

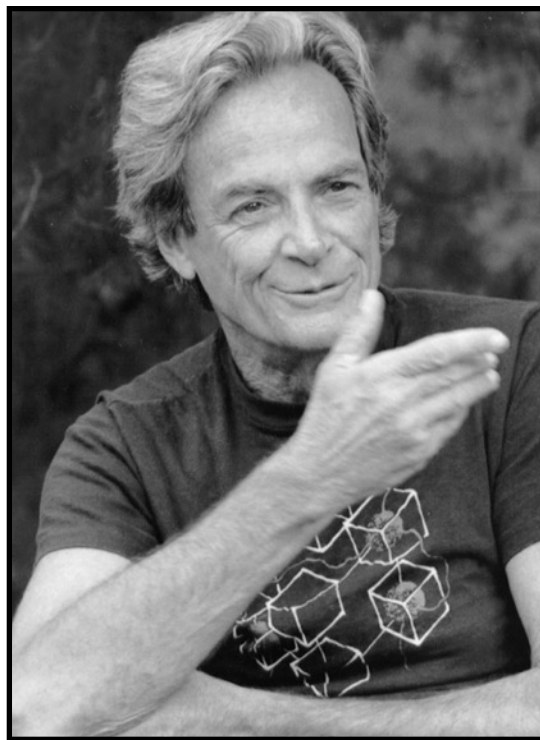
# Quantum algorithms for simulating quantum mechanics

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JOINT CENTER FOR  
QUANTUM INFORMATION  
AND COMPUTER SCIENCE



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

Richard Feynman

*Simulating physics with computers (1981)*

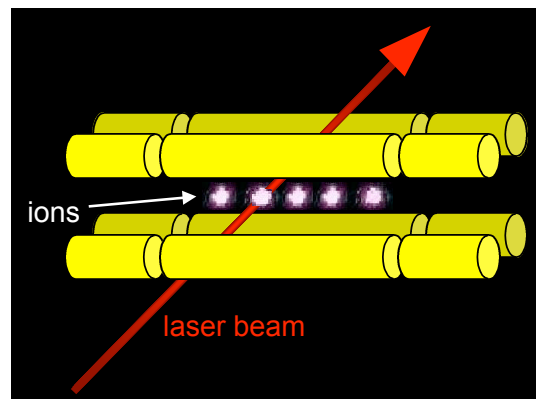
# The ultimate quantum physics lab

## Universal quantum computer

- Prepare system in a pure state of  $n$  qubits
- Apply 2-qubit unitary operations
- Measure in standard basis

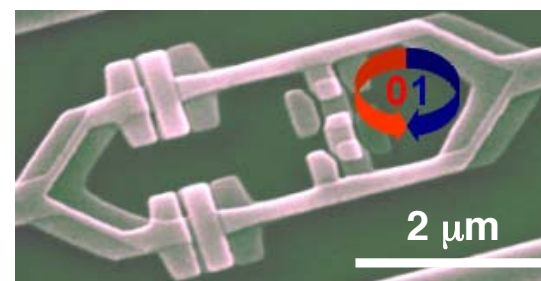
## Many possible implementations

*trapped ions*



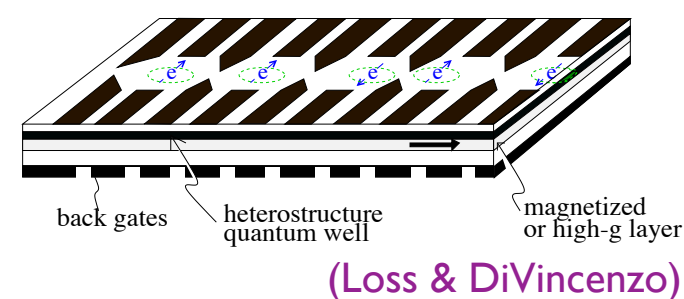
(Monroe & Wineland)

*superconducting circuits*

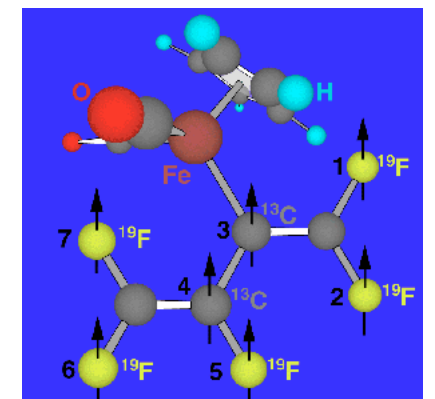


(Nakamura et al.)

