

# Lower Bounds on Number of QAOA Rounds Required for Guaranteed Approximation Ratios

Naphan Benchasattabuse, Andreas Bärtshi, Luis Pedro García-Pintos, John Golden, Nathan Lemons,  
Stephan Eidenbenz  
(arXiv:2308.15442)

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# Combinatorial optimization problem

In the most general form, you're given

- Search space (we only consider binary string of length  $n$ ;  $x \in \{0, 1\}^n$ )
- Objective function  $C(X) \mapsto \mathbb{R}$
- Feasible set (for constrained problem)  $F \subseteq \{0, 1\}^n$

The task is to find a **feasible binary string** which **maximize** the objective value.

# Combinatorial optimization problem

In this work, we consider

- Search space (we only consider binary string of length  $n$ ;  $x \in \{0, 1\}^n$ )
- Objective function  $C(X) \mapsto \mathbb{N}_0$
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If we allow good (not necessarily optimal) solution, the quantity of interest is

*approximation ratio*

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$$C_{max} = \max_z C(z) \quad C_{avg} = \frac{1}{N} \sum_z C(z) \quad \sigma_C = \sqrt{\sum_z \frac{(C(z) - C_{avg})^2}{N}}$$



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*“approximation ratio”* -  $\frac{C(\tilde{z})}{C_{max}}$

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Recast the problem in Hamiltonian

$$H_C = \sum_{z \in F} C(z) |z\rangle \langle z|$$

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Recast the problem in Hamiltonian

more natural to find ground state and  
Hamiltonian with zero ground state energies

$$H_C = \sum_{z \in F} C(z) |z\rangle \langle z|$$

$$H_1 = \mathbb{1}C_{max} - H_C$$

# Quantum Optimization

What quantum algorithms do we have to solve optimization problem?

- (exact) Grover Adaptive Search  
[Dürr, Høyer, arXiv:9607014] [Gilliam, Woerner, Gonciulea, Quantum 5, 428 (2021)]
- (exact/approximate) Quantum Annealing  
[Kadowaki, Nishimori, Phys. Rev. E 58, 5355 (1998)] [Farhi, Goldstone, Gutmann, Sipser, arXiv:0001106]
- (exact) Short-path algorithm  
[Hastings, Quantum 2, 78 (2018)] [Dalzell, Pancotti, Campbell, Brandão, STOC2023]
- (approximate) Quantum Approximate Optimization Algorithm (QAOA)  
[Farhi, Goldstone, Gutmann, arXiv:1411.4028] [Hadfield, Wang, O'Gorman, Rieffel, Venturelli, Biswas, Algorithms 12.2 (2019): 34]

# Why QAOA?

Recent empirical results look promising

(arXiv:2308.02342)

## Evidence of Scaling Advantage for the Quantum Approximate Optimization Algorithm on a Classically Intractable Problem

Ruslan Shaydulin,<sup>1,\*</sup> Changhao Li,<sup>1</sup> Shouvanik Chakrabarti,<sup>1</sup> Matthew DeCross,<sup>2</sup> Dylan Herman,<sup>1</sup>  
Niraj Kumar,<sup>1</sup> Jeffrey Larson,<sup>3</sup> Danylo Lykov,<sup>1,4</sup> Pierre Minssen,<sup>1</sup> Yue Sun,<sup>1</sup> Yuri Alexeev,<sup>4</sup> Joan M. Dreiling,<sup>2</sup>  
John P. Gaebler,<sup>2</sup> Thomas M. Gatterman,<sup>2</sup> Justin A. Gerber,<sup>2</sup> Kevin Gilmore,<sup>2</sup> Dan Gresh,<sup>2</sup> Nathan Hewitt,<sup>2</sup>  
Chandler V. Horst,<sup>2</sup> Shaohan Hu,<sup>1</sup> Jacob Johansen,<sup>2</sup> Mitchell Matheny,<sup>2</sup> Tanner Mengle,<sup>2</sup> Michael Mills,<sup>2</sup>  
Steven A. Moses,<sup>2</sup> Brian Neyenhuis,<sup>2</sup> Peter Siegfried,<sup>2</sup> Romina Yalovetzky,<sup>1</sup> and Marco Pistoia<sup>1</sup>

<sup>1</sup>*Global Technology Applied Research, JPMorgan Chase, New York, NY 10017, USA*

<sup>2</sup>*Quantinuum, Broomfield, CO 80021, USA*

<sup>3</sup>*Mathematics and Computer Science Division, Argonne National Laboratory, Lemont, IL 60439, USA*

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The quantum approximate optimization algorithm (QAOA) is a leading candidate algorithm for

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The quantum approximate optimization algorithm (QAOA) is a leading candidate algorithm for

