Lecture Notes 2025

Optimisation, Control, and Data

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September 21, 2025

Contents

Part I

Optimisation

Chapter 1

Convex Analysis

This chapter closely follows chapter 5 of the lecture notes [2]. For most of the proof in this chapter we refer to [1] or [3].

1.1 Convex sets

Definition 1.1.1
A set $K \subset \mathbb{R}^d$ is *convex* if

$$tx + (1-t)y \in K \qquad \forall x, y \in K,\ t \in [0,1] \tag{1.1}$$

We have the following fact.

Proposition 1.1.1
The set $K \subset \mathbb{R}^d$ is convex if and only if for any $n \in \mathbb{N}$, and $t_1, \dots, t_n \geq 0$ such that $\sum_{i=1}^n t_i = 1$, it holds

$$x_1, \dots, x_n \in K \implies \sum_{i=1}^n t_i x_i \in K. \tag{1.2}$$

Proof: Property (1.2) with $n = 2$ is exactly the definition of K is convex. The statement then follows by induction on n. ■

Definition 1.1.2
The convex hull $\mathrm{conv}(\Omega)$ of $\Omega \subset \mathbb{R}^d$ is the smallest convex set K containing Ω.

By Proposition 1.1.1, it is immediate to observe that

$$\mathrm{conv}(\Omega) = \left\{ \sum_{i=1}^n t_i x_i \mid t_i \geq 0, \sum_{i=1}^n t_i = 1,\ x_i \in \Omega \right\}. \tag{1.3}$$

Example 1.1.1 (Convex sets)

- Unit ball w.r.t. any norm.
- Vector subspaces.
- Hyperplanes, i.e., for any $v \in \mathbb{R}^d$ and $\lambda \in \mathbb{R}$,

$$H_{v,\lambda} := \{x \in \mathbb{R}^d \mid \langle v, x \rangle \geq \lambda\}. \tag{1.4}$$

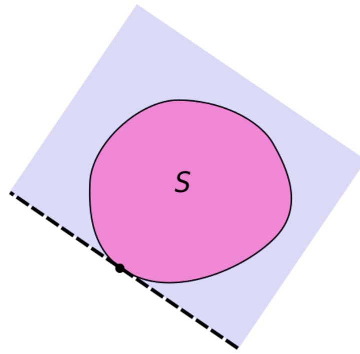

Figure 1.1: Supporting hyperplane for a set S.

An important result (that we will not prove) on convex sets is the following.

Theorem 1.1.1 Separation theorem

Let $K_1, K_2 \subset \mathbb{R}^d$ be two convex sets such with disjoint interior. Then there exists $v \in \mathbb{R}^d$ and $\lambda \in \mathbb{R}$ such that

$$K_1 \subset H_{v,\lambda}, \qquad K_2 \subset \mathbb{R}^d \setminus H_{v,\lambda}. \tag{1.5}$$

Here, $H_{v,\lambda}$ is defined in (1.4).

As a direct consequence, we have the following (see Figure 1.1).

Corollary 1.1.2 Supporting hyperplane theorem

Let $K \subset \mathbb{R}^d$ be a convex set and $x \in \partial K$. Then, there exists a supporting hyperplane of K containing x_0. That is, there exists $v \in \mathbb{R}^d$ and $\lambda \in \mathbb{R}$ such that $K \subset H_{v,\lambda}$ and $x_0 \in \partial H_{v,\lambda}$.

When K is a convex polygon, it is natural to expect it to be determined by its vertices. In order to formalize this intuition we need the following.

Definition 1.1.3

Let $K \subset \mathbb{R}^d$ be a convex set. A point $x \in K$ is an extremum of K if for any $y, z \in K$ and $t \in (0,1)$ we have that

$$x = ty + (1-t)z \implies x = y = z. \tag{1.6}$$

The set of exterma of K is denoted by $\operatorname{extr}(K)$.

In particular, for a convex polygon $\operatorname{extr}(K)$ is the set of its vertices.

Proposition 1.1.2

Let $K \subset \mathbb{R}^d$ be a convex set that is compact. Then,

$$\operatorname{conv}(K) = \operatorname{conv}(\operatorname{extr}(K)). \tag{1.7}$$

Figure 1.2: Two examples of polar cone.

1.2 Cones

Definition 1.2.1
A set $K \subset \mathbb{R}^d$ is a cone if

$$tx \in K \qquad \forall x \in K,\ t \geq 0. \tag{1.8}$$

Observe that every cone contains the origin.

