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Exploration in Policy Search by Multiple Importance Sampling

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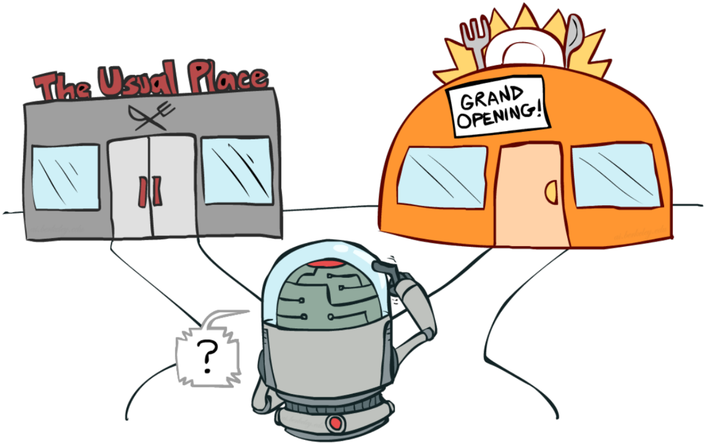
Exploration VS Exploitation



Reinforcement Learning Applications

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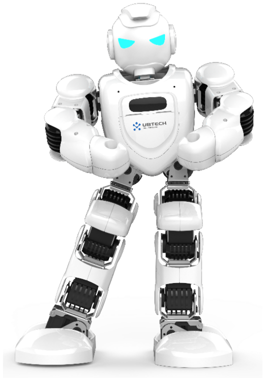


Plan

1. Basics of Reinforcement Learning
2. Exploration in Policy Search
3. Problem Formalization
4. OPTIMIST
5. Experiments
6. Conclusions

The Reinforcement Learning Framework

The Reinforcement Learning Framework

Environment

$\mathcal{P}, \mathcal{R}$

The Reinforcement Learning Framework

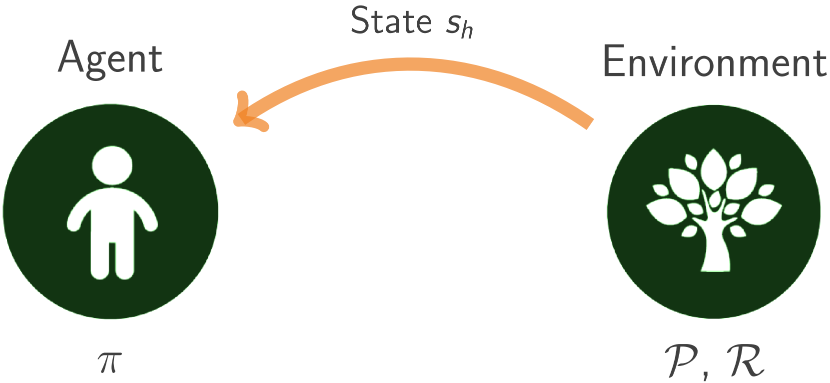
Agent

π

Environment

$\mathcal{P}$, $\mathcal{R}$

The Reinforcement Learning Framework



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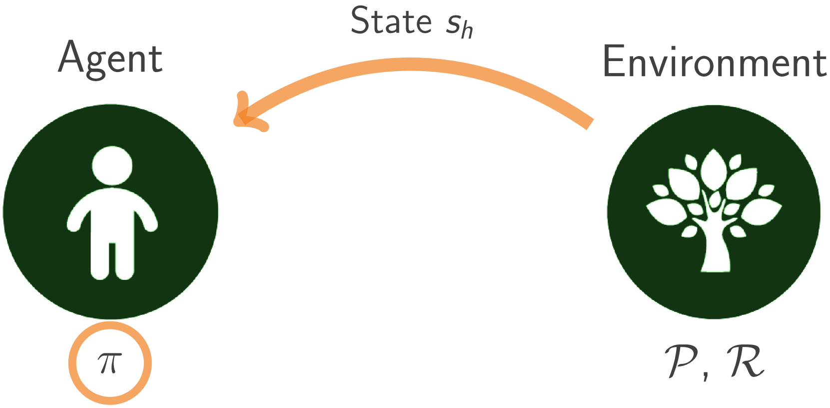

