

Ch 1 Convexity

① Convex Hull $\rightarrow \text{conv}(S) = \left\{ \sum_{i=1}^n \lambda_i x_i : \sum \lambda_i = 1, \lambda_i \geq 0, x_i \in S \right\}$

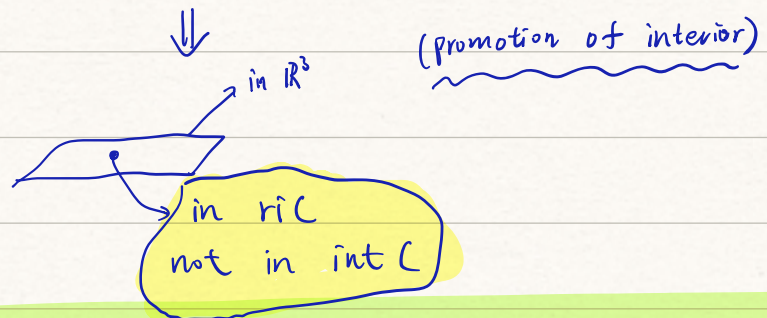
[Caratheodory's Thm]

$S \subset \mathbb{R}^n \Rightarrow \text{conv}(S) = \left\{ \sum_{i=1}^{n+1} \lambda_i x_i : \sum \lambda_i = 1, \lambda_i \geq 0, x_i \in S \right\}$.
 给出一个上界

(Some defn)

② Affine Hull $\rightarrow \text{aff } S = \left\{ \sum \lambda_i x_i : \sum \lambda_i = 1, x_i \in S \right\}$

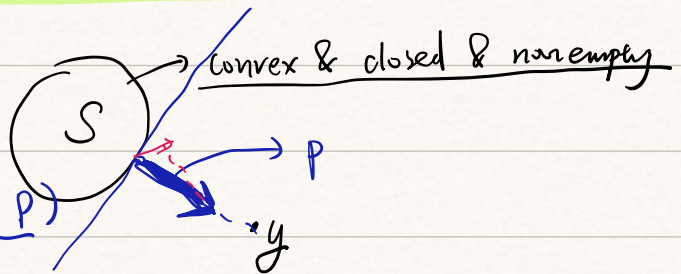
relative int $\rightarrow \text{ri } C = \left\{ x \in C : \exists \varepsilon > 0, (x + \varepsilon B) \cap \text{aff } C \subset C \right\}$



③ Separation Thm



(guarantee the existence of p)



P& Part

\Rightarrow After 'simple' trick, we can get unique \bar{x} .

such that $\|\bar{x} - y\| \leq \|x - y\|$ for all $x \in S$

point \leftrightarrow set

This part is relatively difficult!

Q: How to use this to achieve conclusion?

(*) $\begin{cases} p^T y > \alpha & ① \\ p^T x \leq \alpha & ② \end{cases}$

obviously, we can GUESS that $p = y - \bar{x}, \alpha = p^T \bar{x}$.

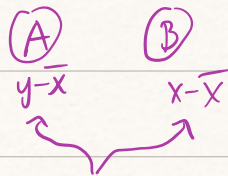
\hookrightarrow How to prove the (*)?

// \hookrightarrow ②

Contradiction!

① obviously true

if for some $x \in S$, $(y-\bar{x})^T (x-\bar{x}) > 0$

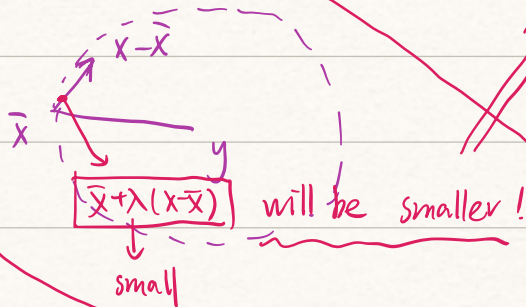


\Downarrow
 $\|x-\bar{x}\|$ not the minimal

$$\|y-x\|^2 = \langle A-B, A-B \rangle$$

$$= \|A\|^2 + \|B\|^2 - 2\langle A, B \rangle$$

Motivation



< 0

\Rightarrow Contradiction

→ Key Point of the Pf.

