

A Note on the Probability of Rectangles for Correlated Binary Strings

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Abstract—Consider two sequences of n independent and identically distributed fair coin tosses, $X = (X_1, \dots, X_n)$ and $Y = (Y_1, \dots, Y_n)$, which are ρ -correlated for each j , i.e. $\mathbb{P}[X_j = Y_j] = \frac{1+\rho}{2}$. We study the question of how large (small) the probability $\mathbb{P}[X \in A, Y \in B]$ can be among all sets $A, B \subset \{0, 1\}^n$ of a given cardinality. For sets $|A|, |B| = \Theta(2^n)$ it is well known that the largest (smallest) probability is approximately attained by concentric (anti-concentric) Hamming balls, and this can be proved via the hypercontractive inequality (reverse hypercontractivity). Here we consider the case of $|A|, |B| = 2^{\Theta(n)}$. By applying a recent extension of the hypercontractive inequality of Polyanskiy-Samorodnitsky (J. Functional Analysis, 2019), we show that Hamming balls of the same size approximately maximize $\mathbb{P}[X \in A, Y \in B]$ in the regime of $\rho \rightarrow 1$. We also prove a similar tight lower bound, i.e. show that for $\rho \rightarrow 0$ the pair of opposite Hamming balls approximately minimizes the probability $\mathbb{P}[X \in A, Y \in B]$.

of a given size, how large/small can the probability of a rectangle be? Previous works addressing similar questions relied on hypercontractive and reverse hypercontractive inequalities, as we describe below. Our main innovation is applying a new tool from [1] that is a refinement of the direct hypercontractive inequality to functions with sparse support.

A direct application of the hypercontractive inequality [2], [3], [4], [5], [6] (see Section III for more details) yields that for A and B of equal cardinalities, i.e. $|A| = |B| \triangleq \eta \cdot 2^n$, we have

$$P_{XY}(A \times B) \leq \eta^{\frac{2}{1+\rho}}, \quad (2)$$

whereas the reverse hypercontractive inequality of [7] was applied in [8] to obtain

$$P_{XY}(A \times B) \geq \eta^{\frac{2}{1-\rho}}. \quad (3)$$

Both bounds become quite tight for the regime of $\eta = \Theta(1)$, i.e. for very large sets of cardinalities $|A| = |B| = \Theta(2^n)$. In particular, (2) is approximately attained by taking A and B as the zero-centered Hamming balls containing all vectors with Hamming weight smaller than $\frac{n}{2} - s\sqrt{n}$, for large s independent of n , whereas (3) is approximately attained by taking A as such zero-centered ball and B as the same ball shifted such that its center is the all-ones vector. A special case of the construction in [9] also gives more constructions of sets approximately attaining (2): namely, for any $k \in \mathbb{Z}_+$ and all sufficiently large $n \geq n_0(k)$ they constructed sets $A = B$ of cardinality 2^{n-k} such that

$$P_{XY}(A \times B) \geq \Omega_\rho(1/\sqrt{k})2^{-k \cdot \frac{2}{1+\rho}}, \quad (4)$$

thus showing that the estimate (2) is tight (up to a polylog factor $(\log \frac{1}{\eta})^{-\frac{1}{2}}$).

In this paper we are interested in estimating the probability of rectangles for sets A, B of much smaller cardinalities (such as those frequently encountered in information and coding theories), namely $|A| = 2^{n\alpha}$, $|B| = 2^{n\beta}$ for $\alpha, \beta < 1$. Our original motivation stems from the bounds on the adder multiple access channel (MAC) zero-error capacity, obtained in [10]. Sets $A, B \subset \{0, 1\}^n$ are called a zero-error code for the adder MAC, if $|A + B| = |A| \cdot |B|$, where $A + B \subset \{0, 1, 2\}^n$ is the

I. INTRODUCTION

Let $X \sim \text{Uniform}(\{0, 1\}^n)$ and $Y \in \{0, 1\}^n$ be a ρ -correlated copy of X , where $0 \leq \rho < 1$, i.e.,

$$\begin{aligned} \Pr(Y = y|X = x) &= \prod_{i=1}^n \left(\frac{1-\rho}{2}\right)^{d(x_i, y_i)} \left(\frac{1+\rho}{2}\right)^{1-d(x_i, y_i)} \\ &= \left(\frac{1+\rho}{2}\right)^n \cdot \left(\frac{1-\rho}{1+\rho}\right)^{d(x, y)}, \end{aligned} \quad (1)$$

where $d(x_i, y_i) = \mathbb{1}_{\{x_i \neq y_i\}}$ and $d(x, y) = \sum_{i=1}^n d(x_i, y_i)$. For $A, B \subset \{0, 1\}^n$, we denote $P_{XY}(A \times B) \triangleq \Pr(X \in A, Y \in B)$ – probability of a rectangle with sides A and B . In this paper we are interested in the following question: *Among all sets*

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Minkowski sum (over the reals) of the sets A and B . The problem of finding all pairs $(R_1, R_2) \in [0, 1]^2$ for which there exist a zero-error code with sizes $|A| = 2^{nR_1}$, $|B| = 2^{nR_2}$ is a long standing open problem [11], [12], [13], [14], [15], [16], [17], [18]. One of the first results in the area, due to van Tilborg [12], states that if A, B form a zero error code, then

$$W_d(A, B) \triangleq \frac{1}{n} \log |\{(a, b) \in A \times B : d(a, b) = nd\}| \quad (5)$$

$$\leq \frac{1}{n} \log \binom{n}{nd} + \min(d, 1-d), \quad (6)$$

for all $d \in \{0, \frac{1}{n}, \dots, 1\}$. The basic idea in [10] was to use (6) for upper bounding

$$\begin{aligned} P_{XY}(A \times B) \\ = 2^{-n} \left(\frac{1+\rho}{2}\right)^n \sum_{d=0}^1 2^{nW_d(A, B)} \left(\frac{1-\rho}{1+\rho}\right)^{nd} \end{aligned} \quad (7)$$

for any zero-error code (A, B) , and to contrast this with lower bounds on $P_{XY}(A \times B)$ for sets $|A| = 2^{nR_1}$, $|B| = 2^{nR_2}$ obtained in [8] (see Remark 4 below). A simple modification of this approach [10] yielded the best known outer bounds on (R_1, R_2) to date, and possibly, replacing the lower bound from [8] on $P_{XY}(A \times B)$ with a sharper one, could yield stronger bounds on (R_1, R_2) . For instance, if our main conjecture, stated below, turns out to be true, repeating the arguments in [10] with the improved bounds will yield that as R_1 approaches 1 we must have that $R_2 < 0.4177$, improving upon $R_2 < 0.4228$ established in [10], which is the best known bound to date.

