Optimization Theory and Algorithms

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Outline

- Affine set
- Convex set
- Convexity-preserving operations
- Separating and supporting hyperplane theorem

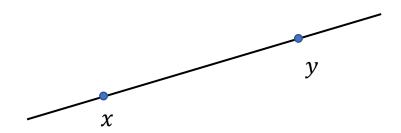
Affine set

Definition: a set $S \subseteq \mathbb{R}^n$ is an affine set, if

for any
$$x,y \in S$$
, $\theta x + (1-\theta)y \in S$, for all $\theta \in \mathbb{R}$.



A line through x,y, if $x \neq y$.



Affine set contains the line through any two distinct points in the set.

Example: $\{x | Ax = b\}$, i.e., solution set of linear equations.

Generalization to more than two points:

Affine combination of x_1 , x_2 ,..., $x_k \in \mathbb{R}^n$:

$$\theta_1 x_1 + \theta_2 x_2 + \dots + \theta_k x_k$$
, where $\sum_{i=1}^k \theta_i = 1$.

Affine set contains the every affine combination of its points in the set.

Affine set: Interpretation

A set $S \subseteq \mathbb{R}^n$ is an affine set



S is the translation of some linear subspace $V \subseteq \mathbb{R}^n$, i.e., *S* is of the form $\{x\} + V = \{x + v : v \in V\}$ for some $x \in \mathbb{R}^n$.

for any $v_1, v_2 \in V, \alpha, \beta \in \mathbb{R}, \alpha v_1 + \beta v_2 \in V$

Affine set = subspace + offset

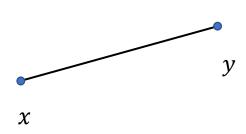
Convex set

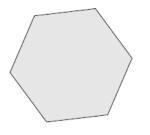
Definition: a set $S \subseteq \mathbb{R}^n$ is a convex set, if

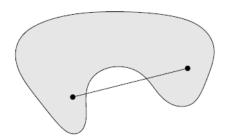
for any
$$x,y \in S$$
, $\theta x + (1-\theta)y \in S$, for $\theta \in [0,1]$.



Line segment between x,y, if $x \neq y$.







Convex set contains the line segment between any two distinct points in the set.

Generalization to more than two points:

Convex combination of $x_1, x_2, ..., x_k \in \mathbb{R}^n$:

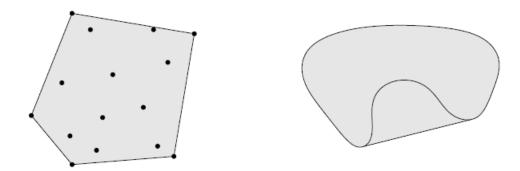
 $\sum_{i=1}^k \theta_i x_i$, where $\sum_{i=1}^k \theta_i = 1$, and $\theta_i \ge 0$ for all i.

Convex set contains the every convex combination of its points in the set.

Convex hull

The convex hull of a set S is the set of all convex combinations of points in S:

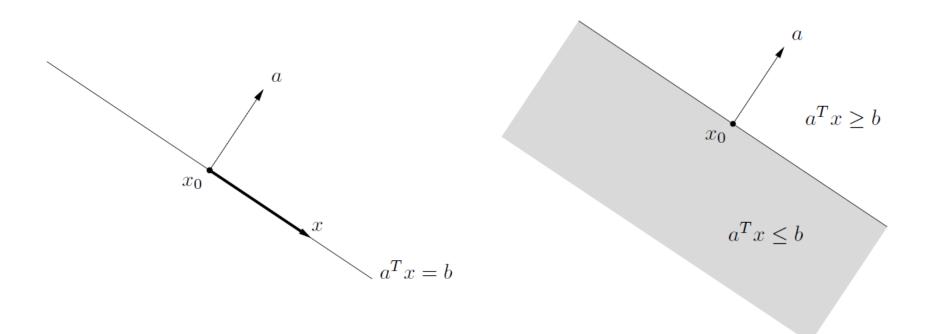
$$conv(S) = \left\{ \sum_{i=1}^k \theta_i x_i \mid x_i \in S, \sum_{i=1}^k \theta_i = 1, \text{ and } \theta_i \ge 0 \text{ for all } i \right\}$$



The convex hull of a set S is the smallest convex set that contains S.

