



Predicting circuit success rates with artificial neural networks



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- Question:

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

- Our approach:

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

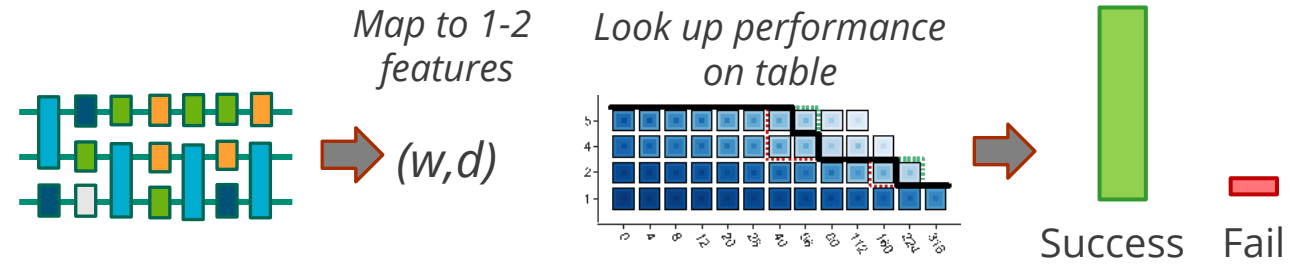
Background – Other Approaches



- Current quantum computers are noisy and error prone

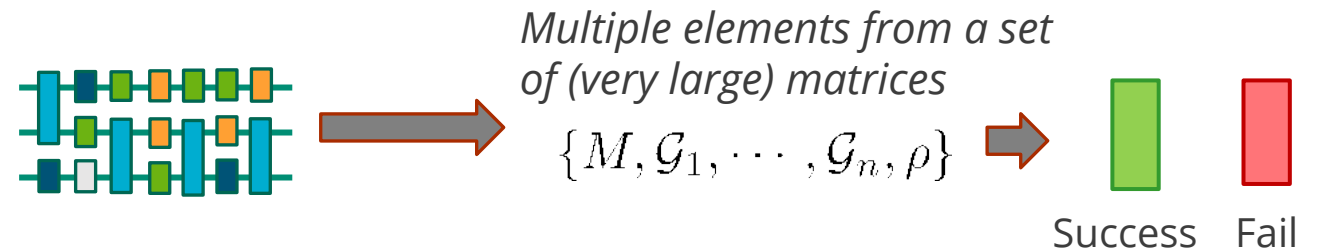
- Phenomenological models¹

- Built on benchmarking tools
- Rely on human extracted features
- Poor performance



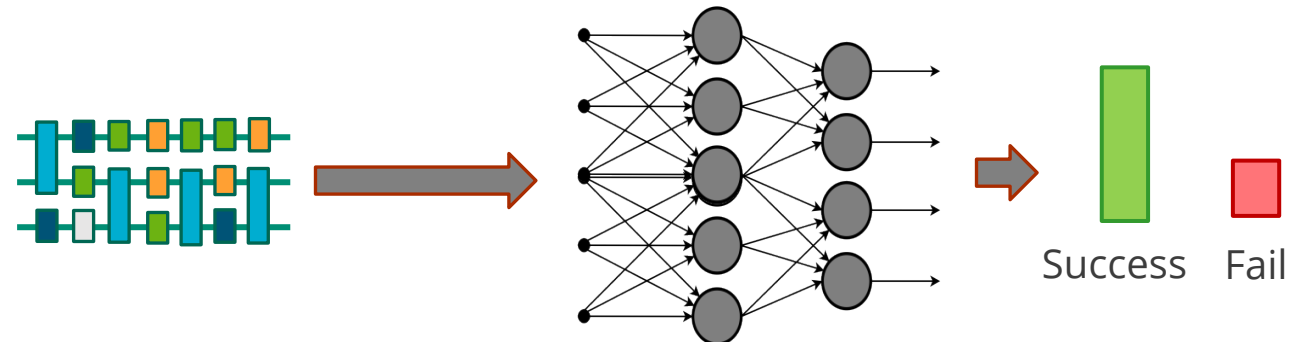
- Quantum process models²

- Informed by “tomography”
- Depend on circuit structure
- Specious assumptions
- Hard to scale



