Variational Quantum Circuits for Reinforcement Learning

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Deep neural networks have had a profound impact on the field of reinforcement learning by recently achieving unprecedented performance in challenging decision-making tasks [1]. Almost in parallel, in the world of near term quantum computers, the idea that limited quantum computations, called variational quantum circuits [2] or quantum neural networks [3], could be used as building blocks of hybrid quantum-classical machine learning systems started gaining increasing traction. Such hybrid systems have already shown the potential to tackle real-world tasks in supervised [4] and generative learning [5], and recent works have established their provable advantages in special artificial tasks [6]. Yet, in the case of reinforcement learning, which is arguably most challenging and where learning boosts would be extremely valuable, no proposal has been successful in solving even standard benchmarking tasks, nor in showing a theoretical learning advantage over classical algorithms. In this work, we achieve both. We find numerically that shallow quantum circuits acting on very few qubits are competitive with deep neural networks on well-established benchmarking environments. Moreover, we demonstrate, and formally prove, the ability of variational quantum circuits to solve certain learning problems that classical models, including deep neural networks, cannot, under the widely-believed classical hardness of the discrete logarithm problem. This constitutes clear evidence of the power of quantum learning agents and suggests that important reinforcement learning applications such as robotics, biology, or healthcare, can be meaningfully impacted by quantum machine learning.

References

[1] D. Silver, *et al.* Mastering the game of go without human knowledge. Nature, **550**(7676) 354–359 (2017)
[2] M. Benedetti, E. Lloyd, S. Sack, M. Fiorentini. Parameterized quantum circuits as machine learning models. Quant. Sci. and Tech., **4**(4) 043001 (2019)
[3] E. Farhi, H. Neven. Classification with quantum neural networks on near term processors. arxiv: 1802.06002 (2018)
[4] M. Schuld, A. Bocharov, K. Svore, N. Wiebe. Circuit-centric quantum classifiers. Phys. Rev. A, **101**(3) 032308 (2020)
[5] D. Zhu, *et al.* Training of quantum circuits on a hybrid quantum computer. Sci. Adv., **5**(10) 9918 (2019)
[6] Y. Liu, S. Arunachalam, K. Temme. A rigorous and robust quantum speed-up in supervised machine learning. Nat. Phys., **17**(9) 1013–1017 (2021)

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