Near-Optimal Averaging Samplers

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Abstract

We present the first efficient averaging sampler that achieves asymptotically optimal randomness complexity and near-optimal sample complexity. For any δ, ε > 0 and any constant α > 0, our sampler uses $O(m + \log(1/\delta))$ random bits to output $t = O((\frac{1}{\epsilon^2} \log \frac{1}{\delta})^{1+\alpha})$ samples $Z_1, \ldots, Z_t \in \{0, 1\}^m$ such that for any function $f : \{0, 1\}^m \to [0, 1]$,

$$\Pr\left[\frac{1}{t} \sum_{i=1}^{t} f(Z_i) - \mathbb{E}f \leq \epsilon\right] \geq 1 - \delta.$$ 

The sample complexity is optimal up to the $O((\frac{1}{\epsilon^2} \log \frac{1}{\delta})^{\alpha})$ factor, and the randomness complexity is optimal up to a constant factor.

We use known connections with randomness extractors and list-decodable codes to give applications to these objects. Specifically, we give the first extractor construction with optimal seed length up to an arbitrarily small constant factor bigger than 1, when the min-entropy $k = \beta n$ for a large enough constant $\beta < 1$.

1 Introduction

Randomization plays a crucial role in computer science, offering significant benefits across various applications. However, obtaining true randomness can be challenging. It’s therefore natural to study whether we can achieve the benefits of randomization while using few random bits.

One of the most basic uses of randomness is sampling. Given oracle access to an arbitrary function $f : \{0, 1\}^m \to [0, 1]$ on a large domain, our goal is to estimate its average value. By drawing $t = O(\log(1/\delta) / \epsilon^2)$ independent random samples $Z_1, \ldots, Z_t \in \{0, 1\}^m$, the Chernoff bound guarantees that the average value $\frac{1}{t} \sum_{i=1}^{t} f(Z_i) - \mathbb{E}f \leq \epsilon$ with probability at least $1 - \delta$. This method uses full independence in sampling, but we can also pursue more efficient strategies. This leads to the following definition:

Definition 1.1 ([BR94]). A function $Samp : \{0, 1\}^n \to (\{0, 1\}^m)^t$ is a $(\delta, \epsilon)$ averaging sampler with $t$ samples using $n$ random bits if for every function $f : \{0, 1\}^m \to [0, 1]$, we have

$$\Pr_{(Z_1, \ldots, Z_t) \sim Samp(U_n)} \left[\frac{1}{t} \sum_{i=1}^{t} f(Z_i) - \mathbb{E}f \leq \epsilon\right] \geq 1 - \delta.$$ 

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We would like to construct explicit samplers using few random bits that have sample complexity close to the optimal. Researchers have made progress towards this goal, and a summary is given in Table 1. Bellare and Rompel [BR94] suggested that interesting choices of parameters are $\varepsilon = 1/poly(m)$ and $\delta = \exp(-poly(m))$. This enables us to use $poly(m)$ random bits and generate $poly(m)$ samples.

<table>
<thead>
<tr>
<th>Due to</th>
<th>Method</th>
<th>Random Bits</th>
<th>Sample Complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>CEG95</td>
<td>Lower Bound</td>
<td>$m + \log(1/\delta) - \log(O(t))$</td>
<td>$\Omega(\log(1/\delta)/\varepsilon^2)$</td>
</tr>
<tr>
<td>CEG95</td>
<td>Non-Explicit</td>
<td>$m + 2\log(2/\delta) + \log(1/\varepsilon)$</td>
<td>$2\log(4/\delta)/\varepsilon^2$</td>
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<tr>
<td>Standard</td>
<td>Full Independence</td>
<td>$O(m \log(1/\delta)/\varepsilon^2)$</td>
<td>$O(1/(\delta \varepsilon^2))$</td>
</tr>
<tr>
<td>CG89</td>
<td>Pairwise Independence</td>
<td>$2m$</td>
<td>$O(1/(\delta \varepsilon^2))$</td>
</tr>
<tr>
<td>Gil98</td>
<td>Expander Walks</td>
<td>$m + O(\log(1/\delta)/\varepsilon^2)$</td>
<td>$O(\log(1/\delta)/\varepsilon^2)$</td>
</tr>
<tr>
<td>BR94</td>
<td>Iterated Sampling</td>
<td>$O(m + (\log m) \log(1/\delta))$</td>
<td>$poly(1/\varepsilon, \log(1/\delta), \log m)$</td>
</tr>
<tr>
<td>Zuc97</td>
<td>Hash-Based Extractors</td>
<td>$(1 + \alpha)(m + \log(1/\delta))$</td>
<td>$poly(1/\varepsilon, \log(1/\delta), m)$</td>
</tr>
<tr>
<td>RVW00</td>
<td>Zig-Zag Extractors</td>
<td>$m + (1 + \alpha) \log(1/\delta)$</td>
<td>$poly(1/\varepsilon, \log(1/\delta))$</td>
</tr>
<tr>
<td>Here</td>
<td>[RVW00] + Almost $\ell$-wise Uniform</td>
<td>$m + O(\log(1/\delta))$</td>
<td>$O(\log(1/\delta)/\varepsilon^{2+\alpha})$</td>
</tr>
</tbody>
</table>

Table 1: Comparison of averaging samplers, $\alpha$ any positive constant, $\varepsilon = 1/poly(m)$, and $\delta = \exp(-poly(m))$.

The best existing randomness-efficient averaging sampler comes from the equivalence between averaging samplers and extractors [Zuc97]. Improving Zuckerman’s construction, Reingold, Vadhan, and Wigderson [RVW00] gave a $(\delta, \varepsilon)$ averaging sampler for domain $\{0, 1\}^m$ that uses $m + (1 + \alpha) \log(1/\delta)$ random bits for any positive constant $\alpha$. This almost matches the lower bound in [CEG95]. However, a notable gap remains in sample complexity: the existing construction’s complexity $poly(1/\varepsilon, \log(1/\delta))$ does not align with the optimal $O(\log(1/\delta)/\varepsilon^2)$. This raised an open problem: Can we design an averaging sampler that not only meets the $O(m + \log(1/\delta))$ random bit requirement but also achieves the more efficient sample complexity of $O(\log(1/\delta)/\varepsilon^2)$ [BR94, Zuc97, Gol11]?

