

Gate Set Tomography on more than two qubits

Erik Nielsen¹

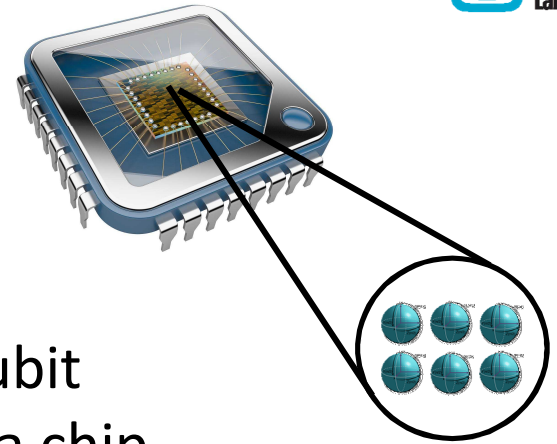
Robin Blume-Kohout², Timothy Proctor¹, Kenneth Rudinger²,
Mohan Sarovar¹, Kevin Young¹

¹(Sandia National Laboratories)

²(Center for Computing Research, Sandia National Laboratories)

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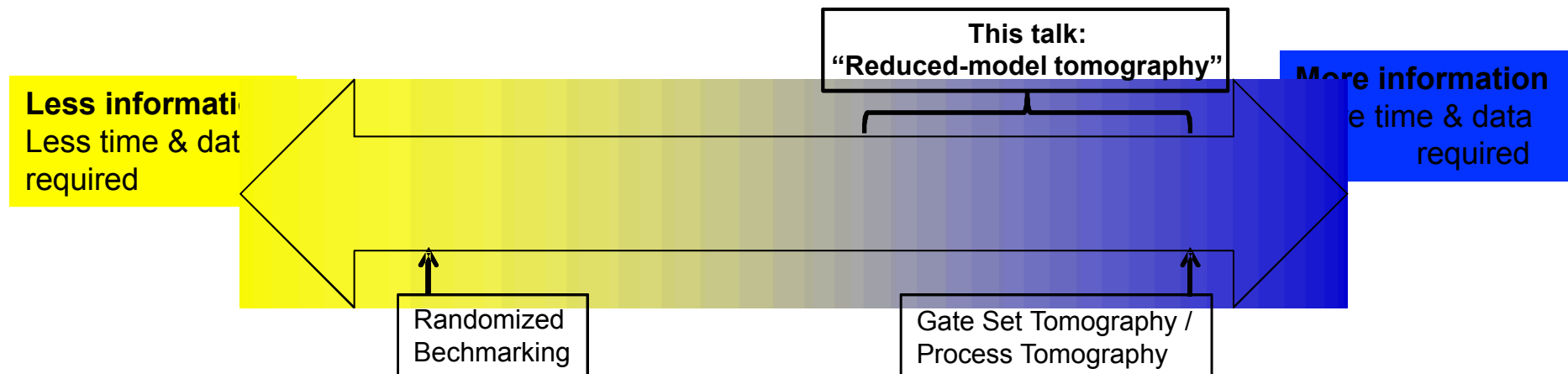
Background



- Ultimate goal is to produce working multi-qubit devices.
- State of the art has moved from single qubit demonstrations to handfuls of qubits on a chip.
- How do we best ensure these collections of qubits will work?
 - What does it mean to “work”?
 - perform algorithms?
 - perform error correction?
 - no “high-weight” errors?
 - Could just “see if they work”, but this is risky, and is difficult to extrapolate from.
 - Characterization? (but how?)

Characterization

- By extracting the information about the system we'd like to:
 - Rough gauge of performance (benchmarking)
 - "Debug" the system of qubits
 - Inform predictive simulations (model-based)
- Tradeoff:** Information vs. Effort (but how in practice?)



- Goal** of this work is to allow us to make this tradeoff.
- Within the context of model-based approaches, tradeoff is captured by the **number of model parameters**

Reduced-parameter models

This talk: “GST”-like characterization using reduced-parameter models.

