Quantum Neural Network Performance with Error Mitigation on IEEE Dataset

Overview

This document provides a structured overview and performance comparison of different Quantum Neural Network (QNN) models evaluated using the IEEE dataset. All models were trained using **PennyLane's lightning.qubit** simulator with **8 qubits**, over a short training period of **3 epochs**. The emphasis was on evaluating how various **Quantum Error Mitigation (QEM)** techniques affect the performance and stability of the QNN.

Quantum Models Evaluated

1. **QNN with No Mitigation (Baseline)**

- Serves as the control model.
- No error mitigation techniques were applied.
- Allows us to evaluate the raw impact of quantum noise on model accuracy and training dynamics.

Quantum Error Mitigation (QEM) Techniques

2. **QNN with Zero-Noise Extrapolation (ZNE)**

- **Core Idea**: Artificially increases the noise in the quantum circuit and then extrapolates back to the zero-noise limit.
- **Process**:
  1. Executes the same quantum circuit multiple times, each time with scaled gate noise.
  2. Extrapolates measurement results to the limit where noise strength = 0.
- **Advantages**:
  - Software-level technique; no hardware change needed.
  - Applicable to a wide range of quantum devices.
- **Challenges**:
  - Requires more executions.
  - Sensitive to the scaling method used.

3. **QNN with Probabilistic Error Cancellation (PCE)**

- **Core Idea**: Simulates an ideal (noiseless) circuit by sampling noisy operations and statistically cancelling errors.
- **Process**:
  1. Decompose noisy gates into a linear combination of ideal gates.
  2. Run multiple executions and apply weighted averaging to cancel out noise.
- **Advantages**:
  - Can in principle fully cancel noise.
  - Theoretically exact mitigation if sufficient samples are used.

- **Challenges**:
  - Requires exponentially more samples as noise increases.
  - Computationally expensive.
- ✅ **Best performing model in this study**.

4. **QNN with Virtual Distillation**

- **Core Idea**: Improves state fidelity by preparing multiple copies of a quantum state and projecting onto the purified subspace.
- **Process**:
  1. Prepare 2 or more noisy copies of the quantum state.
  2. Apply joint measurements to estimate a higher fidelity result.
- **Advantages**:
  - Enhances signal-to-noise ratio significantly.
- **Challenges**:
  - Requires more qubits (to store multiple copies).
  - May increase circuit depth and gate count.

Performance Comparison

All models were trained for **3 epochs** only. This limited training period aims to simulate real-world constraints in quantum training scenarios and test the efficacy of QEM methods under minimal learning steps.

Model Type	Accuracy (3rd Epochs)	Loss (3rd Epochs)	Notes
QNN (No Mitigation)	*0.9617*	*0.3385*	Baseline performance, susceptible to noise
QNN + ZNE	*0.3392*	*0.7225*	Computational expensive, worst performance
QNN + PCE	*0.9617*	*0.5482*	**Best performance**, especially under low epoch count. More stable than baseline
QNN + Virtual Distillation	*0.9248*	*0.5919*	Improved stability over baseline, minor gains

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Conclusions

- **Probabilistic Error Cancellation (PCE)** showed the **best accuracy and loss trends**, even within the limited 3-epoch training window.
- **Virtual Distillation** offers an easy-to-implement strategy with modest improvements.
- Eventhough the 3rd accuracy of QNN without Mitigation and PCE is same, the 1st accuracy of them has a significant gap. The 1st accuracy of QNN without mitigation is 0.4992 (49.9%) while QNN with PCE give a more stable result with 0.9617 (96.2%) since the first training process. However the 3rd epochs' loss of QNN without Mitigation still outperform the model with PCE.

- The results underscore the importance of **choosing appropriate QEM methods** depending on the available hardware resources, noise characteristics, and performance goals.