We note that such algorithms do exist for general samplers, which queries $f$ and computes the estimation of $\mathbb{E} f$ by an arbitrary computation [BGG93]. However, many applications require the use of averaging samplers, such as the original use in interactive proofs [BR94]. Beyond these applications, averaging samplers act as a fundamental combinatorial object that relate to other notions such as randomness extractors, expander graphs, and list-decodable codes [Zuc97, Vad07].

### 1.1 Our Sampler

In this paper, we construct a polynomial-time computable $(\delta, \varepsilon)$ averaging sampler $\text{Samp}$ with near-optimal sample complexity using an asymptotically optimal number of random bits. In fact, the sampler we constructed is a strong sampler, defined as follows:

**Definition 1.2.** A $(\delta, \varepsilon)$ averaging sampler $\text{Samp}$ is strong if for every sequence of $t$ functions $f_1, \ldots, f_t : \{0, 1\}^m \rightarrow [0, 1]$, we have

$$\Pr_{(Z_1, \ldots, Z_t) \sim \text{Samp}(U_m)} \left[ \frac{1}{t} \sum_i (f_i(Z_i) - \mathbb{E} f_i) \right] \leq \varepsilon \leq 1 - \delta.$$

We then state our main theorem:
**Corollary 3.** For every constant $\alpha > 0$, there exists an efficient strong $(\delta, \varepsilon)$ averaging sampler for domain $\{0, 1\}^m$ with $O(\frac{\log(1/\varepsilon)}{\varepsilon^2} \log \frac{1}{\delta})$ samples using $m + O((\log(1/\delta) + 1) \log \frac{1}{\delta})$ random bits.

By setting $s = \varepsilon^{-\alpha} \log^2 (1/\delta)$ for an arbitrarily small constant $\alpha$, this gives us the next sampler as a corollary.

**Corollary 2.** For every constant $\alpha > 0$, given any $(\delta, \varepsilon)$ such that $\delta \leq \varepsilon^\alpha$, there exists an efficient strong $(\delta, \varepsilon)$ averaging sampler for domain $\{0, 1\}^m$ with $O(\frac{\log(1/\varepsilon)}{\varepsilon^2} \log \frac{1}{\delta})$ samples using $m + O((\log(1/\delta) + 1) \log \frac{1}{\delta})$ random bits.

Note that $\delta \leq \varepsilon^\alpha$ is a very mild condition. Almost every application satisfies the stronger but still mild condition that $\delta \leq \varepsilon$. When $\varepsilon = 1/poly(m)$ and $\delta = \exp(-poly(m))$, we can interpret our result as follows:

**Corollary 3.** For every constant $\alpha > 0$, given any $(\delta, \varepsilon)$ such that $\varepsilon = 1/p_1(m)$ and $\delta = \exp(-p_2(m))$ for some polynomials $p_1$ and $p_2$, there exists an efficient strong $(\delta, \varepsilon)$ averaging sampler for domain $\{0, 1\}^m$ with $O(\frac{\log(1/\varepsilon)}{\varepsilon^2} \log \frac{1}{\delta})$ samples using $m + O((\log(1/\delta) + 1) \log \frac{1}{\delta})$ random bits.

Even in the extreme case where $\delta > \varepsilon^\alpha$, we can employ pairwise independence as our sampler (see Table 1). This gives us an efficient strong sampler with $O(1/(\delta^2\varepsilon^2)) \leq O(1/\varepsilon^{2+\alpha})$ samples, using only $2m$ random bits. Therefore, we can give a sampler working for any choices of $\delta$ and $\varepsilon$.

**Corollary 4.** For every constant $\alpha > 0$, and for all $\delta, \varepsilon > 0$, there exists an efficient strong $(\delta, \varepsilon)$ averaging sampler for domain $\{0, 1\}^m$ with $O(\frac{\log(1/\varepsilon)}{\varepsilon^2} \log \frac{1}{\delta})$ samples using $2m + O((\log(1/\delta) + 1) \log \frac{1}{\delta})$ random bits.

### 1.2 Randomness Extractors

Our sampler construction has implications for randomness extractors. A randomness extractor is a function that extracts almost-uniform bits from a low-quality source of randomness. We define the quality of a random source as its min-entropy.

**Definition 1.3.** The min-entropy of a random variable $X$ is

$$H_\infty(X) := \min_{x \in \text{supp}(X)} \log \left( \frac{1}{\Pr[X = x]} \right).$$

An $(n, k)$-source is a random variable on $n$ bits with min-entropy at least $k$.

Then a randomness extractor is defined as:

**Definition 1.4 ([NZ96]).** A function $\text{Ext} : \{0, 1\}^n \times \{0, 1\}^d \rightarrow \{0, 1\}^m$ is a $(k, \varepsilon)$ extractor if for every $(n, k)$-source $X$, the distribution $\text{Ext}(X, U_d) \approx_{\varepsilon} U_m$. We say $\text{Ext}$ is a strong $(k, \varepsilon)$ extractor if for every $(n, k)$-source $X$, the distribution $(\text{Ext}(X, Y), Y) \approx_{\varepsilon} U_{m+d}$, where $Y$ is chosen from $U_d$.

Randomness extractors are used in many areas within theoretical computer science. However, there has been little study of explicit extractors with the right dependence on $\varepsilon$. This is a particular concern in cryptography, where $\varepsilon$ is often very small. Existentially, there are extractors with seed length $d = \log(n - k) + 2 \log(1/\varepsilon) + O(1)$, and there is a matching lower bound [RT00].

Zuckerman [Zuc97] showed that averaging samplers are essentially equivalent to extractors. Specifically, an extractor $\text{Ext} : \{0, 1\}^n \times \{2^d\} \rightarrow \{0, 1\}^m$ can be seen as a sampler that generates $\text{Ext}(X, i)$ as its $i$-th sample point using the random source $X$. Using this equivalence, we give the first extractor construction with optimal seed length up to an arbitrarily small constant factor bigger than 1, when the min-entropy $k = \beta n$ for a large enough constant $\beta < 1$. 

