

# Block Encoding

## with low gate count for second-quantized Hamiltonians

Diyi Liu  
Berkeley Lab

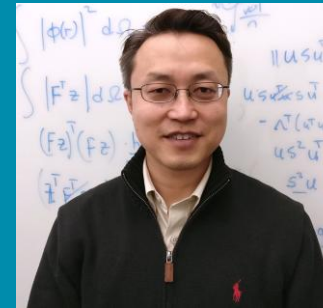
Shuchen Zhu  
Duke University



Lin Lin  
UC Berkeley  
Berkeley Lab



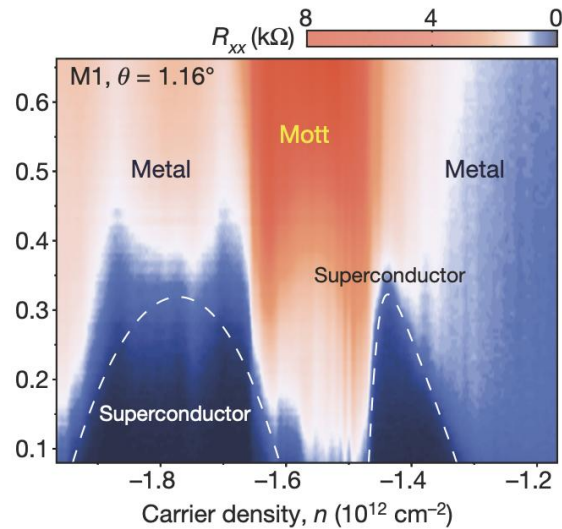
Guang Hao Low  
Google Quantum AI



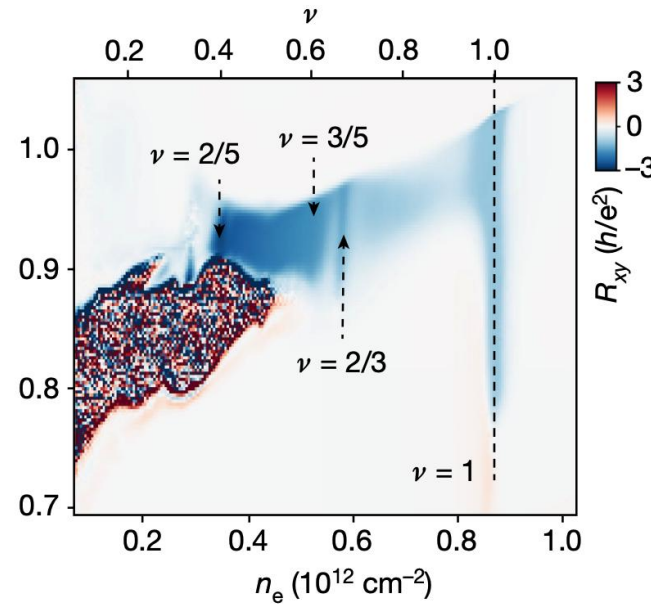
Chao Yang  
Berkeley Lab

# Quantum simulation for Quantum sciences

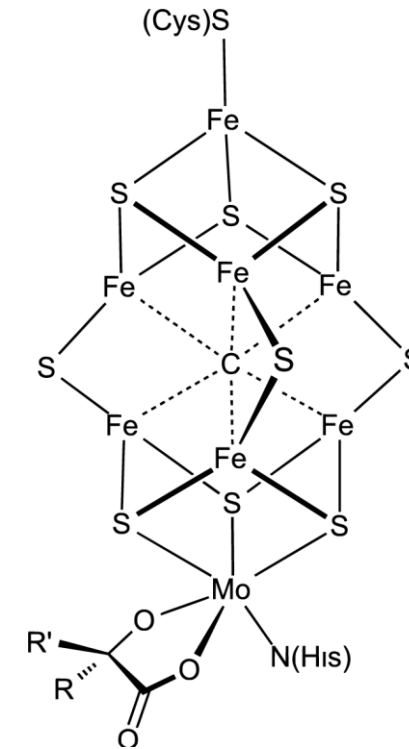
It is hard to understand and predict quantum many-body systems



Superconductivity



Fractional QAH effect



Harber process

# Input model of quantum algorithm

Quantum Algorithms often start with a matrix as input

Quantum dynamics

$$e^{-iHt}\psi_0$$

Computing spectral properties

$$\text{Tr}(g(H))$$

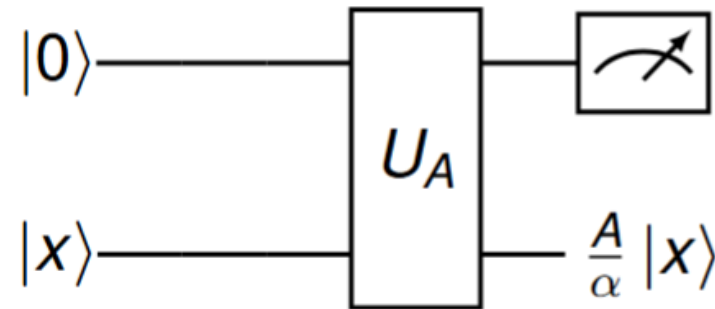
Solving linear systems

$$x = A^{-1}b$$

## Definition (General Idea)

Block encoding is a technique for embedding a properly scaled nonunitary matrix  $A \in \mathbb{C}^{N \times N}$  into a unitary matrix  $U_A$  of the form

$$U_A = \begin{bmatrix} \frac{A}{\alpha} & * \\ * & * \end{bmatrix},$$



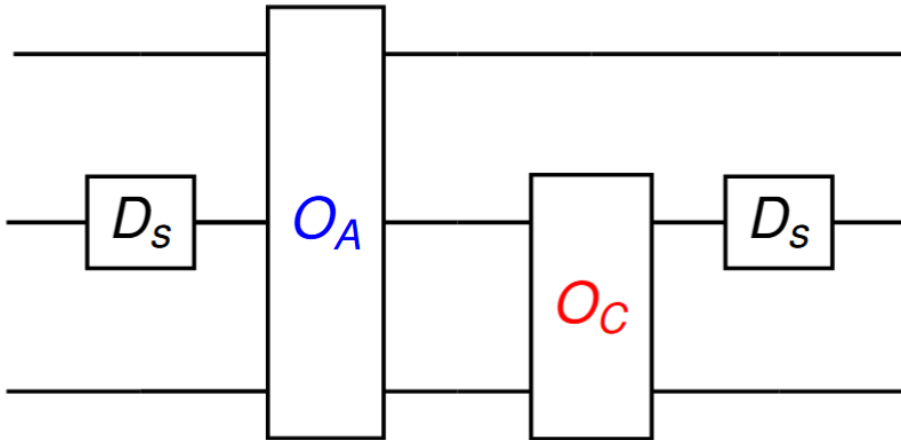
# Block Encoding

## Definition (Block encoding)

Given an  $n$ -qubit matrix  $A \in \mathbb{C}^{2^n \times 2^n}$ , if we find  $\alpha, \epsilon \in \mathcal{R}_+$ , and an  $(m+n)$ -qubit unitary matrix  $U_A$  so that

$$\|A - \alpha(|0^m\rangle\langle 0^m| \otimes I_{2^n}) U_A (|0^m\rangle\langle 0^m| \otimes I_{2^n})\| \leq \epsilon$$

then  $U_A$  is called a  $(\alpha, m, \epsilon)$ -block-encoding of  $A$ .



