# Optimization Algorithms as Quantum Performance Benchmarks

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Collaboration with Tom Lubinski, Carleton Coeffrin, Joshua Apanavicius, Catherin McGeoch and David Bernal.

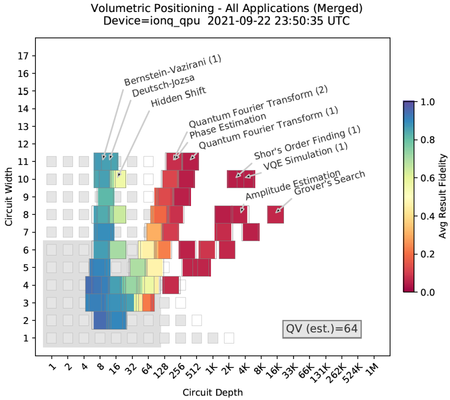
# Background and Motivation

- Component-level benchmarking is valuable, but less informative for the user.
- End-User perspective: Will I be able to solve my problem using a quantum computer?
- Hence, QED-C's approach [1]:
  - Versatile, accessible benchmarking suite.
  - How good an answer does the hardware give?
  - Use out-of-the-box software capabilities.
  - Run algorithms on hardware, and present insightful visualizations.
  - Plug and play

[1] https://github.com/SRI-International/QC-App-Oriented-Benchmarks

# Volumetric Positioning

- Sub-routine and algorithm benchmarking[2]:
  - Quantum Fourier Transform, Phase Estimation, etc.
  - Grover's Algorithm, Hamiltonian Simulation, etc.




*Volumetric Positioning* plot obtained from the first installment of the suite

[2]Lubinski, Thomas, et al. "Application-oriented performance benchmarks for quantum computing. https://arxiv.org/abs/2110.03137

# Performance for Combinatorial Optimization Problems

- Example: Find $s_1, \dots s_N$ (each being 0 or 1) which minimize[3]

$$\text{Cost function } H := \sum_{i,j} J_{ij} s_i s_j + \sum_i h_i s_i$$

- NP-hard
- Digital/Gate model QPUs: Quantum Approximate Optimization Algorithm[4]: A hybrid quantum-classical approach offering potential speed-up.
- Analog QPUs: Quantum Annealing

[3] aka QUBO problems (**Q**uadratic **U**nconstrained **B**inary **O**ptimization).

[4] Farhi, Edward, Jeffrey Goldstone, and Sam Gutmann. "A quantum approximate optimization algorithm." arXiv preprint arXiv:1411.4028 (2014).

# QAOA: **Q**uantum **A**pproximate **O**ptimization **A**lgorithm

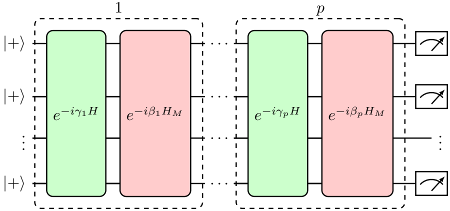
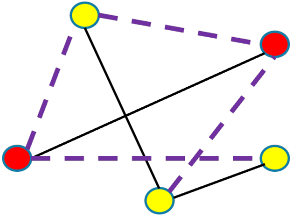



Figure: QAOA Circuit: Each circuit corresponds to a probability distribution over 'solution space'.

1. Choose initial parameters $\beta_1, \ldots, \beta_p$, $\gamma_1, \ldots, \gamma_p$.
2. Implement circuit many times; obtain $\langle H \rangle$.
3. Classical minimizer routine updates angles that result in smaller $C \equiv \langle H \rangle$.
4. If not converged, go back to (2).

# Choice of Problem: The MaxCut Problem

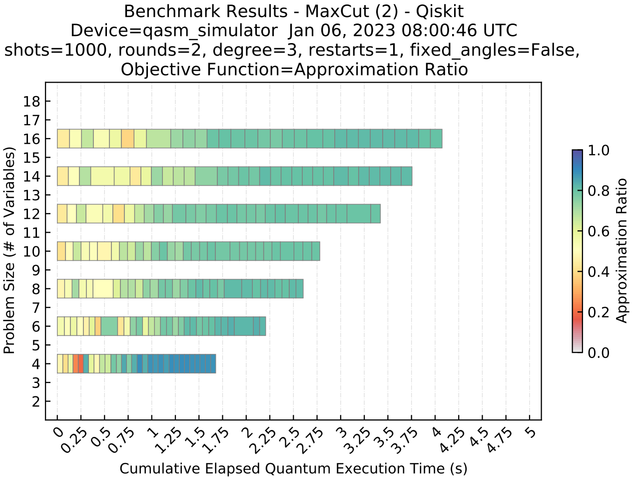


- **Given**: Graph $G$ with vertices $V$ and edges $E$.
- A **'cut'** is a division of the vertices into two groups.
- The **'size'** of a cut is the number of edges that now connect vertices from different groups.
- **Objective**: Find the cut with highest size, i.e. the 'Max Cut'.

