Learning Based Error Mitigation for VQE

QHack2022
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Introduction

Motivation

- Learning based error mitigation (LBEM)
  - Promising new method of error mitigation
  - Doesn’t require prior knowledge of noise models
  - Training circuits can be efficiently simulated

- Variational quantum eigensolver (VQE) for molecule ground state calculation
  - Important application of near-term quantum computers
  - Noise limits its use

⇒ Let’s try LBEM on VQE!

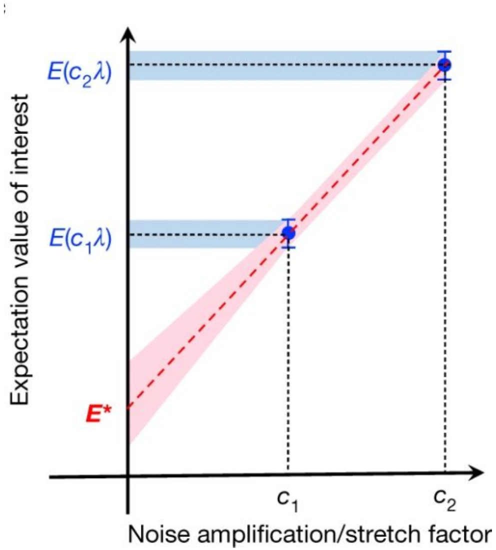
Theory of Learning Based Error Mitigation

Quantum Error Mitigation

- Current quantum hardware is <u>noisy</u>

- Quantum error correction
  - Idea: Use entanglement to preserve quantum state
  - Large overhead → infeasible!

- Quantum error mitigation
  - Idea: noisy measurement results → approximate of accurate result
  - Ex) Zero-noise extrapolation:
  - Expectation values @ different noise levels → extrapolate to zero noise



Zero noise extrapolation diagram

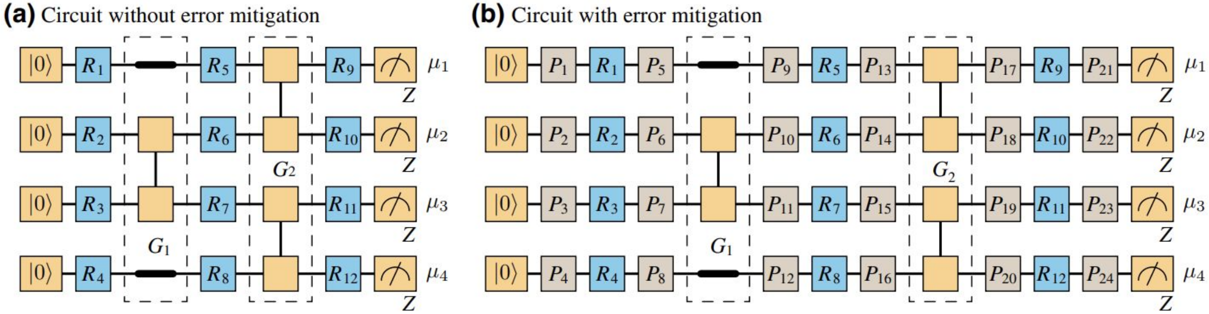
Kandala, A., Temme, K., Córcoles, A.D. *et al.* Error mitigation extends the computational reach of a noisy quantum processor. *Nature* 567, 491–495 (2019)

Learning Based Error Mitigation (LBEM) [1]

- **Model**: $com^{EM}(R,I) = \sum_P q(P)com(R,P)$
  - Error mitigated expectation value of circuit **R**: $com^{EM}(R,I)$
  - Noisy expectation value circuit **R modified by P**: $com(R,P)$
  - **Quasi-probability**: $q(P)$
  - Modify by P: insert Pauli operators **P** before & after single qubit gates in **R**

