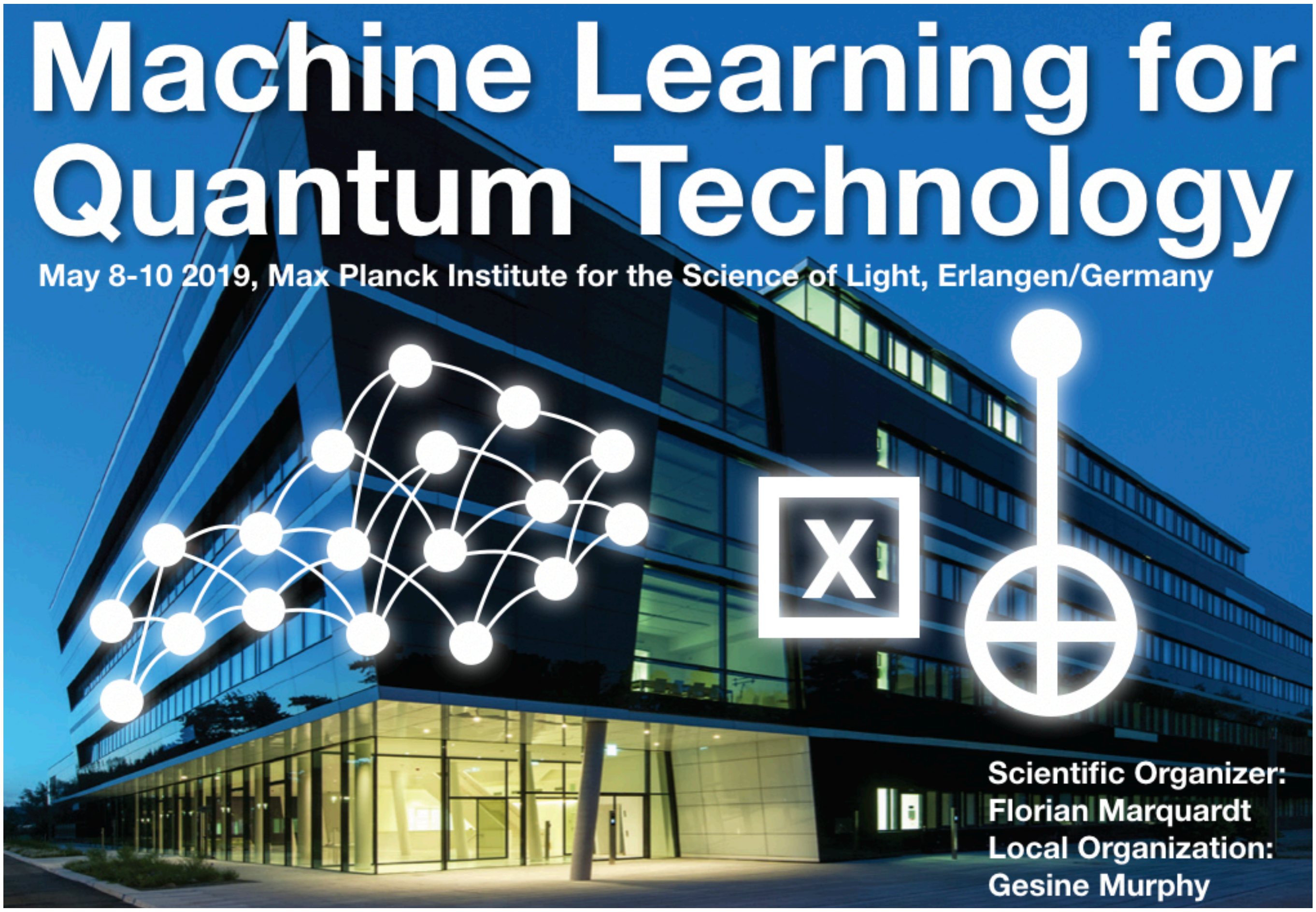
Workshop Machine Learning for Quantum Technology 2019



8th May – 10th May 2019

Max Planck Institute for the Science of Light,

Erlangen, Germany

MAX PLANCK INSTITUTE
for the science of light

Organizer

Florian Marquardt, MPL Erlangen

Workshop Location

Max Planck Institute for the Science of Light,

Staudtstraße 2, 91058 Erlangen, Germany

Workshop rooms (see maps next pages for precise location)

