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Key Derivation Without Entropy Waste

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Abstract

We revisit the classical problem of converting an imperfect source of randomness into a usable cryptographic key. Assume that we have some cryptographic application P that expects a uniformly random m-bit key R and ensures that the best attack (in some complexity class) against $P(R)$ has success probability at most δ. Our goal is to design a key-derivation function (KDF) h that converts any random source X of min-entropy k into a sufficiently "good" key $h(X)$, guaranteeing that $P(h(X))$ has comparable security δ' which is 'close' to δ.

Seeded randomness extractors provide a generic way to solve this problem for *all* applications P, with resulting security $\delta' = O(\delta)$, provided that we start with entropy $k \geq m + 2\log(1/\delta) - O(1)$. By a result of Radhakrishnan and Ta-Shma, this bound on k (called the "RT-bound") is also known to be tight in general. Unfortunately, in many situations the loss of $2\log(1/\delta)$ bits of entropy is unacceptable. This motivates the study KDFs with less entropy waste by placing some restrictions on the source X or the application P.

In this work we obtain the following new positive and negative results in this regard:

- Efficient samplability of the source X does not help beat the RT-bound for general applications. This resolves the SRT (samplable RT) conjecture of Dachman-Soled et al. [DGKM12] in the affirmative, and also shows that the existence of computationally-secure extractors beating the RT-bound implies the existence of one-way functions.
- We continue in the line of work initiated by Barak et al. [BDK$^+$11] and construct new information-theoretic KDFs which beat the RT-bound for large but restricted classes of applications. Specifically, we design efficient KDFs that work for *all unpredictability applications* P (e.g., signatures, MACs, one-way functions, etc.) and can either: (1) extract *all* of the entropy $k = m$ with a very modest security loss $\delta' = O(\delta \cdot \log(1/\delta))$, or alternatively, (2) achieve essentially optimal security $\delta' = O(\delta)$ with a very modest entropy loss $k \geq m + \operatorname{loglog}(1/\delta)$. In comparison, the best prior results from [BDK$^+$11] for this class of applications would only guarantee $\delta' = O(\sqrt{\delta})$ when $k = m$, and would need $k \geq m + \log(1/\delta)$ to get $\delta' = O(\delta)$.
- The weaker bounds of [BDK$^+$11] hold for a larger class of so-called "square-friendly" applications (which includes all unpredictability, but also some important indistinguishability, applications). Unfortunately, we show that these weaker bounds are tight for the larger class of applications.
- We abstract out a clean, information-theoretic notion of (k, δ, δ')-*unpredictability extractors*, which guarantee "induced" security δ' for any δ-secure unpredictability application P, and characterize the parameters achievable for such unpredictability extractors. Of independent interest, we also relate this notion to the previously-known notion of (min-entropy) *condensers*, and improve the state-of-the-art parameters for such condensers.

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1 Introduction

Key Derivation is a fundamental cryptographic task arising in a wide variety of situations where a given application P was designed to work with a uniform m-bit key R, but in reality one only has a "weak" n-bit random source X. Examples of such sources include biometric data [DORS08, BDK$^+$05], physical sources [BST03, BH05], secrets with partial leakage, and group elements from Diffie-Hellman key exchange [GKR04, Kra10], to name a few. We'd like to have a *Key Derivation Function* (KDF) $h : \{0,1\}^n \to \{0,1\}^m$ with the property that the derived key $h(X)$ can be safely used by P, even though the original security of P was only analyzed under the assumption that its key R is uniformly random.

Of course, good key derivation is generally impossible unless X has some amount of entropy k to begin with, where the "right" notion of entropy in this setting is *min-entropy*: a source X has min-entropy $\mathbf{H}_\infty(X) = k$ if for any $x \in \{0,1\}^n$ we must have $\Pr[X = x] \leq 2^{-k}$. We call such a distribution X over n-bits strings an (n,k)*-source*, and generally wish to design a KDF h which "works" for all such (n,k)-sources X. More formally, assuming P was δ-secure (against some class of attackers) with the uniform key $R \equiv U_m$, we would like to conclude that P is still δ'-secure (against nearly the same class of attackers) when using $R = h(X)$ instead. The two most important parameters are: (1) ensuring that the new security δ' is "as close as possible" to the original security δ, and (2) allowing the source entropy k to be "as close as possible" to the application's key length m. Minimizing this threshold k is very important in many practical situations. For example, in the setting of biometrics and physical randomness, many natural sources are believed to have very limited entropy, while in the setting of Diffie-Hellman key exchange reducing the size of the Diffie-Hellman group (which is roughly 2^k) results in substantial efficiency improvements. Additionally, we prefer to achieve *information-theoretic* security for our KDFs (we discuss "computational KDFs" in Section 1.2), so that the derived key can be used for arbitrary (information-theoretic and computational) applications P.

This discussion leads us to the following central question of our work: *Can one find reasonable application scenarios where one can design a* **provably-secure, information-theoretic** *KDF achieving "real security" $\delta' \approx \delta$ when $k \approx m$?* More precisely, for a given (class of) application(s) P,

(A) *What is the best (provably) achievable security δ' (call it δ^*) when $k = m$?*

(B) *What is the smallest (provable) entropy threshold k (call it k^*) to achieve security $\delta' = O(\delta)$?*

Ideally, we would like to get $\delta^* = \delta$ and $k^* = m$, and the question is how close one can come to these "ideal" bounds. In this work we will provide several positive and negative answers to our main question, including a general way to *nearly achieve the above "ideal" for all unpredictability applications*. But first we turn to what is known in the theory of key derivation.

Randomness Extractors. In theory, the cleanest way to design a general, information-theoretically secure KDF is by using so called (strong) *randomness extractors* [NZ96]. Such a (k,ε)-extractor Ext has the property that the output distribution $\mathsf{Ext}(X)$ is ε-statistically close to the uniform distribution U_m, which means that using $\mathsf{Ext}(X)$ as a key will degrade the original security δ of *any* application P by at most ε: $\delta' \leq \delta + \varepsilon$. However, the sound use of randomness extractors comes with two important caveats. The first caveat comes from the fact that no deterministic extractor Ext can work for all (n,k)-sources [CG89] when $k < n$, which means that extractors must be probabilistic, or "seeded". This by itself is not a big limitation, since the extracted randomness $\mathsf{Ext}(X;S)$ is ε-close to U_m even *conditioned on the seed S*, which means that the seed S can be reused and globally shared across many applications.[1] From our perspective, though, a more important limitation/caveat of randomness extractors comes from a non-trivial tradeoff between the min-entropy k and the security ε one can achieve to derive an m-bit key

[1] However, it does come with an important assumption that the source distribution X must be independent of the seed S. Although this assumption could be problematic in some situations, such as leakage-resilient cryptography (and has led to some interesting research [TV00, CDH$^+$00, KZ03, DRV12]), in many situations, such as the Diffie-Hellman key exchange or biometrics, the independence of the source and the seed could be naturally enforced/assumed.

$\mathsf{Ext}(X;S)$. The best randomness extractors, such as the one given by the famous Leftover Hash Lemma (LHL) [HILL99], can only achieve security $\varepsilon = \sqrt{2^{m-k}}$. This gives the following very general bound on δ' for *all* applications P:

$$\delta' \leq \delta_{\mathsf{ALL}} \overset{\text{def}}{=} \delta + \sqrt{2^{m-k}} \tag{1}$$

Translating this bound to answer our main questions (A) and (B) above, we see that $\delta^* = 1$ (no meaningful security is achieved when $k = m$) and min-entropy $k^* \geq m + 2\log(1/\delta) - O(1)$ is required to get $\delta' = O(\delta)$. For example, to derive a 128-bit key for a CBC-MAC with security $\delta \approx \delta' \approx 2^{-64}$, one needs $k \approx 256$ bits of min-entropy, and nothing is theoretically guaranteed when $k = 128$.

Of course, part of the reason why these provable bounds are "not too great" (compared both with the "ideal" bounds, as well as the "real" bounds we will achieve shortly) is their generality: extractors work for *all* (n, k)-sources X and *all* applications P. Unfortunately, Radhakrishnan and Ta-shma [RTS00] showed that in this level of generality nothing better is possible: any (k, ε)-extractor must have $k \geq m + 2\log(1/\varepsilon)$ (we will refer to this as the "RT-bound"). This implies that for any candidate m-bit extractor Ext there exists some application P, some (possibly *inefficiently samplable*) source X of min-entropy k and some (possibly *exponential time*) attacker A, such that $A(S)$ can break P keyed by $R = \mathsf{Ext}(X;S)$ with advantage $\sqrt{2^{m-k}}$.

Thus, there is hope that better results are possible if one restricts the type of applications P (e.g., unpredictability applications), sources X (e.g., efficiently samplable) or attackers A (e.g., polynomial-time) considered. We discuss such options below, stating what was known together with our new results.

1.1 Our Main Results

Efficiently Samplable Sources. One natural restriction is to require that the source X is efficiently sampleable. This restriction is known to be useful for relaxing the assumption that the source distribution X is independent of the seed S [TV00, DRV12], which was the first caveat in using randomness extractors. Unfortunately, it was not clear if efficient samplability of X helps with reducing the entropy loss $L = k - m$ below $2\log(1/\varepsilon)$. In fact, Dachman-Soled et al. [DGKM12] conjectured that this is indeed not the case when Ext is also efficient, naming this conjecture the "SRT assumption" (where SRT stands for "samplable RT").

SRT Assumption [DGKM12]: *For any efficient extractor* Ext *with* m*-bit output there exists an efficiently samplable (polynomial in* n*) distribution* X *of min-entropy* $k = m + 2\log(1/\varepsilon) - O(1)$ *and a (generally inefficient) distinguisher* D *which has at least an* ε*-advantage in distinguishing* $(S, R = \mathsf{Ext}(X;S))$ *from* $(S, R = U_m)$.

As our first result, we show that the SRT assumption is indeed (unfortunately) true, even *without* restricting the extractor Ext to be efficient.

Theorem 1.1. *(Informal) The SRT assumption is true for any (possibly inefficient) extractor* Ext*. Thus, efficiently samplability does not help to reduce the entropy loss of extractors below* $2\log(1/\varepsilon)$*.*

Square-Friendly Applications. The next natural restriction is to limit the class of applications P in question. Perhaps, for some such applications, one can argue that the derived key $R = h_s(X)$ is still "good enough" for P despite *not* being statistically close to U_m (given s). This approach was recently pioneered by Barak et al [BDK+11], and then further extended and generalized by Dodis et al. [DRV12, DY13]. In these works the authors defined a special class of cryptographic applications, called *square-friendly*, where the pessimistic RT-bound can be provably improved. Intuitively, while any traditional application P demands that the expectation (over the uniform distribution $r \leftarrow U_m$) of the attacker's advantage $f(r)$ on key r is at most δ, square-friendly applications additionally require that the expected value of $f(r)^2$ is also bounded by δ. The works of [BDK+11, DY13] then showed that the class of square-friendly applications includes *all unpredictability applications* (signatures, MACs, one-way functions, etc.), and *some, but not all, indistinguishability applications* (including chosen plaintext attack secure encryption, weak pseudorandom functions and others). [2] Additionally, for all such square-friendly applications P, it was shown that universal (and thus also the stronger pairwise independent) hash functions $\{h_s\}$ yield the following improved bound on the security δ' of the derived key $R = h_s(X)$:

$$\delta' \le \delta_{\mathsf{SQF}} \overset{\text{def}}{=} \delta + \sqrt{\delta \cdot 2^{m-k}} \tag{2}$$

This provable (and still relatively general!) bound lies somewhere in between the "ideal" bounds and the fully generic bound (1): in particular, for the first time we get a meaningful security $\delta^* \approx \sqrt{\delta}$ when $k = m$ (giving non-trivial answer to Question (A)), or, alternatively, we get full security $\delta' = O(\delta)$ provided $k^* \ge m + \log(1/\delta)$ (giving much improved answer to Question (B) than the bound $k^* \ge k + 2\log(1/\delta)$ derived by using standard extractors). For example, to derive a 128-bit key for a CBC-MAC having ideal security $\delta = 2^{-64}$, we can either settle for much lower security $\delta' \approx 2^{-32}$ from entropy $k = 128$, or get full security $\delta' \approx 2^{-64}$ from entropy $k = 192$.

