FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
FACULTY OF SCIENCES

Fraunhofer IIS

Master Thesis

Variational Quantum Circuits for Learning Distributions

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. These 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

In this regard, realizations of **quantum generative adversarial networks** (QGANs) – an extension of classical GANs to the domain of quantum data and quantum computation – provide an ideal testing ground for the exploitation of quantum resources for learning of and sampling from complex distributions – a ubiquitous task in statistical modelling and machine learning.
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 QGANs for the task of learning and approximating distributions from data, 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 first approach forms the basis for many model-based reinforcement-learning methods.
The goal of the advertised master thesis will be to implement and test QGAN architectures for learning distributions from a finite set of samples. A special emphasis will be put on the learning of state-transition probabilities from data generated by simulated reinforcement-learning environments with discrete state and action spaces. To leverage the potential quantum advantage offered by QGANs, the combination with dimensionality reduction techniques, such as representation learning approaches, will be explored.

Required Skills

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

Literature

[1] Pierre-Luc Dallaire-Demers, Nathan Killoran, "Quantum generative adversarial networks", Phys. Rev. A 98, 012324 (2018)
[2] Christa Zoufal, Aurélien Lucchi, Stefan Woerner, "Quantum Generative Adversarial Networks for learning and loading random distributions", npj Quantum Information volume 5, 103 (2019)
[3] Jonathan Romero, Alan Aspuru-Guzik, "Variational quantum generators: Generative adversarial quantum machine learning for continuous distributions", arXiv:1901.00848 [quant-ph]
[4] Tingwu Wang, Xuchan Bao, Ignasi Clavera, Jerrick Hoang, Yeming Wen, Eric Langlois, Shunshi Zhang, Guodong Zhang, Pieter Abbeel, Jimmy Ba, "Benchmarking Model-Based Reinforcement Learning", arXiv:1907.02057 [cs.LG]

Contact

Friedrich-Alexander-Universität Erlangen-Nürnberg
Chair for Quantum Theory

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

Fraunhofer Institute for Integrated Circuits IIS
Self-Learning Systems Group

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