Amplitude oracle:

$$O_A |0\rangle |\ell\rangle |j\rangle = \left( A_{c(j,\ell),j} |0\rangle + \sqrt{1 - |A_{c(j,\ell),j}|^2} |1\rangle \right) |\ell\rangle |j\rangle$$

Sparsity oracle:

$$O_c |\ell\rangle |j\rangle = |\ell\rangle |c(j, \ell)\rangle$$

$$U_A = (I_2 \otimes D_s \otimes I_N) (I_2 \otimes O_c) O_A (I_2 \otimes D_s \otimes I_N)$$

Guang Hao Low, and Isaac L. Chuang. "Optimal Hamiltonian simulation by quantum signal processing" *PRL* (2017).

András Gilyén, Yuan Su, Guang Hao Low, and Nathan Wiebe. "Quantum singular value transformation and beyond" *STOC* (2019).

Daan Camps, Lin Lin, Roel Van Beeumen, and Chao Yang. "Explicit quantum circuits for block encodings of certain sparse matrices" *SIAM Matrix Analysis* (2024).

# Second quantized Hamiltonian

$$\mathcal{H} = \sum_{p,q} h_{pq} a_p^\dagger a_q + \sum_{p < q, r < s} h_{pqrs} a_p^\dagger a_q^\dagger a_r a_s \quad \text{General Hamiltonian}$$

$$\mathcal{H} = \sum_{p,q=0}^{n-1} T(p-q) a_p^\dagger a_q \quad \text{Translational Invariant}$$

$$\mathcal{H} = \sum_{p=0}^{n-1} \sum_{q=0}^{n-1} h_{pq} a_p^\dagger a_q \quad |h_{pq}| \leq C e^{-\alpha|p-q|} \quad \text{Nearest-Neighbour}$$

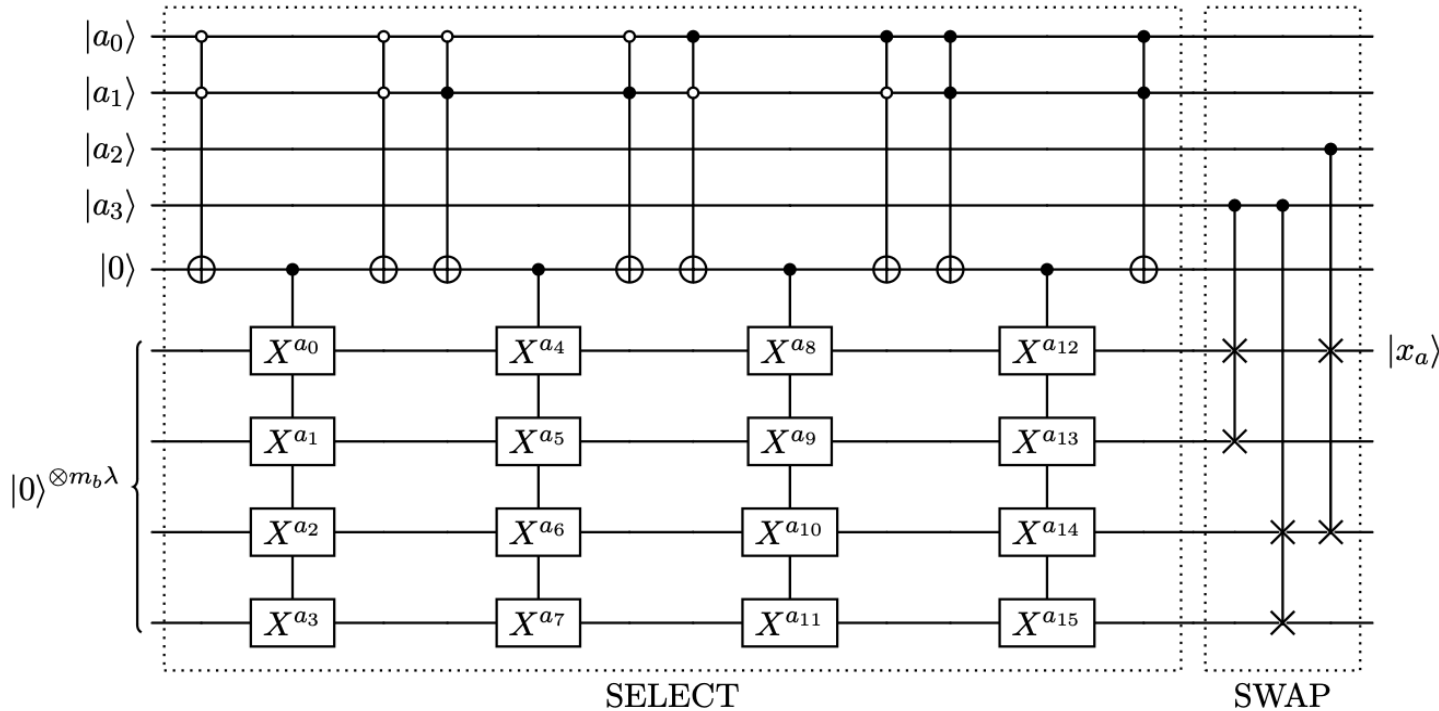
Model	Reference	Qubit	Subnormalization factor	T count
General	2018 Babbush et al. [1]	$\mathcal{O}(n + \log(\frac{n^4}{\epsilon}))$	$\mathcal{O}(n^4)$	$\mathcal{O}(n^4 + \log(\frac{n^4}{\epsilon}))$
	<b>This paper</b>	$\mathcal{O}(n^2 \sqrt{\log(\frac{n^4}{\epsilon})})$	$\mathcal{O}(n^4)$	$\mathcal{O}(n^2 \sqrt{\log(\frac{n^4}{\epsilon})})$
Factorized	2018 Kivlichan et al. [2]	N/A	N/A	$\mathcal{O}(n^2 \log(\frac{1}{\epsilon}))$
TI Factorized	2018 Babbush et al. [1]	$\mathcal{O}(n + \log(\frac{n^2}{\epsilon}))$	$\mathcal{O}(n^2)$	$\mathcal{O}(n + \log(\frac{n^2}{\epsilon}))$
	<b>This paper</b>	$\mathcal{O}(n + \sqrt{n \log(\frac{n^2}{\epsilon})})$	$\mathcal{O}(n^2)$	$\mathcal{O}(n + \sqrt{n \log(\frac{n^2}{\epsilon})})$
Localized	2021 Wan [3]	$\mathcal{O}(n)$	$\mathcal{O}(n^2)$	$\mathcal{O}(n) + \text{PREP}$
	<b>This paper</b>	$\tilde{\mathcal{O}}(n \sqrt{\log^3(\frac{n^2}{\epsilon})})$	$\mathcal{O}(n^2 \log^2(\frac{n^2}{\epsilon}))$	$\tilde{\mathcal{O}}(n \sqrt{\log^3(\frac{n^2}{\epsilon})})$

Babbush et al. "Encoding electronic spectra in quantum circuits with linear T complexity." *PRX* (2018).

