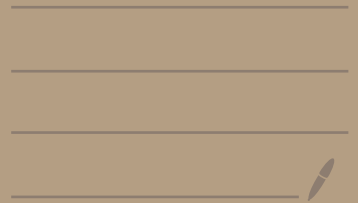


Lec 2 : Convex Sets



Affine set

all points on a line through x_1, x_2

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



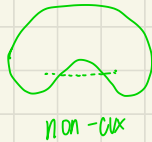
eg. solution set of $\{x \mid Ax=b\}$

Convex Set

line segment between x_1, x_2 ; $x = \theta x_1 + (1-\theta)x_2 \quad \theta \in [0,1]$

convex set: contains line segment between any 2 points in the set
 $x_1, x_2 \in C \quad 0 \leq \theta \leq 1 \Rightarrow \theta x_1 + (1-\theta)x_2 \in C$

eg. convex sets.

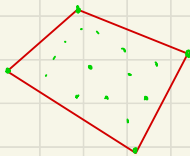


Convex Combination and convex hull

convex combination: $x = \theta_1 x_1 + \dots + \theta_k x_k \quad \sum \theta_i = 1 \quad \theta_i \geq 0$

convex hull:

conv S : set of all convex combination of points in S



convex hull of a conv set is the set itself

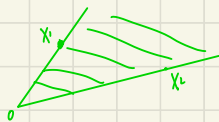
• Convex cone

convex (nonnegative) combination of x_1 and x_2 :

$$x = \theta_1 x_1 + \theta_2 x_2 \quad \theta_1 \geq 0 \quad \theta_2 \geq 0$$

convex cone: set that contains all convex combination of points in the set

any convex cone has to be a convex set

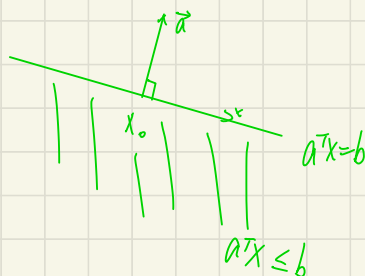


• Hyperplanes and halfspaces

hyperplane: $\{x \mid a^T x = b\} \quad a \neq 0$

halfspace: $\{x \mid a^T x \leq b\} \quad a \neq 0$

hyperplane is convex and affine
halfspace is convex



• Euclidean balls and ellipsoids

Euclidean balls with center x_c and radius r

$$B(x_c, r) = \{x \mid \|x - x_c\|_2 \leq r\} = \{x_c + r \cdot u \mid \|u\|_2 \leq 1\}$$

Ellipsoids:

$$\{x \mid (x - x_c)^T \cdot P^{-1} (x - x_c) \leq 1\} \quad \text{with } P \in S_{++}^n \quad (P \text{ symmetric, pd})$$



other representation: $\{x_c + \lambda u \mid \|u\|_2 \leq 1\}$

$$P = U \Lambda U^T = U \Lambda U^T$$

$$(x - x_c)^T \cdot U \Lambda^{-1} \cdot U^T (x - x_c)$$

$$= v^T \Lambda^{-1} v$$

$$v = U^T (x - x_c) = U^T (x - x_c)$$

where U is the normal axis

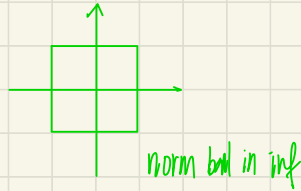
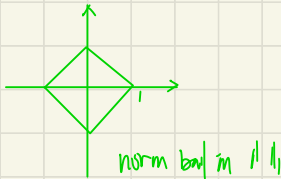
• Norm balls and norm cones

norm: any function that satisfies

- $\|x\| \geq 0$ $\|x\| = 0$ iff $x = 0$
- $\|tx\| = |t| \cdot \|x\|$ for $t \in \mathbb{R}$
- $\|x+y\| \leq \|x\| + \|y\|$