Given these non-trivial improvements, one can wonder if further improvements (for square-friendly applications) are still possible. As a simple (negative) result, we show that the bound in Equation (2) cannot be improved in general for *all* square-friendly applications. Interestingly, the proof of this result uses the proof of Theorem 1.1 to produce the desired source X for the counter-example.

Theorem 1.2. *(Informal) There exists a δ-square friendly application P with an m-bit key such that for any family $\mathcal{H} = \{h_s\}$ of m-bit key derivation functions there exists (even efficiently samplable) (n, k)-source X and a (generally inefficient) distinguisher D such that $D(S)$ has at least $\delta' = \Omega(\sqrt{\delta \cdot 2^{m-k}})$ advantage in breaking P with the derived key $R = h_S(X)$ (for random seed S).*

Hence, to improve the parameters in Equation (2) and still have information-theoretic security, we must place more restrictions on the class of applications P we consider.

Unpredictability Applications. This brings us to our main (positive) result: we get improved information-theoretic key derivation for *all unpredictability applications* (which includes MACs, signatures, one-way functions, identification schemes, etc.; see Footnote 2).

Theorem 1.3. *(Main Result; Informal) Assume P is any unpredictability application which is δ-secure with a uniform m-bit key against some class of attackers $\mathcal{C}$. Then, there is an efficient family of hash functions $\mathcal{H} = \{h_s : \{0,1\}^n \to \{0,1\}^m\}$, such that for any (n, k)-source X, the application P with the derived key $R = h_S(X)$ (for random public seed S) is δ'-secure against class $\mathcal{C}$, where:*

$$\delta' = O\left(1 + \log(1/\delta) \cdot 2^{m-k}\right) \delta. \tag{3}$$

In particular, we get the following nearly optimal answers to Questions (A) and (B):

- *With entropy $k = m$, we get security $\delta^* = (1 + \log(1/\delta))\delta$ (answering Question (A)).*
- *To get security $\delta' \le 3\delta$, we only need entropy $k^* = m + \operatorname{loglog}(1/\delta) + 4$ (answering Question (B)).*

In fact, our basic KDF hash family $\mathcal{H}$ is simply a t-wise independent hash function where $t = O(\log(1/\delta))$. Hence, by using higher than pairwise independence (which was enough for weaker security given by Equations (1) and (2)), we get a largely improved entropy loss: $\operatorname{loglog}(1/\delta)$ instead of $\log(1/\delta)$.

As we can see, the *provable* bounds above nearly match the ideal bounds $\delta^* = \delta$ and $k^* = m$ and provide a vast improvement over what was known previously. For example, to derive a 128-bit key for a CBC-MAC having ideal security $\delta = 2^{-64}$ (so that $\operatorname{loglog}(1/\delta) = 6$), we can either have excellent security $\delta' \le 2^{-57.9}$ starting with minimal entropy $k = 128$, or get essentially full security $\delta' \le 2^{-62.4}$ with only slightly higher entropy $k = 138$. Thus, for the first time we obtained an efficient, *theoretically-sound* key

[2] Recall, in indistinguishability applications the goal of the attack is to win a game with probability noticeably greater than 1/2; in contrast, for unpredictability applications the goal of the attacker is to win with only non-negligible probability.

derivation scheme which nearly matches "dream" parameters $k^* = m$ and $\delta^* = \delta$. Alternatively, as we discuss in Section 1.2, for the first time we can offer a provably-secure *alternative* to the existing practice of using cryptographic hash functions modeled as a random oracle for KDFs, and achieve nearly optimal parameters.

Unpredictability Extractors and Condensers. To better understand the proof of Theorem 1.3, it is helpful to abstract the notion of an *unpredictability extractor* UExt which we define in this work. Recall, standard (k, ε)-extractors ε-fool any distinguisher $D(R, S)$ trying to distinguish $R = \mathsf{Ext}(X; S)$ from R being uniform. In contrast, when dealing with δ-secure unpredictability applications, we only care about "fooling" so called δ-distinguishers D: these are distinguishers s.t. $\Pr[D(U_m, S) = 1] \leq \delta$, which directly corresponds to the emulation of P's security experiment between the "actual attacker" A and the challenger C. Thus, we define (k, δ, δ')-*unpredictability extractors* as having the property that $\Pr[D(\mathsf{UExt}(X; S), S) = 1] \leq \delta'$ for any δ-distinguisher D.[3] With this cleaner notion in mind, our main Theorem 1.3 can be equivalently restated as follows:

Theorem 1.4. *(Main Result; Restated) A family* $\mathcal{H} = \{h_s : \{0,1\}^n \to \{0,1\}^m\}$ *which is* $O(\log(1/\delta))$*-wise independent defines a* $(k, \delta, O(1 + \log(1/\delta) \cdot 2^{m-k})\delta)$*-unpredictability extractor* $\mathsf{UExt}(x; s) = h_s(x)$*.*

In turn, we observe that unpredictability extractors are closely connected to the related notion of a *randomness condenser* [RR99, RSW06]: such a (k, ℓ, ε)-condenser $\mathsf{Cond} : \{0,1\}^n \to \{0,1\}^m$ has the property that the output distribution $\mathsf{Cond}(X; S)$ is ε-close (even given the seed S) to some distribution Y s.t. the conditional min-entropy $\mathbf{H}_\infty(Y|S) \geq m - \ell$ whenever $\mathbf{H}_\infty(X) \geq k$. In particular, instead of requiring the output to be close to uniform, we require it to be close to having almost full entropy, with some small "gap" ℓ. While $\ell = 0$ gives back the definition of (k, ε)-extractors, permitting a small non-zero "entropy gap" ℓ has recently found important applications for key derivation [BDK+11, DRV12, DY13]. In particular, it is easy to see that a (k, ℓ, ε)-condenser is also a $(k, \delta, \varepsilon + \delta \cdot 2^\ell)$-unpredictability extractor. Thus, to show Theorem 1.4 it suffices to show that $O(\log(1/\delta))$-wise independent hashing gives a (k, ℓ, δ)-condenser, where $\ell \approx \operatorname{loglog}(1/\delta)$.

Theorem 1.5. *(Informal) A family* $\mathcal{H} = \{h_s : \{0,1\}^n \to \{0,1\}^m\}$ *of* $O(\log(1/\delta))$*-wise independent hash functions defines a* (k, ℓ, δ)*-condenser* $\mathsf{Cond}(x; s) = h_s(x)$ *for either of the following settings:*

- No Entropy Loss*: min-entropy* $k = m$ *and entropy gap* $\ell = \operatorname{loglog}(1/\delta)$*.*
- Constant Entropy Gap*: min-entropy* $k = m + \operatorname{loglog}(1/\delta) + O(1)$ *and entropy gap* $\ell = 1$*.*

It is instructive to compare this result with the RT-bound for (k, δ)-extractors: to have no entropy gap $\ell = 0$ requires us to start with entropy $k \geq m + 2\log(1/\delta)$. However, already 1-bit entropy gap $\ell = 1$ allows us to get away with $k = m + \operatorname{loglog}(1/\delta)$, while further increasing the gap to $\ell = \operatorname{loglog}(1/\delta)$ results in no entropy loss $k = m$.

Balls and Bins, Max-Load and Balanced Hashing. Finally, to prove Theorem 1.5 (and, thus, Theorem 1.4 and Theorem 1.3) we further reduce the problem of condensers to a very simple balls-and-bins problem. Indeed, we can think of our (k, ℓ, δ)-condenser as a way to hash 2^k items (out of a universe of size 2^n) into 2^m bins, so that the *load* (number of items per bin) is not too much larger than the expected 2^{k-m} for "most" of the bins. More concretely, it boils down to analyzing a version of average-load: if we choose a random item (and a random hash function from the family) then the probability that the item lands in a bin with more than $2^\ell(2^{k-m})$ items should be at most ε. We use Chernoff-type bounds for limited independence [Sie89, BR94] to analyze this version of average load when the hash function is $O(\log 1/\delta)$-independent.

Optimizing Seed Length. The description length d of our $O(\log(1/\delta))$-wise independent KDF h_s is $d = O(n \log(1/\delta))$ bits, which is much larger than that needed by universal hashing for standard

[3] This notion can also be viewed as "one-sided" slice extractors [RTS00]. Unlike this work, though, the authors of [RTS00] did not use slice extractors as an interesting primitive by itself, and did not offer any constructions of such extractors.

extractors. We adapt the elegant "gradual increase of independence" technique of Celis et al. [CRSW11] to reduce the seed length to nearly linear: $d = O(n \log k)$ (e.g., for $k = 128$ and $\delta = 2^{-64}$ this reduces the seed length from $128n$ to roughly $7n$ bits). It is an interesting open problem if the seed length can be reduced even further (and we show non-constructively that the answer is positive).

1.2 Computational Extractors

So far we considered information-theoretic techniques for designing theoretically-sound KDFs. Of course, given the importance of the problem, it is also natural to see if better parameters can be obtained when we assume that the attacker A is *computationally bounded*. We restrict our attention to the study of *computational extractors* [DGH$^+$04, Kra10, DGKM12] Ext, whose output $R = \mathsf{Ext}(X; S)$ looks *pseudo-random* to D (given S) for any *efficiently samplable* (n, k)-source X, which would suffice for our KDF goals if very strong results were possible for such extractors.

Unfortunately, while not ruling out the usefulness of computational extractors, we point out the following three negative results: (1) even "heuristic" computational computational extractors do not appear to beat the information-theoretic bound $k^* \geq m$ (which we managed to nearly match for all unpredictability applications); (2) existing "provably-secure" computational extractors do not appear to offer any improvement to our information-theoretic KDFs, when dealing with the most challenging "low entropy regime" (when k is roughly equal to the security parameter); (3) even for "medium-to-high entropy regimes", computational extractors beating the RT-bound require one-way functions. We expand on these results below.

Heuristic Extractors. In practice, one would typically use so called "cryptographic hash function" h, such as SHA or MD5, for key derivation (or as a computational extractor). As discussed in detail by [DGH$^+$04, Kra10, DRV12], there are several important reasons for this choice. From the perspective of this work, we will focus on the arguably the most important such reason — the common belief that cryptographic hash functions achieve excellent security $\delta' \approx \delta$ already when $k \approx m$. This can be easily *justified in the random oracle model*; assuming the KDF h is a random oracle which can be evaluated on at most q points (where q is the upper bound of the attacker's running time), one can upper bound $\delta' \leq \delta + q/2^k$, where $q/2^k$ is the probability the attacker evaluates $h(X)$. In turn, for most natural computationally-secure applications, in time q the attacker can also test about q out of 2^m possible m-bit keys, and hence achieve advantage $q/2^m$. This means that the ideal security δ of P cannot be lower than $q/2^m$, implying $q \leq \delta \cdot 2^m$. Plugging this bound on q in the bound of $\delta' \leq \delta + q/2^k$ above, we get that using a random oracle (RO) as a computational extractor/KDF achieves real security

$$\delta' \leq \delta_{\mathsf{RO}} \stackrel{\text{def}}{=} \delta + \delta \cdot 2^{m-k} \tag{4}$$

Although this heuristic bound is indeed quite amazing (e.g., $\delta' \leq 2\delta$ even when $k = m$, meaning that $\delta^* = 2\delta$ and $k^* = m$), and, unsurprisingly, beats our provably-secure, information-theoretic bounds, it still requires $k^* \geq m$. So we are not that far off, especially given our nearly matching bound for all unpredictability applications.[4]

And, of course, as with any analysis in the random oracle model [CGH98], the bound above is ultimately a heuristic. Moreover, as was pointed out by [DGH$^+$04, Kra10], existing hash functions, such as SHA and MD5, are far from ideal, since they use a highly structured Merkle-Damgard mode of operation when processing long inputs. In particular, the provable "extraction bounds" [DGH$^+$04] one gets when taking this structure into account are nowhere close to the amazing bound in (4), even under the generous assumption that the "compression function" f of h is "ideal".

