

W21 CSE 203B: Convex Set

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- Affine and convex sets
- Example of convex sets
- Key properties of convex sets
- Proper cone, dual cone and generalized inequality

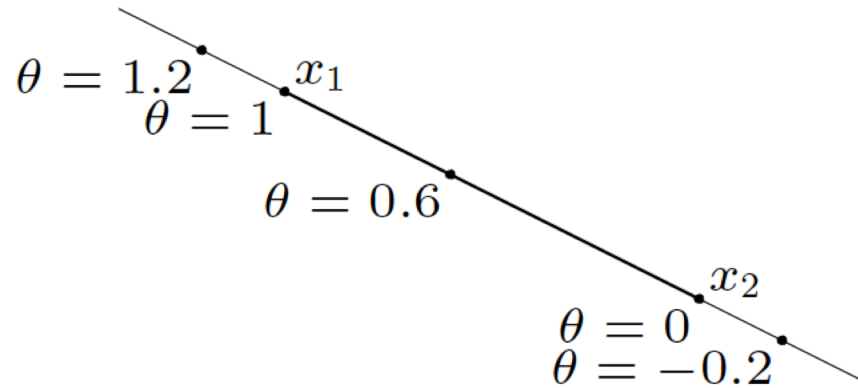
Contents

- Affine and convex sets
 - Definitions
 - Affine/convex/conic combinations
 - Implicit expression and explicit enumeration

Affine set

line through x_1, x_2 : all points

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



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

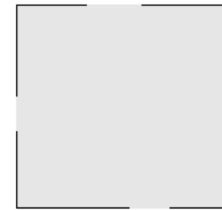
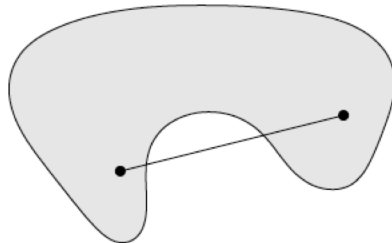
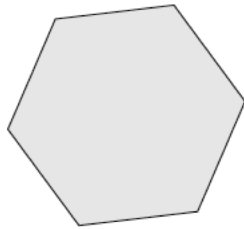
$$x = \theta x_1 + (1 - \theta)x_2$$

with $0 \leq \theta \leq 1$

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

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

examples (one convex, two nonconvex sets)



Convex combination and convex hull

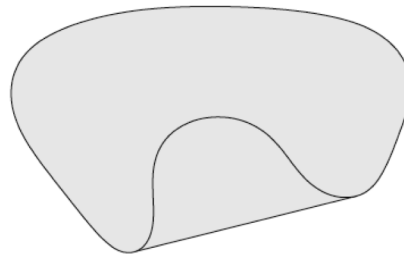
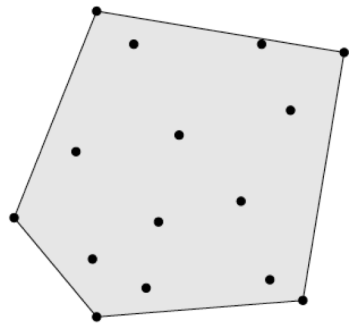
convex combination of x_1, \dots, x_k : any point x of the form

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

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

convex hull $\text{conv}C$: set of all convex combinations of points in C

$$\text{conv}C = \{\theta_1 x_1 + \dots + \theta_k x_k \mid x_i \in C, \theta_i \geq 0, i = 1, \dots, k, \theta_1 + \dots + \theta_k = 1\}.$$



