A Hypercontractive Inequality for Matrix-Valued Functions with Applications to Quantum Computing

Avraham Ben-Aroya* Oded Regev† Ronald de Wolf‡

Abstract

The Bonami-Beckner hypercontractive inequality is a powerful tool in Fourier analysis of real-valued functions on the Boolean cube. In this paper we present a version of this inequality for *matrix-valued* functions on the Boolean cube. Its proof is based on a powerful inequality by Ball, Carlen, and Lieb. We also present a number of applications of this inequality. In particular, we analyze maps that encode n classical bits into m qubits, in such a way that each set of k bits can be recovered with some probability by an appropriate measurement on the quantum encoding; we show that if $m < 0.7n$, then the success probability is exponentially small in k. This result may be viewed as a direct product version of Nayak's quantum random access code bound. It in turn implies strong direct product theorems for the one-way quantum communication complexity of Disjointness and other problems. We also slightly strengthen and simplify a result about 3-party communication complexity of Disjointness due to Beame et al.

*Department of Computer Science, Tel-Aviv University, Tel-Aviv 69978, Israel. Supported by the Israel Science Foundation, and by the European Commission under the Integrated Project QAP funded by the IST directorate as Contract Number 015848.

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‡Centrum voor Wiskunde en Informatica (CWI), Amsterdam, The Netherlands. Supported by a Veni grant from the Netherlands Organization for Scientific Research (NWO) and also partially supported by the European Commission under the Integrated Project QAP funded by the IST directorate as Contract Number 015848.

1 Introduction

1.1 A hypercontractive inequality for matrix-valued functions

Fourier analysis of real-valued functions on the Boolean cube has been widely used in the theory of computing. Applications include analyzing the influence of variables on Boolean functions [25], probabilistically-checkable proofs [20], analysis of threshold phenomena in random graphs [16], analyzing noise [37], learning under the uniform distribution [30, 31, 23, 32], communication complexity [39, 26, 17], etc.

One of the main technical tools in this area is a hypercontractive inequality that is sometimes called the *Bonami-Beckner inequality* [9, 7], though its history would also justify other names (see Lecture 16 of [38] for some background and history). For a fixed $\rho \in [0,1]$, consider the linear operator T_ρ on the space of all functions $f : \{0,1\}^n \to \mathbb{R}$ defined by

$$(T_\rho(f))(x) = \mathbb{E}_y[f(y)]$$

where y is obtained from x by negating each bit independently with probability $(1-\rho)/2$. In other words, the value of $T_\rho(f)$ at a point x is obtained by averaging the values of f over a certain neighborhood of x. One important property of T_ρ for $\rho < 1$ is that it has a "smoothing" effect: any "high peaks" present in f are smoothed out in $T_\rho(f)$. The hypercontractive inequality formalizes this intuition. To state it precisely, define the p-norm of a function f by $\|f\|_p = (\frac{1}{2^n}\sum_x |f(x)|^p)^{1/p}$. It is not difficult to prove that the norm is nondecreasing with p. Also, the higher p is, the more sensitive the norm becomes to peaks in the function f. The hypercontractive inequality says that for certain $q > p$, the q-norm of $T_\rho(f)$ is upper bounded by the p-norm of f. This exactly captures the intuition that $T_\rho(f)$ is a smoothed version of f: even though we are considering a higher norm, the norm does not increase. More precisely, the hypercontractive inequality says that as long as $1 \le p \le q$ and $\rho \le \sqrt{(p-1)/(q-1)}$, we have

$$\|T_\rho(f)\|_q \le \|f\|_p. \tag{1}$$

The most interesting case for us is when $q = 2$, since in this case one can view the inequality as a statement about the Fourier coefficients of f, as we describe next. Let us first recall some basic definitions from Fourier analysis. For every $S \subseteq [n]$ (which by some abuse of notation we will also view as an n-bit string) and $x \in \{0,1\}^n$, define $\chi_S(x) = (-1)^{x \cdot S}$ to be the parity of the bits of x indexed by S. The *Fourier transform* of a function $f : \{0,1\}^n \to \mathbb{R}$ is the function $\widehat{f} : \{0,1\}^n \to \mathbb{R}$ defined by

$$\widehat{f}(S) = \frac{1}{2^n} \sum_{x \in \{0,1\}^n} f(x)\chi_S(x).$$

The values $\widehat{f}(S)$ are called the *Fourier coefficients* of f. The coefficient $\widehat{f}(S)$ may be viewed as measuring the correlation between f and the parity function χ_S. Since the functions χ_S form an orthonormal basis of the space of all functions from $\{0,1\}^n$ to $\mathbb{R}$, we can express f in terms of its Fourier coefficients as

$$f = \sum_{S \subseteq [n]} \widehat{f}(S)\chi_S. \tag{2}$$

Using the same reasoning we obtain Parseval's identity, $\|f\|_2 = \left(\sum_{S \subseteq [n]} \widehat{f}(S)^2\right)^{1/2}$.

The operator T_ρ has a particularly elegant description in terms of the Fourier coefficients. Namely, it simply multiplies each Fourier coefficient $\widehat{f}(S)$ by a factor of $\rho^{|S|}$:

$$T_\rho(f) = \sum_{S \subseteq [n]} \rho^{|S|}\widehat{f}(S)\chi_S.$$

The higher $|S|$ is, the stronger the Fourier coefficient $\widehat{f}(S)$ is "attenuated" by T_ρ. Using Parseval's identity, we can now write the hypercontractive inequality (1) for the case $q = 2$ as follows. For every $p \in [1, 2]$,

$$\left(\sum_{S \subseteq [n]} (p-1)^{|S|} \widehat{f}(S)^2 \right)^{1/2} \leq \left(\frac{1}{2^n} \sum_{x \in \{0,1\}^n} |f(x)|^p \right)^{1/p}. \tag{3}$$

This gives an upper bound on a weighted sum of the squared Fourier coefficients of f, where each coefficient is attenuated by a factor $(p-1)^{|S|}$. We are interested in generalizing this hypercontractive inequality to *matrix-valued* functions. Let $\mathcal{M}$ be the space of $d \times d$ matrices and suppose we have a function $f : \{0,1\}^n \to \mathcal{M}$. For example, a natural scenario where this arises is in quantum information theory, if we assign to every $x \in \{0,1\}^n$ some m-qubit *density matrix* $f(x)$ (so $d = 2^m$). We define the Fourier transform $\widehat{f}$ of a matrix-valued function f exactly as before:

$$\widehat{f}(S) = \frac{1}{2^n} \sum_{x \in \{0,1\}^n} f(x) \chi_S(x).$$

The Fourier coefficients $\widehat{f}(S)$ are now also $d \times d$ matrices. An equivalent definition is by applying the standard Fourier transform to each i, j-entry separately: $\widehat{f}(S)_{ij} = \widehat{f(\cdot)_{ij}}(S)$. This extension of the Fourier transform to matrix-valued functions is quite natural, and has also been used in, e.g., [34, 15].

