Advanced Cryptography
1st Semester 2007-2008

Indistinguishability

Pascal Lafourcade

Université Joseph Fourier, Verimag

Master: October 6th 2007
Last Time (I)

Introduction

• Presentation
• Organization
• Motivation
• Mathematics Recalls
• Birthday Paradox
• Perfect Encryption

Remarks, questions, comments?
Last Time (II)

Exercises done

- 1) Give the security properties for an international airport
- 2) Drug Test
- 9) Perfect Security

Others Exercises

- Expectation properties
- Proofs of different probabilistic theorems.
- Generalization of Birthday Paradox.
- Negligible and Noticeable Functions.
## Second Draft of Instructors Schedule

10th October **PL 3** 17th October **PL 5**

<table>
<thead>
<tr>
<th>Monday</th>
<th>Thursday</th>
</tr>
</thead>
<tbody>
<tr>
<td>22/09/08</td>
<td>Welcome</td>
</tr>
<tr>
<td>29/09/08</td>
<td><strong>PL 1</strong></td>
</tr>
<tr>
<td>06/10/08</td>
<td><strong>PL 2</strong></td>
</tr>
<tr>
<td>13/10/08</td>
<td><strong>PL 4</strong></td>
</tr>
<tr>
<td>20/10/08</td>
<td>Entreprise</td>
</tr>
<tr>
<td>25/09/08</td>
<td>22/09/08 Welcome</td>
</tr>
<tr>
<td>02/10/08</td>
<td>25/09/08 JL 1</td>
</tr>
<tr>
<td>09/10/08</td>
<td>02/10/08 JL 2</td>
</tr>
<tr>
<td>16/10/08</td>
<td>09/10/08 JL 3</td>
</tr>
<tr>
<td>23/10/08</td>
<td>16/10/8 JL 4</td>
</tr>
</tbody>
</table>

**W44 HOLIDAYS**

<table>
<thead>
<tr>
<th>Monday</th>
<th>Thursday</th>
</tr>
</thead>
<tbody>
<tr>
<td>03/11/08</td>
<td><strong>FA 2</strong></td>
</tr>
<tr>
<td>10/11/08</td>
<td><strong>PL 6</strong></td>
</tr>
<tr>
<td>17/11/08</td>
<td><strong>PL 7</strong></td>
</tr>
<tr>
<td>24/11/08</td>
<td><strong>PL 8</strong></td>
</tr>
<tr>
<td>01/12/08</td>
<td><strong>PL 9</strong></td>
</tr>
<tr>
<td>08/12/08</td>
<td>Empty</td>
</tr>
<tr>
<td>06/11/08</td>
<td><strong>FA 3</strong></td>
</tr>
<tr>
<td>13/11/08</td>
<td><strong>FA 4</strong></td>
</tr>
<tr>
<td>20/11/08</td>
<td>06/11/08 FA 3</td>
</tr>
<tr>
<td>27/11/08</td>
<td>13/11/08 FA 4</td>
</tr>
<tr>
<td>04/11/08</td>
<td>20/11/08 JLR 5</td>
</tr>
<tr>
<td>04/11/08</td>
<td>27/11/08 JLR 6</td>
</tr>
<tr>
<td>04/11/08</td>
<td>04/11/08 JLR 7</td>
</tr>
<tr>
<td>04/11/08</td>
<td>04/11/08 JLR 7</td>
</tr>
</tbody>
</table>
Negligible functions

We call a function \( \mu : \mathbb{N} \rightarrow \mathbb{R}^+ \) negligible if for every positive polynomial \( p \) there exists an \( N \) such that for all \( n > N \)

\[
\mu(n) < \frac{1}{p(n)}
\]

Properties

Let \( f \) and \( g \) be two negligible functions, then

1. \( f.g \) is negligible.
2. For any \( k > 0 \), \( f^k \) is negligible.
3. For any \( \lambda, \mu \) in \( \mathbb{R} \), \( \lambda.f + \mu.g \) is negligible.

