Convex Optimization

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Abstract

This document is Antoine Groudiev's class notes while following the class *Convex Optimization* (Optimisation Convexe) at the Computer Science Department of ENS Ulm. It is freely inspired by the lectures of Adrien Taylor.

1 Introduction

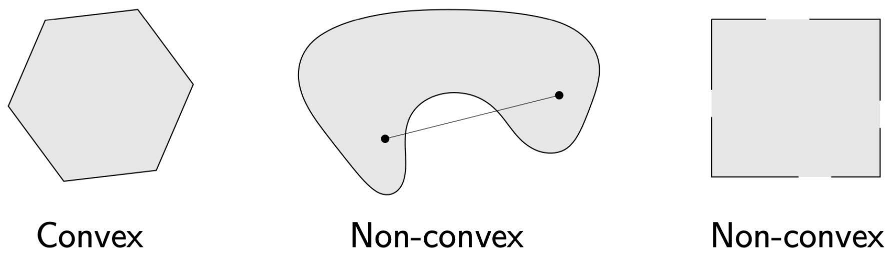
2 Convex sets

2.1 Definitions

Definition (Convex set)**.** A set C is a *convex set* if every segment that connects two points in C is in C. Formally:

$$\forall x, y \in C, \forall \theta \in [0, 1], \quad \theta x + (1 - \theta) y \in C$$

Example. Here are some examples of convex and non-convex sets:



In many cases, we will use proper (i.e. non-empty) convex sets, and closed convex sets.

Definition (Convex hull)**.** The *convex hull* of S, denoted $\mathrm{Conv}(S)$, is the smallest convex set that contains S.

Definition (Convex combinations)**.** The *convex combinations* of $x_1, \dots, x_k$ are all the point x of the form:

$$x = \theta_1 x_1 + \cdots + \theta_k x_k$$

with $\theta_1, \dots, \theta_k \geqslant 0$ and $\sum_{i=1}^k \theta_i = 1$.

Property 2.1. The convex hull of a set S is the set of all convex combinations of points in S:

$$\mathrm{Conv}(S) = \left\{ \sum_{i=1}^k \theta_i x_i \,\middle|\, (x_i) \in S^k, (\theta_i) \in \mathbb{R}_+^k, \sum_{i=1}^k \theta_i = 1 \right\}$$

2.2 Examples

2.2.1 Hyperplanes and halfspaces

Definition (Hyperplane)**.** A *hyperplane* is the set of the form:

$$H = \left\{ x \,\middle|\, a^\top x = b \right\}$$

for some $a \in \mathbb{R}^n \setminus \{0\}$ and $b \in \mathbb{R}$. a is called the *normal vector* of H. Hyperspaces are affine and convex.

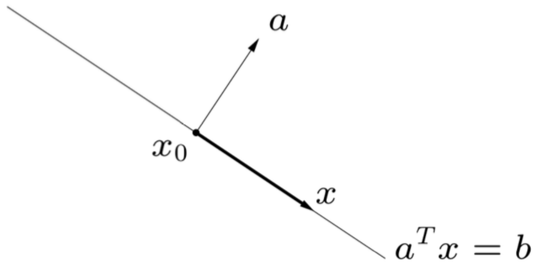


Figure 2.1: Hyperplane

Definition (Halfspace)**.** A *halfspace* is the set of the form:

$$H = \left\{ x \,\middle|\, a^\top x \leqslant b \right\}$$

for some $a \in \mathbb{R}^n \setminus \{0\}$ and $b \in \mathbb{R}$. a is called the *normal vector* of H. Halfspaces are convex.

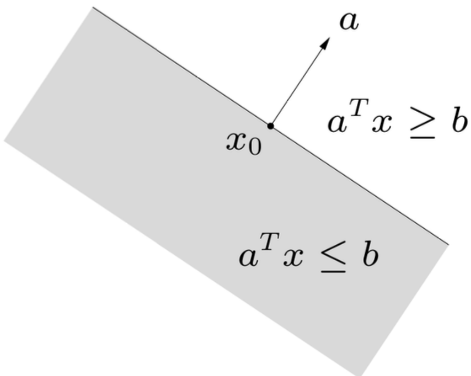


Figure 2.2: Halfspace

2.2.2 Euclidian balls and ellipsoids

Definition (Euclidian ball)**.** The *Euclidian ball* of center x_c and radius r is the set:

$$B(x_c, r) = \{ x \mid \|x - x_c\|_2 \leqslant r \} = \{ x_c + ru \mid \|u\|_2 \leqslant 1 \}$$

Euclidian balls are convex.

Definition (Ellipsoid)**.** An *ellipsoid* is the set of the form:

$$E = \left\{ x \,\middle|\, (x - x_c)^\top P^{-1}(x - x_c) \leqslant 1 \right\}$$

with $P \in \mathbb{S}^n_{++}$[1] and $x_c \in \mathbb{R}^n$. Ellipsoids are convex.

[1] $\mathbb{S}^n_{++}$ denotes the set of symmetric positive definite matrices of size n

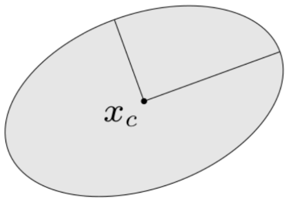


Figure 2.3: Ellipsoid

An alternative representation of an ellipsoid is:

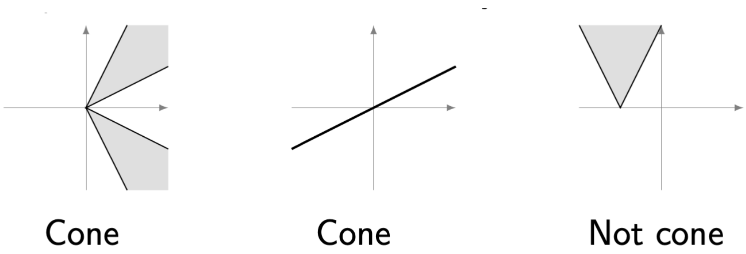
$$E = \{\, x_c + Au \mid \|u\|_2 \leqslant 1 \,\}$$

for some nonsingular matrix $A \in \mathrm{GL}_n(\mathbb{R})$. We can choose A symmetric and positive definite without loss of generality, for instance by choosing $A = P^{1/2}$.

