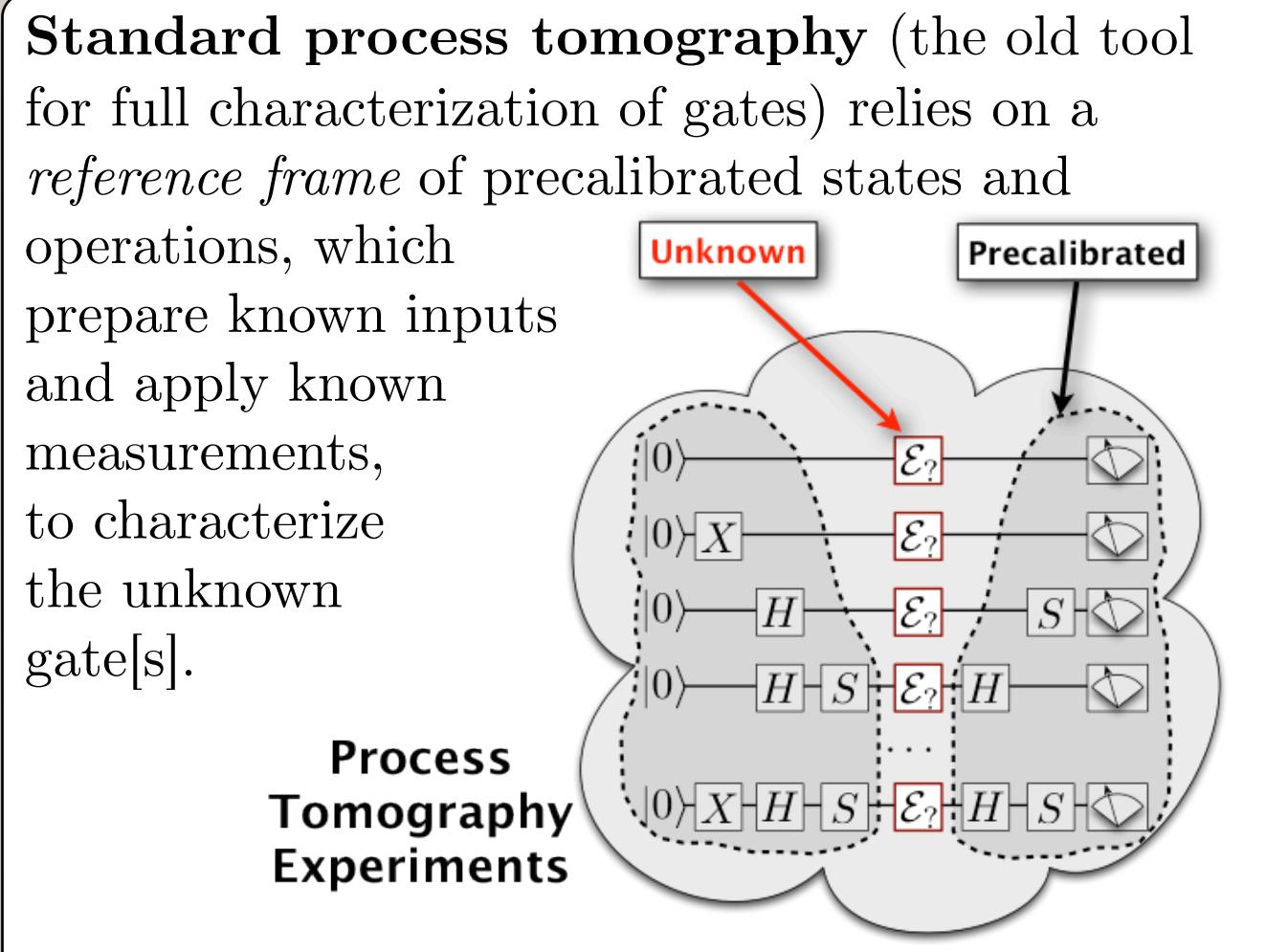


Gate Set Tomography (GST): Robust, accurate, full characterization of quantum logic gates