Example 1.2.1 (Cones)

- The second order cone
$$C = \{x = (x', x_n) \in \mathbb{R}^d \times \mathbb{R} \mid \|x'\|_2 \leq x_n\}.$$
- Positive orthant $\mathbb{R}^d_+ = \{x \in \mathbb{R}^d \mid x_i \geq 0, \quad \forall i \in [\![1, d]\!]\}$.
- The set of positive semidefinite matrices $\mathrm{Sym}_+(\mathbb{R}^d)$.

Definition 1.2.2
The conic hull $\mathrm{cone}(\Omega)$ of a set $\Omega \subset \mathbb{R}^d$ is the smallest cone containing Ω. Namely,

$$\mathrm{cone}(\Omega) = \left\{ \sum_{i=1}^{n} t_i x_i \mid t_i \geq 0 \text{ and } x_i \in \Omega \text{ for any } i \in [\![1, n]\!] \right\}. \tag{1.9}$$

Definition 1.2.3
The polar cone K^* of a cone $K \subset \mathbb{R}^d$ is the set

$$K^* := \left\{ y \in \mathbb{R}^d \mid \rangle x, y \langle \geq 0 \quad \forall x \in K \right\}. \tag{1.10}$$

We have the following properties for the polar cone.

Proposition 1.2.1
The polar cone K^* is a closed, convex cone. If, moreover, the cone K is closed, then $K^{**} = K$.

1.3 Convex functions

We will work with extended functions $F : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$. The domain of an extended function is

$$\mathrm{dom}(F) = \{x \in \mathbb{R}^d \mid F(x) < +\infty\}. \tag{1.11}$$

An extended function such that $\mathrm{dom}(F) \neq \emptyset$ is called *proper*.

Given a standard function $F : \Omega \longrightarrow \mathbb{R}$, we can identify it with the extended function $\bar{F} : \mathbb{R}^d \longrightarrow \mathbb{R} \cup \{+\infty\}$ defined by

$$\bar{F}(x) = \begin{cases} F(x) & \text{if } x \in \Omega, \\ +\infty & \text{if } x \in \mathbb{R}^d \setminus \Omega. \end{cases} \tag{1.12}$$

Definition 1.3.1 Convex functions

Let $F : \mathbb{R}^d \longrightarrow \mathbb{R} \cup \{+\infty\}$ be an extended function. Then,

- F is convex if
$$F(tx + (1-t)y) \leq tF(x) + (1-t)F(y) \qquad \forall x, y \in \mathbb{R}^d,\ t \in [0,1]. \tag{1.13}$$
- F is strictly convex if
$$F(tx + (1-t)y) < tF(x) + (1-t)F(y) \qquad \forall x, y \in \mathbb{R}^d,\ x \neq y,\ t \in [0,1]. \tag{1.14}$$
- F is strongly convex if there exists $\gamma > 0$ such that
$$F(tx + (1-t)y) \leq tF(x) + (1-t)F(y) - \frac{\gamma}{2}t(t-1)\|x-y\|_2^2 \qquad \forall x, y \in \mathbb{R}^d,\ t \in [0,1]. \tag{1.15}$$

We say that F is *concave* if $-F$ is convex.

Observe that it holds

$$\text{convex} \impliedby \text{strongly convex} \impliedby \text{strictly convex} \tag{1.16}$$

We say that a standard function $F : K \longrightarrow \mathbb{R}$ is convex, strictly convex, strongly convex, or concave, if the same is true for its extension $\bar{F}$. Observe that this requires K to be convex.

Example 1.3.1

- The prototypical convex function, used in the definition of strongly convex, is the quadratic function
$$F(x) = \frac{\|x\|_2^2}{2} = \frac{1}{2}\sum_{i=1}^{d} |x_i|^2. \tag{1.17}$$
- More generally, every norm is convex.
- The norm ℓ_p is strictly convex if and only if $p \in (1, +\infty)$.
- $F(x) = x^\top Ax$ is convex if A is positive semidefinite (i.e., $A \in \mathrm{Sym}_{\geq 0}(\mathbb{R}^d)$), and strongly convex if A is positive definite.

