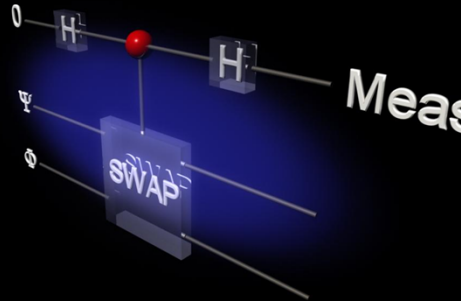


Introduction to Quantum Algorithms

11th Canadian Summer School on Quantum Information

Michele Mosca mmosca@iqc.ca

Canada Research Chair in Quantum Computation



Computational Complexity

- The (computational) complexity of an **algorithm** refers to some measure of the resources (e.g. time, space, basic operations, energy) used by the algorithm.
- E.g. the traditional algorithm for multiplying two n -bit numbers takes $O(n^2)$ **time** steps (with pen and paper, or on a PC).
- E.g. the best-known rigorous probabilistic classical algorithms for factoring an n -digit number into its prime factors with high probability takes **time** in

$$e^{O(\sqrt{n \log n})}$$

- We measure the complexity as a function of the input size.
- Unless stated otherwise, we refer to the “worst-case” complexity, i.e. the running time on a worst-case input.

2

Computational Complexity

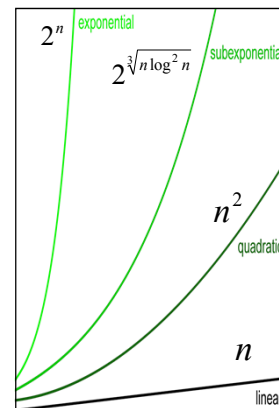
- The (computational) complexity of a **problem** refers to some measure of the resources (e.g. *time, space, basic operations, energy*) required to solve a problem.
- E.g. multiplying two n -bit numbers must take $\Omega(n)$ **time** (even just to write the answer).
- No known algorithm achieves that lower bound.
 - Until 2007, the best known upper bound was (Schönhage-Strassen, 1971) $O(n \log n \log \log n)$
 - In 2007, this was improved (Fürer) to $O(n \log n 2^{\log^* n})$
- Unless stated otherwise, we refer to the “worst-case” complexity, i.e. the resources required to solve the problem on any input of size n .

3

Aside : Computationally secure cryptography

Why do we believe the current cryptographic tools are secure?

- It is easy to multiply two large numbers
 $9287137268623 \times 61649017818402059 = 572542890955285156447699294757$
- It takes between n and n^2 steps to multiply two n -digit numbers.
- It is not known how to easily factor an arbitrary large (non-prime) number (e.g. 6521860808574070658969971) into a product of smaller numbers.
- Best-known heuristic classical methods take roughly $2^{\sqrt[3]{n \log^2 n}}$ steps.
- The best known classical methods for breaking elliptic curve cryptography with n digit keys take roughly 2^n steps.



4

Really big numbers ...

A million GHz computers, running for 100 years, can perform about 2^{71} basic operations

$$10^6 \text{ computers} \times 10^9 \text{ cycles/second/computer} \times 31536000 \text{ seconds/year} \times 100 \text{ years} \\ \approx 2^{20} \times 2^{30} \times 2^{24} \times 2^7 = 2^{71} \text{ cycles}$$

A billion THz computer, running for 1000 years, can perform about 2^{104} basic operations

$$10^9 \text{ computers} \times 10^{12} \text{ cycles/second/computer} \times 31536000 \text{ seconds/year} \times 10^3 \text{ years} \\ \approx 2^{30} \times 2^{40} \times 2^{24} \times 2^{10} = 2^{104} \text{ cycles}$$

Approximate age of the universe: 2^{92} seconds

5

Big numbers ...

www.keylength.com

The best known classical algorithm for cracking 256-bit Elliptic Curve Crypto requires about 2^{128} steps

The best known classical algorithm for cracking 2030-bit RSA requires about 2^{128} steps

The best known classical algorithm for cracking 128-bit AES (a widely used symmetric key cipher) requires about 2^{128} steps



“Polynomial” cost

- We say an algorithm A runs in “polynomial” time if there exists a polynomial $p(n)$ such that the algorithm takes time at most $p(n)$ on inputs of size n .
- One can similarly talk about algorithms that use polynomial space, or a polynomial number of logic gates.
- Algorithm A simulates algorithm B with “polynomial overhead” (in time e.g.) if there is some polynomial $p(n)$ such that when algorithm B uses T time then algorithm A takes time at most $p(T)$ when simulating algorithm B. (similarly for other resources)

7

Why polynomials ??

- Polynomials are closed under addition, multiplication and composition.
- Any known realistic classical computing model can be simulated with polynomial overhead by a classical (probabilistic) Turing machine (or a PC with arbitrary memory and random coins). Thus, in these cases, the Strong Church-Turing thesis holds.
- In general, measuring complexity up to a polynomial factor gives a certain degree of robustness (e.g. against reasonable changes in computing model, and other “details”)

8

Polynomial complexity \approx Efficient

"It should not come as a surprise that our choice of polynomial algorithms as the mathematical concept that is supposed to capture the informal notion of 'practically efficient computation' is open to criticism from all sides. [...]"

Ultimately, our argument for our choice must be this: **Adopting polynomial worst-case performance as our criterion of efficiency results in an elegant and useful theory that says something meaningful about practical computation, and would be impossible without this simplification**" - Christos Papadimitriou

9

How does quantum information change computational complexity?

- We don't think a classical computer efficiently captures the computational power of a quantum universe.
- Quantum Strong Church-Turing thesis:
Any known realistic computing model can be simulated with polynomial overhead by a *quantum* computer.

Different computational models

Increasing (?) capabilities →

	Closed system (i.e. reversible)	Open system (i.e. not necessarily reversible)		
Increasing (?) capabilities ↓	classical	Classical reversible circuit model	(without randomness) Deterministic classical circuit model	(with randomness) Probabilistic classical circuit model
	quantum	Quantum circuit model with unitary gates	Quantum circuit model with general quantum gates	

11

Universal set of quantum gates

To capture the full computational power of quantum information (as defined in previous lectures), it suffices to have a *universal set of unitary quantum gates*.

Definition

A set of gates G is said to be universal if for any integer $n > 0$, any n -qubit unitary operator can be approximated to arbitrary accuracy by a quantum circuit using only gates from G .

Results about universality give us guidelines for useful implementation paradigms, as well as for useful algorithmic paradigms.

12

Definition of *error* or *accuracy*

Suppose we approximate a desired unitary transformation U by some other unitary transformation V .

The *error* in the approximation is defined to be

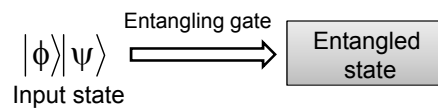
$$E(U, V) \equiv \max_{|\psi\rangle} \|U|\psi\rangle - V|\psi\rangle\|$$

13

Universal set of quantum gates

Definition

A two-qubit gate is said to be entangling if for some input product state, the output of the gate is an entangled state.



14

Universal set of quantum gates

Theorem:

A set composed of any two-qubit entangling gate, together with all one-qubit gates, is universal.

... a bit of an overkill, since such a set allows one to achieve any unitary exactly.

Also unrealistic, since one needs access to an infinite number of one-qubit gates.

Can we achieve universality with a finite set of gates?

15

Arbitrary one-qubit operations

Theorem (one-qubit universality):

Let \hat{n} and \hat{m} be any two non-parallel axes of the Bloch sphere, and let β, γ be real numbers such that

$$\frac{\beta}{\pi}, \frac{\gamma}{\pi}$$

are not rational.

Then

$$G = \{R_{\hat{n}}(\beta), R_{\hat{m}}(\gamma)\}$$

is universal for one-qubit gates.

16

A universal set of gates: an example

Theorem:

The set

$$G = \{H, T, \text{CNOT}\}$$

is a universal set of gates.

i.e. any n -qubit unitary operator U can be approximated with error ε , for any $\varepsilon > 0$, using a finite circuit with gates from G .

17

Efficiency of approximation

How does the size of a circuit scale as the desired accuracy improves?

$$e^{o\left(\frac{1}{\varepsilon}\right)} \quad ? \quad O\left(\frac{1}{\varepsilon}\right) \quad ? \quad O\left(\log \frac{1}{\varepsilon}\right) \quad ?$$


18

Solovay-Kitaev theorem

Theorem:

If G is a finite set of one-qubit gates satisfying the conditions of the one-qubit universality theorem, and

iii) for any gate $g \in G$, its inverse g^{-1} can be implemented exactly by a finite sequence of gates in G

 any one-qubit gate can be approximated with error at most ϵ using $O(\log^c(1/\epsilon))$ gates from G , where c is a positive constant.

19

Efficiency of approximation

Corollary

It is possible to approximate a circuit with T gates from any universal set with $O(T \log^c(T/\epsilon))$ gates from any finite universal set of gates satisfying condition iii).

- Key points are sketched in section 4.4 of KLM textbook.
- More details in Appendix of N&C, or KSV.

20

Bottom line for computer algorithmics

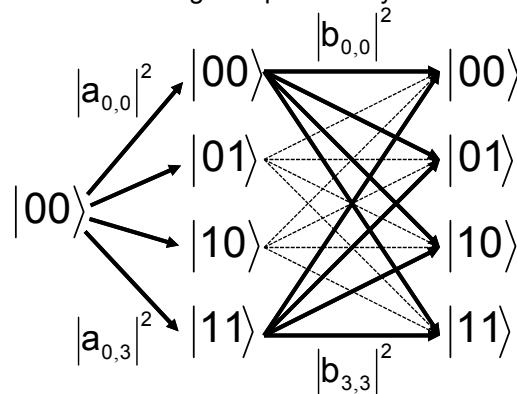
It suffices to design algorithms with your favourite finite universal gate set.

However, one might gain intuition or other practical advantages by working in other equivalent algorithmic paradigms (e.g. quantum walks, adiabatic algorithms, measurement-based, topological, etc)

21

A classical randomized algorithm

The probabilities could correspond to the square of a probability amplitude (due to measuring the quantum system at each time step)

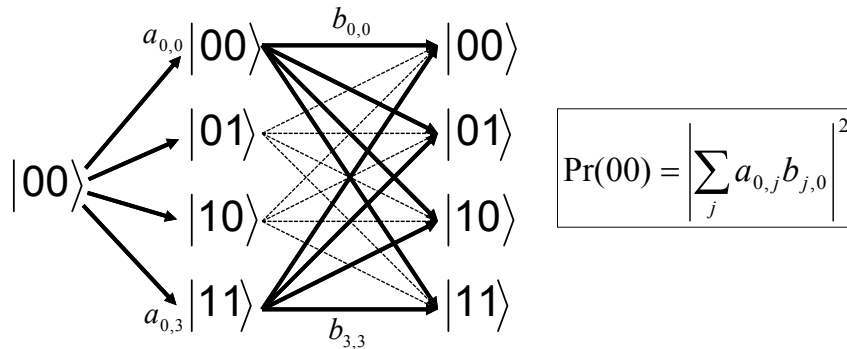


$$\Pr(00) = \sum_j |a_{0,j} b_{j,0}|^2$$

22

A quantum algorithm

If we don't measure at each time step, only at the end, the probability amplitudes first have a chance to interfere.



