Hands-On Introduction to Quantum Machine Learning

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Abstract

This tutorial introduces key concepts in Quantum Machine Learning (QML), covering qubits, gates, entanglement, parameterized circuits, and quantum neural networks (QNNs). It highlights recent advances in quantum-enhanced model compression and quantum architecture search (QAS), which improve QML efficiency and scalability. Attendees will gain hands-on experience with QML implementations on quantum simulators and receive guidance on tools for continued learning. Designed for beginners, the tutorial aims to foster cross-disciplinary innovation at the intersection of quantum computing and AI.

Presenters

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Dr. Samuel Yen-Chi Chen received the Ph.D. and B.S. degree in physics and the M.D. degree in medicine from National Taiwan University, Taipei City, Taiwan. He is now a senior research scientist at Wells Fargo Bank. Prior to that, he was an assistant computational scientist in the Computational Science Initiative, Brookhaven National Laboratory. He is the first one to use variational quantum circuits to perform deep reinforcement learning and the inventor of quantum LSTM. His research interests include building quantum machine learning algorithms as well as applying classical machine learning techniques to solve quantum computing challenges such as quantum error correction and quantum architecture search. He is involved in multiple advanced privacy-preserving quantum AI research projects and is an experienced distributed computing researcher and developer. He won the First Prize In the Software Competition (Research Category) from Xanadu Quantum Technologies, in 2019.

Dr. Huan-Hsin Tseng is a research scientist at the AI Department of the Brookhaven National Lab. He received a Ph.D. and a B.S. degree in Physics and Mathematics from National Tsing Hua University. His background was in High Energy Physics, General Relativity, and Quantum Field Theories in Spacetime. Previously, he was with the University of Michigan, Ann Arbor, working on RL radiotherapy cancer treatments; one of his works received the Best Paper Award in Medical Physics 2018. He was also with the Academia Sinica under Dr. Yu Tsao's Lab researching speech analysis and speech enhancement. His current interests focus on AI/ML, Quantum Computing, and their intersections in Quantum Machine Learning.

Introduction

As quantum computing technology advances, quantum machine learning (QML) has shown promise in domains such as classification (Mitarai et al. 2018; Schuld et al. 2020; Chen et al. 2024a; Lin et al. 2024b; Chen, Chen, and Tseng 2025; Lee, Ismail, and Chen 2024), time-series prediction (Chen, Yoo, and Fang 2022; Chen 2024d), natural lan-

guage processing (Yang et al. 2021; Di Sipio et al. 2022; Li et al. 2023; Yang et al. 2022; Stein et al. 2023), and reinforcement learning (Chen et al. 2020; 2022a; Chen 2023c; 2023a; 2024b; 2023b; 2024d; Kim et al. 2025; Meyer et al. 2022). Quantum neural networks (QNNs) (Chen et al. 2022b; Chen 2024d; Chen et al. 2025b; Tseng et al. 2025) and tensor networks (TNs) (Chen et al. 2022a; 2021) have enabled breakthroughs in modeling complex systems, while recent developments in quantum-enhanced model compression (Liu and Chen 2024; Lin et al. 2024a; Liu et al. 2024; Chen et al. 2024b) and quantum architecture search (QAS) (Martyniuk, Jung, and Paschke 2024) are transforming QML by optimizing QNN architectures, improving scalability, and reducing resource demands. Quantum-enhanced compression leverages entanglement to create efficient models, while QAS identifies optimal QNN structures using reinforcement learning (Kuo, Fang, and Chen 2021; Ye and Chen 2021; Chen 2023d; Dai et al. 2024), evolutionary algorithms (Chen 2024c), and differentiable programming (Zhang et al. 2022; Chen 2024a). This tutorial bridges quantum information science and AI by covering foundational concepts (qubits, gates, entanglement) and QML techniques (parameterized circuits, data encoding, QNNs). Attendees will explore practical applications in classification, time-series modeling, and sequential decision-making. A hands-on session will guide participants through implementing QML models on a quantum computer simulator. Designed for novice audiences, the tutorial provides further reading, software tools, and frameworks to support continued learning. By leveraging FLAIRS's platform, this tutorial aims to foster interdisciplinary collaboration, driving innovation at the intersection of quantum computing and machine learning.

