# The Heisenberg limit and early fault-tolerant quantum algorithms 

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- The basic problem: the ground state energy (lowest eigenvalue of $H$ ).

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## Practical quantum advantage in quantum chemistry

- Can we solve a practically useful problem on a quantum computer faster than on a classical computer?
- Quantum chemistry may be the right place to look.
- The basic problem: the ground state energy (lowest eigenvalue of $H$ ).
- Compare with classical algorithms: need very high accuracy.
- Density functional theory can get to precision of 2-3 kcal•mol ${ }^{-1}$. ${ }^{1}$
- Chemical accuracy: $1 \mathrm{kcal} \cdot \mathrm{mol}^{-1}$.
- We should care very much about how the cost of the quantum algorithm scales with precision.

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- Classical computer: $\lambda=\langle\Psi| H|\Psi\rangle$ (one matrix-vector multiplication, one inner product, machine precision).
- Quantum computer: measure each Pauli operator, obtain $0 / 1$ outputs, take average to get $\langle\Psi| P_{i}|\Psi\rangle$, then add up all Pauli terms.
- Example: to measure $X \otimes X$, we can apply $\mathrm{Had} \otimes \mathrm{Had}$ to the quantum state, so that we can now measure in the computational basis $(Z \otimes Z)$ :

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- Taking average over $N_{s}$ samples, the variance is $\mathcal{O}\left(1 / N_{s}\right)$.
- We need to do this for all terms. Can measure some of them simultaneously (e.g. for $X \otimes X$ and $Z \otimes Z$ because they commute), but this creates correlated error.
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- Quantum phase estimation can do the same by evolving with $H$ for $\mathcal{O}\left(\epsilon^{-1}\right)$ time (Heisenberg limit), with a single copy of $|\Psi\rangle$.


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## Algorithms for different development stages of QC



- NISQ: variational algorithms (VQE, QAOA) $\left(\epsilon^{-2}\right)$
- Early fault-tolerant quantum algorithms
- Need to optimize the total runtime, circuit depth, and number of qubits.
- Fully fault-tolerant quantum algorithms $\left(\epsilon^{-1}\right)$
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## The Heisenberg limit

- The quantum version of parameter estimation: estimate $\theta$ from parameterized quantum state $\rho(\theta),\left\|\frac{\mathrm{d} \rho}{\mathrm{d} \theta}\right\|_{1} \leq 1$ (here $\|\cdot\|_{1}$ is the trace norm).


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- Beyond-SQL example: estimate eigenvalue to precision $\epsilon$ using QPE with exact eigenstate requires runtime $\mathcal{O}\left(\epsilon^{-1}\right)$.
- Information theoretic lower bound: this requires $\Omega\left(\epsilon^{-1}\right)$ total evolution time (how long we evolve with $H$ ). This is the Heisenberg limit.


## Notations

- We have a target Hamiltonian $H$ (Hermitian matrix of size $2^{N} \times 2^{N}, N$ is the number of qubits).


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- $|\Phi\rangle$ is an initial guess for the ground state.
- We can apply control $-e^{-i \tau H}$, where $\tau$ is a rescaling factor.

We will use the following asymptotic notations:

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- $f(x)=\widetilde{\Omega}(g(x))$ if $f(x)=\Omega(g(x) / \operatorname{polylog}(g(x)))$.


## Single-qubit quantum phase estimation



Figure: The Hadamard test circuit: from the measurement outcome $\hat{m}$ we can compute the expectation value $\langle\Phi| e^{-i t H}|\Phi\rangle$. Real and imaginary parts are computed separately (corresponding to Had and $\operatorname{Had} S^{\dagger}$ respectively).

- For the real part, before measurement the quantum state undergoes the transformation

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- We then measure the first qubit to get $\hat{m} \in\{0,1\}$. The expectation value of $(-1)^{\hat{m}}$ is

$$
\mathbb{E}\left[(-1)^{\hat{m}}\right]=\frac{1}{4}\left(\||\Phi\rangle+e^{-i t H}|\Phi\rangle\left\|^{2}-\right\||\Phi\rangle-e^{-i t H}|\Phi\rangle \|^{2}\right)=\operatorname{Re}\langle\Phi| e^{-i t H}|\Phi\rangle
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- For any $t$, we estimate $\langle\Phi| e^{-i t H}|\Phi\rangle$ by

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- Obtain eigenvalues of $H$ by processing the signal and getting the target frequency.


