Master-thesis: Quantum Machine Learning for variational quantum algorithms

1 Background

Quantum computers can outperform classical computers on certain classes of problems and solve problems that are intractable even on any future (classical) supercomputer. The development of chips for quantum computers has been following Moore's law in the last years and the technology is edging ever closer to commercialization. Every new generation of quantum chips represents an improvement not only in the number of quantum bits, but also with respect to the error rates and the connectivity of the quantum bits. Most of these small scale quantum computers are accessible through cloud interfaces today. The first generation of practically-relevant quantum computers will be noisy intermediate-scale quantum (NISQ) computers. This means that calculations will have errors and the length of a computation will be relatively short. A family of methods that lend themselves well to NISQ devices are hybrid methods based on the variational principle. A general overview is provided in, e.g., [1]. For quantum machine learning we refer to, e.g., [3, 4, 2] and references therein.

2 Problems to be studied

The main aim is to apply QML directly at the end of a variational quantum algorithms, either QAOA or VQE. The aim of the thesis is to investigate whether this can lead to advantages wrt to avoiding local minima, faster convergence, etc.

3 Goals of the project

There are three primary goals of the project:

1. Developing a sound theoretical understanding of variational quantum algorithms and QML, including basic principles and current state of the art.
2. Implementing and testing QML for variational quantum algorithms on simulators and actual quantum computers. For execution on real devices, it is suggested to use e.g., IBM's gate based quantum computers available free online.
3. Time allowing, improvements on existing approaches can be developed.

References

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[2] Maria Schuld, Ville Bergholm, Christian Gogolin, Josh Izaac, and Nathan Killoran. Evaluating analytic gradients on quantum hardware. *Physical Review A*, 99(3):032331, 2019.

[3] Maria Schuld and Francesco Petruccione. *Supervised Learning with Quantum Computers*. Springer International Publishing, 2018.

[4] Giacomo Torlai, Guglielmo Mazzola, Giuseppe Carleo, and Antonio Mezzacapo. Precise measurement of quantum observables with neural-network estimators. *Physical Review Research*, 2(2), June 2020.