(Quantum) Physics and Machine Learning

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Machine learning-based device-independent certification of quantum networks

Iris Agresti

University of Vienna

The detection of non-classical features, along with the possibility of carrying out optimizations over the set of quantum behaviors, has a great relevance in the field of quantum technology. In particular this task becomes pivotal, when the goal is assessing the reliability of quantum hardware in a quantitative way. At the state of art, the most widely employed techniques to approximate the set of quantum correlations (which is a hard computational task) rely on semidefinite programming optimization (SDP). However, such a tool has two intrinsic limitations. Firstly, it can be applied only to linear objective functions and enforce linear constraints, therefore excluding quantum networks featuring independent hidden variables. Moreover, such optimizations become computationally unfeasible when the complexity and size of the system grow. To circumvent this issue, we introduce an artificial neural network-based strategy, that allows to carry out numerical optimizations over supersets of the quantum set. This method has two main advantages: on one side, it can be applied to nonlinear optimizations constraints and objective functions. This opens the possibility of studying quantum networks featuring independent sources or to optimize nonlinear entanglement witnesses. On the other hand, it requires less computational resources than the aforementioned SDP-based techniques, allowing a better scalability and promising to be a useful tool to explore more complex scenarios.

Machine learning dynamics of quantum systems

Sabine Andergassen

TU Wien

Quantum effects typically only manifest in systems that are well-isolated from the outside world, and this poses a major obstacle. To faithfully capture and harness quantum effects, knowledge of the quantum state of the system and its environment is required. We here apply machine learning methods to understand the quantum dynamics in physical models and show that it can be learned even in the presence of strong coupling between the system and the environment. In particular, the knowledge acquired during a short evolution interval makes it possible to extrapolate the dynamics to previously unseen times. This may constitute a route for analyzing long-time behavior in situations where this is not accessible by numerical simulations or experiments. In regimes, where the dynamics cannot be described by such an approach, neural networks can nevertheless be utilized to quantify and characterize the system-environment coupling, which can feed into the development of numerical models and simulation algorithms.

Machine learning for tackling quantum device variability

Natalia Ares

University of Oxford

Machine learning is proving to be essential in the tuning and characterization of quantum devices. The search for operation conditions, which often requires navigating large and complex parameter spaces, can now be fully automated, with performances superior to those achieved by human experts. Now these machine learning approaches are not only enabling scalability by automating qubit control, but also by providing us with unprecedented insight into quantum device variability.

We can use these machine learning algorithms for automatic tuning across different semiconductor platforms. This demonstrates not only the robustness of these algorithms against the differences in the characteristics of the material system and device architecture, but that they can provide a tool for their comparison and analysis. I will show that by using a physics-aware machine learning algorithm we are able to infer the disorder potential affecting the operation of quantum dot devices, revealing a hidden characteristic of such devices, and thus narrowing the gap between simulation and reality.

How to tune qubits industrially! Quantum Control Oxford: QuantrolOx

Andrew Briggs

University of Oxford

Eight years ago we recognised that experiments on quantum devices were becoming sufficiently challenging that they would benefit from the capability of machine learning. At the time the main application of machine learning in science research was for classification, whereas we wanted to use machine learning for decision making. The established techniques of deep neural networks thrived on data that were plentiful and cheap, or in some cases free. Our data were sparse and costly to acquire. We therefore turned to some of the newer techniques such as Bayesian optimisation and Gaussian processes, as well as conventional neural networks. Before long our methods were being used in several universities in Europe and beyond. We soon reached the limit of our capacity to help other academics use our techniques, not to mention the growing needs of early stage companies. In 2021 we founded QuantrolOx as a spin-out of the University of Oxford. Even before we had funding we formulated what would become the values of the company. The product is a commercially engineered implementation of the methods developed in our laboratory, and it will automate the tuning and characterising of qubits for scalable quantum computing.