23

Decoherence

- A quantum system that is continually measured (or “leaks” information to an external system) will behave like a classical randomized system.
- Partial measurements will give a probability distribution somewhere in between the two extremes.
- Error-correcting codes will allow a quantum system interacting with the environment to maintain “coherence”.

24

How do quantum algorithms work?

Given a polynomial-time classical algorithm for $f: \{0,1\}^n \rightarrow T$, it is straightforward to construct a quantum algorithm that creates the state

$$\frac{1}{\sqrt{2^n}} \sum_x |x\rangle |f(x)\rangle$$

at the cost of about **one** evaluation of f

Is this exponentially many computations at polynomial cost?

No! — the most straightforward way of extracting information from the state yields just $(x, f(x))$ for a random $x \in \{0,1\}^n$

But we can make some interesting **tradeoffs**:

instead of learning about any $(x, f(x))$ point, one can learn something about a **global property** of f

25

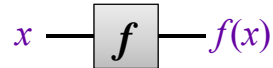
Quantum algorithms

- Quantum Algorithms should exploit quantum parallelism *and* quantum interference.
- This is necessary, but not sufficient, in order to outperform a classical probabilistic algorithm.
E.g. at some point in the execution of the algorithm, the state of the system should have a substantial amount of entanglement (assuming we are in the usual model of unitary operations on pure states).

26

Query scenario

Input: a function f , given as a black box (a.k.a. oracle)



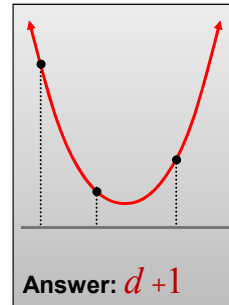
Goal: determine some information about f making as few queries to f as possible (of course, other operations are allowed – but we do not count them)

Example: polynomial interpolation

Let: $f(x) = c_0 + c_1x + c_2x^2 + \dots + c_dx^d$

Goal: determine $c_0, c_1, c_2, \dots, c_d$

Question: How many classical f -queries does one require for this?



27

- Introduction to quantum algorithms
- **Parity problem and Deutsch's algorithm**
- Constant vs. balanced problem
- Computing $H \otimes H \otimes \dots \otimes H$
- Simon's problem

28

Deutsch's problem

Let $f: \{0,1\} \rightarrow \{0,1\}$



There are **four** possibilities:

x	$f_1(x)$	x	$f_2(x)$	x	$f_3(x)$	x	$f_4(x)$
0	0	0	1	0	0	0	1
1	0	1	1	1	1	1	0

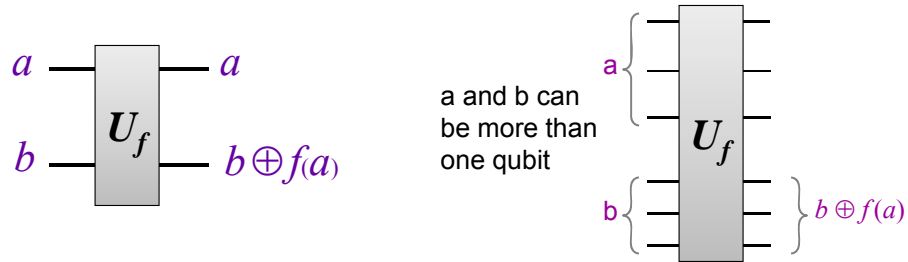
Goal: determine whether or not $f(0) = f(1)$ (i.e. $f(0) \oplus f(1)$)

Any classical method requires **two** queries

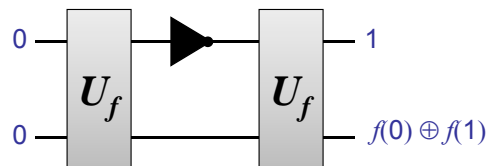
What about a quantum method?

29

Unitary black box for f



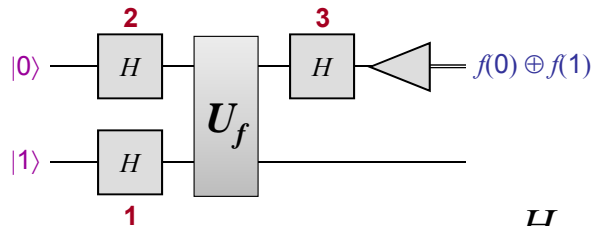
A classical algorithm:
(still requires 2 queries)



2 queries + 1 auxiliary operation

30

Quantum algorithm for Deutsch



1 query + 4 auxiliary operations

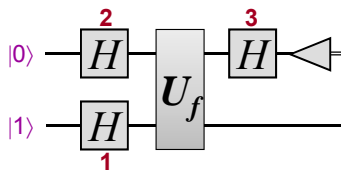
$$H = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

How does this algorithm work?

Each of the three H operations can be seen as playing a different role ...

31

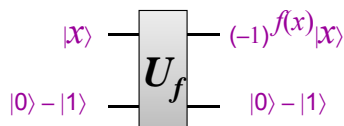
Quantum algorithm (1)



1. Creates the state $|0\rangle - |1\rangle$, which is an eigenvector of

$$\begin{cases} \text{NOT with eigenvalue } -1 \\ \mathbf{I} \text{ with eigenvalue } +1 \end{cases}$$

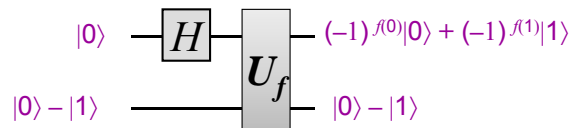
This causes f to induce a **phase shift** of $(-1)^{f(x)}$ to $|x\rangle$



32

Quantum algorithm (2)

2. Causes f to be queried *in superposition* (at $|0\rangle + |1\rangle$)



x	$f_1(x)$
0	0
1	0

x	$f_2(x)$
0	1
1	1

x	$f_3(x)$
0	0
1	1

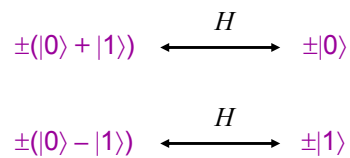
x	$f_4(x)$
0	1
1	0

$\pm(|0\rangle + |1\rangle)$
 $\pm(|0\rangle - |1\rangle)$

33

Quantum algorithm (3)

3. Distinguishes between $\pm(|0\rangle + |1\rangle)$ and $\pm(|0\rangle - |1\rangle)$



34

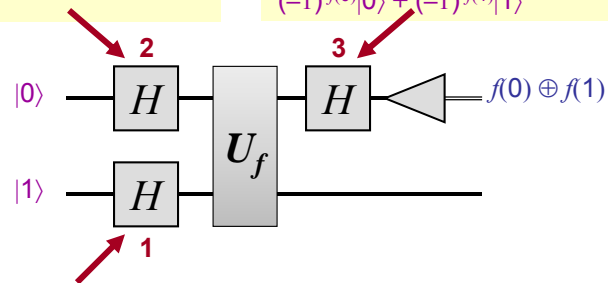
Summary of Deutsch's algorithm

Makes only one query, whereas two are needed classically

produces superpositions of inputs to f : $|0\rangle + |1\rangle$

extracts phase differences from

$$(-1)^{f(0)}|0\rangle + (-1)^{f(1)}|1\rangle$$



constructs eigenvector so f -queries induce phases: $|x\rangle \rightarrow (-1)^{f(x)}|x\rangle$

35

- Introduction to quantum algorithms
- Parity problem and Deutsch's algorithm
- **Constant vs. balanced problem**
- Computing $H \otimes H \otimes \dots \otimes H$
- Simon's problem

36

Constant vs. balanced

Let $f: \{0,1\}^n \rightarrow \{0,1\}$ be either constant or balanced, where

- **constant** means $f(x) = 0$ for all x , or $f(x) = 1$ for all x
- **balanced** means $\sum_x f(x) = 2^{n-1}$

Goal: determine whether f is constant or balanced

How many queries are there needed classically?

$2^{n-1} + 1$

Example: if $f(0000) = f(0001) = f(0010) = \dots = f(0111) = 0$ then it still could be either

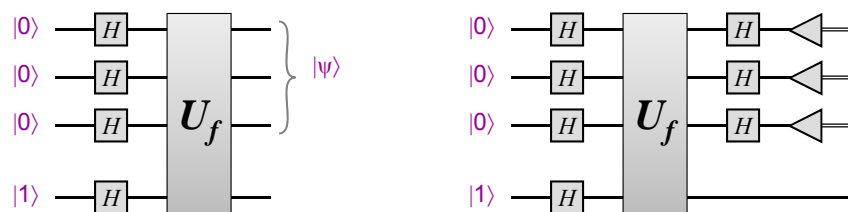
Quantumly?

just 1 query suffices!

[Deutsch & Jozsa, 1992]

37

Quantum algorithm



Constant case: $|\psi\rangle = \pm \sum_x |x\rangle$ **Why?**

Balanced case: $|\psi\rangle$ is **orthogonal** to $\pm \sum_x |x\rangle$ **Why?**

How to distinguish between the cases? What is $H^{\otimes n}|\psi\rangle$?

Constant case: $H^{\otimes n}|\psi\rangle = \pm |00\dots 0\rangle$

Balanced case: $H^{\otimes n}|\psi\rangle$ is orthogonal to $|0\dots 00\rangle$

Last step of the algorithm: if the measured result is 000 then output "constant", otherwise output "balanced"

38

Probabilistic *classical* algorithm solving constant vs. balanced

But here's a classical procedure that makes only 2 queries and performs fairly well probabilistically:

1. pick $x_1, x_2 \in \{0,1\}^n$ randomly
2. **if** $f(x_1) \neq f(x_2)$ **then** output balanced **else** output constant

What happens if f is constant? The algorithm always succeeds

What happens if f is balanced? Succeeds with probability $\frac{1}{2}$

By repeating the above procedure k times:
 $2k$ queries and one-sided error probability $(\frac{1}{2})^k$

Therefore, for "bounded-error" algorithms, the improvement doesn't scale as a function of n , though there is an improvement with respect to error probability.

