A Lower Bound for Sampling Disjoint Sets

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Suppose Alice and Bob each start with private randomness and no other input, and they wish to engage in a protocol in which Alice ends up with a set $x \subseteq [n]$ and Bob ends up with a set $y \subseteq [n]$, such that (x, y) is uniformly distributed over all pairs of disjoint sets. We prove that for some constant $\beta < 1$, this requires $\Omega(n)$ communication even to get within statistical distance $1 - \beta^n$ of the target distribution. Previously, Ambainis, Schulman, Ta-Shma, Vazirani, and Wigderson (FOCS 1998) proved that $\Omega(\sqrt{n})$ communication is required to get within some constant statistical distance $\varepsilon > 0$ of the uniform distribution over all pairs of disjoint sets of size $\sqrt{n}$.

CCS Concepts: • **Theory of computation → Communication complexity**;

Additional Key Words and Phrases: Communication complexity, set disjointness, sampling

ACM Reference format:
Mika Göös and Thomas Watson. 2020. A Lower Bound for Sampling Disjoint Sets. *ACM Trans. Comput. Theory* 12, 3, Article 20 (July 2020), 13 pages.
https://doi.org/10.1145/3404858

1 INTRODUCTION

In most traditional computational problems, the goal is to take an input and produce the "correct" output or produce one of a set of acceptable outputs. In a *sampling* problem, however, the goal is to generate a random sample from a specified probability distribution D or at least from a distribution that is close to D. There has been a surge of interest in studying sampling problems from a complexity theory perspective [1, 7, 13, 15, 32, 36, 49, 61, 75–82]. Unlike more traditional computational problems, sampling problems do not necessarily need to have any real input, besides the uniformly random bits fed into a sampling algorithm.

One commonly studied type of target distribution is "input–output pairs" of a function f, i.e., $(D, f(D))$, where D is perhaps the uniform distribution over inputs to f. This means an outcome should be (x, z) where x is distributed according to D, and $z = f(x)$. Using an algorithm for computing f, one can sample $(D, f(D))$ by first sampling from D and then evaluating f on that input. However, for some functions f, generating an input jointly with the corresponding output may be computationally easier than evaluating f on an adversarially chosen input. Thus, in general, sampling lower bounds tend to be more challenging to prove than lower bounds for functions.

Mika Göös was supported by NSF Grant No. CCF-1412958. Thomas Watson was supported by NSF Grant No. CCF-1657377.
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1942-3454/2020/07-ART20 $15.00
https://doi.org/10.1145/3404858

Many of the above-cited works focus on concrete computational models such as low-depth circuits. We consider the model of two-party communication complexity, for which comparatively less is known about sampling. Which problem should we study? Well, the single most important function in communication complexity is Set-Disjointness, in which Alice gets a set $x \subseteq [n]$, Bob gets a set $y \subseteq [n]$, and the goal is to determine whether $x \cap y = \emptyset$. Identifying the sets with their characteristic bit strings, this can be viewed as $\textsc{Disj} : \{0,1\}^n \times \{0,1\}^n \to \{0,1\}$, where $\textsc{Disj}(x,y) = 1$ iff $x \wedge y = 0^n$. The applications of communication bounds for Set-Disjointness are far too numerous to list, but they span areas such as streaming, circuit complexity, proof complexity, data structures, property testing, combinatorial optimization, fine-grained complexity, cryptography, and game theory. Because of its central role, Set-Disjointness has become the de facto testbed for proving new types of communication bounds. This function has been studied in the contexts of randomized [9, 10, 17, 51, 65] and quantum [2, 25, 44, 66, 69, 73] protocols; multi-party number-in-hand [6, 10, 18, 22, 27, 42, 50] and number-on-forehead [11, 12, 28, 41, 59, 63, 64, 69, 71, 72, 74] models; Merlin–Arthur and related models [3, 4, 29, 35, 38, 39, 52, 67]; with a bounded number of rounds of interaction [19, 23, 48, 54, 83]; with bounds on the sizes of the sets [26, 31, 43, 45, 58, 62, 68]; very precise relationships between communication and error probability [20, 21, 30, 33, 39]; when the goal is to find the intersection [8, 24, 34, 82]; in space-bounded, online, and streaming models [5, 16, 55]; and direct product theorems [12, 14, 47, 53, 56, 70–72]. We contribute one more result to this thorough assault on Set-Disjointness.

