SAND2022-9425C

Sandia National Laboratories

Predicting circuit success rates with artificial neural networks

QPL

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2022 MLDL Workshop

07/27/2022

U.S. DEPARTMENT OF ENERGY NNSA

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Background – Quantum Computing

- Potential exponential speedups
  - Optimization
  - Quantum chemistry
- NISQ era
  - Noisy and error prone
- Need scalable and efficient performance predictors

Motivation

- Question:

Can we use machine learning to better understand the capabilities of a quantum device?

- Our goal:

Train neural networks on classically simulable circuits to predict the performance of generic quantum circuits

Motivation

- Question:

Can we use machine learning to better understand the capabilities of a quantum device?

- This work:

Train neural networks on classically simulable circuits to predict the success rate of (new) classically simulable circuits

Motivation

- Question:

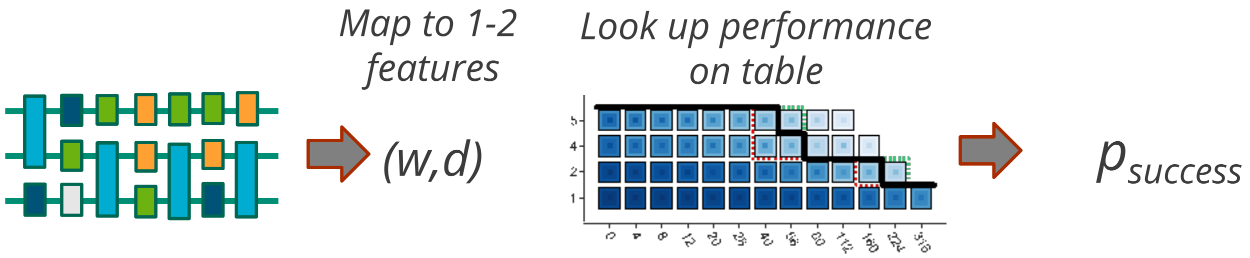
Can we use machine learning to better understand the capabilities of a quantum device?

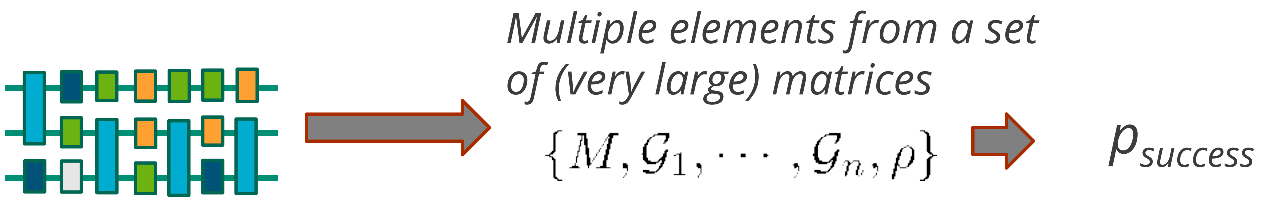
- This work:

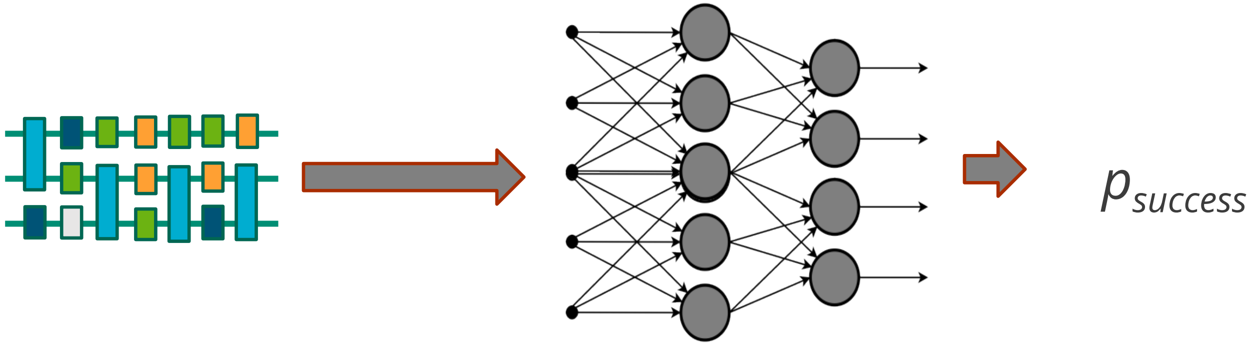
How do dataset size and data quality affect a neural network’s ability to learn?

