

Reachability for weakly nonlinear systems using Carleman linearization

Presentation at:



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Regional del Este



JuliaReach



AALBORG UNIVERSITY
DENMARK

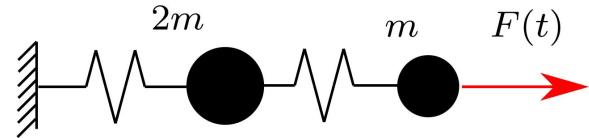
OCTOBER 25-27 2021, LIVERPOOL, UK

15th International Conference on Reachability Problems

What is reachability for continuous dynamical systems?

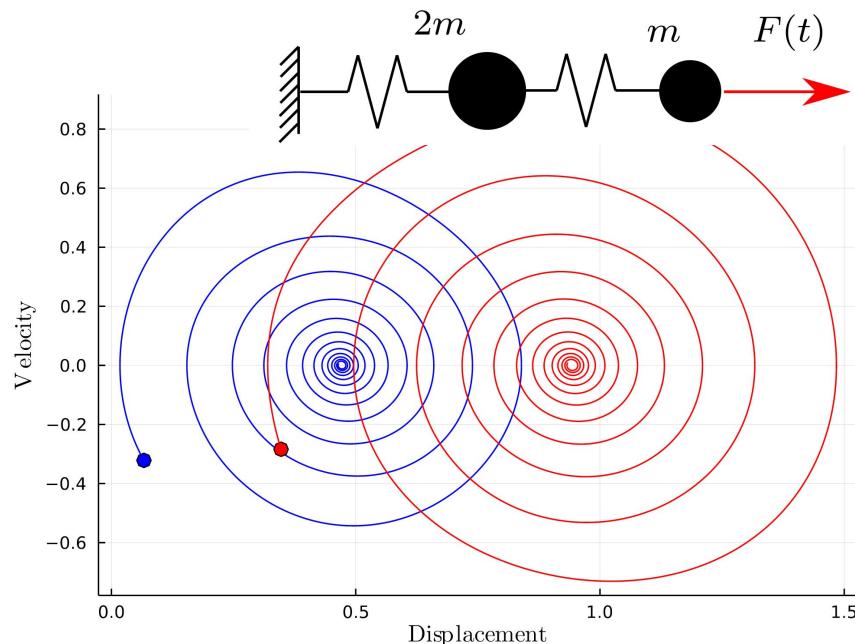
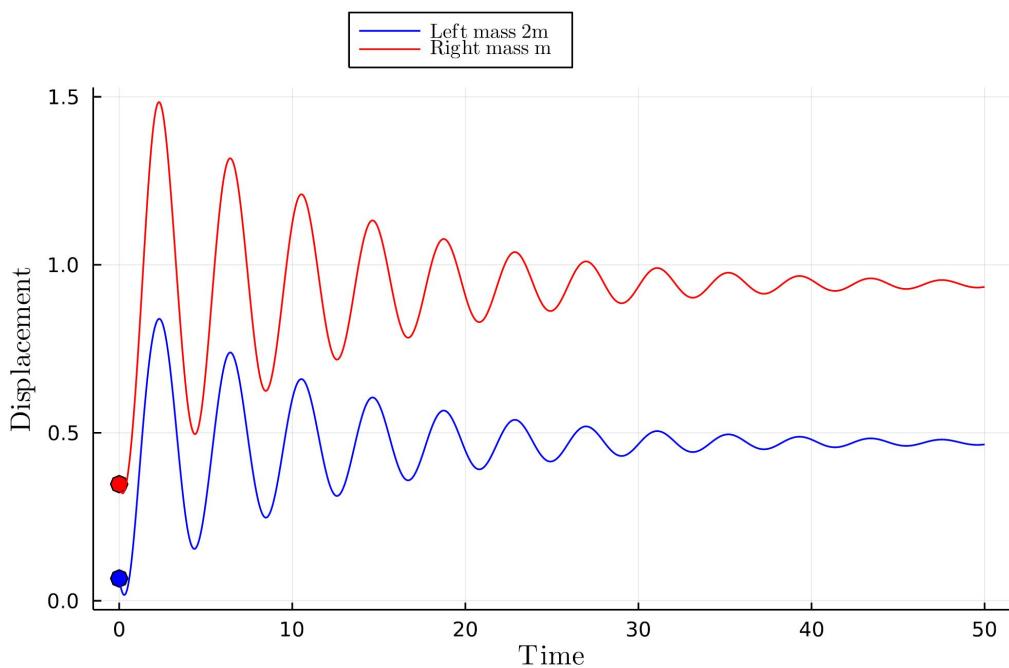
Example (linear differential equation):

