Lecture 10 - Derandomization, Pseudorandom Generators (PRGs)

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• Pseudorandom Generators (PRGs)

• Unpredictability vs Randomness & PRGs from Hard Functions

- Derandomization is the process of "removing randomness" from PTMs
 - Sometimes term is used to simply refer to a deterministic algorithm for the same problem
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Is there a general way to (non-trivially) remove randomness from BPP machines?

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To do the above, cannot use PTMs as a black-box. That is, general derandomization cannot relativize

See literature in [Pap 1994]

Also know that lower bounds cannot relativize. Could we use (strong enough) lower bounds to derandomize BPP?

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In a sense reduce use of non-relativization to proving lower bounds.¹

¹Though admittedly it could be that on the way to prove lower bounds, our non-reltivizing technique also works against BPP, in which case all of the below will be sort of redundant.

- Also know that lower bounds cannot relativize.
 Could we use (strong enough) lower bounds to derandomize BPP?
- In a sense reduce use of non-relativization to proving lower bounds.
- Still interesting that hardness can imply randomness, as we are now using reductions to prove:

some impossible result \Rightarrow possible result!

Usually a reduction $A \leq B$ is used to show that B tractable then A tractable or conversely A intractable then B intractable

Pseudorandom Generators

Definition 1 (Pseudorandom Distributions)

A distribution R over $\{0,1\}^m$ is $(s,\varepsilon)\text{-pseudorandom}$ if for every circuit C such that $S(C)\leq s$

$$\left|\Pr[C(R)=1] - \Pr[C(U_m)=1]\right| < \varepsilon$$

where U_m is the uniform distribution over $\{0,1\}^m$.

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• We say that $G: \{0,1\}^{\ell} \to \{0,1\}^m$ is (s,ε) -pseudorandom if the distribution $G(U_{\ell})$ is (s,ε) -pseudorandom.

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Definition 2 (Pseudorandom Generators)

Let $s: \mathbb{N} \to \mathbb{N}$ be a time-constructible and non-decreasing function. A 2^n -time constructible string function $G: \{0,1\}^* \to \{0,1\}^*$ is an $s(\ell)$ -pseudorandom generator if

•
$$|G(z)| = s(|z|)$$
 for all $z \in \{0, 1\}^*$

▶ for every $\ell \in \mathbb{N}$, $G(U_{\ell})$ is $(s(\ell)^3, 1/10)$ pseudorandom.¹

¹Constants 3 and 1/10 chosen for convenience

Proposition 3

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$$\begin{array}{l} 1. \ s(\ell) = 2^{\gamma \ell} \Rightarrow \mathsf{BPP} = \mathsf{P} \\ 2. \ s(\ell) = 2^{\ell^{\gamma}} \ \text{where} \ \gamma \in (0,1) \ \text{then} \ \mathsf{BPP} \subseteq \mathsf{DTIME}(2^{\mathsf{poly}\log n}) \\ 3. \ \text{if} \ s(\ell) = \ell^c \ \text{then} \ \mathsf{BPP} \subseteq \mathsf{DTIME}(2^{n^{1/c}}) \end{array}$$

Proposition 3

► Say
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 and let $M \in \mathsf{BPTIME}(n^c)$,
 $G_m : \{0, 1\}^{\gamma^{-1} \log m} \to \{0, 1\}^m$

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- If M uses m := m(n) random bits over $\{0,1\}^n$, then

$$\Pr_{r \in U_m}[M(x,r) = L(x)] \ge 2/3$$

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 $s(\ell)$ -PRG \Rightarrow BPTIME $(s(t(n))) \subseteq$ DTIME $(2^{ct(n)}s(t(n)))$ for some constant c > 0, where t(n) is a poly-time computable function.

