

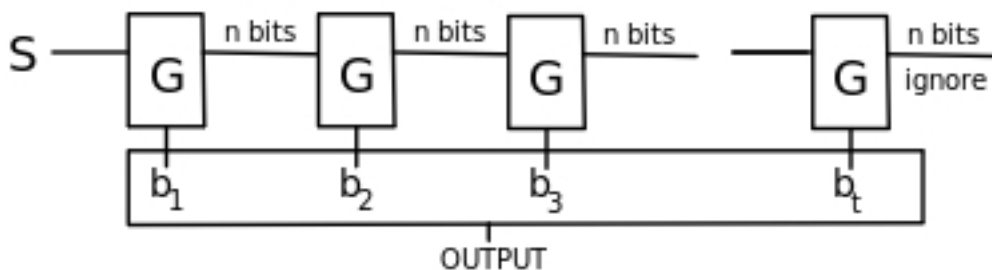
1 Expanding a PRG

In the last lecture we saw the definition of a Pseudorandom Generator (PRG) as a deterministic function that, given a seed of size n , outputs a pseudorandom string of length $\ell(n)$. We can ask the following question: how big can $\ell(n)$ be? Is there any limit on how much pseudorandom data we can generate starting from a seed of a certain size? We will find out that if we can get a PRG with even *one bit* of expansion (i.e., $\ell(n) = n + 1$), then we can get a PRG with *any* polynomial output length.

Theorem 1.1. *Suppose that there exists a PRG G with output of length $\ell(n) = n + 1$. Then for any $t(n) = \text{poly}(n)$ (where $t(n) > n$), there exists a PRG G_t with output length $t(n)$.*

Remark 1.2. The size of the set $\{G_t(s) : s \in \{0, 1\}^n\}$ is at most 2^n (because G_t is deterministic), while the number of possible $t(n)$ -bit string is $|\{0, 1\}^{t(n)}| = 2^{t(n)}$. The ratio of possible output strings that could actually be output by the PRG is at most $2^n / 2^{t(n)} = 2^{n-t(n)}$, which is absurdly small when $t(n) \geq 2n$ (and even smaller when $t(n) = n^{10}$, say).

Proof. We will construct $G_t(s)$ from G . Our construction will apply the function $G(\cdot)$ $t(n)$ times, outputting one new bit at each step and reusing the other n bits of the previous step's output as a seed. See the following picture for intuition about the construction.



Formally, G_t is defined as follows (note that it always applies G on string of the same length, n bits):

Algorithm 1 $G_t(s)$

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if  $t = 0$  then
  return  $\varepsilon$  (the empty string)
else
  let  $(x|b) = G(s)$ , where  $x \in \{0, 1\}^n$ ,  $b \in \{0, 1\}$ 
  return  $b|G_{t-1}(x)$ 
end if
  
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By construction, $|G_t(s)| = t$. We want to show that G_t is a PRG. The function clearly runs in polynomial time (each call to G can be resolved in polynomial time and we only use a polynomial number of steps), so what's left is to prove that $\{G_t(U_n)\} \stackrel{c}{\approx} \{U_{t(n)}\}$. We need to be careful: we already know that G is a PRG, but in our construction we are giving a *pseudorandom* seed to G , instead of a truly random seed. We will see that this fact will not affect the pseudorandomness of G_t . Intuitively, because no efficient algorithm can tell a pseudorandom seed apart from a random string, then in particular neither can G .

To prove that G_t is a PRG we will define a set of “hybrid experiments.” We will build a sequence of distributions, where the first is equal to our “real” construction $G_t(U_n)$, the last is equal to the “ideal” truly uniform distribution $U_{t(n)}$, and each consecutive pair of distributions are computationally indistinguishable. By the hybrid lemma, we conclude that $\{G_t(U_n)\}$ and $\{U_{t(n)}\}$ are computationally indistinguishable and that G_t is a PRG, thus proving the theorem.

