

Predicting a Superconducting Machine's Noise Induced Barren Plateau for Generative AI on QAOA Problems



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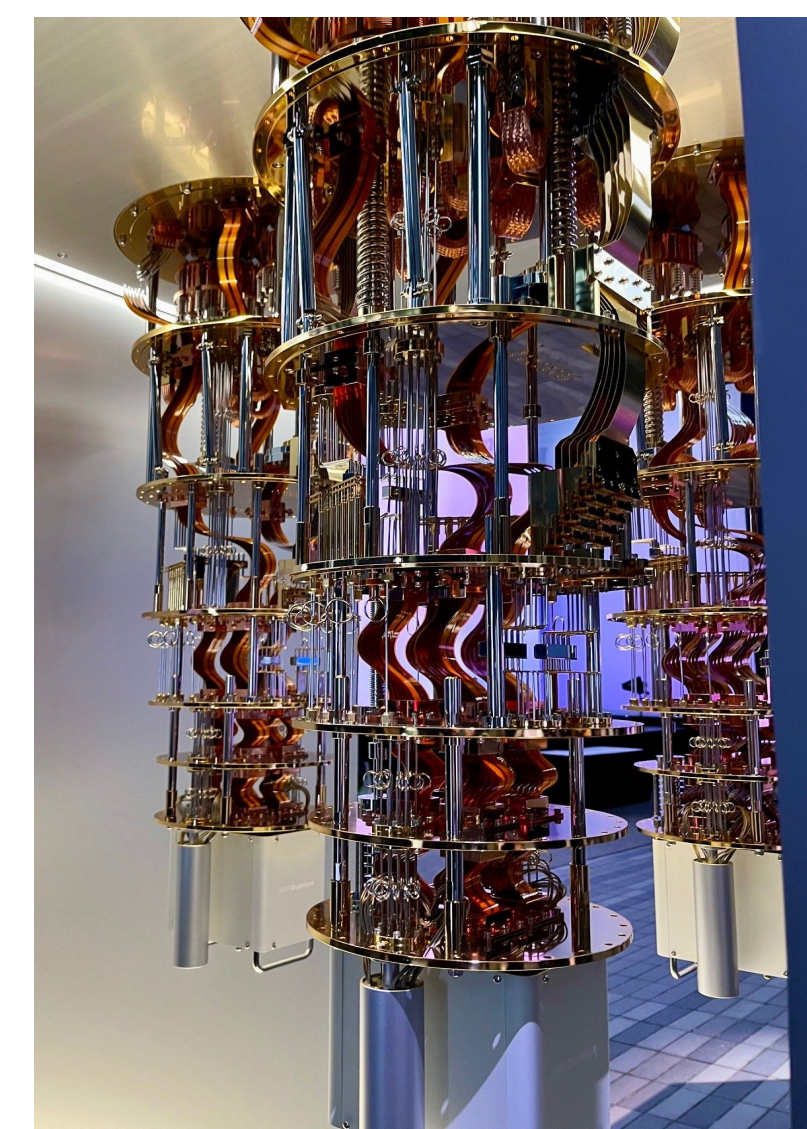
Background

Significance of Quantum Computing

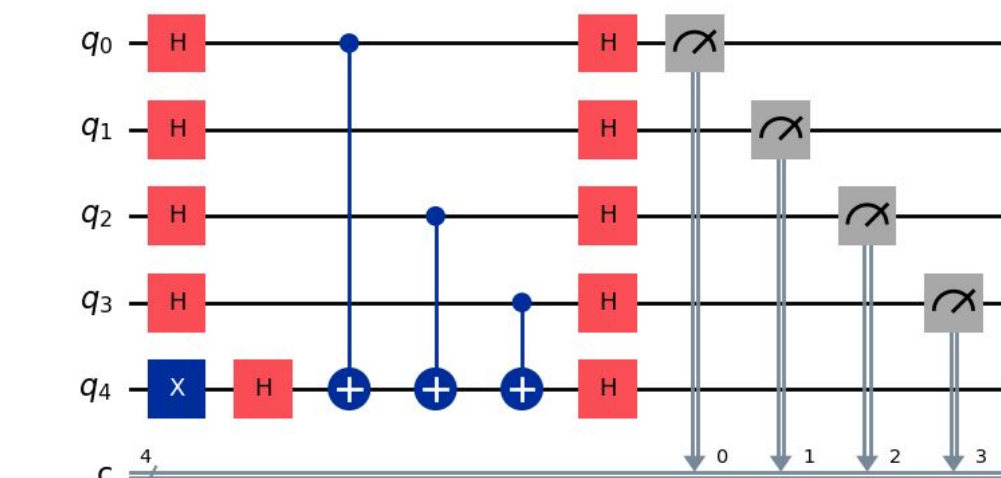
- Quantum Computing is a new paradigm of computation that can solve unique problems
- Entering the age of quantum utility, where we can run useful algorithms

