

# Hamiltonian Decoded Quantum Interferometry

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Joint work with

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# Optimization by decoded quantum interferometry

[Stephen P. Jordan](#) , [Noah Shutty](#) , [Mary Wootters](#), [Adam Zalcman](#), [Alexander Schmidhuber](#), [Robbie King](#), [Sergei V. Isakov](#), [Tanuj Khattar](#) & [Ryan Babbush](#)

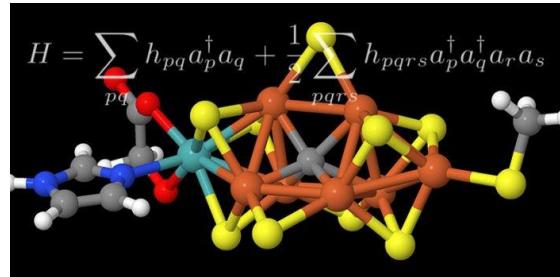
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## Hamiltonian Decoded Quantum Interferometry

Alexander Schmidhuber<sup>\*1,2</sup>, Jonathan Z. Lu<sup>\*2</sup>, Noah Shutty<sup>1</sup>,  
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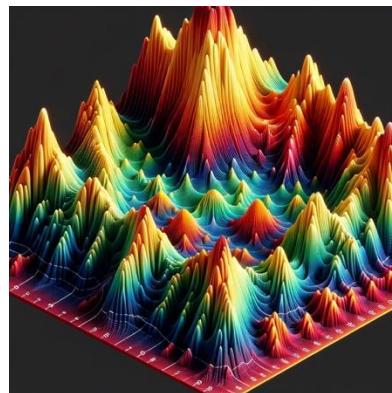
# What are quantum computers good at?



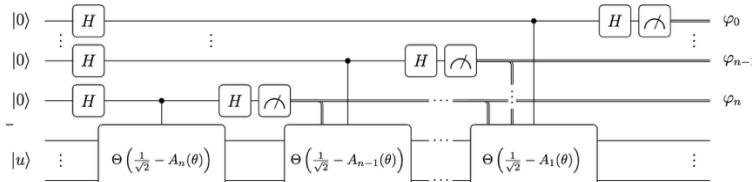
Quantum chemistry /  
Material science

Exponential quantum speedups?

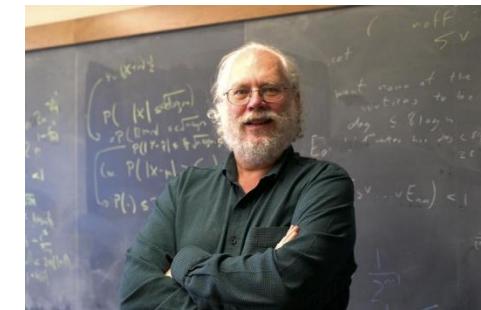
via classical decoding!



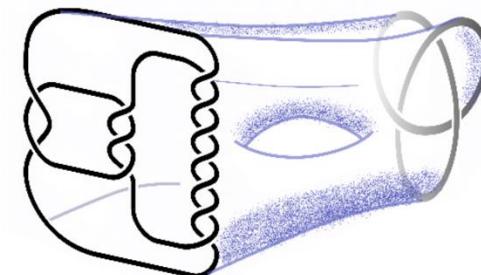
Combinatorial  
optimization?



Matrix inversion / Linear algebra



Integer factorization / HSP



Approximating  
topological invariants

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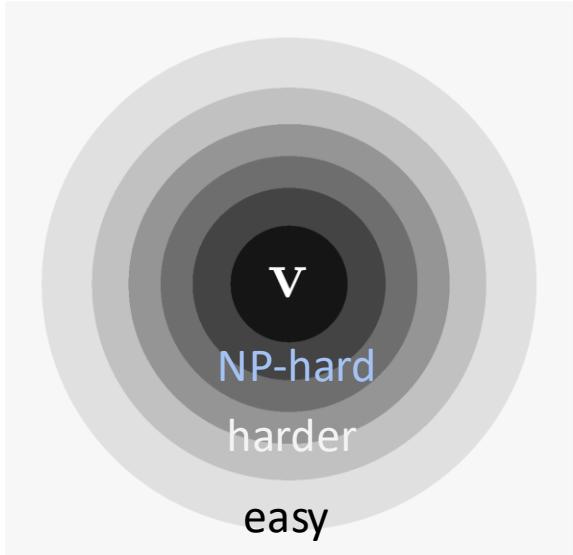
- 01** Recap of DQI
- 02** Hamiltonian DQI
- 03** Algorithmic applications (Putting things into BQP)
- 04** Complexity-theoretic applications (Putting things into QMA)



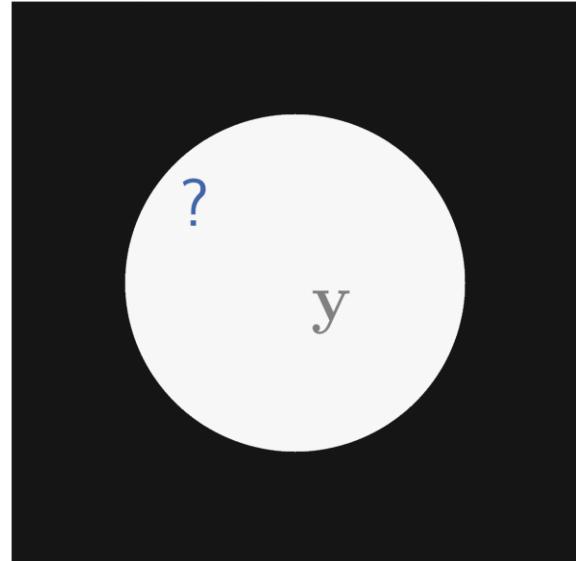
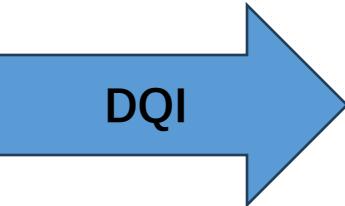
# Decoded Quantum Interferometry

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# DQI is a quantum reduction from classical optimization to classical decoding



$$\max_{\mathbf{x}} f(\mathbf{x})$$



Decode a noisy message

quantum algorithm  
for optimization

=

quantum computer

+

classical decoder

## Example

**Given:**

**$m$  constraints on  $n$  variables** over a binary field mod 2

$$B\mathbf{x} \equiv \mathbf{v}$$

$$B = \begin{bmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \\ \vdots \\ \mathbf{b}_m \end{bmatrix} \in \mathbb{F}_2^{m \times n} \quad \mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_m \end{bmatrix} \in \mathbb{F}_2^m$$

**Goal:**

“satisfy as many  $\mathbf{b}_i \cdot \mathbf{x} = v_i$  as possible”



maximize

$$f(\mathbf{x}) = \sum_{j=1}^m (-1)^{\mathbf{b}_j \cdot \mathbf{x} + v_j} = \#\text{SAT} - \#\text{UNSAT}$$

This defines a code:  $C^\perp = \{\mathbf{d} \in \mathbb{F}_2^m : B^T \mathbf{d} = \mathbf{0}\}$

and a decoding problem: Given  $\mathbf{s} = B^T \mathbf{e}$ , recover  $\mathbf{e}$  provided  $|\mathbf{e}| \leq \ell$

Central claim of DQI:

