

## Convex Optimization for Dynamical Systems Region of Attraction Computation via Polynomial Optimization

Region of Attraction (ROA) estimation problems yield interesting optimization approaches when considering polynomial dynamics. In this study, a method presented in [2] is shown, providing an outer approximation to the ROA, solving a Polynomial Optimization problem, induced by occupation measures, approximating an initial infinite dimensional problem with a hierarchy of finite dimensional linear matrix inequalities, with convergence for an arbitrarily large polynomial degree.

### I. Introduction

The problem relies on computing the Region of Attraction (ROA) of a target set, on a nonlinear dynamical system. The domain sets are  $X, U, X_T$ , respectively for the trajectories, control, and terminal state.

$$\dot{x}(t) = f(t, x(t), u(t)) \quad t \in [0, T] \quad (1.1)$$

where it is considered that each entry is polynomial, i.e.,  $f_i \in \mathbb{R}[t, x, u], i \in \mathbb{Z}_{[1, n]}$ . The set of all admissible trajectories starting from  $x_0$  is given by:

$$\mathcal{X}(x_0) := \{x(\cdot) : \exists u(\cdot) \in \mathcal{U} \text{ s.t. } \dot{x}(t) = f(t, x(t), u(t)) \text{ a.e., } x(0) = x_0, x(t) \in X, x(T) \in X_T, \forall t \in [0, T]\} \quad (1.2)$$

where  $\mathcal{U}$  denotes the set of all control functions, and  $x(\cdot)$  is absolutely continuous. Also, a.e. stands for "almost everywhere" in a Lebesgue measure or a weak sense.

The defined sets  $X, U, X_T$  form semialgebraic constraints that restrict state and control input.

$$x(t) \in X := \{x \in \mathbb{R}^n : g_i^X(x) \geq 0, i \in \mathbb{Z}_{[1, n_X]}\}, \quad t \in [0, T] \quad (1.3)$$

$$u(t) \in U := \{u \in \mathbb{R}^m : g_i^U(u) \geq 0, i \in \mathbb{Z}_{[1, n_U]}\}, \quad t \in [0, T] \quad (1.4)$$

where  $g_i^X \in \mathbb{R}[x], g_i^U \in \mathbb{R}[x]$ , and the terminal state  $x(T)$  is constrained to lie in the basic semialgebraic set

$$X_T := \{x \in \mathbb{R}^n : g_i^{X_T}(x) \geq 0, i \in \mathbb{Z}_{[1, n_T]}\} \subset X, \quad g_i^{X_T} \in \mathbb{R}[x] \quad (1.5)$$

**Definition 1.1** (Region of Attraction (ROA) [2]). The Region of Attraction (ROA) of a dynamical system is the set of all initial states that can be directed to a target set, with an admissible control, while remaining in the state-constraint set. The ROA is denoted by

$$X_0 = \{x_0 \in X : \mathcal{X}(x_0) \neq \emptyset\} \quad (1.6)$$

### A. Assumptions

1. **Assumption 1:  $X, U$ , and  $X_T$  are compact.** Therefore, the sets are also bounded.
2. **Assumption 2:** The control system satisfies  $\lambda(X_0) = \lambda(\bar{X}_0)$ . Thus, the volume of the relaxed region has the same volume as the ROA measure.
3. **Assumption 3:** Archimedian semialgebraic sets. Allows us to use quadratic modules (weighted SOS).

**Definition 1.2** (Quadratic Module [4]). The quadratic module generated by the polynomials  $g_1, \dots, g_m$  is the set

$$Q(g_1, \dots, g_m) := \left\{ \sigma_0 + \sum_{i=1}^m g_i \sigma_i : \sigma_0, \dots, \sigma_m \in \Sigma[x] \right\} \quad (1.7)$$

**Definition I.3** (Archimedean semialgebraic sets). The Quadratic module  $Q(g_1, \dots, g_m)$  is said to be Archimedean if  $\exists N \in \mathbb{N} : N - (x_1^2 + \dots + x_n^2) \in Q(g_1, \dots, g_m)$ .

Assumptions 1 and 3 are sufficient conditions to apply Putinar's theorem [5], and then a Quadratic module can be a representation of the semialgebraic sets.

**Theorem I.4** (Putinar [5]). Suppose the polynomials  $g_1, \dots, g_m$  are such that  $Q(g_1, \dots, g_m)$  is Archimedean. If  $f \in \mathbb{R}[x]$  is positive on the set  $K$ , then  $f \in Q(g_1, \dots, g_m)$ .