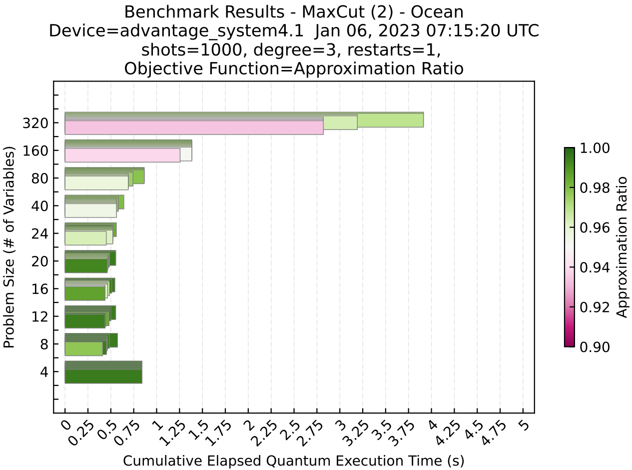
QAOA Formulation: Find ground state of:

$$H = -\frac{1}{2} \sum_{\langle j,k \rangle \in E} (1 - Z_j Z_k),$$

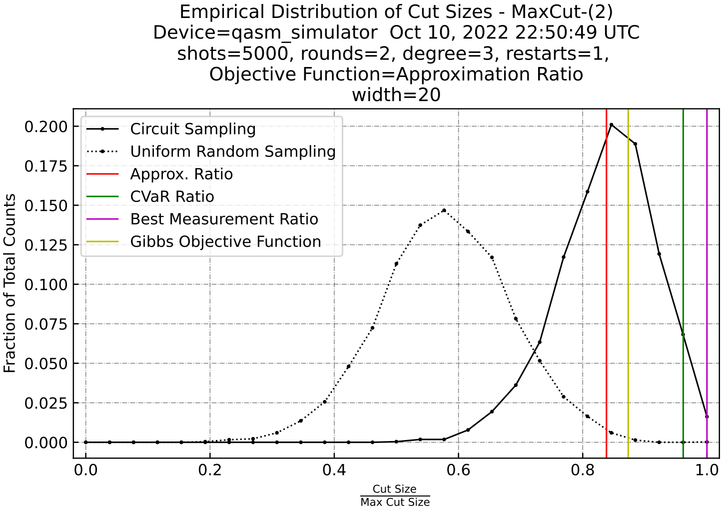
# Area Plots: Time Evolution of Quality



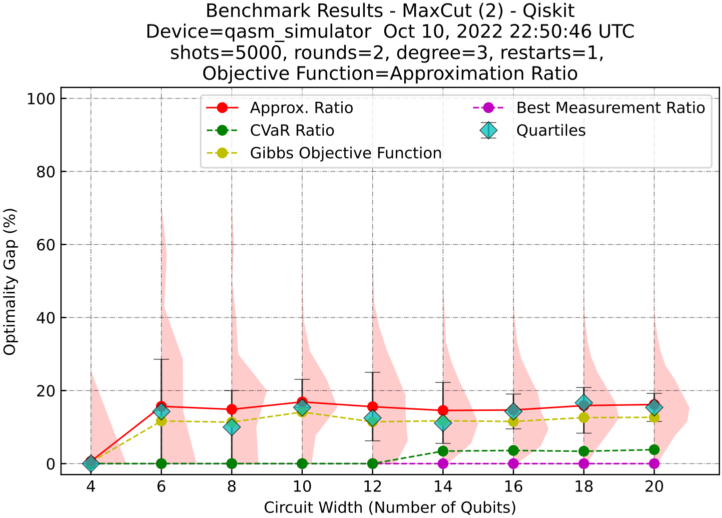
# Area Plots: Time Evolution of Quality



# Distribution of Cut Sizes

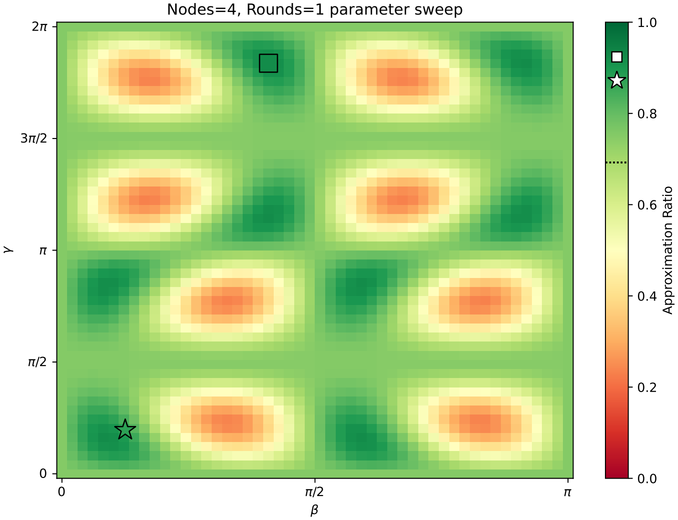