Extract-then-Expand Approach. Turning to provable constructions, one very natural way to build computational extractors is the folklore *extract-then-expand* approach (recently explored in more detail

[4] Also, unlike our bound in Equation (3), one cannot apply the heuristic bound from Equation (4) to derive a key for an *information-theoretically* secure MAC.

by [Kra10, DGKM12]). The idea is to define $\mathsf{Ext}(X;S) = \mathsf{Prg}(\mathsf{Ext}'(X;S))$, where $\mathsf{Prg} : \{0,1\}^{m'} \to \{0,1\}^m$ is a computationally $(t, \delta_{\mathsf{PRG}})$-secure pseudorandom generator (PRG), and Ext' is an information-theoretic (k, ε)-extractor with an m'-bit output. It is clear that the resulting computational extractor has has security $\delta_{\mathsf{PRG}} + \varepsilon$, which means that $R = \mathsf{Ext}(X;S)$ can be used in any computationally (t, δ)-secure application P, and result in (t, δ')-security, where $\delta' \leq \delta + \varepsilon + \delta_{\mathsf{PRG}}$. In particular, it is tempting to set $\delta_{\mathsf{PRG}} \approx \varepsilon \approx \delta$, which gives $\delta' = O(\delta)$, and ask what is the smallest entropy threshold for k where such setting of parameters is possible. In other words, how good is the extract-then-expand approach for answering our Question (B)?

Unfortunately, we show that the resulting parameters must be poor, at least for the low-entropy settings we care about. Indeed, since the best information-theoretic security δ for the extractor Ext' is $\delta = \sqrt{2^{k-m'}}$ [RTS00], we get that the best value of k we can hope for is $k = m' + 2\log(1/\delta)$, where m' is the smallest possible seed length for a (t, δ)-secure PRG. However, it is well known (e.g., see [DTT10]) than any non-trivial (m', δ)-secure PRG with an m'-bit seed must have seed length $m' > 2\log(1/\delta)$. This gives a lower bound $k > 4\log(1/\delta)$ even for linear-time distinguishers (and the bound actually gets worse when t grows). For example, if $\delta = 2^{-64}$, we get $k > 256$, which is already worse that the naive bound we directly got from an information-theoretic secure extractor when $m = 128$ (see Equation (1)). Indeed, in this case the PRG itself must have a longer seed $m' > 128$ than the derived 128-bit key we are looking for! Thus, although the extract-then-expand approach is indeed useful for medium-to-high rage values of k (e.g., $k \gg 256$), it does not appear to be of any use for the more important low-entropy (e.g., $k < 256$) scenarios.

Indeed, the best currently known computational extractor [DY12] closely follows the information-theoretic techniques developed for square-friendly applications [BDK$^+$11], by building a square-friendly computational KDF. (Interestingly, the final construction resembles a "dual" of the extract-then-expand approach, and could be called "expand-then-extract".) It achieves $k \geq m + 2\log(1/\delta) - \log(1/\delta_{\mathsf{PRG}})$, where δ_{PRG} is the security of the given PRG. In practical terms, it could work when $k \approx 192$, which is still not as good as what we would expect from heuristic extractors (which appear to work already when $k \approx 128$).

Beating RT-bound Implies OWFs. Despite provably failing for low-entropy regimes, the extract-then-expand approach at least showed that computational assumptions help in "beating" the RT-bound $k \geq m + 2\log(1/\varepsilon)$ for any (k, ε)-secure extractor, as applying the PRG allows one to increase m essentially arbitrarily (while keeping $k = m' + 2\log(1/\varepsilon)$). Motivated by this, Dachman-Soled et al. [DGKM12] asked an interesting theoretical question if the existence of one-way functions (and, hence, PRGs [HILL99]) is *essential* for beating the RT-bound for unconditional extractors. They also managed to give an affirmative answer to this question *under the SRT assumption* mentioned earlier. Since we unconditionally prove the SRT assumption (see Theorem 1.1), we immediately get the following Corollary, removing the conditional clause from the result of [DGKM12]:

Theorem 1.6. *(Informal) If* Ext *is an efficient* (k, ε)*-computational extractor with an* m*-bit output, where* $m > k - 2\log(1/\varepsilon) - O(1)$*, then one-way functions (and, hence, PRGs) exist.*

2 Preliminaries

We recap some definitions and results from probability theory. Let X, Y be random variables with supports S_X, S_Y, respectively. We define their *statistical difference* as

$$\Delta(X,Y) = \frac{1}{2} \sum_{u \in S_X \cup S_Y} \left| \Pr[X = u] - \Pr[Y = u] \right|.$$

We write $X \approx_\varepsilon Y$ and say that X and Y are ε-statistically close to denote that $\Delta(X,Y) \leq \varepsilon$.

The *min-entropy* of a random variable X is $\mathbf{H}_\infty(X) \stackrel{\text{def}}{=} -\log(\max_x \Pr[X = x])$, and measures the "best guess" for X. The *conditional min-entropy* is defined by $\mathbf{H}_\infty(X|Y = y) \stackrel{\text{def}}{=} -\log(\max_x \Pr[X = x|Y = y])$. Following Dodis et al. [DORS08], we define the *average* conditional min-entropy:

$$\mathbf{H}_\infty(X|Y) \stackrel{\text{def}}{=} -\log\left(\mathop{\mathbb{E}}_{y \leftarrow Y} \left[\ \max_x \Pr[X = x|Y = y] \ \right] \right) = -\log\left(\mathop{\mathbb{E}}_{y \leftarrow Y} \left[2^{-\mathbf{H}_\infty(X|Y=y)} \right] \right).$$

Above, and throughout the paper, all "log" terms are base 2, unless indicated otherwise. We say that a random variable X is an (n, k)*-source* if the support of X is $\{0,1\}^n$ and the entropy of X is $\mathbf{H}_\infty(X) \geq k$.

Lemma 2.1 (A Tail Inequality [BR94])**.** *Let $q \geq 4$ be an even integer. Suppose $X_1, \ldots, X_n$ are q-wise independent random variables taking values in $[0, 1]$. Let $X := X_1 + \cdots + X_n$ and define $\mu := \mathbf{E}[X]$ be the expectation of the sum. Then, for any $A > 0$, $\Pr[|X - \mu| \geq A] \leq 8 \left(\frac{q\mu + q^2}{A^2}\right)^{q/2}$. In particular, for any $\alpha > 0$ and $\mu > q$, we have $\Pr[X \geq (1 + \alpha)\mu] \leq 8 \left(\frac{2q}{\alpha^2 \mu}\right)^{q/2}$.*

3 Defining Extractors for Unpredictability Applications

We start by abstracting out the notion of general unpredictability applications (e.g., one-way functions, signatures, message authentication codes, soundness of an argument, etc.) as follows. The security of such all such primitives is abstractly defined via a security game P which requires that, for all attackers $\mathcal{A}$ (in some complexity class), $\Pr[P^{\mathcal{A}}(U) = 1] \leq \delta$ where $P^{\mathcal{A}}(U)$ denotes the execution of the game P with the attacker $\mathcal{A}$, where P uses the uniform randomness U.[5] For example, in the case of a message-authentication code (MAC), the value U is used as secret key for the MAC scheme and the game P is the standard "existential unforgeability against chosen-message attack game" for the given MAC. Next, we will assume that δ is some small (e.g., negligible) value, and ask the question if we can still use the primitive P if, instead of a uniformly random U, we only have some arbitrary (n, k)-source X?

To formally answer this question, we would like a function $\mathsf{UExt} : \{0,1\}^n \times \{0,1\}^d \to \{0,1\}^m$ (seeded unpredictability extractor) such that, for all attackers $\mathcal{A}$ (in some complexity class), $\Pr[P^{\mathcal{A}(S)}(\mathsf{UExt}(X; S)) = 1] \leq \varepsilon$, where the seed S is chosen uniformly at random and given to the attacker, and ε is not much larger than δ. Since we do not wish to assume much about the application P or the attacker $\mathcal{A}$, we can roll them up into a unified adversarial "distinguisher" defined by $D(R, S) := P^{\mathcal{A}(S)}(R)$. By definition, if $R = U$ is random and independent of S, then $\Pr[D(U, S) = 1] = \Pr[P^{\mathcal{A}(S)}(U) = 1] \leq \delta$. On the other hand, we need to ensure that $\Pr[P^{\mathcal{A}(S)}(\mathsf{UExt}(X; S)) = 1] = \Pr[D(\mathsf{UExt}(X; S), S) = 1] \leq \varepsilon$ for some ε which is not much larger than δ. This motivates the following definition of unpredictability extractor which ensures that the above holds for *all* distinguishers D.

Definition 3.1 (UExtract)**.** *We say that a function $D : \{0,1\}^m \times \{0,1\}^d \to \{0,1\}$ is a δ-distinguisher if $\Pr[D(U, S) = 1] \leq \delta$ where (U, S) is uniform over $\{0,1\}^m \times \{0,1\}^d$. A function $\mathsf{UExt} : \{0,1\}^n \times \{0,1\}^d \to \{0,1\}^m$ is a (k, δ, ε)-*unpredictability extractor (UExtract) *if for any (n, k)-source X and any δ-distinguisher D, we have $\Pr[D(\mathsf{UExt}(X; S), S) = 1] \leq \varepsilon$ where S is uniform over $\{0,1\}^d$.*

Notice that the above definition is essentially the same as that of standard extractors except that: (1) we require that the distinguisher has a "small" probability δ of outputting 1 on the uniform distribution, and (2) we only require a one-sided error that the probability of outputting 1 does not increase too much. A similar notion was also proposed by [RTS00] and called a "slice extractor".

Toward the goal of understanding unpredictability extractors, we show tight connections between the above definition and two seemingly unrelated notions. Firstly, we define "condensers for min-entropy" and show that the they yield "good" unpredictability extractors. Second, we define something called "balanced hash functions" and show that they yield good condensers, and therefore also good unpredictability

[5] In contrast, for *indistinguishability* games we typically require that $\Pr[P^{\mathcal{A}}(U) = 1] \leq \frac{1}{2} + \delta$.

extractors. Lastly, we show that unpredictability extractors also yield balanced hash functions, meaning that all three notions are essentially equivalent up to a small gap in parameters.

Definition 3.2 (Condenser)**.** *A function* $\mathsf{Cond} : \{0,1\}^n \times \{0,1\}^d \to \{0,1\}^m$ *is a* (k,ℓ,ε)*-condenser if for all* (n,k)*-sources* X*, and a uniformly random and independent seed* S *over* $\{0,1\}^d$*, the joint distribution* $(S, \mathsf{Cond}(X;S))$ *is* ε*-statistically-close to some joint distribution* (S,Y) *such that, for all* $s \in \{0,1\}^d$*,* $\mathbf{H}_\infty(Y|S=s) \geq m-\ell$*.*

First, we show that condensers already give us unpredictability extractors. This is similar in spirit to a lemma of [DY13] which shows that, if we use a key with a small entropy gap for an unpredictability application, the security of the application is only reduced by at most a small amount. One difference that prevents us from using that lemma directly is that we need to explicitly include the seed of the condenser and the dependence between the condenser output and the seed.

Lemma 3.3 (Condenser ⇒ UExtract)**.** *Any* (k,ℓ,ε)*-condenser is a* (k,δ,ε^*)*-UExtract where* $\varepsilon^* = \varepsilon + 2^\ell\delta$*.*

Proof. Let $\mathsf{Cond} : \{0,1\}^n \times \{0,1\}^d \to \{0,1\}^m$ be a (k,ℓ,ε)-condenser and let X be an (n,k)-source. Let S be uniform over $\{0,1\}^d$, so that, by definition, there is a joint distribution (S,Y) which has statistical distance at most ε from $(S,\mathsf{Cond}(X;S))$ such that $\mathbf{H}_\infty(Y|S=s) \geq m-\ell$ for all $s \in \{0,1\}^d$. Therefore, for any δ-distinguisher D, we have

$$\begin{aligned}
\Pr[D(\mathsf{Cond}(X;S),S)=1] &\leq \varepsilon + \Pr[D(Y,S)=1] \\
&= \varepsilon + \sum_{y,s} \Pr[S=s]\Pr[Y=y|S=s]\Pr[D(y,s)=1] \\
&\leq \varepsilon + \sum_{y,s} 2^{-d}2^{-\mathbf{H}_\infty(Y|S=s)}\Pr[D(y,s)=1] \\
&\leq \varepsilon + 2^\ell \sum_{y,s} 2^{-(m+d)}\Pr[D(y,s)=1] \leq \varepsilon + 2^\ell\delta.
\end{aligned}$$

