

# Flipping-based Policy for Chance-Constrained Markov Decision Processes

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# Chance-Constrained MDPs

**Maximize**  
 $\pi \in \Pi$

$$\mathbb{E} \left\{ \sum_{k=0}^{\infty} \gamma^k r(\mathbf{s}_k, \mathbf{a}_k) \mid \mathbf{s}_0 = \mathbf{s} \right\} \quad \mathbf{a}_k \sim \pi(\mathbf{s}_k)$$

**Subject to**

$$\Pr_{\mathbf{s}_0, \infty}^{\pi} \{ \mathbf{s}_{k+i} \in \mathcal{S}, \forall i \in [T] \mid \mathbf{s}_k \in \mathcal{S} \} \geq 1 - \alpha, \quad \forall k$$

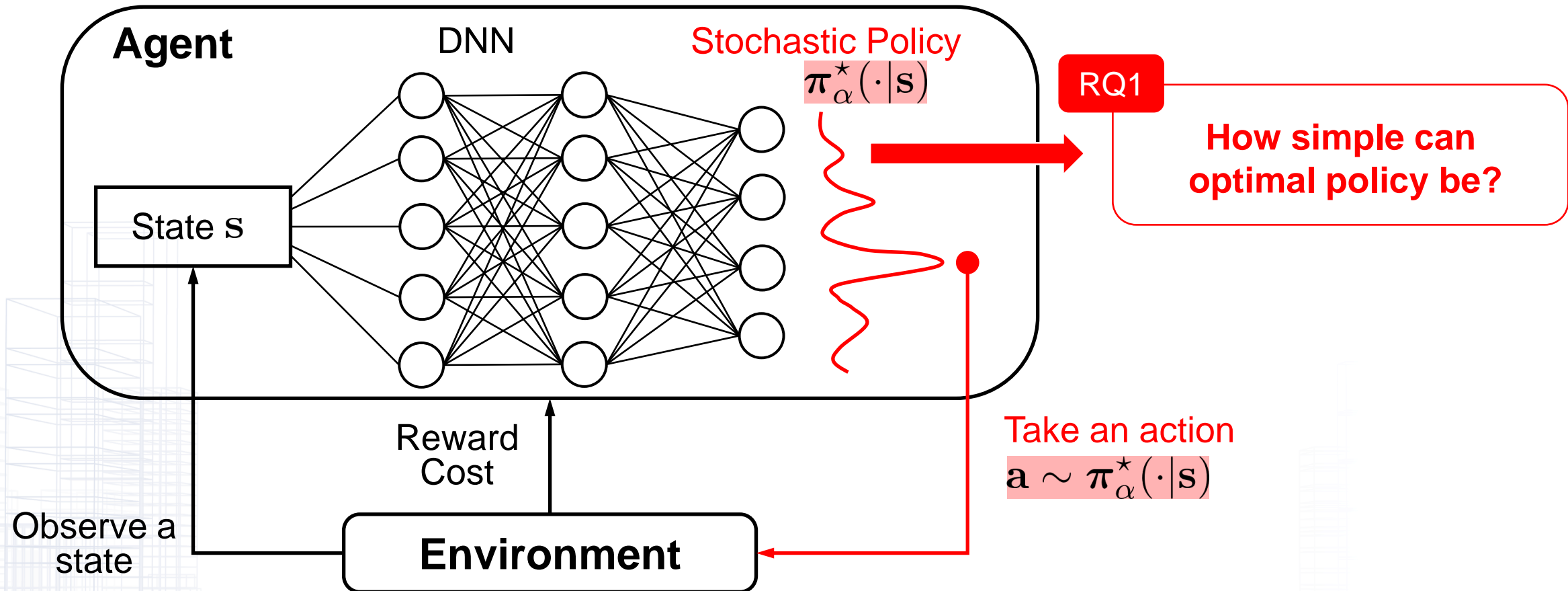


# Research Questions

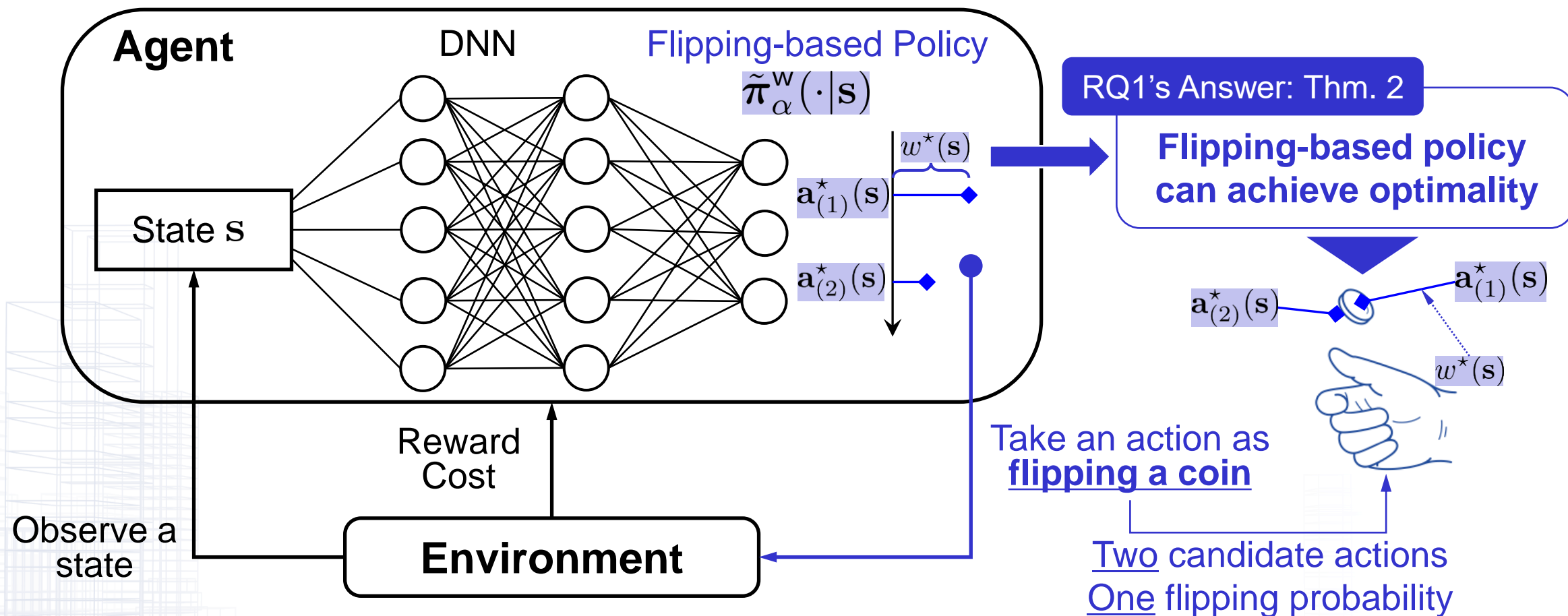
## Regarding the optimal policy for CCMDPs

- RQ1: How can we define and characterize the optimal policy?
- RQ2: How can we use the existing safe RL algorithms to effectively approximate the optimal policy

# Stochastic Policy



# Flipping-based Policy



# Conservative Approximation

Maximize  
 $\pi \in \Pi$

$$\mathbb{E} \left\{ \sum_{k=0}^{\infty} \gamma^k r(\mathbf{s}_k, \mathbf{a}_k) \mid \mathbf{s}_0 = \mathbf{s} \right\} \quad \mathbf{a}_k \sim \pi(\mathbf{s}_k)$$

Intractable

Subject to

$$\Pr_{\mathbf{s}_0, \infty}^{\pi} \{ \mathbf{s}_{k+i} \in \mathcal{S}, \forall i \in [T] \mid \mathbf{s}_k \in \mathcal{S} \} \geq 1 - \alpha, \forall k$$

Joint Chance Constraint

- Conservative Approximation: Thm. 5
- Flipping-based policy can also achieve optimality: Thm. 4

CPO, PCPO,  
CUP, P3O, .....