Quantum optimal control: reinforcement learning for quantum technologies

Tommaso Calarco

Forschungszentrum Jülich

The control of quantum states is essential both for fundamental investigations and for technological applications of quantum physics. In quantum few-body systems, decoherence arising from interaction with the environment hinders the realization of desired processes. In quantum many-body systems, complexity of their dynamics further makes state preparation via external manipulation highly non-trivial. An effective strategy to counter these effects is offered by quantum optimal control theory, in essence a form of reinforcement learning exploiting quantum coherence to dynamically reach a desired goal with high accuracy even under limitations on resources such as time, bandwidth, and precision.

This talk will review our recent results with a variety of quantum technology platforms, and introduce our software for automatic calibration of quantum operations - the fundamental building block of next-generation quantum firmware.

Quantum advantage in shallow circuits

Xavier Coiteux-Roy

TU Munich

Qubits in near-term quantum computers are very short-lived, mainly because of the inevitability of decoherence and the present inability to achieve reliable error correction. For this reason, shallow-depth quantum circuits are expected to be among the first to be experimentally investigated. I will mainly present joint work with Libor Caha and Robert König [1] in which we analyze what is probably the simplest quantum circuit of constant depth that cannot be simulated by a similarly restricted classical circuit. It is based on the fundamental task of gate teleportation and re-exhibits a separation between the respective complexity classes QNC0 and NC0. I will focus on the many open questions our work raise.

[1] Single-qubit gate teleportation provides a quantum advantage, L. Caha, X. Coiteux-Roy, and R. Koenig, arxiv 2209.14158.

Simulating interacting particles with graph neural quantum states

Zakari Denis

EPFL

The classical simulation of quantum many-body systems is a daunting task. Variational approaches have proven to be particularly efficient and versatile to numerically address this issue. Among these, neural quantum states have recently been introduced. These utilise neural-network models as variational Ansätze and are able to generically represent states with an entanglement structure out of reach for standard tensor-network architectures, thereby opening new perspectives for faithfully describing strongly correlated systems. In this talk, I will first give a general introduction to neural quantum states and the associated variational principle. I will then describe the graph neural-network architecture and explain how discrete symmetries of the physical system of interest can be easily encoded in the variational Ansatz. Finally, I will show how this property can be exploited to simulate ensembles of interacting particles with given bosonic/fermionic quantum statistics.

Analogue QFT simulators beyond the linear regime

Sebastian Erne

Atominstitut, TU Wien

By and large, interacting quantum field theories far from equilibrium to date pose an computationally intractable problem, in particular for strongly interacting or strongly correlated theories. I will discuss recent developments and extensions in the realization of an analogue quantum simulator for the sine-Gordon model, emerging from two tunnel coupled superfluids. Within this example, I will focus on the opportunities and challenges for utilizing optimal control theory and machine learning in the design, verification, and measurement / data analysis of analogue cold atom simulators for relativistic quantum field theories.

Exploring the efficiency of learning a rule with a physical learning machine

Federico Fedele

University of Oxford

Learning means using “inputs” to construct a model of the environment that can then be used to produce an appropriate response (“outputs”) to new, previously unseen, inputs. A learning machine is an analogue physical device that learns using algorithms written by the laws of physics and especially the lows of thermodynamics and are therefore promising to perform fast and energy efficient learning.

In this work we realise such a system using a Ge/SiGe quantum dot. By exploiting the non-linearities intrinsic of this system we define a physical perceptron and train it to learn a logic NOT operation. We characterised the stability and the efficiency of the learning performance against noise that arise from temperature and the quantum dot tunnelling dynamics. Our results indicate that although higher temperatures degrade the learning performances, the learning efficiency eventually saturates at low temperatures.

Exploiting symmetry in variational quantum machine learning

Elies Gil-Fuster

Freie Universität Berlin

Variational quantum machine learning is an extensively studied application of near-term quantum computers. The success of variational quantum learning models crucially depends on finding a suitable parametrization of the model that encodes an inductive bias relevant to the learning task. However, precious little is known about guiding principles for the construction of suitable parametrizations.

