Semidefinite Approximations of Reachable Sets for Discrete-time Polynomial Systems

Victor Magron, CNRS VERIMAG

Joint work with
Pierre-Loïc Garoche (ONERA)
Didier Henrion (LAAS)
Xavier Thirioux (IRIT)

SMAI-MODE
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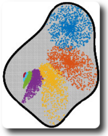
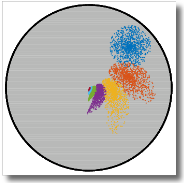


The Problem

- Semialgebraic initial conditions
  $\mathbf{X}_0 := \{\mathbf{x} \in \mathbb{R}^n : g_1^0(\mathbf{x}) \geqslant 0, \ldots, g_{m_0}^0(\mathbf{x}) \geqslant 0\}$

- Polynomial map $f : \mathbb{R}^n \to \mathbb{R}^n$,
  $\mathbf{x} \mapsto f(\mathbf{x}) := (f_1(\mathbf{x}), \ldots, f_n(\mathbf{x}))$



- $\deg f = d := \max\{\deg f_1, \ldots, \deg f_n\}$

- Set of admissible trajectories
  $\mathbf{X}^* := \{(\mathbf{x}_t)_{t \in \mathbb{N}} : \mathbf{x}_{t+1} = f(\mathbf{x}_t), \forall t \in \mathbb{N}, \mathbf{x}_0 \in \mathbf{X}_0\}$

- $\mathbf{X}^* = \bigcup_{t \in \mathbb{N}} f^t(\mathbf{X}_0) \subseteq \mathbf{X}$, with $\mathbf{X} \subset \mathbb{R}^n$ a box or a ball

- Tractable approximations of $\mathbf{X}^*$?

The Problem

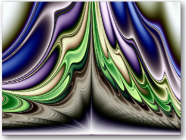
- Occurs in several contexts :

1. program analysis: fixpoint computation

```
toyprogram (x_1,x_2)
requires (0.25 ⩽ x_1 ⩽ 0.75 && 0.25 ⩽ x_2 ⩽ 0.75);
while (x_1^2 + x_2^2 ⩽ 1){
        x_1 = x_1 + 2x_1x_2;
            x_2 = 0.5(x_2 − 2x_1^3);
      }
```

2. hybrid systems, biology: Neuron Model, Growth Model

3. control: integrator, Hénon map



Related work: LP relaxations

1. Contractive methods based on LP relaxations and polyhedra projection [Bertsekas 72]
2. Extension to nonlinear systems [Harwood et al. 16]
3. Bernstein/Krivine-Handelman representations [Ben Sassi- et al. 15, Ben Sassi et al. 12]

$\oplus$ LP relaxations $\implies$ scalability

$\ominus$ Convex approximations of nonconvex sets $\implies$ coarse

$\ominus$ No convergence guarantees (very often)

Related work: SDP relaxations

1. Upper bounds of the volume of a semialgebraic set [Henrion et al. 09]

2. Tractable approximations of sets defined with quantifiers $\exists, \forall$ [Lasserre 15]

3. Semidefinite characterization of region of attraction [Henrion-Korda 14]

4. Convex computation of maximum controlled invariant [Korda-Henrion-Jones 13]

Related work: SDP relaxations

5 SDP approximation of polynomial images of semialgebraic sets [Magron-Henrion-Lasserre 15]

- $\mathbf{X}_1 := f(\mathbf{X}_0) \subseteq \mathbf{X}$, with $\mathbf{X} \subset \mathbb{R}^n$ a box or a ball
  $\implies$ Discrete-time system with a single iteration

- 💡 Approximation of image measure supports
  $\implies$ certified SDP over approximations of $\mathbf{X}_1$

- $\mathbf{X}_t := f^t(\mathbf{X}_0)$

  ⊖ $\deg f^t = d \times t \implies$ very expensive computation

  ⊖ Would only approximate $\mathbf{X}_t$ and not $\mathbf{X}^*$

Contribution

- General framework to approximate $\mathbf{X}^*$
  $\oplus$ **No discretization** is required

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- Finite-dimensional SDP relaxations

- $\mathbf{X}^* \subseteq \mathbf{X}^r := \{\mathbf{x} \in \mathbf{X} : w_r(\mathbf{x}) \geqslant 1\}$
  $\oplus$ Strong convergence guarantees $\lim_{r\to\infty} \text{vol}(\mathbf{X}^r \backslash \mathbf{X}^*) = 0$
  $\oplus$ Compute w_r by solving one **semidefinite program**

Contribution

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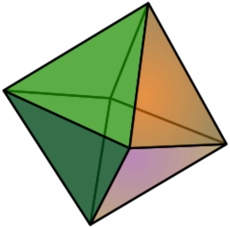
  $\oplus$ Compute w_r by solving one **semidefinite program**

- Work in progress with technical issues
  $\ominus$ Requires strong assumption on attractors of f on $\mathbf{X} \backslash \mathbf{X}^*$

What is Semidefinite Programming?

