

The Space “Just Above” BQP

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Abstract

We explore the space “just above” BQP by defining a complexity class naCQP (non-adaptive Collapse-free Quantum Polynomial time) which is larger than BQP but does not contain NP relative to an oracle. The class is defined by imagining that quantum computers can perform (non-adaptive) measurements that do not collapse the wavefunction. This non-physical model of computation can efficiently solve problems such as Graph Isomorphism and Approximate Shortest Vector which are believed to be intractable for quantum computers. Furthermore, it can search an unstructured N -element list in $\tilde{O}(N^{1/3})$ time, but no faster than $\Omega(N^{1/4})$, and hence cannot solve NP-hard problems in a black box manner. In short, this model of computation is more powerful than standard quantum computation, but only slightly so. This is surprising as most modifications of BQP increase the power of quantum computation to NP or beyond.

1 Introduction

Quantum computers are believed to be strictly more powerful than classical computers, but not so much more powerful that they can solve NP-hard problems efficiently. In particular, it is known that BQP, the class of languages recognizable in polynomial time by a quantum algorithm [11], does not contain NP “relative to an oracle.” This means that there is some “black box” problem \mathcal{O} for which $\text{BQP}^{\mathcal{O}} \not\subseteq \text{NP}^{\mathcal{O}}$. (For more information about the terminology, see [8].) On the other hand, many seemingly innocuous modifications of quantum mechanics—for example, allowing nonlinear transformations, non-unitary transformations, postselection, or measurement statistics based on the p th power of the amplitudes for $p \neq 2$ —increase the power of quantum computation drastically enough that they can solve NP-hard problems (and even #P-hard problems) efficiently [6][3]. As a result, it is difficult to find natural complexity classes which are bigger than BQP but which don’t contain NP. Quantum mechanics appears to be an “island in theoryspace” in terms of its complexity-theoretic properties [3].

In this work, we explore a natural modification of quantum mechanics to obtain a complexity class which is only “slightly more powerful” than BQP. In quantum mechanics, when a system is

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measured, the state of the system “collapses” to its observed value; one cannot observe a quantum system without perturbing it. Here we consider the power of quantum computers which can also make “non-collapsing measurements,” which are identical to usual quantum measurements except that they do not perturb the state. We call the class of problems decidable in polynomial time in this model CQP, which stands for “Collapse-free Quantum Polynomial time.” We additionally consider a weaker version of this model, naCQP (non-adaptive CQP) in which the quantum operations performed must be independent of the non-collapsing measurement outcomes.

We show that quantum computers equipped with this power (even in the non-adaptive case) can solve the Graph Isomorphism problem in polynomial time, and in fact can solve any problem in SZK in a black-box manner. Since standard quantum computers cannot solve SZK-hard problems in a black-box manner [1], this implies that there is an oracle \mathcal{O} for which $\text{BQP}^{\mathcal{O}} \neq \text{naCQP}^{\mathcal{O}}$. This is evidence that quantum computation with non-collapsing measurements is more powerful than standard quantum computation. Furthermore, we upper bound the power of both CQP and naCQP by showing that $\text{naCQP} \subseteq \text{CQP} \subseteq \text{BPP}^{\text{PP}}$, so both naCQP and CQP are in the counting hierarchy. In comparison the best known classical upper bound for BQP is AWPP which is contained in PP [14][7].

We also demonstrate that if (even non-adaptive) non-collapsing measurements are possible, then there is a quantum algorithm that searches an unstructured list of N elements in $\tilde{O}(N^{1/3})$ time. Furthermore any such algorithm takes at least $\Omega(N^{1/4})$ time in the non-adaptive case. While the upper bound is simple, the proof of the lower bound uses a hybrid argument [10] and properties of Markov chains. We conclude that naCQP does not contain NP relative to an oracle. To our knowledge this represents the only known complexity class larger than BQP which provably does not admit polynomial time black-box algorithms for NP-hard problems. This is what we mean when we say naCQP is only “slightly more powerful” than BQP. Proving the analogous lower bound for CQP remains open, so it is possible that CQP could be more powerful than naCQP.

Note that introducing non-collapsing measurements into quantum mechanics allows for many strange phenomena. In particular, it allows for faster-than-light communication, it allows for quantum cloning¹, and it renders quantum query complexity and quantum communication complexity meaningless. We describe these strange consequences of non-collapsing measurements in detail in Appendix A. For this reason, we are not suggesting that “non-collapsing measurements” should be considered seriously as an amendment to quantum theory. Rather we are simply showing that non-collapsing measurements have interesting complexity-theoretic properties - namely, that they can be used to define an complexity class which is “just above” BQP.

2 Relation to Prior Work

Our work is inspired by previous work on quantum computing with hidden variables by Aaronson [2]. Aaronson defines a class DQP (“Dynamical Quantum Polynomial Time”) by imagining a hidden variable theory is true, and that an experimenter can view the evolution of the hidden variables in real time. Additionally, he requires that the quantum operations are non-adaptive to the hidden variable values (similar to our class naCQP). He shows that with this power one can

¹Note, however, that this only arises when the quantum operations can depend on the non-collapsing measurement results. Our definition of naCQP does not allow cloning due to the non-adaptivity restriction. In contrast the class CQP does admit cloning, so might be a more powerful computational model. We discuss this issue in detail in Appendix A, and describe a related open problem in Section 8.

Table 1: Comparison between BQP, naCQP, CQP and DQP

Property	BQP	naCQP	CQP	DQP
Contains SZK	Unknown	Yes	Yes	Yes
Contains $\text{SZK}^O \forall O$	No	Yes	Yes	Yes
Upper Bound for Search	$O(N^{1/2})$	$\tilde{O}(N^{1/3})$	$\tilde{O}(N^{1/3})$	$\tilde{O}(N^{1/3})$
Lower Bound for Search	$\Omega(N^{1/2})$	$\Omega(N^{1/4})$	$\Omega(1)$	$\Omega(1)$
Upper Bound	AWPP	BPP^{PP}	BPP^{PP}	EXP

search in $\tilde{O}(N^{1/3})$ time and solve any problem in SZK in polynomial time. He additionally claims one cannot search in faster than $\Omega(N^{1/3})$ time in this model. Unfortunately, there is an error which invalidates his proof of the lower bound for search. For the interested reader, we describe this error in Appendix B and correct it for a modified version of the computational model in Appendix C. Proving the lower bound for search under Aaronson’s original computational model is challenging because we have few examples of working hidden variable theories, and therefore have little understanding of how hidden variable values could correlate over time. Note, however, that an $\Omega(N^{1/3})$ lower bound for search might hold even for Aaronson’s original model.

The classes CQP and naCQP, which we define by imagining one can perform (non-adaptive) non-collapsing measurements, seem incomparable to DQP - we do not know if either $\text{CQP} \subseteq \text{DQP}$, nor if $\text{DQP} \subseteq \text{CQP}$. However, we suspect that naCQP is a weaker class than DQP for several reasons. First, we can prove a polynomial lower bound for search in naCQP, which we don’t know how to do in DQP. Second, we can prove an upper bound that $\text{naCQP} \subseteq \text{BPP}^{\text{PP}} \subseteq \text{PSPACE}$. In contrast the best known upper bound for DQP is EXP. Table 1 summarizes the relationship between BQP, naCQP, CQP and DQP.

3 Definition of CQP and naCQP

We assume the reader is familiar with the standard definition of BQP and the basics of quantum computing; for an introduction to this topic see [16]. We now give a formal definition of our model of quantum computing with non-collapsing measurements.

Let \mathcal{Q} be an oracle that takes as input a quantum circuit $C = (U_1, M_1, U_2, M_2, \dots, U_T, M_T)$ and an integer $\ell \geq 0$. Here each U_i is a unitary operator on ℓ qubits composed of gates from some finite universal gate set \mathcal{U} , and each M_i is a standard (collapsing) measurement of zero or more qubits in the computational basis. Define a (random) sequence $\{|\psi_t\rangle\}_{t=0}^T$ of quantum states by $|\psi_0\rangle = |0\rangle^{\otimes \ell}$ and for $t > 0$, $|\psi_t\rangle$ is the resulting (random) pure state obtained when measurement M_t is applied to $U_t |\psi_{t-1}\rangle$. Note that we imagine the state of the system $|\psi_t\rangle$ is a (random) pure state for $0 \leq t \leq T$. The oracle \mathcal{Q} samples the sequence $\{|\psi_t\rangle\}_{t=0}^T$ (note that the random variables $|\psi_t\rangle$ are not independent), measures $|\psi_t\rangle$ in the computational basis for every t independently, and outputs the $T + 1$ measurement results, which we label v_0, v_1, \dots, v_T , respectively. The output of \mathcal{Q} is an element of $(\{0, 1\}^\ell)^{T+1}$. Note that once the $|\psi_t\rangle$ are fixed, the $T + 1$ measurement results are independent, however since the $|\psi_t\rangle$ are correlated, the measurement outcomes may be correlated.

naCQP (non-adaptive Collapse-free Quantum Polynomial-time) is then defined as the class of all languages that can be recognized in polynomial time by a deterministic Turing machine with one

query to \mathcal{Q} , with error probability at most $\frac{1}{3}$. Note that because the base machine is polynomially bounded, the circuit C with which it queries \mathcal{Q} must be polynomially sized. Furthermore, since the base machine can use the oracle to output coin flips, it makes no difference if we define the base machine to be deterministic or randomized. This class contains BQP, because one can always query the oracle \mathcal{Q} with a BQP circuit, and then ignore all output except the final measurement outcome. The constant $\frac{1}{3}$ is arbitrary: we can decrease the error probability arbitrarily close to 0 by repetition, which can be accomplished by packing multiple copies of a quantum circuit into a single call to \mathcal{Q} . Furthermore, it turns out that the definition of naCQP is not affected by the choice of universal gate set \mathcal{U} ; this is a consequence of the Solovay-Kitaev Theorem. The proof is omitted here due to lack of space, but can be found in Appendix D.

We can think of the $T + 1$ measurement samples from \mathcal{Q} as the results of *non-collapsing* measurements on the state vector, which give information about the state without changing it. For instance, let $|\psi_1\rangle = U_1|0\rangle^{\otimes \ell}$, let M_1, M_2 and M_3 be empty measurements, and let U_2, U_3 be the identity. Then the oracle \mathcal{Q} will output the result of three independent non-collapsing measurements of $|\psi_1\rangle$ in the computational basis. The key point is that the oracle's samples do not disturb the state of the system; only the unitary operators U_i and collapsing measurements M_i do. The oracle \mathcal{Q} gives us information about the intermediate stages of the quantum computation without collapsing the state; this is what gives naCQP additional power over BQP.

Note that by requiring the quantum circuit C to be specified up front, we have enforced the condition that the circuit is non-adaptive to the non-collapsing measurement outcomes (hence the name naCQP). To define CQP, we consider the case where the base machine can query the oracle \mathcal{Q} adaptively. That is, the base machine can first specify $U_1, M_1, \dots, U_t, M_t$ and receive samples $v_1 \dots v_t$, then based on those samples select $U_{t+1}, M_{t+1} \dots U_{t'}, M_{t'}$ and receive samples $v_{t+1} \dots v_{t'}$, etc. CQP is then defined analogously to be the class of languages which can be decided in polynomial time with adaptive queries to \mathcal{Q} , with error probability at most $1/3$. This class captures the power of generic computations with non-collapsing measurements.

Note that we explicitly allow for intermediate (collapsing) measurements in our model. In the definition of BQP, the principle of deferred measurement tells us that this is not necessary; the power of standard quantum computers is unchanged by the inclusion of intermediate collapsing measurements. However, in our model this makes a crucial difference. Indeed, suppose that we did not allow for intermediate collapsing measurements; then this model would be simulable in BQP with a polynomial amount of overhead. If there are no intermediate measurements M_i , then $|\psi_t\rangle = U_t U_{t-1} \dots U_1 |0\rangle^{\otimes \ell}$ are no longer random variables but are deterministic pure states, each preparable with a polynomially sized quantum circuit. So a BQP machine could simply prepare $|\psi_1\rangle$ and measure it, then prepare $|\psi_2\rangle$ from scratch and measure it, etc. to obtain the samples v_0, \dots, v_T . This would incur at most quadratic overhead.

