

EigenSafe A Spectral Framework for Learning-Based Stochastic Safety Filtering

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Summary

- EigenSafe is a framework based on linear operator theory that correctly captures the evolution of safety probability of stochastic systems.
- The proposed safety Q function is directly tied to the safety probability and can be learned from trajectory data.

Dynamic Programming for Safety Probability

$$\mathbb{P}_\pi[\text{safety}(x, u, t + 1)] = \mathbb{E}_\pi[\mathbb{P}_\pi[\text{safety}(x^+, u^+, t)]]$$

$$\mathbb{P}_\pi[\text{safety}(x, u, 0)] = 1_{\text{safe}}(x, u)$$

$$\mathbb{P}_\pi[\text{safety}(x, u, t)] = A_\pi \circ \dots \circ A_\pi 1_{\text{safe}}(x, u) = A_\pi^t 1_{\text{safe}}(x, u)$$

$$\text{where } A_\pi \beta(x, u) := \begin{cases} \mathbb{E}_\pi[\beta(x^+, u^+)] & (x, u) \text{ safe} \\ 0 & (x, u) \text{ unsafe} \end{cases}$$

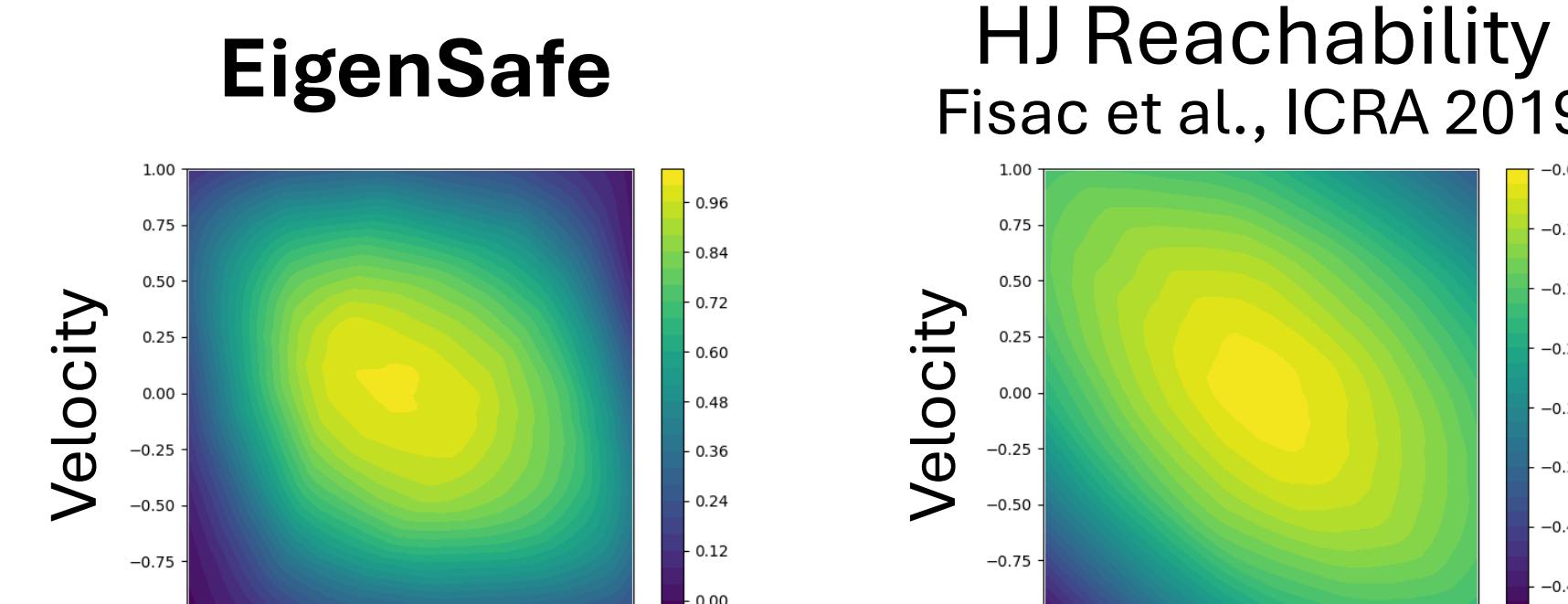
- A_π is a linear operator.
- The spectral properties of A_π describe the long-term safety of the closed-loop system.

