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Automated Model Selection for Gate Set Tomography

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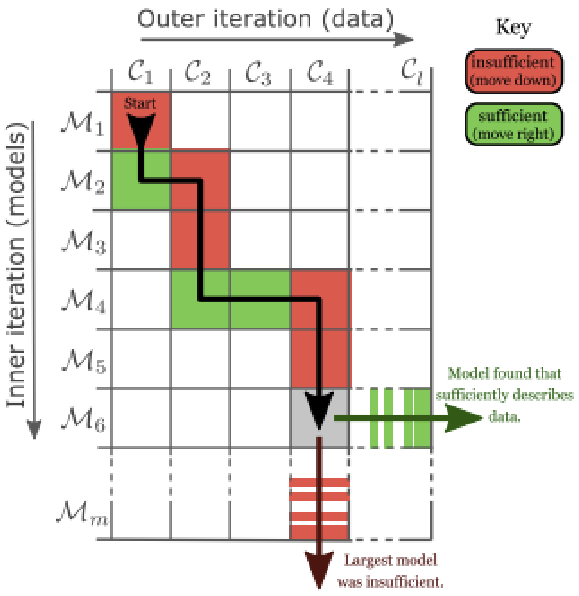
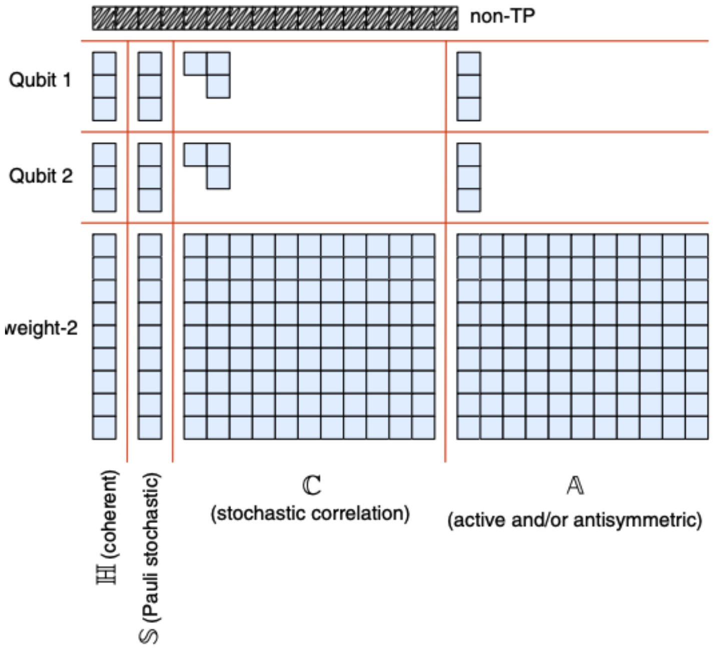
Model Reductions for Gate Set Tomography

- Gate set tomography (GST) is:
  - Accurate (Heisenberg-limited)
  - Robust to SPAM errors
  - Provides detailed process matrices for all gates
- But process matrices are not that useful always – often, we just want *simple* and *intuitive* models
- Two-part solution!
  - **Decrease model size** with a nested model reduction approach
  - Use elementary error generators for **greater interpretability**



Procedure for systematic testing of nested models[1]



Elementary error generators broken up by type (coherent, Pauli stochastic, correlated stochastic, and active), weight, and support[2]