In this work, we holistically explore when and how symmetries of the learning problem can be exploited to construct quantum learning models with outcomes invariant under the symmetry of the learning task. Building on tools from representation theory, we show how a standard gateset can be transformed into an equivariant gateset that respects the symmetries of the problem at hand through a process of gate symmetrization. We benchmark the proposed methods on two toy problems that feature a non-trivial symmetry and observe a substantial increase in generalization performance. As our tools can also be applied in a straightforward way to other variational problems with symmetric structure, we show how equivariant gatesets can be used in variational quantum eigensolvers.

Hybrid variational quantum computing - ingredients to make it work

Zoe Holmes

EPFL

Parameterized quantum circuits serve as ansätze for solving variational problems and provide a flexible paradigm for programming near-term quantum computers. Here we discuss three fundamental criteria for this paradigm to be effective: expressibility, trainability and generalisability. We will introduce these concepts and present recent analytic progress quantifying to what extent these criteria can be achieved. While more generally applicable, the discussion will be framed around the example of trying to variationally learn an unknown quantum process. We will end with some more open-ended dreaming about the applications of these ideas for experimental quantum physics.

Deep learning of quantum entanglement

Miroslav Ježek

Palacky University Olomouc

The detection of quantum correlations, or entanglement, in a physical system is crucial for fundamental research and numerous cutting-edge applications in quantum science and technology. However, the exact quantification of entanglement requires either the full quantum tomography or interference of multiple copies of the system under test. Both methods are experimentally demanding and ultimately not scalable.

Here, we propose a method for direct quantification of entanglement from an incomplete local measurement using deep neural networks. Our method demonstrates significantly lower errors of quantum concurrence and quantum mutual information estimated from undersampled Pauli measurements compared to state-of-the-art approaches for systems consisting of up to five qubits.

We show the performance of our method for photonic entanglement sources based on a nonlinear parametric generator and a semiconductor quantum dot. Additionally, we present a convolutional network that inputs the measurement description alongside the data. This network can accept data from various measurement scenarios and perform, to some extent, independently of the measurement device. We also discuss the issue of incorporating physical constraints into learning models to keep them interpretable and physically sound.

Classical and quantum systems through the lens of compression theory

Maciej Koch-Janusz

Univeristy of Zurich

I will discuss how extracting relevant degrees of freedom from raw configurational data of a statistical system can be re-cast as a problem of finding the optimal compression preserving long-range information. More formally, the RG-relevant operators in the field theory describing the system are solutions to a suitably posed Information Bottleneck (IB) problem. This gives rise to an efficient numerical algorithm using contrastive learning. I will demonstrate applications to coarse-graining and extracting the operator content of classical and quantum statistical model.

Deep learning for quantum physics and astronomy

Johannes Kofler

Johannes Kepler University (JKU) Linz, Austria

In the past decade, Deep Learning has emerged as the most transformative subfield of Artificial Intelligence, leading to enormous advances in not only text, language, music, and video processing, autonomous driving, and board-game strategies, but also in the chemical and physical sciences, e.g., in protein folding, weather forecasts, and material design. In this talk, I will first give a brief introduction about fundamental neural network architectures such as Long Short-Term Memory (LSTM), Residual Neural Networks (ResNets), and Graph Neural Networks (GNNs). I will then report on our work using such networks for various different physical problems:

- Modelling multi-particle high-dimensional photonic quantum experiments by predicting output state characteristics for given setups without the necessity of computing the states themselves [1]
- Predicting the outcome of pairwise planetary collisions using data from Smooth Particle Hydrodynamics simulations [2]
- Approximating the ground states of families of Ising Hamiltonians [3]
- Using classical shadows to learn the ground state properties of quantum Hamiltonians [4]

