Last-Iterate Global Convergence of Policy Gradients for Constrained Reinforcement Learning

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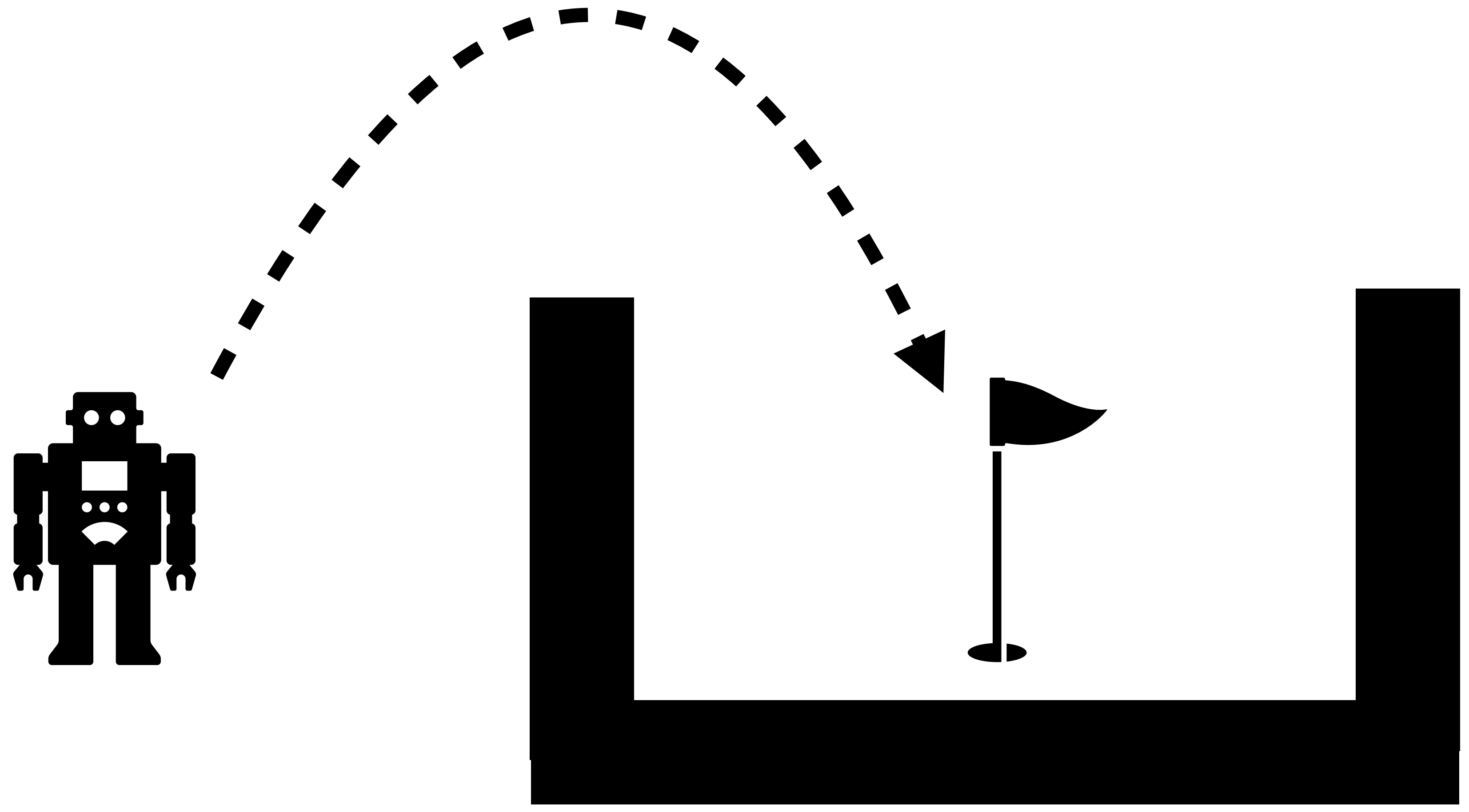
Constrained Reinforcement Learning (CRL)
Introduction

- Real-world scenarios: reach a goal + meet structural/utility-based constraints
- Constrained RL: extension of RL with the possibility to account for constraints