## Single frequency estimation

- We have seen that the Hadamard test circuit can be used to compute

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- The simplest case: if $|\Phi\rangle=\left|\Psi_{0}\right\rangle$, then we can use this to get the ground state energy $\lambda_{0}$.

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S(t)=e^{-i \lambda_{0} t}+e(t)
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We want to estimate $\lambda_{0} \in(-1,1]$ (rescaling the Hamiltonian properly) to precision $\epsilon$.

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- Suppose our samples are $S\left(t_{1}\right), S\left(t_{2}\right), \cdots, S\left(t_{N_{s}}\right)$, then the total evolution time is $t_{1}+t_{2}+\cdots+t_{N_{s}}$.

[^7]Suppose we know $a \leq-\lambda_{0} \leq b$. We want to determine

1. $a \leq-\lambda_{0} \leq \frac{a+2 b}{3}$,
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If we can do that then we can reduce the uncertainty by $1 / 3$ at each step. $\mathcal{O}\left(\log \left(\epsilon^{-1}\right)\right)$ steps are needed for $\epsilon$ precision.

We look at the value of

$$
f_{a, b}\left(-\lambda_{0}\right)=\sin \left(\frac{\pi}{b-a}\left(-\lambda_{0}-\frac{a+b}{2}\right)\right)=\operatorname{Im}\left\langle S\left(t^{*}\right)\right\rangle e^{-i \frac{(a+b) \pi}{2(b-a)}},
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- Evaluating $f_{a, b}\left(-\lambda_{0}\right)$ to precision $\frac{1}{2}$ is enough.
- Can get confidence level $1-\delta^{\prime}$ with $\mathcal{O}\left(\log \left(\delta^{\prime-1}\right)\right)$ samples.
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\mathcal{O}\left(\epsilon^{-1} \log \left(\delta^{\prime-1}\right)\right) \times\left(1+\frac{2}{3}+\left(\frac{2}{3}\right)^{2}+\cdots\right)=\mathcal{O}\left(\epsilon^{-1} \log \left(\delta^{\prime-1}\right)\right)
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This achieves the Heisenberg-limited scaling.

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- Need $\delta^{\prime}=\mathcal{O}\left(\delta / \log \left(\epsilon^{-1}\right)\right)$ to ensure that all steps are successful with probability $1-\delta$.
- Total evolution time is $\mathcal{O}\left(\epsilon^{-1} \log \left(\delta^{-1}\right)\right)$ and the number of samples is $\mathcal{O}\left(\log \left(\epsilon^{-1}\right)\right)$.
- Robust to noise ( $|e(t)| \leq 1 / 2$ w.p. $2 / 3)$.


## Summary: single qubit phase estimation

- A high-level statement: We can use the Hadamard test circuit to estimate the eigenvalue given the corresponding eigenstate with Heisenberg-limited scaling. It is also robust to constant amount of noise.


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- A high-level statement: We can use the Hadamard test circuit to estimate the eigenvalue given the corresponding eigenstate with Heisenberg-limited scaling. It is also robust to constant amount of noise.
- A precise statement: we can do the above with $\mathcal{O}\left(\epsilon^{-1} \log \left(\delta^{-1}\right)\right)$ total evolution time to get confidence level $1-\delta$. We will still get correct estimate when $|e(t)| \leq 1 / 2$ w.p. $2 / 3$.


## Quantum phase estimation



Figure: The quantum phase estimation circuit. Two registers: energy register ( $r$ qubits) and state register ( $N$ qubits). Measuring the energy register yields a bit string $\hat{m}$, which we convert to an energy measurement $\tau \hat{\lambda}=2 \pi \hat{m} / 2^{r}$.