Talks

8th -10th	Leuchs-Russell Auditorium, 1st floor

Lunch

8th – 10th May	MPL Foyer, ground floor

Dinner

8th May	MPL Foyer, ground floor
9th May	Entlas‘ Keller, Erlangen

Poster Session

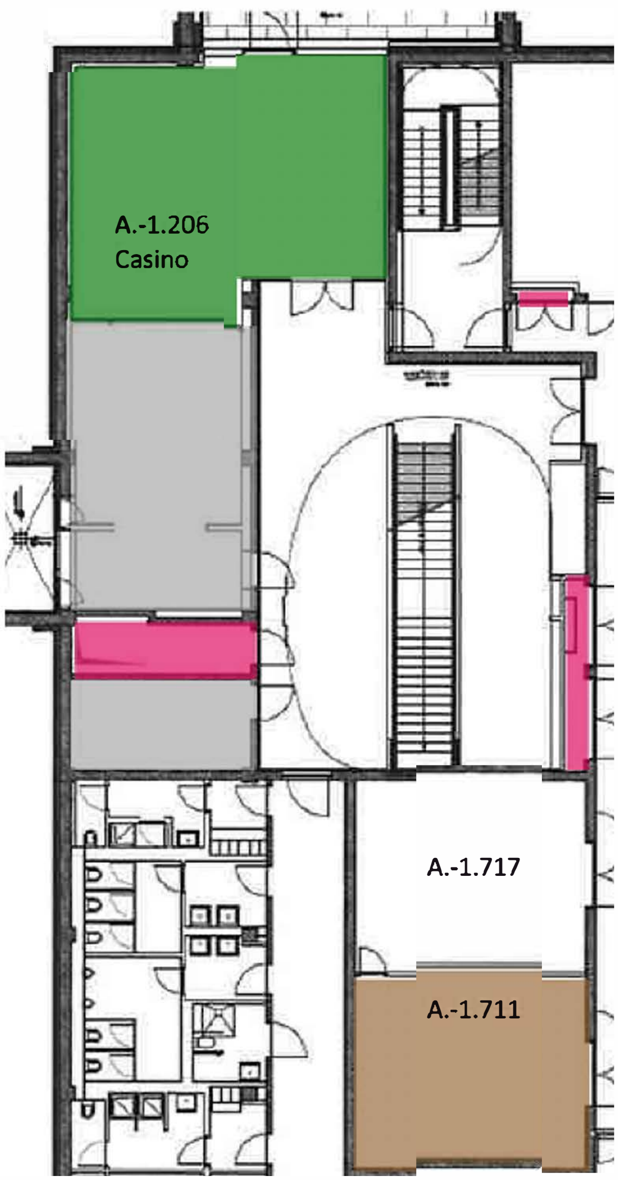
8th May	MPL Foyer, ground floor

Contact

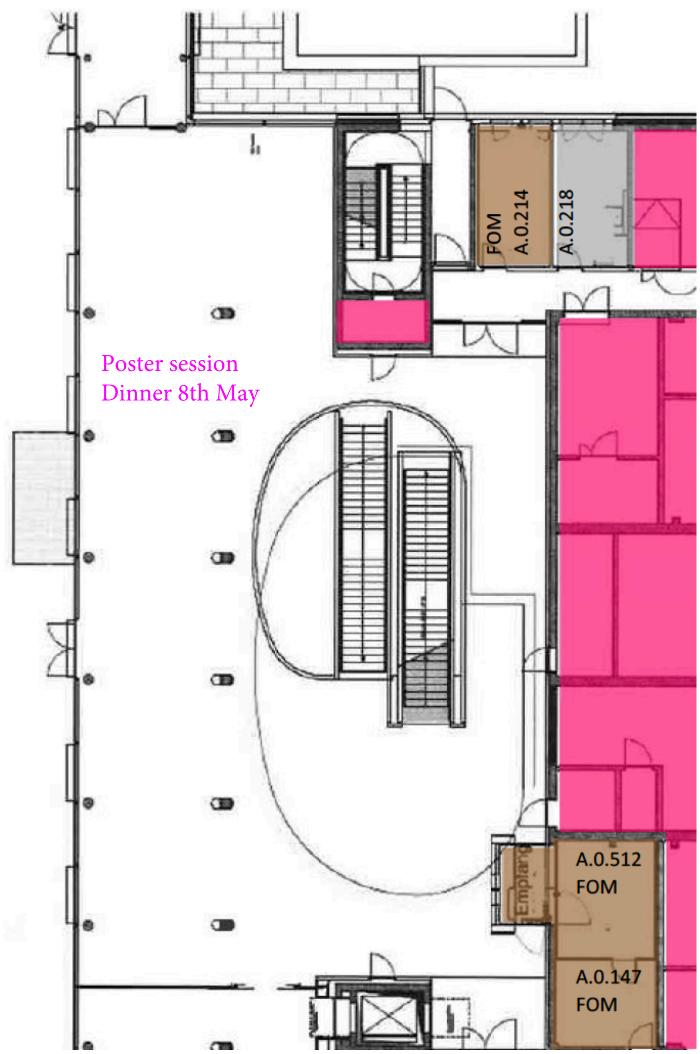
Ms. Gesine Murphy, MPL Room: A.2.108, Tel.: +49 9131 7133 401,

