# Exercises for Convexity

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# Ex. 1 — Existence of a minimizer of an extended-valued function

Prove that the following optimization problem

$$\min_{x \in \mathbb{R}^2} \sqrt{1 + \left\| x - \begin{pmatrix} 1 \\ 0 \end{pmatrix} \right\|_2^2} \quad \text{s.t.} \quad \left\langle x, \begin{pmatrix} \cos(\|x\|_2) \\ \sin(\|x\|_2) \end{pmatrix} \right\rangle \ge 0$$

has a solution.

# Ex. 2 — Meeting the $\ell^1$ ball

We consider the  $\ell^1$  ball,

$$C = \left\{ x \in \mathbb{R}^p \mid \sum_{i=1}^p |x_i| \le 1 \right\}.$$

- 1. Prove that it is a compact convex set.
- 2. What are the extreme points of C?
- 3. What is its (relative) interior?

## Ex. 3 — On a set of positive semi-definite matrices

We denote by  $\mathbb{S}_n(\mathbb{R})$  (resp.  $\mathbb{S}_n^+(\mathbb{R})$ ) the set of real symmetric (resp. positive semi-definite) matrices of size  $n \times n$ . Consider the set

$$C = \left\{ M \in \mathbb{S}_n^+(\mathbb{R}) \mid \operatorname{Tr} M = 1 \right\}.$$

- 1. Prove that C is a compact convex set.
- 2. What are the extreme points of C?
- 3. a) What is the affine hull of C?
  - b) Deduce the dimension of C. What can you conclude about the Minkowski-Carathéodory theorem for this convex?
- 4. What is the relative interior of C?

## Ex. 4 — Some projections

Let  $x \in \mathbb{R}^p$ . Compute the projection of x onto

- 1.  $C = \{ y \in \mathbb{R}^p \mid ||y||_2 \le 1 \} \ (\ell^2 \text{ unit ball}).$
- 2.  $C = \{ y \in \mathbb{R}^p \mid ||y||_{\infty} \le 1 \} \ (\ell^{\infty} \text{ unit cube}).$
- 3.  $C = \left\{ (y, t) \in \mathbb{R}^{p-1} \times \mathbb{R} \mid \sum_{i=1}^{p-1} (y_i)^2 \le 1 \text{ and } 0 \le t \le 1 \right\}$ , for  $p \ge 2$  (cylinder).

### Ex. 5 — Recognizing convex functions

Are the following functions convex?

- 1. f(x) = ||Ax b||, for  $x \in \mathbb{R}^p$ , where  $A \in \mathbb{R}^{m \times N}$ ,  $b \in \mathbb{R}^m$ .
- 2. (ReLU)  $f(x) = \max\{x, 0\}$ , for all  $x \in \mathbb{R}$ .
- 3. (Quadratic over linear function)  $f(x,y) = x^2/y$  for all  $x,y \in \mathbb{R}$  such that y > 0.
- 4. (Log-sum-exp)  $f(x) = \log(e^{x_1} + \dots + e^{x_p})$ , for all  $x = (x_1, \dots, x_p) \in \mathbb{R}^p$ .
- 5. (Maximal eigenvalue)  $f(M) = \lambda_n(M)$  for all  $M \in S_n^+(\mathbb{R})$ . **Hint:** Observe that  $\lambda_n(M) = \sup \left\{ y^\top M y \mid y \in \mathbb{R}^n, \|y\| = 1 \right\}$ .
- 6. (Sum of the k largest components)  $f(x) = x_{[1]} + \cdots + x_{[k]}$  where  $1 \le k \le p$  and  $x_{[1]} \ge \cdots \ge x_{[p]}$  are the ordered components of  $x \in \mathbb{R}^p$ . **Hint:** Write f as the supremum of affine functions.

### Ex. 6 — Subdifferential of separable functions

1. Let  $f_1, \ldots, f_p : \mathbb{R} \to \{+\infty\}$  be convex proper lower semi-continuous functions. Consider the function  $f : \mathbb{R}^p \to \mathbb{R} \cup \{+\infty\}$  defined by  $f(x) = \sum_{i=1}^p f_i(x_i)$  for all  $x = (x_1, \ldots, x_p) \in \mathbb{R}^p$ . Prove that

$$\forall x = (x_1, \dots, x_p) \in \mathbb{R}^p, \quad \partial f(x) = (\partial f_1(x_1)) \times \dots \times (\partial f_n(x_p))$$