2.2.3 Cones

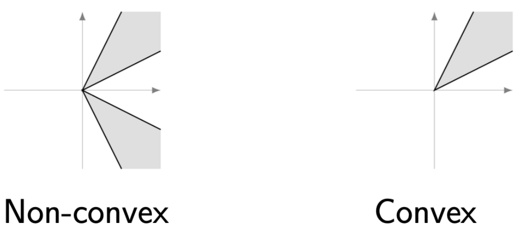
Definition (Cones)**.** A set K is a *cone*, or a *nonnegative homogeneous set*, if:

$$\forall x \in K, \forall \theta \in \mathbb{R}_+^*, \quad \theta x \in K$$



Definition (Convex cone)**.** A set K is a *convex cone* if:

$$\forall x_1, x_2 \in K, \forall \theta_1, \theta_2 \in \mathbb{R}_+^*, \quad \theta_1 x_1 + \theta_2 x_2 \in K$$



In the followings, we will denote by:

- $\mathbb{S}^n \subset \mathbb{R}^{n \times n}$ the set of symmetric matrices of size n
- $\mathbb{S}_+^n$ the set of positive semidefinite matrices of size n, that is matrices verifying:

  $$\forall z \in \mathbb{R}^n, z^\top X z \geqslant 0$$

  also denoted $X \succcurlyeq 0$.

- $\mathbb{S}^n_{++}$ the set of positive definite matrices of size n, that is matrices verifying:

$$\forall z \in \mathbb{R}^n, z^\top X z > 0$$

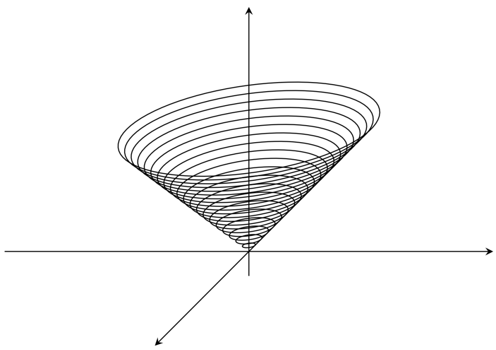
  also denoted $X \succ 0$.

$\mathbb{S}^n_+$ and $\mathbb{S}^n_{++}$ are convex cones.

Special cases of cones include:

Positive orthant $K = \mathbb{R}^n_+ = \{\, x \in \mathbb{R}^n \mid x_i \geqslant 0, \forall i \,\}$

Norm cones $K = \{\, (x, t) \in \mathbb{R}^n \times \mathbb{R} \mid \|x\| \leqslant t \,\}$. A particular case is the second-order cone (SOC), based on the ℓ_2 norm.



Positive polynomials $K_n = \{\, x \in \mathbb{R}^{n+1} \mid \forall t \in \mathbb{R}, \sum_{i=0}^n x_i t^i \geqslant 0 \,\}$

Positive semidefinite cone $\mathbb{S}^n_+ = \left\{ X \in \mathbb{S}^n \,\middle|\, \forall z \in \mathbb{R}^n, z^\top X z \geqslant 0 \right\}$

Co-positive cone $\mathbb{S}^n_+ = \left\{ X \in \mathbb{S}^n \,\middle|\, \forall z \in \mathbb{R}^n_+, z^\top X z \geqslant 0 \right\}$

Exponential cone $\left\{ (x, y, z) \in \mathbb{R} \times \mathbb{R}^*_+ \times \mathbb{R} \,\middle|\, z \geqslant y e^{x/y} \right\}$

Definition (Dual cones)**.** The *dual cone* to a convex cone K is the set:

$$K^* = \left\{ y \,\middle|\, \forall x \in K, \quad y^\top x \geqslant 0 \right\}$$

Convex cones and their duals are particularly useful for convex duality. A convex cone that satisfies $K = K^*$ is called *self-dual.*

Definition (Polar cones)**.** The *polar cone* to a convex cone K is the set:

$$K^\diamond = \left\{ y \,\middle|\, \forall x \in K, \quad y^\top x \leqslant 0 \right\}$$

We have the identity $K^\diamond = -K^*$.

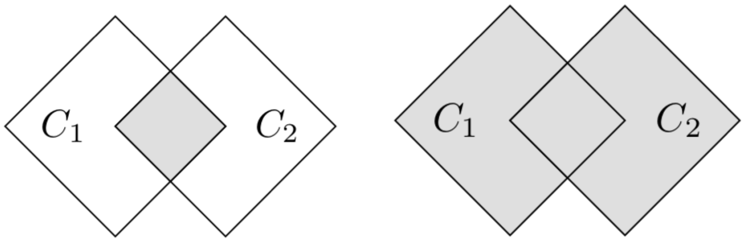
2.3 Convexity-preserving operations

To establish the convexity of a set C, the most basic approach is to apply the definition by proving that every segment that connects two points in C is in C. However, this can be tedious in practice. Instead, we can use operations that preserve convexity.

2.3.1 Intersection and union

Property 2.2 (Convexity is preserved by intersection)**.** For any convex sets C_1 and C_2, the intersection $C_1 \cap C_2$ is convex.

Likewise, the intersection of an arbitrary number of convex sets is convex.

