Advanced Computational Statistics (Fall 2016)

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Preface & Disclaimer

This note is a summary of the lecture Advanced Computational Statistics (M1399.000200) held at Seoul National University, Fall 2016. Lecturer was Jung-Ho Won, and the note was summarized by J.P.Kim, who is a Ph.D student. There are few textbooks and references in this course, which are following.

- *Convex Optimization Theory, Dimitri P. Bertsekas, 2009.*
- *Optimization, Kenneth Lange, 2013.*
- *Convex Optimization, S.Boyd & L.Vandenberghe, 2004.*

Also I referred to following books when I write this note. The list would be updated continuously.

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Chapter 1

Basic Concepts of Convex Analysis

1.1 Convex sets and functions

Definition 1.1.1. *A set $C \subseteq \mathbb{R}^n$ is **convex** if $\alpha x + (1-\alpha)y \in C$ for any $x, y \in C$ and $\alpha \in [0,1]$.*

Note that ϕ is convex by convention.

Proposition 1.1.2. *Let C and C_i be convex sets for $i \in I$. Then,*

(a) $\bigcap_{i \in I} C_i$ is also a convex set.

(b) $C_1 + C_2$ is a convex set.

(c) For any scalar λ, λC is a convex set. Also, for $\lambda_1, \lambda_2 > 0$, $(\lambda_1 + \lambda_2)C = \lambda_1 C + \lambda_2 C$ holds.

(d) $cl(C)$ and $int(C)$ are convex.

(e) For an affine function f, $f(C)$ or $f^{-1}(C)$ is convex.

Proof. (c) Convexity is trivial. Let $x \in (\lambda_1 + \lambda_2)C$. Then for some $y \in C$, $x = (\lambda_1 + \lambda_2)y$ holds. Since $\lambda_1 y \in \lambda_1 C$ and $\lambda_2 y \in \lambda_2 C$, we get $x \in \lambda_1 C + \lambda_2 C$. Thus we showed $(\lambda_1 + \lambda_2)C \subseteq \lambda_1 C + \lambda_2 C$. $\supseteq$ part is similar.

(d) Let $x, y \in cl(C)$. Then $\{x_k\}, \{y_k\} \subseteq C$ exist such that $x_k \to x$ and $y_k \to y$. Note that for any $\alpha \in [0,1]$ we get $\{\alpha x_k + (1-\alpha)y_k\} \subseteq C$, and so $\alpha x + (1-\alpha)y \in cl(C)$ from $\alpha x_k + (1-\alpha)y_k \to \alpha x + (1-\alpha)y$. Next, let $x, y \in int(C)$. Then there exists $r > 0$ such that $B(x,r) \subseteq C$ and $B(y,r) \subseteq C$. Note that $B(x,r) = \{x + z : \|z\| < r\}$. It's enough to show that $B(\alpha x + (1-\alpha)y, r) \subseteq C$. Now $B(\alpha x + (1-\alpha)y, r) = \{\alpha x + (1-\alpha)y + z : \|z\| < r\}$ and hence $\alpha x + (1-\alpha)y + z = \alpha \underbrace{(x+z)}_{\in B(x,r) \subseteq C} + (1-\alpha) \underbrace{(y+z)}_{\in B(y,r) \subseteq C} \in C$ for any z such that $\|z\| < r$.

(e) If $x, y \in f(C)$, $\exists x', y' \in C$ such that $x = f(x')$ and $y = f(y')$. Since f was affine, we get

$$\alpha x + (1-\alpha)y = \alpha f(x') + (1-\alpha)f(y') = f(\alpha x' + (1-\alpha)y') \in f(C)$$

from $\alpha x' + (1-\alpha)y' \in C$. Rest part is similar. □

Example 1.1.3 (Special convex sets)**.** In this example we see some examples of convex set.

(a) *Hyperplane* $\{x : a^T x = b\}$ is convex, for given a and b.

(b) *Half-space* $\{x : a^T x \le b\}$ is also convex.

(c) *Polyhedra*, $\{x : a_j^T x \le b_j,\ a_j \ne 0,\ b_j \in \mathbb{R},\ j = 1, 2, \cdots, r\}$ is intersection of half-spaces, and hence convex.

(d) C is *cone* if $\forall x \in C\ \lambda x \in C$ for any $\lambda > 0$. Note that, cone need not be convex, nor contain the origin. (See figure 1.1.) Rather, we consider *polyhedral cone* $\{x : a_j^T x \le 0,\ j = 1, 2, \cdots, r\}$, which contains the origin at the boundary. Polyhedral cone is convex.

(e) $S = \{x : a^T x = 0\}$ is a convex set, subspace of $\mathbb{R}^n$, a hyperplane, and a polyhedral cone.

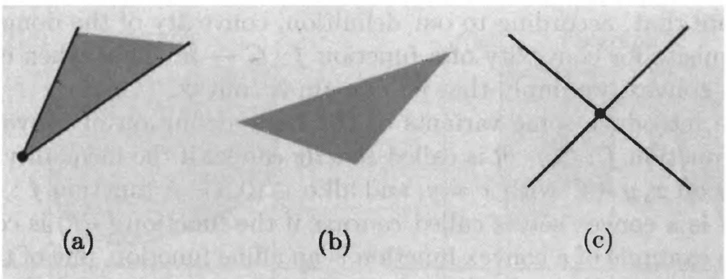

Figure 1.1: (a) Convex cone. (b) Convex cone which does not contain the origin. (c) Nonconvex cone, which consists of 2 lines.

Definition 1.1.4. *Let $C \subseteq \mathbb{R}^n$ be a convex set, and $f : C \to \mathbb{R}$ be a function. f is **convex** if*

$$f(\alpha x + (1-\alpha)y) \le \alpha f(x) + (1-\alpha)f(y)\ \forall x, y \in C,\ \ \alpha \in [0,1].$$

*Remark: Domain is a convex set! Also, f is **strictly convex** if*

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

*Finally, f is **concave** if $-f$ is convex.*

From now on, without mention, C always denote a convex set in $\mathbb{R}^n$.

Example 1.1.5. (a) Affine function $f(x) = a^T x + b$ is both convex and concave.

(b) Any norm $f(x) = \|x\|$ is convex from *triangle inequality.*

Definition 1.1.6 (level set)**.** *Let $f : C \to \mathbb{R}$ be a convex function. Then for any given $\gamma \in \mathbb{R}$,*

*(a) $\{x \in C : f(x) \leq \gamma\}$ is called **sublevel set** of f.*

*(b) $\{x \in C : f(x) \geq \gamma\}$ is called **superlevel set** of f.*

*From now on, we will call a sublevel set as a **level set** in short.*

Remark 1.1.7. It is known that if f is a convex function, then all of its level sets are convex. Note that converse does not hold: See figure 1.2.

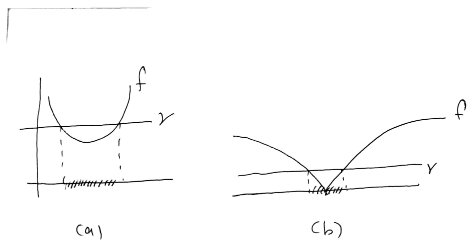

Figure 1.2: (a) Level set of convex function. (b) Even if all of level sets are convex, function need not be a convex one.

In many cases, it is convenient to allow function value be $\pm\infty$, or domain is $\mathbb{R}^n$. For this, we may consider a *extended real valued functions.* Then how to define convexity of such function $f : C \to [-\infty, \infty]$? The rest part of this section handles this issue.

Example 1.1.8. (Motivation for extension to $\bar{\mathbb{R}}$)

(a) We may deal with the function $f(x) = \sup_{i \in I} f_i(x)$. Its value may be ∞.

(b) "Conjugate function" will be handled in section 1.6. To define this notion, extension should be required. For example, conjugate function $f^*(y)$ of $f(x) = |x|$ is

$$f^*(y) = \begin{cases} 0 & |y| \leq 1 \\ +\infty & o.w. \end{cases}.$$

(c) Consider $f(x) = 1/x$ on $(0, \infty)$. For optimization, closed domain is useful and convenient, so we may extend the domain to $[0, \infty]$. In here, $f(0) = \infty$ is reasonable extension.

Remark 1.1.9. Note that we can extend the domain of function $f : C \to \mathbb{R}$ to $\mathbb{R}^n$ as letting $f(x) = \infty$ if $x \notin C$. Thus allowing function to be extended real-valued, we can extend the domain of function. Then how to restrict the origin domain again? *Effective domain*, which is following, can be one answer.