Subject to

$$\mathbb{E} \left\{ \sum_{i=1}^{\infty} \gamma_{\text{unsafe}}^i \mathbb{I}(\mathbf{s}_{k+i} \notin \mathcal{S}) \mid \mathbf{s}_k \in \mathcal{S} \right\} \leq \alpha, \forall k$$

Expected  
Cumulative  
Safety Constraint

# Train Flipping-based Policy

Step 1. Construct the sample set of risk levels

$$\mathcal{Z}_S = \{\tilde{\alpha}_i\}_{i=1}^S, \quad \tilde{\alpha}_i \sim \mathcal{U}(0, 1)$$

Step 2. Optimize a policy parameter  $\tilde{\theta}_i$ , by solving

$$\max_{\theta \in \Theta} J(\theta) := \mathbb{E}_{\tau_\infty \sim \pi_\theta^d} \{R(\tau_\infty)\} \quad \text{s.t.} \quad F^d(\theta) \leq \tilde{\alpha}_i.$$

$$J(\theta) := \mathbb{E}_{\mathbf{s} \sim \mu_0} \left\{ \mathbb{E}_{\pi_\theta^d} \left\{ \sum_{k=0}^{\infty} \gamma^k r(\mathbf{s}_k, \mathbf{a}_k) \mid \mathbf{s}_0 \right\} \right\} \quad F^d(\theta) := \mathbb{E}_{\mathbf{s} \sim \mu_0} \left\{ \mathbb{E}_{\pi_\theta^d} \left\{ \sum_{i=1}^{\infty} \gamma_{\text{unsafe}}^i \mathbb{I}(\mathbf{s}_{k+i} \notin \mathcal{S}) \mid \mathbf{s}_0 \right\} \right\}$$

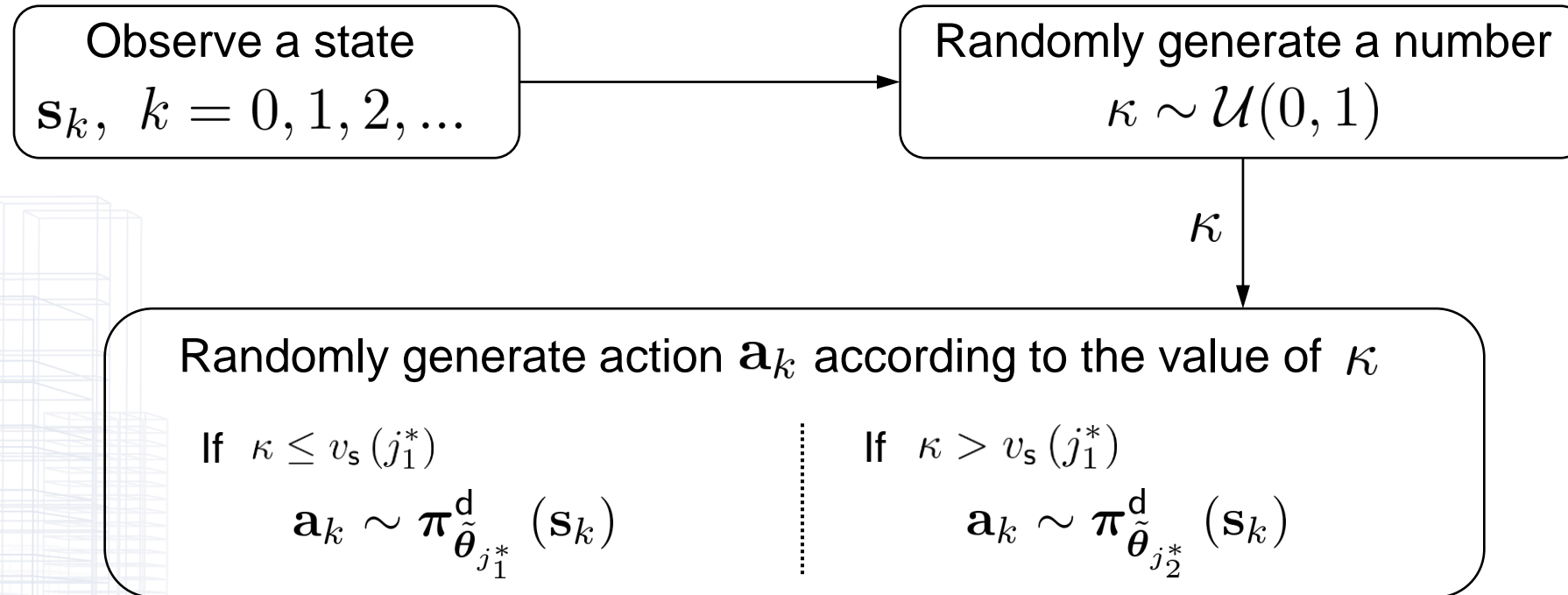
Step 3. Solve a linear program to obtain parameters  $(\nu_s(j_1^*), \nu_s(j_2^*), \tilde{\theta}_{j_1^*}, \tilde{\theta}_{j_2^*})$  for flipping-based policy

$$\max_{\nu_s(1), \dots, \nu_s(S) \in [0, 1]^S} \sum_{i=1}^S J(\tilde{\theta}_i) \nu_s(i) \quad \text{s.t.} \quad \sum_{i=1}^S \nu_s(i) F^d(\tilde{\theta}_i) \geq 1 - \alpha, \quad \sum_{i=1}^S \nu_s(i) = 1.$$

