| MAT 4930: Quantum Algorithms and Complexity   | Spring 2021     |
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| Lecture 9: Amplitude Amplification Algorithms |                 |
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In this lecture, we focus on Grover's algorithm, and its generalization the quantum amplification strategy. The idea is that we are looking for one of M marked elements inside a set of N > M elements. The marked elements  $x \in \{1, \ldots, N\}$  satisfy f(x) = 1 for some function f. If we do not assume any particular structure (such as an ordering of the elements for example), then on the worst case scenario, a classical algorithm would need to evaluate f at N - M elements before finding the correct one. On average, N/M elements could suffice. With a quantum computer however, we can get away with evaluating f only  $\sqrt{M/N}$  time on average. Like the Deutsch-Jozsa algorithm, this result demonstrate the superiority of quantum computers over their classical counterpart for certain comptutational tasks.

## 9.1 Grover's search method

Grover's search algorithm starts with the state  $|0\rangle^{\otimes n}$ , and after applying  $H^{\otimes n}$ , we obtain the state

$$|\psi\rangle := \frac{1}{\sqrt{N}} \sum_{x} |x\rangle.$$

A measurement on the system in the sate  $|\psi\rangle$  would yield a marked element with probability M/N. Grover's algorithm proposes to perform a series of computations aiming to raise the amplitude of the  $|x\rangle$  for x a marked element while reducing all the other ones. At the end of the procedure, a measurement will likely yield a marked element. For this, we need a circuit that evaluates f. More specifically, we need to implement the circuit

$$|x\rangle = \mathcal{O}_f \qquad (-1)^{f(x)} |x\rangle$$
$$|0\rangle^m = |0\rangle^m$$

We call this circuit the "oracle". A typical use case is when we know an efficient classical algorithm for f. Then using the methods previously seen, we can efficiently implement  $\mathcal{O}_f$ . The other essential ingredient is a conditional phase shift circuit called  $\mathcal{O}_{\phi}$  that realizes the following transformation

$$\mathcal{O}_{\phi} |0\rangle = |0\rangle$$
, and  $\mathcal{O}_{\phi} |x\rangle = -|x\rangle$  for  $x \neq 0$ .

Grover's algorithm is the repetition of an elementary step involving  $\mathcal{O}_f$  and  $\mathcal{O}_{\phi}$  that we call the "Grover iterate". It can be represented like this

$$|x\rangle_{i} = |x\rangle_{i+1} = |x\rangle_{i} = \mathcal{O}_{f} = |0\rangle^{m} = |0\rangle^{m} = |0\rangle^{m}$$

**Proposition 9.1** The action of  $H^{\otimes n}\mathcal{O}_{\phi}H^{\otimes n}$  is the linear operator  $2|\psi\rangle\langle\psi|-I$ , and the Grover operators is

$$G = (2 |\psi\rangle \langle \psi| - I) \mathcal{O}_f.$$

**Proof:** The conditional phase shift acts as  $2|0\rangle\langle 0| - I$ . Then by substituting it in  $H^{\otimes n}\mathcal{O}_{\phi}H^{\otimes n}$  we get

$$\begin{aligned} H^{\otimes n} \mathcal{O}_{\phi} H^{\otimes n} &= H^{\otimes n} 2 \left| 0 \right\rangle \langle 0 \right| - I) (H^{\otimes n} \\ &= (2H^{\otimes n} \left| 0 \right\rangle \langle 0 \right| - H^{\otimes n}) H^{\otimes n} \\ &= 2H^{\otimes n} \left| 0 \right\rangle \langle 0 \right| H^{\otimes n} - H^{\otimes n} H^{\otimes n} \\ &= 2 \left| \psi \right\rangle \langle \psi \right| - I \text{ since } H^{\otimes n} H^{\otimes n} = I \text{ and } H^{\otimes n} \left| 0 \right\rangle = \left| \psi \right\rangle \end{aligned}$$

The result on G follows since the Grover iterate is the composition of  $\mathcal{O}_f$  with the above block.