39

- Introduction to quantum algorithms
- Parity problem and Deutsch's algorithm
- Constant vs. balanced problem
- **Computing $H \otimes H \otimes \dots \otimes H$**
- Simon's problem

40

Recap

- Quantum Computational Complexity is an elegant robust framework for studying the efficient computability of computational problems
 - A guiding tool for computationally secure cryptography
 - Notion of polynomial cost and polynomial overhead is critical
 - Quantum Strong Turing thesis
 - Efficient universal quantum computation
- Quantum Algorithms exploit quantum parallelism and quantum interference to solve problems more efficiently than the best-known classical algorithms
 - Black-box (or “query”) complexity is a useful paradigm for studying quantum algorithms and complexity
 - Deutsch’s “constant vs balanced” problem and solution gave us the first quantum algorithm; several developments eventually led to Simon’s algorithm and then Shor’s algorithms

41

About $H \otimes H \otimes \dots \otimes H = H^{\otimes n}$

Theorem: for $x \in \{0,1\}^n$, $H^{\otimes n}|x\rangle = \frac{1}{2^{n/2}} \sum_{y \in \{0,1\}^n} (-1)^{x \cdot y} |y\rangle$

where $x \cdot y = x_1 y_1 \oplus \dots \oplus x_n y_n$

Example: $H \otimes H = \frac{1}{2} \begin{bmatrix} +1 & +1 & +1 & +1 \\ +1 & -1 & +1 & -1 \\ +1 & +1 & -1 & -1 \\ +1 & -1 & -1 & +1 \end{bmatrix}$

Proof: For all $x \in \{0,1\}$, $H|x\rangle = |0\rangle + (-1)^x |1\rangle = \sum_y (-1)^{xy} |y\rangle$

Thus, $H^{\otimes n}|x_1 \dots x_n\rangle = (\sum_{y_1} (-1)^{x_1 y_1} |y_1\rangle) \dots (\sum_{y_n} (-1)^{x_n y_n} |y_n\rangle)$

$$= \sum_y (-1)^{x_1 y_1 \oplus \dots \oplus x_n y_n} |y_1 \dots y_n\rangle \blacksquare$$

42

- Introduction to quantum algorithms
- Parity problem and Deutsch's algorithm
- Constant vs. balanced problem
- Computing $H \otimes H \otimes \dots \otimes H$
- **Simon's problem**

43

Quantum vs. classical separations

Black-box problem	Quantum	Classical	
Deutsch's problem	1 (query)	2 (queries)	
constant vs. balanced	1	$\frac{1}{2} 2^n + 1$	(only for exact)
Simon's problem	$O(n)$	$\theta(2^{n/2})$	(probabilistic)

44

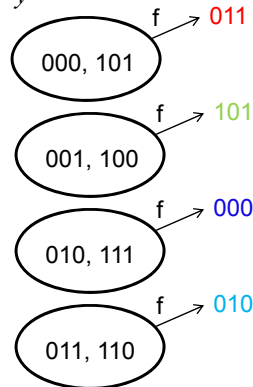
Simon's problem

Let $f: \{0,1\}^n \rightarrow \{0,1\}^n$ have the property that there exists an $r \in \{0,1\}^n$ such that $f(x) = f(y)$ iff $x \oplus y = r$ or $x = y$

Find r .

Example:

x	$f(x)$
000	011
001	101
010	000
011	010
100	101
101	011
110	010
111	000



What is r in this case?

$r = 101$

45

A classical algorithm for Simon

Search for a **collision**, an $x \neq y$ such that $f(x) = f(y)$

1. Choose $x_1, x_2, \dots, x_k \in \{0,1\}^n$ uniformly randomly (independently)
2. For all $i \neq j$, if $f(x_i) = f(x_j)$ then output $x_i \oplus x_j$ and halt

A hard case is where r is chosen randomly from $\{0,1\}^n - \{0^n\}$ and then the "table" for f is filled out randomly subject to the structure implied by r

Question: How big does k have to be for the probability of a collision to be a constant, such as $3/4$?

Answer: order $2^{n/2}$ (each (x_i, x_j) collides with prob. $O(2^{-n})$)

46

Classical lower bound

Theorem: *any* classical algorithm solving Simon's problem must make $\Omega(2^{n/2})$ queries

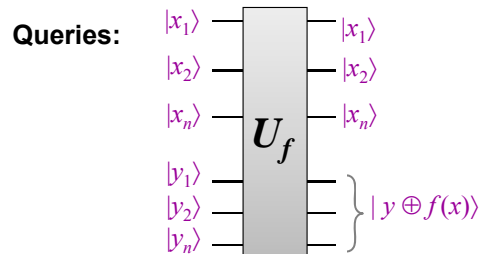
Proof is omitted here

Note: the performance analysis of the previous algorithm does *not* imply the theorem

... how can we know that there isn't a *different* algorithm that performs better?

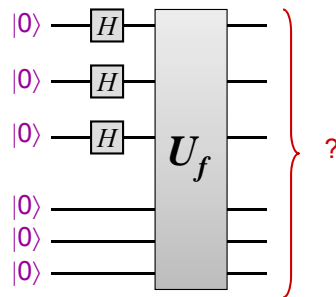
47

A quantum algorithm for Simon (1)



Proposed start of quantum algorithm: query all values of f in superposition

What is the output state of this circuit?



48

A quantum algorithm for Simon (2)

Answer: the output state is $\sum_{x \in \{0,1\}^n} |x\rangle |f(x)\rangle$

Let $T \subseteq \{0,1\}^n$ be such that **one** element from each matched pair is in T (assume $r \neq 00\dots 0$)

Example: could take $T = \{000, 001, 011, 111\}$

Then the output state can be written as:

$$\begin{aligned} & \sum_{x \in T} |x\rangle |f(x)\rangle + |x \oplus r\rangle |f(x \oplus r)\rangle \\ &= \sum_{x \in T} (|x\rangle + |x \oplus r\rangle) |f(x)\rangle \end{aligned}$$

x	$f(x)$
000	011
001	101
010	000
011	010
100	101
101	011
110	010
111	000

49

A quantum algorithm for Simon (3)

Measuring the second register yields $|x\rangle + |x \oplus r\rangle$ in the first register, for a random $x \in T$

How can we use this to obtain **some** information about r ?

Try applying $H^{\otimes n}$ to the state, yielding:

$$\begin{aligned} & \sum_{y \in \{0,1\}^n} (-1)^{x \cdot y} |y\rangle + \sum_{y \in \{0,1\}^n} (-1)^{(x \oplus r) \cdot y} |y\rangle \\ &= \sum_{y \in \{0,1\}^n} (-1)^{x \cdot y} (1 + (-1)^{r \cdot y}) |y\rangle \end{aligned}$$

Measuring this state yields y with prob. $\begin{cases} (1/2)^{n-1} & \text{if } r \cdot y = 0 \\ 0 & \text{if } r \cdot y = 1 \end{cases}$

50

A quantum algorithm for Simon (4)

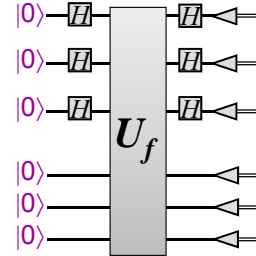
Executing this algorithm $k = n+O(1)$ times yields random $y_1, y_2, \dots, y_k \in \{0,1\}^n$ such that $r \cdot y_1 = r \cdot y_2 = \dots = r \cdot y_k = 0$

How does this help?

This is a system of k linear equations:

$$\begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{k1} & y_{k2} & \cdots & y_{kn} \end{bmatrix} \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_n \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

With high probability, there is a unique non-zero solution that is r (which can be efficiently found by linear algebra)



51

Conclusion of Simon's algorithm

- Any classical algorithm has to query the black box $\Omega(2^{n/2})$ times, even to succeed with probability $\frac{3}{4}$.
- There is a quantum algorithm that queries the black box only $n+O(1)$ times, performs only $O(n^3)$ auxiliary operations (for the Hadamards, measurements, and linear algebra), and succeeds with probability $\frac{3}{4}$.

52

Aside:

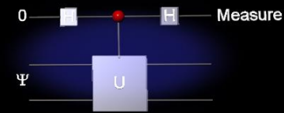
- Note that we assumed that if we know how to classically compute $f(x)$ then we can implement

$$|x\rangle|0\rangle \mapsto |x\rangle|f(x)\rangle$$

- Is that necessarily possible to do with comparable efficiency?

53

Irreversible gates from reversible ones

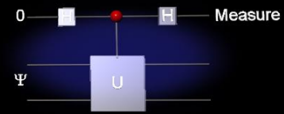


- Note that irreversible gates are really just reversible gates where we hardwire some inputs and throw away some outputs

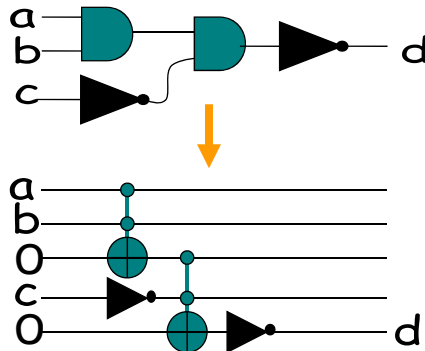


54

Making reversible circuits

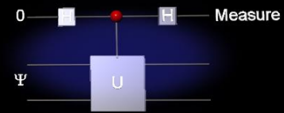


- Replace irreversible gates with their reversible counterparts



55

Making reversible circuits

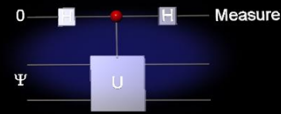


- One problem is that there will be junk left in the extra bits
- Bennett showed how to “uncompute” the junk

$$\begin{aligned}
 &|x\rangle|0\rangle|0\rangle|0\rangle \\
 \xrightarrow{\text{compute } f(x)} &|x\rangle|f(x)\rangle|junk(x)\rangle|0\rangle \\
 \xrightarrow{\text{copy } f(x)} &|x\rangle|f(x)\rangle|junk(x)\rangle|f(x)\rangle \\
 \xrightarrow{\text{uncompute } f(x)} &|x\rangle|0\rangle|0\rangle|f(x)\rangle
 \end{aligned}$$

56

Making reversible circuits



- An irreversible circuit with space S and depth (or “time”) T can thus be simulated by a reversible circuit with space in $O(S+T)$ and time $O(T)$
- Bennett also showed how to implement a reversible version with time $O(T^{1+\epsilon})$ and space $O(S \log(T))$ or time $O(T)$ and space $O(ST^\epsilon)$.
- *Bottom line:* if we know how to classically compute $f(x)$ then we can implement, with similar efficiency,

$$|x\rangle|0\rangle \mapsto |x\rangle|f(x)\rangle$$

57

Recall: Multi-qubit Hadamard

$$|x\rangle \xrightarrow{H^{\otimes n}} \frac{1}{\sqrt{2^n}} \sum_y (-1)^{x \cdot y} |y\rangle$$

$$\frac{1}{\sqrt{2^n}} \sum_y (-1)^{x \cdot y} |y\rangle \xrightarrow{H^{\otimes n}} |x\rangle$$

58

Quantum algorithms

- These algorithms have been computing essentially classical functions on quantum superpositions.
- When information is encoded in the phases of the basis states, measuring basis states would provide little useful information
- However, a quantum transformation might translate the phase information into information that is measurable in the computational basis.