Kivlichan et al. "Quantum simulation of electronic structure with linear depth and connectivity." *PRL* (2018).

Kianna Wan. "Exponentially faster implementations of Select(H) for fermionic Hamiltonians" *Quantum* (2021).

# SELECT-SWAP circuit



Data lookup  $|l\rangle |0^{m_b}\rangle \rightarrow |l\rangle |\text{data}_l\rangle$

Number of Data  $L$

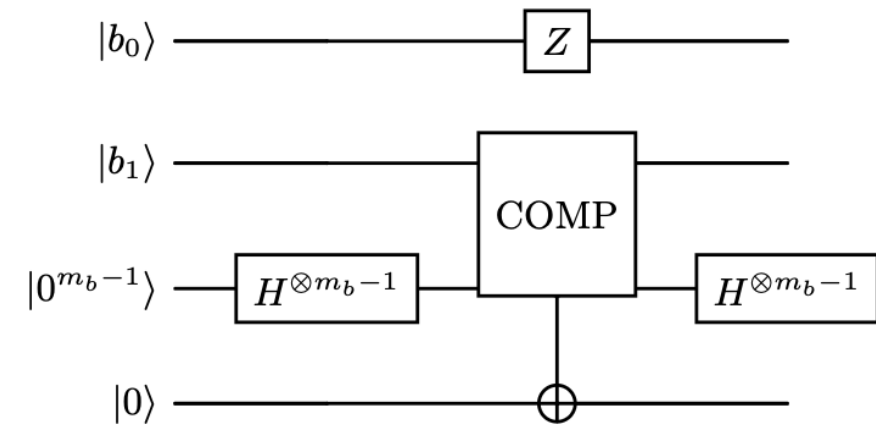
Word length  $m_b$

Qubits  $m_b \lambda + 2 \lceil \log_2(L) \rceil$

T count  $4 \left\lceil \frac{L}{\lambda} \right\rceil + 8m_b \lambda$

T depth  $\frac{L}{\lambda} + \log(\lambda)$

# Construction of amplitude oracle $O_A$



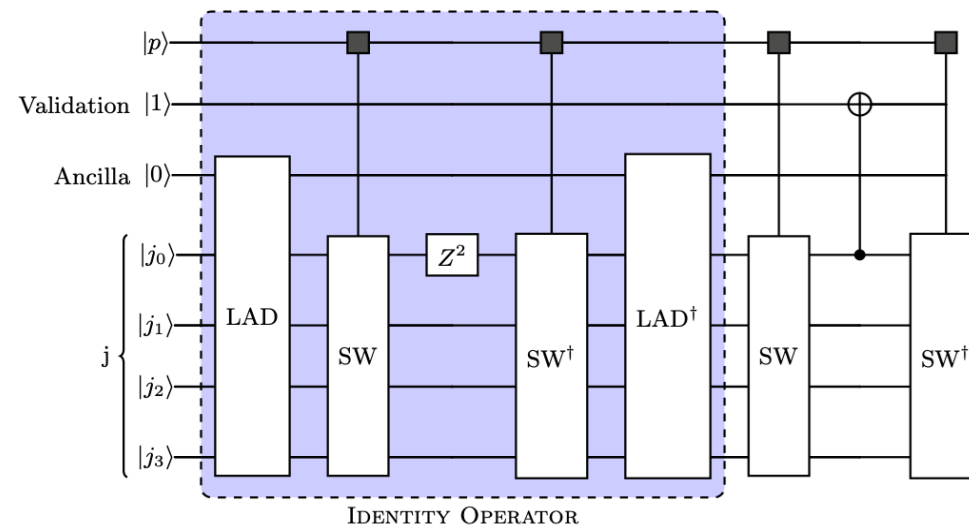
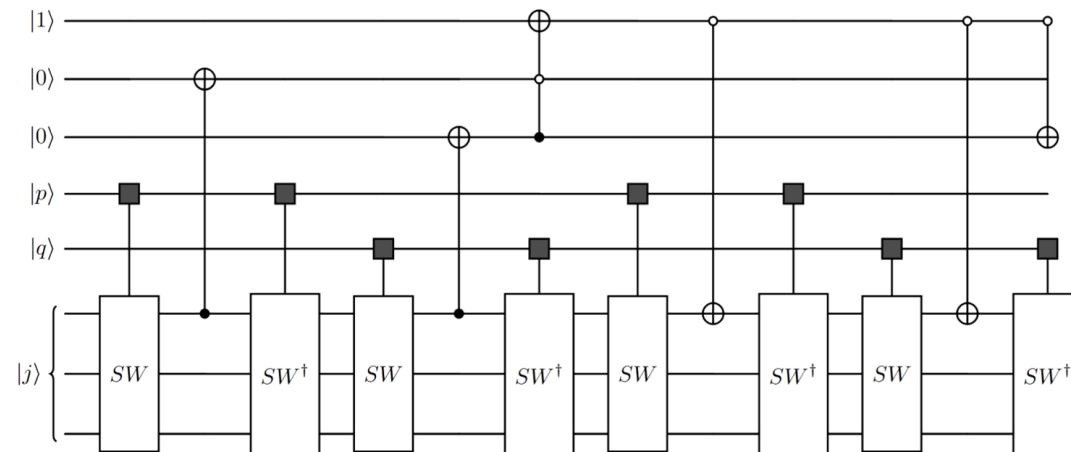
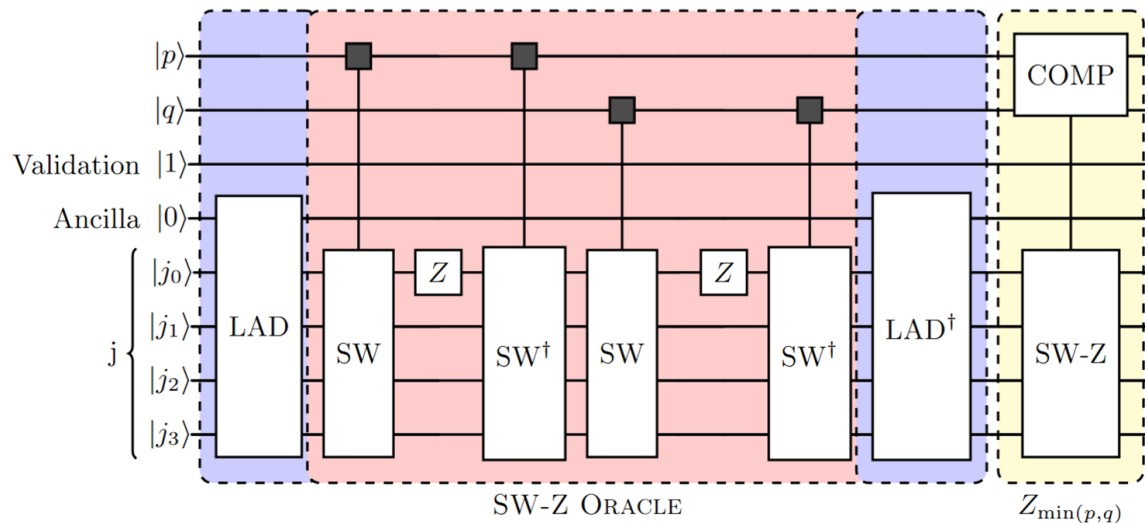
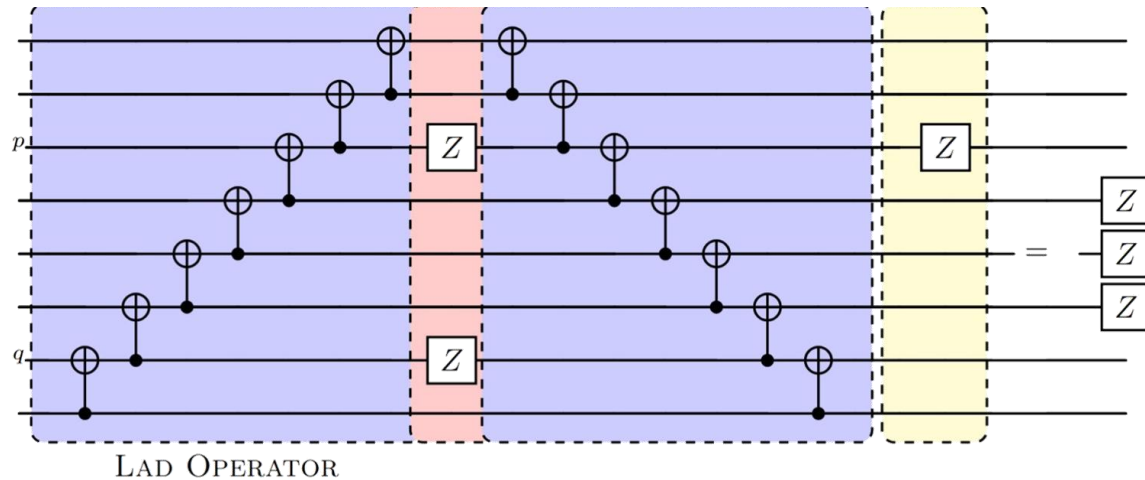
Direct Sampling