Convex set: examples

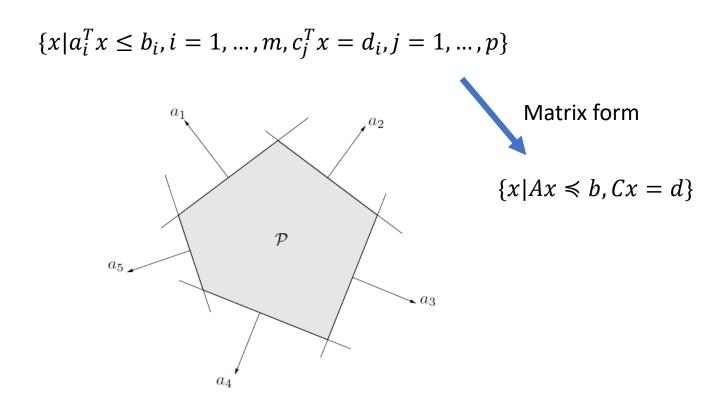
- Simple examples: empty set \emptyset ; any single point; line; the whole space \mathbb{R}^n .
- Hyperplane $\{x \in \mathbb{R}^n | a^T x = b\}$ $(a \in \mathbb{R}^n, a \neq \mathbf{0}, b \in \mathbb{R}).$



• Halfspace $\{x \in \mathbb{R}^n | a^T x \le b\}$ $(a \in \mathbb{R}^n, a \ne \mathbf{0}, b \in \mathbb{R}).$

Convex set: examples

Polyhedron: solution set of finite linear equalities and inequalities



Polyhedron is intersection of finite number of halfspaces and hyperplanes.

Convex set: examples

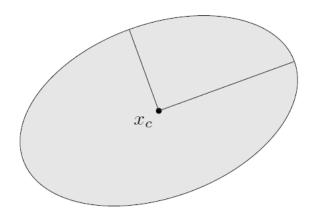
Euclidean ball

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

Ellipsoids

$$E(x_c, Q) = \{x | (x - x_c)^T Q (x - x_c) \le 1\}$$

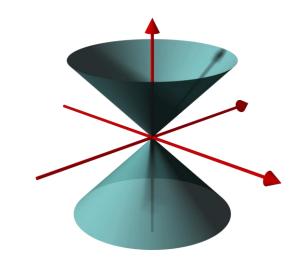
 x_c is the center of the ellipsoid; Q > 0, i.e., positive definite matrix.



Cone

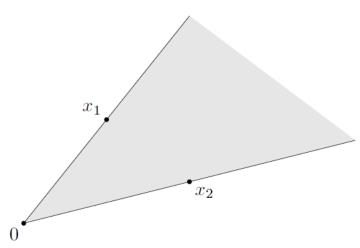
A set $S \subseteq \mathbb{R}^n$ is a cone, if

for any $x \in S$, $\theta x \in S$, for $\theta \ge 0$.



A set $S \subseteq \mathbb{R}^n$ is a convex cone, if

for any $x_1, x_2 \in S$, $\theta_1 x_1 + \theta_2 x_2 \in S$, for $\theta_1, \theta_2 \ge 0$.



Generalization to more than two points:

Conic combination of $x_1, x_2, ..., x_k \in \mathbb{R}^n$:

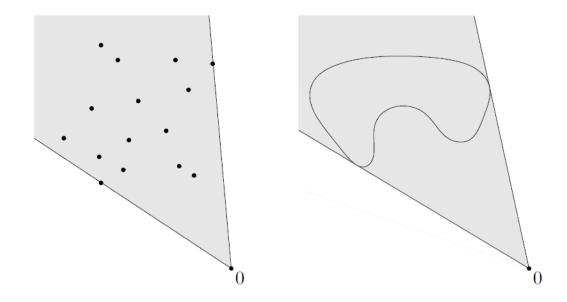
 $\sum_{i=1}^{k} \theta_i x_i$, where $\theta_i \ge 0$ for all i.

Convex cone contains the every conic of its points in the set.