When we add intermediate measurements into our model, this simulation strategy no longer works. Indeed, suppose that we performed measurement M_1 to obtain a random state $|\psi_1\rangle$. If we wanted to reproduce this state with a BQP machine, we could try applying M_1 to $U_1|0\rangle^{\otimes \ell}$. However, it might be that the probability of obtaining the same outcome for M_1 is exponentially small, and hence the BQP machine could not prepare another copy of $|\psi_1\rangle$ in polynomial time.

In short, the power of this model comes from the fact that we can perform intermediate measurements which collapse the wave function, and afterwards we can examine the resulting pure state $|\psi_t\rangle$ (which might not be efficiently preparable with a BQP machine) using multiple non-collapsing measurements. In the next section we will show how to leverage these properties to solve any

problem in SZK in polynomial time.

4 SZK is contained in naCQP

We will now describe how to use the peculiarities of non-collapsing measurements to solve any problem in SZK in polynomial time. The proof uses essentially the ideas of Aaronson [2], with minor simplifications.

SZK was originally defined as the class of languages admitting statistical zero-knowledge proofs. The precise definition of a statistical zero-knowledge proof can be found in [18], but it is not important here. SZK includes important problems such as Graph Isomorphism and Approximate Shortest Vector. It has been a long-standing open problem whether or not these problems can be solved in quantum polynomial time. Ettinger, Høyer and Knill showed that Graph Isomorphism (and indeed any hidden subgroup problem) can be solved in a black box manner with a polynomial number of queries to the black box, but with exponential post-processing time [13]. On the other hand, Aaronson [1] showed that BQP does not admit a black-box algorithm for the collision problem, and hence there is an oracle relative to which SZK is not in BQP.

In contrast, we show that quantum computers with non-collapsing measurements can solve any problem in SZK efficiently, i.e. $\text{SZK} \subseteq \text{naCQP}$. It is enough to prove that Statistical Difference, a problem shown in [18] to be SZK-complete, is in naCQP. The statistical difference problem is to determine, for two functions $P_0, P_1 : \{0, 1\}^n \rightarrow \{0, 1\}^m$ specified by classical circuits, whether the distributions of $P_0(X), P_1(X)$ for uniformly random X are close or far. Here, two distributions are “close” if their total variation distance is less than $\frac{1}{3}$ and they are “far” if their total variation distance is more than $\frac{2}{3}$.

We now show how to solve this efficiently if we have access to non-collapsing measurements.

Theorem 4.1. *The Statistical Difference problem can be solved in polynomial time in naCQP, and therefore $\text{SZK} \subseteq \text{naCQP}$.*

Proof. By the Polarization Lemma of Sahai and Vadhan [18, Lemma 3.3], we can assume that the distributions $P_0(X)$ and $P_1(X)$ have total variation distance less than 2^{-n^c} or more than $1 - 2^{-n^c}$, for any constant c . For now, assume that the distributions have total variation distance equal to either 1 or 0.

Our algorithm for the statistical difference problem is as follows. Prepare the state

$$\frac{1}{2^{(n+1)/2}} \sum_{b \in \{0,1\}, x \in \{0,1\}^n} |b\rangle |x\rangle |P_b(x)\rangle.$$

Now, measure the third register with a collapsing measurement to obtain a state $|\phi\rangle$ on the first two registers. If the distributions P_0, P_1 have total variation distance 1, then $|\phi\rangle$ will be of the form $|b\rangle |\psi\rangle$ for some b and $|\psi\rangle$. On the other hand, if they have total variation distance 0, then $|\phi\rangle$ will be an equal superposition $\frac{1}{\sqrt{2}}(|0\rangle |\psi_0\rangle + |1\rangle |\psi_1\rangle)$ where $|\psi_0\rangle$ and $|\psi_1\rangle$ have unit norm. We can distinguish the two cases by now repeatedly performing non-collapsing measurements and examining the value of the first register. If P_0, P_1 have total variation distance 1, then all of these measurements will give the same value b ; if P_0 and P_1 have total variation distance 0, then each of these measurements will independently give 0 with probability $\frac{1}{2}$ and 1 with probability $\frac{1}{2}$. We can distinguish the two cases with probability $3/4$ by performing three non-collapsing measurements and looking at whether or not they yielded identical values of the first register.

Furthermore, the fact that the total variation distances are merely exponentially close to 0 or 1, rather than actually being equal to 0 or 1, makes little difference. One can show that the probability of seeing the same measurement outcome three times is at most $\frac{1}{4} + O(2^{-n^c})$ if P_0 and P_1 are exponentially close and at least $1 - O(2^{-n^c})$ if P_0 and P_1 are exponentially far apart. We provide a detailed proof of this fact in Appendix E. Therefore our algorithm will have error probability at most $1/3$. □

Hence SZK is in naCQP, and furthermore we can solve SZK problems in naCQP in a black box manner, i.e. relative to any oracle. Since [1] has the result that $\text{SZK} \not\subseteq \text{BQP}$ relative to an oracle, we have the immediate corollary²:

Corollary 4.1. *There exists an oracle \mathcal{O} such that $\text{naCQP}^{\mathcal{O}} \neq \text{BQP}^{\mathcal{O}}$.*

5 Search in $\tilde{O}(N^{1/3})$ time

Suppose that we are given query access to a function $f : \{0, 1\}^n \rightarrow \{0, 1\}$ such that the preimage $f^{-1}(1)$ contains exactly one element, x . In the classical randomized computational model, we can find x in $O(N)$ time, where $N = 2^n$, but no faster. In the quantum computational model, on the other hand, we can find x in $O(N^{1/2})$ time using Grover's search algorithm [15], but no faster [10].

Here we show that quantum computers equipped with (non-adaptive) non-collapsing measurements can search in $\tilde{O}(N^{1/3})$ time, where the tilde hides factors in $\log N$. The basic idea is to run $N^{1/3}$ Grover iterations, and then make $N^{1/3}$ non-collapsing measurements of the resulting state. Then with high probability the the marked item will be seen. This is a simplification of the proof given in [2, Theorem 10] for DQP. We now formalize this idea below:

Theorem 5.1. *Suppose, in the definition of naCQP, that the unitary operators U_1, \dots, U_T are now allowed to query f . That is, we are given access to the n -qubit gate U_f defined by $U_f |y\rangle = (-1)^{f(y)} |y\rangle$ for all $y \in \{0, 1\}^n$, as well as controlled- U_f . Then there is a naCQP algorithm to find the value of x that uses $O(N^{1/3})$ queries and $\tilde{O}(N^{1/3})$ time.*

Proof. Prepare the uniform superposition of all basis states, apply $i = N^{1/3}$ Grover iterations [15], then query the oracle to record whether or not each basis state is marked in an ancilla. We obtain the state

$$\sin((2i+1)\theta) |x\rangle |1\rangle + \cos((2i+1)\theta) \sum_{y \in \{0,1\}^n, y \neq x} 2^{-\frac{N-1}{2}} |y\rangle |0\rangle$$

where $\sin(\theta) = 2^{-n/2}$ and $i = 2^{n/3}$. For small x we have $\sin(x) \approx x$, so for large n we have $\theta = \Theta(2^{-n/2})$, so $\sin((2i+1)\theta) = \Theta(2^{-n/6})$.

Now make $O(N^{1/3} \log N)$ non-collapsing measurements. We claim that with high probability, the marked item x will appear at least once. Indeed, the marked item x appears with probability at least $\Omega(N^{-1/3})$ in each non-collapsing measurement outcome, so it occurs at least once with probability more than $1 - (\log N + 1)e^{-\log N} = 1 - o(1)$. □

²Note that when we say $\text{naCQP}^{\mathcal{O}}$, we mean that circuits given in the input to \mathcal{Q} in the definition of naCQP can contain quantum calls to the oracle.

Note that if we are willing to use an enormous amount of *time*, we can search in the **naCQP** model using only one *query*: just query the oracle in superposition and then perform $O(N)$ non-collapsing measurements. Indeed as we note in the introduction, any function f has query complexity 1 in this model, although this approach requires exponentially many non-collapsing measurements. Therefore in this model of computation, the relevant measure of complexity of an algorithm is the number of queries Q plus the number of non-collapsing measurements T used by the algorithm. Our above algorithm uses $Q + T = \tilde{O}(N^{1/3})$ of each, with $O(N^{1/3})$ post-processing time, so we say it “runs in time $\tilde{O}(N^{1/3})$ ”.

6 Lower bounds for search

We now show that our search algorithm in section 5 cannot be improved by much; in particular there is no way to solve search in faster than $N^{1/4}$ time, even with non-adaptive non-collapsing measurements. Proving the analogous lower bound for adaptive non-collapsing measurements (i.e. for the class **CQP**) remains open.

Theorem 6.1. *Suppose, in the definition of **naCQP**, that the unitary operators U_1, \dots, U_T are now allowed to query f . Let Q be the number of queries to f made by a **naCQP** algorithm, and T be the number of non-collapsing measurements. Then any **naCQP** algorithm to find the value of x obeys $Q + T = \Omega(N^{1/4})$, and hence search requires $\Omega(N^{1/4})$ time.*

In other words, there is no “black box” polynomial-time algorithm for NP-hard problems, even when given access to non-collapsing measurements. This is evidence that the class **naCQP** does not contain NP. The following corollary follows immediately from the well-known “diagonalization method” of Baker, Gill, and Solovay [9]:

Corollary 6.1. *There exists an oracle \mathcal{O} such that $\text{NP}^{\mathcal{O}} \not\subseteq \text{naCQP}^{\mathcal{O}}$.*

We now outline the proof of Theorem 6.1. The following lemma is essential: it bounds the total variation distance between two Markov distributions.

Lemma 6.1. *Suppose that $T \geq 1$, and that $v = (v_0, \dots, v_T)$ is a random variable governed by a Markov distribution. That is, for all $1 \leq i \leq T$, v_i is independent of v_0, \dots, v_{i-2} conditioned on a particular value of v_{i-1} . Let $w = (w_0, \dots, w_T)$ be another random variable governed by a Markov distribution. If $d_{TV}(\cdot, \cdot)$ denotes the total variation distance between random variables, then*

$$d_{TV}(v, w) \leq 2 \sum_{i=1}^T d_{TV}((v_{i-1}, v_i), (w_{i-1}, w_i)).$$

Proof. We proceed by induction on T . The base case $T = 1$ is trivial. For $T > 1$, since w_T depends only on w_{T-1} (by the Markov property), it is equal to $A(w_{T-1})$ for some randomized process A ; let $w'_T := A(v_{T-1})$ be a variable that depends on v_{T-1} in exactly the same way that w_T depends on w_{T-1} . Then, define the random variable $v' = (v_0, \dots, v_{T-1}, w'_T)$. By the triangle inequality,

$$d_{TV}(v, w) \leq d_{TV}(v, v') + d_{TV}(v', w). \tag{1}$$

Applying the same randomized process to two random variables cannot increase their total variation distance [18]. We can generate random variables identically distributed to v and v'

by applying a suitable randomized process to (v_{T-1}, v_T) and (v_{T-1}, w'_T) . We can also generate random variables identically distributed to v' and w by applying a suitable randomized process to (v_0, \dots, v_{T-1}) and (w_0, \dots, w_{T-1}) . Therefore, the right hand side of (1) is bounded above by

$$d_{TV}((v_{T-1}, v_T), (v_{T-1}, w'_T)) + d_{TV}((v_0, \dots, v_{T-1}), (w_0, \dots, w_{T-1})).$$

