

## QI 2: Quantum Machine Learning I

Time: Monday 11:00–12:45

Location: HS VIII

QI 2.1 Mon 11:00 HS VIII

**Self-Adaptive Physics-Informed Quantum Machine Learning for Solving Differential Equations** — ●ABHISHEK SETTY<sup>1,2,3</sup>, RASUL ABDUSALAMOV<sup>1</sup>, and FELIX MOTZOI<sup>2,3</sup> — <sup>1</sup>Department of Continuum Mechanics, RWTH Aachen University, Germany — <sup>2</sup>Forschungszentrum Jülich, Institute of Quantum Control (PGI-8), D-52425 Jülich, Germany — <sup>3</sup>Institute for Theoretical Physics, University of Cologne, D-50937 Cologne, Germany

Chebyshev polynomials have shown significant promise as an efficient tool for both classical and quantum neural networks to solve linear and nonlinear differential equations. In this work, we adapt and generalize this framework in a quantum machine learning setting for a variety of problems, including the 2D Poisson's equation, second-order linear differential equation, system of differential equations, nonlinear Duffing and Riccati equation. In particular, we propose in the quantum setting a modified Self-Adaptive Physics-Informed Neural Network (SAPINN) approach, where self-adaptive weights are applied to problems with multi-objective loss functions. We further explore capturing correlations in our loss function using a quantum-correlated measurement, resulting in improved accuracy for initial value problems. We analyse also the use of entangling layers and their impact on the solution accuracy for second-order differential equations. The results indicate a promising approach to the near-term evaluation of differential equations on quantum devices.

QI 2.2 Mon 11:15 HS VIII

**Automation of Quantum Machine Learning** — ●MARCO ROTH — Fraunhofer IPA, Stuttgart

Applying quantum machine learning (QML) presents unique challenges that often demand expertise in fields such as machine learning and quantum computing. To address these challenges and facilitate broader applications, automation offers a promising solution. In this talk, we introduce two approaches that leverage this concept. The first is AutoQML, a framework designed to create end-to-end QML pipelines for a range of supervised learning scenarios, including time series classification and tabular regression and classification tasks. Additionally, we propose a novel method that employs reinforcement learning techniques to develop problem-specific encoding circuits, enhancing the performance of QML models in a sample-efficient way.

QI 2.3 Mon 11:30 HS VIII

**Expressive power of reservoir-based quantum machine learning** — ●NILS-ERIK SCHÜTTE<sup>1,2</sup>, NICLAS GÖTTING<sup>2</sup>, HAUKE MÜNTINGA<sup>1</sup>, MEIKE LIST<sup>1,3</sup>, and CHRISTOPHER GIES<sup>2</sup> — <sup>1</sup>German Aerospace Center, Institute for Satellite Geodesy and Inertial Sensing, Bremen, Germany — <sup>2</sup>Institut für Physik, Fakultät V, Carl von Ossietzky Universität Oldenburg — <sup>3</sup>University of Bremen

Quantum machine learning merges quantum computing and artificial intelligence, two transformative technologies for data processing. While gate-based quantum computing employs precise unitary operations on qubits, noisy intermediate-scale quantum (NISQ) devices face limitations in implementing high-depth circuits, yet remain promising for machine learning applications. In contrast, quantum reservoir computing (QRC) leverages physical systems as quantum neural networks, relying on Hamiltonian dynamics rather than controlled gate operations, with learning performed at the output layer. Despite their differing foundations, these approaches share connections and can be formally mapped onto each other.

We discuss this analogy by realizing a transverse-field Ising model on a gate-based quantum computing architecture. We quantify expressivities of either approach and explore the potential of gate-based quantum computers over QRC that rely on quantum circuit design and the possibility to optimize the circuits for specific tasks. Furthermore, we discuss the balance of the influence of the input encoding and the complexity of the reservoir on the output functions that a QRC approach has access to.

QI 2.4 Mon 11:45 HS VIII

**Generating reservoir state descriptions with random matrices** — ●TOBIAS FELLNER<sup>1</sup>, SAMUEL TOVEY<sup>1</sup>, CHRISTIAN HOLM<sup>1</sup>, and MICHAEL SPANNOVSKY<sup>2</sup> — <sup>1</sup>Institute for Computational Physics, University of Stuttgart — <sup>2</sup>Institute of Particle Physics Phenomenology,

University of Durham

We demonstrate a novel approach to reservoir computation measurements using random matrices. We do so to motivate how atomic-scale devices could be used for real-world computational applications. Our approach uses random matrices to construct reservoir measurements, introducing a simple, scalable means of generating state descriptions. In our studies, two reservoirs, a five-atom Heisenberg spin chain and a five-qubit quantum circuit, perform time series prediction and data interpolation. The performance of the measurement technique and current limitations are discussed in detail, along with an exploration of the diversity of measurements provided by the random matrices. In addition, we explore the role of reservoir parameters such as coupling strength and measurement dimension, providing insight into how these learning machines could be automatically tuned for different problems. This research highlights the use of random matrices to measure simple quantum reservoirs for natural learning devices, and outlines a path forward for improving their performance and experimental realization.

