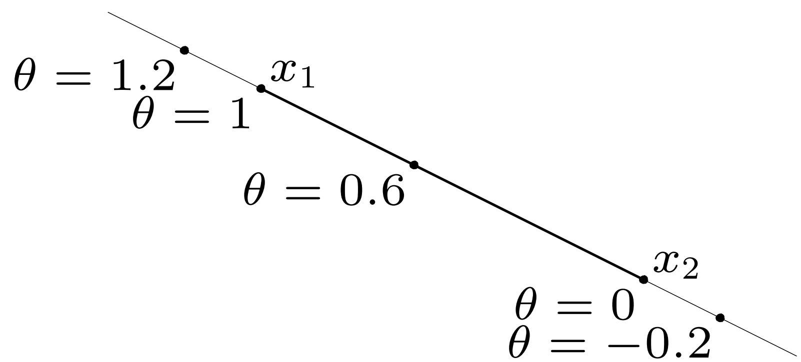
2. Convex sets

- affine and convex sets
- some important examples
- operations that preserve convexity
- generalized inequalities
- separating and supporting hyperplanes
- dual cones and generalized inequalities

Affine set

line through x_1, x_2: all points

$$x = \theta x_1 + (1-\theta)x_2 \qquad (\theta \in \mathbf{R})$$



affine set: contains the line through any two distinct points in the set

example: solution set of linear equations $\{x \mid Ax = b\}$

(conversely, every affine set can be expressed as solution set of system of linear equations)

Convex set

line segment between x_1 and x_2: all points

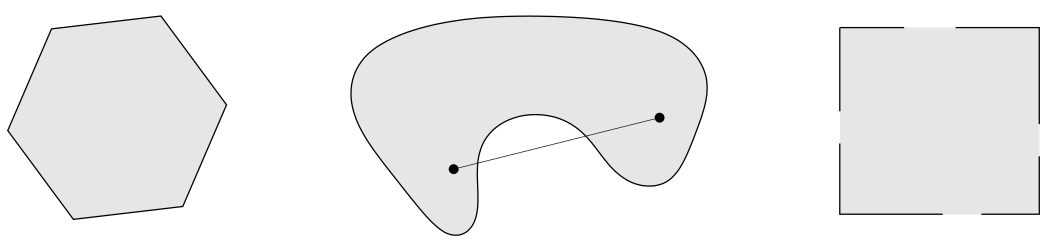
$$x = \theta x_1 + (1 - \theta) x_2$$

with $0 \leq \theta \leq 1$

convex set: contains line segment between any two points in the set

$$x_1, x_2 \in C, \quad 0 \leq \theta \leq 1 \quad \Longrightarrow \quad \theta x_1 + (1 - \theta) x_2 \in C$$

examples (one convex, two nonconvex sets)



