Optimistic Policy Optimization via Multiple Importance Sampling

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Multi Armed Bandits

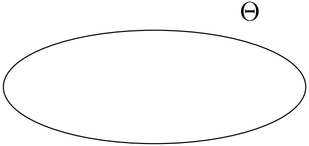
Per collegarsi al tema del workshop e menzionare directed exploration

Reinforcement Learning

Schema RL, policy, traiettoria, return

Policy Optimization

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



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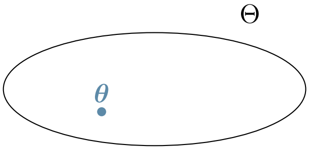

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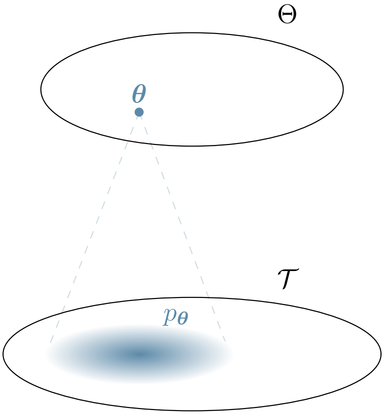

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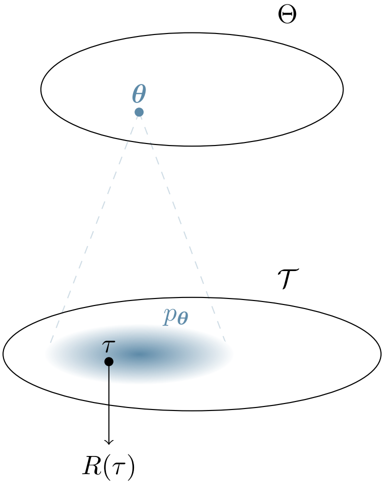

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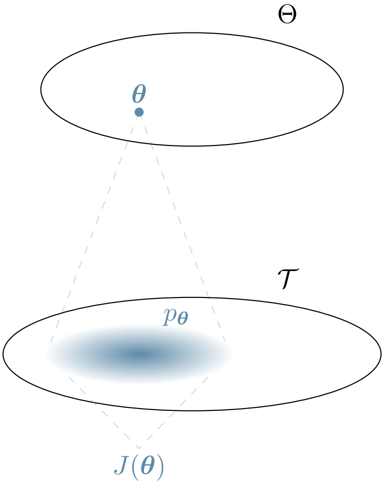

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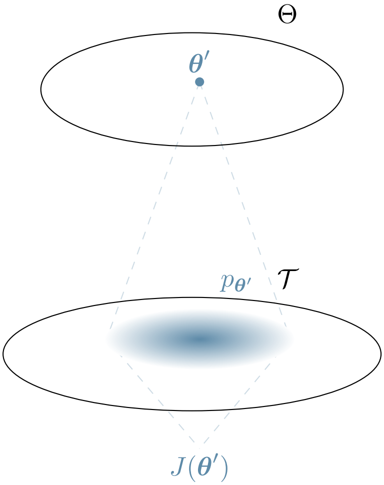

Policy Gradient Methods

Common algorithms, greediness

Exploration in Policy Optimization

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

Add more

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

Policy Optimization as a MAB

- **Arms:** parameters $\boldsymbol{\theta}$
- **Payoff:** expected return $J(\boldsymbol{\theta})$
- **Continuous MAB** [3]: we *need* structure

More on continuous MAB

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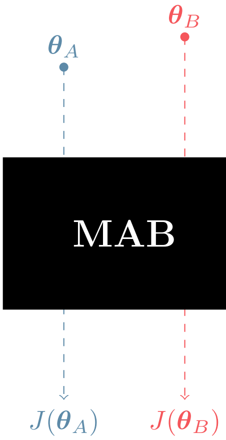

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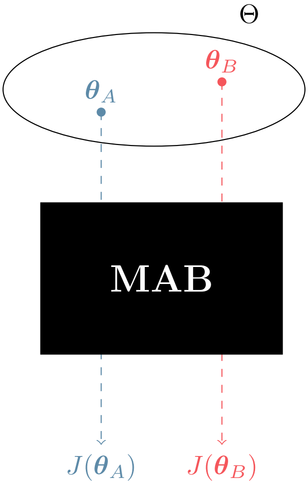

Correlated MAB

Just the idea

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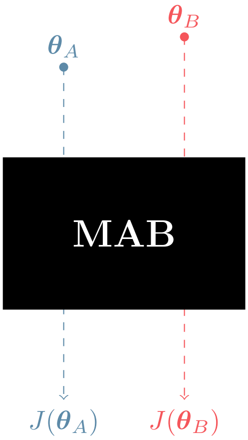