Proposition 1.3.1

A function $F : K \longrightarrow \mathbb{R}$ is convex if and only if its epigraph $\mathrm{epi}(F) \subset \mathbb{R}^{d+1}$ is convex. Here, we let

$$\mathrm{epi}(F) = \{(x, r) \mid r \geq F(x)\}. \tag{1.18}$$

Proof: Assume F is convex and let $(x, r), (y, s) \in \mathrm{epi}(F)$. In particular, $r \geq F(x)$ and $s \geq F(y)$. Let $t \in [0,1]$ and observe that

$$tr + (1-t)s \geq tF(x) + (1-t)F(y) \geq F(tx + (1-t)y). \tag{1.19}$$

Hence, $t(x, r) + (1-t)(y, s) \in \mathrm{epi}(F)$. A similar reasoning proves the opposite implication. ∎

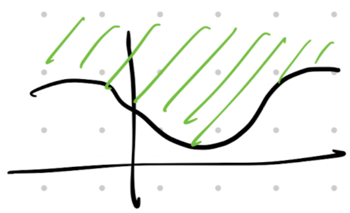

Figure 1.3: Epigraph of a function.

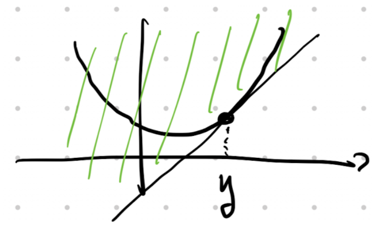

Figure 1.4: Graphical representation of Proposition 1.3.2.

Proposition 1.3.2 Differential characterisations of convexity

Let $F : \mathbb{R}^d \longrightarrow \mathbb{R}$ be an everywhere differentiable function. Then,

- F is convex if and only if
$$F(y) \geq F(x) + \langle \nabla F(x), y - x \rangle, \qquad \forall x, y \in \mathbb{R}^d. \tag{1.20}$$
- F is strongly convex with parameter $\gamma > 0$ if and only if
$$F(y) \geq F(x) + \langle \nabla F(x), y - x \rangle + \frac{\gamma}{2}\|x - y\|_2^2, \qquad \forall x, y \in \mathbb{R}^d. \tag{1.21}$$
- If F is everywhere twice differentiable, then it is convex if and only if
$$\operatorname{Hess} F(x) \geq 0 \qquad \forall x \in \mathbb{R}^d. \tag{1.22}$$
Here, we denoted by $\operatorname{Hess} F(x)$ the Hessian of F at x.

Proposition 1.3.3

Let $F : K \longrightarrow \mathbb{R}$ be convex. Then, F is continuous on the interior of K.

Proof: Let $x_0 \in \operatorname{int}(K)$ and consider $r > 0$ such that $B(x_0, r) \subset K$. Without loss of generality, we assume $x_0 = 0$ (otherwise, replace the function F by its translation $G(x) = F(x) - F(x_0)$).

Convexity will allow to bound the difference $F(y) - F(0)$ with the values of F on the sphere $\partial B(0, r)$. However, without continuity, the function F need not be bounded on the compact set $\partial B(0, r)$, and hence we need some additional care.

Pick $d + 1$ linearly independent points $v_0, \dots v_{d+1} \in \partial B(0, r)$, and consider the corresponding symplex
$$\Delta = \operatorname{conv}(\{v_0, \dots, v_{d+1}\}) = \left\{ \sum_{i=1}^{d+1} t_i v_i \mid t_i \geq 0, \sum_i t_i = 1 \right\} \subset B(0, r). \tag{1.23}$$
Then, letting $M = \max_{i \in [\![1, d+1]\!]} F(v_i)$, the fact that F is convex yields that for any $x = \sum_{i=1}^{d+1} t_i v_i \in \Delta$ it holds
$$F(x) \leq \sum_{i=1}^{d+1} t_i F(v_i) \leq M. \tag{1.24}$$
In particular, we can fix a radius $r' < r$ such that $B(0, r') \subset \Delta$ where F is bounded.

We now proceed to bound the difference $F(x) - F(0)$. Let $x \in U \subset B(0, r')$ and set $t = \|x\|/r'$. In particular, $t \in [0, 1]$ and the ray $\{sx \mid s \geq 0$ meets the sphere $\partial B(x_0, r')$ at the point
$$y = \frac{r'}{\|x\|}(x). \tag{1.25}$$
In particular, $x = (1 - t)0 + ty$. By convexity and (1.24), we have
$$F(x) \leq (1 - t)F(0) + tF(y) \leq .(1 - t)F(0) + tM \implies F(x) - F(0) \leq t(M - F(0)). \tag{1.26}$$
To derive a bound from below, we proceed similarly, considering
$$z = \frac{r'}{\|x\| - r'} x. \tag{1.27}$$

Indeed, we then have $0 = (1-t)x + tx$, where $t = \|x\|/r'$ as above. Then, convexity and the fact that $z \in B(0, r')$ yield

$$F(0) \le (1-t)F(x) + tM \implies F(x) - F(0) \ge -\frac{t}{1-t}(M - F(0)). \tag{1.28}$$

Combining (1.26) and (1.28), we obtain

$$-\frac{t}{1-t}(M - F(0)) \le F(x) - F(0) \le t(M - F(0)), \qquad t = \frac{\|x\|}{r'} \tag{1.29}$$

Since x was arbitrary in $B(0, r')$ we can take the limit as $x \to 0$, which implies $t \to 0$ and thus that

$$\lim_{x\to 0} |F(x) - F(0)| = 0, \tag{1.30}$$

concluding the proof. ■

The following result is at the core of the relation between optimisation and convexity.

