

Convex Analysis

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Chapter 1

Affine Sets

1.1 Definitions

Definition (Affine Combination). *Let S be a set in \mathbb{E} . We define an **affine combination** of S to be a point x in the space of the form*

$$x = \sum_{i=1}^n \lambda_i v_i$$

where (1) $n \in \mathbb{N}$, (2) $v_i \in S$ for all i , (3) $\lambda_i \in \mathbb{R}$ for all i , and (4) $\sum_{i=1}^n \lambda_i = 1$.

Definition (Affine Span). *Let S be a set in \mathbb{E} . We define the **affine span** of S , denoted by $\text{affspan}(S)$, to be the set of all affine combinations of S .*

Definition (Affine Set). *Let S be a set in \mathbb{E} . We say that S is an **affine set** if $S = \text{aff}(S)$.*

Definition (Affine Hull). *Let S be a set in \mathbb{E} . We define the **affine hull** of S , denoted by $\text{affhull}(S)$, to be the smallest affine set containing S .*

Chapter 2

Relative Topology

2.1 Definitions

Definition (Relative Interior). *Let \mathbb{E} be some Euclidean space. Let S be a set in the space. We define the **relative interior** of S , denoted by $\text{ri}(S)$, to be the interior of S for the topology relative to the affine hull $\text{aff}(S)$. i.e., the set given by*

$$\text{ri}(S) := \{x \in \text{aff}(S) : \exists r > 0, \text{ball}(x, r) \cap \text{aff}(S) \subseteq S\}.$$

A quick result. For a singleton set S , $\text{ri}(S) = S = \text{cl}(S)$.

2.2 Basic Properties

Proposition 2.2.1. *For any set S , we have $\text{ri}(S) \subseteq S$.*

Remark. *The relative interior operator is not monotonic.*

Example 2.2.1. *Consider \mathbb{R} with the usual topology and sets $\{0\}$ and $[0, 1]$. Then $\text{ri}(\{0\}) = \{0\}$ and $\text{ri}([0, 1]) = (0, 1)$.*

Proposition 2.2.2. *Let S be a set in some Euclidean space \mathbb{E} . Then if $\text{int}(S) \neq \emptyset$, $\text{ri}(S) = \text{int}(S)$.*

Proof.

It suffices to show that $\text{aff}(S) = \mathbb{R}^n$.

Since $\text{int}(S) \neq \emptyset$, $\exists x \in \text{int}(S)$.

Since $x \in \text{int}(S)$, $\exists r > 0$, $\text{ball}(x, r) \subseteq S$.

$\mathbb{E} = \text{aff}(\text{ball}(x, r)) \subseteq \text{aff}(S) \subseteq \mathbb{E}$.

This shows $\text{aff}(S) = \mathbb{E}$.

■

2.3 Arithmetic Properties

Proposition 2.3.1. *Let C_1 and C_2 be convex subsets of \mathbb{E} . Let λ_1 and λ_2 be scalars in \mathbb{R} . Then*

$$\text{ri}(\lambda_1 C_1 + \lambda_2 C_2) = \lambda_1 \text{ri}(C_1) + \lambda_2 \text{ri}(C_2).$$

Proposition 2.3.2. *Let C_1 be a convex set in \mathbb{E}_1 . Let C_2 be a convex set in \mathbb{E}_2 . Then*

$$\text{ri}(C_1 \oplus C_2) = \text{ri}(C_1) \oplus \text{ri}(C_2).$$

Chapter 3

Convex Sets

3.1 Definitions

Definition (Convex Combination). *Let S be a set in \mathbb{E} . We define a **convex combination** of S to be a point x in the space of the form*

$$x = \sum_{i=1}^n \lambda_i v_i$$

where (1) $n \in \mathbb{N}$, (2) $v_i \in S$ for all i , (3) $\lambda_i \in \mathbb{R}_+$ for all i , and (4) $\sum_{i=1}^n \lambda_i = 1$.

Definition (Convex Span). *Let S be a set in \mathbb{E} . We define a **convex span** of S , denoted by $\text{convspan}(S)$, to be the set of all convex combinations of S .*

Definition (Convex Sets). *Let S be a set in \mathbb{E} . We say that S is **convex** if $S = \text{convspan}(S)$, or equivalently, $\alpha x + \beta y \in S$ for any $x, y \in S$ and any $\alpha, \beta \in [0, 1]$ such that $\alpha + \beta = 1$.*

Definition (Convex Hull). *Let S be a set in \mathbb{E} . We define the **convex hull** of S , denoted by $\text{convhull}(S)$, to be the smallest convex set containing S .*

Definition (Closed Convex Hull). *Let S be a set in some Euclidean space. We define the **closed convex hull** of S to be the intersection of all closed convex supersets of S .*

Proposition 3.1.1. *For any set S , $\text{convspan}(S) = \text{convhull}(S)$. They will both be denoted by $\text{conv}(S)$ from now on.*

Proof.

For one direction, let x be an arbitrary point in $\text{convspan}(S)$.

We are to prove that $x \in \text{convhull}(S)$.

Let C be an arbitrary convex set containing S .

Since x is a convex combination of S , x is also a convex combination of C .

Since x is a convex combination of C and C is convex, $x \in C$.

Since x is in any convex set containing S , $x \in \text{convhull}(S)$.

Since $x \in \text{convhull}(S)$ for any $x \in \text{convspan}(S)$, $\text{convspan}(S) \subseteq \text{convhull}(S)$.

For the reverse direction,

proof incomplete.

■

Proposition 3.1.2. *The closed convex hull is the closure of the convex hull.*

3.2 Basic Properties

Proposition 3.2.1 (The conv Operator).

(1) *For any set S in a Euclidean space, we have*

$$S \subseteq \text{conv}(S).$$

(2) *(Monotonic) For any sets S_1 and S_2 in \mathbb{E} , if $S_1 \subseteq S_2$, then*

$$\text{conv}(S_1) \subseteq \text{conv}(S_2).$$

(3) *(Idempotent) For any set S in \mathbb{E} , we have*

$$\text{conv}(\text{conv}(S)) = \text{conv}(S).$$

Theorem 1 (Carathéodory). *Let \mathbb{E} be some Euclidean space. Let S be some set in the space. Let x be some point in $\text{conv}(S)$. Then x can be represented as a convex combination of at most $d + 1$ points in S . i.e., x lies in some r -simplex with vertices in S , where $r \leq d$.*

3.3 Arithmetic Properties

Proposition 3.3.1. *Let C be a convex set. Let λ_1 and λ_2 be in \mathbb{R}_+ . Then*

$$(\lambda_1 + \lambda_2)C = \lambda_1 C + \lambda_2 C.$$

Proof.

The case where any of λ_1 and λ_2 is 0 is trivial. I will assume that $\lambda_1, \lambda_2 > 0$.

For one direction, let x be an arbitrary point in $(\lambda_1 + \lambda_2)C$.

Since $x \in (\lambda_1 + \lambda_2)C$, $\exists c \in C, x = (\lambda_1 + \lambda_2)c$.

Since $\begin{cases} (\lambda_1 + \lambda_2)c = \lambda_1 c + \lambda_2 c \\ x = (\lambda_1 + \lambda_2)c \end{cases}$, we get $x = \lambda_1 c + \lambda_2 c$.

Since $\begin{cases} x = \lambda_1 c + \lambda_2 c \\ \lambda_1 c \in \lambda_1 C \\ \lambda_2 c \in \lambda_2 C \end{cases}$, we get $x \in \lambda_1 C + \lambda_2 C$.

Since $x \in \lambda_1 C + \lambda_2 C$ for any $x \in (\lambda_1 + \lambda_2)C$, $\lambda_1 C + \lambda_2 C \subseteq (\lambda_1 + \lambda_2)C$.

For the reverse direction, let x be an arbitrary point in $\lambda_1 C + \lambda_2 C$.

Since $x \in \lambda_1 C + \lambda_2 C$, $\exists c_1, c_2 \in C, x = \lambda_1 c_1 + \lambda_2 c_2$.

Define scalars $\mu_1 := \frac{\lambda_1}{\lambda_1 + \lambda_2}$ and $\mu_2 := \frac{\lambda_2}{\lambda_1 + \lambda_2}$.

Then $x = (\lambda_1 + \lambda_2)c$.

Since $\lambda_1, \lambda_2 > 0$, $\mu_1, \mu_2 \in [0, 1]$.

Define point $c := \mu_1 c_1 + \mu_2 c_2$.

Since $\begin{cases} c = \mu_1 c_1 + \mu_2 c_2 \\ c_1, c_2 \in C \\ \mu_1, \mu_2 \in [0, 1] \\ \mu_1 + \mu_2 = 1 \\ C \text{ is convex} \end{cases}$, we get $c \in C$.

Since $x = (\lambda_1 + \lambda_2)c$ and $c \in C$, $x \in (\lambda_1 + \lambda_2)C$.

Since $x \in (\lambda_1 + \lambda_2)C$ for any $x \in \lambda_1 C + \lambda_2 C$, $(\lambda_1 + \lambda_2)C \subseteq \lambda_1 C + \lambda_2 C$.

Since $\lambda_1 C + \lambda_2 C \subseteq (\lambda_1 + \lambda_2)C$ and $(\lambda_1 + \lambda_2)C \subseteq \lambda_1 C + \lambda_2 C$, $(\lambda_1 + \lambda_2)C = \lambda_1 C + \lambda_2 C$ ■

3.4 Stability of Convexity

Proposition 3.4.1. *Convexity is stable under intersection. i.e., the intersection of any collection of convex sets is convex.*

Proof. Let $\{C_i\}_{i \in I}$ be an arbitrary collection of convex sets where I is an index set and C_i is convex for any $i \in I$. Let C denote their intersection. If $C = \emptyset$, then we are done. Else, let x and y be two arbitrary points in C . Let λ be an arbitrary number in $(0, 1)$. Define a point $z := \lambda x + (1 - \lambda)y$. Since $x \in C$ and $C = \bigcap_{i \in I} C_i$, we get $x \in C_i$ for any $i \in I$. Since $y \in C$ and $C = \bigcap_{i \in I} C_i$, we get $y \in C_i$ for any $i \in I$. Let i be an arbitrary index in I . Since $x \in C_i$ and $y \in C_i$ and $\lambda \in (0, 1)$ and C_i is convex and $z = \lambda x + (1 - \lambda)y$, we get $z \in C_i$. Since $z \in C_i$ for any $i \in I$ and $C = \bigcap_{i \in I} C_i$, we get $z \in C$. Since

$$\forall x, y \in C, \forall \lambda \in (0, 1), \quad \lambda x + (1 - \lambda)y \in C,$$

by definition of convex sets, we get C is convex. ■

Proposition 3.4.2. *Convexity is stable under affine mapping. i.e., the affine image of a convex set is convex.*

Proposition 3.4.3 (Linear Combinations). *Convexity is stable under linear combination. i.e., if C_1 and C_2 are convex sets and λ_1 and λ_2 are real numbers, then the set $C := \lambda_1 C_1 + \lambda_2 C_2$ is convex.*

Proof.

If $C_1 = \emptyset$ or $C_2 = \emptyset$, then $\lambda_1 C_1 + \lambda_2 C_2 = \emptyset$ and we are done.

Now assume $C_1, C_2 \neq \emptyset$.

Let x and y be arbitrary points in C .

Since $x \in C$,

$$\exists x_1 \in C_1, x_2 \in C_2 \text{ such that } x = \lambda_1 x_1 + \lambda_2 x_2.$$

Since $y \in C$,

$$\exists y_1 \in C_1, y_2 \in C_2 \text{ such that } y = \lambda_1 y_1 + \lambda_2 y_2.$$

Let $\lambda \in [0, 1]$ be arbitrary.

Define $z := \lambda x + (1 - \lambda)y$.

$$\text{Since } \begin{cases} z = \lambda \mathbf{x} + (1 - \lambda)\mathbf{y} \\ \mathbf{x} = \lambda_1 x_1 + \lambda_2 x_2, \text{ substitute } x \text{ and } y \text{ into } z, \text{ we get} \\ \mathbf{y} = \lambda_1 y_1 + \lambda_2 y_2 \end{cases}$$

$$\begin{aligned} z &= \lambda(\lambda_1 \mathbf{x}_1 + \lambda_2 \mathbf{x}_2) + (1 - \lambda)(\lambda_1 \mathbf{y}_1 + \lambda_2 \mathbf{y}_2) \\ &= \lambda_1(\lambda \mathbf{x}_1 + (1 - \lambda)\mathbf{y}_1) + \lambda_2(\lambda \mathbf{x}_2 + (1 - \lambda)\mathbf{y}_2). \end{aligned}$$

Since (1) $x_1, y_1 \in C_1$ and (2) $\lambda \in [0, 1]$ and (3) C_1 is convex, we get

$$\lambda x_1 + (1 - \lambda)y_1 \in C_1.$$

Since (1) $x_2, y_2 \in C_2$ and (2) $\lambda \in [0, 1]$ and (3) C_2 is convex, we get

$$\lambda x_2 + (1 - \lambda)y_2 \in C_2.$$

$$\text{Since } \begin{cases} z = \lambda_1(\lambda x_1 + (1 - \lambda)y_1) + \lambda_2(\lambda x_2 + (1 - \lambda)y_2) \\ \lambda x_1 + (1 - \lambda)y_1 \in C_1 \\ \lambda x_2 + (1 - \lambda)y_2 \in C_2 \end{cases}, \text{ we get}$$

$$z \in \lambda_1 C_1 + \lambda_2 C_2.$$

Since $\forall x \in C, \forall y \in C, \forall \lambda \in [0, 1], \lambda x + (1 - \lambda)y \in C$, we get C is convex. ■

Corollary. *The Minkowski sum of two convex sets is convex.*

Lemma 1. *Let C be a convex set in \mathbb{E} . Let $x \in \text{int}(C)$. Let $y \in \text{cl}(C)$. Then*

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

Proof.

Since $x \in \text{int}(S)$, there exists some radius r_x such that $\text{ball}(x, r_x) \subseteq S$.

Define $r_z := \lambda r_x$.

Let z' be an arbitrary point in $\text{ball}(z, r_z)$.

Define $x' := \frac{1}{\lambda}(z' - (1 - \lambda)y)$.

Notice

$$\begin{aligned}
 & \|x - x'\| \\
 &= \frac{1}{|\lambda|} \|\lambda x - \lambda x'\| \\
 &= \frac{1}{|\lambda|} \|(z - (1 - \lambda)y) - (z' - (1 - \lambda)y)\| \\
 &= \frac{1}{|\lambda|} \|z - z'\| \\
 &\leq \frac{1}{|\lambda|} r_z, \text{ since } z' \in \text{ball}(z, r_z) \\
 &= \frac{1}{|\lambda|} \lambda r_x \\
 &= r_x.
 \end{aligned}$$

That is,

$$\|x - x'\| \leq r_x.$$

So $x' \in \text{ball}(x, r_x)$.

Since $x' \in \text{ball}(x, r_x)$ and $\text{ball}(x, r_x) \subseteq S$, we get $x' \in S$.

$$\text{Since } \begin{cases} z' = \lambda x' + (1 - \lambda)y \\ x', y \in S \\ \lambda \in (0, 1] \\ S \text{ is convex} \end{cases}, \text{ we get } z' \in S.$$

Since $z' \in S$ for any $z' \in \text{ball}(z, r_z)$, $\text{ball}(z, r_z) \subseteq S$.

Since there exists some radius r_z such that $\text{ball}(z, r_z) \subseteq S$, $z \in \text{int}(S)$.

