

# Convex Sets (I)

Lecture 1, Nonlinear Programming, (Part b)

National Taiwan University

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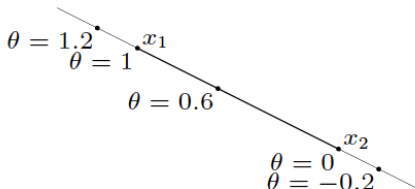
# Line

## Line

Let  $x_1, x_2 \in \mathbf{R}^n$  and  $x_1 \neq x_2$ . The set of all points

$$\{\theta x_1 + (1 - \theta)x_2 \mid \theta \in \mathbf{R}\}$$

is called a **line** passing through  $x_1$  and  $x_2$ .



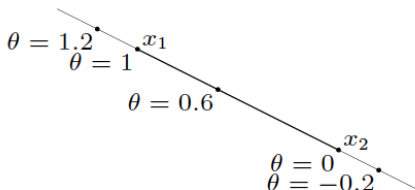
# Line Segment

## Line Segment

Let  $x_1, x_2 \in \mathbf{R}^n$  and  $x_1 \neq x_2$ . The set of all points

$$\{\theta x_1 + (1 - \theta)x_2 \mid \theta \in \mathbf{R}, 0 \leq \theta \leq 1\}$$

is called a **(closed) line segment** between  $x_1$  and  $x_2$ .



# Line and Line Segment

## Line and Line Segment

Let  $x_1, x_2 \in \mathbf{R}^n$  and  $x_1 \neq x_2$ . The set of all points

$$\{\theta x_1 + (1 - \theta)x_2 \mid \theta \in \mathbf{R}\}$$

is called a **line** passing through  $x_1$  and  $x_2$ . The set of all points

$$\{\theta x_1 + (1 - \theta)x_2 \mid \theta \in \mathbf{R}, 0 \leq \theta \leq 1\}$$

is called a **(closed) line segment** between  $x_1$  and  $x_2$ .

Another interpretation:

$$y = x_2 + \theta(x_1 - x_2)$$

is the sum of the **base point**  $x_2$  and the **direction**  $x_1 - x_2$  scaled by the parameter  $\theta$ .

# Affine Sets

## Affine Sets

A set  $C \subseteq \mathbf{R}^n$  is **affine** if the line through any two distinct points in  $C$  lies in  $C$ . That is,

$$x_1, x_2 \in C, \theta \in \mathbf{R} \Rightarrow \theta x_1 + (1 - \theta)x_2 \in C.$$

## Affine Combination

Let  $x_1, x_2, \dots, x_k \in \mathbf{R}^n$ . Then, a point of the form

$$\theta_1 x_1 + \dots + \theta_k x_k$$

with  $\theta_1 + \dots + \theta_k = 1$  is referred to as an **affine combination** of the points  $x_1, x_2, \dots, x_k$ .

# Affine Sets

## Affine Sets and Subspaces

If  $C$  is an **affine set** and  $x_0 \in C$ , then the set

$$V = C - x_0 = \{x - x_0 \mid x \in C\}$$

is a **subspace**.

\* Note that the subspace  $V$  associated with  $C$  does not depend on the choice of  $x_0$ .

Proof:

# Dimension of Affine Set

## Dimension of Affine Set

The **dimension** of an affine set  $C$  is defined as the **dimension** of the **subspace**  $V = C - x_0$  where  $x_0$  is any element of  $C$ .



## Example: Solution set of linear equations (1/2)

### Solution set of linear equations

The solution set of a system of linear equations

$$C = \{x \mid Ax = b\}$$

where  $A \in \mathbf{R}^{m \times n}$  and  $b \in \mathbf{R}^m$  is an **affine set**.

Proof:

## Example: Solution set of linear equations (2/2)

### Solution set of linear equations

The solution set of a system of linear equations

$$C = \{x \mid Ax = b\}$$

where  $A \in \mathbf{R}^{m \times n}$  and  $b \in \mathbf{R}^m$  is an **affine set**.

- The **subspace** associated with the **affine set**  $C$  is the **nullspace** of  $A$ .
- Converse: every **affine set** can be expressed as the solution set of **system of linear equations**.