By the triangle inequality,

$$\begin{aligned} d_{TV}((v_{T-1}, v_T), (v_{T-1}, w'_T)) &\leq d_{TV}((v_{T-1}, v_T), (w_{T-1}, w_T)) + d_{TV}((w_{T-1}, w_T), (v_{T-1}, w'_T)) \\ &= d_{TV}((v_{T-1}, v_T), (w_{T-1}, w_T)) + d_{TV}(v_{T-1}, w_{T-1}) \\ &\leq 2d_{TV}((v_{T-1}, v_T), (w_{T-1}, w_T)). \end{aligned}$$

Putting all of this together, we get that $d_{TV}(v, w)$ is upper bounded by

$$\begin{aligned} &2d_{TV}((v_{T-1}, v_T), (w_{T-1}, w_T)) \\ &+ d_{TV}((v_0, \dots, v_{T-1}), (w_0, \dots, w_{T-1})). \end{aligned}$$

The result follows from induction. \square

Lemma 6.2. *The trace distance between two pure states $|\psi\rangle$ and $|\phi\rangle$ is less than or equal to the 2-norm $\| |\psi\rangle - |\phi\rangle \|_2$.*

Proof. The trace distance between $|\psi\rangle$ and $|\phi\rangle$ is equal to $\sqrt{1 - |\langle\psi|\phi\rangle|^2}$ [16], and the 2-norm $\| |\psi\rangle - |\phi\rangle \|_2$ is $\sqrt{2 - 2\text{Re}(\langle\psi|\phi\rangle)}$. The inequality follows from $|\langle\psi|\phi\rangle| \leq 1$. \square

From the hybrid argument of [10], we have the following:

Lemma 6.3. *For all t , if there are no measurements made before time t , we have*

$$\sum_{x=0}^{N-1} \| |\psi_t\rangle - |\psi_t(x)\rangle \|_2^2 \leq 4Q^2.$$

With these facts, we can now prove Theorem 6.1. We provide an outline of the proof here, and the full proof can be found in Appendix F. The basic idea is to realize that the non-collapsing measurement outcomes form a Markov chain, because the distribution of any non-collapsing measurement is independent once the results of the previous intermediate collapsing measurements are fixed. So, letting v and $v(x)$ be the distributions on non-collapsing measurement outcomes when the marked item is absent or present at x , by applying Lemma 6.1, we have that

$$\frac{1}{3} \leq d_{TV}(v, v(x)) \leq 2 \sum_{i=1}^T d_{TV}((v_{i-1}, v_i), (v_{i-1}(x), v_i(x))).$$

Here the lower bound on d_{TV} comes from the fact that our algorithm can distinguish whether or not a marked item is present with probability $2/3$, and hence these distributions must be $1/3$ -far apart for all x .

Lemma 6.3 tells us that there is some x for which the marginal distributions v_i and $v_i(x)$ are close. However, this isn't sufficient to upper bound the quantity on the right of this inequality, because the correlations between the distributions at steps $i-1$ and i (which are induced by the

intermediate collapsing measurements) might make the distributions easier to distinguish³. Hence in order to prove this lower bound, we have to substantially strengthen the hybrid argument [10] to show that the correlations induced by the collapsing measurement outcomes do not allow $d_{TV}((v_{i-1}, v_i), (v_{i-1}(x), v_i(x)))$ to be large. By carefully keeping track of these induced correlations, we show in Appendix F that there is some x for which

$$d_{TV}(v, v(x)) \leq 2 \sum_{i=1}^T d_{TV}((v_{i-1}, v_i), (v_{i-1}(x), v_i(x))) \leq \frac{20TQ}{\sqrt{N}}.$$

where Q is the number of queries made by the algorithm and T is the number of non-collapsing measurements. Combining this with the fact that $d_{TV}(v, v(x)) \geq \frac{1}{3}$ for all x , this implies

$$\frac{20TQ}{\sqrt{N}} \geq \frac{1}{3},$$

and hence the running time of the algorithm is at least $T + Q = \Omega(N^{1/4})$.

7 An upper bound on CQP

We now show that CQP is contained in the class BPP^{PP} . Since $\text{naCQP} \subseteq \text{CQP}$, this places both classes in the second level of the counting hierarchy. By comparison, the best known upper bound for BQP is AWPP which is contained in PP [14][7].

Theorem 7.1. $\text{CQP} \subseteq \text{BPP}^{\text{PP}}$.

Proof. First note that $\text{BPP}^{\text{PP}} = \text{BPP}^{\#P}$, because one can always use a PP oracle to count with only polynomial overhead. Therefore it suffices to show $\text{CQP} \subseteq \text{BPP}^{\#P}$. We now show how to simulate the sampling oracle \mathcal{Q} in $\text{BPP}^{\#P}$. Our algorithm will work for adaptive queries as well. Since $\text{CQP} = \text{BPP}^{\mathcal{Q},1}$, this implies the claim.

Suppose we wish to simulate a sample from the oracle \mathcal{Q} with input circuit $C = (U_1, M_1, \dots, U_T, M_T)$ on n qubits. Since the choice of gate set does not matter (see Appendix D), without loss of generality we can assume our circuit is composed of only Toffoli and Hadamard gates, which are universal by a result of Shi [19].

We first simulate the result of the measurement M_1 . Suppose without loss of generality that M_1 measures the first k qubits and gets outcome $x_1 \dots x_k \in \{0, 1\}^k$. Following the techniques of Adleman, DeMarrais, and Huang [7], we can write the probability that x_1 is 0 or 1 as an exponential sum of poly-time-computable terms (since U_1 is specified by a poly-sized circuit). Since we chose Hadamard and Toffoli as our gate set, all terms in the sum are of the form $\frac{\pm 1}{2^k}$, where k is the number of Hadamard gates in U_1 . Hence using the $\#P$ oracle, we can compute $\Pr[x_1 = 1]$ exactly in binary, and then flip a coin with bias p using the base BPP machine to obtain outcome $x_1 \in 0, 1$ with this probability.

We've now sampled the value of x_1 . To sample the value of x_2 , note that we can also express $\Pr[x_2 = 1 | x_1 = 0]$ as a sum of exponentially many terms, each of which is poly-time computable

³To see how this could happen in general, consider the following two Markov distributions on two bits: D_1 outputs 00 or 11 with equal probability, and D_2 outputs 01 or 10 with equal probability. These have identical marginals on each bit, but are perfectly distinguishable due to the correlations between their bits.

and takes values in $\frac{\pm 1}{2^k}$. Therefore using the #P oracle, we can exactly compute the *conditional* probability that $x_2 = 1$ given our sampled value of x_1 ; in other words the #P oracle can compute the probabilities of measurement outcomes under post-selection. In this way we can sample x_2 , then x_3 , etc. obtain a sample $x_1 \dots x_k \in \{0, 1\}^k$ as desired.

Now suppose we wish to sample the variable $v_1 \in \{0, 1\}^n$ which is the result of a non-collapsing measurement on the state remaining after measurement M_1 yields value $x_1 \dots x_k$. As noted above, using the #P oracle, we can compute the marginal probability that any qubit is 1, postselected on a particular measurement outcome. Hence using the #P oracle, we can draw the sample v_1 using n queries to the oracle. We can continue this process to simulate M_2 , then sample v_2 , etc. Therefore we can draw a sample from \mathcal{Q} using $O(nT)$ queries to the #P oracle. Note that this simulation works when the U_i and the M_i are chosen adaptively, since for each t the base BPP machine receives the non-collapsing measurement samples $v_0 \dots v_t$ before proposing the next unitary U_{t+1} and measurement M_{t+1} . Hence this shows $\text{CQP} \subseteq \text{BPP}^{\text{PP}}$. □

An open question is whether or not we can improve this upper bound to show $\text{naCQP} \subseteq \text{PP}$. This seems difficult because $\text{SZK} \subseteq \text{naCQP}$, and it is open whether or not $\text{SZK} \subseteq \text{PP}$. In fact, Aaronson [4] showed that there is an oracle separation between SZK and a weaker class A_0PP , and left open the problem of finding an oracle relative to which SZK is not contained in PP. If such an oracle exists, it would imply one could not show $\text{naCQP} \subseteq \text{PP}$ with a relativizing proof.

One natural approach to showing $\text{naCQP} \subseteq \text{PP}$ is to use the fact that $\text{PP} = \text{PostBQP}$ [3], and design a post-selected quantum circuit to simulate the oracle \mathcal{Q} . However, the most naive way of trying to do this fails. Suppose that one tried the following: to simulate the oracle's output under $C = (U_1, M_1, \dots, U_T, M_T)$ on n qubits, create a post-selected circuit C' on nT qubits which runs $U_1 M_1$ on the first n qubits, $U_1 M_1 U_2 M_2$ on the second n qubits, etc, and post-selects on them receiving the same outcomes for the intermediate measurements. While this superficially looks like what the oracle \mathcal{Q} performs, this approach does not sample from the correct distribution on outputs. Suppose the probability that the outcome of M_1 is 1 is p . Then the probability one sees $M_1 = 1$ in the final output of C' will be $\frac{p^T}{p^T + (1-p)^T}$, while the quantum oracle \mathcal{Q} will sample $M_1 = 1$ with probability p . For this reason it seems difficult to generate a sample from \mathcal{Q} with a post-selected circuit, and hence difficult to place naCQP in PP.

8 Open questions

We leave many questions about the complexity classes DQP, CQP and naCQP unanswered.

1. We demonstrated a $\tilde{O}(N^{1/3})$ -time algorithm for the search problem in the naCQP model, as well as the result that any search algorithm takes $\Omega(N^{1/4})$ time. Is it possible to close the gap between these two bounds? If we disallow intermediate collapsing measurements, then we can prove an $N^{1/3}$ lower bound for search (a proof is included in Appendix G). However proving an $N^{1/3}$ lower bound when there are intermediate measurements remains open.
2. Can we demonstrate a lower bound, superpolynomial in $\log N$, for the running time of a search algorithm in the DQP model? The proof given in [2] of an $\Omega(N^{1/3})$ lower bound is flawed (as discussed in Appendix B).

3. Is there a hierarchy of computational models for which the k th allows searching in $\tilde{O}(N^{1/k})$ time?
4. Can we improve the upper bound $\text{naCQP} \subseteq \text{BPP}^{\text{PP}}$ to $\text{naCQP} \subseteq \text{P}^{\text{PP}}$ or $\text{naCQP} \subseteq \text{PP}$? One possible way to approach this problem is to use the alternative formulation of PP as PostBQP [3], however a straightforward application of this result does not seem to work.
5. How powerful is the class CQP ? In particular, can one prove a polynomial lower bound for search in CQP ?
6. More generally, what is the power of quantum computers which have the ability to clone quantum states? Such devices could clearly simulate computations in naCQP and CQP - to simulate a non-collapsing measurement, simply clone the state and measure in the computational basis - but may be more powerful than either class. For a further discussion see Appendix A.

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References

- [1] Scott Aaronson. Quantum lower bound for the collision problem. In *Proceedings of the thirty-fourth annual ACM symposium on Theory of computing*, STOC '02, pages 635–642, New York, NY, USA, 2002. ACM.
- [2] Scott Aaronson. Quantum computing and hidden variables. *Phys. Rev. A*, 71:032325, Mar 2005.
- [3] Scott Aaronson. Quantum computing, postselection, and probabilistic polynomial-time. In *Proceedings of the Royal Society A*, page 0412187, 2005.
- [4] Scott Aaronson. Impossibility of Succinct Quantum Proofs for Collision-Freeness. *Quantum Information and Computation*, 12:21-28, 2012.
- [5] Scott Aaronson, Adam Bouland, Joseph Fitzsimons, and Mitchell Lee. The space "just above" BQP . Technical report, arXiv:1412.6507, 2014.
- [6] Daniel S. Abrams and Seth Lloyd. Nonlinear quantum mechanics implies polynomial-time solution for NP-complete and $\#\text{P}$ problems. *Phys. Rev. Lett.*, 81, 3992–3995, 1998.
- [7] Leonard M. Adleman, Jonathan Demarrais, Ming-deh, and A. Huang. Quantum computability. *SIAM Journal of Computation*, pages 1524–1540, 1997.