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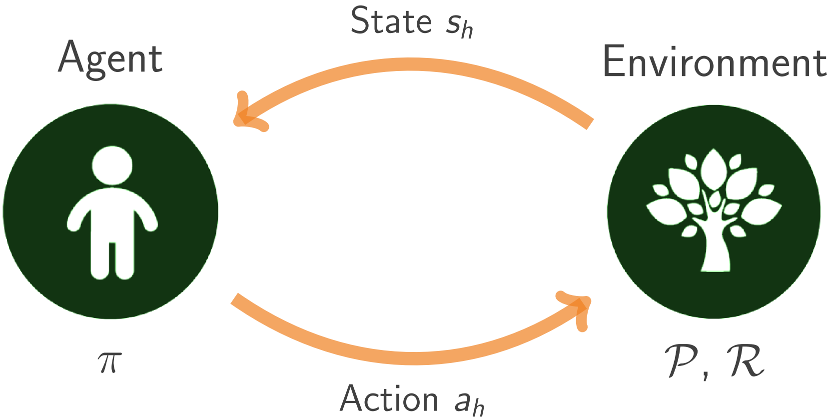

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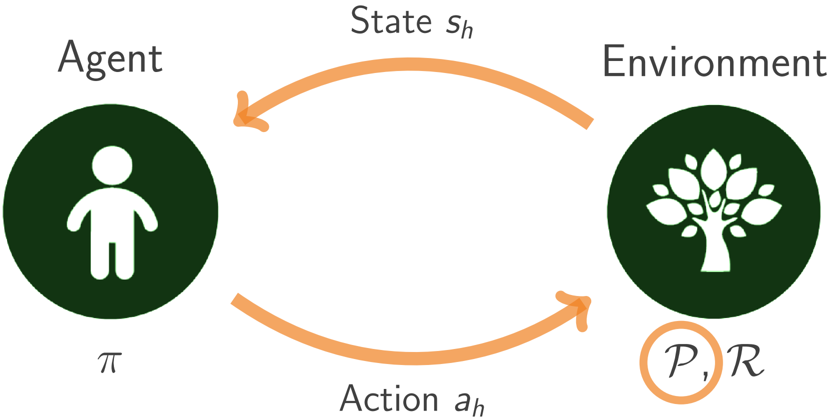

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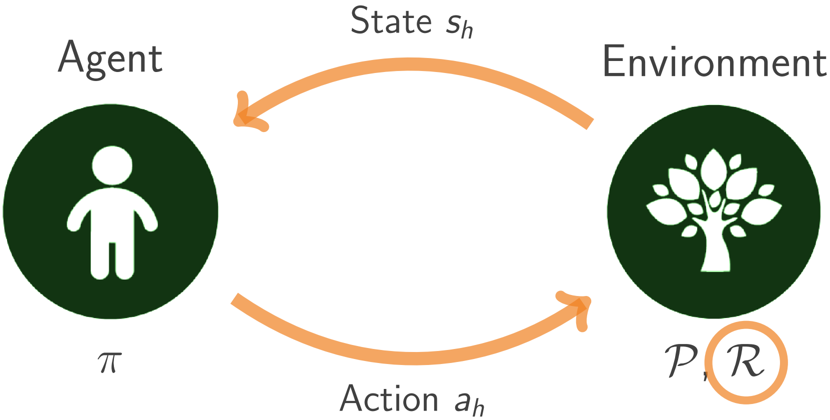

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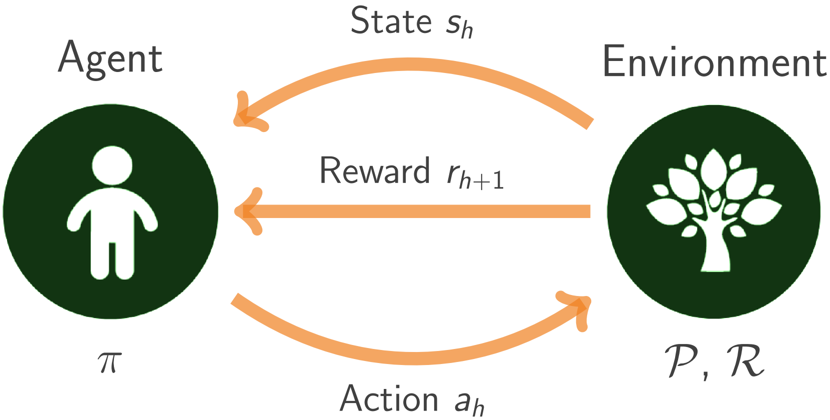