$$\begin{aligned}
 & |b_0\rangle |b_1\rangle |0^{m_b-1}\rangle |0\rangle \\
 & \xrightarrow{H^{\otimes m_b-1}} \sum_i^{2^{m_b-1}-1} \frac{1}{\sqrt{2^{m_b-1}}} |b_0\rangle |b_1\rangle |i\rangle |0\rangle \\
 & \xrightarrow{\text{COMP}} \frac{1}{\sqrt{2^{m_b-1}}} \sum_{i=0}^{b_1-1} |b_0\rangle |b_1\rangle |i\rangle |0\rangle + \frac{1}{\sqrt{2^{m_b-1}}} \sum_{i=b_1}^{2^{m_b-1}-1} |b_0\rangle |b_1\rangle |i\rangle |1\rangle \\
 & \xrightarrow{H^{\otimes m_b-1}, Z} |b_0\rangle |b_1\rangle |0^{m_b-1}\rangle \left( r_b |0\rangle + \sqrt{1 - r_b^2} |1\rangle \right) + |b\rangle |\Psi\rangle
 \end{aligned}$$

# Construction of sparsity oracle $O_C$

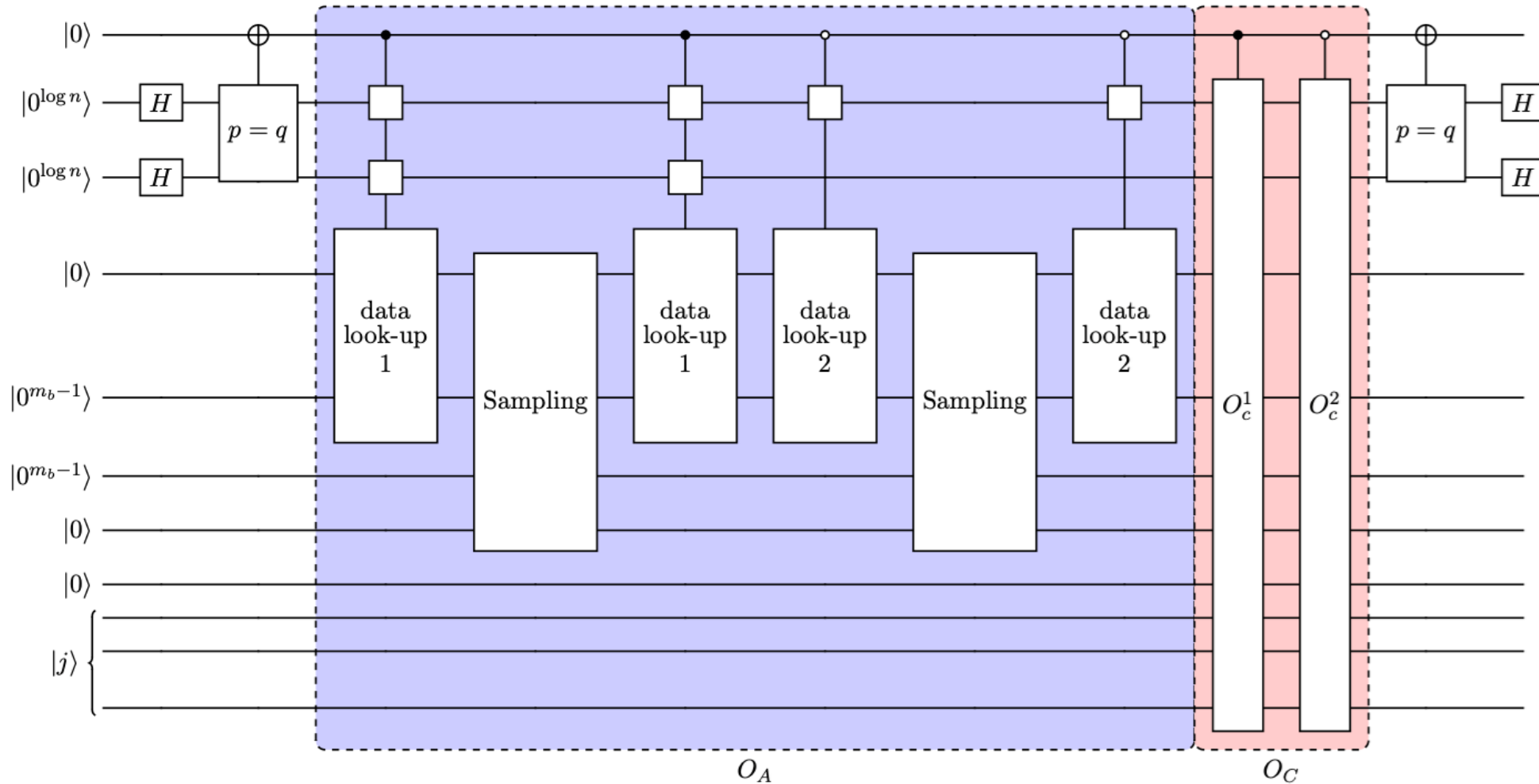
$$a_2^\dagger a_0 |110\rangle = a_2^\dagger a_0 a_0^\dagger a_1^\dagger |vac\rangle = a_2^\dagger a_1^\dagger |vac\rangle = -|011\rangle,$$

$$\sum_{p,q=0}^{n-1} |o(j,p,q)\rangle \langle 0| \otimes |i\rangle \langle i| \otimes a_p^\dagger a_q$$