*quantum dots*



*nuclear spins*



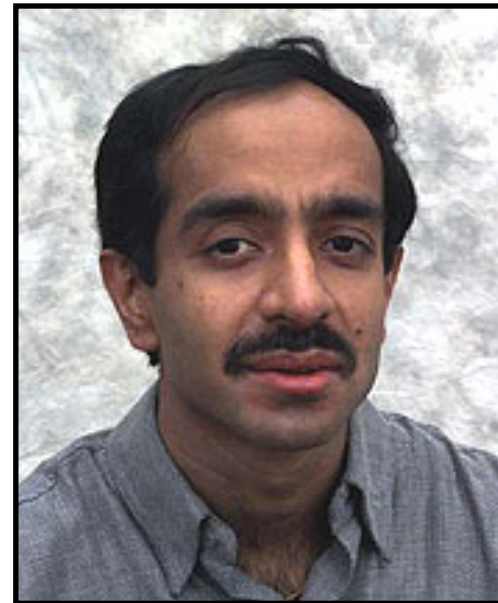
(Chuang et al.)

**Fault-tolerance Threshold Theorem:** If we can manipulate qubits sufficiently well (constant error rate, say  $10^{-4}$ ), we can effectively make them perfect through an encoding with reasonable overhead.

# Fast algorithms for classically hard problems



3107418240490043721350750035888567  
9300373460228427275457201619488232  
0644051808150455634682967172328678  
2437916272838033415471073108501919  
5485290073377248227835257423864540  
14691736602477652346609  
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163473364580925384844313388386509  
085984178367003309231218111085238  
9333100104508151212118167511579  
×  
190087128166482211312685157393541  
397547189678996851549366663853908  
8027103802104498957191261465571

[illegible]

- Computing discrete logarithms
- Decomposing Abelian groups
- Computations in number fields
- Approximating Gauss sums
- Shifted Legendre symbol
- Counting points on algebraic curves
- Approximating the Jones polynomial (and other topological invariants)
- Simulating quantum mechanics
- Linear systems
- Computing effective resistance
- ...

- Formula evaluation
- Collision finding ( $k$ -distinctness,  $k$ -sum, etc.)
- Minimum spanning tree, connectivity, shortest paths, bipartiteness of graphs
- Network flows, maximal matchings
- Finding subgraphs
- Minor-closed graph properties
- Property testing (distance between distributions, bipartiteness/expansion of graphs, etc.)
- Checking matrix multiplication
- Group commutativity
- Subset sum
- ...

# Two kinds of quantum simulation

**Analog simulation:** Build a device whose Hamiltonian effectively models a desired target system

Ex: Use an optical lattice to simulate spin models

**Digital simulation:** Build a universal, fault-tolerant quantum computer and perform a controlled approximation of the dynamics of the target system

# Why simulate quantum mechanics?

## Computational chemistry/physics

- chemical reactions
- properties of materials

## Implementing quantum algorithms

- continuous-time quantum walk (e.g., for formula evaluation)
- adiabatic quantum computation (e.g., for optimization)
- linear/differential equations

# Quantum dynamics

The dynamics of a quantum system are determined by its *Hamiltonian*.

$$i \frac{d}{dt} |\psi(t)\rangle = H |\psi(t)\rangle$$
$$\Downarrow$$
$$|\psi(t)\rangle = e^{-iHt} |\psi(0)\rangle$$

**Quantum simulation problem:** Given a description of the Hamiltonian  $H$ , an evolution time  $t$ , and an initial state  $|\psi(0)\rangle$ , produce the final state  $|\psi(t)\rangle$  (to within some error tolerance  $\epsilon$ )

A classical computer cannot even represent the state efficiently

A quantum computer cannot produce a complete description of the state, but by performing measurements on the state, it can answer questions that (apparently) a classical computer cannot

# Local Hamiltonians

Simple class of systems that can be simulated efficiently [Lloyd 96]:

$$H = \sum_{j=1}^m H_j \text{ where each } H_j \text{ acts on } k = O(1) \text{ qubits}$$

Ex: Spin system on a lattice

Lie Product Formula:

$$\lim_{r \rightarrow \infty} \left( e^{-iAt/r} e^{-iBt/r} \right)^r = e^{-i(A+B)t}$$

