



Quantum algorithms for Dynamics Simulation: Hamiltonian Simulation and Linear Differential Equations

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Outline

- 1 Hamiltonian Simulation Problem
 - Motivations
 - Expected cost

- 2 Hamiltonian Simulation Algorithms
 - Trotterization
 - Block-encoding, Truncated Taylor series, Optimal Ham Sim by QSVT

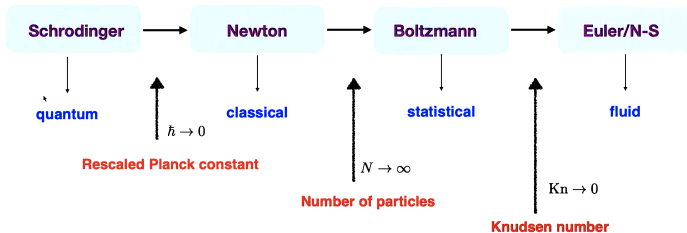
Part 1: Hamiltonian Simulation

(time-independent case)

Different Levels of Physics

multiscale physics fig by Prof. Qin Li

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Different Levels of Physics

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Paul A. M. Dirac (1929)

Different Levels of Physics

“the underlying physical laws necessary for the mathematical theory of a large part of physics and the whole of chemistry are thus completely known, and the difficulty is only that the exact application of these laws leads to equations much too complicated to be soluble.”

Paul A. M. Dirac (1929)

Schrödinger equation for Molecular Dynamics

To describe its behaviour: (x : nuclei coordinates, y : electronic coordinates, M : mass of a nucleus, m : mass of an electron.)

$$\hat{H}_{\text{total}} = \frac{\tilde{p}^2}{2M} + \frac{\tilde{p}^2}{2m} + V(x; y); \quad x \in \mathbb{R}^d; y \in \mathbb{R}^n$$

$$i\hbar \frac{\partial}{\partial t} \Psi = \hat{H}_{\text{total}} \Psi$$

Quantum Computing 101

“... 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.”

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Hamiltonian Simulation Problem (original motivation for quantum computers): Given a description of the Hamiltonian $H(t)$, an evolution time t and an initial state $|j(0)\rangle_i$, to produce the final state $|j(t)\rangle_i$ within in some error tolerance ϵ .

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$$i\partial_t |j(t)\rangle = H(t) |j(t)\rangle; \quad |j(0)\rangle = |j_0\rangle :$$

To simulate $T e^{i \int_0^t H(s) ds}$ for H of very high dimension!

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Time-independent: $H(t) = H$ is a $2^n \times 2^n$ matrix

$$|i\rangle \langle j| (t) = H^t |j(0)\rangle \langle i| ; |j(0)\rangle = |j_0\rangle :$$

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Examples of H : many-body Hamiltonian

$$H = \sum_{E \in \mathcal{S}} \sum_{\{I; X; Y; Z\}} g_E \cdot \sigma^X \sigma^Y \sigma^Z$$

k -local Hamiltonian (TFIM, Heisenberg models, etc), etc.

Error Metrics: Specific case v.s. Worst case

Taking into account **initial conditions** : consider **vector norm**, instead of operator norm.

$$U_{\text{app}} |j\rangle \langle i| e^{iHt} |j\rangle \langle i| \quad U_{\text{app}} e^{iHt} :$$

[Sahinoglu-Somma 2021], [An-Fang-Lin 2020], [Tres-Fang 2022], [BornsWeil-Fang 2022], [Zhao-Zhou-Shaw-Li-Childs 2022], etc

Error Metrics: Specific case v.s. Worst case

Taking into account **initial conditions** : consider **vector norm**, instead of operator norm.

$$\|U_{\text{app}}|j\rangle - |j\rangle\| = \|U_{\text{app}} - I\|$$

Taking into account the **observable** : consider **observable error bounds**. $\|O - U_{\text{app}}^\dagger O U_{\text{app}}\|$

$$\begin{aligned} & \|U_{\text{app}}^\dagger O U_{\text{app}} - O\| \\ = & \|U_{\text{app}}^\dagger O U_{\text{app}} - U_{\text{app}}^\dagger O U_{\text{app}} + U_{\text{app}}^\dagger O U_{\text{app}} - O\| \\ & \leq \|U_{\text{app}}^\dagger O U_{\text{app}} - U_{\text{app}}^\dagger O U_{\text{app}}\| + \|U_{\text{app}}^\dagger O U_{\text{app}} - O\| \\ & \leq 2 \|U_{\text{app}} - I\| : \end{aligned}$$

