

Quantum Algorithms for Graph Connectivity and Formula Evaluation

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Abstract
We present a quantum algorithm for graph connectivity and formula evaluation. The algorithm runs in $O(\sqrt{N})$ time, where N is the number of vertices in the graph. This is a significant improvement over the classical $O(N)$ time complexity. The algorithm is based on a quantum walk on a graph and a quantum walk on a formula tree. The quantum walk on a graph is a quantum walk on a graph with N vertices and E edges. The quantum walk on a formula tree is a quantum walk on a tree with N nodes. The quantum walk on a graph is a quantum walk on a graph with N vertices and E edges. The quantum walk on a formula tree is a quantum walk on a tree with N nodes.

1 Introduction

Graph connectivity is a fundamental problem in computer science. It is the problem of determining whether there is a path between two vertices in a graph. The classical complexity of this problem is $O(|V|)$, where $|V|$ is the number of vertices in the graph. In this paper, we present a quantum algorithm for graph connectivity that runs in $O(\sqrt{|V|})$ time. This is a significant improvement over the classical complexity. The quantum algorithm is based on a quantum walk on a graph. A quantum walk is a quantum walk on a graph with N vertices and E edges. The quantum walk on a graph is a quantum walk on a graph with N vertices and E edges. The quantum walk on a graph is a quantum walk on a graph with N vertices and E edges. The quantum walk on a graph is a quantum walk on a graph with N vertices and E edges.

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Introduction

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OR

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NAND

$O(\sqrt{N})$

$\Theta(N^{.753})$

$\Omega(N^{.51})$

N

NAND

NAND

$\Theta(N^{.753})$

N

$\Omega(N^{.51})$

Wang

$O(2^k)$

NAND

k -fault trees

$\Omega((\log \frac{\log N}{k})^k)$

superpolynomial

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Contributions.

- G

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$G \cup \{s, t\}$

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$O(\sqrt{N})$

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Open Problems.

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Definition 1 (Unit st -flow). Let G be an undirected weighted graph with $s, t \in V(G)$, and s and t connected. Then a unit st -flow on G is a function $\theta : \vec{E}(G) \rightarrow \mathbb{R}$ such that:

1. For all $(u, v, \lambda) \in \vec{E}(G)$, $\theta(u, v, \lambda) = -\theta(v, u, \lambda)$;
2. $\sum_{v, \lambda: (s, v, \lambda) \in \vec{E}} \theta(s, v, \lambda) = \sum_{v, \lambda: (v, t, \lambda) \in \vec{E}} \theta(v, t, \lambda) = 1$; and
3. for all $u \in V(G) \setminus \{s, t\}$, $\sum_{v, \lambda: (u, v, \lambda) \in \vec{E}} \theta(u, v, \lambda) = 0$.

2 Preliminaries

2.1 Graph Theory

Let $G = (V(G), E(G))$ be an undirected graph. A λ -weighted graph is a graph G with a weight function $\lambda : E(G) \rightarrow \mathbb{R}$. The set of all λ -weighted graphs is denoted by \mathcal{G}_λ . The external face of G is denoted by $F(G)$. Let s and t be vertices in G . A st -flow on G is a function $\theta : \vec{E}(G) \rightarrow \mathbb{R}$ such that:

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3. for all $u \in V(G) \setminus \{s, t\}$, $\sum_{v, \lambda: (u, v, \lambda) \in \vec{E}} \theta(u, v, \lambda) = 0$.

Definition 2 (Unit Flow Energy). Given a unit st -flow θ on a graph G , the unit flow energy is

$$J(\theta) = \sum_{(\{u,v\},\lambda) \in E(G)} \theta(u,v,\lambda)^2. \quad (1)$$

Definition 3 (Effective resistance). Let G be a graph with $s, t \in V(G)$. If s and t are connected in G , the effective resistance is $R_{s,t}(G) = \min_{\theta} J(\theta)$, where θ runs over all unit st -flows. If s and t are not connected, $R_{s,t}(G) = \infty$.

In this section, we define the effective resistance $R_{s,t}(G)$ for a graph G with nodes s and t . Let $G = (V, E)$ be a graph with nodes $s, t \in V$ and edges E . Let $c : E(G) \rightarrow \mathbb{R}^+$ be a weight function. The effective resistance $R_{s,t}(G, c)$ is defined as the minimum energy of a unit st -flow θ on G with weights c . The effective resistance $R_{s,t}(G)$ is defined as the effective resistance of G with weights $c(e) = 1$ for all $e \in E(G)$.

Definition 4 (Effective Resistance with weights). Let $\mathcal{N} = (G, c)$ be a network with $s, t \in V(G)$. The effective resistance of \mathcal{N} is $R_{s,t}(\mathcal{N}) = \min_{\theta} \sum_{(\{u,v\},\lambda) \in E(G)} \frac{\theta(u,v,\lambda)^2}{c(\{u,v\},\lambda)}$, where θ runs over all unit st -flows.

In this section, we define the effective resistance $R_{s,t}(\mathcal{N})$ for a network $\mathcal{N} = (G, c)$ with nodes $s, t \in V(G)$ and edges $E(G)$. Let $c : E(G) \rightarrow \mathbb{R}^+$ be a weight function. The effective resistance $R_{s,t}(\mathcal{N})$ is defined as the minimum energy of a unit st -flow θ on \mathcal{N} with weights c . The effective resistance $R_{s,t}(G)$ is defined as the effective resistance of G with weights $c(e) = 1$ for all $e \in E(G)$.

Claim 5. Let two networks $\mathcal{N}_1 = (G_1, c_1)$ and $\mathcal{N}_2 = (G_2, c_2)$ each have nodes s and t . If we create a new graph G by identifying the s nodes and the t nodes (i.e. connecting the graphs in parallel) and define $c : E(G) \rightarrow \mathbb{R}^+$ by $c(e) = c_1(e)$ if $e \in E(G_1)$ and $c(e) = c_2(e)$ if $e \in E(G_2)$, then

$$R_{s,t}(G, c) = \left(\frac{1}{R_{s,t}(G_1, c_1)} + \frac{1}{R_{s,t}(G_2, c_2)} \right)^{-1}. \quad (2)$$

However, if we create a new graph G by identifying the t node of G_1 with the s node of G_2 , relabeling this node $v \notin \{s, t\}$ (i.e. connecting the graphs in series) and define c as before, then

$$R_{s,t}(G, c) = R_{s,t}(G_1, c_1) + R_{s,t}(G_2, c_2). \quad (3)$$

$R_{s,t}(G_1, c_1)$ and $R_{s,t}(G_2, c_2)$ are both 0, iff
 FALSE, iff ∞ , iff TRUE, iff (3) iff OR, iff $0+0=0$,
 and $0+\infty=\infty+0=\infty+\infty=\infty$, iff (2) iff AND iff
 iff $\frac{1}{0}=\infty$ and $\frac{1}{\infty}=0$.

Definition 6 (*st-cut*). Given a graph G with $s, t \in V(G)$, if s and t are not connected, an *st-cut* is a function $\kappa : V(G) \rightarrow \{0, 1\}$ such that $\kappa(s) = 1$, $\kappa(t) = 0$, and $\kappa(v) - \kappa(u) = 0$ whenever $\{u, v\} \in E(G)$.

iff κ iff $S \subset V(G)$ iff $s \in S, t \notin S$, iff
 iff G iff $S, \text{ iff } \bar{S}$. A iff s and t
 iff $G, \text{ iff } s$ and t .
 iff

Definition 7 (*Dual Graph*). Let G be a planar graph (with an implicit embedding). The dual graph, G^\dagger , is defined as follows. For every face $f \in F(G)$, G^\dagger has a vertex v_f , and any two vertices are adjacent if their corresponding faces share an edge, e . We call the edge between two such vertices the dual edge to e , e^\dagger . By convention, e and e^\dagger will always have the same label, so that if $e = (\{u, v\}, \lambda)$, then $e^\dagger = (\{v_f, v_{f'}\}, \lambda)$ for f and f' the faces of G on either side of the edge e .

2.2 Span Programs and Quantum Query Algorithms

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Definition 8 (*Span Program*). A span program $P = (H, U, \tau, A)$ on $\{0, 1\}^N$ is made up of (I) finite-dimensional inner product spaces $H = H_1 \oplus \dots \oplus H_N$, and $\{H_{j,b} \subseteq H_j\}_{j \in [N], b \in \{0,1\}}$ such that $H_{j,0} + H_{j,1} = H_j$, (II) a vector space U , (III) a non-zero target vector $\tau \in U$, and (IV) a linear operator $A : H \rightarrow U$. For every string $x \in \{0, 1\}^N$, we associate the subspace $H(x) := H_{1,x_1} \oplus \dots \oplus H_{N,x_N}$, and an operator $A(x) := A\Pi_{H(x)}$, where $\Pi_{H(x)}$ is the orthogonal projector onto $H(x)$.

Definition 9 (*Positive and Negative Witness*). Let P be a span program on $\{0, 1\}^N$ and let x be a string $x \in \{0, 1\}^N$. Then we call $|w\rangle$ a positive witness for x in P if $|w\rangle \in H(x)$, and $A|w\rangle = \tau$. We define the positive witness size of x as:

$$w_+(x, P) = w_+(x) = \min\{\| |w\rangle \|^2 : |w\rangle \in H(x), A|w\rangle = \tau\}, \quad (4)$$

if there exists a positive witness for x , and $w_+(x) = \infty$ otherwise. Let $\mathcal{L}(U, \mathbb{R})$ denote the set of linear maps from U to \mathbb{R} . We call a linear map $\omega \in \mathcal{L}(U, \mathbb{R})$ a negative witness for x in P if $\omega A\Pi_{H(x)} = 0$ and $\omega\tau = 1$. We define the negative witness size of x as:

$$w_-(x, P) = w_-(x) = \min\{\|\omega A\|^2 : \omega \in \mathcal{L}(U, \mathbb{R}), \omega A\Pi_{H(x)} = 0, \omega\tau = 1\}, \quad (5)$$

if there exists a negative witness, and $w_-(x) = \infty$ otherwise. If $w_+(x)$ is finite, we say that x is positive (wrt. P), and if $w_-(x)$ is finite, we say that x is negative. We let P_1 denote the set of positive inputs, and P_0 the set of negative inputs for P . In this way, the span program defines a partition (P_0, P_1) of $[N]$.

iff $f : X \rightarrow \{0, 1\}$, iff $X \subseteq \{0, 1\}^N$, iff P decides f iff $f^{-1}(0) \subseteq P_0$
 and $f^{-1}(1) \subseteq P_1$. iff P decides f ,
 iff $x \in X$ iff $\mathcal{O}_x : |i, b\rangle \mapsto |i, b \oplus x_i\rangle$.

Theorem 10 ([21]). Fix $X \subseteq \{0, 1\}^N$ and $f : X \rightarrow \{0, 1\}$, and let P be a span program on $\{0, 1\}^N$ that decides f . Let $W_+(f, P) = \max_{x \in f^{-1}(1)} w_+(x, P)$ and $W_-(f, P) = \max_{x \in f^{-1}(0)} w_-(x, P)$. Then there is a bounded error quantum algorithm that decides f with quantum query complexity $O(\sqrt{W_+(f, P)W_-(f, P)})$.

2.3 Boolean Formulas

Boolean formula	x_1, \dots, x_N	
$\{ \wedge, \vee, \neg \}$		\neg (NOT)
	\wedge (AND) \vee (OR)	fan-in
	depth	
	AND-OR formula	monotone formula
		$\wedge \vee$
AND-OR read-once formula		NOT
		formula, σ
AND-OR read-once formula		
	x_i	
	$x \in \{0, 1\}^N$	
	$\phi, \phi(x)$	ϕ
	$\phi = x_i$	$\phi(x) = x_i$
	ϕ	ϕ_1, \dots, ϕ_l $\phi = \phi_1 \wedge \dots \wedge \phi_l$
	\wedge $\phi = \phi_1 \vee \dots \vee \phi_l$	\vee
	$\phi(x) = \phi_1(x) \wedge \dots \wedge \phi_l(x)$	$\phi(x) = \phi_1(x) \vee \dots \vee \phi_l(x)$
	$\phi = \phi_N$ N	EVAL $_{\phi, n}$
	$x \in \{0, 1\}^N$	$\phi_N(x)$ $\phi(x) = 0$ x 0
	$\phi(x) = 1, x$	$\phi_1 \circ \phi_2$ ϕ_1 ϕ_2
	$\phi_1 : \{0, 1\}^{N_1} \rightarrow \{0, 1\}$ $\phi_2 : \{0, 1\}^{N_2} \rightarrow \{0, 1\}$	$\phi_1 \circ \phi_2 : \{0, 1\}^{N_1 N_2} \rightarrow \{0, 1\}$
	$\phi_1 \circ \phi_2(x) = \phi_1(\phi_2(x^1), \dots, \phi_2(x^{N_1}))$	$x = (x^1, \dots, x^{N_1})$ $x^i \in \{0, 1\}^{N_2}$
		NAND $_d$ NAND $_d$
	d	
	d	
\vee		\wedge
NAND $_d$	NAND $_d$	d NAND $_d$
	NAND $_d$	d
AND	OR	d
NAND $_d$	NAND $_d$	$x \in \{0, 1\}^N$ $N = 2^d$
	NAND $_2(x_1, x_2, x_3, x_4) = (x_1 \wedge x_2) \vee (x_3 \wedge x_4)$	NAND $_d$ 2. NAND $_0$
	A NAND $_d$ $x \in \{0, 1\}^{2^d}$	
	NAND $_d$	x_i
	A	B
1	A	0 B

$\text{st-CONN}_{G,D}$ is a linear-time algorithm for computing the st -connectivity of a graph G with respect to a set of nodes D . The algorithm takes as input a graph G and a set of nodes D , and outputs a binary string x of length $|D|$ such that $x_i = 1$ if and only if s and t are connected in G with respect to D . The algorithm is based on the following observation:

3 Improved Analysis of st -connectivity Algorithm

Let G be a graph with n nodes and m edges. Let $D \subseteq \{0, 1\}^{E(G)}$ be a set of nodes. Let $x \in D$ be a node in D . Let $e \in E(G)$ be an edge in G . Let s and t be nodes in G . Let O_x be a linear operator on \mathbb{R}^E defined by $O_x(e) = |e|b \oplus x_e$. Let $P_{G,c}$ be a linear operator on \mathbb{R}^E defined by $P_{G,c}(e) = \sum_{(u,v,\lambda) \in \vec{E}(G)} \sqrt{c(\{u,v\}, \lambda)} (|u| - |v|) \langle u, v, \lambda \rangle$.

$$\forall e \in \vec{E}(G) : H_{e,0} = \{0\}, \quad H_{e,1} = \text{span}\{|e\rangle\}, \quad H = \text{span}\{|e\rangle : e \in \vec{E}(G)\}$$

$$U = \text{span}\{|u\rangle : u \in V(G)\}, \quad \tau = |s\rangle - |t\rangle, \quad A = \sum_{(u,v,\lambda) \in \vec{E}(G)} \sqrt{c(\{u,v\}, \lambda)} (|u| - |v|) \langle u, v, \lambda \rangle.$$

$$P_{G,c} = \sum_{(u,v,\lambda) \in \vec{E}(G)} \sqrt{c(\{u,v\}, \lambda)} (|u\rangle\langle v| - |v\rangle\langle u|) \langle u, v, \lambda \rangle.$$

$$O \left(\sqrt{\max_{x \in D: s, t \text{ are connected}} R_{s,t}(G(x)) \times |E(G)|} \right).$$

$$O \left(\sqrt{\max_{x \in D: s, t \text{ are connected}} R_{s,t}(G(x)) \times \max_{x \in D: s, t \text{ are not connected}} (C_{s,t}(G(x)))} \right).$$

$$C_{s,t}(G(x)) = \begin{cases} \min_{\kappa: \kappa \text{ is an } st\text{-cut of } G(x)} \sum_{(u,v,\lambda) \in E(G)} |\kappa(u) - \kappa(v)| & \text{if } s \text{ and } t \text{ not connected} \\ \infty & \text{otherwise.} \end{cases}$$

The algorithm runs in time $O(\sqrt{k|V|})$ where k is the number of nodes in D .

$k = |V|$, $O(|V|^{3/2})$
 G is a planar graph with vertices s and t on the same face. \bar{G} is obtained from G by adding an edge $(\{s, t\}, \emptyset)$. \bar{G}^\dagger is the planar dual of \bar{G} . G' is obtained from \bar{G}^\dagger by removing the edge $(\{s, t\}, \emptyset)^\dagger$.



Figure 1: Example of how to derive \bar{G} , \bar{G}^\dagger , and G' from a planar graph G where s and t are on the same face. \bar{G} is obtained from G by adding an edge $(\{s, t\}, \emptyset)$. \bar{G}^\dagger is the planar dual of \bar{G} . (In the diagram labeled by \bar{G}^\dagger , \bar{G} is the gray graph, while \bar{G}^\dagger is black). G' is obtained from \bar{G}^\dagger by removing the edge $(\{s, t\}, \emptyset)^\dagger$. Note that dual edges inherit their labels (in this case 1, 2, 3, 4, \emptyset).

$G(x) \in G$ if $x_e = 1$, $G'(x) \in G'$ if $x_e = 0$.
 $e \in E(G)$, $e \in E(G(x))$ if $x_e = 1$, $e^\dagger \notin E(G'(x))$ if $x_e = 1$.
 $\kappa(v) = 1$ if v is above t , $\kappa(v) = 0$ if v is below t .
 $c'(e^\dagger) = 1/c(e)$.
 $R_{s,t}(G(x), c)$ if s to t in $G(x)$, $R_{s',t'}(G'(x), c')$ if s' to t' in $G'(x)$.