- [8] Sanjeev Arora and Boaz Barak. *Computational Complexity: A Modern Approach*. Cambridge University Press, New York, NY, USA, 1st edition, 2009.
- [9] T. Baker, J. Gill, and R. Solovay. Relativizations of the $\mathcal{P} = ?\mathcal{NP}$ question. *SIAM Journal on Computing*, 4(4):431–442, 1975.
- [10] Charles H. Bennett, Ethan Bernstein, Gilles Brassard, and Umesh Vazirani. Strengths and weaknesses of quantum computing. *SIAM J. Comput.*, 26(5):1510–1523, October 1997.
- [11] Ethan Bernstein and Umesh Vazirani. Quantum complexity theory. In *in Proc. 25th Annual ACM Symposium on Theory of Computing*, ACM, pages 11–20, 1993.
- [12] Christopher M. Dawson and Michael A. Nielsen. The Solovay-Kitaev algorithm. *Quantum Info. Comput.*, 6(1):81–95, January 2006.
- [13] Mark Ettinger, Peter Høyer, and Emanuel Knill. The quantum query complexity of the hidden subgroup problem is polynomial. *Information Processing Letters*, 91(1):43–48, July 2004.
- [14] Lance Fortnow and John Rogers. Complexity limitations on quantum computation. In *Proc. IEEE CCC'98*, p. 202–209, 1998.
- [15] Lov K. Grover. A fast quantum mechanical algorithm for database search. In *Proceedings of the twenty-eighth annual ACM symposium on Theory of computing*, STOC '96, pages 212–219, New York, NY, USA, 1996. ACM.
- [16] Michael A. Nielsen and Isaac L. Chuang. *Quantum Computation and Quantum Information (Cambridge Series on Information and the Natural Sciences)*. Cambridge University Press, 1 edition, January 2004.
- [17] A Peres. Two simple proofs of the Kochen-Specker theorem. *Journal of Physics A: Mathematical and General*, 24(4):L175, 1991.
- [18] A. Sahai and S.P. Vadhan. A complete promise problem for statistical zero-knowledge. In *Foundations of Computer Science, 1997. Proceedings., 38th Annual Symposium on*, pages 448–457, 1997.
- [19] Y. Shi. Both Toffoli and controlled-NOT need little help to do universal quantum computing. *Quantum Information & Computation*, 3:1 pp. 84–92 (2003).

Appendix

A Strange properties of noncollapsing measurements

Here we show why allowing non-collapsing measurements in quantum mechanics allows for faster than light communication, renders quantum query complexity and quantum communication complexity meaningless, and allows for quantum cloning. We also discuss the relationship between naCQP and quantum computers which have the ability to clone.

To see that non-collapsing measurements allow for faster-than-light communication: suppose two players Alice and Bob share n EPR pairs. Then Alice can send a bit of information to Bob

with probability $1 - 2^{-n}$. To see this, suppose Alice makes collapsing measurements in the 0/1 basis on her share of the EPR pairs to send a 0, and measures in the +/- basis to send a 1. Now Bob makes two non-collapsing measurements in the 0/1 basis on his half of the EPR pairs. If Alice had sent a 0, then Bob will see the same outcome each time. If Alice had sent a 1, then Bob will see a random string each time, so with probability $1 - 2^{-n}$ Bob will see two different outcomes. Thus Bob can tell which basis Alice measured in with high probability, and Alice and Bob can communicate faster than light.

We now explain why with non-collapsing measurements, the quantum query complexity and quantum communication complexity of any function is 1. Suppose one wishes to evaluate $f(x)$ where $x = x_1 \dots x_N$. Then one can prepare the superposition $\sum_i |i\rangle |x_i\rangle$ with one query to the oracle, and make $O(N \log N)$ non-collapsing measurements of this state to observe the value of each x_i and compute the function. Similarly, in the context of communication complexity, one player can simply encode their input $x \in \{0, 1\}^n$ into the state $\cos \theta_x |0\rangle + \sin \theta_x |1\rangle$ where $\theta_x = \frac{x}{2^n} \frac{\pi}{2}$. By performing roughly 2^n non-collapsing measurements, the other player can learn θ_x and hence x , with only one quantum bit of communication. Note that although these example algorithms use only one query or one qubit of communication, respectively, they use a large number of non-collapsing measurements. For this reason, when we prove lower bounds for naCQP, we lower bound the number of queries *plus* the number of non-collapsing measurements required, rather than the number of queries alone.

To see that non-collapsing measurements allow for cloning: given a quantum state ψ on n qubits, one could perform $2^{O(n)}$ non-collapsing measurements to characterize the state using tomography, and then (approximately) reproduce the state. This “approximate cloning” operation take exponential time for generic states, and is non-unitary.

Note, that the class of computations considered in naCQP cannot clone, even for states of $O(\log(n))$ qubits, since the naCQP machine cannot perform further quantum computations after receiving the non-collapsing measurement results (i.e. because of the non-adaptivity restriction). In contrast, if the circuit could depend on the non-collapsing measurement results (as in CQP), then one could clone states of $O(\log(n))$ qubits to polynomial accuracy, which is a non-unitary operation. Hence following the result of Abrams and Lloyd [6], the power of CQP class might include NP or even #P, though we do not know if this is the case. A broader related open problem is: what is the power of quantum computers which are given the ability to clone? Such devices could clearly simulate naCQP and CQP computations - to simulate a non-collapsing measurement, simply clone and measure in the computational basis. However, it’s unclear how powerful such quantum devices would be.

B The error in the DQP search time lower bound, and a roadmap for correcting it

We now describe the error in Aaronson’s original proof of an $\Omega(N^{1/3})$ lower bound for search in the DQP model, which is related to the fact that hidden variable theories can have strong correlations between their values at different times.

B.1 The class DQP

We first describe the formal definition of the complexity class DQP, which is based on the notion of a hidden-variable theory. A hidden-variable theory is an interpretation of quantum mechanics in

which a quantum system is described by both a state vector and a definite state (called the “hidden variable”), which determines the result of measurements on the system. When a transformation is applied to the system, the state vector evolves by a unitary linear transformation, like in ordinary quantum mechanics, and the hidden variable evolves stochastically according to the state vector and the unitary linear transformation. According to the Kochen-Specker theorem [17], it is impossible for the hidden variable to determine a result for all possible measurements on the system. Therefore, in what follows, we will only ever measure the quantum system in some fixed basis.

Suppose that our quantum system is described by a Hilbert space with N basis states $|1\rangle, |2\rangle, \dots, |N\rangle$. Then, the hidden variable has one of the values $1, \dots, N$. The hidden-variable theory specifies the probabilities that the hidden variable changes from i to j given that the state was $|\psi\rangle$ and was transformed by the unitary U . More precisely, a hidden variable theory \mathcal{T} is specified by a stochastic matrix $S_{\mathcal{T}}(|\psi\rangle, U)$ for every state $|\psi\rangle$ and unitary transformation U of dimension N , which indicates how the hidden variable evolves when the state transforms from $|\psi\rangle$ to $U|\psi\rangle$. If \mathcal{T} is understood from context, then we simply write $S(|\psi\rangle, U)$. Suppose $|\psi\rangle = \sum_i \alpha_i |i\rangle$ and $U|\psi\rangle = \sum_j \beta_j |j\rangle$. The hidden-variable theory must be consistent with the predictions of quantum mechanics, which is to say that the probability that the hidden variable is equal to i is equal to $|\alpha_i|^2$. This means that the stochastic matrix $S = S(|\psi\rangle, U)$ must satisfy

$$|\beta_j|^2 = \sum_{i=1}^n |\alpha_i|^2 (S)_{ij}.$$

Other “reasonable” properties that we might expect a hidden-variable theory to have, for example that $S(|\psi\rangle, WV) = S(|\psi\rangle, V)S(V|\psi\rangle, W)$, need not be satisfied.

Sometimes, the hidden-variable theory is described instead by the matrix $P = P(|\psi\rangle, U)$ of joint probabilities, defined by $(P)_{ij} = |\alpha_i|^2 (S)_{ij}$. The matrix S is then recovered by

$$S(|\psi\rangle, U) = \lim_{\epsilon \rightarrow 0^+} \frac{(P(|\psi_\epsilon\rangle, U))_{ij}}{(|\psi_\epsilon\rangle)_i^2}$$

where $|\psi_\epsilon\rangle = \sqrt{1-\epsilon}|\psi\rangle + \sqrt{\epsilon}\frac{1}{\sqrt{2^{N/2}}}\sum_i |i\rangle$. The function $P(|\psi\rangle, U)$ only defines a hidden-variable theory if this limit actually exists.

The hidden-variable theory is called *local* if unitary transformations on some subsystem A of the system do not affect the value of the hidden variable on a separate subsystem B . A stronger property is *indifference*, which is the property that if U is block-diagonal, then $S(|\psi\rangle, U)$ is block-diagonal with the same block structure or some refinement thereof. It is called *commutative* if the order of unitaries applied to separate subsystems is irrelevant. A theorem of Bell states that no hidden-variable theory satisfies both locality and commutativity. The theory is called *robust* if for every polynomial $q(N)$, there is a polynomial $p(N)$ such that perturbing the unitary U and density matrix $|\psi\rangle$ by at most $\frac{1}{p(N)}$ in the infinity norm changes the matrix $P(|\psi\rangle, U)$ by at most $\frac{1}{q(N)}$ in the infinity norm. An example of a robust indifferent hidden variable theory is the flow theory \mathcal{FT} defined in [2], which is based on network flows. For a more detailed treatment of hidden variable theories, see [2].

The complexity class DQP (Dynamical Quantum Polynomial Time) is the class of all problems solvable efficiently in the dynamic quantum model of computation. The basic idea is that a dynamic quantum algorithm is allowed to see the whole history of a hidden variable through some quantum computation (and postprocess it classically), as opposed to a quantum algorithm which can only see the final value of the hidden variable.

More formally, suppose that U_1, \dots, U_T are unitary transformations on ℓ qubits, each specified by a sequence of gates from some finite universal gate set \mathcal{U} . Then, a *history* of the hidden variable is a sequence (v_0, \dots, v_T) of computational basis states, with $v_0 = |0\rangle^{\otimes \ell}$. For any hidden-variable theory \mathcal{T} , the rule

$$\Pr[v = (v_0, \dots, v_T)] = \prod_{k=0}^{T-1} (S_{\mathcal{T}}(U_k \cdots U_1 |0\rangle^{\otimes \ell}, U_{k+1}))_{v_k v_{k+1}}$$

defines a Markov distribution on histories. The oracle $\mathcal{O}(\mathcal{T})$ takes as input the unitaries (U_1, U_2, \dots, U_T) , specified by sequences of gates from \mathcal{U} , and outputs a sample from this distribution.

Now, we are ready to define the complexity class DQP. The computational model is a deterministic classical polynomial-time Turing machine A that is allowed one oracle query to $\mathcal{O}(\mathcal{T})$. A language L is in DQP if there is such a Turing machine A , such that for *any* robust indifferent hidden-variable theory \mathcal{T} , the machine A correctly decides, with probability at least $2/3$, whether a string of length n is in L , for all sufficiently large n . It follows from the principle of deferred measurement that $\text{DQP} \supset \text{BQP}$, because viewing the entire history of a quantum system is at least as powerful as observing it only at the end of a computation [2]. It is important that there is one machine A that works for all robust indifferent hidden-variable theories \mathcal{T} .

