



**Carnegie Mellon University**  
Electrical & Computer Engineering

# Myopically Verifiable Probabilistic Certificate for Long-term Safety

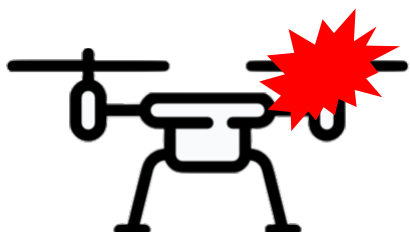
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*Zhuoyuan (Jacob) Wang, Haoming Jing, Christian  
Kurniawan, Albert Chern and Yorie Nakahira*

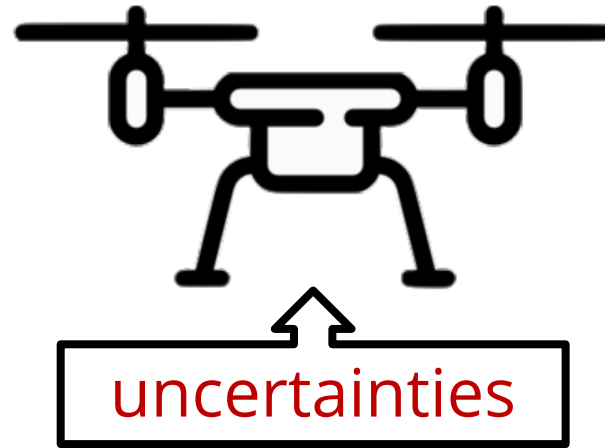
internal:

$$\dot{x} = ??????$$

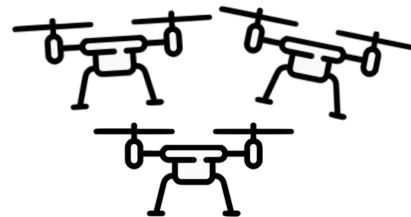
unmodeled dynamics




mechanical faults



external:

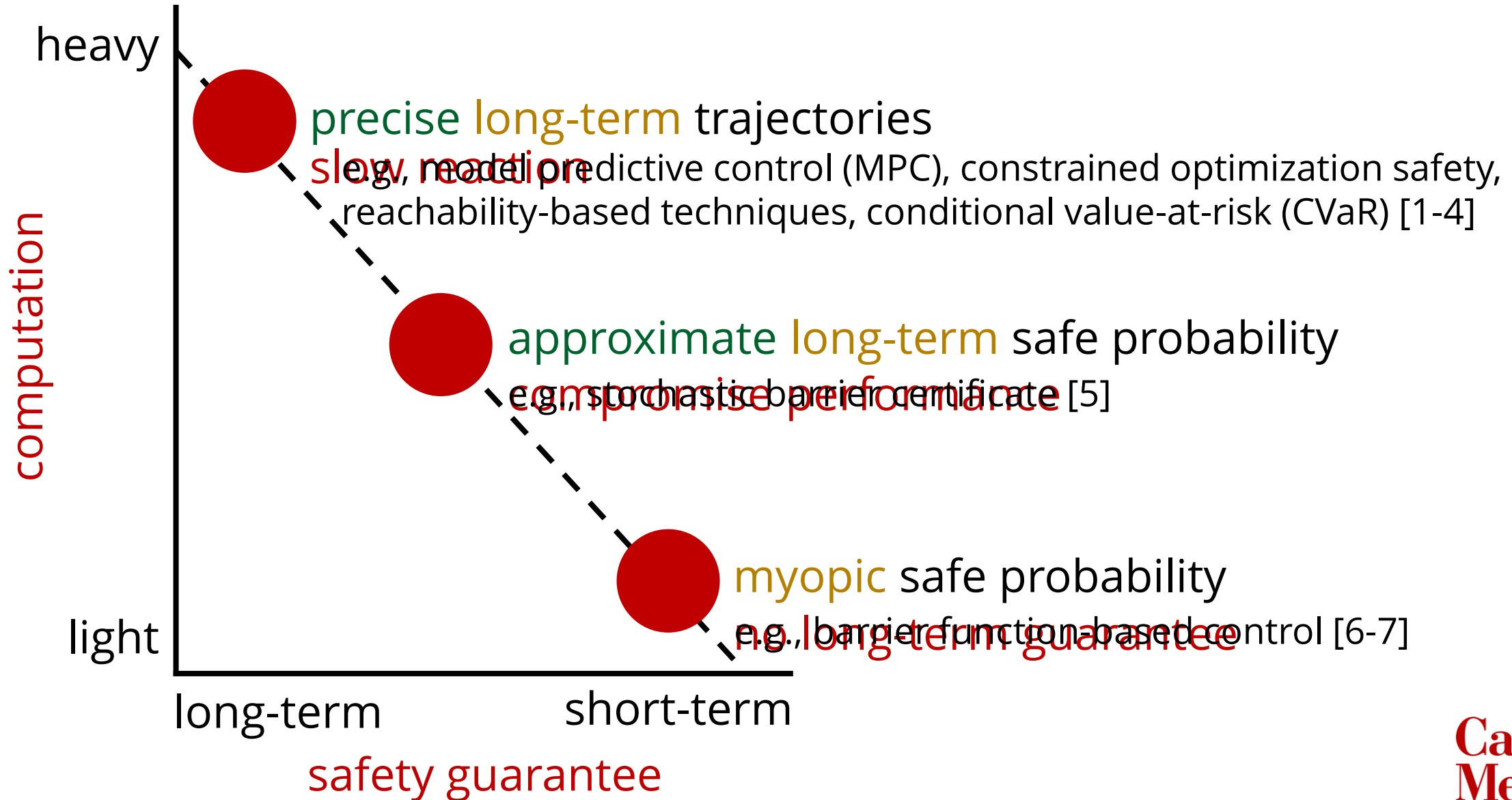


other agents

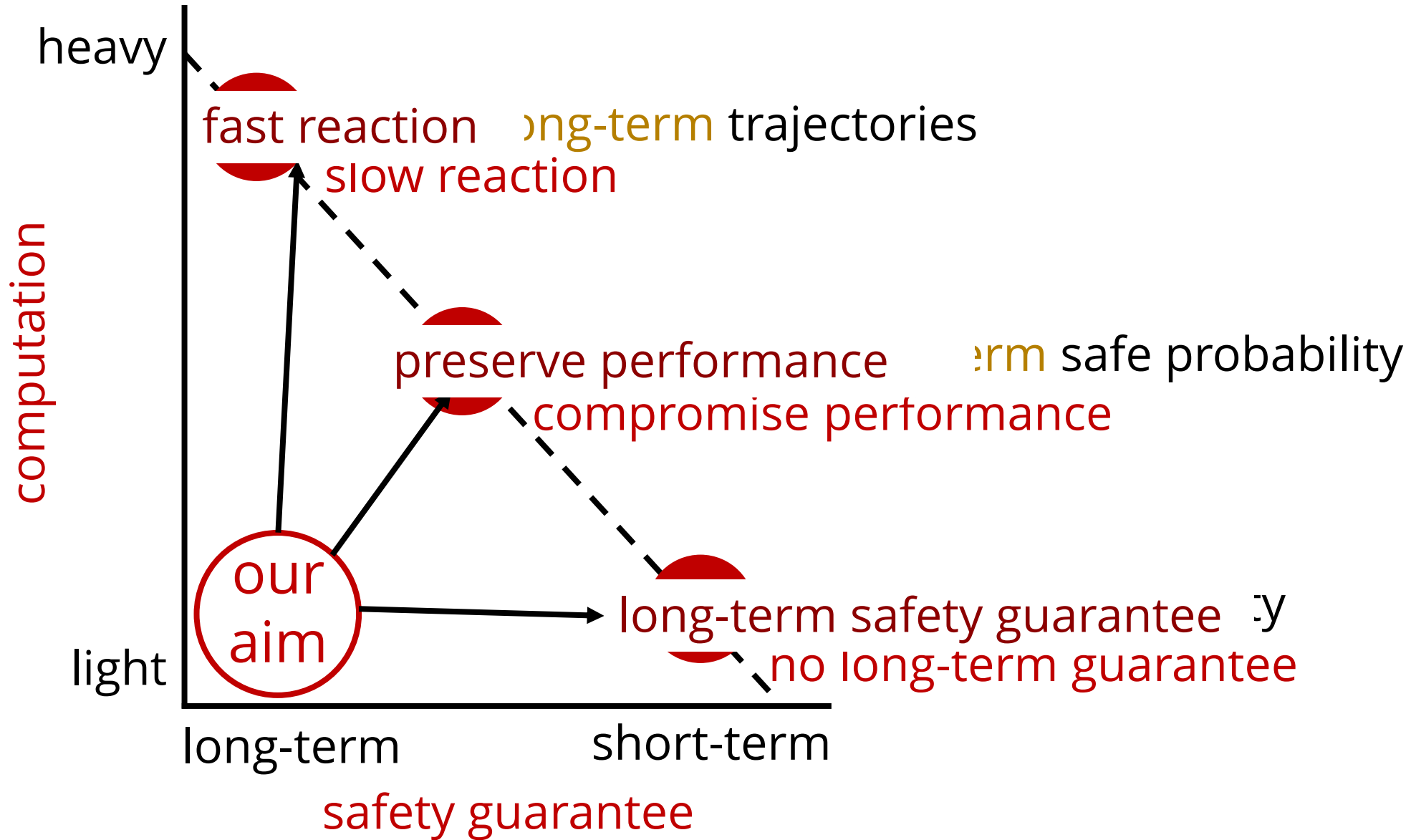


wind

# Current Challenges

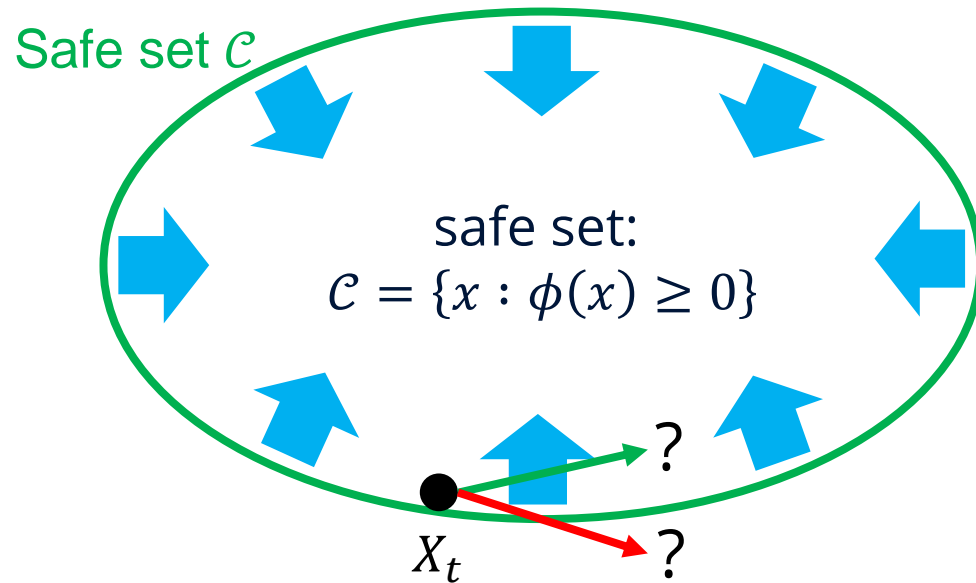


# Aims



# Proposed Method: Intuitions

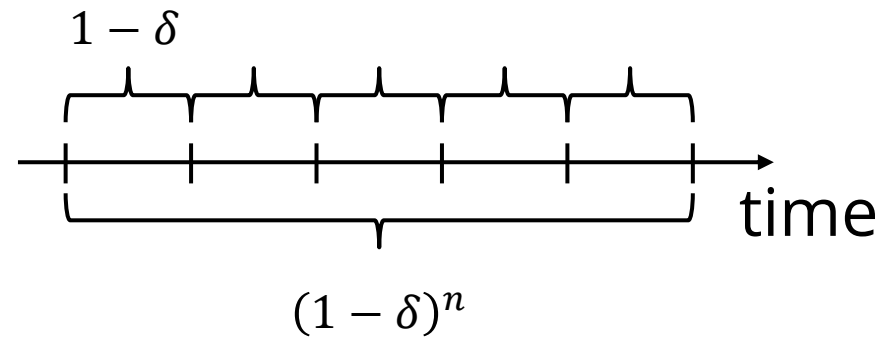
Existing approach:  
Control barrier function...



Under stochastic  
uncertainties

safe at next time  $\Rightarrow$  safe at all time **X**

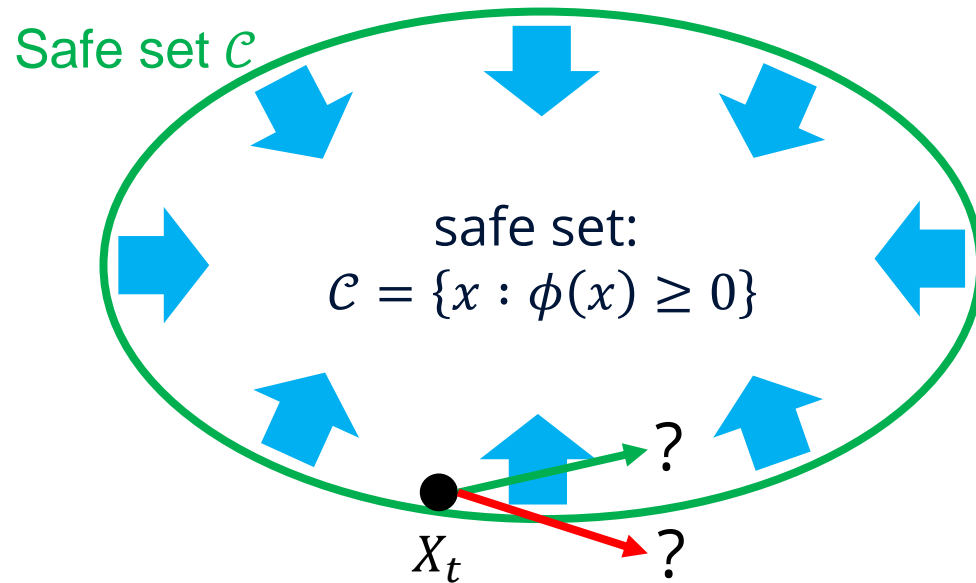
safe with probability  
 $1 - \delta$  at each step



unsafe with high  
probability in a long term

# Proposed Method: Intuitions

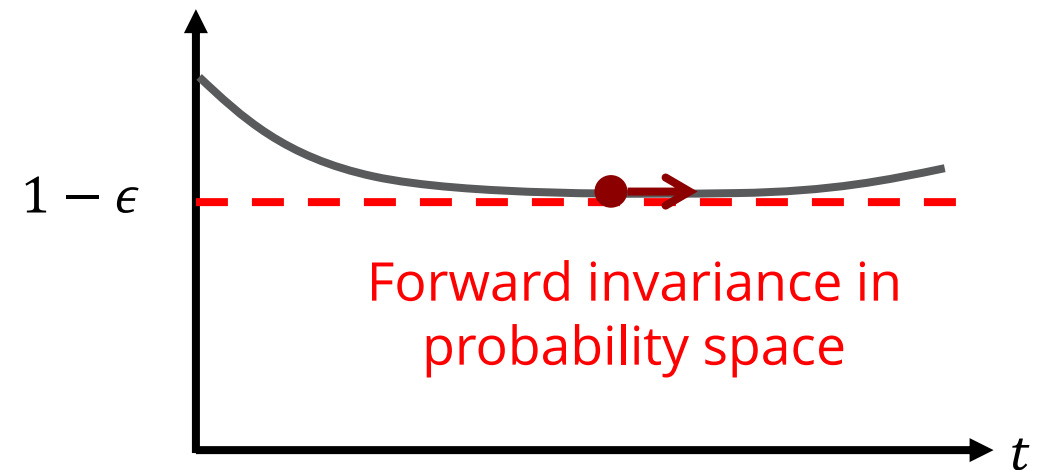
Existing approach:  
Control barrier function...



