Predictive Tomography

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Problem

- Quantum process tomography is a way of characterizing the action of a quantum channel.
- This can be useful for identifying errors caused by noise, but in practice requires large numbers of trials that scale exponentially with the number of qubits.
- As a result, process tomography is not the favored experimental method of characterizing errors.

Abstract

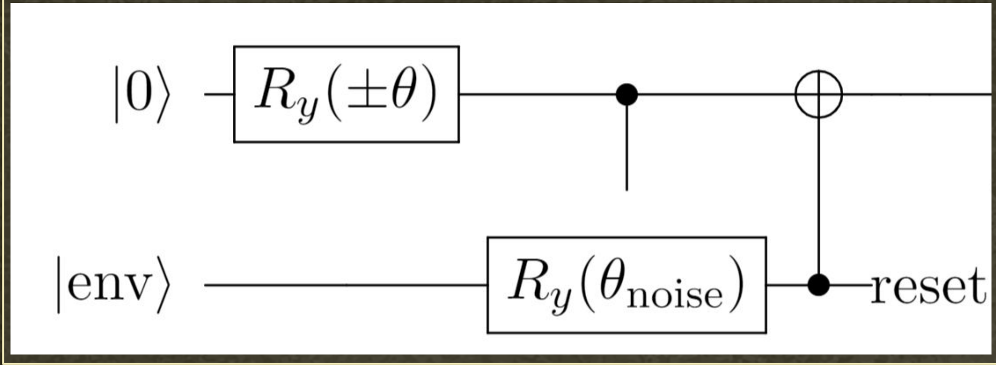
- ★ We perform quantum process tomography on 33 randomized circuits.
- ★ All of these trials contain amplitude damping and dephasing channels.
  - ○ Tomography is performed for 25 combinations of these noise parameters.
- ★ This generates a Pauli Transfer Matrix for each of the 825 unique channels.
- ★ The resulting dataset is used to test two approaches toward predictive tomography of an arbitrary channel:
  - ○ Non-linear neural network.
  - ○ Weighted function based on similarity of channel with known channels.

Noise Channels

- Real quantum computers contain noise, which can be simulated by introducing an environment qubit to the noisy circuit.
- We use two forms of noise:
  - Amplitude damping (spontaneous loss of energy)
  - Dephasing (loss of phase)
- Amplitude damping can be simulated with a controlled-Ry gate targeting the environment followed by a controlled-NOT gate targeting the qubit.
- Dephasing can be simulated with a Ry gate on the environment followed by a CZ gate on the pair.

Noise Channels Part 2

- ★ The angles for both of these rotation are linked to experimentally determinable decoherence times. We therefore take the error angles as input parameters.
- ★ The circuit for one step of Markovian amplitude damping is shown below, along with its relationship to gate time (time to enact a gate), and decoherence times (characteristic error time). This error channel is for an Ry gate on the qubit.



$$\theta_{\mathrm{noise}} = 2\arcsin\sqrt{1 - e^{-\frac{t}{T_1}}}$$

State Tomography

- Density matrices can be vectorized in terms of Pauli operators as follows: [2]
  - $\rho = \frac{\Sigma(S_i\rho)S_i^\dagger}{2}$, where the set S = (I, X, Y, Z)
- Using this formalism, we find that each Pauli operator has an expectation value:
  - $< S_i >= trace(S_i\rho)$
- For some given input state, state tomography can be performed on the input and output, yielding a mapping of operators.

Process Tomography

- ★ First, initialize the qubit in each of |0>, |1>, |+>, and |i>.
- ★ Perform state tomography on each input and output, yielding 4 mapping equations of inputs and outputs of the form: $[I_{in}, X_{in}, Y_{in}, Z_{in}] = [I_{out}, X_{out}, Y_{out}, Z_{out}]$
- ★ We can solve this system for each input operator in terms of its output operator.
- ★ This information can be condensed into the Pauli transfer matrix, R, with terms given by:[3] $R_{ij} = \frac{1}{d} Trace(S_i \Lambda(S_j))$
  - ○ Λ refers to the quantum channel's action on an operator, while d is twice the number of qubits.

Generating Data Sets and Fidelity

- ★ We iterate through noise angles from 0.05 to 0.25 for both amplitude damping and dephasing.
- ★ These are put into a searchable array of 825 Pauli transfer matrices.
- ★ This data serves as an input to a simple guessing function as well as a training set for a non-linear neural network.
- ★ To check accuracy of these predictive procedures, we use fidelity, defined as: [4]

$$F = \frac{Trace\left(R^{\dagger}_{desired} R_{predicted}\right) + d}{d^2 + d}$$

Simple predictive function

- Accepts input for an ideal transfer matrix and noise parameters.
- Algorithm references the 33 lowest noise matrices in the set and assigns a weight to each index given by: $2 - |R_{ij} - T_{ij}|$, here R and T refer to the input and a training set matrix.
- Querying the noise parameters next, it references the 33 equivalently noisy matrices in the training set, and creates a predicted Pauli transfer matrix based on a weighted average of each of these.
- Across 825 trials, the predicted matrix had an average fidelity of 0.514 compared with the matrix calculated through quantum process tomography.

Neural Network

- ★ Non-linear Neural network with 8 layers.
- ★ Input channels are the ideal matrix, and error angles.
- ★ Model predicts a noisy matrix using input parameters.
- ★ Fidelity is used as a loss function.
- ★ As a test, we give it training data of one matrix across each noise combination, and check how often it can correctly predict the noisy matrix.
- ★ Across 50 epochs, the model had an accuracy of 5.4%

Further Work

- ★ The results as well as qualitative observation showed that the decay of terms and emergence of errors in Pauli transfer matrices are highly unpredictable prior to simulation.
- ★ Other variables, such as the specific circuit rather than just its transfer matrix may be important in characterizing these errors. Additionally, it may be simpler to focus on a single type of error first.
- ★ We have also implemented functionality for twirling and Pauli conjugation of these circuits, and these procedures could be extended to those channels.

Thank you!

Works Cited

[2] Nielsen, Michael A, and Isaac L Chuang. *Quantum Computation and Quantum Information*. Cambridge University Press.

[3] Greenbaum, Daniel. (2015). Introduction to Quantum Gate Set Tomography.

[4] Chow, Jerry M., et al. "Universal Quantum Gate Set Approaching Fault-Tolerant Thresholds with Superconducting Qubits." Physical Review Letters, vol. 109, no. 6, 2012, https://doi.org/10.1103/physrevlett.109.060501.