Email: gesine.murphy@mpl.mpg.de

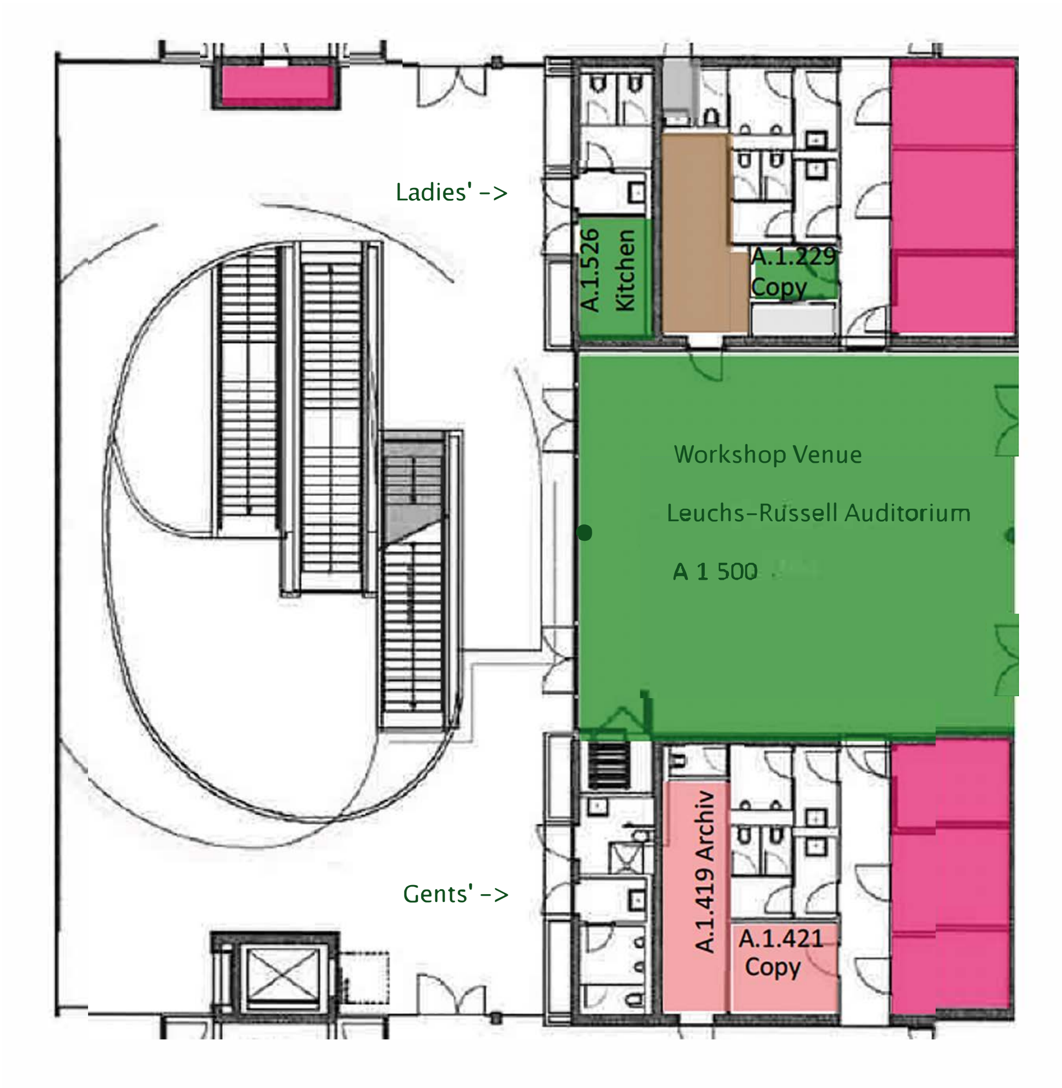
MPL UG/Basement



MPL EG/Ground floor

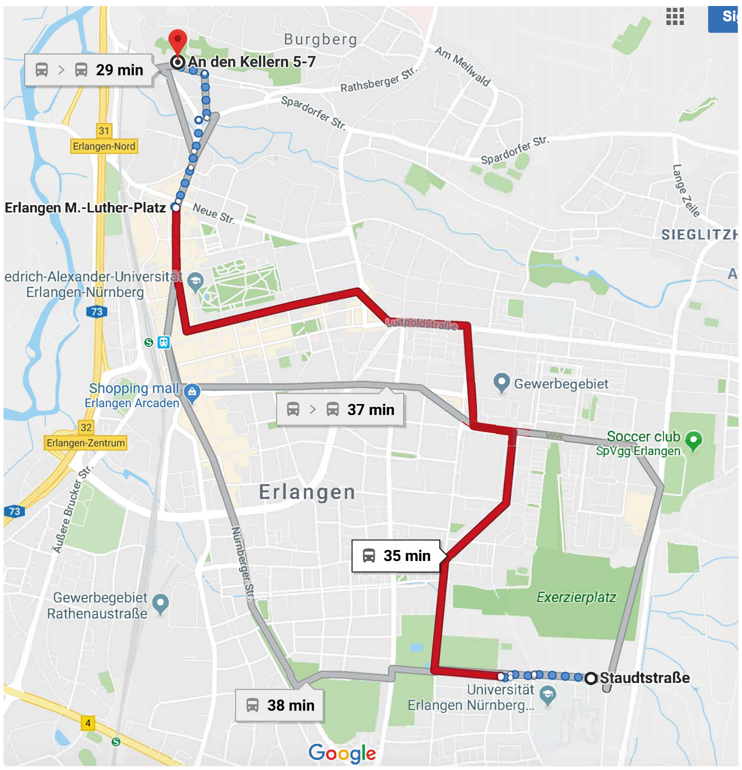


MPL 1st floor



Dinner on 9th May 2019 -
How to get to Entla‘s Keller, An den Kellern 5-7, 91054 Erlangen

By bus, e. g. bus 293 at 17:39, 17:59, 18:19



6:13 PM Staudtstraße
Erlangen

Walk
About 6 min , 450 m

6:19 PM Erlangen Fridericianum

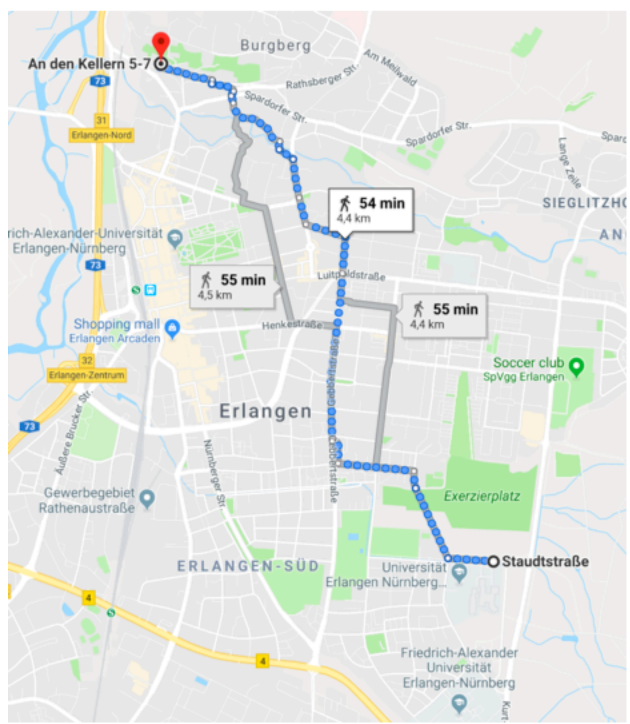
293 Büchenbach/ER Zambellistr.
18 min (12 stops)

6:37 PM Erlangen M.-Luther-Platz

Walk
About 11 min , 800 m

6:48 PM An den Kellern 5-7
91054 Erlangen

Or on foot:



Schedule Wednesday, 8th May 2019

09:30 – 09:45	Registration
09:45 – 10:00	Welcome and Opening Remarks
10:00 – 10:40	Reinforcement learning and AI for quantum experiment Hans-Jürgen Briegel, University of Innsbruck (Austria)
10:40 – 11:15	Topological quality control Paul Baireuther, Bosch Center for Artificial Intelligence (Germany)
11:15 – 11:35	Quantum error correction via Hamiltonian learning Eliska Greplova, ETH Zurich (Switzerland)
11:35 – 11:50	Coffee break
11:50 – 12:25	Supervised learning of time-independent Hamiltonians for gate design Mauro Paternostro, Queen's University Belfast (UK)
12:25 – 12:45	Reinforcement learning for quantum memory Thomas Fösel, MPL (Germany)
12:45 – 13:20	Efficiently measuring and tuning quantum devices using machine learning Natalia Ares, University of Oxford (UK)
13:20 – 14:00	Lunch

Schedule Wednesday 8th May 2019

14:30 – 15:05	Integrating neural networks with Rydberg quantum simulators Evert van Nieuwenburg, Caltech (USA)
15:05 – 15:25	Emulating entanglement on temporally sampling deep neural networks Stefanie Czischek, University of Heidelberg (Germany)
15:25 – 15:40	Coffee break
15:40 – 16:15	Reinforcement learning to prepare quantum states away from equilibrium Marin Bukov, Berkeley (USA)
16:15 – 16:35	Variational neural network ansatz for steady-states in open quantum systems Filippo Vicentini, Université Paris Diderot (France)
17:00 – 18:00	Discussion time
18:30 – 19:30	Dinner at MPL
19:30 – 21:00	Poster session

Schedule Thursday, 9th May 2019

10:00 – 10:40	Generative models for wavefunction reconstruction Roger Melko, University of Waterloo (Canada)
10:40 – 11:15	Reinforcement learning decoders for fault-tolerant quantum computation and other perspectives of quantum machine learning Jens Eisert, Freie Universität Berlin (Germany)
11:15 – 11:35	Speedup problem for quantum walks and quantum annealing algorithms implementation Aleksandr Alodzhants, ITMO University St. Petersburg (Russia)
11:35 – 11:50	Coffee break
11:50 – 12:25	Machine learning for certification of photonic quantum information Fabio Sciarrino, Sapienza Università die Roma (Italy)
12:25 – 12:45	Error correction for the toric code using deep reinforcement learning Mats Granath, University of Gothenburg (Sweden)
12:45 – 13:20	Using a recurrent neural network to reconstruct quantum dynamics of a superconducting qubit from physical observations Emmanuel Flurin, Quantronics – CEA (France)
13:20 – 14:00	Lunch

Schedule Thursday, 9th May 2019

14:30 – 15:05	Learning the dynamics of quantum systems using statistical inference Raffaele Santagati, University of Bristol (UK)
15:05 – 15:25	Neural network decoders for large-distance 2D Toric codes Xiaotong Ni, TU Delft (Netherlands)
15:25 – 15:40	Coffee break
15:40 – 16:15	Deep reinforcement learning for steering qubits Enrico Prati, Consiglio Nazionale delle Ricerche (Italy)
16:15 – 16:35	Divergence of predictive model output as indication of phase transitions Niels Loerch, University of Basel (Switzerland)
17:00 -18:00	Discussion time
18:30 – 20:30	Dinner at Entla's Keller
20:30 – 21:00	Scientific Walk 'n Talk