□

Definition 3.4 (Balanced Hashing)**.** *Let* $h := \{h_s : \{0,1\}^n \to \{0,1\}^m\}_{s\in\{0,1\}^d}$ *be a hash function family. For* $\mathcal{X} \subseteq \{0,1\}^n, s \in \{0,1\}^d, x \in \mathcal{X}$ *we define* $\mathsf{Load}_{\mathcal{X}}(x,s) := |\{x' \in \mathcal{X} : h_s(x') = h_s(x)\}|$*.*[6] *We say that the family* h *is* (k,t,ε)*-balanced if for all* $\mathcal{X} \subseteq \{0,1\}^n$ *of size* $|\mathcal{X}| = 2^k$*, we have*

$$\Pr\left[\mathsf{Load}_{\mathcal{X}}(X,S) > t2^{k-m}\ \right] \leq \varepsilon$$

where S, X *are uniformly random and independent over* $\{0,1\}^d, \mathcal{X}$ *respectively.*

Lemma 3.5 (Balanced ⇒ Condenser)**.** *Let* $\mathcal{H} := \{h_s : \{0,1\}^n \to \{0,1\}^m\}_{s\in\{0,1\}^d}$ *be a* (k,t,ε)*-balanced hash function family. Then the function* $\mathsf{Cond} : \{0,1\}^n \times \{0,1\}^d \to \{0,1\}^m$ *defined by* $\mathsf{Cond}(x;s) = h_s(x)$ *is a* (k,ℓ,ε)*-condenser for* $\ell = \log(t)$*.*

Proof. Without loss of generality, we can restrict ourselves to showing that Cond satisfies the condenser definition for every *flat source* X which is uniformly random over some subset $\mathcal{X} \subseteq \{0,1\}^n$, $|\mathcal{X}| = 2^k$. Let us take such a source X over the set $\mathcal{X}$, and define a *modified* hash family $\tilde{h} = \{\tilde{h}_s : \mathcal{X} \to \{0,1\}^m\}_{s\in\{0,1\}^d}$ which depends on $\mathcal{X}$ and essentially "re-balances" h on the set $\mathcal{X}$. In particular, for every pair (s,x) such that $\mathsf{Load}^h_{\mathcal{X}}(x,s) \leq t2^{k-m}$ we set $\tilde{h}_s(x) := h_s(x)$, and for all other pairs (s,x) we define $\tilde{h}_s(x)$ in such a way that $\mathsf{Load}^{\tilde{h}}_{\mathcal{X}}(x,s) \leq t2^{k-m}$ (the super-script is used to denote the hash function with respect to which we are computing the load). It is easy to see that this "re-balancing" is always possible. We

[6] Note that we allow $x' = x$ and so $\mathsf{Load}_{\mathcal{X}}(x,s) \geq 1$.

use the re-balanced hash function $\tilde{h}$ to define a joint distribution (S, Y) by choosing S uniformly at random over $\{0,1\}^d$, choosing X uniformly/independently over $\mathcal{X}$ and setting $Y = \tilde{h}_S(X)$. It's easy to check that the statistical distance between $(S, \mathsf{Cond}(X;S))$ and (S, Y) is at most $\Pr[h_S(X) \neq \tilde{h}_S(X)] \leq \Pr[\mathsf{Load}^h_{\mathcal{X}}(X, S) > t2^{k-m}] \leq \varepsilon$. Furthermore, for every $s \in \{0,1\}^d$, we have:

$$\begin{aligned}\mathbf{H}_\infty(Y|S=s) &= -\log(\max_y \Pr[Y = y|S = s]) \\ &= -\log(\max_y \Pr[X \in \tilde{h}_s^{-1}(y)]) \geq -\log(t2^{k-m}/2^k) = m - \log t.\end{aligned}$$

Therefore Cond is a $(k, \ell = \log t, \varepsilon)$-condenser. □

Lemma 3.6 (UExtract ⇒ Balanced). *Let* $\mathsf{UExt} : \{0,1\}^n \times \{0,1\}^d \to \{0,1\}^m$ *be a* (k, δ, ε)*-UExtractor for some,* $\varepsilon > \delta > 0$*. Then the hash family* $\mathcal{H} = \{h_s : \{0,1\}^n \to \{0,1\}^m\}_{s \in \{0,1\}^d}$ *defined by* $h_s(x) = \mathsf{UExt}(x; s)$ *is* $(k, \varepsilon/\delta, \varepsilon)$*-balanced.*

Proof. Let $t = \varepsilon/\delta$ and assume that $\mathcal{H}$ is *not* (k, t, ε)-balanced. Then there exists some set $\mathcal{X} \subseteq \{0,1\}^n$, $|\mathcal{X}| = 2^k$ such that $\hat{\varepsilon} := \Pr[\mathsf{Load}_{\mathcal{X}}(X, S) > t2^{k-m}] > \varepsilon$ where X is uniform over $\mathcal{X}$ and S is uniform over $\{0,1\}^d$. Let $\mathcal{X}_s \subseteq \mathcal{X}$ be defined by $\mathcal{X}_s := \{x \in \mathcal{X} \ : \ \mathsf{Load}_{\mathcal{X}}(x, s) > t2^{k-m}\}$ and let $\varepsilon_s \stackrel{\text{def}}{=} |\mathcal{X}_s|/2^k$. By definition $\hat{\varepsilon} = \sum_s 2^{-d}\varepsilon_s$. Define $\mathcal{Y}_s \subseteq \{0,1\}^m$ via $\mathcal{Y}_s := h_s(\mathcal{X}_s)$. Now by definition, each $y \in \mathcal{Y}_s$ has at least $t2^{k-m}$ pre-images in $\mathcal{X}_s$ and therefore $\delta_s \stackrel{\text{def}}{=} |\mathcal{Y}_s|/2^m \leq |\mathcal{X}_s|/(t2^{k-m}2^m) \leq \varepsilon_s/t$ and $\delta := \sum_s 2^{-d}\delta_s \leq \hat{\varepsilon}/t$.

Define the distinguisher D via $D(y, s) = 1$ iff $y \in \mathcal{Y}_s$. Then D is a δ-distinguisher for $\delta \leq \hat{\varepsilon}/t \leq \varepsilon/t$ but $\Pr[D(h_S(X), S) = 1] = \hat{\varepsilon} \geq \varepsilon$. Therefore, UExt is not a $(k, \varepsilon/t, \varepsilon)$-UExtractor. □

Summary. Taking all of the above lemmata together, we see that they are close to tight. In particular, for any $\varepsilon > \delta > 0$, we get:

$$(k, \delta, \varepsilon)\text{-UExt} \overset{Lem.3.6}{\Rightarrow} (k, \varepsilon/\delta, \varepsilon)\text{-Balanced} \overset{Lem.3.5}{\Rightarrow} (k, \log(\varepsilon/\delta), \varepsilon)\text{-Condenser} \overset{Lem.3.3}{\Rightarrow} (k, \delta, 2\varepsilon)\text{-UExt}$$

4 Constructing Unpredictability Extractors

Given the connections established in the previous section, we have paved the road for constructing unpredictability extractors via balanced hash functions, which is a seemingly simpler property to analyze. Indeed, we will give relatively simple lemmas showing that "sufficiently independent" hash functions are balanced. This will lead to the following parameters (restating Theorem 1.3 from the introduction):

Theorem 4.1. *There exists an efficient* (k, δ, ε)*-unpredictability extractor* $\mathsf{UExt} : \{0,1\}^n \times \{0,1\}^d \to \{0,1\}^m$ *for the following parameters:*

1. *When* $k = m$ *(no entropy loss), we get* $\varepsilon = (1 + \log(1/\delta))\delta$*.*
2. *When* $k \geq m + \log\log 1/\delta + 4$*, we get* $\varepsilon = 3\delta$*.*
3. *In general,* $\varepsilon = O(1 + 2^{m-k}\log(1/\delta))\delta$*.*

In all cases, the function UExt *is simply a* $(\log(1/\delta) + O(1))$*-wise independent hash function and the seed length is* $d = O(n\log(1/\delta))$*.*

Although these constructions may already be practical, the level of independence we will need is $O(\log 1/\delta)$, which will result in a large seed $O(n\log(1/\delta))$. We will show how to achieve similar parameters with a shorter seed $O(n \log k)$ in Section 4.2. We now proceed to prove all of the parts of Theorem 4.1 by constructing "good" balanced hash functions and using our connections between balanced hashing and unpredictability extractors from the previous section.

4.1 Sufficient Independence Provides Balance

First we start with a simple case where the output m is equal to the entropy k.

Lemma 4.2. *Let $\mathcal{H} := \{h_s : \{0,1\}^n \to \{0,1\}^k\}_{s\in\{0,1\}^d}$ be $(t+1)$-wise independent. Then it is (k, t, ε)-balanced where $\varepsilon \le \left(\frac{e}{t}\right)^t$ and e is the base of the natural logarithm.*

Proof. Fix any set $\mathcal{X} \subseteq \{0,1\}^n$ of size $|\mathcal{X}| = 2^k$. Let X be uniform over $\mathcal{X}$ and S be uniform/independent over $\{0,1\}^d$. Then

$$\begin{aligned}
\Pr[\mathsf{Load}_{\mathcal{X}}(X,S) > t] &\le \Pr[\ \exists \mathcal{C} \subseteq \mathcal{X}, |\mathcal{C}| = t\ \ \forall x' \in \mathcal{C}\ :\ h_S(x') = h_S(X) \wedge x' \neq X] \\
&\le \sum_{\mathcal{C}\subseteq\mathcal{X}, |\mathcal{C}|=t} \Pr[\forall x' \in \mathcal{C}\ :\ h_S(x') = h_S(X) \wedge x' \neq X] \\
&\le \binom{2^k}{t} 2^{-tk} \le \left(\frac{e2^k}{t}\right)^t 2^{-tk} \le \left(\frac{e}{t}\right)^t .
\end{aligned}$$

□

Corollary 4.3. *For any $0 < \varepsilon < 2^{-2e}$, any $\delta > 0$, a $(\lceil\log(1/\varepsilon)\rceil + 1)$-wise independent hash family $\mathcal{H} = \{h_s\ :\ \{0,1\}^n \to \{0,1\}^k\}_{s\in\{0,1\}^d}$ is:*

$$(k, \log(1/\varepsilon), \varepsilon)\text{-balanced}, \quad (k, \log\log(1/\varepsilon), \varepsilon)\text{-condenser}, \quad (k, \delta, \log(1/\varepsilon)\delta + \varepsilon)\text{-UExtractor.}$$

In particular, setting $\delta = \varepsilon$, it is a $(k, \delta, (1 + \log(1/\delta))\delta)$-UExtractor.

Proof. Set $t = \lceil\log(1/\varepsilon)\rceil$ in Lemma 4.2 and notice that $\left(\frac{e}{t}\right)^t \le 2^{-t} \le \varepsilon$ as long as $t \ge 2e$. □

This establishes part (1) of Theorem 4.1. Next we look at a more general case where k may be larger than m. This also covers the case $k = m$ but gets a somewhat weaker bound. It also requires a more complex tail bound for q-wise independent variables.

Lemma 4.4. *Let $\mathcal{H} := \{h_s : \{0,1\}^n \to \{0,1\}^m\}_{s\in\{0,1\}^d}$ be $(q+1)$-wise independent for some even q. Then, for any $\alpha > 0$, it is $(k, 1+\alpha, \varepsilon)$-balanced where $\varepsilon \le 8\left(\frac{q2^{k-m}+q^2}{(\alpha 2^{k-m}-1)^2}\right)^{q/2}$.*

Proof. Let $\mathcal{X} \subseteq \{0,1\}^n$ be a set of size $|\mathcal{X}| = 2^k$, X be uniform over $\mathcal{X}$, and S be uniform/independent over $\{0,1\}^d$. Define the indicator random variables $C(x^*, x)$ to be 1 if $h_S(x) = h_S(x^*)$ and 0 otherwise. Then:

$$\begin{aligned}
\Pr[\mathsf{Load}_{\mathcal{X}}(X,S) > (1+\alpha)2^{k-m}] &= \sum_{x^*\in\mathcal{X}} \Pr[X = x^*] \Pr[\mathsf{Load}_{\mathcal{X}}(x^*,S) > (1+\alpha)2^{k-m}] \\
&= 2^{-k} \sum_{x^*\in\mathcal{X}} \Pr\left[\sum_{x\in\mathcal{X}\setminus\{x^*\}} C(x^*,x) + 1 > (1+\alpha)2^{k-m}\right] \\
&\le 8\left(\frac{q2^{k-m}+q^2}{(\alpha 2^{k-m}-1)^2}\right)^{q/2}
\end{aligned}$$

Where the last line follows from the tail inequality Lemma 2.1 with the random variables $\{C(x^*,x)\}_{x\in\mathcal{X}\setminus\{x^*\}}$ which are q-wise independent and have expected value $\mu = \mathbb{E}[\sum_{x\in\mathcal{X}\setminus\{x^*\}} C(x^*,x)] = (2^k - 1)2^{-m} \le 2^{k-m}$, and by setting $A = (1+\alpha)2^{k-m} - 1 - \mu \ge \alpha 2^{k-m} - 1$; recall that $C(x^*, x^*)$ is always 1 and $C(x^*, x)$ for $x \neq x^*$ is 1 with probability 2^{-m}. □

Corollary 4.5. *For any $0 < \varepsilon < 2^{-5}$, $k \ge m + \log\log(1/\varepsilon) + 4$, a $(\lceil\log(1/\varepsilon)\rceil + 6)$-wise independent hash function family $\mathcal{H} = \{h_s\ :\ \{0,1\}^n \to \{0,1\}^m\}_{s\in\{0,1\}^d}$ is:*

$(k, 2, \varepsilon)$-balanced, $\quad (k, 1, \varepsilon)$-condenser, $\quad (k, \delta, 2\delta + \varepsilon)$-UExt for any $\delta > 0$.