- Initial state is $|00 \cdots 0\rangle|\Phi\rangle$.
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- Apply Hadamard gates:

$$
|++\cdots+\rangle|\Phi\rangle=\frac{1}{\sqrt{2^{r}}} \sum_{j=0}^{2^{r}-1}|j\rangle|\Phi\rangle
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$$

- Controlled time evolution:

$$
\frac{1}{\sqrt{2^{r}}} \sum_{j=0}^{2^{r}-1}|j\rangle|\Phi\rangle \mapsto \frac{1}{\sqrt{2^{r}}} \sum_{j=0}^{2^{r}-1}|j\rangle e^{-i j \tau H}|\Phi\rangle
$$

- Eigenbasis expansion: let $|\Phi\rangle=\sum_{k} c_{k}\left|\Psi_{k}\right\rangle$

$$
\frac{1}{\sqrt{2^{r}}} \sum_{j=0}^{r-1}|j\rangle e^{-i j \tau H}|\Phi\rangle=\sum_{k} c_{k} \frac{1}{\sqrt{2^{r}}} \sum_{j=0}^{r-1}|j\rangle e^{-i j \tau \lambda_{k}}\left|\Psi_{k}\right\rangle
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$$

- Inverse QFT: $|j\rangle \mapsto \frac{1}{\sqrt{2^{r}}} \sum_{m=0}^{2^{r}-1} e^{i 2 \pi j m / 2^{r}}|m\rangle$.

$$
\sum_{k} c_{k} \sum_{m=0}^{2^{r}-1}|m\rangle \underbrace{\frac{1}{2^{r}} \sum_{j=0}^{2^{r}-1} e^{i 2 \pi j m / 2^{r}-i j \tau \lambda_{k}}}_{\Gamma\left(2 \pi m / 2^{r}-\tau \lambda_{k}\right)}\left|\Psi_{k}\right\rangle
$$

- The reason why QPE works: $\Gamma(\theta)$ approximates the Dirac delta function.

$$
\begin{aligned}
& \sum_{k} c_{k} \sum_{m=0}^{2^{r}-1}|m\rangle \Gamma\left(2 \pi m / 2^{r}-\tau \lambda_{k}\right)\left|\Psi_{k}\right\rangle \\
& \approx \sum_{k} c_{k} \sum_{m=0}^{2^{r}-1}|m\rangle \delta\left(2 \pi m / 2^{r}-\tau \lambda_{k}\right)\left|\Psi_{k}\right\rangle \\
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- From the energy register we can directly read off $\frac{2^{r} \tau \lambda_{k}}{2 \pi}$ (binary representation of rescaled $\lambda_{k}$ ).
- This is the idealized version of QPE. Next we will see what actually happens.
- The kernel function (resembling the Dirac delta function)

$$
\Gamma(\theta)=\frac{1}{2^{r}} \sum_{j=0}^{r-1} e^{i j \theta}=\frac{1}{2^{r}} \frac{1-e^{i 2^{r} \theta}}{1-e^{i \theta}}
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$$

- Measuring the energy register $|m\rangle$ yields $m$ with probability

$$
\operatorname{Pr}[\hat{m}=m]=\sum_{k}\left|c_{k}\right|^{2}\left|\Gamma\left(2 \pi m / 2^{r}-\tau \lambda_{k}\right)\right|^{2}
$$

- Suppose we are given a hidden random variable $\hat{k}$, with

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\operatorname{Pr}[\hat{k}=k]=\left|c_{k}\right|^{2}
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- Need to show that $\operatorname{Pr}[\hat{m}=m \mid \hat{k}=k]$ is concentrated around $\frac{2^{r} \tau \lambda_{k}}{2 \pi}$.


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Figure: $|\Gamma(\Delta \theta)|^{2}$ for $\Delta \theta \in[-\pi, \pi]$. The kernel is $2 \pi$-periodic.

