

Note: Some of these notes deviate from the lecture a bit; in particular, the optimality argument for Grover's algorithm. These arguments are covered again at the beginning of next week's lecture.

Topics

- Simon's Algorithm (complementary lower bound, classical version)
- Grover's Algorithm (quantum lower bound)

Algorithmic Beginnings

Can quantum computers do what classical computers can do? Last time, we figured that if we have a classical computer that can perform:

$$x \rightarrow f(x)$$

then we can construct a quantum circuit that performs:

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

or

$$|x\rangle |y\rangle \rightarrow |x\rangle |f(x) \oplus y\rangle$$

in the general case. We can perform a change of basis with a Hadamard transformation:

$$H : |0\rangle \rightarrow \frac{1}{\sqrt{2}} (|0\rangle + |1\rangle)$$
$$|1\rangle \rightarrow \frac{1}{\sqrt{2}} (|0\rangle - |1\rangle)$$

The action of the gate $H^{\otimes n}$ on some example inputs is:

$$|00000000\dots\rangle \rightarrow \frac{1}{\sqrt{2}} (|0\rangle + |1\rangle) \otimes \frac{1}{\sqrt{2}} (|0\rangle + |1\rangle) \otimes \dots$$

= uniform superposition over all n-bit states

$$|10000000\dots\rangle \rightarrow \frac{1}{\sqrt{2}} (|0\rangle - |1\rangle) \otimes \frac{1}{\sqrt{2}} (|0\rangle + |1\rangle) \otimes \dots$$

= superposition over all n-bit states, where qubits with a leading 1 are negative

$$|x_0 x_1 \dots x_n\rangle \rightarrow \sum_y (-1)^{x \cdot y} |y\rangle$$

Hence, the operation $H^{\otimes n}$ is in some sense a Fourier transformation.

The purpose of the Hadamard gate is to take a classical 0-1 state and bring it to a state of maximal quantum superposition. Consider the sequence of operations:

$$|0\rangle^{\otimes n} \xrightarrow{H^{\otimes n}} \sum_{y=[0..2^n-1]} |y\rangle \xrightarrow{f} \sum |y\rangle |f(y)\rangle$$

where the coefficients were dropped for convenience. Suppose we take the output state $\sum_y |y\rangle |f(y)\rangle$, and we perform a measurement on the second ket ($|f(y)\rangle$). If the result of the measurement is a state $|z\rangle$, then we are told something about the first ket. In particular, the first ket is projected onto a space of preimages of z :

$$\sum_y |y\rangle |f(y)\rangle \rightarrow \sum_z |f^{-1}(z)\rangle |z\rangle$$

We will see that this measurement is useful for Simon's Algorithm.

Simon's Problem

Suppose we have a function $f_s : \mathbb{Z}_2^n \rightarrow \mathbb{Z}_2^n$, which is 2-to-1; that is, each output has two possible inputs. We are given the following property, for some s :

$$f_s(x) = f_s(x \oplus s) \quad s \in \mathbb{Z}_2^n$$

Given that we can only query the function f_s (but cannot look inside it – it is a black box), how fast can we determine s ?

Classical Solution

The problem is reduced to finding a collision: we want to find two inputs x and y ($x \neq y$) where $f(x) = f(y)$. Since we are given (above) that the only two inputs that map to the same output are x and $x \oplus s$, we can conclude that $y = x \oplus s$ and hence $s = x \oplus y$, revealing s . So how fast can we find a collision?

The best deterministic bound is $O(2^{n-1} + 1)$. We query all numbers from 0 to $2^{n-1} + 1$ and look for a collision. Once we find a collision x, y s.t. $f(x) = f(y)$ we can determine $s = x \oplus y$.

If we allow a probabilistic algorithm then finding collisions in this way becomes much easier! See: *birthday paradox*. The bound becomes $O(\sqrt{2^n})$. If we know that $f(x) \neq f(y)$ all we can say for sure is that $s \neq x \oplus y$. Thus if we have a set of n integers then we can at most eliminate the value given by the XOR of every pair. This is at most $n(n-1)/2$. Thus the number of values eliminated is quadratic in the number of queries done. So it will take at least $O(\sqrt{2^n})$ queries.

Quantum Solution (Simon's Algorithm)

Assume that we have a black box that can perform the oracle f in quantum superposition. We can do much better than $O(\sqrt{2^n})$ with the following procedure:

1. Prepare the state. Start with $|0\rangle^{\otimes n}$ and apply $H^{\otimes n}$ and f :

$$|0\rangle^{\otimes n} \xrightarrow{H^{\otimes n}} \sum_y |y\rangle$$

$$\xrightarrow{f} \sum_y |y\rangle |f(y)\rangle$$

Note the following:

$$\sum_y |y\rangle |f(y)\rangle = \sum_z (|z\rangle + |z \oplus s\rangle) |f(z)\rangle$$

The reason the above is true is because for every output $f(z)$ there are two corresponding inputs z and $z \oplus s$ that map to it.