Lemma 11. Let G be a planar multigraph with $s, t \in V(G)$ such that $G \cup \{\{s, t\}\}$ is also planar, and let c be a weight function on $E(G)$. Let $x \in \{0, 1\}^{E(G)}$. Then $w_+(x, P_{G,c}) = \frac{1}{2}R_{s,t}(G(x), c)$ and $w_-(x, P_{G,c}) = 2R_{s',t'}(G'(x), c')$.

Theorem 12. Let G be a planar multigraph with $s, t \in V(G)$ such that $G \cup \{\{s, t\}\}$ is also planar. Then the bounded error quantum query complexity of evaluating $st\text{-CONN}_{G,D}$ is

$$O\left(\min_c \sqrt{\max_{x \in D: st\text{-CONN}_G(x)=1} R_{s,t}(G(x), c) \times \max_{x \in D: st\text{-CONN}_G(x)=0} R_{s',t'}(G'(x), c')}\right) \quad (10)$$

where the minimization is over all positive real-valued functions c on $E(G)$.

$U_{G,c} : |u\rangle|0\rangle \mapsto \frac{1}{\sqrt{\sum_{v,\lambda:(u,v,\lambda) \in \vec{E}(G)} c(\{u,v\}, \lambda)}} \sum_{v,\lambda:(u,v,\lambda) \in \vec{E}(G)} \sqrt{c(\{u,v\}, \lambda)} |u, v, \lambda\rangle.$

Theorem 13. Let $P_{G,c} = (H, U, A, \tau)$ be defined as in (6). Let $S_{G,c}$ be an upper bound on the time complexity of implementing $U_{G,c}$. If G has the property that $G \cup \{s, t\}$ is planar, then the time complexity of deciding $st\text{-CONN}_{G,D}$ is at most

$$O\left(\min_c S_{G,c} \sqrt{\max_{x \in D: s,t \text{ are connected}} R_{s,t}(G(x), c) \times \max_{x \in D: s,t \text{ are not connected}} R_{s',t'}(G'(x), c')}\right).$$

$O(\max\{\log |E(G)|, \log |V(G)|\} + S'_{G,c}).$

3.1 Comparison to Previous Quantum Algorithm

$C_{s,t}(G(x)) = (\text{shortest path length from } s' \text{ to } t' \text{ in } G'(x)) \geq R_{s',t'}(G'(x)).$

$C_{s,t}(G(x)) \leq R_{s',t'}(G(x))$

G is a graph with N nodes and $N+1$ edges. The nodes are arranged in a line from s to t . The edges are $(s, u_1), (u_1, u_2), \dots, (u_{N-1}, u_N), (u_N, t)$. The cost of each edge is $c(e) = N^{-1}$. The set D is defined as $D = \{1^N\} \cup \{x \in \{0, 1\}^N : |x| \leq N - h\}$. The graph G' is a graph with nodes s' and t' . The edges between s' and t' are (s', t') and $(s', u_i), (u_i, t')$ for $i = 1, \dots, h$. The cost of each edge is $c'(e) = 1/h$.

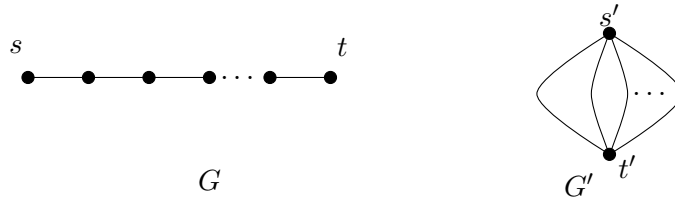


Figure 2: Example of graph for which our analysis does better than the analysis of [4], even with $c = 1$ for all edges, under the promise that $G'(x)$ always contains at least h edges, if s' and t' are connected.

$$\max_{x \in D: st\text{-CONN}_G(x)=1} R_{s,t}(G(x)) = N \quad (14)$$

$$\max_{x \in D: st\text{-CONN}_G(x)=0} R_{s',t'}(G'(x)) \leq 1/h, \quad (15)$$

$$\max_{x \in D: st\text{-CONN}_G(x)=0} C_{s,t}(G(x)) = 1. \quad (16)$$

$$C_{s,t}(G(x)) \leq \frac{1}{N} \quad \text{if } \kappa(u) = 1 \text{ and } \kappa(v) = 0 \text{ for any } (u, v) \in E(G(x)).$$

$$\max_{x \in D: st\text{-CONN}_G(x)=1} R_{s,t}(G(x), c) = 2N, \quad (17)$$

$$\max_{x \in D: st\text{-CONN}_G(x)=0} R_{s',t'}(G'(x), c') \leq 1, \quad (18)$$

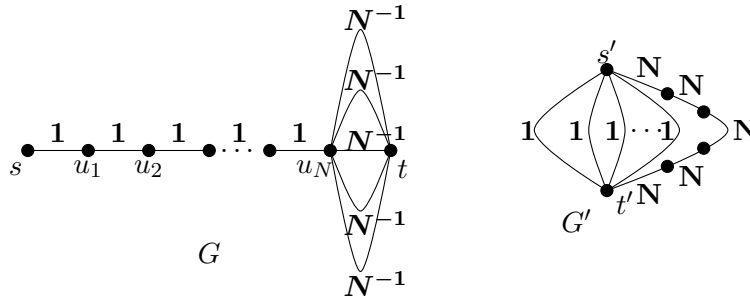


Figure 3: Example of graph for which our analysis does quadratically better than the analysis of [4] by taking advantage of a non-trivial weight function c . The values of c for each edge of G , and of c' for each edge of G' , are shown in boldface.

$$\max_{x \in D: st\text{-CONN}_G(x)=0} C_{s,t}(G(x)) = N \quad (19)$$

$$\max_{x \in D: st\text{-CONN}_G(x)=1} R_{s,t}(G(x)) = N + 1, \quad (20)$$

Our analysis shows that the complexity is $O(N^{1/2})$.

4 AND-OR Formulas and st-Connectivity

AND-OR formulas are represented by graphs G_ϕ . The set of variables $x = (x_1, \dots, x_N)$ is a solution if $O_x(\phi) = 1$. The graph G_ϕ has nodes s and t and edges (s, t, x_i) . The set of solutions is $\{x_i\}_{i \in [N]}$. The graph G_ϕ is a series of graphs $G_{\phi_1}, \dots, G_{\phi_l}$ in series, where $\phi = \phi_1 \wedge \dots \wedge \phi_l$. The graph G_ϕ is a parallel of graphs $G_{\phi_1}, \dots, G_{\phi_l}$ in parallel, where $\phi = \phi_1 \vee \dots \vee \phi_l$.

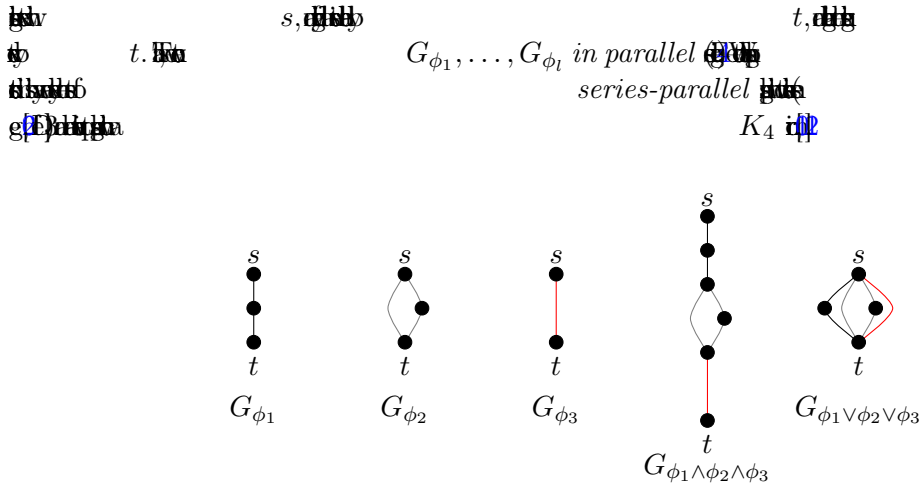


Figure 4: Let $\phi_1 = x_1 \wedge x_2$, $\phi_2 = x_3 \vee (x_4 \wedge x_5)$, and $\phi_3 = x_6$. Then we obtain $G_{\phi_1 \wedge \phi_2 \wedge \phi_3}$ by connecting G_{ϕ_1} , G_{ϕ_2} , and G_{ϕ_3} in series, and $G_{\phi_1 \vee \phi_2 \vee \phi_3}$ by connecting them in parallel.

Let ϕ be any AND-OR formula on N variables. For every $x \in \{0, 1\}^N$, there exists a path from s to t in $G_\phi(x)$ if and only if $\phi(x) = 1$. Furthermore, for every $x \in \{0, 1\}^N$, there exists a path from s' to t' in $G'_\phi(x)$ if and only if $\phi(x) = 0$.

Lemma 14. Let ϕ be any AND-OR formula on N variables. For every $x \in \{0, 1\}^N$, there exists a path from s to t in $G_\phi(x)$ if and only if $\phi(x) = 1$. Furthermore, for every $x \in \{0, 1\}^N$, there exists a path from s' to t' in $G'_\phi(x)$ if and only if $\phi(x) = 0$.

Let $\phi = \phi_1 \vee \dots \vee \phi_l$ (OR) or $\phi = \phi_1 \wedge \dots \wedge \phi_l$ (AND). In $G_\phi(x)$, if $\phi(x) = 1$, then there is a path from s to t . If $\phi(x) = 0$, then there is no path from s to t in $G_\phi(x)$. In $G'_\phi(x)$, if $\phi(x) = 0$, then there is a path from s' to t' . If $\phi(x) = 1$, then there is no path from s' to t' in $G'_\phi(x)$. This is the EVAL $_\phi$ problem.

Theorem 15. For any family ϕ of AND-OR formulas, the bounded error quantum query complexity of EVAL $_\phi$ when the input is promised to come from a set D is

$$O\left(\min_c \sqrt{\max_{x \in D: \phi(x)=1} R_{s,t}(G_\phi(x), c) \times \max_{x \in D: \phi(x)=0} R_{s',t'}(G'_\phi(x), c')}\right), \quad (21)$$

where the minimization is over all positive real-valued functions c on $E(G_\phi)$.

Proof. By Lemma 14, the query complexity of EVAL $_\phi$ on D is at most the query complexity of st -CONN $_{G_\phi, D}$. Since G_ϕ is planar, and has s and t on the same face, we can apply Theorem 12, which immediately implies the result. \square

4.1 Comparison to Existing Boolean Formula Algorithms

Definition 16.

is $O(\sqrt{N})$ queries.

N

Theorem 16. Let ϕ be a read-once formula on N variables. Then there exists a choice of c on $E(G_\phi)$ such that the quantum algorithm obtained from the span program $P_{G_\phi, c}$ computes EVAL_ϕ with bounded error in $O(\sqrt{N})$ queries.

Lemma 17.

Claim 17. If $\phi = \phi_1 \vee \phi_2 \vee \dots \vee \phi_l$, then $G'_\phi(x)$ is formed by composing $\{G'_{\phi_i}(x)\}_i$ in series, and if $\phi = \phi_1 \wedge \phi_2 \wedge \dots \wedge \phi_l$, then $G'_\phi(x)$ is formed by composing $\{G'_{\phi_i}(x)\}_i$ in parallel.

Lemma 18.

6 G_ϕ , is the span

G'_ϕ is the

G'_ϕ

is the span

an ϕ on N variables

ϕ' on N variables

h \vee ϕ \wedge

\wedge ϕ \vee

h $x \in \{0, 1\}^N$, $\phi(x) = \neg\phi'(\bar{x})$, \bar{x} is the

x . \bar{x} is the

is $G'_\phi = G'_{\phi'}$

x , $G'_\phi(\bar{x}) = G'_{\phi'}(x)$

Proof of Theorem 16. We will make use of the following fact: for any network (G, c) , and any positive real number W :

$$R_{s,t}(G, c/W) = \min_{\theta} \sum_{e \in E(G)} \frac{\theta(e)^2}{c(e)/W} = W \min_{\theta} \sum_{e \in E(G)} \frac{\theta(e)^2}{c(e)} = WR_{s,t}(G, c). \quad (22)$$

We now proceed with the proof. For any formula ϕ in $\{\wedge, \vee, \neg\}$, by repeated applications of de Morgan's law, we can push all NOT-gates to distance-1 from a leaf. Since x_i and $\neg x_i$ can both be learned in one query, we can restrict our attention to AND-OR formulas.

If ϕ has only $N = 1$ variable, it's easy to see that $W_+(P_{G_\phi, c})W_-(P_{G_\phi, c}) \leq N$ for c taking value 1 on the single edge in G_ϕ . We will prove by induction that this is true for any ϕ , for some choice of c , completing the proof, since the complexity of our algorithm obtained from $P_{G_\phi, c}$ is $O(\sqrt{W_+(P_{G_\phi, c})W_-(P_{G_\phi, c})})$.

Suppose $\phi = \phi_1 \wedge \dots \wedge \phi_l$ for formulas ϕ_i on N_i variables, so ϕ has $N = \sum_i N_i$ variables. For $x \in \{0, 1\}^N$, we will let $x^i \in \{0, 1\}^{N_i}$ denote the $(N_1 + \dots + N_{i-1} + 1)$ -th to $(N_1 + \dots + N_i)$ -th bits of x . For each G_{ϕ_i} , by the induction hypothesis, there is some weight function c_i on $E(G_{\phi_i})$ such that $W_+(P_{G_{\phi_i}, c_i})W_-(P_{G_{\phi_i}, c_i}) \leq N_i$.

Using our construction, G_ϕ is formed by composing $\{G_{\phi_i}\}_i$ in series. Thus every edge $(\{u, v\}, \lambda) \in E(G_\phi)$ corresponds to an edge $(\{u, v\}, \lambda) \in E(G_{\phi_i})$ for some i . We create a weight function $c : E(G_\phi) \rightarrow \mathbb{R}^+$ such that $c(\{u, v\}, \lambda) = \frac{c_i(\{u, v\}, \lambda)}{W_-(P_{G_{\phi_i}, c_i})}$ if $(\{u, v\}, \lambda)$ is an edge originating from the graph G_{ϕ_i} . That is, our new weight function is the same as combining all of the old weight functions, up to scaling factors $\{W_-(P_{G_{\phi_i}, c_i})\}_i$.

Using Lemma 11, Claim 5, and Eq. (22), for any 1-instance x ,

$$\begin{aligned} w_+(x, P_{G_\phi, c}) &= \frac{1}{2} R_{s,t}(G_\phi(x), c) = \frac{1}{2} \sum_{i=1}^l R_{s,t} \left(G_{\phi_i}(x), \frac{c_i}{W_-(P_{G_{\phi_i}, c_i})} \right) \\ &= \frac{1}{2} \sum_{i=1}^l W_-(P_{G_{\phi_i}, c_i}) R_{s,t}(G_{\phi_i}(x), c_i) \leq \sum_{i=1}^l W_-(\phi_i, P_{G_{\phi_i}, c_i}) W_+(P_{G_{\phi_i}, c_i}). \end{aligned} \quad (23)$$

Thus

$$W_+(P_{G_\phi, c}) \leq \sum_{i=1}^l W_-(P_{G_{\phi_i, c_i}}) W_+(P_{G_{\phi_i, c_i}}) \leq \sum_{i=1}^l N_i = N. \quad (24)$$

Recall that for a weight function c on G_ϕ , we define a weight function c' on G'_ϕ by $c'(e^\dagger) = 1/c(e)$. Then for an edge $e \in E(G_{\phi_i}(x^i))$, we have $c'(e^\dagger) = W_-(P_{G_{\phi_i, c_i}})/c_i(e) = W_-(P_{G_{\phi_i, c_i}})c'_i(e^\dagger)$. By Claim 17, G'_ϕ is formed by composing $\{G'_{\phi_i}\}_i$ in parallel, so by Lemma 11, Claim 5, and Eq. (22):

$$\begin{aligned} w_-(x, P_{G_\phi, c}) &= 2R_{s', t'}(G'_\phi(x), c') = 2 \left(\sum_{i=1}^l \frac{1}{R_{s', t'}(G'_{\phi_i}(x^i), c')} \right)^{-1} \\ &= 2 \left(\sum_{i=1}^l \frac{1}{R_{s', t'}(G'_{\phi_i}(x^i), W_-(P_{G_{\phi_i, c_i}})c'_i)} \right)^{-1} = 2 \left(\sum_{i=1}^l \frac{W_-(P_{G_{\phi_i, c_i}})}{R_{s', t'}(G'_{\phi_i}(x^i), c'_i)} \right)^{-1} \\ &= 2 \left(\sum_{i=1}^l \frac{W_-(P_{G_{\phi_i, c_i}})}{w_-(x^i, P_{G_{\phi_i, c_i}})} \right)^{-1}. \end{aligned} \quad (25)$$

Whenever x is a 0-instance of ϕ , the set $S \subseteq [l]$ of i such that x^i is a 0-instance of ϕ_i is non-empty. This is exactly the set of i such that $w_-(x^i, P_{G_{\phi_i, c_i}}) < \infty$. Continuing from above, we have:

$$w_-(x, P_{G_\phi, c}) = \left(\sum_{i \in S} \frac{W_-(P_{G_{\phi_i, c_i}})}{w_-(x^i, P_{G_{\phi_i, c_i}})} \right)^{-1} \leq \left(\sum_{i \in S} \frac{W_-(P_{G_{\phi_i, c_i}})}{W_-(P_{G_{\phi_i, c_i}})} \right)^{-1} = \frac{1}{|S|} \leq 1. \quad (26)$$

Thus $W_-(P_{G_{\phi_i, c_i}}) \leq 1$. Combining this with Eq. (24) we have $W_+(P_{G_\phi, c})W_-(P_{G_\phi, c}) \leq N$, as desired.

