Quantum lower bounds by quantum arguments

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Abstract

We propose a new method for proving lower bounds on quantum query algorithms. Instead of a classical adversary that runs the algorithm with one input and then modifies the input, we use a quantum adversary that runs the algorithm with a superposition of inputs. If the algorithm works correctly, its state becomes entangled with the superposition over inputs. We bound the number of queries needed to achieve a sufficient entanglement and this implies a lower bound on the number of queries for the computation.

Using this method, we prove two new $\Omega(\sqrt{N})$ lower bounds on computing AND of ORs and inverting a permutation and also provide more uniform proofs for several known lower bounds which have been previously proven via variety of different techniques.

1 Introduction

In the query model, algorithms access the input only by querying input items and the complexity of the algorithm is measured by the number of queries that it makes. Many quantum algorithms can be naturally expressed in this model. The most famous examples are Grover's algorithm[9] for searching an N-element list with $O(\sqrt{N})$ quantum queries and period-finding which is the basis of Shor's factoring algorithm[11, 17].

In the query setting, one can not only construct efficient quantum algorithms but also prove lower bounds on the number of queries that any quantum algorithm needs. For example, it can be shown that any algorithm solving the unordered search problem needs $\Omega(\sqrt{N})$ queries[4]. (This implies that Grover's algorithm is optimal.)

The lower bounds in quantum query model provide insights into the limitations of quantum computing. For example, the unordered search problem provides an abstract model for NP-complete problems and the $\Omega(\sqrt{N})$ lower bound of [4] provided evidence of the difficulty of solving these problems on a quantum computer.

For two related problems - inverting a permutation (often used to model one-way permutation) and AND of ORs only weaker lower bounds have been known. Both of these problems can be solved using Grover's algorithm with $O(\sqrt{N})$ queries for inverting a permutation and $O(\sqrt{N}\log N)$ queries for AND of ORs[7]. However, the best lower bounds have been $\Omega(\sqrt[3]{N})[4]$ and $\Omega(\sqrt[4]{N})$, respectively.

We present a new method for proving lower bounds on quantum query algorithms and use it to prove $\Omega(\sqrt{N})$ lower bounds for inverting a permutation and AND of ORs. It also provides a unified proof for several other results that have been previously proven via variety of different techniques.

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In contrast to [4, 18] that use a classical adversary argument (an adversary runs the algorithm with one input and, after that, changes the input slightly so that the correct answer changes but the algorithm does not notice that), we use a quantum adversary. In other words, instead of running the algorithm with one input, we run it with a superposition of inputs. This gives stronger bounds and can also simplify the proofs.

More formally, we consider a bipartite quantum system consisting of the algorithm and an oracle answering algorithm's queries. At the beginning, the algorithm part is in its starting state (normally $|0\rangle$), the oracle part is in a uniform superposition over some set of inputs and the two parts are not entangled.

In the query model, the algorithm can either perform a unitary transformation that does not depend on the input or a query transformation that accesses the input. The unitary transformations of the first type become unitary transformations over the algorithm part of the superposition. The queries become transformations entangling the algorithm part with the oracle part.

If the algorithm works correctly, the algorithm part becomes entangled with the oracle part because the algorithm part must contain different answers for different inputs. We obtain lower bounds on quantum algorithms by bounding the number of query transformations needed to achieve such entanglement.

Previously, two main lower bound methods were classical adversary[4] (called 'hybrid argument' in [18]) and polynomials methods. The classical adversary/hybrid method of [4, 18] starts with running the algorithm on one input. Then the input is modified so that the behavior of algorithm does not change much but the correct answer does change. That implies that the problem cannot be solved with a small number of queries. Polynomials method[3] uses the fact that any function computable with a small number of queries can be approximated by a polynomial of a small degree and then applies results about inapproximability by polynomials.

Our "quantum adversary" method can be used to give more unified proofs for many (but not all) results that were previously shown using different variants of hybrid and/or polynomials method.

There is also a new proof of the $\Omega(\sqrt{N})$ lower bound on unordered search by Grover[10]. This proof is based on considering the sum of distances between superpositions on different inputs. While the motivation for Grover's proof (sum of distances) is fairly different from ours (quantum adversary), these two methods are, in fact, closely related. We discuss this relation in section 7.

2 The model

We consider computing a Boolean function $f(x_1, ..., x_N) : \{0, 1\}^N \to \{0, 1\}$ in the quantum query model[3]. In this model, the input bits can be accessed by queries to an oracle X and the complexity of f is the number of queries needed to compute f.

A quantum computation with T queries is just a sequence of unitary transformations

$$U_0 \to O \to U_1 \to O \to \ldots \to U_{T-1} \to O \to U_T.$$

 U_j 's can be arbitrary unitary transformations that do not depend on the input bits x_1, \ldots, x_N . O are query (oracle) transformations. To define O, we represent basis states as $|i,b,z\rangle$ where i consists of $\lceil \log N \rceil$ bits, b is one bit and z consists of all other bits. Then, O maps $|i,b,z\rangle$ maps to $|i,b\oplus x_i,z\rangle$. (i.e., the first $\lceil \log N \rceil$ bits are interpreted as an index i for an input bit x_i and this input bit is XORed on the next qubit.) We use O_x to denote the query transformation corresponding to an input $x = (x_1, \ldots, x_n)$.

Also, we can define that O maps $|i,b,z\rangle$ to $(-1)^{b\cdot\hat{x}_i}|i,b,z\rangle$ (i.e., instead of XORing x_i on an extra qubit we change phase depending on x_i). It is well known that both definitions are equivalent up to a constant factor: one query of the 1st type can be simulated with a one query of the 2nd type and one query of the 2nd type can be simulated with 2 queries of the 1st type. For technical convenience, we use the 2nd definition in most of this paper.

The computation starts with a state $|0\rangle$. Then, we apply $U_0, O, ..., O, U_T$ and measure the final state. The result of the computation is the rightmost bit of the state obtained by the measurement.