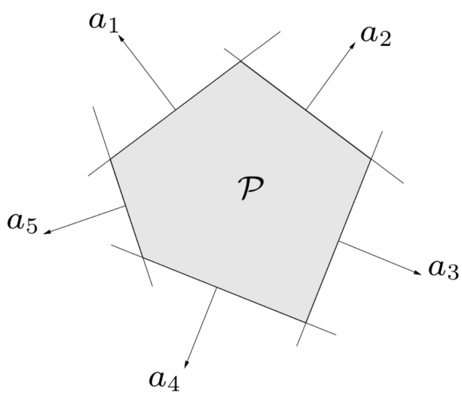


Remark. *The union of convex sets is not necessarily convex. For instance in* $\mathbb{R}$*, both* $[0,1]$ *and* $[2,3]$ *are convex, but their union* $[0,1] \cup [2,3]$ *is not.*

Definition (Polyhedron)**.** A *polyhedron* is the solution set of finitely many linear inequalities and equalities:

$$S = \{\, x \in \mathbb{R}^n \mid Ax \leqslant b, Cx = d \,\}$$

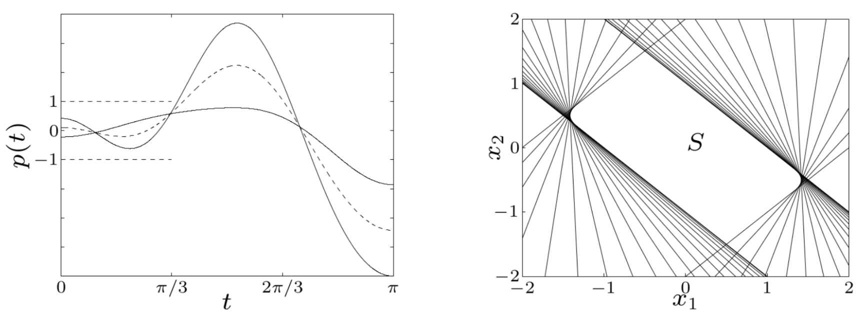
for $A \in \mathscr{M}_{m,n}(\mathbb{R})$ and $C \in \mathscr{M}_{p,n}(\mathbb{R})$. Polyhedra are convex, since they are the intersection of halfspaces and hyperplanes which are convex.



Example. Let:

$$S = \left\{ x \in \mathbb{R}^m \;\middle|\; \forall t \in \mathbb{R}, \quad |t| \leqslant \frac{\pi}{3} \implies \left| \sum_{k=1}^{m} x_k \cos(kt) \right| \leqslant 1 \right\}$$

S is convex, since it can be written as the intersection of convex sets.



Example. $\mathbb{S}_+^n$ is convex since it is the intersection of convex sets:

$$\mathbb{S}_+^n = \left\{ X \in \mathbb{S}^n \,\middle|\, \forall z \in \mathbb{R}^n, z^\top X z \geqslant 0 \right\} = \mathbb{S}^n \cap \bigcap_{z \in \mathbb{R}^n} \left\{ X \in \mathscr{M}_n(\mathbb{R}) \,\middle|\, z^\top X z \geqslant 0 \right\}$$

Each set $\left\{ X \in \mathscr{M}_n(\mathbb{R}) \,\middle|\, z^\top X z \geqslant 0 \right\}$ being convex, their intersection is convex. In particular, it doesn't matter if the number of sets is finite, countable or uncountable.

2.3.2 Affine functions

Property 2.3 (The image of a convex set by an affine function is convex)**.** If $L : \mathbb{R}^n \to \mathbb{R}^m$ is an affine function, then if C is convex, $L(C)$ is convex.

More explicitly, let $A \in \mathscr{M}_{m,n}(\mathbb{R})$ and $b \in \mathbb{R}^m$. The affine function $L(x) = Ax + b$ maps C to $L(C) = \{ y \in \mathbb{R}^m \mid \exists x \in C, y = Ax + b \}$, which is convex if C is convex.

Property 2.4 (The pre-image of a convex set by an affine function is convex)**.** If $L : \mathbb{R}^n \to \mathbb{R}^m$ is an affine function, then $L^{-1}(C)$, the pre-image of C by L defined by:

$$L^{-1}(C) = \{ x \in \mathbb{R}^n \mid L(x) \in C \}$$

is convex if C is convex.

Example (Linear matrix inequalities)**.** Let $A_1, \dots, A_m \in \mathbb{S}^n(\mathbb{R})$. The set:

$$\left\{ x \in \mathbb{R}^m \,\middle|\, \sum_{i=1}^{m} x_i A_i \succcurlyeq 0 \right\}$$

is an affine pre-image of $\mathbb{S}_+^n$ for the mapping $L : \mathbb{R}^m \to \mathbb{S}^n$ defined by:

$$L(x) = \sum_{i=1}^{m} x_i A_i$$

$\mathbb{S}_+^n$ being convex, the set is convex. $\sum_{i=1}^m x_i A_i \succcurlyeq 0$ is called a *linear matrix inequality.*

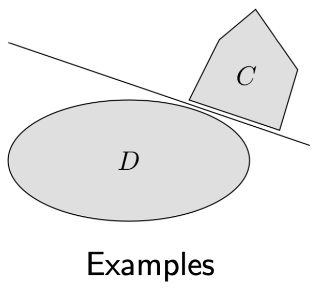
2.4 Geometric elements

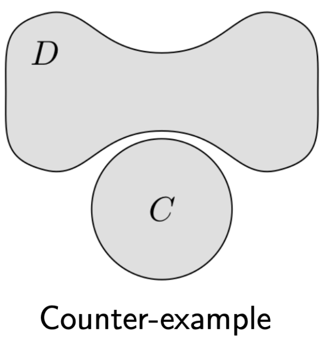
2.4.1 Separating and supporting hyperplanes