Optimal solution has two non-zero element



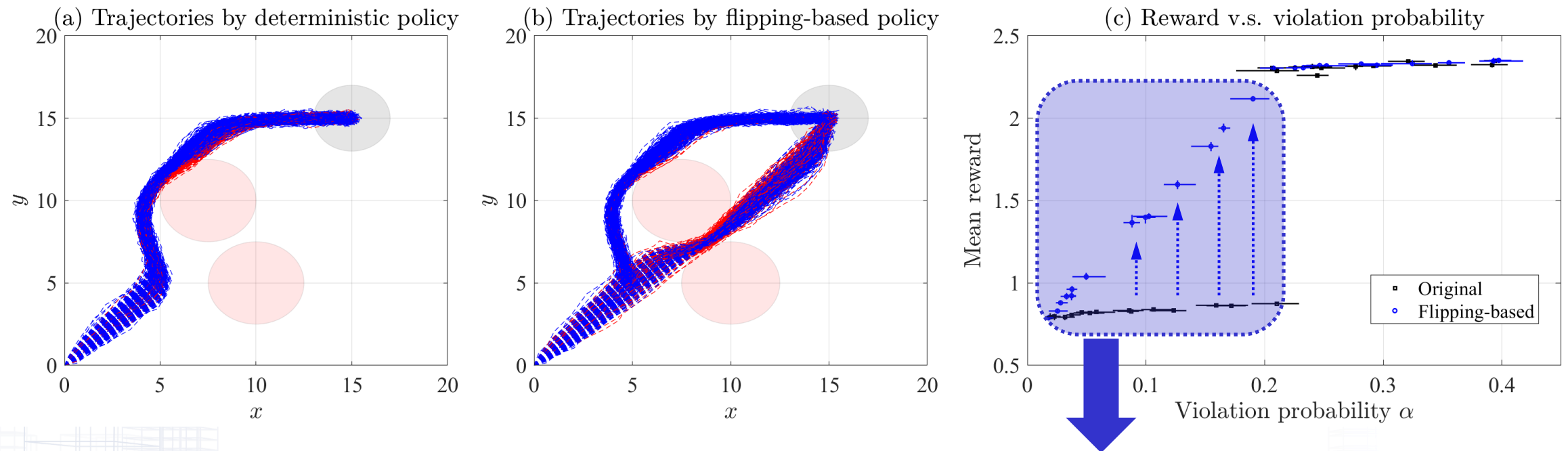
# Implement Flipping-based Policy





# Numerical Example