The quantum computation computes f with bounded error if, for every $x = (x_1, \ldots, x_N)$, the probability that the rightmost bit of $U_T O_x U_{T-1} \ldots O_x U_0 | 0 \rangle$ equals $f(x_1, \ldots, x_N)$ is at least $1 - \epsilon$ for some fixed $\epsilon < 1/2$.

This model can be easily extended to functions defined on a larger set (for example, $\{1, ..., N\}$) or functions having more than 2 values. In the first case, we replace one bit b with several bits ($\lceil \log N \rceil$ bits in the case of $\{1, ..., N\}$). In the second case, we measure several rightmost bits to obtain the answer.

3 The main idea

Let S be a subset of the set of possible inputs $\{0,1\}^N$. We run the algorithm on a superposition of inputs in S. More formally, let \mathcal{H}_A be the workspace of the algorithm. We consider a bipartite system $\mathcal{H} = \mathcal{H}_A \otimes \mathcal{H}_I$ where \mathcal{H}_I is an "input subspace" spanned by basis vectors $|x\rangle$ corresponding to inputs $x \in S$.

Let $U_TOU_{T-1}...U_0$ be the sequence of unitary transformations on \mathcal{H}_A performed by the algorithm A (with $U_0, ..., U_T$ being the transformations that do not depend on the input and O being the query transformations). We transform it into a sequence of unitary transformations on \mathcal{H} . A unitary transformation U_i on \mathcal{H}_A corresponds to the transformation $U_i' = U_i \otimes I$ on the whole \mathcal{H} . The query transformation O corresponds to a transformation O' that is equal to O_x on subspace $H_A \otimes |x\rangle$.

We perform the sequence of transformations $U'_TO'U'_{T-1}\dots U'_0$ on the starting state

$$|\psi_{start}\rangle = |0\rangle \otimes \sum_{x \in S} \alpha_x |x\rangle.$$

Then, the final state is

$$|\psi_{end}\rangle = \sum_{x \in S} \alpha_x |\psi_x\rangle \otimes |x\rangle$$

where $|\psi_x\rangle$ is the final state of $A = U_T O U_{T-1} \dots U_0$ on the input x. This follows from the fact that the restrictions of $U'_T, O', U'_{T-1}, \dots, U'_0$ to $\mathcal{H}_A \otimes |x\rangle$ are $U_T, O_x, U_{T-1}, \dots, U_0$ and these are exactly the transformations of the algorithm A on the input x.

In the starting state, the \mathcal{H}_A and \mathcal{H}_I parts of the superposition are unentangled. In the final state, however, they must be entangled (if the algorithm works correctly). To see that, consider a simple example where the algorithm has to recover the whole input.

Let $\alpha_x = 1/\sqrt{m}$ (where m = |S|) for all $x \in S$. In the exact model (the algorithm is not allowed to give the wrong answer even with a small probability), $|\psi_x\rangle$ must be $|x\rangle|\varphi_x\rangle$ where $|x\rangle$ is the answer of the algorithm and $|\varphi_x\rangle$ are algorithm's workbits. This means that the final state is

$$\frac{1}{\sqrt{m}} \sum_{x \in S} |x\rangle |\varphi_x\rangle \otimes |x\rangle,$$

i.e., it is fully entangled state. In the bounded error model (the algorithm can give a wrong answer with a probability at most ϵ), $|\psi_x\rangle$ must be $(1-\epsilon)|x\rangle|\varphi_x\rangle + |\psi_x'\rangle$ and the final state must be

$$\frac{1}{\sqrt{m}} \sum_{x \in S} ((1 - \epsilon)|x\rangle |\varphi_x\rangle + |\psi_x'\rangle) \otimes |x\rangle$$

which is also quite highly entangled.

In the general case (we have to compute some function f instead of learning the whole input x), the parts of \mathcal{H}_I corresponding to inputs with f(x) = z must become entangled with parts of \mathcal{H}_A corresponding to the answer z.

Thus, we can show a lower bound on quantum query algorithms by showing that, given an unentangled start state, we cannot achieve a highly entangled end state with less than a certain number of query transformations.

Next, we describe more formally how we bound this entanglement. If we trace out \mathcal{H}_A from the states $|\psi_{start}\rangle$ and $|\psi_{end}\rangle$, we obtain mixed states over \mathcal{H}_I . Let ρ_{start} and ρ_{end} be the density matrices describing these states.

 ho_{start} is a $m \times m$ matrix corresponding to the pure state $\sum_{x \in S} \alpha_x |x\rangle$. Entries of this matrix are $(\rho_{start})_{xy} = \alpha_x^* \alpha_y$. In particular, if the start state is $\frac{1}{\sqrt{m}} \sum_{x \in S} |x\rangle$, all entries of the ρ_{start} are 1/m.

For ρ_{end} we have

Lemma 1 Let A be an algorithm that computes f with probability at least $1 - \epsilon$. Let x, y be such that $f(x) \neq f(y)$. Then,

$$|(\rho_{end})_{xy}| \le 2\sqrt{\epsilon(1-\epsilon)}|\alpha_x||\alpha_y|.$$

Proof: Let $|\psi_x\rangle$, $|\psi_y\rangle$ be the final superpositions of the algorithm A on inputs x,y. We take a basis for \mathcal{H}_A consisting of the vectors of the form $|z\rangle|v\rangle$ where $|z\rangle$ is a basis for the answer part (the part which is measured at the end of algorithm to obtain the answer) and $|v\rangle$ is a basis for the rest of \mathcal{H}_A (workbits). We express $|\psi_x\rangle$ and $|\psi_y\rangle$ in this basis. Let

$$|\psi_x\rangle = \sum_{z,v} a_{z,v} |z\rangle |v\rangle, \ |\psi_y\rangle = \sum_{z,v} b_{z,v} |z\rangle |v\rangle.$$