Target Audience and Objectives

This tutorial is designed for researchers, practitioners, and students with backgrounds in artificial intelligence, machine learning, or quantum computing who are interested in exploring the intersection of these fields. No prior experience with quantum programming is required, making the session accessible to beginners while still providing depth for more advanced participants.

Objectives:

- Introduce the fundamentals of quantum information science (QIS), including qubits, gates, measurements, and entanglement.
- Explain core Quantum Machine Learning (QML) techniques such as parameterized quantum circuits, data encoding, and quantum neural networks (QNNs).
- Explore advanced QML architectures including quantum convolutional, recurrent, and tensor neural networks.
- Highlight cutting-edge developments in quantum-enhanced model compression and quantum architecture search (QAS).
- Demonstrate practical applications of QML in classification, time-series modeling, and reinforcement learning.
- Provide hands-on experience using open-source quantum simulators to implement QML models.
- Offer resources, software tools, and reading materials to support continued learning and research.

Relevance

This tutorial aligns with FLAIRS's mission of advancing intelligent systems by introducing cutting-edge Quantum Machine Learning techniques that expand the frontiers of AI, offering novel approaches to learning, optimization, and decision-making under the emerging paradigm of quantum computing.

Structure and Scope

Part 1:

- Qubits, Single and Multiple Qubit Gates, Measurements, Entanglement
  - Introduction to qubits and their representation
  - Single-qubit and multi-qubit gate operations
  - Quantum measurements and key properties
  - Understanding quantum entanglement and its implications
- Concepts of Quantum Machine Learning
  - Overview of Quantum Machine Learning (QML) principles
  - Classical vs. quantum computational paradigms in machine learning
- Parameterized or Variational Quantum Circuits
  - Structure and role of variational quantum circuits (VQCs) in QML
  - Quantum circuit parameterization and optimization
- Data Encoding or Embedding and Quantum Circuit Design
  - Techniques for embedding classical data into quantum states
  - Designing efficient quantum circuits for machine learning tasks

Part 2:

- Quantum Feed-forward Neural Network
  - Overview of quantum feed-forward network architecture
  - Training methodologies for quantum neural networks
- Quantum Convolutional Neural Network
  - Quantum convolutional layers and pooling mechanisms (Chen et al. 2022b)
  - Applications of quantum CNNs in feature extraction and classification
- Quantum Recurrent Neural Networks
  - Design of quantum recurrent layers for sequence-based learning

  - Discussion of hybrid quantum-classical RNNs for temporal data
- Quantum Tensor Networks
  - Concepts of Quantum Tensor Neural Networks
  - Quantum Tensor Neural Networks as QML models (Chen et al. 2022a; 2021)
  - Advantages of Quantum Tensor Neural Networks
- Quantum Neural Networks as Model Compressor
  - Concepts of quantum-enhanced model compression
  - Examples of quantum-enhanced model compression

Part 3:

- Quantum Reinforcement Learning
  - Quantum-enhanced reinforcement learning frameworks (Chen et al. 2020; 2022a; Chen 2023c; 2023a; Meyer et al. 2022)
  - Implementation of quantum policy and value functions (Lockwood and Si 2020; Skolik, Jerbi, and Dunjko 2022; Jerbi et al. 2021)
- Quantum Distributed/Federated Learning
  - Quantum protocols for distributed learning systems (Chen and Yoo 2021; Chehimi et al. 2023; 2024; Chen and Yoo 2024; Liu et al. 2025; Chen et al. 2025a)
  - Security and privacy considerations in quantum federated learning (Rofougaran et al. 2024; Lee et al. 2025)
- Quantum Architecture Search and Optimization
  - Concepts of quantum neural architecture search (QNAS)
  - Evolutionary QAS (Chen 2024c)
  - QAS as a reinforcement learning (RL) problem (Kuo, Fang, and Chen 2021; Ye and Chen 2021; Chen 2023d; Dai et al. 2024)
  - Differentiable Programming for QAS (Zhang et al. 2022; Chen 2024a)
  - Optimization challenges and performance tuning in QML
- Challenges in Quantum Machine Learning
  - Key limitations and open research problems
  - Scalability and noise resilience in practical QML systems
- Concluding Remarks
  - Summary of key points
  - Future directions and potential breakthroughs in QML

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