Application Part

① if we have a closed & convex set S.

② and a point $y \notin S$

\Downarrow
there exists one (p) and (α) .

$$\text{such that } \begin{cases} p^T y > \alpha \\ p^T x \leq \alpha \text{ for all } x \in S. \end{cases}$$

used in Farkas's Lemma etc.

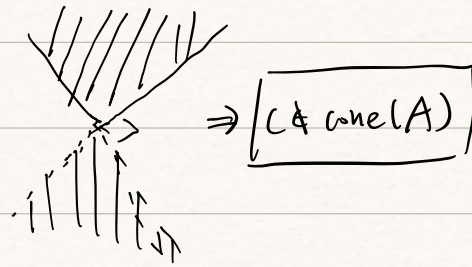
① Farkas's Lemma:

$$\begin{cases} Ax \leq 0 \\ c^T x > 0. \end{cases} \text{ for some } x. \quad \text{①}$$

$$\left\{ \begin{array}{l} A^T y = c \\ y \geq 0 \end{array} \right. \text{ for some } y \quad (2)$$

Geometric

$$(1) \Rightarrow A = \begin{pmatrix} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{pmatrix} = \begin{pmatrix} a_1^T \\ \vdots \\ a_m^T \end{pmatrix}$$



$$(2) \Rightarrow c \rightarrow \text{linear combination of } \{a_1, \dots, a_m\} \Rightarrow c \in \text{cone}(A)$$

Formally (Pf).

key point: use separation Thm through (2) \Rightarrow (1) \checkmark

(is apparent) \leftarrow (2) $\checkmark \Rightarrow$ (1) \times

$$S = \{z : z = A^T y, y \geq 0\}$$

closed \rightarrow DIFFICULT

\hookrightarrow (1) minimal rep..

(2) A_k^T linearly independ.

$$(3) z = A_k^T y_k$$

\hookrightarrow row (column) full rank.

$\Rightarrow \{z\}$ Bounded

$$(y_k \text{ Bounded}) \Leftrightarrow \{y\} \text{ Bounded}$$

$$(4) z_k \rightarrow z \Rightarrow \underline{z \in S}$$

$$z_k = A^T y_k$$

$$y_{k_t} \rightarrow y$$

$$\Rightarrow [z = A^T y, y \geq 0] \checkmark$$

Outline:

(2) Farkas's Lemma \Leftrightarrow Gordan's Theorem \Rightarrow Use the equivalence to prove this

$$\downarrow$$

$$S \neq \emptyset : Ax \leq 0, c^T x > 0 \text{ for some } x$$

$$S_2: A^T y = c \quad y \geq 0 \quad \text{for some } y$$

Analysis

$$\begin{cases} S_1': Ax \leq 0 \quad \text{for some } x \\ S_2': A^T y = 0, y \geq 0 \quad \text{for some } y \neq 0 \end{cases}$$

\swarrow ky is also soln.

$$S_1' \Leftrightarrow Ax + s \cdot e \leq 0 \quad s > 0$$

Key: Construction

Farkas's Lemma!

$$\Leftrightarrow \begin{bmatrix} A & e \end{bmatrix} \begin{bmatrix} x \\ s \end{bmatrix} \leq 0 \quad \begin{bmatrix} 0, \dots, 0, 1 \end{bmatrix} \begin{bmatrix} x \\ s \end{bmatrix} > 0$$

$$S_2' \Leftrightarrow A^T y = 0, y \geq 0 \quad e^T y = 1$$

$$\Leftrightarrow \begin{bmatrix} A^T \\ e^T \end{bmatrix} y = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix} \quad y \geq 0$$

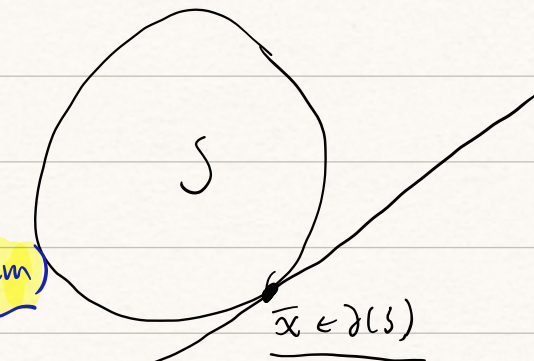
Supporting Hyperplane

$\Rightarrow S \rightarrow \text{convex} \Rightarrow$ existence of Supporting Hyperplane

relatively trivial

(use separating thm)

subgradient!



