Algorithm selection and configuration for Noisy Intermediate Scale Quantum methods for industrial applications

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Propositions

accompanying the thesis

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1. In practice, quantum optimization will have to compete with classical heuristic methods, which have the advantage of decades of empirical domain-specific enhancements. Consequently, we will face the issue of algorithm selection. [Chapter 3]

2. Resorting to machine learning for algorithm selection can be motivated by several considerations: machine learning methods are flexible and can equally be applied to many quantum algorithms in other regimes (e.g., when considering real-world noise), complexity-theoretical arguments about why exact decisions are likely computationally intractable, and employing explainability techniques to identify problem characteristics/features that make them better suited for a quantum treatment, which may guide other more theoretical research. [Chapter 3]

3. Near-term hardware constraints make quantum algorithms unlikely to be competitive when compared to high-performing classical heuristics on large practical problems. One option to achieve advantages with near-term devices is to use them in combination with classical heuristics. [Chapter 5]

4. Using quantum methods such as QAOA to sample from classically intractable distributions -- which is the most probable approach to attain a true provable quantum separation in the near term -- can be used to solve optimization problems faster. [Chapter 5]

5. The value of quantum machine learning on real-world datasets is still to be investigated in any larger-scale systematic fashion. Currently, common practices from machine learning, such as large-scale benchmarking, hyperparameter importance, and analysis have been challenging tools to use in the quantum community. [Chapter 7]

6. There is currently limited intuition as to which hyperparameters are important to optimize and which are not. Such insights, which can be obtained using hyperparameter importance techniques such as functional ANOVA, can lead to much more efficient hyperparameter optimization. [Chapter 7]

7. Optimizing variational quantum algorithms can be challenging and calls for tailored optimization procedures. [Chapters 4, 6, and 8]

8. Variational quantum algorithms for quantum machine learning require long run times and large resource overheads during training (as many iterations and shots to achieve respectable performances). Developing resource-frugal optimizers can help in reducing the cost of running such algorithms on quantum devices. [Chapter 8]

9. Variational quantum algorithms are hybrid quantum-classical algorithms most often used as heuristics and designed to tackle relevant applications for industries in the NISQ era. Such hybrid algorithms can be complex with many components or hyperparameters to work with. Learning to configure these algorithms will be key to apply them successfully in practice.

10. The path to quantum computing in practice is paved with many challenges to overcome. Dealing with them require a high flexibility technically but also mentally. Even if quantum computing in practice fails, the lessons learned along the way can be valuable and applied anywhere else.