**Explicit expression of
convex hull**

The convex hull is the **smallest** convex set that contains C

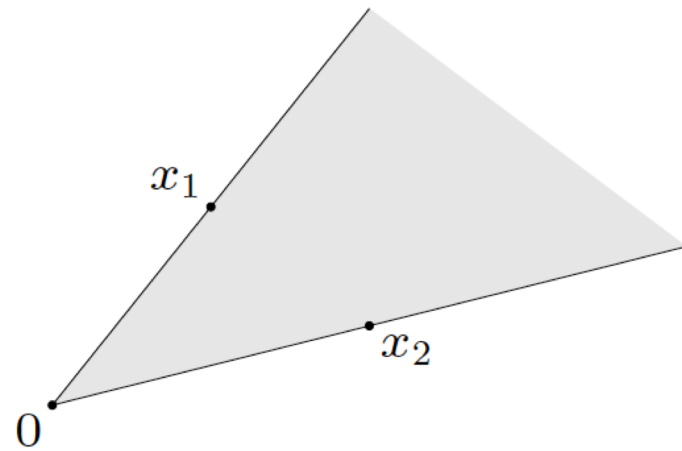
Cone

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

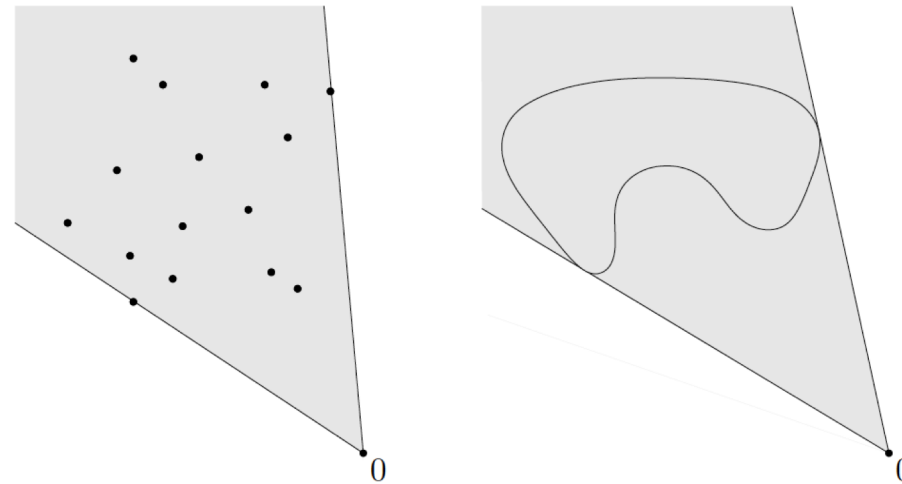
$$x = \theta_1 x_1 + \theta_2 x_2$$

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

A cone formed with x_1, x_2



Conic hull of sets



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

Set Specification via Implicit or Explicit Enumeration

Implicit Expression

$$S_I = \{x \mid Ax \leq b, x \in R^n\}$$

Explicit Enumeration

$$S_E = \{Ax \mid x \in R^n\}$$

Implicit Expression:

Constraints

Min $f_o(x)$

Subject to

$$Ax \leq b, x \in R^n$$

Explicit Expression:

Enumeration

Min $f_o(Ax), x \in R^n$

Contents

- Example of convex sets
 - Simple examples
 - Hyperplanes and halfspaces
 - Prove the convexity of sets with operations that preserve the convexity

Examples of convex sets

- Empty set, point, line.
- Norm ball: $\{x : \|x\| \leq r\}$, for given norm $\|\cdot\|$, radius r .
- Hyperplane: $\{x : a^T x = b\}$, for given a, b .
- Halfspace: $\{x : a^T x \leq b\}$.
- Affine space: $\{x : Ax = b\}$, for given A, b .
- Polyhedron: $\{x : Ax \leq b\}$, where \leq is interpreted componentwise. The set $\{x : Ax \leq b, Cx = d\}$ is also a polyhedron.
- Simplex: special case of polyhedra, given by $\text{conv}\{x_0, \dots, x_k\}$, where these points are affinely independent. The canonical example is the probability simplex,

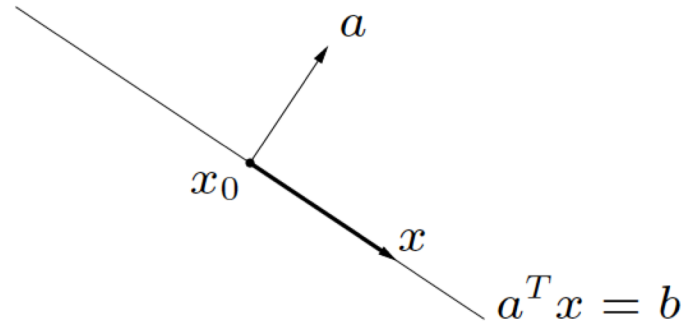
$$\text{conv}\{e_1, \dots, e_n\} = \{w : w \geq 0, 1^T w = 1\}$$