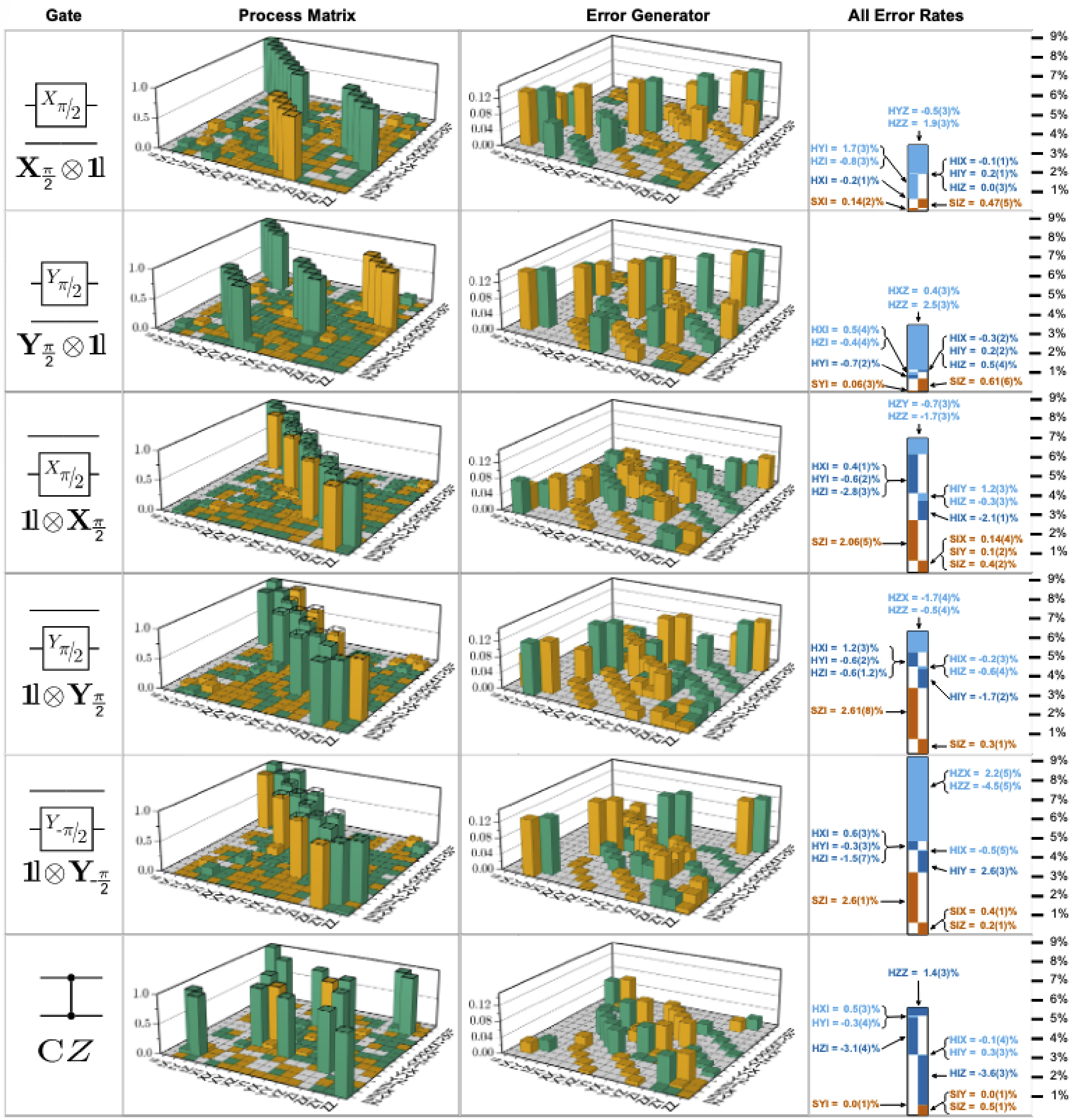
[1] Nielsen *et al.*, *New J. Phys.*, 23, 093020 (2021)
[2] Blume-Kohout *et al.*, *PRX Quantum*, 3, 020335 (2022)

Reduced GST models are powerful… but not always easy to find

- For example: Reduced GST models provided evidence for an unexpected ZZ coherent error in a recent silicon spin qubit experiment[1]

