# Saving Private Randomness in One-Way Functions and Pseudorandom Generators 

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#### Abstract

Can a one-way function $f$ on $n$ input bits be used with fewer than $n$ bits while retaining comparable hardness of inversion? We show that the answer to this fundamental question is negative, if one is limited black-box reductions.

Instead, we ask whether one can save on secret random bits at the expense of more public random bits. Using a shorter secret input is highly desirable, not only because it saves resources, but also because it can yield tighter reductions from higher-level primitives to one-way functions. Our first main result shows that if the number of output elements of $f$ is at most $2^{k}$, then a simple construction using pairwiseindependent hash functions results in a new one-way function that uses only $k$ secret bits. We also demonstrate that it is not the knowledge of security of $f$, but rather of its structure, that enables the savings: a black-box reduction cannot, for a general $f$, reduce the secret-input length, even given the knowledge that security of $f$ is only $2^{-k}$; nor can a black-box reduction use fewer than $k$ secret input bits when $f$ has $2^{k}$ distinct outputs.

Our second main result is an application of the public-randomness approach: we show a construction of a pseudorandom generator based on any regular one-way function with output range of known size $2^{k}$. The construction requires a seed of only $2 n+\mathcal{O}(k \log k)$ bits (as opposed to $\mathcal{O}(n \log n)$ in previous constructions); the savings come from the reusability of public randomness. The secret part of the seed is of length only $k$ (as opposed to $n$ in previous constructions), less than the length of the one-way function input.


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## 1 Introduction

PRG Seed Length It is important to keep the seed required for a pseudorandom generator (PRG) as short as possible, lest the amount of true random bits needed to run it exceed the amount of pseudorandom bits its application requires, thus rendering it pointless. Moreover, in reductions from PRGs (or other constructs) to one-way functions, the blowup in the input length turns out to be the most central parameter in determining the security of the construct. It is therefore a major goal to reduce this parameter (as was addressed in [GIL+90, HL92, HHR06b, Hol06, HHR06a]). The ultimate goal is a linear blowup, a necessary, although not a sufficient, condition to achieve a reduction with tight security preservation, i.e. a linear preserving one [HL92, HILL99].

Consider, therefore, the following problem: when is it possible to build a pseudorandom generator out of a one-way function $f$ while keeping the generator seed length linear in the one-way function input length $n$ ? Certainly this is possible if $f$ is a permutation-in fact, in the original PRG construction of [BM82, Yao82] the seed length is equal to the one-way function input length. However, no broader class of one-way functions satisfying this condition is currently known: even one-way bijections, if their output range is not easily mapped to $\{0,1\}^{n}$, are not known to satisfy this condition (the best constructions for them are the same as for other regular one-way functions, discussed below).

In this paper we demonstrate constructions of PRGs with the linear input length condition for a large class of known regular one-way functions. Specifically, if every output of $f$ has $\alpha$ preimages (thus $f$ has $2^{k}$ distinct outputs where $k=n-\log \alpha$ ) and (a lowerbound on) $\alpha$ is known, then we can build a PRG with seed length $2 n+\mathcal{O}(k \log k)$. Thus, for functions with high enough degeneracy, where $k=\mathcal{O}(n / \log n)$, our PRG has a linear-length seed, like the Blum-Micali-Yao PRG built from one-way permutations. The construction, described in Section 4, builds upon the techniques of Haitner, Harnik and Reingold [HHR06b], which require longer seed length of $\mathcal{O}(n \log n)$, but assume only regularity rather than known regularity.

New Tool: One-Way Functions with Short Secret Inputs We arrive at our pseudorandom generator as part of a study of a more fundamental problem: when is it possible to reduce the input length of a oneway function while maintaining some of its security? In other words, given a one-way function $f$ with input length $n$, when is it possible to build another function $g$ of input length $\ell(n)<n$ with comparable security? Indeed, if this were possible, then one could, for example, build a pseudorandom generator from $g$ rather than from $f$, and maintain a reasonable seed length even if the PRG construction blows up the input size. However, we show that in general it is impossible to significantly reduce the input length of one-way function in a black-box manner, even for regular one-way functions (Theorem 5). That is, one must invest essentially the full $n$ random bits when calling a one-way function.

This result, however, does not doom all efforts of using the one-way function with a shorter input. The insight is to use the paradigm introduced by Herzberg and Luby [HL92], which separates public randomness from secret randomness. It turns out to be possible to reduce the amount of secret randomness at the cost of additional public randomness. In Theorem 1 we show how to convert any one-way function $f$ with $2^{k}$ distinct outputs into a collection of one-way functions $f_{h}$ with inputs of length $k$, where the index $h$ into the collection is the public randomness. The simple construction uses a pairwise independent family of expanding hash functions. The choice of the function from the collection is a choice of a hash function $h$, and we define $f_{h}(x)=f(h(x))$. This choice is made using $2 n$ public random coins, which are available to any potential inverter.

One way to achieve such a result is by using a technical Lemma of Dodis and Smith [DS05, Lemma 12], which shows the same construction secure if it uses $k+2 \log \frac{1}{\varepsilon}+1$ secret input bits, where $\varepsilon$ is the additive security loss. In particular, even if one needs to ensure that extra security loss is exponentially

Figure 1: Our pseudorandom generator on seed $x . \hat{h}$ is a pairwise-independent hash function from $k$ bits to $n$ bits; $h^{1}, h^{2}, \ldots, h^{k}$ are almost-pairwise independent hash functions from the output space of $f$ to $k$ bits, generated by a bounded space generator from a common seed $s$ of length $\mathcal{O}(k \log k) ; b_{r}$ is the GoldreichLevin hardcore bit (the same $r$ is used throughout). $\hat{h}, s$ and $r$ are included in the output or, equivalently, are public.
small, the result of [DS05] requires only linearly more input bits. However, the linear improvement we achieve over [DS05] is crucial for building our pseudorandom generator, as we explain shortly. To achieve this improvement, we take a different path from [DS05]: instead of showing that the distributions $(f(x), h)$ and $(f(h(x)), h)$ are statistically close, we show they have polynomially related subset weights, a relation between distributions that we call $g$-domination.

The secret input to our one-way function need not consist of $k$ uniform independent bits: inputs from any distribution of entropy ${ }^{1} k$ suffice (the same is true for our pseudorandom generator construction). This is beneficial, because uniform random bits may be harder to obtain that simply strings of high entropy. ${ }^{2}$ Moreover, this enables our pseudorandom generator construction.

Application: The PRG Construction We construct our pseudorandom generator by applying the randomized iterate construction of [HHR06b] (henceforth called "the HHR construction") to $f_{h}$ for a known regular $f$. Because $f_{h}$ is secure even when $h$ is public, the coins for $h$ can be given only once and used for all iterations, resulting in a shorter seed. As compared to the HHR construction, we replace the need for many large hash functions with one large hash function (the $\hat{h}$ used for $f_{\hat{h}}$ ), and many small ones ( $h^{1}, \ldots, h^{k}$ used in the randomized iterate construction). Our construction is illustrated in Figure 1.

To get some intuition for the construction, observe that if $f$ is regular, then the number of secret random input bits we require for $f_{h}$ is the entropy of the output of $f_{h}$. This enables iteration, because the output of $f_{h}$ has enough entropy to be used (after an appropriate transformation) as an input to the next $f_{h}$. We could not use the result of [DS05], because it requires more input entropy than is output; nor could we use functions that are not regular, because they produce less output entropy than the input requires. The proof of pseudorandomness is not as simple as applying the HHR result to $f_{\hat{h}}$, because the HHR construction needs to start with a regular one-way function, and $f_{\hat{h}}$ is not necessarily regular even if $f$ is.

In Appendix A we show how one can further exploit the knowledge of the regularity and further shorten the seed of our PRG to $2 n+\mathcal{O}(k \log \log k)$, albeit at the cost of lowering its security.

In addition to considering the overall PRG seed length, it is also important to consider how much of the generator seed must be secret, because secret random bits tend to be much harder to obtain than nonsecret ones (again, this was already observed in [HL92]). Our PRG is the first to require a sublinear number of secret bits, namely, just $k$ (the HHR generator, like the generators of [BM82, GKL93], requires $n$ secret bits). Moreover, just like for our one-way function, the secret input to our PRG need not consist of uniform independent bits, but can come from any distribution of entropy $k$.

[^1]Example: One-way Function and PRG Based on Factoring Consider the problem of building a oneway function based on the hardness of factoring products of two $b$-bit randomly chosen primes. If one is willing to assume a trusted party with secret coins, then it is easy: the trusted party chooses two secret random $b$-bit primes $p$ and $q$, publishes $N=p q$, and the function can be, for example, squaring modulo $N$.

However, without trusted setup, there is no such easy construction. In order to work on the domain $\{0,1\}^{n}$, the one-way function needs to include the process of generating the two random primes. A natural way to do this is to test some number of random integers for primality. To guarantee that two primes are found with probability $2^{-s}$ for some security parameter $s$, the number of integers tested should be $\Theta(s b)$ (because the probability that a random $b$-bit integer is prime is $\Theta(1 / b)$ ). The natural function therefore gets $n=\Theta\left(s b^{2}\right)$ bits as input, splits them into $\Theta(s b)$ integers of length $b$ each, finds the first two such integers $p, q$ that are prime (if they do not exist, output 0 ), and outputs their product $N=p q$. We call this function $f_{\text {mult }}$ (observe that, for sufficiently large $s$, it is one-way under the assumption that factoring is hard).

For reasonably secure values for $b$ (e.g., 2048) and $s$ (e.g., 64), the input length $n$ of $f_{\text {mult }}$ will be on the order of tens of megabytes. To come up with such a long secret input is, naturally, quite costly. Because the output of $f_{\text {mult }}$ is short, however, we can apply our result on converting one-way functions to families with shorter secret inputs. Setting $k=2 b=o(\sqrt{n})$, we obtain a family of one-way functions with secret inputs of length only $2 b$-as short as the description of the two primes $p$ and $q$. To sample a function from this family, one still needs $\Theta(n)$ random bits, but they can be public, and are therefore much less expensive to obtain (e.g., from adversarially observable sources such as user behavior or ambient noise). Finally we note that using our techniques, one can generate a product $N=p q$ of two secret $b$-bit primes $p, q$ using private randomness of entropy $2 b$ (and the appropriate amount of public randomness). This can be used, for example, for generating public/secret key pairs for RSA or Paillier functions, from a modest amount of private randomness.

Consider now trying to make a PRG out of $f_{\text {mult }}$. The prior most efficient way (in terms of seed length) to achieve this is to notice that $f_{\text {mult }}$ is a regular one-way function (except the negligible $2^{-s}$ portion that leads to the 0 output) and use the HHR construction, which takes a seed of $\mathcal{O}(n \log n)$ bits with $\mathcal{O}(n)$ of the bits being secret. ${ }^{3}$ For reasonable parameter settings, it would be useful only in applications that can afford to gather tens of megabytes of secret randomness and gigabytes of public randomness before invoking the PRG.

Instead, observe that $f_{\text {mult }}$ is also a known ${ }^{4}$ regular one-way function, with $k<2 b$. Applying our PRG construction, we get a pseudorandom generator with just $2 b=o(\sqrt{n})$ secret seed bits (which is roughly what's required to describe the two primes, anyway) and $\mathcal{O}(n)$ seed bits total (which is linear in what's anyway required as an input to $\left.f_{\text {mult }}\right)$.

Impossibility Results As already mentioned, Theorem 5 shows that the total input length of a one-way function cannot be reduced in a black-box manner, thus leading us to use public randomness in order to reduce the amount of secret randomness. It is natural to ask if this approach can also work for one-way functions with a large number of outputs. On the positive side, we show in Theorem 2 that if a sufficiently large portion of the inputs goes to a sufficiently small portion of the outputs, then the answer is yes. In general, however, this appears unlikely to be the case, for the following reasons. In Theorem 6 we show that the number of secret random bits used when calling a one-way permutation $f$ cannot be reduced to

[^2]be substantially smaller than $n$ by use of black-box reductions. This theorem is actually more general, and shows that our positive result is indeed tight for regular one-way functions, and the number of secret bits cannot be reduced any further in a black-box manner. Moreover, Theorem 7 shows that there is no blackbox reduction that takes a one-way function $f$ with hardness $2^{s}$ on $n$ input bits and produce a collection of one-way functions on $n-s+\mathcal{O}(\log n)$ input bits. Thus, unless $f$ has hardness very close to $2^{n}$, in general the number of secret inputs bits must remain linear if one wants to have any hardness at all.

Discussion Ideally, one would like to use only as many secret bits as the security one gets from the oneway function (it is clear that at least that many bits are necessary: a one-way function with $n$ secret input bits can be easily inverted with probability $2^{-n}$ ). Indeed, typical conjectured one-way functions, for example, RSA or discrete logarithm, are known to provide less security than $2^{n}$ (for the above examples, at most roughly $2^{n^{1 / 3}}$ ). Our negative results show that this is not possible in general with a black-box reduction (although we do not rule it out for specific functions such as discrete logarithm, of course). Our positive result, however, shows that if this weaker than optimal security manifests itself in a "structural" way, i.e., with the function having fewer outputs (a one-way function with $k$ output bits can be easily inverted with probability $2^{-k}$ ), then reduction in the number of inputs bits is possible.

It is natural to ask, of course, if one can not simply use the same one-way function $f$ on a shorter input. It should be noted that our negative results do not consider such constructions, and hence do not rule them out. However, this option is unavailable when $f$ is a fixed-length function secure in a concrete sense, such as a 128 -bit block cipher or a hardware device implementing modular exponentiation for a 2,048 -bit modulus. In this case, our impossibility results indicate that if we are given a hardware implementation of a one-way function we should use it with its full input length (unless we can look inside the box and learn something from there). This last observation adds motivation to results that take as input an exponentially hard one-way function and construct from it a pseudorandom generator with weaker security (of $n^{\log n}$ ) (e.g., some of the results stated in [Hol06, HHR06a] and the one in Appendix A in this paper). These results would be less interesting if there was a direct method of trading input length for security.

Even when the one-way function has variable input length, using it on a shorter input will reduce security. Of course, our construction also reduces security, but the security loss (i.e., security of $f_{h}$ with $n$-bit $f$ as compared to security of $f$ on $n$ bits) is polynomial. In contrast, simply using $f$ on a shorter input can reduce security more than polynomially when the reduction in input length is superlinear.