## II. Occupation measures

[2] shows that it is possible to compute the ROA by solving a convex linear program (LP), with infinite dimensionality. However, the infinite dimensional problem can be converted to an equivalent optimization problem, with finite dimensionality, which is more suitable for numerical simulation.

**Definition II.1** (Occupation measure). Given an initial condition  $x_0$  and admissible  $x(\cdot|x_0) \in \mathcal{X}_0$ , with  $u(\cdot|x_0) \in \mathcal{U}$ , the occupation measure  $\mu(\cdot|x_0)$  is defined by

$$\mu(A \times B \times C|x_0) = \int_0^T \mathbb{I}_{A \times B \times C}(t, x(t|x_0), u(t|x_0)) dt, \quad \forall A \times B \times C \subset [0, T] \times X \times U \quad (II.1)$$

where  $\mu(A \times B \times C|x_0)$  quantifies the amount of time of  $A \subset [0, T]$  spent with the trajectory state and control  $(x(\cdot|x_0), u(\cdot|x_0)) \in B \times C \subset X \times U$ .

For any measurable function  $g(t, x, u)$  we have the property

$$\int_0^T g(t, x(t|x_0), u(t|x_0)) dt = \int_{[0, T] \times X \times U} g(t, x, u) d\mu(t, x, u|x_0) \quad (II.2)$$

which relates the measure  $\mu(\cdot|x_0)$  to the trajectory state and control in the given time.

Furthermore, a particularly relevant relation between a measure  $\mu$  and the function  $f$  is the Liouville equation, with the derivative of the measure in a weak or distributional sense:

$$\partial_t \mu + \text{div}_x(f\mu) = 0, \quad \mu \in M([0, T] \times X) \quad (II.3)$$

And with a test function, initially with flexible regularity  $C_0^\infty([0, T] \times X)$ , we integrate with time and space. By integrating by parts and shifting the derivative to the test function with the first term, and applying the divergence theorem with the second term:

$$\int_0^T \int_X (\partial_t \mu + \text{div}_x(f\mu)) v dx dt = \int_0^T \int_X \partial_t \mu \cdot v dx dt + \int_0^T \int_X \text{div}(f\mu) \cdot v dx dt \quad (II.4)$$

$$= - \int_0^T \int_X \mu \cdot \partial_t v dx dt - \int_0^T \int_X f\mu \cdot \nabla v dx dt = 0 \quad (II.5)$$

$$\int_0^T \int_X (\partial_t v + \nabla v \cdot f) \mu dx dt = 0 \quad (II.6)$$

$$\Rightarrow \int_0^T \int_X (\partial_t v + \nabla v \cdot f) d\mu(t, x) = 0, \quad \forall v \in C_0^\infty([0, T] \times X) \quad (II.7)$$

We then reformulate II.3 via the Linear Operator  $\mathcal{L} : C^1([0, T] \times X) \rightarrow C([0, T] \times X \times U)$  with

$$v \mapsto Lv := \frac{\partial v}{\partial t} + \nabla v \cdot f \quad (II.8)$$

which has an adjoint  $\mathcal{L}' : C([0, T] \times X \times U)' \rightarrow C_1([0, T] \times X)'$ , with

$$\langle \mathcal{L}'\nu, v \rangle := \langle \nu, Lv \rangle = \int_{[0, T] \times X \times U} \mathcal{L}v(t, x, u) d\nu(t, x, u) \quad (II.9)$$

$$\forall \nu \in M([0, T] \times X \times U) = C([0, T] \times X \times U)', v \in C^1([0, T] \times X)$$

Often the adjoint is expressed with  $\mathcal{L}'\nu = -\partial_t \nu - \nabla \cdot f\nu$ . Note that the liouville equation II.3 is denoted with the given adjoint.

