Master-thesis: Extended QAOA

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., [3].

2 Problems to be studied

Since its inception, there have been several extensions/variants of the QAOA proposed. A recent approach, dubbed *ADAPT-QAOA*, presented in [4] is to create an iterative version that is problem-tailored and can adapt to specific hardware constraints. The method is exemplified on a class of MAX-CUT problems, requiring fewer CNOT gates as the original method. A non-local version of QAOA is proposed in [1]. Dubbed *R-QAOA*, the algorithm recursively removes variables from the Hamiltonian until the remaining instance is small enough to be solved classically. Numerical evidence is provided that shows this procedure significantly outperforms standard QAOA for frustrated Ising models on random 3-regular graphs for the MAX-CUT problem. Another recent approach, dubbed *WS-QAOA* is using the solutions of classical algorithms to improve QAOA, see [2][1]. An example is provided with MAX-CUT, which shows numerically that warm-starting QAOA and R-QAOA provides an advantage at low depth, in the form of a systematic increase in the size of the obtained cut for fully connected graphs with random weights. Warm starting results in a change of the mixer operator only.

3 Goals of the project

There are three primary goals of the project:

1. Developing a sound theoretical understanding of QAOA for various optimization problems, including basic principles and current state of the art.
2. Implementing and testing extensions of QAOA 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

[1] Sergey Bravyi, Alexander Kliesch, Robert Koenig, and Eugene Tang. Obstacles to state preparation and variational optimization from symmetry protection. *arXiv preprint arXiv:1910.08980*, 2019.

[2] Daniel J Egger, Jakub Marecek, and Stefan Woerner. Warm-starting quantum optimization. *arXiv preprint arXiv:2009.10095*, 2020.

[3] Nikolaj Moll, Panagiotis Barkoutsos, Lev S Bishop, Jerry M Chow, Andrew Cross, Daniel J Egger, Stefan Filipp, Andreas Fuhrer, Jay M Gambetta, Marc Ganzhorn, Abhinav Kandala, Antonio Mezzacapo, Peter Müller, Walter Riess, Gian Salis, John Smolin, Ivano Tavernelli, and Kristan Temme. Quantum optimization using variational algorithms on near-term quantum devices. *Quantum Science and Technology*, 3(3):030503, June 2018.

[1] See also the tutorial here `https://qiskit.org/documentation/optimization/tutorials/10_warm_start_qaoa.html`

[4] Linghua Zhu, Ho Lun Tang, George S Barron, Nicholas J Mayhall, Edwin Barnes, and Sophia E Economou. An adaptive quantum approximate optimization algorithm for solving combinatorial problems on a quantum computer. *arXiv preprint arXiv:2005.10258*, 2020.