3
**Theorem 5.** For every constant $\alpha > 0$, there exists $\beta < 1$ such that for all $\varepsilon > 0$ and $k \geq \beta n$, there is an efficient strong $(k, \varepsilon)$ extractor $\text{Ext} : \{0, 1\}^n \times \{0, 1\} \rightarrow \{0, 1\}^m$ with $m = \Omega(n) - \log(1/\varepsilon)$ and $d = (1 + \alpha) \log(n - k) + (2 + \alpha) \log(1/\varepsilon) + O(1)$.

Prior to our work, extractors with a seed length dependence on $\varepsilon$ achieving $2 \log(1/\varepsilon)$ or close to it were based on the leftover hash lemma [BBR88, IZ89, HILL99] and expander random walks [Gil98, Zuc07]. Extractors using the leftover hash lemma have a seed length of $O(\log(1/\varepsilon))$, which is far from optimal. Expander random walks give a $(k, \varepsilon)$ extractor with $k > (1 - \Omega(\varepsilon^2))n$ and an optimal seed length of $\log(n - k) + 2 \log(1/\varepsilon) + O(1)$. Our extractor allows for smaller $k$ for all $\varepsilon = \Theta(1)$.

In fact, if we aim to remove the $\alpha$ and achieve the optimal seed length of $\log(n - k) + 2 \log(1/\varepsilon) + O(1)$ to match expander random walks, we can set $s = 1$ in Theorem 1 and get the following extractor for entropy rate $1 - O(1/\log n)$ for $\varepsilon = 1/\log(n)$:

**Theorem 6.** There exists $\beta < 1$ such that for all $\varepsilon > 0$ and $k \geq (1 - \frac{\beta}{\log n + \log(1/\varepsilon)})n$, there is an efficient strong $(k, \varepsilon)$ extractor $\text{Ext} : \{0, 1\}^n \times \{0, 1\} \rightarrow \{0, 1\}^m$ with $m = \Omega(n) - \log^2(1/\varepsilon)$ and $d = \log(n - k) + 2 \log(1/\varepsilon) + O(1)$.

This is better than extractor random walks’ entropy rate of $1 - O(\varepsilon^2)$ for all $\varepsilon \leq o(1/\sqrt{\log n})$.

### 1.3 Techniques

Our construction is very simple, and is based on two observations:

1. Rather than querying every sample point produced by a sampler $\text{Samp}$, we can use a second sampler $\text{Samp}'$ to pick certain samples for querying. This reduces the sample complexity because the number of queried samples just depends on $\text{Samp}'$. Since the domain of $\text{Samp}'$ is much smaller than the original domain, this allows more efficient sampling strategies. This observation has been utilized in previous sampler constructions [BR94, Gol11].

2. The bottleneck of generating an almost $\ell$-wise uniform sequence over a large domain $\{0, 1\}^m$ lies in sampling $\ell$ independent random points, which costs $\ell m$ random bits. Since we can only afford $O(m)$ random bits, we are restricted to generating constant-wise uniform samples. However, for a much smaller domain, we can use few random bits to generate an almost $\ell$-wise uniform sequence for large $\ell$.

Our construction is outlined as follows. Let $\text{Samp}_E : \{0, 1\}^n \times [t'] \rightarrow \{0, 1\}^m$ be the extractor-based sampler in [RVW00]. Let $Y_1, \ldots, Y_t$ be an almost $\ell$-wise uniform sequence over domain $[t']$, thinking of $t \ll t'$. Our sampler is then defined by

$$\text{Samp} := (\text{Samp}_E(X, Y_1), \text{Samp}_E(X, Y_2), \ldots, \text{Samp}_E(X, Y_t)).$$

In this construction, we use the almost $\ell$-wise uniform sequence to sub-sample from the extractor-based sampler. This can be viewed as a composition, similar to other cases such as Justesen codes [Jus72] and the first PCP theorem [ALM+98], where the goal is to optimize two main parameters simultaneously by combining two simpler schemes, each optimizing one parameter without significantly compromising the other.

Previous works have also applied almost $\ell$-wise independence in extractor constructions. Srinivasan and Zuckerman [SZ99] proved a randomness-efficient leftover hash lemma by sampling an almost $\ell$-wise independent function using uniform seeds and inputting a weak random source. Our construction inverts this process: we generate an $\ell$-wise uniform sequence using a weak random
source and then choose an index uniformly. Furthermore, Ran Raz’s two-source extractor [Raz05] utilized two weak random sources to sample an almost \( \ell \)-wise uniform sequence and an index separately. This is a more general construction, but if we directly apply Raz’s error bound in our analysis Lemma 3.3, the final sample complexity will be off by a \( \log(1/\delta) \) factor.

It might be of independent interest to readers who are familiar with the Nisan-Zuckerman pseudorandom generator [NZ96]. Our sampler has the same structure as the Nisan-Zuckerman generator, and one can view our construction from the perspective of pseudorandom generators. In the classical analysis of the Nisan-Zuckerman generator, ensuring a success probability of \( 1 - \delta \) demands an extractor error smaller than \( \delta \), since an error at any step implies a complete loss of control. However, in our setting, every output sample has a very small effect on the final answer. This enables us to use an extractor with much larger error than \( \delta \) here.

1.4 List-Decodable Codes

Another perspective on averaging samplers is its connection to error-correcting codes. Ta-Shma and Zuckerman [ TZ04] showed that strong randomness extractors are equivalent to codes with good soft-decision decoding, which is related to list recovery. From this perspective, the composition scheme in our construction is similar to code concatenation.

For codes over the binary alphabet, soft decision decoding amounts to list decodability, which we focus on here. We give good list-decodable codes without using the composition. That is, by just applying our almost \( \ell \)-wise uniform sampler on the binary alphabet, we can get a binary list-decodable code with rate \( \Omega(\varepsilon^{2+\alpha}) \) and non-trivial list size, although the list size is still exponential.

**Theorem 7.** For every constant \( \alpha > 0 \): there exists an explicit binary code with rate \( \Omega(\varepsilon^{2+\alpha}) \) that is \( (\rho = \frac{1}{2} - \varepsilon, L) \) list-decodable with list size \( L = 2^{(1-c)n} \) for some constant \( c = c(\alpha) > 0 \).

Prior to our work, the best known code rate was \( \Omega(\varepsilon^3) \) by Guruswami and Rudra [GR08]. We emphasize that their code achieved a list size of \( L = \text{poly}(n) \), while our list size is exponentially large, making our code unlikely to be useful.

