

Convex Sets

- (1) $\{C_i\}_{i \in I}$ family of convex sets $\implies \bigcap_{i \in I} C_i$ is convex
 (2) $C_i \subseteq \mathbb{R}^{n_i}$ convex for $i = 1, \dots, k \implies C_1 \times \dots \times C_k \subseteq \mathbb{R}^{n_1} \times \dots \times \mathbb{R}^{n_k}$ is convex
 (3) $C_i \subseteq \mathbb{R}^n$ convex and $\alpha_i \in \mathbb{R}$ for $i = 1, \dots, k \implies \alpha_1 C_1 + \dots + \alpha_k C_k \subseteq \mathbb{R}^n$ is convex
 (4) $C \subseteq \mathbb{R}^n$ convex and T affine $\implies T(C)$ is convex
 (5) $D \subseteq \mathbb{R}^n$ convex and T affine $\implies T^{-1}(D)$ is convex

Proposition 0.1. Let $V \subseteq \mathbb{R}^n$ be an affine manifold and $S \subseteq V$ be given. Then:

- (a) $\text{int}_V S \neq \emptyset \implies V = \text{aff } S$ and hence $\text{ri } S \neq \emptyset$.
 (a) $\text{int } S \neq \emptyset \implies \mathbb{R}^n = \text{aff } S$ and hence $\text{ri } S = \text{int } S \neq \emptyset$.

Proposition 0.2. If $\emptyset \neq C \subseteq \mathbb{R}^n$ convex, then $\text{ri } C \neq \emptyset$.

Proposition 0.3. (resolution lemma) Let $\emptyset \neq C \subseteq \mathbb{R}^n$ convex, $x \in \text{cl } C$ and $y \in \text{ri } C$. Then $[y, x] \subseteq C$.

Proposition 0.4. Assume that $\bar{x} \in \text{ri } C$. Then

- (a) $\exists \delta > 0$ such that $\bar{B}(\bar{x}; \delta) \cap \text{aff } C \subseteq \text{ri } C$
 (b) Given any $x \in \text{aff } C$, $\exists \varepsilon > 0$ s.t. $\bar{x} + t(x - \bar{x}) \in \text{ri } C$, for all t s.t. $|t| \leq \varepsilon$
 (c) Given any u lying in the subspace parallel to $\text{aff } C$, $\exists \varepsilon > 0$ s.t. $\bar{x} + tu \in \text{ri } C$, for all t s.t. $|t| < \varepsilon$.

Proposition 0.5. Let $\emptyset \neq C \subseteq \mathbb{R}^n$ be convex. Then,

- (a) $\text{aff}(\text{ri } C) = \text{aff } C = \text{aff}(\text{cl } C)$
 (b) $\text{ri}(\text{ri } C) = \text{ri } C = \text{ri}(\text{cl } C)$
 (c) $\text{cl}(\text{ri } C) = \text{cl } C = \text{cl}(\text{cl } C)$

Proposition 0.6. The sets $\text{ri } C$, C , and $\text{cl } C$ all have the same ri , cl , and aff .

Proposition 0.7. Let C_1, C_2 convex. Then the following are equivalent:

- (1) $\text{ri } C_1 = \text{ri } C_2$,
 (2) $\text{cl } C_1 = \text{cl } C_2$,
 (3) $\text{ri } C_1 \subseteq C_2 \subseteq \text{cl } C_1$.

Proposition 0.8. If $C \subseteq \mathbb{R}^m$ is convex and $A : \mathbb{R}^m \mapsto \mathbb{R}^n$ is affine, then

- (1) $\text{ri } A(C) = A(\text{ri } C)$
 (2) $\text{cl } A(C) \supseteq A(\text{cl } C)$ (no need for convexity)
 (3) $\text{aff } A(C) = \text{aff}(A(\text{ri } C)) = \text{aff}(A(\text{cl } C)) = A(\text{aff } C)$

Corollary 0.1. If $\alpha_1, \dots, \alpha_k \in \mathbb{R}$ and $C_1, \dots, C_k \in \mathbb{R}^n$ convex. Then,

$$\text{ri}(\alpha_1 C_1 + \dots + \alpha_k C_k) = \alpha_1 \text{ri } C_1 + \dots + \alpha_k \text{ri } C_k.$$

Lemma 0.1. For $S_i \subseteq \mathbb{R}^n$, $i = 1, \dots, k$,

$$\text{ri}(S_1 \times \dots \times S_k) = \text{ri } S_1 \times \dots \times \text{ri } S_k.$$

Proposition 0.9. Let $A : \mathbb{R}^n \mapsto \mathbb{R}^n$ be affine and $D \subseteq \mathbb{R}^n$ be convex. If $A^{-1}(\text{ri } D) \neq \emptyset$ then

$$\begin{aligned} \text{ri } A^{-1}(D) &= A^{-1}(\text{ri } D) \\ \text{cl } A^{-1}(D) &= A^{-1}(\text{cl } D). \end{aligned}$$

The sets $A^{-1}(\text{ri } D)$, $A^{-1}(D)$, $A^{-1}(\text{cl } D)$ have the same affine hull, namely $A^{-1}(\text{aff } D)$.

Proposition 0.10. If $C_1, \dots, C_k \subseteq \mathbb{R}^n$ are convex and $\bigcap_{i=1}^k \text{ri } C_i \neq \emptyset$ then

$$\begin{aligned} \text{ri} \left(\bigcap_{i=1}^k C_i \right) &= \bigcap_{i=1}^k \text{ri } C_i \\ \text{cl} \left(\bigcap_{i=1}^k C_i \right) &= \bigcap_{i=1}^k \text{cl } C_i. \end{aligned}$$

Asymptotic or Recession Cone

Definition 0.1. Let $\emptyset \neq C \subseteq \mathbb{R}^n$ be closed and convex. Its **asymptotic cone**, denoted by C_∞ , is defined as

$$C_\infty := \{d \in \mathbb{R}^n : x + td \in C, \forall t > 0, \forall x \in C\}.$$

Proposition 0.11. C_∞ is a closed convex cone containing 0.

Proposition 0.12. If for source $x_0 \in C$ and $d \in \mathbb{R}^n$ we have

$$\{x_0 + td : t > 0\} \subseteq C$$

then $d \in C_\infty$.

Lemma 0.2. If $d = \lim_{k \rightarrow \infty} \alpha_k x^k$ where $\{x^k\} \subseteq C$ and $\{\alpha_k\} \subseteq \mathbb{R}_{++} \rightarrow 0$ then $d \in C_\infty$.

Proposition 0.13. C is bounded $\iff C_\infty = \{0\}$.

Proposition 0.14. (a) If $\{C_j\}_{j \in J}$ is a family of closed convex sets such that $\bigcap_{j \in J} C_j \neq \emptyset$ then

$$\left(\bigcap_{j \in J} C_j \right)_\infty = \bigcap_{j \in J} (C_j)_\infty$$

(b) If $C_i \subseteq \mathbb{R}^{n_i}$ is a non-empty closed convex set for $i = 1, 2, \dots, k$ then

$$(C_1 \times \dots \times C_k)_\infty = (C_1)_\infty \times \dots \times (C_k)_\infty.$$

(c) Let $A : \mathbb{R}^n \mapsto \mathbb{R}^m$ be linear. Then,

(i) If $\emptyset \neq C$ is closed convex and $A(C)$ is closed then $A(C_\infty) \subseteq [A(C)]_\infty$.

(ii) If $\emptyset \neq D$ is closed convex and $A^{-1}(D) \neq \emptyset$ then $A^{-1}(D_\infty) = [A^{-1}(D)]_\infty$.

Proposition 0.15. Let $A : \mathbb{R}^n \mapsto \mathbb{R}^m$ be linear, $\emptyset \neq C \subseteq \mathbb{R}^n$ closed convex such that $A^{-1}(0) \cap C_\infty = \{0\}$ (or $\subseteq -C_\infty$) then:

- (i) $A(C)$ is closed
 (ii) $A(C_\infty) = [A(C)]_\infty$

Definition 0.2. The **linearity space** of C is defined as $C_\infty \cap (-C_\infty)$ which you can prove is the largest subspace contained in C_∞ .

