

Pseudodeterministic Constructions in Subexponential Time*

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ABSTRACT

We study *pseudodeterministic constructions*, i.e., randomized algorithms which output the *same solution* on most computation paths. We establish unconditionally that there is an infinite sequence $\{p_n\}_{n \in \mathbb{N}}$ of increasing primes and a randomized algorithm A running in expected sub-exponential time such that for each n , on input $1^{|p_n|}$, A outputs p_n with probability 1. In other words, our result provides a pseudodeterministic construction of primes in sub-exponential time which works infinitely often.

This result follows from a much more general theorem about pseudodeterministic constructions. A property $Q \subseteq \{0, 1\}^*$ is γ -dense if for large enough n , $|Q \cap \{0, 1\}^n| \geq \gamma 2^n$. We show that for each $c > 0$ at least one of the following holds: (1) There is a pseudodeterministic polynomial time construction of a family $\{H_n\}$ of sets, $H_n \subseteq \{0, 1\}^n$, such that for each $(1/n^c)$ -dense property $Q \in \text{DTIME}(n^c)$ and every large enough n , $H_n \cap Q \neq \emptyset$; or (2) There is a deterministic sub-exponential time construction of a family $\{H'_n\}$ of sets, $H'_n \subseteq \{0, 1\}^n$, such that for each $(1/n^c)$ -dense property $Q \in \text{DTIME}(n^c)$ and for infinitely many values of n , $H'_n \cap Q \neq \emptyset$.

We provide further algorithmic applications that might be of independent interest. Perhaps intriguingly, while our main results are unconditional, they have a non-constructive element, arising from a sequence of applications of the hardness versus randomness paradigm.

CCS CONCEPTS

• Theory of computation \rightarrow Pseudorandomness and derandomization;

KEYWORDS

Explicit constructions, pseudorandomness, derandomization, prime numbers.

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1 INTRODUCTION

Number theory tells us that a significant fraction of n -bit integers are prime, but can we efficiently generate an n -bit prime deterministically? This is a fundamental question in computational number theory and cryptography. A naive solution is to test the n -bit numbers for primality in order, starting with $2^{n-1} + 1$, using the AKS primality test [1], until we find one that is prime. Known results about the distribution of prime numbers guarantee that this procedure works in time $2^{0.525n+o(n)}$ [5]. Despite all the progress that has been made in understanding the behaviour of prime numbers, the best known deterministic algorithm for generating n -bit primes runs in time $2^{n/2+o(n)}$ [23], which is not significantly better.

If we are allowed randomness in our generating algorithm, the problem becomes almost trivial: we repeatedly guess an n -bit number at random and test it for primality, halting if a prime is found. Using the Prime Number Theorem, we will succeed with probability $1 - o(1)$ after $\tilde{O}(n)$ tests, each of which can be implemented in $\text{poly}(n)$ time. Thus the efficient deterministic generation problem reduces to *derandomizing* this algorithm. Under a strong hardness hypothesis, such as the assumption that linear exponential time requires exponential size circuits almost everywhere, this derandomization can be performed using known results from the theory of hardness-randomness tradeoffs [19]. However, we appear to be very far from proving such strong circuit lower bounds.

A few years ago, the Polymath 4 project considered precisely this question of efficient generation of primes, with the goal of using the state of the art in complexity theory and in number theory to obtain better results. It was observed during the project that several famous number-theoretic conjectures, such as Cramer's conjecture and Schinzel's hypothesis H, imply better generation algorithms, as do circuit lower bound assumptions, as described above. All of these conjectures seem far beyond our reach at present. The Polymath 4 project established [28] an improved algorithm for determining the *parity* of the number of primes in a large interval, but this has not yet yielded an unconditional improvement to the best known deterministic generation algorithm. The project posed the following question of interest to complexity theorists: does $\text{BPP} = \text{P}$ imply more efficient deterministic

generation of primes? This is not clear because the randomized generation algorithm for primes is not an algorithm for a decision problem.

Given the difficulty of finding more efficient deterministic generation algorithms, a natural approach is to relax the question. We know that randomized generation is easy, and we do not know of good deterministic generation algorithms. Is there an intermediate notion that could perhaps be useful?

Such a notion of *pseudodeterministic algorithms* was defined by Goldwasser and Gat [11], motivated by applications in cryptography and distributed computing, and further studied in [14–16]. A pseudodeterministic algorithm is a randomized algorithm, but the algorithm generates the *same* output with high probability. Thus, while the algorithm is not deterministic, the output of the algorithm *looks* deterministic to a computationally bounded observer. In the context of generating primes, pseudodeterministic generation means that the *same* prime is output on most computation paths. Note that the naive random generation algorithm does not have this property.

Goldwasser and Gat [11] describe the question of pseudodeterministic generation of primes as “perhaps the most compelling challenge for finding a unique output”. To the best of our knowledge, it is not known how to do better for this problem than to use the fastest deterministic algorithm.

1.1 Main Results

The main application of our techniques is that there is unconditionally a subexponential-time pseudodeterministic algorithm for generating infinitely many primes.

THEOREM 1.1. *Let $\varepsilon > 0$ be any constant. There is an infinite sequence $\{p_n\}_{n \in \mathbb{N}}$ of increasing primes, and a randomized algorithm A running in expected time $O(2^{m^\varepsilon})$ on inputs of length m such that for each $n \in \mathbb{N}$, A on input $1^{|p_n|}$ outputs p_n with probability 1.*

Note that the algorithm A is *zero-error*: on input $1^{|p_n|}$, it outputs the same prime p_n on all computation paths. In fact, on any input 1^m , the algorithm either operates deterministically and halts without output, or else it outputs the same m -bit prime on all computation paths.

Using the proof idea of Theorem 1.1, we answer a variant of the question from Polymath 4: under the assumption that $\text{ZPP} \subseteq \text{i.o. DTIME}(2^{n^c})$ for some fixed $c > 0$ (which is much weaker than $\text{BPP} = \text{P}$), we show that there is a subexponential-time *deterministic* algorithm for generating infinitely many primes (see Theorem 3.8 in Section 3.2).

Theorem 1.1 has some unusual features: we show that an algorithm *exists* satisfying the described properties, but we are not able to *explicitly* give such an algorithm. Similarly, while we show the existence of an infinite sequence of primes $\{p_n\}$, we are unable to bound $|p_{n+1}|$ as a function of $|p_n|$. These non-constructive features, which are surprising in the context of an algorithmic solution to a natural problem, arise because Theorem 1.1 is proved as a corollary of the following generic result about explicit constructions.

THEOREM 1.2. *Call a property $Q \subseteq \{0, 1\}^*$ γ -dense if for each large enough n , $|Q \cap \{0, 1\}^n|/2^n \geq \gamma(n)$. For each $c > 0$ at least one of the following holds:*

1. *There is a deterministic sub-exponential time construction of a family $\{H_n\}$ of sets, where each $H_n \subseteq \{0, 1\}^n$, such that for each $(1/n^c)$ -dense property $Q \in \text{DTIME}(n^c)$ and for infinitely many values of n , $H_n \cap Q \neq \emptyset$.*
2. *There is a zero-error pseudodeterministic polynomial time algorithm outputting a family $\{H'_n\}$ of sets, $H'_n \subseteq \{0, 1\}^n$, such that for each $(1/n^c)$ -dense property $Q \in \text{DTIME}(n^c)$ and every large enough n , $H'_n \cap Q \neq \emptyset$.*

We derive Theorem 1.1 by taking Q to be the set of primes in Theorem 1.2, and observing that the statement of Theorem 1.1 follows both from the first and second item of Theorem 1.2. The non-constructivity comes from not knowing which of these two items holds, and we discuss this issue in more detail in Section 1.4.

Consider any property Q as in the statement of Theorem 1.2, namely with polynomial density and decidable in deterministic polynomial time. For any such property, there is a randomized generation algorithm in polynomial time analogous to the one we described for Primes: generate strings of length n at random and test for membership in Q , halting if a string in Q is found. What Theorem 1.2 says is that this randomized generation algorithm can *unconditionally* be made pseudodeterministic in a generic fashion, albeit at the cost of increasing the running time to subexponential, and only succeeding for infinitely many input lengths n .

Theorem 1.2 is a very general result, and the generality of our techniques enables us to apply them to give unconditional pseudodeterministic algorithms in other contexts. Even if Theorem 1.1 does not give an explicit algorithm for generating primes of every input length, it does provide evidence that such algorithms might not be out of reach of current techniques. More explicit and more efficient algorithms could perhaps be designed by tailoring them more closely to the property at hand.

Nevertheless, we are interested in the question of whether there is a fundamental bottleneck to constructivity in our proof technique for Theorem 1.2. By refining some aspects of our approach, we are able to get *somewhat explicit* algorithms for generating primes as follows.

THEOREM 1.3. *For each $\varepsilon > 0$, there is a constant $k > 1$, an infinite sequence $\{q_n\}_{n \in \mathbb{N}}$ of increasing primes, and an explicit randomized algorithm A halting in time $O(2^{m^\varepsilon})$ on inputs of length m such that for each $n \in \mathbb{N}$, $A(1^{|q_n|})$ outputs q_n with probability $1 - o(1)$, and moreover $|q_{n+1}| < |q_n|^k$ for each $n \in \mathbb{N}$.*

The algorithm in Theorem 1.3 is explicit, but we still cannot say for sure on which input lengths it will succeed. We do have the guarantee that the gaps between successive input lengths on which the algorithm succeeds are not superpolynomially large. Theorem 1.3 does not strictly improve on

Theorem 1.1 – it is not necessarily true, for example, that the *same* prime is output on *all* computation paths. Namely, we get a *bounded-error* pseudodeterministic algorithm rather than a zero-error one. However, the issue of non-constructivity is somewhat mitigated in Theorem 1.3.

Theorem 1.2 yields subexponential-time pseudodeterministic generation algorithms for properties that are both easy and dense. A more general context is polynomial-time *sampling*. Here we are given a sampler that either outputs a string (with high probability) or aborts, and we wish to design a new sampler that outputs a *fixed* string with high probability, with the constraint that this fixed string should belong to the range of the original sampler. It is possible to adapt our ideas to give an analogue of Theorem 1.2 for this problem. We refer to the full version of the paper for more details.