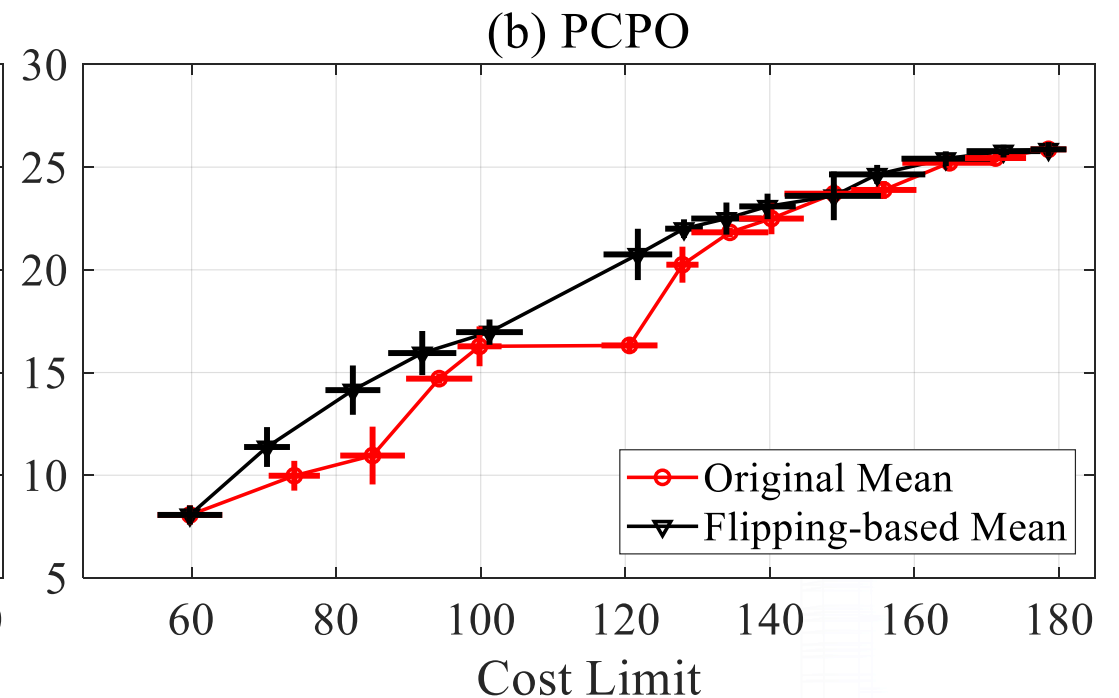
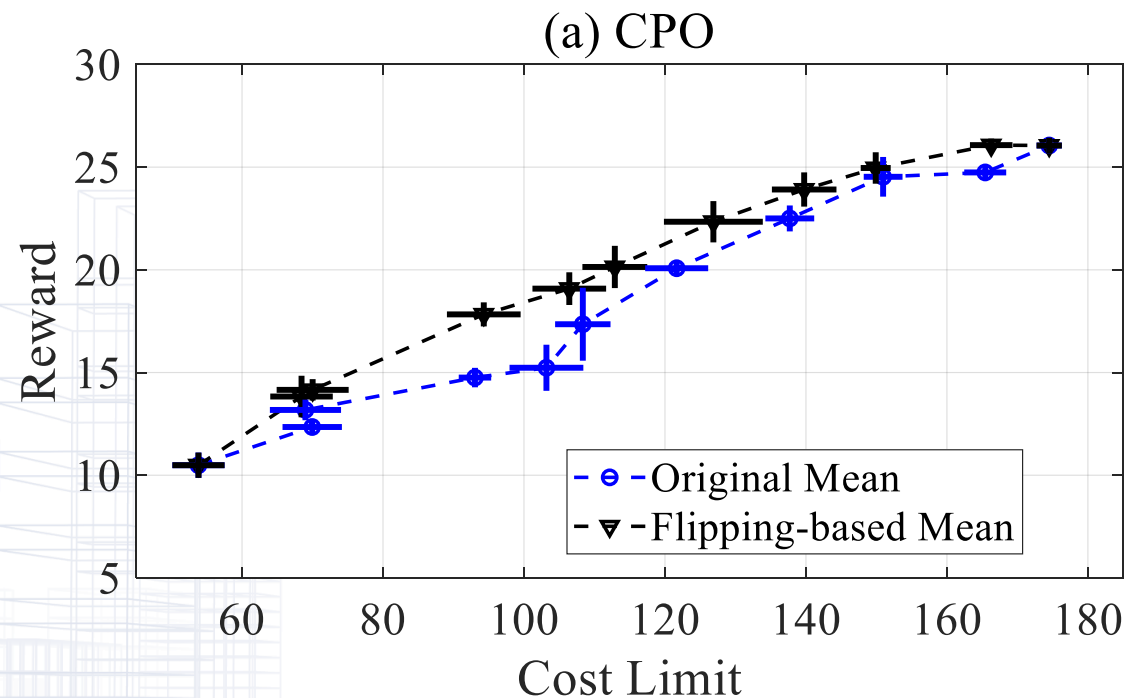
- Intuitive example of trajectory planning and control