1. The superscript $(\cdot)^+$ denotes the state/action at the next time step.
2. The subscript $(\cdot)_\pi$ on \mathbb{P} or \mathbb{E} means that the probability/expectation was evaluated with respect to the trajectory induced by the feedback policy π .
3. $\text{safety}(x, u, t)$ means that the system remains within the safe region throughout the time window $[0, t]$, given initial state x and initial input u .
4. 1_{safe} is the one-step safety indicator function returning 1 if the state-action pair is safe and 0 otherwise.

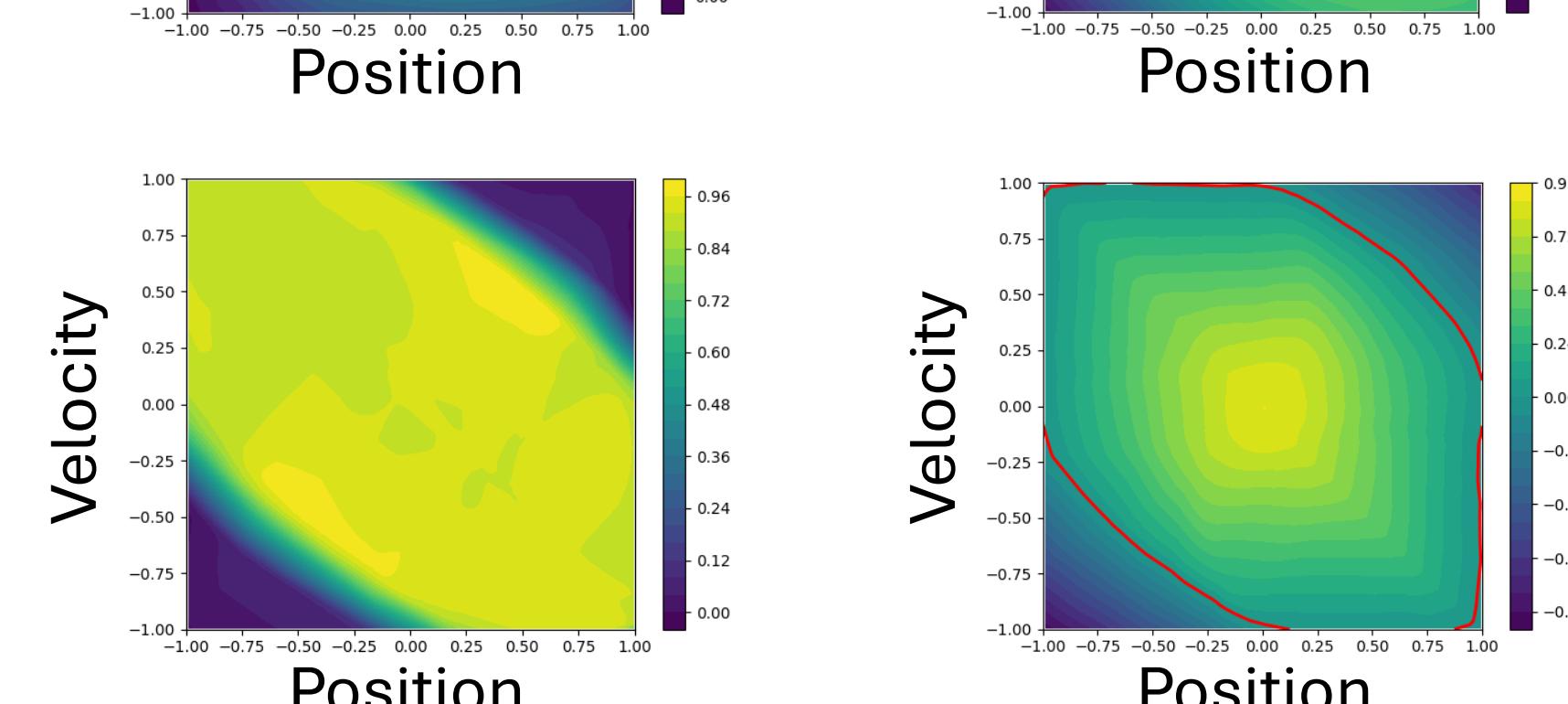
Experiments

(a) Double Integrator (Safety Value Function)

Stochastic Double Integrator
(Gaussian noise on accel.)



Deterministic Double Integrator
(No noise)



- EigenSafe properly evaluates relative safety across state-action pairs.
- EigenSafe generalizes to deterministic systems, with ψ_π being the indicator for the invariant set and γ_π being 1.

