

Optimization and Optimal Control in Banach Spaces

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1 Convex non-smooth optimization with proximal operators

Remark 1.1 (Motivation). Convex optimization:

- easier to solve, global optimality,
- convexity is strong regularity property, even if functions are not differentiable, even in infinite dimensions,
- usually strong duality,
- special class of algorithms for non-smooth, convex problems; easy to implement and to parallelize. Objective function may assume value $+\infty$, i.e. well suited for implementing constraints.

So if possible: formulate convex optimization problems.

Of course: some phenomena can only be described by non-convex problems, e.g. formation of transport networks.

Definition 1.2. Throughout this section H is Hilbert space, possibly infinite dimensional.

1.1 Convex sets

Definition 1.3 (Convex set). A set $A \subset H$ is convex if for any $a, b \in A$, $\lambda \in [0, 1]$ one has $\lambda \cdot a + (1 - \lambda) \cdot b \in A$.

Comment: Line segment between any two points in A is contained in A

Sketch: Positive example with ellipsoid, counterexample with ‘kidney’

Comment: Study of geometry of convex sets is whole branch of mathematical research. See lecture by Prof. Wirth in previous semester for more details. In this lecture: no focus on convex sets, will repeat all relevant properties where required.

Proposition 1.4 (Intersection of convex sets). If $\{C_i\}_{i \in I}$ is family of convex sets, then $C \stackrel{\text{def.}}{=} \bigcap_{i \in I} C_i$ is convex.

Proof. • Let $x, y \in C$ then for all $i \in I$ have $x, y \in C_i$, thus $\lambda \cdot x + (1 - \lambda) \cdot y \in C_i$ for all $\lambda \in [0, 1]$ and consequently $\lambda \cdot x + (1 - \lambda) \cdot y \in C$.

□

Definition 1.5 (Convex hull). The *convex hull* $\text{conv } C$ of a set C is the intersection of all convex sets that contain C .

Proposition 1.6. Let $C \subset H$, let T be the set of all convex combinations of elements of C , i.e.,

$$T \stackrel{\text{def.}}{=} \left\{ \sum_{i=1}^k \lambda_i x_i \mid k \in \mathbb{N}, x_1, \dots, x_k \in C, \lambda_1, \dots, \lambda_k > 0, \sum_{i=1}^k \lambda_i = 1 \right\}.$$

Then $T = \text{conv } C$.

Proof. $\text{conv } C \subset T$. T is convex: any $x, y \in T$ are (finite) convex combinations of points in C . Thus, so is any convex combination of x and y . Also, $C \subset T$. So $\text{conv } C \subset T$.

$\text{conv } C \supset T$. Let S be convex and $S \supset C$. We will show that $S \supset T$ and thus $\text{conv } C \supset T$, which with the previous step implies equality of the two sets.

We show $S \supset T$ by recursion. For some $k \in \mathbb{N}$, $x_1, \dots, x_k \in C$, $\lambda_1, \dots, \lambda_k > 0$, $\sum_{i=1}^k \lambda_i = 1$ let

$$s_k = \sum_{i=1}^k \lambda_i x_i.$$

When $k = 1$ clearly $s_k \in S$.

Otherwise, set $\tilde{\lambda}_i = \lambda_i / (1 - \lambda_k)$ for $i = 1, \dots, k-1$. Then

$$s_k = \lambda_k x_k + (1 - \lambda_k) \cdot \underbrace{\sum_{i=1}^{k-1} \tilde{\lambda}_i x_i}_{\stackrel{\text{def.}}{=} s_{k-1}}.$$

We find that $s_k \in S$ if $s_{k-1} \in S$. Applying this argument recursively to s_{k-1} until we reach s_1 , we have shown that $s_k \in S$. \square

Proposition 1.7 (Carathéodory). Let $H = \mathbb{R}^n$. Every $x \in \text{conv } C$ can be written as convex combination of at most $n + 1$ elements of C .

Proof. Consider arbitrary convex combination $x = \sum_{i=1}^k \lambda_i x_i$ for $k > n + 1$.

Claim: without changing x can change $(\lambda_i)_i$ such that one λ_i becomes 0.

- The vectors $\{x_2 - x_1, \dots, x_k - x_1\}$ are linearly dependent, since $k - 1 > n$.
- \Rightarrow There are $(\beta_2, \dots, \beta_k) \in \mathbb{R}^{k-1} \setminus \{0\}$ such that

$$0 = \sum_{i=2}^k \beta_i (x_i - x_1) = \sum_{i=2}^k \beta_i x_i - \underbrace{\sum_{i=2}^k \beta_i x_1}_{\stackrel{\text{def.}}{=} -\beta_1}.$$

- Define $\tilde{\lambda}_i = \lambda_i - t^* \beta_i$ for $t^* = \frac{\lambda_{i^*}}{\beta_{i^*}}$ and $i^* = \text{argmin}_{i=1, \dots, k: \beta_i \neq 0} \frac{\lambda_i}{|\beta_i|}$.
- $\tilde{\lambda}_i \geq 0$: $\tilde{\lambda}_i = \lambda_i \cdot \underbrace{\left(1 - \frac{\lambda_{i^*}/\beta_{i^*}}{\lambda_i/\beta_i}\right)}_{|\cdot| \leq 1}$

- $\tilde{\lambda}_{i^*} = 0$
- $\sum_{i=1}^k \tilde{\lambda}_i = \underbrace{\sum_{i=1}^k \lambda_i}_{=1} - t^* \underbrace{\sum_{i=1}^k \beta_i}_{=0} = 1$
- $\sum_{i=1}^k \tilde{\lambda}_i x_i = \underbrace{\sum_{i=1}^k \lambda_i x_i}_{=x} - t^* \underbrace{\sum_{i=1}^k \beta_i x_i}_{=0} = x$

□

1.2 Convex functions

Definition 1.8 (Convex function). A function $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ is convex if for all $x, y \in H$, $\lambda \in [0, 1]$ one has $f(\lambda \cdot x + (1 - \lambda) \cdot y) \leq \lambda \cdot f(x) + (1 - \lambda) \cdot f(y)$. Set of convex functions over H is denoted by $\text{Conv}(H)$.

- f is *strictly convex* if for $x \neq y$ and $\lambda \in (0, 1)$: $f(\lambda \cdot x + (1 - \lambda) \cdot y) < \lambda \cdot f(x) + (1 - \lambda) \cdot f(y)$.
- f is *concave* if $-f$ is convex.
- The *domain* of f , denoted by $\text{dom } f$ is the set $\{x \in H : f(x) < +\infty\}$. f is called *proper* if $\text{dom } f \neq \emptyset$.
- The *graph* of f is the set $\{(x, f(x)) | x \in \text{dom } f\}$.
- The *epigraph* of f is the set ‘above the graph’, $\text{epi } f = \{(x, r) \in H \times \mathbb{R} : r \geq f(x)\}$.
- The *sublevel set* of f with respect to $r \in \mathbb{R}$ is $S_r(f) = \{x \in H : f(x) \leq r\}$.

Sketch: Strictly convex, graph, secant, epigraph, sublevel set

Proposition 1.9. (i) f convex \Rightarrow $\text{dom } f$ convex.

(ii) $[f \text{ convex}] \Leftrightarrow [\text{epi } f \text{ convex}]$.

(iii) $[(x, r) \in \text{epi } f] \Leftrightarrow [x \in S_r(f)]$.

Example 1.10. (i) *characteristic or indicator function* of convex set $C \subset H$:

$$\iota_C(x) = \begin{cases} 0 & \text{if } x \in C \\ +\infty & \text{else.} \end{cases} \quad \text{Do not confuse with} \quad \chi_C(x) = \begin{cases} 1 & \text{if } x \in C \\ 0 & \text{else.} \end{cases}$$

(ii) any *norm* on H is convex: For all $x, y \in H$, $\lambda \in [0, 1]$:

$$\|\lambda \cdot x + (1 - \lambda) \cdot y\| \leq \|\lambda \cdot x\| + \|(1 - \lambda) \cdot y\| = \lambda \cdot \|x\| + (1 - \lambda) \cdot \|y\|$$

(iii) for $H = \mathbb{R}^n$ the *maximum function*

$$\mathbb{R}^n \ni x \mapsto \max\{x_i | i = 1, \dots, n\}$$

is convex.

(iv) *linear and affine functions* are convex.

Example 1.11 (Optimization with constraints). Assume we want to solve an optimization problem with linear constraints, e.g.,

$$\min\{f(x) | x \in \mathbb{R}^n, Ax = y\}$$

where $f : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{\infty\}$, $A \in \mathbb{R}^{m \times n}$, $y \in \mathbb{R}^m$. This can be formally rewritten as unconstrained problem:

$$\min\{f(x) + g(Ax) | x \in \mathbb{R}^n\} \quad \text{where} \quad g = \iota_{\{y\}}.$$

We will later discuss algorithms that are particularly suited for problems of this form where one only has to ‘interact’ with f and g separately, but not their combination.

As mentioned in the motivation: convexity is a strong regularity property. Here we give some examples of consequences of convexity.

Definition 1.12. A function $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ is (sequentially) continuous in x if for every convergent sequence $(x_k)_k$ with limit x one has $\lim_{k \rightarrow \infty} f(x_k) = f(x)$. The set of points x where $f(x) \in \mathbb{R}$ and f is continuous in x is denoted by $\text{cont } f$.

Remark 1.13 (Continuity in infinite dimensions). If H is infinite dimensional, it is a priori not clear, whether closedness and sequential closedness coincide. But since H is a Hilbert space, it has an inner product, which induces a norm, which induces a metric. On metric spaces the notions of closedness and sequential closedness coincide and thus so do the corresponding notions of continuity.

Proposition 1.14 (On convexity and continuity I). Let $f \in \text{Conv}(H)$ be proper and let $x_0 \in \text{dom } f$. Then the following are equivalent:

- (i) f is locally Lipschitz continuous near x_0 .
- (ii) f is bounded on a neighbourhood of x_0 .
- (iii) f is bounded from above on a neighbourhood of x_0 .

Proof. The implications (i) \Rightarrow (ii) \Rightarrow (iii) are clear. We show (iii) \Rightarrow (i).

- If f is bounded from above in an environment of x_0 then there is some $\rho \in \mathbb{R}_{++}$ such that $\sup f(\overline{B(x_0, \rho)}) = \eta < +\infty$.
- Let $x \in H$, $x \neq x_0$, such that $\alpha \stackrel{\text{def.}}{=} \|x - x_0\|/\rho \in (0, 1]$

Sketch: Draw position of \tilde{x} .

- Let $\tilde{x} = x_0 + \frac{1}{\alpha}(x - x_0) \in \overline{B(x_0, \rho)}$. Then $x = (1 - \alpha) \cdot x_0 + \alpha \cdot \tilde{x}$ and therefore by convexity of f

$$\begin{aligned} f(x) &\leq (1 - \alpha) \cdot f(x_0) + \alpha \cdot f(\tilde{x}) \\ f(x) - f(x_0) &\leq \alpha \cdot (\eta - f(x_0)) = \|x - x_0\| \cdot \frac{\eta - f(x_0)}{\rho} \end{aligned}$$

Sketch: Draw position of new \tilde{x} .

- Now let $\tilde{x} = x_0 + \frac{1}{\alpha}(x_0 - x) \in \overline{B(x_0, \rho)}$. Then $x_0 = \frac{\alpha}{1+\alpha} \cdot \tilde{x} + \frac{1}{1+\alpha} \cdot x$. So:

$$\begin{aligned} f(x_0) &\leq \frac{1}{1+\alpha} \cdot f(x) + \frac{\alpha}{1+\alpha} \cdot f(\tilde{x}) \\ f(x_0) - f(x) &\leq \frac{\alpha}{1+\alpha} \cdot (f(\tilde{x}) - f(x_0)) + f(x_0) - f(x) \\ f(x_0) - f(x) &\leq \alpha \cdot (\eta - f(x_0)) = \|x - x_0\| \cdot \frac{\eta - f(x_0)}{\rho} \end{aligned}$$

We combine to get:

$$|f(x) - f(x_0)| \leq \|x - x_0\| \cdot \frac{\eta - f(x_0)}{\rho}$$

- Now need to extend to other ‘base points’ near x_0 . For every $x_1 \in \overline{B(x_0, \rho/4)}$ have $\sup f(\overline{B(x_1, \rho/2)}) \leq \eta$ and $f(x_1) \geq f(x_0) - \frac{\rho}{4} \cdot \frac{\eta - f(x_0)}{\rho} \geq 2f(x_0) - \eta$. With arguments above get for every $x \in \overline{B(x_1, \rho/2)}$ that

$$|f(x) - f(x_1)| \leq \|x - x_1\| \cdot \frac{\eta - f(x_1)}{\rho/2} \leq \|x - x_1\| \cdot \frac{4(\eta - f(x_0))}{\rho}.$$

- For every $x_1, x_2 \in \overline{B(x_0, \rho/4)}$ have $\|x_1 - x_2\| \leq \rho/2$ and thus

$$|f(x_1) - f(x_2)| \leq \|x_1 - x_2\| \cdot \frac{4(\eta - f(x_0))}{\rho}.$$

□

Proposition 1.15 (On convexity and continuity II). If any of the conditions of Proposition 1.14 hold, then f is locally Lipschitz continuous on $\text{int dom } f$.

Proof. Sketch: Positions of x_0, x, y and balls $B(x_0, \rho), B(x, \alpha \cdot \rho)$

- By assumption there is some $x_0 \in \text{dom } f$, $\rho \in \mathbb{R}_{++}$ and $\eta < \infty$ such that $\sup f(\overline{B(x_0, \rho)}) \leq \eta$.
- For any $x \in \text{int dom } f$ there is some $y \in \text{dom } f$ such that $x = \gamma \cdot x_0 + (1 - \gamma) \cdot y$ for some $\gamma \in (0, 1)$.
- Further, there is some $\alpha \in (0, \gamma)$ such that $\overline{B(x, \alpha \cdot \rho)} \subset \text{dom } f$ and $y \notin \overline{B(x, \alpha \cdot \rho)}$.
- Then, $\overline{B(x, \alpha \cdot \rho)} \subset \text{conv}(\overline{B(x_0, \rho)} \cup \{y\})$.
- So for any $z \in \overline{B(x, \alpha \cdot \rho)}$ there is some $w \in B(x_0, \rho)$ and some $\beta \in [0, 1]$ such that $z = \beta \cdot w + (1 - \beta) \cdot y$. Therefore,

$$f(z) \leq \beta \cdot f(w) + (1 - \beta) \cdot f(y) \leq \max\{\eta, f(y)\}.$$

- So f is bounded from above on $\overline{B(x, \alpha \cdot \rho)}$ and thus by Proposition 1.14 f is locally Lipschitz near x .

□

Remark 1.16. One can show: If $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ is proper, convex and lower semicontinuous, then $\text{cont } f = \text{int dom } f$.

Proposition 1.17 (On convexity and continuity in finite dimensions). If $f \in \text{Conv}(H = \mathbb{R}^n)$ then f is locally Lipschitz continuous at every point in $\text{int dom } f$.

Proof. • Let $x_0 \in \text{int dom } f$.

- If H is finite-dimensional then there is a finite set $\{x_i\}_{i \in I} \subset \text{dom } f$ such that $x_0 \in \text{int conv}(\{x_i\}_{i \in I}) \subset \text{dom } f$.
- For example: along every axis $i = 1, \dots, n$ pick $x_{2i-1} = x + \varepsilon \cdot e_i$, $x_{2i} = x - \varepsilon \cdot e_i$ for sufficiently small ε where e_i denotes the canonical i -th Euclidean basis vector.
- Since every point in $\text{conv}(\{x_i\}_{i \in I})$ can be written as convex combination of $\{x_i\}_{i \in I}$ we find $\sup f(\text{conv}(\{x_i\}_{i \in I})) \leq \max_{i \in I} f(x_i) < +\infty$.
- So f is bounded from above on an environment of x_0 and thus Lipschitz continuous in x_0 by the previous Proposition. □

Comment: Why is interior necessary in Proposition above?

Example 1.18. The above result does not extend to infinite dimensions.

- For instance, the H^1 -norm is not continuous with respect to the topology induced by the L^2 -norm.
- An unbounded linear functional is convex but not continuous.

Definition 1.19 (Lower semi-continuity). A function $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ is called (sequentially, see Remark 1.13) *lower semicontinuous* in $x \in H$ if for every sequence $(x_n)_n$ that converges to x one has

$$\liminf_{n \rightarrow \infty} f(x_n) \geq f(x).$$

f is called lower semicontinuous if it is lower semicontinuous on H .

Example 1.20. $f(x) = \begin{cases} 0 & \text{if } x \leq 0, \\ 1 & \text{if } x > 0 \end{cases}$ is lower semicontinuous, $f(x) = \begin{cases} 0 & \text{if } x < 0, \\ 1 & \text{if } x \geq 0 \end{cases}$ is not.

Sketch: Plot the two graphs.

Comment: Assuming continuity is sometimes impractically strong. Lower semi-continuity is a weaker assumption and also sufficient for well-posedness of minimization problems: If $(x_n)_n$ is a convergent minimizing sequence of a lower semicontinuous function f with limit x then x is a minimizer.

Proposition 1.21. Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$. The following are equivalent:

- (i) f is lower semicontinuous.
- (ii) $\text{epi } f$ is closed in $H \times \mathbb{R}$.
- (iii) The sublevel sets $S_r(f)$ are closed for all $r \in \mathbb{R}$.

Proof. (i) \Rightarrow (ii). Let $(y_k, r_k)_k$ be a converging sequence in $\text{epi } f$ with limit (y, r) . Then

$$r = \lim_{k \rightarrow \infty} r_k \geq \liminf_{k \rightarrow \infty} f(y_k) \geq f(y) \quad \Rightarrow \quad (y, r) \in \text{epi } f.$$

(ii) \Rightarrow (iii). For $r \in \mathbb{R}$ let $A_r : H \rightarrow H \times \mathbb{R}$, $x \mapsto (x, r)$ and $Q_r = \text{epi } f \cap (H \times \{r\})$. Q_r is closed, A_r is continuous.

$$S_r(f) = \{x \in H : f(x) \leq r\} = \{x \in H : (x, y) \in Q_r\} = A_r^{-1}(Q_r) \quad \text{is closed.}$$

(iii) \Rightarrow (i). Assume (i) is false. Then there is a sequence $(y_k)_k$ in H converging to $y \in H$ such that $\rho \stackrel{\text{def.}}{=} \lim_{k \rightarrow \infty} f(y_k) < f(y)$. Let $r \in (\rho, f(y))$. For $k \geq k_0$ sufficiently large, $f(y_k) \leq r < f(y)$, i.e. $y_k \in S_r(f)$ but $y \notin S_r(f)$. Contradiction. \square

1.3 Subdifferential

Definition 1.22. The power set of H is the set of all subsets of H and denoted by 2^H .

Comment: Meaning of notation.

Definition 1.23 (Subdifferential). Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ be proper. The *subdifferential* of f is the set-valued operator

$$\partial f : H \rightarrow 2^H, \quad x \mapsto \{u \in H : f(y) \geq f(x) + \langle y - x, u \rangle \text{ for all } y \in H\}$$

For $x \in H$, f is *subdifferentiable* at x if $\partial f(x) \neq \emptyset$. Elements of $\partial f(x)$ are called *subgradients* of f at x .

Sketch: Subgradients are slopes of affine functions that touch graph of function in x from below.

Definition 1.24. The *domain* $\text{dom } A$ of a set-valued operator A are the points where $A(x) \neq \emptyset$.

Definition 1.25. Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ be proper. x is a *minimizer* of f if $f(x) = \inf f(H)$. The set of minimizers of f is denoted by $\text{argmin } f$.

The following is an adaption of first order optimality condition for differentiable functions to convex non-smooth functions.

Proposition 1.26 (Fermat's rule). Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ be proper. Then

$$\text{argmin } f = \{x \in H : 0 \in \partial f(x)\}.$$

Proof. Let $x \in H$. Then

$$[x \in \text{argmin } f] \Leftrightarrow [f(y) \geq f(x) = f(x) + \langle y - x, 0 \rangle \text{ for all } y \in H] \Leftrightarrow [0 \in \partial f(x)].$$

□

Proposition 1.27 (Basic properties of subdifferential). Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$.

- (i) $\partial f(x)$ is closed and convex.
- (ii) If $x \in \text{dom } \partial f$ then f is lower semicontinuous at x .

Proof. (i):

$$\partial f(x) = \bigcap_{y \in \text{dom } f} \{u \in H : f(y) \geq f(x) + \langle y - x, u \rangle\}$$

So $\partial f(x)$ is the intersection of closed and convex sets. Therefore it is closed and convex.

(ii): Let $u \in \partial f(x)$. Then for all $y \in H$: $f(y) \geq f(x) + \langle y - x, u \rangle$. So, for any sequence $(x_k)_k$ converging to x one finds

$$\liminf_{k \rightarrow \infty} f(x_k) \geq f(x) + \liminf_{k \rightarrow \infty} \langle y - x, u \rangle = f(x).$$

□

Definition 1.28 (Monotonicity). A set-valued function $A : H \rightarrow 2^H$ is monotone if

$$\langle x - y, u - v \rangle \geq 0$$

for every tuple $(x, y, u, v) \in H^4$ such that $u \in A(x)$ and $v \in A(y)$.

Proposition 1.29. The subdifferential of a proper function is monotone.

Proof. Let $u \in \partial f(x)$, $v \in \partial f(y)$. We get:

$$\begin{aligned} f(y) &\geq f(x) + \langle y - x, u \rangle, \\ f(x) &\geq f(y) + \langle x - y, v \rangle, \end{aligned}$$

and by combining:

$$0 \geq \langle y - x, u - v \rangle$$

□

Proposition 1.30. Let I be a finite index set, let $H = \bigotimes_{i \in I} H_i$ a product of several Hilbert spaces. Let $f_i : H_i \rightarrow \mathbb{R} \cup \{\infty\}$ be proper and let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$, $x = (x_i)_{i \in I} \mapsto \sum_{i \in I} f_i(x_i)$. Then $\partial f(x) = \bigotimes_{i \in I} \partial f_i(x_i)$.

Proof. $\partial f(x) \supset \bigotimes_{i \in I} \partial f_i(x_i)$: For $x \in H$ let $p_i \in \partial f_i(x_i)$. Then

$$f(x + y) = \sum_{i \in I} f_i(x_i + y_i) \geq \sum_{i \in I} f_i(x_i) + \langle y_i, p_i \rangle = f(x) + \langle y, p \rangle.$$

Therefore $p = (p_i)_{i \in I} \in \partial f(x)$.

$\partial f(x) \subset \bigotimes_{i \in I} \partial f_i(x_i)$: Let $p = (p_i)_{i \in I} \in \partial f(x)$. For $j \in I$ let $y_j \in H_j$ and let $y = (\tilde{y}_i)_{i \in I}$ where $\tilde{y}_i = 0$ if $i \neq j$ and $\tilde{y}_j = y_j$. We get

$$f(x + y) = \sum_{i \in I} f_i(x_i + \tilde{y}_i) = \sum_{i \in I \setminus \{j\}} f_i(x_i) + f_j(x_j + y_j) \geq f(x) + \langle y, p \rangle = \sum_{i \in I} f_i(x_i) + \langle y_j, p_j \rangle$$

This holds for all $y_j \in H_j$. Therefore, $p_j \in \partial f_j(x_j)$. □

Example 1.31. • $f(x) = \frac{1}{2}\|x\|^2$: f is Gâteaux differentiable (see below) with $\nabla f(x) = x$. We will show that this implies $\partial f(x) = \{\nabla f(x)\} = \{x\}$.

- $f(x) = \|x\|$:
 - For $x \neq 0$ f is again Gâteaux differentiable with $\nabla f(x) = \frac{x}{\|x\|}$.
 - For $x = 0$ we get $\overline{f(y)} \geq \langle y, p \rangle = f(0) + \langle y - 0, p \rangle$ for $\|p\| \leq 1$ via the Cauchy-Schwarz inequality. So $\overline{B(0, 1)} \subset \partial f(0)$.
 - Assume some $p \in \partial f(0)$ has $\|p\| > 1$. Then $\frac{p}{\|p\|} \in \partial f(p)$. We test: $\left\langle p - 0, \frac{p}{\|p\|} - p \right\rangle = \|p\| - \|p\|^2 < 0$ which contradicts monotonicity of the subdifferential. Therefore $\partial f(0) = \overline{B(0, 1)}$.

Sketch: Draw ‘graph’ of subdifferential.

- $H = \mathbb{R}$, $f(x) = |x|$ is a special case of the above.

$$\partial f(x) = \begin{cases} \{-1\} & \text{if } x < 0, \\ [-1, 1] & \text{if } x = 0, \\ \{+1\} & \text{if } x > 0 \end{cases}$$

- $H = \mathbb{R}^n$, $f(x) = \|x\|_1$. The L_1 norm is not induced by an inner product. Therefore the above does not apply. We can use Proposition 1.30:

$$\partial f(x) = \bigotimes_{k=1}^n \partial \text{abs}(x_k)$$

Sketch: Draw subdifferential ‘graph’ for 2D.

Proposition 1.32. Let $f, g : H \rightarrow \mathbb{R} \cup \{\infty\}$. For $x \in H$ one finds $\partial f(x) + \partial g(x) \subset \partial(f+g)(x)$.

Proof. Let $u \in \partial f(x)$, $v \in \partial g(x)$. Then

$$f(x+y) + g(x+y) \geq f(x) + \langle u, y \rangle + g(x) + \langle v, y \rangle = f(x) + g(x) + \langle u+v, y \rangle.$$

Therefore, $u+v \in \partial(f+g)(x)$. □

Remark 1.33. The converse inclusion is not true in general and much harder to prove. A simple counter-example is $f(x) = \|x\|^2$ and $g(x) = -\|x\|^2/2$. The subdifferential of g is empty but the subdifferential of $f+g$ is not.

An application of the sub-differential is a simple proof of Jensen’s inequality.

Proposition 1.34 (Jensen’s inequality). Let $f : H = \mathbb{R}^n \rightarrow \mathbb{R} \cup \{\infty\}$ be convex. Let μ be a probability measure on H such that

$$\bar{x} = \int_H x \, d\mu(x) \in H$$

and $\bar{x} \in \text{dom } \partial f$. Then

$$\int_H f(x) \, d\mu(x) \geq f(\bar{x}).$$

Proof. Let $u \in \partial f(\bar{x})$.

$$\int_H f(x) \, d\mu(x) \geq \int_H f(\bar{x}) + \langle x - \bar{x}, u \rangle \, d\mu(x) = f(\bar{x})$$

□

Let us examine the subdifferential of differentiable functions.

