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## Optimal Set Containment Using Sublevel Set Volume Minimization

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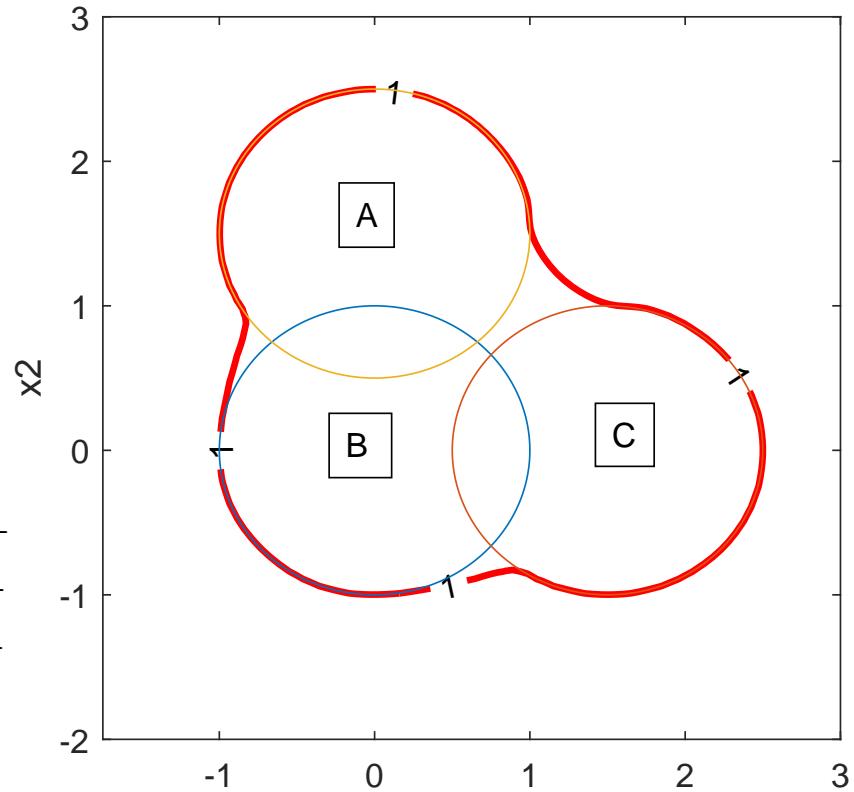
# Optimal Set Containment

## Goal

For  $S \subset \mathbb{R}^n$  find  $V : \mathbb{R}^n \rightarrow \mathbb{R}$  such that  $S \subseteq \{x \in \mathbb{R}^n : V(x) < 1\}$ .

## Example:

$$\begin{aligned}V(x_1, x_2) = & 0.15361x_1^6 + 0.2062x_1^5x_2 + \\& 0.57102x_1^4x_2^2 + 0.49633x_1^3x_2^3 + \\& 0.57102x_1^2x_2^4 + 0.2062x_1x_2^5 + \\& 0.15361x_2^6 - 0.644x_1^5 - 1.011x_1^4x_2 - \\& 1.6852x_1^3x_2^2 - 1.6852x_1^2x_2^3 - \\& 1.011x_1x_2^4 - 0.644x_2^5 + 0.47172x_1^4 + \\& 1.043x_1^3x_2 + 0.67683x_1^2x_2^2 + 1.043x_1x_2^3 + \\& 0.47172x_2^4 + 0.73992x_1^3 + 1.0435x_1^2x_2 + \\& 1.0435x_1x_2^2 + 0.73992x_2^3 - 0.67654x_1^2 - \\& 1.347x_1x_2 - 0.67654x_2^2 - 0.15349x_1 - \\& 0.15349x_2 + 0.99181.\end{aligned}$$



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## 1. Applications:

- Region of Attraction (ROA) estimation.
- Relaxing Optimization Problems.
- Finding domains where determinism fails.

## 2. General problem formulation and sublevel set volume minimization.

## 3. Formulation of SOS program for approximation of:

- Unions of semialgebraic sets.
- Attractor sets.
- Reachable sets.

# Regions Of Attraction

Consider the ODE,

$$\begin{aligned}\dot{x}(t) &= f(x(t)) \\ \text{Given } x(0) &= x_0.\end{aligned}\tag{1}$$

Where  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  and  $x_0 \in \mathbb{R}^n$ .

## The Solution Map

We say  $\phi_f(x_0, t)$  is the solution map of the ODE (1) if,

$$\begin{aligned}\frac{\delta}{\delta t} \phi_f(x, t) &= f(\phi_f(x, t)) \\ \phi_f(x, 0) &= x.\end{aligned}$$

## The Region of Attraction

The Region of Attraction (ROA) for the ODE (1) is defined by,

$$ROA_f := \{x \in \mathbb{R}^n : \lim_{t \rightarrow \infty} \phi_f(x, t) = 0\}. \tag{2}$$

## Estimation of ROA's Using Trajectory Data

Given data,  $D = \{x_1, \dots, x_N\} \subset ROA_f$ , we can find  $V : \mathbb{R}^n \rightarrow \mathbb{R}$  such that  $D \subseteq \{x \in \mathbb{R}^n : V(x) < 1\}$ .

