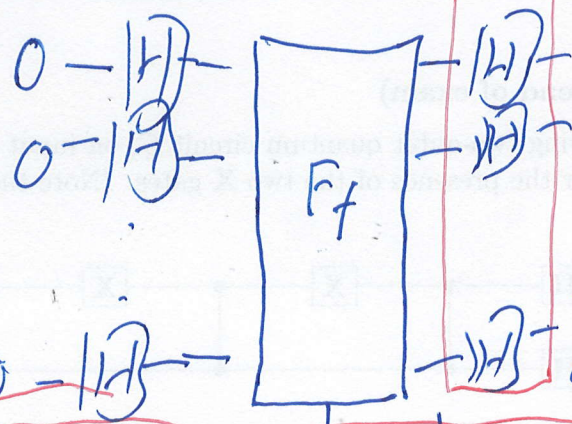


CSB 439 Lecture on Chs 9 & 10

Deutsch's Algorithm

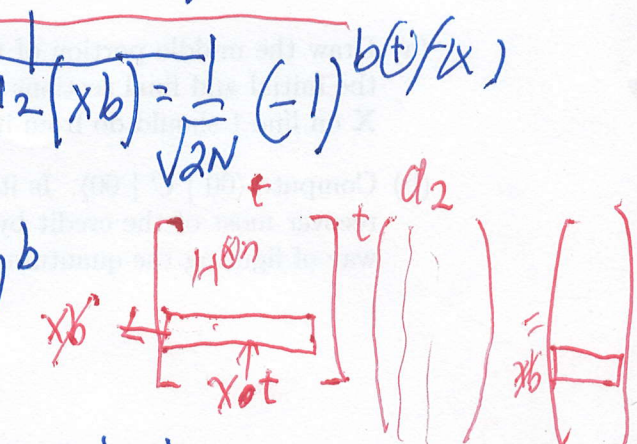
$f = \{0,1\}^n \rightarrow \{0,1\}$   
 promise = either  
 f is constant or  
 f is balanced.



$a_3(xb) = \frac{1}{\sqrt{N}} \sum_t (-1)^{x \cdot t} a_2(tb)$   
 $= \frac{1}{N\sqrt{2}} \sum_t (-1)^{x \cdot t} (-1)^{f(t) \oplus b}$   
 (continued see below)

$F_f(xb) = \begin{bmatrix} x \\ b \oplus f(x) \end{bmatrix}$

$a_0 = |0^n\rangle$   
 $a_1 = |+\rangle^{\otimes n} |0\rangle$   
 $a_2(xb) = \frac{1}{\sqrt{2N}} (-1)^b$



$= \frac{1}{N\sqrt{2}} \sum_t (-1)^{x \cdot t} (-1)^b (-1)^{f(t)}$

If f is constant = c, then this equals  $\frac{1}{\sqrt{2}} \sum_t (-1)^{x \cdot t} (-1)^{b+c} = \frac{1}{\sqrt{2}} (-1)^{b+c} \sum_t (-1)^{x \cdot t}$

Analysis is about measuring on the first n qubits - i.e. getting  $0^n$  or  $0^n.1$

$a_3(0^n b) = \frac{1}{\sqrt{2}} \frac{1}{N} \sum_{t \in \{0,1\}^n} (+1) = \frac{1}{\sqrt{2}}$

∴ Half the probability is on  $0^n.0$ , the other half on  $0^n.1$   
 ∴ With certainty, we will get  $0^n$  on the first n qubits

To make the distinction we need that if f is balanced, then we never get  $0^n$  on the first n qubits

Generally,  $a_3(0^n b) = \frac{1}{\sqrt{2}} (-1)^{b+c}$

$a_3(xb) = \frac{1}{N\sqrt{2}} \sum_t (-1)^{x \cdot t} (-1)^{f(t)}$

∴  $a_3(0^n b) = \frac{1}{N\sqrt{2}} \sum_t (+1) \cdot (-1)^{f(t)}$

This finishes the proof.  
 No classical algorithm able to query only  $f(x)$  is able to get certainty. But you can get "high probb."