- Linear Programming (LP):

$$\begin{aligned} \min_{\mathbf{z}} \quad & \mathbf{c}^\top \mathbf{z} \\ \text{s.t.} \quad & \mathbf{A}\,\mathbf{z} \geqslant \mathbf{d} \,. \end{aligned}$$



Polyhedron

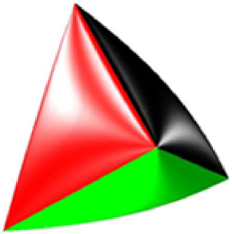
  - Linear cost $\mathbf{c}$
  - Linear inequalities "$\sum_i A_{ij}\, z_j \geqslant d_i$"

What is Semidefinite Programming?

- Semidefinite Programming (SDP):

$$\min_{\mathbf{z}} \quad \mathbf{c}^\top \mathbf{z}$$
$$\text{s.t.} \quad \sum_i \mathbf{F}_i z_i \succcurlyeq \mathbf{F}_0 \ .$$

  - Linear cost $\mathbf{c}$
  - Symmetric matrices $\mathbf{F}_0, \mathbf{F}_i$
  - Linear matrix inequalities "$\mathbf{F} \succcurlyeq 0$" ($\mathbf{F}$ has nonnegative eigenvalues)

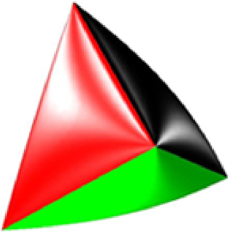


Spectrahedron

What is Semidefinite Programming?

- Semidefinite Programming (SDP):

$$\min_{\mathbf{z}} \quad \mathbf{c}^\top \mathbf{z}$$
$$\text{s.t.} \quad \sum_i \mathbf{F}_i z_i \succcurlyeq \mathbf{F}_0 \ , \quad \mathbf{A}\,\mathbf{z} = \mathbf{d} \ .$$



Spectrahedron

- Linear cost $\mathbf{c}$
- Symmetric matrices $\mathbf{F}_0, \mathbf{F}_i$
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Applications of SDP

- Combinatorial optimization
- Control theory
- Matrix completion
- Unique Games Conjecture (Khot ’02) :
  “A *single concrete algorithm* provides **optimal guarantees** among all efficient algorithms for a large class of computational problems.”
  (Barak and Steurer survey at ICM’14)
- Solving polynomial optimization (Lasserre ’01)

Polynomial Optimization

- Semialgebraic set $\mathbf{X} := \{\mathbf{x} \in \mathbb{R}^n : g_1(\mathbf{x}) \geqslant 0, \ldots, g_l(\mathbf{x}) \geqslant 0\}$
- $p^* := \inf_{\mathbf{x} \in \mathbf{X}} f(\mathbf{x})$: NP hard
- Sums of squares $\Sigma[\mathbf{x}]$
  e.g. $x_1^2 - 2x_1x_2 + x_2^2 = (x_1 - x_2)^2$
- $\mathcal{Q}(\mathbf{X}) := \left\{ \sigma_0(\mathbf{x}) + \sum_{j=1}^{l} \sigma_j(\mathbf{x}) g_j(\mathbf{x}), \text{ with } \sigma_j \in \Sigma[\mathbf{x}] \right\}$
- **REMEMBER**: $f \in \mathcal{Q}(\mathbf{X}) \implies \forall \mathbf{x} \in \mathbf{X}, f(\mathbf{x}) \geqslant 0$

Infinite LP Reformulation

- Borel σ-algebra $\mathcal{B}(\mathbf{X})$ (generated by the open sets of $\mathbf{X}$)

- $\mathcal{M}_+(\mathbf{X})$: set of probability measures supported on $\mathbf{X}$.
  If $\mu \in \mathcal{M}_+(\mathbf{X})$ then

  1. $\mu : \mathcal{B} \to [0, \infty)$, $\mu(\emptyset) = 0$

  2. $\mu(\bigcup_i B_i) = \sum_i \mu(B_i)$, for any disjoint countable $(B_i) \subset \mathcal{B}(\mathbf{X})$

