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Do quantum computers have applications in machine learning and combinatorial optimization?

Jens Eisert

Freie Universität Berlin

Abstract

There has been substantial excitement recently in identifying tasks for which quantum devices could possibly outperform classical devices. Recent experimental implementations on random circuit sampling have provided strong evidence that near-term quantum devices can outperform classical computers on paradigmatic tasks [1]. These developments invite further studies to see what applications of quantum devices could be found.

Notions of quantum-assisted machine learning are seen as candidates for this. We will have a careful look at such notions. We will discuss the comparative power of classical and quantum learners for generative modelling within the PAC framework, for which we prove a separation [2, 3]. Going further, will discuss how much structure is actually expected to be required for quantum advantages in machine learning [4]. We prove that the injection of a single T-gate into Clifford circuits renders the task of learning evaluators from samples infeasible in polynomial time. This is in stark contrast to the case of Clifford circuits for which we provide an efficient learning algorithm [5].

Finally, we will have a look at the sense in which quantum computers may assist in solving problems of combinatorial optimization. These problems are usually NP-hard in worst case complexity, so it is far from

clear what type of quantum advantage one can even hope for, despite commonly made claims of expectations of such advantages in the literature. We discuss a proven super-exponential quantum advantage for combinatorial optimization [6].

At the end of the talk, we will put these findings into perspective and discuss the potential for near-term quantum computing, including limitations of quantum error mitigation in NISQ devices [7], noise being helpful in variational quantum algorithms [8], classical surrogates simulating variational quantum algorithms in execution but not in training [9, 10] and the exploitation of symmetry [10, 11].

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[3] Phys. Rev. A 107, 042416 (2023).
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[6] arXiv:2212.08678 (2022).
[7] arXiv:2210.11505 (2022).
[8] arXiv:2210.06723 (2022).
[9] Phys. Rev. Lett. 131, 100803 (2023).
[10] arXiv:2309.11647 (2023).
[11] PRX Quantum 4, 010328 (2023).