Definition 1.35 (Gâteaux differentiability). A function $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ is *Gâteaux differentiable* in $x \in \text{dom } f$ if there is a unique *Gâteaux gradient* $\nabla f(x) \in H$ such that for any $y \in H$ the directional derivative is given by

$$\lim_{\alpha \searrow 0} \frac{f(x+\alpha \cdot y) - f(x)}{\alpha} = \langle y, \nabla f(x) \rangle.$$

Proposition 1.36. Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ be proper and convex, let $x \in \text{dom } f$. If f is Gâteaux differentiable in x then $\partial f(x) = \{\nabla f(x)\}$.

Proof. $\nabla f(x) \in \partial f(x)$:

- For fixed $y \in H$ consider the function $\phi : \mathbb{R}_+ \rightarrow \mathbb{R} \cup \{\infty\}$, $\alpha \mapsto \frac{f(x+\alpha \cdot y) - f(x)}{\alpha}$.
- ϕ is increasing: let $\beta \in (0, \alpha)$. Then $x + \beta \cdot y = (1 - \beta/\alpha) \cdot x + \beta/\alpha \cdot (x + \alpha \cdot y)$. So

$$\begin{aligned} f(x + \beta \cdot y) &\leq (1 - \beta/\alpha) \cdot f(x) + \beta/\alpha \cdot f(x + \alpha \cdot y), \\ \phi(\beta) &\leq \frac{(1 - \beta/\alpha) \cdot f(x) + \beta/\alpha \cdot f(x + \alpha \cdot y) - f(x)}{\beta} \\ &= \frac{\beta/\alpha \cdot (f(x + \alpha \cdot y) - f(x))}{\beta} = \phi(\alpha). \end{aligned}$$

- Therefore,

$$\langle y, \nabla f(x) \rangle = \lim_{\alpha \searrow 0} \frac{f(x + \alpha \cdot y) - f(x)}{\alpha} = \inf_{\alpha \in \mathbb{R}_+} \phi(\alpha) \leq f(x + y) - f(x).$$

(We set $\alpha = 1$ to get the last inequality.)

$\partial f(x) \subset \{\nabla f(x)\}$:

- For $u \in \partial f(x)$ we find for any $y \in H$

$$\langle y, \nabla f(x) \rangle = \lim_{\alpha \searrow 0} \frac{f(x + \alpha \cdot y) - f(x)}{\alpha} \geq \lim_{\alpha \searrow 0} \frac{f(x) + \langle \alpha \cdot y, u \rangle - f(x)}{\alpha} = \langle y, u \rangle.$$

- This inequality holds for any y and $-y$ simultaneously. Therefore $u = \nabla f(x)$.

□

Remark 1.37. For differentiable functions in one dimension this implies monotonicity of the derivative: Let $f \in C^1(\mathbb{R})$. With Propositions 1.36 and 1.29 we get: if $x \geq y$ then $f'(x) \geq f'(y)$.

1.4 Cones and support functions

Cones are a special class of sets with many applications in convex analysis.

Definition 1.38. A set $C \subset H$ is a *cone* if for any $x \in C$, $\lambda \in \mathbb{R}_{++}$ one has $\lambda \cdot x \in C$. In short notation: $C = \mathbb{R}_{++} \cdot C$.

Remark 1.39. A cone need not contain 0, but for any $x \in C$ it must contain the open line segment $(0, x]$.

Proposition 1.40. The intersection of a family $\{C_i\}_{i \in I}$ of cones is cone. The *conical hull* of a set $C \subset H$, denoted by $\text{cone } C$ is the smallest cone that contains C . It is given by $\mathbb{R}_{++} \cdot C$.

Proof. • Let $C = \bigcap_{i \in I} C_i$. If $x \in C$ then $x \in C_i$ for all $i \in I$ and for any $\lambda \in \mathbb{R}_{++}$ one has $\lambda \cdot x \in C_i$ for all $i \in I$. Hence $\lambda \cdot x \in C$ and C is also a cone.

- Let $D = \mathbb{R}_{++} \cdot C$. Then D is a cone, $C \subset D$ and therefore $\text{cone } C \subset D$. Conversely, let $y \in D$. Then there are $x \in C$ and $\lambda \in \mathbb{R}_{++}$ such that $y = \lambda \cdot x$. So $x \in \text{cone } C$, therefore $y \in \text{cone } C$ and thus $D \subset \text{cone } C$.

□

Proposition 1.41. A cone C is convex if and only if $C + C \subset C$.

Proof. C **convex** $\Rightarrow C + C \subset C$: Let $a, b \in C$. $\Rightarrow \frac{1}{2} \cdot a + \frac{1}{2} \cdot b \in C \Rightarrow a + b \in C \Rightarrow C + C \subset C$.
 $C + C \subset C \Rightarrow C$ **convex**: Let $a, b \in C$. $\Rightarrow a + b \in C$ and $\lambda \cdot a, (1 - \lambda) \cdot b \in C$ for all $\lambda \in (0, 1)$.
 $\Rightarrow \lambda \cdot a + (1 - \lambda) \cdot b \in C$. $\Rightarrow [a, b] \in C \Rightarrow C$ convex. □

Definition 1.42. Let $C \subset H$. The *polar cone* of C is

$$C^\ominus = \{y \in H : \sup \langle C, y \rangle \leq 0\}.$$

Sketch: Draw a cone in 2D with angle $< \pi/2$ and its polar cone.

Proposition 1.43. Let C be a linear subspace of H . Then $C^\ominus = C^\perp$.

Proof. • Since C is a linear subspace, if $\langle x, y \rangle \neq 0$ for some $y \in H$, $x \in C$ then $\sup \langle C, y \rangle = \infty$.

- Therefore, $C^\ominus = \{y \in H : \langle x, y \rangle = 0 \text{ for all } x \in C\}$.

□

Definition 1.44. Let $C \subset H$ convex, non-empty and $x \in H$. The *tangent cone* to C at x is

$$T_C x = \begin{cases} \overline{\text{cone}(C - x)} & \text{if } x \in C, \\ \emptyset & \text{else.} \end{cases}$$

The *normal cone* to C at x is

$$N_C x = \begin{cases} (C - x)^\ominus = \{u \in H : \sup \langle C - x, u \rangle \leq 0\} & \text{if } x \in C, \\ \emptyset & \text{else.} \end{cases}$$

Example 1.45. Let $C = \overline{B(0, 1)}$. Then for $x \in C$:

$$T_C x = \begin{cases} \{y \in H : \langle y, x \rangle \leq 0\} & \text{if } \|x\| = 1, \\ H & \text{if } \|x\| < 1. \end{cases}$$

Note: the \leq in the $\|x\| = 1$ case comes from the closure in the definition of $T_C x$. Without closure it would merely be $<$.

$$N_C x = \begin{cases} \mathbb{R}_+ \cdot x & \text{if } \|x\| = 1, \\ \{0\} & \text{if } \|x\| < 1. \end{cases}$$

Example 1.46. What are tangent and normal cone for the L_1 -norm ball in \mathbb{R}^2 ?

We start to see connections between different concepts introduced so far.

Proposition 1.47. Let $C \subset H$ be a convex set. Then $\partial \iota_C(x) = N_C x$.

Proof. • $x \notin C$: $\partial \iota_C(x) = \emptyset = N_C x$.

• $x \in C$:

$$\begin{aligned} [u \in \partial \iota_C(x)] &\Leftrightarrow [\iota_C(y) \geq \iota_C(x) + \langle y - x, u \rangle \ \forall y \in C] \Leftrightarrow [0 \geq \langle y - x, u \rangle \ \forall y \in C] \\ &\Leftrightarrow [\sup \langle C - x, u \rangle \leq 0] \Leftrightarrow [u \in N_C x] \end{aligned}$$

□

Comment: This will become relevant, when doing constrained optimization, where parts of the objective are given by indicator functions.

Now we introduce the projection onto convex sets. It will play an important role in analysis and numerical methods for constrained optimization.

Proposition 1.48 (Projection). Let $C \subset H$ be non-empty, closed convex. For $x \in H$ the problem

$$\inf \{\|x - p\| \mid p \in C\}$$

has a unique minimizer. This minimizer is called the *projection* of x onto C and is denoted by $P_C x$.

Proof. • We will need the following inequality for any $x, y, z \in H$, which can be shown by careful expansion:

$$\|x - y\|^2 = 2\|x - z\|^2 + 2\|y - z\|^2 - 4\|(x + y)/2 - z\|^2$$

- C is non-empty, $y \mapsto \|x - y\|$ is bounded from below, so the infimal value is a real number, denoted by d .
- Let $(p_k)_{k \in \mathbb{N}}$ be a minimizing sequence. For $k, l \in \mathbb{N}$ one has $\frac{1}{2}(p_k + p_l) \in C$ by convexity and therefore $\|x - \frac{1}{2}(p_k + p_l)\| \geq d$.
- With the above inequality we find:

$$\|p_k - p_l\|^2 = 2\|p_k - x\|^2 + 2\|p_l - x\|^2 - 4\|\frac{p_k + p_l}{2} - x\|^2 \leq 2\|p_k - x\|^2 + 2\|p_l - x\|^2 - 4d^2$$

- So by sending $k, l \rightarrow \infty$ we find that $(p_k)_k$ is a Cauchy sequence which converges to a limit p . Since C is closed, $p \in C$. And since $y \mapsto \|x - y\|$ is continuous, p is a minimizer.
- Uniqueness of p , quick answer: the optimization problem is equivalent to minimizing $y \mapsto \|x - y\|^2$, which is strictly convex. Therefore p must be unique.
- Uniqueness of p , detailed answer: assume there is another minimizer $q \neq p$. Then $\frac{1}{2}(p+q) \in C$ and we find:

$$\|x - p\|^2 + \|x - q\|^2 - 2\|x - \frac{1}{2}(p+q)\|^2 = \frac{1}{2}\|p - q\|^2 > 0$$

So the sum of the objectives at p and q is strictly larger than twice the objective at the midpoint. Therefore, neither p nor q can be optimal. □

Proposition 1.49 (Characterization of projection). Let $C \subset H$ be non-empty, convex, closed. Then $p = P_C x$ if and only if

$$[p \in C] \wedge [\langle y - p, x - p \rangle \leq 0 \text{ for all } y \in C].$$

Sketch: Illustrate inequality.

Proof. • It is clear that $[p = P_C x] \Rightarrow [p \in C]$, and that $[p \notin C] \Rightarrow [p \neq P_C x]$.

- So, need to show that for $p \in C$ one has $[p = P_C x] \Leftrightarrow [\langle y - p, x - p \rangle \leq 0 \text{ for all } y \in C]$.
- For some $y \in C$ and some $\varepsilon \in \mathbb{R}_{++}$ consider:

$$\begin{aligned} \|x - (p + \varepsilon \cdot (y - p))\|^2 - \|x - p\|^2 &= \|p + \varepsilon \cdot (y - p)\|^2 - \|p\|^2 - 2\varepsilon \langle x, y - p \rangle \\ &= \varepsilon^2 \|y - p\|^2 - 2\varepsilon \langle x - p, y - p \rangle \end{aligned}$$

If $\langle x - p, y - p \rangle > 0$ then this is negative for sufficiently small ε and thus p cannot be the projection. Conversely, if $\langle x - p, y - p \rangle \leq 0$ for all $y \in C$, then for $\varepsilon = 1$ we see that p is indeed the minimizer of $y \mapsto \|x - y\|^2$ over C and thus the projection. □

Corollary 1.50 (Projection and normal cone). Let $C \subset H$ be non-empty, closed, convex. Then $[p = P_C x] \Leftrightarrow [x \in p + N_C p]$.

Proof. $[p = P_C x] \Leftrightarrow [p \in C \wedge \sup \langle C - p, x - p \rangle \geq 0] \Leftrightarrow [x - p \in N_C p]$. □

Comment: This condition is actually useful for computing projections.

Example 1.51 (Projection onto L_1 -ball in \mathbb{R}^2). Let $C = \{(x, y) \in \mathbb{R}^2 : |x| + |y| \leq 1\}$. We find:

$$N_C(x, y) = \begin{cases} \emptyset & \text{if } |x| + |y| > 1, \\ \{0\} & \text{if } |x| + |y| < 1, \\ \text{cone}\{(1, 1), (-1, 1)\} & \text{if } (x, y) = (0, 1), \\ \text{cone}\{(1, 1), (1, -1)\} & \text{if } (x, y) = (1, 0), \\ \text{cone}\{(1, 1)\} & \text{if } x + y = 1, x \in (0, 1), \\ \dots & \end{cases}$$

Sketch: Draw normal cones attached to points in C .

Now compute projection of $(a, b) \in \mathbb{R}^2$. W.l.o.g. assume $(a, b) \in \mathbb{R}_+^2$. Then

$$P_C(a, b) = \begin{cases} (0, 1) & \text{if } [a + b \geq 1] \wedge [b - a \geq 1], \\ (1, 0) & \text{if } [a + b \geq 1] \wedge [a - b \geq 1], \\ ((1 + a - b)/2, (1 - a + b)/2) & \text{else.} \end{cases}$$

Comment: Do computation in detail.

Comment: Result is very intuitive, but not so trivial to prove rigorously due to non-smoothness of problem. Comment: Eistüte.

We now establish a sequence of results that will later allow us to analyze the subdifferential via cones and prepare results for the study of the Fenchel–Legendre conjugate.

Proposition 1.52. Let $K \subset H$ be a non-empty, closed, convex cone. Let $x, p \in H$. Then

$$[p = P_K x] \Leftrightarrow [p \in K, x - p \perp p, x - p \in K^\ominus].$$

Proof. • By virtue of Corollary 1.50 (Characterization of projection with normal cone inclusion) we need to show

$$[x - p \in N_K p] \Leftrightarrow [p \in K, x - p \perp p, x - p \in K^\ominus].$$

- \Rightarrow : Let $x - p \in N_K p$. Then $p \in K$. By definition have $\sup \langle K - p, x - p \rangle \leq 0$. Since $2p, 0 \in K$ (K is closed) this implies $\langle p, x - p \rangle = 0$. Further, since K is convex, we have (Prop. 1.41) $K + K \subset K$, and in particular $K + p \subset K$. Therefore $\sup \langle K + p - p, x - p \rangle \leq \sup \langle K - p, x - p \rangle \leq 0$ and thus $x - p \in K^\ominus$.

Sketch: Recall that $K + p \subset K$. Counter-example for non-convex K .

- \Leftarrow : Since $p \perp x - p$ have $\sup \langle K - p, x - p \rangle = \sup \langle K, x - p \rangle \leq 0$ since $x - p \in K^\ominus$. Then, since $p \in K$ have $x - p \in N_K p$.

□

Proposition 1.53. Let $K \subset H$ be a non-empty, closed, convex cone. Then $K^{\ominus\ominus} = K$.

Proof. • $K \subset K^{\ominus\ominus}$: Recall: $K^\ominus = \{u \in H : \sup \langle K, u \rangle \leq 0\}$.

- Let $x \in K$. Then $\langle x, u \rangle \leq 0$ for all $u \in K^\ominus$. Therefore $\sup \langle x, K^\ominus \rangle \leq 0$ and so $x \in K^{\ominus\ominus}$. Therefore: $K \subset K^{\ominus\ominus}$.
- $K^{\ominus\ominus} \subset K$: Let $x \in K^{\ominus\ominus}$, set $p \in P_K x$. Then by Proposition 1.52 (Projection onto closed, convex cone): $x - p \perp p, x - p \in K^\ominus$.
- $[x \in K^{\ominus\ominus}] \wedge [x - p \in K^\ominus] \Rightarrow \langle x, x - p \rangle \leq 0$.
- $\|x - p\|^2 = \langle x, x - p \rangle - \langle p, x - p \rangle \leq 0 \Rightarrow x = p \Rightarrow x \in K$. Therefore $K^{\ominus\ominus} \subset K$.

□

For subsequent results we need the following Lemma that once more illustrates that convexity implies strong regularity.

Proposition 1.54. Let $C \subset H$ be convex. Then the following hold:

- (i) For all $x \in \text{int } C$, $y \in \overline{C}$, $[x, y) \subset \text{int } C$.
- (ii) \overline{C} is convex.
- (iii) $\text{int } C$ is convex.
- (iv) If $\text{int } C \neq \emptyset$ then $\text{int } C = \text{int } \overline{C}$ and $\overline{C} = \overline{\text{int } C}$.

Proof. • **(i):** Assume $x \neq y$ (otherwise the result is trivial). Then for $z \in [x, y)$ there is some $\alpha \in (0, 1]$ such that $z = \alpha \cdot x + (1 - \alpha) \cdot y$.

- Since $x \in \text{int } C$ there is some $\varepsilon \in \mathbb{R}_{++}$ such that $B(x, \varepsilon \cdot (2 - \alpha)/\alpha) \subset C$.
- Since $y \in \overline{C}$, one has $y \in C + B(0, \varepsilon)$.
- By convexity of C :

$$\begin{aligned} B(z, \varepsilon) &= \alpha \cdot x + (1 - \alpha) \cdot y + B(0, \varepsilon) \\ &\subset \alpha \cdot x + (1 - \alpha) \cdot (C + B(0, \varepsilon)) + B(0, \varepsilon) \\ &= \alpha \cdot B(x, \varepsilon \cdot \frac{2-\alpha}{\alpha}) + (1 - \alpha) \cdot C \\ &\subset \alpha \cdot C + (1 - \alpha) \cdot C = C \end{aligned}$$

- Therefore $z \in \text{int } C$.
- **(ii):** Let $x, y \in \overline{C}$. By definition there are sequences $(x_k)_k, (y_k)_k$ in C that converge to x and y . For $\lambda \in [0, 1]$ the sequence $(\lambda \cdot x_k + (1 - \lambda) \cdot y_k)_k$ converges to $\lambda \cdot x + (1 - \lambda) \cdot y \in \overline{C}$.
- **(iii):** Let $x, y \in \text{int } C$. Then $y \in \overline{C}$. By (i) therefore $(x, y) \in \text{int } C$.
- **(iv):** By definition $\text{int } C \subset \text{int } \overline{C}$. Show converse inclusion. Let $y \in \text{int } \overline{C}$. Then there is $\varepsilon \in \mathbb{R}_{++}$ such that $B(y, \varepsilon) \subset \overline{C}$. Let $x \in \text{int } C$, $x \neq y$. Then there is some $\alpha \in \mathbb{R}_{++}$ such that $y + \alpha \cdot (y - x) \in B(y, \varepsilon) \subset \overline{C}$.
- Since $y \in (x, y + \alpha \cdot (y - x))$ it follows from (i) that $y \in \text{int } C$.
- Similarly, it is clear that $\overline{\text{int } C} \subset \overline{C}$. We show the converse inclusion. Let $x \in \text{int } C$, $y \in \overline{C}$. For $\alpha \in (0, 1]$ let $y_\alpha = (1 - \alpha) \cdot y + \alpha \cdot x$. Then $y_\alpha \in \text{int } C$ by (i) and thus $y = \lim_{\alpha \rightarrow 0} y_\alpha \in \overline{\text{int } C}$.

□

Example 1.55. Let $H = \mathbb{R}$, $C = \mathbb{Q} \cup [0, 1]$. $\text{int } C = (0, 1) \neq \emptyset$ but C is not convex. We find $\text{int } C = (0, 1) \neq \text{int } \overline{C} = \text{int } \mathbb{R} = \mathbb{R}$ and $\overline{C} = \mathbb{R} \neq \overline{\text{int } C} = [0, 1]$.

We can characterize the tangent and normal cones of a convex set, depending on the base point position.

Proposition 1.56. Let $C \subset H$ be convex with $\text{int } C \neq \emptyset$ and $x \in C$. Then

$$[x \in \text{int } C] \Leftrightarrow [T_C x = H] \Leftrightarrow [N_C x = \{0\}].$$

Proof. • $[x \in \text{int } C] \Leftrightarrow [T_C x = H]$: Let $D = C - x$. Then $0 \in D$, $[x \in \text{int } C] \Leftrightarrow [0 \in \text{int } D]$ and $T_C x = \text{cone } \overline{D}$.

- One can show: if $D \subset H$ is convex with $\text{int } D \neq \emptyset$ and $0 \in D$, then $[0 \in \text{int } D] \Leftrightarrow [\overline{\text{cone } D} = H]$.
- Sketch: assume $0 \in \text{int } D$. Then $\overline{\text{cone } D} = \text{cone } D = H$ since there is some $\varepsilon > 0$ such that for any $u \in H \setminus \{0\}$ one has $\varepsilon \frac{u}{\|u\|} \in D$. The converse conclusion is more tedious. It relies on Proposition 1.54. See [Bauschke, Combettes; Prop. 6.17] for details.
- $[T_C x = H] \Leftrightarrow [N_C x = \{0\}]$: Recall $N_C x = \{u \in H : \sup \langle C - x, u \rangle \leq 0\}$. We can extend the supremum to $\text{cone}(C - x)$ and we can then extend it to the closure $\overline{\text{cone}(C - x)}$ without changing whether it will be ≤ 0 (why?). So $N_C x = \{u \in H : \sup \langle T_C x, u \rangle \leq 0\} = (T_C x)^\ominus$.
- Now, if $T_C x = H$ then $N_C x = \{0\}$.
- Conversely, since for $x \in C$, $T_C x$ is a non-empty, closed, convex cone, one has $(T_C x)^{\ominus\ominus} = T_C x$ (Prop. 1.53) and therefore $T_C x = (N_C x)^\ominus$. So if $N_C x = \{0\}$ then $T_C x = H$.

□

Comment: Observation: subdifferential describes affine functions that touch graph in one point and always lie below graph. Similarly: for convex sets there are hyperplanes, that touch set in one point and separate the set from the opposite half-space. These are called ‘supporting hyperplanes’. The study of the subdifferential is thus related to the study of supporting hyperplanes. Supporting hyperplanes, in turn, are again closely related to normal cones, as we will learn.

Definition 1.57. Let $C \subset H$, $x \in C$ and let $u \in H \setminus \{0\}$. If

$$\sup \langle C, u \rangle \leq \langle x, u \rangle$$

then the set $\{y \in H : \langle y, u \rangle = \langle x, u \rangle\}$ is a *supporting hyperplane* of C at x and x is a *support point* at C with *normal vector* u . The set of support points of C is denoted by $\text{spts } C$.

Proposition 1.58. Let $C \subset H$, $C \neq \emptyset$ and convex. Then:

$$\text{spts } C = \{x \in C : N_C x \neq \{0\}\}$$

Proof. Let $x \in C$. Then:

$$[x \in \text{spts } C] \Leftrightarrow [\exists u \in H \setminus \{0\} : \sup \langle C - x, u \rangle \leq 0] \Leftrightarrow [0 \neq u \in N_C x]$$

□

Proposition 1.59. Let $C \subset H$ convex, $\text{int } C \neq \emptyset$. Then

$$\text{bdry } C \subset \text{spts } \overline{C} \quad \text{and} \quad C \cap \text{bdry } C \subset \text{spts } C.$$

Proof. • If $C = H$ the result is clear. (Why?) So assume $C \neq H$.

- Let $x \in \text{bdry } C \subset \overline{C}$. So $x \in \overline{C} \setminus \text{int } C = \overline{C} \setminus \text{int } \overline{C}$ (Prop. 1.54).
- Consequence of Prop. 1.56: $\exists u \in N_{\overline{C}} x \setminus \{0\}$.
- Consequence of Prop. 1.58: $x \in \text{spts } \overline{C}$. Therefore $\text{bdry } C \subset \text{spts } \overline{C}$.
- Show $\text{spts } C = C \cap \text{spts } \overline{C}$: For this use $\sup \langle \overline{C}, u \rangle = \sup \langle C, u \rangle$ (why?).

- Let $x \in \text{spts } C$: $\Rightarrow x \in C \subset \overline{C}$, $\exists u \neq 0$ s.t. $\sup \langle C, u \rangle \leq \langle x, u \rangle$. $\Rightarrow x \in C \cap \text{spts } \overline{C}$.
- Let $x \in \text{spts } \overline{C} \cap C$: $\Rightarrow x \in C$, $\exists u \neq 0$ s.t. $\sup \langle \overline{C}, u \rangle \leq \langle x, u \rangle$. $\Rightarrow x \in \text{spts } C$.
- So: $C \cap \text{bdry } C \subset C \cap \text{spts } \overline{C} = \text{spts } C$.

□

Example 1.60. Let $H = \mathbb{R}$, $C = [-1, 1)$. Then $\text{int } C = (-1, 1)$, $\overline{C} = [-1, 1]$, $\text{bdry } C = \{-1, 1\}$, $\text{spts } C = \{-1\}$, $\text{spts } \overline{C} = \{-1, 1\}$.

An application of the previous results is to show that the subdifferential of a convex function is non-empty in a point of its domain where the function is continuous.

Proposition 1.61. Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ be proper and convex and let $x \in \text{dom } f$. If $x \in \text{cont } f$ then $\partial f(x) \neq \emptyset$.

Proof. • Since f is proper and convex, $\text{epi } f$ is non-empty and convex.