Alternative Expressing:

Define $B := \text{ball}(0, 1)$.

$$\begin{aligned}
 & (1 - \lambda)x + \lambda y + \varepsilon B \\
 &\subseteq (1 - \lambda)x + \lambda(C + \varepsilon B) + \varepsilon B \\
 &= (1 - \lambda)x + \lambda C + \lambda \varepsilon B + \varepsilon B \\
 &= (1 - \lambda)x + (1 + \lambda)\varepsilon B + \lambda C \\
 &= (1 - \lambda)\left(x + \frac{1 + \lambda}{1 - \lambda}\varepsilon B\right) + \lambda C
 \end{aligned}$$

$$\begin{aligned}
&\subseteq (1 - \lambda)C + \lambda C \\
&= C.
\end{aligned}$$

■

Lemma 2. *Let C be a convex set in \mathbb{E} . Let $x \in \text{ri}(C)$. Let $y \in \text{cl}(C)$. Then*

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

Proof.

Case 1. $\text{int}(C) \neq \emptyset$.

Then $\text{int}(C) = \text{ri}(C)$.

Since $x \in \text{int}(C)$ and $y \in \text{cl}(C)$, $\forall t \in (0, 1], z := tx + (1 - t)y \in C$.

Case 2. $\text{int}(C) = \emptyset$.

Now $\dim(C) < d$.

Say $\dim(C) = l$.

Apply case 1 in \mathbb{R}^l .

■

Proposition 3.4.4. *Convexity is stable under interior. i.e., the interior of a convex set is convex.*

Proof. Let S be a convex set in \mathbb{E} . If $\text{int}(S) = \emptyset$, then we are done. Else: let x and y be two arbitrary points in $\text{int}(S)$. Let λ be an arbitrary number in $(0, 1)$. Define a point z by $z := \lambda x + (1 - \lambda)y$. Since $x, y \in \text{int}(S)$ and $\lambda \in (0, 1)$, by the lemma, we get $z \in \text{int}(S)$. Since

$$\forall x, y \in \text{int}(S), \forall \lambda \in (0, 1), \quad \lambda x + (1 - \lambda)y \in \text{int}(S),$$

we get $\text{int}(S)$ is convex.

■

Proposition 3.4.5. *Convexity is stable under relative interior. i.e., the relative interior of a convex set is convex.*

Proof. Let S be a convex set in \mathbb{E} . If $\text{ri}(S) = \emptyset$, then we are done. Else: let x and y be two arbitrary points in $\text{ri}(S)$. Let λ be an arbitrary number in $(0, 1)$. Define a point z by $z := \lambda x + (1 - \lambda)y$. Since $x, y \in \text{ri}(S)$ and $\lambda \in (0, 1)$, by the lemma, we get $z \in \text{ri}(S)$. Since

$$\forall x, y \in \text{ri}(S), \forall \lambda \in (0, 1), \quad \lambda x + (1 - \lambda)y \in \text{ri}(S),$$

we get $\text{ri}(S)$ is convex.

■

Proposition 3.4.6. *Convexity is stable under closure. i.e., the closure of a convex set is convex.*

Proof Approach 1.

Let $x, y \in \text{cl}(C)$.

Let $t \in [0, 1]$.

Since $x \in \text{cl}(C)$, $\exists \{x_i\}_{i \in \mathbb{N}} \subseteq C$, $\lim_{i \rightarrow \infty} x_i = x$.

Since $y \in \text{cl}(C)$, $\exists \{y_i\}_{i \in \mathbb{N}} \subseteq C$, $\lim_{i \rightarrow \infty} y_i = y$.

Since $\lim_{i \rightarrow \infty} x_i = x$ and $\lim_{i \rightarrow \infty} y_i = y$, $\lim_{i \rightarrow \infty} (tx_i + (1-t)y_i) = tx + (1-t)y$.

Since $x_i, y_i \in C$ and C is convex, $tx_i + (1-t)y_i \in C$.

Since $tx_i + (1-t)y_i \in C$, $\lim_{i \rightarrow \infty} (tx_i + (1-t)y_i) = tx + (1-t)y$, $tx + (1-t)y \in \text{cl}(C)$.

Since $\forall x, y \in \text{cl}(C)$, $\forall t \in [0, 1]$, $tx + (1-t)y \in \text{cl}(C)$, we get $\text{cl}(C)$ is convex. ■

Proof Approach 2.

$\text{cl}(C) = \bigcap_{\varepsilon > 0} [C + \varepsilon \text{ball}(0, 1)]$. This is an intersection of linear combinations of convex sets and hence convex. ■

Proposition 3.4.7. *Convexity is stable under conical hull. i.e., if C is convex, then $\text{cone}(C)$ is convex.*

Proof.

Let x and y be arbitrary points in $\text{cone}(C)$.

Let λ be an arbitrary number in $(0, 1)$.

Define point z as $z := \lambda x + (1-\lambda)y$.

Since $x \in \text{cone}(C)$, $\exists x' \in C$ and $\exists \alpha > 0$ such that $x = \alpha x'$.

Since $y \in \text{cone}(C)$, $\exists y' \in C$ and $\exists \beta > 0$ such that $y = \beta y'$.

Define point z' as $z' := \frac{\lambda\alpha}{\lambda\alpha + (1-\lambda)\beta} x' + \frac{(1-\lambda)\beta}{\lambda\alpha + (1-\lambda)\beta} y'$.

Since $x', y' \in C$ and $\frac{\lambda\alpha}{\lambda\alpha + (1-\lambda)\beta} \in (0, 1)$ and $\frac{\lambda\alpha}{\lambda\alpha + (1-\lambda)\beta} + \frac{(1-\lambda)\beta}{\lambda\alpha + (1-\lambda)\beta} = 1$ and C is convex and $z' := \frac{\lambda\alpha}{\lambda\alpha + (1-\lambda)\beta} x' + \frac{(1-\lambda)\beta}{\lambda\alpha + (1-\lambda)\beta} y'$, we get $z' \in C$.

Since $z' \in C$ and $z = (\lambda\alpha + (1-\lambda)\beta)z'$, $z \in \text{cone}(C)$.

That is, $\lambda x + (1-\lambda)y \in \text{cone}(C)$.

Since $\forall x, y \in \text{cone}(C)$, $\forall \lambda \in (0, 1)$, $\lambda x + (1-\lambda)y \in \text{cone}(C)$, we get $\text{cone}(C)$ is convex. ■

3.5 Topological Properties

Proposition 3.5.1. *A closed convex hull does not distinguish a set from its closure. i.e., for any set S , we have $\overline{\text{conv}}(S) = \overline{\text{conv}}(\text{cl}(S))$.*

Proposition 3.5.2. *The convex hull of a bounded set is bounded.*

Proposition 3.5.3. *The convex hull of a compact set is compact.*

Proposition 3.5.4. *If S is bounded, then the closure operation and the convex hull operation commute. i.e., $\text{conv}(\text{cl}(S)) = \text{cl}(\text{conv}(S))$.*

Remark. *The closure operation and the convex hull operation do not commute in general.*

Theorem 2. *Let C be a convex set such that $\text{int}(C) \neq \emptyset$. Then*

$$(1) \text{ int}(C) = \text{int}(\text{cl}(C)), \text{ and}$$

$$(2) \text{ cl}(C) = \text{cl}(\text{int}(C)).$$

Proof of (1). $\text{int}(C) \subseteq \text{int}(\text{cl}(C))$ is clear. For $\text{int}(\text{cl}(C)) \subseteq \text{int}(C)$, let x be an arbitrary point in $\text{int}(\text{cl}(C))$.

Since $x \in \text{int}(\text{cl}(C))$,

$$\exists r > 0 \text{ such that } \text{ball}(x, r) \subseteq \text{cl}(C).$$

Since $\text{int}(C) \neq \emptyset$, pick $y \in \text{int}(C)$.

Define a scalar λ by

$$\lambda := \frac{r}{2\|x - y\|}.$$

Define a point z by

$$z := x + \lambda(x - y).$$

Since $\lambda = \frac{r}{2\|x - y\|}$ and $z = x + \lambda(x - y)$,

$$\begin{aligned} & \|z - x\| \\ &= \|x + \lambda(x - y) - x\| \\ &= \|\lambda(x - y)\| \\ &= \lambda\|x - y\| \\ &= \frac{r}{2\|x - y\|}\|x - y\| \\ &= \frac{r}{2} \\ &< r. \end{aligned}$$

That is,

$$\|z - x\| < r.$$

So $z \in \text{ball}(x, r)$. It follows that $z \in \text{cl}(C)$.

Since $z = x + \lambda(x - y)$, rearranging this yields

$$x = \frac{1}{1 + \lambda}z + \frac{\lambda}{1 + \lambda}y.$$

$$\text{Since } \begin{cases} x = \frac{1}{1+\lambda}z + \frac{\lambda}{1+\lambda}y \\ z \in \text{cl}(C) \\ y \in \text{int}(C) \\ \frac{1}{1+\lambda}, \frac{\lambda}{1+\lambda} \in (0, 1) \\ \frac{1}{1+\lambda} + \frac{\lambda}{1+\lambda} = 1 \end{cases}, \text{ by the lemma, we get}$$

$$x \in \text{int}(C).$$

Since $\forall x \in \text{int}(\text{cl}(C)), x \in \text{int}(C)$, we get $\text{int}(\text{cl}(C)) \subseteq \text{int}(C)$. ■

Proof of (2). $\text{cl}(\text{int}(C)) \subseteq \text{cl}(C)$ is clear. For $\text{cl}(C) \subseteq \text{cl}(\text{int}(C))$, let x be an arbitrary point in $\text{cl}(C)$.

Since $\text{int}(C) \neq \emptyset$, pick $y \in \text{int}(C)$.

Let $\lambda \in [0, 1)$.

Define a point z by

$$z(\lambda) := \lambda x + (1 - \lambda)y.$$

$$\text{Since } \begin{cases} z(\lambda) := \lambda x + (1 - \lambda)y \\ x \in \text{cl}(C) \\ y \in \text{int}(C) \\ \lambda \in [0, 1) \end{cases}, \text{ by the lemma, we get}$$

$$z(\lambda) \in \text{int}(C).$$

$$\text{Since } \begin{cases} z(\lambda) \in \text{int}(C) \\ \lim_{\lambda \rightarrow 1} z(\lambda) = x \end{cases}, \text{ we get}$$

$$x \in \text{cl}(\text{int}(C)).$$

Since $\forall x \in \text{cl}(C), x \in \text{cl}(\text{int}(C))$, we get $\text{cl}(C) \subseteq \text{cl}(\text{int}(C))$. ■

Proposition 3.5.5. *If C is convex, then*

- (1) $\text{aff}(\text{ri}(C)) = \text{aff}(C) = \text{aff}(\text{cl}(C))$,
- (2) $\text{ri}(\text{ri}(C)) = \text{ri}(C) = \text{ri}(\text{cl}(C))$, and
- (3) $\text{cl}(\text{ri}(C)) = \text{cl}(C) = \text{cl}(\text{cl}(C))$.

Proposition 3.5.6. *Let C be a convex set. Then*

$$C \neq \emptyset \iff \text{ri}(C) \neq \emptyset.$$

Proof.

For one direction, assume that $C \neq \emptyset$. We are to prove that $\text{ri}(C) \neq \emptyset$. Since $C \neq \emptyset$, $\text{aff}(C) \neq \emptyset$. Since C is convex, $\text{aff}(C) = \text{aff}(\text{ri}(C))$. Since $\begin{cases} \text{aff}(C) \neq \emptyset \\ \text{aff}(C) = \text{aff}(\text{ri}(C)) \end{cases}$, we get

$$\text{aff}(\text{ri}(C)) \neq \emptyset.$$

Since $\text{aff}(\text{ri}(C)) \neq \emptyset$, we get $\text{ri}(C) \neq \emptyset$.

For the reverse direction, assume that $\text{ri}(C) \neq \emptyset$. We are to prove that $C \neq \emptyset$. Since $\text{ri}(C) \neq \emptyset$ and $\text{ri}(C) \subseteq C$, we get $C \neq \emptyset$. ■

3.6 Examples of Convex Sets

Example 3.6.1. Let I be an index set. Let b_i for $i \in I$ be vectors in \mathbb{E} . Let β_i for $i \in I$ be reals. Then the set C given by

$$C := \{x \in \mathbb{E} : \forall i \in I, \langle x, b_i \rangle \leq \beta_i\}$$

is convex.

Proof.

Each of $C_i := \{x \in \mathbb{E} : \langle x, b_i \rangle \leq \beta_i\}$ is convex and $C = \bigcap_{i \in I} C_i$.

$$\begin{aligned} \langle z, b_i \rangle &= \langle \lambda x + (1 - \lambda)y, b_i \rangle \\ &= \lambda \langle x, b_i \rangle + (1 - \lambda) \langle y, b_i \rangle \\ &\leq \lambda \beta_i + (1 - \lambda) \beta_i \\ &= \beta_i. \end{aligned}$$
■

Chapter 4

Cones (in Analysis)

4.1 Definitions

Definition (Conical Combination). *Let S be a set in \mathbb{E} . We define a **conical combination** of S to be a point x in the space of the form*

$$x = \sum_{i=1}^n \lambda_i v_i$$

where (1) $n \in \mathbb{N}$, (2) $v_i \in S$ for all i , and (3) $\lambda_i \in \mathbb{R}_{++}$ for all i .

Definition (Cone). *Let S be a set in \mathbb{E} . We say that S is a **cone** if $S = \mathbb{R}_{++}S$.*

Definition (Conical Hull). *Let S be a set in \mathbb{E} . We define the **conical hull** of S , denoted by $\text{cone}(S)$, to be the intersection of all cones containing S .*

Proposition 4.1.1. *Let S be a set in \mathbb{E} . Then $\text{cone}(S) = \mathbb{R}_{++}S$.*

Proof. For one direction, we are to prove $\text{cone}(S) \subseteq \mathbb{R}_{++}S$. Since $\mathbb{R}_{++}\mathbb{R}_{++}S = \mathbb{R}_{++}S$, $\mathbb{R}_{++}S$ is a cone. Since $1 \in \mathbb{R}_{++}$, $S \subseteq \mathbb{R}_{++}S$. Since $\mathbb{R}_{++}S$ is a cone containing S and $\text{cone}(S)$ is the smallest cone containing S , we get

$$\text{cone}(S) \subseteq \mathbb{R}_{++}S.$$

For the reverse direction, we are to prove $\mathbb{R}_{++}S \subseteq \text{cone}(S)$. Let C be an arbitrary cone containing S . Since $S \subseteq C$, $\mathbb{R}_{++}S \subseteq \mathbb{R}_{++}C$. Since C is a cone, $\mathbb{R}_{++}C = C$. So $\mathbb{R}_{++}S \subseteq C$. Since $\mathbb{R}_{++}S \subseteq C$ for any cone C containing S , we get

$$\mathbb{R}_{++}S \subseteq \text{cone}(S).$$

■

Definition (Closed Conical Hull). *Let S be a set in \mathbb{E} . We define the **closed conical hull** of S , denoted by $\text{clcone}(S)$, to be the intersection of all closed cones containing S .*

Proposition 4.1.2. *For any set S in \mathbb{E} , we have*

$$\text{clcone}(S) = \text{cl}(\text{cone}(S)).$$

Proof.

For $\text{clcone}(S) \subseteq \text{cl}(\text{cone}(S))$.

Since $\text{cl}(\text{cone}(S))$ is a closed cone containing S and $\text{clcone}(S)$ is the smallest closed cone containing S , $\text{clcone}(S) \subseteq \text{cl}(\text{cone}(S))$.

For $\text{cl}(\text{cone}(S)) \subseteq \text{clcone}(S)$.

