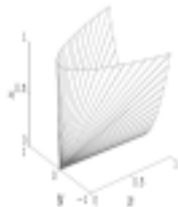


Positive semidefinite cone: **Primal Description**

Consider a positive semi-definite matrix S in \mathbb{R}^2 . Then S must be of the form

$$S = \begin{bmatrix} x & y \\ y & z \end{bmatrix} \quad (33)$$

We can represent the space of matrices \mathcal{S}_+^2 of the form $S \in \mathcal{S}_+^2$ as a three dimensional space with non-negative x , y and z coordinates and a non-negative determinant. This space



corresponds to a cone as shown in the Figure above.

Positive semidefinite cone: Dual Description

Instead of all vectors $\mathbf{z} \in \Re^n$, we can, without loss of generality, only require the above inequality to hold for all \mathbf{y} with $\|\mathbf{y}\|_2 = 1$.

① $S_+^n = \{A \in S^n | A \succeq 0\} = \{A \in S^n | \mathbf{y}^T A \mathbf{y} \succeq 0, \forall \|\mathbf{y}\|_2 = 1\}$

② So, $S_+^n = \bigcap_{\|\mathbf{y}\|=1} \{A \in S | \langle \mathbf{y}^T \mathbf{y}, A \rangle \succeq 0\}$

③ $\mathbf{y}^T A \mathbf{y} = \sum_i \sum_j y_i a_{ij} y_j = \sum_i \sum_j (y_i y_j) a_{ij} = \langle \mathbf{y} \mathbf{y}^T, A \rangle = \text{tr}((\mathbf{y} \mathbf{y}^T)^T A) = \text{tr}(\mathbf{y} \mathbf{y}^T A)$

▶ One parametrization for \mathbf{y} such that $\|\mathbf{y}\|_2 = 1$ is **Frobenius inner product**

$$\mathbf{y} = \begin{bmatrix} \cos(\theta) \\ \sin(\theta) \end{bmatrix} \quad (34)$$

$$\mathbf{y} \mathbf{y}^T = \begin{bmatrix} \cos^2(\theta) & \cos(\theta) \sin(\theta) \\ \cos(\theta) \sin(\theta) & \sin^2(\theta) \end{bmatrix} \quad (35)$$

▶ Assignment 1: Plot a finite # of halfspaces parameterized by (θ) .

Positive semidefinite cone: **Dual Description**

- 1 S_+^n = intersection of infinite # of half spaces belonging to $R^{n(n+1)/2}$ [Dual Representation]
 - 1 Cone boundary consists of all singular p.s.d. matrices having at-least one 0 eigenvalue.
 - 2 Origin = O = matrix with all 0 eigenvalues.
 - 3 Interior consists of all full rank matrices A ($\text{rank } A = m$) i.e. $A \succ 0$.

$$\text{HW: } N = \|\cdot\|_\infty, \quad M_N(A) = \sup_{\mathbf{x} \neq 0} \frac{N(A\mathbf{x})}{N(\mathbf{x})} = \sup_{\|\mathbf{x}\|=1} N(A\mathbf{x})$$

$$\textcircled{1} \text{ If } N(\mathbf{x}) = \max_i |x_i| \text{ then } N(A\mathbf{x}) = \max_i \left| \sum_{j=1}^m a_{ij} x_j \right| \leq \max_i \sum_{j=1}^m |a_{ij}| |x_j| \leq \max_i \sum_{j=1}^m |a_{ij}|$$

where the last inequality is attained by considering a $\mathbf{x} = [1, 1, \dots, 1]$ which has 1 in all positions. Then $\|\mathbf{x}\|_\infty = 1$ and for such an \mathbf{x} , the upper bounded on the supremum is indeed attained.

