Cost Efficient Exploration for Reinforcement Learning

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Motivation

Background

Exploration and Exploitation Dilemma

RL maintains this balance

Information Theory guided exploration

Motivation

Minimize the cost of exploration while achieving good performance

Related Works

Literature Review

- Curiosity Based
  - Induce Exploration by Leveraging Uncertainty about the Environment
  - Paper: Formal theory of creativity, fun, and intrinsic motivation: Schmidhuber [2010]; Curiosity-driven exploration in deep reinforcement learning via bayesian neural networks;Houthooft et al. [2016]
- Information Theory Based
  - Occupancy Information Ratio

Occupancy Information Ratio: Infinite-Horizon, Information-Directed, Parameterized Policy Search

- Information-directed exploration to infinite-horizon, parameterized policy search problems.

$$\rho(\theta) = \frac{J(\theta)}{\kappa + H(d_\theta)}$$

Cost

Entropy of Steady State Estimate

Goals

→ Incorporate exploration cost in OIR

→ OIR Validation

→ Comparative Study

Methodology

Incorporating exploration cost in OIR

- OIR induces a uniform state occupancy limited by the reward maximization
- Non uniform policy induces over exploration in certain states
- Penalize over exploration

$$\rho(\theta) = \frac{J(\theta) + \alpha . \mathbb{1}_{\sum_s N^t(\theta,s)/N^t_{tot} > N} \cdot \sum_t p}{\kappa + H^t\left(d_\theta\right)}$$

Intuition

$$D_{\mathrm{TV}}(P,Q) := \sup_{A\in\mathcal{F}} |P(A) - Q(A)|$$

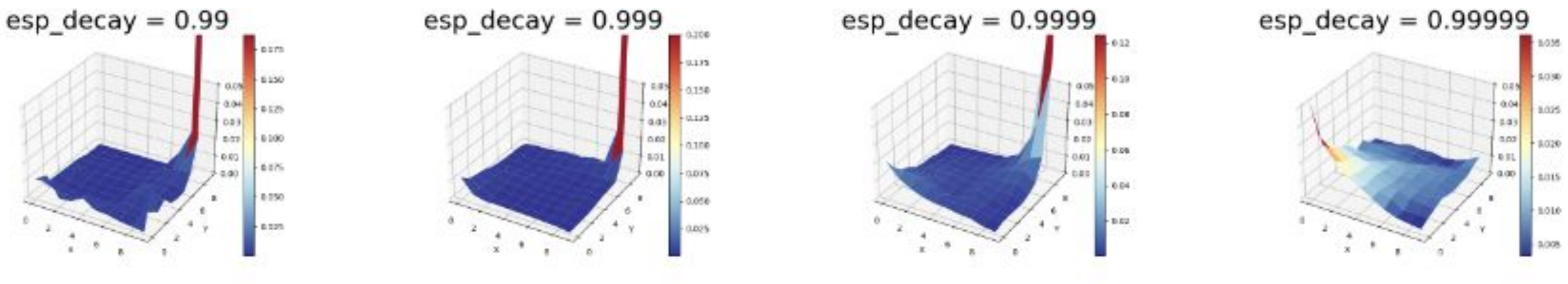
$$d_{mix}(t) = \sup_{s\in\Omega} D_{\mathrm{TV}}\left(P^t(s,\cdot),\mu\right)$$
$$\tau_{mix}(\epsilon) = \inf t : d_{mix}(t) \leq \epsilon$$