The proof for the case $\phi = \phi_1 \vee \dots \vee \phi_l$ is similar. \square

References

Corollary 18. *Deciding st-connectivity on subgraphs of two-terminal series-parallel graphs of N edges can be accomplished using $O(\sqrt{N})$ queries, if s and t are chosen to be the two terminal nodes.*

Appendix

Graphs

Graphs with terminals

Graphs with terminals

Graphs

$$\begin{aligned} \text{AND-OR} & \quad N, h \in \mathbb{Z}^+, \quad D_{N,h} = \{x \in \{0, 1\}^N : |x| = N \text{ or } |x| \leq N - h\} \\ \text{AND-OR} & \quad D'_{N,h} = \{x \in \{0, 1\}^N : |x| = 0 \text{ or } |x| \geq h\}. \\ \text{AND} & \quad \text{AND}_{D_{N,h}} \quad \text{AND}_{D'_{N,h}} \\ \text{OR} & \quad \text{OR}_{D_{N,h}} \quad \text{OR}_{D'_{N,h}} \\ \text{OR} & \quad 1, \quad h. \end{aligned}$$

Graphs

Graphs

Graphs

Theorem 19. Let $\phi = \phi_1 \circ \phi_2 \circ \dots \circ \phi_l$, where for each $i \in [l]$, $\phi_i = \text{OR}|_{D_{N_i, h_i}}$ or $\phi_i = \text{AND}|_{D_{N_i, h_i}}$. Then the randomized bounded-error query complexity of evaluating ϕ is $\Omega\left(\prod_{i=1}^l N_i/h_i\right)$, and the bounded-error quantum query complexity of evaluating ϕ is $O\left(\prod_{i=1}^l \sqrt{N_i/h_i}\right)$.

Lemma 19.1. Let $D_1 \subseteq \{0, 1\}^{N_1}$ and $D_2 \subseteq \{0, 1\}^{N_2}$, $\phi = \phi_1 \circ \phi_2$ with $x = (x^1, \dots, x^{N_1}) \in \{0, 1\}^{N_1}$ and $x^i \in D_2$ for $i \in [N_1]$, and $(\phi_2(x^1), \dots, \phi_2(x^{N_1})) \in D_1$.

$$\frac{\prod_{i=1}^l N_i}{\prod_{i=1}^l h_i} = \left(\max_{x \in D: \phi(x)=1} R_{s,t}(G_\phi(x)) \right) \left(\max_{x \in D: \phi(x)=0} R_{s,t}(G'_\phi(x)) \right), \quad (27)$$

Lemma 19.2. Let $\phi = \text{AND}|_{D_{N,h}}$ and $\phi = \text{OR}|_{D_{N,h}}$. Then the randomized bounded-error query complexity of evaluating ϕ is $\Omega(N/h)$ and the bounded-error quantum query complexity of evaluating ϕ is $O(\sqrt{N/h})$.

5 NAND-tree Results

5.1 Query Separations

Theorem 20. Using the st -connectivity approach to formula evaluation (Theorem 15), one can solve $\text{EVAL}_{\text{NAND}_d}$ when the input is promised to be from $F_{\log d}^d$ with $O(d)$ queries, while any classical algorithm requires $\Omega(d^{\log \log(d)})$ queries.

Theorem 21. Consider the problem $st\text{-CONN}_{G_{\text{NAND}_d}, F_1^d}$. The analysis of [4] gives a bound of $O(N^{1/4})$ quantum queries to decide this problem (where $N = 2^d$ is the number of edges in G_{NAND_d}), while our analysis shows this problem can be decided with $O(1)$ quantum queries.

Theorem 21.1. Consider the problem $st\text{-CONN}_{G_{\text{NAND}_d}, F_1^d}$. The analysis of [4] gives a bound of $O(N^{1/4})$ quantum queries to decide this problem (where $N = 2^d$ is the number of edges in G_{NAND_d}), while our analysis shows this problem can be decided with $O(1)$ quantum queries.

NAND_d . If $x \in \{0, 1\}^{2^d}$, then $G_{\text{NAND}_d}(x) \leq G'_{\text{NAND}_d}(x)$. For $x \in \{0, 1\}^{2^d}$, let Z be the set of x such that $\nu_Z(x) > 0$. For $x \in Z$, let $\mathcal{P}_A(x)$ and $\mathcal{P}_B(x)$ be the sets of paths from the root to the leaves. For $x \in Z$, let $\nu_Z(p)$ be the number of paths in $\mathcal{P}_Z(x)$ that contain p . For $x \in Z$, let $\nu_A(p)$ and $\nu_B(p)$ be the number of paths in $\mathcal{P}_A(x)$ and $\mathcal{P}_B(x)$ that contain p , respectively. For $x \in Z$, let $f_Z(p)$ be the number of faults in p . For $x \in Z$, let $\mathcal{F}(x) = \min\{\mathcal{F}_A(x), \mathcal{F}_B(x)\}$. For $x \notin Z$, let $\mathcal{F}(x) = \infty$.

$$\mathcal{F}_Z(x) = \begin{cases} 2^{\max_{p \in \mathcal{P}_Z(x)} f_Z(p)} & \text{if } x \text{ is } Z\text{-winnable} \\ \infty & \text{otherwise.} \end{cases} \quad (28)$$

For $k = 0, \dots, d/2$, let F_k^d be the set of $x \in \{0, 1\}^{2^d}$ such that $\log \mathcal{F}(x) \leq k$.

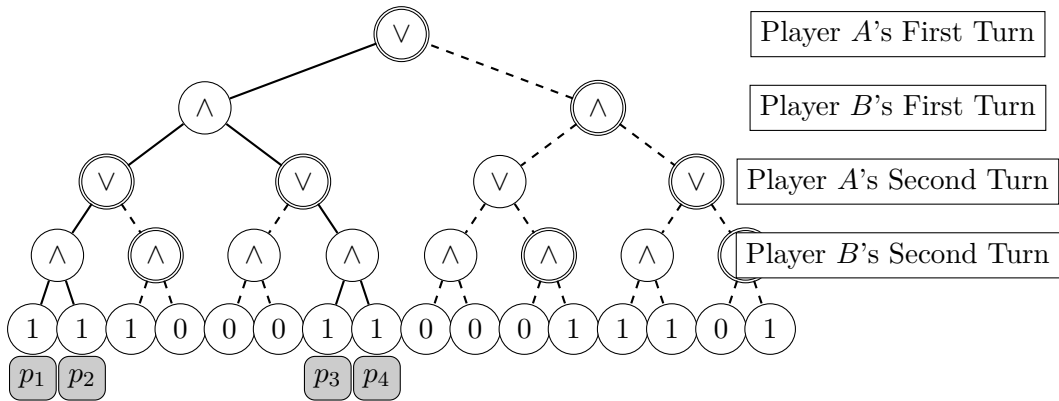


Figure 5: Depiction of a depth-4 NAND-tree as a two-player game. Let x be the input to NAND_4 shown in the figure. This instance is A -winnable, and $\mathcal{P}_A(x)$ consists of the paths $\{p_1, p_2, p_3, p_4\}$, shown using solid lines. Fault nodes are those with double circles. Each path in $\mathcal{P}_A(x)$ encounters two faults at nodes where Player A makes decisions. Therefore, $\mathcal{F}_A(x) = 4$.

$\mathcal{F}(x)$: $G_{\text{NAND}_d}(x) \leq G'_{\text{NAND}_d}(x)$

¹We have actually used the more refined definition of k -fault from [19].

Lemma 22. For any $x \in \{0, 1\}^{2^d}$, if d is even, then we have $R_{s,t}(G_{\text{NAND}_d}(x)) \leq \mathcal{F}_A(x)$ and $R_{s',t'}(G'_{\text{NAND}_d}(x)) \leq \mathcal{F}_B(x)$, while if d is odd, we have $R_{s,t}(G_{\text{NAND}_d}(x)) \leq 2\mathcal{F}_A(x)$ and $R_{s',t'}(G'_{\text{NAND}_d}(x)) \leq 2\mathcal{F}_B(x)$.

Corollary 23. The span program P_{G_ϕ} for $\phi = \text{NAND}_d$ decides $\text{EVAL}_{\text{NAND}_d}$ restricted to the domain X in $O(\max_{x \in X} \mathcal{F}(x))$ queries. In particular, it decides k -fault trees (on domain F_k^d) in $O(2^k)$ queries.

Proof of Theorem 20. Theorem 20 is now an immediate consequence of Corollary 23, with k set to $\log(d)$, along with the fact from [27] that the classical query complexity of evaluating such formulas is $\Omega(d^{\log \log(d)})$. \square

Claim 24. Let two graphs G_1 and G_2 each have nodes s and t and let $x^1 \in \{0, 1\}^{E(G_1)}$ and $x^2 \in \{0, 1\}^{E(G_2)}$. Suppose we create a new graph G by identifying the s nodes and the t nodes (i.e. connecting the graphs in parallel), then

$$C_{s,t}(G(x^1, x^2)) = C_{s,t}(G_1(x^1)) + C_{s,t}(G_2(x^2)) \quad (29)$$

If we create a new graph G by identifying the t node of G_1 with the s node of G_2 and relabeling this node $v \notin \{s, t\}$ (i.e. connecting the graphs in series), then

$$C_{s,t}(G(x^1, x^2)) = \min\{C_{s,t}(G_1(x^1)), C_{s,t}(G_2(x^2))\}. \quad (30)$$

Proof of Theorem 21. Using Corollary 23, our analysis shows that $st\text{-CONN}_{G_{\text{NAND}_d}, F_1^d}$ can be decided in $O(1)$ queries.

We apply Eq. (8) to compare to the analysis of [4]. We must characterize the quantity $\max\{C_{s,t}(G_{\text{NAND}_d}(x)) : x \in F_1^d, \text{ and } s, t \text{ are not connected}\}$, since we already have

$$\max_{x \in F_1^d : s, t \text{ are connected}} R_{s,t}(G(x)) = O(1). \quad (31)$$

We now prove that for every $x \in \{0, 1\}^{2^d}$ such that $\text{NAND}_d(x) = 0$, $C_{s,t}(G_{\text{NAND}_d}(x)) = 2^{\lfloor d/2 \rfloor}$. Thus, for any promise D on the input, as long as there exists some $x \in D$ such that $\text{NAND}_d(x) = 0$, we have $\max_{x \in D : \text{NAND}_d(x) = 0} C_{s,t}(G_{\text{NAND}_d}(x)) = 2^{\lfloor d/2 \rfloor}$. Intuitively, this is because every st -cut on any subgraph of G_{NAND_d} cuts across $2^{\lfloor d/2 \rfloor}$ edges of G_{NAND_d} .

The proof is by induction on d . For the base even case, $d = 0$ and G_{NAND_0} is a single edge connecting s and t . The only input $x \in \{0, 1\}^{2^0}$ such that $\text{NAND}_d(x) = 0$ is $x = 0$, in which case, the st -cut is $\kappa(s) = 1$ and $\kappa(t) = 0$, so the cut is across the unique edge in G_{NAND_0} , so $C_{s,t}(G_{\text{NAND}_0}(x)) = 1$.

For the induction step, we treat even and odd separately. Suppose $d > 0$ is odd. Then $\text{NAND}_d(x) = \text{NAND}_{d-1}(x^0) \wedge \text{NAND}_{d-1}(x^1)$, where $x^0 = (x_1, \dots, x_{2^{d-1}})$ and $x^1 = (x_{2^{d-1}+1}, \dots, x_{2^d})$. Thus $G_{\text{NAND}_d}(x)$ involves composing two graphs $G_{\text{NAND}_{d-1}}(x^0)$ and $G_{\text{NAND}_{d-1}}(x^1)$ in series. Since we are assuming s and t are not connected in $G_{\text{NAND}_d}(x)$, at least one of $G_{\text{NAND}_{d-1}}(x^0)$ and $G_{\text{NAND}_{d-1}}(x^1)$ must not be connected. Without loss of generality, suppose $G_{\text{NAND}_{d-1}}(x^0)$ is not connected and $C_{s,t}(G_{\text{NAND}_{d-1}}(x^0)) \leq C_{s,t}(G_{\text{NAND}_{d-1}}(x^1))$. By induction, $C_{s,t}(G_{\text{NAND}_{d-1}}(x^0)) = 2^{(d-1)/2}$. Thus using Eq. (30) in Claim 24,

$$C_{s,t}(G_{\text{NAND}_d}(x)) = 2^{(d-1)/2} = 2^{\lfloor d/2 \rfloor}. \quad (32)$$

Now suppose $d > 0$ is even. Then $\text{NAND}_d(x) = \text{NAND}_{d-1}(x^0) \vee \text{NAND}_{d-1}(x^1)$. Thus $G_{\text{NAND}_d}(x)$ involves composing two graphs $G_{\text{NAND}_{d-1}}(x^0)$ and $G_{\text{NAND}_{d-1}}(x^1)$ in parallel. Since we are assuming s and t are not connected in $G_{\text{NAND}_d}(x)$, both of $G_{\text{NAND}_{d-1}}(x^0)$ and $G_{\text{NAND}_{d-1}}(x^1)$ must not be connected, and so by induction, we have $C_{s,t}(G_{\text{NAND}_{d-1}}(x^0)) = C_{s,t}(G_{\text{NAND}_{d-1}}(x^1)) = 2^{\lfloor (d-1)/2 \rfloor} = 2^{d/2-1}$, since d is even. Thus using Eq. (29) in Claim 24,

$$C_{s,t}(G_{\text{NAND}_d}(x)) = 2^{d/2-1} + 2^{d/2-1} = 2^{d/2} = 2^{\lfloor d/2 \rfloor}. \quad (33)$$

Therefore, using Eq. (8), we have that the analysis of [4] for d -depth NAND-trees with inputs in F_1^d gives a query complexity of $O(\sqrt{2^{\lfloor d/2 \rfloor}}) = O(N^{1/4})$, where $N = 2^d$ is the number of input variables. Comparing with our analysis, which gives a query complexity of $O(1)$, we see there is a polynomial to constant improvement. \square

5.2 Winning the NAND-tree Game

Let ϕ be an AND-OR formula with constant fan-in l , \vee -depth d_\vee and \wedge -depth d_\wedge . Then the quantum query complexity of estimating $R_{s,t}(G_\phi(x))$ (resp. $R_{s,t}(G'_\phi(x))$) to relative accuracy ϵ is $\tilde{O}\left(\frac{1}{\epsilon^{3/2}} \sqrt{R_{s,t}(G_\phi(x)) l^{d_\vee}}\right)$ (resp. $\tilde{O}\left(\frac{1}{\epsilon^{3/2}} \sqrt{R_{s,t}(G'_\phi(x)) l^{d_\wedge}}\right)$).

$$O\left(2 \sum_{i=0}^{\frac{d}{2}} 2^{\frac{d-2i}{2}} \log d\right) = O\left(2 \sum_{i=0}^{\frac{d}{2}} 2^i \log d\right) = O\left(2^{\frac{d}{2}} \log d\right) = O\left(\sqrt{N} \log \log N\right). \quad (34)$$

Let ϕ be an AND-OR formula with constant fan-in l , \vee -depth d_\vee and \wedge -depth d_\wedge . Then the quantum query complexity of estimating $R_{s,t}(G_\phi(x))$ (resp. $R_{s,t}(G'_\phi(x))$) to relative accuracy ϵ is $\tilde{O}\left(\frac{1}{\epsilon^{3/2}} \sqrt{R_{s,t}(G_\phi(x)) l^{d_\vee}}\right)$ (resp. $\tilde{O}\left(\frac{1}{\epsilon^{3/2}} \sqrt{R_{s,t}(G'_\phi(x)) l^{d_\wedge}}\right)$).

Lemma 25 (Est Algorithm). *Let ϕ be an AND-OR formula with constant fan-in l , \vee -depth d_\vee and \wedge -depth d_\wedge . Then the quantum query complexity of estimating $R_{s,t}(G_\phi(x))$ (resp. $R_{s,t}(G'_\phi(x))$) to relative accuracy ϵ is $\tilde{O}\left(\frac{1}{\epsilon^{3/2}} \sqrt{R_{s,t}(G_\phi(x)) l^{d_\vee}}\right)$ (resp. $\tilde{O}\left(\frac{1}{\epsilon^{3/2}} \sqrt{R_{s,t}(G'_\phi(x)) l^{d_\wedge}}\right)$).*

$\epsilon = \frac{1}{3}, d \quad \phi = \text{NAND}_d, s \quad l = 2, d$
 $d \vee d \quad d \wedge d \quad [d/2].$
 $\text{Est}(x)$
 $\text{Est}(x)$
 $\text{Est}(x)$
 $x \in \{0, 1\}^{2^d}$
 $\{0, 1\}^{2^{d-1}}$
 $\bar{b} = b \oplus 1.$ **Select**
 $\text{Est}(x^b)$
 $p(d)\sqrt{w_b}2^{d/4}$
 $b.$
 $\text{Est}(x^0)$
 $\text{Est}(x^1)$
 w_b
 x^b
 b
 $w_b \leq w_{\bar{b}}.$

Lemma 26. Let $x^0, x^1 \in \{0, 1\}^{2^d}$ be instances of NAND_d with at least one of them a 1-instance. Let $N = 2^d$, and $w_{\min} = \min\{R_{s,t}(G_{\text{NAND}_d}(x^0)), R_{s,t}(G_{\text{NAND}_d}(x^1))\}$. Then **Select** (x^0, x^1) terminates after $\tilde{O}(N^{1/4}\sqrt{w_{\min}})$ queries to (x^0, x^1) and outputs b such that $R_{s,t}(G_{\text{NAND}_d}(x^b)) \leq 2R_{s,t}(G_{\text{NAND}_d}(x^{\bar{b}}))$ with bounded error.