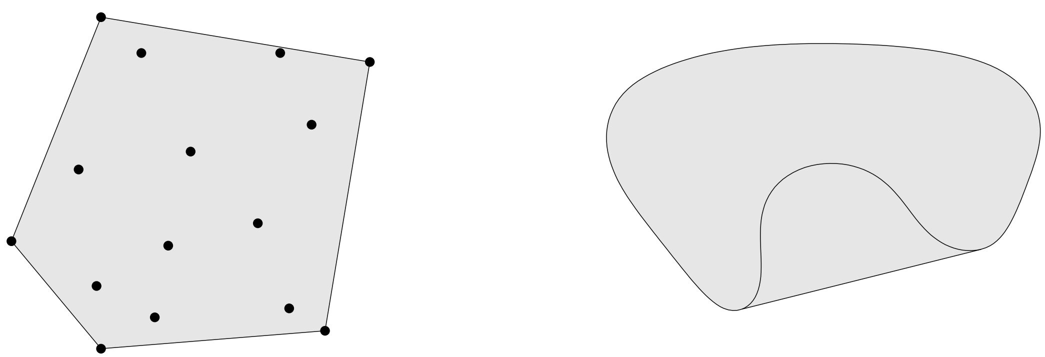
Convex combination and convex hull

convex combination of x_1,. . . , x_k: any point x of the form

$$x = \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_k x_k$$

with $\theta_1 + \cdots + \theta_k = 1$, $\theta_i \geq 0$

convex hull $\mathbf{conv}\, S$: set of all convex combinations of points in S

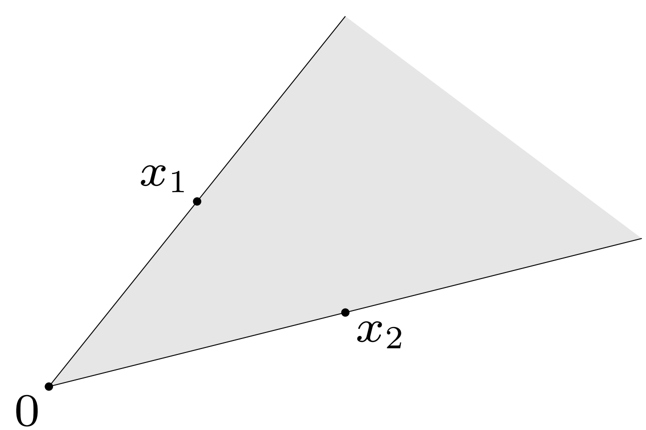


Convex cone

conic (nonnegative) combination of x_1 and x_2: any point of the form

$$x = \theta_1 x_1 + \theta_2 x_2$$

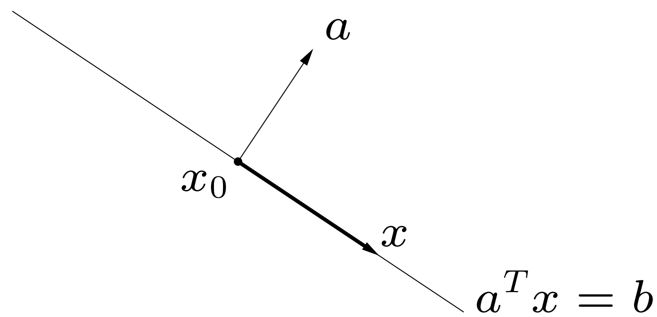
with $\theta_1 \geq 0$, $\theta_2 \geq 0$



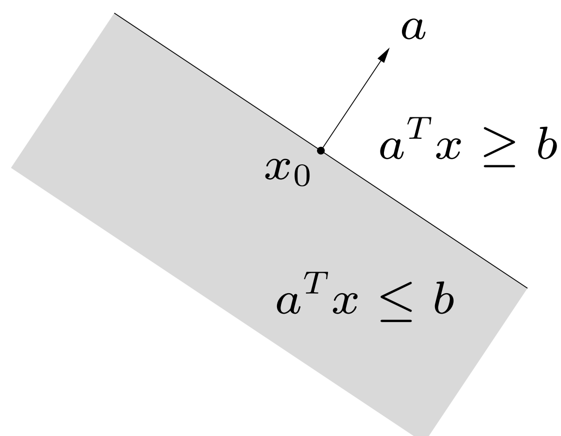
convex cone: set that contains all conic combinations of points in the set

Hyperplanes and halfspaces

hyperplane: set of the form $\{x \mid a^T x = b\}$ $(a \neq 0)$



halfspace: set of the form $\{x \mid a^T x \leq b\}$ $(a \neq 0)$



- a is the normal vector
- hyperplanes are affine and convex; halfspaces are convex

Euclidean balls and ellipsoids

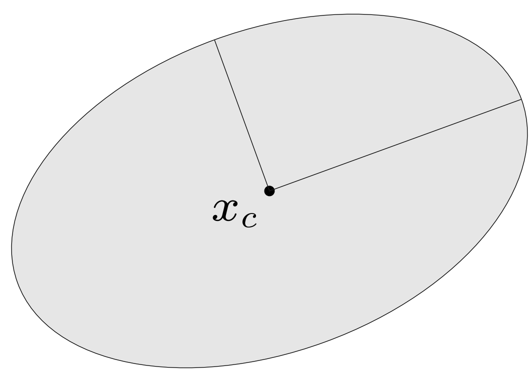
(Euclidean) ball with center x_c and radius r:

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

ellipsoid: set of the form

$$\{x \mid (x - x_c)^T P^{-1}(x - x_c) \leq 1\}$$

with $P \in \mathbf{S}^n_{++}$ (*i.e.*, P symmetric positive definite)



other representation: $\{x_c + Au \mid \|u\|_2 \leq 1\}$ with A square and nonsingular