$$Mx''(t) + Cx'(t) + Kx(t) = F(t)$$



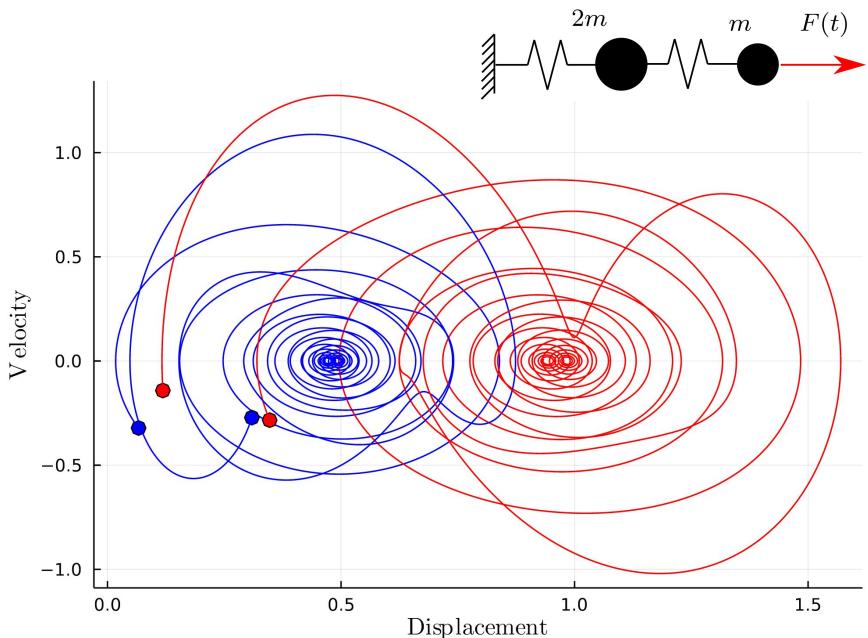
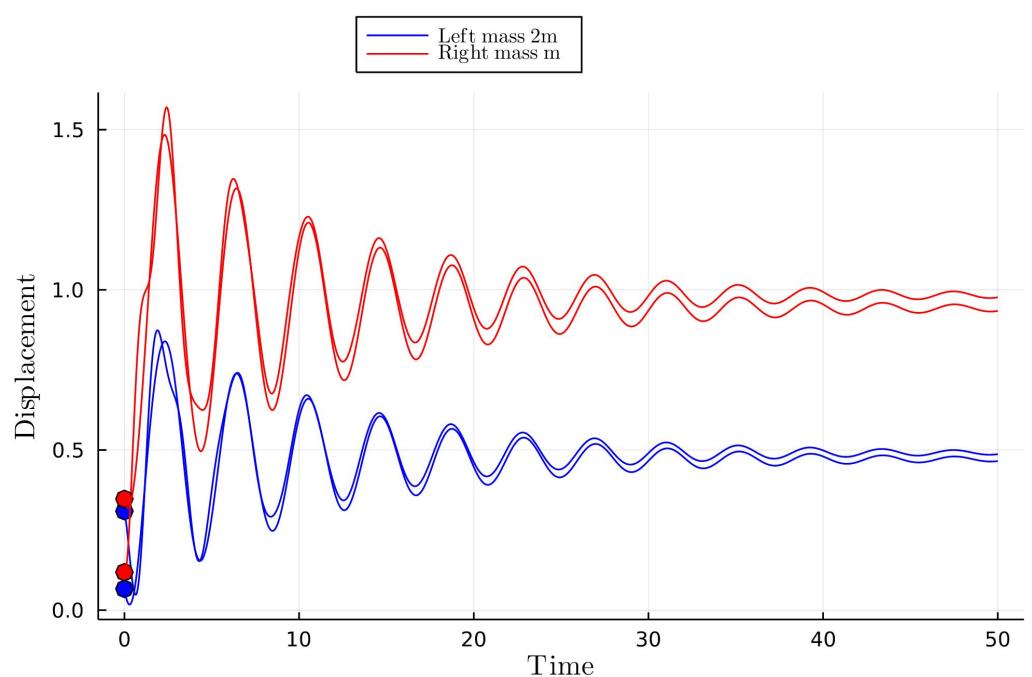
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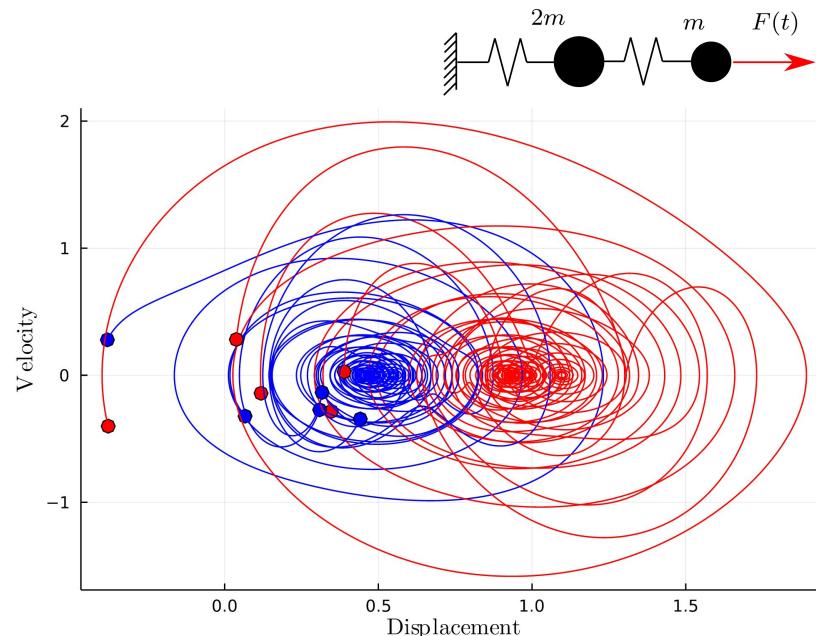
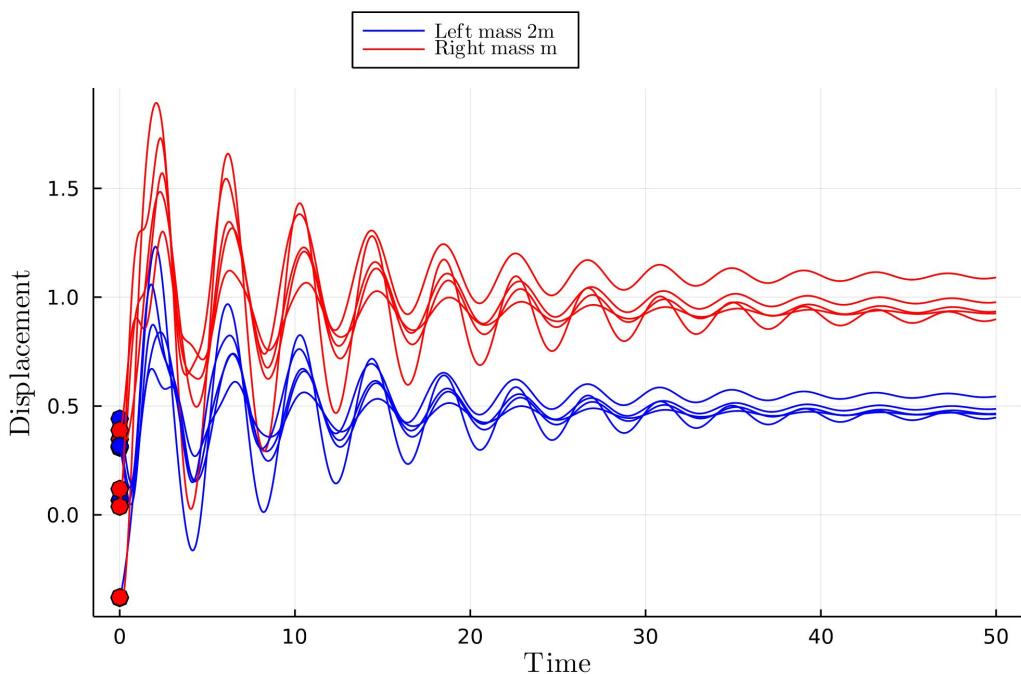
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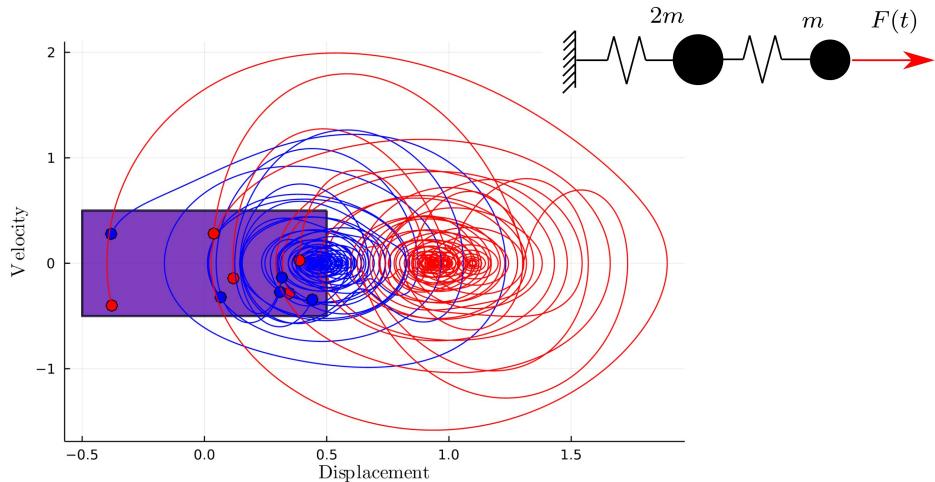
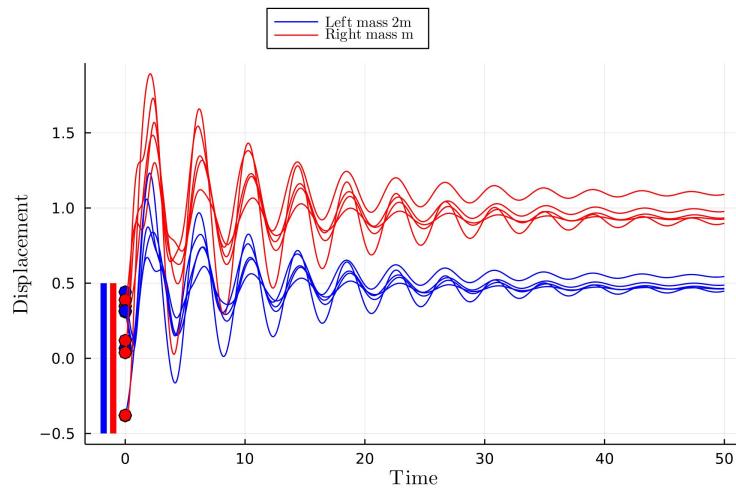
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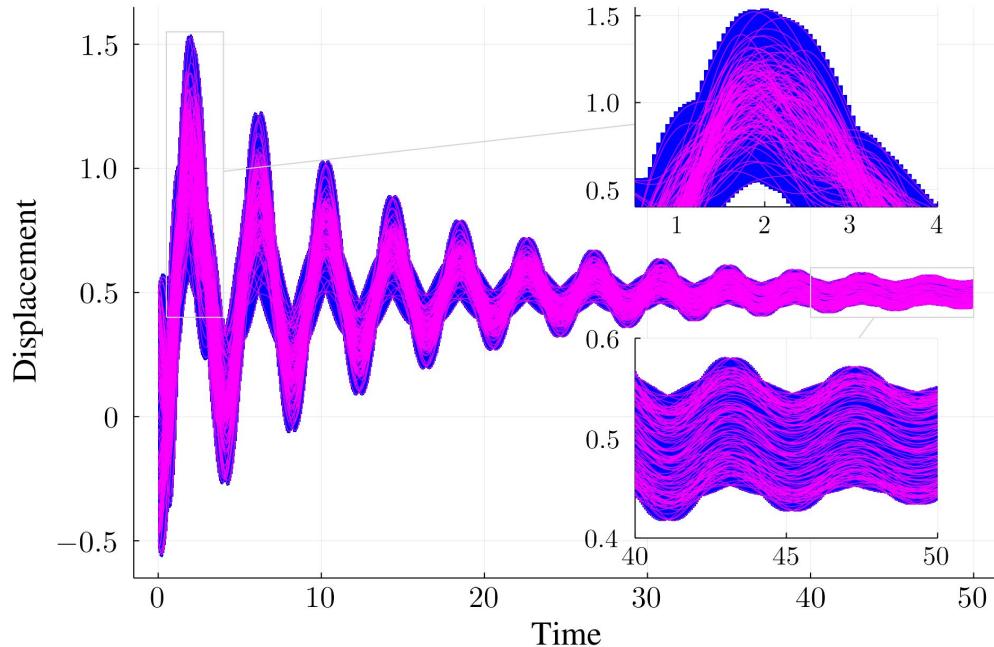
What is reachability for continuous dynamical systems?



Reachability is a numerical method to compute sets of states reachable by dynamical systems for *all initial states* and all admissible *parameters* and *inputs*

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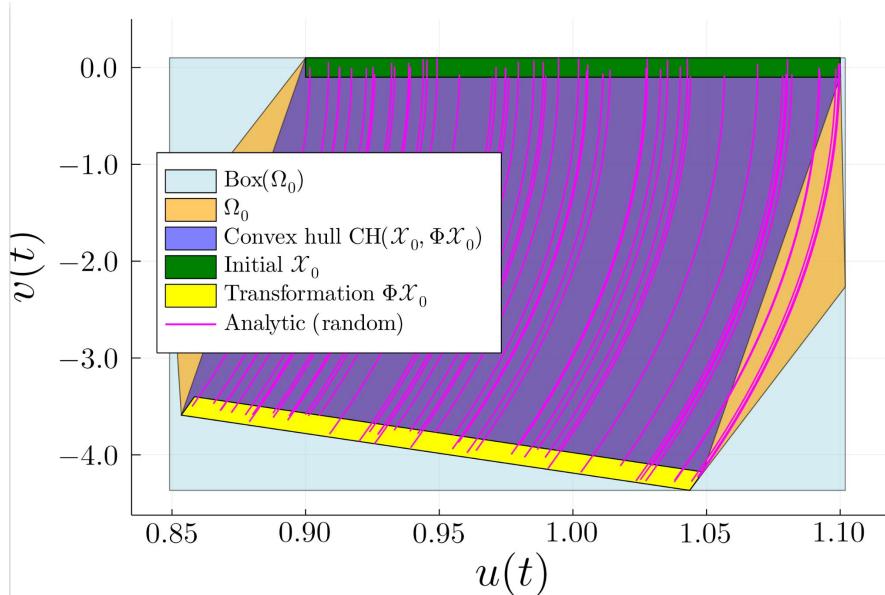
What is reachability for continuous dynamical systems?