59

Quantum phase estimation

- Suppose we wish to estimate a number $\omega \in [0,1)$ given the quantum state

$$\sum_{y=0}^{2^n-1} e^{2\pi i \omega y} |y\rangle$$

- Note that in binary we can express

$$\omega = 0.x_1x_2x_3 \dots$$

$$2\omega = x_1.x_2x_3 \dots$$

$$2^{n-1} \omega = x_1x_2x_3 \dots x_{n-1}.x_nx_{n+1} \dots$$

60

Quantum phase estimation

- Since $e^{2\pi ik} = 1$ for any integer k , we have

$$e^{2\pi i(2\omega)} = e^{2\pi i(x_1.x_2x_3\dots)} = e^{2\pi ix_1} e^{2\pi i(0.x_2x_3\dots)} = e^{2\pi i(0.x_2x_3\dots)}$$

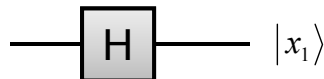
$$e^{2\pi i(2^k \omega)} = e^{2\pi i(0.x_{k+1}x_{k+2}\dots)}$$

61

Quantum phase estimation

- If $\omega = 0.x_1$ then we can do the following

$$\frac{|0\rangle + e^{2\pi i(0.x_1)}|1\rangle}{\sqrt{2}} = \frac{|0\rangle + (-1)^{x_1}|1\rangle}{\sqrt{2}}$$



62

Useful identity

- We can show that

$$\sum_{y=0}^{2^n-1} e^{2\pi i \omega y} |y\rangle$$

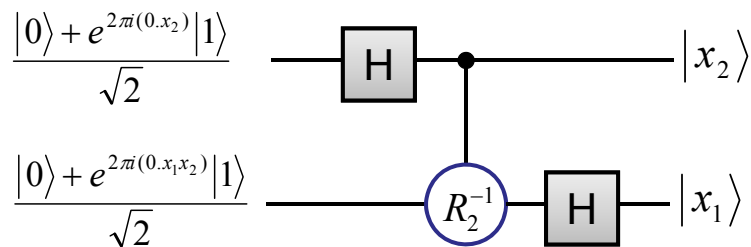
$$= \left(|0\rangle + e^{2\pi i (2^{n-1} \omega)} |1\rangle \right) \otimes \left(|0\rangle + e^{2\pi i (2^{n-2} \omega)} |1\rangle \right) \otimes \dots \otimes \left(|0\rangle + e^{2\pi i (\omega)} |1\rangle \right)$$

$$= \left(|0\rangle + e^{2\pi i (0.x_n x_{n+1} \dots)} |1\rangle \right) \otimes \left(|0\rangle + e^{2\pi i (0.x_{n-1} x_n x_{n+1} \dots)} |1\rangle \right) \otimes \dots \otimes \left(|0\rangle + e^{2\pi i (0.x_1 x_2 \dots)} |1\rangle \right)$$

63

Quantum phase estimation

- So if $\omega = 0.x_1 x_2$ then we can do the following

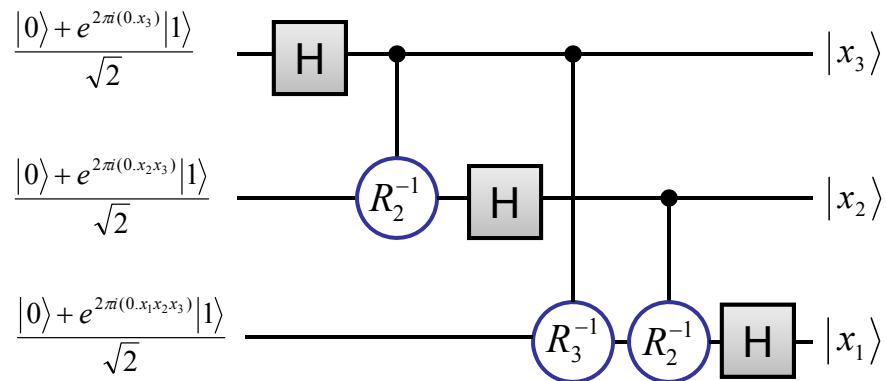


$$R_k = \begin{bmatrix} 1 & 0 \\ 0 & e^{2\pi i / 2^k} \end{bmatrix}$$

64

Quantum phase estimation

- So if $\omega = 0.x_1x_2x_3$ then we can do the following



65

Quantum phase estimation

- Generalizing this network (and reversing the order of the qubits at the end) gives us a network with $O(n^2)$ gates that implements

$$\sum_{y=0}^{2^n-1} e^{2\pi i \frac{x}{2^n} y} |y\rangle \mapsto |x\rangle$$

66

Discrete Fourier transform

- The discrete Fourier transform maps vectors of dimension N by transforming the X^{th} elementary vector according to

$$(0,0,\dots,0,1,0,\dots,0) \mapsto \frac{1}{\sqrt{N}} (1, e^{2\pi i \frac{x}{N}}, e^{2\pi i \frac{2x}{N}}, \dots, e^{2\pi i \frac{(N-1)x}{N}})$$

- The quantum Fourier transform maps vectors in a Hilbert space of dimension N according to

$$|x\rangle \mapsto \frac{1}{\sqrt{N}} \sum_{y=0}^{N-1} e^{2\pi i \frac{x}{N} y} |y\rangle$$

67

Discrete Fourier transform

- Thus we have illustrated how to implement (the inverse of) the quantum Fourier transform in a Hilbert space of dimension 2^n

68

Estimating arbitrary $\omega \in [0,1)$

- What if ω is not necessarily of the form $\frac{x}{2^n}$ for some integer x ?

- The QFT will map

$$\sum_{x=0}^{2^n-1} e^{2\pi i \omega x} |z\rangle$$

to a superposition

$$|\tilde{\omega}\rangle = \sum_y \alpha_y |y\rangle$$

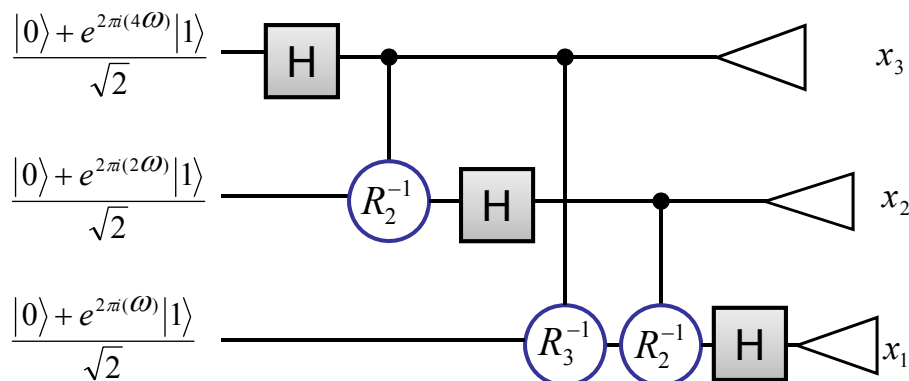
where

$$\text{Prob}\left(\left|\frac{y}{N} - \omega\right| \leq \frac{1}{N}\right) \geq \frac{8}{\pi^2} \quad |\alpha_y| \in O\left(\frac{1}{\left|\frac{y}{N} - \omega\right|}\right)$$

69

Quantum phase estimation

- For any real $\omega \in [0,1)$

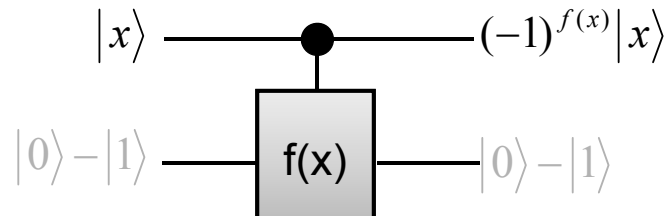


- With high probability $\frac{4x_1 + 2x_2 + x_3}{8} \approx \omega$

70

Eigenvalue kick-back

- Recall the “trick”:

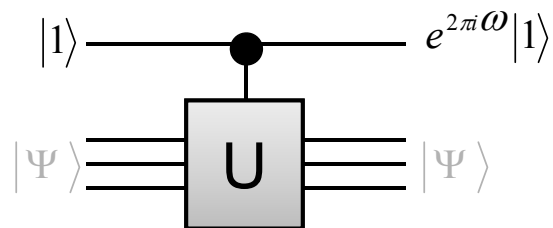


$$\begin{aligned}
 |x\rangle(|0\rangle - |1\rangle) &\rightarrow |x\rangle(|f(x)\rangle - |f(x) \oplus 1\rangle) \\
 &= |x\rangle(-1)^{f(x)}(|0\rangle - |1\rangle) \\
 &= (-1)^{f(x)}|x\rangle(|0\rangle - |1\rangle)
 \end{aligned}$$

71

Eigenvalue kick-back (Kitaev)

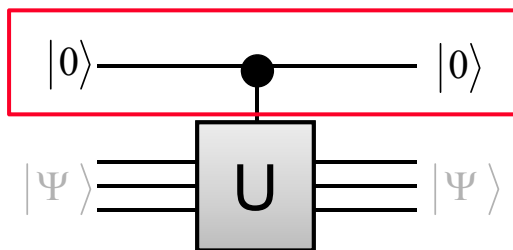
- Consider a unitary operation U with eigenvalue $e^{2\pi i \omega}$ and eigenvector $|\Psi\rangle$



$$\begin{aligned}
 |1\rangle|\Psi\rangle &\rightarrow |1\rangle U|\Psi\rangle = |1\rangle e^{2\pi i \omega} |\Psi\rangle \\
 &= e^{2\pi i \omega} |1\rangle |\Psi\rangle
 \end{aligned}$$

72

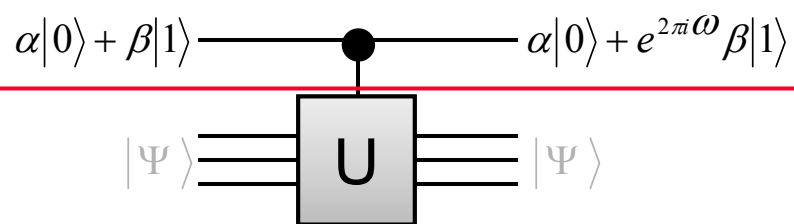
Eigenvalue kick-back



73

Eigenvalue kick-back

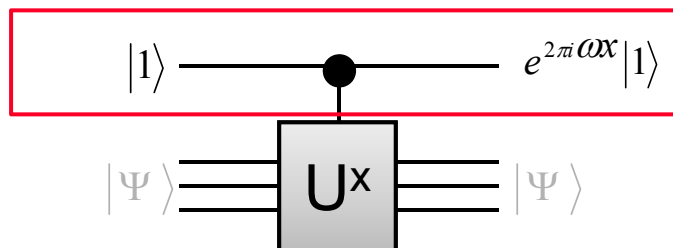
- As a relative phase, $e^{2\pi i \omega}$ becomes measurable