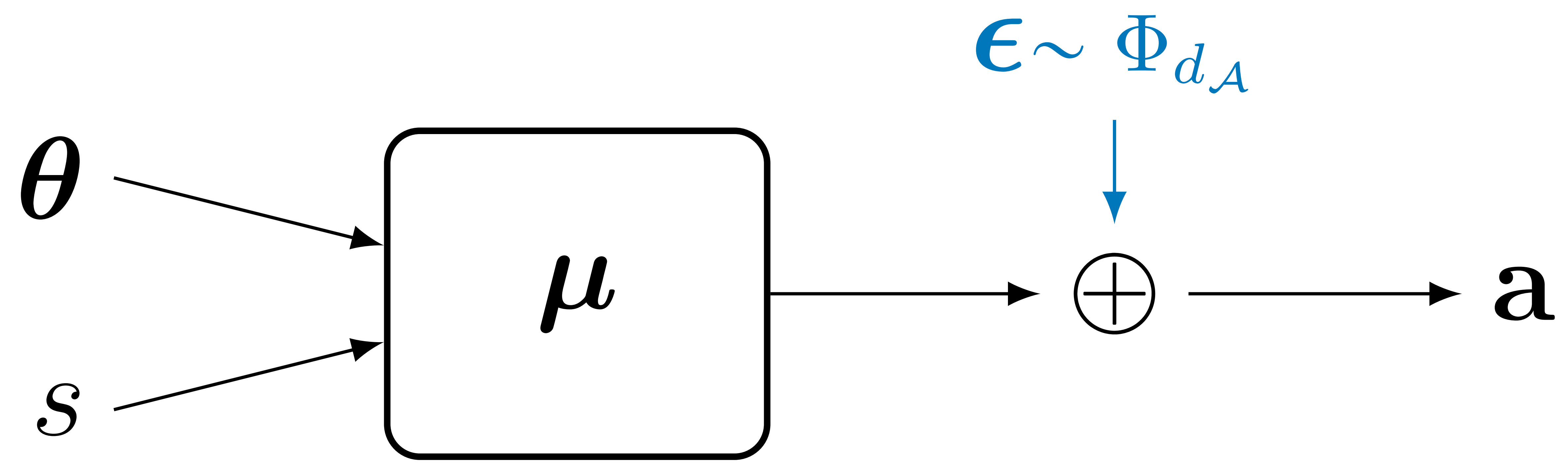
Policy Gradients (PGs) for CRL

Introduction

- Continuous State and Action Spaces
- Robustness to Actuators and Sensors Noise
- Robustness to Partial Observability
- Possibility to incorporate expert-knowledge in the Policy-design Phase

Action-based (AB) Exploration

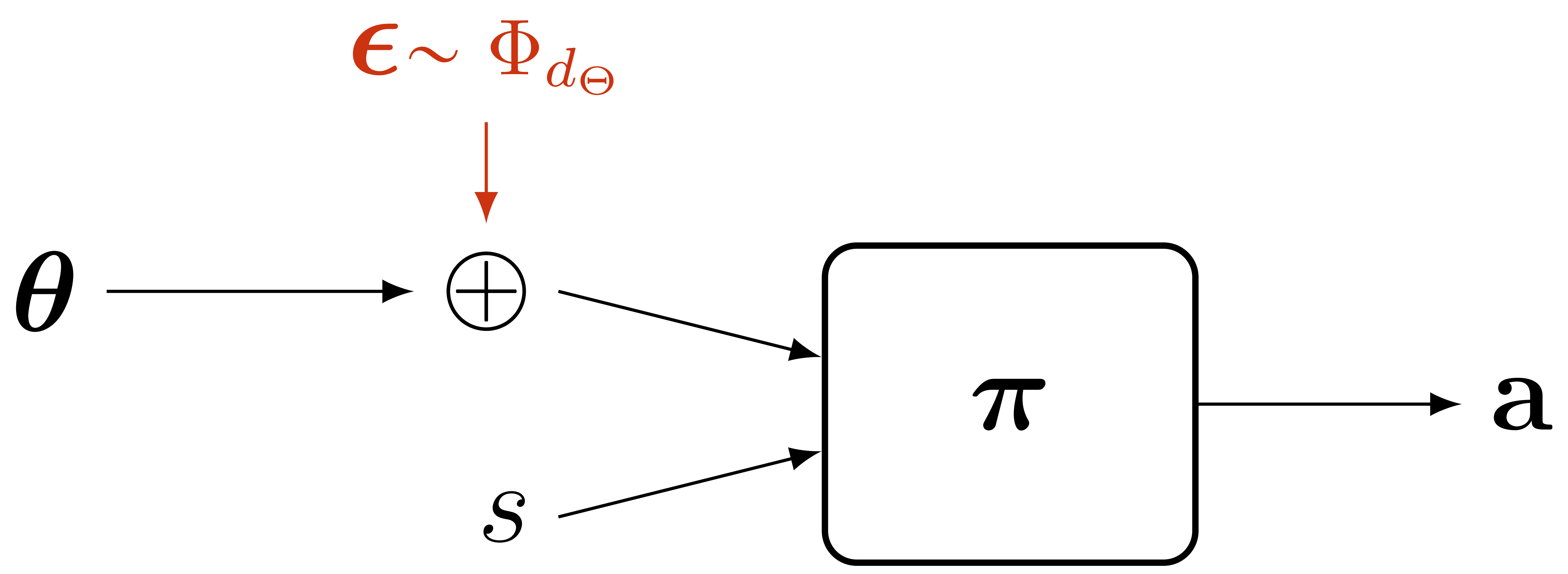
PGs Exploration Approaches



$$J_{\mathrm{A}}(\boldsymbol{\theta}) = \mathbb{E}_{\tau \sim p_{\mathrm{A}}(\cdot|\boldsymbol{\theta})}\left[R(\tau)\right]$$

