## Exploration of Quantum Computing for Fusion Energy Science Applications

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## Quantum computing may be a game-changer for fusion and science in general

- Polynomial to exponential gains in memory and computational power
- Exponential speedup for the Fourier transform, linear solvers, factoring integers, ...
- Quadratic speedup for unstructured search, optimization, sums \& integrals, ...
- Great progress has been made on quantum hardware \& technology
- Multiple platforms: ion traps, neutral atom traps, superconducting circuits, NMR, ...
- Google, IBM, \& others now claim to have achieved quantum supremacy ...
- But, we are still in the Noisy Intermediate-Scale Quantum (NISQ) era
- Many qubits, but no error correction
- $1 \%$ error rate per gate $\rightarrow$ can only perform $\sim 100$ gate operations



## The key insight ...



Nature isn't classical, dammit, and if you want to make a simulation of nature, you'd better make it quantum mechanical, and by golly it's a wonderful problem, because it doesn't look so easy.

- Richard P. Feymman -


## Outline: Quantum Computing for Fusion Energy Sciences

- Intro to Quantum Computing
- Qubits
—Quantum Algorithms
- Quantum Simulation Algorithms
- Linear
- Nonlinear
- Testing Quantum Hardware Platforms
- Error Mitigation
- Error Utilization
- Conclusions \& Outlook



## The qubit is the simplest complex Hilbert space



- Pure State: wavefunction $\psi \in \mathbb{C}^{2}$ is a normalized superposition of the basis states $|0\rangle$ and $|1\rangle$

$$
\boldsymbol{\psi}=\left(\begin{array}{cc}
\cos \theta & e^{-i \phi / 2} \\
\sin \theta & e^{+i \phi / 2} \\
\sin \rangle
\end{array}\right)
$$

- Mixed State: probability density matrix $\rho=\rho^{\dagger} \in \mathbb{H}_{4} \sim \mathbb{R}^{4}$ is a mixture of pure states

$$
\boldsymbol{\rho}=\left(\begin{array}{ll}
\rho_{00}|\mathbf{0}\rangle\langle\mathbf{0}| & \rho_{01}|\mathbf{0}\rangle\langle\mathbf{1}| \\
\rho_{01}^{*}|\mathbf{1}\rangle\langle\mathbf{0}| & \rho_{11}|\mathbf{1}\rangle\langle\mathbf{1}|
\end{array}\right)
$$

- PDF: probability distribution function $f \in \mathbb{R}^{2}$

$$
\boldsymbol{f}=\operatorname{Diag}(\boldsymbol{\rho})=\left(\begin{array}{ll}
\rho_{00}|\mathbf{0}\rangle\langle\mathbf{0}| & \\
& \rho_{11}|\mathbf{1}\rangle\langle\mathbf{1}|
\end{array}\right)
$$

## Quantum memory registers are "exponentially large"

Qubit: Dimension 2

n Qubits $\rightarrow$ Hilbert Space Dimension: $\mathbf{N}=\mathbf{2}^{\mathbf{n}}$


- For n qubits, the number of states is $\mathbf{N}=\mathbf{2}^{\mathbf{n}}$
- Pure State: $\psi \in \mathbb{C}^{N}$ has $2(N-1)$ real DOFs
- Mixed State: $\rho=\rho^{\dagger} \in \mathbb{H}_{N \times N}$ has $\left(N^{2}-1\right)$ real DOFs
- Classical PDF: $f \in \mathbb{R}^{N}$ has $(N-1)$ real DOFs
- Direct quantum simulation is extremely difficult due to exponentially large Hilbert space!


## Let's use "quantum machines" to simulate quantum physics!

## Qubit: Dimension 2


n Qubits $\rightarrow$ Hilbert Space Dimension: $\mathbf{N}=\mathbf{2}^{\mathbf{n}}$


## - A brief history of quantum algorithms:

- Early-1980's: Turn the challenge into an opportunity - Feynman, Manin, Bennett \& Brassard
- Mid-1990's: Factoring integers, unstructured search, quantum counting - Shor, Grover, Brassard, Hoyer, Tapp
- Late-1990's: Efficient simulation algorithms based on Trotter-Suzuki decompositions - Lloyd \& Abrams
- Early 2000's: Linear solver algorithms - Harrow Hassidim \& Lloyd, Ambianis, Childs Kothari \& Somma, ...
- 2015-present: Accelerated linear solver, linear diff eq \& simulation algorithms - Berry, Childs, Low \& Chuang


## Digital quantum computing model has power and simplicity

- Quantum states can be transformed efficiently via linear unitary operations
$-\psi=\mathbf{U} \psi_{\mathbf{0}}$ where $\mathbf{U}=e^{-i \mathbf{H} t}$ is a unitary $\mathbf{U} \mathbf{U}^{\dagger}=\mathrm{I}$ evolution operator and $\mathbf{H}=\mathbf{H}^{\dagger}$ a Hermitian Hamiltonian
- This is amazing! because $\psi$ is an exponentially large vector and $\mathbf{U}$ is a dense exponentially large matrix!