Generative AI for Quantum

- Generative transformer models can be used to create circuits
- Current models struggle with performance across different processors



Early IBM Quantum Computer in New York



Circuit map of the Deutsch-Jozsa circuit. This circuit is commonly described as the first circuit to show quantum advantage. Qubits are represented by the lines, gates are performed left to right.

Noisy Intermediate-Scale Quantum (NISQ)

- Currently in the age of NISQ machines
- Types of noise: Decoherence, Crosstalk, Gate, and Readout
- Noise limits the scale of our circuits and restricts the progress of generative models [1, 2]
- Each machine has vastly different noise profiles

NIBP Estimation

Noise Induced Barren Plateau

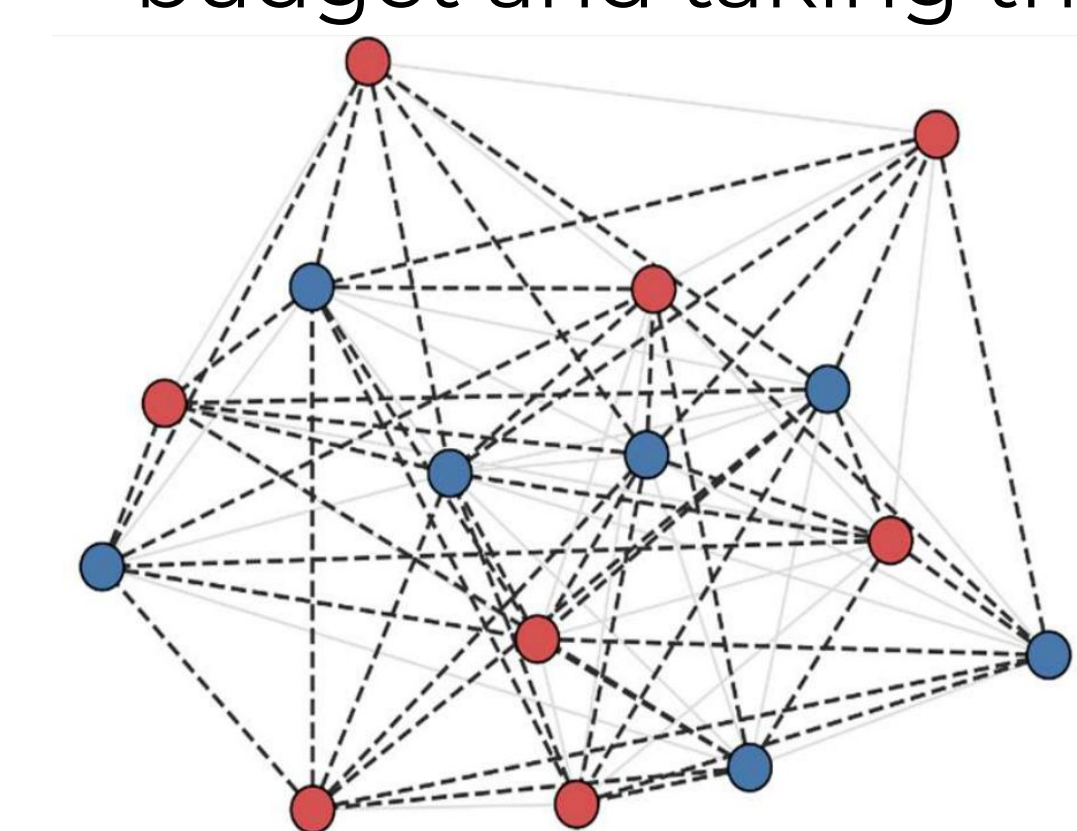
- Defines the relationship between a noise budget and the fidelity of a circuit
- In this work, we introduce a machine-specific definition to find how a machine's noise profile affects circuit accuracy

