



### **Master Thesis**

# **Variational Quantum Circuits for Policy Approximation**

### Motivation

Spurred by the recent experimental demonstration of so-called quantum advantage for a classically hard random-number generation problem with actual quantum hardware, the research community has increased its efforts to propose new types of quantum algorithms for the still imperfect, noisy intermediate scale quantum (NISQ) computing devices we have today.

One class of algorithms that have emerged as viable candidates for achieving quantum advantage with NISQ devices also in other application domains beyond random number generation are **variational quantum circuits** (VQCs). These adaptive quantum circuits lend themselves as a platform for **quantum machine learning**, here understood as the generation of quantum algorithms from data. While the requirements on the expressivity of these circuits to reach quantum advantage and related complexity-theoretic problems pose open research questions, experimentation with available architectures might uncover promising directions.

## **Project Idea**

Within the framework of a joint master thesis project between the Chair for Quantum Theory at Friedrich-Alexander University Erlangen-Nürnberg and the Self-Learning Systems group at the Fraunhofer Institute for Integrated Circuits, the potential of VQCs for the task of learning and approximating complex multimodal distributions, as well as for the task of efficient sampling from these distributions, is to be investigated. In the context of reinforcement learning, the learning of distributions from data plays a crucial role, both when generating surrogate models for the system dynamics from observational data, and when training the reinforcement-learning policy to approximately solve the underlying stochastic optimization problem. The latter case is closely tied to the trade-off between exploration and exploitation during the training phase of the reinforcement-learning procedure. To properly balance exploration and exploitation, it is particularly relevant to employ methods capable of learning conditional, multimodal distributions. In order to analyze the potential of quantum-enhanced learning algorithms in the context of model-free reinforcement learning, the goal of the advertised master thesis is to provide a proof-of-principle implementation of a VQC-based policy learning procedure. While actions are sampled according to the state prepared by the quantum circuit, the parameter updates for policy improvement need to be provided by an appropriate generalization of the so-called policy gradient.

The algorithm will be developed and tested for simple reinforcement-learning tasks (e.g. bandits and grid world problems) with discrete state and action spaces. In order to empirically gain insight on the possibility of quantum advantage, the quantum policy gradient approach is to be benchmarked against classical methods.

## **Required Skills**

Basic knowledge of variational quantum circuits and machine learning, Python programming

### Literature

[1] Marcello Benedetti, Erika Lloyd, Stefan Sack, Mattia Fiorentini, "Parameterized quantum circuits as machine learning models", Quantum Science and Technology 4, 043001 (2019)

[2] Samuel Yen-Chi Chen, Chao-Han Huck Yang, Jun Qi, Pin-Yu Chen, Xiaoli Ma, Hsi-Sheng Goan, "Variational Quantum Circuits for Deep Reinforcement Learning", arXiv:1907.00397 [cs.LG]

[3] Tuomas Haarnoja, Haoran Tang, Pieter Abbeel, Sergey Levine, "Reinforcement Learning with Deep Energy-Based Policies", arXiv:1702.08165 [cs.LG]

[4] Sofiene Jerbi, Hendrik Poulsen Nautrup, Lea M. Trenkwalder, Hans J. Briegel, Vedran Dunjko, "A framework for deep energy-based reinforcement learning with quantum speed-up", arXiv:1910.12760 [quant-ph]

### Contact

Friedrich-Alexander-Universität Erlangen-Nürnberg Chair for Quantum Theory Fraunhofer Institute for Integrated Circuits IIS Self-Learning Systems Group

Prof. Dr. Michael J. Hartmann michael.j.hartmann@fau.de

Dr. Daniel D. Scherer daniel.scherer2@iis.fraunhofer.de