# All Metrics and Distribution all Widths

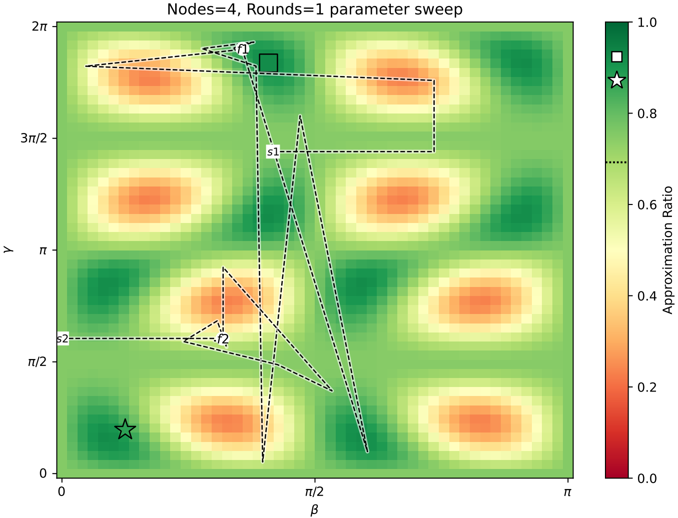


# Cost Function Landscape

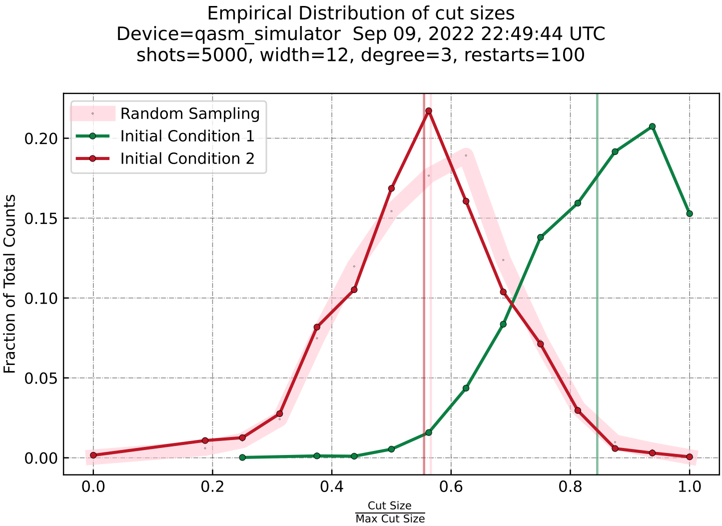
Created using state-vector simulator $\beta \in (0, \pi]$ and $\gamma \in (0, 2\pi]$



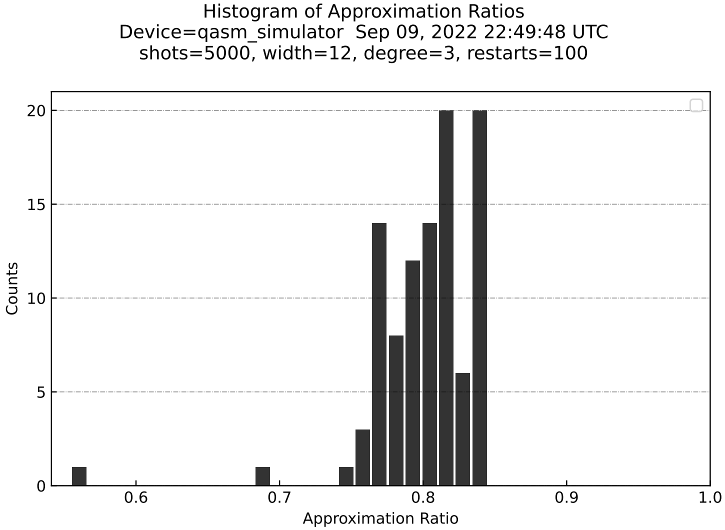
QAOA with 30 rounds, random initial conditions

