Foundation of Cryptography (0368-4162-01), Lecture 3 Hardcore Predicates for Any One-way Function

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Definition 1 (hardcore predicates)

An efficiently computable function $b : \{0, 1\}^n \mapsto \{0, 1\}$ is an hardcore predicate of $f : \{0, 1\}^n \mapsto \{0, 1\}^n$, if

$$\Pr[P(f(U_n)) = b(U_n)] \le \frac{1}{2} + \operatorname{neg}(n),$$

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Theorem 2 (Goldreich-Levin)

Let $f: \{0,1\}^n \mapsto \{0,1\}^n$ be a OWF, and define $g: \{0,1\}^n \times \{0,1\}^n \mapsto \{0,1\}^n \times \{0,1\}^n$ as g(x,r) = f(x), r. Then $b(x,r) = \langle x,r \rangle_2$, is an hardcore predicate of g.

Note that if *f* is one-to-one, then so is *g*.

Section 1

The Information Theoretic Case

Definition 3 (min-entropy)

The min entropy of a random variable X, is defined

$$\mathsf{H}_{\infty}(X) := \min_{y \in \mathsf{Supp}(X)} \log \frac{1}{\mathsf{Pr}_{X}[y]}.$$

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Examples

- X is uniform over a set of size 2^k
- (X | f(X) = y), where $f: \{0, 1\}^n \mapsto \{0, 1\}^n$ is 2^k to 1 and X is uniform over $\{0, 1\}^n$

Pairwise independent hashing

Pairwise independent hashing

Definition 4 (pairwise independent hash functions)

A function family \mathcal{H} from $\{0,1\}^n$ to $\{0,1\}^m$ is pairwise independent, if for every $x \neq x' \in \{0,1\}^n$ and $y, y' \in \{0,1\}^m$, it holds that $\Pr_{h \leftarrow \mathcal{H}}[h(x) = y \land h(x') = y')] = 2^{-2m}$. Pairwise independent hashing

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Lemma 5 (leftover hash lemma)

Let X be a random variable over $\{0,1\}^n$ with $H_{\infty}(X) \ge k$ and let \mathcal{H} be a family of pairwise independent hash functions from $\{0,1\}^n$ to $\{0,1\}^m$, then

 $\mathrm{SD}((h,h(x))_{h\leftarrow\mathcal{H},x\leftarrow X},(h,y)_{h\leftarrow\mathcal{H},y\leftarrow\{0,1\}^m})\leq 2^{(m-k-2))/2}.$

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* We typically simply write $SD((H, H(X)), (H, U_m))$, where *H* is uniformly distributed over \mathcal{H} .

efficient function families

efficient function families

Definition 6 (efficient function family)

An ensemble of function families $\mathcal{F} = \{\mathcal{F}_n\}_{n \in \mathbb{N}}$ is efficient, if the following hold:

Samplable. \mathcal{F} is samplable in polynomial-time: there exists a PPT that given 1^{*n*}, outputs (the description of) a uniform element in \mathcal{F}_n .

Efficient. There exists a polynomial-time algorithm that given $x \in \{0, 1\}^n$ and (a description of) $f \in \mathcal{F}_n$, outputs f(x).

hardcore predicate for regular functions

hardcore predicate for regular OWF

Lemma 7

Let $f : \{0,1\}^n \mapsto \{0,1\}^n$ be a $d(n) \in 2^{\omega(\log n)}$ regular function and let $\mathcal{H} = \{\mathcal{H}_n\}$ be an efficient family of Boolean pairwise independent hash functions over $\{0,1\}^n$. Define $g : \{0,1\}^n \times \mathcal{H}_n \mapsto \{0,1\}^n \times \mathcal{H}_n$ as

$$g(x,h)=(f(x),h),$$

then b(x, h) = h(x) is an hardcore predicate of g.

The Information Theoretic Case $\circ \circ \bullet \circ \circ \circ$

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How does it relate to the computational case?

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How does it relate to the computational case? Proof: We prove the claim by showing that

Claim 8

SD (($f(U_n), H, H(U_n)$), ($f(U_n), H, U_1$)) = neg(n), where the rv H = H(n) is uniformly distributed over \mathcal{H}_n .

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Does this conclude the proof?

The Computational Case

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Proving Claim 8

Proof: For $y \in f(\{0, 1\}^n) := \{f(x) : x \in \{0, 1\}^n\}$, let the rv X_y be uniformly distributed over $f^{-1}(y) := \{x \in \{0, 1\}^n : f(x) = y\}$.