Schedule Friday, 10th May 2019

10:00 – 10:40	Learning for adaptive quantum control Barry Sanders, University of Calgary (Canada)
10:40 – 11:15	Discovering physical concepts with neural networks Renato Renner, ETH Zurich (Switzerland)
11:15 – 11:30	Coffee break
11:30 – 11:50	Experimental Protocol for Quantum State Engineering throughone-dimensional Quantum Walk Alessia Suprano, Università di Roma Sapienza (Italy)
11:50 – 12:10	Reinforcement learning in quantum optics experiments Alexey Melnikov, University of Basel (Switzerland)
12:10 – 12:30	QAR-Lab Site Report and the PlanQK Initiative Thomas Gabor, Christoph Roch, LMU Munich (Germany)
12:30 – 13:30	Lunch
13:45 – 14:20	Stochastic estimation of dynamical variables Stefan Krastanov, Yale Quantum Institute (USA)
14:20 – 14:55	Neural-network approach to dissipative quantum many-body dynamics Michael Hartmann, Heriot-Watt University (UK)
14:55 – 15:00	Closing remarks

Poster session Wednesday, 8th May 2019, 18:30

Sudoku and other NP-hard optimization problems with Neural Networks
Shahnawaz Ahmed, Chalmers University of Technology (Sweden)

Quantum digital simulation of three toy models using IBM quantum hardware
Pedro Cruz, University of Porto (Portugal)

Exploring graph complexity with quantum spin systems
Durga B. Rao Dasari, University of Stuttgart

Entanglement Stabilization in a Superconducting Quantum Processor using Parity Detection and Real-Time Feedback
Christopher Eichler, ETH Zürich

Quantum Model Learning
Brian Flynn, University of Bristol (UK)

The contribution of quantum computing in developing an artificial general intelligence
Marc Gänsler, LMU Munich (Germany)

Tbd
Ilia Iakovlev, Ural Federal University

Supervised learning of time-independent Hamiltonians for gate design
Luca Innocenti, Queen's University Belfast (UK)

Infrared Molecular Fingerprinting:A Machine-Learning Analysis
Kosmas Kepesidis, LMU Munich (Germany)

A Reinforcement Learning approach for Quantum State Engineering
Jelena Mackeprang, University of Stuttgart (Germany)

Tbd
Rodrigo Martinez-Pena, IFISC (Spain)

Theoretical preparation of quantum nanoskyrmion state for experimental realization on quantum computer
Vladimir Mazurenko, Ural Federal University (Russia)

Self-learning Monte Carlo simulations of classical and quantum many-body systems
Kai Meinerz, University of Cologne (Germany)

Tbd
André Melo, TU Delft (Netherlands)

Machine learning to create ordered states in ultra-cold systems
Rick Mukherjee, Imperial College London (UK)

Numerical optimisation of silicon nitride photonic crystal nanobeam cavities
Jan Olthaus, University of Münster (Germany)

A novel method of data remapping for quantum information science
Syed Adil Rab, Cogisen Srl (Italy)

Design of robust control of quantum systems with polychromatic low-frequency radiation
German Sinuco Leon, University of Sussex (UK)

Machine learning to create ordered states in ultra-cold systems
Frederic Sauvage, Imperial College London (UK)

Divergence of predictive model output as indication of phase transitions
Frank Schäfer, University of Basel (Switzerland)

Improving Quantum Metrology with Reinforcement Learning
Jonas Schuff, University of Tübingen (Germany)

Neural network agent playing spin Hamiltonian games on a quantum computer
Oleg Sotnikov, Ural Federal University (Russia)

Machine learning for long-distance quantum communication
Julius Wallnöfer, University of Innsbruck (Austria)

Quantum State Tomography using Quartic Potentials and Neural Networks
Talitha Weiß, University of Innsbruck (Austria)

Quantum Circuit Design for Training Perceptron Models
Yu Zheng, Chalmers University of Technology

Abstracts Talks

Natalia Ares

Efficiently measuring and tuning quantum devices using machine learning

Fulfilling the promise of quantum technologies requires to be able to measure and tune several devices; fault-tolerant factorization using a surface code will require ~10^8 physical qubits. A long-term approach, based on the success of integrated circuits, is to use electron spins in semiconducting devices. A major obstacle to creating large circuits in this platform is device variability. It is very time consuming to fully characterize and tune each of these devices and this task will rapidly become intractable for humans without the aid of automation.

I will present efficient measurements on a quantum dot performed by a machine learning algorithm. This algorithm employs a probabilistic deep-generative model, capable of generating multiple full-resolution reconstructions from scattered partial measurements. Information theory is then used to select the most informative measurements to perform next. The algorithm outperforms standard grid scan techniques in different measurement configurations, reducing the number of measurements required by up to 4 times. I will also show the use of Bayesian optimisation to tune a quantum dot device. By generating a score function, we can efficiently navigate a multi-dimensional parameter space. We tune the device to the single-electron tunnelling regime with no previous knowledge of the device characteristics in less than a thousandth part of the time that it requires manually.

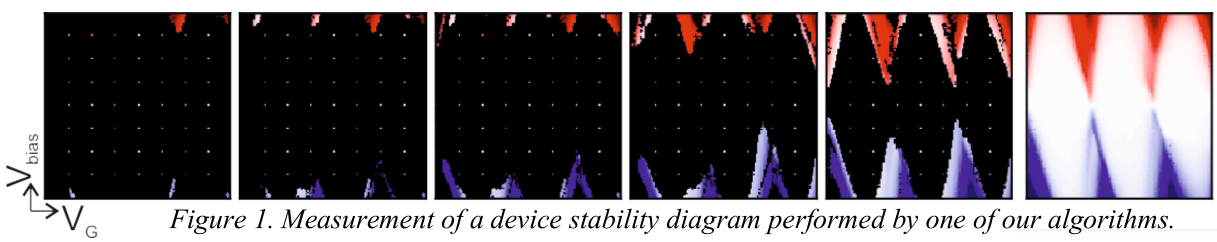


Figure 1. Measurement of a device stability diagram performed by one of our algorithms.

Paul Baireuther

Topological quality control

The continuous effort towards topological quantum devices calls for an efficient and non-invasive method to assess the conformity of components in different topological phases. In this talk, I will discuss how machine learning can assist in measuring local topological invariants [1].