$$\lambda_i = \sum_n \sum_{idle} \frac{t}{T_e} \quad (1) \text{ Accumulated idle decoherence of a circuit}$$

$$\Lambda = N_2 \varepsilon_2 + N_1 \varepsilon_1 + n \varepsilon_r + \lambda_i \quad (1) \text{ Effective noise budget of a circuit}$$

NIBP Decay Rate

- Defines the relationship between circuit accuracy and the effective noise budget on a machine
- Found by plotting the log scaled signal against the noise budget and taking the slope of the least squares line of best fit



Example of a MaxCut problem to solve using QAOA

Experiment Design

- We test MaxCut problems and collect the approximation ratio against the optimum result
- Normalize signal by using noiseless simulations
- Looking to identify how each machine's noise profile affects the accuracy of circuits at different depths

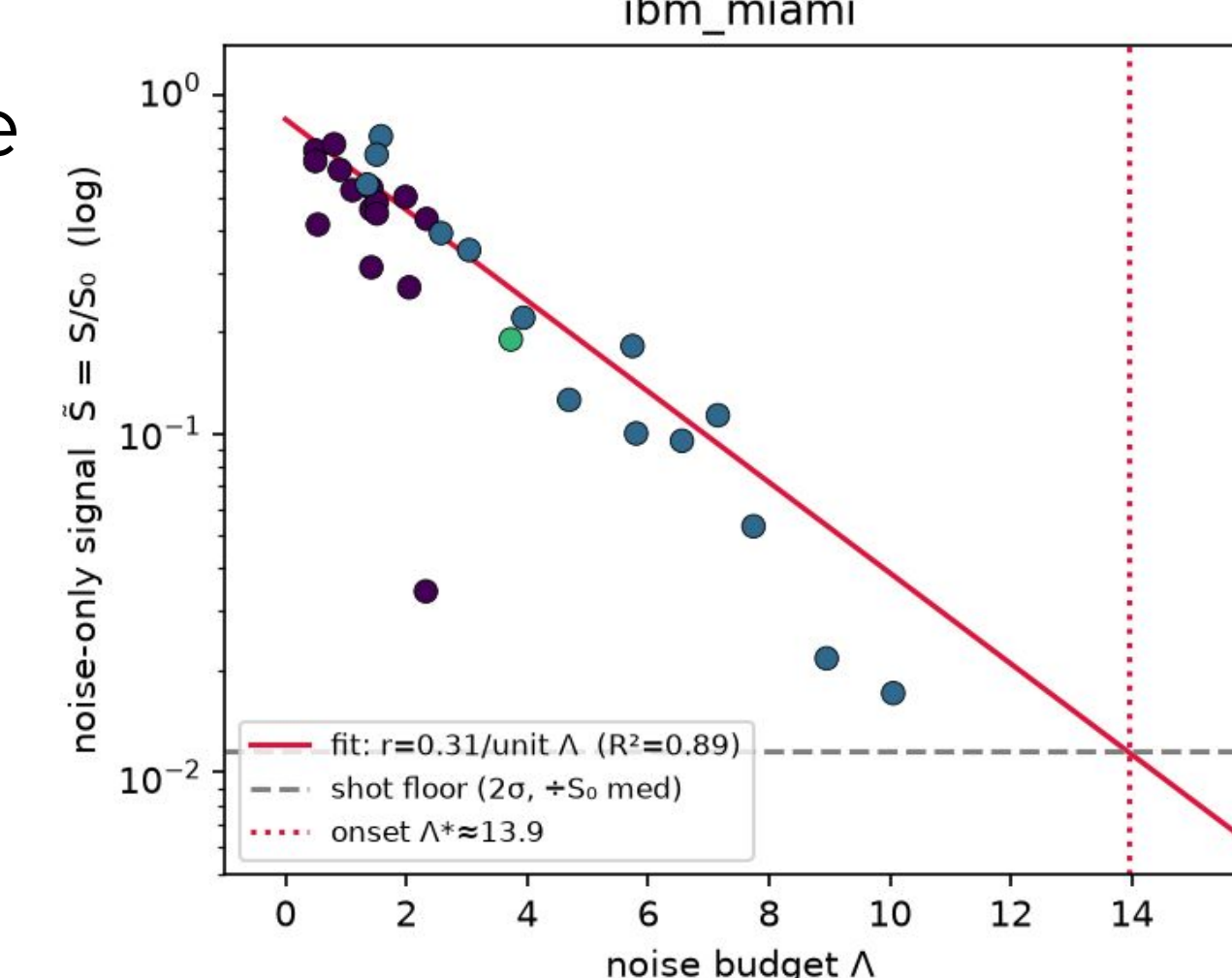
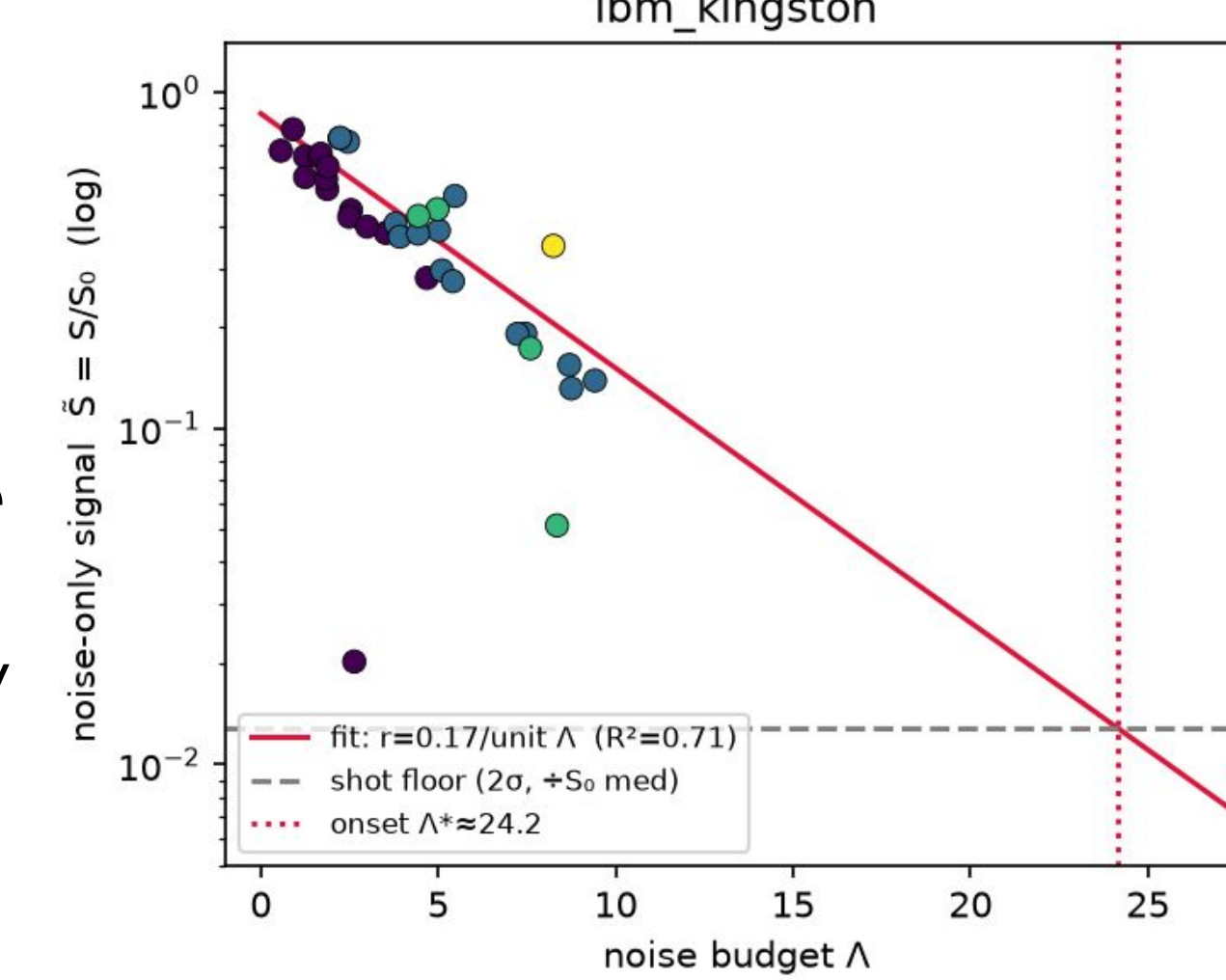
QAOA GPT Models