Limit on number of samples

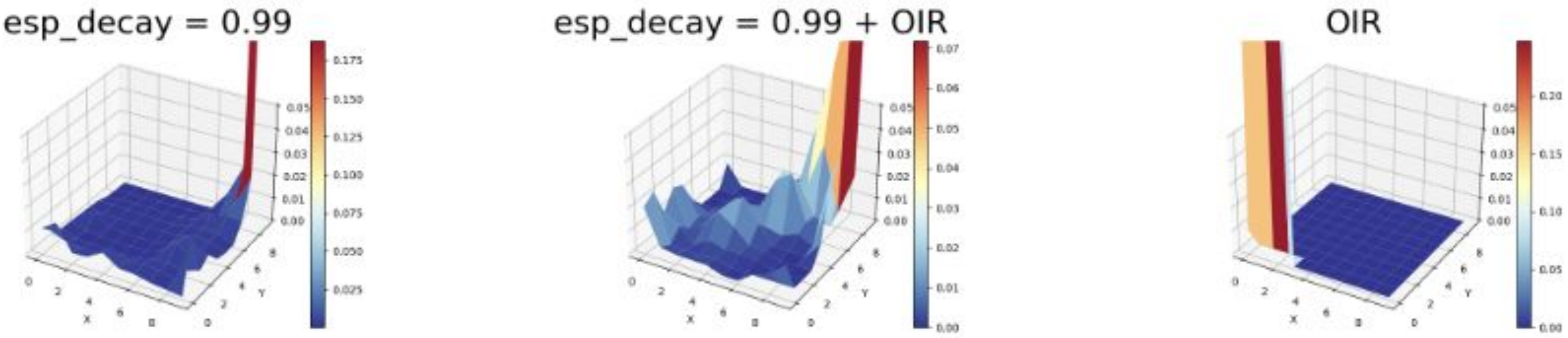
$$P(|d_\theta - d_\theta^*| > \delta) \leq 2e^{-2n\delta^2}$$

$$\begin{aligned} P(|d_\theta - d_\theta^*| > \delta) &\leq \alpha \\ 2e^{-2n\delta^2} &\leq \alpha \\ -2n\delta^2 &\leq \ln \frac{\alpha}{2} \\ n &\geq \frac{1}{2\delta^2} \ln \frac{2}{\alpha} \end{aligned}$$

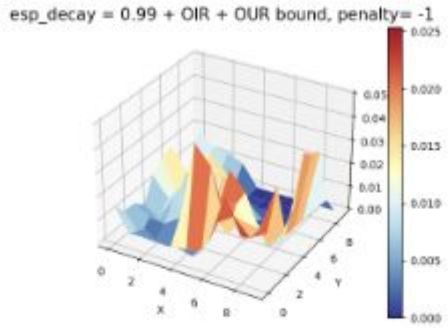
Exploration vs State Occupancy

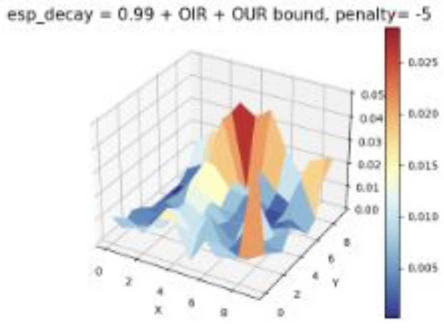


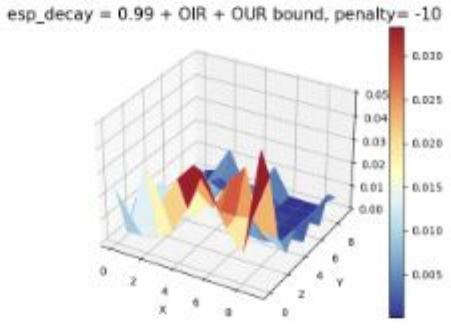
State Occupancy in OIR



State Occupancy in our work







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OIR Validation and Comparative Study

