# QI 2: Quantum Computing and Algorithms I

Time: Monday 10:45–12:45 Location: H5

QI 2.1 Mon 10:45 H5

**Training variational quantum algorithms is NP-hard** — •Lennart Bittel and Martin Kliesch — Heinrich-Heine-Universität, Düsseldorf, Deutschland

Variational quantum algorithms (VQAs) are proposed to solve relevant computational problems on near term quantum devices. Popular versions are variational quantum eigensolvers (VQEs) and quantum approximate optimization algorithms (QAOAs) that solve ground state problems from quantum chemistry and binary optimization problems, respectively. They are based on the idea to use a classical computer to train a parameterized quantum circuit. We show that the corresponding classical optimization problems are NP-hard. Moreover, the hardness is robust in the sense that for every polynomial time algorithm, there exists instances for which the relative error resulting from the classical optimization problem can be arbitrarily large, assuming P =/= NP. Even for classically tractable systems, composed of only logarithmically many qubits or free fermions, we show that the optimization is NP-hard. This elucidates that the classical optimization is intrinsically hard and does not merely inherit the hardness from the ground state problem. Our analysis shows that the training landscape can have many far from optimal persistent local minima. This means gradient and higher order decent algorithms will generally converge to far from optimal solutions.

QI 2.2 Mon 11:00 H5

**Linear growth of quantum circuit complexity** — •Jonas Haferkamp[1], Philippe Faist[1], Naga Kothakonda[1], Jens Eisert[1], and Nicole Yunger Halpern[2] — [1]Freie Universität Berlin — [2]Harvard-Smithsonian, ITAMP

Quantifying quantum states' complexity is a key problem in various subfields of science, from quantum computing to black-hole physics. We prove a prominent conjecture by Brown and Susskind about how random quantum circuits' complexity increases. Consider constructing a unitary from Haar-random two-qubit quantum gates. Implementing the unitary exactly requires a circuit of some minimal number of gates - the unitary's exact circuit complexity. We prove that this complexity grows linearly in the number of random gates, with unit probability, until saturating after exponentially many random gates. Our proof is surprisingly short, given the established difficulty of lower-bounding the exact circuit complexity. Our strategy combines differential topology and elementary algebraic geometry with an inductive construction of Clifford circuits.

QI 2.3 Mon 11:15 H5

**Understanding Variational Quantum Learning Models** — Matthias C. Caro[1,2], Jens Eisert[3,4], Elies Gil-Fuster[3], •Johannes Jakob Meyer[3,5], Maria Schuld[6], and Ryan Sweke[3] — [1]Department of Mathematics, Technical University of Munich, Garching, Germany — [2]Munich Center for Quantum Science and Technology (MCQST), Munich, Germany — [3]Dahlem Center for Complex Quantum Systems, Freie Universität Berlin, Berlin, Germany — [4]Helmholtz-Zentrum Berlin für Materialien und Energie, Berlin, Germany — [5]QMATH, University of Copenhagen, Copenhagen, Denmark — [6]Xanadu, Toronto, ON, M5G 2C8, Canada

Finding practically relevant applications for noisy intermediate-scale quantum devices is an active frontier of quantum information research. Using them to execute parametrized quantum circuits used as learning models is a possible candidate. We show that the possible output functions of such learning models can be elegantly expressed by generalized trigonometric polynomials, whose available frequencies are determined by the spectra of the Hamiltonians used for the data encoding [1]. This approach allows for an intuitive understanding of quantum learning models and underlines the important role of data encoding in quantum machine learning. Building on this, we exploit this natural connection to give generalization bounds which explicitly take into account how a given quantum learning model is encoding the data [2]. These bounds can act as a guideline to select and optimize quantum learning models in a structural risk minimization approach. Based on [1] arXiv:2008.08605 and [2] arXiv:2106.03880.

QI 2.4 Mon 11:30 H5

**Generalization in quantum machine learning from few training data** — •Matthias C. Caro[1,2], Hsin-Yuan Huang[3,4], Marco Cerezo[5,6], Kunal Sharma[7,8], Andrew Sornborger[9,10], Lukasz Cincio[5], and Patrick J. Coles[5] — [1]Department of Mathematics, TU Munich, Garching, Germany — [2]MCQST, Munich, Germany — [3]IQIM, Caltech, Pasadena, CA, USA — [4]Department of Computing and Mathematical Sciences, Caltech, Pasadena, CA, USA — [5]Theoretical Division, LANL, Los Alamos, NM, USA — [6]Center for Nonlinear Studies, LANL, Los Alamos, NM, USA — [7]QuICS, University of Maryland, College Park, MD, USA — [8]Department of Physics and Astronomy, Louisiana State University, Baton Rouge, LA USA — [9]Information Sciences, LANL, Los Alamos, NM, USA — [10]Quantum Science Center, Oak Ridge, TN, USA

Modern quantum machine learning (QML) methods involve variationally optimizing a parameterized quantum circuit on training data, and then make predictions on testing data. We study the generalization performance in QML after training on $N$ data points. We show: The generalization error of a quantum circuit with $T$ trainable gates scales at worst as $\sqrt{T/N}$. When only $K \ll T$ gates have undergone substantial change in the optimization process, this improves to $\sqrt{K/N}$.