Game Theory

Theorem 27. Let $x \in \{0, 1\}^N$ for $N = 2^d$ be an A -winnable input to NAND_d . At every node v where Player A makes a decision, let Player A use the **Select** algorithm in the following way. Let v_0 and v_1 be the two children of v , with inputs to the respective subtrees of v_0 and v_1 given by x^0 and x^1 respectively. Then Player A moves to v_b where b is the outcome that occurs a majority of times when **Select** (x^0, x^1) is run $O(\log d)$ times. Then if Player B , at his decision nodes, chooses left and right with equal probability, Player A will win the game with probability at least $2/3$, and will use $\tilde{O}(N^{1/4}\sqrt{R_{s,t}(G_{\text{NAND}_d}(x))})$ queries on average, where the average is taken over the randomness of Player B 's choices.

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A Analysis of the Span Program for st -Connectivity

[arXiv:1608.03389v1 \[quant-ph\]](#) $P_{G,c}$
 G .
 k

Definition 28 (Circulation). *A circulation on a graph G is a function $\theta : \vec{E}(G) \rightarrow \mathbb{R}$ such that:*

1. For all $(u, v, \lambda) \in \vec{E}(G)$, $\theta(u, v, \lambda) = -\theta(v, u, \lambda)$;
2. for all $u \in V(G)$, $\sum_{v, \lambda: (u, v, \lambda) \in \vec{E}(G)} \theta(u, v, \lambda) = 0$.

[arXiv:1608.03389v1 \[quant-ph\]](#)
 θ

Claim 29. *Let θ be a unit st -flow in some multigraph G . We can consider the corresponding vector $|\theta\rangle = \sum_{(u, v, \lambda) \in \vec{E}(G)} \theta(u, v, \lambda) |u, v, \lambda\rangle$. Then $|\theta\rangle$ can be written as a linear combination*

of vectors corresponding to self-avoiding st -paths and cycles that are edge-disjoint from these paths.

Let σ be a circulation on G . Then $|\sigma\rangle$ can be written as a linear combination of cycles in G . Furthermore, $|\sigma\rangle$ can be written as a linear combination of cycles such that each cycle goes around a face of G .

~~Abstract~~

~~stflow~~

Claim 30. Fix a span program $P_{G,c}$ as in (6). Call $|w\rangle \in H$ a positive witness in $P_{G,c}$ if $A|w\rangle = \tau$ (note that such a $|w\rangle$ is not necessarily a positive witness for any particular input x). Then if θ is a unit st -flow in G , $\frac{1}{2} \sum_{(u,v,\lambda) \in \vec{E}(G)} \frac{\theta(u,v,\lambda)}{\sqrt{c(\{u,v\},\lambda)}} |u,v,\lambda\rangle$ is a positive witness in $P_{G,c}$, and furthermore, if $|w\rangle$ is a positive witness in $P_{G,c}$, then $\theta(u,v,\lambda) = \sqrt{c(\{u,v\},\lambda)}(\langle w|u,v,\lambda\rangle - \langle w|v,u,\lambda\rangle)$ is a unit st -flow in G .

Proof. The proof is a straightforward calculation. Let θ be a unit st -flow on G . Then

$$\begin{aligned}
& A \left(\frac{1}{2} \sum_{(u,v,\lambda) \in \vec{E}(G)} \frac{\theta(u,v,\lambda)}{\sqrt{c(\{u,v\},\lambda)}} |u,v,\lambda\rangle \right) \\
&= \frac{1}{2} \sum_{(u,v,\lambda) \in \vec{E}(G)} \theta(u,v,\lambda) (|u\rangle - |v\rangle) \\
&= \frac{1}{2} \sum_{u \in V(G)} \left(\sum_{v,\lambda:(u,v,\lambda) \in \vec{E}(G)} \theta(u,v,\lambda) \right) |u\rangle + \frac{1}{2} \sum_{v \in V(G)} \left(\sum_{u,\lambda:(v,u,\lambda) \in \vec{E}(G)} \theta(v,u,\lambda) \right) |v\rangle \\
&= \frac{1}{2} (|s\rangle - |t\rangle) + \frac{1}{2} (|s\rangle - |t\rangle) = \tau. \tag{35}
\end{aligned}$$

Above we have used that $\theta(u,v,\lambda) = -\theta(v,u,\lambda)$, and $\sum_{v,\lambda:(u,v,\lambda) \in \vec{E}(G)} \theta(u,v,\lambda) = 0$ when $u \notin \{s,t\}$, 1 when $u = s$, and -1 when $u = t$.

To prove the second half of the claim, let $|w\rangle$ be such that $A|w\rangle = \tau$, and define $\theta(u,v,\lambda) = \sqrt{c(\{u,v\},\lambda)}(\langle w|u,v,\lambda\rangle - \langle w|v,u,\lambda\rangle)$. We immediately see that $\theta(u,v,\lambda) = -\theta(v,u,\lambda)$ for all (u,v,λ) . Furthermore, we have:

$$\begin{aligned}
|s\rangle - |t\rangle = A|w\rangle &= \sum_{u \in V(G)} \left(\sum_{(u,v,\lambda) \in \vec{E}(G)} \sqrt{c(\{u,v\},\lambda)} \langle u,v,\lambda|w\rangle \right) |u\rangle \\
&\quad - \sum_{v \in V(G)} \left(\sum_{(u,v,\lambda) \in \vec{E}(G)} \sqrt{c(\{u,v\},\lambda)} \langle u,v,\lambda|w\rangle \right) |v\rangle \\
&= \sum_{u \in V(G)} \left(\sum_{(u,v,\lambda) \in \vec{E}(G)} \sqrt{c(\{u,v\},\lambda)} (\langle u,v,\lambda|w\rangle - \langle v,u,\lambda|w\rangle) \right) |u\rangle \\
&= \sum_{u \in V(G)} \left(\sum_{(u,v,\lambda) \in \vec{E}(G)} \theta(u,v,\lambda) \right) |u\rangle. \tag{36}
\end{aligned}$$

Thus, for all $u \in V(G(x)) \setminus \{s,t\}$, $\sum_{(u,v,\lambda) \in \vec{E}(G)} \theta(u,v,\lambda) = 0$, and $\sum_{(s,v,\lambda) \in \vec{E}(G)} \theta(s,v,\lambda) = \sum_{(v,t,\lambda) \in \vec{E}(G)} \theta(v,t,\lambda) = 1$. Thus, θ is a unit st -flow on G . \square

~~Abstract~~

~~s'tflow~~

Claim 31. For a planar graph G , fix a span program $P_{G,c}$ as in (6). Call a linear function $\omega : V(G) \rightarrow \mathbb{R}$ a negative witness if $\omega\tau = 1$. Then $\theta((u, v, \lambda)^\dagger) = \omega(u) - \omega(v)$ is a unit $s't'$ -flow on G' , and furthermore, for every $s't'$ -flow θ on G' there is a negative witness ω such that $\theta((u, v, \lambda)^\dagger) = \omega(u) - \omega(v)$ for all $(u, v, \lambda) \in \vec{E}(G)$.

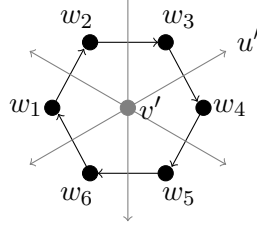


Figure 6: The duality between a cycle and a star.

Proof. When we consider the edges of G as directed edges, we assign edge directions to the dual by orienting each dual edge $\pi/2$ radians counter-clockwise from the primal edge.

Note that without loss of generality, if ω is a negative witness, we can assume $\omega(s) = 1$ and $\omega(t) = 0$. This is because $\|\omega A\|$ and $\|\omega A \Pi_{H(x)}\|$ are invariant under affine transformations of ω .

We first show that if ω is a negative witness in $P_{G,c}$, then $\theta : \vec{E}(G') \rightarrow \mathbb{R}$ defined $\theta((u, v, \lambda)^\dagger) = \omega(u) - \omega(v)$ is a unit $s't'$ -flow on G' . To begin with, we will define $\theta'((u, v, \lambda)^\dagger) = \omega(u) - \omega(v)$ on $\vec{E}(\overline{G}^\dagger)$, so θ' agrees with θ everywhere θ is defined, and in addition, $\theta'(s', t', \emptyset) = \theta'((s, t, \emptyset)^\dagger) = \omega(s) - \omega(t) = 1$, and $\theta'(t', s', \emptyset) = -1$. Then clearly we have $\theta'(u', v', \lambda) = -\theta'(v', u', \lambda)$ for all $(\{u', v'\}, \lambda) \in E(\overline{G}^\dagger)$.

Next, every $v' \in V(\overline{G}^\dagger)$ corresponds to a face $f_{v'}$ of \overline{G} , and the edges coming out of v' are dual to edges going clockwise around the face $f_{v'}$ (see Figure 6). If $(w_1, w_2, \lambda_1), \dots, (w_k, w_{k+1}, \lambda_k)$, for $w_{k+1} = w_1$, are the directed edges going clockwise around $f_{v'}$, then we have:

$$0 = \sum_{i=1}^k (\omega(w_i) - \omega(w_{i+1})) = \sum_{i=1}^k \theta'((w_i, w_{i+1}, \lambda_i)^\dagger) = \sum_{\substack{u', \lambda: \\ (\{v', u'\}, \lambda) \in E(\overline{G}^\dagger)}} \theta'(v', u', \lambda). \quad (37)$$

Thus, θ' is a circulation. Then, since $\theta'(s', t', \emptyset) = 1$, if we remove the flow on this edge, which recovers θ , we get a unit $s't'$ -flow on G' .

Next we will show that if θ is a unit $s't'$ -flow on G' , then there exists a negative witness ω in $P_{G,c}$ such that for all $(u, v, \lambda) \in \vec{E}(G)$, $\theta((u, v, \lambda)^\dagger) = \omega(u) - \omega(v)$.

Define θ' to be the circulation on \overline{G}^\dagger obtained from defining $\theta'(u', v', \lambda) = \theta(u', v', \lambda)$ for all $(u', v', \lambda) \in \vec{E}(G')$, and $\theta'(s', t', \emptyset) = -\theta'(t', s', \emptyset) = 1$. Then if we define $|\theta'\rangle = \sum_{(u, v, \lambda) \in \vec{E}(\overline{G}^\dagger)} \theta'(u, v, \lambda) |u, v, \lambda\rangle$, we can express $|\theta'\rangle$ as a linear combination of cycles around the faces of \overline{G}^\dagger , $|\theta'\rangle = \sum_{f \in F(\overline{G}^\dagger)} \alpha_f |\vec{C}_f\rangle + \sum_{f \in F(\overline{G}^\dagger)} \alpha'_f |\overleftarrow{C}_f\rangle$, where if $w_{k+1} = w_1$ and $(w_1, w_2, \lambda_1), \dots, (w_k, w_{k+1}, \lambda_k)$ is a clockwise cycle around f , $|\vec{C}_f\rangle = \sum_{i=1}^k |w_i, w_{i+1}, \lambda_i\rangle$ is the clockwise cycle around the face f , and $|\overleftarrow{C}_f\rangle = \sum_{i=1}^k |w_{i+1}, w_i, \lambda_i\rangle$ is the counter-clockwise cycle around f . There is a one-to-one correspondance between vertices in $V(\overline{G}) = V(G)$ and faces in $F(\overline{G}^\dagger)$, so we can define $\omega : V(G) \rightarrow \mathbb{R}$ by $\omega(v_f) = \frac{1}{2}(\alpha_f - \alpha'_f)$.

We claim that for all $(u, v, \lambda) \in \vec{E}(G)$, $\omega(u) - \omega(v) = \theta'((u, v, \lambda)^\dagger)$. Let (u', v', λ) be any edge in $\vec{E}(\overline{G}^\dagger)$. This edge is part of a clockwise cycle around one face in \overline{G}^\dagger , call it f ,

and a counter clockwise cycle around one face in \overline{G}^\dagger , call it g . Since these are the only two faces containing the edge (u', v', λ) , we must have $\theta'(u', v', \lambda) = \langle u', v', \lambda | \theta' \rangle = \alpha_f + \alpha'_g$. Since $\theta'(u', v', \lambda) = -\theta'(v', u', \lambda)$, we have $\alpha_f + \alpha'_g = -\alpha'_f - \alpha_g$. Thus:

$$\omega(v_f) - \omega(v_g) = \frac{1}{2} (\alpha_f - \alpha'_f - \alpha_g + \alpha'_g) = \frac{1}{2} (\theta'(u', v', \lambda) - \theta'(v', u', \lambda)) = \theta'((v_f, v_g, d)^\dagger). \quad (38)$$

In particular, this means that $\omega(s) - \omega(t) = \theta'((s, t, \emptyset)^\dagger) = \theta'(s', t', \emptyset) = 1$, so ω is a negative witness, and for all $(u, v, \lambda) \in \vec{E}(G)$, $\omega(u) - \omega(v) = \theta((u, v, \lambda)^\dagger)$. \square

Lemma 11

Lemma 11. *Let G be a planar multigraph with $s, t \in V(G)$ such that $G \cup \{\{s, t\}\}$ is also planar, and let c be a weight function on $E(G)$. Let $x \in \{0, 1\}^{E(G)}$. Then $w_+(x, P_{G,c}) = \frac{1}{2} R_{s,t}(G(x), c)$ and $w_-(x, P_{G,c}) = 2R_{s',t'}(G'(x), c')$.*

Proof. If x is a 1-instance, s and t are connected in $G(x)$, so there exists a unit st -flow on $G(x)$, which is a unit st -flow on G that is supported only on $\vec{E}(G(x))$. Let θ be the flow on $G(x)$ such that $R_{s,t}(G(x), c) = \sum_{(u,v,\lambda) \in E(G(x))} \frac{\theta(u,v,\lambda)^2}{c(\{u,v\},\lambda)}$. By Claim 30, $|w\rangle = \frac{1}{2} \sum_{(u,v,\lambda)} \frac{\theta(u,v,\lambda)}{\sqrt{c(\{u,v\},\lambda)}} |u, v, \lambda\rangle$ is a positive witness in $P_{G,c}$, and since θ is supported on $\vec{E}(G(x))$, $|w\rangle \in H(x)$, and so $|w\rangle$ is a positive witness for x in $P_{G,c}$. Thus

$$w_+(x, P_{G,c}) \leq \| |w\rangle \|^2 = \frac{1}{4} \sum_{(u,v,\lambda) \in \vec{E}(G(x))} c(\{u,v\}, \lambda) \theta(u,v,\lambda)^2 = \frac{1}{2} R_{s,t}(G(x), c). \quad (39)$$

On the other hand, let $|w\rangle$ be an optimal positive witness for x . By Claim 30, $\theta(u, v, \lambda) = \sqrt{c(\{u, v\}, \lambda)} (\langle u, v, \lambda | w \rangle - \langle v, u, \lambda | w \rangle)$ is a unit st -flow on G , and since $|w\rangle \in H(x)$, $\theta(u, v, \lambda)$ is only non-zero on $\vec{E}(G(x))$, so θ is a unit st -flow on $G(x)$. Thus,

$$\begin{aligned} R_{s,t}(G(x), c) &\leq \sum_{(u,v,\lambda) \in E(G(x))} \frac{\theta(u,v,\lambda)^2}{c(\{u,v\},\lambda)} = \frac{1}{2} \sum_{(u,v,\lambda) \in \vec{E}(G(x))} (\langle u, v, \lambda | w \rangle - \langle v, u, \lambda | w \rangle)^2 \\ &= \sum_{(u,v,\lambda) \in \vec{E}(G(x))} \langle u, v, \lambda | w \rangle^2 - \sum_{(u,v,\lambda) \in \vec{E}(G(x))} \langle u, v, \lambda | w \rangle \langle v, u, \lambda | w \rangle \leq 2 \| |w\rangle \|^2 \end{aligned} \quad (40)$$

where the last inequality is by Cauchy-Schwarz. Thus, $w_+(x, P_{G,c}) = \frac{1}{2} R_{s,t}(G(x))$.