2. Apply $H^{\otimes n}$ to the state.

$$H^{\otimes n} \left[\sum_z (|z\rangle + |z \oplus s\rangle) |f(z)\rangle \right]$$

$$= \sum_y \sum_z \left((-1)^{y \cdot z} + (-1)^{y \cdot (z \oplus s)} \right) |y\rangle |f(z)\rangle$$

If $y \cdot z = 0$:

$$(-1)^0 + (-1)^{y \cdot s}$$

If $y \cdot z = 1$:

$$(-1)^1 + (-1)^{1+y \cdot s}$$

$$= -(1 + (-1)^{y \cdot s})$$

In both cases, if $y \cdot s = 1$, the amplitude vanishes! Hence, if after we perform the Hadamard transformation, we measure the first ket to be $|y\rangle$, then we can guarantee that the resulting state has the property $y \cdot s = 0$ since all other amplitudes vanish.

3. If we repeat this measurement multiple times we get outputs:

$$y_1, y_2, y_3, \dots \quad y_i \cdot s = 0 \quad \forall i$$

Now if at some iteration we have $n - 1$ linearly independent vectors, then they will span the entire vector space perpendicular to s , and we can fully determine s . Hence, all we need to complete the analysis is the expected time for this process to give $n - 1$ independent vectors. For that analysis, let S_i denote the Span(y_1, y_2, \dots, y_i) and D_i denote Dimension(S_i).

We note that $P(D_{i+1} = k + 1 | D_i = k) = (2^n - |S_i|)/2^n$ since each vector has a $1/2^n$ probability of being picked. Also, $P(D_{i+1} = k | D_i = k) = |S_i|/2^n$ and since one vector can increase the dimension of a space by at most one, there is no other value that D_{i+1} can take.

Note that since \mathbb{Z}_2 is a field of cardinality 2, and S_i is a vector space over it, the number of elements in S_i given that $D_i = k$ is simply 2^k . Thus the process from the state $D_i = k$ can also be viewed in the following way: Toss a coin with probability of failure as $2^k/2^n$. On failure D_{i+1} remains k , on success it gets updated to $k + 1$. Thus the expected waiting time at state k is $2^n/(2^n - 2^k)$. Hence the total expected time to hit $n - 1$ is:

$$\sum_{i=0}^{n-1} \frac{2^n}{2^n - 2^i} < \sum_{i=0}^{n-1} 2 = 2n$$

So we can see that the quantum algorithm operates in $O(n)$ queries while the classical algorithm operates in $O(2^n)$ queries. Note that this is only true given the "black box" assumption at the beginning – that we can apply the oracle in superposition easily.

Grover's Search Problem

We have a function $f : \{0, 1, \dots, n - 1\} \rightarrow \{0, 1\}$. Find x s.t. $f(x) = 1$. We consider the hardest case, where $f(x) = 1$ for only one input. That is:

$$\begin{cases} f(x) = 1 & \text{if } x = a \\ f(x) = 0 & \text{else} \end{cases}$$

Classically we can do it in $O(n)$ time – we just query every $n!$ And we can't do better, since we know nothing else about f . Can we do better quantumly?

Quantum Lower Bound

To analyse this problem firstly let us initiate a state space. But this time instead of having the oracle registry initially as $|0\rangle$, we will have it to be $|0\rangle - |1\rangle$. Then as the oracle performs a XOR of the original registry value and $f(i)$ we have:

$$\begin{aligned} \sum_i \alpha_i |i\rangle (|0\rangle - |1\rangle) &\xrightarrow{f} \sum_i \alpha_i |i\rangle (|0 \oplus f(i)\rangle - |1 \oplus f(i)\rangle) \\ &= \sum_{i:f(i)=0} \alpha_i |i\rangle (|0\rangle - |1\rangle) + \sum_{i:f(i)=1} -\alpha_i |i\rangle (|0\rangle - |1\rangle) \end{aligned}$$

Thus the oracle essentially reverses the amplitude of the basis vector containing $|i\rangle$ where $f(i) = 1$. This was the reason for initialising the system to have registry values as $|0\rangle - |1\rangle$. For clarity, we will simply denote the state $|i\rangle (|0\rangle - |1\rangle)$ as $|i\rangle$, and define the oracle operator F , where:

$$F |i\rangle = \begin{cases} -|i\rangle & \text{if } f(i) = 1 \\ |i\rangle & \text{if } f(i) = 0 \end{cases}$$

Now, the essential idea is that if we could somehow amplify the negative vectors enough then we could measure the required state with high probability. Grover's algorithm is thus less of a search algorithm and more of an amplification algorithm.

