Quantitative Security of Block Ciphers: Designs and Cryptanalysis Tools

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PhD Defense
November 14, 2008

Prologue

Cryptography: the Basics

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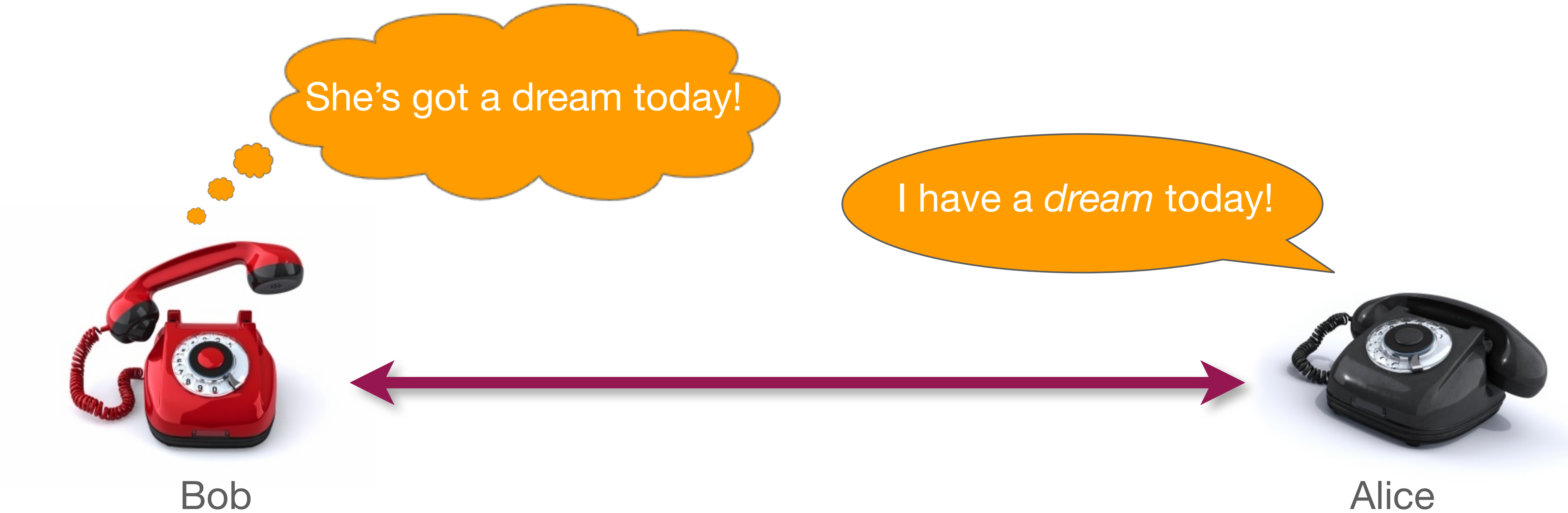

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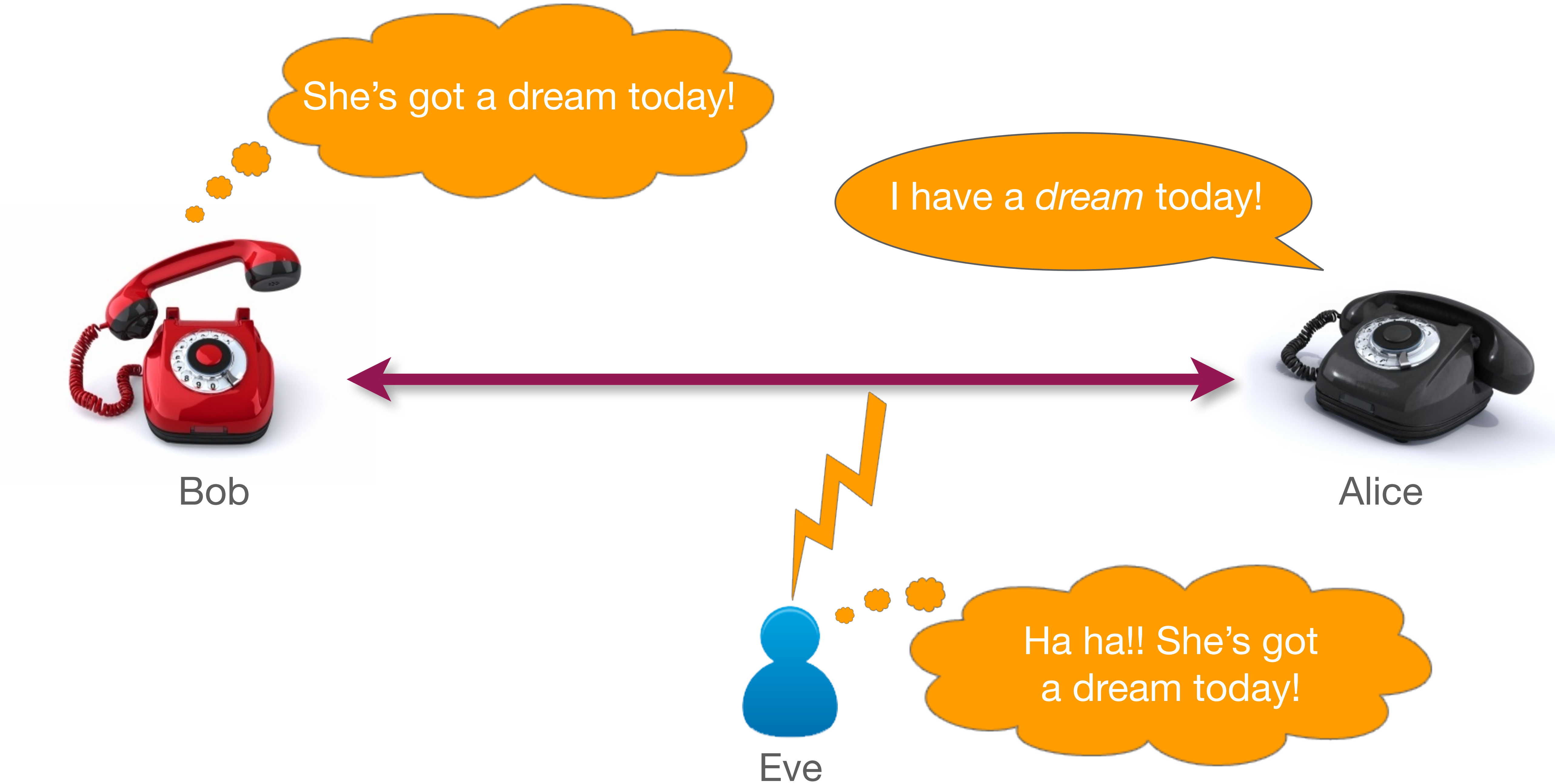

