



Quantum Computer Algorithms

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Crash Course on Computational Complexity

- Computational Complexity
- Computing Models
- Some notation
- Uniformity

Computational Complexity

- We usually measure the amount of resources (e.g. time, space, gates) used by an algorithm as a function of the input size.
- E.g. The grade-school algorithm for multiplying two n -bit integers uses $O(n^2)$ time steps. FFT methods use $O(n(\log n)(\log \log n))$ time steps. The best known lower bound is $\Omega(n)$ steps.

“polynomial” cost

- When we say an algorithm uses a polynomial amount of some resource (e.g. time, space, gates, energy), we mean that there is some polynomial $p(n)$ such that the amount of that resource used by the algorithm is in $O(p(n))$
- E.g. we can multiply n -bit numbers in polynomial time.

“polynomial” cost

- If the cost is not bounded above by a polynomial, we say its “super-polynomial”; sometimes people abuse the term “exponential” to mean super-polynomial
- E.g. the best rigorous probabilistic classical algorithm for factoring n -bit numbers uses time in $e^{O(\sqrt{n \log n})}$
- So there is no known polynomial time classical algorithm for factoring

What's so special about polynomials?

- The Strong Church-Turing thesis states that a probabilistic Turing machine can simulate any reasonable algorithmic process with at most a polynomial overhead
- Using polynomial cost as our notion of "efficiency" is very convenient.

Computing Models

- Two commonly used models are the Turing machine model and the circuit model

Turing machines

- Turing machines can take inputs of any size.
- We measure the time complexity of a computation on a Turing machine by the number of steps taken before the TM stops
- The space complexity is the number of tape positions used for the computation
- We usually consider the *worst case* complexity for an input of a fixed size n .

Asymptotic Notation

- A function $f(n)$ is in $O(g(n))$ if for some constant m there exists a positive constant c such that $f(n) \leq c g(n)$ for all $n \geq m$
- A function $f(n)$ is in $\Omega(g(n))$ if for some constant m there exists a positive constant c such that $f(n) \geq c g(n)$ for all $n \geq m$
- A function $f(n)$ is in $\Theta(g(n))$ if for some constant m there exists positive constants $c_1 \leq c_2$ such that $c_1 g(n) \leq f(n) \leq c_2 g(n)$ for all $n \geq m$

Circuits

- We usually measure the complexity of a circuit C_n by its size, $|C_n|$, which is the number of gates in it.
- We can also measure the depth (or time), and the space (or width).
- Circuits only take a fixed size input. So how can we fairly compare them to Turing machines?

Families of Circuits

- We consider families of circuits $\{C_n\}$ where C_n takes inputs of size n .
- We can, e.g., design a family of multiplication circuits where C_n has size $O(n^2)$ or $O(n \log n \log \log n)$.
- Recall that the description of a Turing machine is finite. Where do we keep an infinite family of circuits?

Families of Circuits

- We have a procedure (e.g. a Turing machine) that generates the circuit diagrams for us
- For the size of the circuit C_n to fairly reflect the complexity of solving a problem on an input of size n , the complexity of generating the circuit must be “reasonable”

Families of Circuits

- The definition of "reasonable" varies depending on what you are trying to prove, but as a bare minimum, we expect the time and space complexities of generating C_n to be at most polynomial in the size of C_n
- For most of the circuits we will encounter, it will be clear that we can efficiently generate C_n given the integer n

Families of Circuits

- A family of circuits that can be efficiently generated is a *uniform family* of circuits
- Non-uniform families of circuits can require exponential resources to construct. It is possible to hide valuable information in the circuit C_n that we might not be able to compute from scratch using $\text{poly}(|C_n|)$ resources. It is not appropriate to use $|C_n|$ as a measure of the complexity of solving a problem "from scratch"

Uniform Families of Acyclic Quantum Circuits

- The computing model we will use for most of this course is *uniform families of acyclic circuits*
- The word "circuit" seems to refer to particular physical implementation of a computer. We will often use the terms "network" or "array of gates" instead.

Quantum Algorithms Overview

- Eigenvalue Estimation lets us factor integers
- Eigenvalue 'kick-back' turns eigenvalue estimation problem into phase estimation problem
- Quantum Fourier Transform and Phase Estimation
- Generalization to finding hidden subgroups
- Finding Hidden Affine Functions

Integer Factorization

- 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 $a^r \equiv 1 \pmod{N}$

Simple operator

Since we know how to efficiently multiply by $a \bmod N$, 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. $U_a^r = I$

Interesting eigenvalues

If $U_a^r = \mathbf{I}$ then the eigenvalues of

U_a are of the form $e^{2\pi i \frac{k}{r}}$

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

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

Checking the eigenvalue

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

Finding r

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

Where do we get $|\Psi_k\rangle$?

Since most k are good, a random $|\Psi_k\rangle$
suffices. Try
$$|1\rangle = \sum_{k=0}^{r-1} \frac{1}{\sqrt{r}} |\Psi_k\rangle$$

Estimating Random Eigenvalue lets us Factor

In summary:

Factoring large numbers can be reduced to
estimating a random eigenvalue of U_a

Must make the "global" phase a "relative" phase

A global phase has no physical significance.
In other words, states that differ only by a global phase are equivalent

$$U\left(\sum_x a_x |x\rangle\right) = \sum_x b_x |x\rangle$$
$$U\left(e^{i\theta} \sum_x a_x |x\rangle\right) = e^{i\theta} \sum_x b_x |x\rangle$$

so $e^{i\theta} |\Phi\rangle \approx |\Phi\rangle$

Must make the "global" phase a "relative" phase

A relative phase can affect outcome probabilities

E.g.

$$|0\rangle + e^{i\varphi} |1\rangle \xrightarrow{H} \left(\frac{1 + e^{i\varphi}}{2} \right) |0\rangle + \left(\frac{1 - e^{i\varphi}}{2} \right) |1\rangle$$
$$p_0 = \cos^2 \left(\frac{\varphi}{2} \right)$$

Eigenvalue "kick-back"