B.2 The error

We now describe the error in Aaronson's proof that any algorithm for the search problem in DQP takes at least $\Omega(N^{1/3})$ time. His proof is based on the hybrid argument: it shows that changing the marked item from x to x^* does not affect the distribution of any particular entry v_i of the hidden-variable history by very much (in the total variation distance). This part of the proof is correct. However, from there he claims that this implies the total variation distance between the entire hidden variable histories v, w is small, using the following inequality

$$d_{TV}(v, w) \leq \sum_{i=0}^T d_{TV}(v_i, w_i).$$

While this inequality looks quite similar to Lemma 6.1 of our paper, it is false. The reason is that correlations between the v_i 's in a Markov chain can cause the total variation distance between the Markov chains to be high, while the total variation distance between the marginals is small. A specific counterexample is $T = 1$, where v is $(0, 0)$ with probability $\frac{1}{2}$ and $(1, 1)$ with probability $\frac{1}{2}$, and w is $(0, 1)$ with probability $\frac{1}{2}$ and $(1, 0)$ with probability $\frac{1}{2}$. These distributions are perfectly distinguishable, but they have the property that their marginals on any entry are identical (a 50-50 coin flip). Hence

$$d_{TV}(v, w) = 1$$

for this distribution whereas

$$\sum_{i=0}^T d_{TV}(v_i, w_i) = 0$$

Although $d_{TV}(v, w)$ cannot be upper bounded in this way, this sort of argument does show that for some item location, the probability of seeing the marked item in the hidden variable history is upper bounded by $O\left(\frac{Q^2 T}{N}\right)$ (this follows from the hybrid argument and the union bound). So

any search algorithm in DQP which is required to see the marked item takes at least $\Omega(N^{1/3})$ time. However, it is possible that a DQP algorithm could infer the marked item's presence by observing correlations in the hidden variable history, without ever seeing the marked item itself. This possibility is what breaks the proof.

In order to fix this step in Aaronson's proof, one would have to show that the quantity $d_{TV}((v_{i-1}, v_i), (w_{i-1}, w_i))$ is small for each i , and then apply Lemma 6.1 of our paper to bound the total variation distance between v and w . Furthermore, since a DQP algorithm is required to work for all indifferent or robust hidden variable theories, one would only need to exhibit a single hidden variable theory in which this is small. However, we only know of one indifferent and robust hidden variable theory ("flow theory"), and it remains open whether or not it satisfies this property.

B.3 A proposed roadmap for fixing the error

One way to fix this lower bound would be to find a hidden variable theory which is extremely robust to small perturbations. By the hybrid argument, we know that for any search algorithm making few queries, there will exist a marked item x for which the state of the system $|\psi^x\rangle$ with the item x present is ϵ -close (where $\epsilon \approx \frac{Q}{\sqrt{N}}$) to the state $|\psi\rangle$ without the marked item.

Call a hidden variable theory *strongly robust* if, for all states ψ, ϕ that are ϵ -close, and all U, U' that are ϵ -close,

$$|P(\psi, U) - P(\phi, U')|_1 \leq \text{poly}(\epsilon)\text{polylog}(N)$$

In other words, perturbing the states only perturbs the joint probability matrices by a small amount, which increases only polynomially in the number of qubits. In contrast, a robust theory is only required to obey $|P(\psi, U) - P(\phi, U')|_1 \leq \text{poly}(\epsilon)\text{poly}(N)$, i.e. the joint probability matrices can be perturbed by an amount which increases polynomially in the dimension of the Hilbert space.

If a strongly robust theory exists, it would immediately imply a lower bound for search in DQP which is polynomial in N - the reason is that for this marked item x , we would have

$$|P(\psi, U) - P(\psi^x, U^x)|_1 \leq \text{poly}(\epsilon)\text{polylog}(N) = \text{poly}\left(\frac{Q}{\sqrt{N}}\right)\text{polylog}(N)$$

at all stages of the algorithm, and hence by Lemma 6.1,

$$\begin{aligned} d_{TV}(v, v^x) &\leq \sum_i d_{TV}((v_{i-1}, v_i), (v_{i-1}^x, v_i^x)) \\ &= \sum_t |P(\psi_t^x, U_t^x) - P(\psi_t, U_t)|_1 \\ &\leq T \text{poly}\left(\frac{Q}{\sqrt{N}}\right)\text{polylog}(N) \end{aligned}$$

Since the DQP search algorithm must work for this strongly robust theory, we must have

$$\frac{TQ^c \text{polylog}(N)}{N^{c/2}} \geq d_{TV}(v, v^x) \geq \Omega(1)$$

for some constant c which is the exponent of the polynomial in ϵ . This implies $T+Q = \tilde{\Omega}(N^{c/(2+2c)})$. Note that perturbing a state by ϵ has to perturb the resulting P matrices by at least ϵ (since it

must alter their row sums by ϵ), and hence we must have $0 < c \leq 1$. Therefore even if a strongly robust theory exists, the best possible lower bound one could prove using this technique is $N^{1/4}$.

Unfortunately we do not know of any theories which are strongly robust. The only provably robust theory we know of is flow theory, which in [2] is shown to obey

$$|P(\psi, U) - P(\psi^x, U^x)|_1 \leq 4\epsilon N^2$$

which does not meet the criteria for strong robustness. An interesting open problem is to determine if flow theory, Schödinger theory (described in [2]), or any hidden variable theory is strongly robust.

C An $N^{1/4}$ lower bound for search in a modified version of DQP

Although we do not know how to prove a polynomial lower bound for search in DQP, we can show an $N^{1/4}$ lower bound for search in a modified version of DQP, which we describe below:

We first modify the definition of a hidden variable theory. A hidden variable theory is a function $P(\psi, C)$ which depends on

1. A quantum state $\psi = \sum_i \alpha_i |i\rangle$
2. A quantum circuit C which specifies product of unitary gate elements g^k , $k = 1 \dots poly(n)$, from some universal gate set \mathcal{U} . Note $U = \prod_k g^k$.

Unlike before, we now allow $P(\psi, C)$ to depend on the circuit generating the unitary U , rather than only the unitary itself. The output of $P(\psi, C)$ is a joint probability matrix P_{ij} , $i, j = 1 \dots N$ which satisfies

1. $\sum_j P_{ij} = |\alpha_i|^2$ where $\psi = \sum_i \alpha_i |i\rangle$
2. $\sum_i P_{ij} = |\beta_j|^2$ where we have $U\psi = \sum_j \beta_j |j\rangle$

as before.

We call $B \subseteq [N]$ a *circuit block* for circuit $C = \prod_k g^k$, where each g^k is a gate from a universal gate set \mathcal{U} , if for all k , $g^k_{ij} = 0$ for all $i \in B, j \notin B$ and $g^k_{ij} = 0$ for all $i \notin B, j \in B$. In other words, a circuit block B is valid if for all circuit elements g_k , indices i, j are in the same block in the unitary g_k . The *circuit block structure* of C is a minimal collection of circuit blocks which partition $[N]$.

In contrast, the block structure of C is the block structure of the resulting unitary. Note that block structure of C is always a refinement of its circuit block structure; if all gates in C have B as a valid block, then the final unitary will have B as a valid block, but the converse is not true. For example, suppose that $C = HH$ on a single qubit. Since $U = HH = I$ the block structure of C is $\{1\}, \{2\}$. However the circuit block structure of C is $\{1, 2\}$, i.e. the trivial circuit block structure, because the individual circuit elements do not have any block structure.

We call a hidden variable theory *circuit-indifferent* if $P(\psi, C)$'s block structure respects the circuit block structure of C . Since the block structure of a unitary U is always a refinement of the circuit block structure of the circuit C producing U , an indifferent theory is always circuit-indifferent. Hence the set of circuit-indifferent theories is larger than the set of indifferent theories.

We define a new version of DQP, which we call CDQP (for ‘‘circuit-indifferent DQP’’), as before, except

1. We require the algorithms to work for all circuit-indifferent hidden variable theories

2. We no longer require the hidden variable theories to be robust. As a result the definition of our class is gate set dependent. Assume we have all 1 and 2-qubit gates at our disposal.
3. When given access to a search oracle $f : \{0, 1\}^n \rightarrow \{0, 1\}$, we assume it is a phase oracle, i.e. $\mathcal{O}_f |x\rangle = (-1)^{f(x)} |i\rangle$. This distinction did not matter in the definition of DQP or naCQP, but it does matter here, because our hidden variable theories depend on the block structure of individual circuit elements, including the oracle.

We can now prove a lower bound for search in this version of CDQP.

Theorem C.1. *Any algorithm correctly deciding search in CDQP using Q queries and T time satisfies $Q + T = \Omega(N^{1/4})$.*

Proof. We will describe a circuit-indifferent hidden variable theory, which we call Dieks theory for circuit block structure, which foils any search algorithm A which uses $Q + T = o(N^{1/4})$ time. This contradicts the requirement that A work for all circuit-indifferent hidden variable theories.

Suppose that A generates quantum circuits $C_1 \dots C_T$ when there is no marked item, and quantum circuits $C_1^x \dots C_T^x$ when there is a marked item at location x . Clearly the circuits C_t and C_t^x differ only in their search oracles. The search oracles are diagonal, hence C_t and C_t^x have the same circuit block structure I . This will be crucial in proving our result.

Let ψ_t be the quantum state after t steps of the algorithm when there is no marked item, and let ψ_t^x be the quantum state after t steps when there is a marked item at location x . By the hybrid argument, there exists an item x such that

$$\|\psi_t - \psi_t^x\| \leq \frac{4Q}{\sqrt{N}} \quad (2)$$

for all $t = 1 \dots T$, where $\|\psi_t - \psi_t^x\|$ indicates the trace norm.

We will show that if $P(\psi_t, C_{t+1}, t)$ and $P(\psi_t^x, C_{t+1}^x, t)$ are given by Dieks theory for circuit block structure, then

$$|P(\psi_t, C_{t+1}) - P(\psi_t^x, C_{t+1}^x)|_1 \leq \frac{12Q}{\sqrt{N}} \quad (3)$$

From this the lower bound will follow, because the trace distance between the hidden variable histories with and without a marked item is upper bounded by

$$\sum_t |P(\psi_t, C_{t+1}) - P(\psi_t^x, C_{t+1}^x)|_1 \leq O\left(\frac{TQ}{\sqrt{N}}\right)$$

by Lemma 6.1. The quantity must be $\Omega(1)$ because A distinguishes the presense of a marked item with $\Omega(1)$ probability. Hence we have $TQ = \Omega(N^{1/2})$ so $T + Q = \Omega(N^{1/4})$ as desired.

We now define Dieks theory for circuit block structure. Let I be the circuit block structure of C . Let $P := P(\psi_t, C_{t+1})$ be the joint probability matrix of Dieks theory with block structure I . That is,

$$P_{ij} = |\alpha_i|^2 \frac{|\beta_j|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2}$$

if i, j are in the same block $B \in I$ and 0 otherwise. Note P is a valid, circuit indifferent matrix. Indeed the column and row sums are

$$\sum_j P_{ij} = |\alpha_i|^2 \sum_{j \in B} \frac{|\beta_j|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2} = |\alpha_i|^2 \quad (4)$$

$$\sum_i P_{ij} = \sum_{i \in B} |\alpha_i|^2 \frac{|\beta_j|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2} \quad (5)$$

$$= |\beta_j|^2 \frac{\sum_{i \in B} |\alpha_i|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2} = |\beta_j|^2 \quad (6)$$

where in line 6 we used the fact that the actual block structure of U is a refinement of the circuit block structure of C , hence U restricted to any block B of I is also unitary, and so $\sum_{i \in B} |\alpha_i|^2 = \sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2$. Hence $P(\psi, C)$ is a valid circuit-indifferent hidden variable theory.

The following Lemma, combined with the equation 2 and the fact that C and C^x have the same circuit block structure, implies equation 3.

Lemma C.1. *Suppose that $\|\psi - \psi_x\| \leq \|U\psi - U^x\psi_x\| \leq \epsilon$ where U (U^x) is the unitary produced by circuit C (C^x). Furthermore suppose C and C^x have the same circuit block structure. Then if P is given by Dieks theory for circuit block structure, then $|P(\psi, C) - P(\psi^x, C^x)| \leq 3\epsilon$.*

Proof. Let $\alpha_i, \alpha_i^x, \beta_i, \beta_i^x$ be defined by $\psi = \sum_i \alpha_i |i\rangle$, $\psi^x = \sum_i \alpha_i^x |i\rangle$, $U\psi = \sum_i \beta_i |i\rangle$, and $U\psi^x = \sum_i \beta_i^x |i\rangle$ as usual.