  3. Lebesgue **Volume** of $B \in \mathcal{B}(\mathbf{X})$

$$\operatorname{vol} B := \int_{\mathbf{X}} \lambda_B \,, \text{ with } \lambda_B(d\mathbf{x}) := \mathbf{1}_B(\mathbf{x})\, d\mathbf{x}$$

- $\operatorname{supp} \mu$ is the smallest set $\mathbf{X}$ such that $\mu(\mathbb{R}^n \backslash \mathbf{X}) = 0$

Infinite LP Reformulation

$$p^* = \inf_{\mathbf{x} \in \mathbf{X}} f(\mathbf{x}) = \inf_{\mu \in \mathcal{M}_+(\mathbf{X})} \int_{\mathbf{X}} f \, d\mu$$

Primal-dual Moment-SOS [Lasserre 01]

- Let $(\mathbf{x}^\alpha)_{\alpha \in \mathbb{N}^n}$ be the monomial basis

Definition

A sequence $\mathbf{z}$ has a representing measure on $\mathbf{X}$ if there exists a finite measure μ supported on $\mathbf{X}$ such that

$$\mathbf{z}_\alpha = \int_{\mathbf{X}} \mathbf{x}^\alpha \mu(d\mathbf{x}), \quad \forall \alpha \in \mathbb{N}^n .$$

Primal-dual Moment-SOS [Lasserre 01]

- $\mathcal{M}_+(\mathbf{X})$: space of probability measures supported on $\mathbf{X}$
- $\mathcal{Q}(\mathbf{X})$: quadratic module

Polynomial Optimization Problems (POP)

(Primal) $\qquad$ (Dual)

$$\begin{aligned} \inf \quad & \int_{\mathbf{X}} f \, d\mu \\ \text{s.t.} \quad & \mu \in \mathcal{M}_+(\mathbf{X}) \end{aligned} \qquad = \qquad \begin{aligned} \sup \quad & m \\ \text{s.t.} \quad & m \in \mathbb{R} \ , \\ & f - m \in \mathcal{Q}(\mathbf{X}) \end{aligned}$$

Primal-dual Moment-SOS [Lasserre 01]

- Finite moment sequences $\mathbf{z}$ of measures in $\mathcal{M}_+(\mathbf{X})$
- Truncated quadratic module $\mathcal{Q}_r(\mathbf{X}) := \mathcal{Q}(\mathbf{X}) \cap \mathbb{R}_{2r}[\mathbf{x}]$

Polynomial Optimization Problems (POP)

$$
\begin{array}{llll}
 & \text{(Moment)} & & \text{(SOS)} \\
\inf & \sum_\alpha f_\alpha \mathbf{z}_\alpha & = \sup & m \\
\text{s.t.} & \mathbf{M}_{r-v_j}(g_j\, \mathbf{z}) \succcurlyeq 0\,, \quad 0 \leqslant j \leqslant l, & \text{s.t.} & m \in \mathbb{R}\ , \\
 & \mathbf{z}_1 = 1 & & f - m \in \mathcal{Q}_r(\mathbf{X})
\end{array}
$$

Semidefinite Optimization

- F_0, F_α symmetric real matrices, cost vector c

Primal-dual pair of semidefinite programs:

$$
(SDP) \begin{cases} \mathcal{P}: & \inf_{\mathbf{z}} & \sum_\alpha c_\alpha \mathbf{z}_\alpha \\ & \text{s.t.} & \sum_\alpha F_\alpha \mathbf{z}_\alpha - F_0 \succcurlyeq 0 \\ & & \\ \mathcal{D}: & \sup_{\mathbf{Y}} & \text{Trace}\,(F_0\,\mathbf{Y}) \\ & \text{s.t.} & \text{Trace}\,(F_\alpha\,\mathbf{Y}) = c_\alpha \ , \quad \mathbf{Y} \succcurlyeq 0 \ . \end{cases}
$$

- Freely available SDP solvers (CSDP, SDPA, SEDUMI)

Pushforward and Liouville's Equation

- Let $\mu_0 \in \mathcal{M}_+(\mathbf{X}_0)$

- **Pushforward** $f_\# : \mathcal{M}_+(\mathbf{X}_0) \to \mathcal{M}_+(\mathbf{X})$:

$$f_\# \mu_0(\mathbf{A}) := \mu_0(\{\mathbf{x} \in \mathbf{X}_0 : f(\mathbf{x}) \in \mathbf{A}\}), \quad \forall \mathbf{A} \in \mathcal{B}(\mathbf{X})$$