74

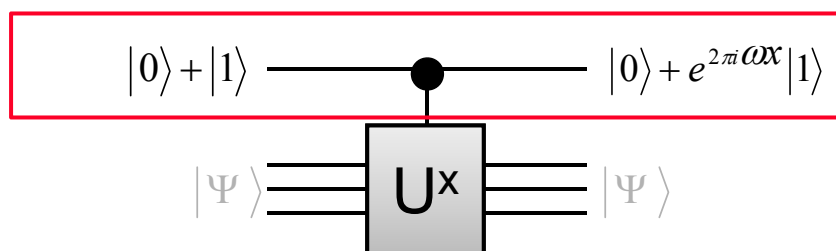
Eigenvalue kick-back

- If we exponentiate U , we get multiples of ω



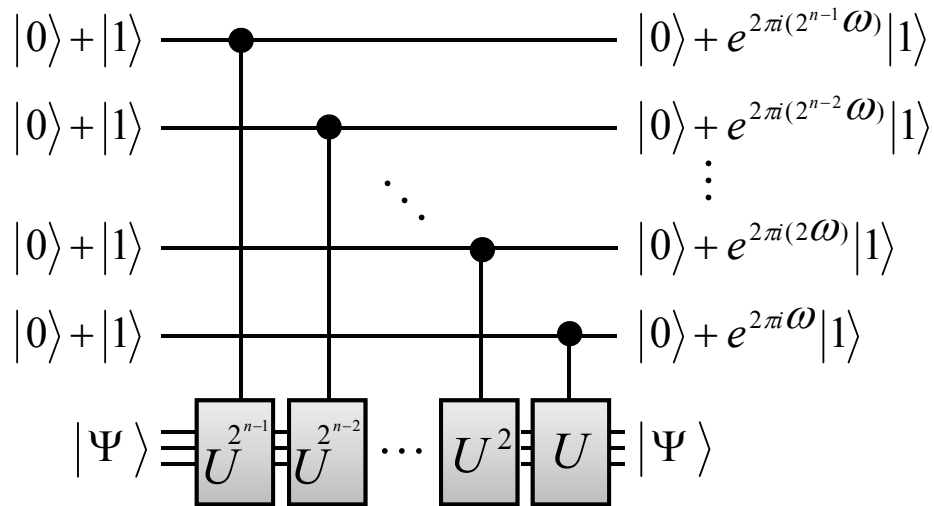
75

Eigenvalue kick-back



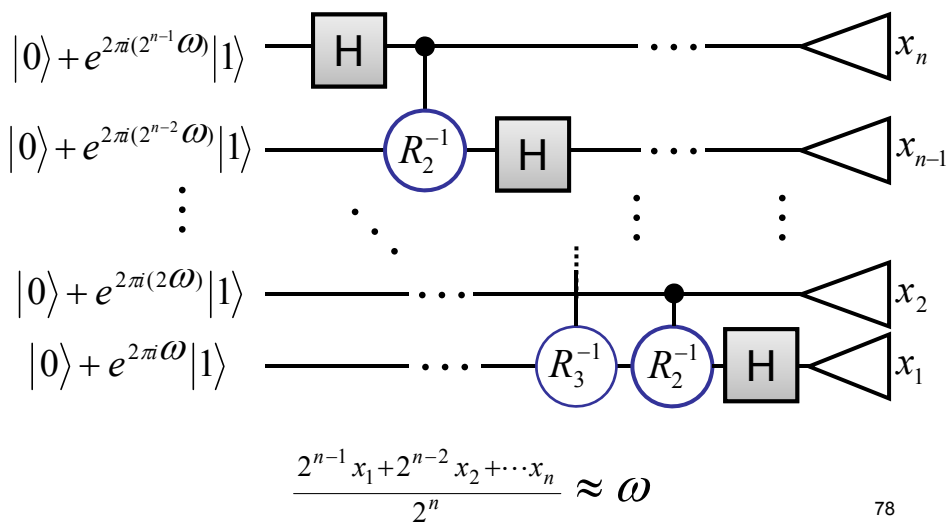
76

Eigenvalue kick-back



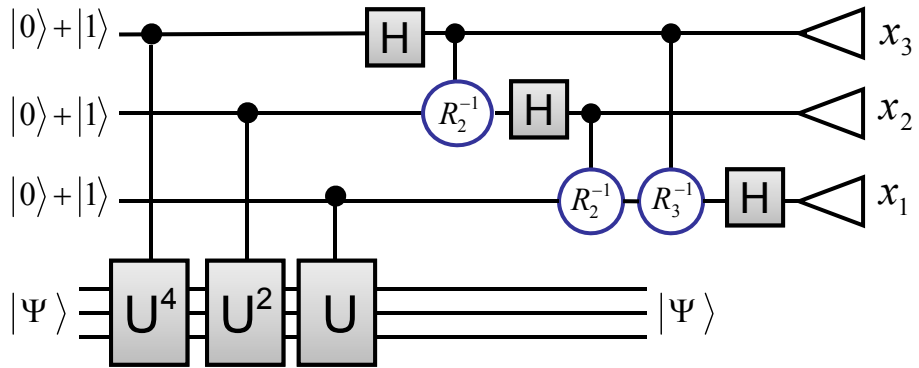
77

Phase estimation



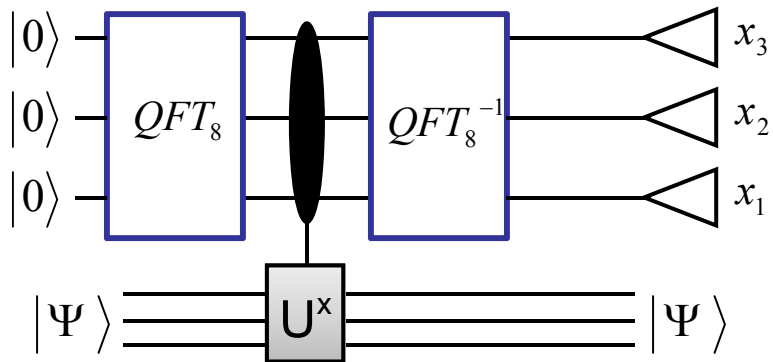
78

Eigenvalue estimation



79

Eigenvalue estimation



80

Eigenvalue estimation

- Given \mathbf{U} with eigenvector $|\Psi\rangle$ and eigenvalue $e^{2\pi i\Omega}$, we thus have an algorithm that maps

$$|0\rangle|\Psi\rangle \rightarrow |\tilde{\omega}\rangle|\Psi\rangle$$

81

Eigenvalue estimation

- Given \mathbf{U} with eigenvectors $|\Psi_k\rangle$ and respective eigenvalues $e^{2\pi i\Omega_k}$ we thus have an algorithm that maps

$$|0\rangle|\Psi_k\rangle \mapsto |\tilde{\omega}_k\rangle|\Psi_k\rangle$$

and therefore

$$|0\rangle\sum_k \alpha_k |\Psi_k\rangle = \sum_k \alpha_k |0\rangle|\Psi_k\rangle \mapsto \sum_k \alpha_k |\tilde{\omega}_k\rangle|\Psi_k\rangle$$

82

Eigenvalue estimation

- Measuring the first register of

$$\sum_k \alpha_k |\tilde{\omega}_k\rangle |\Psi_k\rangle$$

is equivalent to measuring $|\tilde{\omega}_k\rangle$ with probability $|\alpha_k|^2$.

83

Example

- Suppose we have a group G and we wish to find the order of $a \in G$ (i.e. the smallest positive r such that $a^r \equiv 1$).
- If we can efficiently do arithmetic in the group, then we can realize a unitary operator U_a that maps $|x\rangle \mapsto |ax\rangle$.

- Notice that

$$U_a^r = U_{a^r} = I$$

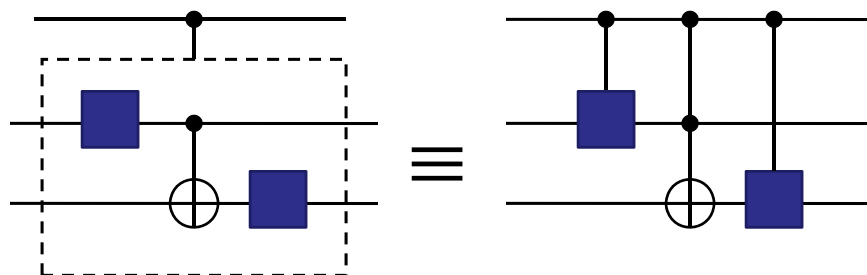
- This means that the eigenvalues of U_a are of the form $e^{2\pi i \frac{k}{r}}$ where k is an integer.

84

How do we implement c-U ?

Replace every gate G in the circuit with a c-G.

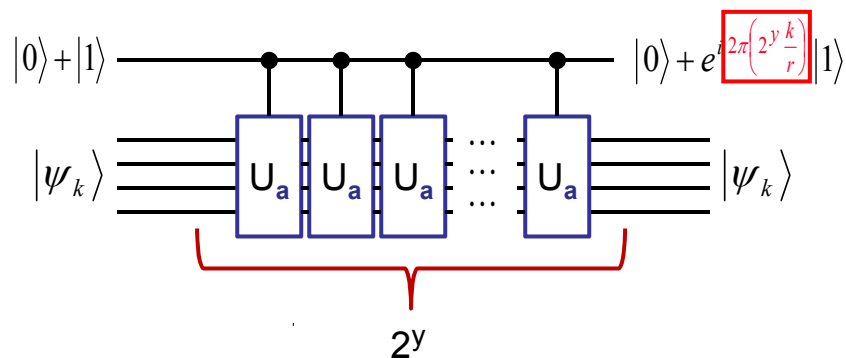
For example,



85

Inefficient exponentiation

We can effect a relative phase shift of $e^{i2\pi\left(2^y \frac{k}{r}\right)}$

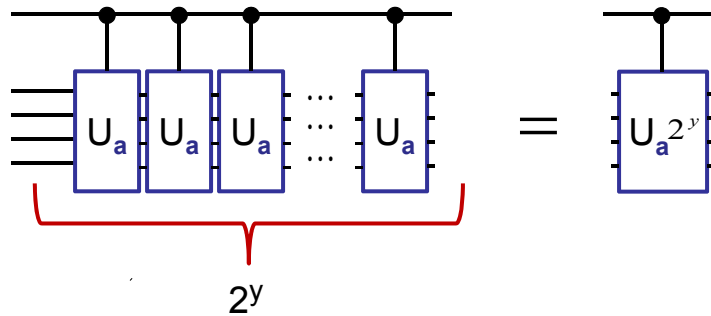


86

Efficient exponentiation

But we can also do it **efficiently** by noticing that

$$U_a^{2^y} = U_a^{2^y}$$



87

Quantum factoring

- The security of many public key cryptosystems used in industry today relies on the difficulty of factoring large numbers into smaller factors.
- Factoring the integer N into smaller factors can be reduced to the following task:

Given integer a , find the smallest positive integer r so that $a^r \equiv 1 \pmod{N}$

88

(Aside: how does factoring reduce to order-finding ?)