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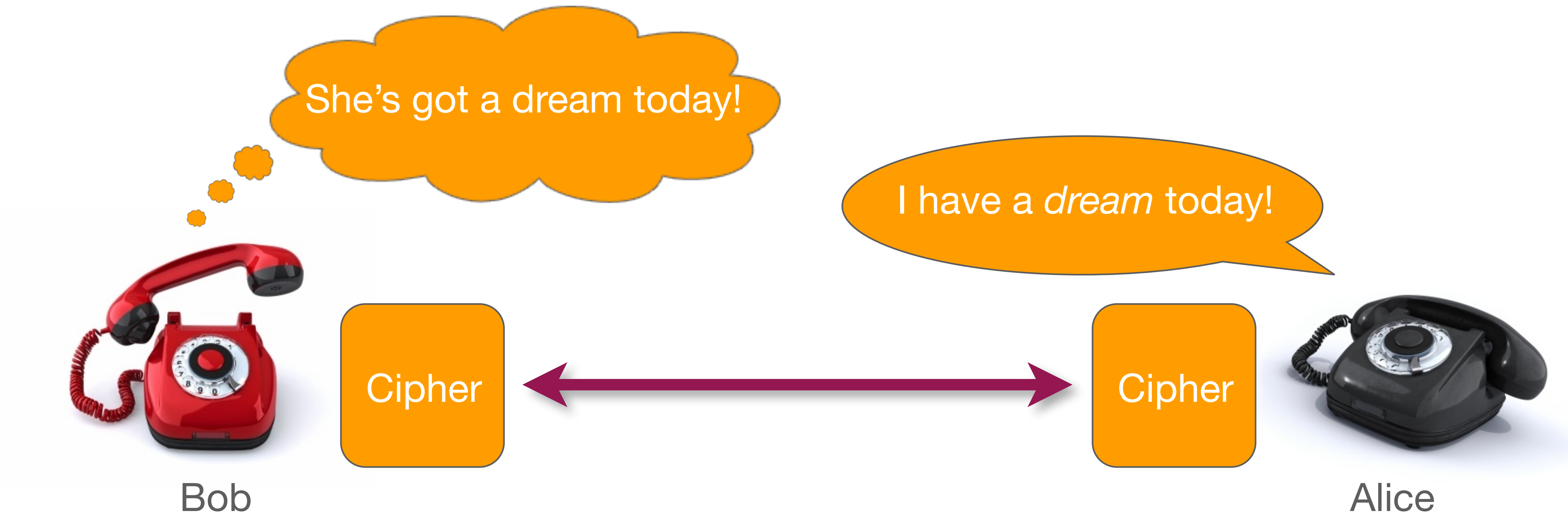

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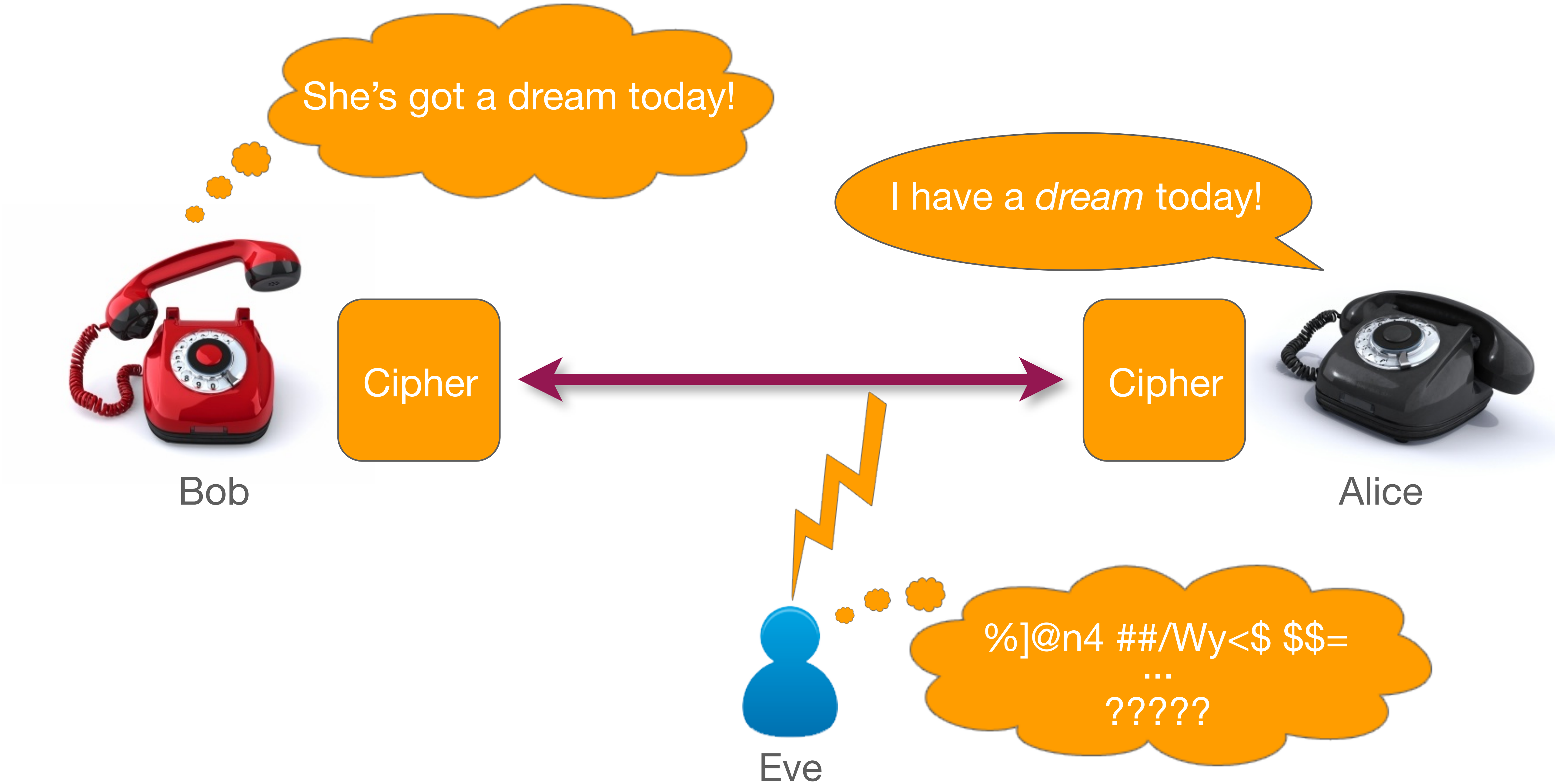