Our main result, which we prove in Section 3, is an extension of the hypercontractive inequality to matrix-valued functions. For $M \in \mathcal{M}$ with singular values $\sigma_1, \ldots, \sigma_d$, we define its (normalized Schatten) p-norm as $\|M\|_p = (\frac{1}{d} \sum_{i=1}^d \sigma_i^p)^{1/p}$.

Theorem 1. *For every $f : \{0,1\}^n \to \mathcal{M}$ and $1 \leq p \leq 2$,*

$$\left(\sum_{S \subseteq [n]} (p-1)^{|S|} \left\| \widehat{f}(S) \right\|_p^2 \right)^{1/2} \leq \left(\frac{1}{2^n} \sum_{x \in \{0,1\}^n} \|f(x)\|_p^p \right)^{1/p}.$$

This is the analogue of Eq. (3) for matrix-valued functions, with p-norms replacing absolute values. The case $n = 1$ can be seen as a geometrical statement that extends the familiar parallelogram law in Euclidean geometry and is closely related to the notion of uniform convexity. This case was first proven for certain values of p by Tomczak-Jaegermann [41] and then in full generality by Ball, Carlen, and Lieb [4]. Among its applications are the work of Carlen and Lieb on fermion fields [13], and the more recent work of Lee and Naor on metric embeddings [29].

To the best of our knowledge, the general case $n \geq 1$ has not appeared before.[1] Its proof is not difficult, and follows by induction on n, similar to the proof of the usual hypercontractive inequality.[2] Although one might justly regard Theorem 1 as a 'standard' corollary of the result by Ball, Carlen, and Lieb, such 'tensorized inequalities' tend to be extremely useful (see, e.g., [8, 18]) and we believe that the matrix-valued hypercontractive inequality will have more applications in the future.

[1] A different generalization of the Bonami-Beckner inequality was given by Borell [10]. His generalization, however, is an easy corollary of the Bonami-Beckner inequality and is therefore relatively weak (although it does apply to any Banach space, and not just to the space of matrices with the Schatten p-norm).

[2] We remark that Carlen and Lieb's proof in [13] also uses induction and has some superficial resemblance to our proof. Their induction, however, is on the *dimension* of the matrices (or more precisely, the number of fermions), and moreover leads to an entirely different inequality.

1.2 Application: k-out-of-n random access codes

Our main application of Theorem 1 is for the following information-theoretic problem. Suppose we want to encode an n-bit string x into m bits or qubits, in such a way that for any set $S \subseteq [n]$ of k indices, the k-bit substring x_S can be recovered with probability at least p by making an appropriate measurement on the encoding. We are allowed to use probabilistic encodings here, so the encoding need not be a function mapping x to a fixed classical string or a fixed quantum pure state. We will call such encodings *k-out-of-n random access codes*, since they allow us to access any set of k out of n bits. As far as we know, for $k > 1$ neither the classical nor the quantum case has been studied before. Here we focus on the quantum case, because our lower bounds for quantum encodings of course also apply to classical encodings.

We are interested in the tradeoff between the length m of the quantum random access code, and the success probability p. Clearly, if $m \geq n$ then we can just use the identity encoding to obtain $p = 1$. If $m < n$ then by Holevo's theorem [21] our encoding will be "lossy", and p will be less than 1. The case $k = 1$ was first studied by Ambainis et al. [2], who showed that if p is bounded away from 1/2, then $m = \Omega(n/\log n)$. Nayak [33] subsequently strengthened this bound to $m \geq (1-H(p))n$, where $H(\cdot)$ is the binary entropy function. This bound is optimal up to an additive $\log n$ term both for classical and quantum encodings. The intuition of Nayak's proof is that, for average i, the encoding only contains $m/n < 1$ bits of information about the bit x_i, which limits our ability to predict x_i given the encoding.

Now suppose that $k > 1$, and m is much smaller than n. Clearly, for predicting one specific bit x_i, with i uniformly chosen, Nayak's result applies, and we will have a success probability that is bounded away from 1. But intuitively this should apply to each of the k bits that we need to predict. Moreover, these k success probabilities should not be very correlated, so we expect an overall success probability that is exponentially small in k. Nayak's proof does not generalize to the case $k \gg 1$ (or at least, we do not know how to do it). The reason it fails is the following. Suppose we probabilistically encode $x \in \{0,1\}^n$ as follows: with probability 1/4 our encoding is x itself, and with probability 3/4 our encoding is the empty string. Then the average length of the output (and hence the entropy or amount of information in the encoding) is only $n/4$ bits, or 1/4 bit for an average x_i. Yet from this encoding one can predict *all of* x with success probability $1/4$! Hence, if we want to prove our intuition it is crucial to make use of the fact that the encoding is always confined to a 2^m-dimensional space (a property which the above example lacks). Entropy-based arguments, such as the ones used in [33], do not seem capable of capturing this condition. The new hypercontractive inequality offers an alternative approach—in fact the only alternative approach to entropy-based methods that we are aware of in quantum information. Applying the inequality to the matrix-valued function that gives the encoding implies $p \leq 2^{-\Omega(k)}$ if $m \ll n$. More precisely:

Theorem 2. *For any $\eta > 2\ln 2$ there exists a constant C_η such that if n/k is large enough then for any k-out-of-n quantum random access code on m qubits, the success probability satisfies*

$$p \leq C_\eta \left(\frac{1}{2} + \frac{1}{2}\sqrt{\frac{\eta m}{n}}\right)^k.$$

In particular, the success probability is exponentially small in k if $m/n < 1/(2\ln 2) \approx 0.721$. Notice that for very small m/n the bound on p gets close to 2^{-k}, which is what one gets by guessing the k-bit answer randomly. We also obtain bounds if k is close to n, but these are a bit harder to state. We believe that the theorem can be extended to the case that $m/n > 1/(2\ln 2)$, although proving this would probably require a strengthening of the inequality by Ball, Carlen, and Lieb. Luckily, in all our applications we are free to choose a small enough m. Finally, we note that in contrast to Nayak's approach, our proof does not use the strong subadditivity of von Neumann entropy.