Definition 1.1.10 (epigraph)**.** ***Epigraph*** *of function* $f : X \to \bar{\mathbb{R}}$ *is defined as*

$$epi(f) = \{(x, w) : x \in X,\ w \in \mathbb{R},\ f(x) \le w\}.$$

Note that w *is not allowed to be* $\pm\infty$*.*

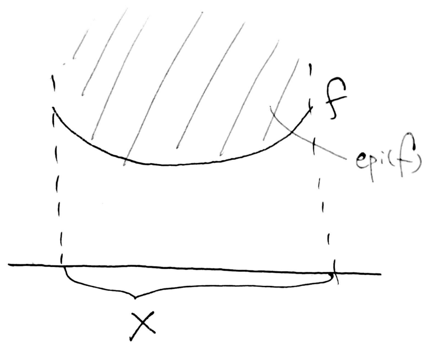

Figure 1.3: Epigraph of a function

Proposition 1.1.11. *Epigraph of convex function is a convex set.*

Proof. Easy. □

Definition 1.1.12 (effective domain)**.** *Let* $f : X \to \bar{\mathbb{R}}$ *be a function.* ***Effective domain*** *of* f *is defined as*

$$dom(f) = \{x \in X : f(x) < \infty\}.$$

There are some remarks.

Remark 1.1.13.

(a) Since we usually deal with a convex function f, the point whose functional value is $-\infty$ is out of interest.

(b) Note that

$$dom(f) = \{x \in \mathbb{R}^n : \exists w \in \mathbb{R}\ s.t.\ (x, w) \in epi(f)\},$$

so it is "projection of $epi(f)$ onto $\mathbb{R}^n$. If we want to handle real valued function, we can think restriction on $dom(f)$. Or, as mentioned above, we can enlarge domain from X to $\mathbb{R}^n$. Extended or restricted functions have the same epigraph.

Example 1.1.14.

(a) Consider a function $f : [0, \infty) \to [-\infty, \infty]$ defined as

$$f(x) = \begin{cases} \dfrac{1}{x} & x \neq 0 \\ +\infty & x = 0 \end{cases}.$$

Then $dom(f) = (0, \infty)$, and

$$epi(f) = \{(x, y) : 0 < x < \infty, y \geq 1/x.\}$$

(b) Suppose that $f(x) = -\infty$ for some $x \in X$. Then its epigraph $epi(f)$ may contain a vertical line.

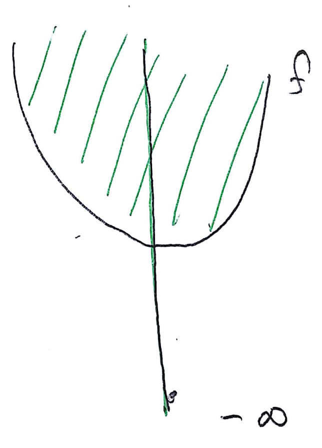

Figure 1.4: Epigraph of nonproper function

Definition 1.1.15 (proper function)**.** *Let $f : X \to \bar{\mathbb{R}}$. f is a* ***proper function*** *if*

(1) $f(x) < \infty$ for at least one $x \in X$, and

(2) $f(x) > -\infty$ for all $x \in X$.

Remark 1.1.16. Note that, f is proper function $\Leftrightarrow$ $epi(f)$ is nonempty and does not contain vertical line.

Now we can extend the definition of convex function *to extended real valued function.*

Definition 1.1.17. *$f : C \to \bar{\mathbb{R}}$ is a convex function if epi(f) is a convex subset of* $\mathbb{R}^{n+1}$.

Remark 1.1.18. Note that this definition satisfies followings.

(1) $dom(f)$ is convex.

(2) All of level sets are convex.

(3) If $f(x) < \infty \ \forall x$ or $f(x) > -\infty \ \forall x$, it satisfies Jensen's inequality.

Definition 1.1.19 (Indicator function)**.** *Let $X \subseteq \mathbb{R}^n$ be a set. An* ***indicator function*** *δ_X of X is defined as*

$$\delta_X(x) = \begin{cases} 0 & x \in X \\ +\infty & o.w. \end{cases}.$$

Note that effective domain of δ_X is X. Also, note that

$$X \text{ is (strictly) convex set } \Leftrightarrow \delta_X \text{ is (strictly) convex function.}$$

Also, if $X \neq \phi$, δ_X is proper.

Remark 1.1.20. Now we can give a correspondence between convex sets and convex functions. Epigrpah of convex function is convex set, and indicator of convex set is convex function.

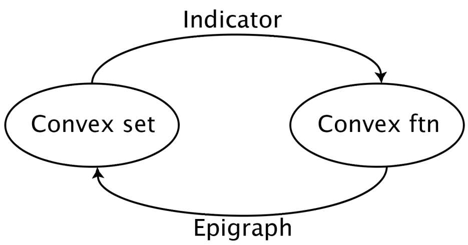

Figure 1.5: Correspondence between convex sets and functions

Now, we are ready for extension of convexity to nonconvex domain.

Definition 1.1.21. *Let C be a convex set, and $C \subseteq X \subseteq \mathbb{R}^n$. Then $f : X \to \bar{\mathbb{R}}$ is* ***convex over C*** *if $f|_C : C \to \bar{\mathbb{R}}$ (restriction on C of f) is convex function.*

1.1.1 Closedness and Semicontinuity

Definition 1.1.22. *A function $f : X \to \bar{\mathbb{R}}$ is a closed function if its epigraph epi(f) is closed set.*

It is reasonable definition because of correspondence between sets and functions. In Appendix A, we defined lower and upper semicontinuity of function. There is an important relationship between two notions of function. In fact, *they are equivalent.*

Theorem 1.1.23. *Let $f : \mathbb{R}^n \to \bar{\mathbb{R}}$ be a function. Then TFAE*[1]

(i) For any $\gamma \in \mathbb{R}$, $V_\gamma = \{x : f(x) \le \gamma\}$ is closed.

(ii) f is lower semicontinuous function.

(iii) f is closed function. (epi(f) is closed)

Proof. If $f(x) \equiv \infty$, it is trivial, so assume not.

(i)⇒(ii): Suppose that $\bar{x}$ and a sequence $\{x_k\}$ exist such that $x_k \xrightarrow[k\to\infty]{} \bar{x}$ and $f(x) > \liminf_{k\to\infty} f(x_k)$. Then $\exists\gamma$ such that $f(\bar{x}) > \gamma > \liminf_{k\to\infty} f(x_k)$. Then there is a subsequence $\{x_{kj}\}$ which satisfies

$$f(x_{kj}) \le \gamma \ \forall j,$$

by definition of $\liminf$. Hence $V_\gamma := \{x : f(x) \le \gamma\} \supseteq \{x_{kj}\}$, and from closedness of V_γ, $\bar{x} \in V_\gamma$ should be held, which yields contradiction.

(ii) ⇒ (iii): Choose a sequence $\{(x_k, w_k)\} \subseteq epi(f)$ such that $(x_k, w_k) \to (\bar{x}, \bar{w})$. Then since f is l.s.c.,

$$f(\bar{x}) \le \liminf_{k\to\infty} f(x_k) \le \liminf_{k\to\infty} w_k$$

holds by definition of epigraph. Thus we get

$$f(\bar{x}) \le \bar{w}$$

by letting $k \to \infty$. Therefore $(\bar{x}, \bar{w}) \in epi(f)$ holds.

(iii) ⇒ (i): Note that $(x, \gamma) \in epi(f) \Leftrightarrow x \in V_\gamma$. Let $\gamma \in \mathbb{R}$, and $\{x_k\} \subseteq V_\gamma$ be a sequence converging to $\bar{x}$. Then $(x_k, \gamma) \in epi(f)$ and $(x_k, \gamma) \xrightarrow[k\to\infty]{} (\bar{x}, \gamma)$ hold, which imply $(\bar{x}, \gamma) \in epi(f)$ since $epi(f)$ is closed. Therefore $\bar{x} \in V_\gamma$ is obtained. □

Remark 1.1.24. We will often use the condition that a function is *closed*, rather than *lower semicontinuity*, even though they are equivalent on $\mathbb{R}^n$. It's because closedness of epigraph is more convenient to handle, due to the 'domain dependency' of semicontinuity. For example,

[1] The followings are equivalent.

consider a function

$$f:\mathbb{R}\to(-\infty,\infty],\ f(x)=\begin{cases}0 & 0<x<1\\ \infty & o.w.\end{cases}.$$

Then its epigraph is $epi(f)=(0,1)\times[0,\infty)$ so it is not closed, nor lower semicontinuous. However, if we restrict the domain,

$$\tilde{f}:(0,1)\to(-\infty,\infty],\ \tilde{f}(x)=0$$

is lower semicontinuous, while its epigraph does not change, which means that $\tilde{f}$ is not closed. For this reason, we often consider the epigraph while we deal with closedness or semicontinuity of function.

Then our question is: Cannot we think similar thing as theorem 1.1.23 for a function on restricted domain? Next theorem gives the answer.

Proposition 1.1.25. *Let $f:X\to\bar{\mathbb{R}}$ and suppose that $dom(f)$ is closed, and f is l.s.c. at x for any $x\in dom(f)$. Then, f is closed.*

Proof. Similar as 1.1.23. □

Example 1.1.26. Let $X\subseteq\mathbb{R}^n$. Then,

(a) Indicator δ_X of X is closed iff X is closed.