[1] T. Adler, M. Erhard, M. Krenn, J. Brandstetter, J. Kofler, and S. Hochreiter, Quantum Optical Experiments Modeled by Long Short-Term Memory, Photonics 8 (12), 535 (2021), NeurIPS 2019 Workshop on Machine Learning and the Physical Sciences

[2] P. M. Winter, C. Burger, S. Lehner, J. Kofler, T. I. Maindl, and C. M. Schäfer, Residual Neural Networks for the Prediction of Planetary Collision Outcomes, Monthly Notices of the Royal Astronomical Society, stac2933 (2022)

[3] S. Sanokowski, W. Berghammer, J. Kofler, S. Hochreiter, and S. Lehner, One Network to Approximate Them All: Amortized Variational Inference of Ising Ground States, Machine Learning and the Physical Sciences, NeurIPS 2022, 129 (2022)

[4] V. T. Tran, L. Lewis, H. Y. Huang, J. Kofler, R. Kueng, S. Hochreiter, and S. Lehner, Using Shadows to Learn Ground State Properties of Quantum Hamiltonians, Machine Learning and the Physical Sciences, NeurIPS 2022, 184 (2022)

Towards an artificial muse for new ideas in quantum physics

Mario Krenn

Max Planck Institute for the Science of Light

Artificial intelligence (AI) is a potentially disruptive tool for physics and science in general. One crucial question is how this technology can contribute at a conceptual level to help acquire new scientific understanding or inspire new surprising ideas. I will talk about how AI can be used as an artificial muse in quantum physics, which suggests surprising and unconventional ideas and techniques that the human scientist can interpret, understand and generalize to its fullest potential.

[1] Krenn, Kottmann, Tischler, Aspuru-Guzik, Conceptual understanding through efficient automated design of quantum optical experiments. Physical Review X 11(3), 031044 (2021).

[2] Krenn, Pollice, Guo, Aldeghi, Cervera-Lierta, Friederich, Gomes, Häse, Jinich, Nigam, Yao, Aspuru-Guzik, On scientific understanding with artificial intelligence. Nature Reviews Physics 4, 761–769 (2022).

[3] Krenn, Zeilinger, Predicting research trends with semantic and neural networks with an application in quantum physics. PNAS 117(4), 1910-1916 (2020).

Neural network ansatz for quantum network tasks

Tamás Kriváchy

Atominstitut, TU Wien

Many concepts in quantum foundations, such as Bell nonlocality, EPR steering, and certain quantum state preparation tasks, have efficient numerical solutions. However, when examining these tasks on networks, such methods are lacking or unsatisfactory. We discuss how using neural networks as variational ansätze may be useful in Bell nonlocality and in fixed network protocols.

Optimizing optical potentials with physics-inspired learning algorithms

Yevhenii Kuriatnikov

TU Wien

Shaping and control of light beams play a crucial role in various optical experiments, and setups with ultracold atoms and have applications in other fields. We present an experimental combination of a superluminescent diode's broadband beam shaped by a digital micromirror device with fast learning algorithms for designing 1D optical potentials. We build a physics-inspired model using machine learning algorithms to act as a digital twin of the optical system predicting the behavior of the optical apparatus including all its imperfections. Implementation of iterative learning control allows us to minimize the required amount of experimental iteration for optimizing the potential to a given error level. Our methods provide a new route to fast optimization of optical potential.

Designing and learning quantum many-body matter with generative adversarial networks

Jose Lado

Aalto University

The design of many-body quantum matter provides a promising strategy to engineer new phenomena in the quantum world. However, the connection between the Hamiltonian description of a system and its observed phenomena is a greatly challenging task. Here we demonstrate that conditional generative adversarial networks (cGANs) allow both exploring phase spaces of many-body systems [1] and the design of specific regimes in combination with an experimental platform for topological superconductivity [2]. First [1], we show that the cGAN algorithm provides the whole dynamical excitation spectra for a Hamiltonian instantly and with an accuracy analogous to the exact calculation. Second, we adapt our algorithm for an experimental realization of a topological superconductor, allowing us to extract the parameter regime solely from a measurement of the conductance. Our methodology puts forward generative adversarial learning as a powerful technique to explore complex many-body phenomena, providing a starting point to design large-scale quantum many-body matter.

