phi(\Phi^\top \Phi)^{-1} \Phi^\top \in \mathbb{R}^{n \times n}$ .

- Show that

$$\mathbb{E}[\widehat{R}(\hat{\theta})] = \frac{n-d}{n} \sigma^2.$$

Hint:  $\Pi := \mathbf{I} - \Phi(\Phi^\top \Phi)^{-1} \Phi^\top \in \mathbb{R}^{n \times n}$  is an orthogonal projection matrix.

**Exercise IV (On the Moore–Penrose inverse) .** The goal of this exercise is to explore fundamental properties of the Moore–Penrose inverse, as defined via the Singular Value Decomposition (SVD) in the lecture slides.

1. Given  $A := \begin{pmatrix} 1 & 0 \\ 1 & 0 \end{pmatrix}$

- (a) Compute the Moore–Penrose inverse of  $A$ .
- (b) As seen in the lecture slide 68, compute  $A^\dagger A$  and  $\mathbf{I}_2 - A^\dagger A$ .
- (c) What are the properties of the previous matrices?

2. Show the following equalities for  $M \in \mathbb{R}^{m \times n}$ :

- (a)  $MM^\dagger M = M$ .
- (b)  $M^\dagger MM^\dagger = M^\dagger$ .