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Capturing dynamics with noisy quantum computers

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Summary

Quantum computing represents a fundamentally new paradigm of computation, enabling approaches to problems that are intractable for classical computers. Since currently available quantum devices are small, noisy, unreliable, and expensive, much of today's progress relies on theoretical analysis and classical simulations to understand their capabilities and limitations.

Dynamics describes how the state of a system changes over time, and can be mathematically represented by models such as differential equations or time series. In this thesis, we investigate the application of quantum computing to capturing such dynamics from several complementary perspectives.

In the introductory Chapter 1, we present the foundational concepts. We introduce quantum computing, variational quantum algorithms, and shot noise. As applications of variational quantum computing, we discuss solving differential equations, quantum machine learning, and applications to finance. Finally, we outline several research questions and describe the overall structure of the thesis.

In Chapter 2, we explore the role of derivatives in quantum machine learning. We demonstrate that parameterized quantum circuits can approximate both functions and their derivatives arbitrarily well, provided that the input data are appropriately rescaled. Furthermore, we show that incorporating both function values and derivative values in the training data set enhances the guaranteed approximation of the trained quantum models, allowing approximation in stronger norms that would otherwise be unattainable. As the dynamics of a function are governed by its derivatives, these insights clarify how quantum machine learning can effectively capture dynamical behavior.

In Chapter 3, we analyze a class of quantum algorithms designed to solve differential equations. We conduct an error analysis and resource estimation, focusing on errors arising from the classical Runge-Kutta subroutines as well as from shot noise in evaluating quantum circuits. We apply these estimates to a differential equation from financial option pricing and compare how different Runge-Kutta methods affect the total computational resources required.

Quantum state tomography is the process of reconstructing a quantum state from measurement data and constitutes an important subroutine in many quantum algorithms. In Chapter 4, we present a method for mitigating shot noise in quantum state tomography by formulating both measurement data and physical constraints as a semidefinite program. We show that, depending on the underlying quantum state, there exist noise regimes in which our method outperforms other state-of-the-art tomography techniques.

Finally, in Chapter 5, we demonstrate the application of quantum generative adversarial networks to generating synthetic financial time series. We simulate the quantum circuits using both full-state and tensor network-based simulations. For classical models, generating synthetic financial time series that both follow the target distributions and exhibit realistic temporal correlations remains challenging. We show that our quantum models can qualitatively capture these statistical and temporal properties well.