- Define the energy measurement $\tau \hat{\lambda}=2 \pi \hat{m} / 2^{r}$ which we get from running the QPE circuit.
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- Define distance on torus $|x|_{a}=\min _{k \in \mathbb{Z}}|x-k a|$.
- The concentration of the kernel $\Gamma(\Delta \theta)$ guarantees that

$$
\operatorname{Pr}\left[\left|\tau \hat{\lambda}-\tau \lambda_{k}\right|_{2 \pi} \geq \epsilon \mid \hat{k}=k\right] \leq \mathcal{O}\left(\frac{1}{2^{r} \epsilon}\right)
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## An operational understanding of QPE

- We first sample $\hat{k}=k$ w.p. $\left|c_{k}\right|^{2}$ (remember $|\Phi\rangle=\sum_{k} c_{k}\left|\Psi_{k}\right\rangle$ ).


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- In this sense we are sampling from the spectrum of $\tau H$, and each sample is close to an (rescaled) eigenvalue with large probability (exact in the limit of $r \rightarrow \infty$ ).
- The rescaled eigenvalues are determined modulo $2 \pi$. We need to choose $\tau$ appropriately to get $\lambda_{k}$.


## Proof of the concentration inequality

- Want to prove $\operatorname{Pr}\left[\left|\tau \hat{\lambda}-\tau \lambda_{k}\right|_{2 \pi} \geq \epsilon \mid \hat{k}=k\right] \leq \mathcal{O}\left(\frac{1}{2^{r} \epsilon}\right)$.


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- The probability of deviation larger than $\epsilon=2 \pi \ell / 2^{r}$

$$
\begin{aligned}
& \operatorname{Pr}\left[\left.\left|\frac{2 \pi \hat{m}}{2^{r}}-\tau \lambda_{k}\right|_{2 \pi} \geq \frac{2 \pi \ell}{2^{r}} \right\rvert\, \hat{k}=k\right] \\
& =\sum_{m: \left\lvert\, \begin{array}{c}
m-\left.\frac{2^{r} \tau \lambda_{k}}{2 \pi}\right|_{2^{r}} \\
0 \leq m \leq 2^{r}-1
\end{array}\right.} \frac{1}{4^{r}} \frac{\sin ^{2}\left(2^{r-1}\left(2 \pi m / 2^{r}-\tau \lambda_{k}\right)\right)}{\sin ^{2}\left(\left(2 \pi m / 2^{r}-\tau \lambda_{k}\right) / 2\right)}
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0 \leq m \leq 2^{r}-1\right.}} \frac{1}{2_{2} \geq \ell}<\frac{1}{4\left|m-2^{r-1} \tau \lambda_{k} / \pi\right|_{2^{r}}^{2}}
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$$
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\leq 2 \times \frac{1}{4} \sum_{n=\ell}^{\infty} \frac{1}{n^{2}}
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& \leq m-2^{r-1} \tau \lambda_{k} /\left.\pi\right|_{2^{r}} ^{2}
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$$

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[^10]Summary: quantum phase estimation (textbook version) ${ }^{3}$

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- Runtime of the algorithm: apply control- $e^{-i \tau H} 2^{r}$ times. $2^{r}=\mathcal{O}\left(\epsilon^{-1}\right)$ for constant success probability.

[^11]
## Use QPE for ground state energy

- Recall that the ground state energy is $\lambda_{0}$, the lowest eigenvalue of $H$.


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- We need to ensure that the energy we get correspond to the ground state rather than excited states (ensure $\hat{k}=0$ ): generate $\mathcal{O}\left(1 /\left|c_{0}\right|^{2}\right)$ samples for $\hat{\lambda}$ and take the minimum.


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- Make sure in all of these samples the energy estimate is close to some eigenvalue. This happens with probability

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- We therefore need $\epsilon 2^{r}=\Omega\left(1 /\left|c_{0}\right|^{2}\right)$.
- Total cost (number of times to apply control- $-e^{-i \tau H}$ ) for getting the ground state energy is

$$
\underbrace{\frac{1}{\left|c_{0}\right|^{2}}}_{\# \text { runs }} \times \underbrace{\mathcal{O}\left(\frac{1}{\epsilon\left|c_{0}\right|^{2}}\right)}_{\text {cost of single run }}=\mathcal{O}\left(\frac{1}{\epsilon\left|c_{0}\right|^{4}}\right) .
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- We do not need to know $c_{0}$, but assume $\left|c_{0}\right|^{2} \geq \eta$. Then the total cost is $\mathcal{O}\left(\epsilon^{-1} \eta^{-2}\right)$ (Heisenberg-limited scaling).
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- $2^{r}=\mathcal{O}\left(\epsilon^{-1} \eta^{-1}\right)$ is how deep the circuit is in each run. This is called the the circuit depth. $r=\mathcal{O}\left(\log \left(\epsilon^{-1} \eta^{-1}\right)\right)$ is the number of ancilla qubits.
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- Both achieve the Heisenberg-limited scaling.
- Coming up next: can we have all the good features?