The QAOA-GPT Model

- A current leader in the field of generative AI for QAOA problems [3]
- Works with FEATHER graph embedding and ADAPT-QAOA for circuit generation
- Utilizes a simplified gate-based dictionary for tokenization
- Multi-shot generation, highest signal to the original problem Hamiltonian is selected

NIBP Estimator Tool

- An XG-Boost Decision Tree model is trained on NIBP estimator data
- Goal is to predict the slope of the line of best fit for a machine
- Needs to run efficiently, so we try to optimize for fewer k-circuit count for predictions
- This model is provided to a 250k parameter QAOA-GPT to score a circuit's noise budget against the machine's NIBP decay rate



Top graph shows normalized signal graphed against circuit noise budget for ibm_kingston

Bottom graph shows the same for ibm_miami

Evaluation of Tool's Effectiveness

- The model will be able to shrink and grow the circuit to keep the circuit above the shot floor using the NIBP estimator
- We will evaluate the optimum signal strength across 3 variations of the model:
 - Base Model
 - k=0 (shared decay assumed)
 - k=12 estimator

Scope Limitations

- To limit the scope of the project, results will be tested across two machines: ibm_miami (Nighthawk r1 processor) and ibm_kingston (Heron r2 processor)
- 540 MaxCut problems, Erdős-Rényi graphs, will be examined across each model variation

References & Acknowledgements

References

- [1] S. Singhal, V. Srivastava, P. Rohith, P. Jain and D. Bhowmik, "Performance Comparison for Quantum Approximate Optimization Algorithm (QAOA) across Noiseless Simulation, Experimentally Benchmarked Noisy Simulation, and Experimental Hardware Platforms," 2024 8th IEEE Electron Devices Technology & Manufacturing Conference (EDTM), Bangalore, India, 2024, pp. 1-3, doi: 10.1109/EDTM58488.2024.10512142.
- [2] Shaydulin, R., Hadfield, S., Hogg, T. et al. Classical symmetries and the Quantum Approximate Optimization Algorithm. Quantum Inf Process 20, 359 (2021). <https://doi.org/10.1007/s11128-021-03298-4>.
- [3] I. Tyagin, M. H. Farag, K. Sherbert, K. Shirali, Y. Alexeev, and I. Safro, "QAOA-GPT: Efficient generation of adaptive and regular quantum approximate optimization algorithm circuits," arXiv preprint arXiv:2504.16350, Apr. 2025, doi: 10.48550/arXiv.2504.16350.