Policy Search Formulation

Cumulative return of a trajectory τ:

$$\mathcal{R}(\tau) = \sum_{h=0}^{H-1} \gamma^h r_{h+1}, \text{ with } \tau = [s_0, a_0, s_1, a_1, \ldots, s_{H-1}, a_{H-1}]$$

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Parametric policy:

$$\pi_{\boldsymbol{\theta}} : \mathcal{S} \to \Delta(\mathcal{A}), \text{ i.e., } \pi_{\boldsymbol{\theta}}(a|s) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{1}{2} \left(\frac{a - \boldsymbol{\theta}^T \phi(s)}{\sigma} \right)^2 \right)$$

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Performance:

$\mu(\boldsymbol{\theta}) = \underset{\tau \sim p_{\boldsymbol{\theta}}}{\mathbb{E}} [\mathcal{R}(\tau)]$, where $p_{\boldsymbol{\theta}}$ is the **distribution over trajectories** $\tau \in \mathcal{T}$ induced by $\pi_{\boldsymbol{\theta}}$

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Objective:

$$\boldsymbol{\theta}^* = \arg\max_{\boldsymbol{\theta} \in \Theta} \mu(\boldsymbol{\theta}).$$

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Undirected exploration

Generate actions based on randomness, without any knowledge of the learning process.

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Leverage on the knowledge acquired during learning.

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- Count-based techniques.

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The parameter space $\Theta \subseteq \mathbb{R}^d$.

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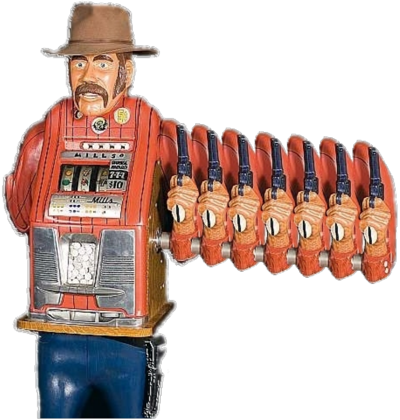
Goal

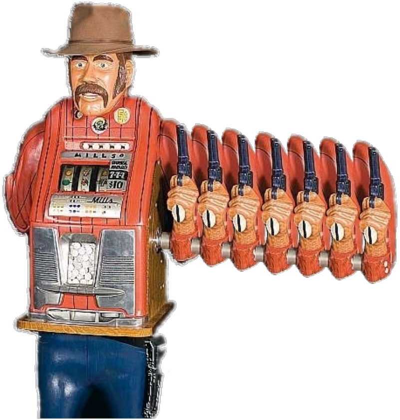
Minimize $Regret(T) = \sum_{t=0}^{T} \mu(\boldsymbol{\theta}^*) - \mu(\boldsymbol{\theta}_t)$, where $\boldsymbol{\theta}^* = \arg\max_{\boldsymbol{\theta} \in \Theta} \mu(\boldsymbol{\theta})$

Problem Formulation



Multi Armed Bandits

Problem Formulation



Multi Armed Bandits

- Simpler framework;

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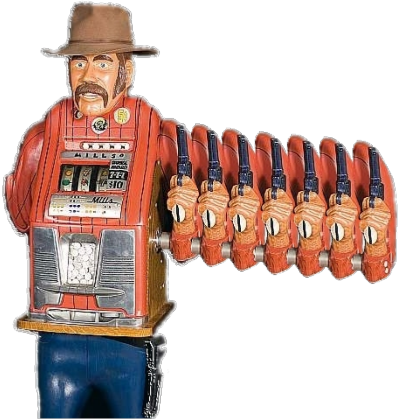