- While there are a huge number, $\mathbf{N}^{\mathbf{2}}=\mathbf{2}^{\mathbf{2 n}}$, of unitary operations, they are generated by a small number $\sim \mathrm{O}(\mathrm{n})$ of basic operations called a "gate set"
- Single qubit operations can be achieved efficiently with a few standard gates, e.g. RX and RZ
- Adding one nontrivial 2-qubit gate, e.g. CNOT or CZ, between nearest neighbors generates the rest


## Many useful computations can be performed in $O(p o l y(n))$ basic gate operations!

- The key resource is quantum parallelism: superposition and interference ;)
- Any reversible classical computation can also be performed, but typically without a speedup



## 3 qubit FFT

- Approximating an arbitrary unitary is exponentially hard : $^{2}$
- Only certain unitaries can be performed efficiently
- Initializing all quantum information is exponentially hard
- Measuring all quantum information is exponentially hard
- Measuring exponentially small probabilities is hard $)^{2}$
- Central limit theorem implies direct sampling converges as $1 /$ sqrt(\# samples)

Central limit theorem implies direct sampling converges as 1/sqrt(\# samples)

## A few essential subroutines power the majority of quantum algorithms

## - Quantum Fourier Transform: Cost of $(\log \mathbf{N})^{2}$ rather than classical $\mathbf{N} \log \mathbf{N}$

- Phase estimation, factoring integers, and taking discrete logarithms - Peter Shor 1994
- Powers many Hamiltonian simulation algorithms
- Hamiltonian simulation powers linear solvers, linear diff. eq. solvers, and variational eigensolvers, etc.


## - Amplitude Amplification: Cost of sqrt(N) rather than classical $\mathbf{N}$

- Amplitude amplification first used in Grover's search algorithm - Lov Grover 1996
- Amplitude estimation \& Quantum counting - Brassard, Hoyer, Mosca, Tapp 2000
- Powers many Monte Carlo and integration algorithms - Heinrich \& Novaks 2000, Montanaro 2015


## - Quantum Walks: Cost of $\mathbf{N}$ rather than classical $\mathbf{N}^{2}$

- Early models turned into a computational framework - Aharonov, Ambianis, Kempe, Vazirani 2001
- Graph search, element uniqueness, ... - Ambianis, Childs, Kempe
- Hamiltonian simulation, state preparation - Szegedy 2004, Childs 2010
- Qubitization, Quantum Signal Processing, Quantum Singular Value Transformation - Low \& Chuang 2017


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## Hamiltonian simulation can speed up the solution of linear PDEs

- Simple PDEs, e.g. Poisson or wave equation, have simple/sparse Hamiltonians and can typically be solved with exponential speedup - The output is a wavefunction that encodes the solution
- And a few robust physical observables $\left\langle\mathrm{O}_{1}\right\rangle,\left\langle\mathrm{O}_{2}\right\rangle,\left\langle\mathrm{O}_{3}\right\rangle$

$$
|\psi\rangle=\sum_{x} \psi_{x}|x\rangle
$$

- However, outputting the data $\left\{\psi_{x}\right\}$ to a classical register, requires an exponential amount of work \& reduces speedup to quadratic at best [1,2]
- The same problem occurs for nontrivial initial condition and/or source functions
- "Hidden Spectral Problem": if you promise there is a basis in which the solution is exponentially sparse, then we can get exponential speedup - Like doing "X-ray crystallography"


## Hamiltonian simulation can speed up the solution of linear PDEs

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## Amplitude Estimation yields up to quadratic speedup for output

- Central limit theorem: direct sampling requires computational cost ~ 1/accuracy ${ }^{2}$
- Classical randomized Monte Carlo algorithms can also often provide an exponential speedup over Eulerian methods
- Amplitude estimation only requires computational cost ~ 1/accuracy


|  | function space | deterministic | randomized | quantum |
| :--- | :--- | :--- | :--- | :--- |
|  | $L_{p}^{N}, 2 \leq p \leq \infty$ | 1 | $n^{-1 / 2}$ | $n^{-1}$ |
| Holder class | $F_{d}^{k, \alpha}$ | $n^{-(k+\alpha) / d}$ | $n^{-(k+\alpha) / d-1 / 2}$ | $n^{-(k+\alpha) / d-1}$ |
| Sobolev class | $W_{p, d}^{k}, 2 \leq p \leq \infty$ | $n^{-k / d}$ | $n^{-k / d-1 / 2}$ | $n^{-k / d-1}$ |

Convergence [1] of error with number of function calls $n$

## - Relative to deterministic algorithms, speedups increase for

 high dimensions $\boldsymbol{d} \rightarrow \infty$ and for solutions that are not smooth $\boldsymbol{k}, \boldsymbol{\alpha} \rightarrow \mathbf{0}$- Key Assumption: location of discontinuities are unknown $\rightarrow$ stochastic / randomized functions
- No-Cloning Theorem:

An unknown quantum state cannot be copied

- The only way to do this is to measure all components and prepare an identical state from scratch

- If a state preparation process is reproducible, we can form multiple replicas of the state
- A fault-tolerant quantum computer can run the same quantum program to create identical outputs

