

# Complexity-Theoretic Cryptography

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## Information Theoretic Approach



adversary:

- Is there plaintext information left in the ciphertext?
- I have **unlimited** computational power!



## Complexity Theoretic Approach



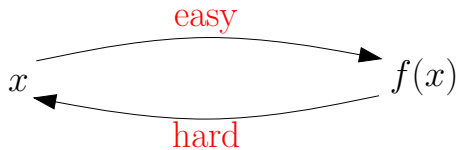
adversary:

- Can I efficiently extract plaintext information?
- I only have **limited** computational resources!



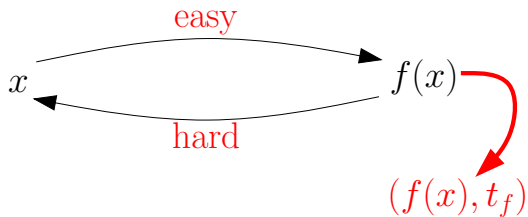
# One-Way Function

Informal Definition.



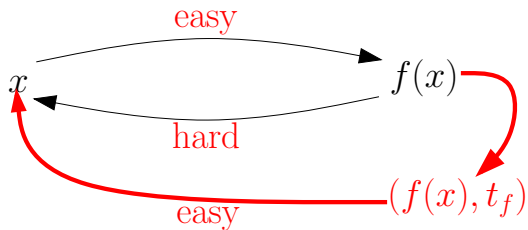
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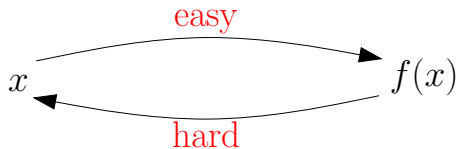
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Informal Definition.



## Definition

A function  $f$  is called **one-way**, if  $f$  is **easy** to compute but **hard** to invert.



# One-Way Function

Road Map to Formalize the Definition.

- Find proper definitions of **easy** and **hard**.
- Use computational complexity theory:
  - Classify problems according to their computational difficulty.
  - Classify problems according to needed resources (like time, storage space,...).
  - Our focus: `time complexity`.
  - Computational models: Turing machine, boolean circuits,...
- Basic definitions of complexity theory.

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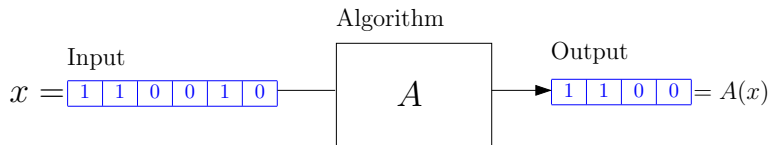
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# Complexity Theory - Basic Definitions

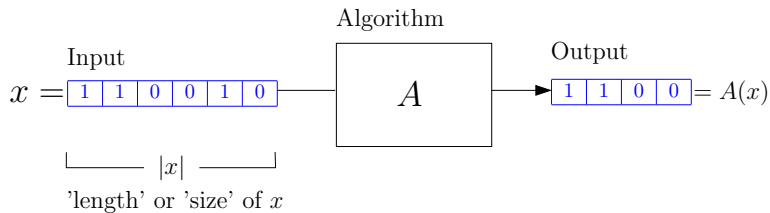
Algorithm; Running Time.





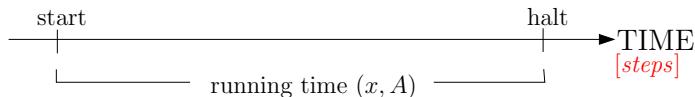
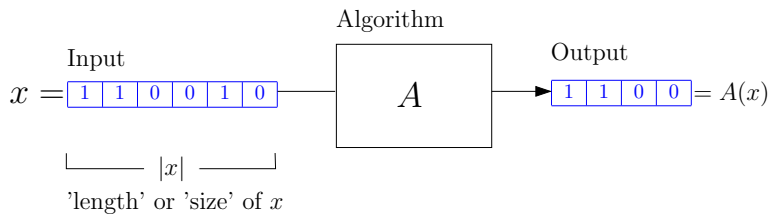
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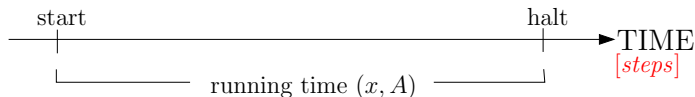
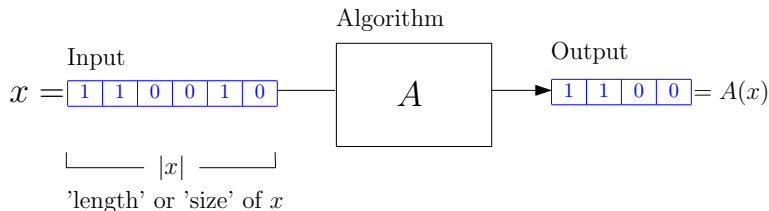
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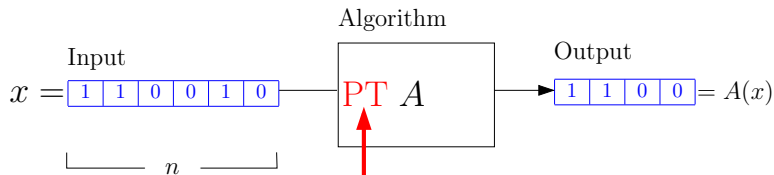
Algorithm; Running Time.



worst case running time  $(n) \geq$  running time  $(x, A) \quad \forall x : |x| \leq n$

# Complexity Theory - Basic Definitions

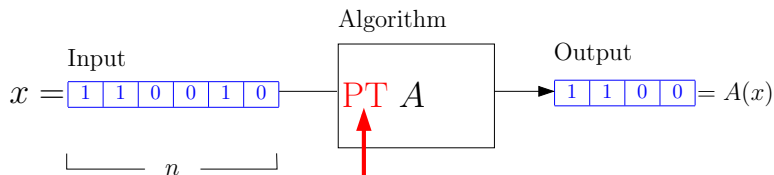
## Polynomial Time Algorithm



worst case running time  $(n) \leq \text{poly}(n) \quad \forall n$

# Complexity Theory - Basic Definitions

## Polynomial Time Algorithm



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Otherwise: Exponential time algorithm

# Complexity Theory - Basic Definitions

Polynomial Time vs. Exponential Time.