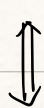
Polyhedron, extreme points & direction

Form

characterization

Polyhedron $\rightarrow S = \{x: p_i^T x \leq \alpha_i, i \in \mathbb{N}\}$

$= \{x: p^T x \leq \alpha\}$



没什么意义?

$\{x: Ax=b, x \geq 0\}$

Useful Conclusion

Defn of Extreme Point $\rightarrow x \in \text{E.P.} \Leftrightarrow$

$$x = \lambda x_1 + (1-\lambda)x_2$$

$$0 < \lambda < 1$$

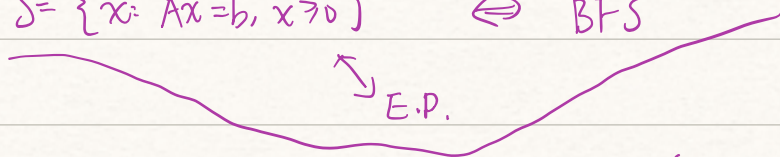
$$\Leftrightarrow x_1 = x_2 = x$$

Defn of Extreme Direction \rightarrow

- ① Recession Direction d
 $x \in S \Rightarrow x + \lambda d \in S \quad \text{all } \lambda \geq 0$
- ② Extreme Direction d
 $d = \lambda d_1 + \lambda_2 d_2 \quad \lambda_1, \lambda_2 \geq 0$
 $\Rightarrow d_1 = \alpha d_2 \quad \text{for some } \alpha$

① Characterization of E.P.

$S = \{x: Ax=b, x \geq 0\} \Leftrightarrow \text{BFS}$



$A = (a_1 \dots a_n)$

pf: " \Leftarrow " obvious

" \Rightarrow " $x \in S$ E.P. $x = \begin{bmatrix} x_1 \\ \vdots \\ x_n \\ 0 \end{bmatrix}$

Claim 1: $\{a_1, \dots, a_k\}$ linearly independ.

of E.P.

$\leq \binom{m}{n}$



$\Rightarrow k \leq m$

$\sum \alpha_i a_i = 0$ (if not)

$x + \lambda \alpha$ $x - \lambda \alpha$ \Rightarrow Contradiction

$\Rightarrow k \leq m \Rightarrow \begin{cases} k=m & \checkmark \\ k < m & \Rightarrow \text{basis can be expanded} \end{cases}$

② Characterization of Extreme Direction.

$$S = \{x: Ax=b, x \geq 0\} \quad \text{E.D.} \Leftrightarrow d = \begin{pmatrix} -A_B^{-1} a_j \\ e_j \end{pmatrix}$$

" \Leftarrow "

Pf: $\begin{pmatrix} -A_B^{-1} a_j \\ e_j \end{pmatrix} = \lambda_1 \begin{pmatrix} d_{11} \\ d_{12} \end{pmatrix} + \lambda_2 \begin{pmatrix} d_{21} \\ d_{22} \end{pmatrix}$

$$\downarrow \begin{pmatrix} d_{11} \\ d_{12} \end{pmatrix}$$

$$\downarrow \begin{pmatrix} d_{21} \\ d_{22} \end{pmatrix}$$

→ find the Analysis
Solu of $\begin{pmatrix} d_{11} \\ \infty \end{pmatrix}$ & $\begin{pmatrix} d_{21} \\ \infty \end{pmatrix}$

$$\Rightarrow \begin{pmatrix} d_{11} \\ \infty \end{pmatrix} = \alpha \begin{pmatrix} d_{21} \\ \infty \end{pmatrix}$$

recession dire.

