Recurrent Quantum Neural Network Adaptability

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Introduction
Recurrent neural networks are the foundation of many sequence-to-sequence models in machine learning, such as those used in speech synthesis and machine translation. Quantum machine learning techniques such as variational quantum eigensolver have already been applied, however applied quantum computing is still in its early stages of development.
Neural networks and other classical deep learning techniques were developed during the early stages of quantum learning. Still, there haven't been any workable models for sequence learning, much less frameworks for transfer learning or quantum computing-based transformers.
Motivation
According to current research, QRNNs may be able to handle increasingly difficult problems like financial time series prediction or natural language processing. QRNNs can also be used for transfer learning, where their effectiveness on a larger range of tasks is compared to that of classical RNNs and other quantum machine learning models.
Taking advantage of the entanglement and parallelism that come with quantum computing, this project seeks to investigate new architectures that go beyond traditional constraints. Combining transformer design with quantum principles could potentially lead to quantum transfer learning, and further provide improvement in classical model performance.
Problem Statement
The objective is to explore the feasibility and efficacy of transformer topologies based on quantum computing and investigate potential ways to gain an advantage over classical counterparts in terms of solving more complex tasks in sequence/time data.
Methodology
Our methodology focuses on developing a quantum recurrent neural network (QRNN) leveraging parameterized quantum neurons. This approach integrates the model within the PyTorch framework, facilitating the establishment of a robust QRNN training protocol. We meticulously analyze various network topologies to optimize the QRNN's structure. Our evaluation encompasses applying the QRNN to the MNIST dataset classification task, aiming to benchmark its performance against classical models.
Expected Outcomes
- The project outcomes demonstrate the QRNN's capability in complex tasks like sequence learning and digit classification, with a detailed evaluation on the MNIST dataset through pixel-wise image processing and advanced data augmentation techniques.
- Additionally, we will explore the QRNN's adaptability via transfer learning, highlighting its potential for broader applications in quantum-enhanced machine learning.

References

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