- Neural Networks

- Extract their own features
- Rely on no assumptions
- Potentially scalable



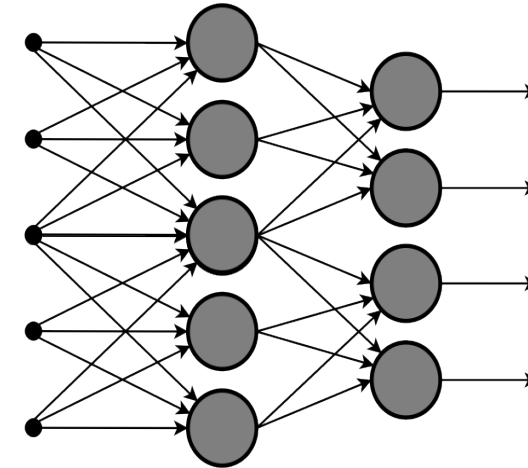
¹Characterizing Quantum Gates via Randomized Benchmarking, Magesan et al, arXiv:1109.6887

²Gate Set Tomography, Nielsen et al, arXiv:2009.07301

Background – Neural Networks



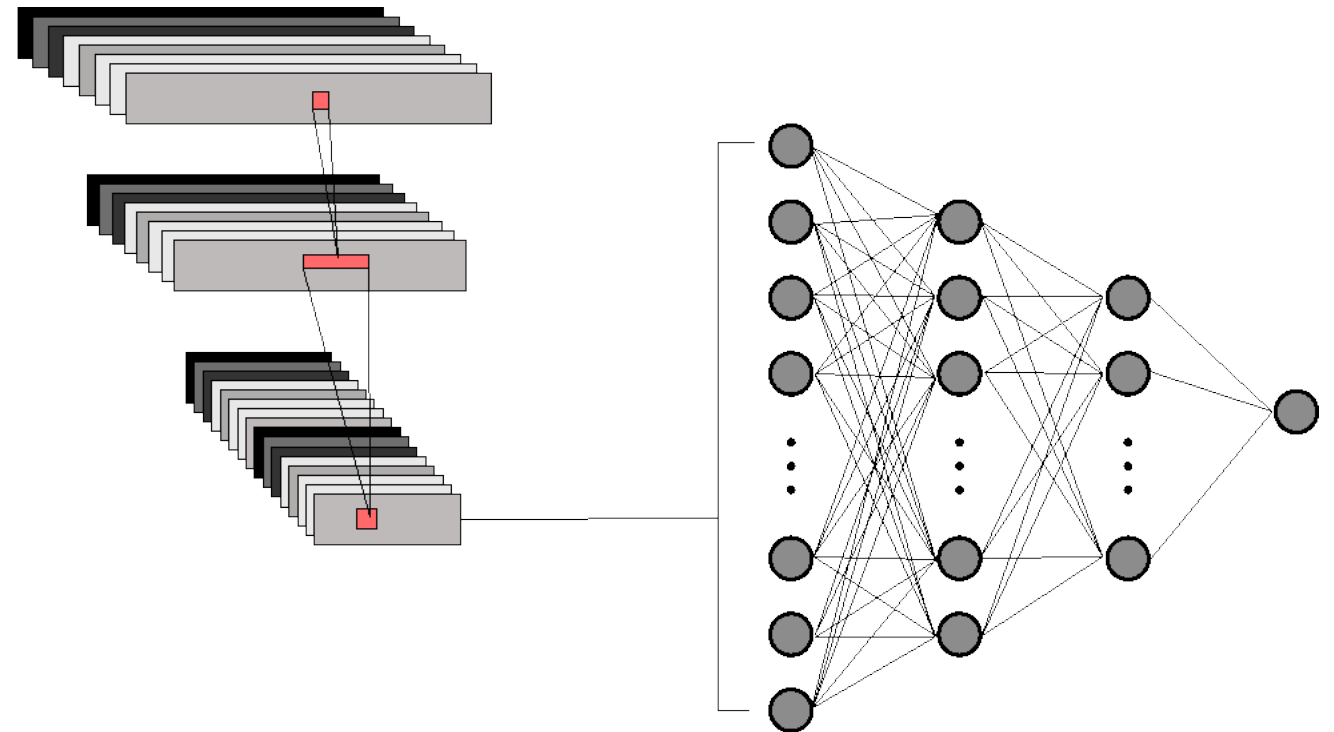
- Basic structure
 - Layers of “neurons”
 - “Neurons” perform different operations
 - Previous layer feeds into the next layer
- Universal approximation theorem
 - Capable of learning “most” “reasonable” functions
- Convolutional Neural Networks
 - Process images
 - Learns weights for convolutional filters
 - Extracts useful features
- Multilayer Perceptron
 - “Vanilla” (deep) neural network
 - Dot products and activation functions