Security comparison of the original $f$ and our construction $f_{h}$ depends on what parameters are set to equal each other. For example, we can compare the security of $f$ on $n$ bits to the security of $f_{h}$ with a $n$-bit $f$ (thus equating the input length to $f$, and hence the output length and likely most of the computational cost). In that case, $f_{h}$ incurs a polynomial deterioration in security. Herzberg and Luby [HL92] advocate equating the secret input length. In that comparison, our constructions can actually be more secure that $f$, because $f$ needs all $n$ bits to be secret, while $f_{h}$ and our PRG need only $k<n$ secret bits.

## 2 Definitions and Notation

If $Y$ is a set, we denote by $Y$ also the uniform distribution over that set, unless another distribution on $Y$ is specified. We denote by $U_{n}$ the uniform distribution over $\{0,1\}^{n}$. Given a distribution $X$ and a function $f: X \rightarrow Y$, we denote by $f(X)$ the induced distribution on $Y$.

Let $P$ and $Q$ be distributions over some finite domain $X$. The collision-probability of $P$ is $C P(P)=$ $\sum_{x \in X} P(x)^{2} . P$ and $Q \varepsilon$-close (or have statistical distance $\varepsilon$ ) if for every $A \subseteq X$ it holds that $\mid \operatorname{Pr}_{x \leftarrow P}(A)-$ $\operatorname{Pr}_{x \leftarrow Q}(A) \mid \leq \varepsilon$ (equivalently, $\frac{1}{2} \sum_{x \in X}\left|\operatorname{Pr}_{P}[x]-\operatorname{Pr}_{Q}[x]\right| \leq \varepsilon$ ).

We assume familiarity with the standard notions of computational indistinguishability, one-way functions and pseudorandom generators (with public inputs, or equivalently, as public-coin collections), which, for completeness, are recalled in Appendix B.

Definition 1 (Regular functions) A function $f:\{0,1\}^{*} \rightarrow\{0,1\}^{*}$ is regular if for any $x, y \in\{0,1\}^{n}$, $\left|f^{-1}(f(x))\right|=\left|f^{-1}(f(y))\right|$. If $k(n)=-\log \left(\left|\left\{f(x) \mid x \in\{0,1\}^{n}\right\}\right|\right)$ then $f$ is said to be regular with output entropy $k$. When $k$ is also polynomial-time computable on input $1^{n}, f$ is known-regular.

It is also customary to say that $f$ is an $\alpha$-regular function (for some $\alpha: \mathbb{N} \rightarrow \mathbb{N}$ ) - this means that $f$ is a regular function with output entropy $k(n)=n-\log \alpha(n)$, i.e. preimage sizes are equal to $\alpha(n)$.

Definition 2 (Family of almost pairwise-independent hash functions) Let $\left\{X_{n}\right\}_{n \in \mathbb{N}},\left\{Y_{n}\right\}_{n \in \mathbb{N}}$ be two families of subsets of $\{0,1\}^{*}$. For any $n \in \mathbb{N}$ let $\mathcal{H}_{n}$ be a collection of functions where each $h \in \mathcal{H}_{n}$ is from $X_{n}$ to $Y_{n} .\left\{\mathcal{H}_{n}\right\}_{n \in \mathbb{N}}$ is an (efficient) family of $\delta$-almost pairwise-independent hash functions if: 1. there is a polynomial-time sampler which on $n \in \mathbb{N}$ outputs a description of randomly chosen $h \in \mathcal{H}_{n}$, 2. for any $h \in \mathcal{H}_{n},|h|$ (i.e., the description length of $h$ ) is polynomial in $\log \left|X_{n}\right|$, 3. each $h \in \mathcal{H}_{n}$ is a polynomially-computable function, and 4. for all $x \neq x^{\prime} \in X_{n}$ and all $y, y^{\prime} \in Y_{n}$,

$$
\left|\underset{h \leftarrow \operatorname{Pr}_{n}}{ }\left[h(x)=y \bigwedge h\left(x^{\prime}\right)=y^{\prime}\right]-\frac{1}{\left|Y_{n}\right|^{2}}\right| \leq \delta(n)
$$

A 0-almost pairwise independent family is called simply pairwise independent.
There are various constructions of efficient families of pairwise-independent hash functions (i.e. $\delta=0$ ) for any $X_{n}=\{0,1\}^{n}$ and $Y_{n}=\{0,1\}^{\ell(n)}$ whose description length (i.e., $|h|$ ) is linear in $\max \{n, \ell(n)\}$ (e.g., [CW77]). It is possible to construct $\delta$-almost pairwise independent families for $\delta>0$ whose description size depends very mildly on the input size. In particular, using [CW77], [WC81] and [NN93] one gets constructions of efficient families of almost pairwise-independent hash functions for $X_{n}=\{0,1\}^{n}$ and $Y_{n}=\{0,1\}^{\ell(n)}$ whose description length is $\mathcal{O}(\log (n)+\ell(n)+\log (1 / \delta))$.

Proposition 1 Let $\left\{\mathcal{H}_{n}\right\}$ be a family of $\delta$-almost pairwise independent hash functions from $X_{n}$ to $Y_{n}$. Then for any $n$, and any distinct $x_{1}, x_{2} \in X_{n}$ the following distributions have statistical distance at most $\delta\left|Y_{n}\right|^{2} / 2$ : 1. uniform on $Y_{n} \times Y_{n}$, 2. $\left(h\left(x_{1}\right), h\left(x_{2}\right)\right)$ for uniformly random $h \in \mathcal{H}_{n}$.

Proof: For any $y_{1}, y_{2} \in Y_{n}$,
$\left|\operatorname{Pr}_{h}\left[\left(h\left(x_{1}\right), h\left(x_{2}\right)\right)=\left(y_{1}, y_{2}\right)\right]-\operatorname{Pr}_{\left(z_{1}, z_{2}\right) \in Y_{n} \times Y_{n}}\left[\left(z_{1}, z_{2}\right)=\left(y_{1}, y_{2}\right)\right]\right| \leq \delta$ by definition. Summing over all $y_{1}, y_{2} \in Y_{n}$ and dividing by 2 , we get the desired result.

To simplify exposition, we will often work with (almost) pairwise independent hash functions on some fixed domain and range $X$ and $Y$ (rather than consider families $\left\{X_{n}\right\},\left\{Y_{n}\right\}$ ).

Definition 3 ( $g$-Domination) Let $B$ and $C$ be distributions on the same set $\Pi$, and $g$ a real-valued function. We will say that $C$-dominates $B$ if $\forall S \subseteq \Pi, \operatorname{Pr}_{C}[S] \geq g\left(\operatorname{Pr}_{B}[S]\right)$ (this is a generalization of the notion of "dominates" from [Lev86], which contemplated linear g).

Lemma 1 If $C$-dominates $B$ for a convex function $g$, then for any distribution $D$ on a set $\Phi, D \times C$ $g$-dominates $D \times B$.

Proof: Let $E \subset \Phi \times \Pi$. Let $p(\pi)$, for $\pi \in \Pi$, be $\operatorname{Pr}_{\phi \leftarrow D}[(\phi, \pi) \in E]$.

$$
\begin{aligned}
\operatorname{Pr}_{D \times C}[E] & =\underset{\pi}{\mathbb{E}} \underset{\leftarrow C}{ } p(\pi) \\
& =\int_{0}^{1} \underset{\pi}{\operatorname{Pr}}[p(\pi)>\alpha] d \alpha \quad \text { (using } \mathbb{E}(x)=\int \operatorname{Pr}[x>\alpha] d \alpha \text { ) } \\
& \geq \int_{0}^{1} g\left(\operatorname{Pr}_{\pi \leftarrow B}[p(\pi)>\alpha]\right) d \alpha \\
& \geq g\left(\int_{0}^{1} \underset{\pi}{\operatorname{Pr}}[p(\pi)>\alpha] d \alpha\right) \quad \text { (Jensen's inequality, since } g \text { is convex) } \\
& =g\left(\underset{\pi}{\mathbb{E}}{ }_{B} p(\pi)\right)=g\left(\operatorname{Pr}_{D \times B}[E]\right) .
\end{aligned}
$$

A common approach in cryptographic reduction is to focus only on the subset of $B$ for which $p(\pi)$ is large, and use Markov's inequality to obtain $g^{\prime}$-domination of $D \times B$ by $D \times C$, for $g^{\prime} \in \omega(g)$. Instead, this lemma, which takes all subsets into account, saves the increase in $g$ and the corresponding loss of tightness in reductions.

## 3 One-way Functions and Public Randomness

Here we show that a one-way function needs only as many secret input bits as the number of output bits it produces. We state our theorem in terms of bits in order to get a more concise statement; neither the domain nor the range need to be restricted to bit strings of a particular length, as shown in Lemma 2.

Theorem 1 Let $f:\{0,1\}^{*} \rightarrow\{0,1\}^{*}$ be a one-way function that on $n$-bit inputs has at most $2^{k}$ distinct outputs. Let $\mathcal{H}_{k, n}$ be a family of pairwise-independent functions from $\{0,1\}^{k}$ to $\{0,1\}^{n}$. Define the domainsampled $f$ as $f_{h}(x) \stackrel{\text { def }}{=} f(h(x))$ for $h \in \mathcal{H}_{k, n}$ and $x \in\{0,1\}^{k}$. Then $\left\{f_{h}\right\}_{h \in \mathcal{H}_{k, n}}$ is a public-coin collection of one-way functions.

The theorem is immediate from the following lemma.
Lemma 2 Let $f: Y \rightarrow Z$ be a function, where $|Z|=K$. Let $X$ be a distribution with collision probability at most $1 / K$, and let $\mathcal{H}_{X, Y}$ be a family of pairwise-independent functions from the elements of $X$ to $Y$. For every $h \in \mathcal{H}_{X, Y}$ define $f_{h}: X \rightarrow Z$ as $f_{h}(x) \stackrel{\text { def }}{=} f(h(x))$. Then any adversary $A$ that inverts $f_{h}$ with probability at least $\varepsilon$ over $x \in X$ and $h \in \mathcal{H}_{X, Y}$ can be used to invert $f$ on uniformly random inputs from $Y$ with probability at least $\varepsilon^{4} / 21-1 /\left(4 K^{2}\right)\left(\varepsilon^{2} / 2\right.$ if $f$ is regular) in the same running time as $A$ (plus the time required to pick and evaluate a random hash function from $\mathcal{H}_{X, Y}$ ).

Proof: Suppose that an algorithm $A$, when given $\left(f_{h}(x), h\right)$ computes $x^{\prime}$ such that $f_{h}\left(x^{\prime}\right)=f_{h}(x)$ with probability $\varepsilon$. That is,

$$
\operatorname{Pr}_{(x, h) \leftarrow\left(X, \mathcal{H}_{X, Y}\right)}\left[f_{h}\left(A\left(f_{h}(x), h\right)\right)=f_{h}(x)\right] \geq \varepsilon
$$

Consider the following procedure $M^{A}$ for inverting $f$ : on input $z \in Z$, choose a random $h^{\prime} \in \mathcal{H}_{X, Y}$, let $x^{\prime}=A\left(z, h^{\prime}\right)$, and output $h^{\prime}\left(x^{\prime}\right)$. Note that the notation $h^{\prime}$ in $M^{A}$, rather than $h$, emphasizes that the $h^{\prime}$ does not necessarily have to be consistent with $z$. While there exist many $h$ with $x$ such that $z=f_{h}(x)$, the chosen $h^{\prime}$ might not be one of them.

We will analyze the success probability of $M^{A}$ as follows. The success of $A$ (and therefore $M^{A}$ ) is determined by its internal coin flips and its input $\left(z, h^{\prime}\right)$. We will show that the distribution of (coinflips, input) pairs that $A$ sees when run within $M g$-dominates the distribution for which $A$ is designed, for a polynomial $g$; therefore, the probability of the event that $M^{A}$ succeeds in inverting $f$ is polynomially related to the probability of the event that $A$ inverts the domain-sampled $f$. We will first show $g$-domination for inputs only, ignoring the coinflips, and take care of the coinflips later.

It is worth comparing the following proposition, about $g$-domination of inputs, to the aforementioned lemma by Dodis and Smith [DS05, Lemma 12], which analyzes the same construction but with longer inputs to $h$, showing that $\left(f(y), h^{\prime}\right)$ is close to $(f(h(x)), h)$. Our proof technique is entirely different and builds on the technique of [HHR06b].

Proposition 2 For any (not necessarily one-way) $f: Y \rightarrow Z$ with $K$ distinct outputs, distribution $X$ with $C P(X) \leq 1 / K$, and pairwise-independent hash family $\mathcal{H}_{X, Y}$, the distribution $\left(f(y), h^{\prime}\right)$ (where $y \leftarrow$ $\left.Y, h^{\prime} \leftarrow \mathcal{H}_{X, Y}\right) g$-dominates $(f(h(x)), h)$ (where $\left.x \leftarrow X, h \leftarrow \mathcal{H}_{X, Y}\right)$, for $g(\delta)=\delta^{4} / 21-1 /\left(4 K^{2}\right)$, or $g(\delta)=\delta^{2} / 2$ if $f$ is regular.

Proof: We need show that for any $S \subseteq Z \times \mathcal{H}_{X, Y}$,
(replace the right-hand-side with $\delta^{2} / 2$ if $f$ is regular).
First we give a one-paragraph outline of the proof of this proposition. Call the points in $S$ good. Let $(y, h) \in Y \times \mathcal{H}_{X, Y}$ be called good if and only if $(f(y), h)$ is good. We will divide the space $Y$ of inputs to $f$ into $K$ equal-size chunks, producing a set of chunks called $C$. Call $(c, h) \in C \times \mathcal{H}_{X, Y} \operatorname{good}$ if $\exists y \in c$ such that $(y, h)$ is good (i.e., a chunk is good if contains a preimage of a good point in $Z$ ). We will show, simply using properties of $\mathcal{H}_{X, Y}$, that the fraction of good chunks (under the uniform distribution) is at least $\delta^{2} / 2.125$. This will imply that $A$ works on some portion of sufficiently many chunks. Then, using the fact that $f$ has only $K$ outputs, we will show that $A$ works on a sufficiently large portion of most of these chunks. The actual proof is in Appendix C.
$M^{A}$ succeeds whenever $A$ succeeds; in turn, the success or failure of $A$ depends on the point $\left(z, h^{\prime}\right)$ chosen, and on the coin flips of $A$. Let $\Phi$, with probability distribution $D$, be the space of all coin flips of $A$. Let $\Pi=Z \times \mathcal{H}_{X, Y}$, let $B$ be the distribution on $\Pi$ obtained by choosing $x \leftarrow X, h \in \mathcal{H}_{X, Y}$, and $z=f_{h}(x)$, and let $C$ be the distribution on $\Pi$ obtained by choosing a uniform $y \in Y, h^{\prime} \in \mathcal{H}_{X, Y}$, and $z=f(y)$. Applying Lemma 1 below to the event $E$ that that $A$ succeeds (here $g(\delta)=\delta^{4} / 21-1 / 4 K^{2}$, or $\delta^{2} / 2$ in the case of regular functions), we obtain the desired statement.

