OFVF

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Abstract

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1. Introduction

Markov decision processes (MDPs) provide a versatile methodology for modeling dynamic decision problems under uncertainty. MDPs assume that transition probabilities are known precisely, but this is rarely the case in reinforcement learning. Errors in transition probabilities often results in probabilities often results in policies that are brittle and fail in real-world deployments. The agent has to learn the true dynamics of the MDP as it optimize the performance while interacts with its environment. The key to evaluate RL algorithms is to check how they balance between exploration that gains information about unknown states (actions) and exploitation to achieve near-term performance.

OFU-RL

Posterior sampling

Our work

2. Problem formulation

We consider the problem of learning and solving an uncertain MDP :$(S, A, P^M a, R^M,)$

3. OFVF and Bayes UCRL

Algorithm 1 Bayesian Confidence Interval (BCI)

Distribution θ over $p^\star_{s,a}$, confidence level δ, sample count m Nominal point $\bar{p}_{s,a}$ and L_1 norm size $\psi_{s,a}$ Sample $X_1, \ldots, X_m \in \Delta^S$ from θ: $X_i \sim \theta$ $Nominalpoint$:$\bar{p}_{s,a} \leftarrow (1/m)\sum_{i=1}^m X_i$ $Computedistances$d$_i \leftarrow \bar{p}_{s,a} - X_{i1}$ and sort *increasingly* $Normsize$:$\psi_{s,a} \leftarrow d_{(1-\delta)\,m}$ $\bar{p}_{s,a}$ and $\psi_{s,a}$

Algorithm 2 Bayes UCRL

Desired confidence level δ and prior distribution Policy with an optimistic return estimate num episodes Initialize MDP: M $Computeposterior$:$\tilde{p} \leftarrow$ compute_posterior(prior, samples) $s \in \mathcal{S}, a \in \mathcal{A} \bar{p}_{s,a}, \psi_{s,a} \leftarrow$ Invoke Algortihm **??** with $\tilde{p}$, δ M $\leftarrow$ $addtransitionwith \bar{p}_{s,a}, \psi_{s,a}$ $ComputepolicybysolvingMDP$:$\hat{\pi} \leftarrow$ Solve M $Collectsamplesbyexecutingthepolicy$: $samples \leftarrow$ execute $\hat{\pi}$ $prior \leftarrow$ posterior $(\pi_k, p_0^{\mathsf{T}} v_k)$

4. Some shortcomings of existing UCRL2 and PSRL

5. Analysis

6. Simulation results

7. Conclusion

Acknowledgements

Do not include acknowledgements in the initial version of the paper submitted for blind review.

If a paper is accepted, the final camera-ready version can (and probably should) include acknowledgements. In this case, please place such acknowledgements in an unnumbered section at the end of the paper. Typically, this will include thanks to reviewers who gave useful comments, to colleagues who contributed to the ideas, and to funding agencies and corporate sponsors that provided financial support.

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References

Langley, P. Crafting papers on machine learning. In Langley, P. (ed.), *Proceedings of the 17th International Conference on Machine Learning (ICML 2000)*, pp. 1207–1216, Stanford, CA, 2000. Morgan Kaufmann.

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