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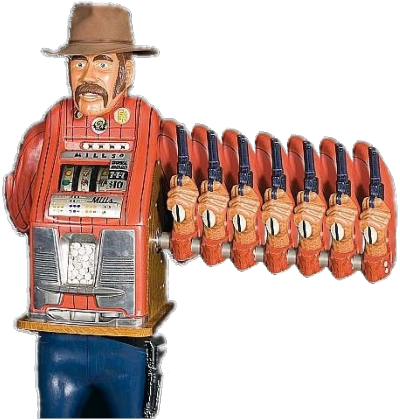

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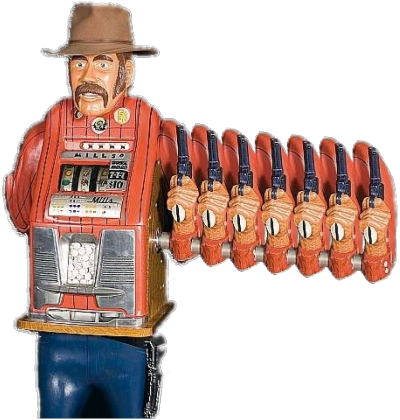

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- Simpler framework;
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Desideratum

sub-linear $Regret(T) \Leftrightarrow \lim_{T \to \infty} Regret(T)/T = 0$

E.g. $Regret(T) = \mathcal{O}(\log T)$

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Algorithm 1 OPTIMIST

1: **Input:** initial parameters $\boldsymbol{\theta}_0$, confidence schedule $(\delta_t)_{t=1}^T$, order $\epsilon \in (0, 1]$

Discrete Decision Set

Algorithm 2 OPTIMIST

1: **Input:** initial parameters $\boldsymbol{\theta}_0$, confidence schedule $(\delta_t)_{t=1}^T$, order $\epsilon \in (0, 1]$
2: Draw trajectory $\tau_0 \sim p_{\boldsymbol{\theta}_0}$ and observe return $\mathcal{R}(\tau_0)$

Discrete Decision Set

Algorithm 3 OPTIMIST

1: **Input:** initial parameters $\boldsymbol{\theta}_0$, confidence schedule $(\delta_t)_{t=1}^{T}$, order $\epsilon \in (0, 1]$
2: Draw trajectory $\tau_0 \sim p_{\boldsymbol{\theta}_0}$ and observe return $\mathcal{R}(\tau_0)$
3: **for** $t = 1, \ldots, T$ **do**

Discrete Decision Set

Algorithm 4 OPTIMIST

1: **Input:** initial parameters $\boldsymbol{\theta}_0$, confidence schedule $(\delta_t)_{t=1}^{T}$, order $\epsilon \in (0, 1]$
2: Draw trajectory $\tau_0 \sim p_{\boldsymbol{\theta}_0}$ and observe return $\mathcal{R}(\tau_0)$
3: **for** $t = 1, \ldots, T$ **do**
4: Select arm $\boldsymbol{\theta}_t = \arg\max_{\boldsymbol{\theta} \in \Theta} B_t^{\epsilon}(\boldsymbol{\theta}, \delta_t)$

Discrete Decision Set

Algorithm 5 OPTIMIST

1: **Input:** initial parameters $\boldsymbol{\theta}_0$, confidence schedule $(\delta_t)_{t=1}^{T}$, order $\epsilon \in (0, 1]$
2: Draw trajectory $\tau_0 \sim p_{\boldsymbol{\theta}_0}$ and observe return $\mathcal{R}(\tau_0)$
3: **for** $t = 1, \dots, T$ **do**
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5: Draw trajectory $\tau_t \sim p_{\boldsymbol{\theta}_t}$ and observe return $\mathcal{R}(\tau_t)$
6: **end for**

