FUNDAMENTALS OF MACHINE LEARNING
AA 2025-2026
Prova Intermedia (FACSIMILE)

4 November, 2025

Istruzioni: Niente libri, niente appunti, niente dispositivi elettronici, e niente carta per appunti. Usare matita o penna di qualsiasi colore. Usare lo spazio fornito per le risposte.
Instructions: No books, no notes, no electronic devices, and no scratch paper. Use pen or pencil. Use the space provided for your answers.
This exam has 5 questions, for a total of 100 points and 10 bonus points.

Nome: ____________________

Matricola: ____________________

1. **Multiple Choice**: Select the correct answer from the list of choices.
   (a) [5 points] True or False: Adding an L_2 regularizer to least squares regression will reduce bias. ◯ True ◯ False
   (b) [5 points] True or False: A zero-mean Gaussian Prior (i.e. $p(\mathbf{w}) = \mathcal{N}(\mathbf{0}, \sigma I)$) on model parameters in a MAP estimate corresponds to adding an L2 regularization term (e.g. $||\mathbf{w}||_2$) to the loss in an MLE estimate. ◯ True ◯ False
   (c) [5 points] True or False: In the Primal Form of the SVM, increasing hyperparameter C will decrease the complexity of the resulting classifier. ◯ True ◯ False
   (d) [5 points] True or False: The Maximum a Priori (MAP) and Maximum Likelihood (ML) solution for linear regression are always equivalent. ◯ True ◯ False
   (e) [5 points] If a hard-margin support vector machine tries to minimize $||\mathbf{w}||_2$ subject to $y_n(\mathbf{w}^T\mathbf{x}_n + b) \geq 2$, what will be the size of the margin?
   ◯ $\frac{1}{||\mathbf{w}||}$ ◯ $\frac{2}{||\mathbf{w}||}$ ◯ $\frac{1}{2||\mathbf{w}||}$ ◯ $\frac{1}{4||\mathbf{w}||}$
   (f) [5 points] The posterior distribution of B given A is:
   ◯ $P(B \mid A) = \frac{P(A|B)P(A)}{P(B)}$
   ◯ $P(B \mid A) = \frac{P(A,B)P(B)}{P(A)}$
   ◯ $P(B \mid A) = \frac{P(A|B)P(B)}{P(A)}$
   ◯ $P(B \mid A) = \frac{P(A|B)P(B)}{P(A,B)}$
   (g) [5 points] Let $\mathbf{w}^*$ be the solution obtained using unregularized least-squares regression. What solution will you obtain if you scale all input features by a factor of c before solving?
   ◯ $c\mathbf{w}^*$ ◯ $c^2\mathbf{w}^*$ ◯ $\frac{1}{c^2}\mathbf{w}^*$ ◯ $\frac{1}{c}\mathbf{w}^*$

Total Question 1: 35

2. **Multiple Answer**: Select **ALL** correct choices: there may be more than one correct choice, but there is always at least one correct choice.

(a) [5 points] What are support vectors?

◯ The examples $\mathbf{x}_n$ from the training set required to compute the decision function $f(\mathbf{x})$ in an SVM.

◯ The class means.

◯ The training samples farthest from the decision boundary.

◯ The training samples $\mathbf{x}_n$ that are on the margin (i.e. $y_n f(\mathbf{x}_n) = 1$).

(b) [5 points] Which of the following are true about the relationship between the MAP and MLE estimators for linear regression?

◯ They are equal in the limit of infinite training samples.

◯ They are equal if $p(\mathbf{w}) = \mathcal{N}(\mathbf{0}, \sigma)$ for very small σ.

◯ They are equal if $p(\mathbf{w}) = 1$.

◯ They are never equal.

(c) [5 points] You train a linear classifier on 10,000 training points and discover that the training accuracy is only 67%. Which of the following, done in isolation, has a good chance of improving your training accuracy?

◯ Add novel features.

◯ Train on more data.

◯ Regularize the model.

◯ Train on less data.

(d) [5 points] What assumption does the quadratic Bayes generative classifier make about class-conditional covariance matrices?

◯ That they are equal.

◯ That they are diagonal.

◯ That their determinants are equal.

◯ None of the above.

(e) [5 points] Which of the following are reasons why you might adjust your model in ways that increase the bias?

◯ You observe high training error and high validation error.

◯ You have few data points.

◯ You observe low training error and high validation error.

◯ Your data are not linearly separable.

(f) [5 points] Which of the following are true of polynomial regression (i.e. least squares regression with polynomial basis mapping)?

◯ If we increase the degree of polynomial, we increase variance.

◯ The regression function is nonlinear in the model parameters.

◯ The regression function is linear in the original input variables.

◯ If we increase the degree of polynomial, we decrease bias.

(g) [5 points] Which of the following classifiers can be used on non linearly separable datasets?

◯ The hard margin SVM.

◯ Logistic regression.

◯ The linear generative Bayes classifiers.

◯ Fisher's Linear Discriminant.

Total Question 2: 35

3. [15 points] Assume the class conditional distributions for a two-class classification problem are $p(\mathbf{x} \mid \mathcal{C}_1) = \mathcal{N}(\boldsymbol{\mu}_1, \beta^{-1}I)$ and $p(\mathbf{x} \mid \mathcal{C}_2) = \mathcal{N}(\boldsymbol{\mu}_2, \beta^{-1}I)$. Moreover, assume that the class priors are equal: $p(\mathcal{C}_1) = p(\mathcal{C}_2)$. Show that the optimal decision boundary is *linear*, i.e. that it can be written as $H = \{\mathbf{x} \mid \mathbf{w}^T\mathbf{x} + b = 0\}$ for some $\mathbf{w}$ and b.

   Hint: Remember that points $\mathbf{x}$ on the optimal decision boundary will satisfy $p(\mathcal{C}_1 \mid \mathbf{x}) = p(\mathcal{C}_2 \mid \mathbf{x})$, and that the formula for the multivariate Gaussian density is:

$$\mathcal{N}(\mathbf{x} \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{D/2}|\boldsymbol{\Sigma}|^{1/2}} \exp\{-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\}$$

4. [15 points] Suppose that the data $\mathcal{D} = \{(\mathbf{x}_n, y_n)\}_{n=1}^{N}$ in a regression problem are generated as:

$$y_n = \mathbf{w}^T \mathbf{x}_n + \varepsilon,$$

where $\varepsilon \sim \mathcal{N}(0, \beta^{-1})$ is a zero-mean random variable. Show that the maximum likelihood solution $\mathbf{w}_{\mathrm{ML}}$ to this problem is equivalent to the solution that minimizes the squared error on $\mathcal{D}$.

Hint: Recall that the formula for the univariate Gaussian density is given by:

$$\mathcal{N}(y \mid \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\mu)^2}{2\sigma^2}}.$$

5. [10 points (bonus)] Consider the dataset with 1-dimensional inputs:

$$\mathcal{D} = \{(+1, +1), (-1, +1), (+2, -1), (-2, -1)\}.$$

Find a nonlinear embedding $\phi : \mathbb{R} \to \mathbb{R}^2$ that makes $\mathcal{D}$ linearly separable. Show that the resulting embedded dataset is indeed linearly separable by solving for the optimal hard-margin SVM solution $(\mathbf{w}^*, b^*)$.