

Learning and Control with Safety and Stability Guarantees for Nonlinear Systems

Part II: Applications

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Overview

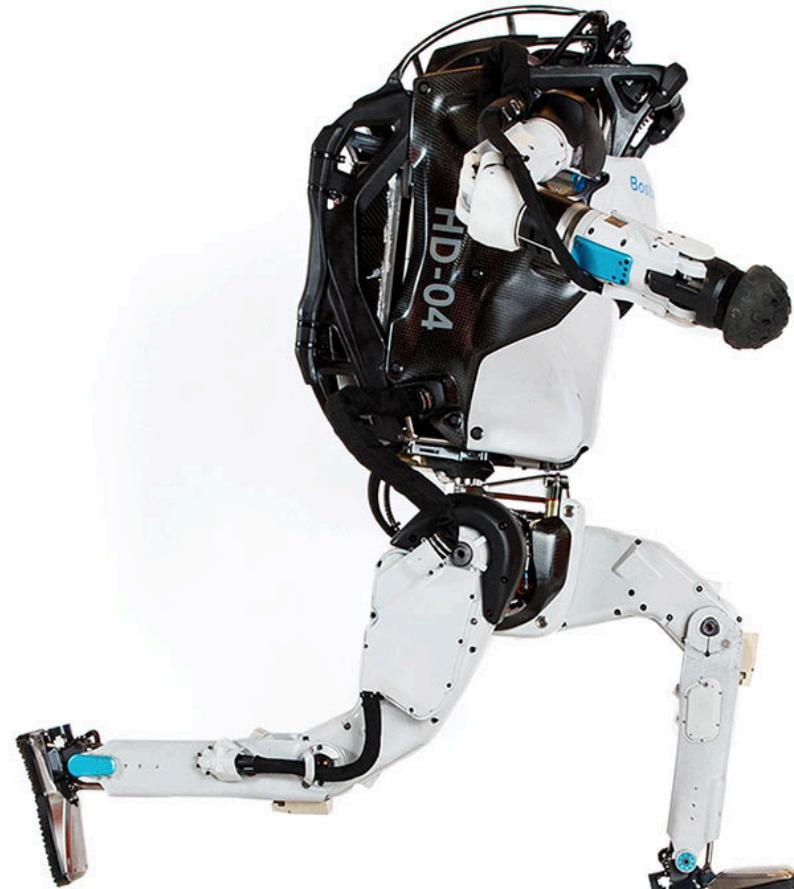
- In Part I, we covered a wide variety of foundational tools:
 - Concentration inequalities.
 - Uniform convergence / empirical process theory.
 - Nonlinear stability theory.
- In Part II, we will apply these tools to several applications:
 - Learning stability certificates from data.
 - Stability constrained imitation learning.
 - Regret bounds for adaptive nonlinear control.

Learning Stability Certificates from Data

Nicholas M. Boffi, Stephen Tu, Nikolai Matni, Jean-Jacques E. Slotine, and Vikas Sindhwani

arxiv.org/abs/2008.05952

Lab-to-Reality Transfer?



Lab-to-Reality Transfer?

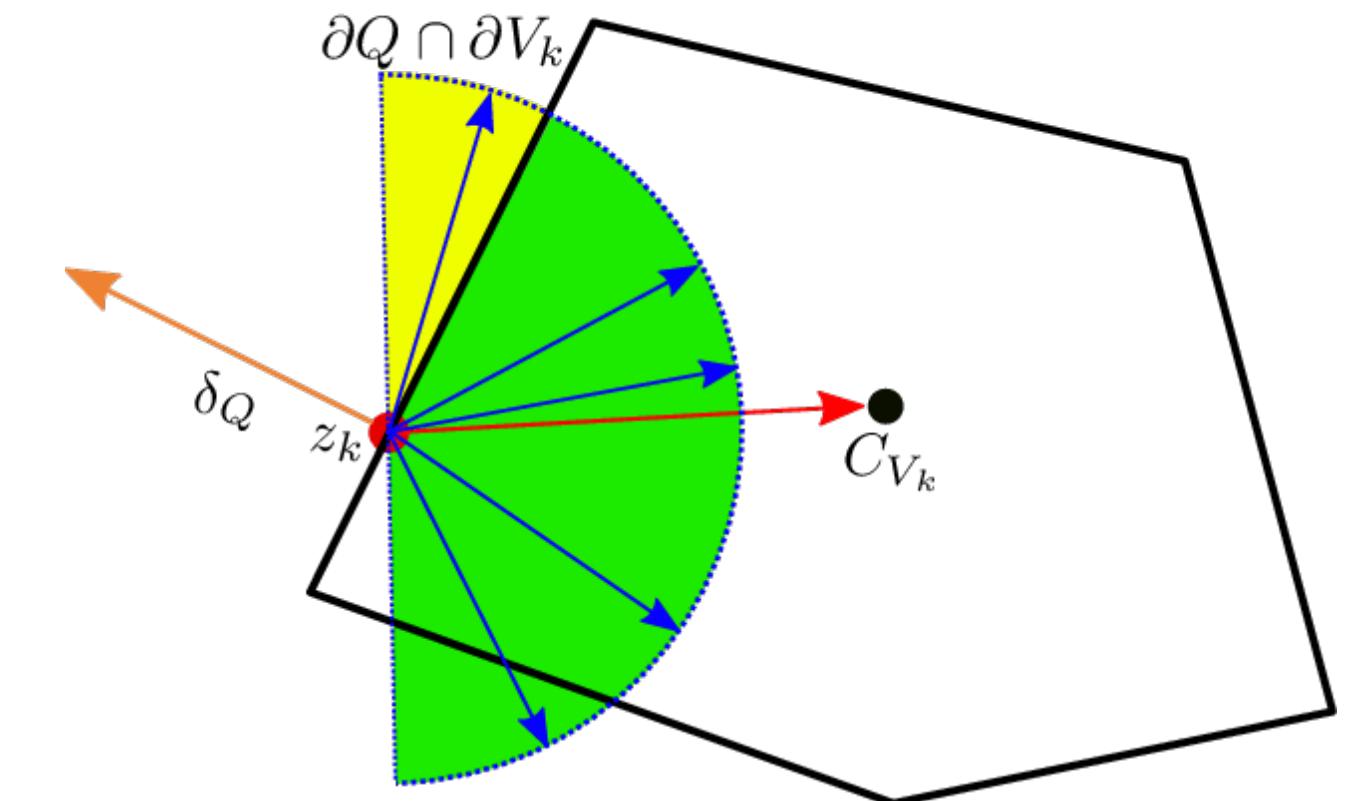
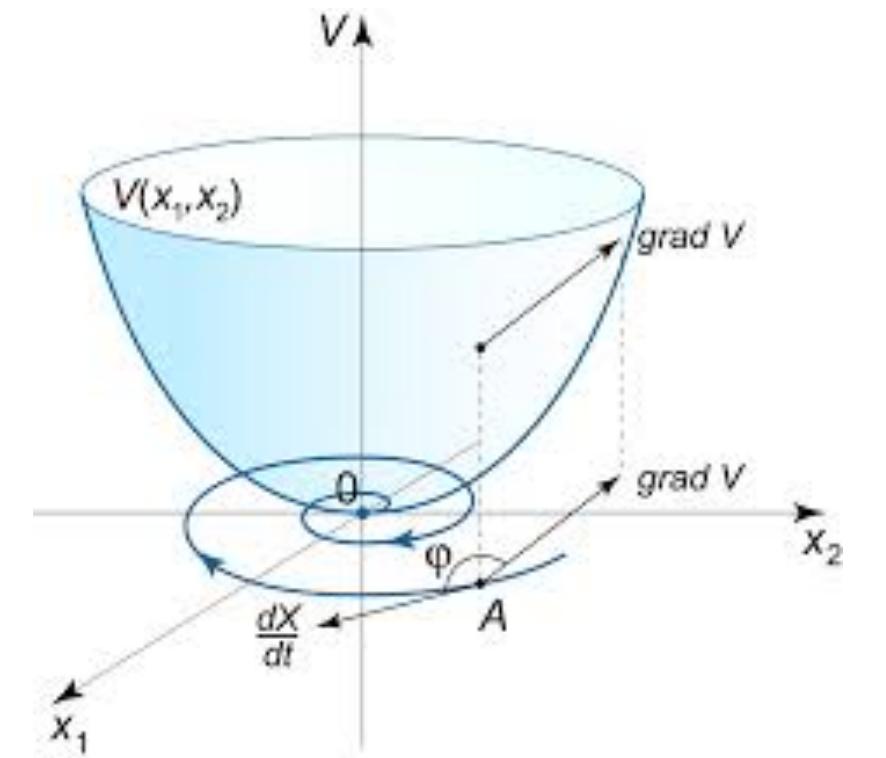
- **How do we deploy these demos out into the real world at scale?**
- A lot of research has focused on:
 - Algorithmic improvements
 - Better models/simulators
- Less emphasis on **provable** stability and safety guarantees.
 - Understanding limits is key to real-world deployment.
- **This talk:** an algorithmic framework for provably certifying guarantees of a dynamical system **from trajectory data**.

Problem formulation

- **Dynamical system:** $\dot{x} = f(x)$, $x \in \mathbb{R}^n$.
- Let $\varphi_t(\xi)$ denote the **flow-map** at time $t \in T$ starting at $x(0) = \xi \in X$.
- **Certificate function space:** $\mathcal{V} \subseteq C^1(\mathbb{R}^n, \mathbb{R})$.
- **Evaluation function** $h \in C(\mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R} \times \mathbb{R}^n, \mathbb{R})$.
- **Goal:** Find $V \in \mathcal{V}$ such that:
$$h(\varphi_t(\xi), \dot{\varphi}_t(\xi), V(\varphi_t(\xi)), \nabla V(\varphi_t(\xi))) \leq 0 \quad \forall \xi \in X, t \in T.$$

Why?

- V can be used to **certify** desirable system behavior.
- **Lyapunov stability:** Conditions (a) & (b) imply $x = 0$ is (locally) asymptotically stable:
 - (a) $V(x) > 0, V(0) = 0,$
 - (b) $\langle \nabla V(x), f(x) \rangle \leq -\alpha(x) \quad \forall x \in \mathbb{B}_2^n(0, \varepsilon)$ [α is class \mathcal{K}].
- **Barrier function:** Conditions (a) & (b) imply $\mathcal{C} := \{x : V(x) \geq 0\}$ is invariant:
 - (a) $V(x) = 0 \implies \nabla V(x) \neq 0,$
 - (b) $\langle \nabla V(x), f(x) \rangle \geq -\alpha(V(x)) \quad \forall x \in \mathcal{C}$ [α is class \mathcal{K}].



Why?

- Recall we want to find $V \in \mathcal{V}$ such that:
$$h(\varphi_t(\xi), \dot{\varphi}_t(\xi), V(\varphi_t(\xi)), \nabla V(\varphi_t(\xi))) \leq 0 \quad \forall \xi \in X, t \in T.$$
- **Lyapunov stability:** set $h(x, \dot{x}, V(x), \nabla V(x)) = \langle \nabla V(x), \dot{x} \rangle + \alpha(x)$.
- **Barrier function:** set $h(x, \dot{x}, V(x), \nabla V(x)) = -\langle \nabla V(x), \dot{x} \rangle - \alpha(V(x))$.
- Note: can handle **incremental stability** by drawing **pairs** of initial conditions.

What about sum-of-squares programming?

- Given knowledge of dynamics $f(x)$, can search for V satisfying $h \leq 0$ using sum-of-squares programming.
 - Caveat: only if $f(x)$, $V(x)$, $h(x)$ are polynomials.
 - Caveat: only if degree of polynomials and state dimension is not too large (SDP does not scale well in # of decision variables).
- **Goal:** search for V using only trajectories of $\dot{x} = f(x)$.

Problem formulation

- Let \mathcal{D} denote a distribution over X .
- **Observations:** $D = \{\{\varphi_t(\xi_i)\}_{t \in T}\}_{i=1,\dots,m}$, where ξ_1, \dots, ξ_m are i.i.d. samples from \mathcal{D} .
- We study the following empirical estimate:

$$\begin{aligned} \text{find } V \in \mathcal{V} \text{ s.t. } h(\varphi_t(\xi_i), \dot{\varphi}_t(\xi_i), V(\varphi_t(\xi_i)), \nabla V(\varphi_t(\xi_i))) \leq -\gamma \\ i = 1, \dots, m, \quad t \in T. \end{aligned}$$

- Supposing problem is feasible, let $\hat{V}_m \in \mathcal{V}$ denote a solution. Define the **generalization error** of \hat{V}_m as:

$$\text{err}(\hat{V}_m) := \mathbb{P}_{\xi \sim \mathcal{D}} \left\{ \max_{t \in T} h \left(\varphi_t(\xi), \dot{\varphi}_t(\xi), \hat{V}_m(\varphi_t(\xi)), \nabla \hat{V}_m(\varphi_t(\xi)) \right) > 0 \right\}.$$

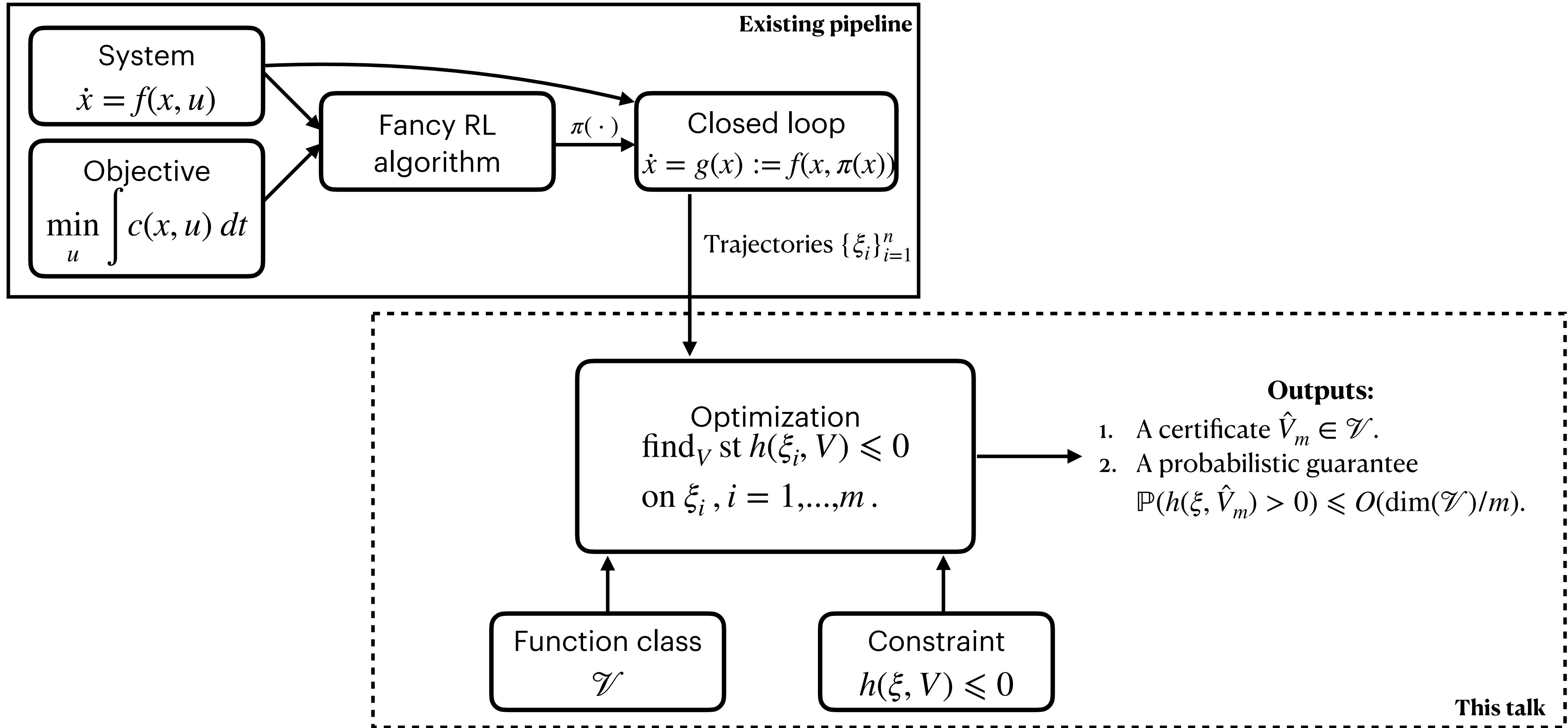
Problem formulation

- Generalization error:

$$\text{err}(\hat{V}_m) := \mathbb{P}_{\xi \sim \mathcal{D}} \left\{ \max_{t \in T} h \left(\varphi_t(\xi), \dot{\varphi}_t(\xi), \hat{V}_m(\varphi_t(\xi)), \nabla \hat{V}_m(\varphi_t(\xi)) \right) > 0 \right\}.$$

- Measures the probability that \hat{V}_m **fails to certify** a trajectory $\{\varphi_t(\xi)\}_{t \in T}$ when initialized at $\xi \sim \mathcal{D}$.
- **Question:** How many trajectories $m = m(\varepsilon, \delta)$ do we need such that $\text{err}(\hat{V}_m) \leq \varepsilon$ with probability at least $1 - \delta$ (over ξ_1, \dots, ξ_m)?

Algorithmic Framework



Supervised learning reduction

- Let $h(\xi, V)$ be shorthand for:

$$h(\xi, V) := \max_{t \in T} h \left(\varphi_t(\xi), \dot{\varphi}_t(\xi), V(\varphi_t(\xi)), \nabla V(\varphi_t(\xi)) \right).$$

- For any $V \in \mathcal{V}$, define the empirical (margin) risk $\hat{R}_\gamma(V)$ and true risk $R(V)$ as:

$$\hat{R}_\gamma(V) := \frac{1}{m} \sum_{i=1}^m \mathbf{1}\{h(\xi_i, V) > -\gamma\}, \quad R(V) := \mathbb{P}_{\xi \sim \mathcal{D}} (h(\xi, V) > 0).$$

- By definition of \hat{V}_m , we have $\hat{R}_\gamma(\hat{V}_m) = 0$ (all constraints are satisfied).
- To proceed, we want to upper bound $R(\hat{V}_m)$ by some expression containing $\hat{R}_\gamma(\hat{V}_m)$ (via a uniform convergence argument).

Supervised learning reduction

- We will use a result from [Srebro et al. 2010] which yields uniform convergence for H -smooth losses (H -Lipschitz gradients).
- Let us review the setup of supervised learning:
 - $\mathcal{H} \subseteq F(\mathcal{X}, \mathbb{R})$ is a hypothesis class.
 - $\phi : \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}_{\geq 0}$ is a non-negative loss function.
 - \mathcal{D} is a distribution over $\mathcal{X} \times \mathbb{R}$.
 - $L(h) := \mathbb{E}_{(x,y) \sim \mathcal{D}} \phi(h(x), y)$.
 - $\hat{L}(h) = \frac{1}{m} \sum_{i=1}^m \phi(h(x_i), y_i)$ with $(x_i, y_i) \sim_{\text{i.i.d.}} \mathcal{D}$.

Supervised learning reduction

- **Theorem** [Srebro et al. 2010]:
 - Suppose $\sup_{x \in \mathcal{X}} \sup_{y \in \mathbb{R}} \sup_{h \in \mathcal{H}} |\phi(h(x), y)| \leq b$ and that $t \mapsto \phi(t, y)$ is H -smooth for every $y \in \mathbb{R}$.
 - Define $\mathcal{R}_m(\mathcal{H}) := \sup_{x_1, \dots, x_m \in \mathcal{X}} \mathbb{E}_{\{\varepsilon_i\}} \sup_{h \in \mathcal{H}} \frac{1}{m} \sum_{i=1}^m \varepsilon_i h(x_i)$.
 - Define $\Gamma(\mathcal{H}, m, \delta) := H \log^3 m \cdot \mathcal{R}_m^2(\mathcal{H}) + \frac{b \log(1/\delta)}{m}$.
 - Then, with probability at least $1 - \delta$ (over $(x_1, y_1), \dots, (x_m, y_m)$ drawn i.i.d. from \mathcal{D}), for any $h \in \mathcal{H}$,
$$L(h) \leq \hat{L}(h) + O(1)\sqrt{\hat{L}(h)\Gamma(\mathcal{H}, m, \delta)} + O(1)\Gamma(\mathcal{H}, m, \delta).$$
 - **Fast rate:** Therefore, if $\hat{h} \in \arg \min_{h \in \mathcal{H}} \hat{L}(h)$ satisfies $\hat{L}(\hat{h}) = 0$, then $L(\hat{h}) \leq O(1)\Gamma(\mathcal{H}, m, \delta)$.

Supervised learning reduction

- Define $\phi_\gamma(t) := \begin{cases} 0 & \text{if } t \leq -\gamma, \\ \frac{1 + \cos(-\pi t/\gamma)}{2} & \text{if } t \in (-\gamma, 0), \\ 1 & \text{if } t \geq 0 \end{cases}$.