- Since $x \in \text{cont } f$, f is bounded in an environment of x . Let $\varepsilon > 0$, $\eta < +\infty$ such that $f(y) < f(x) + \eta$ for $\|x - y\| < \varepsilon$. Therefore, $\text{int epi } f \neq \emptyset$ because it contains $B(x, \varepsilon/2) \times (f(x) + 2\eta, \infty)$.
- Further: consider sequence $(y_k = (x, f(x) - 1/k))_{k=1}^\infty$. Clearly $y_k \notin \text{epi } f$ but $\lim_{k \rightarrow \infty} y_k = (x, f(x)) \in \text{epi } f$. Therefore $(x, f(x)) \in \text{bdry epi } f$.
- So by Proposition 1.59 there is some $(u, r) \in N_{\text{epi } f}(x, f(x)) \setminus \{(0, 0)\}$.
- By definition of normal cone: For every $(v, s) \in \text{epi } f$ have:

$$\left\langle \begin{pmatrix} v \\ s \end{pmatrix} - \begin{pmatrix} x \\ f(x) \end{pmatrix}, \begin{pmatrix} u \\ r \end{pmatrix} \right\rangle \leq 0$$

- So in particular for $y \in \text{dom } f$ have $(y, f(y)) \in \text{epi } f$ and therefore:

$$\langle y - x, u \rangle + (f(y) - f(x)) \cdot r \leq 0$$

- If $r < 0$ we could divide by r and get that $u/|r| \in \partial f(x)$. So need to show $r < 0$.
- Show that $r \leq 0$: For any $\delta > 0$ have:

$$[(x, f(x) + \delta) \in \text{epi } f] \Leftrightarrow \left[\left\langle \begin{pmatrix} x \\ f(x) + \delta \end{pmatrix} - \begin{pmatrix} x \\ f(x) \end{pmatrix}, \begin{pmatrix} u \\ r \end{pmatrix} \right\rangle \leq 0 \right] \Leftrightarrow [\delta \cdot r \leq 0] \Leftrightarrow [r \leq 0]$$

- Assume $r = 0$: Then must have $u \neq 0$. Then there is some $\rho > 0$ such that $\|\rho \cdot u\| < \varepsilon$ and therefore $(x + \rho \cdot u, f(x) + \eta) \in \text{epi } f$. Then:

$$\left[\left\langle \begin{pmatrix} x + \rho \cdot u \\ f(x) + \eta \end{pmatrix} - \begin{pmatrix} x \\ f(x) \end{pmatrix}, \begin{pmatrix} u \\ 0 \end{pmatrix} \right\rangle \leq 0 \right] \Leftrightarrow [\rho \cdot \langle u, u \rangle \leq 0]$$

This is a contradiction, therefore $r \neq 0$.

□

Corollary 1.62. Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ convex, proper, lower semicontinuous. Then

$$\text{int dom } f = \text{cont } f \subset \text{dom } \partial f \subset \text{dom } f$$

Proof. • The first inclusion was cited in Remark 1.16 (see e.g. [Bauschke, Combettes; Corollary 8.30]).

- The second inclusion is shown in Prop. 1.61.
- The third inclusion follows from contraposition of $[x \notin \text{dom } f] \Rightarrow [\partial f(x) = \emptyset]$.

□

Finally, we show that closed, convex sets can be expressed solely in terms of their supporting hyperplanes.

For notational convenience introduce ‘support function’.

Definition 1.63. Let $C \subset H$. The *support function* of C is

$$\sigma_C : H \mapsto [-\infty, \infty], \quad u \mapsto \sup \langle C, u \rangle .$$

Sketch: Definition.

We will later learn that each convex, lower semicontinuous and 1-homogeneous function is the support function of a suitable auxiliary set.

Sketch: Following remark.

Remark 1.64. If $C \neq \emptyset$, $u \in H \setminus \{0\}$ and $\sigma_C(u) < +\infty$, then $\{x \in H : \langle x, u \rangle \leq \sigma_C(u)\}$ is smallest closed half-space with outer normal u that contains C . If $x \in C$ and $\sigma_C(u) = \langle x, u \rangle$ then $x \in \text{spts } C$ and $\{y \in H : \langle y, u \rangle = \sigma_C(u) = \langle x, u \rangle\}$ is a supporting hyperplane of C at x .

Proposition 1.65. Let $C \subset H$ and set for $u \in H$

$$A_u = \{x \in H : \langle x, u \rangle \leq \sigma_C(u)\} .$$

Then $\overline{\text{conv } C} = \bigcap_{u \in H} A_u$.

Proof. • If $C = \emptyset$ then $\sigma_C(u) = -\infty$ and $A_u = \emptyset$ for all $u \in H$. Hence, the result is trivial.

- Otherwise, $\sigma_C(u) > -\infty$. Let $D = \bigcap_{u \in H} A_u$.
- Each A_u is closed, convex and contains C . Therefore D is closed, convex and $\text{conv } C \subset D$. Since D is closed, also $\overline{\text{conv } C} \subset D$.
- Now, let $x \in D$, set $p = P_{\overline{\text{conv } C}} x$.
- Then $\langle x - p, y - p \rangle \leq 0$ for all $y \in \overline{\text{conv } C}$ and thus $\sigma_{\overline{\text{conv } C}}(x - p) = \sup \langle \overline{\text{conv } C}, x - p \rangle = \langle p, x - p \rangle$.
- Moreover, $x \in D \subset A_{x-p}$. So $\langle x, x - p \rangle \leq \sigma_C(x - p)$.
- Since $C \subset \overline{\text{conv } C}$ we get $\sigma_C \leq \sigma_{\overline{\text{conv } C}}$.
- Now: $\|x - p\|^2 = \langle x, x - p \rangle - \langle p, x - p \rangle \leq \sigma_C(x - p) - \sigma_{\overline{\text{conv } C}}(x - p) \leq 0$. Therefore $x = p \in \overline{\text{conv } C}$ and thus $D \subset \overline{\text{conv } C}$.

□

Corollary 1.66. Any closed convex subset of H is the intersection of all closed half-spaces of which it is a subset.

1.5 The Fenchel–Legendre conjugate

Remark 1.67 (Motivation). Previous result (Cor. 1.66): closed, convex set is intersection of all half-spaces that contain set.

Analogous idea: is convex, lower semicontinuous function f pointwise supremum over all affine lower bounds $x \mapsto \langle x, u \rangle - a_u$? How to get minimal offset a_u for given slope u ?

$$\begin{aligned} a_u &= \inf\{r \in \mathbb{R} : f(x) \geq \langle x, u \rangle - r \text{ for all } x \in H\} \\ &= \inf\{r \in \mathbb{R} : r \geq \sup_{x \in H} \langle x, u \rangle - f(x)\} \\ &= \sup_{x \in H} \langle x, u \rangle - f(x) \end{aligned}$$

For given slopes and offsets (u, a_u) , how do we reconstruct f ? Pointwise-supremum (\equiv intersection of all half-spaces containing $\text{epi } f$):

$$f(x) = \sup_{u \in H} \langle x, u \rangle - a_u$$

Note: same formula for obtaining a_u and reconstructing f . Write $a_u = f^*(u)$ and call this *Fenchel–Legendre conjugate*. Reconstruction of f is then bi-conjugate f^{**} . When is $f^{**} = f$ and what happens if $f^{**} \neq f$?

The Fenchel–Legendre conjugate and the bi-conjugate are fundamental in convex analysis and optimization. We start by a formal definition of f^* , by studying some examples and showing some basic properties of f^* . We return to a systematic study of f^{**} in second half of this subsection.

Definition 1.68 (Fenchel–Legendre conjugate). Let $f : H \mapsto [-\infty, \infty]$. The *Fenchel–Legendre conjugate* of f is

$$f^* : H \mapsto [-\infty, \infty], \quad u \mapsto \sup_{x \in H} \langle x, u \rangle - f(x).$$

The *biconjugate* of f is $(f^*)^* = f^{**}$.

Example 1.69. (i) $f(x) = \frac{1}{2}\|x\|^2$:

$$f^*(u) = \sup_{x \in H} \langle x, u \rangle - \frac{1}{2}\|x\|^2 = - \left(\inf_{x \in H} \frac{1}{2}\|x\|^2 - \langle x, u \rangle \right) = - \inf_{x \in H} \tilde{f}(x)$$

Convex optimization problem. Fermat’s rule (Prop. 1.26): y is optimizer if $0 \in \partial \tilde{f}(y)$. Minkowski sum of subdifferentials (Prop. 1.32): $y - u \in \partial \tilde{f}(y)$. \Rightarrow sufficient optimality condition: $y = u$, so u is minimizer. $\Rightarrow f^*(u) = \frac{1}{2}\|u\|^2$, f is *self-conjugate*.

(ii) $f(x) = \|x\|$:

$$f^*(u) = \sup_{x \in H} \langle x, u \rangle - \|x\|$$

If $\|u\| > 1$ consider sequence $x_k = u \cdot k$. Then

$$f^*(u)|_{[\|u\|>1]} \geq \limsup_{k \rightarrow \infty} (\|u\|^2 - \|u\|) \cdot k = \infty$$

If $\|u\| \leq 1$ then by Cauchy-Schwarz:

$$f^*(u)|_{\|u\| \leq 1} \leq \sup_{x \in H} (\|u\| \cdot \|x\| - \|x\|) \leq 0$$

And by setting $x = 0$ get $f^*(u)|_{\|u\| \leq 1} \geq 0$. We summarize

$$f^*(u) = \begin{cases} +\infty & \text{if } \|u\| > 1, \\ 0 & \text{if } \|u\| \leq 1 \end{cases} = \iota_{\overline{B(0,1)}}(u)$$

(iii) special case: $H = \mathbb{R}$, $f(x) = |x|$: $f^* = \iota_{[-1,1]}$

(iv) $H = \mathbb{R}^n$, $f(x) = \|x\|_1 = \sum_{k=1}^n |x_k|$:

$$f^*(u) = \sup_{x \in H} \langle u, x \rangle - f(x) = \sup_{x \in H} \sum_{k=1}^n u_k \cdot x_k - |x_k| = \sum_{k=1}^n \sup_{s \in \mathbb{R}} u_k \cdot s - |s| = \sum_{k=1}^n \text{abs}^*(u_k)$$

(v) $f(x) = 0$:

$$f^*(u) = \sup_{x \in H} \langle u, x \rangle = \begin{cases} 0 & \text{if } u = 0, \\ +\infty & \text{else.} \end{cases}$$

From Examples 1.69 we learn a result on conjugation.

Proposition 1.70. Let $(H_k)_{k=1}^n$ be a tuple of Hilbert spaces, $f_k : H_k \rightarrow [-\infty, \infty]$, let $H = \bigotimes_{k=1}^n H_k$, $f : H \rightarrow [-\infty, \infty]$, $((x_k)_k) \mapsto \sum_{k=1}^n f_k(x_k)$. Then $f^*((u_k)_k) = \sum_{k=1}^n f_k^*(u_k)$.

Proof. The proof is completely analogous to Example 1.69, (iv). \square

A few simple ‘transformation rules’:

Proposition 1.71. Let $f : H \rightarrow [-\infty, \infty]$, $\gamma \in \mathbb{R}_{++}$.

- (i) Let $h : x \mapsto f(\gamma \cdot x)$. Then $h^*(u) = f^*(u/\gamma)$.
- (ii) Let $h : x \mapsto \gamma \cdot f(x)$. Then $h^*(u) = \gamma \cdot f^*(u/\gamma)$.
- (iii) Let $h : x \mapsto f(-x)$. Then $h^*(u) = f^*(-u)$.
- (iv) Let $h : x \mapsto f(x) - a$ for $a \in \mathbb{R}$. Then $h^*(u) = f^*(u) + a$. (Adding offset to function adds same offset to all affine lower bounds.)
- (v) Let $h : x \mapsto f(x - y)$ for $y \in H$. Then $h^*(u) = f^*(u) + \langle u, y \rangle$. (Shifting the effective origin of a function requires adjustment of all offsets \equiv axis intercept at origin.)

Proof. All points follow from direct computation. \square

Proposition 1.72 (Fenchel–Young inequality). Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ be proper. Then for all $x, u \in H$:

$$f(x) + f^*(u) \geq \langle x, u \rangle$$

Proof. • Let $x, u \in H$.

- Since f is proper, have $f^* > -\infty$ (why?).
- So if $f(x) = \infty$, the inequality holds trivially.
- Otherwise: $f^*(u) = \sup_{y \in H} \langle u, y \rangle - f(y) \geq \langle u, x \rangle - f(x)$.

□

Now we establish some basic properties of the conjugate. We need an auxiliary Lemma.

Proposition 1.73. Let $(f_i)_{i \in I}$ be an arbitrary set of functions $H \rightarrow [-\infty, \infty]$. Set $f : H \rightarrow [-\infty, \infty]$, $x \mapsto \sup_{i \in I} f_i(x)$. Then:

- (i) $\text{epi } f = \bigcap_{i \in I} \text{epi } f_i$
- (ii) If all f_i are lower semicontinuous, so is f .
- (iii) If all f_i are convex, so is f .

Proof. • **(i):** $[(x, r) \in \text{epi } f] \Leftrightarrow [\mathbb{R} \ni r \geq f(x)] \Leftrightarrow [\mathbb{R} \ni r \geq f_i(x) \text{ for all } i \in I] \Leftrightarrow [(x, r) \in \text{epi } f_i \text{ for all } i \in I] \Leftrightarrow [(x, r) \in \bigcap_{i \in I} \text{epi } f_i]$.

- **(ii):** If all f_i are lower semicontinuous, all $\text{epi } f_i$ are closed (Prop. 1.21). Then $\text{epi } f = \bigcap_{i \in I} \text{epi } f_i$ is closed, i.e. f is lower semicontinuous.
- **(iii):** If all f_i are convex, all $\text{epi } f_i$ are convex (Prop. 1.9). Then $\text{epi } f = \bigcap_{i \in I} \text{epi } f_i$ is convex (Prop. 1.4), i.e. f is convex.

□

Proposition 1.74 (Basic properties of conjugate). Let $f : H \rightarrow [-\infty, \infty]$. Then f^* is convex and lower semicontinuous.

Proof. • The result is trivial if $f(x) = -\infty$ for some $x \in H$. So assume $f > -\infty$ from now on.

- Can write conjugate as: $f^*(u) = \sup_{x \in \text{dom } f} \langle u, x \rangle - f(x)$.
- So conjugate is pointwise supremum over family of convex, lower semicontinuous functions: $(y \mapsto \langle y, x \rangle - f(x))_{x \in \text{dom } f}$.
- By Proposition 1.73 have: f^* is convex and lower semicontinuous.

□

Now, we return to the initial motivation and start to study the bi-conjugate f^{**} . We first give some related background.

Definition 1.75. Let $f : H \rightarrow [-\infty, \infty]$.

- The *lower semicontinuous envelope* or *closure* of f is given by

$$\bar{f} : x \mapsto \sup\{g(x) \mid g : H \rightarrow [-\infty, \infty], g \text{ is lsc}, g \leq f\}.$$

- The *convex lower semicontinuous envelope* of f is given by

$$\overline{\text{conv } f} : x \mapsto \sup\{g(x) \mid g : H \rightarrow [-\infty, \infty], g \text{ is convex, lsc}, g \leq f\}.$$

Proposition 1.76. \bar{f} is lower semicontinuous and $\overline{\text{conv } f}$ is convex, lower continuous.

Proof. This follows directly from Prop. 1.73. □

Proposition 1.77. Let $f : H \rightarrow [-\infty, \infty]$. Then $\text{epi } \overline{\text{conv } f} = \overline{\text{conv epi } f}$.

Proof. • Set $F = \overline{\text{conv } f}$ and $D = \overline{\text{conv epi } f}$.

- Since $F \leq f \Rightarrow \text{epi } f \subset \text{epi } F$. Since $\text{epi } F$ is convex, have $\text{conv epi } f \subset \text{epi } F$. Since $\text{epi } F$ is also closed (why?), have $D = \overline{\text{conv epi } f} \subset \text{epi } F$.
- Show converse inclusion. Let $(x, \zeta) \in \text{epi } F \setminus D$. Since D is closed and convex, the projection onto D is well defined. Let $(p, \pi) = P_D(x, \zeta)$. Characterization of projection:

$$\left\langle \begin{pmatrix} x - p \\ \zeta - \pi \end{pmatrix}, \begin{pmatrix} y - p \\ \eta - \pi \end{pmatrix} \right\rangle \leq 0 \quad \text{for all } (y, \eta) \in D$$

- For some $(y, \eta) \in D$, send $\eta \rightarrow \infty$ (which is still in D , why?). We deduce: $\zeta - \pi \leq 0$.
- Note that $(y, \eta) \in D \Rightarrow y \in \overline{\text{conv dom } f}$. (Details: any $(y, \eta) \in D = \overline{\text{conv epi } f}$ can be written as limit of sequence $(y_k, \eta_k)_k$ in $\text{conv epi } f$. Any (y_k, η_k) can be written as finite convex combination of some $(y_{k,i}, \eta_{k,i})_i$ in $\text{epi } f$. So all $y_{k,i} \in \text{dom } f$ and thus the convex combination $y_k \in \text{conv dom } f$ and therefore the limit $y \in \overline{\text{conv dom } f}$.)
- Also note: $\text{dom } F \subset \overline{\text{conv dom } f} = E$: Define function

$$g(x) = \begin{cases} F(x) & \text{if } x \in E, \\ +\infty & \text{else.} \end{cases}$$

Since E is closed and convex, and F is lsc and convex, g is lsc and convex. Since $F \leq f$ and $g(x) = F(x)$ for $x \in \text{dom } f \subset E$, have $g \leq f$. Since F is the convex lower semicontinuous envelope of f we must therefore have $g \leq F$ and therefore $\text{dom } F \subset E$.

- Assume $\zeta = \pi$. Then projection characterization yields: $\langle x - p, y - p \rangle \leq 0$ for all $y \in \overline{\text{conv dom } f}$. Since $[(x, \zeta) \in \text{epi } F] \Rightarrow [x \in \text{dom } F \subset \overline{\text{conv dom } f}]$ we may set $y = x$ and obtain $\|x - p\|^2 \leq 0$. Therefore $x = p$ which contradicts $(x, \zeta) \notin D$.
- Now assume $\zeta < \pi$. Set $u = \frac{x-p}{\pi-\zeta}$ and let $\eta = f(y)$. Then from characterization pf projection get:

$$\langle u, y - p \rangle + \pi \leq f(y)$$

Once more, set $y = x$ and use $\zeta \geq f(x)$ to get

$$\left[\zeta \geq \pi + \left\langle x - p, \frac{x-p}{\pi-\zeta} \right\rangle \right] \Leftrightarrow [-(\pi - \zeta)^2 \geq \|x - p\|^2] .$$

This is a contradiction and therefore there cannot be any $(x, \zeta) \in \text{epi } F \setminus D$. □

Now some basic properties of the biconjugate.

Proposition 1.78. Let $f : H \rightarrow [-\infty, \infty]$. Then $f^{**} \leq f$ and f^{**} is the pointwise supremum over all continuous affine lower bounds on f .

Proof. • We find:

$$\begin{aligned}
f^*(u) &= \sup_{y \in H} \langle u, y \rangle - f(y) \\
f^{**}(x) &= \sup_{u \in H} \langle u, x \rangle - \left(\sup_{y \in H} \langle u, y \rangle - f(y) \right) = \sup_{u \in H} \inf_{y \in H} \langle u, x \rangle - \langle u, y \rangle + f(y) \\
&\leq \sup_{v \in H} \langle u, x - x \rangle + f(x) = f(x) \quad (\text{set } y = x \text{ in infimum})
\end{aligned}$$

- By Prop. 1.72 (Fenchel–Young): $f(x) \geq \langle u, x \rangle - f^*(u)$ for all $x, u \in H$. So $f^{**}(x) = \sup_{u \in H} \langle u, x \rangle - f^*(u)$ is the pointwise supremum over a family of continuous affine lower bounds on f .
- So f^{**} is pointwise supremum over family of convex, lsc functions $\Rightarrow f^{**}$ is convex lsc (Prop. 1.73).
- On the other hand, let $g(x) = \langle v, x \rangle - r \leq f(x)$ for some $(v, r) \in H \times \mathbb{R}$ be a continuous affine lower bound. Then:

$$\begin{aligned}
f^*(v) &= \sup_{x \in H} \langle v, x \rangle - \underbrace{f(x)}_{\geq g(x)} \leq \sup_{x \in H} \langle v, x \rangle - \langle v, x \rangle + r = r \\
f^{**}(x) &= \sup_{u \in H} \langle u, x \rangle - f^*(u) \geq \langle v, x \rangle - \underbrace{f^*(v)}_{\leq r} \geq \langle v, x \rangle - r = g(x)
\end{aligned}$$

So f^{**} is larger (or equal) than any continuous affine lower bound on f . □

We now prove the main result of this subsection.

Proposition 1.79. Assume $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ has a continuous affine lower bound. Then $f^{**} = \overline{\text{conv } f}$.

Proof. • Let $F = \overline{\text{conv } f}$. By Prop. 1.77 have $\text{epi } F = \overline{\text{conv epi } f}$ and by Prop. 1.65 $\text{epi } F$ is the intersection of all closed halfspaces that contain $\text{epi } f$.

- Let $(v, r) \in H \times \mathbb{R}$ be the outward normal of a closed halfspace that contains $\text{epi } F$. If $r > 0$ then $\text{epi } F = \emptyset$ and then $f = +\infty = f^{**}$ and we are done.
- So assume that $\text{epi } F \neq \emptyset$ and therefore $r \leq 0$ for all closed halfspaces that contain $\text{epi } F$.
- Similarly, f^{**} is the pointwise supremum over all continuous affine lower bounds on f . Therefore, $\text{epi } f^{**}$ is the intersection of all closed halfspaces that contain $\text{epi } f^{**}$ and for which the outward normal (v, r) has $r < 0$.
- Therefore, $\text{epi } F \subset \text{epi } f^{**}$ which implies $f^{**} \leq F$. (Also follows from f^{**} convex, lsc and $f^{**} \leq f$, why?)
- Let $(u, a) \in H \times \mathbb{R}$ such that $x \mapsto \langle u, x \rangle - a$ is a continuous affine lower bound of f . Then it is also a lower bound on f^{**} and finally F .
- Assume $(z, \zeta) \in \text{epi } f^{**} \setminus \text{epi } F$.

- Then there must be a closed halfspace in $H \times \mathbb{R}$ with horizontal outward normal (i.e. $r = 0$) that contains $\text{epi } F$, but not (z, ζ) . That is, there is some $(v, y) \in H^2$ such that $\langle x - y, v \rangle \leq 0$ for all $x \in \text{dom } F$ but $\langle z - y, v \rangle > 0$.

Sketch: $\text{epi } F, (z, \zeta), (y, v) \in H \times H, (u, a) \in H \times \mathbb{R}$

- For $s \geq 0$ let $g_s(x) = \langle u, x \rangle - a + s \cdot \langle x - y, v \rangle$. Recall that g_0 is a continuous affine lower bound on f .
- For $x \in \text{dom } f \subset \text{dom } F$ (follows from $F \leq f$) have $g_s(x) = g_0(x) + s \cdot \langle x - y, v \rangle \leq f(x)$. So for $s \geq 0$, g_s is a continuous affine lower bound on f , and thus on f^{**} .
- But for $s \rightarrow \infty$ have $g_s(z) = g_0(z) + s \cdot \langle z - y, v \rangle \rightarrow \infty > \zeta \geq f^{**}(z)$.
- This is a contradiction, thus points like (z, ζ) cannot exist and $\text{epi } f^{**} = \text{epi } F$.

□

We obtain the famous Fenchel–Moreau Theorem as a corollary.

Corollary 1.80 (Fenchel–Moreau). Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ be proper. Then

$$[f \text{ is convex, lsc}] \quad \Leftrightarrow \quad [f^{**} = f] \quad \Rightarrow \quad [f^* \text{ is proper}].$$

Proof. • **\Leftarrow of equivalence:** If $f = f^{**}$ then f is the conjugate of f^* . Therefore, it is convex and lsc.

- **\Rightarrow of equivalence:** f is convex, lsc. $\Rightarrow \text{epi } f$ is convex, closed. \Rightarrow it is intersection of all closed halfspaces that contain $\text{epi } f$. If f has no continuous affine lower bound then all these halfspaces must have ‘horizontal’ normals ($r = 0$) $\Rightarrow f(H) \subset \{-\infty, +\infty\}$, which contradicts assumptions. So f must have continuous affine lower bound.
- By previous result $f^{**} = \overline{\text{conv } f}$ which equals f since f convex, lsc.
- **f^* is proper:** we have just shown that f has continuous affine lower bound, say $f(x) \geq \langle x, v \rangle - a$ for some $(v, a) \in H \times \mathbb{R}$. Recall: this implies $f^*(v) \leq a$. Conversely, f is proper, i.e. $f(x_0) < \infty$ for some x_0 and then $f^*(u) \geq \langle x_0, u \rangle - f(x_0)$.

□

Comment: We showed in proof: A convex lsc function must have a continuous affine lower bound. This is not true for general convex (but not lsc) functions. Recall: unbounded linear functions are convex.

A few applications: The following result is helpful to translate knowledge from ∂f or f^* onto the other. It gives the ‘extreme cases’ of the Fenchel–Young inequality.

Proposition 1.81. Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ be convex, lsc. Let $x, u \in H$. Then:

$$[u \in \partial f(x)] \quad \Leftrightarrow \quad [f(x) + f^*(u) = \langle x, u \rangle] \quad \Leftrightarrow \quad [x \in \partial f^*(u)]$$

Comment: Intuitive interpretation: conjugate $f^*(u)$ computes minimal offset a such that $y \mapsto \langle u, y \rangle - a$ is lower bound on f . If $u \in \partial f(x)$ then $y \mapsto \langle u, y - x \rangle + f(x)$ is affine lower bound for f that touches graph in x . So offset $\langle u, x \rangle - f(x)$ is minimal for slope u .

Proof. • Consider first equivalence.

- \Rightarrow : By Prop. 1.72 (Fenchel–Young): $f^*(u) \geq \langle u, x \rangle - f(x)$.
- Have $f(y) \geq f(x) + \langle u, y - x \rangle$ for all $y \in H$. Get:

$$f^*(u) = \sup_{y \in H} \langle u, y \rangle - f(y) \leq \sup_{y \in H} \langle u, y \rangle - \langle u, y - x \rangle - f(x) = \langle u, x \rangle - f(x)$$

- So $f^*(u) + f(x) = \langle u, x \rangle$.
- \Leftarrow :

$$f^*(u) = \langle x, u \rangle - f(x) = \sup_{y \in H} \langle y, u \rangle - f(y) \geq \langle y, u \rangle - f(y) \text{ for all } y \in H$$

So $f(y) \geq \langle u, y - x \rangle + f(x)$ for all $y \in H$. $\Rightarrow u \in \partial f(x)$.

- For second equivalence, apply first equivalence to f^* and use that $f^{**} = f$.

□

Now we can relate one-homogeneous functions and indicator functions:

Definition 1.82. A function $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ is *positively 1-homogeneous* if $f(\lambda \cdot x) = \lambda \cdot f(x)$ for all $x \in H$, $\lambda \in \mathbb{R}_{++}$.

Proposition 1.83. Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$. Then f is a convex, lsc, positively 1-homogeneous function if and only if $f = (\iota_C)^* = \sigma_C$ for some closed, convex, non-empty $C \subset H$.