[1] M. D. Caio, M. Caccin, P. Baireuther, T. Hyart, and M. Fruchart, arXiv:1901.03346

Marin Bukov

Reinforcement learning to prepare quantum states away from equilibrium

The ability to prepare a physical system in a desired quantum state is central to many areas of physics such as nuclear magnetic resonance, cold atoms, and quantum computing. Yet, preparing states quickly and with high fidelity remains a formidable challenge. In this work I will show how a Q-Learning agent succeeds in the task of finding short, high-fidelity driving protocols from an initial to a target state in non-integrable many-body quantum systems of interacting qubits. RL methods learn about the underlying physical system solely through a single scalar reward (the fidelity of the resulting state) calculated from numerical simulations of the physical system. If time permits, I will demonstrate that quantum state manipulation, viewed as an optimization problem, exhibits a spin-glass-like phase transition in the space of protocols as a function of the protocol duration. Our study highlights the potential usefulness of RL for applications in out-of-equilibrium quantum physics.

Jens Eisert

Reinforcement learning decoders for fault-tolerant quantum computation and other perspectives of quantum machine learning

Quantum machine learning comes in many facets: It either makes use of a methodology of machine learning for particularly suitable classes of problems involving quantum data. It can also refer to making use of ideas of coherent notions of learning in the quantum information context. The main part of the talk will be concerned with an instance of the first kind for which ideas of machine learning seem particularly suitable [1]. Topological error correcting codes, and particularly the surface code, currently provide the most feasible roadmap towards large-scale fault-tolerant quantum computation. As such, obtaining fast and flexible decoding algorithms for these codes, within the experimentally relevant context of faulty syndrome measurements, is of critical importance. In this work, we show that the problem of decoding such codes, in the full fault-tolerant setting, can be naturally reformulated as a process of repeated interactions between a decoding agent and a code environment, to which the machinery of reinforcement learning can be applied to obtain decoding agents. As a demonstration, by using deepQ learning, we obtain fast decoding agents for the surface code, for a variety of noise-models. In an outlook, depending on the time, I may elaborate on further perspectives and some ideas towards a statistical basis of quantum learning theory [2].

R. Sweke, M. S. Kesselring, E. P. L. van Nieuwenburg, J. Eisert, arXiv:1810.07207.

In preparation.

Emmanuel Flurin

Using a Recurrent Neural Network to Reconstruct Quantum Dynamics of a Superconducting Qubit from Physical Observations

E. Flurin [1], L. S. Martin [2], S. Hacohen-Gourgy [3], I. Siddiqi [2]

[1] Quantronics group, SPEC, IRAMIS, DSM, CEA Saclay, 91191 Gif-sur-Yvette, France.

[2] Quantum Nanoelectronics Laboratory,Department of Physics, UC Berkeley CA 94720, USA.

[3] Technion Israel Institute of Technology, Israel.

Quantum mechanics provides us with an accurate set of rules to optimally predict the outcome of experiments, however it is also infamous for being abstract and highly counter intuitive. Neural networks are powerful tools to extract non-trivial correlation in vast datasets, they recently outperformed state-of-the-art techniques in language translation, medical diagnosis or image recognitions. It remains to be seen if they can be of aid in learning non-intuitive dynamics such as ones found in quantum systems without any prior. Here, we demonstrate that a recurrent neural network can be trained in real time to infer the quantum evolution of a superconducting qubit under non-trivial unitary evolution and continuous measurement from raw experimental observations only. These predictions are exploited to extract the system Hamiltonian, measurement operators and parameters such as quantum efficiency with a greater accuracy than usual calibration methods. Also, the quantum tomography of an unknown initial state is performed without prior calibration. This work shows that quantum mechanics can be inferred from observation based on deep learning methods and can be readily extended to larger quantum system in a model independent fashion to enhance quantum sensing or QCVV.

Michael J. Hartmann

Neural-Network Approach to Dissipative Quantum Many-Body Dynamics

In experimentally realistic situations, quantum systems are never perfectly isolated and the coupling to their environment needs to be taken into account. Often, the effect of the environment can be well approximated by a Markovian master equation. However, solving this master equation for quantum many-body systems, becomes exceedingly hard due to the high dimension of the Hilbert space. Here we present an approach to the effective simulation of the dynamics of open quantum many-body systems based on machine learning techniques. We represent the mixed many-body quantum states with neural networks in the form of restricted Boltzmann machines and derive a variational Monte-Carlo algorithm for their time evolution and stationary states. We document the accuracy of the approach with numerical examples for a dissipative spin lattice system.

Stefan Krastanov

Stochastic Estimation of Dynamical Variables

Stefan Krastanov[1], Sisi Zhou[1], Steven T. Flammia[1,2], Liang Jiang[1]

Estimating the parameters governing the dynamics of a system is a prerequisite for its optimal control. We present a simple but powerful method that we call STEADY, for STochastic Estimation Algorithm for DYnamical variables, to estimate the Hamiltonian (or Lindbladian) governing a quantum system of a few

qubits. STEADY makes efficient use of all measurements and it saturates the information-theoretic limits for such an estimator. Importantly, it is inherently robust to state preparation and measurement errors. It is not limited to evaluating only a fixed set of possible gates, rather it estimates the complete Hamiltonian of the system. The estimator is applicable to any Hamiltonian that can be written as a piecewise-differentiable function and it can easily include estimators for the non-unitary parameters as well. Moreover, it can be extended to work on Stochastic Master Equations. At the heart of our approach is a stochastic gradient descent over the difference between experimental measurement and model prediction. Described in arxiv:1812.05120

[1] Yale Quantum Institute, Yale University, New Haven, Connecticut 06520, USA

[2] Centre for Engineered Quantum Systems, School of Physics, University of Sydney, Sydney NSW, Australia

Roger Melko

Generative Models for Wavefunction Reconstruction

The quantum wavefunction presents the ultimate "big data" problem in physics. When a large number of qubits are highly entangled, the resulting complexity presents a daunting challenge for any computational strategy seeking to characterize the underlying quantum state. Recently, a new computational toolbox based on modern machine learning techniques has been rapidly adopted into the field of quantum physics. In this talk, I will discuss how generative modelling can provide a practical route to approximate reconstruction of certain quantum wavefunctions. Such methods raise important theoretical questions, the most pressing being how the structure of typical physical wavefunctions affects their learnability from experimentally-accessible measurement data.

Evert van Nieuwenburg

Integrating neural networks with Rydberg quantum simulators

Recent theoretical studies have demonstrated the efficacy of neural network models in unsuper- vised reconstruction of pure and mixed quantum states. So far, however, these analyses have been restricted to training on error-free projective measurement results sampled from numerical algo- rithms. Here, we demonstrate an extension of this reconstruction technique to noisy experimental quantum simulator data, by expanding the network model to include an explicit description of the measurement process. We extract Restricted Boltzmann Machine (RBM) wavefunctions from data produced by a Rydberg atom array experiment in a single measurement basis, and apply a novel regularization technique for mitigating the effects of measurement errors in the training data. Re- constructions of modest complexity are able to capture one- and two-body observables not accessible to experimentalists, as well as more sophisticated observables such as the Renyi mutual information. Our results open the door to deeper integration of machine learning architectures with quantum hardware.