## growing of poly., sub-exp., exp. functions

$f(x)$ $x$	$n^2$	$n^3$	$\exp(\sqrt{n \ln n})$	$2^n$
10	$10^2$	$10^3$	$1.2 \cdot 10^2$	$10^3$
50	$2.5 \cdot 10^3$	$1.2 \cdot 10^5$	$10^6$	$10^{15}$
100	$10^4$	$10^6$	$2 \cdot 10^9$	$10^{30}$

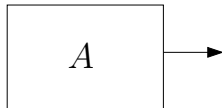
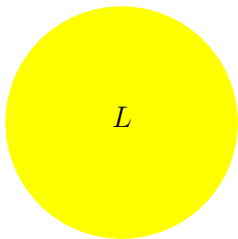
## Notes

- polynomial time algorithm  $\Leftrightarrow$  efficient
- exponential time algorithm  $\Leftrightarrow$  inefficient

# Complexity Theory - Basic Definitions

## Complexity Classes

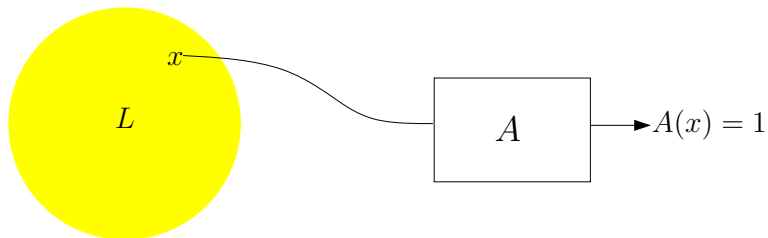
decision problem  $L$



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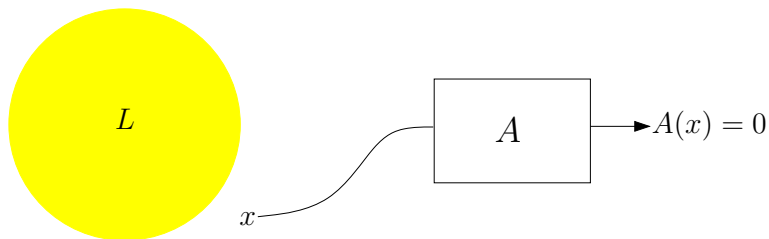




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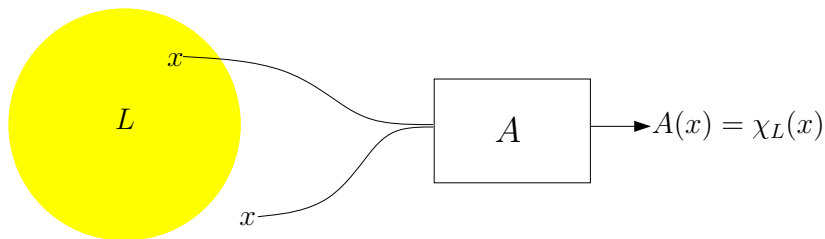
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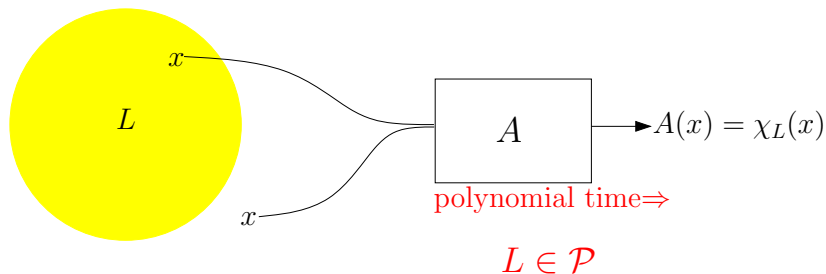
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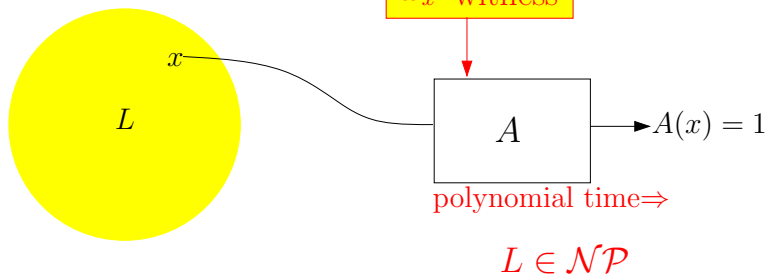
decision problem  $L$



# Complexity Theory - Basic Definitions

## Complexity Classes

decision problem  $L$



## Fact

- $\mathcal{P} \subseteq \mathcal{NP}$

## Examples

- $\text{PRIMES} \in \mathcal{P}$
- 3-Coloring-Problem: It is widely assumed that  $3\text{COL} := \{G : G \text{ is 3-colorable finite Graph}\} \notin \mathcal{P}$   
But  $\forall G \in 3\text{COL}$  exists a **PT C** that makes  $G$  3-colored  $\Rightarrow 3\text{COL} \in \mathcal{NP}$ .

### Definition (temporary)

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- $f$  is easy to compute
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### Example (FACTORING)

Let  $f_{mult}(p, q) := pq$ ,  $p, q$  primes.

Assumption:  $\text{FACTORING} \notin \mathcal{P} \Rightarrow f_{mult}$  is one-way (according to the above definition)

## Observation of $f_{mult}$

- for  $p, q \in \text{PRIMES}$  :  $|p| \approx |q|$  huge, inverting  $f_{mult}(p, q)$  is indeed hard
- But for half of the integers, finding an inverse of  $n := f_{mult}(p, q)$  is very easy:

$$f_{mult}(n/2, 2) \in f_{mult}^{-1}(n)$$

⇒ Definition has to be improved.

- Substitute: *worst-case complexity* ⇒ **average-case complexity**
- **success probability** of an inverting algorithm should be negligible

⇒ **randomized algorithms**

# Complexity Theory - Intermezzo

One-Way Function - Definition I (to be improved?)