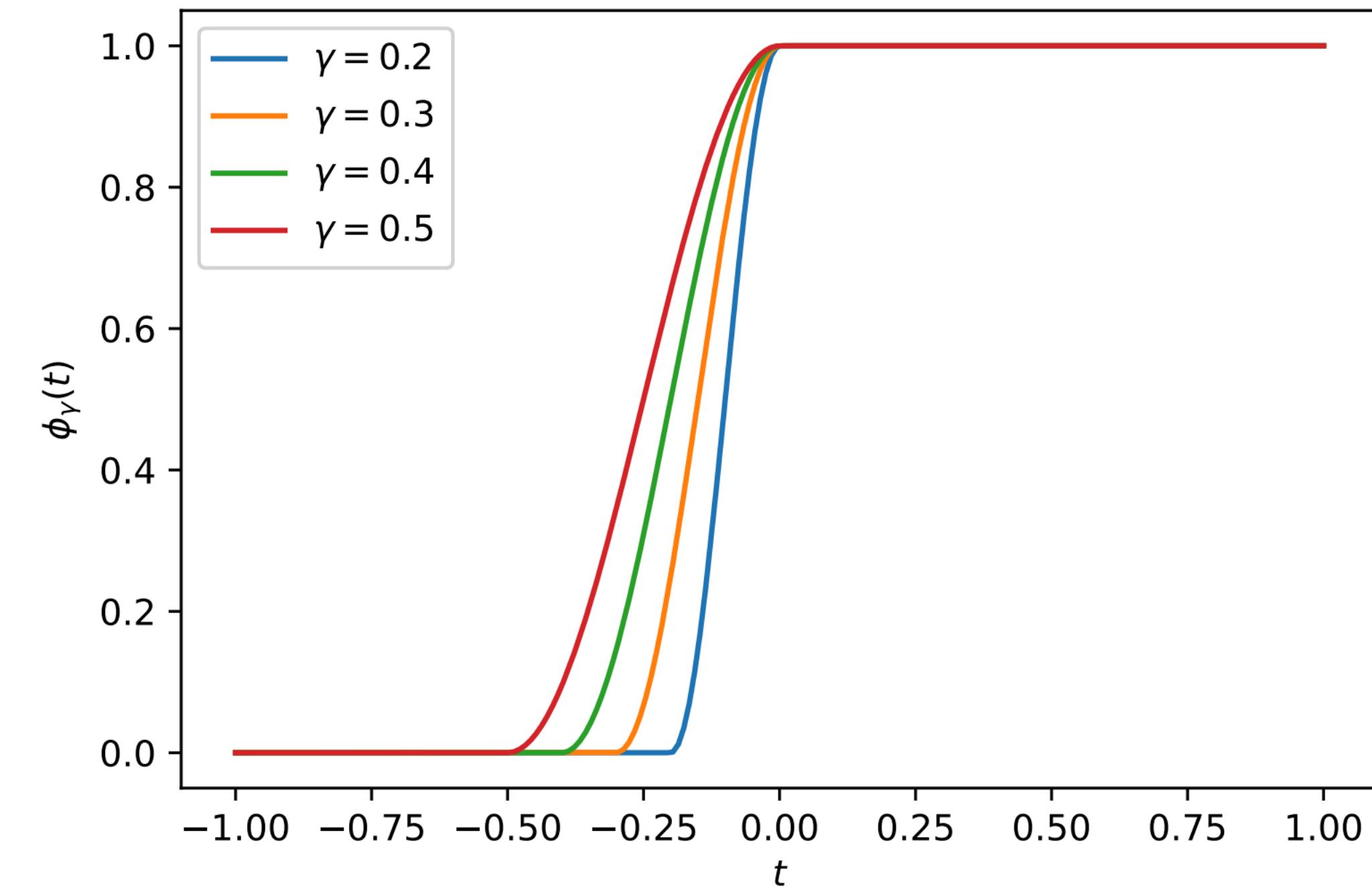
- Observe the relationship for all $t \in \mathbb{R}$:

$$\mathbf{1}\{t > 0\} \leq \phi_\gamma(t) \leq \mathbf{1}\{t > -\gamma\}.$$

- Therefore:

- $\mathbb{E}\mathbf{1}\{h(\xi, \hat{V}_m) > 0\} \leq \mathbb{E}\phi_\gamma(h(\xi, \hat{V}_m))$

- $\frac{1}{m} \sum_{i=1}^m \phi_\gamma(h(\xi_i, \hat{V}_m)) \leq \frac{1}{m} \sum_{i=1}^m \mathbf{1}\{h(\xi_i, \hat{V}_m) > -\gamma\} = 0.$



Supervised learning reduction

- We can apply [Srebro et al. 2010]’s result as follows.
- First, $\text{err}(\hat{V}_m) = \mathbb{P}(h(\xi, \hat{V}_m) > 0) = \mathbb{E}\mathbf{1}\{h(\xi, \hat{V}_m) > 0\} \leq \mathbb{E}\phi_\gamma(h(\xi, \hat{V}_m))$.
- Next, one can check that ϕ_γ is $\frac{\pi^2}{4\gamma^2}$ -smooth.
- Define $\mathcal{R}_m(\mathcal{V}) := \sup_{\xi_1, \dots, \xi_m \in X} \mathbb{E}_{\{\varepsilon_i\}} \sup_{V \in \mathcal{V}} \frac{1}{m} \sum_{i=1}^m \varepsilon_i h(\xi_i, V)$.
- [Srebro et al. 2010]’s result implies $\text{err}(\hat{V}_m) \leq O(1) \left(\frac{\log^3 m}{\gamma^2} \mathcal{R}_m^2(\mathcal{V}) + \frac{\log(1/\delta)}{m} \right)$.
- It remains to bound the Rademacher complexity $\mathcal{R}_m(\mathcal{V})$.

Rademacher complexity bounds

- We bound the Rademacher complexity $\mathcal{R}_m(\mathcal{V})$ by using Dudley's inequality.
- We need the following two assumptions.
- **Assumption** (stability i.s.L.): There exists a compact S such that $\bigcup_{t \in T} \varphi_t(X) \subseteq S$.
- **Assumption** (regularity of \mathcal{V}):
 - $\sup_{V \in \mathcal{V}} \sup_{x \in S} |V(x)| \leq B_V$
 - $\sup_{V \in \mathcal{V}} \sup_{x \in S} \|\nabla V(x)\|_2 \leq B_{\nabla V}$

Rademacher complexity bounds

- Let L_h denote an upper bound such that $(V, \nabla V) \mapsto h(x, f(x), V, \nabla V)$ is L_h -Lipschitz for all $x \in S$.
- Define the following norm on \mathcal{V} : $\|V\|_{\mathcal{V}} := \sup_{x \in S} \left\| \begin{bmatrix} V(x) \\ \nabla V(X) \end{bmatrix} \right\|_2$.

- **Claim:** for any $\xi \in X$ and $V_1, V_2 \in \mathcal{V}$, we have:

$$|h(\xi, V_1) - h(\xi, V_2)| \leq L_h \|V_1 - V_2\|_{\mathcal{V}}.$$

- **Proof of claim** $|h(\xi, V_1) - h(\xi, V_2)| \leq L_h \|V_1 - V_2\|_{\mathcal{V}}$:
- Define $h_t(\xi, V) := h(\varphi_t(\xi), \dot{\varphi}_t(\xi), V(\varphi_t(\xi)), \nabla V(\varphi_t(\xi)))$.
- Let t_i be such that $h(\xi, V_i) = h_{t_i}(\xi, V_i)$ for $i \in \{1, 2\}$.
- Observe that:

$$\begin{aligned}
h(\xi, V_1) - h(\xi, V_2) &= h_{t_1}(\xi, V_1) - h_{t_2}(\xi, V_2) \\
&\leq h_{t_1}(\xi, V_1) - h_{t_1}(\xi, V_2) && [h_{t_1}(\xi, V_2) \leq h_{t_2}(\xi, V_2)] \\
&\leq L_h \left\| \begin{bmatrix} V_1(\varphi_{t_1}(\xi)) - V_2(\varphi_{t_1}(\xi)) \\ \nabla V_1(\varphi_{t_1}(\xi)) - \nabla V_2(\varphi_{t_1}(\xi)) \end{bmatrix} \right\|_2 && [\text{definition of } L_h] \\
&\leq L_h \sup_{x \in S} \left\| \begin{bmatrix} V_1(x) - V_2(x) \\ \nabla V_1(x) - \nabla V_2(x) \end{bmatrix} \right\|_2 && [\text{stability i.s.L.}] \\
&= L_h \|V_1 - V_2\|_{\mathcal{V}}.
\end{aligned}$$

- An identical bound holds for $h(\xi, V_2) - h(\xi, V_1)$. ■

Rademacher complexity bounds

- Therefore by Dudley's inequality, we have:

$$\mathcal{R}_m(\mathcal{V}) \leq \frac{24L_h}{\sqrt{m}} \int_0^\infty \sqrt{\log N(\varepsilon; \mathcal{V}, \|\cdot\|_{\mathcal{V}})} d\varepsilon.$$

- Here, $N(\varepsilon; \mathcal{V}, \|\cdot\|_{\mathcal{V}})$ is the **covering number** of \mathcal{V} in the $\|\cdot\|_{\mathcal{V}}$ -norm at resolution ε .
- To further specialize this bound, we need to specialize the function class \mathcal{V} .

Rademacher complexity bounds

- Consider $\mathcal{V} = \{V_\theta(x) = g(x, \theta) : \theta \in \mathbb{R}^k, \|\theta\|_2 \leq B_\theta\}$ with $g \in C^1(\mathbb{R}^n \times \mathbb{R}^k, \mathbb{R})$.
- Let L_g be such that $\theta \mapsto g(x, \theta)$ is L_g -Lipschitz on $\mathbb{B}_2^k(0, B_\theta)$ for all $x \in S$.
- Let $L_{\nabla g}$ be such that $\theta \mapsto \nabla_x g(x, \theta)$ is $L_{\nabla g}$ -Lipschitz on $\mathbb{B}_2^k(0, B_\theta)$ for all $x \in S$.
- **Claim:** $\mathcal{R}_m(\mathcal{V}) \leq 32.5B_\theta L_h(L_g + L_{\nabla g})\sqrt{\frac{k}{m}}$.

Rademacher complexity bounds

- **Proof:** by Lipschitz assumptions, for all $\theta_1, \theta_2 \in \mathbb{B}_2^k(0, B_\theta)$:

$$\|V_1 - V_2\|_{\mathcal{V}} \leq (L_g + L_{\nabla g}) \|\theta_1 - \theta_2\|_2.$$

- Therefore:

$$\mathcal{R}_m(\mathcal{V}) \leq \frac{24L_h}{\sqrt{m}} \int_0^\infty \sqrt{\log N(\varepsilon; \mathcal{V}, \|\cdot\|_{\mathcal{V}})} d\varepsilon \quad [\text{Dudley's inequality}]$$

$$\leq \frac{24B_\theta L_h(L_g + L_{\nabla g})}{\sqrt{m}} \int_0^\infty \sqrt{\log N(\varepsilon; \mathbb{B}_2^k(0,1), \|\cdot\|_2)} d\varepsilon \quad [\text{Lipschitz inequality above}]$$

$$\leq 24B_\theta L_h(L_g + L_{\nabla g}) \sqrt{\frac{k}{m}} \int_0^1 \sqrt{\log(1 + 2/\varepsilon)} d\varepsilon \quad [N(\varepsilon; \mathbb{B}_2^k(0,1), \|\cdot\|_2) \leq (1 + 2/\varepsilon)^k]$$

$$\leq 32.5B_\theta L_h(L_g + L_{\nabla g}) \sqrt{\frac{k}{m}}.$$

■

Rademacher complexity bounds

- Let us add some more structure to \mathcal{V} .
- A natural way to enforce non-negativity of \mathcal{V} is to use the representation $\mathcal{V} = \{x \mapsto \psi(x)^T Q \psi(x) : Q \in \mathbb{R}^{p \times p}, Q = Q^T \geq 0, \|Q\|_F \leq B_Q\}$, where $\psi \in C^1(\mathbb{R}^n, \mathbb{R}^p)$ is a feature map.
- If we use the previous analysis, we have $\mathcal{R}_m(\mathcal{V}) \lesssim \sqrt{\frac{p^2}{m}}$ since there are $\Theta(p^2)$ parameters.
- **Claim:** $\mathcal{R}_m(\mathcal{V}) \lesssim \sqrt{\frac{p \log^2 p}{m}}$.

Rademacher complexity bounds

- **Proof:** Let $\sup_{x \in S} \|\psi(x)\|_2 \leq B_\psi$ and $\sup_{x \in S} \left\| \frac{\partial \psi}{\partial x}(x) \right\|_{\text{op}} \leq B_{D\psi}$.
- We have that $\nabla V(x) = 2 \frac{\partial \psi^T}{\partial x}(x) Q \psi(x)$.
- Not hard to check that $\|V_1 - V_2\|_{\mathcal{V}} \leq B_\psi (B_\psi + 2B_{D\psi}) \|Q_1 - Q_2\|_{\text{op}}$.
- Therefore, $\mathcal{R}_m(\mathcal{V}) \leq \frac{24B_Q B_\psi (B_\psi + 2B_{D\psi}) L_h}{\sqrt{m}} \int_0^\infty \sqrt{\log N(\varepsilon; \mathbb{B}_2^{p \times p}(0,1), \|\cdot\|_{\text{op}})} d\varepsilon$.

Rademacher complexity bounds

- The mismatch in norms in the covering number $\log N(\varepsilon; \mathbb{B}_2^{p \times p}(0,1), \|\cdot\|_{\text{op}})$ allows for some wins.
- First, the trivial bound. Because $\|Q\|_{\text{op}} \leq \|Q\|_F$, we have:

$$\log N(\varepsilon; \mathbb{B}_2^{p \times p}(0,1), \|\cdot\|_{\text{op}}) \leq \log N(\varepsilon; \mathbb{B}_2^{p \times p}(0,1), \|\cdot\|_F) \leq p^2 \log(1 + 2/\varepsilon).$$

- Next, by the dual Sudakov inequality [Vershynin 2010], we can improve the dependence on p at the expense of a worse dependence on ε :

$$\log N(\varepsilon; \mathbb{B}_2^{p \times p}(0,1), \|\cdot\|_{\text{op}}) \leq cp/\varepsilon^2.$$

- Combining both inequalities:

$$\log N(\varepsilon; \mathbb{B}_2^{p \times p}(0,1), \|\cdot\|_{\text{op}}) \leq \min\{p^2 \log(1 + 2/\varepsilon), cp/\varepsilon^2\}.$$

- Now for any $\tau \in (0,1)$:

$$\int_0^1 \sqrt{\log N(\varepsilon; \mathbb{B}_2^{p \times p}(0,1), \|\cdot\|_{\text{op}})} d\varepsilon$$

$$\leq p \int_0^\tau \sqrt{\log(1 + 2/\varepsilon)} d\varepsilon + \sqrt{cp} \int_\tau^1 1/\varepsilon d\varepsilon \quad [\log N(\varepsilon; \mathbb{B}_2^{p \times p}(0,1), \|\cdot\|_{\text{op}}) \leq \min\{p^2 \log(1 + 2/\varepsilon), cp/\varepsilon^2\}]$$

$$\leq p \int_0^\tau \sqrt{\log(3/\varepsilon)} d\varepsilon + \sqrt{cp} \log(1/\tau).$$

- From Mathematica:

$$\int_0^\tau \sqrt{\log(3/\varepsilon)} d\varepsilon = \tau \sqrt{\log(3/\tau)} + \frac{3\sqrt{\pi}}{2} \operatorname{erfc}\left(\sqrt{\log(3/\tau)}\right)$$

$$\leq \tau \sqrt{\log(3/\tau)} + \frac{3\sqrt{\pi}}{2} \exp(-\log(3/\tau)) \quad [\operatorname{erfc}(x) \leq \exp(-x^2) \text{ for } x > 0]$$

$$= \tau \sqrt{\log(3/\tau)} + \tau \frac{\sqrt{\pi}}{2}.$$

- Therefore, setting $\tau = 1/\sqrt{p}$, we have $\int_0^1 \sqrt{\log N(\varepsilon; \mathbb{B}_2^{p \times p}(0,1), \|\cdot\|_{\text{op}})} d\varepsilon \leq O(1)\sqrt{p} \log p$.

Rademacher complexity bounds

- Therefore, we have the bound:

$$\mathcal{R}_m(\mathcal{V}) \leq O(1)B_Q B_\psi (B_\psi + B_{D\psi}) L_h \sqrt{\frac{p \log^2 p}{m}}. \quad \blacksquare$$

Generalization error bounds

- With bounds on $\mathcal{R}_m(\mathcal{V})$, we can obtain bounds on $\text{err}(\hat{V}_m)$.
- When $\mathcal{V} = \{V_\theta(x) = g(x, \theta) : \theta \in \mathbb{R}^k, \|\theta\|_2 \leq B_\theta\}$, we have with probability at least $1 - \exp(-k)$,

$$\text{err}(\hat{V}_m) \leq O(1)B_\theta^2 L_h^2 (L_g^2 + L_{\nabla g}^2) \frac{k \log^3 m}{m}.$$

- When $\mathcal{V} = \{x \mapsto \psi(x)^T Q \psi(x) : Q \in \mathbb{R}^{p \times p}, Q = Q^T \geq 0, \|Q\|_F \leq B_Q\}$, we have with probability at least $1 - \exp(-p)$,

$$\text{err}(\hat{V}_m) \leq O(1)B_Q^2 B_\psi^2 (B_\psi^2 + B_{D\psi}^2) L_h^2 \frac{p \log^2 p \log^3 m}{m}.$$

Random convex programs (RCP)

- In certain special cases, we can actually obtain sharper bounds on $\text{err}(\hat{V}_m)$ using results on random convex programs [Calafiore 2010].
- Suppose again that $\mathcal{V} = \{V_\theta(x) = g(x, \theta) : \theta \in \mathbb{R}^k\}$. Suppose furthermore that $\theta \mapsto h(\xi, V_\theta)$ is convex for every $\xi \in X$.
- Then the feasibility problem find_θ s.t. $h(\xi_i, V_\theta) \leq 0, i = 1, \dots, m$ is a random convex program.
- **Theorem** [Calafiore 2010]: For any $\varepsilon \in (0, 1)$, define $\beta(\varepsilon) := \sum_{i=0}^{k-1} \binom{m}{i} \varepsilon^i (1 - \varepsilon)^{m-i}$. With probability at least $1 - \beta(\varepsilon)$ (over ξ_1, \dots, ξ_m), we have $\text{err}(\hat{V}_m) \leq \varepsilon$.

Random convex programs (RCP)

- To compare this bound with ours, we need to invert $\beta(\varepsilon) = \delta$.
- While this can be done numerically, there is no closed form formula for this.
- We can get an upper bound using the Chernoff inequality, which yields that with probability at least $1 - \delta$:

$$\text{err}(\hat{V}_m) \leq O(1) \frac{k - 1 + \log(1/\delta)}{m}.$$

- Order-wise, this matches our parametric bound. However, the RCP constants are **much sharper**.

Random convex programs (RCP)

- Let's see an example where $\theta \mapsto h(\xi, V_\theta)$ is convex.
- Suppose $h(x, \dot{x}, V(x), \nabla V(x)) = \langle \nabla V(x), \dot{x} \rangle + \rho V(x)$.
- Now suppose $V(x) = \psi(x)^T Q \psi(x)$. Then,
$$h(x, \dot{x}, V(x), \nabla V(x)) = \left\langle 2 \frac{\partial \psi}{\partial x}(x)^T Q \psi(x), \dot{x} \right\rangle + \rho \psi(x)^T Q \psi(x)$$
, which is convex (linear) in the parameters Q .

An aside: Towards practical bounds

- Uniform convergence laws typically give the right scaling, but the **constants are not practical**.
- **Randomized convex programs** (cf. [Calafiore 2010], [Campi and Garatti 2008]) give sharp generalization bounds, but only apply to convex optimization problems.
- **PAC-Bayes bounds** [McAllester 1999] have been shown to give non-vacuous bounds (cf. [Dziugaite and Roy 2017], [Majumdar and Goldstein 2018]) for both deep learning and control problems, but require delicate/expensive joint training of empirical risk + bound.

An aside: Towards practical bounds

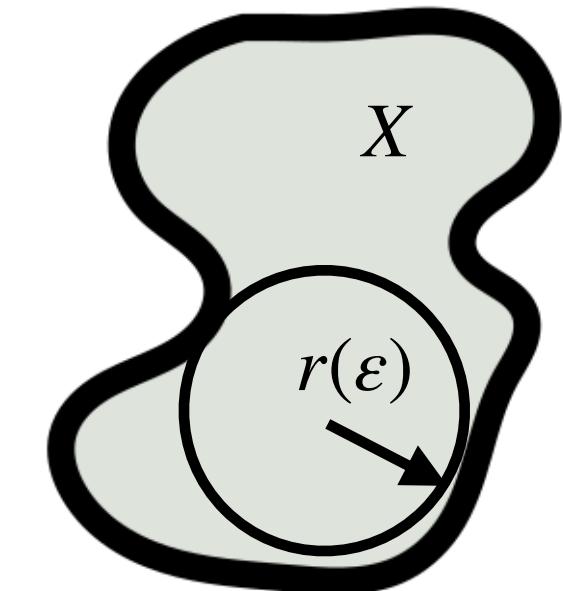
- A basic **holdout set bound** [Langford 2005] can be very powerful in practical.
- Procedure:
 - Split available data into train and holdout set.
 - Compute \hat{V} on the training set.
 - Compute $\hat{p} = \frac{1}{m_h} \sum_{i=1}^{m_h} 1\{h(\xi_i, \hat{V}) > 0\}$ from holdout set.
 - Compute UCB on $\text{err}(\hat{V})$: $\sup\{p \in (0,1) : \text{KL}(\hat{p}, p) \leq m_h^{-1} \log(1/\delta)\}$.
 - (Set $m_h = 0.1m$ (say) for the UCB to tend to zero.)

Deterministic guarantees

- We have given bounds on $\text{err}(\hat{V}_m)$, which is the probability that \hat{V}_m will **fail to certify** a trajectory randomly initialized at $\xi \sim \mathcal{D}$.
- Can we convert this probabilistic bound into a **deterministic bound** regarding the “size” of the state space for which the certificate condition is violated?

