

Homework 2 : Convex Optimization

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$$1. \Rightarrow C = \{x \in \mathbb{R}^n \mid A_0 - \left(\sum_{i=1}^n \alpha_i A_i \right) \succeq 0\}$$

$\Rightarrow A_i$ are all ~~not~~ symmetric matrices of size $m \times m$.

\Rightarrow For C to be a convex set

$$\text{if } \underline{x}_1, \underline{x}_2 \in C, \quad \theta \in [0, 1], \quad \theta \underline{x}_1 + (1-\theta) \underline{x}_2 \in C$$

$$\Rightarrow \underline{x}_1 = [(x_1)_1, (x_1)_2, \dots, (x_1)_n] \in C$$

$$\underline{x}_2 = [(x_2)_1, (x_2)_2, \dots, (x_2)_n] \in C$$

$$\Rightarrow A_0 - \sum_{i=1}^n (\alpha_1)_i A_i \succeq 0 \quad \text{and} \quad A_0 - \sum_{i=1}^n (\alpha_2)_i A_i \succeq 0$$

$$\Rightarrow A_0 - \sum_{i=1}^n (\theta x_1)_i + (1-\theta)(x_2)_i A_i \text{ is PSD} \Leftrightarrow$$

$$= \theta \left[A_0 - \sum_{i=1}^n (x_1)_i A_i \right] + (1-\theta) \left[A_0 - \sum_{i=1}^n (x_2)_i A_i \right]$$

$$= \theta M + (1-\theta)N$$

$$\text{where } M = A_0 - \sum_{i=1}^n (x_1)_i A_i \in S_+$$

$$N = A_0 - \sum_{i=1}^n (x_2)_i A_i \in S_+$$

M, N are PSD $\Leftrightarrow \theta(1-\theta) \geq 0$

$$\Rightarrow M, N \in S_+, \theta \in [0, 1].$$

$$\theta M + (1-\theta)N \in S_+ \text{ i.e. } \theta M + (1-\theta)N \succeq 0$$

$$M \in S_+ \rightarrow Z^T M Z \geq 0$$

$$N \in S_+ \rightarrow Z^T N Z \geq 0$$

$$Z^T (\theta M + (1-\theta)N) Z \geq 0 = \theta Z^T M Z + (1-\theta) Z^T N Z$$

$$\Rightarrow Z^T (\theta M + (1-\theta)N) Z \geq 0$$

$$\theta M + (1-\theta)N \in S_+$$

$$\Rightarrow A_0 - \sum_{i=1}^n (\theta(x_1)_i + (1-\theta)(x_2)_i) A_i \succeq 0$$

$$\Rightarrow \theta x_1 + (1-\theta)x_2 \in C$$

$\Rightarrow C$ is convex

2. $\Rightarrow P = \text{set of probability density functions}$

$$\Rightarrow P = \left\{ f : \Omega \rightarrow \mathbb{R} \text{ measurable} \mid f(x) \geq 0 \forall x \in \Omega \text{ and } \int f(\tilde{x}) d\mu = 1 \right\}$$

$$\Rightarrow \text{Take any } f_1, f_2 \in P, [\theta \in [0, 1]]$$

$$\Rightarrow \text{Let } g = \theta f_1 + (1-\theta)f_2$$

\Rightarrow We know that $(f_1 \geq 0, f_2 \geq 0) \Theta \in [0, 1]$

$$\Theta f_1 \geq 0, (1-\Theta) f_2 \geq 0$$

$$g(x) = \Theta f_1(x) + (1-\Theta) f_2(x) \geq 0 \quad \forall x \in S$$

$$\begin{aligned} \Rightarrow \int g(x) dx &= \int [\Theta f_1(x) + (1-\Theta) f_2(x)] dx \\ &= \Theta \int f_1(x) dx + (1-\Theta) \int f_2(x) dx \\ &= \Theta(1) + (1-\Theta)1 = 1 \end{aligned}$$

$$\Rightarrow g \in P \text{ i.e. } \Theta f_1 + (1-\Theta) f_2 \in P$$

$\Rightarrow P$ is a convex set

$$3. \Rightarrow K_M = \left\{ \begin{bmatrix} \underline{x} \\ y \end{bmatrix} \mid \|\underline{x}\|_M \leq y, \underline{x} \in \mathbb{R}^n, y \in \mathbb{R} \right\}$$

$$\Rightarrow \|\underline{x}\|_M = M\text{-norm of } \underline{x} \quad (\text{viz } (0, -1) + M)$$

$$\Rightarrow \|\underline{x}\|_M = \sqrt{\underline{x}^T M \underline{x}} \quad (\text{if } M \succ 0)$$

i.e. M is positive definite

\Rightarrow Find dual cone of K_M

\Rightarrow Let K be a cone. The set

$$K^* = \{ y \mid \underline{x}^T y \geq 0 \quad \forall \underline{x} \in K \}$$

K^* is called dual cone of K

$$\Rightarrow K_M^* = \left\{ \begin{bmatrix} u \\ v \end{bmatrix} \mid u \in \mathbb{R}^n, v \in \mathbb{R}, \underline{x}^T u + yv \geq 0 \right\}$$

$$\{ v = \inf \{ \underline{x}^T u \mid \underline{x} \in K_M \}$$

for all $\begin{bmatrix} \underline{x} \\ y \end{bmatrix} \in K_M$

⇒ By eigenvalue decomposition (EVD) of M

$$M = Q \Lambda Q^T$$

Q is orthogonal, $\lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$

$$\lambda_i \geq 0. \quad \text{let } \underline{x} = Q^T \underline{x}$$

$$\Rightarrow \|\underline{x}\|_M = \sqrt{\underline{x}^T M \underline{x}} = \sqrt{\underline{x}^T Q \lambda Q^T \underline{x}}$$

$$= \sqrt{\underline{x}^T \lambda \underline{x}} = \sqrt{\underline{x}^T \lambda^{1/2} \lambda^{1/2} \underline{x}}$$

$$\Rightarrow \|\underline{x}\|_M = \|\lambda^{1/2} \underline{x}\|_2 = \|W\|_2$$

$$\Rightarrow \text{let } \underline{z} = \lambda^{1/2} \underline{x} = \lambda^{1/2} Q^T \underline{x}$$