The classical case. For future reference, we give a few comments regarding the special case of classical (probabilistic) m-bit encodings. First, in this case the encodings are represented by diagonal matrices. For such matrices, the base case $n = 1$ of Theorem 1 can be derived directly from the Bonami-Beckner inequality, without requiring the full strength of the Ball, Carlen, Lieb inequality (see [4] for details). Alternatively, one can derive Theorem 2 in the classical case directly from the Bonami-Beckner inequality by conditioning on a fixed m-bit string of the encoding (this step is already impossible in the quantum case) and then analyzing the resulting distribution on $\{0,1\}^n$. This proof is very similar to the one we give in Section 4 (and in fact slightly less elegant due to the conditioning step) and we therefore omit the details.

Interestingly, in the classical case there is a simpler argument that avoids Bonami-Beckner altogether. This argument was used in [42] and was communicated to us by the authors of that paper. We briefly sketch it here. Suppose we have a classical m-bit encoding that allows to recover any k-bit set with probability p. Use this repeatedly to decode $\ell = 100n/k$ uniformly and independently chosen k-sets. With probability at least p^ℓ, all decodings will be correct, and with probability $1 - 2^{-\Theta(n)}$ the union of the ℓ k-sets will have at least $9n/10$ elements. Thus we have a way to recover 90% of the bits of x from an m-bit encoding, with probability at least $p^\ell - 2^{-\Theta(n)}$. A simple counting argument shows that this is impossible unless $p \leq 2^{-\Omega(k)}$ or m is close to n. This argument does not work for quantum encodings, of course, because these cannot just be reused (a quantum measurement changes the state).

1.3 Applications in communication complexity

1.3.1 Direct product theorem for one-way quantum communication complexity

Our result for k-out-of-n random access codes has the flavor of a direct product theorem: the success probability of performing a certain task on k instances (i.e. k distinct indices) goes down exponentially with k. We use this to prove a new strong direct product theorem for one-way communication complexity.

Consider the 2-party Disjointness function: Alice receives input $x \in \{0,1\}^n$, Bob receives input $y \in \{0,1\}^n$, and they want to determine whether the sets represented by their inputs are disjoint, i.e. whether $x_i y_i = 0$ for all $i \in [n]$. They want to do this while communicating as few qubits as possible (allowing some error probability). We can either consider one-way protocols, where Alice sends one message to Bob who then computes the output; or two-way protocols, which are interactive. The quantum communication complexity of Disjointness is fairly well understood: it is $\Theta(n)$ qubits for one-way protocols [12], and $\Theta(\sqrt{n})$ qubits for two-way protocols [11, 22, 1, 40].

Now consider the case of k independent instances: Alice receives inputs $x_1, \ldots, x_k$ (each of n bits), Bob receives $y_1, \ldots, y_k$, and their goal is to compute all k bits $\mathrm{DISJ}_n(x_1, y_1), \ldots, \mathrm{DISJ}_n(x_k, y_k)$. Klauck et al. [27] proved an optimal direct product theorem for *two-way* quantum communication: every protocol that communicates fewer than $\alpha k\sqrt{n}$ qubits (for some small constant $\alpha > 0$) will have a success probability that is exponentially small in k. Surprisingly, no strong direct product theorem was known for the usually simpler case of *one-way* communication—not even for *classical* one-way communication. In Section 5 we derive such a theorem from our k-out-of-n random access code lower bound: if $\eta > 2\ln 2$, then every one-way quantum protocol that sends fewer than kn/η qubits will have success probability at most $2^{-\Omega(k)}$.

These results can straightforwardly be generalized to get a bound for all functions in terms of their *VC-dimension*. If f has VC-dimension d, then any one-way quantum protocol for computing k independent copies of f that sends kd/η qubits, has success probability $2^{-\Omega(k)}$. For simplicity, Section 5 only presents the case of Disjointness.

1.3.2 3-party NOF communication complexity of Disjointness

Though often studied in the standard 2-player setting, communication complexity is also interesting with more than two players. Suppose there are ℓ players, and ℓ inputs $x_1, \ldots, x_\ell$. The players want to compute some function $f(x_1, \ldots, x_\ell)$. There are two main models here: the "number in the hand" (NIH) model where player j sees only input x_j, and the "number on the forehead" (NOF) model where player j sees all inputs *except* x_j. In the ℓ-party version of the Disjointness problem, the ℓ players want to figure out whether there is an index $i \in [n]$ where all ℓ input strings have a 1. Nearly tight bounds were obtained for this function in the NIH model by Chakrabarti et al. [14]. On the other hand, very little is known about lower bounds in the NOF model. This is all the more unfortunate because even slightly superlogarithmic lower bounds would already imply interesting lower bounds for Lovász-Schrijver proof systems [5].

Probably the best results known so far for three players are due to Beame et al. [6], in settings that limit the communication to less than full interaction. Suppose we have a classical protocol where Charlie first sends a message to Bob, and then Alice and Bob are allowed two-way communication between each other to compute $\mathrm{DISJ}_n(x_1, x_2, x_3)$. Beame et al. showed (using a direct product theorem) that any bounded-error protocol of this form requires $\Omega(n^{1/3})$ bits of communication.[3] Moreover, if Bob only has one-way communication to Alice, then the bound becomes $\Omega(\sqrt{n})$ bits. As Beame et al. noted, this follows from a lower bound for the pointer-jumping problem due to Wigderson, included in the appendix of [3].[4]

In Section 6 we slightly strengthen the two 3-player results, with simpler proofs, showing the same bounds for protocols where Alice and Bob can send *quantum* bits. These results will follow easily from the two direct product theorems: the one for two-way communication from [27], and the new one for one-way communication that we prove here.

2 Preliminaries

Norms: Recall that we define the p-norm of a d-dimensional vector v by

$$\|v\|_p = \left(\frac{1}{d}\sum_{i=1}^{d} |v_i|^p\right)^{1/p}.$$

We extend this to matrices by defining the (normalized Schatten) p-norm of a matrix $A \in \mathbb{C}^{d\times d}$ as

$$\|A\|_p = \left(\frac{1}{d}\mathrm{Tr}|A|^p\right)^{1/p}.$$

This is equivalent to the p-norm of the vector of singular values of A. For diagonal matrices this definition coincides with the one for vectors. For convenience we defined all norms to be under the normalized counting measure, even though for matrices this is nonstandard. The advantage of the normalized norm is that it is nondecreasing with p. We also define the *trace norm* $\|A\|_{\mathrm{tr}}$ of a matrix A as the sum of its singular values, hence we have $\|A\|_{\mathrm{tr}} = d\|A\|_1$ for any $d \times d$ matrix A.