Convex Functions

Notation 1. Let us denote $\bar{\mathbb{R}} = \mathbb{R} \cup \{\pm\infty\} = [-\infty, \infty]$ and for $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ we denote

$$\begin{aligned} \text{dom } f &= \{x \in \mathbb{R}^n : f(x) < \infty\} \\ \text{epi } f &= \{(x, r) \in \mathbb{R}^n \times \mathbb{R} : f(x) \leq r\} \\ \text{epi}_s f &= \{(x, r) \in \mathbb{R}^n \times \mathbb{R} : f(x) < r\} \end{aligned}$$

$$f^{-1}(-\infty, r] = \{x \in \mathbb{R}^n : f(x) \leq r\}$$

$$f^{-1}(-\infty, r) = \{x \in \mathbb{R}^n : f(x) < r\}.$$

Definition 0.3. A **convex function** $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is a function where its **epigraph** $\text{epi } f$ is convex. We say such functions $f \in E\text{-Conv } \mathbb{R}^n$.

Definition 0.4. $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is **proper convex** if $f \in E\text{-Conv } \mathbb{R}^n$, $f(x) > -\infty$ for all $x \in \mathbb{R}^n$, and $f \neq \infty$ (or equivalently, $\exists x \in \mathbb{R}^n$ such that $f(x) < \infty$). We say that such functions $f \in \text{Conv } \mathbb{R}^n$.

Proposition 0.16. Let $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ be given. Then the following are equivalent:

- (a) $f \in E\text{-Conv } \mathbb{R}^n$
- (b) $\text{epi}_S f$ is a convex set
- (c) $f(\alpha x_0 + (1-\alpha)x_1) \leq \alpha f(x_0) + (1-\alpha)f(x_1)$ for all $\alpha \in (0, 1)$ and $\forall x_0, x_1 \in \text{dom } f$.

Proposition 0.17. Let $f \in E\text{-Conv } \mathbb{R}^n$. Then

- (a) $f^{-1}[-\infty, r]$ is convex for all $r \in \bar{\mathbb{R}}$
- (b) $f^{-1}[-\infty, r]$ is convex for all $r \in \bar{\mathbb{R}}$

So $\text{dom } f$ is convex.

Proposition 0.18. (Jensen's inequality) If $f \in E\text{-Conv } \mathbb{R}^n$ then

$$f(\alpha_0 x_0 + \dots + \alpha_k x_k) \leq \sum_{i=1}^k \alpha_i f(x_i)$$

for all $(\alpha_0, \dots, \alpha_k) \in \Delta_k$ the k -dimensional probability simplex and $x_i \in \text{dom } f$ for $i = 0, 1, \dots, k$.

Definition 0.5. A function $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is **strictly convex** if f is proper and

$$f(\alpha x_0 + (1-\alpha)x_1) < \alpha f(x_0) + (1-\alpha)f(x_1)$$

for all $\alpha \in (0, 1)$ and $x_0 \neq x_1 \in \text{dom } f$.

Definition 0.6. A function $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is **β -strongly convex** if f is proper and

$$f(\alpha x_0 + (1-\alpha)x_1) \leq \alpha f(x_0) + (1-\alpha)f(x_1) - \frac{\beta}{2} \alpha(1-\alpha) \|x_0 - x_1\|^2$$

for all $\alpha \in (0, 1)$ and $x_0 \neq x_1 \in \text{dom } f$.

Remark 0.1. We have f is β -strongly convex $\implies f$ is strictly convex $\implies f$ convex

Proposition 0.19. f is β -strongly convex $\iff f - \frac{\beta}{2} \|\cdot\|^2$ is convex.

Proposition 0.20. (a) If $f_1, \dots, f_k \in \text{Conv } \mathbb{R}^n$ and $\alpha_1, \dots, \alpha_n \geq 0$ then

$$\alpha_1 f_1 + \dots + \alpha_n f_k \in \begin{cases} \text{Conv } \mathbb{R}^n, & \text{if } \bigcap_{i=1}^k \text{dom } f_i \neq \emptyset \\ \infty, & \text{otherwise.} \end{cases}$$

(b) If $\{f_i\}_{i \in I} \in E\text{-Conv } \mathbb{R}^n$ then $\sup_{i \in I} f_i \in \text{Conv } \mathbb{R}^n$ or $f = \infty$. Note that this can follow from $\text{epi}(\sup_{i \in I} f_i) = \bigcap_{i \in I} \text{epi } f_i$.

(c) If $f \in \text{Conv } \mathbb{R}^n$ and $A : \mathbb{R}^n \mapsto \mathbb{R}^m$ is affine such that $A(\mathbb{R}^n) \cap \text{dom } f \neq \emptyset$ then $f \circ A \in \text{Conv } \mathbb{R}^n$.

Proposition 0.21. If $f \in \text{Conv } \mathbb{R}^n$ then $\forall x_0 \in \text{ri}(\text{dom } f)$, $\exists L = L(x_0) \geq 0$ and neighbourhood $N(x_0)$ of x_0 such that

$$|f(x) - f(\tilde{x})| \leq L \|x - \tilde{x}\|$$

for all $x, \tilde{x} \in N(x_0) \cap \text{aff}(\text{dom } f)$. In particular, this result implies that f is continuous on $\text{ri}(\text{dom } f)$.

Continuity

Proposition 0.22. If $f \in \text{Conv } \mathbb{R}^n$ then for all compact set $K \subseteq \text{ri}(\text{dom } f)$ there exists $L = L(K)$ such that

$$|f(x) - f(\tilde{x})| \leq L \|x - \tilde{x}\|.$$

Corollary 0.2. If $f \in \text{Conv } \mathbb{R}^n$ finite everywhere, then f is continuous on \mathbb{R}^n and for every bounded set $C \subseteq \mathbb{R}^n$ there exists $L = L(C)$ such that

$$|f(x) - f(\tilde{x})| \leq L \|x - \tilde{x}\|, \forall x, \tilde{x} \in C.$$

Definition 0.7. The **lower semi-continuous hull** of $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$, denoted by $\text{lsc } f$ is defined as

$$\begin{aligned} (\text{lsc } f)(x) &= \liminf_{y \rightarrow x} f(y) \\ &= \inf \left\{ v : \exists \{y_k\} \rightarrow x \text{ s.t. } \lim_{k \rightarrow \infty} f(y_k) = v \right\} \leq f(x). \end{aligned}$$

Definition 0.8. A function $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is lower semi-continuous (lsc) at $x \in \mathbb{R}^n$ if $f(x) = (\text{lsc } f)(x)$. The function f is **lower semi-continuous** if $(\text{lsc } f) = f$.

Proposition 0.23. Let $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$. Then:

- (a) $\text{epi}(\text{lsc } f) = \text{cl}(\text{epi } f)$
- (b) If $f \in E\text{-Conv } \mathbb{R}^n$ then $\text{lsc } f \in E\text{-Conv } \mathbb{R}^n$

Proposition 0.24. For $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ the following are equivalent:

- (a) $\text{epi } f$ is closed
- (b) $f^{-1}[-\infty, r]$ is (possibly empty) closed for all $\forall r \in \mathbb{R}$
- (c) f is lsc

Proposition 0.25. Let $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$. Then,

- (a) $\text{lsc } f$ is lsc and $\text{lsc } f \leq f$.
- (b) $\text{lsc } f = \sup\{g : g \leq f, g \text{ lsc}\} =: h$
- (c) $\text{lsc } f$ is the largest lsc function minorizing f , i.e. if g is lsc with $g \leq f$ then $g \leq \text{lsc } f$.

Proposition 0.26. Assume that $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is lsc and $K \subseteq \mathbb{R}^n$ is compact and non-empty. Then $\exists x^* \in K$ such that

$$f(x^*) = \inf\{f(x) : x \in K\}.$$

Definition 0.9. A function $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is **0-coercive** if $\lim_{\|x\| \rightarrow \infty} f(x) = \infty$ or equivalently $\forall r \in \mathbb{R}, \exists M > 0$ such that $\|x\| > M \implies f(x) > r$. Also equivalently, $\forall r \in \mathbb{R}, \exists M > 0$ such that $x \in f^{-1}[-\infty, r] \implies \|x\| \leq M$ or equivalently $\forall r \in \mathbb{R}, \exists M > 0$ such that $f^{-1}[-\infty, r] \subseteq \bar{B}(0; M)$ or equivalently $\forall r \in \mathbb{R}, f^{-1}[-\infty, r]$ is bounded.