Comment: Relation between indicator functions and support functions: $\iota_C^* = \sigma_C$.

Proof. • \Leftarrow : ι_C^* is lsc and convex. Moreover, for $x \in H$, $\lambda \in \mathbb{R}_{++}$

$$\iota_C^*(\lambda \cdot x) = \sigma_C(\lambda \cdot x) = \sup_{y \in C} \langle y, \lambda \cdot x \rangle = \lambda \sup_{y \in C} \langle y, x \rangle = \lambda \cdot \sigma_C(x).$$

So ι_C^* is positively 1-homogeneous.

- \Rightarrow : Observe: $f(0) = 0$ (why?). So

$$f^*(u) = \sup_{x \in H} \langle u, x \rangle - f(x) \geq 0 \quad (\text{set } x = 0 \text{ in sup}).$$

- If, for fixed $u \in H$ there is some $x \in H$ such that $\langle u, x \rangle - f(x) > 0$, then

$$f^*(u) \geq \limsup_{k \rightarrow \infty} \langle u, k \cdot x \rangle - f(k \cdot x) = \limsup_{k \rightarrow \infty} k \cdot (\langle u, x \rangle - f(x)) = \infty.$$

- So $f^*(H) \subset \{0, +\infty\}$ and therefore $f^* = \iota_C$ for some $C \subset H$. Since f^* is convex, lsc $\Rightarrow C$ is convex, closed (why?).
- Since f is convex, lsc have $f = f^{**} = \iota_C^*$.

□

This allows us to describe subdifferential of 1-homogeneous functions.

Corollary 1.84. If $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ is convex, lsc, positively 1-homogeneous, then $f = \sigma_C$ where $C = \partial f(0)$.

Proof. • By assumption, $f = \sigma_C$ for some closed, convex $C \subset H$, $f^* = \iota_C$.

- Then $[u \in \partial f(0)] \Leftrightarrow [0 \in \partial f^*(u) = \partial \iota_C(u)] \Leftrightarrow [u \in C]$.

□

Example 1.85. Go through Examples [1.69](#) and study biconjugates. Note the relation between positively 1-homogeneous functions and indicator functions.

1.6 Convex variational problems

Remark 1.86 (Motivation). We want to find minimizers of functionals. Standard argument: minimizing sequence + compactness: Weierstrass provides cluster point. Lower semicontinuity: cluster point is minimizer.

Problem: compactness in infinite dimensions is far from trivial. Example: orthonormal sequences $(x_k)_{k \in \mathbb{N}}$, $\langle x_i, x_j \rangle = \delta_{i,j}$ (e.g. ‘traveling bumps’ in $L^2(\mathbb{R})$ or canonical ‘basis vectors’ in $\ell^2(\mathbb{N})$). \Rightarrow closed unit ball in infinite-dimensional Hilbert spaces is not compact.

Recall: avoided this problem for proof of existence of projection via Cauchy sequence, but this argument will not work in general. \Rightarrow we need a different tool.

Definition 1.87 (Weak convergence on Hilbert space). A sequence $(x_k)_k$ in H is said to *converge weakly* to some $x \in H$, we write $x_k \rightharpoonup x$, if for all $u \in H$

$$\lim_{k \rightarrow \infty} \langle u, x_k \rangle = \langle u, x \rangle .$$

Comment: For now only use weak convergence for Hilbert spaces. More general and detailed discussion will follow later.

Remark 1.88. Weak convergence corresponds to weak topology. Weak topology is coarsest topology in which all maps $x \mapsto \langle u, x \rangle$ for all $u \in H$ are continuous (this implies precisely that $\langle u, x_k \rangle \rightarrow \langle u, x \rangle$ for weakly converging sequences $x_k \rightharpoonup x$). So, subbasis is given by all open halfspaces. Weak topology still yields Hausdorff space (e.g. for any two distinct points $x, y \in H$ can find open halfspace A such that $x \in A, y \notin A$). Need Hausdorff property for uniqueness of limits.

In general it is easier to obtain compactness with respect to the weak topology due to the following theorem.

Theorem 1.89 (Banach–Alaoglu). The closed unit ball of H is weakly compact.

Corollary 1.90. Weakly closed, bounded subsets of H are weakly compact.

Proof. Let $C \subset H$ be weakly closed and bounded. Then there is some $\rho \in \mathbb{R}_{++}$ such that $C \subset \overline{B(0, \rho)}$, which is weakly compact by Banach–Alaoglu. C is a weakly closed subset of a weakly compact set, therefore it is weakly compact. \square

Example 1.91 (Orthonormal sequence and Bessel’s inequality). Let $(x_k)_{k \in \mathbb{N}}$ be an orthonormal sequence in H , i.e. $\langle x_i, x_j \rangle = \delta_{i,j}$ for all $i, j \in \mathbb{N}$, and let $u \in H$. Then for all $N \in \mathbb{N}$

$$\begin{aligned} 0 &\leq \left\| u - \sum_{k=1}^N x_k \langle x_k, u \rangle \right\|^2 = \|u\|^2 - 2 \left\langle u, \sum_{k=1}^N x_k \langle x_k, u \rangle \right\rangle + \left\| \sum_{k=1}^N x_k \langle x_k, u \rangle \right\|^2 \\ &= \|u\|^2 - 2 \sum_{k=1}^N \langle u, x_k \rangle^2 + \sum_{k=1}^N \langle u, x_k \rangle^2 = \|u\|^2 - \sum_{k=1}^N \langle u, x_k \rangle^2 . \end{aligned}$$

So $\|u\|^2 \geq \sum_{k=1}^N \langle u, x_k \rangle^2$ for all N (which then also holds in the limit $N \rightarrow \infty$) and $\langle u, x_k \rangle \rightarrow 0$ as $k \rightarrow \infty$. Therefore $x_k \rightharpoonup 0$. (But clearly not $x_k \rightarrow 0$.)

The previous example shows that weak convergence does in general not imply strong convergence. We require an additional condition.

Proposition 1.92. Let $(x_k)_{k \in \mathbb{N}}$ be a sequence in H and let $x \in H$. Then the following are equivalent:

$$[x_k \rightarrow x] \quad \Leftrightarrow \quad [x_k \rightharpoonup x \text{ and } \|x_k\| \rightarrow \|x\|]$$

Proof. • \Rightarrow : For every $u \in H$ have $y \mapsto \langle u, y \rangle$ is continuous. Therefore, if $x_k \rightarrow x$ one finds $\langle u, x_k \rangle \rightarrow \langle u, x \rangle$ for all $u \in H$, therefore $x_k \rightharpoonup x$. The norm function is also (strongly) continuous, therefore it also implies $\|x_k\| \rightarrow \|x\|$.

• \Leftarrow :

$$\|x_k - x\|^2 = \underbrace{\|x_k\|^2}_{\rightarrow \|x\|^2} - 2 \underbrace{\langle x_k, x \rangle}_{\rightarrow \langle x, x \rangle} + \|x\|^2 \rightarrow 0$$

□

Remark 1.93. In the previous example we find indeed $\lim_{k \rightarrow \infty} \|x_k\| = 1 \neq \|0\|$. Therefore, the sequence cannot converge strongly.

Theorem 1.94 (Characterization of infinite-dimensional Hilbert spaces). The following are equivalent:

- (i) H is finite-dimensional.
- (ii) The closed unit ball $\overline{B(0, 1)}$ is compact.
- (iii) The weak topology of H coincides with its strong topology.
- (iv) The weak topology of H is metrizable.

Remark 1.95. Note that item (iv) implies that for the weak topology we can in general not equate sequential closedness and closedness, as for the strong topology (cf. Remark 1.13). We will now show that it remains at least equivalent for convex sets (and functions).

Proposition 1.96. Let $C \subset H$ be convex. Then the following are equivalent:

- (i) C is weakly sequentially closed.
- (ii) C is sequentially closed.
- (iii) C is closed.
- (iv) C is weakly closed.

Proof. • (i) \Rightarrow (ii): Let $(x_k)_k$ be a sequence in C that converges strongly to some $x \in H$. Prop. 1.92: $[x_k \rightarrow x] \Rightarrow [x_k \rightharpoonup x]$. Therefore, $x \in C$ since C is weakly sequentially closed. Therefore, C is (strongly) sequentially closed.

- (ii) \Leftrightarrow (iii): The two are equivalent because the strong topology is metrizable (cf. Remark 1.13).
- (iii) \Rightarrow (iv): For this need convexity. C is closed and convex. Therefore, C is the intersection of all closed halfspaces that contain C .

- A subbasis for the open sets of the weak topology are open halfspaces. So subbasis for weakly closed sets are closed halfspaces. C can be written as intersection of weakly closed sets. $\Rightarrow C$ is weakly closed.
- (iv) \Rightarrow (i): Sequential closedness is implied by ‘full’ closedness. (Proof: Let C be weakly closed. Let $(x_k)_k$ be a sequence in C with $x_k \rightharpoonup x$ for some $x \in H$. Assume $x \notin C$. Then there is some weakly open U such that $x \in U$, $U \cap C = \emptyset$. But since $x_k \rightharpoonup x$, for sufficiently large k one must have $x_k \in U$ which is a contradiction.)

□

Corollary 1.97. For a convex function $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ the notions of weak, strong, sequential and ‘full’ lower semicontinuity coincide.

Proof. When f is convex, all its sublevel sets are convex and for these all corresponding notions of closedness coincide. □

Corollary 1.98. The norm $x \mapsto \|x\|$ is (sequentially) weakly lower semicontinuous.

Remark 1.99. Note: the norm is not (sequentially) weakly continuous in infinite dimensions. Recall an orthonormal sequence $(x_k)_{k \in \mathbb{N}}$. Then $x_k \rightharpoonup 0$ but $\|x_k\| \rightarrow 1$.

Corollary 1.100. The closed unit ball $\overline{B(0,1)}$ is weakly closed. But in infinite dimensions the (strongly) open unit ball $B(0,1)$ is not weakly open.

Proof. • $\overline{B(0,1)}$ is a convex set. Therefore the notion of strong and weak closure coincide.

- Consider once more an orthonormal sequence $(x_k)_{k \in \mathbb{N}}$. Then $x_k \notin B(0,1)$ for all k , but $x_k \rightharpoonup 0 \in B(0,1)$.

□

So in the following we resort to weak topology to obtain minimizers via compactness. We do not have to worry too much about the new notion of lower semicontinuity. But since (strongly) open balls are no longer weakly open, we will face some subtleties when we try to extract converging subsequences from minimizing sequences: we do not know whether weak compactness implies weak sequential compactness. This is provided by the following theorem:

Theorem 1.101 (Eberlein–Šmulian). For subsets of H weak compactness and weak sequential compactness are equivalent.

Now we give a prototypical theorem for the existence of minimizers.

Proposition 1.102. Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ be convex, lower semicontinuous. Let $C \subset H$ be closed, convex such that for some $r \in \mathbb{R}$ the set $C \cap S_r(f)$ is non-empty and bounded. Then f has a minimizer over C .

Proof. • The sets C and $S_r(f)$ are closed and convex. So $D = C \cap S_r(f)$ is closed and convex and by assumption bounded.

- D closed, convex $\Rightarrow D$ is weakly closed (Prop. 1.96).
- D bounded, weakly closed \Rightarrow weakly compact (Cor. 1.90 of Banach–Alaoglu).
- D weakly compact \Rightarrow weakly sequentially compact (Thm. 1.101, Eberlein–Šmulian).

- Since $D = C \cap S_r(f)$ is non-empty, we can confine minimization of f over C to minimization of f over D .
- Let $(x_k)_{k \in \mathbb{N}}$ be minimizing sequence of f over D . Since D is weakly sequentially compact, there is a subsequence of $(x_k)_k$ that converges to some $x \in D$ in the weak topology.
- Since f is convex and lower semicontinuous, it is weakly sequentially lower semicontinuous (Cor. 1.97). Therefore, x is a minimizer.

□

A useful criterion to check whether the sublevel sets of a function are bounded is coerciveness.

Definition 1.103 (Coerciveness). A function $f : H \rightarrow [-\infty, \infty]$ is *coercive* if $\lim_{\|x\| \rightarrow \infty} f(x) = \infty$.

Proposition 1.104. Let $f : H \rightarrow [-\infty, \infty]$. Then f is coercive if and only if its sublevel sets $S_r(f)$ are bounded for all $r \in \mathbb{R}$.

Proof. • Assume $S_r(f)$ is unbounded for some $r \in \mathbb{R}$. Then we can find a sequence (x_k) in $S_r(f)$ with $\|x_k\| \rightarrow \infty$ but $\limsup f(x_k) \leq r$.

- Assume $S_r(f)$ is bounded for every $r \in \mathbb{R}$. Let $(x_k)_k$ be an unbounded sequence with $\lim \|x_k\| \rightarrow \infty$. Then for any $s \in \mathbb{R}$ there is some $N \in \mathbb{N}$ such that $x_k \notin S_s(f)$ for $k \geq N$. Hence, $\liminf f(x_k) \geq s$. Since this holds for any $s \in \mathbb{R}$, have $\lim f(x_k) = \infty$.

□

Once existence of minimizers is ensured, uniqueness is simpler to handle. ‘Mere’ convexity is not sufficient for uniqueness. We require additional assumptions. Strict convexity is sufficient.

Proposition 1.105. Consider the setting of Prop. 1.102. If f is strictly convex then there is a unique minimizer.

Proof. Assume x and $y \in C$ are two distinct minimizers. Then $f(x) = f(y)$. Then $z = (x + y)/2 \in C$ and $f(z) < \frac{1}{2}f(x) + \frac{1}{2}f(y) = f(x) = f(y)$. So neither x nor y can be minimizers. □

1.7 Proximal operators

Definition 1.106. Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ convex, lsc and proper. Then the map $\text{Prox}_f : H \rightarrow H$ is given by

$$x \mapsto \underset{y \in H}{\operatorname{argmin}} \left(\frac{1}{2} \|x - y\|^2 + f(y) \right).$$

The minimizer exists and is unique, so the map is well-defined.

Remark 1.107 (Motivation). Interpretation: near point x try to minimize f , but penalize if we move too far from x . Intuitively: do small step in direction where f decreases, similarly to gradient descent, but Prox_f is also defined for non-smooth f .

The proximal operator will be our basic tool for optimization. Later we will show that we can optimize $f + g$ by only knowing the proximal operators of f and g separately. This is the basis for the *proximal splitting* strategy. One tries to decompose the objective into components such that the proximal operator for each component is easy to compute.

Proof that Prox_f is well-defined. • Since f is convex and lsc $\Rightarrow f^*$ is proper. Therefore f has a continuous affine lower bound, which we denote by $\tilde{f} : y \mapsto \langle u, y \rangle - r$.

- For fixed $x \in H$ let $g : y \mapsto \frac{1}{2} \|x - y\|^2$. By ‘completing the square’ we get

$$\tilde{f}(y) + g(y) = \frac{1}{2} \|x - y\|^2 + \langle u, y \rangle - r = \frac{1}{2} \|y - v\|^2 + C$$

for some $v \in H, C \in \mathbb{R}$. So sublevel sets of $\tilde{f} + g$ are bounded.

- Since $\tilde{f} \leq f$ have $S_r(f + g) \subset S_r(\tilde{f} + g)$, so sublevel sets of $f + g$ are bounded.
- Since f is proper and g is finite, there is some $r \in \mathbb{R}$ such that $S_r(f + g)$ is non-empty.
- Using Prop. 1.102 with $C = H$ and $f = f + g$ we find that $f + g$ has a minimizer over H .
- Since f is convex and g is strictly convex, $f + g$ is strictly convex. Prop. 1.105 \Rightarrow this minimizer is unique.

□

Characterization of proximal operator.

Proposition 1.108. Let f be convex, lsc, proper, let $x \in H$. Then

$$[p = \text{Prox}_f(x)] \quad \Leftrightarrow \quad [\langle y - p, x - p \rangle + f(p) \leq f(y) \text{ for all } y \in H] \quad \Leftrightarrow \quad [x - p \in \partial f(p)]$$

Proof. • The second equivalence is trivial. We prove the first.

- \Rightarrow : Assume $p = \text{Prox}_f(x)$, let $y \in H$. For $\alpha \in [0, 1]$ let $p_\alpha = \alpha \cdot y + (1 - \alpha) \cdot p$.
- Then $f(p_\alpha) + \frac{1}{2} \|x - p_\alpha\|^2 \geq f(p) + \frac{1}{2} \|x - p\|^2$.
- By convexity of f : $f(p_\alpha) \leq \alpha \cdot f(y) + (1 - \alpha) \cdot f(p)$.
- We get:

$$\alpha \cdot f(y) + (1 - \alpha) \cdot f(p) + \frac{1}{2} \|x - p_\alpha\|^2 \geq f(p) + \frac{1}{2} \|x - p\|^2$$

- Setting $g(\alpha) = \alpha \cdot f(y) + (1 - \alpha) \cdot f(p) + \frac{1}{2}\|x - p_\alpha\|^2$ this translates to $g(\alpha) \geq g(0)$ for $\alpha \in [0, 1]$.
- Note that g is differentiable, so we must have $\partial_\alpha g(\alpha)|_{\alpha=0} \geq 0$. This implies:

$$f(y) - f(p) + \langle x - p, y - p \rangle \geq 0.$$

- \Leftarrow : For fixed x let $g : y \mapsto \frac{1}{2}\|x - y\|^2$. Then $\partial g(y) = \{y - x\}$. Then

$$\begin{aligned} [x - p \in \partial f(p)] &\Leftrightarrow [0 \in p - x + \partial f(p) = \partial g(p) + \partial f(p)] \\ &\Rightarrow (\partial f + \partial g \subset \partial(f + g), \text{Prop. 1.32}) \quad [0 \in \partial(g + f)(p)] \\ &\Leftrightarrow [p \in \operatorname{argmin}(g + f)] \Leftrightarrow [p = \operatorname{Prox}_f(x)] \end{aligned}$$

□

Comment: Since we did not prove any results of the form $\partial(f + g) = \partial f + \partial g$ we had to ‘manually’ do the \Rightarrow -argument.

Example 1.109 (Projections). Projections are special cases of proximal operators. Let $C \subset H$ be non-empty, closed, convex. We find

$$P_C x = \operatorname{argmin}_{p \in C} \frac{1}{2}\|x - p\|^2 = \operatorname{argmin}_{p \in H} \frac{1}{2}\|x - p\|^2 + \iota_C(p) = \operatorname{Prox}_{\iota_C}(x).$$

Then the characterization for projections (Prop. 1.49) is a special case of Prop. 1.108:

$$\begin{aligned} [p = \operatorname{Prox}_{\iota_C}(x)] &\Leftrightarrow [\langle y - p, x - p \rangle + \iota_C(p) \leq \iota_C(y) \text{ for all } y \in H] \\ &\Leftrightarrow [p \in C \wedge \langle y - p, x - p \rangle \leq 0 \text{ for all } y \in C] \Leftrightarrow [p = P_C x] \end{aligned}$$

Similarly, the characterization of projections via the normal cone (Cor. 1.50) is a special case of the characterization of the proximal operator via the subdifferential: Recall $\partial \iota_C(y) = N_C y$ (Prop. 1.47). Then:

$$[x \in p + \partial \iota_C(p)] \Leftrightarrow [x \in p + N_C p]$$

So, conversely we may think of the proximal operator as a generalization of projections with ‘soft walls’: instead of paying an infinite penalty when we leave C , the penalty is now controlled by a more general function f .

A few more examples, that are not projections:

Example 1.110. Let $\lambda > 0$.

- $f(y) = \frac{\lambda}{2}\|y\|^2$: $[p = \operatorname{Prox}_f(x)] \Leftrightarrow [x - p \in \partial f(p) = \{\lambda \cdot p\}] \Leftrightarrow [p = x/(1 + \lambda)]$. So $\operatorname{Prox}_f(x) = x/(1 + \lambda)$.
- $f(y) = \lambda \cdot \|y\|$: Recall:

$$\partial f(y) = \lambda \cdot \begin{cases} \frac{y}{\|y\|} & \text{if } y \neq 0, \\ B(0, 1) & \text{if } y = 0. \end{cases}$$

If $x \in \lambda \cdot \overline{B(0, 1)}$ we find that $p = 0$ is a solution to $x \in p + \partial f(p)$. Otherwise, we need to solve $x = p + \frac{\lambda p}{\|p\|}$ for some $p \neq 0$. We deduce that $p = \rho \cdot x$ for some $\rho \in \mathbb{R} \setminus \{0\}$ (since p and x must be linearly dependent) and get:

$$[x = \rho \cdot x + \frac{\lambda \rho x}{\|\rho \cdot x\|}] \Leftrightarrow [1 = \rho + \frac{\lambda}{\|x\|}] \Leftrightarrow [\rho = 1 - \frac{\lambda}{\|x\|}] \Leftrightarrow [p = x - \frac{\lambda x}{\|x\|}]$$

We summarize:

$$\text{Prox}_f(x) = \begin{cases} 0 & \text{if } x \in \overline{B(0, \lambda)} \\ x - \frac{\lambda x}{\|x\|} & \text{else.} \end{cases}$$

Interpretation: if $\|x\| > \lambda$ we move towards the origin with stepsize λ , otherwise, go directly to origin.

Example 1.111 (Comparison with explicit gradient descent). Assume f is Gâteaux differentiable. Then $\partial f(x) = \{\nabla f(x)\}$. Consider a naive discrete gradient descent with stepsize $\lambda > 0$ for some initial $x^{(0)} \in H$:

$$x^{(\ell+1)} \stackrel{\text{def.}}{=} x^{(\ell)} - \lambda \nabla f(x^{(\ell)})$$

For comparison consider repeated application of the proximal operator on some initial $y^{(0)} \in H$:

$$y^{(\ell+1)} \stackrel{\text{def.}}{=} \text{Prox}_{\lambda f}(y^{(\ell)})$$

We find $y^{(\ell)} \in y^{(\ell+1)} + \lambda \partial f(y^{(\ell+1)}) = \{y^{(\ell+1)} + \lambda \nabla f(y^{(\ell+1)})\}$, so

$$y^{(\ell+1)} = y^{(\ell)} - \lambda \nabla f(y^{(\ell+1)}).$$

This is called an *implicit* gradient descent, since the new iterate depends on the gradient at the position of the new iterate, and it is thus only implicitly defined. For comparison, the above rule for $x^{(\ell+1)}$ is called *explicit*.

Usually, the explicit gradient scheme is much easier to implement, but the proximal operator has several important advantages:

- The proximal scheme also works, when f is not differentiable. (But it must be convex.)
- The proximal scheme can be started from any point in H , even from outside of $\text{dom } f$.
- The proximal scheme tends to converge more robustly.

As an illustration of the latter point return to two previous examples:

(i) $f(x) = \frac{1}{2}\|x\|^2$. Then $\nabla f(x) = x$ and we get

$$x^{(\ell+1)} = x^{(\ell)} - \lambda x^{(\ell)} = x^{(0)} (1 - \lambda)^\ell.$$

This converges geometrically to $x^{(\ell)} \rightarrow 0$ for $|1 - \lambda| < 1 \Leftrightarrow \lambda \in (0, 2)$. For $\lambda > 1$ the solution oscillates around the minimizer, for $\lambda > 2$ the sequence diverges.

For comparison we get

$$y^{(\ell+1)} = y^{(\ell)} / (1 + \lambda) = y^{(0)} (1 + \lambda)^{-\ell}$$

This converges geometrically for all $\lambda > 0$. For very small positive λ we have $(1 + \lambda)^{-1} \approx 1 - \lambda$ and the implicit and explicit scheme act similarly (for the first few iterations). Intuitively, this stems from the fact that if f is continuously differentiable and the stepsize is small, then $\nabla f(x^{(\ell)}) \approx \nabla f(x^{(\ell+1)})$.

(ii) $f(x) = \|x\|$. Then $\nabla f(x) = x/\|x\|$ for $x \neq 0$ and we obtain

$$x^{(\ell+1)} = x^{(\ell)} - \frac{\lambda x^{(\ell)}}{\|x^{(\ell)}\|}$$

For $\|x\| > \lambda$ this is the same effect as the proximal operator, but for $\|x\| < \lambda$ it does not jump to the origin and terminate, but oscillates around the minimizer.

The examples indicate that $\text{Prox}_f(x)$ moves from x towards a minimum of f . We also observe that a prefactor λ acts like a stepsize. We establish a few corresponding results.

Proposition 1.112. Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ be convex, lsc, proper. Let $\lambda \in \mathbb{R}_{++}$.

- (i) $[x \in \text{argmin } f] \Leftrightarrow [x = \text{Prox}_f(x)]$.
- (ii) $[x \notin \text{argmin } f] \Rightarrow [f(\text{Prox}_f(x)) < f(x)]$.
- (iii) Let $p = \text{Prox}_f(x)$, $C = S_{f(p)}(f)$. Then $p = P_C x$.
- (iv) The function $\lambda \mapsto \|x - \text{Prox}_{\lambda f}(x)\|$ is increasing.
- (v) The function $\lambda \mapsto f(\text{Prox}_f(x))$ is decreasing.

Proof. • **(i):** Assume $x \in \text{argmin } f$. Then for all $p \in H$

$$f(x) = \frac{1}{2}\|x - x\|^2 + f(x) \leq \frac{1}{2}\|x - p\|^2 + f(p)$$

Therefore, $x = \text{Prox}_f(x)$.

- Conversely, assume $x = \text{Prox}_f(x)$. $\Rightarrow [x \in x + \partial f(x)] \Rightarrow [0 \in \partial f(x)] \Rightarrow$ (Fermat's rule, Prop. 1.26) $[x \in \text{argmin } f]$.
- **(ii):** By assumption $x \notin \text{argmin } f$. Let $p = \text{Prox}_f(x)$. By **(i)** $p \neq x$ and then

$$\frac{1}{2}\|x - p\|^2 + f(p) < \frac{1}{2}\|x - x\|^2 + f(x) = f(x)$$

which implies $f(x) - f(p) > \frac{1}{2}\|x - p\|^2 > 0$.

- **(iii):** By construction $p \in C$. Let $p' = P_C x$. So $p' \in C = S_{f(p)}(f) \Rightarrow f(p') \leq f(p)$. Assume $p' \neq p$. Then $\|x - p\| > \|x - p'\|$ (p' is point that minimizes distance to x among all points in C). Then

$$\frac{1}{2}\|x - p'\|^2 + f(p') < \frac{1}{2}\|x - p\|^2 + f(p)$$

and therefore p' is a better candidate for $\text{Prox}_f(x)$ than p . Therefore we must have $p' = p$.