We also study the relationship between pseudodeterminism and derandomization. A natural problem associated with derandomization is the Circuit Acceptance Probability Problem (CAPP): given a circuit C , output a small-error additive approximation to the acceptance probability of C . There is a simple randomized polynomial-time algorithm for this problem – sample polynomially many inputs of C at random, and output the fraction of these inputs on which C accepts. This algorithm outputs different estimations of the acceptance probability of C on different computation paths. We show how to get a pseudodeterministic algorithm as in Theorem 1.2 for infinitely many input lengths, but our algorithm is only guaranteed to succeed distributionally rather than in the worst case. (We refer to Section 4 for a precise formulation of the result.)

THEOREM 1.4. *For any $\varepsilon > 0$ and any polynomial-time samplable sequence $\mathfrak{D} = \{\mathcal{D}_n\}$ of distributions over Boolean circuits, CAPP is pseudodeterministically solvable for infinitely many input lengths n in time $2^{O(n^\varepsilon)}$ with high probability over \mathcal{D}_n .*

One of the main questions in the theory of derandomization concerns the relationship between “white-box” and “black-box” derandomization. Black-box derandomization refers to derandomization using a fixed pseudorandom generator, while in white-box derandomization, we are given a circuit and asked to approximate its acceptance probability deterministically. Black-box derandomization implies white-box derandomization of randomized algorithms, and white-box derandomization implies deterministic simulations of languages in BPP. However, it is unknown whether these implications can be reversed in general (cf. [9, 13]), and separations are known in relativized worlds [9].

We prove that these notions are all in fact *equivalent* in the setting of subexponential-time derandomization that works infinitely often on average over polynomial-time samplable distributions. (While Theorem 1.4 provides a randomized algorithm, we stress that the algorithms postulated in Theorem 1.5 below are all *deterministic*. We refer to Section 4 for definitions.)

THEOREM 1.5. *The following statements are equivalent:*

1. *For each polynomial-time samplable distribution \mathfrak{D} of Boolean circuits and each $\varepsilon > 0$, there is an i.o.PRG \mathfrak{G} on average over \mathfrak{D} with seed length n^ε that is computable in time $2^{O(n^\varepsilon)}$.*
2. *For each polynomial-time samplable distribution \mathfrak{D} over Boolean circuits and each $\varepsilon > 0$, CAPP is solvable infinitely often in time $2^{O(n^\varepsilon)}$ on average over \mathfrak{D} .*
3. *For each polynomial-time samplable distribution \mathfrak{D} over input strings and each $\varepsilon > 0$, BPP is solvable infinitely often in time $2^{O(n^\varepsilon)}$ with $O(\log(n))$ bits of advice on average over \mathfrak{D} .*
4. *For each $\varepsilon > 0$, BPP is solvable infinitely often in time $2^{O(n^\varepsilon)}$ on average over U_n .*

Therefore, in order to establish all these items it is necessary and sufficient to turn the (unconditional) pseudodeterministic algorithm from Theorem 1.4 into a deterministic algorithm.

1.2 Related Work

There has been a lot of work on explicitly constructing combinatorial objects that can be shown to exist by the probabilistic method. Vadhan [31] surveys known unconditional constructions of such objects, and connections to the theory of pseudorandomness. There are important properties, such as the Ramsey property, for which optimal explicit constructions are still not known, though there has been much recent progress (cf. [7, 8]). However, in many cases, such constructions do exist if the notion of explicitness is weakened or if a sufficiently strong derandomization hypothesis is made [26, 29].

The techniques used to show explicit constructions of combinatorial objects do not seem to be directly relevant to constructions of algebraic objects such as irreducible polynomials or number-theoretic objects such as primes. Shoup [27] shows how to deterministically construct an irreducible polynomial of degree n over the field \mathbb{F}_p in time polynomial in n and p . This is useful for constructions of irreducible polynomials over fields of small characteristic, but the large-characteristic case is still open – ideally we would like the construction algorithm to operate in time $\text{poly}(n, \log(p))$.

For primes, known results are even weaker. The fastest known algorithm generates n -bit primes in time $2^{(\gamma+o(1))n}$, for $\gamma = 1/2$ [23]. There are algorithms that achieve an arbitrarily small constant $\gamma > 0$, but assume certain number-theoretic conjectures. Faster running times can be obtained under stronger conjectures, and we refer to the introduction of [28] for more information.

Assuming standard (but hard to prove) derandomization hypotheses, stronger explicit constructions are known. It is folklore that the existence of hitting sets against a class \mathcal{C} of algorithms yields explicit deterministic constructions for every dense property computed by \mathcal{C} -algorithms. References that discuss this include [13, 26, 29]). As an example, the assumption that E requires exponential-size Boolean circuits

implies polynomial-time explicit constructions of irreducible polynomials and of primes. However, in this work, we are interested in *unconditional*, albeit pseudodeterministic, constructions for properties decidable in polynomial time. (While there are unconditional pseudorandom generators against restricted classes of algorithms such as small-depth polynomial size circuits, it is known that such circuits cannot decide several properties of interest, such as prime numbers [2].)

Perhaps the most closely related result is a certain unconditional derandomization of one-sided polynomial time randomized algorithms in subexponential time established in [22]. However, the focus there is on decision problems, and as remarked above, such results do not immediately imply pseudodeterministic constructions. The *easy witness* method from [22] is an important tool in some of our proofs.

The investigation of the power and limitations of pseudodeterministic algorithms is fairly recent. A sequence of works [11, 14–16] has started the development of a more general theory of pseudodeterministic computation. These papers give pseudodeterministic algorithms that are faster than their known deterministic counterparts for various concrete search problems of interest, and also give some structural results.

Connections between black-box derandomization, white-box derandomization and deterministic simulation of BPP are explored by Fortnow [9], who shows relativized separations between these notions. Goldreich [13] shows an equivalence between white-box derandomization and black-box derandomization in the average-case setting; however he considers pseudo-random generators that work against uniform algorithms, rather than against non-uniform circuits. Impagliazzo, Kabanets and Wigderson [18] give an equivalence between white-box and black-box derandomization in the setting where we allow the derandomization to be done *non-deterministically* with a small amount of advice, and the derandomization is only required to be correct for infinitely many input lengths.

1.3 Techniques

Suppose we wish to pseudodeterministically generate strings satisfying some property Q that is dense and is decidable in polynomial time, such as **Primes**. (For concreteness, we let $\text{Primes} = \{w \in \{0, 1\}^* \mid w = w_{n-1}w_{n-2} \dots w_0, w_{n-1} = 1, \text{ and } \sum_{i=0}^{n-1} 2^i w_i \text{ is prime}\}$.) It is well-known that using standard hardness-randomness tradeoffs, efficient deterministic generation can be done under a strong enough circuit lower bound assumption for $E \stackrel{\text{def}}{=} \text{DTIME}(2^{O(n)})$ (linear exponential time).

Our first observation is that efficient pseudodeterministic generation follows from *weaker* circuit lower bound assumptions, namely circuit lower bounds for the probabilistic classes $\text{BPE} = \text{BPTIME}(2^{O(n)})$ (bounded-error linear exponential time) and $\text{ZPE} = \text{ZPTIME}(2^{O(n)})$ (zero-error linear exponential time). Pseudodeterministic algorithms come in two flavours: *zero-error*, where the algorithm outputs a fixed string (with high probability) or else aborts, and *bounded-error*, where it outputs a fixed string on most computation

paths but might output other strings on exceptional computation paths. It turns out that strong enough circuit lower bounds for BPE imply efficient bounded-error pseudodeterministic generation, and strong enough circuit lower bounds for ZPE imply efficient zero-error pseudodeterministic generation. This is because a hard function in BPE (resp. a hard function in ZPE) yields a bounded-error (resp. zero-error) pseudodeterministic construction of a *discrepancy set* (see Section 2). In turn, once such a discrepancy set is obtained, its elements can be checked in some fixed order for membership in Q , and the first such element belonging to Q can then be output pseudodeterministically.

Note that circuit lower bounds for BPE do not seem useful for decision problems: using a sufficiently hard function in BPE in a pseudorandom generator would merely yield the tautologous inclusion $\text{BPP} \subseteq \text{BPP}$. However, such circuit lower bounds *are* useful for pseudo-derandomization of search problems. (It is natural to wonder if there are techniques tailored to BPE and ZPE lower bounds. We refer the interested reader to the approaches outlined in [24].)

To turn our conditional pseudodeterministic generation algorithms into unconditional ones, we use the uniform hardness-randomness tradeoffs of [20, 30] and win-win analysis, showing that both the success and the failure of certain pseudorandom generators can be exploited to give non-trivial pseudodeterministic constructions. The specific win-win analysis we use depends on the intended application. In order to make some constructions zero-error, we further combine the arguments with the easy witness method [22].

We describe next the main conceptual ideas behind the proof of each main result stated in Section 1.1.

Theorem 1.1 (Non-constructive zero-error pseudodeterministic algorithm for **Primes**). Recall that Theorem 1.1 is a straightforward consequence of Theorem 1.2. In each case, it follows that there is a pseudodeterministic subexponential time algorithm which simply outputs the lexicographic first n -bit prime in the hitting set. The non-constructive aspect of Theorem 1.1 arises because we do not know which of items (1) and (2) holds in Theorem 1.2.

Theorem 1.2 (Unconditional pseudodeterministic hitting set generators). Here we use a win-win analysis. We try two different candidate hitting set generators $\mathcal{H}^{\text{easy}}$ and $\mathcal{H}^{\text{hard}}$, both computable in deterministic subexponential time. The first generator is based on the easy witness method of Kabanets [22], and the second is the generator of Trevisan-Vadhan [30]. If either of the corresponding hitting set families intersects $Q \cap \{0, 1\}^n$ infinitely often, we have that the first item of Theorem 1.2 holds. If not, then we show that we have the complexity collapse $\text{PSPACE} = \text{ZPP}$. We exploit this collapse to derive strong circuit lower bounds in ZPE, and are then able to use our conditional argument for efficient pseudodeterministic generation to conclude the second item.