Here is the definition of our two-party sampling model: Let D be a probability distribution over $\{0,1\}^n \times \{0,1\}^n$; we also think of D as a matrix with rows and columns both indexed by $\{0,1\}^n$, where $D_{x,y}$ is the probability of outcome (x,y). We define $\textsc{Samp}(D)$ as the minimum communication cost of any protocol where Alice and Bob each start with private randomness and no other input, and at the end Alice outputs some $x \in \{0,1\}^n$ and Bob outputs some $y \in \{0,1\}^n$ such that (x,y) is distributed according to D. Note that $\textsc{Samp}(D) = 0$ iff D is a product distribution (x and y are independent), and $\textsc{Samp}(D) \leq n$ for all D (since Alice can privately sample (x,y) and send y to Bob). Allowing public randomness would not make sense, since Alice and Bob could read a properly distributed (x,y) off of the randomness without communicating. We define $\textsc{Samp}_\varepsilon(D)$ as the minimum of $\textsc{Samp}(D')$ over all distributions D' with $\Delta(D,D') \leq \varepsilon$, where Δ denotes statistical (total variation) distance, defined as

$$\Delta(D,D') \coloneqq \max_{\text{event } E} \left| \mathbb{P}_D[E] - \mathbb{P}_{D'}[E] \right| = \frac{1}{2} \sum_{\text{outcome } o} \left| \mathbb{P}_D[o] - \mathbb{P}_{D'}[o] \right|.$$

1.1 A Story

Our story begins with Reference [7], which proved that $\textsc{Samp}_\varepsilon\big((D, \textsc{Disj}(D))\big) \geq \Omega(\sqrt{n})$ for some constant $\varepsilon > 0$, where D is uniform over the set of all pairs of sets of size $\sqrt{n}$ (note that this D is a product distribution and is approximately balanced between 0-inputs and 1-inputs of $\textsc{Disj}$); here it does not matter which party is responsible for outputting the bit $\textsc{Disj}(D)$. The main tool in the proof was a lemma that was originally employed in Reference [9] to prove an $\Omega(\sqrt{n})$ bound on the randomized communication complexity of *computing* $\textsc{Disj}$. The latter bound was improved to $\Omega(n)$ via several different proofs [10, 51, 65], which leads to a natural question: Can we improve the sampling bound of [7] to $\Omega(n)$ by using the techniques of References [10, 51, 65] instead of Reference [9]?

For starters, the answer is "no" for the particular D considered in Reference [7]—there is a trivial exact protocol with $O(\sqrt{n} \log n)$ communication, since it only takes that many bits to specify a set of size $\sqrt{n}$. What about other interesting distributions D? The following illuminates the situation.

Observation 1. *For any D and constants $\varepsilon > \delta > 0$, if* $\mathsf{Samp}_\varepsilon\big((D, \textsc{Disj}(D))\big) \geq \omega(\sqrt{n})$ *then* $\mathsf{Samp}_\delta(D) \geq \Omega\Big(\mathsf{Samp}_\varepsilon\big((D, \textsc{Disj}(D))\big)\Big)$.

Proof. It suffices to show $\mathsf{Samp}_\varepsilon\big((D, \textsc{Disj}(D))\big) \leq \mathsf{Samp}_\delta(D) + O(\sqrt{n})$. First, note that for any sampling protocol, if we condition on a particular transcript, then the output distribution becomes product (Alice and Bob are independent after they stop communicating). Second, Reference [17] proved that for every product distribution and every constant $\gamma > 0$, there exists a deterministic protocol that uses $O(\sqrt{n})$ bits of communication and computes Disj with error probability $\leq \gamma$ on a random input from the distribution. Now to ε-sample $(D, \textsc{Disj}(D))$, Alice and Bob can δ-sample D to obtain (x, y), and then conditioned on that sampler's transcript, they can run the average-case protocol from Reference [17] for the corresponding product distribution with error $\varepsilon - \delta$. A simple calculation shows this indeed gives statistical distance ε. □

The upshot is that to get an improved bound, *the hardness of sampling* $(D, \textsc{Disj}(D))$ *would come entirely from the hardness of just sampling* D. Thus, such a result would not really be "about" the Set-Disjointness function, it would be about the distribution on inputs. Instead of abandoning this line of inquiry, we realize that if D itself is somehow defined in terms of Disj, then a bound for sampling D would still be saying something about the complexity of Set-Disjointness. In fact, the proof in Reference [7] actually shows something stronger than the previously stated result: If D is instead defined as the uniform distribution over pairs of *disjoint* sets of size $\sqrt{n}$ (which are 1-inputs of Disj), then $\mathsf{Samp}_\varepsilon(D) \geq \Omega(\sqrt{n})$. After this pivot, we are now facing a direction in which we can hope for an improvement. We prove that by removing the restriction on the sizes of the sets, the sampling problem becomes maximally hard. Our result holds for error $\varepsilon < 1$ that is exponentially close to 1, but the result is already new and interesting for constant $\varepsilon > 0$.

Theorem 1. *Let U be the uniform distribution over the set of all $(x, y) \in \{0,1\}^n \times \{0,1\}^n$ with $x \wedge y = 0^n$. There exists a constant $\beta < 1$ such that* $\mathsf{Samp}_{1-\beta^n}(U) = \Omega(n)$.

The proof from Reference [7] was a relatively short application of the technique from Reference [9], but for Theorem 1, harnessing known techniques for proving linear communication lower bounds turns out to be more involved.