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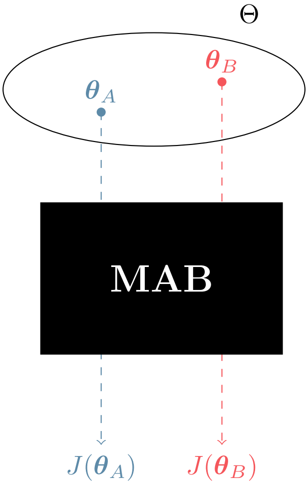

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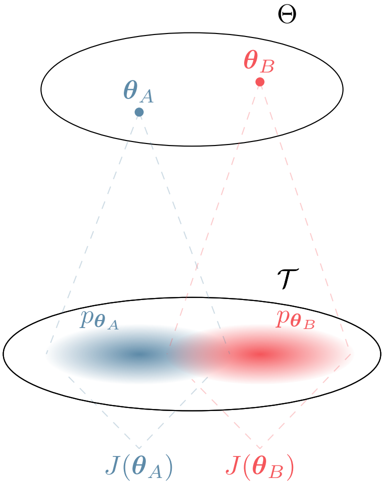

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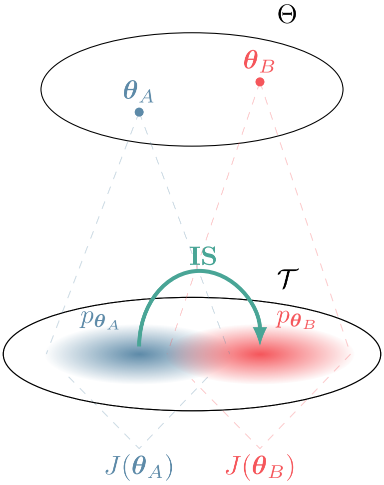


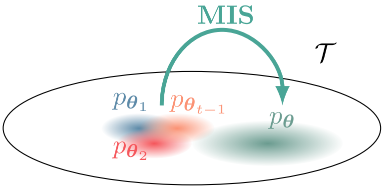
Essential pseudocode (UCB)

The OPTIMIST index

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

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

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



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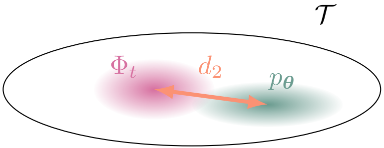
a **robust multiple** importance sampling estimator [8, 1]

distributional distance from previous solutions



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

distributional distance from previous solutions

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

Robust Multiple Importance Sampling Estimator

why MIS, heavy tails, truncation

Exploration Bonus

Variance bound, mixture, more insight on d_2

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

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

Add proof idea

Sublinear Regret

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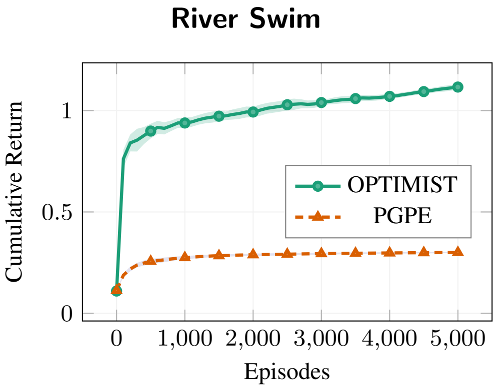
Optimist in Practice

Parameter-based exploration, discretization, further regret bounds

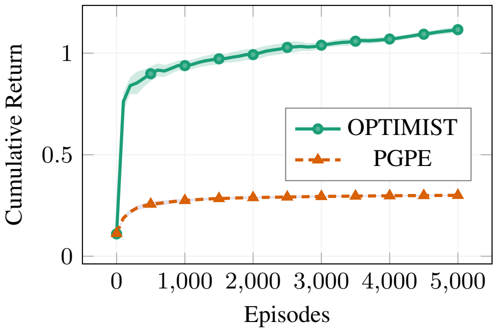
Empirical Results



Remove caveats, add another experiment

Empirical Results

River Swim



Remove caveats, add another experiment

Caveats

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

Future Work

Future

The Abstract Problem

maybe?

Thank You for Your Attention!

Papini, Matteo, Alberto Maria Metelli, Lorenzo Lupo, and Marcello Restelli. ”Optimistic Policy Optimization via Multiple Importance Sampling.” In International Conference on Machine Learning, pp. 4989-4999. 2019.

Code: `github.com/WolfLo/optimist`

Contact: matteo.papini@polimi.it

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

References

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[2] Haarnoja, T., Zhou, A., Abbeel, P., and Levine, S. (2018). Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. In *Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018*, pages 1856–1865.

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