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## Solving boolean satisfiability problems with the quantum approximate optimization algorithm

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2023 IEEE International Conference on Quantum Computing and Engineering (QCE)

## Numerical Evidence for Exponential Speed-up of QAOA over Unstructured Search for Approximate Constrained Optimization

John Golden<sup>\*†</sup>, Andreas Bärttschi<sup>\*†</sup>, Daniel O'Malley<sup>‡</sup>, Stephan Eidenbenz<sup>†</sup>

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**Abstract**—Despite much recent work, the true promise and limitations of the Quantum Alternating Operator Ansatz the optimal operators for each problem, and the amount of phasing and mixing for each round, generates a large number

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## The Quantum Alternating Operator Ansatz for Satisfiability Problems

John Golden<sup>\*†</sup>, Andreas Bärttschi<sup>\*†</sup>, Daniel O'Malley<sup>‡</sup>, Stephan Eidenbenz<sup>†</sup>

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**Abstract**—We comparatively study, through large-scale numerical simulation, the performance across a large set of Quantum Alternating Operator Ansatz (QAOA) variants. Overall, the connection between mixers, phase separators, and QAOA performance is not well understood. In this



# QAOA

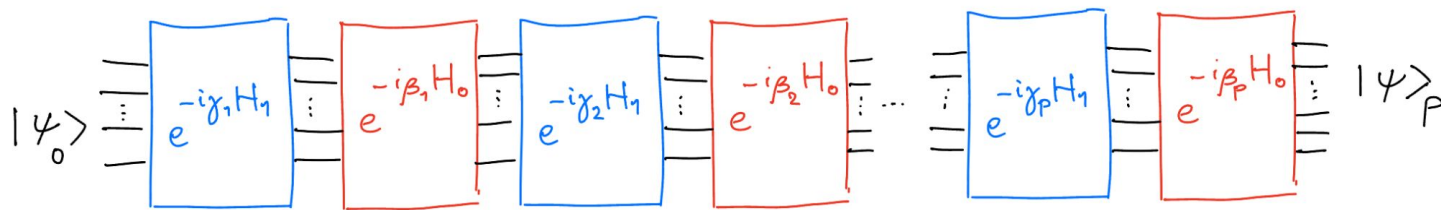
Quantum approximate optimization algorithm or quantum alternating operator ansatz

- Two non-commuting Hamiltonians  $H_0$ (mixing) and  $H_1$  (problem)
- Hyperparameter  $p$
- Two set of angles (parameters)  $\vec{\beta} = (\beta_1, \beta_2, \dots, \beta_p)$   $\vec{\gamma} = (\gamma_1, \gamma_2, \dots, \gamma_p)$

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$$|\psi(\vec{\beta}, \vec{\gamma})\rangle_p = (e^{-i\beta_p H_0} e^{-i\gamma_p H_1})(e^{-i\beta_{p-1} H_0} e^{-i\gamma_{p-1} H_1}) \dots (e^{-i\beta_1 H_0} e^{-i\gamma_1 H_1}) |\psi_0\rangle$$

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The goal is to **get a good string** “ $\tilde{z}$ ”

And we use the **expectation value** to guide the parameter adjustment

$$|\psi(\vec{\beta}, \vec{\gamma})\rangle_p = (e^{-i\beta_p H_0} e^{-i\gamma_p H_1})(e^{-i\beta_{p-1} H_0} e^{-i\gamma_{p-1} H_1}) \dots (e^{-i\beta_1 H_0} e^{-i\gamma_1 H_1}) |\psi_0\rangle$$

$$\lambda = \frac{\langle H_C \rangle_p}{C_{max}} = \max_{|\psi_p\rangle} \frac{\langle \psi_p | H_C | \psi_p \rangle}{C_{max}}$$

# Quantum Annealing

Consists of (1) set of driving Hamiltonians (2) annealing schedule

- Two non-commuting Hamiltonians  $H_0$ (mixing) and  $H_1$  (problem)
- Annealing schedule  $g(t)$  ranges between 0 and 1  
that satisfies  $g(0) = 0$  and  $g(t_f) = 1$
- The system is driven by time-dependent Hamiltonian

$$H(t) = (1 - g(t))H_0 + g(t)H_1$$

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$$t_{\text{anneal}} = \sum_{j=1}^p (|\beta_j| + |\gamma_j|)$$

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Results on quantum annealing also applies to QAOA!