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$$\|U_{\text{app}}|j\rangle - |j\rangle\| = \|U_{\text{app}} - I\|$$

Taking into account the **observable** : consider **observable error bounds**. $\|K\| \leq 1$

$$\begin{aligned} & \|U_{\text{app}}^\dagger O U_{\text{app}} - e^{iHt} O e^{-iHt}\| \\ = & \|U_{\text{app}}^\dagger O U_{\text{app}} - U_{\text{app}}^\dagger O e^{iHt} + U_{\text{app}}^\dagger O e^{iHt} - e^{iHt} O e^{-iHt}\| \\ \leq & 2 \|U_{\text{app}} - I\| : \end{aligned}$$

Taking into account **both** and consider **observable expectation**

$$\langle j | U_{\text{app}}^\dagger O U_{\text{app}} | j \rangle - \langle j | e^{iHt} O e^{-iHt} | j \rangle$$

[Sahinoglu-Somma 2021], [An-Fang-Lin 2020], [Tres-Fang 2022], [BornsWeil-Fang 2022], [Zhao-Zhou-Shaw-Li-Childs 2022], etc

Specific case v.s. Worst case: Take-away

“Spectrum” of various error measurements:

Observable
expectation

Vector norm
Observable error bounds

Operator norm

¹The cost can be improved for product formulas.

Specific case v.s. Worst case: Take-away

“Spectrum” of various error measurements:



Specific case v.s. Worst case

Taking into account the specific instance, the error (and hence the cost) can be improved.¹

In this lecture, we only focus on the worst case, i.e. error in the operator norm of unitaries.

¹The cost can be improved for product formulas.

Expected cost

Expected Complexity?

²[Feymann 1985]

Expected Complexity?

No-fast-forwarding Theorem: (informal)

Simulating Hamiltonian dynamics for time t requires complexity $(t)^2$.

²[Feymann 1985]

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Simulating Hamiltonian dynamics for time t requires complexity (t) .

Exponential Quantum Advantage (EQA)? (often this is also used to refer superpolynomial speedup)

Criteria to claim EQA:

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Expected Complexity?

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Simulating Hamiltonian dynamics for time t requires complexity $\Omega(t)$.

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There is a QA with quantum complexity $\ll \text{poly}(n)$.

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≥ (A) **Best-known** Classical Alg. has complexity $e^{\text{poly}(n)}$

≥ (B) Show that the task is BQP-hard or BQP-complete

∴ (Any Classical Alg. under reasonable complexity conjectures)

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Hamiltonian Simulation is BQP-hard.

(Any quantum circuit can be efficiently implemented by the dynamics of a local Hamiltonian. ²)

²[Feymann 1985]

Hamiltonian Simulation Algorithms

Trotterization (= Product Formulae = Time/Operator Splitting)

1st-order Trotter formula (Lie-Trotter) for $H = H_1 + H_2$

$$e^{-iHt} \approx e^{-iH_2t/L} e^{-iH_1t/L} \quad L$$

Cost/Complexity?

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$$e^{-iHt} = e^{-iH_2t/L} e^{-iH_1t/L} \quad L + O(k[H_1; H_2]kt^2=L)$$

The number of Trotter steps $L = O(k[H_1; H_2]kt^2=)$

Hamiltonian Simulation Algorithms

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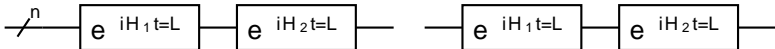
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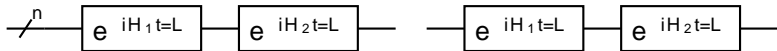
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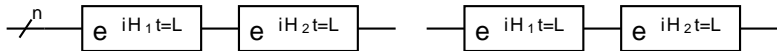
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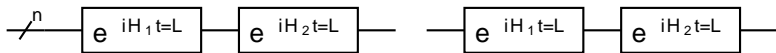
) $O(k[H_1; H_2]kt^2) =$ queries to $e^{iH_1 s}$ and $e^{iH_2 s}$.

High order (p-th): query complexity $O_H t^{1+p} = 1+p \cdot 3$

Hamiltonian Simulation Algorithms

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Everything is unitary! No ancilla needed.

But it needs $e^{iH_j s}$ of efficiently implementable.