The final state of the algorithm is $\sum_{x \in S} \alpha_x |\psi_x\rangle \otimes |x\rangle$. By tracing out \mathcal{H}_A in the $|z\rangle |v\rangle$ basis, we get

$$(\rho_{end})_{xy} = \alpha_x \alpha_y \sum_{z,v} a_{z,v}^* b_{z,v}.$$

Define $\epsilon_1 = \sum_{z,v:z \neq f(x)} |a_{z,v}|^2$ and $\epsilon_2 = \sum_{z,v:z = f(x)} |b_{z,v}|^2$. Then, $\epsilon_1 \leq \epsilon$ and $\epsilon_2 \leq \epsilon$ (because these are the probabilities that the measurement at the end of algorithm gives us a wrong answer: not f(x) for the input x and f(x) for the input y). We have

$$\begin{split} |\sum_{z,v} a_{z,v}^* b_{z,v}| & \leq \sum_{z,v} |a_{z,v}| |b_{z,v}| = \sum_{z,v:z=f(x)} |a_{z,v}| |b_{z,v}| + \sum_{z,v:z\neq f(x)} |a_{z,v}| |b_{z,v}| \\ & \leq \sqrt{\sum_{z,v:z=f(x)} |a_{z,v}|^2} \sqrt{\sum_{z,v:z=f(x)} |b_{z,v}|^2} + \sqrt{\sum_{z,v:z\neq f(x)} |a_{z,v}|^2} \sqrt{\sum_{z,v:z\neq f(x)} |b_{z,v}|^2} = \sqrt{(1-\epsilon_1)\epsilon_2} + \sqrt{\epsilon_1(1-\epsilon_2)}. \end{split}$$

This expression is maximized by $\epsilon_1 = \epsilon_2 = \epsilon$, giving us $2\sqrt{\epsilon(1-\epsilon)}$. Therefore,

$$|(\rho_{end})_{xy}| = |\alpha_x||\alpha_y||\sum_{z,v} a_{z,v}^* b_{z,v}| \le 2\sqrt{\epsilon(1-\epsilon)}|\alpha_x||\alpha_y|.$$

In particular, if $|\psi_{start}\rangle$ is the uniform $\frac{1}{\sqrt{m}}\sum_{x\in S}|x\rangle$, we have $(\rho_{end})_{xy}\leq 2\sqrt{\epsilon(1-\epsilon)}/m$. Note that, for any $\epsilon<1/2$, $2\sqrt{\epsilon(1-\epsilon)}<1$. Thus, if the algorithm A works correctly, the absolute value of every entry of ρ_{end} that corresponds to inputs x,y with $f(x)\neq f(y)$ must be smaller than the corresponding entry of ρ_{start} by a constant fraction.

To prove a lower bound on the number of queries, we bound the change in ρ_{xy} caused by one query. Together with Lemma 1, this implies a lower bound on the number of queries.

4 Lower bound on search

Next, we apply this technique to several problems. We start with the simplest case: the lower bound on unordered search problem (Theorem 1). Then, we show two general lower bound theorems (Theorems 2 and 6).

Each of these theorems is a special case of the next one: Theorem 2 implies Theorem 1 and Theorem 6 implies Theorem 2. However, more general theorems have more complicated proofs and it is easier to see the main idea in the simple case of unordered search. Therefore, we show this case first, before general theorems 2 and 6.

Problem: We are given $x_1, \ldots, x_N \in \{0, 1\}$ and we have to find i such that $x_i = 1$.

Theorem 1 [4] Any quantum algorithm that finds i with probability $1 - \epsilon$ uses $\Omega(\sqrt{N})$ queries.

Proof: Let S be the set of inputs with one x_i equal to 1 and the rest 0. Then, |S| = N and \mathcal{H}_I is an N-dimensional space. To simplify the notation, we use $|i\rangle$ to denote the basis state of \mathcal{H}_I corresponding to the input (x_1, \ldots, x_N) with $x_i = 1$.

Let ρ_k be the density matrix of \mathcal{H}_I after k queries. Note that $\rho_0 = \rho_{start}$ and $\rho_T = \rho_{end}$. We consider the sum of absolute values of all its off-diagonal entries $S_k = \sum_{x,y,x\neq y} |(\rho_k)_{xy}|$. We will show that

- 1. $S_0 = N 1$,
- 2. $S_T \leq 2\sqrt{\epsilon(1-\epsilon)}(N-1)$
- 3. $S_{k-1} S_k \le 2\sqrt{N-1}$ for all $k \in \{1, \dots, T\}$.

This implies that the number of queries T is at least $(1-2\sqrt{\epsilon(1-\epsilon)})\sqrt{N-1}/2$.

The first two properties follow straightforwardly from the results at the end of section 3. $N \times N$ matrices ρ_i have N(N-1) non-diagonal entries and each of these entries is 1/N in ρ_{start} and at most $2\sqrt{\epsilon(1-\epsilon)}/N$ in ρ_{end} (Lemma 1 together with the fact that each of these entries corresponds to two inputs with different answers).

It remains to prove the third part. First, notice that

$$S_{k-1} - S_k = \sum_{x,y:x \neq y} |(\rho_{k-1})_{xy}| - \sum_{x,y:x \neq y} |(\rho_k)_{xy}| \le \sum_{x,y:x \neq y} |(\rho_{k-1})_{xy} - (\rho_k)_{xy}|.$$

Therefore, it suffices to bound the sum of $|(\rho_{k-1})_{xy} - (\rho_k)_{xy}|$.

A query corresponds to representing the pure state before the query as

$$|\psi_{k-1}\rangle = \sum_{i,z} \sqrt{p_{i,z}} |i,z\rangle \otimes |\psi_{i,z}\rangle,$$

$$|\psi_{i,z}\rangle = \sum_{j=1}^{n} \alpha_{i,z,j} |j\rangle$$

and changing the phase on the $|i\rangle$ component of $|\psi_{i,z}\rangle$. If we consider just the H_I part, the density matrix ρ_{k-1} before the query is $\sum_{i,z} p_{i,z} |\psi_{i,z}\rangle \langle \psi_{i,z}|$. The density matrix ρ_k after the query is $\sum_{i,z} p_{i,z} |\psi_{i,z}'\rangle \langle \psi_{i,z}'|$ where

$$|\psi'_{i,z}\rangle = \sum_{j \neq i} \alpha_{i,z,j} |j\rangle - \alpha_{i,z,i} |i\rangle.$$

Consider $\rho_{i,z} = |\psi_{i,z}\rangle\langle\psi_{i,z}|$ and $\rho'_{i,z} = |\psi'_{i,z}\rangle\langle\psi'_{i,z}|$. Then, $\rho_{k-1} = \sum_{i,z} p_{i,z}\rho_{i,z}$ and $\rho_k = \sum_{i,z} p_{i,z}\rho'_{i,z}$.