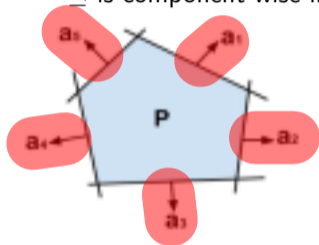
$$\textcircled{2} \text{ Therefore, it must be that } \|A\mathbf{x}\|_1 = \max_i \sum_{j=1}^m |a_{ij}| \text{ (the maximum absolute row sum)}$$

$\textcircled{3}$ That is,

$$M_N(A) = \|A\mathbf{x}\|_1 = \max_i \sum_{j=1}^m |a_{ij}|$$

Convex Polyhedron

- Solution set of finitely many inequalities or equalities: $Ax \preceq b$, $Cx \equiv d$
 - ▶ $A \in \mathbb{R}^{m \times n}$
 - ▶ $C \in \mathbb{R}^{p \times n}$
 - ▶ \preceq is component wise inequality



- This is a **Dual or H Description**: Intersection of finite number of half-spaces and hyperplanes.
- **Primal or V Description**: Can you define convex polyhedra in terms of convex hull?
 - 1 Convex hull of finite # of points \Rightarrow **Convex Polytope**
 - 2 Conic hull of finite # of points \Rightarrow **Polyhedral Cone**
 - 3 Convex hull of $n + 1$ affinely independent points \Rightarrow **Simplex**

V = vertices or points

Convex combinations and Convex Hull

- **Convex combination** of points $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_k$ is any point \mathbf{x} of the form

$$\mathbf{x} = \theta_1 \mathbf{x}_1 + \theta_2 \mathbf{x}_2 + \dots + \theta_k \mathbf{x}_k = \text{conv}(\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_k\})$$

with $\theta_1 + \theta_2 + \dots + \theta_k = 1, \theta_i \geq 0$.

- Equivalent Definition of Convex Set: C is convex iff it is closed under generalized convex combinations.
- **Convex hull** or $\text{conv}(S)$ is the set of all convex combinations of points in the set S .
- $\text{conv}(S) =$ The smallest convex set that contains S . S may not be convex but $\text{conv}(S)$ is.
 - ▶ Prove by contradiction that if a point lies in another smallest convex set, and not in $\text{conv}(S)$, then it must be in $\text{conv}(S)$.

S is a
finite
set
of points



Original set was not convex, whereas the convex hull is

- The idea of convex combination can be generalized to include infinite sums, integrals, and, in most general form, probability distributions.

Basic Prerequisite Topological Concepts in \mathbb{R}^n

Definition

[Balls in \mathbb{R}^n]: Consider a point $\mathbf{x} \in \mathbb{R}^n$. Then the closed ball around \mathbf{x} of radius ϵ is

$$\mathcal{B}[\mathbf{x}, \epsilon] = \{\mathbf{y} \in \mathbb{R}^n \mid \|\mathbf{y} - \mathbf{x}\| \leq \epsilon\}$$

Likewise, the open ball around \mathbf{x} of radius ϵ is defined as

$$\mathcal{B}(\mathbf{x}, \epsilon) = \{\mathbf{y} \in \mathbb{R}^n \mid \|\mathbf{y} - \mathbf{x}\| < \epsilon\}$$

For the 1-D case, open and closed balls degenerate to open and closed intervals respectively.

Definition

[Boundedness in \mathbb{R}^n]: We say that a set $\mathcal{S} \subset \mathbb{R}^n$ is *bounded* when there exists an $\epsilon > 0$ such that $\mathcal{S} \subseteq \mathcal{B}[0, \epsilon]$.

In other words, a set $\mathcal{S} \subseteq \mathbb{R}^n$ is bounded means that there exists a number $\epsilon > 0$ such that for all $\mathbf{x} \in \mathcal{S}$, $\|\mathbf{x}\| \leq \epsilon$.

Convex Polytope: **Primal** and **Dual** Descriptions

Dual or H Description: A Convex Polytope P is a **Bounded Convex Polyhedron**. That is, is solution set of finitely many inequalities or equalities: $P = \{\mathbf{x} \mid A\mathbf{x} \preceq \mathbf{b}, C\mathbf{x} = \mathbf{d}\}$ where $A \in \mathbb{R}^{m \times n}$, $C \in \mathbb{R}^{p \times n}$ such that P is also bounded.

Primal or V Description : If $\exists S \subset P$ s.t. $|S|$ is finite and $P = \text{conv}(S)$, then P is a **Convex Polytope**.

