Problem-tailored variational quantum algorithms

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Outline

- VQEs for quantum simulation
- Choice of ansatz
- Adaptive, problem tailored VQE (ADAPT-VQE)
- Beyond digitized gates: ctrl-VQE

Observable (Hamiltonian) in second quantized form

Fermionic Hamiltonian
$$H = -\sum_{i} \frac{\nabla_{r_i}^2}{2} - \sum_{i,j} \frac{Z_i}{|R_i - r_j|} + \sum_{i,j>i} \frac{Z_i Z_j}{|R_i - R_j|} + \sum_{i,j>i} \frac{1}{|r_i - r_j|}$$

Ο

• Second quantization (basis chosen, Coulomb integrals computed—*classical preprocessing step*)

$$\hat{H} = \sum_{i,j} h_{ij} a_i^{\dagger} a_j + \frac{1}{2} \sum_{i,j,k,l} h_{ijkl} a_i^{\dagger} a_j^{\dagger} a_k a_l$$

 ○ Wavefunction antisymmetric under exchange of two particles → fermionic operators satisfy anticommutation relations

$$\left\{ \hat{a}_{\alpha}, \hat{a}_{\beta} \right\} = 0, \quad \left\{ \hat{a}_{\alpha}^{\dagger}, \hat{a}_{\beta}^{\dagger} \right\} = 0, \quad \left\{ \hat{a}_{\alpha}, \hat{a}_{\beta}^{\dagger} \right\} = \delta_{\alpha,\beta}$$

Mapping fermions to qubits: Jordan-Wigner

• Fermionic Hamiltonian

$$\hat{H} = \sum_{i,j} h_{ij} a_i^{\dagger} a_j + \frac{1}{2} \sum_{i,j,k,l} h_{ijkl} a_i^{\dagger} a_j^{\dagger} a_k a_l$$

- Jordan-Wigner mapping:
- Each orbital is mapped onto a qubit: $|0> \rightarrow$ unoccupied orbital, $|1> \rightarrow$ occupied orbital

$$a_{3}^{\dagger}|1001\rangle = a_{3}^{\dagger}a_{1}^{\dagger}a_{4}^{\dagger}|0000\rangle = -a_{1}^{\dagger}a_{3}^{\dagger}a_{4}^{\dagger}|0000\rangle$$

• Fermions satisfy Pauli exclusion principle but qubits are distinguishable → impose on qubits through Z strings

$$a_i^{\dagger} = \frac{1}{2} (X_i - iY_i) \bigotimes_{j < i} Z_j$$

Review: Rev. Mod. Phys. 92, 015003 (2020)

VQE overview



Objective function form

$$\langle A(\vec{\theta})\rangle = \langle \Psi(\vec{\theta})|A|\Psi(\vec{\theta})\rangle$$

Depends on:

- Observable measured (e.g., Hamiltonian)
- Ansatz (parameterized wavefunction)
 - Reference state
 - Parameterized circuit



Cerezo et al, arXiv:2012.09265

Most widely considered ansatze

I. Hardware-efficient ansatz

- Natural for hardware
 - Kandala et al (IBM group), Nature **549**, 242 (2017)
- Inefficient—too much of the Hilbert space sampled
- Difficult to optimize (barren plateaus) McClean et al., Nat. Commun. 9, 4812 (2018)
- II. Chemistry-inspired ansatz (UCC)
- Naturally generalizes classical simulation





Figures from Bharti et al. review on NISQ algorithms, arXiv:2101.08448

UCC is not unique in NISQ devices

$$U_{\text{UCC}}(\boldsymbol{\theta}) = e^{T(\boldsymbol{\theta}) - T(\boldsymbol{\theta})^{\dagger}} \qquad T(\boldsymbol{\theta}) = \sum_{ij} \theta_i^j a_j^{\dagger} a_i + \sum_{i_k, j_l} \theta_{i_k}^{j_l} a_{j_2}^{\dagger} a_{i_2} a_{j_1}^{\dagger} a_{i_1} + \cdots$$

- To implement this on quantum processors, we need to use the terms entering in the *T*'s as separate gates
- These don't generally commute with each other
- Need to trotterize
- Finite-order trotterization not unique
- Different choices of trotterization give qualitatively different results!

