

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 semi-continuous, 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 semi-continuous* 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 semi-continuous if it is lower semi-continuous on H .

Example 1.20. $f(x) = \begin{cases} 0 & \text{if } x \leq 0, \\ 1 & \text{if } x > 0 \end{cases}$ is lower semi-continuous, $f(x) = \begin{cases} 0 & \text{if } x < 0, \\ 1 & \text{if } x \geq 0 \end{cases}$ 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 semi-continuous 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 semi-continuous.
- (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 semi-continuous 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 $f(y) \geq \langle y, p \rangle = f(0) + \langle y - 0, p \rangle$ 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: $\langle p - 0, \frac{p}{\|p\|} - p \rangle = \|p\| - \|p\|^2 < 0$ 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

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

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

• $x \in C$:

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

□

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

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

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

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

- \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 $T_C x = \text{cone } D$.

- 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 semi-continuous. 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.