Mauro Paternostro

Supervised learning of time-independent Hamiltonians for gate design

I will illustrate the application of machine learning to a problem of "quantum gate synthesis", i.e. the identification of the best suited configuration of interactions among the elements of a computational register that realises a desired unitary transformation. I will then show how the same logic can be applied to problems of quantum state engineering in large Hilbert spaces, illustrating a recent experiment performed on a quantum network involving a multimode setting where coherent absorption effects are emulated through a simple learning approach.

Enrico Prati

Deep reinforcement learning for steering qubits

The diffusion of deep learning algorithms has boosted the research in several fields. The paradigm shift from knowledge-based to representation-based artificial intelligence has opened the chance to apply novel methods to physics. I review quantum computer architectures [1] and I show how to improve quantum computers by exploiting deep reinforcement learning [2]. I present two practical examples of how to steer a qubit by exploiting deep reinforcement learning, namely in the case of spatial coherent transport by adiabatic passage (CTAP) [3] of quantum states [4] and in the field of quantum compiling, managed by using A2C and TRPO deep reinforcement learning algorithms. By reverse engineering the network, it is possible to achieve better understanding of the physical process itself by identifying those physical quantities more contributing to the process.

D. Rotta, F. Sebastiano, E. Charbon, and E. Prati, "Quantum information density scaling and qubit operation time constraints of cmos silicon-based quantum computer architectures," npj Quantum Information, vol. 3, no. 1, p. 26, 2017.

A. Bonarini, C. Caccia, A. Lazaric, and M. Restelli, "Batch reinforcement learning for controlling a mobile wheeled pendulum robot," in IFIP International Conference on Artificial Intelligence in Theory and Practice, pp. 151–160, Springer, 2008.

E. Ferraro, M. D. Michielis, M. Fanciulli, and E. Prati, "Coherent tunneling by adiabatic passage of an exchange-only spin qubit in a double quantum dot chain," Phys. Rev. B, vol. 91, p. 075435., 2015.

R. Porotti, D. Tamascelli, M. Restelli, and E. Prati, Coherent Transport of Quantum States by Deep Reinforcement Learning, arXiv:submit/2546122 [quant-ph] 20 Jan 2019

Renato Renner

Discovering physical concepts with neural networks

Suppose that a neural network has been trained to successfully predict certain physical observations, e.g., the position of a planet at a particular time. Does this mean that the network has gained an understanding of the underlying physical concepts, such as Kepler's laws? And, if yes, is there a way to extract this conceptual knowledge from the network? Once these questions can be answered in the affirmative, neural networks may become a valuable tool in research on the foundations of physics. In my talk, I will describe some very first steps we took in this direction. One of these steps consists of the proposal of a neural network architecture that models the physical reasoning process. The architecture enables the extraction of physical relations from the trained network. This is illustrated by several simple examples.

The talk will be based on arXiv:1807.10300, which is joint work with Raban Iten, Tony Metger, Henrik Wilming, and Lidia del Rio

Barry Sanders

Learning for adaptive quantum control

We develop a framework for connecting adaptive quantum control to machine learning, with applications to adaptive quantum metrology and to quantum logic gates in superconducting circuits and ion traps. Our framework suggests how to systematically study the intriguing topic of quantum reinforcement learning.

Raffaele Santagati

Learning the dynamics of quantum systems using statistical inference

R. Santagati, A.A. Gentile, B. Flynn, S. Paesani, N. Wiebe, C. Granade, S. Knauer, J. Wang, S. Schmidt, L.P. McGuinness, J. Rarity, F. Jelezko, A. Laing

Statistical inference algorithms have found a wide range of applications in quantum technologies thanks to their noise-resilience properties and flexibility. In this talk, I will present some of the most recent research, carried out at Bristol's Quantum engineering and technology labs (QETLabs), on the characterisation and optimisation of quantum technologies using Bayesian inference.

Bayesian inference protocols, such as Quantum likelihood estimation (QLE) [1], have been experimentally applied to the characterisation of quantum systems [2] and the efficient estimation of magnetic fields using single spin quantum sensors [3]. Starting from these two demonstrations, we will explore new applications, considering those cases where prior knowledge of the model describing the system under study is limited [4, 5].

Wiebe et al. Hamiltonian Learning and Certification Using Quantum Resources. Phys. Rev. Lett. 112, (2014)

Wang et al. Experimental quantum Hamiltonian learning - Nature Physics 1, 149 (2017)

Santagati et al. Magnetic-field-learning using a single electronic spin in diamond with one-photon-readout at room temperature - Phys. Rev. X (2019)

Gentile et al. Characterising open quantum systems with Bayesian inference - manuscript in preparation (2019)

Flynn et al. Exploring acyclic graphs for the study of quantum systems – manuscript in preparation (2019)

Aleksandr Alodzhants

Speedup problem for quantum walks and quantum annealing algorithms implementation

The speedup problem of algorithms implementation for quantum computing is one of extensively discussed now. Although quantum parallelism, in general, represents the necessary ingredient for acceleration of computational algorithms on quantum "hardware", sufficient criterion is still unknown in many cases. In my talk I discuss two important examples with quantum annealing, and quantum walks processes.

First, I will focus on the quantum annealing problem that is relevant to the searching algorithm for the global minimum of the potential energy landscape consisting of a set of barriers and wells. In a purely classical (thermal) regime the bosonic particles cross barriers stochastically at finite temperature with the help of thermal activation process if the thermal energy is large enough. Contrary, in a quantum limit the same system undergoes quantum tunneling through the barrier. To be more specific we study the effect of a finite effective temperature on the coupling of quasi-equilibrium exciton-polariton condensates accounting for the competing thermal and quantum annealing effects [1]. We demonstrate the crossover from thermal to quantum annealing regime for a model system of two condensates localized by a W-shape potential. The transition between thermal activation (classical) and tunneling (quantum) regimes exhibits universal features of the first and second order phase transition phase transition depending on the potential energy landscape for polariton condensates that might be described as transition from the thermal to the quantum annealing regime. We show that improvement of the annealing algorithm in the quantum domain strongly depends on the particle number and governed by the ratio which depends on the effective action difference taken at a given temperature T.

In another example, I discuss a new machine learning method to detect a speedup of quantum transport [2]. It is known that quantum particles propagate faster than classical analogs on certain graphs. However, there is not much known about the possible speedups on large scale graphs without apparent symmetries. In order to distinguish between quantum and classical regimes, we train a discriminative classifier that is a specially designed convolutional neural network (CQCNN). We generate training examples, each consisting of an adjacency matrix and a corresponding label ("classical" or "quantum"), by simulating the random walk dynamics of classical and quantum particles. By training CQCNN we show that the neural network is able to learn to classify the quantum speedup. First, we demonstrate that CQCNN learns to approximate given examples well by representing the quantum and classical properties of graphs in its weights. Second, we demonstrate that CQCNN correctly classifies not only previously unseen graphs of the same size, but also of larger sizes that were not used in the training phase. Our findings pave the way to an automated elaboration of novel large-scale quantum circuits utilizing quantum walk based algorithms, and to simulating high-efficiency energy transfer in biophotonics and material science.

