



# **MECH 6v29.002 – Model Predictive Control**

Tuesday and Thursday 8:30 – 9:45am

L3 – Math Background

- Mathematical Background for MPC
  - Vectors
  - Matrices
  - Sets
  - Functions
- Note:
  - Not intended to be complete, focus on common assumptions and operations for MPC
  - Notation is not always consistent in the literature, so ask questions throughout the semester
  - Let me know what topics are new to you so that I can improve this review in the future!



## Functions:

- Continuous
- Convex
- Lipschitz
- Comparison

Cost  
function

$$\min_{U_t} \sum_{k=t}^{t+N-1} J(x_k, u_k) + J_T(x_{t+N}, u_{t+N})$$

$$s.t. \quad \forall k = t, \dots, t + N - 1$$

$$x_{k+1} = Ax_k + Bu_k$$

Model

Constraints

$$u_k \in \mathcal{U}, \quad x_k \in \mathcal{X}, \quad y_k = g(x_k, u_k) \in \mathcal{Y}$$

$$x_t = x(t)$$

## Vectors and Matrices:

- Notation
- Norms
- Spaces

## Sets

- Compact
- Convex
- Representations
- Operations

For more mathematical background, see:

- Appendix A of *Model Predictive Control: Theory, Computation, and Design 2<sup>nd</sup> Edition* by Rawlings, Mayne, and Diehl, 2019.
- Appendix A of *Convex Optimization* by Boyd and Vandenberghe, 2009.

- Vector notation

- $x$  is a vector,  $x_i$  are scalars

$$x \in \mathbb{R}^n$$

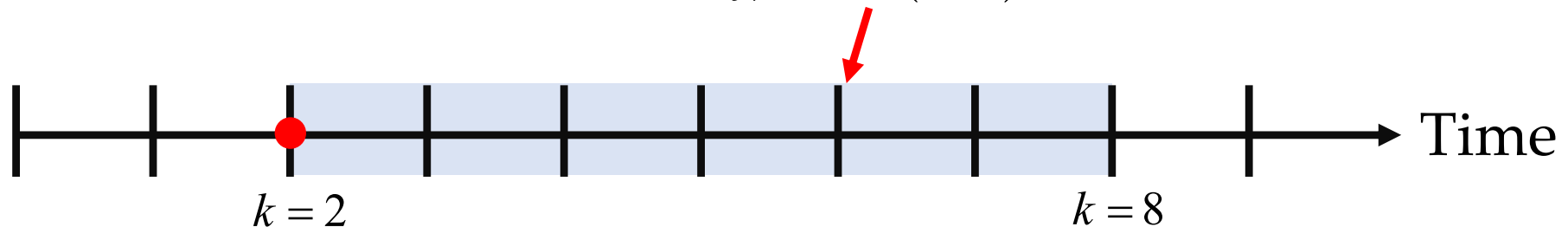
$$x_1, x_2, \dots, x_n \in \mathbb{R}$$

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = [x_1 \quad x_2 \quad \cdots \quad x_n]^T$$

$$x = [x_i], i \in 1, \dots, n$$

- State at time  $t - x(t)$
  - Predicted state at time step  $k - x(k), x[k], x_k$
  - Predicted state at time step  $j$  determined at time step  $k$

(double-index notation)  $x(j|k), x_{j|k}$   $x(6|2)$



- Vector spaces
  - Mostly dealing with **Euclidean space**  $\mathbb{R}^n$
  - Frequently use  $n$ -dimensional state space and  $m$ -dimensional input space

$$x_k \in \mathbb{R}^n \quad u_k \in \mathbb{R}^m$$

- Vector spaces must satisfy a set of axioms
  - [https://en.wikipedia.org/wiki/Vector\\_space](https://en.wikipedia.org/wiki/Vector_space)
  - Most importantly, if  $\mathcal{V}$  is a vector space and  $x$  and  $y$  are elements of this vector space  $x, y \in \mathcal{V}$ , then

$$\alpha x + \beta y \in \mathcal{V} \text{ for all scalars } \alpha, \beta \in \mathbb{R}$$

- Not to be confused with set, which can be finite
- (Linear) subspaces contained in a vector space  $\mathcal{S} \subset \mathcal{V}$

$$\alpha x + \beta y \in \mathcal{S} \quad \text{for all scalars } \alpha, \beta \in \mathbb{R}$$