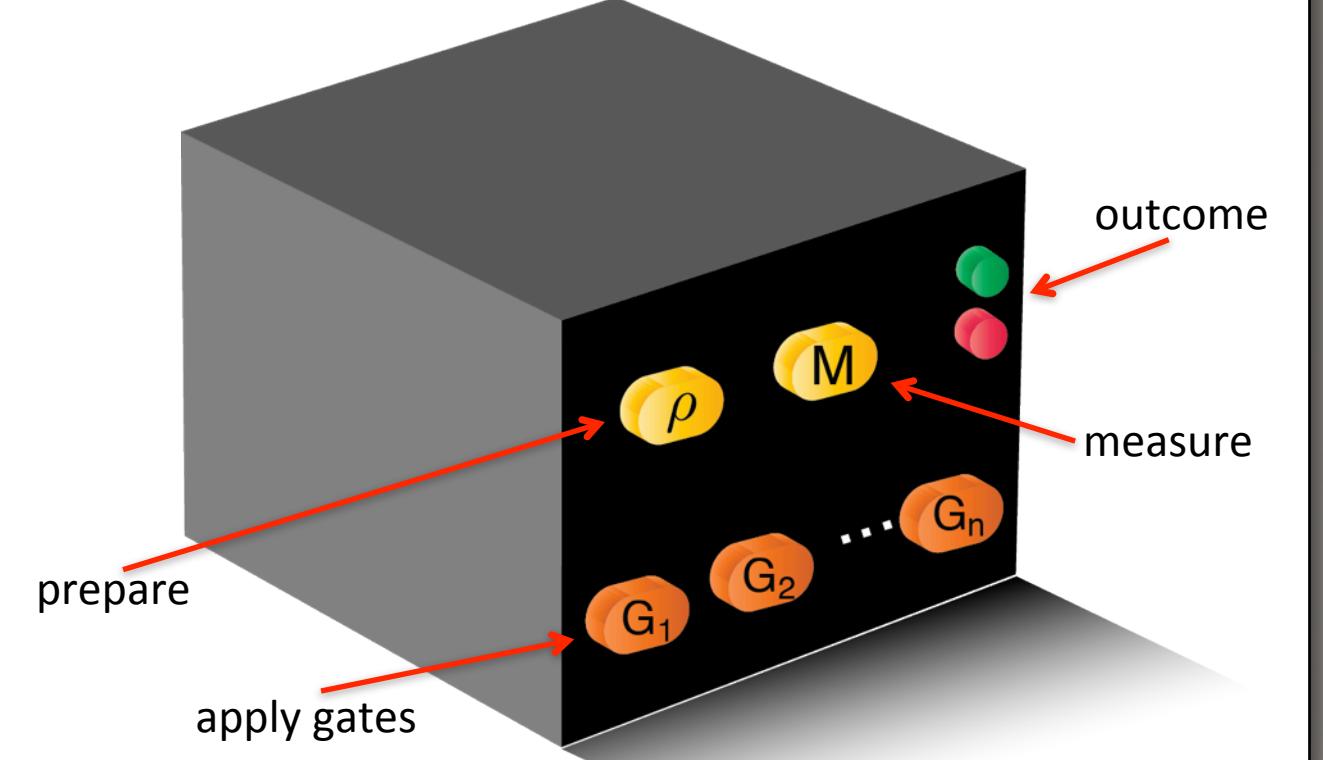
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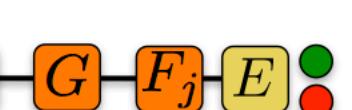
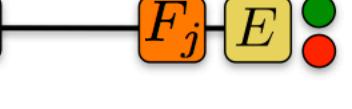
Summary Of Results

- Process tomography is unreliable, depending on precalibrated gates.
- We developed GST as a robust, calibration-free alternative.
- Use of structured data allows a *closed-form* linear inversion algorithm, which (unlike MLE) is guaranteed to give a pretty good answer.
- Within GST we can also use and analyze *long circuits* involving many gates. These amplify errors, and yield very accurate estimates.
- GST supports a rich error analysis, and detects non-Markovian noise.