We can also efficiently implement

$$C-U_a |0\rangle|x\rangle = |0\rangle|x\rangle$$

$$C-U_a |1\rangle|x\rangle = |1\rangle|ax\rangle$$

so

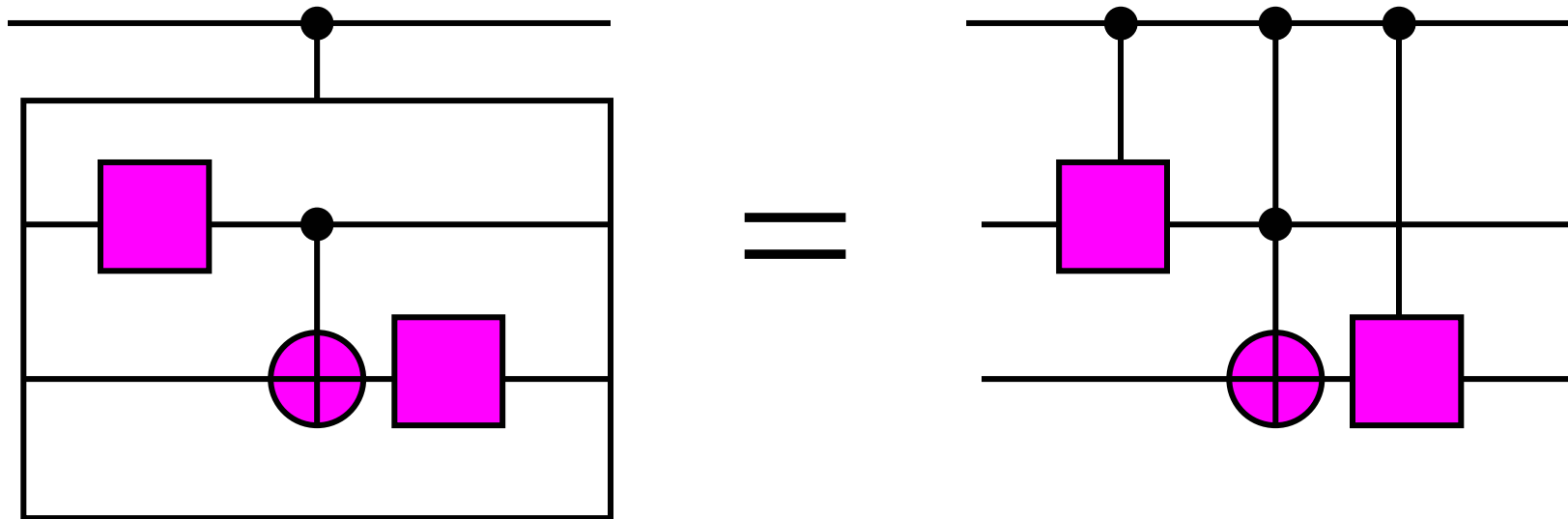
$$C-U_a |0\rangle|\psi_k\rangle = |0\rangle|\psi_k\rangle$$

$$C-U_a |1\rangle|\psi_k\rangle = e^{2\pi i \frac{k}{r}} |1\rangle|\psi_k\rangle$$

How do we implement c-U?

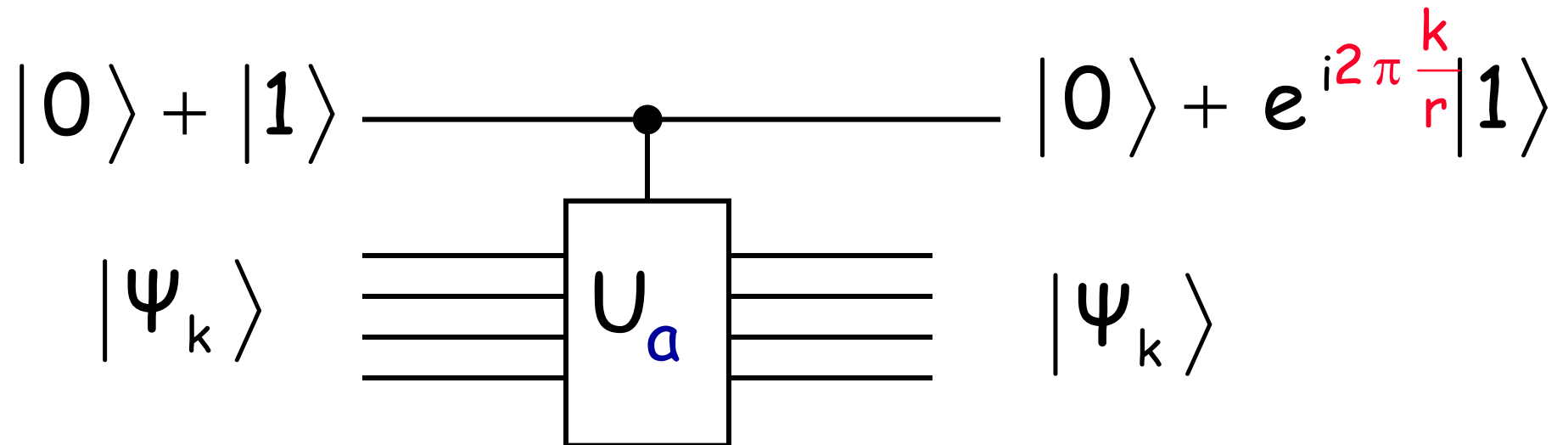
Replace every gate G in the circuit for
with a c- G .