Our interest is in the greatest and smallest exponential decay rate of $P_{XY}(A \times B)$ among all possible sets A, B of sizes $2^{n\alpha}$ and $2^{n\beta}$, respectively. To that end, for fixed $0 < \alpha, \beta < 1$ we define

$$\overline{E}(\alpha, \beta, \rho) \triangleq - \limsup_{n \rightarrow \infty} \max_{\{A\}, \{B\}} \frac{1}{n} \log P_{XY}(A \times B), \quad (8)$$

$$\underline{E}(\alpha, \beta, \rho) \triangleq - \liminf_{n \rightarrow \infty} \min_{\{A\}, \{B\}} \frac{1}{n} \log P_{XY}(A \times B), \quad (9)$$

where $\max_{\{A\}, \{B\}}$ and $\min_{\{A\}, \{B\}}$ denote optimizations over the sequences of sets $A_n \subset \{0, 1\}^n$, $B_n \subset \{0, 1\}^n$, $n \in \mathbb{Z}_+$ such that

$$|A_n| = 2^{n\alpha + o(n)}, \quad |B_n| = 2^{n\beta + o(n)}.$$

Our **main conjecture** is that both $\overline{E}(\alpha, \beta, \rho)$ and $\underline{E}(\alpha, \beta, \rho)$ are optimized by concentric (resp., anti-concentric) Hamming balls. In this work we show partial progress towards establishing this conjecture. Our conjecture is in line with the well-known facts that among

all pairs of sets $A, B \subset \{0, 1\}^n$ of given sizes, the maximal distance $d_{\max}(A, B) = \max_{a \in A, b \in B} d(a, b)$ is minimized by concentric Hamming (quasi) balls [19], [20], whereas the minimum distance $d_{\min}(A, B) = \min_{a \in A, b \in B} d(a, b)$ is maximized by anti-concentric Hamming (quasi) balls [21].

Notation: Logarithms are taken to base 2 throughout, unless stated otherwise. We denote the Shannon entropy of a random variable V by $H(V)$. For a binary random variable $V \sim \text{Ber}(p)$ we denote the entropy by $h(p) \triangleq -p \log p - (1-p) \log(1-p)$ and its inverse restricted to $[0, 1/2]$ by $h^{-1}(\cdot)$. For $0 \leq p, q \leq 1$ we denote $p * q \triangleq p(1-q) + q(1-p)$.

Our main results characterize $\overline{E}(\alpha, \alpha, \rho)$ in the low noise (large ρ) regime, and $\underline{E}(\alpha, \beta, \rho)$ in the high noise (small ρ) regime, as follows.

Theorem 1: As $\rho \rightarrow 1$ we have

$$\begin{aligned} \overline{E}(\alpha, \alpha, \rho) &= (1-\alpha) \\ &+ \frac{\frac{1}{2} - \sqrt{h^{-1}(\alpha)(1-h^{-1}(\alpha))}}{\ln 2} (1-\rho) + o(1-\rho). \end{aligned} \quad (10)$$

Theorem 1 will follow from combining Proposition 1 and Proposition 3, proved in Section II and Section III, respectively.

Theorem 2: As $\rho \rightarrow 0$ we have

$$\begin{aligned} \underline{E}(\alpha, \beta, \rho) &= (1-\alpha) + (1-\beta) \\ &+ \rho \log e (1 - 2h^{-1}(\alpha) * h^{-1}(\beta)) + o(\rho). \end{aligned} \quad (11)$$

Theorem 2 will follow from combining Proposition 2 and Proposition 6, proved in Section II and Section IV, respectively.

In both cases, the optimal exponents are obtained (up to $o(\rho)$ and $o(1-\rho)$ terms) by taking A and B to be Hamming spheres. In Section II we compute $P_{XY}(A \times B)$ for Hamming spheres, and prove the corresponding upper bound for $\overline{E}(\alpha, \alpha, \rho)$ obtained by concentric spheres, and the lower bound on $\underline{E}(\alpha, \beta, \rho)$, obtained by spheres with opposite centers. In Section III we prove the lower bound on $\overline{E}(\alpha, \alpha, \rho)$. What is interesting is that while (2) is shown via the classical hypercontractivity inequality [2], [3], [4], [5], [6], our result is shown by applying a recent improvement [1] of this inequality for functions of small support (cf. Section III). In Section IV we prove the upper bound on $\underline{E}(\alpha, \beta, \rho)$ by bounding the maximal average Hamming distance between members of A and B , subject to the cardinality constraint – another combinatorial optimization problem of possible interest.

Remark 1: After this work had been completed, we have learned from Naomi Kirshner and Alex Samorodnitsky about their concurrent work [22] in which, among

other things, they were able to prove that $\overline{E}(\alpha, \alpha, \rho)$ is attained by concentric spheres for all $0 < \rho < 1$. Their result subsumes our Theorem 1 and relies on a different strengthening of a hypercontractive inequality.¹ The problems of characterizing $\overline{E}(\alpha, \beta, \rho)$ for $\alpha \neq \beta$ and that of $\underline{E}(\alpha, \beta, \rho)$ remain open.

II. BOUNDS VIA SPHERES

For $x = (x_1, \dots, x_n) \in \{0, 1\}^n$ denote the Hamming weight of x and the Hamming sphere centered at zero as

$$|x| \triangleq |\{j : x_j = 1\}| \quad (12)$$

$$\mathbb{S}_j \triangleq \{x : |x| = j\}. \quad (13)$$

For the size of Hamming spheres we have [23, Exc. 5.8]

$$|\mathbb{S}_{[dn]}| = \binom{n}{[dn]} = 2^{nh(d) - \frac{1}{2} \log n + O(1)}, \quad n \rightarrow \infty \quad (14)$$

where the estimate is a consequence of Stirling's formula, $O(1)$ is uniform in δ on compact subsets of $(0, 1)$.

Existential results (an upper bound on \overline{E} and a lower bound on \underline{E}) follow from taking A and B as Hamming spheres $\mathbb{S}_i, \mathbb{S}_j$ for a suitable i, j . Here we compute the probability of such spherical rectangles.

For any two sets $A, B \subset \{0, 1\}^n$, we have

$$\begin{aligned} P_{XY}(A \times B) &= \sum_{x \in A, y \in B} 2^{-n(2 - \log(1 + \rho) - \frac{d(x, y)}{n} \log(\frac{1 - \rho}{1 + \rho}))} \\ &= 2^{-n(1 + o(1))E(A, B, \rho)}, \end{aligned} \quad (15)$$

where

$$\begin{aligned} E(A, B, \rho) &\triangleq \min_{0 \leq d \leq 1} \left(2 - \log(1 + \rho) \right. \\ &\quad \left. - W_d(A, B) - d \log\left(\frac{1 - \rho}{1 + \rho}\right) \right), \end{aligned} \quad (16)$$

and $W_d(A, B)$ is as defined in (5). Note that if $nd \notin \mathbb{N}$ we have that $W_d(A, B) = -\infty$, and therefore the minimization in (16) can indeed be performed on $[0, 1]$ and need not be restricted to $d \in \{0, \frac{1}{n}, \dots, 1\}$.