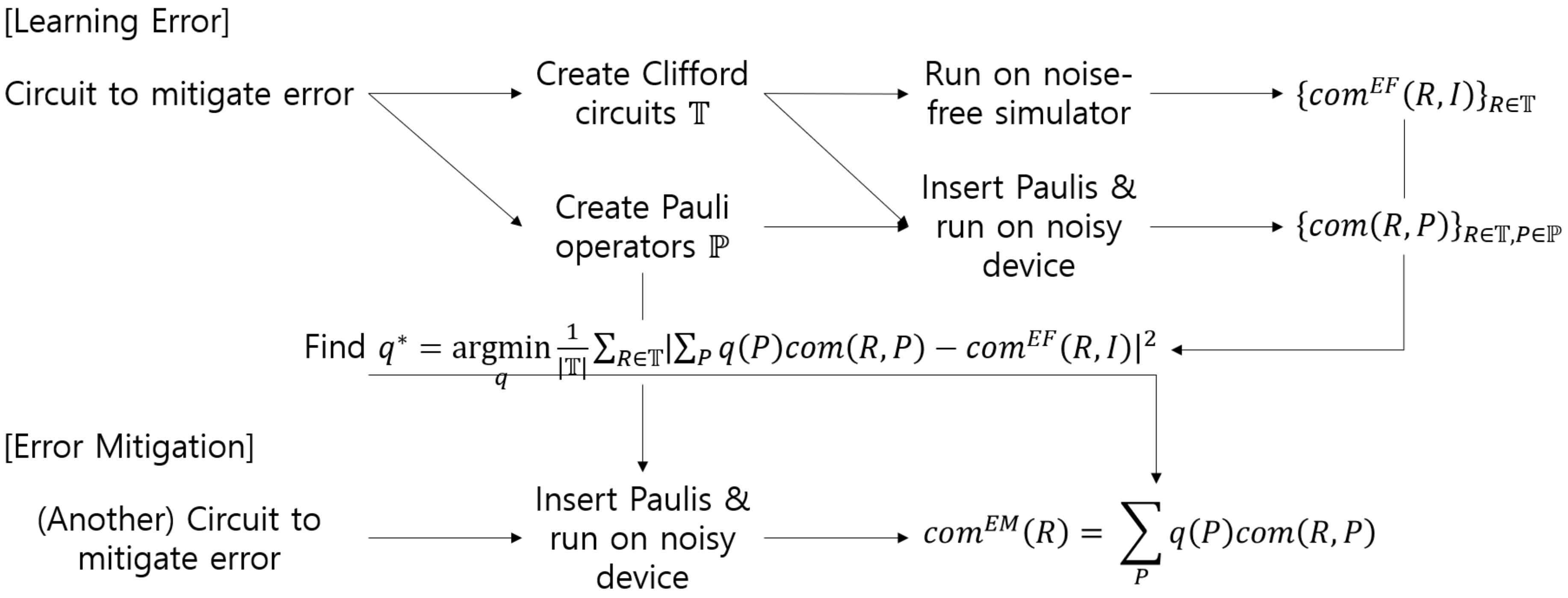
⇒ Learn $q(P)$ by minimizing empirical error of training set

- Training set: clifford gates → efficient to classically simulate, noise-model independent



[1] Strikis, Armands, et al. "Learning-based quantum error mitigation." PRX Quantum 2.4 (2021): 040330.

[LBEM Diagram]



Experiment Design

Experiment Flow

- Training Session
  - Create Ansatz & Hamiltonian
  - Generate training/error-mitigated circuits
    - Generate training circuits by substituting the *R* gates in Ansatz with single-qubit Clifford gates
    - Generate error-mitigated circuits by inserting a Pauli gate before each R gate
    - For Ansatz with more than one R gate, truncate the number of circuits by using only a portion of Clifford group and Pauli words
  - Calculate expectation values
    - Append measurement circuits to training/error-mitigated circuits with respect to the given Hamiltonian
    - Calculate the expectation value of Hamiltonian with training circuits on a simulator
    - Calculate the expectation value of Hamiltonian with error-mitigated circuits on a noisy backend
  - Optimize $q(P)$ to minimize the prediction error

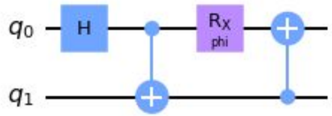
- Testing Session
  - Calculate the expectation value with optimized $q(P)$

Experiment Results

1. LBEM - simple circuit

- Objective: Determine expectation value of a given pauli sum.