The Dominant Eigenfunction as Safety Q function

$$\mathbb{P}_\pi[\text{safety}(x, u, t)] = A_\pi^t 1_{\text{safe}}(x, u) \approx c \cdot \psi_\pi(x, u) \cdot \gamma_\pi^t$$

The dominant eigenfunction ψ_π

- Measures safety of each state-action pair (x, u)
- Always nonnegative

The dominant eigenvalue γ_π

- Safety of the overall closed-loop system
- Always between 0 and 1

Learning

1. Eigenpair Learning

$$(\gamma_\pi, \psi_\pi) = \arg \min_{\lambda, \psi} W_\lambda \mathbb{E}_{(x, u, x^+) \sim \mathcal{D}, u^+ \sim \pi} [(\psi(x^+, u^+) - \lambda \psi(x, u))^2] + W_n (\|\psi\| - 1)^2$$

Eigenpair Loss

Encourages (γ_π, ψ_π) to converge to the dominant eigenpair

Normalization Loss

Prevents ψ from collapsing to zero

* $W_{(\cdot)}$ -s are positive weights. $\|\psi\|$ is an estimate of any function norm of ψ from data (e.g., the supremum norm $\sup_{(x, u) \sim \mathcal{D}} |\psi(x, u)|$).

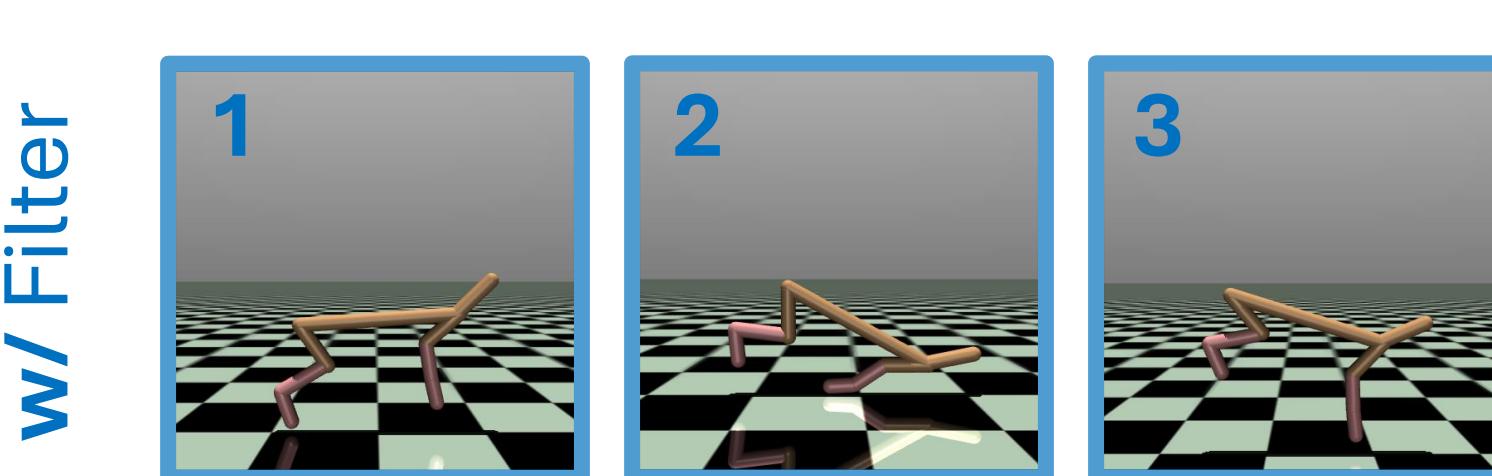
2. Backup Policy Optimization (DDPG Style)

$$\pi = \arg \max_\pi \mathbb{E}_{(x, \cdot, \cdot) \sim \mathcal{D}} \psi(x, \pi(x))$$

- Solve for the policy π that maximizes safety Q function value.
- This will give the safest backup policy possible for the given system.