For two natural numbers $j \geq i$ and $d \in [0, 1]$ such that $j - i + nd$ is even, we have that

$$\begin{aligned} W_d(\mathbb{S}_i, \mathbb{S}_j) &= \frac{1}{n} \log \binom{n}{i} \binom{i}{\frac{1}{2}(j + i - nd)} \binom{n - i}{\frac{1}{2}(j - i + nd)} \\ &\quad (17) \end{aligned}$$

¹In the notation of Section III, our work leverages the inequality $\|T_\rho f\|_{q_0} \leq \|f\|_q$ among all support-constrained functions f (with the best possible q), whereas the work [22] uses the inequality $\|T_\rho f\|_{q_0} \leq e^{-n\lambda} \|f\|_{1 + (q_0 - 1)\rho^2}$ with the largest possible λ , which depends on the support size of f .

for $j - i \leq nd \leq j + i$, and $W_d(\mathbb{S}_i, \mathbb{S}_j) = -\infty$ otherwise. Let $0 < \alpha \leq \beta \leq 1$ and $d \in [0, 1]$ be such that $i = nh^{-1}(\alpha)$ and $j = nh^{-1}(\beta)$ are integers and $j - i + nd$ is an even integer. Approximating $\binom{n}{k} = 2^{n(h(k/n) + o(1))}$ as in (14), we have (18), (19) and (20) at the top of the next page, and it therefore follows from (17) that

$$W_d(\mathbb{S}_i, \mathbb{S}_j) = w_d(\alpha, \beta) + o(1), \quad (21)$$

where

$$\begin{aligned} w_d(\alpha, \beta) &\triangleq \alpha + h^{-1}(\alpha)h \left(\frac{1}{2} + \frac{h^{-1}(\beta) - d}{2h^{-1}(\alpha)} \right) \\ &\quad + (1 - h^{-1}(\alpha))h \left(\frac{1}{2} + \frac{d - (1 - h^{-1}(\beta))}{2(1 - h^{-1}(\alpha))} \right) \end{aligned} \quad (22)$$

for $h^{-1}(\beta) - h^{-1}(\alpha) \leq d \leq h^{-1}(\beta) + h^{-1}(\alpha)$, and $w_d(\alpha, \beta) = -\infty$ otherwise. Since the values of $d \in [0, 1]$ for which $j - i + nd$ is an even integer become arbitrarily dense as n grows, by continuity of $d \mapsto w_d(\alpha, \beta)$, we have that

$$\begin{aligned} E(\mathbb{S}_{nh^{-1}(\alpha)}, \mathbb{S}_{nh^{-1}(\beta)}, \rho) &= \min_{0 \leq d \leq 1} \left(2 - \log(1 + \rho) \right. \\ &\quad \left. - w_d(\alpha, \beta) - d \log\left(\frac{1 - \rho}{1 + \rho}\right) \right) + o(1). \end{aligned} \quad (23)$$

Proposition 1: For large ρ we have

$$\begin{aligned} \overline{E}(\alpha, \alpha, \rho) &\leq (1 - \alpha) \\ &\quad + \frac{\frac{1}{2} - \sqrt{h^{-1}(\alpha)(1 - h^{-1}(\alpha))}}{\ln 2} (1 - \rho) + o(1 - \rho). \end{aligned} \quad (24)$$

Proof. Let $0 < \alpha \leq 1$. We establish the claim by evaluating $P_{XY}(A \times B)$ for $A = B = \mathbb{S}_{nh^{-1}(\alpha)}$ and $\rho = 1 - \epsilon$. By (23), it holds that

$$\begin{aligned} &E\left(\mathbb{S}_{nh^{-1}(\alpha)}, \mathbb{S}_{nh^{-1}(\alpha)}, 1 - \epsilon\right) \\ &= \min_d \left(2 - \log(2 - \epsilon) - w_d(\alpha, \alpha) + d \log\left(\frac{2 - \epsilon}{\epsilon}\right) \right) \\ &\quad + o(1) \\ &= 1 + \frac{\epsilon}{2} \log(e) - \max_d \left(w_d(\alpha, \alpha) - d \log\left(\frac{2}{\epsilon}\right) \right) + d \frac{\epsilon}{2} \log(e) \\ &\quad + o(\epsilon) + o(1). \end{aligned} \quad (25)$$

Denoting $r = r_\alpha = h^{-1}(\alpha)$, we have that

$$w_d(\alpha, \alpha) = h(r) + r \cdot h\left(\frac{d/2}{r}\right) + (1 - r) \cdot h\left(\frac{d/2}{1 - r}\right). \quad (26)$$

$$\frac{1}{n} \log \binom{n}{i} = h(h^{-1}(\alpha)) + o(1), \quad (18)$$

$$\frac{1}{n} \log \binom{i}{\frac{1}{2}(j+i-nd)} = h^{-1}(\alpha) h \left(\frac{\frac{1}{2}h^{-1}(\alpha) + h^{-1}(\beta) - d}{h^{-1}(\alpha)} \right) + o(1), \quad (19)$$

$$\frac{1}{n} \log \binom{n-i}{\frac{1}{2}(j-i+nd)} = (1 - h^{-1}(\alpha)) h \left(\frac{\frac{1}{2}h^{-1}(\beta) - h^{-1}(\alpha) + d}{1 - h^{-1}(\alpha)} \right). \quad (20)$$

The function $d \mapsto w_d(\alpha, \alpha) - d \log \left(\frac{2}{\epsilon} \right) + d \frac{\epsilon}{2} \log(e)$ is concave and its derivative

$$\begin{aligned} & \frac{1}{2} \log \left(\frac{1 - \frac{d/2}{r}}{\frac{d/2}{r}} \right) + \frac{1}{2} \log \left(\frac{1 - \frac{d/2}{1-r}}{\frac{d/2}{1-r}} \right) \\ & - \log \left(\frac{2}{\epsilon} \right) + \frac{\epsilon}{2} \log(e) \end{aligned} \quad (27)$$

equals zero at $d^* = \epsilon \sqrt{r(1-r)} + o(\epsilon)$. Thus, the optimizing d in (25) is $d^* = \epsilon \sqrt{r(1-r)} + o(\epsilon)$, and therefore

$$\begin{aligned} & E \left(\mathbb{S}_{nh^{-1}(\alpha)}, \mathbb{S}_{nh^{-1}(\alpha)}, 1 - \epsilon \right) = 1 - h(r) \\ & + \frac{\epsilon}{2} \log(e) + \epsilon \sqrt{r(1-r)} + \epsilon \log \left(\frac{1}{\epsilon} \right) \sqrt{r(1-r)} \\ & - \left[r \cdot h \left(\sqrt{\frac{1-r}{r}} \frac{\epsilon}{2} \right) + (1-r) \cdot h \left(\sqrt{\frac{r}{1-r}} \frac{\epsilon}{2} \right) \right] \\ & + o(\epsilon) + o(1) \end{aligned} \quad (28)$$