# Affine Hull

## Affine Hull

The set of all **affine combinations** of points in some set  $C \subseteq \mathbb{R}^n$  is called the **affine hull** of  $C$ , denoted **aff**  $C$ :

$$\text{aff } C = \{\theta_1 x_1 + \cdots + \theta_k x_k \mid x_1, \dots, x_k \in C, \theta_1 + \cdots + \theta_k = 1\}.$$

The **affine hull** is the smallest affine set that contains  $C$ :

- If  $S$  is any affine set with  $C \subseteq S$ , then **aff**  $C \subseteq S$ .

# Affine Dimension

## Affine dimension

The **affine dimension** of  $C$ , a subset of  $\mathbf{R}^n$ , is defined by the **dimension** of its **affine hull**.

## Example

Let  $C = \{x \in \mathbf{R}^2 \mid x_1^2 + x_2^2 = 1\}$ . What is the **affine dimension** of  $C$ ?

# Interior

## Interior point

An element  $x \in C \subseteq \mathbf{R}^n$  is called an **interior point** of  $C$  if there exists an  $\epsilon > 0$  for which

$$\{y \mid \|y - x\|_2 \leq \epsilon\}$$

is a subset of  $C$ .

## Interior

The set of all points **interior** to  $C$  is called the **interior** of  $C$ , denoted **int**  $C$ :

$$\text{int}C = \{y \mid y \in C \text{ and } y \text{ is an interior point of } C\}$$

# Relative Interior

Consider a set  $C \subseteq \mathbf{R}^n$  whose affine dimension is less than  $n$ . That is,  $\text{aff } C \neq \mathbf{R}^n$ . What is the **interior** of  $C$ ?

## Relative Interior

The **relative interior** of the set  $C$ , denoted **relint** $C$ , is defined as its **interior** relative to **aff**  $C$ :

$$\text{relint } C = \{x \in C \mid B(x, r) \cap \text{aff } C \subseteq C \text{ for some } r > 0\}$$

where  $B(x, r) = \{y \mid \|y - x\|_2 \leq r\}$ .

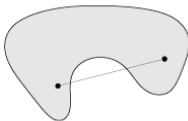
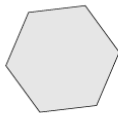
# Convex Sets

## Convex Set

A set  $C$  is **convex** if the **line segment** between any two points in  $C$  lies in  $C$ . That is, for any  $x_1, x_2 \in C$  and any  $\theta$  with  $0 \leq \theta \leq 1$ , we have

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

Example: which of following is convex?



Example: Every **affine set** is also **convex**. Any **line segment** is also convex.

# Convex Combination

## Convex combination

A point of the form  $\theta_1 x_1 + \dots + \theta_k x_k$ , where  $\theta_1 + \dots + \theta_k = 1$  and  $\theta_i \geq 0$ ,  $i = 1, \dots, k$ , is called a **convex combination** of the points  $x_1, \dots, x_k$ .

## Property

A set is **convex** if and only if it contains every **convex combination** of its points.



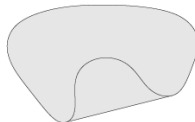
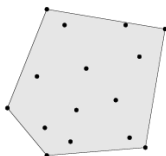
# Convex Hull

## Convex Hull

The **convex hull** of a set  $C$ , denoted **conv**  $C$ , is the set of all **convex combinations** of points in  $C$ :

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

Property: the **convex hull** **conv**  $C$  is always **convex**. It is the smallest convex set that contains  $C$ .



# Generalized Definitions of Convex Combinations

- Infinite sum:
  - If  $C$  is convex and let  $x_1, x_2, \dots \in C$ , then  $\sum_{i=1}^{\infty} \theta_i x_i \in C$  where  $\theta_i \geq 0, i = 1, 2, \dots$  and  $\sum_{i=1}^{\infty} \theta_i = 1$ .
- Integral:
  - Let  $C$  be a convex set. Consider a function  $p : \mathbf{R}^n \rightarrow \mathbf{R}$  that satisfies  $p(x) \geq 0 \forall x \in C$  and  $\int_C p(x) dx = 1$ . Then  $\int_C p(x)x dx \in C$ .
- Probability distributions (most general form)
  - Suppose  $C \subseteq \mathbf{R}^n$  is convex and  $x$  is a random vector with  $x \in C$  with probability one. Then  $\mathbf{E}[x] \in C$ .

# On Various Types of “Combinations”

Compare “linear combination,” “affine combination,” and “convex combination”. All of these three types of combinations can be defined as the set  $\{\theta_1 x_1 + \dots + \theta_k x_k\}$  with certain constraints on the coefficients  $\theta_1, \dots, \theta_k$ .

