



Optimization, Verification and Engineered Reliability of Quantum Computers



<https://overqc.sandia.gov>



Dartmouth



THE UNIVERSITY OF
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Integrating ASCR Research to Deliver Scientific
Discovery Quantum Computing Workshop

December 2019

Mohan Sarovar

People

- **SNL**: Jon Aytac, Andrew Baczewski, Matthew Grace, Lucas Kocia, Alicia Magann, Ojas Parekh, Denis Ridzal, Kenneth Rudingger, Antonio Russo, Mohan Sarovar, Greg von Winckel, Wayne Witzel.
- **LANL**: Lukasz Cincio, Patrick Coles, Yigit Subasi.
- **Dartmouth**: James Brown, James Whitfield, Jun Yang.
- **UNM**: Robert Carr, Deepak Kapur.

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Project structure

Thrust 1: Formal verification of quantum algorithm implementations

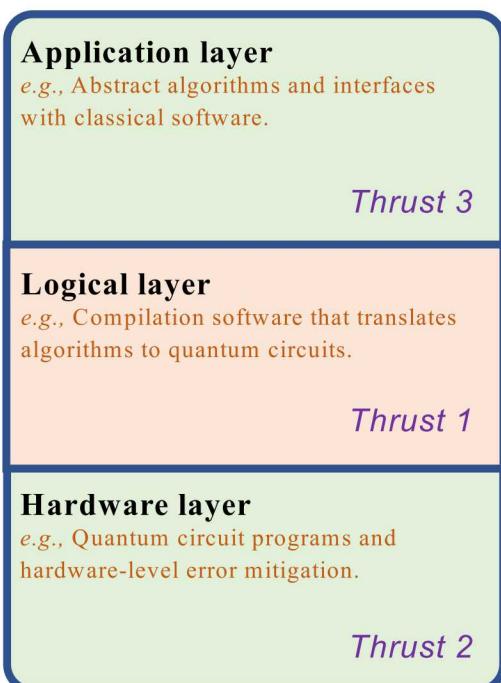
Goal: generate machine-assisted proofs of circuit implementations of quantum algorithms.

Thrust 2: Engineered reliability of NISQ devices

Goal: produce classical software and analysis tools to make near-term devices more reliable.