Property 2.5 (Separating hyperplanes)**.** Soppose that $C, D \subseteq \mathbb{R}^n$ are two non-intersecting convex sets (that is $C \cap D = \varnothing$). Then there exists a hyperplane that separates C and D, that is:

$$\exists s \in \mathbb{R}^n \setminus \{0\}, \exists r \in \mathbb{R}, \quad \forall x \in C, s^\top x \leqslant r \quad \text{and} \quad \forall x \in D, s^\top x \geqslant r$$

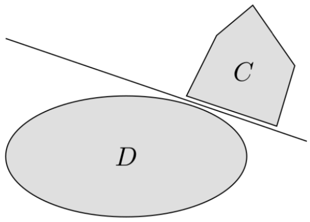
where $\left\{ x \in \mathbb{R}^n \,\middle|\, s^\top x = t \right\}$ is called the *separating hyperplane.*

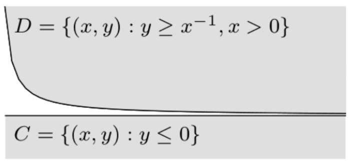




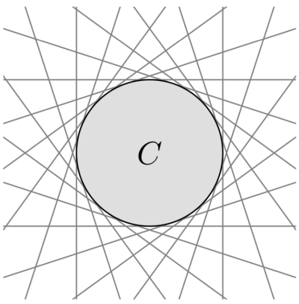
Property 2.6 (Strict separating hyperplanes)**.** Suppose that $C, D \subseteq \mathbb{R}^n$ are two non-intersecting **closed** convex sets, and that one of them is compact (closed and bounded in finite dimension). Then there exists a hyperplane that strictly separates C and D, that is:

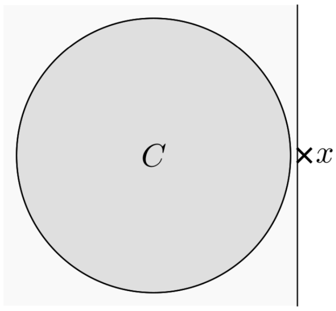
$$\exists s \in \mathbb{R}^n \setminus \{0\}, \exists r \in \mathbb{R}, \quad \forall x \in C, s^\top x < r \quad \text{and} \quad \forall x \in D, s^\top x > r$$





Note that a closed convex set C is the intersection of all halfspaces that contain it.

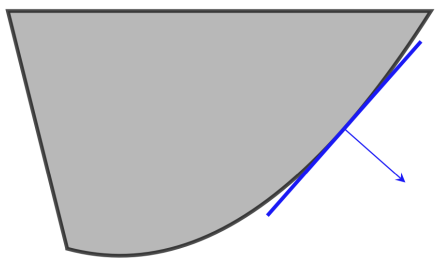




Definition (Supporting hyperplanes)**.** Supporting hyperplanes touch the boundary of a convex set, and have the entire set on one side. Formally, a hyperplane $H = \left\{ y \,\middle|\, s^\top y = r \right\}$ is a *supporting hyperplane* to a convex set C at a point $x \in \partial C$ if:

$$x^\top x = r \qquad \text{and} \qquad \forall y \in C, \quad a^\top y \leqslant r = s^\top x$$

We also say that H *supports* C at x.



Property 2.7. Let $C \subseteq \mathbb{R}^n$ be a non-empty convex set, and let $x \in \partial C$. Then there exists a supporting hyperplane to C at x.

2.4.2 Cone operators

Definition (Normal cone operator)**.** The *normal cone operator* to a set C at a point x is the set:

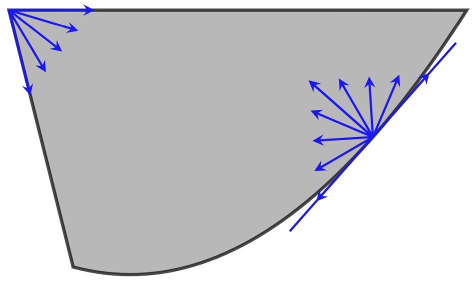
$$N_C(x) = \begin{cases} \left\{ g \in \mathbb{R}^n \,\middle|\, \forall y \in C, \quad g^\top (y - x) \leqslant 0 \right\} & \text{if } x \in C \\ \varnothing & \text{if } x \notin C \end{cases}$$

Intuitively, it is the set of vectors g that form obtuse angles for all $y - x$ with $y \in C$.

For $x \in \mathring{C}$, we have $N_c(x) = \{0\}$. For $x \in \partial C$, $N_C(x)$ is the set of the normal vectors to the supporting hyperplanes to C at x. If $x \notin C$, $N_C(x)$ is empty.

Definition (Tangent vector)**.** Let $C \subseteq \mathbb{R}^n$ be a convex set. A vector $d \in \mathbb{R}^n$ is tangent to C at x if:

$$\exists \{x_k\}_k \subseteq C, \exists \{\lambda_k\}_k \subset \mathbb{R}_+, \quad \lim_{k \to +\infty} \lambda_k (x_k - x) = d$$



Definition (Tangent cone)**.** The tangent cone of a convex set C at x is:

$$T_C(x) = N_C^\diamond(x)$$

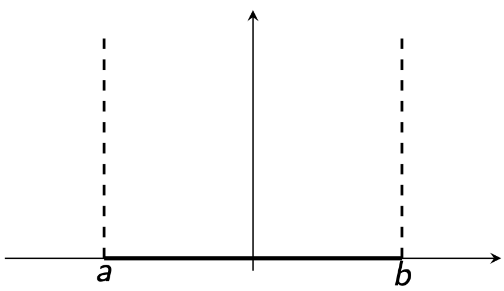
3 Convex functions

3.1 Extended-valued functions

Definition (Extended-valued function)**.** A function $f : \mathbb{R}^n \longrightarrow \mathbb{R}$ is *extended-valued* if its domain is $\mathbb{R}^n$ and its range is $\bar{\mathbb{R}} := \mathbb{R} \cup \{+\infty\}$.