- Examples?
  - Line, plane, origin, empty set

- **Absolute value** for a scalar  $x \in \mathbb{R}$   $|x| \in \mathbb{R}_+$
- Absolute value of a vector  $x \in \mathbb{R}^n$ 
  - Apply element-wise
  - Need to be careful with notation
$$|x| = \begin{bmatrix} |x_1| \\ \vdots \\ |x_n| \end{bmatrix} \in \mathbb{R}_+^n$$
- **Norm** of a vector  $x \in \mathbb{R}^n$   $\|x\| \in \mathbb{R}$ 
  - All norms are:
    - Nonnegative  $\|x\| \geq 0, \forall x \in \mathbb{R}^n$
    - Definite  $\|x\| = 0$  only if  $x = 0$
    - Homogeneous  $\|\alpha x\| = |\alpha| \|x\| \quad \forall x \in \mathbb{R}^n, \alpha \in \mathbb{R}$
    - Satisfy triangle inequality
$$\|x + y\| \leq \|x\| + \|y\| \quad \forall x, y \in \mathbb{R}^n$$

- Vector norms (continued)
  - Common types of norms

$$\ell_1 - \text{norm} : \|x\|_1 = |x_1| + |x_2| + \dots + |x_n|$$

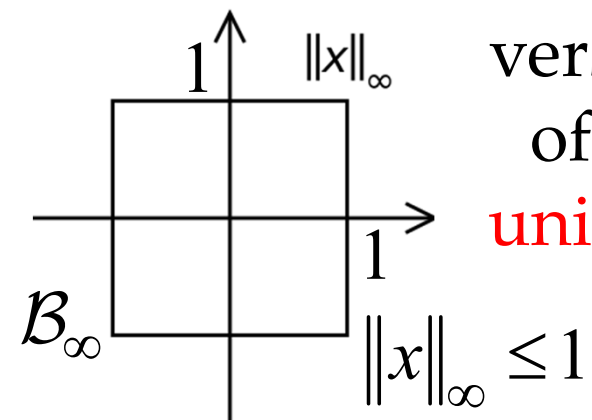
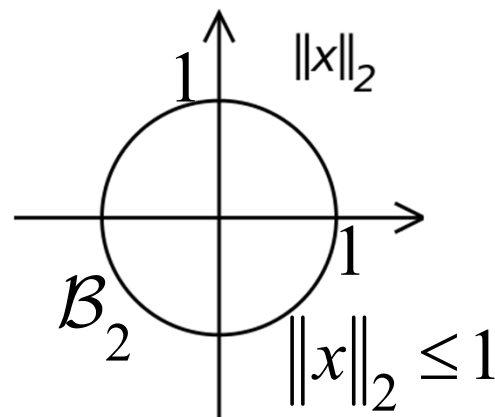
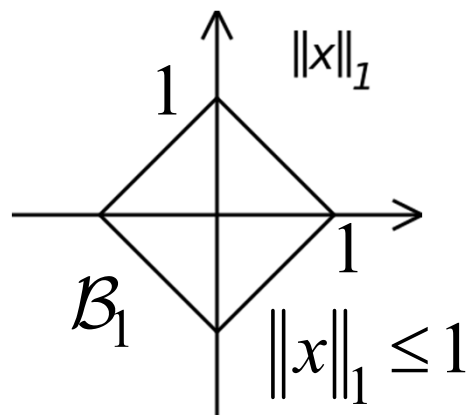
sum-absolute-value

$$\ell_2 - \text{norm} : \|x\|_2 = \left( x^T x \right)^{1/2} = \left( x_1^2 + x_2^2 + \dots + x_n^2 \right)^{1/2}$$

Root-sum-square

$$\ell_p - \text{norm} : \|x\|_p = \left( |x_1|^p + |x_2|^p + \dots + |x_n|^p \right)^{1/p} \quad p \geq 1$$

$$\ell_\infty - \text{norm} : \|x\|_\infty = \max \{ |x_1|, |x_2|, \dots, |x_n| \}$$



Different  
versions  
of the  
**unit ball**

- Vector norms (continued)
  - Common types of norms

$$\ell_1 - norm: \quad \|x\|_1 = |x_1| + |x_2| + \dots + |x_n|$$

$$\ell_2 - norm: \quad \|x\|_2 = \left( x^T x \right)^{1/2} = \left( x_1^2 + x_2^2 + \dots + x_n^2 \right)^{1/2}$$

$$\ell_p - norm: \quad \|x\|_p = \left( |x_1|^p + |x_2|^p + \dots + |x_n|^p \right)^{1/p} \quad p \geq 1$$

$$\ell_\infty - norm: \quad \|x\|_\infty = \max \{ |x_1|, |x_2|, \dots, |x_n| \}$$

- **Norm equivalence**

- For any two norms, there exists positive constants such that

$$\alpha \|x\|_a \leq \|x\|_b \leq \beta \|x\|_a$$

- Common relationships

$$\|x\|_\infty \leq \|x\|_2 \leq \|x\|_1 \leq \sqrt{n} \|x\|_2 \leq n \|x\|_\infty$$



