

Abstract

The development of scalable quantum computing requires efficient methods for characterizing, modeling, and controlling complex quantum systems from experimentally accessible data. In solid-state systems, such data are often only indirectly related to the quantities of interest: tomographic measurements must be inverted to reconstruct quantum states, while transport spectra must be interpreted in terms of Hamiltonian parameters or topological regimes. This dissertation investigates how machine learning can bridge this gap, with a particular focus on quantum state analysis, measurement-based inference, and physics-informed control of solid-state quantum systems.

The first part of the dissertation concerns the identification of quantum correlations. An unsupervised neural network approach is developed to learn the structure of separable three-qubit states and detect correlated states as anomalies. This direction is extended through supervised and semisupervised Siamese neural networks, where entanglement-preserving symmetries, such as local unitary transformations and qubit permutations, are incorporated into the learning process to improve entanglement detection and generalization beyond the training data.

The second part focuses on analyzing experimentally motivated measurement representations. Neural networks and random forests are trained to infer entanglement directly from tomography data, revealing that different models may rely on qualitatively different measurement features. The dissertation further develops learning-based quantum tomography from informationally incomplete measurements, using neural networks to refine pseudoinverse reconstruction and recurrent architectures to jointly reconstruct quantum states and optimize the order of measurements.

The final part addresses solid-state quantum simulators and topological platforms. A physics-informed neural network is utilized for autotuning quantum dot Hamiltonians toward regimes supporting Majorana zero modes, using conductance maps as input and a differentiable modes-scoring quasi-metric as the training objective. In addition, a physics decoder autoencoder framework is developed for Hamiltonian learning, where a neural encoder predicts effective Hamiltonian parameters from transport measurements while a scattering-matrix-based decoder enforces the underlying physical model.

Across these directions, the dissertation shows that combining data-driven learning with physical constraints improves accuracy, interpretability, and generalization in quantum-data analysis and device control. The presented results demonstrate that physics-informed machine learning can serve as a unifying framework for extracting quantum correlations, reconstructing states from incomplete data, learning effective Hamiltonians, and guiding quantum systems toward desired operational regimes.