GST treats the QIP (e.g. qubit) as a black box. Precalibrated states/gates are not available, and GST therefore does not use or rely upon them.



The 1st stage of GST is *Linear GST*. Simple, efficient, and 100% reliable, LGST provides a rough estimate that can be iteratively improved:

- (1) Choose a set of *fiducial sequences*:
 $\{F_1, F_2, F_3, F_4\} \stackrel{\text{e.g.}}{=} \{G_1, G_2, G_3, G_2^2\}$
- (2) Do "tomography" by measuring:
 $(\tilde{G}_i)_{j,k} = \langle\langle E | F_j G_i F_k | \rho \rangle\rangle$ 
 and $\tilde{1}_{j,k} = \langle\langle E | F_j F_k | \rho \rangle\rangle$ 
- (3) Use linear algebra to get the estimate:
 $\hat{G}_i = \tilde{1}^{-1} \tilde{G}_i$, etc. $\iff \hat{G}_i = B^{-1} G_i B$, $\langle\langle \hat{E} \rangle\rangle = \langle\langle E | B, | \rho \rangle\rangle = B^{-1} | \rho \rangle\rangle$
- (4) Transform the estimated gateset by a *gauge transformation* to make it as close as possible to the desired target gateset:
 $\hat{G}_i \rightarrow S^{-1} \hat{G}_i S$ and $\langle\langle \hat{E} \rangle\rangle \rightarrow \langle\langle \hat{E} | S \text{ and } | \hat{\rho} \rangle\rangle \rightarrow S^{-1} | \hat{\rho} \rangle\rangle$

All forms of GST contain a gauge freedom. It's annoying but unavoidable.

Every observable probability

$$p(\bullet) = \langle\langle E | G_{s_1} \dots G_{s_L} | \rho \rangle\rangle$$

is totally invariant under the **gauge** transformation

$$G_i \rightarrow B^{-1} G_i B \text{ and } \langle\langle E | B, | \rho \rangle\rangle \rightarrow B^{-1} | \rho \rangle\rangle$$

This can change the gates a *lot*. But it doesn't change *anything* observable. So these gatesets are *equivalent*.

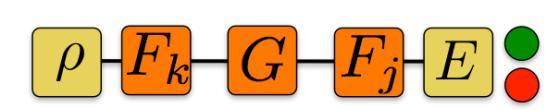
So we can choose the gauge to best match our target gates.

Or to get as close as possible to a set of CPTP gates.

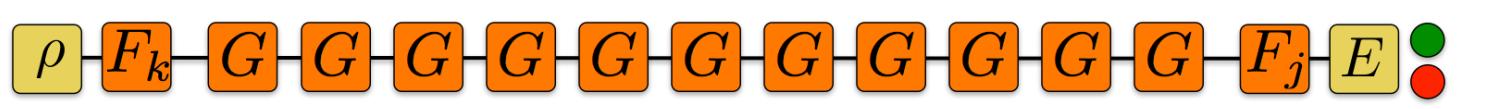
Argh...

GST is (necessarily) capable of analyzing *nonlinear* data -- i.e., experiments in which the unknown gate is used multiple times.

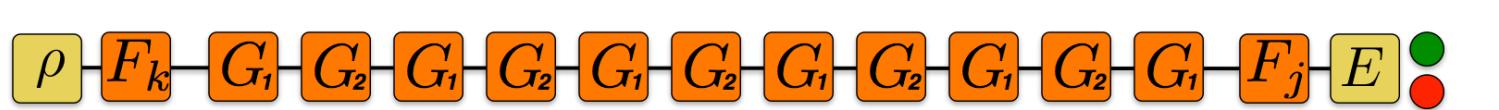
- We care deeply about very small errors (0.01%) in gates. These are very hard to detect in a single use of the gate.