To give some intuition about how we design the hybrid experiments, we imagine that instead of invoking the first G on n uniform bits, what if we replaced its output with $n + 1$ truly uniform bits? Intuitively, these two cases should not be distinguishable, because G is a PRG. And then what if we replaced the first two invocations of G , and so on? Eventually, we would end up with $t = t(n)$ truly uniform output bits, as desired.

Formally, the hybrid experiments are defined as follows:

- $H_0 = G_t(U_n)$
- $H_1 = U_1 | G_{t-1}(U_n)$
- In general, $H_i = U_i | G_{t-i}(U_n)$ for $i \in \{0\} \cup [t]$
- $H_t = U_t$

We now show that for all $i \in [t - 1]$, $H_i \stackrel{c}{\approx} H_{i+1}$. We will do this by using the simulation/composition lemma, and the fact that G is a PRG. For each i , we design a PPT “simulator” algorithm \mathcal{S}_i such that $\mathcal{S}_i(G(U_n)) = H_{i-1}$, and $\mathcal{S}_i(U_{n+1}) = H_i$. Since we know that $G(U_n) \stackrel{c}{\approx} U_{n+1}$ from the fact that G is a PRG, the composition lemma implies that $H_{i-1} \approx H_i$.

We define \mathcal{S}_i as follows:

Algorithm 2 $\mathcal{S}_i(y \in \{0, 1\}^{n+1})$

parse y as $(x|b)$ for $x \in \{0, 1\}^n$, $b \in \{0, 1\}$
return $U_{i-1} | b | G_{t-i}(x)$

This algorithm clearly runs in polynomial time. We need to check that it maps $G(U_n)$ to H_{i-1} , and U_{n+1} to H_i . First suppose that the input of \mathcal{S}_i comes from U_{n+1} :

$$\mathcal{S}_i(U_{n+1}) = U_{i-1} | b | G_{t-i}(x) = U_{i-1} | U_1 | G_{t-i}(U_n) = U_i | G_{t-i}(U_n) = H_i.$$

Now suppose that the input comes from $G(U_n)$. By the definition of G_t , we can see the following:

$$\mathcal{S}_i(G(U_n)) = U_{i-1} | b | G_{t-i}(x) = U_{i-1} | G_{t-i+1}(U_n) = H_{i-1}.$$

This completes the proof. □

To recap, our proof of [Theorem 1.1](#) took the following path:

- We defined a construction: the actual PRG G_t having a pseudorandom output of polynomial length.
- We defined the sequence of hybrid (“imaginary”) experiments. In each step, we replaced *one* “real” invocation of a crypto primitive ($G(U_n)$) with its “ideal” counterpart (U_{n+1}).
- We proved that consecutive pairs of hybrids are computationally indistinguishable, using the composition lemma and the security properties of the underlying primitives (i.e., that G is a PRG).
 - To apply the composition lemma, we defined a “simulator” (reduction) for each pair of adjacent hybrids and analyzed its behavior.

2 Obtaining a PRG

Thanks to [Theorem 1.1](#), we know that all we need is to obtain a PRG with one extra bit of output. We describe a number-theoretic construction, due to Blum and Micali, of such an object.

2.1 Number Theory Background

Theorem 2.1 (Euler’s theorem). *Let G be a finite abelian (i.e., commutative) multiplicative group. For every $a \in G$, we have $a^{|G|} = 1$.*

Proof. Consider the set $A = a \cdot G = \{ax : x \in G\}$. Because G is a group, a is invertible, and we have $A = G$. Taking products over all elements in $A = G$, we have

$$\prod_{x \in G} (ax) = \prod_{x \in G} x.$$

Because G is commutative, the LHS is $a^{|G|} \cdot \prod_{x \in G} x$, and we can multiply by the inverse of the RHS to obtain $a^{|G|} = 1$. \square

When $G = \mathbb{Z}_p^*$ for a prime p , we have $|\mathbb{Z}_p^*| = \varphi(p) = p - 1$, so we obtain the following corollary:

Corollary 2.2 (Fermat’s “little” theorem). *Let p be a prime. For any $a \in \mathbb{Z}_p^*$, we have $a^{p-1} = 1 \pmod{p}$.*

The following structural theorem will be very useful. (Its proof is elementary but rather tedious, so we won’t go through it today.)