Proposition 0.27. Assume $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is lsc and 0-coercive. Then $\exists x^* \in \mathbb{R}^n$ such that

$$f(x^*) = \inf\{f(x) : x \in \mathbb{R}^n\}.$$

Closures of Convex Functions

Definition 0.10. For $f \in E\text{-Conv } \mathbb{R}^n$ the closure of f , denoted by $\text{cl } f$ is defined as

$$\text{cl } f = \begin{cases} \text{lsc } f, & \text{if } f \in \text{Conv } \mathbb{R}^n \text{ or } f = \infty \\ -\infty, & \text{otherwise.} \end{cases}$$

Definition 0.11. f is closed if $f = \text{cl } f$.

Notation 2. $E\text{-Conv } \mathbb{R}^n$ is the set of all **closed convex functions**. $\text{Conv } \mathbb{R}^n$ is the set of all **proper closed convex functions**.

Lemma 0.3. For $f \in E\text{-Conv } \mathbb{R}^n$,

$$\text{ri}(\text{epi } f) = \{(x, r) \in \mathbb{R}^n \times \mathbb{R} : x \in \text{ri}(\text{dom } f), r > f(x)\}$$

Proposition 0.28. Suppose $f \in E\text{-Conv } \mathbb{R}^n$ and $x_0 \in \text{ri}(\text{dom } f)$. Then $\forall x \in \mathbb{R}^n$ we have

$$(\text{lsc } f)(x) = \lim_{t \downarrow 0} f(x + t(x_0 - x)).$$

Proposition 0.29. Suppose that $f \in E\text{-Conv } \mathbb{R}^n$. Then:

- (a) $f(x) = (\text{lsc } f)(x)$ for all $x \in \mathbb{R}^n \setminus \text{rbd}(\text{dom } f)$
- (b) $\text{dom } f \subseteq \text{dom}(\text{lsc } f) \subseteq \text{cl}(\text{dom } f)$

Corollary 0.3. If $f \in \text{Conv } \mathbb{R}^n$ then

- (a) $f(x) = (\text{cl } f)(x)$ for all $x \in \mathbb{R}^n \setminus \text{rbd}(\text{dom } f)$
- (b) $\text{dom } f \subseteq \text{dom}(\text{cl } f) \subseteq \text{cl}(\text{dom } f)$

Corollary 0.4. If $f \in \text{Conv } \mathbb{R}^n$ and $\text{dom } f$ is an affine manifold then $f \in \text{Conv } \mathbb{R}^n$.

Proposition 0.30. Suppose $f \in E\text{-Conv } \mathbb{R}^n$ and $(\text{lsc } f)(x_0) = -\infty$ for some $x_0 \in \mathbb{R}^n$ (e.g. $f(x_0) = -\infty$ for some $x_0 \in \mathbb{R}^n$). Then,

- (a) $(\text{lsc } f)(x) = -\infty$ for all $x \in \text{cl}(\text{dom } f)$ and $\text{dom}(\text{lsc } f) = \text{cl}(\text{dom } f)$
- (b) $f(x) = -\infty$ for all $x \in \text{ri}(\text{dom } f)$

As a consequence of (a) and (b), $\text{cl } f, \text{lsc } f$ agree on $\text{cl}(\text{dom } f)$ and $f, \text{cl } f$ agree on $\text{ri}(\text{dom } f)$.

Definition 0.12. The **convex hull** of denoted by $\text{co } f$, is defined as

$$\text{co } f = \sup\{g \in E\text{-Conv } \mathbb{R}^n : g \leq f\}$$

Definition 0.13. The **closed convex hull** of $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$, denoted by $\overline{\text{co } f}$, is defined as $\overline{\text{co } f} = \text{cl}(\text{co } f)$.

Proposition 0.31. (1) $\text{co } f \in E\text{-Conv } \mathbb{R}^n$, $\text{co } f \leq f$
 (2) if $g \in E\text{-Conv } \mathbb{R}^n$, $g \leq f$, then $g \leq \text{co } f$.

Proposition 0.32. (1) $\overline{\text{co } f} \in E\text{-Conv } \mathbb{R}^n$, $\overline{\text{co } f} \leq f$
 (2) if $g \in E\text{-Conv } \mathbb{R}^n$, $g \leq f$, then $g \leq \overline{\text{co } f}$.

Proposition 0.33. (1) $\text{cl } f \in E\text{-Conv } \mathbb{R}^n$

(2) If $g \in E\text{-Conv } \mathbb{R}^n$, $g \leq f \implies g \leq \text{cl } f$.

Derivatives

Definition 0.14. Let $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ and $\bar{x} \in \mathbb{R}^n$ such that $f(\bar{x}) \in \mathbb{R}$. The **directional derivative** of f at \bar{x} along d is

$$f'(\bar{x}; d) = \lim_{t \downarrow 0} \frac{f(\bar{x} + td) - f(\bar{x})}{t}$$

whenever it exists where $\pm\infty$ is possible.

Definition 0.15. $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is **differentiable** at \bar{x} if $f(\bar{x}) \in \mathbb{R}$ and \exists linear map $f'(\bar{x}) : \mathbb{R}^n \mapsto \mathbb{R}$ such that

$$\lim_{\substack{h \rightarrow 0 \\ h \in \mathbb{R}^n}} \frac{f(\bar{x} + h) - [f(\bar{x}) + f'(\bar{x})h]}{\|h\|} = 0.$$

Remark 0.2. (1) $f'(\bar{x})$ is unique

(2) f is differentiable at $\bar{x} \implies \bar{x} \in \text{int}(\text{dom } f)$.

(3) f is differentiable at $\bar{x} \implies f'(\bar{x}; d) = f'(\bar{x})d$.

Remark 0.3. The gradient is $T : \mathbb{R}^n \mapsto \mathbb{R}$ over inner product $\langle \cdot, \cdot \rangle$ on \mathbb{R}^n where $\exists! a \in \mathbb{R}^n$ such that $T(\cdot) = \langle a, \cdot \rangle$. In particular, $T = f'(\bar{x})$ and $f'(\bar{x})d = \langle a, d \rangle$.

Proposition 0.34. Let $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ and $\bar{x} \in \mathbb{R}^n$ be such that $f(\bar{x}) \in \mathbb{R}$. If \bar{x} is a local minimum of $\inf\{f(x) : x \in \mathbb{R}^n\}$ then

$$f'(\bar{x}; d) \geq 0, \forall d \in \mathbb{R}^n$$

whenever it exists. As a consequence, if f is differentiable at \bar{x} then $f'(\bar{x}) = 0$.

Proposition 0.35. Assume $f \in E\text{-Conv } \mathbb{R}^n$ and $\bar{x}, d \in \mathbb{R}^n$ are such that $f(\bar{x}) \in \mathbb{R}$. Define

$$\Delta f(\cdot; \bar{x}, d) : \mathbb{R}_{++} \mapsto \bar{\mathbb{R}}$$

as

$$\Delta f(t; \bar{x}, d) = \frac{f(\bar{x} + td) - f(\bar{x})}{t}.$$

Then,

- (1) $\Delta f(\cdot; \bar{x}, d)$ is non-decreasing
- (2) if $f(\cdot)$ is strictly convex and $d \neq 0$ then $\Delta f(\cdot; \bar{x}, d)$ is increasing
- (3) if f is β -strongly convex, then for all $0 < t_1 < t_2$,

$$\Delta f(t_1) \leq \Delta f(t_2) - \frac{\beta}{2}(t_2 - t_1)\|d\|^2.$$

Proposition 0.36. Assume that $f \in E\text{-Conv } \mathbb{R}^n$ and $\bar{x} \in \mathbb{R}^n$ such that $f(\bar{x}) \in \mathbb{R}$. Then,

- (a) $\forall d \in \mathbb{R}^n$, $f'(\bar{x}; d)$ exists and $f'(\bar{x}; d) = \inf_{t>0} \Delta f(t; \bar{x}, d)$
- (b) $f(x) - f(\bar{x}) \geq f'(\bar{x}; x - \bar{x})$, $\forall x \in \mathbb{R}^n$
- (c) $f(x) - f(\bar{x}) > f'(\bar{x}; x - \bar{x})$, $\forall x \in \mathbb{R}^n \setminus \{\bar{x}\}$ if f is strictly convex
- (d) $f(x) - f(\bar{x}) \geq f'(\bar{x}; x - \bar{x}) + \frac{\beta}{2}\|x - \bar{x}\|^2$, $\forall x \in \text{dom } f$ if f is β -strongly convex

Proposition 0.37. Assume that $f \in E\text{-Conv } \mathbb{R}^n$ and $\bar{x} \in \mathbb{R}^n$ such that $f(\bar{x}) \in \mathbb{R}$. Then the following are equivalent:

- (a) \bar{x} is a global min of $f(x)$ on \mathbb{R}^n
 - (b) \bar{x} is a local min of $f(x)$ on \mathbb{R}^n
 - (c) $f'(\bar{x}; d) \geq 0$ for all $d \in \mathbb{R}^n$
 - (d) $f'(\bar{x}; x - \bar{x}) \geq 0$ for all $x \in \text{dom } f$
- If f is differentiable at \bar{x} then,
- (e) $f'(\bar{x}) = 0$

Corollary 0.5. Assume f is β -strongly convex and \bar{x} is a global minimum of f over \mathbb{R}^n . Then:

$$f(x) - f(\bar{x}) \geq \frac{\beta}{2} \|x - \bar{x}\|^2.$$

Definition 0.16. If $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is proper and $\emptyset \neq C \subseteq \text{dom } f$ is convex, we say f is **convex on** C if

$$f_C(x) = \begin{cases} f(x), & x \in C \\ +\infty, & \text{otherwise} \end{cases}$$

is convex.

