Optimistic Policy Optimization via Multiple Importance Sampling

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Lorenzo Lupo Marcello Restelli

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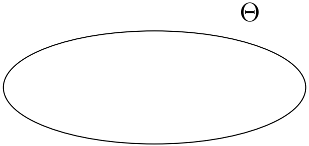
Policy Optimization



- **Parameter space** $\Theta \subseteq \mathbb{R}^d$
- A parametric **policy** for each $\boldsymbol{\theta} \in \Theta$
- Each inducing a distribution $p_{\boldsymbol{\theta}}$ over **trajectories**
- A **return** $R(\tau)$ for every trajectory τ
- **Goal:** $\max_{\boldsymbol{\theta} \in \Theta} J(\boldsymbol{\theta}) = \mathbb{E}_{\tau \sim p_{\boldsymbol{\theta}}}[R(\tau)]$
- Iterative optimization (e.g., gradient ascent)

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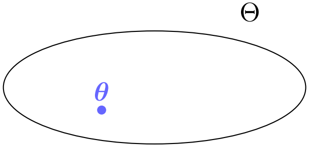

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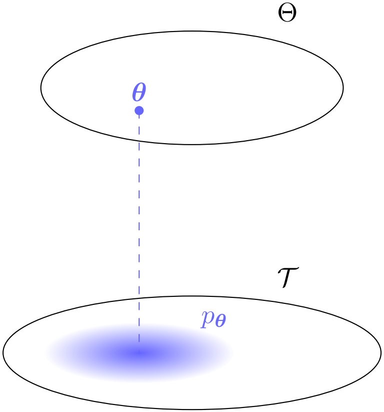

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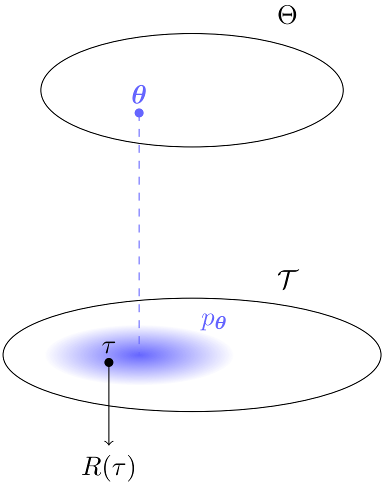

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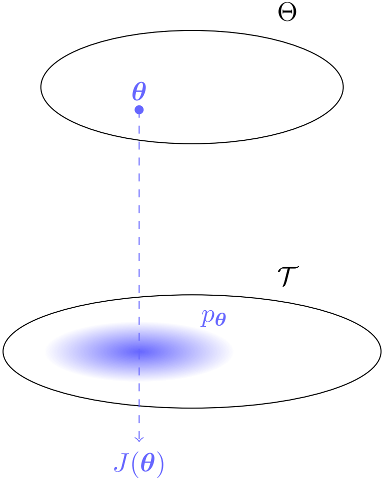

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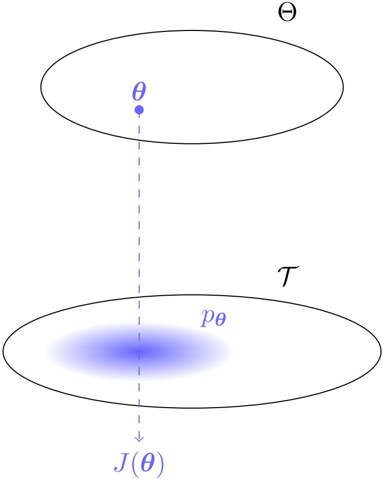

Exploration in Policy Optimization

- **Exploration-exploitation** trade-off
- The underlying Markov process is often **continuous**
- **Undirected** exploration: entropy bonus [3]
- **Directed** exploration: pseudo-counts [1]

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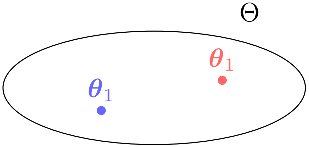
Lack of theoretical guarantees

Policy Optimization as a MAB



- **Arms:** parameters $\boldsymbol{\theta}$
- **Payoff:** expected return $J(\boldsymbol{\theta})$
- **Continuous MAB** [4]: we *need* structure
- **Arm correlation** [6] through trajectory distributions