Let I be the circuit block structure of C and C^x . By the definition of Dieks theory for circuit indifference, we have that $P := P(\psi, C)$ and $\hat{P} := P(\psi^x, C^x)$ are given by

$$P_{ij} = \begin{cases} |\alpha_i|^2 \frac{|\beta_j|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2} & i, j \in B \in I \\ 0 & \text{o.w.} \end{cases} \quad \hat{P}_{ij} = \begin{cases} |\alpha_i^x|^2 \frac{|\beta_j^x|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}^x|^2} & i, j \in B \in I \\ 0 & \text{o.w.} \end{cases}$$

We can now show \hat{P} is close to P in trace distance. Note that

$$|P - \hat{P}|_1 = \sum_{i,j} \left| |\alpha_i|^2 \frac{|\beta_j|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2} - |\alpha_i^x|^2 \frac{|\beta_j^x|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}^x|^2} \right| \quad (7)$$

$$\leq \sum_B \sum_{i,j \in B} \left| |\alpha_i|^2 \frac{|\beta_j|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2} - |\alpha_i|^2 \frac{|\beta_j^x|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}^x|^2} \right| + \left| |\alpha_i|^2 \frac{|\beta_j^x|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}^x|^2} - |\alpha_i^x|^2 \frac{|\beta_j^x|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}^x|^2} \right| \quad (8)$$

$$= \sum_B \sum_{i,j \in B} |\alpha_i|^2 \left| \frac{|\beta_j|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2} - \frac{|\beta_j^x|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}^x|^2} \right| + \sum_B \sum_{i,j \in B} \frac{|\beta_j^x|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}^x|^2} \left| |\alpha_i|^2 - |\alpha_i^x|^2 \right| \quad (9)$$

$$= \sum_B \sum_{j \in B} \sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2 \left| \frac{|\beta_j|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2} - \frac{|\beta_j^x|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}^x|^2} \right| + \sum_i \left| |\alpha_i|^2 - |\alpha_i^x|^2 \right| \quad (10)$$

$$\leq \sum_B \sum_{j \in B} \left| |\beta_j|^2 - |\beta_j^x|^2 \frac{\sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}^x|^2} \right| + \epsilon \quad (11)$$

$$\leq \sum_B \sum_{j \in B} \left| |\beta_j|^2 - |\beta_j^x|^2 \right| + \left| |\beta_j^x|^2 - |\beta_j^x|^2 \frac{\sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}^x|^2} \right| + \epsilon \quad (12)$$

$$\leq \epsilon + \sum_B \sum_{j \in B} |\beta_j^x|^2 \left| 1 - \frac{\sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2}{\sum_{\hat{j} \in B} |\beta_{\hat{j}}^x|^2} \right| + \epsilon \quad (13)$$

$$= \epsilon + \sum_B \left| \sum_{j \in B} |\beta_j^x|^2 - \sum_{\hat{j} \in B} |\beta_{\hat{j}}|^2 \right| + \epsilon \quad (14)$$

$$\leq 3\epsilon \quad (15)$$

where line (8) follows from the triangle inequality, line (10) from the fact that U has block structure I so $\sum_{i \in B} |\alpha_i|^2 = \sum_{j \in B} |\beta_j|^2$ as well as an evaluation of the second sum, line (11) from our upper bound on the trace distance of ψ and ψ_x , line (12) by the triangle inequality, and lines (13) and (15) by our upper bound on the trace distance of $U\psi$ and $U\psi^x$. This completes the proof. \square

Hence Dieks theory for circuit block structure foils any CDQP algorithm taking less than $N^{1/4}$ time, which completes the proof. \square

D Universal gate set does not matter

We prove that the universal gate set \mathcal{U} used in the definition of naCQP does not matter. Our proof relies on Lemma 6.1 and the Solovay-Kitaev theorem [12] to show that any computation using a particular universal gate set \mathcal{U} can be done using a different gate set \mathcal{U}' in such a way that the distributions of the histories does not change significantly in total variation distance.

To do so, we will first give an alternative definition of naCQP which will make the proof easier. Our alternative definition is framed in the notation of DQP; for an introduction to this notation please see Appendix B.

D.1 An alternative definition of naCQP

If B is a partition of $\{0, 1\}^\ell$ and U is a unitary operator on $(\mathbb{C}^2)^{\otimes \ell}$, then we say that U respects the block structure B if $U_{ij} = 0$ whenever i and j are in different parts of B . If $|\psi\rangle$ is a pure state and U is a unitary that respects the block structure B , then the stochastic matrix $S_{\mathcal{PT}_B}(|\psi\rangle, U)$ is formed by applying the ‘‘product theory’’ \mathcal{PT} separately on each block of B . More precisely, let \sim be the equivalence relation on $\{1, \dots, n\}$ defined by $i \sim j$ if and only if i and j are in the same block of B . Let $|\psi\rangle = \sum_i \alpha_i |i\rangle$ and $U|\psi\rangle = \sum_j \beta_j |j\rangle$. Then,

$$(S_{\mathcal{PT}_B}(|\psi\rangle, U))_{ij} = \begin{cases} \frac{|\beta_j|^2}{\sum_{k \sim j} |\beta_k|^2} & \text{if } i \sim j \\ 0 & \text{otherwise} \end{cases}$$

where the sum over k ranges over all k with $k \sim j$.

Suppose that $\mathcal{V} = (U_1, \dots, U_T)$ are unitary operators on ℓ qubits, and $\mathcal{B} = (B_1, \dots, B_T)$ are partitions of $\{0, \dots, 1\}^n$ such that for every i , B_{i+1} is a refinement of B_i , and U_i respects the block structure B_i . Then they define a probability distribution $\Omega = \Omega_{\mathcal{PT}}(\mathcal{V}, \mathcal{B})$ over hidden variable

histories $v = (v_0, \dots, v_T)$ by

$$\Omega_{(v_0, \dots, v_T)} = \prod_{k=1}^T (S_{\mathcal{PT}_{B_k}}(U_{k-1} \cdots U_1 |0\rangle^{\otimes \ell}, U_k))_{v_{k-1}v_k}.$$

The oracle \mathcal{Q}_B takes as input the unitaries U_1, \dots, U_T specified by sequences of gates from some finite universal gate set \mathcal{U} . It also takes as input the partitions B_1, \dots, B_T , specified by polynomial-time computable functions $b_1, \dots, b_T : \{0, 1\}^\ell \rightarrow \{0, 1\}^m$ satisfying the property that x and y are in the same part of the partition B_i if and only if $b_i(x) = b_i(y)$. It outputs a sample from the distribution $\Omega_{\mathcal{PT}}(\mathcal{V}, \mathcal{B})$. Then, let naCQP' be the class of all languages that can be recognized by a polynomial-time Turing machine with one query to \mathcal{Q}_B , with error probability at most $\frac{1}{3}$.

Lemma D.1. $\text{naCQP}' = \text{naCQP}$.

Proof. We first demonstrate a procedure for converting oracle queries to \mathcal{Q}_B to oracle queries to \mathcal{Q}_P . Suppose that B_1, \dots, B_T are specified by polynomial-time computable functions $b_1, \dots, b_T : \{0, 1\}^\ell \rightarrow \{0, 1\}^m$ (so that x, y are in the same part of the partition B_i if and only if $b_i(x) = b_i(y)$). Now, add an extra T registers of m qubits each, which start in the state $|0 \cdots 0\rangle$. Create a quantum circuit with the same unitary operators U_1, \dots, U_T , but before applying the unitary U_i , apply a unitary that writes the value $|b_i(x)\rangle$ to the i th register when the first ℓ qubits are $|x\rangle$. Then measure the i th register. The effect is that the non-collapsing measurement results will never jump from one part of B_i to a different part, which is exactly what is desired.

To convert a query $C = (U_1, M_1, \dots, U_T, M_T)$ to \mathcal{Q}_P to a query to \mathcal{Q}_B , we first assume, as in the proof of Theorem 6.1, that measured qubits are never modified again. Keep the unitaries U_1, \dots, U_T and let B_i be the partition of $\{0, 1\}^\ell$ induced by the measurements M_1, \dots, M_{i-1} . By the principle of deferred measurement, $\Omega_{\mathcal{V}, \mathcal{B}}$ is the same distribution that we would have seen had we queried \mathcal{Q}_P instead. \square

Now that we have given an alternative definition of naCQP , we can easily show that the choice of gate set does not matter:

Theorem D.1. *Any universal gate set \mathcal{U} yields the same complexity class naCQP .*

Proof. If A is an operator, denote by $\|A\|$ the maximum value of $\|A|\phi\rangle\|_2$ over all ϕ with $\|\phi\|_2 = 1$.

Lemma D.2. *Suppose that V_1, \dots, V_m and V'_1, \dots, V'_m are unitary operators. Then,*

$$\|V_1 \cdots V_m - V'_1 \cdots V'_m\| \leq \sum_{k=1}^m \|V_k - V'_k\|.$$

Proof. By induction, it suffices to prove the statement for $m = 2$. We have

$$\begin{aligned} \|V_1 V_2 - V'_1 V'_2\| &= \max_{\|\phi\|_2=1} \|V_1 V_2 |\phi\rangle - V'_1 V'_2 |\phi\rangle\|_2 \\ &\leq \max_{\|\phi\|_2=1} (\|V_1 V_2 |\phi\rangle - V'_1 V_2 |\phi\rangle\|_2 + \|V'_1 V_2 |\phi\rangle - V_1 V_2 |\phi\rangle\|_2) \\ &= \max_{\|\phi\|_2=1} (\|(V_1 - V'_1) V_2 |\phi\rangle\|_2 + \|(V_2 - V'_2) |\phi\rangle\|_2) \\ &\leq \|V_1 - V'_1\| + \|V_2 - V'_2\|. \end{aligned}$$

\square

If $|\psi\rangle = \sum_i \alpha_i |i\rangle$ is a pure state and U is a unitary operator on ℓ qubits that respects the block structure B , such that $U|\psi\rangle = \sum_j \beta_j |j\rangle$, then define the joint probabilities matrix $P_{\mathcal{PT}_B}(|\psi\rangle, U)$ by

$$(P_{\mathcal{PT}_B}(|\psi\rangle, U))_{ij} = \begin{cases} \frac{|\alpha_i|^2 |\beta_j|^2}{\sum_{k \sim j} |\beta_k|^2} & \text{if } i \sim j \\ 0 & \text{otherwise} \end{cases}.$$

It is straightforward to show that

$$\|P_{\mathcal{PT}_B}(|\psi\rangle, U) - P_{\mathcal{PT}_B}(|\psi'\rangle, U')\|_1 \leq 2^{2\ell} (\|\psi\rangle - |\psi'\rangle\|_{tr} + \|U - U'\|)$$

whenever $|\psi\rangle, |\psi'\rangle$ are state vectors and U, U' are unitary operators.