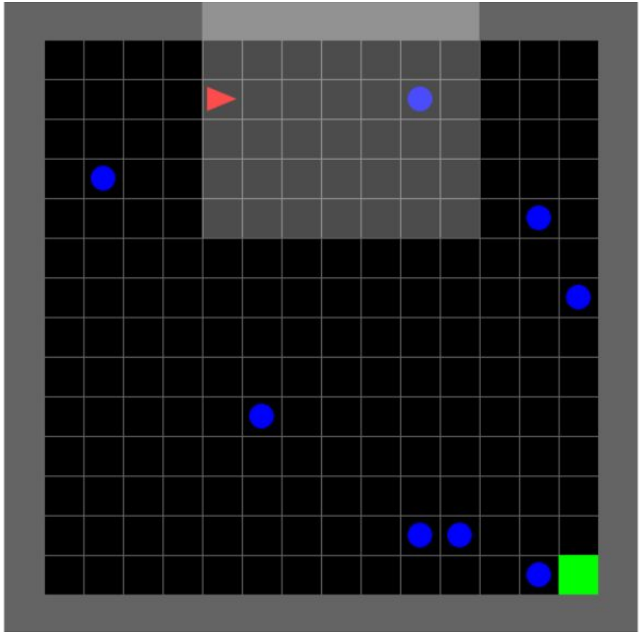
OIR Validation

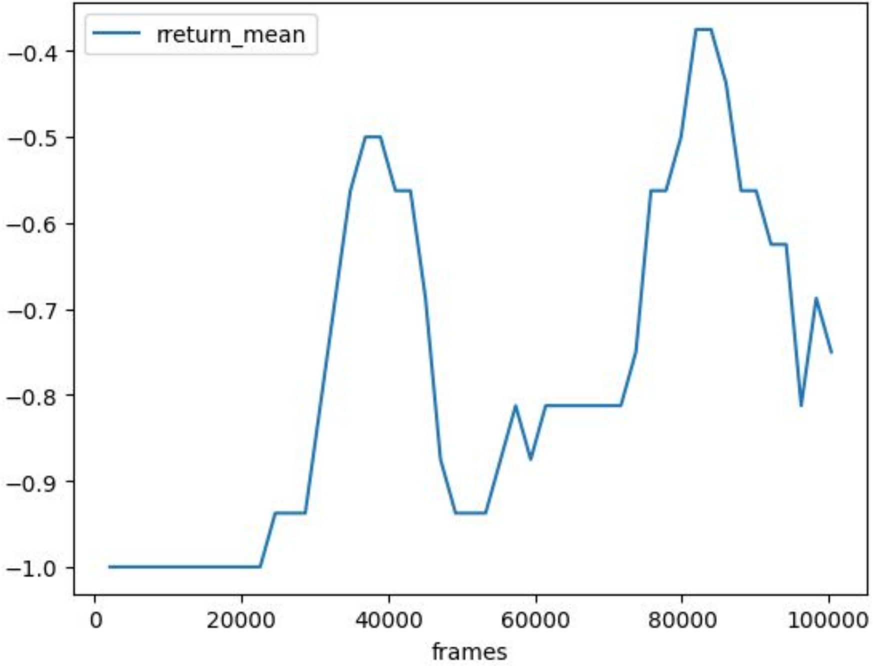
- GridWorld
- IDAC

Comparative Study

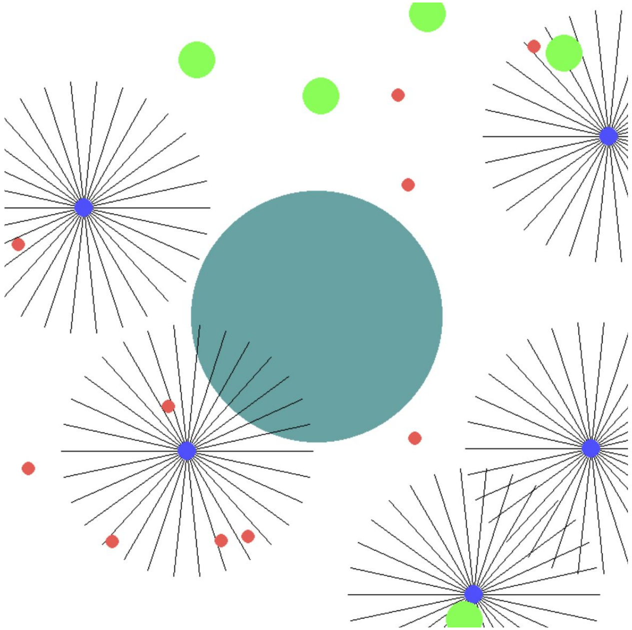
- WaterWorld
- PPO and DDPG
- Both vanilla and OIR versions