**Proposition 9.2** The operator  $2 |\psi\rangle \langle \psi| - I$  realizes the following operation

$$\sum_{x} \alpha_x \left| x \right\rangle \longmapsto \sum_{x} \left( -\alpha_x + 2 \langle \alpha \rangle \right) \left| x \right\rangle,$$

where  $\langle \alpha \rangle := \frac{1}{N} \sum_{x} \alpha_{x}$ . We call this operation the inversion about the mean.

**Proof:** We have the following identities

$$(2 |\psi\rangle \langle \psi| - I) \left(\sum_{x} \alpha_{x} |x\rangle\right) = 2 |\psi\rangle \langle \psi| \left(\sum_{x} \alpha_{x} |x\rangle\right) - \sum_{x} \alpha_{x} |x\rangle$$
$$= 2 |\psi\rangle \sum_{x} \alpha_{x} \langle \psi|x\rangle - \sum_{x} \alpha_{x} |x\rangle$$
$$= 2 |\psi\rangle \sum_{x} \left(\frac{1}{\sqrt{N}} \sum_{x} \alpha_{x}\right) - \sum_{x} \alpha_{x} |x\rangle$$
$$= 2 \langle \alpha \rangle \sqrt{N} |\psi\rangle - \sum_{x} \alpha_{x} |x\rangle$$
$$= 2 \langle \alpha \rangle \sum_{x} |x\rangle - \sum_{x} \alpha_{x} |x\rangle$$

There is an elegant interpretation of the action of the Grover iterate that helps quantifying how many interations are required to ensure the optimum probability of measuring a marked element. Let  $S \subseteq \{1, \ldots, N\}$  be the set of marked elements of cardinality |S| = M < N. Additionally, we define the states

$$|\alpha\rangle = \frac{1}{\sqrt{N-M}} \sum_{x \notin S} |x\rangle \text{ and } |\beta\rangle = \frac{1}{\sqrt{M}} \sum_{x \in S} |x\rangle$$

We clearly see that  $|\alpha\rangle \perp |\beta\rangle$ , and that

$$\left|\psi\right\rangle = \sqrt{\frac{N-M}{N}} \left|\alpha\right\rangle + \sqrt{\frac{M}{N}} \left|\beta\right\rangle$$

**Proposition 9.3** The Grover iterate G acts on  $\text{Span}\{|\alpha\rangle, |\beta\rangle\}$  as

$$G = \begin{pmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{pmatrix},$$

where  $\theta$  is defined by  $\cos(\theta/2) = \sqrt{\frac{N-M}{N}}$  and  $\sin(\theta/2) = \sqrt{\frac{M}{N}}$ . This means that G acts as a rotation of angle  $\theta$ .