For calibration, the uniform distribution over *all* (x, y) achieves statistical distance $1 - 0.75^n$ from U, since there are 4^n inputs and 3^n disjoint inputs (for a disjoint input, each coordinate $i \in [n]$ has 3 possibilities $x_i y_i \in \{00, 01, 10\}$). We can do a little better: Suppose for each coordinate independently, Alice picks 0 with probability $\sqrt{1/3}$ and picks 1 with probability $1 - \sqrt{1/3}$, and Bob does the same. This again involves no communication, and it achieves statistical distance $1 - \left(2\sqrt{1/3} - 1/3\right)^n \leq 1 - 0.82^n$ from U. Theorem 1 shows that the constant 0.82 cannot be improved arbitrarily close to 1 without a lot of communication. (In the setting of lower bounds for circuit samplers, significant effort has gone into handling statistical distances exponentially close to the maximum possible [13, 32, 79].)

1.2 Interpreting the Result

As an important step in the proof of Theorem 1, we first observe that our sampling model is equivalent to two other models. One of these we call (for lack of a better word) "synthesizing" the distribution D: Alice and Bob get inputs $x, y \in \{0,1\}^n$, respectively, in addition to their private randomness, and their goal is to accept with probability exactly $D_{x,y}$. We let $\mathsf{Synth}(D)$ denote the minimum communication cost of any synthesizing protocol for D, and $\mathsf{Synth}_\varepsilon(D)$ denote the minimum of $\mathsf{Synth}(D')$ over all D' with $\Delta(D, D') \leq \varepsilon$. The other model is the nonnegative rank of

a matrix: $\mathrm{rank}_+(D)$ is defined as the minimum k for which D (viewed as a $2^n \times 2^n$ matrix) can be written as a sum of k many nonnegative rank-1 matrices.

Observation 2. *For every distribution D, the following are all within $\pm O(1)$ of each other:*

$$\mathrm{Samp}(D), \quad \mathrm{Synth}(D), \quad \log \mathrm{rank}_+(D).$$

Proof. $\mathrm{Synth}(D) \leq \mathrm{Samp}(D) + 2$, since a synthesizing protocol can just run a sampling protocol and accept iff the result equals the given input (x, y). (Only this part of Observation 2 is needed in the proof of Theorem 1.)

$\log \mathrm{rank}_+(D) \leq \mathrm{Synth}(D)$, since for each transcript of a synthesizing protocol, the matrix that records the probability of getting that transcript on each particular input has rank 1 (since Alice's private randomness being consistent with the transcript, and Bob's private randomness being consistent with the transcript, are independent events); summing these matrices over all accepting transcripts yields a nonnegative rank decomposition of D.

To see that $\mathrm{Samp}(D) \leq \lceil \log \mathrm{rank}_+(D) \rceil$, suppose $D = M^{(1)} + M^{(2)} + \cdots + M^{(k)}$ is a sum of nonnegative rank-1 matrices. For each i, by scaling we can write $M^{(i)}_{x,y} = p_i \, u^{(i)}_x v^{(i)}_y$ for some distributions $u^{(i)}$ and $v^{(i)}$ over $\{0,1\}^n$, where p_i is the sum of all entries of $M^{(i)}$. Since D is a distribution, $p \coloneqq (p_1, \ldots, p_k)$ is a distribution over $[k]$. To sample from D, Alice can privately sample $i \sim p$ and send it to Bob using $\lceil \log k \rceil$ bits, then Alice can sample $x \sim u^{(i)}$ and Bob can independently sample $y \sim v^{(i)}$ with no further communication. □

By this characterization, Theorem 1 can be viewed as a lower bound on the approximate nonnegative rank of the Disj matrix, where the approximation is in ℓ_1 (which has an average-case flavor). In the recent literature, "approximate nonnegative rank" generally refers to approximation in ℓ_∞ (which is a worst-case requirement), and this model is equivalent to the so-called smooth rectangle bound and WAPP communication complexity [37, 46, 57].

Observation 2 combined with a result of Reference [60] shows that the deterministic communication complexity of any total two-party Boolean function f is quadratically related to the communication complexity of exactly sampling the uniform distribution over $f^{-1}(1)$.

2 PROOF

2.1 Overview

Our proof of Theorem 1 is by a black-box reduction to the well-known *corruption lemma* for Set-Disjointness due to Razborov [65]. We start with a high-level overview.

For notation: Let $|z|$ denote the Hamming weight of a string $z \in \{0,1\}^n$. For $\ell \in \mathbb{N}$, let U^ℓ be the uniform distribution over all $(x, y) \in \{0,1\}^n \times \{0,1\}^n$ with $|x \wedge y| = \ell$. Note that $U = U^0$. For a distribution D over $\{0,1\}^n \times \{0,1\}^n$ and an event $E \subseteq \{0,1\}^n \times \{0,1\}^n$, let $D_E \coloneqq \sum_{(x,y)\in E} D_{x,y}$. For a randomized protocol Π, let $\mathrm{acc}_\Pi(x, y)$ denote the probability that Π accepts (x, y).