[1] Rouven Koch and Jose L. Lado, Phys. Rev. Research 4, 033223 (2022)

[2] Rouven Koch, David van Driel, Alberto Bordin, Jose L. Lado,and Eliska Greplova, to appear (2023)

Tuning semiconductor spin qubit devices using machine learning

Edward Laird

Lancaster University

Semiconductor spin qubits are among the most scalable candidates for making a scalable quantum computer. However, unavoidable variation between devices means that each qubit must be tuned individually by adjusting its control voltages to create the necessary potential in which electrons can be trapped, and to adjust the energy levels and transition rates for optimum operation. This is a task well-suited to machine learning.

I will present a demonstration of this approach using gate-defined lateral quantum dots in gallium arsenide. First, I will show how a single quantum dot can be characterised efficiently by a machine learning algorithm which chooses the order in which it makes measurements [1]. Second, I will show how a double quantum dot can be tuned by searching for desirable features in the multi-dimensional map of current versus gate voltage [2].

[1] DT Lennon et al., “Efficiently measuring a quantum device using machine learning”. npj Quantum Information 5 79 (2019)

[2] H Moon et al., “Machine learning enables completely automatic tuning of a quantum device faster than human experts”. Nature Communications 11 4161 (2020)

Reinforcement learning for quantum technologies

Florian Marquardt

Max Planck Institute for the Science of Light

I will give a brief overview of recent developments in the field of reinforcement learning applied to quantum technologies.

ML, randomness and physics

Gorka Muñoz-Gil

University of Innsbruck

In this talk, I will review recent results on the application of a variety of ML paradigms to the understanding of stochastic processes in (classical and quantum) physics. The latter range from the animal foraging to the motion of atoms in magneto-optical traps. For the former, I will show how to leverage Reinforcement Learning to model how foragers converge to well known theoretically optimal strategies. For the latter, I will show how supervised and unsupervised learning can be extended from the usual deterministic data and help us better analyze experimental systems. To conclude, I will briefly comment on the suitability of creating community driven projects, as e.g. ML competitions, to push our knowledge in particular fields.

Safety of complex systems controlled by deep neural networks

Sophie A. Neubauer (née Gruenbacher)

DatenVorsprung

Neural networks (NN) are increasingly deployed to control complex systems where traditional control approaches are not capable to do so. When controlling complex systems, in robotics as well as in physics, the big open question is: How to provide safety-guarantees, predictable behavior, strong assurances, and thus trustworthiness, such that the use of NN controllers becomes a feasible strategy?

In reachability analysis, this question is addressed by giving over-approximations of the solution space of the AI systems, considering the desired accuracy, speed and computational power.

Continuous-depth neural networks (CDNN) are especially suited for the task of controlling nonlinear dynamical systems as they are more robust than traditional NN and capable of handling varying control input timings. The over-approximations of the reachable states over a given time horizon (Reachtube), reflects the behavior of the system given by the system dynamics. The main problem is how to construct Reachtubes in as tight a way and with as little system executions as possible for a given time horizon.

The main focus of this talk is the presentation of two complementary approaches: The first, a set of conservative, symbolic techniques and an algorithm (LRT-NG) for the reachability analysis of nonlinear ordinary differential equations. The second, a statistical verification algorithm (GoTube) that formally quantifies the behavioral robustness of any time-continuous process by computing statistical upper bounds of local Lipschitz constants.