\downarrow
E.D.

d recession direc. $\Rightarrow Ax=b, x \geq 0, x+\lambda d \in S$

$$A(x+\lambda d) = b, x+\lambda d \geq 0$$

$$\Downarrow$$

 $Ad=0$

$$\Downarrow$$

 $d \geq 0$

" \Rightarrow " d is **E.D.** \Rightarrow ① $Ad=0 \quad d \geq 0$

② $d = (d_1, \dots, d_k, \dots, d_j, \dots, 0)^T$

$$\underbrace{\hspace{1cm}}_{\{a_1, \dots, a_k\}}$$

\downarrow
linearly independent

$$\begin{cases} \text{①, } k=m & A_B d_m + d_j a_j = 0 \\ & \Rightarrow d_m = -d_j A_B^{-1} a_j \\ & \Rightarrow d = \begin{pmatrix} d_m \\ d_j \end{pmatrix} = d_j \begin{pmatrix} -A_B^{-1} a_j \\ e_j \end{pmatrix} \quad \checkmark \end{cases}$$

② $k < m$. claim: a_j cannot lie in the

linearly independent part

if so, $A_B d_m = 0 \Rightarrow \boxed{d_m = 0}$

$$\{a_1, \dots, a_k\} \xrightarrow{\text{expanded}} \{a_1, \dots, a_m\}$$

$$Ad = (A_B \ A_K) \begin{pmatrix} d_1 \\ d_m \\ \vdots \\ d_j \\ 0 \end{pmatrix}$$

$$= A_B d + A_K d_j = 0 \Rightarrow \text{SAME!}$$

contradicts to d is recession dir.
(extreme dir.)

③ Representation of Polyhedron (with EP and ED)

$$S = \{x : Ax = b, x \geq 0\} \Leftrightarrow$$

$$x = \sum \lambda_i x_i + \sum \mu_j d_j$$

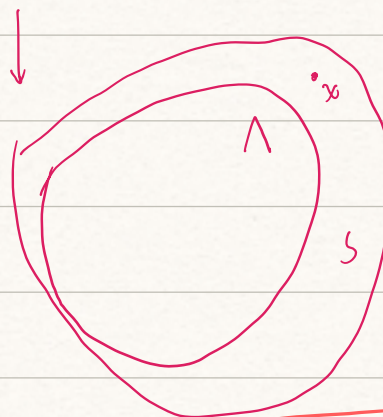
\Rightarrow finite

$$\boxed{\sum \lambda_i = 1 \quad \mu_j \geq 0}$$

Pf: \Leftarrow obviously True (\supseteq)

$$\Rightarrow (\subseteq) \quad L \subseteq R$$

if $\exists x \in S, x \notin R$



①

[Separating Thm]

② rewrite

$$\begin{cases} p^T z > p^T x_i \\ p^T d_j \leq 0 \end{cases}$$

③ Find contradiction

$$\text{choose } \bar{x} = \arg \max \{p^T x_i : x_i \in ED\}$$

use z to construct \tilde{x} .

$$\Lambda = \{\sum \lambda_i x_i + \sum \mu_j d_j : \sum \lambda_i = 1, \mu_j \geq 0\}$$

$$C_k = \sum \lambda_i^k x_i + \sum \mu_j^k d_j$$

$$C_k \rightarrow C \Rightarrow C \in \Lambda$$

$$C_k = \sum \bar{\lambda}_i^k x_i + \sum \bar{\mu}_j^k d_j$$

$$\text{st } \lambda_i^k \rightarrow \lambda_i^*$$

$$\Rightarrow C_k - \sum \bar{\lambda}_i^k x_i = d \bar{\mu}^k = (d_1, \dots, d_s) \bar{\mu}^k$$

$$\Rightarrow \bar{\mu}^k = \frac{C_k - \sum \bar{\lambda}_i^k x_i}{d}$$

\Rightarrow Bounded

subsequence convergent

$$\Rightarrow C_k^* = \sum \bar{\lambda}_i^k x_i + \sum \bar{\mu}_j^k d_j$$

最小输出

$$\text{s.t. } \begin{cases} \tilde{x} \rightarrow ED \\ p^T \tilde{x} > p^T \bar{x} \quad (\text{use } p^T z > p^T \bar{x}) \end{cases}$$

$$\begin{aligned} \lambda_1^* &\rightarrow \bar{c}_k \rightarrow c^* \\ \lambda_2^* &\rightarrow c^* \end{aligned}$$