Since $S \subseteq \text{clcone}(S)$, by the monotonicity of the cone operator, $\text{cone}(S) \subseteq \text{cone}(\text{clcone}(S))$.

Since $\text{cone}(S) \subseteq \text{cone}(\text{clcone}(S))$, by the monotonicity of the closure operator, $\text{cl}(\text{cone}(S)) \subseteq \text{cl}(\text{cone}(\text{clcone}(S)))$.

Since $\text{clcone}(S)$ is a cone, $\text{cone}(\text{clcone}(S)) = \text{clcone}(S)$.

Since $\text{clcone}(S)$ is closed, $\text{cl}(\text{clcone}(S)) = \text{clcone}(S)$.

Since $\text{cone}(\text{clcone}(S)) = \text{clcone}(S)$ and $\text{cl}(\text{clcone}(S)) = \text{clcone}(S)$, we get $\text{cl}(\text{cone}(\text{clcone}(S))) = \text{clcone}(S)$.

Since $\text{cl}(\text{cone}(S)) \subseteq \text{cl}(\text{cone}(\text{clcone}(S)))$ and $\text{cl}(\text{cone}(\text{clcone}(S))) = \text{clcone}(S)$, we get $\text{cl}(\text{cone}(S)) \subseteq \text{clcone}(S)$.

Since $\text{clcone}(S) \subseteq \text{cl}(\text{cone}(S))$ and $\text{cl}(\text{cone}(S)) \subseteq \text{clcone}(S)$, we get $\text{clcone}(S) = \text{cl}(\text{cone}(S))$. ■

4.2 The cone Operator

Proposition 4.2.1 (The cone Operator). *The cone operator has the following properties.*

$$(1) \quad \forall S \subseteq \mathbb{E},$$

$$S \subseteq \text{cone}(S).$$

$$(2) \quad \forall S_1, S_2 \subseteq \mathbb{E},$$

$$S_1 \subseteq S_2 \implies \text{cone}(S_1) \subseteq \text{cone}(S_2).$$

$$(3) \quad \forall S \subseteq \mathbb{E},$$

$$\text{cone}(\text{cone}(S)) = \text{cone}(S).$$

Proposition 4.2.2. *The conv operator and the cone operator commute. Let S be a set in \mathbb{E} . Then*

$$\text{conv}(\text{cone}(S)) = \text{cone}(\text{conv}(S)).$$

Proof.

For $\text{cone}(\text{conv}(S)) \subseteq \text{conv}(\text{cone}(S))$, let x be an arbitrary point in $\text{cone}(\text{conv}(S))$.

Since $x \in \text{cone}(\text{conv}(S))$, we get $\exists \lambda \in \mathbb{R}_+$, $\exists n \in \mathbb{N}$, $\exists v_1, \dots, v_n \in S$, $\exists \mu_1, \dots, \mu_n \in [0, 1]$, $\sum_{i=1}^n \mu_i = 1$ such that $x = \lambda \sum_{i=1}^n \mu_i v_i$.

Since $x = \lambda \sum_{i=1}^n \mu_i v_i$, $x = \sum_{i=1}^n \mu_i (\lambda v_i)$.

Since $\lambda \in \mathbb{R}_+$ and $v_i \in S$, $\lambda v_i \in \text{cone}(S)$.

Since $\lambda v_i \in \text{cone}(S)$ and $\mu_i \in [0, 1]$, $\sum_{i=1}^n \mu_i = 1$, $\sum_{i=1}^n \mu_i (\lambda v_i) \in \text{conv}(\text{cone}(S))$.

Since $\forall x \in \text{cone}(\text{conv}(S))$, $x \in \text{conv}(\text{cone}(S))$, $\text{cone}(\text{conv}(S)) \subseteq \text{conv}(\text{cone}(S))$.

For $\text{conv}(\text{cone}(S)) \subseteq \text{cone}(\text{conv}(S))$, let x be an arbitrary point in $\text{conv}(\text{cone}(S))$.

Since $x \in \text{conv}(\text{cone}(S))$, $\exists n \in \mathbb{N}$, $\exists \lambda_i \in [0, 1]$, $\sum_{i=1}^n \lambda_i = 1$, $\exists \mu_i \in \mathbb{R}_+$, $\exists v_i \in S$ such that $x = \sum_{i=1}^n \lambda_i \mu_i v_i$.

Define $\alpha := \sum_{i=1}^n \lambda_i \mu_i$.

Define $\beta_i := \lambda_i \mu_i / \alpha$.

Then $\alpha \in \mathbb{R}_+$ and $\beta_i \in [0, 1]$ and $\sum_{i=1}^n \beta_i = 1$ and $x = \alpha \sum_{i=1}^n \beta_i v_i$.

Since $\beta_i \in [0, 1]$ and $\sum_{i=1}^n \beta_i = 1$ and $v_i \in S$, we get $\sum_{i=1}^n \beta_i v_i \in \text{conv}(S)$.

Since $\alpha \in \mathbb{R}_+$ and $\sum_{i=1}^n \beta_i v_i \in \text{conv}(S)$ and $x = \alpha \sum_{i=1}^n \beta_i v_i$, we get $x \in \text{cone}(\text{conv}(S))$.

Since $\forall x \in \text{conv}(\text{cone}(S))$, $x \in \text{cone}(\text{conv}(S))$, we get $\text{conv}(\text{cone}(S)) \subseteq \text{cone}(\text{conv}(S))$.

Since $\text{cone}(\text{conv}(S)) \subseteq \text{conv}(\text{cone}(S))$ and $\text{conv}(\text{cone}(S)) \subseteq \text{cone}(\text{conv}(S))$, we get $\text{conv}(\text{cone}(S)) = \text{cone}(\text{conv}(S))$. ■

4.3 Other Properties

Proposition 4.3.1. *Let C be a convex set in \mathbb{E} . Assume $\text{int}(C) \neq \emptyset$ and $0 \in C$. Then $\text{int}(\text{cone}(C)) = \text{cone}(\text{int}(C))$.*

Proof.

For one direction, let x be an arbitrary point in $\text{int}(\text{cone}(C))$. We are to prove that $x \in \text{cone}(\text{int}(C))$.

Since $x \in \text{int}(\text{cone}(C))$, $\exists r$ such that $\text{ball}(x, r) \subseteq \text{cone}(C)$.

Since $x \in \text{int}(\text{cone}(C))$, $x \in \text{cone}(C)$.

Since $x \in \text{cone}(C)$, $\exists n \in \mathbb{N}$, $\exists \lambda_1, \dots, \lambda_n > 0$, $\exists v_1, \dots, v_n \in C$ such that $x = \sum_{i=1}^n \lambda_i v_i$.

Assume for the sake of contradiction that $\exists k \in \{1, \dots, n\}$ such that $\forall r_k > 0$, $\text{ball}(v_k, r_k) \cap \mathbb{E} \setminus C \neq \emptyset$.

not finished

For the reverse direction, let x be an arbitrary point in $\text{cone}(\text{int}(C))$. We are to prove that $x \in \text{int}(\text{cone}(C))$.

Since $x \in \text{cone}(\text{int}(C))$, $\exists n \in \mathbb{N}$, $\exists \lambda_1, \dots, \lambda_n > 0$, $\exists v_1, \dots, v_n \in \text{int}(C)$ such that $x = \sum_{i=1}^n \lambda_i v_i$.

Since $v_i \in \text{int}(C)$ for each $i \in \{1, \dots, n\}$, $\exists r_i$ such that $\text{ball}(v_i, r_i) \subseteq C$.

Define $R := \min\{\lambda_i r_i\}_{i=1}^n$.

Say $R = \lambda_k r_k$ for some $k \in \{1, \dots, n\}$.

Let y be an arbitrary point in $\text{ball}(x, R)$.

Since $y \in \text{ball}(x, R)$, $\exists w$ such that $\|w\| < R$ and $y = x + w$.

$$\begin{aligned} y &= \sum_{i=1}^n \lambda_i v_i + w \\ &= \sum_{i \neq k} \lambda_i v_i + \lambda_k v_k + w \\ &= \sum_{i \neq k} \lambda_i v_i + \lambda_k (v_k + w/\lambda_k). \end{aligned}$$

Since $\|w\| < R$, $\|w/\lambda_k\| < R/\lambda_k = r_k$.

Since $\|w/\lambda_k\| < r_k$, $v_k + w/\lambda_k \in \text{ball}(v_k, r_k)$.

So $v_k + w/\lambda_k \in C$.

So $y \in \text{cone}(C)$.

Since $\forall y \in \text{ball}(x, R)$, $y \in \text{cone}(C)$, $\text{ball}(x, R) \subseteq \text{cone}(C)$.

Since $\exists r$ such that $\text{ball}(x, r) \subseteq \text{cone}(C)$, $x \in \text{int}(\text{cone}(C))$.

This proves $\text{cone}(\text{int}(C)) \subseteq \text{int}(\text{cone}(C))$. ■

Proposition 4.3.2. *Let C be a convex set in \mathbb{E} . Assume $\text{int}(C) \neq \emptyset$ and $0 \in C$. Then*

$$0 \in \text{int}(C) \iff \text{cone}(C) = \mathbb{E}.$$

Proof. For one direction, assume that $0 \in \text{int}(C)$. We are to prove that $\text{cone}(C) = \mathbb{E}$. Clearly

$$\text{cone}(C) \subseteq \mathbb{E}.$$

Since $0 \in \text{int}(C)$, $\exists r > 0$ such that $\text{ball}(0, r) \subseteq C$. Since $\text{ball}(0, r) \subseteq C$, $\text{cone}(\text{ball}(0, r)) \subseteq \text{cone}(C)$. Since $\text{cone}(\text{ball}(0, r)) = \mathbb{E}$ and $\text{cone}(\text{ball}(0, r)) \subseteq \text{cone}(C)$, we get

$$\mathbb{E} \subseteq \text{cone}(C).$$

For the reverse direction, assume that $\text{cone}(C) = \mathbb{E}$. We are to prove that $0 \in \text{int}(C)$.

$$\mathbb{E} = \text{int}(\mathbb{E}) = \text{int}(\text{cone}(C)) = \text{cone}(\text{int}(C)).$$

If $0 \notin \text{int}(C)$, then $0 \notin \text{cone}(\text{int}(C))$. So $0 \in \text{int}(C)$. ■

Chapter 5

Tangent Cones and Normal Cones

5.1 Definitions

Definition (Tangent Cones). *Let C be a non-empty convex set in \mathbb{E} . Let x be a point in \mathbb{E} . We define the **tangent cone** to C at point x , denoted by $T_C(x)$, to be a set given by*

$$T_C(x) := \begin{cases} \text{clcone}(C - x), & \text{if } x \in C, \text{ or} \\ \emptyset, & \text{if } x \notin C. \end{cases}$$

Definition (Normal Cones). *Let C be a non-empty convex set in \mathbb{E} . Let x be a point in \mathbb{E} . We define the **normal cone** to C at point x , denoted by $N_C(x)$, to be a set given by*

$$N_C(x) := \begin{cases} \{v \in \mathbb{E} : \forall y \in C - x, \langle y, v \rangle \leq 0\}, & \text{if } x \in C, \text{ or} \\ \emptyset, & \text{if } x \notin C. \end{cases}$$

5.2 Basic Properties

Proposition 5.2.1. *Let C be a closed convex set in \mathbb{E} . Let x be a point in \mathbb{E} . Then $T_C(x)$ and $N_C(x)$ are closed convex cones.*

Proof.

If $C = \emptyset$, then $T_C(x) = N_C(x) = \emptyset$.

If $C \neq \emptyset$ and $x \notin C$, then $T_C(x) = N_C(x) = \emptyset$.

So now I assume that $C \neq \emptyset$ and $x \in C$.

Tangent Cone is Closed:

By definition, $T_C(x) = \text{clcone}(C - x)$. So $T_C(x)$ is a closed.

Tangent Cone is Convex:

$$\begin{array}{ll}
C \text{ is convex} & \\
\Downarrow & \text{since affine mapping preserves convexity} \\
C - x \text{ is convex} & \\
\Downarrow & \text{since the cone operator preserves convexity} \\
\text{cone}(C - x) \text{ is convex} & \\
\Downarrow & \text{since the cl operator preserves convexity} \\
\text{cl}(\text{cone}(C - x)) \text{ is convex} & \\
\Downarrow & \text{since } \text{cl} \circ \text{cone} = \text{clcone} \\
\text{clcone}(C - x) \text{ is convex} &
\end{array}$$

That is, $T_C(x)$ is convex.

Tangent Cone is a Cone

By definition, $T_C(x) = \text{clcone}(C - x)$. So $T_C(x)$ is a cone.

Normal Cone is Closed:

Let $\{x_i\}_{i \in \mathbb{N}}$ be an arbitrary sequence in $N_C(x)$ that converges to some point in \mathbb{E} .

Say $x_i \rightarrow x_\infty$.

Let y be an arbitrary point in $C - x$.

Since $x_i \in N_C(x)$ and $y \in C - x$, by definition of $N_C(x)$, we get $\langle x_i, y \rangle \leq 0$.

Since $\langle x_i, y \rangle \leq 0$ for any $i \in \mathbb{N}$ and $x_i \rightarrow x_\infty$, we get $\langle x_\infty, y \rangle \leq 0$.

Since $\forall y \in C - x$, $\langle x_\infty, y \rangle \leq 0$, by definition of $N_C(x)$, we get $x_\infty \in N_C(x)$.

Since any convergent sequence whose terms are in $N_C(x)$ has its limit also in $N_C(x)$, $N_C(x)$ is closed.

Normal Cone is Convex:

Let u and v be arbitrary points in $N_C(x)$.

Let λ be an arbitrary number in $(0, 1)$.

Define point z as $z := \lambda u + (1 - \lambda)v$.

Let y be an arbitrary point in $C - x$.

Since $u \in N_C(x)$, $\langle u, y \rangle \leq 0$.

Since $v \in N_C(x)$, $\langle v, y \rangle \leq 0$.

$$\begin{aligned}
& \langle z, y \rangle \\
&= \langle \lambda u + (1 - \lambda)v, y \rangle \\
&= \lambda \langle u, y \rangle + (1 - \lambda) \langle v, y \rangle \\
&\leq \lambda 0 + (1 - \lambda) 0
\end{aligned}$$

$$= 0.$$

That is, $\langle z, y \rangle \leq 0$.

Since $\forall y \in C - x$, $\langle z, y \rangle \leq 0$, we get $z \in N_C(x)$.

That is, $\lambda u + (1 - \lambda)v \in N_C(x)$.

Since $\forall u, v \in N_C(x)$, $\forall \lambda \in (0, 1)$, $\lambda u + (1 - \lambda)v \in N_C(x)$, we get $N_C(x)$ is convex.

Normal Cone is a Cone:

Let v be an arbitrary point in $N_C(x)$.

Let λ be an arbitrary number such that $\lambda > 0$.

Let y be an arbitrary point in $C - x$.

Since $v \in N_C(x)$, $\langle v, y \rangle \leq 0$.

Since $\langle v, y \rangle \leq 0$ and $\lambda > 0$, $\langle \lambda v, y \rangle \leq 0$.

Since $\forall y \in C - x$, $\langle \lambda v, y \rangle \leq 0$, we get $\lambda v \in N_C(x)$.

Since $\forall v \in N_C(x)$, $\forall \lambda > 0$, $\lambda v \in N_C(x)$, we get $N_C(x)$ is a cone. ■

Proposition 5.2.2. *Let C be a non-empty closed convex set in \mathbb{E} . Let x be a point in C . Let n be a point in \mathbb{E} . Then*

$$n \in N_C(x) \iff \forall t \in T_C(x), \langle n, t \rangle \leq 0.$$

Proof.

For one direction, assume that $n \in N_C(x)$.