(b) Let

$$f_X(x)=\begin{cases}f(x) & x\in X\\ \infty & o.w.\end{cases}\qquad\text{(“extension to the whole domain”)}$$

Then f_X is closed iff X is closed.

Proof. (From HW1) Let δ_X be indicator of X. Then

$$epi(\delta_X)=\{(x,w):x\in X,w\geq 0\}=X\times[0,\infty)$$

is closed iff X is closed. Next,

$$epi(f_X)=\{(x,w):x\in X,f(x)\leq w\}.$$

If $epi(f_X)$ is closed, $\forall(x_k,w_k)\to(\bar{x},\bar{w})$ s.t. $\{(x_k,w_k)\}\subseteq epi(f_X)$, $(\bar{x},\bar{w})\in epi(f_X)$. Thus $\bar{x}\in X$. Note that $\forall x_k\to\bar{x}\ \exists w_k$ s.t. $(x_k,w_k)\to(\bar{x},\bar{w})$ and $\{(x_k,w_k)\}\subseteq epi(f_X)$. Conversely, if X is closed, $\forall (x_k, w_k) \to (\bar{x}, \bar{w})$ since $x_k \to \bar{x}$ so $\bar{x} \in X$ and $f(x_k) \le w_k \Leftrightarrow f(\bar{x}) \le \bar{w}$ so $(\bar{x}, \bar{w}) \in epi(f_X)$. (continuity of f is used) Hence $epi(f_X)$ is closed. □

In optimization, we usually consider a *proper, convex and closed* functions. Following proposition says that 'proper' condition is needed to make the function reasonable.

Proposition 1.1.27. *Improper closed convex function* ***cannot*** *take a finite value anywhere.*

Proof. Let $f : \mathbb{R}^n \to \bar{\mathbb{R}}$ be an improper closed convex function. Suppose that $\exists x$ such that $f(x) \in \mathbb{R}$ (i.e., f has a finite value). Then $f \not\equiv \infty$ and so $\exists \bar{x}$ s.t. $f(\bar{x}) = -\infty$. Define a sequence $\{x_k\}$ as

$$x_k = \frac{k-1}{k}x + \frac{1}{k}\bar{x}.$$

Note that $x_k \to x$ as $k \to \infty$. By convexity,

$$f(x_k) \le \frac{k-1}{k}f(x) + \frac{1}{k}f(\bar{x}) = -\infty,$$

so we get $\forall k \; f(x_k) = -\infty$. Now by closedness, f is lower semicontinuous, and so

$$f(x) \le \liminf_{k\to\infty} f(x_k) = -\infty,$$

which yields contradiction. □

Remark 1.1.28. Note that by previous proposition, improper closed convex can have only the form as

$$f(x) = \begin{cases} -\infty & x \in dom(f) \\ \infty & o.w. \end{cases}.$$

1.1.2 Operations that preserve convexity of functions

Following operations preserve convexity.

(a) Composition with a linear transform, $f(Ax)$, where f: convex and A is $m \times n$ matrix. (It also preserves closedness)

(b) Summation or positive scalar multiplication, $\lambda_1 f_1(x) + \cdots + \lambda_m f_m(x)$ where f_i's are convex and $\lambda_i > 0$.

(c) Taking sup (See proposition 1.1.29)

(d) Taking partial minimum. If $f(x, z)$ is convex in (x, z), then $x \mapsto \inf_z f(x, z)$ is convex (Will be shown at section 3.3.).

Proposition 1.1.29. *Let $f_i : \mathbb{R}^n \to \mathbb{R}$ be convex functions where $i \in I$. Then*

$$f(x) := \sup_{i \in I} f_i(x)$$

is also convex.

Proof. We use the definition of convexity of *extended real-valued* function. Note that

$$(x, w) \in epi(f) \Leftrightarrow f(x) \le w \Leftrightarrow f_i(x) \le w \ \forall i \in I \Leftrightarrow (x, w) \in epi(f_i) \ \forall i \in I \Leftrightarrow (w, x) \in \bigcap_{i \in I} epi(f_i)$$

so we obtain

$$epi(f) = \bigcap_{i \in I} epi(f_i),$$

which yields the desired result. □

Remark 1.1.30. Note that $epi(f) = \bigcap_{i \in I} epi(f_i)$ also implies that f is closed, i.e., taking supremum preserves closedness as well as convexity.

1.1.3 Differentiable convex functions

In this subsection we deal with *differentiable* convex functions. Since we can define a gradient of function, There are some more things that we can say.

Proposition 1.1.31. *Let $C \subseteq \mathbb{R}^n$ be a nonempty convex set, and $f : \mathbb{R}^n \to \mathbb{R}$ be differentiable over an open set containing C. Then*

(a) f is convex over $C \Leftrightarrow f(z) \ge f(x) + \langle \nabla f(x), z - x \rangle \ \forall x, z \in C$

(b) f is (strictly) convex over $C \Leftrightarrow f(z) \ge f(x) + \langle \nabla f(x), z - x \rangle \ \forall x, z \in C$ s.t. $x \ne z$

Proof. Only a proof for (a) would be given.

$\Leftarrow$) Let $x, y \in C$, $\alpha \in [0, 1]$, and $z = \alpha x + (1 - \alpha) y$. Then by the assumption,

$$f(x) \ge f(z) + \langle \nabla f(z), x - z \rangle$$

$$f(y) \ge f(z) + \langle \nabla f(z), y - z \rangle$$

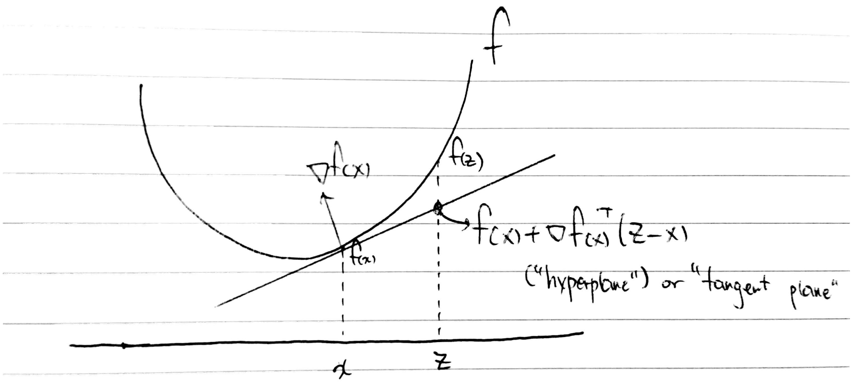

Figure 1.6: Convex differentiable function. See proposition 1.1.31.

holds. Thus, we get

$$\alpha f(x)+(1-\alpha y) \geq f(z)+\langle\nabla f(z), \alpha(x-z)+(1-\alpha)(y-z)\rangle = f(z)+\langle\nabla f(z), \underbrace{\alpha x+(1-\alpha)y}_{=z}-z\rangle$$

and therefore

$$\alpha f(x)+(1-\alpha)y \geq f(z) = f(\alpha x+(1-\alpha)y).$$

$\Rightarrow$) Let $x, y \in C$ and $x \neq y$. Define

$$g(\alpha) = \frac{f(x+\alpha(z-x))-f(x)}{\alpha} \text{ for } \alpha \in (0,1]. \qquad (\text{“Average rate on the direction of } z-x\text{”})$$

Then we get

$$\lim_{\alpha \searrow 0} g(\alpha) = \langle\nabla f(x), z-x\rangle \qquad (\text{“Directional derivative”})$$

and

$$g(1) = f(z)-f(x).$$

Thus if we can show that g is monotonely increasing,

$$g(1) \geq \lim_{\alpha \searrow 0} g(\alpha)$$

holds, which is the desired result. So our claim is:

Claim. g is monotonely increasing.

Choose $0<\alpha_1<\alpha_2<1$. Then

$$f\left(x+\alpha_1(z-x)\right) = f\left(\frac{\alpha_1}{\alpha_2}(x+\alpha_2(z-x))+\left(1-\frac{\alpha_1}{\alpha_2}\right)x\right)$$

$$\leq \frac{\alpha_1}{\alpha_2} f(x + \alpha_2(z - x)) + \left(1 - \frac{\alpha_1}{\alpha_2}\right) f(x)$$

so

$$\frac{f(x + \alpha_1(z - x)) - f(x)}{\alpha_1} \leq \frac{f(x + \alpha_2(z - x)) - f(x)}{\alpha_2}$$

is obtained. □

Remark 1.1.32. Proposition 1.1.31 has some siginficant consequences.