Proposition 0.38. Assume $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is proper, $\emptyset \neq C \subseteq \text{dom } f$ is convex, and f is convex on C . Then following are equivalent:

- (a) $\bar{x} \in C$ is a global minimum of f over C
- (b) $\bar{x} \in C$ is a local minimum of f over C
- (c) $f'(\bar{x}; d) \geq 0$ for all $d \in \mathbb{R}_+ \cdot (C - \bar{x})$
- (d) $f'(\bar{x}; x - \bar{x}) \geq 0$ for all $x \in C$

Proposition 0.39. Assume $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is proper, $\emptyset \neq C \subseteq \text{dom } f$ is convex, and f is strictly convex on C . Assume \bar{x} is a global minimum of f over C . then \bar{x} is the unique global minimum of f over C .

Asymptotic Function

Definition 0.17. For $f \in \overline{\text{Conv}} \mathbb{R}^n$, its **asymptotic function** $f'_\infty : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is defined as

$$f'_\infty(d) = \sup_{\substack{t > 0 \\ x \in \text{dom } f}} \frac{f(x + td) - f(x)}{t}.$$

Proposition 0.40. For $f \in \overline{\text{Conv}} \mathbb{R}^n$, have:

- (a) $\text{epi } f'_\infty = (\text{epi } f)_\infty$
- (b) If $x_0 \in \text{dom } f$ then

$$f'_\infty(d) = \sup_{t > 0} \underbrace{\frac{f'(x_0 + td) - f(x_0)}{t}}_{:=h_1(d)} \stackrel{(o)}{=} \sup_{x \in \text{dom } f} \underbrace{f(x + d) - f(x)}_{:=h_2(d)}.$$

Proposition 0.41. Let $f \in \overline{\text{Conv}} \mathbb{R}^n$. Then,

- (a) $f'_\infty \in \overline{\text{Conv}} \mathbb{R}^n$
- (b) $f'_\infty(\alpha d) = \alpha f'_\infty(d)$ for all $\alpha \geq 0, d \in \mathbb{R}^n$
- (c) $\forall r \in \mathbb{R}$ s.t. $f^{-1}[-\infty, r] \neq \emptyset$, we have $(f^{-1}[\infty, r])_\infty = (f'_\infty)^{-1}[-\infty, 0]$.

Proposition 0.42. Let $f \in \overline{\text{Conv}} \mathbb{R}^n$. Then the following are equivalent:

- (a) $\forall r \in \mathbb{R}, f^{-1}[-\infty, r]$ is bounded (i.e. f is coercive).
- (b) $\exists r_0 \in \mathbb{R}$ s.t. $f^{-1}[-\infty, r_0] \neq \emptyset$ and bounded.
- (c) the set of optimal solutions of $\min_{x \in \mathbb{R}^n} f(x) \neq \emptyset$ and bounded.
- (d) $f'_\infty(d) > 0, \forall d \in \mathbb{R}^n \setminus \{0\}$.

Proposition 0.43. (1) If $f_1, \dots, f_k \in \overline{\text{Conv}} \mathbb{R}^n$ such that $\bigcap_{i=1}^k \text{dom } f_i \neq \emptyset$ then for all $\alpha_1, \dots, \alpha_k \geq 0$

$$(\alpha_1 f_1 + \dots + \alpha_k f_k)_\infty = \alpha_1 (f_1)_\infty + \dots + \alpha_k (f_k)_\infty$$

and $\alpha_1 f_1 + \dots + \alpha_k f_k \in \overline{\text{Conv}} \mathbb{R}^n$.

(2) If $\{f_i\}_{i \in I} \subseteq \overline{\text{Conv}} \mathbb{R}^n$ such that $\sup_{i \in I} f_i(x_0) < \infty$ for some $x_0 \in \mathbb{R}^n$ then $f := \sup_{i \in I} f_i \in \overline{\text{Conv}} \mathbb{R}^n$ and $f'_\infty = \sup_{i \in I} (f_i)_\infty$.

(3) If $f \in \overline{\text{Conv}} \mathbb{R}^n$, $A : \mathbb{R}^n \mapsto \mathbb{R}^m$ affine such that $A(\mathbb{R}^n) \cap \text{dom } f \neq \emptyset$ then $f \circ A \in \overline{\text{Conv}} \mathbb{R}^n$ and

$$(f \circ A)'_\infty = f'_\infty \circ (A_0) \text{ where } A_0(\cdot) = A(\cdot) - A(0).$$

Corollary 0.6. We have

$$(f_C)'_\infty(d) = (f + I_C)'_\infty(d) = f'_\infty(d) + (I_C)'_\infty = f'_\infty(d) + I_{C_\infty}(d).$$

Differentiable Functions

Proposition 0.44. Let $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ be differentiable on a nonempty convex set $C \subseteq \text{dom } f$. Then the following are equivalent:

- (a) f is convex on C , i.e.

$$f(\alpha x + (1 - \alpha)y) \leq \alpha f(x) + (1 - \alpha)f(y), \forall x, y \in C, \alpha \in (0, 1)$$

$$(b) f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle, \forall x, y \in C$$

$$(c) [f'(y) - f'(x)](y - x) \geq 0, \forall x, y \in C.$$

Corollary 0.7. Assume $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is differentiable on a nonempty convex set $C \subseteq \text{dom } f$. Then for all $\forall \beta \in \mathbb{R}$, the following are equivalent,

- (a) $\forall x, y \in C, \forall \alpha \in (0, 1)$ we have

$$f(\alpha x + (1 - \alpha)y) + \frac{\beta}{2} \alpha(1 - \alpha) \leq \alpha f(x) + (1 - \alpha)f(y)$$

- (b) $f - \frac{\beta}{2} \|\cdot\|^2$ is convex.

$$(c) \forall x, y \in C, f(y) \geq f(x) + f'(x)(y - x) + \frac{\beta}{2} \|y - x\|^2$$

$$(d) \forall x, y \in C, [f'(y) - f'(x)](y - x) \geq \beta \|y - x\|^2.$$

Corollary 0.8. Assume $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is differentiable on a nonempty convex set $C \subseteq \text{dom } f$. Then $\forall L \in \mathbb{R}$ the following are equivalent:

- (a) $\forall x, y \in C, \forall \alpha \in (0, 1)$ we have

$$f(\alpha x + (1 - \alpha)y) + \frac{L}{2} \alpha(1 - \alpha) \geq \alpha f(x) + (1 - \alpha)f(y)$$

- (b) $\frac{L}{2} \|\cdot\|^2 - f$ is convex.

$$(c) \forall x, y \in C, f(y) \leq f(x) + f'(x)(y - x) + \frac{L}{2} \|y - x\|^2$$

$$(d) \forall x, y \in C, [f'(y) - f'(x)](y - x) \leq L \|y - x\|^2.$$

Separation Theory

Proposition 0.45. $\bar{c} = \Pi_C(x) \iff \langle c - \bar{c}, x - \bar{c} \rangle \leq 0$ for all $c \in C$.

Proposition 0.46. For every $(x, y) \in \mathbb{R}^n \times \mathbb{R}^n$,

$$\|\Pi_C(x) - \Pi_C(y)\|^2 \leq \langle x - y, \Pi_C(x) - \Pi_C(y) \rangle$$

and as a consequence,

$$\|\Pi_C(x) - \Pi_C(y)\| \leq \|x - y\|.$$

Definition 0.18. Let $C_1, C_2 \subseteq \mathbb{R}^n$ be nonempty and H be a hyperplane.