Decode up to  $\ell$  errors on  $C^\perp \implies$  Sample  $\mathbf{x} \sim P(f(x))^2$ ,

where  $P$  is an arbitrary degree- $\ell$  polynomial

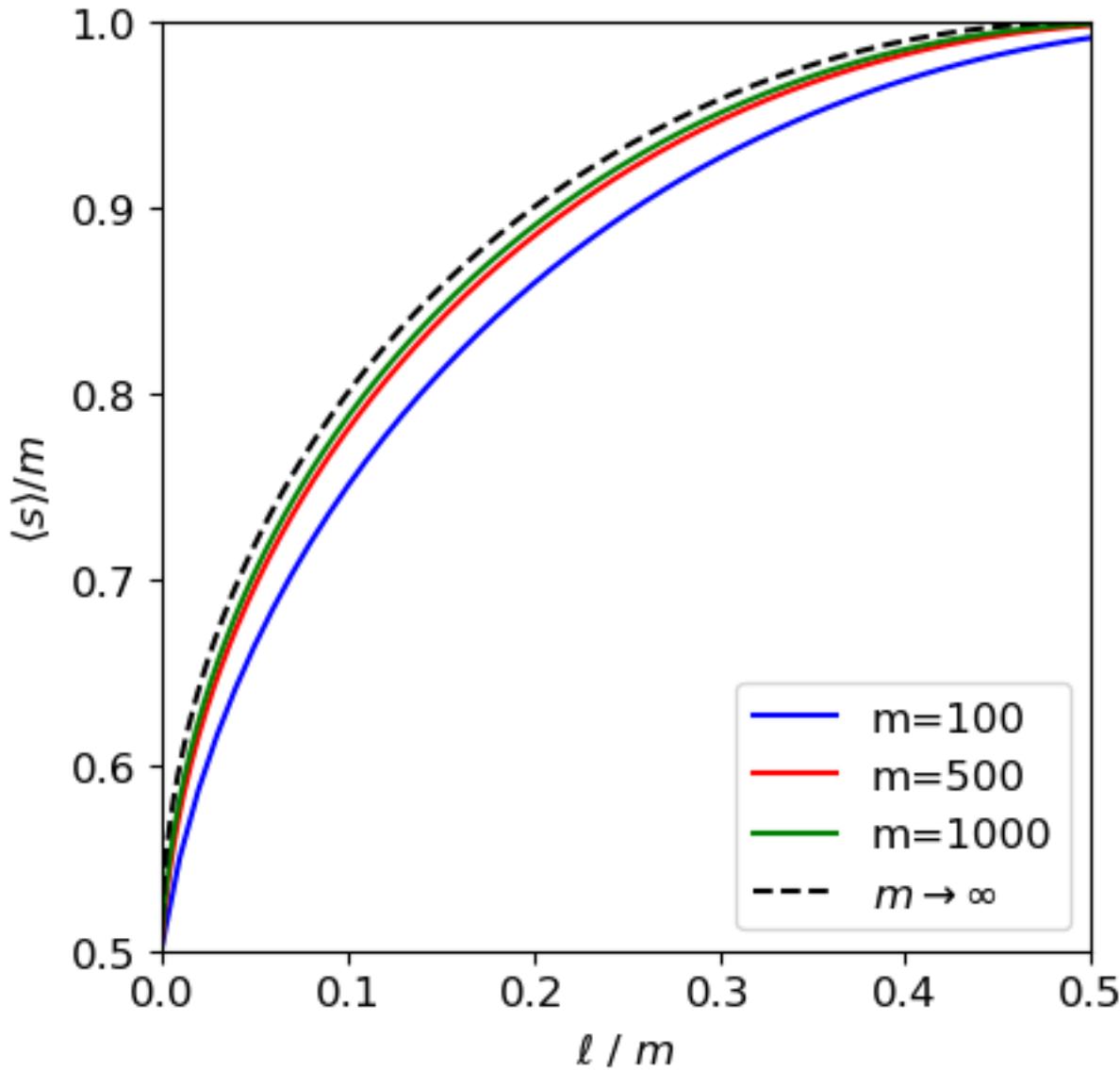
# Performance of DQI

- How can we predict the performance of DQI?

$$B\mathbf{x} \equiv \mathbf{v}$$

If one can correct weight- $\ell$  errors on  $C^\perp$ , then DQI find a solution  $\mathbf{x}$  that satisfies  $s$  constraints given by

$$\frac{\langle s \rangle}{m} = \frac{1}{2} + \sqrt{\frac{\ell}{m} \left(1 - \frac{\ell}{m}\right)}$$



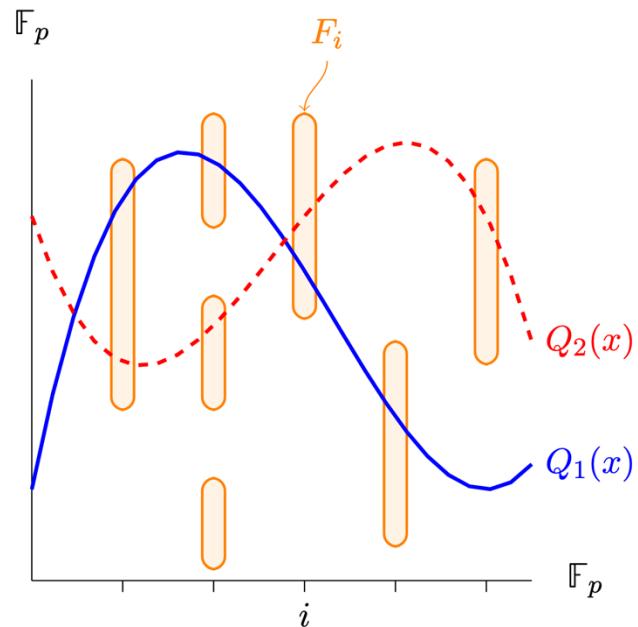
## What kind of structure benefits DQI?