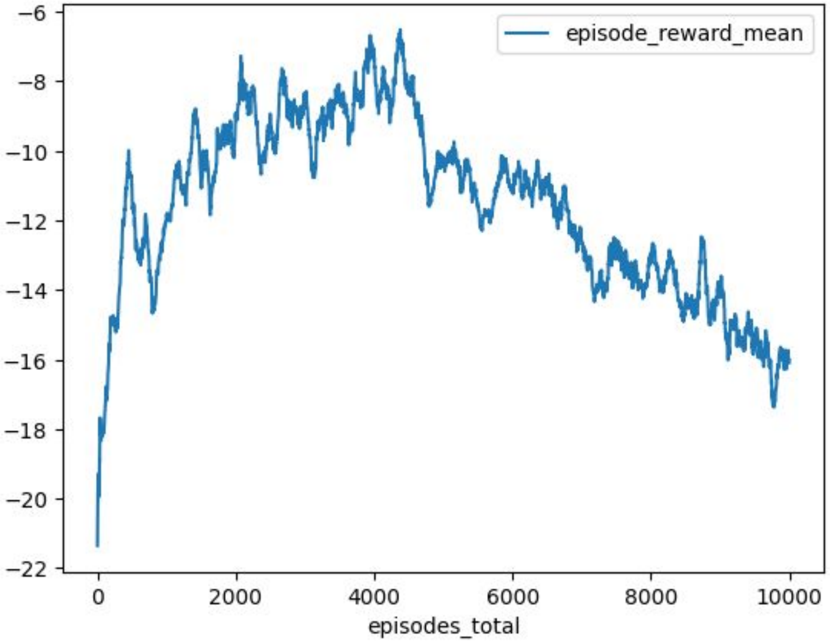
A2C Algorithm for Gridworld



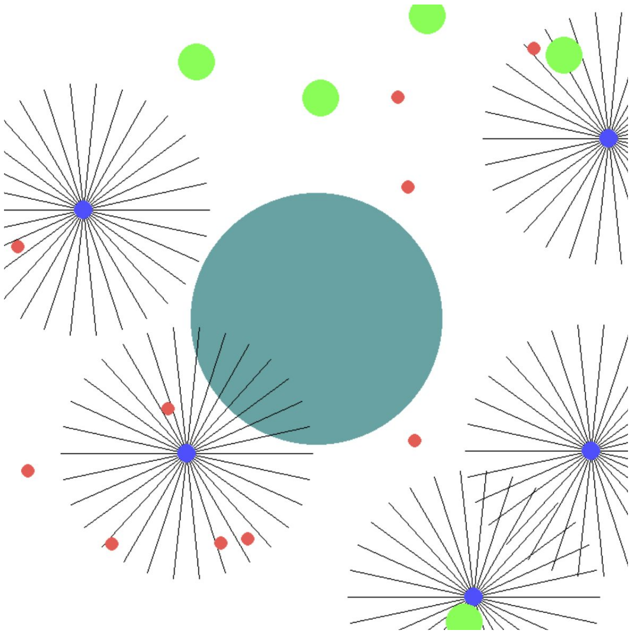


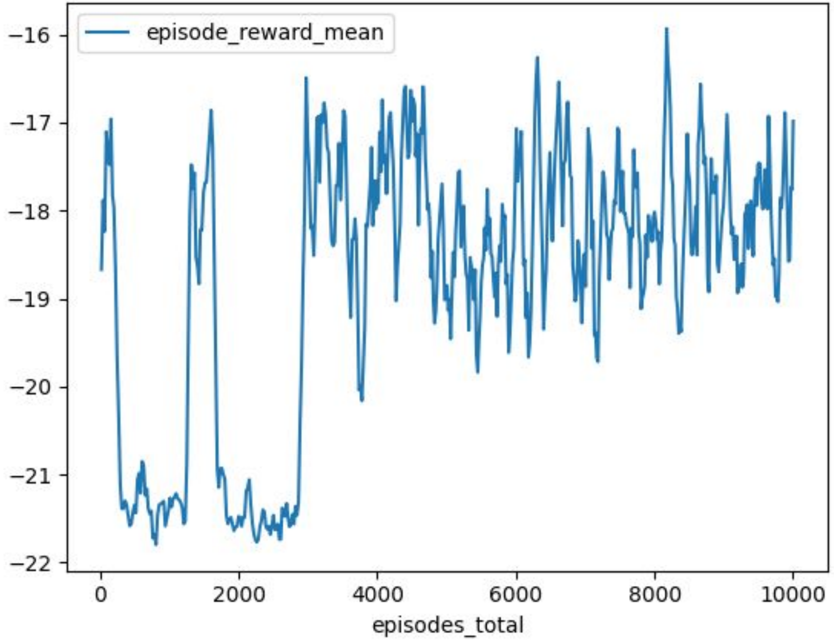
PPO Algorithm for WaterWorld





APEX DDPG Algorithm for Waterworld





Unachieved Objectives

Density Estimation

- Learning based method
- Kernel based Density Estimate
- Multi-Agent Implementation

$$\rho(\theta) = \frac{J(\theta)}{\kappa + H(d_\theta)}$$

Future Work

- Completing implementation of Density Estimator
- Applying OIR to Heterogeneous case (Pursuit Evasion)
- Extend to Large Scale Environment for ORI cost

Questions?