Norm balls and norm cones

norm: a function $\|\cdot\|$ that satisfies

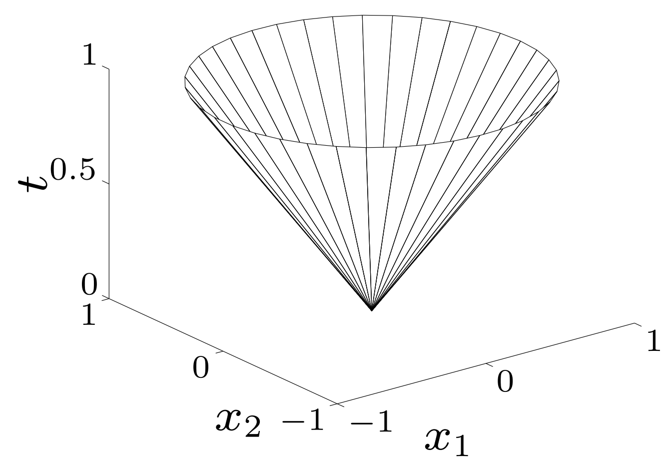
- $\|x\| \geq 0$; $\|x\| = 0$ if and only if $x = 0$
- $\|tx\| = |t|\,\|x\|$ for $t \in \mathbf{R}$
- $\|x + y\| \leq \|x\| + \|y\|$

notation: $\|\cdot\|$ is general (unspecified) norm; $\|\cdot\|_{\text{symb}}$ is particular norm

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



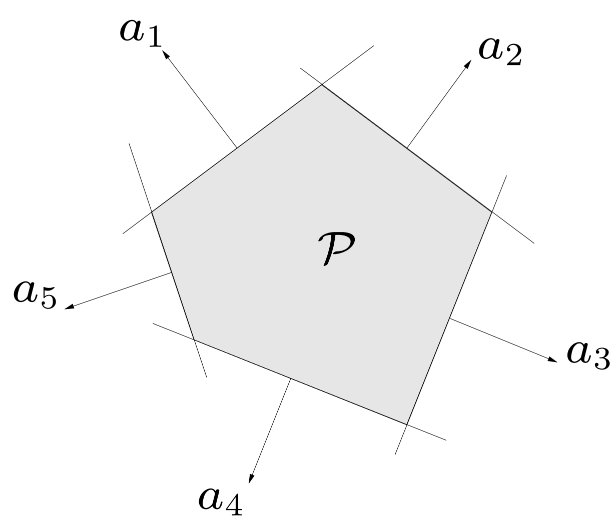
norm balls and cones are convex

Polyhedra

solution set of finitely many linear inequalities and equalities

$$Ax \preceq b, \qquad Cx = d$$

($A \in \mathbf{R}^{m \times n}$, $C \in \mathbf{R}^{p \times n}$, $\preceq$ is componentwise inequality)



polyhedron is intersection of finite number of halfspaces and hyperplanes

Positive semidefinite cone

notation:

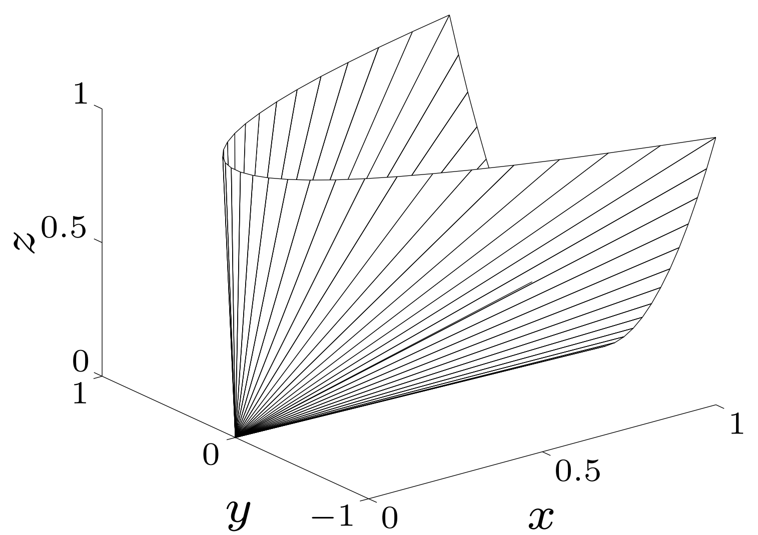
- $\mathbf{S}^n$ is set of symmetric $n \times n$ matrices
- $\mathbf{S}^n_+ = \{X \in \mathbf{S}^n \mid X \succeq 0\}$: positive semidefinite $n \times n$ matrices

$$X \in \mathbf{S}^n_+ \quad \Longleftrightarrow \quad z^T X z \geq 0 \text{ for all } z$$

