

# Approximating regions of attraction of a sparse polynomial differential system

POP brainstorming  
MAC team

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Le réseau  
de transport  
d'électricité

# Outline

- 1 An illustrative toy example
- 2 Exploiting sparsity
- 3 Computing a dimension 20 ROA

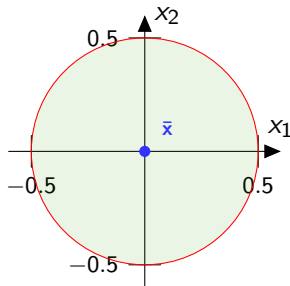
- 1 **An illustrative toy example**
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# A radial system

$$\begin{cases} \dot{x}_1 = (x_1^2 + x_2^2 - \frac{1}{4}) x_1 \\ \dot{x}_2 = (x_1^2 + x_2^2 - \frac{1}{4}) x_2 \end{cases} \quad \text{summarized into } \dot{\mathbf{x}} = \left( |\mathbf{x}|^2 - \frac{1}{4} \right) \mathbf{x}$$

## Stability analysis

- $\bar{\mathbf{x}} = (0, 0)$  locally asymptotically stable equilibrium point
- $D(0, \frac{1}{2}) := \{(x_1, x_2) \in \mathbb{R}^2 : x_1^2 + x_2^2 < \frac{1}{4}\}$  ROA of  $\bar{\mathbf{x}}$
- $C(0, \frac{1}{2}) := \{(x_1, x_2) \in \mathbb{R}^2 : x_1^2 + x_2^2 = \frac{1}{4}\}$  set of unstable EPs



# A sparse system

$$\begin{cases} \dot{x}_1 = (x_1^2 + x_2^2 - \frac{1}{4}) x_1 \\ \dot{x}_2 = (x_2^2 + x_3^2 - \frac{1}{4}) x_2 \\ \dot{x}_3 = (x_2^2 + x_3^2 - \frac{1}{4}) x_3 \end{cases} \quad \text{summarized into } \dot{\mathbf{x}} = \mathbf{f}(\mathbf{x})$$

## Stability analysis

💡  $V(\mathbf{x}) := |\mathbf{x}|^2 = x_1^2 + x_2^2 + x_3^2$  Lyapunov function ( $V$  &  $-\dot{V}$  p.d.) on

$$\mathcal{D} := \left\{ \mathbf{x} \in \mathbb{R}^3 : x_1^2 + x_2^2 < \frac{1}{4}, x_2^2 + x_3^2 < \frac{1}{4} \right\}$$

⇒  $\bar{\mathbf{x}} = (0, 0, 0)$  locally asymptotically stable equilibrium point

💡  $\mathcal{D}$  is positively invariant ⇒ it is included in the ROA of  $\bar{\mathbf{x}}$

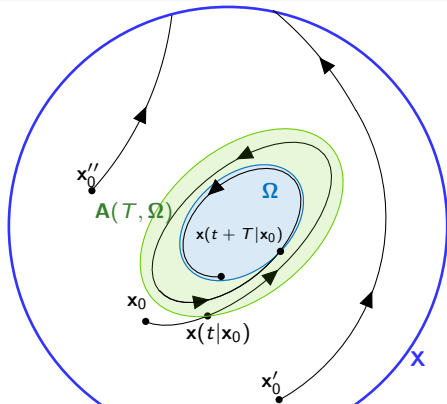
→ what is the ROA of  $\bar{\mathbf{x}}$ ?