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$$SD((f(U_n), H, H(U_n)), (f(U_n), H, U_1)) = \sum_{y \in f(\{0,1\}^n)} Pr[f(U_n) = y] \cdot SD((f(U_n), H, H(U_n) | f(U_n) = y))$$

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- $\leq \max_{y \in f(\{0,1\}^n)} SD((y, H, H(X_y)), (y, H, U_1))$

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hardcore predicate for regular functions

Proving Claim 8 cont.

Since $H_{\infty}(X_y) = \log(d(n))$ for any $y \in f(\{0,1\}^n)$,

hardcore predicate for regular functions

Proving Claim 8 cont.

Since $H_{\infty}(X_y) = \log(d(n))$ for any $y \in f(\{0, 1\}^n)$, The leftover hash lemma yields that

$$\begin{aligned} \mathsf{SD}((H, H(X_y)), (H, U_1)) &\leq 2^{(1-H_\infty(X_y)-2))/2} \\ &= 2^{(1-\log(d(n)))/2} = \operatorname{neg}(n). \quad \Box \end{aligned}$$

hardcore predicate for regular functions

Further remarks

Remark 9

- We can output $\Theta(\log d(n))$ bits,
- g and b are not defined over all input length.

Section 2

The Computational Case

Theorem 10 (Goldreich-Levin)

Let $f: \{0,1\}^n \mapsto \{0,1\}^n$ be a OWF, and define $g: \{0,1\}^n \times \{0,1\}^n \mapsto \{0,1\}^n \times \{0,1\}^n$ as g(x,r) = f(x), r. Then $b(x,r) = \langle x,r \rangle_2$, is an hardcore predicate of g.

Note that if b(x, r) is (almost) a family of pairwise independent hash functions.

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Proof: Assume $\exists \text{ PPT A}, p \in \text{poly and infinite set } \mathcal{I} \subseteq \mathbb{N} \text{ with}$ $\Pr[A(g(U_n, R_n)) = b(U_n, R_n)] \ge \frac{1}{2} + \frac{1}{p(n)}, \quad (1)$

for any $n \in \mathcal{I}$, where U_n and R_n are uniformly (and independently) distributed over $\{0, 1\}^n$.

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for every $n \in \mathcal{I}$.

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for every $n \in \mathcal{I}$. In the following fix $n \in \mathcal{I}$.

Claim 11

There exists a set $S \subseteq \{0, 1\}^n$ with

•
$$\frac{|S|}{2^n} \ge \frac{1}{2p(n)}$$
, and

$$2 \ \alpha(x) := \Pr[\mathsf{A}(f(x), R_n) = b(x, R_n)] \ge \frac{1}{2} + \frac{1}{2p(n)}, \forall x \in S.$$

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We will present $q \in poly$ and a PPT B such that

$$\Pr[\mathsf{B}(y = f(x)) \in f^{-1}(y) \ge \frac{1}{q(n)},$$
(3)

for every $x \in S$.

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We will present $q \in poly$ and a PPT B such that

$$\Pr[\mathsf{B}(y = f(x)) \in f^{-1}(y) \ge \frac{1}{q(n)}, \tag{3}$$

for every $x \in S$. Fix $x \in S$.

Perfect case

The perfect case $\alpha(x) = 1$

For every $i \in [n]$, it holds that

$$A(f(x), e^{i}) = b(x, e^{i}),$$

where $e^{i} = (\underbrace{0, \dots, 0}_{i-1}, 1, \underbrace{0, \dots, 0}_{n-i}).$

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• Hence, $x_{i} = \langle x, e^{i} \rangle_{2} = A(f(x), e^{i})$

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• Hence, $x_i = \langle x, e^i \rangle_2 = \mathsf{A}(f(x), e^i)$

We let $B(f(x)) = (A(f(x), e^1), ..., A(f(x), e^n))$

Easy case

Easy case: $\alpha(x) \ge 1 - \operatorname{neg}(n)$

Fact 12

∀r ∈ {0,1}ⁿ, the rv (r ⊕ R_n) is uniformly dist. over {0,1}ⁿ
 ∀w, y ∈ {0,1}ⁿ, it holds that b(x, w) ⊕ b(x, y) = b(x, w ⊕ y)

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Hence, $\forall i \in [n]$:

● $\forall r \in \{0,1\}^n$ it holds that $x_i = b(x,r) \oplus b(x,r \oplus e^i)$

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- $\forall r \in \{0,1\}^n$ it holds that $x_i = b(x,r) \oplus b(x,r \oplus e^i)$
- ② $\Pr[A(f(x), R_n) = b(x, R_n) \land A(f(x), R_n \oplus e^i) = b(x, R_n \oplus e^i)]$ ≥ 1 - neg(n)

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We let $B(f(x)) = (A(f(x), R_n) \oplus A(f(x), R_n \oplus e^1)), \dots, A(f(x), R_n) \oplus A(f(x), R_n \oplus e^n)).$