# Block Encoding of one-body interactions



# Second quantized Hamiltonian

$$\mathcal{H} = \sum_{p,q} h_{pq} a_p^\dagger a_q + \sum_{p<q, r<s} h_{pqrs} a_p^\dagger a_q^\dagger a_r a_s$$

General Hamiltonian [H, n]=0

$$\mathcal{H} = \sum_{p,q=0}^{n-1} T(p-q) a_p^\dagger a_q$$

Translational Invariant

$$\mathcal{H} = \sum_{p=0}^{n-1} \sum_{q=0}^{n-1} h_{pq} a_p^\dagger a_q \quad |h_{pq}| \leq C e^{-\alpha|p-q|}$$

Nearest-Neighbour

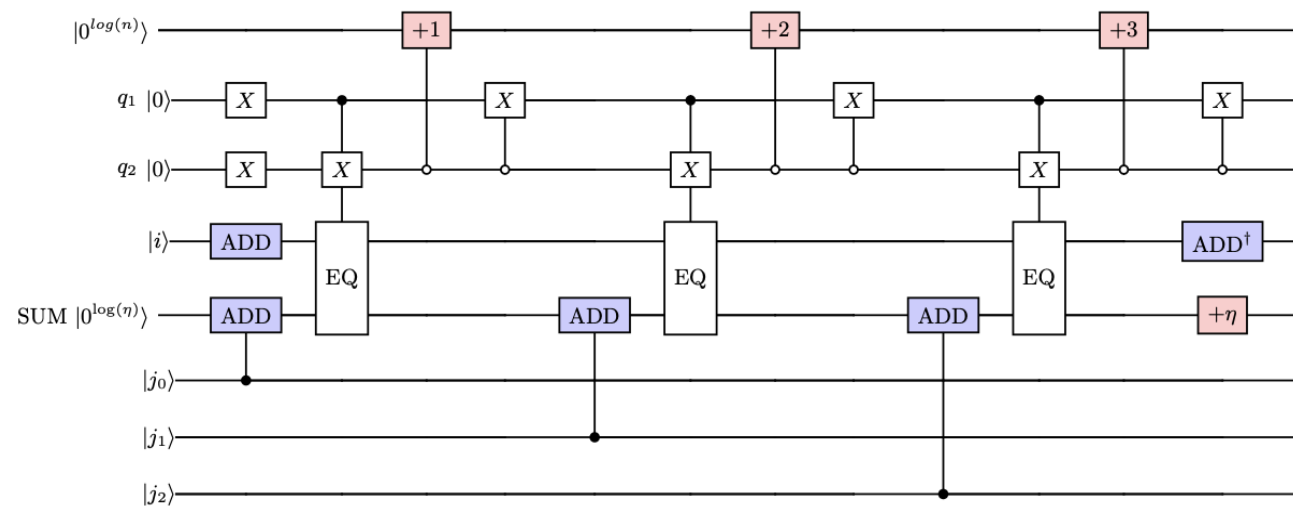
Model	Reference	Qubit	Subnormalization factor	T count
General	2018 Babbush et al. [1]	$\mathcal{O}(n + \log(\frac{n^4}{\epsilon}))$	$\mathcal{O}(n^4)$	$\mathcal{O}(n^4 + \log(\frac{n^4}{\epsilon}))$
	<b>This paper</b>	$\mathcal{O}(n + \lambda_1 \log(\frac{n^4}{\epsilon}))$	$\mathcal{O}(n^4)$	$\mathcal{O}(\frac{n^4}{\lambda_1} + \lambda_1 \log(\frac{n^4}{\epsilon}))$
Factorized	2018 Kivlichan et al. [2]	N/A	N/A	$\mathcal{O}(n^2 \log(\frac{1}{\epsilon}))$
TI Factorized	2018 Babbush et al. [1]	$\mathcal{O}(n + \log(\frac{n^2}{\epsilon}))$	$\mathcal{O}(n^2)$	$\mathcal{O}(n + \log(\frac{n^2}{\epsilon}))$
	<b>This paper</b>	$\mathcal{O}(n + \lambda_2 \log(\frac{n^2}{\epsilon}))$	$\mathcal{O}(n^2)$	$\mathcal{O}(n + \frac{n}{\lambda_2} + \lambda_2 \log(\frac{n^2}{\epsilon}))$
Localized	2021 Wan [3]	$\mathcal{O}(n)$	$\mathcal{O}(n^2)$	$\mathcal{O}(n) + \text{PREP}$
	<b>This paper</b>	$\tilde{\mathcal{O}}(n + \lambda_3 \log(\frac{n^2}{\epsilon}))$	$\mathcal{O}(n^2 \log^2(\frac{n^2}{\epsilon}))$	$\tilde{\mathcal{O}}\left(\frac{n^2}{\lambda_3} \log^2(\frac{n^2}{\epsilon}) + \lambda_3 \log(\frac{n^2}{\epsilon})\right)$

# $\eta$ –particle Hamiltonian Block Encoding

$$H = \sum_{p=0}^{n-1} h_p a_p^\dagger a_p.$$

$$|0\rangle |0^{\log(\eta)}\rangle |j\rangle \xrightarrow[O_A]{H} \frac{1}{\sqrt{\eta}} \sum_{i=0}^{\eta-1} \left( h_{add_i(j)} |0\rangle + \sqrt{1 - h_{add_i(j)}^2} |1\rangle \right) |i\rangle |j\rangle$$

State-dependent amplitude oracle  $O_A$



$$|0^{\log(\eta)}\rangle |0^{\log(n)}\rangle |j\rangle \xrightarrow{H^{\otimes \log(\eta)}} \frac{1}{\sqrt{\eta}} \sum_{i=0}^{\eta-1} |i\rangle |0^{\log(n)}\rangle |j\rangle$$

$$|i\rangle |0^{\log(n)}\rangle |j\rangle \xrightarrow{O_{occ}} |i\rangle |add_i(j)\rangle |j\rangle$$

$$\xrightarrow{O_{\text{IDF}}} \frac{1}{\sqrt{\eta}} \sum_{i=0}^{\eta} |i\rangle |add_i(j)\rangle |j\rangle$$

