

# Reachability of Chen-Fliess series: A Gradient Descent Approach\*

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The University of Vermont

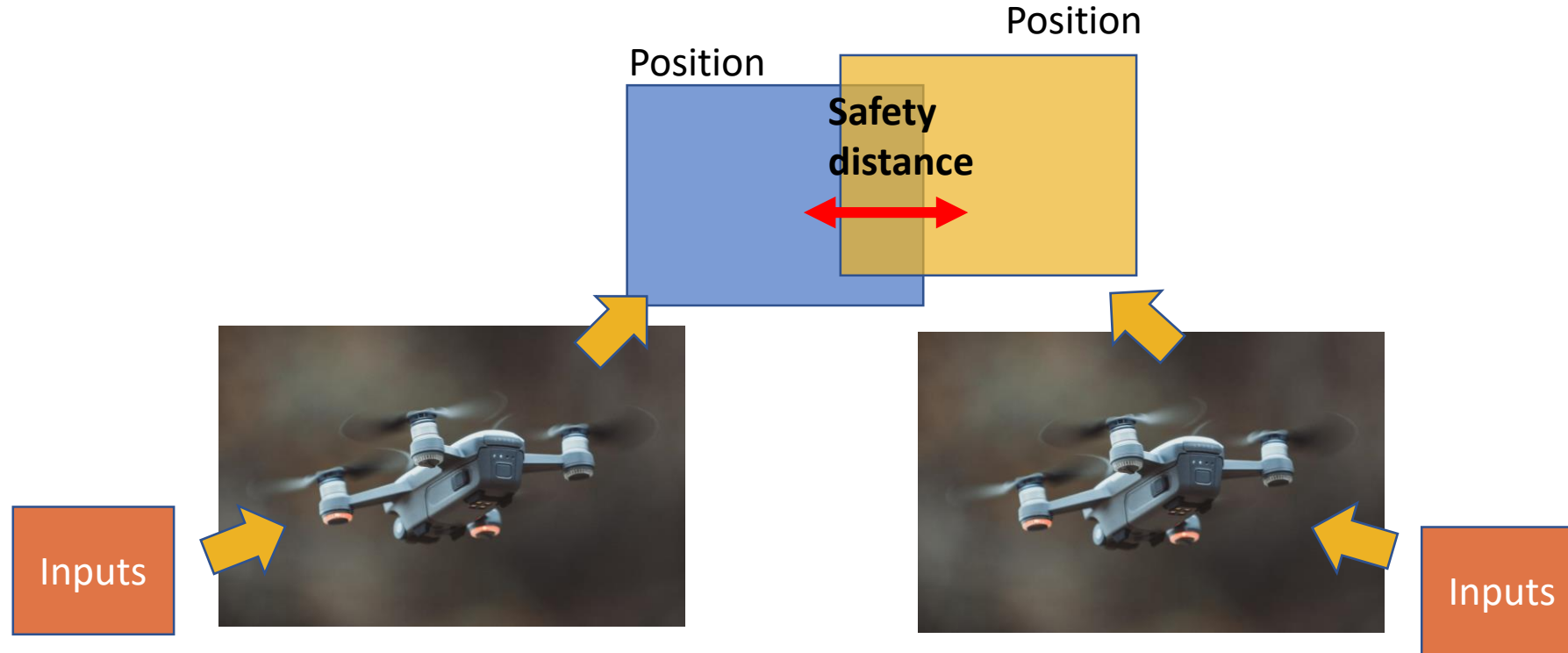
# Outline

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  - 2.2. Mixed-Monotonicity
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4. Illustrative Simulations
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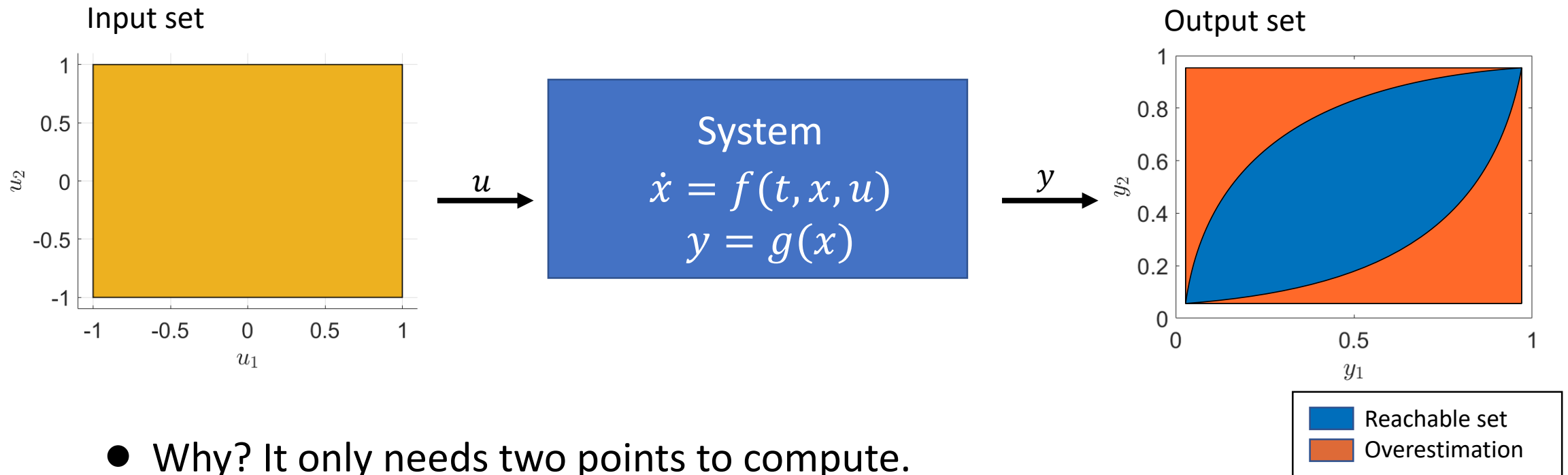
# 1. Motivation and Problem Statement