Deterministic guarantees

- We first study the following technical question.
- Let μ_{Leb} denote the Lebesgue measure and $X \subseteq \mathbb{R}^n$ be a compact set with $\mu_{\text{Leb}}(X) > 0$.
- Let μ_X denote the uniform measure on X , i.e., $\mu_X(A) = \frac{\mu_{\text{Leb}}(A)}{\mu_{\text{Leb}}(X)}$ for all measurable $A \subseteq X$.
- **Question:** Fix an $\varepsilon \in (0,1)$. What is the largest radius $r(\varepsilon)$ such that there exists a $U \subseteq X$ with $\mu_X(U) \leq \varepsilon$ which contains a ℓ_2^n -ball of radius $r(\varepsilon)$?
- Mathematically, $r(\varepsilon) = \sup_{U \subseteq X: \mu_X(U) \leq \varepsilon} \sup\{r > 0 : \exists x \in U \text{ s.t. } \mathbb{B}_2^n(x, r) \subseteq U\}$.



$$\mu(X) \leq \varepsilon$$

- **Claim:** $r(\varepsilon) \leq \left(\frac{\varepsilon \mu_{\text{Leb}}(X)}{\mu_{\text{Leb}}(\mathbb{B}_2^n(0,1))} \right)^{1/n}$.
- **Proof:** for any x, r such that $\mathbb{B}_2^n(x, r) \subseteq U$, then by translation invariance:

$$\mu_{\text{Leb}}(U) \geq \mu_{\text{Leb}}(\mathbb{B}_2^n(x, r)) = \mu_{\text{Leb}}(\mathbb{B}_2^n(0, r)) = r^n \mu_{\text{Leb}}(\mathbb{B}_2^n(0, 1)).$$

- But since $\mu_X(U) \leq \varepsilon$, we have $\mu_{\text{Leb}}(U) \leq \varepsilon \mu_{\text{Leb}}(X)$.
- Therefore, $r^n \mu_{\text{Leb}}(\mathbb{B}_2^n(0, 1)) \leq \varepsilon \mu_{\text{Leb}}(X)$, which implies the claim. ■

Deterministic guarantees

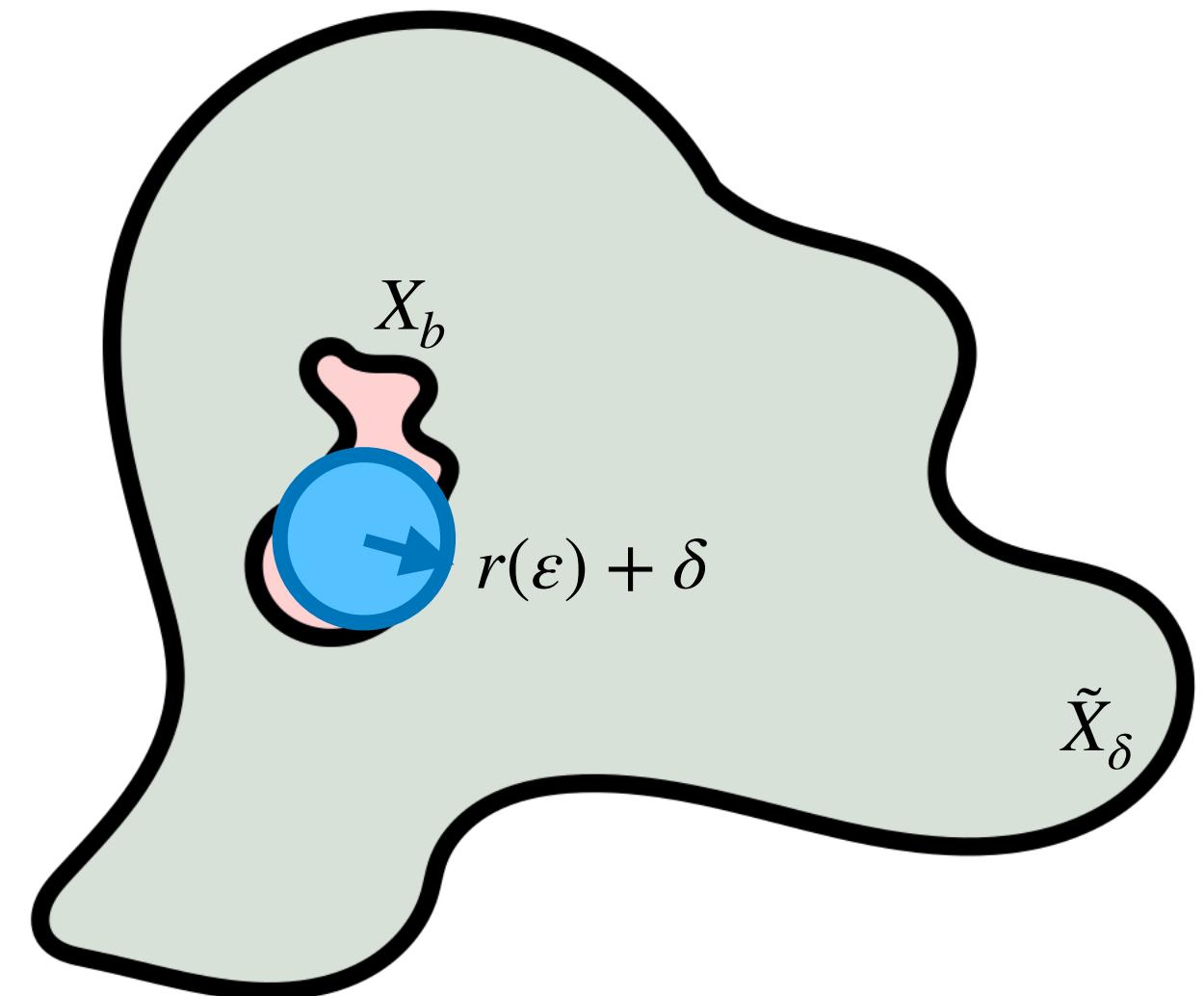
- Let us consider certifying exponential Lyapunov stability.
- Let $V \in C^1(\mathbb{R}^n, \mathbb{R})$ satisfy $V(x) \geq \nu \|x\|_2^2$. Define the “bad” set X_b as:
$$X_b := \left\{ \xi \in X : \max_{t \in T} \langle \nabla V(\varphi_t(\xi)), f(\varphi_t(\xi)) \rangle > -\lambda V(\varphi_t(\xi)) \right\}.$$
- Assume that $\mu_X(X_b) \leq \varepsilon$ (if \mathcal{D} is uniform over X , then $\mu_X(X_b) = \text{err}(\hat{V}_m)$).
- For which $x \in S$ can we assert that $\langle \nabla V(x), f(x) \rangle \leq -\lambda V(x)$?
- **Assumption (incremental stability):** There exists a class \mathcal{KL} function β such that for all $\xi_1, \xi_2 \in X, t \in T$: $\|\varphi_t(\xi_1) - \varphi_t(\xi_2)\|_2 \leq \beta(\|\xi_1 - \xi_2\|_2, t)$.

Deterministic guarantees

- For $\delta > 0$, define:
 - $\tilde{X}_\delta := \{\xi \in X : \mathbb{B}_2^n(\xi, r(\varepsilon) + \delta) \subseteq X\}$,
 - $\tilde{S}_\delta := \bigcup_{t \in T} \varphi_t(\tilde{X}_\delta)$ and $\tilde{S} := \bigcap_{\delta > 0} \tilde{S}_\delta$.
- Let L_V denote the Lipschitz constant of V over S .
- Define $q(x) := \langle \nabla V(x), f(x) \rangle$ and let L_q denote its Lipschitz constant over S .
- **Theorem:** For all $\eta \in (0,1)$:

$$\langle \nabla V(x), f(x) \rangle \leq - (1 - \eta)\lambda V(x) \quad \forall x \in \tilde{S} \setminus \mathbb{B}_2^n \left(0, \sqrt{\frac{(L_q + \lambda L_V)\beta(r(\varepsilon), 0)}{\eta \lambda \nu}} \right).$$

- **Proof:** Let $x \in \tilde{S}_\delta$. By definition of \tilde{S}_δ , there exists a $\xi \in \tilde{X}_\delta$, $t \in T$ such that $\varphi_t(\xi) = x$.
- Define the “good” set as $X_g := X \setminus X_b$.
- **Claim:** there must exist a $\xi' \in X_g$ satisfying $\|\xi - \xi'\|_2 \leq r(\varepsilon) + \delta$.
- If $\xi \in X_g$, there is nothing to prove, so suppose that $\xi \in X_b$.
- We know that $\mathbb{B}_2^n(\xi, r(\varepsilon) + \delta) \not\subseteq X_b$ since $\mu_X(X_b) \leq \varepsilon$.
- Furthermore, since $\xi \in \tilde{X}_\delta$, we have $\mathbb{B}_2^n(\xi, r(\varepsilon) + \delta) \subseteq X$.
- Therefore, $\mathbb{B}_2^n(\xi, r(\varepsilon) + \delta) \cap X_g$ is non-empty, proving the claim.



- Therefore:
$$\begin{aligned}
q(\varphi_t(\xi)) &\leq q(\varphi_t(\xi')) + L_q \|\varphi_t(\xi) - \varphi_t(\xi')\|_2 \\
&\leq -\lambda V(\varphi_t(\xi')) + L_q \|\varphi_t(\xi) - \varphi_t(\xi')\|_2 & [\xi' \in X_g] \\
&\leq -\lambda V(\varphi_t(\xi)) + (L_q + \lambda L_V) \|\varphi_t(\xi) - \varphi_t(\xi')\|_2 \\
&\leq -\lambda V(\varphi_t(\xi)) + (L_q + \lambda L_V) \beta(\|\xi - \xi'\|_2, t) & [\text{incremental stability}] \\
&\leq -\lambda V(\varphi_t(\xi)) + (L_q + \lambda L_V) \beta(r(\varepsilon) + \delta, 0). & [\text{properties of class KL function}]
\end{aligned}$$
- This shows for any $x \in \tilde{S}_\delta$, we have $q(x) \leq -\lambda V(x) + (L_q + \lambda L_V) \beta(r(\varepsilon) + \delta, 0)$.
- Taking $\delta \rightarrow 0$, by continuity of β in its first argument, for any $x \in \tilde{S}$:

$$q(x) \leq -\lambda V(x) + (L_q + \lambda L_V) \beta(r(\varepsilon), 0).$$
- Therefore, for any $\eta \in (0, 1)$, since $V(x) \geq \nu \|x\|_2^2$:

$$q(x) \leq -(1 - \eta)\lambda V(x) - \eta\lambda\nu \|x\|_2^2 + (L_q + \lambda L_V) \beta(r(\varepsilon), 0). \blacksquare$$

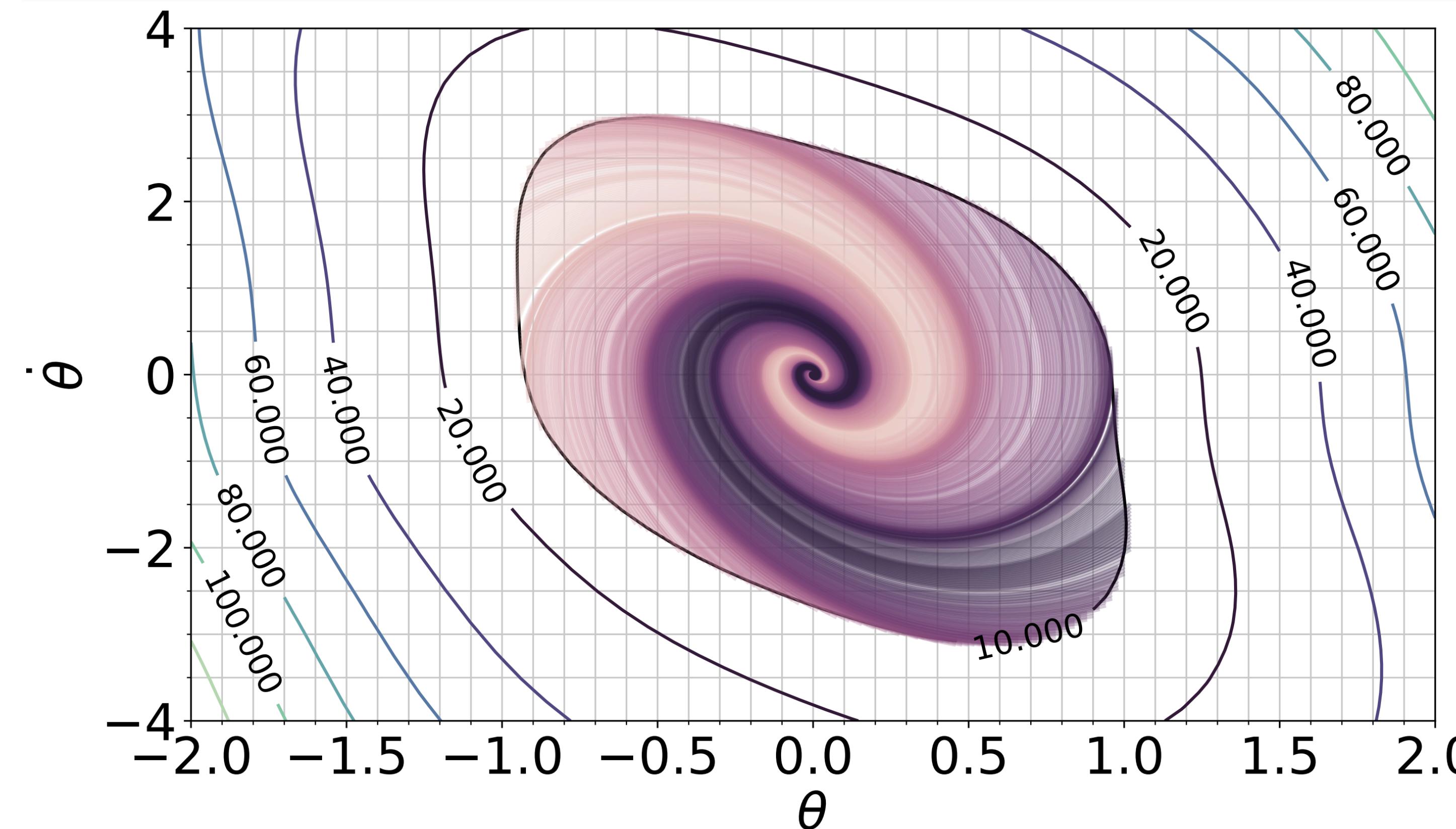
Deterministic guarantees

- We have shown that the Lyapunov condition holds for all $x \in \tilde{S}$ except in a radius around the origin of size $r_b \lesssim \sqrt{\beta(r(\varepsilon), 0)}$. If $\beta(s, 0) \lesssim s$, then $r_b \lesssim \varepsilon^{\frac{1}{2n}}$.
- We know that $\text{err}(\hat{V}_m) \lesssim \frac{k}{m}$. Hence if we want $r_b \leq \zeta$, we need $m \gtrsim k\zeta^{-2n}$ trajectories.
- This exponential dependence on ζ in state dimension is (probably) unavoidable.

Damped pendulum

- We rollout $m = 1000$ trajectories for $T = 8$ seconds ($dt = 0.02$) initialized from $X = [-2,2] \times [-2,2]$.
- We fit a neural network Lyapunov function of the form $V_\theta(x) = x^T(L_\theta(x)L_\theta(x) + I)x$ where $L_\theta(x)$ is a reshaped fully connected NN.
- We use a soft loss
$$\ell(\theta) = \sum_{i=1}^{1000} \sum_{k=1}^{400} \text{ReLU}(\langle \nabla V_\theta(x_i(k)), \dot{x}_i(k) \rangle + \gamma V_\theta(x_i(k))) + \lambda \|\theta\|_2^2.$$
- Time derivatives $\dot{x}_i(k)$ are computed by finite differencing (savgol_filter in scipy).

Damped pendulum



Level sets of the learned Lyapunov function.

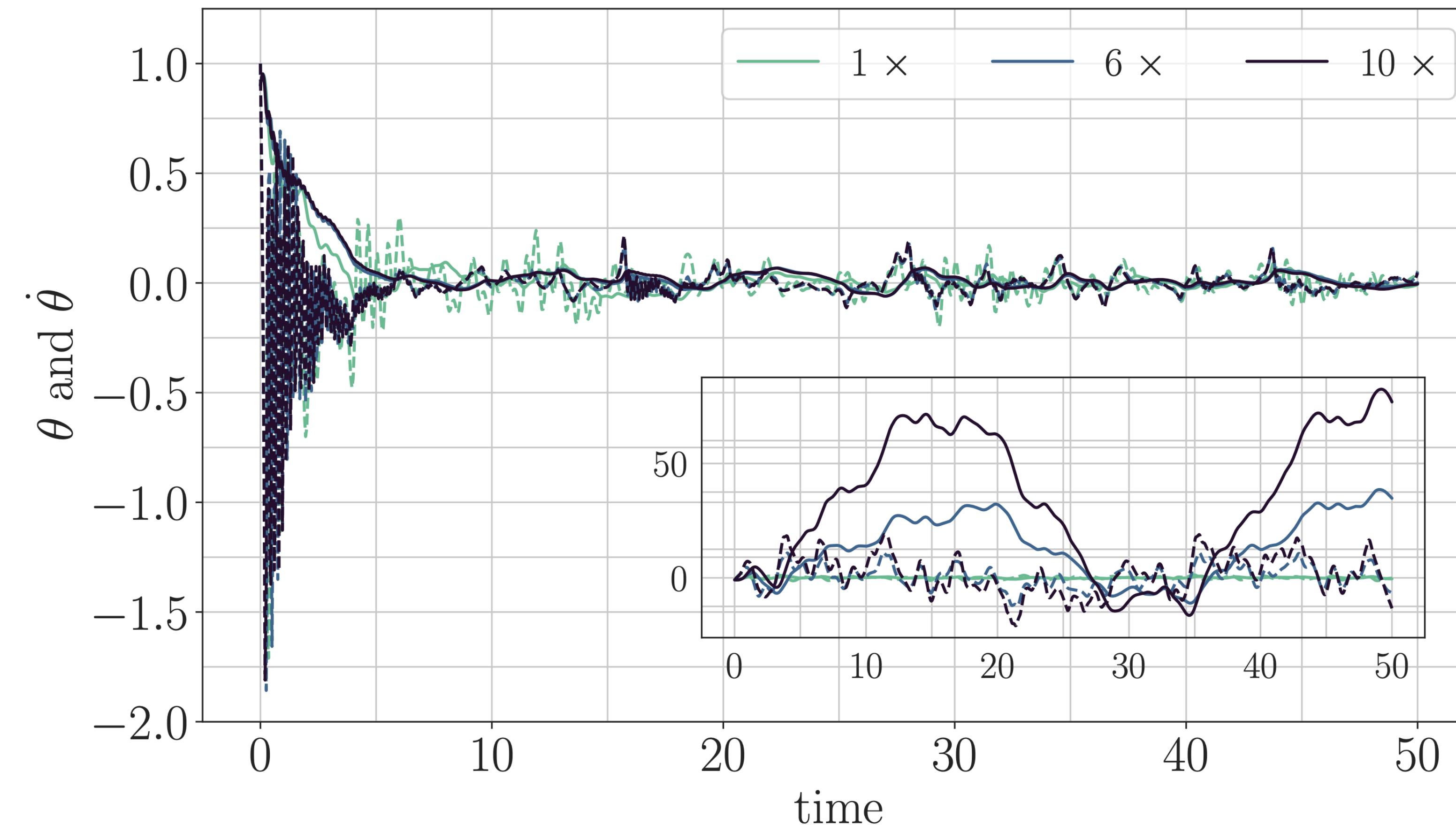
Damped pendulum

- To show that the learned Lyapunov function can perform useful downstream tasks, we add a disturbance to the pendulum dynamics (here a is unknown):
$$m\ell^2\ddot{\theta} + b\dot{\theta} + mg\ell \sin \theta + \langle a, \kappa\phi(t) \rangle = u.$$
- We use a “speed-gradient” (cf. [Fradkov et al. 1999]) adaptive controller to reject the disturbance:

$$u(t) = \langle \hat{a}(t), \kappa\phi(t) \rangle ,$$

$$\dot{\hat{a}}(t) = -\gamma\phi(t)\langle \nabla_x V_\theta(x(t)), e_2 \rangle .$$

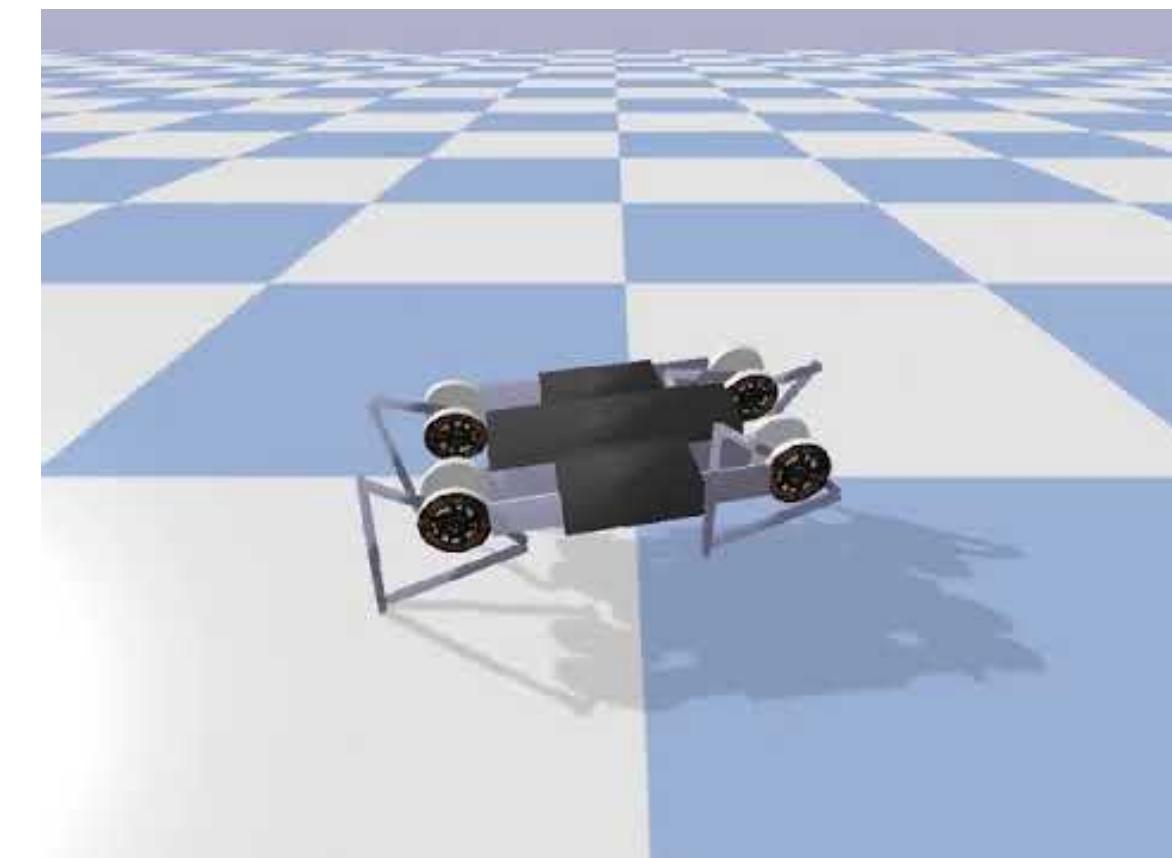
Damped pendulum



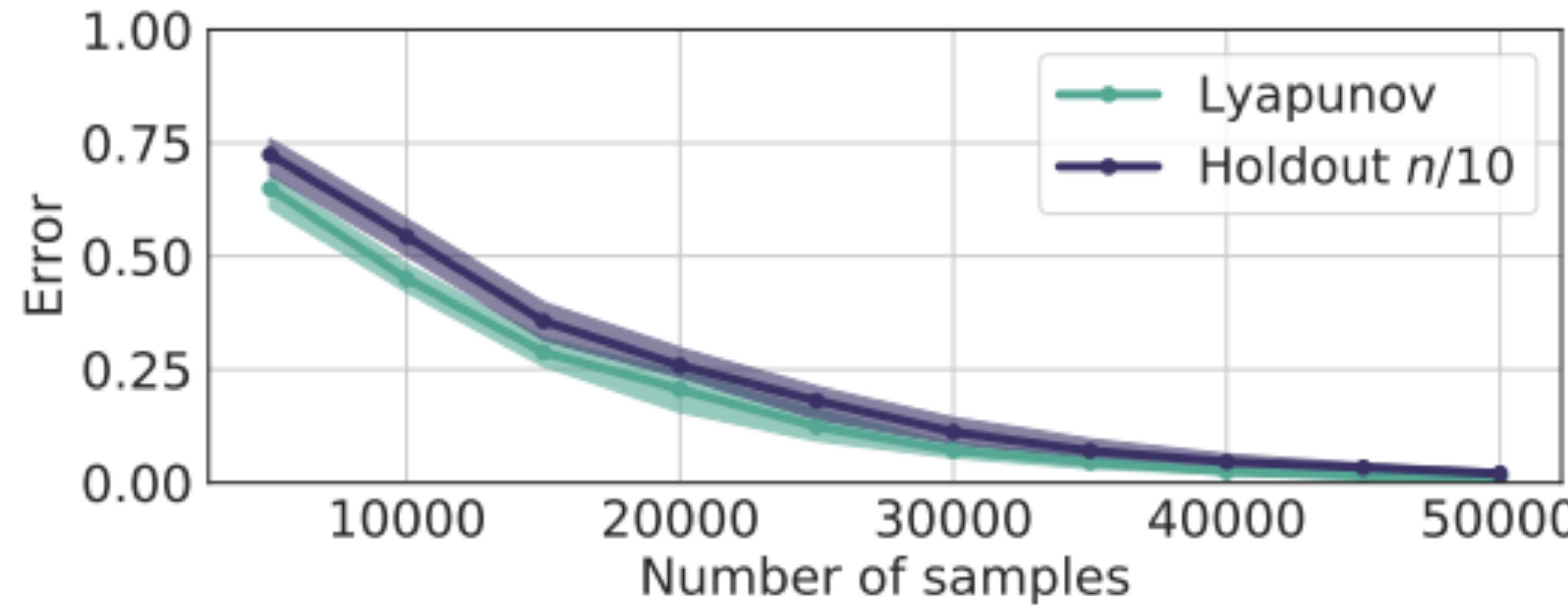
Different colors correspond to various values of κ .
Inset shows performance without adaptation.