algebraic structure

**Optimization problem:** “Optimal Polynomial Intersection”



**Decoding problem:** Reed-Solomon code

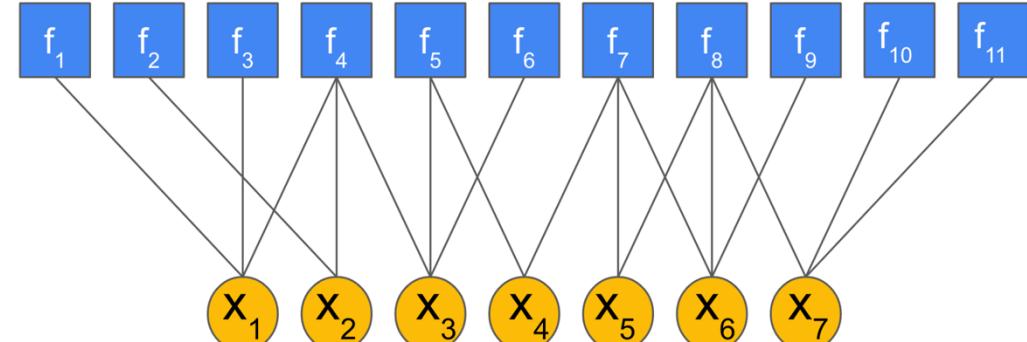


sparsity

**Optimization problem:** Sparse CSP



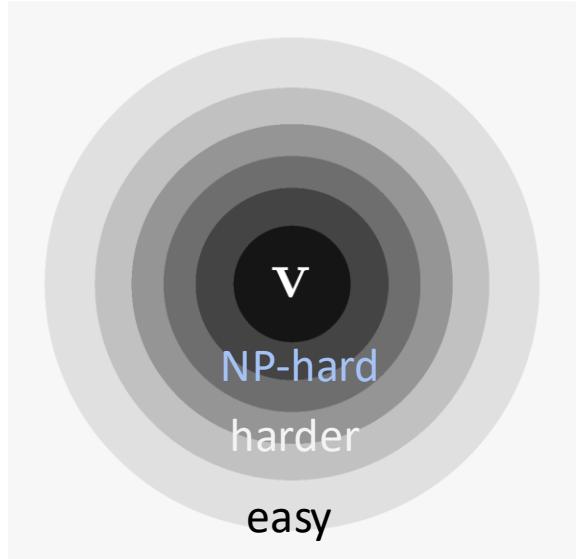
**Decoding problem:** LDPC code



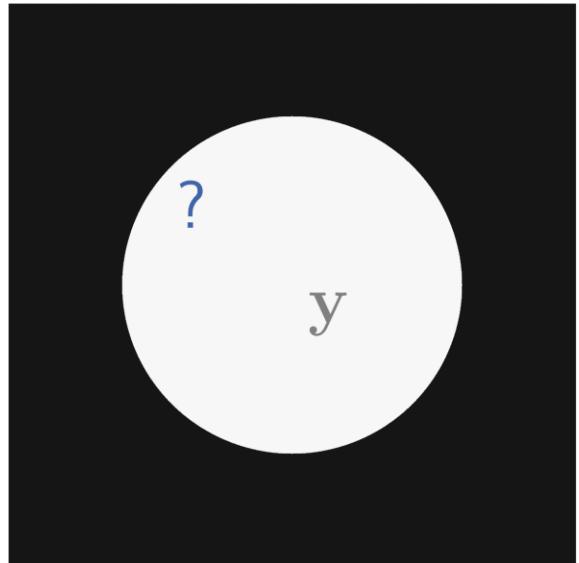
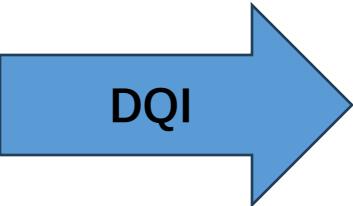


## Hamiltonian DQI

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$$\max_{\mathbf{x}} f(\mathbf{x})$$



Decode a noisy message

quantum algorithm  
for optimization

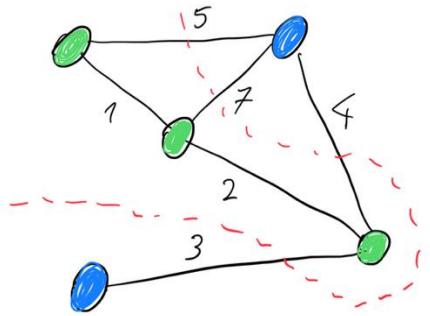
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quantum computer

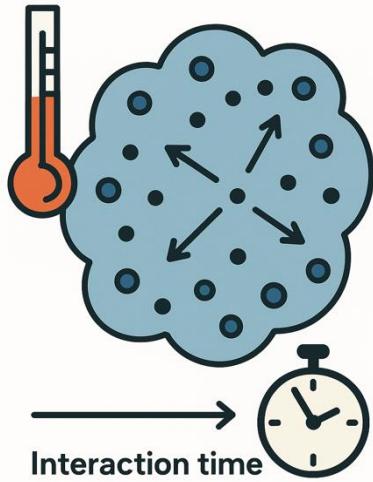
+

classical decoder

## Hamiltonian Optimization



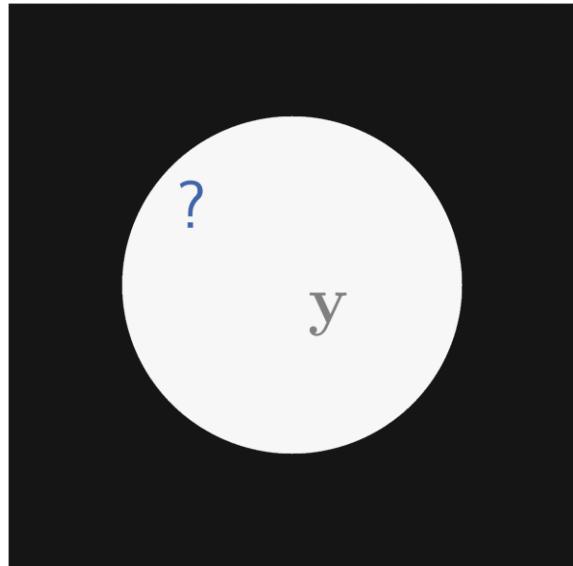
## Gibbs sampling



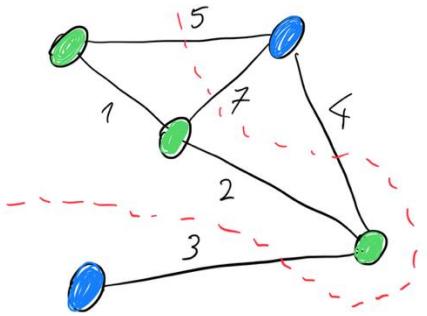
## Hamiltonian simulation

$$e^{-iHt}$$

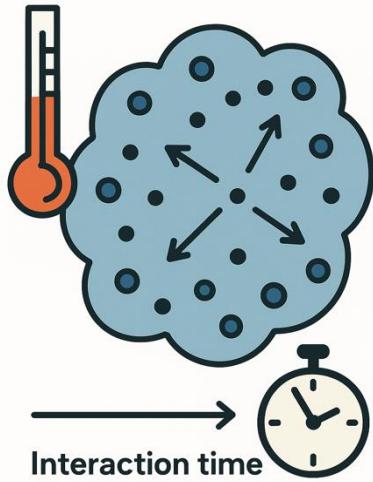
?



