HK 46: Computing II

Time: Thursday 14:00–14:30 Location: SR 0.01 Erw. Physik

HK 46.1 Thu 14:00 SR 0.01 Erw. Physik

Variational Quantum Eigensolver for (2+1)-Dimensional QED at Finite Density — •Emil Rosanowski[1], Lena Funcke[1], Karl Jansen[2], Paulo Itaborai[2], Arianna Crippa[2], and Stefan Kühn[2] — [1]Universität Bonn — [2]DESY Zeuthen

In this talk, we present an implementation of multiple fermion flavors in both the Kogut-Susskind and Wilson formulations for quantum simulations of (2+1)-dimensional Quantum Electrodynamics (QED). Our first results show a particular type of level crossing with one flavor of fermions at zero density, as expected from analytical Chern number calculations. Moving forward, we explore the multi-flavor system at finite density by including a chemical potential. Finally, we present results from inference runs executed on real quantum hardware.

HK 46.2 Thu 14:15 SR 0.01 Erw. Physik

Machine Learning Enhanced Optimization of Variational Quantum Eigensolvers — •Luca Johannes Wagner, Kim Nicoli, and Lena Funcke — Helmholz Institut für Strahlen- und Kernphysik, Bonn, Germany

Variational Quantum Eigensolvers (VQEs) are a powerful class of hybrid quantum-classical algorithms designed to approximate the ground state of a quantum system described by its Hamiltonian. VQEs hold promise for various applications, including lattice field theory and quantum chemistry. However, the inherent noise present in Noisy Intermediate-Scale Quantum (NISQ) devices poses a significant challenge for running VQEs. These algorithms are particularly susceptible to noise, such as measurement shot noise and hardware noise.

Within this work, we propose to enhance VQEs using Gaussian Processes and Bayesian Optimization. These established machine-learning techniques excel at learning from noisy data, making them ideal candidates for improving VQEs. The contributions of this work are twofold. First, we introduce a "VQE-kernel", a custom kernel function specifically designed to incorporate valuable prior physics information in the Gaussian Process by design. Second, we propose a physics-informed acquisition function for Bayesian Optimization termed "Expected Maximum Improvement over Confident Regions" (EMICoRe).

Extensive numerical experiments demonstrate that our approach outperforms state-of-the-art baselines.