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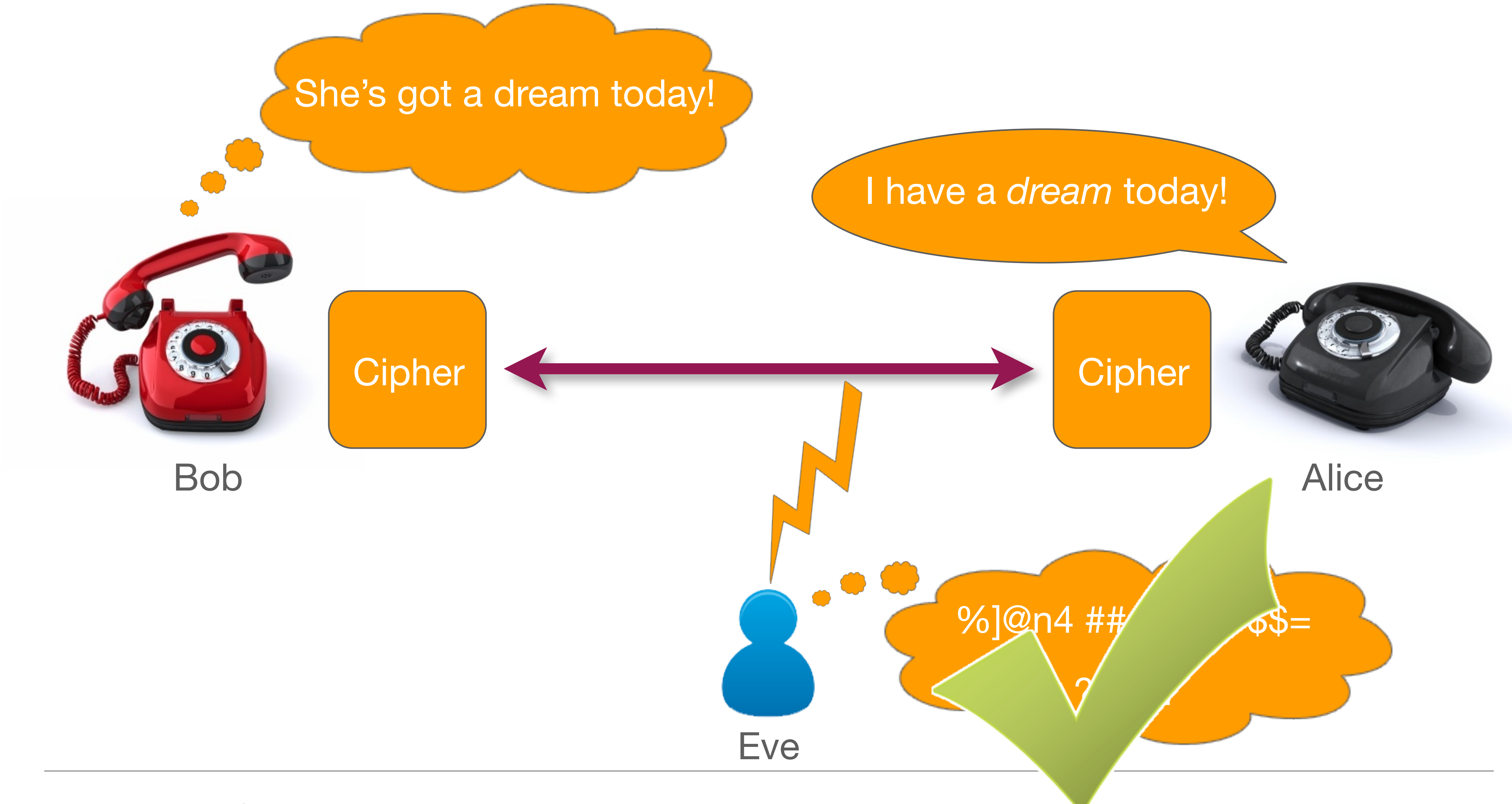

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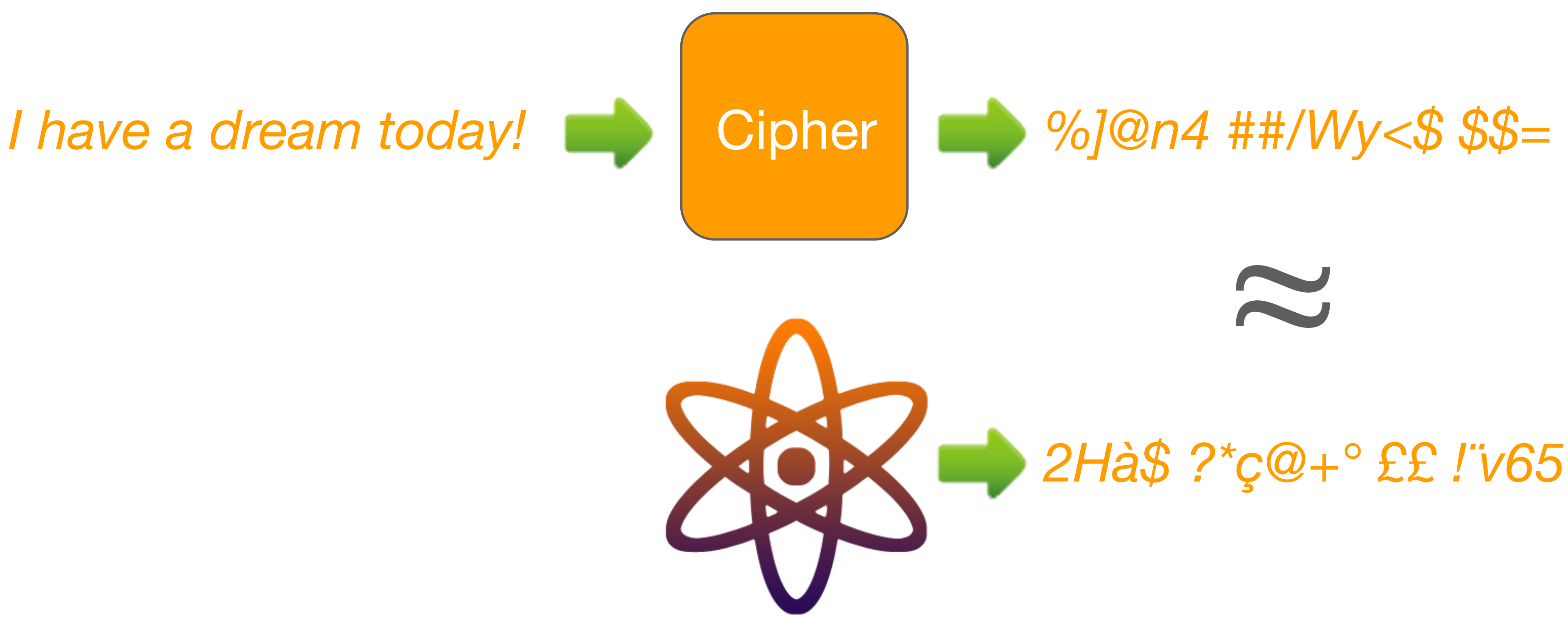

It should be hard for Eve to guess wether she's looking at an encrypted message (ciphertext) or to pure rubish (random string).

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... or “Cryptographers will never grow up”.