  $\mathbf{S}^n_+$ is a convex cone

- $\mathbf{S}^n_{++} = \{X \in \mathbf{S}^n \mid X \succ 0\}$: positive definite $n \times n$ matrices

example: $\begin{bmatrix} x & y \\ y & z \end{bmatrix} \in \mathbf{S}^2_+$



Operations that preserve convexity

practical methods for establishing convexity of a set C

1. apply definition

$$x_1, x_2 \in C, \quad 0 \le \theta \le 1 \quad \Longrightarrow \quad \theta x_1 + (1-\theta) x_2 \in C$$

2. show that C is obtained from simple convex sets (hyperplanes, halfspaces, norm balls, . . .) by operations that preserve convexity
   - intersection
   - affine functions
   - perspective function
   - linear-fractional functions

Intersection

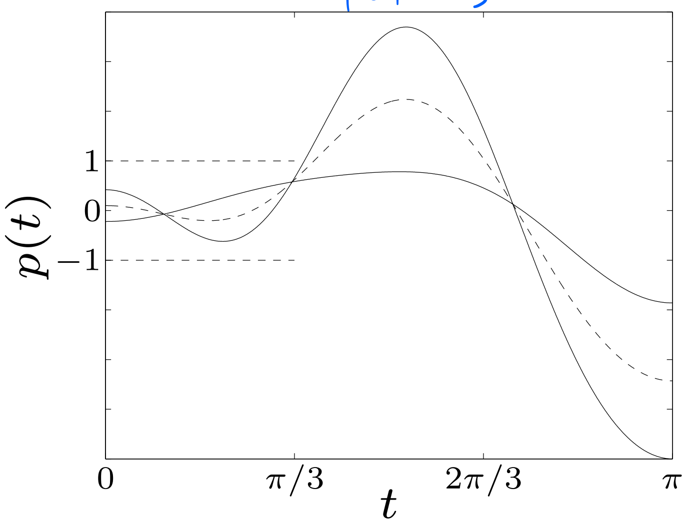
the intersection of (any number of) convex sets is convex

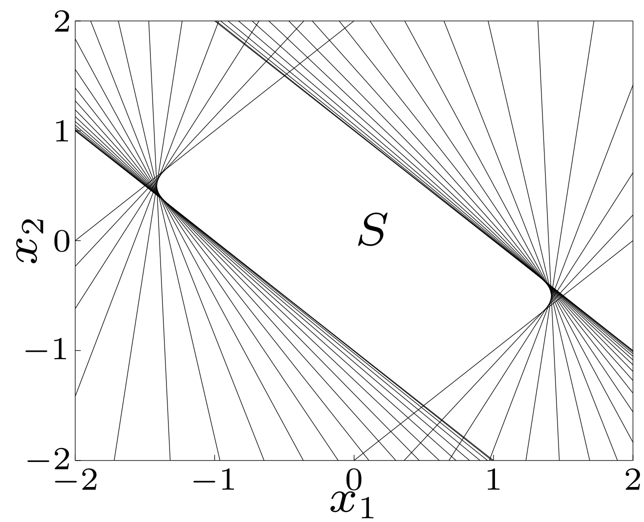
example:

$$S = \{x \in \mathbf{R}^m \mid |p(t)| \leq 1 \text{ for } |t| \leq \pi/3\}$$

where $p(t) = x_1 \cos t + x_2 \cos 2t + \cdots + x_m \cos mt$

for $m = 2$: $S = \bigcap_{|t| \leq \frac{\pi}{3}} S_t$, $S_t = \{x \mid x^T a(t) \leq 1, x^T a(t) \geq -1\}$





Affine function 仿射变换

suppose $f : \mathbf{R}^n \to \mathbf{R}^m$ is affine ($f(x) = Ax + b$ with $A \in \mathbf{R}^{m\times n}$, $b \in \mathbf{R}^m$)

- the image of a convex set under f is convex

$$S \subseteq \mathbf{R}^n \text{ convex} \quad \Longrightarrow \quad f(S) = \{f(x) \mid x \in S\} \text{ convex}$$

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

$$C \subseteq \mathbf{R}^m \text{ convex} \quad \Longrightarrow \quad f^{-1}(C) = \{x \in \mathbf{R}^n \mid f(x) \in C\} \text{ convex}$$