**Definition 1 (Reachable set):** The set of outputs of the system as a response to a set of inputs and a set of initial conditions.

**Application:** Collision avoidance of quadcopters

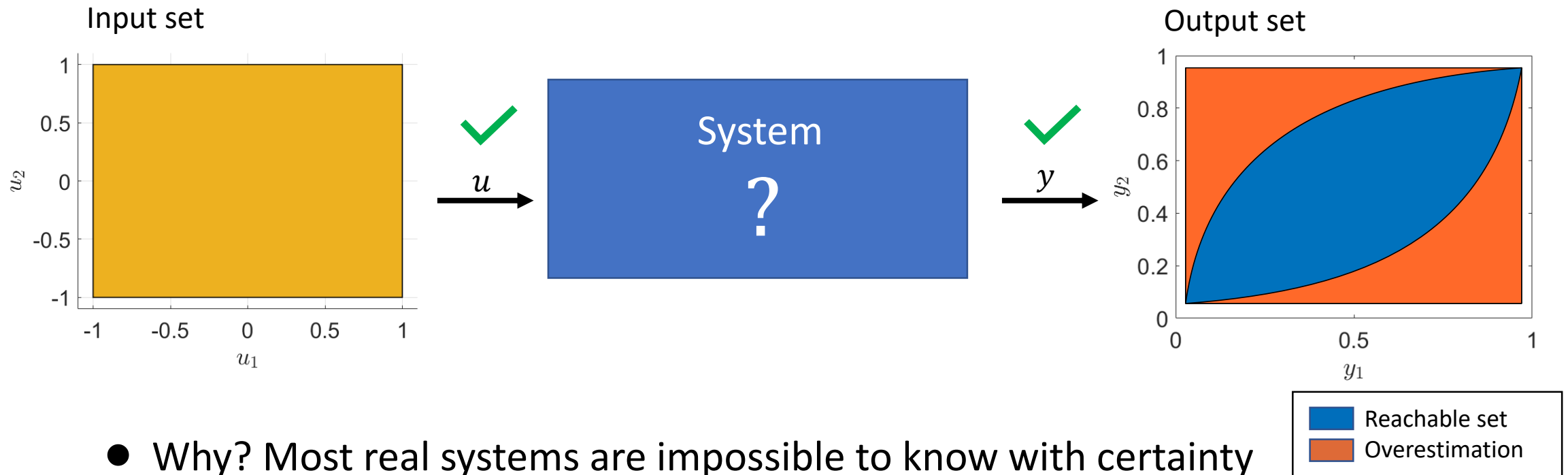


# 1. Motivation and Problem Statement



- Why? It only needs two points to compute.
- Approaches: mixed-monotonicity, Hamilton-Jacobi reachability, neural networks

# 1. Motivation and Problem Statement



- Why? Most real systems are impossible to know with certainty
- What to do? Use a data-driven approach
- Data-driven approaches: neural networks, **Chen-Fliess series**