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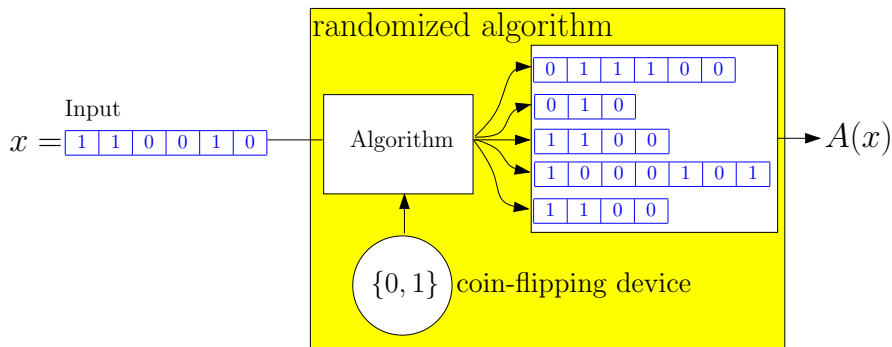
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# Complexity Theory - Basic Definitions

## Randomized Algorithm

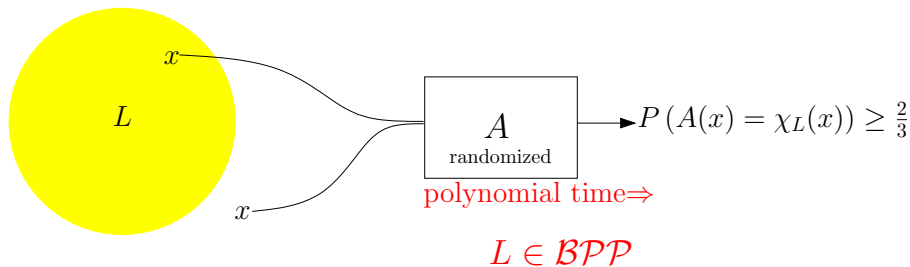


probabilistic polynomial time, if worst case running time  $(n) \leq \text{poly}(n) \forall n$

# Complexity Theory - Basic Definitions

Complexity Class  $BPP$

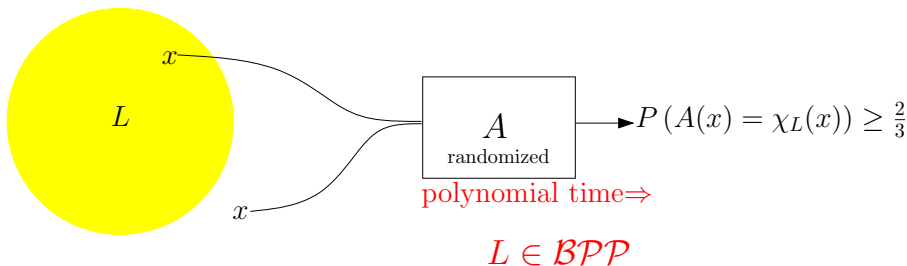
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# Complexity Theory - Basic Definitions

Complexity Class  $\mathcal{BPP}$

decision problem  $L$



## Notes

- $\mathcal{BPP}$  remains same with  $\mathbf{P}(A(x) = \chi_L(x)) \geq \frac{1}{2} + \frac{1}{p(|x|)}$ ,  $p$  polynomial instead.
- $\mathcal{BPP} \Leftrightarrow$  'efficiently' computable.



# One-Way Function

Definition.

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A function  $f : \{0, 1\}^* \rightarrow \{0, 1\}^*$  is called **one-way** if the following two conditions hold

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for all polynomials  $p$  and sufficiently large integers  $n$

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## Notes

- Adversary is not unable to invert  $f$ , but has low probability to do so.

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- Adversary is not unable to invert  $f$ , but has low probability to do so.
- Definition works with asymptotic complexity: A sufficiently large *security parameter*  $n$  makes inversion infeasible.
- If  $f$  is 1 – 1 then  $f^{-1}(f(x)) = x$ .

# One-Way Function

Length Preserving One-way Functions.

## Definition

A function  $f : \{0, 1\}^* \rightarrow \{0, 1\}^*$  is called **length preserving** if

$$\forall x \in \{0, 1\}^* : |f(x)| = |x|$$

A permutation is a length-preserving function  $f$  which is 1-1.

## Lemma (Length-preserving)

*If there exists a one-way function, then we can construct a **length-preserving one-way** function  $f$ :*

$$\forall x \in \{0, 1\}^* : |f(x)| = |x|$$

*Proof by reducibility arguments.*

# One-Way Function - In Search of Examples

Factoring.

## FACTORING-problem

FACTORING

Instance: positive integer  $n$

Question: Find the prime factorization  $n = \prod_i p_i^{e_i}$

## Algorithms

- NUMBER FIELD SIEVE (1990)  
sub-exponential expected running time  $\exp(1.9(\log n)^{1/3}(\log \log n)^{2/3})$
- Special-purpose algorithms, like POLLARD'S  $p - 1$

# Candidates Based on Factoring.

A One-Way Function by Rivest, Shamir, Adleman

## RSA function

$\text{RSA}_{n,e}$  where  $n = pq$ ,  $|p| = |q|$  primes,  $\text{gcd}(e, \varphi(n)) = 1$

input:  $x$  positive integer

output:  $\text{RSA}_{n,e}(x) := x^e \pmod n$

- $\text{RSA}_{n,e}$  assumed to be one-way

## Fact (FACTORING vs. INVERTING-RSA)

If  $n$  can be factored by a **PPT**  $\Rightarrow$   $\text{RSA}_{n,e}$  can be inverted by a **PPT**

**INVERTING-RSA**  $\leq_P$  **FACTORING**

## Open Problem -FACTORING vs. INVERTING-RSA

Are **FACTORING** and **INVERTING-RSA** computationally equivalent?

# Candidates Based on Factoring.

The SQUARE-Function by Rabin

## Rabin's SQUARE function

$\text{SQUARE}_n$  where  $n = pq$ ,  $p, q$  primes and  $|p| = |q|$

input:  $x \in \mathbb{Z}_n^*$

output:  $\text{SQUARE}_n(x) := x^2 \pmod n$

- $\text{SQUARE}_n$  is not 1-1
- But  $\text{SQUARE}_n$  restricted to  $Q_n$  is a permutation, if  
 $n \in \{pq : p, q \text{ distinct odd primes, } |p| = |q|, p \equiv q \equiv 3 \pmod 4\}$   
 $Q_n := \{x : x \in \mathbb{Z}_p^*, \exists y \in \mathbb{Z} : y^2 \equiv x \pmod n\}$  quadratic-residues

## Fact (FACTORING vs. INVERTING-SQUARE)

*FACTORING( $n$ ) and INVERTING-SQUARE $_n$  are computationally equivalent!*

# One-Way Function - In Search of Examples

DLP The Discrete Logarithm Problem

## DLP - discrete logarithm problem

DLP

Instance: a finite cyclic Group  $G$  of order  $n$   
a generator  $\alpha$  of  $G$   
an element  $\beta \in G$

Question: Find the integer  $x, 0 \leq x \leq n - 1$  :  
 $\alpha^x = \beta$

- Given the prime factorization  $n = \prod_i p_i^{e_i}$  the DLP in  $G$  can be reduced to **DLP's** in the groups  $\mathbb{Z}_{p_i}^*$

## Algorithms

- Best randomized algorithms in sub-exponential running time.