Example (Indicator function)**.** We consider the indicator function of interval $[a, b]$:

$$\mathbb{1}_{[a,b]}(x) := \begin{cases} 0 & \text{if } x \in [a, b] \\ +\infty & \text{otherwise} \end{cases}$$



Definition (Effective domain)**.** The *effective domain* of $f : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ is the set of points where f is finite:

$$\operatorname{dom} f := \{\, x \in \mathbb{R}^n \mid f(x) < +\infty \,\} \tag{3.1.1}$$

A function is said to be *proper* if its effective domain is non-empty: $\operatorname{dom} f \neq \varnothing$.

3.2 Definition and first properties

Definition (Convex function)**.** A function $f : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ is *convex* if its graph is below any line connecting two points of the graph $(x, f(x))$ and $(y, f(y))$. That is:

$$\forall x, y \in \mathbb{R}^n, \forall \theta \in [0,1], \quad f(\theta \cdot x + (1-\theta) \cdot y) \leqslant \theta \cdot f(x) + (1-\theta) \cdot f(y) \tag{3.2.1}$$

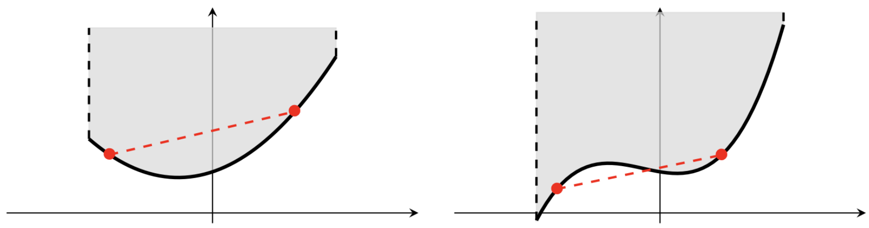
Definition (Concave function)**.** A function $f : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ is *concave* if $-f$ is convex. That is:

$$\forall x, y \in \mathbb{R}^n, \forall \theta \in [0,1], \quad f(\theta \cdot x + (1-\theta) \cdot y) \geqslant \theta \cdot f(x) + (1-\theta) \cdot f(y)$$

Definition (Epigraph)**.** The *epigraph* of a function $f : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ is the set of points lying above the graph of f:

$$\operatorname{epi} f := \{\, (x,t) \in \mathbb{R}^n \times \mathbb{R} \mid f(x) \leqslant t \,\} \tag{3.2.2}$$

Property 3.1 (Convexity and epigraph)**.** A function $f : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ is convex if and only if its epigraph is a convex set.



The following property allows to check the convexity of a multivariate function f by checking the convexity of functions of one variable.

Property 3.2. Let $f : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ be a function, and let $x \in \operatorname{dom} f$. We define:

$$\begin{aligned} g_{x,v} : \mathbb{R} &\longrightarrow \bar{\mathbb{R}} \\ t &\longmapsto f(x + tv) \end{aligned}$$

with $\operatorname{dom} g_{x,v} = \{\, t \in \mathbb{R} \mid x + tv \in \operatorname{dom} f \,\}$. Then, f is convex if and only if $g_{x,v}$ is convex in t for all $x \in \operatorname{dom} f$ and all $v \in \mathbb{R}^n$.

Definition (Sublevel sets)**.** Let $f : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ be a function. The *sublevel set* of f at level $\alpha \in \mathbb{R}$ is the set of points lying below the level α:

$$S_\alpha(f) = \{\, x \in \mathbb{R}^n \mid f(x) \leqslant \alpha \,\}$$

Property 3.3. If f is convex, then its sublevel sets are convex:

$$f \text{ is convex} \implies \forall \alpha \in \mathbb{R}, \quad S_\alpha(f) \text{ is convex}$$

The converse is not true.

3.3 First-order conditions

Property 3.4 (First-order condition for convexity)**.** Let $f : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ be a differentiable function, that is that $\nabla f(x)$ exists for all $x \in \operatorname{dom} f$. Then, f is convex if and only if $\operatorname{dom} f$ is convex and:

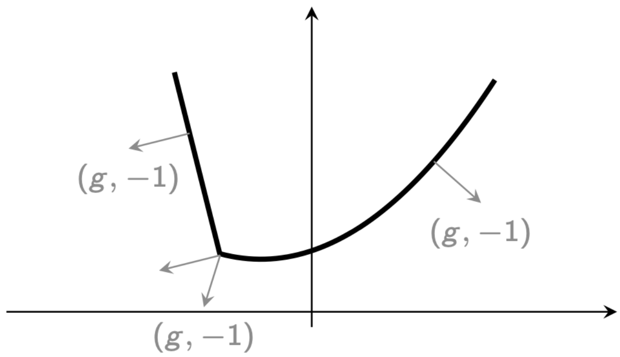
$$\forall x, y \in \operatorname{dom} f, \quad f(y) \geqslant f(x) + \nabla f(x)^\top (y - x)$$

In general, the function f might not be differentiable. In this case, we can use the subdifferential, a generalization of the local variation of a function, to characterize the convexity of f.

Recall that a supporting hyperplane $(g, -1)$ of $\operatorname{epi} f$ at $(x, f(x))$ is a hyperplane such that:

$$\forall y \in \mathbb{R}^n, \quad f(y) \geqslant f(x) + g^\top (y - x)$$

This motivates the following definition.



Definition (Subdifferential)**.** The *subdifferential* of a function $f : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ is the function associating to each point x the set of all supporting hyperplanes of $\operatorname{epi} f$ at $(x, f(x))$:

$$\begin{aligned} \partial f(x) : \mathbb{R}^n &\longrightarrow \mathcal{P}(\mathbb{R}^n) \\ x &\longmapsto \left\{ g \in \mathbb{R}^n \,\middle|\, \forall y \in \mathbb{R}^n, \quad f(y) \geqslant f(x) + g^\top (y - x) \right\} \end{aligned}$$

Any $g \in \partial f(x)$ is called a *subgradient* of f at x.