### 3.1 The Case of Many Outputs

Theorem 1 can be used to reduce the number of secret input bits to a one-way function provided the function has a sufficiently small output range. As we show in this section, the same technique is useful even if the function has large output range, as long as an appreciable fraction of the inputs falls into a rather small subset of the output range. Namely, suppose there is a set of outputs $O_{H}$ of size $2^{k}$ such that $\operatorname{Pr}_{y \in\{0,1\}^{n}}[f(y) \in$ $\left.O_{H}\right] \geq p_{H}$. If $k<\sqrt{p_{H} n}$, then it is possible to reduce the number of secret input bits from $n$ to $k^{2} / p_{H}$, as follows.

Let $X$ be a distribution of collision probability $1 / 2^{k}$, and $\mathcal{H}_{X, Y}$ and $f_{h}(x)$ as above. Lemma 4 below states that $f_{h}(x)$ is a collection of weak one-way functions, i.e., is not invertible with probability appreciably more than $1-p_{H}$.

We can then use the standard hardness amplification technique of Yao [Yao82] in order to convert the weak one-way function collection into a strong one. The technique simply concatenates many independent copies of the weak one-way function. The number of repetitions needed to reduce the easily invertible fraction of inputs to (negligibly more than) $1 / 2^{k}$ from $1-p_{H}$ is $k / p_{H}$ (thus requiring $k^{2} / p_{H}$ secret bits) This gives the following result, whose proof is similar to the proof of Theorem 1 and is outlined in Appendix D.

Theorem 2 Let $f:\{0,1\}^{*} \rightarrow\{0,1\}^{*}$ be a one-way function and suppose for every $n$ there exists a set $O_{H}(n)$ of size $k(n)$ such that $\operatorname{Pr}_{y \in\{0,1\}^{n}}\left[f(y) \in O_{H}(n)\right] \geq p_{H}(n)$. For every $n \in \mathbb{N}$ let $\mathcal{H}_{k, n}$ be a family of pairwise-independent functions from $k$ bits to $n$ bits. Denote $\ell=k / p_{H}$ and define $\overline{f_{\bar{h}}}\left(x_{1}, \ldots, x_{\ell}\right) \stackrel{\text { def }}{=}$ $\left(f_{h_{1}}\left(x_{1}\right), \ldots, f_{h_{\ell}}\left(x_{\ell}\right)\right)$ for $\bar{h}=\left(h_{1}, \ldots, h_{\ell}\right) \in \mathcal{H}_{k, n}^{\ell}$ and $x_{1}, \ldots, x_{\ell} \in\{0,1\}^{k}$. Then $\left\{\overline{f_{\bar{h}}}\right\}_{\bar{h} \in \mathcal{H}_{k, n}^{\ell}}$ is a public-coin collection of one-way functions.

## 4 Pseudorandom Generator Collection from any Known Regular OWF

In this section we show a construction of a pseudorandom generator collection from any regular one-way function. Unlike in the randomized iterate constructions of [GKL93, HHR06b], here the underlying function $f$ has known (i.e. efficiently computable) regularity. We use this knowledge to get a PRG collection with particularly short secret input and little security loss.

Namely, suppose $f$ is a regular OWF with output entropy $k(n)$, and that $(t(n), \epsilon(n))$ is the security of $f$. On secret seed of length $s_{S}(n)=k(n)$, our PRG collection attains the security of (poly $(n)+$ $t(n)$, $\operatorname{poly}(\epsilon(n)))$ (Theorem 3). For example, if $k(n)=n^{1 / 3}$, then we get security comparable to $(t(n), \epsilon(n))$ using only $n^{1 / 3}$ secret bits. And since, for sufficiently small $k$, the public index of our PRG collection is of linear size $\mathcal{O}(n)$, one can also view it as a PRG, rather than collection, with good security preservation: on seed length $\mathcal{O}(n)$ it attains security $(\operatorname{poly}(n)+t(n)$, poly $(\epsilon(n)))$.

Our construction in fact requires a somewhat weaker condition on $f$ than known regularity: $f$ still must be regular, but it is sufficient to have an efficiently computable upper bound $k(n)$ on the output entropy of $f$. Note that a more accurate bound leads to greater savings in the number of secret seed bits.

Theorem 3 Let $f$ be a regular one-way function with security $(t(n), \epsilon(n))$ and output entropy at most $k(n)$ (for $k$ computable in time polynomial in $n$ ). Then there is a public-coin PRG collection $G$, which is (poly $(n)+t(n), \operatorname{poly}(\epsilon(n)))$-indistinguishable on secret seeds of length $s_{S}(n)=k(n)$ and public seeds of length $s_{P}(n)=2 n+\mathcal{O}(k(n) \log k(n))$. (In particular $s_{P}(n)=\mathcal{O}(n)$ if $k=\mathcal{O}(n / \log n)$.)

Before the actual construction we present the basic tool of the randomized iterate [GKL93, HHR06b]. We define it slightly differently than [GKL93, HHR06b]: theirs outputs a value in $\operatorname{Im}(f)$, and ours outputs a hash function image.

Definition 4 (The $m^{\text {th }}$ Randomized Iterate of $f$ ) Let $f:\{0,1\}^{k} \rightarrow\{0,1\}^{\ell}$ and let $\mathcal{H}$ be a family of functions from $\{0,1\}^{\ell}$ to $\{0,1\}^{k}$. For input $x \in\{0,1\}^{k}$ and $\bar{h}=\left(h^{1}, \ldots, h^{t}\right) \in \mathcal{H}^{t}$ define the $m^{\text {th }}$ Randomized Iterate $f^{m}:\{0,1\}^{k} \times \mathcal{H}^{t} \rightarrow \operatorname{Im}(f)$ for every $m \in[t]$ recursively as:

$$
f^{m}(x, \bar{h})=h^{m}\left(f\left(f^{m-1}(x, \bar{h})\right)\right)
$$

where $f^{0}(x, \bar{h})=x$.
We first show a construction with public seed length $2 n+\mathcal{O}\left(k^{2}\right)$ and then describe how it may be reduced to as low as $2 n+\mathcal{O}(k \log k)$, following the same technique as in the HHR construction.

Construction 1 The generator takes the following as inputs:

1. A secret random $x \in\{0,1\}^{k}$
2. A (public) description of one hash function $\hat{h}$ from a family $\mathcal{H}_{k, n}$ of pairwise independent hash functions from $k$ bits to $n$ bits (requires $2 n$ bits).
3. (Public) descriptions of $k$ hash functions $\bar{h}=\left(h^{1}, \ldots, h^{k}\right)$ from a family $\mathcal{H}_{\ell, k}$ of $2^{-3 k}$-almost pairwise independent hash functions from $\ell$ bits to $k$ bits (requires $\mathcal{O}(k)$ bits each).
4. A (public) random string $r \in\{0,1\}^{k}$ for the Goldreich-Levin [GL89] hardcore bit $b_{r}$ (requires $k$ bits). The generator is defined as follows:

$$
G_{\hat{h}, \overline{\bar{h}}, r}(x)=b_{r}(x), b_{r}\left(f_{\hat{h}}^{1}(x, \bar{h})\right), \ldots, b_{r}\left(f_{\hat{h}}^{k}(x, \bar{h})\right),
$$

where $f_{\hat{h}}^{i}$ denotes the $i^{\text {th }}$ randomized iterate of the function $f_{\hat{h}}=\hat{h} \circ f$ (see Figure 1).
Theorem 4 Suppose $f$ is regular one-way with output entropy at most $k(n)$ and security $(t(n), \epsilon(n))$. Then $G$ in Construction 1 is a public-coin pseudorandom generator collection. It is $(\operatorname{poly}(n)+t(n), \operatorname{poly}(\epsilon(n)))-$ indistinguishable on secret seeds of length $s_{S}(n)=k(n)$ (and public seeds of length $s_{P}(n)=2 n+\mathcal{O}\left(k^{2}\right)$ ). (In particular, $s_{P}(n)=\mathcal{O}(n)$ if $k(n)=\mathcal{O}(\sqrt{n})$ ).

Proof: $G$ takes $k$ bits and outputs $k+1$ bits. Thus it is expanding. We must now prove that it is indistinguishable. It is tempting to first fix $\hat{h}$ and since by Theorem $1 f_{\hat{h}}$ is a one-way function, simply plug $f_{\hat{h}}$ in the HHR construction. However, the HHR construction relies heavily on the fact that the underlying function is regular or at least very close to regular. The function $f_{\hat{h}}$ on the other hand is not guaranteed to be regular once $\hat{h}$ is fixed, even if $f$ is regular to begin with. If $\hat{h}$ were from a $k$-wise independent family (rather than a pairwise independent one) then one can prove that with overwhelming probability $f_{\hat{h}}$ is close to regular. This is not the case with pairwise independent $\hat{h}$ and on the contrary, it is likely that with noticeable probability $f_{\hat{h}}$ will deviate too much from a regular function. Our proof follows the basic structure of the proof of the HHR construction, so we give a sketch, detailing the parts which differ from [HHR06b].

As in the previous iterative constructions (such as [BM82, Yao82, Lev87],
[GKL93, HHR06b]), the key to the proof is the unpredictability of the sequence

$$
\left(f_{\hat{h}}^{k}(x, \bar{h}), f_{\hat{h}}^{k-1}(x, \bar{h}), \ldots, f_{\hat{h}}^{1}(x, \bar{h}), x\right),
$$

even for an adversary who is given $(\bar{h}, \hat{h})$. Once this is shown (Lemma 3), it follows from the stronger Goldreich-Levin theorem [Lev93], that the output of the PRG is next-bit unpredictable with essentially the same security. Next-bit unpredictability is equivalent to indistinguishability with a security loss $1 / k^{\mathcal{O}(1)}$ (see [Gol01], Theorem 3.3.7). Thus the output of $G$ is indeed pseudorandom, with security essentially the same as of the above sequence. We now turn to the proof of unpredictability.

Let $\operatorname{Supp}(n)=\mathcal{H}_{\ell, k}^{k} \times \mathcal{H}_{k, n} \times\{0,1\}^{k}$, and call an element of Supp an instance. Let $\Phi=\{0,1\}^{\mathbb{N}}$ denote the set of all coin toss sequences. We say that an algorithm $A$ inverts $i$-th iteration (on random coins $\omega$ and instance $\left(\bar{h}, \hat{h}, f_{\hat{h}}^{i}(x, \bar{h})\right)$ ) if

$$
A\left(\omega, \bar{h}, \hat{h}, f_{\hat{h}}^{i}(x, \bar{h})\right)=f_{\hat{h}}^{i-1}(x, \bar{h})
$$

Let $D(n)$ be the distribution of instances produced by the generator, i.e.
$\left(\bar{h}, \hat{h}, f_{\hat{h}}^{i}(x, \bar{h})\right)$ for uniform $(\bar{h}, \hat{h}, x)$. Let $Z(n)$ be the uniform distribution of instances, i.e. uniform ( $\bar{h}, \hat{h}, z$ ).

Lemma 3 Let $A$ be an algorithm with running time $\leq t(n)$. Suppose that

$$
\operatorname{Pr}\left[\text { A inverts } i \text {-th iteration on }\left(\omega, \bar{h}, \hat{h}, f_{\hat{h}}^{i}(x, \bar{h})\right)\right] \geq \epsilon(n),
$$

where $\omega$ is uniform and $\left(\bar{h}, \hat{h}, f_{\hat{h}}^{i}(x, \bar{h})\right)$ is distributed according to $D(n)$. Then there is an algorithm $B$ which runs in time $\leq \operatorname{poly}(n)+t(n)$ and inverts $f(x)$ with probability $\geq \epsilon^{2.5}(n) /(16(k+1))($ for $|x|=n)$.

Proof: On input $y$, the algorithm $B$ generates random $(\bar{h}, \hat{h})$, sets $u \leftarrow A\left(\bar{h}, \hat{h}, h^{i}(y)\right)$, and outputs $\hat{h}(u)$.

Fix some $n$ and then we can omit it from the notation. $B$ chooses the hash functions independently of $y$, i.e. it produces instances distributed according to $Z$. However, $A$ is guaranteed to invert with probability $\epsilon$ on a different distribution $D$. The bulk of the proof is devoted to proving that $A$ inverts with comparable probability $\approx \epsilon^{2}$ also on distribution $Z$. The basic idea of the proof is similar to [HHR06b]: we show that collision probabilities of $Z$ and $D$ are closely related $C P(Z) \geq \mathcal{O}(k) \cdot C P(D)$, and from that we conclude that event probabilities are closely related as well $\operatorname{Pr}_{Z}[S] \geq\left(\operatorname{Pr}_{D}[S]\right)^{2} / \mathcal{O}(k)$. In particular, the inversion event happens with probability $\epsilon^{2} / \mathcal{O}(k)$ under $Z$. The actual proof is more involved than this simple outline, the main complications being: 1 . there is a single expanding hash function $\hat{h}$ which is used in every iteration, so the technique of [HHR06b] is not directly applicable, 2 . contracting hash functions $h^{i}$ cause collisions, so an inverse of $i$-th iteration may be unrelated to $y$. The proof continues in Appendix E.