Step I: Uniform Corruption. The corruption lemma states that if a rectangle $R \subseteq \{0,1\}^n \times \{0,1\}^n$ contains a noticeable fraction of *disjoint* pairs, then it must contain about as large a fraction of *uniquely intersecting* pairs. More quantitatively, there exist a constant $C > 0$ and two distributions D^ℓ, $\ell = 0, 1$, defined over disjoint ($\ell = 0$) and uniquely intersecting pairs ($\ell = 1$) such that for every rectangle R,

$$\text{if} \quad D^0_R \geq 2^{-o(n)}, \quad \text{then} \quad D^1_R \geq C \cdot D^0_R.$$

The original proof [65] defined D^ℓ as the uniform distribution over all pairs (x, y) with fixed sizes $|x| = |y| = \lceil n/4 \rceil$ and $|x \wedge y| = \ell$. For our purpose, we need the corruption lemma to hold relative to the aforementioned distributions U^ℓ, $\ell = 0, 1$, which have no restrictions on set sizes. We derive in Section 2.2 a corruption lemma for U^ℓ from the original lemma for D^ℓ. To do this, we exhibit

a reduction that uses public randomness and no communication to transform a sample from D^ℓ into a sample from a distribution that is close to U^ℓ in a suitable sense, for $\ell = 0, 1$.

Step II: Truncate and Scale. For simplicity, let us think about proving Theorem 1 for a small error $\varepsilon > 0$. Assume for contradiction there is some distribution D, $\Delta(U, D) \le \varepsilon$, such that $\mathsf{Synth}(D) \le o(n)$ as witnessed by a private-randomness synthesizing protocol Π' with $\mathrm{acc}_{\Pi'}(x, y) = D_{x,y}$. Note that the total acceptance probability over disjoint inputs is close to 1:

$$\textstyle\sum_{x,y\,:\,|x\wedge y|=0} \mathrm{acc}_{\Pi'}(x,y) \;\ge\; 1-\varepsilon \quad \text{and thus} \quad \mathbb{E}_{(x,y)\sim U^0}[\mathrm{acc}_{\Pi'}(x,y)] \;\ge\; (1-\varepsilon)3^{-n}.$$

Our eventual goal (in Step III) is to apply our corruption lemma to the transcript rectangles, but the above threshold $(1-\varepsilon)3^{-n}$ is too low for this. To raise the threshold to $2^{-o(n)}$ as needed for corruption, we would like to scale up all the acceptance probabilities accordingly. To "make room" for the scaling, we first carry out a certain truncation step. Specifically, in Section 2.3, we transform Π' into a public-randomness protocol Π:

(1) First, we **truncate** (using a *truncation lemma* [37]) the values $\mathrm{acc}_{\Pi'}(x, y)$, which has the effect of decreasing some of them, but any $\mathrm{acc}_{\Pi'}(x, y)$ that is under 3^{-n} remains approximately the same. This results in an intermediate protocol Π'' that still satisfies $\mathbb{E}_{(x,y)\sim U^0}[\mathrm{acc}_{\Pi''}(x, y))] \ge \Omega((1-\varepsilon)3^{-n})$ (using the assumption that $\Delta(U, D) \le \varepsilon$).
(2) Second, we **scale** (using the low cost of Π'') the truncated probabilities up by a large factor $3^n 2^{-o(n)}$. This results in a protocol Π with large typical acceptance probabilities:

$$\mathbb{E}_{(x,y)\sim U^0}[\mathrm{acc}_{\Pi}(x,y)] \;\ge\; 2^{-o(n)}. \tag{1}$$

Step III: Iterate Corruption. Because Π has such large acceptance probabilities Equation (1), our corruption lemma can be applied: there is some constant $C' > 0$, such that

$$\mathbb{E}_{(x,y)\sim U^1}[\mathrm{acc}_{\Pi}(x,y)] \;\ge\; C' \cdot \mathbb{E}_{(x,y)\sim U^0}[\mathrm{acc}_{\Pi}(x,y)]. \tag{2}$$

Since Π is a truncated-and-scaled version of Π', this allows us to infer that

$$\mathbb{E}_{(x,y)\sim U^1}[\mathrm{acc}_{\Pi'}(x,y)] \;\ge\; \Omega((1-\varepsilon)3^{-n}) \quad \text{and thus} \quad \textstyle\sum_{x,y\,:\,|x\wedge y|=1} \mathrm{acc}_{\Pi'}(x,y) \;\ge\; \Omega((1-\varepsilon)n)$$

using the fact that $|\mathrm{supp}(U^1)| = n3^{n-1} = (n/3) \cdot |\mathrm{supp}(U^0)|$. Thus, for $\varepsilon = 1 - \omega(1/n)$, this means Π' must have placed a total probability mass > 1 on uniquely intersecting inputs, which is the sought contradiction.