用定义

examples

- scaling, translation, projection
- solution set of linear matrix inequality $\{x \mid x_1A_1 + \cdots + x_mA_m \preceq B\}$ $= f^{-1}(C)$ (with $A_i, B \in \mathbf{S}^p$) $C = \{Z \mid Z \succeq 0\} = S_+^n$, $f(x) = B - \sum x_iA_i$ (Affine)
- hyperbolic cone $\{x \mid x^TPx \leq (c^Tx)^2,\ c^Tx \geq 0\}$ (with $P \in \mathbf{S}^n_+$) $= f^{-1}(C)$

$C = \{(x,t) \mid \|x\|_2 \leq t\}$ 已 $f(x) = \begin{pmatrix} P^{\frac{1}{2}}x \\ c^Tx \end{pmatrix}$

Perspective and linear-fractional function

perspective function $P : \mathbf{R}^{n+1} \to \mathbf{R}^n$:

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

images and inverse images of convex sets under perspective are convex

事实上有 $P([x,y]) = [P(x), P(y)]$

linear-fractional function $f : \mathbf{R}^n \to \mathbf{R}^m$:

$$f(x) = \frac{Ax+b}{c^Tx+d}, \qquad \mathbf{dom}\, f = \{x \mid c^Tx + d > 0\}$$

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

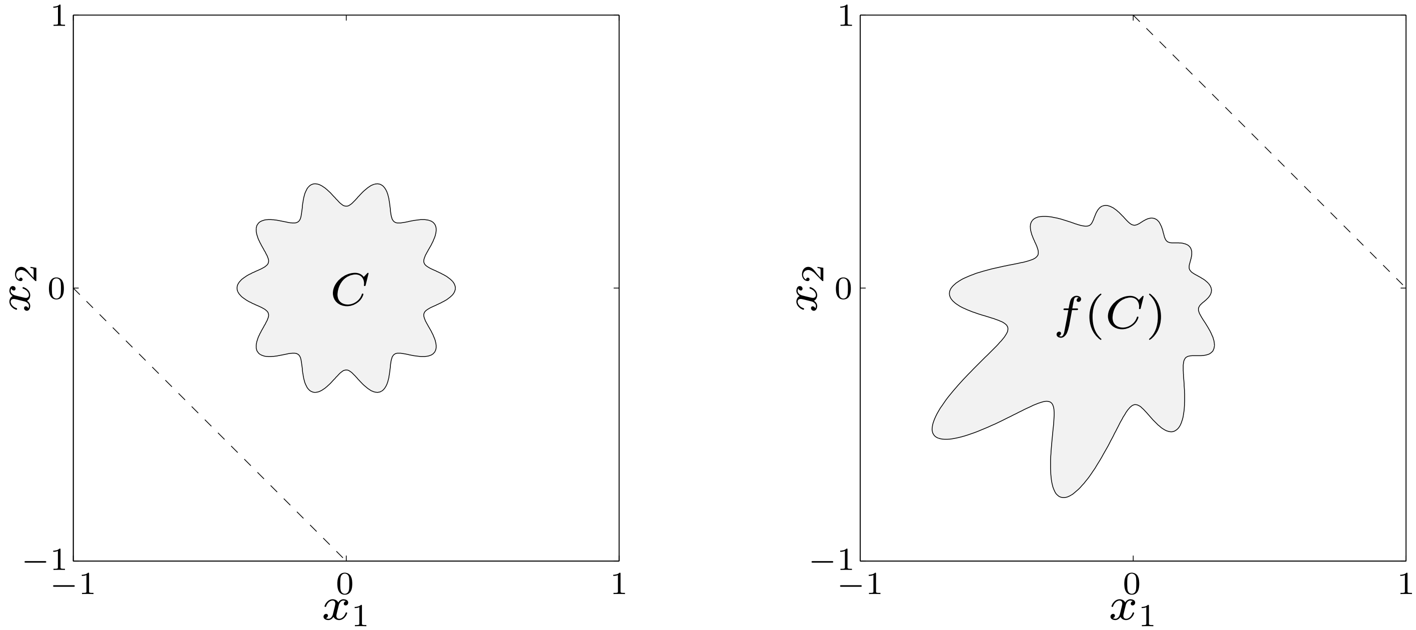
$f = P \circ h$: $h(x) = (Ax+b,\ c^Tx+d)^T$

$P(x,t) = \frac{x}{t}$.