(1) If $f : \mathbb{R}^n \to \mathbb{R}$ is a differentiable convex function, then for x^* s.t. $\nabla f(x^*) = 0$ ("critical point") we get

$$f(x) \geq f(x^*) + \langle \nabla f(x^*), x - x^* \rangle \ \forall x$$

and hence

$$x^* \in \arg\min_{x \in \mathbb{R}^n} f(x). \qquad \text{("Unconstrained Optimization")}$$

(2) If $\langle \nabla f(x^{**}), z - x^{**} \rangle \geq 0 \ \forall z \in C$ holds, then we get

$$f(z) \geq f(x^{**}) + \langle \nabla f(x^{**}), z - x^{**} \rangle \geq f(x^{**}) \ \forall z \in C$$

so

$$x^{**} \in \arg\min_{x \in C} f(x). \qquad \text{("Constrained Optimization")}$$

(3) In fact, converse of (2) also holds. In other words, if $x^{**} \in C$ minimizes f over C, then $\langle \nabla f(x^{**}), z - x^{**} \rangle \geq 0 \ \forall z \in C$. To see this, assume that $\langle \nabla f(x^{**}), z - x^{**} \rangle < 0$ for some $z \in C$. Then since $\langle \nabla f(x^{**}), z - x^{**} \rangle$ is a directional derivative, we get

$$\lim_{\alpha \searrow 0} \frac{f(x^{**} + \alpha(z - x^{**})) - f(x^{**})}{\alpha} = \langle \nabla f(x^{**}), z - x^{**} \rangle < 0,$$

so for small α, we get

$$f(x^{**} + \alpha(z - x^{**})) < f(x^{**}),$$

which yields contradiction to minimization assumption of x^{**}.

(4) Later, proposition 1.1.31 will be extended to *subdifferential functions* using *subgradients.*

Proposition 1.1.33 (Projection Theorem)**.** *Let $C \subseteq \mathbb{R}^n$ be a nonempty closed convex set, and*

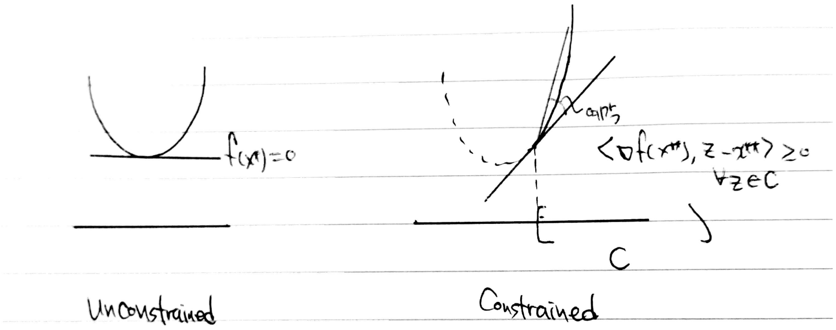

Figure 1.7: Unconstrained and Constrained Optimization

$z \in \mathbb{R}^n$ be a vector. Then there is a unique vector x^* such that

$$\|z - x^*\| \le \|z - x\| \ \forall x \in C.$$

In this case, we denote $x^* = \mathcal{P}_C(z) = \arg\min_{x \in C} \|z - x\|$. Furthermore,

$$x^* = \mathcal{P}_C(z) \ \Leftrightarrow \ \langle z - x^*, x - x^* \rangle \le 0 \ \forall x \in C.$$

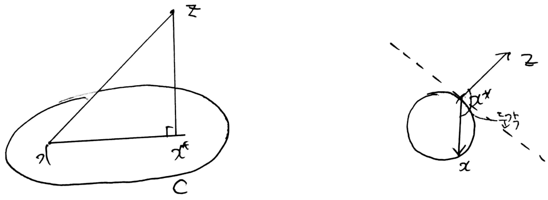

Figure 1.8: Projection Theorem

Proof. (Existence) Let $\tilde{C} = C \cap \{x : \|z - x\| \le \|z - w\|\}$ for some $w \in C$. Since we think minimization, we get

$$\min_{x \in C} f(x) = \min_{x \in \tilde{C}} f(x) \ . \qquad \text{("Restriction to bounded ball")}$$

(See figure 1.9) Then since $\tilde{C}$ is compact, by max-min theorem, we get $\exists x^* = \arg\min_{x \in \tilde{C}} f(x)$.

(Uniqueness) Let x_1^*, x_2^* be minimizers. Then by the fact that will be shown, we get

$$\langle z - x_1^*, x_2^* - x_1^* \rangle \le 0$$

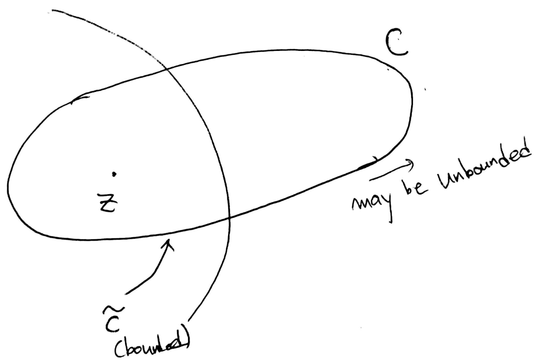

Figure 1.9: Restriction to bounded ball

$$\langle z - x_2^*, x_1^* - x_2^* \rangle \le 0,$$

which implies $\langle x_2^* - x_1^*, x_2^* - x_1^* \rangle \le 0$, and hence $x_1^* = x_2^*$.

(Rest part) Let $f(x) = \|z - x\|^2/2$. Then from previous theorem,

$$x^* = \arg\min_{x \in C} f(x) \ \Leftrightarrow\ \langle \nabla f(x^*), x - x^* \rangle \ge 0 \ \forall x \in C$$

holds, so from $\nabla f(x^*) = x^* - z$, we get $\langle z - x^*, x - x^* \rangle \le 0$. □

Now consider a $\mathcal{C}^2$ function.

Proposition 1.1.34. *Let $C \subseteq \mathbb{R}^n$ be a nonempty convex set, and $f : \mathbb{R}^n \to \mathbb{R}$ be twice continuously differentiable function over an open set that contains C. Then,*

(a) $\nabla^2 f(x) \ge 0\ \forall x \in C \ \Rightarrow f$*: convex over C.*

(b) $\nabla^2 f(x) > 0\ \forall x \in C \ \Rightarrow f$*: strictly convex over C.*

(c) If C is open and f is convex over C, then $\nabla^2 f(x) \ge 0\ \forall x \in C$.

Proof. By Taylor's theorem, for any $x, y \in C$, there is $\alpha \in [0, 1]$ such that

$$f(y) = f(x) + \nabla f(x)^T (y - x) + \frac{1}{2}(y - x)\nabla^2 f\left(x + \alpha(y - x)\right)(y - x).$$

Thus by theorem 1.1.31 we get (a) and (b). For (c), assume not. Then $\exists x \in C$ and $\exists z \in \mathbb{R}^n$ such that $z^T \nabla^2 f(x) z < 0$. WLOG z has very small norm. Then $x + z \in C$ from openness of C, and since $\nabla^2 f$ is continuous, for any $\alpha \in [0, 1]$, we get $z^T f(x + \alpha z) z < 0$. Using Taylor theorem again, we can yield contradiction. □

Remark 1.1.35. In (c), if open condition of C is omitted, then the assertion does not hold. For example, let $C = \{(x_1, 0) : x_1 \in \mathbb{R}\}$ and $f(x_1, x_2) = x_1^2 - x_2^2$. Then f is convex over C but

$$\nabla^2 f(x_1, x_2) = \begin{pmatrix} 2 & 0 \\ 0 & -2 \end{pmatrix}$$

is not positive definite.

1.2 Convex and Affine hulls

In this section, our goal is "convexification" of nonconvex sets. Let $x_1, \cdots, x_k \in \mathbb{R}^n$, $\alpha_1, \cdots, \alpha_k \in \mathbb{R}$ and $S \subseteq \mathbb{R}^n$ be a nonempty set. We can summarize definitions and facts about hulls as table 1.1.