To prove Theorem 1 for very large error $\varepsilon = 1 - \beta^n$, in Section 2.4, we iterate the above argument for U^ℓ over $0 \le \ell \le o(n)$. Namely, analogously to Equation (2), we show that the average acceptance probability of Π over $U^{\ell+1}$ is at least a constant times the average over U^ℓ. Meanwhile, the support sizes increase as $|\mathrm{supp}(U^{\ell+1})| \ge \omega(1) \cdot |\mathrm{supp}(U^\ell)|$ for $\ell \le o(n)$. These facts together imply a large constant factor increase in the total probability mass that Π' places on $\mathrm{supp}(U^{\ell+1})$ as compared to $\mathrm{supp}(U^\ell)$. Starting with even a tiny probability mass over $\mathrm{supp}(U^0)$, this iteration will eventually lead to a contradiction.

2.2 Step I: Uniform Corruption

The goal of this step is to derive Lemma 2 from Lemma 1.

Lemma 1 (Corruption [65]). *For every rectangle $R \subseteq \{0,1\}^n \times \{0,1\}^n$, we have $D^1_R \ge \frac{1}{45} D^0_R - 2^{-0.017n}$ where, assuming $n = 4k - 1$, D^ℓ is the uniform distribution over all (x, y) with $|x| = |y| = k$ and $|x \wedge y| = \ell$.*

Lemma 2 (Uniform Corruption). *For every rectangle $R \subseteq \{0,1\}^n \times \{0,1\}^n$, we have $U^1_R \ge \frac{1}{765} U^0_R - 2^{-0.008n}$.*

Proof. Assume for convenience that $n/2$ has the form $4k-1$ (otherwise use the nearest such number instead of $n/2$ throughout). We prove that Lemma 1 for $n/2$ implies Lemma 2 for n by the contrapositive. Thus, D^0 and D^1 are distributions over $\{0,1\}^{n/2}\times\{0,1\}^{n/2}$ while U^0 and U^1 are distributions over $\{0,1\}^n\times\{0,1\}^n$. Assume there exists a rectangle $R\subseteq\{0,1\}^n\times\{0,1\}^n$ such that $U^1_R < \frac{1}{765}U^0_R - 2^{-0.008n}$. We exhibit a distribution over rectangles $Q\subseteq\{0,1\}^{n/2}\times\{0,1\}^{n/2}$ such that $\mathbb{E}[D^1_Q] < \frac{1}{45}\mathbb{E}[D^0_Q] - 2^{-0.017n/2}$; by linearity of expectation this implies that there exists such a Q with $D^1_Q < \frac{1}{45}D^0_Q - 2^{-0.017n/2}$.

To this end, we define a distribution F over functions $f:\{0,1\}^{n/2}\times\{0,1\}^{n/2}\to\{0,1\}^n\times\{0,1\}^n$ of the form $f(x,y)=(f_1(x),f_2(y))$ and then let Q_f be the rectangle $f^{-1}(R) \coloneqq \{(x,y) : f(x,y)\in R\}$. Let H be the distribution over $\{(v,w)\in\mathbb{N}\times\mathbb{N} : v+w\le n\}$ obtained by sampling $(x,y)\sim U^0$ and outputting $(|x|,|y|)$; i.e., $H_{v,w} \coloneqq \frac{n!}{v!\,w!\,(n-v-w)!}\cdot 3^{-n}$. To sample $f\sim F$:

1. Sample (v,w) from H conditioned on $v\ge k$, $w\ge k$, and $v+w\le 2k+n/2$.
2. Sample a uniformly random permutation π of $[n]$.
3. Given $(x,y)\in\{0,1\}^{n/2}\times\{0,1\}^{n/2}$, define $(x',y')\in\{0,1\}^n\times\{0,1\}^n$ by letting

$$x'_iy'_i \coloneqq \begin{cases} x_iy_i & \text{for the first } n/2 \text{ coordinates } i;\\ 10 & \text{for the next } v-k \text{ coordinates } i;\\ 01 & \text{for the next } w-k \text{ coordinates } i;\\ 00 & \text{for the remaining } n/2-(v-k)-(w-k)\ge 0 \text{ coordinates } i. \end{cases}$$

4. Let $f(x,y) \coloneqq (\pi(x'),\pi(y'))$ (i.e., permute the coordinates according to π).

For $\ell\in\{0,1\}$ let $F(D^\ell)$ denote the distribution obtained by sampling $(x,y)\sim D^\ell$ and $f\sim F$ and outputting $f(x,y)$, and note that $F(D^\ell)_R = \mathbb{E}_F[D^\ell_{Q_F}]$. Now, we claim that $F(D^\ell)$ and U^ℓ are close, in the following senses:

(1) For every event E, $F(D^0)_E \ge U^0_E - 2^{-0.01n}$.
(2) For every event E, $F(D^1)_E \le U^1_E\cdot 17$.