For example,



Eigenvalue kick-back

We can thus efficiently implement

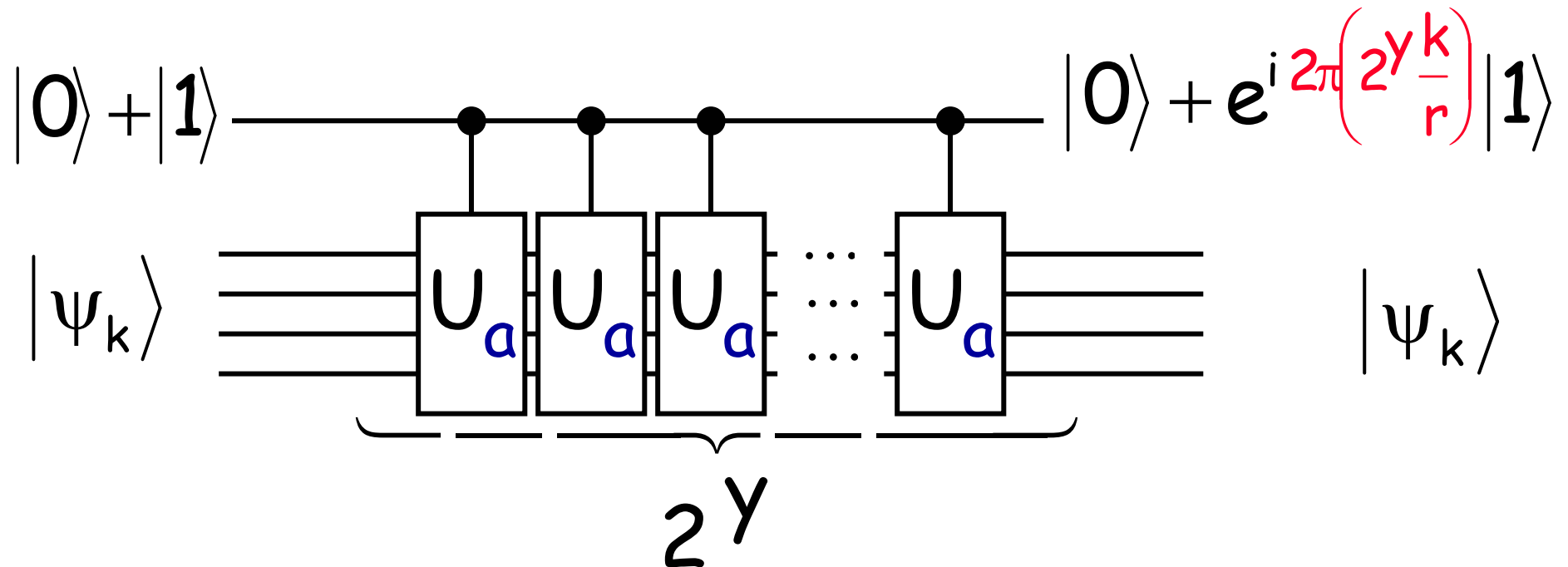


This gives us a relative phase shift of

$$\varphi = 2\pi \frac{k}{r} \quad \text{in the control qubit}$$

Inefficient exponentiation

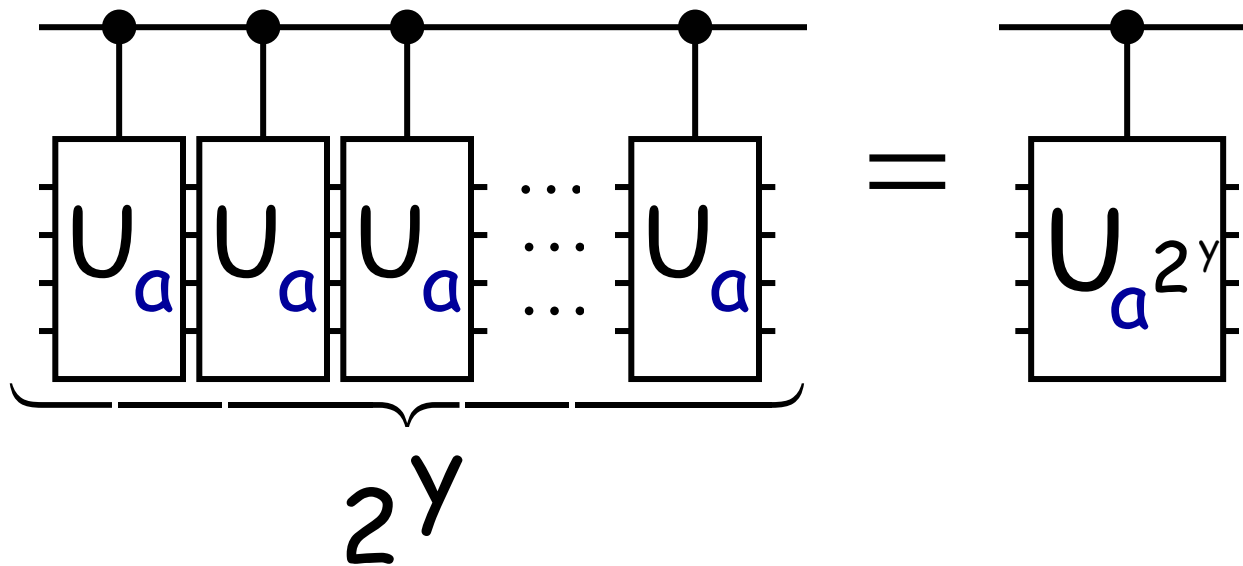
We can effect a relative phase shift of $e^{i2\pi\left(\frac{2\gamma k}{r}\right)}$



Efficient Exponentiation

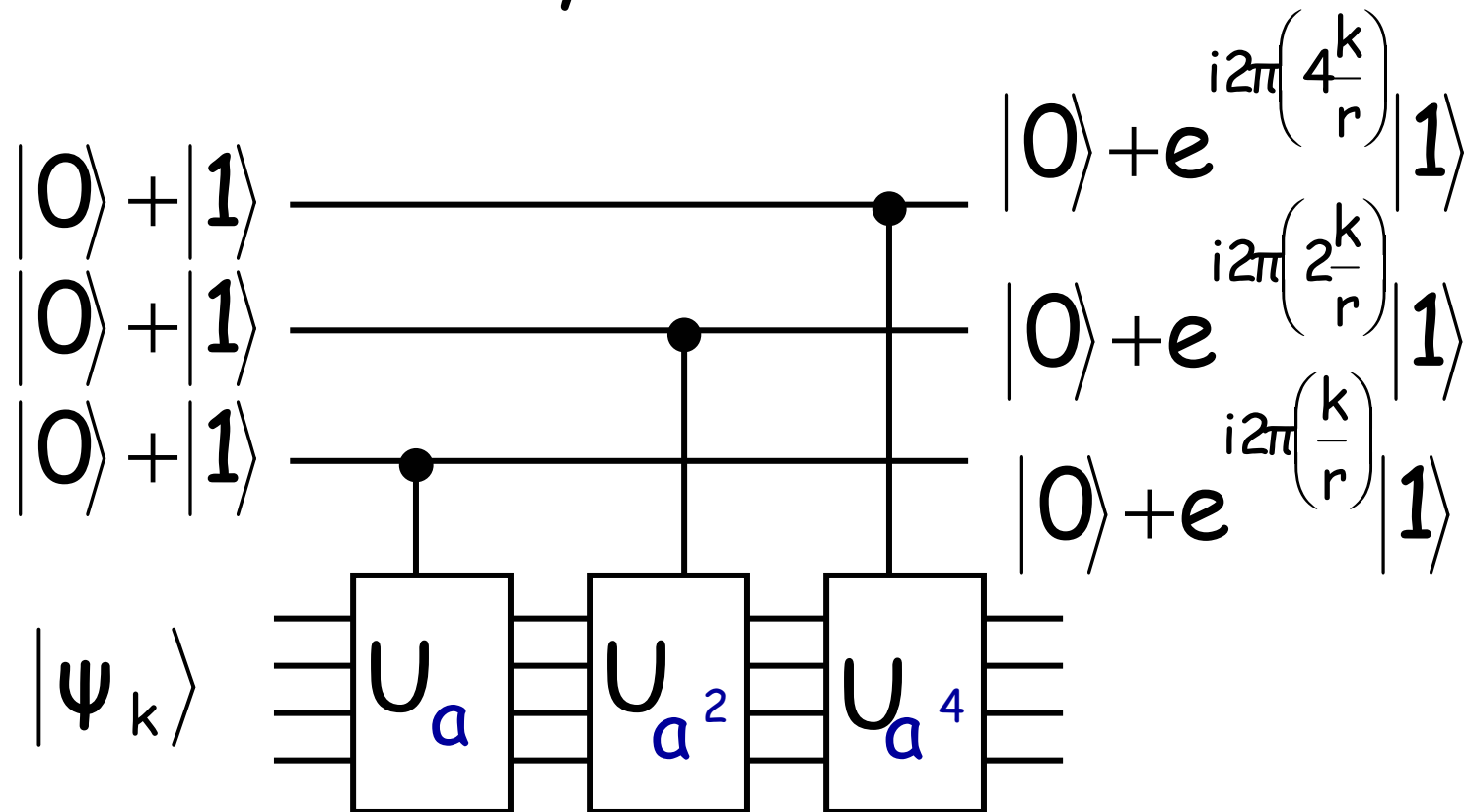
But we can also do it **efficiently** by noticing