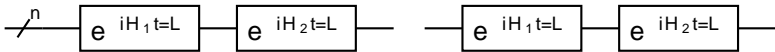
³[Suzuki 91], [Descombes-Thalhammer 2010], [Childs-Su-et Al. 2021]

⁴truncated Taylor [Berry-Childs-Cleve-Kothari-Somma 2015], QSP/QSVT [Low-Chuang 2016 and 2017], [Childs-Su-Low-Wiebe 2019]

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Post-Trotter, e.g., **truncated Taylor series**, quantum signal processing (QSP), quantum singular value transformation (QSVT)³, etc.

$$e^{iHt} \approx \sum_{k=0}^{\infty} \frac{(iHt)^k}{k!} = \sum_{k=0}^{\infty} \sum_{j_1, \dots, j_k} \frac{(it)^k}{k!} H_{j_1} H_{j_2} \dots H_{j_k}$$

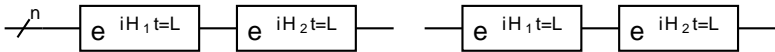
Upshot: $O(t \log(t))$

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Upshot: $O(t \log(t))$ Even better, say, $O(t + \log(1/t))$

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Block-Encoding – Definition

Let A be a general $2^n \times 2^n$ matrix.

Idea:

$$U_A = \begin{matrix} & & A \\ & & \\ & & \end{matrix} \quad ! \text{ ancilla qubits}$$

Block-Encoding – Definition

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Definition (Block-encoding)

U_A is an $(\gamma; m; n)$ -block-encoding of A , if

$$\| \langle k | A | j \rangle - \langle \langle n | U_A | j \rangle \langle k | \rangle \| \leq \gamma$$

for some $\|A\| \leq 1$, $m > 0$ and $\gamma > 0$. Here γ is called the subnormalization factor and m is the number of ancilla qubits, and n is the number of system qubits. When $\gamma = 0$, it is also called an $(\gamma; m)$ -block-encoding.

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Understanding: $U_A : 2^{m+n} \rightarrow 2^{m+n}$.

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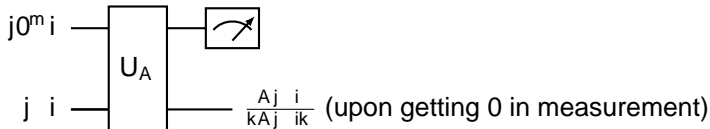
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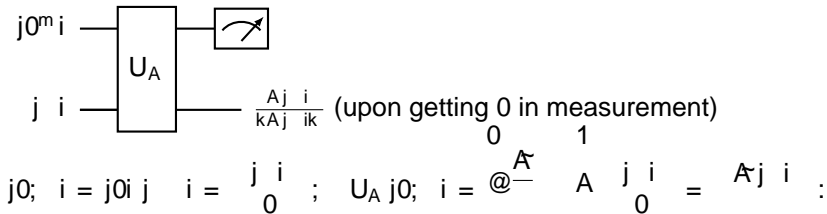
U_A is an $(\lceil m \rceil, \gamma)$ -block-encoding of A , if

$$\| \|A - (\langle j|0^m\rangle \langle 0^m|) U_A (\langle 0^m|i\rangle \langle i|) \| \| \leq \gamma$$

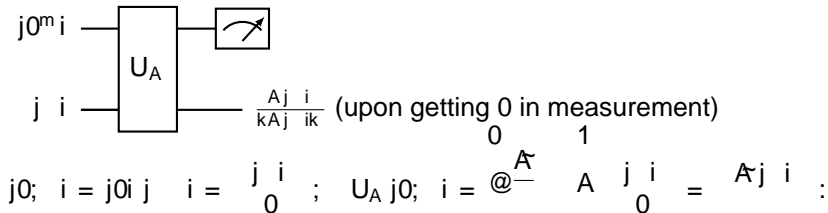
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Block-Encoding – Definition cont'd

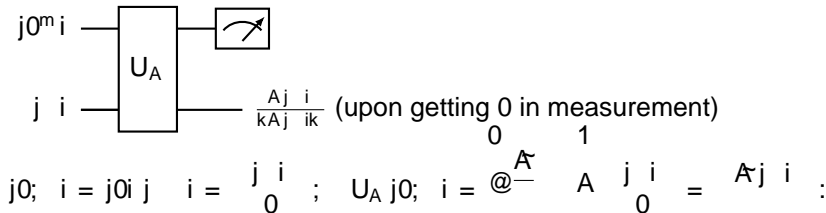


Block-Encoding – Definition cont'd



Question: Well-defined? Not an empty set?