- **(iv):** We use the monotonicity of the subdifferential for this (Prop. 1.29). Let $0 < \lambda_1 \leq \lambda_2$. Let $p_i = \text{Prox}_{\lambda_i f}(x)$ and set $u_i = x - p_i$ for $i = 1, 2$.
- Let $\Delta u = u_2 - u_1$, $\Delta p = p_2 - p_1$. From $x = p_i + u_i$ we get $\Delta u = -\Delta p$.
- By characterization of the proximal operator we find: $u_i \in \lambda_i \partial f(p_i)$.

Sketch: x, p_1, u_1 , then transition from p_1 to p_2 'towards' x and change of u_1 to u_2 as dictated by $\lambda_2 \geq \lambda_1$ and monotonicity of subdifferential.

- By monotonicity of the subdifferential:

$$0 \leq \left\langle \frac{u_2}{\lambda_2} - \frac{u_1}{\lambda_1}, p_2 - p_1 \right\rangle$$

$$0 \leq \left\langle u_2 - \frac{\lambda_2}{\lambda_1} u_1, \Delta p \right\rangle = \left\langle \Delta u - \frac{\lambda_2 - \lambda_1}{\lambda_1} u_1, \Delta p \right\rangle = -\|\Delta p\|^2 - \frac{\lambda_2 - \lambda_1}{\lambda_1} \langle u_1, \Delta p \rangle$$

We deduce $\langle u_1, \Delta p \rangle \leq 0$. Then

$$\begin{aligned} \|x - p_2\|^2 &= \|x - p_1 - (p_2 - p_1)\|^2 = \|x - p_1 - \Delta p\|^2 \\ &= \|x - p_1\|^2 - 2 \langle u_1, \Delta p \rangle + \|\Delta p\|^2 \geq \|x - p_1\|^2. \end{aligned}$$

- **(v):** Use notation from previous point. Assume $f(p_2) > f(p_1)$, let $C = S_{f(p_2)}(f)$. Then $p_1 \neq p_2$ and $p_1 \in C$. By (iii) have $p_2 = P_C x$, therefore $\|x - p_2\| < \|x - p_1\|$, which contradicts (iv). Therefore we must have $f(p_2) \leq f(p_1)$. □

It turns out that there is a surprisingly simple relation between the proximal operators for f and f^* . This can be used to compute one via the other, in case one seems easier to implement.

Proposition 1.113 (Moreau decomposition). Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ be convex, lsc and proper, $x \in H$. Then $\text{Prox}_f(x) + \text{Prox}_{f^*}(x) = x$.

Proof. Let $p \in H$. Then:

$$\begin{aligned} [p = \text{Prox}_f(x)] &\Leftrightarrow [x - p \in \partial f(p)] \Leftrightarrow (\text{Prop. 1.81}) [p \in \partial f^*(x - p)] \\ &\Leftrightarrow [x - (x - p) \in \partial f^*(x - p)] \Leftrightarrow [x - p = \text{Prox}_{f^*}(x)] \end{aligned}$$

□

Example 1.114 (Moreau decomposition for projections). Let C be a closed subspace of H . Then ι_C is convex, lsc. Consider the conjugate

$$\iota_C^*(x) = \sup_{y \in H} \langle x, y \rangle - \iota_C(y) = \sup_{y \in C} \langle x, y \rangle = \begin{cases} 0 & \text{if } x \perp y \text{ for all } y \in C, \\ +\infty & \text{else} \end{cases} = \iota_{C^\perp}(x)$$

So ι_C^* is the indicator of the orthogonal complement of C . Then $\text{Prox}_{\iota_C} = P_C$ and $\text{Prox}_{\iota_C^*} = P_{C^\perp}$ and the Moreau decomposition yields:

$$x = P_C x + P_{C^\perp} x$$

which is the orthogonal decomposition of x . So we may interpret the Moreau decomposition as a generalization in the same sense that the proximal operator generalizes the projection.

Example 1.115. In an implicit descent scheme $x^{(\ell+1)} = \text{Prox}_f(x^{(\ell)})$ we now find that $x^{(\ell+1)} + \text{Prox}_{f^*}(x^{(\ell)}) = x^{(\ell)}$, $\Rightarrow x^{(\ell+1)} = x^{(\ell)} - \text{Prox}_{f^*}(x^{(\ell)})$, so Prox_{f^*} gives the ‘implicit gradient steps’ $\Delta x^{(\ell+1)}$.

Let $f(x) = \|x\|$. Then $f^* = \iota_{\overline{B(0,1)}}$ and

$$\text{Prox}_f(x) = \begin{cases} 0 = x - x & \text{if } x \in \overline{B(0,1)}, \\ x - \frac{x}{\|x\|} & \text{else.} \end{cases} \quad \text{Prox}_{f^*}(x) = \begin{cases} x & \text{if } x \in \overline{B(0,1)}, \\ \frac{x}{\|x\|} & \text{else.} \end{cases}$$

Interpretation: if $x^{(\ell)} \in \overline{B(0,1)}$ then $\Delta x^{(\ell+1)} = -x^{(\ell)}$ (i.e. we jump directly to the origin). Otherwise we move by $-\frac{x^{(\ell)}}{\|x^{(\ell)}\|}$.

1.8 Proximal algorithm

Now we discuss the simplest possible algorithm built from the proximal iterator: simple iteration of the proximal operator of the objective. We have already discussed this in the context of simple examples (Example 1.111) and shown some preliminary results that support our intuition (Prop. 1.112).

Proposition 1.116 (Proximal algorithm). Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ be proper, convex, lsc with $\operatorname{argmin} f \neq \emptyset$. For some $\gamma \in \mathbb{R}_{++}$ and $x^{(0)} \in H$ set

$$x^{(\ell+1)} = \operatorname{Prox}_{\gamma f}(x^{(\ell)}).$$

Then

- (i) $(x^{(\ell)})_\ell$ is a minimizing sequence of f .
- (ii) $(x^{(\ell)})_\ell$ converges weakly to some point in $\operatorname{argmin} f$.

For the proof we need to gather some auxiliary definitions and results.

Definition 1.117. Let $C \subset H$ be non-empty. Let $(x_k)_k$ be a sequence in H . $(x_k)_k$ is *Fejér monotone* with respect to C if for all $y \in C$ and $k \in \mathbb{N}$

$$\|x_{k+1} - y\| \leq \|x_k - y\|.$$

Proposition 1.118 (Basic consequences of Fejér monotonicity). If $(x_k)_k$ is Fejér monotone with respect to some C then:

- (i) $(x_k)_k$ is bounded.
- (ii) For all $y \in C$ the sequence $(\|x_k - y\|)_k$ converges.
- (iii) Let $d_C(z) = \inf_{y \in C} \|y - z\|$. The sequence $(d_C(x_k))_k$ is decreasing and converges.

Proof. • **(i):** Let $y \in C$. Then by definition $\|x_k - y\| \leq \|x_0 - y\|$, so $(x_k)_k$ is in $\overline{B(y, \|x_0 - y\|)}$.

- **(ii):** By definition, the sequence $(\|x_k - y\|)_k$ is decreasing and bounded from below. Therefore $\lim_{k \rightarrow \infty} \|x_k - y\| = \inf_k \|x_k - y\|$.
- **(iii):** We find: $d_C(x_{k+1}) = \inf_{y \in C} \|x_{k+1} - y\| \leq \inf_{y \in C} \|x_k - y\| = d_C(x_k)$. Therefore, the sequence is decreasing. Also clearly $d_C(x_k) \geq 0$ for all k . Therefore the sequence $(d_C(x_k))_k$ is converging.

□

Lemma 1.119. Let $(x_k)_k$ be a bounded sequence in H . Then $(x_k)_k$ converges weakly if and only if it has at most one weak sequential cluster point.

Proof. • Assume $(x_k)_k$ converges weakly. Since the weak topology is Hausdorff, it has a unique limit which is its only cluster point.

- Assume $(x_k)_k$ has at most one weak sequential cluster point. Since $(x_k)_k$ is bounded, by Banach–Alaoglu and Eberlein–Šmulian (Theorems 1.89 and 1.101) it has at least one weak sequential cluster point. So it has precisely one. Let this cluster point be x .

- Assume x_k does not converge weakly to x . Then there is a weakly open environment U of x such that $H \setminus U$ contains an infinite number of elements of the sequence.
- U is weakly open $\Rightarrow H \setminus U$ is weakly closed \Rightarrow weakly sequentially closed.
- Apply Banach–Alaoglu and Eberlein–Šmulian to the sequence in $H \setminus U$ to get a cluster point in $H \setminus U$.
- This cluster point cannot be x which contradicts the assumption of a unique cluster point. Hence, x_k must converge weakly to x .

□

Remark 1.120. One can in fact show a slightly stronger result: $[(x_k)_k \text{ converges weakly}] \Leftrightarrow [(x_k)_k \text{ is bounded and has at most one cluster point}]$. See [Bauschke, Combettes; Lemma 2.38].

Lemma 1.121. Let $(x_k)_k$ be a sequence in H , let $C \subset H$ nonempty. Suppose that for every $y \in C$ the sequence $(\|x_k - y\|)_k$ converges (to a finite value) and that every weak sequential cluster point of $(x_k)_k$ lies in C . Then $(x_k)_k$ converges weakly to a point in C .

Proof. • By assumption $(x_k)_k$ is bounded. Therefore by Lemma 1.119 it suffices to show that $(x_k)_k$ can have at most one weak sequential cluster point.

- Let x and y be two weak sequential cluster points of $(x_k)_k$, i.e. $x_{i_k} \rightharpoonup x$ and $x_{j_k} \rightharpoonup y$.
- By assumption $x, y \in C$. Therefore $(\|x_k - x\|)_k$ and $(\|x_k - y\|)_k$ converge.
- Therefore, by

$$\|x_k - y\|^2 - \|x_k - x\|^2 - \|y\|^2 + \|x\|^2 = 2 \langle x_k, x - y \rangle$$

we find that $(\langle x_k, x - y \rangle)_k$ converges, call the limit $r \in \mathbb{R}$.

- Further, by weak convergence of the two extracted subsequences we find

$$\lim_k \langle x_{i_k}, x - y \rangle = \langle x, x - y \rangle, \quad \lim_k \langle x_{j_k}, x - y \rangle = \langle y, x - y \rangle.$$

- Both sequences are subsequences of the converging sequence $(\langle x_k, x - y \rangle)_k$. Therefore, their limits must therefore coincide and equal r . Then

$$\|x - y\|^2 = \langle x - y, x - y \rangle = r - r = 0$$

and therefore the two cluster points must coincide.

□

Corollary 1.122. Let $(x_k)_k$ be Fejér monotone with respect to C and every weak sequential cluster point of $(x_k)_k$ is in C . Then $(x_k)_k$ converges weakly to some $x \in C$.

Proof. • From Prop. 1.118 (ii) the sequence $(\|x_k - y\|)_k$ converges for all $y \in C$ (to a finite value).

- Then the result follows from Lemma 1.121.

□

Finally, we can give the proof for the convergence of the proximal minimization scheme.

Proof of Prop. 1.116. • Let $z \in \operatorname{argmin} f$. From $x^{(\ell+1)} = \operatorname{Prox}_{\gamma f}(x^{(\ell)})$ we deduce $x^{(\ell)} - x^{(\ell+1)} \in \gamma \partial f(x^{(\ell+1)})$. Therefore:

$$\begin{aligned} f(x^{(\ell)}) &\geq f(x^{(\ell+1)}) + \left\langle x^{(\ell)} - x^{(\ell+1)}, x^{(\ell)} - x^{(\ell+1)} \right\rangle / \gamma, \\ f(z) &\geq f(x^{(\ell+1)}) + \left\langle z - x^{(\ell+1)}, x^{(\ell)} - x^{(\ell+1)} \right\rangle / \gamma. \end{aligned}$$

- The first inequality implies that $(f(x^{(\ell)}))_\ell$ is decreasing.
- The second inequality implies:

$$\begin{aligned} \|x^{(\ell+1)} - z\|^2 &= \|(x^{(\ell+1)} - x^{(\ell)}) - (z - x^{(\ell)})\|^2 \\ &= \|x^{(\ell+1)} - x^{(\ell)}\|^2 + \|z - x^{(\ell)}\|^2 - 2 \left\langle x^{(\ell+1)} - x^{(\ell)}, z - (x^{(\ell+1)} - x^{(\ell+1)}) - x^{(\ell)} \right\rangle \\ &= \|x^{(\ell)} - z\|^2 - \|x^{(\ell+1)} - x^{(\ell)}\|^2 + 2 \left\langle z - x^{(\ell+1)}, x^{(\ell)} - x^{(\ell+1)} \right\rangle \\ &\leq \|x^{(\ell)} - z\|^2 + 2\gamma(f(z) - f(x^{(\ell+1)})) \end{aligned}$$

- Therefore, $(x^{(\ell)})_\ell$ is Fejér monotone with respect to $\operatorname{argmin} f$.
- Summing the above inequality over $\ell = 0, \dots, N$ we obtain:

$$\begin{aligned} \sum_{\ell=0}^N f(x^{(\ell+1)}) - f(z) &\leq \frac{1}{2\gamma} \sum_{\ell=0}^N \|x^{(\ell)} - z\|^2 - \|x^{(\ell+1)} - z\|^2 \\ &= \frac{1}{2\gamma} \left(\|x^{(0)} - z\|^2 - \|x^{(N+1)} - z\|^2 \right) \leq \infty \end{aligned}$$

- **(i):** So $(f(x^{(\ell)}) - f(z))_\ell$ is monotone decreasing, nonnegative (since z is minimizer) and the sum over its elements is bounded. Therefore $\lim_\ell f(x^{(\ell)}) = f(z)$ and $(x^{(\ell)})_\ell$ is a minimizing sequence.
- **(ii):** Let x be a weak sequential cluster point of $(x^{(\ell)})_\ell$. Since f is convex and lsc, it is weakly sequentially lsc (Cor. 1.97). Therefore, $x \in \operatorname{argmin} f$.
- Now apply Cor. 1.122.

□

Remark 1.123. Observe that the proximal algorithm converges for all step sizes $\gamma > 0$, unlike the explicit gradient step scheme.

1.9 The Douglas–Rachford algorithm

Now we introduce the first true proximal splitting method that minimizes the sum $f + g$ of two convex lsc proper functions by only applying the proximal operators of f and g separately. The algorithm will therefore be much more practical and easier to implement than the simple proximal algorithm. But its convergence analysis is more involved.

Proposition 1.124 (Douglas–Rachford algorithm). Let f and g be convex, lsc, proper such that $\exists z \in H$ with $0 \in \partial f(z) + \partial g(z)$. Further, let $\lambda \in (0, 2)$ and $\gamma \in \mathbb{R}_{++}$. For some $x^{(0)} \in H$ set by iteration for $\ell = 0, 1, \dots$:

$$\begin{aligned} y^{(\ell)} &= \text{Prox}_{\gamma g}(x^{(\ell)}), \\ z^{(\ell)} &= \text{Prox}_{\gamma f}(2y^{(\ell)} - x^{(\ell)}), \\ x^{(\ell+1)} &= x^{(\ell)} + \lambda \cdot (z^{(\ell)} - y^{(\ell)}) \end{aligned}$$

Then there exists some $x \in H$ such that

- (i) $\text{Prox}_{\gamma g}(x) \in \text{argmin}(f + g)$.
- (ii) $y^{(\ell)} - z^{(\ell)} \rightarrow 0$ strongly.
- (iii) $x^{(\ell)} \rightharpoonup x$ weakly.

Remark 1.125. One can in addition show that $y^{(\ell)} \rightharpoonup \text{Prox}_{\gamma g}(x) \in \text{argmin } f$.

We start by going through an explicit example.

Example 1.126. Let $H = \mathbb{R}^2$. $f(x) = \frac{1}{2}\|x\|^2$, $C = \{x \in H : x_1 = 1\}$, $g(x) = \iota_C(x)$. Then $\text{Prox}_{\gamma f}(x) = \frac{1}{1+\gamma}x$. Further $\text{Prox}_{\gamma g}(x) = P_C x$. Recall $[y = P_C x] \Leftrightarrow [y \in C \wedge x \in y + N_C y]$. For the normal cone we get:

$$N_C x = \begin{cases} \emptyset & \text{if } x \notin C, \\ \mathbb{R} \cdot (1, 0) & \text{else.} \end{cases}$$

This implies

$$y_1 = 1, \quad \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} + \lambda \begin{pmatrix} 1 \\ 0 \end{pmatrix}.$$

We obtain $\lambda = x_1 - 1$, $y_1 = 1$, $y_2 = x_2$. So $P_C(x_1, x_2) = (1, x_2)$. For the iterations we get:

$$\begin{aligned} y^{(\ell)} &= (1, x_2^{(\ell)}), & v^{(\ell)} &= 2y^{(\ell)} - x^{(\ell)} = (2 - x_1^{(\ell)}, x_2^{(\ell)}) \\ z^{(\ell)} &= \frac{1}{1+\gamma}(2 - x_1^{(\ell)}, x_2^{(\ell)}), & x^{(\ell+1)} &= \left(x_1^{(\ell)} \cdot \left(1 - \frac{\lambda}{1+\gamma}\right) + \frac{\lambda(1-\gamma)}{1+\gamma}, x_2^{(\ell)} \cdot \left(1 - \frac{\lambda\gamma}{1+\gamma}\right) \right) \end{aligned}$$

Iterations for $x_1^{(\ell)}$ and $x_2^{(\ell)}$ separate. Both are affine maps. For the slopes we find:

$$\begin{aligned} 1 - \frac{\lambda}{1+\gamma} &< 1, & 1 - \frac{\lambda}{1+\gamma} &> -1, \\ (1 - \frac{\lambda\gamma}{1+\gamma}) &< 1, & (1 - \frac{\lambda\gamma}{1+\gamma}) &> -1. \end{aligned}$$

So by the Banach fixed-point theorem both coordinates converge to a unique limit. Determine the fixed point of $x_1^{(\ell)}$:

$$r = r \cdot \left(1 - \frac{\lambda}{1+\gamma}\right) + \frac{\lambda(1-\gamma)}{1+\gamma} \quad \Leftrightarrow \quad r = 1 - \gamma$$

For the fixed-point of $x_2^{(\ell)}$ we immediately find $r = 0$. So we deduce $x^{(\ell)} \rightarrow x = (1 - \gamma, 0)$. Note in particular that this is not optimal (in fact $g(x) = +\infty$). Then $y^{(\ell)} = P_C x^{(\ell)} \rightarrow y = (1, 0)$ which is indeed the minimizer. Further, $v^{(\ell)} = 2y^{(\ell)} - x^{(\ell)} \rightarrow 2y - x = (1 + \gamma, 0)$ such that $z^{(\ell)} = \text{Prox}_{\gamma f}(v^{(\ell)}) = \frac{1}{1+\gamma} v^{(\ell)} \rightarrow (1, 0) = y$.

Remark 1.127 (Interpretation of Douglas–Rachford algorithm). The goal is to find a minimizer $y = z$ and an offset vector Δx such that $x = y + \Delta x$ ‘lies on the f side of the minimizer’ and $v = y - \Delta x$ ‘lies on the g side’, i.e. $y = \text{Prox}_{\gamma g}(y + \Delta x) = \text{Prox}_{\gamma f}(y - \Delta x)$. Unless $\text{argmin } f \cap \text{argmin } g \neq \emptyset$ there can be no such point for $\Delta x = 0$, which is why mere alternating application of $\text{Prox}_{\gamma f}$ and $\text{Prox}_{\gamma g}$ is in general too simplistic and a more sophisticated combination of proximal operators is required.

Sketch: Compare interpretation with example: $x_2^{(\ell)}$ iteration simply approaches 0. For $x_1^{(\ell)}$ iterations the sign of the $x_2^{(\ell)}$ -update depends on whether $x_2^{(\ell)}$ was too close to 0 or too close to 1.

Now we start proving Prop. 1.124. We need considerable auxiliary definitions and results. First note, that if $\text{argmin } f$ contains more than one element, then Prox_f has more than one fixed-point (Prop. 1.112 (i)). So Prox_f cannot be a contraction and therefore convergence proofs cannot rely e.g. on the Banach fixed-point theorem. We need a refined notion of contraction.

Definition 1.128. A map $T : H \mapsto H$ is called

- (i) *nonexpansive* if it is Lipschitz continuous with constant 1. That is

$$\|T(x) - T(y)\| \leq \|x - y\| \quad \text{for all } x, y \in H;$$

- (ii) *firmly nonexpansive* if

$$\|T(x) - T(y)\|^2 + \|(T(x) - x) - (T(y) - y)\|^2 \leq \|x - y\|^2 \quad \text{for all } x, y \in H.$$

Proposition 1.129. Let $f : H \rightarrow \mathbb{R} \cup \{\infty\}$ be proper, convex lsc. Then

- (i) Prox_f is firmly nonexpansive.
- (ii) $\text{id} - \text{Prox}_f$ is firmly nonexpansive.
- (iii) $2 \text{Prox}_f - \text{id}$ is nonexpansive.

Proof. • **(i)** Use monotonicity of subdifferential. Let $x, y \in H$, set $p = \text{Prox}_f(x)$, $q = \text{Prox}_f(y)$. Denote $\Delta x = x - y$ and $\Delta p = p - q$.

- From $x - p \in \partial f(p)$, $y - q \in \partial f(q)$ and monotonicity of the subdifferential we get:

$$\begin{aligned} [\langle (x - p) - (y - q), p - q \rangle \geq 0] &\Leftrightarrow [\langle \Delta x - \Delta p, \Delta p \rangle \geq 0] \Leftrightarrow [2\|\Delta p\|^2 - 2\langle \Delta p, \Delta x \rangle \leq 0] \\ &\Leftrightarrow [\|\Delta p\|^2 + \|\Delta p\|^2 - 2\langle \Delta p, \Delta x \rangle + \|\Delta x\|^2 \leq \|\Delta x\|^2] \Leftrightarrow [\|\Delta p\|^2 + \|\Delta p - \Delta x\|^2 \leq \|\Delta x\|^2] \end{aligned}$$

- (ii) By the Moreau decomposition (Prop. 1.113), $\text{id} - \text{Prox}_f = \text{Prox}_{f^*}$. Since f^* is convex, lsc, proper, Prox_{f^*} is firmly nonexpansive by (i).
- (iii) Use the above notation. Then we need to bound:

$$\|(2p - x) - (2q - y)\|^2 = \|2\Delta p - \Delta x\|^2 = \underbrace{4\|\Delta p\|^2 - 4\langle \Delta p, \Delta x \rangle}_{\leq 0, \text{ see (i)}} + \|\Delta x\|^2 \leq \|\Delta x\|^2$$

□

We need a result to identify fixed-points of nonexpansive maps in the context of weak convergence.

Proposition 1.130. Let $T : H \rightarrow H$ be nonexpansive. Let $(x_k)_k$ be a bounded sequence in H and let $x \in H$. If $x_k \rightharpoonup x$ and $x_k - T(x_k) \rightarrow 0$ then $x = T(x)$.

Proof.

$$\begin{aligned} \|x - T(x)\|^2 &= \|(x - x_k) - (T(x) - x_k)\|^2 \\ &= \|x - x_k\|^2 + \|T(x) - x_k\|^2 - 2\langle x - x_k, T(x) - x + x - x_k \rangle \\ &= \|T(x) - x_k\|^2 - \|x - x_k\|^2 - 2\langle x - x_k, T(x) - x \rangle \\ &= \|(T(x) - T(x_k)) - (x_k - T(x_k))\|^2 - \|x - x_k\|^2 - 2\langle x - x_k, T(x) - x \rangle \end{aligned}$$

(use nonexpansiveness of T to bound $\|T(x) - T(x_k)\| \leq \|x - x_k\|$)

$$\leq \|x_k - T(x_k)\|^2 - 2\langle T(x) - T(x_k), x_k - T(x_k) \rangle - 2\langle x - x_k, T(x) - x \rangle$$

Now, recall $x_k \rightharpoonup x$, $x_k - T(x_k) \rightarrow 0$ and $(x_k)_k$ bounded, i.e. $\|x_k\| \leq C_1$ for some $C_1 < +\infty$. Further, since T is nonexpansive: $\|T(x_k)\| = \|T(x_k) - T(0) + T(0)\| \leq \|T(x_k) - T(0)\| + \|T(0)\| \leq C + \|T(0)\| \stackrel{\text{def.}}{=} C_2$. Then

$$\begin{aligned} \|x_k - T(x_k)\|^2 &\rightarrow 0, \\ \limsup_k |\langle T(x) - T(x_k), x_k - T(x_k) \rangle| &\leq \limsup_k (\|T(x)\| + C_2) \cdot \|x_k - T(x_k)\| = 0 \end{aligned}$$

(here have used Cauchy-Schwarz and $\|T(x) - T(x_k)\| \leq \|T(x)\| + \|T(x_k)\| \leq \|T(x)\| + C_2$)

$$\langle x - x_k, T(x) - x \rangle \rightarrow \langle x - x, T(x) - x \rangle = 0.$$

Therefore, by going to the limit in the above upper bound on $\|x - T(x)\|^2$ we get $\|x - T(x)\| \leq 0$, i.e. $T(x) = x$.

□

Definition 1.131. In the following, for an operator $T : H \rightarrow H$ denote by

$\text{Fix } T = \{x \in H : T(x) = x\}$ the set of fixed-points of T .

$\text{zer } T = \{x \in H : T(x) = 0\}$ the set of ‘roots’ of T .

Analogously, for $T : H \rightarrow 2^H$ let

$$\text{zer } T = \{x \in H : 0 \in T(x)\}.$$

We will shortly show that the Douglas–Rachford iteration can be compactly rewritten as an iteration as analyzed in the following Proposition.

Proposition 1.132. Let $T : H \rightarrow H$ be nonexpansive, let $\text{Fix } T \neq \emptyset$, $\lambda \in (0, 1)$ and $x^{(0)} \in H$. Set

$$x^{(\ell+1)} = x^{(\ell)} + \lambda (T(x^{(\ell)}) - x^{(\ell)}).$$

Then:

- (i) $(x^{(\ell)})_\ell$ is Fejér monotone with respect to $\text{Fix } T$.
- (ii) $(T(x^{(\ell)}) - x^{(\ell)})_\ell$ converges strongly to 0.
- (iii) $(x^{(\ell)})_\ell$ converges weakly to a point in $\text{Fix } T$.