Using R as the event E, we have

$$\begin{aligned} F(D^1)_R &\le U^1_R\cdot 17\\ &< 17\Big(\tfrac{1}{765}U^0_R - 2^{-0.008n}\Big)\\ &\le 17\Big(\tfrac{1}{765}(F(D^0)_R + 2^{-0.01n}) - 2^{-0.008n}\Big)\\ &\le \tfrac{1}{45}F(D^0)_R - 2^{-0.017n/2} \end{aligned}$$

as desired. To see *(1)*, note that $F(D^0)$ is precisely U^0 conditioned on $v\ge k$, $w\ge k$, and $v+w\le 2k+n/2$, and this conditioning event has probability $\ge 1-2^{-0.01n}$ by Chernoff bounds:

$$\begin{aligned} \mathbb{P}[v<k] \;=\; \mathbb{P}[w<k] \;&=\; \mathbb{P}[\mathrm{Bin}(n,1/3) < n/8+1/4] \;\le\; 2^{-0.12n},\\ \mathbb{P}[v+w>2k+n/2] \;&=\; \mathbb{P}[\mathrm{Bin}(n,2/3) > 3n/4+1/2] \;\le\; 2^{-0.02n}. \end{aligned}$$

Thus, letting C be the complement of the conditioning event, we have $F(D^0)_E \ge U^0_{E\setminus C} \ge U^0_E - U^0_C \ge U^0_E - 2^{-0.01n}$. To see *(2)*, consider any outcome $(x,y)\in\{0,1\}^n\times\{0,1\}^n$ with $|x\wedge y|=1$. We have $U^1_{x,y} = 1/(n3^{n-1})$. Abbreviating $a\coloneqq|x|$ and $b\coloneqq|y|$, assume $a\ge k$, $b\ge k$, and $a+b\le 2k+n/2$, since otherwise $F(D^1)_{x,y}=0$, and there would be nothing to prove. Henceforth, consider the

probability space with the randomness of D^1 and of F. Let I be the event that $F_1(D^1) \wedge F_2(D^1) = x \wedge y$, i.e., that the intersecting coordinate of $F(D^1)$ is the same as for (x, y). We have

$$F(D^1)_{x,y} = \underbrace{\mathbb{P}[I]}_{(*)} \cdot \underbrace{\mathbb{P}[v = a \text{ and } w = b]}_{(**)} \cdot \underbrace{\mathbb{P}\left[F(D^1) = (x, y) \,\middle|\, I \text{ and } v = a \text{ and } w = b\right]}_{(***)}.$$

For the three terms on the right-hand side, we have

$$(*) = \tfrac{1}{n}, \quad (**) \le H_{a,b}/(1 - 2^{-0.01n}) \le \tfrac{n!}{a!\,b!\,(n-a-b)!} \cdot 3^{-n} \cdot 1.01, \quad (***) = 1/\tfrac{(n-1)!}{(a-1)!\,(b-1)!\,(n-a-b+1)!}.$$

We have

$$\tfrac{n!}{a!\,b!\,(n-a-b)!} \,/\, \tfrac{(n-1)!}{(a-1)!\,(b-1)!\,(n-a-b+1)!} = \tfrac{n\cdot(n-a-b+1)}{a\cdot b} \le \tfrac{n\cdot(n-2k+1)}{k\cdot k} \le \tfrac{n\cdot(n-2n/8+1)}{(n/8)\cdot(n/8)} = (\tfrac{3}{4} + \tfrac{1}{n}) \cdot 64.$$

Combining, we get

$$F(D^1)_{x,y} \,/\, U^1_{x,y} = (*) \cdot (**) \cdot (***) \cdot n3^{n-1} \le \tfrac{1.01}{3} \cdot (\tfrac{3}{4} + \tfrac{1}{n}) \cdot 64 \le 17. \qquad \square$$

2.3 Step II: Truncate and Scale

The goal of this step is to construct a truncated-and-scaled protocol Π from any given low-cost Π' that synthesizes a distribution close to U.

For a nonnegative matrix M, we define its *truncation* $\overline{M}$ to be the same matrix but where each entry > 1 is replaced with 1. We let $a \pm b$ denote the real interval $[a - b, a + b]$.