- By using the unknown gate many times in an experimental test circuit, we can *amplify* errors



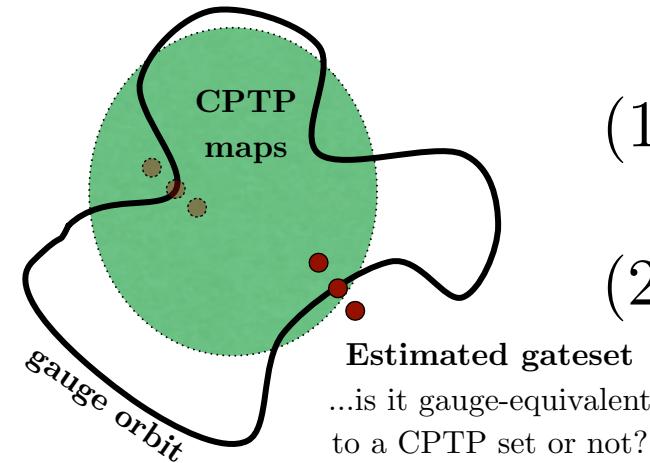
- We developed sequences that can amplify *all* errors.



Brute-force maximum likelihood GST (and why we don't do it any more)

In principle, GST could be done on data from *any* circuits by numerically maximizing $\mathcal{L} = \Pr(\text{data} | \{G_k\})$

But nonlinearity makes the likelihood horrible. And the gauge plays very badly with the CPTP constraint. In practice, brute-force MLE fails:



- (1) It takes about a day to analyze typical single-qubit data!
- (2) Even with sophisticated codes, we don't reliably find global maxima.

Efficient analysis of long circuits/sequences: eLGST and least squares GST.

We're developing reliable, fast (1-100s running time) alternatives to MLE for analyzing long sequences.

Extended LGST (eLGST) uses LGST to directly estimate the process matrix of long periodic sequences like $(G_1 G_2)^{32}$. Then, the estimates of $\{G_k\}$ are adjusted (iteratively) to fit these direct-LGST estimates of long gate sequence products.

Least squares GST (LSGST) analyzes the same structured data as eLGST, but iteratively adjusts estimates of $\{G_k\}$ by weighted least-squares fitting directly to the data.

Glossary: Hilbert-Schmidt notation

1. States (ρ) and measurement outcomes (E) live in the *Hilbert-Schmidt space* of Hermitian $d \times d$ matrices.

$$|\rho\rangle\rangle = \begin{pmatrix} \rho_{11} \\ \rho_{12} \\ \rho_{21} \\ \rho_{22} \end{pmatrix}$$

2. Gates (processes) are $d^2 \times d^2$ linear *superoperators* that act on states:

$$|\rho_{\text{out}}\rangle\rangle = G |\rho_{\text{in}}\rangle\rangle$$

3. Observable probabilities are inner products:

$$Pr = \langle\langle E | \rho \rangle\rangle \quad \text{or} \quad Pr = \langle\langle E | G_1 G_2 \dots G_L | \rho \rangle\rangle$$