Given a test function  $v \in C^1([0, T] \times X)$ ,

$$\begin{aligned} v(T, x(T|x_0)) &= v(0, x_0) + \int_0^T \frac{d}{dt} v(t, x(t|x_0)) dt = v(0, x_0) + \int_0^T \mathcal{L}v(t, x(t|x_0), u(t|x_0)) dt \\ &= v(0, x_0) + \int_{[0, T] \times X \times U} \mathcal{L}v(t, x, u) d\mu(t, x, u) = v(0, x_0) + \langle \mathcal{L}'\mu(\cdot|x_0), v \rangle \\ &\Rightarrow v(T, x(T|x_0)) = v(0, x_0) + \langle \mathcal{L}'\mu(\cdot|x_0), v \rangle \end{aligned} \quad (II.10)$$

The average occupation measure  $\mu$  quantifies the average time spent with the given control and state. By integrating II.10 w.r.t  $\mu_0$ , we obtain

$$\int_{X_T} v(T, x(T|x_0)) d\mu_T(x) = \int_X v(0, x_0) d\mu_0(x) + \int_{[0, T] \times X \times U} \mathcal{L}v(t, x, u) d\mu(t, x, u) \quad (II.11)$$

$$\langle \mu_T, v(T, \cdot) \rangle = \langle \mu_0, v(0, \cdot) \rangle + \langle \mu, \mathcal{L}v \rangle \quad (II.12)$$

which relate the nonnegative measures  $\mu \geq 0, \mu_0 \geq 0, \mu_T \geq 0$ .

We can rewrite II.12 with the Dirac  $\delta_t$  measure as  $\langle \mu_0, v(0, \cdot) \rangle = \langle \delta_0 \otimes \mu_0, v \rangle$ , obtaining

$$\langle \delta_T \otimes \mu_T, v \rangle = \langle \delta_0 \otimes \mu_0, v \rangle + \underbrace{\langle \mu, \mathcal{L}v \rangle}_{\langle \mathcal{L}'\mu, v \rangle} \quad \forall v \in C^1([0, T] \times X) \quad (II.13)$$

And finally, we obtain the linear operator equation:

$$\delta_T \otimes \mu_T = \delta_0 \otimes \mu_0 + \mathcal{L}'\mu \quad (II.14)$$

Relaxation can be obtained by assuming suitable changes:

$$\rightarrow \dot{x}(t) \in f(t, x(t), U) \quad (II.15)$$

$$\rightarrow \dot{x}(t) \in \text{conv}f(t, x(t), U) \quad (II.16)$$

which can be shown to satisfy Liouville's equation II.14.

Then, the set of admissible trajectories and the ROA are defined with

$$\begin{aligned} \bar{\mathcal{X}}(x_0) &:= \{x(\cdot) : \exists u(\cdot) \in U \text{ s.t. } \dot{x}(t) \in \text{conv}f(t, x(t), U) \text{ a.e.}, \\ &\quad x(0) = x_0 \in X, x(T) \in X_T, \forall t \in [0, T]\} \end{aligned} \quad (II.17)$$

$$\bar{X}_0 = \{x_0 \in X : \bar{\mathcal{X}}(x_0) \neq \emptyset\} \quad (II.18)$$

### III. ROA via Optimization

Computing the ROA then can be determined with the optimization problem below

$$\begin{aligned} q^* &= \sup \lambda(\text{spt } \mu_0) \\ \text{s.t. } &\delta_T \otimes \mu_T = \delta_0 \otimes \mu_0 + \mathcal{L}'\mu \\ &\mu \geq 0, \mu_0 \geq 0, \mu_T \geq 0 \\ &\text{spt } \mu \subset [0, T] \times X \times U \\ &\text{spt } \mu_0 \subset X, \text{spt } \mu_T \subset X_T \end{aligned} \quad (III.1)$$

**Lemma III.1** (ROA computation via III.1). *It can be shown that the volume in III.1 equals to the volume of the ROA, i.e.,  $q^* = \lambda(X_0)$ .*

*Proof.* By definition, for  $x_0 \in X_0$ , there is an admissible trajectory in  $\mathcal{X}(x_0)$ , thus, for  $\mu_0$  with  $\text{spt } \mu_0 \subset X_0$ , there exist  $\mu, \mu_T$  satisfying the constraints.

With Assumption 2,  $\lambda(X_0) = \lambda(\bar{X}_0)$ , then  $q^* \geq \lambda(X_0) = \lambda(\bar{X}_0)$ .