## 2. Preliminaries

### 2.1 Chen-Fliess Series

**Definition 2 (Chen-Fliess series):**

$$F_c[u](t) := \sum_{\eta \in X^*} (c, \eta) E_{x_{i\eta}}[u](t)$$

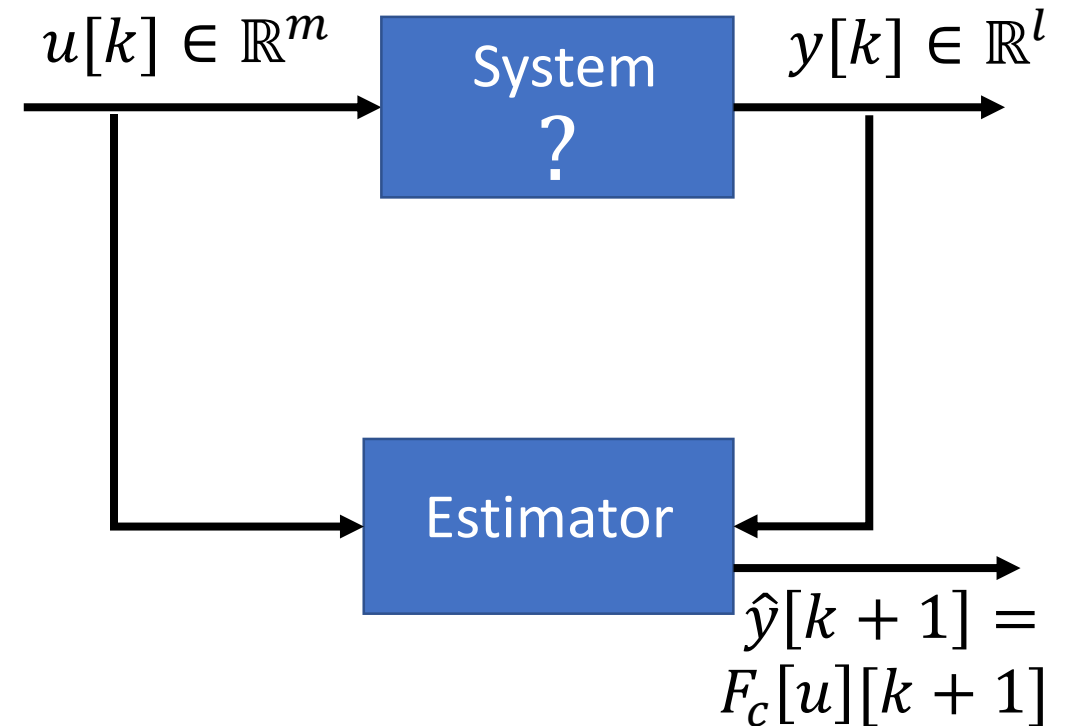
words  $\nearrow$   $\eta \in X^*$   $\nwarrow$  words  
 $\nwarrow$  Space of all words  $\nearrow$  Vector in  $\mathbb{R}^l$   
 $\nwarrow$  Iterative integral  $\nearrow$

**Definition 3 (Iterative integral):**

$$E_{x_{i\eta}}[u](t) := \int_0^t u_i(\tau) E_\eta[u](\tau) d\tau,$$

$$E_\phi[u](t) := 1 \quad [\text{Fliess, 1981}]$$

**Remark:** we need to truncate to a word length to use them.

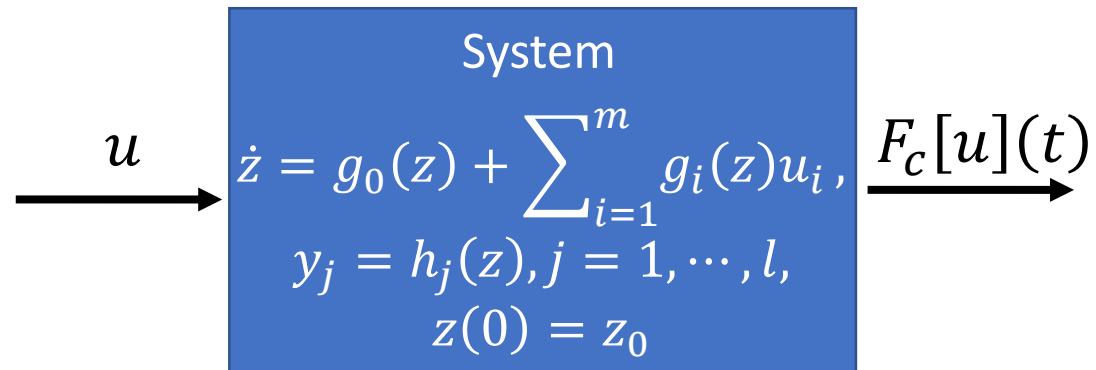


**Remark:** Chen-Fliess series does not estimate the system.

[Gray, Venkatesh, Duffaut Espinosa, 2019]

## 2. Preliminaries

### 2.1 Chen-Fliess Series



**Remark:** the coefficients are computed deterministically.

[Fliess, 1981]