Discrete Decision Set

Algorithm 6 OPTIMIST

Input: initial parameters $\boldsymbol{\theta}_0$, confidence schedule $(\delta_t)_{t=1}^T$, order $\epsilon \in (0, 1]$
Draw trajectory $\tau_0 \sim p_{\boldsymbol{\theta}_0}$ and observe return $\mathcal{R}(\tau_0)$
for $t = 1, \dots, T$ **do**
    Select arm $\boldsymbol{\theta}_t = \arg\max_{\boldsymbol{\theta} \in \Theta} B_t^{\epsilon}(\boldsymbol{\theta}, \delta_t)$
    Draw trajectory $\tau_t \sim p_{\boldsymbol{\theta}_t}$ and observe return $\mathcal{R}(\tau_t)$
end for

$$\mu(\boldsymbol{\theta}) \leqslant B_t^{\epsilon}(\boldsymbol{\theta}, \delta_t) \;=\; \check{\mu}_t^{MIS}(\boldsymbol{\theta}) \;+\; \|f\|_{\infty} \left(\sqrt{2} + \frac{4}{3}\right) \left(\frac{d_{1+\epsilon}(p_{\boldsymbol{\theta}_t} \| \Phi_t) \;\; \log \frac{1}{\delta_t}}{t} \right)^{\frac{\epsilon}{1+\epsilon}}$$

Discrete Decision Set

Algorithm 7 OPTIMIST

Input: initial parameters $\boldsymbol{\theta}_0$, confidence schedule $(\delta_t)_{t=1}^T$, order $\epsilon \in (0,1]$
Draw trajectory $\tau_0 \sim p_{\boldsymbol{\theta}_0}$ and observe return $\mathcal{R}(\tau_0)$
for $t = 1, \dots, T$ **do**
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    Draw trajectory $\tau_t \sim p_{\boldsymbol{\theta}_t}$ and observe return $\mathcal{R}(\tau_t)$
end for

Upper Confidence Bound

$$\boxed{\mu(\boldsymbol{\theta}) \leqslant B_t^{\epsilon}(\boldsymbol{\theta}, \delta_t)} = \check{\mu}_t^{MIS}(\boldsymbol{\theta}) + \|f\|_\infty \left(\sqrt{2} + \frac{4}{3}\right) \left(\frac{d_{1+\epsilon}(p_{\boldsymbol{\theta}_t} \| \Phi_t) \ \log \frac{1}{\delta_t}}{t}\right)^{\frac{\epsilon}{1+\epsilon}}$$

Discrete Decision Set

Algorithm 8 OPTIMIST

1: **Input:** initial parameters $\boldsymbol{\theta}_0$, confidence schedule $(\delta_t)_{t=1}^{T}$, order $\epsilon \in (0, 1]$
2: Draw trajectory $\tau_0 \sim p_{\boldsymbol{\theta}_0}$ and observe return $\mathcal{R}(\tau_0)$
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6: **end for**

Truncated Multiple Importance Sampling Estimator

$$\mu(\boldsymbol{\theta}) \leqslant B_t^{\epsilon}(\boldsymbol{\theta}, \delta_t) = \boxed{\check{\mu}_t^{MIS}(\boldsymbol{\theta})} + \|f\|_{\infty} \left(\sqrt{2} + \frac{4}{3}\right) \left(\frac{d_{1+\epsilon}(p_{\boldsymbol{\theta}_t} \| \Phi_t) \ \log \frac{1}{\delta_t}}{t} \right)^{\frac{\epsilon}{1+\epsilon}}$$

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Algorithm 9 OPTIMIST

1: **Input:** initial parameters $\boldsymbol{\theta}_0$, confidence schedule $(\delta_t)_{t=1}^T$, order $\epsilon \in (0, 1]$
2: Draw trajectory $\tau_0 \sim p_{\boldsymbol{\theta}_0}$ and observe return $\mathcal{R}(\tau_0)$
3: **for** $t = 1, \dots, T$ **do**
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6: **end for**

Exploration Bonus

$$\mu(\boldsymbol{\theta}) \leqslant B_t^{\epsilon}(\boldsymbol{\theta}, \delta_t) = \check{\mu}_t^{MIS}(\boldsymbol{\theta}) + \boxed{\|f\|_\infty \left(\sqrt{2} + \frac{4}{3}\right) \left(\frac{d_{1+\epsilon}(p_{\boldsymbol{\theta}_t} \| \Phi_t) \ \log \frac{1}{\delta_t}}{t} \right)^{\frac{\epsilon}{1+\epsilon}}}$$