Improve average reward through the linear combination of risks

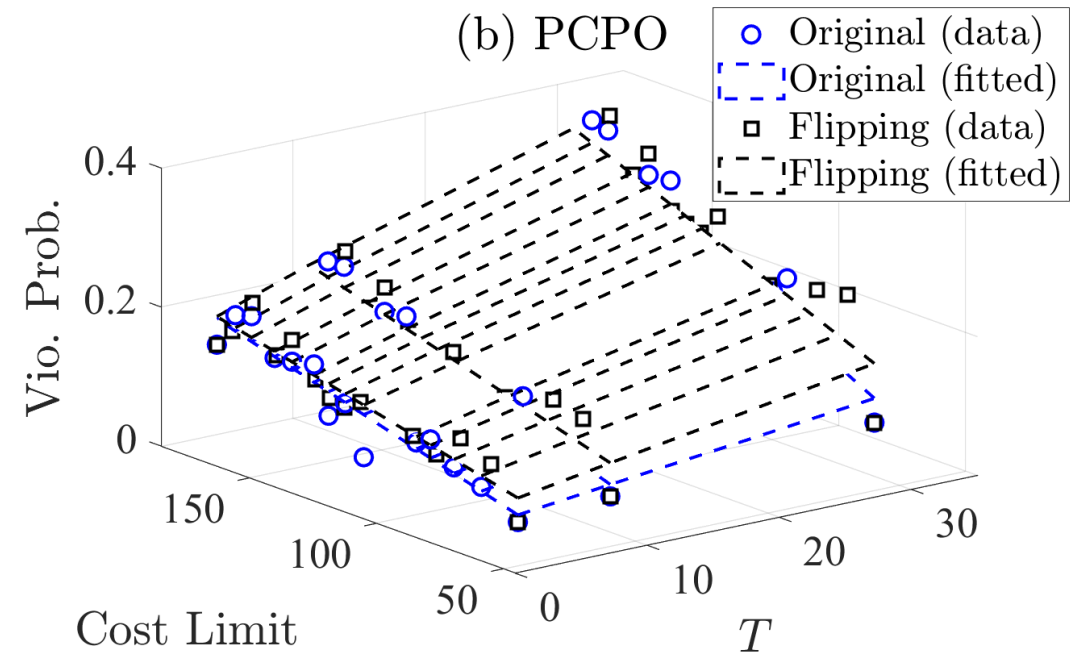
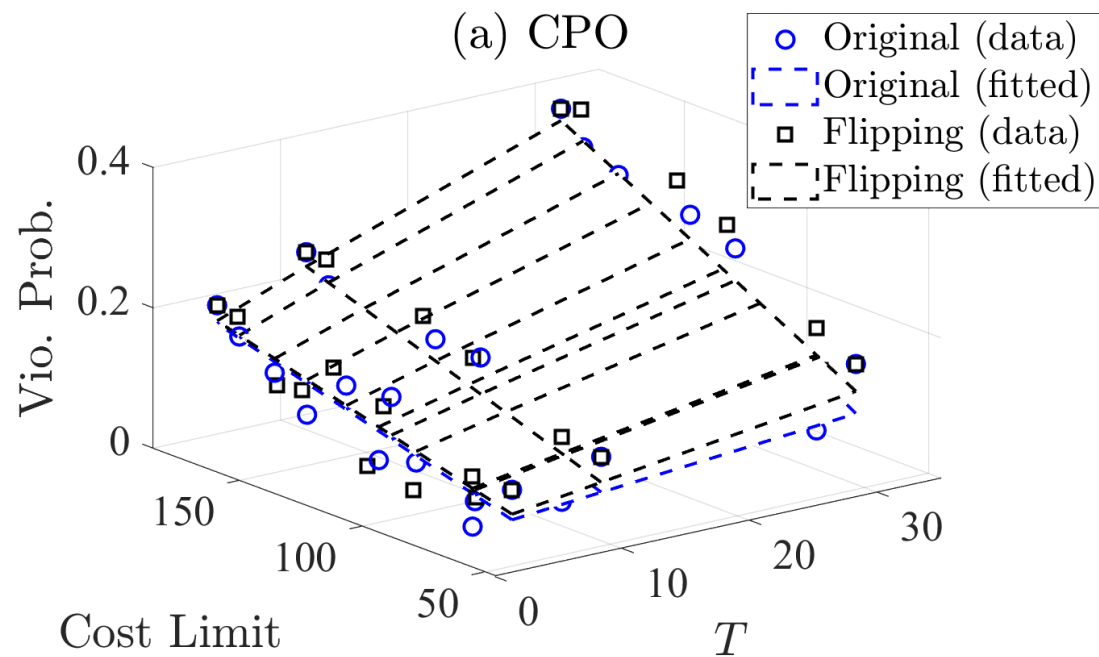
# Experimental Validation

- Enhance existing safe RL algorithms (e.g., CPO, PCPO)
- Increase the expected reward under the required level of risk



# Experimental Validation

- Expected cumulative safety (average cost) v.s. violation probability



**Thanks for your kind attention!**