- $f_\# \mu_0$ is the **image measure** of μ_0 under f

Pushforward and Liouville's Equation

- Let $\mu_0 \in \mathcal{M}_+(\mathbf{X}_0)$, $\alpha > 1$ and define

$$\begin{aligned}
\mu_1 &:= \alpha f_{\#} \mu_0 \\
&\dots \\
\mu_t &:= \alpha f_{\#} \mu_{t-1} \\
\mu &:= \sum_{i=0}^{t-1} \mu_i = \sum_{i=0}^{t-1} \alpha^i f_{\#}^i \mu_0
\end{aligned}$$

- The measures μ_t, μ, μ_0 satisfy **Liouville's Equation**:

$$\mu_t + \mu = \alpha f_{\#} \mu + \mu_0$$

Pushforward and Liouville's Equation

- Let $\mu_t := \lambda_{\mathbf{X}_t}$: Lebesgue measure restriction on $\mathbf{X}_t = f^t(\mathbf{X}_0)$

- $\exists\, \mu_0 \in \mathcal{M}_+(\mathbf{X}_0)$ s.t. $\mu_t = \alpha^t f^t_{\#} \mu_0$
  $\implies \mu_t$ satisfies **Liouville's Equation**!

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Proof

Define $\mu := \sum_{i=0}^{t-1} \alpha^i f^i_{\#}\, \mu_0$. Then, $\mu_t + \mu = \alpha f_{\#}\, \mu + \mu_0$.

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- Let $\lambda_{\mathbf{X}(T)}$: Lebesgue measure restriction on $\bigcup_{t=0}^{T} \mathbf{X}_t$
  $\implies \lambda_{\mathbf{X}(T)}$ satisfies **Liouville's Equation** by superposition

Pushforward and Liouville's Equation

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- Let $\lambda_{\mathbf{X}(T)}$: Lebesgue measure restriction on $\bigcup_{t=0}^{T} \mathbf{X}_t$
  $\implies \lambda_{\mathbf{X}(T)}$ satisfies **Liouville's Equation** by superposition

Lemma

$\alpha > 1 \implies \lambda_{\mathbf{X}^*}$ satisfies **Liouville's Equation**

Infinite Primal LP

$$
\begin{aligned}
p^* := \sup_{\mu_\infty, \mu, \mu_0} \quad & \int_{\mathbf{X}} \mu_\infty \\
\text{s.t.} \quad & \mu_\infty + \mu = \alpha f_\# \mu + \mu_0 \,, \\
& \mu_\infty \leqslant \lambda_{\mathbf{X}} \,, \\
& \mu_\infty, \mu \in \mathcal{M}_+(\mathbf{X}) \,, \quad \mu_0 \in \mathcal{M}_+(\mathbf{X}_0) \,.
\end{aligned}
$$

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\end{aligned}
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- **Question**: $\lambda_{\mathbf{X}^*}$ optimal for this infinite primal LP ?

Infinite Primal LP

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- **Answer** (in general): No!

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\end{aligned}
$$

- **Question**: $\lambda_{\mathbf{X}^*}$ optimal for this infinite primal LP ?
- **Answer** (in general): No!

Proof

Let μ be any invariant measure w.r.t. f on $\mathbf{X} \backslash \mathbf{X}^*$:

- $\mu = f_\# \mu$, $\mu_{\text{inv}} := (\alpha - 1)\, \mu$ satisfies Liouville's Equation
- $\lambda_{\mathbf{X}^*} + \mu_{\text{inv}}$ satisfies Liouville's Equation

$\text{vol}(\text{supp}\, \mu) > 0 \implies \text{vol}\, \mathbf{X}^* < \int_{\mathbf{X}} (\lambda_{\mathbf{X}^*} + \mu_{\text{inv}}) \leqslant \text{vol}\, \mathbf{X}$.

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& \mu_\infty \leqslant \lambda_{\mathbf{X}} \,, \\
& \mu_\infty, \mu \in \mathcal{M}_+(\mathbf{X}) \,, \quad \mu_0 \in \mathcal{M}_+(\mathbf{X}_0) \,.
\end{aligned}
$$

Lemma

Let μ_{inv} be invariant w.r.t. f with maximal support $\mathbf{X}^{\text{inv}}$.
Then the above LP has optimal solution $\lambda_{\mathbf{X}^*} + \mu_{\text{inv}}$ and
$p^* = \text{vol}(\mathbf{X}^* \cup \mathbf{X}^{\text{inv}})$.

Infinite Primal LP

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Lemma

Let μ_{inv} be invariant w.r.t. f with maximal support $\mathbf{X}^{\text{inv}}$. Then the above LP has optimal solution $\lambda_{\mathbf{X}^*} + \mu_{\text{inv}}$ and $p^* = \text{vol}(\mathbf{X}^* \cup \mathbf{X}^{\text{inv}})$.