$$\cancel{\lambda^{-1/2} \underline{z} = Q^T \underline{x} = Q^{-1} \underline{x}} \quad (\text{Q is orthogonal})$$

$$\cancel{\underline{x} = Q \lambda^{-1/2} \underline{z}} \rightarrow \|\underline{z}\|_2 \leq y$$

$$\Rightarrow \|\underline{x}\|_M \leq y$$

$$\Rightarrow u^T \underline{x} + vy \geq 0. \quad (\because \underline{x}^T u = \underline{u}^T \underline{x})$$

$$u^T Q \lambda^{-1/2} \underline{z} + vy \geq 0 \quad \forall \underline{z} \in \mathbb{R}^n, \|\underline{z}\|_2 \leq y$$

$$\text{let } \underline{w} = \lambda^{-1/2} Q^T u$$

$$\underline{w}^T \underline{z} + vy \geq 0 \quad \forall \underline{z} \in \mathbb{R}^n, \|\underline{z}\|_2 \leq y$$

$$\boxed{\underline{w}^T \underline{z} + \sqrt{\|\underline{z}\|_2} \geq 0 \quad \forall \underline{z}}$$

$$\therefore \underline{w} = 0.$$

$$\Rightarrow \text{if } v=0, \quad \underline{w}^T \underline{z} \geq 0 \quad \forall \underline{z}. \quad \text{So,}$$

$$\Rightarrow \text{if } v>0, \quad \left(\frac{\underline{w}}{\sqrt{v}}\right)^T \underline{z} + \|\underline{z}\|_2 \geq 0. \quad \forall \underline{z}$$

$$\Rightarrow \min_{\underline{z}} \left(\frac{\underline{w}}{\sqrt{v}}\right)^T \underline{z} = -\left\|\frac{\underline{w}}{\sqrt{v}}\right\|_2 \|\underline{z}\|_2$$

$$\Rightarrow -\left\|\frac{\underline{w}}{\sqrt{v}}\right\|_2 \|\underline{z}\|_2 + \|\underline{z}\|_2 \geq 0$$

$$\Rightarrow \|\underline{w}\|_2 \leq v$$

$$\Rightarrow \|\underline{w}\|_2 = \sqrt{\underline{w}^T \underline{w}} = M$$

$$= \sqrt{(\lambda^{-1/2} Q^T \underline{u})^T \lambda^{-1/2} Q^T \underline{u}}$$

$$= \sqrt{\underline{u}^T Q \lambda^{-1/2} M^{-1/2} \lambda^{-1/2} Q^T \underline{u}} = \|M^{-1/2} \underline{u}\|$$

$$= \sqrt{\underline{u}^T Q \lambda^{-1} Q^T \underline{u}} \leq v$$

$$\Rightarrow \|\underline{w}\|_2 = \sqrt{\underline{u}^T M^{-1} \underline{u}} \leq \| \underline{u} \|_{M^{-1}} \leq v$$

$$\Rightarrow K_M^* = \left\{ \underline{u} \in \mathbb{R}^n \mid \underline{u}^T M^{-1} \underline{u} \geq v \right\}$$

K_M

$$K_M^* = K_M^{-1}$$

$$4. \Rightarrow K_M = \left\{ \underline{x} \mid \underline{x}^T M \underline{x} \leq (\underline{c}^T \underline{x})^2 \right\}$$

$$\underline{x} \in \mathbb{R}^n, \underline{c}^T \underline{x} \geq 0$$

$\Rightarrow K_M$ is a hyperbolic cone

\Rightarrow Show that K_M is a convex set

$$\Rightarrow \text{let } (\underline{x}^T M \underline{x})^T = \underline{x}^T M^T \underline{x}$$

$$\underline{x}^T (M + M^T) \underline{x} = \underline{x}^T S \underline{x}$$

$S = M$
M is a PSD matrix

$$\underline{x}^T M \underline{x} = \underline{x}^T (M + M^T) \underline{x}$$

$$\text{As } \underline{x}^T (M - M^T) \underline{x} = 0, \text{ let } S = M + M^T$$

$$\Rightarrow \underline{x}^T S \underline{x} \leq (\underline{c}^T \underline{x})^2, \underline{x} \in \mathbb{R}^n, \underline{c}^T \underline{x} \geq 0$$

$\Rightarrow S$ is symmetric PSD matrix.

$\Rightarrow \exists$ matrix L such that $S = L^T L$
(Cholesky decomposition)

$$\Rightarrow K_M = \{ \underline{x} \in R^n \mid \underline{x}^T L^T S \underline{x} = \underline{x}^T L^T L \underline{x} \text{ and } \\ \text{condition } L \underline{x} \geq 0 \} = \{ \underline{x} \mid \| L^T \underline{x} \|_2^2 \leq (L^T \underline{x})^2 \}$$

where $\underline{x} \in R^n$, $L^T \underline{x} \geq 0$

$$\Rightarrow K_M = \{ \underline{x} \mid \| L^T \underline{x} \|_2 \leq L^T \underline{x}, \underline{x} \in R^n \}$$

$\Rightarrow \{ \underline{x} \mid \| L^T \underline{x} \|_2 \leq L^T \underline{x} \}$ is obvious

$$\Rightarrow K_M = \{ \underline{x} \in R^n \mid \| L^T \underline{x} \|_2 \leq L^T \underline{x} \}$$

\Rightarrow Consider linear mapping $f: R^n \rightarrow R^k$

$$f(\underline{x}) = (L^T \underline{x}, C^T \underline{x})$$

$R^k = \text{no. of columns of } L$

\Rightarrow Consider linear mapping

$$f: R^n \rightarrow R^k \times R$$

$$f(\underline{x}) = (L^T \underline{x}, C^T \underline{x})$$

$k = \text{no. of columns of } L$

$$\Rightarrow Q = \{ (\underline{x}, t) \mid \| \underline{x} \|_2 \leq t \}$$

$$\Rightarrow K_M = \{ \underline{x} \in R^n \mid (L^T \underline{x}, C^T \underline{x}) \in Q \}$$

$$K_M = \{ \underline{x} \in R^n \mid f(\underline{x}) \in Q \}$$

$$K_M = f^{-1}(Q)$$

Q is convex. Inverse image of convex set under linear map is convex

$\Rightarrow K_M$ is convex

5. \Rightarrow Geometric interpretation of PSD cone

\Rightarrow Set of symmetric 2×2 matrices

$$C = \{A \in S^2 \mid A \succeq 0\}$$

$\Rightarrow S^2 \Rightarrow$ Space of 2×2 symmetric matrices

$\Rightarrow A \succeq 0 \rightarrow A$ is PSD

\Rightarrow A symmetric matrix (2×2) is PSD iff

$$\det(A) \geq 0 \geq \|x^T z\| / \|x\| \|z\|$$

(a) $\Rightarrow A = \begin{bmatrix} x & y \\ y & z \end{bmatrix}$ is symmetric 2×2 matrix