Exercises:

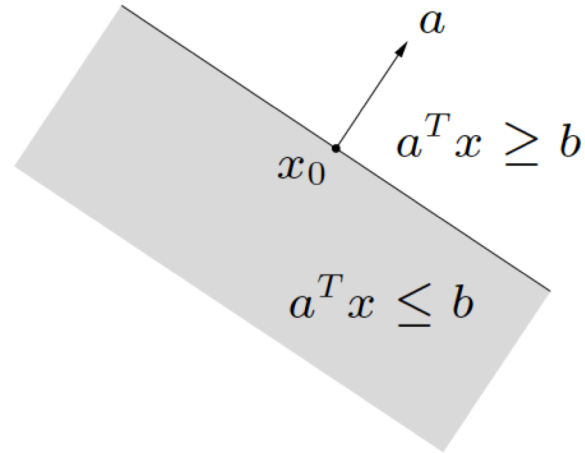
- 1) **Prove the convexity of the sets using the definition.**
- 2) **The above convex sets are described with implicit expression, find the explicit enumeration.**

Hyperplane 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

Hyperplane and Halfspaces

- Example of plane in \mathbb{R}^3 : $3x + 4y + 6z = 12$

- Implicit express of the hyperplane

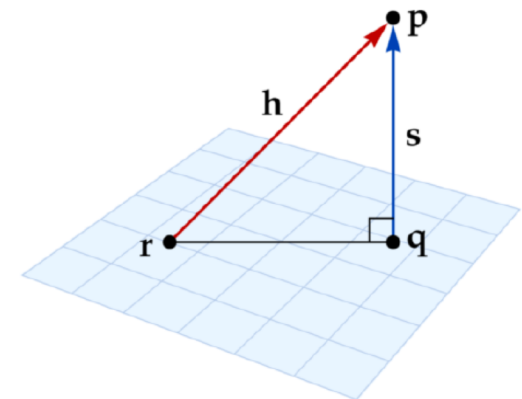
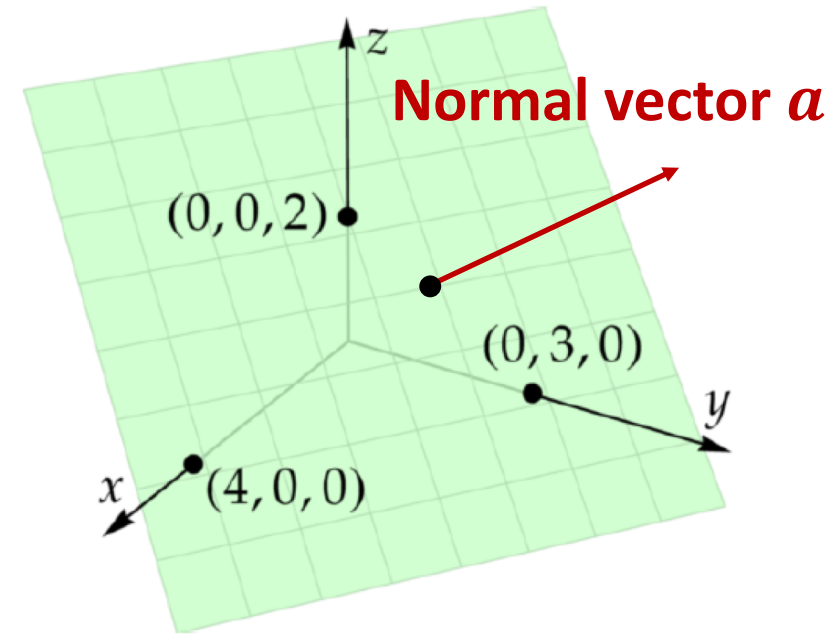
$$\{x \mid a^T x = b\} \text{ where } a^T = [3, 4, 6], b = 12$$

- Let x_0 be any point in the hyperplane, then the expression becomes

$$\{x \mid a^T (x - x_0) = 0\} = x_0 + a^\perp$$

Q: Write the explicit expression of the hyperplane.