### Example: Single Machine Infinite Bus System

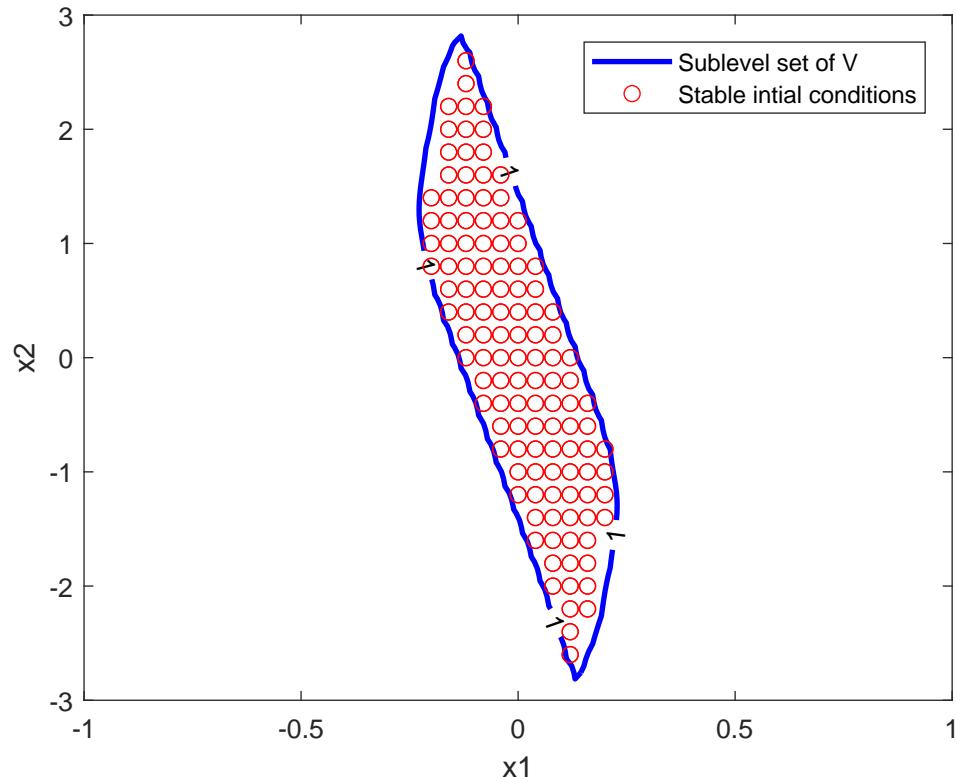
Consider the nonlinear, non-polynomial, switching system:

$$\begin{bmatrix} \dot{\theta}(t) \\ \dot{\omega}(t) \end{bmatrix} = \begin{cases} \begin{bmatrix} \omega(t) \\ \frac{1}{M} \left( P_m - \frac{vE_s}{X_t} \sin(\theta(t)) - D\omega(t) \right) \end{bmatrix} & \forall \omega \in [-3, 3], \delta \in [-\pi, \pi] \\ \begin{bmatrix} 0 \\ 0 \end{bmatrix} & \text{otherwise} \end{cases}$$

where  $M = 0.0212$ ,  $X_t = 0.28$ ,  $P_m = 1$ ,  $v = 1$ ,  $E_s = 1.21$ ,  $D = 0.02$ .

# Estimation of ROA of Single Machine Infinite Bus

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Stable initial conditions were generated using a numerical ODE solver or from the real time output of the machine.

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# Relaxing Optimization Problems