[3] Their conference paper had an $\Omega(n^{1/3}/\log n)$ bound, but the journal version [6] managed to get rid of the $\log n$.

[4] Very recently, Viola and Wigderson [42] generalized the one-way pointer-jumping lower bound to $\Omega(n^{1/(\ell-1)})$ for any constant ℓ players, and obtained the same lower bound for the one-way complexity of ℓ-player Disjointness.

Quantum states: An m-qubit *pure state* is a superposition $|\phi\rangle = \sum_{z\in\{0,1\}^m} \alpha_z |z\rangle$ over all classical m-bit states. The α_z's are complex numbers called *amplitudes*, and $\sum_z |\alpha_z|^2 = 1$. Hence a pure state $|\phi\rangle$ is a unit vector in $\mathbb{C}^{2^m}$. Its complex conjugate (a row vector with entries conjugated) is denoted $\langle\phi|$. The inner product between $|\phi\rangle = \sum_z \alpha_z|z\rangle$ and $|\psi\rangle = \sum_z \beta_z|z\rangle$ is the dot product $\langle\phi|\cdot|\psi\rangle = \langle\phi|\psi\rangle = \sum_z \alpha_z^*\beta_z$. Second, an m-qubit *mixed state* (or *density matrix*) $\rho = \sum_i p_i|\phi_i\rangle\langle\phi_i|$ corresponds to a probability distribution over m-qubit pure states, where $|\phi_i\rangle$ is given with probability p_i. The eigenvalues $\lambda_1, \ldots, \lambda_d$ of ρ are non-negative reals that sum to 1, so they form a probability distribution. If ρ is pure then one eigenvalue is 1 while all others are 0. Hence for any $p \geq 1$, the maximal p-norm is achieved by pure states:

$$\|\rho\|_p^p = \frac{1}{d}\sum_{i=1}^{d} \lambda_i^p \leq \frac{1}{d}\sum_{i=1}^{d} \lambda_i = \frac{1}{d}. \tag{4}$$

A k-outcome *positive operator-valued measurement* (POVM) is given by k positive semidefinite operators $E_1, \ldots, E_k$ with the property that $\sum_{i=1}^k E_i = I$. When this POVM is applied to a mixed state ρ, the probability of the ith outcome is given by the trace $\mathrm{Tr}(E_i\rho)$. The following well known fact gives the close relationship between trace distance and distinguishability of density matrices:

Fact 3. *The best possible measurement to distinguish two density matrices ρ_0 and ρ_1 has bias $\frac{1}{2}\|\rho_0 - \rho_1\|_{\mathrm{tr}}$.*

Here "bias" is defined as twice the success probability, minus 1. We refer to Nielsen and Chuang [36] for more details.

3 The hypercontractive inequality for matrix-valued functions

Here we prove Theorem 1. The proof relies on the following powerful inequality by Ball et al. [4] (they state this inequality for the usual unnormalized Schatten p-norm, but both statements are clearly equivalent).

Lemma 4. *([4, Theorem 1]) For any matrices A, B and any $1 \leq p \leq 2$, it holds that*

$$\left(\left\|\frac{A+B}{2}\right\|_p^2 + (p-1)\left\|\frac{A-B}{2}\right\|_p^2\right)^{1/2} \leq \left(\frac{\|A\|_p^p + \|B\|_p^p}{2}\right)^{1/p}.$$

Theorem 1. *For any $f : \{0,1\}^n \to \mathcal{M}$ and for any $1 \leq p \leq 2$,*

$$\left(\sum_{S\subseteq[n]} (p-1)^{|S|}\left\|\widehat{f}(S)\right\|_p^2\right)^{1/2} \leq \left(\frac{1}{2^n}\sum_{x\in\{0,1\}^n} \|f(x)\|_p^p\right)^{1/p}.$$

Proof: By induction. The case $n = 1$ follows from Lemma 4 by setting $A = f(0)$ and $B = f(1)$, and noting that $(A+B)/2$ and $(A-B)/2$ are exactly the Fourier coefficients $\widehat{f}(0)$ and $\widehat{f}(1)$.

We now assume the lemma holds for n and prove it for $n+1$. Let $f : \{0,1\}^{n+1} \to \mathcal{M}$ be some matrix-valued function. For $i \in \{0,1\}$, let $g_i = f|_{x_{n+1}=i}$ be the function obtained by fixing the last input bit of f to i. We apply the induction hypothesis on g_0 and g_1 to obtain

$$\left(\sum_{S\subseteq[n]} (p-1)^{|S|}\|\widehat{g_0}(S)\|_p^2\right)^{1/2} \leq \left(\frac{1}{2^n}\sum_{x\in\{0,1\}^n} \|g_0(x)\|_p^p\right)^{1/p}$$

$$\left(\sum_{S\subseteq[n]} (p-1)^{|S|}\|\widehat{g_1}(S)\|_p^2\right)^{1/2} \leq \left(\frac{1}{2^n}\sum_{x\in\{0,1\}^n} \|g_1(x)\|_p^p\right)^{1/p}.$$

Take the L_p average of these two inequalities: raise each to the pth power, average them and take the pth root. We get

$$\left(\frac{1}{2}\sum_{i\in\{0,1\}}\left(\sum_{S\subseteq[n]}(p-1)^{|S|}\|\widehat{g}_i(S)\|_p^2\right)^{p/2}\right)^{1/p} \leq \left(\frac{1}{2^{n+1}}\sum_{x\in\{0,1\}^n}\left(\|g_0(x)\|_p^p+\|g_1(x)\|_p^p\right)\right)^{1/p} \tag{5}$$
$$= \left(\frac{1}{2^{n+1}}\sum_{x\in\{0,1\}^{n+1}}\|f(x)\|_p^p\right)^{1/p}.$$

The right-hand side is the expression we wish to lower bound. To bound the left-hand side, we need the following inequality (to get a sense of why this holds, consider the case where $q_1 = 1$ and $q_2 = \infty$).

