Fast Estimation of Physical Error Contributions of Quantum Gates

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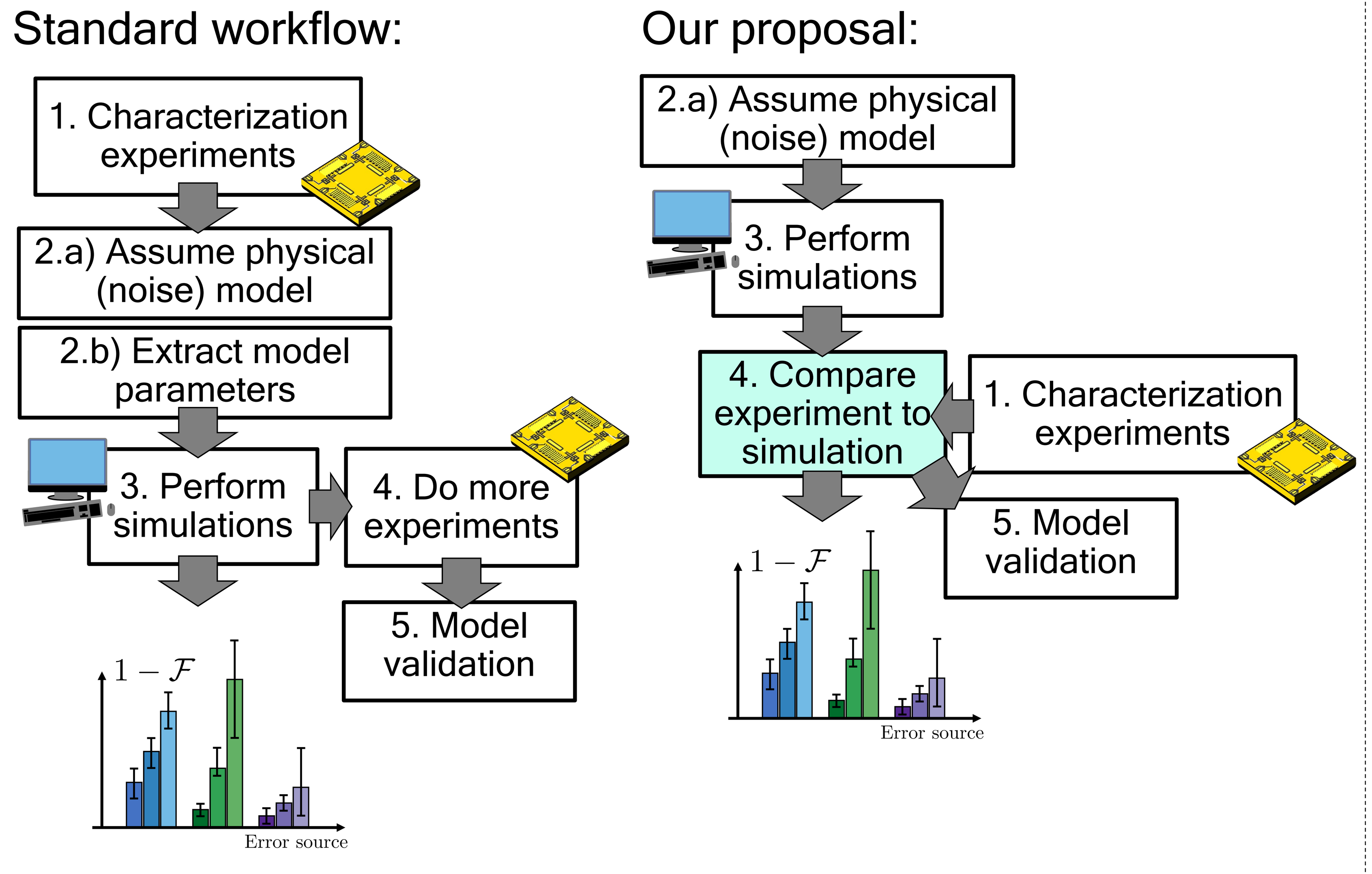
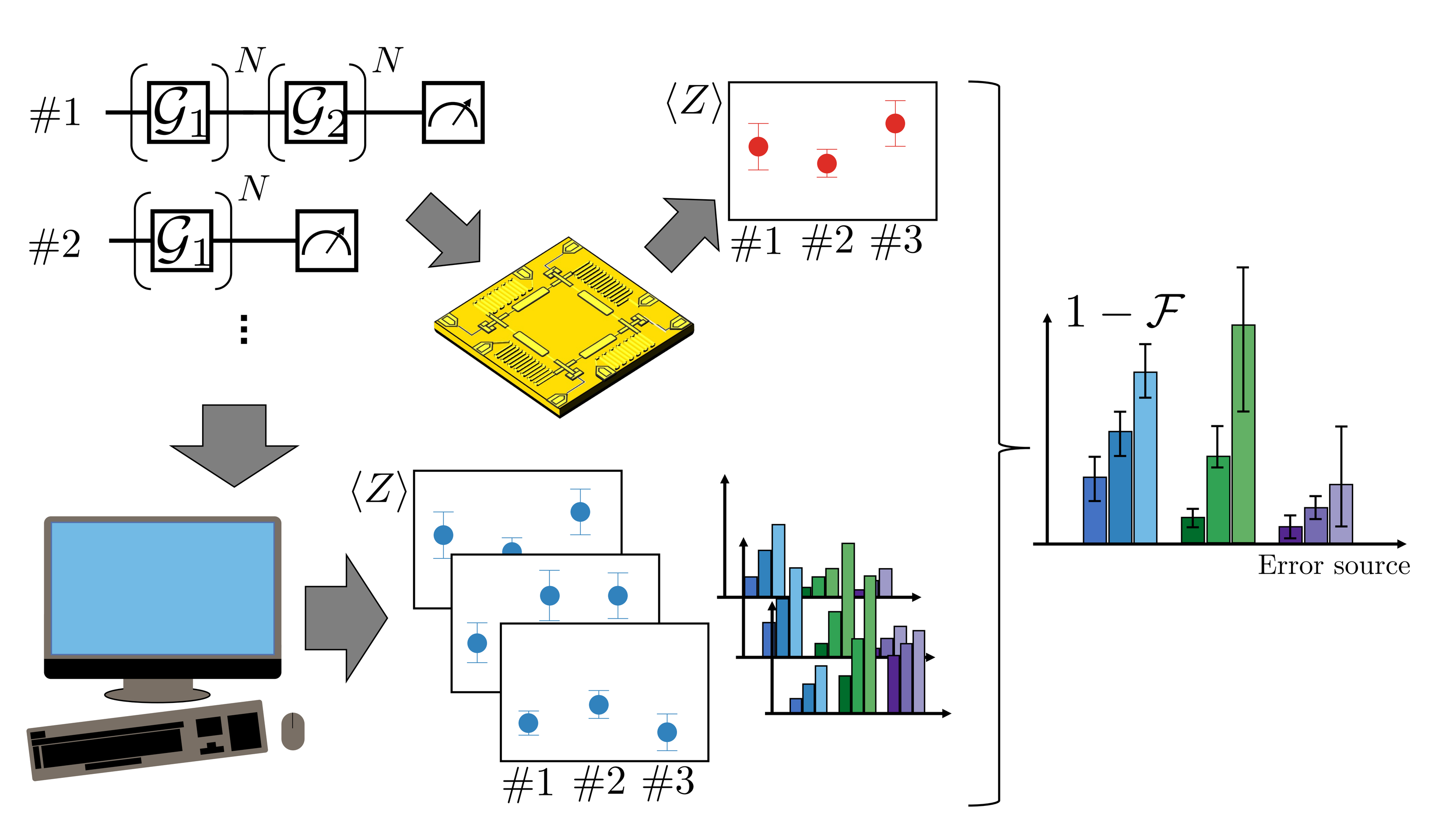
Overview

