International Workshop on Quantum Boltzmann Machines

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Organizers

Xin Wang, The Hong Kong University of Science and Technology (GZ)

Mark M. Wilde (Cornell University)

Dec. 8-11, 2025

Ithaca, NY, USA

Guangzhou, Guangdong, China

Contact Information

wilde@cornell.edu

felixxinwang@hkust-gz.edu.cn

Agenda

For time zone: Ithaca, NY, USA			
Time	Mon. 12.08	Tue. 12.09	Wed. 12.10
7:50-8:00	Introductory Remarks		
8:00 –8:30	Nathan Wiebe	Sabre Kais	Mingrui Jing
8:30-9:00	Christa Zoufal	Cenk Tüysüz	Ángela Capel
9:00-9:30	Dongling Deng	Maria Demidik	Nana Liu
9:30-10:00	Ruchira V Bhat	Qi Zhao	Dhrumil Patel
10:00-11:00	Discussion	Discussion	Discussion
Break			
20:00-20:30	Masahito Hayashi	Tongyang Li	Yuxuan Du
20:30-21:00	Adit Vishnu	Eric R. Anschuetz	Ge Bai
21:00-21:30	Mohammad Amin	Jiaqiang Jiang	Yixian Qiu
21:30-22:00	Yadong Wu	Lei Zhang	Discussion
22:00-23:00	Discussion	Discussion	

For time zone: Guangzhou, Guangdong Province, China				
Time	Mon. 12.08	Tue. 12.09	Wed. 12.10	Thu. 12.11
9:00 –9:30		Masahito Hayashi	Tongyang Li	Yuxuan Du
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10:00-10:30		Mohammad Amin	Jiaqiang Jiang	Yixian Qiu
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11:00-12:00		Discussion	Discussion	
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21:30-22:00	Christa Zoufal	Cenk Tüysüz	Ángela Capel	
22:00-22:30	Dongling Deng	Maria Demidik	Nana Liu	
22:30-23:00	Ruchira V Bhat	Qi Zhao	Dhrumil Patel	
23:00-24:00	Discussion	Discussion	Discussion	

Abstracts

Speaker: Mohammad Amin

Title: Quantum Boltzmann machine: A path to practical quantum generative AI

Abstract: Recent technological developments, marked by experimental demonstrations of scaling advantage (Nature 2023) and quantum computational supremacy (Science 2025) on D-Wave processors, have advanced the field of quantum annealing into a new era. These results show that large-scale transverse-field Ising dynamics can reach low-energy configurations more efficiently than leading classical heuristics and generate sampling distributions that lie beyond the capabilities of state-of-the-art classical simulators. Such capabilities can provide a powerful new platform for generative AI. In this talk, I will connect these hardware-level advances to machine learning by explaining how the demonstrated sampling power of quantum annealing processors naturally supports quantum Boltzmann machines (QBM), especially within variational autoencoder framework. I will then present recent results illustrating applications across multiple domains, including drug discovery, high-energy physics, and image generation.

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: Ge Bai

Title: Proper and improper mixed states serve as different prior beliefs for quantum state retrodiction

Abstract: A mixed quantum state can be taken as capturing an unspecified form of ignorance; or as describing the lack of knowledge about the true pure state of the system ("proper mixture"); or as arising from entanglement with another system that has been disregarded ("improper mixture"). These different views yield identical density matrices and therefore identical predictions for future measurements. But when used as prior beliefs for inferring the past state from later observations ("retrodiction"), they lead to different updated beliefs. This is a purely quantum feature of Bayesian agency. Based on this observation, we establish a framework for retrodicting on any quantum belief and we prove a necessary and sufficient condition for the equivalence of beliefs. We also illustrate how these differences have operational consequences in quantum state recovery.

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: Angela Capel

Title: Efficient preparation of the Gibbs state of the 2D toric code

Abstract: In this talk, we will review and compare two methods to efficiently prepare the Gibbs state of the 2D toric code at any positive temperature. We will first show that the Davies generator associated to the 2D toric code satisfies a modified logarithmic Sobolev inequality at any positive temperature, and hence mixes rapidly towards the Gibbs state. This allows for efficient Gibbs sampling via dissipation. Secondly, we will show that the 2D toric code can be mapped with a circuit of polynomial depth to two decoupled Ising chains, and thus can be efficiently sampled by sampling the Ising chains and conjugating with the circuit. Both methods are extended to larger families of CSS codes.

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: 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: Yuxuan Du

Title: Efficient Classical Learning Surrogates for Quantum Circuits at Scale

Abstract: The expansive state space of large-qubit quantum computers poses a challenge for comprehensive characterization via classical simulations or quantum tomography. Recent advancements in quantum learning theory offer a promising avenue: Can a learner accurately predict a quantum circuit's expectation values with new classical controls, using data obtained from incoherent measurements? This presentation affirms this possibility. First, I will establish that achieving low prediction errors entails sample complexity scaling linearly with circuit size but exponentially increasing runtime. Subsequently, I will briefly introduce two classical learning surrogates that can balance prediction error and computational complexity, transitioning from exponential to polynomial scaling. Numerical simulations across diverse scenarios, including quantum information processing protocols, Hamiltonian simulation, and variational quantum algorithms up to 60 qubits, validate the efficacy of the proposed approach. I will also demonstrate our recent experimental demonstrations of using classical learning surrogates to identify non-equilibrium Floquet symmetry-protected topological phases on a 20-qubit superconducting processor. I will end this talk by discussing how to harness advanced deep learning and large language models to further improve the capability of classical learning surrogates.