Reducing the public seed length. To reduce the public seed length of the above construction from $2 n+\mathcal{O}\left(k^{2}\right)$ to $2 n+\mathcal{O}(k \log k)$, we follow exactly the same derandomization technique as in the HHR construction. The idea is to not use independent choices of hash functions for $\bar{h}=\left(h_{1}, \ldots, h_{k}\right)$ but rather choose functions that are correlated yet satisfy the proof of the previous section. The central observation is that the collision probability of a randomized iterate can be computed by a bounded space program. More precisely, there is a simple bounded space branching program such that its input tape consists of the choice of $\bar{h}$ and its acceptance probability is precisely the collision probability of $f_{\hat{h}}^{k}$ (the probability is over inputs $x, \bar{h})$ for every fixed $\hat{h}$. Thus replacing the hash functions in the input tape by the output of a generator that fools bounded space programs (such as the generators of [Nis92, INW94]) changes the collision probability only by a small additive error. This is sufficient to make the proof of the previous section go through. Loosely speaking, the bounded space program takes two initial inputs $x_{1}$ and $x_{2} .{ }^{5}$ At the first step the program reads the randomizing hash function $h^{1}$ and computes $f_{\hat{h}}^{1}\left(x_{1}, h^{1}\right)$ and $f_{\hat{h}}^{1}\left(x_{2}, h^{1}\right)$ and stores only these two intermediate values (not storing $x_{1}$ and $x_{2}$ ). At each iteration the program reads a new randomizing hash and computes the next randomized iterate of the two values, while not storing the previous one. At the end the program simply compares the two values and outputs 1 only if they are the same value. An accurate account of such a program, bounded space generators and the revisions needed in the proof appears in [HHR06b].

Construction 2 The generator takes the following as inputs:

1. A secret random $x \in\{0,1\}^{k}$
2. Description of one hash function $\hat{h}$ from a family $\mathcal{H}_{k, n}$ of pairwise independent hash functions from $k$ bits to $n$ bits (requires $2 n$ bits).

[^3]3. Seed $s \in\{0,1\}^{\mathcal{O}(k \log k)}$ to a bounded space generator $B S G$ with space bound $2 k$ and error $2^{-k}$. The output $B S G(s)=\left(h^{1}, \ldots, h^{k}\right)$ of the generator consists of the descriptions of $k$ hash functions from a family $\mathcal{H}_{\ell, k}$ of almost pairwise independent hash functions from $\ell$ bits to $k$ bits.
4. A random string $r \in\{0,1\}^{k}$ for the Goldreich-Levin hardcore bit $b_{r}$ (requires $k$ bits).

The generator is defined as follows:

$$
G^{\prime}(x, \hat{h}, s, r)=b_{r}(x), b_{r}\left(f_{\hat{h}}^{1}(x, B S G(s))\right), \ldots, b_{r}\left(f_{\hat{h}}^{k}(x, B S G(s))\right), \hat{h}, s, r
$$

Where $f_{\hat{h}}^{i}$ denotes the $i^{\text {th }}$ randomized iterate of the function $f_{\hat{h}}=\hat{h} \circ f$.
The seed length of the aforementioned generators is $\mathcal{O}\left(\log \left|\mathcal{H}_{\ell, k}\right| \cdot \log k\right)$ (which equals $\mathcal{O}(k \log k)$ with our choice of parameters) and thus the overall construction takes seed length $2 n+\mathcal{O}(k \log k)$.

On using secret seeds from non-uniform distributions. A simple modification makes our PRG secure even when used with secret seed drawn from any distribution $X$ as long as $C P(X) \leq 2^{-k}$. The modification can be applied to either Construction 2 or Construction 1. The public seed then increases by only $\mathcal{O}(k)$ bits, therefore it remains unchanged asymptotically. Please see Appendix E. 2 for a brief description of the modification.

## 5 Black-Box Separations

As discussed in the introduction, it is natural to ask under which conditions one can reduce the input length to a one-way function below its "native" length $n$. More abstractly, we want to know: Is there a generic way of securely using a OWF on n-bit inputs, if we are given only $\ell<n$ random bits? How small can $\ell$ be?

We formalize these questions using circuits, where it is easy to talk about security on fixed-length input. (It is possible to formulate them in the uniform context, but they become too cumbersome.) We then give some indications that improving upon our results requires non-black-box reductions. Roughly, by "no blackbox reduction of $P$ to $Q$ " we mean that the security proof "if $Q$ is secure then $P$ is too" is necessarily non-black-box (the construction of $P$ from $Q$, however, may be black-box). Before elaborating, let us informally summarize the optimality results:

1. For any $l<n$, there is no black-box reduction of $l$-bit input OWF to regular $n$-bit-input OWF (and, as a corollary, no black-box reduction to either OWF of known hardness, or arbitrary OWF).
2. For any $l<n-\log \alpha$, there is no black-box reduction of $l$-bit input one-way-collection to $\alpha$-regular $n$ -bit-input OWF (and, as a corollary, no black-box reduction to either OWF of known hardness $<2^{n} / \alpha$, or arbitrary OWF).
3. For any $s<n$ and $l<n-s$, there is no black-box reduction of $l$-bit input one-way-collection to an $n$-bit input OWF of hardness at most $s$.

### 5.1 Formal Statements

Let $\mathcal{F}^{n}$ denote the set of all $f:\{0,1\}^{n} \rightarrow\{0,1\}^{n}$. Let $\nu(n)$ denote a negligible function (one decaying faster than any inverse polynomial). Note that $1 / \nu(n)$ is then a superpolynomial function.
Circuits, oracle circuits. Let $|A|$ denote the size of the circuit $A$. For an oracle circuit $A$ and a function $f:\{0,1\}^{n} \rightarrow\{0,1\}^{m}, A^{f}$ denotes the oracle circuit in which each oracle gate with input $x$ outputs $f(x)$. If $\mathcal{G}=\left\{g_{i}\right\}_{i \in\{0,1\}^{n}}$ is a collection of functions $g_{i}:\{0,1\}^{n} \rightarrow\{0,1\}^{m}$ then $A^{\mathcal{G}}$ denotes the oracle circuit in which each oracle gate, on input $(i, x)$ outputs $g_{i}(x)$.

Inverter. A circuit $A:\{0,1\}^{l} \rightarrow\{0,1\}^{n}$ is a $p$-inverter for $f:\{0,1\}^{n} \rightarrow\{0,1\}^{l}$ if $\operatorname{Pr}_{x \in\{0,1\}^{n}}[A(f(x)) \in$ $\left.f^{-1}(f(x))\right] \geq p$. A 1-inverter is called perfect.
Black-box reduction. Let $\mathcal{F} \subseteq \mathcal{F}^{n}$. A pair of circuits $(R, g)$ is an $(l, p)$-reduction to $\mathcal{F}$ if for any $f \in \mathcal{F}$ :

1. $g$ has $l$ input wires.
2. If $V$ is a perfect inverter for $g^{f}$, then $R^{V, f}$ is a $p$-inverter for $f$.

A sequence $\left(R_{n}, g_{n}\right)$ of $\left(l_{n}, p_{n}\right)$-reductions to $\mathcal{H}_{n} \subseteq \mathcal{F}^{n}$ is called $d(n)$-saving if: $1 .\left(\left|R_{n}\right|+\left|g_{n}\right|\right) / p_{n}$ is polynomial in $n, 2$. $n-l_{n}=d(n)$.

Let $\mathcal{F}_{\text {REG }}^{n, \alpha} \subseteq \mathcal{F}_{\text {ALL }}$ denote its subset of all $\alpha$-regular functions. Let $\mathcal{F}_{\text {Low }}^{n, s} \subseteq \mathcal{F}_{\text {ALL }}$ denote the subset of all at most $s$-hard permutations (permutations which have a $1 / 2$-inverter of size $<s$ ).
Black-box collection reduction. A pair of circuits $(R, g)$ is a $(l, m, p)$-collection-reduction to $\mathcal{F}$ if:

1. For any $f \in \mathcal{F}$, and any $(i, x) \in\{0,1\}^{m} \times\{0,1\}^{l}, g^{f}(i, x)$ is of the form $(i, y)$.
2. If $V$ is a perfect inverter for $g^{f}$, then $R^{V, f}$ is a $p$-inverter for $f$.

A sequence $\left(R_{n}, g_{n}\right)$ of $\left(l_{n}, m_{n}, p_{n}\right)$-reductions to $\mathcal{H}_{n} \subseteq \mathcal{F}^{n}$ is called $d(n)$-saving if: $1 . m_{n}\left(\left|R_{n}\right|+\left|g_{n}\right|\right) / p_{n}$ is polynomial in $n$, 2. $n-l_{n}=d(n)$.

Theorem 5 Let $\alpha(n)=\nu(n) 2^{n}$. There is no $\omega(\log n)$-saving reduction to $\mathcal{F}_{\mathrm{REG}}^{n, \alpha(n)}$.
Proof: Suppose to the contrary that $(R, g)$ is a $\omega(\log n)$-saving reduction to $\mathcal{F}_{\text {REG }}^{n, \alpha(n)}$. Consider some particular $f$, and let $D$ be the set of all possible oracle queries that $g^{f}$ can ask, on any input. Then $|S| \leq|g| 2^{l}$, because on each of the $2^{l}$ distinct inputs, $g$ asks at most $|g|$ queries. The basic idea of the lower bound proof is that, for $l<n-\omega(\log n)$, and polynomial-sized $g, S$ occupies a negligible fraction of $f$ 's domain. But the one-way $f$ can be easy on $S$, and $g^{f}$ is then not one-way.

Formally: apply Lemma 6 of Appendix F to $\left(R_{n}, g_{n}\right)$ with $c=\omega(\log (n))$ and $p=p(n)$. Since $2^{c / 2}=1 / \nu(n)$ and $2^{n-\log \alpha(n)}=2^{n} / \alpha(n)=1 / \nu(n)$ we conclude that $\left|R_{n}\right|+\left|g_{n}\right|$ is superpolynomial.

Theorem 6 Let $\alpha(n)=\nu(n) 2^{n}$. There is no $(\omega(\log (n))+\log \alpha(n))$-saving collection-reduction to $\mathcal{F}_{\mathrm{REG}}^{n, \alpha(n)}$. Proof: Suppose that $(R, g)$ is the collection-reduction which contradicts the theorem statement, and let $l$ be the number of $g$ 's input wires. We show that it is possible to build from $(R, g)$ a circuit $B$ of size about $2^{l}$ which inverts any $f \in \mathcal{F}_{\mathrm{REG}}^{n, \alpha(n)}$. To do this, note that $R^{V}$ inverts any $f \in \mathcal{F}_{\mathrm{REG}}^{n, \alpha(n)}$ as long as it is given an inverter $V$ for $g^{f}$. But $V$ can be implemented as a circuit of size $2^{l} / \nu(n)$. Therefore $R^{V}$ can be implemented (without any oracle) as a circuit of size about $|R| 2^{l} / \nu(n)$. But this is too small to invert any function $f \in \mathcal{F}_{\mathrm{REG}}^{n, \alpha(n)}$. The formal argument follows.

If $\left|g_{n}\right|$ is superpolynomial we are done. Else suppose $\left|g_{n}\right|$ grows polynomially fast. Apply Lemma 9 of Appendix F with $d=\omega(\log (n))$ (and $\log |I|<\left|g_{n}\right|$ since $\log |I|$ is at most the number of input wires of $g_{n}$ ), to get that $\left|R_{n}\right|>p(n) 2^{\omega(\log (n))} /\left|g_{n}\right|$ which is superpolynomial.

Theorem 7 Let $s(n)<n$. There is no $(\omega(\log (n))+s(n))$-saving collection-reduction to $\mathcal{F}_{\text {Low }}^{n, s(n)}$.
Proof Sketch: Let $f$ be a random permutation and let $h(p, y)$ output $x=f^{-1}(y)$ if $p$ is an $s$-bit prefix of $x$. This ensures that $f$ is "exactly" $s$-hard. For any construction $g^{f}$ with input size $l=n-s-d$ (and description of family index $m$ polynomial in $n$ ), we can show an oracle $V$ which inverts it, but such that $V$ does not significantly reduce the hardness of $f$. Some minor modifications are needed to ensure that $(f, h)$ is a permutation.
$V$, on input $(i, y)$, simply outputs a random $x$ for which $g_{i}^{f}(x)=y$. To see that $f$ is still $s$-hard, suppose there is a poly-size inverter $A^{(f, h), V}$ for $f$. From it one can build a circuit $B^{f}$ which perfectly simulates $A^{(f, h), V}$. Each call to $h$ can be simulated using $2^{n-s}$ queries to $f$, and each call to $V$ using $\approx 2^{l}$ queries to $f$. So $B^{f}$ calls $f$ about $|B|\left(2^{l}+2^{n-s}\right)<|B|\left(2 \cdot 2^{n-s}\right)$ times. With this many queries, the probability of inverting $f$ cannot exceed $\approx 2^{-s}$, so $f$ is still $s$-hard.

Corollary 1 (To Theorem 5) There is no $\omega(\log n)$-saving reduction to $\mathcal{F}^{n}$.
Corollary 2 (To Theorem 6) There is no $(\omega(\log n)+\log \alpha(n))$-saving reduction to $\mathcal{F}^{n}$.

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## A Further Shortening the PRG Seed

In our pseudorandom generator, the output of the last hash function has, intuitively, almost $k$ bits of entropy. It entropy can be converted to pseudorandomness using an extractor with a public seed (of length $k$ ). To get this pseudorandomness to be, e.g., $n^{\log ^{c} n}$-close to uniform for some $c$, one will $\operatorname{lose}^{\Theta}\left(\log ^{c+1} n\right)$ bits. If we take this approach, then the we need to run the randomized iterate construction not $k$ times, but $\Theta\left(\log ^{c+1} n\right)$ times; thus, we need the space-bounded generator to produce not $k$, but $\Theta\left(\log ^{c+1} n\right)$ hash functions, which can be done in space $\mathcal{O}\left(k \log \left(\log ^{c+1} n\right)\right)=\mathcal{O}(k \log \log k)$. The result is a PRG with seed length $2 n+\mathcal{O}(k \log \log k)$ of which only $k$ bits needs to be secret, but security reduced to the bare minimum $n^{\log ^{c} n}$.

## B Standard Definitions

A function $\varepsilon(n)$ is negligible in $n$ (denoted $\varepsilon(n) \in \operatorname{neg}(n)$ ) if $\varepsilon(n)=o(1 / p(n))$ for every positive polynomial $p$.