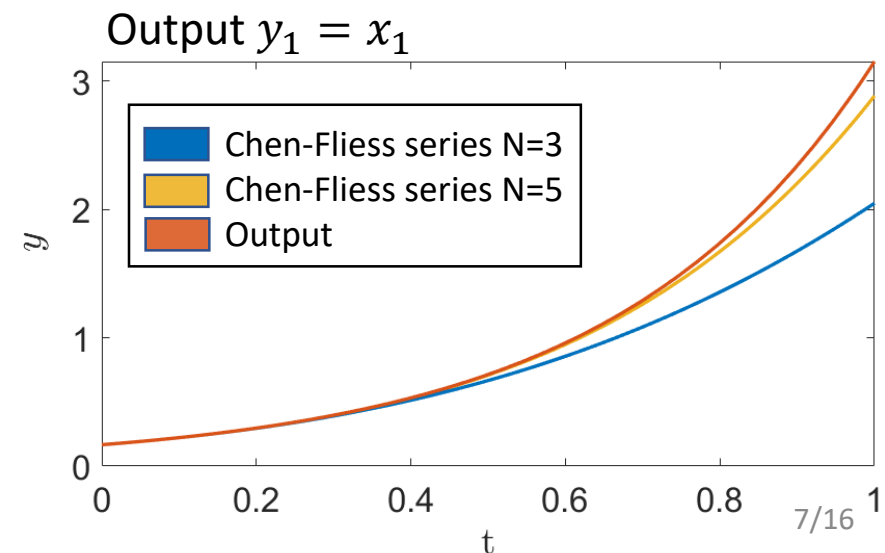
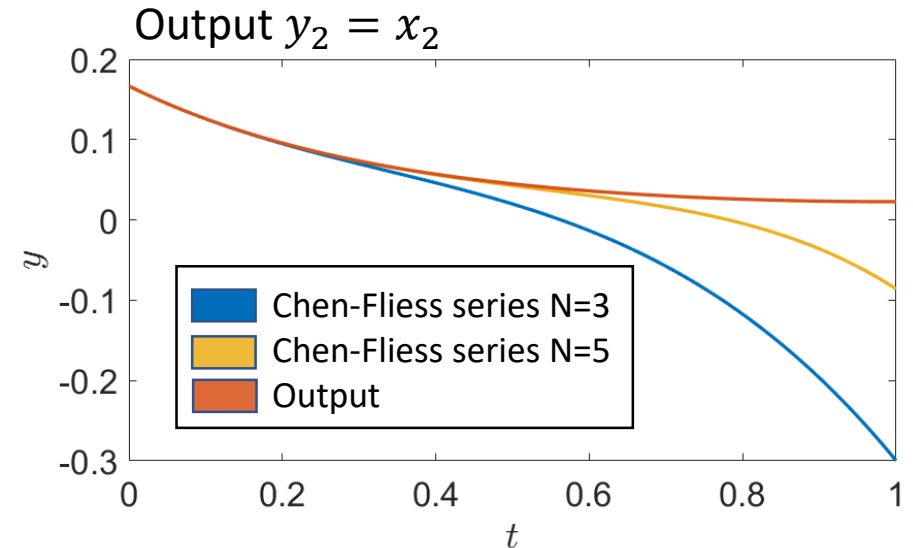
**Example:** Lotka-Volterra system

$$\dot{x}_1 = -x_1x_2 + x_1u_1,$$

$$\dot{x}_2 = x_1x_2 - x_2u_2,$$

$$y = x,$$

$$x(0) = (1/6, 1/6),$$

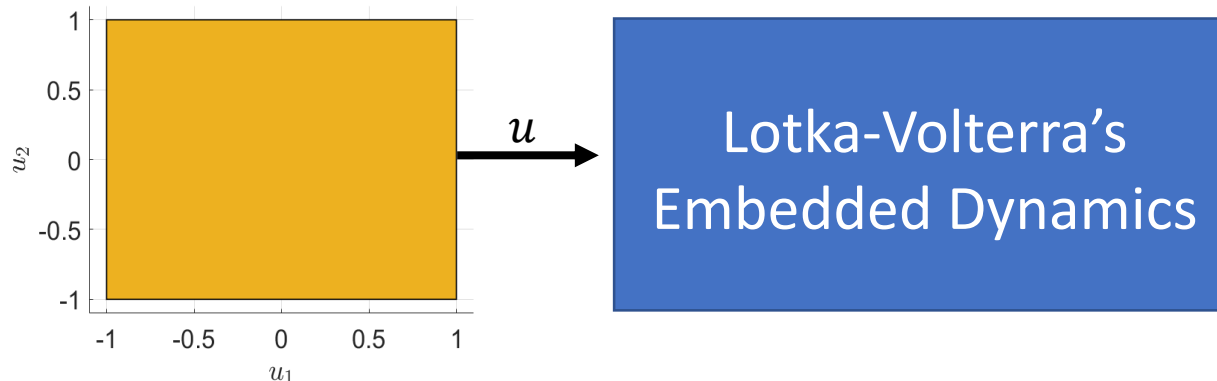


## 2. Preliminaries

### 2.2 Mixed-Monotonicity (MM)

**Definition 4 (Mixed-Monotone system):** A system is mixed-monotone with respect to the decomposition function  $d: \mathcal{X} \times \mathcal{W} \times \mathcal{X} \times \mathcal{W} \rightarrow \mathbb{R}^n$  if

- i.  $d(x, w, x, w) = f(x, w)$ ,
- ii.  $\frac{\partial d_i}{\partial x_j}(x, w, \hat{x}, \hat{w}) \geq 0$  for all  $i \neq j$ ,
- iii.  $\frac{\partial d_i}{\partial \hat{x}_j}(x, w, \hat{x}, \hat{w}) \leq 0$  for all  $i, j$ ,
- iv.  $\frac{\partial d_i}{\partial w_k}(x, w, \hat{x}, \hat{w}) \geq 0$  and  $\frac{\partial d_i}{\partial \hat{w}_k}(x, w, \hat{x}, \hat{w}) \leq 0$  for all  $i, k$