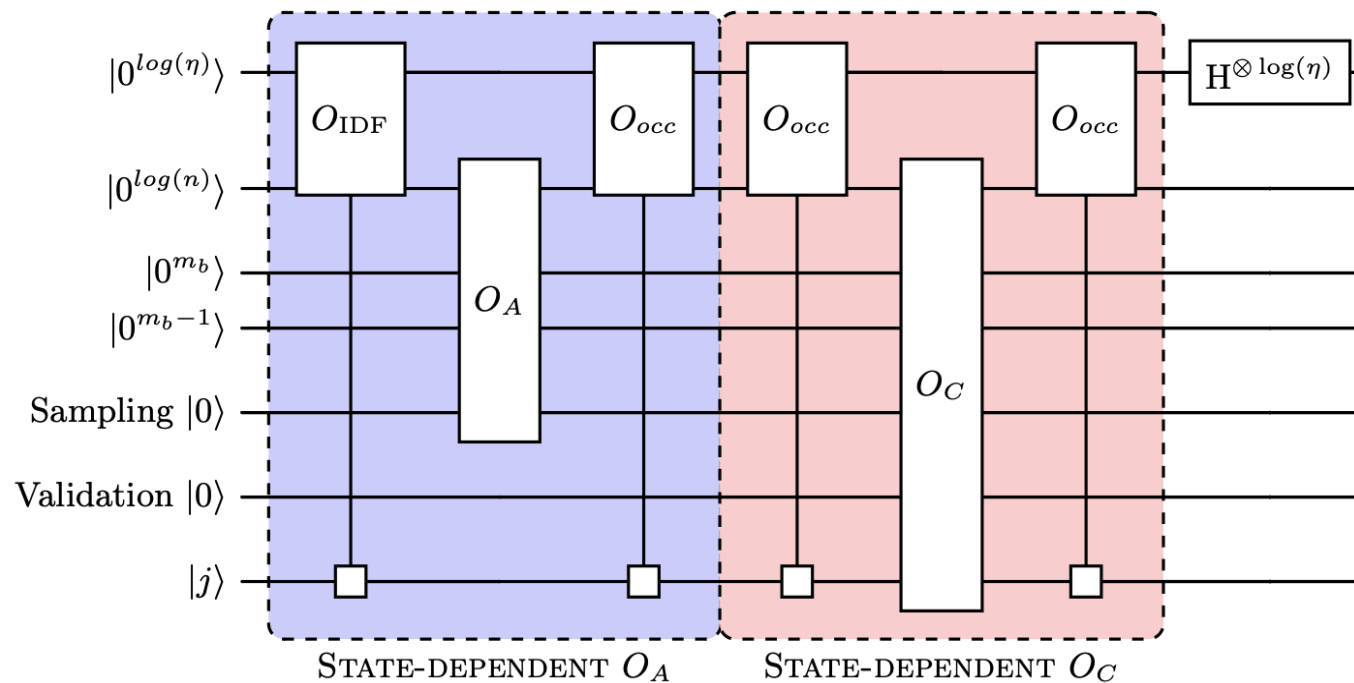
## Indirect diffusion

# $\eta$ –particle Hamiltonian Block Encoding

$$H = \sum_{p=0}^{n-1} h_p a_p^\dagger a_p.$$

$$\sum_{i=0}^{\eta-1} |o(j, add_i(j))\rangle \langle 0| \otimes |i\rangle \langle i| \otimes a_{add_i(j)}^\dagger a_{add_i(j)}$$

State-dependent sparse oracle  $O_C$



$$\xrightarrow{X} \frac{1}{\sqrt{\eta}} \sum_{i=0}^{\eta-1} |1\rangle |i\rangle |add_i(j)\rangle |j_0\rangle |j_1\rangle \dots |j_{n-1}\rangle$$

$$\xrightarrow{SW} \frac{1}{\sqrt{\eta}} \sum_{i=0}^{\eta-1} |1\rangle |i\rangle |add_i(j)\rangle |j_{add_i(j)}\rangle ** \dots$$

$$\xrightarrow{CNOT} \frac{1}{\sqrt{\eta}} \sum_{i=0}^{\eta-1} |o(j, add_i(j))\rangle |i\rangle |add_i(j)\rangle |j_{add_i(j)}\rangle ** \dots$$

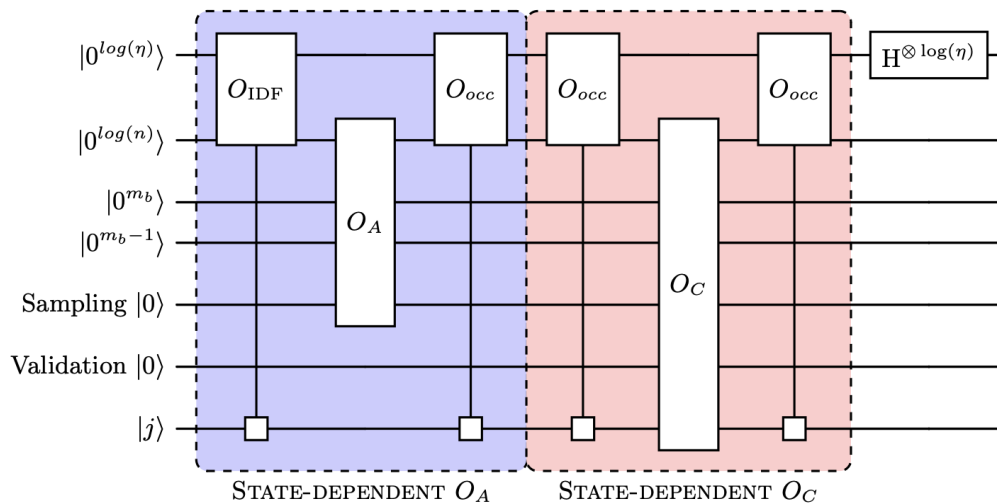
$$\xrightarrow{SW^\dagger} \frac{1}{\sqrt{\eta}} \sum_{i=0}^{\eta-1} |o(j, add_i(j))\rangle |i\rangle |add_i(j)\rangle |j\rangle$$