Theorem 1.3 (Constructive bounded-error pseudodeterministic algorithm for **Primes**). The proof for Theorem 1.2 gives no information on the sparsity of input lengths for which the construction succeeds, nor does it give us an explicit algorithm. An important reason for this is that we prove item (2) to hold in Theorem 1.2 only if the candidate hitting set generators in item (1) fail almost everywhere. We first show a refinement of the main technical lemma which allows us to derive a consequence for item (2) from a failure of item (1) for all input lengths in a polynomially large range of input lengths. We then crucially use the fact that item (1) gives deterministically generatable hitting sets which can be checked for correctness somewhat efficiently to guarantee that either item (1) or item (2) must hold in every large enough polynomial range of input lengths.¹ The details are somewhat technical, and we provide a more intuitive explanation in Section 3.3.

Theorem 1.4 (Pseudodeterministic algorithm for **CAPP**). We use a win-win analysis once again, relying on the fact that pseudo-random generators can be employed to approximate the acceptance probability of circuits in a deterministic fashion. If the candidate pseudo-random generator we use succeeds infinitely often, we can solve **CAPP** deterministically infinitely often; if it fails in an average-case sense, we adapt the arguments used in the proof of Theorem 1.2 to show how to solve **CAPP** pseudodeterministically in polynomial time.

Theorem 1.5 (Equivalences for deterministic algorithms in the average-case). The most interesting implications rely on results from previous works. The simulation in (3) assuming (2) introduces advice, and this advice is eliminated in item (4) as follows. Under assumption (3), it follows by diagonalization that $\text{EXP} \neq \text{BPP}$. In turn, [20] showed that this hypothesis provides sub-exponential time simulations of **BPP**, as required in (4). Perhaps a more surprising connection is that (4) implies (1). Our argument is based on another win-win analysis, and relies on results from [4, 20, 30]. Under (4), it can be shown that $\text{EXP} \neq \text{BPP}$, and that this implies that either $\text{EXP} \not\subseteq \text{P/poly}$, or $\text{PSPACE} \neq \text{BPP}$. In each case, we argue that any samplable distribution admits an average-case pseudo-random generator satisfying the conditions in (1).

1.4 Constructivity: **PSEUDO** versus **SPARSE**

Note the quantification in the statement of Theorem 1.2: there is a pseudodeterministic polynomial time algorithm producing a hitting set family which works for *every* sufficiently dense easy property, or there is a deterministic subexponential time algorithm producing hitting set families which work infinitely often for *every* sufficiently dense easy property. Thus

¹The possible sparsity of the sequence of primes produced by our algorithm is an artifact of our complexity-theoretic techniques. In contrast, constructions using standard number-theoretic techniques typically use analytic methods and succeed for every large enough input length (James Maynard, personal communication).

we provably live in one of two worlds:² a world **PSEUDO** where there is a generic hitting set family for sufficiently dense easy properties that is computable in zero-error pseudodeterministic polynomial time, or a world **SPARSE** where generic hitting set families are computable deterministically but only in subexponential time, and moreover the hitting sets only work infinitely often. These two worlds could co-exist. Indeed many complexity theorists believe that linear exponential time requires exponential size circuits on almost all input lengths, which would imply the co-existence of the two worlds. However, given the available techniques at this point in time, we are only able to establish that we live in one of the two worlds.

The fact that we can show that we live in one of these two worlds, but don't know which one, leads to a certain *non-constructivity* in our results, which is ironic given that we are motivated by explicit constructions! We can show that we live in one of the worlds **PSEUDO** or **SPARSE**, and in the latter case, our proof provides an explicit algorithm witnessing that we live in that world, namely the algorithm producing the union of the hitting set families $\mathcal{H}^{\text{easy}}$ and $\mathcal{H}^{\text{hard}}$. However, in the former case, the proof does not provide an explicit algorithm witnessing that we live in that world. This is because the proof relies on the existence of an easy dense property which acts as distinguisher for the hitting set families, and we do not know a priori which property this is.

A further element of non-constructivity in Theorem 1.2 is that in case we live in the world **SPARSE**, we have no information on the set of input lengths for which the hitting set works, except that this set is infinite. This set could be arbitrarily sparse. The reason is that we can only show the second item based on the hitting set families $\mathcal{H}^{\text{easy}}$ and $\mathcal{H}^{\text{hard}}$ failing to work on all large enough input lengths.

We partially address both issues in Section 3.3, and we refer to that section for further discussions on **PSEUDO** and **SPARSE**.

2 PRELIMINARIES

2.1 Basic Definitions and Notation

We refer to algorithms in a sufficiently strong computational model, such as the 2-tape Turing Machine over the alphabet $\{0, 1, \perp\}$. We use standard encodings of objects such as numbers and finite sets by strings. For convenience, we let $\mathbb{N} \stackrel{\text{def}}{=} \{1, 2, \dots\}$. Given a string $u \in \{0, 1\}^{\geq n}$, we let $\text{left}_n(u)$ denote its leftmost n bits.

Properties and Density. A *property* is an arbitrary set $Q \subseteq \{0, 1\}^*$.³ Let $Q_n \stackrel{\text{def}}{=} Q \cap \{0, 1\}^n$, and $Q_{\leq n} \stackrel{\text{def}}{=} \bigcup_{m \leq n} Q_m$. Given a function $\gamma: \mathbb{N} \rightarrow \mathbb{R}$, we say that Q is γ -dense if $|Q_n|/2^n \geq \gamma(n)$ for every large enough n . We say that Q is *dense* if there is $c > 0$ such that Q is γ -dense with $\gamma(n) \geq n^{-c}$.

²Inspired by the worlds of Impagliazzo [17].

³We use the term “property” rather than “language” or “Boolean function” to highlight that in our setting, we are more interested in the *efficient constructibility* of positive instances than in efficient recognizability.

for every sufficiently large n . We say that Q is *easy* if Q is decidable in deterministic polynomial time.

Hitting Sets and Discrepancy Sets. Let $\mathcal{H} = \{H_n\}_{n \in \mathbb{N}}$ be a sequence, where $H_n \subseteq \{0, 1\}^n$ for each $n \in \mathbb{N}$, and let $Q \subseteq \{0, 1\}^*$ be a property. We say that \mathcal{H} is a *hitting set* for Q at length n if $H_n \cap Q_n \neq \emptyset$. Given a set $S \subseteq \mathbb{N}$ of input lengths, we say that \mathcal{H} is a *hitting set family* for Q on S if it is a hitting set for Q at length n for each $n \in S$. We say that \mathcal{H} is a hitting set family for Q in case it is a hitting set family for Q on some co-finite set S , and we say that \mathcal{H} is an *i.o. hitting set family* for Q if it is a hitting set for Q on some infinite set S .

Let $\gamma: \mathbb{N} \rightarrow \mathbb{R}$ be an arbitrary function. We say that a sequence \mathcal{H} of (multi-) sets H_n is a γ -*discrepancy set* for Q at length n if $||Q_n|/2^n - |H_n \cap Q_n||/|H_n| < \gamma(n)$. The notions of being a γ -discrepancy set family at a set $S \subseteq \mathbb{N}$ of input lengths, an *i.o. γ -discrepancy set family* and a γ -discrepancy set family are defined in analogy to the previous paragraph. Note that if Q is γ -dense, then a γ -discrepancy set family \mathcal{H} for Q is also a hitting set family for Q .

Pseudodeterministic Algorithms. By default, we consider randomized algorithms whose input and output are both strings. Let p be a real-valued parameter. A randomized algorithm $A(\cdot)$ is said to be a *bounded-error pseudodeterministic* algorithm with success probability p if there is a function $f: \{0, 1\}^* \rightarrow \{0, 1\}^*$ such that $A(x) = f(x)$ with probability at least p over the random choices of A . We call such a function f a *p -canonical function* for A , and an output $f(x)$ of the function a *p -canonical output* of $A(x)$. A randomized algorithm $A(\cdot)$ is said to be a *zero-error pseudodeterministic* algorithm with success probability p if there is a function $f: \{0, 1\}^* \rightarrow \{0, 1\}^*$ such that on each computation path, $A(x)$ outputs either $f(x)$ or \perp , and $A(x) = f(x)$ with probability at least p over the random choices of A .

Given a set S of inputs, we say that an algorithm is *pseudodeterministic on S* if the pseudodeterministic promise is only required to hold for inputs in S . When the algorithm takes a unary input, we sometimes identify subsets of inputs with subsets of \mathbb{N} , in the natural way.

For any bounded-error pseudodeterministic algorithm with success probability $> 1/2$ or any zero-error pseudodeterministic algorithm with success probability > 0 , there is a *unique p -canonical function*, defined in the former case by the unique output produced with probability $> 1/2$, and in the latter case by the unique non- \perp output. In both cases, we simply call the function and the corresponding output *canonical*.

Let Q be a property, p a real-valued parameter, and $T: \mathbb{N} \rightarrow \mathbb{N}$ be a time function. We say that there is a *bounded-error pseudodeterministic construction* with success probability p for Q in time T if there is a bounded-error pseudodeterministic algorithm A with success probability p such that for all large enough n , $A(1^n)$ halts in time $T(n)$ and has a p -canonical output in Q_n . Similarly, we say that there is a *zero-error pseudodeterministic construction* with

success probability p for Q in time T if there is a zero-error pseudodeterministic algorithm A with success probability p , such that for all large enough n , $A(1^n)$ halts in time $T(n)$ and has a p -canonical output in Q_n .

As with hitting sets and discrepancy sets, given a set $S \subseteq \mathbb{N}$, we can generalize the notion of a pseudodeterministic construction to the notion of a pseudodeterministic construction on S , which means that $A(1^n)$ has a p -canonical output in Q_n for each $n \in S$. An *i.o. pseudodeterministic construction* is a pseudodeterministic construction on some infinite set S .

When the parameter $p = p(n)$ for a pseudodeterministic algorithm is omitted, it is taken by default to be $1 - o(1)$. For such a pseudodeterministic algorithm A on input x of length n , for a large enough n , we will sometimes abuse notation and use $A(x)$ to refer to the canonical output of A on x . Indeed, as observed next, bounded-error pseudodeterministic constructions and zero-error pseudodeterministic constructions are largely robust to variations in the success probability.