## Hamiltonian Optimization



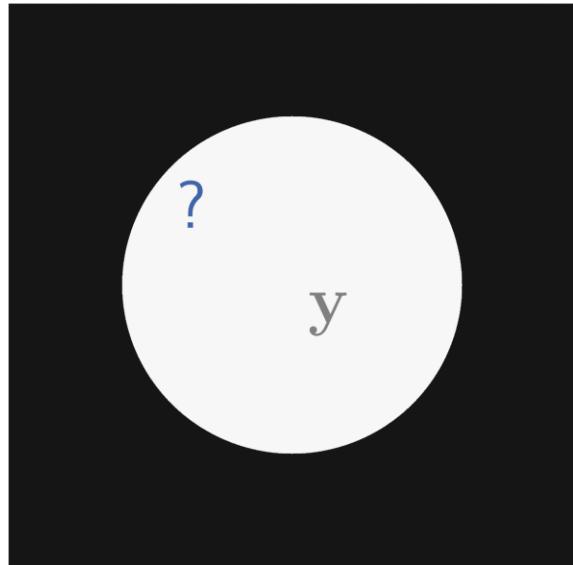
## Gibbs sampling



## Hamiltonian simulation

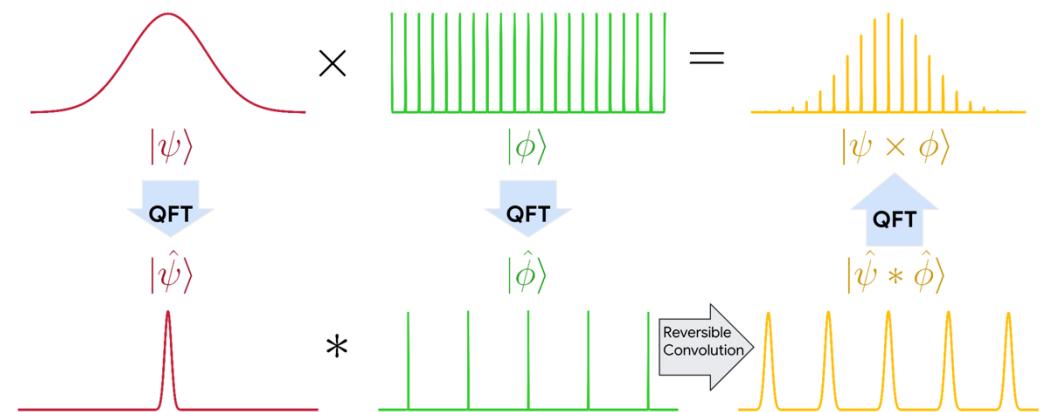
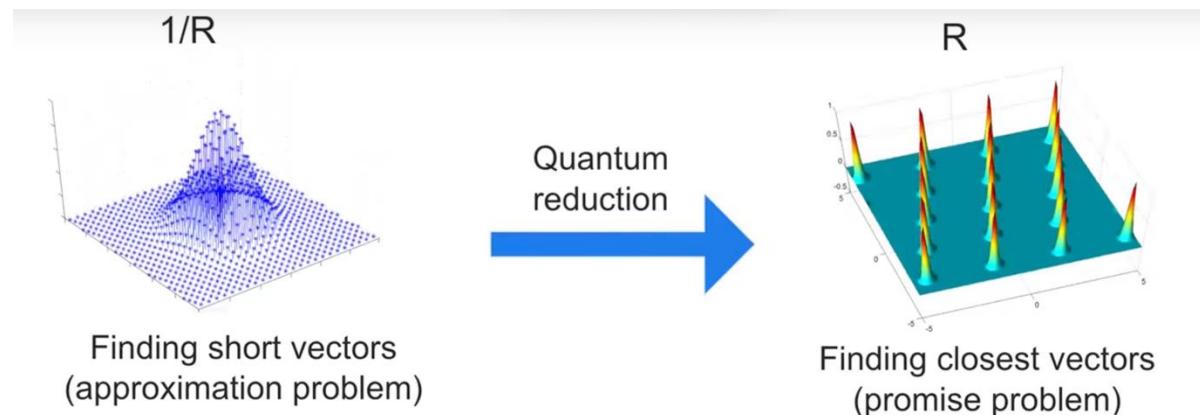
$$e^{-iHt}$$

Hamiltonian DQI



Decode a noisy message

# Alternative: Non-abelian Regev's reduction



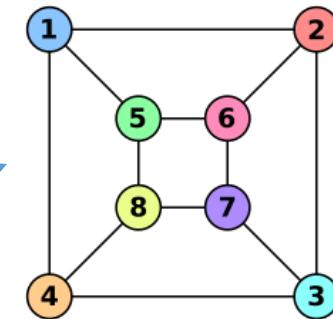
Abelian groups:

$$\mathbb{F}_2, \mathbb{R}, V$$

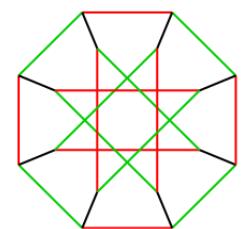
Non-abelian groups:

$$\begin{pmatrix} 1 & 2 & 3 & 4 & 5 \\ 3 & 5 & 1 & 2 & 4 \end{pmatrix}$$

$i < j$   
 $\pi(i) > \pi(j)$



$$X = \sigma_1 = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, \quad Y = \sigma_2 = \begin{pmatrix} 0 & -i \\ i & 0 \end{pmatrix}, \quad Z = \sigma_3 = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix},$$



## Hamiltonian optimization

**Given:**

***m* constraints on *n* variables** over a binary field mod 2

$$B = \begin{bmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \\ \vdots \\ \mathbf{b}_m \end{bmatrix} \in \mathbb{F}_2^{m \times n} \quad \mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_m \end{bmatrix} \in \mathbb{F}_2^m$$

$$H = \sum_i (-1)^{v_i} Z^{b_i} \quad H|x\rangle = f(x)|x\rangle \quad f(\mathbf{x}) = \sum_{j=1}^m (-1)^{\mathbf{b}_j \cdot \mathbf{x} + v_j} = \#\text{SAT} - \#\text{UNSAT}$$