For simplicity, we consider the reduced problem where there is only one satisfying predicate. That is, $f(i) = 1$ iff $i = a$, and $f(i) = 0$ elsewhere.

We can write the operator F as:

$$F = I - 2|a\rangle\langle a|$$

(You should confirm that this agrees with our previous definition above). We also define an initial state $|s\rangle$:

$$|s\rangle = \frac{1}{\sqrt{N}} \sum_i |i\rangle$$

representing maximal ignorance of the correct element. Note that the action of F on $|s\rangle$ is:

$$\begin{aligned} F|s\rangle &= (I - 2|a\rangle\langle a|)|s\rangle \\ &= |s\rangle - \frac{2}{\sqrt{N}}|a\rangle \\ &= \frac{1}{\sqrt{N}} \left[\left(\sum_{i \neq a} |i\rangle \right) - |a\rangle \right] \end{aligned}$$

That is, **applying the oracle to the initial state negates the amplitude of the satisfying element.**

We now introduce the Grover diffusion operator:

$$U = 2|s\rangle\langle s| - I$$

One iteration of the algorithm consists of applying the operator $A = UF$ (that is, querying the oracle and then applying the diffusion operator). After one step of amplification:

$$\begin{aligned} A|s\rangle &= UF|s\rangle \\ &= (2|s\rangle\langle s| - I)(I - 2|a\rangle\langle a|)|s\rangle \\ &= \left(2|s\rangle\langle s| + 2|a\rangle\langle a| - \frac{4|s\rangle\langle a|}{\sqrt{N}} - I \right) |s\rangle \\ &= \left(1 - \frac{4}{N} \right) |s\rangle + \frac{2}{\sqrt{N}} |a\rangle \end{aligned}$$

We see that after one iteration, the probability of measuring a has increased. With some calculation, it can be checked that the transformation A rotates the state vector by $2\sqrt{N-1}/N \approx 2/\sqrt{N}$. Since we start out almost orthogonal to $|a\rangle$ (assuming N is large), we need to rotate an angle of $\pi/2$ in total, and thus we need to apply A about $\pi\sqrt{N}/4$ times to get a vector close enough to $|a\rangle$. Hence the algorithm runs in $O(\sqrt{N})$ queries of the oracle.

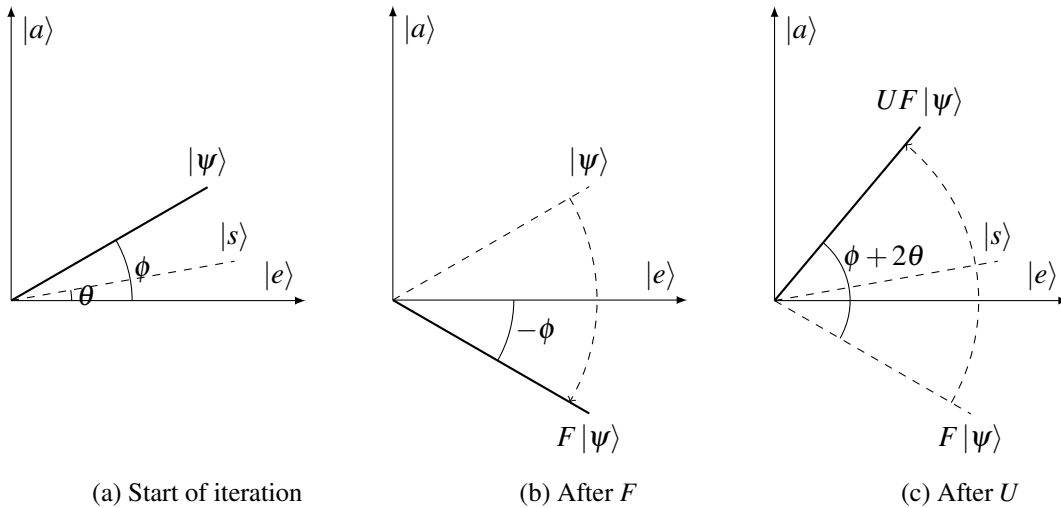


Figure 1: One iteration of Grover's algorithm

Geometric Visualization of Grover's Algorithm

We can visualize the operators in Grover's algorithm as reflections in state space. Consider the target vector $|a\rangle$ and the hyperplane of all other vectors $|e\rangle \equiv \frac{1}{\sqrt{N-1}} \sum_{i \neq a} |i\rangle$ (see figure).