- (a) H **separates** C_1, C_2 if $C_1 \subseteq H^\leq$ and $C_2 \subseteq H^\geq$.
- (b) H **properly separates** C_1, C_2 if H separates them and $C_1 \cup C_2 \subseteq H$.
- (c) H **strongly separates** C_1, C_2 if H separates $C_1 + \bar{B}(0; \delta_1), C_2 + \bar{B}(0; \delta_2)$ for some $\delta_1, \delta_2 > 0$.

Proposition 0.47. Let $\emptyset \neq C_1, C_2 \subseteq \mathbb{R}^n$ be given

- (a) \exists hyperplane separating $C_1, C_2 \iff \exists 0 \neq s \in \mathbb{R}^n$ s.t. $\sup_{x_1 \in C_1} \langle s, x_1 \rangle \leq \inf_{x_2 \in C_2} \langle s, x_2 \rangle$ (*).
- (b) \exists hyperplane properly separating $C_1, C_2 \iff \exists s \in \mathbb{R}^n$ s.t. (*) holds and $\inf_{x_1 \in C_1} \langle s, x_1 \rangle < \sup_{x_2 \in C_2} \langle s, x_2 \rangle$.
- (c) \exists hyperplane strongly separating $C_1, C_2 \iff \exists s \in \mathbb{R}^n$ s.t. (*) holds strictly.

Proposition 0.48. Let $\emptyset \neq C_1, C_2 \subseteq \mathbb{R}^n$ be given. Then C_1, C_2 can be separated $\iff \{0\}, C = C_1 - C_2$ can be separated.

Proposition 0.49. Let $\emptyset \neq C \subseteq \mathbb{R}^n$ be a convex set and $x \in \mathbb{R}^n$. Then,

- (a) x, C (C_1, C_2) can be strongly separated $\iff x \notin \text{cl } C$ ($0 \notin \text{cl}(C_1 - C_2)$)
- (b) x, C (C_1, C_2) can be properly separated $\iff x \notin \text{ri } C$ ($0 \notin \text{ri}(C_1 - C_2)$).

Proposition 0.50. Let $\emptyset \neq C \subseteq \mathbb{R}^n$ be a convex set and $x \in \mathbb{R}^n$. Then,

$$\text{cl } C = \bigcap \{H^\leq : H \text{ is a hyperplane}, C \subseteq H^\leq\}.$$

Corollary 0.9. If $f \in E\text{-Conv } \mathbb{R}^n$ then

$$\text{epi}(\text{lsc } f) = \text{cl}(\text{epi } f) = \bigcap \{H^\leq : H \text{ is a hyperplane}, \text{epi } f \subseteq H^\leq\}.$$

Remark 0.4. A closed halfspace has one of the following representations:

- (1) $H^+(s, \beta) = \{(x, t) : \langle s, t \rangle + t \leq \beta\}$
- (2) $H^-(s, \beta) = \{(x, t) : \langle s, t \rangle - t \leq \beta\}$
- (3) $H^0(s, \beta) = \{(x, t) : \langle s, t \rangle \leq \beta\}$

Observe that

- (1) $H^+(s, \beta)$ is **not** an epigraph
- (2) $H^-(s, \beta) = \text{epi}(\langle s, \cdot \rangle - \beta)$
- (3) $H^0(s, \beta) = H_{s, \beta}^\leq \times \mathbb{R}$

Proposition 0.51. If $f \in E\text{-Conv } \mathbb{R}^n$ then

$$\begin{aligned} \text{cl } f &= \sup \{A : A \text{ is affine}, A \leq f\} \\ &= \sup_{(s, \beta)} \{\langle s, \cdot \rangle - \beta : \langle s, \cdot \rangle - \beta \leq f\}. \end{aligned}$$

Also if $f \in \text{Conv } \mathbb{R}^n$ then \exists affine function minorizing f .

Conjugate Functions

Definition 0.19. The **conjugate** of $f : \mathbb{R}^n \mapsto \mathbb{R}$, denoted by f^* , is defined as $f^* : \mathbb{R}^n \mapsto \mathbb{R}$ where

$$s \mapsto f^*(s) = \sup_{x \in \mathbb{R}^n} \langle x, s \rangle - f(x).$$

Observe that $\forall s \in \mathbb{R}^n$ we have

$$f^*(s) = \sup_{x \in \text{dom } f} \langle x, s \rangle - f(x) = \sup_{(x, t) \in \text{epi } f} \langle x, s \rangle - t.$$

Proposition 0.52. We have:

- (a) if $f = \infty$ then $f^* = -\infty$
- (b) if $f(x_0) = -\infty$ for some x_0 then $f^* = \infty$
- (c) $\text{epi } f^* = \{(s, \beta) : \langle s, \cdot \rangle - \beta \leq f\}$
- (d) $f^*(s) = \inf \{\beta : \langle s, \cdot \rangle - \beta \leq f\}$
- (e) $-f^*(0) = \inf \{f(x) : x \in \mathbb{R}^n\}$
- (f) $\forall x, s \in \mathbb{R}^n, f^*(s) \geq \langle x, s \rangle - f(x)$

Proposition 0.53. For any $f \in E\text{-Conv } \mathbb{R}^n$,

$$f^* = (\text{cl } f)^* = (\text{lsc } f)^*.$$

Proof. Let $A = \langle s, \cdot \rangle - \beta$. Then $A \leq f \iff A \leq \text{lsc } f \iff A \leq \text{cl } f$. \square

Definition 0.20. **Fenchel's inequality** is

$$f^*(x) \geq \langle x, s \rangle - f(x).$$

Proposition 0.54. Let $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ be such that

- (1) $f \neq \infty$
- (2) f is minorized by an affine function

Then, $f^* \in \overline{\text{Conv}} \mathbb{R}^n$. As a consequence, if $f \in \text{Conv } \mathbb{R}^n$ then $f^* \in \overline{\text{Conv}} \mathbb{R}^n$.

Proposition 0.55. Assume that $f \in E\text{-Conv } \mathbb{R}^n$. Then

$$\text{cl } f = f^{**} = (f^*)^*.$$

Subgradients

Definition 0.21. We say $s \in \partial f(\bar{x})$ where ∂f is the subgradient of f if and only if

$$f(x) \geq f(\bar{x}) + \langle s, x - \bar{x} \rangle, \forall x \in \mathbb{R}^n.$$

Remark 0.5. We have

- $f(\bar{x}) = +\infty \implies \partial f(\bar{x}) = \mathbb{R}^n$
- $f(\bar{x}) = -\infty$ then $\partial f(\bar{x}) \neq \emptyset \iff f = +\infty$ in which case $\partial f(\bar{x}) = \mathbb{R}^n$.

Assumption. (A) $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ and $\bar{x} \in \mathbb{R}^n$ such that $f(\bar{x}) \in \mathbb{R}$.

Proposition 0.56. If (A) holds then

- (a) \bar{x} is a global minimum of f over $\mathbb{R}^n \iff 0 \in \partial f(\bar{x})$.
 (b) $\partial f(\bar{x})$ is a (possibly empty) closed convex set.

Proposition 0.57. Assume that $f \in E\text{-Conv } \mathbb{R}^n$ and $\bar{x} \in \mathbb{R}^n$ such that $f(\bar{x}) \in \mathbb{R}$. Then,

$$\partial f(\bar{x}) = \{s \in \mathbb{R}^n : \langle s, \cdot \rangle \leq f'(\bar{x}; \cdot)\}$$

and also

$$\text{cl } f'(\bar{x}; \cdot) = \sigma_{\partial f(\bar{x})} = \sup_{s \in \partial f(\bar{x})} \langle s, \cdot \rangle.$$

Proposition 0.58. Let $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ and $\bar{x} \in \mathbb{R}^n$ be given. Then $s \in \partial f(x) \iff f^*(s) \leq \langle x, s \rangle - f(x)$.

Definition 0.22. or a multivalued map $A : \mathbb{R}^n \rightrightarrows \mathbb{R}^n$, define $A^{-1}(y) = \{x : y \in A(x)\}$.

Lemma 0.4. Let $f : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ and $\bar{x} \in \mathbb{R}^n$ such that $\partial f(\bar{x}) \neq \emptyset$ be given. Then:

- (a) $(\text{lsc } f)(\bar{x}) = f(\bar{x})$, i.e. f is lsc at \bar{x}
 (b) If $f \in E\text{-Conv } \mathbb{R}^n$ then $(\text{cl } f)(\bar{x}) = f(\bar{x})$.