Under stochastic  
uncertainties

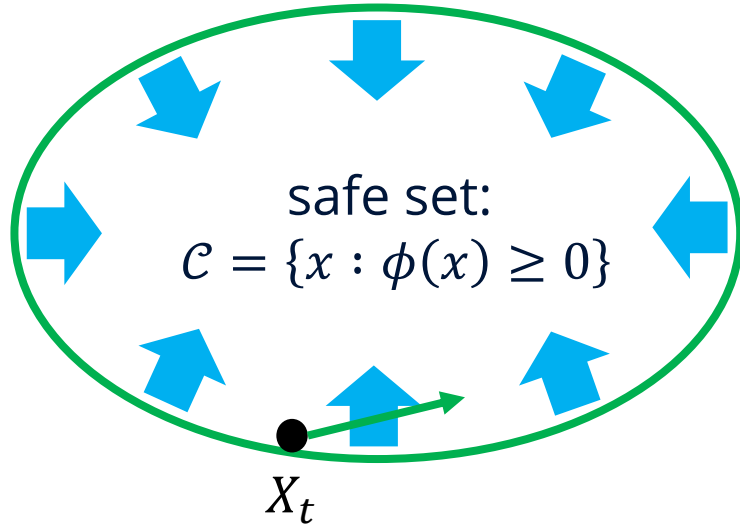
Proposed approach:

Long-term safety probability  
 $F(X_t) = \Pr(X_\tau \in \mathcal{C}, \tau \in [t, t + T] | X_t)$



# Proposed Method: Intuition

Control barrier functions:



Reachability:

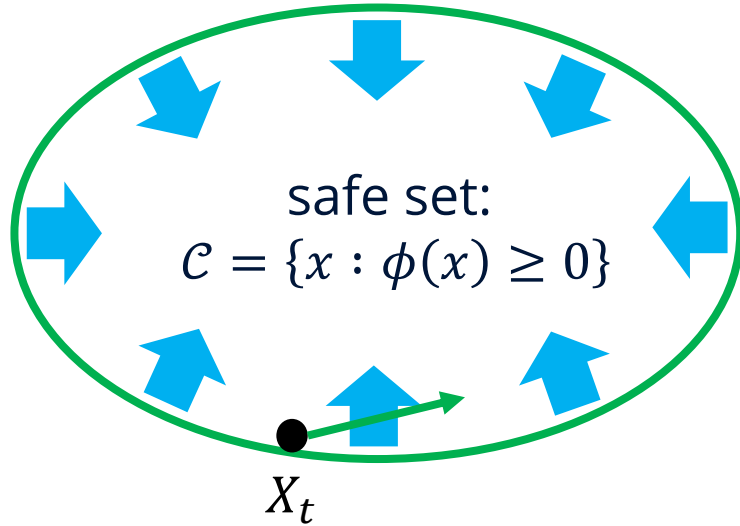


$X_t$

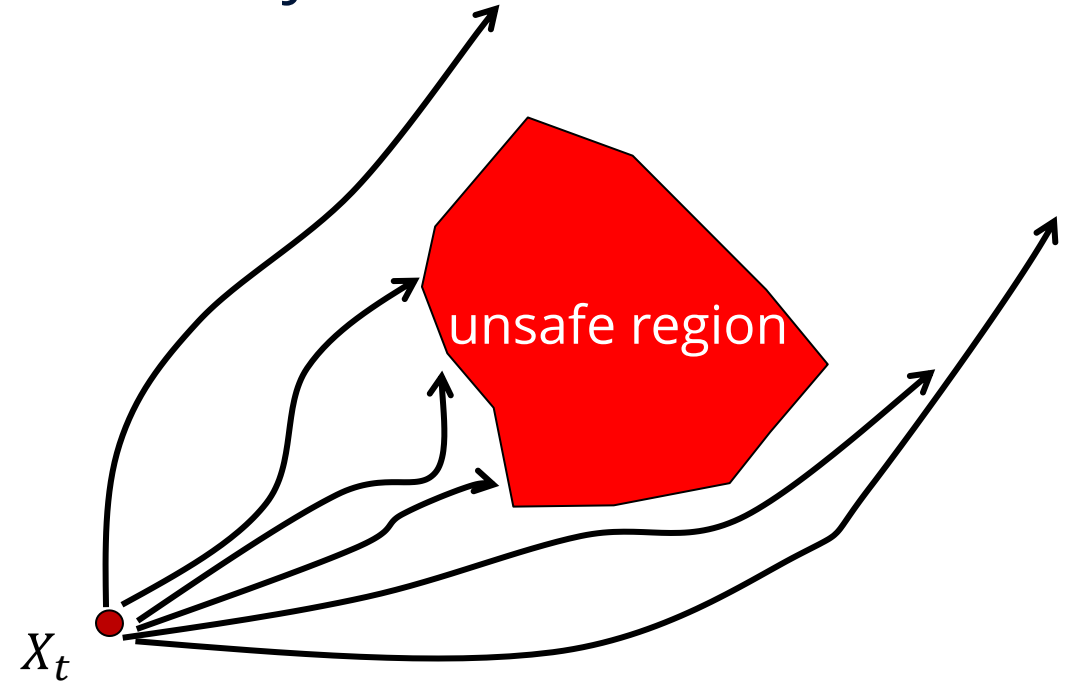
A red dot labeled  $X_t$  is located to the left of the unsafe region, representing a state that is not in the safe set.

# Proposed Method: Intuition

Control barrier functions:



Reachability:

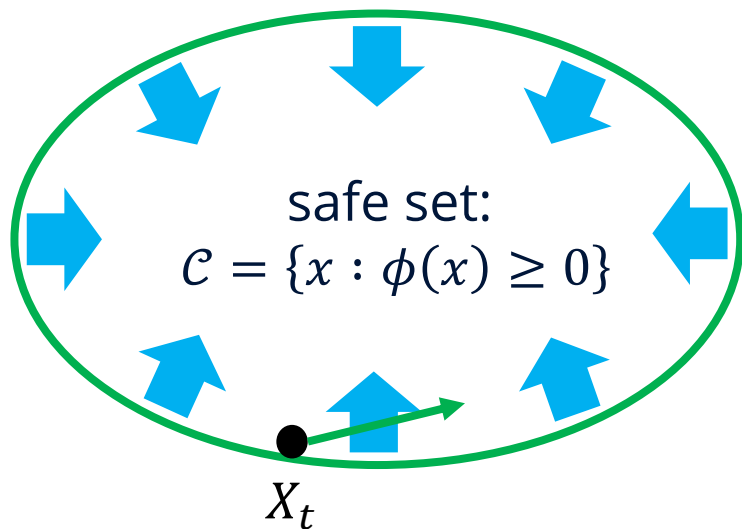


Forward rollout trajectories

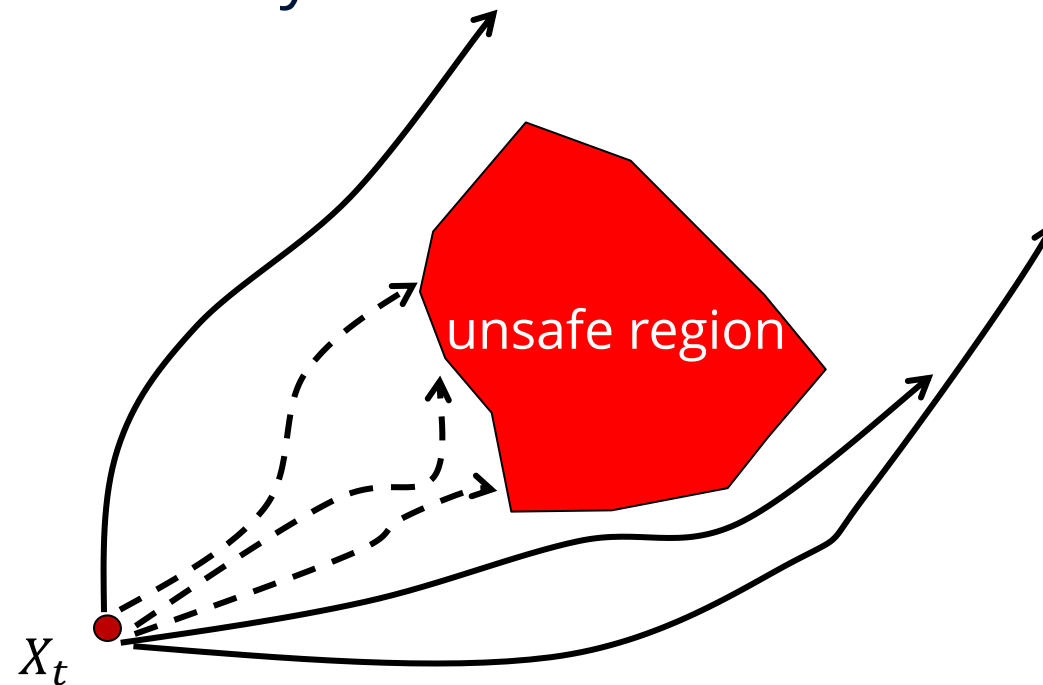


# Proposed Method: Intuition

Control barrier functions:



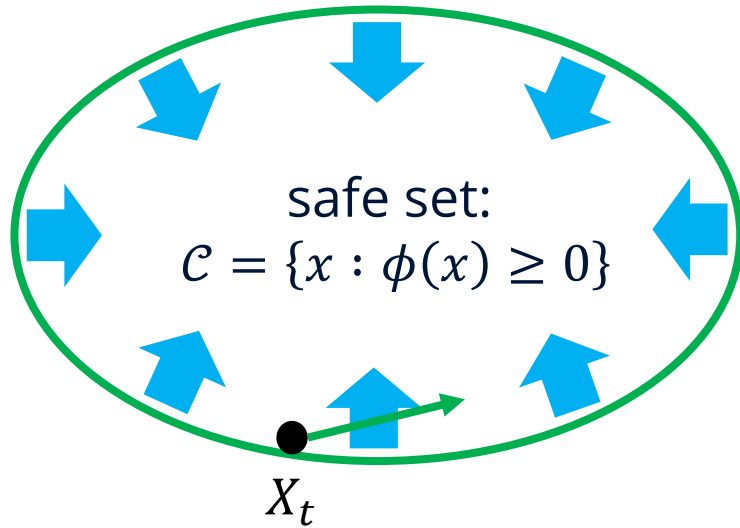
Reachability:



Forward rollout trajectories

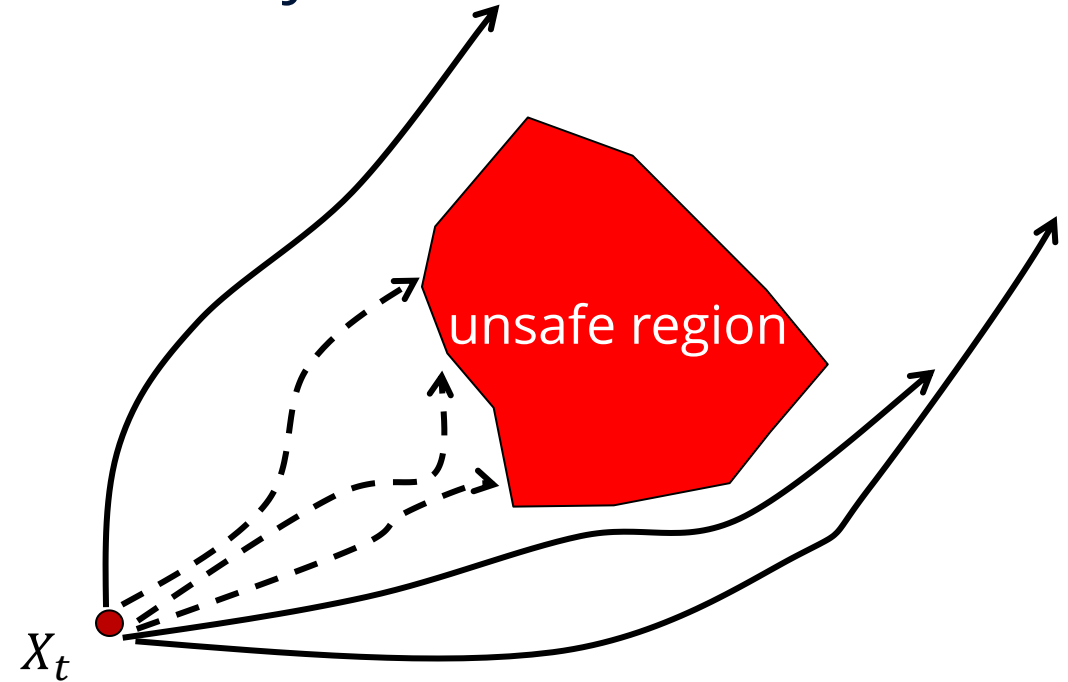
# Proposed Method: Intuition

Control barrier functions:



Encoded safety probability  $F(X_t)$

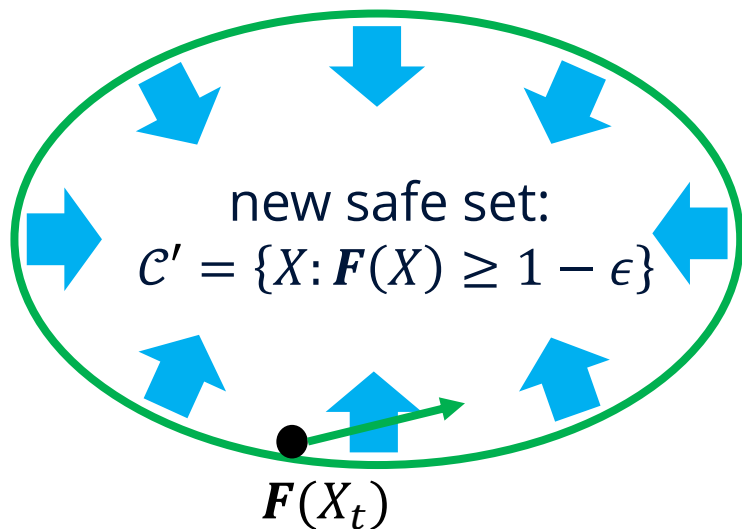
Reachability:



← Forward rollout trajectories

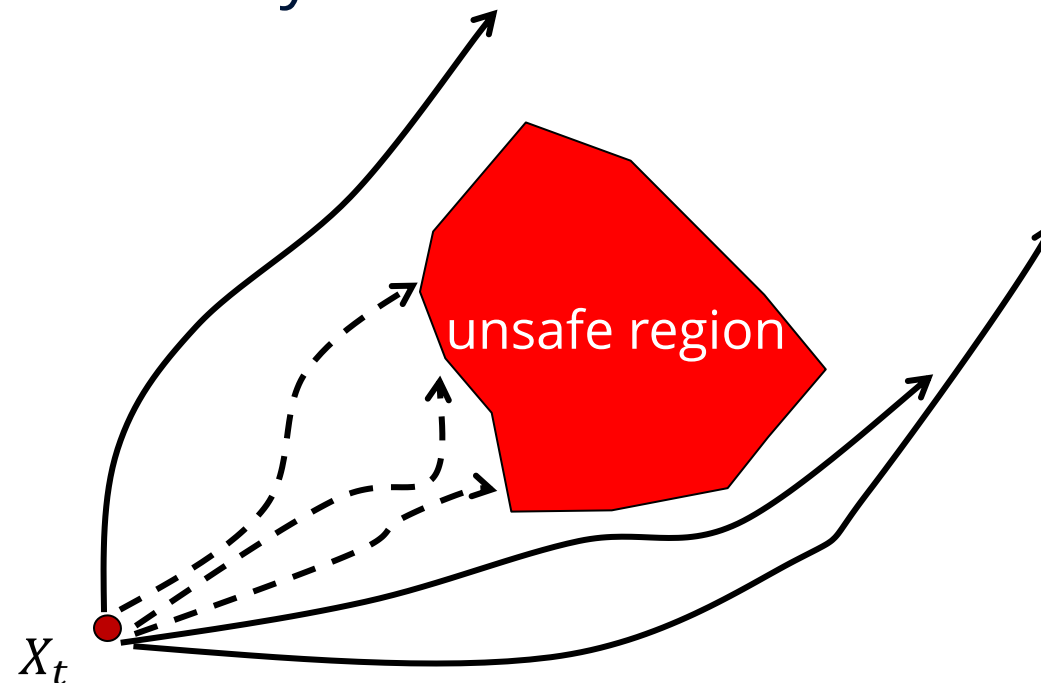
# Proposed Method: Intuition

Control barrier functions:



Encoded safety probability  $F(X_t)$

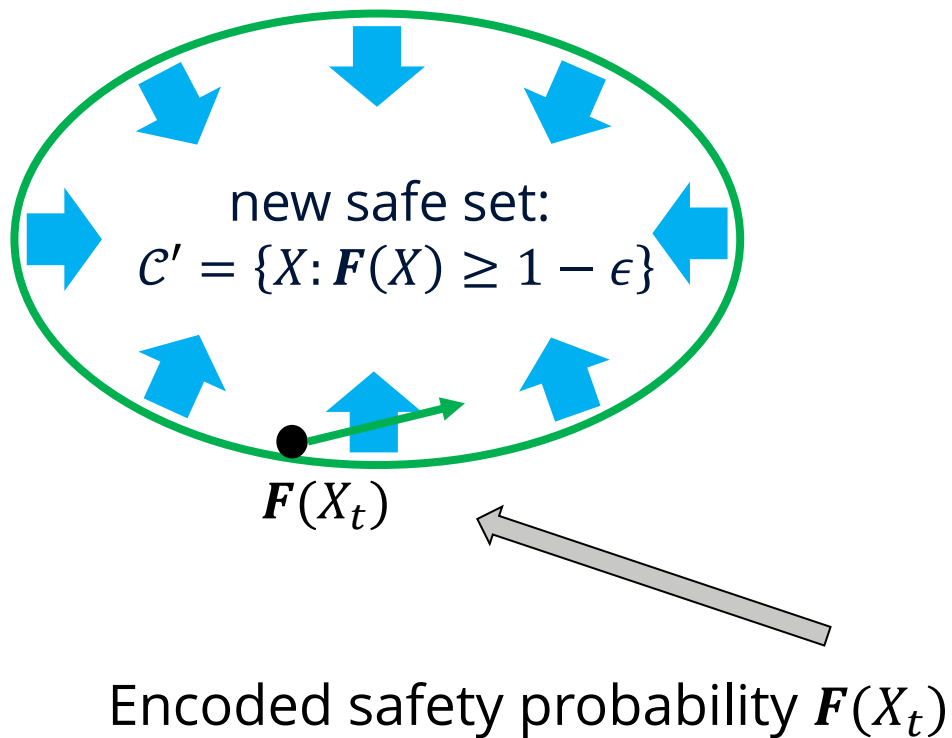
Reachability:



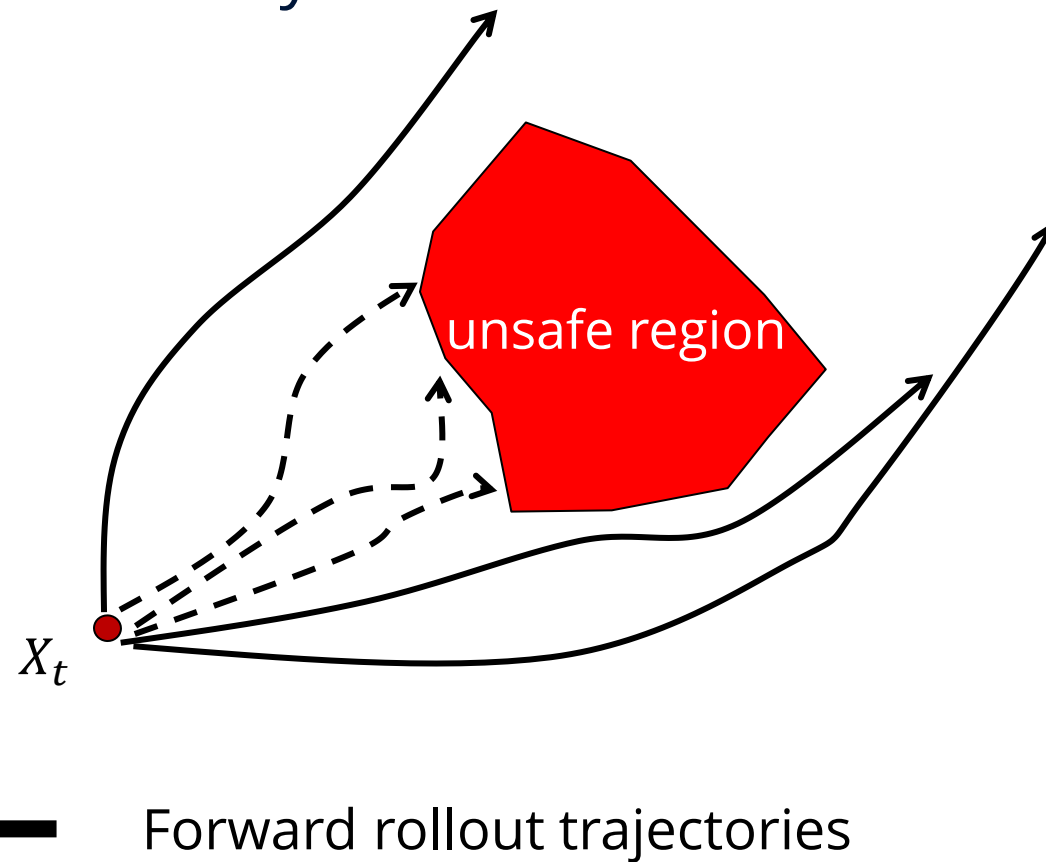
← Forward rollout trajectories

# Proposed Method: Intuition

Control barrier functions:



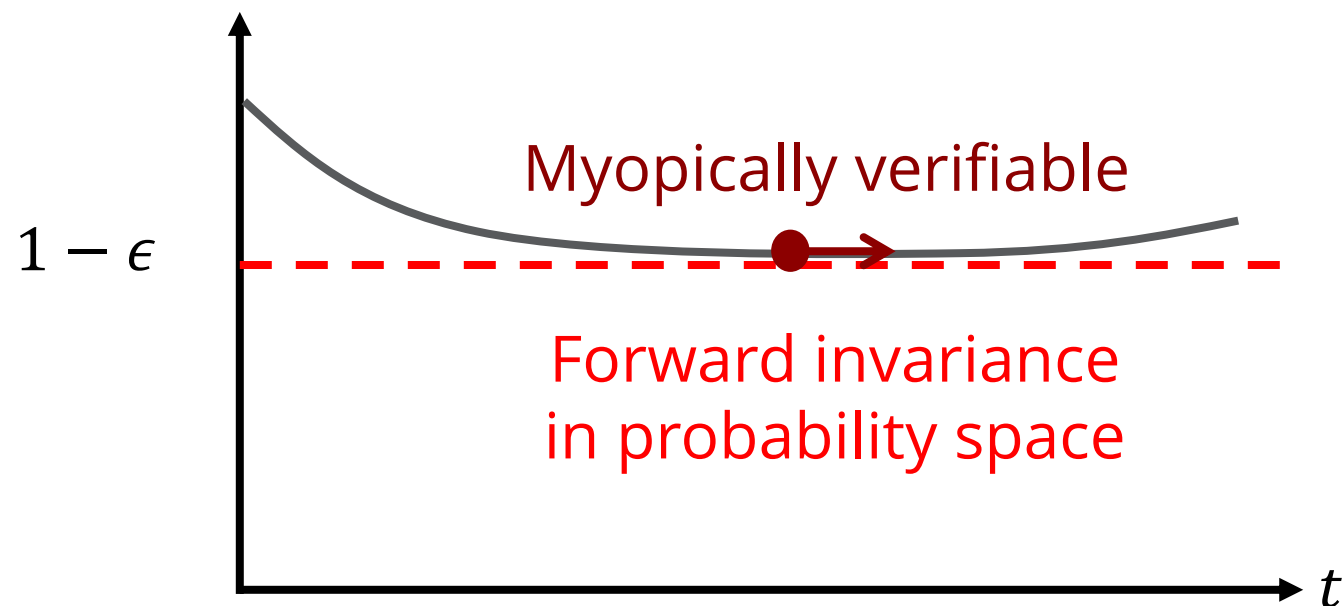
Reachability:



# Proposed Method

Long-term safe probability

$$F(X_t) = \Pr(X_\tau \in \mathcal{C}, \tau \in [t, t + T] | X_t)$$



**Proposed Safety Condition:**

$$AF(X_t) \geq -\alpha(F(X_t) - (1 - \epsilon))$$

time derivative of safety probability

desired safety probability

$A$ : infinitesimal generator

$\alpha: \mathbb{R} \rightarrow \mathbb{R}$  monotonically increasing, concave,  $\alpha(0) \leq 0$ .

$$A\mathbf{F}(X_t) \geq -\alpha(\mathbf{F}(X_t) - (1 - \epsilon))$$

linear with respect to  $u$

$$A\mathbf{F}(X_t) = \mathcal{L}_f\mathbf{F}(X_t) + (\mathcal{L}_g\mathbf{F}(X_t))u + \frac{1}{2}\text{tr}([\sigma(X_t)]^\top \text{Hess}\mathbf{F}(X_t)[\sigma(X_t)])$$

constant given system dynamics

$$dX_t = (f(X_t) + g(X_t)U_t)dt + \sigma(X_t)dW$$

**Theorem:** Given

$$F(X_0) > 1 - \epsilon,$$

if we choose the control action to satisfy

$$AF(X_t) \geq -\alpha(F(X_t) - (1 - \epsilon)) \text{ for } t > 0,$$

then we have

$$\Pr(X_\tau \in \mathcal{C}, \tau \in [t, t + T]) \geq 1 - \epsilon \text{ for } \forall t > 0$$

$\alpha: \mathbb{R} \rightarrow \mathbb{R}$  is a monotonically increasing concave function that satisfies  $\alpha(0) \leq 0$ .

system dynamic:

$$dx_t = (2x_t + 2.5u_t) dt + 2dw_t$$

initial state:

$$x_0 = 3$$

safe set:

$$\mathcal{C} = \{x \in \mathbb{R} : x - 1 > 0\}$$

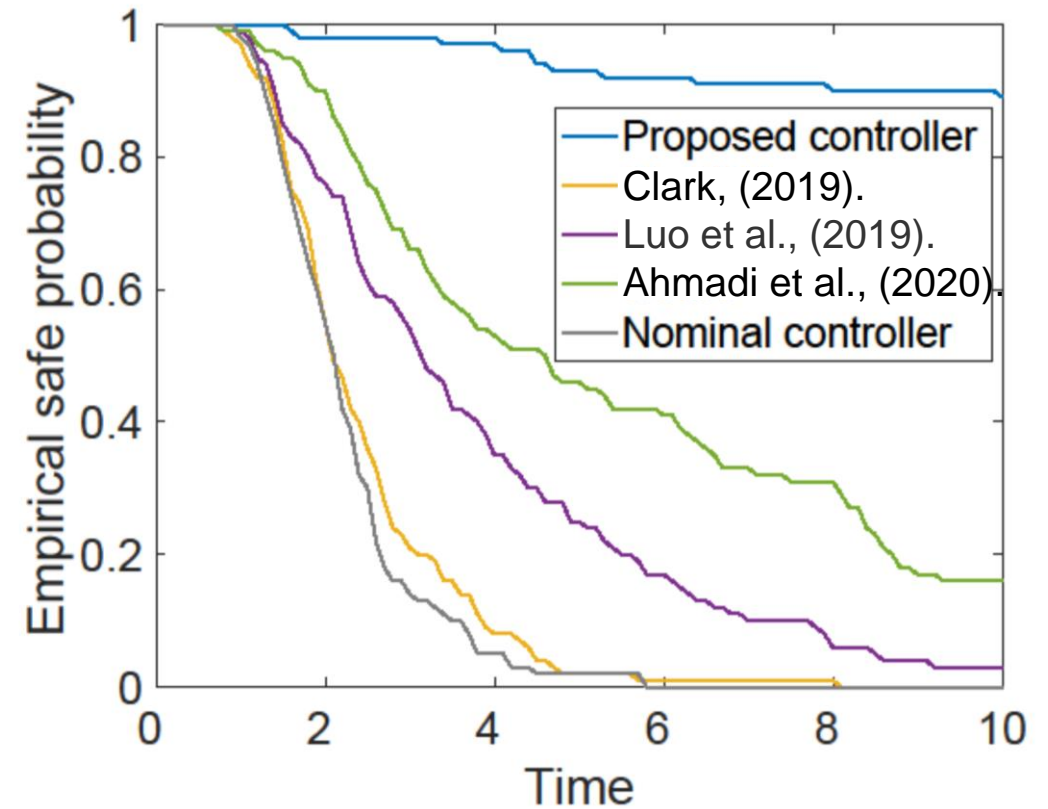
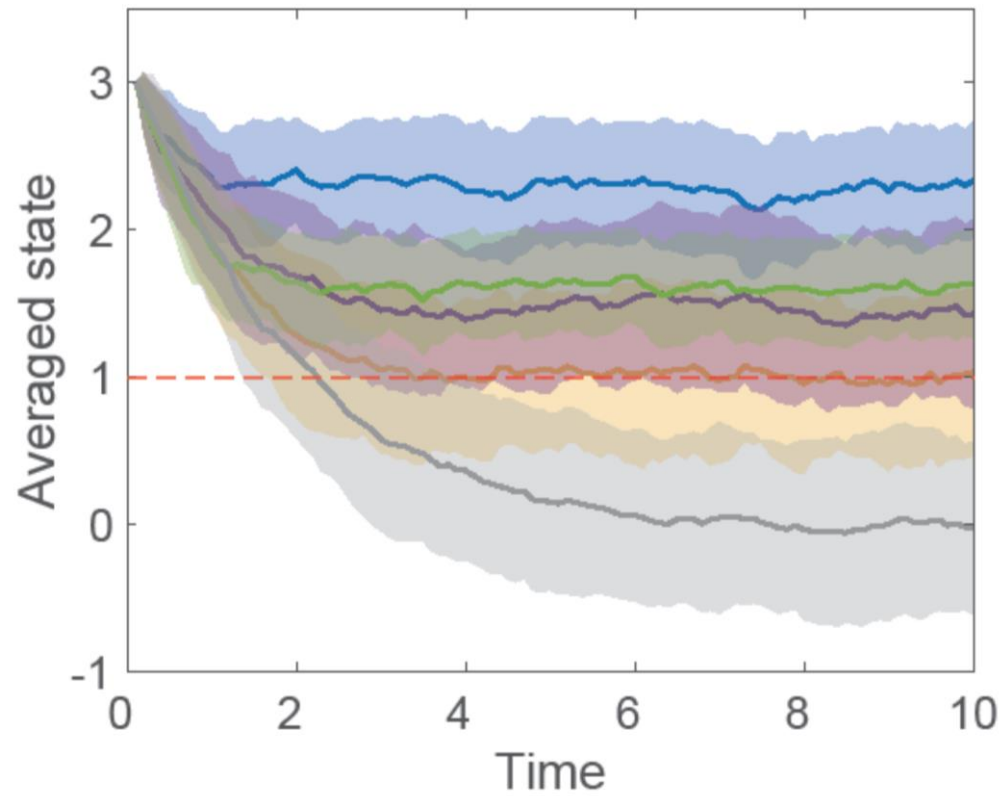
nominal controller:

