WRITE FIRST NAME, LAST NAME, AND ID NUMBER ("MATRICOLA") BELOW AND READ ALL INSTRUCTIONS BEFORE STARTING WITH THE EXAM! TIME: 2.5 hours.

FIRST NAME:	 	 	 
LAST NAME: .	 	 	 
ID NUMBER:	 	 	 

#### **INSTRUCTIONS**

- solutions to exercises must be in the appropriate spaces, that is:
  - Exercise 1: pag. 1, 2, 3
  - Exercise 2: pag. 4, 5
  - Exercise 3: pag. 6, 7, 8
  - Exercise 4: pag. 9, 10, 11, 12

Solutions written outside the appropriate spaces (including other papersheets) will not be considered.

- the use of notes, books, or any other material is forbidden and will make your exam invalid;
- electronic devices (smartphones, calculators, etc.) must be turned off; their use will make your exam invalid;
- this booklet must be returned in its entirety.

## Exercise 1 [8 points]

In the context of supervised learning:

- 1. provide the definition of the regression task
- 2. consider the following model class that is linear in the parameter:

$$h(x) := \mathbf{w}^{\mathsf{T}} \Psi(x) \quad \Psi(x) = [\psi_1(x), ..., \psi_L(x)]^{\mathsf{T}} \quad x \in \mathbb{R}, \mathbf{w} \in \mathbb{R}^L$$

where  $\Psi(x) = [\psi_1(x), ..., \psi_L(x)]^{\top}$  can be a generic function, e.g., recall the polynomial regression case where  $\Psi(x) = [1, x, x^2, ...., x^{L-1}]^{\top}$ . Write the explicit expression of the least squares estimator of  $\mathbf{w}$  given data  $(x_k, y_k)$ , k = 1, ..m.

3. Recalling the answer to the previous question, consider the one-hidden-layer neural network

$$h(x) := \sum_{i=1}^{L} w_i \sigma(\alpha_i(x - \beta_i)) \quad x \in \mathbb{R}$$

where  $\alpha_i, w_i, \beta_i, i = 1, ..., L$ , are the network parameters. Show that for  $\alpha_i$  and  $\beta_i$  fixed, the optimal  $w_i$  can be found in closed form under the square loss.

[Solution: Exercise 1]

[Solution: Exercise 1]

[Solution: Exercise 1]

### Exercise 2 [8 points]

Consider a generic machine learning problem and assume that a regularized loss function has been used by the selected algorithm A. In the loss function the relevance of the regularization term is controlled by a parameter  $\lambda$ . Let us denote with  $h_A$  the solution found by algorithm A and with  $L_S(h_A)$  its empirical risk while the true risk (generalization error) of  $h_A$  is  $L_D(h_A)$ .

- 1. Which is the impact of the  $\lambda$  parameter on the empirical risk  $L_S(h_A)$  of the solution found by A?
- 2. Which is the expected behavior of the true risk  $L_D(h_A)$  of the found solution as a function of the  $\lambda$  parameter?
- 3. Describe how the behavior of the empirical risk and of the true risk in the answers to the previous questions are related to the bias-complexity trade-off.

[Solution: Exercise 2]

[Solution: Exercise 2]

# Exercise 3 [8 points]

Consider a classification problem with 0-1 loss.

- 1. Provide the definition of VC dimension  $VCdim(\mathcal{H})$  of a hypothesis set  $\mathcal{H}$ , and of empirical error and true risk (generalization error) for an arbitrary hypothesis  $h \in \mathcal{H}$ . What is the relation between the empirical error and the true risk in terms of the VC dimension of  $\mathcal{H}$ ?
- 2. Consider the hypothesis set  $\mathcal{H}$  defined as:  $\mathcal{H} = \{h_{a,b} : a, b \in \mathbb{R}, a < b\}$  where  $h_{a,b} : \mathbb{R} \mapsto \{0,1\}$  is

$$h_{a,b}(x) = \begin{cases} 1 & \text{if } x \le a \ OR \ x \ge b \\ 0 & \text{otherwise} \end{cases}$$

What's the value of  $VCdim(\mathcal{H})$ ? Provide a proof of your claim.

3. Assume that you have many hypothesis sets, denoted by  $\mathcal{H}_i$ , i = 1, 2, ..., n. Describe one strategy to choose a good hypothesis set  $\mathcal{H}_i$  and a good model  $\hat{h}_i \in \mathcal{H}_i$ .

[Solution: Exercise 3]

[Solution: Exercise 3]

[Solution: Exercise 3]

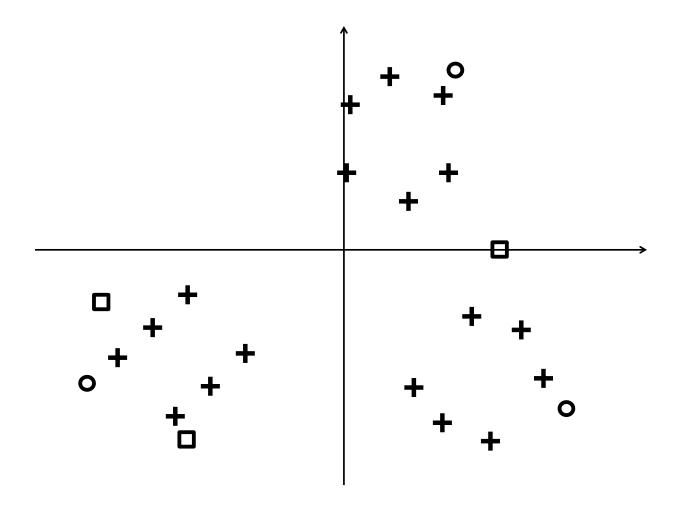
[Solution: Exercise 3]

# Exercise 4 [8 points]

Consider the problem of clustering.

- 1. Introduce the k-means clustering problem, rigorously defining its cost function.
- 2. Consider Lloyd's algorithm. What is the rule that is used to update the cluster centers after the points are assigned to clusters? Prove that such rule minimizes the k-means cost for the given assignment of points to clusters (i.e., once the assignment of points to clusters is fixed).
- 3. Consider the data in the figure below where each point  $\mathbf{x} \in \mathbb{R}^2$  is represented by a cross. Draw (approximately) the output of Lloyd's algorithm for k = 3 when
  - (a) the initial centers for the algorithm are the circles;
  - (b) the initial centers for the algorithm are the squares.

Which one of the two resulting clusterings has a lower cost?



[Solution: Exercise 4]

[Solution: Exercise 4]

[Solution: Exercise 4]