- Large-scale quantum computation requires a fast assessment of the main sources of error.
- Realistic errors are not necessarily Markovian (e.g. 1/f noise) or trace-preserving (leakage).
- We provide a learning-based framework that allows to extract the contribution of each physical noise source to the infidelity of a series of gates with a small number of experimental measurements and low classical overhead [1].
- Demonstration on superconducting transmon qubits with tunable couplers.

Error Budget Reconstruction

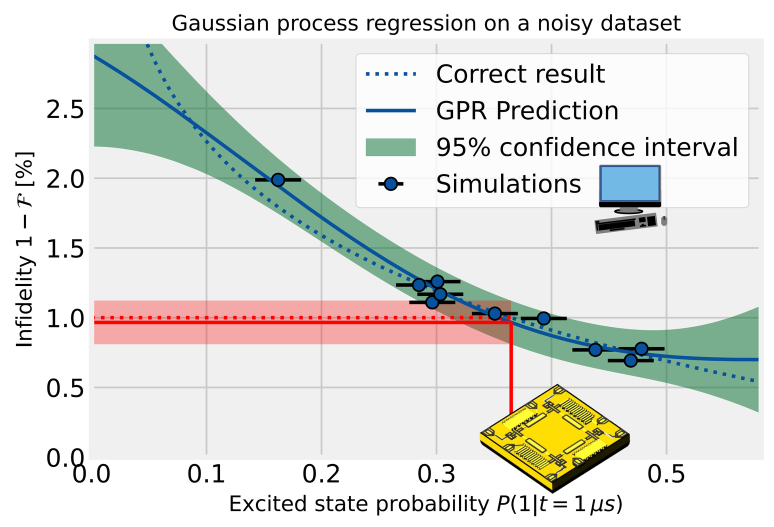




- Use noise models to simulate quantum circuits.
- Compare a set of simulated circuits to experimental results.
- Low classical overhead after training.

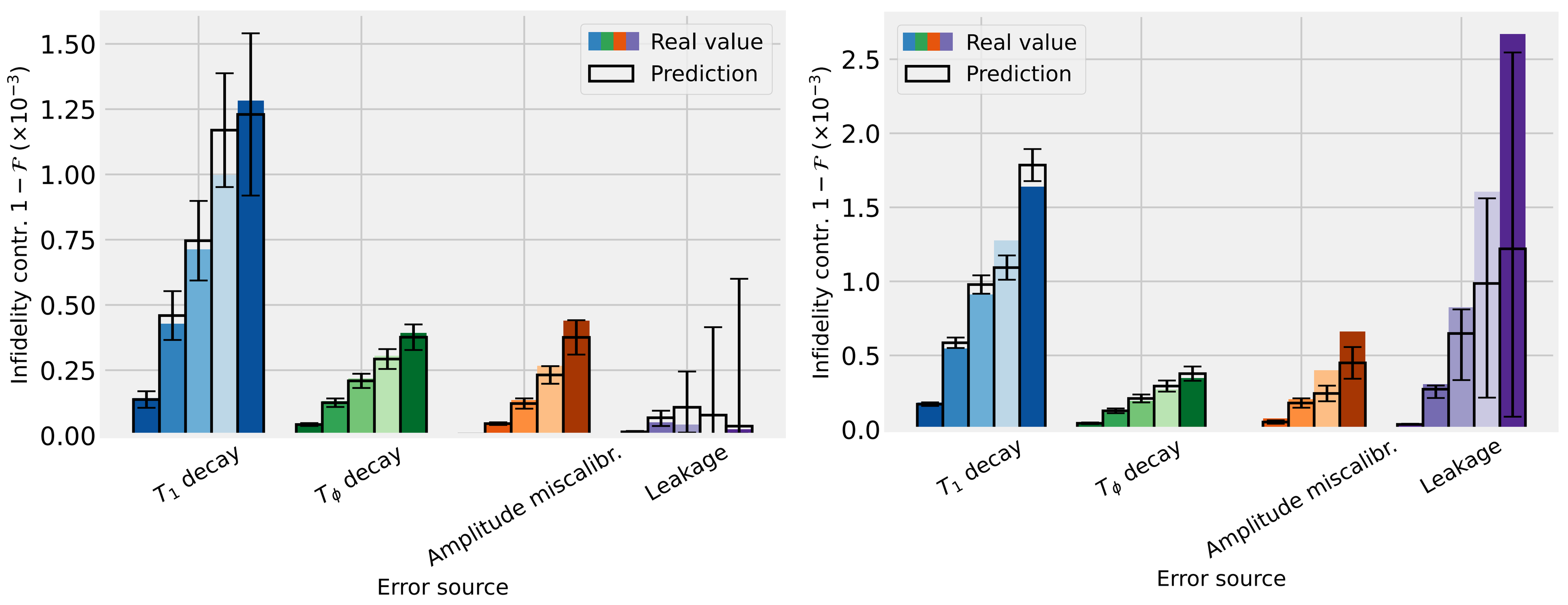
Gaussian Process Regression (GPR)

- Supervised learning (interpolation) technique.
- Inherent uncertainty of predictions.
- Small number of training samples.

