Unveiling the Best Performers: A Comparative Analysis of RL Algorithms in QRL with TensorFlow Quantum

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I. Introduction

Reinforcement learning (RL) has achieved significant success in various domains but faces challenges when applied to quantum systems due to their inherent complexity. Quantum reinforcement learning (QRL) seeks to address this by marrying RL techniques with the power of quantum computing. This project aims to analyse and compare the performance of different RL algorithms within the framework of QRL, utilizing the capabilities of TensorFlow Quantum (TFQ) (Broughton et al., 2021).

II. Problem Statement

With the growing interest in QRL, a comprehensive understanding of different RL algorithms' effectiveness in this unique setting is crucial. This study seeks to address the following:

1. How does the performance of various RL algorithms differ when applied to QRL problems?
2. Which specific algorithms are best suited for different types of QRL tasks?

III. Methodology

This project will leverage TensorFlow Quantum (TFQ), a leading library for constructing and training quantum machine learning models. We will integrate various well-established RL algorithms, including Deep Q-Learning (DQN), Soft Actor-Critic (SAC), and Proximal Policy Optimization (PPO), with Parametrized Quantum Circuits (PQCs) within the TFQ framework (Jerbi et al., 2021). Each algorithm will be evaluated on a set of standardized QRL benchmarks, potentially sourced from the OpenAI Gym library, which facilitates the active learning of RL agents (Skolik et al., 2022). This comprehensive approach allows for a rigorous comparative analysis of the algorithms' effectiveness, assessed through metrics like reward accumulation and learning efficiency.

IV. Outcomes

Through this study, we expect to gain valuable insights into the performance of different RL algorithms in QRL environments. The project aims to:

1. Identify the strengths and weaknesses of each algorithm in the context of QRL.
2. Provide recommendations for choosing the most suitable RL algorithm for different QRL applications.
3. Offer valuable resources for further research in the field of QRL.

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Note: Driven by our unique interests in our respective majors, CSAI and RCPS, we aim to unlock the potential of QRL by analyzing RL algorithms in this domain of Quantum Computing, thus paving our path into this interesting field!

Thank You!