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# Lower bound on annealing time

**Theorem 1** (García-Pintos et al. [31]). *Given two driving Hamiltonians with zero ground state energies  $H_0$  and  $H_1$ . For a quantum annealing protocol that starts in the ground state of  $H_0$  and ends at time  $t_f$ , it holds that*

$$t_f \geq \tau_{\text{anneal}} := \frac{\langle H_0 \rangle_{t_f} + \langle H_1 \rangle_0 - \langle H_1 \rangle_{t_f}}{\|[H_1, H_0]\|}. \quad (7)$$

[García-Pintos, Brady, Bringewatt, Liu, Phys. Rev. Lett. 130, 140601]

$$\langle H \rangle_t = \langle \psi_t | H | \psi_t \rangle$$



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$$\sum_{j=1}^p (|\beta_j| + |\gamma_j|) \geq \frac{\langle H_0 \rangle_p - \langle H_1 \rangle_0 - \langle H_1 \rangle_p}{\|[H_1, H_0]\|}$$

for QAOA

# Assumptions

- Periodic driving Hamiltonians  $e^{iH(t+\theta)} = e^{iHt}$  (here  $\theta = 2\pi$ )
  - With  $C(X) \mapsto \mathbb{N}_0$ , we have periodicity for
  - Most mixers used in literature are periodic (e.g., transverse field, Grover-M, clique-M)
- Both QA and QAOA always start from a ground state of  $H_0$

# Lower bound on QAOA rounds


Derivations:

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2 pi period 

# Lower bound on QAOA rounds

Derivations:

$$\begin{aligned} \sum_{j=1}^p (|\beta_j| + |\gamma_j|) &\geq \frac{\langle H_0 \rangle_p - \langle H_1 \rangle_0 - \langle H_1 \rangle_p}{\|[H_1, H_0]\|} \\ \text{2 pi period} \swarrow \searrow & \\ p(2\pi + 2\pi) &\geq \frac{\langle H_0 \rangle_p - \langle H_1 \rangle_0 - \langle H_1 \rangle_p}{\|[H_1, H_0]\|} \\ p &\geq \frac{\langle H_0 \rangle_p - \langle H_1 \rangle_0 - \langle H_1 \rangle_p}{4\pi \|[H_1, H_0]\|} \end{aligned}$$

# Lower bound on QAOA rounds

**Theorem 2.** *Given a classical objective function  $C(x)$  for a maximization task, represented by the Hamiltonian  $H_C$ , encoded into the phase separator Hamiltonian  $H_1 = \mathbb{1}C_{max} - H_C$  and a mixing Hamiltonian  $H_0$ , where all Hamiltonians are  $2\pi$  periodic with zero ground state energies. Let  $C_{max}$  and  $C_{avg}$  denote the global maximum and the average of  $C(x)$ . If a QAOA protocol with  $p$  rounds driven by  $H_0$  and  $H_1$  that starts from the ground state  $|\psi_0\rangle = |+\rangle^{\otimes n}$  of  $H_0$  reaches a state with approximation ratio  $\lambda$ , then*

$$p \geq \frac{\langle H_0 \rangle_p + \lambda C_{max} - C_{avg}}{4\pi \| [H_C, H_0] \|}. \quad (10)$$

**We have a lower bound now what?**

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Calculating this term is super hard!



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Calculating this term is super hard!

If you're an expert in spectral graph theory or matrix analysis. **We need your help!**

# What mixers do people use?

## Unconstrained Problems

- Transverse field (go-to mixer)
- Grover-mixer

$$H_{TF} = \mathbb{1} \frac{n}{2} - \frac{1}{2} \sum_{j=1}^n X_j$$

$$\begin{aligned} H_{Grover} &= \mathbb{1} - |\psi_0\rangle \langle \psi_0| \\ &= \mathbb{1} - \frac{1}{N} \sum_x \sum_y |y\rangle \langle x| \end{aligned}$$

## Constrained Problems (starts from a superposition of feasible states)

- Grover-mixer
- Clique-mixer (Hamming weight preserving)
- Ring-type mixer (Hamming weight preserving)

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# Lower Bound with Grover-Mixer

**Theorem 3.** *Given a classical objective function  $C(x)$  for a maximization task, represented by the Hamiltonian  $H_C$ , encoded into the phase separator Hamiltonian  $H_1 = \mathbb{1}C_{max} - H_C$  and the mixing Hamiltonian  $H_{Grover}$ , where all Hamiltonians are  $2\pi$  periodic with zero ground state energies. Let  $C_{max}$ ,  $C_{avg}$ , and  $\sigma_C$  denote the global maximum, the average, and the standard deviation of  $C(x)$ . If a QAOA protocol with  $p$  rounds driven by  $H_{Grover}$  and  $H_1$  starts from the ground state  $|\psi_0\rangle = |+\rangle^{\otimes n}$  of  $H_{Grover}$  and reaches a state with approximation ratio  $\lambda$ , then*

$$p \geq \frac{1 - |\langle \psi_0 | \psi_p \rangle|^2 + \lambda C_{max} - C_{avg}}{4\pi\sigma_C}$$