2 Preliminaries

**Notations.** We use \([t]\) to represent set \( \{1, \ldots, t\} \). For integer \( m \), \( U_m \) is a random variable distributed uniformly over \( \{0, 1\}^m \). For random variables \( X \) and \( Y \), we use \( X \approx \varepsilon \ Y \) to represent the statistical distance (total variation distance) between \( X \) and \( Y \) is at most \( \varepsilon \), i.e.,

\[
\max_{T \subseteq \supp(X)} \left| \Pr_{x \sim X}[x \in T] - \Pr_{y \sim Y}[y \in T] \right| \leq \varepsilon.
\]

We use the term “efficient” to mean polynomial-time computable.

2.1 Extractor-Based Sampler

As mentioned above, averaging samplers are equivalent to extractors. We will introduce this in detail in Section 4.1. Reingold, Vadhan, and Wigderson used this equivalence to achieve the following:

**Theorem 2.1** ([RVW00, Corollary 7.3], see also [Gol11, Theorem 6.1]). For every constant \( \alpha > 0 \), there exists an efficient \( (\delta, \varepsilon) \) averaging sampler over \( \{0, 1\}^m \) with \( \text{poly}(1/\varepsilon, \log(1/\delta)) \) samples using \( m + (1 + \alpha) \cdot \log_2(1/\delta) \) random bits.
For ease of presentation, we often denote an extractor-based averaging sampler by $\text{Samp}_E: \{0,1\}^n \times \{0,1\}^d \to \{0,1\}^m$, where $\text{Samp}_E(X, i)$ is the $i$-th output sample point of the sampler using randomness input $X$. Therefore, the sample complexity of $\text{Samp}_E$ is $2^d$.

### 2.2 Almost $\ell$-wise Uniform

A sequence $Z_1, \ldots, Z_t$ is pairwise independent if the marginal distribution of every pair $(Z_{i_1}, Z_{i_2})$ is uniformly random. Chor and Goldreich [CG89] proved that using pairwise independence, we can have a sampler using few random bits but with unsatisfied sample complexity.

**Lemma 2.2 ([CG89]).** There exists an efficient strong $(\delta, \varepsilon)$ for domain $\{0,1\}^m$ sampler with $O(1/(\delta \varepsilon^2))$ samples using $2m$ random bits.

Generalizing pairwise independence, an almost $\ell$-wise uniform sequence is a sequence of random variables such that the marginal distribution of every $\ell$ of them is close to uniform.

**Definition 2.3 ([NN93]).** A sequence of random variables $Z_1, \ldots, Z_t \in \{0,1\}^m$ is said to be $\gamma$-almost $\ell$-wise uniform if for all subsets $S \subseteq [t]$ such that $|S| \leq \ell$,

$$(Z_i)_{i \in |S|} \approx_{\gamma} U_{m \times |S|}.$$  

In particular, the pairwise independent sequence mentioned above is a 0-almost 2-wise uniform sequence. Naor and Naor proved that such sequences can be randomness-efficiently generated.

**Lemma 2.4 ([NN93], see also [AGHP92]).** There exists an efficient algorithm that uses $O(\ell m + \log(1/\gamma) + \log \log t)$ random bits to generate a $\gamma$-almost $\ell$-wise uniform sequence $z_1, \ldots, z_t \in \{0,1\}^m$.

Using standard techniques, we have the following concentration bound for almost $\ell$-wise uniform sequences (see Appendix A for the proof). Similar bounds for exact $\ell$-wise uniform sequences have been shown in [BR94, Dod00].

**Lemma 2.5.** Let $Z_1, \ldots, Z_t \in \{0,1\}^m$ be a sequence of $\gamma$-almost $\ell$-wise uniform variables for an even integer $\ell$. Then for every sequence of functions $f_1, \ldots, f_t: \{0,1\}^m \to [0,1]$,

$$\Pr \left[ \left| \frac{1}{t} \sum_{i=1}^{t} (f_i(Z_i) - \mathbb{E} f_i) \right| \leq \varepsilon \right] \geq 1 - \left( \frac{5 \sqrt{\ell}}{\varepsilon \sqrt{t}} \right)^{\ell} - \frac{\gamma \varepsilon}{\varepsilon^m}.$$

### 2.3 Composition of Samplers

The idea of composing samplers has been studied before. More specifically, Goldreich proved the following proposition.

**Proposition 2.6 ([Gol11]).** Suppose we are given two efficient samplers:

- A $(\delta, \varepsilon)$ averaging sampler for domain $\{0,1\}^m$ with $t_1$ samples using $n_1$ random bits.
- A $(\delta', \varepsilon')$ averaging sampler for domain $\{0,1\}^{\log t_1}$ with $t_2$ samples using $n_2$ random bits.

Then, there exists an efficient $(\delta + \delta', \varepsilon + \varepsilon')$ averaging sampler for domain $\{0,1\}^m$ with $t_2$ samples using $O(n_1 + n_2)$ random bits.
3 Main Results

Our construction is based on a reduction lemma that constructs a sampler for domain \( \{0,1\}^m \) based on a sampler for domain \( \{0,1\}^{O(\log(1/\varepsilon)+\log \log(1/\delta))} \). We exploit the fact that when composing averaging samplers, the final sample complexity depends on only one of the samplers. Our strategy is:

- Apply the extractor sampler in Theorem 2.1 as a \((\delta/2, \varepsilon/2)\) sampler over domain \( \{0,1\}^m \). This uses \( m + O(\log(1/\delta)) \) random bits and generates \( \text{poly}(1/\varepsilon, \log(1/\delta)) \) samples.
- By Proposition 2.6, we only need to design a \((\delta/2, \varepsilon/2)\) averaging sampler over domain \( \{0,1\}^{O(\log(1/\varepsilon)+\log \log(1/\delta))} \) using \( O(\log(1/\delta)) \) random bits. The total sample complexity will be equal to the sample complexity of this sampler. For this sampler, we use almost \( \ell \)-wise uniformity.

To formally prove the reduction lemma, we establish the next lemma, which demonstrates the explicit composition of samplers and proves that this composition maintains the properties of a strong sampler. The proof follows from the idea of Proposition 2.6.