**Example:** Lotka-Volterra system

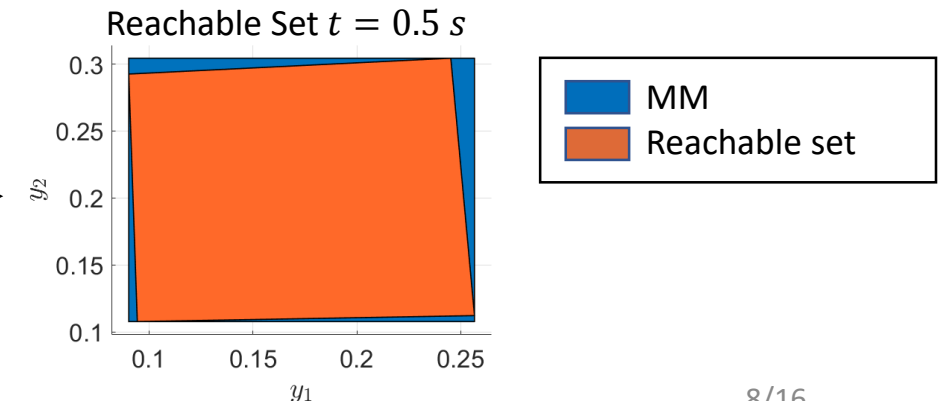
$$\dot{x}_1 = -x_1x_2 + x_1u_1,$$

$$\dot{x}_2 = x_1x_2 - x_2u_2,$$

$$y = x,$$

$$x(0) = (1/6, 1/6)$$

$$u_{1,2} \in [-1, 1]$$





## 2. Preliminaries

### 2.3 Input-Output Mixed-Monotonicity (IOMM)

- Alphabets:  $X = \{x_1, \dots, x_n\}$ ,  $Y = \{y_1, \dots, y_n\}$
- Word substitution:  $\sigma_Y(x_i) = y_i$
- Extended Iterative Integral:

$$\mathcal{E}_{z_i \eta}[u, v](t) = \begin{cases} \int_0^t u_i(\tau) \mathcal{E}[u, v](\tau) d\tau, & z_i \in X \\ \int_0^t v_i(\tau) \mathcal{E}[u, v](\tau) d\tau, & z_i \in Y \end{cases}$$

**Definition 5 (IOMM):** A Chen-Fliess series  $F_c[u](t)$  is input-output mixed-monotone if there exists a decomposition function  $d[u, \hat{u}](t)$  such that

- $d[u, u](t) = F_c[u](t)$ ,
- $d[u, \hat{u}](t)$  is non-decreasing in  $u$ ,
- $d[u, \hat{u}](t)$  is non-increasing in  $\hat{u}$ ,

**Lemma 1:** Every Chen-Fliess series is expressed as

$$F_c[u](t) = \mathcal{F}_{c^+}[u](t) - \mathcal{F}_{c^-}[u](t)$$

where

$$\mathcal{F}_{c^+}[u](t) = \sum_{k=0}^{\infty} \sum_{\eta \in X^*} \sum_{\xi \in \mathbb{S}_{\eta, Y^k}} (c^+, \xi) \mathcal{E}_{\xi}[u^+, u^-](t),$$

$$\mathcal{F}_{c^-}[u](t) = \sum_{k=0}^{\infty} \sum_{\eta \in X^*} \sum_{\xi \in \mathbb{S}_{\eta, Y^k}} (c^-, \xi) \mathcal{E}_{\xi}[u^+, u^-](t),$$

$$(c^+, \xi) = \max\{(-1)^k (c, \sigma_X(\xi)), 0\}$$

$$(c^-, \xi) = -\min\{(-1)^k (c, \sigma_X(\xi)), 0\}$$

**Theorem 1:** The following is decomposition function of the Chen-Fliess series

$$d[u, \hat{u}](t) := \mathcal{F}_{c^+}[u](t) - \mathcal{F}_{c^-}[\hat{u}](t)$$

[Perez Avellaneda & Duffaut Espinosa, 2022a]

## 2. Preliminaries

### 2.3 Input-Output Mixed-Monotonicity (IOMM)

**Theorem 2:** Consider the Chen-Fliess series  $F_c[u](t)$  taking values in the hyper-rectangle  $U = [u, \hat{u}] \subset K$ . Then