Exercise: Proofs
Example Negligible functions (I)

Prove that $f(n) := (\frac{1}{2})^n$ is negligible.
Example Negligible functions (II)

\( f(n) := (\frac{1}{2})^n \) is negligible? Show that for any positive polynomial \( p \) we have \( f(n) \leq p(n) \) for sufficiently large \( n \). Let \( d \) be the degree of \( p \).

\[
\lim_{n \to \infty} \frac{f(n)}{\frac{1}{p(n)}} = \lim_{n \to \infty} \frac{p(n)}{2^n} = \lim_{n \to \infty} \frac{\delta^d p(n)}{\delta^d 2^n} = \lim_{n \to \infty} \frac{0}{(\ln 2)^d 2^n} = 0
\]

Using L'Hôpital's rule:

\[
\lim_{x \to c} f(x) = \lim_{x \to c} g(x) = \pm \infty,
\]

then:

\[
\lim_{x \to c} \frac{f(x)}{g(x)} = \lim_{x \to c} \frac{f'(x)}{g'(x)}
\]

Since \( \frac{f(n)}{1/p(n)} \) converges to 0, and since \( p \) is positive, for sufficiently large \( n \) we have \( f(n) \leq \frac{1}{p(n)} \). So \( f \) is negligible.
Independent Random Variables

Definition

Two random variables $X$, $Y$ are **independent** if for all $x$ in the image of $X$ and all $y$ in the image of $Y$, the events $X = x$ and $Y = y$ are independent:

$$P[X = x \land Y = y] = P[X = x]P[Y = y]$$

Equivalently, $X$ and $Y$ are independent if and only if their joint distribution is equal to the product of their individual distributions.

**Exercise:** Prove that $X$ and $Y$ are independent if and only if for all values $x$ taken by $X$ with non-zero probability, the conditional distribution of $Y$ given the event $X = x$ is the same as the distribution of $Y$. 
Pairwise Independent Random Variables

Let $X_1, ..., X_n$ be a collection of random variables, and let $X_i$ be the image of $X_i$ for $i = 1, ..., n$. We say $X_1, ..., X_n$ are **pairwise independent** if for all $i, j = 1, ..., n$ with $i \neq j$, the variables $X_i$ and $X_j$ are independent.
Mutually Independent Random Variables

We say that $X_1, \ldots, X_n$ are **mutually independent** if for all $x_1 = X_1, \ldots, x_n = X_n$, we have

$$P[X_1 = x_1 \land \ldots \land X_n = x_n] = \prod_{i=1}^{n} P[X_i = x_i]$$

More generally, for $k = 2, \ldots, n$, we say that $X_1, \ldots, X_n$ are $k$-wise independent if any $k$ of them are mutually independent.
Example

We toss three coins, and set $X_i := 0$ if the $i$th coin is "tails," and $X_i := 1$ otherwise.

Show that the variables $X_1, X_2, X_3$ are mutually independent.

Let us set $Y_{12} := X_1 \oplus X_2$, $Y_{13} := X_1 \oplus X_3$, and $Y_{23} := X_2 \oplus X_3$, where "\(\oplus\)" denotes "exclusive or," that is, addition modulo 2.

Show that the variables $Y_{12}, Y_{13}, Y_{23}$ are pairwise independent, but not mutually independent.
Probability Notation

\[ Pr[A(X_n) = 1] = \sum_x Pr[X_n = x] \cdot Pr[A(x) = 1] \]
Outline of Today: **Indistinguishability**

1. Introduction
Outline of Today: Indistinguishability

1 Introduction

2 Definitions
Outline of Today: Indistinguishability

1. Introduction
2. Definitions
3. Hybrid Technique
Outline of Today: **Indistinguishability**

1. Introduction
2. Definitions
3. Hybrid Technique
4. Application: Pseudo-Random Generators
Outline of Today: Indistinguishability

1 Introduction
2 Definitions
3 Hybrid Technique
4 Application: Pseudo-Random Generators
5 Conclusion
Outline

1 Introduction
2 Definitions
3 Hybrid Technique
4 Application: Pseudo-Random Generators
5 Conclusion
Notion of Indistinguishability

Objects are considered to be computationally equivalent if they cannot be differentiated by any efficient procedure.

Hence, two distributions are said to be computationally indistinguishable if no efficient procedure can tell them apart.
Example with Distributions

Given an efficient algorithm \( D \), we consider the probability that \( D \) accepts a string taken from the first distribution, and the probability for the second distribution. If these two probabilities are close, we say that \( D \) does not distinguish the two distributions.
Concrete Example (I)

Consider that in Box 1 there are 9 blue numerated balls and in Box 2 there are 9 red numerated balls, with uniform distributions.