\Rightarrow For A to be PSD, $\det(A) \geq 0$.

$$xz - y^2 \geq 0, x \geq 0, z \geq 0$$

(b) \Rightarrow Boundary of C is given by quadratic surface $xz = y^2, x \geq 0, z \geq 0$, which forms curved bowl shaped surface opening outward in (x, z) directions, $x \geq 0, z \geq 0$.

\Rightarrow This surface curves outward i.e. line segments b/w points inside surface remains inside the region.

$\Rightarrow C$ consists of all points lying on or above surface, so it is a solid convex cone.

\Rightarrow As boundary does not go inward, interior

is filled, any convex combination of PSD matrices is PSD

\Rightarrow Outward curvature of boundary implies convexity of set C

6.

$$(a) \Rightarrow C = \text{slab} = \{\underline{x} \in \mathbb{R}^n \mid \alpha \leq \underline{a}^T \underline{x} \leq \beta\}$$

\Rightarrow Take $\underline{x}_1, \underline{x}_2 \in C, \theta \in [0, 1]$

$$\Rightarrow \underline{a}^T \underline{x}_1 \geq \alpha, \underline{a}^T \underline{x}_2 \geq \alpha, \underline{a}^T \underline{x}_1 \leq \beta, \underline{a}^T \underline{x}_2 \leq \beta$$

$$\Rightarrow \underline{a}^T (\theta \underline{x}_1 + (1-\theta) \underline{x}_2) = \theta \underline{a}^T \underline{x}_1 + (1-\theta) \underline{a}^T \underline{x}_2$$

$$\geq \theta \alpha + (1-\theta) \alpha \geq \alpha$$

$$\Rightarrow \underline{a}^T (\theta \underline{x}_1 + (1-\theta) \underline{x}_2) = \theta \underline{a}^T \underline{x}_1 + (1-\theta) \underline{a}^T \underline{x}_2$$

$$\leq \theta \beta + (1-\theta) \beta = \beta$$

$$\Rightarrow \alpha \leq \underline{a}^T (\theta \underline{x}_1 + (1-\theta) \underline{x}_2) \leq \beta$$

$$\Rightarrow \theta \underline{x}_1 + (1-\theta) \underline{x}_2 \in C. \boxed{C \text{ is convex}}$$

$$\Rightarrow \text{Slab is the region sandwiched between 2 hyperplanes } \{\underline{x} \in \mathbb{R}^n \mid \underline{a}^T \underline{x} = \alpha\}, \{\underline{x} \in \mathbb{R}^n \mid \underline{a}^T \underline{x} = \beta\}$$

$$\Rightarrow \text{In R, } C = \{\underline{x} \in \mathbb{R} \mid \alpha \leq \underline{x} \leq \beta\}$$

6.(b) $\Rightarrow C = \text{rectangle}$ (hyper rectangle when $n > 2$)

$$\Rightarrow C = \{\underline{x} \in \mathbb{R}^n \mid d_i \leq x_i \leq p_i, i=1 \dots n\}$$

\Rightarrow Take $\underline{x}_1, \underline{x}_2 \in C$

$$\Rightarrow \underline{x}_1 = [x_{11} \ x_{12} \ \dots \ x_{1n}]^T$$

$$\underline{x}_2 = [x_{21} \ x_{22} \ \dots \ x_{2n}]^T$$

$$\Rightarrow d_i \leq x_{1i} \leq p_i \quad d_i \leq x_{2i} \leq p_i$$

$$\Rightarrow \theta d_i \leq \theta x_{1i} \leq \theta p_i, \quad \theta d_i \leq \theta x_{2i} \leq \theta p_i$$

$$\Rightarrow \theta d_i \leq \theta x_i \leq \theta p_i, \quad (1-\theta)d_i \leq (1-\theta)x_i \leq (1-\theta)p_i$$

$$\Rightarrow x_{1i} \geq \alpha_i, \quad x_{2i} \geq \alpha_i$$

$$\theta x_{1i} + (1-\theta)x_{2i} \geq \theta \alpha_i + (1-\theta)\alpha_i = \alpha_i$$

$$\Rightarrow x_{1i} \leq \beta_i, \quad x_{2i} \leq \beta_i$$

$$\theta x_{1i} + (1-\theta)x_{2i} \leq \theta \beta_i + (1-\theta)\beta_i = \beta_i$$

$$\begin{aligned} & \theta x_{1i} + (1-\theta)x_{2i} \leq \theta b_i + (1-\theta)\beta_i \\ \Rightarrow & x_i \leq \theta x_{1i} + (1-\theta)x_{2i} \leq b_i \\ \Rightarrow & \theta x_1 + (1-\theta)x_2 \in C; \quad \boxed{C \text{ is convex}} \\ \Rightarrow & \text{In } \mathbb{R}, \quad C = \{x \in \mathbb{R} \mid x_1 \leq x \leq \beta_1\} \end{aligned}$$

$\Rightarrow \mathbb{R}^n$ — hyper rectangle.

6. (c) $\Rightarrow C = \text{wedge} = \left\{ \underline{x} \in \mathbb{R}^n \mid \underline{a}_1^T \underline{x} \leq b_1, \underline{a}_2^T \underline{x} \leq b_2 \right\}$

\Rightarrow Take $\underline{x}_1, \underline{x}_2 \in C, \theta \in [0, 1]$.