$$\text{Reach}(F_c, U)(t) \subset [d[u, \hat{u}](t), d[\hat{u}, u](t)].$$

**Example:** Lotka-Volterra system

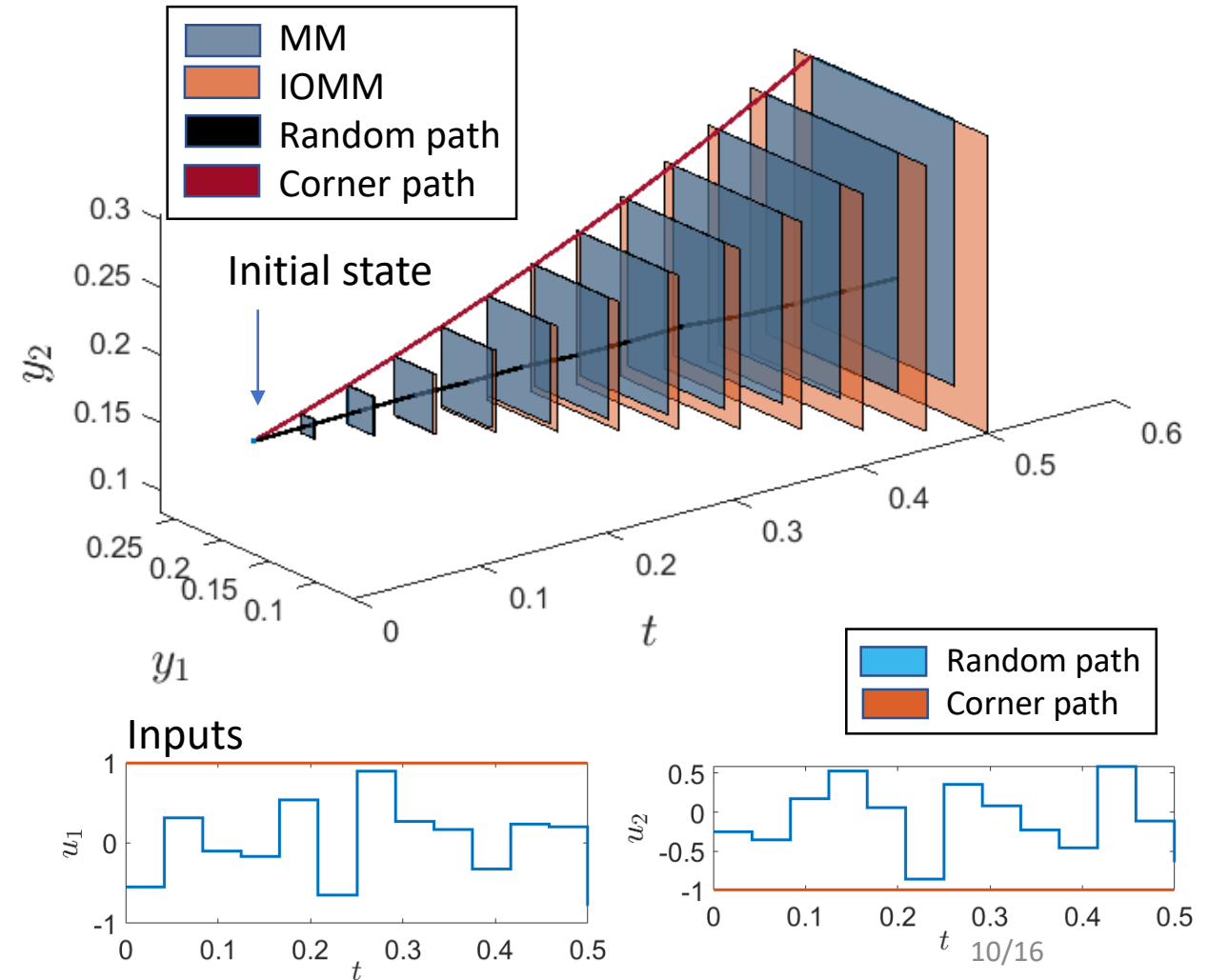
$$\dot{x}_1 = -x_1 x_2 + x_1 u_1,$$

$$\dot{x}_2 = x_1 x_2 - x_2 u_2,$$

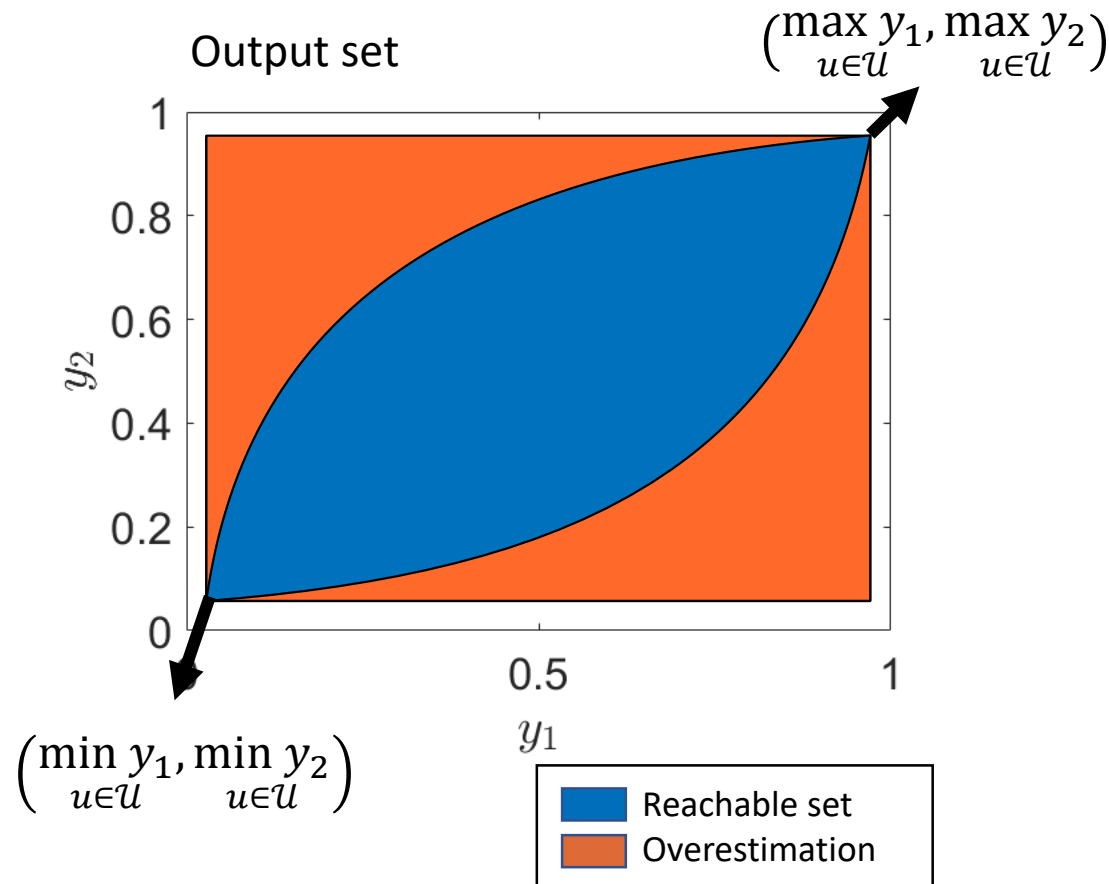
$$y = x,$$

$$x(0) = (1/6, 1/6),$$

$$(u_1, u_2) \in [-1, 1] \times [-1, 1]$$



### 3. Gradient Descent Method



**Problem:**

$$\min_{u \in \mathcal{U}} F_c[u](t)$$

function

Chen-Fliess series

**Definition 6 (Gateaux derivative):** Given  $c \in \mathbb{R}^l \langle \langle X \rangle \rangle$  and the input functions  $u, v \in L_p^m[0, t]$ , the Chen-Fliess series is Gateaux differentiable at  $u$  the direction of  $v$  if and only if there exists  $\frac{\partial}{\partial v} F_c[u](t) \in \mathbb{R}^l$  such that the following limit is satisfied:

$$\lim_{\varepsilon \rightarrow 0} \frac{1}{\varepsilon} \left( F_c[u + \varepsilon v](t) - F_c[u](t) - \frac{\partial}{\partial v} F_c[u](t) \varepsilon \right) = 0$$

# 3. Gradient Descent Method

**Theorem 2:** Let  $X$  and  $Y$  be alphabets associated to  $u, v \in L_p^m[t_0, t_1]$ , respectively. The Chen-Fliess series is Gâteaux differentiable in the direction of  $v$  if and only if

$$\lim_{\varepsilon \rightarrow 0} \sum_{k=2}^{\infty} \sum_{\eta \in X^*} \sum_{\xi \in \mathbb{S}_{\eta, Y^k}} (c, \sigma_X(\xi)) \mathcal{E}_{\xi}[u, v](t) \varepsilon^k = 0$$

And the Gâteaux derivative is expressed as