Proposition 0.59. Let $f \in E\text{-Conv } \mathbb{R}^n$ and $x \in \mathbb{R}^n$ be given. Then for $s \in \mathbb{R}^n$ the following are equivalent

- (a) $s \in \partial f(x)$
 (b) $s \in \partial(\text{cl } f)(x)$ and $(\text{cl } f)(x) = f(x)$
 (c) $x \in \partial f^*(s)$ and $(\text{cl } f)(x) = f(x)$.

Corollary 0.10. If $f \in E\text{-Conv } \mathbb{R}^n$ then $s \in \partial f(x) \iff x \in \partial f^*(s)$.

Corollary 0.11. If $f \in \overline{\text{Conv}} \mathbb{R}^n$ then $\partial f^*(0) = \text{argmin}_{x \in \mathbb{R}^n} f(x)$.

Sublinear Functions

Definition 0.23. $\sigma : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is **sublinear** if $\text{epi } \sigma$ is a convex cone.

Definition 0.24. $\sigma : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ is **subadditive** if $\sigma(x_0 + x_1) \leq \sigma(x_0) + \sigma(x_1)$ and is **positively homogeneous** (of degree 1) if $\sigma(tx) = t\sigma(x)$ for all $t > 0$ and for all $x \in \mathbb{R}^n$.

Proposition 0.60. Let $\sigma : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$. Then the following are equivalent:

- (a) σ is sublinear
 (b) σ is convex and positively homogeneous
 (c) σ is subadditive and positively homogeneous
 (d) $\sigma(t_0x_0 + t_1x_1) \leq t_0\sigma(x_0) + t_1\sigma(x_1)$ for all $t_0, t_1 > 0$ and for all $x_0, x_1 \in \text{dom } \sigma$

Proposition 0.61. Let $\sigma : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ be sublinear. Then,

- (a) $\text{dom } \sigma$ is a convex cone
 (b) $\sigma(0) \in \{-\infty, 0, +\infty\}$
 (c) if σ is proper then $\sigma(x) + \sigma(-x) \geq \sigma(0) \geq 0$
 (d) if σ is proper closed then $\sigma(0) = 0$

Remark 0.6. $\sigma_C(s) = \sup_{x \in C} \langle s, x \rangle = (I_C)^*$.

Proposition 0.62. For any $C \subseteq \mathbb{R}^n$ we have

$$\text{lsc } I_C = I_{\text{cl } C}$$

$$\text{co } I_C = I_{\text{co } C}$$

$$\overline{\text{co}} I_C = I_{\overline{\text{co}} C}.$$

Proposition 0.63. For any $C \subseteq \mathbb{R}^n$ we have

$$\sigma_C = \sigma_{\text{cl } C} = \sigma_{\text{co } C} = \sigma_{\overline{\text{co}} C}.$$

Proposition 0.64. Let $C_1, C_2 \subseteq \mathbb{R}^n$ be closed convex. Then,

$$C_1 \subseteq C_2 \iff \sigma_{C_1} \leq \sigma_{C_2}$$

and in particular, $C_1 = C_2 \iff \sigma_{C_1} = \sigma_{C_2}$.

Corollary 0.12. Σ is one-to-one.

Corollary 0.13. For any $C \subseteq \mathbb{R}^n$,

$$\overline{\text{co}} C = \{x \in \mathbb{R}^n : \langle x, \cdot \rangle \leq \sigma_C(\cdot)\}.$$

Proposition 0.65. (Σ is onto) If σ is a closed sublinear function such that $\sigma \neq \infty$ then $\sigma = \sigma_C$ where

$$C = C(\sigma) = \{x \in \mathbb{R}^n : \langle x, \cdot \rangle \leq \sigma\}.$$

By the previous result,

$$C = \overline{\text{co}} C = \{x \in \mathbb{R}^n : \langle x, \cdot \rangle \leq \sigma_C\} = \{x \in \mathbb{R}^n : \langle x, \cdot \rangle \leq \sigma\} = C(\sigma).$$

Proposition 0.66. Assume $f \in E\text{-Conv } \mathbb{R}^n$ and $\bar{x} \in \mathbb{R}^n$ is such that $f(\bar{x}) \in \mathbb{R}$. Then,

- (a) $\text{dom } (f'(\bar{x}; \cdot)) = \mathbb{R}_{++} \cdot (\text{dom } f - \bar{x})$
 (b) $f'(\bar{x}; \cdot)$ is sublinear.

Proposition 0.67. Assume $f \in E\text{-Conv } \mathbb{R}^n$ and $\bar{x} \in \mathbb{R}^n$ is such that $f(\bar{x}) \in \mathbb{R}$. Then,

$$\text{cl } f'(\bar{x}; \cdot) = \sigma_{\partial f(\bar{x})}.$$

Proposition 0.68. Assume $f \in E\text{-Conv } \mathbb{R}^n$ and $\bar{x} \in \mathbb{R}^n$ is such that $f(\bar{x}) \in \mathbb{R}$. Then,

$$\partial f(\bar{x}) = \emptyset \iff \exists d_0 \in \mathbb{R}^n \text{ s.t. } f'(\bar{x}; d_0) = -\infty$$

in which case

$$f'(\bar{x}; d) = -\infty, \forall d \in \text{ri}(\text{dom } f - \bar{x}).$$

Proposition 0.69. Assume $f \in E\text{-Conv } \mathbb{R}^n$ and $\bar{x} \in \mathbb{R}^n$ is s.t. $f(\bar{x}) \in \mathbb{R}$. Then:

- (a) if $\bar{x} \in \text{ri}(\text{dom } f)$, then $\partial f(\bar{x}) \neq \emptyset$ and $f'(\bar{x}; \cdot) = \sigma_{\partial f(\bar{x})}$.
 (b) $\bar{x} \in \text{int}(\text{dom } f)$ iff $\partial f(\bar{x}) \neq \emptyset$ and bounded, in which case $f'(\bar{x}; d) = \max \{\langle d, s \rangle : s \in \partial f(\bar{x})\}$.

Duality [ECP]

Definition 0.25. Define the **Lagrangian function** for (ECP) $\mathcal{L} : \mathbb{R}^n \times \mathbb{R}^E \mapsto (-\infty, +\infty]$ by

$$(x, \lambda) \mapsto \begin{cases} f(x) + \sum_{i \in E} \lambda_i g_i(x), & \text{if } x \in X \\ +\infty, & \text{otherwise} \end{cases} = \begin{cases} f(x) + \langle \lambda, g_E(x) \rangle, \\ +\infty, \end{cases}$$

Note that (ECP) $\iff \inf_x \sup_\lambda \mathcal{L}(x, \lambda) \geq \sup_\lambda \inf_x \mathcal{L}(x, \lambda)$ which we call the dual. Also, *Proof.* Follows from $f_* \geq \theta_* \geq \theta(\lambda^*)$. So

$$\sup_{\lambda \in \mathbb{R}^E} \mathcal{L}(x, \lambda) = \begin{cases} f(x), & \text{if } g_E(x) = 0, x \in X \\ +\infty, & \text{otherwise} \end{cases}$$

and so (ECP) $\iff \inf_{x \in \mathbb{R}^n} \sup_{\lambda \in \mathbb{R}^E} \mathcal{L}(x, \lambda)$.

Definition 0.26. The **dual function** $\theta : \mathbb{R}^E \mapsto [-\infty, \infty)$ is defined as $\theta(\lambda) = \inf_{x \in \mathbb{R}^n} \mathcal{L}(x, \lambda)$. The dual (DECP) is

$$(DECP) \quad \theta^* = \sup_{\lambda \in \mathbb{R}^E} \theta(\lambda) = \sup_{\lambda \in \mathbb{R}^E} \inf_{x \in \mathbb{R}^n} \mathcal{L}(x, \lambda).$$

Note that $-\theta \in \overline{\text{Conv}} \mathbb{R}^n$.