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



Reduction to phase estimation

We can efficiently construct



Phase Estimation

Given the qubits

$$\left(|0\rangle + e^{i2\pi\left(\frac{k}{r}\right)} |1\rangle \right) \left(|0\rangle + e^{i2\pi\left(\frac{2^k}{r}\right)} |1\rangle \right) \cdots \left(|0\rangle + e^{i2\pi\left(\frac{2^j k}{r}\right)} |1\rangle \right)$$

Estimate $\frac{k}{r}$

Special Case

$$\left(|0\rangle + e^{i(\varphi)} |1\rangle \right) \quad \left(|0\rangle + e^{i(2\varphi)} |1\rangle \right) \quad \left(|0\rangle + e^{i(4\varphi)} |1\rangle \right)$$

Where

$$\frac{\varphi}{2\pi} = \frac{x}{8} = \frac{x_1 x_2 x_3}{8} = \frac{4x_1 + 2x_2 + x_3}{8} = 0.x_1 x_2 x_3$$

Since $e^{i2\pi} = 1$ then we have the state

$$\left(|0\rangle + e^{i2\pi(0.x_1 x_2 x_3)} |1\rangle \right) \left(|0\rangle + e^{i2\pi(0.x_2 x_3)} |1\rangle \right) \left(|0\rangle + e^{i2\pi(0.x_3)} |1\rangle \right)$$

Recall Hadamard transform

$$|b\rangle \xleftrightarrow{H} (|0\rangle + (-1)^b |1\rangle) = (|0\rangle + e^{i2\pi(0.b)} |1\rangle)$$

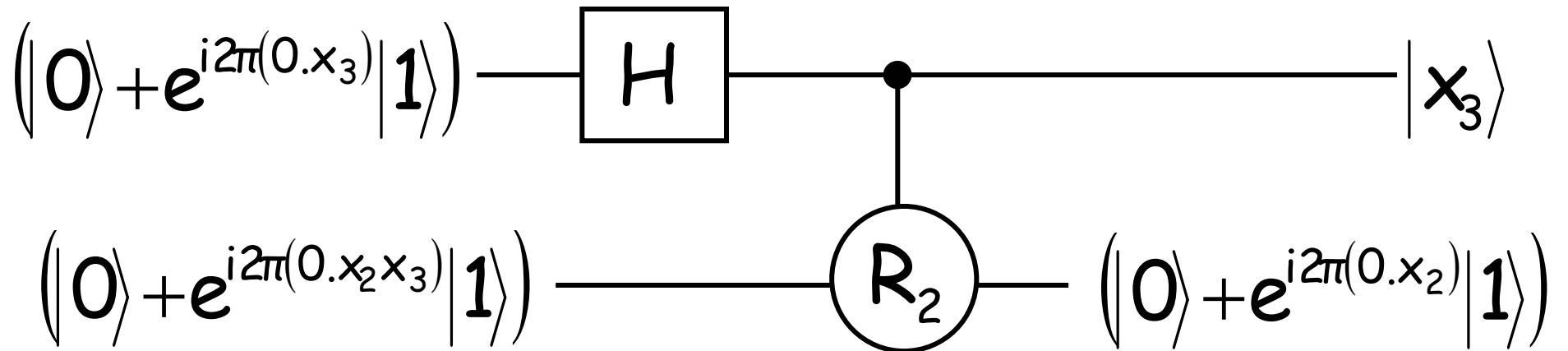
Obvious Phase Estimation Algorithm

$$\left(|0\rangle + e^{i2\pi(0.x_3)} |1\rangle \right) \text{ --- } \boxed{H} \text{ --- } |x_3\rangle$$

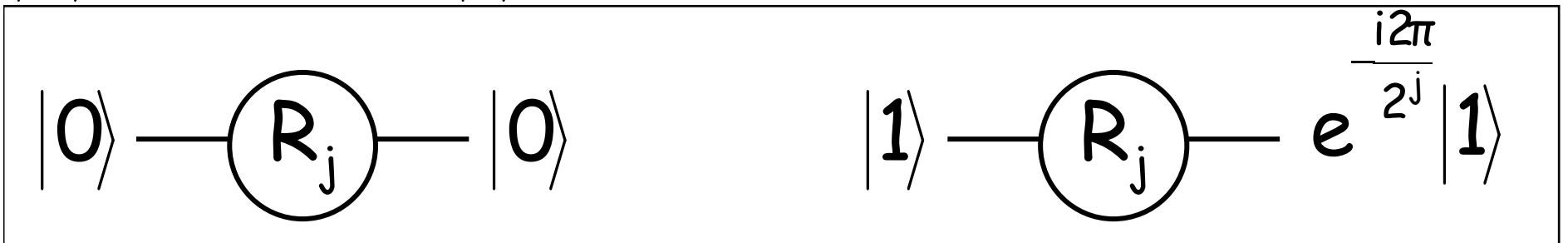
$$\left(|0\rangle + e^{i2\pi(0.x_2x_3)} |1\rangle \right)$$