Now we prove that $w_-(x, P_{G,c}) = 2R_{s',t'}(G'(x), c')$. Let $x \in \{0, 1\}^{\vec{E}(G)}$ be such that s and t are not connected in $G(x)$. Fix an optimal negative witness ω for x . By Claim 31 the linear function $\theta : \vec{E}(G') \rightarrow \mathbb{R}$ defined by $\theta((u, v, \lambda)^\dagger) = \omega(u) - \omega(v)$ is a unit $s't'$ -flow on G' . Since ω is a negative witness for x , we also have:

$$\begin{aligned} 0 &= \left\| \omega A \Pi_{H(x)} \right\|^2 = \sum_{(u,v,\lambda) \in \vec{E}(G(x))} c(\{u,v\}, \lambda) (\omega(u) - \omega(v))^2 \\ &= \sum_{(u,v,\lambda) \in \vec{E}(G(x))} c(\{u,v\}, \lambda) \theta((u,v,\lambda)^\dagger)^2 \\ &= \sum_{(u',v',\lambda) \in \vec{E}(G') \setminus \vec{E}(G'(x))} \frac{\theta(u',v',\lambda)^2}{c'(\{u',v'\},\lambda)}, \end{aligned} \quad (41)$$

since $(u, v, \lambda) \in \vec{E}(G(x))$ exactly when $(u, v, \lambda)^\dagger \notin \vec{E}(G'(x))$. So θ is only supported on $\vec{E}(G'(x))$, and so it is a unit $s't'$ -flow on $G'(x)$. Thus

$$\begin{aligned} w_-(x, P_{G,c}) = \|\omega A\|^2 &= \sum_{(u,v,\lambda) \in \vec{E}(G)} c(\{u, v\}, \lambda) (\omega(u) - \omega(v))^2 \\ &= \sum_{(u',v',\lambda) \in \vec{E}(G'(x))} \frac{\theta(u', v', \lambda)^2}{c'(\{u', v'\}, \lambda)} \geq 2R_{s',t'}(G'(x), c'). \end{aligned} \quad (42)$$

For the other direction, let θ be an $s't'$ -flow in $G'(x)$ with minimal energy. By Claim 31, there is a negative witness ω such that $\theta((u, v, \lambda)^\dagger) = \omega(u) - \omega(v)$. Since θ is supported on edges $(u', v', \lambda) \in \vec{E}(G'(x))$, which are exactly those edges such that $(u', v', \lambda)^\dagger \notin \vec{E}(G(x))$, we have

$$0 = \sum_{\substack{(u,v,\lambda) \\ \in \vec{E}(G(x))}} c(\{u, v\}, \lambda) \theta((u, v, \lambda)^\dagger)^2 = \sum_{\substack{(u,v,\lambda) \\ \in \vec{E}(G(x))}} c(\{u, v\}, \lambda) (\omega(u) - \omega(v))^2 = \|\omega A \Pi_{H(x)}\|^2, \quad (43)$$

so ω is a negative witness for x in $P_{G,c}$. Thus:

$$\begin{aligned} w_-(x, P_{G,c}) \leq \|\omega A\|^2 &= \sum_{(u,v,\lambda) \in \vec{E}(G)} c(\{u, v\}, \lambda) (\omega(u) - \omega(v))^2 \\ &= \sum_{(u',v',\lambda) \in \vec{E}(G'(x))} \frac{\theta(u', v', \lambda)^2}{c'(\{u', v'\}, \lambda)} = 2R_{s',t'}(G'(x), c'), \end{aligned} \quad (44)$$

completing the proof. \square

A.1 Time and Space Analysis of the Span Program Algorithm for st -Connectivity

is designed to run in st -CONN $_G$ in G, \mathbb{F} with time $O(\max\{\log |E(G)|, \log |V(G)|\})$.
 We show that Π_S is a span program for st -CONN $_G$ in G, \mathbb{F} .
 Let $P = (H, U, A, \tau)$ be a span program for st -CONN $_G$ in G, \mathbb{F} .
 Let $w_0 = A^+ \tau$, and let $\Pi_{H(x)}$ be the projection onto $H(x)$.
 Let $A_{\ker A}$ be the restriction of A to $\ker A$.
 Let f be the function $f(x) = \max_{x \in D: f(x)=1} w_+(x) \times \max_{x \in D: f(x)=0} w_-(x)$.
 Let D be the domain of f .
 Let $P_{G,c}$ be the span program in (6).
 Let $O(1)$ be a constant.
 Let x be an element of G .
 Let $\Pi_{\ker A}$ be the projection onto $\ker A$.
 Let G be a graph.
 Let n be the number of vertices in G .
 Let $O(\log n)$ be a function of n .

Let G be a graph with vertex set $V(G)$ and edge set $E(G)$. Let c, c' be functions on $E(G)$. Let $U_{G,c}$ be a quantum walk step on G with coin c and $U_{G,c}$ be a quantum walk step on G with coin c' .

$$U_{G,c} : |u\rangle|0\rangle \mapsto \frac{1}{\sqrt{\sum_{v,\lambda:(u,v,\lambda)\in\vec{E}(G)} c(\{u,v\},\lambda)}} \sum_{v,\lambda:(u,v,\lambda)\in\vec{E}(G)} \sqrt{c(\{u,v\},\lambda)} |u\rangle|u,v,\lambda\rangle. \quad (45)$$

Theorem 13. Let $P_{G,c} = (H, U, A, \tau)$ be defined as in (6). Let $S_{G,c}$ be an upper bound on the time complexity of implementing $U_{G,c}$. If G has the property that $G \cup \{\{s, t\}\}$ is planar, then the time complexity of deciding $st\text{-CONN}_{G,D}$ is at most

$$O\left(\min_c S_{G,c} \sqrt{\max_{x \in D: s,t \text{ are connected}} R_{s,t}(G(x), c) \times \max_{x \in D: s,t \text{ are not connected}} R_{s',t'}(G'(x), c')}\right). \quad (12)$$

Lemma 31. Let A be defined as in (6). Let $S_{G,c}$ be an upper bound on the time complexity of implementing $U_{G,c}$. Then $2\Pi_{\ker A} - I$ can be implemented in time complexity $O(S_{G,c})$.

Lemma 32. Let A be defined as in (6). Let $S_{G,c}$ be an upper bound on the time complexity of implementing $U_{G,c}$. Then $2\Pi_{\ker A} - I$ can be implemented in time complexity $O(S_{G,c})$.

Proof. This analysis follows [4] (see also [17]). Let

$$d(u) = \sum_{v,\lambda:(u,v,\lambda)\in\vec{E}(G)} c(\{u,v\},\lambda). \quad (46)$$

Define spaces Z and Y as follows.

$$Z = \text{span} \left\{ |z_u\rangle := \sum_{v,\lambda:(u,v,\lambda)\in\vec{E}(G)} \frac{\sqrt{c(\{u,v\},\lambda)}}{\sqrt{2d(u)}} (|0, u, u, v, \lambda\rangle + |1, u, v, u, \lambda\rangle) : u \in V(G) \right\} \quad (47)$$

$$Y = \text{span} \left\{ |y_{u,v,\lambda}\rangle := \frac{|0, u, u, v, \lambda\rangle - |1, v, u, v, \lambda\rangle}{\sqrt{2}} : (u, v, \lambda) \in \vec{E}(G) \right\} \quad (48)$$

Define isometries whose column-spaces are Z and Y respectively:

$$M_Z = \sum_{u \in V(G)} |z_u\rangle\langle u| \quad \text{and} \quad M_Y = \sum_{(u,v,\lambda) \in \vec{E}(G)} |y_{u,v,\lambda}\rangle\langle u, v, \lambda|. \quad (49)$$

Now we note that for any $(\{u, v\}, \lambda) \in E(G)$, we have the following:

$$\langle z_u | y_{u,v,\lambda} \rangle = \frac{\sqrt{c(\{u, v\}, \lambda)}}{2\sqrt{d(u)}}, \quad \text{and} \quad \langle z_v | y_{u,v,\lambda} \rangle = -\frac{\sqrt{c(\{u, v\}, \lambda)}}{2\sqrt{d(v)}}. \quad (50)$$

Thus, we can calculate:

$$\begin{aligned} M_Z^\dagger M_Y &= \sum_{(u,v,\lambda) \in \vec{E}(G)} \left(\frac{|u\rangle}{2\sqrt{d(u)}} - \frac{|v\rangle}{2\sqrt{d(v)}} \right) \sqrt{c(\{u, v\}, \lambda)} \langle u, v, \lambda| \\ &= \sum_{u' \in V(G)} \frac{|u'\rangle\langle u'|}{2\sqrt{d(u')}} \sum_{(u,v,\lambda) \in \vec{E}(G)} \sqrt{c(\{u, v\}, \lambda)} (|u\rangle - |v\rangle) \langle u, v, \lambda| \\ &= \sum_{u' \in V(G)} \frac{|u'\rangle\langle u'|}{2\sqrt{d(u')}} A. \end{aligned} \quad (51)$$

Note that the rows of $M_Z^\dagger M_Y$ are non-zero multiples of the rows of A , so $\text{row}(M_Z^\dagger M_Y) = \text{row}(A)$, and thus $\ker(M_Z^\dagger M_Y) = \ker A$.

Define $W = (2\Pi_Z - I)(2\Pi_Y - I)$. We now claim that M_Y maps $\ker A$ to the (-1) -eigenspace of W , and $(\ker A)^\perp$ to the 1-eigenspace of W , so that $2\Pi_{\ker A} - I = M_Y^\dagger W M_Y$. To see this, note that if $|\psi\rangle \in \ker A$, then $|\psi\rangle \in \ker(M_Z^\dagger M_Y)$ so $M_Y|\psi\rangle \in \ker M_Z^\dagger = Z^\perp$. Thus $M_Y|\psi\rangle \in Y \cap Z^\perp$, which is in the (-1) -eigenspace of W .

Next, suppose $|\psi\rangle \in (\ker A)^\perp = (\ker(M_Z^\dagger M_Y))^\perp$, so since M_Y is an isometry, $M_Y|\psi\rangle \in (\ker M_Z)^\perp = \text{row} M_Z = Z$. Thus $M_Y|\psi\rangle \in Y \cap Z$, which is in the 1-eigenspace of W .

Thus, we can implement $2\Pi_{\ker A} - I$ by $M_Y^\dagger W M_Y$. It only remains to argue that each of M_Y , $2\Pi_Z - I$ and $2\Pi_Y - I$ can be implemented in time complexity at most $O(S_{G,c})$.

We first show that we can implement the isometry M_Y , or rather a unitary U_Y that acts as $|0\rangle|0\rangle|u, v, \lambda\rangle \mapsto M_Y|u, v, \lambda\rangle = |y_{u,v,\lambda}\rangle$. First, use HX on the first qubit to perform the map:

$$|0\rangle|0\rangle|u, v, \lambda\rangle \mapsto |-\rangle|0\rangle|u, v, \lambda\rangle. \quad (52)$$

Conditioned on the value of the first register, copy either u or v into the second register to get:

$$\frac{1}{\sqrt{2}}(|0, u, u, v, \lambda\rangle - |1, v, u, v, \lambda\rangle) = |y_{u,v,\lambda}\rangle. \quad (53)$$

Thus, we can implement U_Y in the time it takes to write down a vertex of G , $O(\log |V(G)|)$, which is at most $O(S_{G,c})$. Using the ability to implement U_Y , we can implement $2\Pi_Y - I$ as $U_Y R_Y U_Y^\dagger$, where R_Y is the reflection that acts as the identity on computational basis states of the form $|0\rangle|0\rangle|u, v, \lambda\rangle$, and reflects computational basis states without this form.

Next, we implement a unitary U_Z that acts as $|0\rangle|u\rangle|0\rangle \mapsto M_Z|u\rangle = |z_u\rangle$. First, use the quantum walk step $U_{G,c}$, which can be implemented in time $S_{G,c}$, to perform:

$$|+\rangle|u\rangle|0\rangle \mapsto \frac{1}{2\sqrt{d(u)}} \sum_{v,\lambda:(u,v,\lambda) \in \vec{E}(G)} \sqrt{c(\{u, v\}, \lambda)} (|0\rangle + |1\rangle)|u\rangle|u, v, \lambda\rangle. \quad (54)$$

Conditioned on the bit in the first register, swap the third and fourth registers, to get:

$$\frac{1}{2\sqrt{d(u)}} \sum_{v,\lambda:(u,v,\lambda) \in \vec{E}(G)} \sqrt{c(\{u, v\}, \lambda)} (|0\rangle|u\rangle|u, v, \lambda\rangle + |1\rangle|u\rangle|v, u, \lambda\rangle) = |z_u\rangle. \quad (55)$$

The total cost of implementing U_Z is $O(S_{G,c} + \log |V(G)|) = O(S_{G,c})$. Thus, we can implement $2\Pi_Z - I$ in $O(S_{G,c})$ quantum gates. \square

Lemma 33. *Let A and τ be defined as in (6). Let $S_{G,c}$ be an upper bound on the complexity of implementing $U_{G,c}$. Then the initial state of the algorithm, $\frac{|w_0\rangle}{\| |w_0\rangle \|}$ where $|w_0\rangle = A^+\tau$, can be approximated in time $O(S_{G,c})$.*

Proof. Without loss of generality, we can assume that G includes the edge $(\{s, t\}, \emptyset)$ (we can simply not include it in any subgraph). Furthermore, we set $c(\{s, t\}, \emptyset) = 1/r$, for some positive r to be specified later, so that $A|s, t, \emptyset\rangle = r^{-1/2}\tau$. This has no effect on other edges in G . Note that

$$\Pi_{(\ker A)^\perp}|s, t, \emptyset\rangle = A^+ A|s, t, \emptyset\rangle = r^{-1/2} A^+\tau = r^{-1/2}|w_0\rangle, \quad (56)$$

so

$$|s, t, \emptyset\rangle = r^{-1/2}|w_0\rangle + |w_0^\perp\rangle \quad (57)$$

for some $|w_0^\perp\rangle \in \ker A$. Thus, constant precision phase estimation on $2\Pi_{\ker A} - I$ maps $|s, t, \emptyset\rangle$ to

$$r^{-1/2}|0\rangle|w_0\rangle + |1\rangle|w_0^\perp\rangle. \quad (58)$$

Using quantum amplitude amplification [7], we can amplify the amplitude on the $|0\rangle|w_0\rangle$ part of this arbitrarily close to 1 using a number of calls to $2\Pi_{\ker A} - I$ proportional to $\|r^{-1/2}|w_0\rangle\|^{-1}$.

In fact, it is straightforward to show that for any $|\mu\rangle \in \text{row} A$, the vector $|\nu\rangle$ with smallest norm that satisfies $A|\nu\rangle = |\mu\rangle$, is $A^+|\mu\rangle$ [17]. Using this fact along with Claim 30 and Definition 9, we have $\|w_0\|^2 = R_{s,t}(G, c)$.

Let $R = R_{s,t}(G \setminus \{(s, t, \emptyset)\}, c)$ be the effective resistance of G without the edge (s, t, \emptyset) . Now we can think of $(\{s, t, \emptyset\})$ and $G \setminus \{(s, t, \emptyset)\}$ as two graphs in parallel, so using Claim 5, we have

$$\|w_0\|^2 = \frac{1}{1/R + 1/r}. \quad (59)$$

Setting $r = R$, we have $\|w_0\|^2 = R/2$ and $\|r^{-1/2}|w_0\rangle\|^{-1} = O(1)$. Thus, using $O(1)$ calls to $2\Pi_{\ker A} - I$, we can approximate the initial state $|w_0\rangle$. \square

$$O\left(\min_c \sqrt{\max_{x \in D: \phi(x)=1} R_{s,t}(G_\phi(x), c) \times \max_{x \in D: \phi(x)=0} R_{s',t'}(G'_\phi(x), c')}\right) = O(|E(G)|). \quad (60)$$

$$O(\log(|E(G)|))$$

B Formula Evaluation and st -Connectivity

$$G_\phi \quad \phi, \mathbf{st}$$

Definition 34 (G_ϕ). If $\phi = x_i$ is a single-variable formula, then $V(G_\phi) = \{s, t\}$ and $E(G_\phi) = \{(\{s, t\}, x_i)\}$.

If $\phi = \phi_1 \wedge \dots \wedge \phi_l$, then define $V(G_\phi) = \{(i, v) : i \in [l], v \in V(G_{\phi_i}) \setminus \{s, t\}\} \cup \{s, s_2, \dots, s_l, t\}$ and, letting $s_1 = s$ and $s_{l+1} = t$, define:

$$\begin{aligned} E(G_\phi) = & \{(\{(i, u), (i, v)\}, x_j) : i \in [l], u, v \in V(G_{\phi_i}) \setminus \{s, t\}, (\{u, v\}, x_j) \in E(G_{\phi_i})\} \\ & \cup \{(\{(i, u), s_i\}, x_j) : i \in [l], u \in V(G_{\phi_i}), (\{s, u\}, x_j) \in E(G_{\phi_i})\} \\ & \cup \{(\{(i, u), s_{i+1}\}, x_j) : i \in [l], u \in V(G_{\phi_i}), (\{t, u\}, x_j) \in E(G_{\phi_i})\}. \end{aligned} \quad (61)$$

If $\phi = \phi_1 \vee \dots \vee \phi_l$ define $V(G_\phi) = \{(i, v) : i \in [l], v \in V(G_{\phi_i}) \setminus \{s, t\}\} \cup \{s, t\}$ and

$$E(G_\phi) = \{(\{(i, u), (i, v)\}, x_j) : i \in [l], u, v \in V(G_{\phi_i}) \setminus \{s, t\}, (\{u, v\}, x_j) \in E(G_{\phi_i})\} \\ \cup \{(\{(i, u), s\}, x_j) : i \in [l], u \in V(G_{\phi_i}), (\{u, s\}, x_j) \in E(G_{\phi_i})\} \\ \cup \{(\{(i, u), t\}, x_j) : i \in [l], u \in V(G_{\phi_i}), (\{u, t\}, x_j) \in E(G_{\phi_i})\}. \quad (62)$$

Bitwise Complement

Lemma 35. For an AND-OR formula ϕ on $\{0, 1\}^N$, define ϕ' to be the formula obtained by replacing \vee -nodes with \wedge -nodes and \wedge -nodes with \vee -nodes in ϕ . Then for all $x \in \{0, 1\}^N$, if \bar{x} denotes the bitwise complement of x , then $\phi'(x) = \neg\phi(\bar{x})$. Furthermore up to an isomorphism that maps s to s' , t to t' , and an edge labeled by any label λ to an edge labeled by λ , we have $G'_\phi = G_{\phi'}$ and $G'_\phi(x) = G_{\phi'}(\bar{x})$.