Proof. • For the proof we use the following equality which can be verified by expansion: For $\lambda \in [0, 1]$, $x, y \in H$:

$$\|\lambda x + (1 - \lambda)y\|^2 = \lambda\|x\|^2 + (1 - \lambda)\|y\|^2 - \lambda(1 - \lambda)\|x - y\|^2$$

- (i) Let $y \in \text{Fix } T$. Then

$$\begin{aligned} \|x^{(\ell+1)} - y\|^2 &= \|(1 - \lambda)(x^{(\ell)} - y) + \lambda(T(x^{(\ell)}) - y)\|^2 \\ &= (1 - \lambda)\|x^{(\ell)} - y\|^2 + \lambda\|T(x^{(\ell)}) - T(y)\|^2 - \lambda(1 - \lambda)\|x^{(\ell)} - T(x^{(\ell)})\|^2 \\ &\leq \|x^{(\ell)} - y\|^2 - \lambda(1 - \lambda)\|x^{(\ell)} - T(x^{(\ell)})\|^2 \end{aligned}$$

So $(x^{(\ell)})_\ell$ is Fejér monotone with respect to $\text{Fix } T$.

- (ii) From the above bound we find:

$$\sum_{\ell=0}^N \lambda(1 - \lambda)\|x^{(\ell)} - T(x^{(\ell)})\|^2 \leq \|x^{(0)} - y\|^2 - \|x^{(N+1)} - y\|^2 < \infty$$

Therefore $\|x^{(\ell)} - T(x^{(\ell)})\| \rightarrow 0 \Rightarrow x^{(\ell)} - T(x^{(\ell)}) \rightarrow 0$. (Here use that $\lambda(1 - \lambda) > 0$.)

- (iii) $(x^{(\ell)})_\ell$ is bounded due to Fejér monotonicity (Prop. 1.118). From (ii) we have $T(x^{(\ell)}) - x^{(\ell)} \rightarrow 0$. So by the previous result, Prop. 1.130, we obtain that any weak sequential cluster point of $(x^{(\ell)})_\ell$ is in $\text{Fix } T$.
- It follows then from Cor. 1.122 that $(x^{(\ell)})_\ell$ converges weakly to a point in $\text{Fix } T$. □

Proposition 1.133. Let $f, g : H \rightarrow \mathbb{R} \cup \{\infty\}$ be proper, convex, lsc. Let

$$R_f = 2\text{Prox}_f - \text{id}, \quad R_g = 2\text{Prox}_g - \text{id}.$$

Then $\text{zer}(\partial f + \partial g) = \text{Prox}_g(\text{Fix } R_f R_g)$.

Comment: We will shortly show that fixed-points of $(x^{(\ell)})_\ell$ in the Douglas–Rachford iterations are precisely the fixed-points of $R_f R_g$.

Proof. We find:

$$\begin{aligned}
[0 \in \partial f(x) + \partial g(x)] &\Leftrightarrow [\exists u \in H : [u \in \partial f(x)] \wedge [-u \in \partial g(x)]] \\
&\Leftrightarrow [\exists y \in H : [x - y \in \partial f(x)] \wedge [y - x \in \partial g(x)]] \\
&\Leftrightarrow [\exists y \in H : [x = \text{Prox}_f(2x - y)] \wedge [x = \text{Prox}_g(y)]] \\
&\Leftrightarrow [\exists y \in H : [x = \text{Prox}_f(R_g(y))] \wedge [x = \text{Prox}_g(y)]]
\end{aligned}$$

$$\begin{aligned}
(\Rightarrow: R_g(y) = 2 \text{Prox}_g(y) - y = 2x - y \Rightarrow y = 2x - R_g(y) = 2 \text{Prox}_f(R_g(y)) - R_g(y) = R_f(R_g(y)), \\
(\Leftarrow: y = R_f(R_g(y)) = 2 \text{Prox}_f(R_g(y)) - 2 \text{Prox}_g(y) + y \Rightarrow x = \text{Prox}_g(y) = \text{Prox}_f(R_g(y)))
\end{aligned}$$

$$\Leftrightarrow [\exists y \in H : [y = R_f(R_g(y))] \wedge [x = \text{Prox}_g(y)]]$$

□

Now we are ready to assemble the proof of Prop. 1.124.

Proof of Prop. 1.124. • Let

$$R_f = 2 \text{Prox}_{\gamma f} - \text{id}, \quad R_g = 2 \text{Prox}_{\gamma g} - \text{id}, \quad T = R_f R_g.$$

- Conversely $\text{Prox}_{\gamma g} = \frac{1}{2}(R_g + \text{id})$. Then we can rewrite the Douglas–Rachford iterations as follows:

$$\begin{aligned}
x^{(\ell+1)} &= x^{(\ell)} + \lambda \cdot \left(\text{Prox}_{\gamma f}(2y^{(\ell)} - x^{(\ell)}) - y^{(\ell)} \right) \\
&= x^{(\ell)} + \lambda \cdot \left(\text{Prox}_{\gamma f}(2 \text{Prox}_{\gamma g}(x^{(\ell)}) - x^{(\ell)}) - \text{Prox}_{\gamma g}(x^{(\ell)}) \right) \\
&= x^{(\ell)} + \lambda \cdot \left(\text{Prox}_{\gamma f}(R_g(x^{(\ell)})) - \frac{1}{2}R_g(x^{(\ell)}) - \frac{1}{2}x^{(\ell)} \right) \\
&= x^{(\ell)} + \lambda \cdot \left(\frac{1}{2}R_f(R_g(x^{(\ell)})) - \frac{1}{2}x^{(\ell)} \right) = x^{(\ell)} + \frac{\lambda}{2} \cdot \left(T(x^{(\ell)}) - x^{(\ell)} \right)
\end{aligned}$$

Note that $z^{(\ell)} - y^{(\ell)} = \frac{1}{2}(T(x^{(\ell)}) - x^{(\ell)})$.

- Apply Prop. 1.133 to γf and γg to obtain

$$\text{zer}(\partial f + \partial g) = \text{zer}(\partial \gamma f + \partial \gamma g) = \text{Prox}_{\gamma g}(\text{Fix } T).$$

Since by assumption $\text{zer}(\partial f + \partial g) \neq \emptyset$ this implies also $\text{Fix } T \neq \emptyset$.

- In view of (i) we note that for every $x \in \text{Fix } T$ have therefore $\text{Prox}_{\gamma g}(x) \in \text{argmin}(f + g)$.
- Due to Prop. 1.129(iii) the operators R_f and R_g are nonexpansive. Then so is their composition $T = R_f R_g$.
- (ii) From Prop. 1.132(ii) we find $z^{(\ell)} - y^{(\ell)} = \frac{1}{2}(T(x^{(\ell)}) - x^{(\ell)}) \rightarrow 0$ strongly.
- From Prop. 1.132(iii) we get: there is some $x \in \text{Fix } T$ such that $x^{(\ell)} \rightharpoonup x$ weakly. Since $\text{Prox}_{\gamma g}(x) \in \text{argmin}(f + g)$ (see above) this establishes (i) and (iii).

□

1.10 Primal-Dual Methods

In this subsection we study an alternative approach to optimizing objectives of the form $f + g$ that is intimately linked to conjugation.

Definition 1.134. • For convex functions $f, g : H \rightarrow \mathbb{R} \cup \{\infty\}$ let

$$P(x) = f(x) + g(x), \quad D(y) = -f^*(-y) - g^*(y), \quad L(x, y) = f(x) - g^*(y) + \langle x, y \rangle.$$

- The problem $\inf_{x \in H} P(x)$ is called *primal problem*, the problem $\sup_{y \in H} D(y)$ is called *dual problem* and L is called *Lagrangian*.
- Note that since D is concave, the dual problem is also a convex optimization problem.
- For all $(x, y) \in H^2$ one has

$$P(x) \geq L(x, y) \geq D(y).$$

This follows quickly from the Fenchel–Young inequality (Prop. 1.72).

- In particular:

$$P(x) \geq \inf_{x' \in H} P(x') \geq \sup_{y' \in H} D(y') \geq D(y)$$

- So for every feasible pair $(x, y) \in H^2$ of primal and dual problem the value $\Delta(x, y) = P(x) - D(y)$ is an upper bound on the combined suboptimality of x and y with respect to primal and dual problem. Therefore $\Delta(x, y)$ is called the *duality gap*.
- If $\Delta(x, y) = 0$ then x and y must be optimizers of primal and dual problem respectively.

We give a simple variant of the famous Fenchel–Rockafellar duality.

Proposition 1.135 (Duality). Assume there exists some $x_0 \in H$ such that $f(x_0) < \infty$, $g(x_0) < \infty$ and f is continuous in x_0 . Then

$$\inf_{x \in H} \{f(x) + g(x)\} = \max_{y \in H} \{-f^*(-y) - g^*(y)\}.$$

In particular, a maximizer for the dual problem exists.

Comment: Sometimes one tries to show that a given optimization problem is the dual problem of some auxiliary problem to use the above Proposition for showing that a solution exists.

For the proof we need an auxiliary result on separating points from convex sets via hyperplanes.

Proposition 1.136. Let $C \subset H$ be convex, $0 \notin \text{int } C$, $\text{int } C \neq \emptyset$. Then there is some $z \in H \setminus \{0\}$ such that $\langle z, x \rangle \geq 0$ for all $x \in C$.

Comment: This means, the hyperplane with normal z through the origin separates C from 0.

Proof. • Let $D = \overline{C}$. By Prop. 1.54 we have $\text{int } D = \text{int } C \neq \emptyset$ and in particular $0 \notin C \supset \text{int } D$.

- Since D is closed and convex, it is the intersection of all closed halfspaces that contain D (Cor. 1.66).

- If $0 \notin D$ there must be a closed halfspace $A_u = \{x \in H : \langle u, x \rangle - r \geq 0\}$, $u \neq 0$, such that $D \subset A_u$ and $0 \notin A_u$.
- $0 \notin A_u \Rightarrow \langle 0, x \rangle - r < 0 \Rightarrow r > 0$.
- $x \in D \subset A_u \Rightarrow 0 \leq \langle u, x \rangle - r < \langle u, x \rangle$. So setting $z = u$ we have found an appropriate z .
- Alternatively, must have $0 \in D$, but $0 \notin \text{int } D$. Then by Prop. 1.56 there is some $u \in N_D 0$ with $u \neq 0$. By definition $\sup \langle u, D \rangle \leq 0$. Then set $z = -u$ above:

$$\langle -u, x \rangle \geq \inf \langle -u, D \rangle = -\sup \langle u, D \rangle \geq 0$$

□

Proof of Prop. 1.135. • The inequality $\inf_{x \in H} P(x) \geq \sup_{y \in H} D(y)$ is clear by Def. 1.134. We need to show the converse inequality.

- Denote by $m = \inf_{x \in H} P(x)$. We have $m \leq f(x_0) + g(x_0) < \infty$. If $m = -\infty$ the converse inequality is trivial. Hence, assume $m \in \mathbb{R}$.
- Assume we had some $z \in H$ such that for all $a, b \in H$ one has

$$f(a) + g(b) + \langle z, a - b \rangle \geq m.$$

- Then we find:

$$\begin{aligned} \sup_{y \in H} -f^*(-y) - g^*(y) &= \sup_{y \in H} \inf_{a, b \in H} [f(a) - \langle a, -y \rangle + g(b) - \langle b, y \rangle] \\ &\geq \inf_{a, b \in H} [f(a) + g(b) + \langle z, a - b \rangle] \geq m \end{aligned}$$

- Since also $\sup_{y \in H} -f^*(-y) - g^*(y) \leq m$, z must therefore be a dual maximizer and primal and dual problem have the same optimal value.
- Now we show existence of a suitable z .
- Let

$$\begin{aligned} A &= \{(a, \lambda) \in H \times \mathbb{R} : \lambda > f(a)\}, \\ B &= \{(b, \mu) \in H \times \mathbb{R} : \mu \leq m - g(b)\}. \end{aligned}$$

- A and B are convex. Since f is continuous in x_0 and $f(x_0) < \infty$, we have $\text{int } A \neq \emptyset$.
- Assume there were some $(a, \lambda) \in A \cap B$. Then we would find

$$f(a) + g(a) < \lambda + (m - \lambda) = m$$

which is a contradiction. Therefore $A \cap B = \emptyset$.

- This implies $0 \notin A - B$ and in particular $0 \notin \text{int}(A - B)$. $A - B$ is convex. Also, $\emptyset \neq \text{int } A - B \subset \text{int}(A - B)$. So by Prop. 1.136 there is some $(u, r) \in H \times \mathbb{R} \setminus \{(0, 0)\}$ such that $\langle (u, r), (a, \lambda) \rangle \geq 0$ for all $(a, \lambda) \in A - B$. This implies

$$\langle (u, r), (a, \lambda) \rangle \geq \langle (u, r), (b, \mu) \rangle \Leftrightarrow \langle u, a \rangle + r \cdot \lambda \geq \langle u, b \rangle + r \cdot \mu$$

for all $(a, \lambda) \in A$, $(b, \mu) \in B$.

- Since we can send $\lambda \rightarrow \infty$ and $\mu \rightarrow -\infty$ (and remain in A, B respectively) we find that $r \geq 0$.
- If $r = 0$, we can violate the inequality by setting $b = x_0$ (where g is finite) and $a = x_0 - \varepsilon \cdot u$ for sufficiently small $\varepsilon > 0$ (which works since f is continuous in x_0). So must have $r > 0$.
- Set now $z = u/r$. The above inequality yields

$$\langle z, a - b \rangle + \lambda - \mu \geq 0$$

for all $\lambda > f(a)$, $\mu \leq m - g(b)$, i.e. for $\lambda - \mu > f(a) + g(b) - m$. Therefore, the given z is as needed above and the proof is complete. \square

Remark 1.137. There are considerably more general variants of Prop. 1.135 on Banach spaces and their dual spaces. Then the auxiliary separation result, Prop. 1.136, must usually be provided by the Hahn–Banach theorem.

Finally, we give another proximal splitting algorithm, specialized for primal-dual problem pairs as above.

Proposition 1.138. Assume that f and g are proper, convex, lsc and that primal and dual problem have solutions. For $\tau \in (0, 1)$ and $x^{(0)}, y^{(0)} \in H$ set

$$\begin{aligned} x^{(\ell+1)} &= \text{Prox}_{\tau f}(x^{(\ell)} - \tau \cdot y^{(\ell)}), \\ y^{(\ell+1)} &= \text{Prox}_{\tau g^*}(y^{(\ell)} + \tau \cdot (2x^{(\ell+1)} - x^{(\ell)})). \end{aligned}$$

Then $(x^{(\ell)})_\ell$ and $(y^{(\ell)})_\ell$ converge weakly to solutions of the primal and dual problem, respectively.

Remark 1.139. For more details on such algorithms and generalizations, see for instance [Chambolle, Pock: A First-Order Primal-Dual Algorithm for Convex Problems with Applications to Imaging, 2011].

Proposition 1.140. A pair $(x, y) \in H^2$ are solutions to the primal and dual problem if and only if $x \in g^*(y)$ and $-y \in \partial f(x)$.

Proof.

$$\begin{aligned} [(x, y) \text{ are solutions}] &\Leftrightarrow [P(x) = D(y)] \Leftrightarrow [f(x) + g(x) = -f^*(-y) - g^*(y)] \\ &\Leftrightarrow [(f(x) + f^*(-y) - \langle x, -y \rangle) + (g(x) + g^*(y) - \langle x, y \rangle) = 0] \end{aligned}$$

(By Fenchel–Young (Prop. 1.72) this is 0 if and only if both parantheses are 0, which, by Prop. 1.81, is equivalent to:)

$$\Leftrightarrow [-y \in \partial f(x)] \wedge [x \in \partial g^*(y)]$$

\square

Remark 1.141. The strategy for the convergence proof of Prop. 1.138 is as follows: we show that the optimality condition of Prop. 1.140 can be written as zeros of a monotone operator acting on the pair (x, y) . These zeros can be identified with fixed-points of carefully constructed firmly nonexpansive operators and corresponding metrics. If we choose the right metric, this operator can be identified with the iterations of Prop. 1.138. We then generalize the original proximal optimization algorithm (Prop. 1.116) to firmly nonexpansive operators.

Proposition 1.142. Let $A : H \rightarrow 2^H$ be monotone. Let $M : H \rightarrow H$ be linear, continuous, self-adjoint and positive definite, i.e. $\langle x, Mx \rangle \geq C\|x\|^2$ for some $C \in \mathbb{R}_{++}$. Let the operator $T : K \rightarrow H$ be given by

$$[y = T(x)] \Leftrightarrow [Mx \in My + A(y)]$$

where $K \subset H$ is the set such that the above inclusion has a solution y for fixed $x \in K$.

- (i) This inclusion has at most one solution, i.e. T is well-defined on K .
- (ii) $\text{Fix } T = \text{zer } A$.
- (iii) T is firmly nonexpansive with respect to the inner product induced by M , $\langle x, y \rangle_M = \langle x, My \rangle$.

Proof. • (i) For fixed $x \in H$ and $y_1, y_2 \in H$ assume:

$$[Mx \in My_1 + A(y_1)] \wedge [Mx \in My_2 + A(y_2)]$$

By monotonicity of A we get:

$$0 \leq \langle M(x - y_1) - M(x - y_2), y_1 - y_2 \rangle = -\langle M(y_1 - y_2), (y_1 - y_2) \rangle \leq -C\|y_1 - y_2\|^2$$

Therefore $y_1 = y_2$ and thus, T is well-defined on K .

- (ii)

$$[x \in \text{zer}(A)] \Leftrightarrow [0 \in A(x)] \Leftrightarrow [Mx \in Mx + A(x)] \Leftrightarrow [T(x) = x] \Leftrightarrow [x \in \text{Fix } T]$$

- (iii) Let $p = T(x)$, $q = T(y)$, $\Delta x = x - y$, $\Delta p = p - q$. Then

$$M(x - p) \in A(p), \quad M(y - q) \in A(q).$$

By monotonicity:

$$\begin{aligned} [\langle M(x - p) - M(y - q), p - q \rangle \geq 0] &\Leftrightarrow [\langle \Delta x - \Delta p, \Delta p \rangle_M \geq 0] \\ &\Leftrightarrow [\|\Delta p\|_M^2 - \langle \Delta p, \Delta x \rangle_M \leq 0] \\ &\Leftrightarrow [\|p - q\|_M^2 + \|(p - x) - (q - y)\|_M^2 \leq \|x - y\|_M^2] \end{aligned}$$

□

Now we generalize Prop. 1.116 to arbitrary firmly nonexpansive operators.

Proposition 1.143. Assume $T : H \rightarrow H$ is firmly nonexpansive and $\text{Fix } T \neq \emptyset$. For $x^{(0)} \in H$ set

$$x^{(\ell+1)} = T(x^{(\ell)}).$$

Then $(x^{(\ell)})_\ell$ converges weakly to some point $x \in \text{Fix } T$.

Proof. • Let $z \in \text{Fix } T$. Then by firm nonexpansiveness:

$$\begin{aligned} \|x^{(\ell+1)} - z\|^2 &= \|T(x^{(\ell)}) - T(z)\|^2 \leq \|x^{(\ell)} - z\|^2 - \|(T(x^{(\ell)}) - x^{(\ell)}) - (T(z) - z)\|^2 \\ &= \|x^{(\ell)} - z\|^2 - \|T(x^{(\ell)}) - x^{(\ell)}\|^2 \end{aligned}$$

- So $(x^{(\ell)})_\ell$ is Fejér monotone with respect to $\text{Fix } T$.
- Further $\sum_{\ell=0}^N \|T(x^{(\ell)}) - x^{(\ell)}\|^2 \leq \|x^{(0)} - z\|^2$. Therefore $T(x^{(\ell)}) - x^{(\ell)} \rightarrow 0$ strongly.
- By Prop. 1.130 every weak sequential cluster point of $(x^{(\ell)})_\ell$ is a fixed-point of T .
- By Cor. 1.122 $x^{(\ell)} \rightharpoonup x$ for some $x \in \text{Fix } T$.

□

Proof of Proposition 1.138. • Define set valued operator $A : H \times H \rightarrow 2^H \times 2^H$ as follows:

$$\begin{pmatrix} x \\ y \end{pmatrix} \mapsto \begin{pmatrix} \partial f(x) + y \\ \partial g^*(y) - x \end{pmatrix}$$

- By Prop. 1.140 the primal and dual optimizers are given precisely by $\text{zer } A$, and therefore by assumption $\text{zer } A \neq \emptyset$.
- Note that $2^H \times 2^H$ can be identified with a subset of $2^{(H \times H)}$. So formally A can be interpreted as $H \times H \rightarrow 2^{H \times H}$.

Sketch: $2^H \times 2^H$ vs $2^{(H \times H)}$ for $H = \mathbb{R}$: product of two intervals vs general 2d sets.

- A is monotonous: let $[a_i \in \partial f(x_i) \wedge b_i \in \partial g^*(y_i)] \Leftrightarrow (a_i + y_i, b_i - x_i) \in A(x_i, y_i)$ for $i = 1, 2$. Denote by $\Delta x, \Delta y, \Delta a, \Delta b$ all pairwise differences. Then by monotonicity of ∂f and ∂g^* :

$$\begin{aligned} & \langle (a_2 + y_2, b_2 - x_2) - (a_1 + y_1, b_1 - x_1), (x_2 - x_1, y_2 - y_1) \rangle = \\ & \langle (\Delta a + \Delta y, \Delta b - \Delta x), (\Delta x, \Delta y) \rangle = \langle \Delta a, \Delta x \rangle + \langle \Delta y, \Delta x \rangle + \langle \Delta b, \Delta y \rangle - \langle \Delta x, \Delta y \rangle \geq 0 \end{aligned}$$

- Now set $M : H^2 \rightarrow H^2$ as

$$M = \begin{pmatrix} \frac{1}{\tau} \text{id} & -\text{id} \\ -\text{id} & \frac{1}{\tau} \text{id} \end{pmatrix}$$

M is continuous, linear and symmetric. Furthermore, it is positive definite, since for $x, y \in H$:

$$\langle (x, y), M(x, y) \rangle = \frac{1}{\tau} \|x\|^2 + \frac{1}{\tau} \|y\|^2 - 2 \langle x, y \rangle \geq \left(\frac{1}{\tau} - 1\right) \cdot (\|x\|^2 + \|y\|^2) + \|x - y\|^2$$

- Now analyze operator T constructed from A and M via Prop. 1.142: From $(a, b) = T(x, y)$ we obtain the following inclusion condition:

$$\begin{aligned} & M \begin{pmatrix} x - a \\ y - b \end{pmatrix} \in A \begin{pmatrix} a \\ b \end{pmatrix} \\ & \Leftrightarrow \begin{pmatrix} \frac{1}{\tau} x - \frac{1}{\tau} a - y + b \\ \frac{1}{\tau} y - \frac{1}{\tau} b - x + a \end{pmatrix} \in \begin{pmatrix} \partial f(a) + b \\ \partial g^*(b) - a \end{pmatrix} \\ & \Leftrightarrow \begin{pmatrix} x - \tau y \\ y + \tau(2a - x) \end{pmatrix} \in \begin{pmatrix} a + \partial \tau f(a) \\ b + \partial \tau g^*(b) \end{pmatrix} \\ & \Leftrightarrow a = \text{Prox}_{\tau f}(x - \tau y) \wedge b = \text{Prox}_{\tau g^*}(y + \tau(2a - x)) \end{aligned}$$

So the iterations of the algorithm, Prop. 1.138, correspond to the induced operator T , i.e. $(x^{(\ell+1)}, y^{(\ell+1)}) = T(x^{(\ell)}, y^{(\ell)})$. This also implies that the domain of T is H^2 .

- By Prop. 1.142 (ii) have $\text{Fix } T = \text{zer } A \neq \emptyset$.
- Now consider the Hilbert space $H \times H$, equipped with the inner product induced by M . Note that the topology induced by M is the same as the product topology on $H \times H$. Therefore, both topologies induce the same weak topology.
- On this space T is firmly nonexpansive by Prop. 1.142 (iii). So by Prop. 1.143 the sequence $(x^{(\ell)}, y^{(\ell)})_{\ell}$ converges weakly to some $(x, y) \in \text{Fix } T = \text{zer } A$, which is therefore a pair of solutions to primal and dual problem.
- Note: the iteration would converge to a fixed-point for every positive definite M . We chose M carefully such that computing $x^{(\ell+1)}$ does not depend on $y^{(\ell+1)}$ and thus the two updates can be computed subsequently and separately.

□

Remark 1.144. • Prop. 1.143 studies convergence to fixed-points of general firmly nonexpansive operators, it is a generalization of Prop. 1.116, which only treated the special case of the proximal operator.

- Prop. 1.142 defines a firmly nonexpansive operator from a monotone operator. T is usually called *resolvent* of A . This is a generalization of the relation between the subdifferential and the proximal operator, Prop. 1.108.
- Generalize minimization problems to finding zeros of monotone operators via their resolvents. Douglas–Rachford algorithm can also be generalized to finding zero of sum of two monotone operators. In fact, this was application of the algorithm in first publication.

2 Optimization in Banach spaces

Remark 2.1 (Motivation). • We go through some fundamental aspects of analysis in Banach spaces. Goal: ensure that minimization problems are well-defined (e.g. minimizers exist, sufficient and necessary criteria for optimality).

- For numerical solution we need to discretize, i.e. approximate by finite-dimensional problem. Must ensure ‘quality’ of approximations. Will introduce Γ -convergence, essentially notion of convergence for minimization problems.
- Discrete problems always finite dimensional. Still: must analyze infinite dimensional problems, to ensure that limit of solutions as we choose finer and finer discretizations is reasonable.

Definition 2.2. Throughout this subsection V is a real vector space.

2.1 Foundations

Definition 2.3 (Norm and inner product). • A map $\|\cdot\| : V \rightarrow \mathbb{R}_+$ on V is a *norm* if for all $x, y \in V$, $\lambda \in \mathbb{R}$ have

- (i) (positive definite) $\|x\| = 0 \Rightarrow x = 0$,
- (ii) (subadditive) $\|x + y\| \leq \|x\| + \|y\|$,
- (iii) (homogeneity) $\|\lambda \cdot x\| = |\lambda| \cdot \|x\|$.