Notation 3. For $\lambda \in \mathbb{R}^E$, denote $X(\lambda) = \{x \in \mathbb{R}^n : \mathcal{L}(x, \lambda) = \theta(\lambda)\}$. Observe that:

- (1) if $\theta(\lambda) = -\infty$ then $X(\lambda) = \emptyset$
- (2) $\theta(\lambda) < \infty$ for all $\lambda \in \mathbb{R}^E$
- (3) $X(\lambda) = \{x \in X : \theta(\lambda) = f(x) + \langle \lambda, g_E(x) \rangle\}$

Proposition 0.70. (Everett) Assume $x_\lambda \in X(\lambda)$ for some $\lambda \in \mathbb{R}^E$. Then x_λ is an optimal solution of

$$(P_\lambda) \quad \inf_{x \in X} f(x) \quad \text{s.t. } g_E(x) = g_E(x_\lambda)$$

Definition 0.27. $\lambda^* \in \mathbb{R}^E$ is a **Lagrange multiplier** (LM) of (ECP) if $f_* \in \mathbb{R}$ and $f_* \in \theta(\lambda^*)$ ($\iff f_* = \inf_{x \in X} f(x) + \langle \lambda^*, g_E(x) \rangle$).

Remark 0.7. Consider the set

$$S = \left\{ \begin{pmatrix} g_E(x) \\ f(x) \end{pmatrix} \in \mathbb{R}^E \times \mathbb{R} : x \in X \right\}$$

and let $\eta^* = \begin{pmatrix} \lambda^* \\ 1 \end{pmatrix}$, $s^* = \begin{pmatrix} 0 \\ f^* \end{pmatrix}$. Let $H^\geq = \{s : (\eta^*)^T(s - s^*) \geq 0\}$. Then $S \subseteq H^\geq$ since $f_* \leq f(x) + \langle \lambda^*, g_E(x) \rangle$ for all $x \in X$ or equivalently,

$$\begin{pmatrix} \lambda^* \\ 1 \end{pmatrix}^T \begin{pmatrix} g_E(x) - 0 \\ f(x) - f_* \end{pmatrix} \geq 0.$$

Proposition 0.71. For a given $(x^*, \lambda^*) \in \mathbb{R}^n \times \mathbb{R}^E$, then following are equivalent:

- (a) x^* is an optimal solution and λ^* is a Lagrange multiplier for (ECP)
- (b) $x^* \in X(\lambda^*)$, $g_E(x^*) = 0$.

Proposition 0.72. (Weak Duality) For every feasible x of (ECP) and $\lambda \in \mathbb{R}^E$, we have $f(x) \geq \theta(\lambda)$. As a consequence, $f_* \geq \theta^*$.

Proof. $f(x) = \mathcal{L}(x, \lambda) \geq \inf_u \mathcal{L}(u, \lambda) = \theta$. \square

Proposition 0.73. λ^* is a LM of (ECP) $\iff f_* = \theta_*$ and λ^* is an optimal solution of (DECP).

$$\mathbb{R} \ni f_* = \theta(\lambda^*) \iff f_* = \theta_* \text{ and } \theta_* = \theta(\lambda^*).$$

\square

Corollary 0.14. Assume $f_* = \theta_* \in \mathbb{R}$. Then the set of LM's is equal to the set of dual optimal solutions.

Definition 0.28. The **value function** for (ECP) is defined as

$$v(b) = \inf_{x \in X} f(x) \quad \text{s.t. } g_E(x) + b = 0 \quad (\iff g_E(x) = -b)$$

Observe that $f_* = v(0)$.

Proposition 0.74. For all $\lambda \in \mathbb{R}^E$, $v^*(\lambda) = (-\theta)(\lambda)$.

Corollary 0.15. $(-\theta)^* = \overline{\text{cov}}$ using the fact that $v^{**} = \overline{\text{cov}}$.

Proposition 0.75. $\theta_* = (\overline{\text{cov}})(0)$.

Corollary 0.16. $f_* = \theta_* \iff v(0) = (\overline{\text{cov}})(0)$.

Proposition 0.76. The set of dual optimal solutions is equal to $\partial(\overline{\text{cov}})(0)$.

Remark 0.8. Observe that $(-\theta)^*(0) = \theta_*$. Also if Λ^* is the set of optimal solutions of (DECP), then $\Lambda^* = \partial(-\theta)^*(0)$.

Corollary 0.17. $\overline{\text{cov}}(0) = \theta_*$ and $\partial(\overline{\text{cov}})(0) = \Lambda^*$.

Proposition 0.77. λ^* is a Lagrange multiplier (L.M.) of (ECP) $\iff v(0) \in \mathbb{R}$ and $\lambda^* \in \partial v(0)$ (or $f_* \in \mathbb{R}$).

Proposition 0.78. Assume $f_* \in \mathbb{R}$, $v \in E\text{-Conv } \mathbb{R}^n$, and $0 \in \text{ri}(\text{dom } v)$. Then (ECP) has a LM.

Duality [ICP]

Definition 0.29. The **Lagrangian function** for (ICP) is defined as

$$\mathcal{L}(x, \lambda) = \begin{cases} f(x) + \langle \lambda, g_I(x) \rangle, & \text{if } x \in X, \lambda \geq 0 \\ -\infty & \text{if } x \in X, \lambda \not\geq 0 \\ +\infty & \text{if } x \notin X. \end{cases}$$

Define

$$\widetilde{(ECP)} \quad f_* = \inf_{x \in X, s \in \mathbb{R}_+^I} f(x) \quad \text{s.t. } g_i(x) + s = 0, i \in I$$

Proposition 0.79. We relate $\widetilde{(ECP)}$ to (ICP):

- (a) $f_* = \tilde{f}_*$ and $v = \tilde{v}$ (i.e. x^* is an optimal solution of (ICP) $\iff (x^*, -g_I(x^*))$ is an optimal solution of $\widetilde{(ECP)}$)
- (b) $\theta = \tilde{\theta}$ and

$$\tilde{X}S(\lambda) = \begin{cases} X(\lambda) \times \{s \in \mathbb{R}_+^I, \langle s, \lambda \rangle \geq 0\}, & \text{if } \lambda \geq 0 \\ \emptyset, & \text{otherwise.} \end{cases}$$

- (c) $\theta^* = \tilde{\theta}^*$ and $\Lambda^* = \tilde{\Lambda}^*$.

Proposition 0.80. For $(x^*, \lambda^*) \in \mathbb{R}^n \times \mathbb{R}^I$, we have:

$$\begin{aligned} x^* \text{ is an optimal solution of (ICP)} &\iff \lambda^* \geq 0, g(x^*) \leq 0 \\ \lambda^* \text{ is a LM of (ICP)} &\iff \langle \lambda^*, g(x^*) \rangle = 0 \\ &\iff x \in X(\lambda^*) \end{aligned}$$

$$\text{and } x^* \in X(\lambda^*) \iff x^* \in \operatorname{argmin}_{x \in X} f(x) + \langle \lambda^*, g_I(x) \rangle.$$

Proposition 0.81. The following are equivalent:

- (a) $f_* = \theta_* \in \mathbb{R}$ and $\lambda^* \in \Lambda^*$
- (b) λ^* is a LM of ICP
- (c) $v(0) \in \mathbb{R}$ and $\lambda^* \in \partial v(0)$

Proposition 0.82. Assume that $f_* \in \mathbb{R}$, $v \in E\text{-Conv } \mathbb{R}^n$ and $0 \in \operatorname{ri}(\operatorname{dom} v)$. Then (ICP) has a LM.

Assumption 1. Suppose X is convex and f, g_i are convex for $i \in I$.

Proposition 0.83. Under assumption ?? and assumption 1, the value function v is convex and

$$\operatorname{ri}(\operatorname{dom} v) = \left\{ b \in \mathbb{R}^I : \exists x \in \operatorname{ri}(X) \text{ s.t. } g_I(x) + b < 0 \right\}.$$

Proposition 0.84. Let $f_1, \dots, f_m : \mathbb{R}^n \mapsto \bar{\mathbb{R}}$ and convex set $X \subseteq \mathbb{R}^n$ such that $\emptyset \neq X \subseteq \bigcap_{i=1}^m \operatorname{dom} f_i$ be given. If each f_i is convex on X then

$$U = \{(x, r) \in X \times \mathbb{R}^m : f_i(x) \leq r_i, i = 1, 2, \dots, m\}$$

is convex and

$$\operatorname{ri} U = \{(x, r) \in \operatorname{ri} X \times \mathbb{R}^m : f_i(x) < r_i, i = 1, 2, \dots, m\}.$$

Theorem 0.1. Consider the problem

$$\begin{aligned} (NLP) \quad f_* &= \inf f(x) \\ \text{s.t. } g_I(x) &\leq 0, \quad g_i, i \in I \text{ convex} \\ g_E(x) &= 0, \quad g_i, i \in I \text{ affine} \\ x &\in X. \end{aligned}$$

and define

$$\begin{aligned} I_a &= \{i \in I : g_i \text{ is affine}\} \\ I_c &= I \setminus I_a. \end{aligned}$$

If $f_* \in \mathbb{R}$ and $\exists x^0 \in \operatorname{ri} X$ such that $g_E(x^0) = 0$, $g_{I_a}(x^0) \leq 0$, $g_{I_c}(x^0) < 0$ then (NLP) has a LM.

