

# Exercises on Chapter 1: Convexity

Mathematics of Data Science, M1 IDD

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## Convex sets

### Exercise 1.1: Partial sum

Let  $\mathcal{C}_1$  and  $\mathcal{C}_2$  be two convex sets in  $\mathbb{R}^{m+n}$ . Show that the set

$$\mathcal{C} := \left\{ \begin{bmatrix} x \\ y_1 + y_2 \end{bmatrix} \middle| x \in \mathbb{R}^m, y_1 \in \mathbb{R}^n, y_2 \in \mathbb{R}^n, \begin{bmatrix} x \\ y_1 \end{bmatrix} \in \mathcal{C}_1, \begin{bmatrix} x \\ y_2 \end{bmatrix} \in \mathcal{C}_2 \right\}$$

is also convex.

### Exercise 1.2: Characterizing convexity

Show that a set  $\mathcal{C} \subseteq \mathbb{R}^n$  is convex if and only if  $(\alpha + \beta)\mathcal{C} = \alpha\mathcal{C} + \beta\mathcal{C}$  for any  $\alpha \geq 0$  and  $\beta \geq 0$ .

### Exercise 1.3: Normal cone

Let  $\mathcal{X} \subseteq \mathbb{R}^n$  be an arbitrary set (not necessarily convex) and let  $x_0 \in \mathcal{X}$ . The *normal cone* of  $\mathcal{X}$  at  $x_0$  is defined by

$$\mathcal{N}_{\mathcal{X}}(x_0) := \{y \in \mathbb{R}^n \mid y^T(x - x_0) \leq 0 \forall x \in \mathcal{X}\}.$$

Show that  $\mathcal{N}_{\mathcal{X}}(x_0)$  is a convex cone.

### Exercise 1.4: Convex and affine hulls

Show that the following properties hold for any set  $\mathcal{X} \subseteq \mathbb{R}^n$ :

- a)  $\text{conv}(\mathcal{X}) \subseteq \text{aff}(\mathcal{X})$ ;
- b)  $\text{aff}(\mathcal{X}) = \text{aff}(\text{conv}(\mathcal{X}))$ .
- c)  $\text{aff}(\mathcal{X})$  is a closed set and  $\text{aff}(\mathcal{X}) = \text{aff}(\text{cl}(\mathcal{X}))$

### Exercise 1.5: Retraction set

Let  $\mathcal{C} \subset \mathbb{R}^n$  be a convex set and  $r \geq 0$ . The purpose of this exercise is to establish that the retraction set

$$\mathcal{C}_{-r} := \{\mathbf{x} \in \mathbb{R}^n \mid \mathcal{B}_r(\mathbf{x}) \subseteq \mathcal{C}\}$$

is convex.

- a) Given any  $\mathbf{x}, \mathbf{y} \in \mathcal{C}_{-r}$  and  $t \in [0, 1]$ , show that  $t\mathbf{x} + (1 - t)\mathbf{y} \in \mathcal{C}$ .
- b) Consider now  $\mathbf{z} \in \mathcal{B}_r(t\mathbf{x} + (1 - t)\mathbf{y})$ , and write

$$\mathbf{z} = \mathbf{w} + t\mathbf{x} + (1 - t)\mathbf{y}.$$

Show that  $\mathbf{w} + \mathbf{x} \in \mathcal{B}_r(\mathbf{x})$  and  $\mathbf{w} + \mathbf{y} \in \mathcal{B}_r(\mathbf{y})$ .

- c) Show finally that  $\mathbf{z} \in \mathcal{C}$ , and explain how it proves the desired result.

## Convex functions

### Exercise 1.6: Convexity and upper bounds

Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be convex and differentiable. Suppose that there exists  $M \in \mathbb{R}$  such that  $f(\mathbf{x}) \leq M$  for all  $\mathbf{x} \in \mathbb{R}^n$ . Show then that the gradient of  $f$  is zero at every point, which implies that the function  $f$  is constant.