In particular, setting $\delta = \varepsilon$, it is a $(k, \delta, 3\delta)$-UExt.

Proof. Set $\alpha := 1$ and choose $q \in (\log(1/\varepsilon) + 3, \log(1/\varepsilon) + 5)$ to be an even integer. Notice that $2^{k-m} \geq 16\log(1/\varepsilon) \geq 8(\log(1/\varepsilon) + 5) \geq 8q$ since $\log(1/\varepsilon) \geq 5$. Then we apply Lemma 4.4

$$8\left(\frac{q2^{k-m} + q^2}{(\alpha 2^{k-m} - 1)^2}\right)^{q/2} = 8\left(\frac{q(1 + q/2^{k-m})}{2^{k-m}(1 - 1/2^{k-m})^2}\right)^{q/2} \leq 8\left(\frac{2q}{2^{k-m}}\right)^{q/2} \leq \varepsilon.$$

□

The above corollary establishes part (2) of Theorem 4.1. The next corollary gives us a general bound which establishes part (3) of the theorem. Asymptotically it implies variants of Corollary 4.5 and Corollary 4.3, but with worse constants.

Corollary 4.6. *For any $\varepsilon > 0$ and $q := \lceil \log(1/\varepsilon) \rceil + 3$, a $(q+1)$-wise independent hash function family $\mathcal{H} = \{h_s : \{0,1\}^n \to \{0,1\}^m\}_{s \in \{0,1\}^d}$ is $(k, 1 + \alpha, \varepsilon)$-balanced for*

$$\alpha = 4\sqrt{q2^{m-k} + (q2^{m-k})^2} = O(2^{m-k}\log(1/\varepsilon) + 1).$$

By setting $\delta = \varepsilon$, a $(\log\frac{1}{\delta} + 4)-$wise independent hash function is a $(k, \delta, O(1 + 2^{m-k}\log\frac{1}{\delta})\delta)$-UExtactor.

Proof. The first part follows from Lemma 4.4 by noting that

$$8\left(\frac{q2^{k-m} + q^2}{(\alpha 2^{k-m} - 1)^2}\right)^{q/2} \leq 8\left(\frac{q2^{k-m} + q^2}{\frac{1}{4}(\alpha 2^{k-m})^2}\right)^{q/2} \leq 8\left(\frac{1}{4}\right)^{q/2} \leq \varepsilon.$$

For the second part, we can consider two cases. If $q2^{m-k} \leq 1$ then $\alpha \leq 4\sqrt{2}$ and we are done. Else, $\alpha \leq 4\sqrt{2}(q2^{m-k}) = 4\sqrt{2}(\log(1/\varepsilon) + 3)2^{m-k}$. □

4.2 Minimizing the Seed Length

In both of the above constructions (Corollary 4.3, Corollary 4.5), to get an (k, δ, ε)-UExtractor, we need a $O(\log(1/\varepsilon))$-wise independent hash function $h_s : \{0,1\}^n \to \{0,1\}^m$, which requires a seed-length $d = O(\log(1/\varepsilon) \cdot n)$. Since in many applications, we envision $\varepsilon \approx 2^{-k}$, this gives a seed $d = O(kn)$. We should contrast this with standard extractors constructed using universal hash functions (via the leftover-hash lemma), where the seed-length is $d = n$. We now show how to optimize the seed-length of UExtractors, first to $d = O(n \log k)$ and eventually to $d = O(k \log k)$. We adapt the technique of Celis et al. [CRSW11] which shows how to construct hash functions with a small seed that achieve essentially optimal "max-load" (e.g., minimize the hash value with the most items inside it). We show that a lightly modified analysis can also be used to show that such hash functions are "balanced" with essentially optimal parameters.

Almost Independence. We start by recalling the notion of q-wise δ-dependent hash functions.

Definition 4.7 ((Almost) Independent Hashing)**.** *A hash family $\mathcal{H}$: $\{h : \{0,1\}^n \to \{0,1\}^m\}_{s \in \{0,1\}^d}$ is q-wise δ-dependent if for any distinct $x_1, \ldots, x_q \in \{0,1\}^n$,*

$$(h_S(x_1), \ldots, h_S(x_q)) \approx_\delta (U_1, \ldots, U_q)$$

where S is uniformly random over $\{0,1\}^d$ and U_i are uniformly random/independent over $\{0,1\}^m$.

Such almost independent hash functions can be constructed using ε-biased distributions [NN93, AGHP92]. The following parameters are stated in [CRSW11].

Lemma 4.8. *For any integers n, ℓ, there exists a family of q-wise δ-dependent hash functions from n-bits to ℓ-bits with seed-length $d = O(n + \ell \cdot q + \log(1/\delta))$.*

We will also rely on the following tail-bound from [CRSW11].

Lemma 4.9 ([CRSW11], Lemma 2.2)**.** *Suppose that $X_1, \ldots, X_n$ are q-wise δ-dependent random variables taking values in $[0,1]$. Let $X := X_1 + \cdots + X_n$ and define $\mu := \mathbf{E}[X]$ be the expectation of the sum. Then, for any $\alpha > 0$, $\Pr[X \geq (1+\alpha)\mu] \leq 2\left(\frac{qn}{(\alpha\mu)^2}\right)^{q/2} + \delta\left(\frac{n}{\alpha\mu}\right)^q$.*

Construction. Our goal is to construct a hash function family $\mathcal{H} = \{h_s : \{0,1\}^n \to \{0,1\}^k\}_{s \in \{0,1\}^d}$ such that $\mathcal{H}$ is (k, t, ε)-balanced for some small $\varepsilon \approx 2^{-t}$. Assume that $n \geq k \geq t$. We will choose h_s to be a concatenation of several hash functions with gradually increasing levels of independence q_i and gradually decreasing output size ℓ_i while keeping the product $q_i \ell_i = O(t)$ essentially constant. More precisely, let $\mathcal{H}_1, \ldots, \mathcal{H}_r, \mathcal{H}_{r+1}$ be hash function families, where each family $\mathcal{H}_i = \{h_{s_i} : \{0,1\}^n \to \{0,1\}^{\ell_i}\}_{s_i \in \{0,1\}^{d_i}}$ is q_i-wise δ_i-dependent with the parameters q_i, ℓ_i and δ_i being chosen as follows:

- For $i = 1, \ldots, r$ (where r will be specified later), set ℓ_i so that $\sum_{j=1}^{i} \ell_i = \lfloor \left(1 - \left(\frac{3}{4}\right)^i\right) k \rfloor$. Note that this means $\ell_i = \frac{1}{4}(\frac{3}{4})^{i-1}k \pm 1$ and $k - \sum_{j=1}^{i} \ell_i = 3\ell_i \pm 4 = 4\ell_{i+1} \pm 5$.
- For $i = 1, \ldots, r$, set $q_i := 4\lceil t/\ell_i \rceil + 1$.
- Set r be the largest integer such that $\ell_r \geq \log t + 2 \log \log_{4/3} k + 7$. Note that $r \leq \log_{4/3} k = O(\log k)$.
- Set $\ell_{r+1} := k - \sum_{i=1}^{r} \ell_i$. This gives $\ell_{r+1} = O(\log t + \log \log k)$. Set $q_{r+1} = 4t + 1$
- For $i = 1, \ldots, r$, set $\delta_i := 2^{-18k}$ and set $\delta_{r+1} = 2^{-t\ell_{r+1} - 2t} = 2^{-O(k \log k)}$.

Let $\mathcal{H} := \mathcal{H}_1 \circ \ldots \circ \mathcal{H}_{r+1}$ meaning that $\mathcal{H} = \{h_s : \{0,1\}^n \to \{0,1\}^k\}_{s \in \{0,1\}^d}$ is defined by

$$h_s(x) := h_{s_1}(x) || \cdots || h_{s_{r+1}}(x)$$

where $s = (s_1, \ldots, s_r, s_{r+1})$ and $h_{s_i} \in \mathcal{H}_i$ and '$||$' denotes concatenation. Notice that, using the parameters of Lemma 4.8 for the function families $\mathcal{H}_i$, we can get the total seed-length to be $d = |s| = \sum_{i=1}^{r+1} d_i = O(n \log k)$, assuming $n \geq k \geq t$.

Theorem 4.10. *The above family $\mathcal{H} : \{h_s : \{0,1\}^n \to \{0,1\}^k\}_{s \in \{0,1\}^d}$ is $(k, t, 2^{-t})$-balanced for any*

$$n \geq k \geq t \geq \log \log_{4/3} k + 4 = \log \log k + O(1).$$

The seed length is $d = O(n \log k)$. In particular, $\mathcal{H}$ is also $(k, \log(t), 2^{-t})$-condenser and a $(k, \delta, t\delta + 2^{-t})$-UExtract for any $\delta > 0$.

We can also consider the family $\mathcal{H}' : \mathcal{H}_1 \circ \ldots \circ \mathcal{H}_r$, defined analogously to the above but excluding $\mathcal{H}_{r+1}$, so that $\mathcal{H}' = \{h_s : \{0,1\}^n \to \{0,1\}^m\}_{s \in \{0,1\}^{d'}}$ where $d' = \sum_{i=1}^{r} d_i$ and $m = k - \ell_{r+1} = k - O(\log t + \log \log k)$.

Theorem 4.11. *The above family $\mathcal{H}' : \{h_s : \{0,1\}^n \to \{0,1\}^m\}_{s \in \{0,1\}^{d'}}$ is $(k, (e+1), \varepsilon)$-balanced for any*

$$n \geq k \geq t \geq \log \log_{4/3} k + 4 = \log \log k + O(1), m = k - \ell_{r+1} = k - O(\log t + \log \log k)$$

with $\varepsilon = 2^{-t}$. The seed length is $d = O(n \log k)$. In particular, $\mathcal{H}$ is also $(k, \log(e+1), \varepsilon)$-condenser and a $(k, \delta, (e+1)\delta + \varepsilon)$-UExtract for any $\delta > 0$.