Calculus of Conjugate Functions

Definition 0.30. Let $A : \mathbb{R}^n \mapsto \mathbb{R}^m$ affine and $f : \mathbb{R}^n \mapsto [-\infty, +\infty]$. Define $Af : \mathbb{R}^m \mapsto [-\infty, +\infty]$ as

$$\begin{aligned} y \mapsto (Af)(y) &= \inf f(x) \\ \text{s.t. } Ax &= y \end{aligned}$$

Proposition. (1) $f \in E\text{-Conv } \mathbb{R}^n \implies Af \in E\text{-Conv } \mathbb{R}^m$

(2) $\operatorname{dom}(Af) = A(\operatorname{dom} f)$

Proposition 0.85. $(Af)^* = f^* \circ A^*$

Proposition 0.86. For any $g \in E\text{-Conv } \mathbb{R}^n$ and $B : \mathbb{R}^n \mapsto \mathbb{R}^m$ linear, we have

$$(\operatorname{cl} g \circ B)^* = \operatorname{cl}(B^* g^*).$$

Proposition 0.87. Let $g \in E\text{-Conv } \mathbb{R}^m$ and $B : \mathbb{R}^n \mapsto \mathbb{R}^m$ linear be such that

$$(*) \quad \operatorname{Im} B \cap \operatorname{ri}(\operatorname{dom} g) \neq \emptyset.$$

Then $(g \circ B)^* = B^* g^*$ and for every $s \in \mathbb{R}^n$ such that $B^* g^*(s)$ is finite, the infimum

$$\begin{aligned} (B^* g^*)(s) &= \inf g^*(y) \\ \text{s.t. } B^* y &= s \end{aligned}$$

is achieved.

Proposition 0.88. Let $g \in E\text{-Conv } \mathbb{R}^m$ and $B : \mathbb{R}^n \mapsto \mathbb{R}^m$ be linear. Then,

$$B^*(\partial g(Bx)) \subseteq \partial(g \circ B)(x), \forall x.$$

If, in addition, $\operatorname{Im} B \cap \operatorname{ri}(\operatorname{dom} g) \neq \emptyset$ then equality holds.

Definition 0.31. The ϵ -subgradient is defined as

$$s \in \partial_\epsilon f(x) \iff f(x') \geq f(x) + \langle s, x' - x \rangle - \epsilon, \forall x'.$$

An equivalent characterization is

$$s \in \partial_\epsilon f(x) \iff f^*(s) \leq \langle x, s \rangle - f(x) + \epsilon.$$

Corollary 0.18. Let $\epsilon > 0$, $g \in E\text{-Conv } \mathbb{R}^m$, and $B : \mathbb{R}^n \mapsto \mathbb{R}^m$ be linear. Then,

$$B^*(\partial_{g_\epsilon}(Bx)) \subseteq \partial_\epsilon(g \circ B)(x), \forall x.$$

If, in addition, $\operatorname{Im} B \cap \operatorname{ri}(\operatorname{dom} g) \neq \emptyset$ then equality holds.

Infimal Convolution

Definition 0.32. For $f_1, \dots, f_m : \mathbb{R}^n \mapsto (-\infty, +\infty]$, their **infimal convolution** is defined as

$$(f_1 \square \dots \square f_m)(x) = \left[\begin{array}{l} \inf f_1(x_1) + \dots + f_m(x_m) \\ \text{s.t. } x_1 + \dots + x_m = x \end{array} \right].$$

Proposition 0.89. $f_1, \dots, f_m \in \operatorname{Conv } \mathbb{R}^n$ implies that $f_1 \square \dots \square f_m \in E\text{-Conv } \mathbb{R}^n$ and

$$\operatorname{dom}(f_1 \square \dots \square f_m) = \operatorname{dom} f_1 + \dots + \operatorname{dom} f_m.$$

Remark 0.9. Let $f(x_1, \dots, x_m) = f_1(x_1) + \dots + f_m(x_m)$ and $A(x_1, \dots, x_m) = x$. Then $f_1 \square \dots \square f_m = Af$ and $f \circ A^* = (f_1 + \dots + f_m)^*$.

Proposition 0.90. Let $f_i : \mathbb{R}^m \mapsto (-\infty, \infty]$, $i = 1, 2, \dots, m$ be given. Then:

(i) $(f_1 \square \dots \square f_m)^* = f_1^* + \dots + f_m^*$

(ii) If $f_i \in \operatorname{Conv } \mathbb{R}^n$ for $i = 1, 2, \dots, m$ then $(\operatorname{cl}[f_1 + \dots + f_m])^* = \operatorname{cl}(f_1^* \square \dots \square f_m^*)$.

(iii) If $f_i \in \operatorname{Conv } \mathbb{R}^n$ for $i = 1, 2, \dots, m$ and

$$\bigcap_{i=1}^m \operatorname{ri}(\operatorname{dom} f_i) \neq \emptyset$$

then

$$(f_1 + \dots + f_m)^* = (f_1^* \square \dots \square f_m^*).$$

Corollary 0.19. *We have*

$$\begin{aligned}\partial(f_1 + \dots + f_m)(x) &= \partial(f \circ A^*)(x) \\ &= A[\partial f(A^*x)] \\ &= A(\partial f_1(x) \times \dots \times \partial f_m(x)) \\ &\stackrel{(*)}{=} \partial f_1(x) + \dots + \partial f_m(x)\end{aligned}$$

if the standard constraint qualification holds, where $(*)$ is left as an exercise. Note that \supseteq always holds regardless of the constraint set.

Corollary 0.20. *If $0 \leq \epsilon_1 + \dots + \epsilon_m \leq \epsilon$ then*

$$\partial_\epsilon(f_1 + \dots + f_m)(x) = \partial_{\epsilon_1} f_1(x) + \dots + \partial_{\epsilon_m} f_m(x)$$

when the standard constraint qualification holds. Note that \supseteq always holds regardless of the constraint set.

Applications

(1) Consider the problem

$$\begin{aligned}\min & f(x) \\ \text{s.t. } & x \in C\end{aligned}$$

where $f : \mathbb{R}^n \mapsto (-\infty, \infty]$ and $C \subseteq \mathbb{R}^n$. This is equivalent to

$$\begin{aligned} (*) \quad \min & f(x) + I_C(x) = (f + I_C)(x) \\ \text{s.t. } & x \in \mathbb{R}^n.\end{aligned}$$

Now x^* is a global min of $(*) \iff 0 \in \partial(f + I_C)(x^*) \iff 0 \in \partial f(x^*) + \partial I_C(x^*) \iff 0 \in \partial f(x^*) + N_C(x^*) \iff -\partial f(x^*) \cap N_C(x^*) \neq \emptyset$. All the statements are equivalent if f is convex, C is convex, $\text{ri}(\text{dom } f) \cap \text{ri } C \neq \emptyset$. The last expression is a generalization of the requirement $-\nabla f(x^*) \in N_C(x^*)$.

Proposition 0.91. *Consider ICP with $\emptyset \neq X \subseteq \text{dom } f \cap \bigcap_{i \in I} \text{dom } g_i$. Let \bar{x} be a feasible point of $(*)$, i.e. $g_I(\bar{x}) \leq 0$, $\bar{x} \in X$. If $\exists \bar{\lambda} \in \mathbb{R}_+^m$ s.t.*

$$\begin{cases} \partial f(\bar{x}) + \sum_{i \in I} \bar{\lambda}_i \partial g_i(\bar{x}) + N_X(\bar{x}), \\ \bar{\lambda}^T g_I(\bar{x}) = 0 \end{cases} \quad (a) \quad (*)$$

then \bar{x} is an optimal solution and $\bar{\lambda}$ is a Lagrange multiplier of $(**)$.

Conversely suppose that $f, \{g_i\}_{i \in I}$ are convex, X is convex and $\exists x^0 \in \text{ri}(\text{dom } f) \cap \bigcap_{i \in I} \text{ri}(\text{dom } g_i) \cap \text{ri } X$ such that $g_I(x^0) < 0$. Then if \bar{x} is a global minimum of (2), $\exists \bar{\lambda} \in \mathbb{R}_+^m$ satisfying $(*)$.