We are to prove that

$$\forall t \in T_C(x), \quad \langle n, t \rangle \leq 0.$$

Let t be an arbitrary point in $T_C(x)$.

Since $t \in T_C(x) = \text{cl}(\text{cone}(C - x))$,

$$\exists \{t_i\}_{i \in \mathbb{N}} \subseteq \text{cone}(C - x), \text{ such that } t_i \rightarrow t. \quad (1)$$

Since $t_i \in \text{cone}(C - x)$,

$$\forall i \in \mathbb{N}, \exists \lambda_i \in \mathbb{R}_{++}, \exists c_i \in C \text{ such that } t_i = \lambda_i(c_i - x). \quad (2)$$

Since $n \in N_C(x)$ and $c_i \in C$,

$$\langle n, c_i - x \rangle \leq 0. \quad (3)$$

Now using (2) and (3), we have

$$\begin{aligned} & \langle n, t_i \rangle \\ &= \langle n, \lambda_i(c_i - x) \rangle, & \text{since } t_i = \lambda_i(c_i - x) \\ &= \lambda_i \langle n, c_i - x \rangle \end{aligned}$$

$$\begin{aligned}
&\leq \lambda_i \cdot 0, & \text{since } \langle n, c_i - x \rangle \leq 0 \\
&= 0.
\end{aligned}$$

That is,

$$\forall i \in \mathbb{N}, \quad \langle n, t_i \rangle \leq 0.$$

Since $\langle n, t_i \rangle \leq 0$ for each $i \in \mathbb{N}$ and $t_i \rightarrow t$, we get

$$\langle n, t \rangle \leq 0.$$

For the reverse direction, assume that n is a vector such that

$$\forall t \in T_C(x), \quad \langle n, t \rangle \leq 0.$$

We are to prove that $n \in N_C(x)$.

Let y be an arbitrary point in $C - x$.

Since $C - x \subseteq \text{clcone}(C - x) = T_C(x)$ and $y \in C - x$, we get $y \in T_C(x)$.

Since $y \in T_C(x)$ and $\forall t \in T_C(x), \langle n, t \rangle \leq 0$, we get $\langle n, y \rangle \leq 0$.

Since $\forall y \in C - x, \langle n, y \rangle \leq 0$, we get $n \in N_C(x)$. ■

Theorem 3. Let C be a closed convex set in \mathbb{E} such that $\text{int}(C) \neq \emptyset$. Let x be a point in \mathbb{E} . Then

$$x \in \text{int}(C) \iff T_C(x) = \mathbb{E} \iff N_C(x) = \{0\}.$$

Proof.

Part 1.

$x \in \text{int}(C)$ if and only if $0 \in \text{int}(C - x)$, if and only if $\text{clcone}(C - x) = \mathbb{E}$.

Part 2.

For one direction, assume that $T_C(x) = \mathbb{E}$.

We are to prove that $N_C(x) = \{0\}$.

Consider $n = 0$.

Since

$$\forall t \in T_C(x), \quad \langle 0, t \rangle = 0 \leq 0,$$

we get $0 \in N_C(x)$.

Let n be an arbitrary vector in $N_C(x)$.

By another proposition, we have

$$\begin{aligned}
&n \in N_C(x) \\
&\iff \forall t \in T_C(x) = \mathbb{E}, \langle n, t \rangle \leq 0 \\
&\implies \text{for } t = n, \langle n, t \rangle = \langle n, n \rangle \leq 0
\end{aligned}$$

$$\implies n = 0.$$

That is, $n \in N_C(x) \implies n = 0$.

So $N_C(x) = \{0\}$.

For the reverse direction, assume that $N_C(x) = \{0\}$.

We are to prove that $T_C(x) = \mathbb{E}$.

Clearly $T_C(x) \subseteq \mathbb{E}$.

For $\mathbb{E} \subseteq T_C(x)$, let x be an arbitrary point in \mathbb{E} .

Define $p := \text{proj}_{T_C(x)}(x)$.

Since $p = \text{proj}_{T_C(x)}(x)$,

$$\forall y \in T_C(x), \quad \langle x - p, y - p \rangle \leq 0. \quad (1)$$

Since $p = \text{proj}_{T_C(x)}(x)$, $p \in T_C(x)$.

Since $p \in T_C(x)$ and $T_C(x)$ is a cone,

$$2p \in T_C(x). \quad (2)$$

Apply (1) to $y = 2p$, we get

$$\langle x - p, 2p - p \rangle = \langle x - p, p \rangle \leq 0. \quad (3)$$

Since $T_C(x)$ is a closed cone,

$$0 \in T_C(x). \quad (4)$$

Apply (1) to $y = 0$, we get

$$\langle x - p, 0 - p \rangle = \langle x - p, -p \rangle \leq 0. \quad (5)$$

From (3) and (5), we get

$$\langle x - p, p \rangle = 0.$$

So (1) becomes

$$\forall y \in T_C(x), \quad \langle x - p, y \rangle \leq 0.$$

So $x - p \in N_C(x)$.

So $x - p = 0$.

So $x = p$.

So $x \in T_C(x)$.

Since $\forall x \in \mathbb{E}, x \in T_C(x)$, we get

$$\mathbb{E} \subseteq T_C(x).$$

■

5.3 Arithmetic Properties

Proposition 5.3.1. *Let C and D be convex subsets of \mathbb{E} . Let x be a point in \mathbb{E} . Then*

$$N_C(x) + N_D(x) \subseteq N_{C \cap D}(x).$$

Proof.

If C or D is empty, then $N_C(x) + N_D(x) = N_{C \cap D}(x) = \emptyset$.

So now I assume that $C, D \neq \emptyset$.

If $x \notin C \cap D$, then $N_C(x) + N_D(x) = N_{C \cap D}(x) = \emptyset$.

So now I assume that $x \in C \cap D$.

Let v be an arbitrary point in $N_C(x) + N_D(x)$.

Since $v \in N_C(x) + N_D(x)$, $\exists u \in N_C(x)$, $\exists w \in N_D(x)$ such that $v = u + w$.

Since $u \in N_C(x)$, $\forall y \in C - x$, $\langle u, y \rangle \leq 0$.

Since $w \in N_D(x)$, $\forall y \in D - x$, $\langle w, y \rangle \leq 0$.

Let y be an arbitrary point in $C \cap D - x$.

Since $y \in C \cap D - x$, we get $y \in C - x$ and $y \in D - x$.

$$\begin{aligned} & \langle v, y \rangle \\ &= \langle u + w, y \rangle \\ &= \langle u, y \rangle + \langle w, y \rangle \\ &\leq 0 + 0 = 0. \end{aligned}$$

This is true for any $y \in C \cap D - x$.

So $v \in N_{C \cap D}(x)$.

This is true for any $v \in N_C(x) + N_D(x)$.

So $N_C(x) + N_D(x) \subseteq N_{C \cap D}(x)$.

■

Theorem 4. *Let C and D be convex sets in \mathbb{E} . Assume that $\text{ri}(C) \cap \text{ri}(D) \neq \emptyset$. Let x be a point in $C \cap D$. Then*

$$N_{C \cap D}(x) = N_C(x) + N_D(x).$$

5.4 Other Properties

Proposition 5.4.1. *Let f be a proper, convex, and lower semi-continuous function from \mathbb{E} to \mathbb{R}^* . Let x be a point in $\text{dom}(f)$. Let u be a point in \mathbb{E} . Then $u \in \partial f(x)$ if and only if $(u, -1) \in N_{\text{epi}(f)}(x, f(x))$.*

Proof.

$$\begin{aligned}
& u \in \partial f(x) \\
\iff & \forall y \in \mathbb{E}, f(y) \geq f(x) + \langle u, y - x \rangle \\
\iff & \forall y \in \text{dom}(f), f(y) \geq f(x) + \langle u, y - x \rangle \\
\iff & \forall (y, \beta) \in \text{epi}(f), f(x) + \langle u, y - x \rangle \leq \beta \\
\iff & \forall (y, \beta) \in \text{epi}(f), \langle (u, -1), (y - x, \beta - f(x)) \rangle \leq 0 \\
\iff & \forall (y, \beta) \in \text{epi}(f), \langle (u, -1), (y, \beta) - (x, f(x)) \rangle \leq 0 \\
\iff & (u, -1) \in N_{\text{epi}(f)}(x, f(x)).
\end{aligned}$$

■

Chapter 6

Dual Cones and Polar Cones

6.1 Definitions

Definition (Dual Cone). *Let K be a cone in \mathbb{E} . We define the **dual cone** of K , denoted by K^* , to be the set given by*

$$K^* := \{x \in \mathbb{E} : \forall k \in K, x \cdot k \geq 0\}.$$

Definition (Polar Cone). *Let \mathbb{E} be some Euclidean space. Let S be some set in the space. We define the **polar cone** of S , denoted by C° , to be the set given by*

$$C^\circ := \{y \in \mathbb{E} : \forall x \in C, \langle y, x \rangle \leq 0\}.$$

6.2 Properties

Proposition 6.2.1. *If S is a linear subspace of some Euclidean space \mathbb{E} , then $S^\circ = S^\perp$.*

Chapter 7

Extreme Points

7.1 Definitions

Definition (Extreme Points). *Let \mathbb{E} be some Euclidean space. Let C be a nonempty convex set in the space. Let x be some point in C . We say that x is an **extreme point** of C if it does not lie between any two distinct points in C .*

Definition (Extreme Points). *Let \mathbb{E} be some Euclidean space. Let C be a nonempty convex set in the space. Let x be some point in C . We say that x is an **extreme point** of C if $C \setminus \{x\}$ is convex.*

Definition (Extreme Points). *Let \mathbb{E} be some Euclidean space. Let C be a nonempty convex set in the space. Let x be some point in C . We say that x is an **extreme point** of C if $\{x\}$ is a face of C .*

Proposition 7.1.1. *The three definitions of extreme point are equivalent.*

Def 1 \iff Def 2.

For one direction, assume that x does not lie between any two distinct points in C . We are to prove that $C \setminus \{x\}$ is convex. Let x_1 and x_2 be two arbitrary distinct points in $C \setminus \{x\}$. Let λ be an arbitrary number in $(0, 1)$. Define a point y as $y := \lambda x_1 + (1 - \lambda)x_2$. Since C is convex, $x_1, x_2 \in C$, and $\lambda \in (0, 1)$, we get $y \in C$. Since x does not lie between any two distinct points in C , $y \neq x$. So $y \in C \setminus \{x\}$. That is, I have proved that

$$\forall x_1, x_2 \in C \setminus \{x\}, \forall \lambda \in (0, 1), \quad y = \lambda x_1 + (1 - \lambda)x_2 \in C \setminus \{x\}.$$

By definition, $C \setminus \{x\}$ is convex.

For the reverse direction, assume that $C \setminus \{x\}$ is convex. We are to prove that x does not lie between any two distinct points in C . Assume for the sake of contradiction that

x does lie between two distinct points in C . Say $x = \lambda x_1 + (1 - \lambda)x_2$ where $x_1, x_2 \in C$, $x_1 \neq x_2$, and $\lambda \in (0, 1)$. Clearly $x \neq x_1$ and $x \neq x_2$. So $x_1, x_2 \in C \setminus \{x\}$. Since $C \setminus \{x\}$ is convex, $x_1, x_2 \in C \setminus \{x\}$, and $\lambda \in (0, 1)$, we get $x = \lambda x_1 + (1 - \lambda)x_2 \in C \setminus \{x\}$. This leads to a contradiction. So the assumption that x lies between two distinct points in C does not hold. i.e. x does not lie between two distinct points in C . ■

7.2 Properties

Proposition 7.2.1. *If C is nonempty, convex, and compact, then $\text{extr}(C) \neq \emptyset$.*

Theorem 5 (Minkowski). *A compact convex set is the convex hull of its extreme points.*

Chapter 8

Projection

8.1 Definitions

Definition (Projection). Let \mathcal{H} be a Hilbert space. Let S be a non-empty set in the space. Let x be a point in the space. We define the **projection** of x onto S , denoted by $\text{proj}_S(x)$, to be a point given by

$$\text{proj}_S(x) := \operatorname{argmin}_{p \in S} \|p - x\|.$$

i.e., $\text{proj}_S(x)$ is the closest point in S to x .

Proposition 8.1.1 (Existence). If S is non-empty and closed, then the projection $\text{proj}_S(x)$ exists.

Proof. Define for an $n \in \mathbb{N}$ a point c_n to be a point in S that satisfies

$$\lim_{i \in \mathbb{N}} \|c_i - x\| = d_S(x) \text{ where } d_S(x) = \inf_{p \in S} \|p - x\|.$$

Since \mathcal{H} is a Hilbert space, the norm $\|\cdot\|$ on \mathcal{H} satisfies the Parallelogram Law. So

$$\begin{aligned} \|c_m - c_n\|^2 &= 2\|c_m - x\|^2 + 2\|c_n - x\|^2 - \|c_m + c_n - 2x\|^2 \\ &= 2\|c_m - x\|^2 + 2\|c_n - x\|^2 - 4\left\|\frac{c_m + c_n}{2} - x\right\|^2 \\ &\leq 2\|c_m - x\|^2 + 2\|c_n - x\|^2 - 4d_S(x) \\ &\rightarrow 2d_S(x) + 2d_S(x) - 4d_S(x) = 0. \end{aligned}$$

So the sequence $(c_i)_{i \in \mathbb{N}}$ is Cauchy. Since \mathcal{H} is a Hilbert space, it is complete. So $(c_i)_{i \in \mathbb{N}}$ converges. Since S is closed, and $(c_i)_{i \in \mathbb{N}}$ is a Cauchy sequence in S , $p := \lim_{i \in \mathbb{N}} c_i \in S$. So $\|p - x\| = \|\lim_{i \in \mathbb{N}} c_i - x\| = \lim_{i \in \mathbb{N}} \|c_i - x\| = d_S(x)$. So p is the minimizer of the distance to the point x over S . So $p = \text{proj}_S(x)$. ■

Proposition 8.1.2 (Uniqueness). *If S is non-empty, closed, and convex, then the projection $\text{proj}_S(x)$ is unique.*

Proof. Let p denote $\text{proj}_S(x)$. Then $\|p - x\| = d_S(x)$. Let q be a point in S such that $\|q - x\| = d_S(x)$. Then by the Parallelogram Law,

$$\begin{aligned} 0 \leq \|p - q\|^2 &= 2\|x - p\|^2 + 2\|q - x\|^2 - 4\left\|x - \frac{1}{2}(p + q)\right\|^2 \\ &\leq 2d_S^2(x) + 2d_S^2(x) - 4d_S^2(x) \\ &= 0. \end{aligned}$$

This shows $\|p - q\| = 0$ and hence $p = q$. Thus the projection is unique. ■

8.2 Properties of the Projection Operator

Proposition 8.2.1 (Idempotent). *The projection operator is idempotent. i.e., if C is a nonempty closed convex set in \mathbb{E} , then $\text{proj}_C = \text{proj}_C \text{proj}_C$.*

Proof. Let x be an arbitrary point in \mathbb{E} . By definition, $\text{proj}_C(x) \in C$. Since $\text{proj}_C(x) \in C$, the closest point in C to $\text{proj}_C(x)$ is $\text{proj}_C(x)$. So $\text{proj}_C \text{proj}_C(x) = \text{proj}_C(x)$. This is true for any $x \in \mathbb{E}$. So $\text{proj}_C = \text{proj}_C \text{proj}_C$. ■

Proposition 8.2.2. *Let C be a nonempty closed convex set in \mathbb{E} . Then the set of fixed points of the operator proj_C is C .*

Proof. For one direction, let x be an arbitrary fixed point of proj_C . We are to prove that $x \in C$. Since x is a fixed point of proj_C , $x = \text{proj}_C(x)$. By definition of projection, $\text{proj}_C(x) \in C$. So $x = \text{proj}_C(x) \in C$.