We approximate the term in the square brackets in equations (29), (30) and (31) at the bottom of the page. Substituting (31) into (28), we obtain

$$\begin{aligned} r \cdot h \left(\sqrt{\frac{1-r}{r}} \frac{\epsilon}{2} \right) &= -\sqrt{r(1-r)} \frac{\epsilon}{2} \log \left(\sqrt{\frac{1-r}{r}} \frac{\epsilon}{2} \right) - r \left(1 - \sqrt{\frac{1-r}{r}} \frac{\epsilon}{2} \right) \log \left(1 - \sqrt{\frac{1-r}{r}} \frac{\epsilon}{2} \right) \\ &= -\sqrt{r(1-r)} \frac{\epsilon}{2} \log \left(\sqrt{\frac{1-r}{r}} \frac{\epsilon}{2} \right) + \frac{\epsilon}{2} \sqrt{r(1-r)} \log(e) + o(\epsilon), \end{aligned} \quad (29)$$

$$\begin{aligned} (1-r) \cdot h \left(\sqrt{\frac{r}{1-r}} \frac{\epsilon}{2} \right) &= -\sqrt{r(1-r)} \frac{\epsilon}{2} \log \left(\sqrt{\frac{r}{1-r}} \frac{\epsilon}{2} \right) - (1-r) \left(1 - \sqrt{\frac{r}{1-r}} \frac{\epsilon}{2} \right) \log \left(1 - \sqrt{\frac{r}{1-r}} \frac{\epsilon}{2} \right) \\ &= -\sqrt{r(1-r)} \frac{\epsilon}{2} \log \left(\sqrt{\frac{r}{1-r}} \frac{\epsilon}{2} \right) + \frac{\epsilon}{2} \sqrt{r(1-r)} \log(e) + o(\epsilon), \end{aligned} \quad (30)$$

$$\begin{aligned} r \cdot h \left(\sqrt{\frac{1-r}{r}} \frac{\epsilon}{2} \right) + (1-r) \cdot h \left(\sqrt{\frac{r}{1-r}} \frac{\epsilon}{2} \right) &= -\sqrt{r(1-r)} \epsilon \log \left(\frac{\epsilon}{2} \right) + \epsilon \sqrt{r(1-r)} \log(e) + o(\epsilon) \\ &= \sqrt{r(1-r)} \epsilon \log \left(\frac{1}{\epsilon} \right) + \epsilon \sqrt{r(1-r)} + \epsilon \sqrt{r(1-r)} \log(e) + o(\epsilon). \end{aligned} \quad (31)$$

$$\begin{aligned} & E \left(\mathbb{S}_{nh^{-1}(\alpha)}, \mathbb{S}_{nh^{-1}(\alpha)}, 1 - \epsilon \right) = 1 - h(r) \\ & + \left(\frac{1}{2} - \sqrt{r(1-r)} \right) \epsilon \log(e) + o(\epsilon) + o(1). \end{aligned} \quad (32)$$

The claim now follows by definition of $\bar{E}(\alpha, \alpha, \rho)$. ■

Proposition 2: For small ρ we have that

$$\begin{aligned} \underline{E}(\alpha, \beta, \rho) &\geq (1 - \alpha) + (1 - \beta) \\ &+ \rho \log e (1 - 2h^{-1}(\alpha) * h^{-1}(\beta)) + o(\rho). \end{aligned} \quad (33)$$

Proof. We establish the claim by evaluating $P_{XY}(A \times B)$ for $A = \mathbb{S}_{nh^{-1}(\alpha)}$ and $B = 1^n + \mathbb{S}_{nh^{-1}(\beta)}$, i.e., a zero-centered Hamming sphere and a Hamming sphere centered around the all-ones vector 1^n . First, note that for any $A, B \subset \{0, 1\}^n$ it holds that

$$W_d(A, 1^n + B) = W_{1-d}(A, B). \quad (34)$$

Thus, applying (23), we see that for $0 < \alpha \leq \beta \leq 1$ it

holds that

$$\begin{aligned}
& E(\mathbb{S}_{nh^{-1}(\alpha)}, 1^n + \mathbb{S}_{nh^{-1}(\beta)}, \rho) \\
&= \min_{0 \leq d \leq 1} \left(2 - \log(1 + \rho) - w_d(\alpha, \beta) \right. \\
&\quad \left. - (1 - d) \log \left(\frac{1 - \rho}{1 + \rho} \right) \right) + o(1) \\
&= 2 - \log(1 + \rho) - \max_{0 \leq d \leq 1} \left(w_d(\alpha, \beta) - d \log \left(\frac{1 - \rho}{1 + \rho} \right) \right) \\
&+ o(1) \tag{35}
\end{aligned}$$

Let us consider the case of $\rho \ll 1$. In this case, we have that $\log(1 + \rho) = \rho \log e + o(\rho)$, so that (35) reads

$$\begin{aligned}
& E(\mathbb{S}_{nh^{-1}(\alpha)}, 1^n + \mathbb{S}_{nh^{-1}(\beta)}, \rho) = 2 + \rho \log e \\
&\quad - \max_d (w_d(\alpha, \beta) + 2d\rho \log e) + o(\rho) + o(1). \tag{36}
\end{aligned}$$

The function $d \mapsto w_d(\alpha, \beta) \triangleq g(d)$ is strictly concave, and it is straightforward to verify that $g'(h^{-1}(\alpha) * h^{-1}(\beta)) = 0$ and that $g(h^{-1}(\alpha) * h^{-1}(\beta)) = \alpha + \beta$. Denoting $c = 2g''(h^{-1}(\alpha) * h^{-1}(\beta)) < 0$ and setting $\delta = d - h^{-1}(\alpha) * h^{-1}(\beta)$, we therefore have

$$g(d) = \alpha + \beta + c\delta^2 + o(\delta^2). \tag{37}$$

Consequently,

$$\begin{aligned}
& w_d(\alpha, \beta) + 2d\rho \log e = g(d) + 2d\rho \log e \\
&= \alpha + \beta + c\delta^2 + 2(h^{-1}(\alpha) * h^{-1}(\beta) + \delta)\rho \log e + o(\delta^2) \\
&= \alpha + \beta + \rho \log e \cdot 2h^{-1}(\alpha) * h^{-1}(\beta) \\
&+ \delta(2\rho \log e + c\delta + o(\delta)) \\
&\leq \alpha + \beta + \rho \log e \cdot 2h^{-1}(\alpha) * h^{-1}(\beta) + o(\rho), \tag{38}
\end{aligned}$$

where the last inequality follows since $c < 0$. Substituting (38) into (36) we obtain

$$\begin{aligned}
& E(\mathbb{S}_{nh^{-1}(\alpha)}, 1^n + \mathbb{S}_{nh^{-1}(\beta)}, \rho) \geq (1 - \alpha) + (1 - \beta) \\
&\quad + \rho \log e (1 - 2h^{-1}(\alpha) * h^{-1}(\beta)) + o(\rho) + o(1). \tag{39}
\end{aligned}$$