- The most common approach for factoring integers is the difference of squares technique:

➤ “Randomly” find two integers x and y satisfying

$$x^2 = y^2 \pmod{N}$$

➤ So N divides $x^2 - y^2 = (x - y)(x + y)$

➤ Hope that $\gcd(N, x - y)$ is non-trivial

- If r is even, then let

so that
$$x = a^{r/2} \pmod{N}$$

$$x^2 = 1^2 \pmod{N}$$

89

Quantum factoring

Since we know how to efficiently multiply by $a \pmod{N}$, we can efficiently implement

$$U_a|x\rangle = |ax\rangle$$

Note that

$$U_{a^r}|x\rangle = |a^r x\rangle = |x\rangle$$

i.e.

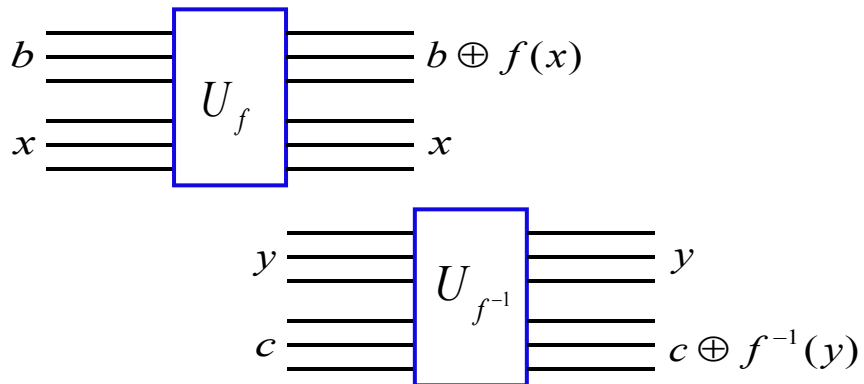
$$U_a^r = I$$

Remember that $|x\rangle$ represents the state corresponding to the binary representation of x (e.g. for four qubits, $|2\rangle$ represents $|0010\rangle$)

90

(Aside : more on reversible computing)

If we know how to efficiently compute f and f^{-1} then we can efficiently and reversibly map

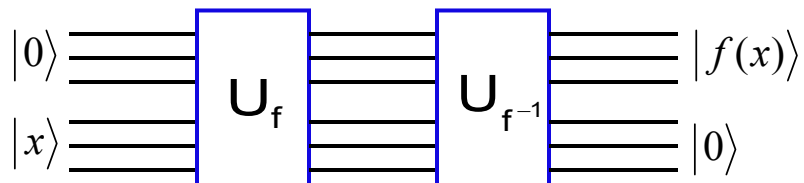


91

(Aside : more on reversible computing)

And therefore we can efficiently map

$$|x\rangle \mapsto |f(x)\rangle$$



92

Interesting eigenvalues

If $U_a^r = I$ then the eigenvalues of U_a are of the form

$$e^{i2\pi \frac{k}{r}}$$
$$\Rightarrow U_a |\psi_k\rangle = e^{i2\pi \frac{k}{r}} |\psi_k\rangle$$
$$|\psi_k\rangle = \sum_{j=0}^{r-1} e^{i2\pi j \frac{k}{r}} |a^j\rangle$$

93

Checking the eigenvalues

$$U_a |\psi_k\rangle = \sum_{j=0}^{r-1} e^{-i2\pi j \frac{k}{r}} U_a |a^j\rangle$$
$$= \sum_{j=0}^{r-1} e^{-i2\pi j \frac{k}{r}} |a^{j+1}\rangle = e^{i2\pi \frac{k}{r}} \left(\sum_{j=1}^r e^{-i2\pi j \frac{k}{r}} |a^j\rangle \right)$$
$$= e^{i2\pi \frac{k}{r}} \left(\sum_{j=0}^{r-1} e^{-i2\pi j \frac{k}{r}} |a^j\rangle \right) = e^{i2\pi \frac{k}{r}} |\psi_k\rangle$$

94

Finding r

For most integers k , a good estimate of $\frac{k}{r}$ (with error at most $\frac{1}{2r^2}$) allows us to determine r (even if we don't know k).

(using continued fractions)

95

Complexity comparison

- The best known rigorous classical algorithms use

$$e^{O(\sqrt{\log(N)} \log \log(N))}$$

operations

- The best known heuristic classical algorithms use

$$e^{O((\log(N))^{\frac{1}{3}} \log \log(N)^{\frac{2}{3}})}$$

operations

- The quantum algorithm uses $\text{poly}(\log(N))$

$$= e^{O(\log \log(N))}$$

operations

96

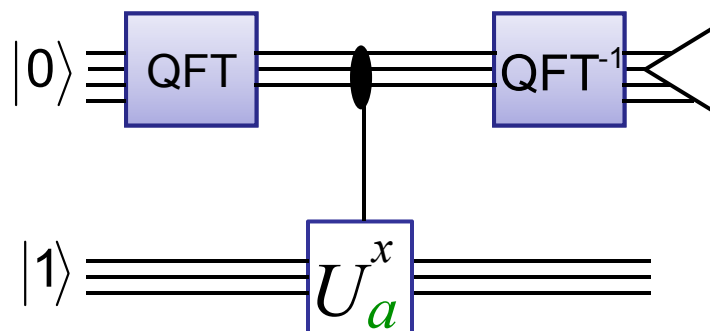
Shor's Factoring Algorithm

$$\begin{aligned} \sum_x |x\rangle|1\rangle &\mapsto \sum_x |x\rangle|a^x\rangle \\ &= \sum_{w=0}^{r-1} \sum_y |w+yr\rangle|a^w\rangle \end{aligned}$$

$$\xrightarrow{\text{QFT}^{-1}} \sum_w \left(\underbrace{\quad}_{\frac{0}{r}} \quad \underbrace{\quad}_{\frac{1}{r}} \quad \underbrace{\quad}_{\frac{k}{r}} \quad \underbrace{\quad}_{\frac{1}{r}} \right) |a^w\rangle$$

97

A circuit for Shor's Factoring Algorithm



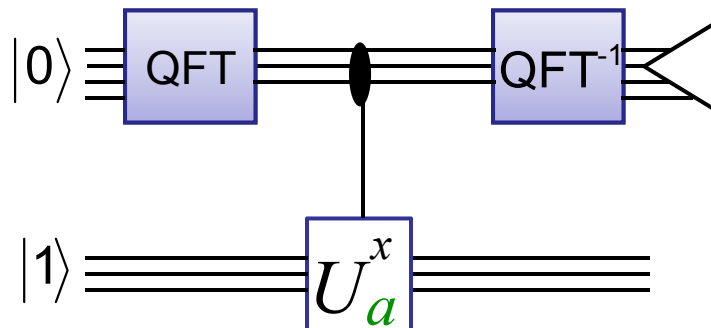
98

Eigenvalue Estimation Factoring Algorithm

$$\begin{aligned}
 |0\rangle|1\rangle &= \sum_{k=0}^{r-1} |0\rangle|\psi_k\rangle \mapsto \sum_{k=0}^{r-1} \sum_x |x\rangle|\psi_k\rangle \\
 &\mapsto \sum_{k=0}^{r-1} \sum_x e^{2\pi i kx/r} |x\rangle|\psi_k\rangle \\
 &\rightarrow \sum_k \left(\underbrace{\quad}_{\frac{k}{r}} \right) |\psi_k\rangle
 \end{aligned}$$

99

A circuit for Eigenvalue Estimation Factoring Algorithm



100

Equivalence

$$\sum_x |x\rangle|1\rangle = \sum_{k=0}^{r-1} \sum_x |x\rangle|\psi_k\rangle$$

$$\sum_{w=0}^{r-1} \sum_y |w + yr\rangle|a^w\rangle = \sum_{k=0}^{r-1} \sum_x e^{2\pi i kx/r} |x\rangle|\psi_k\rangle$$

$$\sum_w \left(\bigwedge_{\frac{0}{r}} \bigwedge_{\frac{1}{r}} \bigwedge_{\frac{k}{r}} \bigwedge \right) |a^w\rangle = \sum_k \left(\bigwedge_{\frac{k}{r}} \right) |\psi_k\rangle$$

101

Discrete Logarithm Problem

Consider two elements $a, b \in G$ from a group G satisfying

$$a^r = 1$$

$$b = a^s$$

Find s .

$$U_a |x\rangle = |ax\rangle$$

102

Discrete Logarithm Problem

We know U_a has eigenvectors

$$|\psi_k\rangle = \sum_{j=0}^{r-1} e^{-i2\pi j \frac{k}{r}} |a^j\rangle$$

$$U_a |\psi_k\rangle = e^{i2\pi \frac{k}{r}} |\psi_k\rangle$$

103

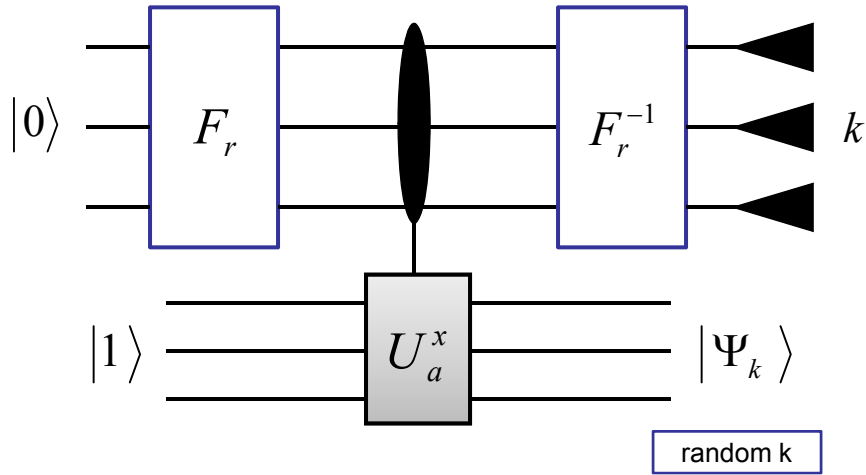
Discrete Logarithm Problem

Thus U_b has the same eigenvectors but with eigenvalues exponentiated to the power of s

$$U_b |\psi_k\rangle = U_{a^s} |\psi_k\rangle = e^{i2\pi \frac{ks}{r}} |\psi_k\rangle$$