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▶ Given x, r, note that M(x, r) is deterministic TM, hence (Proposition 2, Lecture 6), $M(x, r) \in SIZE(t^2(n))$, thus

$$\Pr_{r \in G_m(U_\ell)}[M(x,r)] - \Pr_{r \in U_m}[M(x,r)]| < 1/10$$

• Then, if $\ell := \gamma^{-1} \log m$,

$$\Pr_{r \in G_m(U_\ell)}[M(x,r) = L(x)] > 2/3 - 1/10 > 5/9$$

Proposition 3

 $s(\ell)$ -PRG \Rightarrow BPTIME $(s(t(n))) \subseteq$ DTIME $(2^{ct(n)}s(t(n)))$ for some constant c > 0, where t(n) is a poly-time computable function.

► The above shows why it's ok to let the PRG run in 2^ℓ time for inputs of length ℓ - for derandomization we will have to go over all seeds! • Pseudorandom Generators (PRGs)

• Unpredictability vs Randomness & PRGs from Hard Functions

Constructing PRGs

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- As we will see soon, it turns out that one can use hard boolean functions to construct PRGs
- ► Idea:
 - 1. unpredictability equivalent to pseudorandomness ([Yao 1982])
 - 2. a hard function should be hard to predict

Unpredictability vs Pseudorandomness

Lemma 4 If $f : \{0,1\}^{\ell} \to \{0,1\}$ and there is a circuit D with $S(D) \le s$ s.t. $|\Pr_{x}[D(x \circ f(x)) = 1] - \Pr_{x,b}[D(x \circ b) = 1]| > \varepsilon$

then there is a circuit A with $S(A) \leq s+3$ s.t.

$$\Pr_x[A(x) = f(x)] > 1/2 + \varepsilon.$$

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Lemma 4 If $f : \{0,1\}^{\ell} \to \{0,1\}$ and there is a circuit D with $S(D) \le s$ s.t. $|\Pr_{x}[D(x \circ f(x)) = 1] - \Pr_{x,b}[D(x \circ b) = 1]| > \varepsilon$

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- Above lemma shows that hard functions (on average), should "look random" to "efficient computation"
- Can assume there is circuit D' of size $\leq s + 1$ s.t.

$$\Pr_x[D'(x \circ f(x)) = 1] - \Pr_{x,b}[D'(x \circ b) = 1] > \varepsilon$$

Since either D or $\neg D$ will do.

Let's use D^\prime as our circuit D

Main idea: guess random bit b and compute D(x, b) to check whether b is a good guess for f(x).

Let A_b be the procedure:

- Sample $b \sim \{0, 1\}$
- ▶ If D(x,b) = 1 then output b
- ▶ Else, output 1 b

$$\Pr_{x,b}[A_b(x) = f(x)] > 1/2 + \varepsilon$$

$$\Pr_{x,b}[A_b(x) = f(x)] = \Pr_{x,b}[A_b(x) = f(x) \mid b = f(x)] \cdot \Pr_{x,b}[b = f(x)] + \Pr_{x,b}[A_b(x) = f(x) \mid b \neq f(x)] \cdot \Pr_{x,b}[b \neq f(x)]$$

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$$\begin{aligned} \Pr_{x,b}[A_b(x) &= f(x)] &= \Pr_{x,b}[A_b(x) = f(x) \mid b = f(x)] \cdot \Pr_{x,b}[b = f(x)] \\ &+ \Pr_{x,b}[A_b(x) = f(x) \mid b \neq f(x)] \cdot \Pr_{x,b}[b \neq f(x)] \\ &= \frac{1}{2} \cdot \Pr_{x,b}[A_b(x) = f(x) \mid b = f(x)] \\ &+ \frac{1}{2} \cdot \Pr_{x,b}[A_b(x) = f(x) \mid b \neq f(x)] \\ &= \frac{1}{2} \cdot \Pr_{x,b}[D(x \circ b) = 1 \mid b = f(x)] \\ &+ \frac{1}{2} \cdot \Pr_{x,b}[D(x \circ b) = 0 \mid b \neq f(x)] \end{aligned}$$