**Task:** Sample  $x \sim P(f(x))^2$

## (Pauli) Hamiltonian generalization:

**Given:**

$$H = \sum_{i=1}^m v_i P_i \quad H |\lambda\rangle = \lambda |\lambda\rangle$$

**Task:** Sample  $|\lambda\rangle \sim \mathcal{P}(\lambda)^2$

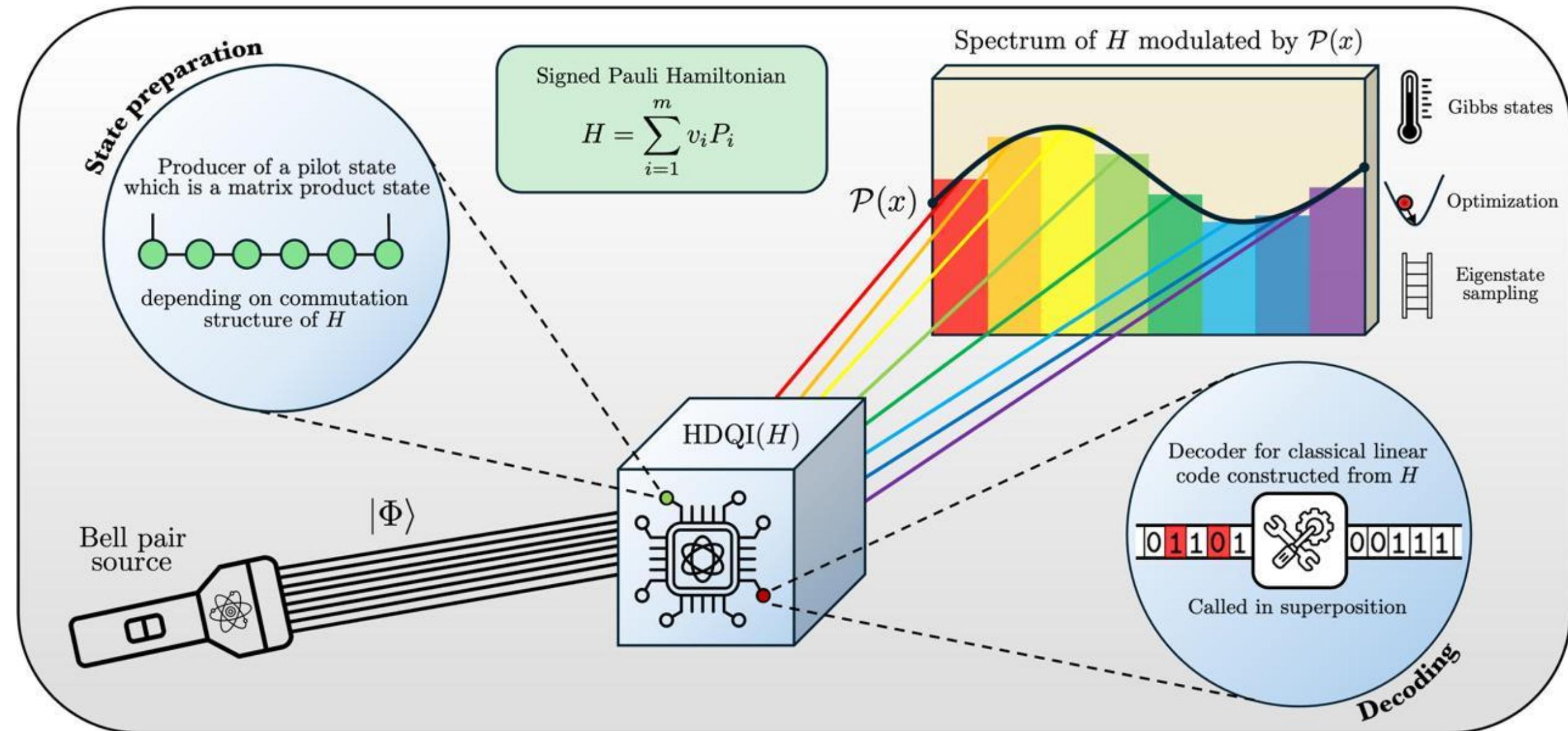
**HDQI reduces this task to:**

$$\rho_{\mathcal{P}}(H) = \frac{\mathcal{P}^2(H)}{\text{Tr} [\mathcal{P}^2(H)]}$$

Decoding

+

Preparing a Pilot state



# Algorithm

**Goal:** Sample  $|\lambda\rangle \sim \mathcal{P}(\lambda)^2$

DQI prepares

$$\propto \sum_{\mathbf{x} \in \mathbb{F}_2^n} \mathcal{P}(f(\mathbf{x})) |\mathbf{x}\rangle$$

Naïve approach for HDQI:

$$\propto \mathcal{P}(H) \sum_{\lambda} |\lambda\rangle = \sum_{\lambda} \mathcal{P}(\lambda) |\lambda\rangle$$

## Two issues

Resolution:

$$|\Phi^n\rangle = \frac{1}{2^{n/2}} \sum_{x \in \mathbb{F}_2^n} |x\rangle \otimes |x\rangle = \frac{1}{2^{n/2}} \sum_{\lambda} |\lambda\rangle \otimes |\bar{\lambda}\rangle$$

$$(\mathcal{P}(H) \otimes \mathbb{1}) |\Phi^n\rangle = \frac{1}{2^{n/2}} \sum_{\lambda} \mathcal{P}(\lambda) |\lambda\rangle \otimes |\bar{\lambda}\rangle \xrightarrow{\text{Partial trace}} \rho_{\mathcal{P}}(H) = \frac{\mathcal{P}^2(H)}{\text{Tr}[\mathcal{P}^2(H)]}$$

# Algorithm (commuting case)

**Input:**

$$H = \sum_{i=1}^m v_i P_i$$

**Goal:** Prepare

$$(\mathcal{P}(H) \otimes \mathbb{1}) |\Psi\rangle := (\mathcal{P}(H) \otimes \mathbb{1}) \frac{1}{2^{n/2}} \sum_{x \in \mathbb{F}_2^n} |x\rangle \otimes |x\rangle$$

**1. Expand**

$$\mathcal{P}(H) = \sum_{k=0}^{\ell} w_k \sum_{y \in \mathbb{F}_2^m, |y|=k} \left( \prod_{i \in y} v_i \right) P_y, \quad P_y := \prod_{i \in y} P_i,$$

**2. Prepare pilot state**

$$\sum_{k=0}^{\ell} w_k \sum_{y \in \mathbb{F}_2^m, |y|=k} |y\rangle |\Phi^n\rangle,$$

**3. Controlled Paulis**

$$\sum_{k=0}^{\ell} w_k \sum_{y \in \mathbb{F}_2^m, |y|=k} |y\rangle \left( \prod_{i \in y} v_i \right) P_y |\Phi^n\rangle.$$

**4. Uncompute!**

$$|y\rangle P_y |\Phi^n\rangle \mapsto |0^m\rangle P_y |\Phi^n\rangle$$

# Decoding problem:

Recover  $y \in \mathbb{F}_2^m$  (with  $|y| \leq \ell$ ) given

$$P_y \sum_x |x\rangle|x\rangle$$

$$P_y := \prod_{i \in y} P_i$$

Step 1: Recover  $P_y$  from  $P_y \sum_x |x\rangle|x\rangle$

Information theoretically possible:  $\forall P, Q \in \{X, Y, Z, \mathbb{1}\}^{\otimes n} : \langle \Psi | PQ | \Psi \rangle = \frac{1}{2^n} \text{tr}\{PQ\} = \delta_{P,Q}$ .

Efficiently possible (Bell measurement):  $|\Psi\rangle = \left(|\Phi^+\rangle_{1,1'}\right) \otimes \left(|\Phi^+\rangle_{2,2'}\right) \otimes \cdots \otimes \left(|\Phi^+\rangle_{n,n'}\right)$

Step 2: Recover  $y \in \mathbb{F}_2^m$  (with  $|y| \leq \ell$ ) from  $P_y$

Classical decoding problem

## Decoding problem

$$G_n \equiv \{\pm I, \pm iI, \pm X, \pm iX, \pm Y, \pm iY, \pm Z, \pm iZ\}^{\otimes n}$$

$$P_{\mathbf{a}} = i^{\mathbf{a}^T \mathbf{Y} \mathbf{a}} \prod_{j=1}^n X_j^{\mathbf{a}_{2j-1}} Z_j^{\mathbf{a}_{2j}}, \mathbf{a} = \text{symp}(\mathbf{P}_i) \in \mathbb{F}_2^{2n}$$

Group homomorphism

$$\text{symp}(P_i P_j) = \text{symp}(P_i) \oplus \text{symp}(P_j) \in \mathbb{F}_2^{2n}$$

**Bell measurement maps**  $P_y \sum_x |x\rangle|x\rangle$  to  $\text{symp}(P_y)$

# Decoding problem:

Recover  $y$  from

$$P_y \sum_x |x\rangle|x\rangle$$

$$P_y := \prod_{i \in y} P_i$$

Step 2: Recover  $y \in \mathbb{F}_2^m$  (with  $|y| \leq \ell$ ) from  $\text{symp}(P_y)$

This is just a classical bounded-distance syndrome decoding problem

$$B^T y \mapsto y \text{ given } |y| \leq \ell \quad B \in \mathbb{F}_2^{m \times 2n}$$

Symplectic code defined by parity check matrix

$$B^T = \begin{bmatrix} & & & \\ & | & | & | \\ \text{symp}(P_1) & \text{symp}(P_2) & \cdots & \text{symp}(P_m) \\ & | & | & | \end{bmatrix} \in \mathbb{F}_2^{2n \times m}$$