- Matrix notation

- $M$  is a matrix

$$M \in \mathbb{R}^{m \times n}$$

$$M = \begin{bmatrix} m_{11} & m_{12} & \cdots & m_{1n} \\ m_{21} & \ddots & & \vdots \\ \vdots & & & \\ m_{m1} & \cdots & & m_{mn} \end{bmatrix}$$

$$M = [x_{ij}], i \in 1, \dots, m, j \in 1, \dots, n$$

- Matrices are **linear transformations** (linear mappings)

$$\mathbb{R}^n \rightarrow \mathbb{R}^m$$

- Maps each vector  $x \in \mathbb{R}^n$  to  $y = Mx \in \mathbb{R}^m$

- Matrix notation  $M \in \mathbb{R}^{m \times n}$   $x \in \mathbb{R}^n$   $y = Mx \in \mathbb{R}^m$ 
  - It makes sense to think about where this mapping can take you (and where it cannot)
  - **Range** of  $M$  :  $\mathcal{R}(M) = \{y = Mx \mid x \in \mathbb{R}^n\}$ 
    - Set of vectors that can be written as linear combinations of the columns of  $M$

$\mathcal{R}(M)$  is a subspace of  $\mathbb{R}^m$

with dimension equal to the # of linearly independent columns of  $M$  (= rank of  $M$ )

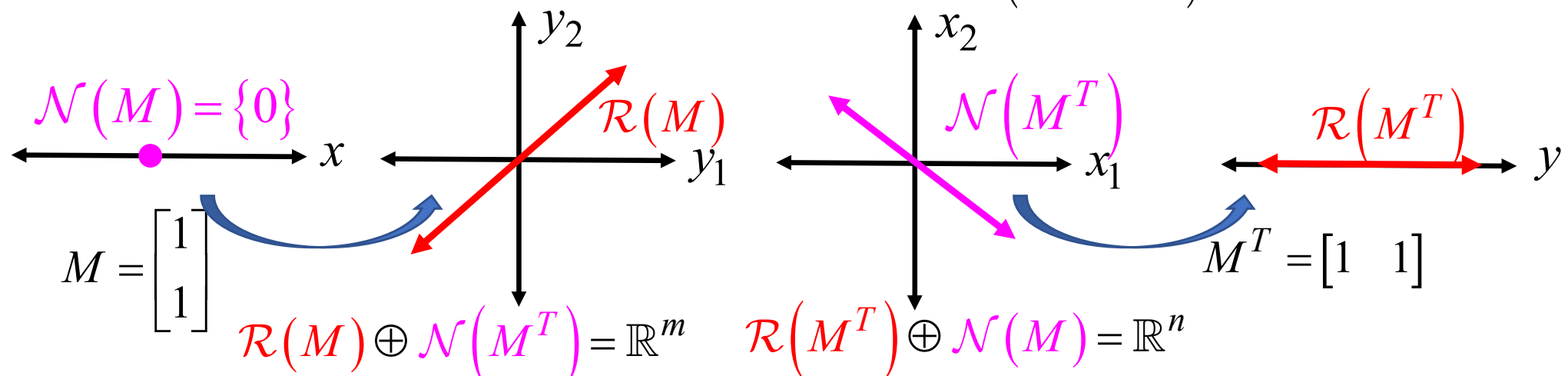
- **Nullspace** of  $M$  :  $\mathcal{N}(M) = \{x \mid Mx = 0\}$ 
  - Set for vectors  $x$  that are mapped to zero by  $M$

$\mathcal{N}(M)$  is a subspace of  $\mathbb{R}^n$

with dimension equal to  $n - \text{rank}(M)$

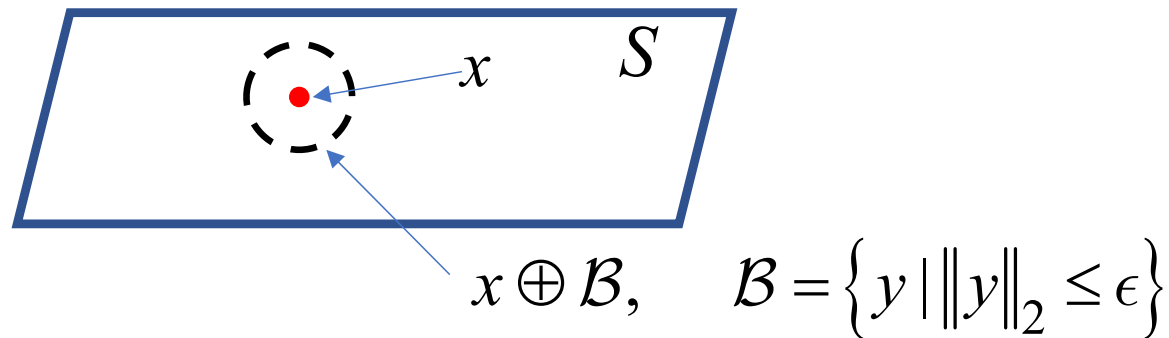
*i.e.* sum of the dimensions of  $\mathcal{R}(M)$  and  $\mathcal{N}(M) = n$