Our Approach



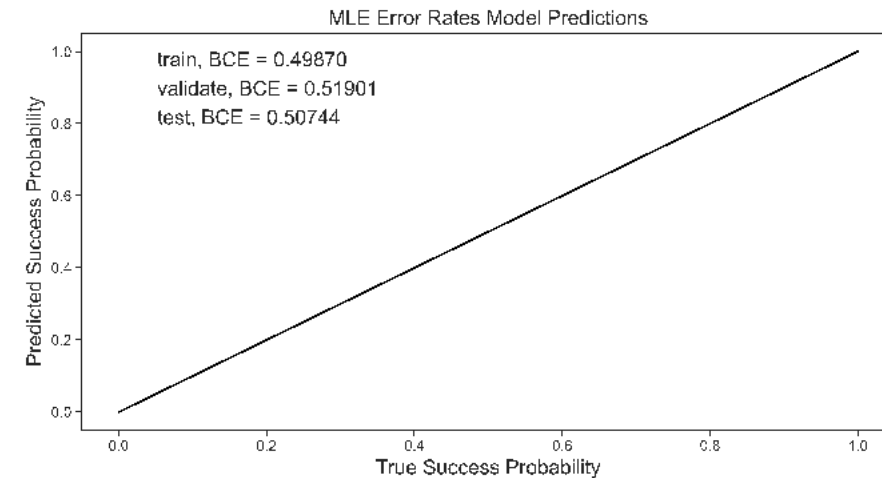
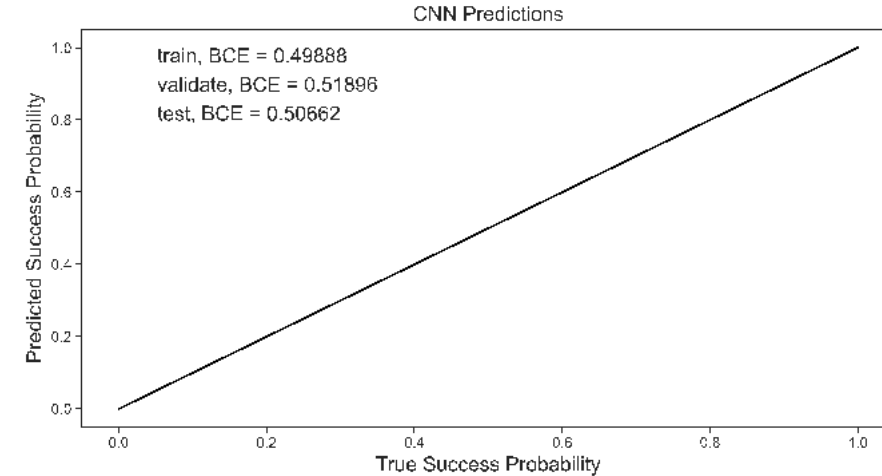
- Encode circuits as images
- Feed images into convolutional layers
- Extracted features are input into a deep multilayer perceptron
- Predict success probability with a softmax function



Preliminary Results – Simulated Data



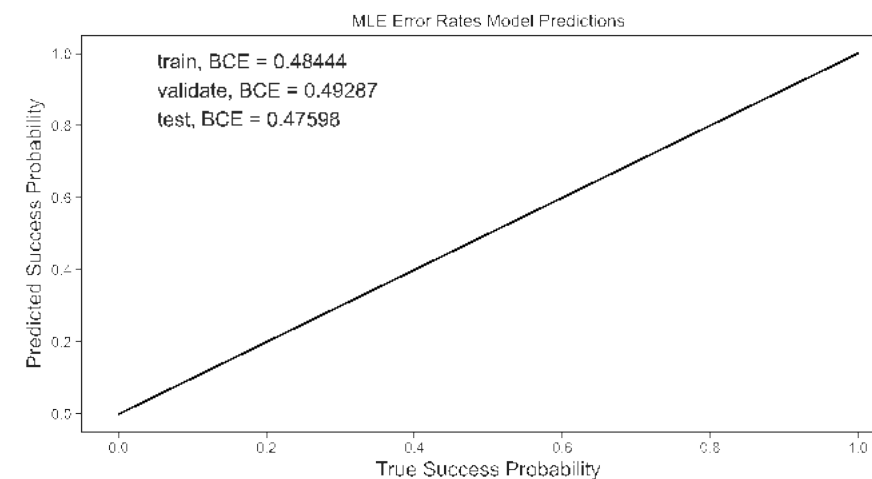
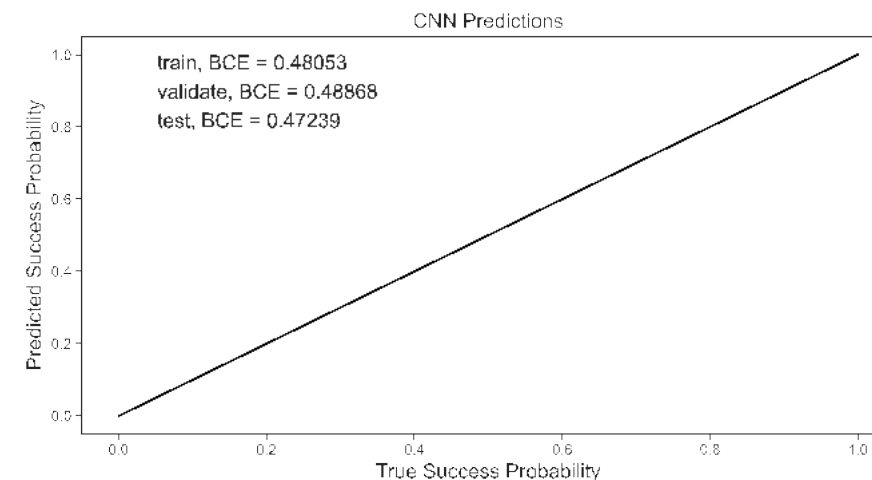
- Biased stochastic error model
- Mirror Clifford Circuits
- Neural networks provided with stabilizer information
- Outperforms models based on per gate error rates estimated from the data