If f is balanced, the sum cancels, leaving zero amplitude on  $a_3(0^n b)$  ( $b=0$  or  $b=1$ )

# Chapter 10: Simon's Algorithm $f(x) = y$ (2)

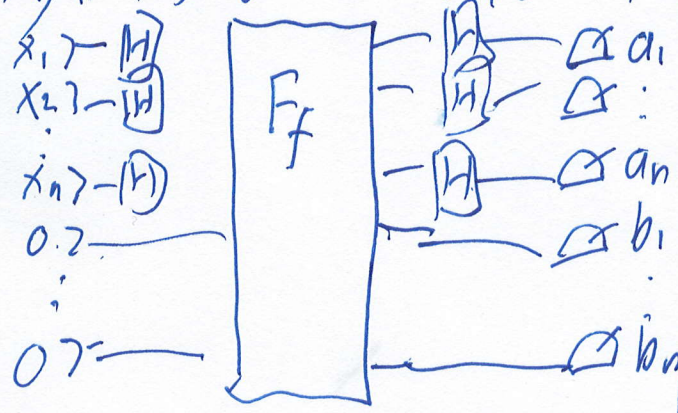
Now we are given  $f: \{0,1\}^n \rightarrow \{0,1\}^n$  with the promise that there is a "hidden vector"  $s \in \{0,1\}^n$  st  $\forall x, z \in \{0,1\}^n, f(x) = f(z) \iff x = z \oplus s$ .  
 When  $s = 0^n$ , this says  $f$  is 1-1, else  $f$  is 2-1 in this special way.

Goal: Given ability to query  $F(y, w) = [y, w \oplus f(y)]$  in quantum, compute  $s$ .  
 In particular, this distinguishes the case  $s = 0^n$  from the case  $f$  is 2-1 with  $s$ .

Simon's Theorems:  
 Proof really long; skipped

1. We can build a classical algorithm with a quantum sampling subroutine that computes  $s$  w.h.p. in  $n^{O(1)}$  time.
2. No classical algorithm able to query  $f(y) \rightarrow z$  is able to distinguish  $s = 0^n$  from  $s \neq 0^n$  in  $2^{o(n)}$  time w.h.p.

Begin Proof of (1)  
 The quantum circuit is @ W



Classical part

$E = \emptyset;$   
 while  $(\text{rank}(E) < n)$   
 Sample  $c \rightarrow \begin{bmatrix} \alpha \\ \beta \end{bmatrix}$   
 if  $c \notin \text{span}(E)$   
 }  $E = E \cup \{c\}$

Inner Lemma:  $c$  always gives  $c \cdot s = 0$   
 Thus when  $\text{rank}(E) < n$  we can solve for  $s$

Outer Lemma: Given that the  $c$  we measure is uniformly random st.  $c \cdot s = 0$ , with prob. at least  $1/2$  on each sample,  $c \notin \text{span}(E)$ . So we make progress.

Thursday's lecture went to here.

Proof of Inner Lemma: The state after  $F_f$  is  $\frac{1}{\sqrt{N}} \sum_x |x\rangle |f(x)\rangle$ . In "function-vector" form:  
 The state  $v$  after the Hadamard transform on the "x space" is:

$$u(x, y) = \begin{cases} 1/\sqrt{N} & \text{if } y = f(x) \\ 0 & \text{otherwise} \end{cases}$$

$$v(x, y) = \sum_{t \in \{0,1\}^n} (-1)^{x \cdot t} u(t, y) = \frac{1}{N} \sum_t (-1)^{x \cdot t} \begin{cases} 1 & \text{if } y = f(t) \\ 0 & \text{otherwise} \end{cases}$$

(with constant  $1/\sqrt{N}$  again,  $N = 2^n$ )

(searchwork page)  
 Immediately we can deduce that the measurement outcome  $xy$  has nonzero amplitude only if  $y \in R = \text{Ran}(f)$ .

Continuing the proof of Simon's Algorithm: We measure the state (3)

$$V(xy) = \frac{1}{N} \sum_{t \in \{0,1\}^n} \begin{cases} (-1)^{x \bullet t} & \text{if } y = f(t) \\ 0 & \text{otherwise} \end{cases}$$

where  $N = 2^n$   
and we multiplied  
 $\frac{1}{\sqrt{N}} \cdot \frac{1}{\sqrt{N}} = \frac{1}{N}$

Now suppose we measure and get the result  $\begin{bmatrix} a \\ b \end{bmatrix}$ ,  $a \in \{0,1\}^n$ ,  $b \in \{0,1\}^n$ .  
We know  $b \in \text{Ran}(f)$ . If  $f$  is 1-to-1, then  $s = 0^n$  and automatically,  $a \bullet s = 0$ . Moreover, the amplitude and hence probability for getting  $b$  will be the same: there is exactly one  $t$  such that  $f(t) = b$ , so the sum over  $t$  has only the single nonzero term  $(-1)^{a \bullet t}$ . Thus the  $b$  given as a sampling of the quantum circuit  $\mathcal{C}$  will be a uniformly random string in the space of  $b \in \{0,1\}^n$  such that  $b \bullet s = 0$  which is all of  $\{0,1\}^n$  in this case. Since  $f$  is 1-to-1, the  $a$  we get will be uniformly random as well.