- Starting point: standard-GST’s very rich model
 - Gates are $4^N \times 4^N$ matrices; $\approx 3N \cdot 16^N$ total parameters.
 - Hero computation at $N=3$; impossible beyond that.
 - Even if we could compute it, way too much information

$$\underset{\text{(gate)}}{G_i} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ \tau_x & \lambda_{xx} & \lambda_{xy} & \lambda_{xz} \\ \tau_y & \lambda_{yx} & \lambda_{yy} & \lambda_{yz} \\ \tau_z & \lambda_{zx} & \lambda_{zy} & \lambda_{zz} \end{pmatrix}$$

λ, τ parameters

- Key idea:** (leading to natural reduction in #parameters)

- Write gates as:

$$\underset{\text{(gate)}}{G_i} = e^{\overset{\text{“Error generator”}}{\Gamma}} \underset{\text{Ideal unitary}}{U_0}$$

$$\Gamma = \sum_i \theta_i H_i + \sum_{ij} \theta_{ij} S_{ij}$$

$$H_i: \rho \rightarrow -\frac{i}{\hbar} [A_i, \rho]$$

$$S_{ij}: \rho \rightarrow A_i \rho A_j^\dagger - \frac{1}{2} (\rho A_j^\dagger A_i - A_j^\dagger A_i \rho)$$

- Strategy: Limit terms in Γ to reduce the parameters of G_i**
 - Pauli-channel; limited weight; locality of terms; system-specific physics
 - Nested** models allow application of standard selection criteria.

Linear-chain models

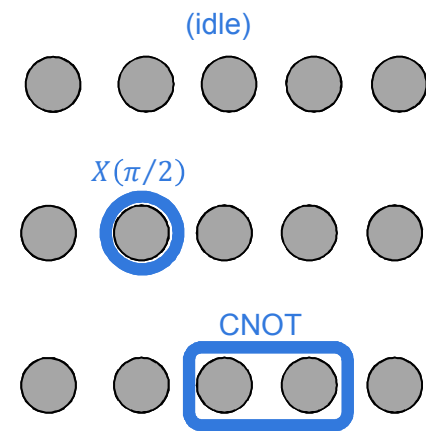
Consider a chain of N qubits.

■ Ideal operations:

1. Global idle gate
2. $X(\pi/2)$ and $Y(\pi/2)$ gates on each qubit
3. CNOT gates between adjacent qubits.

Recall:

$$G_i = e^{\Gamma} U_0$$



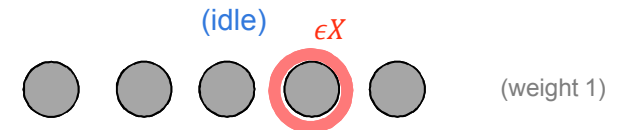
Example:
5-qubit chain

Linear-chain models (cont.)

■ Errors included in model:

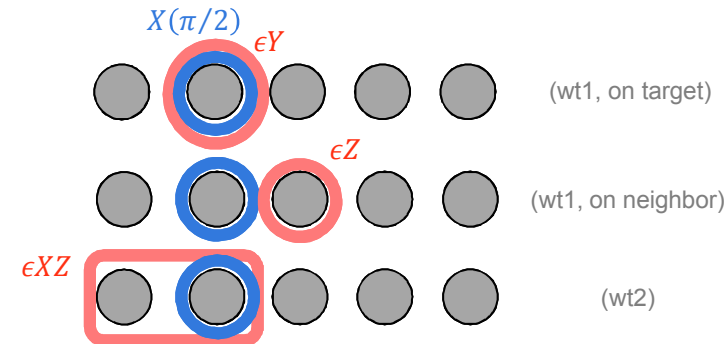
■ Idle gate

- weight-1 errors* on all qubits



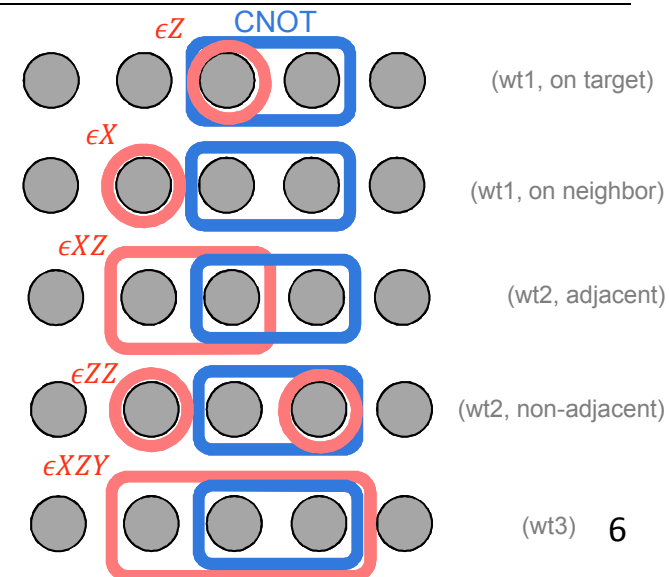
■ X,Y gates:

- weight-1 & 2 errors* on target qubit and its neighbors
- Same weight-1 errors* as global idle on all other qubits