- A norm induces a metric on V via $d(x, y) = \|x - y\|$.
- A map $\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{R}$ is an *inner product* on V if for all $x, y, z \in V$, $\lambda \in \mathbb{R}$ it satisfies
 - (i) (symmetry) $\langle x, y \rangle = \langle y, x \rangle$,
 - (ii) (linearity in first argument) $\langle \lambda \cdot x, y \rangle = \lambda \cdot \langle x, y \rangle$, $\langle x + y, z \rangle = \langle x, z \rangle + \langle y, z \rangle$,
 - (iii) (positive definite) $\langle x, x \rangle \geq 0$, $[\langle x, x \rangle = 0] \Rightarrow [x = 0]$.
- From the axioms for the inner product we quickly obtain the *Cauchy-Schwarz inequality*, $\langle x, y \rangle \leq \|x\| \cdot \|y\|$, and that an inner product induces a norm via $\|x\| = \sqrt{\langle x, x \rangle}$.
- A vector space V with a norm $\|\cdot\|$ is called a *normed space*. A vector space with an inner product $\langle \cdot, \cdot \rangle$ is called *pre-Hilbert space*.

Definition 2.4 (Convergence in metric). We say a sequence $(x_k)_k$ on a metric space (X, d) converges to some $x \in X$ if $d(x_k, x) \rightarrow 0$. x is called the *limit* of $(x_k)_k$ and is unique.

Definition 2.5 (Cauchy sequence and complete metric spaces). A sequence $(x_k)_k$ on a metric space (X, d) is a Cauchy sequence if for all $\varepsilon > 0$ there is some $N \in \mathbb{N}$ such that $d(x_i, x_j) \leq \varepsilon$ whenever $i, j \geq N$. A metric space is called *complete* if all Cauchy sequences converge.

Definition 2.6 (Banach and Hilbert spaces). A complete normed space is called *Banach space*. A complete pre-Hilbert space is called *Hilbert space*.

Definition 2.7. • A finite set $\{x_1, \dots, x_n\} \subset V$ is linearly independent if for all $(\alpha_i)_{i=1}^n \in \mathbb{R}^n$ one has $\sum_{i=1}^n \alpha_i \cdot x_i = 0 \Rightarrow \alpha_i = 0$.

- The span of a finite set $\{x_1, \dots, x_n\}$ is $\text{span}\{x_1, \dots, x_n\} = \{\sum_{i=1}^n \alpha_i \cdot x_i \mid (\alpha_i)_{i=1}^n \in \mathbb{R}^n\}$.
- A basis of V is a linearly independent finite set $X \subset V$ such that $\text{span } X = V$.
- The dimension of V is the cardinality of any basis. If no basis exists, the dimension is ∞ .
- On an ∞ -dimensional normed vector space a *Schauder basis* is a sequence $(x_k)_k$ in V such that for any $x \in V$ there is a unique sequence $(\lambda_k)_k$ such that

$$\lim_{n \rightarrow \infty} \left\| x - \sum_{k=1}^n \lambda_k \cdot x_k \right\| = 0.$$

Remark 2.8 (Convexity in Banach spaces). The notions of convex sets, convex hull, convex functions, lower semicontinuity and cones can be defined on Banach spaces just as in the previous part, since these do not rely on the inner product. For definitions such as subdifferential, normal cone, conjugation we need to be more careful, but generalizations exist. Some more details later.

2.2 Reminders on topology

We recall a few basic facts about topologies.

Definition 2.9. Let X be a set. A set $T \subset 2^X$ of subsets of X is called a *topology* for X if

- (i) $X, \emptyset \in T$,
- (ii) For arbitrary subsets $S \subset T$ their union is also in T , i.e.

$$\bigcup_{s \in S} s \in T.$$

- (iii) For finite subsets $S = \{s_1, \dots, s_n\} \subset T$ their intersection is also in T , i.e.

$$\bigcap_{i=1}^n s_i \in T.$$

Sets in T are called *open*. A set is *closed*, if its complement in X is open. The set X with a corresponding topology T is called *topological space*. If not required, we may drop the explicit reference to T .

Remark 2.10. The restriction that only finite intersections of open sets are open is necessary. Recall basic example from $X = \mathbb{R}$: for every $\varepsilon > 0$ the set $(-\varepsilon, \varepsilon)$ is open. But

$$\bigcap_{n=1}^{\infty} (-1/n, 1/n) = \{0\}$$

which is not open.

Proposition 2.11 (de Morgan's law). Let $(A_i)_{i \in I}$ be a set of subsets of X where I is an arbitrary index set. Then

$$\bigcap_{i \in I} A_i = X \setminus \left(\bigcup_{i \in I} (X \setminus A_i) \right).$$

Proof.

$$\begin{aligned}
[x \in \bigcap_{i \in I} A_i] &\Leftrightarrow [x \in A_i \forall i \in I] \Leftrightarrow [x \notin X \setminus A_i \forall i \in I] \\
&\Leftrightarrow [x \notin \bigcup_{i \in I} (X \setminus A_i)] \Leftrightarrow [x \in X \setminus (\bigcup_{i \in I} (X \setminus A_i))]
\end{aligned}$$

□

Corollary 2.12. With this we quickly find that arbitrary intersections of closed sets are closed and finite unions of closed sets are closed.

Definition 2.13. Let (X, T) be a topological space. The interior $\text{int } A$ of a set $A \subset X$ is the union of all open sets contained in A :

$$\text{int } A = \bigcup \{U \in T : U \subset A\}$$

Since this set is by construction open and contains all open sets contained in A it is also referred to as ‘largest open set contained in A ’. Similarly, the closure $\text{cl } A$ of A is the intersection of all closed sets that contain A .

Definition 2.14 (Convergence of sequences). A sequence $(x_k)_k$ in a topological space (X, T) is said to converge to a point $x \in X$ if for any any $t \in T$ with $x \in t$ there is some $N \in \mathbb{N}$ such that $x_k \in t$ for $k \geq N$.

Definition 2.15 (Continuous maps). Let (X, T) , (Y, S) be two topological spaces and let $f : X \rightarrow Y$. f is called *continuous* if $f^{-1}(s) \in T$ for all $s \in S$. (‘Preimages of open sets are open.’)

Proposition 2.16. Let $\{T_i\}_{i \in I}$ be a set of topologies over a set X , where I is an arbitrary index set. Then their *intersection* T , where $t \in T$ iff $t \in T_i$ for all $i \in I$, is a topology.

Definition 2.17 (Induced topology). Let $(f_i : X \rightarrow Y_i)_{i \in I}$ be a family of maps from X to topological spaces Y_i . Then the intersection T of all topologies $(T_j)_{j \in J}$ such that all maps $(f_i)_{i \in I}$ are continuous is the *induced topology*. Since T only contains sets that are contained in all other T_j , T also referred to as *coarsest topology* in which the family $(f_i)_{i \in I}$ is continuous.

Comment: Transition from metric to metric topology often simply ‘stated as fact’. Take some time to re-check.

Proposition 2.18 (Metric topology). • Let (X, d) be a metric space. The metric topology on X is the topology induced by the family of maps $(y \mapsto d(x, y))_{x \in X}$ from X to \mathbb{R} where \mathbb{R} is equipped with the standard topology.

- For $x \in X$, $\varepsilon > 0$ the set $B(x, \varepsilon) = \{y \in X : d(x, y) < \varepsilon\}$ is called the *open ball* of radius ε around x . $B(x, \varepsilon)$ is open in the metric topology.
- Any open set in the metric topology can be written as union of open balls.

Proof. • Note that $B(x, \varepsilon) = d(x, \cdot)^{-1}((-\varepsilon, \varepsilon))$. Since $(-\varepsilon, \varepsilon)$ is open in \mathbb{R} , $B(x, \varepsilon)$ is therefore open in the metric topology by construction.

- The intersection of two open balls can be written as union of open balls: For $x_1, x_2 \in X$, $r_1, r_2 > 0$ and $x \in B(x_1, r_1) \cap B(x_2, r_2)$ set $\varepsilon_i = r_i - d(x_i, x)$. Let $\varepsilon = \min\{\varepsilon_1, \varepsilon_2\}/2$. Then for $z \in B(x, \varepsilon)$ have $d(z, x_i) \leq d(z, x) + d(x, x_i) < \varepsilon + r_i - \varepsilon_i \leq \varepsilon_i/2 + r_i - \varepsilon_i = r_i - \varepsilon_i/2$. So $z \in B(x_i, r_i)$ and $B(x, \varepsilon) \subset B(x_i, r_i)$.
- More generally, for any $y \in B(x_1, r_1) \cap B(x_2, r_2)$ denote by $\varepsilon_y > 0$ a positive radius such that $B(y, \varepsilon_y) \subset B(x_1, r_1) \cap B(x_2, r_2)$. Then

$$B(x_1, r_1) \cap B(x_2, r_2) = \bigcup_{y \in B(x_1, r_1) \cap B(x_2, r_2)} B(y, \varepsilon_y)$$

- Finite intersections of arbitrary unions of open balls can be written as unions of open balls. We start with the intersection of two unions. The rest follows by induction. Let

$$S = \left(\bigcup_{i \in I} A_i \right) \cap \left(\bigcup_{j \in J} B_j \right)$$

where I and J are some index sets and $(A_i)_{i \in I}$, $(B_j)_{j \in J}$ are families of open balls. Then $x \in S \Leftrightarrow \exists i_x \in I, j_x \in J$ such that $x \in A_{i_x} \cap B_{j_x} \subset S$. So

$$S = \bigcup_{x \in S} (A_{i_x} \cap B_{j_x}).$$

By the previous point we can rewrite the intersection $A_{i_x} \cap B_{j_x}$ of two open balls as union of open balls, therefore we can rewrite S as union of open balls.

- Now set $T = \{\bigcup_{i \in I} B_i \mid \text{index sets } I, \text{ open balls } (B_i)_{i \in I}\}$ be the set of unions of open balls. We set by convention that $X, \emptyset \in T$. Then T is a topology (see previous point for the intersection property) and it contains all open balls. Therefore, the metric topology is a subset of T .
- The metric topology must contain at least all open balls, and therefore all arbitrary unions thereof. So T is contained in the metric topology. Therefore, the two coincide. \square

Corollary 2.19. The metric topology is Hausdorff. That is, for every distinct pair $x_1, x_2 \in X$ there are open sets $A_1, A_2 \subset X$ with $x_i \in A_i$, $A_1 \cap A_2 = \emptyset$.

Proof. Since $x_1 \neq x_2$ have $d(x_1, x_2) > 0$. Set $A_i = B(x_i, d(x_1, x_2)/3)$. \square

Corollary 2.20. Let $A \subset X$ be open. Then for every $x \in A$ there is some $\varepsilon > 0$ such that $B(x, \varepsilon) \subset A$.

Proof. By Prop. 2.18 A can be written as union of open balls. Therefore, we must have some $y \in A$, $\delta > 0$ such that $x \in B(y, \delta) \subset A$. Set $\varepsilon = (\delta - d(x, y))/2$. By triangle inequality $B(x, \varepsilon) \subset B(y, \delta) \subset A$. \square

Corollary 2.21 (Convergence in metric topology). Convergence in the metric (Def. 2.4) is equivalent to convergence in the metric topology (Prop. 2.18).

Proof. • Assume $d(x_k, x) \rightarrow 0$. For any open set U containing x , by Cor. 2.20, there is some $\varepsilon > 0$ such that $B(x, \varepsilon) \subset U$ and consequentially some $N \in \mathbb{N}$ such that $d(x_k, x) < \varepsilon$ for $k > N$, i.e. $x_k \in U$. This implies convergence in metric topology.

- Assume convergence in metric topology. Then for any $\varepsilon > 0$ there is some $N \in \mathbb{N}$ such that $x_k \in B(x, \varepsilon)$ for $k > N$, i.e. $d(x_k, x) < \varepsilon$. This implies $d(x_k, x) \rightarrow 0$. □

2.3 Examples

Let $\Omega \subset \mathbb{R}^n$ be open, bounded, non-empty. For a ‘multiindex’ $a \in \{0, 1, 2, \dots\}^n$ let $|a| = a_1 + \dots + a_n$ and $D^a f \stackrel{\text{def.}}{=} \frac{\partial^{|a|}}{\partial x_1^{a_1} \dots \partial x_n^{a_n}} f$.

Definition 2.22. The space of k times continuously differentiable functions on $\overline{\Omega}$ is denoted by $C^k(\overline{\Omega})$. It is a Banach space when equipped with the norm

$$\|f\|_{C^k(\overline{\Omega})} \stackrel{\text{def.}}{=} \max_{a: |a| \leq k} \max_{x \in \overline{\Omega}} |D^a f(x)|.$$

Remark 2.23. The maximizer in the definition of the norm exists since $D^a f$ is continuous for $|a| \leq k$ and $\overline{\Omega}$ is compact (since Ω is bounded).

Proof. • Start with $C^0(\overline{\Omega})$. $\|f\|_{C^0(\overline{\Omega})} = \max_{x \in \overline{\Omega}} |f(x)|$.

- $\|f\|_{C^0(\overline{\Omega})}$ is a norm: finiteness, positive definiteness and homogeneity are immediate. Check subadditivity: $\|f+g\|_{C^0(\overline{\Omega})} = \max_{x \in \overline{\Omega}} |f(x)+g(x)| \leq \max_{x, y \in \overline{\Omega}} |f(x)| + |g(y)| = \|f\|_{C^0(\overline{\Omega})} + \|g\|_{C^0(\overline{\Omega})}$.
- Now assume $(f_k)_k$ is Cauchy sequence in $C^0(\overline{\Omega})$. Then for any $\varepsilon > 0$ there is some N such that for $i, j > N$ one finds for all $x \in \overline{\Omega}$

$$|f_i(x) - f_j(x)| \leq \|f_i - f_j\|_{C^0(\overline{\Omega})} < \varepsilon.$$

So $(f_k(x))_k$ is a Cauchy sequence in \mathbb{R} and thus, for every $x \in \overline{\Omega}$ there is a limit. We denote the limits by $f(x)$.

- $\|f_i - f\|_{C^0(\overline{\Omega})} \rightarrow 0$: For $\varepsilon > 0$ there is some N such that $|f_i(x) - f_j(x)| < \varepsilon/3$ for all $i, j > N$, $x \in \overline{\Omega}$.
- For all $x \in \overline{\Omega}$ there is some $j_x > N$ such that $|f_{j_x}(x) - f(x)| < \varepsilon/3$. Therefore

$$|f_i(x) - f(x)| \leq |f_i(x) - f_{j_x}(x)| + |f_{j_x}(x) - f(x)| < 2\varepsilon/3$$

for all $i > N$ and $x \in \overline{\Omega}$.

- $f \in C^0(\overline{\Omega})$: For $x \in \overline{\Omega}$ and $\varepsilon > 0$ choose $i \in \mathbb{N}$ such that $\|f_i - f\|_{C^0(\overline{\Omega})} < \varepsilon/3$. Then there exists some $\delta > 0$ such that $|f_i(x) - f_i(y)| < \varepsilon/3$ for $y \in B(x, \delta)$. Finally, for $y \in B(x, \delta)$ get

$$\begin{aligned} |f(x) - f(y)| &\leq |f(x) - f_i(x)| + |f_i(x) - f_i(y)| + |f_i(y) - f(y)| \\ &\leq 2\|f_i - f\|_{C^0(\overline{\Omega})} + |f_i(x) - f_i(y)| < \varepsilon. \end{aligned}$$

- Now $C^1(\overline{\Omega})$. $\|f\|_{C^1(\overline{\Omega})} = \max \left\{ \|f\|_{C^0(\overline{\Omega})}, \|\nabla f\|_{C^0(\overline{\Omega}, \mathbb{R}^n)} \right\}$ where the norm $\|\cdot\|_{C^0(\overline{\Omega}, \mathbb{R}^n)}$ is the maximum of the $\|\cdot\|_{C^0(\overline{\Omega})}$ norm of each component. We show analogously that this is indeed a norm.
- Now let $(f_i)_i$ be a Cauchy sequence in $C^1(\overline{\Omega})$. Then $(f_i)_i$ is a Cauchy sequence in $C^0(\overline{\Omega})$ and $(\nabla f_i)_i$ is a Cauchy sequence in $C^0(\overline{\Omega}, \mathbb{R}^n)$. Therefore, they have limits in $C^0(\overline{\Omega})$ and $C^0(\overline{\Omega}, \mathbb{R}^n)$, which we denote by f and g .
- Now show: $\nabla f = g$: For $x, y \in \overline{\Omega}$, $i \in \mathbb{N}$ we get:

$$\|f_i(y) - f_i(x) - \langle y - x, \nabla f_i(x) \rangle\| = \left\| \int_0^1 \langle \nabla f_i(x_t) - \nabla f_i(x), y - x \rangle dt \right\|$$

(Where $x_t = x + (y - x) \cdot t$. Note also: $\|\nabla f_i(z) - g(z)\| \leq \sqrt{n} \|\nabla f_i - g\|_{C^0(\overline{\Omega}, \mathbb{R}^n)}$.)

$$\leq \left\| \int_0^1 \langle g(x_t) - g(x), y - x \rangle dt \right\| + 2\sqrt{n} \|\nabla f_i - g\|_{C^0(\overline{\Omega}, \mathbb{R}^n)} \cdot \|x - y\|$$

By sending $i \rightarrow \infty$ for $x \neq y$ we obtain

$$\left\| \frac{f(y) - f(x)}{\|y - x\|} - \frac{\langle y - x, g(x) \rangle}{\|y - x\|} \right\| \leq \left\| \int_0^1 \|g(x_t) - g(x)\| dt \right\| \xrightarrow{y \rightarrow x} 0$$

- General $C^{k+1}(\overline{\Omega})$, $k \geq 1$, follow by recursion. Assume we have dealt with $C^k(\overline{\Omega})$. Then for a Cauchy sequence $(f_i)_i$ in $C^{k+1}(\overline{\Omega})$ each component of $(\nabla f_i)_i$ converges in $C^k(\overline{\Omega})$. With the above argument we show that the gradient of the limit f is the limit of the gradients $(\nabla f_i)_i$.

□

We give a prototypical result for the relation between different function spaces.

Proposition 2.24 (Relation between $C^k([0, 1])$). For some integers $k > 0$ the space $C^0([0, 1])$ is the completion of $C^k([0, 1])$ with respect to the norm $\|\cdot\|_{C^0([0, 1])}$. More precisely,

- (i) any sequence $(f_i)_i$ in $C^k([0, 1])$ that is Cauchy with respect to the norm $\|\cdot\|_{C^0([0, 1])}$ has a limit in $C^0([0, 1])$,
- (ii) and any $f \in C^0([0, 1])$ can be reached as limit of such a sequence.

Comment: Result sometimes allows to ‘temporarily’ restrict an optimization problem to a space with higher regularity, since the regularity is only lost ‘in the limit’.

Comment: Approximating sequences are in general not Cauchy in $C^k([0, 1])$.

Proof. • (i) follows directly from $C^k([0, 1]) \subset C^0([0, 1])$. We turn to (ii).

- By the famous Weierstrass approximation theorem any $f \in C^0([0, 1])$ can be approximated to any given precision $\varepsilon > 0$ in the norm $\|\cdot\|_{C^0([0, 1])}$ by a polynomial, see e.g. [Narici, Beckenstein: Topological Vector Spaces; Section 16.5].

- So any f can be written as limit of a convergent (in $\|\cdot\|_{C^0([0,1])}$) sequence $(f_i)_i$ of polynomials; therefore $(f_i)_i$ is Cauchy with respect to this norm. And clearly $f_i \in C^k([0,1])$. \square

Definition 2.25. For an exponent $\beta \in (0, 1]$ a function $f : \overline{\Omega} \rightarrow \mathbb{R}$ is *Hölder continuous* with exponent β if there is a constant $C < \infty$ such that for all $x, y \in \overline{\Omega}$

$$|f(x) - f(y)| \leq C \cdot |x - y|^\beta$$

The space of k times Hölder continuously differentiable functions on $\overline{\Omega}$ with exponent β is denoted by $C^{k,\beta}(\overline{\Omega})$. It is a Banach space when equipped with the norm

$$\|f\|_{C^{k,\beta}(\overline{\Omega})} = \|f\|_{C^k(\overline{\Omega})} + \max_{a: |a|=k} \sup_{\substack{x, y \in \overline{\Omega}: \\ x \neq y}} \frac{|D^a f(x) - D^a f(y)|}{|x - y|^\beta}$$

Proof. • When all derivatives of f up to k -th order are Hölder continuous, $\|f\|_{C^{k,\beta}(\overline{\Omega})}$ is finite. Moreover, $\|\cdot\|_{C^{k,\beta}(\overline{\Omega})}$ is positive definite, homogeneous and subadditive and thus is a norm on $C^{k,\beta}(\overline{\Omega})$.

- Completeness for $k = 0$: Let $(f_i)_i$ be a Cauchy sequence in $C^{0,\beta}(\overline{\Omega})$. Then it is a Cauchy sequence in $C^0(\overline{\Omega})$ and thus its pointwise limit f exists and is in $C^0(\overline{\Omega})$. Then for any $x, y \in \overline{\Omega}$, $x \neq y$

$$\frac{|(f - f_i)(x) - (f - f_i)(y)|}{\|x - y\|^\beta} = \lim_{j \rightarrow \infty} \underbrace{\frac{|(f_j - f_i)(x) - (f_j - f_i)(y)|}{\|x - y\|^\beta}}_{\leq \|f_i - f_j\|_{C^{0,\beta}(\overline{\Omega})}}$$

The right-hand-side is bounded, therefore $\|f\|_{C^{0,\beta}(\overline{\Omega})} \leq \|f - f_i\|_{C^{0,\beta}(\overline{\Omega})} + \|f_i\|_{C^{0,\beta}(\overline{\Omega})} < \infty$ and thus $f \in C^{0,\beta}(\overline{\Omega})$. Moreover, as $i \rightarrow \infty$ the right-hand-side goes to zero, therefore $\|f - f_i\|_{C^{0,\beta}(\overline{\Omega})} \rightarrow 0$.

- Extension to $C^{k,\beta}$, $k > 0$ as above. \square

The following family of spaces will often serve as useful examples.

Definition 2.26. For $p \in [1, \infty]$ let $\ell^p = \{x = (x_1, x_2, \dots) \in \mathbb{R}^{\mathbb{N}} \mid \|x\|_{\ell^p} < \infty\}$ where

$$\|x\|_{\ell^p} = \begin{cases} (\sum_{i=1}^{\infty} |x_i|^p)^{1/p} & \text{if } p < \infty, \\ \sup_i |x_i| & \text{if } p = \infty. \end{cases}$$

The following inequalities are often useful when one must derive upper bounds. They will also allow to prove that ℓ^p is a Banach space.

Proposition 2.27 (Hölder inequality for ℓ^p). For $p, q \in [1, \infty]$ with $\frac{1}{p} + \frac{1}{q} = 1$, $x \in \ell^p$, $y \in \ell^q$ we have $\sum_{i=1}^{\infty} |x_i y_i| \leq \|x\|_{\ell^p} \cdot \|y\|_{\ell^q}$. For $p, q \in (1, \infty)$ there is equality if and only if $\left(\frac{|x_i|}{\|x\|_{\ell^p}}\right)^p = \left(\frac{|y_i|}{\|y\|_{\ell^q}}\right)^q$.

Proof. • For $p = 1$ or $q = 1$ the inequality is immediate. So assume $p, q \in (1, \infty)$.

- For $a, b \geq 0$, $\lambda \in (0, 1)$ one has $a^\lambda b^{1-\lambda} \leq \lambda \cdot a + (1 - \lambda) \cdot b$ ('geometric average \leq arithmetic average'), with equality only if $a = b$.
- The statement is trivial if $a = 0$ or $b = 0$ since then the left-hand-side is zero.
- So assume $a, b > 0$. Then both expressions are well defined for $\lambda \in [0, 1]$. We find equality for $\lambda = 0$ and $\lambda = 1$.
- Let $g(\lambda) = a^\lambda b^{1-\lambda} = \exp(\lambda \log(a) + (1 - \lambda) \log(b))$. We find $\frac{\partial^k}{\partial \lambda^k} g(\lambda) = g(\lambda) \cdot (\log(a) - \log(b))^k$. So $\frac{\partial^2}{\partial \lambda^2} g(\lambda) \geq 0$ and therefore g is convex and so $g(\lambda) \leq g(0) \cdot (1 - \lambda) + g(1) \cdot \lambda$.
- If $a \neq b$ then $\frac{\partial^2}{\partial \lambda^2} g(\lambda) > 0$ and thus the function is strictly convex. So equality can only happen if $a = b$.
- Now set

$$a = \left(\frac{|x_i|}{\|x\|_{\ell^p}} \right)^p, \quad b = \left(\frac{|y_i|}{\|y\|_{\ell^q}} \right)^q, \quad \lambda = \frac{1}{p}, \quad 1 - \lambda = \frac{1}{q}.$$

- Then

$$\frac{|x_i|}{\|x\|_{\ell^p}} \frac{|y_i|}{\|y\|_{\ell^q}} \leq \frac{1}{p} \left(\frac{|x_i|}{\|x\|_{\ell^p}} \right)^p + \frac{1}{q} \left(\frac{|y_i|}{\|y\|_{\ell^q}} \right)^q$$

- Now sum both sides over i to get:

$$\sum_{i=1}^{\infty} \frac{|x_i y_i|}{\|x\|_{\ell^p} \|y\|_{\ell^q}} = \sum_{i=1}^{\infty} \frac{|x_i|}{\|x\|_{\ell^p}} \frac{|y_i|}{\|y\|_{\ell^q}} \leq \sum_{i=1}^{\infty} \left[\frac{1}{p} \left(\frac{|x_i|}{\|x\|_{\ell^p}} \right)^p + \frac{1}{q} \left(\frac{|y_i|}{\|y\|_{\ell^q}} \right)^q \right] = \frac{1}{p} + \frac{1}{q} = 1$$

□

Proposition 2.28 (Minkowski inequality for ℓ^p). For $p \in [1, \infty]$ find $x, y \in \ell^p \Rightarrow x + y \in \ell^p$ with $\|x + y\|_{\ell^p} \leq \|x\|_{\ell^p} + \|y\|_{\ell^p}$. For $p \in (1, \infty)$ there is equality if and only if $x = q \cdot y$ for some $q \geq 0$.