Lemma 3 (Truncation Lemma [37]). *For every $2^n \times 2^n$ nonnegative rank-1 matrix M and every natural number d, there exists a $O(d + \log n)$-communication public-randomness protocol Π such that for every (x, y) we have $\mathrm{acc}_\Pi(x, y) \in \overline{M}_{x,y} \pm 2^{-d}$.*

Let $c \ge 1$ be the hidden constant in the big O in Lemma 3, and let $\delta := 0.00005/c$. Toward proving Theorem 1, suppose for contradiction $\mathrm{Samp}(D) \le \delta n$ for some distribution D with $\Delta(U, D) \le 1 - 2^{-\delta n}$ (so $\beta := 2^{-\delta}$ in Theorem 1) and thus

$$\begin{aligned}
\textstyle\sum_{x,y\,:\,|x\wedge y|=0} \min(3^{-n}, D_{x,y}) &= \textstyle\sum_{x,y} \min(U_{x,y}, D_{x,y}) \\
&= \textstyle\sum_{x,y} U_{x,y} - \sum_{x,y\,:\,U_{x,y} > D_{x,y}} (U_{x,y} - D_{x,y}) \\
&= 1 - \Delta(U, D) \\
&\ge 2^{-\delta n}.
\end{aligned}$$

By Observation 2, $\mathrm{Synth}(D) \le \delta n + 2$, so consider a synthesizing protocol Π' for D with communication cost $\le \delta n + 2$. Let A be the set of all accepting transcripts of Π'. For each $\tau \in A$ let N^τ be the nonnegative rank-1 matrix such that $N^\tau_{x,y}$ is the probability Π' generates τ on input (x, y); thus, $D_{x,y} = \sum_{\tau\in A} N^\tau_{x,y}$. Let Π^τ be the public-randomness protocol from Lemma 3 applied to $M^\tau := 3^n N^\tau$ and $d := 15\delta n$. Let Π be the public-randomness protocol that picks a uniformly random $\tau \in A$ and then runs Π^τ. The communication cost of Π is $\le c \cdot (d + \log n) \le 0.001n$.

Claim 1. *For every input (x, y), we have $\frac{3^n}{|A|} \min(3^{-n}, D_{x,y}) - 2^{-d} \le \mathrm{acc}_\Pi(x, y) \le \frac{3^n}{|A|} D_{x,y} + 2^{-d}$.*

Proof. We have

$$\begin{aligned}
\mathrm{acc}_\Pi(x, y) &= \tfrac{1}{|A|} \textstyle\sum_{\tau\in A} \mathrm{acc}_{\Pi^\tau}(x, y) \\
&\in \tfrac{1}{|A|} \textstyle\sum_{\tau\in A} (\overline{M}^\tau_{x,y} \pm 2^{-d}) \\
&\subseteq \tfrac{1}{|A|} \textstyle\sum_{\tau\in A} \min(1, 3^n N^\tau_{x,y}) \pm 2^{-d} \\
&= \tfrac{3^n}{|A|} \textstyle\sum_{\tau\in A} \min(3^{-n}, N^\tau_{x,y}) \pm 2^{-d}.
\end{aligned}$$

From this, it follows that

$$\begin{aligned}\mathrm{acc}_\Pi(x,y) &\geq \tfrac{3^n}{|A|}\min\Big(3^{-n}, \textstyle\sum_{\tau\in A} N^\tau_{x,y}\Big) - 2^{-d} = \tfrac{3^n}{|A|}\min(3^{-n}, D_{x,y}) - 2^{-d},\\ \mathrm{acc}_\Pi(x,y) &\leq \tfrac{3^n}{|A|}\textstyle\sum_{\tau\in A} N^\tau_{x,y} + 2^{-d} = \tfrac{3^n}{|A|}D_{x,y} + 2^{-d}.\end{aligned}$$ □

We can now formally state the large typical acceptance probability property (Equation (1) from the overview): writing $U_\Pi := \mathbb{E}_{(x,y)\sim U}[\mathrm{acc}_\Pi(x,y)]$ (and similarly for other input distributions),

$$\begin{aligned}U_\Pi &\geq \tfrac{1}{3^n}\textstyle\sum_{x,y\,:\,|x\wedge y|=0}\Big(\tfrac{3^n}{|A|}\min(3^{-n}, D_{x,y}) - 2^{-d}\Big) && \text{(by Claim 1)}\\ &= \tfrac{1}{|A|}\textstyle\sum_{x,y\,:\,|x\wedge y|=0}\min(3^{-n}, D_{x,y}) - 2^{-d}\\ &\geq \tfrac{1}{|A|}2^{-\delta n} - 2^{-15\delta n}\\ &\geq \tfrac{1}{|A|}2^{-\delta n-1}, && (3)\end{aligned}$$

where the last line follows because $|A| \leq 2^{\delta n+2}$ and $2^{-2\delta n-2}$ is at least twice $2^{-15\delta n}$.

2.4 Step III: Iterate Corruption

Here, we derive the final contradiction: Π' places an acceptance probability mass exceeding 1 on $\mathrm{supp}(U^{\delta n})$. This is achieved by iterating our corruption lemma, starting with Equation (3) as the base case.