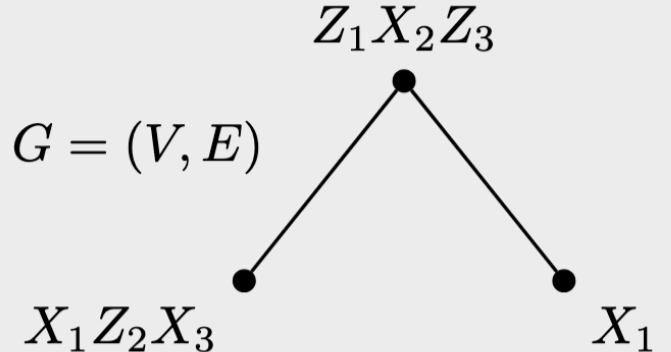
# Non-commuting case:

There are now cancellations!

$$\mathcal{P}(H) = \sum_{k=0}^{\ell} w_k \sum_{y \in \mathbb{F}_2^m, |y|=k} \alpha(y) P_y,$$

$$\alpha(y) = \frac{1}{|y|!} \sum_{\sigma \in S^{|y|}} \text{sgn}_y(\sigma) \quad \text{sgn}_y(\sigma) := \frac{\sigma(P_y)}{P_y}$$

$$H = X_1 Z_2 X_3 + Z_1 X_2 Z_3 - X_1$$



New goal:  
Prepare the pilot state

$$\sum_{k=0}^{\ell} w_k \sum_{y \in \mathbb{F}_2^m, |y|=k} \alpha(y) |y\rangle |\Psi\rangle$$

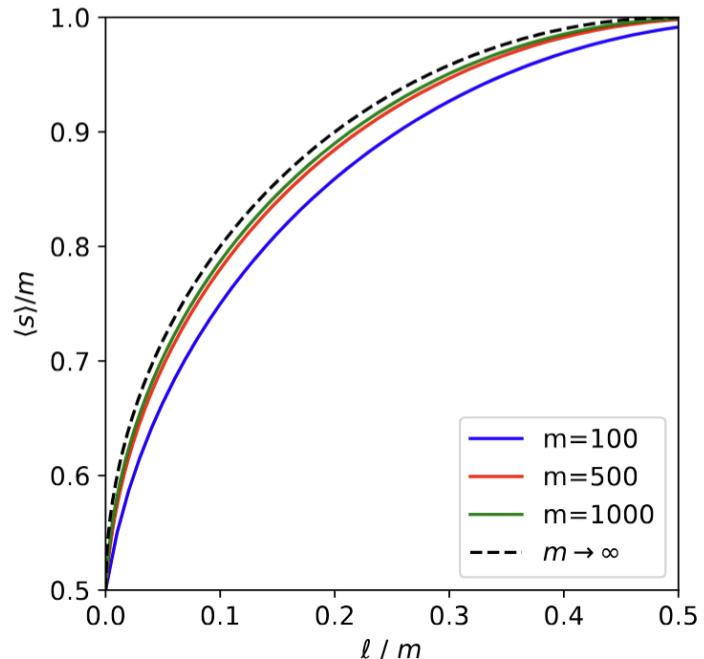
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## Applications of HDQI

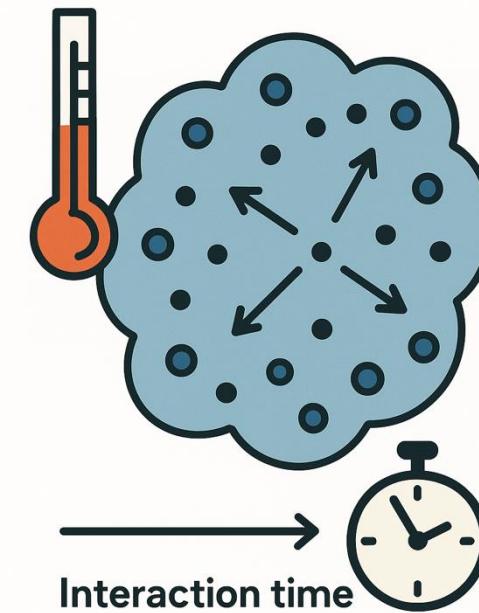
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# Applications:

## Optimization and Gibbs sampling

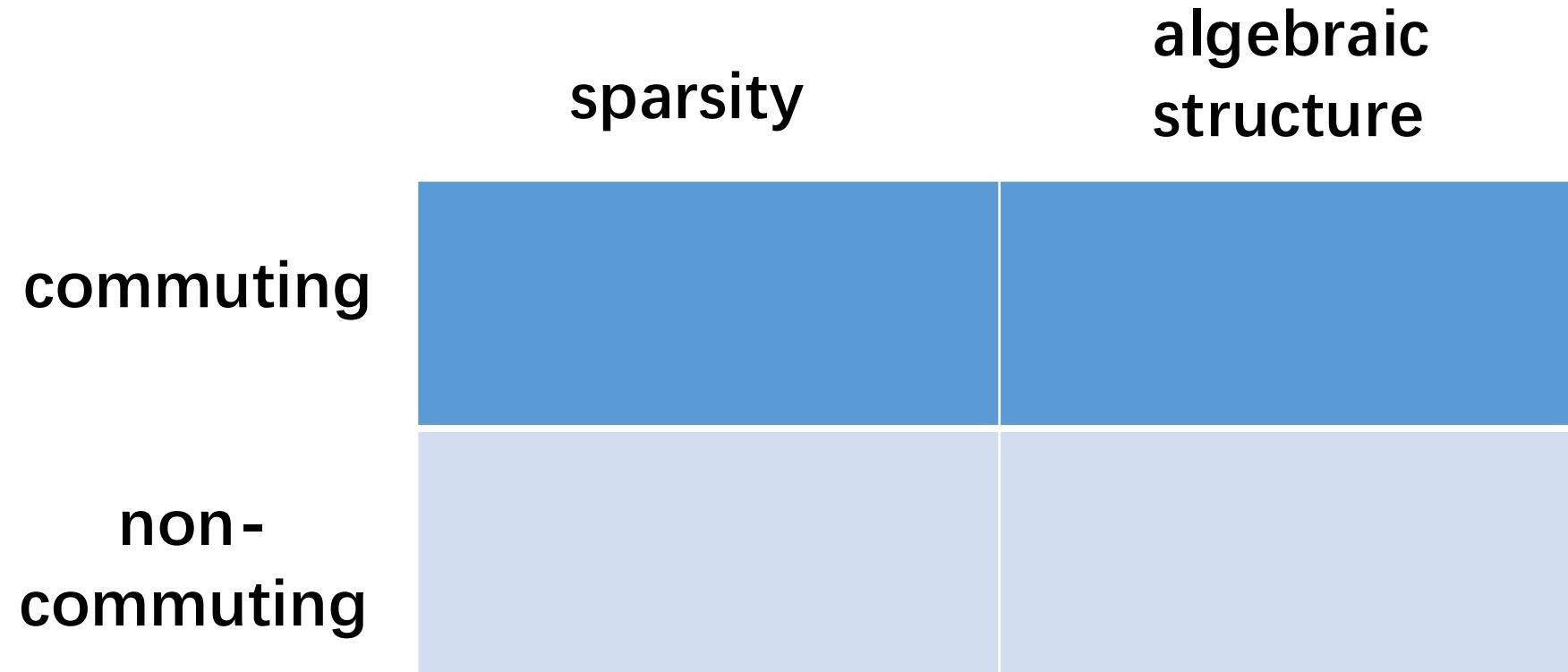


$$\frac{\langle E \rangle}{m} = \left( \sqrt{\frac{\ell}{2m}} + \sqrt{\left(\frac{1}{2} - \frac{\ell}{2m}\right)} \right)^2$$



$$\beta ||H|| = \frac{1}{\sqrt{2}} \ell$$

# Applications



## Random commuting local Hamiltonians

$$H = \sum_i v_i P_i \quad [P_i, P_j] = 0 \quad P_j \in \mathcal{P}_n^{(k)} := \{k\text{-local Paulis on } n \text{ qubits}\}$$

$$B^T = \begin{bmatrix} & & & \\ | & | & & | \\ \text{symp}(P_1) & \text{symp}(P_2) & \cdots & \text{symp}(P_m) \\ | & | & & | \end{bmatrix} \quad \text{Local Hamiltonian} \rightarrow \text{LDPC code!}$$