## The spectral density

- The Hamiltonian $H$ has eigenvalues $\lambda_{0}, \lambda_{1}, \cdots$. For simplicity we assume $\operatorname{spec}(H) \subset(-\pi / 4, \pi / 4)$.


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\mu(x)=\sum_{k} p_{k} \delta\left(x-\lambda_{k}\right)
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- If $X \sim \mu(x)$ then $X=\lambda_{k}$ w.p. $p_{k}$. Note that $\sum_{k} p_{k}=1$.


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where $p_{k}=\left|\left\langle\Psi_{k} \mid \Phi\right\rangle\right|^{2}$ and $\delta(\cdot)$ is the Dirac delta function.

- If $X \sim \mu(x)$ then $X=\lambda_{k}$ w.p. $p_{k}$. Note that $\sum_{k} p_{k}=1$.
- This distribution contains all the information about the spectrum.


Figure: The Hadamard test circuit.


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- The Hadamard test circuit outputs the expectation value

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\begin{aligned}
\langle\Phi| e^{-i t H}|\Phi\rangle & =\sum_{k} p_{k} e^{-i t \lambda_{k}} \\
& =\int_{-\pi}^{\pi} e^{-i t x} \mu(x) \mathrm{d} x
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- This is the Fourier transform (either on $\mathbb{R}$ or on the torus) of the distribution $\mu(x)$.
- We can try recovering the spectrum density $\mu(x)$ through inverse Fourier transform. If we can then we will have the ground state energy.
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- Problem: we can only run the Hadamard test for a finite number of times, and the cost grow with $t$.
- $\mu(x)$ is a linear combination of Dirac delta functions. The Fourier coefficients do not decay.
- We can instead compute a smeared spectral density:

$$
\widetilde{\mu}(x)=\mu * M(x)=\int \mu(y) M(x-y) \mathrm{d} y
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where $M(\cdot)$ is a kernel (mollifier).

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- We want the kernel $M(x)$ to be $2 \pi$-periodic finite-degree trigonometric polynomial (the cost depend on the degree), and integrates to 1 .

An example of such a kernel ${ }^{a}$

$$
M(x)=\frac{1}{\mathcal{N}_{d, \delta}} T_{d}\left(1+2 \frac{\cos (x)-\cos (\delta)}{1+\cos (\delta)}\right)
$$

where $T_{d}$ is the $d$ th Chebyshev polynomial of the first kind, and
$\mathcal{N}_{d, \delta}=\int_{-\pi}^{\pi} T_{d}\left(1+2 \frac{\cos (x)-\cos (\delta)}{1+\cos (\delta)}\right) \mathrm{d} x$.

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[^13]

Figure: The kernel function $M(x)$. The degree is $\mathcal{O}\left(\delta^{-1} \log \left(\epsilon^{-1}\right)\right)$.

- The quantum eigenvalue estimation problem (QEEP) ${ }^{a}$
- With $\left|\left\langle\Phi \mid \Psi_{0}\right\rangle\right|^{2} \geq \eta$ and to estimate ground state energy to precision $\epsilon$ : total runtime $\mathcal{O}\left(\epsilon^{-4} \eta^{-2}\right)$, circuit depth $\mathcal{O}\left(\epsilon^{-1}\right)$, single ancilla, imperfect initial guess.
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- Number of terms in the Fourier expansion $\mathcal{O}\left(\epsilon^{-1}\right)$.
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Other relevant works:

- O'Brien et al., 2020, Error mitigation via verified phase estimation.
- Lu et al., 2020, Algorithms for Quantum Simulation at Finite Energies.
- Russo et al., 2020, Evaluating energy differences on a quantum computer with robust phase estimation.

