Physics-Informed Neural Networks for Simulating Open Quantum Systems

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In the rapidly evolving field of quantum computing, the study of open quantum systems remains crucial. Understanding the dynamics of these systems drives the development of better quantum devices, error mitigation and error correction strategies. An open quantum system can be represented by a density matrix that evolves according to the Gorini-Kossakowski-Sudarshan-Lindblad master equation [1, 2]. When working with continuous-variable open quantum systems, it is beneficial to transform the master equation into a partial differential equation describing the evolution of a quasi-probability distribution [3]. In this work, we make use of the Husimi Q-Function representation that evolves according to Fokker-Planck equations. Using this representation, we are able to simulate open quantum systems using state-of-the-art physics-informed neural networks (PINNs) [4, 5]. PINNs provide a powerful alternative to traditional numerical approaches for solving differential equations such as finite difference and finite element schemes. Unlike these traditional approaches, PINNs do not require costly evaluations on fine grids and can incorporate experimental data. In this work, we train PINNs to solve several equations that govern the dynamics of the Husimi Q-Function. We evaluate the performance of several architectures for PINNs and compare the obtained solutions to analytical solutions where possible. We further demonstrate the effectiveness of the physics-informed neural networks by estimating observables, including the average photon number and average displacement.

References

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