Background – Other Approaches

- Current quantum computers are noisy and error prone
- Phenomenological models[1]
  - Built on benchmarking tools
  - Rely on human extracted features
  - Poor performance
- Quantum process models[2]
  - Informed by "tomography"
  - Depend on circuit structure
  - Specious assumptions
  - Hard to scale
- Neural network models
  - Extract their own features
  - Few assumptions
  - Potentially scalable





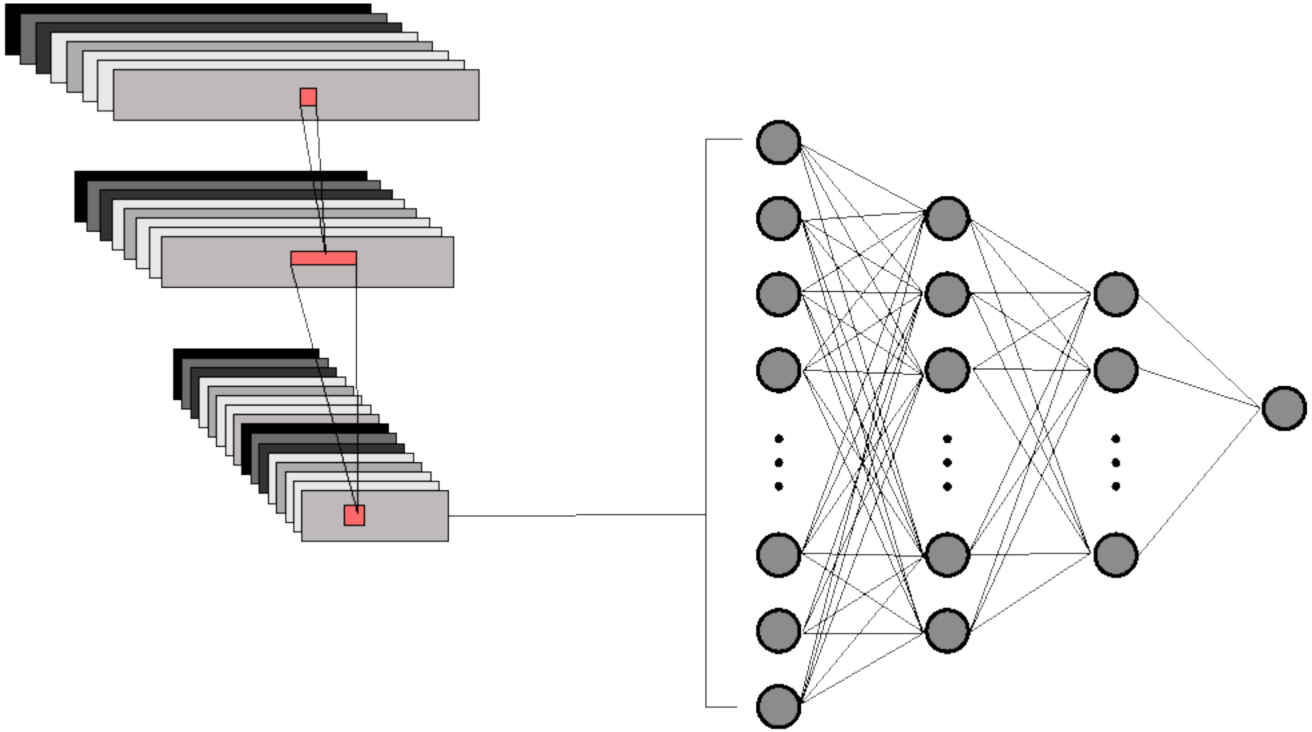


[1] *Characterizing Quantum Gates via Randomized Benchmarking*, Magesan et al, Phys. Rev. A **85,** 042311, 11 April 2012

[2] *Gate Set Tomography*, Nielsen et al, Quantum **5**, 2021

Our Approach

- Encode circuits as images
- Feed images into convolutional layers
- Extracted features are input into a deep multilayer perceptron
- Predict success probability with a softmax function