The claim now follows by definition of $\underline{E}(\alpha, \beta, \rho)$. ■

III. LOWER BOUND ON $\bar{E}(\alpha, \alpha, \rho)$

For a function $f : \{0, 1\}^n \rightarrow \mathbb{R}^+$ and $p \geq 1$ we define $\|f\|_p = \mathbb{E}^{1/p}[|f(X)|^p]$. For a set $A \subset \{0, 1\}^n$ denote

$$\mathbf{1}_A(x) \triangleq \begin{cases} 0, & x \notin A \\ 1, & x \in A \end{cases}$$

We have that

$$\begin{aligned}
P_{XY}(A \times B) &= \mathbb{E}[\mathbf{1}_A(X)\mathbf{1}_B(Y)] \\
&= \mathbb{E}[\mathbf{1}_B(Y)\mathbb{E}[\mathbf{1}_A(X)|Y]] \\
&= \mathbb{E}[\mathbf{1}_B(Y)(T_\rho \mathbf{1}_A)(Y)], \tag{40}
\end{aligned}$$

where

$$(T_\rho f)(y) \triangleq \mathbb{E}[f(X)|Y = y]. \tag{41}$$

Denoting the inner-product $(f, g) = \mathbb{E}[f(Y)g(Y)]$ and noticing that T_ρ is self-adjoint and satisfies the semi-group property $T_{\rho_1}T_{\rho_2} = T_{\rho_1\rho_2}$ (for $0 < \rho_1, \rho_2 < 1$), we obtain

$$\begin{aligned}
P_{XY}(A \times B) &= (\mathbf{1}_B, T_\rho \mathbf{1}_A) \\
&= (T_{\rho_1} \mathbf{1}_B, T_{\rho_2} \mathbf{1}_A) \quad \forall \rho_1 \rho_2 = \rho \tag{42} \\
&\leq \|T_{\rho_1} \mathbf{1}_B\|_2 \|T_{\rho_2} \mathbf{1}_A\|_2, \tag{43}
\end{aligned}$$

where the last step is Cauchy-Schwarz inequality.

The next step is to use the hypercontractivity inequality to upper bound $\|T_\rho f\|_p$. Denote the support size of f by $\|f\|_0$. Since $\|f\|_0 \ll 2^n$, we will use an improved hypercontractivity inequality from [1], that takes $\|f\|_0$ into account. The following result is a key ingredient:

Theorem 3 (Theorem 7 in [1]): Fix $1 < p_0 < \infty$ and $0 \leq \lambda_0 \leq (1 - p_0^{-1}) \ln 2$. For any $f : \{0, 1\}^n \rightarrow \mathbb{R}_+$ with $\|f\|_{p_0} \geq e^{n\lambda_0} \|f\|_1$ we have

$$\|T_{e^{-t}} f\|_{p(t)} \leq \|f\|_{p_0}, \quad p(t) = 1 + e^{u(t)}, \tag{44}$$

where $u(t)$ is the unique solution on $[0, \infty)$ of the following ODE with initial condition $u(0) = \ln(p_0 - 1)$

$$u'(t) = C \left(\lambda_0 (1 + e^{-u(t)}) \right) \tag{45a}$$

$$C(\ln 2(1 - h(y))) = \frac{2 - 4\sqrt{y(1-y)}}{\ln 2(1 - h(y))}. \tag{45b}$$

Furthermore, the function $C : [0, \ln 2] \rightarrow [2, 2/\ln 2]$ is a smooth, convex and strictly increasing bijection.

From this result we derive the following implication for indicator functions.

Theorem 4: Fix $0 < \alpha < 1$ and $1 < q_0 < \infty$. Then there exists a function $q = q(t)$ defined on an interval $t \in [0, \epsilon)$ for some $\epsilon > 0$ such that for all sets $A \subset \{0, 1\}^n$ with $|A| \leq 2^{n\alpha}$ we have

$$\|T_{e^{-t}} \mathbf{1}_A\|_{q_0} \leq \|\mathbf{1}_A\|_{q(t)} \quad \forall t \in [0, \epsilon). \tag{46}$$

The function $q(t)$ satisfies

$$q(t) = q_0 - (q_0 - 1)C((1 - \alpha) \ln 2)t + O(t^2) \quad \text{as } t \rightarrow 0. \tag{47}$$

Remark 2: Note that the standard hypercontractivity estimate [2], [3], [4], [5] yields the same result without restriction on the size of the set A but with a strictly worse (larger) function $q(t) = (q_0 - 1)e^{-2t} + 1$. See [1, Remark 3].

Proof. Denote by $u_f(a, b, t)$ the solution of the ordinary differential equation (ODE)

$$\frac{d}{dt} u(t) = C(b(1 + e^{-u(t)})),$$

with $u(0) = a$. Here $C(\cdot)$ is a function defined in (60), $a \in \mathbb{R}$ and $0 < b < (1 + e^{-a})^{-1} \ln 2$. For a fixed a, b the standard results on ODEs imply that this solution exists and is unique in some neighborhood $-\epsilon < t < \epsilon$ of zero. Furthermore, for any a_0, b_0 satisfying $0 < b_0 < (1 + e^{-a_0})^{-1} \ln 2$ there exists an $\epsilon_1 > 0$ such that the map

$$(a, b, t) \mapsto u_f(a, b, t)$$

is smooth for $|a - a_0| < \epsilon_1, |b - b_0| < \epsilon_1, |t| < \epsilon_1$ (for both of these results, cf. [24, Chapter 2, Section 7, Corollary 6]). We set $a_0 = \ln(q_0 - 1)$ and $b_0 = (1 - \alpha)(1 - q_0^{-1}) \ln 2$. We will call triplets (a, b, t) in the above neighborhood of $(a_0, b_0, 0)$ *admissible*.

From (44) we have for any admissible (a, b, s) with $s \geq 0$ and any A with $|A| \leq 2^{n\alpha}$:

$$\|T_{e^{-s}} 1_A\|_{1+e^{u_f(a,b,s)}} \leq \|1_A\|_{1+e^a}, \quad (48)$$

provided that $b(1 + e^{-a}) \leq (1 - \alpha) \ln 2$ (this is just the condition $\|f\|_{p_0} \geq e^{n\lambda_0} \|f\|_1$ of Theorem 3).