PROPOSITION 2.1. *Let $Q \subseteq \{0, 1\}^*$ be a property, and $T: \mathbb{N} \rightarrow \mathbb{N}$ be a time function.*

- (i) *There exists a bounded-error pseudodeterministic construction for Q with success probability $\geq 1/2 + 1/\text{poly}(n)$ in time $T \cdot \text{poly}(n)$ if and only if there is a bounded-error pseudodeterministic construction for Q with success probability $\geq 1 - 2^{-n}$ in time $T \cdot \text{poly}(n)$.*
- (ii) *There exists a zero-error pseudodeterministic construction for Q with success probability $\geq 1/\text{poly}(n)$ in time $T \cdot \text{poly}(n)$ if and only if there is a zero-error pseudodeterministic construction for Q with success probability $\geq 1 - 2^{-n}$ in time $T \cdot \text{poly}(n)$.*

We refer to the full version of this paper for a proof of Proposition 2.1.

As opposed to Theorem 1.1, the algorithm from Theorem 1.3 might generate different primes on inputs 1^ℓ for which it is not the case that $\ell = |q_n|$ for some n . It is not excluded that on some inputs of this form each prime is generated with approximately equal and non-negligible probability. This can be partially addressed using the following simple proposition.

PROPOSITION 2.2 (PURIFYING INFINITELY-OFTEN PSEUDODETERMINISTIC CONSTRUCTORS). *Let $S \subseteq \mathbb{N}$ be arbitrary, and let A be a bounded-error pseudodeterministic construction for Q with success probability $\geq 2/3$ on every input 1^m with $m \in S$. Then there is a bounded-error pseudodeterministic construction A' for Q for which the following holds:*

- (i) *On every input 1^m with $m \in S$, A' outputs the same canonical solution $A(1^m)$ with high probability.*
- (ii) *On an arbitrary input 1^n with $n \in \mathbb{N}$, there exists a set $V'_n \subseteq \{0, 1\}^n \cup \{\perp\}$ satisfying $|V'_n \cap \{0, 1\}^n| \leq 1$ such that $A'(1^n) \in V'_n$ with high probability.*
- (iii) *The running time of A' is at most a polynomial factor larger than the running time of A .*

The proof of Proposition 2.2 appears in the full version of this paper.

Complexity Classes. We use the standard definitions for classes such as P, BPP, RP, ZPP, and PSPACE. We will also use $\text{BPE} \stackrel{\text{def}}{=} \text{BPTIME}(2^{O(n)})$, $\text{ZPE} \stackrel{\text{def}}{=} \text{ZPTIME}(2^{O(n)})$ and $\text{ESPACE} \stackrel{\text{def}}{=} \text{DSpace}(2^{O(n)})$. We refer to standard textbooks such as [3, 12] for more information about complexity theory.

Boolean Circuits and Pseudorandom Generators. We consider Boolean circuits consisting of fan-in two gates over the standard B_2 basis, and measure circuit size by the number of wires in the circuit. The precise details will not be important here, and we refer to [21] for more background in circuit complexity. Given a size function $s: \mathbb{N} \rightarrow \mathbb{N}$, $\text{SIZE}(s)$ is the class of properties Q such that Q_n has Boolean circuits of size $s(n)$, for each $n \in \mathbb{N}$.

We say that a function $G: \{0, 1\}^\ell \rightarrow \{0, 1\}^m$ ε -fools algorithms (circuits) of running time (circuit size) t if for every such algorithm (circuit) D ,

$$\left| \Pr_{w \sim \{0, 1\}^\ell} [D(G(w)) = 1] - \Pr_{u \sim \{0, 1\}^m} [D(u) = 1] \right| < \varepsilon.$$

Otherwise, we say that D ε -distinguishes G (on seed length ℓ).

We will consider a sequence $\{G_\ell\}_{\ell \in \mathbb{N}}$ of pseudorandom generators $G_\ell: \{0, 1\}^\ell \rightarrow \{0, 1\}^{m(\ell)}$, which we also view as a single function $G: \{0, 1\}^* \rightarrow \{0, 1\}^*$. The function $m(\cdot)$ is the *stretch* of G . We say that a generator G with stretch $m(\cdot)$ is *quick* if on every input $w \in \{0, 1\}^\ell$, $G(w)$ can be computed in time $O(m(\ell)^d)$, where d is a fixed constant independent of the remaining parameters. Finally, we say that an algorithm D is a $t(m)$ -*distinguisher* for G if D runs in time at most $t(m)$, and on every sufficiently large ℓ , D $1/t(m)$ -distinguishes G_ℓ .

2.2 Technical Results

We make use of the following “hardness versus randomness” results.

THEOREM 2.3 (IMPAGLIAZZO AND WIGDERSON [19]). *There is a function $F: \{0, 1\}^* \times \{0, 1\}^* \rightarrow \{0, 1\}^*$, computable in polynomial time, for which the following holds. For every $\gamma > 0$, there exist constants $a, b \geq 1$ such that for every $r \in \mathbb{N}$,*

$$F(\{0, 1\}^{r^a} \times \{0, 1\}^{b \log r}) \subseteq \{0, 1\}^r,$$

and if $T_h \in \{0, 1\}^{r^a}$ is the truth-table of a boolean function $h: \{0, 1\}^{a \log r} \rightarrow \{0, 1\}$ of circuit complexity $\geq r^{\gamma a}$, then

$$G_h: \{0, 1\}^{b \log r} \rightarrow \{0, 1\}^r, \text{ given by } G_h(w) \stackrel{\text{def}}{=} F(T_h, w),$$

is a (quick) pseudorandom generator that $(1/r)$ -fools size- r circuits.

The next generator is based on a downward-self-reducible and self-correctable PSPACE-complete language L^* described in [30], and the corresponding result can be seen as a uniform “low-end” version of Theorem 2.3. The following formulation is sufficient for our purposes.

THEOREM 2.4 (IMPAGLIAZZO AND WIGDERSON [20], TREVISAN AND VADHAN [30]). *For every integers $b, c \geq 1$, there*

exists an integer $d \geq 1$ and a function $G^: \{0, 1\}^* \rightarrow \{0, 1\}^*$ with restrictions*

$$G_\ell^*: \{0, 1\}^\ell \rightarrow \{0, 1\}^{m(\ell)}, \text{ where } m(\ell) = \ell^b,$$

such that G^ can be computed in time $O(m(\ell)^d) = \text{poly}(\ell)$ when given oracle access to $L_{\leq \ell}^*$, and the following holds. If the output of G_ℓ^* can be $(1/m(\ell)^c)$ -distinguished from random for every large enough $\ell \in \mathbb{N}$ by an algorithm running in time $O(m(\ell)^c)$, then $\text{PSPACE} \subseteq \text{BPP}$.*

3 PSEUDODETERMINISTIC CONSTRUCTIONS

3.1 Conditional Constructions

LEMMA 3.1. *If there is an $\varepsilon > 0$ and a Boolean function $h \in \text{BPE}$ (resp. $h \in \text{ZPE}$) that requires circuits of size $2^{\varepsilon m}$ on all large enough input lengths $m \in \mathbb{N}$, then for each constant $c > 0$, there is a bounded-error (resp. zero-error) pseudodeterministic algorithm A running in polynomial time such that $\{A(1^n)\}$ is a $(1/n^c)$ -discrepancy set family for every property Q decidable in deterministic time n^c .*

PROOF. We give the proof for the case that $h \in \text{BPE}$; the case that $h \in \text{ZPE}$ is exactly analogous. Assume without loss of generality that the probabilistic exponential-time machine N computing h has failure probability $< 2^{-2^m}$ on any input of length m .

We define the behaviour of pseudodeterministic algorithm A on input 1^n using Theorem 2.3 as follows. We apply this result with constants a and b corresponding to the choice $\gamma = \varepsilon$. Let $r = n^{2^c}$. The algorithm A first computes the truth table T_h of the function h on input size $a \log r$ by evaluating h on every input of size $a \log r$ using the probabilistic exponential-time machine N . (We assume here that r is a power of 2; if not, the same argument works by setting r to be the smallest power of 2 larger than n^{2^c} .) Note that by a union bound, A computes the entire truth table correctly with probability $1 - o(1)$, and runs in time $\text{poly}(n)$. A then computes $F(T_h, y)$ for each string $y \in \{0, 1\}^{b \log r}$, using the polynomial-time algorithm for F guaranteed by Theorem 2.3, and forms a multi-set $H'_n \subseteq \{0, 1\}^{n^{2^c}}$ composed of the union of these strings. It then forms the (multi-) set $H_n \stackrel{\text{def}}{=} \{\text{left}_n(u) \mid u \in H'_n\}$, and outputs H_n .

Note that the same set H_n is output whenever the correct truth table T_h is computed, which happens with probability $1 - o(1)$ as argued before. Hence A is a pseudodeterministic algorithm with success probability $1 - o(1)$. Let H_n be the canonical output of $A(1^n)$.

It remains to argue that H_n is a $1/n^c$ -discrepancy set for Q_n for large enough n , where Q is any property decidable in time n^c for n large enough. Let M be a deterministic machine deciding Q with a running time of this form, and let D_n be the Boolean circuit of size n^{2^c} obtained by translating M 's computation on inputs of length n into a circuit, as in the proof of the Cook-Levin theorem. Let C_n be the circuit of size n^{2^c} on input x of size n^{2^c} , which simulates D_n on $\text{left}_n(x)$ and outputs the answer. Finally, let n be large enough that

h requires circuits of size at least $m^{2ac\epsilon}$ on inputs of size $2ac\log m$ for any $m \geq n$ that is a power of two. By Theorem 2.3, $G_h: \{0, 1\}^{b\log r} \rightarrow \{0, 1\}^r$ $1/n^{2c}$ -fools C_n . It follows that H_n is a $1/n^c$ -discrepancy set for Q_n for n large enough, using the facts that C_n accepts a string u of length n^{2c} if and only if D_n accepts $\text{left}_n(u)$, and that D_n accepts a string $z \in \{0, 1\}^n$ if and only if $z \in Q_n$. \square

REMARK 1. *We note that the conclusion of Lemma 3.1 holds even for properties decidable by Boolean circuits of size $\leq n^c$, since we do not take advantage of uniformity in the argument above.*

COROLLARY 3.2. *Let Q be any property that is easy and dense. If there is an $\epsilon > 0$ and a Boolean function $f \in \text{BPE}$ (resp. $f \in \text{ZPE}$) that requires circuits of size $2^{\epsilon m}$ on all large enough input lengths $m \in \mathbb{N}$, then there is a bounded-error (resp. zero-error) pseudodeterministic construction for Q in polynomial time.*

PROOF. Again we give the proof for the case that $f \in \text{BPE}$; the case that $f \in \text{ZPE}$ is exactly analogous. Let Q be any property that is easy and dense. Let M be a polynomial-time Turing machine deciding Q . Let c be a constant chosen large enough such that Q_n is $1/n^c$ -dense and M runs in time at most n^c for n large enough. Using Lemma 3.1, we have that there is a bounded-error pseudodeterministic algorithm A running in polynomial time such that the canonical output H_n of $A(1^n)$ is a $1/n^c$ -discrepancy set for Q_n . Hence, by the density condition on Q , we have that H_n is a hitting set for Q_n for n large enough.