If  $f$  is 2-to-1, then there are two distinct  $t_1$  and  $t_2$  such that  $f(t_1) = b$  and  $f(t_2) = b$  and  $t_2 = t_1 \oplus s$ . These will be the only two terms of the sum for  $V(ab)$  that can give a nonzero result. So we get

$$V(ab) = \frac{1}{N} \left( (-1)^{a \bullet t_1} + (-1)^{a \bullet t_2} \right) = \frac{1}{N} \left( (-1)^{a \bullet t_1} + (-1)^{a \bullet (t_1 \oplus s)} \right)$$

The  $\bullet$  denotes the "Boolean dot product of binary strings modulo 2", but we can still use the distributive law over  $\oplus$ , which is addition modulo 2. So we get:

$$= \frac{1}{N} \left( (-1)^{a \bullet t_1} + (-1)^{a \bullet t_1} (-1)^{a \bullet s} \right)$$

Now if  $a \bullet s = 1$ , then the second term is the negative of the first term. So they cancel, so  $V(ab) = 0$ . This means  $ab$  has zero amplitude - so we could not have gotten  $\begin{bmatrix} a \\ b \end{bmatrix}$  as a result of the measurement. This means:

The only  $\begin{bmatrix} a \\ b \end{bmatrix}$  we can get from the measurement are cases where  $a \bullet s = 0$ .

Moreover the amplitude has the same <sup>magnitude</sup> for any  $a$ : it is  $\frac{1}{N} (2 \cdot (-1)^{a \bullet t_1})$  which is  $\frac{\pm 2}{N}$  depending on whether  $a \bullet t_1 = 0$  or  $1$ . So the probability is  $\frac{4}{N^2}$  for any  $a$ . Thus  $a$  is uniformly at random from the subspace of  $a$  such that  $a \bullet s = 0$ .  $\square$

Technote: we do not get  $f(a) = b$ , only that  $b \in \text{Ran}(f)$ . There are  $\frac{1}{2}N$  such  $b$  and  $\frac{1}{2}N$   $a$ 's such that  $a \bullet s = 0$ . So we get  $\frac{1}{4}N^2$  possible outputs, each equally likely. So the probabilities do sum to 1.

Proof of the Outer Lemma: First suppose  $f$  is 1-to-1, i.e.,  $S = 0^n$ .  
 Let  $a_1, \dots, a_m$  be the  $n$ -vectors sampled thus far. They are members of the vector space  $\mathbb{Z}_2^n$  with addition modulo 2. Let  $A = \langle a_1, \dots, a_m \rangle$  be the subspace spanned by the sampled vectors, and let  $r = \dim(A)$ . We can calculate  $r$  as the rank of the  $m \times n$  matrix with  $a_1, \dots, a_m$  as its rows. Then  $r \leq n$ .

- If  $r = n$ , then we know that  $f$  is 1-to-1, and can say so.
- If  $r < n$ , then  $A$  is not the entire space. Since it is a linear subspace, its cardinality is at most half of the space:  $|\mathbb{Z}_2^n| = 2^n$ . Since  $c$  gives a random member of the whole space, in this case, with probability at least  $1/2$  the next sampled vector  $a_{m+1}$  is not in  $A$ . Then the new  $r$  goes up by 1, so we make progress.

It follows that the expected number of iterations to get  $r = n$  is  $\leq 2n$ . (Initially the chance of making progress is much better than  $1/2$ . It only equals  $1/2$  on the last step where  $r = n-1$ .) Furthermore, if you do  $4n$  iterations and still don't have  $r = n$ , then you can "give up" and conclude what that  $f$  is not 1-to-1.

If  $f$  is 2-to-1 (with period  $S$ ), then  $S = \{x : x \circ S = 0\}$  is a subspace of dimension  $n-1$ . Since  $a_1, \dots, a_m$  always belong to  $S$ , it follows that we will never get  $r = n$ . Thus when we "give up" after  $4n$  iterations, we will be correct in this case. Moreover, by reasoning similar to the first part, we always have at least a  $1/2$  chance of incrementing  $r$ . This is because when  $r = \dim(A)$  is  $< n-1$ , then  $A$  is at most half the subspace  $S$ . Since the inner lemma gives a uniformly random  $a_{m+1} \in S$  on the next iteration, it has at least a  $1/2$  chance of giving  $a_{m+1} \in S \setminus A$ , which means  $r$  goes up by 1. Hence with high probability we get  $r = n-1$  and the  $n-1$  evaluations allow us to calculate  $S$ .  $\square$