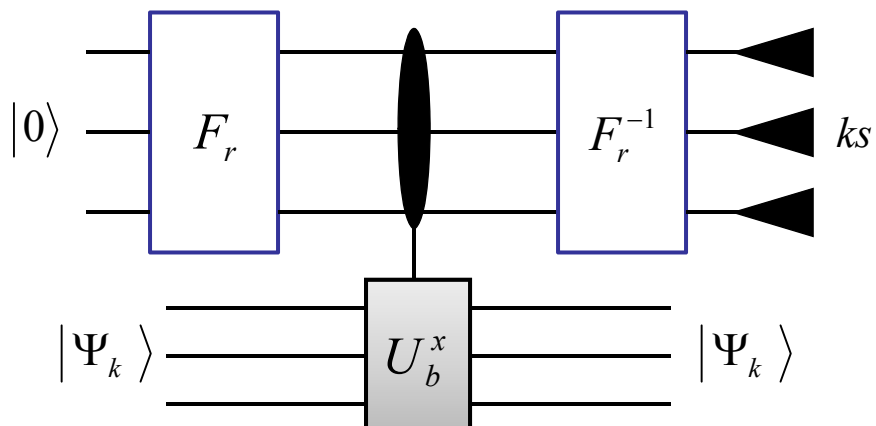
104

Discrete Logarithm Problem



105

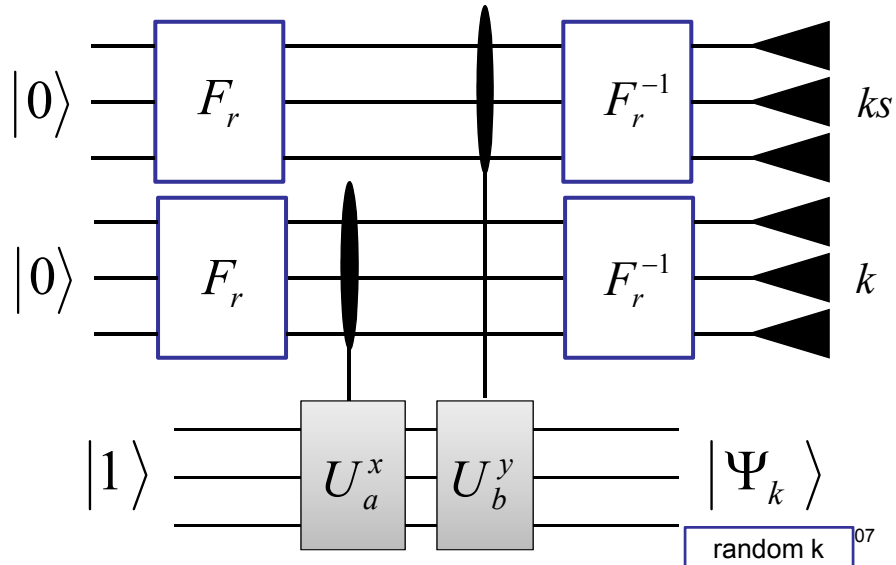
Discrete Logarithm Problem



Given k and ks , we can compute $s \pmod r$
 (provided k and r are coprime)

106

Complete Circuit



Generalization of Simon's problem, order-finding and DLP: "Hidden subgroup problem"

- A unifying framework was developed for these problems

$$f : G \rightarrow X$$

$$f(x) = f(y) \text{ iff } x + S = y + S \\ \text{for some } S \leq G$$

- If G is Abelian, finitely generated, and represented in a reasonable way, we can efficiently find S .

108

Example (I)

Deutsch's Problem:

$$G = \{0,1\} \quad X = \{0,1\}$$

$$S = \{0\} \text{ or } \{0,1\}$$

Order finding:

$$G = \mathbb{Z} \quad X \text{ any group}$$

$$f(x) = a^x$$

$$S = r\mathbb{Z}$$

109

Example (II)

Discrete Log of $b = a^k$ to base a :

$$G = \mathbb{Z}_r \times \mathbb{Z}_r \quad X \text{ any group}$$

$$f(x, y) = a^x b^y$$

$$S = \langle (k, -1) \rangle$$

110

What about non-Abelian HSP

- Consider the symmetric group $G = S_n$
- S_n is the set of permutations of n elements
- Let G be an n -vertex graph
- Let $X_G = \{\pi(G) \mid \pi \in S_n\}$
- Define $f_G : S_n \rightarrow X_G \quad f_G(\pi) = \pi(G)$
- Then $f_G(\pi_1) = f_G(\pi_2) \Leftrightarrow \pi_1 S = \pi_2 S$
where $S = \text{AUT}(G) = \{\pi \mid \pi(G) = G\}$

111

Further reading

<http://math.nist.gov/quantum/zoo/> (maintained by S. Jordan)

Quantum algorithms for algebraic problems

Andrew M. Childs
Department of Mathematics & Optimization and Institute for Quantum Computing
University of Waterloo, Waterloo, Ontario, Canada N2L 2G7
amc@uwaterloo.ca

Department of Computer Science and Physics
University of Guelph, Guelph, Ontario, Canada N1G 2W1

Quantum computers can execute algorithms for (classically) intractable algebraic computation. As the field of quantum computing grows, it is important to understand the limits of quantum computation. This article surveys the state of the art in quantum algorithms for algebraic computation, with a focus on the complexity of quantum algorithms for solving systems of linear equations over finite fields. The article surveys the complexity of quantum algorithms for solving systems of linear equations over finite fields, and the complexity of quantum algorithms for solving systems of linear equations over finite fields.

MSC numbers: 68Q12

Contents

I. Introduction	1	VII. Non-Abelian Hidden Subgroup Problem	11
II. Complexity of Quantum Computation	2	A. The problem and its applications	11
III. Quantum Algorithms for Algebraic Problems	3	B. The problem and its applications	11
IV. Hidden Subgroup Problem	4	C. The problem and its applications	11
V. Quantum Algorithms for Linear Equations	5	D. The problem and its applications	11
VI. Quantum Algorithms for Solving Systems of Linear Equations	6	E. The problem and its applications	11
VIII. Quantum Algorithms for Solving Systems of Linear Equations	7	F. The problem and its applications	11
IX. Quantum Algorithms for Solving Systems of Linear Equations	8	G. The problem and its applications	11
X. Quantum Algorithms for Solving Systems of Linear Equations	9	H. The problem and its applications	11
XI. Quantum Algorithms for Solving Systems of Linear Equations	10	I. The problem and its applications	11
XII. Quantum Algorithms for Solving Systems of Linear Equations	11	J. The problem and its applications	11
XIII. Quantum Algorithms for Solving Systems of Linear Equations	12	K. The problem and its applications	11
XIV. Quantum Algorithms for Solving Systems of Linear Equations	13	L. The problem and its applications	11
XV. Quantum Algorithms for Solving Systems of Linear Equations	14	M. The problem and its applications	11
XVI. Quantum Algorithms for Solving Systems of Linear Equations	15	N. The problem and its applications	11
XVII. Quantum Algorithms for Solving Systems of Linear Equations	16	O. The problem and its applications	11
XVIII. Quantum Algorithms for Solving Systems of Linear Equations	17	P. The problem and its applications	11
XIX. Quantum Algorithms for Solving Systems of Linear Equations	18	Q. The problem and its applications	11
XX. Quantum Algorithms for Solving Systems of Linear Equations	19	R. The problem and its applications	11
XXI. Quantum Algorithms for Solving Systems of Linear Equations	20	S. The problem and its applications	11
XXII. Quantum Algorithms for Solving Systems of Linear Equations	21	T. The problem and its applications	11
XXIII. Quantum Algorithms for Solving Systems of Linear Equations	22	U. The problem and its applications	11
XXIV. Quantum Algorithms for Solving Systems of Linear Equations	23	V. The problem and its applications	11
XXV. Quantum Algorithms for Solving Systems of Linear Equations	24	W. The problem and its applications	11
XXVI. Quantum Algorithms for Solving Systems of Linear Equations	25	X. The problem and its applications	11
XXVII. Quantum Algorithms for Solving Systems of Linear Equations	26	Y. The problem and its applications	11
XXVIII. Quantum Algorithms for Solving Systems of Linear Equations	27	Z. The problem and its applications	11
XXIX. Quantum Algorithms for Solving Systems of Linear Equations	28	aa. The problem and its applications	11
XXX. Quantum Algorithms for Solving Systems of Linear Equations	29	ab. The problem and its applications	11
XXXI. Quantum Algorithms for Solving Systems of Linear Equations	30	ac. The problem and its applications	11
XXXII. Quantum Algorithms for Solving Systems of Linear Equations	31	ad. The problem and its applications	11
XXXIII. Quantum Algorithms for Solving Systems of Linear Equations	32	ae. The problem and its applications	11
XXXIV. Quantum Algorithms for Solving Systems of Linear Equations	33	af. The problem and its applications	11
XXXV. Quantum Algorithms for Solving Systems of Linear Equations	34	ag. The problem and its applications	11
XXXVI. Quantum Algorithms for Solving Systems of Linear Equations	35	ah. The problem and its applications	11
XXXVII. Quantum Algorithms for Solving Systems of Linear Equations	36	ai. The problem and its applications	11
XXXVIII. Quantum Algorithms for Solving Systems of Linear Equations	37	aj. The problem and its applications	11
XXXIX. Quantum Algorithms for Solving Systems of Linear Equations	38	ak. The problem and its applications	11
XL. Quantum Algorithms for Solving Systems of Linear Equations	39	al. The problem and its applications	11
XLI. Quantum Algorithms for Solving Systems of Linear Equations	40	am. The problem and its applications	11
XLII. Quantum Algorithms for Solving Systems of Linear Equations	41	an. The problem and its applications	11
XLIII. Quantum Algorithms for Solving Systems of Linear Equations	42	ao. The problem and its applications	11
XLIV. Quantum Algorithms for Solving Systems of Linear Equations	43	ap. The problem and its applications	11
XLV. Quantum Algorithms for Solving Systems of Linear Equations	44	aq. The problem and its applications	11
XLVI. Quantum Algorithms for Solving Systems of Linear Equations	45	ar. The problem and its applications	11
XLVII. Quantum Algorithms for Solving Systems of Linear Equations	46	as. The problem and its applications	11
XLVIII. Quantum Algorithms for Solving Systems of Linear Equations	47	at. The problem and its applications	11
XLIX. Quantum Algorithms for Solving Systems of Linear Equations	48	au. The problem and its applications	11
L. Quantum Algorithms for Solving Systems of Linear Equations	49	av. The problem and its applications	11
LII. Quantum Algorithms for Solving Systems of Linear Equations	50	aw. The problem and its applications	11
LIII. Quantum Algorithms for Solving Systems of Linear Equations	51	ax. The problem and its applications	11
LIV. Quantum Algorithms for Solving Systems of Linear Equations	52	ay. The problem and its applications	11
LV. Quantum Algorithms for Solving Systems of Linear Equations	53	az. The problem and its applications	11
LVI. Quantum Algorithms for Solving Systems of Linear Equations	54	ba. The problem and its applications	11
LVII. Quantum Algorithms for Solving Systems of Linear Equations	55	bb. The problem and its applications	11
LVIII. Quantum Algorithms for Solving Systems of Linear Equations	56	bc. The problem and its applications	11
LIX. Quantum Algorithms for Solving Systems of Linear Equations	57	bd. The problem and its applications	11
LX. Quantum Algorithms for Solving Systems of Linear Equations	58	be. The problem and its applications	11
LXI. Quantum Algorithms for Solving Systems of Linear Equations	59	bf. The problem and its applications	11
LXII. Quantum Algorithms for Solving Systems of Linear Equations	60	bg. The problem and its applications	11
LXIII. Quantum Algorithms for Solving Systems of Linear Equations	61	bh. The problem and its applications	11
LXIV. Quantum Algorithms for Solving Systems of Linear Equations	62	bi. The problem and its applications	11
LXV. Quantum Algorithms for Solving Systems of Linear Equations	63	bj. The problem and its applications	11
LXVI. Quantum Algorithms for Solving Systems of Linear Equations	64	bk. The problem and its applications	11
LXVII. Quantum Algorithms for Solving Systems of Linear Equations	65	bl. The problem and its applications	11
LXVIII. Quantum Algorithms for Solving Systems of Linear Equations	66	bm. The problem and its applications	11
LXIX. Quantum Algorithms for Solving Systems of Linear Equations	67	bn. The problem and its applications	11
LXX. Quantum Algorithms for Solving Systems of Linear Equations	68	bo. The problem and its applications	11
LXXI. Quantum Algorithms for Solving Systems of Linear Equations	69	bp. The problem and its applications	11
LXXII. Quantum Algorithms for Solving Systems of Linear Equations	70	bq. The problem and its applications	11
LXXIII. Quantum Algorithms for Solving Systems of Linear Equations	71	br. The problem and its applications	11
LXXIV. Quantum Algorithms for Solving Systems of Linear Equations	72	bs. The problem and its applications	11
LXXV. Quantum Algorithms for Solving Systems of Linear Equations	73	bt. The problem and its applications	11
LXXVI. Quantum Algorithms for Solving Systems of Linear Equations	74	bu. The problem and its applications	11
LXXVII. Quantum Algorithms for Solving Systems of Linear Equations	75	bv. The problem and its applications	11
LXXVIII. Quantum Algorithms for Solving Systems of Linear Equations	76	bw. The problem and its applications	11
LXXIX. Quantum Algorithms for Solving Systems of Linear Equations	77	bx. The problem and its applications	11
LXXX. Quantum Algorithms for Solving Systems of Linear Equations	78	by. The problem and its applications	11
LXXXI. Quantum Algorithms for Solving Systems of Linear Equations	79	bz. The problem and its applications	11
LXXXII. Quantum Algorithms for Solving Systems of Linear Equations	80	ca. The problem and its applications	11
LXXXIII. Quantum Algorithms for Solving Systems of Linear Equations	81	cb. The problem and its applications	11
LXXXIV. Quantum Algorithms for Solving Systems of Linear Equations	82	cc. The problem and its applications	11
LXXXV. Quantum Algorithms for Solving Systems of Linear Equations	83	cd. The problem and its applications	11
LXXXVI. Quantum Algorithms for Solving Systems of Linear Equations	84	ce. The problem and its applications	11
LXXXVII. Quantum Algorithms for Solving Systems of Linear Equations	85	cf. The problem and its applications	11
LXXXVIII. Quantum Algorithms for Solving Systems of Linear Equations	86	cg. The problem and its applications	11
LXXXIX. Quantum Algorithms for Solving Systems of Linear Equations	87	ch. The problem and its applications	11
LXXXX. Quantum Algorithms for Solving Systems of Linear Equations	88	ci. The problem and its applications	11
LXXXXI. Quantum Algorithms for Solving Systems of Linear Equations	89	cj. The problem and its applications	11
LXXXXII. Quantum Algorithms for Solving Systems of Linear Equations	90	ck. The problem and its applications	11
LXXXXIII. Quantum Algorithms for Solving Systems of Linear Equations	91	cl. The problem and its applications	11
LXXXXIV. Quantum Algorithms for Solving Systems of Linear Equations	92	cm. The problem and its applications	11
LXXXXV. Quantum Algorithms for Solving Systems of Linear Equations	93	cn. The problem and its applications	11
LXXXXVI. Quantum Algorithms for Solving Systems of Linear Equations	94	co. The problem and its applications	11
LXXXXVII. Quantum Algorithms for Solving Systems of Linear Equations	95	cp. The problem and its applications	11
LXXXXVIII. Quantum Algorithms for Solving Systems of Linear Equations	96	cq. The problem and its applications	11
LXXXXIX. Quantum Algorithms for Solving Systems of Linear Equations	97	cr. The problem and its applications	11
LXXXXX. Quantum Algorithms for Solving Systems of Linear Equations	98	cs. The problem and its applications	11
LXXXXXI. Quantum Algorithms for Solving Systems of Linear Equations	99	ct. The problem and its applications	11
LXXXXXII. Quantum Algorithms for Solving Systems of Linear Equations	100	cu. The problem and its applications	11