We define a bounded-error pseudodeterministic algorithm A_Q running in polynomial time, whose canonical output on input 1^n belongs to Q_n for n large enough. $A_Q(1^n)$ first simulates $A(1^n)$ to obtain a subset S_n of $\{0, 1\}^n$; if the output of $A(1^n)$ is not such a subset, it outputs an arbitrary string. With probability $1 - o(1)$, S_n is the canonical output of $A(1^n)$, which is the hitting set $H_n \subseteq \{0, 1\}^n$ of size $\text{poly}(n)$. A_Q then orders the strings in S_n in lexicographic order to obtain a list y_1, y_2, \dots, y_m , where $m = \text{poly}(n)$, and each y_i , $i = 1, \dots, m$, is an n -bit string. A_Q simulates M on each of the y_i 's, in order, until it finds a y_i on which M accepts. If it finds such a y_i , it outputs y_i , otherwise it rejects.

For n large enough, let z_n be the smallest element of H_n in lexicographic order which belongs to Q_n . Since H_n is a hitting set for Q_n for n large enough, such a string z_n exists. It is easy to see that A_Q outputs z_n with probability $1 - o(1)$, and hence that z_n is the canonical output of $A_Q(1^n)$. This is because $S_n = H_n$ with probability $1 - o(1)$, and whenever $S_n = H_n$, the string z_n is output by A_Q . Clearly A_Q runs in time $\text{poly}(n)$ and is a pseudodeterministic algorithm with success probability $1 - o(1)$ whose canonical output is in Q_n for n large enough. \square

The proof of Corollary 3.2 can easily be adapted to give a bounded-error pseudodeterministic construction in polynomial time even when the condition on easiness of Q is relaxed to $Q \in \text{BPP}$, and a zero-error pseudodeterministic

construction in polynomial time even when the condition on easiness of Q is relaxed to $Q \in \text{ZPP}$. There is also a natural tradeoff between the hardness assumption and the running time of the corresponding pseudodeterministic construction, which can be obtained by using a generalization of Theorem 2.3 giving a hardness-randomness tradeoff based on circuit lower bounds varying from superpolynomial to exponential.

Note that the easiness assumption on Q is used twice to obtain Corollary 3.2, the first time in the proof of Lemma 3.1 to obtain pseudodeterministic algorithms outputting discrepancy sets based on the hardness assumption, and the second time in the proof of Corollary 3.2 to obtain a pseudodeterministic construction for Q from the discrepancy set. The first use of the assumption can be eliminated by using a stronger hardness assumption with respects to circuits that have oracle access to Q , but the second use seems essential.

3.2 Unconditional Constructions that Work Infinitely Often

By using in addition uniform hardness-randomness tradeoffs, we obtain *unconditionally* that there are pseudodeterministic constructions for easy dense sets in polynomial time, or else there are deterministic constructions for easy dense sets in subexponential time which work infinitely often. In fact, we obtain the following stronger result stating that in either case, there is a *generic* hitting set family that works simultaneously for *all* easy dense sets where the easiness and density parameters are fixed in advance.

THEOREM 3.3 (RESTATEMENT OF THEOREM 1.2). *Let $c > 0$ be any constant. At least one of the following is true:*

1. *There is a pseudodeterministic algorithm A running in polynomial time such that $\{A(1^n)\}$ is a hitting set family for every $1/n^c$ -dense property Q decidable in time n^c .*
2. *For each $\epsilon > 0$, there is a deterministic algorithm B_ϵ running in time $O(2^{n^\epsilon})$, such that $\{B_\epsilon(1^n)\}$ is an i.o. hitting set family for every $1/n^c$ -dense property Q decidable in time n^c .*

We now give the proof of Theorem 3.3. Informally, the proof is a “win-win-win” argument using uniform hardness-randomness tradeoffs. We will describe two candidate hitting set families $\mathcal{H}^{\text{easy}}$ and $\mathcal{H}^{\text{hard}}$ computable in sub-exponential time, the first based on the “easy witness” method of Kabanets [22], and the second based on the uniform hardness-randomness tradeoffs of Impagliazzo-Wigderson and Trevisan-Vadhan [20, 30]. We will show that if there is a sufficiently easy dense property Q such that $\mathcal{H}^{\text{easy}}$ is not an i.o. hitting set family for Q , then $\text{BPP} = \text{ZPP}$. We will also show that if there is a sufficiently easy dense property Q such that $\mathcal{H}^{\text{hard}}$ is not an i.o. hitting set family for Q , then $\text{PSPACE} = \text{BPP}$. Thus, in each of these cases, we either “win” for each sufficiently easy dense property Q by computing an i.o. hitting set family in sub-exponential time, or we have a complexity collapse. Finally, we show how to “win” in the case that both complexity collapses occur, by using Lemma 3.1. The win in

this case is in the form of a polynomial-time pseudodeterministic algorithm which outputs a hitting set family for each sufficiently easy dense property. When either of the first two wins occur, item 2 of Theorem 3.3 holds, and when the third win occurs, item 1 holds.

Fix a $c > 0$ as in the statement of Theorem 3.3, and let $\varepsilon > 0$ be any constant. The candidate hitting set families $\mathcal{H}^{\text{easy}}$ and $\mathcal{H}^{\text{hard}}$ depend on ε , but we work with a fixed arbitrarily small $\varepsilon > 0$ through the proof, and therefore do not need to formalize this dependence.

We first define the candidate hitting set family $\mathcal{H}^{\text{easy}}$. Consider the set \mathcal{C}_n of all Boolean circuits C on $\lceil \log n \rceil$ input variables and of size at most n^δ , where $\delta \stackrel{\text{def}}{=} \varepsilon/10$. Each circuit $C \in \mathcal{C}_n$ computes a Boolean function $f_C: \{0, 1\}^{\lceil \log n \rceil} \rightarrow \{0, 1\}$, and its truth-table $\text{tt}(f_C)$ is a string of length $\geq n$. We consider the following family $\mathcal{H}^{\text{easy}} = \{H_n^{\text{easy}}\}$ obtained from \mathcal{C}_n :

$$H_n^{\text{easy}} \stackrel{\text{def}}{=} \{\text{left}_n(\text{tt}(f_C)) \mid C \in \mathcal{C}_n\} \subseteq \{0, 1\}^n.$$

By our choice of $\delta = \varepsilon/10$ and a standard upper bound on the number of small circuits (cf. [3]), there are at most $O(2^{n^{2\delta}}) \leq O(2^{n^{\varepsilon/2}})$ strings in $\mathcal{H}_n^{\text{easy}}$. Furthermore, an ordered list containing all such strings can be printed in time $O(2^{n^\varepsilon})$.

The following lemma is key to our analysis of $\mathcal{H}^{\text{easy}}$.

LEMMA 3.4. *If there is a $1/n^c$ -dense property Q decidable in deterministic time n^c such that $\mathcal{H}^{\text{easy}}$ is not an i.o. hitting set family for Q , then $\text{BPP} \subseteq \text{ZPP}$.*

PROOF. Let $L \in \text{BPP}$, and V_L be a polynomial time verifier that decides L in time $n^{c_L/2}$, where $c_L \geq 1$. In other words, if $x \in L$ then $\Pr_y[V_L(x, y) = 1] \geq 2/3$, while if $x \notin L$ we have $\Pr_y[V_L(x, y) = 1] \leq 1/3$. By assumption, there is a $1/n^c$ -dense property Q decidable in deterministic time n^c such that $H_n^{\text{easy}} \cap Q_n = \emptyset$ whenever $n \geq n_0$, where n_0 is a fixed constant. Let V be a deterministic Turing machine running in time n^c for n large enough, and deciding Q .

The following zero-error algorithm B_1 decides L in polynomial time. Let $x \in \{0, 1\}^n$ be the input string of B_1 . If $n < n_0$, B_1 outputs the correct answer by storing it on its code. Otherwise, consider the Boolean circuit D_x of size at most n^{c_L} obtained from V_L by fixing its first input to x . In order to decide L on x it is enough to estimate the acceptance probability of D_x with additive error at most $1/10$.

Let $m \stackrel{\text{def}}{=} n^{c_L}$, $\gamma \stackrel{\text{def}}{=} \delta$, and assume from now on that $n \geq n_0$. Let F be the polynomial time computable function from Theorem 2.3, and $a, b \geq 1$ be the respective constants for our choice of γ . Finally, set $\ell \stackrel{\text{def}}{=} a \cdot \log(r) = a \cdot c_L \cdot \log(n)$, and $m \stackrel{\text{def}}{=} 2^\ell = n^{a \cdot c_L} \leq \text{poly}(n)$.

Algorithm B_1 samples $k \stackrel{\text{def}}{=} m^{10c}$ independent uniformly distributed strings $z_1, \dots, z_k \sim \{0, 1\}^m$. Let z_i be the first string on this list such that $V(z_i) = 1$, if such string exists. Otherwise, B_1 aborts its computation. Using the hypothesis that Q is n^{-c} -dense, we get that whenever n is sufficiently large, algorithm B_1 succeeds with high probability in finding

a string z_i of this form. By redefining n_0 , we can assume without loss of generality that B_1 succeeds whenever $n \geq n_0$.

Since $m \geq n \geq n_0$ and $z_i \in Q$, it follows from our previous discussion that $z_i \notin H_m^{\text{easy}}$. In other words, z_i is *not* the leftmost segment of the truth-table of a Boolean function $f: \{0, 1\}^{a \cdot \log r} \rightarrow \{0, 1\}$ of circuit complexity at most $m^\delta = r^{\gamma a}$.