$$N(x_t) = 2.5x_t$$

desired safety probability:

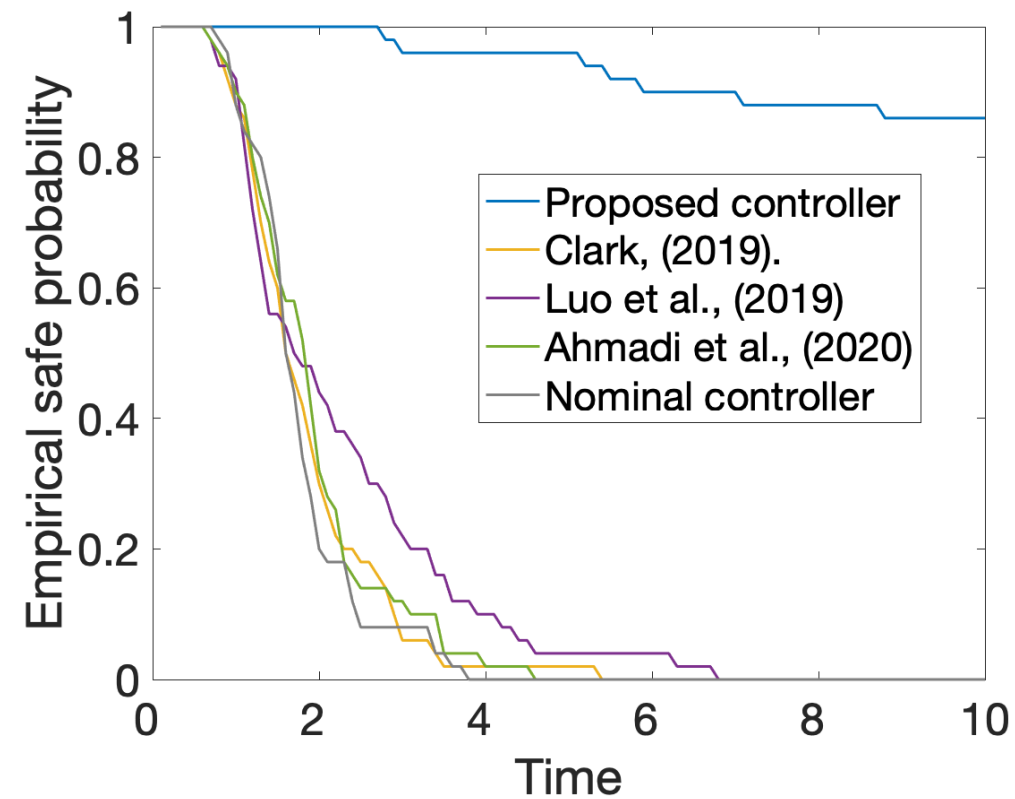
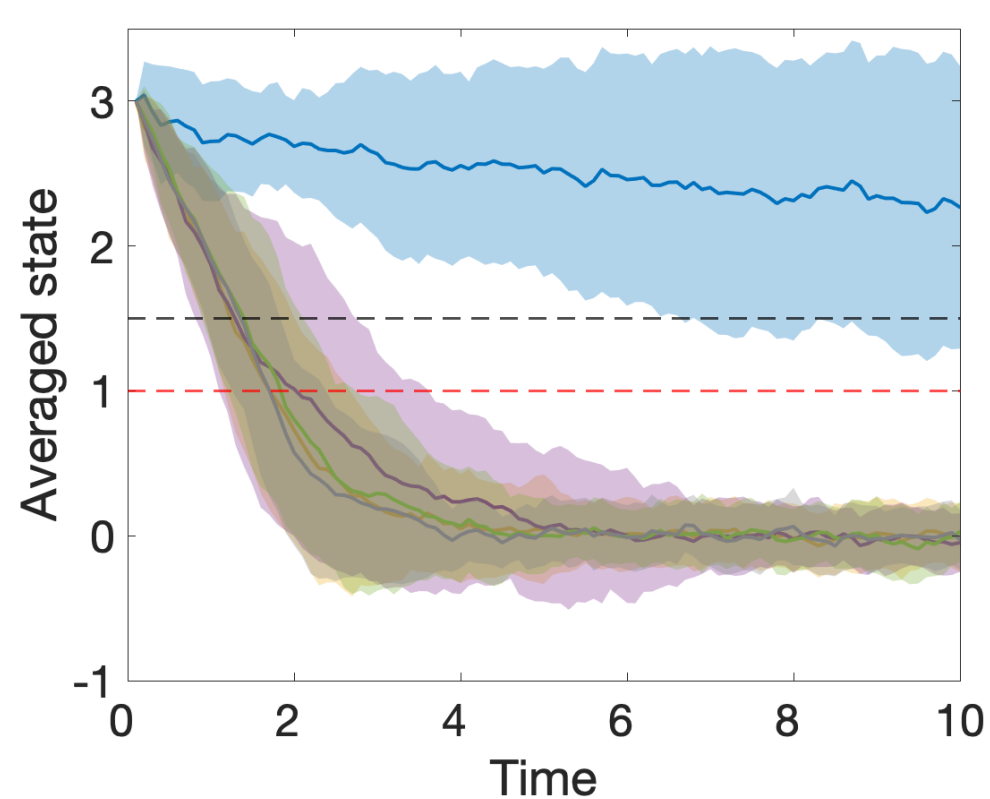
$$1 - \epsilon = 0.9$$