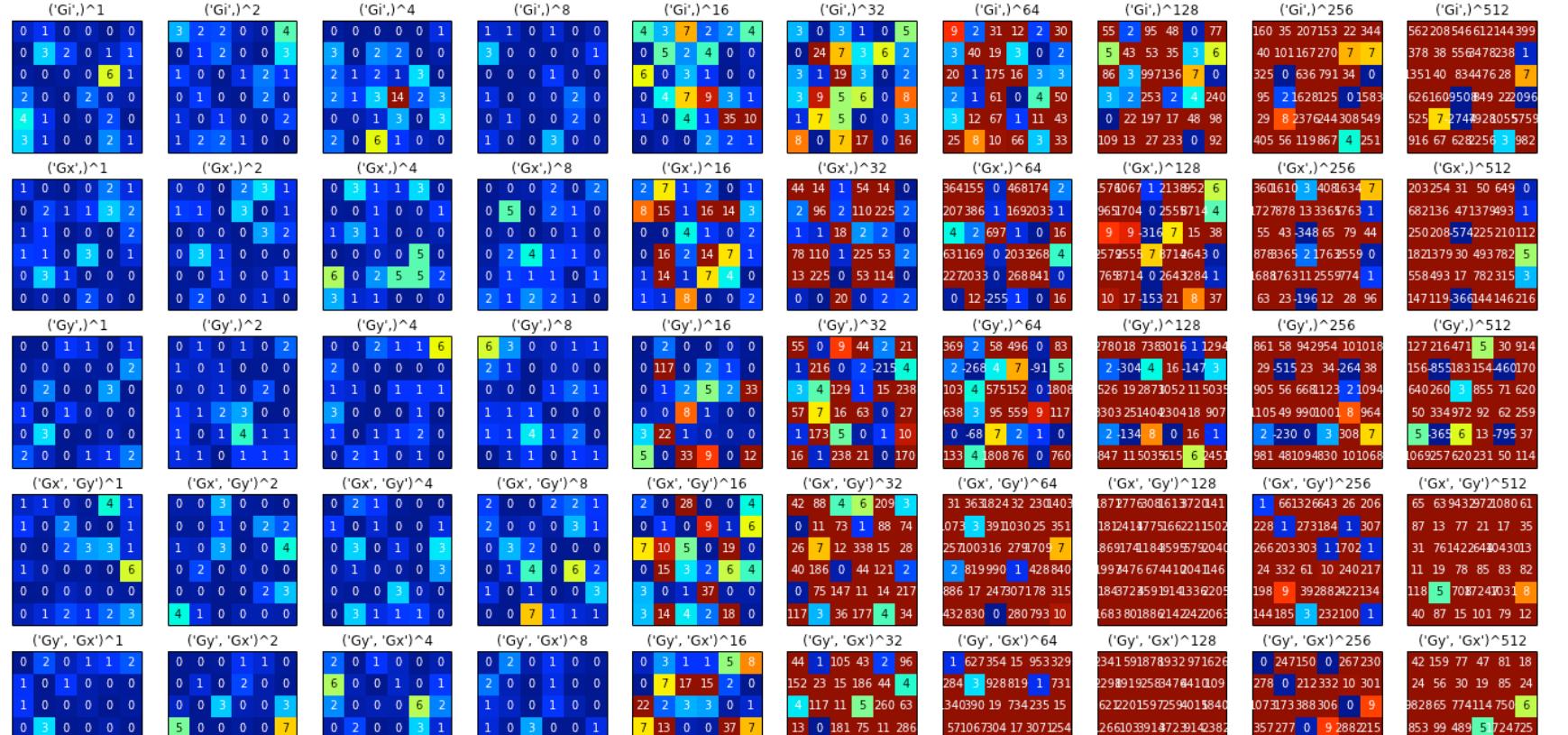
Error analysis and badness-of-fit.

When you get a tomographic estimate, it's critical that you ask how *good* it is -- e.g., can we rely on it? what are the error bars? did tomography work?

GST data is usually highly overcomplete -- $O(1000)$ observed frequencies for $O(100)$ gate parameters. So we can measure *badness-of-fit* by computing log-likelihood ratio or X2 statistics. These diagnose *whether* and *which data* our estimate fails to fit!