Grimsley et al., JCTC 2020, 16, 1, 1-6

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- II. Chemistry-inspired ansatz (UCC)
- Naturally generalizes classical simulation
- Impractically long circuits
- Inconsistent under low-order Trotterization
 Grimsley et al., JCTC 2020, 16, 1, 1-6

Neither are problem-tailored





Figures from Bharti et al. review on NISQ algorithms, arXiv:2101.08448

Properties of a good ansatz

$$|\Psi(\vec{\theta})\rangle = T(\vec{\theta})|\Psi_{ref}\rangle$$

- Quantum coherence is very limited \rightarrow shallow circuit
- Classical optimization is not infinitely powerful \rightarrow not too many optimization parameters
- Need to span the space where the solution lives; *it should help to have some input from the Hamiltonian*

Our approach: problem-tailored ansatze

Features:

✓ shallow circuits

✓ small/minimal number of optimization parameters

✓ Exactness

Key idea:

✓ Use the quantum computer to help determine the ansatz

ADAPT-VQE

- Adaptive, Problem tailored (ADAPT)-VQE introduced the first dynamically created ansatz
- Start from a simple/short depth ansatz (e.g., Hartree-Fock)
- Use measurements on the QC to determine how to grow the ansatz further
- The resulting ansatz depends on the Hamiltonian, hence problem-tailored

ADAPT-VQE ingredients: (i) operator pool

- ADAPT-VQE uses a pool of operators, $A_{\rm m}$
- Applies unitaries one by one : $U_m = \exp(\theta_m A_m)$ to a reference state



ADAPT-VQE ingredients: (ii) update criterion

- Identify which $e^{\theta A}$ to apply to reference state $|\Psi_0\rangle$
- Take gradient of mean energy wrt θ

$$\frac{\partial}{\partial \theta} \langle \Psi_0 | e^{-\theta A} H e^{\theta A} | \Psi_0 \rangle |_{\theta=0} = \langle \Psi_0 | [H, A] | \Psi_0 \rangle$$

New Hermitian operator \rightarrow measure on hardware



Grimsley, Economou, Barnes, Mayhall, Nature Communications 10, 3007 (2019)

Results



$$\epsilon_1 = 0.1$$

 $\epsilon_2 = 0.01$
 $\epsilon_3 = 0.001$



Comparing ADAPT to other pseudo-Trotter orderings



BeH₂ bond distance 2.39 Å

Grimsley, Economou, Barnes, Mayhall, Nature Commun. 10, 3007 (2019)

Hardware-efficient pool $\{e^{i\theta_j P_j}\}$, where P_j is a Pauli string with up to 4 Paulis

Qubit ADAPT-VQE—results



Tang, Shkolnikov, Barron, Grimsley, Mayhall, Barnes, Economou, PRX Quantum 2, 020310 (2021)

How should the operator pool be chosen?



- We can choose it according to hardware constraints
- However, how can we guarantee that it contains enough and the right type of operators?

Complete pools

$$|\psi^{ADAPT}(\vec{\theta})\rangle = e^{\theta_n A_n} \dots e^{\theta_2 A_2} e^{\theta_1 A_1} |\psi^{ref}\rangle = e^{\sum_i \phi_i B_i} |\psi^{ref}\rangle$$

where
$$\{B_i\} = \{A_1, A_2, ..., [A_1, A_2], ..., [A_1, [A_2, A_3]], ...\}$$

We have a complete pool and qubit-ADAPT is capable of converging to the exact ground state* when states $B_i |\psi\rangle$ form a complete basis (where $|\psi\rangle$ is an arbitrary *real* state)

*We are assuming throughout that we have time reversal symmetry \rightarrow all eigenstates are real

Complete vs incomplete pool convergence

Test complete vs incomplete pools for random Hamiltonians for (a) 3 qubits, (b) 4 qubits, (c) 5 qubits

For pools that satisfy completeness criterion ADAPT always converges



Minimal complete pools (MCPs)

Minimal complete pool: smallest sized complete pool

The minimal size of complete pools is linear in the nr of qubits: 2n-2

Example of min complete pool "G pool"

$$G_{1} = ZYII \dots I, \quad G_{2} = IZYII \dots I,$$

$$G_{3} = IIZYII \dots I, \quad \dots, \quad G_{n-2} = II \dots IZYI, \quad G_{n-1} = II \dots IZY,$$

$$G_{n} = YII \dots I, \quad G_{n+1} = IYII \dots I,$$

$$G_{n+2} = IIYII \dots I, \quad \dots, \quad G_{2n-3} = II \dots IYII, \quad G_{2n-2} = II \dots IYI$$

Proof of *G* pool completeness—outline

Show that any real state can be transformed into |000...> with G operators

• Define alternate pool V, which is comprised of products of G operators:

$$V_1 = ZZ \dots ZY, \quad V_2 = ZZ \dots ZYI,$$

$$V_3 = ZZ \dots ZYII, \quad \dots, \quad V_{n-1} = ZYII \dots I, \quad V_n = YII \dots I,$$

$$V_{n+1} = ZZ \dots ZIYI, \quad V_{n+2} = ZZ \dots ZIYII,$$

$$\dots, \quad V_{2n-3} = ZIYII \dots I, \quad V_{2n-2} = IYII \dots I.$$

- Prove that any 3-qubit real state can be transformed to |000> using only V operators
- Inductive proof: assume it holds for *n* qubits and prove it holds for *n*+1 qubits