# Candidates Based on DLP.

The EXP Function

## EXP function

$\text{EXP}_{p,\alpha}$  where  $p$  prime and  $\alpha$  generator of  $\mathbb{Z}_p^*$

input:  $x \in \mathbb{Z}_p^*$

output:  $\text{EXP}_{p,\alpha}(x) := \alpha^x \pmod p$

- EXP is one-way, *assuming* DLP is hard

# One-Way Function

## Necessary Assumptions

### Assumptions for concrete candidates:

FACTORING efficiently computable  $\Rightarrow$  RSA not one-way

FACTORING efficiently computable  $\Leftrightarrow$  SQUARING not one-way

DLP efficiently computable  $\Leftrightarrow$  EXP not one-way

### Traditional assumption. *hard to break in worst case*

$f$  computable by **PT**  $\Rightarrow$  inverse under  $f$  computable by *non-det.* **PT**:

$\hookrightarrow \mathcal{P} = \mathcal{NP} \Rightarrow$  One-Way Function not exist.

### Intractability assumption. *hard to break in average*

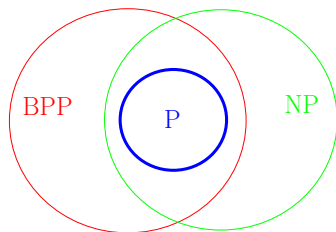
We assume the adversary uses a **PPT**

$\hookrightarrow \mathcal{NP} \subseteq \mathcal{BPP} \Rightarrow$  One-Way Function not exist. ( $\mathcal{NP} \not\subseteq \mathcal{BPP} \Rightarrow \mathcal{P} \neq \mathcal{NP}$ )



# One-Way Function

Existence of One-Way Function cannot be proved yet.



## Problem

- Traditional assumption and Intractability assumption are **only necessary** but not sufficient conditions.
- Existence of **One-Way Functions not provable** yet.
- Implementation based on reasonable 'intractability assumptions', like FACTORING, DLP.



# Collection Of One-Way Functions

Motivation

One-way function - up to now...

$$f : \{0, 1\}^* \rightarrow \{0, 1\}^*$$

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infinite domain

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$$f : \{0, 1\}^* \rightarrow \{0, 1\}^*$$

infinite domain

- Suitable for abstract discussion
- ..but not for natural candidates:

$$EXP_{p,\alpha} : \{1, \dots, p-2\} \rightarrow \{0, 1\}^*$$

finite domain

## A larger View: Collection

$$f_i : D_i \rightarrow \{0, 1\}^*$$



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- The  $f_i$  sharing a common **Domain Sampler  $S_D$**

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Security parameter

$$n \in \mathbb{N}$$

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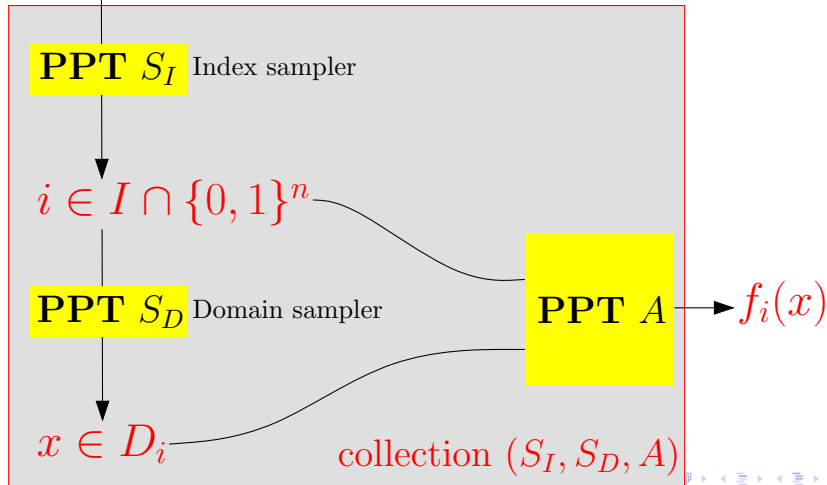
$$f_i(x)$$

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# Collection Of One Way Functions

Definition.

## Definition

Let  $I$  be a set of indices and  $D_i \subset \{0, 1\}^*$  **finite**  $\forall i \in I$ .

A collection of one-way functions is a set

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satisfying the following two conditions

1 There exists tree **PPT**  $\mathbf{S}_I$ ,  $\mathbf{S}_D$ ,  $\mathbf{A}$ , such that

$\mathbf{S}_I$  on input  $1^n$  outputs an  $i \in \{0, 1\}^n \cap I$

$\mathbf{S}_D$  on input  $i \in I$  outputs an  $x \in D_i$

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- 2 The probability of finding an inverse for every **PPT** given  $i$  and an element in range is negligible, if we consider the distribution induced by  $\mathbf{S}_I$ ,  $\mathbf{S}_D$ .

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For every **PPT**  $\mathbf{A}'$ , every polynomial  $p(\cdot)$  and sufficiently large  $n$ :

$$\mathbf{P}(\mathbf{A}'(f_{I_n}(X_n), I_n) \in f_{I_n}^{-1}(f_{I_n}(X_n))) < \frac{1}{p(n)}$$

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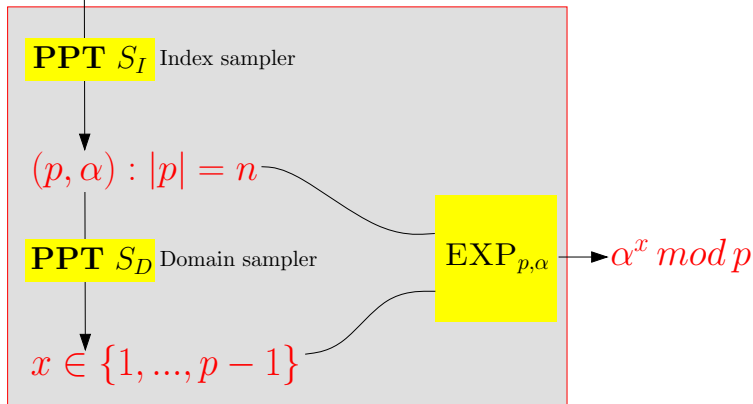
$I_n, X_n$  random variable describing output distribution of  $\mathbf{S}_I, \mathbf{S}_D$