Lemma 3.1. Let \( \text{Samp}_E : \{0,1\}^n \times \{0,1\}^d \rightarrow \{0,1\}^m \) be a \((\delta, \varepsilon)\) averaging sampler, and let \( \text{Samp}_{\text{base}} \) be a \((\delta', \varepsilon')\) averaging sampler for domain \( \{0,1\}^d \). Suppose \( Y_1, \ldots, Y_t \in \{0,1\}^d \) are the samples generated by \( \text{Samp}_{\text{base}} \), i.e., for uniformly random source \( R \),

\[
\text{Samp}_{\text{base}}(R) = (Y_1, \ldots, Y_t).
\]

Then, for a uniformly random \( X \in \{0,1\}^n \),

\[
\text{Samp}(R, X) := (\text{Samp}_E(X, Y_1), \ldots, \text{Samp}_E(X, Y_t))
\]

is a \((\delta' + \delta, \varepsilon' + \varepsilon)\) averaging sampler for domain \( \{0,1\}^m \). Furthermore, if \( \text{Samp}_{\text{base}} \) is strong, then \( \text{Samp} \) is also a strong \((\delta' + t\delta, \varepsilon' + \varepsilon)\) averaging sampler.

Proof. We only prove the case when \( \text{Samp}_{\text{base}} \) is a strong sampler, and the non-strong case follows similarly. Let \( f_1, \ldots, f_t : \{0,1\}^m \rightarrow [0,1] \) be an arbitrary sequence of functions. By the definition of strong samplers, we have for every \( f_i \),

\[
\Pr_{X \sim U_n} \left[ \left| \frac{1}{Y \sim U_d} \sum_{Y} \left( \mathbb{E}_{Y \sim U_d} f_i(\text{Samp}_E(X, Y)) - \mathbb{E}_{X \sim U_n} f_i(\text{Samp}_E(X, Y)) \right) \right| \leq \varepsilon \right] \geq 1 - \delta.
\]

By a union bound over all \( f_1, \ldots, f_t \), we have \(^1\)

\[
\Pr_{X \sim U_n} \left[ \forall i \in [t] : \left| \frac{1}{Y \sim U_d} \sum_{Y} \left( \mathbb{E}_{Y \sim U_d} f_i(\text{Samp}_E(X, Y)) - \mathbb{E}_{X \sim U_n} f_i(\text{Samp}_E(X, Y)) \right) \right| \leq \varepsilon \right] \geq 1 - t\delta. \tag{1}
\]

For an arbitrary \( x \), view \( f_i(\text{Samp}_E(x, \cdot)) \) as a Boolean function on domain \( \{0,1\}^d \). Therefore, since \( Y_1, \ldots, Y_t \) are generated by a strong \((\delta, \varepsilon)\) sampler,

\[
\Pr_{Y_1, \ldots, Y_t} \left[ \left| \frac{1}{t} \sum_{i=1}^t \left( f_i(\text{Samp}_E(x, Y_i)) - \mathbb{E}_{Y \sim U_d} f_i(\text{Samp}_E(x, Y)) \right) \right| \leq \varepsilon' \right] \geq 1 - \delta'. \tag{2}
\]

\(^1\)Note that for the non-strong case, we don’t need a union bound here. Thus, we can save a factor of \( t \) in the error parameter.
By the triangle inequality and a union bound over equations (1) and (2), we have

\[ \Pr_{X,Y_1,...,Y_t} \left[ \left| \frac{1}{t} \sum_{i=1}^{t} (f_i(S_{\text{amp}}_E(X,Y_i)) - \mathbb{E} f_i) \right| \leq \varepsilon' + \varepsilon \right] \geq 1 - \delta' - t\delta. \]

This proves that \( (S_{\text{amp}}_E(X,Y_1), \ldots, S_{\text{amp}}_E(X,Y_t)) \) is a strong \((\delta' + t\delta, \varepsilon' + \varepsilon)\) averaging sampler. \(\square\)

Instantiating Lemma 3.1 with the extractor-based sampler from Theorem 2.1 gives:

**Lemma 3.2** (Main Reduction Lemma). For any \(\alpha > 0\): For a sufficiently large constant \(C > 0\), suppose there exists an efficient \((\delta', \varepsilon')\) averaging sampler \(S_{\text{amp}}_\text{base}\) for domain \(\{0,1\}^C(\log(1/\varepsilon) + \log(1/\delta))\) with \(t\) samples using \(n\) random bits. Then

- There exists an efficient \((\delta + \delta', \varepsilon + \varepsilon')\) averaging sampler \(S_{\text{amp}}\) for domain \(\{0,1\}^m\) with \(t\) samples using \(m + (1 + \alpha)\log(t/\delta) + n\) random bits.
- If \(S_{\text{amp}}_\text{base}\) is strong, then there exists an efficient \((\delta + \delta', \varepsilon + \varepsilon')\) averaging sampler \(S_{\text{amp}}\) for domain \(\{0,1\}^m\) with \(t\) samples using \(m + (1 + \alpha)\log(t/\delta) + n\) random bits.

**Proof.** By Theorem 2.1, there exists an explicit \((\delta/t, \varepsilon)\) averaging sampler \(S_{\text{amp}}_E: \{0,1\}^{n'} \times \{0,1\}^d \to \{0,1\}^m\) with \(n' = m + (1 + \alpha)\log(t/\delta)\) and \(d = \log(\text{poly}(1/\varepsilon, \log(t/\delta))) \leq C(\log(1/\varepsilon) + \log(1/\delta))\) for some large enough constant \(C\).

First, we need to verify that \(S_{\text{amp}}_\text{base}\) can work for domain \(\{0,1\}^d\), i.e., that \(d \leq C(\log(1/\varepsilon) + \log(1/\delta))\). Without loss of generality, we assume \(\log t \leq C(\log(1/\varepsilon) + \log(1/\delta));\) otherwise, we can just use the trivial sampler that outputs the whole domain. Thus, \(S_{\text{amp}}_\text{base}\) can successfully work for \(\{0,1\}^d\) since

\[ d \leq C \left( \log(1/\varepsilon) + \log(1/\delta) \right) + \frac{C}{2} \log \log t \leq C \left( \log(1/\varepsilon) + \log(1/\delta) \right) \]

Next, we analyze the number of random bits that \(S_{\text{amp}}\) needs. We need \(n'\) random bits to generate \(x\) and we need \(n\) bits to generate \(y_1, \ldots, y_t\).