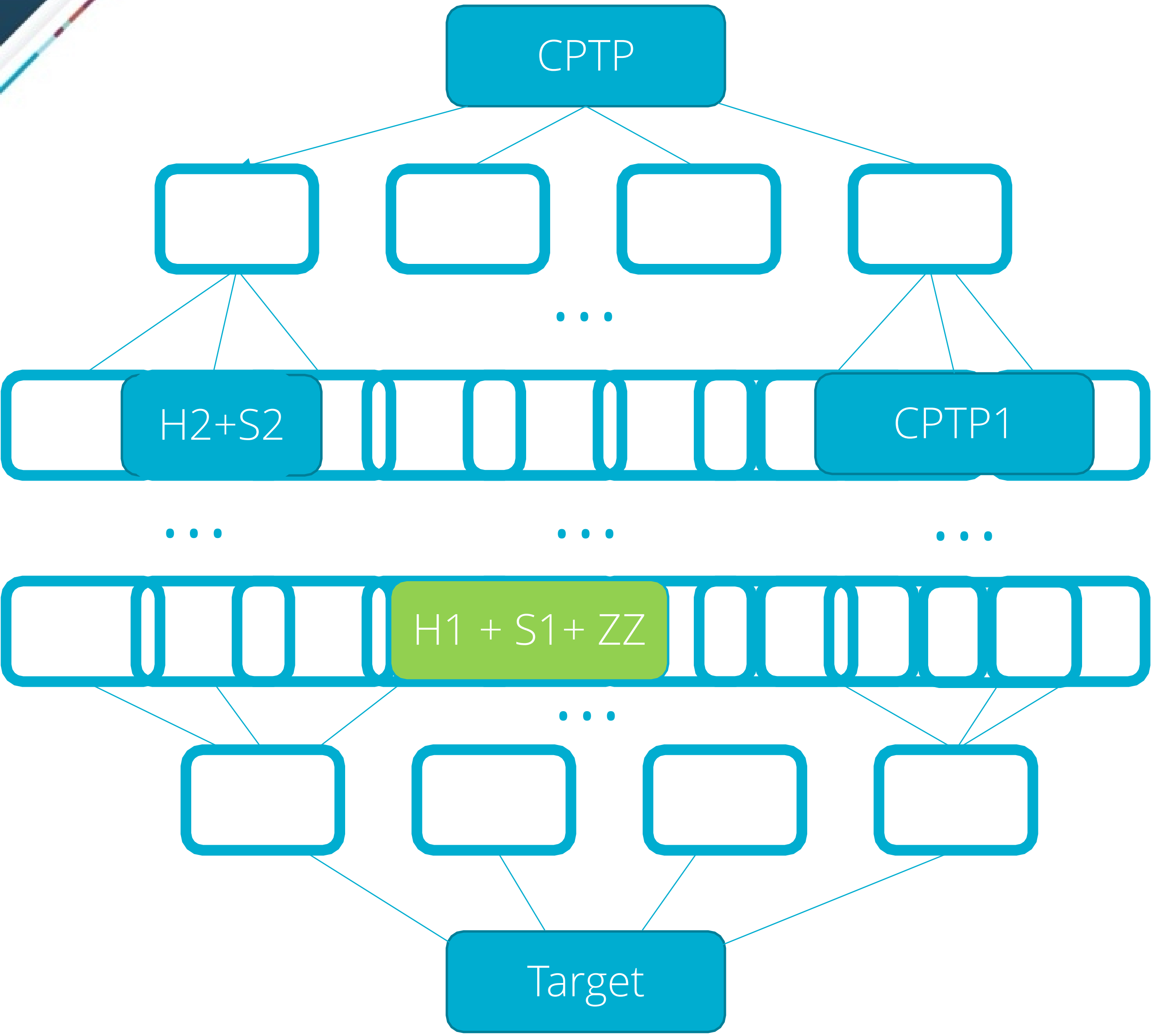
- However, this reduced model was hand-tuned with hours of data analysis and input from physics modeling

- We would like to do these types of analyses consistently – and that means doing it automatically!



[1] Madzik *et al.*, *Nature*, **601**, 348-353 (2022)

Searching for a Needle in a Haystack



- Unfortunately, there are a lot of valid reduced models… so brute force search is exponential
- We have some intuition that some form of sparsification should work
  - Adding the next most significant error generator seems like a reasonable thing to do?
- So we really just need to find a “good” path through this graph

How well does a greedy search do?