- The four fundamental subspaces [1]  $M \in \mathbb{R}^{m \times n}$   $x \in \mathbb{R}^n$   
 $y = Mx \in \mathbb{R}^m$ 
  - Column space** (Range):  $\mathcal{R}(M) \subset \mathbb{R}^m$ 
    - All linear combination of columns of  $M$
  - Nullspace**:  $\mathcal{N}(M) \subset \mathbb{R}^n$ 
    - All solutions  $x$  such that  $Mx = 0$
  - Row space** (Range of transpose):  $\mathcal{R}(M^T) \subset \mathbb{R}^n$ 
    - All linear combination of rows of  $M$
  - Left nullspace** (Nullspace of transpose):  $\mathcal{N}(M^T) \subset \mathbb{R}^m$ 
    - All solutions  $x$  such that  $M^T x = 0$  ( $x^T M = 0$ )



- Some square matrices can be positive definite or positive semidefinite
- Let  $Q$  be a real, symmetric matrix
  - Then  $Q$  is **positive definite**  $Q > 0$  if
$$x^T Q x > 0, \quad \forall x \in \mathbb{R}^n$$
  - Then  $Q$  is **positive semidefinite**  $Q \geq 0$  if
$$x^T Q x \geq 0, \quad \forall x \in \mathbb{R}^n$$
- **Lecture Assignment:**
  - Prove one of the following
$$Q > 0 \text{ if and only if } \lambda(Q) > 0, \quad \lambda \in \text{eig}(Q)$$
$$Q \geq 0 \text{ if and only if } \lambda(Q) \geq 0, \quad \lambda \in \text{eig}(Q)$$
  - Remember to go both directions, i.e.
    - Assume  $Q > 0$  and show  $\lambda(Q) > 0, \quad \lambda \in \text{eig}(Q)$
    - Then assume  $\lambda(Q) > 0, \quad \lambda \in \text{eig}(Q)$  and show  $Q > 0$

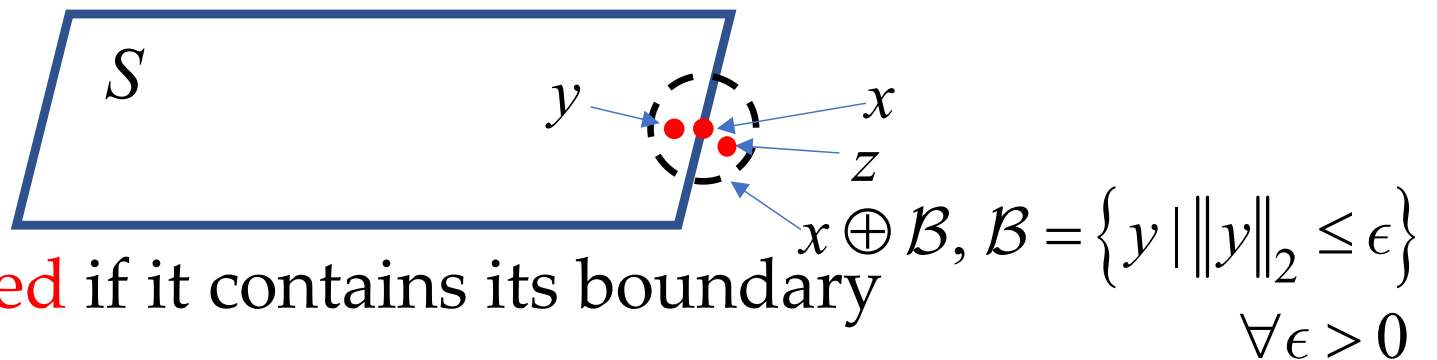
- Consider a set  $S \in \mathbb{R}^n$ 
  - An element of this set,  $x \in S$ , is an **interior point** if the set of “nearby points” are also elements of this set
  - Formally,  $\exists \epsilon > 0$  s.t.  $\{y \mid \|y - x\|_2 \leq \epsilon\} \subseteq S$
  - Alternatively, we can think about the existence of an epsilon-ball centered at  $x$  that lies entirely in the set