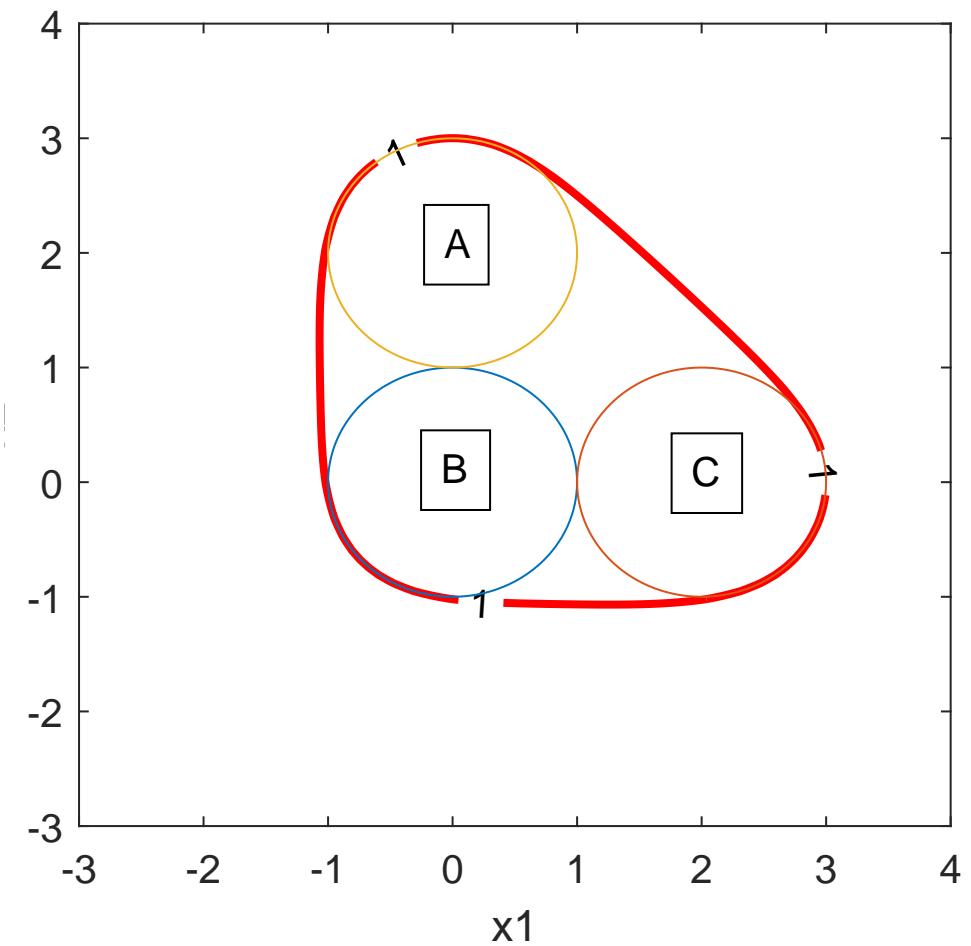
$$\min_{x \in X} f(x) \quad (3)$$

$$\min_{x \in C} f(x) \quad (4)$$

## Fact

Suppose  $X \subseteq C$  then  $\min_{x \in C} f(x) \leq \min_{x \in X} f(x)$ .

- Replacing  $X$  with a set,  $C$ , such that  $X \subset C$  allows us to provide a **bound** for  $\min_{x \in X} f(x)$ .
- Finding a set  $C$  that is **convex** can make the bound of  $\min_{x \in X} f(x)$  **tractable** to compute.



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# The Butterfly Effect

## Chaos: The Butterfly Effect

When a **small change** in the initial conditions for a system results in a **large change** in a later stage.

## Classical Example

A tornado can be influenced by small perturbations such as a **butterfly flapping its wings** several weeks earlier.



# How Chaos Undermines Modeling Physical Systems Mathematically

## Experimental error

You can never measure phenomena in nature without error.



## Definition: Chaotic Region

A compact set  $A \subset \mathbb{R}^n$  is a **chaotic region** of  $\dot{x}(t) = f(x(t)), x(0) = x_0$  if  $\forall x_0 \in A$  the limit  $\lim_{t \rightarrow \infty} \phi(x_0, t)$  is neither **convergent**, **divergent** or **recurrent**.

ODE's loose the ability to predict future natural phenomena inside chaotic regions!

Our Goal is to estimate chaotic regions of ODE's

# The Lorenz System

In 1963 E.N. Lorenz proposed a **3D nonlinear model** convection rolls in the atmosphere.

$$\dot{x}_1(t) = \sigma(x_2(t) - x_1(t))$$

$$\dot{x}_2(t) = \rho x_1(t) - x_2(t) - x_1(t)x_3(t)$$

$$\dot{x}_3(t) = x_1(t)x_2(t) - \beta x_3(t)$$

- |                                 |   |   |
|---------------------------------|---|---|
| • $x_1(t)$ = rate of convection | • $x_2(t)$ = horizontal temperature variation | • $x_3(t)$ = vertical temperature variation |
| • $\sigma$ = Prandtl number     | • $\rho$ = Rayleigh number                    | • $\beta$ = aspect ratio                    |

For the classical parameter choice  $\sigma = 10$ ,  $\rho = 28$  and  $\beta = \frac{8}{3}$  the Lorenz system exhibits chaotic properties.

# Chaos Simulation of Lorenz System

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## We Are Able to Generate an Approximation of the Lorenz Attractor

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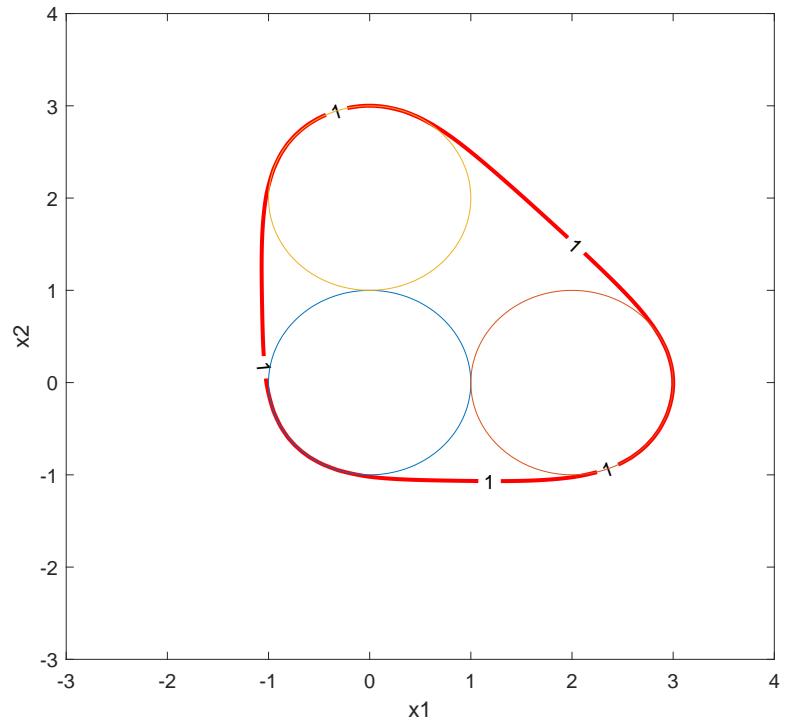
# An Optimization Problem for Outer Set Approximation