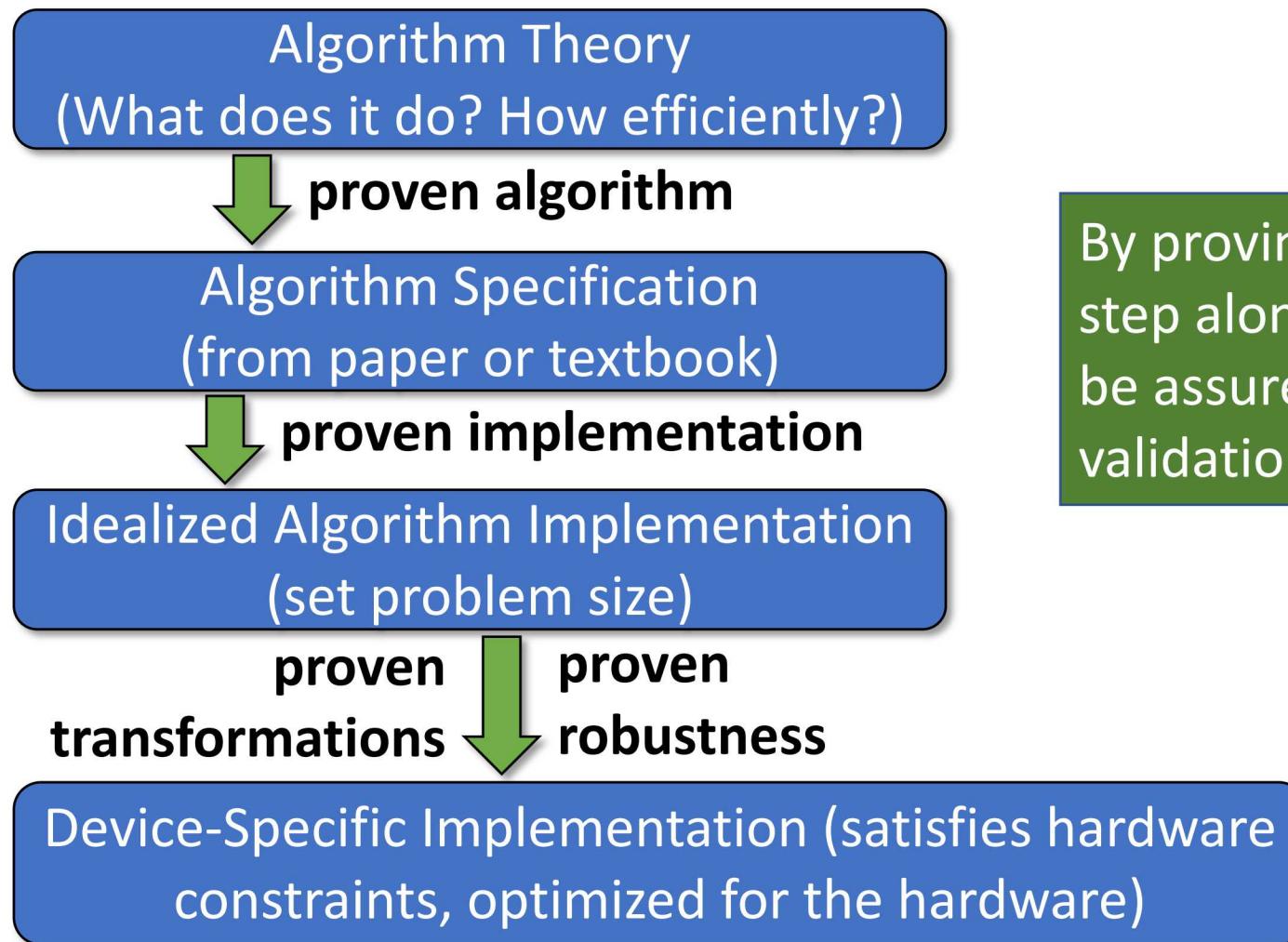
Thrust 3: Variational devices and classical heuristics

Goal: develop tools to explore synergies between classical heuristics and near-term variational devices (VD).



Highlight 1: Program verification using ProveIt

[Wayne Witzel, Kenny Rüdinger, Deepak Kapur, et al.]

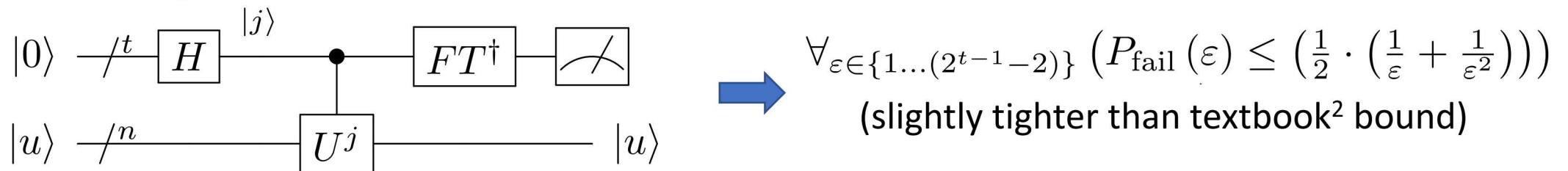


By proving the validity each step along the way, we can be assured that complete validation is feasible.

Highlight 1: Program verification using ProveIt

Prove-It: <http://pyproveit.org>

- Our open-source Python-based general-purpose theorem-proving assistant.
- Use Jupyter notebooks to render mathematical expressions via LaTeX.
Example: $\forall_{l \in \mathbb{N}} [\forall_{x, y_1, \dots, y_l} ((x \in \{y_1, \dots, y_l\}) = ((x = y_1) \vee \dots \vee (x = y_l)))]$
- In a proof-of-concept demonstration,¹ we derived the accuracy of the Quantum Phase Estimation algorithm:



- ... and uncovered 3 minor mistakes in the textbook² proof and improved the bound of the probability distribution.