Standing minitaur

- We use the minitaur environment in PyBullet. The state dimension is 16 (excluding the base).
- A random impulse force (kick) is applied to the minitaur at time $t = 0$, and a simple PD controller is used to return the minitaur to a desired standing position.
- We learn a discrete-time Lyapunov function to satisfy $V_\theta(e_i(k + 1)) \leq \rho V_\theta(e_i(k)) + \gamma$, where $e_i(k)$ is the error of the i -th trajectory at timestep k .



Standing minitaur



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On the Sample Complexity of Stability Constrained Imitation Learning

Stephen Tu, Alexander Robey, Tingnan Zhang, and Nikolai Matni.

arxiv.org/abs/2102.09161

Imitation learning

- In many tasks, there exists an expert policy which solves the task.
- However, relying on this expert may be undesirable:
 - Expert could be a human demonstrator.
 - Expert could require lots of computation (e.g. solution to non-convex optimization problem).
 - Expert could be a black-box policy.
- **Goal:** imitate (via supervised learning) a policy from demonstrations, so that the learned policy can solve the desired task.

Problem notation

- Discrete-time control-affine dynamical system:
$$x_{t+1} = f(x_t) + g(x_t)u_t, \quad f(0) = 0, \quad x_t \in \mathbb{R}^n, \quad u_t \in \mathbb{R}^d.$$
- \mathcal{D} is a distribution over initial states $\xi \in X$ (can also generalize to include environment stochasticity).
- For policy $\pi : \mathbb{R}^n \rightarrow \mathbb{R}^d$, let $\varphi_t^\pi(\xi)$ denote the state x_t with $u_t = \pi(x_t)$.
- **Expert policy** $\pi_\star : \mathbb{R}^n \rightarrow \mathbb{R}^d$.
- (Weighted) **Policy deviation** $\Delta_{\pi_1, \pi_2}(x) := g(x)(\pi_1(x) - \pi_2(x))$.
- **Imitation loss** $\ell_{\pi'}(\xi; \pi_1, \pi_2) := \sum_{t=0}^{T-1} \|\Delta_{\pi_1, \pi_2}(\varphi_t^{\pi'}(\xi))\|_2$.
- The **generalization error** of a learned policy π is $\text{err}(\pi) := \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi}(\xi; \pi, \pi_\star)$.

Behavior cloning

- Most basic imitation learning algorithm.
- Observe m **expert trajectories** $\{\{\varphi_t^{\pi_\star}(\xi_i)\}_{t=0}^T\}_{i=1}^m$, with ξ_1, \dots, ξ_m i.i.d. from \mathcal{D} .
- The behavior cloning policy is $\pi_{bc} \in \arg \min_{\pi \in \Pi} \frac{1}{m} \sum_{i=1}^m \ell_{\pi_\star}(\xi_i; \pi, \pi_\star)$.
- **Note:** A bound on the generalization error $\text{err}(\pi_{bc})$ is not immediate from supervised learning theory, which yields bounds on the related (but not the same) quantity: $\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_\star}(\xi; \pi_{bc}, \pi_\star)$.
- This **distribution shift** $\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_\star}(\xi; \pi_{bc}, \pi_\star)$ vs $\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_{bc}}(\xi; \pi_{bc}, \pi_\star)$ is what makes imitation learning trickier to analyze.

Distribution shift

- The key technical question in analyzing imitation learning is the following.
- Given two policies π_1, π_2 , define $\text{disc}_T(\xi; \pi_1, \pi_2) := \sum_{t=0}^T \|\varphi_t^{\pi_1}(\xi) - \varphi_t^{\pi_2}(\xi)\|_2$.
- Can we upper bound $\text{disc}_T(\xi; \pi_1, \pi_2)$ by some function of the imitation loss $\ell_{\pi_1}(\xi; \pi_1, \pi_2)$ under π_1 ?
- **Claim** (Gronwall bound): Suppose f, g, π_1, π_2 are B -bounded and L -Lipschitz. Then:
$$\text{disc}_T(\xi; \pi_1, \pi_2) \leq \frac{(L(1 + 2B))^T - 1}{L(1 + 2B) - 1} \ell_{\pi_1}(\xi; \pi_1, \pi_2).$$

- **Proof:** let us consider two trajectories:

$$x_{t+1} = f(x_t) + g(x_t)\pi_1(x_t), \quad x_0 = \xi,$$

$$y_{t+1} = f(y_t) + g(y_t)\pi_2(y_t), \quad y_0 = \xi.$$

- We have:

$$x_{t+1} - y_{t+1} = f(x_t) - f(y_t) + g(x_t)\pi_1(x_t) - g(y_t)\pi_2(y_t)$$

$$= f(x_t) - f(y_t) + g(x_t)\pi_1(x_t) - g(x_t)\pi_2(x_t) + g(x_t)\pi_2(x_t) - g(y_t)\pi_2(y_t).$$

- Because f, g, π_1, π_2 are B -bounded and L -Lipschitz, by triangle inequality:

$$\|x_{t+1} - y_{t+1}\|_2 \leq L(1 + 2B)\|x_t - y_t\|_2 + \|g(x_t)(\pi_1(x_t) - \pi_2(x_t))\|_2$$

$$= L(1 + 2B)\|x_t - y_t\|_2 + \|\Delta_{\pi_1, \pi_2}(x_t)\|_2.$$

- Previously we showed:

$$\|x_{t+1} - y_{t+1}\|_2 \leq L(1 + 2B)\|x_t - y_t\|_2 + \|\Delta_{\pi_1, \pi_2}(x_t)\|_2.$$

- Unrolling this recursion, we obtain:

$$\|x_t - y_t\|_2 \leq \sum_{i=0}^{t-1} (L(1 + 2B))^{t-1-i} \|\Delta_{\pi_1, \pi_2}(x_i)\|_2.$$

- Therefore:

$$\begin{aligned} \sum_{t=0}^T \|x_t - y_t\|_2 &\leq \sum_{t=0}^{T-1} \left(\frac{(L(1 + 2B))^{T-t} - 1}{L(1 + 2B) - 1} \right) \|\Delta_{\pi_1, \pi_2}(x_t)\|_2 \\ &\leq \frac{(L(1 + 2B))^T - 1}{L(1 + 2B) - 1} \sum_{t=0}^{T-1} \|\Delta_{\pi_1, \pi_2}(x_t)\|_2. \end{aligned}$$

■

Incremental ISS

- Gronwall bound is **exponential** in horizon length T !
- To improve the dependence on the horizon length, we need to use some stability theory.
- We start with the following definition of incremental input-to-state stability [Tran et al. 2016].
- **Notation:** for dynamics $x_{t+1} = f(x_t, u_t)$, let $\varphi_t(\xi; \{u_t\}_{t \geq 0})$ denote the state x_t initialized at $x_0 = \xi$ with input signal $\{u_t\}_{t \geq 0}$.
- **Definition:** the dynamics $x_{t+1} = f(x_t, u_t)$ is δ ISS if there exists class \mathcal{KL} function ζ and class \mathcal{K}_∞ function γ such that for every $\xi_1, \xi_2 \in X$, $\{u_t\}_{t \geq 0} \subseteq U$, and $t \in \mathbb{N}_{\geq 0}$:

$$\|\varphi_t(\xi_1, \{u_t\}_{t \geq 0}) - \varphi_t(\xi_2, \{0\}_{t \geq 0})\|_X \leq \zeta(\|\xi_1 - \xi_2\|_X, t) + \gamma \left(\max_{0 \leq k \leq t-1} \|u_k\|_U \right).$$

Incremental ISS

- Now suppose that $\tilde{f}(x, u) = f(x) + g(x)\pi_2(x) + u$ is δ ISS.
- Write $x_{t+1} = f(x_t) + g(x_t)\pi_1(x_t) = f(x_t) + g(x_t)\pi_2(x_t) + g(x_t)(\pi_1(x_t) - \pi_2(x_t))$.
- We can now treat $\Delta_{\pi_1, \pi_2}(x_t) = g(x_t)(\pi_1(x_t) - \pi_2(x_t))$ as an input signal to $\tilde{f}(x, u)$:

- $\varphi_t^{\pi_1}(\xi) = \varphi_t(\xi, \{\Delta_{\pi_1, \pi_2}(\varphi_t^{\pi_1}(\xi))\}_{t \geq 0})$ and $\varphi_t^{\pi_2}(\xi) = \varphi_t(\xi, \{0\}_{t \geq 0})$.
- Therefore, by δ ISS:

$$\|\varphi_t^{\pi_1}(\xi) - \varphi_t^{\pi_2}(\xi)\|_2 \leq \gamma \left(\max_{0 \leq k \leq t-1} \|\Delta_{\pi_1, \pi_2}(\varphi_k^{\pi_1}(\xi))\|_2 \right) \leq \gamma \left(\sum_{k=0}^{t-1} \|\Delta_{\pi_1, \pi_2}(\varphi_k^{\pi_1}(\xi))\|_2 \right).$$

- Hence:

$$\text{disc}_T(\xi; \pi_1, \pi_2) = \sum_{t=0}^T \|\varphi_t^{\pi_1}(\xi) - \varphi_t^{\pi_2}(\xi)\|_2 \leq \sum_{t=0}^{T-1} \gamma \left(\sum_{k=0}^{t-1} \|\Delta_{\pi_1, \pi_2}(\varphi_k^{\pi_1}(\xi))\|_2 \right) \leq T\gamma \left(\ell_{\pi_1}(\xi; \pi_1, \pi_2) \right).$$

Incremental ISS

- The bound $\text{disc}_T(\xi; \pi_1, \pi_2) \leq T\gamma(\ell_{\pi_1}(\xi; \pi_1, \pi_2))$ improves the dependence on T when compared to the Gronwall bound.
- However, this bound is not sharp: consider the Gronwall bound when $L(1 + 2B) < 1$, in which case $\text{disc}_T(\xi; \pi_1, \pi_2) \leq O(1)\ell_{\pi_1}(\xi; \pi_1, \pi_2)$ is independent of T .
- This motivates a more **quantitative** definition of δ ISS.

Incremental gain stability (IGS)

- **Definition:** Let $\Psi = (a, a_0, a_1, b_0, b_1, \zeta, \gamma)$ with $a, a_0, a_1, b_0, b_1 \in [1, \infty)$, $a_0 \leq a_1$, $b_0 \leq b_1$, and ζ, γ positive. The dynamics $x_{t+1} = f(x_t, u_t)$ is Ψ -IGS if for every $\xi_1, \xi_2 \in X$, $\{u_t\}_{t \geq 0} \subseteq U$, $T \in \mathbb{N}_{\geq 0}$, letting $\Delta_t := \varphi_t(\xi_1, \{u_t\}_{t \geq 0}) - \varphi_t(\xi_2, \{0\}_{t \geq 0})$:

$$\sum_{t=0}^T \min\{\|\Delta_t\|_X^{a \wedge a_0}, \|\Delta_t\|_X^{a \vee a_1}\} \leq \zeta \|\xi_1 - \xi_2\|_X^a + \gamma \sum_{t=0}^{T-1} \max\{\|u_t\|_U^{b_0}, \|u_t\|_U^{b_1}\}.$$
- **Claim:** If $\tilde{f}(x, u) = f(x) + g(x)\pi_2(x) + u$ is Ψ -IGS, then:

$$\text{disc}_T(\xi; \pi_1, \pi_2) \leq 4(\gamma \vee 1)^{\frac{1}{a \wedge a_0}} T^{1 - \frac{1}{a \vee a_1}} \max \left\{ \ell_{\pi_1}(\xi; \pi_1, \pi_2)^{\frac{b_0}{a \vee a_1}}, \ell_{\pi_1}(\xi; \pi_1, \pi_2)^{\frac{b_1}{a \vee a_0}} \right\}.$$

- **Proof** (of simple case when $a = a_0$ and $b_0 = b_1$).
- We have $\varphi_t^{\pi_1}(\xi) = \varphi_t(\xi, \{\Delta_{\pi_1, \pi_2}(\varphi_t^{\pi_1}(\xi))\}_{t \geq 0})$ and $\varphi_t^{\pi_2}(\xi) = \varphi_t(\xi, \{0\}_{t \geq 0})$.
- Since $f(x) + g(x)\pi_2(x) + u$ is Ψ -IGS:

$$\sum_{t=0}^T \min\{\|\Delta_t\|_X^{a_0}, \|\Delta_t\|_X^{a_1}\} \leq \gamma \sum_{t=0}^{T-1} \|u_t\|_U^{b_0}.$$

- Let $I := \{t \in \{0, \dots, T\} : \|\Delta_t\|_2^{a_0} \leq \|\Delta_t\|_2^{a_1}\}$. Then,

$$\text{disc}_T(\xi; \pi_1, \pi_2) = \sum_{t \in I} \|\Delta_t\|_2 + \sum_{t \in I^c} \|\Delta_t\|_2$$

$$\leq |I|^{1/a_0} \left(\sum_{t \in I} \|\Delta_t\|_2^{a_0} \right)^{1/a_0} + |I^c|^{1/a_1} \left(\sum_{t \in I^c} \|\Delta_t\|_2^{a_1} \right)^{1/a_1}$$

[Holder's inequality]

$$\leq T^{1/a_0} \left(\sum_{t \in I} \min\{\|\Delta_t\|_2^{a_0}, \|\Delta_t\|_2^{a_1}\} \right)^{1/a_0} + T^{1/a_1} \left(\sum_{t \in I^c} \min\{\|\Delta_t\|_2^{a_0}, \|\Delta_t\|_2^{a_1}\} \right)^{1/a_1}$$

[$|I|, |I^c| \leq T$]

$$\leq T^{1/a_0} \left(\sum_{t=0}^T \min\{\|\Delta_t\|_2^{a_0}, \|\Delta_t\|_2^{a_1}\} \right)^{1/a_0} + T^{1/a_1} \left(\sum_{t=0}^T \min\{\|\Delta_t\|_2^{a_0}, \|\Delta_t\|_2^{a_1}\} \right)^{1/a_1}$$

$[I \subseteq \{0, \dots, T\}]$

$$\leq T^{1/a_0} \left(\gamma \sum_{t=0}^{T-1} \|u_t\|_2^{b_0} \right)^{1/a_0} + T^{1/a_1} \left(\gamma \sum_{t=0}^{T-1} \|u_t\|_2^{b_0} \right)^{1/a_1}$$

[Ψ -IGS with $u_t = \Delta_{\pi_1, \pi_2}(\varphi_t^{\pi_1}(\xi))$]

$$\leq T^{1/a_0} \gamma^{1/a_0} \left(\sum_{t=0}^{T-1} \|u_t\|_2 \right)^{b_0/a_0} + T^{1/a_1} \gamma^{1/a_1} \left(\sum_{t=0}^{T-1} \|u_t\|_2 \right)^{b_1/a_1}$$

$$\left[\sum_t \|u_t\|_2^{b_0} \leq \left(\sum_t \|u_t\|_2 \right)^{b_0} \right]$$

$$\leq 2(\gamma \vee 1)^{1/a_0} T^{1-1/a_1} \max \left\{ \ell_{\pi_1}(\xi; \pi_1, \pi_2)^{b_0/a_0}, \ell_{\pi_1}(\xi; \pi_1, \pi_2)^{b_1/a_1} \right\}.$$

$[a + b \leq 2 \max\{a, b\}, 1 \leq a_0 \leq a_1]$



Incremental gain stability

- **Claim (IGS implies bounded state):** if f is Ψ -IGS, then for all $\xi_1, \xi_2 \in X$, defining $\Delta_t := \varphi_t(\xi_1, \{0\}_{t \geq 0}) - \varphi_t(\xi_2, \{0\}_{t \geq 0})$, we have:

$$\sum_{t=0}^{T-1} \|\Delta_t\|_X \leq 2(\zeta \vee 1)^{\frac{1}{a \wedge a_0}} T^{1-\frac{1}{a \vee a_1}} \max \left\{ \|\xi_1 - \xi_2\|_X^{\frac{a}{a \wedge a_0}}, \|\xi_1 - \xi_2\|_X^{\frac{a}{a \vee a_1}} \right\}.$$

- Similar proof to bound on $\text{disc}_T(\xi; \pi_1, \pi_2)$.

Incremental gain stability

- **Claim (Lyapunov characterization of IGS):** Suppose there exists $V: \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}_{\geq 0}$ satisfying:
 - $\underline{\alpha} \|x - y\|_X^a \leq V(x, y) \leq \bar{\alpha} \|x - y\|_X^a$,
 - $V(f(x, u), f(y, 0)) - V(x, y) \leq -\mathfrak{a} \min\{\|x - y\|_X^{a_0}, \|x - y\|_X^{a_1}\} + \mathfrak{b} \max\{\|u\|_U^{b_0}, \|u\|_U^{b_1}\}$.
- Then f is Ψ -IGS with $\Psi = \left(a, a_0, a_1, b_0, b_1, \frac{\bar{\alpha}}{\underline{\alpha} \wedge \mathfrak{a}}, \frac{\mathfrak{b}}{\underline{\alpha} \wedge \mathfrak{a}} \right)$.