Lemma 5 (Minkowski's inequality, [19, Theorem 26])**.** *For any $r_1 \times r_2$ matrix whose rows are given by $u_1, \ldots, u_{r_1}$ and whose columns are given by $v_1, \ldots, v_{r_2}$, and any $1 \leq q_1 < q_2 \leq \infty$,*

$$\left\|\left(\|v_1\|_{q_2}, \ldots, \|v_{r_2}\|_{q_2}\right)\right\|_{q_1} \geq \left\|\left(\|u_1\|_{q_1}, \ldots, \|u_{r_1}\|_{q_1}\right)\right\|_{q_2},$$

i.e., the value obtained by taking the q_2-norm of each column and then taking the q_1-norm of the results, is at least that obtained by first taking the q_1-norm of each row and then taking the q_2-norm of the results.

Consider now the $2^n \times 2$ matrix whose entries are given by

$$c_{S,i} = 2^{n/2}\left\|(p-1)^{|S|/2}\widehat{g}_i(S)\right\|_p$$

where $i \in \{0,1\}$ and $S \subseteq [n]$. The left-hand side of (5) is then

$$\left(\frac{1}{2}\sum_{i\in\{0,1\}}\left(\frac{1}{2^n}\sum_{S\subseteq[n]}c_{S,i}^2\right)^{p/2}\right)^{1/p} \geq \left(\frac{1}{2^n}\sum_{S\subseteq[n]}\left(\frac{1}{2}\sum_{i\in\{0,1\}}c_{S,i}^p\right)^{2/p}\right)^{1/2}$$
$$= \left(\sum_{S\subseteq[n]}(p-1)^{|S|}\left(\frac{\|\widehat{g}_0(S)\|_p^p+\|\widehat{g}_1(S)\|_p^p}{2}\right)^{2/p}\right)^{1/2},$$

where the inequality follows from Lemma 5 with $q_1 = p$, $q_2 = 2$. We now apply Lemma 4 to deduce that the above is lower bounded by

$$\left(\sum_{S\subseteq[n]}(p-1)^{|S|}\left(\left\|\frac{\widehat{g}_0(S)+\widehat{g}_1(S)}{2}\right\|_p^2+(p-1)\left\|\frac{\widehat{g}_0(S)-\widehat{g}_1(S)}{2}\right\|_p^2\right)\right)^{1/2} = \left(\sum_{S\subseteq[n+1]}(p-1)^{|S|}\left\|\widehat{f}(S)\right\|_p^2\right)^{1/2}$$

where we used $\widehat{f}(S) = \frac{1}{2}(\widehat{g_0}(S)+\widehat{g_1}(S))$ and $\widehat{f}(S\cup\{n+1\}) = \frac{1}{2}(\widehat{g_0}(S)-\widehat{g_1}(S))$ for any $S \subseteq [n]$. ■

4 Bounds for k-out-of-n quantum random access codes

In this section we prove Theorem 2. Recall that a k-out-of-n random access code allows us to encode n bits into m qubits, such that we can recover any k-bit substring with probability at least p. We now define this notion formally. In fact, we consider a somewhat weaker notion where we only measure the success probability for a random k subset, and a random input $x \in \{0,1\}^n$. Since we only prove impossibility results, this clearly makes our results stronger.

Definition 1. *A k-out-of-n quantum random access code on m qubits with success probability p (for short (k,n,m,p)-QRAC), is a map*

$$f : \{0,1\}^n \to \mathbb{C}^{2^m \times 2^m}$$

that assigns an m-qubit density matrix $f(x)$ to every $x \in \{0,1\}^n$, and a quantum measurement $\{M_{S,z}\}_{z\in\{0,1\}^k}$ to every set $S \in \binom{[n]}{k}$, with the property that

$$\mathbb{E}_{x,S}[\mathrm{Tr}(M_{S,x_S} \cdot f(x))] \geq p,$$

where the expectation is taken over a uniform choice of $x \in \{0,1\}^n$ and $S \in \binom{[n]}{k}$, and x_S denotes the k-bit substring of x specified by S.

In order to prove Theorem 2, we introduce another notion of QRAC, which we call *XOR-QRAC*. Here, the goal is to predict the XOR of the k bits indexed by S (as opposed to guessing all the bits in S). Since one can always predict a bit with probability $\frac{1}{2}$, it is convenient to define the *bias* of the prediction as $\varepsilon = 2p - 1$ where p is the probability of a correct prediction. Hence a bias of 1 means that the prediction is always correct, whereas a bias of -1 means that it is always wrong. The advantage of dealing with an XOR-QRAC is that it is easy to express the best achievable prediction bias without any need to introduce measurements. Namely, if $f : \{0,1\}^n \to \mathbb{C}^{2^m \times 2^m}$ is the encoding function, then the best achievable bias in predicting the XOR of the bits in S (over a random $\{0,1\}^n$) is exactly half the trace distance between the average of $f(x)$ over all x with the XOR of the bits in S being 0 and the average of $f(x)$ over all x with the XOR of the bits in S being 1. Using our notation for Fourier coefficients, this can be written simply as $\left\|\widehat{f}(S)\right\|_{\mathrm{tr}}$.

Definition 2. *A k-out-of-n XOR quantum random access code on m qubits with bias ε (for short (k,n,m,ε)-XOR-QRAC), is a map*

$$f : \{0,1\}^n \to \mathbb{C}^{2^m \times 2^m}$$

that assigns an m-qubit density matrix $f(x)$ to every $x \in \{0,1\}^n$ and has the property that

$$\mathbb{E}_{S\sim\binom{[n]}{k}}\left[\left\|\widehat{f}(S)\right\|_{\mathrm{tr}}\right] \geq \varepsilon.$$

Our new hypercontractive inequality allows us to easily derive the following key lemma:

Lemma 6. *Let $f : \{0,1\}^n \to \mathbb{C}^{2^m \times 2^m}$ be any mapping from n-bit strings to m-qubit density matrices. Then for any $0 \leq \delta \leq 1$, we have*

$$\sum_{S\subseteq[n]} \delta^{|S|}\left\|\widehat{f}(S)\right\|_{\mathrm{tr}}^2 \leq 2^{2\delta m}.$$

Proof: Let $p = 1 + \delta$. On one hand, by Theorem 1 and Eq. (4) we have

$$\sum_{S\subseteq[n]} (p-1)^{|S|}\left\|\widehat{f}(S)\right\|_p^2 \leq \left(\frac{1}{2^n}\sum_{x\in\{0,1\}^n}\left\|f(x)\right\|_p^p\right)^{2/p} \leq \left(\frac{1}{2^n}\cdot 2^n \cdot \frac{1}{2^m}\right)^{2/p} = 2^{-2m/p}.$$