$$\min_{X \in C} \{D(X, Y)\}$$

subject to:  $Y \subseteq X$

where,

- $D : P(\mathbb{R}^n) \times P(\mathbb{R}^n) \rightarrow \mathbb{R}$  is some metric that measures the distance between two subsets of  $\mathbb{R}^n$ .
- $Y \subset \mathbb{R}^n$ .
- $C \subset P(\mathbb{R}^n) := \{X : X \subset \mathbb{R}^n\}$ .



## Example

- $Y = B((0,0), 1) \cup B((0,2), 1) \cup B((2,0), 1)$ .
- $C = \{X \subset \mathbb{R}^n : X = \{x \in \mathbb{R}^n : g(x) \leq 1\}, g \in \Sigma_{sos}, X \text{ is convex}\}$ .

# Volume is a Metric for Set Approximation

## Definition: Volume

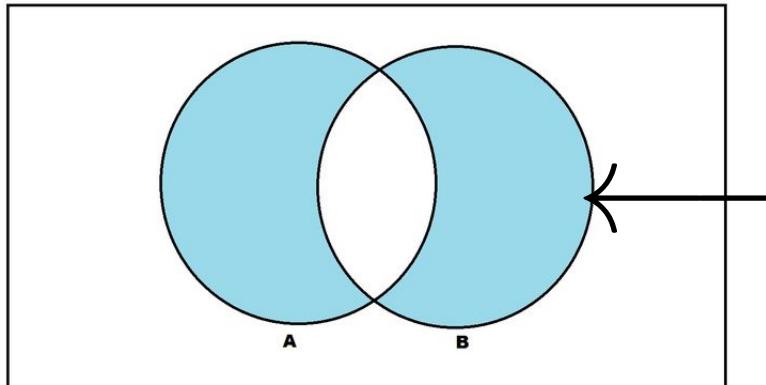
For  $A \subset \mathbb{R}^n$  we define

$$vol\{A\} = \int_{\mathbb{R}^n} \mathbf{1}_A(x) dx$$

## Definition: Volume Metric

For  $A, B \subset \mathbb{R}^n$  we define,

$$D_V(A, B) = vol\{(A/B) \cup (B/A)\}$$



$$\text{Blue Area} = D_V(A, B)$$

# Outer Set Approximation Using the Volume Metric

$$\min_{X \in C} \{D_V(X, Y)\} \quad (5)$$

subject to:  $Y \subseteq X$

$$\min_{X \in C} \{vol\{X\}\} \quad (6)$$

subject to:  $Y \subseteq X$

**Lemma:** The above optimization problems are equivalent

If  $X_1$  solves (5) and  $X_2$  solves (6) then  $X_1 = X_2$ .

To make the problem tractable we consider Sum-of-Square (SOS) polynomial sublevel set outer approximations parameterized by a positive matrix  $A \in S_{++}^n$ ,

$$\{x \in \mathbb{R}^n : z_d(x)^T A z_d(x) < 1\}$$

where  $z_d : \mathbb{R}^n \rightarrow \mathbb{R}^N$  is a monomial vector of degree  $d$ .

Sublevel set volume minimization is hard!

# Determinants are Related to Volumes of Ellipses

For an invertible square matrix  $A \in GL(n, \mathbb{R})$  and a fixed function  $g : \mathbb{R}^n \rightarrow \mathbb{R}$ ,

$$\det(A) \propto \text{vol}\{x \in \mathbb{R}^n : g(A^{-1}x) < 1\}.$$



$$\det(A) \propto \text{vol}\{x \in \mathbb{R}^n : x^T A x < 1\}.$$

We can formulate a **convex objective function** that is minimized by the matrix with minimum feasible determinant.

## Lemma: **logdet is convex**

$f : S_{++}^n \rightarrow \mathbb{R}$  given by  $f(X) = -\log \det(X)$  is **convex**.

## $-\log \det A$ objective functions increase eigenvalues

### Fact

Minimizing

$$\text{vol}\{x \in \mathbb{R}^n : x^T A x < 1\}$$

is equivalent to minimizing  
 $-\log \det A$ .

### Question

Can we use  $-\log \det A$  to minimize

$$\text{vol}\{x \in \mathbb{R}^n : z_d(x)^T A z_d(x) < 1\}?$$

For  $A \in S_{++}^n$  there exists unitary  $T \in \mathbb{R}^{n \times n}$  and a diagonal matrix  $\Lambda \in \mathbb{R}^{n \times n}$  such that  $A = T^T \Lambda T$ .