- Find the distance from a point p to the plane.

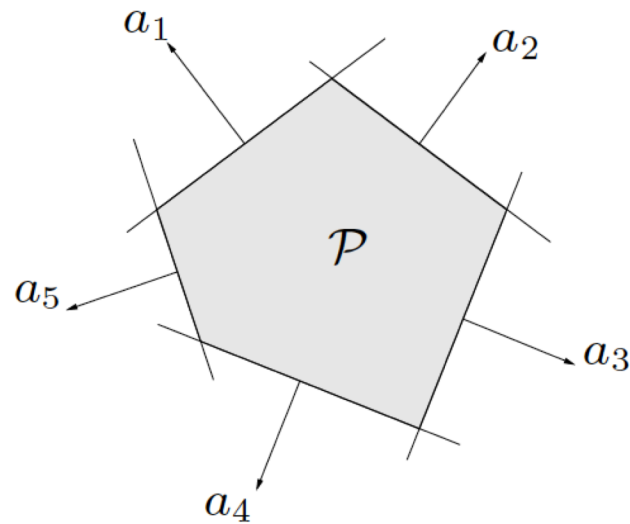


Prove the convexity of polyhedron

solution set of finitely many linear inequalities and equalities

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

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



Use the definition of convex set:

$$x_1, x_2 \in C, 0 \leq \theta \leq 1$$

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

Proof:

pick any two points in the polyhedron
 $x_1, x_2 \in P$, for $0 \leq \theta \leq 1$ is the point

$$\theta x_1 + (1 - \theta)x_2 \in P ?$$

polyhedron is intersection of finite number of halfspaces and hyperplanes

Positive semidefinite cone

notation:

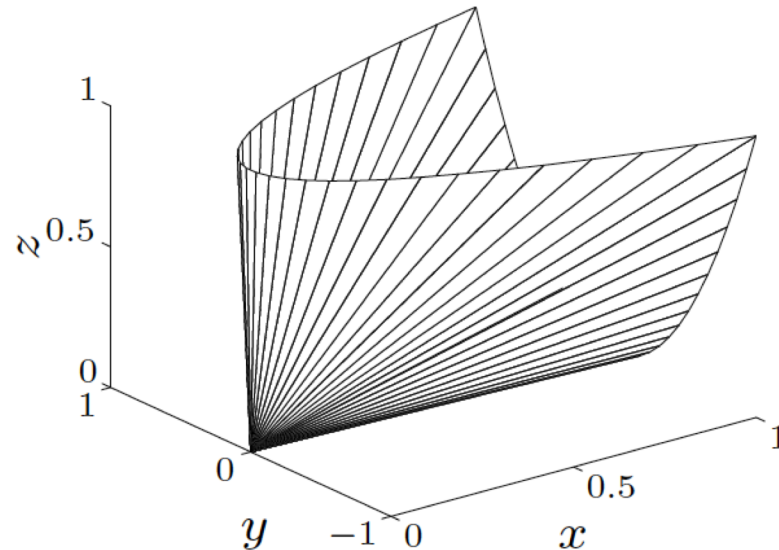
- \mathbf{S}^n is set of symmetric $n \times n$ matrices
- $\mathbf{S}_+^n = \{X \in \mathbf{S}^n \mid X \succeq 0\}$: positive semidefinite $n \times n$ matrices

$$X \in \mathbf{S}_+^n \iff z^T X z \geq 0 \text{ for all } z$$

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



Intersections preserve convexity

- Polyhedron: intersection of halfspaces and hyperplanes (convex)

⇒ *Is the intersection of a finite number of convex sets still convex?*

prove with the definition of convex sets.