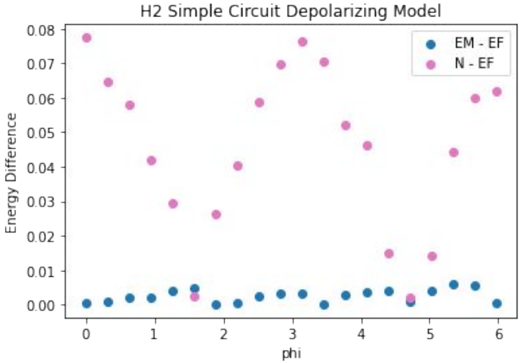
- Ansatz:
  - 1 parameterized gates
  - 4[1] Pauli gates
  - 24[1] Clifford gates

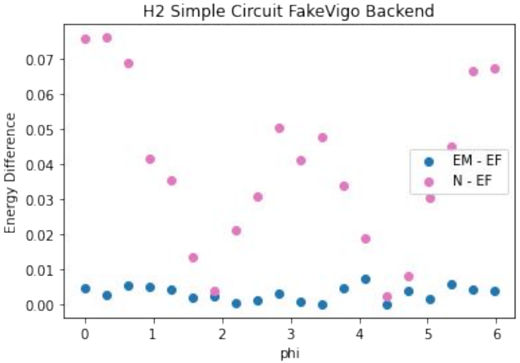


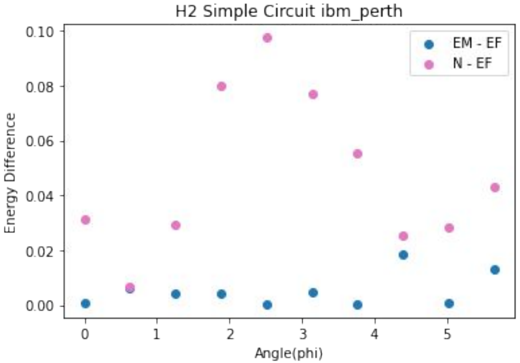
|Ψ(Φ)>

- Results:

<Ψ(Φ) |H |Ψ(Φ)>





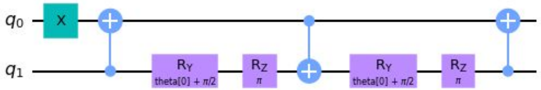


⇒ Error is mitigated for both simulated noise models and real hardware

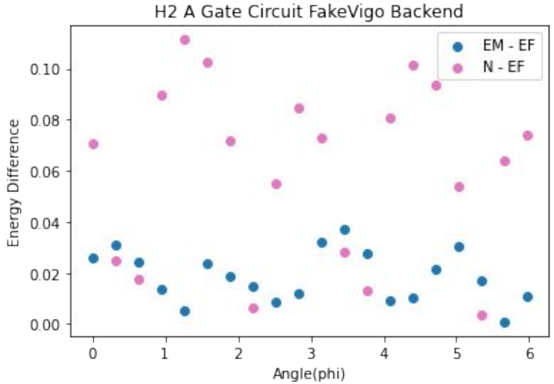
2. LBEM - A Gate circuit

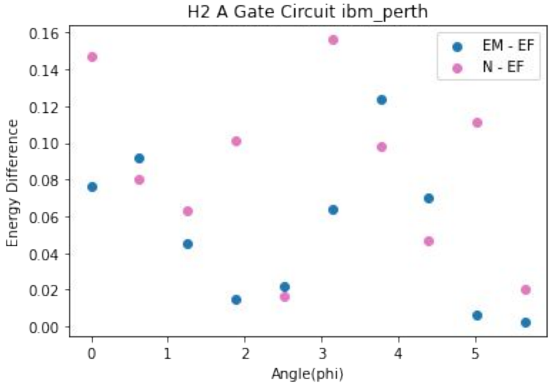
- Objective: Try for a more complex circuit with 2 parametrized gates

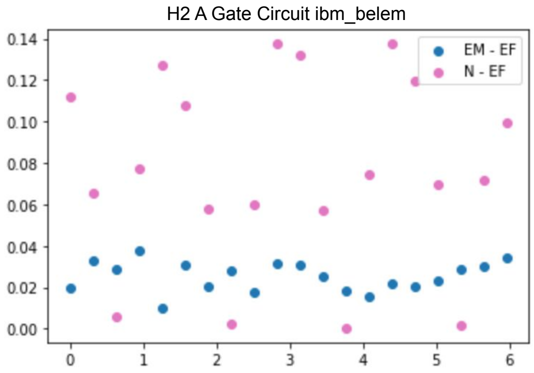
- Ansatz:
  - 2 parameterized gates
  - 4^2 Pauli gates
  - 24^2 Clifford gates



- Results:

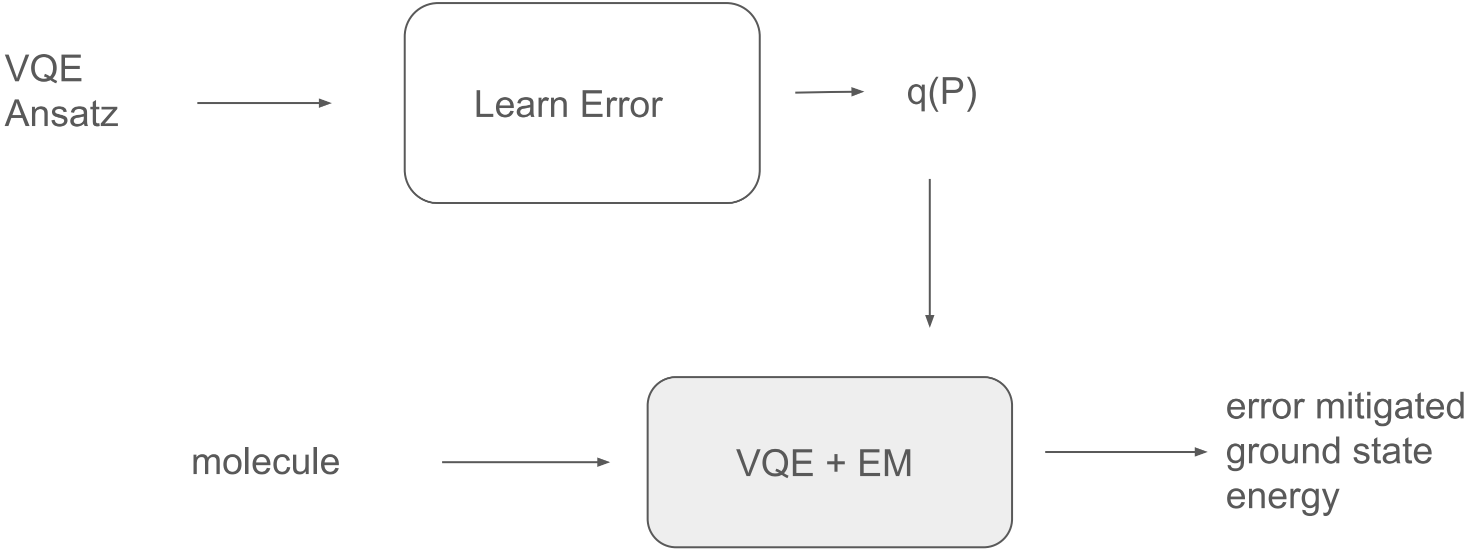




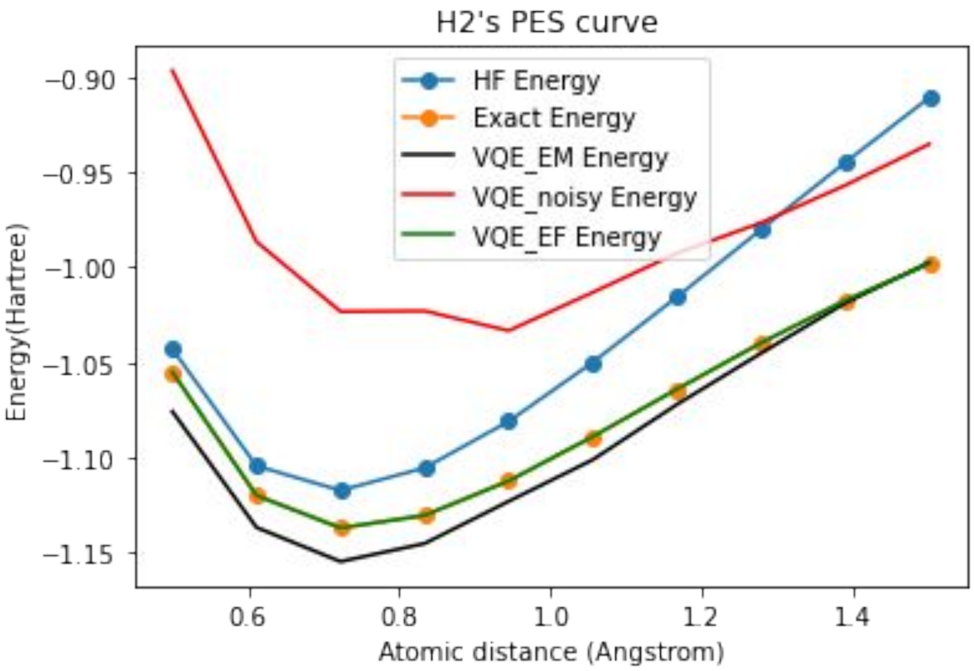


⇒ Error is mitigated for both simulated noise models and real hardware (hardware: train set truncate to 50 training circuits)