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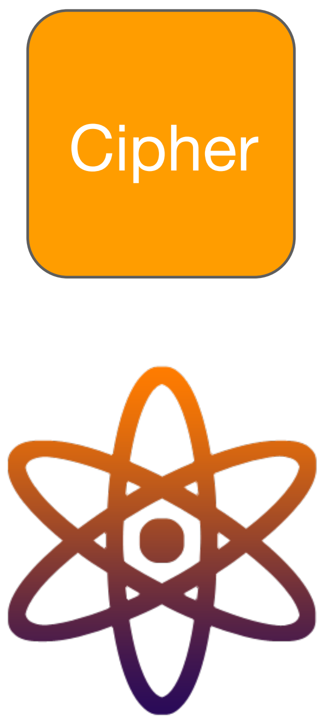

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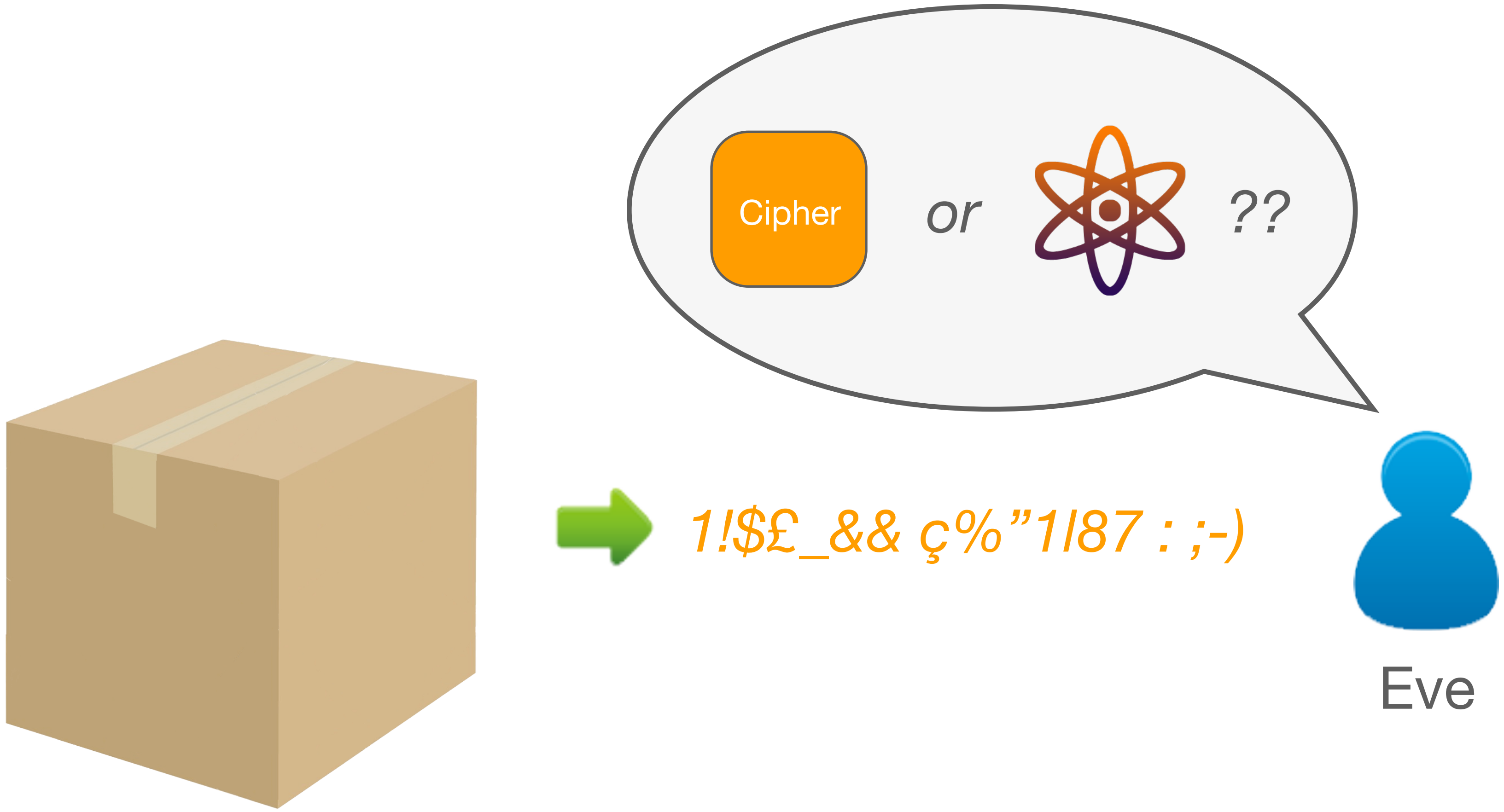

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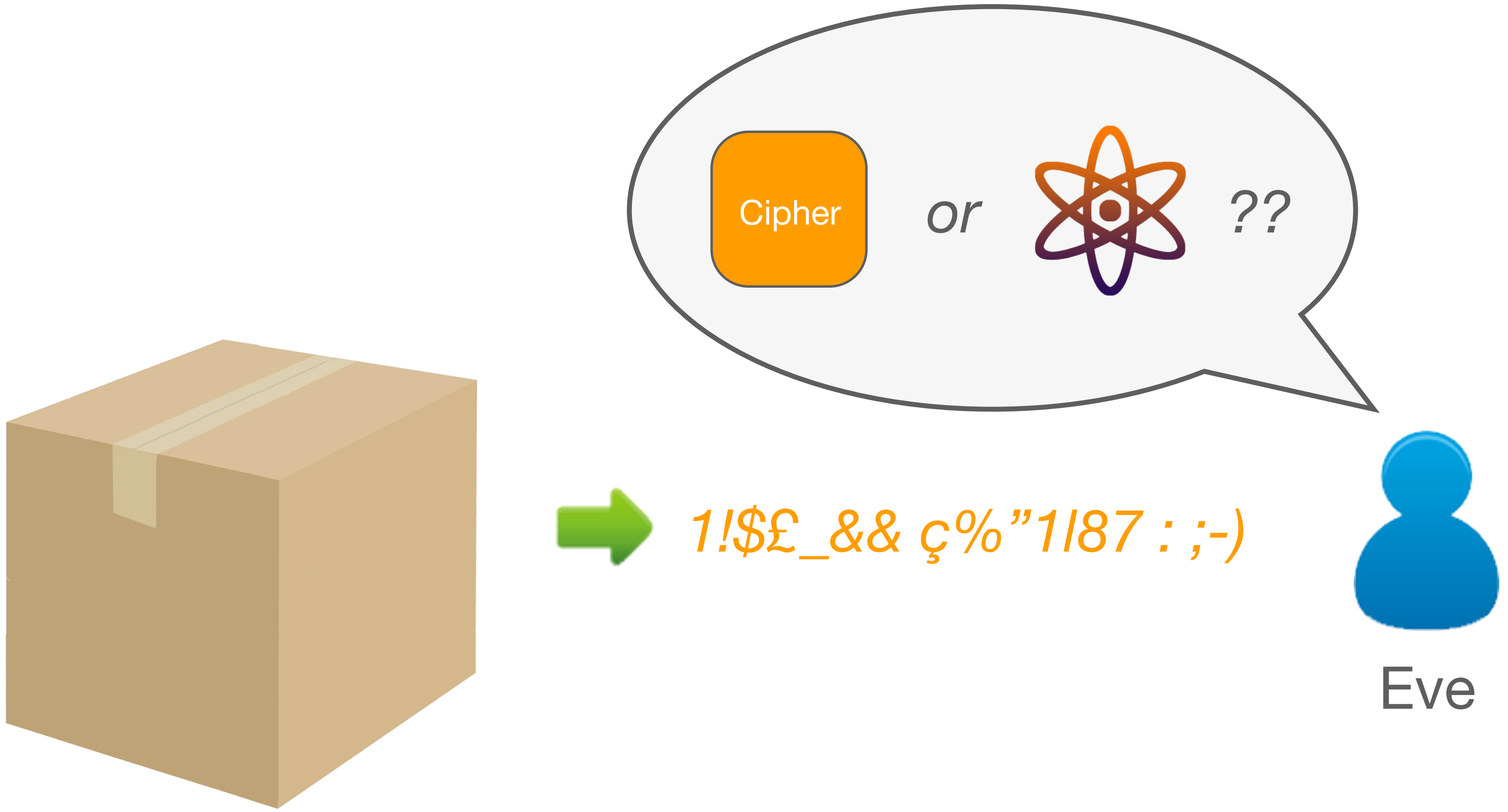