# $\eta$ –particle Hamiltonian Block Encoding

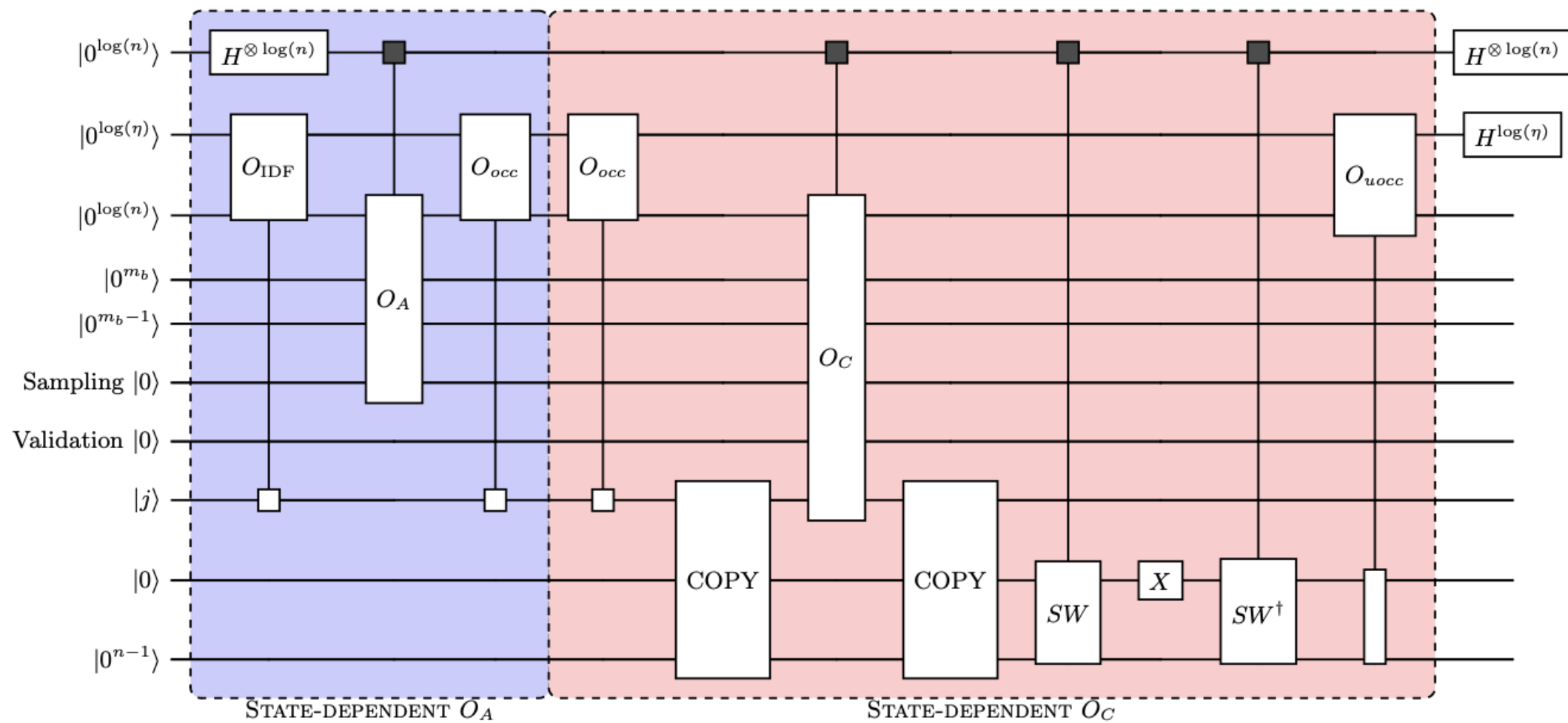
$$H = \sum_{p=0}^{n-1} h_p a_p^\dagger a_p.$$

$$\sum_{i=0}^{\eta-1} |o(j, add_i(j))\rangle \langle 0| \otimes |i\rangle \langle i| \otimes a_{add_i(j)}^\dagger a_{add_i(j)}$$

State-dependent sparse oracle  $O_C$



$$\begin{aligned} & \xrightarrow{O_{IDF}, O_A} \frac{1}{\sqrt{\eta}} \sum_{i=0}^{\eta-1} |0\rangle |i\rangle \left( h_{add_i(j)} |0\rangle + \sqrt{1 - h_{add_i(j)}^2} |1\rangle \right) |j\rangle \\ & \xrightarrow{O_C} \frac{1}{\sqrt{\eta}} \sum_{i=0}^{\eta-1} |o(j, add_i(j))\rangle |i\rangle \left( h_{add_i(j)} |0\rangle + \sqrt{1 - h_{add_i(j)}^2} |1\rangle \right) a_{add_i(j)}^\dagger a_{add_i(j)} |j\rangle \\ & = \frac{1}{\sqrt{\eta}} \sum_{i=0}^{\eta-1} |0\rangle |i\rangle \left( h_{add_i(j)} |0\rangle + \sqrt{1 - h_{add_i(j)}^2} |1\rangle \right) a_{add_i(j)}^\dagger a_{add_i(j)} |j\rangle \\ & \xrightarrow{H} \frac{1}{\eta} \sum_{i=0}^{\eta-1} |0\rangle |0^{\log(\eta)}\rangle |0\rangle \left( h_{add_i(j)} a_{add_i(j)}^\dagger a_{add_i(j)} \right) |j\rangle + * \\ & = \frac{1}{\eta} |0\rangle |0^{\log(\eta)}\rangle |0\rangle \sum_{p=0}^{n-1} h_p a_p^\dagger a_p |j\rangle + * \end{aligned}$$