Alice picks one ball into one of the two boxes and says the number of the ball.

Where did Alice pick the ball?

\[
|Pr[A(Box1|Number) = 1] - Pr[A(Box2|Number) = 1]| \text{ is negligible.}
\]
Concrete Example (II)

Consider now that Alice has $\frac{1}{2}$ probability to pick ball number 1 between the red balls and $\frac{1}{16}$ for the others ($2, \ldots, 9$).

Hence an adversary has a non negligible advantage to know which Box the ball comes from.
Medical Issue

Consider two sets of patients following two indistinguishable distributions of probability. We give in similar conditions to the first set a new medicine and only water to the second set.

If the results are significant then the treatment is efficient, i.e., the probability of distribution for the results whit medicine is distinguishable from the fictive one.
Cryptographic Issue

For a perfect encryption scheme we wish:

$$\left| \Pr[Enc(1) = 1] - \Pr[Enc(0) = 1] \right|$$

is negligible.
Outline

1. Introduction
2. Definitions
3. Hybrid Technique
4. Application: Pseudo-Random Generators
5. Conclusion
Probability Ensemble

Let \( I \) be a countable index set. An ensemble indexed by \( I \) is a sequence of random variable indexed by \( I \). Namely, any \( X = \{X_i\}_{i \in I} \), where each \( X_i \) is a random variable, is an ensemble indexed by \( I \).

Notations

- \( X = \{X_n\}_{n \in \mathbb{N}} \) has each \( X_n \) ranging over strings of length \( \text{poly}(n) \).
- \( X = \{X_w\}_{w \in \{0,1\}^*} \) has each \( X_w \) ranging over string of length \( \text{poly}(|w|) \).
Example

Sequences \( \{x_n\}_{n \in \mathbb{N}} \) and \( \{y_n\}_{n \in \mathbb{N}} \) are said to be computationally indistinguishable if no efficient procedure can tell them apart.
Polynomial-Time Indistinguishability

- Two ensembles, $X := \{X_n\}_{n \in \mathbb{N}}$ and $Y := \{Y_n\}_{n \in \mathbb{N}}$, are indistinguishable in polynomial time if for every probabilistic polynomial-time algorithm $D$, every positive polynomial $p(.)$, and all sufficiently large $n$’s,

$$|Pr[D(X_n, 1^n) = 1] - Pr[D(Y_n, 1^n) = 1]| < \frac{1}{p(n)}$$

- Two ensembles, $X := \{X_w\}_{w \in S}$ and $Y := \{Y_w\}_{w \in S}$, are indistinguishable in polynomial time if for every probabilistic polynomial-time algorithm $D$, every positive polynomial $p(.)$, and all sufficiently long $w \in S$,

$$|Pr[D(X_w, w) = 1] - Pr[D(Y_w, w) = 1]| < \frac{1}{p(|w|)}$$
Example (I)

Let $b$ be a string generated by flipping a “fair” coin until head appears (head = 1). Let $X$ be random variable which represents the size of $b$. Define random variables $B_1, B_2, ...$, where $B_i$ represents the value of the bit assigned to $b$ in the $i$th flip, if $X \geq i$, and $\star$ otherwise.

Note: exactly one $B_i$ will take the value 1, in which case $X$ takes the value $i$. Evidently, for each $i \geq 1$, then $B_i$ is uniformly distributed over \{0, 1\}, and otherwise, $B_i = \star$.

$$P[B_i = 0|X \geq i] = \frac{1}{2}$$

$$P[B_i = 1|X \geq i] = \frac{1}{2}$$

$$P[B_i \neq \star|X < i] = 1$$
Example (II)

\[ P[X \geq 1] = 1 \]
\[ P[X \geq 2] = P[B_1 = 0|X \geq 1]P[X \geq 1] = \frac{1}{2} \]
\[ P[X \geq 3] = P[B_2 = 0|X \geq 2]P[X \geq 2] = \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{4} \]

By induction on \( i \)

\[ P[X \geq i] = P[B_{i-1} = 0|X \geq i - 1]P[X \geq i - 1] = \frac{1}{2} \cdot \frac{1}{2^{i-2}} = \frac{1}{2^{i-1}} \]

\( X \) has a geometric distribution with success \( 1/2 \).
Example (III)

The following simple probabilistic algorithm corresponds to flipping a coin until head appears

repeat
    \( b \leftarrow_R \{0, 1\} \)
until \( b = 1 \)
Example (I)