The Computational Case

Intermediate case

Intermediate case:
$$\alpha(x) \ge \frac{3}{4} + \frac{1}{q(n)}$$

For any $i \in [n]$, it holds that

$$\Pr[A(f(x), R_n) \oplus A(f(x), R_n \oplus e^i) = x_i]$$

$$\geq \Pr[A(f(x), R_n) = b(x, R_n) \land A(f(x), R_n \oplus e^i) = b(x, R_n \oplus e^i)]$$
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$$\geq \Pr[A(f(x), R_n) = b(x, R_n) \wedge A(f(x), R_n \oplus e^i) = b(x, R_n \oplus e^i)]$$

$$\geq \frac{1}{2} + \frac{2}{q(n)}$$

$$(4)$$

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$$\geq \Pr[A(f(x), R_n) = b(x, R_n) \wedge A(f(x), R_n \oplus e^i) = b(x, R_n \oplus e^i)]$$

$$\geq \frac{1}{2} + \frac{2}{q(n)}$$
(4)

Algorithm 13 (B)

Input: $f(x) \in \{0, 1\}^n$

- For every $i \in [n]$
 - Sample $r^1, \ldots, r^{\nu} \in \{0, 1\}^n$ uniformly at random
 - Let $m_i = \operatorname{maj}_{j \in [v]} \{ (A(f(x), r^j) \oplus A(f(x), r^j \oplus e^j) \}$

Output (*m*₁,..., *m_n*)

The Computational Case

Intermediate case

B's success provability

The following holds for "large enough" v = v(n).

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• The W^j are iids and $E[W^j] \ge \frac{1}{2} + \frac{2}{q(n)}$, for every $j \in [v]$

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Let X^1, \ldots, X^{ν} be iid over [0, 1] with expectation μ . Then, $\Pr\left[\left|\frac{\sum_{j=i}^{\nu} X^j}{\nu} - \mu\right| \ge \varepsilon\right] \le 2 \cdot \exp(-2\varepsilon^2 \nu)$ for every $\varepsilon > 0$.

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We complete the proof taking $X^j = W^j$, $\varepsilon = 1/4q(n)$ and $v \in \omega(\log(n) \cdot q(n)^2)$.

Actual case

The actual case: $\alpha(x) \ge \frac{1}{2} + \frac{1}{q(n)}$

• What goes wrong?

The Computational Case

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Actual case

F

Algorithm B

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The Computational Case



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Algorithm 16 (B)

Input: $f(x) \in \{0, 1\}^n$

• Sample uniformly (and independently) $t_1, \ldots, t_\ell \in \{0, 1\}^n$

2 For all
$$\mathcal{L} \subseteq [\ell]$$
, set $r^{\mathcal{L}} = \bigoplus_{i \in \mathcal{L}} t^i$

3 Guess $\{b(x, t^i)\}$, and compute $\{b(x, r^{\mathcal{L}})\}$ (how?)

③ For all *i* ∈ [*n*], let

$$m_i = \operatorname{maj}_{\mathcal{L} \subseteq \{0,1\}^n} \{ \mathsf{A}(f(x), r^{\mathcal{L}} \oplus e^i) \oplus b(x, r^{\mathcal{L}}) \}$$

Output $(m_1, ..., m_n)$

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Analyzing B's success probability

• Let
$$T^1, ..., T^{\ell}$$
 be iid over $\{0, 1\}^n$.

2 For every $\mathcal{L} \subseteq [\ell]$, let $\mathcal{R}^{\mathcal{L}} = \bigoplus_{i \in \mathcal{L}} T^i$.

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Fact 17

•
$$\forall \mathcal{L} \subseteq [\ell], R^{\mathcal{L}}$$
 is uniformly distributed over $\{0, 1\}^n$

2 ∀w, y ∈ {0,1}ⁿ and ∀L ≠ L' ⊆ [ℓ], it holds that

$$\Pr[R^{\mathcal{L}} = w \land R^{\mathcal{L}'} = y] = \Pr[R^{\mathcal{L}} = w] \cdot \Pr[R^{\mathcal{L}'} = y]$$

That is, the $R^{\mathcal{L}}$'s are *pairwise independent*.

Actual case

Proving Fact 17(2)

Assume wlg. that $1 \in (\mathcal{L}' \setminus \mathcal{L})$.