Therefore, the total number of random bits we need is \(n' + n = m + (1 + \alpha)\log(t/\delta) + n\). The lemma then follows from Lemma 3.1. \(\square\)

Next, we show that for domain \(\{0,1\}^m\) with \(m \leq O(\log(1/\varepsilon) + \log(1/\delta))\), we can use an almost \(\ell\)-wise uniform sequence to design a strong averaging sampler with near-optimal sample complexity.

**Lemma 3.3.** For any \(1 < s < 1/\delta\), there exists an efficient strong \((\delta, \varepsilon)\) averaging sampler for domain \(\{0,1\}^m\) with \(O \left( \frac{s \log 1}{\delta^2} \right)\) samples using \(O \left( \frac{m + \log(1/\varepsilon)}{\log s} \frac{\log(1/\delta)}{\log s} + \log(1/\delta) \right)\) random bits.

**Proof.** We begin by setting \(\ell = \frac{2 \log(2/\delta)}{\log s}\), \(\gamma = \frac{4\ell}{2}\), and \(t = \frac{50\ell \log(2/\delta)}{\varepsilon^2 \log s}\). We then define our sampler by outputting a \(\gamma\)-almost \(\ell\)-wise uniform sequence \(Z_1, \ldots, Z_t \in \{0,1\}^m\). Taking the parameters of Lemma 2.5, observe

\[ \left( \frac{25\ell}{\varepsilon^2 t} \right)^{\ell/2} = \left( \frac{1}{s} \right)^{\ell/2} \left( \frac{1}{s} \right)^{\log(2/\delta) \log s} = \delta \]

and

\[ \frac{\gamma}{\varepsilon} = \frac{\delta}{2}. \]
Therefore, for every sequence of functions \( f_1, \ldots, f_t : \{0,1\}^m \rightarrow [0,1] \),
\[
\Pr \left[ \frac{1}{t} \sum_{i=1}^{t} (f_i(Z_i) - \mathbb{E} f_i) \leq \varepsilon \right] \geq 1 - \delta.
\]

Furthermore, Lemma 2.4 shows that we have an efficient algorithm that uses only \( O\left(\frac{m+\log(1/\varepsilon)}{\log s} \log(1/\delta) + \log(1/\delta)\right) \) random bits to generate this \( \gamma \)-almost \( \ell \)-wise uniform sequence.

Combining Lemma 3.2 and Lemma 3.3, we can prove our main theorem.

**Theorem 1.** For any \( 1 \leq s \leq 1/\delta \), there exists an efficient strong \((\delta, \varepsilon)\) averaging sampler for domain \( \{0,1\}^m \) with \( O\left(\frac{s}{\varepsilon^2} \log \frac{1}{\delta}\right) \) samples using \( m + O\left(\frac{\log(1/\varepsilon) + \log\log(1/\delta)}{\log s} + 1\right) \log \frac{1}{\delta} \) random bits.

**Proof.** By Lemma 3.2, our goal is to design an efficient strong \((\delta/2, \varepsilon/2)\) averaging sampler \( \text{Samp}_{\text{base}} \) for domain \( \{0,1\}^C(\log(1/\varepsilon) + \log\log(1/\delta)) \) for some large enough constant \( C \). The theorem is proved if for any \( 1 < s < 1/\delta \), \( \text{Samp}_{\text{base}} \) generates \( O\left(\frac{s}{\varepsilon^2} \log \frac{1}{\delta}\right) \) samples using \( O\left(\frac{\log(1/\varepsilon) + \log\log(1/\delta)}{\log s} + 1\right) \log(1/\delta) \) random bits. The almost \( \ell \)-wise uniform sampler defined in Lemma 3.3 for \( m = C(\log(1/\varepsilon) + \log\log(1/\delta)) \) satisfies these conditions, and proves the theorem.

For an arbitrarily small constant \( \alpha \), by setting \( s = \varepsilon^\alpha \log^\alpha(1/\delta) \), we get the next corollary:

**Corollary 2.** For every constant \( \alpha > 0 \), given any \((\delta, \varepsilon)\) such that \( \delta \leq \varepsilon^\alpha \), there exists an efficient strong \((\delta, \varepsilon)\) averaging sampler for domain \( \{0,1\}^m \) with \( O\left(\frac{1}{\varepsilon^2} \log \frac{1}{\delta} \right)^{1+\alpha} \) samples using \( m + O(\log(1/\delta)) \) random bits.

Combining with the pairwise independence sampler in Lemma 2.2, we can get a sampler working for arbitrary \( \delta \) and \( \varepsilon \).

**Corollary 4.** For every constant \( \alpha > 0 \), and for all \( \delta, \varepsilon > 0 \), there exists an efficient strong \((\delta, \varepsilon)\) averaging sampler for domain \( \{0,1\}^m \) with \( O\left(\frac{1}{\varepsilon^2} \log \frac{1}{\delta} \right)^{1+\alpha} \) samples using \( 2m + O(\log(1/\delta)) \) random bits.

**Proof.** Suppose \( \delta \geq \varepsilon^\alpha \), then the sampler in Corollary 2 satisfies the requirement. When \( \delta < \varepsilon^\alpha \), we can use the pairwise independence sampler in Lemma 2.2, which uses \( 2m \) random bits and generates \( O(1/(\delta^2)) < O(1/\varepsilon^{2+\alpha}) \) samples.

We can also set \( s = 1 \) in Theorem 1 and get the following sampler with asymptotically optimal sample complexity but a worse randomness complexity.

**Corollary 3.4.** There exists an efficient strong \((\delta, \varepsilon)\) averaging sampler for domain \( \{0,1\}^m \) with \( O\left(\frac{1}{\varepsilon^2} \log \frac{1}{\delta} \right) \) samples using \( m + O(\log \frac{1}{\delta} (\log \frac{1}{\varepsilon} + \log \log \frac{1}{\delta})) \) random bits.

### 4 Applications to Extractors and Codes

#### 4.1 Applications to Extractors

Zuckerman showed that averaging samplers are equivalent to randomness extractors [Zuc97]. Here we state the only direction that we need.

