International Workshop on Quantum Boltzmann Machines

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Dec. 8-11, 2025

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Abstracts

Speaker: Eric R. Anschuetz

Title: Average-case quantum complexity from glassiness

Abstract: Glassiness--a phenomenon in physics characterized by a rough free-energy landscape--implies hardness for stable classical algorithms. For example, it can obstruct constant-time Langevin dynamics and message-passing in random k-SAT and max-cut instances. We provide an analogous framework for average-case quantum complexity showing that a natural family of quantum algorithms (e.g., Lindbladian evolution) fails for natural Hamiltonian ensembles (e.g., random 3-local Hamiltonians). Specifically, we prove that the standard notion of quantum glassiness based on replica symmetry breaking obstructs stable quantum algorithms for Gibbs sampling, which we define by a Lipschitz temperature dependence in quantum Wasserstein complexity. Our proof relies on showing that such algorithms fail to capture a structural phase transition in the Gibbs state, where glassiness causes the Gibbs state to decompose into clusters extensively separated in quantum Wasserstein distance. This yields average-case lower bounds for constant-time local Lindbladian evolution and shallow variational circuits. Unlike mixing time lower bounds, our results hold even when dynamics are initialized from the maximally mixed state. We apply these lower bounds to non-commuting, non-stoquastic Hamiltonians by showing a glass transition via the replica trick. We find that the ensemble of all 3-local Pauli strings with independent Gaussian coefficients is average-case hard, while providing analytical evidence that the general p-local Pauli ensemble is non-glassy for sufficiently large constant p, in contrast to its classical (Ising p-spin, always glassy) and fermionic (SYK, never glassy) counterparts.

Speaker: Ruchira V Bhat

Title: Meta-learning of Gibbs states for many-body Hamiltonians with applications to Quantum Boltzmann Machines

Abstract: The preparation of quantum Gibbs states is a fundamental challenge in quantum computing, essential for applications ranging from modeling open quantum systems to quantum machine learning. Building on the Meta-Variational Quantum Eigensolver framework proposed by Cervera-Lierta *et al*. (2021) and a problem driven ansatz design, we introduce two meta-learning algorithms: Meta-Variational Quantum Thermalizer (Meta-VQT) and Neural Network Meta-VQT (NN-Meta VQT) for efficient thermal state preparation of parametrized Hamiltonians on Noisy Intermediate-Scale Quantum (NISQ) devices. Meta-VQT utilizes a fully quantum ansatz, while NN Meta-VQT integrates a quantum classical hybrid architecture. Both leverage collective optimization over training sets to generalize Gibbs state preparation to unseen parameters. We validate our methods on up to 8-qubit Transverse Field Ising Model and the 2-qubit Heisenberg model with all field terms, demonstrating efficient thermal state generation beyond training data. For larger systems, we show that our meta-learned parameters when combined with appropriately designed ansatz serve as warm start initializations, significantly outperforming random initializations in the

optimization tasks. Furthermore, a 3-qubit Kitaev ring example showcases our algorithm's effectiveness across finite-temperature crossover regimes. Finally, we apply our algorithms to train a Quantum Boltzmann Machine (QBM) on a 2-qubit Heisenberg model with all field terms, achieving enhanced training efficiency, improved Gibbs state accuracy, and a 30-fold runtime speedup over existing techniques such as variational quantum imaginary time (VarQITE)-based QBM highlighting the scalability and practicality of meta-algorithm-based QBMs.

Speaker: Dongling Deng

Title: Quantum automated learning

Abstract: Quantum artificial intelligence, an emerging research frontier at the intersection of quantum computing and machine learning, holds unprecedented potential to revolutionize AI technologies. However, the field remains in its infancy, with fundamental challenges impeding its scalability and real-life applications. In this talk, I will first give a brief introduction to quantum AI and the challenges faced in scaling up. Then, I introduce a new paradigm, called quantum automated learning, that may circumvent these challenges. This approach is inherently gradient-free and scalable, with provable and explainable trainability. I will give a couple of concrete examples regarding classification of both real-life images and quantum datasets to show its effectiveness and sample efficiency.