Supposing by contradiction  $(\mu_0, \mu, \mu_T)$  satisfy the constraints and  $\lambda(\text{spt } \mu_0 \setminus \bar{X}_0) > 0$ . However, no trajectory from  $\text{spt } \mu_0 \setminus \bar{X}_0$  can be admissible, then  $\lambda(\text{spt } \mu_0 \setminus \bar{X}_0) = 0 \Rightarrow \lambda(\text{spt } \mu_0) \leq \lambda(\bar{X}_0)$ . Then,  $q^* \leq \lambda(\bar{X}_0) = \lambda(X_0)$ .  $\square$

It is possible to reformulate III.1, by using that for any feasible  $\mu_0$ :

$$\lambda(\text{spt } \mu_0) \leq \lambda(X_0) \quad (\text{III.2})$$

$$\mu_0 \leq \lambda \Rightarrow \mu_0(X) = \mu_0(\text{spt } \mu_0) \leq \lambda(\text{spt } \mu_0) \leq \lambda(X_0) \quad (\text{III.3})$$

$$\therefore \mu_0(X) \leq \lambda(X_0) \quad (\text{III.4})$$

Also, by definition  $\mu_0(X) \geq \lambda(X_0)$ . Thus:  $p^* := \mu_0(X) = \lambda(X_0)$ , and we obtain:

$$\begin{aligned} p^* &= \sup \mu_0(X) \\ \text{s.t. } &\delta_T \otimes \mu_T = \delta_0 \otimes \mu_0 + \mathcal{L}'\mu \\ &\mu \geq 0, \quad \lambda \geq \mu_0 \geq 0, \quad \mu_T \geq 0 \\ &\text{spt } \mu \subset [0, T] \times X \times U \\ &\text{spt } \mu_0 \subset X, \text{spt } \mu_T \subset X_T \end{aligned} \quad (\text{III.5})$$

**Theorem III.2.** *The optimal value of the infinite-dimensional problem is equal to the volume of the ROA, i.e.,*

$$p^* = \lambda(X_0) \quad (\text{III.6})$$

*Proof.* From Lemma III.1  $\lambda(\text{spt } \mu_0) \leq \lambda(X_0)$  for any feasible  $\mu_0$ .

With the constraint  $\mu_0 \leq \lambda$ , we get the inequality  $\mu_0 \leq \lambda \Rightarrow \mu_0(X) = \mu_0(\text{spt } \mu_0) \leq \lambda(\text{spt } \mu_0) \leq \lambda(X_0)$ , for any feasible  $\mu_0$ , then  $p^* \leq \lambda(X_0)$ .

However, by definition,  $\lambda(X_0)$  is feasible, so  $p^* \leq \lambda(X_0)$ . Therefore,  $p^* = \lambda(X_0)$ . □

Adding a slack variable  $\hat{\mu} \in M(X)$ , s.t.,

$$\lambda \geq \mu_0 \geq 0, \quad \mu_0 + \hat{\mu}_0 = \lambda, \quad \mu_0 \geq 0, \quad \hat{\mu}_0 \geq 0 \quad (\text{III.7})$$

Then:

$$\begin{aligned} p^* &= \sup \mu_0(X) \\ \text{s.t. } &\delta_T \otimes \mu_T = \delta_0 \otimes \mu_0 + \mathcal{L}'\mu \\ &\mu_0 + \hat{\mu}_0 = \lambda \\ &\mu \geq 0, \mu_0 \geq 0, \mu_T \geq 0, \hat{\mu}_0 \geq 0 \\ &\text{spt } \mu \subset [0, T] \times X \times U \\ &\text{spt } \mu_0 \subset X, \text{spt } \mu_T \subset X_T \\ &\text{spt } \hat{\mu}_0 \subset X \end{aligned} \quad (\text{III.8})$$

It can be shown that the primal problem III.8 it is associated with the dual shown below.

$$\begin{aligned} d^* &= \inf \int_X w(x) d\lambda(x) \\ \text{s.t. } &\mathcal{L}v(t, x, u) \leq 0, \quad \forall (t, x, u) \in [0, T] \times X \times U \\ &w(x) \geq v(0, x) + 1, \quad \forall x \in X \\ &v(T, x) \geq 0, \quad \forall (t, x) \in X_T \\ &w(x) \geq 0, \quad \forall x \in X \end{aligned} \quad (\text{III.9})$$

**Theorem III.3** (Strong duality in  $\infty$ -dim LP problem [2]). *There is no duality gap between the primal infinite-dimensional problem and the dual infinite-dimensional problem, i.e.,*

$$p^* = d^* \quad (\text{III.10})$$

*Proof:* [2]