# Collection Of One-Way Functions

$$EXP := \{EXP_{p,\alpha} : \mathbb{Z}_{p-1} \rightarrow \{0, 1\}^*\}$$

Security parameter

$$n \in \mathbb{N}$$



# Collection Of Trapdoor Functions

Security parameter

$$n \in \mathbb{N}$$

**PPT**  $S_I$  Index sampler

$$i \in I \cap \{0, 1\}^n$$

**PPT**  $S_D$  Domain sampler

$$x \in D_i$$

**PPT**  $A$

$$f_i(x)$$

collection  $(S_I, S_D, A)$



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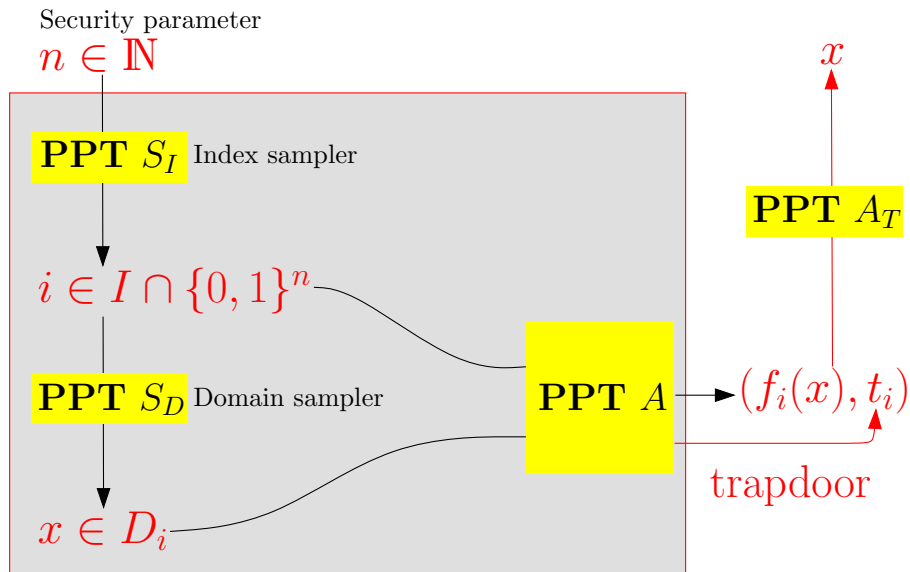
**PPT**  $A$

$$(f_i(x), t_i)$$

trapdoor

collection  $(S_I, S_D, A)$

# Collection Of Trapdoor Functions





# Hard-Core Predicate - Motivation

Bit-Security of EXP

How secure is *EXP*?

$x$   $\longrightarrow$   $\text{EXP}_{p,\alpha}(x)$

1	1	0	0	1	0
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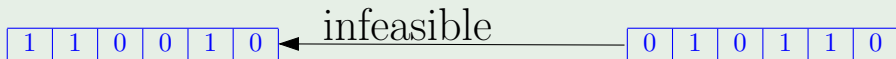
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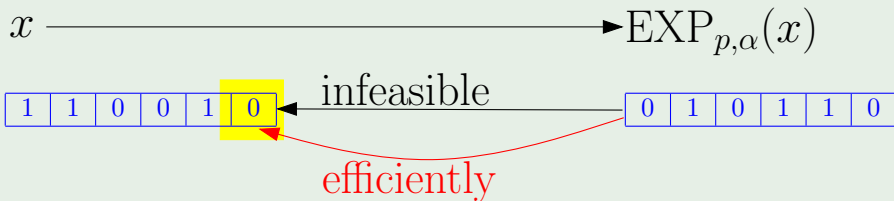
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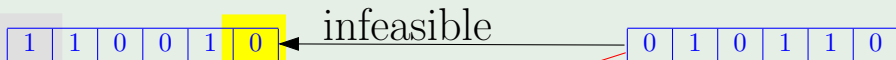


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efficiently

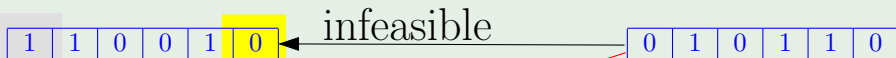
as hard as inverting

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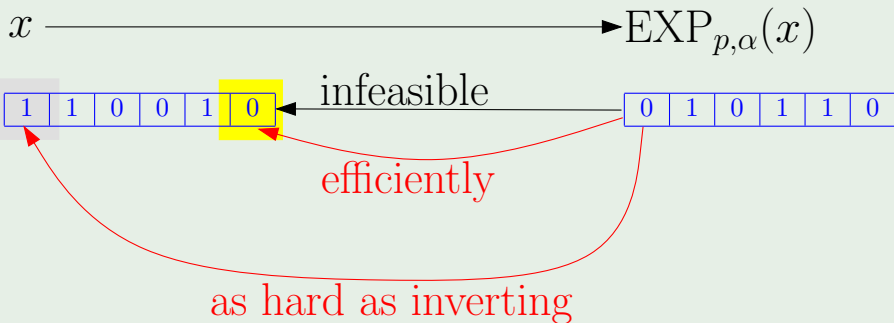
- A one-way function doesn't hide partial information



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## How secure is $EXP$ ?



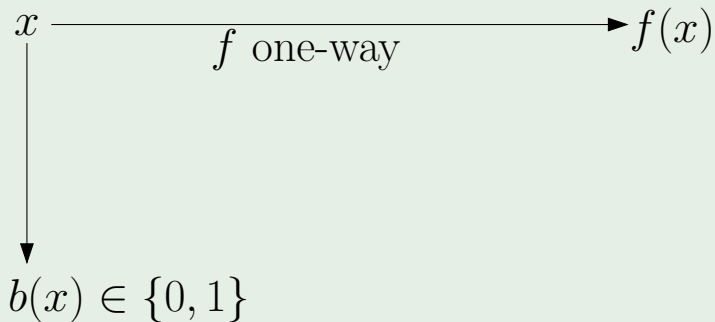
- A one-way function doesn't hide partial information
- But at least one Bit of information is hard to guess

## Idea of hard-core predicate.



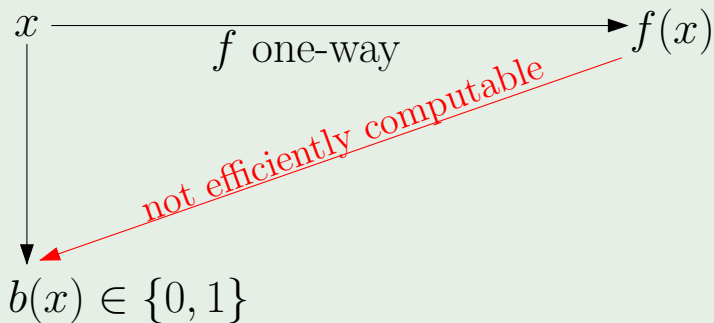
# Hard-Core Predicate - Definition

## Idea of hard-core predicate.



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## Idea of hard-core predicate.