- **Proof:** Define two dynamics:

$$x_{t+1} = f(x_t, u_t), \quad x_0 = \xi_1,$$

$$y_{t+1} = f(y_t, 0), \quad y_0 = \xi_2.$$

- With $V_t := V(x_t, y_t)$, we have:

$$V_{t+1} = V(x_{t+1}, y_{t+1}) = V(f(x_t, u_t), f(y_t, 0))$$

$$\leq V(x_t, y_t) - \alpha \min\{\|x_t - y_t\|_X^{a_0}, \|x_t - y_t\|_X^{a_1}\} + \beta \max\{\|u_t\|_U^{b_0}, \|u_t\|_U^{b_1}\}$$

$$= V_t - \alpha \min\{\|x_t - y_t\|_X^{a_0}, \|x_t - y_t\|_X^{a_1}\} + \beta \max\{\|u_t\|_U^{b_0}, \|u_t\|_U^{b_1}\}.$$

- Unrolling, we obtain:

$$V_T + \alpha \sum_{t=0}^{T-1} \min\{\|x_t - y_t\|_X^{a_0}, \|x_t - y_t\|_X^{a_1}\} \leq V_0 + \beta \sum_{t=0}^{T-1} \max\{\|u_t\|_U^{b_0}, \|u_t\|_U^{b_1}\}$$

$$\leq \bar{\alpha} \|\xi_1 - \xi_2\|_X^a + \beta \sum_{t=0}^{T-1} \max\{\|u_t\|_U^{b_0}, \|u_t\|_U^{b_1}\}.$$

- Previously, we showed:

$$V_T + \mathfrak{a} \sum_{t=0}^{T-1} \min\{\|x_t - y_t\|_X^{a_0}, \|x_t - y_t\|_X^{a_1}\} \leq \bar{\alpha} \|\xi_1 - \xi_2\|_X^a + \mathfrak{b} \sum_{t=0}^{T-1} \max\{\|u_t\|_U^{b_0}, \|u_t\|_U^{b_1}\}.$$

- We can lower bound the LHS by:

$$\begin{aligned} V_T + \mathfrak{a} \sum_{t=0}^{T-1} \min\{\|x_t - y_t\|_X^{a_0}, \|x_t - y_t\|_X^{a_1}\} &\geq \underline{\alpha} \|x_T - y_T\|_X^a + \mathfrak{a} \sum_{t=0}^{T-1} \min\{\|x_t - y_t\|_X^{a_0}, \|x_t - y_t\|_X^{a_1}\} \\ &\geq (\underline{\alpha} \wedge \mathfrak{a}) \sum_{t=0}^T \min\{\|x_t - y_t\|_X^{a_0}, \|x_t - y_t\|_X^a, \|x_t - y_t\|_X^{a_1}\} \\ &= (\underline{\alpha} \wedge \mathfrak{a}) \sum_{t=0}^T \min\{\|x_t - y_t\|_X^{a_0 \wedge a}, \|x_t - y_t\|_X^{a_1 \vee a}\}. \end{aligned}$$

- Therefore:

$$\sum_{t=0}^T \min\{\|x_t - y_t\|_X^{a_0 \wedge a}, \|x_t - y_t\|_X^{a_1 \vee a}\} \leq \frac{\bar{\alpha}}{\underline{\alpha} \wedge a} \|\xi_1 - \xi_2\|_X^a + \frac{\mathfrak{b}}{\underline{\alpha} \wedge a} \sum_{t=0}^{T-1} \max\{\|u_t\|_U^{b_0}, \|u_t\|_U^{b_1}\}.$$
■

Contraction implies exponential IGS

- Suppose there exists $\mu I \preceq M \preceq LI$, and $\rho \in (0,1)$ such that:
 - $\|f(x,0) - f(y,0)\|_M \leq \rho \|x - y\|_M \quad \forall x, y \in \mathbb{R}^n.$
 - $\|f(x,u) - f(x,0)\|_M \leq L_u \|u\|_2 \quad \forall x \in \mathbb{R}^n, u \in \mathbb{R}^d.$
- Note that the first condition is equivalent to the contraction condition
$$\frac{\partial f}{\partial x}(x,0)^T M \frac{\partial f}{\partial x}(x,0) \leq \rho^2 M \quad \forall x \in \mathbb{R}^n.$$
- **Claim:** f is Ψ -IGS with $\Psi = \left(1, 1, 1, 1, 1, \frac{L}{(1-\rho)\mu}, \frac{L_u}{(1-\rho)\mu} \right)$, or equivalently:
$$\sum_{t=0}^T \|\Delta_t\|_2 \leq \frac{L}{(1-\rho)\mu} \|\xi_1 - \xi_2\|_2 + \frac{L_u}{(1-\rho)\mu} \sum_{t=0}^{T-1} \|u_t\|_2.$$

- **Proof:** Letting $V(x, y) = \|x - y\|_M$,

$$\begin{aligned} V(f(x, u), f(y, 0)) &= \|f(x, u) - f(y, 0)\|_M \\ &\leq \|f(x, u) - f(x, 0)\|_M + \|f(x, 0) - f(y, 0)\|_M \\ &\leq \rho \|x - y\|_M + L_u \|u\|_2. \end{aligned}$$
- Therefore the IGS Lyapunov condition is verified:

$$V(f(x, u), f(y, 0)) - V(x, y) \leq -(1 - \rho)\mu \|x - y\|_2 + L_u \|u\|_2. \blacksquare$$

Contraction implies exponential IGS

- The same conclusion applies if the metric $M(x)$ is allowed to depend on the state (although the proof is a bit more technical):

$$\frac{\partial f}{\partial x}(x,0)^T M(x) \frac{\partial f}{\partial x}(x,0) \leq \rho^2 M(x) \quad \forall x \in \mathbb{R}^n.$$

- Examples of contracting systems:

- $f(x, u) = \sum_{i=1}^K A_i \mathbf{1}\{x \in \mathcal{C}_i\} x + B(x)u$ for $\{A_i\}$ with common quadratic Lyapunov function P and $B(x)$ bounded (metric is $M(x) = P$).
- $f(x, u) = \log(1 + x^2) + u$ with metric $M(x) = 2[1 + \exp(-|x|)]^{-1}$,
- $f(x, u) = x - \eta[\nabla V(x) + u]$ with $V \in C^2(\mathbb{R}^n, \mathbb{R})$ satisfying $\mu I \leq \nabla^2 V(x) \leq L I$ and $\eta \in (0, 1/L]$.

Tunable Ψ -IGS system

- **Claim:** consider the scalar dynamics $f(x_t, u_t) = x_t - \eta x_t \frac{|x_t|^p}{1 + |x_t|^p} + \eta u_t$ for $p \in (0, \infty)$ and $0 < \eta < \frac{4}{5+p}$. Then f is Ψ -IGS with
 $\Psi = \left(1, 1, 1 + p, 1, 1, \frac{2^{2+p}}{\eta}, 2^{2+p} \right)$, i.e.,
$$\sum_{t=0}^T \min\{ |\Delta_t|, |\Delta_t|^{1+p} \} \leq \frac{2^{2+p}}{\eta} |\xi_1 - \xi_2| + 2^{2+p} \sum_{t=0}^{T-1} |u_t|.$$
- **Proof idea:** Show $V(x, y) = |x - y|$ is an IGS Lyapunov function.

Behavior cloning

- Let us now use IGS to analyze **stability constrained** behavior cloning.
- Recall we observe m **expert trajectories** $\{\{\varphi_t^{\pi_\star}(\xi_i)\}_{t=0}^T\}_{i=1}^m$, with ξ_1, \dots, ξ_m i.i.d. from \mathcal{D} .
- The standard behavior cloning policy is $\hat{\pi}_{bc} \in \arg \min_{\pi \in \Pi} \frac{1}{m} \sum_{i=1}^m \ell_{\pi_\star}(\xi_i; \pi, \pi_\star)$.
- **Stability constrained** BC policy is $\hat{\pi}_{bc} \in \arg \min_{\pi \in \Pi_\Psi} \frac{1}{m} \sum_{i=1}^m \ell_{\pi_\star}(\xi_i; \pi, \pi_\star)$, where Π_Ψ is the set of policies such that $\tilde{f}(x, u) = f(x) + g(x)\pi(x) + u$ is Ψ -IGS.

Behavior cloning

- **Main assumptions for analysis:**
 - **Policy preserves fixed point:** $\pi(0) = 0$ for $\pi \in \Pi$.
 - **Realizability+stability:** $\pi_\star \in \Pi_\Psi$ with $\Psi = (a, a_0, a_1, b_0, b_1, \zeta, \gamma)$ satisfying $a = a_0$, $b_0 = b_1$, $a_1 \leq b_0$, $\zeta \geq 1$, $\gamma \geq 1$ (simplifications made for clarity, not actually necessary).
 - **Lipschitz+bounded:** Δ_{π_1, π_2} is L_Δ -Lipschitz for all $\pi_1, \pi_2 \in \Pi$ and $\sup_{x \in \mathbb{R}^n} \|g(x)\|_{\text{op}} \leq B_g$.

Behavior cloning

- **Basic inequality:**

$$\text{err}(\hat{\pi}_{\text{bc}}) = \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\hat{\pi}_{\text{bc}}}(\xi; \hat{\pi}_{\text{bc}}, \pi_\star)$$

$$\leq L_\Delta \mathbb{E}_{\xi \sim \mathcal{D}} \sum_{t=0}^{T-1} \|\varphi_t^{\hat{\pi}_{\text{bc}}}(\xi) - \varphi_t^{\pi_\star}(\xi)\|_2 = L_\Delta \mathbb{E}_{\xi \sim \mathcal{D}} \text{disc}_T(\xi; \hat{\pi}_{\text{bc}}, \pi_\star).$$

- Because $\hat{\pi}_{\text{bc}} \in \Pi_\Psi$, by Ψ -IGS + Jensen's inequality, assuming $\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_\star}(\xi; \hat{\pi}_{\text{bc}}, \pi_\star) \leq 1$:

$$\mathbb{E}_{\xi \sim \mathcal{D}} \text{disc}_T(\xi; \hat{\pi}_{\text{bc}}, \pi_\star) \leq 8\gamma^{\frac{1}{a_0}} T^{1-\frac{1}{a_1}} \left(\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_\star}(\xi; \hat{\pi}_{\text{bc}}, \pi_\star) \right)^{\frac{b_0}{a_1}}.$$

- We now use uniform convergence to obtain a bound on $\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_\star}(\xi; \hat{\pi}_{\text{bc}}, \pi_\star)$.

Uniform convergence of imitation loss

- In stability constrained BC, we minimized $\hat{\pi}_{bc} \in \arg \min_{\pi \in \Pi_\Psi} \frac{1}{m} \sum_{i=1}^m \ell_{\pi_\star}(\xi_i; \pi, \pi_\star)$, but now we want a bound on $\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_\star}(\xi; \hat{\pi}_{bc}, \pi_\star)$.
- Because $\hat{\pi}_{bc}$ is a function of ξ_1, \dots, ξ_m , $\mathbb{E}_{\{\xi_i\}} \frac{1}{m} \sum_{i=1}^m \ell_{\pi_\star}(\xi_i; \hat{\pi}_{bc}, \pi_\star) \neq \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_\star}(\xi; \hat{\pi}_{bc}, \pi_\star)$, and hence a standard Hoeffding inequality is insufficient.
- We need a uniform law of the form:

$$\sup_{\pi_d \in \Pi_\Psi, \pi_g \in \Pi} \mathbb{P}_{\{\xi_i\}} \left(\sup_{\pi \in \Pi} \left| \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_d}(\xi; \pi, \pi_g) - \frac{1}{m} \sum_{i=1}^m \ell_{\pi_d}(\xi_i; \pi, \pi_g) \right| \geq f(m, \delta, \Pi) \right) \leq \delta$$

Uniform convergence of imitation loss

- Define the following:
 - **[Uniform bound]** $B_\ell := \sup_{\pi_d \in \Pi_\Psi} \sup_{\pi_1, \pi_2 \in \Pi} \sup_{\xi \in X} \ell_{\pi_d}(\xi; \pi_1, \pi_2).$
 - **[Rademacher complexity]** $\mathcal{R}_m(\Pi) := \sup_{\pi_d \in \Pi_\Psi} \sup_{\pi_g \in \Pi} \mathbb{E}_{\{\xi_i\}} \mathbb{E}_{\{\varepsilon_i\}} \sup_{\pi \in \Pi} \frac{1}{m} \sum_{i=1}^m \varepsilon_i \ell_{\pi_d}(\xi_i; \pi, \pi_g).$
- From uniform convergence results (cf. lecture this morning), for any fixed $\pi_d \in \Pi_\Psi, \pi_g \in \Pi$, with probability at least $1 - \delta$:

$$\sup_{\pi \in \Pi} \left| \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_d}(\xi; \pi, \pi_g) - \frac{1}{m} \sum_{i=1}^m \ell_{\pi_d}(\xi_i; \pi, \pi_g) \right| \leq 2\mathcal{R}_m(\Pi) + B_\ell \sqrt{\frac{\log(2/\delta)}{m}}.$$

Uniform convergence of imitation loss

- **Claim:** $B_\ell \leq 2\zeta^{\frac{1}{a_0}} B_0 L_\Delta T^{1-\frac{1}{a_1}}$, with $B_0 = \sup_{\xi \in X} \|\xi\|_2$.
- Proof is simple and uses IGS => boundedness of state.

Uniform convergence of imitation loss

- Rademacher complexity bound is more involved.
- Need to fix policy class Π to obtain concrete bounds.
- For simplicity, we consider a parametric policy class
 $\Pi = \{x \mapsto \pi(x, \theta) : \theta \in \mathbb{R}^q, \|\theta\|_2 \leq B_\theta\}$ with $\pi \in C^2(\mathbb{R}^n \times \mathbb{R}^q, \mathbb{R}^d)$.

- Define $L_{\partial^2\pi} := \sup_{\|x\|_2 \leq \zeta^{\frac{1}{a_0}}B_0, \|\theta\|_2 \leq B_\theta} \left\| \frac{\partial^2\pi}{\partial\theta\partial x}(x, \theta) \right\|_{\ell_2^q \rightarrow M(\mathbb{R}^{d \times n})}$.

- **Claim:** $\mathcal{R}_m(\Pi) \leq 65\zeta^{\frac{1}{a_0}}B_0B_gB_\theta L_{\partial^2\pi}T^{1-\frac{1}{a_1}}\sqrt{\frac{q}{m}}$.

- **Proof:** Again, our main tool will be Dudley's inequality.

- By Taylor's theorem, not hard to check that:

$$\|\pi(x, \theta_1) - \pi(x, \theta_2)\|_2 \leq L_{\partial^2 \pi} \|x\|_2 \|\theta_1 - \theta_2\|_2 \quad \forall x \in \mathbb{B}_2^n(0, \zeta^{\frac{1}{a_0}} B_0), \quad \theta_1, \theta_2 \in \mathbb{B}_2^q(0, B_\theta).$$

- Therefore, for two policies $\pi_1, \pi_2 \in \Pi$:

$$\begin{aligned}
|\ell_{\pi_d}(\xi; \pi_1, \pi_g) - \ell_{\pi_d}(\xi; \pi_2, \pi_g)| &\leq \sum_{t=0}^{T-1} \|\Delta_{\pi_1, \pi_g}(\varphi_t^{\pi_d}(\xi)) - \Delta_{\pi_2, \pi_g}(\varphi_t^{\pi_d}(\xi))\|_2 && [\text{reverse triangle inequality}] \\
&= \sum_{t=0}^{T-1} \|\Delta_{\pi_1, \pi_2}(\varphi_t^{\pi_d}(\xi))\|_2 && [\Delta_{\pi_1, \pi_g}(x) - \Delta_{\pi_2, \pi_g}(x) = \Delta_{\pi_1, \pi_2}(x)] \\
&\leq B_g \sum_{t=0}^{T-1} \|\pi(\varphi_t^{\pi_d}(\xi), \theta_1) - \pi(\varphi_t^{\pi_d}(\xi), \theta_2)\|_2 && [\|g(x)\|_{\text{op}} \leq B_g] \\
&\leq B_g L_{\partial^2 \pi} \left(\sum_{t=0}^{T-1} \|\varphi_t^{\pi_d}(\xi)\|_2 \right) \|\theta_1 - \theta_2\|_2 && [\|\varphi_t^{\pi_d}(\xi)\|_2 \leq \zeta^{\frac{1}{a_0}} B_0] \\
&\leq 2\zeta^{\frac{1}{a_0}} B_0 B_g L_{\partial^2 \pi} T^{1-\frac{1}{a_1}} \|\theta_1 - \theta_2\|_2 && [\text{IGS bounded state}] .
\end{aligned}$$

- Therefore by Dudley's inequality:

$$\mathcal{R}_m(\Pi) \leq 48\zeta^{\frac{1}{a_0}}B_0B_gL_{\partial^2\pi}T^{1-\frac{1}{a_1}}\frac{1}{\sqrt{m}}\int_0^\infty \sqrt{\log N(\varepsilon; \mathbb{B}_2^q(0, B_\theta), \|\cdot\|_2)} d\varepsilon$$

$$\leq 48\zeta^{\frac{1}{a_0}}B_\theta B_0B_gL_{\partial^2\pi}T^{1-\frac{1}{a_1}}\sqrt{\frac{q}{m}}\int_0^1 \sqrt{\log(1+2/\varepsilon)} d\varepsilon$$

[$N(\varepsilon; \mathbb{B}_2^q(0, 1), \|\cdot\|_2) \leq (1+2/\varepsilon)^q$]

$$\leq 65\zeta^{\frac{1}{a_0}}B_\theta B_0B_gL_{\partial^2\pi}T^{1-\frac{1}{a_1}}\sqrt{\frac{q}{m}}.$$

■

Behavior cloning

- **Theorem:** With probability at least $1 - 2e^{-q}$,

$$\text{err}(\hat{\pi}_{\text{bc}}) \leq O(1)\gamma^{\frac{1}{a_0}}\zeta^{\frac{b_0}{a_0a_1}}B_0^{\frac{b_0}{a_1}}L_{\Delta} \max\{(B_{\theta}B_gL_{\partial^2\pi})^{\frac{b_0}{a_1}}, L_{\Delta}^{\frac{b_0}{a_1}}\}T^{(1-\frac{1}{a_1})(1+\frac{b_0}{a_1})}\left(\frac{q}{m}\right)^{\frac{b_0}{2a_1}}.$$

- **Proof:** Recall the basic inequality $\text{err}(\hat{\pi}_{\text{bc}}) \leq 4\gamma^{\frac{1}{a_0}}L_{\Delta}T^{1-\frac{1}{a_1}}\left(\mathbb{E}_{\xi \sim \mathcal{D}}\ell_{\pi_{\star}}(\xi; \hat{\pi}_{\text{bc}}, \pi_{\star})\right)^{\frac{b_0}{a_1}}$.

- From uniform convergence, with probability at least $1 - \delta$:

$$\mathbb{E}_{\xi \sim \mathcal{D}}\ell_{\pi_{\star}}(\xi; \hat{\pi}_{\text{bc}}, \pi_{\star}) \leq \frac{1}{m} \sum_{i=1}^m \ell_{\pi_{\star}}(\xi; \hat{\pi}_{\text{bc}}, \pi_{\star}) + 2\mathcal{R}_m(\Pi) + B_{\ell}\sqrt{\frac{\log(2/\delta)}{m}}.$$

- Since $\pi_{\star} \in \Pi_{\psi}$, then π_{\star} is feasible for the optimization defining $\hat{\pi}_{\text{bc}}$, and therefore

$$\frac{1}{m} \sum_{i=1}^m \ell_{\pi_{\star}}(\xi; \hat{\pi}_{\text{bc}}, \pi_{\star}) \leq \frac{1}{m} \sum_{i=1}^m \ell_{\pi_{\star}}(\xi; \pi_{\star}, \pi_{\star}) = 0.$$

- Therefore, with probability at least $1 - 2e^{-q}$:

$$\begin{aligned}
\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_\star}(\xi; \hat{\pi}_{\text{bc}}, \pi_\star) &\leq 2\mathcal{R}_m(\Pi) + B_\ell \sqrt{\frac{q}{m}} \\
&\leq O(1)\zeta^{\frac{1}{a_0}}B_\theta B_0 B_g L_{\partial^2 \pi} T^{1-\frac{1}{a_1}} \sqrt{\frac{q}{m}} + O(1)\zeta^{\frac{1}{a_0}}B_0 L_\Delta T^{1-\frac{1}{a_1}} \sqrt{\frac{q}{m}} \\
&\leq O(1)\zeta^{\frac{1}{a_0}}B_0 \max\{B_\theta B_g L_{\partial^2 \pi}, L_\Delta\} T^{1-\frac{1}{a_1}} \sqrt{\frac{q}{m}}.
\end{aligned}$$

- Claim follows by plugging this bound into the basic inequality

$$\text{err}(\hat{\pi}_{\text{bc}}) \leq 8\gamma^{\frac{1}{a_0}}L_\Delta T^{1-\frac{1}{a_1}} \left(\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_\star}(\xi; \hat{\pi}_{\text{bc}}, \pi_\star) \right)^{\frac{b_0}{a_1}}. \quad \blacksquare$$

Behavior cloning

- Only focusing on T, q, m : $\text{err}(\hat{\pi}_{\text{bc}}) \leq O(1)T^{(1-\frac{1}{a_1})(1+\frac{b_0}{a_1})} \left(\frac{q}{m}\right)^{\frac{b_0}{2a_1}}$.
- For contraction, $b_0 = a_1 = 1$ which yields $\text{err}(\hat{\pi}_{\text{bc}}) \leq O(1)\left(\frac{q}{m}\right)^{1/2}$.
 - Implies $m \geq \Omega(1)q/\varepsilon^2$ trajectories suffice for $\text{err}(\hat{\pi}_{\text{bc}}) \leq \varepsilon$.
- For tunable Ψ -IGS system, $b_0 = 1$ and $a_1 = 1 + p$ for $p \in (0, 1)$, which yields $\text{err}(\hat{\pi}_{\text{bc}}) \leq O(1)T^{1-\frac{1}{(1+p)^2}} \left(\frac{q}{m}\right)^{\frac{1}{2(1+p)}}$.
 - Implies $m \geq \Omega(1)q \frac{T^{\frac{p(p+2)}{1+p}}}{\varepsilon^{2(1+p)}}$ trajectories suffice for $\text{err}(\hat{\pi}_{\text{bc}}) \leq \varepsilon$.
 - Note that for $p \in (0, (\sqrt{5} - 1)/2) \approx (0, 0.618)$, $\frac{p(p+2)}{1+p} < 1$ and hence sublinear in T trajectories suffice.

Epoch based algorithms

- In practice, behavior cloning is not desirable due to compounding errors.
- Two more practical algorithms are SMILe [Ross and Bagnell 2010] and DAgger [Ross et al. 2011].

SMILe

- Fix number of epochs E , mixing weight $\alpha \in (0,1]$.
- Set $\pi_0 = \pi_\star$.
- For $k \in \{0, \dots, E-2\}$:
 - Collect rollouts $\{\{\varphi_t^{\pi_k}(\xi_i^k)\}_{t=0}^T\}_{i=1}^{m/E}$ and set $\hat{\pi}_k \in \arg \min_{\pi \in \Pi} \frac{1}{m/E} \sum_{i=1}^{m/E} \ell_{\pi_k}(\xi_i^k; \pi, \pi_\star)$.
 - $\pi_{k+1} = (1 - \alpha)\pi_k + \alpha\hat{\pi}_k$.
- Collect rollouts $\{\{\varphi_t^{\pi_{E-1}}(\xi_i^{E-1})\}_{t=0}^T\}_{i=1}^{m/E}$ and set $\hat{\pi}_{E-1} \in \arg \min_{\pi \in \Pi} \frac{1}{m/E} \sum_{i=1}^{m/E} \ell_{\pi_{E-1}}(\xi_i^{E-1}; \pi, \pi_\star)$.
- Return $\pi_E = \frac{1}{1 - (1 - \alpha)^E} [(1 - \alpha)\pi_{E-1} + \alpha\hat{\pi}_{E-1} - (1 - \alpha)^E \pi_\star]$.

DAgger

- Fix number of epochs E , mixing weight $\alpha \in (0,1]$.
- Set $\hat{\pi}_0 \in \Pi$ arbitrarily.
- For $k \in \{0, \dots, E-1\}$:
 - Set $\pi_k = \alpha^k \pi_\star + (1 - \alpha^k) \hat{\pi}_k$.
 - Rollout policy π_k : $\{ \{ \varphi_t^{\pi_k}(\xi_i^k) \}_{t=0}^T \}_{i=1}^{m/E}$.
 - $\hat{\pi}_{k+1} \in \arg \min_{\pi \in \Pi} \sum_{j=0}^k \frac{1}{m/E} \sum_{i=1}^m \ell_{\pi_j}(\xi_i^j; \pi, \pi_\star)$.
- Return best of $\hat{\pi}_1, \dots, \hat{\pi}_E$.

SMILe

- To analyze SMILe using our IGS machinery, we need to make a few modifications.
- We make the following modifications:
 - The learned policies are constrained to be IGS stable.
 - The learned policies are constrained to not change too much from epoch to epoch (trust-region constraint).
- We call these modifications CMILe (Constrained SMILe).