Therefore,

$$-\log \det A = -\sum_{i=1}^n \log(\Lambda_{i,i}).$$

$\implies$  Increasing the eigenvalues of  $A$  minimizes  $-\log \det A$ .

# Increasing Eigenvalues Decreases Volume

Consider the following set

$$\{x \in \mathbb{R}^n : V(x) < 1\},$$

where  $V(x) = z_d(x)^T A z_d(x)$ .

As  $A \in S_{++}^n$  it follows

$$V(x) = (T z_d(x))^T \Lambda T z_d(x) = \sum_{i=1}^n \Lambda_{i,i} (p_i(x))^2,$$

for some  $p_i : \mathbb{R}^n \rightarrow \mathbb{R}$ .

Minimizing  $-\log \det A$  results in:

- ⇒ Larger eigenvalues of  $A$
- ⇒ Larger value of  $V(x) = z_d(x)^T A z_d(x)$  for all  $x \in \mathbb{R}^n$
- ⇒ Less elements in  $\{x \in \mathbb{R}^n : z_d(x)^T A z_d(x) < 1\}$
- ⇒ Smaller  $\text{vol}\{x \in \mathbb{R}^n : z_d(x)^T A z_d(x) < 1\}$ .

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3. **Formulation of SOS program for approximation of:**
  - Unions of semialgebraic sets.
  - Attractor sets.
  - Reachable sets.

# SOS Approximation of Unions of Semialgebraic Sets

## Optimization for approximation of semialgebraic sets

$$\min_{A \in S_{++}^n} \{-\log \det A\}$$

$$\text{subject to: } Y \subseteq \{x \in \mathbb{R}^n : z_d(x)^T A z_d(x) < 1\}$$

where  $Y = \bigcup_{i=1}^m S_i$  and  $S_i = \{x \in \mathbb{R}^n : g_{i,1}(x) \leq 0, \dots, g_{i,m}(x) \leq 0\}$ .

## Tightened SOS optimization problem

$$\min_{A \in S_{++}^N} \{-\log \det A\} \quad \text{subject to,}$$

$$(1 - z_d^T A z_d) + \sum_{j=1}^k s_{i,j} g_{i,j} \in \sum_{sos} \quad \forall i \in \{1, \dots, m\}$$

$$s_{i,j} \in \sum_{sos} \quad \forall i, j$$

# Numerics: Sublevel Set Approximation of balls

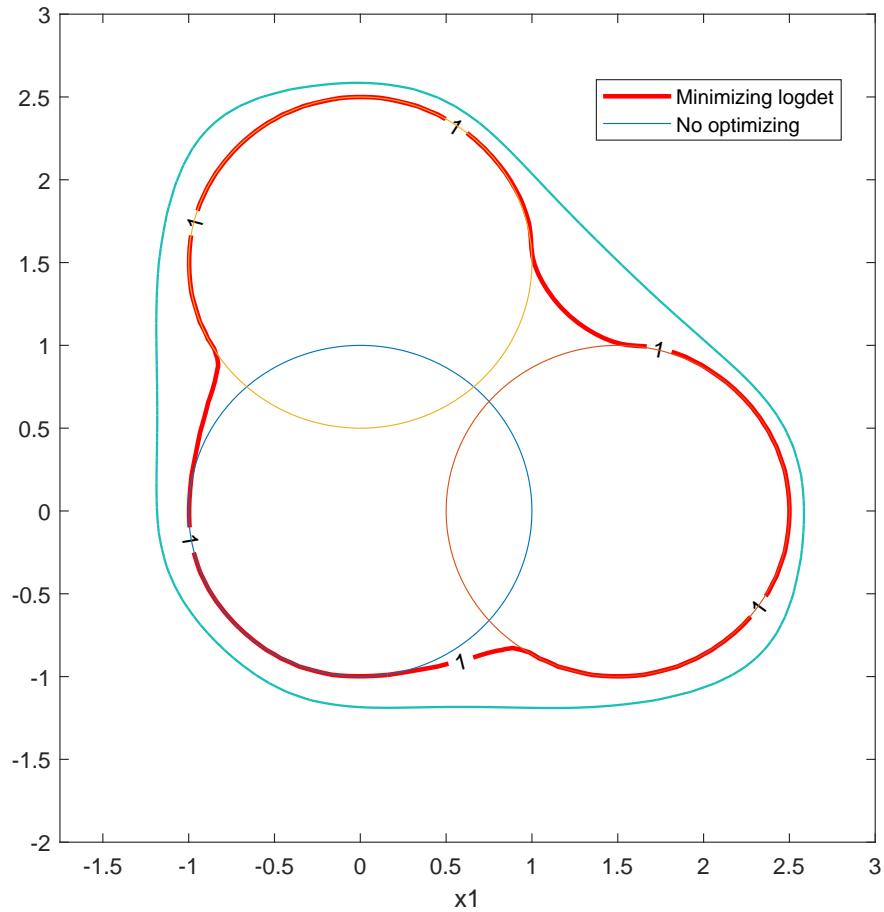
- Outer approx for  $S = \bigcup_{i=1}^3 S_i$  where,

$$S_1 = \{(x_1, x_2) : x_1^2 + x_2^2 \leq 1\}$$

$$S_2 = \{(x_1, x_2) : (x_1 - 1.5)^2 + (x_2)^2 \leq 1\}$$

$$S_3 = \{(x_1, x_2) : (x_1)^2 + (x_2 - 1.5)^2 \leq 1\}.$$

- degree=8.