$b(x) \in \{0, 1\}$  hard-core predicate of  $f$

# Hard-Core Predicate

Definition.

## Instance

- a function  $f : \{0, 1\}^* \rightarrow \{0, 1\}^*$
- a predicate  $b : \{0, 1\}^* \rightarrow \{0, 1\}$

## Definition

$b$  is a **hard-core predicate** of  $f$ , iff

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$b$  is a **hard-core predicate** of  $f$ , iff

- $\exists$  PPT  $A$ , such that  $\forall x : A(x) = b(x)$
- Every efficient algorithm given  $f(x)$  can guess  $b(x)$  only with success **probability negligible better than  $\frac{1}{2}$**

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- $\exists$  PPT  $\mathbf{A}$ , such that  $\forall x : \mathbf{A}(x) = b(x)$
- $\forall$  PPT  $\mathbf{G}$ ,  $\forall p$  polynomial and sufficiently large  $n$ :

$$\mathbf{P}(G(f(U_n)) = b(U_n)) < \frac{1}{2} + \frac{1}{p(n)}$$



# A Generic Hard-Core Predicate

A Hard-Core Predicate for 'any' One-Way Function.

## Instance

- $f : \{0, 1\}^* \rightarrow \{0, 1\}^*$  length preserving
- $g(x, r) := (f(x), r)$ , where  $|x| = |r|$
- $b(x, r) := \langle x, r \rangle_{\text{mod}2} := \sum_i (x_i r_i \text{ mod } 2)$

## Theorem

Let  $f$  be a length-preserving one-way function, and let  $g, b$  defined like above. Then  $b$  is a **hard-core predicate** of the function  $g$ .

## Notes

It means: it is infeasible to guess the exclusive-or of a random subset of the bits of  $x$ , when given  $f(x)$  and the subset itself, denoted by  $r$ .

$$x = \begin{array}{|c|c|c|c|c|c|} \hline 1 & 1 & 0 & 0 & 1 & 0 \\ \hline \end{array}$$

$f$

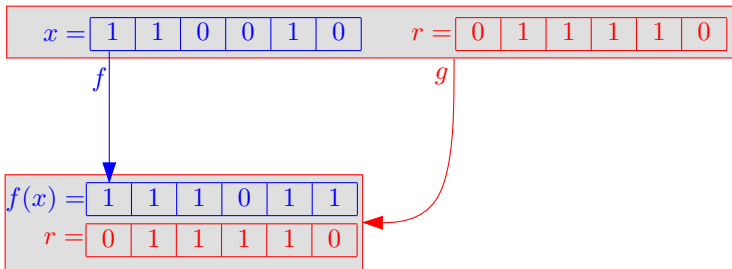
$$f(x) = \begin{array}{|c|c|c|c|c|c|} \hline 1 & 1 & 1 & 0 & 1 & 1 \\ \hline \end{array}$$

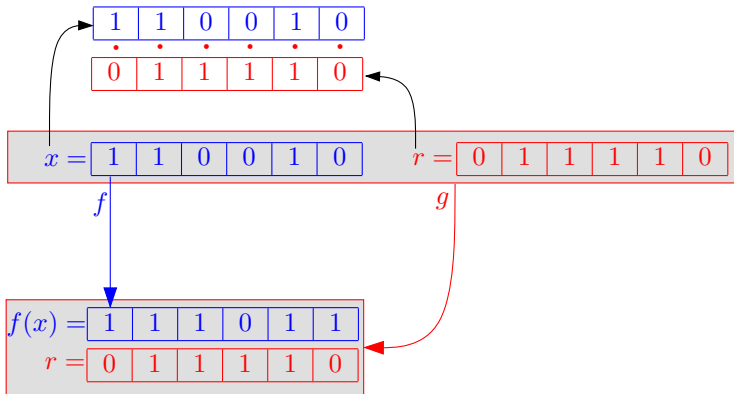
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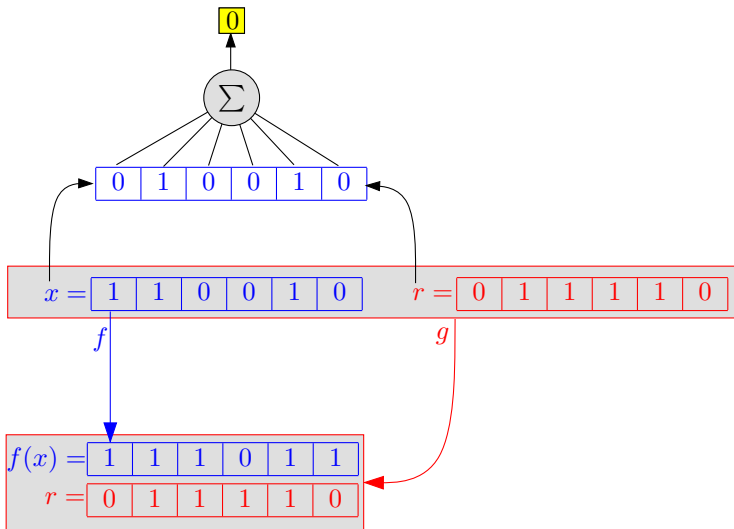
$f$

$$f(x) = \begin{array}{|c|c|c|c|c|c|} \hline 1 & 1 & 1 & 0 & 1 & 1 \\ \hline \end{array}$$

$$r = \begin{array}{|c|c|c|c|c|c|} \hline 0 & 1 & 1 & 1 & 1 & 0 \\ \hline \end{array}$$