- Consider a set  $S \in \mathbb{R}^n$ 
  - An element of this set,  $x \in S$ , is a **boundary point** if there are both “nearby points” that are in and not in the set
  - Formally,  $\forall \epsilon > 0 \exists y \in S$  and  $z \notin S$  such that

$$\|y - x\|_2 \leq \epsilon \quad \|z - x\|_2 \leq \epsilon$$



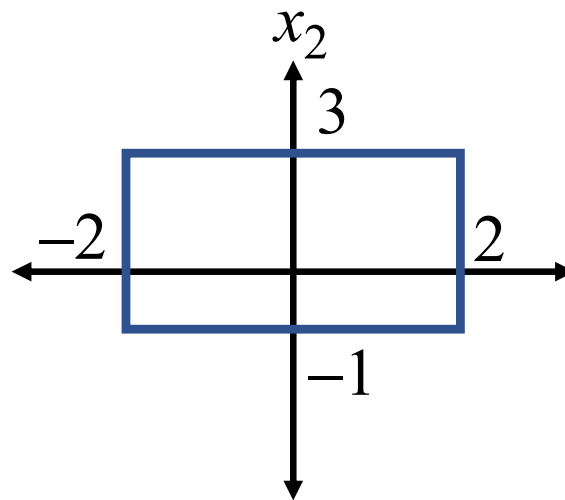
- A set is **closed** if it contains its boundary
- A set is **open** if it contains no boundary points
- A set is **bounded** if there exists a finite number that bounds the norm of every element of the set

$$\exists M < \infty, \text{ s.t. } \|x\| \leq M, \forall x \in S$$

- A set is **compact** if it is closed and bounded

- A set is **convex** if for any two elements in the set, all of the points on a straight line connecting these elements are also in the set
- Formally,  $\forall x, y \in S$  and  $\lambda \in [0, 1]$ ,  $(\lambda x + (1 - \lambda)y) \in S$
- We will primarily deal with convex sets
- Sets can be defined using different representations
  - **Intervals:**

$$S = [\underline{x}, \bar{x}] = \left\{ x \in \mathbb{R}^n \mid \underline{x} \leq x \leq \bar{x} \right\}$$

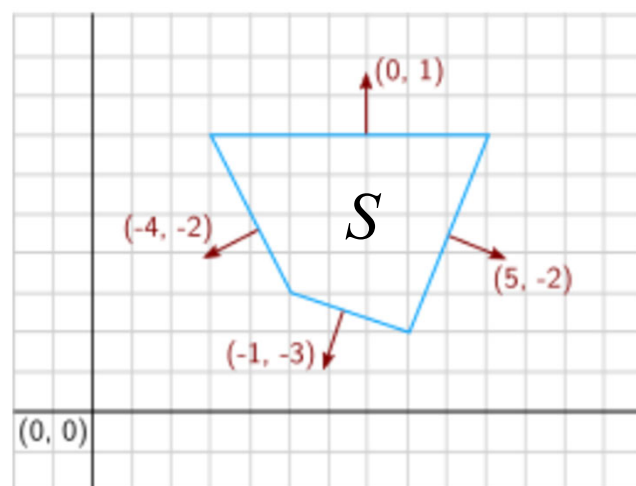


$$S = [\underline{x}, \bar{x}], \quad \underline{x} = \begin{bmatrix} -2 \\ -1 \end{bmatrix}, \quad \bar{x} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$$

- Sets can be defined using different representations
  - Halfspace-Representation (**H-Rep**):

$$S = \left\{ x \in \mathbb{R}^n \mid Ax \leq b \right\}, \quad A \in \mathbb{R}^{n_h \times n}, \quad b \in \mathbb{R}^{n_h} \quad n_h = \# \text{ of halfspaces}$$

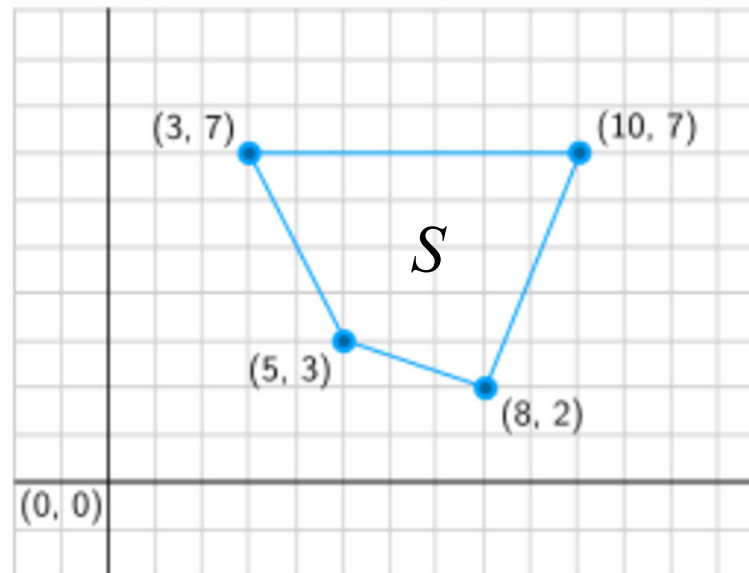
$$\begin{bmatrix} 0 & 1 \\ 5 & -2 \\ -1 & -3 \\ -4 & -2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \leq \begin{bmatrix} 7 \\ 36 \\ -14 \\ -26 \end{bmatrix}$$