**Lemma III.4.** *Let  $(v, w)$  be a feasible pair V.1, then  $v(0, \cdot) \geq 0$  on  $X_0$ , and  $w \geq 1$  on  $X_0$ .*

*Proof.* Given any  $x_0 \in X_0$ , there exist  $u(t)$  such that  $x(t) \in X$ ,  $u(t) \in U$ ,  $\forall t \in [0, T]$  and  $x(T) \in X_T$ . Note that

$$v(T, \cdot) \geq 0 \text{ on } X_T \quad (\text{III.11})$$

$$\mathcal{L}v \leq 0 \text{ on } [0, T] \times X \times U \quad (\text{III.12})$$

and since  $\frac{d}{dt}v(t, x(t)) = \frac{dv}{dt} + \frac{dv}{dx} \frac{dx}{dt} = \dot{v} + \nabla v \cdot f = \mathcal{L}v$ , and obviously  $\int_0^T \frac{d}{dt}v(t, x(t))dt = v(T, x(T)) - v(0, x_0)$ , then we can obtain:

$$\begin{aligned} 0 &\leq v(T, x(T)) = v(0, x_0) + \int_0^T \frac{d}{dt}v(t, x(t))dt \\ &= v(0, x_0) + \int_0^T \mathcal{L}v(t, x(t), u(t))dt \leq v(0, x_0) \leq w(x_0) - 1 \end{aligned} \quad (\text{III.13})$$

Therefore,  $w(x_0) \geq 1$  and  $v(0, x_0) \geq 0$ , on  $X_0$ .  $\square$

By Theorem III.2, the primal is related to the integral:

$$p^* = \int_X \mathbb{I}_{X_0}(x) d\lambda(x) \quad (\text{III.14})$$

Then, by Theorem III.3, there is no duality gap, i.e.,  $p^* = d^*$ , and  $\exists (v_k, w_k) \in C^1([0, T] \times X) \times C(X)$  feasible such that

$$p^* = d^* = \lim_{k \rightarrow \infty} \int_X w_k(x) d\lambda(x) \quad (\text{III.15})$$

and it can be shown (by the previous Lemma) that

$$\lim_{k \rightarrow \infty} \int_X (w_k(x) - \mathbb{I}_{X_0}(x)) d\lambda(x) = 0 \quad (\text{III.16})$$

concluding that  $w_k \xrightarrow{L^1} \mathbb{I}_{X_0}$ .

**Theorem III.5** (Convergence of  $w_k$  to  $\mathbb{I}_{X_0}$  [2]). *Given  $w_k \in \mathbb{R}_{2k}[x]$  as an optimal solution to the dual LMI, then  $w_k \searrow \mathbb{I}_{X_0}$  (converges from above) in  $L^1$ .*

*Proof:* [2]

It is shown in [2] that the  $\infty$ -dim LP problem can be approximated by a series of LMI problems, with vanishing error as the relaxation order increases.

Given the primal and dual,  $p^*$  and  $d^*$ , which approximate the  $\infty$ -dim problem, one can see that the following sets are outer approximations of the ROA:

$$X_{0k} := \{x \in X : v_k(0, x) \geq 0\} \quad \text{and} \quad \bar{X}_{0k} := \{x \in X_{\bar{v}_k} : v_k(0, x) \geq 0\} \quad (\text{III.17})$$

where  $\bar{w}_k := \min_{i \geq k} w_i$  and  $\bar{v}_k := \min_{i \geq k} v_i$ , for polynomials  $(w_k, v_k)$  with degree up to  $2k$ .

Furthermore,  $X_{0k} \supset \bar{X}_{0k} \supset X_0$ .

#### IV. Convergence Analysis

**Corollary IV.1** (The sequence of LMI converge monotonically to the  $\infty$ -dim LP).

$$d^* \leq d_{k+1}^* \leq d_k^* \quad \text{and} \quad p^* \leq p_{k+1}^* \leq p_k^* \quad (\text{IV.1})$$

*Proof.* From Theorem III.5 and relaxation of constraint with  $k \rightarrow \infty$ , we get convergence of dual optima  $d_k^*$ .

For the primal, weak duality:  $d_k^* \geq p_k^*$ , and from strong duality III.3:  $d^* \rightarrow d^* = p^*$ , then,  $p_k^* \geq p^*$ .