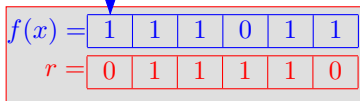
$$b(x, r) = \boxed{0}$$

$b$



$f$

$g$



$$b(x, r) = \boxed{0}$$

'unpredictable'  
by PPT  
 $G(f(x), r)$

$$x = \boxed{1} \boxed{1} \boxed{0} \boxed{0} \boxed{1} \boxed{0}$$

$f$

$$f(x) = \boxed{1} \boxed{1} \boxed{1} \boxed{0} \boxed{1} \boxed{1}$$
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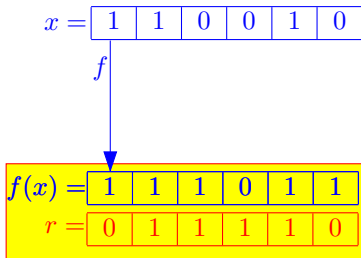


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If we can predict  $b$  with  
non-negligible probability...

by PPT

$$G(f(x), r)$$

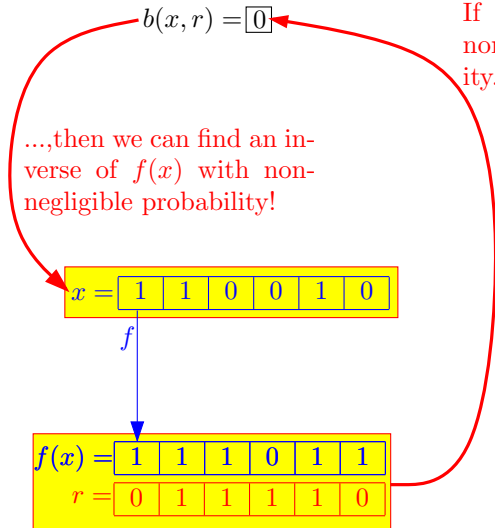


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..., then we can find an inverse of  $f(x)$  with non-negligible probability!

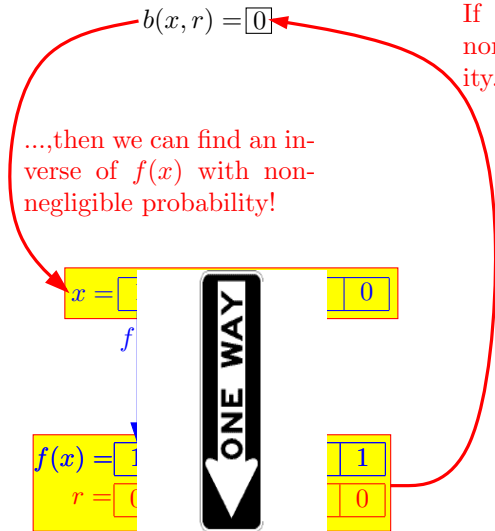


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# A Generic Hard-Core Predicate - Proof

Sketch.

## Proof sketch.

We use a 'reducibility argument' and proof by contradiction:

- 1 Suppose:  $b$  is not hard-core predicate of  $g$   
Then there exists an *efficient* algorithm  $\mathbf{G}$ , that can guess  $b$  with non-negligible probability better  $\frac{1}{2}$ :

$\Rightarrow \exists \mathbf{PPT} \mathbf{G}, \exists p$  polynomial:

$$\varepsilon(n) := \mathbf{P}(\mathbf{G}(f(X_n, R_n)) = b(X_n, R_n)) - \frac{1}{2} > \frac{1}{p(n)}$$

- 2 Construct an *efficient* algorithm  $\mathbf{A}$  (using  $\mathbf{G}$ ), which inverts  $f$  on input  $(f(x), r)$  with non-negligible probability
- 3 Conclude:  
 $\exists \mathbf{G} \Rightarrow \exists \mathbf{A} \Rightarrow f$  not one-way  
 $\Rightarrow$  **contradiction** to  $f$  one-way.



# Proof - Inverting Algorithm A

Idea I - a mental experiment

## Important Observation

$$b(x, \alpha) \oplus b(x, \beta) = b(x, \alpha \oplus \beta)$$

$$x_i = b(x, \alpha) \oplus b(x, \alpha \oplus e_i)$$

## Mental Experiment

Suppose: Guessing by **G** works very good for a subset  $S_n \subseteq \{0, 1\}^n$ :

- $\mathbf{P}(\mathbf{G} \text{ correct guess}) = \mathbf{P}(\mathbf{G}(f(x), r) = b(x, r)) > \frac{3}{4} + \frac{1}{2p(n)}$
- for all inputs  $f(x)$  with  $x \in S_n$
- for all sufficiently large  $n \in \mathbb{N}$

Algorithm **A** (guessing the  $i^{\text{th}}$  bit of the inverse):

- 1 Randomly select  $r \in \{0, 1\}^n$
- 2 Compute  $z_i := \mathbf{G}(f(x), r) \oplus \mathbf{G}(f(x), r \oplus e_i)$

Success probability:  $\mathbf{P}(\mathbf{A}(f(x)) \in f^{-1}(f(x))) > \frac{1}{2} + \frac{3}{4p(n)}$

↪ Repetition and rule by majority ⇒ efficiently computes  $x_i$

# Proof - Inverting Algorithm A

Idea II - Use **G** and Make Own Guess

Notice:  $b(x, \alpha) \oplus b(x, \alpha \oplus e_i) = x_i \quad \forall x, \alpha, i$

Idea to construct **A** inverting  $f(x)$  for all  $x \in S_n$

- Select a special subset  $S_n$ , where **G** works sufficiently successful.
- Use **G** to guess  $b(x, r \oplus e_i)$
- Make own guess  $\rho$  for  $b(x, r)$
- Both guess correct:  $x_i = \rho \oplus \mathbf{G}(f(x), r \oplus e_i)$

Claim I ( $S_n$ , where **G** guesses sufficiently good)

If  $b$  not hard-core,  $n$  sufficiently large, then there exists a subset  $S_n \subseteq \{0, 1\}^n$ , such that

- 'Large enough':  $|S_n| \geq \frac{\varepsilon(n)}{2} 2^n$
- 'Successful enough':  $\forall x \in S_n : \pi(x) := \mathbf{P}(\mathbf{G}(x, R_n) = b(x, R_n)) \geq \frac{1}{2} + \frac{\varepsilon(n)}{2}$