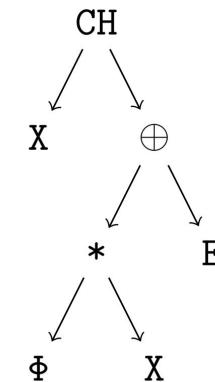
```
1 using ReachabilityAnalysis
2
3 # model parameters
4 m = 0.25; k = 2.0
5
6 # finite-element method assembled matrices
7 M = [2m 0; 0 m]; K = [2k -k; -k k]; C = (M+K)/20
8 F = [0.0, 1.0]; ΔF₀ = Interval(0.9, 1.1)
9
10 # initial-value problem with uncertain initial conditions
11 U₀ = BallInf(zeros(4), 0.5)
12 sys = SecondOrderLinearContinuousSystem(M, C, K, F)
13 prob = InitialValueProblem(homogenize(sys), U₀ × ΔF₀)
14
15 # solve using support function method (box directions)
16 solA = solve(prob, 50, LGG09(δ=5e-2, dirs=:box, dim=5))
```

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Conservative time discretization (step 1/2)



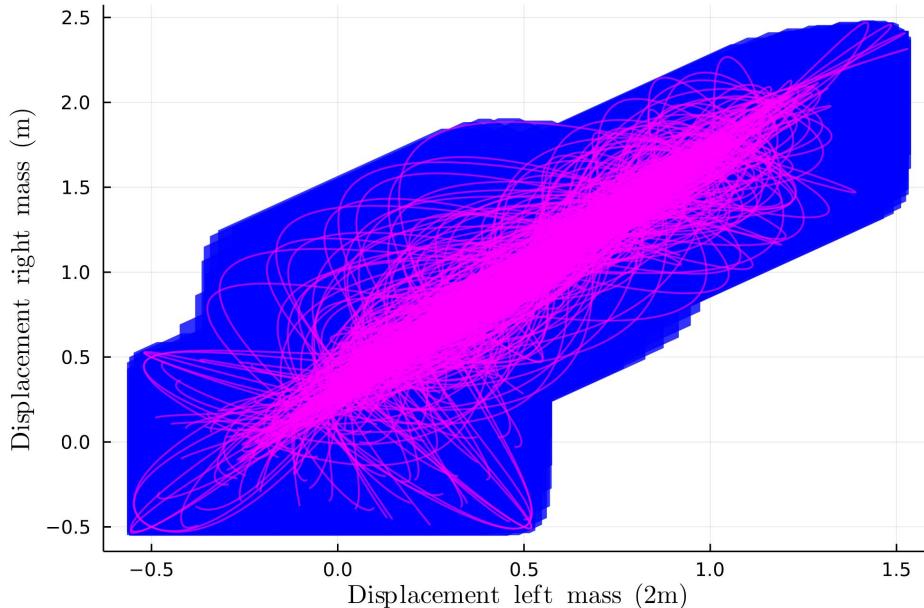
```
1 julia> Ω₀ = CH(Χ₀, Φ*X₀ ⊕ E+)
```



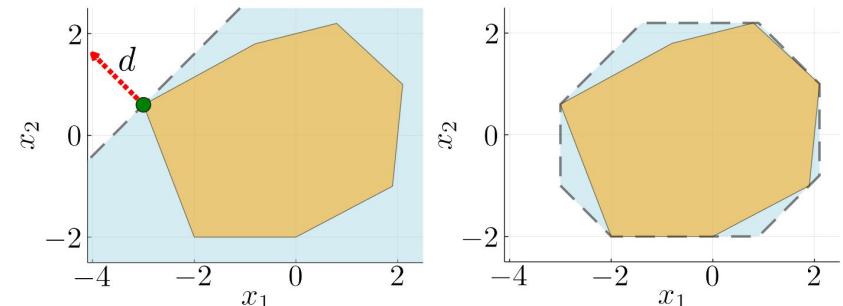
Efficient set computations require specialized algorithms based on different combinations of *set type representations* and *operations* involved.

See: *LazySets.jl: Scalable Symbolic-Numeric Set Computations*. Marcelo Forets and Christian Schilling. arXiv preprint [arXiv:2110.01711](https://arxiv.org/abs/2110.01711) (2021). Submitted to JuliaCon'2021 (full paper).

Set propagation (step 2/2)

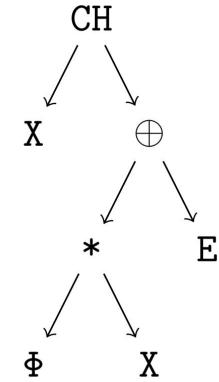
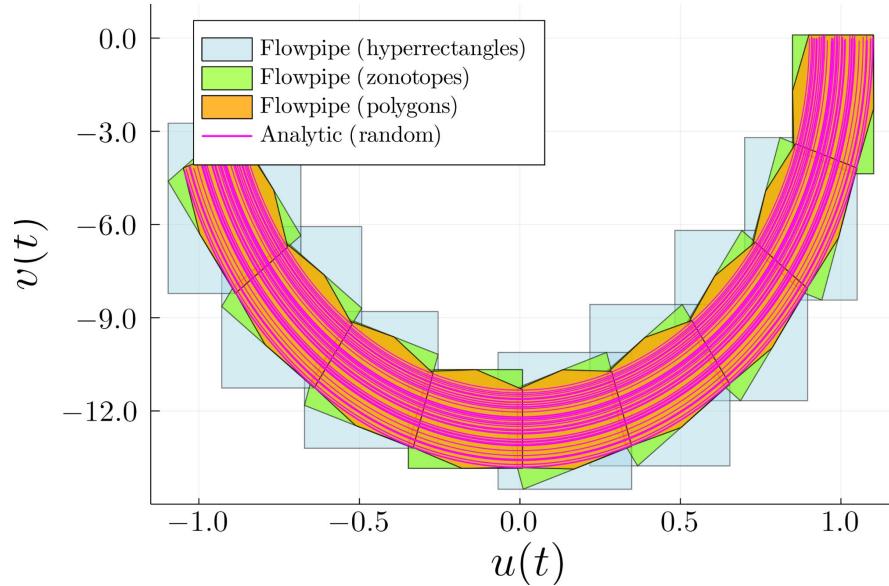


```
1 # solve using octagonal template directions  
2 solB = solve(prob, 50, LGG09(δ=5e-2, dirs=:oct, dim=5))
```



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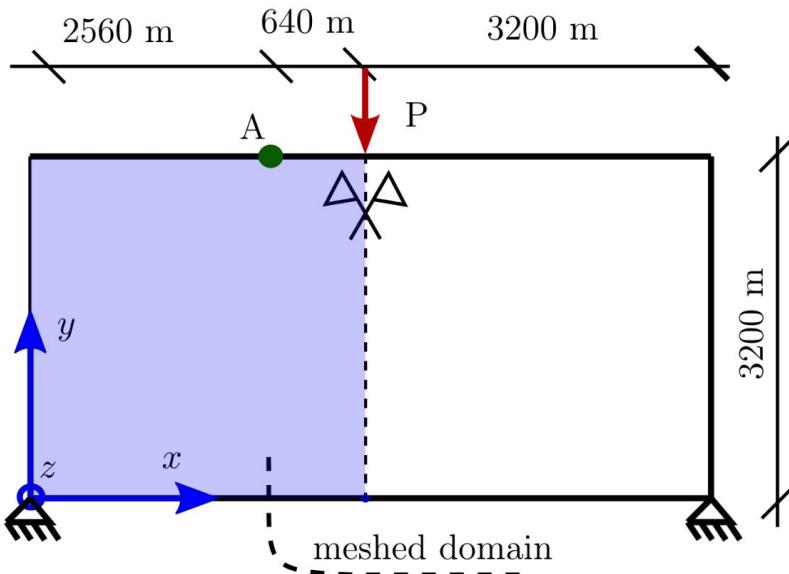
Set propagation (step 2/2)



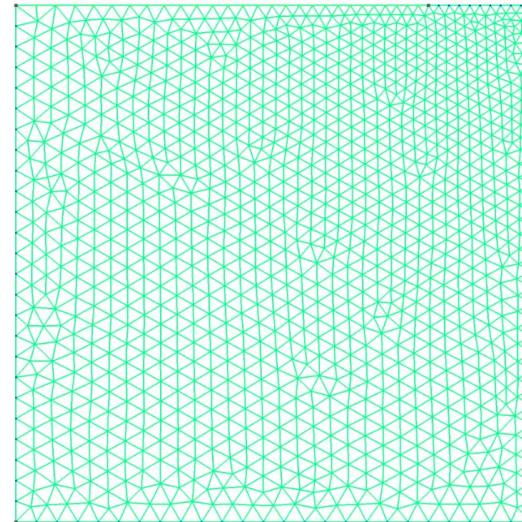
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Example in higher dimensions



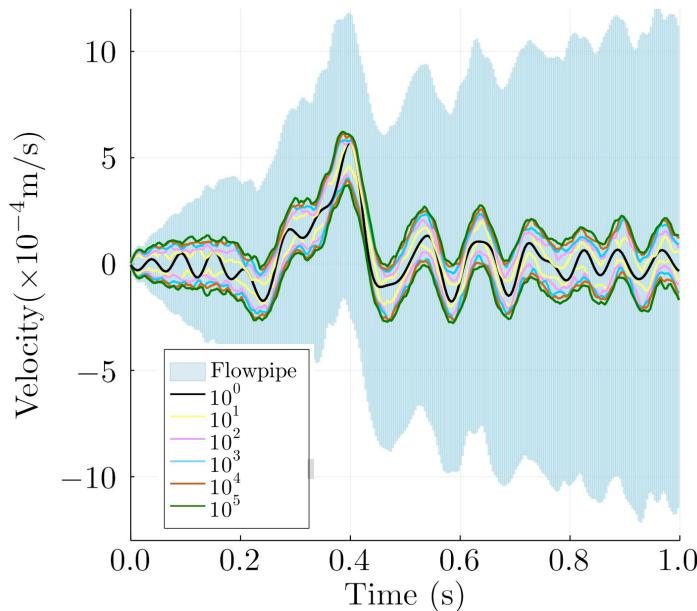
(a) Diagram of domain and boundary conditions considered.