$(m/n, k)$	HDQI and BP	Clifford SA
(3, 3)	$69.15 \pm 0.04\%$	$77.92 \pm 0.29\%$
(3, 4)	$69.73 \pm 0.04\%$	$76.87 \pm 0.32\%$
(3, 5)	$69.25 \pm 0.03\%$	$75.68 \pm 0.30\%$
(3, 6)	$68.57 \pm 0.03\%$	$74.60 \pm 0.51\%$
(6, 3)	$61.56 \pm 0.04\%$	$70.10 \pm 0.26\%$
(6, 4)	$62.38 \pm 0.02\%$	$69.35 \pm 0.29\%$
(6, 5)	$62.31 \pm 0.02\%$	$68.56 \pm 0.28\%$
(6, 6)	$62.00 \pm 0.02\%$	$67.46 \pm 0.21\%$
(10, 3)	$58.02 \pm 0.03\%$	$65.44 \pm 0.31\%$
(10, 4)	$58.83 \pm 0.02\%$	$64.81 \pm 0.18\%$
(10, 5)	$58.90 \pm 0.02\%$	$64.31 \pm 0.27\%$
(10, 6)	$58.75 \pm 0.01\%$	$63.60 \pm 0.32\%$

Fig: Energy (in percentages) achieved by HDQI and a classical Clifford SA algorithm.

# Structured commuting Hamiltonians

if  $\dim \text{Ker } B^T = \text{const}$

$$B^T = \begin{bmatrix} & & & \\ \text{symp}(P_1) & \text{symp}(P_2) & \cdots & \text{symp}(P_m) \\ & & & \end{bmatrix}$$

Theorem:

HDQI efficiently prepares

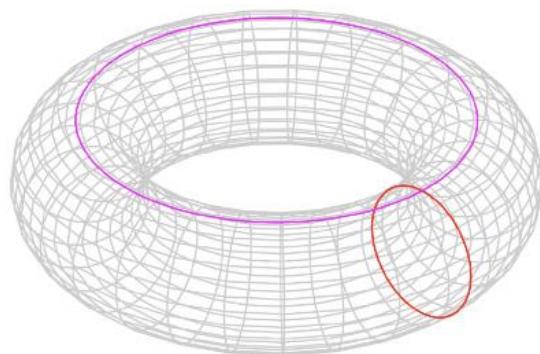
$$\rho_H = f(H) / \text{Tr}[f(H)]$$

for any non-zero function  $f : \text{Spec}(H) \rightarrow \mathbb{R}_{\geq 0}$

Example: Toric code

$$H_{\text{TC}} = - \sum_v A_v - \sum_p B_p$$

$$A_v = \prod_{i \in v} X_i, \quad B_p = \prod_{i \in p} Z_i$$



Two relations:

$$\prod_{v \in V} A_v = \prod_{p \in F} B_p = \mathbb{1}.$$

$$\dim \text{Ker } B^T = 2^2 = 4$$

# HDQI prepares arbitrary Gibbs states of the 2D Toric code

Polynomial-Time Preparation of Low-Temperature Gibbs States for  
2D Toric Code

Zhiyan Ding<sup>\*1</sup>, Zeph Landau<sup>†2</sup>, Bowen Li<sup>‡3</sup>, Lin Lin<sup>§1,4</sup>, and Ruizhe Zhang<sup>¶5</sup>

Gibbs state preparation for commuting Hamiltonian:  
Mapping to classical Gibbs sampling

Yeongwoo Hwang<sup>‡ \*1</sup> and Jiaqing Jiang<sup>‡ †2</sup>

**Efficient and simple Gibbs state preparation of the 2D toric code  
via duality to classical Ising chains**

Pablo Páez Velasco,<sup>1, 2, \*</sup> Niclas Schilling,<sup>3, †</sup> Samuel O. Scalet,<sup>4, 5, ‡</sup> Frank Verstraete,<sup>4, 6, §</sup> and Ángela Capel<sup>4, 7, ¶</sup>

# Structured commuting Hamiltonians

if  $\dim \text{Ker } B^T = \text{const}$

$$B^T = \begin{bmatrix} & & & \\ | & | & \cdots & | \\ \text{symp}(P_1) & \text{symp}(P_2) & \cdots & \text{symp}(P_m) \\ | & | & & | \end{bmatrix}$$

Theorem:

HDQI efficiently prepares

$$\rho_H = f(H) / \text{Tr}[f(H)]$$

for any non-zero function  $f : \text{Spec}(H) \rightarrow \mathbb{R}_{\geq 0}$

Model	Geometry	$\dim \text{Symp}(H)$	Reason / remarks
Ising (ring)	1D, periodic	1	Unique cycle relation $\prod ZZ = I$ .
Surface/toric	2D, closed	2	Global star and plaquette products; homology on closed surfaces.
Color code (stabilizer)	2D, closed	4	Two independent two-color products per Pauli sector.
TI Pauli in 2D	2D, closed	$2K$	LC-equivalent to $K$ toric copies; $K$ constant.
Cluster (1D, 2D, 3D)	periodic	0	Unique stabilizer ground state.
Finite stack of 2D codes	embedded in 3D	$2K$	Sum over $K$ decoupled layers.
Haah (generic sizes)	3D, periodic	$O(1)$	No local relations; global count constant for many $L$ .
Counterexamples			
3D toric code	3D, periodic	$\Theta(L^3)$	Cube-local plaquette identities.
X-cube / checkerboard	3D, periodic	$\Theta(L^3)$	Many local relations (type-I fracton).

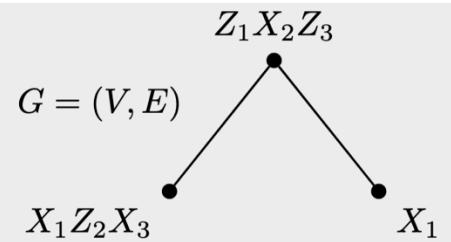


**Noah Shutty**

“This is also classically easy!”

# Non-commuting Hamiltonians

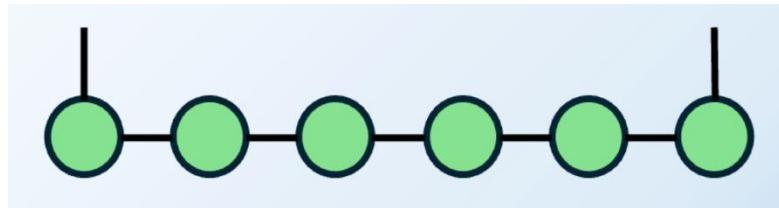
If the anti-commutation graph factorizes into connected components of size  $O(\log(n))$



Theorem:



The pilot state can be prepared efficiently as a Matrix Product State (MPS).