Approximate version:

$$\left( e^{-iAt/r} e^{-iBt/r} \right)^r = e^{-i(A+B)t} + O(t^2/r)$$

Complexity (number of elementary gates):  $\text{poly}(\log N) (\|H\|t)^2 / \epsilon$

where  $H$  is  $N \times N$



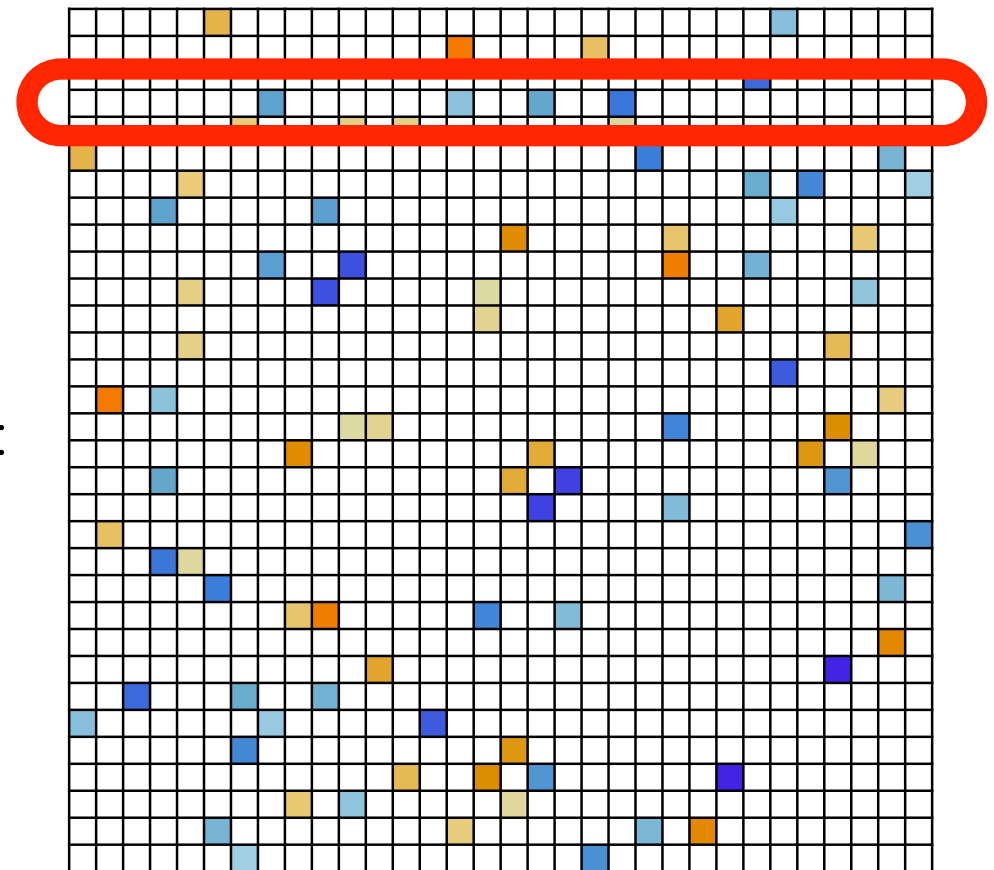
# Sparse Hamiltonians

More general class of Hamiltonians that can be simulated efficiently  
[Aharonov, Ta-Shma 03]:

At most  $d$  nonzero entries  
per row,  $d = \text{poly}(\log N)$   
(where  $H$  is  $N \times N$ )

In any given row, the  
location of the  $j$ th nonzero  
entry and its value can be  
computed efficiently (or is  
given by a black box)

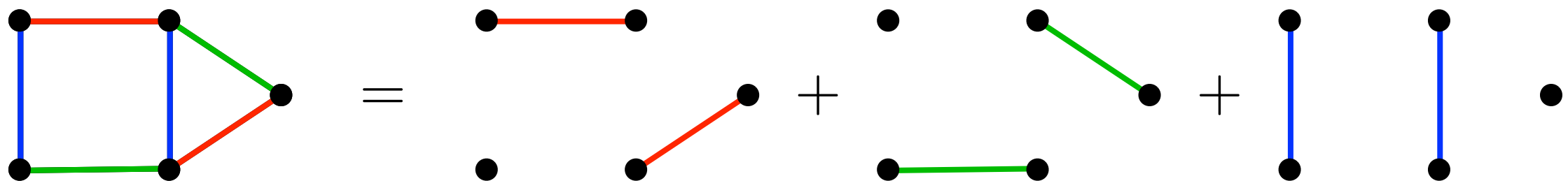
$$H =$$



Note: A  $k$ -local Hamiltonian with  $m$  terms is  $d$ -sparse with  $d = 2^k m$

# Sparse Hamiltonians and coloring

**Strategy** [Childs, Cleve, Deotto, Farhi, Gutmann, Spielman 03; Aharonov, Ta-Shma 03]: Color the edges of the graph of  $H$ . Then the simulation breaks into small pieces that are easy to handle.