Type	Constraints on $\theta_i$	Set of all combinations
linear combination	$\theta_1, \dots, \theta_k \in \mathbf{R}$	span
affine combination	$\theta_1 + \dots + \theta_k = 1$	affine hull
convex combination	$\theta_1 + \dots + \theta_k = 1, \theta_i \geq 0$	convex hull

# Cones

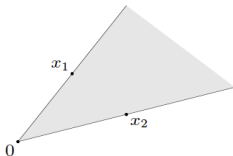
## Cone

A set  $C$  is called a **cone** if for every  $x \in C$  and  $\theta \geq 0$  we have  $\theta x \in C$ . The set  $C$  is also said to be **nonnegative homogeneous**.

## Convex Cone

A set  $C$  is called a **convex cone** if it is convex and is a cone. That is, for any  $x_1, x_2 \in C$  and  $\theta_1, \theta_2 \geq 0$  we have

$$\theta_1 x_1 + \theta_2 x_2 \in C.$$



# Conic Combination

## Conic combination

A point of the form  $\theta_1 x_1 + \cdots + \theta_k x_k$  with  $\theta_1, \dots, \theta_k \geq 0$  is called a **conic combination** (or a **nonnegative linear combination**) of  $x_1, x_2, \dots, x_k$ .

- Property: If  $x_i$  are in a **convex cone**  $C$ , then every **conic combination** of  $x_i$  is in  $C$ .
- Property: A set  $C$  is a **convex cone** if and only if it contains all **conic combinations** of its elements.
- Generalized definitions: the idea of **conic combination** can be generalized to **infinite sums** and **integrals**.

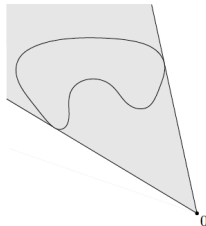
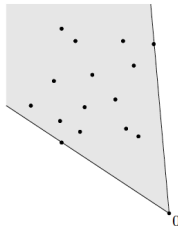
# Conic Hull

## Conic hull

The **conic hull** of a set  $C$  is the set of all conic combinations of points in  $C$ :

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

Property: The **conic hull** of a set  $C$  is the smallest **convex cone** that contains  $C$ .



# Some Simple Examples of Affine / Convex Sets / Cones

- The empty set  $\phi$  is **affine** (and hence **convex**).
- Any single point (i.e., **singleton**)  $\{x_0\}$  is **affine** (and **convex**).
- The whole space  $\mathbf{R}^n$  is **affine** (and **convex**).
- Any **subspace** is **affine**, and a **convex cone**.
- Any **line** is **affine**. If it passes through zero, it is a **subspace**, and also a **convex cone**.
- A **line segment** is **convex**, but is in general not **affine**.
- A **ray**, having the form  $\{x_0 + \theta v \mid \theta \geq 0\}$ , where  $v \neq 0$ , is **convex** but not **affine**. If  $x_0 = 0$ , then it is a **convex cone**.

# Hyperplane

## Hyperplane

A **hyperplane** is a set of the form

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

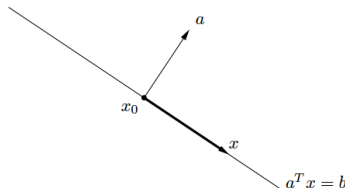
where  $a \in \mathbf{R}^n$ ,  $a \neq 0$ , and  $b \in \mathbf{R}$ .

- A **hyperplane** is the solution set of a nontrivial linear equation among components of  $x$ . So, a **hyperplane** is **affine**.
- The vector  $a$  is called the **normal vector** of the **hyperplane**. Every point in the hyperplane has a constant inner product with the normal vector  $a$ .
- The constant  $b \in \mathbf{R}$  determines the offset of the hyperplane from 0.



# Hyperplane

- The hyperplane  $\{x \mid a^T x = b\}$  can be rewritten as  $\{x \mid a^T (x - x_0) = 0\}$ , where  $x_0$  is any point in the hyperplane.



- Further, we can write

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

where  $a^\perp$  denotes the **orthogonal complement** of  $a$ :  
 $a^\perp = \{v \mid a^T v = 0\}$ .

# Halfspaces

A **hyperplane** divides  $\mathbf{R}^n$  into two **halfspaces**.

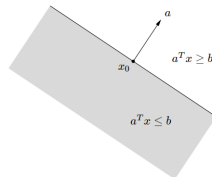
## Halfspaces

A (closed) **halfspace** is a set of the form

$$\{x \mid a^T x \leq b\},$$

where  $a \neq 0$ .