We use the alternative formulation naCQP' (Lemma D.1). Suppose that \mathcal{U} and \mathcal{U}' are two universal gate sets, and that $\mathcal{V} = (U_1, \dots, U_T)$ and $\mathcal{B} = (B_1, \dots, B_T)$ are a query to the \mathcal{Q}_B oracle, where the operators U_t are specified by sequences of gates from \mathcal{U} . It is enough to be able to compute in polynomial time a sequence $\mathcal{V}' = (U'_1, \dots, U'_T)$ of unitary operators, specified by sequences of gates from \mathcal{U}' , such that

$$d_{TV}(\Omega_{\mathcal{PT}}(\mathcal{V}, \mathcal{B}), \Omega_{\mathcal{PT}}(\mathcal{V}', \mathcal{B})) < \frac{1}{8}.$$

Let $\epsilon = 2^{-\ell^2 T - 10}$. Then, by the Solovay-Kitaev theorem [12], it is possible to compute in polynomial time a sequence $\mathcal{V}' = (U'_1, \dots, U'_T)$ such that

$$\|U_t - U'_t\| \leq \epsilon$$

for all t . Suppose that $v = (v_0, \dots, v_T)$ is sampled from $\Omega_{\mathcal{PT}}(\mathcal{V}, \mathcal{B})$, and that $v' = (v'_0, \dots, v'_T)$ is sampled from $\Omega_{\mathcal{PT}}(\mathcal{V}', \mathcal{B})$. Then,

$$d_{TV}(\Omega_{\mathcal{PT}}(\mathcal{V}, \mathcal{B}), \Omega_{\mathcal{PT}}(\mathcal{V}', \mathcal{B})) = d_{TV}(v, v').$$

By Lemma 6.1,

$$\begin{aligned} d_{TV}(v, v') &\leq 2 \sum_{i=1}^T d_{TV}((v_{i-1}, v_i), (v'_{i-1}, v'_i)) \\ &= 2 \sum_{i=1}^T \left\| P_{\mathcal{PT}_{B_i}}(U_{i-1} \cdots U_1 |0\rangle^{\otimes \ell}, U_i) - P_{\mathcal{PT}_{B_i}}(U'_{i-1} \cdots U'_1 |0\rangle^{\otimes \ell}, U'_i) \right\|_1 \\ &\leq 2^{2\ell+1} \sum_{i=1}^T \left(\left\| U_{i-1} \cdots U_1 |0\rangle^{\otimes \ell} - U'_{i-1} \cdots U'_1 |0\rangle^{\otimes \ell} \right\|_2 + \|U_i - U'_i\| \right) \\ &\leq 2^{2\ell+1} \sum_{i=1}^T (\|U_{i-1} \cdots U_1 - U'_{i-1} \cdots U'_1\| + \epsilon) \\ &\leq 2^{2\ell+1} \sum_{i=1}^T \left(\sum_{k=0}^{i-1} \|U_k - U'_k\| + \epsilon \right) \\ &\leq 2^{2\ell+1} \sum_{i=1}^T (T\epsilon + \epsilon) \\ &\leq \frac{1}{8}, \end{aligned}$$

as desired. □

E A detailed proof that $\text{SZK} \subseteq \text{naCQP}$

Here we provide a detailed analysis of the probability of error in our naCQP algorithm for solving the Statistical Difference problem, which is SZK-complete.

Let's briefly recap the algorithm. Suppose we're given an instance of Statistical Difference, and apply the Polarization Lemma of Sahai and Vadhan [18] to obtain two circuits P_0 and P_1 which encode probability distributions D_0 and D_1 which satisfy either $d_{TV}(D_0, D_1) \leq \epsilon$ or $d_{TV}(D_0, D_1) \geq 1 - \epsilon$, where $\epsilon = 2^{-O(n^c)}$ for some constant c . We now prepare the state

$$\frac{1}{2^{(n+1)/2}} \sum_{b \in \{0,1\}, x \in \{0,1\}^n} |b\rangle |x\rangle |P_b(x)\rangle$$

Now, measure the third register with a collapsing measurement to obtain some outcome y , and then perform three non-collapsing measurements on the b register to obtain outcomes b_1, b_2, b_3 . If $b_1 = b_2 = b_3$ then output the distributions were $(1 - \epsilon)$ -far in total variation distance, otherwise output they were ϵ -close in total variation distance.

We will now compute the probability this algorithm makes an error when the input distributions are ϵ -close in total variation distance.

Let $D_b(x)$ denote the probability that distribution D_b outputs string x . The probability of seeing outcome y in the $P_b(x)$ register under our collapsing measurement is

$$\frac{1}{2}(D_0(y) + D_1(y)).$$

Conditioned on seeing outcome y , one can easily compute that the probability of obtaining outcome $b_1 = b_2 = b_3$ (which causes the algorithm to err) is $\frac{D_0(y)^3 + D_1(y)^3}{(D_0(y) + D_1(y))^3}$.

Hence the total probability of error in this case is given by

$$\Pr[\text{error}] = \sum_y \frac{D_0(y) + D_1(y)}{2} \frac{D_0(y)^3 + D_1(y)^3}{(D_0(y) + D_1(y))^3}$$

Let $\delta(y) = D_1(y) - D_0(y)$. So $\sum_y \delta(y) = 0$ and $\sum_y |\delta(y)| \leq 2\epsilon$ by our promise on the total variation distance between D_0 and D_1 . Hence we have by direct calculation that

$$\begin{aligned} \Pr[\text{error}] &= \frac{1}{2} \sum_y \frac{D_0(y)^3 + D_1(y)^3}{(D_0(y) + D_1(y))^2} \\ &= \frac{1}{2} \sum_y \frac{D_0(y)^3 + (D_0(y) + \delta(y))^3}{(2D_0(y) + \delta(y))^2} \\ &= \frac{1}{2} \sum_y \frac{2D_0(y)^3 + 3D_0(y)^2\delta(y) + 3D_0(y)\delta(y)^2 + \delta(y)^3}{4D_0(y)^2 + 4D_0(y)\delta(y) + \delta(y)^2} \\ &= \frac{1}{2} \sum_y \frac{D_0(y)}{2} + \frac{D_0(y)^2\delta(y) + \frac{5}{2}D_0(y)\delta(y)^2 + \delta(y)^3}{4D_0(y)^2 + 4D_0(y)\delta(y) + \delta(y)^2} \\ &= \frac{1}{4} + \frac{1}{2} \sum_y \delta(y) \frac{D_0(y)^2 + \frac{5}{2}D_0(y)\delta(y) + \delta(y)^2}{4D_0(y)^2 + 4D_0(y)\delta(y) + \delta(y)^2} \end{aligned}$$

$$\begin{aligned}
&\leq \frac{1}{4} + \frac{1}{2} \sum_y |\delta(y)| \frac{D_0(y)^2 + \frac{5}{2}D_0(y)|\delta(y)| + |\delta(y)|^2}{4D_0(y)^2 + 4D_0(y)\delta(y) + \delta(y)^2} \\
&\leq \frac{1}{4} + \frac{1}{2} \sum_y |\delta(y)| \frac{4D_0(y)^2 + 4D_0(y)|\delta(y)| + |\delta(y)|^2}{4D_0(y)^2 + 4D_0(y)\delta(y) + \delta(y)^2} \\
&= \frac{1}{4} + \frac{1}{2} \sum_y |\delta(y)| \leq \frac{1}{4} + \epsilon
\end{aligned}$$

Where the last two lines follow from the fact that all terms in the sum are non-negative, and the fact that $\sum_y |\delta(y)| \leq 2\epsilon$. Hence the probability of error in the case is upper bounded by $\frac{1}{4} + \epsilon = \frac{1}{4} + O(2^{-n^c})$, so the algorithm has probability of error $< \frac{1}{3}$ for sufficiently large n as desired.

We now bound the probability of error in the case that the distributions are far apart. In this case, the probability of getting an outcome where b_1, b_2, b_3 are not all at the same, conditioned on measuring y , is given by

$$\frac{3D_0(y)^2D_1(y) + 3D_0(y)D_1(y)^2}{(D_0(y) + D_1(y))^3}.$$

Hence by direct calculation we have that the probability of error is

$$\begin{aligned}
\Pr[\text{error}] &= \sum_y \frac{D_0(y) + D_1(y)}{2} \frac{3D_0(y)^2D_1(y) + 3D_0(y)D_1(y)^2}{(D_0(y) + D_1(y))^3} \\
&= \frac{3}{2} \sum_y \frac{D_0(y)^2D_1(y)}{(D_0(y) + D_1(y))^2} + \frac{D_0(y)D_1(y)^2}{(D_0(y) + D_1(y))^2}
\end{aligned}$$

Let us upper bound the first of these terms; the upper bound on the second term follows analogously by switching D_0 and D_1 .

Since D_0 and D_1 are $1 - \epsilon$ -far in total variation distance, there must exist some set S of y 's, and its complement \bar{S} , such that $\sum_{y \in S} D_0(y) \geq 1 - \epsilon$ and $\sum_{y \in S} D_1(y) \leq \epsilon$, which implies that $\sum_{y \in \bar{S}} D_0(y) \leq \epsilon$ and $\sum_{y \in \bar{S}} D_1(y) \geq 1 - \epsilon$. Hence we have that

$$\begin{aligned}
\sum_y \frac{D_0(y)^2D_1(y)}{(D_0(y) + D_1(y))^2} &= \sum_{y \in S} \frac{D_0(y)^2D_1(y)}{(D_0(y) + D_1(y))^2} + \sum_{y \in \bar{S}} \frac{D_0(y)^2D_1(y)}{(D_0(y) + D_1(y))^2} \\
&\leq \sum_{y \in S} \frac{D_0(y)^2D_1(y)}{(D_0(y))^2} + \sum_{y \in \bar{S}} \frac{D_0(y)^2D_1(y)}{(D_1(y))^2} \\
&\leq \sum_{y \in S} D_1(y) + \sum_{y \in \bar{S}} D_0(y) \\
&\leq 2\epsilon
\end{aligned}$$

By applying an analogous bound to the second term, we have that $\Pr[\text{error}] = O(\epsilon) = O(2^{-n^c})$ as desired, so the probability of error in this case is vanishingly small.

Hence the net probability that the algorithm errs is $\frac{1}{4} + \epsilon$ in the case the distributions are ϵ -close and $O(\epsilon)$ in the case the distributions are $(1 - \epsilon)$ -far.

F An $N^{1/4}$ Lower Bound for Search in naCQP

Here we show that any naCQP algorithm for search requires at least $N^{1/4}$ time.

Proof of Theorem 6.1. Since it is always possible to copy measured qubits, we can assume that qubits which are measured in an intermediate step of the algorithm are never directly modified again. Now, assume that the algorithm uses ℓ qubits and applies unitary operators U_1, \dots, U_T , each of which is either a (controlled) query to the search function f or a gate from the finite universal gate set \mathcal{U} . The measurements $M_1 \dots M_T$ (which may or may not be empty) are applied between the operators $U_1 \dots U_T$.

Let $v(x) = (v_0(x), v_1(x), \dots, v_T(x))$ be the non-collapsing measurement results when the marked item is x , so that $v_i(x)$ is sampled immediately before the application of U_{i+1} . Let $v = (v_0, \dots, v_T)$ be the non-collapsing measurement results when there is no marked item. In general, both $v(x)$ and v are random variables. Since the postprocessing step can distinguish the distributions of v and $v(x)$ with success probability $2/3$, $d_{TV}(v, v(x)) \geq \frac{1}{3}$ for all x . On the other hand, each v and $v(x)$ is a Markov process. Therefore, by Lemma 6.1,

$$d_{TV}(v, v(x)) \leq 2 \sum_{i=1}^T d_{TV}((v_{i-1}, v_i), (v_{i-1}(x), v_i(x))).$$

Now, we bound the term

$$d_{x,i} := d_{TV}((v_{i-1}, v_i), (v_{i-1}(x), v_i(x))).$$

Since it is possible to defer measurements in a quantum circuit to a later stage [16], we can assume that all intermediate measurements that occurred before the application of U_i occurred immediately before the sampling of v_i . Suppose that these measurements were applied to the first k qubits of the state. Let $|\phi\rangle$ and $|\phi(x)\rangle$ be the state vectors immediately before these measurements. Then, we decompose $|\phi\rangle = \sum_{s \in \{0,1\}^k} \alpha_s |s\rangle |\phi_s\rangle$ and $|\phi(x)\rangle = \sum_{s \in \{0,1\}^k} \beta_s |s\rangle |\phi_s(x)\rangle$. Possible values for (v_{i-1}, v_i) and $(v_{i-1}(x), v_i(x))$ can be written in the form (st_1, st_2) , where s is a k -bit string and t_1, t_2 are $(\ell - k)$ -bit strings.