$\Rightarrow \underline{a}_1^T \underline{x}_1 \leq b_1, \underline{a}_1^T \underline{x}_2 \leq b_1$

$\underline{a}_1^T (\theta \underline{x}_1 + (1-\theta) \underline{x}_2) \leq \theta \underline{a}_1^T \underline{x}_1 + (1-\theta) \underline{a}_1^T \underline{x}_2$

$\leq \theta b_1 + (1-\theta) b_1 \leq b_1$

$\Rightarrow \underline{a}_2^T \underline{x}_1 \leq b_2, \underline{a}_2^T \underline{x}_2 \leq b_2$

$\underline{a}_2^T (\theta \underline{x}_1 + (1-\theta) \underline{x}_2) \leq \theta \underline{a}_2^T \underline{x}_1 + (1-\theta) \underline{a}_2^T \underline{x}_2$

$\leq \theta b_2 + (1-\theta) b_2 \leq b_2$

$\Rightarrow \underline{a}_1^T (\theta \underline{x}_1 + (1-\theta) \underline{x}_2) \leq b_1, \underline{a}_2^T (\theta \underline{x}_1 + (1-\theta) \underline{x}_2) \leq b_2$

C is convex

$\Rightarrow \theta \underline{x}_1 + (1-\theta) \underline{x}_2 \in C$

\Rightarrow This is intersection of 2 halfspaces
 convexity is preserved

$$\{ \underline{x} \in R^n \mid g_1^T \underline{x} \leq b_1 \} \cap \{ \underline{x} \in R^n \mid g_2^T \underline{x} \leq b_2 \}$$

$$\Rightarrow \text{In } \mathbb{R}, C = \left\{ x \in \mathbb{R} \mid a_1 x \leq b_1, a_2 x \leq b_2 \right\}$$

6.(d) $\Rightarrow C = \text{set of points closer to given point than given set}$

$$\Rightarrow S \subseteq \mathbb{R}^n$$

$$\Rightarrow C = \left\{ \underline{x} \in \mathbb{R}^n \mid \|\underline{x} - \underline{x}_0\|_2 \leq \|\underline{x} - \underline{y}\|_2, \forall \underline{y} \in S \right\}$$

\Rightarrow Take any $\underline{y} \in S$.

$$\|\underline{x} - \underline{x}_0\|_2 \leq \|\underline{x} - \underline{y}\|_2$$

$$\|\underline{x} - \underline{x}_0\|_2^2 \leq \|\underline{x} - \underline{y}\|_2^2$$

$$\langle \underline{x} - \underline{x}_0, \underline{x} - \underline{x}_0 \rangle \leq \langle \underline{x} - \underline{y}, \underline{x} - \underline{y} \rangle$$

$$(\underline{x} - \underline{x}_0)^T (\underline{x} - \underline{x}_0) \leq (\underline{x} - \underline{y})^T (\underline{x} - \underline{y})$$

$$\underline{x}^T \underline{x} - 2 \underline{x}^T \underline{x}_0 + \underline{x}_0^T \underline{x}_0 \leq \underline{x}^T \underline{x} - 2 \underline{x}^T \underline{y} + \underline{y}^T \underline{y}$$

$$2 \underline{x}^T (\underline{y} - \underline{x}_0) \leq \|\underline{y}\|_2^2 - \|\underline{x}_0\|_2^2$$

$$(\underline{y} - \underline{x}_0)^T \underline{x} \leq \frac{1}{2} (\|\underline{y}\|_2^2 - \|\underline{x}_0\|_2^2)$$

This is of the form $\underline{a}^T \underline{x} \leq b$ so it is a halfspace
which is convex set.

$$\Rightarrow C = \bigcap_{\underline{y} \in S} \left\{ \underline{x} \in \mathbb{R}^n \mid \|\underline{x} - \underline{x}_0\|_2 \leq \|\underline{x} - \underline{y}\|_2 \right\}$$

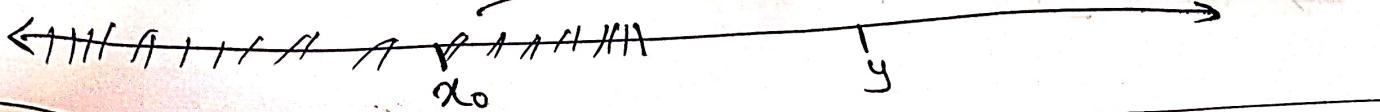
\Rightarrow Intersection is an operation preserving convexity.

\Rightarrow Intersection of convex sets is a convex set.
So, intersection of convex sets is a convex set.

$\Rightarrow C$ is convex

$$\Rightarrow \text{In } \mathbb{R}, C = \left\{ x \in \mathbb{R} \mid |x - x_0| \leq |x - y|, y \in \mathbb{R} \right\}$$

$$S = \{y\} \subseteq \mathbb{R} \rightarrow C \subseteq \mathbb{R}$$



$$6.(e) \Rightarrow C = \{x \in R^n \mid x_0 + s_2 \subseteq S_1\}$$

$\Rightarrow S_1 \subseteq R^n, S_2 \subseteq R^n, S_1$ is convex

\Rightarrow Take $x_1, x_2 \in C, \theta \in [0, 1]$

$$\Rightarrow \underline{x_1} + \underline{y} \in S_1 \quad \underline{\underline{y}} \in S_2$$

$$\Rightarrow \underline{x_1} + \underline{y} \in S_1 \quad \underline{y} \in S_2$$

$$\underline{x_2} + \underline{y} \in S_1 \quad \underline{y} \in S_2$$

$$\Rightarrow \theta \underline{x_1} + \theta \underline{y} \in S_1 \quad \underline{y} \in S_2$$

$$(1-\theta) \underline{x_2} + (1-\theta) \underline{y} \in S_1 \quad \underline{y} \in S_2$$

$$\Rightarrow \theta (\underline{x_1} + \underline{y}) + (1-\theta) (\underline{x_2} + \underline{y}) \in S_1 \quad \underline{y} \in S_2$$

since S_1 is convex

$$\Rightarrow \theta \underline{x_1} + (1-\theta) \underline{x_2} + \underline{y} \in S_1 \quad \underline{y} \in S_2$$

$$\Rightarrow \theta \underline{x_1} + (1-\theta) \underline{x_2} \in C$$

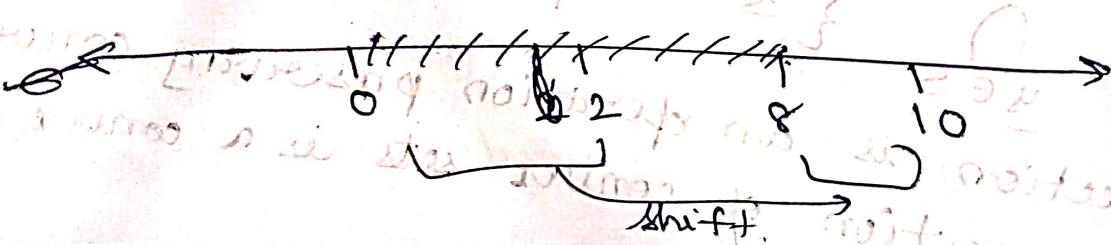
\Rightarrow C is convex

$$\Rightarrow \text{In } R, C = \{x \in R \mid x + s_2 \subseteq S_1\}$$

$S_1 \subseteq R, S_2 \subseteq R, S_1$ is convex.