Parameter-based (PB) Exploration

PGs Exploration Approaches



$$J_{\mathrm{P}}(\boldsymbol{\theta}) = \mathbb{E}_{\boldsymbol{\theta} \sim \nu_{\boldsymbol{\rho}}} \left[\mathbb{E}_{\tau \sim p_{\mathrm{A}}(\cdot|\boldsymbol{\theta})} \left[R(\tau) \right] \right]$$

Constrained Optimization Problem

Setting

- Continuous State and Action spaces
- Multiple constraints on cost functions c_i
- Both exploration paradigms are supported
- Inexact Gradients

Constrained Optimization Problem

Setting

$$\min_{\boldsymbol{v}\in\mathcal{V}} J_{\dagger,0}(\boldsymbol{v}) \quad \text{s.t.} \quad J_{\dagger,i}(\boldsymbol{v}) \leqslant b_i, \quad \forall i \in [\![U]\!]$$

Constrained Optimization Problem

Setting

$$\min_{\boldsymbol{v}\in\mathcal{V}} \boxed{J_{\dagger,0}(\boldsymbol{v})} \quad \text{s.t.} \quad \boxed{J_{\dagger,i}(\boldsymbol{v})} \leqslant b_i, \quad \forall i \in [\![U]\!]$$

AB or PB approaches on costs c_i with $i \in \{0,1,\ldots,U\}$

Constrained Optimization Problem

Setting

$$\min_{\boldsymbol{v}\in\mathcal{V}} J_{\dagger,0}(\boldsymbol{v}) \quad \text{s.t.} \quad J_{\dagger,i}(\boldsymbol{v}) \leqslant \boxed{b_i,} \quad \forall i \in [\![U]\!]$$

i-th threshold

C-PG

Exploration-Agnostic Algorithm

Algorithm

Projected Alternate Ascent Descent on the ω-Regularized Lagrangian w.r.t. the Dual Variable

$$\downarrow \widehat{\nabla}_v \mathscr{L}_\omega(v, \lambda) \qquad \uparrow \widehat{\nabla}_\lambda \mathscr{L}_\omega(v, \lambda)$$

C-PG: Convergence

Exploration-Agnostic Algorithm

Assumptions:

1. ψ-Gradient Domination on parameterization ($\psi \in [1,2]$)
2. Regularity of $\mathscr{L}_\omega$
3. Existence of a saddle point

C-PG: Convergence

Exploration-Agnostic Algorithm

Theorem

$$\mathbb{E}[J_0(\boldsymbol{v}_k) - J_0(\boldsymbol{v}_0^*)] \leqslant \epsilon + \frac{\beta_1}{\alpha_1} + \frac{\omega}{2}\|\boldsymbol{\lambda}_0^*\|_2^2 \quad \text{and} \quad \mathbb{E}[(J_i(\boldsymbol{v}_k) - b_i)^+] \leqslant 4\epsilon + 4\frac{\beta_1}{\alpha_1} + \omega\|\boldsymbol{\lambda}_0^*\|_2 \ , \ \forall i \in [\![U]\!]$$

Holds for both exploration approaches

C-PG: Convergence

Exploration-Agnostic Algorithm

	$\boxed{\psi = 1}$	$\boxed{\psi = 2}$
Exact Gradients	$\mathcal{O}(\epsilon^{-2})$	$\mathcal{O}(\epsilon^{-1}\log(\epsilon^{-1}))$
Estimated Gradients	$\mathcal{O}(\epsilon^{-6}\log(\epsilon^{-1}))$	$\mathcal{O}(\epsilon^{-4}\log(\epsilon^{-1}))$

Enforcing Constraints on Risks

Risk and Exploration Agnostic Algorithms

- AB and PB explorations have a **semantic difference** when enforcing constraints
- In order to induce safer behaviors, we can enforce **constraints on risk** measures
- We introduce a **unified risk measure** that extends the framework previously described
- **Additional parameter** to learn required

Conclusions

Our Contribution

- **Framework** to handle CRL with PGs (both AB and PB) in continuous spaces and with multiple constraints
- Both approaches exhibit **last-iterate global convergence** to a feasible (hyper)policy guarantees
- We extend the framework to handle **risk-based constraints**
- We **numerically** validate our results

Thank you!