- If f is differentiable at x and $\partial f(x) \neq \varnothing$, then $\partial f(x) = \{\nabla f(x)\}$.
- If f is convex, and $\partial f(x)$ is a singleton, then $\partial f(x) = \{\nabla f(x)\}$.
- If f is convex but not differentiable at $x \in \operatorname{int} \operatorname{dom} f$, then:

$$\partial f(x) = \overline{\operatorname{Conv} S(x)} \tag{3.3.1}$$

  where $S(x) = \left\{ s \in \mathbb{R}^n \,\middle|\, \nabla f(x_k) \xrightarrow[x_k \to x]{} s \right\}$
- In general, for a convex function f:

$$\partial f(x) = \overline{\operatorname{Conv} S(x)} + N_{\operatorname{dom} f}(x) \tag{3.3.2}$$

Property 3.5 (Existence of subgradient)**.** For finite-valued convex functions, a subgradient exists for every x.

Property 3.6 (Existence of subgradient for extended-valued functions)**.** In the extendevalued setting, let $f : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ be a convex function. Then:

1. Subgradients exist for all x in the relative interior of $\operatorname{dom} f$.

2. Subgradients sometimes exist for x on the relative boundary of $\operatorname{dom} f$.
3. No subgradient exists for x ourside of $\operatorname{dom} f$.

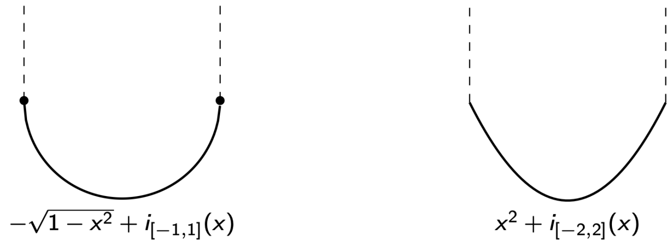


Figure 3.1: Examples for the second case, where boundary points exist on the relative boundary of $\operatorname{dom} f$. No subgradient (affine minorizer) exists for the left function at $x = \pm 1$.

3.4 Second-order conditions

Property 3.7 (Second-order condition for convexity)**.** Let $f : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ be a twice differentiable function (i.e. $\nabla^2 f(x)$ exists for all $x \in \operatorname{dom} f$ which is open). Then, f is convex if and only if $\operatorname{dom} f$ is convex and:

$$\forall x \in \operatorname{dom} f, \quad \nabla^2 f(x) \succcurlyeq 0 \tag{3.4.1}$$

3.5 Examples

In practice, we showed multiple practical ways to establish the convexity of a function:

- By definition, using the convexity criterion.
- By the existence of subgradients for all points of the domain.
- For twice differentiable functions, by checking the positive semidefiniteness of the Hessian.
- By decomposing the function into simpler functions through operations that preserve convexity.

3.5.1 One-dimensional examples

The following functions are convex:

- affine functions: $x \longmapsto ax + b$, $a, b \in \mathbb{R}$
- exponential functions: $x \longmapsto e^{ax}$, $a \in \mathbb{R}$
- power functions: $x : \mathbb{R}_+^* \longmapsto x^\alpha$, $a \geqslant 1$ or $\alpha \leqslant 0$
- powers of absolute value: $x \longmapsto |x|^p$, $p \geqslant 1$
- negative entropy: $x : \mathbb{R}_+^* \longmapsto x \log x$

The following functions are concave:

- affine functions: $x :\longmapsto ax + b$, $a, b \in \mathbb{R}$ (both convex and concave)
- power functions: $x : \mathbb{R}_+^* \longmapsto x^\alpha$, for $0 \leqslant \alpha \leqslant 1$
- logarithm: $x : \mathbb{R}_+^* \longmapsto \log x$

3.5.2 Examples on vectors

The following functions are convex on $\mathbb{R}^n$:

- affine functions $x \longmapsto a^\top x + b$, $a \in \mathbb{R}^n$, $b \in \mathbb{R}$
- norms: $x \longmapsto \|x\|_p = (\sum_{i=1}^n |x_i|^p)^{1/p}$, $p \geqslant 1$

- quadratic functions:
$$f : x \longmapsto \frac{1}{2}x^\top Px + q^\top x + r$$
with $P \in \mathbb{S}^n$, $q \in \mathbb{R}^n$, $r \in \mathbb{R}$. Indeed, we have;
$$\nabla f(x) = Px + q \quad \text{and} \quad \nabla^2 f(x) = P \succcurlyeq 0$$

- least-squares objective:
$$f : x \longmapsto \|Ax - b\|_2^2$$
with $A \in \mathcal{M}_{m,n}(\mathbb{R})$, $b \in \mathbb{R}^m$. Indeed, we have:
$$\nabla f(x) = 2A^\top (Ax - b) \quad \text{and} \quad \nabla^2 f(x) = 2A^\top A \succcurlyeq 0$$

3.5.3 Examples on matrices

The following functions are convex on $\mathcal{M}_{m,n}(\mathbb{R})$:

- affine functions (convex and concave):
$$X \longmapsto \mathrm{Tr}(A^\top X) + b = \sum_{i=1}^{m}\sum_{j=1}^{n} A_{i,j}X_{i,j} + b$$

- spectral norm (maximum singular value):
$$X \longmapsto \|X\|_2 = \sigma_{\max}(X) = \sqrt{\lambda_{\max}(X^\top X)}$$

- in general, all norms are convex

3.5.4 Log-determinant function

The $\log\det$ function, defined on $\mathbb{S}^n$, is concave:
$$f : \mathbb{S}^n \longrightarrow \mathbb{R}X \quad \longmapsto \log\det X$$
with $\operatorname{dom} f = \mathbb{S}^n_{++}$. To show this, we will use Property 3.2; we define:
$$\begin{aligned} g_{X,V} : \mathbb{R} &\longrightarrow \mathbb{R} \\ t &\longmapsto \log\det(X + tV) \end{aligned}$$
Note that:
$$\begin{aligned} g_{X,V}(t) &= \log\det(X + tV) \\ &= \log\det X + \log\det(I + tX^{-1/2}VX^{-1/2}) \\ &= \log\det X + \sum_{i=1}^{n} \log(1 + t\lambda_i) \end{aligned}$$
where λ_i are the eigenvalues of $X^{-1/2}VX^{-1/2}$.