$$\text{Eg: } S_1 = [0, 10], S_2 = [0, 2]$$

$$C = [0, 8]$$



$$6.(f) \Rightarrow C = \{x \in R^n \mid \|x - a\|_2 \leq \theta \|x - b\|_2\}$$

$$\Rightarrow a \neq b, \theta \in [0, 1]$$

Case 1: $0 < \theta < 1$

$$\Rightarrow \|\underline{x} - \underline{a}\|_2^2 \leq \theta^2 \|\underline{x} - \underline{b}\|_2^2$$

$$\Rightarrow \langle \underline{x} - \underline{a}, \underline{x} - \underline{a} \rangle \leq \theta^2 \langle \underline{x} - \underline{b}, \underline{x} - \underline{b} \rangle$$

$$\Rightarrow \|\underline{x}\|_2^2 - 2\underline{x}^T \underline{a} + \|\underline{a}\|_2^2 \leq \theta^2 \|\underline{x}\|_2^2 - 2\theta^2 \underline{x}^T \underline{b} + \theta^2 \|\underline{b}\|_2^2$$

$$\Rightarrow (1 - \theta^2) \|\underline{x}\|_2^2 - 2\underline{x}^T (\underline{a} - \theta^2 \underline{b}) + (\|\underline{a}\|_2^2 - \theta^2 \|\underline{b}\|_2^2)$$

$$\Rightarrow 1 - \theta^2 > 0. \text{ So, this can be written } \leq 0 \quad (1)$$

as $\left\| \underline{x} - \frac{\underline{a} - \theta^2 \underline{b}}{1 - \theta^2} \right\|_2 \leq \frac{\theta}{1 - \theta^2} \|\underline{a} - \underline{b}\|_2$

This is closed ball \rightarrow [Convex]

Case 2: $\theta = 0$

$$\Rightarrow \|\underline{x} - \underline{a}\|_2 \leq 0 \Rightarrow \underline{x} = \underline{a}. \quad [C \text{ is convex}]$$

Case 3: $\theta = 1$

$$\Rightarrow -2 \underline{x}^T (\underline{a} - \underline{b}) + (\|\underline{a}\|_2^2 - \|\underline{b}\|_2^2) \leq 0 \quad (2)$$

$$\Rightarrow 2(\underline{b} - \underline{a})^T \underline{x} + \|\underline{a}\|_2^2 - \|\underline{b}\|_2^2 \leq 0$$

\Rightarrow closed halfspace \rightarrow [convex]

$\Rightarrow [C \text{ is convex}]$

$$\Rightarrow \text{In } \mathbb{R}, C = \{x \in \mathbb{R} \mid |x - a| \leq \theta|x - b|\}$$

wLOG, $a < b$.

$$a \neq b, \theta \in [0, 1].$$

$$(1 - \theta^2)x^2 - 2(\underline{a} - \theta^2 \underline{b})x + (\underline{a}^2 - \theta^2 \underline{b}^2) \leq 0$$

$$(x - a)^2 = \theta^2(x - b)^2 \Rightarrow (x - a) = \theta(x - b) \Rightarrow x = \frac{a - \theta b}{1 - \theta}$$

① $x - a = \theta(x - b)$

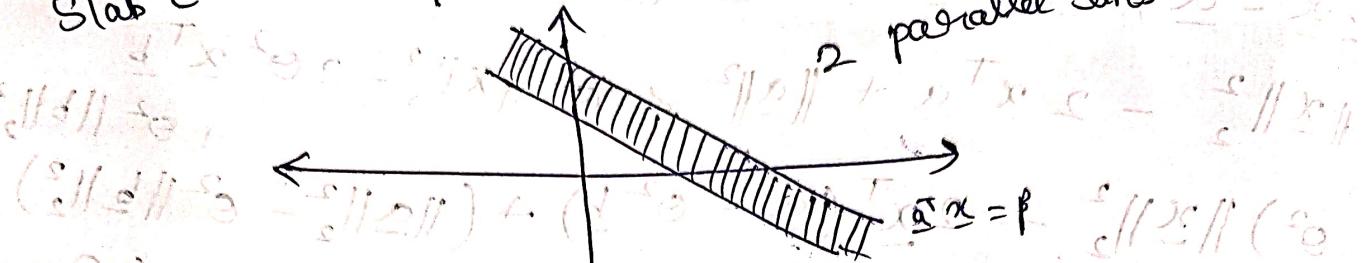
② $x - a = -\theta(x - b) \rightarrow x = \frac{a + \theta b}{1 + \theta}$

$\xleftarrow{\frac{a - \theta b}{1 - \theta}} \quad \xrightarrow{\frac{a + \theta b}{1 + \theta}}$