- A **halfspace** is the solution set of one (nontrivial) linear inequality.
- **Halfspaces** are **convex**, but not **affine**.

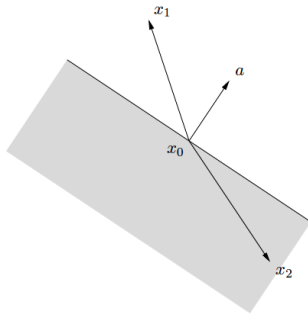


# Halfspaces

- The halfspace  $\{x \mid a^T x \leq b\}$  can also be rewritten as

$$\{x \mid a^T (x - x_0) \leq 0\},$$

where  $x_0$  is any point on the associated hyperplane (i.e.,  $a^T x_0 = b$ ).



# Halfspaces

- The boundary of the halfspace  $\{x \mid a^T x \leq b\}$  is the hyperplane  $\{x \mid a^T x = b\}$ .
- The set

$$\{x \mid a^T x < b\}$$

is the **interior** of the **halfspace**  $\{x \mid a^T x \leq b\}$ . It is called an **open halfspace**.

# Euclidean Balls

## Euclidean ball

A **Euclidean ball** (or just **ball**) in  $\mathbb{R}^n$  has the form

$$B(x_c, r) = \{x \mid \|x - x_c\|_2 \leq r\} = \left\{x \mid (x - x_c)^T (x - x_c) \leq r^2\right\}$$

where  $r > 0$  and  $\|\cdot\|_2$  denotes the **Euclidean norm**.

The vector  $x_c$  is the **center** of the **ball**. The scalar  $r$  is its **radius**.

- $B(x_c, r)$  consists of all points within a distance  $r$  of the **center**  $x_c$ .
- The Euclidean ball can be rewritten as

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

# Euclidean Balls

## Property

A **Euclidean ball** is a convex set.

Proof:

# Ellipsoid

## Ellipsoid

An **ellipsoid** has the form

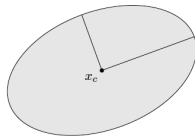
$$\mathcal{E} = \left\{ x \mid (x - x_c)^T P^{-1} (x - x_c) \leq 1 \right\},$$

where  $P$  is **symmetric** and **positive definite**:  $P = P^T \succ 0$ .

The vector  $x_c \in \mathbb{R}^n$  is the **center** of the **ellipsoid**.

- The lengths of the semi-axes of  $\mathcal{E}$  are given by  $\sqrt{\lambda_i}$  where  $\lambda_i$  are the eigenvalues of  $P$ .
- A **ball** is an **ellipsoid** with  $P = r^2 I$ .
- An **ellipsoid** is **convex**.

# Ellipsoid



- The ellipsoid  $\mathcal{E} = \{x \mid (x - x_c)^T P^{-1}(x - x_c) \leq 1\}$  can be rewritten as

$$\mathcal{E} = \{x_c + Au \mid \|u\|_2 \leq 1\}$$

where  $A$  is square and nonsingular.

- W.l.o.g., we can assume  $A$  is **symmetric** and **positive definite** (by taking  $A = P^{1/2}$ ).



# Degenerate Ellipsoid

- If  $A$  is symmetric positive semidefinite but singular, then the set  $\mathcal{E} = \{x_c + Au \mid \|u\|_2 \leq 1\}$  is called a **degenerate ellipsoid**.
- Its affine dimension is rank  $A$ .
- Degenerate ellipsoids are also convex.

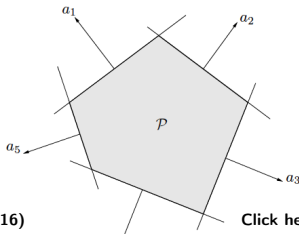
# Polyhedra

## Polyhedron

A **polyhedron** is defined as the solution set of a finite number of linear equations and linear inequalities:

$$\mathcal{P} = \left\{ x \mid a_j^T x \leq b_j, j = 1, \dots, m, c_j^T x = d_j, j = 1, \dots, p \right\}.$$

- A **polyhedron** is the **intersection** of a finite number of **halfspaces** and **hyperplanes**.



# Polyhedra

- Polyhedra are convex sets.
- Affine sets (including subspaces, hyperplanes, and lines) are polyhedra.
- Rays, line segments, and hyperplanes are polyhedra.
- A bounded polyhedron is called a polytope.