Conic combinations and Conic Hull

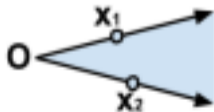


- Recap **Cone**: A set C is a cone if $\forall \mathbf{x} \in C, \theta \mathbf{x} \in C$ for $\theta \geq 0$.
- **Conic (nonnegative) Combination** of points $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_k$ is any point \mathbf{x} of the form

$$\mathbf{x} = \theta_1 \mathbf{x}_1 + \theta_2 \mathbf{x}_2 + \dots + \theta_k \mathbf{x}_k$$

with $\theta_i \geq 0$.

- **Conic hull or conic(S)**: The set that contains all conic combinations of points in set S .



- $\text{conic}(S) =$ Smallest conic set that contains S .

Polyhedral Cone: **Primal** and **Dual** Descriptions

Dual or H Description : A Polyhedral Cone P is a Convex Polyhedron with $\mathbf{b} = 0$. That is, $\{\mathbf{x} | A\mathbf{x} \succeq 0\}$ where $A \in \Re^{m \times n}$ and \succeq is component wise inequality.

Primal or V Description : If $\exists S \subset P$ s.t. $|S|$ is finite and $P = \text{cone}(S)$, then P is a **Polyhedral Cone**.

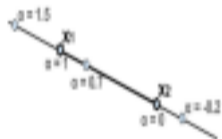
Affine combinations, Affine hull and Dimension of a set S

- **Affine Combination** of points $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_k$ is any point \mathbf{x} of the form

$$\mathbf{x} = \theta_1 \mathbf{x}_1 + \theta_2 \mathbf{x}_2 + \dots + \theta_k \mathbf{x}_k$$

$$\text{with } \sum_i \theta_i = 1$$

- **Affine hull or $\text{aff}(S)$** : The set that contains all affine combinations of points in set S = Smallest affine set that contains S .



-
- Dimension of a set S = dimension of $\text{aff}(S)$ = dimension of vector space V such that $\text{aff}(S) = \mathbf{v} + V$ for some $\mathbf{v} \in \text{aff}(S)$.
- $S = \{\mathbf{x}_0, \mathbf{x}_1, \dots, \mathbf{x}_{n+1}\}$ is set of $n+1$ *affinely independent* points if $\{\mathbf{x}_1 - \mathbf{x}_0, \mathbf{x}_2 - \mathbf{x}_0, \dots, \mathbf{x}_{n+1} - \mathbf{x}_0\}$ are linearly independent.

Simplex (plural: simplexes) Polytope: **Primal** and **Dual** Descriptions

Dual or H Description: An n Simplex S is a convex Polytope with of affine dimension n and having $n + 1$ corners. That is, is solution set of finitely many inequalities or equalities: $S = \{\mathbf{x} \mid A\mathbf{x} \preceq \mathbf{b}, C\mathbf{x} = \mathbf{d}\}$ where $A \in \mathbb{R}^{m \times n}$, $C \in \mathbb{R}^{p \times n}$ such that S with affine dimension n and having $n + 1$ corners.

Primal or V Description: Convex hull of $n + 1$ affinely independent points. Specifically, let $S = \{\mathbf{x}_0, \mathbf{x}_1, \dots, \mathbf{x}_{n+1}\}$ be a set of $n + 1$ affinely independent points, then an n -dimensional simplex is $\text{conv}(S)$.

Simplex is a generalization of the notion of a triangle or tetrahedron to arbitrary dimensions.

Convexity preserving operations

Assignment 1 is about ascertaining convexity or non-convexity and other properties of a whole bunch of sets

In practice if you want to establish the convexity of a set \mathcal{C} , you could either

- 1 prove it from first principles, *i.e.*, using the definition of convexity or
- 2 prove that \mathcal{C} can be built from simpler convex sets through some basic operations which preserve convexity.