Our aim is to set $s = t$ in (48) and show that there exists a choice of $a = a(t)$ and $b = b(t)$ and $\epsilon < \epsilon_1$ such that the following conditions are satisfied: (C1) $a(0) = a_0, b(0) = b_0$ and both functions are smooth on $|t| < \epsilon$; (C2) for any $|t| < \epsilon$ the triplet $(a(t), b(t), t)$ is admissible; (C3) for each $|t| < \epsilon$

$$\begin{cases} b(t)(1 + e^{-a(t)}) &= (1 - \alpha) \ln 2 \\ u_f(a(t), b(t), t) &= \ln(q_0 - 1) \end{cases} \quad (49)$$

It is clear that if indeed such a choice of $a(t), b(t)$ were found we get from (48) with $s = t$ the statement of the Theorem with $q(t) = 1 + e^{a(t)}$.

We claim that it is sufficient to show that the system of equations

$$\begin{cases} f(a, b) &= 0, \\ u_f(a, b, t) &= \ln(q_0 - 1) \end{cases} \quad (50)$$

where $f(a, b) \triangleq b - (1 - \alpha)(1 - (1 + e^a)^{-1}) \ln 2$, is uniquely solvable (for a, b) in the interval $-\epsilon < t < \epsilon$ and that solution $a(t), b(t)$ is smooth. Indeed, since the triplet $(a_0, b_0, 0)$ is a solution, we get (C1). Smoothness of $a(t), b(t)$ implies (C2). And, finally, (C3) is automatic. Smooth solvability, in turn, follows from the fact that the map

$$(a, b, t) \mapsto (f(a, b), u_f(a, b, t), t) \quad (51)$$

has non-trivial Jacobian at $(a_0, b_0, 0)$. Indeed, denoting $\partial_x = \frac{\partial}{\partial x}$ the Jacobian is given by

$$\text{Jac}(a, b, t) = (\partial_a f)(\partial_b u_f) - (\partial_b f)(\partial_a u_f).$$

To evaluate this we note an identity $u_f(a, b, 0) = a$ and thus

$$\left. \frac{\partial}{\partial a} \right|_{t=0} u_f(a, b, t) = 1, \quad (52)$$

$$\left. \frac{\partial}{\partial b} \right|_{t=0} u_f(a, b, t) = 0, \quad (53)$$

$$\left. \frac{\partial}{\partial t} \right|_{t=0} u_f(a, b, t) = C(b(1 + e^{-a})). \quad (54)$$

Therefore, at $(a = a_0, b = b_0, t = 0)$ the Jacobian evaluates to

$$\text{Jac}(a_0, b_0, 0) = -1 \neq 0.$$

Since the Jacobian is non-zero in some neighborhood of $(a_0, b_0, 0)$, the map (51) can be locally inverted, and we take for $a(t), b(t)$ the pre-image of $(0, 0, t)$ under (51).

Finally, we need to show that $q(t) = 1 + e^{a(t)}$ satisfies the expansion (47). To that end, we differentiate over t the identity

$$u_f(a(t), b(t), t) = \ln(q_0 - 1) \quad (55)$$

to get

$$\begin{aligned} \dot{a}(t) \partial_a u_f(a(t), b(t), t) + \dot{b}(t) \partial_b u_f(a(t), b(t), t) \\ + \partial_t u_f(a(t), b(t), t) = 0 \end{aligned} \quad (56)$$

where $\dot{a}(t) \triangleq \frac{da(t)}{dt}$ and $\dot{b}(t) \triangleq \frac{db(t)}{dt}$. At $t = 0$ this is evaluated via (52)-(54) to give

$$\dot{a}(0) + C((1 - \alpha) \ln 2) = 0. \quad (57)$$

This clearly implies that $q(t) = 1 + e^{a(t)}$ satisfies (47). \blacksquare

The following application of the previous result establishes the hard direction of Theorem 1.

Proposition 3: Fix $\rho \in (0, 1)$. Then for any sets A, B with $|A| \leq 2^{n\alpha}, |B| \leq 2^{n\alpha}$ we have

$$P_{XY}(A \times B) \leq 2^{-n\psi(\alpha, \rho)}, \quad (58)$$

where as $\rho \rightarrow 1$ we have

$$\begin{aligned} \psi(\alpha, \rho) &= (1 - \alpha) \\ &+ \frac{1}{\ln 2} (1/2 - \sqrt{h^{-1}(\alpha)(1 - h^{-1}(\alpha))}) (1 - \rho) \\ &+ o(1 - \rho). \end{aligned} \quad (59)$$

Remark 3: For bounding $\overline{E}(\alpha, \beta, \rho)$ with $\alpha \neq \beta$ this method does not give a bound matching that attained by Hamming spheres. The main reason is that if we take A, B as concentric (but grossly unequal) Hamming balls the Cauchy-Schwarz inequality (43) is applied to functions $T_{\rho_1} \mathbb{1}_A, T_{\rho_2} \mathbb{1}_B$ which have effectively disjoint supports for $\rho \rightarrow 1$.

Proof. Let $\rho = e^{-2t}$ for some fixed t . Suppose the sets A, B both have sizes at most $2^{n\alpha}$. Then from Theorem 4 we obtain

$$\|T_{e^{-t}}\mathbb{1}_A\|_2 \leq \|\mathbb{1}_A\|_{p(t)} \quad (60a)$$

$$\|T_{e^{-t}}\mathbb{1}_B\|_2 \leq \|\mathbb{1}_B\|_{p(t)} \quad (60b)$$

$$p(t) = 2 - (2-1)C((1-\alpha)\ln 2)t + o(t). \quad (60c)$$

Since $\|\mathbb{1}_A\|_q = 2^{-n(1-\alpha)/q}$ we get from (43) the following:

$$\frac{1}{n} \log P_{X,Y}(A \times B) \leq -\frac{2}{p(t)}(1-\alpha) \quad (61)$$

$$= -(1-\alpha) \left(1 + \frac{t}{2} C((1-\alpha)\ln 2) + o(t) \right) \quad (62)$$

$$= -(1-\alpha) - \frac{t(1-\alpha)}{2} \frac{2 - 4\sqrt{h^{-1}(\alpha)(1-h^{-1}(\alpha))}}{(1-\alpha)\ln 2} + o(t). \quad (63)$$