- Eve wins if she guesses correctly.

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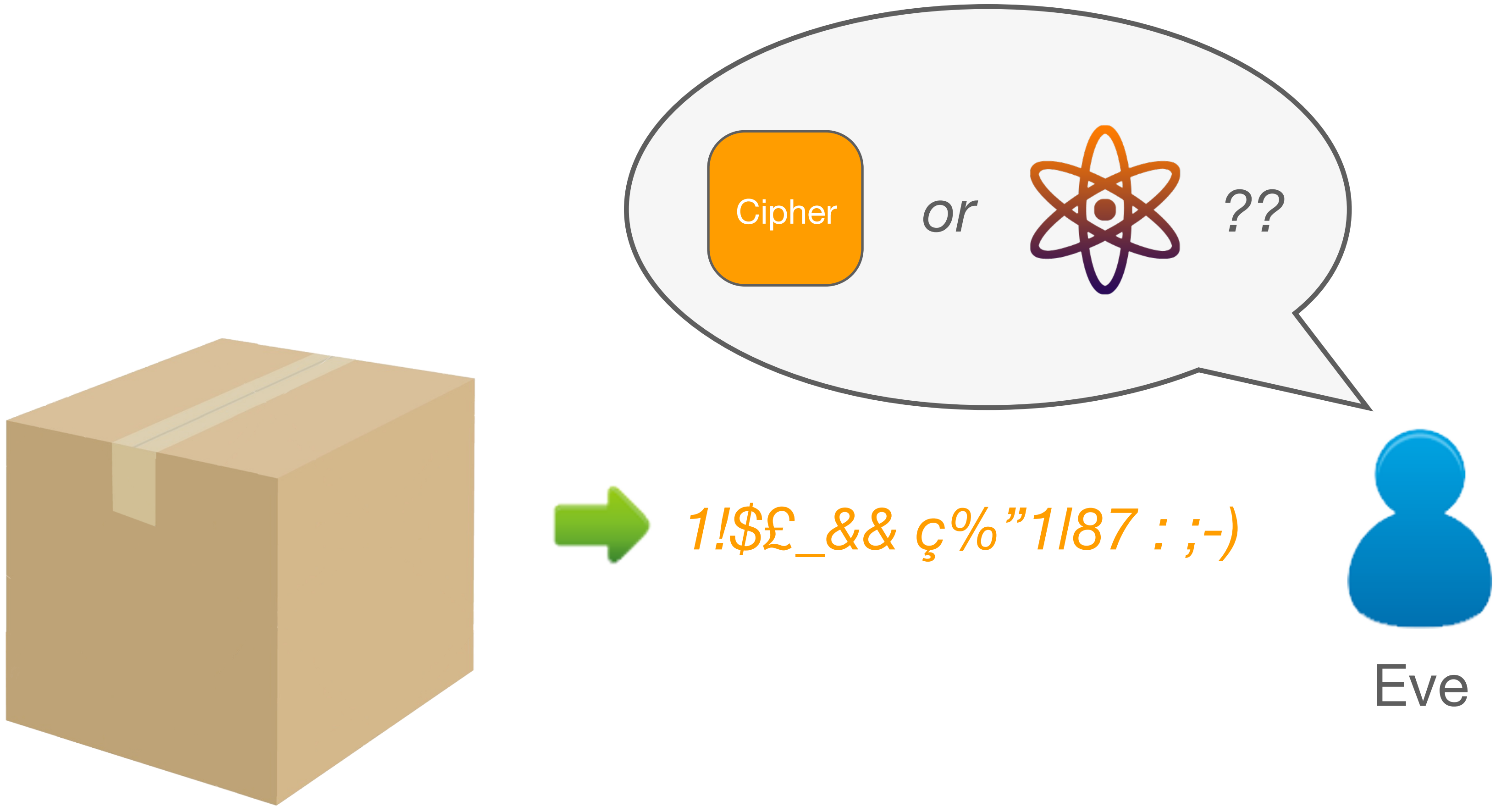

- Eve wins if she guesses correctly.
- Objective for the cryptographer: make sure that Eve cannot do better than guessing correctly 50% of the time.

Part I: On the (In)Security of Block Ciphers: Tools for the Security Analysis

Outline

Distinguishers between two sources

Projection-based distinguishers
between two sources

Practical Implications for block ciphers

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- Distinguishers between two sources
- Projection-based distinguishers between two sources
- Practical Implications for block ciphers

- The game: distinguishing between two sources of randomness
- The optimal solution
- Complexity analysis: How many samples do we need to distinguish with a given efficiency?

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Distinguishers between two sources

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Practical Implications for block ciphers

- What if the optimal solution cannot be implemented?
- Distinguishing in practice using compression
- Example: Generalized linear distinguisher

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[BJVa04] [BSVsac07] [BVicits08]

Part I: On the (In)Security of Block Ciphers:
Tools for the Security Analysis

- Distinguisher between two Sources

The Game

- P_0 and P_1 are two arbitrary distributions over a finite set $\mathcal{Z}$.