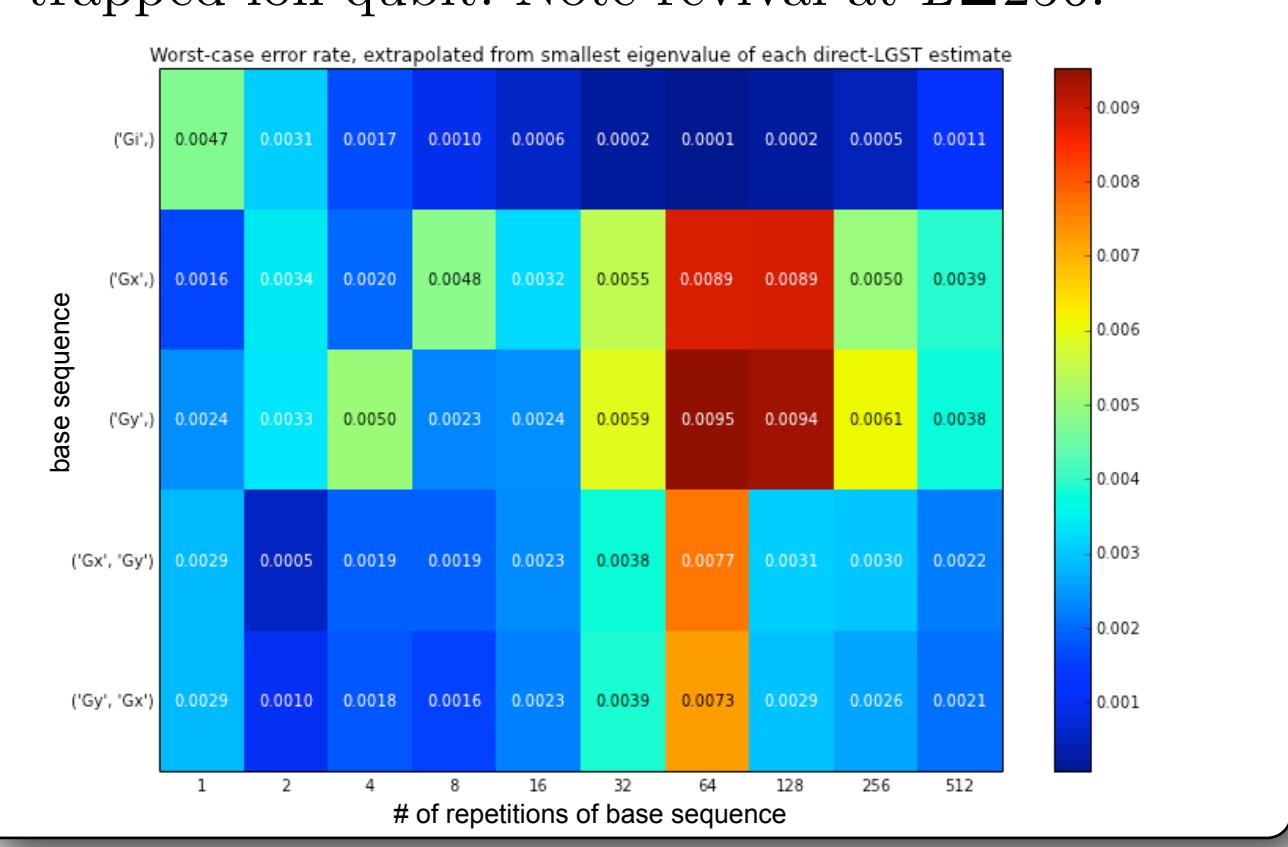
(Below): we fit the gates to data from sequences of lengths $L=1, 2, 4, 8$ -- but we show the X2 b-o-f for data from $L=1 \dots 512$. As expected, we fit the $L=1..8$ data well but fail for $L > 16$ data.

However, fits to *all* the data (not shown) fail across the board! No Markovian gates fit this data well! This is a clear signature



Experimental Result:

Experiments in 3 different qubits (ion, Si-dot, superconducting) have *all* revealed significant non-Markovian noise! Figure below shows error-per-gate vs. circuit length for SNL trapped-ion qubit. Note revival at $L \geq 256$!



Conclusions

- GST is ready for use, robust, and capable of unprecedented accuracy.
- Long-sequence experiments reveal non-Markovian noise in multiple qubit techs.