The Computational Case

Proving Fact 17(2)

$$\Pr[\mathcal{R}^{\mathcal{L}} = \mathbf{w} \land \mathcal{R}^{\mathcal{L}'} = \mathbf{y}]$$

= $\sum_{(t^2, \dots, t^{\ell}) \in \{0, 1\}^{(\ell-1)n}} \Pr[(\mathcal{T}^2, \dots, \mathcal{T}^{\ell}) = (t^2, \dots, t^{\ell})] \cdot$
$$\Pr[\mathcal{R}^{\mathcal{L}} = \mathbf{w} \land \mathcal{R}^{\mathcal{L}'} = \mathbf{y} \mid (\mathcal{T}^2, \dots, \mathcal{T}^{\ell}) = (t^2, \dots, t^{\ell})]$$

Proving Fact 17(2)

$$\Pr[R^{\mathcal{L}} = w \land R^{\mathcal{L}'} = y] = \sum_{\substack{(t^2, \dots, t^{\ell}) \in \{0, 1\}^{(\ell-1)n}}} \Pr[(T^2, \dots, T^{\ell}) = (t^2, \dots, t^{\ell})] \cdot \\ \Pr[R^{\mathcal{L}} = w \land R^{\mathcal{L}'} = y \mid (T^2, \dots, T^{\ell}) = (t^2, \dots, t^{\ell})] \\ = \sum_{\substack{(t^2, \dots, t^{\ell}): \ (\bigoplus_{i \in \mathcal{L}} t^i) = w}} \Pr[(T^2, \dots, T^{\ell}) = (t^2, \dots, t^{\ell})] \\ \cdot \Pr[R^{\mathcal{L}} = w \land R^{\mathcal{L}'} = y \mid (T^2, \dots, T^{\ell}) = (t^2, \dots, t^{\ell})]$$

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Pairwise independence variables

Definition 18 (pairwise independent random variables)

A sequence of random variables X^1, \ldots, X^{ν} is pairwise independent, if $\forall i \neq j \in [\nu]$ and $\forall a, b$, it holds that $\Pr[X^i = a \land X^j = b] = \Pr[X^i = a] \cdot \Pr[X^j = b]$

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Lemma 19 (Chebyshev's inequality)

Let X^1, \ldots, X^{ν} be pairwise-independent random variables with expectation μ and variance σ^2 . Then, for every $\varepsilon > 0$,

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B's success provability cont

Assuming that B always guesses $\{b(x, t^i)\}$ correctly, then for every $\mathcal{L} \subseteq [\ell]$

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$$E[W^{\mathcal{L}}] \ge \frac{1}{2} + \frac{1}{q(n)}$$

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$$Var(W^{\mathcal{L}}) := E[W^{\mathcal{L}}]^2 - E[(W^{\mathcal{L}})^2] \le 1$$

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$$\Pr[m_i = x_i] = \Pr\left[\frac{\sum_{\mathcal{L} \subseteq [\ell]} W^{\mathcal{L}}}{v} > \frac{1}{2}\right] \ge 1 - \frac{1}{2n}$$
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and by a union bound, B outputs *x* with probability $\frac{1}{2}$. Taking the guessing into account, yields that B outputs *x* with probability at least $2^{-\ell-1} \in \Omega(n/q(n)^2)$. The Information Theoretic Case

Reflections



Reflections

Hardcore functions. Similar ideas allows to output log *n* "pseudorandom bits"

The Information Theoretic Case

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Hardcore functions. Similar ideas allows to output log *n* "pseudorandom bits"

Alternative proof for the LHL. Let X be a rv with over $\{0,1\}^n$ with $H_{\infty}(X) \ge t$, and assume that $SD((R_n, \langle R_n, X \rangle_2), (R_n, U_1)) > \alpha = 2^{-c \cdot t}$ for some universal c > 0.



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- 2 $\exists A \text{ that predicts } \langle R_n, X \rangle_2 \text{ given } R_n \text{ with prob}$ $\frac{1}{2} + \alpha$
- ③ (by GL) ∃B that guesses *X* "from nothing", with prob $\alpha^{O(1)} > 2^{-t}$

List decoding. An efficient encoding $C: \{0,1\}^n \mapsto \{0,1\}^m$, and a decoder D. Such that the following holds for any $x \in \{0,1\}^n$ and c of hamming distance $\frac{1}{2} - \delta$ from C(x): $D(c, \delta)$ outputs a list of size at most poly $(1/\delta)$ that whp. contains x

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Reflections cont.

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LPN - learning parity with noise. Find *x* given polynomially many samples of $\langle x, R_n \rangle_2 + N$, where $\Pr[N = 1] \le \frac{1}{2} - \delta$.

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LPN - learning parity with noise. Find *x* given polynomially many samples of $\langle x, R_n \rangle_2 + N$, where $\Pr[N = 1] \le \frac{1}{2} - \delta$. The difference comparing to Goldreich-Levin – no control over the R_n 's.