Discrete Decision Set

Algorithm 10 OPTIMIST

Input: initial parameters $\boldsymbol{\theta}_0$, confidence schedule $(\delta_t)_{t=1}^T$, order $\epsilon \in (0, 1]$
Draw trajectory $\tau_0 \sim p_{\boldsymbol{\theta}_0}$ and observe return $\mathcal{R}(\tau_0)$
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Continuous Decision Set

Algorithm 11 OPTIMIST2

Input: initial arm $\boldsymbol{\theta}_0$, confidence schedule $(\delta_t)_{t=1}^{T}$, discretization schedule $(\nu_t)_{t=1}^{T}$, order $\epsilon \in (0, 1]$

Draw sample $\nu_0 \sim p_{\boldsymbol{\theta}_0}$ and observe return $f(\tau_0)$

for $t = 1, \dots, T$ **do**

    Discretize Θ with a uniform grid $\widetilde{\Theta}_t$ of ν_t^d points

    Select arm $\boldsymbol{\theta}_t = \arg\max_{\boldsymbol{\theta} \in \widetilde{\Theta}_t} B_t^{\epsilon}(\boldsymbol{\theta}, \delta_t)$

    Draw sample $\tau_t \sim p_{\boldsymbol{\theta}_t}$ and observe return $\mathcal{R}(\tau_t)$

end for

Continuous Decision Set

Algorithm 12 OPTIMIST2

Input: initial arm $\boldsymbol{\theta}_0$, confidence schedule $(\delta_t)_{t=1}^T$, $\boxed{\text{discretization schedule } (\nu_t)_{t=1}^T}$, order $\epsilon \in (0, 1]$
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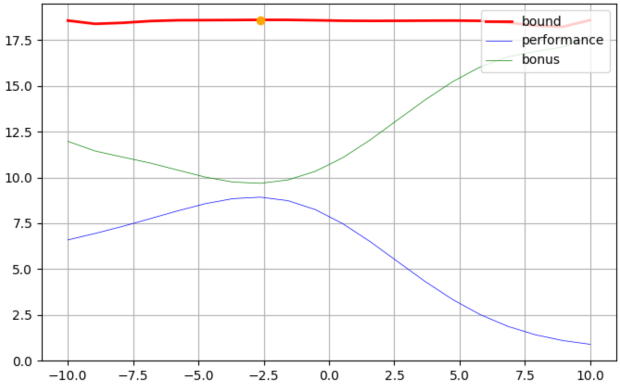
The Upper Confidence Bound



Regret Analysis

Theorem (1)

*Let $\mathcal{X}$ be a discrete arm set with $|\mathcal{X}| = K \in \mathbb{N}_+$. Under Assumption (**??**), Algorithm 1 with confidence schedule $\delta_t = \dfrac{3\delta}{t^2\pi^2 K}$ guarantees, with probability at least $1 - \delta$:*

$$\mathit{Regret}(T) \leqslant \Delta_0 + CT^{\frac{1}{1+\epsilon}} \left[v_\epsilon \left(2 \log T + \log \frac{\pi^2 K}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}},$$

where $C = (1+\epsilon)\left(2\sqrt{2} + \dfrac{5}{3}\right) \|f\|_\infty$, and Δ_0 is the instantaneous regret of the initial arm $\boldsymbol{x}_0$.

This yields a $\mathcal{O}(\sqrt{T \log T})$ regret when $\epsilon = 1$.