Let $h: \{0, 1\}^{a \cdot \log m} \rightarrow \{0, 1\}$ be the Boolean function encoded by the string z_i completed with zeroes until the next power of two. The previous paragraph implies that h has circuit complexity greater than $r^{\gamma a}$. It follows from Theorem 2.3 that $G_h: \{0, 1\}^{b \cdot \log r} \rightarrow \{0, 1\}^r$ is a generator that $(1/10)$ -fools circuits of size at most $r = n^{c_L}$. Since F and h are efficiently computable in n , B_1 can compute $G_h(w) = F(z_i, w)$ on every input $w \in \{0, 1\}^{a \cdot \log r}$ in time $\text{poly}(n)$. Moreover, the seed length of G_h is $O(\log n)$. By standard methods, i.e. by trying all possible seeds of G_h and taking a majority vote using D_x , it follows that B_1 can efficiently decide whether x is in L . In addition, it is clear that B_1 decides L with zero-error, since it aborts (with a small probability) when a good string z_i is not found. Consequently, $L \in \text{ZPP}$, which completes the proof of Lemma 3.4. \square

Next we define the candidate hitting set family $\mathcal{H}^{\text{hard}}$. Assume that the PSPACE -complete language L^* from Theorem 2.4 can be decided in space $O(n^a)$, where $a \in \mathbb{N}$. Let $\delta \stackrel{\text{def}}{=} \varepsilon/(10a)$. Consider the function G^* obtained from an application of Theorem 2.4 with stretch parameter $b = 1/\delta$ and the parameter c set as in the statement of Theorem 3.6. This gives a sequence $\{G_\ell^*\}_{\ell \in \mathbb{N}}$ of functions computable with oracle access to $L_{\leq \ell}^*$ in time $\text{poly}(\ell)$, where each $G_\ell^*: \{0, 1\}^\ell \rightarrow \{0, 1\}^{\ell^b}$. Consider a seed function $s(n) \stackrel{\text{def}}{=} \lceil n^\delta \rceil$, and let $G_n \stackrel{\text{def}}{=} G_{s(n)}^*$. Since $b = 1/\delta$, we have

$$G_n: \{0, 1\}^{\lceil n^\delta \rceil} \rightarrow \{0, 1\}^{\geq n}.$$

In addition, G_n can be computed in time $O(2^{n^{\varepsilon/5}})$ without access to an oracle. This is because the oracle answers to $L_{\leq n^\delta}$ can be computed within this running time due to our choice of parameters and the fact that bounded-space algorithms run in time at most exponential.

Each set H_n^{hard} is obtained from G_n as follows:

$$H_n^{\text{hard}} \stackrel{\text{def}}{=} \{\text{left}_n(G_n(w)) \mid w \in \{0, 1\}^{s(n)}\}.$$

The following lemma is key to our analysis of $\mathcal{H}^{\text{hard}}$.

LEMMA 3.5. *If there is a $1/n^c$ -dense property Q decidable in deterministic time n^c such that $\mathcal{H}^{\text{hard}}$ is not an i.o. hitting set family for Q , then $\text{PSPACE} \subseteq \text{BPP}$.*

PROOF. If $\mathcal{H}^{\text{hard}}$ is not an i.o. hitting set family for Q , it must be the case that $H_n^{\text{hard}} \cap Q_n = \emptyset$ for every large enough n . Equivalently, $\text{left}_n(G_{s(n)}^*(\{0, 1\}^{s(n)})) \cap Q_n = \emptyset$, where $s(n) = n^\delta$. Since $s(\cdot)$ is surjective as a function in $\mathbb{N} \rightarrow \mathbb{N}$, for every large enough ℓ ,

$$G_\ell^*(\{0, 1\}^\ell) \cap Q_{\ell^b} = \emptyset.$$

On the other hand, Q is a n^{-c} -dense property, and for large enough ℓ ,

$$\Pr_{y \sim \{0,1\}^{\ell^b}}[y \in E_{\ell^b}] = \Pr_{y \sim \{0,1\}^{\ell^b}}[V(y) = 1] \geq \ell^{-bc} = m^{-c},$$

using $m = \ell^b$ as in Theorem 2.4. Furthermore, by assumption there is a deterministic Turing machine V running in time at most m^c on inputs of length m for large enough m , and deciding Q . Therefore, it can be used as a distinguisher against G^* , matching the parameters of Theorem 2.4. Thus $\text{PSPACE} \subseteq \text{BPP}$, completing the proof of Lemma 3.5. \square

We complete the proof of Theorem 3.3 using a third and final application of the hardness versus randomness paradigm. If $\mathcal{H}^{\text{easy}}$ is an i.o. hitting set family for every n^{-c} -dense property Q decidable in deterministic time n^c , the second item of Theorem 3.3 holds by letting B_ε be the deterministic algorithm which, on input 1^n , outputs H_n^{easy} in time $2^{O(n^\varepsilon)}$. If not, then we have $\text{BPP} = \text{ZPP}$ by Lemma 3.4. If $\mathcal{H}^{\text{hard}}$ is an i.o. hitting set family for every n^{-c} -dense property Q decidable in deterministic time n^c , then again, the second item of Theorem 3.3 holds by letting B_ε be the deterministic algorithm which, on input 1^n , outputs H_n^{hard} in time $2^{O(n^\varepsilon)}$. If not, then we have $\text{PSPACE} = \text{BPP}$ by Lemma 3.5. Thus, if the second item of Theorem 3.3 fails to hold, we have the complexity collapse $\text{PSPACE} = \text{ZPP}$. This facilitates a zero-error pseudodeterministic construction of an unconditional hitting set in polynomial time as follows.

First, it follows by direct diagonalization that there is a language computed in $\text{DSPACE}(2^{O(m)})$ that requires circuits of size $\geq 2^{m/2}$ for every large m . From $\text{PSPACE} \subseteq \text{ZPP}$, a standard padding argument implies that this language can be computed in $\text{ZPTIME}(2^{O(m)})$. In other words, there is a function $h: \{0,1\}^* \rightarrow \{0,1\}$ in $\text{ZPTIME}(2^{O(m)})$ that for every large m cannot be computed by circuits of size $\leq 2^{m/2}$.

Now, by setting $\varepsilon = 1/2$ in Lemma 3.1, we have that there is a pseudodeterministic algorithm A running in polynomial time such that $\{A(1^n)\}$ is a $1/n^c$ -discrepancy set family for every property Q decidable in deterministic time n^c , and consequently a hitting set family for every $1/n^c$ -dense property Q decidable in deterministic time n^c . This completes the proof of Theorem 3.3. \square

REMARK 2. Observe that the argument presented above provides a stronger discrepancy set in the first case of Theorem 3.3. While this is not needed in our applications, it might be helpful elsewhere.

The generic Theorem 3.3 can be used to show unconditionally the existence of certain kinds of explicit constructions for easy dense properties.

COROLLARY 3.6. *Let $Q \subseteq \{0,1\}^*$ be any easy dense property. Then for each $\varepsilon > 0$, there is an i.o. zero-error pseudodeterministic construction for Q in time $O(2^{n^\varepsilon})$.*

To establish Corollary 3.6, note that if the first item of Theorem 3.3 holds, a zero-error pseudodeterministic construction for Q in polynomial time follows exactly as Corollary

3.2 follows from Lemma 3.1. On the other hand, if the second item of Theorem 3.3 holds, for every $\varepsilon > 0$, there is an i.o. deterministic construction for Q in time $O(2^{n^\varepsilon})$, just by computing the i.o. hitting sets for Q and outputting the lexicographically first element of the hitting set in Q , if such an element exists, and an arbitrary fixed string otherwise. Thus, in either case, for every $\varepsilon > 0$ there is an i.o. zero-error pseudodeterministic construction for Q in time $O(2^{n^\varepsilon})$.

We could trade off the parameters of items (1) and (2) of Theorem 3.3 to obtain a stronger bound on the running time of the construction in Corollary 3.6 by using a more general version of Theorem 2.3, but we do not pursue this direction here, as a polynomial-time bound for the construction does not appear to be provable using such an approach.

Corollary 3.6 also has a non-constructive element. We know that for any easy dense Q , there is an i.o. zero-error pseudodeterministic construction, but we are unable to say explicitly what this construction is, as we do not know which of the worlds **PSEUDO** or **SPARSE** we live in. Also, similarly to Theorem 3.3, we do not have any information on the set of input lengths for which the construction works, except that it is infinite. This can be a somewhat unsatisfactory situation where explicit constructions are concerned, and we show how to address both issues in Section 3.3.

COROLLARY 3.7 (RESTATEMENT OF THEOREM 1.1). *For each $\varepsilon > 0$, there is an i.o. zero-error pseudodeterministic construction for Primes in time $O(2^{n^\varepsilon})$.*

Corollary 3.7 follows from Corollary 3.6 because Primes is $1/\text{poly}(n)$ -dense by the Prime Number Theorem, and is in deterministic polynomial time by the Agrawal-Kayal-Saxena algorithm [1].

Using the ideas of the proof of Theorem 3.3, we can partially answer a question of the Polymath 4 Project on generating primes. The following question was posed there: does $\text{BPP} = \text{P}$ imply a polynomial-time algorithm for generating primes? We consider a much weaker assumption, namely that $\text{ZPP} \subseteq \text{i.o. DTIME}(2^{n^c})$ for some fixed constant c . Under this assumption, we show that there is a subexponential-time deterministic algorithm for generating infinitely many primes.

THEOREM 3.8. *If there is a $c \geq 1$ such that $\text{ZPP} \subseteq \text{i.o. DTIME}(2^{n^c})$, then for each $\varepsilon > 0$ there is a deterministic algorithm A running in time $O(2^{n^\varepsilon})$ such that for infinitely many n , $A(1^n)$ is an n -bit prime.*

We refer to the full version of the paper for a proof of Theorem 3.8.

3.3 Unconditional Constructions that are Explicit

In this section, we show how to make our constructions for easy dense properties explicit, in the sense that the algorithm implementing the construction is an explicit algorithm. Consider for instance the problem of pseudodeterministically generating primes. Since Theorem 1.1 establishes that some algorithm runs in sub-exponential time and outputs a

canonical prime infinitely often, a natural approach would be to employ a universal search procedure that runs all algorithms with short descriptions until a prime is produced. Unfortunately, this idea does not seem to work when the algorithms involved are randomized and we would like to maintain pseudodeterminism.