Also, the higher the relaxation order, the higher the constraints, so  $p_{k+1}^* \leq p_k^*$ .  $\square$

**Theorem IV.2** (Convergence to ROA). *Given  $(v_k, w_k) \in \mathbb{R}_{2k}[t, x] \times \mathbb{R}_{2k}[x]$  be a solution to the dual LMI problem. Then, the sets  $X_{0k}$  and  $\bar{X}_{0k}$  converge to the ROA  $X_0$  from the outside, such that*

$$X_{0k} \supset \bar{X}_{0k} \supset X_0 \quad (\text{IV.2})$$

$$\lim_{k \rightarrow \infty} \lambda(X_{0k} \setminus X_0) = 0 \quad \text{and} \quad \lim_{k \rightarrow \infty} \lambda(\bar{X}_{0k} \setminus X_0) = 0 \quad (\text{IV.3})$$

*Proof.* From Lemma III.4 and  $\bar{X}_{0k} = \cup_{i=1}^k X_{0i}$  it follows that  $X_{0k} \supset \bar{X}_{0k} \supset X_0$ . Then, monotonicity of the sequence  $\bar{X}_{0k}$  is implied.

Also from Lemma III.4, we have  $w_k \geq \mathbb{I}_{X_0}$ , and then since  $w_k \geq v_k(0, \cdot) + 1 \Rightarrow w_k \geq \mathbb{I}_{X_{0k}} \geq \mathbb{I}_{\bar{X}_{0k}} \geq \mathbb{I}_{X_0}$ .

From Theorem III.5,  $w_k \rightarrow \mathbb{I}_{X_0}$ , then

$$\lambda(X_0) = \int_X \mathbb{I}_{X_0} d\lambda \stackrel{\text{III.5}}{=} \lim_{k \rightarrow \infty} \int_X w_k d\lambda \geq \lim_{k \rightarrow \infty} \int_X \mathbb{I}_{X_{0k}} d\lambda = \lim_{k \rightarrow \infty} \lambda(X_{0k}) \geq \lim_{k \rightarrow \infty} \lambda(\bar{X}_{0k}) \quad (\text{IV.4})$$

But  $X_0 \subset \bar{X}_{0k} \subset X_{0k}$ , then  $\lambda(X_0) \leq \lambda(\bar{X}_{0k}) \leq \lambda(X_{0k})$ .  $\square$

## V. Polynomial Optimization Problem

Utilizing the Weierstrass theorem, [3], one can approximate continuous functions with polynomials in a compact set. Furthermore, the domain sets are defined as semialgebraic Quadratic modules. The problem then yields a Polynomial Optimization problem (POP), which can be implemented and solved with a variety of computational tools, for example, with a the Mosek [1] optimization solver, as later will be shown in numerical examples. The POP is formulated from the dual below.

$$\begin{aligned}
 & \inf \int_X w(x) d\lambda(x) \\
 \text{s.t. } & \mathcal{L}v(t, x, u) \leq 0, \quad \forall (t, x, u) \in [0, T] \times X \times U \\
 & w(x) \geq v(0, x) + 1, \quad \forall x \in X \\
 & v(t, x) \geq 0, \quad \forall (t, x) \in [0, T] \times X_T \\
 & w(x) \geq 0, \quad \forall x \in X
 \end{aligned} \tag{V.1}$$

Where, the constraints are written as nonnegativity certificates, which are related to sums of squares and quadratic modules.

$$\begin{aligned}
 & w(x) - v(0, x) - 1 \geq 0, \quad \forall x \in X \\
 & v(t, x) \geq 0, \quad \forall (t, x) \in [0, T] \times X_T \\
 & w(x) \geq 0, \quad \forall x \in X
 \end{aligned} \tag{V.2}$$

It is imperative to design suitable semialgebraic sets, then, given  $X = [a, b]$ , in order to find a semialgebraic domain such that

$$K = \{(t, x) \in \mathbb{R}^2 : g_1(t, x) \geq 0 \wedge g_2(t, x) \geq 0\} = [0, T] \times X \tag{V.3}$$

a simple concave quadratic polynomial is a possible representation, obtaining:

$$K = \{(t, x) \in \mathbb{R}^2 : -t(t - T) \geq 0 \wedge -(x - a)(x - b) \geq 0\} = [0, T] \times [a, b] \tag{V.4}$$

Similarly, for the remaining domains:

$$X = \{x \in \mathbb{R} : -(x - a)(x - b) \geq 0\} \tag{V.5}$$

$$K_T = \{(t, x) \in \mathbb{R}^2 : -t(t - T) \geq 0 \wedge -(x - \alpha)(x - \beta) \geq 0\} = [0, T] \times X_T \tag{V.6}$$

## VI. Numerical Simulations

All implementations are available at [https://github.com/pedroblossbraga/ROA\\_computation/tree/main](https://github.com/pedroblossbraga/ROA_computation/tree/main).