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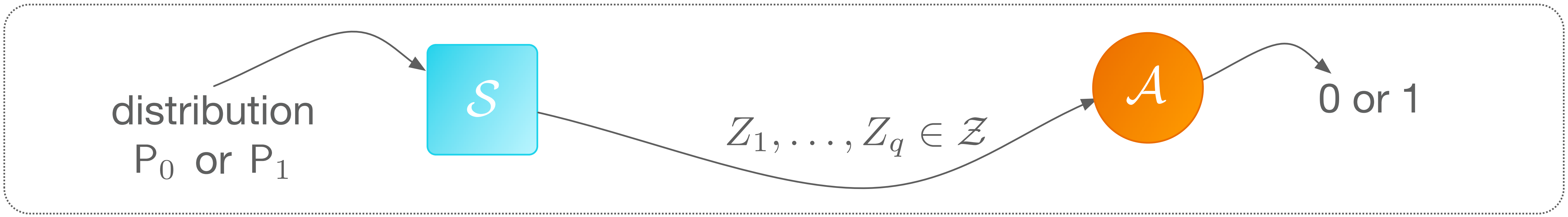

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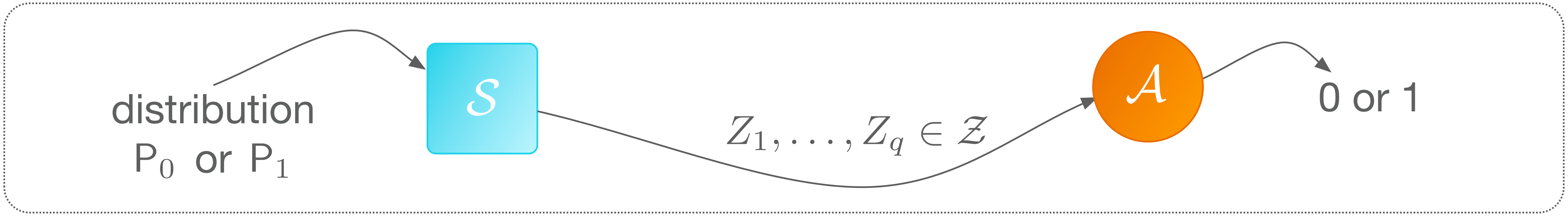

- The ability of $\mathcal{A}$ to distinguish P_0 from P_1 is its advantage:

$$\mathrm{Adv}_{\mathcal{A}}(\mathsf{P}_0, \mathsf{P}_1) = \left|\Pr_{\mathsf{P}_0}[\mathcal{A}(Z_1, \ldots, Z_q) = 1] - \Pr_{\mathsf{P}_1}[\mathcal{A}(Z_1, \ldots, Z_q) = 1]\right|$$

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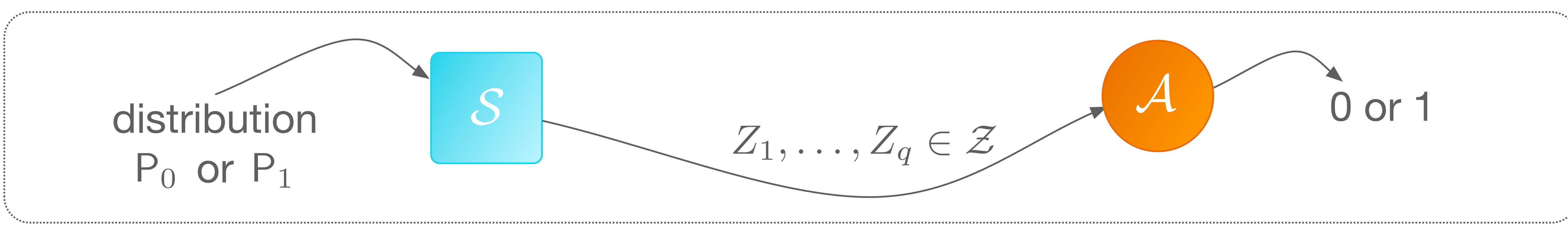

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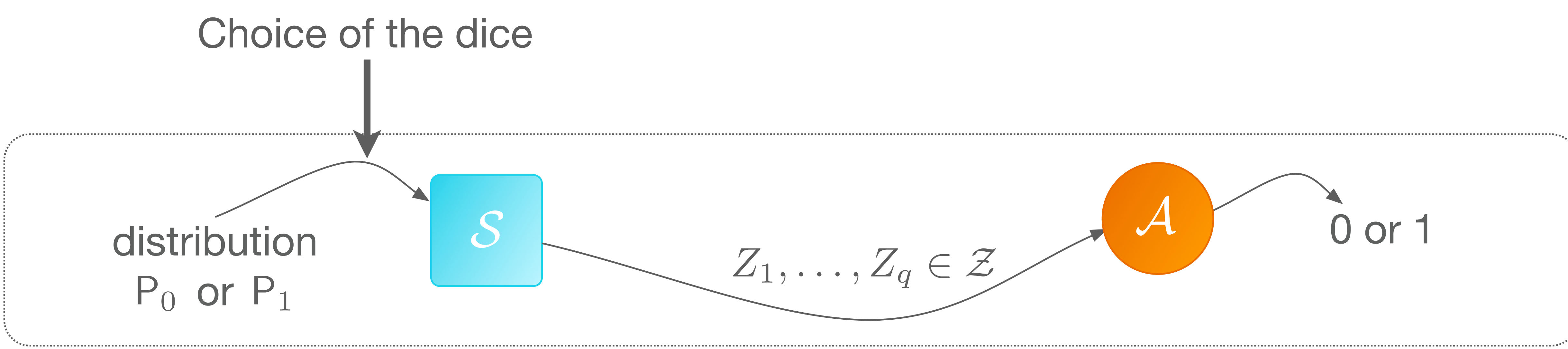

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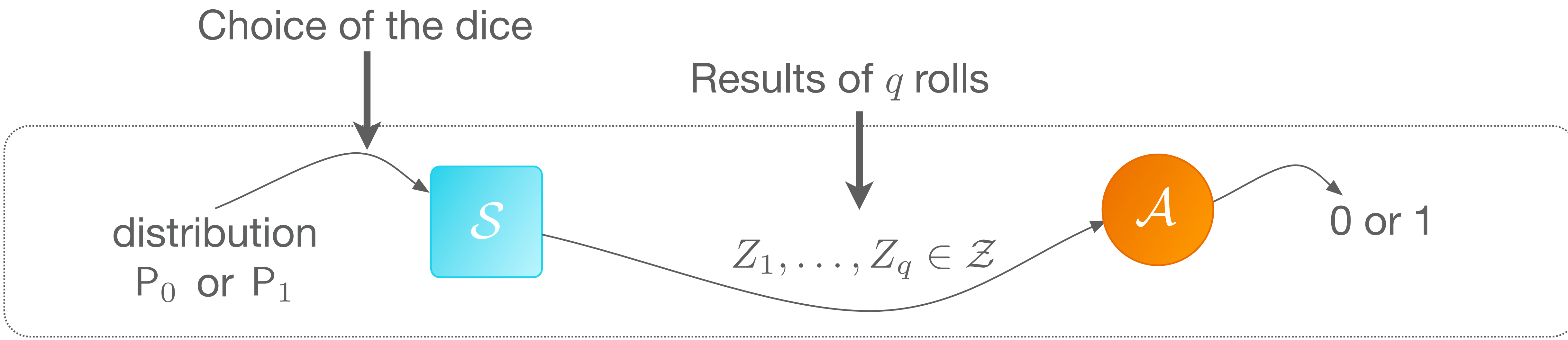