[^16]
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- Some degree of noise-robustness.
- Early fault-tolerant quantum algorithms are the ones that take the above factors into account.

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- We should not evaluate each term and sum them up: $\mathcal{O}\left(\epsilon^{-1}\right)$ terms and $\mathcal{O}\left(\epsilon^{-1}\right)$ average time makes the cost at least $\mathcal{O}\left(\epsilon^{-2}\right)$.
- Not all terms are equally important.


## The cumulative distribution function

- Define the cumulative distribution function (CDF):

$$
C(x)=\int_{-\pi}^{x} \mu(y) \mathrm{d} y=\sum_{k} p_{k} H\left(x-\lambda_{k}\right)=(H * \mu)(x)
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- $C(x)$ is a monotonously increasing function. We can therefore find the first jump by binary search.
- $C(x)$ can be approximated using Hadamard-test data.


Figure: Evaluating the CDF by sampling from the quantum circuit. Note that we do not need to re-sample for each point.


Figure: Zoom-in around the ground state energy

## The approximate CDF

- We can approximate $C(x)$ with a smooth function

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which guarantees that we can find the first jump within error $\delta$.

- We can evaluate $\widetilde{C}(x)$ through its Fourier transform

$$
\hat{\widetilde{C}}_{k}=\hat{M}_{k} \hat{H}_{k} \hat{\mu}_{k}
$$

$k=-d,-d+1, \cdots, d$, where $\hat{M}_{k}$ and $\hat{H}_{k}$ are known and $\hat{\mu}_{k}$ is computed from the Hadamard test.

## Importance sampling

- If we want to evaluate $\widetilde{C}(x)$, then we need

$$
\widetilde{C}(x)=\frac{1}{2 \pi} \sum_{k=-d}^{d} \hat{\widetilde{C}}_{k} e^{i k x}=\frac{1}{2 \pi} \sum_{k=-d}^{d} \hat{M}_{k} \hat{H}_{k} \hat{\mu}_{k} e^{i k x}
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- If we compute each $\hat{\mu}_{k}(k=-d,-d+1, \cdots, d)$ individually, then each will require evolution time $\mathcal{O}(|k|)$, which means the total evolution time is at least $\mathcal{O}\left(d^{2}\right)=\mathcal{O}\left(\epsilon_{\mathrm{gs}}^{-2}\right)$. Impossible to achieve the Heisenberg limit.


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- Notice that

$$
\sum_{k=-d}^{d}\left|\hat{M}_{k} \hat{H}_{k}\right| \leq 2 \pi \sum_{k=-d}^{d}\left|\hat{H}_{k}\right| \leq \sum_{k=-d}^{d} \frac{C}{1+|k|}=\mathcal{O}(\log (d))
$$

Many terms are unimportant. We can use importance sampling.

- Sample random variable $K$ with distribution

$$
K=k \text { w.p. } \frac{\left|\hat{M}_{k} \hat{H}_{k}\right|}{\sum_{k^{\prime}=-d}^{d}\left|\hat{M}_{k^{\prime}} \hat{H}_{k^{\prime}}\right|} .
$$

Then

$$
\widetilde{C}(x)=\left(\sum_{k^{\prime}=-d}^{d}\left|\hat{M}_{k^{\prime}} \hat{H}_{k^{\prime}}\right|\right) \mathbb{E}\left[e^{i \theta_{K}} \hat{\mu}_{K}\right] .
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$$

- We can therefore randomly sample $K=k_{1}, k_{2}, \cdots, k_{\mathrm{N}_{\mathrm{s}}}$, compute $e^{i \theta_{k_{l}}} \hat{\mu}_{k_{l}}$, take average, and then multiply by $\sum_{k^{\prime}=-d}^{d}\left|\hat{M}_{k^{\prime}} \hat{H}_{k^{\prime}}\right|$.
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- The variance is

$$
\frac{\mathcal{O}\left(\log (d)^{2}\right)}{N_{s}}
$$

- Locating the first jump only requires precision $\eta$ (lower bound of the initial overlap $\left|\left\langle\Psi_{0} \mid \Phi\right\rangle\right|^{2}$ ). Therefore we need

$$
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- If we want to compute the ground-state energy to precision $\epsilon_{\mathrm{gs}}$, we need $d \sim \epsilon_{\mathrm{gs}}^{-1}$. Then the total evolution time is

$$
\mathcal{O}(d) \times N_{s}=\mathcal{O}\left(\epsilon_{\mathrm{gs}}^{-1} \eta^{-2}\right)
$$