Proof of Theorem 4.10 and Theorem 4.11. We start with the proof of Theorem 4.10. Let us choose some arbitrary set $\mathcal{X} \subseteq \{0,1\}^n$, $|\mathcal{X}| = 2^k$ and some arbitrary $x \in \mathcal{X}$. For a seed $s = (s_1, \ldots, s_{r+1}) \leftarrow \{0,1\}^{d=\sum_i^{r+1} d_i}$ we will iteratively define $\mathcal{X}_0 = \mathcal{X} \setminus \{x\}$ and for $i > 0$, $\mathcal{X}_i = \{x' \in \mathcal{X}_{i-1} \ : \ h_{s_i}(x') = h_{s_i}(x)\}$. We start with the following lemma:

Lemma 4.12. *Let $\alpha = 1/r$ and assume that for some $i \in \{1, \ldots, r\}$, we have $|\mathcal{X}_{i-1}| \leq (1+\alpha)^{i-1} 2^{k-\sum_{j=1}^{i-1} \ell_j}$. Then*

$$\Pr_{s_i \leftarrow \{0,1\}^{d_i}} \left[|\mathcal{X}_i| > (1+\alpha)^i 2^{k-\sum_{j=1}^{i} \ell_j} \right] < 3 \cdot 2^{-2t}$$

Proof. Without loss of generality, assume the worst-case scenario that $|\mathcal{X}_{i-1}| = \lfloor (1+\alpha)^{i-1} 2^{k-\sum_{j=1}^{i-1} \ell_j} \rfloor \geq 2^{k-\sum_{j=1}^{i-1} \ell_j}$. In this case, we can write the above as:

$$\begin{aligned}
\Pr_{s_i \leftarrow \{0,1\}^{d_i}} \left[|\mathcal{X}_i| > (1+\alpha)^i 2^{k-\sum_{j=1}^{i-1} \ell_j} \right] &\leq \Pr_{s_i \leftarrow \{0,1\}^{d_i}} \left[\sum_{x' \in \mathcal{X}_{i-1}} \left\{ \begin{array}{cc} 1 & \text{if } h_{s_i}(x') = h_{s_i}(x) \\ 0 & \text{otherwise} \end{array} \right\} > (1+\alpha) \frac{|\mathcal{X}_{i-1}|}{2^{\ell_i}} \right] \\
&\leq 2 \left(\frac{4\lceil t/\ell_i \rceil |\mathcal{X}_{i-1}|}{(\alpha |\mathcal{X}_{i-1}|/2^{\ell_i})^2} \right)^{2\lceil t/\ell_i \rceil} + \delta_i \left(\frac{|\mathcal{X}_{i-1}|}{\alpha |\mathcal{X}_{i-1}|/2^{\ell_i}} \right)^{4\lceil t/\ell_i \rceil} && (5) \\
&\leq 2 \left(\frac{4\lceil t/\ell_i \rceil 2^{2\ell_i} r^2}{2^{k-\sum_{j=1}^{i-1} \ell_j}} \right)^{2\lceil t/\ell_i \rceil} + \delta_i (2^{4\lceil t/\ell_i \rceil (\ell_i + \log r)}) \\
&\leq 2 \left(\frac{4\lceil t/\ell_i \rceil r^2}{2^{2\ell_i - 5}} \right)^{2\lceil t/\ell_i \rceil} + \delta_i 2^{4(t+\ell_i+t\log r/\ell_i + \log r)} && (6) \\
&\leq 2 \cdot 2^{-2t} + 2^{-2t} \leq 3 \cdot 2^{-2t} && (7)
\end{aligned}$$

Line (5) follows from Lemma 4.9 and the fact that the variables being summed are $(q_i - 1)$-wise δ_i-dependent with mean $\mu = \frac{|\mathcal{X}_{i-1}|}{2^{\ell_i}}$. Line (6) follows from the fact that $k - \sum_{j=1}^{i-1} \ell_j \geq 4\ell_i - 5$. Line (7) follows from the fact that

$$2^{\ell_i} \geq 2^{\ell_r} \geq 2^{\log t + 2\log r + 7} \geq 4tr^2 2^5 \geq 4\lceil t/\ell_i \rceil r^2 / 2^{-5}$$

which gives the bound for the left-hand summand, and

$$4(t + \ell_i + t\log r/\ell_i + \log r) \leq 4(t + k + t + \log\log_{4/3} k) \leq 16k$$

which gives the bound for the right hand summand as long as $\delta_i \leq 2^{-18k} \leq 2^{-16k-2t}$.

□

By using Lemma 4.12 inductively, we get $\Pr_{s_1,\ldots,s_r} \left[|\mathcal{X}_r| \geq (1+1/r)^r 2^{k-\sum_{j=1}^{r} \ell_j} \right] \leq (3r) 2^{-2t}$. Since $(1+1/r)^r \leq e$ and $\ell_{r+1} = k - \sum_{j=1}^{r} \ell_j$, we can rewrite the above as:

$$\Pr_{s_1,\ldots,s_r} \left[|\mathcal{X}_r| \geq e 2^{\ell_{r+1}} \right] \leq (3r) 2^{-2t} \tag{8}$$

Assuming that $|\mathcal{X}_r| \leq e 2^{\ell_{r+1}}$. Then

$$\begin{aligned}
\Pr[|\mathcal{X}_{r+1}| \geq t] &= \Pr_{s_{r+1} \leftarrow \{0,1\}^{d_{r+1}}} [\ \exists \mathcal{C} \subseteq \mathcal{X}_r, |\mathcal{C}| = t \ \ \forall x' \in \mathcal{C} \ : \ h_{s_{r+1}}(x') = h_{s_{r+1}}(x)] \\
&\leq \sum_{\mathcal{C} \subseteq \mathcal{X}_r, |\mathcal{C}| = t} \Pr[\forall x' \in \mathcal{C} \ : \ h_{s_{r+1}}(x') = h_{s_{r+1}}(x)] \\
&\leq \binom{|\mathcal{X}_r|}{t} (2^{-t\ell_{r+1}} + \delta_{r+1}) \left(\frac{e^2 2^{\ell_{r+1}}}{t} \right)^t (2^{-t\ell_{r+1}} + \delta_{r+1}) \\
&\leq (e^2/t)^t + \delta_{r+1} 2^{t\ell_{r+1}} \leq 2^{-2t} + 2^{-2t} \leq 2 \cdot 2^{-2t}.
\end{aligned}$$

Therefore, altogether, we have

$$\Pr_{s \leftarrow \{0,1\}^s}[\mathcal{X}_{r+1} \geq t] \leq 3(r+1)2^{-2t} \leq 3(\log_{4/3} k + 1)2^{-2t} \leq 2^{-(t+1)}$$

since we chose t so that $2^{t-1} \geq 3(\log_{4/3} k + 1)$. Moreover, we have $\mathsf{Load}^{\mathcal{H}}_{\mathcal{X}}(x, s) = |\mathcal{X}_{r+1}| + 1$ (since we must also include the point x itself). Therefore $\Pr[\mathsf{Load}^{\mathcal{H}}_{\mathcal{X}}(X, S) \geq t + 1] \leq 2^{-(t+1)}$ which proves the Theorem 4.10.

To prove Theorem 4.11, we go back to equation (8) and notice that $\Pr_{s_1,\ldots,s_r}\left[|\mathcal{X}_r| \geq e2^{\ell_{r+1}}\right] \leq (3r)2^{-2t} \leq 3(r+1)2^{-2t} \leq 2^{-t}$. Combining this with the fact that $\mathsf{Load}^{\mathcal{H}'}_{\mathcal{X}}(x, s) = |\mathcal{X}_{r+1}| + 1$, we get for every $\mathcal{X}$ and $x \in \mathcal{X}$:

$$\Pr_{s \leftarrow \{0,1\}^{d'}}[\mathsf{Load}^{\mathcal{H}'}_{\mathcal{X}}(x, s) \geq (e+1)2^{k-m}] = \Pr[|\mathcal{X}_{r+1}| \geq e2^{\ell_{r+1}}] \leq 2^{-t}.$$

This concludes the proof. □

Additional Optimization. We note that it is easy to reduce the seed further from $d = O(n \log k)$ to $d = O(k \log k)$ while achieving essentially the same bounds as Theorem 4.10 and Theorem 4.11. The idea is that we can always covert an (n, k) source into an (n', k) source for some $n' = O(k)$. We simply first hash the n bit input into a smaller n' bit input using a universal hash function.

Lemma 4.13. *Let X be any (n, k)-source and let $\mathcal{H} = \{h_s : \{0,1\}^n \to \{0,1\}^{n'}\}_{s \in \{0,1\}^d}$ be a ρ-universal hash function, meaning that for any $x \neq x' \in \{0,1\}^n$, $\Pr_{s \leftarrow \{0,1\}^d}[h_s(x) = h_s(x')] \leq \rho$. Then $\Pr_{s \leftarrow \{0,1\}^d}[h_s(X)$ is a $(n', k) - source] \geq 1 - 2^{2k}\rho$.*

Proof. It suffices to show that the above holds for all flat sources X, distributed uniformly at random over some $\mathcal{X} \subseteq \{0,1\}^n$, $|\mathcal{X}| = 2^k$. Moreover $h_s(X)$ is an (n', k)-source as long as $|h_s(\mathcal{X})| = 2^k$, meaning that there are no collisions. The probability that this does *not* happen is:

$$\Pr_{s \leftarrow \{0,1\}^d}[|h_s(\mathcal{X})| < 2^k] \leq \Pr_{s \leftarrow \{0,1\}^d}[\exists x_1 \neq x_2 \in \mathcal{X} \ : \ h_s(x_1) = h_s(x_2)] \leq 2^{2k}\rho.$$

□

Polynomial evaluation over the field $\mathbb{F}_{2^{n'}}$ gives us a hash family $\mathcal{H} = \{h_s : \{0,1\}^n \to \{0,1\}^{n'}\}_{s \in \{0,1\}^{n'}}$ which is ρ-universal for $\rho = \lceil n/n' \rceil 2^{-n'}$. Setting $n' = 3k$ and plugging this into the above lemma, we see that $h_s(X)$ is a $(3k, k)$ source with probability $1 - \lceil n/3k \rceil 2^{-k} \geq 1 - 2^{-(k - \log n)}$. Therefore, by first applying the above universal hash function from n bits to $n' = 3k$ bits and then a (k, t, ε)-balanced hash from $n' = 3k$ bits to m bits, we get a $(k, t, \varepsilon + 2^{-(k - \log n)})$-balanced hash from n to m bits. Therefore, we can efficiently achieve essentially the same parameters as Theorem 4.10 and Theorem 4.11 but with reduced seed length $d = O(n' \log k + n') = O(k \log k)$.

4.3 A Probabilistic Method Bound

We also give a probabilistic method argument showing the existence of unpredictability extractors with very small seed length $d \approx \log(1/\delta) + \log(n - k)$. In other words, unpredictability extractors with small entropy loss do not, in principle, require a larger seed than standard randomness extractors (with much larger entropy loss).

See e.g., Theorem 4.1 of [MR95], for the following Chernoff tail-bound.

Lemma 4.14 (Multiplicative Chernoff Bound). *Let $X_1, \ldots, X_n$ be independent (but not necessarily identical) random variables taking on values in $\{0,1\}$ with $\mu := \mathbb{E}[\sum_{i=1}^n X_i]$. Then, for any $\alpha > 1$:*

$$\Pr\left[\sum_{i=1}^{n} X_i > \alpha\mu\right] < \left(\frac{e^{(\alpha-1)}}{\alpha^\alpha}\right)^{\delta n} \leq \left\{ \begin{array}{ll} e^{-\mu(\alpha-1)^2/4} & 1 < \alpha \leq 2e \\ 2^{-\alpha\mu} & \alpha \geq 2e \end{array} \right.$$

We use the above tail-bound to prove the following theorem.

Theorem 4.15. *There exists a (k, δ, ε)-UExtract* $\mathsf{UExt} : \{0,1\}^n \times \{0,1\}^d \to \{0,1\}^m$ *as long as either:*

$$\begin{aligned} \varepsilon &\geq \max\{\ 2e\delta\ ,\ \ (n-k+2)2^{-d} + \log(e/\delta)\delta 2^{m-k}\ \ \} \\ 2e\delta \geq \varepsilon &\geq \delta + 2\delta\sqrt{(1/\delta)(n-k+2)2^{-d} + \log(e/\delta)2^{m-k}} \end{aligned}$$

In particular, as long as the seed-length $d \geq \log(1/\delta) + \log(n-k+2) + 3$ *we get:*

- *In general:* $\varepsilon = O(1 + \log(1/\delta)2^{m-k})\delta$.
- *When* $k = m$ *and* $\delta < 2^{-2e}$*:* $\varepsilon = (2 + \log(1/\delta))\delta$.
- *When* $k \geq m + \log\log(e/\delta) + 3$*:* $\varepsilon = 2\delta$.