Note that $F = I - 2|a\rangle\langle a|$ corresponds to a flip over $|e\rangle$ and $U = 2|s\rangle\langle s| - I$ corresponds to a flip over $|s\rangle$. If we define θ as the angle between $|s\rangle$ and $|e\rangle$, and ϕ as the angle between $|\psi\rangle$ and $|e\rangle$ (where $|\psi\rangle$ is the state at the current iteration), we see that the transformations perform the following rotations:

$$\phi \xrightarrow{F} (-\phi) \xrightarrow{U} \phi + 2\theta$$

Hence, after one iteration we rotate our state forward by $2\theta = 2 \arcsin \frac{1}{\sqrt{N}} \approx \frac{2}{\sqrt{N}}$. Given that we start with $\phi = \theta \approx \frac{1}{\sqrt{N}}$ and want to rotate by $\pi/2$ in total, we will need $\frac{\pi/2 - \theta}{2\theta} \approx O(\sqrt{N})$ iterations (for large N).

Optimality of Grover's Algorithm

Note: We will sometimes abbreviate state vectors with their labels, e.g. $v \iff |v\rangle$.

To prove optimality, we show that any sequence of unitary operators (combined with calls to the oracle) that distinguish between the function that has 0 everywhere and the function which is 1 at the a 'th position requires at least $O(\sqrt{N})$ calls of the oracle. So let U_1, U_2, \dots be some unitary operators and $|v_{a,k}\rangle = U_k F_a U_{k-1} F_a \dots U_1 |s\rangle$, where F_a is the oracle corresponding to the function $f(x)$ which is 1 iff $x = a$. Also, let $|s_k\rangle = U_k U_{k-1} \dots U_1 |s\rangle$. Essentially, s_k is the state we would have been in if f had no 1's. Note that since the oracle depends on a , F changes with a and thus so does a_k . However since no measurement is done before the end, we can glean no information about a a priori, and thus the U_i 's are independent of a , implying that s_k is independent of a .

Now define $t_{a,k} = |v_{a,k} - s_k|$. Essentially, $t_{a,k}$ is a measurement of the error between a run of the algorithm with a function which is always 0 or a function which is 1 at position a .

Then we are first going to prove that $t_{a,k} \leq \sum_{i=1}^{k-1} 2(a \cdot s_i)$. We will prove this by induction. Note that at $k = 1$ $v_{a,1} = U_1 |s\rangle = s_1$. Thus $t_{a,1} = 0$ and the inequality is trivially true.

Now let us assume by induction that for some k , $t_{a,k} \leq \sum_{i=1}^{k-1} 2(a \cdot s_i)$. Then for $k+1$:

$$\begin{aligned}
 t_{a,k+1} &= |v_{a,k+1} - s_{k+1}| \\
 &= |U_{k+1} F_a v_{a,k} - U_{k+1} s_k| \\
 &= |F_a v_{a,k} - s_k| \quad [U_{k+1} \text{ is unitary}] \\
 &= |F_a v_{a,k} - F_a s_k + F_a s_k - s_k| \\
 &\leq |F_a(v_{a,k} - s_k)| + |(F_a - I)s_k| \quad [\text{by triangle inequality}] \\
 &= |v_{a,k} - s_k| + 2(a \cdot s_k) \\
 &= t_k + 2(a \cdot s_k) \\
 &\leq \sum_{i=1}^k 2(a \cdot s_i) \quad [\text{by Induction on } k]
 \end{aligned}$$

Thus by induction we have that:

$$t_{a,k} \leq \sum_{i=1}^{k-1} 2(a \cdot s_i) \tag{1}$$

Now since our algorithm needs to distinguish between the function which is 0 everywhere and the one which has 1 at a , $t_{a,T}$ must be large, since this is the difference between the output vectors when these two functions are used as inputs. So for the sake of argument say $t_{a,T} > 1/2$.

Now applying Cauchy Schwartz on the R.H.S. of (1) we get:

$$\begin{aligned}
 1/2 &< t_{a,T} \\
 &\leq \sum_{i=1}^{T-1} 2(a \cdot s_i) \\
 &\leq \sqrt{T-1} \sqrt{\sum_{i=1}^{T-1} (a \cdot s_i)^2}
 \end{aligned} \tag{2}$$

But as the different vectors a are an orthonormal basis for the space and as each s_i is unit norm we have $\sum_a (a \cdot s_i)^2 = 1 \Rightarrow \sum_a \sum_{i=1}^{T-1} (a \cdot s_i)^2 = T-1$. Since there are N such vectors a , there is at least one choice of a for which $\sum_{i=1}^{T-1} (a \cdot s_i)^2 < (T-1)/N$.

Plugging this value of a into (2), we get that there is a choice of a , such that $1/2 < \sqrt{T-1} \sqrt{(T-1)/N} = (T-1)/\sqrt{N}$.

Thus we get that $T = O(\sqrt{N})$ as desired.