## Recent advances in Complexity CIS 6930/CIS 4930

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Lecture 23

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Recall that we had split the proof of  $(2)\Rightarrow(3)$  of the main theorem into two subparts (Lecture 22). In this lecture we present proofs of these subparts.

**Exercise 1** Show that subparts 1 and 2 imply  $(2) \Rightarrow (3)$  of the main theorem.

## 1 Proof of Subpart 1

**Lemma 1** Let m, n, l be integers. Let  $f : \{0, 1\}^m \longrightarrow \{0, 1\}, H_f(m) \ge n^2$ , and let A be a Boolean  $n \times l$  matrix which is a (logn, m) design. Then  $G : \{0, 1\}^l \longrightarrow \{0, 1\}^n$  defined from A as  $G(x) = f(x_1), \ldots, f(x_n)$  is a pseudo random generator satisfying

$$|P[C(y) = 1] - P[C(G(x)) = 1]| \le \frac{1}{n},$$

for all circuits C of size n.

**Proof.** Before presenting the proof note that in the main theorem we will apply the lemma for  $l = m^2$  and  $n = s(l^c)$ .

The proof involves a series of bias preservations. The idea is to decompose an event into a bunch of events. If the bias holds for the original event, it also holds for at least one event in the union. Assume that G does not satisfy the given condition, i.e.,

$$|P[C(y)=1]-P[C(G(x))=1]|>\frac{1}{n}.$$

In other words the circuit C is able to distinguish between y and G(x). We will arrive at a contradiction that f could not have assumed the hardness property as G was constructed from f. It is first shown that  $\exists i$  such that C can predict  $f(x_i)$  from  $f(x_1), \ldots, f(x_{i-1})$ . Since  $x_i$  is uncorrelated to  $x_1, x_2, \ldots, x_{i-1}$ , it follows that C could not have got information about  $x_i$  from those. So  $f(x_i)$  has been independently computed from scratch contradicting the fact that f is hard. The details of the proof follow.

Define  $E_i$  to be a distribution on  $\{0,1\}^n$ , such that  $E_0$  is uniform over  $\{0,1\}_n$ ,  $E_n$  is the distribution G(x), where x is uniform over  $\{0,1\}^l$  and in general  $E_i$  is obtained by choosing  $f(x_1), \ldots, f(x_i)$ , where x is uniform and the remaining bits are uniform over  $\{0,1\}^{n-i+1}$ . Observe that the definitions of  $E_0$ 

and  $E_n$  are consistent with  $E_0 = E_i$ , i = 0 and  $E_n = E_i$ , i = n. Also define  $P_i = P[C(z) = 1]$  where z is chosen from  $E_i$ . We have  $P_0 - P_n = \sum_i [P_{i-1} - P_i]$ . This is a telescoping sum (refer to Henry's notes for more on this) and clearly  $\exists i$  such that  $|P_{i-1} - P_i| \ge 1/n^2$ , i.e., C distinguishes well between two types of strings; strings having i - 1 bits defined from applying f on the design and the rest random  $(E_{i-1})$  and those having i bits defined from applying f on the design and the rest random  $(E_i)$ .

Using this we build a circuit D that predicts  $f(x_i)$  from  $f(x_1),\ldots,f(x_{i-1})$ . D takes as inputs the first i-1 bits,  $z_1,z_2,\ldots,z_{i-1}$ , of a string z in  $E_{i-1}$ , i.e.,  $f(x_1),\ldots,f(x_{i-1})$  for some  $x\in\{0,1\}^l$ . It will output a bit  $z_i$ , which is a good approximation of  $f(x_i)$ . D is a probabilistic circuit (at start) that chooses n-i+1 random bits  $r_i,\ldots,r_n$ , computes  $C(z_1,\ldots,z_{i-1},r_i,\ldots,r_n)$ , and if the output is 1 it predicts  $z_i=r_i$  and if the output is 0 it predicts  $z_i=\bar{r_i}$ . Using the same proof as Yao's XOR lemma,  $P[D(z_1,z_2,\ldots,z_{i-1})=f(x_i)]-1/2\geq 1/n^2$ . This bias is true for the probability taken over the collection of  $r_i,\ldots,r_n$  and the  $z_i,\ldots,z_n$ . We can now claim that  $\exists\{r_i,\ldots,r_n\}$  (fixed values for the random bits) such that the prediction works with the bias. Note that once  $r_i,\ldots,r_n$  are fixed the circuit is no longer probabilistic. However it still works with the same bias when the probability is taken over  $z_1,\ldots,z_{i-1}$ . Also note that D has the same size as C. This completes the first part of what we are trying to do: prediction of  $f(x_i)$  from  $f(x_1),\ldots,f(x_{i-1})$ .