■ CNOT gates:

- weight-1, 2 & 3 errors* on target qubits and their neighbors
- Same weight-1 errors* as global idle on all other qubits



* “errors” = Hamiltonian + *Pauli*-stochastic only

Sparse-model Gate Set Tomography

- **Method:**

- Input:
 - Parameterized qubit error model
 - outcome counts for a pre-defined set of gate sequences
- Maximize Likelihood(model-parameters | data)
- Output: best-fit model parameters (= qubit errors)

- **Result:**

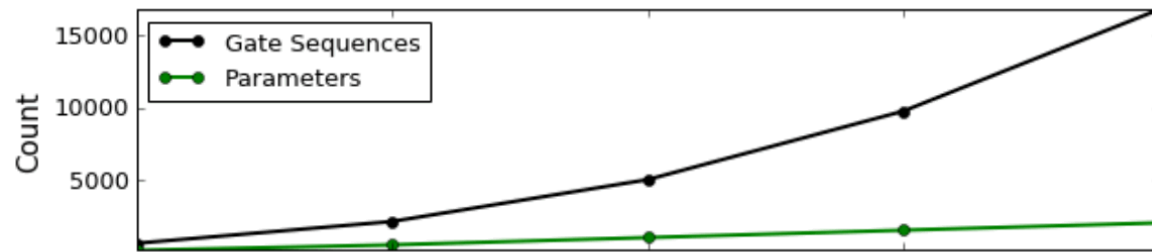
- Using the “base” model and an over-complete set of sequences, this **method succeeds in identifying the errors in simulated 3,4,5 & 6-qubit processors.**
- Computation time: < 15 hours on < 100-cores.

- **Significance:**

- **Proof of principle:** ML gradient ascent algorithms are able to fit simulated-processor data using the aforementioned models.
- **Capability:** methods/framework in open-source pyGSTi package.

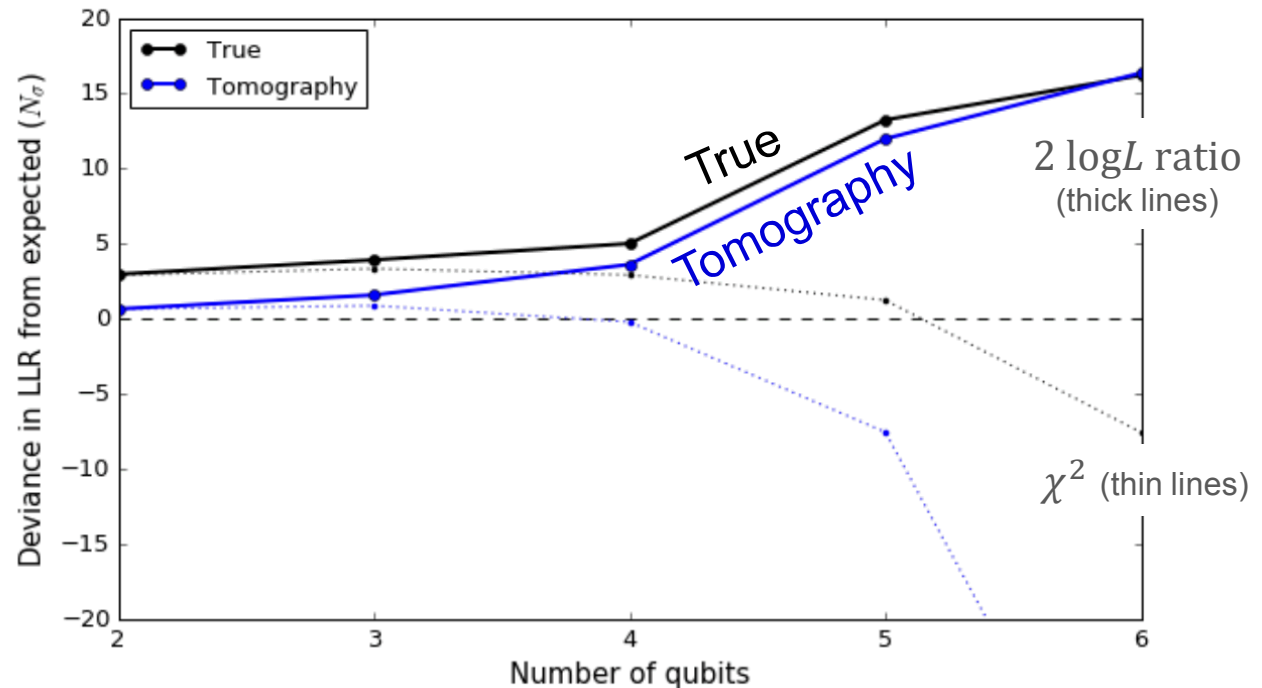
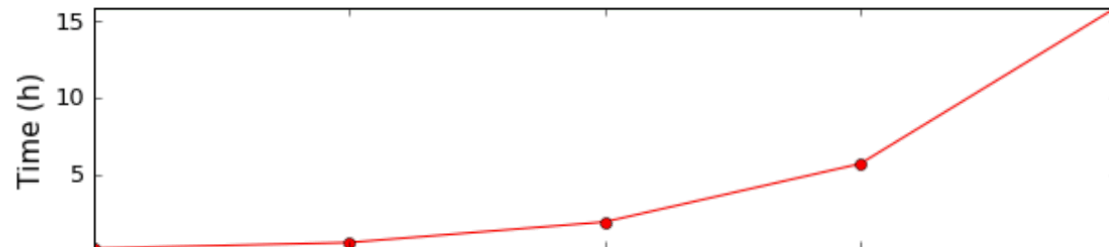