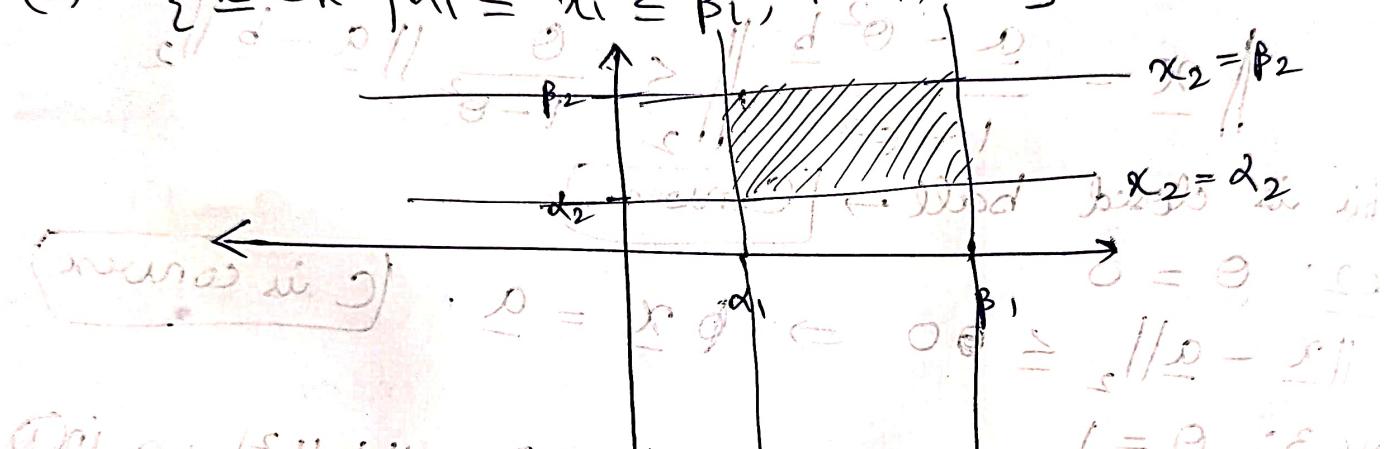
6. Figures drawn in Cartesian plane: (\mathbb{R}^2)

(a) $\{\underline{x} \in \mathbb{R}^2 \mid \underline{a}^T \underline{x} \geq d, \underline{a}^T \underline{x} \leq b\}$

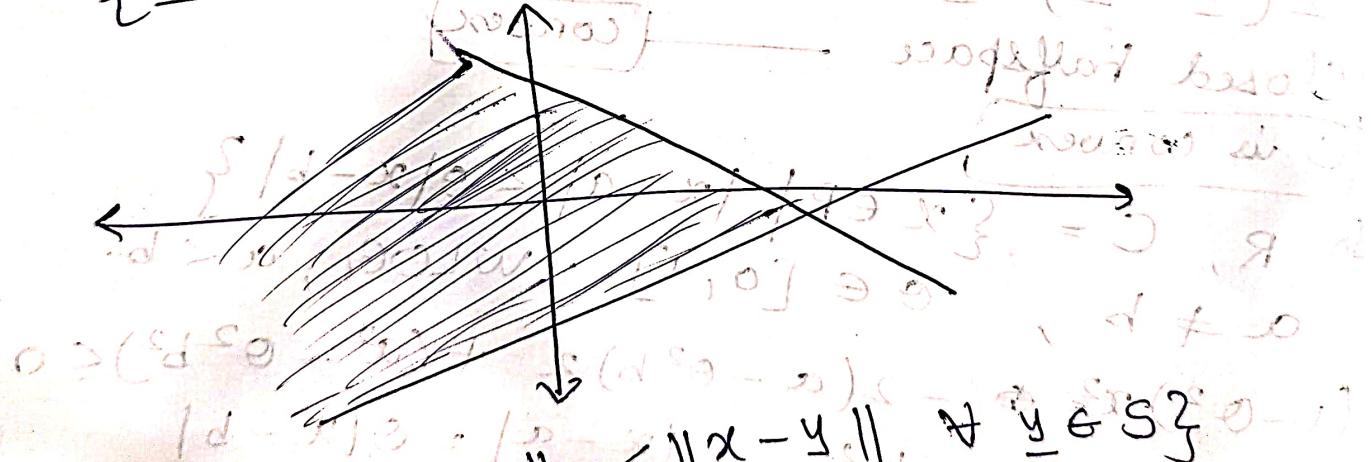
Slab parallel lines



(b) $\{\underline{x} \in \mathbb{R}^2 \mid a_i \leq x_i \leq b_i, i=1, 2\}$

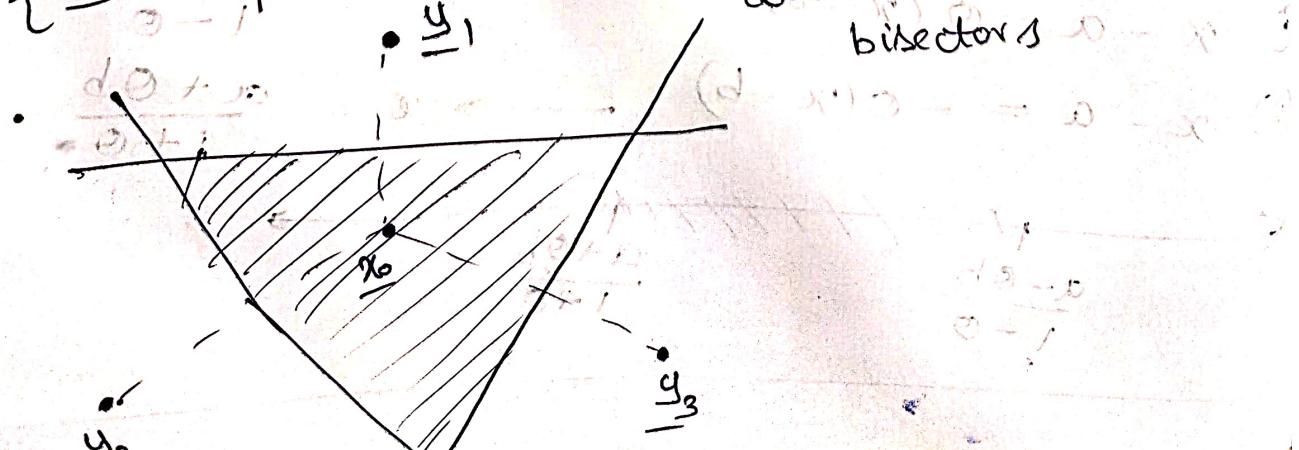


(c) $\{\underline{x} \in \mathbb{R}^2 \mid \underline{a}_1^T \underline{x} \leq b_1 + \underline{a}_2^T \underline{x} \leq b_2\}$