Policy Optimization as a Correlated MAB

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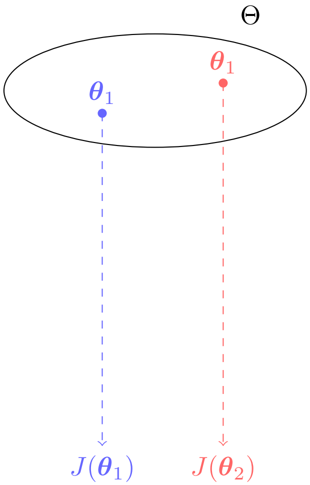

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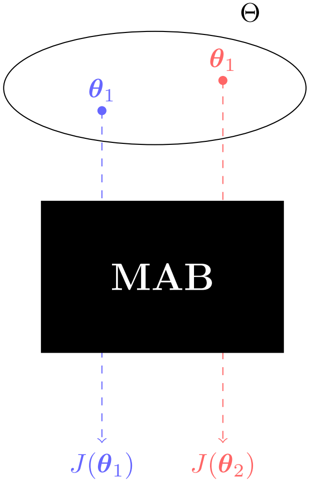

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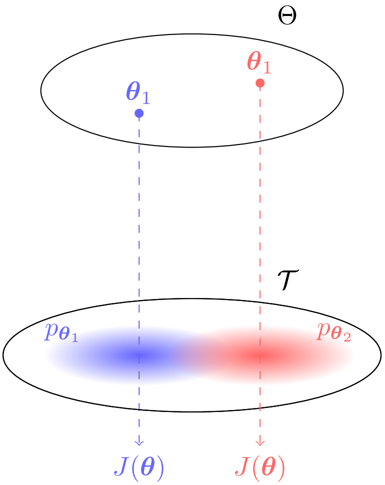
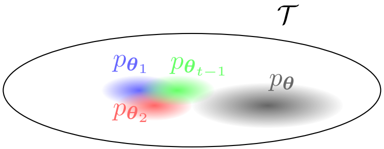


OPTIMIST

- A **UCB-like** index [5]:

$$B_t(\boldsymbol{\theta}) = \underbrace{\check{J}_t(\boldsymbol{\theta})}_{\textbf{ESTIMATE}}$$

a **truncated** **multiple**
importance sampling estimator [8, 2]



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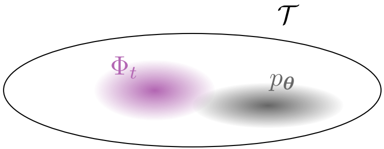
distributional distance from previous solutions



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- Select $\boldsymbol{\theta}_t = \arg\max_{\boldsymbol{\theta}\in\Theta} B_t(\boldsymbol{\theta})$

Sublinear Regret

- $Regret(T) = \sum_{t=0}^{T} J(\boldsymbol{\theta}^*) - J(\boldsymbol{\theta}_t)$

- **Compact**, d-dimensional parameter space Θ

- Under **mild assumptions** on the policy class, with high probability:

$$Regret(T) = \widetilde{\mathcal{O}}\left(\sqrt{dT}\right)$$

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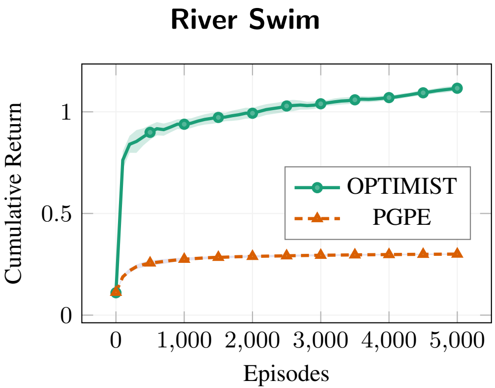
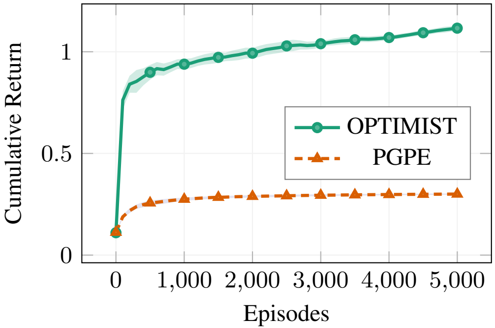
Empirical Results



Empirical Results

River Swim



Caveats

- Easy implementation only for parameter-based exploration [7]
- Difficult optimization $\Longrightarrow$ discretization
- ...

Thank You for Your Attention!

Poster **#103**

Code: `github.com/WolfLo/optimist`

Contact: matteo.papini@polimi.it

Web page: `t3p.github.io/icml19`

References

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