Consider the algorithm $D_1$ which flips a coin and outputs its outcome $(0 - 1)$, with probability $1/2$. Prove that

$$|\Pr[D_1(X) = 1] - \Pr[D_1(Y) = 1]|$$

is negligible.
Where $X$ is the event obtain 1 and $Y$ obtain 0
Exercises (I)

Consider the algorithm $D_2$ that outputs 1 iff the input string contains more zeros than ones. If $D_2$ can be implemented in polynomial time, then prove that $X$ and $Y$ are polynomial-time-indistinguishable.
### Exercises (II)

#### Transitivity

Let $X := \{X_n\}_{n \in \mathbb{N}}$, $Y := \{Y_n\}_{n \in \mathbb{N}}$ and $Z := \{Z_n\}_{n \in \mathbb{N}}$ three ensembles. If $X$ and $Y$ are indistinguishable in polynomial time, $Y$ and $Z$ are indistinguishable in polynomial time then $X$ and $Z$ are indistinguishable in polynomial time.
Indistinguishability by Repeated Sampling

Two ensembles, $X := \{X_n\}_{n \in \mathbb{N}}$ and $Y := \{Y_n\}_{n \in \mathbb{N}}$ are indistinguishable by polynomial-time sampling if for every probabilistic polynomial-time algorithm $D$, every positive polynomials $m(.)$ and $p(.)$, and all sufficiently large $n$’s:

$$|Pr[D(X_1^n, \ldots, X_{m(n)}^n) = 1] - Pr[D(Y_1^n, \ldots, Y_{m(n)}^n) = 1]| < \frac{1}{p(n)}$$

where $X_n^1$ through $X_n^{m(n)}$ and $Y_n^1$ through $Y_n^{m(n)}$ are independent random variables, with each $X_n^i$ identical to $X_n$ and $Y_n^i$ identical to $Y_n$. 
Efficiently Constructible Ensembles

An ensemble $\mathcal{X} := \{X_n\}_{n \in \mathbb{N}}$ is said to be polynomial-time-constructible if there exists a probabilistic polynomial-time algorithm $S$ such that for every $n$, the random variables $S(1^n)$ and $X_n$ are identically distributed.
Outline

1. Introduction
2. Definitions
3. Hybrid Technique
4. Application: Pseudo-Random Generators
5. Conclusion
Theorem

Let \( X := \{X_n\}_{n \in \mathbb{N}} \) and \( Y := \{Y_n\}_{n \in \mathbb{N}} \) be two polynomial-time-constructible ensemble, and suppose that \( X \) and \( Y \) are indistinguishable in polynomial time. Then \( X \) and \( Y \) are indistinguishable by polynomial-time sampling.
Proof by contradiction

We prove that the existence of an efficient algorithm that distinguishes $X$ and $Y$ using several samples implies the existence of an efficient algorithm which distinguishes the ensembles $X$ and $Y$. 
Proof (I)

We assume that there is $D$ a polynomial-time algorithm such that for many $n$’s holds:

$$\Delta(n) := |\Pr[D(X_n^{(1)}, \ldots, X_n^{(m)}) = 1] - \Pr[D(Y_n^{(1)}, \ldots, Y_n^{(m)}) = 1]| > \frac{1}{p(n)}$$

where $m := m(n)$ and the $X_n^{(i)}$ and $Y_n^{(i)}$ are defined by repeated sampling.

GOAL: Finding a probabilistic polynomial-time algorithm $D'$ that distinguishes $X$ and $Y$. 
Introducing $H^k_n$

For every $0 \leq k \leq m$, we define the hybrid random variable

$$H^k_n := (X^{(1)}_n, \ldots, X^{(k)}_n, Y^{(k+1)}_n, \ldots, Y^{(m)}_n)$$

where $X^{(1)}_n$ through $X^{m(n)}_n$ and $Y^{(1)}_n$ through $Y^{m(n)}_n$ are independent random variables, with each $X^{(i)}_n$ identical to $X_n$ and $Y^{(i)}_n$ identical to $Y_n$.

Clearly we have

$$H^m_n := (X^{(1)}_n, \ldots, X^{(m)}_n)$$

and

$$H^0_n := (Y^{(1)}_n, \ldots, Y^{(m)}_n)$$
Idea of the Proof

By hypothesis, $D$ distinguishes $H^0_n$ and $H^m_n$.