Using LBEM for a VQE



2. LBEM for H_2 simulation (PES curve)



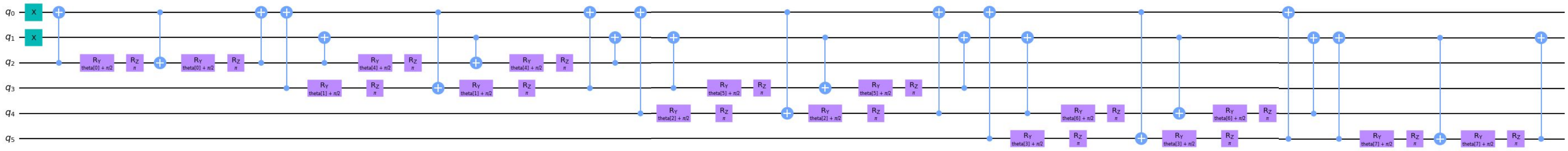
Backend: FakeVigo

The exact energy is calculated using NumpyEigenSolver

The error mitigated value is closer to the exact energy value than the noisy one.

3. Effects of Training Set Truncation - LiH

- Objective: calculate LiH energy at certain parameters
- Particle preserving ansatz:
  - 16 parameterized gates
  - 4^{16} Pauli gates
  - 24^{16} Clifford gates



- Problem: # parameterized gates ↑ → # training circuits, paulis increase **exponentially**

⇒ Randomly truncate training circuits & paulis (# training circuits = 3 * # paulis, following [1])

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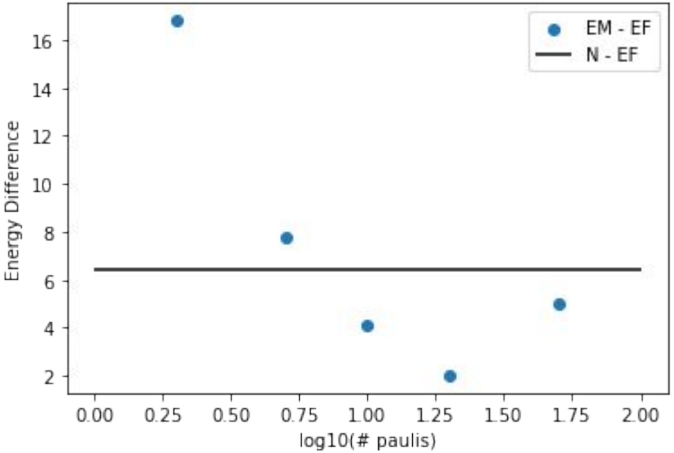
3. Effects of Training Set Truncation - LiH

- Classical simulation LBEM for |P| = 2, 5, 10, 20, 50
- Depolarizing error model used



⇒ High |P| generally mitigated more error

Results Summary

1. H_2 Simulation with simple ansatz
   a. Error mitigated for depolarizing model, FakeVigo model, and ibm_perth hardware

2. H_2 Simulation with A gate ansatz
   a. Error mitigated for FakeVigo model
   b. Simulated noisy VQE with error mitigation gave accurate results

3. Effects of Training Set Truncation - LiH
   a. Number of training circuits increase exponentially → truncate
   b. Larger number of training circuits give better mitigation results

Discussion

Future Work

- Apply effective truncation methods for feasible training
  - As the problem size grows, the size of possible combinations of single-qubit Clifford gates and Pauli gates to be used in the circuit grows exponentially
  - Simulating LBEM using noise models might provide insights into dominant Pauli words in $q(P)$, which, in turn, can be selected for efficient training on real QPU

- Compare LBEM to other mitigation methods
  - Error mitigation methods such as Zero Noise Extrapolation, Clifford Data Regression, Dynamic Decoupling, etc. have been proposed
  - Analytical comparison to such methods could reveal the dominant factor of errors on existing quantum devices

- Combine LBEM with other mitigation methods
  - Different mitigation methods are proposed to combat different types of noises
  - Careful combination of error mitigation methods can lead to efficiency and better performance