# Polyhedra

The polyhedron

$$\mathcal{P} = \left\{ x \mid a_j^T x \leq b_j, j = 1, \dots, m, c_j^T x = d_j, j = 1, \dots, p \right\}$$

can be rewritten as

$$P = \{x \mid Ax \preceq b, Cx = d\}$$

where

$$A = \begin{bmatrix} a_1^T \\ \vdots \\ a_m^T \end{bmatrix} \text{ and } C = \begin{bmatrix} c_1^T \\ \vdots \\ c_p^T \end{bmatrix},$$

and the symbol  $\preceq$  denotes **vector inequality** or **componentwise inequality** in  $\mathbf{R}^m$ :  $u \preceq v$  means  $u_i \leq v_i$  for  $i = 1, \dots, m$ .

## Polyhedra – An example

The set of nonnegative numbers

Let  $\mathbf{R}_+$  denote the set of **nonnegative numbers**. Let  $\mathbf{R}_{++}$  denote the set of **positive numbers**.

Nonnegative orthant

The **nonnegative orthant** in  $\mathbf{R}^n$  is

$$\mathbf{R}_+^n = \{x \in \mathbf{R}^n \mid x_i \geq 0, i = 1, \dots, n\} = \{x \in \mathbf{R}^n \mid x \succeq 0\}.$$

- The **nonnegative orthant** is a **polyhedron** and a **cone** (called a **polyhedral cone**).

# Simplexes – Another example of polyhedra

## Affinely Independent

The  $k + 1$  points  $v_0, v_1, \dots, v_k \in \mathbf{R}^n$  are called **affinely independent** if  $\{v_1 - v_0, \dots, v_k - v_0\}$  is **linearly independent**.

## Simplex

Suppose the  $k + 1$  points  $v_0, v_1, \dots, v_k \in \mathbf{R}^n$  are **affinely independent**. The **simplex** determined by these  $k + 1$  points is

$$C = \text{conv} \{v_0, \dots, v_k\} = \left\{ \theta_0 v_0 + \dots + \theta_k v_k \mid \theta \succeq 0, \mathbf{1}^T \theta = 1 \right\}$$

where  $\mathbf{1}$  is the vector with all entries one.

- The above defined simplex is sometimes called a  **$k$ -dimensional simplex in  $\mathbf{R}^n$** , since its **affine dimension** is  $k$ .

# Examples of Simplexes

- A 1-dimensional simplex is a line segment.
- A 2-dimensional simplex is a triangle (including its interior).
- A 3-dimensional simplex is a tetrahedron.

## Unit Simplex

The unit simplex in  $\mathbb{R}^n$  is the  $n$ -dimensional simplex determined by the zero vector and the unit vectors:  $\{0, e_1, \dots, e_n\}$ .

The unit simplex can be expressed as

$$\left\{ x \mid x \succeq 0, \mathbf{1}^T x \leq 1 \right\}.$$

## Example of Simplexes – Probability Simplex

- The **probability simplex** in  $\mathbf{R}^n$  is the  $(n - 1)$ -dimensional **simplex** determined by the **unit vectors**  $\{e_1, \dots, e_n\}$ .
- It can be expressed as

$$\left\{ x \mid x \succeq 0, \mathbf{1}^T x = 1 \right\}.$$

- Vectors in the **probability simplex** corresponds to **probability distributions** on a set with  $n$  elements.



# Expressing A Simplex as A Polyhedron

- Consider the simplex

$$C = \text{conv} \{v_0, \dots, v_k\} = \left\{ \theta_0 v_0 + \dots + \theta_k v_k \mid \theta \succeq 0, \mathbf{1}^T \theta = 1 \right\}$$

- Let

$$B = \begin{bmatrix} v_1 - v_0 & \dots & v_k - v_0 \end{bmatrix} \in \mathbf{R}^{n \times k}$$

and  $A = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix} \in \mathbf{R}^{n \times n}$  be a **nonsingular matrix** such that

$$AB = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix} B = \begin{bmatrix} I_k \\ 0_{(n-k) \times k} \end{bmatrix}.$$

- Then, we have  $x \in C$  if and only if

$$A_2 x = A_2 v_0, \quad A_1 x \succeq A_1 v_0, \quad \mathbf{1}^T A_1 x \leq 1 + \mathbf{1}^T A_1 v_0.$$

(a form of a polyhedron)