We use $D$ to build $D'$ which distinguishes $X$ and $Y$:

1. Selects $k$ uniformly in the set $\{0, 1, \ldots, m - 1\}$.
2. Generates $k$ independent samples of $X_n$ denoted $x^1, \ldots, x^k$.
3. Generates $m - k - 1$ independent samples of $Y_n$ denoted $y^{k+2}, \ldots, y^m$.
4. Invokes $D$ with the input $\alpha$ and halts with the output

$$D'(\alpha) = D(x^1, \ldots, x^k, \alpha, y^{k+2}, \ldots, y^m)$$
Claim 1

\[ \Pr[D'(X_n) = 1] = \frac{1}{m} \sum_{k=0}^{m-1} \Pr[D(H_n^{k+1}) = 1] \]

and

\[ \Pr[D'(Y_n) = 1] = \frac{1}{m} \sum_{k=0}^{m-1} \Pr[D(H_n^k) = 1] \]
Claim 1

\[ Pr[D'(X_n) = 1] = \frac{1}{m} \sum_{k=0}^{m-1} Pr[D(H_n^{k+1}) = 1] \]

and

\[ Pr[D'(Y_n) = 1] = \frac{1}{m} \sum_{k=0}^{m-1} Pr[D(H_n^k) = 1] \]

Remark

- \( \sum_{k=0}^{m-1} Pr[D(H_n^{k+1}) = 1] \) corresponds to all \( H_n^i \) except \( H_n^0 \)
- \( \sum_{k=0}^{m-1} Pr[D(H_n^k) = 1] \) corresponds to all \( H_n^i \) except \( H_n^m \)
Proof of Claim 1

By construction of the algorithm $D'$, we have

$$D'(\alpha) = D(X_n^{(1)}, \ldots, X_n^{(k)}, \alpha, Y_n^{(k+2)}, \ldots, Y_n^{(m)})$$

where $k$ is uniformly distributed in $\{0, 1, \ldots, m - 1\}$.

$$Pr[D'(X_n) = 1] = \sum_{l=0}^{m-1} Pr[k = l]Pr[D(X_n^{(1)}, \ldots, X_n^{(k)}, X_n^{(l)}, Y_n^{(k+2)}, \ldots, Y_n^{(m)}) = 1]$$

Using the definition of the hybrids $H_n^k$, the claim follows.

$$Pr[D'(X_n) = 1] = \frac{1}{m} \sum_{l=0}^{m-1} Pr[D(H_n^{k+1}) = 1]$$
Claim 2

For $\Delta(n)$ we have:

$$|Pr[D'(X_n) = 1] - Pr[D'(Y_n) = 1]| = \frac{\Delta(n)}{m(n)}$$

where

$$\Delta(n) := |Pr[D(X_n^{(1)}, \ldots, X_n^{(m)}) = 1] - Pr[D(Y_n^{(1)}, \ldots, Y_n^{(m)}) = 1]|$$

where $m := m(n)$ and the $X_n^i$ and $Y_n^i$ are defined by repeated sampling.
Proof of Claim 2

Using Claim 1 we get,

\[ |Pr[D'(X_n) = 1] - Pr[D'(Y_n) = 1]| \]

\[ = \frac{1}{m} \sum_{k=0}^{m-1} Pr[D(H_n^{k+1}) = 1] - \sum_{k=0}^{m-1} Pr[D(H_n^k) = 1]| \]

\[ = \frac{1}{m} |Pr[D(H_n^m) = 1] - Pr[D(H_n^0) = 1]| = \frac{\Delta(n)}{m} \]

where the last equality follows by recalling that:

\[ H_n^m := (X_n^{(1)}, \ldots, X_n^{(m)}) \]

\[ H_n^0 := (Y_n^{(1)}, \ldots, Y_n^{(m)}) \]

Using the definition of \( \Delta(n) \)
End of the Proof

Our hypotheses said that $\Delta(n) > \frac{1}{p(n)}$ for infinitely many n’s, hence $D'$ distinguishes $X$ and $Y$, which contradicts the hypothesis of the theorem.
Hybrid Argument: A digest

- Extreme hybrids collide with the complex ensembles
- Neighboring hybrids are easily related to the basic ensembles
- Number of hybrid is “small” (polynomial)
Outline