⊖ Assuming that vol $\mathbf{X}^{\text{inv}} = 0$ is a **strong hypothesis**!

$f(x) = x, \mathbf{X}_0 := [0, 1/2], \mathbf{X} = [0, 1]$

$\implies \mathbf{X}^* = \mathbf{X}_0$ and $p^* = \text{vol}\, \mathbf{X}$.

LP Primal-dual conic formulation

The LP can be cast as follows:

$$
\begin{aligned}
p^* = \sup_{x} \quad & \langle x, c \rangle_1 \\
\text{s.t.} \quad & \mathcal{A}\, x = b\,, \\
& x \in E_1^+\,,
\end{aligned}
$$

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with

- $E_1 := \mathcal{M}(\mathbf{X})^3 \times \mathcal{M}(\mathbf{X}_0) \quad F_1 := \mathcal{C}(\mathbf{X})^3 \times \mathcal{C}(\mathbf{X}_0)$
- $x := (\mu_\infty, \hat{\mu}_\infty, \mu, \mu_0) \quad c := (1, 0, 0, 0) \in F_1 \quad b := (0, \lambda_{\mathbf{X}})$
- the linear operator $\mathcal{A} : E_1 \to E_2$ given by

$$\mathcal{A}\,(\mu_\infty, \hat{\mu}_\infty, \mu, \mu_0) := \begin{bmatrix} \mu_\infty + \mu - \alpha\, f_{\#}\, \mu - \mu_0 \\ \mu_\infty + \hat{\mu}_\infty \end{bmatrix}.$$

LP Primal-dual conic formulation

Primal LP	Dual LP
$$\begin{aligned} p^* = \sup_x \quad & \langle x, c \rangle_1 \\ \text{s.t.} \quad & \mathcal{A}\, x = b \,, \\ & x \in E_1^+ \,. \end{aligned}$$	$$\begin{aligned} d^* = \inf_y \quad & \langle b, y \rangle_2 \\ \text{s.t.} \quad & \mathcal{A}'\, y - c \, \in F_1^+ \,. \end{aligned}$$

with

- $y := (v, w) \in \mathcal{M}(\mathbf{X})^2$
- $\mathcal{A}'\,(v, w) := \begin{bmatrix} v + w \\ v - \alpha\, v \circ f \\ w \\ -v \end{bmatrix}$.

LP Primal-dual conic formulation

Primal LP

$$
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& \mu_\infty \leqslant \lambda_{\mathbf{X}} \,, \\
& \mu_\infty, \mu \in \mathcal{M}_+(\mathbf{X}) \,, \\
& \mu_0 \in \mathcal{M}_+(\mathbf{X}_0) \,.
\end{aligned}
$$

Dual LP

$$
\begin{aligned}
d^* := \inf_{v, w} \quad & \int w(\mathbf{x}) \, \lambda_{\mathbf{X}}(d\mathbf{x}) \\
\text{s.t.} \quad & w - v - 1 \in \mathcal{C}_+(\mathbf{X}) \,, \\
& \alpha \, v \circ f - v \in \mathcal{C}_+(\mathbf{X}) \,, \\
& w \in \mathcal{C}_+(\mathbf{X}) \,, \\
& v \in \mathcal{C}_+(\mathbf{X}_0) \,.
\end{aligned}
$$

Zero duality gap

Lemma

$p^* = d^*$

Strong convergence property

Strengthening of the dual LP:

$$\begin{aligned} d_r^* := \inf_{v,w} \quad & \sum_{\beta \in \mathbb{N}_{2r}^n} w_\beta z_\beta^{\mathbf{X}} \\ \text{s.t.} \quad & w - v - 1 \in \mathcal{Q}_r(\mathbf{X}) \,, \\ & \alpha\, v \circ f - v \in \mathcal{Q}_{rd}(\mathbf{X}) \,, \\ & w \in \mathcal{Q}_r(\mathbf{X}) \,, \\ & v \in \mathcal{Q}_r(\mathbf{X}_0) \,. \end{aligned}$$

Strong convergence property

Theorem

Assume that $\mathbf{X}^* \cup \mathbf{X}^{\text{inv}}$ has nonempty interior and $\mathcal{Q}_r(\mathbf{X}_0)$ (resp. $\mathcal{Q}_r(\mathbf{X})$) is Archimedean.