	Linear	Affine	Convex
combination	$\sum_{i=1}^k \alpha_i x_i$	$\sum_{i=1}^k \alpha_i x_i$, where $\sum_{i=1}^k \alpha_i = 1$	$\sum_{i=1}^k \alpha_i x_i$, where $\sum_{i=1}^k \alpha_i = 1$, $\forall \alpha_i \geq 0$.
set	X is a linear set $\Leftrightarrow X = \left\{\sum_{i=1}^k \alpha_i x_i : x_i \in X\right\}$ $\Leftrightarrow X$ is a subspace	X is an affine set $\overset{(a)}{\Leftrightarrow} X = \left\{\sum_{i=1}^k \alpha_i x_i : x_i \in X, \sum_{i=1}^k \alpha_i = 1\right\}$	X is a conex set $\overset{(e)}{\Leftrightarrow} X = \left\{\sum_{i=1}^k \alpha_i x_i : x_i \in X, \sum_{i=1}^k \alpha_i = 1, \forall \alpha_i \geq 0\right\}$
hull generation	$\mathrm{lin}(S) = \bigcap(\text{linear} \supseteq S) = \left\{\sum_{i=1}^k \alpha_i x_i : x_i \in S\right\}$	$\mathrm{aff}(S) = \bigcap(\text{affine} \supseteq S) \overset{(b)}{=} \left\{\sum_{i=1}^k \alpha_i x_i : x_i \in S, \sum_{i=1}^k \alpha_i = 1\right\}$	$\mathrm{conv}(S) = \bigcap(\text{convex} \supseteq S) \overset{(f)}{=} \left\{\sum_{i=1}^k \alpha_i x_i : x_i \in S, \sum_{i=1}^k \alpha_i = 1, \forall \alpha_i \geq 0\right\}$
independence	$x_1, \cdots, x_k$ is linearly indep if $\sum_{i=1}^k \alpha_i x_i = 0 \Rightarrow \forall \alpha_i = 0$	$x_1, \cdots, x_k$ is affinely indep if $x_1 + \langle x_2 - x_1, \cdots, x_k - x_1 \rangle$ has dimension $k-1$ ((c))	N/A
cardinality	$\forall x \in \mathrm{lin}(S)$ can be represented as a linear combination of no more than n points from S $(k \leq n)$	(d) $\forall x \in \mathrm{aff}(S)$ can be represented as a affine combination of no more than $n+1$ points from S $(k \leq n+1)$	(g) $\forall x \in \mathrm{conv}(S)$ can be represented as a convex combination of no more than $n+1$ points from S $(k \leq n+1)$

Table 1.1: Linear, affine, and convex hull

Remark 1.2.1. Some remarks or proofs about table 1.1.

(a) Note that for some $x_0 \in X$, we get $X = x_0 + (X - x_0)$, and $X - x_0$ is a subspace. Then we get

$$X = x_0 + \left\{ \sum_{i=1}^{k} \alpha_i (x_i - x_0) : x_i \in X,\ i = 1, 2, \cdots, k \right\} = \left\{ \sum_{i=0}^{k} \alpha_i x_i : x_i \in X,\ i = 1, 2, \cdots, k \right\}$$

letting $\alpha_0 = 1 - \alpha_1 - \cdots - \alpha_k$.

(b) Take $x_0 \in S$ and A be an affine set that contains S. Then $A = x_0 + (A - x_0)$ holds, and $A - x_0$ is a subspace that contains $S - x_0$. Thus $\mathrm{aff}(S) = x_0 + \mathrm{span}(S - x_0)$. Now from

$$\mathrm{span}(S - x_0) = \left\{ \sum_{i=1}^{k} \alpha_i (x_i - x_0) : x_i \in S,\ i = 1, 2, \cdots, k \right\},$$

we get

$$\mathrm{aff}(S) = \left\{ \sum_{i=0}^{k} \alpha_i x_i : x_i \in S,\ i = 1, 2, \cdots, k \right\}.$$

(c) By index changing, we get

$$x_1 + \mathrm{span}(x_2 - x_1, \cdots, x_k - x_1) = x_k + \mathrm{span}(x_1 - x_k, \cdots, x_{k-1} - x_k) = x_k + \mathrm{span}(x_1 - x_k, \cdots, x_k - x_k).$$

(In the table, $\mathrm{span}(\cdot, \cdot)$ is represented as $\langle \cdot, \cdot \rangle$) Now by definition, $x_1, \cdots, x_k$ are affinely independent if $x_i - x_k,\ i = 1, 2, \cdots, k-1$ are linearly independent, i.e.,

$$\sum_{i=1}^{k-1} \alpha_i (x_i - x_k) = 0 \ \Rightarrow \alpha_1 = \alpha_2 = \cdots = \alpha_{k-1} = 0.$$

Now letting $\alpha_k = -(\alpha_1 + \cdots + \alpha_{k-1})$, we get

$$\sum_{i=1}^{k} \alpha_i = 0 \text{ and } \sum_{i=1}^{k} \alpha_i x_i = \sum_{i=1}^{k-1} \alpha_i (x_i - x_k).$$

Therefore, affinely independent condition is equivalent to

$$\sum_{i=1}^{k} \alpha_i x_i = 0,\ \sum_{i=1}^{k} \alpha_i = 0 \Rightarrow \alpha_1 = \cdots = \alpha_k = 0$$

holds, which means that

$$\sum_{i=1}^{k} \alpha_i \begin{pmatrix} x_i \\ 1 \end{pmatrix} = 0$$

has a unique solution. In other words, $x_1, \cdots, x_k$ is affinely independent iff k vectors $\begin{pmatrix} x_1 \\ 1 \end{pmatrix}, \cdots, \begin{pmatrix} x_k \\ 1 \end{pmatrix}$ in $\mathbb{R}^{n+1}$ are linearly independent.

(d) Since affinely independent condition in $\mathbb{R}^n$ is equivalent to linearly independent condition in $\mathbb{R}^{n+1}$, at most $n+1$ points determine $\text{aff}(S)$.

(e) $\Leftarrow$ part is trivial. For $\Rightarrow$ part, let $x_1, \cdots, x_k \in X$ and $\alpha_1, \cdots, \alpha_k \in \mathbb{R}$, $\sum \alpha_i = 1$, and $\alpha_i \geq 0$. As summation is 1, at least one α_i is positive. WLOG $\alpha_1 > 0$. Now

$$\begin{aligned}
y_2 &= \frac{\alpha_1}{\alpha_1 + \alpha_2} x_1 + \frac{\alpha_2}{\alpha_1 + \alpha_2} x_2 \in X \ (\because \text{convexity}) \\
y_3 &= \frac{\alpha_1 + \alpha_2}{\alpha_1 + \alpha_2 + \alpha_3} y_2 + \frac{\alpha_3}{\alpha_1 + \alpha_2 + \alpha_3} x_3 = \frac{\alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3}{\alpha_1 + \alpha_2 + \alpha_3} \in X \\
&\vdots \\
y_k &= \frac{\alpha_1 + \cdots + \alpha_{k-1}}{\alpha_1 + \cdots + \alpha_k} y_{k-1} + \frac{\alpha_k}{\alpha_1 + \cdots + \alpha_k} x_k = \frac{\alpha_1 x_1 + \cdots + \alpha_k x_k}{\alpha_1 + \cdots + \alpha_k} \in X
\end{aligned}$$

hold, and from $\sum \alpha_i = 1$, we get $y_k = \alpha_1 x_1 + \cdots + \alpha_k x_k \in X$.

(f) Let

$$T := \left\{ \sum_{i=1}^{k} \alpha_i x_i : x_i \in S,\ \sum_{i=1}^{k} \alpha_i = 1,\ \forall \alpha_i \geq 0 \text{ for some } k \right\}.$$

Then clearly T is convex, so $T \supseteq \text{conv}(S)$. Now if $S' \supseteq S$ is a convex set, then by (e)

$$S' = \left\{ \sum_{i=1}^{k} \alpha_i x_i : x_i \in S',\ \sum_{i=1}^{k} \alpha_i = 1,\ \forall \alpha_i \geq 0 \text{ for some } k \right\}$$

and it contains T from $S' \supseteq S$. Take intersection on S' and we obtain $\text{conv}(S) \supseteq T$. Therefore $\text{conv}(S) = T$.

(g) It is the result of *Carathéodory theorem*; any $x \in \text{conv}(S)$ can be represented as a convex combination of at most $n+1$ points from S. It means that for

$$C_k := \left\{ \sum_{i=1}^{k} \alpha_i x_i : x_i \in S,\ \alpha_i \geq 0,\ \sum_{i=1}^{k} \alpha_i = 1 \right\},$$

we get $S \subseteq C_1 \subseteq C_2 \subseteq \cdots$ "$\to$"conv(S), or $C_{n+1} = \text{conv}(S)$. Our goal of the rest part of this section is to prove Carathéodory theorem.

Remark 1.2.2. There are some consequences of Carathéodory theorem. First, $\text{aff}(\text{conv}(S)) = \text{aff}(S)$. For the proof, showing '$\subseteq$' part is enough. It is clear because *any affine combination of convex combination is indeed an affine combination.* Precisely, let $x \in \text{aff}(\text{conv}(S))$, and we get

$$x = \sum_{i=1}^{k} \alpha_i x_i \text{ for some } k \text{ and } x_i \in \text{conv}(S),\ \forall \alpha_i \geq 0$$

where

$$x_i = \sum_{j=1}^{k_i} \beta_{ij} y_{ij} \text{ for some } k_i \text{ and } y_{ij} \in S,\ \forall \beta_{ij} \geq 0,\ \sum_{j=1}^{k_i} \beta_{ij} = 1.$$

It implies that

$$x = \sum_{i=1}^{k} \sum_{j=1}^{k_i} \alpha_i \beta_{ij} y_{ij},\ \forall \alpha_i \beta_{ij} \geq 0,$$

and hence $x \in \text{aff}(S)$.