By a Distribution Ensemble we mean a series $\left\{D_{n}\right\}_{n \in \mathbb{N}}$ where $D_{n}$ is a distribution over $\{0,1\}^{n}$. Let $\left\{X_{n}\right\}$ and $\left\{Y_{n}\right\}$ be distribution ensembles. Define the distinguishing advantage of an algorithm $A$ between the ensembles $\left\{X_{n}\right\}$ and $\left\{Y_{n}\right\}$ denoted as $\Delta^{A}\left(\left\{X_{n}\right\},\left\{Y_{n}\right\}\right)$, by:

$$
\Delta^{A}\left(\left\{X_{n}\right\},\left\{Y_{n}\right\}\right)=\left|\operatorname{Pr}\left[A\left(1^{n}, X_{n}\right)=1\right]-\operatorname{Pr}\left[A\left(1^{n}, Y_{n}\right)=1\right]\right|
$$

where the probabilities are taken over the distributions $X_{n}$ and $Y_{n}$, and the randomness of $A$. We say that $\left\{X_{n}\right\}$ and $\left\{Y_{n}\right\}$ are computationally-indistinguishable [GM84] if for every PPT $A, \Delta^{A}\left(\left\{X_{n}\right\},\left\{Y_{n}\right\}\right) \in$ neg $(n)$.

Definition 5 (One-way functions) Let $f:\{0,1\}^{*} \rightarrow\{0,1\}^{*}$ be a polynomial-time computable function. $f$ is one-way iffor every PPT $A, \operatorname{Pr}_{x} \leftarrow\{0,1\}^{n}\left[A\left(1^{n}, f(x)\right) \in f^{-1}(f(x))\right]$ is negligible in $n$.

A few convention remarks: When the value of the security-parameter (i.e., $1^{n}$ ) is clear, we allow ourselves to omit it from the adversary's parameters list. Since any one-way function is w.l.o.g. length-regular (i.e., inputs of same length are mapped to outputs of the same length), it can be viewed as an ensemble of functions mapping inputs of a given length to outputs of some polynomial (in the input) length. Therefore we can write: let $f:\{0,1\}^{n} \rightarrow\{0,1\}^{\ell(n)}$ be a one-way function, where $\ell(n)$ is a polynomial-time computable function of $n$.

The following definition follows the definition of one-way functions with public randomness from [HL92] (though we do not require the amounts of public randomness and secret randomness to be polynomially related-it is possible to imagine, for instance, that for $k$ secret random bits a one-way function could need $k^{\log k}$ public ones).

Definition 6 (Public-coin collection of one-way functions) Let $s_{P}, s_{S}: \mathbb{N} \rightarrow \mathbb{N}$. A collection of functions $\left\{f_{i}\right\}_{i \in\{0,1\}^{*}}$ is public-coin one-way if it is:

1. Easy to compute: There exists an efficient (randomized) algorithm $f$ such that for any $i, x, f(i, x)=$ $f_{i}(x)$.
2. Hard to invert: For every РРT $A$ :

$$
\underset{i \leftarrow\{0,1\}^{s_{P}(n)}, x \leftarrow\{0,1\}^{s_{S}(n)}}{\operatorname{Pr}}\left[A\left(i, f_{i}(x)\right) \in f_{i}^{-1}\left(f_{i}(x)\right)\right] \in \operatorname{neg}(n) .
$$

For ease of notation, in the rest of the paper we use in place of $i$ something more meaningful, as long as it can be computed in polynomial-time from public coins, such as a description $h$ of a member of a hash function family.

Definition 7 (Pseudorandom-Generator (PRG) [BM82, Yao82]) Let $G:\{0,1\}^{n} \rightarrow\{0,1\}^{\ell(n)}$ be a poly-nomial-time computable function where $\ell(n)>n$. We say that $G$ is a Pseudorandom-Generator if $G\left(U_{n}\right)$ is computationally-indistinguishable from $U_{\ell(n)}$.

The following definition follows the definition of pseudorandom generators with public randomness from [HL92].

Definition 8 (Public-coin collection of PRGs) Let $d, s_{P}, s_{S}: \mathbb{N} \rightarrow \mathbb{N}$ and $d>0$. A collection offunctions $\left\{G_{i}\right\}_{i \in\{0,1\}^{*}}$ is said to be a public-coin collection of PRGs if it is:

1. Easy to compute: There is an efficient algorithm $G$ such that for any $i, x, G(i, x)=G_{i}(x)$.
2. Expanding: If $|i|=s_{P}(n)$ then $G_{i}:\{0,1\}^{s_{S}(n)} \rightarrow\{0,1\}^{s_{S}(n)+d(n)}$.
3. Indistinguishable: The ensembles $\left(i, G_{i}(x)\right)$ and $(i, Z)$ are indistinguishable ( $i, x$ and $Z$ are uniform on $\{0,1\}^{s_{P}(n)},\{0,1\}^{s_{S}(n)}$ and $B^{s_{S}(n)+d(n)}$, respectively).

The functions $d, s_{P}$ and $s_{S}$ are called expansion, public seed length and secret seed length, respectively.

## C Proof of Proposition 2

We continue where we left off on page 7. The division into chunks is as follows. Call two points $y_{1}, y_{2}$ of $Y$ siblings if $f\left(y_{1}\right)=f\left(y_{2}\right)$; a sibling set is the set $f^{-1}(z)$ for some $z \in Z$. Order all the points of $Y$ by the number of siblings they have, in increasing order, keeping sibling sets together. Let $\sigma=\lfloor|Y| / K\rfloor$, and let $R=|Y| \bmod K$ be the remainder (note that $R=0$ if $f$ is regular). Put the first $\sigma+1$ points into the first chunk, the next $\sigma+1$ points into the second chunk, and so on for the first $R$ chunks; then put the next $\sigma$ points into chunk $R+1$, the next $\sigma$ points into chunk $R+2$, and so on, obtaining a total of $K$ chunks. (Each chunk contains precisely one sibling set if $f$ is regular.) For a point $y \in Y$, let $c(y)$ be the chunk that contains $y$. Call the set of the $K$ chunks $C$, and define the function $\hat{h}: X \rightarrow C$ as $\hat{h}(x)=c(h(x))$.

The following claim is adapted from [HHR06b]. It says, essentially, that if a set of chunks is heavy under the distribution imposed by $\hat{h}(x)$, then it also heavy under the uniform distribution.

Claim 1 For any set $T \subseteq C \times \mathcal{H}_{X, Y}$, if $\operatorname{Pr}_{(x, h) \leftarrow X \times \mathcal{H}_{X, Y}}[(\hat{h}(x), h) \in T] \geq \delta$, then

$$
\operatorname{Pr}_{\left(c, h^{\prime}\right) \leftarrow C \times \mathcal{H}_{X, Y}}\left[\left(c, h^{\prime}\right) \in T\right] \geq \delta^{2} / 2.125\left(\delta^{2} / 2 \text { if } f \text { is regular }\right) .
$$

Proof: The statement we want to prove is equivalent to $|T| \geq \delta^{2}\left|\mathcal{H}_{X, Y}\right| K / 2.125$. We will prove it by showing that if $T$ is too small, then collision probability $p$ of the distribution $(\hat{h}(x), h)$ is too high.

On the one hand, the collision probability $C P_{(x, \hat{h}) \leftarrow X \times \mathcal{H}_{X, Y}}(\hat{h}(x), \hat{h})$ is equal to

$$
\begin{aligned}
p & =\underset{\left(x_{1}, h_{1}\right),\left(x_{2}, h_{2}\right) \leftarrow X \times \mathcal{H}_{X, Y}}{\operatorname{Pr}}\left[\left(\hat{h}_{1}\left(x_{1}\right), h_{1}\right)=\left(\hat{h}_{2}\left(x_{2}\right), h_{2}\right)\right] \\
& =\operatorname{Pr}_{h_{1}, h_{2} \leftarrow \mathcal{H}_{X, Y}}^{\operatorname{Pr}}\left[h_{1}=h_{2}\right] \quad \operatorname{Pr}_{\left(x_{1}, h_{1}\right),\left(x_{2}, h_{2}\right) \leftarrow X \times \mathcal{H}_{X, Y}}\left[\left(\hat{h}_{1}\left(x_{1}\right), h_{1}\right)=\left(\hat{h}_{2}\left(x_{2}\right), h_{2}\right) \mid h_{1}=h_{2}\right] \\
& \left.=\frac{1}{\left|\mathcal{H}_{X, Y}\right|}{ }_{h \leftarrow \mathcal{H}_{X, Y}, x_{1}, x_{2} \leftarrow X} \operatorname{Pr}^{[\hat{h}}\left(x_{1}\right)=\hat{h}\left(x_{2}\right)\right] .
\end{aligned}
$$

The event $\hat{h}\left(x_{1}\right)=\hat{h}\left(x_{2}\right)$ happens if $x_{1}=x_{2}$ (whose probability, by the assumption on collision probability of $X$, is at most $1 / K$ ), or if $x_{1} \neq x_{2}$, but the choice of $h$ mapped them to the same chunk. The probability of the latter event is analyzed easily if we assume all chunks are of size $\sigma$, i.e., $K$ divides $|Y|$ (in particular, if $f$ is regular). In such a case, for any fixed $x_{1} \neq x_{2}, \operatorname{Pr}_{h \leftarrow \mathcal{H}_{X, Y}}\left\{\hat{h}\left(x_{1}\right)=\hat{h}\left(x_{2}\right)\right]=$ $\sum_{c \in C} \sum_{y_{1}, y_{2} \in c} \operatorname{Pr}_{h \leftarrow \mathcal{H}_{X, Y}}\left[y_{1}=h\left(x_{1}\right) \wedge y_{2}=h\left(x_{2}\right)\right]=K \cdot\left(\frac{|Y|}{K}\right)^{2} \cdot \frac{1}{|Y|^{2}}=\frac{1}{K}$. The general case is a bit messier: for any fixed $x_{1} \neq x_{2}$,

$$
\begin{aligned}
\operatorname{Pr}_{h \leftarrow \mathcal{H}_{X, Y}}\left[\hat{h}\left(x_{1}\right)=\hat{h}\left(x_{2}\right)\right]= & \\
= & \sum_{c \in\left\{c_{1}, \ldots, c_{R}\right\}} \sum_{y_{1}, y_{2} \in c} \operatorname{Pr}_{h \leftarrow \mathcal{H}_{X, Y}}\left[y_{1}=h\left(x_{1}\right) \wedge y_{2}=h\left(x_{2}\right)\right]+ \\
& \sum_{c \in\left\{c_{R+1}, \ldots c_{K}\right\}} \sum_{y_{1}, y_{2} \in c} \operatorname{Pr}_{\leftarrow \leftarrow \mathcal{H}_{X, Y}}\left[y_{1}=h\left(x_{1}\right) \wedge y_{2}=h\left(x_{2}\right)\right] \\
= & \frac{R(\sigma+1)^{2}}{|Y|^{2}}+\frac{(K-R) \sigma^{2}}{|Y|^{2}}=\frac{K \sigma^{2}+2 R \sigma+R}{(K \sigma+R)^{2}} .
\end{aligned}
$$

Looking at signs of partial derivatives with respect to $\sigma$ and $R$, and observing that $|Y| \geq K$, hence $\sigma \geq 1$, shows that the maximum of this expression occurs at $\sigma=1$ and $R=K / 3$. Thus, $\operatorname{Pr}_{h \leftarrow \mathcal{H}_{X, Y}}\left[\hat{h}\left(x_{1}\right)=\right.$ $\left.\hat{h}\left(x_{2}\right)\right] \leq 2 K /(4 K / 3)^{2}=9 /(8 K)$.

Hence, $p \leq 1 /\left|\mathcal{H}_{X, Y}\right|(1 / K+9 /(8 K))=2.125 /\left(K\left|\mathcal{H}_{X, Y}\right|\right)$, and $p \leq 2 /\left(K\left|\mathcal{H}_{X, Y}\right|\right)$ for regular $f$.
On the other hand, $p$ is at least the probability that a collision occurs, and happens inside $T: p \geq$ $\operatorname{Pr}_{\left(x_{1}, h_{1}\right),\left(x_{2}, h_{2}\right) \leftarrow X \times \mathcal{H}_{X, Y}}\left[\left(\hat{h}_{1}\left(x_{1}\right), h_{1}\right)=\left(\hat{h}_{2}\left(x_{2}\right), h_{2}\right) \wedge\left(\hat{h}_{1}\left(x_{1}\right), h_{1}\right) \in T\right]$. If both $\left(\hat{h}_{1}\left(x_{1}\right), h_{1}\right)$ and ( $\hat{h}_{2}\left(x_{2}\right), h_{2}$ ) end up in $T$ (which happens with probability $\delta^{2}$ ), then they collide with probability at least $1 /|T|$ (no matter what the distribution is inside $T, 1 /|T|$ is the lowest possible collision probability), and hence $p \geq \delta^{2} /|T|$.

Thus, the two bounds on $p$ show that $\delta^{2} /|T| \leq 2.125 /\left(K\left|\mathcal{H}_{X, Y}\right|\right)(2$ instead of 2.125 for regular $f$ ), which is exactly what we needed to show.

Applying this claim to the set $T$ of good pairs $(c, h)$ (and observing that $\operatorname{Pr}_{(x, h) \leftarrow X \times \mathcal{H}_{X, Y}}[(\hat{h}(x), h) \in$ $T] \geq \delta$, because if $(f(h(x)), h) \in S$, then $(\hat{h}(x), h) \in T)$ ), we see that $\operatorname{Pr}_{\left(c, h^{\prime}\right) \leftarrow C \times \mathcal{H}_{X, Y}}\left[\left(c, h^{\prime}\right) \in T\right] \geq$ $\delta^{2} / 2.125$. For regular $f$ (replacing 2.125 with 2 ), this concludes the proof of the proposition, because a good chunk gives exactly $|Y| / K$ good elements of $Y$. For general $f$, we have to work harder.