The statement now follows since $t = \frac{1-\rho}{2} + o(1-\rho)$. ■

IV. UPPER BOUND ON $\underline{E}(\alpha, \beta, \rho)$

Note that

$$\begin{aligned} P_{XY}(A \times B) &= \sum_{a \in A, b \in B} \Pr(X = a, Y = b) \\ &= |A| \cdot |B| \\ &\cdot \frac{1}{|A| \cdot |B|} \sum_{a \in A, b \in B} 2^{-n} \left(\frac{1+\rho}{2} \right)^n \cdot \left(\frac{1-\rho}{1+\rho} \right)^{d(a,b)} \\ &\geq |A| \cdot |B| \\ &\cdot 2^{-n} \left(\frac{1+\rho}{2} \right)^n \cdot \left(\frac{1-\rho}{1+\rho} \right)^{\frac{1}{|A| \cdot |B|} \sum_{a \in A, b \in B} d(a,b)} \end{aligned} \quad (64)$$

$$= 2^{-n \left(2 - \frac{\log(|A| \cdot |B|)}{n} - \log(1+\rho) - \frac{\log \frac{1-\rho}{1+\rho}}{|A| \cdot |B|} \sum_{a \in A, b \in B} \frac{d(a,b)}{n} \right)}, \quad (65)$$

where we have used Jensen's inequality in (64). As $\frac{1-\rho}{1+\rho} < 1$, we need to upper bound $\frac{1}{|A| \cdot |B|} \sum_{a \in A, b \in B} d(a,b)$ in terms of $|A|$ and $|B|$ in order to further lower bound (65). Consequently, we define

$$\begin{aligned} \bar{d}(n, \alpha, \beta) &= \frac{1}{n} \max_{A, B: |A|=2^{n\alpha}, |B|=2^{n\beta}} \frac{1}{|A| \cdot |B|} \sum_{a \in A, b \in B} d(a,b) \end{aligned} \quad (66)$$

$$\begin{aligned} \underline{d}(n, \alpha, \beta) &= \frac{1}{n} \min_{A, B: |A|=2^{n\alpha}, |B|=2^{n\beta}} \frac{1}{|A| \cdot |B|} \sum_{a \in A, b \in B} d(a,b). \end{aligned} \quad (67)$$

With these definitions we relax (65) to

$$\begin{aligned} P_{XY}(A \times B) &\geq 2^{-n((1-\alpha)+(1-\beta)-\log(1+\rho)-\bar{d}(n, \alpha, \beta) \log \frac{1-\rho}{1+\rho})}. \end{aligned} \quad (68)$$

It is obvious that $\bar{d}(n, \alpha, \beta) = 1 - \underline{d}(n, \alpha, \beta)$, since if the sets (A, B) achieve the minimal average distance, the sets $(A, B' = 1^n + B)$ must achieve the maximal average distance. A quantity similar to $\underline{d}(n, \alpha, \beta)$, where the optimization in (66) is performed over all families A of size $2^{n\alpha}$ while $B = A$ was defined in [20, p.10 eq. 1], and its asymptotic (in n) value, was characterized in [25]. Below we prove a lower bound on $\underline{d}(n, \alpha, \beta)$. The technique is quite similar to that of [25], and requires the following simple proposition.

Proposition 4: The function $\varphi(x, y) = h^{-1}(x) * h^{-1}(y)$ is jointly convex in $(x, y) \in [0, 1]^2$.

The function $\varphi(x, y)$ is plotted in Figure 1. To prove Proposition 4, we will rely on the following simpler statement, which is essentially proved in [25]. For completeness we provide the proof in the appendix.

Proposition 5: The function $x \mapsto h^{-1}(x)(1-h^{-1}(x))$ is convex in $[0, 1]$.

Proof of Proposition 4. Let (X, Y) be two (possibly dependent) random variables on $[0, 1]^2$. We use the identity $a * b = \frac{1}{2}(1 - (1-2a)(1-2b))$ to write

$$\begin{aligned} \mathbb{E}[\varphi(X, Y)] &= \frac{1}{2} (1 - \mathbb{E}[(1-2h^{-1}(X))(1-2h^{-1}(Y))]) \\ &\geq \frac{1}{2} \left(1 - \sqrt{\mathbb{E}[(1-2h^{-1}(X))^2]} \right) \end{aligned} \quad (69)$$

$$\sqrt{\mathbb{E}[(1-2h^{-1}(Y))^2]} \quad (70)$$

$$\geq \frac{1}{2} \left(1 - \sqrt{(1-2h^{-1}(\mathbb{E}[X]))^2} \sqrt{(1-2h^{-1}(\mathbb{E}[Y]))^2} \right) \quad (71)$$

$$= \varphi(\mathbb{E}[X], \mathbb{E}[Y]), \quad (72)$$

where (70) follows from the Cauchy-Schwarz inequality, and (71) from Jensen's inequality and the fact that $t \mapsto (1-2h^{-1}(t))^2 = 1 - 4h^{-1}(t)(1-h^{-1}(t))$ is concave due to Proposition 5. ■

Lemma 1: For any two independent n -dimensional random binary vectors V and W

$$\begin{aligned} h^{-1} \left(\frac{H(V)}{n} \right) * h^{-1} \left(\frac{H(W)}{n} \right) &\leq \frac{\mathbb{E}d(V, W)}{n} \\ &\leq 1 - h^{-1} \left(\frac{H(V)}{n} \right) * h^{-1} \left(\frac{H(W)}{n} \right). \end{aligned} \quad (73)$$

Proof. Let V and W be two independent random vectors with $H(V) = n\alpha$ and $H(W) = n\beta$. Further, let $a_i \triangleq$

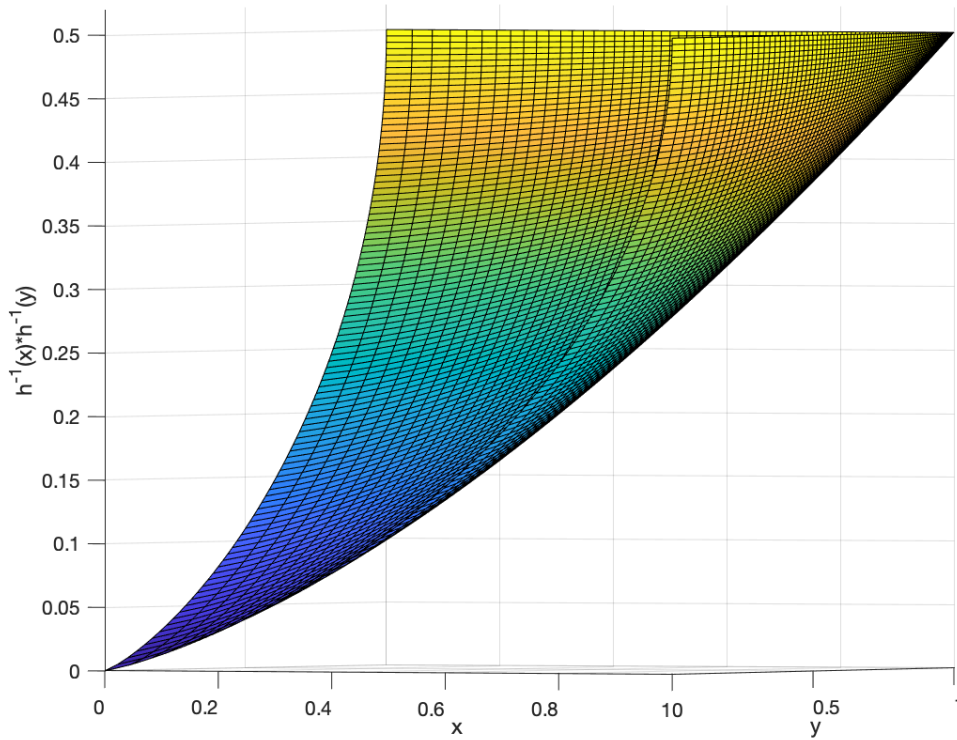


Fig. 1. Illustration of the function $h^{-1}(x) * h^{-1}(y)$.