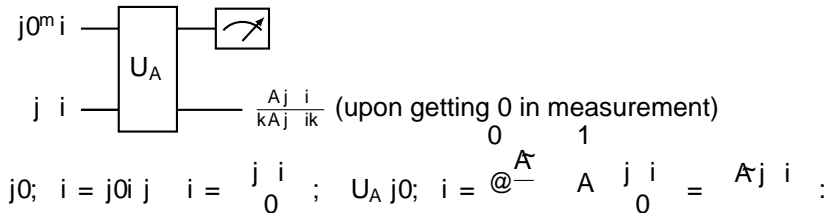
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Trivial example (unitary): U is a $(1; 0; 0)$ -block-encoding of U .

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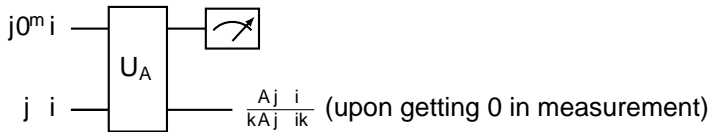


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$(; 1)$ -block-encoding is general. WLOG, assume $k A_{j,i} = 1$.

Block-Encoding – Definition cont'd



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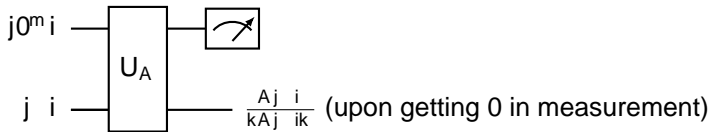
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Proof: $A = W V^y$. All singular values $\in [0; 1]$.

References: Lecture notes by Lin Lin, QSVT [Gilyen-Su-Low-Wiebe 2018/2019], see also QSP [Low-Chuang 2017], qubitization [Low-Chuang 2016]

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$$\begin{aligned}
 U_A &:= \begin{pmatrix} W & 0 \\ 0 & I_n \end{pmatrix} \begin{pmatrix} p \frac{1}{\|k\rangle\|^2} & \\ & p \frac{1}{\|k\rangle\|^2} \end{pmatrix} \begin{pmatrix} V^y & 0 \\ 0 & I_n \end{pmatrix} \\
 &= \begin{pmatrix} p \frac{1}{\|k\rangle\|^2} & \\ & p \frac{1}{\|k\rangle\|^2} \end{pmatrix} W V^y
 \end{aligned}$$

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Sparse Input Model

Question: Efficient to construct?

[Gilyen-Su-Low-Wiebe 2018], see also [Berry-Childs 2012], [Low-Chuang 2017]



Sparse Input Model

Question: Efficient to construct?

Upshot: sparse matrix (Hamiltonian) is ok!

[Gilyen-Su-Low-Wiebe 2018], see also [Berry-Childs 2012], [Low-Chuang 2017]

Sparse Input Model

Question: Efficient to construct?

Upshot: **sparse matrix (Hamiltonian) is ok!**

We assume that H is a s -sparse matrix with $\|H\|_{\max} \leq 1$. The information of H is given through the following oracles:

$$\begin{aligned}
 U_{\text{row}} &|j\rangle|s\rangle|i\rangle = |j\rangle|\text{row}(j; s)\rangle|i\rangle; \\
 U_{\text{col}} &|j\rangle|s\rangle|i\rangle = |j\rangle|\text{col}(j; s)\rangle|i\rangle; \\
 U_{\text{val}} &|j\rangle|k\rangle|z\rangle|i\rangle = |j\rangle|k\rangle|z\rangle|H_{jk}(t)\rangle|i\rangle;
 \end{aligned} \tag{1}$$

Here $\text{row}(j; s)$ is the row index of the s th nonzero element in the j th column, $\text{col}(j; s)$ is the column index of the s th nonzero element in the j th row.

A $(s; n+3;)$ -block-encoding of H can be constructed via $O(1)$ queries to above oracles and $O(n + \log^{5=2}(s))$ primitive gates.

[Gilyen-Su-Low-Wiebe 2018], see also [Berry-Childs 2012], [Low-Chuang 2017]



Block-Encoding – Properties

Properties: Let U_A be an $(\gamma; a; \epsilon)$ -BE of A ; U_B be a $(\gamma; b; \epsilon)$ -BE of B

Block-Encoding – Properties

Properties: Let U_A be an $(c; a)$ -BE of A ; U_B be a $(c; b)$ -BE of B
 (BE of cA)

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(BE of AB)

$W = (I_b \oplus U_A)(I_a \oplus U_B)$ is an $(c; a + b; c)$ -BE of AB .