Sketch of proof for three qubits

Three-qubit V pool: $\{V_i\}_{n=3} = \{iZ_3Z_2Y_1, iZ_3Y_2, iY_3, iY_2\}$

Arbitrary 3-qubit state $\xrightarrow{Y_3}$

$$|0
angle|\psi_0
angle+|1
angle|\psi_1
angle$$
 such that $\langle\psi_0|\psi_0
angle=\langle\psi_1|\psi_1
angle$

$$\xrightarrow{(I\pm Z_3)Y_2} |00\rangle |y_0\rangle + |01\rangle |y_1\rangle + |10\rangle |\chi_0\rangle + |11\rangle |\chi_1\rangle$$

such that $\langle y_0 | y_0 \rangle = \langle y_1 | y_1 \rangle = \langle \chi_0 | \chi_0 \rangle = \langle \chi_1 | \chi_1 \rangle$

$$\xrightarrow{Z_3 Z_2 Y_1, (I+Z_3)Y_2} \sqrt{2} |00\rangle |y'\rangle + |1\rangle (|0\rangle |\chi'_0\rangle + |1\rangle |\chi'_1\rangle)$$

 $\xrightarrow{Z_3 Z_2 Y_1, \, (I-Z_3) Y_2} |0\rangle |0\rangle |y\rangle + |1\rangle |0\rangle |\chi\rangle$

 $\xrightarrow{Z_3Z_2Y_1,Y_3,Z_3Z_2Y_1} |0\rangle|0\rangle|0\rangle$

Inductive proof

Define *n*-qubit pool $\{V_i\}_n = \{Z_n\{V_i\}_{n-1}, iY_n, iY_{n-1}\}$ Assume that V_n is complete Using this assumption, prove that V_{n+1} is complete

The proof follows the same logic of the one for n=3

So far

- There exist complete pools of size 2n-2
- We have explicit examples of such pools, including a local (nearest-neighbor) one

→Pools that are complete and scale linearly with the number of qubits are available to ADAPT-VQE

Can we have even smaller complete pools?

Size of minimal complete pools—proof

- Need operators with odd number of Y Paulis ("odd Paulis") to transform between arbitrary real states
- Algebra should contain odd operators that flip all possible 2ⁿ combinations of qubits; e.g., YIIIZIZ, YYZIYXZ etc
- Instead of working with the algebra, we will work with the product group
- Can generate all possible flippings with product group generators: $\{Y_1, Y_2, \dots, Y_{n-1}, Z_{n-1}Y_n, Z_1, Z_2, \dots, Z_k\}$

Must have $k \ge n - 2 \Rightarrow 2n - 2$ is MCP size

Need to determine k such that we can generate all odd flippings

- This generator set can yield a pool through products that give odd Paulis O
- The algebra generated by this pool is contained in the product group

[A,B]=0	$\{A,B\}=0$
$O \cdot O = E$	$O \cdot O = O$
$E \cdot E = E$	$E \cdot E = O$
$O \cdot E = O$	$O \cdot E = E$

Criteria for MCPs

- Given a 2n 2 odd pool operators, how can we check for completeness?
- For an MCP, the following statements are equivalent*:
 - (a) The pool $O_1, O_2, ..., O_{2n-2}$ is complete.
 - (b) The pool $O_1, O_2, ..., O_{2n-2}$ cannot be split into two mutually commuting sets.
 - (c) The algebra generated by O_1 , O_2 , ..., O_{2n-2} spans all odd strings from the group G.

where G is the product group

*We proved that (b) is necessary but not that it is sufficient; it is attractive because it takes polynomial time

Shkolnikov, Mayhall, Economou, Barnes, arXiv:2109.05340

The role of symmetries

- Physical Hamiltonians typically have structure due to symmetries
- In this case, common issues with a random MCP are:
 - Qubit-ADAPT won't start
 - Qubit-ADAPT won't converge to g.s.
- This is because generically the pool operators do not respect symmetries
- Then the gradient criterion may not allow exiting a symmetry subspace

qubit-ADAPT won't find the path from HF to the g.s.