A sparse graph can be efficiently colored using only local information [Linial 87], so this gives efficient simulations.

Can also use other decompositions (e.g., stars [Childs, Kothari 10])

# Higher-order product formulas

$$\left(e^{-iAt/r} e^{-iBt/r}\right)^r = e^{-i(A+B)t} + O(t^2/r)$$

$$\left(e^{-iAt/2r} e^{-iBt/r} e^{-iAt/2r}\right)^r = e^{-i(A+B)t} + O(t^3/r^2)$$

⋮

[Suzuki 91]: Systematic construction of arbitrarily high-order formulas

Number of terms in the formula grows exponentially with order

Complexity of best known simulation, using  $p$ th order:

$$O\left(5^{2p} d^3 \|H\| t \left(\frac{d \|H\| t}{\epsilon}\right)^{1/2p}\right)$$

[Berry, Ahokas, Cleve, Sanders 07;  
Childs, Kothari 11; Berry, Childs,  
Cleve, Kothari, Somma 14]

# High-precision simulation

We have recently developed a novel approach that directly implements the Taylor series of the evolution operator

New tools:

- Implementing linear combinations of unitary operations
- Oblivious amplitude amplification

Dependence on simulation error is  $\text{poly}(\log(1/\epsilon))$ , an exponential improvement over previous work

Algorithms are also simpler, with less overhead

[Berry, Childs, Cleve, Kothari, Somma 14 & 15]

# Linear combinations of unitaries

**LCU Lemma:** Given the ability to perform unitaries  $V_j$  with unit complexity, one can perform the operation  $U = \sum_j \beta_j V_j$  with complexity  $O(\sum_j |\beta_j|)$ . Furthermore, if  $U$  is (nearly) unitary then this implementation can be made (nearly) deterministic.

Main ideas:

- Using controlled- $V_j$  operations, implement  $U$  with some amplitude:

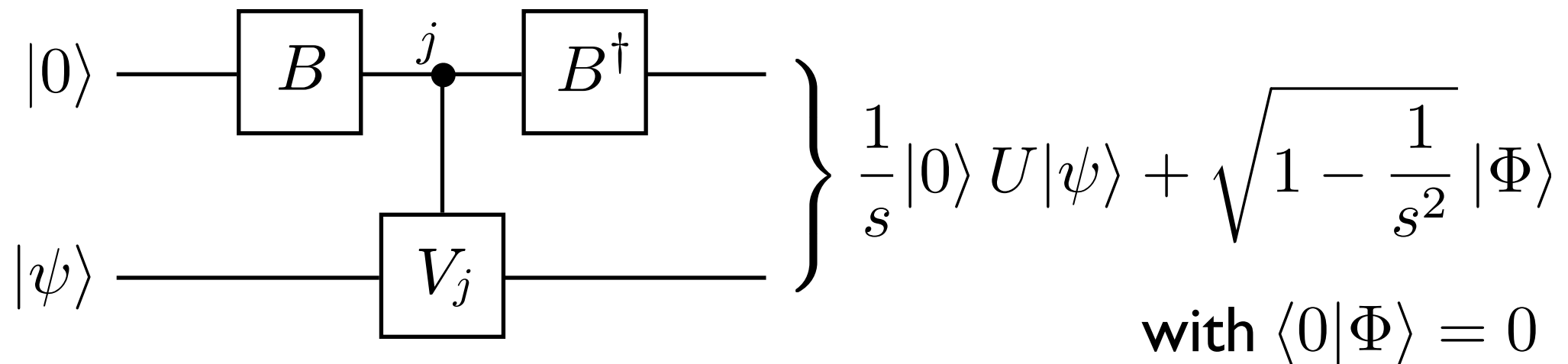
$$|0\rangle|\psi\rangle \mapsto \sin \theta |0\rangle U|\psi\rangle + \cos \theta |\Phi\rangle$$