Conic hull

The conic hull of a set S is the set of all conic combinations of points in S:

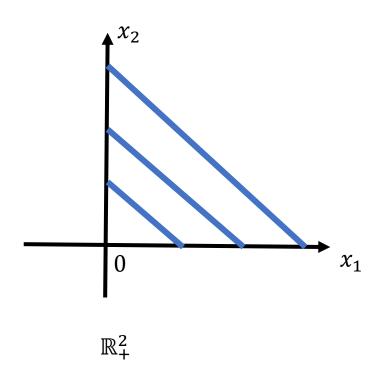
$$conv(S) = \left\{ \sum_{i=1}^{k} \theta_i x_i \mid x_i \in S, \text{ and } \theta_i \ge 0 \text{ for all } i \right\}$$



The convex hull of a set S is the smallest convex cone that contains S.

Convex cone: example

• Non-negative orthant: $\mathbb{R}^n_+ \triangleq \{(x_1, x_2, ..., x_n) | x_i \geq 0, i = 1, ..., n\}$

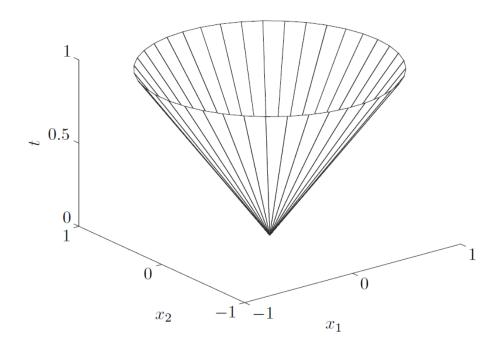


Convex cone: example

• Norm cone: $\{(x,t)| ||x|| \le t\} \subseteq \mathbb{R}^{n+1}$, for a norm $||\cdot||$.

For a I2-norm (Euclidean norm) $\|\cdot\|_2$:

 $\{(x,t)| \|x\|_2 \le t\}$ is second-order cone, also called ice cream cone.



Boundary of second-order cone in \mathbb{R}^3 , $\{(x_1, x_2, t) | (x_1^2 + x_2^2)^{1/2} \le t\}$.

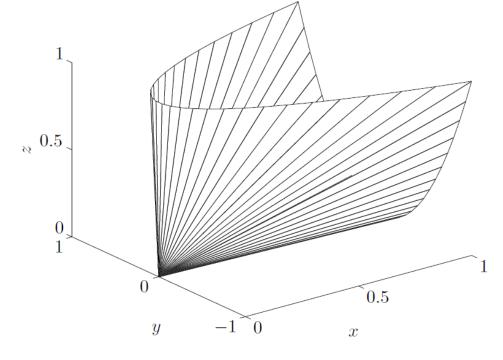
Convex cone: positive semidefinite cone

• Positive semidefinite matrix $S_+^n \triangleq \{X \in S^n | X \geq 0\}$.

$$z^T X z \ge 0$$
 for all $z \in \mathbb{R}^n$

• Example: positive semidefinite cone in S_+^2

$$X = \begin{bmatrix} x & y \\ y & z \end{bmatrix} \in \mathbf{S}_{+}^{n} \iff x \ge 0, z \ge 0, xz \ge y^{2}. \quad \approx 0.5$$

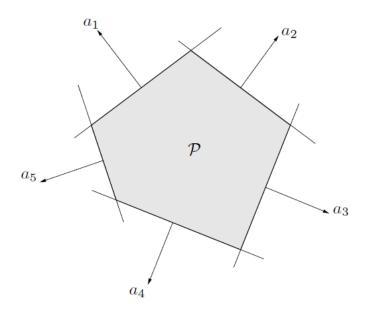


Boundary in \mathbb{R}^3

Operations that preserve convexity

Intersection: the intersection of convex sets is convex.

$$\{x | a_i^T x \le b_i, i = 1, ..., m, c_j^T x = d_i, j = 1, ..., p\}$$



Polyhedron is intersection of finite number of halfspaces and hyperplanes.