**Lemma 4.1 ([Zuc97]).** An efficient strong \((\delta, \varepsilon)\) averaging sampler \( \text{Samp} : \{0,1\}^n \rightarrow (\{0,1\}^m)^t \) gives an efficient strong \((n - \log(1/\delta) + \log(1/\varepsilon), 2\varepsilon)\) extractor \( \text{Ext} : \{0,1\}^n \times \{0,1\}^{\log t} \rightarrow \{0,1\}^m \).
Applying Lemma 4.1 on Corollary 4 gives Theorem 5:

**Theorem 5.** For every constant \( \alpha > 0 \), there exists \( \beta < 1 \) such that for all \( \varepsilon > 0 \) and \( k \geq \beta n \), there is an efficient strong \((k, \varepsilon)\) extractor \( \text{Ext} : \{0,1\}^n \times \{0,1\}^d \rightarrow \{0,1\}^m \) with \( m = \Omega(n) - \log(1/\varepsilon) \) and \( d = (1 + \alpha) \log(n - k) + (2 + \alpha) \log(1/\varepsilon) + O(1) \).

**Proof.** By Corollary 4, for any positive constant \( \alpha > 0 \), there exists a constant \( \lambda > 1 \) such that there exists an efficient strong \((\delta, \varepsilon)\) averaging sampler for domain \( \{0,1\}^m \) with \( O(\frac{1}{\epsilon^{1+\alpha}} \log^{1+\alpha} \frac{1}{\lambda}) \) samples using \( \lambda(m + \log \frac{1}{\delta}) \) random bits.

To construct the required strong \((k, \varepsilon)\) extractor for every \( n \), we set \( \delta = \frac{n}{2\lambda} + \log(1/\varepsilon) \). Then, we construct an efficient strong \((\delta, \varepsilon)\) sampler \( \text{Samp} \) for domain \( \{0,1\}^m \) where

\[
m = \frac{n}{\lambda} - \log(1/\delta) > \frac{n}{2\lambda} - \log(1/\varepsilon) = \Omega(n) - \log(1/\varepsilon).
\]

By the above, \( \text{Samp} \) uses \( n \) random bits and generates \( O(\frac{1}{\epsilon^{1+\alpha}} \log^{1+\alpha} \frac{1}{\lambda}) \) samples.

By Lemma 4.1, \( \text{Samp} \) implies an efficient strong \((n - \log(1/\delta) + \log(1/\varepsilon), 2\varepsilon)\) extractor \( \text{Ext} : \{0,1\}^n \times \{0,1\}^d \rightarrow \{0,1\}^m \) with \( d \leq (1 + \alpha) \log(n - k) + (2 + \alpha) \log(1/\varepsilon) + O(1) \). It is only left to verify that \( n - \log(1/\delta) + \log(1/\varepsilon) \leq \beta n \) for some constant \( \beta < 1 \). We have

\[
n - \log(1/\delta) + \log(1/\varepsilon) = n - \frac{2\lambda - 1}{2\lambda} n.
\]

This proves the theorem. \(\square\)

If we would like an extractor with the optimal seed length of \( d = \log(n - k) + 2 \log(1/\varepsilon) + O(1) \), we can have the following extractor using Corollary 3.4.

**Theorem 6.** There exists \( \beta < 1 \) such that for all \( \varepsilon > 0 \) and \( k \geq (1 - \frac{\beta}{\log n + \log(1/\varepsilon)}) n \), there is an efficient strong \((k, \varepsilon)\) extractor \( \text{Ext} : \{0,1\}^n \times \{0,1\}^d \rightarrow \{0,1\}^m \) with \( m = \Omega(n) - \log^2(1/\varepsilon) \) and \( d = \log(n - k) + 2 \log(1/\varepsilon) + O(1) \).

**Proof.** By Corollary 3.4, there exists a constant \( \lambda > 1 \) such that there exists an efficient strong \((\delta, \varepsilon)\) averaging sampler for domain \( \{0,1\}^m \) with \( O(\frac{1}{\epsilon} \log \frac{1}{\delta}) \) samples using \( m + \lambda \log \frac{1}{\delta} \log(1/\delta) + \log(1/\varepsilon) \) random bits.

To construct the required strong \((k, \varepsilon)\) extractor for every \( n \), we set \( \delta \) such that \( \log(1/\delta) = \frac{1}{2\lambda} \log^{1+\alpha} \frac{n}{\lambda} + \log(1/\varepsilon) \). Then, we construct an efficient strong \((\delta, \varepsilon)\) sampler \( \text{Samp} \) for domain \( \{0,1\}^m \) where

\[
m = n - \lambda \log \frac{1}{\delta} (\log \log(1/\delta) + \log(1/\varepsilon)) \geq n - \frac{n}{2} \frac{\log \log(1/\delta) + \log(1/\varepsilon)}{\log n + \log(1/\varepsilon)} - \log^2(1/\varepsilon) - \log(1/\varepsilon) \log n \geq \Omega(n) - \log^2(1/\varepsilon).
\]

By the above, \( \text{Samp} \) uses \( n \) random bits and generates \( O(\frac{1}{\epsilon} \log \frac{1}{\delta}) \) samples.

By Lemma 4.1, \( \text{Samp} \) implies an efficient strong \((n - \log(1/\delta) + \log(1/\varepsilon), 2\varepsilon)\) extractor \( \text{Ext} : \{0,1\}^n \times \{0,1\}^d \rightarrow \{0,1\}^m \) with \( d = \log(n - k) + 2 \log(1/\varepsilon) + O(1) \). It is only left to verify that \( n - \log(1/\delta) + \log(1/\varepsilon) \leq (1 - \frac{\beta}{\log n + \log(1/\varepsilon)}) n \) for some constant \( \beta < 1 \). We have

\[
n - \log(1/\delta) + \log(1/\varepsilon) = n - \frac{1}{2\lambda} \left( \frac{n}{\log n + \log(1/\varepsilon)} \right) \leq (1 - \frac{1}{2\lambda(\log n + \log(1/\varepsilon))}) n.
\]

This proves the theorem. \(\square\)
4.2 Application to List-Decodable Codes

Error-correcting codes are combinatorial objects that enable messages to be accurately transmitted, even when parts of the data get corrupted. Codes have been extensively studied and have proven to be extremely useful in computer science. Here we focus on the combinatorial property of list-decodability, defined below.