- Boost the amplitude for success by oblivious amplitude amplification

# Implementing $U$ with some amplitude

$$U = \sum_j \beta_j V_j \quad (\text{WLOG } \beta_j > 0)$$

Ancilla state:  $B|0\rangle = \frac{1}{\sqrt{s}} \sum_j \sqrt{\beta_j} |j\rangle$   $s := \sum_j \beta_j$



# Oblivious amplitude amplification

Suppose  $W$  implements  $U$  with amplitude  $\sin \theta$ :

$$W|0\rangle|\psi\rangle = \sin \theta|0\rangle U|\psi\rangle + \cos \theta|\Phi\rangle$$

To perform  $U$  with amplitude close to 1: use amplitude amplification?

But the input state is unknown!

Using ideas from [Marriott, Watrous 05], we can show that a  $|\psi\rangle$ -independent reflection suffices to do effective amplitude amplification.

With this *oblivious amplitude amplification*, we can perform the ideal evolution with only about  $1/\sin \theta$  steps.

We also give a robust version that works even when  $U$  is not exactly unitary.

# Simulating the Taylor series

Taylor series of the dynamics generated by  $H$ :

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

Write  $H = \sum_{\ell} \alpha_{\ell} H_{\ell}$  where each  $H_{\ell}$  is unitary

Then 
$$e^{-iHt} \approx \sum_{k=0}^K \sum_{\ell_1, \dots, \ell_k} \frac{(-it)^k}{k!} \alpha_{\ell_1} \cdots \alpha_{\ell_k} H_{\ell_1} \cdots H_{\ell_k}$$

is a linear combination of unitaries



# Decomposing sparse Hamiltonians

To express  $H$  as a linear combination of unitaries:

- Edge coloring:  $H = \sum_{j=1}^{d^2} H_j$  where each  $H_j$  is 1-sparse  
 new trick:  $H$  is bipartite wlog since it suffices to simulate  $H \otimes \sigma_x$   
 $d^2$ -coloring:  $\text{color}(\ell, r) = (\text{idx}(\ell, r), \text{idx}(r, \ell))$
- Approximately decompose into terms with all nonzero entries equal

Ex: 
$$\begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 3 \\ 0 & 0 & 0 & 0 & 3 & 0 \end{pmatrix} = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} + \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} + \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$

- Remove zero blocks so that all terms are rescaled unitaries

Ex: 
$$\begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix} = \frac{1}{2} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix} + \frac{1}{2} \begin{pmatrix} -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

# Why $\text{poly}(\log(1/\epsilon))$ ?

Lowest-order product formula:

$$(e^{-iA/r} e^{-iB/r})^r = e^{-i(A+B)} + O(1/r)$$

so we must take  $r = O(1/\epsilon)$  to achieve error at most  $\epsilon$

Higher-order formulas exist, but they only improve the power of  $\epsilon$

The approximation  $e^{-iHt} \approx \sum_{k=0}^K \frac{(-iHt)^k}{k!}$  has error  $\epsilon$  provided

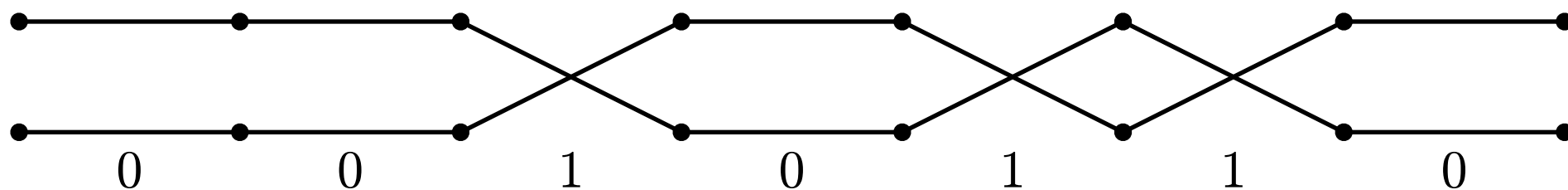
$$K = O\left(\frac{\log(1/\epsilon)}{\log \log(1/\epsilon)}\right)$$

# Lower bounds

No-fast-forwarding theorem [BACS 07]:  $\Omega(t)$

Main idea:

- Query complexity of computing the parity of  $n$  bits is  $\Omega(n)$ .
- There is a Hamiltonian that can compute parity by running for time  $O(n)$ .