Next we show that the prediction has not used  $f(x_1), \ldots, f(x_i)$ , since  $x_i$  is unrelated to  $x_1, \ldots, x_{i-1}$ , and so the prediction comes down to computing  $f(x_i)$  directly from x. In order to do this we construct a circuit that uses D to compute  $f(x_i)$  from x, while still preserving the size. Call this new circuit D'.

In constructing D' we make use of the fact that the restrictions  $x_1,\ldots,x_{i-1}$  have a certain relationship to the restriction  $x_i$ . Each shares at most logn bits of x with  $x_i$ . Without loss assume that  $x_i = x^1, x^2, \ldots, x^m$ , the first m bits of x. Since  $z_i$  does not depend on the other bits of x, we can rewrite the probability that D predicts  $z_i$  correctly as  $P[D(z_1, z_2, \ldots, z_{i-1}) = z_i]$  (where x is chosen as random) over all possible choices of the bits  $x^{m+1}, \ldots, x^l$  of the same probability over the distribution where only  $x_1, \ldots, x_m$  are chosen at random i.e.,  $E_{i-1,x^1,\ldots,x^l} = \bigcup E_{i-1,x^1,\ldots,x^m}^{c_{m+1},\ldots,c_l}$ , where the union is over all possible choices  $c_{m+1},\ldots,c_l$  of  $x^{m+1},\ldots,x^l$ .

Applying the bias preservation property note that there exists some element of this union, i.e., some choice of  $x^{m+1}, \ldots, x^l$ , such that the bias on the probability is preserved. Once these l-m bits are fixed, the probability is over the remaining m bits. Now  $z_1, \ldots, z_{i-1}$ , each depend only on log n of the bits in  $x_i$ . This allows D' to incorporate the computation of f on log n bits for each  $x_j$ . Recall that f is assumed by the Theorem to be computable in exponential time. There are  $2^{log n} = n$  such values of f for each  $x_j$  that can actually be tabulated within D'. Each of these sets of values requires O(n) space and there are O(n) of such  $x_j$  resulting in a  $O(n^2)$  additional size to the circuit D' (besides the size of the circuit C). The  $f(x_j)$ s obtained can now be fed into a copy of D in D' to give  $x_i$  as output. We have constructed the required circuit D', which contradicts hardness of f at m.

## 2 Proof of Subpart 2

**Lemma 2** For all integers  $n, m, logn \le m \le n$ ,  $\exists (logn, m)$  design that can be constructed by an algorithm in DPACE(logn).

**Proof.** The design has n rows of subsets of  $\{0,1,\ldots,l\}$  of size m with intersections of size logn. Without loss, assume that m is a prime power. Also let  $l=m^2$ . If m is not a prime power pick the smallest power of 2 greater than m. Note that this doubles m at most. Consider numbers in  $\{0,1,\ldots,l\}$  as pairs of elements in GF(m), i.e., construct subsets of  $\{< a,b>|a,b\in GF(m)\}$ . Given a polynomial q on GF(m), define a set  $S_q=\{< a,q(a)>|a\in GF(m)\}$ . We take sets of this form and q varies over polynomials of degree at most logn. Now the following facts can be verified:

- (1) The size of each set is exactly m.
- (2) Any two sets intersect in at most log n points.
- (3) There are at least n different sets (the number of polynomials over GF(m) of degree at most log n is  $m^{log n+1} \ge n$ ).

Note that the sets can be effectively constructed using simple arithmetic in GF(m). Since m has length of  $O(\log n)$  bits, everything can be computed in  $O(\log n)$  space.