Let $\alpha_{h}=\operatorname{Pr}_{c \leftarrow C}[(c, h) \in T]$; we have just shown that $\mathbb{E}_{h \leftarrow \mathcal{H}_{X, Y}} \alpha_{h} \geq \delta^{2} / 2.125$. Now fix $h$, and call $z, y$ or $c$ good if $(z, h),(y, h)$, or $(c, h)$, respectively, is good. We will show that the fraction of good points $y$ is polynomially related to $\alpha_{h}$. (Of course, each chunk that contains a good point may also contain many points that are not good, so this is not immediate. )

Claim 2 If, for a fixed $h, \operatorname{Pr}_{c \leftarrow C}[c$ is good $]=\alpha_{h}$, then $\operatorname{Pr}_{y \in Y}[y$ is good $]>2 \alpha_{h}^{2} / 9-1 /\left(4 K^{2}\right)$.
Proof: To prove this, we will make use of two facts: first, if $y$ is good, then so are all of its siblings (because the definition of good depends only on $f(y)$ ); second, many $y$ values have to have many siblings, because the total number of outputs of $f$ is only $K$.

Let $T_{h}$ be the set of good chunks; recall that $\operatorname{Pr}_{c \leftarrow C}\left[c \in T_{h}\right]=\alpha_{h}$, i.e., $\left|T_{h}\right|=\alpha_{h} K$. To see an intuitive explanation for the second fact, assume for a moment that sibling sets do not cross chunk boundaries. Then the average number of siblings sets per chunk in $T_{h}$ cannot exceed $1 / \alpha_{h}$ : else, the total number of distinct sibling sets (and hence outputs of $f$ ) would exceed $\left(1 / \alpha_{h}\right) \cdot\left(\alpha_{h} K\right)=K$. The actual math involved, unfortunately, is uglier, both because sibling sets can cross chunk boundaries, and because average number of sibling sets (and hence the weight of the average sibling set) is insufficient for our analysis: it is possible that only below-average sets are the ones that cause chunks to be included in $T_{h}$.

We now proceed to the formal argument. Call the chunks in $T_{h} c_{1}, c_{2}, \ldots, c_{t}$ according to the ordering of points described at the beginning of the proof (i.e., $c_{1}$ contains elements with smaller sibling sets, and $c_{t}$ contains elements with larger sibling sets); note that $t=\alpha_{h} K$.

First, we will count all the large sibling sets. Namely, consider all good $y$ whose sibling sets are of size greater than $\sigma$. These $y$ belong to chunks $c_{d+1}, \ldots, c_{t}$ for some $d$. Note that all elements of such a sibling set are good, as long as a single element is good; and every chunk must contain at least one good element.

Sub-Claim 1 If a sibling set of size at least $\sigma+1$ intersects with $v$ chunks, then it contains more than $(\sigma+1) v / 3$ elements.

Proof: Note that the statement is trivial for $v<3$; and if a sibling set intersects with 3 chunks, then it must contain at least $\sigma+2$ elements; so we consider only $v \geq 4$. If the sibling set contains $w$ elements, then it can intersect with at most $(w-2) / \sigma+2$ chunks, because the rightmost and the leftmost chunk require at least one element each from the sibling set, and the remaining chunks require at least $\sigma$ elements. Therefore, $v \leq(w-2) / \sigma+2$, and hence $w \geq(v-2) \sigma+2 \geq v \sigma / 3+(2 v / 3-2) \sigma+2 \geq v \sigma / 3+(2 v / 3-2)+2 \geq$ $v \sigma / 3+v / 3$.

Therefore, the total number of good $y$ s in $c_{d+1}, \ldots, c+t$ is at least $(t-d)(\sigma+1) / 3 \geq(t-d)|Y| /(3 K)$.
We will now count good $y$ s in smaller sibling sets, those overlapping with chunks $c_{1}, \ldots, c_{d}$.

Sub-Claim 2 If $y \in c_{i}$, then the size of the sibling set of $y\left(i . e .,\left|f^{-1}(f(y))\right|\right)$ is greater than $(i-1)|Y| / K^{2}$.
Proof: There are $i-1$ chunks that come before $y$, and their average size is least $|Y| / K$ (because we arranged for chunks of size $\sigma+1>|Y| / K$ to come before the chunks of size $\sigma$ ). Thus, total number of points that come before (and including) $y$ in the ordering is at least $1+(i-1)|Y| / K$. They are contained in at most $K$ distinct sibling sets; hence, the size of the average sibling set is greater than $(i-1)|Y| / K^{2}$. The sibling set that contains $y$ is the largest of them (because of the ordering), and hence no smaller than the average.

Consider now the chunk $c_{d}$. It is in $T_{h}$ because of some good $y \in c_{d}$; neither this $y$ nor its siblings have been counted above, when we were counting members of large sibling sets, because no good $y$ in $c_{1}, \ldots, c_{d}$ has a sibling set of size greater than $\sigma$. The sibling set of that $y$ (and note that every element of that sibling set is good) is of size greater than $(d-1)|Y| / K^{2}$, by the above sub-claim. The chunk $c_{d-1}$ may be in $T_{h}$ because of some other element of the same sibling set, and hence we will not count any points in it. However, no elements of the same sibling set are in chunks preceding $c_{d-1}$, because the size of the sibling set of size no greater than $\sigma$. Therefore, we can proceed to $c_{d-2}$, and similarly identify a good $y$ in it, and count its sibling set, of size greater than $(d-3)|Y| / K^{2}$. Continuing in this manner, we get that the number of good points is more than

$$
\frac{(t-d)|Y|}{3 K}+\frac{|Y|}{K^{2}}((d-1)+(d-3)+(d-5)+\ldots)=\frac{|Y|}{K}\left(\frac{t-d}{3}+\frac{d^{2}-1}{4 K}\right)
$$

(because $\left.(d-1)+(d-3)+(d-5)+\cdots \geq\left(d^{2}-1\right) / 4\right)$. To get rid of the variable $d$, we use the fact that $(t-d) / 3+d^{2} /(4 K) \geq 2 t^{2} /(9 K)$ (this can be shown as follows: because $d \leq t$, if $t<2 K / 3$, then the derivative with respect to $d$ is negative, with the minimum reached when $t=d$ and $(t-d) / 3+d^{2} /(4 K) \geq$ $t^{2} /(4 K)>2 t^{2} /(9 K)$; if $t \geq 2 K / 3$, then the minimum is reached at the zero of the derivative, when $d=2 K / 3$ and $(t-d) / 3+d^{2} /(4 K)=t / 3-K / 9 \geq 2 t^{2} / 9 K$, with the last inequality holding because the quadratic $2 t^{2} / 9 K-t / 3+K / 9$ has roots $t=K / 2$ and $t=K$, and $K / 2<t \leq K$ ). Thus, remembering that $t / K=\alpha_{h}$, we get that the number of good points is more than

$$
\frac{|Y|}{K}\left(\frac{2 t^{2}}{9 K}-\frac{1}{4 K}\right)=|Y|\left(\frac{2 \alpha_{h}^{2}}{9}-\frac{1}{4 K^{2}}\right)
$$

and hence the probability that a uniformly chosen point in $Y$ is good is more than $2 \alpha^{2} / 9-1 /\left(4 K^{2}\right)$. This concludes the proof of Claim 2.

By Claim 2, $\operatorname{Pr}_{(y, h) \leftarrow Y \times \mathcal{H}_{X, Y}}[(f(y), h)$ is good $] \geq \mathbb{E}_{h \leftarrow \mathcal{H}_{X, Y}}\left(2 \alpha_{h}^{2} / 9-1 /\left(4 K^{2}\right)\right)$. Because average of squares is no less than the square of the average (by Jensen's inequality), we have $\mathbb{E}_{h \leftarrow \mathcal{H}_{X, Y}} \alpha_{h}^{2} \geq$ $\left(\mathbb{E}_{h \leftarrow \mathcal{H}_{X, Y}} \alpha_{h}\right)^{2} \geq\left(8 \delta^{2} / 17\right)^{2}$ by Claim 1. Thus, $\operatorname{Pr}_{(y, h) \leftarrow Y \times \mathcal{H}_{X, Y}}[(f(y), h)$ is good $] \geq 2 \cdot 8^{2} \delta^{4} /(9$. $\left.17^{2}\right)-1 /\left(4 K^{2}\right)$. This proves Proposition 2.

## D Proof of Theorem 2

We state and prove the technical lemma that immediately implies the theorem.
Lemma 4 Let $f: Y \rightarrow Z$ be a function, let $O_{H} \subset Z$ be a set of size $K$, and $I_{H}=f^{-1}\left(O_{H}\right)$. Suppose $\left|I_{H}\right|=p_{H}|Y|$. Let $X$ be a distribution with collision probability at most $1 / K$, and let $\mathcal{H}_{X, Y}$ be a family of pairwise-independent functions from the elements of $X$ to $Y$. For every $h \in \mathcal{H}_{X, Y}$ define $f_{h}: X \rightarrow Z$ as $f_{h}(x) \stackrel{\text { def }}{=} f(h(x))$. Then any adversary $A$ that inverts $f_{h}$ with probability at least $\left(1-p_{H}\right)+\varepsilon$ over $x \in X$ and $h \in \mathcal{H}_{X, Y}($ for $\varepsilon>0)$ can be used to invert $f$ on uniformly random inputs from $Y$ with probability at least $\varepsilon^{4} /\left(21 p_{H}\right)-p_{H} /\left(4 K^{2}\right)$ in the same running time as $A$ (plus the time required to pick and evaluate $a$ random hash function from $\mathcal{H}_{X, Y}$ ).

Proof: The proof is very similar to the proof of Lemma 2. We construct the same $M^{A}$ and analyze its success probability. We highlight the differences in the analysis.

Proposition 3 For any $S^{\prime} \subseteq Z \times \mathcal{H}_{X, Y}$, if

$$
\operatorname{Pr}_{(x, h) \leftarrow X \times \mathcal{H}_{X, Y}}\left[\left(f_{h}(x), h\right) \in S^{\prime}\right] \geq\left(1-p_{H}\right)+\delta
$$

for $\delta>0$, then

$$
\underset{\left(y, h^{\prime}\right) \leftarrow Y \times \mathcal{H}_{X, Y}}{ }\left[\left(f(y), h^{\prime}\right) \in S^{\prime}\right] \geq \frac{\delta^{4}}{21 p_{H}}-\frac{p_{H}}{4 K^{2}} .
$$

Proof: Let $S=S^{\prime} \cap O_{H} \times \mathcal{H}_{X, Y}$. Note that the weight of $S$ with respect to $\left(f_{h}(x), h\right)$ is least $\delta$ : $\left.\left.\operatorname{Pr}_{(x, h) \leftarrow X \times \mathcal{H}_{X, Y}}\left[f_{h}(x), h\right) \in S\right] \geq \operatorname{Pr}_{(x, h) \leftarrow X \times \mathcal{H}_{X, Y}}\left[f_{h}(x), h\right) \in S^{\prime}\right]-\operatorname{Pr}_{(x, h) \leftarrow X \times \mathcal{H}_{X, Y}}\left[f_{h}(x) \notin O_{H}\right]$. Because for any fixed $x$ and random $h$, the value $h(x)$ is uniformly distributed, $\operatorname{Pr}_{(x, h) \leftarrow X \times \mathcal{H}_{X, Y}}\left[f_{h}(x) \notin\right.$ $\left.O_{H}\right]=\operatorname{Pr}_{(x, h) \leftarrow X \times \mathcal{H}_{X, Y}}\left[h(x) \notin I_{H}\right]=1-p_{H}$. We will work with $S$ instead of $S^{\prime}$ from now on.

Instead of dividing the entire $Y$ into $K$ chunks as in Proposition 2 we divide only $I_{H}$ into $K$ chunks. We do not define $\hat{h}(x)$, because not every point in $Y$ belongs to a chunk. However, for every $y \in I_{H}$, we define $c(y)$ as the chunk to which $y$ belongs.

Claim 3 For any set $T \subseteq C \times \mathcal{H}_{X, Y}$, if $\operatorname{Pr}_{(x, h) \leftarrow X \times \mathcal{H}_{X, Y}}\left[h(x) \in I_{H} \wedge(c(h(x)), h) \in T\right] \geq \delta$, then $\operatorname{Pr}_{\left(c, h^{\prime}\right)} \leftarrow C \times \mathcal{H}_{X, Y}\left[\left(c, h^{\prime}\right) \in T\right] \geq \delta^{2} /\left(p_{H}+1.125 p_{H}^{2}\right) \geq \delta^{2} /\left(2.125 p_{H}\right)$.

Proof: The proof is essentially the same as of Claim 1. Consider the probability

$$
p=\operatorname{Pr}_{\left(x_{1}, h_{1}\right),\left(x_{2}, h_{2}\right) \leftarrow X \times \mathcal{H}_{X, Y}}\left[h_{1}\left(x_{1}\right) \in I_{H} \wedge h_{2}\left(x_{2}\right) \in I_{H} \wedge\left(c\left(h_{1}\left(x_{1}\right)\right), h_{1}\right)=c\left(\left(h_{2}\left(x_{2}\right)\right), h_{2}\right)\right] .
$$

On the one hand $p \leq 1 /\left(\left|\mathcal{H}_{X, Y}\right| K\right)\left(p_{H}+1.125 p_{H}^{2}\right)$. On the other hand, $p \geq \delta^{2} /|T|$. This gives the desired bound.

Observe that if $(f(h(x)), h) \in S$, then $h(x) \in I_{H}$ and $(c(h(x)), h)$ is good. Hence, we can apply the above claim to the set $T$ of $\operatorname{good}(c, h)$ pairs.