**New lower bound:**  $\Omega\left(\frac{\log(1/\epsilon)}{\log \log(1/\epsilon)}\right)$


Main idea:

- Query complexity of parity is  $\Omega(n)$  even for *unbounded error*.
- The same Hamiltonian as above computes parity with unbounded error by running for any positive time. Running for constant time gives the parity with probability  $\Theta(1/n!)$ .

# Discrete-time quantum walk

Quantum walk: quantum analog of a random walk on a graph

In general, locality is inconsistent with unitarity [Severini 03]

Ex:  no unitary matrix has this pattern: 
$$\begin{pmatrix} 0 & \bullet & 0 \\ \bullet & 0 & \bullet \\ 0 & \bullet & 0 \end{pmatrix}$$

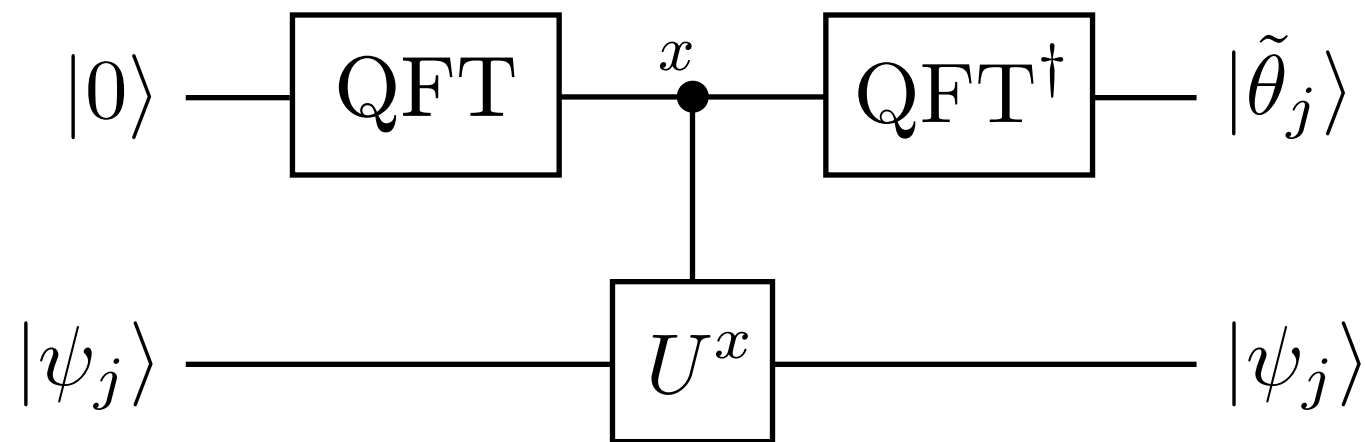
Natural definition of a discrete-time quantum walk [Szegedy 04]:

- Represent state by two locations:  $|u, v\rangle$  ( $u$  is the current vertex;  $v$  is the next vertex)
- Conditioned on  $u$ , reflect about some superposition of its neighbors
- Swap the two registers

Such walks have many nice properties and have been used extensively to construct quantum algorithms

# Phase estimation

**Problem:** Given a unitary operator  $U$  with eigenvectors  $|\psi_j\rangle$ , where  $U|\psi_j\rangle = e^{i\theta_j}|\psi_j\rangle$ , produce an estimate of  $\theta_j$



$$\sum_j \alpha_j |0\rangle |\psi_j\rangle \mapsto \sum_j \alpha_j |\tilde{\theta}_j\rangle |\psi_j\rangle$$

To get an estimate with precision  $\epsilon$ , we need  $O(1/\epsilon)$  uses of  $U$ .

# Quantum walk simulation

Define a Szegedy walk operator for any given Hamiltonian  $H$

Each eigenvalue  $\lambda$  of  $H$  corresponds to two eigenvalues  $\pm e^{\pm i \arcsin \lambda}$  of the walk operator (with eigenvectors closely related to those of  $H$ )

**Strategy:** Use phase estimation to determine and correct the phase

$$\begin{aligned} |\psi\rangle &\mapsto |\psi\rangle \widetilde{|\arcsin \lambda\rangle} \\ &\mapsto e^{-i\lambda t} |\psi\rangle \widetilde{|\arcsin \lambda\rangle} \\ &\mapsto e^{-i\lambda t} |\psi\rangle \end{aligned}$$

**Complexity:**  $O(\tau/\sqrt{\epsilon})$  where  $\tau := d\|H\|_{\max}t$

This matches the no fast-forwarding bound: real-time simulation!