# How does the subspace influence complexity

$$\mathcal{H} = \sum_{p=0}^{n-1} h_p a_p^\dagger a_p$$

$$\mathcal{H} = \sum_{p=0}^{n-1} \sum_{q=0}^{n-1} h_{pq} a_p^\dagger a_q.$$

Number of data :  $n$

Number of data :  $n^2$

Word length  $m_b$  :  $\log\left(\frac{\eta}{\epsilon}\right)$

Word length  $m_b$  :  $\log\left(\frac{n\eta}{\epsilon}\right)$

$\alpha$  :  $\eta$

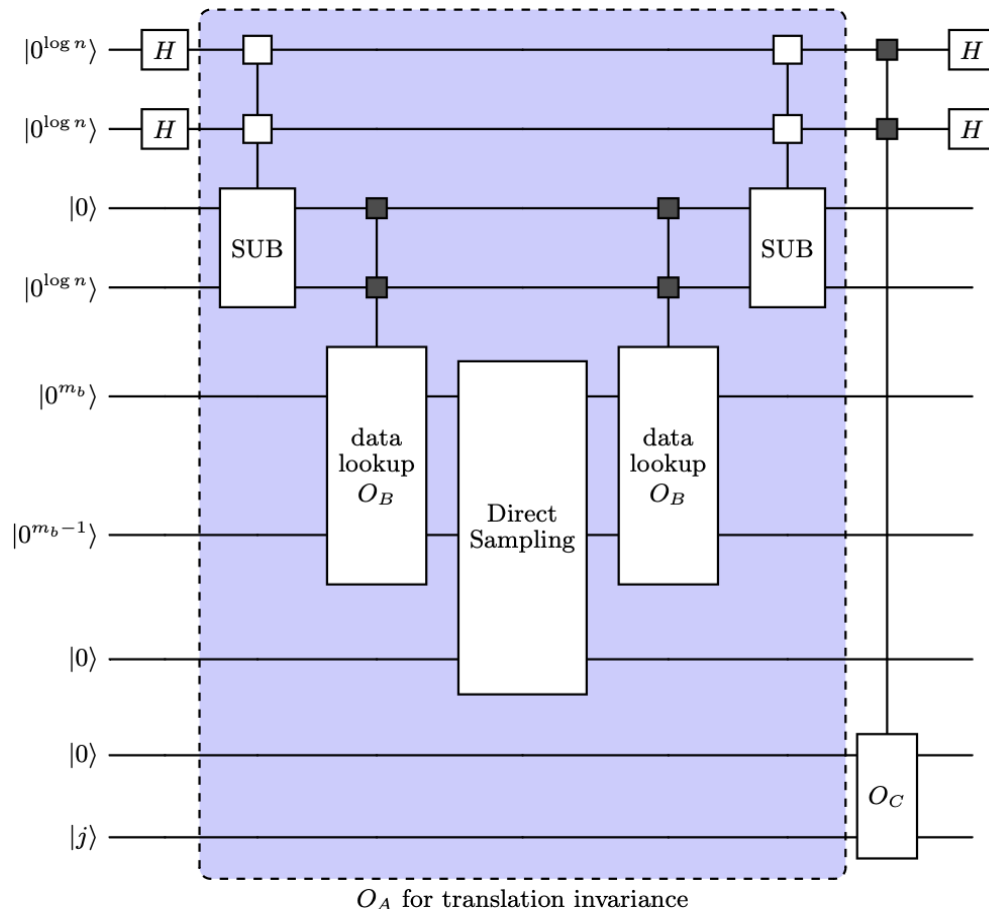
$\alpha$  :  $n\eta$

Model	Reference	Qubit	Subnormalization factor	T count
General	2018 Babbush et al. [1]	$\mathcal{O}(n + \log(\frac{n^4}{\epsilon}))$	$\mathcal{O}(n^4)$	$\mathcal{O}(n^4 + \log(\frac{n^4}{\epsilon}))$
	<b>This paper</b>	$\mathcal{O}(n + \tilde{\lambda}_1 \log(\frac{n^2 \eta^2}{\epsilon}))$	$\mathcal{O}(n^2 \eta^2)$	$\mathcal{O}(n \log(\eta) + \frac{n^4}{\tilde{\lambda}_1} + \tilde{\lambda}_1 \log(\frac{n^2 \eta^2}{\epsilon}))$
Factorized	2018 Kivlichan et al. [2]	N/A	N/A	$\mathcal{O}(n^2 \log(\frac{1}{\epsilon}))$
TI Factorized	2018 Babbush et al. [1]	$\mathcal{O}(n + \log \frac{n^2}{\epsilon})$	$\mathcal{O}(n^2)$	$\mathcal{O}(n + \log(\frac{1}{\epsilon}))$
	<b>This paper</b>	$\mathcal{O}(n + \tilde{\lambda}_2 \log(\frac{n\eta}{\epsilon}))$	$\mathcal{O}(n\eta)$	$\mathcal{O}(n \log(\eta) + \frac{n}{\tilde{\lambda}_2} + \tilde{\lambda}_2 \log(\frac{n\eta}{\epsilon}))$
Localized	2021 Wan [3]	$\mathcal{O}(n)$	$\mathcal{O}(n^2)$	$\mathcal{O}(n) + \text{PREP}$
	<b>This paper</b>	$\tilde{\mathcal{O}}(n + \tilde{\lambda}_3 \log(\frac{\eta^2}{\epsilon}))$	$\mathcal{O}(\eta^2 \log^2(\frac{\eta^2}{\epsilon}))$	$\tilde{\mathcal{O}}(n \log(\eta) + \frac{n^2}{\tilde{\lambda}_3} \log(\frac{\eta^2}{\epsilon}) + \tilde{\lambda}_3 \log(\frac{\eta^2}{\epsilon}))$

# Block Encoding for Structured Hamiltonian

Translational Invariant

$$\mathcal{H} = \sum_{p,q=0}^{n-1} T(p-q) a_p^\dagger a_q$$



Number of data :

$n$

Word length  $m_b$  :

$\log\left(\frac{n^2}{\epsilon}\right)$

$\alpha :$

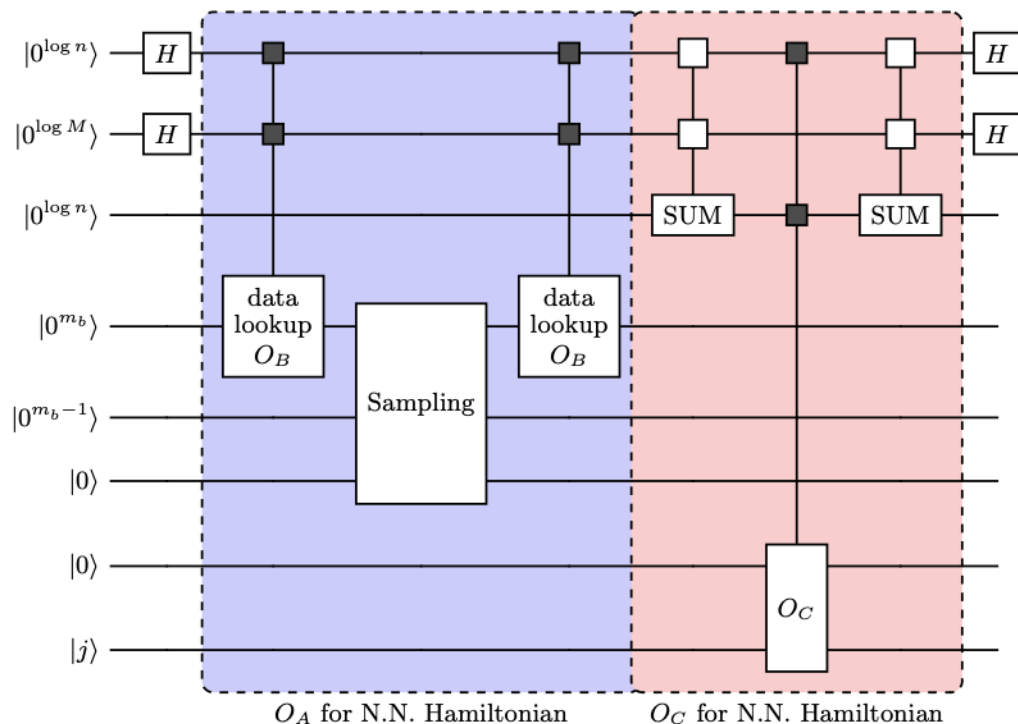
$n^2$



# Block Encoding for Structured Hamiltonian

## Nearest-Neighbour

$$\mathcal{H} = \sum_{p=0}^{n-1} \sum_{q=0}^{n-1} h_{pq} a_p^\dagger a_q \quad |h_{pq}| \leq C e^{-\alpha|p-q|}$$



Less data       $|p - q| \leq C' \log \left( \frac{n}{\epsilon} \right)$

Number of data :       $n \log \left( \frac{n}{\epsilon} \right)$

Word length  $m_b$  :       $\log \left( \frac{n}{\epsilon} \right) + \log \left( \log \left( \frac{n}{\epsilon} \right) \right)$

$\alpha$  :       $n \log \left( \frac{n}{\epsilon} \right)$

Large  $\alpha$

$$\frac{1}{\sqrt{2n}} \sum_{p=0}^{n-1} |p\rangle |p-1\rangle |0\rangle + \frac{1}{\sqrt{2n}} \sum_{p=0}^{n-1} |p\rangle |p+1\rangle |1\rangle$$

# Conclusion

- We develop Block Encoding with **reduced T gate count** for general second-quantized Hamiltonian
- We develop  $\eta$  particle Hamiltonian with **state-dependent**  $O_A$  and **state-dependent**  $O_C$ , through **indirect diffusion**. This gives **smaller subnormalization factor** and **smaller T gate count**.
- We extend the frameworks to structured Hamiltonians

## Future work

- Non-binary block encoding
- More structured Hamiltonians: lower bound and construction

# Thank You