1. The sequence (w_r) converges to $\mathbf{1}_{\mathbf{X}^* \cup \mathbf{X}^{\text{inv}}}$ w.r.t the $L_1(\mathbf{X})$-norm:

$$\lim_{r \to \infty} \int_{\mathbf{X}} |w_r - \mathbf{1}_{\mathbf{X}^* \cup \mathbf{X}^{\text{inv}}}| = 0 \ .$$

Strong convergence property

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$$\lim_{r\to\infty} \int_{\mathbf{X}} |w_r - \mathbf{1}_{\mathbf{X}^* \cup \mathbf{X}^{\text{inv}}}| = 0 \ .$$

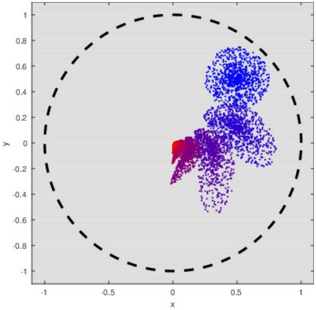
2. Let $\mathbf{X}^r := \{\mathbf{x} \in \mathbf{X} : w_r(\mathbf{x}) \geqslant 1\}$. Then,

$$\lim_{r\to\infty} \text{vol}(\mathbf{X}^r \backslash \mathbf{X}^* \cup \mathbf{X}^{\text{inv}}) = 0 \ .$$

Toy Example

Trajectories from $\mathbf{X}_0 := \{\mathbf{x} \in \mathbb{R}^2 : (x_1 - \frac{1}{2})^2 + (x_2 - \frac{1}{2})^2 \leqslant \frac{1}{4}\}$ under

$$x_1^+ := \frac{1}{2}(x_1 + 2x_1x_2)\,,$$
$$x_2^+ := \frac{1}{2}(x_2 - 2x_1^3)\,,$$

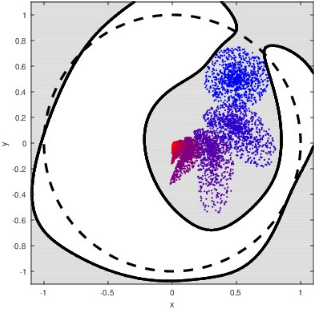


$\mathbf{X}^4$

Toy Example

Trajectories from $\mathbf{X}_0 := \{\mathbf{x} \in \mathbb{R}^2 : (x_1 - \frac{1}{2})^2 + (x_2 - \frac{1}{2})^2 \leqslant \frac{1}{4}\}$ under

$$x_1^+ := \frac{1}{2}(x_1 + 2x_1x_2)\,,$$
$$x_2^+ := \frac{1}{2}(x_2 - 2x_1^3)\,,$$

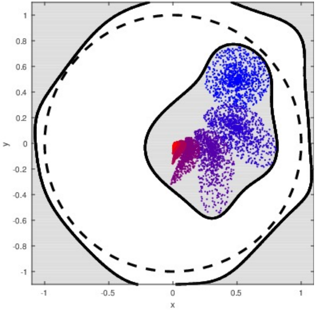


$\mathbf{X}^6$

Toy Example

Trajectories from $\mathbf{X}_0 := \{\mathbf{x} \in \mathbb{R}^2 : (x_1 - \frac{1}{2})^2 + (x_2 - \frac{1}{2})^2 \leqslant \frac{1}{4}\}$ under

$$x_1^+ := \frac{1}{2}(x_1 + 2x_1x_2),$$
$$x_2^+ := \frac{1}{2}(x_2 - 2x_1^3),$$

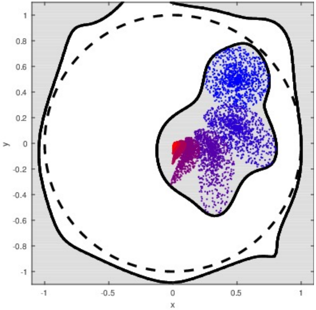


$\mathbf{X}^8$

Toy Example

Trajectories from $\mathbf{X}_0 := \{\mathbf{x} \in \mathbb{R}^2 : (x_1 - \frac{1}{2})^2 + (x_2 - \frac{1}{2})^2 \leqslant \frac{1}{4}\}$ under

$$x_1^+ := \frac{1}{2}(x_1 + 2x_1x_2),$$
$$x_2^+ := \frac{1}{2}(x_2 - 2x_1^3),$$



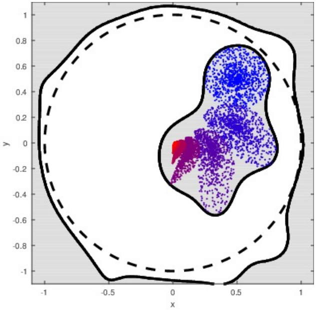
$\mathbf{X}^{10}$

Toy Example

Trajectories from $\mathbf{X}_0 := \{\mathbf{x} \in \mathbb{R}^2 : (x_1 - \frac{1}{2})^2 + (x_2 - \frac{1}{2})^2 \leqslant \frac{1}{4}\}$ under