$$\frac{\partial}{\partial v} F_c[u](t) = \sum_{\eta \in X^*} \sum_{\xi \in \mathbb{S}_{\eta, Y^k}} (c, \sigma_X(\eta)) \mathcal{E}_{\xi}[u, v](t)$$

**Definition 7 (Gradient):** the gradient of a Chen-Fliess series is defined as

$$\nabla F_c[u](t) = \left( \frac{\partial}{\partial e_1} F_c[u](t), \dots, \frac{\partial}{\partial e_m} F_c[u](t) \right)$$

where  $e_i(t) = (0, \dots, \underbrace{1}_{i\text{-th}}, \dots, 0)$

**Example:** Consider the system:

$$\dot{x} = Ax + Bu, y = Cx, x(0) = x_0$$

The output is expressed as

$$y(t) = C \exp(-At) x_0 + \int_0^t C \exp A(t - \tau) B u(\tau) d\tau$$

The Chen-Fliess series of the system is

$$F_c[u] = \sum_{k=0}^{\infty} C A^k x_0 \frac{t^k}{k!} + \sum_{k=0}^{\infty} C A^k B E_{x_0^k x_1}[u](t)$$

The Gâteaux derivative is the following

$$\nabla F_c[u](t) = \sum_{k=0}^{\infty} C A^k B \frac{t^{k+1}}{(k+1)!} = -\frac{dy}{du}$$

# 3. Gradient Descent Method

**Theorem 3:** Consider the constant vector  $v \in \mathbb{R}^m$ , the function  $u \in L_p^m[0, t]$  and  $c \in R_{LC}\langle\langle X \rangle\rangle$ . Then there exists  $\varepsilon_0 \in (0, \varepsilon)$  such that

$$F_c[u + \varepsilon v] = F_c[u] + v^T \nabla F_c[u + \varepsilon_0 v](t) \varepsilon$$

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## Algorithm 2 Gradient Descent

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**Input:**  $R, u_0, \varepsilon, \mathcal{U}$

