

## Exercices

Luxformel

# Mathematics for Machine Learning

### Exercise 1 : Basic vector operations

Let

$$\mathbf{u} = (1, 2, -1)^\top, \quad \mathbf{v} = (0, 1, 3)^\top.$$

Compute:

1.  $\mathbf{u}, \mathbf{v}$
2.  $\|\mathbf{u}\|_2$  and  $\|\mathbf{v}\|_2$
3. Projection of  $\mathbf{u}$  onto  $\mathbf{v}$ .

### Exercise 2 : Linear system

Solve:

$$A = \begin{pmatrix} 2 & -1 & 0 \\ 1 & 1 & 1 \\ 0 & 2 & -1 \end{pmatrix}, \quad \mathbf{b} = \begin{pmatrix} 1 \\ 3 \\ -1 \end{pmatrix}, \quad A\mathbf{x} = \mathbf{b}.$$

### Exercise 3 : Data interpretation

Given points  $(1,2)$ ,  $(2,3)$ ,  $(3,5)$ , form the design matrix  $\mathbf{X}$  for

$$y = w_0 + w_1 x$$

and write the **normal equations** for least squares.

**Exercise 4 : Partial derivatives**

For

$$f(x, y) = 3x^2y - 4xy + \sin y,$$

compute  $\frac{\partial f}{\partial x}$  and  $\frac{\partial f}{\partial y}$ .

**Exercise 5 : Gradient and Hessian**

Let

$$f(\mathbf{x}) = \frac{1}{2}\mathbf{x}^\top A\mathbf{x} - \mathbf{b}^\top \mathbf{x},$$

compute  $\nabla f(\mathbf{x})$ ,  $H(f)$ , and state when  $f$  is convex.

**Exercise 6 : Chain rule**

Let

$$g(\mathbf{x}) = \log(1 + e^{\mathbf{a}^\top \mathbf{x}}),$$

compute  $\nabla g(\mathbf{x})$ .

**Exercise 7 : One-dimensional GD**

For

$$f(x) = x^2 - 4x + 5,$$

starting from  $x_0 = 0$ , apply gradient descent with  $\eta = 0.1$  for three iterations.

**Exercise 8 : Quadratic form**

For

$$f(\mathbf{x}) = \frac{1}{2}\mathbf{x}^\top \begin{pmatrix} 3 & 0 \\ 0 & 1 \end{pmatrix} \mathbf{x},$$

find the largest  $\eta$  guaranteeing convergence.

**Exercise 9 : Least squares**

For

$$J(w) = \frac{1}{2m} \|Xw - y\|_2^2,$$

derive  $\nabla_w J(w)$  and write one gradient descent update.

**Exercise 10 : Ridge closed form**

Show that

$$w^* = (X^\top X + \lambda I)^{-1} X^\top y.$$

Why does  $\lambda I$  improve conditioning?

**Exercise 11 : L1 vs L2 regularization**

Explain why **L1** produces sparse models while **L2** does not.

**Exercise 12 : Regularized gradient**

For

$$J_\lambda(w) = \frac{1}{2m} \|Xw - y\|_2^2 + \frac{\lambda}{2} \|w\|_2^2,$$

compute  $\nabla_w J_\lambda(w)$ .

**Exercise 13 : Eigenpairs & PCA intuition**

Given

$$C = \frac{1}{m} X^\top X,$$

explain why eigenvectors with largest eigenvalues are **principal components**, and find the projection of a point  $\mathbf{x}$ .

**Exercise 14 : Gradient descent rate**

For

$$f(\mathbf{x}) = \frac{1}{2} \mathbf{x}^\top A \mathbf{x} - \mathbf{b}^\top \mathbf{x},$$

show that gradient descent with

$$0 < \eta < \frac{2}{\lambda_{\max}}$$

converges linearly with rate involving

$$\kappa = \frac{\lambda_{\max}}{\lambda_{\min}}.$$