With this fact, we can define a dimension of convex hull, or a convex set, as $\dim(\text{conv}(S)) = \dim(\text{aff}(\text{conv}(S))) = \dim(\text{aff}(S))$. Or, for any convex set C, we can define $\dim(C) = \dim(\text{aff}(C))$. This definition coincides to our intuition, e.g., disk $\{(x, y) : x^2 + y^2 \leq 1\}$ on the plane has dimension 2. Furthermore, we get $\text{aff}(S) = \text{aff}(\text{cl}(S))$, where $\text{cl}(X)$ denotes the closure of X (It is clear because affine space is closed).

Example 1.2.3 (Convex hulls)**.** (a) $\text{conv}(\{x_1, x_2, \cdots, x_m\}) = \left\{ \sum_{i=1}^{m} \alpha_i x_i : \forall \alpha_i \geq 0, \sum_{i=1}^{m} \alpha_i = 1 \right\}$.

(b) If $C_1, C_2, \cdots, C_m$ are convex sets and $S = \bigcup_{i=1}^{m} C_i$, then

$$\text{conv}(S) = \left\{ \sum_{i=1}^{m} \alpha_i x_i : x_i \in C_i, \forall \alpha_i \geq 0, \sum_{i=1}^{m} \alpha_i = 1 \right\}.$$

(c) Let $A \in \mathbb{R}^{m \times n}$. Then

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

Proof. (b) Note that

$$\text{conv}(S) = \left\{ \sum_{i=1}^{k} \alpha_i x_i : x_i \in S,\ \forall \alpha_i \geq 0,\ \sum_{i=1}^{k} \alpha_i = 1 \text{ for some } k \right\}.$$

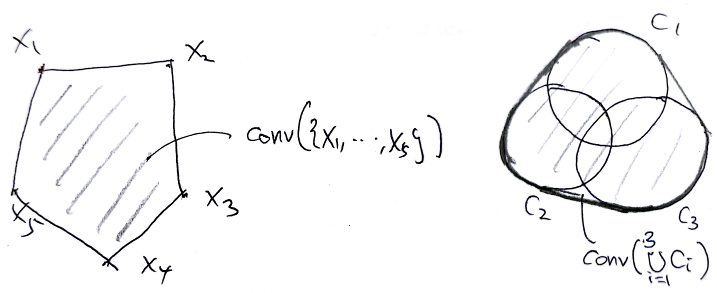

Figure 1.10: (a) and (b)

Let $x \in \mathrm{conv}(S)$, and we get

$$x = \sum_{i=1}^{k} \alpha_i x_i \text{ for some } x_i \in S,\ \forall \alpha_i \geq 0,\ \sum_{i=1}^{k} \alpha_i = 1.$$

For any x_j, there is $C_{\pi(j)}$ for some $\pi(j) \in \{1, 2, \cdots, m\}$ such that $x_j \in C_{\pi(j)}$. (If there are many such C_k's, choose $\pi(j)$ be the smallest one, so that $\pi(j)$ can be well-defined) Then with rearrangement of index

$$\begin{aligned} x = \sum_{i=1}^{k} \alpha_i x_i &= \sum_{l=1}^{m} \sum_{\pi(j)=l} \alpha_j x_j \\ &= \sum_{l=1}^{m} \underbrace{\left(\sum_{\pi(i)=l} \alpha_i \right)}_{=:\beta_l} \underbrace{\sum_{\pi(j)=l} \frac{\alpha_j}{\sum_{\pi(i)=l} \alpha_i} x_j}_{=:y_l \in C_l} \\ &= \sum_{l=1}^{m} \beta_l y_l \end{aligned}$$

holds, which implies

$$x = \sum_{l=1}^{m} \beta_l y_l \in \left\{ \sum_{i=1}^{m} \alpha_i x_i : x_i \in C_i, \forall \alpha_i \geq 0, \sum_{i=1}^{m} \alpha_i = 1 \right\},$$

and '$\subseteq$' part is shown. '$\supseteq$' is trivial.

(c) Note that for $A \in \mathbb{R}^{m \times n}$,

If C is convex, $A \cdot C$ is convex,

and if C' is convex, $A^{-1}(C')$ is convex.

Thus, $A \cdot \text{conv}(S)$ is a convex set, containing $A \cdot S$, and we get $\text{conv}(A \cdot S) \subseteq A \cdot \text{conv}(S)$. Conversely, let

$$x \in \text{conv}(S), \text{ and represent } x = \sum_{i=1}^{k} \alpha_i x_i \text{ for some } k \text{ and } x_i \in S, \forall \alpha_i \geq 0, \sum_{i=1}^{k} \alpha_i = 1.$$

Then each Ax_i belongs to $A \cdot S$, and so $Ax = \sum_{i=1}^{k} \alpha_i \cdot Ax_i \in \text{conv}(A \cdot S)$, which implies $\text{conv}(A \cdot S) \supseteq A \cdot \text{conv}(S)$. □

Remark 1.2.4. Using the definition of convex hull, we can define "convexification" of non-convex function. Note that a function is convex iff its epigraph is. If we find a function whose epigraph is a convex hull of epigraph of given function, we can find "the nearest convex function" with given one. See figure 1.11.

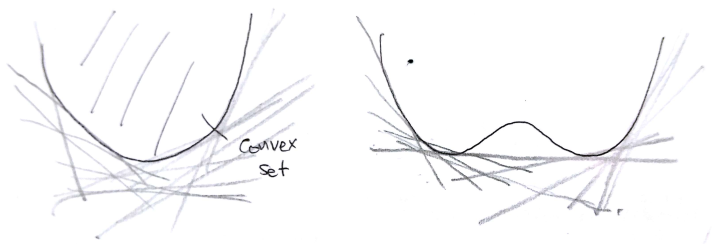

Figure 1.11: Convexification of non-convex function.

Now, we introduce a "conic hull."

Definition 1.2.5. $\sum_{i=1}^{k} \alpha_i x_i$ *is called a* ***conic combination*** *(or nonnegative combination) if* $\forall \alpha_i \geq 0$.

Note that comparing to convex combination, the condition $\sum \alpha_i = 1$ is omitted.

Proposition 1.2.6. *X is a convex cone if and only if*

$$X = \left\{ \sum_{i=1}^{k} \alpha_i x_i,\ x_i \in X,\ \forall \alpha_i \geq 0, \exists \alpha_i > 0,\ i = 1, 2, \cdots, k \text{ for some } k \right\}.$$

Recall that cone need not be convex. Also recall that even if convex cone cannot contain the origin. For convenience, we would consider convex cones containing 0.

Definition 1.2.7 (Convex hull)**.** ***Conic hull*** *of S is "defined" as*

$$cone(S) = \left\{ \sum_{i=1}^{k} \alpha_i x_i : x_i \in S,\ \alpha_i \geq 0,\ i = 1, 2, \cdots, k \text{ for some } k \right\}.$$

We defined cone(S) as the smallest "convex cone" that contains S and 0.

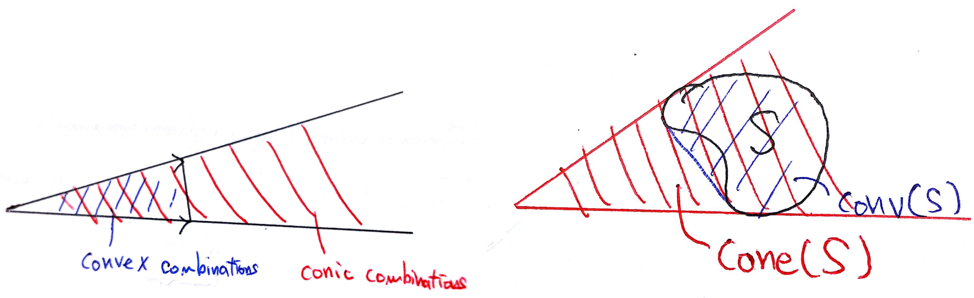

Figure 1.12: Conic combination and conic hull

Remark 1.2.8. (1) $0 \in \text{cone}(S)$, by definition of conic hull.

(2) Also, by definition of conic hull, cone(S) is a convex cone.

(3)

$$\text{cone}(S) = \bigcup_{\lambda \geq 0} \lambda \cdot \text{conv}(S) = \text{conv}\left(\bigcup_{\lambda \geq 0} \lambda \cdot S\right)$$

holds, which implies cone$(S) \supseteq$ conv(S). It can be shown as following. First,

$$x \in \text{cone}(S) \Leftrightarrow x = \sum_{i=1}^{k} \alpha_i x_i \ \forall \alpha_i \geq 0, x_i \in S \Leftrightarrow x = \sum_{j=1}^{k} \alpha_j \sum_{i=1}^{k} \frac{\alpha_i}{\sum_j \alpha_j} x_i$$

$$\Leftrightarrow x \in \sum_{j=1}^{k} \alpha_j \cdot \text{conv}(S) \subseteq \bigcup_{\lambda \geq 0} \lambda \cdot \text{conv}(S).$$

Next,

$$x \in \text{cone}(S) \Rightarrow x = \sum_{i=1}^{k} \frac{\alpha_i}{\sum_j \alpha_j} \left(\sum_{j=1}^{k} \alpha_j x_i\right) \in \text{conv}\left(\bigcup_{\lambda \geq 0} \lambda \cdot S\right)$$

and

$$x \in \text{conv}\left(\bigcup_{\lambda \geq 0} \lambda \cdot S\right) \Rightarrow x = \sum_{i=1}^{k} \alpha_i \lambda_i x_i \ \forall \alpha_i \geq 0, \sum \alpha_i = 1, \ x_i \in S \in \text{cone}(S)$$

yields the result.