$$\left(|0\rangle + e^{i2\pi(0.x_1x_2x_3)} |1\rangle \right)$$

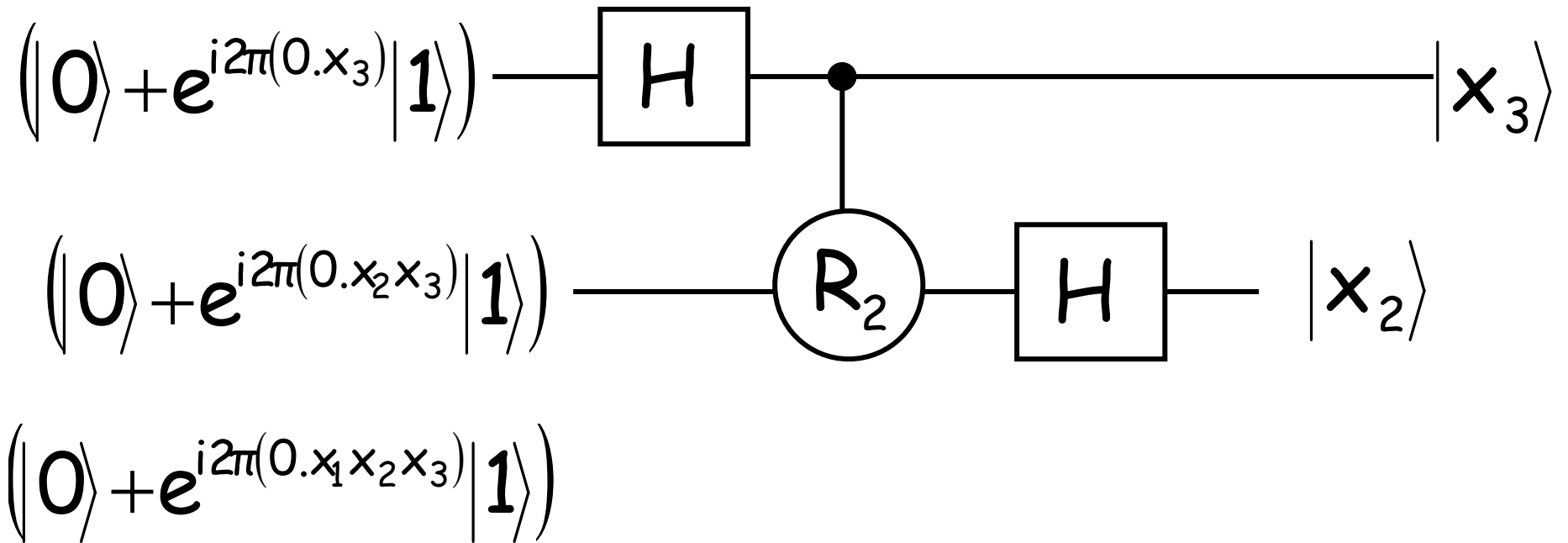
Phase Estimation



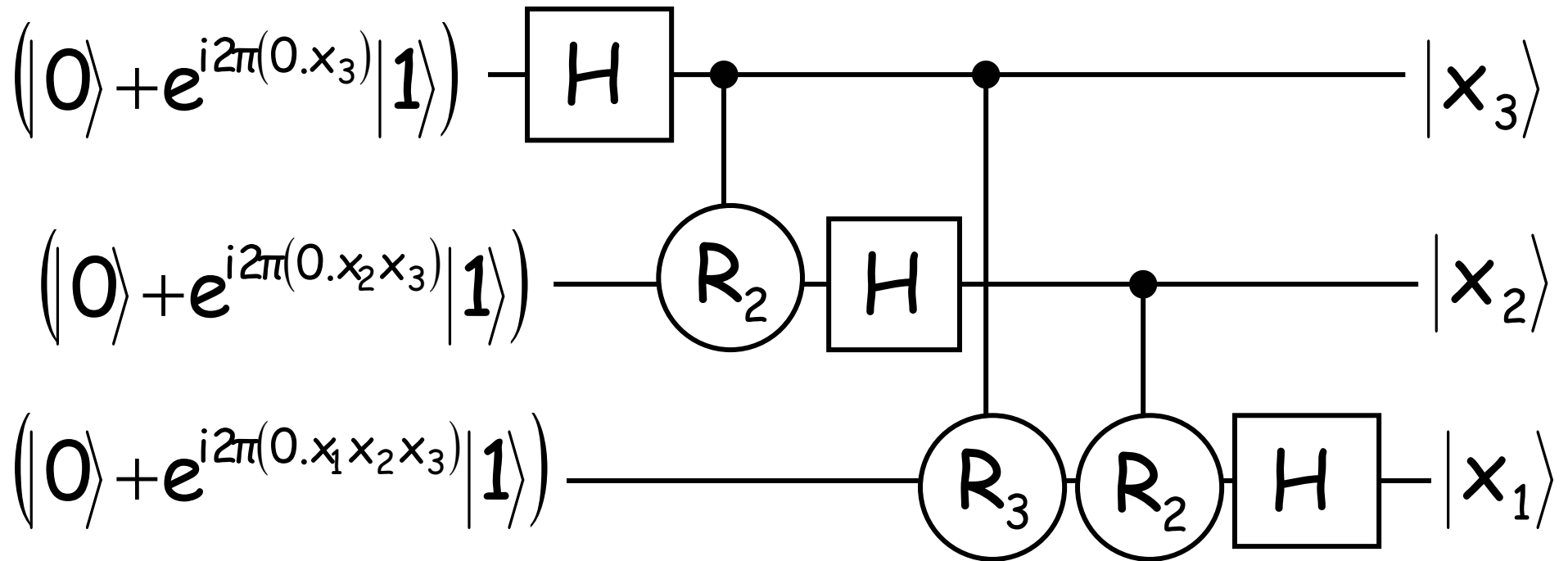
$$(|0\rangle + e^{i2\pi(0.x_1 x_2 x_3)}|1\rangle)$$



Natural Phase Estimation

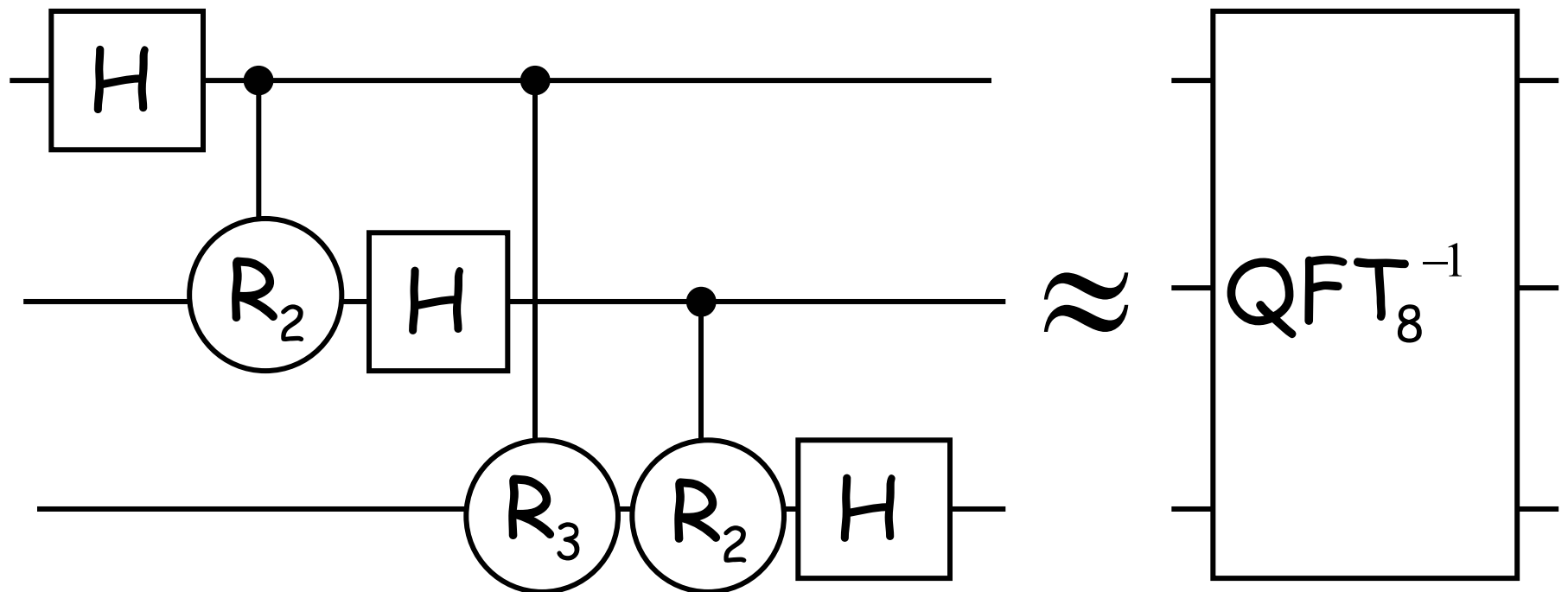


Phase Estimation



Inverse Quantum Fourier Transform

If we reorder the final qubits, we have



What is a (Q)FT?