$$x_1^+ := \frac{1}{2}(x_1 + 2x_1x_2),$$

$$x_2^+ := \frac{1}{2}(x_2 - 2x_1^3),$$

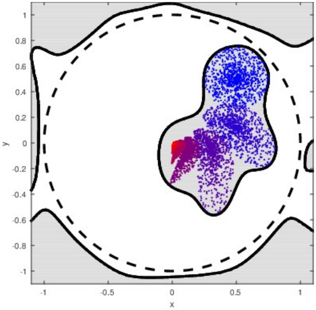


$\mathbf{X}^{12}$

Toy Example

Trajectories from $\mathbf{X}_0 := \{\mathbf{x} \in \mathbb{R}^2 : (x_1 - \frac{1}{2})^2 + (x_2 - \frac{1}{2})^2 \leqslant \frac{1}{4}\}$ under

$$x_1^+ := \frac{1}{2}(x_1 + 2x_1 x_2)\,,$$
$$x_2^+ := \frac{1}{2}(x_2 - 2x_1^3)\,,$$

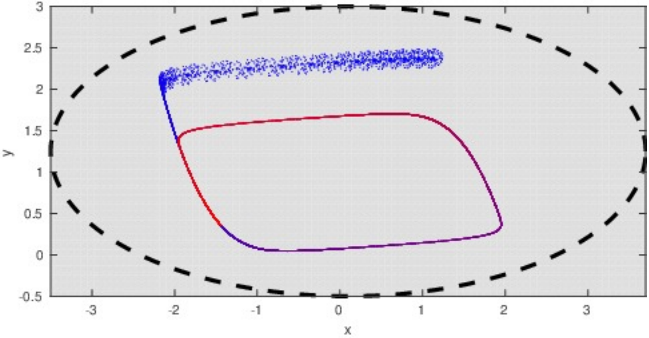


$\mathbf{X}^{14}$

FitzHugh-Nagumo Neuron Model

Trajectories from $\mathbf{X}_0 := [1, 1.25] \times [2.25, 2.5]$ under

$$x_1^+ := x_1 + 0.2(x_1 - x_1^3/3 - x_2 + 0.875)\,,$$
$$x_2^+ := x_2 + 0.2(0.08(x_1 + 0.7 - 0.8x_2))\,,$$

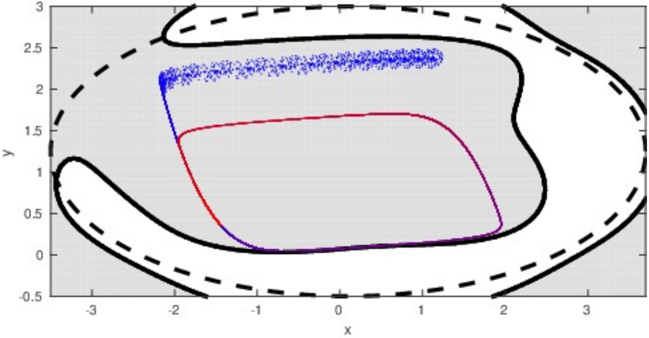


$\mathbf{X}^4$

FitzHugh-Nagumo Neuron Model

Trajectories from $\mathbf{X}_0 := [1, 1.25] \times [2.25, 2.5]$ under

$$x_1^+ := x_1 + 0.2(x_1 - x_1^3/3 - x_2 + 0.875)\,,$$
$$x_2^+ := x_2 + 0.2(0.08(x_1 + 0.7 - 0.8x_2))\,,$$

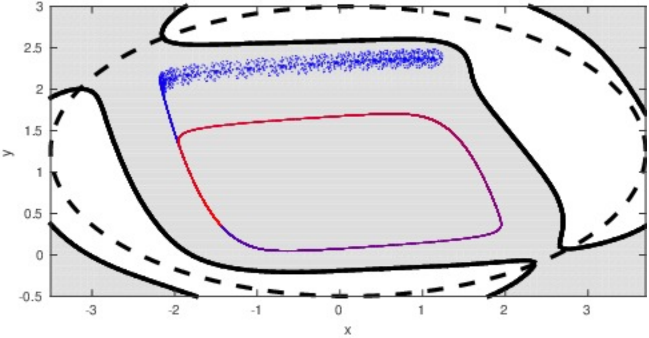


$\mathbf{X}^6$

FitzHugh-Nagumo Neuron Model

Trajectories from $\mathbf{X}_0 := [1, 1.25] \times [2.25, 2.5]$ under

$$x_1^+ := x_1 + 0.2(x_1 - x_1^3/3 - x_2 + 0.875)\,,$$
$$x_2^+ := x_2 + 0.2(0.08(x_1 + 0.7 - 0.8x_2))\,,$$