norm ball with center x_c and radius r

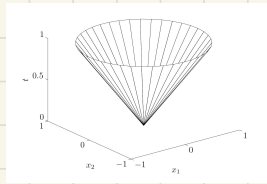
$$\{x \mid \|x - x_c\| \leq r\}$$



norm cone:

$$\{(x, t) \mid \|x\| \leq t\}$$

Euclidean norm cone is called second-order cone



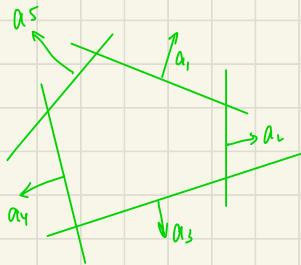
norm balls and norm cones are convex

• Polyhedra

solution set of finitely many linear inequalities and equalities

$$Ax \leq b \quad Cx = d$$

polyhedron is intersection of finite number of halfspaces and hyperplanes



Positive Semi-definite Cone

S^n is set of symmetric $n \times n$ matrices

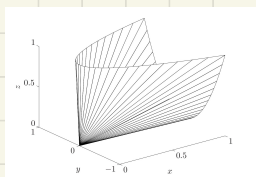
S_+^n is set of symmetric semi-def matrices ($X \in S_+^n \iff z^T X z \geq 0$)

$X_1 \in S_+^n \quad X_2 \in S_+^n \quad \forall \alpha_1, \alpha_2 \geq 0 \quad \alpha_1 X_1 + \alpha_2 X_2 \in S_+^n$

S_+^n is a convex cone

S_+^n set of symmetric def matrices

$$\begin{bmatrix} x & y \\ y & z \end{bmatrix} \in S_+^2$$



Operations that preserve convexity

Intersection

intersection of any number of convex sets is a convex set

Affine functions

suppose $f: \mathbb{R}^n \rightarrow \mathbb{R}^m$ is an affine function $f(x) = Ax + b$

the image of a convex set under f is convex

$S \subseteq \mathbb{R}^n$ convex $\Rightarrow f(S) = \{f(x) \mid x \in S\}$ is convex

the inverse image $f^{-1}(C)$ of a convex set under f is convex

$C \subseteq \mathbb{R}^m$ convex $\Rightarrow f^{-1}(C) = \{x \in \mathbb{R}^n \mid f(x) \in C\}$ is convex

eg. scaling, translation, projection

solution set of linear matrix inequalities $\{x \mid x_1 A_1 + \dots + x_n A_n \leq B\} \quad A_i, B \in S_+^p$

$$f(x) = B - Ax$$

$$= B - x_1 A_1 - \dots - x_n A_n$$

$A_i, B \in S_+^p$ is a convex set

$$f^{-1}(S_+^p) = \{x \in \mathbb{R}^n \mid B - A(x) \in S_+^p\}$$

$\{x \mid A(x) \leq B\}$ is convex

eg. hyperbolic cone

$A = \{ (z, u) \mid \|z\| \leq u, u \geq 0 \}$ is a cvx cone

$$f(x) = \begin{bmatrix} P^T x \\ c^T x \end{bmatrix}$$

$\Downarrow$

$$\{x \mid x^T P x \leq (c^T x)^2, c^T x \geq 0\}$$

$$= \{x \mid f(x) \in A\}$$

f is a affine mapping $\left. \begin{array}{l} \{x \mid f(x) \in A\} \\ A \text{ is a cvx set} \end{array} \right\} \{x \mid f(x) \in A\}$ is a cvx set

• perspective and linear-fractional function

perspective function $P: \mathbb{R}^{n+1} \rightarrow \mathbb{R}^n$

$$P(x, t) = x/t \quad \text{dom } P = \{(x, t) \mid t > 0\}$$

$$\begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \Rightarrow \begin{bmatrix} 1/3 \\ 2/3 \\ 1 \end{bmatrix}$$

images and inverse images of convex sets under perspective functions are convex



linear fractional function (generalization of perspective function)

$$f(x) = \frac{Ax+b}{c^T x+d} \quad \text{dom } f = \{x \mid c^T x+d > 0\} \quad \begin{bmatrix} A \\ c^T \end{bmatrix} x + \begin{bmatrix} b \\ d \end{bmatrix}$$