QI 2.5 Mon 12:00 HS VIII

**Quantum reservoir computing maps data onto the Krylov space** — ●SAUD CINDRAK, LINA JAURIGUE, and KATHY LÜDGE — Technische Universität Ilmenau, Ilmenau, Deutschland

The field of Krylov complexity has deepened our understanding of quantum systems, from field theories to chaos, and shed light on quantum evolution. However, classical computation of these complexities becomes infeasible for larger systems. We address this by defining a measurable basis to construct the Krylov space and introducing **Krylov expressivity** to capture the phase space dimension [1]. Additionally, we define **Krylov observability**, which quantifies how much of the phase space is observed. This work examines fidelity, spread complexity, Krylov expressivity, and Krylov observability as expressivity measures in quantum reservoir computing. In this approach, data is encoded into the system's state, evolved through the quantum system, and measured observables construct a readout vector, which is trained to predict chaotic attractors and compute the information processing capacity. Our findings show that fidelity and spread complexity provide limited insights, while **Krylov expressivity** effectively captures task performance [2]. Notably, **Krylov observability** and the information processing capacity exhibit almost identical behavior, demonstrating that a quantum reservoir maps data onto the Krylov space.

[1] S. Čindrak, L. Jaurigue, K.Lüdge, J. High Energ. Phys 2024, 83

[2] S. Čindrak, L. Jaurigue, K.Lüdge, arxiv.org/abs/2409.12079

QI 2.6 Mon 12:15 HS VIII

**Investigating the Quantum Circuit Born Machine** — ●MICHAEL KREBSBACH<sup>1</sup>, FLORENTIN REITER<sup>1</sup>, ABEDI ALI<sup>2</sup>, HAGEN-HENRIK KOWALSKI<sup>2</sup>, and THOMAS WELLENS<sup>1</sup> — <sup>1</sup>Fraunhofer IAF, Tullastraße 72, 79108 Freiburg — <sup>2</sup>Bundesdruckerei GmbH, Kommandantenstraße 18, 10969 Berlin

The Quantum Circuit Born Machine (QCBM) is a generative quantum machine learning algorithm that can be used to synthetically extend a dataset that is expensive or otherwise difficult to enlarge. This is achieved by training a parameterized quantum circuit to encode the data distribution  $p(x)$  in its output state  $|\psi\rangle \approx \frac{1}{\sqrt{N}} \sum_x p(x)|x\rangle$ . Measuring  $|\psi\rangle$  in the computational basis allows to efficiently sample new data points from the distribution.

In this talk, we present our investigation of the trainability and generalization properties of QCBMs. We discuss how the type of data can affect the trainability, and show how it can be improved using several simple techniques. Lastly, we outline how QCBMs could be extended to solve a wider range of tasks including conditional generation and classification.

QI 2.7 Mon 12:30 HS VIII

**Optimal recoil-free state preparation in an optical atom tweezer** — ●LIA KLEY<sup>1,2</sup>, NICOLAS HEIMANN<sup>1,2,3</sup>, ASLAM PARVEJ<sup>1,2</sup>, LUKAS BROERS<sup>1,2</sup>, and LUDWIG MATHEY<sup>1,2,3</sup> — <sup>1</sup>Zentrum für Optische Quantentechnologien, Universität Hamburg, 22761 Hamburg, Germany — <sup>2</sup>Institut für Quantenphysik, Universität Hamburg, 22761 Hamburg, Germany — <sup>3</sup>The Hamburg Centre for Ultrafast Imaging, 22761 Hamburg, Germany

Quantum computing in atom tweezers requires high-fidelity implementations of quantum operations. Here, we demonstrate the optimal implementation of the transition  $|0\rangle \rightarrow |1\rangle$  of two levels, serving as a qubit, of an atom in a tweezer potential, driven by a single-photon Rabi pulse. The Rabi pulse generates a photon recoil of the atom, due to the Lamb-Dicke coupling between the internal and motional degree of freedom, driving the system out of the logical subspace. This detrimental effect is strongly suppressed in the protocols that we propose. Using pulse engineering, we generate optimal protocols composed of

a Rabi protocol and a force protocol, corresponding to dynamically displacing the tweezer. We generate these for a large parameter space, from small to large values of the Rabi frequency, and a range of pulse lengths. We identify three main regimes for the optimal protocols, and discuss their properties. In all of these regimes, we demonstrate infidelity well below the current technological standard, thus mitigating a universal challenge in atom tweezers and other quantum technology platforms.