为透射与仿射变换的复合

example of a linear-fractional function

$$f(x) = \frac{1}{x_1 + x_2 + 1} x$$



Generalized inequalities

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

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

有正常锥就可以
定义序关系

examples

- nonnegative orthant $K = \mathbf{R}^n_+ = \{x \in \mathbf{R}^n \mid x_i \geq 0, \ i = 1, \ldots, n\}$
- positive semidefinite cone $K = \mathbf{S}^n_+$
- nonnegative polynomials on $[0, 1]$:

$$K = \{x \in \mathbf{R}^n \mid x_1 + x_2 t + x_3 t^2 + \cdots + x_n t^{n-1} \geq 0 \text{ for } t \in [0, 1]\}$$

$a(t) = \begin{pmatrix} 1 \\ t \\ \vdots \\ t^{n-1} \end{pmatrix}$ $\quad K = \bigcap_{t \in [0,1]} \{x \mid x^T a(t) \geq 0\}$

$\mathrm{int}\, K = \bigcap_{t \in [0,1]} \{x \mid x^T a(t) > 0\}$

generalized inequality defined by a proper cone K:

$$x \preceq_K y \quad \Longleftrightarrow \quad y - x \in K, \qquad x \prec_K y \quad \Longleftrightarrow \quad y - x \in \mathbf{int}\, K$$

examples

- componentwise inequality ($K = \mathbf{R}^n_+$)

$$x \preceq_{\mathbf{R}^n_+} y \quad \Longleftrightarrow \quad x_i \leq y_i, \quad i = 1, \ldots, n$$

- matrix inequality ($K = \mathbf{S}^n_+$)

$$X \preceq_{\mathbf{S}^n_+} Y \quad \Longleftrightarrow \quad Y - X \text{ positive semidefinite}$$

these two types are so common that we drop the subscript in $\preceq_K$

properties: many properties of $\preceq_K$ are similar to $\leq$ on **R**, *e.g.*,

$$x \preceq_K y, \quad u \preceq_K v \quad \Longrightarrow \quad x + u \preceq_K y + v$$

$a \in K,\ b \in K \Rightarrow a+b \in K.$

由凸锥

Minimum and minimal elements

$\preceq_K$ is not in general a *linear ordering*: we can have $x \not\preceq_K y$ and $y \not\preceq_K x$

