Description

One of the biggest bottlenecks in today's Noisy Intermediate-Scale Quantum (NISQ) era is the lack of reliable error correction. While full-fledged quantum error correction (QEC) demands significant hardware overhead, error mitigation techniques aim to reduce noise without requiring extra qubits. However, most existing approaches (e.g., Zero Noise Extrapolation, Probabilistic Error Cancellation) rely on classical post-processing and often fail to generalize across varying circuits, devices, or noise profiles.

This project proposes a novel hybrid quantum-classical framework: a Physics-Embedded Liquid Neural Network (PE-LiNN) designed to learn noise patterns from quantum circuits while embedding physical constraints from error models (e.g., depolarizing, amplitude damping, crosstalk). Unlike static machine learning mitigators, the liquid dynamics of LNNs adapt to changing noise environments, while physics embedding ensures predictions remain consistent with quantum mechanics.

Over the 3-month QAMP timeline, the team will:

Design noise-aware datasets using Qiskit Aer simulators (with parameterized noise models).

Implement PE-LiNN-QEM to map noisy expectation values to mitigated (noise-free) estimates.

Benchmark against baseline error mitigation methods on standard workloads such as VQE, QAOA, and random circuits.

The project targets a practical, generalizable error mitigation tool that can adapt to real IBM Quantum backends.

Deliverables

Primary Deliverables:

A Python module implementing PE-LiNN-QEM, built on top of Qiskit + PyTorch.

Interactive Jupyter notebooks demonstrating mitigation on VQE and QAOA circuits under realistic noise.

A benchmarking study comparing PE-LiNN-QEM with ZNE, Clifford Data Regression (CDR), and PEC.

A short research-style technical report (ArXiv-ready) summarizing methodology, results, and open challenges.

Minimal Viable Product (MVP):

Train a PE-LiNN model on synthetic noisy vs. noiseless expectation value pairs for small circuits (≤6 qubits) and show improved fidelity vs. raw noisy outputs.

Mentors

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What I do: I work at the intersection of quantum computing and machine learning, focusing on noise resilience, hybrid algorithms, and quantum error mitigation. I have experience with Qiskit, variational algorithms, and applying physics-informed deep learning architectures to quantum simulation challenges.

Mentoring approach: I provide structured weekly check-ins, code review, and technical guidance. I encourage independent exploration while ensuring the project stays scoped and achievable within 3 months.

This proposal is novel because:

It introduces Liquid Neural Networks (LNNs) into quantum error mitigation (not widely explored yet).

It embeds physics priors (e.g., noise channels, Kraus operators) directly into the ML model.

It addresses a critical technical issue in NISQ computing: noise and error mitigation.

Remark from Bram:

I am embedded software engineer and qiskit advocate for many years.
Why I think Liquid Neural Networks (LNNs) are fascinating?
LNNs (or Liquid Time-Constant networks) are continuous-time recurrent neural networks with strong stability guarantees.
They are designed for non-stationary, time-drifting signals. Noise in NISQ devices is exactly that: drift in gate errors, crosstalk, and decoherence over time. This property makes them more suitable than static deep nets, which often overfit to a single calibration.

Furthermore we can ask why embedding physics (Kraus/Choi/PTM layers) matters
General neural networks may learn unphysical mappings (e.g., predicting expectation values outside $[-1,1]$, or violating complete positivity). By embedding CPTP constraints (Kraus operators, Choi matrices, Pauli transfer matrices) into the NN as a differentiable layer, the mitigation remains consistent with quantum mechanics.
This aligns with the principle in Nielsen & Chuang: all valid noise processes must be completely positive and trace-preserving maps.
Training with such constraints ensures that the learned correction is not just a black-box regression but a channel-aware mitigation.

However we have to take care for the fact that in quantum error mitigation (QEM), "physical consistency" does not mean that the learned inverse channel must itself be a valid physical process. Mitigation often corresponds to applying some form of the inverse of a noisy quantum channel. But in general the mathematical inverse of a quantum channel is not completely positive and trace-preserving (CPTP). For example, probabilistic error cancellation (PEC) achieves a quasi-inverse by representing it as a quasiprobability mixture of CPTP maps, not as a single physical channel.

So a possible design choice is:
Do not force the inverse to be CPTP. That would unnecessarily constrain the model and prevent recovery of useful quasi-inverse behavior. Instead, embed physics only in the forward noise layer, i.e. ensure that the neural network's noise representation is always CPTP (via Kraus, Choi, or Pauli transfer matrix parametrization). Then, train the model to map from noisy forward expectations to the "clean" latent expectations.