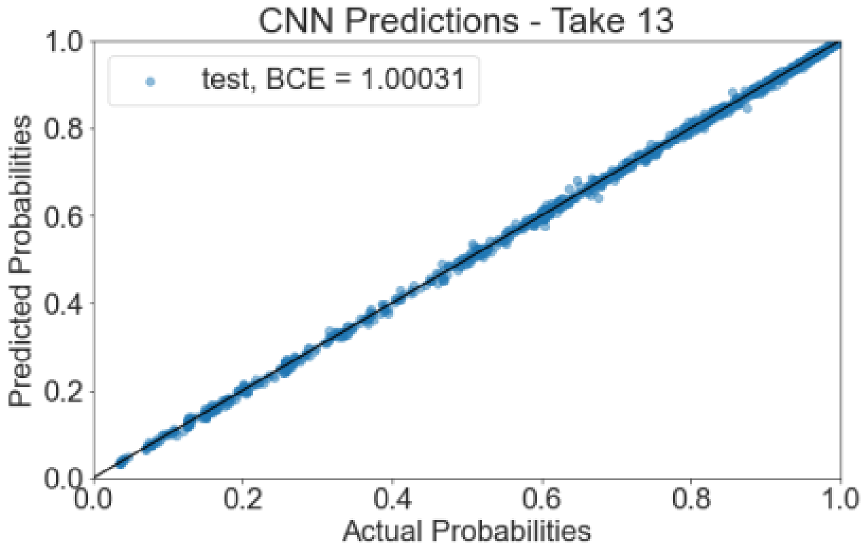


Some more details

- Multiple datasets with 100, 300, 500, 1000, 16600 circuits
  - 11 different 100 circuit datasets
  - 5 different datasets per circuit count for the rest
- Each dataset was simulated at four levels of precision (shot count)
  - Same error model
- Hyperparameter tuning
  - Once per level of precision and dataset size (except for 16600 circuits)
  - Remaining models use the same architecture
  - 16600 circuit models use the best architecture from the corresponding 1000 circuit model