$x \in S$ is **the minimum element** of S with respect to $\preceq_K$ if

最小元

$$y \in S \quad \Longrightarrow \quad x \preceq_K y$$

若存在 则必唯一

任一都小于

$S \subseteq x + K$

$x \in S$ is **a minimal element** of S with respect to $\preceq_K$ if

不存在大于

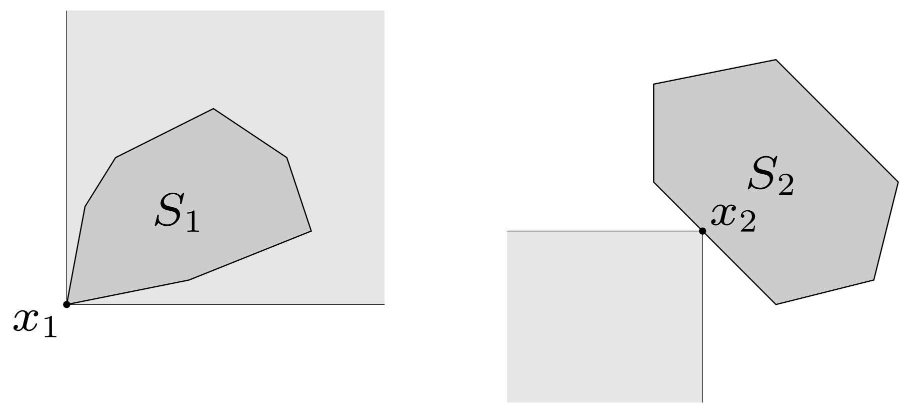
极小元

$$y \in S, \quad y \preceq_K x \quad \Longrightarrow \quad y = x$$

$S \cap (x - K) = \{x\}$

example $(K = \mathbf{R}^2_+)$

x_1 is the minimum element of S_1
x_2 is a minimal element of S_2

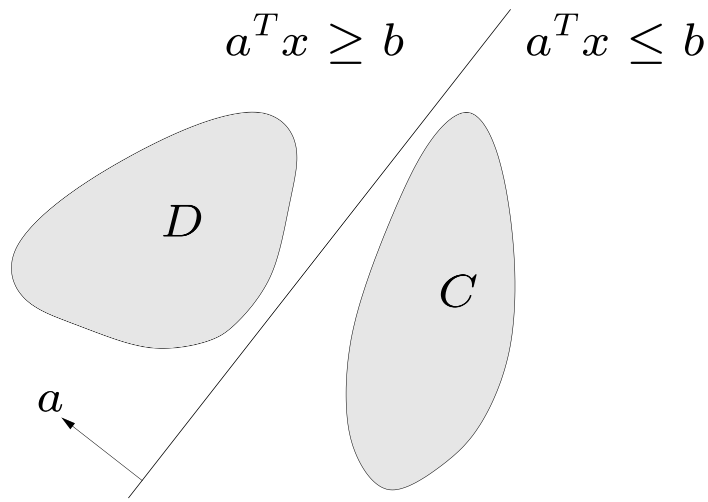


Separating hyperplane theorem

非空 不交 凸

if C and D are nonempty disjoint convex sets, there exist $a \neq 0$, b s.t.

$$a^T x \leq b \text{ for } x \in C, \qquad a^T x \geq b \text{ for } x \in D$$



the hyperplane $\{x \mid a^T x = b\}$ separates C and D

strict separation requires additional assumptions (*e.g.*, C is closed, D is a singleton)

对 C 为闭凸集，$y \notin C$，$\exists!\ x \in C$ 使 $\|y-x\| = d(y,C)$

进而 $\exists\ a \neq 0,\ b$ 使 $a^T y < b \leq a^T x\ \ \forall x \in C$. 强分离

(取 $a = x - y \neq 0$，$b = \frac{1}{2}(|x|^2 - |y|^2)$)

而若 C 为凸集，$y \notin C$ 则 $\exists\ a \neq 0,\ b$ s.t. $a^T y \leq b \leq a^T x\ \ \forall x \in C$.

proof: ① $y \notin \bar{C}$ ② $y \in \bar{C} \to y \in \partial \bar{C} \Rightarrow$ ⓐ $\text{int}\, C = \phi$ 此时 $\dim C \leq n-1$ 在超平面内

ⓑ 若 $\text{int}\, C \neq \phi$ 取 $S_{-\varepsilon} = \{z \mid B(z,\varepsilon) \subseteq C\}$ $\Rightarrow S_{-\varepsilon}$ 为凸 而 $\text{dist}(y, S_{-\varepsilon}) \geq \varepsilon$

$\Rightarrow y \notin \overline{S_{-\varepsilon}} \Rightarrow \exists\ a_\varepsilon \neq 0,\ b$ s.t. $a_\varepsilon^T x > b \geq a_\varepsilon^T y$ (不妨设 $y = 0$)

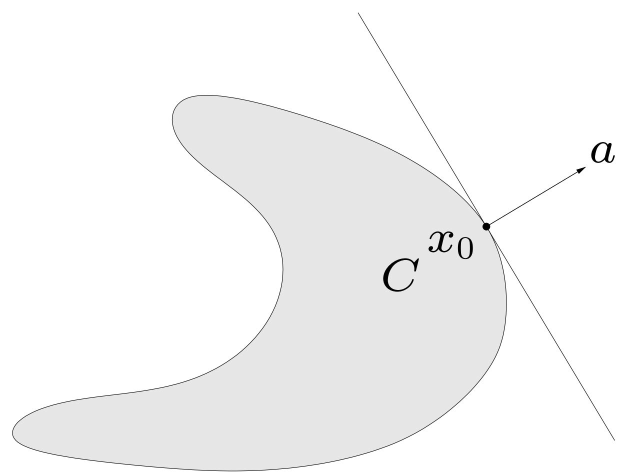
取 $\bar{a}_\varepsilon = \frac{a_\varepsilon}{\|a_\varepsilon\|} \Rightarrow \|\bar{a}_\varepsilon\| = 1$ 有界 $\therefore \exists\ \bar{a}_{\varepsilon_k} \to \bar{a}$ 进而有 $\bar{a}^T x \geq 0\ \ \forall x \in \text{int}\, C$.