(4)

$$\text{cone}(S) = \bigcap (\text{convex cone} \supseteq S) \cup \{0\}.$$

(5) Remark that, cone(S) need not be closed, even if S is compact. For example, let $S = \{(x_1, x_2) : x_1^2 + (x_2 - 1)^2 \le 1\}$. Then S is compact, but

$$\text{cone}(S) = \{(x_1, x_2) : x_2 > 0\} \cup \{0\}$$

is not closed.

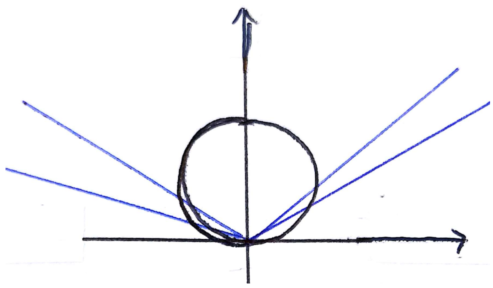

Figure 1.13: Example in (5)

Now we are ready to prove Carathéodory theorem. Indeed, it also says similar argument about conic hull.

Theorem 1.2.9 (Carathéodory)**.** *Let $\phi \neq S \subseteq \mathbb{R}^n$ be a nonempty set.*

(a) For any $0 \neq x \in cone(S)$ can be represented as a "positive combination" of linearly independent points (vectors) from S, i.e.,

$$x = \sum_{i=1}^{k} \alpha_i x_i, \ \ x_i \in S, \ \ \alpha_i > 0, \ \ i = 1, 2, \cdots, k$$

for some k, where $x_1, \cdots, x_k$ are linearly independent vectors.

(b) For any $x \in conv(S)$ can be represented as a convex combination of at most $n+1$ points from S.

Proof. (a) We can find a conic combination representation. Leaving zero coefficients out, we can find "the smallest integer" m such that

$$x = \sum_{i=1}^{m} \alpha_i x_i, \ \text{ where } \alpha_i > 0, \ \ x_i \in S, \ \ i = 1, 2, \cdots, m.$$

If x_i's are linearly dependent, then $\exists \lambda_1, \cdots, \lambda_m$ s.t. $\sum_{i=1}^{m} \lambda_i x_i = 0$, $(\lambda_1, \cdots, \lambda_m) \neq 0$, and at least one $\lambda_i > 0$. (If all of λ_i's are negative, consider $-\lambda_i$ instead.) Let $\mathcal{I} = \{i : \lambda_i > 0\}$. Choose

k such that

$$\gamma := \frac{\alpha_k}{\lambda_k} = \min\left\{\frac{\alpha_i}{\lambda_i} : i \in \mathcal{I}\right\},$$

and then for $\gamma > 0$, we get

$$x = \sum_{i=1}^m \alpha_i x_i - \underbrace{\gamma \sum_{i=1}^m \lambda_i x_i}_{=0} = \sum_{i=1}^m \underbrace{(\alpha_i - \gamma\lambda_i)}_{\geq 0} x_i,$$

where $\alpha_k - \gamma\lambda_k = 0$. It is contradictory to the assumption that m is minimal.

(b) $\square$

Appendix

A Mathematical Background

In this section, we introduce some basic background used oftenly.

A.1 Basic notions

- We often consider *extended real numbers* $\bar{\mathbb{R}} := \mathbb{R} \cup \{-\infty, \infty\}$. Also we define
  - $x \cdot 0 = 0 \ \forall x \in \bar{\mathbb{R}}$
  - $x \cdot \infty = \infty$ if $x > 0$
  - $x \cdot \infty = -\infty$ if $x < 0$
  - $x + \infty = \infty, \ x - \infty = -\infty \ \forall x \in \mathbb{R}$,
  - and we do not allow $\infty - \infty$.
- For nonempty subset X of $\mathbb{R}$, we define $\sup X$ as the smallest $y \in \mathbb{R}$ such that $y \geq x$ for any $x \in X$, and if such y does not exist, we define $\sup X = \infty$. Also, we define $\sup \phi = -\infty$. We can define $\inf X$ similarly.
- If $\sup X := \bar{x}$ is contained in X, we say that $\bar{x} = \max X$. ("maximum is attained")

  If $\inf X := \bar{x}$ is contained in X, we say that $\bar{x} = \min X$. ("minimum is attained")
- Vector space. In this course, we only consider $\mathbb{R}^n$. In here, inner product $\langle x, y \rangle = x^T y$ is defined.
- Also, for $x \in \mathbb{R}^n$, define the notation $x > 0$ or $x \geq 0$ componentwisely. Also define $x > y \Leftrightarrow x - y > 0$.
- Let $f : X \to Y$ be a function. For $U \subseteq X$ and $V \subseteq Y$, we define
  - $f(U) := \{f(x) : x \in U\}$ ("image of U")

- $f^{-1}(V) := \{x \in X : f(x) \in V\}$ ("inverse image of V")

A.2 Linear Algebra

- Let $X, X_1, X_2 \subseteq \mathbb{R}^n$ and λ be a scalar. we define
  - $\lambda X := \{\lambda x : x \in X\}$
  - $X_1 + X_2 := \{x_1 + x_2 : x_1 \in X_1,\ x_2 \in X_2\}$
  - $\overline{x} + X := \{\overline{x}\} + X$ for $\overline{x} \in \mathbb{R}$
  - and $X_1 - X_2 = \{x_1 - x_2 : x_1 \in X_1,\ x_2 \in X_2\}$.
  - To prevent abuse of notation, we will use $X_1 \backslash X_2$ for "set difference."
- If $X_i \subseteq \mathbb{R}^{n_i}$, $i = 1, 2, \cdots, m$, we define "Cartesian Product" as

$$X_1 \times \cdots \times X_m := \{(x_1, \cdots, x_m) : x_i \in X_i,\ i = 1, 2, \cdots, m\} \subseteq \mathbb{R}^{n_1 + \cdots + n_m}.$$

- $S \subseteq \mathbb{R}^n$ is called subspace if $ax + by \in S$ for any $x, y \in S$ and $a, b \in \mathbb{R}$.
- Also, for $\bar{x} \in \mathbb{R}$, $X := \bar{x} + S$ is called an affine set, if S is a subspace.

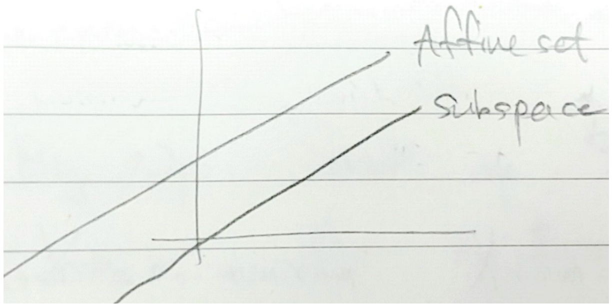

Figure 14: Affine set and subspace

- Facts:
  1. $\exists$ unique subspace associate with an affine set.
  2. $X(\neq \phi)$ is a subspace *if and only if* $0 \in X$ and $\alpha x + (1-\alpha)y \in X$ for any $\alpha \in \mathbb{R}$ and $x, y \in S$.
  3. $X(\neq \phi)$ is an affine set *if and only if* $\alpha x + (1-\alpha)y \in X$ for any $\alpha \in \mathbb{R}$ and $x, y \in S$.
  4. Note that intersection of subspaces is also a subspace.

- $\text{span}(x_1, \cdots, x_m)$ is a subspace generated by $x_1, \cdots, x_m$, and it is a set of linear combinations.

- We say that $x_1, \cdots, x_m$ are linearly independent if $\nexists(\alpha_1, \cdots, \alpha_m) \neq 0$ such that $\sum_{k=1}^m \alpha_k x_k = 0$.

- Let S be a nontrivial subspace. Then $\{x_1, \cdots, x_m\}$ is a basis for S if $x_1, \cdots, x_m \in S$, span $(x_1, \cdots, x_m) = S$ and they are linearly independent. In this case, we say $\dim S = m$. Also we define $\dim(\{0\}) = 0$.

- Dimension of the affine set is defined as that of associated subspace. In other words, $\dim(\bar{x} + S) = \dim S$.

- For given a and b, we define $\{x \in \mathbb{R}^n : a^T x = b\}$ as a hyperplane.

- Let $X \subseteq \mathbb{R}^n$. Then $X^\perp := \{y : \langle y, x \rangle = 0 \ \forall x \in X\}$ is a subspace of $\mathbb{R}^n$. In particular, if S is a subspace, then $S^\perp$ is an orthogoanl complement of S. We can say that $\mathbb{R}^n = S \oplus S^\perp$, and $\left(S^\perp\right)^\perp = S$.