Theorem 2.3. *Let p be a prime. The multiplicative group \mathbb{Z}_p^* is cyclic, i.e., there exists some generator $g \in \mathbb{Z}_p^*$ such that $\mathbb{Z}_p^* = \langle g \rangle := \{g^1, g^2, \dots, g^{p-1} = g^0 = 1\}$. (Equivalently, we can write the group as $\mathbb{Z}_p^* = \{g^0, g^1, \dots, g^{p-2}\}$.)*

Question 1. Suppose there is a “black box” B that outputs a uniformly random element of \mathbb{Z}_{p-1} for some known prime p . Show that there exists an algorithm that, using B as its only source of randomness, samples a uniformly random element of \mathbb{Z}_p^* .

2.2 Discrete Logarithm Problem and One-Way Function

[Theorem 2.3](#) leads naturally to the so-called *discrete logarithm problem*, which is: given $y \in \mathbb{Z}_p^*$ (and prime p and generator g of \mathbb{Z}_p^*), find $\log_g y$, i.e., the $x \in \{1, \dots, p-1\}$ for which $y = g^x \pmod{p}$. This problem is believed to be infeasible for large values of p .

Conjecture 2.4 (Discrete logarithm assumption). Let $S(1^n)$ be a PPT algorithm that outputs some prime p and generator g of \mathbb{Z}_p^* . For every non-uniform PPT algorithm \mathcal{A} ,

$$\Pr_{(p,g) \leftarrow S(1^n), y \leftarrow \mathbb{Z}_p^*} [\mathcal{A}(p, g, y) = \log_g y] = \text{negl}(n).$$

We would like to design a collection of OWFs based on the discrete logarithm assumption. The collection is made up of the functions $f_{p,g}: \{1, \dots, p-1\} \rightarrow \mathbb{Z}_p^*$ (for prime p and generator g of \mathbb{Z}_p^*), defined as

$$f_{p,g}(x) = g^x \pmod{p}.$$

Moreover, these functions are even *permutations* if we identify $\{1, \dots, p-1\}$ with \mathbb{Z}_p^* in the natural way.

It is a tautology that the collection is one-way under the discrete logarithm assumption. It is also clear that we can efficiently sample from the domain of $f_{p,g}$. But we still need to check that $f_{p,g}$ can be evaluated efficiently, and that (p, g) can be generated efficiently.

For the first, we use the standard “repeated squaring” technique for exponentiation, which requires $O(|x|)$ multiplications modulo p . The solution to the second issue is not entirely straightforward. Given only the prime p , it is unknown (in general) how to find a generator g of \mathbb{Z}_p^* efficiently. However, given the *factorization* of $p-1$, which can be generated along with p , it is possible: every element in \mathbb{Z}_p^* has order dividing $p-1$, so g is a generator if and only if $g^{(p-1)/q} \neq 1 \pmod p$ for every prime divisor q of $p-1$. The number of non-generators is at most the sum of $(p-1)/q$ over all prime divisors q of $p-1$, so the density of generators is typically large enough. An often-used special case is $p = 2q + 1$ for prime q , for which there are $q = (p-1)/2$ generators. However, it is not even known whether there exist infinitely many such “Sophie Germain” primes of this form! (Empirically, though, they are abundant.)

2.3 Blum-Micali PRG

We now present a PRG that uses the ideas presented in the previous section. From [Section 1](#) we know that if we have a PRG that is able to generate one extra bit of randomness, we can generate a polynomial number of pseudorandom bits. Our goal will be the following: we want to construct a PRG $G_{p,g}: \mathbb{Z}_p^* \rightarrow \mathbb{Z}_p^* \times \{0, 1\}$.¹

Our solution is a function with the following form:

$$G_{p,g}(x) = (f_{p,g}(x) = g^x \pmod p, h(x)).$$

Note that $f_{p,g}(x)$ performs the modular exponentiation function (which is a one-way under the discrete log assumption), while $h: \mathbb{Z}_p^* \rightarrow \{0, 1\}$ is some function (yet to be defined) that provides the additional bit.