$$\text{FT}_{2^n}: \mathbb{C}^{2^n} \rightarrow \mathbb{C}^{2^n}$$

$$e_j = (0, 0, \dots, 1, \dots, 0, 0)$$

$$\mapsto \frac{1}{\sqrt{2^n}} \left(1, e^{i2\pi \frac{j}{2^n}}, e^{i2\pi \left(2 \frac{j}{2^n}\right)}, \dots, e^{i2\pi \left((2^n-1) \frac{j}{2^n}\right)} \right)$$

$$\text{FT}_{2^n}^{-1}: \frac{1}{\sqrt{2^n}} \left(1, e^{i2\pi \frac{j}{2^n}}, e^{i2\pi \left(2 \frac{j}{2^n}\right)}, \dots, e^{i2\pi \left((2^n-1) \frac{j}{2^n}\right)} \right) \mapsto e_j$$

What is a (Q)FT?

$$\text{FT}_{2^n}^{-1}: \frac{1}{\sqrt{2^n}} (1, e^{i\varphi}, e^{i2\varphi}, \dots, e^{i(2^n-1)\varphi})$$

$$\mapsto (a_0, a_1, \dots, a_{2^n-1})$$

$$|a_j| = \frac{\sin\left(2^n\left(\frac{\varphi}{2\pi} - \frac{j}{2^n}\right)\pi\right)}{2^n \sin\left(\left(\frac{\varphi}{2\pi} - \frac{j}{2^n}\right)\pi\right)}$$

What is a (Q)FT?

$$\text{QFT}_{2^n}: H_{2^n} \rightarrow H_{2^n}$$

$$|j\rangle \mapsto \frac{1}{\sqrt{2^n}} \sum_{x=0}^{2^n-1} e^{i2\pi \left(x \frac{j}{2^n}\right)} |x\rangle$$

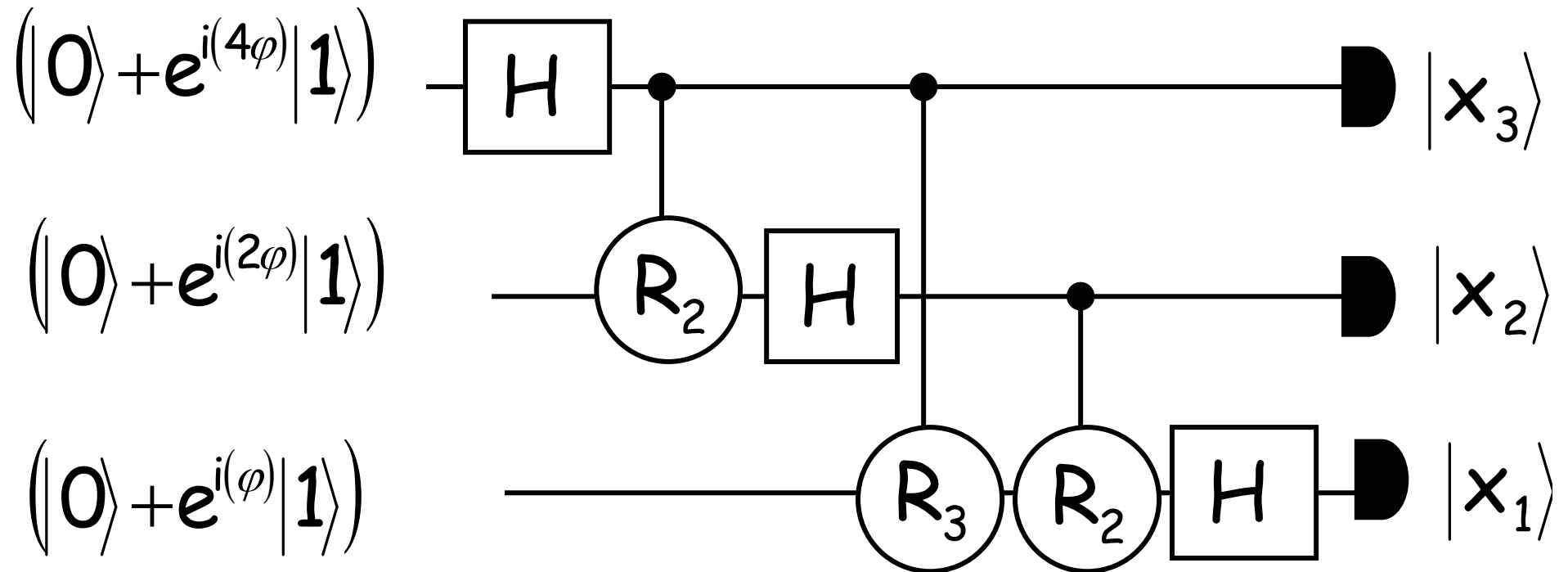
$$\text{QFT}_{2^n}^{-1}: \frac{1}{\sqrt{2^n}} \sum_{x=0}^{2^n-1} e^{i2\pi \left(x \frac{j}{2^n}\right)} |x\rangle \mapsto |j\rangle$$

What is a (Q)FT?

$$\text{QFT}_{2^n}^{-1}: \frac{1}{\sqrt{2^n}} \sum_{x=0}^{2^n-1} e^{ix\varphi} |x\rangle \mapsto \sum_j a_j |j\rangle$$

$$|a_j| = \frac{\sin\left(2^n \left(\frac{\varphi}{2\pi} - \frac{j}{2^n}\right) \pi\right)}{2^n \sin\left(\left(\frac{\varphi}{2\pi} - \frac{j}{2^n}\right) \pi\right)}$$