We will employ a different strategy which will actually give us a bit more. In addition to addressing the issue of explicitness, we also control the gaps between input lengths on which the construction succeeds. However, this comes at the cost of tailoring the construction to a specific easy dense property, and the proof becomes more intricate. For simplicity, we will focus on bounded-error pseudodeterministic constructions for **Primes**. This corresponds to a simpler version of Theorem 3.3, where we not consider the hitting set family $\mathcal{H}^{\text{easy}}$ obtained using the easy witness method, and do a win-win analysis based on the hitting set family $\mathcal{H}^{\text{hard}}$ rather than a win-win-win analysis. In this variant setting, we will consider *bounded-error* pseudodeterministic polynomial time constructions for **Primes**, rather than *zero-error* ones.

Recall that a fundamental issue with obtaining an explicit algorithm using the proof of Theorem 1.2 is that we do not know which of the worlds **PSEUDO** and **SPARSE** we live in (Section 1.4). There is an explicit algorithm corresponding to the world **SPARSE**, but we only obtain an explicit algorithm corresponding to the world **PSEUDO** if the algorithm for **SPARSE** fails on all large enough input lengths, and we do not know a priori if this is the case.

Imagine the following ideal situation: the win-win analysis we carry out works input length by input length. Namely, for each large enough input length n , a given candidate hitting set H_n constructible in deterministic subexponential time works, or else a different candidate hitting set H'_n constructible in pseudodeterministic subexponential time works. If we were in this ideal world, we would get an explicit construction for each large enough length as follows. We first test each element in H_n for primality, in some fixed order. If at least one of the tests succeed, we output the first element satisfying a test. If not, we generate H'_n and again test the elements in some fixed order for primality. Now we are guaranteed to succeed by the assumption that the win-win analysis succeeds on each large enough input length, and as H'_n is generated pseudodeterministically, we will output a fixed prime with high probability.

However, we are quite far from being in this ideal situation. Indeed, our argument that a pseudodeterministic algorithm succeeds relies on the hitting set family failing for all large enough input lengths, rather than on a single input length n . This enables us to obtain the complexity collapse $\text{PSPACE} = \text{BPP}$ and apply Lemma 3.1.

If we are to have any hope of controlling the set of input lengths on which the construction succeeds using such an argument, we need to mitigate this issue. Note that if we are only interested in a pseudodeterministic construction in subexponential time, the collapse $\text{PSPACE} = \text{BPP}$ is overkill; it is enough to have $\text{PSPACE} \subseteq \text{BPSUBEXP}$.

Consider the PSPACE -complete language L^* in the statement of Theorem 2.4. The first element of our new argument is a refined version of Theorem 2.4, which for any $\delta > 0$, yields a probabilistic algorithm solving L^* correctly on inputs of length n in time 2^{n^δ} assuming that the hitting set family $\{H_\ell\}$ fails at all input lengths $\ell \in [n^{1/D}, n^D]$, where D is some constant depending on δ . Thus we now only need the failure of the hitting set family on some polynomially bounded range of input lengths to obtain a complexity collapse consequence, albeit a milder one than before.

We also observe that this refined version can be used in an alternative argument for generating primes pseudodeterministically, by reducing the search version of **Primes** on input length n to the PSPACE -complete language L^* on some polynomially larger input length n^k . Hence, if we knew that the probabilistic algorithm based on the failure of the hitting set family for a polynomially bounded range of input lengths solved L^* correctly at some fixed input length n^k , we would be able to construct primes pseudodeterministically at length n in subexponential time.

However, we have no easy way of knowing this. The straightforward method would be to explicitly test the success of the hitting set family on the appropriate range of input lengths, but this could take more than exponential time.

Imagine instead the pseudodeterministic algorithm we wish to define being given a single *advice bit* per input length. If this advice bit is 0 at length n , it indicates to the algorithm $A(1^n)$ that the hitting set family does indeed fail on all input lengths in $[n^{k/D}, n^{kD}]$; if the advice bit is 1, it indicates that the hitting set family succeeds somewhere on that range. The point is that the requisite information is just a single bit depending on the input length n . The advice bit can be thought of as information for the algorithm about whether the world looks *locally* like **PSEUDO** or **SPARSE**, even if we do not know what the global picture is.

If the algorithm somehow had access to this advice bit, it could act as follows: if the advice bit were 0, it would know that the probabilistic algorithm given by the refined version of Theorem 2.4 solves L^* correctly at input length n^k , and by using the reduction from the search version of **Primes** to L^* and simulating the probabilistic algorithm when needed, it could pseudodeterministically output a prime in subexponential time. If the advice bit were 1, “all bets are off”, and the algorithm simply halts without an output.

For those readers familiar with the work on hierarchies for probabilistic polynomial time with advice [6, 10], the use of a advice bit here might be reminiscent of that work. The similarity is that the advice bit is a way around constructibility issues, but the details are different.

An advantage in our setting is that while the advice bit might be conceptually useful, it is *not really needed*. The reason is that while the algorithm might not have the time to check if the hitting set family fails on all input lengths in a polynomially large range around n , it certainly can check if H_n is a hitting set for **Primes** _{n} in deterministic subexponential time. If it is, the algorithm outputs the first prime in H_n ,

and we are done. If not, then the algorithm behaves *as if* the advice bit were 0. The algorithm with this behaviour will not always be correct, but it will always succeed on some input length in any polynomially large enough interval of input lengths. Moreover, the algorithm is *explicit*. We are exploiting here the fact that the world **SPARSE** is a deterministic world, and that we can check *deterministically* and not too inefficiently whether a given hitting set works at an input length.

We now give details, but first some extra notation.

Polynomial Gaps. We call a set $S \subseteq \mathbb{N}$ *polynomially gapped* if S is non-empty and there is a constant $k > 1$ such that for any $n \in S$, there is $m \in S$, $n < m \leq n^k$.

We require the following refinement of Theorem 2.4, which holds for the same language L^* discussed before.

THEOREM 3.9. *For any integers $b, c \geq 1$, there exists an integer $d \geq 1$ and a function $G^*: \{0, 1\}^* \rightarrow \{0, 1\}^*$ with restrictions*

$$G_\ell^*: \{0, 1\}^\ell \rightarrow \{0, 1\}^{m(\ell)}, \quad \text{where } m(\ell) = \ell^b,$$

such that G^ can be computed in time $O(m(\ell)^d) = \text{poly}(\ell)$ when given oracle access to $L_{\leq \ell}^*$, and the following holds. For every $\delta > 0$, there is a $\delta' > 0$ and a probabilistic algorithm B_δ such that for any large enough $n \in \mathbb{N}$ for which the output of G_ℓ^* can be $(1/m(\ell)^c)$ -distinguished from random for every $\ell \in [n^{\delta'}, n^3]$ by an algorithm A running in time $O(m(\ell)^c)$, B_δ when given access to 1^n , $x \in \{0, 1\}^{\leq n}$ and to the description of A , runs in time $O(2^{n^\delta})$, and computes $L^*(x)$ with error at most $1/n^2$ over its internal randomness.*

The proof of Theorem 3.9 refines the proof of Theorem 2.4, and is described in the full version.

THEOREM 3.10 (RESTATEMENT OF THEOREM 1.3). *For every $\varepsilon > 0$, there is a polynomially gapped set S and a (bounded-error) pseudodeterministic construction for **Primes** on S , running in time $O(2^{n^\varepsilon})$.*

PROOF. Let $\varepsilon > 0$ be any constant. We show that there is a polynomially gapped set S and a pseudodeterministic algorithm A_ε on S such that for each $n \in S$, the canonical output of $A_\varepsilon(1^n)$ is an n -bit prime, and moreover A_ε always halts in time $O(2^{n^\varepsilon})$.

Define the language **LexFirstPrime** to consist of all tuples $\langle 1^n, i \rangle$ such that the i 'th bit of the lexicographical first n -bit prime is 1, where $n \geq 2$. By Bertrand's Postulate, **LexFirstPrime** is well-defined. It is easy to see that this language is decidable in polynomial space, as follows. Enumerate the n -bit integers in order and check each one for primality until an integer p_n is found that passes the primality test. Accept on input $\langle 1^n, i \rangle$ iff the i 'th bit of p_n is 1. Since **LexFirstPrime** is in PSPACE and L^* is PSPACE-complete, there is a constant $k \geq 1$ such that **LexFirstPrime** reduces to L^* in deterministic time n^k .

Let $C > 0$ be an integer to be determined later. We partition \mathbb{N} into intervals I_i , where $I_i = (2^{C^{i-1}}, 2^{C^i}]$ for

$i \geq 1$, and $I_0 = [1, 2]$. We define the algorithm A_ε and show that it satisfies the required properties for at least one input length in each I_i , when i is large enough. The algorithm operates in two phases, the first of which is deterministic and the second probabilistic.

Let $a > 0$ be a constant such that L^* is computable in deterministic time 2^{ℓ^a} on inputs of length ℓ , and let $c > 1$ be a constant such that the Primality algorithm of [1] runs in deterministic time n^c . A_ε operates as follows on input 1^n . It first invokes the generator G^* from Theorem 3.9 using parameters $b = \lceil 2a/\varepsilon \rceil$ and c as chosen above, on input length $\ell = \lceil n^{\varepsilon/2a} \rceil$. It computes $H_n = \{\text{left}_n(u) \mid u \in G^*(\{0, 1\}^\ell)\}$ in time $O(2^{n^\varepsilon})$, exploiting the efficiency guarantee for G^* from Theorem 3.9 and the fact that L^* is computable in deterministic time 2^{ℓ^a} . It checks each element of H_n in lexicographic order for primality, outputting the first n -bit prime in H_n that it finds, if such a prime exists. Given H_n , the total time required for this testing is $O(2^\ell \cdot \text{poly}(n))$, which is $O(2^{n^\varepsilon})$.