 $\begin{aligned} \langle \psi_{HF} | [\hat{P}, \hat{H}] | \psi_{HF} \rangle &= \\ &= \langle (\hat{P}\psi_{HF}) | \hat{H} | \psi_{HF} \rangle - \langle \psi_{HF} | \hat{H} | (\hat{P}\psi_{HF}) \rangle = 0 \end{aligned}$

P = Pauli string that violates particle number or spin



 $\langle +, + | [\hat{H}, \hat{P}] | +, + \rangle =$ 2Im $\langle +, + | \hat{H} | +, - \rangle = 0$

P = Pauli string that violates parity (inversion or particle nr)

Incorporating symmetries

- These issues can be addressed using symmetry-preserving MCPs
- For starting the algorithm, include "starters", operators that preserve symmetries
- These need to involve two-particle excitations (four nontrivial Paulis), since HF is the lowest-energy uncorrelated state
- For convergence, ensure pool operators respect parity symmetries
- Symmetry-preserving MCPs have fewer than 2n 2 operators
- This is because we do not need to span the full Hilbert space



Shkolnikov, Mayhall, Economou, Barnes, arXiv:2109.05340

Trainability of ADAPT

- ADAPT produces compact, problem tailored ansatze
- We numerically found that ADAPT converges before BPs set in
- Shallow circuit → the landscape is generally too rugged
- Trainability?
- ADAPT avoids the issues associated with trainability



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Hardware currently noisy even for VQEs

Pulse-level optimization:

- Instead of circuit, parameterize pulse directly
- Measure <H>
- Classical optimization \rightarrow update pulse parameters
- Repeat until convergence

Meitei et al, npj Quantum Information 7, 155 (2021) Yang et al, Phys. Rev. X 7, 021027 (2017) Magann et al, PRX Quantum 2, 010101 (2021)



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FIG. 2: Bond energies are co ments.

Classical Simulation:

- 1. Pick a hardware Hamiltonian
- 2. Pick controls: 1 qubit microwave drives
- 3. Compute time evolution
- 4. Numerically optimize time-domain drives

Device Hamiltonian: Transmons

$$\hat{H}_D = \sum_{k=1}^N \left(\omega_k \hat{a}_k^{\dagger} \hat{a}_k - \frac{\delta_k}{2} \hat{a}_k^{\dagger} \hat{a}_k \hat{a}_k \right) + \sum_{\langle kl \rangle} g(\hat{a}_k^{\dagger} \hat{a}_l + \hat{a}_l^{\dagger} \hat{a}_k)$$
Control Hamiltonian: RWA

$$\hat{H}_C = \sum_{k=1}^N \Omega_k(t) (e^{i\nu_k t} \hat{a}_k + e^{-i\nu_k t} \hat{a}_k^{\dagger})$$
VQE Ansatz: Time evolution operator
where:

$$|\psi^{\text{trial}}(\Omega_n(t), \nu_n)\rangle = \mathcal{T}e^{-i\int_0^T dt \hat{H}_C(t, \Omega_n(t), \nu_n)} |\psi_0\rangle$$

$$\hat{H}(t)_C = e^{i\hat{H}_D t} \hat{H}_C(t)e^{-i\hat{H}_D t}$$
Dbjective Function: Molecular Energy

$$E(\Omega_n(t), \nu_n) = \langle \psi^{\text{trial'}} | \hat{H}^{\text{molecule}} | \psi^{\text{trial'}} \rangle$$

- Fix pulse duration
- Only optimize amplitude and frequency (frequency fixed throughout evolution)
- Numerically, we can optimize arbitrarily complex pulse shapes using analytic gradients
- Experimentally, this is difficult as finite differentiation is used
- To avoid this we propose the following adaptive parameterization to minimize the number of experimental gradients needed (split into n segments):

Nr of parameters: (n+1) per qubit





FIG. 5: Energy difference between ctrl-VQE and FCI (top) Rough comparison of coherence requirements for gate-based vsact lange (botom) Holong the time evolution steps with optimal pulses of different durations for H_2 with a bond distance 80,000ns (gate-based UCCSD) vs. 50ns (ctrl-VQE) of 0.75 Å. The red and purple lines with T = 29 ns are dis-

tinct solutions to the same optimization. Optimized pulse parameters are provided in the SI.

Meitei et al, npj Quantum Information 7, 155 (2021)

Conclusions

- Adaptive, problem tailored (ADAPT) VQE leverages the quantum computer to create an ansatz that is ideally suited to a given Hamiltonian
- Minimal complete pools scale linearly (2n-2) with the nr of qubits
- ADAPT-VQE burrows into the minimum, is immune to rugged landscape
- Even more near term: pulse-level instead of gate-level optimization

Grimsley, Economou, Barnes, Mayhall, Nature Commun. **10**, 3007 (2019) Tang, Shkolnikov, Barron, et al, PRX Quantum **2**, 020310 (2021) Shkolnikov, Mayhall, Economou, Barnes, arXiv:2109.05340 Meitei et al, npj Quantum Information **7**, 155 (2021)



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