Assume for now that U_i does not contain a query to f . Then, since it does not affect the first k qubits, it can be decomposed into the sum $\sum_{s \in \{0,1\}^k} |s\rangle V_s \langle s|$ for some unitary operators V_s . The transformation U_i can be thought of as applying the unitary V_s to the last $\ell - k$ qubits if the (measured) first k qubits are equal to s . Then, the probability that $(v_{i-1}, v_i) = (st_1, st_2)$ is equal to

$$|\alpha_s|^2 |\langle t_1 | \phi_s \rangle|^2 |\langle t_2 | V_s | \phi_s \rangle|^2,$$

and the probability that $(v_{i-1}(x), v_i(x)) = (st_1, st_2)$ is equal to $|\beta_s|^2 |\langle t_1 | \phi_s(x) \rangle|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2$. Therefore, the total variation distance $d_{x,i}$ is by the triangle inequality

$$\begin{aligned} d_{x,i} &= \frac{1}{2} \sum_{s, t_1, t_2} \left| |\alpha_s|^2 |\langle t_1 | \phi_s \rangle|^2 |\langle t_2 | V_s | \phi_s \rangle|^2 - |\beta_s|^2 |\langle t_1 | \phi_s(x) \rangle|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2 \right| \\ &\leq \frac{1}{2} \sum_{s, t_1, t_2} \left(\left| |\alpha_s|^2 |\langle t_1 | \phi_s(x) \rangle|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2 - |\beta_s|^2 |\langle t_1 | \phi_s(x) \rangle|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2 \right| \right) \\ &\quad + \frac{1}{2} \sum_{s, t_1, t_2} \left(\left| |\alpha_s|^2 |\langle t_1 | \phi_s \rangle|^2 |\langle t_2 | V_s | \phi_s \rangle|^2 - |\beta_s|^2 |\langle t_1 | \phi_s(x) \rangle|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2 \right| \right) \end{aligned}$$

$$\begin{aligned}
& + \frac{1}{2} \sum_{s,t_1,t_2} \left(|\alpha_s|^2 |\langle t_1 | \phi_s(x) \rangle|^2 |\langle t_2 | V_s | \phi_s \rangle|^2 - |\langle t_1 | \phi_s(x) \rangle|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2 \right) \\
& =: \frac{1}{2} (S_1 + S_2 + S_3)
\end{aligned}$$

where S_1, S_2, S_3 are the three sums written above, which range over $s \in \{0, 1\}^k$ and $t_1, t_2 \in \{0, 1\}^{\ell-k}$. Now, we have:

$$\begin{aligned}
S_1 & := \sum_{s,t_1,t_2} \left(|\alpha_s|^2 |\langle t_1 | \phi_s(x) \rangle|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2 - |\beta_s|^2 |\langle t_1 | \phi_s(x) \rangle|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2 \right) \\
& = \sum_s \left(|\alpha_s|^2 - |\beta_s|^2 \right) \left(\sum_{t_1,t_2} |\langle t_1 | \phi_s(x) \rangle|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2 \right) \\
& = \sum_s \left(|\alpha_s|^2 - |\beta_s|^2 \right) \\
& \leq \|\phi\| \langle \phi | - |\phi(x)\rangle \langle \phi(x) | \|_{tr} \\
& \leq 2 \|\phi(x)\rangle - |\phi\rangle\|_2.
\end{aligned}$$

Additionally,

$$\begin{aligned}
S_2 & := \sum_{s,t_1,t_2} \left(|\alpha_s|^2 |\langle t_1 | \phi_s \rangle|^2 |\langle t_2 | V_s | \phi_s \rangle|^2 |\langle t_1 | \phi_s(x) \rangle|^2 |\langle t_2 | V_s | \phi_s \rangle|^2 \right) \\
& = \sum_{s,t_1} \left(|\alpha_s|^2 |\langle t_1 | \phi_s \rangle|^2 - |\langle t_1 | \phi_s(x) \rangle|^2 \right) \\
& \leq \sum_{s,t_1} \left(|\alpha_s|^2 |\langle t_1 | \phi_s \rangle|^2 - |\beta_s|^2 |\langle t_1 | \phi_s(x) \rangle|^2 \right) + \sum_{s,t_1} \left(|\alpha_s|^2 |\langle t_1 | \phi_s(x) \rangle|^2 - |\beta_s|^2 |\langle t_1 | \phi_s(x) \rangle|^2 \right) \\
& = \sum_{s,t_1} \left(|\alpha_s|^2 |\langle t_1 | \phi_s \rangle|^2 - |\beta_s|^2 |\langle t_1 | \phi_s(x) \rangle|^2 \right) + \sum_s \left(|\alpha_s|^2 - |\beta_s|^2 \right) \\
& \leq 2 \|\phi\| \langle \phi | - |\phi(x)\rangle \langle \phi(x) | \|_{tr} \\
& \leq 4 \|\phi(x)\rangle - |\phi\rangle\|_2.
\end{aligned}$$

Finally,

$$\begin{aligned}
S_3 & = \sum_{s,t_1,t_2} \left(|\alpha_s|^2 |\langle t_1 | \phi_s(x) \rangle|^2 |\langle t_2 | V_s | \phi_s \rangle|^2 - |\langle t_1 | \phi_s(x) \rangle|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2 \right) \\
& = \sum_{s,t_2} \left(|\alpha_s|^2 |\langle t_2 | V_s | \phi_s \rangle|^2 - |\langle t_2 | V_s | \phi_s(x) \rangle|^2 \right) \\
& \leq \sum_{s,t_2} \left(|\alpha_s|^2 |\langle t_2 | V_s | \phi_s \rangle|^2 - |\beta_s|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2 \right) \\
& + \sum_{s,t_2} \left(|\alpha_s|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2 - |\beta_s|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2 \right) \\
& = \sum_{s,t_2} \left(|\alpha_s|^2 |\langle t_2 | V_s | \phi_s \rangle|^2 - |\beta_s|^2 |\langle t_2 | V_s | \phi_s(x) \rangle|^2 \right) + \sum_s \left(|\alpha_s|^2 - |\beta_s|^2 \right) \\
& \leq 2 \|\phi\| \langle \phi | - |\phi(x)\rangle \langle \phi(x) | \|_{tr}
\end{aligned}$$

$$= 4 \|\phi(x)\rangle - |\phi\rangle\|_2$$

Therefore,

$$d_{x,i} \leq \frac{1}{2}(S_1 + S_2 + S_3) \leq 5 \|\phi(x)\rangle - |\phi\rangle\|_2.$$

On the other hand, if U_i is a query to f , then it only applies a local phase of -1 to some of the probability amplitudes of $|\phi\rangle$ and $|\phi_x\rangle$. Therefore, the same argument still shows that $d_{x,i} \leq 5 \|\phi(x)\rangle - |\phi\rangle\|_2$.

By the Cauchy-Schwarz inequality and Lemma 6.3,

$$\begin{aligned} \frac{1}{N} \sum_{x=0}^{N-1} d_{x,i} &\leq 5 \cdot \frac{1}{N} \sum_{x=0}^{N-1} \|\phi(x)\rangle - |\phi\rangle\|_2 \\ &\leq 5 \sqrt{\frac{1}{N} \sum_{x=0}^{N-1} \|\phi(x)\rangle - |\phi\rangle\|_2^2} \\ &\leq \frac{10Q}{\sqrt{N}} \end{aligned}$$

for all i . Therefore, there is some x for which

$$d_{TV}(v, v(x)) \leq 2 \sum_{i=1}^T d_{x,i} \leq \frac{20TQ}{\sqrt{N}}.$$

On the other hand, $d_{TV}(v, v(x)) \geq \frac{1}{3}$ for all x , so

$$\frac{20TQ}{\sqrt{N}} \geq \frac{1}{3},$$

and the running time of the algorithm is at least $T + Q = \Omega(N^{1/4})$. \square

G An $N^{1/3}$ lower bound for search in naCQP if there are no collapsing measurements

Assume that intermediate measurements are not allowed in our search algorithm. As we discuss in Section 3, this gives a model with only the power of BQP, because then the states $|\psi_t\rangle = U_t U_{t-1} \dots U_1 |0\rangle^{\otimes n}$ can be generated with poly-sized circuits, and hence a BQP machine could prepare and and measure them to sample from \mathcal{Q} . Trivially one can prove a lower bound of $N^{1/4}$ for search in this model, either by noting that this class can achieve at most quadratic speedups over BQP by the previous comment, or by using the argument put forth in Theorem 6.1. Here we tighten this result to give an $N^{1/3}$ lower bound for search in this class.

Suppose that an algorithm A searches with Q queries and T timesteps, where $Q + T = o(N^{1/3})$. Let ψ_t be the quantum state after t steps with no marked item, and let ψ_t^x be defined likewise when the marked item is at location x . By the hybrid argument we have that $\forall t$

$$\sum_x \|\psi_t - \psi_t^x\|_2^2 \leq 4Q^2$$

where $\|a\|_2^2$ is the 2-norm squared of a . This implies

$$\sum_t \sum_x \|\psi_t - \psi_t^x\|_2^2 \leq 4TQ^2$$

Hence there must exist x such that

$$\sum_t \|\psi_t - \psi_t^x\|_2^2 \leq \frac{4TQ^2}{N} \quad (16)$$

Since we assumed $Q + T = o(N^{1/3})$, we have that $\frac{4TQ^2}{N} = o(1)$. Therefore for sufficiently large N and for all t we have

$$\|\psi_t - \psi_t^x\|_2^2 \leq 0.01$$

(The choice of constant here is arbitrary, we simply need it to be less than around 0.5.) Now consider the states $\Psi := \bigotimes_t |\psi_t\rangle$ and $\Psi^x := \bigotimes_t |\psi_t^x\rangle$. Let V the distribution on samples with no marked item, and let V^x be defined likewise. Then clearly we have that

$$|V - V^x|_1 \leq \|\Psi - \Psi^x\|$$

where $\|a\|$ denotes the trace norm of a . This is because the output distributions of V and V^x can be obtained by (independent) measurements on the states Ψ and Ψ^x in the computational basis. Note that $|V - V^x|_1$ must be $\Omega(1)$ in order to distinguish the presence of a marked item at x in postprocessing. Therefore we have

$$\Omega(1) \leq |V - V^x|_1 \leq \|\Psi - \Psi^x\| \quad (17)$$

$$= \sqrt{1 - |\langle \Psi | \Psi^x \rangle|^2} \quad (18)$$

$$= \sqrt{1 - |\prod_t \langle \psi_t | \psi_t^x \rangle|^2} \quad (19)$$

$$\leq \sqrt{1 - \prod_t e^{-\|\psi_t - \psi_t^x\|_2^2}} \quad (20)$$

$$= \sqrt{1 - e^{-\sum_t \|\psi_t - \psi_t^x\|_2^2}} \quad (21)$$

$$\leq \sqrt{1 - e^{-\frac{4TQ^2}{N}}} \quad (22)$$

$$= o(1) \quad (23)$$

Where in line 18 we use the formula for trace distance of pure states, in line 22 we used equation 16, in line 23 we used the fact that $T + Q = o(N^{1/3})$, and in line 20 we use the inequality

$$|\langle \psi_t | \psi_t^x \rangle| \geq \text{Re}(\langle \psi_t | \psi_t^x \rangle) \quad (24)$$

$$= 1 - \frac{\|\psi_t - \psi_t^x\|_2^2}{2} \quad (25)$$

$$\geq e^{-\|\psi_t - \psi_t^x\|_2^2} \quad (26)$$

where we have use the fact that $1 - x \geq e^{-2x}$ for $0 \leq x \leq 0.01$. Therefore we have shown $\Omega(1) = o(1)$, a contradiction. Hence such an algorithm A cannot exist, so searching takes $Q + T = \Omega(N^{1/3})$ time when there are non-collapsing measurements, but no collapsing measurements, in the model.