We then apply the second-order condition to $g_{X,V}$:
$$g''_{X,V}(t) = -\sum_{i=1}^{n} \frac{\lambda_i}{(1 + t\lambda_i)^2} \leqslant 0$$
Therefore, $g_{X,V}$ is concave for any X, V, hence f is concave.

3.5.5 Softmax function

The softmax function, defined on $\mathbb{R}^n$, is convex:

$$\begin{aligned} f : \mathbb{R}^n &\longrightarrow \mathbb{R} \\ x &\longmapsto \log \sum_{i=1}^{n} e^{x_i} \end{aligned}$$

If we denote by $z_i = e^{x_i} / \sum_j e^{x_j}$, then we get:

$$\nabla^2 f(x) = \operatorname{diag}(z) - zz^\top$$

with $z_i \geqslant 0$ and $\sum_i z_i = 1$. To show that $\nabla^2 f(x) \succcurlyeq 0$, we show that $\operatorname{diag}(z) - zz^\top$ is positive semidefinite. Let $v \in \mathbb{R}^n$, then:

$$\begin{aligned} v^\top \nabla^2 f(x) v &= v^\top (\operatorname{diag}(z) - zz^\top) v \\ &= \sum_{i=1}^{n} z_i v_i^2 - \left(\sum_{i=1}^{n} z_i v_i \right)^2 \end{aligned}$$

According to the Cauchy-Schwarz inequality applied to $\sqrt{z_i} \times \sqrt{z_i} v_i$, we have:

$$\left(\sum_{i=1}^{n} z_i v_i \right)^2 \leqslant \sum_{i=1}^{n} z_i \sum_{i=1}^{n} z_i v_i^2 = \sum_{i=1}^{n} z_i v_i^2$$

Therefore, $v^\top \nabla^2 f(x) v \geqslant 0$, and f is convex.

3.6 Convexity-preserving operations

3.6.1 Nonnegative weighted sum

Property 3.8 (Nonnegative scaling)**.** Let $f : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ be a convex function, and $\alpha > 0$. Then, αf is convex.

Property 3.9 (Sum)**.** Let $f_1, f_2 : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ be convex functions. Then, $f_1 + f_2$ is convex; this extends to infinite sums and integrals.

Property 3.10 (Nonnegative weighted sum)**.** Let $f_1, f_2 : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ be convex functions, and $\alpha_1, \alpha_2 > 0$. Then, $\alpha_1 f_1 + \alpha_2 f_2$ is convex; this extends to infinite sums and integrals.

3.6.2 Compositions by an affine function

Property 3.11 (Composition by an affine function)**.** Let $f : \mathbb{R}^n \longrightarrow \bar{R}$ be a convex function and let $A \in \mathcal{M}_{m,}(\mathbb{R})$, $b \in \mathbb{R}^m$. Then:

$$x \longmapsto f(Ax + b) \text{ is convex}$$

Example. The log barrier function for linear inequalities:

$$f(x) = -\sum_{i=1}^{m} \log(b_i - a_i^\top x)$$

with $\operatorname{dom} f = \left\{ x \in \mathbb{R}^n \,\middle|\, \forall i \in [\![1, m]\!], \quad a_i^\top x < b_i \right\}$, is convex.

Example. Any norm of an affine function:

$$f(x) = \|Ax + b\|$$

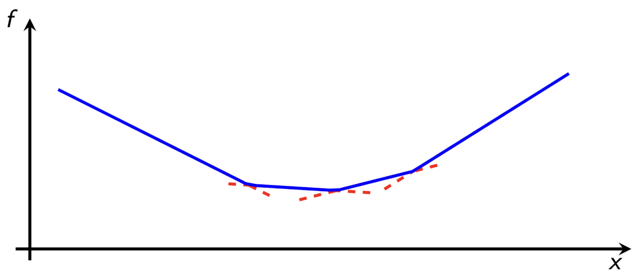
is convex.

3.6.3 Pointwise maximum

Property 3.12 (Pointwise maximum)**.** Let $f_1, f_2 : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ be convex functions. Then, $\max(f_1, f_2)$ is convex. This extends to the pointwise maximum of any finite number of convex functions.

Example. The following piecewise linear function is convex:

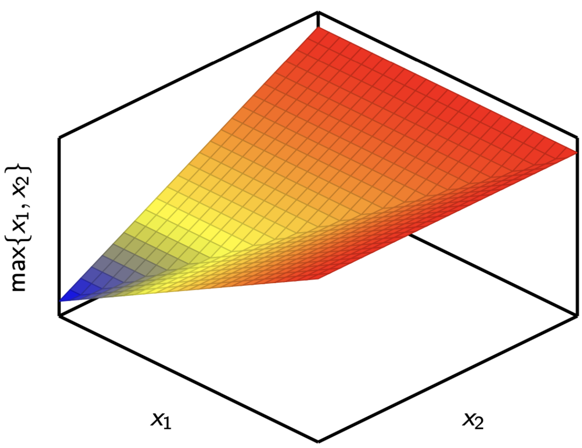
$$f(x) = \max_{i \in [\![1,m]\!]} a_i^\top x + b_i$$



Example (Sum of r largest components)**.** The sum of the r largest components of a vector $x \in \mathbb{R}^n$ is convex:

$$f(x) = x_{(1)} + \cdots + x_{(r)}$$

where $x_{(1)} \geqslant \ldots \geqslant x_{(n)}$ are the components of x sorted in decreasing order.



