

# Codes and Cryptography

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## PART IX

## The Setting (I)

**Perfect environment:** No storage or communication errors or excessive message delivery delays

**Users:** divided into

- good guys (honest)
- bad guys (corrupted by an adversary)

Alternative model: Rational Cryptography (from Game Theory).  
Only selfish guys (not necessarily honest, can collude).

Simplest case: One honest user, one bad user.  
E.g.: Secure binary data storage.

## Outline

- 1 Cryptography: The setting
- 2 Symmetric Encryption (I)

## The Setting (II)

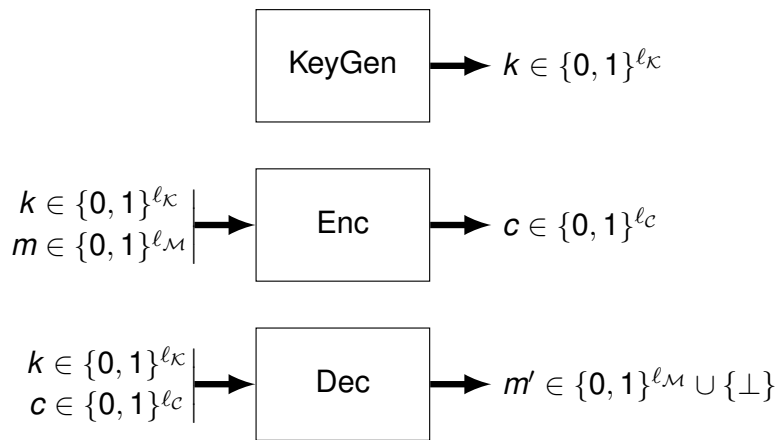
Adversarial behavior:

- **static:** corrupted users are fixed before starting the actual attack
- **dynamic:** corrupted users are decided on-the-fly
  
- **passive:** corrupted users only try to learn more than they are allowed to
- **active:** corrupted users deviate from the protocols in unpredictable ways
  
- **bounded:** the adversary has limited resources (computational power, memory)
- **unbounded:** the adversary has unlimited resources

# Outline

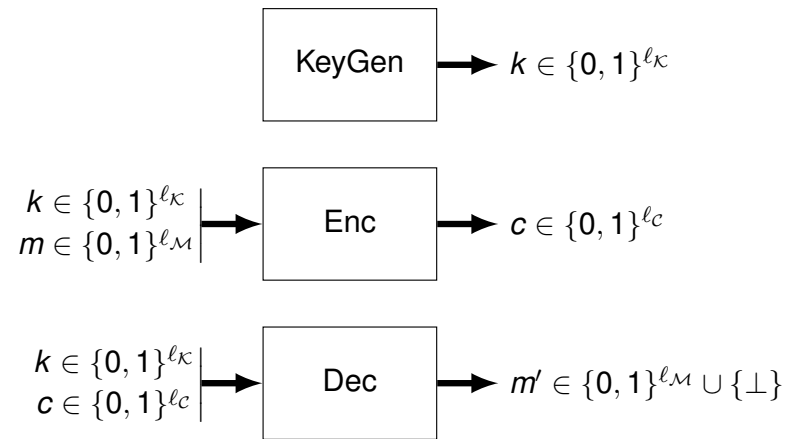
- 1 Cryptography: The setting
- 2 Symmetric Encryption (I)

# Symmetric Encryption: Correctness



$$\forall m \in \{0, 1\}^{l_M}, \forall k \in \{0, 1\}^{l_K}, \quad m = \text{Dec}(k, \text{Enc}(k, m))$$

# Symmetric Encryption: Syntax



# Symmetric Encryption: Privacy

Informal definition:  
“Impossible to find  $m$  from  $c$  without  $k$ ”

More formally:

For any fixed  $c \in \{0, 1\}^{l_C}$ , and for uniformly distributed  $k \in \{0, 1\}^{l_K}$ ,  $\Pr[c = \text{Enc}(k, m)]$  is the same for all  $m \in \{0, 1\}^{l_M}$ .

or:

### Definition (Perfect Privacy)

For any probability distribution (source) of  $M \in \{0, 1\}^{l_M}$  and for a uniformly distributed  $K \in \{0, 1\}^{l_K}$ , **the random variables  $M$  and  $\text{Enc}(K, M)$  are independent.**

## Bounds for Perfect Symmetric Encryption

### Theorem

For any correct and perfectly private symmetric encryption scheme  $\ell_C \geq \ell_M$  and  $\ell_K \geq \ell_M$

Proof: (A simple combinatorial argument)

[▶ details...](#)

**Caveat: We assume that all elements in  $\{0, 1\}^{\ell_M}$  are possible messages** (e.g., consider compression codes for redundant sources)

**No perfect solution for binary private storage!**

**The key can only be used once!**

## A Generalization for Redundant Sources

Replace the sets  $\{0, 1\}^{\ell_M}$ ,  $\{0, 1\}^{\ell_K}$ ,  $\{0, 1\}^{\ell_C}$  by probability distributions  $M$ ,  $K$ ,  $C$  on some finite sets  $\mathcal{M}$ ,  $\mathcal{K}$ ,  $\mathcal{C}$ .