(d) $\{\underline{x} \in \mathbb{R}^2 \mid \|\underline{x} - \underline{x}_0\|_2 \leq \|\underline{x} - \underline{y}\|_2 \text{ and } \underline{y} \in S\}$

all axes perpendicular bisectors



e) $\{\underline{x} \in \mathbb{R}^n \mid \underline{x} + S_2 \subseteq S_1\}$, $S_1, S_2 \subseteq \mathbb{R}^n$, S_1 convex

$$S_1 - S_2 = \{\underline{x} \mid \underline{x} + S_2 \subseteq S_1\}$$

f) $\{\underline{x} \mid \|\underline{x} - \underline{a}\|_2 \leq \theta \|\underline{x} - \underline{b}\|_2\}$, $\underline{a} \neq \underline{b}$
 $\theta \leq \theta \leq 1$

After solving the above, we find that the boundary is defined by (d)
 i.e., $\|\underline{x} - \underline{a}\|_2 = \theta \|\underline{x} - \underline{b}\|_2$. This is the equation of an ellipse.
 To draw the ellipse, we need to know the center, major axis length, minor axis length, and orientation.

7. \Rightarrow Voronoi sets and Polyhedral decomposition
 $\Rightarrow \underline{x}_0, \underline{x}_1, \dots, \underline{x}_K \in \mathbb{R}^n$ be distinct
 \Rightarrow Set of points that are closer in Euclidean norm
 to \underline{x}_0 than to other \underline{x}_i i.e.,
 $\underline{x} \in \{\underline{x} \in \mathbb{R}^n \mid \|\underline{x} - \underline{x}_0\|_2 \leq \|\underline{x} - \underline{x}_i\|_2, i=1, \dots, K\}$

$V = \text{Voronoi region around } \underline{x}_0$ with $\underline{x}_i, i=1 \dots K$

(a) $\|\underline{x} - \underline{x}_0\|_2 \leq \|\underline{x} - \underline{x}_i\|_2$ for $i=1 \dots K$
 $\Rightarrow \|\underline{x} - \underline{x}_0\|_2^2 \leq \|\underline{x} - \underline{x}_i\|_2^2$ for $i=1 \dots K$
 $\Rightarrow \langle \underline{x} - \underline{x}_0, \underline{x} - \underline{x}_i \rangle \leq \langle \underline{x} - \underline{x}_i, \underline{x} - \underline{x}_i \rangle$, $i=1 \dots K$
 $\Rightarrow \underline{x}^T \underline{x} - 2\underline{x}_0^T \underline{x} + \underline{x}_0^T \underline{x}_0 \leq \underline{x}^T \underline{x} - 2\underline{x}_i^T \underline{x} + \underline{x}_i^T \underline{x}_i$
 $\Rightarrow 2(\underline{x}_i^T - \underline{x}_0^T) \underline{x} \leq \|\underline{x}_i\|_2^2 - \|\underline{x}_0\|_2^2$, $i=1 \dots K$

$\Rightarrow V$ is intersection of K halfspaces (polyhedron)

$$V = \bigcap_{i \in \{1, 2, \dots, K\}} \{x \in \mathbb{R}^n \mid \|x - x_0\|_2 \leq \|x - x_i\|_2\}$$

$$\Rightarrow V = \{x \mid Ax \leq b\}$$

$$A = \begin{bmatrix} 2(x_1 - x_0)^T \\ 2(x_2 - x_0)^T \\ \vdots \\ 2(x_K - x_0)^T \end{bmatrix}$$

$$b = \begin{bmatrix} \|x_1\|_2^2 - \|x_0\|_2^2 \\ \|x_2\|_2^2 - \|x_0\|_2^2 \\ \vdots \\ \|x_K\|_2^2 - \|x_0\|_2^2 \end{bmatrix}$$

(b) \Rightarrow Given a polyhedron P with non-empty interior

\Rightarrow Find x_0, \dots, x_K such that polyhedron is the Voronoi region of x_0 wrt x_1, \dots, x_K .

$$\Rightarrow P \subset \mathbb{R}^n. \text{ Let } P = \{x \mid a_i^T x \leq b_i, i=1 \text{ to } m\}$$

with each $a_i \neq 0$, boundary lines are non-parallel

$\Rightarrow \text{int } P \neq \emptyset$. Pick $x_0 \in \text{int } P$.

then $a_i^T x_0 < b_i$ tends to the interior of the

$$a_i^T x_0 + d_i = 4(b_i - a_i^T x_0), \text{ and } d_i > 0$$

$$\Rightarrow \forall i, \text{ define } x_i = \frac{x_0 + d_i a_i}{\|a_i\|_2}, \text{ and } d_i > 0$$

$$\Rightarrow x_i = x_0 + \frac{d_i a_i}{2} \text{ lies on the upper boundary of } V$$

Justification: choose $\|x_i\| = \|x_0 + t_i a_i\|$

Solve for t_i so that perpendicular bisector

$$\text{equals } a_i^T x = b_i \Rightarrow t_i = \frac{d_i}{2}$$

$$\Rightarrow x_i \neq x_0 \Rightarrow x_i^T x \leq \frac{\|x_i\|_2^2 - \|x_0\|_2^2}{2}$$

$$\Rightarrow a_i^T x_i \leq b_i$$

Choose $\underline{x}_i = \underline{x}_0 + t_i \underline{a}_i$ taking \underline{x}_i bisection gives $t_i = \frac{\underline{x}_i - \underline{x}_0}{\underline{a}_i} = \frac{\underline{a}_i^T \underline{x}_0}{\underline{a}_i^T \underline{a}_i}$

$$\|\underline{x}_i\|_2^2 = \|\underline{x}_0\|_2^2 + \left(\frac{\underline{a}_i^T \underline{x}_0}{\underline{a}_i^T \underline{a}_i}\right)^2 = \frac{\underline{a}_i^T \underline{a}_i}{\underline{a}_i^T \underline{a}_i} = 1$$

$$= \underline{a}_i \underline{a}_i^T \underline{x}_0 + \frac{\underline{a}_i^2}{4} \|\underline{a}_i\|_2^2$$

$$= \frac{4(b_i - \underline{a}_i^T \underline{x}_0)}{\|\underline{a}_i\|_2^2} \underline{a}_i^T \underline{x}_0 + \frac{16}{4} \left(\frac{(b_i - \underline{a}_i^T \underline{x}_0)^2}{\|\underline{a}_i\|_2^2} \right)$$

$$= d_i b_i$$

$$\Rightarrow \underline{a}_i \underline{a}_i^T \underline{x}_0 \leq d_i b_i \Leftrightarrow \underline{a}_i^T \underline{x}_0 \leq b_i$$

$$\Rightarrow V = \{ \underline{x} \in \mathbb{R}^n \mid \|\underline{x} - \underline{x}_0\|_2 \leq \|\underline{x} - \underline{x}_i\|_2, i=1 \dots m \}$$

$$V = \{ \underline{x} \in \mathbb{R}^n \mid \underline{a}_i^T \underline{x} \leq b_i, i=1 \dots m \} = P$$

