



POLITECNICO
MILANO 1863

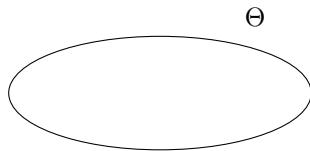
Optimistic Policy Optimization via Multiple Importance Sampling

Matteo Papini Alberto Maria Metelli
Lorenzo Lupo Marcello Restelli

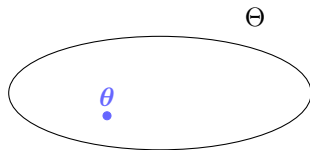
11th June 2019

Thirty-sixth International Conference on Machine Learning, Long Beach, CA, USA

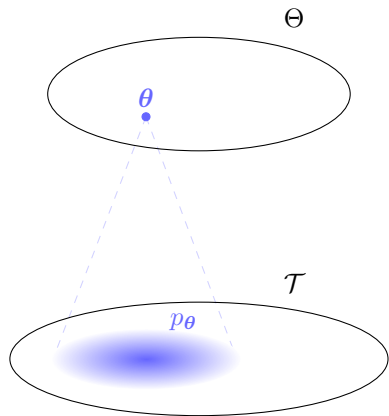
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- A parametric **policy** for each $\theta \in \Theta$
- Each inducing a distribution p_θ over **trajectories**
- A **return** $R(\tau)$ for every trajectory τ
- **Goal:** $\max_{\theta \in \Theta} J(\theta) = \mathbb{E}_{\tau \sim p_\theta} [R(\tau)]$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



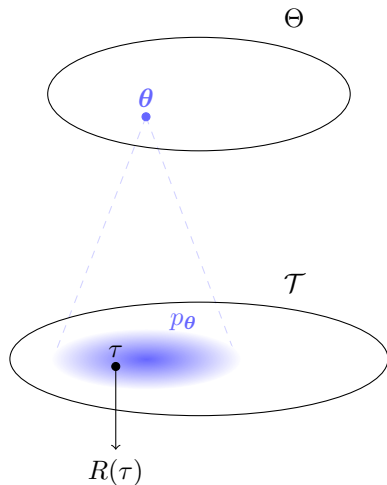
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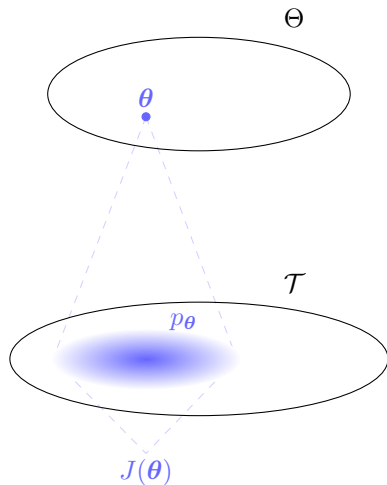
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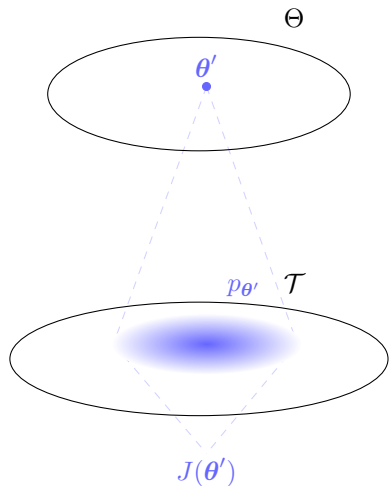
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- Policy gradient methods tend to be **greedy** (e.g., TRPO [6], PGPE [7])
- Mainly **undirected** (e.g., entropy bonus [2])
- **Lack of theoretical guarantees**

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If only this were a Multi-Armed Bandit...