- Iterative algorithms that require nonlinear operations are exponentially costly [1]
- If each iteration needs 2 replicas, then the next iteration needs 4 replicas, and $T$ iterations needs $2^{\top}$ replicas


## How about embedding a nonlinear differential equation within a larger linear system?

- Quantization is a natural embedding for Hamiltonian systems
- Dissipation can be included by embedding the system within a much larger ideal system [1]


## - Exact Koopman-von Neumann (KvN) [2] and Carleman [3] approaches

- The conservation of the probability distribution function (PDF) is a perfect embedding of a nonlinear system ... in an infinite-dimensional system of equations
- Carleman embedding [4] is a complex analytic form of Koopman [2] that works well near fixed points
- Special classes of PDEs may have more efficient types of embedding
- PDEs that are reducible to ODEs can be embedded using the KvN approach for ODEs [4]:

Hamilton-Jacobi equation, advection equation

- Integrable systems also have special types of embedding


## Approach \# 1: Quantize the dynamics $i \hbar \partial_{t} \psi=\mathbf{H} \psi$

## - Point Example: Quantum Sawtooth Map*

- Model for chaotic wave-particle interactions
- Converges to classical result as \# of qubits increases


## - Advantages

- Quantum version may be the more accurate physical model
- Many quantum algorithms for quantum simulation
- Quantum algorithms can efficiently calculate classical quantities:

Lyapunov exponent* \& diffusion coefficient


## - Disadvantages

- Quantum $=$ Classical: interference, diffraction, \& tunneling
- Semiclassical limit requires very large quantum numbers
- Non-Hamiltonian systems, e.g. with dissipation, require embedding in a much larger ideal system


## Approach \# 2: Nonlinear dynamics acts linearly on function spaces

- Consider a set of nonlinear Diff Eq's $d z / d t=V(z, t)$ with initial conditions $z_{0}:=z(t=0)$

$$
\left.\underset{\text { picture }}{\underset{L_{0}}{\text { Lagrangian }}} \quad \partial_{t} Z\right|_{z_{0}}=+\left.V \cdot \nabla z \quad \stackrel{\text { chain rule }}{\longleftrightarrow} \partial_{t} z_{0}\right|_{z}=-V \cdot \nabla z_{0}
$$

- The advection equation expresses the evolution of a scalar function: $\theta(z, t)$

Koopman
evolution

$$
\left.\partial_{t} \theta\right|_{z_{0}}=+V \cdot \nabla \theta \quad \text { chain rule }\left.\quad \partial_{t} \theta\right|_{z}=-V \cdot \nabla \theta
$$

Eulerian picture

- The Liouville equation expresses conservation of probability: $f(z, t)$

$$
\left.\partial_{t} f\right|_{z_{0}}=+\left.\nabla \cdot(V f) \stackrel{\text { chain rule }}{\longleftrightarrow} \partial_{t} f\right|_{z}=-\nabla \cdot(V f)
$$

## Semiclassical wavefunction yields efficient unitary representation [1]

- Since quantum algorithms act naturally on wavefunctions, consider the "semiclassical" ansatz

$$
\psi(z, t)=\sqrt{f(z, t)} e^{i \theta(z, t)}
$$

- Where $f(z, t)$ evolves as a PDF and the phase $\theta(z, t)$ evolves as a scalar field with a source

$$
\left.\partial_{t} \theta\right|_{z}=-V \cdot \nabla \theta+L(z, t) / \hbar
$$

- Inserting the definitions leads to the generalized Koopman-von Neumann equation [1-2]

$$
\left.i \hbar \partial_{t} \psi\right|_{z}=-i \hbar(V \cdot \nabla \psi+\nabla \cdot V \psi) / 2-L \psi
$$

- The classical Lagrangian $L(z, t)=p \cdot \partial_{p} H-H(x, p)$ agrees with Feynman's prescription for the path integral and leads to the semiclassical Koopman-van Hove equation [2]

Choice of numerical advection operator is important for accuracy

| ODE | KvN |
| :---: | :---: |
| $\frac{d x}{d t}=-x^{2}$ | $\partial_{t} \psi=\frac{1}{2} \partial_{x}\left(x^{2} \psi\right)+\frac{1}{2} x^{2} \partial_{x} \psi$ |

Upwind discretization

## Killer App? Use quantum machine learning to develop reduced-order models for native quantum simulation / data

- Quantum machine learning [1] and principle component analysis [2] are potentially powerful techniques
- But, they have the I/O problem of getting the database of information in and out


$$
|\psi\rangle=\sum_{x} \psi_{x}|x\rangle
$$



- Quantum algorithms for reduced-order modeling of native quantum simulation or experimental data [3] could be the killer app!
- Quantum data assimilation [4] and closure of dynamical systems [5]
qDMD: quantum Dynamic Mode Decomposition
qSINDy: quantum Sparse Identification of Nonlinear Dynamics
[1] P. Rebentrost PRL 2014, M. Schuld PRA 2016, J. Biamonte, Nature Phys 2017 [2] S. Lloyd, Nature Phys., 2014
LLNL- PRES-857541
[3] B. Kiani PRA 2022 [4] D. Giannakis PRE 2019, D. Freeman PNAS 2023 [5] D. Freeman arXiv:2208.03390