For the reverse direction, let x be an arbitrary point in C . We are to prove that x is a fixed point of C . Since $x \in C$, the closest point in C to x is x . So $x = \text{proj}_C(x)$. So x is a fixed point of proj_C . ■

Proposition 8.2.3 (Linearity). *Let C be a nonempty closed convex set in \mathbb{E} . Then the operator proj_C is linear if and only if C is a linear subspace.*

Proposition 8.2.4 (Non-expansive). *The projection operator is non-expansive. i.e., if C is a nonempty closed convex set in \mathbb{E} , then $\|\text{proj}_C(x)\| \leq \|x\|$ for any $x \in \mathbb{E}$.*

this is not true. I guess it will be true when C is a linear subspace.

Proposition 8.2.5. *Let C be a nonempty closed convex set in \mathbb{E} . Then proj_C is Lipschitz with constant 1.*

Proof. Let x and y be two arbitrary points in \mathbb{E} . If $\|\text{proj}_C(x) - \text{proj}_C(y)\| = 0$, then $\|\text{proj}_C(x) - \text{proj}_C(y)\| \leq \|x - y\|$. Otherwise,

$$\begin{aligned}
& \|\text{proj}_C(x) - \text{proj}_C(y)\|^2 \\
&= \langle \text{proj}_C(x) - \text{proj}_C(y), \text{proj}_C(x) - \text{proj}_C(y) \rangle \\
&= \langle \text{proj}_C(x) - \text{proj}_C(y), \text{proj}_C(x) - x \rangle \\
&+ \langle \text{proj}_C(x) - \text{proj}_C(y), x - y \rangle \\
&+ \langle \text{proj}_C(x) - \text{proj}_C(y), y - \text{proj}_C(y) \rangle \\
&= \langle x - \text{proj}_C(x), \text{proj}_C(y) - \text{proj}_C(x) \rangle \\
&+ \langle y - \text{proj}_C(y), \text{proj}_C(x) - \text{proj}_C(y) \rangle \\
&+ \langle \text{proj}_C(x) - \text{proj}_C(y), x - y \rangle \\
&\leq 0 + 0 + \langle \text{proj}_C(x) - \text{proj}_C(y), x - y \rangle \\
&= \langle \text{proj}_C(x) - \text{proj}_C(y), x - y \rangle \\
&\leq \|\text{proj}_C(x) - \text{proj}_C(y)\| \|x - y\|.
\end{aligned}$$

That is,

$$\|\text{proj}_C(x) - \text{proj}_C(y)\|^2 \leq \|\text{proj}_C(x) - \text{proj}_C(y)\| \|x - y\|.$$

Dividing both sides by $\|\text{proj}_C(x) - \text{proj}_C(y)\|$ gives

$$\|\text{proj}_C(x) - \text{proj}_C(y)\| \leq \|x - y\|.$$

So proj_C is Lipschitz with constant 1. ■

Proposition 8.2.6 (Firmly Non-expansive). *Let C be a nonempty closed convex set in \mathbb{E} . Then proj_C is firmly non-expansive.*

Proof. This is to prove.

$$\forall x, y \in \mathbb{E}, \quad \|\text{proj}_C(y) - \text{proj}_C(x)\|^2 \leq \langle \text{proj}_C(y) - \text{proj}_C(x), y - x \rangle.$$

$$\begin{aligned}
& \|\text{proj}_C(y) - \text{proj}_C(x)\|^2 \\
&= \langle \text{proj}_C(y) - \text{proj}_C(x), \text{proj}_C(y) - \text{proj}_C(x) \rangle \\
&= \langle \text{proj}_C(y) - \text{proj}_C(x), \text{proj}_C(y) - y \rangle \\
&+ \langle \text{proj}_C(y) - \text{proj}_C(x), y - x \rangle \\
&+ \langle \text{proj}_C(y) - \text{proj}_C(x), x - \text{proj}_C(x) \rangle \\
&\leq 0 + \langle \text{proj}_C(y) - \text{proj}_C(x), y - x \rangle + 0 \\
&= \langle \text{proj}_C(y) - \text{proj}_C(x), y - x \rangle.
\end{aligned}$$
■

8.3 Characterization

Theorem 6 (Projection Theorem). *Let C be a nonempty closed convex set in \mathbb{E} . Let x and p be points in \mathbb{E} . Then $p = \text{proj}_C(x)$ if and only if*

$$\forall y \in C, \quad \langle y - p, x - p \rangle \leq 0.$$

Proof. Let y be an arbitrary point in C . Let α be an arbitrary number in $[0, 1]$. Define $y_\alpha := \alpha y + (1 - \alpha)p$. Now

$$\begin{aligned} p &= \text{proj}_C(x) \\ \iff \forall y \in C, \forall \alpha \in [0, 1], \|x - p\|^2 &\leq \|x - y_\alpha\|^2 \\ \iff \forall y \in C, \forall \alpha \in [0, 1], \|x - p\|^2 &\leq \|x - p - \alpha(y - p)\|^2 \\ \iff \forall y \in C, \langle x - p, y - p \rangle &\leq 0. \end{aligned}$$

■

Chapter 9

Separation

9.1 Definitions

Definition (Separated). Let S_1 and S_2 be two sets in \mathbb{E} . We say that S_1 and S_2 are **separated** if $\exists b \in \mathbb{E} \setminus \{\vec{0}\}$ such that

$$\sup_{s_1 \in S_1} \langle s_1, b \rangle \leq \inf_{s_2 \in S_2} \langle s_2, b \rangle.$$

We say that they are **strongly separated** if the inequality holds strictly.

Definition (Strongly Separated). Let S_1 and S_2 be two sets in \mathbb{E} . We say that they are **strongly separated** if the inequality holds strictly.

Definition (Properly Separated). Let S_1 and S_2 be two sets in \mathbb{E} . We say that S_1 and S_2 are **properly separated** if $\exists b \in \mathbb{E}$ such that

$$\begin{aligned} \sup_{x \in S_1} \langle x, b \rangle &\leq \inf_{y \in S_2} \langle y, b \rangle, \text{ and} \\ \inf_{x \in S_1} \langle x, b \rangle &> \sup_{y \in S_2} \langle y, b \rangle. \end{aligned}$$

Definition (Hyperplane). A **hyperplane** is a set in some Euclidean space \mathbb{E} of the form $\{x \in \mathbb{E} : a^T x = b\}$ for some $a, b \in \mathbb{E}$ and $a \neq \vec{0}$.

Definition (Polyhedrons). A **polyhedron** is a set that is the solution set of finitely many linear inequalities, or equivalently, the intersection of finitely many half spaces.

9.2 Main Results

Proposition 9.2.1. Let C be a nonempty closed convex set in \mathbb{E} . Let x be a point in \mathbb{E} such that $x \notin C$. Then x and C are strongly separated.

Proof.

Define a point p by

$$p := \text{proj}_C(x).$$

Define a point a by

$$a := x - p.$$

To prove that x is strongly separated from C , it suffices to prove that

$$\forall y \in C, \quad \langle y, a \rangle < \langle x, a \rangle.$$

Since $x \notin C$ and C is closed,

$$a \neq 0. \tag{1}$$

Let y be an arbitrary point in C . Since $p = \text{proj}_C(x)$ and $y \in C$,

$$\langle y - p, x - p \rangle \leq 0. \tag{2}$$

$$\begin{aligned} & \langle y, a \rangle \\ & < \langle y, a \rangle + \langle a, a \rangle, \text{ since } a \neq 0 \\ & = \langle y + a, a \rangle \\ & = \langle y + x - p, x - p \rangle, \text{ substitute } a = x - p \\ & = \langle y - p, x - p \rangle + \langle x, x - p \rangle \\ & \leq 0 + \langle x, x - p \rangle, \text{ since } \langle y - p, x - p \rangle \leq 0 \\ & = \langle x, x - p \rangle \\ & = \langle x, a \rangle. \end{aligned}$$

That is,

$$\forall y \in C, \quad \langle y, a \rangle < \langle x, a \rangle.$$

So x is strongly separated from C . ■

Proposition 9.2.2. *Let C_1 be a non-empty closed convex set in \mathbb{E} . Let C_2 be a non-empty compact convex set in \mathbb{E} . Assume that C_1 and C_2 are disjoint. Then C_1 and C_2 are strongly separated.*

Proof. Since C_1 is non-empty closed and convex and C_2 is non-empty compact and convex, we get $C_1 - C_2$ is non-empty closed and convex. Since $C_1 \cap C_2 = \emptyset$, $0 \notin C_1 - C_2$. Since $C_1 - C_2$ is non-empty closed and convex and $0 \in C_1 - C_2$, 0 and $C_1 - C_2$ are strongly separated. Since 0 is strongly separated from $C_1 - C_2$,

$$\exists a \neq 0 \text{ such that } \forall c_1 \in C_1, c_2 \in C_2, \quad \langle c_1 - c_2, a \rangle < \langle 0, a \rangle.$$

That is,

$$\langle c_1, a \rangle < \langle c_2, a \rangle.$$

So C_1 and C_2 are strongly separated. ■

Theorem 7. *Let C_1 and C_2 be non-empty closed convex sets in \mathbb{E} . Assume that C_1 and C_2 are disjoint. Then C_1 and C_2 are separated.*

Proof. For $n \in \mathbb{N}$, define

$$D_n := C_2 \cap \text{ball}(0, n).$$

Then D_n is compact for any $n \in \mathbb{N}$. Since $\{C_1$ is non-empty closed and convex D_n is non-empty compact and convex we get C_1 and D_n are strongly separated for any $n \in \mathbb{N}$. So

$$\forall n \in \mathbb{N}, \exists a_n \in \mathbb{E}, \|a_n\| = 1 \text{ such that } \forall c_1 \in C_1, \forall d_2 \in D_n, \quad \langle c_1, a_n \rangle < \langle d_2, a_n \rangle.$$

Since $\|a_n\| = 1$ for any $n \in \mathbb{N}$, there exists a subsequence $\{a_n\}_{n \in I}$ where I is some infinite subset of \mathbb{N} such that $\{a_n\}_{n \in I}$ converges to some point $a \in \mathbb{E}$. Let x be an arbitrary point in C_1 . Let y be an arbitrary point in C_2 . For large enough n , $y \in D_n$. Since

$$\begin{cases} \langle x, a_n \rangle < \langle y, a_n \rangle \text{ for large enough } n \\ \lim_{n \in I, n \rightarrow \infty} \langle x, a_n \rangle = \langle x, a \rangle \\ \lim_{n \in I, n \rightarrow \infty} \langle y, a_n \rangle = \langle y, a \rangle \end{cases}, \text{ we get}$$

$$\langle x, a \rangle \leq \langle y, a \rangle.$$

Since

$$\exists a \neq 0 \text{ such that } \forall x \in C_1, \forall y \in C_2, \quad \langle x, a \rangle \leq \langle y, a \rangle,$$

by definition of separated, C_1 and C_2 are separated. ■

Proposition 9.2.3. *Let C_1 and C_2 be non-empty convex subsets of \mathbb{E} . Then C_1 and C_2 are properly separated if and only if*

$$\text{ri}(C_1) \cap \text{ri}(C_2) = \emptyset.$$

Proposition 9.2.4. *Polyhedrons are convex.*

Chapter 10

Convex Functions

10.1 Preliminaries

Definition (Epigraph). Let f be a function from \mathbb{E} to \mathbb{R}^* . We define the **epigraph** of f , denoted by $\text{epi}(f)$, to be the set given by

$$\text{epi}(f) := \{(x, \alpha) \in \mathbb{E} \times \mathbb{R} : f(x) \leq \alpha\}.$$

Definition (Domain). Let f be a function from \mathbb{E} to \mathbb{R}^* . We define the **domain** of f , denoted by $\text{dom}(f)$, to be a set given by

$$\text{dom}(f) := \{x \in \mathbb{E} : f(x) < +\infty\}.$$

Definition (Proper). Let f be a function from \mathbb{E} to \mathbb{R}^* . We say that f is **proper** if

$$\begin{aligned} \exists x \in \mathbb{E}, \quad f(x) &\neq +\infty, \text{ and} \\ \forall x \in \mathbb{E}, \quad f(x) &\neq -\infty \end{aligned}$$

10.2 The Indicator Function

Definition (The Indicator Function). Let S be a subset of \mathbb{E} . We define the **indicator function** of S , denoted by δ_S , to be a function from \mathbb{E} to \mathbb{R}^* given by

$$\delta_S(x) = \begin{cases} 0, & x \in S \\ +\infty, & x \notin S. \end{cases}$$

Proposition 10.2.1. Let S be a subset of \mathbb{E} . Then

(1) S is non-empty if and only if δ_S is proper.

(2) S is convex if and only if δ_S is convex.

(3) S is closed if and only if δ_S is lower semi-continuous.

Proof of (1).

For one direction, assume that S is not empty.

We are to prove that δ_S is proper.

Since $S \neq \emptyset$, pick $p \in S$.

Since $p \in S$, $\delta_S(p) = 0$.

Since $\delta_S(p) = 0$, $\exists x_0 \in \mathbb{E}$ such that $\delta_S(x_0) \neq +\infty$.

By definition of the indicator function, it never takes $-\infty$.

Since $\exists x_0 \in \mathbb{E}$ such that $\delta_S(x_0) \neq +\infty$ and $\forall x \in \mathbb{E}$, $\delta_S(x) \neq -\infty$, we get δ_S is proper.

For the reverse direction, assume that δ_S is proper.

We are to prove that S is non-empty.

Assume for the sake of contradiction that S is empty.

Let x be an arbitrary point in \mathbb{E} .

Since $S = \emptyset$, $x \notin S$.

Since $x \notin S$, $\delta_S(x) = +\infty$.

Since $\forall x \in \mathbb{E}$, $\delta_S(x) = +\infty$, by definition of proper function, δ_S is not proper.

This contradicts to the assumption that δ_S is proper.

So the assumption that $S = \emptyset$ is false.

i.e., S is non-empty. ■

Proof of (2).

For one direction, assume that S is convex.

We are to prove that δ_S is convex.

Let x and y be arbitrary points in $\text{dom}(\delta_S)$.

By definition of indicator functions, $\text{dom}(\delta_S) = S$.

So $x, y \in S$.

Let λ be an arbitrary number in $(0, 1)$.

Define point z as $z := \lambda x + (1 - \lambda)y$.

Since $x, y \in S$ and $\lambda \in (0, 1)$ and S is convex and $z = \lambda x + (1 - \lambda)y$, we get $z \in S$.

Since $z \in S$, $\delta_S(z) = 0$.

Since $\lambda \in (0, 1)$ and $\text{range}(\delta_S) = \{0, +\infty\}$, we get $\lambda\delta_S(x) + (1 - \lambda)\delta_S(y) \geq 0$.

Since $\delta_S(z) = 0$ and $\lambda\delta_S(x) + (1 - \lambda)\delta_S(y) \geq 0$, we get $\delta_S(z) \leq \lambda\delta_S(x) + (1 - \lambda)\delta_S(y)$.

That is, $\delta_S(\lambda x + (1 - \lambda)y) \leq \lambda\delta_S(x) + (1 - \lambda)\delta_S(y)$.

Since $\forall x, y \in \text{dom}(\delta_S)$, $\forall \lambda \in (0, 1)$, $\delta_S(\lambda x + (1 - \lambda)y) \leq \lambda\delta_S(x) + (1 - \lambda)\delta_S(y)$, we get δ_S is convex.