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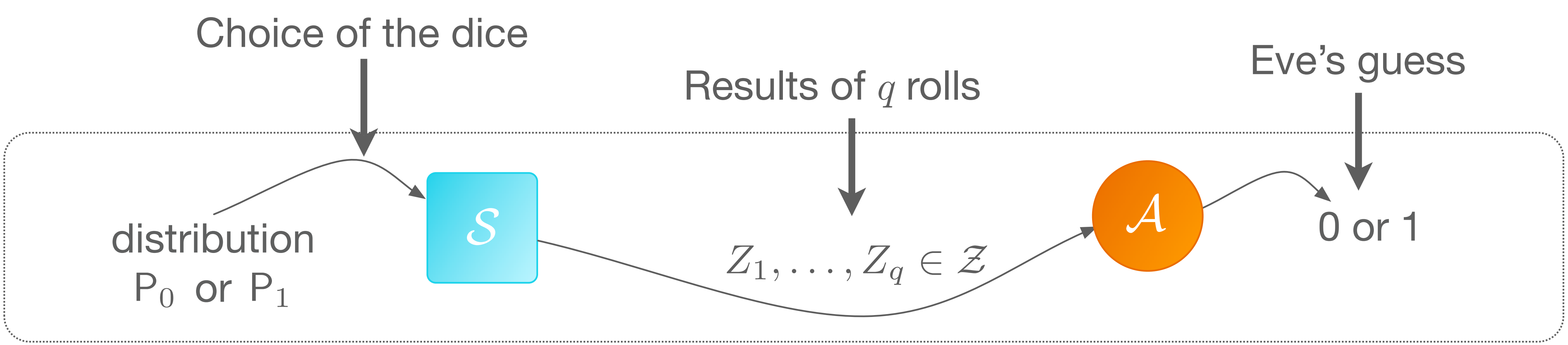

An Optimal Distinguisher

Using maximum-likelihood techniques, the q-limited distinguisher $\mathcal{A}^\star$ which outputs 1 when by

$$\boxed{\mathrm{D}(\mathsf{P}\|\mathsf{P}_1) \leq \mathrm{D}(\mathsf{P}\|\mathsf{P}_0)}$$

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can be shown to be optimal.

$$\left(\mathrm{D}(p\|q) = \sum_{a \in \mathcal{Z}} p[a] \log \frac{p[a]}{q[a]} \right)$$

always non-negative, 0 iff $p=q$, infinite iff $\mathsf{Supp}(p) \not\subseteq \mathsf{Supp}(q)$

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Using the theory of types & Sanov's theorem asymptotic data complexity of $\mathcal{A}^{\star}$.

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Theorem

Let P_0 and P_1 be two distributions s.t. $\mathrm{Supp}(\mathsf{P}_0) \cup \mathrm{Supp}(\mathsf{P}_1) = \mathcal{Z}$. The advantage of $\mathcal{A}^\star$ verifies

$$\boxed{1 - \mathrm{BestAdv}_q(\mathsf{P}_0, \mathsf{P}_1) \doteq 2^{-q\mathrm{C}(\mathsf{P}_0, \mathsf{P}_1)}}$$

where

$$\mathrm{C}(\mathsf{P}_0, \mathsf{P}_1) = - \inf_{0<\lambda<1} \log \sum_{a \in \mathsf{Supp}(\mathsf{P}_0) \cap \mathsf{Supp}(\mathsf{P}_1)} \mathsf{P}_0[a]^{1-\lambda} \mathsf{P}_1[a]^{\lambda}$$

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…

is the … information between P_0 and P_1.

Heuristic: $q \approx 1/\mathrm{C}(\mathrm{P}_0, \mathrm{P}_1)$ allows $\mathcal{A}^\star$ to reach a non-negligible advantage

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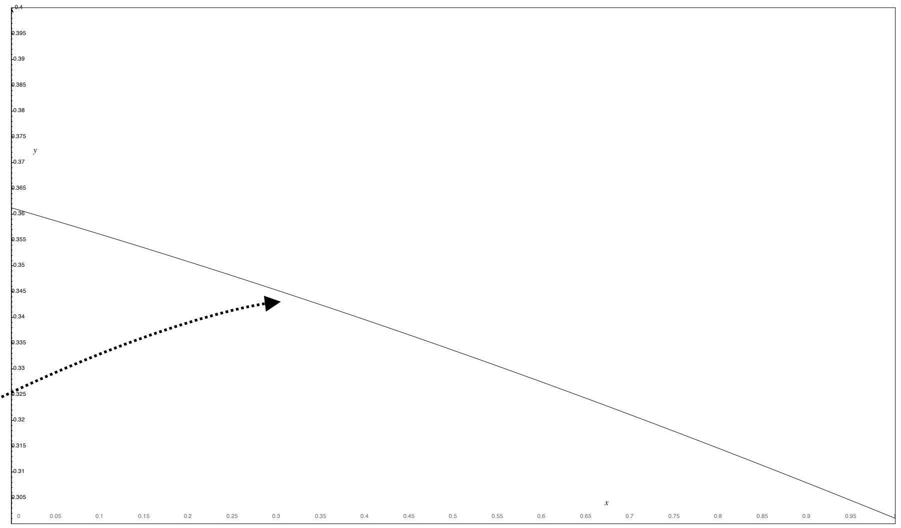

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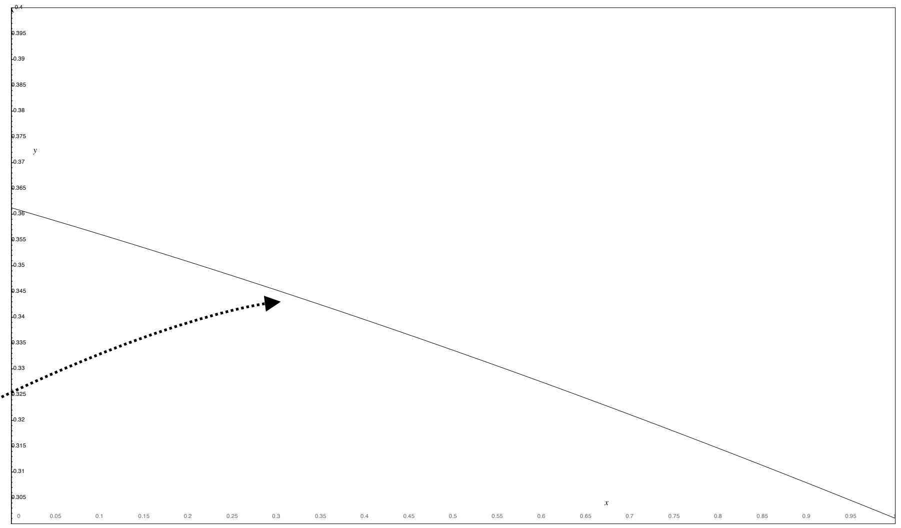

