Optimistic Policy Optimization via Multiple Importance Sampling

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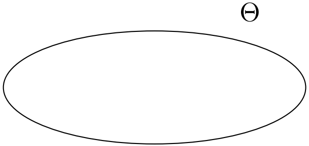
11th June 2019
Thirty-sixth International Conference on Machine Learning, Long Beach, CA, USA

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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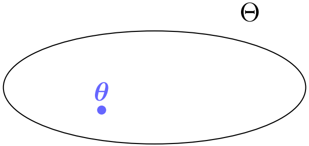

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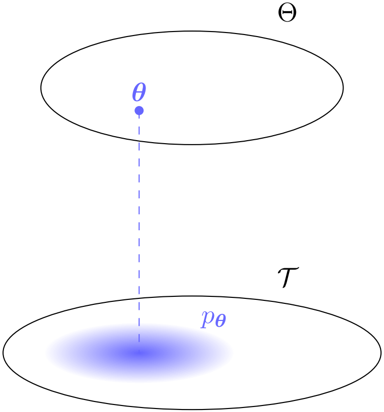

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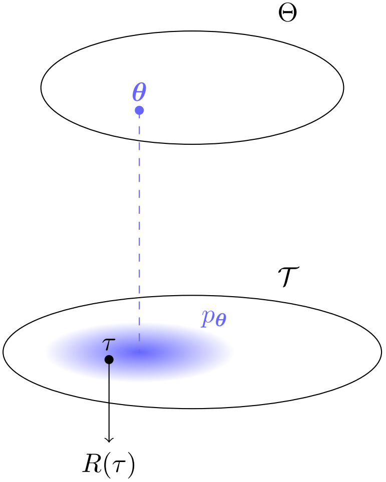

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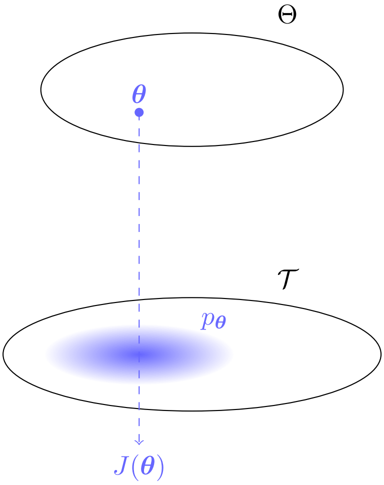

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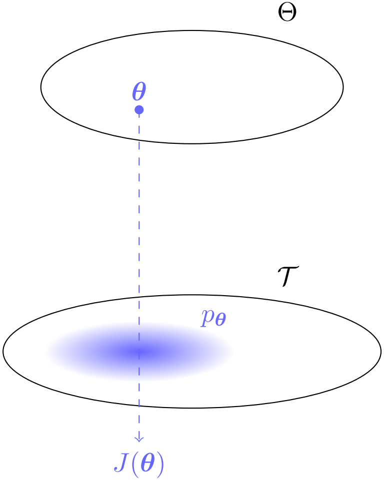


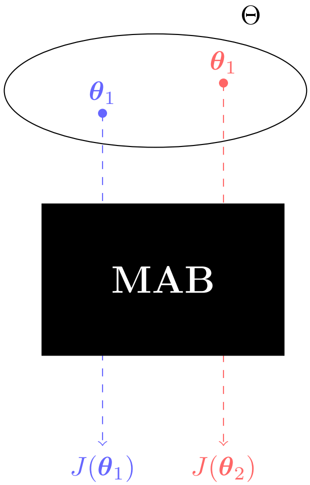
Exploration in Policy Optimization

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

Lack of theoretical guarantees

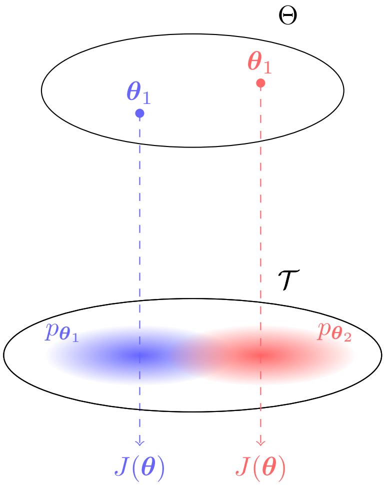
Policy Optimization as a MAB

- **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

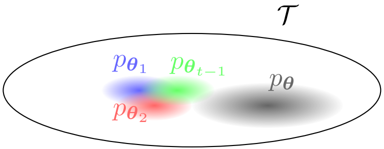
- **Arms:** parameters $\boldsymbol{\theta}$
- **Payoff:** expected return $J(\boldsymbol{\theta})$
- **Continuous MAB** [4]
- **Arm correlation** [6] through trajectory distributions



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

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

a **truncated** **multiple**
importance sampling estimator [7, 2]



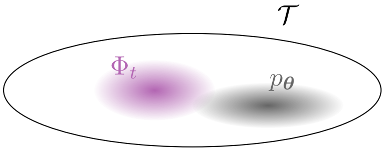
OPTIMIST

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

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

a **truncated** **multiple** importance sampling estimator [7, 2]

distributional distance from previous solutions



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ESTIMATE: a **truncated multiple** importance sampling estimator [7, 2]

EXPLORATION BONUS: **distributional** distance from previous solutions

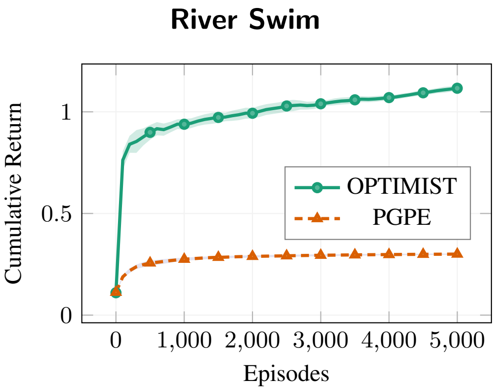
- Select $\boldsymbol{\theta}_t = \arg\max_{\boldsymbol{\theta}\in\Theta} B_t(\boldsymbol{\theta})$

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:

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

Empirical Results



Caveats

- Easy implementation only for parameter-based exploration
- 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

[1] Bellemare, M., Srinivasan, S., Ostrovski, G., Schaul, T., Saxton, D., and Munos, R. (2016). Unifying count-based exploration and intrinsic motivation. In *Advances in Neural Information Processing Systems*, pages 1471–1479.

[2] Bubeck, S., Cesa-Bianchi, N., and Lugosi, G. (2013). Bandits with heavy tail. *IEEE Transactions on Information Theory*, 59(11):7711–7717.

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[4] Kleinberg, R., Slivkins, A., and Upfal, E. (2013). Bandits and experts in metric spaces. *arXiv preprint arXiv:1312.1277*.

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[6] Pandey, S., Chakrabarti, D., and Agarwal, D. (2007). Multi-armed bandit problems with dependent arms. In *Proceedings of the 24th international conference on Machine learning*, pages 721–728. ACM.

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