# Numerical Examples

- Outer approx for  $S = \cup_{i=1}^3 S_i$  where,

$$S_1 = \{(x_1, x_2) : x_1^2 + x_2^2 \leq 1\}$$

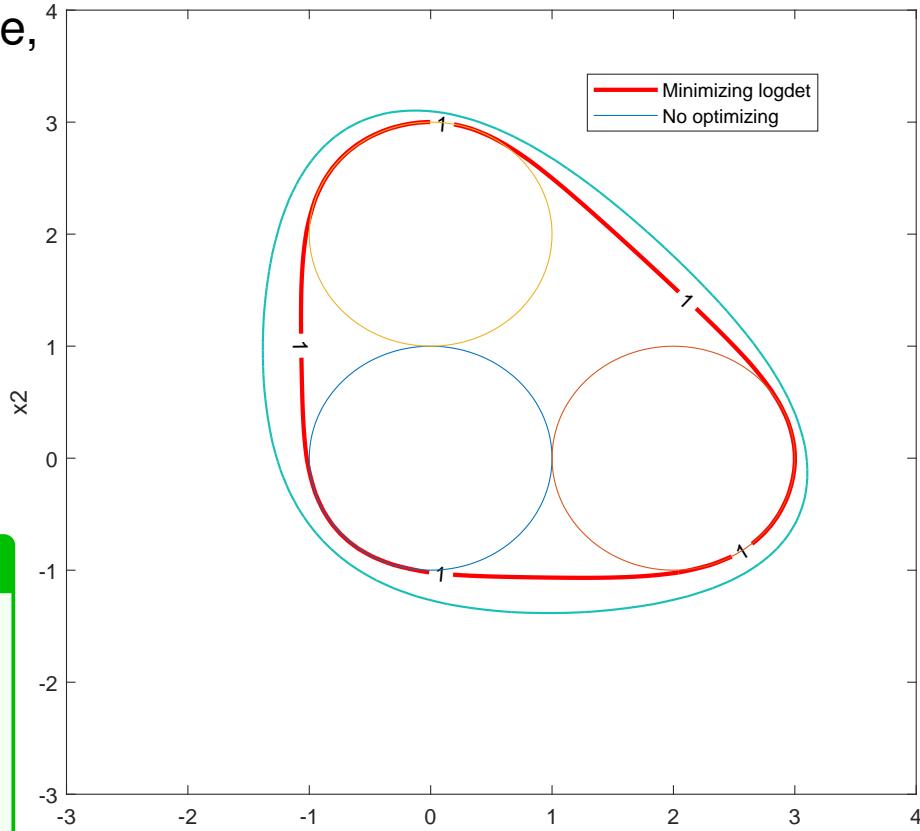
$$S_2 = \{(x_1, x_2) : (x_1 - 2)^2 + (x_2)^2 \leq 1\}$$

$$S_3 = \{(x_1, x_2) : (x_1)^2 + (x_2 - 2)^2 \leq 1\}.$$

- degree=6.

## Convex Constraint

Adding the constraint  $\nabla^2(z_d^T A z_d) \in \Sigma_{SOS}$  to the optimization problem ensures the function  $V(x) = z_d(x)^T A z_d(x)$  is convex and thus its **1-sublevel set** is also convex.



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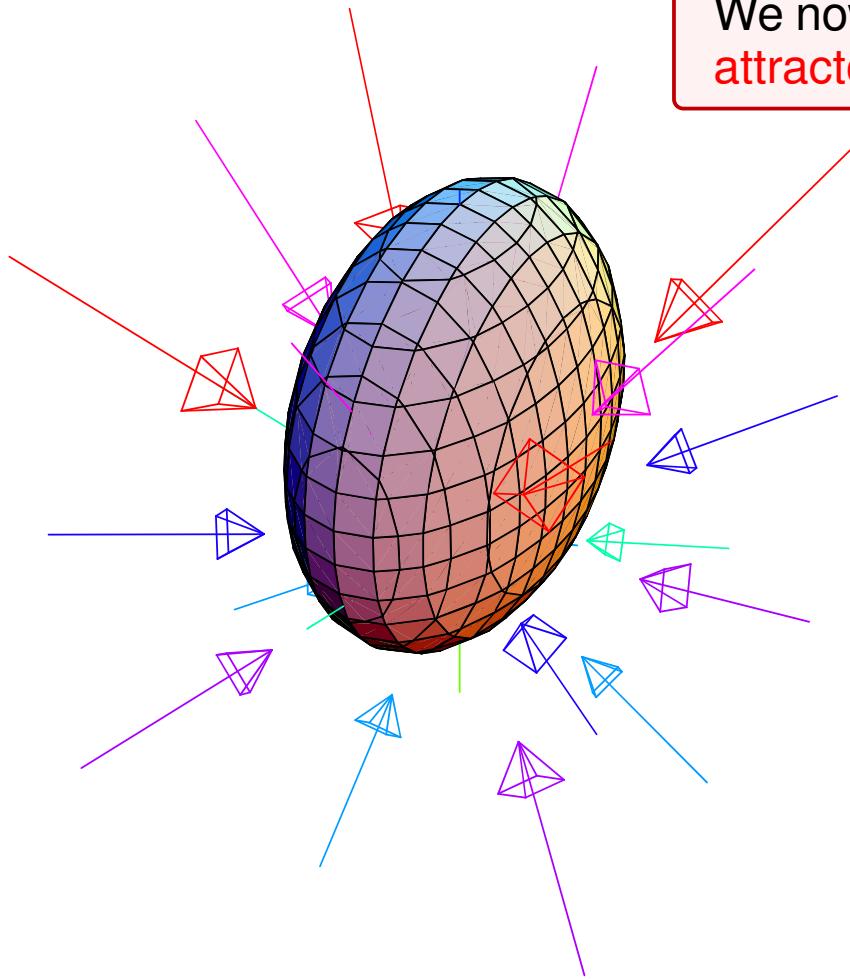
- ~~Unions of semialgebraic sets.~~
- ~~Attractor sets.~~
- Reachable sets.