Block-Encoding – Properties

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$W = (I_b \otimes U_A)(I_a \otimes U_B)$ is an $(c; a + b; c)$ -BE of AB .

Proof:

$$\begin{aligned}
 & AB \quad (|c\rangle\langle c| \otimes I)(I_b \otimes U_A)(I_a \otimes U_B)(|c\rangle\langle c| \otimes I) \\
 = & AB \quad \left| \underbrace{(|c\rangle\langle c| \otimes I) U_A (|c\rangle\langle c| \otimes I)}_{A^c} \right| \left| \underbrace{(|c\rangle\langle c| \otimes I) U_B (|c\rangle\langle c| \otimes I)}_{B^c} \right|
 \end{aligned}$$

Block-Encoding – Properties

Properties: Let U_A be an $(c; a; c)$ -BE of A ; U_B be a $(c; b; c)$ -BE of B

(BE of cA) U_A is an $(c; a; c)$ -BE of cA .

(BE of AB)

$W = (I_b \otimes U_A)(I_a \otimes U_B)$ is an $(c; a + b; c)$ -BE of AB .

Proof:

$$\begin{aligned}
 & AB \quad (|0\rangle\langle 0|^{a+b} \otimes I)(I_b \otimes U_A)(I_a \otimes U_B)(|0\rangle\langle 0|^{a+b} \otimes I) \\
 = & AB \quad \left| \underbrace{(|0\rangle\langle 0|^a \otimes I) U_A (|0\rangle\langle 0|^a \otimes I)}_{\mathcal{Z}^A} \right| \left| \underbrace{(|0\rangle\langle 0|^b \otimes I) U_B (|0\rangle\langle 0|^b \otimes I)}_{\mathcal{Z}^B} \right| \\
 = & AB \quad \mathcal{Z}^A \mathcal{Z}^B + \mathcal{Z}^B \mathcal{Z}^A = (A \otimes I)B + A(I \otimes B)
 \end{aligned}$$

Block-Encoding – Properties

Properties: Let U_A be an $(c; a; c)$ -BE of A ; U_B be a $(c; b; c)$ -BE of B

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 = & AB \quad AB + A'B = (A \otimes A')B + A'(B \otimes B') \\
 & + \dots
 \end{aligned}$$

Block-Encoding – Properties

Properties: Let U_A be an $(n; a)$ -BE of A ; U_B be a $(m; b)$ -BE of B

(BE of cA) U_A is an $(n; a; c)$ -BE of cA .

(BE of AB)

$W = (I_b \otimes U_A)(I_a \otimes U_B)$ is an $(n + m; a + b; a + b)$ -BE of AB .

(BE of $A + B$)

Block-Encoding – Properties

Properties: Let U_A be an $(n; a; \epsilon)$ -BE of A ; U_B be a $(m; b; \epsilon)$ -BE of B

(BE of cA) U_A is an $(n; a; c\epsilon)$ -BE of cA .

(BE of AB)

$W = (I_b \otimes U_A)(I_a \otimes U_B)$ is an $(n + m; a + b; \epsilon)$ -BE of AB .

(BE of $A + B$) $U_A: (n; m; \epsilon)$ -BE of A ; $U_B: (n; m; \epsilon)$ -BE of B

Block-Encoding – Properties

Properties: Let U_A be an $(c; a; c)$ -BE of A ; U_B be a $(c; b; c)$ -BE of B

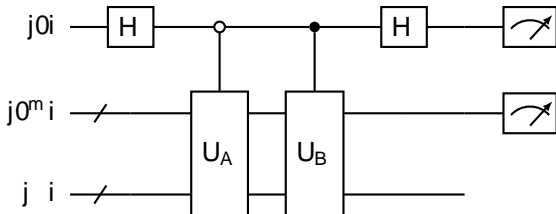
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The following circuit constructs a $(2; m; c)$ -BE of $A + B$.



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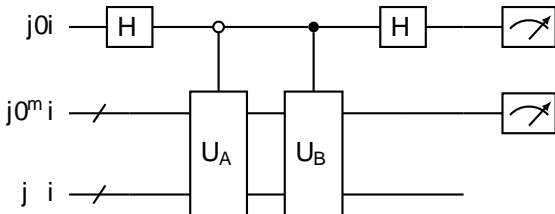
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The following circuit constructs a $(2; m; c)$ -BE of $A + B$.



More generally, linear combination of block-encodings can be constructed via [Linear Combination of Unitaries \(LCU\) Lemma](#).