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 $x \in C$



supporting hyperplane theorem: if C is convex, then there exists a supporting hyperplane at every boundary point of C

Dual cones and generalized inequalities

类似地 Polar Cone 极锥：

$K^\circ = \{y \mid y^T x \le 0 \ \forall x \in K\}$

dual cone of a cone K:

对偶锥

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

Normal cone 范数锥：

$N_K(\bar{x}) = \{g \mid g^T(x-\bar{x}) \le 0 \ \forall x \in K\}$

examples

易见 若 $\bar{x} \in \operatorname{int} K$ 则 $N_K(\bar{x}) = \phi$

- $K = \mathbf{R}^n_+$: $K^* = \mathbf{R}^n_+$
- $K = \mathbf{S}^n_+$: $K^* = \mathbf{S}^n_+$
- $K = \{(x,t) \mid \|x\|_2 \le t\}$: $K^* = \{(x,t) \mid \|x\|_2 \le t\}$
- $K = \{(x,t) \mid \|x\|_1 \le t\}$: $K^* = \{(x,t) \mid \|x\|_\infty \le t\}$

一般 对 $K = \{(x,t) \mid \|x\| \le t\}$

有 $K^* = \{(u,v) \mid \|u\|_* \le v\}$

对偶范数

$\|u\|_* = \sup\{u^T x \mid \|x\| \le 1\}$

first three examples are **self-dual** cones

dual cones of proper cones are proper, hence define generalized inequalities:

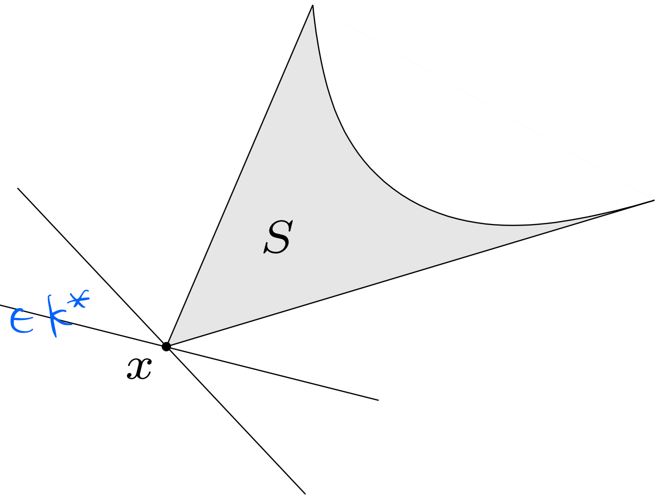
$$y \succeq_{K^*} 0 \quad \Longleftrightarrow \quad y^T x \ge 0 \text{ for all } x \succeq_K 0$$

Minimum and minimal elements via dual inequalities

minimum element w.r.t. $\preceq_K$

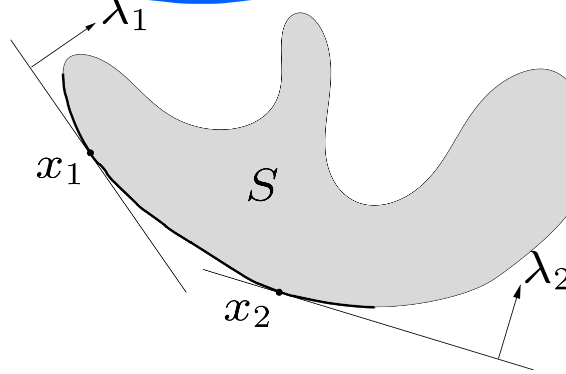
x is minimum element of S iff for all $\lambda \succ_{K^*} 0$, x is the unique minimizer of $\lambda^T z$ over S

$x = \arg\min_{z \in S} \{ \lambda^T z \} \quad \forall \lambda \in K^*$



minimal element w.r.t. $\preceq_K$

- if x minimizes $\lambda^T z$ over S for some $\lambda \succ_{K^*} 0$, then x is minimal



$\exists\, \lambda \in K^*$ 使 x minimize

$\Rightarrow$ x 为 minimal

反之需要 S 为凸集

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

$\underbrace{(x-K) \setminus \{x\}}_{凸} \cap \underbrace{S}_{凸} = \phi \Rightarrow \exists\, a \neq 0,\ b.$ s.t $a^T z_1 \le b \le a^T z_2$, $z_1 \in x-K$, $z_2 \in S$

取 $\lambda = a$.

optimal production frontier

- different production methods use different amounts of resources $x \in \mathbf{R}^n$
- production set P: resource vectors x for all possible production methods
- efficient (Pareto optimal) methods correspond to resource vectors x that are minimal w.r.t. $\mathbf{R}^n_+$

example $(n = 2)$

x_1, x_2, x_3 are efficient; x_4, x_5 are not