Proof. • For $p = 1$, $p = \infty$ the inequality follows directly (for $p = 1$ from subadditivity of the function $s \mapsto |s|$; for $p = \infty$ as for the $C^0(\overline{\Omega})$ space).

- Inequality is also trivial if $x = 0$ or $y = 0$. So assume $p \in (1, \infty)$, $x, y \neq 0$. In the following let $q \in (1, \infty)$ such that $\frac{1}{p} + \frac{1}{q} = 1$. In particular $(p - 1) \cdot q = p$ and $\frac{1}{q} = \frac{1}{p}(p - 1)$. Then:

$$\begin{aligned} \|x + y\|_{\ell^p}^p &= \sum_{i=1}^{\infty} |x_i + y_i|^p \leq \sum_{i=1}^{\infty} |x_i + y_i|^{p-1} (|x_i| + |y_i|) \\ &\leq \sum_{i=1}^{\infty} |x_i + y_i|^{p-1} |x_i| + \sum_{i=1}^{\infty} |x_i + y_i|^{p-1} |y_i| \end{aligned}$$

(using Hölder inequality)

$$\leq \left(\sum_{i=1}^{\infty} |x_i + y_i|^{(p-1)q} \right)^{1/q} (\|x\|_{\ell^p} + \|y\|_{\ell^p}) = \|x + y\|_{\ell^p}^{p-1} (\|x\|_{\ell^p} + \|y\|_{\ell^p})$$

- This implies the inequality. If $x = q \cdot y$ for some $q \geq 0$ we have equality. Conversely, for Hölders inequality to yield equality it is necessary that

$$\left(\frac{|x_i|}{\|x\|_{\ell^p}} \right)^p = \left(\frac{|x_i + y_i|^{p-1}}{\|x + y\|_{\ell^q}^{p-1}} \right)^q = \left(\frac{|x_i + y_i|}{\|x + y\|_{\ell^p}} \right)^p$$

which requires existence of some q .

□

Proposition 2.29. For $p \in [1, \infty]$ the space ℓ^p equipped with $\|\cdot\|_{\ell^p}$ is a Banach space.

Proof. • Finiteness, positive definiteness and homogeneity of $\|\cdot\|_{\ell^p}$ are immediate. Subadditivity follows from the Minkowski inequality. So ℓ^p is normed space.

- For $p = \infty$ the proof for completeness is analogous to $C^0(\overline{\Omega})$. So let $p < \infty$.
- Let $(x_k)_k$ be a Cauchy sequence in ℓ^p , where for each k $(x_{k,i})_i$ is a sequence in \mathbb{R} . Then $|x_{k,i} - x_{j,i}| \leq \|x_k - x_j\|_{\ell^p}$, so for each i $(x_{k,i})_k$ is a Cauchy sequence in \mathbb{R} . Denote the sequence of limits by $(z_i)_i$.
- Since $(x_k)_k$ is Cauchy, $\|x_k\|_{\ell^p} < M$ for some $M < \infty$. So for all $n \in \mathbb{N}$

$$\sum_{i=1}^n |x_{k,i}|^p \leq M^p \quad \Rightarrow \quad \sum_{i=1}^n |z_i|^p \leq M^p$$

and consequently as $n \rightarrow \infty$ find $\|z\|_{\ell^p} \leq M$, i.e. $z \in \ell^p$.

- For any $\varepsilon > 0 \exists N$ such that $\forall m, n > N, k \in \mathbb{N}$ get

$$\sum_{i=1}^k |x_{m,i} - x_{n,i}|^p \leq \|x_m - x_n\|_{\ell^p}^p \leq \varepsilon$$

Now let $m \rightarrow \infty$, then $k \rightarrow \infty$ to get $\|z - x_n\|_{\ell^p}^p \leq \varepsilon$.

□

Remark 2.30. Other prominent examples that are also very common in applications are L^p spaces and Sobolev spaces.

2.4 Compactness, topological dual and convex duality in Banach spaces

We introduce the topological dual of a Banach space, which can be interpreted as an ‘approximation’ for an inner product on Banach spaces. We study related questions on compactness and see how far we can adapt notions of convex duality to this setting.

In Hilbert spaces we have shown that projections onto closed convex sets, i.e. points of minimal distance, exist (and are unique). This is in general no longer true in Banach spaces, due to a lack of a notion of orthogonality.

To gain some intuition, we first give an example where projections exist and then give a counterexample.

Example 2.31. • Let $X = C^0([0, 1])$, equipped with the norm $\|\cdot\| = \|\cdot\|_{C^0([0,1])}$.

- Let $Y = \{f \in X : \int_0^1 f(x) dx = 0\}$. Y is a closed subspace of X .

- Consider now the projection problem from X onto Y . For $f \in X$ study $\inf_{g \in Y} \|f - g\|$.
- Intuition: for given $f \neq Y$, how do we change ‘mean’ of f with minimal perturbation in the norm? \Rightarrow change each point of f by same value.
- Let $g \in Y$ and set $h = f - g$. From $\int_0^1 g \, dx = 0$ we find that we need to find $h \in X$ with $\int_0^1 f \, dx = \int_0^1 h \, dx$ that has minimal norm.
- This implies that $\|h\| \geq |\int_0^1 f \, dx|$ (otherwise $|\int_0^1 h \, dx| \leq \int_0^1 \|h\| \, dx < |\int_0^1 f \, dx|$).
- Try constant function $h(x) = \int_0^1 f(y) \, dy$. This satisfies integral constraint and we find $\|h\| = |\int_0^1 f(y) \, dy|$. So h is optimal and $g(x) = f(x) - \int_0^1 f(y) \, dy$.
- Note: h is unique. Assume, h were not constant. Then $\|h\| > |\int_0^1 h \, dx|$.

Now, by giving a counterexample, we show that projections onto closed convex sets do not always exist in Banach spaces.

Proposition 2.32. For a Banach space $(X, \|\cdot\|)$ and a closed subspace $Y \subset X$ and some fixed $x \in X$, there is not always a minimizer of $\inf_{y \in Y} \|x - y\|$.

Proof. • The proof is a slight modification of the example above.

- Let $X = \{f \in C^0([0, 1]) : f(0) = 0\}$ with norm $\|\cdot\| = \|\cdot\|_{C^0([0, 1])}$. X is a closed subspace of $C^0([0, 1])$ (why? check Cauchy sequences) and therefore X is a Banach space.
- Let $Y = \{g \in X : \int_0^1 g(x) \, dx = 0\}$.
- Analogous to above: fix $f \in X \setminus Y$, rewrite problem. Let $g \in Y$, set $h = f - g$. Solve $s = \inf\{\|h\| : h \in X : \int_0^1 h \, dx = \int_0^1 f \, dx\}$. Almost as above, but now have additional constraint $h(0) = 0$, since we may not change $f(0) = 0$.
- So constant shift no longer works, infimal norm of h cannot be smaller than above, i.e. $s \geq |\int_0^1 f \, dx|$. Since feasible h cannot be constant, must have $\|h\| > |\int_0^1 f \, dx|$ for all feasible h .
- Now show that infimum $s = |\int_0^1 f \, dx|$ which then implies that no minimizer exists. Do this by ‘approximating’ constant shift as good as possible, while obeying the $h(0) = 0$ constraint.
- Set $h_i(x) = (\int_0^1 f(y) \, dy) \cdot (1 + 1/i) \cdot x^{1/i}$. $h_i(0) = 0$, $\int_0^1 h_i(x) \, dx = \int_0^1 f(y) \, dy$ and $\|h_i\| = |h_i(1)| = |\int_0^1 f(y) \, dy| \cdot (1 + 1/i)$. So $(h_i)_i$ is a minimizing sequence.

Sketch: h_i , approximation of constant shift.

Comment: $(h_i)_i$ is not Cauchy. Its pointwise limit is $h_\infty(x) = 1$ for $x \in (0, 1]$, $h(0) = 0$, which is not in $X \subset C^0([0, 1])$.

□

So the projection does not exist, but we can find a sequence $(h_i)_i$ that is approximately orthogonal to the subspace. Such a sequence exists in general.

Proposition 2.33 (Almost orthogonal element). For a Banach space X let Y be a subspace, $Y \neq X$. For any $x \in X$ and $\theta > 1$ there are some $x_\theta \in X$, $y_\theta \in Y$ such that $x = x_\theta + y_\theta$ and $\text{dist}(x, Y) = \text{dist}(x_\theta, Y) \leq \|x_\theta\| \leq \theta \cdot \text{dist}(x, Y)$.

Proof. • $\text{dist}(x, Y) = \inf_{y \in Y} \|x - y\|$ is finite and non-negative.

- Let $y_\theta \in Y$ such that $\|x - y_\theta\| < \theta \cdot \text{dist}(x, Y)$ (take from a minimizing sequence) and set $x_\theta = x - y_\theta$.
- $\text{dist}(x_\theta, Y) = \inf_{y \in Y} \|x - y_\theta - y\| = \inf_{y \in Y} \|x - y\| = \text{dist}(x, Y)$.

□

Remark 2.34. If Y is not closed, then may have $\text{dist}(x, Y) = 0$ even when $x \notin Y$ and $\|x_\theta\| \rightarrow 0$ as $\theta \searrow 1$.

Corollary 2.35. If Y is closed and $Y \neq X$ then for any $\theta > 1$ there is some x_θ with $\|x_\theta\| = 1$ and $\text{dist}(x_\theta, Y) \geq \frac{1}{\theta}$.

We have learned that an important ingredient for existence of minimizers is compactness. Now study (strong) compactness on Banach spaces.

Proposition 2.36. On a normed space X the notions of compactness and sequential compactness are equivalent.

Proof. • **compactness \Rightarrow sequential compactness:** Let $A \subset X$ be compact, let $(x_k)_k$ be a sequence in A . Assume $(x_k)_k$ has no cluster point. Then $\forall y \in A \exists \delta_y > 0$ such that $N_y = \{k \in \mathbb{N} : x_k \in B(y, \delta_y)\}$ is finite.

- The sets $B(y, \delta_y)$ for $y \in A$ form an open cover of A . Since A is compact, there is a finite subcover for some (y_1, \dots, y_n) :

$$A \subset \bigcup_{y \in A} B(y, \delta_y) \Rightarrow A \subset \bigcup_{i=1}^n B(y_i, \delta_{y_i}) \Rightarrow \mathbb{N} = \bigcup_{i=1}^n N_i$$

- This implies that \mathbb{N} is finite. So $(x_k)_k$ must have at least one cluster point and thus A is sequentially compact.
- **sequential compactness \Rightarrow compactness:** For any $\varepsilon > 0$ can cover A with finitely many ε -balls (otherwise, we could define sequence in A without cluster points via $x_k \in A \setminus \bigcup_{i=1}^{k-1} B(x_i, \varepsilon)$).
- For an open cover $A \subset \bigcup_{i \in I} U_i$, $\exists \varepsilon_0 > 0$ such that $\forall x \in A \exists i_x \in I$ such that $B(x, \varepsilon_0) \subset U_{i_x}$. Prove this by contradiction.
- Assume $\forall k \in \mathbb{N} \exists x_k \in A$ such that $\forall i \in I B(x_k, 1/k) \not\subset U_i$. Since A is sequentially compact, $(x_k)_k$ has cluster point $x \in A$. Let $(x_{k_j})_j$ be subsequence converging to x . $\exists \delta > 0$ such that $B(x, \delta) \subset U_i$ for some $i \in I$.
- $\exists j \in \mathbb{N}$ such that $\frac{1}{k_j} < \frac{\delta}{2}$ and $\|x_{k_j} - x\| < \frac{\delta}{2} \Rightarrow B(x_{k_j}, 1/k_j) \subset U_i$, which is a contradiction.
- So for this ε_0 chose $x_1, \dots, x_n \in A$ such that

$$A \subset \bigcup_{k=1}^n B(x_k, \varepsilon_0) \subset \bigcup_{k=1}^n U_{i_{x_k}}$$

□

Corollary 2.37. Projections onto compact sets exist in Banach spaces.

Proof. Can extract cluster point from any minimizing sequence of $\text{dist}(x, Y)$. Is minimizer (and therefore, projection) since $y \mapsto d(x, y)$ is continuous (by construction of metric topology). \square

Proposition 2.38. For a Banach space X we find: $[\overline{B(0, 1)} \text{ compact}] \Leftrightarrow [X \text{ is finite-dimensional}]$

Proof. $\bullet \Rightarrow$: $\overline{B(0, 1)} \subset \bigcup_{y \in B(0, 1)} B(y, \frac{1}{2}) \Rightarrow$ (finite subcover from compactness) $\overline{B(0, 1)} \subset \bigcup_{i=1}^n B(y_i, \frac{1}{2})$.

- $\bullet Y = \text{span}\{y_1, \dots, y_n\}$ is closed subspace. Assume $Y \neq X$.
- \bullet By Corollary 2.35 for $\theta > 1$ there is some x_θ with $\|x_\theta\| = 1$ and $\text{dist}(x_\theta, \{y_1, \dots, y_n\}) \geq \text{dist}(x_\theta, Y) \geq \frac{1}{\theta}$.
- \bullet But since $\|x_\theta\| = 1 \Rightarrow x_\theta \in \overline{B(0, 1)} \subset \bigcup_{i=1}^n B(y_i, \frac{1}{2}) \Rightarrow \text{dist}(x_\theta, \{y_1, \dots, y_n\}) < \frac{1}{2}$. For $\theta < 2$ this is a contradiction.
- $\bullet \Leftarrow$: If X is finite dimensional, identify it with \mathbb{R}^n . All norms are equivalent on \mathbb{R}^n . Therefore compactness of $\overline{B(0, 1)}$ follows from Heine–Borel. \square

So $\overline{B(0, 1)}$ in $C^0([0, 1])$ is not compact. However, one can show that $\overline{B(0, 1)}$ of $C^1([0, 1])$ is compact with respect to the $C^0([0, 1])$ topology.

Definition 2.39 (Equicontinuity). A family of functions $f_i : V \rightarrow \mathbb{R}$, $i \in I$ is equicontinuous if for any $x \in V$ and $\varepsilon > 0$ there is some $\delta > 0$ such that $|f_i(y) - f_i(x)| < \varepsilon$ for all y with $\|y - x\| < \delta$, $i \in I$.

Proposition 2.40 (Arzelà–Ascoli). A set $A \subset C^0([0, 1])$ is (sequentially, equivalent, why?) pre-compact (the closure of A is compact) if and only if it is bounded and equicontinuous.

Corollary 2.41. The set $A = B(0, 1)$ of $C^1([0, 1])$ is pre-compact with respect to the $C^0([0, 1])$ topology.

Proof. \bullet For every $f \in A$, $x \in [0, 1]$ have $|f(x)| \leq 1$ and $|f'(x)| \leq 1$. Therefore A is bounded in $C^0([0, 1])$ and A is equicontinuous: $|f(x) - f(y)| \leq |x - y|$. \square

Definition 2.42 (Separable metric space). A topological space X is *separable* if it contains a countable, dense subset A .

Remark 2.43. A dense in X means that any point in X can be reached as the limit of a sequence in A , or equivalently that any non-empty open set in X has non-empty intersection with A . Intuitively, separability is a bound on the cardinality of the space. Even if X is uncountable, it can be ‘reasonably approximated’ by countable elements. On separable spaces many proofs are constructive and one can avoid the axiom of choice.

Example 2.44. (i) The set \mathbb{R} with the usual topology is separable, as \mathbb{Q} is dense in \mathbb{R} .

(ii) The set \mathbb{R} with the discrete topology (all sets are open) is not separable, since the only set that is dense in this space is \mathbb{R} itself, which is not countable.

More examples:

Proposition 2.45. A compact metric space (X, d) is separable.

Proof. • For $n \in \mathbb{N}$ have $X \subset \bigcup_{x \in X} B(x, \frac{1}{n})$ as an open cover. Therefore, there is a finite subcover $X \subset \bigcup_{i=1}^{k_n} B(x_{n,i}, \frac{1}{n})$.

- The countable set $A = \bigcup_{n=1}^{\infty} \{x_{n,1}, \dots, x_{n,k_n}\}$ is dense in X : For $x \in X$ and $\varepsilon > 0$, set $n > 1/\varepsilon$, then $x \in B(x_{n,i}, \frac{1}{n}) \subset B(x_{n,i}, \varepsilon)$ for some $i \in \{1, \dots, k_n\}$.
- So we can generate a sequence in A that converges to x .

□

Proposition 2.46. An infinite-dimensional Banach space with a Schauder basis is separable.

Remark 2.47. The converse implication is not true in general, see e.g. [Narici, Beckenstein: Topological Vector Spaces; Section 11.1] (which is primarily a very interesting brief historical summary of the mathematical life of Stefan Banach).

Proof. • Let $(x_i)_i$ be a Schauder basis of X . In particular it is countable. W.l.o.g. we can assume that $\{\|x_i\|\}_i$ is bounded by some $C < \infty$.

- Let $A_n = \{\sum_{i=1}^n s_i x_i \mid (s_i)_i \in \mathbb{Q}^n\}$. Since \mathbb{Q} is countable and A_n is a finite union of countable sets $\{\mathbb{Q} \cdot x_i\}$, A_n is countable.
- Let $A = \bigcup_{n=1}^{\infty} A_n$. Since A is a countable union of countable sets, A is countable.
- Fix now $x \in X$ and some $\varepsilon > 0$.
- By definition there is a (unique) sequence $(\alpha_i)_i$ in \mathbb{R} such that $\lim_{n \rightarrow \infty} \|x - \sum_{i=1}^n \alpha_i x_i\| \rightarrow 0$, in particular there is some n such that $\|x - \sum_{i=1}^n \alpha_i x_i\| < \varepsilon/2$.
- Let now $\beta_i \in \mathbb{Q}$ such that $|\alpha_i - \beta_i| < \frac{\varepsilon}{2^{i+1}C}$. Let $z_n = \sum_{i=1}^n \alpha_i x_i$, $y_n = \sum_{i=1}^n \beta_i x_i \in A$.

$$\|x - y_n\| \leq \|x - z_n\| + \|z_n - y_n\| < \frac{\varepsilon}{2} + \sum_{i=1}^n |\alpha_i - \beta_i| \cdot \|x_i\| < \frac{\varepsilon}{2} + \varepsilon \sum_{i=1}^n 2^{-i-1} < \varepsilon$$

□

Proposition 2.48. $C^0([0, 1])$ is separable.

We use a small auxiliary Lemma for the proof that is often helpful when working on compact spaces.

Lemma 2.49. Let (X, d) be a compact metric space. A continuous function $f : X \rightarrow \mathbb{R}$ is uniformly continuous, i.e. $\forall \varepsilon > 0 \exists \delta > 0$ such that $|f(x) - f(y)| < \varepsilon$ when $d(x, y) < \delta$.

Proof. • For every $\varepsilon > 0$, $x \in X \exists \delta_x > 0$ such that $|f(x) - f(y)| < \varepsilon/2$ if $y \in B(x, \delta_x)$.

- The sets $(B(x, \delta_x/2))_{x \in X}$ form an open cover of X and X is compact \Rightarrow there is a finite subcover with midpoints $\{x_1, \dots, x_n\}$. Let $\delta = \min\{\delta_{x_1}, \dots, \delta_{x_n}\} > 0$.
- Now let $x, y \in X$, $d(x, y) < \delta/2$. Then $x \in B(x_i, \delta_{x_i}/2)$ for some i and therefore $y \in B(x_i, \delta_{x_i})$.

- So $|f(x) - f(y)| \leq |f(x) - f(x_i)| + |f(y) - f(x_i)| < \varepsilon$.

□

Proof of Proposition 2.48. • By Lemma 2.49 any $f \in C^0([0, 1])$ is uniformly continuous. So for any $\varepsilon > 0$ can find $n \in \mathbb{N}$ such that $|f(x) - f(y)| < \varepsilon$ for $|x - y| < 2^{-n}$. So we can uniformly approximate f by piecewise affine interpolation between values at points $i \cdot 2^{-n}$ for $i \in \{0, \dots, 2^n\}$.

- Define set of ‘tent functions’ of scale n for $i \in \{0, \dots, 2^n\}$:

$$f_{n,i}(x) = \begin{cases} 0 & \text{if } |x - i \cdot 2^{-n}| \geq 2^{-n}, \\ 1 - |2^n x - i| & \text{else} \end{cases}$$

Sketch: Tent functions.

- So piecewise affine interpolation with resolution n can be written as superposition of functions $f_{n,i}$. The functions $(f_{n,i})_{n,i}$ are an ‘overcomplete’ Schauder basis of $C^0([0, 1])$. The decomposition may not be unique, since the $f_{n,i}$ are not all linearly independent.
- Could re-establish uniqueness, by iteratively removing linearly dependent elements. But reasoning of Prop. 2.46 does not depend on uniqueness of the decomposition. So separability of $C^0([0, 1])$ follows.

□

Remark 2.50. (i) Since $C^k([0, 1])$ can be parametrized by $C^0([0, 1])$ and a finite number of integration constants, this argument extends to $C^k([0, 1])$.

(ii) For spaces X that can be written as subsets of $C^k([0, 1])$ with respect to coarser norms by construction $C^k([0, 1])$ is dense in X and thus X is then also separable. This covers many spaces of integrable functions and Sobolev spaces.

Comment: Many ‘practical’ spaces remain separable, even if they ‘look’ very high dimensional. For this need ‘sufficiently coarse’ topology. (Recall \mathbb{R} with discrete topology is not separable.)

Proposition 2.51. The spaces ℓ^p for $p \in [1, \infty)$ have a Schauder basis and are separable.

Proof. • Let $e_i \in \ell^p$ with $e_{i,j} = \delta_{i,j}$. Claim: $(e_i)_{i \in \mathbb{N}}$ is a Schauder basis of ℓ^p .

- Let $x \in \ell^p$. Set $z_i = \sum_{j=1}^i e_j x_j$, $z_{i,j} = x_j \delta_{j \leq i}$. Find:

$$\|x - z_i\|_{\ell^p}^p = \sum_{j=1}^{\infty} |x_j - z_{i,j}|^p = \sum_{j=1}^{\infty} |x_j - x_j \delta_{j \leq i}|^p = \sum_{j=i+1}^{\infty} |x_j|^p = \|x\|_{\ell^p}^p - \sum_{j=1}^i |x_j|^p \rightarrow 0$$

as $i \rightarrow \infty$. So $z_i \rightarrow x$.

- This decomposition is unique. Let $(y_i)_i$ be another sequence such that $\lim_{i \rightarrow \infty} v_i \rightarrow x$ for $v_i = \sum_{j=1}^i y_j \cdot e_j$ with $|y_{i_0} - x_{i_0}| > \delta$ for some i_0 . Then $\|v_i - x\| \geq \delta$ for all $i \geq i_0$ and thus this sequence cannot converge to x .

□

Proposition 2.52. The space ℓ^∞ is not separable.

Proof. • Let $A \subset \ell^\infty$ be countable, i.e. $A = (a_k)_{k \in \mathbb{N}}$ where for each $k \in \mathbb{N}$ have $a_k = (a_{k,1}, a_{k,2}, \dots) \in \ell^\infty$.

- Define sequence $(b_k)_k$ by

$$b_k = \begin{cases} a_{k,k} + 1 & \text{if } |a_{k,k}| \leq 1, \\ 0 & \text{if } |a_{k,k}| > 1. \end{cases}$$

- $\sup_{k \in \mathbb{N}} |b_k| \leq 2$, i.e. $\|b\|_{\ell^\infty} \leq 2$ and thus $b \in \ell^\infty$.
- $\|b - a_k\|_{\ell^\infty} \geq |b_k - a_{k,k}| \geq 1$ for all $k \in \mathbb{N}$. Therefore, b cannot be approximated by a sequence in A and thus no countable set can be dense in ℓ^∞ . □

Proposition 2.53. An infinite-dimensional Hilbert space H is separable if and only if it has a orthonormal Schauder basis.

Proof. • \Leftarrow : If H has a orthonormal Schauder basis, separability follows from Prop. 2.46.

- \Rightarrow : Let $\{a_k\}_k$ be a countable set that is dense in H . Apply Gram-Schmidt orthonormalization to $(a_k)_k$ to generate orthonormal sequence $(x_i)_i$. (Start with smallest k such that $a_k \neq 0$, set $x_1 = a_k / \|a_k\|$, $i = 1$. Then increase k until $a_k \notin \text{span}\{x_j\}_{j=1}^i$. Add orthonormal component of a_k as new basis vector to $(x_i)_i$, increase i . Since H is infinite-dimensional and $\{a_k\}_k$ is dense, i will tend to ∞ . Note that $i \leq k$ throughout the process and that $a_k \in \text{span}\{x_j\}_{j=1}^k$ at all steps.)
- $(x_i)_i$ is orthonormal by construction. Show that it is Schauder basis.
- By construction $a_k = \sum_{i=1}^k x_i \langle x_i, a_k \rangle$. For any $z \in H$ by density there is a subsequence $(a_{k_j})_j$ that converges to z . So

$$\begin{aligned} \left\| z - \sum_{i=1}^{k_j} x_i \langle x_i, z \rangle \right\| &\leq \|z - a_{k_j}\| + \left\| \sum_{i=1}^{k_j} x_i \langle x_i, a_{k_j} - z \rangle \right\| \\ &\leq \|z - a_{k_j}\| + \left(\left\langle \sum_{i=1}^{k_j} x_i \langle x_i, a_{k_j} - z \rangle, \sum_{i=1}^{k_j} x_i \langle x_i, a_{k_j} - z \rangle \right\rangle \right)^{1/2} \end{aligned}$$

(Bessel inequality, cf. Example 1.91)

$$\leq 2\|z - a_{k_j}\| \rightarrow 0 \quad \text{as } j \rightarrow \infty.$$

- By orthonormality of $(x_i)_i$ the coefficients $\langle x_i, z \rangle$ are unique. □

Corollary 2.54. Every separable Hilbert space H is isomorphic to ℓ^2 , i.e. there is a bijection $\phi : H \rightarrow \ell^2$ such that $\langle x, y \rangle_H = \langle \phi(x), \phi(y) \rangle_{\ell^2}$.

Definition 2.55 (Linear transformations and functionals). • For two normed spaces X, Y , $D \subset X$ a map $T : D \rightarrow Y$ is called *transformation* from X to Y with domain D .