Quantum machine learning: on the design, trainability and noise-robustness of near-term algorithms

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Propositions

accompanying the thesis

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1. Restricting the complexity of a (quantum) machine learning model can improve its trainability. (Chapter 6)

2. An arbitrarily complex quantum machine learning model can fail to solve a simple problem under the wrong choice of data encoding or measurement observable. (Chapter 5)

3. Variational quantum machine learning models exhibit a certain robustness to quantum hardware noise. (Chapter 7)

4. In certain cases, the noise present during the optimization of a variational quantum algorithm can improve its performance. (Chapter 7)

5. Preventing that a parametrized quantum circuit reaches a regime close to Haar-randomness can dampen the effect of barren plateaus. (Chapter 4)

6. Integrating domain knowledge about a problem into an algorithm can greatly improve its performance compared to algorithms that do not utilize any prior knowledge.

7. The number of trainable parameters to solve a learning task alone is not an indicator that one model outperforms another model.

8. The same optimization technique can be more costly for one model than for another, depending on its specific implementation.

9. While heuristics often do not come with theoretical guarantees, they are of great value to solve real-world problems.

10. Technological advancement is both a curse and a blessing.