Regret Analysis

Theorem (2)

*Let $\mathcal{X}$ be a d-dimensional compact arm set with $\mathcal{X} \subseteq [-D, D]^d$. For any $\kappa \geqslant 2$, under Assumptions (**??**) and (**??**), Algorithm 11 with confidence schedule*

$\delta_t = \dfrac{6\delta}{\pi^2 t^2 \left(1 + \lceil t^{1/\kappa} \rceil^d\right)}$ *and discretization schedule* $\tau_t = \lceil t^{\frac{1}{\kappa}} \rceil$ *guarantees, with probability at least* $1 - \delta$*:*

$$\text{Regret}(T) \leqslant \Delta_0 + C_1 T^{\left(1-\frac{1}{\kappa}\right)} d + C_2 T^{\frac{1}{1+\epsilon}} \cdot \left[v_\epsilon \left((2 + {d}/{\kappa}) \log T + d \log 2 + \log \frac{\pi^2}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}},$$

where $C_1 = \dfrac{\kappa}{\kappa - 1} LD$, $C_2 = (1+\epsilon)\left(2\sqrt{2} + \dfrac{5}{3}\right) \|f\|_\infty$, *and* Δ_0 *is the instantaneous regret of the initial arm* $\boldsymbol{x}_0$.

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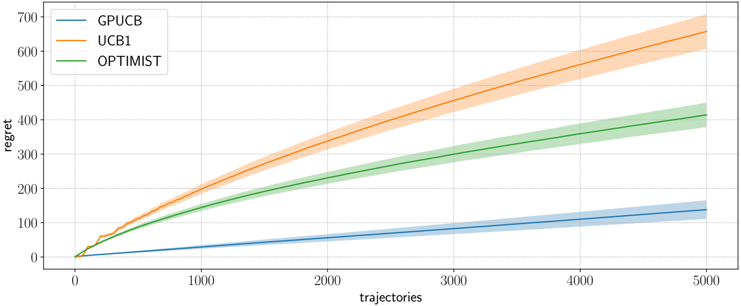
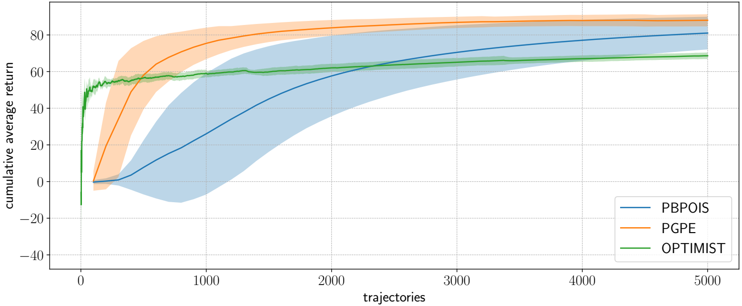
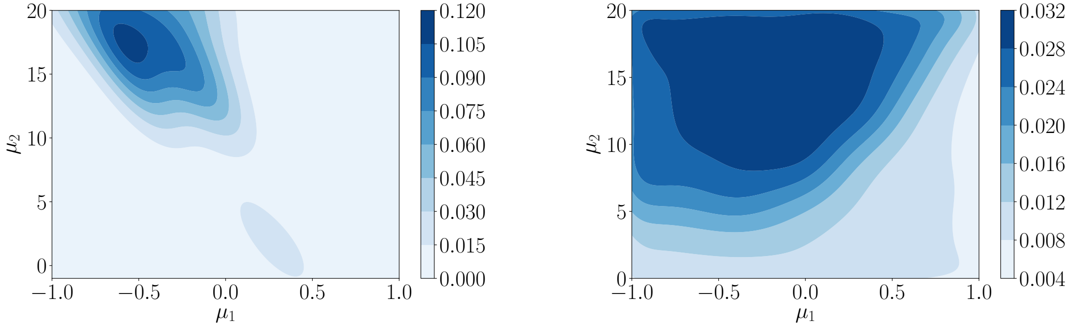
Linear Quadratic Gaussian Regulator



Mountain Car - Performance



Mountain Car - Exploration



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Original Contributions

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Paper submission at **ICML2019** (International Conference on Machine Learning)

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Future Works

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Future Works

1. Optimization problem

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1. Algorithmic contributions: OPTIMIST and OPTIMIST2.
2. Theoretical contributions:
   2.1 novel problem formalization of Policy Search;
   2.2 proved sub-linear regret for both algorithms.
3. Experimental contributions
   3.1 Linear Quadratic Gaussian regulation;
   3.2 Continuous Mountain Car;
   3.3 Inverted Pendulum.

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Future Works

1. Optimization problem
2. Posterior sampling

Thank you for your attention!

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