2. Consider the  $\ell^1$ -norm, i.e. the function  $f: x \mapsto ||x||_1 \stackrel{\text{def.}}{=} \sum_{i=1}^p |x_i|$  and let  $q \in \mathbb{R}^p$ . Prove that  $q \in \partial f(x)$  if and only if

$$\begin{cases} q_i = \operatorname{sign}(x_i) & \text{for all } i \in \{1, \dots, p\} \text{ such that } x_i \neq 0, \\ q_i \in [-1, 1] & \text{for all } i \in \{1, \dots, p\} \text{ such that } x_i = 0 \end{cases}$$

### Ex. 7 — $\ell^1$ -regularization

Consider the minimization problem, for fixed  $y \in \mathbb{R}^p$ , and  $\lambda > 0$ ,

$$\min_{x \in \mathbb{R}^p} \lambda \left\| x \right\|_1 + \frac{1}{2} \left\| x - y \right\|_2^2.$$

Such a problem arises when considering the denoising of signals using the  $\ell^1$  norm. As it amounts to computing the proximity operator of the  $\ell^1$ -norm, so it also appears in proximal algorithms.

1. Prove that there is a unique minimizer.

2. Prove that the solution is given by the soft thresholding of y,

$$\forall i \in \{1, \dots, p\}, \quad x_i = \begin{cases} y_i + \lambda & \text{if } y_i < -\lambda, \\ 0 & \text{if } -\lambda \le y_i \le \lambda, \\ y_i - \lambda & \text{if } y_i > \lambda. \end{cases}$$
 (1)

(you may use the result of the previous exercise).

**Ex. 8** — **Projection onto a convex set** Let  $C \subseteq \mathbb{R}^p$  be a nonempty closed convex set, and  $\chi_C(x) \stackrel{\text{def.}}{=} 0$  if  $x \in C$ ,  $+\infty$  otherwise. Let  $y \in \mathbb{R}^p$  and consider the problem

$$\min_{x \in \mathbb{R}^p} \frac{1}{2} ||x - y||^2 + \chi_C(x).$$

- 1. Prove that there is a unique minimizer to that problem.
- 2. Let  $q \in \mathbb{R}^p$ , what does  $q \in \partial \chi_C(x)$  mean?
- 3. Using the subdifferential, provide a characterization of the projection onto  ${\cal C}.$
- 4. Let  $f \in \mathcal{C}^1(X)$ , convex and coercive (w.r.t. the set C).

Ex. 9 — The Moreau-Yosida regularization and the proximal point Let f be a proper convex lower semi-continuous function, and  $\lambda > 0$ . Define the Moreau-Yosida regularization of f,

$$\forall x \in \mathbb{R}^p, \quad f_{\lambda}(x) \stackrel{\text{def.}}{=} \inf_{y \in \mathbb{R}^p} \left( f(y) + \frac{1}{2\lambda} ||x - y||^2 \right)$$
 (2)

- 1. Draw  $f_{\lambda}$  for  $f(x) = \chi_{[-1,1]}(x), x \in \mathbb{R}$ .
- 2. Prove that there is a unique minimizer y in (2). It is called the proximal point of f at x. It is often denoted by  $\operatorname{prox}_{\lambda f}(x)$ .

**Hint:** To prove that f is coercive, justify that there exists some affine function which is below f.

- 3. Prove that  $f_{\lambda}$  is convex proper, and that dom  $f_{\lambda} = \mathbb{R}^p$  (hence  $f_{\lambda}$  is continuous on  $\mathbb{R}^p$ ).
- 4. Prove the following properties
  - 1.  $f_{\lambda}(x) \leq f(x)$  for all  $x \in \mathbb{R}^p$ ,  $\lambda > 0$ .
  - 2.  $\lim_{\lambda \to 0^+} \operatorname{prox}_{\lambda f}(x) = x$  for all  $x \in \operatorname{dom} f$ .
  - 3.  $\lim_{\lambda \to 0^+} f_{\lambda}(x) = f(x)$  for all  $x \in \mathbb{R}^p$ .

#### Ex. 10 — Convex conjugate.

1. Let  $f: \mathbb{R}^p \to \mathbb{R}$  defined by  $f(x) = \frac{1}{2} \|x\|_2^2$ . Compute its Legendre-Fenchel transform  $f^*$ .

2. Compute the conjugate function of the  $\ell^q$  norm:  $x\mapsto \|x\|_q$ . Hint: Remember the Hölder inequality:  $|\langle x,y\rangle|\leq \|x\|_q\|y\|_{q'}$  for  $q,q'\in [1,+\infty]$  such that 1/q+1/q'=1. What is the equality case?