The only entries where $\rho_{i,z}$ and $\rho'_{i,z}$ differ are the entries in the i^{th} column and the i^{th} row. These entries are $\alpha^*_{i,z,j}\alpha_{i,z,i}$ in $\rho_{i,z}$ and $-\alpha^*_{i,z,j}\alpha_{i,z,i}$ in $\rho'_{i,z}$. The sum of absolute values of the differences of all entries in the i^{th} row is

$$\sum_{j\neq i} 2|\alpha_{i,z,j}^*\alpha_{i,z,i}| \le 2|\alpha_{i,z,i}| \sum_{j\neq i} |\alpha_{i,z,j}|.$$

Similarly, the sum of absolute values of the differences of all entries in the i^{th} column is at most $2|\alpha_{i,z,i}|\sum_{j\neq i}|\alpha_{i,z,j}|$ as well. So, the sum of absolute values of all differences is at most $4|\alpha_{i,z,i}|\sum_{j\neq i}|\alpha_{i,z,j}|$.

By Cauchy-Schwartz inequality,

$$\sum_{j \neq i} |\alpha_{i,z,j}| \le \sqrt{N-1} \sqrt{\sum_{j \neq i} |\alpha_{i,z,j}|^2} = \sqrt{N-1} \sqrt{1 - |\alpha_{i,z,i}|^2}.$$

Therefore,

$$\sum_{j \neq i} 4|\alpha_{i,z,j}^* \alpha_{i,z,i}| \le 4\sqrt{N-1}|\alpha_{i,z,i}| \sqrt{1-|\alpha_{i,z,i}|^2} \le 2\sqrt{N-1}.$$

Define $S_{i,z} = \sum_{x,y:x\neq y} |(\rho_{i,z})_{xy} - (\rho'_{i,z})_{xy}|$. Then, we have just shown $S_{i,z} \leq 2\sqrt{N-1}$. This implies a bound on the sum $\sum_{x,y:x\neq y} |(\rho_{k-1})_{xy} - (\rho_k)_{xy}|$.

$$\sum_{x,y:x\neq y} |(\rho_{k-1})_{xy} - (\rho_k)_{xy}| = \sum_{x,y:x\neq y} |\sum_{i,z} p_{i,z}(\rho_{i,z})_{xy} - \sum_{i,z} p_{i,z}(\rho'_{i,z})_{xy}|$$

$$\leq \sum_{i,z} p_{i,z} \sum_{x,y:x \neq y} |(\rho_{i,z})_{xy} - (\rho'_{i,z})_{xy}| \leq \sum_{i,z} p_{i,z} 2\sqrt{N-1} = 2\sqrt{N-1}.$$

This completes the proof. \Box

5 The general lower bound

5.1 The result

Next, we obtain a general lower bound theorem.

Theorem 2 Let $f(x_1,...,x_N)$ be a function of $n \{0,1\}$ -valued variables and X,Y be two sets of inputs such that $f(x) \neq f(y)$ if $x \in X$ and $y \in Y$. Let $R \subset X \times Y$ be such that

- 1. For every $x \in X$, there exist at least m different $y \in Y$ such that $(x,y) \in R$.
- 2. For every $y \in Y$, there exist at least m' different $x \in X$ such that $(x,y) \in R$.
- 3. For every $x \in X$ and $i \in \{1, ..., n\}$, there are at most l different $y \in Y$ such that $(x, y) \in R$ and $x_i \neq y_i$.
- 4. For every $y \in Y$ and $i \in \{1, ..., n\}$, there are at most l' different $x \in X$ such that $(x, y) \in R$ and $x_i \neq y_i$.

Then, any quantum algorithm computing f uses $\Omega(\sqrt{\frac{mm'}{ll'}})$ queries.

Proof: Consider the set of inputs $S = X \cup Y$ and the superposition

$$\frac{1}{\sqrt{2|X|}} \sum_{x \in X} |x\rangle + \frac{1}{\sqrt{2|Y|}} \sum_{y \in Y} |y\rangle$$

over this set of inputs. Let S_i be the sum of $|(\rho_i)_{xy}|$ over all x, y such that $(x, y) \in R$. Then, the theorem follows from

1.
$$S_0 - S_T \ge (1 - 2\sqrt{\epsilon(1 - \epsilon)})\sqrt{mm'}$$

2.
$$S_{k-1} - S_k < \sqrt{ll'}$$

To show the first part, let $(x,y) \in R$. Then, $(\rho_0)_{xy} = \frac{1}{\sqrt{|X||Y|}}$ and $|(\rho_T)_{xy}| \leq \frac{2\sqrt{\epsilon(1-\epsilon)}}{\sqrt{|X||Y|}}$ (Lemma 1). Therefore,

$$|(\rho_0)_{xy}| - |(\rho_T)_{xy}| \ge \frac{1 - 2\sqrt{\epsilon(1 - \epsilon)}}{\sqrt{|X||Y|}}.$$

The number of $(x, y) \in R$ is at least $\max(|X|m, |Y|m')$ because for every $x \in X$, there are at least m possible $y \in Y$ and, for every $y \in Y$, there are at least m' possible $x \in X$. We have

$$\max(|X|m,|Y|m') \ge \frac{|X|m+|Y|m'}{2} \ge \sqrt{|X||Y|mm'},$$

$$S_0 - S_T \ge \sqrt{|X||Y|mm'} \frac{1 - 2\sqrt{\epsilon(1 - \epsilon)}}{\sqrt{|X||Y|}} = (1 - 2\sqrt{\epsilon(1 - \epsilon)})\sqrt{mm'}.$$