For the reverse direction, assume that δ_S is convex.

We are to prove that S is convex.

The case where S is empty is trivial.

So now I assume $S \neq \emptyset$.

Let x and y be arbitrary points in S .

Let λ be an arbitrary number in $(0, 1)$.

Define point z as $z := \lambda x + (1 - \lambda)y$.

Since $x \in S$, $\delta_S(x) = 0$.

Since $y \in S$, $\delta_S(y) = 0$.

Since $\delta_S(x) = \delta_S(y) = 0$, we get $\lambda\delta_S(x) + (1 - \lambda)\delta_S(y) = 0$.

Since $\lambda \in (0, 1)$ and δ_S is convex, $\delta_S(z) \leq \lambda\delta_S(x) + (1 - \lambda)\delta_S(y)$.

Since $\delta_S(z) \leq \lambda\delta_S(x) + (1 - \lambda)\delta_S(y)$ and $\lambda\delta_S(x) + (1 - \lambda)\delta_S(y) = 0$, we get $\delta_S(z) \leq 0$.

By definition of the indicator function, $\delta_S(z) \geq 0$.

Since $\delta_S(z) \leq 0$ and $\delta_S(z) \geq 0$, we get $\delta_S(z) = 0$.

Since $\delta_S(z) = 0$, $z \in S$.

That is, $\lambda x + (1 - \lambda)y \in S$.

Since $\forall x, y \in S, \forall \lambda \in (0, 1), \lambda x + (1 - \lambda)y \in S$, we get S is convex. ■

Proof of (3).

For one direction, assume that S is closed.

We are to prove that δ_S is lower semi-continuous.

Let $\{(x_i, \alpha_i)\}_{i \in \mathbb{N}}$ be an arbitrary sequence in $\text{epi}(\delta_S)$ that converges.

Say its limit is $(x_\infty, \alpha_\infty)$.

Since $(x_i, \alpha_i) \rightarrow (x_\infty, \alpha_\infty)$, $x_i \rightarrow x_\infty$.

Since $(x_i, \alpha_i) \in \text{epi}(\delta_S)$, $\delta_S(x_i) \leq \alpha_i$.

Since $\delta_S(x_i) \leq \alpha_i$ and $\alpha_i \in \mathbb{R}$, we get $\delta_S(x_i) \neq +\infty$.

Since $\delta_S(x_i) \neq +\infty$, $x_i \in S$.

Since $x_i \in S$ and $x_i \rightarrow x_\infty$ and S is closed, $x_\infty \in S$.

Since $x_\infty \in S$, $\delta_S(x_\infty) = 0$.

Since $x_i \in S$, $\delta_S(x_i) = 0$.

Since $\delta_S(x_i) = 0$ and $\delta_S(x_i) \leq \alpha_i$, $\alpha_i \geq 0$.

Since $(x_i, \alpha_i) \rightarrow (x_\infty, \alpha_\infty)$, $\alpha_i \rightarrow \alpha_\infty$.

Since $\alpha_i \geq 0$ and $\alpha_i \rightarrow \alpha_\infty$, $\alpha_\infty \geq 0$.

Since $\delta_S(x_\infty) = 0$ and $\alpha_\infty \geq 0$, $\delta_S(x_\infty) \leq \alpha_\infty$.

Since $\delta_S(x_\infty) \leq \alpha_\infty$, $(x_\infty, \alpha_\infty) \in \text{epi}(\delta_S)$.

Since for any convergent sequence in $\text{epi}(\delta_S)$, its limit is also in $\text{epi}(\delta_S)$, we get $\text{epi}(\delta_S)$ is closed.

For the reverse direction, assume that δ_S is lower semi-continuous.

We are to prove that S is closed.

Let $\{x_i\}_{i \in \mathbb{N}}$ be an arbitrary sequence in S that converges.

Say its limit is x_∞ .

Since $x_i \in S$, $\delta_S(x_i) = 0$.

Since $\delta_S(x_i) = 0$, $(x_i, 0) \in \text{epi}(\delta_S)$.

Since $x_i \rightarrow x_\infty$, $(x_i, 0) \rightarrow (x_\infty, 0)$.

Since $(x_i, 0) \in \text{epi}(\delta_S)$ and $(x_i, 0) \rightarrow (x_\infty, 0)$, $(x_\infty, 0) \in \text{epi}(\delta_S)$.

Since $(x_\infty, 0) \in \text{epi}(\delta_S)$, $\delta_S(x_\infty) \leq 0$.

By definition of the indicator function, $\delta_S(x_\infty) \geq 0$.

Since $\delta_S(x_\infty) \leq 0$ and $\delta_S(x_\infty) \geq 0$, we get $\delta_S(x_\infty) = 0$.

Since $\delta_S(x_\infty) = 0$, $x_\infty \in S$.

Since for any convergent sequence in S , its limit is also in S , we get S is closed. ■

10.3 Definitions

Definition (Convex Function). *Let f be a function from \mathbb{E} to \mathbb{R}^* . We say that f is **convex** if*

$$\forall x, y \in \text{dom}(f), \forall \lambda \in [0, 1], \quad f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y).$$

Definition (Convex Function). *Let f be a function from \mathbb{E} to \mathbb{R}^* . We say that f is **convex** if the epigraph of f is convex.*

Proposition 10.3.1. *The two definitions of convexity of functions are equivalent.*

Proof.

The case where $\text{dom}(f), \text{epi}(f) = \emptyset$ is trivial.

So now I assume that $\text{dom}(f), \text{epi}(f) \neq \emptyset$.

For one direction, assume that $\forall x, y \in \text{dom}(f), \forall \lambda \in [0, 1]$, we have $f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y)$.

We are to prove that the epigraph of f is convex.

Let (x, α) and (y, β) be two arbitrary points in $\text{epi}(f)$.

Since $(x, \alpha), (y, \beta) \in \text{epi}(f)$, $x, y \in \text{dom}(f)$.

Let λ be an arbitrary number in $[0, 1]$.

Define a point $(z, \gamma) := \lambda(x, \alpha) + (1 - \lambda)(y, \beta)$.

Then $z = \lambda x + (1 - \lambda)y$ and $\gamma = \lambda \alpha + (1 - \lambda)\beta$.

Since $x, y \in \text{dom}(f)$, $\lambda \in [0, 1]$, we get $f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y)$.

Since $(x, \alpha) \in \text{epi}(f)$, $f(x) \leq \alpha$.

Since $(y, \beta) \in \text{epi}(f)$, $f(y) \leq \beta$.

Since $f(x) \leq \alpha$ and $f(y) \leq \beta$ and $f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y)$, we get $f(\lambda x + (1 - \lambda)y) \leq \lambda \alpha + (1 - \lambda)\beta$.

Since $z = \lambda x + (1 - \lambda)y$ and $\gamma = \lambda\alpha + (1 - \lambda)\beta$ and $f(\lambda x + (1 - \lambda)y) \leq \lambda\alpha + (1 - \lambda)\beta$, we get $f(z) \leq \gamma$.

Since $f(z) \leq \gamma$, $(z, \gamma) \in \text{epi}(f)$.

For the reverse direction, assume that $\text{epi}(f)$ is convex.

We are to prove that $\forall x, y \in \text{dom}(f)$, $\forall \lambda \in [0, 1]$, we have $f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y)$.

Let x and y be two arbitrary points in $\text{dom}(f)$.

Let λ be an arbitrary number in $[0, 1]$.

Define $z := \lambda x + (1 - \lambda)y$.

Define $\gamma := \lambda f(x) + (1 - \lambda)f(y)$.

Since $(x, f(x)) \in \text{epi}(f)$ and $(y, f(y)) \in \text{epi}(f)$ and $\lambda \in [0, 1]$ and $\text{epi}(f)$ is convex, we get $\lambda(x, f(x)) + (1 - \lambda)(y, f(y)) \in \text{epi}(f)$.

Since $z = \lambda x + (1 - \lambda)y$ and $\gamma = \lambda f(x) + (1 - \lambda)f(y)$ and $\lambda(x, f(x)) + (1 - \lambda)(y, f(y)) \in \text{epi}(f)$, we get $(z, \gamma) \in \text{epi}(f)$.

Since $(z, \gamma) \in \text{epi}(f)$, $f(z) \leq \gamma$.

That is, $f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y)$. ■

10.4 Basic Properties

Proposition 10.4.1 (Necessary Condition). *The domain of a convex function is convex.*

Proof. Follows from the fact that convexity is stable under affine transformations. Define $A((x, \alpha)) := x$. Then $\text{dom}(f) = A(\text{epi}(f))$. ■

Proposition 10.4.2. *The level sets of a convex function are convex.*

Proposition 10.4.3 (Restriction to a Line). *A function $f : \mathbb{E} \rightarrow \mathbb{R}$ is convex if and only if $\forall x \in \text{dom}(f)$, $\forall v \in \mathbb{E}$, the function $g_{x,v} : \mathbb{R} \rightarrow \mathbb{R}$ given by*

$$g_{x,v}(t) = f(x + tv)$$

is convex.

10.5 Differentiable Convex Functions

Proposition 10.5.1. *Let f be a proper convex function from \mathbb{E} to \mathbb{R}^* . Let $x \in \text{dom}(f)$. If f is differentiable at point x , then $\nabla(f)(x)$ is the unique subgradient of f at point x . i.e., $\partial(f)(x) = \{\nabla(f)(x)\}$. Conversely, if the subgradient $\partial(f)(x)$ of f at point x is a singleton set $\{v\}$, then f is differentiable at point x and $\nabla(f)(x) = v$.*

Proof. ■

Proposition 10.5.2 (First-Order Condition). *Let f be a proper function from \mathbb{E} to \mathbb{R}^* . Assume that $\text{dom}(f)$ is convex and open and that f is differentiable on $\text{dom}(f)$. Then f is convex if and only if*

$$\forall x, y \in \text{dom}(f), \quad f(y) - f(x) \geq \langle \nabla(f)(x), y - x \rangle.$$

i.e., the first-order approximation of f is a global under-estimator.

Proof.

Part 1.

For one direction, assume that f is convex. We are to prove that

$$\forall x, y \in \text{dom}(f), \quad f(y) - f(x) \geq \langle \nabla(f)(x), y - x \rangle.$$

Let x and y be arbitrary points in $\text{dom}(f)$. Since f is convex and differentiable at point x , $\nabla(f)(x) = \partial(f)(x)$. So $\nabla(f)(x)$ satisfies the subgradient inequality. That is,

$$f(y) - f(x) \geq \langle \nabla(f)(x), y - x \rangle.$$

Part 2.

For the reverse direction, assume that

$$\forall x, y \in \text{dom}(f), \quad f(y) - f(x) \geq \langle \nabla(f)(x), y - x \rangle.$$

We are to prove that f is convex.

Not Finished. ■

Proposition 10.5.3. *Let f be a proper function from \mathbb{E} to \mathbb{R}^* . Assume that $\text{dom}(f)$ is convex and open and that f is differentiable on $\text{dom}(f)$. Then f is convex if and only if*

$$\forall x, y \in \text{dom}(f), \quad \langle \nabla(f)(x) - \nabla(f)(y), x - y \rangle \geq 0.$$

Proof.

Part 1.

For one direction, assume that f is convex. We are to prove that

$$\forall x, y \in \text{dom}(f), \quad \langle \nabla(f)(x) - \nabla(f)(y), x - y \rangle \geq 0.$$

Let x and y be arbitrary points in $\text{dom}(f)$. Since f is convex and differentiable at point x , $\nabla(f)(x) = \partial(f)(x)$. So $\nabla(f)(x)$ satisfies the subgradient inequality. That is,

$$f(y) - f(x) \geq \langle \nabla(f)(x), y - x \rangle. \tag{1}$$

Since f is convex and differentiable at point y , $\nabla(f)(y) = \partial(f)(y)$. So $\nabla(f)(y)$ satisfies the subgradient inequality. That is,

$$f(x) - f(y) \geq \langle \nabla(f)(y), x - y \rangle. \quad (2)$$

Take the sum of inequalities (1) and (2), we get

$$\begin{aligned} & (f(y) - f(x)) + (f(x) - f(y)) \geq \langle \nabla(f)(x), y - x \rangle + \langle \nabla(f)(y), x - y \rangle \\ \implies & 0 \geq -\langle \nabla(f)(x), x - y \rangle + \langle \nabla(f)(y), x - y \rangle \\ \implies & \langle \nabla(f)(x), x - y \rangle - \langle \nabla(f)(y), x - y \rangle \geq 0 \\ \implies & \langle \nabla(f)(x) - \nabla(f)(y), x - y \rangle \geq 0. \end{aligned}$$

Part 2.

For the reverse direction, assume that

$$\forall x, y \in \text{dom}(f), \quad \langle \nabla(f)(x) - \nabla(f)(y), x - y \rangle \geq 0.$$

We are to prove that f is convex. Let x and y be arbitrary points in $\text{dom}(f)$. Define a function φ on $(0, 1)$ by

$$\varphi(\lambda) := f(\lambda x + (1 - \lambda)y).$$

Notice φ is differentiable and

$$\varphi'(\lambda) = \langle \nabla(f)(\lambda x + (1 - \lambda)y), x - y \rangle.$$

Let α and β be arbitrary numbers in $(0, 1)$. Assume that $\alpha < \beta$. Define two points z_α and z_β by $z_\alpha := \alpha x + (1 - \alpha)y$ and $z_\beta := \beta x + (1 - \beta)y$. Then

$$\begin{aligned} & \varphi'(\beta) - \varphi'(\alpha) \\ &= \langle \nabla(f)(\beta x + (1 - \beta)y), x - y \rangle - \langle \nabla(f)(\alpha x + (1 - \alpha)y), x - y \rangle \\ &= \langle \nabla(f)(z_\beta), x - y \rangle - \langle \nabla(f)(z_\alpha), x - y \rangle \\ &= \langle \nabla(f)(z_\beta) - \nabla(f)(z_\alpha), x - y \rangle \\ &= \left\langle \nabla(f)(z_\beta) - \nabla(f)(z_\alpha), \frac{z_\beta - z_\alpha}{\beta - \alpha} \right\rangle \\ &= \frac{1}{\beta - \alpha} \langle \nabla(f)(z_\beta) - \nabla(f)(z_\alpha), z_\beta - z_\alpha \rangle \\ &\geq \frac{1}{\beta - \alpha} \cdot 0, \text{ by assumption} \\ &= 0. \end{aligned}$$

That is,

$$\forall \alpha, \beta \in (0, 1), \quad \beta > \alpha \implies \varphi'(\beta) - \varphi'(\alpha) \geq 0.$$

So φ' is increasing. So φ is convex. So

$$\varphi(\lambda) \leq \lambda\varphi(1) + (1 - \lambda)\varphi(0).$$

That is,

$$f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y).$$

By definition, f is convex. ■

Proposition 10.5.4 (Second-Order Condition). *A twice continuously differentiable real-valued function f defined on a convex set is convex if and only if*

$$\forall x \in \text{dom}(f), \quad \nabla^2 f(x) \geq 0$$

where $\nabla^2 f(x) = \begin{bmatrix} \frac{\partial^2 f(x)}{\partial x_1 \partial x_1} & \cdots & \frac{\partial^2 f(x)}{\partial x_1 \partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f(x)}{\partial x_n \partial x_1} & \cdots & \frac{\partial^2 f(x)}{\partial x_n \partial x_n} \end{bmatrix}$ denotes the Hessian matrix of f at x_0 .

Proposition 10.5.5. *Let f be a twice continuously differentiable function from \mathbb{E} to \mathbb{R} . Then f is convex if and only if $\forall x \in \mathbb{E}$, $\nabla^2 f(x)$ is positive semi-definite.*

10.6 Convexity and Lipschitz-ness

Theorem 8. *Let f be a differentiable convex function from \mathbb{E} to \mathbb{R} . Then the following statements are equivalent.*

(1) ∇f is Lipschitz with constant L .