1. W. Witzel, M. Sarovar, and K. Rudinger. (2015) Versatile Formal Methods Applied to Quantum Information. [Online]. Available: prod.sandia.gov/techlib/access-control.cgi/2015/159617r.pdf

2. M. A. Nielsen and I. L. Chuang, Quantum computation and quantum information. Cambridge University Press, 2010.

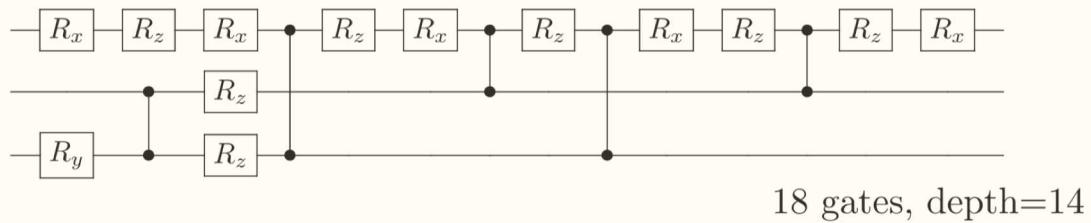
Highlight 2: Machine-learned circuit compilations



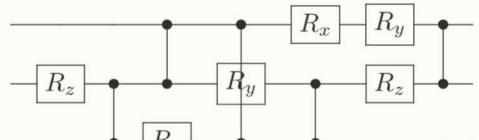
[Lukasz Cincio, Patrick Coles, *et al.*]

- Compilation of algorithms into circuits typically only consider coarse-grained noise models into account (e.g., limited connectivity, dead qubits)
- Recent characterization tools (e.g., gate-set tomography) yield a wealth of fine-grained error information.
- Can we use this information to improve circuit performance?

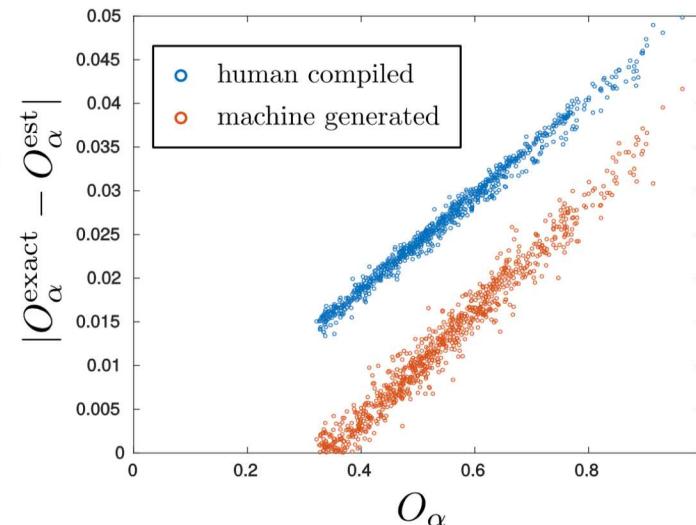
Example: state overlap between two qubits via SWAP test circuit



Human compiled (e.g., Linke et al., PRA 2018)



Machine compiled



Input:

1. Computational task
2. Noise model

- Vary circuit layout and parameters
- Optimize cost function capturing task

Output:

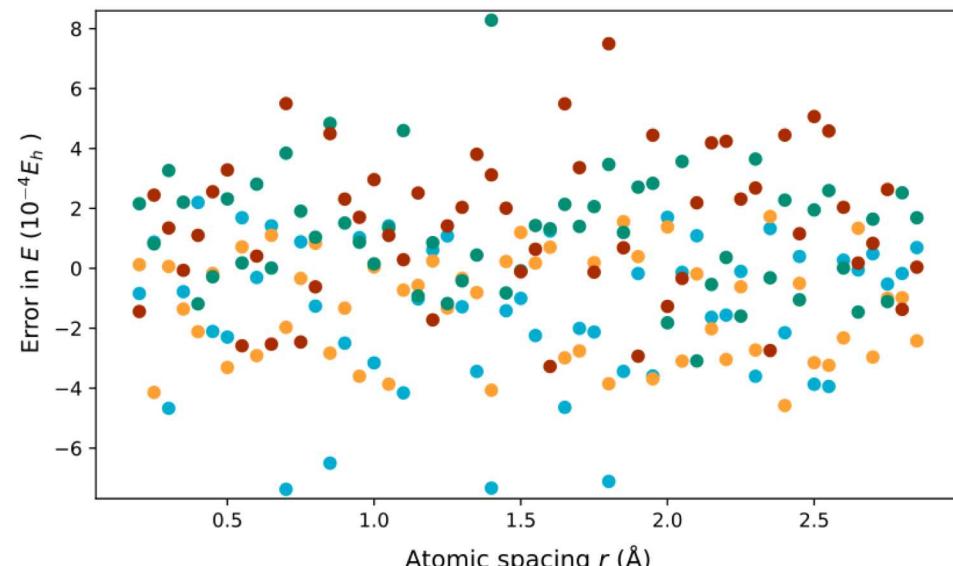
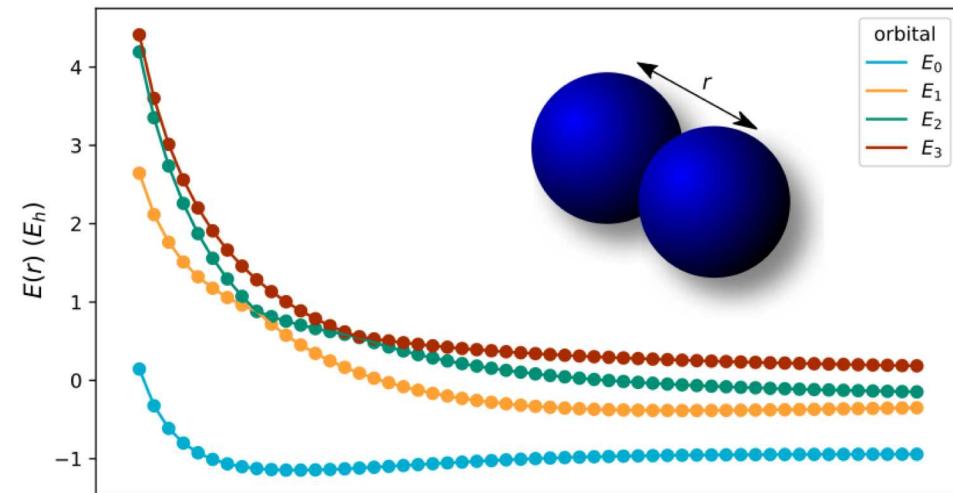
Optimal circuit layout and parameters

Highlight 3: Improved Q. simulation with RPE

[Antonio Russo, Kenny Ruderger, Andrew Baczewski, et al.]

- Robust Phase Estimation (RPE) [Kimmel, Low, Yoder, PRA, 2015] determines the relative phase induced by a unitary between two eigenvectors
- Corresponds to energy differences in the context of Hamiltonian simulation (i.e., molecular spectra)
- **Advantages:**
 - Naturally robust to noise ($\sim 31.6\%$)
 - Does not require controlled unitaries
 - Relies on preparation of superposition of eigenvector pairs
 - Heisenberg scaling

Molecular H_2 energy vs nuclear separation (exact and quantum hardware)



Other work

- 1. Large scale QAOA coupled with large-scale classical optimization techniques**
 - QAOA simulations up to 30 qubits
 - Seamless interface with Rapid Optimization Library (<https://trilinos.org/packages/rol/>)
- 2. Development of proxy models for variational QC**
 - Apply probabilistic manifold learning to learn optimization landscape
 - Fewer samples from quantum co-processor
 - Smooths sampling noise and generates smooth landscape for optimizers
- 3. New (classical) optimization algorithm tailored to variational QC**
- 4. Improved classical solvers for potential inversion when performing TD-DFT with hybrid quantum-classical methods.**
- 5. New variational algorithm for quantum linear systems solving**
- 6. New analog simulation method for generating, and sampling from, many-body thermal states**

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