(b) Finite Element Method mesh used, formed by triangular elements.

See: *Combining Set Propagation with Finite Element Methods for Time Integration in Transient Solid Mechanics Problems*.
Forets, Marcelo, Daniel F. Caporale, and Jorge M. Pérez Zerpa. arXiv preprint [arXiv:2105.05841](https://arxiv.org/abs/2105.05841).
Accepted in Computers & Structures Journal (2021).

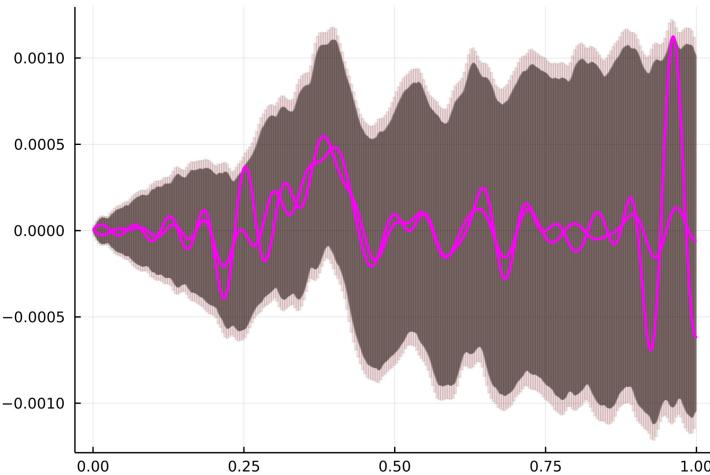
Example in higher dimensions



Method	# Trajectories	Time (s)	$\ v_{env}\ _{L_1} (10^{-5})$	$\ v_{env}\ _{L_\infty} (10^{-5})$
Newmark	1	0.3	9.27	56.98
Newmark	10	2.0	13.52	57.53
Newmark	100	17.7	16.61	57.59
Newmark	1000	175.5	18.52	58.22
Newmark	10000	1771.4	19.98	61.18
Newmark	100000	17796.1	21.42	62.21
Set Propagation	-	8.5	81.33	122.25

The initial set is propagated exponentially faster than using simulations over randomly sampled initial states

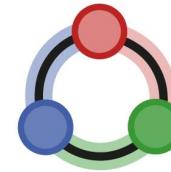
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The sequence of sets obtained (flowpipe) converges to the exact reachable states when the time-step decreases

JuliaReach project



JuliaReach

To advance state-of-the-art
working on *fundamental*
problems

To build comprehensive,
efficient, correct,
reproducible, well
documented libraries

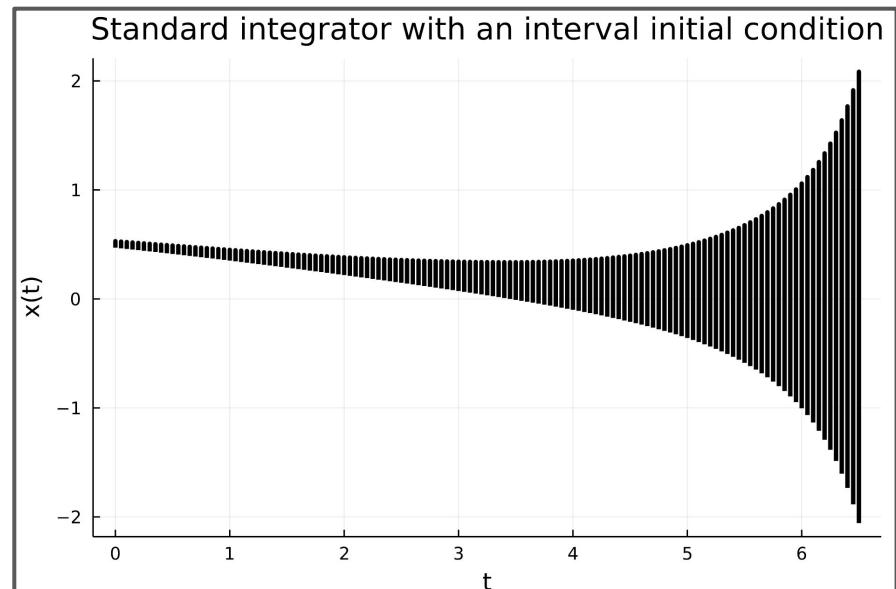
To widen the applicability of
reachability analysis for
scientists & engineers

Reachability for a nonlinear differential equation

$$\frac{dx(t)}{dt} = rx(1 - x/K)$$

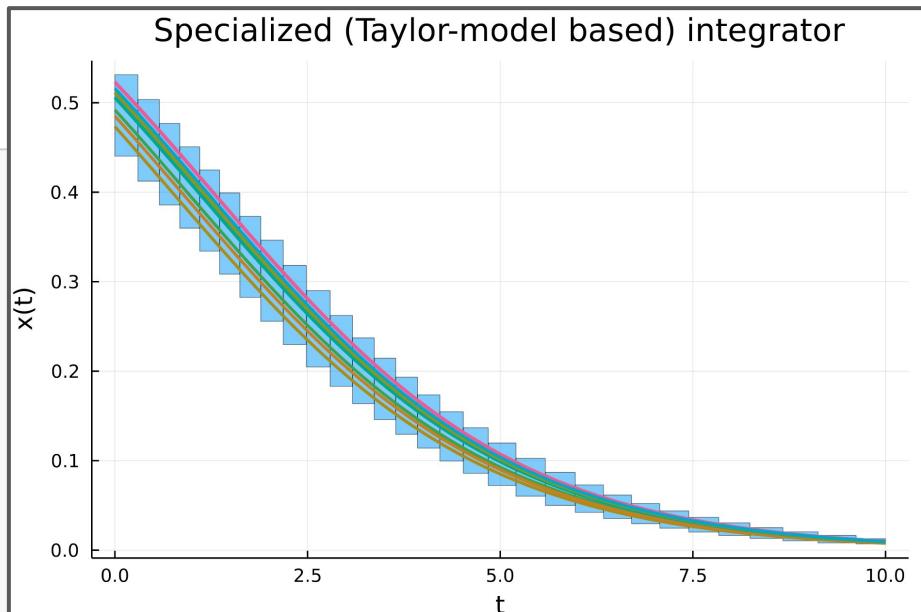
Logistic equation (population dynamics)

```
1 using DifferentialEquations,  
2   IntervalArithmetic  
3  
4 # define the problem  
5 function f(dx, x, p, t)  
6   r = -0.5  
7   K = 0.8  
8   dx[1] = r*x[1]*(1 - x[1]/K)|  
9 end  
10  
11 x₀ = [0.47 .. 0.53] # initial condition  
12 prob = ODEProblem(f, x₀, (0.0, 6.5))  
13 sol = solve(prob, RK4(), adaptive=false,  
14           dt=0.05, reltol=1e-6)
```

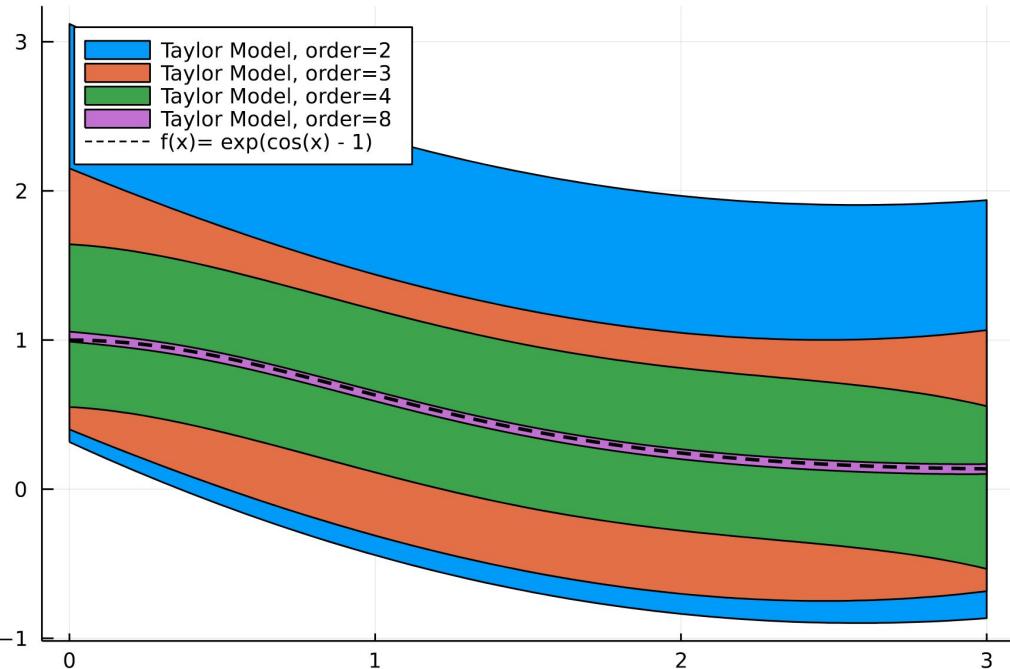


Reachability for a nonlinear differential equation

```
1 using ReachabilityAnalysis, Plots
2
3 # define the model (same as before)
4 function f(dx, x, p, t)
5     r = -0.5
6     K = 0.8
7     dx[1] = r*x[1]*(1 - x[1]/K)
8 end
9
10 X0 = 0.47 .. 0.53 # interval initial states
11 # initial-value problem
12 prob = @ivp(x' = f(x), x(0) ∈ X0, dim=1)
13
14 # solve it
15 sol = solve(prob, alg=TMJets21a(abstol=1e-10), T=10.0);
```