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## First plasma application: simulating three-wave interactions [1]

## - Cubic couplings are ubiquitous in plasmas, fluids, \& nonlinear media

- Examples: nonlinear optics, laser-plasma interactions, weak turbulence, gauge theory, lattice QED ...
- Interaction Hamiltonian
$H_{I}=i g A_{1} A_{2}^{\dagger} A_{3}^{\dagger}-i g^{*} A_{1}^{\dagger} A_{2} A_{3}$

$$
\begin{aligned}
& \omega_{1}=\omega_{2}+\omega_{3} \\
& \mathbf{k}_{1}=\mathbf{k}_{2}+\mathbf{k}_{3}
\end{aligned}
$$

- Envelope equations for resonant interactions
$d_{t} A_{1}=-g^{*} A_{2} A_{3} \quad d_{t} A_{2}=g^{*} A_{1} A_{3}^{\dagger} \quad d_{t} A_{3}=g^{*} A_{1} A_{2}^{\dagger}$
- Quantized version $\left[A_{j}, A_{k}^{\dagger}\right]=\delta_{j k}$
- Developed a new quantum algorithm for simulating 3-wave dynamics [1]
- Transform to action-angle variables
- Evolve a sparse tridiagonal Hamiltonian system


- Results of LLNL QuDIT (blue) are close to analytic solution (black) \& match Lindblad Master Equation (ME) simulation (purple)
- Results of Rigetti Aspen-4 platform (red) perform well for first ${ }^{\sim 9}$ time-steps, but use 17x as many gates per step
- On both platforms, decay and dephasing noise limit the fidelity after $\sim 100$ gate repetitions
- Combining gates into single control pulse improves long-term fidelity
rigetti


## Optimal control approach compresses many standard gates into one

- Optimal control pulse $\mathrm{c}(\mathrm{t})$ generates the desired unitary transformation $\mathrm{U}(T)$ for a single time step of length $T$
- Although the dynamics is nontrivial, populations achieve the desired levels by the end of the pulse
- Density matrix evolution is well-described by an experimentally calibrated decoherence model: the Lindblad Master Equation (ME)

$$
\partial_{t} \boldsymbol{\rho}=\frac{1}{i \hbar}[\mathbf{H}, \boldsymbol{\rho}]+v^{j k}\left(\mathbf{L}_{k} \boldsymbol{\rho} \mathbf{L}_{j}^{\dagger}-\frac{1}{2}\left\{\mathbf{L}_{j} \mathbf{L}_{k}^{\dagger}, \boldsymbol{\rho}\right\}\right)
$$

$$
\mathbf{U}(T)=\mathcal{J} e^{-i \int_{0}^{T}\left(\mathbf{H}_{0}+c(t) \mathbf{H}_{c}\right) d t}
$$






## We now improved the performance of the Rigetti platform for a chaotic 3 -wave and 4 -wave mixing problem using error mitigation

- Fast-forwarding: Directly compiling $U(N \Delta t)$ rather than using $U^{N}(\Delta \mathrm{t})$ results in fewer gates
- Randomized compilation ${ }^{1}$ : suppresses coherent errors, turning them into incoherent errors
- Compile $U(\Delta t)$ to multiple equivalent circuits, select randomly for each time step
- Rescaling ${ }^{2}$ : probability $P$ to extract signal $S$ from incoherent noise using ansatz $P=S e^{-\gamma G}+1 / 2^{n}$
- Signal decay rate $\gamma$ calibrated with cycle benchmarking



## The quantum sawtooth map (QSM) is the most efficient chaotic system to simulate on a quantum computer [1]

- Classical sawtooth map depends on kicking strength $K$

$$
H_{\text {saw }}=\frac{1}{2} p^{2}-\frac{1}{2} K q^{2} \sum_{n} \delta(t-n) \quad \text { for } q \bmod 2 \pi
$$

- Quantum sawtooth map also depends on $\hbar$
- Map eigenvalues of $p$ to $n$ qubits that represent $N=2^{n}$ states
- $\hbar$ is quantized in order to match periodicity in $p$

$$
\Delta p=2 \pi=\hbar N \quad \hbar=2 \pi / N
$$

- Quantum propagator has four stages:

$$
U_{Q S M}=\hat{\mathcal{T}} e^{-i \int H_{\text {saw }} d t / \hbar}=U_{k i n}(\hbar) U_{Q F T}^{-1} U_{p o t}(K / \hbar) U_{Q F T}
$$

Classical Map: K=-0.1


Quantum Map: K=-0.1


Noisy quantum computers can efficiently compute key signatures of chaos: Lyapunov rate $\lambda=$ exponential separation of trajectories $[1,2]$


## Semiclassical theory predicts that fidelity has two components that decay at different rates*

*M. D. Porter, I. Joseph, Quantum 6, 799 (2022)

$$
f(t) \approx f_{\text {Quantum }} e^{-\Gamma_{\text {noise }} t}+f_{\text {Classical }} e^{-\lambda_{\text {Lyap }} t}+1 / N
$$



## Fidelity phase diagram determines whether the Lyapunov rate

 can be observed*

## Key Limitations

- Dynamics must be chaotic
- Lyapunov rate < noise decay rate
- Overall decay rate cannot be too fast
- Noise cannot be too strong or too weak


## Key Requirements

- At least 6 qubits
- Noise must be reduced by 10-100x
- Depends on architecture
- Parallelization, layout, etc.