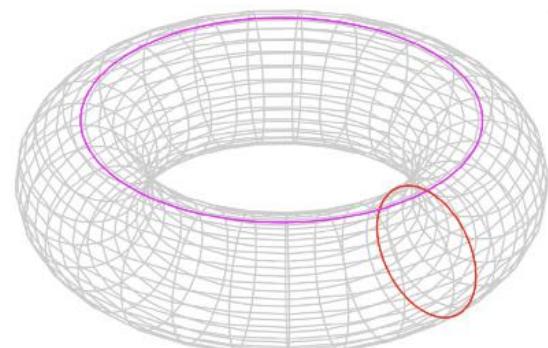
Semi-classical spin glass:

$$H(p) = \sum_{i=1}^m v_i P(\mathbf{b}_i)$$

$$P(\mathbf{b}_i) = \begin{cases} Z^{\mathbf{b}_i} & \text{with probability } 1-p \\ X^{\mathbf{b}_i} & \text{with probability } p \end{cases}$$

Commuting Hamiltonians with random defects:

$$H_{\text{TC}} = - \sum_v A_v - \sum_p B_p$$



## The Pilot state as a QMA witness

- Consider a Hamiltonian  $H$  for which the decoding problem is easy.
- Then the Pilot state acts as a witness for certifying the ground state energy.

$$\sum_{k=0}^{\ell} w_k \sum_{y \in \mathbb{F}_2^m, |y|=k} \alpha(y) |y\rangle |\Psi\rangle \quad \alpha(y) = \frac{1}{|y|!} \sum_{\sigma \in S^{|y|}} \text{sgn}_y(\sigma) \quad \text{sgn}_y(\sigma) := \frac{\sigma(P_y)}{P_y}$$

- Given this state, there is an efficient quantum algorithm (not QPE!) that computes the ground state energy.
- The Pilot state only depends on the anti-commutation graph (not on, e.g., signs!)
- QMA with advice?

# Future directions

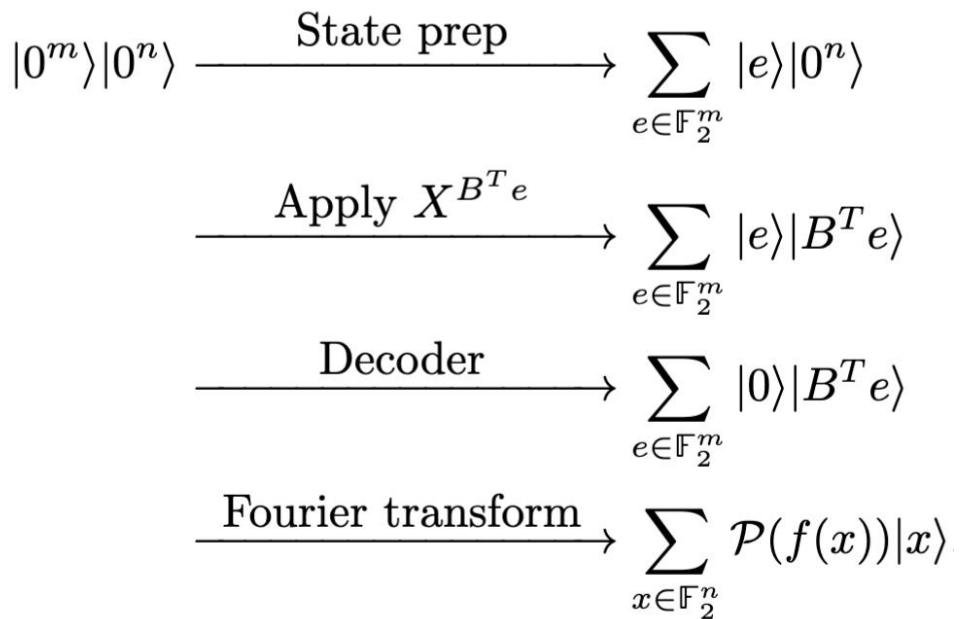
- **When can the pilot state be efficiently prepared?**
  - Beyond  $\log(n)$ -sized connected components?
  - Exploit structure beyond sparsity?
- **What interesting quantum Hamiltonians correspond to good classical codes?**
  - Random local Hamiltonians
  - Topological code Hamiltonians
  - ...?
- **Generalizations to other non-abelian groups?**

Thank you

# Alternative view of HDQI

**Decoded Quantum Interferometry:**  
QFT over the abelian group  $\mathbb{F}_2^n$

$$H^{\otimes n}$$

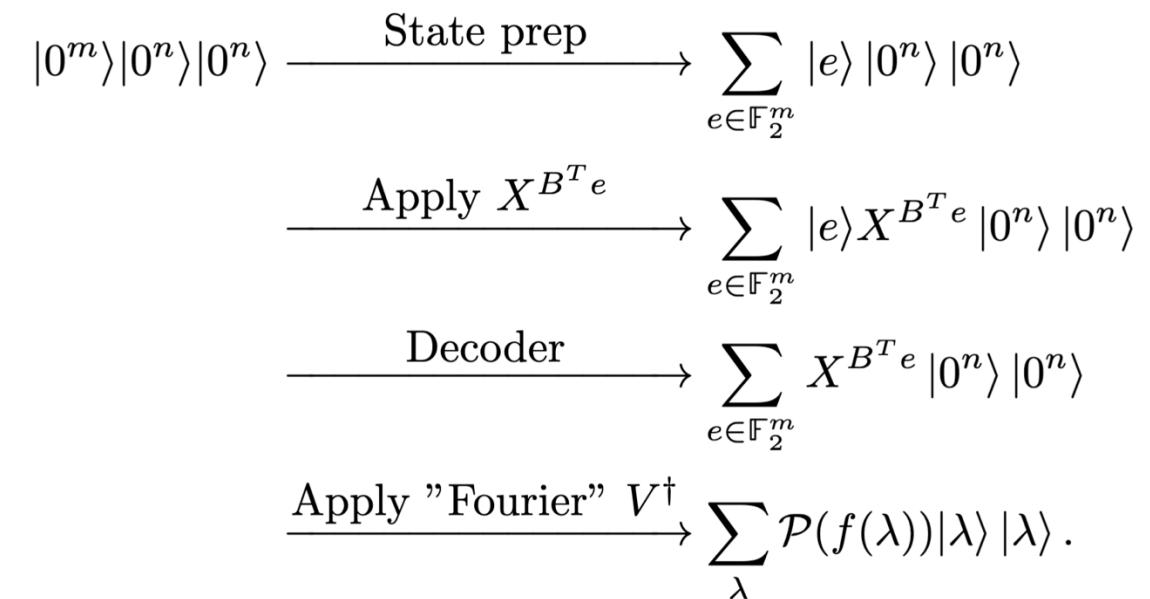


**Hamiltonian DQI:**  
QFT over non-abelian group  $\{\pm 1, \pm i\} \times \{I, X, Y, Z\}^{\otimes n}$

$$V = (H^{\otimes n} \otimes \mathbb{1}) \text{ CNOT}^{\otimes n}$$

Bell state preparation unitary

Non-abelian QFT over Pauli group



# Further Hamiltonians

## Further Hamiltonians

- Can the pilot state be prepared beyond  $\log(n)$ -size connected components?
- Is there structure beyond sparsity in the commutation graph that can be exploited?
- Hardness of semi-classical spin glass?