Taylor models



$$f_{T_3} = 0.39484468326455857 - 0.393855592043663 t + 0.18246938526101011 t^2 + 0.014258580485865105 t^3 + [-0.946548, 0.803778]$$

$$f_{T_8} = 0.39484468326455857 - 0.393855592043663 t + 0.18246938526101011 t^2 + 0.014258580485865105 t^3 - 0.054727422711077306 t^4 + 0.024706768559030104 t^5 + 0.0007709727046973829 t^6 - 0.00520692104599662 t^7 + 0.0019470348640809945 t^8 + [-0.0410741, 0.0258577]$$

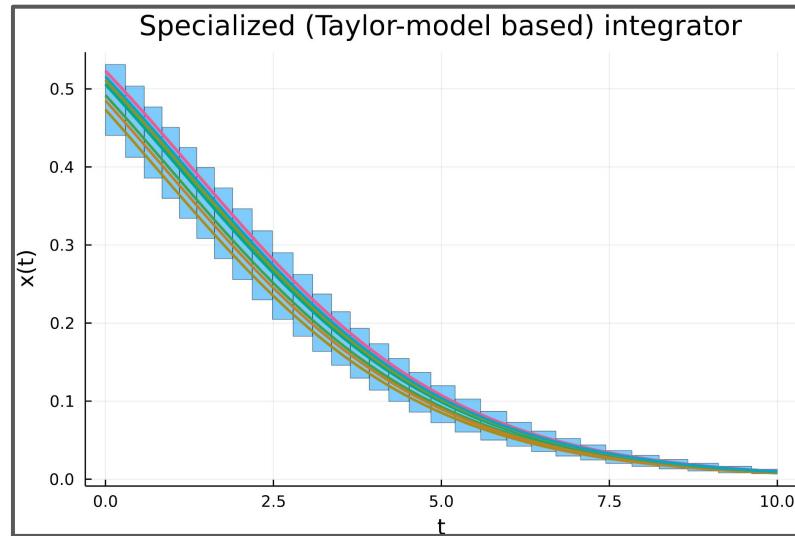
Reachability for a nonlinear differential equation

Example:

Taylor model reach-set at
the final computed interval

```
1 tspan(sol[end])
```

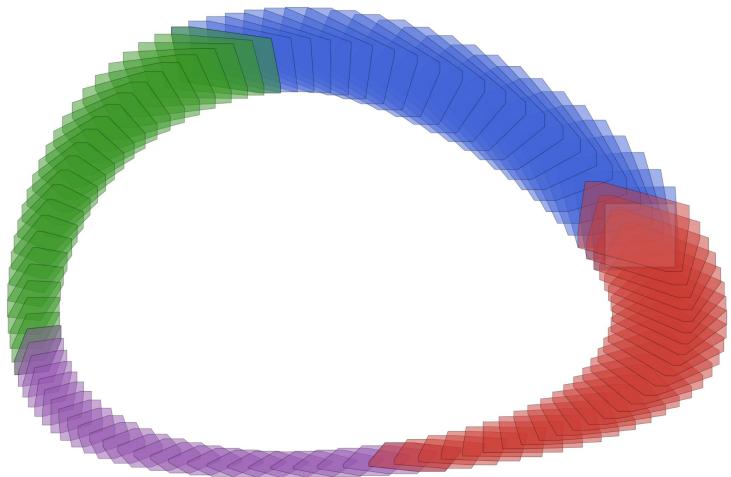
```
[9.61803, 10]
```



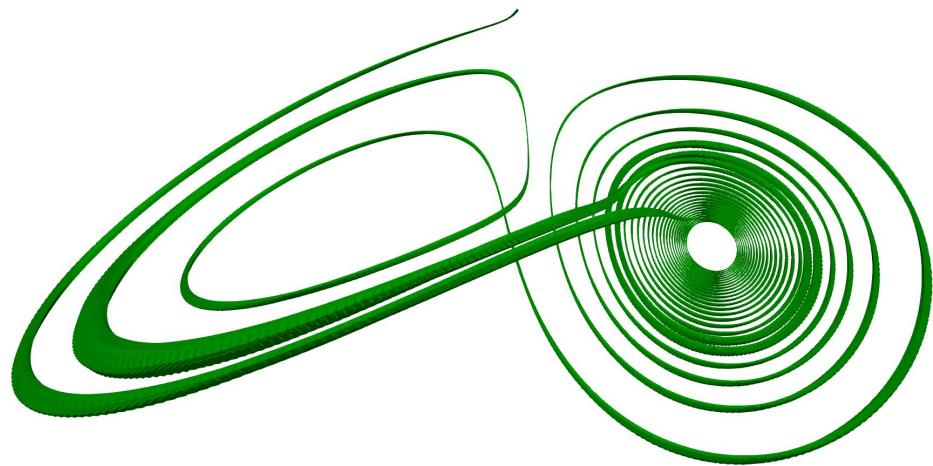
```
1 sol[end]
```

```
TaylorModelReachSet{Float64}(TaylorModels.TaylorModel1{TaylorN{Float64}, Float64}[
  0.010728640000425796 + 0.0016935
  616569102134 x₁ + 0.0001657222430356068 x₁² + (- 0.0052923801775511875 - 0.0008240688117857138 x₁ - 7.8846059232215
  5e-5 x₁²) t + ( 0.0012876075183438367 + 0.00019488963434660352 x₁ + 1.7762397657259186e-5 x₁²) t² + (- 0.0002030100
  35766464 - 2.888459368553032e-5 x₁ - 2.339217437712025e-6 x₁²) t³ + ( 2.2566088815570262e-5 + 2.752383693482914e-6 x
 ₁ + 1.474683203606484e-7 x₁²) t⁴ + (- 1.7202398083315093e-6 - 1.1552580809843272e-7 x₁ + 1.1261821093858127e-8 x₁²)
  t⁵ + ( 6.016969171459992e-8 - 1.413785130768101e-8 x₁ - 4.570779684951191e-9 x₁²) t⁶ + ( 6.311540762007901e-9 + 3.82
  8591659395892e-9 x₁ + 7.063749944165518e-10 x₁²) t⁷ + (- 1.4955436168686581e-9 - 4.920337196748677e-10 x₁ - 6.83032
  0243727477e-11 x₁²) t⁸ + [-1.13178e-10, 1.0917e-10]], [9.61803, 10])
```

Nonlinear reachability



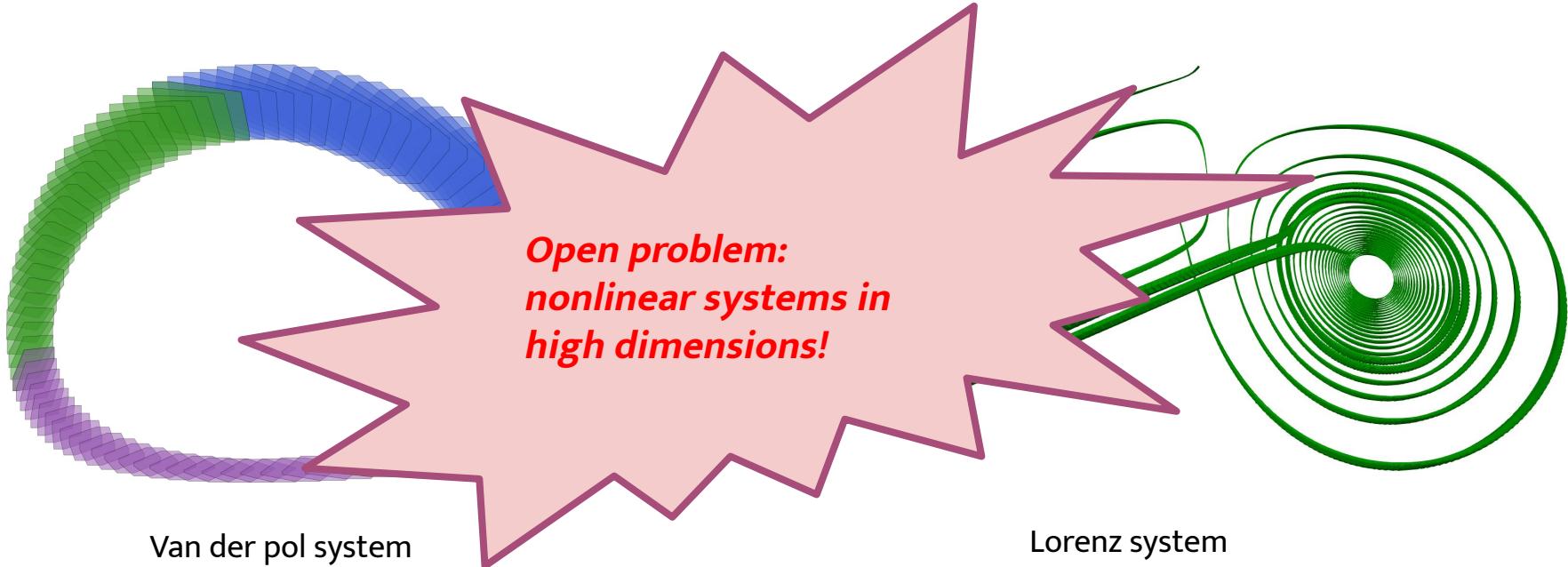
Van der pol system



Lorenz system

Main nonlinear reachability approaches are: invariant generation, optimization based-approaches, solution-space abstractions, and state-space abstractions.