Next, we prove the second part. Similarly to the previous proof, we represent

$$|\psi_{k-1}\rangle = \sum_{i,z} \sqrt{p_{i,z}} |i,z\rangle \otimes |\psi_{i,z}\rangle,$$

$$|\psi_{i,z}\rangle = \sum_{x \in S} \alpha_{i,z,x} |x\rangle.$$

A query corresponds to changing the sign on all components with $x_i = 1$. It transforms $|\psi_{i,z}\rangle$ to

$$|\psi'_{i,z}\rangle = \sum_{x \in S: x_i = 0} \alpha_{i,z,x} |x\rangle - \sum_{x \in S: x_i = 1} \alpha_{i,z,x} |x\rangle.$$

Let $\rho_{i,z} = |\psi_{i,z}\rangle\langle\psi_{i,z}|$ and $\rho'_{i,z} = |\psi'_{i,z}\rangle\langle\psi'_{i,z}|$. We define $S_{i,z} = \sum_{(x,y)\in R} |(\rho_{i,z})_{xy} - (\rho'_{i,z})_{xy}|$. If $x_i = y_i$, then $(\rho_{i,z})_{xy}$ and $(\rho'_{i,z})_{xy}$ are the same. If one of x_i , y_i is 0 and the other is 1, $(\rho_{i,z})_{xy} = (\rho_{i,z})_{xy}$ $-(\rho'_{i,z})_{xy}$ and $|(\rho_{i,z})_{xy} - (\rho'_{i,z})_{xy}| = 2|(\rho_{i,z})_{xy}| = 2|\alpha_{i,z,x}||\alpha_{i,z,y}|$. Therefore,

$$S_{i,z} = \sum_{(x,y) \in R: x_i \neq y_i} 2|\alpha_{i,z,x}| |\alpha_{i,z,y}| \le \sum_{(x,y) \in R: x_i \neq y_i} \sqrt{\frac{l'}{l}} |\alpha_{i,z,x}|^2 + \sqrt{\frac{l}{l'}} |\alpha_{i,z,y}|^2$$

$$\leq \sum_{x \in X} l \sqrt{\frac{l'}{l}} |\alpha_{i,z,x}|^2 + \sum_{y \in Y} l' \sqrt{\frac{l}{l'}} |\alpha_{i,z,y}|^2 = \sqrt{ll'} \sum_{x \in X \cup Y} |\alpha_{i,z,x}|^2 = \sqrt{ll'}.$$

Similarly to the previous proof, this implies the same bound on $S_{k-1} - S_k$. \square

Relation to block sensitivity bound

Our Theorem 2 generalizes the block sensitivity bound of [3, 18].

Let f be a Boolean function and $x = (x_1, \ldots, x_n)$ an input to f. For a set $S \subseteq \{1, \ldots, n\}$, $x^{(S)}$ denotes the input obtained from x by flipping all variables x_i , $i \in S$. f is sensitive to S on input x if $f(x) \neq f(x^{(S)})$.

The block sensitivity of f on input x is the maximal number t such that there exist t pairwise disjoint sets S_1, S_2, \ldots, S_t such that, for all $i \in \{1, \ldots, t\}$, f is sensitive to S_i on x. We denote it by $bs_x(f)$. The block sensitivity of f, bs(f) is just the maximum of $bs_x(f)$ over all inputs x[14].

Theorem 3 [3, 18] Let f be any Boolean function. Then, any quantum query algorithm computing f uses $\Omega(\sqrt{bs(f)})$ queries.

To see that this is a particular case of Theorem 2, let x be the input on which f achieves bs(f) block sensitivity. Then, we can take $X = \{x\}$ and $Y = \{x^{(S_1)}, \ldots, x^{(S_{bs(f)})}\}$.

Let $R = \{(x, x^{(S_1)}), (x, x^{(S_2)}), \dots, (x, x^{(S_{bs(f)})})\}$. Then, m = bs(f), m' = 1. Also, l = 1 (because, by the definition of the block sensitivity, m blocks of input variables have to be disjoint) and l' = 1. Therefore, we get $\frac{mm'}{ll'} = bs(f)$ and Theorem 2 gives the $\Omega(\sqrt{bs(f)})$ lower bound for any Boolean function f.

In the next subsection we show some problems for which our method gives a better bound than the block-sensitivity method.

5.3 Applications

For a first application, consider AND of ORs:

$$f(x_1, \dots, x_N) = (x_1 ORx_2 \dots ORx_{\sqrt{N}}) AND$$
$$(x_{\sqrt{N}+1} \dots x_{2\sqrt{N}}) AND \dots AND(x_{N-\sqrt{N}+1} OR \dots ORx_N)$$

where $x_1, ..., x_N \in \{0, 1\}.$

f can be computed with $O(\sqrt{N} \log N)$ queries by a two-level version of Grover's algorithm (see [7]). However, a straightforward application of lower bound methods from [4, 3] only gives an $\Omega(\sqrt[4]{N})$ bound because the block sensitivity of f is $\Theta(\sqrt{N})$ and the lower bound on the number of queries given by hybrid or polynomials method is the square root of block sensitivity[3, 18]. Our method gives

Theorem 4 Any quantum algorithm computing AND of ORs uses $\Omega(\sqrt{N})$ queries.

Proof: For this problem, let X be the set of all $x = (x_1, \ldots, x_n)$ such that, for every $i \in \{1, \ldots, \sqrt{N}\}$, there is exactly one $j \in \{1, \ldots, \sqrt{n}\}$ with $x_{(i-1)\sqrt{N}+j} = 1$. Y is the set of all $y = (y_1, \ldots, y_n)$ such that $y_{(i-1)\sqrt{N}+1} = \ldots = y_{i\sqrt{N}} = 0$ for some i and, for every $i' \neq i$, there is a unique $j \in \{1, \ldots, \sqrt{N}\}$ with $y_{(i-1)\sqrt{N}+j} = 1$. R consists of all pairs $(x, y), x \in X, y \in Y$ such that there is exactly one i with $x_i \neq y_i$.