[1]

- Sets can be defined using different representations
  - Vertex-Representation (**V-Rep**): (convex hull of vertices)

$$S = \left\{ x \in \mathbb{R}^n \mid x = \sum_{i=1}^{n_v} \lambda_i v_i, \lambda_i \geq 0, \sum_{i=1}^{n_v} \lambda_i = 1 \right\}, \quad n_v = \# \text{ of vertices}$$



[1]

- H-rep and V-rep can be used to represent **any convex polytope**
  - A polytope is a geometric object with “flat” sides
  - Also a bounded cases of a more general (potentially unbounded) polyhedron

- Common set operations

- **Linear transformation:**  $MS = \{Mx \mid x \in S\}$ ,  $M \in \mathbb{R}^{m \times n}$

- **Minkowski sum:**

$$S_1 \oplus S_2 = \{x_1 + x_2 \mid x_1 \in S_1, x_2 \in S_2\}$$

- **Pontryagin difference:**

$$\begin{aligned} S_1 \ominus S_2 &= \{x_1 \in S_1 \mid x_1 \oplus S_2 \subseteq S_1\} \\ &= \{x_1 \in S_1 \mid x_1 + x_2 \in S_1, \forall x_2 \in S_2\} \end{aligned}$$

- **Intersection:**

$$S_1 \cap S_2 = \{x_1 \in S_1 \mid x_1 \in S_2\}$$

- **Convex hull:**

$$CH(S_1, S_2) = \{\lambda x_1 + (1 - \lambda)x_2 \mid x_1 \in S_1, x_2 \in S_2, \lambda \in [0, 1]\}$$



- **Lecture Assignment:**

- Explore the computational geometry features of the Multi-Parametric Toolbox (MPT)

- <https://www.mpt3.org/>

## Multi-Parametric Toolbox 3

The Multi-Parametric Toolbox (or MPT for short) is an open source, Matlab-based toolbox for

### Installation

- [Installation & updating instructions](#)
- [License](#)
- [How to cite MPT3](#)

### Contact

Questions and comments should be posted via the [MPT forum at Google Groups](#).

### First steps with MPT3

- [Quick start using demos](#)
- [Parametric optimization](#)
- [Computational geometry features](#)
- [MPC synthesis \(regulation, tracking\)](#)
  - [Modeling of dynamical systems](#)
  - [Closed-loop simulations](#)
  - [Additional constraints](#) (move blocking, soft & rate constraints, terminal sets, etc.)
  - [Fine-tuning MPC setups via YALMIP](#)
  - [Code generation](#)
  - [Low-complexity explicit MPC algorithms](#)
- [Computation of invariant sets](#)
- [Construction of Lyapunov functions](#)

Particularly  
these ones

<https://www.mpt3.org/Geometry/Geometry>

### Tour on the computational geometry

Objects for representing sets and functions

- [Construction and properties of basic sets](#)
- [Construction of function objects](#)

Objects for representing unions of sets

- [Construction and properties of unions of sets](#)