Results: (more details)

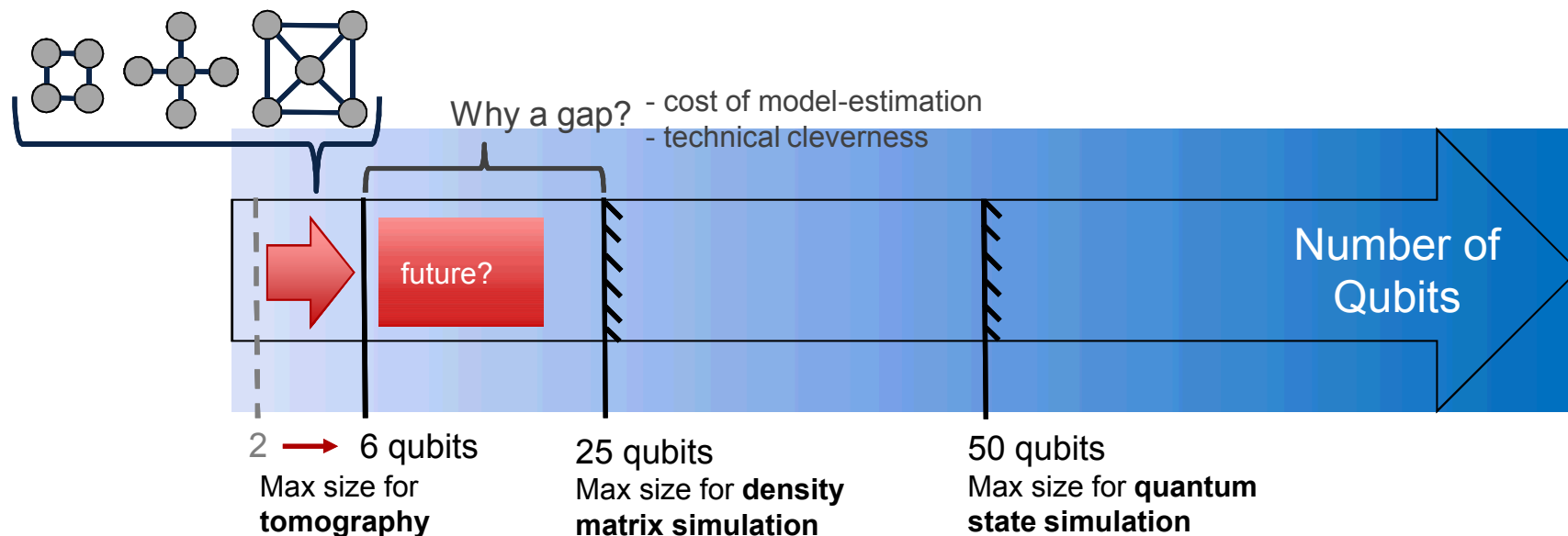


Tomography results fit:

- Within what we expect (χ^2 theory)
- Better than the “True” processor model which generated the data.