Replace binary length by a measure of the average information given by a random variable (Shannon's entropy)

### Definition (Perfect Privacy)

For any probability distribution (source) of  $M \in \{0, 1\}^{\ell_M}$  and for a uniformly distributed  $K \in \{0, 1\}^{\ell_K}$ , **the random variables  $M$  and  $\text{Enc}(K, M)$  are independent.**

### Theorem (Shannon)

For any correct and perfectly private symmetric encryption scheme  $H(C) \geq H(M)$  and  $H(K) \geq H(M)$

## Bounds for Perfect Symmetric Encryption: Details

Plot of Enc function:

$$G = \{(m, k, c = \text{Enc}(k, m))\}_{m \in \{0, 1\}^{\ell_M}, k \in \{0, 1\}^{\ell_K}}$$

Correctness implies

$$(m, k, c), (m', k, c) \in G \Rightarrow m' = m$$

Then fixing  $k$ , we obtain  $\ell_C \geq \ell_M$

In addition, Perfect Privacy implies

$$(m, k, c) \in G \Rightarrow \forall m' \exists k' (m', k', c) \in G$$

Then fixing  $c$ , we obtain  $\ell_K \geq \ell_M$

[◀ go back...](#)

## Shannon's Entropy of a Discrete Random Variable (I)

It is a measure of the average amount of information in a random variable.

### Definition (Shannon's Entropy)

Let  $X$  be a random variable with range a finite set  $\mathcal{X}$ .

$$H(X) = - \sum_{x \in \mathcal{X}} \Pr[X = x] \log_2 \Pr[X = x]$$

Main properties:

- For any joint distribution  $(X, Y, Z)$   
 $H(X, Y, Z) + H(Z) \leq H(X, Z) + H(Y, Z)$
- For a trivial (deterministic) random variable  $H(0) = 0$
- For a uniform distribution  $H(U_{\mathcal{X}}) = \log_2 |\mathcal{X}|$

[▶ details...](#)

## Shannon's Entropy Main Inequality (Submodularity)

The map  $t \mapsto t \log_2 t$  is convex in  $[0, +\infty)$

By discrete Jensen's inequality for convex functions, for positive numbers  $a_i, t_i, i \in \mathcal{I}$

$$\sum_{i \in \mathcal{I}} a_i t_i = 1 \quad \Rightarrow \quad \sum_{i \in \mathcal{I}} a_i t_i \log_2 t_i \geq -\log_2 \sum_{i \in \mathcal{I}} a_i$$

Then use

$$t_{x,y,z} = \frac{\Pr[X = x, Y = y, Z = z] \Pr[Z = z]}{\Pr[X = x, Z = z] \Pr[Y = y, Z = z]}$$

$$a_{x,y,z} = \frac{\Pr[X = x, Z = z] \Pr[Y = y, Z = z]}{\Pr[Z = z]}$$

◀ go back ...

## Proof of Shannon's Theorem

Assume that  $C = \text{Enc}(K, M)$ , and  $K$  and  $M$  are independent

Correctness implies

$$H(M, K, C) = H(\text{Dec}(K, C), K, C) = H(K, C) \leq H(K) + H(C)$$

Perfect Privacy implies

$$H(M, C) = H(M) + H(C)$$

Therefore,

$$H(K) + H(C) \geq H(M, K, C) \geq H(M, C) = H(M) + H(C) \quad \Rightarrow$$

$$H(K) \geq H(M)$$

Moreover,

$$H(K) + H(M) = H(K, M) = H(K, \text{Dec}(K, C)) \leq H(K, C) \leq$$

$$H(K) + H(C) \quad \Rightarrow \quad H(M) \leq H(C)$$

## Shannon's Entropy of a Discrete Random Variable (II)

Other properties:

- $0 \leq H(X) \leq \log_2 |\mathcal{X}|$  (with r.h.s. equality for the uniform distribution)
- $H(X) \leq H(X, Y) \leq H(X) + H(Y)$  (with r.h.s. equality for independent variables)
- $H(g(X)) \leq H(X)$  (with equality for injective maps)
- $H(X, g(X)) = H(X)$

## The One-Time Pad

For fixed length binary strings,  $\ell_M = \ell_K = \ell_C = \ell$ , and  $\text{Enc}(k, m) = k \oplus m$  and  $\text{Dec}(k, c) = k \oplus c$

For an abelian (additive) group  $\mathcal{G}$ , let  $\mathcal{M} = \mathcal{K} = \mathcal{C} = \mathcal{G}$ , and  $\text{Enc}(k, m) = m + k$  and  $\text{Dec}(k, c) = c - k$

Perfect secrecy is guaranteed if  $k$  is uniformly distributed in  $\mathcal{G}$

Normally used as an "information theoretical" piece in other protocols

## Weakening Secrecy

To overcome the previous limitations, consider only **computationally bounded adversaries**

### Definition (Perfect Privacy)

For any probability distribution (source) of  $M \in \{0, 1\}^{\ell_M}$  and for a uniformly distributed  $K \in \{0, 1\}^{\ell_K}$ , **the random variables  $M$  and  $\text{Enc}(K, M)$  are independent.**

### Definition (Informal Computational Privacy)

For any probability distribution (source) of  $M \in \{0, 1\}^{\ell_M}$  and for a uniformly distributed  $K \in \{0, 1\}^{\ell_K}$ , **the random variables  $M$  and  $\text{Enc}(K, M)$  behave as if they were independent for a bounded adversary.**

## Codes and Cryptography

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**END OF PART IX**

## Weakening Secrecy

### Definition (Informal Computational Privacy)

For any probability distribution (source) of  $M \in \{0, 1\}^{\ell_M}$  and for a uniformly distributed  $K \in \{0, 1\}^{\ell_K}$ , **the random variables  $M$  and  $\text{Enc}(K, M)$  behave as if they were independent for a bounded adversary.**

Based on efficient statistical tests a computationally bounded adversary can run

Needs some extra assumptions from Complexity Theory  
(similarly as working with the Riemann Hypothesis)