## We performed the first gate-based quantum simulation proving that fidelity depends on dynamics in addition to gate-count*

*M. D. Porter, I. Joseph, arXiv:2206.04829

- Decay rate is faster for chaotic dynamics with same \# of gates
- Only single-qubit rotation angles change
- Saturates at low and high values of $K$
- Increases during the transition to chaos, but does not keep increasing with Lyapunov rate
- Chaos generates delocalized entangled states that are more sensitive to noise
- Actual error rates are $3-5 x$ larger than reported
- Lindblad decoherence model infers $3 x$ larger dephasing rate $1 / T_{2}{ }^{*}$
fidelity IBM manilla: $\mathbf{3}$ qubits



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## Conclusions \& Outlook

## - Quantum computing holds great promise for accelerating scientific discovery

- Efficient Fourier transforms, sparse linear solvers, sparse Hamiltonian simulation, variational eigensolvers, ...
- Chemistry, materials science, high-energy physics, nuclear physics, ..., fusion energy science!
- Quantum simulation of the PDF of nonlinear dynamical systems can achieve exponential speedup over Eulerian methods and up to quadratic speedup over Monte Carlo methods
- Simulations of fluids, plasmas, molecular dynamics, finance, ecology, epidemiology, ...
- Quadratic speedup attained for high dimension and lack of smoothness
- Exponential speedup for end-to-end app's likely requires problems with special structure
- Algorithms that utilize noise have potential for near-term quantum advantage
- Simulate open system dynamics with an open quantum system
- Passive and active error mitigation, e.g. quantum optimal control, are under extensive development
- Decoherence controls the "information confinement time"


## Quantum Computing for Fusion Energy Science Applications

I. Joseph (LLNL), M. D. Porter (Sandia), Y. Shi (U Colorado Boulder), B. Evert (Rigetti), et al.

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Classical

- Algorithms that utilize noise have potential for near-term quantum advantage
- Simulate open system dynamics with an open quantum system
- Passive and active error mitigation are under extensive development
- Decoherence controls the "information confinement time"
phase space


Quantum phase space


## Our team consists of experts in MFE, HEDS and QIS

## - Core Team

- MFE: Ilon Joseph (PI), Vasily Geyko, Jeff Parker (FY20)
-HEDS: Frank Graziani, Stephen Libby, Yuan Shi (U Colorado Boulder)
-QIS: Jonathan DuBois, Al Castelli, Max Porter (Sandia), Gabriel Woolls (Caltech/Berkeley)


Al Castelli


Jonathan DuBois


Vasily Geyko


Ilon Joseph


Frank Graziani


Steve Libby


Max Porter


Yuan Shi


Gabriel Woolls

## -LLNL Collaborators

—Quantum Coherent Device Physics Group: Kristi Beck (formerly IonQ), Yujin Cho, Yaniv Rosen, Xian Wu (now at Rigetti)

- NACS: Roger Minich, Kyle Wendt, Sofia Quaglioni; CASC: Anders Petersson, Stephanie Gunther
-Students: Jessica Tucker (SJSU), Chris Yang (Caltech, SSGF Fellowship)


## -External Collaborators

-Robin Blume-Kohut (Sandia), Denys Bondar (Tulane), Frank Gaitan (LPS), Cesare Tronci (U. Surrey, Tulane), R. Tyler Sutherland (Quantinuum)

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## Quantum information science (QIS) may soon lead to game-changing capabilities for science in general

- Quantum Sensing: improves measurement sensitivity
- Heisenberg limit for noise/signal ratio scales as $1 / \mathrm{N}$ instead of $1 /$ sqrt(N)

Quantum-Enhanced Advanced LIGO Detectors in the Era of Gravitational-Wave Astronomy
M. Tse et al. Phys. Rev. Lett. 123, 231107 (2019)

China Demonstrates Quantum Encryption By Hosting a Video Call
A. Nordrum, IEEE Spectrum (2017-10-03)

- Quantum Computing: polynomial or exponential gains in effective memory and computational power
- Fourier transform, linear solvers, Hamiltonian simulation, ...
- Today = Noisy Intermediate-Scale Quantum (NISQ) era


## Quantum supremacy using a programmable superconducting processor

F. Arute, et al. Nature. 127, 180502 (2019)

Strong Quantum Computational Advantage Using a Superconducting Quantum Processor

Yulin Wu, et al. Phys. Rev. Lett. 127, 180501 (2021)