(2) $\forall x, y \in \mathbb{E}$, we have

$$f(y) - f(x) \leq \langle \nabla f(x), y - x \rangle + \frac{L}{2} \|y - x\|^2.$$

(3) $\forall x, y \in \mathbb{E}$, we have

$$f(y) - f(x) \geq \langle \nabla f(x), y - x \rangle + \frac{1}{2L} \|\nabla f(y) - \nabla f(x)\|^2.$$

(4) $\forall x, y \in \mathbb{E}$, we have

$$L \langle \nabla f(y) - \nabla f(x), y - x \rangle \geq \|\nabla f(y) - \nabla f(x)\|^2.$$

(1) \implies (2).

Assume that ∇f is Lipschitz with constant L .

Let x and y be two arbitrary points in \mathbb{E} .

$$\begin{aligned}
& f(y) - f(x) \\
&= \int_0^1 \langle \nabla f(x + t(y - x)), y - x \rangle dt \\
&= \langle \nabla f(x), y - x \rangle + \int_0^1 \langle \nabla f(x + t(y - x)) - \nabla f(x), y - x \rangle dt \\
&\leq \langle \nabla f(x), y - x \rangle + \int_0^1 \| \nabla f(x + t(y - x)) - \nabla f(x) \| \|y - x\| dt \\
&\leq \langle \nabla f(x), y - x \rangle + \int_0^1 L \|x + t(y - x) - x\| \|y - x\| dt \\
&= \langle \nabla f(x), y - x \rangle + L \|y - x\|^2 \int_0^1 t dt \\
&= \langle \nabla f(x), y - x \rangle + \frac{L}{2} \|y - x\|^2
\end{aligned}$$

That is,

$$f(y) - f(x) \leq \langle \nabla f(x), y - x \rangle + \frac{L}{2} \|y - x\|^2.$$

■

Theorem 9. *Let f be a twice continuously differentiable function from \mathbb{E} to \mathbb{R} . Let L be some non-negative number. Then the following statements are equivalent.*

- (1) ∇f is L -Lipschitz.
- (2) $\forall x \in \mathbb{E}, \|\nabla^2 f(x)\| \leq L$.

10.7 Stability of Convexity

Proposition 10.7.1 (Linear Combination). *A non-negative linear combination of convex functions is again convex.*

Proof.

It suffices to prove that non-negative scalar multiples of convex functions are convex and sum of convex functions are convex.

Notice $\text{dom}(f) = \text{dom}(\lambda f)$. To prove that λf is convex, take arbitrary points x and y in $\text{dom}(\lambda f) = \text{dom}(f)$. Let α be an arbitrary number in $(0, 1)$. Define point z as $z := \alpha x + (1 - \alpha)y$. Since f is convex, we get $f(z) \leq \alpha f(x) + (1 - \alpha)f(y)$. Multiplying both sides by λ gives $\lambda f(z) \leq \lambda \alpha f(x) + \lambda(1 - \alpha)f(y)$. That is, $(\lambda f)(z) \leq \alpha(\lambda f)(x) + (1 - \alpha)(\lambda f)(y)$. Notice the preceding inequality holds for any $x, y \in \text{dom}(\lambda f)$ and any $\alpha \in (0, 1)$. So λf is convex.

Since f is proper, $\text{dom}(f) \neq \emptyset$. Let x and y be two arbitrary points in $\text{dom}(f)$. Let $\lambda \in (0, 1)$ be arbitrary. Define point z as $z := \lambda x + (1 - \lambda)y$. Since $x, y \in \text{dom}(f)$, $f(x), f(y) \neq +\infty$. Since $f(x), f(y) \neq +\infty$, $f_i(x), f_i(y) \neq +\infty$ for each $i \in I$. Indeed, if $f_i(x) = +\infty$ for any i , since f_i cannot take $-\infty$, $f(x)$ must be $+\infty$. So $x, y \in \text{dom}(f_i)$ for each $i \in I$. Since $x, y \in \text{dom}(f_i)$ and $\lambda \in (0, 1)$ and f_i is convex and $z = \lambda x + (1 - \lambda)y$, we get $f_i(z) \leq \lambda f_i(x) + (1 - \lambda)f_i(y)$. This is true for any $i \in I$. So summing both sides gives

$$\sum_{i \in I} f_i(z) \leq \sum_{i \in I} (\lambda f_i(x) + (1 - \lambda)f_i(y)).$$

That is,

$$f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y).$$

This is true for any $x, y \in \text{dom}(f)$ and any $\lambda \in (0, 1)$. So f is convex. ■

Proposition 10.7.2 (Composition). *The composition of a convex function with an affine function is convex. i.e., if f is convex, then $f(Ax + b)$ is convex.*

Proof. Let x and y be arbitrary points in \mathbb{E} . Let λ be an arbitrary number in $(0, 1)$. Define a point z by $z := \lambda x + (1 - \lambda)y$.

$$\begin{aligned} & g(\lambda x + (1 - \lambda)y) \\ &= f(A(\lambda x + (1 - \lambda)y) + b) \\ &= f(\lambda Ax + (1 - \lambda)Ay + b), && \text{by linearity of } A \\ &= f(\lambda Ax + (1 - \lambda)Ay + \lambda b + (1 - \lambda)b), && \text{decompose } b \\ &= f(\lambda(Ax + b) + (1 - \lambda)(Ay + b)) \\ &\leq \lambda f(Ax + b) + (1 - \lambda)f(Ay + b), && \text{by convexity of } f \\ &= \lambda g(x) + (1 - \lambda)g(y). \end{aligned}$$

That is,

$$\forall x, y \in \mathbb{E}, \forall \lambda \in (0, 1), \quad g(\lambda x + (1 - \lambda)y) \leq \lambda g(x) + (1 - \lambda)g(y).$$

So g is convex. ■

Proposition 10.7.3 (Supremum). *The supremum of a collection of convex functions is again convex. i.e., Let $\{f_i\}_{i \in I}$ be a collection of convex functions where I is some index set. Then the function F given by $F := \sup_{i \in I} f_i$ is convex.*

Proof.

$$(x, \alpha) \in \text{epi}(F)$$

$$\begin{aligned}
&\iff \sup_{i \in I} f_i(x) \leq \alpha \\
&\iff \forall i \in I, f_i(x) \leq \alpha \\
&\iff \forall i \in I, (x, \alpha) \in \text{epi}(f_i) \\
&\iff (x, \alpha) \in \bigcap_{i \in I} \text{epi}(f_i).
\end{aligned}$$

So $\text{epi}(F) = \bigcap_{i \in I} \text{epi}(f_i)$. Since f_i are convex, $\text{epi}(f_i)$ are convex. Since $\text{epi}(f_i)$ are convex, $\bigcap_{i \in I} \text{epi}(f_i)$ is convex. That is, $\text{epi}(F)$ is convex. Since $\text{epi}(F)$ is convex, F is convex. ■

Proposition 10.7.4 (Pointwise Supremum). *If $f(x, y)$ is convex in x for each y in some set \mathcal{A} , then the function g given by*

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

is convex.

10.8 Examples

Example 10.8.1. *Affine functions are convex.*

Example 10.8.2. *Norms are convex.*

Proof.

$$\begin{aligned}
&\|\alpha x + \beta y\| \\
&\leq \|\alpha x\| + \|\beta y\| \\
&= |\alpha| \|x\| + |\beta| \|y\| \\
&= \alpha \|x\| + \beta \|y\|.
\end{aligned}$$

■

Example 10.8.3. *Square norms are convex.*

Proof Approach 1. Notice $\|\cdot\|^2$ is the direct sum of m squares and squares are convex. So by CO 463 Assignment 2 Problem 3, $\|\cdot\|^2$ is convex. ■

Proof Approach 2. The domain is \mathbb{E} . Let x and y be two points in \mathbb{E} . Let λ be an arbitrary number in $(0, 1)$. Define a point z as $z := \lambda x + (1 - \lambda)y$.

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

$$\begin{aligned}
&= \|\lambda x\|^2 + \|(1-\lambda)y\|^2 + 2\langle \lambda x, (1-\lambda)y \rangle \\
&= \lambda^2 \|x\|^2 + (1-\lambda)^2 \|y\|^2 + 2\lambda(1-\lambda)\langle x, y \rangle \\
&\leq \lambda^2 \|x\|^2 + (1-\lambda)^2 \|y\|^2 + 2\lambda(1-\lambda)\|x\|\|y\| \\
&\leq \lambda(\lambda-1)\|x\|^2 + \lambda(\lambda-1)\|y\|^2 + 2\lambda(1-\lambda)\|x\|\|y\| \\
&\quad + \lambda\|x\|^2 + (1-\lambda)\|y\|^2 \\
&= \lambda\|x\|^2 + (1-\lambda)\|y\|^2 \\
&\quad + \lambda(\lambda-1)[\|x\|^2 + \|y\|^2 - 2\|x\|\|y\|] \\
&\leq \lambda\|x\|^2 + (1-\lambda)\|y\|^2
\end{aligned}$$

That is,

$$\forall x, y \in \mathbb{E}, \forall \lambda \in (0, 1), \quad \|\lambda x + (1-\lambda)y\|^2 \leq \lambda\|x\|^2 + (1-\lambda)\|y\|^2.$$

So by definition, $\|\cdot\|^2$ is convex. ■

Example 10.8.4. *The distance function to a convex set is convex.*

Example 10.8.5. *The perspective of a convex function is convex. i.e., if $f : \mathbb{E} \rightarrow \mathbb{R}$*

Chapter 11

More Convex Functions

11.1 Strictly Convex

Definition (Strictly Convex). Let f be a proper function from \mathbb{E} to \mathbb{R}^* . We say that f is **strictly convex** if $\forall x, y \in \text{dom}(f)$, $\forall \lambda \in [0, 1]$, we have $f(\lambda x + (1 - \lambda)y) < \lambda f(x) + (1 - \lambda)f(y)$, except when $\lambda x + (1 - \lambda)y = x$ or y .

Proposition 11.1.1. Strictly convex functions are convex.

11.2 Strongly Convex

Definition (Strongly Convex). Let f be a proper function from \mathbb{E} to \mathbb{R}^* . We say that f is **strongly convex** with constant β if $\forall x, y \in \text{dom}(f)$, $\forall \lambda \in [0, 1]$, we have

$$f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y) - \frac{\beta}{2}\lambda(1 - \lambda)\|x - y\|^2,$$

for some positive constant β .

Proposition 11.2.1. Strongly convex functions are strictly convex.

Proposition 11.2.2. Let f be a function from \mathbb{E} to \mathbb{R}^* . Then f is β -strongly convex if and only if $f - \frac{\beta}{2}\|\cdot\|^2$ is convex.

Proof. Let β be some positive constnat. Let g denote $f - \frac{\beta}{2}\|\cdot\|^2$. Let $x, y \in \mathbb{E}$ be arbitrary. Let $\lambda \in (0, 1)$ be arbitrary.

$$\begin{aligned} & f \text{ is } \beta\text{-strongly convex} \\ \iff & f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y) \\ & \quad - \frac{\beta}{2}\lambda(1 - \lambda)\|x - y\|^2 \end{aligned}$$

$$\begin{aligned}
&\iff f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y) \\
&\quad - \frac{\beta}{2}\lambda(1 - \lambda)(\|x\|^2 + \|y\|^2 - 2\langle x, y \rangle) \\
&\iff f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y) \\
&\quad - \lambda \frac{\beta}{2}\|x\|^2 + \frac{\beta}{2}\lambda^2\|x\|^2 \\
&\quad - (1 - \lambda) \frac{\beta}{2}\|y\|^2 + \frac{\beta}{2}(1 - \lambda)^2\|y\|^2 \\
&\quad + \beta\lambda(1 - \lambda)\langle x, y \rangle \\
&\iff f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y) \\
&\quad - \lambda \frac{\beta}{2}\|x\|^2 - (1 - \lambda) \frac{\beta}{2}\|y\|^2 \\
&\quad + \frac{\beta}{2}\|\lambda x\|^2 + \frac{\beta}{2}\|(1 - \lambda)y\|^2 + \beta\langle \lambda x, (1 - \lambda)y \rangle \\
&\iff f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y) \\
&\quad - \lambda \frac{\beta}{2}\|x\|^2 - (1 - \lambda) \frac{\beta}{2}\|y\|^2 \\
&\quad + \frac{\beta}{2}\|\lambda x + (1 - \lambda)y\|^2 \\
&\iff g(\lambda x + (1 - \lambda)y) \leq \lambda g(x) + (1 - \lambda)g(y) \\
&\iff f - \frac{\beta}{2}\|\cdot\|^2 \text{ is } \beta \text{ convex.}
\end{aligned}$$

■

Question: Can we allow f to take on $-\infty$? Do we need f to be proper?

Proposition 11.2.3. *Let f and g be functions from \mathbb{E} to \mathbb{R}^* . Assume that f is β -strongly convex for some positive constant β and that g is convex. Then $f + g$ is β -strongly convex.*

Question: Can we allow f or g to take on $-\infty$? Do we need f and g to be proper?

Proof.

Since f is β -strongly convex, $f - \frac{\beta}{2}\|\cdot\|^2$ is convex.

Since $f - \frac{\beta}{2}\|\cdot\|^2$ and g are convex, $f + g - \frac{\beta}{2}\|\cdot\|^2$ is convex.

Since $f + g - \frac{\beta}{2}\|\cdot\|^2$ is convex, $f + g$ is β -strongly convex.

■

11.3 Quasiconvex

Definition (Quasiconvex). *Let $f : \mathbb{E} \rightarrow \mathbb{R}$ be a function with convex domain. We say that f is **quasiconvex** if any level set of f is convex.*

Proposition 11.3.1 (Jensen's Inequality for Quasiconvex Functions). *Let f be a quasiconvex function. Then $\forall x, y \in \text{dom}(f)$, $\forall \alpha, \beta \in [0, 1]$ such that $\alpha + \beta = 1$,*

$$f(\alpha x + \beta y) \leq \max\{f(x), f(y)\}.$$

Proposition 11.3.2. *A differentiable real-valued function f with convex domain is convex if and only if $\forall x, y \in \text{dom}(f)$,*

$$f(y) \leq f(x) \implies \nabla f(x) \cdot (y - x) \leq 0. \quad ???$$

Not sure where did this come from but I don't think this is correct.

Chapter 12

Support

12.1 Definitions

Definition (Support Function). *Let S be a subset of \mathbb{E} . We define the **support function** of S , denoted by σ_S , to be a function from \mathbb{E} to \mathbb{R}^* given by*

$$\sigma_S(x) = \sup_{s \in S} \langle x, s \rangle.$$

Definition (Supporting Hyperplane). *Let S be a set in \mathbb{E} with nonempty boundary. Let x_0 be a point in the boundary of S . We define a **supporting hyperplane** H to set S at point x_0 to be a set of the form*

$$H = \{x \in \mathbb{E} : a^T x = a^T x_0\},$$

such that $a \in \mathbb{E}$ and $a \neq \vec{0}$ and $\forall x \in S, a^T x \leq a^T x_0$.

12.2 Properties

Proposition 12.2.1. *The support function of a non-empty set S is proper, convex, and lower semi-continuous.*

Proof.

Part 1. Proper.

Define f_s to be a function from \mathbb{E} to \mathbb{R} by $f_s(x) = \langle s, x \rangle$.

These functions are linear and hence proper, convex, and lower semi-continuous.

Notice $\sigma_S = \sup_{s \in S} f_s$.