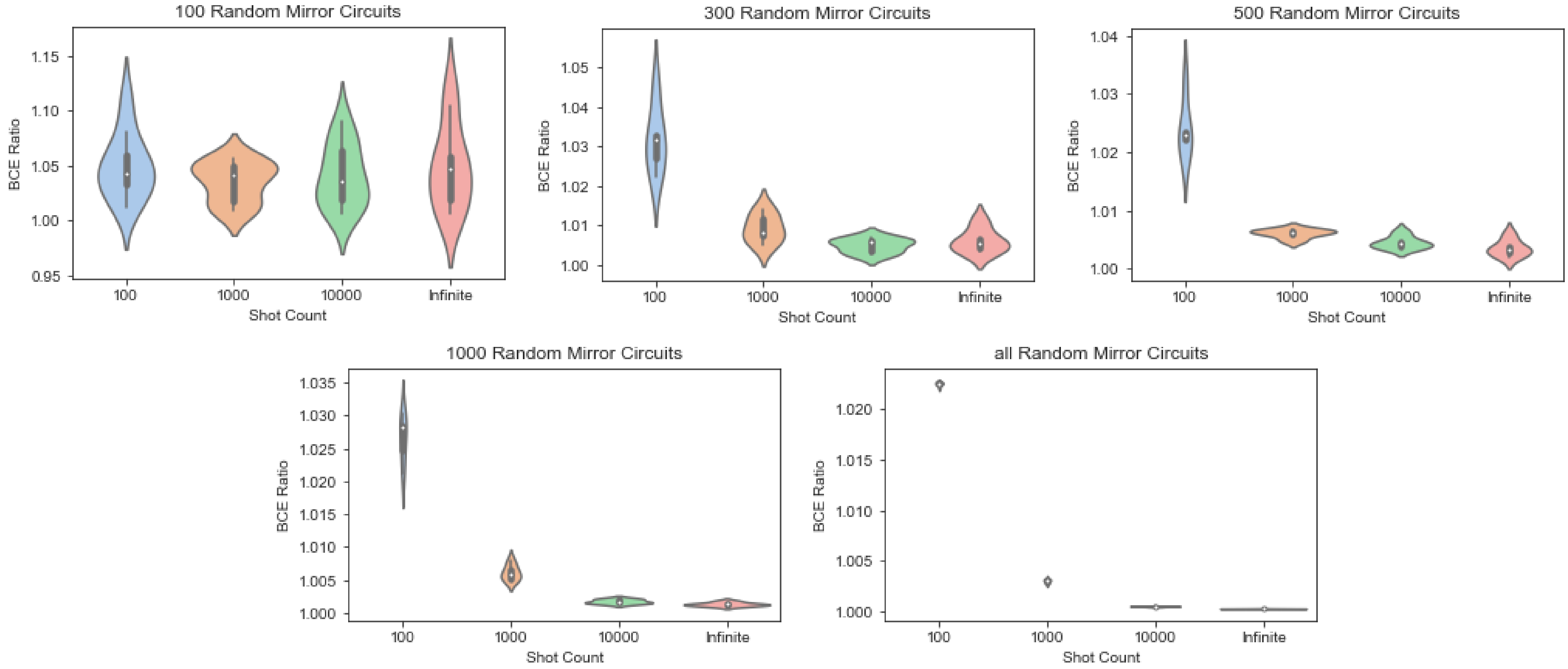
Results – Simulated Data

- Biased local stochastic error model
- Mirror Clifford circuits
  - Width: 1 to 5 qubits
  - Depth: 3 to 1033 layers
- Neural networks provided with additional information
- Outperforms models based on per gate error rates estimated from the data

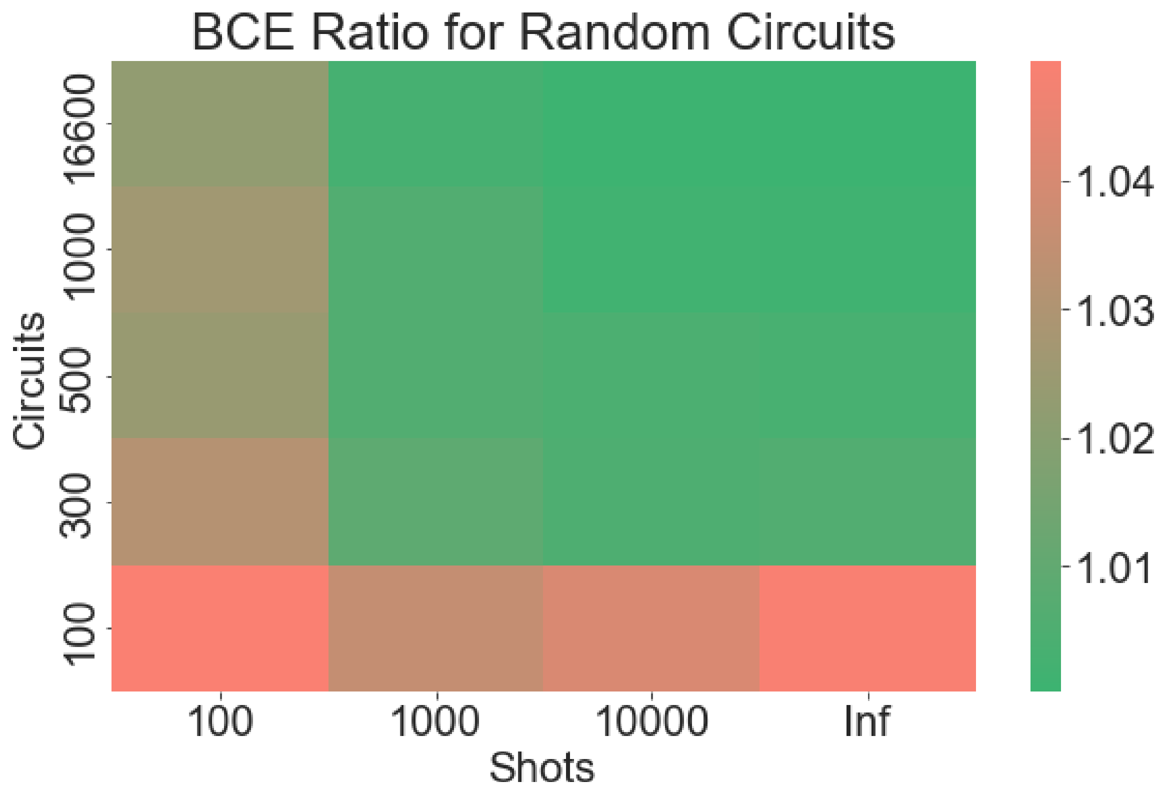


Data: 16600 circuits, Infinite Precision

Results – Simulated Data cont.