LCU Lemma

LCU Lemma: $T = \sum_{j \in [L]} c_j U_j$ for unitaries U_j . $\|T\|_1 = \sum_{j \in [L]} c_j$.

LCU [Berry-Childs-Kothari 2015], General LCBE [Gilyen-Su-Low-Wiebe 2018]

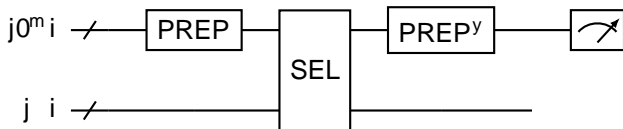
LCU Lemma

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One can get a $(\|T\|_1; \log_2 L e)$ -block-encoding by:

$$\text{SEL} := \sum_{j \in [L]} |j\rangle\langle j| \otimes U_j$$

$$\text{PREP} |0\rangle = \frac{1}{\|T\|_1} \sum_{j \in [L]} c_j |j\rangle.$$



LCU [Berry-Childs-Kothari 2015], General LCBE [Gilyen-Su-Low-Wiebe 2018]

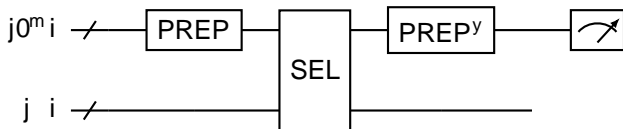
LCU Lemma

LCU Lemma: $T = \sum_{j \in [L]} c_j U_j$ for unitaries U_j . $\|T\|_1 = \sum_{j \in [L]} c_j$.

One can get a $(\|T\|_1; d \log_2 L e)$ -block-encoding by:

$$\text{SEL} := \sum_{j \in [L]} |j\rangle\langle j| \otimes U_j$$

$$\text{PREP} |j\rangle = \frac{1}{\|T\|_1} \sum_{i \in [L]} p_i |i\rangle$$



General LCBE: $\max_j m_j + d \log_2 L e$ ancillas

LCU [Berry-Childs-Kothari 2015], General LCBE [Gilyen-Su-Low-Wiebe 2018]



Matrix Function and Truncated Taylor series

We can “+” and “ ”) we can BE $\text{poly}(A)$



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e.g., e^{iHt} Hamiltonian Simulation, $e^{-\beta H}$ Gibbs distribution, A^{-1} matrix inversion, etc.

Matrix Function and Truncated Taylor series

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) **We can BE f(A): Super Powerful!!!**

e.g., e^{-iHt} Hamiltonian Simulation, $e^{-\beta H}$ Gibbs distribution, A^{-1} matrix inversion, etc.

Truncated Taylor Series $\|kH\| \leq \dots$

$$e^{-iHt} = \sum_{k=0}^{\infty} \frac{(-iHt)^k}{k!} = \sum_{k=0}^{\infty} \frac{(-i)^k t^k}{k!} H^k$$

Number of time steps $L = t = O(t)$; $K = O\left(\frac{\log(t)}{\log\log(t)}\right)$

) Query Complexity: $O\left(t \frac{\log(t)}{\log\log(t)}\right)$.

Matrix Function and Truncated Taylor series

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e.g., e^{iHt} Hamiltonian Simulation, $e^{-\beta H}$ Gibbs distribution, A^{-1} matrix inversion, etc.

Truncated Taylor Series $\sum_{k=0}^K \frac{(iHt)^k}{k!}$

$$e^{iHt} = \sum_{k=0}^K \frac{(iHt)^k}{k!} = \sum_{k=0}^K \frac{(iHt)^k}{k!} H^k$$

Number of time steps $L = t = O(\frac{t}{\epsilon})$; $K = O(\frac{\log(t/\epsilon)}{\log \log(t/\epsilon)})$

) Query Complexity: $O(t \frac{\log(t/\epsilon)}{\log \log(t/\epsilon)})$.

But $A + A^2 + \dots + A^d$

Number of ancillas: $m; 2m; \dots; dm$) $dm + \log(d)$ **HUGE!**

Question: Can we do better?

Matrix Function and Truncated Taylor series

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But $A + A^2 + \dots + A^d$

Number of ancillas: $m; 2m; \dots; dm$) $dm + \log(d)$ **HUGE!**

Question: Can we do better? Yes! 1 additional ancilla is sufficient!