CMILe

- Fix number of epochs E , mixing weight $\alpha \in (0,1]$, trust-region weights $\{c_k\}$.
- Set $\pi_0 = \pi_\star$.
- For $k \in \{0, \dots, E-2\}$:
 - Collect rollouts $\{\{\varphi_t^{\pi_k}(\xi_i^k)\}_{t=0}^T\}_{i=1}^{m/E}$ and set:

$$\hat{\pi}_k \in \arg \min_{\pi \in \Pi} \frac{1}{m/E} \sum_{i=1}^{m/E} \ell_{\pi_k}(\xi_i^k; \pi, \pi_\star)$$

s.t. $(1 - \alpha)\pi_k + \alpha\pi \in \Pi_\Psi$, $\frac{1}{m/E} \sum_{i=1}^m \ell_{\pi_k}(\xi_i^k; \pi, \pi_k) \leq c_k$.
 - $\pi_{k+1} = (1 - \alpha)\pi_k + \alpha\hat{\pi}_k$.
- Collect rollouts $\{\{\varphi_t^{\pi_{E-1}}(\xi_i^{E-1})\}_{t=0}^T\}_{i=1}^{m/E}$ and set :

$$\hat{\pi}_{E-1} \in \arg \min_{\pi \in \Pi} \frac{1}{m/E} \sum_{i=1}^{m/E} \ell_{\pi_{E-1}}(\xi_i^{E-1}; \pi, \pi_\star)$$

s.t. $\frac{1}{1 - (1 - \alpha)^E} [(1 - \alpha)\pi_{E-1} + \alpha\pi - (1 - \alpha)^E \pi_\star] \in \Pi_\Psi$, $\frac{1}{m/E} \sum_{i=1}^M \ell_{\pi_{E-1}}(\xi_i^{E-1}; \pi, \pi_{E-1}) \leq c_{E-1}$.
- Return $\pi_E = \frac{1}{1 - (1 - \alpha)^E} [(1 - \alpha)\pi_{E-1} + \alpha\hat{\pi}_{E-1} - (1 - \alpha)^E \pi_\star]$.

Analysis of CMILe

- We will analyze CMILe similar to how we analyzed BC.
- The key idea is to bound $\text{err}(\pi_{k+1})$ by some function of $\text{err}(\pi_k)$.

- We start with the basic algebraic identity:

$$\begin{aligned}\Delta_{\pi_{k+1}, \pi_\star}(x) &= g(x)(\pi_{k+1}(x) - \pi_\star(x)) \\ &= (1 - \alpha)g(x)(\pi_k(x) - \pi_\star(x)) + \alpha g(x)(\hat{\pi}_k(x) - \pi_\star(x)) \\ &= (1 - \alpha)\Delta_{\pi_k, \pi_\star}(x) + \alpha\Delta_{\hat{\pi}_k, \pi_\star}(x).\end{aligned}$$

- With this identity, we derive the following CMILe **basic inequality**:

$$\begin{aligned}\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_{k+1}}(\xi; \pi_{k+1}, \pi_\star) &= \mathbb{E}_{\xi \sim \mathcal{D}} \sum_{t=0}^{T-1} \|\Delta_{\pi_{k+1}, \pi_\star}(\varphi_t^{\pi_{k+1}}(\xi))\|_2 \\ &\leq \mathbb{E}_{\xi \sim \mathcal{D}} \sum_{t=0}^{T-1} \|\Delta_{\pi_{k+1}, \pi_\star}(\varphi_t^{\pi_k}(\xi))\|_2 + L_\Delta \mathbb{E}_{\xi \sim \mathcal{D}} \text{disc}_T(\xi; \pi_{k+1}, \pi_k) \\ &\leq (1 - \alpha) \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_k}(\xi; \pi_k, \pi_\star) + \alpha \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\hat{\pi}_k}(\xi; \hat{\pi}_k, \pi_\star) + L_\Delta \mathbb{E}_{\xi \sim \mathcal{D}} \text{disc}_T(\xi; \pi_{k+1}, \pi_k).\end{aligned}$$

- We first focus on bounding $\mathbb{E}_{\xi \sim \mathcal{D}} \text{disc}_T(\xi; \pi_{k+1}, \pi_k)$.
- Due to the update $\pi_{k+1} = (1 - \alpha)\pi_k + \alpha\hat{\pi}_k$, we have $\pi_{k+1} - \pi_k = \alpha(\hat{\pi}_k - \pi_k)$. Therefore $\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_k}(\xi; \pi_{k+1}, \pi_k) = \alpha \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_k}(\xi; \hat{\pi}_k, \pi_k)$.
- Because π_{k+1} is Ψ -IGS, as long as $\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_k}(\xi; \hat{\pi}_k, \pi_k) \leq 1$:
$$\mathbb{E}_{\xi \sim \mathcal{D}} \text{disc}_T(\xi; \pi_{k+1}, \pi_k) \leq 8\gamma^{\frac{1}{a_0}} T^{1-\frac{1}{a_1}} \left(\alpha \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_k}(\xi; \hat{\pi}_k, \pi_k) \right)^{\frac{b_0}{a_1}}.$$
- By uniform convergence:
$$\begin{aligned} \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_k}(\xi; \hat{\pi}_k, \pi_k) &\leq \frac{1}{m/E} \sum_{i=1}^{m/E} \ell_{\pi_k}(\xi_i^k; \hat{\pi}_k, \pi_k) + 2\mathcal{R}_{m/E}(\Pi) + B_\ell \sqrt{\frac{\log(2/\delta)}{m/E}} \\ &\leq c_k + 2\mathcal{R}_{m/E}(\Pi) + B_\ell \sqrt{\frac{\log(2/\delta)}{m/E}} \end{aligned} \quad [\text{trust region constraint}] .$$

- Next, we turn to bounding $\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_k}(\xi; \hat{\pi}_k, \pi_\star)$.

- By uniform convergence,

$$\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_k}(\xi; \hat{\pi}_k, \pi_\star) \leq \frac{1}{m/E} \sum_{i=1}^{m/E} \ell_{\pi_k}(\xi_i^k; \hat{\pi}_k, \pi_\star) + 2\mathcal{R}_{m/E}(\Pi) + B_\ell \sqrt{\frac{\log(2/\delta)}{m/E}}$$

$$\leq \frac{1}{m/E} \sum_{i=1}^{m/E} \ell_{\pi_k}(\xi_i^k; \pi_k, \pi_\star) + 2\mathcal{R}_{m/E}(\Pi) + B_\ell \sqrt{\frac{\log(2/\delta)}{m/E}}$$

$[\pi_k$ is feasible]

$$\leq \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_k}(\xi; \pi_k, \pi_\star) + 4\mathcal{R}_{m/E}(\Pi) + 2B_\ell \sqrt{\frac{\log(2/\delta)}{m/E}}$$

[uniform convergence].

- Recall our basic inequality:

$$\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_{k+1}}(\xi; \pi_{k+1}, \pi_\star) \leq (1 - \alpha) \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_k}(\xi; \pi_k, \pi_\star) + \alpha \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_k}(\xi; \hat{\pi}_k, \pi_\star) + L_\Delta \mathbb{E}_{\xi \sim \mathcal{D}} \text{disc}_T(\xi; \pi_{k+1}, \pi_k).$$

- Combining bounds on $\mathbb{E}_{\xi \sim \mathcal{D}} \text{disc}_T(\xi; \pi_{k+1}, \pi_k)$ and $\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_k}(\xi; \hat{\pi}_k, \pi_\star)$, with probability at least $1 - 3\delta$,

$$\begin{aligned} \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_{k+1}}(\xi; \pi_{k+1}, \pi_\star) &\leq \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_k}(\xi; \pi_k, \pi_\star) + 4\alpha \mathcal{R}_{m/E}(\Pi) + 2\alpha B_\ell \sqrt{\frac{\log(2/\delta)}{m/E}} \\ &\quad + 8\gamma^{\frac{1}{a_0}} T^{1-\frac{1}{a_1}} L_\Delta \left[\alpha c_k + 2\alpha \mathcal{R}_{m/E}(\Pi) + \alpha B_\ell \sqrt{\frac{\log(2/\delta)}{m/E}} \right]^{\frac{b_0}{a_1}}. \end{aligned}$$

- This recursion yields a bound on $\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_{E-1}}(\xi; \pi_{E-1}, \pi_\star)$.
- Obtaining a bound on the final policy (with no expert) $\mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_E}(\xi; \pi_E, \pi_\star)$ is more involved but follows similar ideas.

CMILe

- **Theorem:** Suppose that:

- $m \geq \Omega(1)E(q \vee \log E)\zeta^{\frac{2}{a_0}}B_0^2T^{2(1-\frac{1}{a_1})}\max\{B_gB_\theta L_{\partial^2\pi}, L_\Delta\}^2,$

- $c_k \leq O(1)\zeta^{\frac{1}{a_0}}B_0T^{1-\frac{1}{a_1}}\max\{B_gB_\theta L_{\partial^2\pi}, L_\Delta\}\sqrt{\frac{E(q \vee \log E)}{m}},$

- $E \geq \frac{1}{\alpha} \log(1/\alpha)$ and $\alpha \leq \min \left\{ \frac{1}{2}, \frac{1}{L_\Delta \gamma^{\frac{1}{a_0}} T^{1-\frac{1}{a_1}}} \right\}.$

- Then with probability at least $1 - e^{-q}$:

$$\text{err}(\pi_E) \leq O(1)\zeta^{\frac{b_0}{a_0 a_1}}\gamma^{\left(1-\frac{b_0^2}{a_1^2}\right)\frac{1}{a_0}}B_0^{\frac{b_0}{a_1}}T^{1-\frac{1}{a_1}}L^{1-\frac{b_0^2}{a_1^2}}\max\{B_gB_\theta L_{\partial^2\pi}, L_\Delta\}^{\frac{b_0}{a_1}}E^{1+\frac{b_0}{2a_1}}\left(\frac{q \vee \log E}{m}\right)^{\frac{b_0^2}{2a_1^2}}.$$

CMILe

- Only focusing on the dependence on T, q, m : $\text{err}(\pi_E) \leq \tilde{O}(1)T^{\left(1-\frac{1}{a_1}\right)\left(2+\frac{b_0}{2a_1}\right)} \left(\frac{q}{m}\right)^{\frac{b_0^2}{2a_1^2}}$.
- For contraction, we have $\text{err}(\pi_E) \leq \tilde{O}(1)\sqrt{\frac{q}{m}}$.
 - $m \geq \tilde{\Omega}(1)q/\varepsilon^2$ trajectories suffice for $\text{err}(\pi_E) \leq \varepsilon$.
- For the tunable Ψ -IGS system, $\text{err}(\pi_E) \leq O(1)T^{\left(1-\frac{1}{1+p}\right)\left(2+\frac{1}{2(1+p)}\right)} \left(\frac{q}{m}\right)^{\frac{1}{2(1+p)^2}}$,
 - $m \geq \tilde{\Omega}(1)\frac{q}{\varepsilon^{2(1+p)^2}}T^{\frac{2p}{1+p}\left(2(1+p)^2 + \frac{1}{2(1+p)}\right)}$ trajectories suffice for $\text{err}(\pi_E) \leq \varepsilon$.
 - For $p \in (0, 0.183)$, we have that $\frac{2p}{1+p}\left(2(1+p)^2 + \frac{1}{2(1+p)}\right) < 1$, and hence sublinear in T trajectories suffice.

Why do we care about imitation loss?

- Suppose that $h : \mathbb{R}^{n \times (T+1)} \rightarrow \mathbb{R}^s$ is an L_h -Lipschitz function of the state trajectory.
- Define $h_\pi(\xi) := h(\{\varphi_t^\pi(\xi)\}_{t=0}^T)$.
- Then because $\pi_\star \in \Pi_\Psi$, we have:
$$\mathbb{E}_{\xi \sim \mathcal{D}} \|h_{\pi_\star}(\xi) - h_{\hat{\pi}}(\xi)\|_2 \leq L_h \mathbb{E}_{\xi \sim \mathcal{D}} \text{disc}_T(\xi; \hat{\pi}, \pi_\star) \leq 4L_h \gamma^{\frac{1}{a_0}} T^{1-\frac{1}{a_1}} (\text{err}(\hat{\pi}))^{\frac{b_0}{a_1}}.$$
- Therefore, small $\text{err}(\hat{\pi})$ implies that the performance of the observable h under the learned policy mimics that of the observable h under the expert policy.
 - This observable can encode things like trajectory tracking error and safety constraints.

Practical implementation

- **Trust region policy constraint:** the policy trust region constraints are implemented by constraining the parameters $\hat{\theta}_k$ for $\hat{\pi}_k$ to lie close in Euclidean norm to the parameters $\hat{\theta}_{k-1}$ for $\hat{\pi}_{k-1}$: $\|\hat{\theta}_k - \hat{\theta}_{k-1}\|_2 \leq \kappa$.
- **Ψ -IGS constraint:** while one could use the Lyapunov characterization, it is challenging to ensure that the Lyapunov equality holds for all $x \in \mathbb{R}^n$. In our implementation, we simply drop this constraint and note that it only affects the low-data regime in practice.
 - **Open question:** can we analyze BC/CMILe by arguing that the learned policies are already stable without explicit constraints.

Tunable Ψ -IGS system

- Consider the dynamical system in \mathbb{R}^{10} :

$$x_{t+1} = x_t - 0.5x_t \frac{|x_t|^p}{1 + 0.5|x_t|^p} + \frac{1}{1 + |x_t|^p}(h(x_t) + u_t).$$

- All arithmetic operations are element-wise.
- $h : \mathbb{R}^{10} \rightarrow \mathbb{R}^{10}$ is a randomly initialized two-layer MLP with zero biases, hidden width 32, and tanh activations.
- Expert policy is $\pi_\star = -h$, so expert's closed-loop dynamics are:
$$x_{t+1} = x_t - 0.5x_t \frac{|x_t|^p}{1 + 0.5|x_t|^p},$$
 which is Ψ -IGS with $a_1 = 1 + p.$

Tunable Ψ -IGS system

Table of final $\|x_T^{\text{expert}} - x_t^{\text{IL}}\|_2$ for all IL algorithms

p	BC	CMILe	CMILe+Agg	Dagger
1	0.615 ± 0.154	0.247 ± 0.071	0.239 ± 0.038	0.474 ± 0.131
2	1.194 ± 0.130	0.737 ± 0.059	0.578 ± 0.095	0.865 ± 0.142
3	1.637 ± 0.220	1.115 ± 0.066	0.868 ± 0.065	1.199 ± 0.130
4	1.976 ± 0.106	1.409 ± 0.080	1.111 ± 0.080	1.441 ± 0.126
5	2.107 ± 0.079	1.570 ± 0.055	1.240 ± 0.091	1.594 ± 0.146

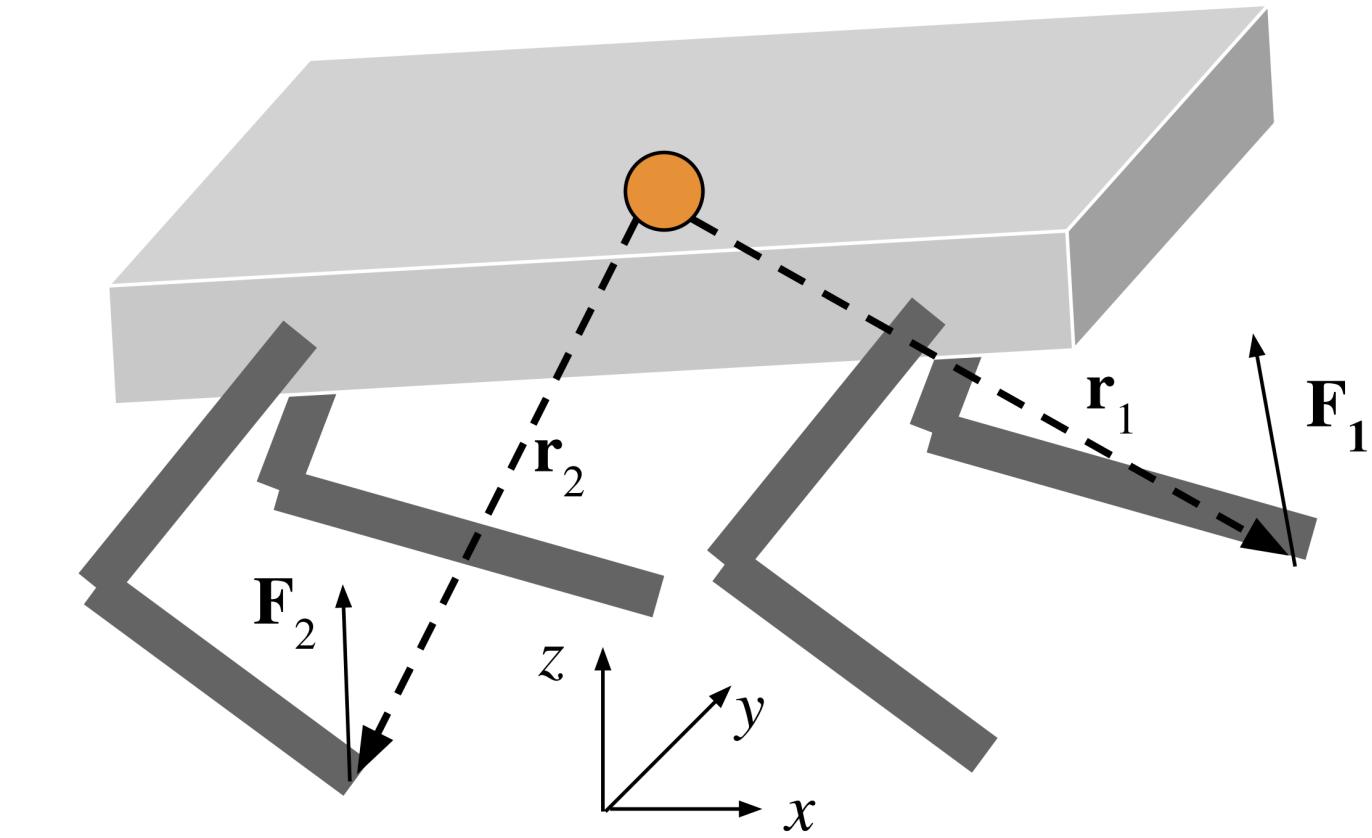
Tunable Ψ -IGS system

Table of final average closed-loop imitation loss $\frac{1}{T} \mathbb{E}_{\xi \sim \mathcal{D}} \ell_{\pi_E}(\xi; \pi_E, \pi_\star)$ for all IL algorithms

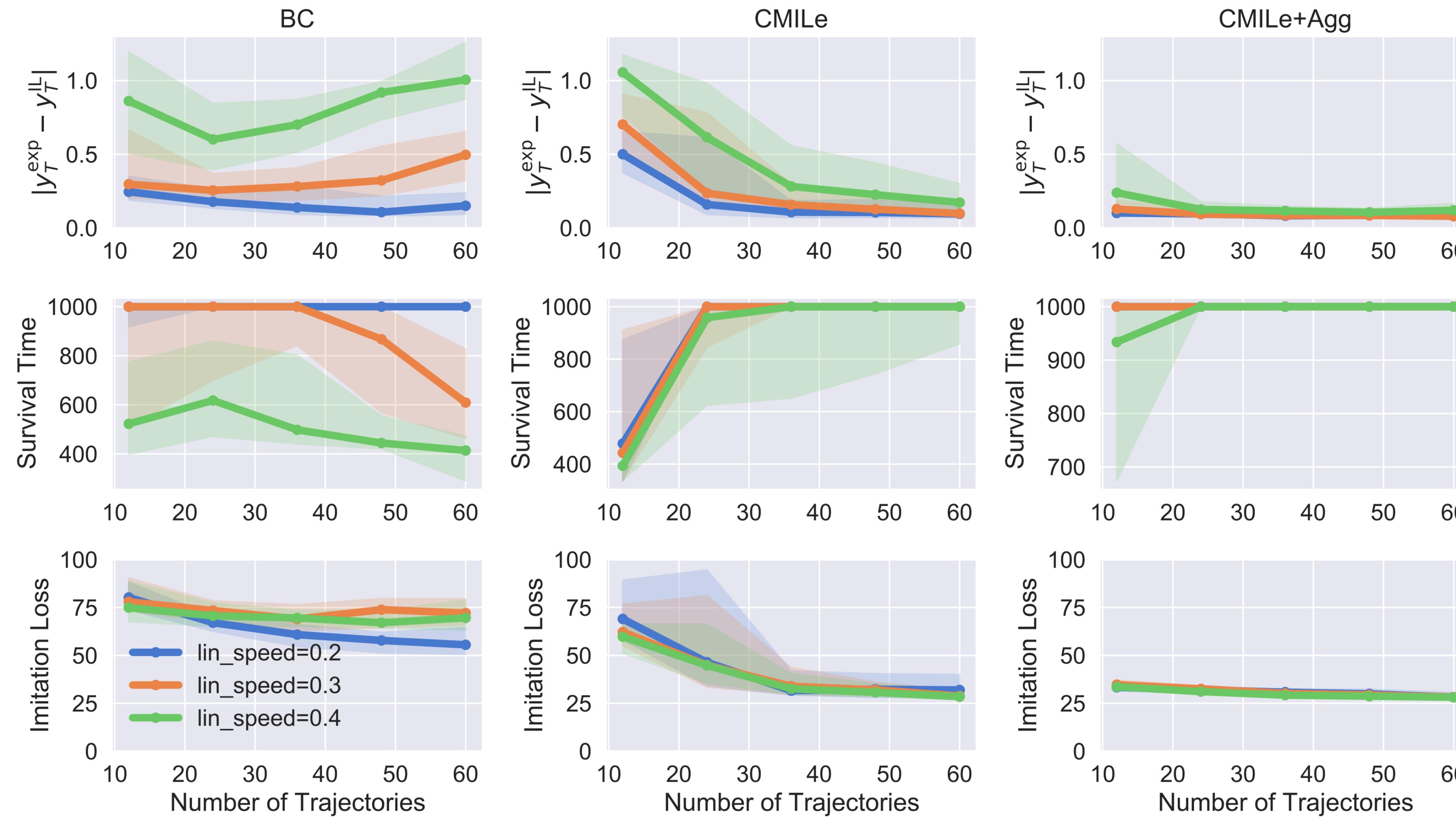
p	BC	CMILe	CMILe+Agg	DAgger
1	0.161 ± 0.088	0.113 ± 0.019	0.021 ± 0.005	0.050 ± 0.017
2	0.324 ± 0.097	0.128 ± 0.013	0.021 ± 0.003	0.052 ± 0.021
3	0.498 ± 0.120	0.151 ± 0.023	0.028 ± 0.007	0.064 ± 0.018
4	0.672 ± 0.139	0.163 ± 0.019	0.031 ± 0.007	0.061 ± 0.023
5	0.905 ± 0.154	0.154 ± 0.030	0.035 ± 0.007	0.058 ± 0.015

Unitree Laikago

- We consider IL for the Unitree Laikago in PyBullet.
- We imitate an expert MPC controller which allows the Laikago to **walk sideways** at varying fixed speeds:
 - Increasing the linear (sideways) velocity decreases task stability.
- MPC controller is based on center-of-mass dynamics as described in [Di Carlo et al. 2018].