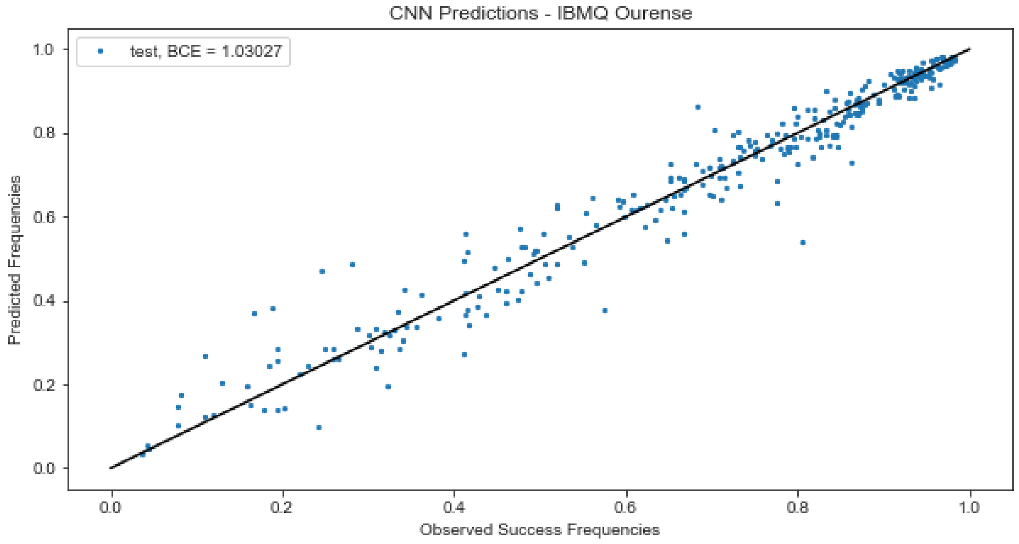
Results – Performance and Data

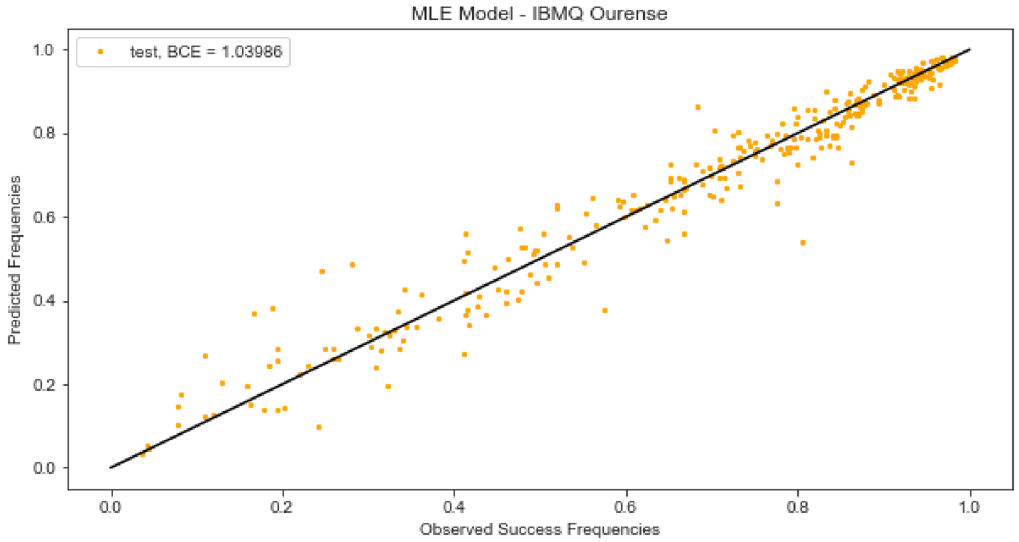


More circuits = Better performance
Increased precision = Better Performance

Preliminary Results – Experimental Data

- Run on IBMQ Ourense
  - Unknown error model
- Mirror Clifford circuits
  - Width: 1 to 5 qubits
  - Depth: 3 to 319 layers
- Neural networks were provided with additional information
- Worse performance than on simulated data
  - Still beats MLE model





Conclusions and Future Work

- CNNs can learn to predict the success rates of some quantum circuits
- Performance scaling
  - Circuit count
  - Measurement precision
- Future work
  - Scaling to wider circuits
  - Different types of networks
  - More complicated error models

Acknowledgements

This work was funded in part by Sandia's Laboratory Directed Research and Development program. This material was funded in part by the U.S. Department of Energy, Office of Science, Office of Advanced Scientific Computing Research Quantum Testbed Program. All statements of fact, opinion or conclusions contained herein are those of the authors and should not be construed as representing the official views or policies of the U.S. Government. Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.