Quantum Singular Value Transformation (QSVT) / Quantum Signal Processing (QSP)

QSVT

$A = W V^y f(A) := W f(\cdot) V^y$ Generalized Matrix Function

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Theorem (QSVT with odd real polynomial)

Let U_A be a $(1; m)$ -block-encoding of $A \in \mathbb{C}^{2^n \times 2^n}$. Given an odd polynomial $P_{<}(x) \in \mathbb{R}[x]$ of odd degree d satisfying

$$|P_{<}(x)| \leq 1; \forall x \in [-1, 1]:$$

We can find a sequence of phase factors $\theta \in \mathbb{R}^{d+1}$ and construct a $(1; m+1)$ -block-encoding of $P_{<}(A)$ that uses $U_A; U_A^y$, m -qubit controlled NOT, and single qubit rotation gates for $O(d)$ times.

QSVT

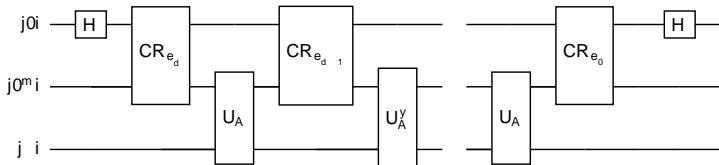
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QSVT (Hermitian matrix + arbitrary parity)

Theorem (QSVT for Polynomial eigenvalue transformation)

Let U_A be a $(1; m; 1)$ -block-encoding of a **Hermitian** matrix $A \in \mathbb{C}^{2^n \times 2^n}$. Given a d -degree polynomial $P_d(x) \in \mathbb{R}[x]$ satisfying

$$|P_d(x)| \leq 1, \forall x \in [-1, 1];$$

Then for $\epsilon > 0$, there is a quantum circuit that constructs a $(1; m+2; 4d \frac{\epsilon}{\|A\|} + 1)$ -block-encoding of $P_d(A)$ that uses a single application of controlled- U_A , and d applications of U_A ; U_A^\dagger , and $O((m+1)d)$ other one- and two-qubit gates.



Optimal Hamiltonian Simulation by QSVT

Given U_H : an $(\epsilon; m; 0)$ -block-encoding of H .

Goal: an algorithm that makes $O(t + \log(1/\epsilon))$ queries to U_H .

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Optimal Hamiltonian Simulation by QSVT

Given U_H : an $(\gamma; m; \epsilon)$ -block-encoding of H .

Goal: an algorithm that makes $O(t + \log(1/\epsilon))$ queries to U_H .

$$e^{iHt} = e^{i \frac{H}{\gamma} t}. \text{ WLOG, assume } \gamma = 1. e^{itx} = \cos(tx) + i \sin(tx)$$

Jacobi-Anger expansion on $[-1; 1]$:

$$\cos(tx) = J_0(t) + 2 \sum_{k=1}^{\infty} (-1)^k J_{2k}(t) T_{2k}(x);$$

$$\sin(tx) = 2 \sum_{k=0}^{\infty} (-1)^k J_{2k+1}(t) T_{2k+1}(x);$$

$J_k(t)$ denotes Bessel functions of the first kind.

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$$\sin(tx) = 2 \sum_{k=0}^{\infty} (-1)^k J_{2k+1}(t) T_{2k+1}(x);$$

This series converges rapidly. Truncating it with

$$r = \left\lceil t + \frac{\log(1/\epsilon)}{\log(e + \log(1/\epsilon))} \right\rceil$$

terms gives a polynomial approximation (with precision ϵ and degree $2r + 1$) of $\cos(tx) + i \sin(tx) = e^{itx}$.

Optimal Hamiltonian Simulation by QSVT

Given U_H : an $(k; m; \epsilon)$ -block-encoding of H .

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$$e^{iHt} = e^{i \frac{H}{t} t}. \text{ WLOG, assume } \|H\| = 1. e^{itx} = \cos(tx) + i \sin(tx)$$

Query Complexity: $O(k H k)$

$$O\left(t + \frac{\log(1/\epsilon)}{\log(e + \log(1/\epsilon))} = O(t)\right)$$

Optimal Hamiltonian Simulation by QSVT cont'd

Given U_H : an $(\epsilon; m; 0)$ -block-encoding of H .

Goal: an algorithm that makes $O(t + \log(1/\epsilon))$ queries to U_H .

We now have block-encodings of both $\cos(tH)$ and $i \sin(tH)$ and use LCU.

⁴[Berry-Childs-Cleve-Kothari-Somma 2014/2015]

Optimal Hamiltonian Simulation by QSVT cont'd

Given U_H : an $(\lceil m \rceil; 0)$ -block-encoding of H .

Goal: an algorithm that makes $O(t + \log(1/\epsilon))$ queries to U_H .