Proof. We use the probabilistic method argument. For simplicity of notation, let $N = 2^n, K = 2^k, D = 2^d, M = 2^m$. Let $R : \{0,1\}^n \times \{0,1\}^d \to \{0,1\}^m$ be chosen uniformly at random from the set $\mathcal{R}$ of all such functions. Then R *fails* to be a (k, δ, ε)-Uextract if there exists some subset $\mathcal{X} \subseteq \{0,1\}^n, |X| = K$ and some (deterministic) δ-distinguisher $\mathcal{D}$ such that $|\{x \in \mathcal{X}, s \in \{0,1\}^d\ :\ \mathcal{D}(R(x;s),s) = 1\}| > \varepsilon KD$. For a fixed $\mathcal{X}, \mathcal{D}$ and a uniformly random R, we can define indicator random variables $\{V^{\mathcal{D}}_{x,s}\}_{x\in\mathcal{X}, s\in\{0,1\}^d}$ via $V^{\mathcal{D}}_{x,s} = 1$ iff $\mathcal{D}(R(x;s),s) = 1$. These variables are mutually independent (but not identically) distributed with $\Pr[V^{\mathcal{D}}_{x,s} = 1] = \delta_s := \frac{|\{y\in\{0,1\}^m : \mathcal{D}(y,s)=1\}|}{2^m}$ and $\mathbb{E}[\sum_{x,s} V^{\mathcal{D}}_{x,s}] = \sum_{x,s}\delta_s = \delta KD$. Therefore, we have:

$$\begin{aligned} \Pr_R[R \text{ is not a } (k,\delta,\varepsilon)\text{-UExtract}] &\leq \Pr_R\left[\exists \mathcal{D}, \mathcal{X} \quad \text{s.t.} \sum_{x\in\mathcal{X}, s\in\{0,1\}^d} V^P_{x,s} > \varepsilon DK\right] \\ &\leq \sum_{\mathcal{D},\mathcal{X}} \Pr_R\left[\sum_{x\in\mathcal{X}, s\in\{0,1\}^d} V^{\mathcal{D}}_{x,s} > (\varepsilon/\delta)\delta KD\right] \qquad (9) \end{aligned}$$

We now divide the analysis into two cases. In the first case, assume that $\varepsilon \geq 2e\delta$. In this case, we continue from (9) and use Chernoff to get:

$$\begin{aligned} \Pr_R[R \text{ is not a } (k,\delta,\varepsilon)\text{-UExtract}] &< \binom{N}{K}\binom{MD}{\delta MD}2^{-\varepsilon KD} \\ &\leq \left(\frac{eN}{K}\right)^K \left(\frac{e}{\delta}\right)^{\delta MD} 2^{-\varepsilon KD} \\ &\leq 2^{(\log e + n - k)K + (\log e + \log(1/\delta))\delta MD - \varepsilon KD} \end{aligned}$$

In particular, the above is strictly less than 1 as long as:

$$\varepsilon > \max\{\ 2e\delta\ ,\ (\log e + n - k)/D + (\log e + \log(1/\delta))\,\delta M/K\ \}.$$

In the second case, assume $\varepsilon < 2e\delta$. In this case, we continue from (9) and use Chernoff to get:

$$\begin{aligned} \Pr_R[R \text{ is not a } (k,\delta,\varepsilon)\text{-UExtract}] &< \binom{N}{K}\binom{MD}{\delta MD}2^{-\delta KD(\varepsilon/\delta - 1)^2/4} \\ &\leq \left(\frac{eN}{K}\right)^K \left(\frac{e}{\delta}\right)^{\delta MD} 2^{-\delta KD(\varepsilon/\delta - 1)^2/4} \\ &\leq 2^{(\log e + n - k)K + (\log e + \log(1/\delta))\delta MD - \delta KD(\varepsilon/\delta - 1)^2/4} \end{aligned}$$

In particular, the above is strictly less than 1 as long as:

$$(\varepsilon/\delta - 1)^2 \geq (\log e + n - k)/(\delta D) + (\log e + \log(1/\delta))M/K$$

which occurs as long as:

$$\varepsilon \geq \delta + 2\delta\sqrt{(\log e + n - k)/(\delta D) + (\log e + \log(1/\delta))M/K}.$$

□

5 SRT Lower-Bound: Samplability Doesn't Improve Entropy Loss

In this section, we prove the 'SRT' conjecture of Dachman-Soled et al. [DGKM12], showing that randomness extractors need to incur a $2\log 1/\varepsilon$ entropy loss (difference between entropy and output length) even if we only require them to work for *efficiently samplable sources*. The lower-bound even holds if the extractor itself is not required to be efficient. The efficient source for which we show a counter-example is sampled via a 4-wise independent hash function. That is, we define the source $X = h_r(Z)$ where $Z \leftarrow \{0,1\}^k$ is chosen uniformly at random and $h_r : \{0,1\}^k \to \{0,1\}^n$ is chosen from some 4-wise independent hash function family. The choice of the seed r will need to be fixed non-uniformly; we show that for any "candidate extractor" $\mathsf{Ext} : \{0,1\}^n \times \{0,1\}^d \to \{0,1\}^m$ there is some seed r such that the above efficiently sampleable (n,k)-source X makes the statistical distance between $(\mathsf{Ext}(X;S), S)$ and the uniform distribution at least $\approx 2^{(m-k)/2}$.

5.1 Preliminaries: Anti-Concentration Bounds

Lemma 5.1 ([Ber91], Theorem 2.3)**.** *For any random variable V, we have: $\mathbb{E}[|V|] \geq \frac{\mathbb{E}[V^2]^{3/2}}{\mathbb{E}[V^4]^{1/2}}$.*

Corollary 5.2. *Let $V_1, \ldots, V_q$ be 4-wise independent random variables over $\mathbb{R}$ such that for all $i \in [q]$ we have $\mathbb{E}[V_i] = 0, \mathbb{E}[V_i^2] \in [p/4, p]$, $\mathbb{E}[V_i^4] \leq p$ for some $p \geq 1/q$. Then $\mathbb{E}[|\sum_{i=1}^q V_i|] \geq \frac{1}{16}\sqrt{q \cdot p}$.*

Proof. Let us define $V := \sum_{i=1}^q V_i$. Then

$$\begin{aligned}
\mathbb{E}[V^2] &= \sum_{i,j\in[q]} \mathbb{E}[V_i \cdot V_j] = \sum_{i\in[q]} \mathbb{E}[V_i^2] \geq qp/4 \\
\mathbb{E}[V^4] &= \sum_{i,j,r,t\in[q]} \mathbb{E}[V_i \cdot V_j \cdot V_r \cdot V_t] = \sum_{i\in[q]} \mathbb{E}[V_i^4] + 3 \sum_{i\neq j\in[q]} \mathbb{E}[V_i^2]\,\mathbb{E}[V_j^2] \\
&\leq qp + 3(qp)^2 \leq 4(qp)^2
\end{aligned}$$

Therefore, by Lemma 5.1, we have

$$\mathbb{E}[|V|] \geq \frac{\mathbb{E}[V^2]^{3/2}}{\mathbb{E}[V^4]^{1/2}} \geq \frac{(\frac{1}{4}qp)^{3/2}}{(4(qp)^2)^{1/2}} = \frac{1}{16}\sqrt{qp}$$

□

5.2 Statement of Lower Bound

Let $\mathsf{Ext} : \{0,1\}^n \times \{0,1\}^d \to \{0,1\}^m$ be a candidate strong extractor, and let X be some random variable over $\{0,1\}^n$. Define the *distinguishability* of Ext on X via:

$$\begin{aligned}
\mathsf{Dist}(X) &\overset{\text{def}}{=} \frac{1}{2} \sum_{s\in\{0,1\}^d, y\in\{0,1\}^m} |\Pr[S = s, \mathsf{Ext}(X;s) = y] - \Pr[S = s, Y = y]| \\
&= \frac{1}{2^{d+1}} \sum_{s\in\{0,1\}^d, y\in\{0,1\}^m} \left|\Pr[\mathsf{Ext}(X,s) = y] - \frac{1}{2^m}\right|.
\end{aligned}$$

where S, Y are uniformly and independently distributed over $\{0,1\}^d$,$\{0,1\}^m$ respectively. Note that $\mathsf{Dist}(X)$ is simply the statistical distance between $(S, \mathsf{Ext}(X; S))$ and (S, U_m) where U_m is uniformly random m bit string.

Theorem 5.3. *For any (possibly inefficient) function* $\mathsf{Ext} : \{0,1\}^n \times \{0,1\}^d \to \{0,1\}^m$*, any positive integer* $k \geq m+2$ *such that* $n > 3k - m + 14$*, there exists a distribution* X *with* $\mathbf{H}_\infty(X) \geq k$*, which is efficiently samplable by a* $\mathrm{poly}(n)$*-size circuit, such that* $\mathsf{Dist}(X) \geq 2^{(m-k)/2-8}$.

Alternatively, for any positive $k \geq m$ *such that* $n > k + \log(k) + 11$*, there exists some distribution* X *with* $\mathbf{H}_\infty(X) \geq k$*, which is efficiently samplable by a* $\mathrm{poly}(n)$*-size circuit such that* $\mathsf{Dist}(X) \geq 2^{(m-k-\log(k))/2-9}$.

5.3 Proof of Lower Bound

Let $\mathcal{X} = \{x_1, \ldots, x_{2^k}\} \subseteq \{0,1\}^n$ be a multiset (i.e, we may have $x_i = x_j$ for $i \neq j$) and let X be a random variable distributed uniformly over $\mathcal{X}$ (i.e., to sample $x \leftarrow X$, choose random $i \in [2^k]$ and output x_i). Define $\mathsf{Dist}(\mathcal{X}) \overset{\text{def}}{=} \mathsf{Dist}(X)$. Then we can write:

$$\begin{aligned}
\mathsf{Dist}(\mathcal{X}) &= \frac{1}{2^{d+1}} \sum_{s\in\{0,1\}^d, y\in\{0,1\}^m} \left| \Pr[\mathsf{Ext}(X, s) = y] - \frac{1}{2^m} \right| \\
&= \frac{1}{2^{d+1}} \sum_{s\in\{0,1\}^d, y\in\{0,1\}^m} \left| \frac{\sum_{i\in[2^k]} b_{i,s,y}}{2^k} - \frac{1}{2^m} \right| \\
&= \frac{1}{2^{d+k+1}} \sum_{s\in\{0,1\}^d, y\in\{0,1\}^m} \left| \sum_{i\in[2^k]} \left(b_{i,s,y} - 2^{-m}\right) \right|
\end{aligned}$$

where $b_{i,s,y} = 1$ if $\mathsf{Ext}(x_i; s) = y$ and 0 otherwise.

Now let us choose the multiset $\mathcal{X}$ randomly via $\mathcal{X} = \{X_1, \ldots, X_{2^k}\}$ where the X_i are *4-wise independent* random variables, each of which is uniform over $\{0,1\}^n$. For example, let $\mathcal{H}$ be a 4-wise independent family of hash functions $h : \{0,1\}^k \to \{0,1\}^n$ and define $X_i = h(i)$ where the randomness is over the choice of $h \leftarrow \mathcal{H}$. Such hash functions can be efficient so that we can compute $h(i)$ in $\mathrm{poly}(n)$-time. In that case, taking an expectation over the choice of $\mathcal{X}$, we can write:

$$\mathbb{E}[\mathsf{Dist}(\mathcal{X})] = \frac{1}{2^{d+k+1}} \sum_{s\in\{0,1\}^d, y\in\{0,1\}^m} \mathbb{E}\left[\left| \sum_{i\in[2^k]} \left(B_{i,s,y} - 2^{-m}\right) \right| \right]$$

where $B_{i,s,y}$ is an indicator random variable which is 1 if $\mathsf{Ext}(X_i; s) = y$ and 0 otherwise. We now prove the following claim, which is the key of the argument, and says that for every s, y the above expectation is sufficiently large.

Claim 5.4. *For all* $s \in \{0,1\}^d, y \in \{0,1\}^m$*, we have* $\mathbb{E}\left[\left|\sum_{i\in[2^k]} \left(B_{i,s,y} - 2^{-m}\right)\right|\right] \geq \frac{1}{64} 2^{(k-m)/2}$

(*Before giving a formal proof, let us give some intuition. For simplicity, assume that the extractor is* regular *so that, for every* s, y *we have* $\mathbb{E}[B_{i,s,y}] = \frac{|\{x\in\{0,1\}^n \,:\, \mathsf{Ext}(x;s)=y\}|}{2^n} = 2^{-m}$*. Then, if we let* $V_i := B_{i,s,y} - 2^{-m}$ *and* $V = \sum V_i$*, we have* $\mathbb{E}[V_i] = 0$*,* $\mathbb{E}[V] = 0$ *and* $\mathbf{Var}[V_i] \approx 2^{-m}$*. The claim boils down to an anti-concentration bound showing that* V *is unlikely to be too close to its mean. If the* V_i *variables were completely independent then, by the central limit theorem,* V *"approaches" a gaussian distribution with mean 0 and and standard deviation* $2^{(k-m)/2}$ *(how closely it approaches this distribution can be quantified e.g., via the Berry-Esseen theorem). Therefore* $|V|$ *is at least* $2^{(k-m)/2}$ *with constant probability and* $\mathbb{E}[|V|] \geq \Omega(2^{(k-m)/2})$*. To prove the above claim, we need to generalize this to the case where the* V_i *are only 4-wise independent and also handle the case where the extractor is not regular.*)

Proof of Claim 5.4. Let us fix some arbitrary $s \in \{0,1\}^d, y \in \{0,1\}^m$. Let $p \overset{\text{def}}{=} \frac{|\{x \in \{0,1\}^n \,:\, \mathsf{Ext}(x;s)=y\}|}{2^n}$, so that for all $i \in [2^k]$ we have, $\mathbb{E}[B_{i,s,y}] = \Pr[B_{i,s,y} = 1] = p$ (if the extractor is regular than $p = 2^{-m}$). First, let us consider the case where the extractor is far from regular at s, y and $|p - 2^{-m}| \geq \frac{1}{64} \cdot 2^{-(k+m)/2}$. In the case, by Jensen's inequality and the linearity of expectation, we have:

$$\begin{aligned} \mathbb{E}\left[\ \left| \sum_{i \in [2^k]} \left(B_{i,s,y} - 2^{-m}\right) \right| \ \right] &\geq \left| \left(\sum_{i \in [2^k]} \mathbb{E}[B_{i,s,y}] \right) - 2^{k-m} \right| \\ &\geq 2^k |p - 2^{-m}| \geq \frac{1}{64} 2^{(k-m)/2} \end{aligned}$$

which matches the claim.