Looking at the function, we can make the following observation: if $x \in \mathbb{Z}_p^*$ is chosen uniformly at random, then also $f_{p,g}(x)$ is uniform (because $f_{p,g}$ is a permutation). We still need to choose the function h , keeping in mind what we want from the function: $h(x)$ should “look like a random bit,” *even given* $f_{p,g}(x)$. That is, $h(x)$ should compute “something about x ” that f hides *completely*.

We can think of many possible candidates for h : apply the xor function to all the bit of x ; take the least significant bit of x (though you will show that this *does not* meet our requirements!); take the “most significant bit” of x (more precisely, test if $x > \frac{p-1}{2}$); etc.

Let’s formalize the security property we want from h . Informally, we want it to be the case that no efficient algorithm, given $f(x)$, should be able to guess $h(x)$ with probability much better than the $\frac{1}{2}$ that is achievable by random guessing.

Definition 2.5 (Hardcore predicate). A predicate $h: \{0, 1\}^* \rightarrow \{0, 1\}$ is *hard-core* for f if for all non-uniform PPT algorithms \mathcal{A} ,

$$\mathbf{Adv}_{f,h}(\mathcal{A}) := \Pr_x[\mathcal{A}(f(x)) = h(x)] - \frac{1}{2} = \text{negl}(n).$$

Next time, we will show that under the discrete log assumption, the “most significant bit” predicate $h(x) = [x > \frac{p-1}{2}]$ is hard-core for $f_{p,g}$.

¹To be pedantic, $G_{p,g}$ is a “collection” of PRGs, where the input seed comes from a set that depends on the function index (p, g) . It is easy to check that our construction from [Section 1](#) is compatible with this collection $G_{p,g}$.

Question 2. Prove that if h is hard-core for a one-way permutation $f: D \rightarrow D$, then

$$(f(x), h(x)) \stackrel{c}{\approx} (U(D), U_1) \equiv (f(x), b),$$

where $x \leftarrow D$ and $b \leftarrow \{0, 1\}$ are independent. This means that $G(x) = (f(x), h(x)) \in D \times \{0, 1\}$ is a PRG that expands by one bit. *Hint:* give a reduction that converts any distinguisher for the above two distributions into a predictor of $h(x)$ given $f(x)$.

Answers

Question 1. Suppose there is a “black box” B that outputs a uniformly random element of \mathbb{Z}_{p-1} for some known prime p . Show that there exists an algorithm that, using B as its only source of randomness, samples a uniformly random element of \mathbb{Z}_p^* .

Answer. By [Theorem 2.3](#), there exists a generator g of \mathbb{Z}_p^* . So, there exists an algorithm A that simply samples an $x \leftarrow B$ and returns g^x . By [Theorem 2.3](#), we know that $\langle g \rangle = \{g^0, \dots, g^{p-2}\} = \mathbb{Z}_p^*$, and since $|\mathbb{Z}_p^*| = p - 1$, it must be the case that for each $x \in \mathbb{Z}_p^*$, there exists a *unique* $i \in \mathbb{Z}_{p-1}$ such that $x = g^i$. Hence, $\Pr[A \text{ outputs } x] = \Pr[B \text{ outputs } i] = 1/(p - 1)$, as needed.

Question 2. Prove that if h is hard-core for a one-way permutation $f: D \rightarrow D$, then

$$(f(x), h(x)) \stackrel{c}{\approx} (U(D), U_1) \equiv (f(x), b),$$

where $x \leftarrow D$ and $b \leftarrow \{0, 1\}$ are independent. This means that $G(x) = (f(x), h(x)) \in D \times \{0, 1\}$ is a PRG that expands by one bit. *Hint:* give a reduction that converts any distinguisher for the above two distributions into a predictor of $h(x)$ given $f(x)$.