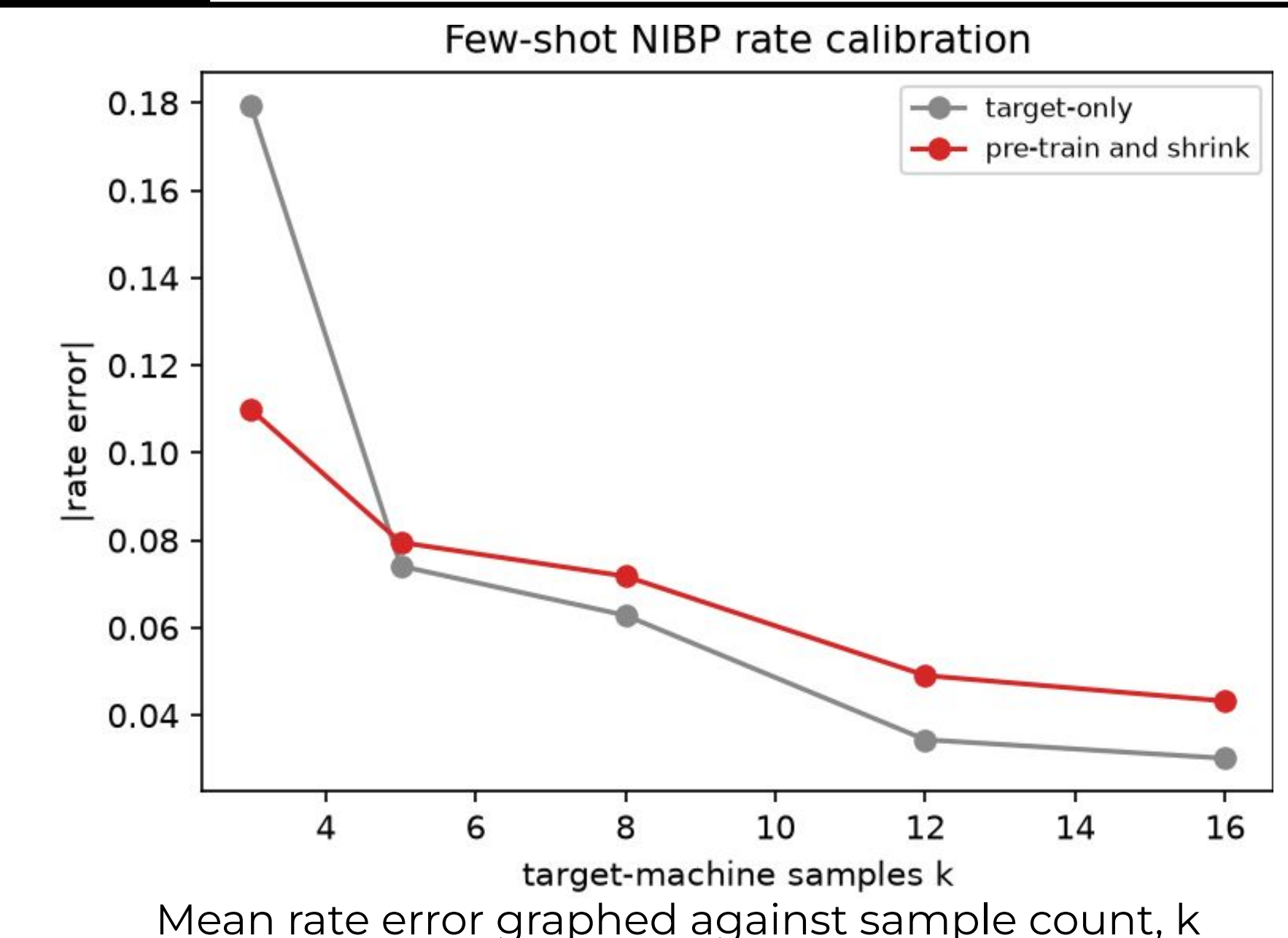
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Results & Future Work

NIBP Estimator

- From scratch prediction (gray) achieves better results at high sample sizes
- Shared assumption & shrinkage succeeds with low sample count
- Shrinkage at low sample counts represents the shared decay rate assumption
- Shows that we can efficiently estimate the NIBP decay rate in 12 samples