Hence polyhedron equals Voronoi region of \underline{x}_0 wrt finitely many points \underline{x}_i .

$$8. \Rightarrow S = \{ \underline{x} \in \mathbb{R}^n \mid P(t) \leq 1 \text{ for } |t| \leq \frac{\pi}{3} \}$$

$$\Rightarrow P(t) = \text{trigonometric polynomial} = \sum_{k=1}^m c_k \sin(kt) + d_k \cos(kt) \text{ in } \mathbb{R}$$

We know that S can be expressed as intersection of infinitely many slabs. $S = \bigcap_{|t| \leq \frac{\pi}{3}} S_t$

Each slab is defined by $S_t = \{ \underline{x} \in \mathbb{R}^m \mid -1 \leq (c_1 \cos t, c_2 \cos 2t, \dots, c_m \cos mt)^T \underline{x} \leq 1 \}$

$$(a)(i) \Rightarrow m = 2$$

$$\Rightarrow P(t) = c_1 \cos t + c_2 \cos 2t$$

$$(a)(ii) \Rightarrow S_t = \{(\alpha_1, \alpha_2) \in \mathbb{R}^2 \mid -1 \leq (\cos t, \cos 2t)^T (\alpha_1, \alpha_2)^T \leq 1\}$$

$$\Rightarrow S_t = \{(\alpha_1, \alpha_2) \in \mathbb{R}^2 \mid -1 \leq \alpha_1 \cos t + \alpha_2 \cos 2t \leq 1\}$$

$$\Rightarrow S = \{(\alpha_1, \alpha_2) \in \mathbb{R}^2 \mid |\alpha_1 \cos t + \alpha_2 \cos 2t| \leq 1\}$$

$$S = \bigcap_{|t| \leq \frac{\pi}{3}} S_t$$

$$\Rightarrow \text{Let } u = \cos t \in [\frac{1}{2}, 1] \quad |t| \leq \frac{\pi}{3}$$

$$P(t) = \alpha_1 u + \alpha_2 (2u^2 - 1)$$

$$|\alpha_1 u + \alpha_2 (2u^2 - 1)| \leq 1 \quad \forall u \in [\frac{1}{2}, 1]$$

\Rightarrow As S_t is a slab, S_t is convex, and intersection is convexity preserving, S is convex.

$$S = \{x \mid (u, 2u^2 - 1)^T (\alpha_1, \alpha_2) \leq 1 \quad \forall u \in [\frac{1}{2}, 1]\}$$

Intersection of infinitely many supporting hyperplanes.

$$\Rightarrow S = \{(\alpha_1, \alpha_2) \in \mathbb{R}^2 \mid \sup_{u \in [\frac{1}{2}, 1]} |\alpha_1 u + \alpha_2 (2u^2 - 1)| \leq 1\}$$

$\Rightarrow S$ is in finite dimensional space.

as $t=0 \rightarrow |\alpha_1 + \alpha_2| \leq 1$ $\Rightarrow S$ is bounded

$t=\frac{\pi}{3} \rightarrow |\alpha_1 - \alpha_2| \leq 2$ $\Rightarrow S$ is closed.

$\Rightarrow S$ is compact.

$$(c) \Rightarrow S = \{(\alpha_1, \alpha_2) \in \mathbb{R}^2 \mid |\alpha_1 \cos t + \alpha_2 \cos 2t| \leq 1 \quad \forall |t| \leq \frac{\pi}{3}\}$$

\Rightarrow Smoothness of boundary:

$$\Rightarrow |(\cos t, \cos 2t)^T (\alpha_1, \alpha_2)| \leq 1$$

\Rightarrow Defines slab whose boundary consists of 2 parallel lines

$$\Rightarrow x_1 \cos t + x_2 \cos 2t = \pm 1$$

$$\Rightarrow \text{let } \alpha(t) = (\cos t, \cos 2t) \quad (\text{normal vector})$$

$$\Rightarrow \alpha(t) \text{ continuously varies with } t \in [-\frac{\pi}{3}, \frac{\pi}{3}]$$

Supporting lines rotate all the time

$S = \text{intersection of infinitely many slabs.}$

\Rightarrow Smooth boundary, continuously curved, no corners, no flat segments

Symmetries of S :

$$\Rightarrow \text{If } \underline{x} \in S, \forall t, |\alpha(t)^T \underline{x}| \leq 1$$

$$|\alpha(t)^T (-\underline{x})| = |-\alpha(t)^T \underline{x}| = |\alpha(t)^T \underline{x}|$$

$$\leftarrow \underline{x} \in S$$

$\Rightarrow S$ is centrally symmetric about origin.

\Rightarrow No independent symmetry wrt x_1, x_2 axes in general.

Average curve:

$$\Rightarrow \text{Let } \underline{x}_1, \underline{x}_2 \in S. \text{ Then } \forall |t| \leq \frac{\pi}{3}$$

$$|\rho^{(1)}(t)| \leq 1, \quad |\rho^{(2)}(t)| \leq 1$$

$$\rho_{\text{avg}}(t) = \frac{1}{2}(\rho^{(1)}(t) + \rho^{(2)}(t))$$

$$\Rightarrow |\rho_{\text{avg}}(t)| = \left| \frac{1}{2}\rho^{(1)}(t) + \frac{1}{2}\rho^{(2)}(t) \right|$$

$$\leq \frac{1}{2}|\rho^{(1)}(t)| + \frac{1}{2}|\rho^{(2)}(t)| \leq \frac{1}{2}(1+1) =$$

$$\Rightarrow |\rho_{\text{avg}}(t)| \leq 1 \quad \forall |t| \leq \frac{\pi}{3}$$