Speaker: Maria Demidik

Title: Bridging expressivity and trainability in quantum Boltzmann machines

Abstract: Quantum computing holds the potential to provide efficient sampling from complex probability distributions, but the trainability and scalability of quantum generative models remain key obstacles. This talk presents two complementary advances that address these challenges. First, we introduce the semi-quantum restricted Boltzmann machine (sqRBM), featuring a partially commuting Hamiltonian that enables closed-form probabilities and gradients. Our theoretical analysis predicts expressive advantages over classical RBMs, supported by simulations with up to hundreds of units. Second, we build on this structure to develop generalized contrastive divergence, a sample-based training framework that achieves constant forward-pass scaling, analogous to backpropagation. Together, these results provide a coherent path toward scalable, resource-efficient quantum generative modeling on future quantum hardware.

Speaker: Masahito Hayashi

Title: Structured quantum learning via em algorithm for Boltzmann machines

Abstract: Quantum Boltzmann machines (QBMs) are generative models with potential advantages in quantum machine learning, yet their training is fundamentally limited by the barren plateau problem, where gradients vanish exponentially with system size. We introduce a quantum version of the em algorithm, an information-geometric generalization of the classical Expectation-Maximization method, which circumvents gradient-based optimization on non-convex functions. Implemented on a semi-quantum restricted Boltzmann machine (sqRBM)—a hybrid architecture with quantum effects confined to the hidden layer—our method achieves stable learning and outperforms gradient descent on multiple benchmark datasets. These results establish a structured and scalable alternative to gradient-based training in QML, offering a pathway to mitigate barren plateaus and enhance quantum generative modeling. This work is joint with Takeshi Kimura and Kohtaro Kato. Details are available at https://arxiv.org/abs/2507.21569

Speaker: Jiaqing Jiang

Title: Quantum Metropolis Sampling via Weak Measurement

Abstract: Gibbs sampling is a crucial computational technique used in physics, statistics, and many other scientific fields. For classical Hamiltonians, the most commonly used Gibbs sampler is the Metropolis algorithm, known for having the Gibbs state as its unique fixed point. For quantum Hamiltonians, designing provably correct Gibbs samplers has been more challenging. [TOV+11] introduced a novel method that uses quantum phase estimation (QPE) and the Marriot-Watrous rewinding technique to mimic the classical Metropolis algorithm for quantum Hamiltonians. The analysis of their algorithm relies upon the use of a boosted and shift-invariant version of QPE which may not exist [CKBG23]. Recent efforts to design quantum Gibbs samplers take a very different approach and are based on simulating Davies generators [CKBG23,CKG23,RWW23,DLL24]. Currently, these are the only provably correct Gibbs samplers for quantum Hamiltonians.

We revisit the inspiration for the Metropolis-style algorithm of [TOV+11] and incorporate weak measurement to design a conceptually simple and provably correct quantum Gibbs sampler, with the Gibbs state as its approximate unique fixed point. Our method uses a Boosted QPE which takes the median of multiple runs of QPE, but we do not require the shift-invariant property. In addition, we do not use the Marriott-Watrous rewinding technique, which simplifies the algorithm significantly.

Speaker: Sabre Kais

Title: Information scrambling and the learning landscape of a quantum machine learning algorithm

Abstract: In this talk, I will focus on quantum machine learning dynamics, with particular emphasis on the Restricted Boltzmann Machine (RBM), which has emerged as a promising framework for harnessing the power of quantum computers. In addition to highlighting successful applications in materials design, I will discuss the training dynamics by examining how quantum information is scrambled within such networks, giving rise to correlations among their constituent subsystems.