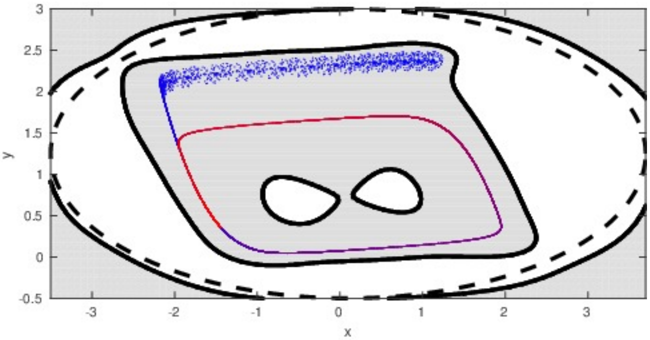


$\mathbf{X}^8$

FitzHugh-Nagumo Neuron Model

Trajectories from $\mathbf{X}_0 := [1, 1.25] \times [2.25, 2.5]$ under

$$x_1^+ := x_1 + 0.2(x_1 - x_1^3/3 - x_2 + 0.875)\,,$$
$$x_2^+ := x_2 + 0.2(0.08(x_1 + 0.7 - 0.8x_2))\,,$$

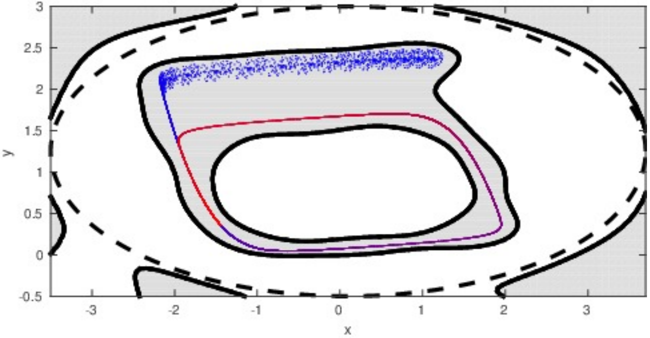


$\mathbf{X}^{10}$

FitzHugh-Nagumo Neuron Model

Trajectories from $\mathbf{X}_0 := [1, 1.25] \times [2.25, 2.5]$ under

$$x_1^+ := x_1 + 0.2(x_1 - x_1^3/3 - x_2 + 0.875)\,,$$
$$x_2^+ := x_2 + 0.2(0.08(x_1 + 0.7 - 0.8x_2))\,,$$

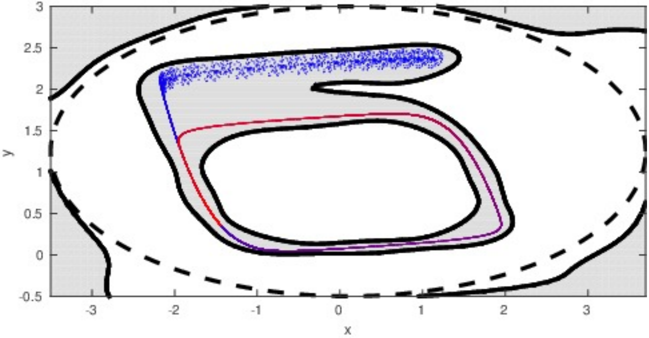


$\mathbf{X}^{12}$

FitzHugh-Nagumo Neuron Model

Trajectories from $\mathbf{X}_0 := [1, 1.25] \times [2.25, 2.5]$ under

$$x_1^+ := x_1 + 0.2(x_1 - x_1^3/3 - x_2 + 0.875)\,,$$
$$x_2^+ := x_2 + 0.2(0.08(x_1 + 0.7 - 0.8x_2))\,,$$



$\mathbf{X}^{14}$

Conclusion

$\oplus$ Certified Approximation of the **whole reachable set** $\mathbf{X}^*$

$\ominus$ Cannot avoid to approximate attractor set $\mathbf{X}^{\text{inv}}$

$\ominus$ Computational complexity: $\binom{n+2rd}{n}$ SDP variables

$\oplus$ **Structure sparsity** can be exploited

Conclusion

Further research:

- Infinite Primal LP characterization of $\mathbf{X}^*$ only ?
- Discrete finite-time, continuous finite/infinite horizon ?
  💡Use previous framework approximating:

  1. region of attraction
  2. maximum controlled invariant

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End

Thank you for your attention!

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