Unitree Laikago



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Regret Bounds for Adaptive Nonlinear Control

Nicholas M. Boffi, Stephen Tu, and Jean-Jacques E. Slotine

arxiv.org/abs/2011.13101

Motivation

- Recent success in **reinforcement learning** (RL) has sparked much interest in analyzing RL for learning to control unknown systems in continuous settings.
- **Adaptive control** from the 90s also studies learning to control unknown systems.
- **Question:** how do these two fields/communities relate to each other?

Comparing RL to adaptive control

	RL	Adaptive Control
Dynamics	Some structure may be known (e.g., linear MDPs, linear Q-functions, low Bellman rank, etc.), but otherwise very general.	Very structured: nominal dynamics known, known basis functions for un-modeled dynamics.
Discrete-time or continuous-time	Discrete-time.	Continuous-time.
Guarantees	Regret bounds, PAC-style guarantees.	Asymptotic convergence, no rates.
Algorithms	Typically optimism/UCB-based, can be intractable.	Typically certainty-equivalence based, computationally efficient.

Goal

- Port over several nice properties of RL to adaptive control:
 - Handle stochasticity.
 - Discrete-time evolution.
 - Finite-time regret bounds.

Problem setup

- Consider the following non-linear system evolving in \mathbb{R}^n :
$$x_{t+1} = f(x_t, t) + B(x_t, t)(u_t - Y(x_t, t)\alpha) + w_t.$$
- $f(x, t)$ and $B(x, t)$ are known **nominal** dynamics. $f(0, t) = 0$ for all t .
- $Y(x, t)$ are known **basis** functions.
- $\alpha \in \mathbb{R}^p$ are **unknown** parameters.
- w_t is zero-mean Gaussian noise.
- Known as **matched uncertainty** setup in adaptive control.

When does this model arise?

- Consider a fully-actuated system: $x_{t+1} = f(x_t) + u_t$.
- We want to drive x_t to the origin, but $f(x_t)$ is unknown.
- Picking any $\rho \in (-1,1)$, and playing $u_t = \rho x_t - \tilde{u}_t$ yields the closed-loop:
$$x_{t+1} = \rho x_t + f(x_t) - \tilde{u}_t.$$
- If $f(x_t)$ is well approximated (e.g., with physical or random basis functions) as
$$f(x_t) \approx Y(x_t)\alpha$$
 for some α , then this follows in our model.

When does this model arise?

- Suppose a controller u_{sim} is designed on model $f_{\text{sim}}(x) + g_{\text{sim}}(x)u$.
- Suppose that u_{real} is optimal for $f_{\text{real}}(x) + g_{\text{real}}(x)u$.
- Then playing u_{sim} on the real system yields the closed-loop dynamics:
$$\begin{aligned} x_{t+1} &= f_{\text{real}}(x) + g_{\text{real}}(x)u_{\text{sim}}(x) \\ &= f_{\text{real}}^{\text{cl}}(x) + g_{\text{real}}(x)(u_{\text{sim}}(x) - u_{\text{real}}(x)) \quad [f_{\text{real}}^{\text{cl}}(x) := f_{\text{real}}(x) + g_{\text{real}}(x)u_{\text{real}}(x)] . \end{aligned}$$
- Now suppose that $u_{\text{real}}(x) \approx Y(x)\alpha$ for α .
- This falls within our model*.

Problem setup

- Model: $x_{t+1} = f(x_t, t) + B(x_t, t)(u_t - Y(x_t, t)\alpha) + w_t$.
- Comparator dynamics: $x_{t+1}^c = f(x_t^c, t) + w_t$, i.e., $u_t = Y(x_t^c, t)\alpha$.
- The regret of a control strategy $\{u_t^a\}$ is:
$$\text{Reg}_T^{\text{Ctrl}} := \mathbb{E} \left[\sum_{t=0}^T \|x_t^a\|_2^2 - \sum_{t=0}^T \|x_t^c\|_2^2 \right].$$
- Here, $x_{t+1}^a = f(x_t^a, t) + B(x_t^a, t)(u_t^a - Y(x_t^a, t)) + w_t$.
- Regret measures the cost of dealing with the uncertain (unmodelled) dynamics.

Online convex optimization primer

- A game played between an adversary and a learner.
- For $t = 1, 2, \dots$:
 - Adversary chooses convex loss function $\ell_t : \mathbb{R}^n \rightarrow \mathbb{R}$.
 - Learner chooses $w_t \in W$, suffers loss $\ell_t(w_t)$, and observes $(\ell_t(w_t), \nabla \ell_t(w_t))$.
- The performance of the learner is measured via the regret, comparing the performance to the best fixed predictor in hindsight:

$$\text{Reg}_T^{\text{Pred}} := \sum_{t=1}^T \ell_t(w_t) - \min_{w \in W} \sum_{t=1}^T \ell_t(w).$$

- A learner that achieves $\text{Reg}_T^{\text{Pred}} \leq o(T)$ is said to be “**no-regret**”.
- See [Hazan 2016] for a thorough treatment of the subject.

Online convex optimization primer

- **Online gradient descent:**
 - Learner updates $w_{t+1} = \Pi_W(w_t - \eta_t \nabla \ell_t(w_t))$, where $\Pi_W(x) = \arg \min_{y \in W} \|x - y\|_2$.
 - Achieves $\text{Reg}_T^{\text{Pred}} \leq O(\sqrt{T})$ with $\eta_t = 1/\sqrt{T}$.
- **Online Newton:**
 - Learner updates $w_{t+1} = \Pi_{t,W}(w_t - \eta A_t^{-1} \nabla \ell_t(w_t))$, with $A_t = \lambda I + \sum_{i=1}^t \nabla \ell_i(w_i) \nabla \ell_i(w_i)^T$ and $\Pi_{t,W}(x) = \arg \min_{y \in W} \|x - y\|_{A_t}$.
 - Achieves $\text{Reg}_T^{\text{Pred}} \leq O(\log T)$ with $\eta \asymp 1$ for exp-concave functions, i.e., $\nabla^2 \ell_t(w) \geq \mu \nabla \ell_t(w) \nabla \ell_t(w)^T$.

Adaptive control with OCO

- We use OCO to estimate $\hat{\alpha}_t$.
- We play the certainty-equivalence controller: $u_t = Y(x_t, t)\hat{\alpha}_t$.
- Closed-loop: $x_{t+1} = f(x_t, t) + G(x_t, t)(\hat{\alpha}_t - \alpha) + w_t$, $G(x, t) := B(x, t)Y(x, t)$.
- After observing x_{t+1} , can obtain necessary signal to update $\hat{\alpha}_t$:
 - **Recursive least-squares:** $y_t := f(x_t, t) + G(x_t, t)\hat{\alpha}_t - x_{t+1} = G(x_t, t)\alpha - w_t$.
 - **Gradient-based:** $\ell_t(\hat{\alpha}) = \frac{1}{2}\|G(x_t, t)(\hat{\alpha} - \alpha) + w_t\|_2^2$,
 $\nabla \ell_t(\hat{\alpha}_t) = G(x_t, t)^T(x_{t+1} - f(x_t, t))$.

Adaptive control with OCO

- Focus on online gradient based algorithms for now.

- Recall $\ell_t(\hat{\alpha}) = \frac{1}{2} \|G_t(\hat{\alpha} - \alpha) + w_t\|_2^2$.

- Online convex optimization bounds give us:

$$\frac{1}{2} \sum_{t=0}^{T-1} \mathbb{E} \|G_t \tilde{\alpha}_t\|_2^2 = \mathbb{E} \left[\sum_{t=0}^{T-1} \ell_t(\hat{\alpha}_t) - \ell_t(\alpha) \right] \leq \text{Reg}_T^{\text{Pred}}.$$

- If $f(x, t) \equiv 0$, then:

$$\text{Reg}_T^{\text{Ctrl}} = \mathbb{E} \left[\sum_{t=0}^T \|x_t^a\|_2^2 - \sum_{t=0}^T \|x_t^c\|_2^2 \right] = \sum_{t=0}^{T-1} \mathbb{E} \|G_t \tilde{\alpha}_t\|_2^2, \text{ so we are done.}$$

- In general though, how do we handle non-zero dynamics?

Adaptive control with OCO

- **Theorem (informal):** under suitable stability assumptions on $f(x, t)$, we have:
$$\text{Reg}_T^{\text{Ctrl}} \lesssim \sqrt{T \cdot \text{Reg}_T^{\text{Pred}}}.$$
- Consequently, if you use either online Newton or online recursive LS, we have
$$\text{Reg}_T^{\text{Ctrl}} \lesssim \sqrt{T \text{polylog}(T)}.$$
- If you use vanilla gradient descent, then $\text{Reg}_T^{\text{Ctrl}} \lesssim T^{3/4}$.
- **Note:** a similar $\sqrt{T \cdot \text{Reg}_T^{\text{Pred}}}$ regret bound found in [Foster and Rakhlin 2020] for contextual bandits.

Main stochastic perturbation result

- The main technical ingredient to show $\text{Reg}_T^{\text{Ctrl}} \lesssim \sqrt{T \cdot \text{Reg}_T^{\text{Pred}}}$ is a stochastic perturbation result.
- Consider two stochastic processes $\{x_t\}, \{y_t\}$ with $\{w_t\}, \{v_t\}$ iid $N(0, \sigma_w^2 I)$.
$$x_{t+1} = f(x_t, t) + d_t(x_0, \dots, x_t) + w_t,$$
$$y_{t+1} = f(y_t, t) + v_t.$$
- **Question:** what assumptions on $f(x, t)$ allow us to bound $\mathbb{E} \left[\sum_{t=0}^T \|x_t\|_2^2 - \sum_{t=0}^T \|y_t\|_2^2 \right]$ by a function of $\mathbb{E} \sum_{t=0}^{T-1} \|d_t\|_2^2$?
- Note that in the context of our adaptive control problem, $\mathbb{E} \sum_{t=0}^{T-1} \|d_t\|_2^2 \asymp \text{Reg}_T^{\text{Pred}}$.

Main stochastic perturbation result

- Recall that $\{y_t\}$ is the **unperturbed** process.
- **Assumption (L2 geometric ergodicity):** there exists a $\rho \in (0,1)$ and positive $R(x)$ such that for all non-negative t, k :
$$|\mathbb{E}[\|y_{t+k}\|_2^2 | y_t = x] - \mathbb{E}[\|y_{t+k}\|_2^2 | y_t = 0]| \leq R(x)\rho^k.$$
- **Theorem:** Under L2 geometric ergodicity, we have:

$$\begin{aligned} & \mathbb{E} \left[\sum_{t=0}^T \|x_t\|_2^2 - \sum_{t=0}^T \|y_t\|_2^2 \right] \\ & \leq \frac{\sqrt{2}}{1-\rho} \sqrt{\mathbb{E} \sum_{t=0}^{T-1} \min \left\{ \frac{\|d_t\|_2^2}{\sigma_w^2}, 1 \right\}} \sqrt{\mathbb{E} \sum_{t=1}^T R(x_t)^2 + \mathbb{E} \sum_{t=0}^{T-1} R(f(x_t, t) + w_t)^2}. \end{aligned}$$

- **Proof:** We build on ideas from [Kakade et al. 2020] and [Yu et al. 2020].

- We start by defining a “cost-to-go” function for the unperturbed dynamics:

$$V_{s:t}(x) := \sum_{k=s}^t \mathbb{E}[\|y_k\|_2^2 | y_s = x].$$

- Now define $h_k(x) := V_{k:T}(x) - V_{k:T}(0)$. We have:

$$|h_k(x)| = \left| \sum_{t=k}^T \mathbb{E}[\|y_t\|_2^2 | y_k = x] - \sum_{t=k}^T \mathbb{E}[\|y_t\|_2^2 | y_k = 0] \right|$$

$$\leq \sum_{t=k}^T |\mathbb{E}[\|y_t\|_2^2 | y_k = x] - \mathbb{E}[\|y_t\|_2^2 | y_k = 0]| \quad [\text{triangle inequality}]$$

$$\leq R(x) \sum_{t=k}^T \rho^{t-k} \quad [\text{L2 geometric ergodicity}]$$

$$\leq \frac{R(x)}{1 - \rho}.$$

- Now define $W_k, k \in \{0, \dots, T\}$ as:

$$W_k = \mathbb{E} \sum_{t=0}^T \|\varphi_t\|_2^2, \quad \varphi_{t+1} = \begin{cases} f(\varphi_t, t) + \textcolor{blue}{d}_t(\varphi_0, \dots, \varphi_t) + w_t & \text{if } t < k \\ f(\varphi_t, t) + w_t & \text{if } t \geq k, \quad \varphi_0 = x_0. \end{cases}$$

- With this notation, we have:

$$\mathbb{E} \sum_{t=0}^T \|x_t\|_2^2 = W_T, \quad \mathbb{E} \sum_{t=0}^T \|y_t\|_2^2 = W_0.$$

- Therefore, we can write the telescoping sum:

$$\mathbb{E} \left[\sum_{t=0}^T \|x_t\|_2^2 - \sum_{t=0}^T \|y_t\|_2^2 \right] = W_T - W_0 = \sum_{k=0}^{T-1} (W_{k+1} - W_k).$$

- Now observe that for $k \in \{0, \dots, T-1\}$, with $\tilde{p}_{0:k}$ denoting the joint distribution of (x_0, \dots, x_k) :

$$W_k = \mathbb{E} \sum_{t=0}^k \|x_t\|_2^2 + \mathbb{E}_{\tilde{p}_{0:k}} \mathbb{E}_{x \sim N(f(x_k, k), \sigma_w^2 I)} V_{k+1:T}(x),$$

$$W_{k+1} = \mathbb{E} \sum_{t=0}^k \|x_t\|_2^2 + \mathbb{E}_{\tilde{p}_{0:k}} \mathbb{E}_{x \sim N(f(x_k, k) + \textcolor{blue}{d}_k(x_0, \dots, x_k), \sigma_w^2 I)} V_{k+1:T}(x).$$

- With this notation, we have the identity:

$$\mathbb{E} \left[\sum_{t=0}^T \|x_t\|_2^2 - \sum_{t=0}^T \|y_t\|_2^2 \right] = \sum_{k=0}^{T-1} (W_{k+1} - W_k)$$

$$= \sum_{k=0}^{T-1} \mathbb{E}_{\tilde{p}_{0:k}} [\mathbb{E}_{x \sim N(f(x_k, k) + \textcolor{blue}{d}_k, \sigma_w^2 I)} V_{k+1:T}(x) - \mathbb{E}_{x \sim N(f(x_k, k), \sigma_w^2 I)} V_{k+1:T}(x)]$$

$$= \sum_{k=0}^{T-1} \mathbb{E}_{\tilde{p}_{0:k}} [\mathbb{E}_{x \sim N(f(x_k, k) + \textcolor{blue}{d}_k, \sigma_w^2 I)} V_{k+1:T}(x) - V_{k+1:T}(0) + V_{k+1:T}(0) - \mathbb{E}_{x \sim N(f(x_k, k), \sigma_w^2 I)} V_{k+1:T}(x)]$$

$$= \sum_{k=0}^{T-1} \mathbb{E}_{\tilde{p}_{0:k}} [\mathbb{E}_{x \sim N(f(x_k, k) + \textcolor{blue}{d}_k, \sigma_w^2 I)} h_{k+1}(x) - \mathbb{E}_{x \sim N(f(x_k, k), \sigma_w^2 I)} h_{k+1}(x)].$$

- We now state a technical lemma from [Kakade et al. 2020].
- **Lemma:** for any measurable g and two Gaussians $N_i = N(\mu_i, \sigma^2 I)$, we have:

$$\mathbb{E}_{N_1} g - \mathbb{E}_{N_2} g \leq \min \left\{ \frac{\|\mu_1 - \mu_2\|_2}{\sigma}, 1 \right\} \left[\sqrt{\mathbb{E}_{N_1} g^2} + \sqrt{\mathbb{E}_{N_2} g^2} \right].$$
- **Note:** this is similar to a classic result which states that for any $g : X \rightarrow [-B, B]$ and any two distributions μ_1, μ_2 , we have:

$$|\mathbb{E}_{\mu_1} g - \mathbb{E}_{\mu_2} g| \leq 2B \|\mu_1 - \mu_2\|_{\text{tv}}.$$
 - But this result requires that g is bounded almost surely, while the lemma above only requires bounded second moments.

- Define $\tilde{N}_k = N(f(x_k, k) + \textcolor{blue}{d}_k, \sigma_w^2 I)$ and $N_k = N(f(x_k, k), \sigma_w^2 I)$.

- With the [Kakade et al. 2020] lemma, we have:

$$\mathbb{E}_{x \sim N(f(x_k, k) + \textcolor{blue}{d}_k, \sigma_w^2 I)} h_{k+1}(x) - \mathbb{E}_{x \sim N(f(x_k, k), \sigma_w^2 I)} h_{k+1}(x)$$

$$\leq \min \left\{ \frac{\|d_k\|_2}{\sigma_w}, 1 \right\} \left[\sqrt{\mathbb{E}_{\tilde{N}_k} h_{k+1}^2} + \sqrt{\mathbb{E}_{N_k} h_{k+1}^2} \right]$$

$$\leq \frac{1}{1-\rho} \min \left\{ \frac{\|d_k\|_2}{\sigma_w}, 1 \right\} \left[\sqrt{\mathbb{E}_{\tilde{N}_k} R^2} + \sqrt{\mathbb{E}_{N_k} R^2} \right].$$

[since $|h_k(x)| \leq \frac{R(x)}{1-\rho}$]

- Therefore:

$$\mathbb{E} \left[\sum_{t=0}^T \|x_t\|_2^2 - \sum_{t=0}^T \|y_t\|_2^2 \right] \leq \frac{1}{1-\rho} \sum_{k=0}^{T-1} \mathbb{E}_{\tilde{p}_{0:k}} \left[\min \left\{ \frac{\|d_k\|_2}{\sigma_w}, 1 \right\} \left[\sqrt{\mathbb{E}_{\tilde{N}_k} R^2} + \sqrt{\mathbb{E}_{N_k} R^2} \right] \right]$$

$$\leq \frac{1}{1-\rho} \sum_{k=0}^{T-1} \sqrt{\mathbb{E}_{\tilde{p}_{0:k}} \min \left\{ \frac{\|d_k\|_2^2}{\sigma_w^2}, 1 \right\}} \sqrt{\mathbb{E}_{\tilde{p}_{0:k}} \left(\sqrt{\mathbb{E}_{\tilde{N}_k} R^2} + \sqrt{\mathbb{E}_{N_k} R^2} \right)^2}$$

$$\leq \frac{1}{1-\rho} \sqrt{\sum_{k=0}^{T-1} \mathbb{E}_{\tilde{p}_{0:k}} \min \left\{ \frac{\|d_k\|_2^2}{\sigma_w^2}, 1 \right\}} \sqrt{\sum_{k=0}^{T-1} \mathbb{E}_{\tilde{p}_{0:k}} \left(\sqrt{\mathbb{E}_{\tilde{N}_k} R^2} + \sqrt{\mathbb{E}_{N_k} R^2} \right)^2}$$

$$\leq \frac{\sqrt{2}}{1-\rho} \sqrt{\sum_{k=0}^{T-1} \mathbb{E}_{\tilde{p}_{0:k}} \min \left\{ \frac{\|d_k\|_2^2}{\sigma_w^2}, 1 \right\}} \sqrt{\sum_{k=0}^{T-1} \mathbb{E}_{\tilde{p}_{0:k}} \mathbb{E}_{\tilde{N}_k} R^2 + \mathbb{E}_{\tilde{p}_{0:k}} \mathbb{E}_{N_k} R^2}$$

$$= \frac{\sqrt{2}}{1-\rho} \sqrt{\sum_{t=0}^{T-1} \mathbb{E} \min \left\{ \frac{\|d_t\|_2^2}{\sigma_w^2}, 1 \right\}} \sqrt{\mathbb{E} \sum_{t=1}^T R(x_t)^2 + \mathbb{E} \sum_{t=0}^{T-1} R(f(x_t, t) + w_t)^2}.$$

■

$[\mathbb{E}AB \leq \sqrt{\mathbb{E}A^2} \sqrt{\mathbb{E}B^2}]$

[Cauchy-Schwarz]

$[(a+b)^2 \leq 2(a^2 + b^2)]$

Wasserstein contraction implies L2 geometric ergodicity

- We show a relationship between contraction in 2-Wasserstein metric and L2 geometric ergodicity.
- Recall that the 2-Wasserstein distance between μ, ν is:

$$W_2(\mu, \nu) := \left(\inf_{(x,y) \in \Gamma(\mu, \nu)} \mathbb{E} \|x - y\|_2^2 \right)^{1/2}.$$

- $\Gamma(\mu, \nu)$ is the set of **couplings** between μ, ν , i.e., distributions (X, Y) such that the marginal of X is μ and the marginal of Y is ν .