**Definition 4.2.** A code \( \text{ECC} : \{0,1\}^n \rightarrow (\{0,1\}^m)^t \) is \((\rho,L)\) list-decodable if for every received message \( r \in (\{0,1\}^m)^t \), there are at most \( L \) messages \( x \in \{0,1\}^n \) such that \( d_H(\text{ECC}(x),r) \leq \rho t \), where \( d_H \) denotes the Hamming distance. A code is binary if \( m = 1 \).

We focus on the binary setting, i.e., \( m = 1 \).

**Lemma 4.3 ([TZ04]).** An efficient strong \((\delta,\varepsilon)\) averaging sampler \( \text{Samp} : \{0,1\}^n \rightarrow \{0,1\}^t \) over the binary domain gives an efficient binary code that is \((\rho = \frac{1}{2} - \varepsilon, \delta^{2^n})\) list-decodable with code rate \( R = \frac{n}{t} \).

To construct our codes, we will use our almost \( \ell \)-wise uniform sampler in Lemma 3.3 directly.

**Lemma 4.4.** For all constant \( \alpha > 0 \), there exists an efficient strong \((\delta,\varepsilon)\) averaging sampler \( \text{Samp} : \{0,1\}^n \rightarrow \{0,1\}^t \) for binary domain with \( O(\frac{1}{\varepsilon^2 \alpha} \log \frac{1}{\delta}) \) samples using \( n = C \log(1/\delta) \) random bits for some constant \( C \geq 1 \).

**Proof.** By setting \( s = \frac{1}{\varepsilon^\alpha} \) and \( m = 1 \) in Lemma 3.3, we have that whenever \( 1/\varepsilon^\alpha \leq 1/\delta \), we have a strong \((\delta,\varepsilon)\) sampler with \( O(\frac{1}{\varepsilon^\alpha} \log \frac{1}{\delta}) \) samples using \( O(\log(1/\delta)) \) random bits. When \( 1/\varepsilon^\alpha > 1/\delta \), using the pairwise independence sampler in Lemma 2.2 for binary domain will satisfy the condition. \( \Box \)

Applying Lemma 4.3 to Lemma 4.4 gives Theorem 7:

**Theorem 7.** For every constant \( \alpha > 0 \): there exists an explicit binary code with rate \( \Omega(\varepsilon^{2+\alpha}) \) that is \((\rho = \frac{1}{2} - \varepsilon, L)\) list-decodable with list size \( L = 2^{(1-c)n} \) for some constant \( c = c(\alpha) > 0 \).

**Proof.** We use the \((\delta,\varepsilon)\) sampler in Lemma 4.4, where we choose \( \delta \) such that \( n = C \log(1/\delta) \). Applying Lemma 4.3 to this sampler implies Theorem 7, where \( c(\alpha) = 1/C \) here. \( \Box \)

5 Open Problems

Our work raises interesting open problems.

- Comparing to the sampler in [RVW00] which uses \( m + (1 + \alpha) \log(1/\delta) \) random bits, our construction requires \( m + O(\log(1/\delta)) \) random bits. Can we improve our randomness efficiency while maintaining a good sample complexity?

- Is there a way to eliminate the additional \( \alpha \) in the sample complexity? For \( \varepsilon = 1/poly(m) \) and \( \delta = \exp(-poly(m)) \), can we design an efficient averaging sampler that is asymptotically optimal in both randomness and sample complexity?

- Is it possible to reduce the list size of the list-decodable codes in Theorem 7 to \( \text{poly}(n) \) using the structure of the list?
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Bibliography


A Proof of Lemma 2.5

**Proposition A.1** (Marcinkiewicz–Zygmund inequality [RL01]). Let \( \{X_i, i \geq 1\} \) be a sequence of independent random variables with \( \mathbb{E} X_i = 0, \mathbb{E}|X_i|^p < \infty \). Then for \( p \geq 2 \):

\[
\mathbb{E} \left| \sum_{i=1}^{n} X_i \right|^p \leq C(p)n^{p/2 - 1} \sum_{i=1}^{n} \mathbb{E}|X_i|^p,
\]

where \( C(p) \leq (3\sqrt{2})^p p^{p/2} \).
Proof of Lemma 2.5. Let $W := f_i(Z_i) - \mathbb{E} f_i$. We have

$$\Pr \left[ \left| \sum_{i=1}^t W_i \right| > t\varepsilon \right] \leq \frac{\mathbb{E} \left[ \left| \sum_{i=1}^t W_i \right|^\ell \right]}{(t\varepsilon)^\ell}.$$ 

Let $W_1', \ldots, W_t'$ be a sequence of independent random variables where $W_i' := f_i(U_{\{0,1\}^m}) - \mathbb{E} f_i$. Since the $W_i$’s are $\gamma$-almost $\ell$-wise independent and $|W_i| \leq 1$, we have

$$\mathbb{E} \left[ \left| \sum_{i=1}^t W_i \right|^\ell \right] = \mathbb{E} \left[ \left( \sum_{i=1}^t W_i \right)^\ell \right] \leq \mathbb{E} \left[ \left( \sum_{i=1}^t W_i' \right)^\ell \right] + \gamma t^\ell = \mathbb{E} \left[ \sum_{i=1}^t W_i' \right]^\ell + \gamma t^\ell.$$ 

Since $\mathbb{E} W_i' = 0$ and $|W_i'| \leq 1$, they satisfy the conditions for Marcinkiewicz-Zygmund inequality. We have

$$\mathbb{E} \left[ \left| \sum_{i=1}^t W_i' \right|^\ell \right] \leq (3\sqrt{2})^{\ell/2} t^{\ell/2 - 1} \sum_{i=1}^t \mathbb{E} |W_i'|^\ell \leq (5\sqrt{\ell})^\ell.$$ 

Therefore,

$$\frac{\mathbb{E} \left[ \left| \sum_{i=1}^t W_i \right|^\ell \right]}{(t\varepsilon)^\ell} \leq \left( \frac{5\sqrt{\ell}}{\varepsilon \sqrt{t}} \right)^\ell + \frac{\gamma t^\ell}{(t\varepsilon)^\ell}.$$ 

$\square$