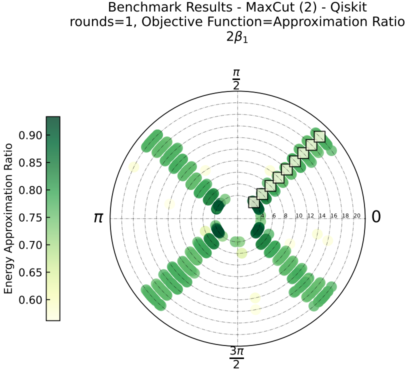


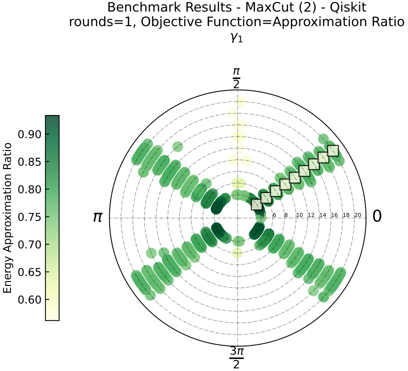
# Initial Conditions Affect Quality Significantly



# Histogram of Approximation Ratios with 100 restarts




Benchmark Results - MaxCut (2) - Qiskit
rounds=1, Objective Function=Approximation Ratio
$2\beta_1$
Energy Approximation Ratio
0.90
0.85
0.80
0.75
0.70
0.65
0.60
$\frac{\pi}{2}$
$\pi$
0
$\frac{3\pi}{2}$
4
6
8
10
12
14
16
18
20


Benchmark Results - MaxCut (2) - Qiskit
rounds=1, Objective Function=Approximation Ratio
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4
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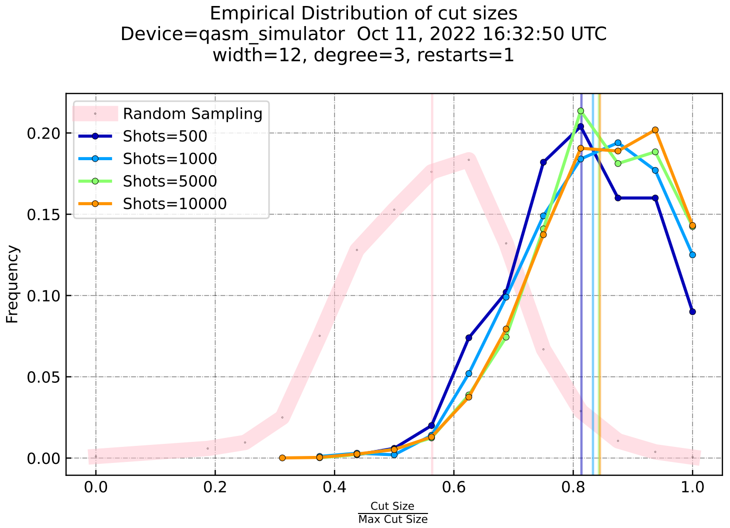
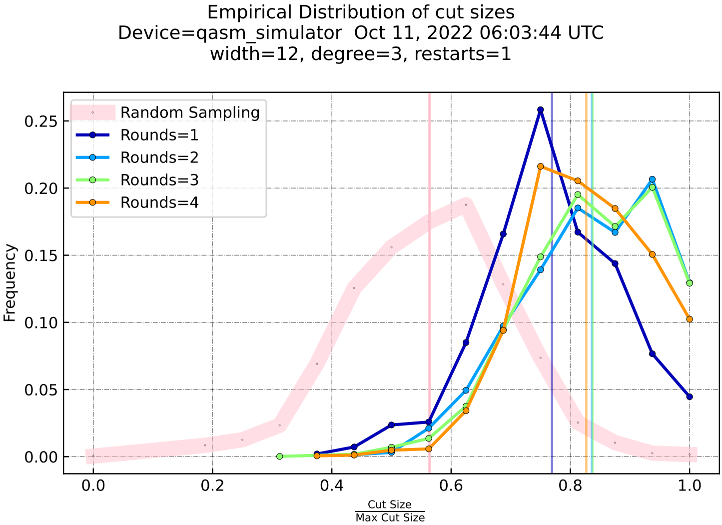
8
10
12
14
16
18
20

Shots $= 1000$

# Effect of Number of Shots



# Effect of Rounds




Same starting angles (all 1's).

# Conclusion and future work

- Open-source benchmarking framework
  - Works on different hardware modalities
  - End-users as well as researchers in mind
  - Also useful to understand effects of parameter choices.
- Details presented in manuscript[5].
- Extend framework:
  - Apply to other iterative hybrid algorithms, such as VQE.
  - Enhancements with 3$^{rd}$ party compiler optimization tools.

[5] Thomas Lubinski, Carleton Coffrin, Catherine McGeoch, Pratik Sathe, Joshua Apanavicius, and David E. Bernal Neira. "Optimization Applications as Quantum Performance Benchmarks." arXiv preprint arXiv:2302.02278 (2023).

Thank you!