For $z \in \{0,1\}^n$ let U^z be the uniform distribution over all $(x,y) \in \{0,1\}^n \times \{0,1\}^n$ with $x \wedge y = z$ (so U^ℓ is the uniform mixture of all U^z with $|z| = \ell$; in particular, $U^0 = U^{0^n}$), and if $|z| < n$, then let $\widehat{U}^z$ be the uniform mixture of $U^{z'}$ over all z' that can be obtained from z by flipping a single 0 to 1 (so $U^{\ell+1}$ is the uniform mixture of all $\widehat{U}^z$ with $|z| = \ell$; in particular, $U^1 = \widehat{U}^{0^n}$).

Claim 2. *For every $z \in \{0,1\}^n$ with $|z| \leq n/2$, we have $\widehat{U}^z_\Pi \geq \frac{1}{765}U^z_\Pi - 2^{-0.003n}$.*

Proof. Since all relevant inputs (x,y) have $x_i y_i = 11$ for all i such that $z_i = 1$, we can ignore those coordinates and think of $\widehat{U}^z$ and U^z as U^1 and U^0, respectively, but defined on the remaining $n - |z| \geq n/2$ coordinates (instead of on all n coordinates). Thus, by Lemma 2, for every outcome of the public randomness of Π and every accepting transcript, say corresponding to rectangle R, we have $\widehat{U}^z_R \geq \frac{1}{765}U^z_R - 2^{-0.008n/2}$. Summing over all the (at most $2^{0.001n}$ many) accepting transcripts, and then taking the expectation over the public randomness, yields the claim, since $2^{0.001n} \cdot 2^{-0.008n/2} \leq 2^{-0.003n}$. □

Claim 3. *For every $\ell = 0, \ldots, \delta n$, we have $U^\ell_\Pi \geq \frac{1}{|A|}2^{-\delta n-1-11\ell}$.*

Proof. We prove this by induction on ℓ. The base case $\ell = 0$ is (3). For the inductive step, assume the claim is true for ℓ. Since $U^{\ell+1}$ and U^ℓ are the uniform mixtures of $\widehat{U}^z$ and U^z, respectively, over all z with $|z| = \ell$ (so $U^{\ell+1}_\Pi = \mathbb{E}_z[\widehat{U}^z_\Pi]$ and $U^\ell_\Pi = \mathbb{E}_z[U^z_\Pi]$), by linearity of expectation Claim 2 implies

$$U^{\ell+1}_\Pi \geq \tfrac{1}{765}U^\ell_\Pi - 2^{-0.003n} \geq \tfrac{1}{|A|}2^{-\delta n-1-11\ell-\log_2(765)} - 2^{-0.003n} \geq \tfrac{1}{|A|}2^{-\delta n-1-11(\ell+1)},$$

where the last inequality follows because $|A| \leq 2^{\delta n+2}$ and $2^{-\delta n-2-\delta n-1-11\delta n-\log_2(765)} \geq 2^{-14\delta n}$ is at least twice $2^{-0.003n}$, which gives $U^{\ell+1}_\Pi \geq \frac{1}{|A|}2^{-\delta n-1-11\ell-\log_2(765)-1}$, and $\log_2(765) + 1 \leq 11$. □

Choosing $\ell = \delta n$, we have

$$U^\ell_\Pi - 2^{-d} \geq \tfrac{1}{|A|}2^{-\delta n-1-11\ell} - 2^{-15\delta n} \geq \tfrac{1}{|A|}2^{-\delta n-2-11\ell}, \qquad (4)$$

because $|A| \leq 2^{\delta n+2}$ and $2^{-\delta n-2-\delta n-1-11\delta n} \geq 2^{-14\delta n}$ is at least twice $2^{-15\delta n}$. Thus, for $\ell = \delta n$,

$$\begin{aligned}
\textstyle\sum_{x,y} D_{x,y} &\geq \textstyle\sum_{x,y\,:\,|x\wedge y|=\ell} D_{x,y} \\
&\geq \textstyle\sum_{x,y\,:\,|x\wedge y|=\ell} \frac{|A|}{3^n}(\mathrm{acc}_\Pi(x,y) - 2^{-d}) && \text{(by Claim 1)} \\
&= \frac{|A|}{3^n}\binom{n}{\ell}3^{n-\ell}(U_\Pi^\ell - 2^{-d}) \\
&\geq \frac{|A|}{3^n}(\tfrac{n}{\ell})^\ell 3^{n-\ell}\tfrac{1}{|A|}2^{-\delta n-2-11\ell} && \text{(using Equation (4))} \\
&= (\tfrac{n}{\ell\cdot 3\cdot 2^{11}})^\ell 2^{-\delta n-2} \\
&= (\tfrac{1}{\delta\cdot 3\cdot 2^{11}\cdot 2})^{\delta n}/4 \\
&\geq 1.6^{\delta n} \\
&> 1,
\end{aligned}$$

contradicting the fact that D is a distribution.

ACKNOWLEDGMENTS

We thank anonymous reviewers for helpful comments. A preliminary version of this article was published as Reference [40].

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Received July 2019; revised March 2020; accepted April 2020