1. Introduction

2. Definitions

3. Hybrid Technique

4. Application: Pseudo-Random Generators

5. Conclusion
Pseudorandom Ensembles

Definition

The ensemble $X = \{X_n\}_{n \in \mathbb{N}}$ is called pseudo random ensemble if there exists a uniform ensemble $U = \{U_l(n)\}_{n \in \mathbb{N}}$ such that $X$ and $U$ are indistinguishable in polynomial time.
Pseudorandom Generator

**Definition**

A pseudo-random generator is a deterministic polynomial-time algorithm $G$ satisfying:

- **Expansion**: There exists a function $l : \mathbb{N} \rightarrow \mathbb{N}$ such that $l(n) > n$ for all $n \in \mathbb{N}$ and $|G(s)| = l(|s|)$ for all $s \in \{0, 1\}^*$. $l$ is called the expansion factor of $G$.

- **Pseudorandomness**: The ensemble $\{G(U_n)\}_{n \in \mathbb{N}}$ is pseudorandom.
Increasing the Expansion Factor

Given a pseudorandom generator $G_1$ with expansion function $l_1(n) = n + 1$, we construct a PRG $G$ with arbitrary polynomial expansion factor

**Construction**

Let $G_1$ be a deterministic polynomial-time algorithm mapping strings of length $n$ into strings of length $n + 1$, and let $p(.)$ be a polynomial. Define $G(s) = \sigma_1 \sigma_2 \ldots \sigma_{p(|s|)}$ where $s_0 = s$, the bit $\sigma_i$ is the first bit of $G_1(s_{i-1})$, and $s_i$ is the $|s|$-bit-long suffix of $G_1(s_{i-1})$ for every $1 \leq i \leq p(|s|)$. 
Incrasing the Expansion Factor

Algorithm: \( G(s_0) = \sigma_1\sigma_2 \ldots \sigma_{p(n)} \)

Let \( s_0 = s \) and \( n = |s| \)

For \( i = 1 \) to \( p(n) \) do

\[ \sigma_i s_i \leftarrow G_1(s_{i-1}), \text{ where } \sigma_i \in \{0, 1\} \text{ and } |s_i| = |s_{i-1}| \]

Output \( \sigma_1\sigma_2 \ldots \sigma_{p(n)} \)
Application of Hybrid Argument

Theorem

Let $G_1, p(.)$, and $G$ defined as in previous construction such that $p(n) > n$. If $G_1$ is a PRG the $G$ is also a PRG.

Proof uses an hybrid argument. Intuitively, we can see that each application of $G_1$ can be replace by a random process. The indistinguishability of each applications of $G_1$ implies that polynomially many applications of $G_1$ are indistinguishable from a random process.
Proof: Idea

To the contrary, suppose $G$ is not a PRG then $\{G(U_n)\}_{n \in \mathbb{N}}$ and $\{U_{p(n)}\}_{n \in \mathbb{N}}$ are indistinguishable, i.e.

$$\Delta(n) = |Pr[D(G(U_n)) = 1] - Pr[D(U_{p(n)})]| > \frac{1}{q(n)}$$

It will contradict the fact that $G_1$ is PRG.

Hybrid Term

We define $\forall k, 0 \leq k \leq p(n)$

$$H^k_n = U^{(1)}_k \cdot \text{pref}_{p(n)-k}(G(U^{(2)}_n))$$

where $U^{(1)}_k$ and $U^{(2)}$ are independent random variable
Proof: Other Representation of $H_n^k$
Proof: Other Representation of $H_n^k$

It is clear that:

- $H_n^0 = G(U_n)$
- $H_n^{p(n)} = U_{p(n)}$
Proof

Idea: If an algorithm $D$ can distinguish extrem hybrid, it can do it for two neighboring hybrids.