On the other hand, by norm monotonicity we have

$$\sum_{S\subseteq[n]} (p-1)^{|S|} \left\|\widehat{f}(S)\right\|_p^2 \;\geq\; \sum_{S\subseteq[n]} (p-1)^{|S|} \left\|\widehat{f}(S)\right\|_1^2 = 2^{-2m} \sum_{S\subseteq[n]} (p-1)^{|S|} \left\|\widehat{f}(S)\right\|_{\mathrm{tr}}^2.$$

By rearranging we have

$$\sum_{S\subseteq[n]} (p-1)^{|S|} \left\|\widehat{f}(S)\right\|_{\mathrm{tr}}^2 \leq 2^{2m(1-1/p)} \leq 2^{2m(p-1)},$$

as required. ∎

The following is our main theorem regarding XOR-QRAC. In particular it shows that if $k = o(n)$ and $m/n < 1/(2\ln 2) \approx 0.721$, then the bias will be exponentially small in k.

Theorem 7. *For any (k, n, m, ε)-XOR-QRAC we have the following bound on the bias*

$$\varepsilon \leq \left(\frac{(2e\ln 2)m}{k}\right)^{k/2} \binom{n}{k}^{-1/2}.$$

In particular, for any $\eta > 2\ln 2$ there exists a constant C_η such that if n/k is large enough then for any (k, n, m, ε)-XOR-QRAC,

$$\varepsilon \leq C_\eta \left(\frac{\eta m}{n}\right)^{k/2}.$$

Proof: Apply Lemma 6 with $\delta = \frac{k}{(2\ln 2)m}$ and only take the sum on S with $|S| = k$. This gives

$$\mathbb{E}_{S\sim\binom{[n]}{k}} \left[\left\|\widehat{f}(S)\right\|_{\mathrm{tr}}^2\right] \leq 2^{2\delta m}\delta^{-k}\binom{n}{k}^{-1} = \left(\frac{(2e\ln 2)m}{k}\right)^{k} \binom{n}{k}^{-1}.$$

The first bound on ε now follows by convexity (Jensen's inequality). To derive the second bound, approximate $\binom{n}{k}$ using Stirling's approximation $n! = \Theta(\sqrt{n}(n/e)^n)$:

$$\binom{n}{k} = \frac{n!}{k!(n-k)!} = \Theta\left(\sqrt{\frac{n}{k(n-k)}} \left(\frac{n}{k}\right)^k \left(1 + \frac{k}{n-k}\right)^{n-k}\right).$$

Now use the fact that for large enough n/k we have $(1 + k/(n-k))^{(n-k)/k} > (2e\ln 2)/\eta$, and notice that the factor $\sqrt{n/k(n-k)} \geq \sqrt{1/k}$ can be absorbed by this approximation. ∎

We now derive Theorem 2 from Theorem 7.

Proof of Theorem 2: Consider a (k, n, m, p)-QRAC, given by encoding function f and measurements $\{M_{T,z}\}_{z\in\{0,1\}^k}$ for all $T \in \binom{[n]}{k}$. Define $p_T(w) = \mathbb{E}_x\left[\Pr[z \oplus x_T = w]\right]$ as the distribution on the "error vector" $w \in \{0,1\}^k$ of the measurement outcome $z \in \{0,1\}^k$ when applying $\{M_{T,z}\}$. By definition, we have that $p \leq \mathbb{E}_T[p_T(0^k)]$.

Now suppose we want to predict the parity of the bits of some set S of size at most k. We can do this as follows: uniformly pick a set $T \in \binom{[n]}{k}$ that contains S, measure $f(x)$ with $\{M_{T,z}\}$, and output the parity

of the bits corresponding to S in the measurement outcome z. Note that our output is correct if and only if the bits corresponding to S in the error vector w have even parity. Hence the bias of our output is

$$\beta_S = \mathbb{E}_{T:T\supseteq S}\left[\sum_{w\in\{0,1\}^k} p_T(w)\chi_S(w)\right] = 2^k\,\mathbb{E}_{T:T\supseteq S}\left[\widehat{p_T}(S)\right].$$

(We slightly abuse notation here by viewing S both as a subset of T and as a subset of $[k]$ obtained by identifying T with $[k]$.) Notice that β_S can be upper bounded by the best-achievable bias $\left\|\widehat{f}(S)\right\|_{\mathrm{tr}}$.

Consider the distribution $\mathcal{S}$ on sets S defined as follows: first pick j from the binomial distribution $B(k,1/2)$ and then uniformly pick $S \in \binom{[n]}{j}$. Notice that the distribution on pairs (S,T) obtained by first choosing $S\sim\mathcal{S}$ and then choosing a uniform $T\supseteq S$ from $\binom{[n]}{k}$ is identical to the one obtained by first choosing uniformly T from $\binom{[n]}{k}$ and then choosing a uniform $S\subseteq T$. This allows us to show that the average bias β_S over $S\sim\mathcal{S}$ is at least p, as follows:

$$\begin{aligned}
\mathbb{E}_{S\sim\mathcal{S}}\left[\beta_S\right] &= 2^k\mathbb{E}_{S\sim\mathcal{S},T\supseteq S}\left[\widehat{p_T}(S)\right] \\
&= 2^k\mathbb{E}_{T\sim\binom{[n]}{k},S\subseteq T}\left[\widehat{p_T}(S)\right] \\
&= \mathbb{E}_{T\sim\binom{[n]}{k}}\left[\sum_{S\subseteq T}\widehat{p_T}(S)\right] \\
&= \mathbb{E}_{T\sim\binom{[n]}{k}}\left[p_T(0^k)\right] \geq p
\end{aligned}$$

where the last equality follows from Eq. (2). On the other hand, using Theorem 7 we obtain

$$\begin{aligned}
\mathbb{E}_{S\sim\mathcal{S}}\left[\beta_S\right] &\leq \mathbb{E}_{S\sim\mathcal{S}}\left[\left\|\widehat{f}(S)\right\|_{\mathrm{tr}}\right] \\
&= \frac{1}{2^k}\sum_{j=0}^{k}\binom{k}{j}\mathbb{E}_{S\sim\binom{[n]}{j}}\left[\left\|\widehat{f}(S)\right\|_{\mathrm{tr}}\right] \\
&\leq \frac{1}{2^k}\sum_{j=0}^{k}\binom{k}{j}C_\eta\left(\frac{\eta m}{n}\right)^{j/2} \\
&= C_\eta\left(\frac{1}{2}+\frac{1}{2}\sqrt{\frac{\eta m}{n}}\right)^k,
\end{aligned}$$

where the last equality uses the binomial theorem. Combining the two inequalities completes the proof. ■

