

Advances in Reinforcement Learning Inspired by Statistical Mechanics

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Reinforcing Rewards



Mountain-Car environment

Reinforcement Learning (RL) is a method of solving sequential decision-making problems by interacting

Basic Idea:

- An agent interacts with the **environment**, by taking **actions**
- Positive behaviors are reinforced relative to undesirable behaviors
 - Reinforcement is implemented via a reward function
- The agent should learn to maximize rewards received
 - Specifically, average reward over (infinitely) long trajectories











Bountiful Bridge

Statistical Physics

- Free Energy
- Ground State
- Correlation Scales
- Hamiltonian MCMC
- Tightening Bounds



Reinforcement Learning

- Value Functions
- Max Reward-Rate
- Mixing Time
- Sampling Methods
- New Algorithms

Fresh Findings

- New proof and perspective of Policy Improvement (PI)
- New algorithm for MaxEnt RL by bounding the Q function [1]
- Ground-state formulation of RL problem
- Extension of Donsker-Varadhan formula to value functions [2]
- Average-Reward Algorithms [3]

[1]: "Boosting Soft Q Learning by Bounding", Under review at RLC, 2024

- [2]: "Eigenvector Based Average-Reward Learning" In Preparation for JMLR
- [3]: "Off-Policy Algorithms for Entropy-Regularized Average-Reward RL", Under review at NeurIPS 2024

Bounds Abound

The optimal Q function can be bounded from arbitrary guess





Friendly Free Energy

The free energy (Q-func) satisfies a variational form (for arb. p):

$$F \doteq -\frac{1}{\beta} \log \sum_{x} p_0(x) e^{-\beta E(x)} \leq \mathbb{E}_p \{E + \beta^{-1} D_{\mathrm{KL}}(p || p_0)\} \doteq F_p$$

How big is the gap between true free energy (F) and variational guess (F_p) ?

$$Q^{*}(s,a) = Q^{\pi}(s,a) - D_{KL}(\pi|\pi^{*})$$

$$F = F_{p} - D_{KL}(p|p^{*})$$

$$p^{*}(x) \propto p_{0}(x)e^{-\beta E(x)}$$





Thank you!