The goal and outlook is a discussion on: How to bridge the gap between trustworthy neural network controllers and their possible use in (quantum) physics? What are the use cases in control tasks as well as in desired over-approximations of system behaviors of complex dynamics?

Interpreting reinforcement learning policies

Hendrik Poulsen Nautrup

University of Innsbruck

Reinforcement learning (RL) has been applied in various areas of science to great success. While RL can learn interesting solutions to complex problems, it still requires an expert to analyze and understand them. Here, we propose to use various techniques from sequence mining and unsupervised learning to automatize the process of interpreting RL policies. We expect that such an approach will aid scientists to distill relevant information from potentially complicated solutions to complex problems.

Extracting information from quantum systems: from machine learning optical potentials to Hamiltonian learning

Maximilian Prüfer

Atominstitut, TU Wien

Quantum simulations in the many-body regime require high level of control and the possibility to efficiently extract physical information. In my talk I will introduce our platform for simulating the dynamics of quantum fields in the laboratory, where we recently we developed a new approach for optimizing optical potential with physics-inspired machine learning models giving us a new level of control.

Using tunnel-coupled superfluids as a quantum simulator for the Sine-Gordon model, I will show how an efficient preparation of these systems in a regime approaching the quantum limit is possible. Finally, I discuss our new approach for learning the realized Hamiltonian from experimental data for continuous quantum systems.

Fisher information in scattering problems and neural networks

Stefan Rotter

Institute for Theoretical Physics, TU Wien

In my talk, I will discuss recent progress in applying the concept of Fisher information to the problem of estimating system parameters in complex scattering environments, such as inside or behind a disordered medium [1,2,3]. We have recently realised that such tools can also be successfully applied to artificial neural networks, in particular to define the performance limit of a network in extracting information from a complex system.

[1] Maximum information states for coherent scattering measurements, D. Bouchet, S. Rotter, and A. P. Mosk, Nature Physics 17, 564 (2021).

[2] Optimal control of coherent light scattering for binary decision problems, D. Bouchet, L. M. Rachbauer, S. Rotter, A. P. Mosk, and E. Bossy, Phys. Rev. Lett. 127, 253902 (2021).

[3] Invariance property of the Fisher information in scattering media, M. Horodynski, D. Bouchet, M. Kühmayer, and S. Rotter, Phys. Rev. Lett. 127, 233201 (2021).

Digital discovery of 100 diverse quantum experiments with Pytheus

Carlos Ruiz Gonzalez

Max Planck Institute for the Science of Light

Photonic technologies are main players in the second quantum revolution, promising better sensors, secure communications, and quantum-enhanced computation. Such endeavors require generating specific quantum states or efficiently performing quantum tasks. The design of the corresponding optical experiments, historically powered by human creativity, is being slowly automated with advanced algorithms, which exploit a graph-based representation of optical setups. Unfortunately, these tools are often restricted to very specific use cases and are difficult to generalize, which limits their practical implementation. To overcome these challenges, we developed PyTheus, a highly-efficient, open-source digital discovery framework that represents a wide range of experimental devices from modern quantum labs. PyTheus produces interpretable designs to solve complex experimental problems, like generating highly entangled quantum states or performing quantum communication protocols. Aiming for the simplest solutions, our software provides inspiration to human researchers, which can often generalize their findings to other systems. Therefore, we hope PyTheus will accelerate the development of quantum optics and related technologies.

Simulating non-equilibrium quantum matter with neural quantum states

Markus Schmitt

FZ Jülich (PGI-8)

The numerical simulation of many-body quantum dynamics constitutes a pivotal challenge of computational physics due to the typical growth of entanglement in the course of the evolution. I will discuss how combining the time-dependent variational principle with artificial neural networks as ansatz for the variational wave function allows us to overcome some of the current limitations. As an application I will address quantum phase transition dynamics in two spatial dimensions of a model that is experimentally realized in Rydberg quantum simulators.