5 Direct product theorem for one-way quantum communication

The setting of communication complexity is by now well-known, so we will not give formal definitions of protocols etc., referring to [28, 43] instead. Consider the n-bit Disjointness problem in 2-party communication complexity. Alice receives n-bit string x and Bob receives n-bit string y. They interpret these strings as subsets of $[n]$ and want to decide whether their sets are disjoint. In other words, $\mathrm{DISJ}_n(x,y)=1$ if and only if $x\cap y=\emptyset$. Let $\mathrm{DISJ}_n^{(k)}$ denote k independent instances of this problem. That is, Alice's input is a k-tuple $x_1,\ldots,x_k$ of n-bit strings, Bob's input is a k-tuple $y_1,\ldots,y_k$, and they should output

all k bits: $\mathrm{DISJ}_n^{(k)}(x_1,\ldots,x_k,y_1,\ldots,y_k) = \mathrm{DISJ}_n(x_1,y_1),\ldots,\mathrm{DISJ}_n(x_k,y_k)$. The trivial protocol where Alice sends all her inputs to Bob has success probability 1 and communication complexity kn. We want to show that if the total one-way communication is much smaller than kn qubits, then the success probability is exponentially small in k. We will do that by deriving a random access code from the protocol's message.

Lemma 8. *Let $\ell \leq k/2$. If there is a c-qubit one-way communication protocol for $\mathrm{DISJ}_n^{(k)}$ with success probability σ, then there is an ℓ-out-of-kn quantum random access code of $c + O(k + \log(kn))$ qubits with success probability $p \geq \frac{1}{2}\sigma \cdot (1-\ell/k)^\ell$.*

Proof: Consider the following one-way communication setting: Alice has a kn-bit string x, and Bob has ℓ distinct indices $i_1,\ldots,i_\ell \in [kn]$ and wants to learn the corresponding bits of x. In order to do this, they use $\lceil \log((kn)!) \rceil$ public coin flips to pick a random permutation $\pi \in S_{kn}$, and Alice sends the c-qubit message corresponding to input $\pi(x)$ in the $\mathrm{DISJ}_n^{(k)}$-protocol. We view $\pi(x) = x_1 \ldots x_k$ as consisting of k disjoint blocks of n bits each. The probability (over the choice of π) that Bob's ℓ permuted indices $\pi(i_1),\ldots,\pi(i_\ell)$ end up in ℓ different blocks is

$$\prod_{i=0}^{\ell-1} \frac{kn-in}{kn-i} \geq \left(\frac{kn-\ell n}{kn}\right)^\ell = \left(1-\frac{\ell}{k}\right)^\ell.$$

If this is the case, Bob chooses his Disjointness inputs $y_1,\ldots,y_k$ as follows. If index $\pi(i_j)$ ended up somewhere in block $b \in [k]$, then he chooses y_b to be the string having a 1 at the position where $\pi(i_j)$ ended up, and 0s elsewhere. Note that the correct output for the b-th instance of Disjointness with inputs $\pi(x)$ and $y_1,\ldots,y_k$ is exactly $1 - x_{i_j}$. Now Bob completes the protocol and gets a k-bit output for the k-fold Disjointness problem. A correct output tells him the ℓ bits he wants to know (he can just disregard the outcomes of the other $k-\ell$ instances). Overall the success probability is at least $\sigma(1-\ell/k)^\ell$.

We will now replace the large public coin by a short coin that Alice flips privately and sends along with her message. By Newman's theorem [35], there exists a set S of only $O(\log(2^{kn}\cdot n^k)/(\sigma(1-\ell/k)^\ell)^2)$ permutations, such that using a random element from this small set instead of a uniformly random permutation changes the success probability in the protocol by at most an additive $\frac{1}{2}\sigma(1-\ell/k)^\ell$, for each of the $2^{kn}\cdot n^k$ inputs that we are considering. Alice's permutation (picked from the small set S, which we hardwire into the protocol so Bob also knows it) can be described by $\log|S| = O(k+\log(kn))$ bits. Here we assume $\sigma \geq 2^{-k}$; the lemma is trivial otherwise. The quantum message corresponding to x together with Alice's private coin, is the quantum random access code. That is, if Alice's message on input x and permutation π is denoted by $\rho_{\pi(x)}$, then the random access code is the mixed quantum state

$$\frac{1}{|S|}\sum_{\pi\in S} \rho_{\pi(x)} \otimes |\pi\rangle\langle\pi|.$$

This has $c + \log|S|$ qubits. ∎

Combining the previous lemma with our earlier upper bound on p for ℓ-out-of-kn quantum random access codes (Theorem 2), we obtain the following upper bound on the success probability σ of c-qubit one-way communication protocols for $\mathrm{DISJ}_n^{(k)}$. For every $\eta > 2\ln 2$ there exists a constant C_η such that:

$$\sigma \leq 2p(1-\ell/k)^{-\ell} \leq 2C_\eta \left(\left(\frac{1}{2}+\frac{1}{2}\sqrt{\frac{\eta(c+O(k+\log(kn)))}{kn}}\right)\left(\frac{k}{k-\ell}\right)\right)^\ell.$$

Choosing ℓ a sufficiently small constant fraction of k (depending on η), we obtain a strong direct product theorem for one-way communication:

Theorem 9. *For any $\eta > 2\ln 2$ the following holds: for any large enough n and any k, every one-way quantum protocol for* $\mathrm{DISJ}_n^{(k)}$ *that communicates $c \leq kn/\eta$ qubits, has success probability $\sigma \leq 2^{-\Omega(k)}$ (where the constant in the $\Omega(\cdot)$ depends on η).*