1. Calculate a GST fit for full model
2. Get all possible nearest-neighbor model reductions
3. Compute GST fits for reduced models
4. Calculate evidence ratio from log-likelihoods L and parameter counts $N_{\mathbf{params}}$

$$\gamma = \frac{2\left(L^{\text{prev}} - L^{\text{curr}}\right)}{\left(N_{\text{params}}^{\text{prev}} - N_{\text{params}}^{\text{curr}}\right)}$$

5. Select model with smallest evidence ratio
6. If $\gamma < 2$ (the AIC), accept model
7. Repeat steps 2 – 6 until model is rejected.

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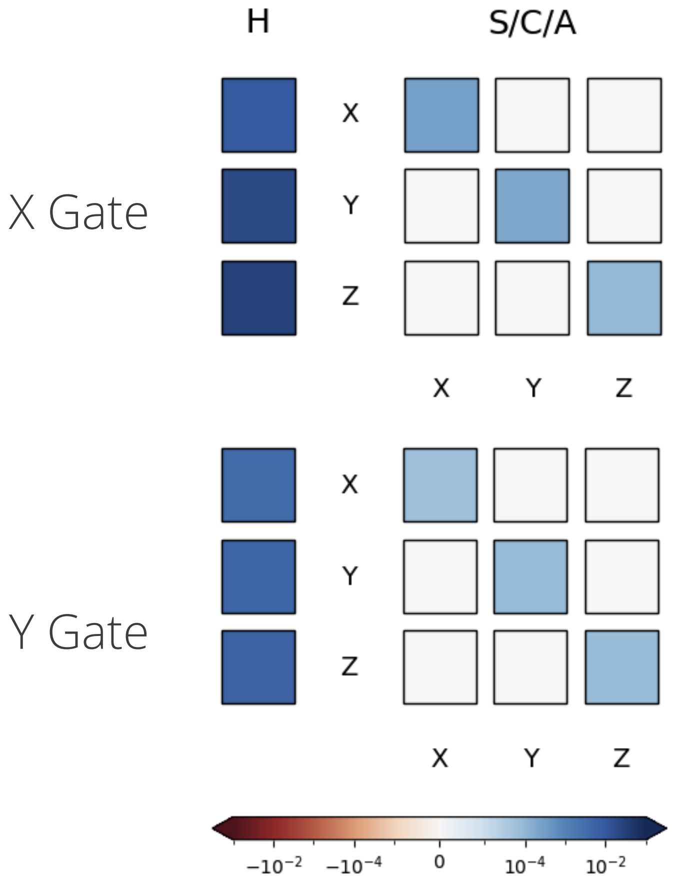
True Model



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7. Repeat steps 2 – 6 until model is rejected.

That's a **fail…**

Improving our search strategy

Faster Evaluations

- In the case of model reduction, we can reuse information to speed up some evaluations
- Do a quadratic expansion around GST (maximum likelihood) estimate $\vec{x_0}$ with Hessian H

$$L(\vec{x}) = \frac{1}{2}(\vec{x} - \vec{x_0})^T H(\vec{x} - \vec{x_0})$$

- Use Lagrange multipliers to do constrained optimization, where Π is the projector that sets the desired parameters of the new estimate $\vec{x}'$ to 0