Neural networks for quantum many-body physics: correlation-enhanced wave-functions and Hamiltonian reconstruction

Agnes Valenti

ETH Zürich

Understanding emergent phenomena that arise from many particles lies at the heart of quantum-many body physics. Seemingly simple interactions and exponential scaling of the Hilbert space induce a formidable challenge, that in general renders an exact solution of the quantum many-body problem infeasible. In this talk, I will discuss applications of neural networks to address this challenge from different perspectives.

On the one hand, neural networks can serve as generic parametrization of quantum states and thus as a powerful tool for a variational solution of the quantum many body problem. However, their parameters are not necessarily physically motivated. In the first part of the talk, I will introduce a neural-network-based variational ansatz that retains the flexibility of these generic methods while allowing for a tunability with respect to the relevant correlations governing the physics of the system.

On the other hand, neural networks have proven to be very successful in extracting information from experimental data. In the second part of the talk, I will illustrate how this property can be applied to address the inverse quantum many body problem: Reconstructing a Hamiltonian from measurements on a state in a quantum simulation.

Deep learning of optimal bidirectional quantum control

Dominik Vasinka

Palacky University Olomouc

Quantum devices share the common aspect of being controlled by classical analog signals, related nontrivially to the device operation. The control signals need to be optimally adjusted to provide a high-fidelity operation of the device. A common approach to predicting control signals required to prepare the target quantum state, i.e., the inverse control model, minimizes an ad hoc selected distance metric in the classical control space. However, the values of control signals are given by the technical implementation and are often ambiguous. We propose and experimentally test a novel idea for constructing the inverse control model. We develop an unsupervised-like deep learning approach combining the inverse and direct control models. The classical control signals play the role of latent variables with no required quantification in the latent space. By minimizing the error in the space of quantum states, various models and devices, even with a different number of control signals, can be optimized and compared. We demonstrate our approach in a use case of polarization state transformation using twisted nematic liquid crystals controlled by several voltage signals. Furthermore, the method is used for local preparation and remote preparation of polarization-encoded qubits with unprecedented accuracy.

Machine learning of many-body propagators

Markus Wallerberger

TU Wien

Electronic propagators are a centrepiece of many-body physics; they are the basic blocks from which diagrammatic theories are built and they are accessible from experiment as response functions. Yet, their numerical treatment is limited by the rapid demand in memory to store them and computational resources to manipulate them.

In this talk, I will discuss two recently developed strategies for tackling this problem: the first is a principal component analysis on the analytic structure of the n-particle propagator, which leads to an optimized basis for the time/frequency dependence, thereby reducing memory and CPU demand by several orders of magnitude.

The second is an automatic decoupling of time and length scales, using a sequence of auxiliary quantum bits, knows as quantics tensor trains (QTT). The propagator is then mapped onto this MPS-like structure using an efficient active learning approach. This model allows us to massively reduce memory for both time and space coordinate of the propagator and also unlocks all MPS manipulation techniques for computations.

Posters

Optimizing optical potentials with physics-inspired learning algorithms

Martino Calzavara

Forschungszentrum Juelich

We present our new experimental and theoretical framework which combines a broadband superluminescent diode (SLED/SLD) with fast learning algorithms to provide speed and accuracy improvements for the optimization of 1D optical dipole potentials, here generated with a Digital Micromirror Device (DMD).

We employ Machine Learning (ML) tools to train a physics-inspired model acting as a digital twin of the optical system predicting the behavior of the optical apparatus including all its imperfections. Implementing an iterative algorithm based on Iterative Learning Control (ILC) we optimize optical potentials an order of magnitude faster than heuristic optimization methods.

We compare iterative model-based offline optimization and experimental feedback-based online optimization. Our methods provide a new route to fast optimization of optical potentials which is relevant for the dynamical manipulation of ultracold gases.