**Proof:** Let us evaluate the action of the Grover iterate on  $|\alpha\rangle$ .

$$\begin{split} G\left|\alpha\right\rangle &= \frac{G}{\sqrt{N-M}} \sum_{x \notin S} \left|x\right\rangle \\ &= \left(2\left|\psi\right\rangle\left\langle\psi\right| - I\right) \frac{1}{\sqrt{N-M}} \sum_{x \notin S} \left|x\right\rangle \\ &= \frac{2}{\sqrt{N-M}} \left|\psi\right\rangle\left\langle\psi\right| \sum_{x \notin S} \left|x\right\rangle - \frac{1}{\sqrt{N-M}} \sum_{x \notin S} \left|x\right\rangle \\ &= \frac{2}{\sqrt{N}\sqrt{N-M}} \left|\psi\right\rangle \sum_{x \notin S} 1 - \frac{1}{\sqrt{N-M}} \sum_{x \notin S} \left|x\right\rangle \\ &= \frac{2\sqrt{N-M}}{N} \sum_{x} \left|x\right\rangle - \frac{1}{\sqrt{N-M}} \sum_{x \notin S} \left|x\right\rangle \\ &= \frac{2\sqrt{N-M}}{N} \sum_{x \in S} \left|x\right\rangle + \left(\frac{2\sqrt{N-M}}{N} - \frac{1}{\sqrt{N-M}}\right) \sum_{x \notin S} \left|x\right\rangle \\ &= \frac{2\sqrt{N-M}}{N} \sum_{x \in S} \left|x\right\rangle + \left(\frac{2\sqrt{N-M}}{N} - \frac{1}{\sqrt{N-M}}\right) \sum_{x \notin S} \left|x\right\rangle \\ &= \underbrace{\frac{2\sqrt{M}\sqrt{N-M}}{N}}_{\sin(\theta)} \underbrace{\frac{1}{\sqrt{M}} \sum_{x \in S} \left|x\right\rangle}_{\left|\beta\right\rangle} + \underbrace{\frac{2(N-M)}{\cos(\theta)} - 1}_{\cos(\theta)} \underbrace{\frac{1}{\sqrt{N-M}} \sum_{x \notin S} \left|x\right\rangle}_{\left|\alpha\right\rangle}. \end{split}$$

Thus  $G |\alpha\rangle = \cos(\theta) |\alpha\rangle + \sin(\theta) |\beta\rangle$ . Likewise, we can prove that  $G |\beta\rangle = -\sin(\theta) |\alpha\rangle + \cos(\theta) |\beta\rangle$ , which shows that G acts like a rotation of angle  $\theta$ .

Since we start with the state  $|\psi\rangle = \cos(\theta/2) |\alpha\rangle + \sin(\theta/2) |\beta\rangle$ , the state we reach after k iterations is

$$G^{k} |\psi\rangle = \cos\left(\frac{2k+1}{2}\theta\right) |\alpha\rangle + \sin\left(\frac{2k+1}{2}\theta\right) |\beta\rangle.$$

To maximize our chances to measure an element in S, we want that  $\frac{2k+1}{2}\theta \approx \frac{\pi}{2}$ . This leads us to choose  $k = \lfloor \frac{\pi}{2\theta} - \frac{1}{2} \rfloor$  where  $\lfloor x \rceil$  denotes the rounding of x to the nearest integer. In particular, this means that

$$\left|\frac{2k+1}{2}\theta - \frac{\pi}{2}\right| \le \theta \left|k - \left(\frac{\pi}{2\theta} - \frac{1}{2}\right)\right| \le \frac{\theta}{2}$$

When we assume that  $M \leq N/2$ , we can choose  $\theta \in [0, \pi/2]$ , and therefore,  $0 \leq \theta/2 \leq \pi/4$ , and we have

$$\frac{\sqrt{2}}{2} \le \sin\left(\frac{2k+1}{2}\theta\right) \le 1$$

**Proposition 9.4** Assuming that  $M \leq N/2$ , a measurement of the state after  $k \leq \left\lceil \frac{\pi}{4} \sqrt{\frac{N}{M}} \right\rceil$  yields  $x \in S$  with probability at least  $\frac{1}{2}$ .

**Proof:** We have seen that after  $k = \lfloor \frac{\pi}{2\theta} - \frac{1}{2} \rfloor$  a projective measurement with respect to  $|\beta\rangle$  leaves the system in the state  $|\beta\rangle$  (a superposition of all solutions) with probability

$$\sin^2\left(\frac{2k+1}{2}\theta\right) \ge \frac{1}{2}.$$

Since we have

$$\frac{\theta}{2} \ge \sin\left(\frac{\theta}{2}\right) = \sqrt{\frac{M}{N}},$$

we can conclude that  $k = \left\lfloor \frac{\pi}{2\theta} - \frac{1}{2} \right\rceil \le \left\lceil \frac{\pi}{4} \sqrt{\frac{N}{M}} \right\rceil$ .