Nonlinear reachability



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Kronecker products, polynomial ODEs and weak nonlinearity

$$x^{\otimes 2} = x \otimes x = (x_1^2, x_1 x_2, x_2 x_1, x_2^2)^T$$

$$x^{\otimes i} := \underbrace{x \otimes \cdots \otimes x}_{i \text{ times}}, \quad x \in \mathbb{R}^n$$

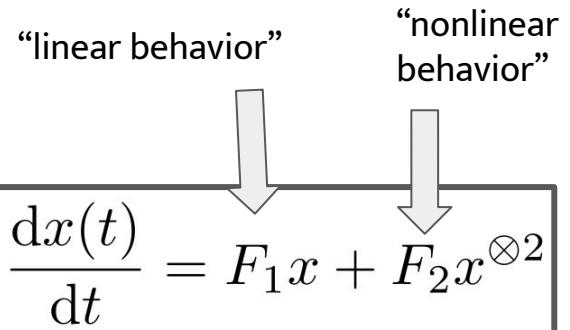
$$A \otimes B := \begin{pmatrix} a_{11}B & \dots & a_{1n}B \\ \vdots & & \vdots \\ a_{m1}B & \dots & a_{mn}B \end{pmatrix}$$

Kronecker products, polynomial ODEs and weak nonlinearity

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$$\|F_2\|_2 / \|F_1\|_2$$

if this ratio is
small



the system is
said to be weakly
nonlinear

Kronecker products, polynomial ODEs and weak nonlinearity

$$x^{\otimes 2} = x \otimes x = (x_1^2, x_1 x_2, x_2 x_1, x_2^2)^T$$

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“linear behavior” “nonlinear behavior”

$$\frac{dx(t)}{dt} = F_1 x + F_2 x^{\otimes 2}$$



General for polynomial ODEs with $f(0) = 0$;
formulation and linearization goes back to
Carleman (1932)

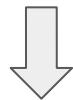
Example: logistic equation

$$\frac{dx(t)}{dt} = rx(1 - x/K)$$



$$x'(t) = ax(t) + bx^2(t)$$

$$a = r \text{ and } b = -r/K$$



$$\hat{y}'_1 = x' = a\hat{y}_1 + b\hat{y}_2$$

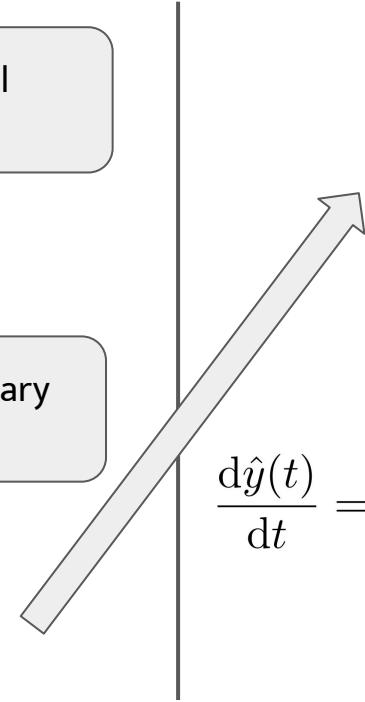
$$\hat{y}'_2 = 2x'x = 2a\hat{y}_2 + 2b\hat{y}_3$$

$$\hat{y}'_j = ja\hat{y}_j + jb\hat{y}_{j+1}, \quad j \in \mathbb{N}$$

Bring to general quadratic form

Truncate to finite order N
(here: N = 4)

Introduce auxiliary variables



$$\frac{d\hat{y}(t)}{dt} = \begin{pmatrix} a & b & 0 & 0 \\ 0 & 2a & 2b & 0 \\ 0 & 0 & 3a & 3b \\ 0 & 0 & 0 & 4a \end{pmatrix} \hat{y}, \quad \hat{y}(0) = \begin{pmatrix} x_0 \\ x_0^2 \\ x_0^3 \\ x_0^4 \end{pmatrix}$$

Example: logistic equation

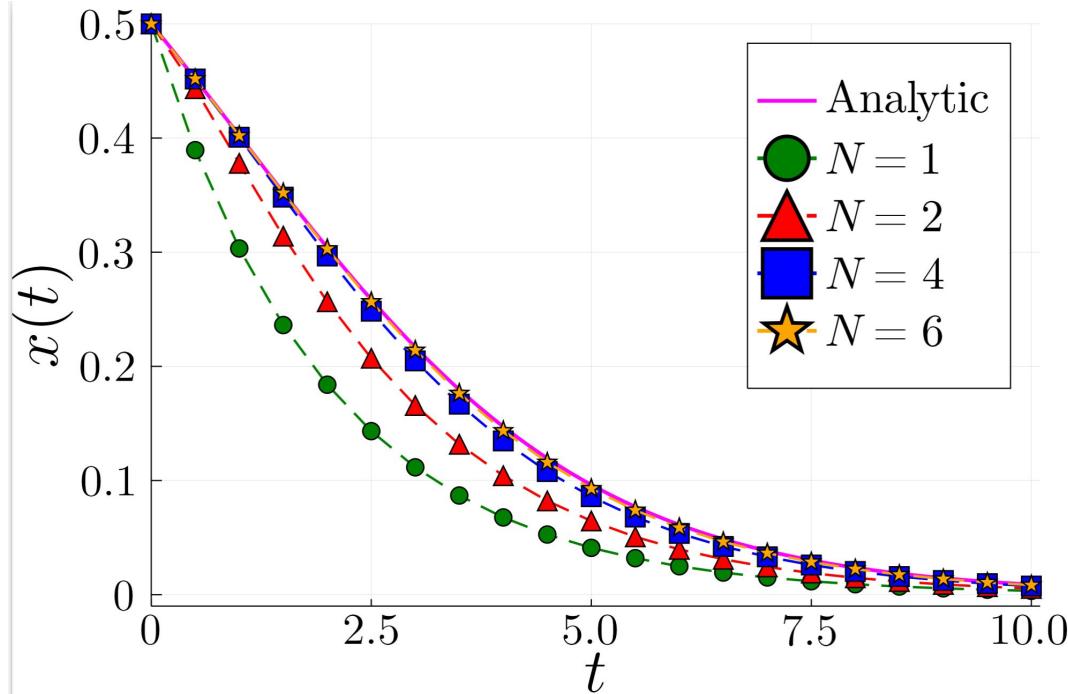
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The analytic solution in this case is:

$$x(t) = \frac{x_0 e^{at}}{1 + (b/a)(1 - e^{at})x_0}$$



b/a controls the “degree” of nonlinearity of the ODE



Example: logistic equation (distributed initial conditions)

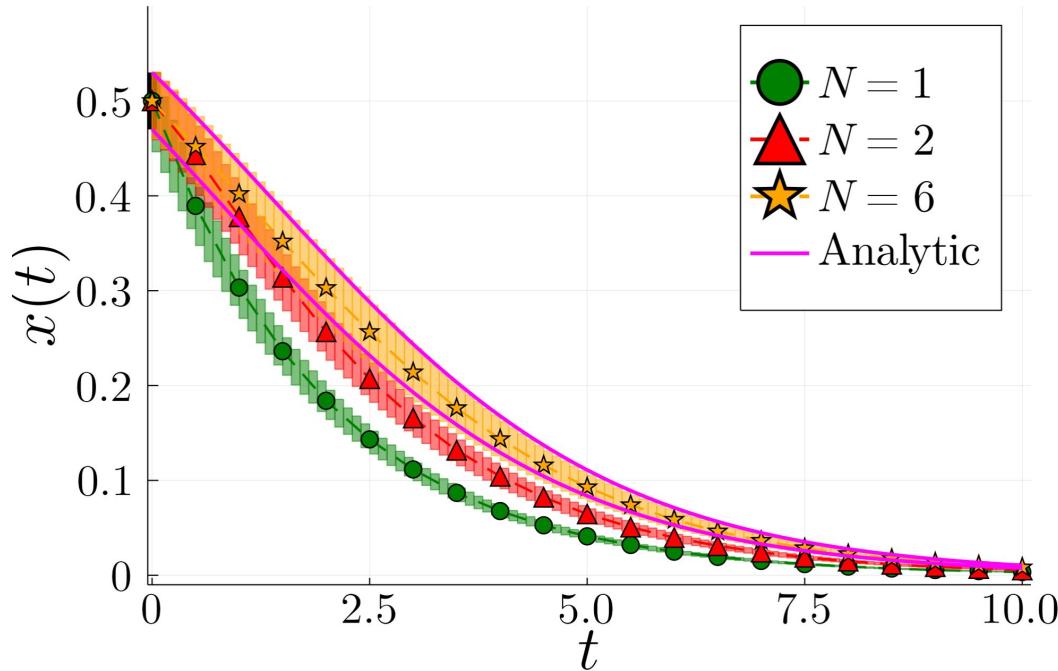
$$\frac{d\hat{y}(t)}{dt} = \begin{pmatrix} a & b & 0 & 0 \\ 0 & 2a & 2b & 0 \\ 0 & 0 & 3a & 3b \\ 0 & 0 & 0 & 4a \end{pmatrix} \hat{y}, \quad \hat{y}(0) = \begin{pmatrix} x_0 \\ x_0^2 \\ x_0^3 \\ x_0^4 \end{pmatrix}$$

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b/a controls the “degree” of nonlinearity of the ODE



Carleman embedding: general case

$$x'(t) = f(x(t)), f : \mathbb{R}^n \rightarrow \mathbb{R}^n$$



Bring to general quadratic form

$$\frac{dx(t)}{dt} = F_1 x + F_2 x^{\otimes 2} \quad (1)$$



Introduce auxiliary variables

$$\hat{y}_j := x^{\otimes j}, j \in \mathbb{N}$$

Truncate to finite order N

$$A = \begin{pmatrix} A_1^1 & A_2^1 & 0 & 0 & \cdots & 0 \\ 0 & A_2^2 & A_3^2 & 0 & \cdots & 0 \\ 0 & 0 & A_3^3 & A_4^3 & 0 & \vdots \\ \vdots & \vdots & \vdots & \ddots & \ddots & 0 \\ 0 & 0 & \cdots & 0 & A_{N-1}^{N-1} & A_N^{N-1} \\ 0 & 0 & \cdots & 0 & 0 & A_N^N \end{pmatrix}$$

$$A_{i+i'-1}^i = \sum_{\nu=1}^i \overbrace{\mathbb{I}_n \otimes \cdots \otimes \underset{\nu\text{-th position}}{F_{i'}} \otimes \cdots \otimes \mathbb{I}_n}^{i \text{ factors}}$$

$$\frac{d\hat{y}}{dt} = A\hat{y}, \quad \hat{y}(0) = \hat{y}_0 \quad (2)$$

Error bounds

Definition 1. System (1) is said to be weakly nonlinear if the ratio

$$R := \frac{\|x_0\| \|F_2\|}{|\Re(\lambda_1)|} \quad (5)$$

satisfies $R < 1$.