Claim 4 If, for a fixed $h, \operatorname{Pr}_{c \leftarrow C}[c$ is good $]=\alpha_{h}$, then $\operatorname{Pr}_{y \in Y}[y$ is good $]>\left(2 \alpha_{h}^{2} / 9-1 /\left(4 K^{2}\right)\right) p_{H}$.
Proof: The proof is essentially the same as of Claim 2, replacing $|Y|$ with $\left|I_{H}\right|$.
Putting the two claims together gives the proof of the proposition.
The proof of Lemma 4 follows by an application of Lemma 1, which is applicable because ( $f(y), h^{\prime}$ ) $g$-dominates $(f(h(x)), h)$, for the convex function

$$
g(\beta)= \begin{cases}\frac{\left(\beta-\left(1-p_{H}\right)\right)^{4}}{21 p_{H}}-\frac{p_{H}}{4 K^{2}} & \text { if } \frac{\left(\beta-\left(1-p_{H}\right)\right)^{4}}{21 p_{H}}-\frac{p_{H}}{4 K^{2}}>0 \\ 0 & \text { otherwise. }\end{cases}
$$

## E Proof of Lemma 3 (Unpredictable Sequence)

Let $E \subseteq \Phi \times$ Supp be the set of coins-instances on which $A$ succeeds:

$$
E=\{(\omega,(\bar{h}, \hat{h}, z)) \mid A \text { inverts } i \text {-th iteration on }(\omega, \bar{h}, \hat{h}, z)\} .
$$

Also let $L \subseteq$ Supp be the set of instances with no more than $2 / \sqrt{\epsilon}$ preimages under $h^{i}$, which fall into $\operatorname{Im}\left(f_{\hat{h}}\right)\left(\right.$ where $f_{\hat{h}}(u)=f(\hat{h}(u))$ ):

$$
L=\left\{(\bar{h}, \hat{h}, z)| |\left(h^{i}\right)^{-1}(z) \cap \operatorname{Im}\left(f_{\hat{h}}\right) \mid \leq 2 / \sqrt{\epsilon}\right\} .
$$

Let us call $(\Phi \times L) \cap E$ the good set of coins-instances. We shall prove that its probability under the uniform distribution is at least $\frac{\epsilon^{2}}{8(k+1)}$ :

$$
\begin{equation*}
\underset{(\omega,(\bar{h}, \hat{h}, z)) \leftarrow \Phi \times Z}{\operatorname{Pr}}[(\Phi \times L) \cap E] \geq \frac{\epsilon^{2}}{8(k+1)} . \tag{1}
\end{equation*}
$$

This inequality is sufficient to claim the lemma. To see that, first note that instances $(\bar{h}, \hat{h}, z)=\left(\bar{h}, \hat{h}, h^{i}(y)\right)$ which $B$ prepares are distributed according to $Z$ (i.e. they are uniform, because $f$ is regular). Suppose that $(\omega,(\bar{h}, \hat{h}, z)) \in(\Phi \times L) \cap E$ (which by (1) happens with probability $\geq \epsilon^{2} / 8(k+1)$ ). By definition of $E$, that means that $A$ 's output $u$ is the inverse of $i$-th iteration on instance $(\bar{h}, \hat{h}, z)$; therefore $h^{i}(f(\hat{h}(u)))=$ $z=h^{i}(y)$. Thus $y$ and $f(\hat{h}(u))$ are siblings under $h^{i}$. But since $z \in L, f(\hat{h}(u))$ has at most $2 / \sqrt{\epsilon}$ such siblings, from which $y$ was chosen at random. The view of $A$ is independent of which sibling is chosen, so with probability $\sqrt{\epsilon} / 2$ we have that $y=f(\hat{h}(u))$, i.e. $B$ 's output is an inverse $f^{-1}(y)$. Thus the overall probability of $B$ 's success is $\epsilon^{2} / 8(k+1) \cdot \sqrt{\epsilon} / 2=\epsilon^{2.5} /(16(k+1))$.

We now turn to proving (1). The first step is to show that the probability of the good set $(\Phi \times L) \cap E$ under the distribution $\Phi \times D$, is at least $\epsilon / 2$. Indeed, $\operatorname{Pr}_{\Phi \times D}[E] \geq \epsilon$ by theorem assumption. We now use $2^{-3 k}$-almost pairwise independence of $h^{i}$ to show that $\operatorname{Pr}_{\Phi \times D}[\Phi \times L] \geq 1-\epsilon / 2$ (in fact this holds for any coins $\omega \in \Phi$, i.e. we prove $\operatorname{Pr}_{D}[L] \geq 1-\epsilon / 2$ ).

Fix arbitrary $\hat{h}$ and $z \in\{0,1\}^{k}$, and let $L_{\hat{h}, z}=\left\{\bar{h}\left|\left(h^{i}\right)^{-1}(z) \cap \operatorname{Im}\left(f_{\hat{h}}\right)\right| \leq 2 / \sqrt{\epsilon}\right\}$. We proceed by a Chebyshev-like argument. For any $x \in \operatorname{Im}\left(f_{\hat{h}}\right)$ define the indicator r.v. $I(x)=1 \Longleftrightarrow h^{i}(x)=z$. Then $V=\sum_{x \in \operatorname{Im}\left(f_{\hat{h}}\right)} I(x)$ is the random variable which counts the number of $z$ 's preimages under $h^{i}$, which are in $\operatorname{Im}\left(f_{\hat{h}}\right)$. We are therefore interested in $\operatorname{Pr}_{h^{i}}[V>2 / \sqrt{\epsilon}]$. Recall that $h^{i}$ are $\delta$-almost pairwise independent where $\delta=2^{-3 k}$ and we have

$$
\begin{aligned}
\underset{h^{i}}{\mathbb{E}}\left(V^{2}\right) & =\mathbb{E}\left(\sum_{x \in \operatorname{Im}\left(f_{\hat{h}}\right)} I(x)\right)^{2}=\mathbb{E} \sum_{x, y}(I(x) I(y))=\sum_{x, y} \mathbb{E}(I(x) I(y))=\sum_{x, y} \operatorname{Pr}_{h^{i}}[(h(x), h(y))=(z, z)] \\
& \leq \sum_{x, y}\left(2^{-2 k}+\delta\right) \leq\left|\operatorname{Im}\left(f_{\hat{h}}\right)\right|^{2}\left(2^{-2 k}+\delta\right) \leq 2^{2 k}\left(2^{-2 k}+\delta\right) \leq 1+2^{-k} \leq 2 .
\end{aligned}
$$

Using Markov's inequality we get that $\operatorname{Pr}\left[V^{2}>4 / \epsilon\right] \leq \epsilon / 2$ or equivalently $\operatorname{Pr}[V>2 / \sqrt{\epsilon}] \leq \epsilon / 2$, i.e. $\operatorname{Pr}\left[L_{\hat{h}, z}\right] \leq 1-\epsilon / 2$. Averaging over $\hat{h}, z$ yields the required $\operatorname{Pr}_{D}[L] \geq 1-\epsilon / 2$.

So we have seen that $\operatorname{Pr}_{\Phi \times D}[\Phi \times L] \geq 1-\epsilon / 2$ and $\operatorname{Pr}_{\Phi \times D}[E] \geq \epsilon$. Therefore

$$
\begin{equation*}
\operatorname{Pr}_{\Phi \times D}[(\Phi \times L) \cap E] \geq \epsilon / 2 . \tag{2}
\end{equation*}
$$

The desired equation (1) now follows from Lemma 1 and the following
Claim 5 For any set of instances $S \subseteq$ Supp

$$
\operatorname{Pr}_{Z}[S] \geq \frac{\left(\operatorname{Pr}_{D}[S]\right)^{2}}{2(k+1)}
$$

Indeed, the above claim says that $Z$ is $g$-dominated by $D$ (see Definition 3), for $g(x)=\frac{x^{2}}{2(k+1)}$. By Lemma 1, $\Phi \times Z$ is $g$-dominated by $\Phi \times D$, and so from (2) we conclude (1).

It remains to prove Claim 5. In other words, in this claim we essentially show that whatever can be done with the knowledge of the randomizing functions $\hat{h}$ and $\bar{h}=\left(h^{1}, \ldots, h^{k}\right)$ can be done about as well when ( $\bar{h}, \hat{h}$ ) are simply chosen at random (as the reduction $B$ does).
Proof: [of Claim 5] We proceed along the lines of [HHR06b] - by showing that the collision probabilities of $D$ and $Z$ are closely related, and using the uniformity of $Z$ we show that event probabilities under those distributions are also closely related. In particular we first show

$$
\begin{equation*}
C P(D) \leq 2(k+1) \cdot C P(Z) \tag{3}
\end{equation*}
$$

and then we use this, as well as the uniformity of $Z$, to conclude that the claim is true.
Proof of (3). Suppose that $i=k$ (i.e. we wish to establish the relation between collision probabilities in the last, $k$-th, iteration). It will be apparent in the proof that the same relation holds for any other $i<k$. By definition, $C P(D)=\operatorname{Pr}\left[\left(\bar{h}, \hat{h}, f_{\hat{h}}^{k}(x, \bar{h}, \hat{h})\right)=\left(\bar{h}^{\prime}, \hat{h}^{\prime}, f_{\hat{h}}^{k}\left(x^{\prime}, \bar{h}^{\prime}, h^{\prime}\right)\right)\right]$. For the collision to happen, we must have $(\bar{h}, \hat{h})=\left(\bar{h}^{\prime}, \hat{h}^{\prime}\right)$ so

$$
C P(D)=\frac{1}{\left|\mathcal{H}_{k, n}\right| \times\left|\mathcal{H}_{\ell, k}^{k}\right|} \cdot \overbrace{\operatorname{Pr}_{x, x^{\prime}, \bar{h}, \hat{h}}\left[f_{\hat{h}}^{k}(x, \bar{h}, \hat{h})=f_{\hat{h}}^{i}\left(x^{\prime}, \bar{h}, \hat{h}\right)\right]}^{b} .
$$

We now show that

$$
b \leq 2(k+1) C P\left(f\left(U_{n}\right)\right)
$$

Define for any $i \leq k$ and any $\hat{h}$ the random variables $y_{i, \hat{h}}=f_{\hat{h}}\left(f_{\hat{h}}^{i}(x, \bar{h}, \hat{h})\right)$ and $y_{i, \hat{h}}^{\prime}=f_{\hat{h}}\left(f_{\hat{h}}^{i}\left(x^{\prime}, \bar{h}, \hat{h}\right)\right)$. For any $\hat{h}$ let $c_{\hat{h}}=C P(f(\hat{h}(x)))$. We first prove that $\operatorname{Pr}\left[y_{k, \hat{h}}=y_{k, \hat{h}}^{\prime}\right] \leq k c_{\hat{h}}+(k-1) 2^{-k}$.

Let $C_{i}$ denote the event that $y_{i, \hat{h}}=y_{i, \hat{h}}^{\prime}$, i.e. a collision in $i$-th iteration. Let $N_{i}$ denote the event $\overline{C_{1} \cup \cdots \cup C_{i}}$, i.e. no collision up to and including $i$-th iteration. We are interested in $\operatorname{Pr}\left[(\exists i \leq k) C_{i}\right]$, which is equal to

$$
\operatorname{Pr}\left[C_{1} \cup\left(C_{2} \cap N_{1}\right) \cup \cdots \cup\left(C_{i} \cap N_{k-1}\right)\right] \leq \operatorname{Pr}\left[C_{1}\right]+\operatorname{Pr}\left[C_{2} \mid N_{1}\right]+\cdots+\operatorname{Pr}\left[C_{k} \mid N_{k-1}\right]
$$

Clearly, $\operatorname{Pr}\left[C_{1}\right]=\operatorname{Pr}\left[f_{\hat{h}}(x)=f_{\hat{h}}\left(x^{\prime}\right)\right]=c_{\hat{h}}$. Let us now upperbound the $i$-th term of the sum: $\operatorname{Pr}\left[C_{i+1} \mid N_{i}\right]$. We are conditioning on $N_{i}$ so $y_{i, \hat{h}} \neq y_{i, \hat{h}}^{\prime}$. Then, by $2^{-3 k}$-almost pairwise independence of $h^{i+1}$, we have that $\left(h^{i+1}\left(y_{i, \hat{h}}\right), h^{i+1}\left(y_{i, \hat{h}}^{\prime}\right)\right)$ is $\left(2^{-3 k} \cdot 2^{2 k} / 2\right)$-close to uniform (see Proposition 1), that is $2^{-k} / 2$-close to uniform. Therefore, by definition of statistical distance, the probability of the collision event $f_{\hat{h}}\left(h^{i+1}\left(y_{i, \hat{h}}\right)\right)=f_{\hat{h}}\left(h^{i+1}\left(y_{i, \hat{h}}^{\prime}\right)\right)$, differs at most by $2^{-k} / 2$ from the probability $c_{\hat{h}}$ of the same event under the uniform distribution. In other words, $\operatorname{Pr}\left[y_{i+1, \hat{h}}=y_{i+1, \hat{h}}^{\prime} \mid N_{i}\right]=\operatorname{Pr}\left[C_{i+1} \mid N_{i}\right] \leq 2^{-k} / 2+c_{\hat{h}}$. Summing up all the $\operatorname{Pr}\left[C_{i+1} \mid N_{i}\right]$ we get the required $\operatorname{Pr}\left[y_{k, \hat{h}}=y_{k, \hat{h}}^{\prime}\right]=\operatorname{Pr}\left[(\exists i \leq k) C_{i}\right] \leq k c_{\hat{h}}+(k-1) 2^{-k} / 2$.

Since $\mathbb{E}_{\hat{h}} c_{\hat{h}}=C P\left(f\left(U_{n}\right)\right)$ we have

$$
\begin{aligned}
b & =\underset{x, x^{\prime}, \bar{h}, \hat{h}}{\operatorname{Pr}}\left[y_{k, \hat{h}}=y_{k, \hat{h}}^{\prime}\right]+\underset{x, x^{\prime}, \overline{h, h},}{\operatorname{Pr}}\left[h^{k}\left(y_{k, \hat{h}}\right)=h^{k}\left(y_{k, \hat{h}}^{\prime}\right) \mid y_{k, \hat{h}} \neq y_{k, \hat{h}}^{\prime}\right] \leq \operatorname{Pr}_{x, x^{\prime}, \bar{h}, \hat{h}}\left[y_{k, \hat{h}}=y_{k, \hat{h}}^{\prime}\right]+2 \cdot 2^{-k} \\
& =\underset{\hat{h}}{\mathbb{E}}\left(k c_{\hat{h}}+(k-1) 2^{-k} / 2\right)+2 \cdot 2^{-k} \leq k C P\left(f\left(U_{n}\right)\right)+(k-1) 2^{-k} / 2+2 \cdot 2^{-k} \\
& \leq k C P\left(f\left(U_{n}\right)\right)+(k+1) 2^{-k} .
\end{aligned}
$$

But the output entropy of $f$ is at most $k$, and since $f$ is regular this means that $2^{-k} \leq C P\left(f\left(U_{n}\right)\right)$. Therefore $b \leq 2(k+1) C P\left(f\left(U_{n}\right)\right)$.