Proof. The first part of the proof is by induction. Suppose ϕ has depth 0, so $\phi = x_i$ for some variable x_i . Then $\phi'(x) = \phi(x) = \neg(\phi(\bar{x}))$. So suppose $\phi = \phi_1 \wedge \dots \wedge \phi_l$. Then $\phi' = \phi'_1 \vee \dots \vee \phi'_l$. Then by the induction hypothesis,

$$\phi'(x) = \phi'_1(x) \vee \dots \vee \phi'_l(x) = (\neg\phi_1(\bar{x})) \vee \dots \vee (\neg\phi_l(\bar{x})) = \neg(\phi_1(\bar{x}) \wedge \dots \wedge \phi_l(\bar{x})) = \neg\phi(\bar{x}) \quad (63)$$

where the second to last equality is de Morgan's law. The case $\phi = \phi_1 \vee \dots \vee \phi_l$ is similar.

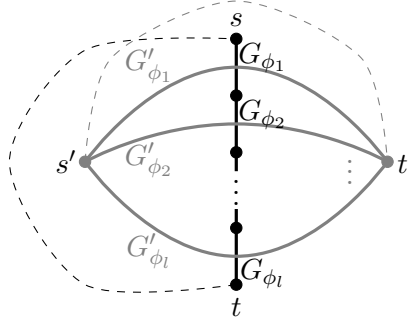


Figure 7: \overline{G}_ϕ shown in black, and its dual, $\overline{G}_{\phi'}$, shown in grey. The thick lines represent graphs. Edges in G_{ϕ_i} are dual to edges in G'_{ϕ_i} , and the dotted edge $(\{s, t\}, \emptyset)$ is dual to $(\{s', t'\}, \emptyset)$.

We will now prove that $\overline{G}_\phi^\dagger = \overline{G}_{\phi'}$, and furthermore, dual edges have the same label, by induction on the depth of ϕ , from which the result follows immediately.

If $\phi = x_i$ is a depth-0 formula, then $\phi' = x_i$. In that case, G_ϕ is just an edge from s to t , labeled by x_i , and G'_ϕ is just an edge from s' to t' labeled x_i , so $G'_\phi = G_{\phi'}$.

For the inductive step, to show that \overline{G}_ϕ and $\overline{G}_{\phi'}$ are dual, and therefore $G'_\phi = G_{\phi'}$. It suffices to exhibit a bijection $\zeta : V(\overline{G}_{\phi'}) \rightarrow F(\overline{G}_\phi)$ such that $(\{u, v\}, x_j) \in E(\overline{G}_{\phi'})$ if and only if the faces $\zeta(u)$ and $\zeta(v)$ are separated by an edge in $E(\overline{G}_\phi)$ with the label x_j . We first consider the case that $\phi = \phi_1 \wedge \dots \wedge \phi_l$, so $\phi' = \phi'_1 \vee \dots \vee \phi'_l$. Then, \overline{G}_ϕ consists of the graphs $G_{\phi_1}, \dots, G_{\phi_l}$, chained together in series as in Figure 7, with an additional edge from s to t , so the faces of \overline{G}_ϕ are exactly all the interior faces of each G_{ϕ_i} , as well as the two faces on either side of the st -edge $(\{s, t\}, \emptyset)$, which we will denote by $f^{s'}$ and $f^{t'}$. That is, adding an i to the label of each internal face of G_{ϕ_i} :

$$F(\overline{G}_\phi) = \{(i, f) : i \in [l], f \in F(\overline{G}_{\phi_i}) \setminus \{f^{s'}, f^{t'}\}\} \cup \{f^{s'}, f^{t'}\}, \quad (64)$$

since $F(\overline{G}_{\phi_i}) \setminus \{f^{s'}, f^{t'}\} = F(G_{\phi_i}) \setminus \{f^E\}$, where f^E is the external face. Since $\phi' = \phi'_1 \vee \dots \vee \phi'_l$ we also have

$$V(\overline{G}_{\phi'}) = V(G_{\phi'}) = \{(i, v) : i \in [l], v \in V(G_{\phi'_i}) \setminus \{s, t\}\} \cup \{s', t'\}, \quad (65)$$

where we will use the labels s' and t' in anticipation of the isometry between $G'_{\phi'}$ and $G_{\phi'}$.

By the induction hypothesis, for each $i \in [l]$, there exists a bijection $\zeta_i : V(\overline{G}_{\phi'_i}) \rightarrow F(\overline{G}_{\phi_i})$ such that for all $u, v \in V(\overline{G}_{\phi'_i}) = V(G_{\phi'_i})$, $(\{u, v\}, x_j) \in E(\overline{G}_{\phi'_i})$ if and only if $\zeta_i(u)$ and $\zeta_i(v)$ are faces separated by an edge with the label x_j . We define ζ by $\zeta(i, v) = (i, \zeta_i(v))$ for all $i \in [l]$ and $v \in V(G_{\phi'_i}) \setminus \{s, t\}$, $\zeta(s') = f^{s'}$, and $\zeta(t') = f^{t'}$. By the induction hypothesis, we can see that for any edge $(\{u, v\}, x_j) \in E(\overline{G}_{\phi'}) \setminus (\{s', t'\}, \emptyset)$, $\zeta(u)$ and $\zeta(v)$ are separated by an edge labeled x_j . This is because this edge is in one of the $G_{\phi'_i}$, and so it has a dual edge in G_{ϕ_i} , by the induction hypothesis (see Figure 7). The only other edge in $\overline{G}_{\phi'}$ is the edge $(\{s', t'\}, \emptyset)$, and $\zeta(s')$ and $\zeta(t')$ are exactly those faces on either side of $(\{s, t\}, \emptyset)$ in \overline{G}_{ϕ} , completing the proof that $\overline{G}_{\phi'}^\dagger = \overline{G}_{\phi}$.

If $\phi = \phi_1 \vee \dots \vee \phi_l$, then $\phi' = \phi'_1 \wedge \dots \wedge \phi'_l$, and a nearly identical proof shows that $\overline{G}_{\phi'}^\dagger = \overline{G}_{\phi}$.

Now that we have shown an isomorphism between $G'_{\phi'}$ and $G_{\phi'}$, note that $G'_{\phi'}(x)$ is the subgraph of $G'_{\phi'}$ that includes all those edges where $x_e = 0$. On the other hand $G_{\phi'}(x)$ is the graph that includes all those edges where $x_e = 1$. Taking the bitwise negation of x , we find that $G'_{\phi'}(x) = G_{\phi'}(\bar{x})$. \square

Lemma 17

Claim 17. *If $\phi = \phi_1 \vee \phi_2 \vee \dots \vee \phi_l$, then $G'_{\phi}(x)$ is formed by composing $\{G'_{\phi_i}(x)\}_i$ in series, and if $\phi = \phi_1 \wedge \phi_2 \wedge \dots \wedge \phi_l$, then $G'_{\phi}(x)$ is formed by composing $\{G'_{\phi_i}(x)\}_i$ in parallel.*

Proof. If $\phi = \phi_1 \vee \dots \vee \phi_l$, then $\phi' = \phi'_1 \wedge \dots \wedge \phi'_l$. From Lemma 35, $G'_{\phi'}(x) = G_{\phi'}(\bar{x})$, which using Definition 34 is composed of $\{G_{\phi'_i}(\bar{x})\}_{i=1}^l$ in series. But using the isomorphism of Lemma 35 again, this is just $\{G'_{\phi_i}(x)\}_{i=1}^l$ composed in series. The proof for $\phi = \phi_1 \wedge \dots \wedge \phi_l$ is similar. \square

Lemma 14

$$\phi(x) : \quad G_{\phi}(x) \text{ } \mathbf{D} \text{ } G'_{\phi}(x)$$

Lemma 14. *Let ϕ be any AND-OR formula on N variables. For every $x \in \{0, 1\}^N$, there exists a path from s to t in $G_{\phi}(x)$ if and only if $\phi(x) = 1$. Furthermore, for every $x \in \{0, 1\}^N$, there exists a path from s' to t' in $G'_{\phi}(x)$ if and only if $\phi(x) = 0$.*

Proof. We will prove the statement by induction on the depth of ϕ . If $\phi = x_j$ has depth 0, then G_{ϕ} is just an edge $(\{s, t\}, x_j)$, and G'_{ϕ} is just an edge $(\{s', t'\}, x_j)$. Thus s and t are connected in $G_{\phi}(x)$ if and only if $x_j = 1$, in which case ϕ evaluates to 1, and s' and t' are connected in $G_{\phi'}$ if and only if $x_j = 0$, in which case ϕ evaluates to 0.

If $\phi = \phi_1 \wedge \dots \wedge \phi_l$, then G_{ϕ} consists of $G_{\phi_1}, \dots, G_{\phi_l}$ connected in series from s to t , and moreover, $G_{\phi}(x)$ consists of $G_{\phi_1}(x), \dots, G_{\phi_l}(x)$ connected in series from s to t . Thus an st -path in $G_{\phi}(x)$ consists of an st -path in $G_{\phi_1}(x)$, followed by an st -path in $G_{\phi_2}(x)$, etc., up to an st -path in $G_{\phi_l}(x)$. Thus, s and t are connected in $G_{\phi}(x)$ if and only if s and t are connected in each $G_{\phi_1}(x), \dots, G_{\phi_l}(x)$, which happens if and only if $\phi_1(x) \wedge \dots \wedge \phi_l(x) = 1$.

On the other hand, by Claim 17, G'_{ϕ} consists of $G'_{\phi_1}, \dots, G'_{\phi_l}$ connected in parallel between s' and t' . So any $s't'$ -path in $G'_{\phi}(x)$ is an $s't'$ -path in one of the $G'_{\phi_i}(x)$, which is equivalent to an st -path in one of $G_{\phi'_i}(\bar{x})$. Thus, by Lemma 35 s' and t' are connected in

$G'_\phi(x)$ if and only if $\phi'_1(\bar{x}) \vee \cdots \vee \phi'_l(\bar{x}) = \neg\phi_1(x) \vee \cdots \vee \neg\phi_l(x) = 1$. By de Morgan's law is true if and only if $\phi(x) = \phi_1(x) \wedge \cdots \wedge \phi_l(x) = 0$.

The case when $\phi = \phi_1 \vee \cdots \vee \phi_l$ is similar. \square

C Classical Lower Bound on Class of Promise Boolean Formulas

Lemma 35. *Let f be a promise Boolean function on D and $R(f)$ its randomized query complexity. Then*

$$R(f) = \Omega(RS(f)), \quad \text{and} \quad RS(f) \leq R(f \circ g),$$

where $f \circ g$ is the composition of f and g . Furthermore, for any $f : D \rightarrow \{0, 1\}$ and $D \subseteq \{0, 1\}^N$, let $f_{\text{sab}} : D_{\text{sab}} \rightarrow \{0, 1\}$ be the sabotaged function on $D_{\text{sab}} = \{x \in \{0, 1, *\}^N \cup \{0, 1, \dagger\}^N : x \text{ is consistent with } y, y' \in D, \text{ s.t. } f(y) \neq f(y')\}$.

Lemma 36. *Let $x \in \{0, 1, *, \dagger\}^N$ and $y \in \{0, 1\}^N$ be consistent with x . Then*

$$f_{\text{sab}}(x) = 1 \text{ if } x \in \{0, 1, *\}^N, \quad f_{\text{sab}}(x) = 0 \text{ if } x \in \{0, 1, \dagger\}^N.$$

Furthermore, $RS(f) = R_0(f_{\text{sab}})$ and $R_0(f) \leq RS(f)$.

Lemma 37. *Let $\text{AND}|_{D_{N,h}}$ and $\text{OR}|_{D'_{N,h}}$ be the promise Boolean functions on $D_{N,h}$ and $D'_{N,h}$ respectively.*

Lemma 36. $RS(\text{OR}|_{D'_{N,h}}) = RS(\text{AND}|_{D_{N,h}}) = \Omega(N/h)$.

Proof. For $x \in [D'_{N,h}]_{\text{sab}}$ to be consistent with $y, y' \in D'_{N,h}$ such that $\text{OR}(y) \neq \text{OR}(y')$, we must have that $x \in \{0, *\}^N \cup \{0, \dagger\}^N$. Furthermore, the number of $*$'s or \dagger 's in x must be at least h . Thus the sabotaged problem reduces to finding at least one marked item out of n , promised there are at least h marked items. The randomized bounded-error query complexity of this task is $\Omega(N/h)$, and so by Theorem 3 in [5],

$$RS(\text{OR}|_{D'_{N,h}}) = R_0((\text{OR}|_{D'_{N,h}})_{\text{sab}}) = \Omega(R((\text{OR}|_{D'_{N,h}})_{\text{sab}})) = \Omega(N/h). \quad (67)$$

The proof for AND is similar. \square

Corollary 37.

Let $\phi = \phi_1 \circ \phi_2 \circ \cdots \circ \phi_l$, where for each $i \in [l]$, $\phi_i = \text{OR}|_{D'_{N_i, h_i}}$ or $\phi_i = \text{AND}|_{D_{N_i, h_i}}$. Then $R(\phi) = \Omega(\prod_{i=1}^l N_i/h_i)$.

Lemma 38. *Let $\phi = \phi_1 \circ \phi_2 \circ \cdots \circ \phi_l$, where for each $i \in [l]$, $\phi_i = \text{OR}|_{D'_{N_i, h_i}}$ or $\phi_i = \text{AND}|_{D_{N_i, h_i}}$. Let D be the domain of ϕ . Then*

$$\frac{\prod_{i=1}^l N_i}{\prod_{i=1}^l h_i} = \left(\max_{x \in D: \phi(x)=1} R_{s,t}(G_\phi(x)) \right) \left(\max_{x \in D: \phi(x)=0} R_{s,t}(G'_\phi(x)) \right). \quad (68)$$

Proof. The proof follows by induction on the number of compositions. First suppose that $\phi = \text{OR}|_{D'_{N,h}}$. Then G_ϕ consists of N edges connected in parallel between s and t , and G'_ϕ consists of N edges connected in series. The only input x such that $\phi(x) = 0$ is the all zeros input. Therefore $\max_{x \in D: \phi(x)=0} R_{s,t}(G'_\phi(x)) = N$. Now notice (using Claim 5) that $R_{s,t}(G_\phi(x)) = 1/|x|$. However because of the domain of OR_{N_i, h_i} , inputs x have $|x| \geq h$, so $\max_{x \in D: \phi(x)=1} R_{s,t}(G_\phi(x)) = 1/h$. Thus

$$N/h = \left(\max_{x \in D: \phi(x)=1} R_{s,t}(G_\phi(x)) \right) \left(\max_{x \in D: \phi(x)=0} R_{s,t}(G'_\phi(x)) \right). \quad (69)$$

A similar analysis holds for the base case $\phi = \text{AND}|_{D_{N,h}}$.

Now for the inductive step, let $\phi = \phi_1 \circ \xi$ for $\xi = \phi_2 \circ \dots \circ \phi_l$, where for each i , ϕ_i is either $\text{OR}|_{D'_{N_i, h_i}}$ or $\text{AND}|_{D_{N_i, h_i}}$. Let D_ξ be the domain of ξ and let $x^j \in D_\xi$ denote the bits of x that are input to the j^{th} copy of ξ . Suppose first that $\phi_1 = \text{OR}|_{D'_{N_1, h_1}}$. G'_ϕ is formed by taking the N_1 graphs G'_ξ and connecting them in series. The only way $\phi(x) = 0$ is if the input $x^j \in D_\xi$ to each of the ξ functions satisfies $\xi(x^j) = 0$, so by Claim 5

$$\max_{x \in D: \phi(x)=0} R_{s,t}(G'_\phi(x)) = N_1 \max_{y \in D_\xi: \xi(y)=0} R_{s,t}(G'_\xi(y)). \quad (70)$$

On the other hand, G_ϕ is formed by taking N_1 graphs G_ξ and connecting them in parallel. Using Claim 5, if $x^j \in D_\xi$ is the input to j^{th} function ξ , we have

$$R_{s,t}(G_\phi(x)) = \left(\sum_{j=1}^{N_1} \frac{1}{R_{s,t}(G_\xi(x^j))} \right)^{-1}. \quad (71)$$

Thus larger values for $R_{s,t}(G_\phi(x))$ come from cases where $R_{s,t}(G_\xi(x^j))$ are large. Now

$$\max_{x \in D_\xi} R_{s,t}(G_\xi(x)) = \infty, \quad (72)$$

which occurs when $\xi(y) = 0$. Because of the promise on the domain of ϕ_1 , there must be at least h_1 of the N_1 subformulas ξ that evaluate to 1. On each of those subformulas, we want to have an input $x^j \in D_\xi$ that maximizes the effective resistance of that subformula. Therefore, we have

$$\max_{x \in D: \phi(x)=1} R_{s,t}(G_\phi(x)) = \left(\frac{h_1}{\max_{y \in D_\xi: \xi(y)=1} R_{s,t}(G_{\xi_j}(y))} \right)^{-1} = \frac{\max_{y \in D_\xi: \xi(y)=1} R_{s,t}(G_{\xi_j}(y))}{h_1}. \quad (73)$$

Therefore, using the inductive assumption,

$$\begin{aligned} & \left(\max_{x \in D: \phi(x)=1} R_{s,t}(G_\phi(x)) \right) \left(\max_{x \in D: \phi(x)=0} R_{s,t}(G'_\phi(x)) \right) \\ &= \frac{N_1}{h_1} \max_{y \in D_\xi: \xi(y)=1} R_{s,t}(G_{\xi_j}(y^j)) \max_{y \in D_\xi: \xi(y)=0} R_{s,t}(G'_\xi(y)) = \frac{\prod_{i=1}^l N_i}{\prod_{i=1}^l h_i}. \end{aligned} \quad (74)$$

The inductive step for $\phi_1 = \text{AND}|_{D_{N,h}}$ is similar. \square

CLAIM

D NAND-tree Proofs

D.1 Relationship Between Faults and Effective Resistance

Lemma 22.