## Examples (Grover-mixer)

**Corollary 1.** *If a QAOA protocol with  $p$  rounds finds an approximate solution with approximation ratio  $\lambda$  to Max-Cut of a graph with  $|E|$  edges driven by the objective value phase separator  $H_1$  and the Grover-mixer  $H_{\text{Grover}}$  that starts in the state  $|\psi_0\rangle = |+\rangle^{\otimes n}$ , then*

$$p \geq \frac{1 - |\langle \psi_0 | \psi_p \rangle|^2 + \lambda C_{\max} - |E|/2}{2\pi\sqrt{|E|}}. \quad (34)$$

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$$p \geq \frac{1 - |\langle \psi_0 | \psi_p \rangle|^2 + \lambda C_{\max} - |E|/2}{2\pi\sqrt{|E|}}.$$

Consider a bipartite graph (easy)

$$\begin{aligned} p &\geq \frac{1 - |\langle \psi_0 | \psi_p \rangle|^2 + \lambda |E| - |E|/2}{2\pi\sqrt{|E|}} \\ &\geq \frac{(2\lambda - 1)}{4\pi} \sqrt{|E|}. \end{aligned}$$

# Examples (Grover-mixer)

**Corollary 1.** If a QAOA protocol with  $p$  rounds finds an approximate solution with approximation ratio  $\lambda$  to Max-Cut of a graph with  $|E|$  edges driven by the objective value phase separator  $H_1$  and the Grover mixer  $H_2$  starting from the state  $|\psi_0\rangle = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle)$ , then

$$p \geq \frac{1 - \langle \psi_0 | \psi_p \rangle^2 + \lambda C_{\max} - 1}{2\pi\sqrt{|E|}}$$

Achieving constant approximation ratio requires a polynomial number of rounds for certain problems with Grover-mixer

h (easy)

$$1 - \langle \psi_0 | \psi_p \rangle^2 + \lambda |E|/2$$

$$\geq \frac{(2\lambda - 1)}{4\pi} \sqrt{|E|}.$$

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To get a non-trivial lower bound, we need (where  $m$  is the number of terms)

$$\|[H_C, H_{TF}]\| = o(m)$$

Is there any problem with this?

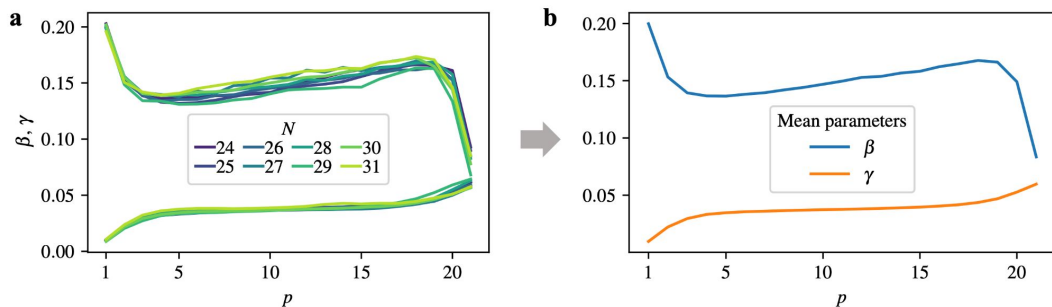
# Are the lower bounds tight?

Grover-mixer:

- Tight for search (makes sense)
- Comb. opt? -> (numerical suggests exponential scaling but we get polynomial)
  - [Golden, Bärttschi, Eidenbenz, O'Malley, arXiv: 2202.00648] [Golden, Bärttschi, O'Malley, Eidenbenz, arXiv:2301.11292]

Transverse field mixer:

- Definitely not?



[Shaydulin et al., arXiv:2308.02342]

# Warm-start QAOA

- Utilizing classical solver to get a starting point and continue with QAOA
  - [Tate, Farhadi, Herold, Mohler, Gupta, ACM TQC Vol 4, Issue 2 (9)] [Egger, Marecek, Woerner, Quantum 5, 479 (2021)]
- With modified mixers (the start states are ground states of the mixer)
- Initial states defined by ( $\theta$ )
  - Small  $\theta$  - starts as close to solution from solver as possible (high initial exp. val.)
  - Larger  $\theta$  - starts from superposition from good set of candidates (lower initial exp. val.)
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Numerical results show that “small”  $\theta$  is bad.



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Lower bound evaluates to

$$p = \Omega(1/\theta)$$

“Theoretical Limitations of Warm-Started QAOA at Low Circuit Depth or Small Initialization Angle”

[Tate, Eidenbenz, (in preparation)]

**Thank you for your attention!**