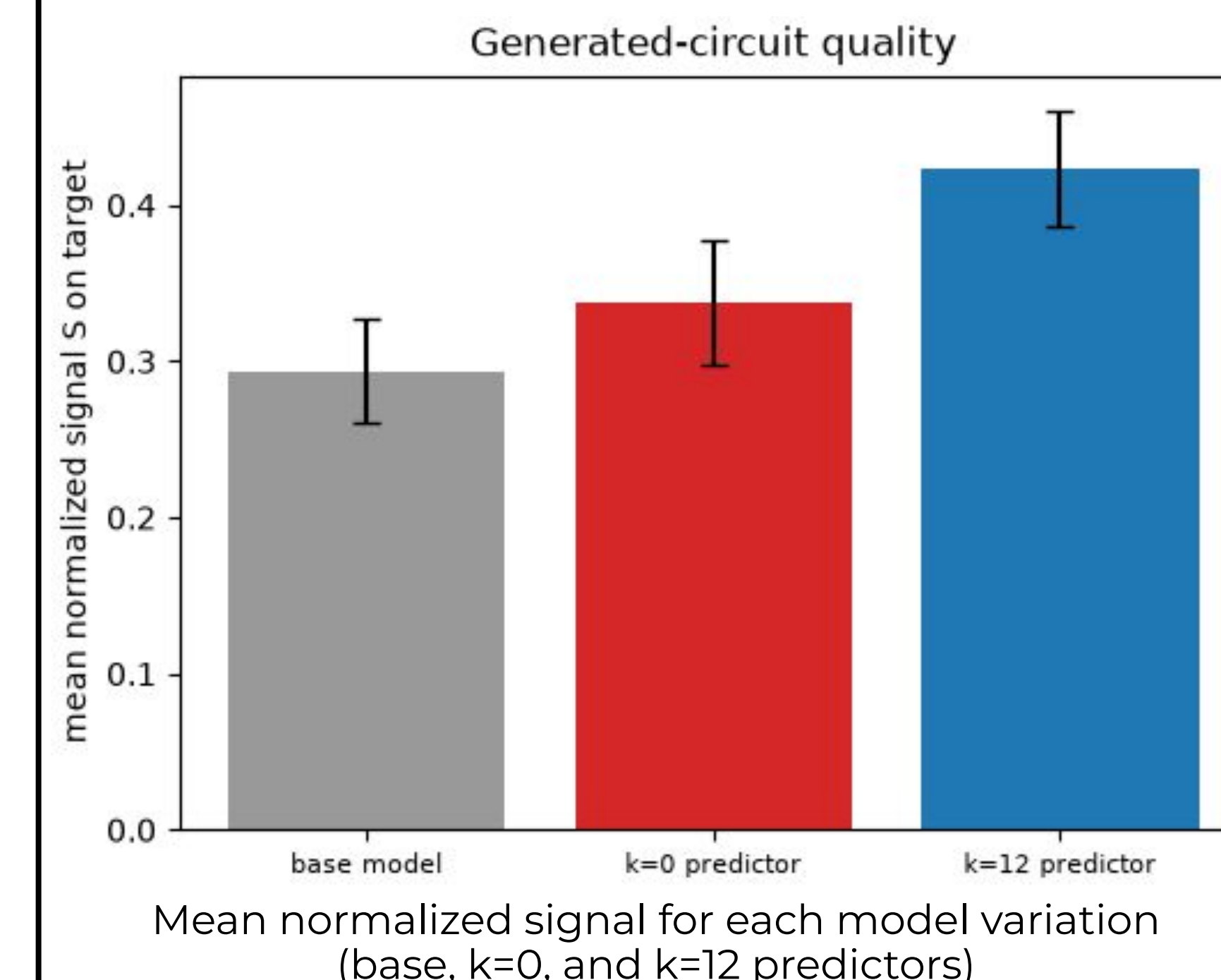
Mean rate error graphed against sample count, k

Gray represents the scratch prediction, red represents starting from the shared assumption and shrinking towards the target

Here, lower is better, representing a better prediction of the machine's decay rate