Operations that preserve convexity

• Affine mapping: f(x) = Ax + b where $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$, i.e., $f: \mathbb{R}^n \to \mathbb{R}^m$

$$S \subseteq \mathbb{R}^n$$
 is convex $\implies f(S) = \{f(x) | x \in S\}$ is convex $T \subseteq \mathbb{R}^n$ is convex $\implies f^{-1}(T) = \{x | f(x) \in T\}$ is convex

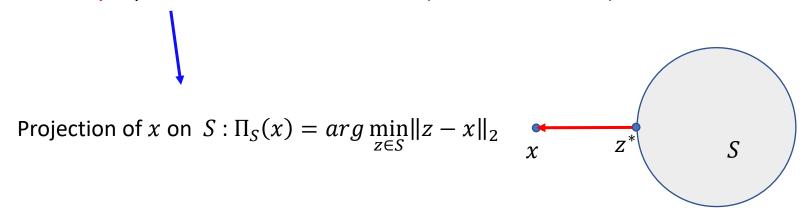
- Examples:
- \triangleright Scaling ($\{\alpha x | x \in S\}$), translation ($\{x + x_0 | x \in S\}$), projection ($\{x_1 | [x_1, x_2]^T \in S\}$)
- ightharpoonup Convexity of ellipsoid: $E(x_c, Q) = \{x | (x x_c)^T Q (x x_c) \le 1\}$

Eclidean ball
$$B(0,r)=\{x|x^Tx\leq r^2\}$$
 is convex Let $f(x)=rQ^{-1/2}x+x_c$

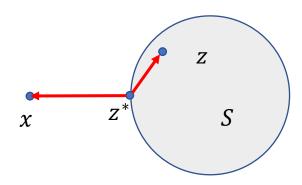
$$f(B(0,r)) = \{f(x)|x^Tx \le r^2\} = \{x|(x-x_c)^TQ(x-x_c) \le 1\}$$
 is convex

Projection onto closed convex sets

Theorem: Let $S \subseteq \mathbb{R}^n$ be non-empty, closed and convex. Then, for every $x \in \mathbb{R}^n$, there exists a unique point $z^* \in S$ that is closest to (in Euclidean norm) x.



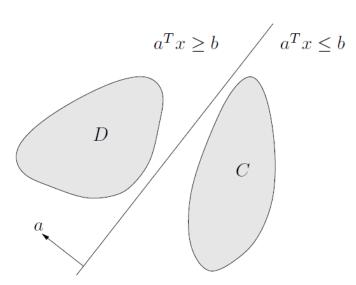
Theorem: Let $S \subseteq \mathbb{R}^n$ be non-empty, closed and convex. Given any $x \in \mathbb{R}^n$, we have $z^* = \Pi_S(x)$ iff $z^* \in S$ and $(z - z^*)^T (x - z^*) \le 0$ for all $z \in S$.



Separating hyperplane theorem

Theorem: If C and D are non-empty, disjoint (i.e., $C \cap D = \emptyset$) convex set, there exists $a \neq 0$ and b such that:

 $a^T x \leq b$ for all $x \in C$ and $a^T x \geq b$ for all $x \in D$.



Hyperplane $\{x | a^T x = b\}$ separates C and D

 $a^Tx < b$ for all $x \in C$ and $a^Tx > b$ for all $x \in D$ strictly separates C and D

Theorem (point-set separation): Let $S \subseteq \mathbb{R}^n$ be non-empty, closed and convex. Let $x \in \mathbb{R}^n \backslash S$. There exists an $a \in \mathbb{R}^n$ such that $\max_{z \in S} a^T z < a^T x$.

Supporting hyperplane theorem

Let $x_0 \in \mathbf{bd}(S)$. If $a \neq 0$ satisfies $a^T x \leq a^T x_0$ for all x in S, then the following hyperplane is a supporting hyperplane to S at the point x_0 :

boundary

$$\{x|a^Tx = a^Tx_0\}$$

Theorem: If S is non-empty convex set, there exists a *supporting hyperplane* at every boundary of S.

Interior point: A point $x \in S$ is an interior point of set S, if there exists an $\varepsilon > 0$ such that

$$\{y \mid ||x - y||_2 \le \varepsilon\} \subseteq S.$$



A ball centered at x that lies entirely in S.

Interior of set S int(S): the set of all interior points.

Closure of set
$$S$$
: **cl** $(S) \triangleq \mathbb{R}^n \setminus \text{int } (\mathbb{R}^n \setminus S)$, i.e., set S + its boundary