1. M. Lebedev, D. Dolinina, K.B. Hong, T. Lu, A.V. Kavokin, A.P. Alodjants. Exciton-polariton Josephson junctions at finite temperatures // Scientific Reports - 2017, Vol. 7, pp. 9515
2. Alexey A. Melnikov, Leonid E. Fedichkin, and Alexander Alodjants, Detecting quantum speedup by quantum walk with convolutional neural networks, arXiv:1901.10632v1 [quant-ph] 30 Jan 2019

Stefanie Czischek

Emulating entanglement on temporally sampling deep neural networks

Representing quantum spin-1/2 systems by artificial neural networks has gained a lot of interest recently. Neural network architectures can be implemented in a controlled manner by means of analog hardware setups. This opens the prospect that neuromorphic computers can be used to efficiently emulate quantum many-body systems.

Here we choose a deep-neural-network ansatz to represent quantum spin-1/2 states to allow for measurements in orthogonal spin bases. We apply our scheme to small systems with non-classical features and show that quantum entanglement can be represented by the classical stochastic network. Using discrete Langevin-type dynamics to sample spin states from the network-encoded distribution, we simulate a spiking neural network, which suggests implementation on neuromorphic hardware, such as the BrainScaleS system.

Thomas Foesel

Reinforcement Learning for Quantum Memory

Machine learning with artificial neural networks is revolutionizing science. In the search for optimal control sequences, where the success can only be judged with some time-delay, reinforcement learning is the method of choice. The power of this technique has been highlighted by spectacular recent successes such as playing Go [1].

We have explored how a network-based "agent" can discover complete quantum-error-correction strategies, protecting a collection of qubits against noise [2]. These strategies require feedback adapted to measurement outcomes. Finding them from scratch without human guidance and tailored to different hardware resources is a formidable challenge due to the combinatorially large search space. Beyond its immediate impact on quantum computation, our work more generally demonstrates the promise of neural-network-based reinforcement learning in physics.

[1] D. Silver et al., Nature 550, 354–359 (2017)

[2] T. Fösel, P. Tighineanu, T. Weiss, and F. Marquardt, Phys. Rev. X 8, 031084 (2018)

Thomas Gabor, Christopher Roch

QAR-Lab Site Report and the PlanQK Initiative

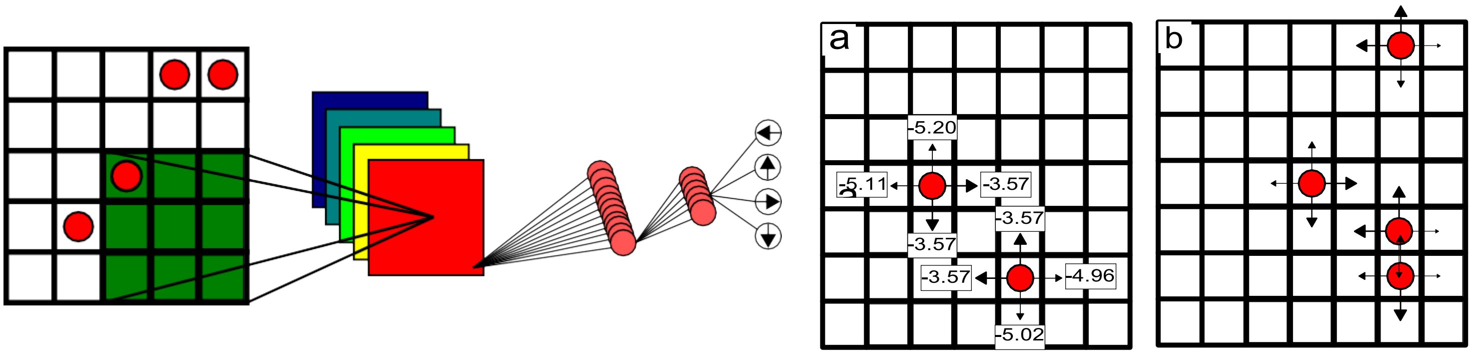
The Quantum Applications and Research Laboratory (QAR-Lab) is situated at the chair for mobile and distributed systems at the LMU Munich. For the past years, we have been investigating near-term applications of quantum computing in corporation with industry partners like the Volkswagen DataLab and Airbus. We present current research regarding the connection of quantum computing and artificial intelligence, like enhancing the computation of Nash equilibria for multi-agent games using quantum annealing, Furthermore, we participate in the PlanQK initiative funded by the German ministry for commerce (BMWi) to build a platform for software developers and users, enabling the practical implementation and advancement of algorithms for quantum artificial intelligence and opening up the domain to the broad public.

Mats Granath

Error correction for the toric code using deep reinforcement learning

We implement a quantum error correction algorithm for bit-flip errors on the toric code using deep reinforcement learning. An action-value Q-function encodes the discounted value of moving a defect (stabilizer error) to a neighboring site on the square grid depending on the full set of defects on the torus. The Q-function is represented by a deep convolutional neural network.

We find performance which is close to, and for small error rates asymptotically equivalent to, that achieved by the Minimum Weight Perfect Matching algorithm for code distances up to $d=7$. The deep Q-network is thus highly versatile in dealing with varying numbers of syndrome defects and may be applicable also to surface codes with boundaries and for different error models.



Philip Andreasson, Joel Johansson, Simon Liljestrand, MG, arXiv:1811.12338

Eliska Greplova

Quantum Error Correction via Hamiltonian Learning

Eliska Greplova, Agnes Valenti, Evert van Nieuwenburg, Sebastian Huber

Successful implementation of error correction is imperative for fault-tolerant quantum computing. At present, the toric code, surface code and related stabilizer codes are state of the art techniques in error correction.

Standard decoders for these codes usually assume uncorrelated single qubit noise, which can prove problematic in a general setting.

In this work, we use the knowledge of topological phases of modified toric codes to identify the underlying Hamiltonians for certain types of imperfections. This Hamiltonian learning is employed to adiabatically remove the underlying noise and approach the ideal toric code Hamiltonian. This approach can be used regardless of correlations. Our method relies on a neural network reconstructing the Hamiltonian given as input a linear amount of expectation values. The knowledge of the Hamiltonian offers significant improvement of standard decoding techniques.