Definition 2. System (1) is said to be dissipative if $\Re(\lambda_1) < 0$ (i.e., the real part of all eigenvalues is negative).

The conditions $\Re(\lambda_1) < 0$ and $R < 1$ ensure arbitrary-time convergence.

Error bounds

Theorem 1 ([30], Corollary 1]). Assuming that (1) is weakly nonlinear and dissipative, the error bound associated with the linearized problem (2) truncated at order N satisfies

$$\|\eta_1(t)\| \leq \varepsilon(t) := \|x_0\| R^N (1 - e^{\Re(\lambda_1)t})^N, \quad (6)$$

with R as defined in (5). This error bound holds for all $t \geq 0$.

[30] Liu, J.P., Kolden, H.Ø., Krovi, H.K., Loureiro, N.F., Trivisa, K., Childs, A.M.:

Efficient quantum algorithm for dissipative nonlinear differential equations. Proceedings of the National Academy of Sciences 118(35) (2021)

Reachability algorithm using Carleman linearization

Algorithm 1: Reachability algorithm

Input: $\mathcal{X}_0 \subseteq \mathbb{R}^n$: hyperrectangular initial states; F_1, F_2 : system matrices;
 N : truncation order; T : time horizon; $post$: algorithm to compute a flowpipe
for linear systems

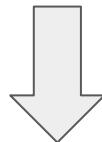
Output: flowpipe overapproximating the reachable states until T

```
1  $A, \hat{\mathcal{X}}_0 \leftarrow linearize(\mathcal{X}_0, F_1, F_2, N)$  ;           // Carleman linearization
2  $(\mathcal{R}_0, \dots, \mathcal{R}_m) \leftarrow post(y' = Ay, y(0) \in \hat{\mathcal{X}}_0)$  ;     // flowpipe for linear system
3 for  $j \leftarrow 0$  to  $m$  do
4    $\varepsilon \leftarrow error(\mathcal{R}_j, \mathcal{X}_0, F_1, F_2, N)$  ;           // linearization error
5    $\mathcal{R}_j^\varepsilon \leftarrow \pi_{1:n}(\mathcal{R}_j) \oplus \mathcal{B}_\varepsilon^n$  ;           // enlarged reach set
6 end
7 return  $(\mathcal{R}_0^\varepsilon, \dots, \mathcal{R}_m^\varepsilon)$ 
```

Numerical results: Burgers' PDE

Continuous partial differential equation (space and time)

$$\partial_t u + x \partial_x u = \nu \partial_x^2 u$$

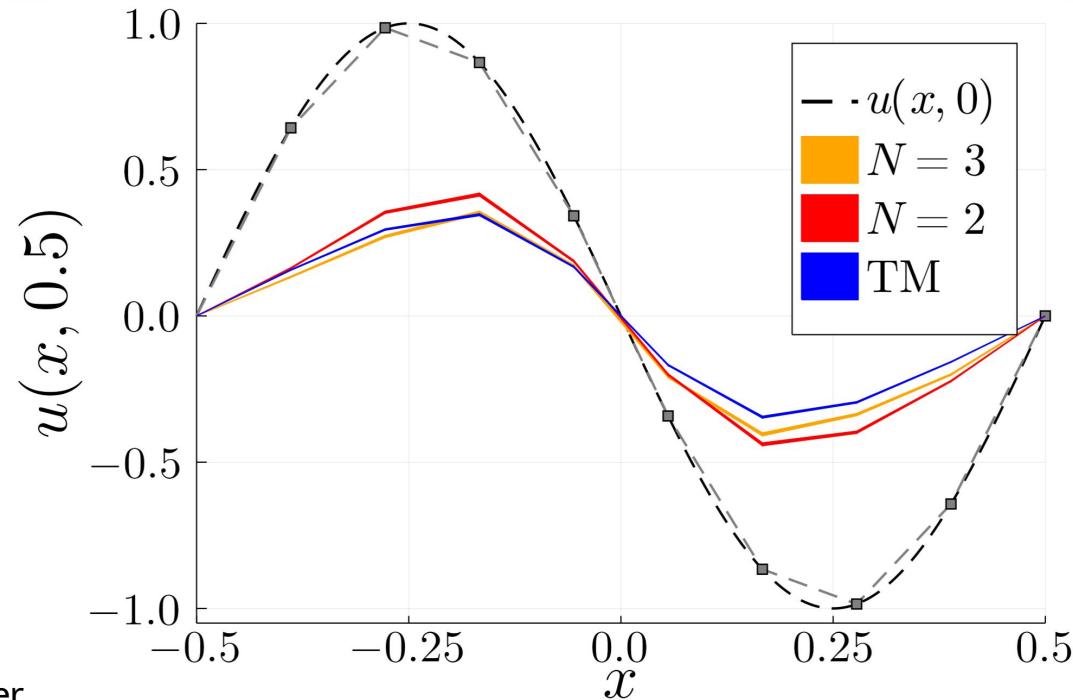


Discretize (space)

$$\partial_t u_i = \nu \frac{u_{i+1} - 2u_i + u_{i-1}}{\Delta x^2} - \frac{u_{i+1}^2 - u_{i-1}^2}{4\Delta x}$$



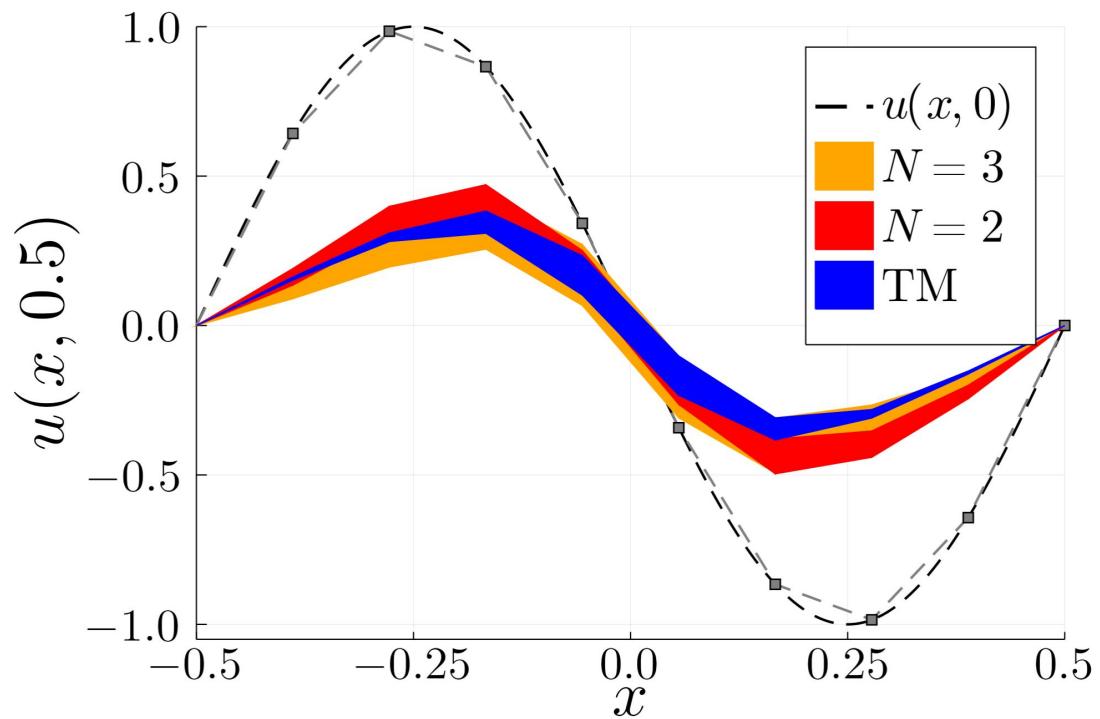
Reachability solver
(integrate in time)



Numerical results: Burgers' PDE (distributed initial conditions)

$$\Re(\lambda_1) \approx -0.488 < 0$$

$$R \approx 18.58$$



Numerical results: Epidemic model (SEIR)