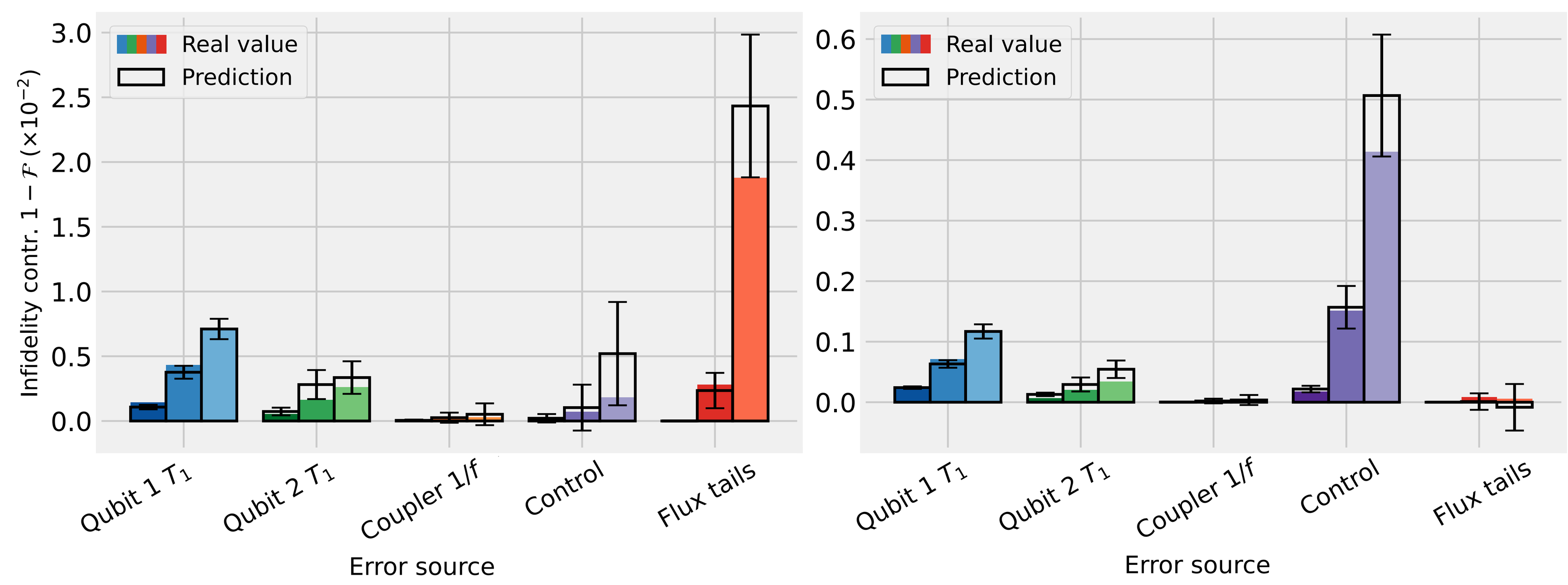


Superconducting Qubit Error Budgets

Single-qubit gates ($\pi/2$ and π rotations) [2]:



Two-qubit diabatic CZ gate [3]:



- Approximately 2x reduction in measurement time needed
- Realistic SPAM errors [4].
- Estimates also for complex errors (such as flux tails and leakage).
- Typical percentage of explained variance: 70-90%.

Conclusions

- GPR can be used to estimate the errors on many qubits, with less experimental shots and low classical overhead.
- Can be used in the presence of non-Markovian errors.
- Prerequisites:
  - Accurate error models of the system,
  - Estimate of realistic parameter ranges.
- Easily adaptable to other systems and co-design chips [5].

References

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