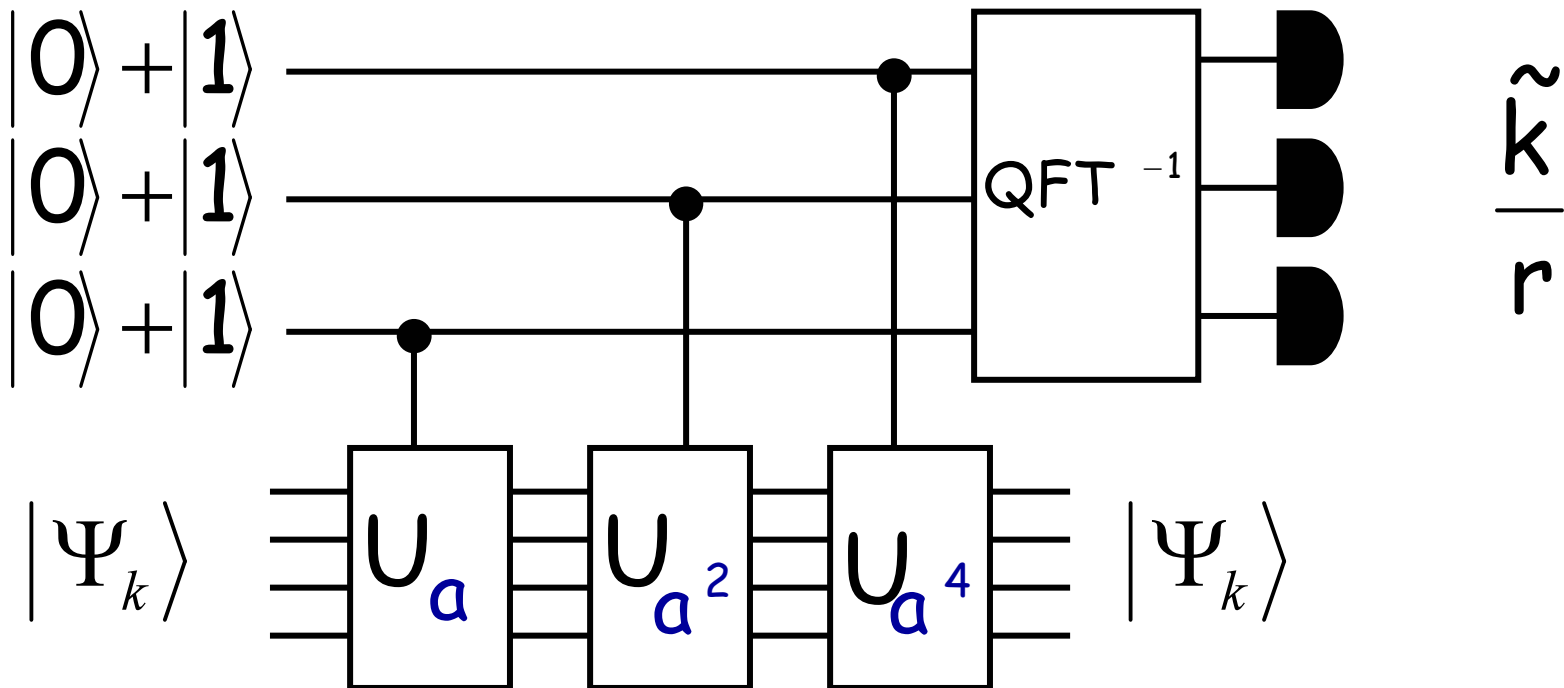
Phase Estimation: Arbitrary φ



$$\tilde{\varphi} = 2\pi \frac{(4x_1 + 2x_2 + x_3)}{8} \quad \mathbb{P}\left(\left|\frac{\tilde{\varphi}}{2\pi} - \frac{\varphi}{2\pi}\right| \leq \frac{1}{8}\right) \geq \frac{8}{\pi^2}$$

Quantum Factoring

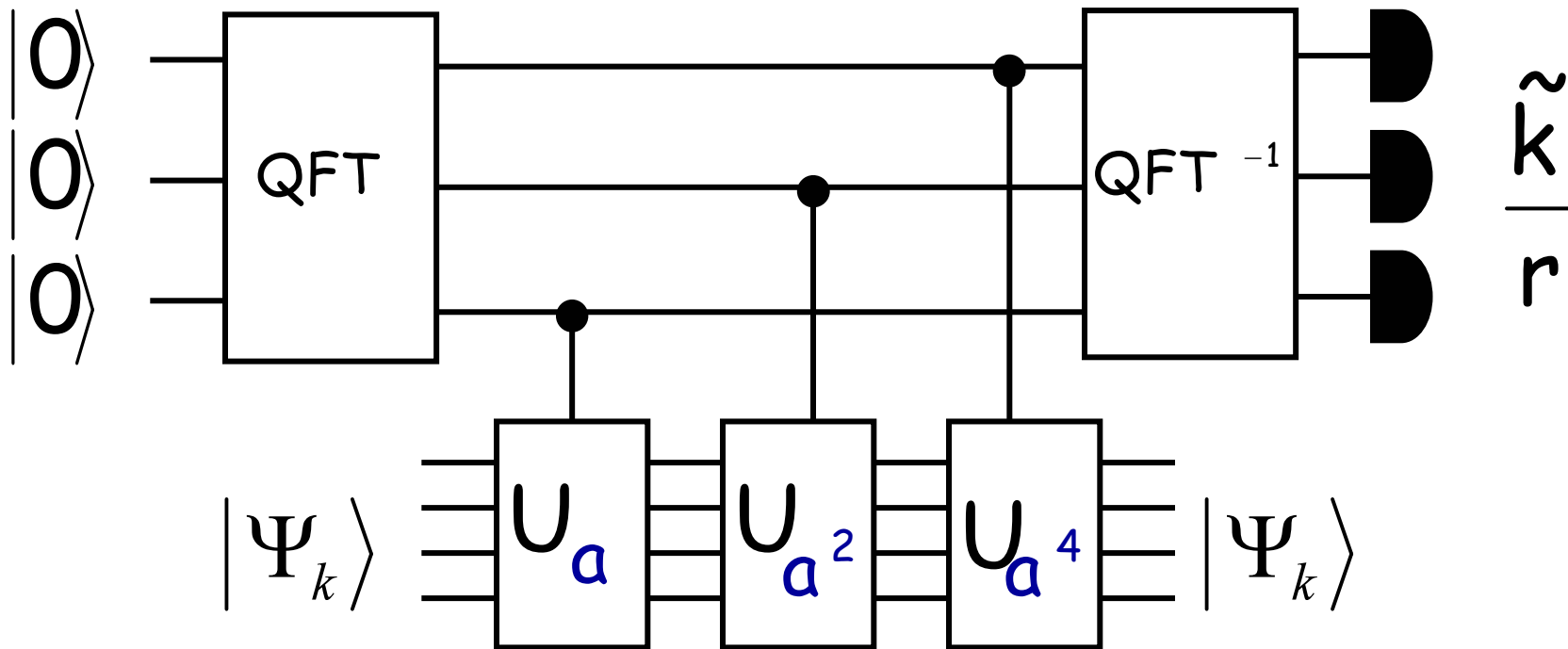
We can efficiently estimate $\frac{k}{r}$



[Kitaev95, CEMM98]

Factoring Network

We are effectively studying the behaviour of the controlled- U_a in a 'very quantum' basis.