## 9.2 Amplitude amplification

Grover's search algorithm can be viewed as a special case of a more general family of search algorithm: *amplitude amplification* algorithms. These algorithms assume the knowledge of an algorithm A that produces a superposition over all possible outcomes with certain weights

$$A\left|0\right\rangle^{\otimes n} = \sum_{x < N} \alpha_x \left|x\right\rangle \left|\mathrm{junk}(x)\right\rangle = \left|\psi\right\rangle$$

In the case of Grover's algorithm,  $A = H^{\otimes n}$ , but in general, the measurement of  $|\psi\rangle$  yields  $x \in S$  with probability

$$1 > p = \sum_{x \in S} |\alpha_x|^2 > 0$$

that is not necessarily M/N (it is hopefully better than that, otherwise we can Grover's algorithm). We define the states

$$|\alpha\rangle = \frac{1}{\sqrt{1-p}} \sum_{x \notin S} \alpha_x |x\rangle |\text{junk}(x)\rangle \quad \text{and} \quad |\beta\rangle = \frac{1}{\sqrt{p}} \sum_{x \in S} \alpha_x |x\rangle |\text{junk}(x)\rangle$$

We clearly see that  $|\alpha\rangle \perp |\beta\rangle$ , and that

$$\left|\psi\right\rangle = \sqrt{1-p} \left|\alpha\right\rangle + \sqrt{p} \left|\beta\right\rangle$$

We define the search iteration as

 $|x\rangle_{i} = Q = |x\rangle_{i+1} = |x\rangle_{i} = O_{f} = O_{f} = |0\rangle^{m} = |0\rangle^{m}$ 

where the states  $|x\rangle_i$  include the qubits necessary to hold the junk space. Similarly to the Grover iterate, we have the following result with the new notations.

**Proposition 9.5** The action of  $A\mathcal{O}_{\phi}A^{\dagger}$  is the linear operator  $2|\psi\rangle\langle\psi|-I$ , and the amplitude amplification iterate is

$$Q = (2 |\psi\rangle \langle \psi| - I) \mathcal{O}_f.$$

Still following the analogy with the Grover search method, we can view the amplitude amplification as a rotation.

**Proposition 9.6** The amplitude amplification iterate Q acts on  $\text{Span}\{|\alpha\rangle, |\beta\rangle\}$  as

$$G = \begin{pmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{pmatrix},$$

where  $\theta$  is defined by  $\cos(\theta/2) = \sqrt{1-p}$  and  $\sin(\theta/2) = \sqrt{p}$ . This means that Q acts as a rotation of angle  $\theta$ .

Since we start with the state  $|\psi\rangle = \cos(\theta/2) |\alpha\rangle + \sin(\theta/2) |\beta\rangle$ , the state we reach after k iterations is

$$Q^{k} |\psi\rangle = \cos\left(\frac{2k+1}{2}\theta\right) |\alpha\rangle + \sin\left(\frac{2k+1}{2}\theta\right) |\beta\rangle.$$

As before, the probability of measuring  $x \in S$  at the end of the procedure is  $\sin\left(\frac{2k+1}{2}\theta\right)^2$ . We perform the minimum number of iterations k such that  $\sin\left(\frac{2k+1}{2}\theta\right) \approx \sin(\pi/2)$ . Following the same arguments as before, we get the following bound on the number of iterations required.

**Proposition 9.7** Assuming that  $p \leq 1/2$ , a measurement of the state after  $k \leq \lfloor \frac{\pi}{4}\sqrt{p} \rfloor$  yields  $x \in S$  with probability at least  $\frac{1}{2}$ .

This means that amplitude amplification uses an algorithm that would take O(1/p) steps to return  $x \in S$  with probability 1/2 as a subroutine of another algorithm that only  $O(1/\sqrt{p})$  steps to return  $x \in S$  with probability 1/2. This generalizes Grover's algorithm that uses the uniform superposition of all x < N, which takes O(M/N) attempts through measurements to return  $x \in S$  as a subroutine of a procedure that only takes  $O\left(\sqrt{\frac{M}{N}}\right)$  steps.