Machine learning stochastic dynamics

Francesco Carnazza

University of Tübingen

Even if the fundamental laws governing physical systems at the microscopic level are well known, in most cases it is not possible to solve them, due to the high number of particles involved.

The approach of statistical physics is to coarse grain the system under investigation and assume that the behaviour of single degrees of freedom will be dictated by a certain probability distribution.

The system is thus assumed to be described by a limited number of dynamical quantities, while the overlooked degrees of freedom give rise to a noise term whose probability distribution is postulated. The origin of noise, which may range from coupling to a thermal bath to quantum fluctuation, is ignored, and one is left with a simplified stochastic model of a more complicated real physical system.
Advancements have been made in machine learning techniques which make possible for such technologies to learn the stochastic differential equations which describes the best the raw data one has.

We address a paradigmatic model of statistical physics, the two dimensional Ising model provided with a dynamics, and set out to search the stochastic differential equation which governs the dynamics of the order parameter, i.e. the magnetisation.

Reinforcement learning guided quantum architecture search for VQE

Onur Danaci

Leiden University

Variational Quantum Eigensolvers for chemistry problems hitherto use ansatze either inspired by domain knowledge, or based on some constraints such as hardware limitations and shrinking gradients. It is well known that high circuit depths and hardware noise lead to barren plateaus in the optimization landscape. These barren plateaus can be mitigated by shallow circuits, where NISQ devices shine, but as a trade-off, they lead to low expressibility. In this work, we use classical reinforcement learning to synthesize ansatze incrementally by solving the VQE problem under physical noise in a classical simulator at each increment, leading the agent to come up with better-performing ansatze. This way we both explore the space of the circuits, and non-local optimization landscapes we encounter at each problem. We found that the hardware-noise constraint leads to shorter circuits.

Predicting and suggesting new research directions via semantic and neural networks

Xuemei Gu

Max Planck Institute for the Science of Light

The rapid growth of scientific literature is posing a significant challenge for human researchers to stay updated and discover new research topics. To address this challenge, we have developed a tool that leverages historical scientific literature to predict and suggest new research directions. Our approach involves creating an evolving knowledge network from a vast collection of scientific papers and applying an artificial neural network to predict and suggest future research directions. Our tool can provide personalized research directions for individual scientists and new research topic suggestions for research collaborations.

Strong interaction between hole spins in silicon and microwave photons

Vincent P. Michal

University of Oxford

The large spin-orbit interaction of holes in semiconductors is key to achieve strong spin-photon coupling in spin circuit-QED experiments [1]. We show that for a single hole this coupling is “reciprocally sweet”, meaning that the coupling can be tuned from fully transverse (allowing coherent spin rotations) to fully longitudinal (modulating the spin resonance frequency) [2, 3]. Based on the longitudinal coupling, we highlight how distant spin-spin coupling and parametrically driven spin-readout can be achieved.

References:

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[2] V. P. Michal, J. C. Abadillo-Uriel, S. Zihlmann, R. Maurand, Y.-M. Niquet, and M. Filippone, Phys. Rev. B 107, L041303 Editors' Suggestion (2023).

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Thermometry of one-dimensional Bose gases with neural networks

Frederik Møller

Atominstitut, TU Wien

One-dimensional Bose gases trapped on an atom chip represent a quantum analog simulator of several important quantum field theory models. To probe the experimental system, absorption images of the atomic cloud following free expansion are taken. Averaging over many images, expectation values and correlations functions can be extracted and compared to known theories. By virtue of the complicated nature of such systems the recorded absorption images contains a large amount of information, much of which is discarded in the extraction process. However, through machine learning techniques more efficient analysis of the experimental data may be possible.

As a demonstration, we train a neural network to predict the temperature of a one-dimensional Bose gas given a single absorption image. We compare our model to the established method of density ripple thermometry, which requires several tens of images to produce accurate results. Here we find the predictions of the two methods compatible, with the neural network reaching similar precision by combining the predictions of much fewer images.