## Semiclassical wavefunction yields efficient unitary representation [1]

- Since quantum algorithms act naturally on wavefunctions, consider a "semiclassical" ansatz

$$
\psi(z, t)=\sqrt{f(z, t)} e^{i \theta(z, t)}
$$

- Assume that the phase evolves as a scalar with a source

$$
\left.\partial_{t} \theta\right|_{z}=-V \cdot \nabla \theta+L(z, t) /\left.\hbar \quad \partial_{t} \theta\right|_{z_{0}}=+V \cdot \nabla \theta-L(z, t) / \hbar
$$

- For classical dynamics, the classical Lagrangian $L(z, t)=p \cdot \partial_{p} H-H(x, p)$ is the natural choice
because it agrees with Feynman's prescription for the path integral \& has special Hamiltonian structure [2]
- Inserting the definitions leads to the "Koopman-van Hove" equation [1-3]

$$
\left.i \hbar \partial_{t} \psi\right|_{z}=-i \hbar(V \cdot \nabla \psi+\nabla \cdot V \psi) / 2-L \psi
$$

$$
\left.i \hbar \partial_{t} \psi\right|_{z_{0}}=+i \hbar(V \cdot \nabla \psi+\nabla \cdot V \psi)+L \psi
$$

## Quantum algorithms for differential equations come in many flavors

## - Linear vs. Nonlinear

- For sparse Hamiltonians, quantum computers can exponentially speed up linear operations
- Koopman \& Carleman: Nonlinear systems can be embedded within an infinite-dimensional linear system


## - Deterministic vs. Stochastic

- Amplitude estimation can quadratically speed up Monte Carlo sums and integrals = observable estimation
- Quantum walks can quadratically speed up the mixing time of Markov chains = time to solution


## - Variational Algorithms and Quantum Machine Learning

- Classical computer can efficiently perform nonlinear operations that drive a quantum computer
- Quantum machine learning can potentially avoid the use of classical computers altogether except for I/O
- Discrete vs. Continuous Variable computation for classical PDEs \& quantum field theory
- Uses a quantum field theory as the computational basis
- Classical limit is a classical field theory, i.e. a set of PDEs such as Maxwell's equations


## Speedup requires exploiting special structure and/or sparsity

- Trotter-Suzuki \& Lie group decompositions [1] work well for specific Hamiltonians

$$
e^{n(A+B)} \approx \prod_{j=1}^{n} e^{B / 2} e^{A} e^{B / 2}=e^{-B / 2}\left(\prod_{j=1}^{n} e^{B} e^{A}\right) e^{B / 2}
$$

- Black box simulation methods work well for sparse Hamiltonians
- "Efficiently row-computable sparse" matrices
- Linear Combination of Unitaries (LCU) [2]; spectral methods [3]
- Quantum signal processing (QSP) \& qubitization [4], eigenvalue \& singular value transformation [5] use block-encoded Hamiltonians - Block encoding allows non-unitary operations to be performed!

I. Novikau, E. Startsev, I. Dodin Phys. Rev. A 105, 062444 (2022)


## Sparse linear evolution can be solved using black-box methods

Choose a basis for finite-dimensional numerical discretization

- Possible choices of basis functions $\phi_{n}(z)$
- Spectral [1,2] $e^{i n z}$, orthogonal polynomials $H_{n}(z)$, etc., ...
- Finite difference \& finite element: local orthogonal polynomials
- Carleman linearization [3,4]: polynomials $z^{k}$
- Reproducing Kernel Hilbert Spaces [2]: allow pointwise evaluation

$$
\begin{aligned}
& \psi(z, t)=\sum_{n} \psi_{n}(t) \phi_{n}(z) \\
& i \hbar \frac{d}{d t} \psi_{n}=\sum_{m} H_{n m} \psi_{m}
\end{aligned}
$$

- If the evolution is unitary, use the quantum Hamiltonian simulation algorithm (QHSA) [1,2]

$$
\psi(t)=\mathbf{U}_{\text {approx }} \psi(0) \approx \mathrm{T} e^{-i \int \mathbf{H} d t / \hbar} \psi(0)
$$

- Otherwise, use the quantum linear differential equation solver algorithm (QLDA) [3,4]
- Uses quantum linear solver algorithm (QLSA) to propagate forward for small timesteps $\Delta t$

$$
1=\alpha+\beta \quad(1+i \alpha \mathbf{H} \Delta t / \hbar) \psi(t+\Delta t) \approx(1-i \beta \mathbf{H} \Delta t / \hbar) \psi(t)
$$

semi-implicit time splitting
[1] I. Joseph, Phys. Rev. Research 2, 043102 (2020)
[2] D. Giannakis, A. Ourmazzi, P. Pfeffer, et al., arXiv:2012.06097 (2022)
[3] Jin-Peng Liu, H. $\emptyset$. Kolden, H.K. Krovi, et al., PNAS 118, e2026805118 (2021)
[4] A. Engel, G. Smith, S. P. Parker, Phys. Plasmas 28, 062305 (2021)

## Quantum walks yield up to quadratic speedup for solving stochastic differential equations (SDEs)

- Quantum walks can speedup random walks [1] and Hamiltonian simulation [2]
- Quadratic speedup of the mixing time of Markov processes [1]
- Quantum algorithms for sums and integrals [3] are based on quantum walks \& accelerate the solution of SDEs [4] and Monte Carlo algorithms [5]
- Algorithm for turbulent mixing rate and turbulent reaction rate [6]
- Algorithm for diffusion, Navier-Stokes [7], and radiation-hydrodynamics
- Also leads to new methods for solving multi-level SDEs [8]
- Algorithms for finance, Monte-Carlo collision operators, ...