Some of the important operations that preserve convexity are:

- 1 Intersection
- 2 Affine Transform
- 3 Perspective and Linear Fractional Function

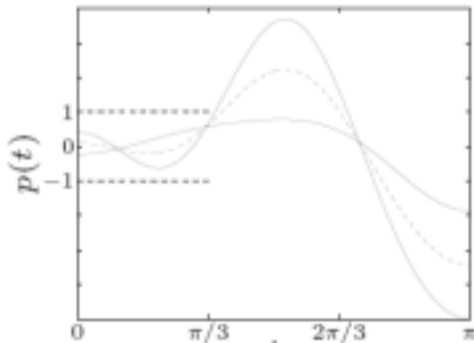
Closure under Intersection

The intersection of any number of convex sets is convex. Consider the set \mathcal{S} :

$$\mathcal{S} = \left\{ \mathbf{x} \in \mathbb{R}^n \mid |p(t)| \leq 1 \text{ for } |t| \leq \frac{\pi}{3} \right\} \quad (36)$$

where

$$p(t) = x_1 \cos t + x_2 \cos 2t + \dots + x_m \cos mt \quad (37)$$



$p(t)$ plotted for
different values of
 $x_1 \dots x_m$

Closure under Intersection (contd.)

Any value of t that satisfies $|p(t)| \leq 1$, defines two regions, viz.,

$$\mathcal{R}^{\leq}(t) = \{ \mathbf{x} \mid x_1 \cos t + x_2 \cos 2t + \dots + x_m \cos mt \leq 1 \}$$

and

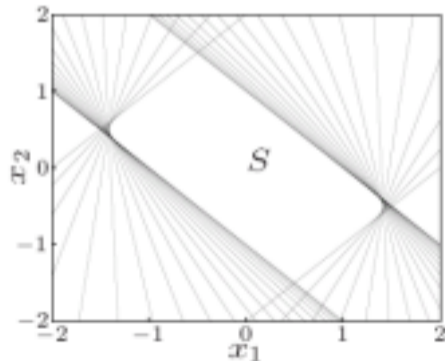
$$\mathcal{R}^{\geq}(t) = \{ \mathbf{x} \mid x_1 \cos t + x_2 \cos 2t + \dots + x_m \cos mt \geq -1 \}$$

Each of these regions is convex and for a given value of t , the set of points that may lie in \mathcal{S} is given by $\mathcal{R}(t) = \mathcal{R}^{\leq}(t) \cap \mathcal{R}^{\geq}(t)$

Closure under Intersection (contd.)

$\mathcal{R}(t)$ is also convex. However, not all the points in $\mathcal{R}(t)$ lie in \mathcal{S} , since the points that lie in \mathcal{S} satisfy the inequalities for every value of t . Thus, \mathcal{S} can be given as:

$$\mathcal{S} = \bigcap_{|t| \leq \frac{\pi}{3}} \mathcal{R}(t)$$



Closure under Affine transform

An affine transform is one that preserves

- Collinearity between points, *i.e.*, three points which lie on a line continue to be collinear after the transformation.
- Ratios of distances along a line, *i.e.*, for distinct collinear points $\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_3$, $\frac{\|\mathbf{p}_2 - \mathbf{p}_1\|}{\|\mathbf{p}_3 - \mathbf{p}_2\|}$ is preserved.

Verify that affine transformation preserves these..

An affine transformation or affine map between two vector spaces $f: \mathbb{R}^n \rightarrow \mathbb{R}^m$ consists of a linear transformation followed by a translation:

$$\mathbf{x} \mapsto A\mathbf{x} + \mathbf{b}$$

where $A \in \mathbb{R}^{n \times m}$ and $\mathbf{b} \in \mathbb{R}^m$.

Closure under Affine transform (contd.)

In the finite-dimensional case each affine transformation is given by a matrix A and a vector \mathbf{b} . The image and pre-image of convex sets under an affine transformation defined as

$$f(\mathbf{x}) = \sum_i^n x_i a_i + b$$

yield convex sets⁸. Here a_i is the i^{th} row of A . The following are examples of convex sets that are either images or inverse images of convex sets under affine transformations:

- 1 the solution set of linear matrix inequality ($A_i, B \in \mathcal{S}^m$)

$$\{\mathbf{x} \in \mathbb{R}^n \mid x_1 A_1 + \dots + x_n A_n \preceq B\}$$

is a convex set. Here $A \preceq B$ means $B - A$ is positive semi-definite⁹. This set is the inverse image under an affine mapping of the **positive semidefinite cone**

⁸Exercise: Prove.