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: Mingrui Jing

Title: Quantum Recurrent Embedding Neural Networks

Abstract: Deep neural networks have revolutionized scientific discovery, accelerating complex tasks from molecular design to material science prediction. However, simulating or predicting the properties of high-dimensional quantum systems remains fundamentally limited due to the exponential scaling of computational resources requirement. Quantum machine learning offers a path toward overcoming this barrier, yet current quantum neural networks face a critical, paradoxical trade-off between guaranteed trainability and sufficient expressive power for achieving quantum advantage. We propose the Quantum Recurrent Embedding Neural Network (QRENN), a versatile framework that tightly integrates tunable QNN components with a ResNet-inspired recurrent data embedding scheme. Through rigorous dynamical Lie algebraic analysis, we prove that deep QRENN can effectively avoid the barren plateau problem while encompassing classically intractable circuits. Building on this foundation, we apply QRENN to accurately classify complex quantum Hamiltonians and detect symmetry-protected topological phases, showcasing its utility in quantum supervised learning. The foundational nature of the recurrent embedding scheme suggests that QRENN may play an equally important part in establishing scalable, expressive quantum supervised learning across the physical science and beyond.

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: Nana Liu

Title: Quantum Boltzmann machines: a bridge between semi-definite optimization and quantum thermodynamics

Abstract: In optimization theory, a semi-definite program (SDP) involves a linear objective function optimized over the cone of positive semi-definite operators intersected with an affine space. In quantum thermodynamics, a system is described by a Hamiltonian and a list of non-commuting charges representing conserved quantities like particle number or electric charge, where a common goal is to determine the system's minimum energy in the presence of these conserved charges. Its equilibrium state, even with non-commuting charges, can be arguably described by a Quantum Boltzmann Machine. These problems arise from differing motivations in the optimization and physics communities and are phrased using very different terminology, yet they are essentially identical mathematically.
By adopting Jaynes' mindset motivated by quantum thermodynamics, we observe that minimizing free energy in the aforementioned thermodynamics problem, instead of energy, leads to an elegant solution in terms of a dual chemical potential maximization problem that is concave in the chemical potential parameters. As such, one can employ standard (stochastic)

gradient ascent methods to find the optimal values of these parameters, and these methods are guaranteed to converge quickly. At low temperature, the minimum free energy provides an excellent approximation for the minimum energy. We then show how this Jaynes-inspired gradient-ascent approach can be used in both first- and second-order classical and hybrid quantum–classical algorithms for minimizing energy, and equivalently, how it can be used for solving SDPs, with guarantees on the runtimes of the algorithms. We benchmark these algorithms on various constrained thermodynamic systems, including spin chains and 2D Heisenberg models, and extend the framework to stabilizer thermodynamic systems.

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: Cenk Tüysüz

Title: Learning to generate high-dimensional distributions with low-dimensional quantum Boltzmann machines

Abstract: In recent years, researchers have been exploring ways to generalize Boltzmann machines (BMs) to quantum systems, leading to the development of variations such as fully-visible and restricted quantum Boltzmann machines (QBMs). Due to the non-commuting nature of their Hamiltonians, restricted QBMs face trainability issues, whereas fully-visible QBMs have emerged as a more tractable option, as recent results demonstrate their sample-efficient trainability. These results position fully-visible QBMs as a favorable choice, offering potential improvements over fully-visible BMs without suffering from the trainability issues associated with restricted QBMs. In this work, we show that low-dimensional, fully-visible QBMs can learn to generate distributions typically associated with higher-dimensional systems. We validate our findings through numerical experiments on both artificial datasets and real-world examples from the high energy physics problem of jet event generation. We find that non-

commuting terms and Hamiltonian connectivity improve the learning capabilities of QBMs, providing flexible resources suitable for various hardware architectures. Furthermore, we provide strategies and future directions to maximize the learning capacity of fully-visible QBMs.

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: Nathan Wiebe

Title: How to Train Your Quantum Neural Network

Abstract: Machine learning has been elevated within the last several years from an application that revolutionized particular domains to one that promises to upend broad swaths of our economy. With this new urgency, an important question to ask is whether quantum can provide advantages within this space. In this talk I will review the quantum Boltzmann machine and argue that it remains the closest analogue of a neural network yet developed for quantum computing. I will provide a high level motivation for quantum Boltzmann machines and provide efficient training algorithms for cases where the Hamiltonian can be easily thermalized. I will discuss issues involving barren plateaus for quantum Boltzmann machines and also show that hidden units in these models can make these issues worse unless steps are taken to mitigate the growth of entanglement between the visible and hidden units. Finally I will argue that exponential advantage is attainable for cases where the input is a quantum state showing that, for cases where data is quantum, these models provide a way to bring the power of machine learning to the quantum realm.

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.

Speaker: Lei Zhang

Title: Quantum Imaginary-Time Evolution with Polynomial Resources in Time

Abstract: Imaginary-time evolution is fundamental to analyzing quantum many-body systems, yet classical simulation requires exponentially growing resources in both system size and evolution time. While quantum approaches reduce the system-size scaling, existing methods rely on heuristic techniques with measurement precision or success probability that deteriorates as evolution time increases. We present a quantum algorithm that prepares normalized imaginary-time evolved states using an adaptive normalization factor to maintain stable success probability over large imaginary times. Our algorithm approximates the target state to polynomially small errors in inverse imaginary time using polynomially many elementary quantum gates and a single ancilla qubit, achieving success probability close to one. When the initial state has reasonable overlap with the ground state, this algorithm also achieves polynomial resource complexity in the system size. We extend this approach to ground-state-related problems and the simulation of open quantum systems, achieving reduced circuit depth compared to existing methods. Numerical experiments validate our theoretical results for evolution time up to 50, demonstrating the algorithm's effectiveness for long-time evolution and its potential applications for early fault-tolerant quantum computing.