**Output:**  $F_c[u](t)$

*Initialization :*  $u_0$

1: **for**  $i = 1$  to  $R$  **do**

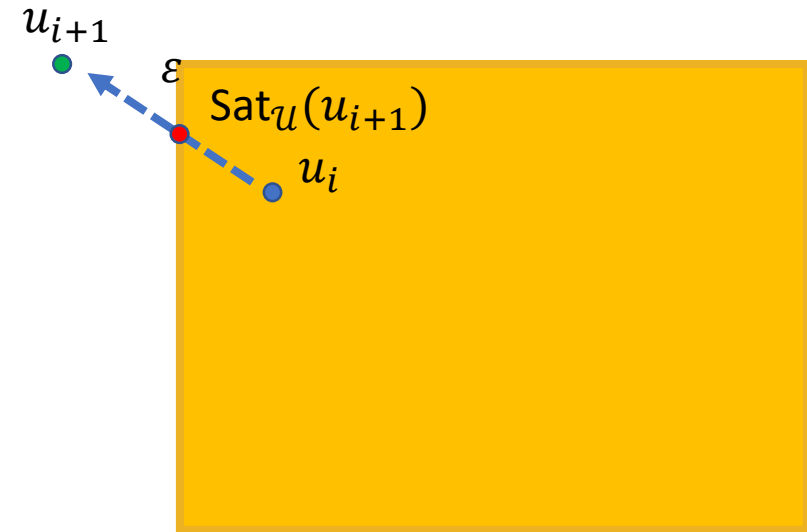
2:    $u_{i+1} = u_i - \varepsilon \nabla F_c[u_i](t),$

3:    $u_{i+1} \leftarrow \text{sat}_{\mathcal{U}}(u_{i+1})$

4: **end for**

5: **return**  $u_R$

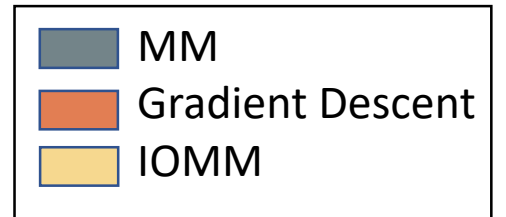
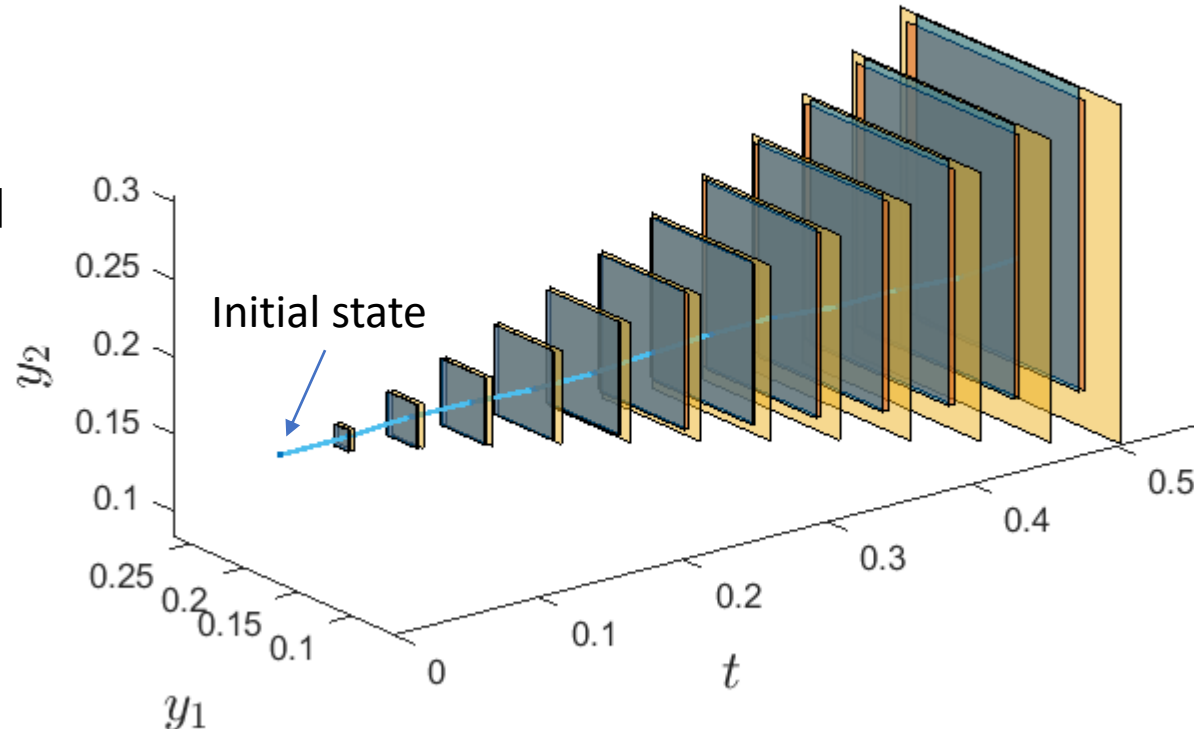
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# 4. Illustrative Simulation

## Example: Lotka-Volterra system

$$\begin{aligned}\dot{x}_1 &= -x_1x_2 + x_1u_1, \\ \dot{x}_2 &= x_1x_2 - x_2u_2, \\ y &= x, \\ x(0) &= (1/6, 1/6), \\ (u_1, u_2) &\in [-1, 1] \times [-1, 1]\end{aligned}$$



Parameters:  
Iterations = 1000,  
 $\varepsilon_1 = 0.1$ ,  
 $\varepsilon_2 = 1$ ,  
 $u_0 = (0, 0)$

**Remark:** the Gradient descent is close to MM in the convergence time range.

# 5. Conclusion

- The gradient descent approach estimates well the real reachable set of a system in the convergence time interval.
- The gradient descent approach outperforms the IOMM approach.
- The performance also depends on the truncation length of the words used in the Chen-Fliess series.

# Questions?

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