[1] M. Szegedy, FOCS 2004 [2] A. Childs, Comm. Math. Phys. 2010
[3] S. Heinrich \& E. Novaks, 2001 [4] B. Kacewicz, J. Complexity 2004 [5] A. Montanaro, PRSA 2015
LLNL- PRES-857541
[6] F. Gaitan, Nature Phys. 2021 [7] G. Xu, et al AIAA J. 2018 [7] D. An, et al, Quantum 2021


## Approach \#3: Hybrid classical-quantum variational algorithms

- Let a classical computer do the nonlinear work ...
- The classical computer iteratively solves a nonlinear optimization problem using standard techniques
The parameters to be optimized are encoded within the quantum program that will be run by the quantum computer
- At each step, the quantum computer evaluates a computationally challenging cost function
e.g. based on a Hamiltonian with many degrees of freedom



## Approach \#3: Hybrid classical-quantum variational algorithms

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e.g. based on a Hamiltonian with many degrees of freedom
- Complete data exchange generically only admits up to quadratic speedup
- Perhaps a high-order linear quantum model interacting with a low-order nonlinear classical reduced model can obtain exponential improvement [2]?


## Variational algorithms have a few key steps ...

- For each time step, iterate until convergence [1]:
- Prepare initial ansatz
- Solve equations using Hamiltonian simulation
- Measure cost function and, potentially, gradients of the cost function
- Execute step of classical optimization algorithm
- Update ansatz



## Variational algorithms have a few key steps ... and a few key limitations

- For each time step, iterate until convergence [1]:
- Prepare initial ansatz
- Solve equations using Hamiltonian simulation
- Measure cost function and, potentially, gradients of the cost function
- Execute step of classical optimization algorithm
- Update ansatz
- Optimization landscape may have intrinsic difficulties such as ...
- Many local maxima and minima
- Barren plateaus with little information on the gradient of the cost function

NASA Earth Observatory:
Himalayas


- NP-complete optimization problems may not have any quantum advantage at all [2]


## PDEs are naturally encoded in the Continuous Variable (CV) model of quantum computing

- Digital quantum computers are actually made out of quantum fields
- Photons, electrons, ions, atoms, ...
- Quantum field theory (QFT) is the quantum counterpart of classical field theory (PDEs)
- In the large number limit, quantum fields approach a classical field
- The Continuous Variable (CV) model of quantum computation uses quantum fields directly
- The CV model has similarities with the analog model of classical computation
- Average position and phase are CV
- The CV model allows one to emulate PDEs and QFTs with basic QFTs: Dirac, Photon, ...
- Similar to a "Wind Tunnel" or "Optics Experiment": works well for the task at hand, but not likely one can control everything perfectly


## Amplitude estimation of physical observables ${ }^{1-3}$ is up to quadratically more

 efficient than best classical methods- Expectation value $\langle\mathcal{O}\rangle=\sum_{x} \mathcal{O}(x) f(x)$ can be found by simulating a reversible classical computation of

$$
\phi(x):=\mathcal{O}^{1 / 2}(x) \psi(x) \quad \phi^{\prime}(x):=\sqrt{1-|\phi(x)|^{2}} \quad|\phi\rangle:=\sum_{x} \phi(x)|x\rangle /\|\phi\|
$$

- Add an ancillary qubit to $|\psi\rangle$ and compute a state proportional to $|\phi\rangle$

$$
\mathcal{R}_{\phi}|\psi\rangle|0\rangle:=\sum_{x=1}^{N}|x\rangle\left(\phi^{\prime}(x)|0\rangle+\phi(x)|1\rangle\right) / N^{1 / 2}=\cos (\theta)\left|\phi^{\prime}\right\rangle|0\rangle+\sin (\theta)|\phi\rangle|1\rangle
$$

- Amplitude estimation of the ancillary $|1\rangle$ state probability yields $\sin ^{2}(\theta)=\langle\mathcal{O}\rangle / N$ with complexity $\sim Q_{H} / \epsilon$

[^0]
## Motivation: Can we simulate chaotic dynamics on near-term universal quantum devices?