Operations that preserve convexity:

- Intersection
- Affine function
- Perspective functions
- Linear-fractional functions

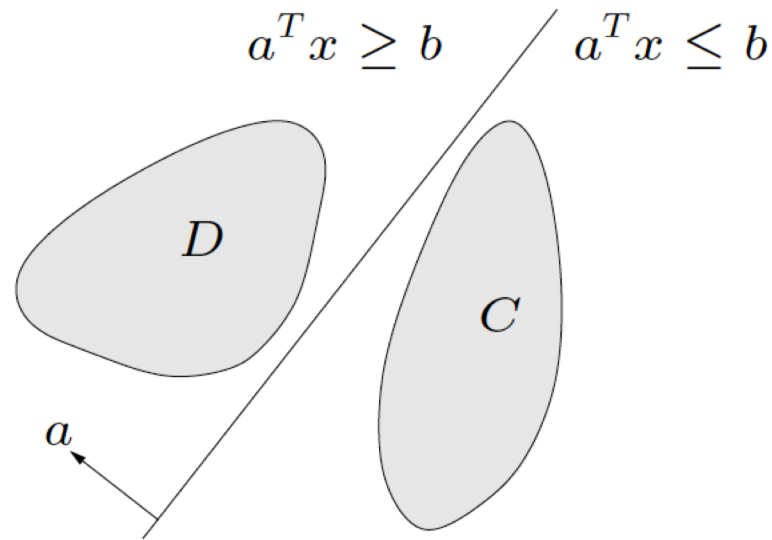
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- Key properties of convex sets
 - Separating hyperplane theorem
 - Supporting hyperplane theorem

Separating hyperplane theorem

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

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



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

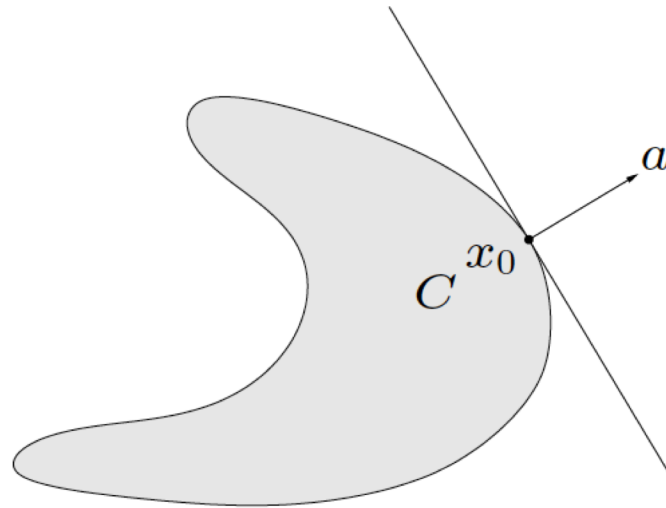
strict separation requires additional assumptions (*e.g.*, C is closed, D is a singleton)

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

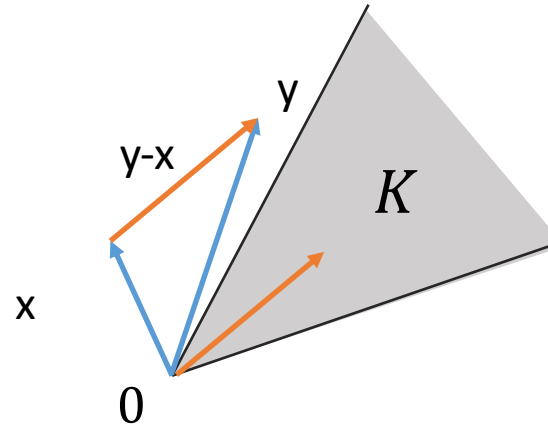
Contents

- Proper cone and generalized inequality
- Dual cone and generalized inequality

Generalized inequality

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)



generalized inequality defined by a proper cone K :

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

Review the properties of proper cones (chap 2.4.1) and generalized inequality (exercise 2.30).