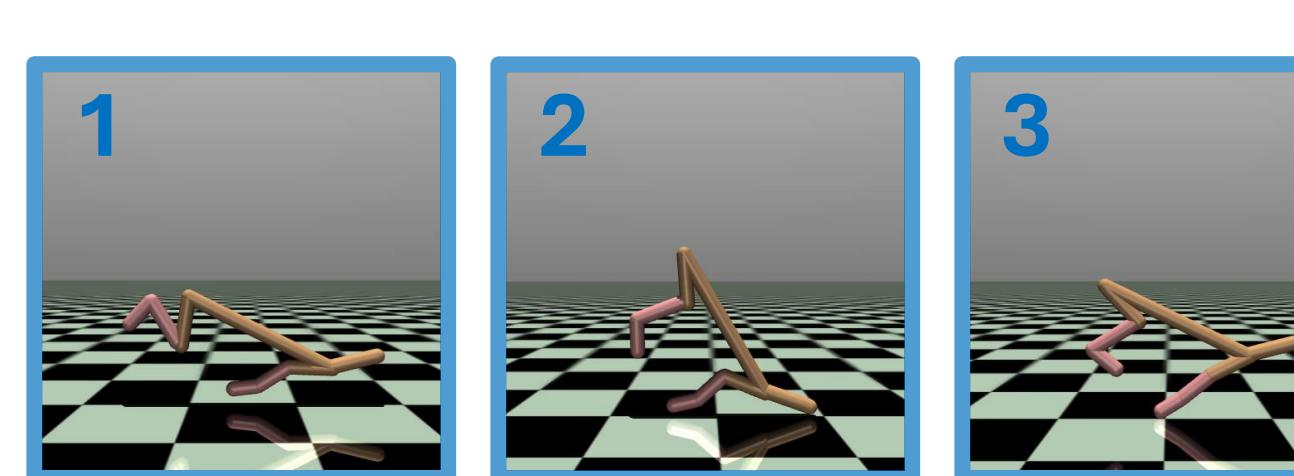
(b1) cheetah_balance

unsafe if cheetah flips



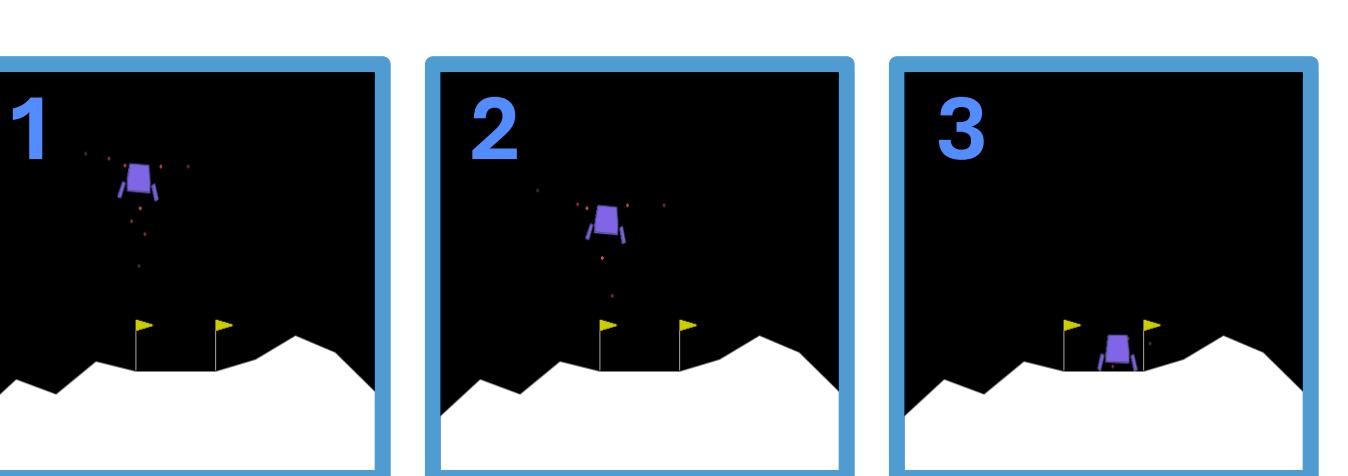
(b2) cheetah_run

unsafe if cheetah moves backward

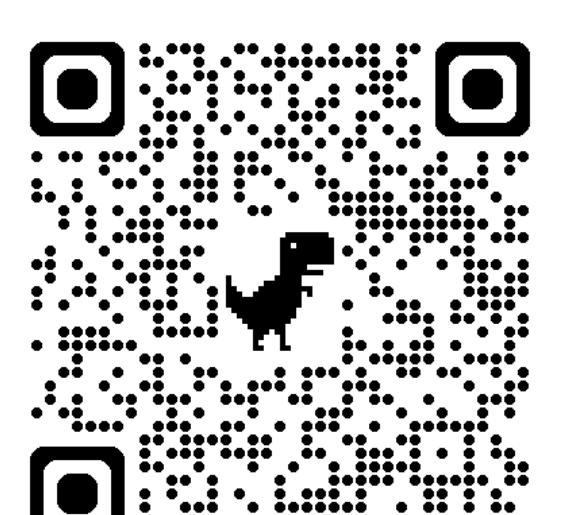


(b3) lunar_lander

unsafe if lander crashes or flies away



Paper
w/ Exp.Details



Experiment Videos
(Gym envs)