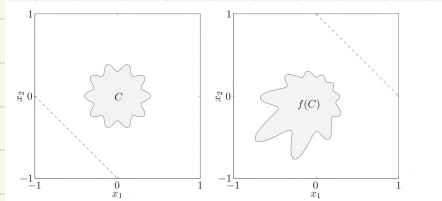
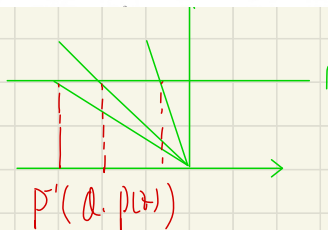
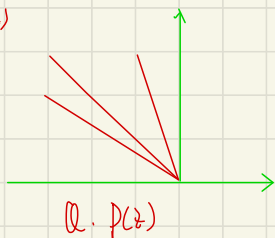
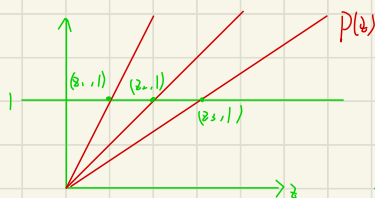
images and inverse images of convex sets under linear-fractional functions are convex functions

projective interpretation

$$a = \begin{bmatrix} A & b \\ c^T & d \end{bmatrix} \in \mathbb{R}^{(m+1) \times (n+1)}$$

$$Q \cdot \begin{bmatrix} x \\ 1 \end{bmatrix} = [a \times b \quad c^T x + d]^T$$

$$P(z) = \{t \cdot (z, 1) \mid t > 0\} \in \mathbb{R}^{n+1}$$



Generalized Inequalities

Proper Cone

A convex cone $K \subseteq \mathbb{R}^n$ is a **proper cone** if

- K is closed (contains its boundary)
- K is solid (nonempty interior)
- K is pointed (contains no line)

eg.

nonnegative orthant $K = \mathbb{R}_+^n$
 psd cone $K = S_+^n$



Generalized Inequality

generalized inequality is defined by a proper cone K

$$x \preceq_K y \Leftrightarrow y - x \in K$$

$$x \preceq_K y \Leftrightarrow y - x \in \text{int}(K)$$

eg1. component-wise inequality ($K = \mathbb{R}_+^n$)

$$x \preceq_K y \Leftrightarrow y - x \in \mathbb{R}_+^n$$



eg2. matrix inequality ($K = S_+^n$)

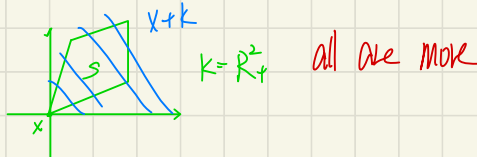
$$x \preceq_{S_+} y \Leftrightarrow y - x \text{ is psd}$$

not a total ordering $x \not\leq_k y$ and $x \not\geq_k y$



• minimum and minimal elements

$x \in S$ is the minimum element of S w.r.t k if
 $y \in S \Rightarrow x \leq_k y$

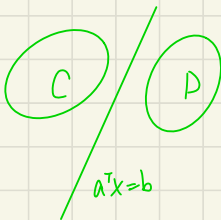


$x \in S$ is the minimal element of S w.r.t k if
 $y \in S \quad y \leq_k x \Rightarrow y = x$



• Separating hyper-plane theorem

if C and D are disjoint convex sets, then there exists $a \neq 0$
 $a^T x \leq b$ for $x \in C$ and $a^T x \geq b$ for $x \in D$



• Supporting hyperplane theorem.