Objects for representing functions over sets

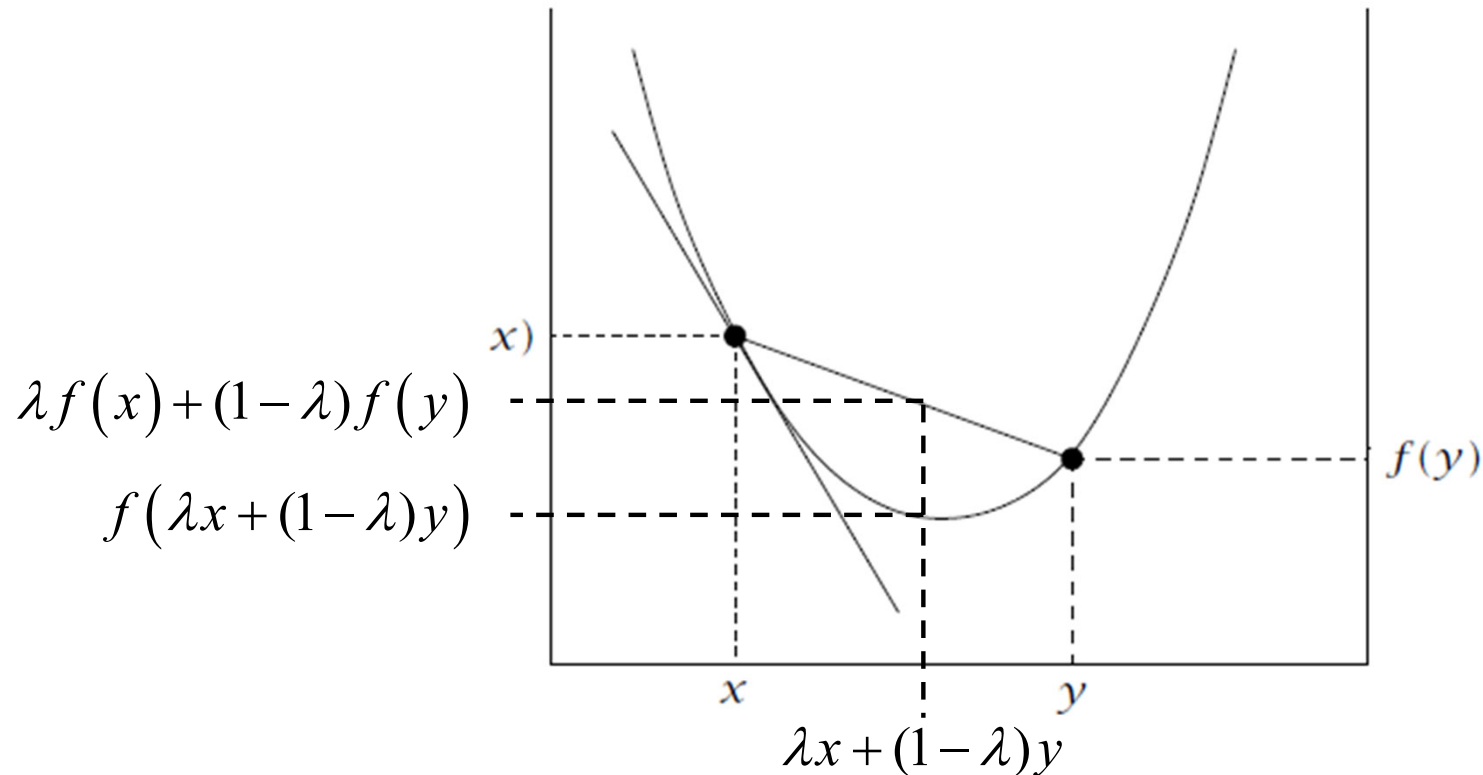
- [Construction of function over sets](#)

Geometric operations

- [Geometric operations with general convex sets](#)
- [Geometric operations with polyhedra](#)

See question on last slide.

- A function  $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$  is **continuous** if  $\forall x \in \mathbb{R}^n$   
 $\exists \delta$  s.t.  $\|y - x\|_2 \leq \delta \Rightarrow \|f(y) - f(x)\|_2 \leq \epsilon, \forall \epsilon > 0$
- A function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is **convex** if  $\forall x, y \in \mathbb{R}^n, \lambda \in [0, 1]$   
 $f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y)$



- The **level set** of a function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is

$$\{x \in \mathbb{R}^n \mid f(x) = \alpha\} \quad \alpha \in \mathcal{R}$$

- The **sublevel set** is similar with

$$\{x \in \mathbb{R}^n \mid f(x) \leq \alpha\} \quad \alpha \in \mathcal{R}$$

- A function is **Lipschitz**, with Lipschitz constant  $L$ , if

$$\forall x, y \in \mathbb{R}^n, \quad \|f(y) - f(x)\|_2 \leq L \|y - x\|_2$$

- **Lecture Assignment:**

- Provide an example of a function that is continuous but not Lipschitz

- A function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is **positive definite** if

$$f(0) = 0 \quad \text{and} \quad f(x) > 0, \quad \forall x \neq 0$$

- A function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is **positive semidefinite** if

$$f(0) = 0 \quad \text{and} \quad f(x) \geq 0, \quad \forall x$$

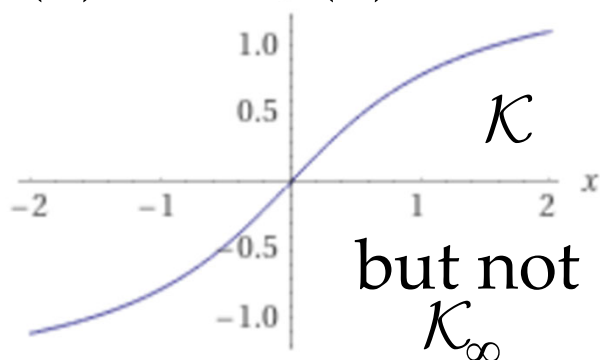
- A **quadratic function**  $f(x) = x^T Q x$ , where  $Q$  is symmetric, is **positive (semi)definite** if  $Q$  is a positive (semi)definite matrix