So σ_S is convex and lower semi-continuous.

Since $\sigma_S(0) = \sup_{s \in S} \langle 0, s \rangle = 0$, $\exists x_0 \in \mathbb{E}, \sigma_S(x) \neq +\infty$.

Since $\sigma_S(x) = \sup_{s \in S} \langle x, s \rangle \geq \langle x, s \rangle \neq -\infty, \forall x \in \mathbb{E}, \sigma_S(x) \neq -\infty$.

Since $\exists x_0 \in \mathbb{E}, \sigma_S(x) \neq +\infty$ and $\forall x \in \mathbb{E}, \sigma_S(x) \neq -\infty$, by definition, σ_S is proper. ■

Proposition 12.2.2. *The support function of a non-empty and bounded set is continuous.*

Proof.

Let x_0 be an arbitrary point in \mathbb{E} . Let ε be an arbitrary positive number. Define $M := \sup_{y \in C} \|y\| + 1$. Since C is bounded, M is finite. Define $\delta := \varepsilon/M$. Let x be an arbitrary point such that $\|x - x_0\| < \delta$. Let y be an arbitrary point in \mathbb{E} . Then by the Cauchy Schwarz inequality, we have

$$\langle x - x_0, y \rangle \leq \|x - x_0\| \|y\|.$$

That is,

$$\langle x, y \rangle \leq \|x - x_0\| \|y\| + \langle x_0, y \rangle.$$

It follows that

$$\begin{aligned} \sup_{y \in C} \langle x, y \rangle &\leq \sup_{y \in C} (\|x - x_0\| \|y\| + \langle x_0, y \rangle) \\ &\leq \|x - x_0\| \sup_{y \in C} \|y\| + \sup_{y \in C} \langle x_0, y \rangle. \end{aligned}$$

That is,

$$\sigma_C(x) \leq \sigma_C(x_0) + \|x - x_0\| \sup_{y \in C} \|y\|.$$

By definition of δ and M ,

$$\sigma_C(x) < \sigma_C(x_0) + \varepsilon. \tag{1}$$

Similarly, reversing the role of x and x_0 , we can prove that

$$\sigma_C(x_0) < \sigma_C(x) + \varepsilon. \tag{2}$$

From (1) and (2) we get

$$|\sigma_C(x) - \sigma_C(x_0)| < \varepsilon.$$

Since $\forall \varepsilon > 0, \exists \delta > 0$ such that $|\sigma_C(x) - \sigma_C(x_0)| < \varepsilon$ whenever $\|x - x_0\| < \delta$, by definition, σ_C is continuous. ■

Proposition 12.2.3. *Let S be a subset of \mathbb{E} . Then $\sigma_S = \sigma_{\text{conv}(S)} = \sigma_{\text{clconv}(S)}$.*

Proof.

Let x be an arbitrary point in \mathbb{E} .

$$\sigma_S(x) = \sup \{ \langle x, s \rangle : s \in S \}$$

$$\begin{aligned}\sigma_{\text{conv}(S)}(x) &= \sup \{ \langle x, s \rangle : s \in \text{conv}(S) \} \\ \sigma_{\text{clconv}(S)}(x) &= \sup \{ \langle x, s \rangle : s \in \text{clconv}(S) \}.\end{aligned}$$

It is easy to see that by the linearity of inner products,

$$\text{conv} \{ \langle x, s \rangle : s \in S \} = \{ \langle x, s \rangle : s \in \text{conv}(S) \}.$$

It is easy to see that by the linearity and the continuity of inner products,

$$\text{clconv} \{ \langle x, s \rangle : s \in S \} = \{ \langle x, s \rangle : s \in \text{clconv}(S) \}.$$

It is also easy to see that for any subset A of the reals,

$$\sup(A) = \sup(\text{conv}(A)),$$

and

$$\sup(A) = \sup(\text{cl}(A)).$$

So

$$\begin{aligned}\sigma_S(x) &= \sup \{ \langle x, s \rangle : s \in S \} \\ &= \sup \text{conv} \{ \langle x, s \rangle : s \in S \} \\ &= \sup \{ \langle x, s \rangle : s \in \text{conv}(S) \} \\ &= \sigma_{\text{conv}(S)}(x).\end{aligned}$$

That is, $\sigma_S(x) = \sigma_{\text{conv}(S)}(x)$.

$$\begin{aligned}\sigma_S(x) &= \sup \{ \langle x, s \rangle : s \in S \} \\ &= \sup \text{conv} \{ \langle x, s \rangle : s \in S \} \\ &= \sup \{ \langle x, s \rangle : s \in \text{conv}(S) \} \\ &= \sup \text{cl} \{ \langle x, s \rangle : s \in \text{conv}(S) \} \\ &= \sup \{ \langle x, s \rangle : s \in \text{cl}(\text{conv}(S)) \} \\ &= \sup \{ \langle x, s \rangle : s \in \text{clconv}(S) \} \\ &= \sigma_{\text{clconv}(S)}(x).\end{aligned}$$

That is, $\sigma_S(x) = \sigma_{\text{clconv}(S)}(x)$. ■

12.3 Supporting Hyperplane

Theorem 10 (Supporting Hyperplane Theorem). *For any boundary point x_0 of a convex set C , there exists a supporting hyperplane to C at x_0 .*

Chapter 13

Conjugacy

13.1 Definition and Examples

Definition (Convex Conjugate (Legendre–Fenchel Transformation)). *Let f be a function from \mathbb{E} to \mathbb{R}^* . We define the **convex conjugate** of f , denoted by f^* , to be a function also from \mathbb{E} to \mathbb{R}^* given by*

$$f^*(x) := \sup_{y \in \mathbb{E}} \{ \langle y, x \rangle - f(y) \}.$$

Example 13.1.1. *Let S be a subset of \mathbb{E} . Then $\delta_S^* = \sigma_S$.*

Proof. Recall that

$$\delta_S(x) = \begin{cases} 0, & x \in S, \\ +\infty, & x \notin S, \end{cases}$$
$$\sigma_S(x) = \sup_{y \in S} \langle x, y \rangle.$$

Now for any $x \in \mathbb{E}$,

$$\begin{aligned} \delta_S^*(x) &= \sup_{y \in S} (\langle x, y \rangle - \delta_S(y)) \\ &= \sup_{y \in S} (\langle x, y \rangle - 0) \\ &= \sup_{y \in S} \langle x, y \rangle \\ &= \sigma_S(x). \end{aligned}$$

So $\delta_S^* = \sigma_S$. ■

13.2 Basic Properties

Proposition 13.2.1. *The convex conjugate function is convex.*

Proof. If $\text{dom}(f) = \emptyset$, then one can see that $f^* \equiv -\infty$. It is a pointwise supremum of affine functions. ■

Proposition 13.2.2. *The convex conjugate function is lower semi-continuous.*

13.3 Double Conjugate

Proposition 13.3.1. *Let f be any function from \mathbb{E} to \mathbb{R}^* . Then $f^{**} \leq f$.*

Proof. Let x be an arbitrary point in \mathbb{E} .

$$\begin{aligned}
 & f^{**}(x) \\
 &= \sup_{y \in \mathbb{E}} \{ \langle y, x \rangle - f^*(y) \} \\
 &= \sup_{y \in \mathbb{E}} \left\{ \langle y, x \rangle - \sup_{z \in \mathbb{E}} \{ \langle z, y \rangle - f(z) \} \right\} \\
 &\leq \sup_{y \in \mathbb{E}} \left\{ \langle y, x \rangle - \{ \langle x, y \rangle - f(x) \} \right\} \\
 &= \sup_{y \in \mathbb{E}} \{ f(x) \} \\
 &= f(x).
 \end{aligned}$$

That is, $f^{**}(x) \leq f(x)$. Since $\forall x \in \mathbb{E}$, $f^{**}(x) \leq f(x)$, we get $f^{**} \leq f$. ■

Proposition 13.3.2. *Let f be a proper function. Then f is convex and lower semi-continuous if and only if*

$$f^{**} = f.$$

Proposition 13.3.3. *Let f and g be functions from \mathbb{E} to \mathbb{R}^* . Then $f \leq g$ implies $f^* \geq g^*$ and $f^{**} \leq g^{**}$.*

Proof. Let x be an arbitrary point in \mathbb{E} .

$$\begin{aligned}
 & f^*(x) \\
 &= \sup_{y \in \mathbb{E}} \{ \langle y, x \rangle - f(y) \} \\
 &\geq \sup_{y \in \mathbb{E}} \{ \langle y, x \rangle - g(y) \} \\
 &= g^*(x).
 \end{aligned}$$

That is, $f^*(x) \geq g^*(x)$. Since $\forall x \in \mathbb{E}$, $f^*(x) \geq g^*(x)$, we get $f^* \geq g^*$.

Let x be an arbitrary point in \mathbb{E} .

$$\begin{aligned}
 f^{**}(x) &= \sup_{y \in \mathbb{E}} \{ \langle y, x \rangle - f^*(y) \} \\
 &= \sup_{y \in \mathbb{E}} \left\{ \langle y, x \rangle - \sup_{z \in \mathbb{E}} \{ \langle z, y \rangle - f(z) \} \right\} \\
 &\leq \sup_{y \in \mathbb{E}} \left\{ \langle y, x \rangle - \sup_{z \in \mathbb{E}} \{ \langle z, y \rangle - g(z) \} \right\} \\
 &= \sup_{y \in \mathbb{E}} \{ \langle y, x \rangle - g^*(y) \} \\
 &= g^{**}(x).
 \end{aligned}$$

That is, $f^{**}(x) \leq g^{**}(x)$. Since $\forall x \in \mathbb{E}$, $f^{**}(x) \leq g^{**}(x)$, we get $f^{**} \leq g^{**}$. ■

Proposition 13.3.4.

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

13.4 Conjugates and Sub-Differentials

Theorem 11 (Fenchel-Young). *Let f be a proper function from \mathbb{E} to \mathbb{R}^* . Then $\forall x, y \in \mathbb{E}$, we have*

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

Proposition 13.4.1. *Let f be a proper closed convex function from \mathbb{E} to \mathbb{R}^* . Then $\forall x, y \in \mathbb{E}$,*

$$y \in \partial f(x) \iff x \in \partial f^*(y) \iff f(x) + f^*(y) = \langle x, y \rangle.$$

Proof of $y \in \partial f(x) \iff x \in \partial f^(y)$.* For one direction, assume that $y \in \partial f(x)$. We are to prove that $x \in \partial f^*(y)$. Consider an arbitrary point $z \in \mathbb{E}$. Since $y \in \partial f(x)$, we get

$$\forall u \in \mathbb{E}, \quad \langle y, u - x \rangle \leq f(u) - f(x).$$

Rearranging yields

$$\forall u \in \mathbb{E}, \quad \langle y, u \rangle - f(u) \leq \langle y, x \rangle - f(x).$$

It follows that

$$\sup_{u \in \mathbb{E}} (\langle y, u \rangle - f(u)) \leq \langle y, x \rangle - f(x). \tag{1}$$

By definition of supremum, we have

$$\sup_{u \in \mathbb{E}} (\langle y, u \rangle - f(u)) \geq \langle y, x \rangle - f(x). \tag{2}$$

From (1) and (2), we get

$$\sup_{u \in \mathbb{E}} (\langle y, u \rangle - f(u)) = \langle y, x \rangle - f(x).$$

That is,

$$f^*(y) = \langle y, x \rangle - f(x).$$

Then

$$\begin{aligned} & f^*(z) - f^*(y) \\ &= \sup_{u \in \mathbb{E}} (\langle z, u \rangle - f(u)) - \sup_{u \in \mathbb{E}} (\langle y, u \rangle - f(u)) \\ &= \sup_{u \in \mathbb{E}} (\langle z, u \rangle - f(u)) - \langle y, x \rangle + f(x) \\ &\geq \langle z, x \rangle - f(x) - \langle y, x \rangle + f(x) \\ &= \langle z - y, x \rangle. \end{aligned}$$

That is,

$$\langle x, z - y \rangle \leq f^*(z) - f^*(y).$$

So $x \in \partial f^*(y)$. This proves

$$y \in \partial f(x) \implies x \in \partial f^*(y).$$

Since $f^{**} = f$, similarly, we can prove that

$$x \in \partial f^*(y) \implies y \in \partial f(x).$$

■

Proposition 13.4.2. *Let f be a proper convex function from \mathbb{E} to \mathbb{R}^* . Let x be a point in \mathbb{E} . Assume that $\partial f(x) \neq \emptyset$. Then $f^{**}(x) = f(x)$.*

Chapter 14

Proximal

14.1 Definition

Definition (Proximal Operator). *Let f be a function from \mathbb{E} to \mathbb{R}^* . We define the **proximal operator** of f , denoted by prox_f , to be a function from \mathbb{E} to $\mathcal{P}(\mathbb{E})$ given by*

$$\text{prox}_f(x) := \underset{y \in \mathbb{E}}{\text{argmin}} \left\{ f(y) + \frac{1}{2} \|y - x\|^2 \right\}.$$

14.2 Basic Properties

Proposition 14.2.1. *Let f be a proper, convex, and lower semi-continuous function from \mathbb{E} to \mathbb{R}^* . Then $\forall x \in \mathbb{E}$, $\text{prox}_f(x)$ is a singleton set.*

Proposition 14.2.2. *Let C be a nonempty closed convex set in \mathbb{E} . Then $\text{prox}_{\delta_C} = \text{proj}_C$.*

Proposition 14.2.3 (Firmly Non-Expansive). *Let f be a proper closed convex function. Then prox_f is firmly non-expansive.*

14.3 Prox Calculus Rules

Proposition 14.3.1 (Scaling and Translation).

Theorem 12 (Norm Composition).

14.4 The Second Prox Theorem

Proposition 14.4.1. *Let f be a proper, convex, and lower semi-continuous function from \mathbb{E} to \mathbb{R}^* . Let x and p be points in \mathbb{E} . Then $p = \text{prox}_f(x)$ if and only if*

$$x - p \in \partial f(p).$$

Proposition 14.4.2. *Let f be a proper, convex, and lower semi-continuous function from \mathbb{E} to \mathbb{R}^* . Let x and p be points in \mathbb{E} . Then $p = \text{prox}_f(x)$ if and only if*

$$\forall y \in \mathbb{E}, \quad \langle y - p, x - p \rangle \leq f(y) - f(p).$$

14.5 Moreau Decomposition

Theorem 13 (Moreau Decomposition). *Let f be a proper closed convex function from \mathbb{E} to \mathbb{R}^* . Then*

$$\text{prox}_f + \text{prox}_{f^*} = \text{id}.$$

Proof. Let x be an arbitrary point in \mathbb{E} . We are to prove that

$$\text{prox}_f(x) + \text{prox}_{f^*}(x) = x.$$

Let p denote $\text{prox}_f(x)$. Since f is proper convex and lower semi-continuous and $p = \text{prox}_f(x)$, we get

$$x - p \in \partial f(p).$$

Since $x - p \in \partial f(p)$, we get $p \in \partial f^*(x - p)$. It follows that $x - p = \text{prox}_{f^*}(x)$. Substitute $p = \text{prox}_f(x)$ and rearrange the equation, we get

$$\text{prox}_f(x) + \text{prox}_{f^*}(x) = x.$$

■

Chapter 15

Ellipsoids

Definition (Ellipsoid). *Let v be a point in some Euclidean space \mathbb{E} . We define an **ellipsoid**, centered at point v , to be a set of the form*

$$\{x \in \mathbb{E} : (x - v)^T A (x - v) = 1\}$$

where A is some d by d positive definite matrix.

15.1 Properties

Proposition 15.1.1. *The eigenvectors of A define the principal axes of the ellipsoid.*