④ Method: $\bar{x} = \begin{pmatrix} A_B^{-1} b \\ 0 \end{pmatrix} \quad \underline{\underline{z = \begin{pmatrix} z_B \\ z_N \end{pmatrix}}}$

$$Az = b \Rightarrow \underline{A_B z_B + A_N z_N = b}$$

$$p^T z - p^T \bar{x} > 0$$

$$\Rightarrow \underbrace{[p_N^T - p_B^T A_B^{-1} A_N]}_{\rightarrow > 0} (z_N) > 0$$

$$\downarrow \quad \text{find a direction}$$

$$\underline{p_j^T - p_B^T A_B^{-1} a_j} > 0 \Leftrightarrow p^T \begin{pmatrix} -A_B^{-1} a_j \\ e_j \end{pmatrix} > 0$$

not E.D.!

$$\underline{\tilde{x} = \bar{x} + \lambda d} \rightarrow \underline{\text{保证 } p^T \tilde{x} > p^T \bar{x}}$$

check \tilde{x} E.P.

$$\underline{\underline{A_{B \cup \{j\}}} / \{r\} = A_{\bar{B}}}$$

$$A_{B \cup \{r\}} = A_{B \cup \{j\}} = (A_B \quad a_j)$$

$$A_{\bar{B}}^{-1} A_{B \cup \{r\}} = (I \quad \underbrace{A_{\bar{B}}^{-1} a_j}_{r\text{-th} \neq 0})$$

$$\Rightarrow A_{\bar{B}}^{-1} A_{\bar{B}} \text{ invertible}$$

$$\Rightarrow A_{\bar{B}} \text{ invertible}$$

$$\Rightarrow \tilde{x} \rightarrow \underline{\underline{E.P.}}$$

Convex Function — Subgradient

$$f: \mathbb{R}^n \rightarrow [-\infty, +\infty]$$

dom f .

$$\text{epi } f = \{ (x, \mu) \in \mathbb{R}^n \times \mathbb{R}, \mu \geq f(x) \}$$

proper

closed $\boxed{\text{epi}(f)}$

$$\text{epi}(cl f) = cl(\text{epi}(f))$$

the closure of f

① Defn of convex

$$f(\lambda x_1 + (1-\lambda)x_2) \leq \lambda f(x_1) + (1-\lambda)f(x_2)$$

② property:

1. φ convex

$$\frac{\varphi(x+\lambda_1 d) - \varphi(x)}{\lambda_1} \leq \frac{\varphi(x+\lambda_2 d) - \varphi(x)}{\lambda_2}$$

2. $\varphi: S \rightarrow \mathbb{R}$ convex. (S convex)

↳ Lipshitz

3. φ convex in $\left(\begin{smallmatrix} \text{open} \\ \text{convex} \end{smallmatrix} \right)$ set S

$$\Leftrightarrow \forall \bar{x} \in S, \exists \beta \text{ s.t. } \underline{\varphi(x) \geq \varphi(\bar{x}) + \beta^T(x - \bar{x})} \text{ for } \underline{\forall x}$$

any $\bar{x} \in S$

$$\varphi \text{ strictly convex} \Rightarrow \varphi(x) > \varphi(\bar{x}) + \beta^T(x - \bar{x})$$

holds for $\forall x \in S$, $\beta \in \partial \varphi(\bar{x})$

$$\forall \bar{x} \in S, \exists \beta \text{ s.t. } \varphi(x) > \varphi(\bar{x}) + \beta^T(x - \bar{x}) \text{ for } \forall x$$

\Rightarrow strictly convex

4. f \mathcal{C}^2 differentiable (twice) convex in open convex S

f convex $\Leftrightarrow \nabla^2 f(x) \succeq 0$ for all $x \in S$