Therefore, we are left to consider the alternate case, where the extractor is close to regular at s, y and $|p - 2^{-m}| < \frac{1}{64} 2^{-(k+m)/2}$. In this case, we have the bounds:

$$\begin{aligned} p &\leq 2^{-m} + 2^{-(k+m)/2} \leq 2^{-m} + 2^{-m-1} \leq \frac{3}{4} \\ 2^k p &\geq 2^k (2^{-m} - 2^{-(k+m)/2}) \geq 2^k (2^{-m} - 2^{-m-1}) \geq 2^{k-m-1} \end{aligned}$$

where the latter also implies $p \geq 2^{-k}$ since $k \geq m+1$. Let us define the random variables $V_i := (B_{i,s,y} - p)$. Then these variables are 4-wise independent, and for all $i \in [2^k]$ we have $\mathbb{E}[V_i] = 0$ and:

$$\begin{aligned} \mathbb{E}[V_i^2] &= p(1-p)^2 + p^2(1-p) = p(1-p) \in [p/4, p] \\ \mathbb{E}[V_i^4] &= p(1-p)^4 + p^4(1-p) \leq p. \end{aligned}$$

Let use define $V := \sum_{i \in [2^k]} V_i$. Then, by applying Corollary 5.2 with $q = 2^k$, we have

$$\mathbb{E}[|V|] \geq \frac{1}{16} (2^k p)^{1/2} \geq \frac{1}{32} 2^{(k-m)/2}.$$

Finally, we have:

$$\begin{aligned} \mathbb{E}\left[\left| \sum_{i \in [2^k]} \left(B_{i,s,y} - 2^{-m}\right) \right| \right] &= \mathbb{E}\left[\ \left| \sum_{i \in [2^k]} (B_{i,s,y} - p) + \sum_{i \in [2^k]} (p - 2^{-m}) \right| \ \right] \\ &\geq \mathbb{E}[|V|] - 2^k |p - 2^{-m}| \geq \frac{1}{64} 2^{(k-m)/2} \end{aligned}$$

which concludes the proof of the claim.

Using the above claim, we get a bound for the expected distinguishing advantage as:

$$\begin{aligned} \mathbb{E}[\mathsf{Dist}(\mathcal{X})] &= \frac{1}{2^{d+k+1}} \sum_{s \in \{0,1\}^d, y \in \{0,1\}^m} \mathbb{E}\left[\left| \sum_{i \in [2^k]} \left(B_{i,s,y} - 2^{-m}\right) \right| \right] \\ &\geq \frac{1}{2} \cdot \frac{2^m}{2^k} \cdot \frac{1}{64} \cdot 2^{(k-m)/2} = \frac{1}{128} 2^{(m-k)/2} = 2^{(m-k)/2 - 7}. \end{aligned}$$

This already shows the *expected* distinguishing advantage for $\mathcal{X}$ is sufficiently high. We now want to show that the distinguishing advantage is high with "good" probability:

$$\begin{aligned} \Pr\left[\mathsf{Dist}(\mathcal{X}) \leq \frac{1}{2} \mathbb{E}[\mathsf{Dist}(\mathcal{X})] \right] &= \Pr\left[1 - \mathsf{Dist}(\mathcal{X}) \geq 1 - \frac{1}{2} \mathbb{E}[\mathsf{Dist}(\mathcal{X})] \right] \\ &\leq \frac{1 - \mathbb{E}[\mathsf{Dist}(\mathcal{X})]}{1 - \frac{1}{2} \mathbb{E}[\mathsf{Dist}(\mathcal{X})]} \leq 1 - \mathbb{E}[\mathsf{Dist}(\mathcal{X})]^2 \leq 1 - 2^{m-k-14} \end{aligned}$$

where the second line follows by Markov inequality and the fact that $\mathsf{Dist}(\mathcal{X}) \in [0,1]$. Therefore, we get:

$$\Pr[\mathsf{Dist}(\mathcal{X}) > 2^{(m-k)/2-8}] > 2^{m-k-14}.$$

Next, we want to show that, if X is uniform over $\mathcal{X}$, then $\mathbf{H}_\infty(X) \geq k$ with overwhelming probability over the choice of $\mathcal{X}$. This happens as long as $X_1, \ldots, X_{2^k}$ are all distinct, which happens with probability $\geq 1 - \Pr[\exists i \neq j \text{ s.t. } X_i = X_j] \geq 1 - 2^{2k-n}$. Therefore, we get:

$$\Pr[(\mathsf{Dist}(\mathcal{X}) > 2^{(m-k)/2-8}) \quad \wedge \quad (\mathbf{H}_\infty(X) \geq k)] > 2^{(m-k)-14} - 2^{2k-n} > 0$$

as long as $n > 3k - m + 14$. This means that, as long as the above inequality is satisfied, there *exits* some choice of $\mathcal{X} = \{x_1, \ldots, x_{2^k}\}$ from the 4-wise independent family (e.g., some hash function $h \in \mathcal{H}$ with $x_i = h(i)$) such that, if X is uniform over $\mathcal{X}$, we have $\mathbf{H}_\infty(X) \geq k$, and $\mathsf{Dist}(X) \geq 2^{(m-k)/2-8}$. As long as the has function h is efficiently computable, we can sample from X efficiently in poly(n)-time. Therefore, this proves the first part of theorem.

For the second part of the theorem, we first generalize our bound on entropy by choosing the elements $X_1, \ldots, X_{2^k}$ of $\mathcal{X}$ via a $(t+1)$-wise independent distribution. In that case, we get $\mathbf{H}_\infty(X) \geq k - \log(t)$ as long as the multiplicity of any element of $\mathcal{X}$ is at most t, which happens with probability

$$\Pr[\mathbf{H}_\infty(X) \geq k - \log(t)] \geq 1 - \binom{2^k}{(t+1)} 2^{-tn} \geq 2^{(t+1)k-tn}.$$

Therefore, we get:

$$\Pr[(\mathsf{Dist}(\mathcal{X}) > 2^{(m-k)/2-8}) \quad \wedge \quad (\mathbf{H}_\infty(X) \geq k - \log(t))] > 2^{(m-k)-14} - 2^{(t+1)k-tn} > 0$$

as long as $n > k + 2k/t - (m-14)/t$.

Finally, to prove the second part of the theorem, for any $k' \geq m$, $n > k' + \log(k') + 11$ let us apply the generalized bound on $k = k' + \log(k') + 2$ and $t = 2k'$. Note, $k \geq m + 2$ and $n > k + 2k/t - (m-14)/t$. Therefore, we get:

$$\Pr[(\mathsf{Dist}(\mathcal{X}) > 2^{(m-k'-\log(k'))/2-9}) \quad \wedge \quad (\mathbf{H}_\infty(X) \geq k')] > 0.$$

This proves the second part of the theorem, by noting that we can $(t = 2k')$-wise independent hash functions can be efficiently computable in poly(n)-time.

6 Lower Bound: Square-Friendly Applications

In this section we prove Theorem 1.2. We define an application P for which we show that it is δ-square secure in Claim 6.1, but a single run can be broken with advantage $\Omega(\sqrt{\delta \cdot 2^{m-k}})$. The two claims imply Theorem 1.2.

We consider the following (artificial) indistinguishability application P between a distinguisher D and a challenger $C(r)$, which is initialized with a key $r \in \{0,1\}^m$ and a bit $b \in \{0,1\}$ (where $b = 0$ means we're playing the random, and $b = 1$ the real game.)

- $C(r)$ flips a biased coin α where $\Pr[\alpha = 1] = \sqrt{\delta}$.
- If $\alpha = 0$, $C(r)$ sends $\perp$ to D.
- If $\alpha = 1$ and $b = 1$ then $C(r)$ sends r to D.
- If $\alpha = 1$ and $b = 0$ then $C(r)$ samples a random $r' \leftarrow \{0,1\}^m$ and sends r' to D.
- D outputs its guess b'.

Let $f_D(r)$ denote the advantage of D (over the choice of b) in the above game

$$f_D(r) = \Pr_{b \leftarrow \{0,1\}}[b = b'] - 1/2$$

By the following claim P is $\delta/4$-square secure (against computationally unbounded distinguishers and any distribution of keys).

Claim 6.1. *For any D and any possible key r, $|f_D(r)| \leq \sqrt{\delta}/2$ (and thus also $\mathbb{E}[f_D(U_m)^2] \leq \delta/4$)*

Proof.

$$\begin{aligned} |\Pr[b = b'] - 1/2| &= |\underbrace{\Pr[\alpha = 1]}_{\sqrt{\delta}} \Pr[b = b'|\alpha = 1] + \underbrace{\Pr[\alpha = 0]}_{1-\sqrt{\delta}} \underbrace{\Pr[b = b'|\alpha = 0]}_{1/2} - 1/2| & (10) \\ &\leq |\sqrt{\delta} \Pr[b = b'|\alpha = 1] - \sqrt{\delta}/2| \leq \sqrt{\delta}/2 & (11) \end{aligned}$$

In the last step we used that any probability is between 0 and 1, in the second step we used that conditioned on $\alpha = 0$, D gets no information about the uniformly random bit b and thus any guess b' will be equal to b with probability exactly 1/2. □

Claim 6.2. *For any family $\mathcal{H} = \{h_s\}$ of functions $\{0,1\}^n \to \{0,1\}^m$, there exists an (even efficiently samplable) (n,k)-source X and a (generally inefficient) distinguisher $D(.)$ such that*

$$\mathbb{E}_S[f_{D(S)}(h_S(X))] = \Omega(\sqrt{\delta \cdot 2^{m-k}})$$

Proof. By Theorem 1.1 there exists an efficiently samplable X such that, for a random S, the statistical distance of the derived key $h_S(X)$ from uniform is

$$\Delta((U_m, S)\ ,\ (h_S(X), S)) = \Omega(\sqrt{2^{m-k}})$$

And thus, we can define a (potentially inefficient) distinguisher $D(S)$ that can distinguish $(h_S(X), S)$ from (U_m, S) with advantage $\Omega(\sqrt{2^{m-k}})$, and thus guess b with the same advantage whenever he gets to see the key (i.e. $\alpha = 1$).

Concretely, the distinguisher $D(s)$ is defined as follows. If it receives $\perp$ (i.e. $\alpha = 0$), it simply outputs a random guess $b' \leftarrow \{0,1\}$. If it receives some $r \in \{0,1\}^m$ (i.e. $\alpha = 1$), then it outputs 1 if $\Pr_X(h_s(X) = r) \geq 2^{-m}$ and 0 otherwise. We have

$$\begin{aligned} \mathbb{E}_S[f_{D(S)}(h_S(X))] &= \underbrace{\Pr[\alpha = 0]}_{1-\sqrt{\delta}} \underbrace{\Pr[b = b'|\alpha = 0]}_{1/2} + \underbrace{\Pr[\alpha = 1]}_{\sqrt{\delta}} \underbrace{\Pr[b = b'|\alpha = 1]}_{1/2+\Omega(\sqrt{2^{m-k}})} - 1/2 \\ &= \Omega(\sqrt{\delta \cdot 2^{m-k}}) \end{aligned}$$

□

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