Then, $m=m'=\sqrt{n}$ because, given $x\in X$, there are \sqrt{n} 1s that can be replaced by 0 and replacing any one of them gives some $y\in Y$. Conversely, if $y\in Y$, there are \sqrt{n} ways to add one more 1 so that we get $x\in X$. On the other hand, l=l'=1 because, given $x\in X$ (or $y\in Y$) and $i\in\{1,\ldots,n\}$, there is only one input that differs from x only in the i^{th} position. Therefore, $\sqrt{\frac{mm'}{ll'}}=\sqrt{n}$ and the result follows from Theorem 2. \square

Our theorem can be also used to give another proof for the following theorem of Nayak and Wu[13].

Theorem 5 [13] Let $f: \{0, 1, ..., n-1\} \rightarrow \{0, 1\}$ be a Boolean function that is equal to 1 either at exactly n/2 points of the domain or at exactly $(1+\epsilon)n/2$ points. Then, any quantum algorithm that determines whether the number of points where f(x) = 1 is n/2 or $(1+\epsilon)n/2$ uses $\Omega(\frac{1}{\epsilon})$ queries.

This result implies lower bounds on the number of quantum queries needed to compute (or to approximate) the median of n numbers[13]. It was shown in [13] using polynomials method. No proof that uses adversary arguments similar to [4, 18] is known.

With our "quantum adversary" method, Theorem 5 can be proven in similarly to other theorems in this paper.

Proof: Let X be the set of all f that are 1 at exactly n/2 points, Y be the set of all f that are 1 at $(1+\epsilon)n/2$ points and R be the set of all (f, f') such that $f \in X$, $f' \in Y$ and they differ in exactly $\epsilon n/2$ points.

Then, $m = \binom{n/2}{\epsilon n/2}$ and $m' = \binom{(1+\epsilon)n/2}{\epsilon n/2}$. On the other hand, $l = \binom{n/2-1}{\epsilon n/2-1}$ and $l' = \binom{(1+\epsilon)n/2-1}{\epsilon n/2-1}$. Therefore,

$$\frac{mm'}{ll'} = \frac{\binom{n/2}{\epsilon n/2} \binom{(1+\epsilon)n/2}{\epsilon n/2}}{\binom{n/2-1}{\epsilon n/2-1} \binom{(1+\epsilon)n/2-1}{\epsilon n/2-1}} = \frac{\frac{n}{2} \frac{(1+\epsilon)n}{2}}{\frac{\epsilon n}{2} \frac{\epsilon n}{2}} = \frac{1+\epsilon}{\epsilon^2} > \frac{1}{\epsilon^2}.$$

By Theorem 2, the number of queries is $\Omega(\sqrt{\frac{mm'}{ll'}}) = \Omega(1/\epsilon)$.

There are several other known lower bounds that also follow from Theorem 2. In particular, Theorem 2 implies $\Omega(N)$ lower bounds for MAJORITY and PARITY of [3].

6 Inverting a permutation

6.1 Extension of Theorem 2

For some lower bounds (like inverting a permutation), we need a following extension of Theorem 2. This is our most general result.

Theorem 6 Let $f(x_1,...,x_N)$ be a function of n variables with values from some finite set and X,Y be two sets of inputs such that $f(x) \neq f(y)$ if $x \in X$ and $y \in Y$. Let $R \subset X \times Y$ be such that

- 1. For every $x \in X$, there exist at least m different $y \in Y$ such that $(x,y) \in R$.
- 2. For every $y \in Y$, there exist at least m' different $x \in X$ such that $(x, y) \in R$.

Let $l_{x,i}$ be the number of $y \in Y$ such that $(x,y) \in R$ and $x_i \neq y_i$ and $l_{y,i}$ be the number of $x \in X$ such that $(x,y) \in R$ and $x_i \neq y_i$. Let l_{max} be the maximum of $l_{x,i}l_{y,i}$ over all $(x,y) \in R$ and $i \in \{1,\ldots,N\}$ such that $x_i \neq y_i$. Then, any quantum algorithm computing f uses $\Omega(\sqrt{\frac{mm'}{l_{max}}})$ queries.

The parameters l and l' of Theorem 2 are just $\max_{x \in X, i} l_{x,i}$ and $\max_{y \in Y, i} l_{y,i}$. It is easy to see that

$$\max_{(x,y)\in R, x_i\neq y_i} l_{x,i}l_{y,i} \leq \max_{x,i} l_{x,i} \max_{y,i} l_{y,i}.$$

Therefore, the lower bound given by Theorem 6 is always greater than or equal to the lower bound of Theorem 2. However, Theorem 6 gives a better bound if, for every $(x, y) \in R$ and i, at least one of $l_{x,i}$ or $l_{y,i}$ is less than its maximal value (which happens for inverting a permutation).

Also, Theorem 6 allows $\{1, \ldots, N\}$ -valued variables instead of only $\{0, 1\}$ -valued in Theorem 2. **Proof:** Similarly to Theorem 6, we consider the set of inputs $S = X \cup Y$ and the superposition

$$\frac{1}{\sqrt{2|X|}} \sum_{x \in X} |x\rangle + \frac{1}{\sqrt{2|Y|}} \sum_{y \in Y} |y\rangle$$

over this set of inputs. Let S_k be the sum of $|(\rho_k)_{xy}|$ over all x, y such that $(x, y) \in R$. The theorem follows from

- 1. $S_T S_0 \ge (1 2\sqrt{\epsilon(1 \epsilon)})\sqrt{mm'}$
- $2. S_{k-1} S_k \le \sqrt{l_{max}}$

The first part is shown in the same way as in the proof of Theorem 2. For the second part, express the state before the k^{th} query as

$$|\psi_{k-1}\rangle = \sum_{i,a,z,x} \alpha_{i,a,z,x} |i,a,z\rangle \otimes |x\rangle$$

where i is the index of the input variable x_i being queried, a are $\log N$ bits for the answer, z is the part of \mathcal{H}_A that does not participate in the query (extra workbits) and x is \mathcal{H}_I part of the superposition. A query changes this to

$$|\psi_k\rangle = \sum_{i,a,z,x} \alpha_{i,a,z,x} |i,a \oplus x_i,z\rangle \otimes |x\rangle = \sum_{i,a,z,x} \alpha_{i,a \oplus x_i,z,x} |i,a,z\rangle \otimes |x\rangle.$$