# Comparison Functions

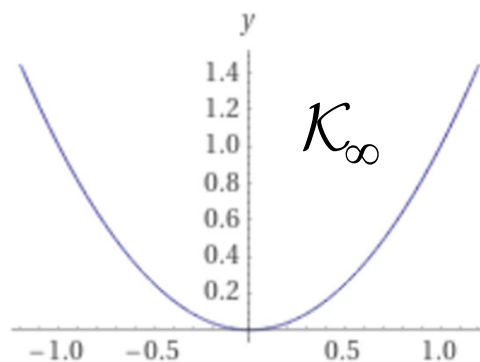
- **Class  $\mathcal{K}$ :** A scalar continuous function  $\alpha(r):[0,a) \rightarrow \mathbb{R}$  belongs to class  $\mathcal{K}$  if it is strictly increasing and  $\alpha(0)=0$
- **Class  $\mathcal{K}_\infty$ :** A scalar continuous function  $\alpha(r):[0,\infty) \rightarrow \mathbb{R}$  belongs to class  $\mathcal{K}_\infty$  if it belongs to class  $\mathcal{K}$  and  $\alpha(r) \rightarrow \infty$  as  $r \rightarrow \infty$
- **Class  $\mathcal{KL}$ :** A scalar continuous function  $\beta(r,s):[0,a) \times [0,\infty) \rightarrow \mathbb{R}$  belongs to class  $\mathcal{KL}$  if for each fixed value of  $s$ ,  $\beta(r,s)$  belongs to class  $\mathcal{K}$  with respect to  $r$  and for each fixed value of  $r$ ,  $\beta(r,s)$  is decreasing with respect to  $s$  and  $\beta(r,s) \rightarrow 0$  as  $s \rightarrow \infty$

- Examples:

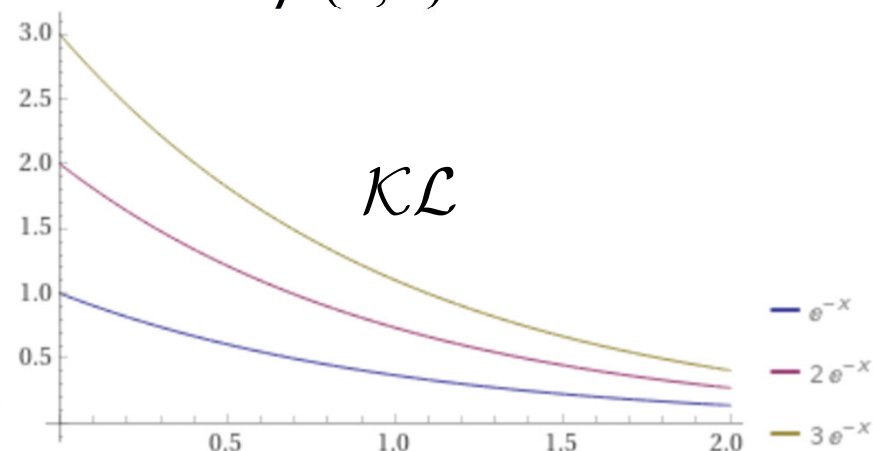
$$\alpha(r) = \tan^{-1}_y(r)$$



$$\alpha(r) = r^2$$



$$\beta(r,s) = re^{-s}$$



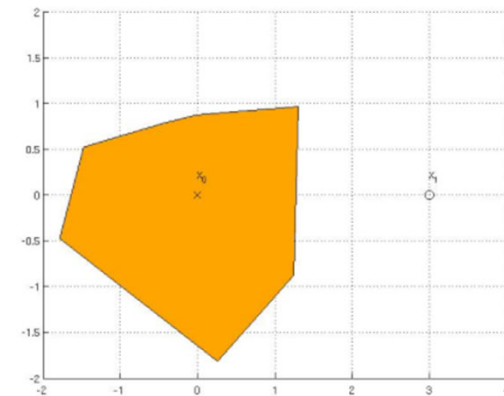


# Summary of Lecture Assignments

- 1) • Prove one of the following
- $Q > 0$  if and only if  $\lambda(Q) > 0$ ,  $\lambda \in \text{eig}(Q)$
  - $Q \geq 0$  if and only if  $\lambda(Q) \geq 0$ ,  $\lambda \in \text{eig}(Q)$
- Remember to go both directions, i.e.
- Assume  $Q > 0$  and show  $\lambda(Q) > 0$ ,  $\lambda \in \text{eig}(Q)$
  - Then assume  $\lambda(Q) > 0$ ,  $\lambda \in \text{eig}(Q)$  and show  $Q > 0$

## 2) MPT Toolbox

- Review computational geometry features
- Determine H-rep of orange set on page
- <https://www.mpt3.org/Geometry/OperationsWithPolyhedra>



- 3) • Provide an example of a function that is continuous but not Lipschitz