# Finite time ROA

## Problem

Let  $\mathbf{X} := \{ \mathbf{x} \in \mathbb{R}^3 : x_1^2 + x_2^2 < 1, x_2^2 + x_3^2 < 1 \}$  be the admissible state set. Given time horizon  $T > 0$  & target set  $\Omega \subset \mathcal{D}$  containing  $\bar{\mathbf{x}}$ , compute

$$\mathbf{A}(T, \Omega) := \left\{ \mathbf{x}^0 \in \mathbb{R}^3 : \begin{array}{l} \forall t \in [0, T] \mathbf{x}(t | \mathbf{x}^0) \in \mathbf{X} \\ \mathbf{x}(T | \mathbf{x}^0) \in \Omega \end{array} \right\}$$



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## Proposition of solution [Korda, Henrion 2012]

For any feasible  $(v, w)$  of LP

$$\inf_{\mathbf{x}} \int_{\mathbf{x}} w(\mathbf{x}) \, d\mathbf{x}$$

$$\text{s.t. } w \geq (v(0, \cdot) + 1)_+ \quad \text{on } \mathbf{X}$$

$$v(T, \cdot) \geq 0 \quad \text{on } \Omega$$

$$\partial_t v(t, \mathbf{x}) + \nabla v(t, \mathbf{x}) \cdot \mathbf{f}(\mathbf{x}) \leq 0 \quad \forall t \in [0, T], \mathbf{x} \in \mathbf{X}$$

- $\mathbf{A}(T, \Omega) \subset \{\mathbf{x} \in \mathbb{R}^3 : v(0, \mathbf{x}) \geq 0\} \subset \{\mathbf{x} \in \mathbb{R}^3 : w(\mathbf{x}) \geq 1\}$
- $\text{vol}(\{\mathbf{x} \in \mathbb{R}^3 : w(\mathbf{x}) \geq 1\} \setminus \mathbf{A}(T, \Omega)) \rightarrow 0$  along minimizing sequences

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# Exploiting sparsity

## “No free lunch” rule

- 💡 minimizing sequence computed using Lasserre hierarchy
- ⇒ reduction to solving LMI / SDP ⇒ sensitive to dimension

## Lower dimensional rephrased LP

Suppose  $\Omega = \{\mathbf{x} \in \mathbb{R}^3 : (x_1, x_2) \in \Omega_1 \ \& \ (x_2, x_3) \in \Omega_2\}$ . Consider

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## Lower dimensional rephrased LP

Suppose  $\Omega = \{\mathbf{x} \in \mathbb{R}^3 : (x_1, x_2) \in \Omega_1 \text{ \& } (x_2, x_3) \in \Omega_2\}$ . Consider

$$\inf_{u, v_i, w_i} \int_{\mathbf{Y}_1} w_1(x_1, x_2) dx_1 dx_2 + \int_{\mathbf{Y}_2} w_2(x_2, x_3) dx_2 dx_3$$

$$\text{s.t. } w_i \geq (v_i(0, \cdot) + 1)_+ \quad \text{on } \mathbf{Y}_i$$

$$v_i(T, \cdot) \geq 0 \quad \text{on } \Omega_i$$

$$\partial_t v_2(t, \cdot) + \partial_2 v_2(t, \cdot) f_2 + \partial_3 v_2(t, \cdot) f_3 \leq 0 \quad \text{on } \mathbf{Y}_2 \quad \forall t \in [0, T]$$

$$v_1(t, x_1, x_2) = v_{11}(t, x_1) + v_{12}(t, x_2) \quad \forall (t, x_1, x_2) \in [0, T] \times \mathbf{Y}_1$$

$$\partial_t v_1(t, x_1, x_2) + \partial_1 v_{11}(t, x_1) f_1(x_1, x_2) \leq u(x_2) \quad \forall (t, x_1, x_2) \in [0, T] \times \mathbf{Y}_1$$

$$u(x_2) + \partial_2 v_{12}(t, x_2) f_2(x_2, x_3) \leq 0 \quad \forall (t, x_2, x_3) \in [0, T] \times \mathbf{Y}_2$$

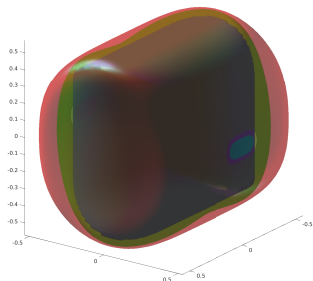
where  $\mathbf{Y}_i := \{(x_i, x_{i+1}) \in \mathbb{R}^2 : x_i^2 + x_{i+1}^2 \leq 1\}$ ,  $i = 1, 2$ .