Preliminary Results – Experimental Data



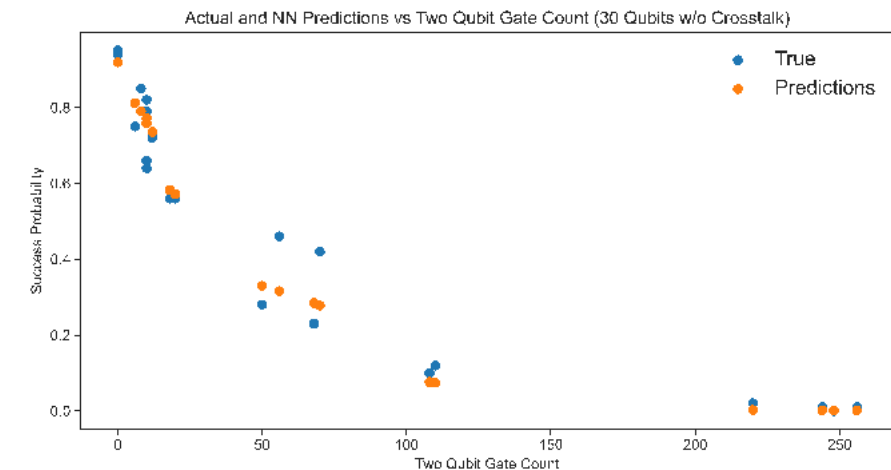
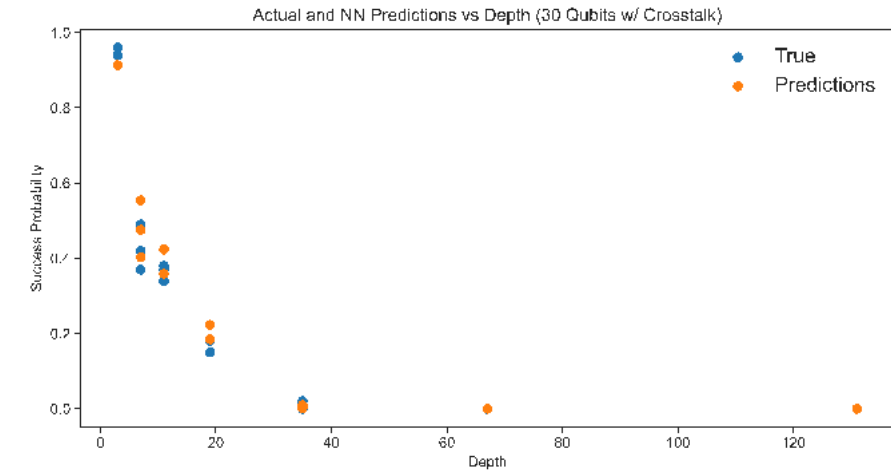
- Run on IBMQ Ourense
- Mirror Clifford Circuits
- Neural Networks not provided with stabilizer information
- Worse performance than on simulated data
 - Still beats MLE model



Scalability



- How scalable is this neural network approach?
- Local depolarization errors
 - Crosstalk free
 - 2Q gate crosstalk
- Deep multilayer perceptron learns useful information
 - Up to 30 qubits
 - Given circuit depth and two qubit gate count
- CNN feature extraction is scalable, but hasn't been performed



Conclusions and Future Work



- Proof of concept
 - CNNs on simulated and experimental data
 - Scalability with human extracted features
- Future work
 - Tune network architecture
 - Different types of networks
 - Try more complicated error models
 - Analyze wider circuits with CNNs

Acknowledgements



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