$$L(\vec{x}') = \frac{1}{2}\vec{x_0}^T \Pi(\Pi H^{-1}\Pi)^{-1}\Pi\vec{x_0}$$

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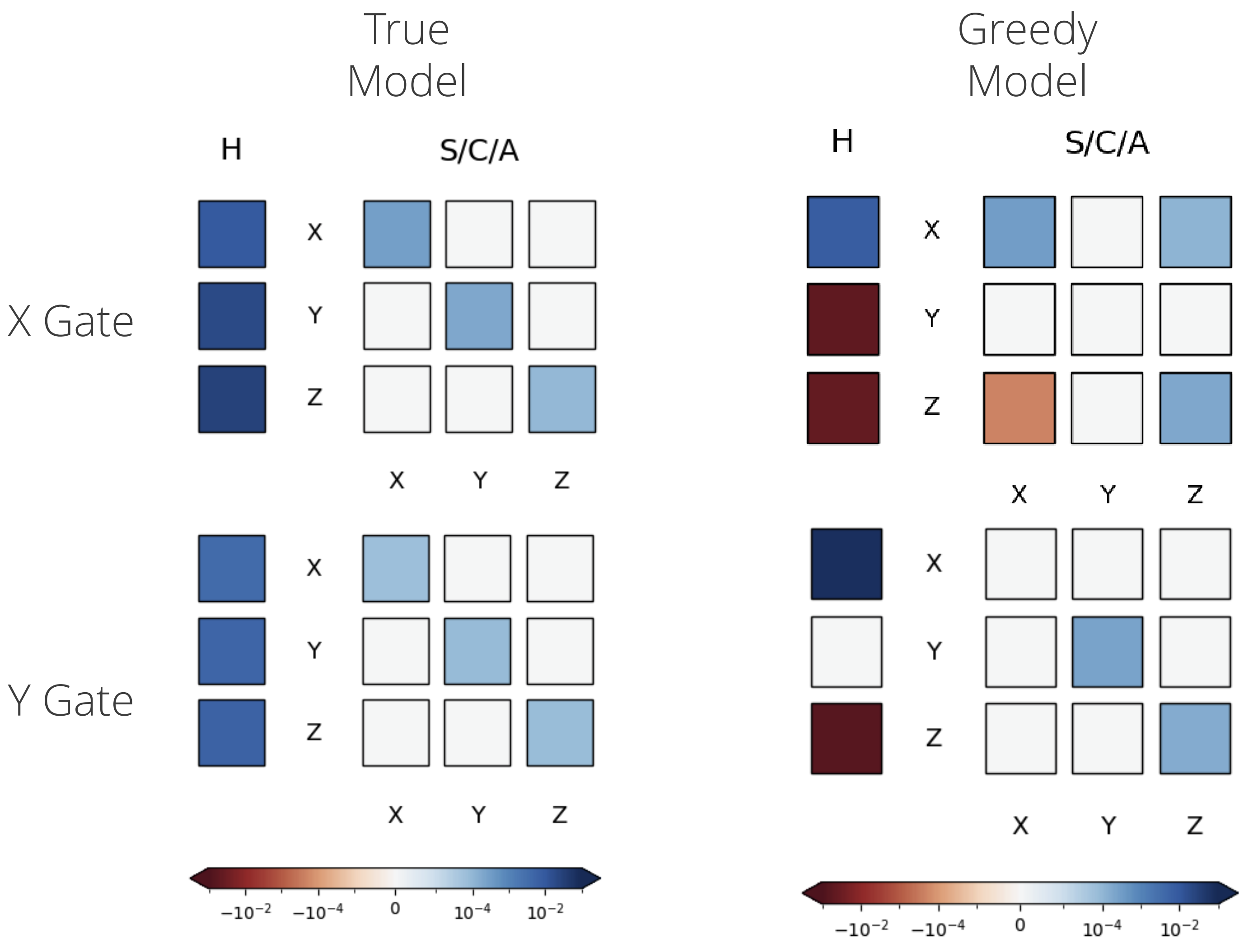
Beam Search

- Part of greedy failure was immediately due to a borderline decision to drop a Hamiltonian generator due to gauge…
- Can we be more robust to these close calls, especially at the beginning?
- Yes! We can do a beam search
  - Instead of keeping single best model at each step, keep some small number of instances instead
  - Still not guaranteed to be optimal, but a good heuristic in practice