Quantum Algorithms

Midale Mera
Institute for Quantum Computing and Dept. of Combinatorics & Optimization
University of Waterloo, Waterloo, Ontario, Canada N2L 2G7
m.mera@utoronto.ca

Abstract

Quantum algorithms for algebraic problems

1. Introduction

2. Background

3. The Quantum Hidden Subgroup Problem

4. The Quantum Hidden Subgroup Problem

5. The Quantum Hidden Subgroup Problem

6. The Quantum Hidden Subgroup Problem

7. The Quantum Hidden Subgroup Problem

8. The Quantum Hidden Subgroup Problem

9. The Quantum Hidden Subgroup Problem

10. The Quantum Hidden Subgroup Problem

11. The Quantum Hidden Subgroup Problem

12. The Quantum Hidden Subgroup Problem

13. The Quantum Hidden Subgroup Problem

14. The Quantum Hidden Subgroup Problem

15. The Quantum Hidden Subgroup Problem

16. The Quantum Hidden Subgroup Problem

17. The Quantum Hidden Subgroup Problem

18. The Quantum Hidden Subgroup Problem

19. The Quantum Hidden Subgroup Problem

20. The Quantum Hidden Subgroup Problem

21. The Quantum Hidden Subgroup Problem

22. The Quantum Hidden Subgroup Problem

23. The Quantum Hidden Subgroup Problem

24. The Quantum Hidden Subgroup Problem

25. The Quantum Hidden Subgroup Problem

26. The Quantum Hidden Subgroup Problem

27. The Quantum Hidden Subgroup Problem

28. The Quantum Hidden Subgroup Problem

29. The Quantum Hidden Subgroup Problem

30. The Quantum Hidden Subgroup Problem

31. The Quantum Hidden Subgroup Problem

32. The Quantum Hidden Subgroup Problem

33. The Quantum Hidden Subgroup Problem

34. The Quantum Hidden Subgroup Problem

35. The Quantum Hidden Subgroup Problem

36. The Quantum Hidden Subgroup Problem

37. The Quantum Hidden Subgroup Problem

38. The Quantum Hidden Subgroup Problem

39. The Quantum Hidden Subgroup Problem

40. The Quantum Hidden Subgroup Problem

41. The Quantum Hidden Subgroup Problem

42. The Quantum Hidden Subgroup Problem

43. The Quantum Hidden Subgroup Problem

44. The Quantum Hidden Subgroup Problem

45. The Quantum Hidden Subgroup Problem

46. The Quantum Hidden Subgroup Problem

47. The Quantum Hidden Subgroup Problem

48. The Quantum Hidden Subgroup Problem

49. The Quantum Hidden Subgroup Problem

50. The Quantum Hidden Subgroup Problem

51. The Quantum Hidden Subgroup Problem

52. The Quantum Hidden Subgroup Problem

53. The Quantum Hidden Subgroup Problem

54. The Quantum Hidden Subgroup Problem

55. The Quantum Hidden Subgroup Problem

56. The Quantum Hidden Subgroup Problem

57. The Quantum Hidden Subgroup Problem

58. The Quantum Hidden Subgroup Problem

59. The Quantum Hidden Subgroup Problem

60. The Quantum Hidden Subgroup Problem

61. The Quantum Hidden Subgroup Problem

62. The Quantum Hidden Subgroup Problem

63. The Quantum Hidden Subgroup Problem

64. The Quantum Hidden Subgroup Problem

65. The Quantum Hidden Subgroup Problem

66. The Quantum Hidden Subgroup Problem

67. The Quantum Hidden Subgroup Problem

68. The Quantum Hidden Subgroup Problem

69. The Quantum Hidden Subgroup Problem

70. The Quantum Hidden Subgroup Problem

71. The Quantum Hidden Subgroup Problem

72. The Quantum Hidden Subgroup Problem

73. The Quantum Hidden Subgroup Problem

74. The Quantum Hidden Subgroup Problem

75. The Quantum Hidden Subgroup Problem

76. The Quantum Hidden Subgroup Problem

77. The Quantum Hidden Subgroup Problem

78. The Quantum Hidden Subgroup Problem

79. The Quantum Hidden Subgroup Problem

80. The Quantum Hidden Subgroup Problem

81. The Quantum Hidden Subgroup Problem

82. The Quantum Hidden Subgroup Problem

83. The Quantum Hidden Subgroup Problem

84. The Quantum Hidden Subgroup Problem

85. The Quantum Hidden Subgroup Problem

86. The Quantum Hidden Subgroup Problem

87. The Quantum Hidden Subgroup Problem

88. The Quantum Hidden Subgroup Problem

89. The Quantum Hidden Subgroup Problem

90. The Quantum Hidden Subgroup Problem

91. The Quantum Hidden Subgroup Problem

92. The Quantum Hidden Subgroup Problem

93. The Quantum Hidden Subgroup Problem

94. The Quantum Hidden Subgroup Problem

95. The Quantum Hidden Subgroup Problem

96. The Quantum Hidden Subgroup Problem

97. The Quantum Hidden Subgroup Problem

98. The Quantum Hidden Subgroup Problem

99. The Quantum Hidden Subgroup Problem

100. The Quantum Hidden Subgroup Problem

112



Graduate Program in Quantum Information

- A cutting-edge interdisciplinary program leading to MMath, MSc, MASc and PhD degrees (e.g. PhD in Applied Mathematics (Quantum Information))
- Students must apply directly to one of the following academic units:
 - Applied Mathematics
 - Chemistry
 - Combinatorics and Optimization
 - David R. Cheriton School of Computer Science
 - Electrical and Computer Engineering
 - Physics and Astronomy
- Applicants will be subject to the normal admission procedures of the home unit
- Students will be subject to the normal program requirements of the home unit, plus additional QI requirements
- Several scholarships available to both domestic and international students
- For more information, visit www.iqc.ca or email grad@iqc.ca

UNIVERSITY OF
WATERLOO

IQC Institute for
Quantum
Computing