Core applications include significantly speeding up the compiling of unitaries into polynomially many native gates and classifying quantum states across a phase transition with a quantum convolutional neural network using a small training data set. Our work injects new hope into QML, as good generalization is guaranteed from few training data.

QI 2.5 Mon 11:45 H5

**Quantum Autoencoders for Error Correction** — •David Locher[1], Lorenzo Cardarelli[2], and Markus Müller[1,2] — [1]Institute for Quantum Information, RWTH Aachen University, D-52056 Aachen, Germany — [2]Peter Grünberg Institute, Theoretical Nanoelectronics, Forschungszentrum Jülich, D-52425 Jülich, Germany

The operation of reliable large-scale quantum computers will foreseeably require quantum error correction procedures, in order to cope with errors that dynamically occur during storage and processing of fragile quantum information. Classical machine learning approaches, e.g. neural networks, have been proposed and successfully used for flexible and scalable strategies for quantum error correction. Complementary to these efforts, we investigate the potential of quantum machine learning for quantum error correction purposes. Specifically, we show how quantum neural networks, in the form of quantum autoencoders, can be trained to learn optimal strategies for active detection and correction of errors, including possibly correlated bit-flip and depolarizing noise, as well as qubit loss. We highlight that the denoising possibilities of quantum autoencoders are not limited to the protection of specific states but extend to entire logical codespaces. In addition, we show that quantum neural networks can discover new encodings, optimally adapted to the underlying noise.

QI 2.6 Mon 12:00 H5

**Gottesman-Kitaev-Preskill bosonic error correcting codes: a lattice perspective** — Jonathan Conrad, •Francesco Arzani, and Jens Eisert — Freie Universität Berlin, Arnimallee 14, 14195 Berlin

Bosonic error correcting codes (ECC) protect the state of a finite-dimensional quantum system by embedding it in the infinite-dimensional Hilbert space of an ensemble of harmonic oscillators. Gottesman-Kitaev-Preskill (GKP) codes are a class of bosonic ECC that rely on translation symmetries of the code-states to detect and correct common errors affecting physical realizations of harmonic oscillators (e.g. photon loss in electromagnetic modes). For example, imposing the correct symmetries on a single oscillator restricts the state-space to that of a qubit. To achieve better noise resilience, the code can be concatenated with a qubit-level ECC. This allows to directly apply the machinery developed for qubits. However, the translation symmetries also establish a formal connection with lattices, which is not fully exploited by usual approaches to concatenated codes (CC). Furthermore, CC are special cases, which are not guaranteed to be optimal given the underlying bosonic nature of the system.

We examine general GKP codes, including concatenated GKP codes, through the lens of lattice theory to understand the structure of this class of stabilizer codes. We derive formal bounds on code parameters, show how different decoding strategies are related and point to natural resource savings that have remained hidden in previous approaches.

QI 2.7 Mon 12:15 H5

**Scalable approach to many-body localization via quantum data** — •Alexander Gresch, Lennart Bittel, and Martin Kliesch — Quantum Technology Group, Heinrich Heine University Düsseldorf

We are interested in how quantum data can allow for practical solutions to otherwise difficult computational problems. Such a notoriously difficult phenomenon from quantum many-body physics is the emergence of many-body localization (MBL). So far, is has evaded a comprehensive analysis. In particular, numerical studies are challenged by the exponential growth of the Hilbert space dimension. As many of these studies rely on exact diagonalization of the system's Hamiltonian, only small system sizes are accessible.

In this work, we propose a highly flexible neural network based learning approach that, once given training data, circumvents any computationally expensive step. In this way, we can efficiently estimate common indicators of MBL such as the adjacent gap ratio or entropic quantities. Moreover, our estimator can be trained on data from various system sizes at once which grants the ability to extrapolate from smaller to larger ones. We hope that our approach can be applied to large-scale quantum experiments to provide new insights into quantum many-body physics.

QI 2.8 Mon 12:30 H5

**Fermion Sampling** — Michal Oszmaniec[1], Ninnat Dangniam[1], Mauro Morales[2], and •Zoltan Zimboras[3,4] — [1]Center for Theoretical Physics, Polish Academy of Sciences — [2]University of Technology Sydney, Australia — [3]Wigner Research Centre for Physics, Budapest, Hungary — [4]BME-MTA Lendület Quantum Information Theory Research Group, Budapest, Hungary and Mathematical Institute, Budapest University of Technology and Economics, Budapest, Hungary

In this talk, we present a quantum advantage scheme which is a fermionic analogue of Boson Sampling: Fermion Sampling with magic input states. We argue that this scheme merges the strengths of Random Circuit Sampling and Boson Sampling. On the one hand side, we provide hardness guarantees for this scheme which is at a comparable level to that of the state-of-the-art hardness guarantees for Random Circuit Sampling, surpassing that of Boson Sampling. On the other hand, we argue that there are verification schemes of Fermion Sampling circuits that are stronger than those for Random Circuit Sampling. We also discuss the experimental feasibility of our scheme.