Generalized inequality

examples

- componentwise inequality ($K = \mathbf{R}_+^n$) **Nonnegative orthant**

$$x \preceq_{\mathbf{R}_+^n} y \iff x_i \leq y_i, \quad i = 1, \dots, n$$

- matrix inequality ($K = \mathbf{S}_+^n$) **Positive semidefinite cone**

$$X \preceq_{\mathbf{S}_+^n} Y \iff Y - X \text{ positive semidefinite}$$

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 \mathbf{R} , *e.g.*, **a partial ordering on \mathbf{R}^n**

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

analogy to ordinary inequality

Minimum and minimal element

\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

$$y \in S \implies x \preceq_K y \iff S \subseteq x + K$$

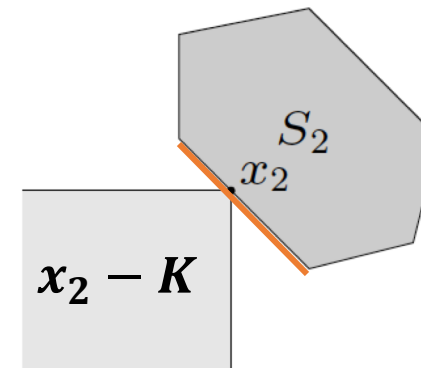
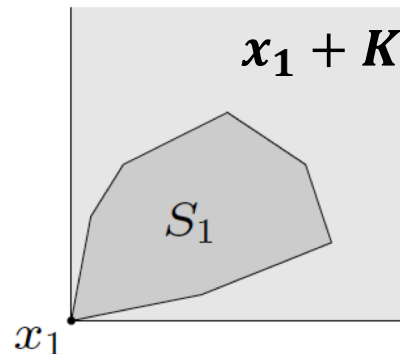
$x \in S$ is a **minimal element** of S with respect to \preceq_K if

$$y \in S, y \preceq_K x \implies y = x \iff (x - K) \cap S = \{x\}$$

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

x_1 is the minimum element of S_1

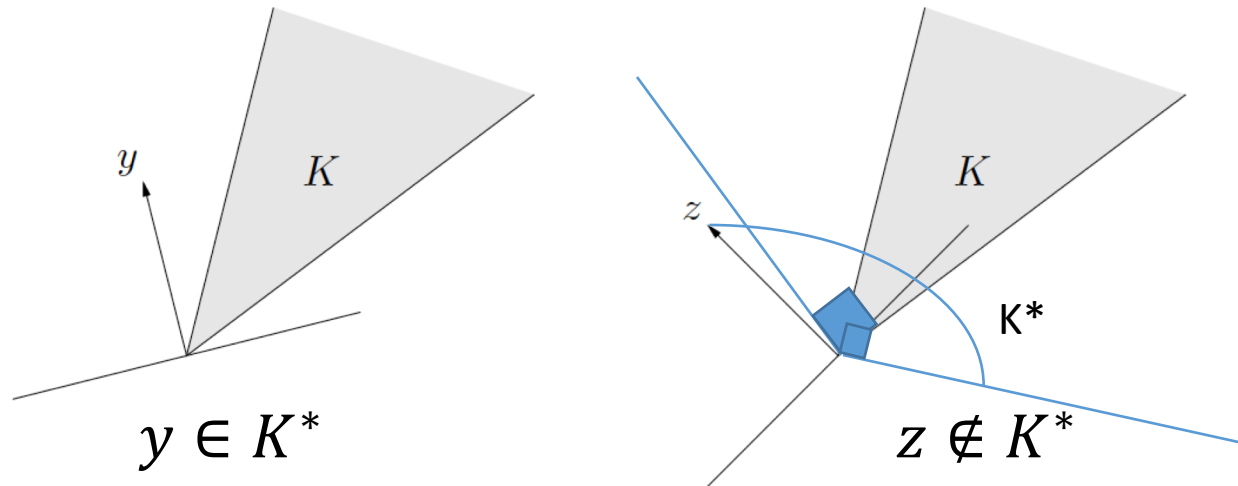
x_2 is a minimal element of S_2



Dual cones

dual cone of a cone K :

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



Find the **dual cones** of

- Subspace $V \in \mathbf{R}^n$
- Nonnegative orthant $K = \mathbf{R}_+^n$
- Positive semidefinite cone $K = \mathcal{S}_+^n$

Review the properties of dual cones (exercise 2.31).

reference

[1] S. Boyd and L. Vandenberghe. Convex Optimization. Cambridge University Press, [http://stanford.edu/ boyd/cvxbook/](http://stanford.edu/boyd/cvxbook/), 2004.