If no element of H_n is prime, A_ε commences its probabilistic phase. It sets $\delta = \varepsilon/k$ in the second part of Theorem 3.9; let $\delta' < \delta$ be the corresponding constant given by the theorem. A_ε attempts to compute an n -bit prime in probabilistic time $O(2^{n^\varepsilon})$ as follows. It tries to determine for each i satisfying $1 \leq i \leq n$, whether $\langle 1^n, i \rangle \in \text{LexFirstPrime}$ by using the reduction from **LexFirstPrime** to L^* , which produces instances of length $\leq n^k$. It answers each query x to L^* by assuming that **Primes** $1/\ell^{bc}$ -distinguishes G_ℓ^* from random for each $\ell \in [n^{k\delta'}, n^{3k}]$, where b is as defined in the previous para, and running the corresponding algorithm B_δ on 1^{n^k} , x , and the code of the AKS primality algorithm. By Theorem 3.9, if **Primes** does indeed distinguish the output of the generator from random for the given range of input lengths, the algorithm B_δ decides $L^*(x)$ correctly with error at most $1/n^{2k}$, since $x \in \{0, 1\}^{\leq n^k}$. Hence, in this case, by a simple union bound, all n queries of A_ε to B_δ are answered correctly with probability at least $1 - 1/n$, using the fact that $k \geq 1$, and hence A_ε correctly determines all the bits of the lexicographically first n -bit prime p_n with error at most $1/n$. Thus, in this case, a fixed prime p_n is output with probability at least $1 - 1/n$, which fulfils the bounded-error pseudodeterministic guarantee for A_ε . Using that $\delta = \varepsilon/k$ and the bound on the running time of B_δ given by Theorem 3.9, it follows that A_ε halts in time $O(2^{n^\varepsilon})$.

We argue that for each interval I_i of input lengths for i large enough, there is $n_i \in I_i$ such that either one of the elements of H_{n_i} is prime, or A_ε outputs a fixed prime with high probability using the reduction to L^* as in the previous para. Note that in the first case, the deterministic phase of the algorithm has an output and the algorithm does not enter its probabilistic phase, while in the second case, the probabilistic phase has a fixed output with high probability. In either case, A_ε operates pseudodeterministically on input 1^{n_i} and outputs a prime.

We set C to be $\lceil 3k/\delta' \rceil$, where k and δ' are as above. If there is no n_i in I_i such that at least one of the elements of

H_{n_i} is prime, and if i is large enough, then it is indeed the case that **Primes** $1/\ell^{bc}$ -distinguishes G_ℓ^* from random for each $\ell \in [n_i^{k\delta'}, n_i^{3k}]$, where $n_i = 2^{C^i/3k}$, just using the fact that **Primes** is $1/n^c$ -dense for large enough n . Hence, in this case, A_ε does output the lexicographically first prime on n_i bits with probability $1 - o(1)$, which concludes the argument. \square

To compare Theorem 3.10 to Corollary 3.7, the advantages of the former are that the algorithm is explicit, and that the input lengths for which it is guaranteed to produce primes are not too far apart. However, a somewhat subtle advantage of Corollary 3.6 is that the construction is guaranteed never to output two different primes on any input length – it either outputs a fixed prime with high probability, or does not output a prime at all. With the construction of Theorem 3.10, this might not be the case. The algorithm has the bounded-error pseudodeterministic guarantee on at least one input length in each large enough interval, but there is no guarantee on the behaviour of the algorithm for other input lengths in the interval. This situation can be improved using Proposition 2.2.

4 PSEUDODETERMINISM AND DERANDOMIZATION

In order to state the results of this section we will need a few additional definitions. Here we work with ensembles $\mathfrak{D} = \{\mathcal{D}_n\}$ of distributions, where we assume that each \mathcal{D}_n is supported over $\{0,1\}^n$. Moreover, we say that such a sequence of distributions is polynomial-time samplable if there is a randomized polynomial-time algorithm B (the sampler) such that for each $n \in \mathbb{N}$ and each $y \in \{0,1\}^n$, $\Pr[B(1^n) = y] = \mathcal{D}_n(y)$, where $\mathcal{D}_n(y) \stackrel{\text{def}}{=} \Pr[y \in \mathcal{D}_n]$. As usual, we use U_n to refer to the uniform distribution on n -bit strings, which is clearly polynomial-time samplable. In some cases we view elements of $\{0,1\}^n$ as descriptions of Boolean circuits of size at most n , under some natural encoding. We may informally refer to \mathfrak{D} as a distribution instead of as an ensemble of distributions.

We define various notions of derandomization on average over polynomial-time samplable distributions \mathfrak{D} . Our setting closely mirrors that of Impagliazzo-Wigderson [20], and our proofs are inspired by their ideas.

Average-Case Definitions. Let $\ell: \mathbb{N} \rightarrow \mathbb{N}$ be a function. We say that a sequence $\mathfrak{G} = \{G_n\}$ with $G_n: \{0,1\}^{\ell(n)} \rightarrow \{0,1\}^n$ is a PRG (resp. i.o.PRG) on average over a distribution \mathfrak{D} of Boolean circuits if for each $c > 0$ and for large enough n (resp. for infinitely many n), G_n $(1/10)$ -fools C_n with probability at least $1 - 1/n^c$ over $C_n \sim \mathcal{D}_n$. We call $\ell(n)$ the seed length of the PRG.

Let $T: \mathbb{N} \rightarrow \mathbb{N}$ be a time bound. We say that the Circuit Acceptance Probability Problem (CAPP) is solvable in time T (resp. solvable infinitely often in time T) on average over \mathfrak{D} if for all $c > 0$ there is a deterministic algorithm A running in time $T(n)$ such that for all $n \in \mathbb{N}$ (resp. for infinitely many n), $\Pr_{C_n \sim \mathcal{D}_n}[|A(C_n) - \Pr_{x \sim U_n}[C_n(x) = 1]| < 1/10] \geq 1 - 1/n^c$.

Let $L \subseteq \{0,1\}^*$ a language. We say that L is solvable in time T (resp. solvable infinitely often in time T) on average over \mathfrak{D} if for all $c > 0$ there is a deterministic algorithm running in time $T(n)$ which for all n (resp. infinitely many n) solves L_n with success probability at least $1 - 1/n^c$ over \mathcal{D}_n . Given a function $a: \mathbb{N} \rightarrow \mathbb{N}$, we also use the notion of being solvable in time T with $a(n)$ bits of advice on average over \mathfrak{D} – here the algorithm solving L gets access to an auxiliary advice string of length $a(n)$ which depends only on the input length.

We say that CAPP is solvable pseudodeterministically in time T (resp. solvable infinitely often pseudodeterministically in time T) on average over \mathfrak{D} if for all $c > 0$ there is a randomized algorithm A running in time $T(n)$ such that for all n (resp. infinitely many n), with probability at least $1 - 1/n^c$ over $C_n \sim \mathcal{D}_n$, $A(C_n)$ outputs the same number $f(C_n)$ with probability $1 - o(1)$ over its internal randomness, and $f(C_n)$ is a $(1/10)$ -additive approximation to the acceptance probability of C_n .

The lemma below is implicit in [30], which itself uses a variation of the argument in [20]. We omit the proof because it is almost identical to the proof of Theorem 2.4.

LEMMA 4.1. [20, 30] *For each $\varepsilon > 0$ there is a sequence $\mathfrak{G} = \{G_n\}$, where $G_n: \{0,1\}^{n^\varepsilon} \rightarrow \{0,1\}^n$ and \mathfrak{G} is computable in time $2^{O(n^\varepsilon)}$, such that if there is a polynomial-time samplable distribution $\mathfrak{D} = \{\mathcal{D}_n\}$ of Boolean circuits and a constant $c > 0$ for which for all large enough n , with probability $\geq 1/n^c$ over $C_n \sim \mathcal{D}_n$, C_n is a $(1/10)$ -distinguisher for G_n , then $\text{PSPACE} = \text{BPP}$.*

We prove the following unconditional result on the (randomized) pseudodeterministic complexity of CAPP.

THEOREM 4.2 (RESTATEMENT OF THEOREM 1.4). *For each $\varepsilon > 0$ and polynomial-time samplable distribution \mathfrak{D} , CAPP is solvable infinitely often pseudodeterministically in time $2^{O(n^\varepsilon)}$ on average over \mathfrak{D} .*

Please check the full version for a proof of Theorem 4.2.

Finally, we establish the following equivalences. Note that all algorithms mentioned below are deterministic.

THEOREM 4.3 (RESTATEMENT OF THEOREM 1.5). *The following statements are equivalent:*

1. *For each polynomial-time samplable distribution \mathfrak{D} of Boolean circuits and each $\varepsilon > 0$, there is an i.o.PRG \mathfrak{G} on average over \mathfrak{D} with seed length n^ε that is computable in time $2^{O(n^\varepsilon)}$.*
2. *For each polynomial-time samplable distribution \mathfrak{D} over Boolean circuits and each $\varepsilon > 0$, CAPP is solvable infinitely often in time $2^{O(n^\varepsilon)}$ on average over \mathfrak{D} .*
3. *For each polynomial-time samplable distribution \mathfrak{D} over input strings and each $\varepsilon > 0$, BPP is solvable infinitely often in time $2^{O(n^\varepsilon)}$ with $O(\log(n))$ bits of advice on average over \mathfrak{D} .*
4. *For each $\varepsilon > 0$, BPP is solvable infinitely often in time $2^{O(n^\varepsilon)}$ on average over U_n .*

We refer to the full version of the paper for the proof of this theorem.

5 FURTHER DIRECTIONS

We propose some directions for further research:

- (1) Theorem 1.1 is proved using general complexity-theoretic considerations, using no information about the set Primes apart from its polynomial density and its decidability by a polynomial-time algorithm. The primes have been intensively studied, and a lot is known about their structure. Can this structural information be leveraged to prove stronger results about generating primes? Perhaps the technique of using complexity-theoretic pseudorandomness applied here could be combined with earlier ideas for generating primes deterministically to show stronger results.
- (2) Can other kinds of probabilistic algorithms be made pseudodeterministic? In very recent work, we use our ideas to give such algorithms unconditionally for various approximate counting problems.
- (3) Are black-box derandomization, white-box derandomization and $\text{BPP} = \text{P}$ equivalent in the standard setting? Here, by the standard setting, we mean that we are interested in worst-case polynomial-time simulations that work for all large enough input lengths. As a first step toward this goal, it would be interesting to get the equivalence for average-case simulations, where we are even prepared to relax the “works almost everywhere” condition on the simulation to “works infinitely often”.

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