Supporting hyperplane to set C at boundary point x_0

$$\{x \mid a^T x = a^T x_0\}$$

where $a \neq 0$ and $a^T x \leq a^T x_0$ for all $x \in C$

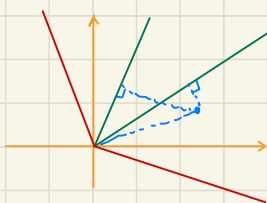


if C is a convex set, then there exists a supporting hyperplane at every boundary point

• Dual Cone and Generalized Inequalities

dual cone of a cone K

$$K^* = \{y \mid y^T x \geq 0 \text{ for all } x \in K\}$$



eg $K = \mathbb{R}_+^n$ $K^* = \mathbb{R}_+^n$

eg $K = S_+^n$ $K^* = S_+^n$ (inner product of 2 mases $\langle X, Y \rangle = \text{tr}(XY^T)$)

Suppose $Y \notin S_+^n$, then there exists some $q \in \mathbb{R}^n$

$$q^T Y q = \text{tr}(q q^T Y) < 0$$

$$X = q q^T \in S_+^n \quad ; \quad \text{tr}(XY) < 0 \quad ; \quad Y \notin (S_+^n)^*$$

$\therefore$ if $Y \notin S_+^n$ then $Y \notin (S_+^n)^*$

Suppose $X, Y \in S_+^n$

$$X = Q \Lambda Q^T = \sum_{i=1}^n \lambda_i q_i q_i^T \quad (\lambda_i \geq 0)$$

$$\text{tr}(XY) = \text{tr}\left(Y \cdot \sum_{i=1}^n \lambda_i q_i q_i^T\right) = \sum_{i=1}^n \lambda_i \cdot q_i^T Y q_i \geq 0$$

$$\therefore Y \in (S_+^n)^*$$

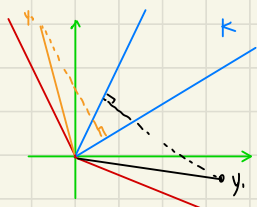
eg. $K = \{(x,t) \mid \|x\|_2 \leq t\}$ $K^* = K$ (euclidean-norm cone)

eg. $K = \{(x,t) \mid \|x\|_1 \leq t\}$ $K^* = \{(x,t) \mid \|x\|_\infty \leq t\}$
 dual cone of 1-norm cone is inf-norm cone

$(K^*)^* = K$ if K is a proper cone

dual cone of proper cones are proper, hence define generalized inequality

$$y \succeq_{K^*} 0 \iff y^T x \geq 0 \text{ for all } x \succeq_K 0$$



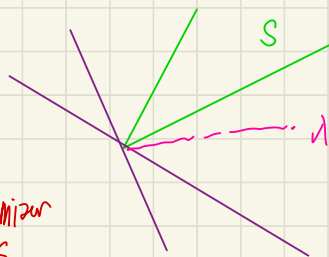
• Minimum and minimal elements via dual inequalities

minimum element w.r.t. K (all are more)

x is the minimum element of S



for all $\lambda \succeq_{K^*} 0$, x is the unique minimizer
 of $\lambda^T z$ over S
 (project S on λ)

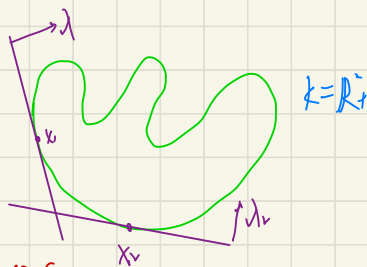


minimal element w.r.t. K (none is less)

x is a minimal



for some $\lambda \succeq_{K^*} 0$, x minimizes $\lambda^T z$ over S



if x is a minimal of a convex set S , then there exists a $\lambda \succeq_{K^*} 0$, $\lambda \neq 0$ such that x minimizes $\lambda^T z$ over S

• optimal production frontier

