Computing and Artificial Intelligence, vol.3, no.2, pp.2923-1-2923-13, December, 2025.

Multifidelity Bayesian optimization for hyperparameter tuning of deep reinforcement learning algorithms

E.C. Garrido Merchán; G. Martínez Martínez; M. Molina González

Abstract-

This research focuses on comparing standard Bayesian optimization and multifidelity Bayesian optimization in the hyperparameter search to improve the performance of reinforcement learning algorithms in environments such as OpenAI LunarLander and CartPole. The primary goal is to determine whether multifidelity Bayesian optimization provides significant improvements in solution quality compared to standard Bayesian optimization. To address this question, several Python implementations were developed, evaluating the solution quality using the mean of the total rewards obtained as the objective function. Various experiments were conducted for each environment and version using different seeds, ensuring that the results were not merely due to the inherent randomness of reinforcement learning algorithms. The results demonstrate that multifidelity Bayesian optimization outperforms standard Bayesian optimization in several key aspects. In the LunarLander environment, multifidelity optimization achieved better convergence and more stable performance, yielding a higher average reward compared to the standard version. In the CartPole environment, although both methods quickly reached the maximum reward, multifidelity did so with greater consistency and in less time. These findings highlight the ability of multifidelity optimization to optimize hyperparameters more efficiently, using fewer resources and less time while achieving superior performance.

Index Terms- deep reinforcement learning; bayesian optimization; meta learning

Citation:
Garrido-Merchán, E.C.; Martínez, G.; Molina, M. "Multifidelity Bayesian optimization for hyperparameter tuning of deep reinforcement learning algorithms", Computing and Artificial Intelligence, vol.3, no.2, pp.2923-1-2923-13, December,

2025.