Denote

$$|\psi_{i,a,z}\rangle = \sum_{x} \alpha_{i,a,z,x} |x\rangle, \ |\psi'_{i,a,z}\rangle = \sum_{x} \alpha_{i,a \oplus x_i,z,x} |x\rangle.$$

 $\rho_{k-1,i} = \sum_{a,z} |\psi_{i,a,z}\rangle\langle\psi_{i,a,z}|$ and $\rho_{k,i} = \sum_{a,z} |\psi'_{i,a,z}\rangle\langle\psi'_{i,a,z}|$ are the parts of ρ_{k-1} and ρ_k corresponding to querying i. We have $\rho_{k-1} = \sum_{i=1}^n \rho_{k-1,i}$ and $\rho_k = \sum_{i=1}^n \rho_{k,i}$. Let $S_{k,i}$ be sum of absolute values of differences $|(\rho_{k-1,i})_{xy} - (\rho_{k,i})_{xy}|$ over all $(x,y) \in R$. Then, for every

x, y,

$$|(\rho_{k-1})_{xy}| - |(\rho_k)_{xy}| \le |(\rho_{k-1})_{xy} - (\rho_k)_{xy}| = |\sum_i (\rho_{k-1,i})_{xy} - \sum_i (\rho_{k,i})_{xy}| \le \sum_i |(\rho_{k-1,i})_{xy} - (\rho_{k,i})_{xy}|.$$

Therefore (by summing over all such x and y), $S_{k-1} - S_k \leq \sum_i S_{k,i}$ and we can bound $S_{k-1} - S_k$ by bounding

Let x, y be two inputs such that $x_i = y_i$. Then, it is easy to see that

$$(\rho_{k-1,i})_{xy} = \sum_{a,z} \alpha_{i,a,z,x}^* \alpha_{i,a,z,y} = \sum_{a,z} \alpha_{i,a \oplus x_i,z,x}^* \alpha_{i,a \oplus y_i,z,y} = (\rho_{k,i})_{xy}.$$

Therefore, the only non-zero entries in $S_{k,i}$ are the entries corresponding to $(x,y) \in R$ with $x_i \neq y_i$. The sum of their differences $|(\rho_{k-1,i})_{xy} - (\rho_{k,i})_{xy}|$ is at most the sum of absolute values of such entries in $\rho_{k-1,i}$ plus the sum of absolute values of them in $\rho_{k,i}$. We bound these two sums.

First, any density matrix is semipositive definite. This implies that

$$|(\rho_{k-1,i})_{xy}| \le \frac{1}{2} \left(\sqrt{\frac{l_{y,i}}{l_{x,i}}} |(\rho_{k-1,i})_{xx}| + \sqrt{\frac{l_{x,i}}{l_{y,i}}} |(\rho_{k-1,i})_{yy}| \right).$$

for any x and y. Therefore,

$$\sum_{\substack{x,y:(x,y)\in R\\x_i\neq y_i}} |(\rho_{k-1,i})_{xy}| \leq \frac{1}{2} \sum_{\substack{x,y:(x,y)\in R\\x_i\neq y_i}} \sqrt{\frac{l_{y,i}}{l_{x,i}}} |(\rho_{k-1,i})_{xx}| + \sqrt{\frac{l_{x,i}}{l_{y,i}}} |(\rho_{k-1,i})_{yy}| = \frac{1}{2} \sum_{x\in X\cup Y} l_{x,i} \sqrt{\frac{l_{y,i}}{l_{x,i}}} |(\rho_{k-1,i})_{xx}|$$

$$= \frac{1}{2} \sum_{x \in X \cup Y} \sqrt{l_{x,i} l_{y,i}} |(\rho_{k-1,i})_{xx}| \le \frac{1}{2} \sqrt{l_{max}} \sum_{x \in X \cup Y} |(\rho_{k-1,i})_{xx}| = \frac{\sqrt{l_{max}}}{2} Tr \rho_{k-1,i}.$$

The same argument shows that a similar sum is at most $\frac{\sqrt{l_{max}}}{2}Tr\rho_{k,i}$ for the matrix $\rho_{k,i}$. Therefore

$$S_{k-1} - S_k \le \sum_{i} S_{k,i} \le \sum_{i} \frac{\sqrt{l_{max}}}{2} (Tr\rho_{k-1,i} + Tr\rho_{k,i}) = \frac{\sqrt{l_{max}}}{2} (Tr\rho_{k-1} + Tr\rho_k) = \sqrt{l_{max}}.$$

This completes the proof. \Box

6.2 Application

We use Theorem 6 to prove a lower bound for inverting a permutation[4].

Problem: We are given $x_1, \ldots, x_N \in \{1, \ldots, N\}$ such that (x_1, \ldots, x_N) is a permutation of $\{1, \ldots, N\}$. We have to find the i such that $x_i = 1$.

This problem was used in [4] to show $NP^A \cap co - NP^A \not\subseteq BQP^A$ for an oracle A. It is easy to see that it can be solved by Grover's algorithm (search for i with $x_i = 1$). This takes $O(\sqrt{N})$ queries.

However, the $\Omega(\sqrt{N})$ lower bound proof for search problem from [4] does not work for this problem. [4] showed a weaker $\Omega(\sqrt[3]{N})$ bound with a more complicated proof.

Theorem 7 Any quantum query algorithm that inverts a permutation with probability $1 - \epsilon$ uses $\Omega(\sqrt{N})$ queries.

Proof: Let X be the set of all permutations x with $x_i = 1$ for an even i and Y be the set of all permutations y with $y_i = 1$ for an odd i. $(x, y) \in R$ if $x = (x_1, ..., x_N)$, $y = (y_1, ..., y_N)$ and there are $i, j, i \neq j$ such that $x_i = y_j = 1$, $x_j = y_i$ and all other elements of x and y are the same.

For every $x \in X$, there are m = n/2 y with $(x, y) \in R$. Similarly, for every $y \in Y$, there are m' = n/2 x such that $(x, y) \in R$.