- Matrices. Let $A \in \mathbb{R}^{m \times n}$. Then we define $AX := \{Ax : x \in X\}$ and $A^{-1}Y := \{x : Ax \in Y\}$.

- Let $\mathbb{S}^n = \{A \in \mathbb{R}^{n \times n} : A^T = A\}$. Then positive definite matrices are elements of the set

$$\mathbb{S}^n_{++} := \{A \in \mathbb{S}^n : x^T A x > 0 \ \forall x \in \mathbb{R}^n \backslash \{0\}\},$$

  and denote as $A \succ 0$ if A is s.p.d.. Also, we define a set of nonnegative definite matrices

$$\mathbb{S}^n_{+} := \{A \in \mathbb{S}^n : x^T A x > 0 \ \forall x \in \mathbb{R}^n \backslash \{0\}\},$$

  and denote as $A \succcurlyeq 0$ if $A \in \mathbb{S}^n_+$.

- If $A \succcurlyeq 0$, then there exists M such that $A = M^T M$.

- For a matrix $A \in \mathbb{R}^{m \times n}$, we define range and null space of A as

$$\mathcal{R}(A) = \{Ax : x \in \mathbb{R}^n\}$$

$$\mathcal{N}(A) = \{x : Ax = 0\}$$

  respectively.

- Rank of matrix A is defined as $rank(A) = \dim(\mathcal{R}(A))$. Note that, $rank(A) = rank(A^T)$, and $\mathcal{R}(A) = \left(\mathcal{N}(A^T)\right)^{\perp}$.
- If $rank(A) = m \wedge n$ we say that A is of full rank.

A.3 Basic Topology

- In here we often use the Euclidean norm $\|x\| = \sqrt{x^T x}$. Then, Cauchy Schwarz inequality $|x^T y| \le \|x\| \cdot \|y\|$ and Pythagoras theorem $\langle x, y\rangle = 0 \Rightarrow \|x+y\|^2 = \|x\|^2 + \|y\|^2$ are known.
- Let $\{x_k\}$ be a sequence in $\mathbb{R}$. We say $\{x_k\}$ converges if $\exists x \in \mathbb{R}$ such that $\forall \epsilon > 0\ \exists K\ s.t.\ \forall k \ge K \Rightarrow |x_k - x| < \epsilon$.
- Also we say that x_k diverges to ∞ if $\forall b \in \mathbb{R}\ \exists K\ s.t.\ \forall k \ge K\ x_k \ge b$.
- $\{x_k\}$ is bounded above if $\exists b$ such that $x_k \le b$ for any k.
- We can define

$$\limsup_{k\to\infty} x_k := \inf_{m\ge 1} \sup_{k \ge m} x_k = \lim_{m\to\infty} \sup_{k\ge m} x_k$$

$$\liminf_{k\to\infty} x_k := \sup_{m\ge 1} \inf_{k \ge m} x_k = \lim_{m\to\infty} \inf_{k\ge m} x_k.$$

- Note that

$$\inf_{k\ge 1} \le \liminf_{k\to\infty} x_k \le \limsup_{k\to\infty} x_k \le \sup_{k\ge 1} x_k$$

  holds.
- Also, if for any k $x_k \le y_k$ holds, then $\liminf x_k \le \liminf y_k$ and $\limsup x_k \le \limsup y_k$.
- Moreover,

$$\liminf_{k\to\infty} x_k + \liminf_{k\to\infty} y_k \le \liminf_{k\to\infty} (x_k + y_k)$$

$$\limsup_{k\to\infty} x_k + \limsup_{k\to\infty} y_k \ge \limsup_{k\to\infty} (x_k + y_k)$$

  hold.
- In general, for $\{x_k\} \subseteq \mathbb{R}^n$, we define $x_k rightarrow x$ as $k \to \infty$ if $x_{ki} \to x_i$ as $k \to \infty$. (componentwisely)
- Now we consider a subsequence $\{x_k : k \in \mathcal{K}\}$. x is called limit point if there exists a subsequence such that converges to x.

- Then we get following **Bolzano-Weierstrass Theorem**, *every bounded sequence has at least one limit point.*

- We can define closure $cl(X)$ and interior $int(X)$ of X. Also we can define boundary $bd(X) := cl(X)\backslash int(X)$ of X.

- <u>Facts</u>:
  - The union of a finite collection of closed sets is closed.
  - The intersection of any collection of closed sets is closed.
  - The union of any collection of open sets is open.
  - The intersection of a finite collection of open sets is open.
  - A set is open if and only if all of its elements are interior points.
  - Every subspace of $\mathbb{R}^n$ is closed.
  - A set X is compact if an only if every sequence of elements of X has a subsequence that converges to an element of X.
  - ("Cantor's intersection theorem", or if underlying space is $\mathbb{R}$, "Nested interval theorem") *If $\{X_k\}$ is a sequence of nonempty and compact sets such that $X_{k+1} \subset X_k$ for all k, then the intersection $\bigcap_{k=0}^{\infty} X_k$ is nonempty and compact.*

- Continuity. A function $f : X \to \mathbb{R}^n$ is continuous at x if for any sequence $\{x_k\}$ converges to x, $\lim_k f(x_k) = f(x)$ holds.

- A function $f : X \to \mathbb{R}^n$ is right-continuous (left-continuous) at x if for any sequence $\{x_k\}$ converges to x satisfying $x_k > x$ ($x_k < x$), $\lim_k f(x_k) = f(x)$ holds.

- A real-valued function $f : X \to \mathbb{R}$ is upper semicontinuous (lower semicontinuous) at $x \in X$ if $f(x) \geq \limsup f(x_k)$ ($f(x) \leq \liminf f(x_k)$) for any sequence $\{x_k\}$ in X that converges to x.

- For example, function

$$f(x) = \begin{cases} \sin(1/x) & x \neq 0 \\ 1 & x = 0 \end{cases}$$

  is upper semicontinuous (Figure 15). For more examples, see figure 16.

- <u>Facts</u>:

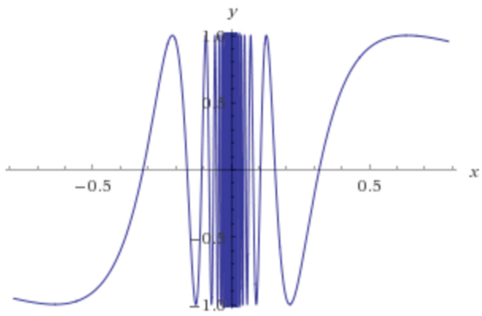

Figure 15: The graph of $y = sin(1/x)$. Image from WolframAlpha.

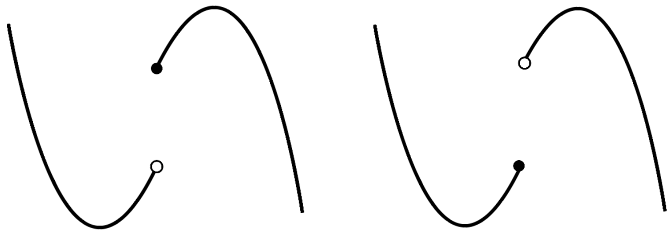

Figure 16: (Left) Such function is upper semicontinuous. (Right) Such function is lower semicontinuous.

- Any vector norm on $\mathbb{R}^n$ is a continuous function.
- Let $f : \mathbb{R}^m \to \mathbb{R}^p$ and $g : \mathbb{R}^n \to \mathbb{R}^m$ be continuous functions. Then $f \circ g$ is also continuous.
- Let $f : \mathbb{R}^n \to \mathbb{R}^m$ be continuous, and Y be an open (closed) subset of $\mathbb{R}^m$. Then $f^{-1}(Y)$ is open (closed).
- Let $f : \mathbb{R}^n \to \mathbb{R}^m$ be continuous, and X be a compact subset of $\mathbb{R}^n$. Then $f(X)$ is compact.

- Following is **Weierstrass' theorem**, or **max-min theorem**: *A continuous function $f : \mathbb{R}^n \to \mathbb{R}$ attains a minimum over any compact subset of $\mathbb{R}^n$.*

  Proof. Let $X \subseteq \mathbb{R}^n$ be a compact set. Define a *level set* $V_\gamma = \{x \in X : f(x) \le \gamma\}$, then it is compact since it is bounded and closed. Let $f^* := \inf_{x\in X} f(x) < \infty$. Then for a sequence $\{\gamma_k\}$ such that $\gamma_k \searrow f^*$ and $\gamma_k > f^*$, V_{γ_k} is nonempty, so by Cantor's intersection theorem, $\cap_k V_{\gamma_k}$ is nonempty compact set. Thus, $X^* := \{x \in X : f(x) = f^*\} = \cap_k V_{\gamma_k}$ is nonempty. $\square$