Semi-reasonable Automated Model Selection



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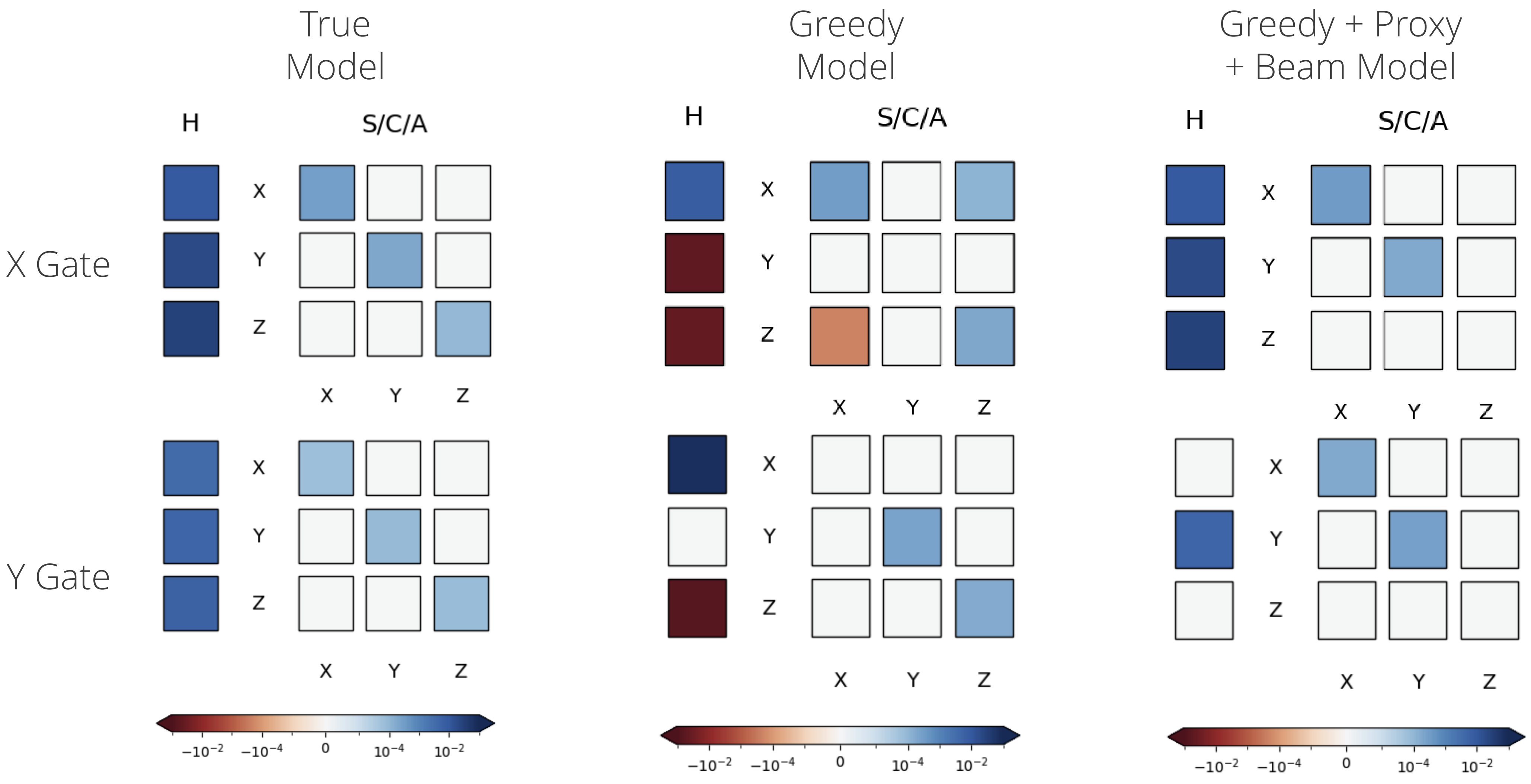