By construction

$$\text{pref}_{j+1}(G(x)) = \text{pref}_1(G_1(x)) \cdot \text{pref}_j(G(\text{suff}_n(G_1(x))))$$

$$H_n^k = U_k(1) \cdot \text{pref}_{p(n)-k-1+1}(G(U_n^{(2)}))$$

$$H_n^{k+1} = U_{k+1}(1) \cdot \text{pref}_{p(n)-(k+1)}(G(U_n^{(2)}))$$

Notation:

$$f_{p(n)-k}(\alpha) = \text{pref}_1(\alpha) \cdot \text{pref}_{p(n)-k-1}(G(\text{suff}_n(\alpha)))$$
Claims

Two Easy Claims

- $H_n^k$ is distributed identically to $U_k^{(1)} \cdot f_{p(n) - k}(G_1(U_n^{(2)}))$
- $H_n^{k+1}$ is distributed identically to $U_k^{(1)} \cdot f_{p(n) - k}(G_1(U_{n+1}^{(3)}))$
Proof of

Claim 1

- $H^k_n$ is distributed identically to $U_k^{(1)} \cdot f_{p(n)-k}(G_1(U_n^{(2)}))$

\[
H^k_n = U_k^{(1)} \cdot \text{pref}_{p(n)-k-1} + 1(G(U_n^{(2)})) \\
= U_k^{(1)} \cdot \text{pref}_1(G_1(U_n^{(2)})) \cdot \text{pref}_{p(n)-k-1}(G(suff_n(G_1(U_n^{(2)})))) \\
= U_k^{(1)} \cdot f_{p(n)-k}(G_1(U_n^{(2)}))
\]
Proof of

Claim 2

- $H^k_n$ is distributed identically to $U^{(1)}_k \cdot f_{p(n)-k}(G_1(U^{(2)}_n))$

\[
H^{k+1}_n = U^{(1)}_{k+1} \cdot pref_{p(n)-(k+1)}(G(U^{(2)}_n))
\]
\[
= U^{(1')}_k \cdot U^{(1'')}_1 \cdot pref_{p(n)-k-1}(G(suff_n(U^{(2')}_{n+1})))
\]
\[
= U^{(1')}_k \cdot pref_1(U^{(2')}_{n+1} \cdot pref_{p(n)-k-1}(G(suff_n(U^{(2')}_{n+1}))))
\]
\[
= U^{(1')}_k \cdot f_{p(n)-k}(G_1(U^{(2')}_{n+1}))
\]
Proof

We derive from $D'$ an algorithm that distinguishes $G_1(U_n)$ from $U_{n+1}$.

**Algorithm $D'$**

1. $D'$ selects an integer $k$ in $\{0, 1, \ldots, p(n) - 1\}$
2. $D'$ selects $\beta$ uniformly in $\{0, 1\}^k$
3. $D'$ halts with output $D(\beta . f_{p(n)-k}(\alpha))$
Two Last Claims

Claims

\[
Pr[D'(G_1(U_n)) = 1] = \frac{1}{p(n)} \sum_{k=0}^{p(n)-1} Pr[D(H_n^k) = 1]
\]

\[
Pr[D'(U_{n+1}) = 1] = \frac{1}{p(n)} \sum_{k=0}^{p(n)-1} Pr[D(H_n^{k+1}) = 1]
\]
Two Last Claims

Claims

\[
Pr[D'(G_1(U_n)) = 1] = \frac{1}{p(n)} \sum_{k=0}^{p(n)-1} Pr[D(H_n^k) = 1]
\]

\[
Pr[D'(U_{n+1}) = 1] = \frac{1}{p(n)} \sum_{k=0}^{p(n)-1} Pr[D(H_n^{k+1}) = 1]
\]

Proof: By construction of \( D' \), we get for every \( \alpha \in \{0, 1\}^{n+1} \)

\[
Pr[D'(\alpha) = 1] = \frac{1}{p(n)} \sum_{k=0}^{p(n)-1} Pr[D(U_k.f_{p(n)-k}(\alpha)) = 1]
\]
δ = |Pr[D'(G_1(U_n)) = 1] - Pr[D'(U_{n+1}) = 1]| \\
= \frac{1}{p(n)} \sum_{k=0}^{p(n)-1} Pr[D(H_n^k) = 1] - \sum_{k=0}^{p(n)-1} Pr[D(H_n^{k+1}) = 1]| \\
= \frac{1}{p(n)} |Pr[D(G(U_n) = 1] - Pr[D(U_{p(n)}) = 1]| \\
= \frac{\Delta(n)}{p(n)} > \frac{1}{q(n)p(n)} \\
Contradiction
Outline

1 Introduction

2 Definitions

3 Hybrid Technique

4 Application: Pseudo-Random Generators

5 Conclusion
Summary

Today

- Indistinguishability
- Not to rush to conclusions regarding complex notions
- Hybrid technique
Thank you for your attention.

Questions ?