*Hint: For any linear function  $g(\mathbf{x}) = \mathbf{A}\mathbf{x} + \mathbf{b}$ ,  $g$  is bounded if and only if  $\mathbf{A} = \mathbf{0}$ .*

### Exercise 1.7: Convexity and extended values

Let  $\mathcal{X} \subset \mathbb{R}^n$  be a convex set and  $f : \mathcal{X} \rightarrow \overline{\mathbb{R}}$  be a convex function. Show that

- a)  $\text{dom}(f)$  is a convex set;
- b) the sublevel sets of  $f$  are convex sets.

### Exercise 1.8: Inequalities and convexity

a) Let  $p > 1$ . We define the  $\ell_p$  norm by

$$\forall \mathbf{x} \in \mathbb{R}^n, \quad \|\mathbf{x}\|_p = \left( \sum_{i=1}^n |x_i|^p \right)^{1/p}.$$

Show that the function  $\mathbf{x} \mapsto \|\mathbf{x}\|_p^p$  is convex.

b) Using the convexity of  $x \mapsto -\ln(x)$ , show that

$$a^\theta b^{1-\theta} \leq \theta a + (1-\theta)b$$

for any  $a, b \geq 0$  and any  $\theta \in [0, 1]$ .

c) Let  $p > 1$  and  $q > 1$  be two values such that  $\frac{1}{p} + \frac{1}{q} = 1$ . Use the previous question to construct  $n$  inequalities that can be combined to show the so-called Hölder inequality:

$$\forall (\mathbf{x}, \mathbf{y}) \in (\mathbb{R}^n)^2, \quad \sum_{i=1}^n x_i y_i \leq \|\mathbf{x}\|_p \|\mathbf{y}\|_q.$$

*Hint: Show that the result holds when  $\sum_{i=1}^n x_i y_i$  is replaced by  $\sum_{i=1}^n |x_i| |y_i|$ , then conclude.*

### Exercise 1.9: Log-concave functions

A function  $f : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$  is called *log-concave* (short for logarithmically concave) if  $f(\mathbf{x}) \geq 0$  for all  $\mathbf{x} \in \text{dom}(f)$  and  $\mathbf{x} \mapsto \ln(f(\mathbf{x}))$  is concave (where we let  $\ln(f(\mathbf{x})) = -\infty$  when  $f(\mathbf{x}) = 0$ ). The concept of *log-convex* functions is defined in a similar way.

a) Given  $a \in \mathbb{R}$ , show that the function  $x \mapsto x^a$  is log-concave on  $\mathbb{R}_{++}$  when  $a \geq 0$  and log-convex on  $\mathbb{R}_{++}$  when  $a \leq 0$ .

b) We will now show that the determinant function is log-concave on  $\mathcal{S}_{++}^n$ . For any  $\mathbf{X} \in \mathcal{S}_{++}^n$ , the determinant of  $\mathbf{X}$  has the expression  $\det(\mathbf{X}) = \prod_{i=1}^n \lambda_i^{\mathbf{X}}$ , where  $\lambda_1^{\mathbf{X}}, \dots, \lambda_n^{\mathbf{X}}$  are positive real numbers corresponding to the eigenvalues of  $\mathbf{X}$ .

(i) Show that the set  $\mathcal{S}_{++}^n$  is convex.

(ii) For any  $\mathbf{X}, \mathbf{Y}$  in  $\mathcal{S}_{++}^n$ , the matrix  $\mathbf{Z} = \mathbf{Y} \mathbf{X}^{-1}$  belongs to  $\mathcal{S}_{++}^n$ . Using this property, show that

$$\ln(\det(\alpha \mathbf{X} + (1-\alpha) \mathbf{Y})) = \sum_{i=1}^n \ln(\lambda_i^{\mathbf{X}}) + \sum_{i=1}^n \ln(\alpha + (1-\alpha) \lambda_i^{\mathbf{Z}}) \quad (1)$$

for any  $\alpha \in [0, 1]$ .

(iii) With the same notations than in the previous question, show that

$$\alpha \ln(\det(\mathbf{X})) + (1-\alpha) \ln(\det(\mathbf{Y})) = \sum_{i=1}^n \ln(\lambda_i^{\mathbf{X}}) + (1-\alpha) \sum_{i=1}^n \ln(\lambda_i^{\mathbf{Z}}). \quad (2)$$

(iv) Conclude that  $\ln \det$  is concave on  $\mathcal{S}_{++}^n$ .