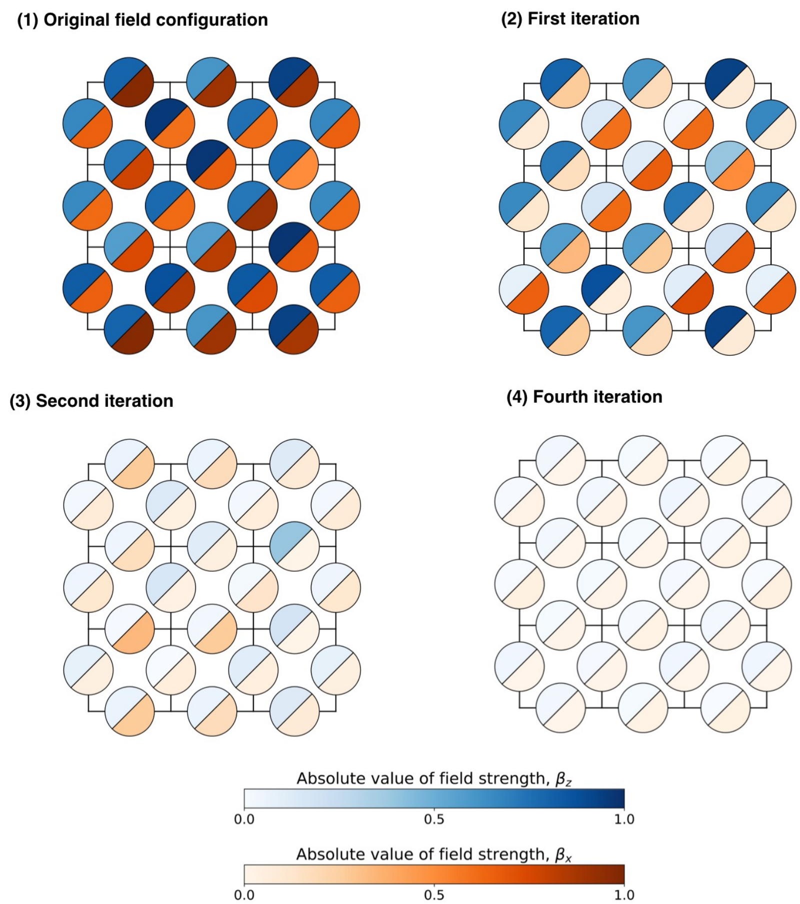


Fig.: Illustration of error correction via Hamiltonian learning technique. We consider imperfect toric code ground state. The imperfections are arbitrary σ_x (orange) and σ_z (blue) fields on every spin. Our machine learning driven protocol reconstructs the Hamiltonian corresponding to faulty ground state and determines the transition to the correct field-free one. (1)-(4) shows 4 iterations of the protocol.

Niels Loerch

Divergence of predictive model output as indication of phase transitions

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(Dated: March 22, 2019)

We introduce a new method to identify phase boundaries in physical systems. It is based on training a predictive model such as a neural network to infer a physical system's parameters from its state. The deviation of the inferred parameters from the underlying correct parameters will be most susceptible and diverge maximally in the vicinity of phase boundaries. Therefore, peaks in the divergence of the model's predictions are used as indication of phase transitions. Our method is applicable for phase diagrams of arbitrary parameter dimension and without prior information about the phases. Application to both the two-dimensional Ising model and the dissipative Kuramoto-Hopf model show promising results.

Alexey Melnikov

Reinforcement learning in quantum optics experiments

Quantum experiments push the envelope of our understanding of fundamental concepts in quantum physics. The designing of modern quantum experiments is difficult and often clashes with human intuition. In my talk, I will address the question of whether a reinforcement learning agent can propose novel quantum experiments. In our works [1,2] we answer this question in the affirmative in the context of quantum optics experiments, although our techniques are more generally applicable. I will talk about reinforcement learning and demonstrate how the projective simulation model can be used to design quantum experiments and discover experimental techniques by considering two examples. In the first example, a reinforcement learning agent learns to create high-dimensional entangled multiphoton states. As a result of this learning process, the agent designs experiments that create a variety of entangled states, improves the efficiency of their realization, and (re)discovers experimental techniques which are only now becoming standard in modern quantum optical experiments. In the second example, our reinforcement learning agent learns to design quantum experiments in which photon pairs violate a Bell inequality. As a result of this learning process, the agent finds several optical setups with high CHSH values for various detection efficiencies, which is an important step towards realistic device-independent quantum cryptography. Our findings highlight the possibility that machine learning could have a significantly more creative role in future quantum experiments.

A.A. Melnikov, H. Poulsen Nautrup, M. Krenn, V. Dunjko, M. Tiersch, A. Zeilinger, and H.J. Briegel. Active learning machine learns to create new quantum experiments. Proc. Natl. Acad. Sci. U.S.A., 115(6):1221, 2018.

A.A. Melnikov, P. Sekatski, and N. Sangouard. Work in progress.

Xiaotong Ni

Neural Network Decoders for Large-Distance 2D Toric Codes (arXiv: 1809.06640)

We still do not have the perfect decoders for topological codes that can satisfy all needs of different experimental setups. Recently, a few neural network based decoders have been studied, with the motivation that they can adapt to a wide range of noise models, and can easily run on dedicated chips without a full-fledged computer. The later feature might lead to fast speed and the ability to operate in low temperature. However, a question which has not been addressed in previous works is whether neural network decoders can handle 2D topological codes with large distances. In this work, we provide a positive answer for the 2D toric code. The structure of our neural network decoder is inspired by the renormalization group decoder. With a fairly strict policy on training time, when the bit-flip error rate is lower than 9% and syndrome extraction is perfect, the neural network decoder performs better when code distance increases. With a less strict policy, we find it is not hard for the neural decoder to achieve a performance close to the minimum-weight perfect matching algorithm. The numerical simulation is done up to code distance d=64.

Alessia Suprano

Experimental Protocol for Quantum State Engineering through one-dimensional Quantum Walk

One dimensional quantum walks can be used to engineer arbitrary quantum states. We imple- ment a state-engineering protocol based on the controlled dynamics of one-dimensional Quan- tum Walk in the orbital angular momentum degree of freedom of single photons. We have demostrated the feasibility of such approach for engineering different qudit states in a six- dimensional space.

Filippo Vicentini

Variational neural network ansatz for steady-states in open quantum systems

The state of a Markovian open quantum system is completely determined by its density matrix which evolves according to a Lindblad master equation. When the system is composed by many interacting particles, the complexity arising from the many-body problem merges with the necessity to represent mixed states. In this work we exploit a variational ansatz described by a neural network to represent a generic nonequilibrium density matrix. By deriving a variational principle, we show that it is possible to define an iterative procedure where the network parameters are varied in order to minimize a cost function quantifying the distance from the asymptotic steady-state. Such a procedure, similar in spirit to supervised learning, can be performed efficiently by means of a Montecarlo sampling of the cost function. As a first application and proof-of-principle, we apply the method to the dissipative quantum transverse Ising model.