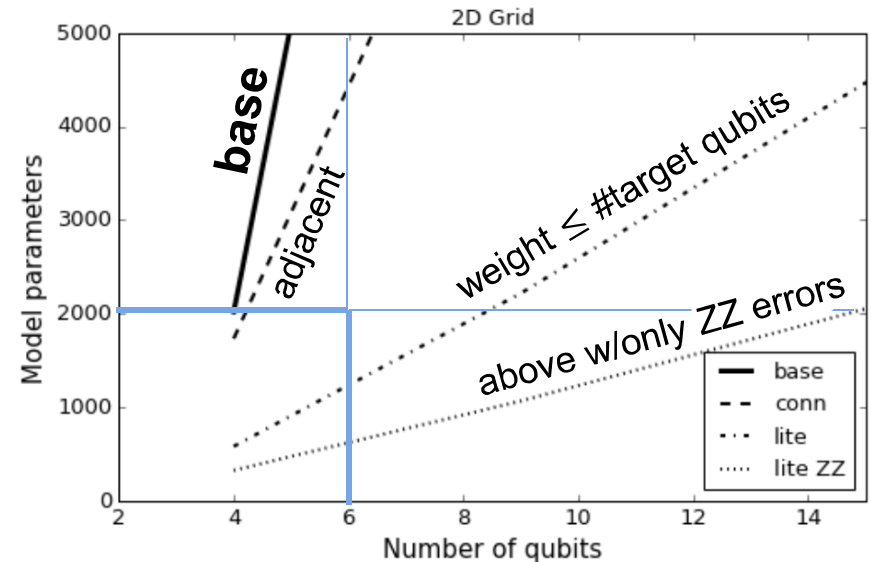
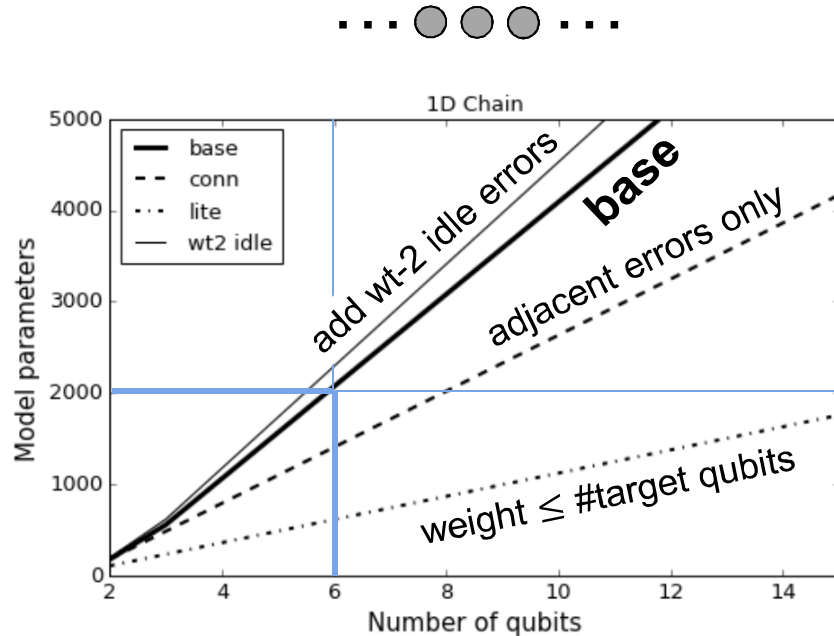


Significance



- Does:
 - Gives users access to the tradeoff space between tomographic detail and required data.
 - Pushed “**#qubits you can perform tomography on**” to > 2 (maybe ~ 6 ?)
 - Provide more direct link with predictive QEC simulations
- Doesn't:
 - push “**#qubits you can simulate**” any higher – *still* limited by cost of forward simulation (density matrix propagation in our case)

Parameter Scaling



- **Linear scaling** of parameters with #qubits
- Ability to tradeoff model richness with qubits or time.
 - Easy to create **nested** models
 - Practical for 2-8(?) qubits
- Pushes reason for tomography's exponential scaling to qubit simulation
($resources \sim parameters * simulation_cost$)

Next steps & open questions

- Faster quantum-state propagation
 - Currently use density-matrix propagation (4^N)
 - Alternatives: state-vector (2^N); compact representations?
 - ...**Or** ways to perform tomography without state propagation.
- Sequence selection (how many & which ones)
- Gauge degrees of freedom
- Efficiency: precision vs. time, # of experiments
- Model selection criteria

Summary

- Suggested a way to construct **reduced-parameter, nested, multi-qubit models**.
- Showed that families of these models can easily have **parameter counts which are polynomial** (even linear) in the number of qubits.
- Showed that it is **possible to use standard likelihood maximization to fit a “base”-type model** to raw count data from a simulated N-qubit linear-chain processor, where $N \leq 6$. (Essentially a “sparse quantum process tomography” on 6 qubits)

Excuses 😊

- Review and Approval
- Early march meeting
- My relatives
- Artic vortex
- El Niño