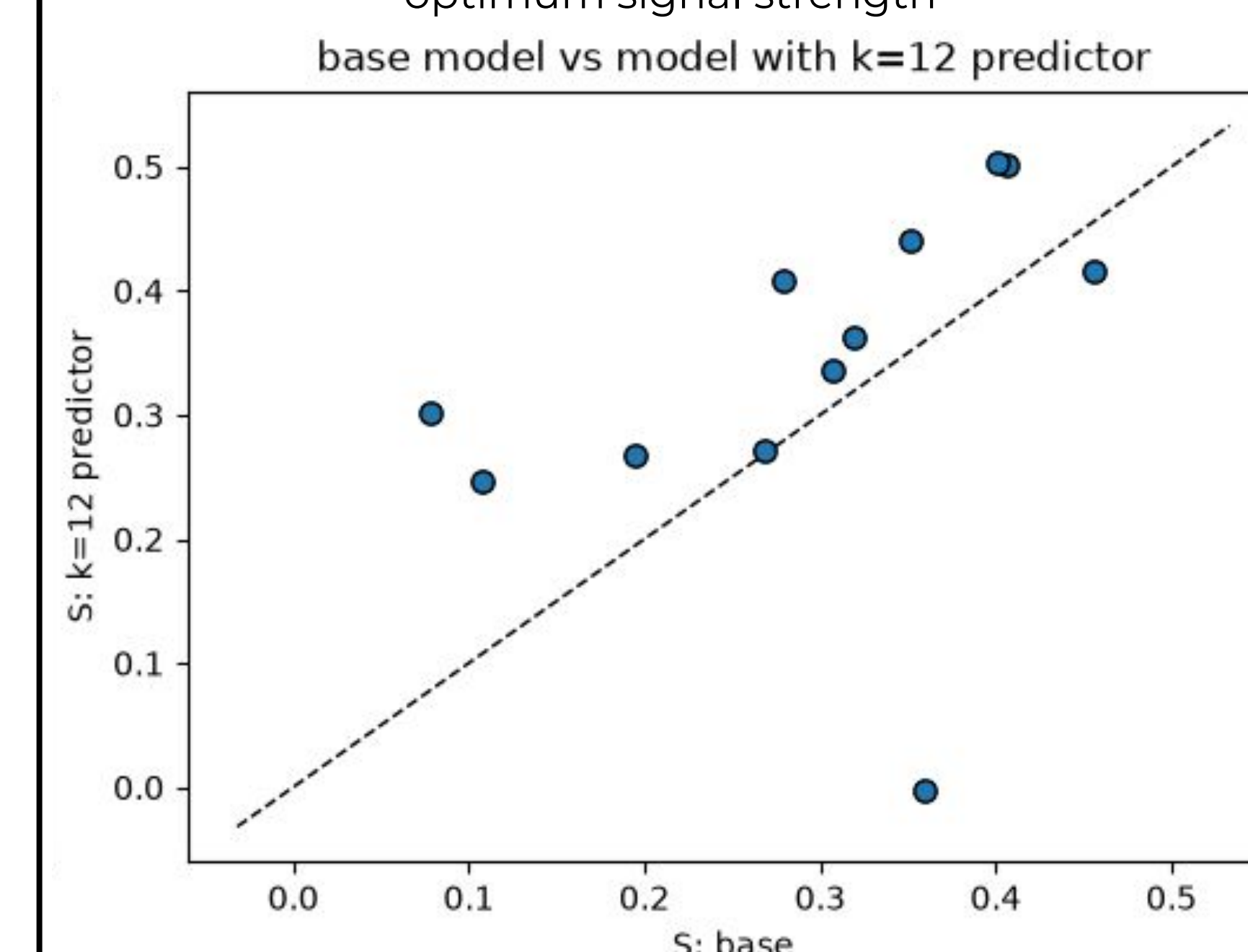
Generated Circuit Qualities

- Model with k=12 predictor consistently outscores the base and shared assumption models
- k=0 predictor outscores the base model, showing that adapting circuits to the machine is a key to improving the quality of generated circuits
- Per graph performance shows that the predictor model can sometimes unnecessarily grow a circuit, causing the circuit to fall below the shot floor
- This opens the door for further research into noise classification for the NIBP estimator and learning better weights for shrink/grow decisions



Mean normalized signal for each model variation (base, k=0, and k=12 predictors)

Here, higher is better, representing a stronger optimum signal strength



k=12 model optimum signal graphed against base model optimum signal strength

Here, points above the dashed line indicate better performance with the k=12 prediction model

Future Work

- A machine's noise profile can change vastly over time, further research to verify that this has a negligible impact on the relationship with its decay rate is needed
- Experiments designed to separate specific instances of noise from different machines could prove to be useful for types of noise that improve at a different rate than other noise such as crosstalk
- More work into decoupling the circuit depth from density could prove useful in preventing instances of unnecessarily growing a circuit
- Now that the pipeline has been verified, growing the problems investigated past MaxCut is a large step forward to a universal generative model for quantum circuits