Finally, if we take a pair $(x,y) \in R$ and a location i such that $x_i \neq y_i$, then one of x_i, y_i is 1. We assume that $x_i = 1$. (The other case is similar.) Then, there are n/2 y' such that $(x,y') \in R$ and $x_i \neq y_i'$. However, the only x' such that $(x',y) \in R$ and $x_i' \neq y_i'$ is x' = x. (Any x' such that $(x',y) \in R$ and $x_i' \neq y_i'$ must also have $x_j' \neq y_j$ where j is the variable for which $y_j = 1$ and x is the only permutation that differs from y only in these two places.)

Therefore, $l_{x,i} = n/2$, $l_{y,i} = 1$ and $l_{max} = n/2$. By Theorem 6, this implies that any quantum algorithm needs $\Omega(\sqrt{\frac{n^2}{n}}) = \Omega(\sqrt{n})$ queries. \square

7 Relation to Grover's proof

Grover[10] presents a proof of the $\Omega(\sqrt{n})$ lower bound on the search problem based on considering the sum of distances

$$\Delta(t) = \sum_{i,j \in \{1,...,n\}, i \neq j} \|\phi_i^t - \phi_0^t\|^2$$

where ϕ_i^t is the state of the algorithm after t queries on the input $x_1 = \ldots = x_{i-1} = 0$, $x_i = 1$, $x_{i+1} = \ldots = x_n = 1$ and ϕ_0^t is the state of the algorithm after t queries on the input $x_1 = \ldots = x_n = 0$.

Grover shows that, after t queries, $\Delta(t) \leq 4t^2$. If the algorithm outputs the correct answer with probability 1, the final vectors $\phi_1^t, \ldots, \phi_n^t$ have to be orthogonal, implying that $\Delta(t) \geq 2N - 2\sqrt{N}$ (cf. [10]). This implies that the number of queries must be $\Omega(\sqrt{N})$.

A similar idea (bounding a certain sum of distances) has been also used by Shi[16] to prove lower bounds on the number of quantum queries in terms of average sensitivity.

These "distance-based" ideas can be generalized to obtain another proof of our Theorems 2 and 6. Namely, for Theorem 2, one can take

$$\Delta(t) = \sum_{(x,y) \in R} \|\phi_x^t - \phi_y^t\|^2$$

where ϕ_x^t , ϕ_y^t are the states of the algorithm after t steps on the inputs x and y. Then,

$$\|\phi_x^t - \phi_y^t\|^2 = 1 - \langle \phi_x^t | \phi_y^t \rangle^2.$$

Let ρ_t be the density matrix of \mathcal{H}_I after t steps. By writing out the expressions for $\langle \phi_x^t | \phi_y^t \rangle$ and $(\rho_t)_{xy}$, we can see that

 $(\rho_t)_{xy} = \frac{1}{4|X||Y|} \langle \phi_x^t | \phi_y^t \rangle.$

This shows that the two quantities (the sum of entries in the density matrix and the sum of distances) are quite similar. Indeed, we can give proofs for Theorems 2 and 6 in terms of distances and their sums $\Delta(t)$. (Namely, $\Delta(0) = 0$ before the first query, $\Delta(T)$ should be large if the algorithm solves the problem with T queries and we can bound the difference $\Delta(t) - \Delta(t-1)$. This gives the same bounds as bounding the entries of density matrices.)

Thus, Theorems 2 and 6 have two proofs that are quite similar algebraically but come from two completely different sources: running a quantum algorithm with a superposition of inputs (our "quantum adversary") and looking at it from a geometric viewpoint (sum of distances).

The "quantum adversary" approach may be more general because one could bound other quantities (besides the sum of entries in the density matrix) which have no simple geometric interpretation.

8 Conclusion and open problems

We introduced a new method for proving lower bounds on quantum algorithms and used it to prove tight (up to a multiplicative or logarithmic factor) lower bounds on Grover's search and 3 other related problems. Two of these bounds (Grover's search and distinguishing between an input with 1/2 of values equal to 1 and $1/2 + \epsilon$ values equal to 1) were known before. For two other problems (inverting a permutation and AND of ORs), only weaker bounds were known. One advantage of our method is that it allows to prove all 4 bounds in a similar way. (Previous methods were quite different for different problems.)

Some open problems:

1. Collision problem[5].

We are given a function $f:\{1,\ldots,n\}\to\{1,\ldots,n/2\}$ and have to find i,j such that f(i)=f(j). Classically, this can be done by querying f(x) for $O(\sqrt{n})$ random values of x and it is easy to see that this is optimal. There is a quantum algorithm that solves this problem with $O(\sqrt[3]{n})$ queries[5]. However, there is no quantum lower bound at all for this problem (except the trivial bound of $\Omega(1)$).

The collision problem is an abstraction for *collision-resistant hash functions*. If it can be solved with $O(\log n)$ queries, there no hash function is collision-resistant against quantum algorithms.

The exact argument that we gave in this paper (with bounding a subset of the entries in the density matrix) does not carry over to the collision problem. However, it may be possible to use our idea of running the algorithm with a superposition of oracles together with some other way of measuring the entanglement between the algorithm and the oracle.

2. Simpler/better lower bound for binary search.

It may be possible to simplify other lower bounds proven previously by different methods. In some cases, it is quite easy to reprove the result by our method (like Theorem 5) but there are two cases in which we could not do that. The first is the bound of [6] on the number of queries needed to achieve very small probability of error in database search problem. The second is the lower bound on the ordered search[1]. It seems unlikely that our technique can be useful in the first case but there is a chance that some variant of our idea may work for ordered search (achieving both simpler proof and better constant under big- Ω).

3. Communication complexity of disjointness.

Quantum communication complexity is often related to query complexity[7]. Can one use our method (either "quantum adversary" or distance-based formulation) to prove lower bounds on quantum communication complexity?

A particularly interesting open problem in quantum communication complexity is set disjointness. The classical (both deterministic and probabilistic) communication complexity of set disjointness is $\Omega(n)[12, 15]$. There is a quantum protocol (based on Grover's search algorithm) that computes set disjointness with an $O(\sqrt{n} \log n)$ communication[7] but the best lower bound is only $\Omega(\log n)[8, 2]$.

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