Speaker: Tongyang Li

Title: QCircuitBench: A Large-Scale Dataset for Benchmarking Quantum Algorithm Design

Abstract: Quantum computing is an emerging field recognized for the significant speedup it offers over classical computing through quantum algorithms. However, designing and implementing quantum algorithms pose challenges due to the complex nature of quantum mechanics and the necessity for precise control over quantum states. Despite the significant advancements in AI, there has been a lack of datasets specifically tailored for this purpose. In this work, we introduce QCircuitBench, the first benchmark dataset designed to evaluate AI's capability in designing and implementing quantum algorithms using quantum programming languages. Unlike using AI for writing traditional codes, this task is fundamentally more complicated due to highly flexible design space. Our key contributions include: 1. A general framework which formulates the key features of quantum algorithm design for Large Language Models. 2. Implementations for quantum algorithms from basic primitives to advanced applications, spanning 3 task suites, 25 algorithms, and 120,290 data points. 3. Automatic validation and verification functions, allowing for iterative evaluation and interactive reasoning without human inspection. 4. Promising potential as a training dataset through preliminary fine-tuning results. We observed several interesting experimental phenomena: LLMs tend to exhibit consistent error patterns, and fine-tuning does not always outperform few-shot learning. In all, QCircuitBench is a comprehensive benchmark for LLM-driven quantum algorithm design, and it reveals limitations of LLMs in this domain.

Speaker: Dhrumil Patel

Title: Natural gradient and parameter estimation for quantum Boltzmann machines

Abstract: Thermal states play a fundamental role in various areas of physics, and they are becoming increasingly important in quantum information science, with applications related to semi-definite programming, quantum Boltzmann machine learning, Hamiltonian learning, and the related task of estimating the parameters of a Hamiltonian. In this talk, I will outline new formulas underlying the basic

geometry of parameterized thermal states and show how the values of these formulas can be estimated using simple quantum algorithms. More specifically, I will present explicit formulas for the Fisher–Bures and Kubo–Mori information matrices and describe quantum algorithms to estimate them using a combination of Hamiltonian simulation, classical sampling, and the Hadamard test. These results have applications in developing a natural gradient descent algorithm for quantum Boltzmann machine learning, which takes into account the geometry of thermal states, and in establishing fundamental limitations on the ability to estimate the parameters of a Hamiltonian, when given access to thermal-state samples. I'll conclude by sketching an asymptotically optimal measurement protocol for single-parameter Hamiltonian estimation and discussing how these tools can generalize to solving broader quantum machine learning problems.

Speaker: Adit Vishnu

Title: Density Operator Expectation Maximization

Abstract: Machine learning with density operators, the mathematical foundation of quantum mechanics, is gaining prominence with rapid advances in quantum computing. Generative models based on density operators cannot yet handle tasks that are routinely handled by probabilistic models. The progress of latent variable models, a broad and influential class of probabilistic unsupervised models, was driven by the Expectation–Maximization framework. Deriving such a framework for density operators is challenging due to the non-commutativity of operators. To tackle this challenge, an inequality arising from the monotonicity of relative entropy is demonstrated to serve as an evidence lower bound for density operators. A minorant-maximization perspective on this bound leads to Density Operator Expectation Maximization (DO-EM), a general framework for training latent variable models defined through density operators. Through an information-geometric argument, the Expectation step in DO-EM is shown to be the Petz recovery map. The DO-EM algorithm is applied to Quantum Restricted Boltzmann Machines, adapting Contrastive Divergence to approximate the Maximization step gradient. Quantum interleaved Deep Boltzmann Machines and Quantum Gaussian–Bernoulli Restricted Boltzmann Machines, new models introduced in this work, outperform their probabilistic counterparts on generative tasks when trained with similar computational resources and identical hyperparameters.

Speaker: Yadong Wu

Title: Learning Phase-space Representations of Continuous-Variable Quantum Systems

Abstract: Characterizing continuous-variable quantum states is essential for quantum communication, sensing, simulation, and computing. However, full characterization of multimode states traditionally requires an exponentially large number of experiments. We first propose an alternative approach that forgoes full reconstruction, instead estimating the state's characteristic function at a specific set of points.

For reflection-symmetric multimode states, we show that estimating the characteristic function at M points requires only O(log M) state copies, independent of the number of modes. Second, we introduce a super-resolution technique, inspired by neural network-based imaging, which reconstructs smooth Wigner functions across the entire phase space from sparse, noisy data. Simulations on GKP states confirm that our methods drastically reduce the required measurement samples, a result we further validate with real experimental data.