# Proof - Inverting Algorithm A

Idea II -  $\rho_J$  our own guess

## Our guess

- Randomly select  $k$  strings  $s_1, \dots, s_k \in \{0, 1\}^n$  and  $k$  predicates  $\sigma_1, \dots, \sigma_k \in \{0, 1\}$  (by Laplace-Experiment)
- for every (non empty) index-subset  $J \subseteq \{1, \dots, k\}$ :

$$r_J := \bigoplus_{j \in J} s_j$$

$$\Rightarrow b(x, r_J) = b(x, \bigoplus_{j \in J} s_j) = \bigoplus_{j \in J} b(x, s_j)$$

$$\Rightarrow \rho_J := \bigoplus_{j \in J} \sigma_j \text{ our guess of } b(x, r_J)$$

- Probability that  $\rho_J = b(x, r_J)$  for all subsets  $J \in \{1, \dots, k\}$  is  $2^{-k}$

# Proof - Inverting Algorithm A

## The Algorithm

### Algorithm (guesses $i^{\text{th}}$ bit)

Let **A** be the following **PPT** algorithm:

- 1 Set  $k := \lceil \log_2(2n \cdot p(n)^2 + 1) \rceil$
- 2 Uniformly and Independent select  $s_1, \dots, s_k \in \{0, 1\}^n, \sigma_1, \dots, \sigma_k \in \{0, 1\}$
- 3  $\forall J \subseteq \{1, \dots, k\}, J$  non-empty compute:
  - $r_J \leftarrow \bigoplus_{j \in J} s_j$
  - $\rho_J \leftarrow \bigoplus_{j \in J} \sigma_j$
  - $z_J \leftarrow \rho_J \oplus \mathbf{G}(f(x), r_J \oplus e_i)$
- 4 Output  $z$  the majority value of the  $z_J$



# Proof - Inverting Algorithm A

Observing Events.

$$\begin{array}{ll} r_J \leftarrow \bigoplus_{j \in J} s_j & s_j \in \{0, 1\}^n \text{ randomly chosen} \\ \rho_J \leftarrow \bigoplus_{j \in J} \sigma_j & \sigma_j \in \{0, 1\} \text{ randomly chosen} \\ z_J \leftarrow \rho_J \oplus \mathbf{G}(f(x), r_J \oplus e_i) & \text{compare: } x_i = b(x, r_J) \oplus b(x, r_J \oplus e_i) \end{array}$$

## Events of interest

- Event  $\mathcal{E}$ :  $\mathbf{G}$  guessing correct for majority of subsets  $J \subseteq \{1, \dots, k\}$ :  
 $\mathcal{E}: |\{J : \mathbf{G}(f(x), r_J \oplus e_i) = b(x, r_J \oplus e_i)\}| > \frac{1}{2}(2^k - 1)$
- Event  $\mathcal{F}$ : our guess correct for all subsets:  
 $\mathcal{F}: \rho_J = b(x, r_J) \quad \forall J \subseteq \{1, \dots, k\}$

## Probabilities

- Event  $\mathcal{E}$ :  
 $\mathbf{P}(\mathcal{E} | x \in S_n) > \frac{1}{2}$  (*this we have to prove!*)
- Event  $\mathcal{F}$ :  
 $\mathbf{P}(\mathcal{F} | x \in S_n) = \mathbf{P}(\forall J : \sigma_J = b(x, s_J) | x \in S_n) = 2^{-k}$  (Bernoulli)

# Proof - Inverting Algorithm A

Success Probability

$$z_J \leftarrow \rho_J \oplus \mathbf{G}(f(x), r_J \oplus e_i)$$

$$\mathbf{P}(\mathcal{E} | x \in S_n) > \frac{1}{2}$$

$$\mathbf{P}(\mathcal{F} | x \in S_n) = 2^{-k}$$

$$|S_n| > \frac{\epsilon}{2} \cdot 2^n \geq \frac{1}{2p(n)} 2^n$$

$\mathcal{E}$ :  $\mathbf{G}$  correct for the majority of all  $J$ 's

$\mathcal{F}$ :  $\rho_J$  correct for all  $J$ 's

$$k := \lceil \log_2(2n \cdot p(n)^2 + 1) \rceil$$

## Success Probability of Algorithm

$$\begin{aligned} & \mathbf{P}(\mathbf{A}(f(x)) \text{ outputs } i^{\text{th}} \text{ bit of an inverse of } f(x)) \\ &= \mathbf{P}(\text{For majority of all } J\text{'s: } z_J = x_i) = \mathbf{P}(\mathcal{E} \wedge \mathcal{F} | x \in S_n) \\ &= \mathbf{P}(\mathcal{E}) \cdot \mathbf{P}(\mathcal{F}) \cdot \mathbf{P}(x \in S_n) \text{ (Independence to be proved!)} \\ &> \frac{1}{2} \cdot 2^{-k} \cdot \frac{|S_n|}{2^n} = \frac{1}{8np(n)^3 + p(n)} = \frac{1}{\text{poly}(n)} \text{ not negligible!!!} \end{aligned}$$

↪ By repeating for all bits: we can efficiently compute  $x$ .

↪ **Contradiction to 'f is one-way' ⇒ b is hard-core Predicate**

## Claim I: There existst $S_n$ , where $\mathbf{G}$ guesses sufficiently good

If  $b$  not hard-core,  $n$  sufficiently large, then there exists a subset  $S_n \subseteq \{0, 1\}^n$ , such that

- 'Large enough':  $|S_n| \geq \frac{\varepsilon(n)}{2} 2^n$
- 'Succesful enough':  $\forall x \in S_n : \pi(x) := \mathbf{P}(\mathbf{G}(x, R_n) = b(x, R_n)) \geq \frac{1}{2} + \frac{\varepsilon(n)}{2}$

## Claim II: $\mathbf{P}(\mathcal{E} | x \in S_n) > \frac{1}{2}$

For every  $x \in S_n$ :

$$\mathbf{P}(|\{J : \mathbf{G}(f(x), r_J \oplus e_i) = b(x, r_J \oplus e_i)\}| > \frac{1}{2}(2^k - 1)) > 1 - \frac{1}{2p(n)}$$

# one-way functions are important primitives.

## Formalizing and abstracting

The concept of one-way functions abstracts the central idea of many common cryptosystems:

- RSA
- RABIN-SQUARE
- ELGAMAL

## As a basis

The introduced concept is a basis for more applicable theories:

- public key cryptosystems
- pseudorandom sequences
- hash functions
- ...

- **Basic definitions of computational complexity theory**
- Formalized the definition of one-way function
- Discussed necessary conditions, like 'intractability assumption'
- Introduced the concept of one-way collections and trapdoor-collection
- Defined the hard-core predicate
- Proved the existence of a generic hard-core predicate

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