For any $x \in \{0, 1\}^{2^d}$, if d is even, then we have $R_{s,t}(G_{\text{NAND}_d}(x)) \leq \mathcal{F}_A(x)$ and $R_{s',t'}(G'_{\text{NAND}_d}(x)) \leq \mathcal{F}_B(x)$, while if d is odd, we have $R_{s,t}(G_{\text{NAND}_d}(x)) \leq 2\mathcal{F}_A(x)$ and $R_{s',t'}(G'_{\text{NAND}_d}(x)) \leq 2\mathcal{F}_B(x)$.

Proof. We will give a proof for $\mathcal{F}_A(x)$; the case of $\mathcal{F}_B(x)$ is similar.

First, $R_{s,t}(G_{\text{NAND}_d}(x)) = \infty$ if and only if s and t are not connected in $G_{\text{NAND}_d}(x)$, which, by Lemma 14, occurs if and only if x is a 0-instance. This means exactly that x is not A -winnable, which, by Eq. (28), holds if and only if $\mathcal{F}_A(x) = \infty$. Thus, suppose this is not the case, so $\mathcal{F}_A(x) < \infty$.

The rest of the proof is by induction. We need to look at both odd and even cases. For the case of $d = 0$, the only A -winnable input in $\{0, 1\}^{2^0}$ is $x = 1$. In that case, using Eq. (28), $\mathcal{F}_A(x) = 1$, since there are no decision nodes for Player A , and since $G_{\text{NAND}_0}(x)$ is just a single edge from s to t , $R_{s,t}(G_{\text{NAND}_0}(x)) = 1$.

Let $x \in \{0, 1\}^{2^d}$ be any A -winnable input with $d > 1$. We let x^0 be the first 2^{d-1} bits of x and x^1 be the last 2^{d-1} bits of x , so $x = (x^0, x^1)$.

We first consider odd $d > 1$. Using the definition of G_ϕ from Section 4, and the fact that for d odd, the root node is an \wedge -node, we see that $G_{\text{NAND}_d}(x)$ consists of $G_{\text{NAND}_{d-1}}(x^0)$ and $G_{\text{NAND}_{d-1}}(x^1)$ connected in series, so by Claim 5

$$R_{s,t}(G_{\text{NAND}_d}(x)) = R_{s,t}(G_{\text{NAND}_{d-1}}(x^0)) + R_{s,t}(G_{\text{NAND}_{d-1}}(x^1)). \quad (75)$$

Now the root can not be a fault, because it is a decision node for Player B , but we know the tree is A -winnable, so no choice Player B makes would allow her to win the game. Therefore, both subtrees connected to the root node must be A -winnable. Using Eq. (28) we have

$$\mathcal{F}_A(x^0) + \mathcal{F}_A(x^1) \leq \max_{b \in \{0,1\}} 2\mathcal{F}_A(x^b) = 2\mathcal{F}_A(x). \quad (76)$$

Combining Eqs. (75) and (76) and the inductive assumption for even depth trees, we have for odd d ,

$$R_{s,t}(G_{\text{NAND}_d}(x)) \leq 2\mathcal{F}_A(x). \quad (77)$$

Now we consider the case that d is even, so the root is a decision node for Player A . Consequently, the root node is a \vee -node, so by Claim 5

$$R_{s,t}(G_{\text{NAND}_d}(x)) = \left(\frac{1}{R_{s,t}(G_{\text{NAND}_{d-1}}(x^0))} + \frac{1}{R_{s,t}(G_{\text{NAND}_{d-1}}(x^1))} \right)^{-1}. \quad (78)$$

Suppose the root is a fault. Without loss of generality, let's assume the subtree with input x^0 is not A -winnable. Then $R_{s,t}(G_{\text{NAND}_{d-1}}(x^0)) = \infty$ so Eq. (78) becomes

$$R_{s,t}(G_{\text{NAND}_d}(x)) = R_{s,t}(G_{\text{NAND}_{d-1}}(x^1)). \quad (79)$$

Using the inductive assumption for odd depth trees, Eq. (28), and the fact that the root is a fault, we have

$$R_{s,t}(G_{\text{NAND}_d}(x)) \leq 2\mathcal{F}(x^1) = \mathcal{F}(x). \quad (80)$$

If the root is not a fault, then both $R_{s,t}(G_{\text{NAND}_{d-1}}(x^0))$ and $R_{s,t}(G_{\text{NAND}_{d-1}}(x^1))$ are finite, so from (78), and using the inductive assumption, we have

$$\begin{aligned} R_{s,t}(G_{\text{NAND}_d}(x)) &\leq \frac{1}{2} \max\{R_{s,t}(G_{\text{NAND}_{d-1}}(x^0)), R_{s,t}(G_{\text{NAND}_{d-1}}(x^1))\} \\ &\leq \max\{\mathcal{F}(x^0), \mathcal{F}(x^1)\} = \mathcal{F}(x). \end{aligned} \quad (81)$$

A similar analysis for $\mathcal{F}_B(x)$ completes the proof. \square

D.2 Estimating Effective Resistances

~~Let $\tilde{w}_\pm(x, P)$ be the approximate positive and negative witness sizes, $\tilde{w}_+(x, P)$ and $\tilde{w}_-(x, P)$. For any span program P on $\{0, 1\}^N$ and $x \in \{0, 1\}^N$, we define the positive error of x in P as:~~

O_x . ~~Witness~~

$G_\phi(x)$ and $G'_\phi(x)$.

~~approximate positive and negative witness sizes, $\tilde{w}_+(x, P)$ and $\tilde{w}_-(x, P)$. For any span program P on $\{0, 1\}^N$ and $x \in \{0, 1\}^N$, we define the positive error of x in P as:~~

$$|w\rangle \in H(x) \quad \omega A \Pi_{H(x)} = 0$$

Definition 39 (Approximate Positive Witness). *For any span program P on $\{0, 1\}^N$ and $x \in \{0, 1\}^N$, we define the positive error of x in P as:*

$$e_+(x) = e_+(x, P) := \min \left\{ \left\| \Pi_{H(x)^\perp} |w\rangle \right\|^2 : A|w\rangle = \tau \right\}. \quad (82)$$

We say $|w\rangle$ is an approximate positive witness for x in P if $\left\| \Pi_{H(x)^\perp} |w\rangle \right\|^2 = e_+(x)$ and $A|w\rangle = \tau$. We define the approximate positive witness size as

$$\tilde{w}_+(x) = \tilde{w}_+(x, P) := \min \left\{ \| |w\rangle \|^2 : A|w\rangle = \tau, \left\| \Pi_{H(x)^\perp} |w\rangle \right\|^2 = e_+(x) \right\}. \quad (83)$$

~~If $x \in P_1$, $e_+(x) = 0$. $\tilde{w}_+(x) = w_+(x)$.~~

Definition 40 (Approximate Negative Witness). *For any span program P on $\{0, 1\}^N$ and $x \in \{0, 1\}^N$, we define the negative error of x in P as:*

$$e_-(x) = e_-(x, P) := \min \left\{ \left\| \omega A \Pi_{H(x)} \right\|^2 : \omega \in \mathcal{L}(U, \mathbb{R}), \omega \tau = 1 \right\}. \quad (84)$$

Any ω such that $\left\| \omega A \Pi_{H(x)} \right\|^2 = e_-(x, P)$ is called an approximate negative witness for x in P . We define the approximate negative witness size as

$$\tilde{w}_-(x) = \tilde{w}_-(x, P) := \min \left\{ \left\| \omega A \right\|^2 : \omega \in \mathcal{L}(U, \mathbb{R}), \omega \tau = 1, \left\| \omega A \Pi_{H(x)} \right\|^2 = e_-(x, P) \right\}. \quad (85)$$

~~If $x \in P_0$, $e_-(x) = 0$. $\tilde{w}_-(x) = w_-(x)$.~~

Theorem 41 ([17]). Fix $X \subseteq \{0, 1\}^N$ and $f : X \rightarrow \mathbb{R}_{\geq 0}$. Let P be a span program such that for all $x \in X$, $f(x) = w_+(x, P)$ and define $\widetilde{W}_- = \widetilde{W}_-(P, f) = \max_{x \in X} \widetilde{w}_-(x, P)$. There exists a quantum algorithm that estimates f to relative error ε and that uses $\widetilde{O}\left(\frac{1}{\varepsilon^{3/2}} \sqrt{w_+(x) \widetilde{W}_-}\right)$ queries. Similarly, let P be a span program such that for all $x \in X$, $f(x) = w_-(x, P)$ and define $\widetilde{W}_+ = \widetilde{W}_+(P, f) = \max_{x \in X} \widetilde{w}_+(x, P)$. Then there exists a quantum algorithm that estimates f to accuracy ε and that uses $\widetilde{O}\left(\frac{1}{\varepsilon^{3/2}} \sqrt{w_-(x) \widetilde{W}_+}\right)$ queries.

Lemma 42. For any formula ϕ , its \wedge -depth is the largest number of \wedge -labeled nodes on any path from the root to a leaf. Let ϕ be any AND-OR formula with maximum fan-in l , \wedge -depth d_\wedge , and \vee -depth d_\vee . Then $\widetilde{W}_+(P_{G_\phi}) \leq \frac{1}{2}l^{d_\wedge}$ and $\widetilde{W}_-(P_{G_\phi}) \leq 2l^{d_\vee}$.

Lemma 25 (Est Algorithm). Let ϕ be an AND-OR formula with constant fan-in l , \vee -depth d_\vee and \wedge -depth d_\wedge . Then the quantum query complexity of estimating $R_{s,t}(G_\phi(x))$ (resp. $R_{s,t}(G'_\phi(x))$) to relative accuracy ε is $\widetilde{O}\left(\frac{1}{\varepsilon^{3/2}} \sqrt{R_{s,t}(G_\phi(x))l^{d_\vee}}\right)$ (resp. $\widetilde{O}\left(\frac{1}{\varepsilon^{3/2}} \sqrt{R_{s,t}(G'_\phi(x))l^{d_\wedge}}\right)$).

Proof of Lemma 25. By Theorem 41, since $R_{s,t}(G_\phi(x)) = \frac{1}{2}w_+(x, P_{G_\phi})$ (Lemma 11), we can estimate this quantity using a number of queries that depends on $\widetilde{W}_-(P_{G_\phi})$. By Lemma 42, we have that $\widetilde{W}_-(P_{G_\phi}) \leq 2l^{d_\vee}$, so we can estimate $w_+(x) = R_{s,t}(G_\phi(x))$ in $\widetilde{O}\left(\frac{1}{\varepsilon^{2/3}} \sqrt{w_+(x) \widetilde{W}_-^{1/2}}\right) = \widetilde{O}\left(\frac{1}{\varepsilon^{2/3}} \sqrt{R_{s,t}(G_\phi(x))l^{d_\vee}}\right)$ queries. Similarly, $R_{s,t}(G'_\phi(x)) = 2w_-(x, P_{G_\phi})$ for all 0-instances, and $\widetilde{W}_+ \leq \frac{1}{2}l^{d_\wedge}$, so we can estimate $R_{s,t}(G'_\phi(x))$ in $\widetilde{O}\left(\frac{1}{\varepsilon^{2/3}} \sqrt{R_{s,t}(G'_\phi(x))l^{d_\wedge}}\right)$ queries. \square

Claim 43. Let ϕ be an AND-OR formula with constant fan-in l . If ϕ has \wedge -depth d_\wedge , then the longest self-avoiding path connecting s and t in G_ϕ has length at most l^{d_\wedge} .

Proof. We will prove the statement by induction. If ϕ has \wedge -depth $d_\wedge = 0$, then it has no \wedge -nodes. Thus, it is easy to see that G_ϕ has only two vertices, s and t , with some number of edges connecting them, so every st -path has length 1.

Suppose ϕ has \wedge -depth $d_\wedge > 0$. First, suppose $\phi = \phi_1 \wedge \dots \wedge \phi_l$. Then since G_ϕ consists of $G_{\phi_1}, \dots, G_{\phi_l}$ connected in series, any st -path in G_ϕ consists of an st -path in G_{ϕ_1} , followed by an st -path in G_{ϕ_2} , etc. up to an st -path in G_{ϕ_l} , so if $d_\wedge(\phi_i)$ is the \wedge -depth of ϕ_i , then the longest st -path in G_ϕ has length at most:

$$l^{d_\wedge(\phi_1)} + \dots + l^{d_\wedge(\phi_l)} \leq ll^{d_\wedge-1} = l^{d_\wedge}. \quad (86)$$

If $\phi = \phi_1 \vee \dots \vee \phi_l$, then $\max_i d_\wedge(\phi_i) = d_\wedge(\phi) = d_\wedge$, and G_ϕ consists of $G_{\phi_1}, \dots, G_{\phi_l}$, connected in parallel. Any self-avoiding st -path must include exactly one edge adjacent to s and one edge adjacent to t . However, any path that includes an edge from G_{ϕ_i} and G_{ϕ_j} for $i \neq j$ must go through s or t , so it must have more than one edge adjacent to s , or more than one edge adjacent to t , so such a path can never be a self-avoiding st -path. Thus, any self-avoiding st -path must be contained completely in one of the G_{ϕ_i} . The longest such path is thus the longest self-avoiding st -path in any of the G_{ϕ_i} , which, by induction, is $\max_i l^{d_\wedge(\phi_i)} = l^{d_\wedge}$. \square

Proof

Proof of Lemma 42. To begin, we will prove the upper bound on \widetilde{W}_+ . Suppose $|\tilde{w}\rangle$ is an optimal approximate positive witness for x . By Claim 30, if $|\tilde{w}\rangle$ is an approximate positive witness, then since $A|\tilde{w}\rangle = \tau$, and c has unit value on all edges of G , $\theta(u, v, \lambda) = \langle u, v, \lambda | \tilde{w} \rangle - \langle v, u, \lambda | \tilde{w} \rangle$ is a unit flow on G . Since $|\tilde{w}\rangle$ is an approximate positive witness for x , it has minimal error for x , so it minimizes $\left\| \Pi_{H(x)^\perp} |\tilde{w}\rangle \right\|^2$, and since it is optimal, it minimizes $\| |\tilde{w}\rangle \|^2$ over all approximate positive witnesses. Define $|\theta\rangle = \sum_{(u,v,\lambda) \in \vec{E}(G)} \theta(u, v, \lambda) |u, v, \lambda\rangle$, so we know that $\frac{1}{2}|\theta\rangle$ also maps to τ under A , so is also a positive witness in P_{G_ϕ} . Then we have

$$\left\| \Pi_{H(x)^\perp} |\theta\rangle \right\|^2 = 2 \sum_{\substack{(u,v,\lambda) \in \\ \vec{E}(G) \setminus \vec{E}(G(x))}} \langle u, v, \lambda | \tilde{w} \rangle^2 - 2 \sum_{\substack{(u,v,\lambda) \in \\ \vec{E}(G) \setminus \vec{E}(G(x))}} \langle u, v, \lambda | \tilde{w} \rangle \langle v, u, \lambda | \tilde{w} \rangle \leq \left\| 2 \Pi_{H(x)^\perp} |\tilde{w}\rangle \right\|^2, \quad (87)$$

where the last inequality uses Cauchy-Schwarz, so $\frac{1}{2}|\theta\rangle$ is also an approximate positive witness for x . Similarly,

$$\| |\theta\rangle \|^2 \leq \| 2|\tilde{w}\rangle \|^2, \quad (88)$$

so $\frac{1}{2}|\theta\rangle$ is optimal.

By Claim 29, we can consider a decomposition of $|\theta\rangle$ into self-avoiding paths p_i and cycles c_i such that all cycles are disjoint from all paths, $|\theta\rangle = \sum_{i=1}^r \alpha_i |p_i\rangle + \sum_{i=1}^{r'} \beta_i |c_i\rangle$, where for each i ,

$$|p_i\rangle = \sum_{j=1}^{L_i} |u_j^{(i)}, u_{j+1}^{(i)}, \lambda_{i,j}\rangle - \sum_{j=1}^{L_i} |u_{j+1}^{(i)}, u_j^{(i)}, \lambda_{i,j}\rangle, \quad (89)$$

$$|c_i\rangle = \sum_{j=1}^{L'_i} |v_j^{(i)}, v_{j+1}^{(i)}, \lambda'_{i,j}\rangle - \sum_{j=1}^{L'_i} |v_{j+1}^{(i)}, v_j^{(i)}, \lambda'_{i,j}\rangle \quad (90)$$

where $v_{L'_i+1}^{(i)} = v_1^{(i)}$ and $\{\lambda_{i,j}\}_{i,j} \cap \{\lambda'_{i,j}\}_{i,j} = \emptyset$. It's easy to see (in the case of unit edge weights) that $A|c_i\rangle = 0$ for all i , so

$$A \frac{1}{2} \sum_{i=1}^r \alpha_i |p_i\rangle = A \frac{1}{2} |\theta\rangle = \tau. \quad (91)$$

Let $|\theta'\rangle = \sum_{i=1}^r \alpha_i |p_i\rangle$. Then since c_i and p_j have no common edges, we have $\langle c_i | p_j \rangle = 0$, and also $\langle c_i | (I - \Pi_{H(x)}) | p_j \rangle = 0$, so the error of $\frac{1}{2}|\theta'\rangle$ is $\frac{1}{4} \left\| \Pi_{H(x)^\perp} |\theta'\rangle \right\|^2 \leq \frac{1}{4} \left\| \Pi_{H(x)^\perp} |\theta\rangle \right\|^2$, so $\frac{1}{2}|\theta'\rangle$ also has minimal error. Furthermore, $\| |\theta'\rangle \|^2 \leq \| |\theta\rangle \|^2$, with equality if and only if there are no cycles in the decomposition. By the optimality of $\frac{1}{2}|\theta\rangle$ as an approximate

positive witness for x , we can conclude that $|\theta\rangle = \sum_{i=1}^r \alpha_i |p_i\rangle$, and since $A|p_i\rangle = 2\tau$ for all i , and $A|\theta\rangle = 2\tau$, we have $\sum_{i=1}^r \alpha_i = 1$. Then

$$\|\theta\|^2 \leq \max_i \| |p_i\rangle \|^2 = \max_i 2L_i. \quad (92)$$

Since the longest self-avoiding st -path in G_ϕ has length at most l^{d_\wedge} , and each L_i is the length of a self-avoiding path in G_ϕ , we have $\tilde{w}_+(x, P_{G_\phi}) \leq \frac{1}{4}2l^{d_\wedge} = \frac{1}{2}l^{d_\wedge}$. Thus $\tilde{W}_+(P_{G_\phi}) \leq \frac{1}{2}l^{d_\wedge}$.