# Attractor Sets

$$\min_{X \in S_{++}^n} \{-\log \det X\}$$

subject to:  $\mathcal{Y} \subseteq \{x \in \mathbb{R}^n : z_d(x)^T X z_d(x) < 1\}$

We now consider the problem when  $\mathcal{Y}$  is an **attractor set**.



## Definition: Attractor set

For a dynamical system  $\dot{x}(t) = f(x(t))$  we say a set  $A \subset \mathbb{R}^n$  is an **attractor set** if  $\forall x_0 \in \mathbb{R}^n$  there exists  $T > 0$  such that  $x(t) \in A$  for all  $t > T$ .

## Definition: Minimal Attractor

$A$  is the **minimal attractor** of a dynamical system  $\dot{x}(t) = f(x(t))$  if it is an attractor set and has no proper subset that is also an attractor set.

## Lyapunov Theory to Enforce Attractor Set Containment Constraints

$$\min_{X \in S_{++}^n} \{-\log \det X\}$$

subject to:  $Y \subseteq \{x \in \mathbb{R}^n : z_d(x)^T X z_d(x) < 1\}$

### Lyapunov theory

Consider some ODE of the  $\dot{x}(t) = f(x(t))$ . Suppose there exists  $V : \mathbb{R}^n \rightarrow \mathbb{R}$  such that,

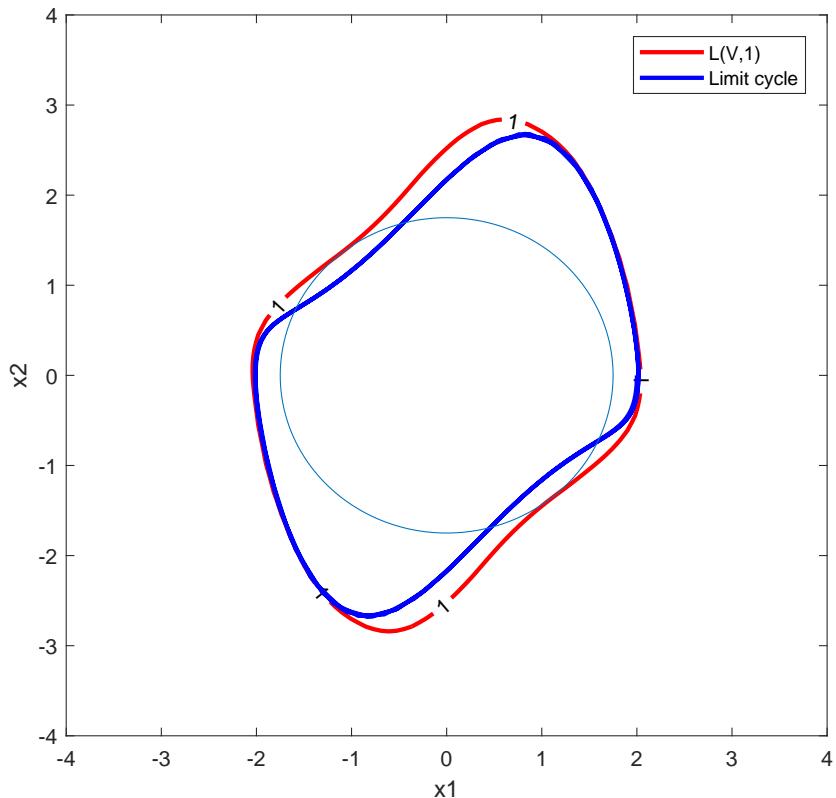
$$\begin{aligned} V(x) &> 0 \text{ for all } x \notin \mathcal{D} \\ \nabla V(x)^T f(x) &< 0 \text{ for all } x \notin \mathcal{D}. \end{aligned}$$

Then if  $\gamma > 0$  is such that  $\mathcal{D} \subset \{x \in \mathbb{R}^n : V(x) < \gamma\}$  we have that

$$\mathcal{A} \subset \{x \in \mathbb{R}^n : V(x) < \gamma\}$$

where  $\mathcal{A}$  is the minimal attractor set.