$\Pr(V_i = 1)$, $b_i \triangleq \Pr(W_i = 1)$, be the induced marginal distributions for each coordinate. Our goal is to minimize and maximize $\sum_{i=1}^n a_i * b_i$ under the entropy constraints $H(V) = n\alpha$, $H(W) = n\beta$. We may and will assume without loss of generality that $a_i, b_i \leq 1/2$ for all i . We have

$$\begin{aligned}
 \inf_{\substack{V, W: \\ H(V) = n\alpha \\ H(W) = n\beta}} \sum_{i=1}^n a_i * b_i &\geq \inf_{\substack{V, W: \\ H(V) \geq n\alpha \\ H(W) \geq n\beta}} \sum_{i=1}^n a_i * b_i \\
 &= \inf_{\substack{\{a_i\}, \{b_i\}: \\ \sum_{i=1}^n h(a_i) \geq n\alpha \\ \sum_{i=1}^n h(b_i) \geq n\beta}} \sum_{i=1}^n a_i * b_i \quad (74) \\
 &= \inf_{\substack{\{\alpha_i\}, \{\beta_i\}: \\ \frac{1}{n} \sum_{i=1}^n \alpha_i \geq \alpha \\ \frac{1}{n} \sum_{i=1}^n \beta_i \geq \beta}} \sum_{i=1}^n h^{-1}(\alpha_i) * h^{-1}(\beta_i) \quad (75)
 \end{aligned}$$

where (74) follows since the cost function $\sum_{i=1}^n a_i * b_i$ depends only on the marginal distributions, and for every feasible distribution V, W the product of the marginalized distributions is also feasible. Our lower bound now immediately follows from Proposition 4. For the upper bound, note that if V and W minimize $\mathbb{E}d(V, W)$ under

the entropy constraints, V and $W' = W + 1^n$ maximizes the expected distance under the same entropy constraints.

■

Taking $V \sim \text{Uniform}(A)$ and $W \sim \text{Uniform}(B)$, we immediately get the following.

Corollary 1:

$$\bar{d}(n, \alpha, \beta) \leq n (1 - h^{-1}(\alpha) * h^{-1}(\beta)), \quad (76)$$

$$\underline{d}(n, \alpha, \beta) \geq n h^{-1}(\alpha) * h^{-1}(\beta). \quad (77)$$

Combining (68) and Corollary 1, gives

$$\begin{aligned}
 \underline{E}(\alpha, \beta, \rho) &\leq (1 - \alpha) + (1 - \beta) - \log(1 + \rho) \\
 &\quad - (1 - h^{-1}(\alpha) * h^{-1}(\beta)) \log \frac{1 - \rho}{1 + \rho} \\
 &= (1 - \alpha) + (1 - \beta) - \log(1 - \rho) \\
 &\quad + (h^{-1}(\alpha) * h^{-1}(\beta)) \log \frac{1 - \rho}{1 + \rho}. \quad (78)
 \end{aligned}$$

We have therefore obtained the following.

Proposition 6: We have

$$\begin{aligned}
 \underline{E}(\alpha, \beta, \rho) &\leq (1 - \alpha) + (1 - \beta) \\
 &\quad + \rho \log(e) (1 - 2h^{-1}(\alpha) * h^{-1}(\beta)) + o(\rho). \quad (79)
 \end{aligned}$$

Remark 4: In [8] the bound

$$\underline{E}(\alpha, \beta, \rho) \leq \frac{(1-\alpha) + (1-\beta) + 2\rho\sqrt{(1-\alpha)(1-\beta)}}{1-\rho^2} \quad (80)$$

was proved, using reverse hypercontractivity. It is easy to verify that for $\alpha = \beta$ the bound (78) is strictly better than (80) for all $\alpha < 1 - \frac{1-\rho}{2\rho} \log\left(\frac{1}{1-\rho}\right)$. Moreover, for any $0 < \alpha, \beta < 1$ the bound (78) is better than (80) for ρ large enough. The reverse hypercontractivity bound states that for $p < 1$ we have $\|T_\rho f\|_{q(\rho,p)} \geq \|f\|_p$ where $q(\rho, p) = 1 - \frac{1-p}{\rho^2} < p$ for $\rho < 1$. The weakness of this bound in our setup is that the function $q(\rho, p)$ does not depend on the support of f , which is exponentially small. It is quite plausible that deriving support dependent reverse hypercontractivity bounds, analogous to the support dependent hypercontractivity bounds of [1], would result in tighter upper bounds on $\underline{E}(\alpha, \beta, \rho)$ in the high-correlation regime.

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APPENDIX

Let $\phi(x) = (1 - 2h^{-1}(x))^2$. Since $h^{-1}(x)(1 - h^{-1}(x)) = 1 - \frac{\phi(x)}{4}$, it suffices to show that $x \mapsto \phi(x)$ is concave. We have

$$\begin{aligned} \phi'(x) &= -\frac{4}{\log\left(\frac{1-h^{-1}(x)}{h^{-1}(x)}\right)} (1 - 2h^{-1}(x)) \\ &= -\frac{4}{\log e} v(h^{-1}(x)), \end{aligned} \quad (81)$$

where

$$v(t) = \frac{1-2t}{\ln\left(\frac{1-t}{t}\right)}. \quad (82)$$

Showing that $x \mapsto \phi(x)$ is concave is equivalent to showing that $x \mapsto \phi'(x)$ is decreasing, which in turn is equivalent to showing that $t \mapsto v(t)$ is increasing in $(0, 1/2)$, due to monotonicity of $x \mapsto h^{-1}(x)$. Thus, it remains to show that $v'(t) \geq 0$ for $t \in (0, 1/2)$. Let $y = y_t = \frac{1-t}{t} \in (1, \infty)$. We have that $v'(t) = \frac{\frac{1-2t}{t(1-t)} - 2\ln\left(\frac{1-t}{t}\right)}{\ln^2\left(\frac{1-t}{t}\right)}$ and since $\frac{1-2t}{t(1-t)} = \frac{y^2-1}{y}$, it suffices to show that $g(y) = \frac{y^2-1}{y} - 2\ln(y) \geq 0$ for all $y > 1$. Noting that $g(1) = 0$ and $g'(y) = 1 + \frac{1}{y^2} - \frac{2}{y} = \frac{(y-1)^2}{y^2} \geq 0$ for all $y \geq 1$, we see that indeed $g(y) \geq 0$ for all $y \geq 1$, which establishes our claim.

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