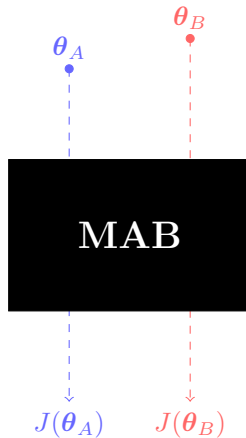
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If only this were a **Correlated Multi-Armed Bandit...**

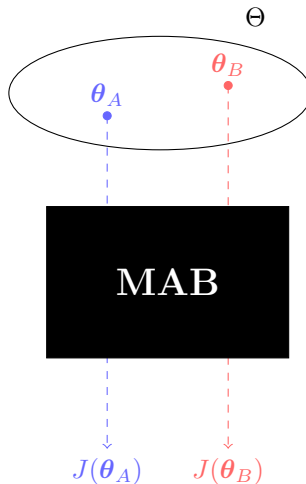
- **Arms:** parameters θ
- **Payoff:** expected return $J(\theta)$
- **Continuous MAB** [3]: we *need* structure
- **Arm correlation** [5] through trajectory distributions
- **Importance Sampling (IS)**



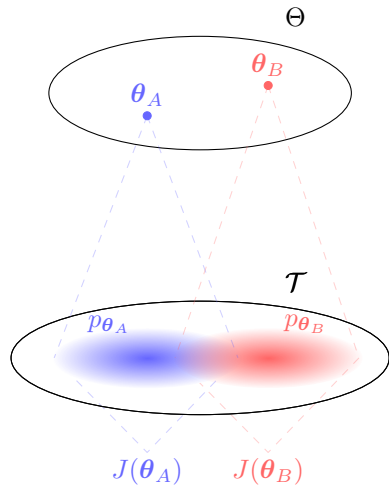
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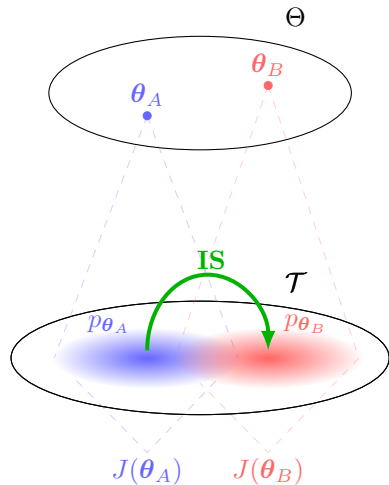
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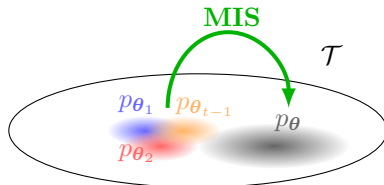
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- A **UCB-like** index [4]:

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

a **truncated multiple**
importance sampling estimator [8, 1]

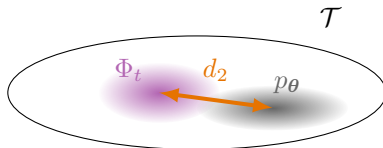


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$$B_t(\theta) = \underbrace{\check{J}_t(\theta)}_{\text{ESTIMATE}} + \underbrace{C \sqrt{\frac{d_2(p_\theta \| \Phi_t) \log \frac{1}{\delta_t}}{t}}}_{\text{EXPLORATION BONUS:}}$$

a **truncated multiple** importance sampling estimator [8, 1]

distributional distance from previous solutions



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

- $Regret(T) = \sum_{t=0}^T J(\boldsymbol{\theta}^*) - J(\boldsymbol{\theta}_t)$
- **Compact**, d -dimensional parameter space Θ
- Under **mild assumptions** on the policy class, with high probability:

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

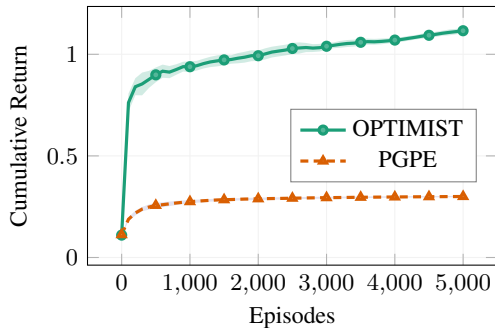
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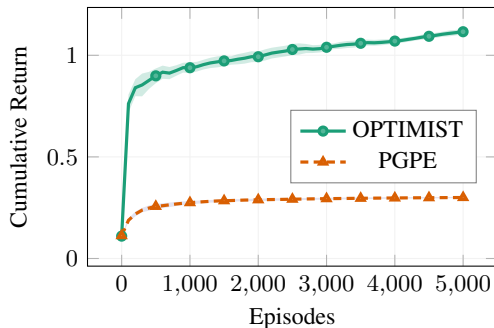
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River Swim



River Swim



Caveats

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

Thank You for Your Attention!

Poster **#103**

Code: github.com/WolfLo/optimist

Contact: matteo.papini@polimi.it

Web page: t3p.github.io/icml19



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