

## COMP3670/6670: Introduction to Machine Learning

**Release Date.** Aug 16th, 2023

**Due Date.** 11:59pm, Sept 17th, 2023

**Maximum credit.** 100

### Exercise 1

#### Orthogonal Projections

(3 + 3 + 3 + 4 + 6 + 3 credits)

Consider the Euclidean vector space  $\mathbb{R}^3$  with the dot product. A subspace  $U \subset \mathbb{R}^3$  and vector  $\mathbf{x} \in \mathbb{R}^3$  are given by:

$$U = \text{span} \left\{ \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \\ -2 \end{bmatrix} \right\}, \mathbf{x} = \begin{bmatrix} 8 \\ 4 \\ 16 \end{bmatrix}$$

1. Show that  $\mathbf{x} \notin U$ .
2. Determine the orthogonal projection of  $\mathbf{x}$  onto  $U$ , denoted  $\pi_U(\mathbf{x})$ .
3. Determine the distance  $d(\mathbf{x}, U) := \min_{\mathbf{y} \in U} \|\mathbf{x} - \mathbf{y}\|$ , where  $\|\cdot\|$  denotes the Euclidean norm.
4. Use Gram-Schmidt orthogonalization to transform the matrix  $\mathbf{A} = \begin{bmatrix} -1 & 2 \\ 1 & -1 \\ 1 & -2 \end{bmatrix}$  into a matrix  $\mathbf{B}$  with orthonormal columns.
5. Let  $\mathbf{Q} \in \mathbb{R}^{m \times n}$  be a matrix with orthonormal columns and  $\mathbf{x} \in \mathbb{R}^m$  be an m-dimensional vector. Find the vector  $\boldsymbol{\theta}$  that minimizes  $\|\mathbf{x} - \mathbf{Q}\boldsymbol{\theta}\|^2 + \lambda\|\boldsymbol{\theta}\|^2$ , where  $\lambda$  is a positive real number.
6. Compute the vector  $\boldsymbol{\theta}$  for the matrix  $\mathbf{B}$  and  $\lambda = 10$ .

### Exercise 2

#### Vector calculus practices

(6 + 8 + 8 credits)

Compute the following gradients over  $\mathbf{x}$  or  $\mathbf{X}$ . Represent the result in numerator layout. **Note that you are only allowed to use the rules demonstrated in the lecture.** Show each step clearly.

1.  $\frac{\partial \mathbf{x}^T \mathbf{A} \mathbf{B} \mathbf{C} \mathbf{x}}{\partial \mathbf{x}}$

2.  $\frac{\partial (\mathbf{B}\mathbf{x} + \mathbf{b})^T \mathbf{C} (\mathbf{D}\mathbf{x} + \mathbf{d})}{\partial \mathbf{x}}$

3.  $\frac{\partial \text{tr}(\mathbf{X}^2)}{\partial \mathbf{X}}$

### Exercise 3

#### Concavity of a function

(8 + 10 + 10 credits)

A function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  with a convex domain is called a **concave** function if and only if its Hessian  $\mathbf{H} = \frac{\partial^2 f}{\partial \mathbf{x}^2}$  is negative semidefinite. Consider the following function:

$$f(\mathbf{x}) = \left( \sum_{i=1}^n x_i^p \right)^{1/p}$$

with convex domain  $\text{dom}(f) = \mathbb{R}_{++}^n$  (n-dim strictly elementwise positive vectors), and  $p < 1, p \neq 0$ .

1. Evaluate the elementwise second order derivatives  $\frac{\partial^2 f}{\partial x_i \partial x_j}$  for arbitrary integer  $i, j \in [1, n]$ .
2. Denote the elementwise power of a vector  $\mathbf{a} \in \mathbb{R}_{++}^n$  to a real number  $t$  as  $\mathbf{a}^t = \begin{bmatrix} a_1^t & a_2^t & \cdots & a_n^t \end{bmatrix}^T$ . Also, the  $\mathbf{diag}(\cdot)$  function returns the diagonal matrix with diagonal values input as a vector. Prove that

$$\mathbf{H} = (1-p)f(\mathbf{x})^{1-2p} \cdot \left( \mathbf{x}^{p-1} \cdot \mathbf{x}^{p-1T} - f(\mathbf{x})^p \cdot \mathbf{diag}(\mathbf{x}^{p-2}) \right)$$

3. Prove  $\mathbf{H}$  is negative semidefinite, hence  $f$  is concave since it has a convex domain.

**Exercise 4      Expectations with respect to a Gaussian distribution      (10+10+8 credits)**

A common objective function in modern machine learning is the variational free-energy,

$$\mathcal{F}(q(\theta)) = \int d\theta q(\theta) \log \frac{q(\theta)}{p(\theta)p(y|\theta, x)} = \int d\theta q(\theta) [\log q(\theta) - \log p(\theta) - \log p(y|\theta, x)]. \quad (1)$$

Consider a simplified setting in which

$$p(\theta) = \mathcal{N}(\theta; 0, 1), \quad (2)$$

$$p(y|\theta, x) = \mathcal{N}(y; \theta x, \sigma_n^2), \quad (3)$$

$$q(\theta) = \mathcal{N}(\theta; \mu, \sigma^2), \quad (4)$$

where  $\mathcal{N}(x; m, v)$  means  $x$  is a univariate Gaussian random variable with mean  $m$  and variance  $v$ .

1. Compute  $\mathcal{F}$ .
2. Find the gradients  $\frac{\partial}{\partial \mu} \mathcal{F}$  and  $\frac{\partial}{\partial \sigma} \mathcal{F}$ .
3. Set these gradients to zero and solve for  $\mu$  and  $\sigma$  in terms of  $y, x$  and  $\sigma_n$ .