Theorem 1.3.1

Let $F : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ be a convex extended function. Then,

- Any local minimum of F is global.
- The set of minima of F is convex.
- If F is strictly convex and admits a minimum, this minimum is unique.
- If F is real-valued and strongly convex, then it has a unique minimum.

Proof: Assume that $x^\star$ is a local minimum, i.e., there exists $r > 0$ such that $F(x^\star) \le F(x)$ for any $x \in B(0, r)$. Let $y \in \mathbb{R}^d$ and consider a point on the ray starting at $x^\star$ and passing through y:

$$z = x^\star + s(y - x^\star) = (1-s)x^\star + sy \qquad s \ge . \tag{1.31}$$

Taking $s < \min\{1, r'/\|x^\star - y\|\}$ we have that $z \in B(0, r)$. Hence, by local minimality of $x^\star$ and convexity of F we have

$$F(x^\star) \le F(z) \le (1-s)F(x^\star) + sF(y) \implies F(x^\star) \le F(y). \tag{1.32}$$

This concludes the proof of the first point.

Assume now that x_1, x_2 are minima for F. This clearly implies that $F(x_1) = F(x_2) =: m$, and thus, by convexity of F, for any $t \in [0,1]$ we have

$$m \le F(tx_1 + (1-t)x_2) \le tF(x_1) + (1-t)F(x_2) = m \implies F(tx_1 + (1-t)x_2). \tag{1.33}$$

This implies that $tx_1 + (1-t)x_2$ is a minimum for any $t \in [0,1]$, thus proving the second point.

The same argument as above in the case of a strictly convex function yields to

$$m \le F(tx_1 + (1-t)x_2) < m \qquad \text{if } x_1 \ne x_2. \tag{1.34}$$

This implies immediately that the minimum is unique.

Assume, finally, that F is strongly convex. Since it is strictly convex, we just need to prove the existence of a minimum. By Proposition 1.3.3 we have that F is continuos, and thus it suffices to prove its coercivity: $F(x) \to +\infty$ if $\|x\| \to +\infty$. We provide a proof of this fact in the case where F is differentiable (the general case can be obtained similarly using Proposition 1.4.2, proven later on). In this case, by Proposition 1.3.2 we have that

$$F(y) \ge F(0) + \langle \nabla F(0), y \rangle + \frac{\gamma}{2}\|y\|_2^2 \qquad \forall y \in \mathbb{R}^d. \tag{1.35}$$

Since $\langle \nabla F(0), y \rangle \le \|y\|_2$, the quadratic term on the right-hand side of the above equation, implies that the limit as $\|y\|_2 \to +\infty$ is $+\infty$. ■

Remark: Strict convexity is not enough to ensure the existence of a minimum. Consider, for example, $F(x) = e^x$.

1.4 Convex conjugate and sub-differential

Definition 1.4.1

The convex conjugate (of Fenchel dual) of an extended function $F : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ is the function $F^* : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ defined by

$$F^*(y) = \sup_{x \in \mathbb{R}^d} \left[\langle x, y \rangle - F(x) \right]. \tag{1.36}$$

Recall the following.

Definition 1.4.2

A function $F : \mathbb{R}^d \to \mathbb{R}$ is *lower semicontinuous* (l.s.c.) if

$$\liminf_{x \to x_0} F(x) \geq F(x_0), \qquad \forall x_0 \in \mathbb{R}^d. \tag{1.37}$$

Equivalently, F is l.s.c. if its epigraph is closed.

Example 1.4.1

- Every continuous function is lower semicontinuous.
- For any set $\Omega \subset \mathbb{R}^d$, the $0 - \infty$ characteristic function

$$\chi_K = \begin{cases} 0 & \text{if } x \in \Omega, \\ +\infty & \text{otherwise,} \end{cases} \tag{1.38}$$

  is lower semicontinuous, but not continuous.