## Numerical Example: Van der Pol Oscillator



Consider the Van-der-Pol system:

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} x_2(t) \\ -x_1(t) + x_2(t)(1 - x_1^2(t)) \end{bmatrix}.$$

This system has a 2D attractor which is a limit cycle shown in blue.

Unlike the Lorenz attractor this attractor is non-chaotic as the solution map is recurrent.

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## Reachable Sets

Consider the ODE,

$$\dot{x}(t) = f(x(t), \mathbf{u}(t)) \quad (7)$$

Given  $x(0) = x_0.$

Where  $f : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}$ ,  
 $\mathbf{u}(t) : \mathbb{R} \rightarrow \mathbb{R}^m$ , and  
 $x_0 \in \mathbb{R}^n.$

### The Solution Map

We say  $\phi_f(x_0, t, \mathbf{u})$  is the solution map of the ODE (7) if,

$$\frac{\delta}{\delta t} \phi_f(x, t, \mathbf{u}) = f(\phi_f(x, t, \mathbf{u}), \mathbf{u}(t))$$
$$\phi_f(x, 0, \mathbf{u}) = x.$$

### The Forward Reachable Set

The forward reachable set for the ODE (7) is defined by,

$$FR_f(X_0, Y, S) := \{y \in \mathbb{R}^n : \exists x \in X_0, \mathbf{u} : \mathbb{R} \rightarrow \mathbb{R}^m, \text{and } t \in S \\ \text{such that } \phi_f(x, t, \mathbf{u}) = y \text{ and } \mathbf{u}(s) \in Y \quad \forall s \in [0, t]\}.$$

$$\min_{X \in S_{++}^n} \{-\log \det X\}$$

subject to:  $Y \subseteq \{x \in \mathbb{R}^n : z_d(x)^T X z_d(x) < 1\}$

### Lyapunov like theorem

Consider some ODE of the  $\dot{x}(t) = f(x(t), \mathbf{u}(t))$ .

For some  $X_0 \subset \mathbb{R}^n$ ,  $T > 0$ ,  $Y \subset \mathbb{R}^{m_u}$ , and  $\gamma \geq 0$ , suppose there exists a function  $V : \mathbb{R}^n \times \mathbb{R} \rightarrow \mathbb{R}$  such that

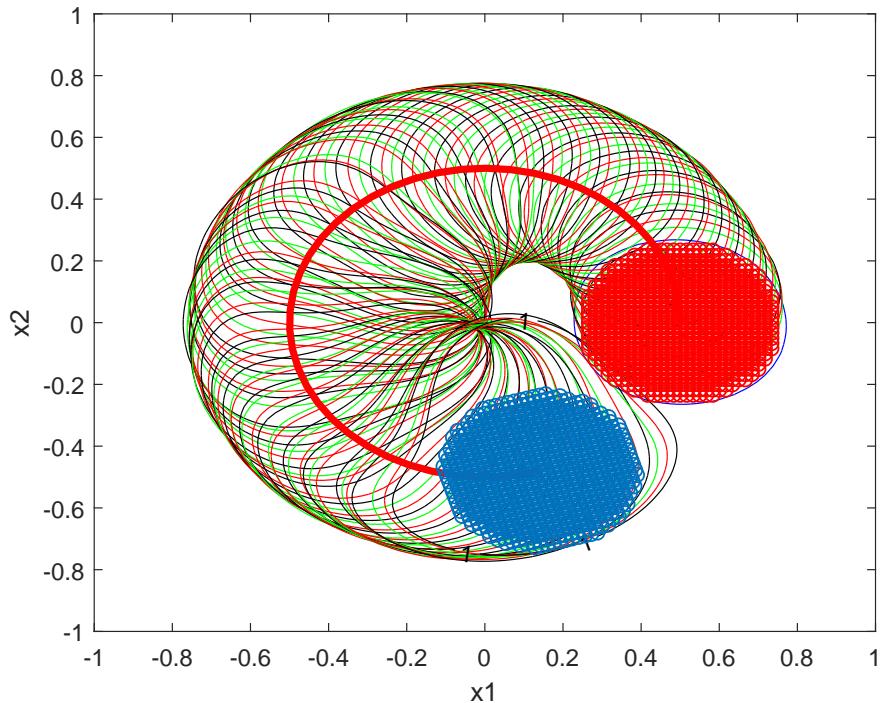
$$V(x, 0) \leq 1 \text{ for all } x \in X_0. \quad (8)$$

$$\frac{\partial V}{\partial t}(x, t) + \nabla_x V(x, t)^T f(x, u) \leq 0, \quad (9)$$

for all  $x \in X_c, t \in [0, T], u \in Y$ .

Then  $FR_f(X_0, Y, S) \subseteq \{x \in \mathbb{R}^n : V(x, T) \leq 1 + \gamma\}$ .

# Sublevel Set Approximation of Reachable Sets



Consider the **linear** system:

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix}. \quad (10)$$

System has eigenvalues  $\pm i$  so produces **circular trajectories**.

We can also find reachable sets of **nonlinear** systems in higher dimensions!

Thanks for your time!