We now have block-encodings of both $\cos(tH)$ and $i \sin(tH)$ and use LCU. Or equivalently, directly use QSVT for polynomial eigenvalue transformation with arbitrary parity. We have a $(\lceil m \rceil + 2; \epsilon)$ of e^{itH} .

⁴[Berry-Childs-Cleve-Kothari-Somma 2014/2015]

Optimal Hamiltonian Simulation by QSVT cont'd

Given U_H : an $(m; 0)$ -block-encoding of H .

Goal: an algorithm that makes $O(t + \log(1/\epsilon))$ queries to U_H .

We now have block-encodings of both $\cos(tH)$ and $i \sin(tH)$ and use LCU. Or equivalently, directly use QSVT for polynomial eigenvalue transformation with arbitrary parity. We have a $(1; m+2; \epsilon)$ of $e^{itH} = 2$.

Last step: We want to turn $e^{itH} = 2$ to e^{itH} .

⁴[Berry-Childs-Cleve-Kothari-Somma 2014/2015]

Optimal Hamiltonian Simulation by QSVT cont'd

Given U_H : an $(\lceil m \rceil; 0)$ -block-encoding of H .

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Last step: We want to turn $e^{itH} = 2$ to e^{itH} . Notice this can be done by QSVT with $P(x) = 3x - 4x^3$.

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Optimal Hamiltonian Simulation by QSVT cont'd

Given U_H : an $(m; 0)$ -block-encoding of H .

Goal: an algorithm that makes $O(t + \log(1/\epsilon))$ queries to U_H .

We now have block-encodings of both $\cos(tH)$ and $i \sin(tH)$ and use LCU. Or equivalently, directly use QSVT for polynomial eigenvalue transformation with arbitrary parity. We have a $(1; m+2; \epsilon)$ of $e^{itH} = 2$.

Last step: We want to turn $e^{itH} = 2$ to e^{itH} . Notice this can be done by QSVT with $P(x) = 3x - 4x^3$.

Oblivious Amplitude Amplification (OAA)⁴

Given a block-encoding U_A of A (and A is close to unitary):

$A = \begin{pmatrix} \hbar j 0_m & I_n \end{pmatrix} U_A \begin{pmatrix} j 0i_s & I_n \end{pmatrix}$. Define $R := \begin{pmatrix} I_m & 2j 0i_m & \hbar j 0_m \end{pmatrix}$ and

$$W = U_A \begin{pmatrix} R & I_n \end{pmatrix} U_A^\dagger \begin{pmatrix} R & I_n \end{pmatrix} U_A:$$

$$\begin{pmatrix} \hbar j 0_m & I_n \end{pmatrix} W \begin{pmatrix} j 0i_m & I_n \end{pmatrix} = \frac{3}{-} A - \frac{4}{3} A A^\dagger A + \left(\frac{3}{-} - \frac{4}{3} \right) A:$$

⁴[Berry-Childs-Cleve-Kothari-Somma 2014/2015]

Summary of Hamiltonian Simulation

Hamiltonian simulation: motivation; set-up

Expected cost: No-fast-forwarding theorem and BQP-hardness

Algorithms

- Trotterization

- Revisit of Block-encoding; truncated Taylor series

- Optimal Hamiltonian Simulation via QSVT

Summary of time-independent Ham Sim cont'd

- **Trotterization:**
1st-order Trotter formula

$$e^{-iHt} = e^{-iH_1 t} e^{-iH_2 t} + O(k[H_1; H_2] k t^2 = L)$$

High order (p -th): $O(k \text{Comm} k^{1+p} \frac{t^{1+1-p}}{1-p})$

Randomized product formula, e.g., qDRIFT: $O(t^2)$:
(*weak convergence* wrt the diamond norm of Quantum channels)

- **LCU, e.g. Truncated Taylor series:**

$$O\left(t \frac{\log(t)}{\log \log(t)}\right) :$$

- **QSP/QSVT:** $O\left(t + \frac{\log(1/\epsilon)}{\log(e + \log(1/\epsilon))} t\right)$

Helpful References

- Lecture notes on Quantum Algorithms for Scientific Computations by Lin Lin (UC Berkeley) [arXiv:2201.08309]
- Lecture notes on Quantum Algorithms by Andrew Childs (U Maryland)
- A. Gilyen, Y. Su, G.H. Low, N. Wiebe. Quantum singular value transformation and beyond: exponential improvements for quantum matrix arithmetics, [arXiv 1806.01838]

Thank you for your attention!