## Comparison with other ground-state energy algorithms:

|  | Runtime | Circ. depth | Ancilla qubits |
| :---: | :---: | :---: | :---: |
| QPE | $\epsilon^{-1} \eta^{-2}$ | $\epsilon^{-1} \eta^{-1}$ | $\log \left(\epsilon^{-1} \eta^{-1}\right)$ |
| Modified QPE |  |  |  |
| Binary search | $\epsilon^{-1} \eta^{-1}$ | $\epsilon^{-1} \eta^{-1 / 2}$ | $\epsilon^{-1}$ |
| QEEP | $\epsilon^{-1}$ | $\log \left(\epsilon^{-1}\right)$ |  |
| CDF-based $^{7}$ | $\epsilon^{-1} \eta^{-2}$ | $\epsilon^{-1}$ | $\epsilon^{-1}$ |

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| QEEP | $\epsilon^{-4} \eta^{-2}$ | $\epsilon^{-1}$ | $\log \left(\epsilon^{-1}\right)$ |
| CDF-based $^{7}$ | $\epsilon^{-1} \eta^{-2}$ | $\epsilon^{-1}$ | 1 |

This algorithm achieves Heisenberg-limit scaling, uses single ancilla qubit, and can use imperfect initial guess.

[^18]
## Extensions

- Computing ground state observable expectation values using a modified circuit. ${ }^{8}$

[^19]
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- Computing ground state observable expectation values using a modified circuit. ${ }^{8}$
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- Lower circuit depth with large gap: $\epsilon^{-1} \rightarrow \Delta^{-1} .^{10}$
- Adding $Z$-rotations (QSP-like) to get better runtime $\widetilde{\mathcal{O}}\left(\epsilon^{-1} \eta^{-1}\right) \cdot{ }^{11}$

[^22]- Using least-squares fitting to get the dominant frequency. Better circuit depth with large overlap. ${ }^{12}$

[^23]- Using least-squares fitting to get the dominant frequency. Better circuit depth with large overlap. ${ }^{12}$
- Robustness under simple noise models. ${ }^{13,14}$

[^24]
## Robustness under simple noise

- In the Hadamard test circuit, consider the following noise model: each time we apply control- $-e^{-i H \tau}$, with probability $1-e^{-\alpha \tau}$ the system decoheres into the maximally mixed state (loses all information).

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- Then the output $\hat{m}$ (when measuring the ancilla qubit) will satisfy

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\mathbb{E}\left[(-1)^{\hat{m}}\right]=e^{-\alpha t}\langle\Phi| e^{-i H t}|\Phi\rangle
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- It is therefore possible to mitigate the error by multiplying $e^{\alpha t}$ (acceptable overhead if $\alpha$ not too large).

[^28]- What happens to the textbook QPE under the same noise model?
- What happens to the textbook QPE under the same noise model?
- Maximally mixed state is invariant under any unitary operation. Therefore the ancilla register has $1-e^{-\alpha 2^{r} \tau}$ probability of returning an uniformly random bit string.

$$
\operatorname{Pr}\left[E_{\text {meas,noisy }}=2 \pi m / 2^{r}\right]=\operatorname{Pr}\left[E_{\text {meas }}=2 \pi m / 2^{r}\right] e^{-\alpha 2^{r} \tau}+\frac{1-e^{-\alpha 2^{r} \tau}}{2^{r}}
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- Disastrous when taking the minimum (it is possible for any bit string to show up).