⁹The inequality induced by positive semi-definiteness corresponds to a generalized inequality \preceq_K with $K = \mathcal{S}_+^n$.

Closure under Affine transform (contd.) H/W: Prove

In the finite-dimensional case each affine transformation is given by a matrix A and a vector \mathbf{b} . The image and pre-image of convex sets under an affine transformation defined as

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$$\{\mathbf{x} \in \mathbb{R}^n \mid x_1 A_1 + \dots + x_n A_n \preceq B\}$$

is a convex set. Here $A \preceq B$ means $B - A$ is positive semi-definite⁹. This set is the inverse image under an affine mapping of the positive semi-definite cone. That is, $f^{-1}(\text{cone}) =$

$$\{\mathbf{x} \in \mathbb{R}^n \mid B - (x_1 A_1 + \dots + x_n A_n) \in \mathcal{S}_+^m\} = \{\mathbf{x} \in \mathbb{R}^n \mid B \succeq (x_1 A_1 + \dots + x_n A_n)\}.$$

⁸Exercise: Prove.

⁹The inequality induced by positive semi-definiteness corresponds to a generalized inequality \preceq_K with $K = \mathcal{S}_+^n$.

Closure under Affine transform (contd.)

- ② hyperbolic cone ($P \in \mathcal{S}_+^n$), which is the inverse image of the

Closure under Affine transform (contd.)

- ② hyperbolic cone ($P \in S_+^n$), which is the inverse image of the norm cone $\mathcal{C}_{m+1} = \{(\mathbf{z}, u) \mid \|\mathbf{z}\| \leq u, u \geq 0, \mathbf{z} \in \mathbb{R}^m\} = \{(\mathbf{z}, u) \mid \mathbf{z}^T \mathbf{z} - u^2 \leq 0, u \geq 0, \mathbf{z} \in \mathbb{R}^m\}$ is a convex set. The inverse image is given by

$$f^{-1}(\mathcal{C}_{m+1}) = \left\{ \mathbf{x} \in \mathbb{R}^n \mid (A\mathbf{x}, \mathbf{c}^T \mathbf{x}) \in \mathcal{C}_{m+1} \right\} = \left\{ \mathbf{x} \in \mathbb{R}^n \mid \mathbf{x}^T A^T A \mathbf{x} - (\mathbf{c}^T \mathbf{x})^2 \leq 0 \right\}.$$

Setting, $P = A^T A$, we get the equation of the hyperbolic cone:

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

Closure under Perspective and linear-fractional functions

H/w: Prove

The perspective function $P: \mathbb{R}^{n+1} \rightarrow \mathbb{R}^n$ is defined as follows:

$$P: \mathbb{R}^{n+1} \rightarrow \mathbb{R}^n \text{ such that } \begin{array}{l} \text{Shrinks from } n+1 \text{ to } n \text{ by division using } t \\ P(x, t) = x/t \end{array} \quad \text{dom } P = \{(x, t) \mid t > 0\} \quad (38)$$

The linear-fractional function f is a generalization of the perspective function and is defined as:
 $\mathbb{R}^n \rightarrow \mathbb{R}^m$:

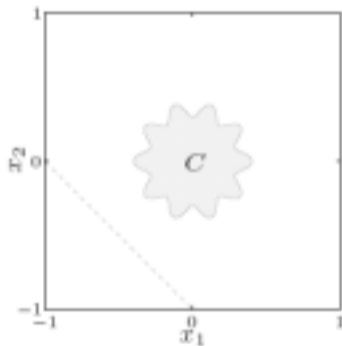
$$f: \mathbb{R}^n \rightarrow \mathbb{R}^m \text{ such that } \quad \text{dom } f = \{x \mid c^T x + d > 0\} \quad (39)$$
$$f(x) = \frac{Ax+b}{c^T x + d}$$

The images and inverse images of convex sets under perspective and linear-fractional functions are convex¹⁰.

¹⁰Exercise: Prove.

Closure under Perspective and linear-fractional functions (contd)

The Figure below shows an example set.



Closure under Perspective and linear-fractional functions (contd)

Consider the linear-fractional function $f = \frac{1}{x_1+x_2+1}x$. The following Figure shows the image of the set (from the previous slide) under the linear-fractional function f .