$$\begin{aligned} \Pr_{x,b}[A_b(x) &= f(x)] > 1/2 + \varepsilon \\ \Pr_{x,b}[A_b(x) &= f(x)] &= \frac{1}{2} \cdot \Pr_{x,b}[D(x \circ b) = 1 \ | \ b = f(x)] \\ &+ \frac{1}{2} \cdot \Pr_{x,b}[D(x \circ b) = 0 \ | \ b \neq f(x)] \\ &= \frac{1}{2} + \frac{1}{2} \cdot \Pr_{x,b}[D(x \circ b) = 1 \ | \ b = f(x)] \\ &- \frac{1}{2} \cdot \Pr_{x,b}[D(x \circ b) = 1 \ | \ b \neq f(x)] \end{aligned}$$

 $\mathbf{T} = [\mathbf{A} (\mathbf{A}) + \mathbf{A} (\mathbf{A})]$

$$\Pr_{x,b}[A_b(x) = f(x)] > 1/2 + \varepsilon$$

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$$-\frac{1}{2} \cdot \Pr_{x,b}[D(x \circ b) = 1 | b \neq f(x)]$$

$$= \frac{1}{2} + \Pr_{x}[D(x \circ f(x)) = 1] - \Pr_{x,b}[D(x \circ b) = 1$$

$$> 1/2 + \varepsilon$$

We will show from our assumption that

$$\Pr_{x,b}[A_b(x) = f(x)] > 1/2 + \varepsilon$$

• Thus, there is bit b^* such that

$$\Pr_x[A_{b^*}(x) = f(x)] > 1/2 + \varepsilon$$

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► Thus, there is bit *b*^{*} such that

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• Circuit for A_{b^*}

$$A_{b^*}(x) = b^* \oplus (\neg D'(x, b^*))$$

Nisan-Wigderson PRG

Definition 5 (Average-Case Hardness)

Given $f: \{0,1\}^n \to \{0,1\}$, its average-case hardness, denoted by H(f), is the smallest $s \in \mathbb{N}$ such that

$$\forall C \text{ circuit s.t. } S(C) \leq s \Rightarrow \Pr_x[C(x) = f(x)] \leq 1/2 + 1/s$$

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Theorem 6 (Special case of [NW 1994])

If there is $L \in E$ and $\delta > 0$ such that for all sufficiently large n, $H(L_n) \ge 2^{\delta n}$, then there is constant c > 0 and family of PRGs $G_m : \{0,1\}^{c \log m} \to \{0,1\}^m$ which are computable in poly(m)time and are (2m, 1/8)-pseudorandom.

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• In particular, the above implies P = BPP.

One can actually obtain derandomization from worst-case hardness.

Theorem 7 ([IW 1997])

If there is $L \in E$ and $\delta > 0$ such that for all sufficiently large n, $S(L \cap \{0,1\}^n) \ge 2^{\delta n}$, then BPP = P.

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If BPP \neq EXP, then for every $L \in$ BPP and $\varepsilon > 0$, there is a deterministic algorithm $A \in DTIME(2^{n^{\varepsilon}})$ and, for infinitely many $n \in \mathbb{N}$ solves $L \cap \{0,1\}^n$ on a 1 - 1/n fraction of its inputs

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- Assumptions in Theorem 7 stronger than in Theorem 8
 - 1. Non-uniform vs uniform
 - 2. exponential hardness vs super-polynomial hardness
- With stronger assumptions, (should) come stronger consequences
 - 1. Theorem 7 works over all inputs
 - 2. running time of simulations

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Turns out worst-case hypothesis \Rightarrow average-case hypothesis

Theorem 9 ([BFNW 1993, I 1995, IW 1997])

If there is $L \in E$ and $\delta > 0$ s.t. for all sufficiently large n, $S(L_n) \ge 2^{\delta n}$, then there is $L' \in E$ and $\delta' > 0$ s.t. for sufficiently large n, $H(L') \ge 2^{\delta' n}$.

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