Proposition 1.4.1

Let $F : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$. Then,

1. The convex conjugate F^* is a lower semicontinuous convex function.
2. We have the Fenchel (or Young, or Fenchel-Young) inequality

$$\langle x, y \rangle \leq F(x) + F^*(y) \tag{1.39}$$

Proof: For any $y_1, y_2 \in \mathbb{R}^d$ and $t \in [0, 1]$ we have

$$\langle x, ty_1 + (1-t)y_2 \rangle - F(x) = t \left(\langle x, y_1 \rangle - F(x) \right) + (1-t) \left(\langle x, y_2 \rangle - F(x) \right). \tag{1.40}$$

Taking the supremum for $x \in \mathbb{R}^d$ of the above, and recalling that $\sup(g(x) + h(x)) \leq \sup g(x) + \sup h(x)$ proves convexity of F^*.

Lower semicontinuity of F^* follows since it is the supremum for $x \in \mathbb{R}^d$ of $g_x(y) := \langle x, y \rangle - F(x)$, which is affine and in particular lower semicontinuous. Indeed, the supremum of a family of l.s.c. functions is l.s.c..

The second point (Fenchel inequality) is a direct consequence of the definition of F^*. ■

Example 1.4.2

- Let $F(x) = \frac{1}{2}\|x\|_2^2$. Then, $F^*(y) = \frac{1}{2}\|y\|_2^2 = F(y)$. This is the only function with this property.

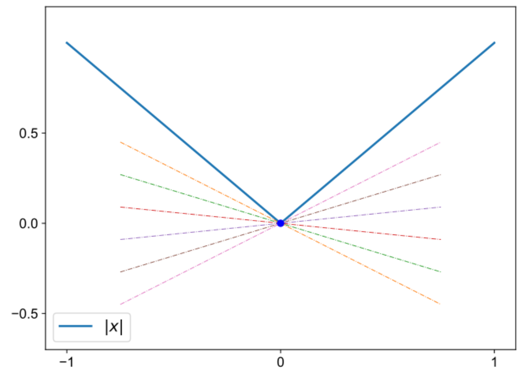

Figure 1.5: Visualization of the subgradients of $F(x) = |x|$ at $x = 0$. Image from this website.

- Let $F = \chi_K$ be the $0 - \infty$ characteristic function of a convex set $K \subset \mathbb{R}^d$ defined in (1.38). Then,

$$F^*(y) = \sup_{x \in K} \langle x, y \rangle. \tag{1.41}$$

Definition 1.4.3

The *subdifferential* of a convex extended function $F : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ at $x \in \mathbb{R}^d$ is the set

$$\partial F(x) = \left\{ v \in \mathbb{R}^d \mid F(y) \geq F(x) + \langle v, y - x \rangle, \qquad \forall y \in \mathbb{R}^d \right\}. \tag{1.42}$$

A vector $v \in \partial F(x)$ is called a *subgradient* for F at x.

Example 1.4.3

Consider $F(x) = |x|$. Then,

$$\partial F(x) = \begin{cases} \{\mathrm{sgn}(x)\} & \text{if } x \neq 0, \\ [-1, 1] & \text{if } x = 0. \end{cases} \tag{1.43}$$

Here, $\mathrm{sgn}(x) = x/|x|$ is the sign function. See Figure 1.5.

Theorem 1.4.1

Let $F : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ be a convex function. Then, $x \in \mathbb{R}^d$ is a minimum for F if and only if $0 \in \partial F(x)$

Proof: The fact that x is a minimum means that $F(x) \leq F(y)$ for any $y \in \mathbb{R}^d$, which is the definition of $0 \in \partial F(x)$. ■

We have the following.

Proposition 1.4.2

Let $F : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ be a convex function. Then,

- For any $x \in \mathbb{R}^d$ the subdifferential $\partial F(x)$ is non-empty.
- It holds that

$$\partial F(x) = \left\{ v \in \mathbb{R}^d \mid F^*(v) + F(x) = \langle x, v \rangle \right\}. \tag{1.44}$$

- If F is differentiable at $x \in \mathbb{R}^d$, then $\partial F(x) = \{\nabla F(x)\}$.

Proof: The first part of the theorem is a consequence of the Supporting Hyperplane Theorem (see Corollary 1.1.2) and Proposition 1.3.1. Indeed, the latter implies that the epigraph $\mathrm{epi}(F)$ is convex and hence, by the former, any of its boundary point admits a supporting hyperplane. Using the fact that $\partial\,\mathrm{epi}(F) = \{(x, F(x)) \mid x \in \mathbb{R}^d\}$ allows to conclude.