The above strong direct product theorem (SDPT) bounds the success probability for protocols that are required to compute *all* k instances correctly. We call this a *zero-error* SDPT. What if we settle for getting a $(1-\varepsilon)$-fraction of the k instances right, for some small $\varepsilon > 0$? An *ε-error SDPT* is a theorem to the effect that even in this case the success probability is exponentially small. An ε-error SDPT follows from a zero-error SDPT as follows. Run an ε-error protocol with success probability p ("success" now means getting $1-\varepsilon$ of the k instances right), guess up to εk positions and change them. With probability at least p the number of errors of the ε-error protocol is at most εk, and with probability at least $1/\sum_{i=0}^{\varepsilon k}\binom{k}{i}$ we now have corrected all those errors. Since $\sum_{i=0}^{\varepsilon k}\binom{k}{i} \leq 2^{kH(\varepsilon)}$ (see, e.g., [24, Corollary 23.6]), we have a protocol that computes all instances correctly with success probability $\sigma \geq p2^{-kH(\varepsilon)}$. If we have a zero-error SDPT that bounds $\sigma \leq 2^{-\gamma k}$ for some $\gamma > H(\varepsilon)$, then it follows that p must be exponentially small as well: $p \leq 2^{-(\gamma - H(\varepsilon))k}$. Hence Theorem 9 implies:

Theorem 10. *For any $\eta > 2\ln 2$ there exists an $\varepsilon > 0$ such that the following holds: for every one-way quantum protocol for* $\mathrm{DISJ}_n^{(k)}$ *that communicates $c \leq kn/\eta$ qubits, its probability to compute at least a $(1-\varepsilon)$-fraction of the k instances correctly is at most $2^{-\Omega(k)}$.*

6 Lower bounds for 3-party Disjointness in the NOF model

We now prove two lower bounds for the communication complexity of 3-party Disjointness in the "number on the forehead" model, slightly improving upon [6]. Here Alice sees n-bit inputs x and z, Bob sees y and z, and Charlie sees x and y. Their goal is to decide if there is an $i \in [n]$ such that $x_i = y_i = z_i = 1$.

6.1 Communication-type $C \to (B \leftrightarrow A)$

Suppose we have a 3-party protocol P for Disjointness with the following "flow" of communication. Charlie sends a message of c_1 classical bits to Alice and Bob (or just to Bob, it doesn't really matter), who then exchange c_2 *qu*bits and compute Disjointness with bounded error probability. Our lower bound approach is similar to the one of Beame et al. [6], the main change being our use of stronger direct product theorems. Combining the (0-error) two-way quantum strong direct product theorem for Disjointness from [27] with the argument from the end of our Section 5, we have the following ε-error strong direct product theorem for k instances of 2-party Disjointness:

Theorem 11. *There exist constants $\varepsilon > 0$ and $\alpha > 0$ such that the following holds: for every two-way quantum protocol for* $\mathrm{DISJ}_n^{(k)}$ *that communicates at most $\alpha k\sqrt{n}$ qubits, its probability to compute at least an $(1-\varepsilon)$-fraction of the k instances correctly, is at most $2^{-\Omega(k)}$.*

Assume without loss of generality that the error probability of our initial 3-party protocol P is at most half the ε of Theorem 11. View the n-bit inputs of protocol P as consisting of t consecutive blocks of n/t bits each. We will restrict attention to inputs $z = z_1 \ldots z_t$ where one z_i is all-1, and the other z_j are all-0. Note that for such a z, we have $\mathrm{DISJ}_n(x,y,z) = \mathrm{DISJ}_{n/t}(x_i, y_i)$. Fixing z thus reduces the 3-party Disjointness on (x,y,z) to 2-party Disjointness on a smaller instance (x_i, y_i). Since Charlie does not see input z, his c_1-bit message is independent of z. Now by going over all t possible z's, and running their

2-party protocol t times starting from Charlie's message, Alice and Bob obtain a protocol P' that computes t independent instances of 2-party Disjointness, namely on each of the t inputs $(x_1, y_1), \ldots, (x_t, y_t)$. This P' uses at most tc_2 qubits of communication. For every x and y, it follows from linearity of expectation that the expected number of instances where P' errs, is at most $\varepsilon t/2$ (expectation taken over Charlie's message, and the t-fold Alice-Bob protocol). Hence by Markov's inequality, the probability that P' errs on more than εt instances, is at most 1/2. Then for every x, y there exists a c_1-bit message m_{xy} such that P', when given that message to start with, with probability at least 1/2 correctly computes $1 - \varepsilon$ of all t instances.

Now replace Charlie's c_1-bit message by a uniformly random message m. Alice and Bob can just generate this by themselves using shared randomness. This gives a new 2-party protocol P''. For each x, y, with probability 2^{-c_1} we have $m = m_{xy}$, hence with probability at least $\frac{1}{2}2^{-c_1}$ the protocol P'' correctly computes $1 - \varepsilon$ of all t instances of Disjointness on n/t bits each. Choosing $t = O(c_1)$ and invoking Theorem 11 gives a lower bound on the communication in P'': $tc_2 = \Omega(t\sqrt{n/t})$. Hence $c_2 = \Omega(\sqrt{n/c_1})$. The overall communication of the original 3-party protocol P is

$$c_1 + c_2 = c_1 + \Omega(\sqrt{n/c_1}) = \Omega(n^{1/3})$$

(the minimizing value is $t = n^{1/3}$).

This generalizes the bound of Beame et al. [6] to the case where we allow Alice and Bob to send each other qubits. Note that this bound is tight for our restricted set of z's, since Alice and Bob know z and can compute the 2-party Disjointness on the relevant (x_i, y_i) in $O(\sqrt{n^{2/3}}) = O(n^{1/3})$ qubits of two-way communication without help from Charlie, using the optimal quantum protocol for 2-party Disjointness [1].

6.2 Communication-type $C \to B \to A$

Now consider an even more restricted type of communication: Charlie sends a classical message to Bob, then Bob sends a quantum message to Alice, and Alice computes the output. We can use a similar argument as before, dividing the inputs into $t = O(n^{1/2})$ equal-sized blocks instead of $O(n^{1/3})$ equal-sized blocks. If we now replace the two-way SDPT (Theorem 11) by the new one-way SDPT (Theorem 10), we obtain a lower bound of $\Omega(\sqrt{n})$ for 3-party bounded-error protocols for Disjointness of this restricted type.

Remark. If Charlie's message is quantum as well, then the same approach works, except we need to reduce the error of the protocol to $\ll 1/t$ at a multiplicative cost of $O(\log t) = O(\log n)$ to both c_1 and c_2 (Charlie's one quantum message needs to be reused t times). This worsens the two communication lower bounds to $\Omega(n^{1/3}/\log n)$ and $\Omega(\sqrt{n}/\log n)$ qubits, respectively.

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