# Actual ROA estimation

Theory: outer approximation

$$\mathbf{A}(T, \Omega) \subset \{\mathbf{x} \in \mathbb{R}^3 : v_i(0, x_i, x_{i+1}) \geq 0, i = 1 \& 2\}$$

Numerics (sparse, dense,  $\mathcal{D}$ )



comparison of the degree 10 relaxations

degree	dense	sparse
4	4	4
6	24	10
8	334	83
10	5542	440
12	-	1865

comparison of the CPU times

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# General sparsity pattern

## “Linear” sparse differential system

$$\begin{cases} \dot{\mathbf{x}}_i = \mathbf{f}_i(\mathbf{x}_i, \mathbf{x}_{i+1}) & i = 1, \dots, N-1 \\ \dot{\mathbf{x}}_N = \mathbf{f}_N(\mathbf{x}_{N-1}, \mathbf{x}_N) \end{cases}$$

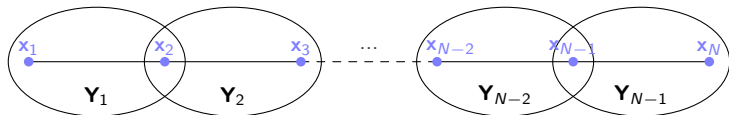
$$\mathbf{x}_j \in \mathbf{X}_j$$

$$j = 1, \dots, N$$

$$\mathbf{Y}_i = \mathbf{X}_i + \mathbf{X}_{i+1}$$

$$i = 1, \dots, N-1$$

$$\mathbf{X} = \mathbf{X}_1 \oplus \dots \oplus \mathbf{X}_N = \mathbf{Y}_1 + \dots + \mathbf{Y}_{N-1}$$



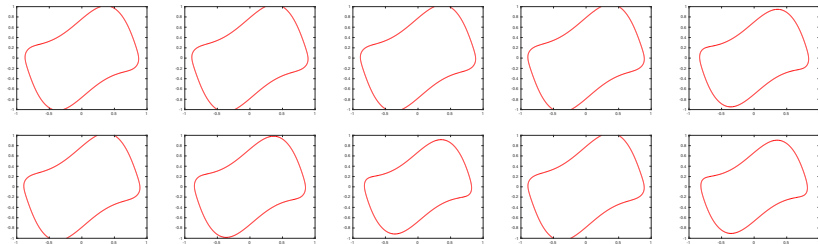
# A chain of Van der Pol oscillators

## Construction

$$\begin{cases} \dot{y}_i = -2z_i & i = 1, \dots, 10 \\ \dot{z}_j = 0.8 y_j + 10 (1.44 y_j^2 - 0.21) z_j + \epsilon_j z_{j+1} y_j & j = 1, \dots, 9 \\ \dot{z}_{10} = 0.8 y_{10} + 10 (1.44 y_{10}^2 - 0.21) z_{10} \end{cases}$$

$\epsilon_j \in [-0.5, 0.5]$  following a uniform probability,  $\mathbf{x}_i = (y_i, z_i)$ .

plots:  $(y_i, z_i)$  projection of finite time ROA outer approx,  $i = 1, \dots, 10$



# Conclusion and future work

## Take-home

Rephrasing Lasserre hierarchy for sparse systems:

- Speed up the computations
- Tackle higher dimensions
- Convergence remains to be studied

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Rephrasing Lasserre hierarchy for sparse systems:

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## Future work

- Tackle more general correlative sparsity patterns as in [Tacchi & al. *Exploiting sparsity for semialgebraic volume computation*, 2020]
- Extend the framework to inner stability region approximations:  
[Korda & al. *Inner approximation of the ROA (...)*, IFAC 2013]  
[Oustry & al. *Inner approximation of the MPI set (...)*, CDC 2019]
- Tackle 'time-scale sparsity' as in [Subotić & al. *A Lyapunov framework for nested dynamical systems (...)*, 2020]
- Apply the results to a simple electrical power network



# Thank you!



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