## Experimental implementation

- A modified version of this algorithm is implemented using superconducting qubits. ${ }^{a}$
- Active space with up to 4 spatial orbitals, 0.1 mHa
- Variational compilation, better Fourier coefficients, ${ }^{b}$ error mitigation.
${ }^{\text {a }}$ Blunt, Caune, Izsák, Campbell, Holzmann, 2023, Statistical phase estimation and error mitigation on a superconducting quantum processor.
${ }^{\text {b }}$ Wan, Berta, and Campbell, 2021, Randomized quantum algorithm for statistical phase estimation.

Compare with Kitaev's iterative phase estimation algorithm.


Figure: O'Malley et al., 2016, Scalable Quantum Simulation of Molecular Energies.

## Conclusions

- For early fault-tolerant quantum computers, we may need to optimize for a number of metrics (circuit depth, number of qubits, error robustness) rather than just the runtime.


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## Conclusions

- For early fault-tolerant quantum computers, we may need to optimize for a number of metrics (circuit depth, number of qubits, error robustness) rather than just the runtime.
- It is possible to optimize for these metrics while keeping the Heisenberg-limited precision scaling.
- We do not know what the first fault-tolerant quantum computer will be like, but the framework of early FTQC algorithms may be flexible enough to be useful.


[^0]:    ${ }^{1}$ Bogojesk et al., 2020, Quantum chemical accuracy from density functional approximations via machine learning.

[^1]:    ${ }^{1}$ Bogojesk et al., 2020, Quantum chemical accuracy from density functional approximations via machine learning.

[^2]:    ${ }^{1}$ Bogojesk et al., 2020, Quantum chemical accuracy from density functional approximations via machine learning.

[^3]:    ${ }^{1}$ Bogojesk et al., 2020, Quantum chemical accuracy from density functional approximations via machine learning.

[^4]:    ${ }^{2}$ Kimmel, Low, Yoder, 2015, Robust Calibration of a Universal Single-Qubit Gate-Set via Robust Phase Estimation.

[^5]:    ${ }^{2}$ Kimmel, Low, Yoder, 2015, Robust Calibration of a Universal Single-Qubit Gate-Set via Robust Phase Estimation.

[^6]:    ${ }^{2}$ Kimmel, Low, Yoder, 2015, Robust Calibration of a Universal Single-Qubit Gate-Set via Robust Phase Estimation.

[^7]:    ${ }^{2}$ Kimmel, Low, Yoder, 2015, Robust Calibration of a Universal Single-Qubit Gate-Set via Robust Phase Estimation.

[^8]:    ${ }^{3}$ Nielsen and Chuang, Quantum Computation and Quantum Information.

[^9]:    ${ }^{3}$ Nielsen and Chuang, Quantum Computation and Quantum Information.

[^10]:    ${ }^{3}$ Nielsen and Chuang, Quantum Computation and Quantum Information.

[^11]:    ${ }^{3}$ Nielsen and Chuang, Quantum Computation and Quantum Information.

[^12]:    ${ }^{a}$ Lin, Tong, 2020, Heisenberg-limited ground-state energy estimation for early fault-tolerant quantum computers.

[^13]:    ${ }^{a}$ Lin, Tong, 2020, Heisenberg-limited ground-state energy estimation for early fault-tolerant quantum computers.

[^14]:    ${ }^{\text {a }}$ Somma, 2019, Quantum eigenvalue estimation via time series analysis.

[^15]:    ${ }^{\text {a }}$ Somma, 2019, Quantum eigenvalue estimation via time series analysis.

[^16]:    ${ }^{\text {a }}$ Somma, 2019, Quantum eigenvalue estimation via time series analysis.

[^17]:    ${ }^{4}$ Knill, Ortiz, Somma, 2006, Optimal quantum measurements of expectation values of observables.
    ${ }^{5}$ Berry, Su, Gyurik, et al., 2022, Quantifying quantum advantage in topological data analysis.
    ${ }^{6}$ Lin, Tong, 2020, Near-optimal ground state preparation.
    ${ }^{7}$ Lin, Tong, 2020, Heisenberg-limited ground-state energy estimation for early fault-tolerant quantum computers.

[^18]:    ${ }^{4}$ Knill, Ortiz, Somma, 2006, Optimal quantum measurements of expectation values of observables.
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