Indeed, we can write f as:

$$f(x) = \max \{ x_{i_1} + x_{i_2} + \cdots + x_{i_r} \mid 1 \leqslant i_1 < i_2 < \cdots < i_r \leqslant n \}$$

3.6.4 Pointwise supremum

Property 3.13 (Pointwise supremum)**.** If $\forall y \in \mathcal{A}, \quad x \longmapsto f(x, y)$ is convex, then:

$$g(x) = \sup_{y \in \mathcal{A}} f(x, y)$$

is convex.

Example (Support function)**.** The support function of a set C is convex:

$$S_C(x) = \sup_{y \in C} y^\top x$$

Example (Distance to farthest point)**.** The distance to the farthest point in a set C is convex:

$$f(x) = \sup_{y \in C} \|x - y\|$$

Example (Legendre-Fenchel conjugate)**.** Let $f : \mathbb{R}^n \longrightarrow \bar{\mathbb{R}}$ be a convex function. Then, its Legendre-Fenchel conjugate is convex:

$$f^*(x) = \sup_{y \in \mathbb{R}^n} x^\top y - f(y)$$

3.6.5 Eigenvalues

Property 3.14 (Maximum eigenvalue)**.** The function associating to a symmetric matrix $X \in \mathbb{S}_n$ its maximum eigenvalue is **convex** on $\mathbb{S}_n$:

$$\lambda_{\max}(X) = \sup_{\|y\|_2 = 1} y^\top X y$$

Property 3.15 (Minimum eigenvalue)**.** The function associating to a symmetric matrix $X \in \mathbb{S}_n$ its minimum eigenvalue is **concave** on $\mathbb{S}_n$:

$$\lambda_{\min}(X) = \inf_{\|y\|_2 = 1} y^\top X y$$

3.6.6 Composition with scalar functions

Property 3.16 (Composition with scalar functions)**.** Let $g : \mathbb{R}^n \to \bar{\mathbb{R}}$ and $h : \bar{\mathbb{R}} \to \bar{\mathbb{R}}$ be two functions. We define the composition:

$$f(x) = h(g(x))$$

If either:

- g is convex, h is convex and nondecreasing,
- g is concave, h is convex and nonincreasing,

then f is convex.

Proof. We will only prove the case where $n = 1$ and g, h are twice differentiable. We have:

$$f''(x) = h''(g(x))g'(x)^2 + h'(g(x))g''(x)$$

If h is convex, then $h''(g(x)) \geqslant 0$ and $h''(g(x))g'(x)^2 \geqslant 0$. In the first case, g convex implies that $g''(x) \geqslant 0$, and h nondecreasing implies that $h'(g(x)) \geqslant 0$. Therefore, $f''(x) \geqslant 0$ and f is convex. In the second case, g concave implies that $g''(x) \leqslant$, and h nonincreasing implies that $h'(g(x)) \leqslant$. Therefore, $f''(x) \geqslant 0$ and f is also convex.

Note that the monotonicity must hold for h on the whole domain of g, including the extended values. □

Example. This allows us to deduce the following properties:

- If g is convex then $\exp g$ is convex.
- If g is concave and positive, then $-\log g$ is convex.
- If g is concave and positive, then $1/g$ is convex.
- If g is convex and nonnegative, then for $\alpha \geqslant 1$ we have that g^α is convex.
- For $\alpha \geqslant 1$, then $\|\cdot\|^\alpha$ is convex (with $h = [\cdot]_+^\alpha$, $g = \|\cdot\|$).

Counter-example. The following counter-example shows the importance of the monotonicity of h:

$$g(x) = x^2 \qquad \text{and} \qquad h = \mathbb{1}_{[1,2]}$$

Then, we have the following composition, which is not convex:

$$h(g(x)) = \mathbb{1}_{\left[-\sqrt{2},-1\right]\cup\left[1,\sqrt{2}\right]}(x)$$

3.6.7 Vector composition

We derive a property similar to Property 3.16 for vector functions.

Property 3.17 (Vector composition). Let $g : \mathbb{R}^n \to \bar{\mathbb{R}}^k$ and $h : \mathbb{R}^k \to \bar{\mathbb{R}}$ be two functions. We define the composition:

$$f(x) = h(g(x)) = h(g_1(x), \ldots, g_k(x))$$

If either:

- the g_i are convex, h is convex and nondecreasing in each argument,
- the g_i are concave, h is convex and nonincreasing in each argument,

then f is convex.

Proof. A proof similar to the one of Property 3.16 can be done, by considering the second derivative of f:

$$f''(x) = g'(x)^\top \nabla^2 h(g(x)) g'(x) + \nabla h(g(x))^\top g''(x)$$

This function is positive for similar reasons as in the scalar case. □

Example. This allows us to deduce the following properties:

- If the g_i are concave and positive, then $-\log \sum_{i=1}^m \log g_i$ is convex.
- If the g_i are convex, then $\log \sum_{i=1}^m \exp g_i$ is convex.

3.6.8 Partial minimization

Property 3.18 (Partial minimization). If $f(x, y)$ is convex in (x, y) and C is a non-empty convex set, then the minimization over one variable is convex:

$$g(x) = \inf_{y \in C} f(x, y)$$

Example (Distance to a convex set). The distance to a convex set S is convex:

$$\operatorname{dist}(x, S) = \inf_{y \in S} \|x - y\|$$

4 Convex problems