# Convex Hull Description of Polyhedra

- Consider the **convex hull** of the finite set  $\{v_1, \dots, v_k\}$ ,

$$\begin{aligned} & \text{conv} \{v_1, \dots, v_k\} \\ &= \{ \theta_1 x_1 + \dots + \theta_k x_k \mid \theta_i \geq 0, i = 1, \dots, k, \theta_1 + \dots + \theta_k = 1 \} \\ &= \left\{ \theta_1 x_1 + \dots + \theta_k x_k \mid \theta \succeq 0, \mathbf{1}^T \theta = 1 \right\} \end{aligned}$$

- It is a **polyhedra** and is **bounded**. (why?)
- How can we express  $\text{conv} \{v_1, \dots, v_k\}$  in the form

$$\mathcal{P} = \left\{ x \mid a_j^T x \leq b_j, j = 1, \dots, m, c_j^T x = d_j, j = 1, \dots, p \right\}?$$

# Convex Hull Description of Polyhedra

- Conversely, how do we express a polyhedron

$$\mathcal{P} = \left\{ x \mid a_j^T x \leq b_j, j = 1, \dots, m, c_j^T x = d_j, j = 1, \dots, p \right\}$$

in the form of convex hull description **conv**  $\{v_1, \dots, v_k\}$ ?

- Example: consider

$$C = \{x \mid |x_i| \leq 1, i = 1, \dots, n\}$$

(with  $2n$  linear inequalities). Then we have

$$C = \mathbf{conv} \{v_1, \dots, v_{2^n}\},$$

where  $v_1, \dots, v_{2^n}$  are the  $2^n$  vectors whose components are all 1 or  $-1$ .

# Notations for Sets of Symmetric Matrices

- The notation  $\mathbf{S}^n$  denotes the set of symmetric  $n \times n$  matrices:

$$\mathbf{S}^n = \{X \in \mathbf{R}^{n \times n} \mid X = X^T\}.$$

- $\mathbf{S}^n$  is a vector space with dimension  $n(n+1)/2$ .
- The notation  $\mathbf{S}_+^n$  denotes the set of symmetric positive semidefinite matrices:

$$\mathbf{S}_+^n = \{X \in \mathbf{S}^n \mid X \succeq 0\}.$$

- The notation  $\mathbf{S}_{++}^n$  denotes the set of symmetric positive definite matrices:

$$\mathbf{S}_{++}^n = \{X \in \mathbf{S}^n \mid X \succ 0\}.$$

# Positive Semidefinite Cone

## Convexity of Positive Semidefinite Cones

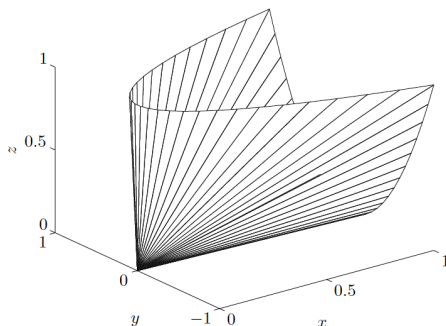
The set  $\mathbf{S}_+^n$  is a **convex cone**:

if  $\theta_1, \theta_2 \geq 0$  and  $A, B \in \mathbf{S}_+^n$ , then  $\theta_1 A + \theta_2 B \in \mathbf{S}_+^n$ .

Proof:

# Positive Semidefinite Cone in $\mathbf{S}^2$

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



# Norm balls and Norm Cones

## Norm balls and Norm Cones

- Suppose  $\|\cdot\|$  is a **norm** on  $\mathbf{R}^n$ .
- It can be shown that a **norm ball** of radius  $r$  and center  $x_c$ , given by  $\{x \mid \|x - x_c\| \leq r\}$ , is **convex**.
- The **norm cone** associated with the norm  $\|\cdot\|$  is the set

$$C = \{(x, t) \mid \|x\| \leq t\} \subseteq \mathbf{R}^{n+1}.$$

## Second-Order Cone

The **second-order cone** is the norm cone for the Euclidean norm, i.e.,

$$\begin{aligned} C &= \left\{ (x, t) \in \mathbf{R}^{n+1} \mid \|x\|_2 \leq t \right\} \\ &= \left\{ \begin{bmatrix} x \\ t \end{bmatrix} \mid \begin{bmatrix} x \\ t \end{bmatrix}^T \begin{bmatrix} I & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} x \\ t \end{bmatrix} \leq 0, \quad t \geq 0 \right\}. \end{aligned}$$

It is also known as the **quadratic cone**, the **Lorentz cone**, or **ice-cream cone**.