Next we prove the bound on \tilde{W}_- . A min-error approximate negative witness for x in P_{G_ϕ} is a function $\omega : V(G_\phi) \rightarrow \mathbb{R}$ such that $\omega\tau = \omega(s) - \omega(t) = 1$, and $\|\omega A \Pi_{H(x)}\|^2 = \sum_{(u,v,\lambda) \in \vec{E}(G_\phi(x))} (\omega(u) - \omega(v))^2$ is minimized. By Claim 31, since $\omega\tau = 1$, the function $\theta : \vec{E}(G'_\phi) \rightarrow \mathbb{R}$ defined by $\theta((u, v, \lambda)^\dagger) = \omega(u) - \omega(v)$ is a unit $s't'$ -flow on $G'_\phi = G_\phi$, and the witness complexity is

$$\|\omega A\|^2 = \sum_{(u,v,\lambda) \in \vec{E}(G_\phi)} (\omega(u) - \omega(v))^2 = \sum_{(u',v',\lambda) \in \vec{E}(G'_\phi)} \theta(u', v', \lambda)^2 = \|\theta\|^2 \quad (93)$$

where we create $|\theta\rangle$ from θ in the usual way. By an argument similar to the previous argument, if ω is an optimal approximate negative witness for x , then $\|\theta\|^2$ is upper bounded by twice the length of the longest self-avoiding $s't'$ -path in $G'_\phi = G_\phi$. By Lemma 35 and Claim 43, this is upper bounded by $2l^{d_\wedge(\phi')} = 2l^{d_\vee(\phi)}$, where $d_\wedge(\phi')$ is the \wedge -depth of ϕ' , and $d_\vee = d_\vee(\phi)$ is the \vee -depth of ϕ . Thus $\tilde{w}_-(x, P_{G_\phi}) \leq 2l^{d_\vee}$, and so $\tilde{W}_- \leq 2l^{d_\vee}$. \square

D.3 Winning the NAND-tree

~~Winning the~~
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NAND ~~tree~~

Lemma 26. *Let $x^0, x^1 \in \{0, 1\}^{2^d}$ be instances of NAND_d with at least one of them a 1-instance. Let $N = 2^d$, and $w_{\min} = \min\{R_{s,t}(G_{\text{NAND}_d}(x^0)), R_{s,t}(G_{\text{NAND}_d}(x^1))\}$. Then $\text{Select}(x^0, x^1)$ terminates after $\tilde{O}(N^{1/4} \sqrt{w_{\min}})$ queries to (x^0, x^1) and outputs b such that $R_{s,t}(G_{\text{NAND}_d}(x^b)) \leq 2R_{s,t}(G_{\text{NAND}_d}(x^{\bar{b}}))$ with bounded error.*

Proof. Since at least one of x^0 and x^1 is a 1-instance, using the description of Select in Section 5.2, at least one of the programs will terminate. Suppose without loss of generality that $\text{Est}(x^0)$ is the first to terminate, outputting w_0 . Then there are two possibilities: $\text{Est}(x^1)$ does not terminate after $p(d)\sqrt{w_0}N^{1/4}$ steps, in which case, $R_{s,t}(G_{\text{NAND}_d}(x^0)) \leq 2R_{s,t}(G_{\text{NAND}_d}(x^1))$, and Select outputs 0; or $\text{Est}(x^1)$ outputs w_1 before $p(d)\sqrt{w_0}N^{1/4}$ steps have passed and Select outputs b such that $w_b \leq w_{\bar{b}}$.

We will prove the first case by contradiction. Suppose

$$2R_{s,t}(G_{\text{NAND}_d}(x^1)) < R_{s,t}(G_{\text{NAND}_d}(x^0)). \quad (94)$$

Then $\text{Est}(x^1)$ must terminate after

$$p(d)\sqrt{R_{s,t}(G_{\text{NAND}_d}(x^1))}N^{1/4} \leq \frac{1}{\sqrt{2}}p(d)\sqrt{R_{s,t}(G_{\text{NAND}_d}(x^0))}N^{1/4} \quad (95)$$

steps. In Select , we run Est to relative accuracy $\varepsilon = 1/3$, so we have

$$|w_0 - R_{s,t}(G_{\text{NAND}_d}(x^0))| \leq \frac{1}{3}R_{s,t}(G_{\text{NAND}_d}(x^0)), \quad (96)$$

and so

$$w_0 \geq \frac{2}{3} R_{s,t}(G_{\text{NAND}_d}(x^0)). \quad (97)$$

Plugging Eq. (97) into Eq. (95), we have $\text{Est}(x^1)$ must terminate after $\frac{1}{\sqrt{2}}p(d)\sqrt{\frac{3}{2}w_0}N^{1/4} < p(d)\sqrt{w_0}N^{1/4}$ steps, which is a contradiction.

Thus, $R_{s,t}(G_{\text{NAND}_d}(x^0)) \leq 2R_{s,t}(G_{\text{NAND}_d}(x^1))$, so outputting 0 is correct. Furthermore, since we terminate after $p(d)\sqrt{w_0}N^{1/4} = \tilde{O}(\sqrt{R_{s,t}(G_{\text{NAND}_d}(x^0))}N^{1/4})$ steps, and since $R_{s,t}(G_{\text{NAND}_d}(x^0)) = O(R_{s,t}(G_{\text{NAND}_d}(x^1)))$, the running time is at most $\tilde{O}(N^{1/4}\sqrt{w_{\min}})$.

We now consider the second case, in which both programs output estimates w_0 and w_1 , such that $|w_b - R_{s,t}(G_{\text{NAND}_d}(x^b))| \leq \varepsilon R_{s,t}(G_{\text{NAND}_d}(x^b))$ for $b = 0, 1$. Suppose $w_b \leq w_{\bar{b}}$. We then have

$$\frac{R_{s,t}(G_{\text{NAND}_d}(x^b))}{R_{s,t}(G_{\text{NAND}_d}(x^{\bar{b}}))} \leq \frac{R_{s,t}(G_{\text{NAND}_d}(x^b))}{w_b} \frac{w_{\bar{b}}}{R_{s,t}(G_{\text{NAND}_d}(x^{\bar{b}}))} \leq \frac{1 + \varepsilon}{1 - \varepsilon} = \frac{4/3}{2/3} = 2. \quad (98)$$

Thus $R_{s,t}(G_{\text{NAND}_d}(x^b)) \leq 2R_{s,t}(G_{\text{NAND}_d}(x^{\bar{b}}))$, as required. Furthermore, the running time of the algorithm is bounded by the running time of $\text{Est}(x^1)$, the second to terminate. We know that $\text{Est}(x^1)$ has running time at most $\tilde{O}(\sqrt{R_{s,t}(G_{\text{NAND}_d}(x^1))}N^{1/4})$ steps, and by assumption, $\text{Est}(x^1)$ terminated after less than $p(d)\sqrt{w_0}N^{1/4} = \tilde{O}(\sqrt{R_{s,t}(G_{\text{NAND}_d}(x^0))}N^{1/4})$ steps, so the total running time is at most $\tilde{O}(N^{1/4}\sqrt{w_{\min}})$. \square

Theorem 27. *Let $x \in \{0, 1\}^N$ for $N = 2^d$ be an A -winnable input to NAND_d . At every node v where Player A makes a decision, let Player A use the **Select** algorithm in the following way. Let v_0 and v_1 be the two children of v , with inputs to the respective subtrees of v_0 and v_1 given by x^0 and x^1 respectively. Then Player A moves to v_b where b is the outcome that occurs a majority of times when **Select** (x^0, x^1) is run $O(\log d)$ times. Then if Player B , at his decision nodes, chooses left and right with equal probability, Player A will win the game with probability at least $2/3$, and will use $\tilde{O}(N^{1/4}\sqrt{R_{s,t}(G_{\text{NAND}_d}(x))})$ queries on average, where the average is taken over the randomness of Player B 's choices.*

Proof. First note that Player A must make $O(d)$ choices over the course of the game. We amplify Player A 's probability of success by repeating **Select** at each decision node $O(\log d)$ times and taking the majority. Then the probability that Player A chooses the wrong direction at any node is $O(1/d)$, and we ensure that her probability of choosing the wrong direction over the course of the algorithm is $< 1/3$. From here on, we analyze the error free case.

Let $p(d)$ be a non-decreasing polynomial function in d such that **Select**, on inputs $x^0, x^1 \in \{0, 1\}^{2^d}$, terminates in at most $p(d)2^{d/4}\sqrt{\min\{R_{s,t}(G_{\text{NAND}_d}(x^0)), R_{s,t}(G_{\text{NAND}_d}(x^1))\}}$ queries. Then we will prove that for trees of odd depth d , the expected number of queries by Player A over the course of the game is at most $p(d)2^{d/4+5}\sqrt{R_{s,t}(G_{\text{NAND}_d}(x))}$, while for even depth trees, it is at most $p(d)2^{d/4+11/2}\sqrt{R_{s,t}(G_{\text{NAND}_d}(x))}$, thus proving the main result.

We prove the result by induction on the depth of the tree. For depth zero trees, there are no decisions, $N = R_{s,t}G_{\text{NAND}_0}(x) = 1$, so the result holds.

For the inductive case, we treat odd and even depth cases separately. First consider an instance of NAND_d with $d > 0$, d odd. Thus $\text{NAND}_d(x) = \text{NAND}_{d-1}(x^0) \wedge \text{NAND}_{d-1}(x^1)$,

where $x = (x^0, x^1)$. Because the root is at odd distance from the leaves, the root is a decision node for Player B . Because we are in an A -winnable tree, no matter which choice Player B makes, we will end up at an A -winnable subtree of depth $d - 1$, so the inductive assumption holds for those trees. That is, the expected number of queries for Player A must make to win the subtree with input x^b (for $b \in \{0, 1\}$) averaged over Player B 's choices is at most

$$p(d-1)2^{(d-1)/4+11/2}\sqrt{R_{s,t}(G_{\text{NAND}_{d-1}}(x^b))}. \quad (99)$$

We are assuming that Player B chooses left and right with equal probability. Thus, the expected number of queries that Player A must make over Player B 's choices throughout the game is at most

$$\begin{aligned} & \frac{1}{2}\left(p(d-1)2^{(d-1)/4+11/2}\sqrt{R_{s,t}(G_{\text{NAND}_{d-1}}(x^0))}\right. \\ & \quad \left.+p(d-1)2^{(d-1)/4+11/2}\sqrt{R_{s,t}(G_{\text{NAND}_{d-1}}(x^1))}\right) \\ & \leq p(d-1)2^{(d-1)/4+11/2}\sqrt{\frac{1}{2}(R_{s,t}(G_{\text{NAND}_{d-1}}(x^0)) + R_{s,t}(G_{\text{NAND}_{d-1}}(x^1)))} \quad \text{by Jensen's ineq.,} \\ & = p(d-1)2^{(d-1)/4+11/2}\sqrt{\frac{1}{2}R_{s,t}(G_{\text{NAND}_d}(x))} \quad \text{by Claim 5,} \\ & \leq p(d)2^{d/4-1/4+11/2-1/2}\sqrt{R_{s,t}(G_{\text{NAND}_d}(x))} \\ & \leq p(d)2^{d/4+5}\sqrt{R_{s,t}(G_{\text{NAND}_d}(x))}, \end{aligned} \quad (100)$$

proving the case for odd d .

Now consider an instance of NAND_d with $d > 0$, d even. Thus $\text{NAND}_d(x) = \text{NAND}_{d-1}(x^0) \vee \text{NAND}_{d-1}(x^1)$, where $x = (x^0, x^1)$. Because the root is at even distance from the leaves, the root is a decision node for Player A . Player A runs $\text{Select}(x^0, x^1)$, which returns $b \in \{0, 1\}$ such that (by Lemma 26)

$$R_{s,t}(G_{\text{NAND}_{d-1}}(x^b)) \leq 2R_{s,t}(G_{\text{NAND}_{d-1}}(x^{\bar{b}})), \quad (101)$$

which requires at most

$$\min_{b^* \in \{0,1\}} p(d-1)2^{(d-1)/4}\sqrt{R_{s,t}(G_{\text{NAND}_{d-1}}(x^{b^*}))} \quad (102)$$

queries.

After making the choice to move to the subtree with input x^b , by the inductive assumption, the expected number of queries that Player A need to make throughout the rest of the game (averaged over Player B 's choices) is

$$p(d-1)2^{d/4+5}\sqrt{R_{s,t}(G_{\text{NAND}_{d-1}}(x^b))}. \quad (103)$$

There are two cases to consider. If $R_{s,t}(G_{\text{NAND}_{d-1}}(x^b)) \leq R_{s,t}(G_{\text{NAND}_{d-1}}(x^{\bar{b}}))$, then combining Eq. (102) and Eq. (103), we have that the total number of queries averaged

over Player B 's choices is

$$\begin{aligned}
& p(d-1)2^{(d-1)/4}\sqrt{R_{s,t}(G_{\text{NAND}_{d-1}}(x^b))} + p(d-1)2^{(d-1)/4+5}\sqrt{R_{s,t}(G_{\text{NAND}_{d-1}}(x^b))} \\
& \leq p(d-1)2^{(d-1)/4}\sqrt{R_{s,t}(G_{\text{NAND}_{d-1}}(x^b))(1+2^5)} \\
& \leq p(d-1)2^{(d-1)/4+5+1/16}\sqrt{R_{s,t}(G_{\text{NAND}_{d-1}}(x^b))} \\
& \leq p(d-1)2^{(d-1)/4+5+1/16+1/2}\sqrt{R_{s,t}(G_{\text{NAND}_d}(x))} \\
& \leq p(d)2^{d/4+11/2}\sqrt{R_{s,t}(G_{\text{NAND}_d}(x))} \tag{104}
\end{aligned}$$

where we've used $R_{s,t}(G_{\text{NAND}_d}(x)) = \left(R_{s,t}(G_{\text{NAND}_{d-1}}(x^0))^{-1} + R_{s,t}(G_{\text{NAND}_{d-1}}(x^1))^{-1}\right)^{-1}$ from Claim 5 and the fact that $R_{s,t}(G_{\text{NAND}_{d-1}}(x^b)) \leq R_{s,t}(G_{\text{NAND}_{d-1}}(x^{\bar{b}}))$ to bound the value $R_{s,t}(G_{\text{NAND}_{d-1}}(x^b))$ by $2R_{s,t}(G_{\text{NAND}_d}(x))$. This proves the even induction step for this case.

The other case is if $R_{s,t}(G_{\text{NAND}_{d-1}}(x^b)) > R_{s,t}(G_{\text{NAND}_{d-1}}(x^{\bar{b}}))$. In that case, again using the fact that $R_{s,t}(G_{\text{NAND}_d}(x)) = \left(R_{s,t}(G_{\text{NAND}_{d-1}}(x^0))^{-1} + R_{s,t}(G_{\text{NAND}_{d-1}}(x^1))^{-1}\right)^{-1}$, we have

$$R_{s,t}(G_{\text{NAND}_{d-1}}(x^{\bar{b}})) = R_{s,t}(G_{\text{NAND}_d}(x)) \left(1 + \frac{R_{s,t}(G_{\text{NAND}_{d-1}}(x^{\bar{b}}))}{R_{s,t}(G_{\text{NAND}_{d-1}}(x^b))}\right)^{-1} \leq \frac{2}{3}R_{s,t}(G_{\text{NAND}_d}(x)), \tag{105}$$

where the inequality follows from Eq. (101). Thus, the average total number of queries is

$$\begin{aligned}
& p(d-1)2^{(d-1)/4}\sqrt{R_{s,t}(G_{\text{NAND}_{d-1}}(x^{\bar{b}}))} + p(d-1)2^{(d-1)/4+5}\sqrt{R_{s,t}(G_{\text{NAND}_{d-1}}(x^b))} \\
& \leq p(d-1)2^{(d-1)/4}\left(\sqrt{R_{s,t}(G_{\text{NAND}_{d-1}}(x^{\bar{b}}))} + 2^5\sqrt{2R_{s,t}(G_{\text{NAND}_{d-1}}(x^{\bar{b}}))}\right) \\
& \leq p(d-1)2^{(d-1)/4}(1+2^{5+1/2})\sqrt{\frac{2}{3}R_{s,t}(G_{\text{NAND}_d}(x))} \\
& \leq p(d)2^{d/4-1/4+5}\sqrt{R_{s,t}(G_{\text{NAND}_d}(x))} \\
& \leq p(d)2^{d/4+5}\sqrt{R_{s,t}(G_{\text{NAND}_d}(x))}. \tag{106}
\end{aligned}$$

This proves the induction step for the other case. \square