[Childs 10], [Berry, Childs 12]

# Linear combination of quantum walk steps

Another approach: find coefficients so that

$$e^{-iH} \approx T^\dagger \sum_{k=-K}^K \beta_k U^k T$$

and implement this using the LCU Lemma

By a generating series for Bessel functions,

$$e^{-i\lambda t} = \sum_{k=-\infty}^{\infty} J_k(-t) e^{ik \arcsin \lambda}$$

Coefficients drop off rapidly for large  $k$ , so we can truncate the series

Query complexity of this approach:  $O\left(\tau \frac{\log(\tau/\epsilon)}{\log \log(\tau/\epsilon)}\right)$   
 $\tau := d \|H\|_{\max} t$

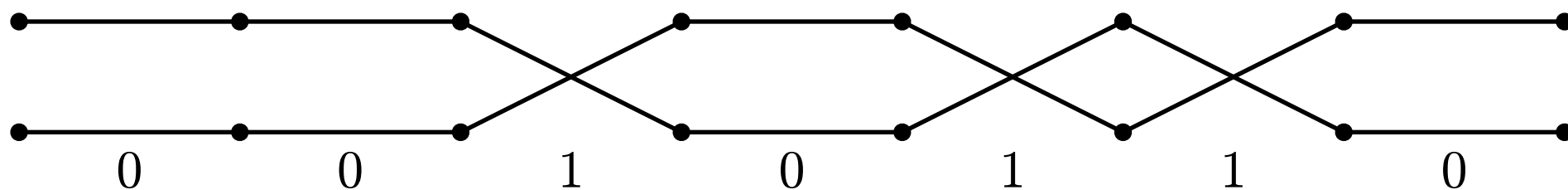
[Berry, Childs, Kothari 15]

# Lower bounds revisited

No-fast-forwarding theorem [BACS 07]:  $\Omega(t)$

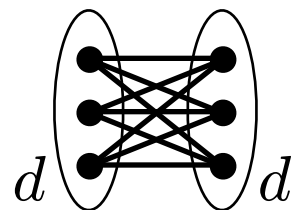
Main idea:

- Query complexity of computing the parity of  $n$  bits is  $\Omega(n)$ .
- There is a Hamiltonian that can compute parity by running for time  $O(n)$ .



**New lower bound:**  $\Omega(dt)$

- Replacing each edge with  $K_{d,d}$  effectively boosts Hamiltonian by  $d$ .



$\Rightarrow$  Our algorithm is (nearly) optimal with respect to each of  $t$ ,  $d$ , and  $\epsilon$



# Query complexity of sparse Hamiltonian simulation

Quantum walk + phase estimation [BC 10]:  $O\left(\frac{\tau}{\sqrt{\epsilon}}\right)$   $\tau := d\|H\|_{\max}t$

Quantum walk + LCU [BCK 15]:  $O\left(\tau \frac{\log(\tau/\epsilon)}{\log \log(\tau/\epsilon)}\right)$

or for  $\alpha \in (0, 1]$ :  $O(\tau^{1+\alpha/2} + \tau^{1-\alpha/2} \log(1/\epsilon))$

Lower bound:  $\Omega\left(\tau + \frac{\log(1/\epsilon)}{\log \log(1/\epsilon)}\right)$

Notes:

- Gate complexity is only slightly larger than query complexity
- These techniques assume time-independent Hamiltonians (otherwise, use fractional queries/LCU on Dyson series [BCCKS 14])

# Summary

Product formulas are the obvious approach to quantum simulation, but they are suboptimal!

Recently-developed algorithms are both

- asymptotically faster
- likely to be competitive in practice

Quantum simulation will probably be the first practical application of quantum computers; recent advances make this all the more likely

# Outlook

## Improved simulation algorithms

- Optimal tradeoff for sparse Hamiltonian simulation
- Faster algorithms for structured problems
- Simulating open quantum systems

## Applications to simulating physics

- What is the cost in practice for simulating molecular systems?
- How do recent algorithms compare to naive methods?

## New quantum algorithms

- Improved algorithms for linear systems
- New applications of linear systems
- Other quantum algorithms from quantum simulation