Addressing learning tasks with quantum devices

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Recent years have witnessed an enormously rapid development of quantum computational devices of intermediate size. For instances of paradigmatic settings such as sampling problems, such existing quantum devices already come close to outperforming or outperform classical supercomputers for the same task, in settings that are equipped with a precise and rigorous complexity theoretic underpinning. In this talk, we start from looking at such quantum advantage schemes that can be efficiently verified by means of local quantum measurements [1], leading to a proof-of-principle-experiment involving trapped ions [2]. These steps suggest to investigate more practically motivated quantum advantages.

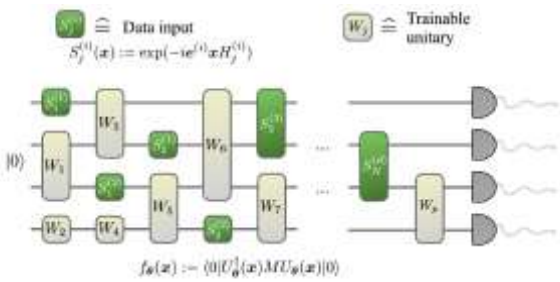

Figure 1: A parametrized quantum circuit.

In the main part of the talk, we will explore to what extent quantum-assisted machine learning tasks could be candidates for this. Specifically, we look in great detail at a proven exponential separation of quantum learners over classical ones in a meaningful quantum machine learning task [3]. Concretely, we study the comparative power of classical and quantum learners for generative modelling within the Probably Approximately Correct (PAC) framework. More specifically we consider the following task: Given samples from some unknown discrete probability distribution, output with high probability an efficient algorithm for generating new samples from a good approximation of the original distribution. Our primary result is the explicit construction of a class of discrete probability distributions which, under the decisional Diffie-Hellman assumption, is provably not efficiently PAC learnable by a classical generative modelling algorithm, but for which we construct an efficient quantum learner. We will investigate encoding non-agnostic generalization bounds (fig. 1) for quantum-assisted machine learning with parameterized quantum circuits [4]. In the last part of the talk, we will explore the possibility of learning output distributions of short quantum circuits [5], and will discuss what degree of structure is needed, after all, to expect a quantum advantage in meaningful quantum-assisted machine learning tasks.

References

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