To prove the second statement, observe that $v \in \partial F(x)$ is equivalent to

$$\langle y, v\rangle - F(y) \le \langle x, v\rangle - F(x), \qquad \forall y \in \mathbb{R}^d. \tag{1.45}$$

Taking the sup for $y \in \mathbb{R}^d$ yields that $F^*(v) \le \langle x, v\rangle - F(x)$. The opposite inequality follows from Fenchel inequality (see Proposition 1.4.1).

Concerning the proof of the last statement, the fact that $\nabla F(x) \in \partial F(x)$ follows from the characterisation of convexity for differentiable functions given in Proposition 1.3.2. To prove the opposite implication, let $v \in \partial F(x)$ and observe that by definition of subgradient the directional derivative $\partial_h F(x)$ of f in the direction $h \in \mathbb{R}^d$ at x satisfies

$$\partial_h F(x) = \lim_{t\to 0} \frac{F(x+th) - F(x)}{t} \ge \langle v, h\rangle. \tag{1.46}$$

Since we know that $\partial_h F(x) = \langle \nabla F(x), h\rangle$, we have that

$$\langle \nabla F(x) - v, h\rangle \ge 0, \qquad \forall h \in \mathbb{R}^d. \tag{1.47}$$

But this implies that $\nabla F(x) = v$, concluding the proof. ■

Thanks to the previous result, we are in a position to prove the following property of the convex biconjugate.

Theorem 1.4.2 Fenchel-Moreau Theorem

The biconjugate F^{**} is the largest convex lower semicontinuous function satisfying $F^{**}(x) \le F(x)$ for any $x \in \mathbb{R}^d$. In particular, $F^{**} = F$ if F is convex and proper.

Proof: We have that $-F^*(y) = \inf_{x\in\mathbb{R}^d} (F(x) - \langle x, y\rangle)$, which implies that for any $y, z \in \mathbb{R}^d$ it holds

$$\langle z, y\rangle - F^*(y) \le \langle z - x, y\rangle + F(x), \qquad \forall x \in \mathbb{R}^d. \tag{1.48}$$

In particular, considering $z = x$ we have

$$F^{**}(x) = \sup_{y\in\mathbb{R}^d} (\langle x, y\rangle - F^*(y)) \le F(x), \tag{1.49}$$

proving the first part of the statement.

Since F^{**} is convex and l.s.c. by Proposition 1.4.1, in order to complete the proof it suffices to show that if F is convex, then

$$F^{**}(x) \ge F(x), \qquad \forall x \in \mathbb{R}^d. \tag{1.50}$$

Let $v \in \partial F(x)$, which exists thanks to Proposition 1.4.2. For such a v, using the characterisation of the subdifferential in Proposition 1.4.2, we have

$$F^*(v) = \langle x, v\rangle - F(x), \tag{1.51}$$

so that $F^{**}(z) \ge \langle v, z - x\rangle + F(x)$ for any $z \in \mathbb{R}^d$. Picking $z = x$ allows to conclude. ■

Proposition 1.4.3

Let $F : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ be a convex function and $x, y \in \mathbb{R}^d$. Then, the following are equivalent:

i. $y \in \partial F(x)$.

ii. $F(x) + F^*(y) = \langle x, y\rangle$.

If, additionally, F is l.s.c. , then the above are also equivalent to

iii. $x \in \partial F^*(y)$.

Proof: To show that i is equivalent to ii, we just need to show that $y \in \partial F(x)$ is equivalent to

$$F(x) + F^*(y) \leq \langle x, y \rangle. \tag{1.52}$$

Indeed, the opposite inequality is always true due to Fenchel's inequality (see Proposition 1.4.1).

Observe that the fact that $y \in \partial F(x)$ means that

$$\langle x, y \rangle F(x) \geq \langle z, y \rangle F(z), \qquad \forall z \in \mathbb{R}^d. \tag{1.53}$$

That is, the function $z \mapsto \langle z, y \rangle F(z)$ attains its maximum at $z = x$. But, by definition of F^*, this is equivalent to (1.52), thus proving that i is equivalent to ii.

To complete the proof, observe that by Theorem 1.4.2 the lower semicontinuity of F yield that $F^{**} = F$, so that ii is equivalent to $F^{**}(x) + F^*(y) = \langle x, y \rangle$. Using the fact that $i \Longleftrightarrow ii$ with F replaced by F^* completes the proof. ∎

1.5 Convex optimization problems

Definition 1.5.1

An optimization problem is a minimization problem of the form

$$\min_{x \in \mathbb{R}^d} F_0(x) \qquad \text{subject to} \qquad Ax = y \qquad \text{and} \qquad F_j(x) \leq 0, \qquad j \in [\![1, M]\!]. \tag{OP}$$

Here,

1. $F_0 : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ is the *objective function*;
2. $F_1, \ldots, F_M : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ are the *constraing functions*;
3. $A \in \mathbb{R}^{m \times n}$ and $y \in \mathbb{R}^m$ provide the *equality constraints*;

The optimization problem is *convex* (resp. *linear*) if $F_0, \ldots, F_M$ are convex (resp. linear) functions.