Answer. We prove this by reduction. Let \mathcal{D} be an nuPPT algorithm that seeks to distinguish $(f(x), h(x))$ from $(f(x), b)$, where $x \leftarrow D, b \leftarrow \{0, 1\}$ are independent. We construct an nuPPT predictor \mathcal{A} against the hard-core predicate h for f , which uses \mathcal{D} as a black box and has the same advantage. The key idea is that \mathcal{A} , given some $y = f(x)$ for unknown x , will simply guess a candidate value b for the hard-core bit $h(x)$, and invoke $\mathcal{D}(y, b)$ to get some indication of whether this guess is correct. Since \mathcal{D} may not be a perfect distinguisher, its answer may not always be “correct,” so it requires some care to analyze this reduction.

Formally, we define the predictor \mathcal{A} to work as follows: given input $y \in D$, choose a uniformly random bit $b \leftarrow \{0, 1\}$ and invoke $\mathcal{D}(y, b)$. If \mathcal{D} accepts (i.e., outputs 1), then output b as the prediction for $h(f^{-1}(y))$; otherwise, output \bar{b} as the prediction. Clearly, \mathcal{A} is nuPPT.

We now relate \mathcal{A} ’s advantage in the prediction game to \mathcal{D} ’s advantage in the distinguishing game. First, observe that \mathcal{A} ’s advantage is

$$\begin{aligned} \text{Adv}(\mathcal{A}) &= \Pr_{x \leftarrow D} [\mathcal{A}(f(x)) = h(x)] - 1/2 \\ &= \frac{1}{2} \left(\Pr_{x \leftarrow D} [\mathcal{D}(f(x), h(x)) = 1] + \Pr_{x \leftarrow D} [\mathcal{D}(f(x), \overline{h(x)}) = 0] - 1 \right) \\ &= \frac{1}{2} \left(\Pr_{x \leftarrow D} [\mathcal{D}(f(x), h(x)) = 1] - \Pr_{x \leftarrow D} [\mathcal{D}(f(x), \overline{h(x)}) = 1] \right), \end{aligned}$$

because $\mathcal{A}(f(x))$ outputs the correct bit $h(x)$ if \mathcal{A} chooses $b = h(x)$ and $\mathcal{D}(f(x), b)$ accepts, or if \mathcal{A} chooses $b = \overline{h(x)}$ and $\mathcal{D}(f(x), b)$ rejects. These events are disjoint, so we can add their probabilities, and b is uniform and independent of x , leading to the $1/2$ factor.

Now let

$$\begin{aligned} p_U &= \Pr_{x \leftarrow D, b \leftarrow \{0, 1\}} [\mathcal{D}(f(x), b) = 1] \\ &= \frac{1}{2} \left(\Pr_{x \leftarrow D} [\mathcal{D}(f(x), h(x)) = 1] + \Pr_{x \leftarrow D} [\mathcal{D}(f(x), \overline{h(x)}) = 1] \right), \end{aligned}$$

because each of $b = h(x)$ and $b = \overline{h(x)}$ occur with probability $1/2$. Similarly, define

$$p_G = \Pr_{x \leftarrow D} [\mathcal{D}(f(x), h(x)) = 1].$$

By definition, \mathcal{D} 's advantage is

$$\begin{aligned} \mathbf{Adv}(\mathcal{D}) &= p_G - p_U = \frac{1}{2} \left(\Pr_{x \leftarrow D} [\mathcal{D}(f(x), h(x)) = 1] - \Pr_{x \leftarrow D} [\mathcal{D}(f(x), \overline{h(x)}) = 1] \right) \\ &= \mathbf{Adv}(\mathcal{A}). \end{aligned}$$

Since \mathcal{A} 's advantage is negligible by the hypothesis that h is hard-core for f , so is \mathcal{D} 's advantage, as desired.