### A. Univariate Cubic Dynamics

Consider the following simple uncontrolled univariate cubic example with dynamics:

$$\dot{x} = x(x - 0.5)(x + 0.5) \tag{VI.1}$$

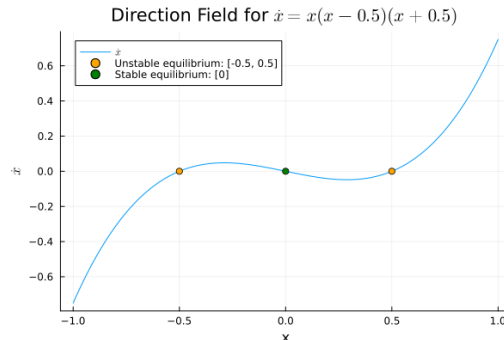


FIG. 1: ROA approximations for  $d \in \{4, 6, 16, 32\}$ .

Additionally, taking  $X = [-1, 1]$ ,  $T = 1$ ,  $X_T = [-0.24, 0.24]$ , the following numerical results are obtained, increasing the velocity of the system with a factor of 10, i.e.,  $\tilde{f} = 10f$ :

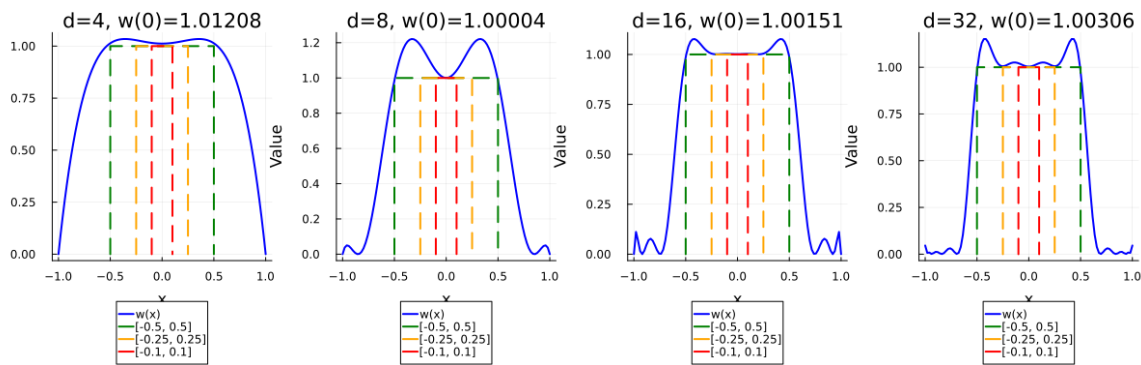


FIG. 2: ROA approximations for  $d \in \{4, 8, 16, 32\}$ .

Note that  $w(x)$  evaluated at the stable equilibrium point  $x = 0$  still satisfies the constraint  $w(x) \geq 1$ . Furthermore, the ROA appears to be located in the interval  $[-0.5, 0.5]$ , with a Gibbs effect in the discontinuity neighborhood, in  $\{-0.5, 0.5\}$ .

And, by reversing the ODE in time, with an initial condition of  $x(0) = 0.24$ , it is possible to verify if the value matches the observed ROA interval of  $[-0.5, 0.5]$ . As the system is symmetric, it is not necessary to verify for the left bound.

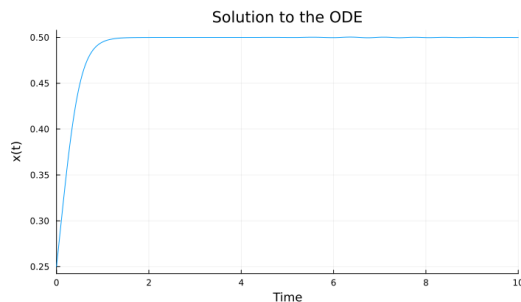


FIG. 3: Reversed ODE solution

The ODE solution converges to the value of 0.5.

## VII. References

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