Factoring Network

The given network maps

$$|000\rangle|\Psi_k\rangle \mapsto \left| \frac{\tilde{k}}{r} \right\rangle |\Psi_k\rangle$$

And therefore

$$|000\rangle|\mathbf{1}\rangle = \frac{1}{\sqrt{r}} \sum_k |000\rangle|\Psi_k\rangle \mapsto \frac{1}{\sqrt{r}} \sum_k \left| \frac{\tilde{k}}{r} \right\rangle |\Psi_k\rangle$$

Partial measurements

$$\sum_k \frac{1}{\sqrt{r}} \left| \frac{\tilde{k}}{r} \right\rangle \left| \psi_k \right\rangle$$

What do we get when we measure the first register?
In general, we can rewrite

$$\sum_{xy} a_{xy} |x\rangle |y\rangle = \sum_x |x\rangle \left(\sum_y a_{xy} |y\rangle \right)$$

$$= \sum_x b_x |x\rangle |\Phi_x\rangle$$

$$|\Phi_x\rangle = \sum_y \frac{a_{xy}}{b_x} |y\rangle$$

$$b_x = \sqrt{\sum_y |a_{xy}|^2}$$

Partial measurements

The probability of measuring x in the first register of $\sum_x b_x |x\rangle |\Phi_x\rangle$ is b_x^2

Partial measurements

Alternatively, we can rewrite

$$\begin{aligned}\sum_{xy} a_{xy} |x\rangle |y\rangle &= \sum_y \left(\sum_x a_{xy} |x\rangle \right) |y\rangle \\ &= \sum_y c_y |\Phi'_y\rangle |y\rangle\end{aligned}$$

$$|\Phi'_y\rangle = \sum_x \frac{a_{xy}}{c_y} |x\rangle \quad c_y = \sqrt{\sum_x |a_{xy}|^2}$$

Partial measurements

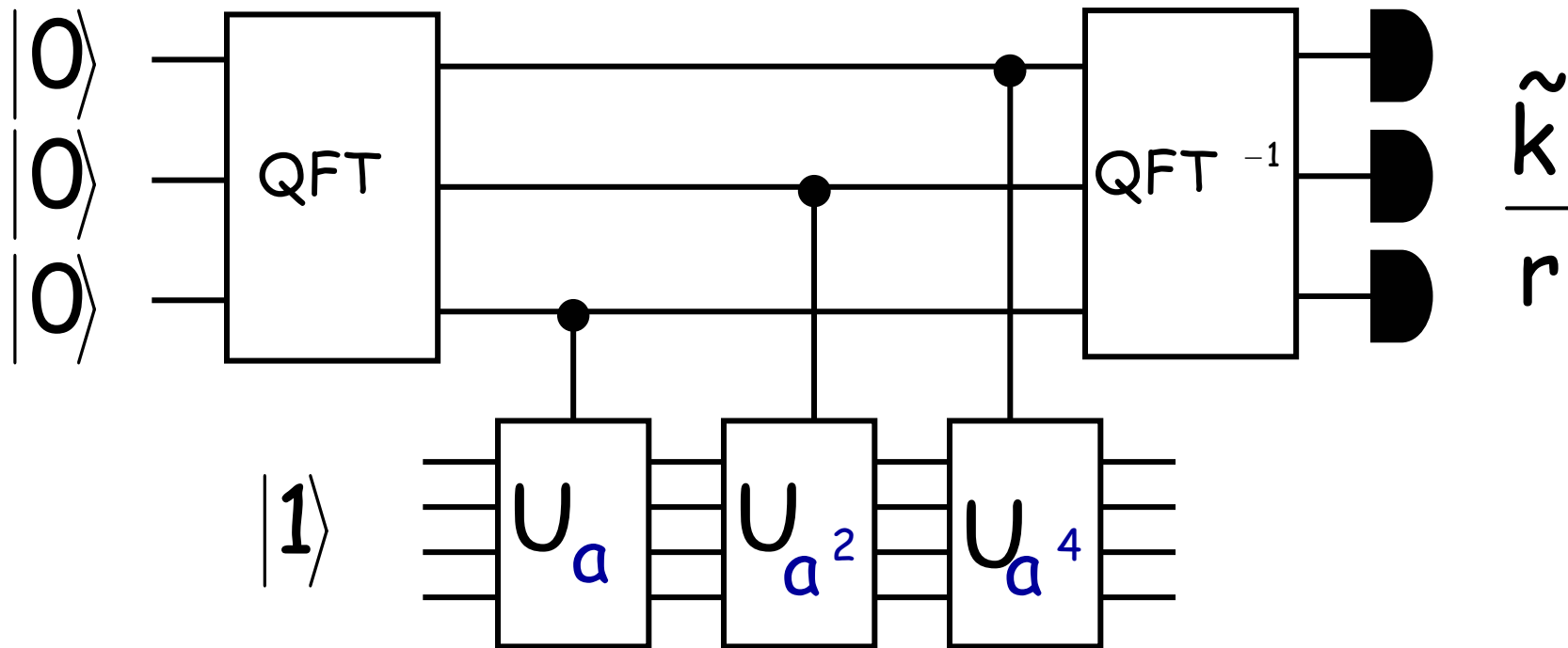
Measuring the first register of $\sum c_y |\Phi'_y\rangle |y\rangle$ is equivalent to performing a measurement on the state $|\Phi'_y\rangle$ with probability c_y^2

Partial measurements

Measuring the first register of $\sum_k \frac{1}{\sqrt{r}} \left| \frac{\tilde{k}}{r} \right\rangle \left| \psi_k \right\rangle$
is equivalent to performing a measurement
on the state $\left| \frac{\tilde{k}}{r} \right\rangle$ with probability $\frac{1}{r}$

Factoring Network

We are effectively studying the behaviour of the controlled- U_a in a 'very quantum' basis.



[CEMM98] show this is equivalent to [Shor94]

Complexity comparison

The best rigorous classical algorithms use $e^{O(\sqrt{\log(N)} \log \log(N))}$ operations

The best 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

Hidden Subgroup

This approach allows us to solve efficiently any “Abelian Hidden Subgroup Problem” (see [ME98],[M99],[NC00])

$$f : G \rightarrow X$$

$$K \leq G$$

$$f(x) = f(y) \Leftrightarrow x - y \in K$$

Find K

Hidden Affine Functions

Hidden Affine Functions:

$$f : \mathbb{Z}_p^n \rightarrow \mathbb{Z}_p^m$$

$$x \rightarrow Mx + b$$

Find M using only m evaluations of f
(instead of $n+1$) (D,BV,CEMM,H,M)