- Interesting quantum simulations usually contain chaotic regions

$$
\mathrm{n}_{\text {qubits }}=6
$$

- Quantum chaotic simulations are important for many body localization, black hole information scrambling, classical chaos, ...
- Efficient detection of quantum chaos can come from quantumclassical correspondence
- Quantum systems recover classical limit at small $\hbar$, but require many qubits
- Quantum fidelity decay of perturbed Hamiltonian evolution can reveal classically chaotic or regular dynamics ${ }^{1,2}$
- For chaotic dynamics, quantum fidelity can decay at the rate of the Lyapunov exponent $\lambda$, which measures the exponential divergence of classical trajectories ${ }^{3}$
- Quantum maps allow efficient simulation of chaotic dynamics ${ }^{4}$
- A quantum map decaying at the Lyapunov rate may be the most resourceefficient signature of quantum chaos

To date, we've used superconducting hardware platforms \& are starting to use ion traps

## - IBM-Quantum Experience

- Open but limited access to 5 qubit devices with relatively good fidelity

IBM-Q Eagle 127 qubits

Rigetti 20 qubit device (Aspen-M series have ~80 qubits)


- Sandia QSCOUT ion trap

Peregrine 6 qubits


LLNL
Quantum Design \& Integration Testbed (QuDIT) $\sim 6$ qubits

## Lack of error-correction limits fidelity of present-day calculations

. "Fidelity" is the figure of merit: $F=\left|\left\langle\psi_{\text {expected }} \mid \psi_{\text {actual }}\right\rangle\right|^{2}$

- Single qubit gate fidelity (IBM-Q):
- Two qubit gate fidelity (IBM-Q):
- State preparation \& measurement (SPAM):
99.9\% --> 700 useful operations before 50\%
99.5\% --> 140 useful operations before 50\%

95\% --> error at beginning and end


- Fidelity does not always decay at an exponential rate
- Coherent gate errors are important and need to be corrected for
- Coherent errors can be much more damaging to intended calculations


## Grover's search algorithm can be modified to directly work on LLNL's 3-level QuDIT




- Search on 3 items has a $92.6 \%$ success probability on the first iteration
- Compare to 2-qubits: search on 4 items has $100 \%$ success on $1^{\text {st }}$ iteration



## The performance of Grover's search can be improved using optimal control [1]



Expt. fidelity after 11 iterations


- Tests on IBM-Q, Rigetti, and LLNL QuDIT demonstrate reasonably good performance for 1-11 iterations
- Optimal control effectively improves hardware performance


## The phase transition between diffusive and localized dynamics is clearly observable on IBM-Q




## What about Generalized Eigenvalue Problems (GEVP)?

- Generalized Eigenvalue Problem: $\mathbf{A} v=\lambda \mathbf{B} v$
- Assume $\mathbf{A}$ is Hermitian and sparse
- Assume B is symmetric positive definite (SPD)
- Any SPD matrix, $\mathbf{B}$, has a unique SPD square root $\mathbf{B}^{1 / 2}$
- The problem can be reduced to standard Hermitian form using the transformation

$$
u=\mathbf{B}^{1 / 2} v \quad \mathbf{H}=\mathbf{B}^{-1 / 2} \mathbf{A} \mathbf{B}^{-1 / 2} \quad \square \quad \mathbf{H} u=\lambda u
$$

- In general, H will not be sparse and, hence, QPE will not be efficient, unless ...
- For special B, e.g. diagonal or block diagonal, then both $\mathbf{B}^{-1 / 2}$ and $\mathbf{H}$ are also sparse


## FES Application: MHD plasma stability is a GEVP

- Linear Ideal MHD is routinely used for plasma stability calculations of magnetic confinement fusion experiments and reactor designs

$$
\mathbf{F} \cdot \boldsymbol{\xi}=-\omega^{2} \rho \boldsymbol{\xi}
$$

- Fundamental Theorem of MHD: Force operator, $\mathbf{F}(\mathbf{x})$, is a self-adjoint 2 nd order differential operator [I. B. Bernstein et al. (1958)]
- Numerical approximations such as finite differences, finite volume, and finite elements in the position, $\boldsymbol{x}$, basis typically lead to a sparse banded matrix for $\mathbf{F}$ and block-diagonal $\boldsymbol{\rho}$
Hermitian form:

$$
\boldsymbol{u}=\rho^{1 / 2} \boldsymbol{\xi}
$$

$$
\mathbf{H}=\rho^{-1 / 2} \mathbf{F} \rho^{-1 / 2}
$$

$$
\mathbf{H} \cdot \boldsymbol{u}=-\omega^{2} \boldsymbol{u}
$$

## Quantum phase estimation can be applied to ideal MHD stability

Is this a route to fast stability calculations for design optimization or feedback control?
mpled, or assumes any legal iiabiity or responsibiitty for the accuracy, completeness, or usefuiness of any information, apparatus, commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or mply its endorsement, recommendation, or favoring by the United States government or Lawrence Livermore National Security, LLC. he views and opinions of authors expressed herein do not necessarily state or reflect those of the United States government or Lawrence Livermore National Security, LLC, and shall not be used for advertising or product endorsement purposes.


[^0]:    ${ }^{1}$ D. S. Abrams and C. P. Williams, arXiv:quant-ph/9908083 (1999)
    ${ }^{2}$ S. Heinrich and H. Novak, Proc. 4th Int. Conf. on Monte Carlo and Quasi-Monte Carlo Methods, Hong Kong 2000, Springer-Verlag (2002)
    ${ }^{3}$ A. Montanaro, Proc. R. Soc. London, Ser. A 471, 20150301 (2015)