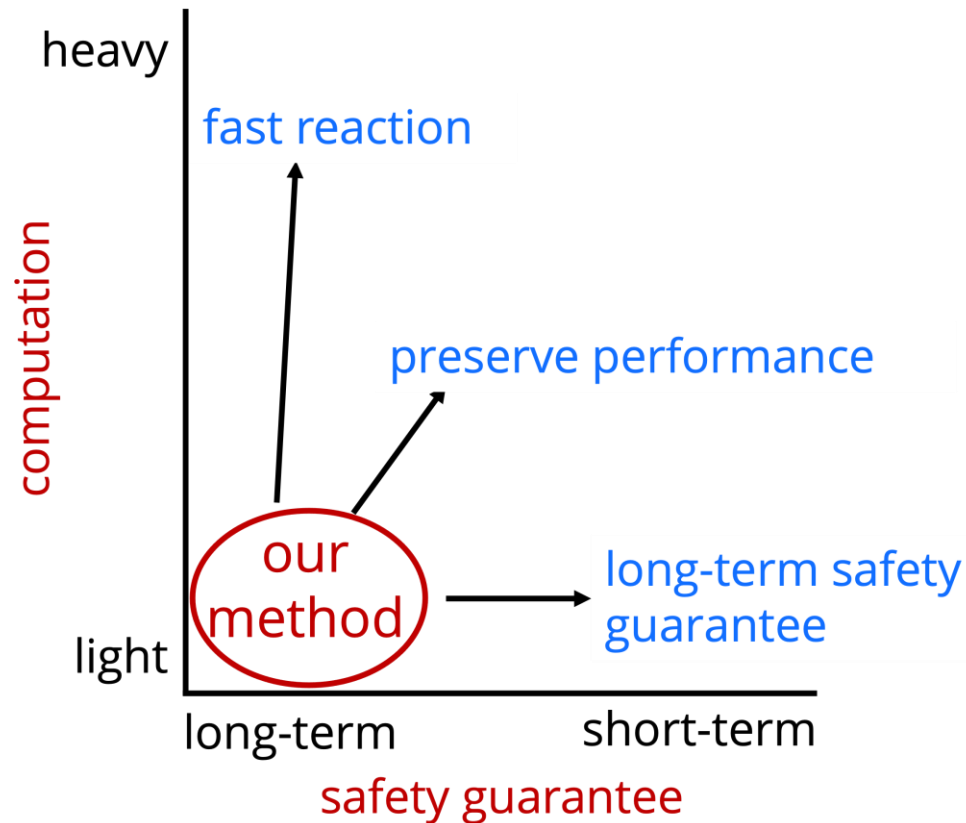




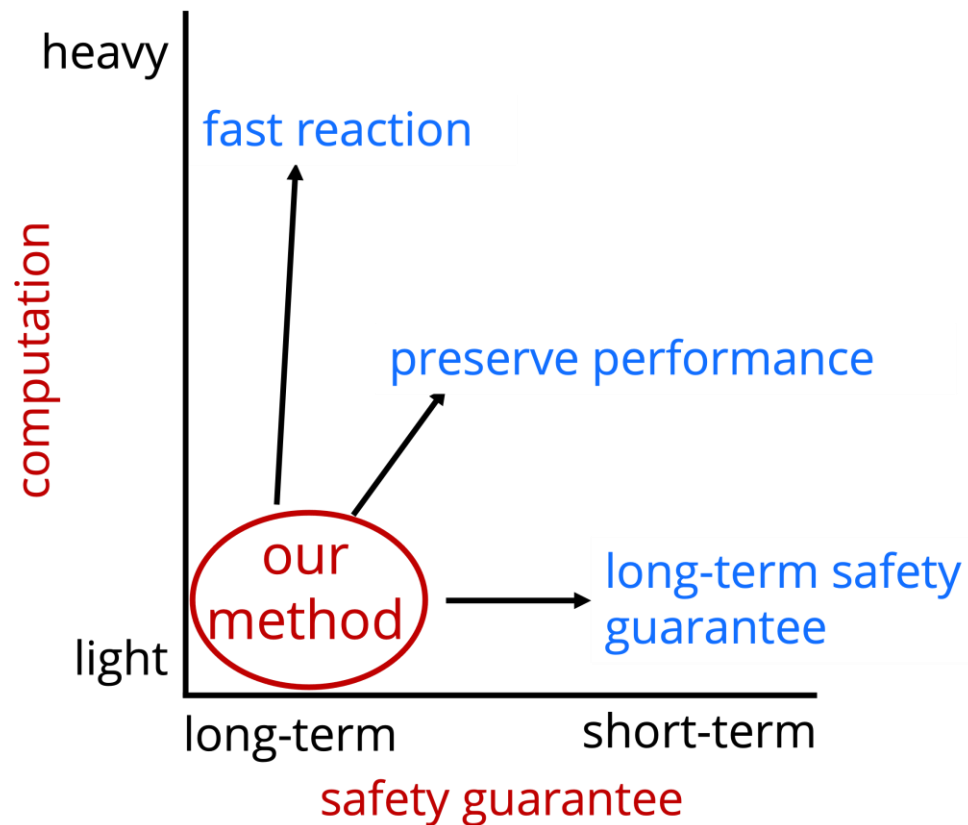
# Simulation – Nonlinear trap

System becomes uncontrollable once reach state  $x = 1.5$





- **Provable long-term safety guarantee**
- **Fast reaction with reduced computation**
- **Controllable safety and performance trade-off**
- **Easy implementation with plug-in usage**



- **Faster and more accurate estimation of safety probability**
- **Compact representation of the safety probability mapping (e.g. DNN)**
- ...

# Thanks for listening!



**Scan for full manuscript on arXiv**

## Application to Autonomous Vehicles

S. Gangadhar, Z. Wang, H. Jing, and Y. Nakahira, "Adaptive Safe Control for Driving in Uncertain Environments," *the 33<sup>rd</sup> IEEE Intelligent Vehicles Symposium (IV)*, 2022.

## Generalization to Distributed Systems

H. Jing, and Y. Nakahira, "Probabilistic safety certificate for multi-agent systems," *submitted to 2022 Control and Decision Conference (CDC)*, 2022.

- [1] Paulson, Joel A., et al. "Stochastic model predictive control with joint chance constraints." *International Journal of Control* 93.1 (2020): 126-139.
- [2] Ahmadi, Mohamadreza, Xiaobin Xiong, and Aaron D. Ames. "Risk-averse control via CVaR barrier functions: Application to bipedal robot locomotion." *IEEE Control Systems Letters* 6 (2021): 878-883.
- [3] Bansal, Somil, et al. "Hamilton-jacobi reachability: A brief overview and recent advances." *2017 IEEE 56th Annual Conference on Decision and Control (CDC)*. IEEE, 2017.
- [4] Oishi, Meeko, et al. "Addressing multiobjective control: Safety and performance through constrained optimization." *International Workshop on Hybrid Systems: Computation and Control*. Springer, Berlin, Heidelberg, 2001.
- [5] Prajna, Stephen, Ali Jadbabaie, and George J. Pappas. "Stochastic safety verification using barrier certificates." *2004 43rd IEEE conference on decision and control (CDC)(IEEE Cat. No. 04CH37601)*. Vol. 1. IEEE, 2004.
- [6] Clark, Andrew. "Control barrier functions for complete and incomplete information stochastic systems." *2019 American Control Conference (ACC)*. IEEE, 2019.

- [7] Luo, Wenhao, Wen Sun, and Ashish Kapoor. "Multi-robot collision avoidance under uncertainty with probabilistic safety barrier certificates." *Advances in Neural Information Processing Systems* 33 (2020): 372-383.
- [8] Wang, Zhuoyuan, et al. "Myopically Verifiable Probabilistic Certificate for Long-term Safety." *arXiv preprint arXiv:2110.13380* (2021).
- [9] Chern, Albert, et al. "Safe Control in the Presence of Stochastic Uncertainties." *arXiv preprint arXiv:2104.01259* (2021).