Definition 1.5.2

Consider an optimization problem (OP). Then,

- The set $\Phi \subset \mathbb{R}^d$ of points $x \in \mathbb{R}^d$ satisfying the constraints is the set of *feasible points*. That is,

$$\Phi = \left\{ x \in \mathbb{R}^d \mid Ax = y, \qquad F_j(x) \leq 0 \qquad \forall j \in [\![1, M]\!] \right\}. \tag{1.54}$$

  In particular, Φ is convex if (OP) is convex.
- Problem (OP) is *feasible* if it admits at least a feasible point (i.e., $\Phi \neq \varnothing$).
- The *optimal value* is $p^\star = \min_{x \in \Phi} F(x_0)$.
- A *minimizer* is a feasible point $x^\star$ such that $F_0(x^\star) \leq F_0(x)$ for all feasible $x \in \Phi$. That is, $F_0(x^\star) = p^\star$.

Observe that the constrained optimization problem (OP) is equivalent to the uncostrained optimization problem

$$\min_{x \in \mathbb{R}^d} F_0(x) + \chi_\Phi, \tag{1.55}$$

where χ_Φ is the $0 - \infty$ characteristic function defined in (1.38).

Let us introduce the notation

$$\mathbb{R}^M = \{ \nu \in \mathbb{R}^M \mid \nu_j \geq 0 \quad \forall j \in [\![1, M]\!] \}. \tag{1.56}$$

Definition 1.5.3 Lagrange and Lagrange dual functions

The *Lagrange function* of the optimization problem (OP) is the function $F : \mathbb{R}^d \times \mathbb{R}^m \times \mathbb{R}_+^M \to \mathbb{R} \cup \{+\infty\}$ defined by

$$L(x, \xi, \nu) = F_0(x) + \langle \xi, Ax - y \rangle + \sum_{j=1}^{m} \nu_j F_j(x). \tag{1.57}$$

The *Lagrange dual function* is the function $H : \mathbb{R}^m \times \mathbb{R}_+^M \to \mathbb{R} \cup \{-\infty\} \cup \{+\infty\}$, defined by

$$H(\xi, \nu) = \inf_{x \in \mathbb{R}^d} L(x, \xi, \nu). \tag{1.58}$$

Proposition 1.5.1

The dual function is always concave. Moreover, if $x^\star$ is a minimizer of (OP), we have

$$H(\xi, \nu) \leq F(x^\star), \qquad \forall \xi \in \mathbb{R}^m,\ \nu \in \mathbb{R}_+^M. \tag{1.59}$$

Proof: Observe that $-H$ is the supremum w.r.t. $x \in \mathbb{R}^d$ of the functions $g_x(\xi, \nu) = -L(x, \xi, \nu)$. The function g_x is affine, and thus convex. Hence, $-H$ is the pointwise supremum of the family $\{g_x\}_{x \in \mathbb{R}^d}$ of convex function. It is immediate to check that it is convex, and thus that H is concave.

On the other hand, for any feasible point $x \in \Phi$, since $\nu_j \geq 0$ for any $j \in [\![1, M]\!]$, we have

$$\langle \xi, Ax - y \rangle + \sum_{j=1}^{m} \nu_j F_j(x) \leq 0. \tag{1.60}$$

Then, $L(x, \xi, \nu) \leq F_0(x) \leq F_0(x^\star)$ and, as a consequence,

$$H(\xi, \nu) \leq \inf_{x \in \Phi} L(x, \xi, \nu) \leq F_0(x^\star). \tag{1.61}$$

This completes the proof of the statement. ∎

The previous result suggests to introduce the following.

Definition 1.5.4 Primal and dual problem

The *dual problem* to (OP), which is called the *primal problem*, it the optimization problem

$$\max_{\xi \in \mathbb{R}^m,\ \nu \in \mathbb{R}^M} H(\xi, \nu) \qquad \text{subject to} \qquad \nu_j \geq 0 \quad \forall j \in [\![1, M]\!]. \tag{DP}$$

- A pair $(\xi, \nu) \in \mathbb{R}^m \times \mathbb{R}_+^M$ is called *dual feasible.*
- The *dual optimal value* is the solution $d^\star$ of (DP).
- A *dual optimal* or *optimal Lagrange multiplier* is a feasible maximizer $(\xi^\star \nu^\star) \in \mathbb{R}^m \times \mathbb{R}_+^M$.
- A *primal-dual optimal* is a triple $(x^\star, \xi^\star, \nu^\star)$ where $x^\star$ is a minimizer for (OP) and $(\xi^\star, \nu^\star)$ is a dual optimal.