We conclude $C P(D)=\frac{b}{\left|\mathcal{H}_{k, n}\right| \cdot\left|\mathcal{H}_{\ell, k}^{k}\right|} \leq \frac{2(k+1) C P\left(f\left(U_{n}\right)\right)}{\left|\mathcal{H}_{k, n}\right| \cdot\left|\mathcal{H}_{\ell, k}^{k}\right|}$. Clearly, $C P(Z) \geq \frac{C P\left(f\left(U_{n}\right)\right)}{\left|\mathcal{H}_{k, n}\right| \cdot\left|\mathcal{H}_{\ell, k}^{k}\right|}$. Thus $C P(D) \leq$ $2(k+1) C P(Z)$, i.e. (3) holds.
Using (3) to show the claim. Take any event $S \subseteq$ Supp. Consider first $C P(D)$, i.e. $\operatorname{Pr}[a=b]$ for $a, b$ independently drawn from $D$. This probability is lower bounded by the probability of the collision occurring within $S$, i.e. $C P(D) \geq \operatorname{Pr}_{D}[a, b \in S \wedge a=b]=\left(\operatorname{Pr}_{D}[S]\right)^{2} \operatorname{Pr}[a=b \mid a, b \in S]$. Denoting $p_{y}=\operatorname{Pr}_{a}[a=y \mid a \in S]$ we therefore have

$$
C P(D) \geq(\underset{D}{\operatorname{Pr}}[S])^{2} \cdot \operatorname{Pr}[a=b \mid a, b \in S]=(\underset{D}{\operatorname{Pr}}[S])^{2} \sum_{y \in S} p_{y}^{2} \geq(\underset{D}{\operatorname{Pr}}[S])^{2} \frac{\left(\sum_{y \in S} p_{y}\right)^{2}}{|S|}=\frac{\left(\operatorname{Pr}_{D}[S]\right)^{2}}{|S|}
$$

where the second inequality follows from $\sum_{i=1}^{m} x_{i}^{2} \geq\left(\sum_{i=1}^{m} x_{i}\right)^{2} / m$.
Now consider $C P(Z)$. Since $Z$ is uniform, its collision probability is simply $1 / \mid$ Supp|, therefore

$$
2(k+1) / \mid \text { Supp } \mid=2(k+1) C P(Z) .
$$

We can now use (3) (which says that $2(k+1) C P(Z) \geq C P(D)$ ), and the above equations to get

$$
2(k+1) / \mid \text { Supp } \left\lvert\,=2(k+1) C P(Z) \geq C P(D) \geq \frac{\left(\operatorname{Pr}_{D}[S]\right)^{2}}{|S|} .\right.
$$

Multiplying by $|S|$ we reach the desired $2(k+1) \operatorname{Pr}_{Z}[S] \geq\left(\operatorname{Pr}_{D}[S]\right)^{2}$.
This concludes the proof of Claim 5, and therefore Lemma 3 and Theorem 4.

## E. 1 Optimizing security preservation

It is possible to save a factor of $\sqrt{\epsilon}$ in the security reduction, at a cost of possibly requiring more public seed bits. Namely, one can change the PRG to extract the Goldreich-Levin hardcore bit from the output of $f$ in each iteration. It is then possible to construct an inverter $B$ which inverts $f(x)$ with probability about $\epsilon^{2}(n) / k$. But the length of the Goldreich-Levin vector $r$ then must be equal to $\ell$, the length of $f$ 's output, so we have $s_{P}(n) \geq \ell(n)$.

## E. 2 On using secret seeds from non-uniform distributions

Suppose $X$ is a distribution with the only guarantee that $C P(X) \leq 2^{-k}$. We outline the modification which makes our PRG secure even when its seed $x$ is drawn from $X$. Namely, suppose that the support of $X$ is $\{0,1\}^{m}$, and let $\mathcal{H}_{m, k}$ be a family of $2^{-3 k}$-almost pairwise independent hash functions from $\{0,1\}^{m}$ to $\{0,1\}^{k}$. The modified generator first pre-processes its seed $x$ by applying a random $h^{0} \in \mathcal{H}_{m, k}$ to $x$, and then uses our PRG (either of Construction 2 or of Construction 1) on secret seed $h^{0}(x)$. The hash function $h^{0}$ need not be secret. As explained in Section 2, $h^{0}$ can be specified using $\mathcal{O}(k)$ bits, therefore the public seed length remains essentially unchanged $\left(\mathcal{O}(k \log k)\right.$ for Construction 2, or $\mathcal{O}\left(k^{2}\right)$ for Construction 1).

The security proof of this modified construction is almost the same as the proof of Theorem 4. The only difference shows up in computing $C P(D)$ in Claim 5: the first collision event $C_{1}$ happens with a higher probability than $c_{\hat{h}}$, since it can be caused by $h^{0}$. But since $h^{0}$ is $2^{-3 k}$-almost pairwise independent, $\operatorname{Pr}\left[C_{1}\right] \leq C P(X)+2 \cdot 2^{-k}+c_{\hat{h}} \leq 3 \cdot 2^{-k}+c_{\hat{h}}$. Therefore $C P(D)$ is still bounded by $\mathcal{O}(k) / 2^{k}$, and the rest of the proof is essentially unchanged.

## F Supporting Lemmas for Black-Box Separations

Lemma 5 Let $A^{f}:\{0,1\}^{l} \rightarrow\{0,1\}^{m}$ be any oracle circuit of size at most $S=2^{n-l-d}$. There is an $\alpha$-regular function $f:\{0,1\}^{n} \rightarrow\{0,1\}^{k}$ and a set $D \subseteq\{0,1\}^{n}$ with $|f(D)|<2^{n-d} / \alpha$ such that for any $x \in\{0,1\}^{l}, A^{f}(x)$ never makes a query outside $D$.

Proof: We construct $f$ and $D$ as follows.

1. Initially let $D=\emptyset, y=0$ and let $f$ be undefined everywhere.
2. For $x \in\{0,1\}^{l}$ :
(a) Run $A(x)$ and answer each its query $f(q)$ as follows:
i. If $f(q)$ is undefined, add $q$ to $D$, answer $y$ and define $f(q):=y$.
ii. If $f(q)$ is defined, then answer $f(q)$.
iii. After answering a query, check if $\left|f^{-1}(y)\right|=\alpha$; if so, set $y \leftarrow y+1$.

In the remaining undefined points, $f$ can be extended arbitrarily to an $\alpha$-regular function. The size of $f(D)$ is the final value of $y$. At least $\alpha$ queries are necessary to increase $y$ by 1 . There are $2^{l}$ inputs, and on each of them $A$ asks at most $S$ queries. Therefore $y \leq S 2^{l} / \alpha \leq 2^{n-d} / \alpha$.

Lemma 6 Let $l=n-c$ and $p \geq 2^{-c / 2+1}$. If $(R, g)$ is an $(l, p)$-reduction to $\mathcal{F}_{\text {REG }}^{n, \alpha}$ then $|g|>2^{c / 2}$ or $|R|>p 2^{n-a+3}$.

Proof: Suppose $|R|<T$ and $|g|=S \leq 2^{c / 2}$. By Lemma 5 there are $f, D$ such that $(\forall x) g^{f}(x)$ never makes a query outside $D$, and $|f(D)|<2^{n-c / 2} / \alpha$. Let $\mathcal{F}$ be the set of all functions which agree with $f$ on $D$ (i.e. all $f^{\prime}:\{0,1\}^{n} \rightarrow\{0,1\}^{n}$ s.t. $x \in D \Longrightarrow f(x)=f^{\prime}(x)$ ). Then for any $x$ and any $f, f^{\prime} \in \mathcal{F}$, $g^{f}(x)=g^{f^{\prime}}(x)$. So $V$, the perfect inverter for $g^{f}$, is in fact a perfect inverter for any $g^{f}$ as long as $f \in \mathcal{F}$.

Therefore $R^{V, f}$ is a $p$-inverter for any $f \in \mathcal{F}$. Let $X:=\{0,1\}^{n} \backslash f^{-1}(D)$ and let $\mathcal{H}^{\prime}$ be the set of all $\alpha$-regular functions $h: X \rightarrow\{0,1\}^{n}$. Since $f^{-1}(D)$ is at most a $p / 2$-fraction of $\{0,1\}^{n}, R^{V, f}$ must work reasonably well on $X$, i.e. it is a $p / 2$-inverter for any $h \in \mathcal{H}$. Its oracle $V$-gates can be replaced by brute-force inverters for $g$, resulting in a circuit $B^{f}$ which makes at most $|T|$ queries to $X$ (recall that $g$ never asks a query outside $D$, so its brute force inverter does not either). Lemma 8 can now be applied, and it follows that at most a $(T / p)(8 \alpha /|X|)$-fraction of $\mathcal{H}$ can be $p / 2$-inverted by $S$. This fraction is smaller than 1 , a contradiction!

Lemma 7 Let $(R, g)$ be a $(l, m, p)$-collection-reduction from $\mathcal{F}_{\mathrm{REG}}^{n, \alpha}$. Then there is a circuit $B$ with $|B| \leq$ $|R|\left(2^{l+1} m\right)$ which is a $p$-inverter for any $f \in \mathcal{F}_{\text {REG }}^{n, \alpha}$.

Proof: We build the required inverter $B$ from $R$ and $g$. Suppose that $V$ is the perfect inverter for $g^{f}$. Then $R^{V, f}$ is a $p$-inverter for $f$. We shall replace each call to the inverting oracle $V$ by a circuit $W^{f}$ which is a brute-force perfect inverter for $\mathcal{G}$. The circuit $W$ only needs oracle access to $f$, and its structure is independent of $f$ - it is determined by $g$. In this way each call to the perfect inverter $I$ is accurately simulated, so $B^{f}(x)=R^{V, f}(x)$ for any $x$, i.e. $B^{f}$ is a $p$-inverter for $f$.

The brute force inverter $W^{f}$ works as follows. On input $(i, y)$ it evaluates $g^{f}(i, x)$ for all $x \in\{0,1\}^{l}$. If either of those is equal to $y$, then it outputs the corresponding $x$. This can be implemented in a circuit of size $\mathcal{O}\left(2^{l}\right)$ times $m$, the size of the circuit evaluating $g^{f}$. Thus $|W| \in \mathcal{O}\left(m 2^{l}\right)$.

Since each call to $V$ is replaced by $W$, the total size of $B$ is $|R| \mathcal{O}\left(m 2^{l}\right)$ as required.

Lemma 8 Let $\alpha \in \mathbb{N}$ and let $A$ be a circuit of size $S<2^{n-\log \alpha-1}$. Let $\mathcal{F}$ denote the set of all $\alpha$-regular functions $f: X \rightarrow Y$. Then

$$
\operatorname{Pr}_{f \in \mathcal{F}}\left[A^{f} p \text {-inverts } f\right]<\frac{S}{p} \frac{4 \alpha}{|X|}
$$

Proof: Let $a=\log \alpha$. Fix some $y \in Y$. Let us compute the probability over $f$, that $A^{f}(y) \in f^{-1}(y)$. Let $Z$ be the set of query answers which $A^{f}(y)$ receives. Since $|Z| \leq S$, we have that $f^{-1}(Z) \leq S \alpha$.

If $A$ never queries any $x \in f^{-1}(y)$, then the probability that he outputs an inverse of $y$ is at most $1 /(|X| / \alpha-S)$.

After making $i$ queries the probability that for the next query $x, f(x)=y$, is at most $1 /(|X| / \alpha-$ $i$. Since there are at most $S$ queries, the probability that any of them gets $y$ as the answer, is at most $\sum_{i=0}^{S-1} 1 /(|X| / \alpha-i)$.

The probability that $A$ outputs an inverse of $y$ is therefore at most $\sum_{i=0}^{S} 1 /(|X| / \alpha-i) \leq 2(S+$ $1) /(|X| / \alpha) \leq S /(|X| / 4 \alpha)$.

It is now easy to see that there is $T \subseteq \mathcal{F}$ with $|T| /|\mathcal{F}|>1-p$, such that

$$
(\forall f \in T) \operatorname{Pr}_{x \in X}\left[A^{f}(f(x)) \in f^{-1}(f(x))\right]<\frac{S}{p} \frac{4 \alpha}{|X|}, .
$$

Lemma 9 Let $l=n-\log \alpha-d$. If $(R, g)$ is a $(l, m, p)$-collection-reduction from $\mathcal{F}_{\text {REG }}^{n, \alpha}$, then $|R|>$ $p 2^{d-4} / m$.

Proof: Suppose $|R|=S \leq p 2^{d-4} / m$. By Lemma 7, there is a $p$-inverter of size $S\left(2^{l+1} m\right) \leq$ $p 2^{n-a-3}$, which works for any $f$. But by Lemma 8 , any algorithm of size $p 2^{n-a-3}$ can $p$-invert at most $p 2^{n-a-3} / p 2^{-n+a+2}=1 / 2$ - fraction of functions.


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    ${ }^{\S}$ Research conducted, in part, at the Institute for Pure and Applied Mathematics at UCLA, whose hospitality the authors gratefully acknowledge.

[^1]:    ${ }^{1}$ Specifically, Renyi entropy of order 2, i.e., negative logarithm of collision probability.
    ${ }^{2}$ Of course, almost uniform independent bits can be obtained from a distribution of high entropy through the use of a strong extractor (whose seed can be public), but extractors necessarily lose entropy, so this approach would require a secret input with entropy higher than $k$, which, as we already pointed out, would create difficulties for our PRG construction.

[^2]:    ${ }^{3}$ It seems fruitless to try to turn $f_{\text {mult }}$ into a permutation to order to apply the efficient construction of [BM82, Yao82]. Indeed, a natural way to build a bijection from $f_{\text {mult }}$ is to include in the output all the unused bits as well as information on where $p$ and $q$ were in the sequence. However, this does not make it a permutation, because the output range (which includes the product of two primes) is not easily mapped back to the input domain of bit strings. Unfortunately, known solutions for bijections are not any better than those for regular functions.
    ${ }^{4}$ Our results apply to a weaker notion of "known": $\alpha$ can be a lower bound on the regularity of $f$, rather than its exact value.

[^3]:    ${ }^{5}$ The program actually computes the collision probability for one fixed pair of inputs $x_{1}, x_{2}$. The actual collision probability is the average over all possible input fixings. But since the generator fools each program separately, it will also fool the average.