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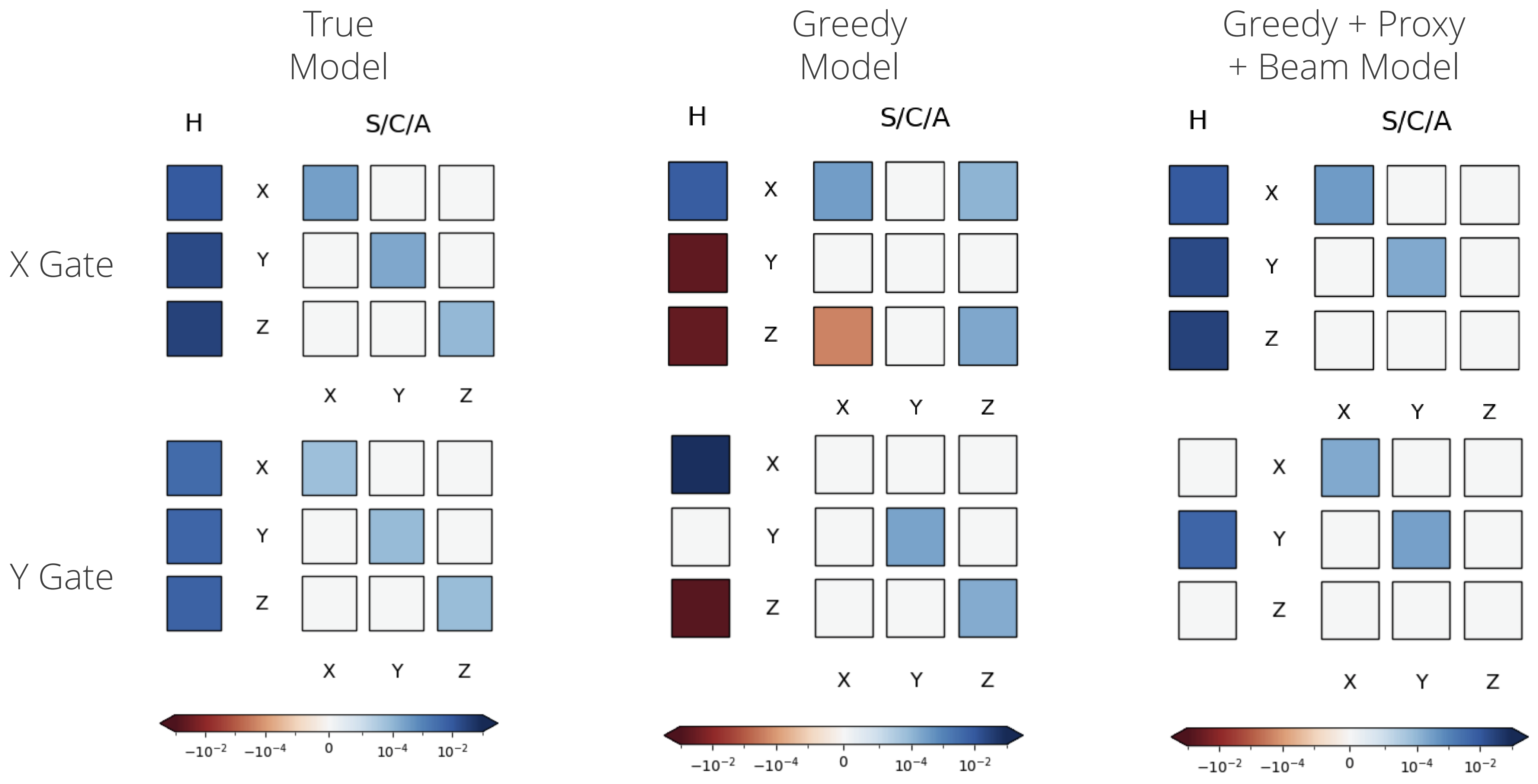

Still some room for improvement,
but on the right track!

Future directions

- Other search strategies
  - Preliminary results for L1 regularization/least-angle regression show comparable performance to greedy or beam, but this is still under investigation

- Use of first-order gauge invariant (FOGI) parameters instead of bare error generators

- Application to existing experimental data – could we have found the ZZ error?

- Currently this is a top-down approach
  - Good for model reduction from a full traditional GST experiment
- Ideally, we also want a bottom-up approach
  - Maybe given some initial data (e.g., RB circuits), guess a good initial model
  - Construct a heavily reduced GST experiment based on that generated model
  - Iterate upwards if needed

Q & A

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6) Postdoc (Nanophotonics): Albuquerque, NM. Req ID 687976