Definition 1.5.5 Duality

The primal-dual problems always satisfy *weak duality*, that is $d^\star \leq p^\star$ where $d^\star$ is the dual optimal value and $p^\star$ is the primal optimal value.
We say that the problems enjoy *strong duality* if it holds

$$p^\star = d^\star. \tag{1.62}$$

The above shows the interest of the dual problem: when strong duality holds, in order to solve the minimization problem (OP) it suffices to solve the dual problem (DP).

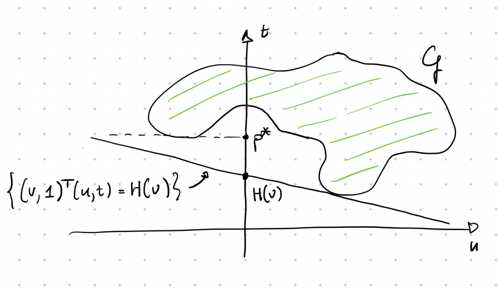

Figure 1.6: Geometric interpretation. The value of the dual function $H(v)$ identifies a supporting hyperplane for the set $\mathcal{G}$.

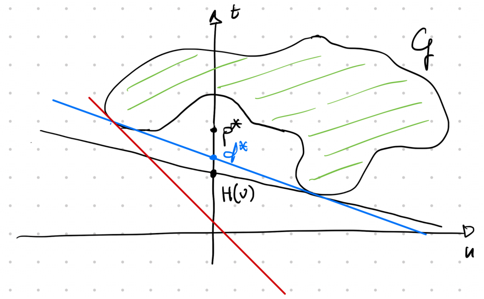

Figure 1.7: Geometric interpretation. Solving the dual problem yields the blue hyperplane. In this case $p^\star > d^\star$ and strong duality does not hold.

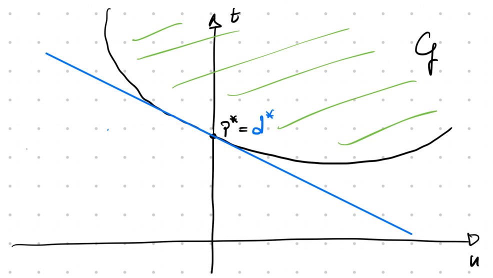

Figure 1.8: Geometric interpretation of Slater's condition. When the set $\mathcal{G}$ is convex and has interior that intersects the left-hand plane, the best supporting hyperplane yields the optimal value $p^\star$.

The following is the most used criterion for strong duality.

Theorem 1.5.1 Slater's constraint quantification

Assume that $F_0, \ldots, F_M$ are convex functions with domain $\mathrm{dom}(\mathbb{R}^d)$ and that $F_0(x) \geq -c$ for some $c \geq 0$. Then, strong duality holds if there exists $x \in \Phi \subset \mathbb{R}^d$ such that $F_j(x) < 0$ for any $j \in [\![1, M]\!]$.

For a proof of the above result, we refer to [1, Section 5.3.2].

Geometric interpretation

Let us follow [1, Section 5.3] and present a geometric interpretation of the previous discussion. Assume that there are no equality constraints and a single inequality constraint, and define

$$\mathcal{G} = \{(F_1(x), F_0(x)) \mid x \in \mathbb{R}^d\}. \tag{1.63}$$

By construction, the problem is feasible if and only if $\mathcal{G}$ intersects the left-half plane. Furthermore, we have

$$p^\star = \min\{t \mid (u,t) \in \mathcal{G},\, u \leq 0\}. \tag{1.64}$$

Since $L(x, v) = (v, 1)^\top (F_1(x), F_0(x))$, we also have

$$H(v) = \inf\{(v, 1)^\top (u, t) \mid (u, t) \in \mathcal{G}\}. \tag{1.65}$$

Hence, if this infimum is finite, the inequality $(v, 1)^\top (u, t) \geq H(v)$ defines a supporting hyperplane for $\mathcal{G}$.

If the problem is convex, then $\mathcal{G}$ is convex and under Slater's condition its interior intersects the left-hand plane. This insures that strong duality holds.

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