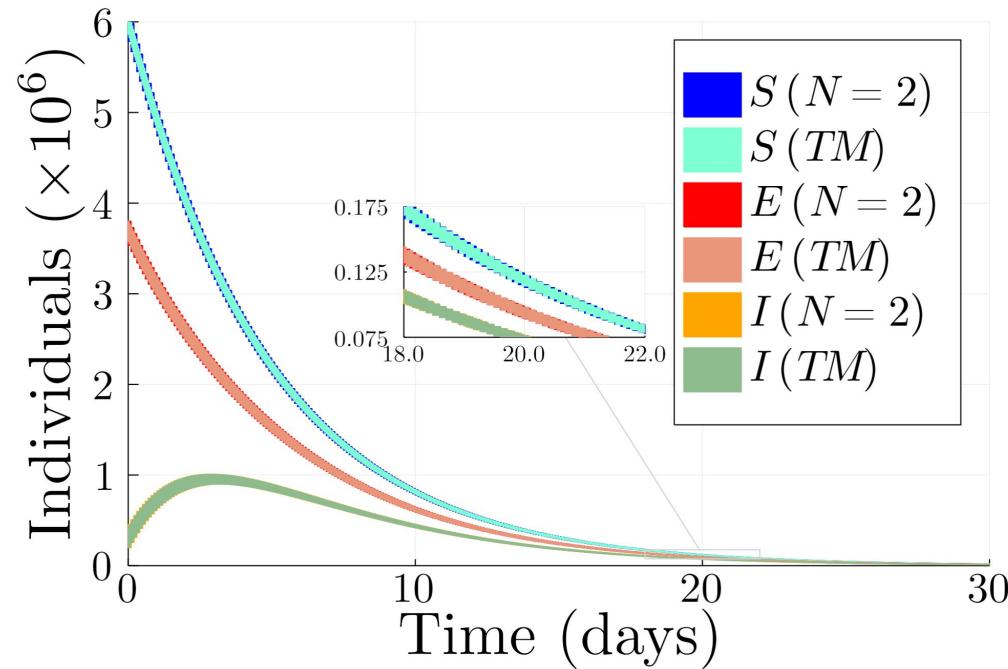
$$\frac{dP_S}{dt} = -\Lambda \frac{P_S}{P} - r_{\text{vac}} P_S - r_{\text{tra}} P_S \frac{P_I}{P} + \Lambda$$

$$\frac{dP_E}{dt} = -\Lambda \frac{P_E}{P} - \frac{P_E}{T_{\text{lat}}} + r_{\text{tra}} P_S \frac{P_I}{P}$$

$$\frac{dP_I}{dt} = -\Lambda \frac{P_I}{P} + \frac{P_E}{T_{\text{lat}}} - \frac{P_I}{T_{\text{inf}}}$$

$$\frac{dP_R}{dt} = -\Lambda \frac{P_R}{P} + r_{\text{vac}} P_S + \frac{P_I}{T_{\text{inf}}}$$

Data from the early spread of the COVID-19 disease from [P20]



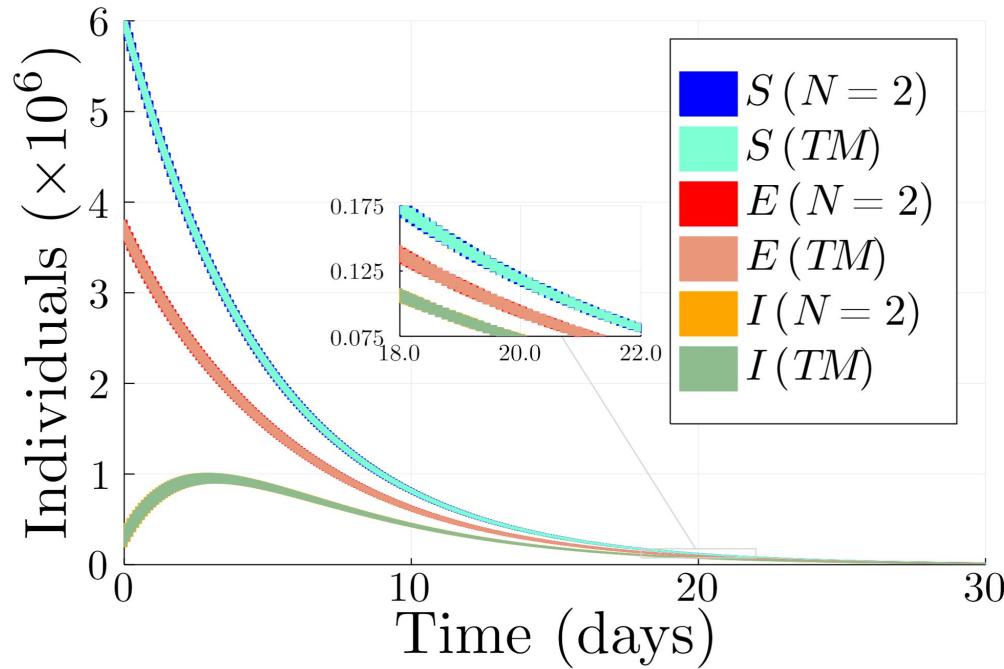
[P20] Pan, A. et al: Association of Public Health Interventions With the Epidemiology of the COVID-19 Outbreak in Wuhan, China. JAMA 323(19), 1915–1923 (2020)

Numerical results: Epidemic model (SEIR)

$$F_1 = \begin{pmatrix} -\frac{\Lambda}{P} - r_{vac} & 0 & 0 \\ 0 & -\frac{\Lambda}{P} - \frac{1}{T_{lat}} & 0 \\ 0 & \frac{1}{T_{lat}} & -\frac{\Lambda}{P} - \frac{1}{T_{inf}} \end{pmatrix}$$

$$F_2 = \begin{pmatrix} 0 & 0 & -\frac{r_{tra}}{P} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{r_{tra}}{P} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

$R \approx 0.68$ and $\Re(\lambda_1) \approx -0.19$



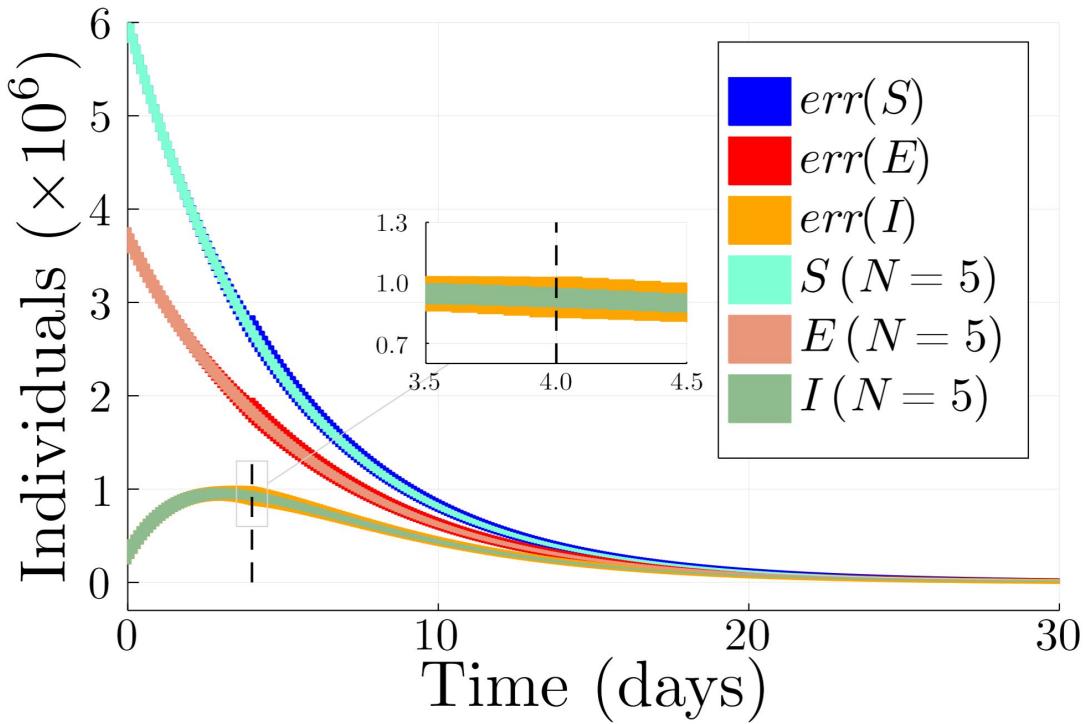
[P20] Pan, A. et al: Association of Public Health Interventions With the Epidemiology of the COVID-19 Outbreak in Wuhan, China. JAMA 323(19), 1915–1923 (2020)

Numerical results: Run-time comparison

	SEIR model		Burgers model	
	no error bound	incl. error bound	initial point	initial set
TM		6.14 s	0.88 s	0.91 s
Carleman	$N = 2$: 0.006 s	$N = 5$: 0.185 s	$N = 2$: 0.0065 s $N = 3$: 0.24 s	$N = 2$: 0.0067 s $N = 3$: 0.29 s

Table 1: Run times for the SEIR model and the Burgers model obtained for the Taylor-model (TM) approach and the Carleman linearization with different truncation orders N .

Idea: time-triggered resets



$$\|\eta_1(t)\| \leq \varepsilon(t) := \|x_0\| R^N (1 - e^{\Re(\lambda_1)t})^N$$

Problem: correction including error term may not converge to zero, even if the true solution does

Idea: re-evaluate the error term at times $t^* > 0 \Rightarrow$ reduce error estimate

Question (open): Automate / optimize when resets happen

Conclusions

We presented a novel reachability method for polynomial ODEs that can leverage established and well-optimized **high-dimensional reachability solvers**

Technique: abstract nonlinear terms into a higher-dimensional space such that the evolution is **approximately linear**

Outperforms other state-of-the-art methods in the set of examples, but requires **weak nonlinearity** and **dissipativity** (for guaranteed bounds)

Still, if the assumptions do not hold, the method returns **relatively good results** (but without guaranteed bounds)

Ideas for possible extensions

Consider time-varying matrices instead of fixed matrices.

Automation of the time-triggered process

Algorithmic specialization for Kronecker products, e.g. Krylov subspace iteration

Automation and specialization of the quadratic formulation [BP21]

How often and when to apply the resets?

Can we exploit the structure of the *linearized system*?

[BP21] Bychkov, Andrey, and Gleb Pogudin. "Optimal monomial quadratization for ODE systems." *ACM Communications in Computer Algebra* 54.3 (2021): 119-123.