Wasserstein contraction implies L2 geometric ergodicity

- **Claim:** $|\mathbb{E}_\mu \|x\|_2^2 - \mathbb{E}_\nu \|x\|_2^2| \leq \sqrt{2} \sqrt{\mathbb{E}_\mu \|x\|_2^2 + \mathbb{E}_\nu \|x\|_2^2} W_2(\mu, \nu).$

- **Proof:** Let $(x, y) \in \Gamma(\mu, \nu)$. We have:

$$\begin{aligned} |\mathbb{E}_\mu \|x\|_2^2 - \mathbb{E}_\nu \|x\|_2^2| &= |\mathbb{E}(\|x\|_2 + \|y\|_2)(\|x\|_2 - \|y\|_2)| \\ &\leq \mathbb{E}(\|x\|_2 + \|y\|_2) \|x - y\|_2 && [\text{reverse triangle}] \\ &\leq \sqrt{\mathbb{E}(\|x\|_2 + \|y\|_2)^2} \sqrt{\mathbb{E}\|x - y\|_2^2} && [\mathbb{E}AB \leq \sqrt{\mathbb{E}A^2} \sqrt{\mathbb{E}B^2}] \\ &\leq \sqrt{2} \sqrt{\mathbb{E}_\mu \|x\|_2^2 + \mathbb{E}_\nu \|x\|_2^2} \sqrt{\mathbb{E}\|x - y\|_2^2} && [(a + b)^2 \leq 2(a^2 + b^2)]. \end{aligned}$$

- Now take the infimum over $(x, y) \in \Gamma(\mu, \nu)$ on RHS which yields the claim. ■

Wasserstein contraction implies L2 geometric ergodicity

- Let $P_t(x, A)$ denote the Markov kernel at time t for the nominal dynamics.
- For a measure μ , let μP_t denote the measure $[\mu P_t](A) = \int P_t(x, A) \mu(dx)$, and let $P_{s:t} = P_s P_{s+1} \dots P_t$.
- **Claim:** Suppose that $W_2(\mu P_{t:t+k-1}, \nu P_{t:t+k-1}) \leq C\gamma^k W_2(\mu, \nu)$ for all $t \in \mathbb{N}_{\geq 0}$. Then the L2 geometric ergodicity condition holds.

- **Proof:**

$$\begin{aligned}
& |\mathbb{E}[\|y_{t+k}\|_2^2 | y_t = x] - \mathbb{E}[\|y_{t+k}\|_2^2 | y_t = 0]| \\
&= |\mathbb{E}_{y_{t+k} \sim \delta_x P_{t:t+k-1}} \|y_{t+k}\|_2^2 - \mathbb{E}_{y_{t+k} \sim \delta_0 P_{t:t+k-1}} \|y_{t+k}\|_2^2| \\
&\leq \sqrt{2} \sqrt{\mathbb{E}_{y_{t+k} \sim \delta_x P_{t:t+k-1}} \|y_{t+k}\|_2^2 + \mathbb{E}_{y_{t+k} \sim \delta_0 P_{t:t+k-1}} \|y_{t+k}\|_2^2} W_2(\delta_x P_{t:t+k-1}, \delta_0 P_{t:t+k-1}) && [\text{Wasserstein inequality}] \\
&\leq \sqrt{2} \sqrt{\mathbb{E}[\|y_{t+k}\|_2^2 | y_t = x] + \mathbb{E}[\|y_{t+k}\|_2^2 | y_t = 0]} C \gamma^k W_2(\delta_x, \delta_0) && [\text{Wasserstein contraction assumption}] \\
&\leq \sqrt{2} \sqrt{\mathbb{E}[\|y_{t+k}\|_2^2 | y_t = x] + \mathbb{E}[\|y_{t+k}\|_2^2 | y_t = 0]} C \gamma^k \|x\|_2 && [W_2(\delta_x, \delta_0) \leq \|x\|_2] \\
&= R(x) \gamma^k. && \blacksquare
\end{aligned}$$

Contraction implies Wasserstein contraction

- Suppose there exists a sequence $\{M_t\}$ of positive definite matrices such that:
 - $\|f(x, t) - f(y, t)\|_{M_{t+1}} \leq \gamma \|x - y\|_{M_t}$ for all x, y, t .
 - $\mu I \leq M_t \leq L I$ for all t .
- **Claim:** $W_2(\mu P_{t:t+k-1}, \nu P_{t:t+k-1}) \leq \sqrt{\frac{L}{\mu}} \gamma^k W_2(\mu, \nu)$.

- **Proof:** Let $\zeta \in \Gamma(\mu, \nu)$ be a coupling. Let $w_t, w_{t+1}, \dots, w_{t+k}$ be iid from $N(0, \sigma_w^2 I)$.

- We construct the following coupled dynamical systems:

$$x_{t+1} = f(x_t, t) + w_t,$$

$$y_{t+1} = f(y_t, t) + w_t,$$

$$(x_t, y_t) \sim \zeta.$$

- Define $V_t := \mathbb{E} \|x_t - y_t\|_{M_t}^2$. Observe that:

$$V_{t+1} = \mathbb{E} \|x_{t+1} - y_{t+1}\|_{M_{t+1}}^2 = \mathbb{E} \|f(x_t, t) - f(y_t, t)\|_{M_{t+1}}^2 \leq \gamma^2 \mathbb{E} \|x_t - y_t\|_{M_t}^2 = \gamma^2 V_t.$$

- Therefore: $V_{t+k} \leq \gamma^{2k} V_t \implies \|x_{t+k} - y_{t+k}\|_2^2 \leq \frac{L}{\mu} \gamma^{2k} \|x_t - y_t\|_2^2$.

- Now taking the infimum over $\zeta \in \Gamma(\mu, \nu)$ yields that:

$$\|x_{t+k} - y_{t+k}\|_2^2 \leq \frac{L}{\mu} \gamma^{2k} W_2^2(\mu, \nu).$$

- The claim now follows since we have constructed a coupling for (x_{t+k}, y_{t+k}) . ■

Contraction implies Wasserstein contraction

- Now we consider the more general form of contraction:

- $\frac{\partial f}{\partial x}(x, t)^T M(f(x, t), t + 1) \frac{\partial f}{\partial x}(x, t) \leq \gamma^2 M(x, t) \quad \forall x \in \mathbb{R}^n, t \in \mathbb{N}_{\geq 0},$
- $\mu I \leq M(x, t) \leq L I \quad \forall x \in \mathbb{R}^n, t \in \mathbb{N}_{\geq 0}.$

- Claim:**

- Define $\Psi := \sup_{x \in \mathbb{R}^n, t \in \mathbb{N}_{\geq 0}} \lambda_{\max}(\mathbb{E}_w[M(x, t)^{-1/2}(M(x + w, t) - M(x, t))M(x, t)^{-1/2}]) \vee 0.$
- Suppose that $\gamma^2(1 + \Psi) < 1$.
- Then: $W_2(\mu P_{t:t+k-1}, \nu P_{t:t+k-1}) \leq \sqrt{\frac{L}{\mu}} [\gamma \sqrt{1 + \Psi}]^k W_2(\mu, \nu).$
- Proof is similar to the state independent metric case, but more technical so we skip it.

Lyapunov stability implies L2 geometric ergodicity

- **Claim:** Suppose there exists a differentiable $Q(x, t)$ such that:
 - $Q(f(x, t), t + 1) \leq \gamma Q(x, t)$
 - $\mu \|x\|_2^2 \leq Q(x, t) \leq \psi \|x\|_2^2$,
 - $x \mapsto \nabla Q(x, t)$ is L -Lipschitz.
- Then we have:
$$|\mathbb{E}[\|y_{t+k}\|_2^2 | y_t = x] - \mathbb{E}[\|y_{t+k}\|_2^2 | y_t = 0]| \lesssim \frac{\psi}{\mu} (1 + \|x\|_2^2) \bar{\alpha}^k.$$
- (Unfortunately, $\bar{\alpha} \approx 1 - \exp(-n)!$)

Lyapunov stability implies L2 geometric ergodicity

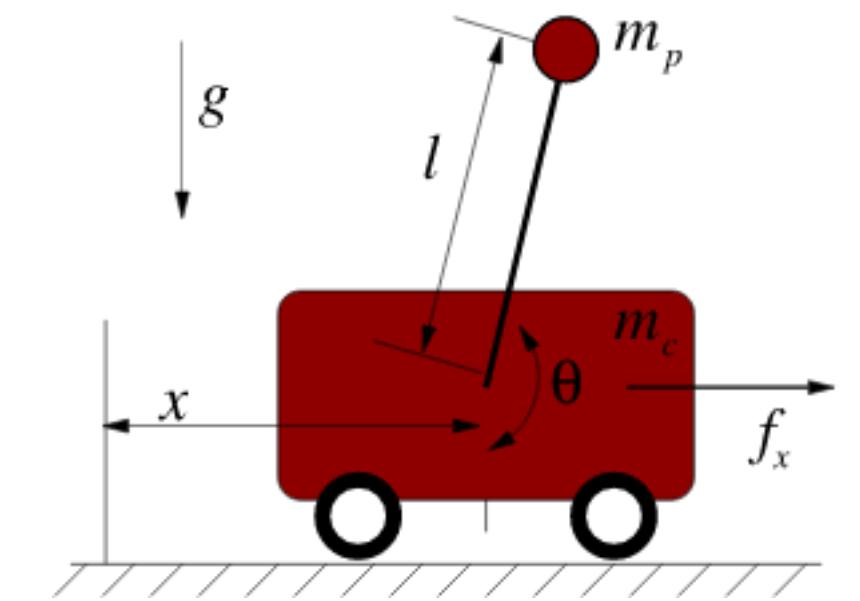
- Proof is based on ideas used to prove ergodicity of Markov chains [Meyn and Tweedie 1993], [Hairer and Mattingly 2008].
- The two key conditions needed are:
 - (Drift condition): $\mathbb{E}[Q(y_{t+1}, t + 1) | y_t] \leq \gamma Q(y_t, t) + R$
 - (“Small-set” minorization): $\inf_{x: Q(x, t) \leq R} P_t(x, A) \geq \alpha(R) \cdot \nu(A).$
- The issue is that $R = O(n)$ and $\alpha(R) = \Omega(\exp(-R))$, yielding the $(1 - \exp(-n))$ convergence rate.

Open question

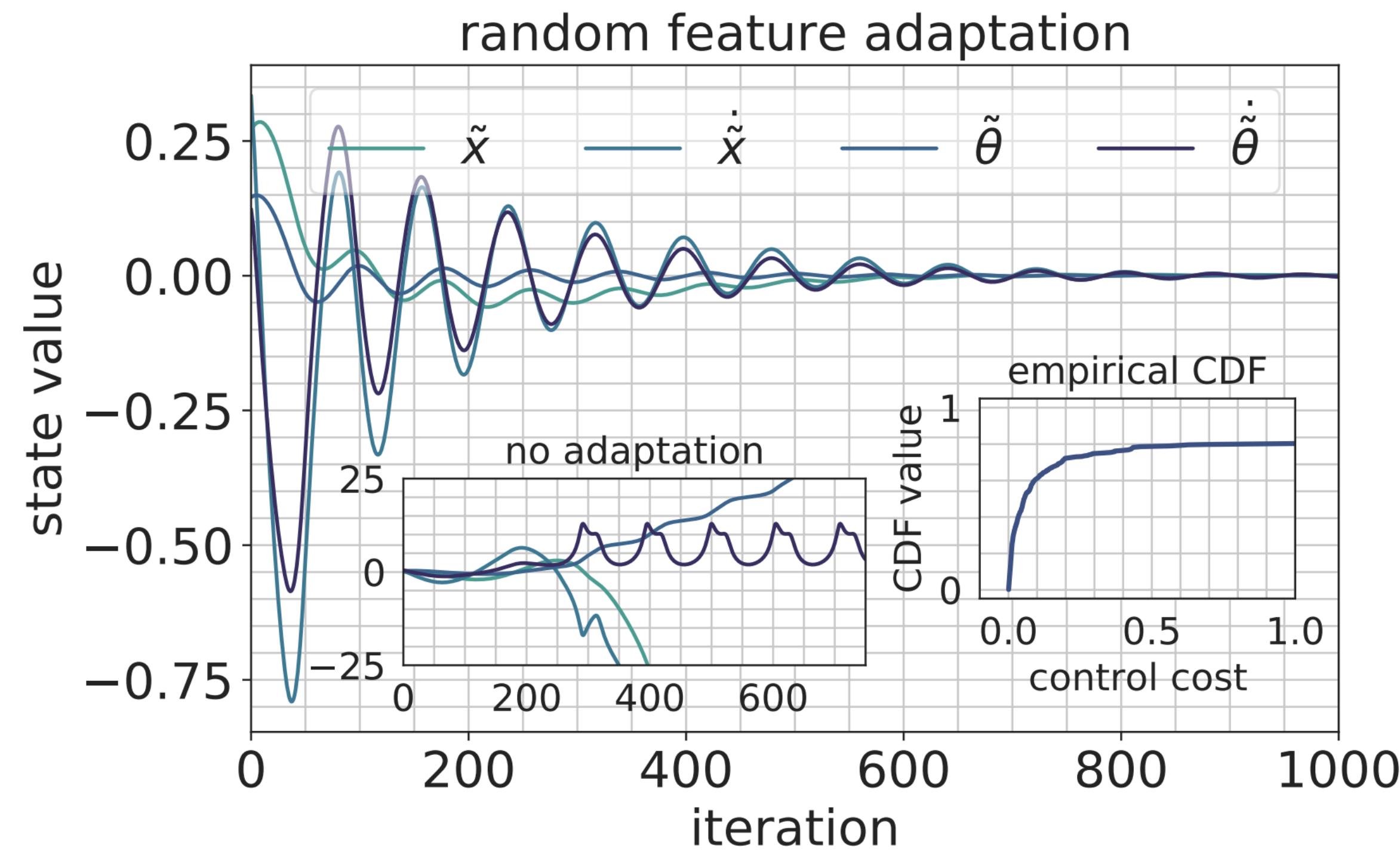
- If we only assume Lyapunov stability, are $1 - \exp(-n)$ rates unavoidable?
 - See <https://mathoverflow.net/questions/389180/convergence-rate-for-ergodic-markov-chains-induced-by-stable-dynamical-systems>.
- Is there some assumption in between Lyapunov stability and smooth contraction metrics that admit rates that do not depend exponentially in n ?

Cartpole

- State is $q = (x, \dot{x}, \theta, \dot{\theta})$.
- We design an LQR controller K using the linearized (RK4 discretized) dynamics about the unstable equilibrium: $q_{\text{eq}} = (0, 0, \pi, 0)$.
 - We use the **wrong** mass and length parameters.
 - LQR gives us an (incorrect) quadratic Lyapunov function:
$$Q(q) = \frac{1}{2}(q - q_{\text{eq}})^T P(q - q_{\text{eq}}).$$
- We then adapt to the model-misspecification using velocity-gradients with $Q(q)$ and with 400 random Fourier features [Rahimi and Recht 2007] as the basis functions.



Cartpole



- Notice the system without adaption is unstable, but adaption manages to correct the model mis-specification.

Semi-contracting system

- We now consider the SDE:

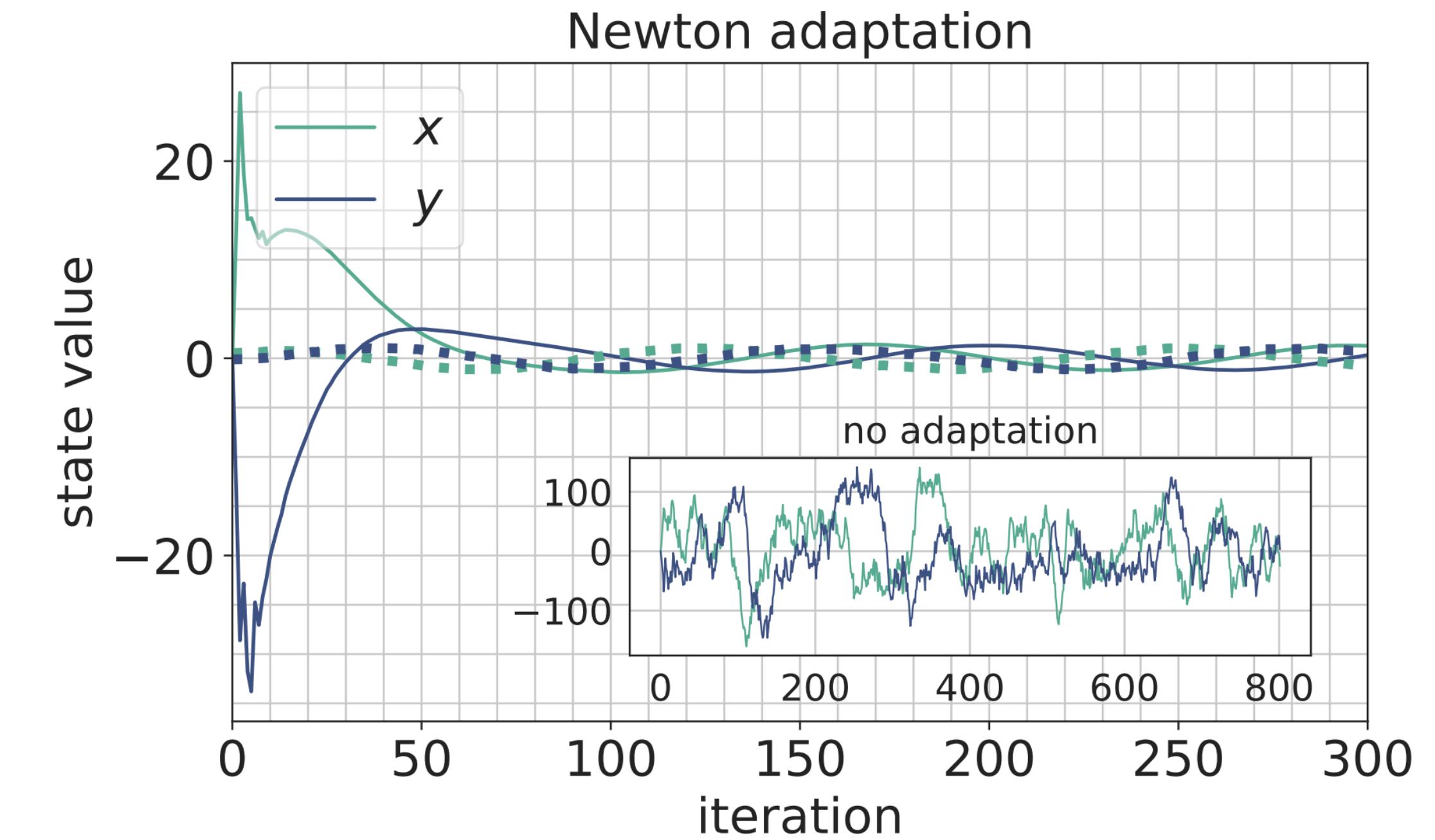
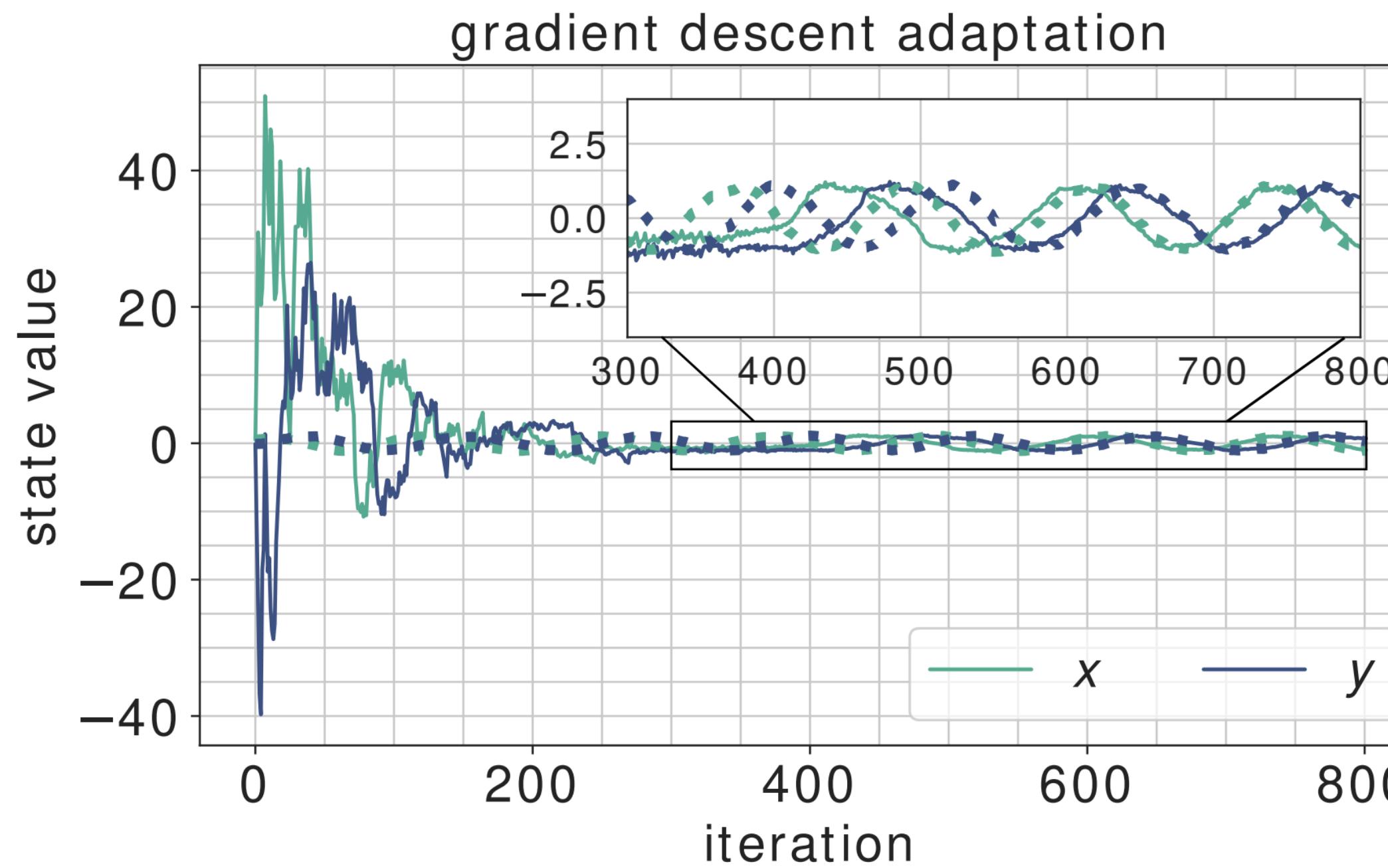
$$dx = \left(-y + \frac{x}{\sqrt{x^2 + y^2}} - x + u_1 - Y_x(x, t)^T \alpha \right) dt + \sigma dw_1,$$

$$dy = \left(x + \frac{y}{\sqrt{x^2 + y^2}} - y + u_2 - Y_y(y, t)^T \alpha \right) dt + \sigma dw_2.$$

- Note the nominal system in polar coordinates is: $\dot{r} = -(r - 1)$, $\dot{\theta} = 1$, which is contracting towards the unit angular velocity limit cycle on the unit circle.

Semi-contracting system

- We apply both GD and online Newton to the discretized SDE:



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