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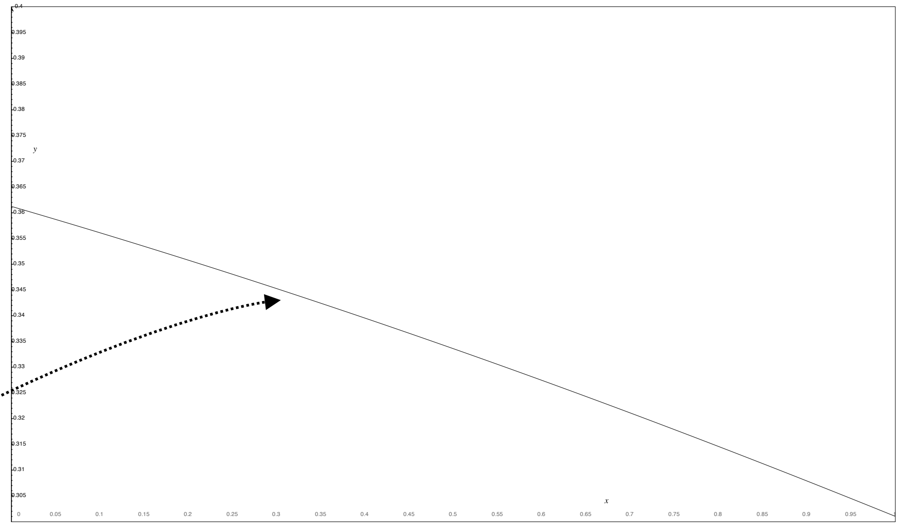

- approx. $\dfrac{1}{0.263} \approx 3.8$ queries (rolls) are sufficient to distinguish one dice from the other.
- This is the proof that all this theory has a practical application...

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$\mathsf{P}_0 = (\frac{1}{2}, \frac{1}{2})$ $\qquad$ $\mathsf{P}_1 = \left(\frac{1}{2}(1-\epsilon), \frac{1}{2}(1+\epsilon)\right)$

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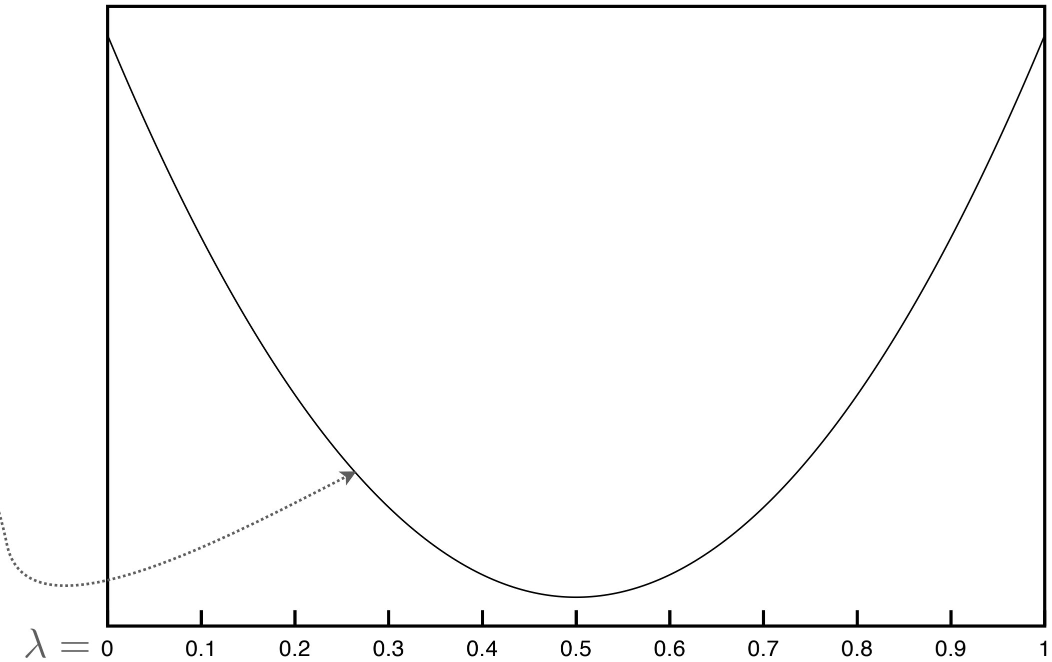
Example with $\epsilon = 0.01$



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Minimum reached for $\lambda \approx \frac{1}{2}$

$$C(\mathsf{P}_0, \mathsf{P}_1) \approx -\log\left(1 - \frac{\epsilon^2}{8}\right) \approx \frac{\epsilon^2}{8 \ln 2}$$

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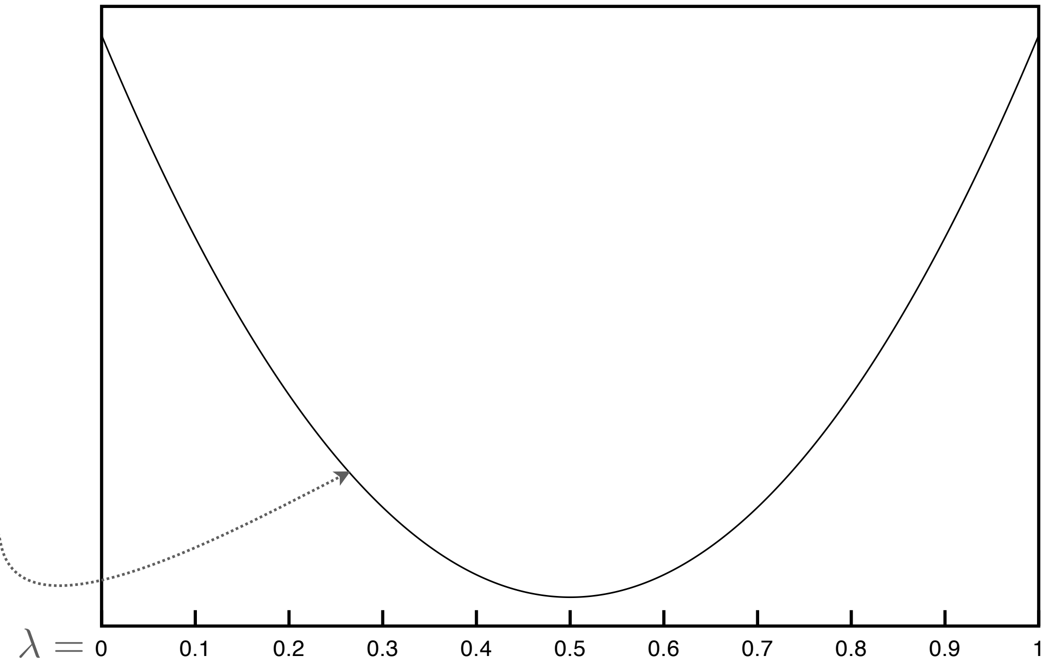

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$q \approx \dfrac{8 \ln 2}{\epsilon^2}$ allow to reach a non-negligible advantage.

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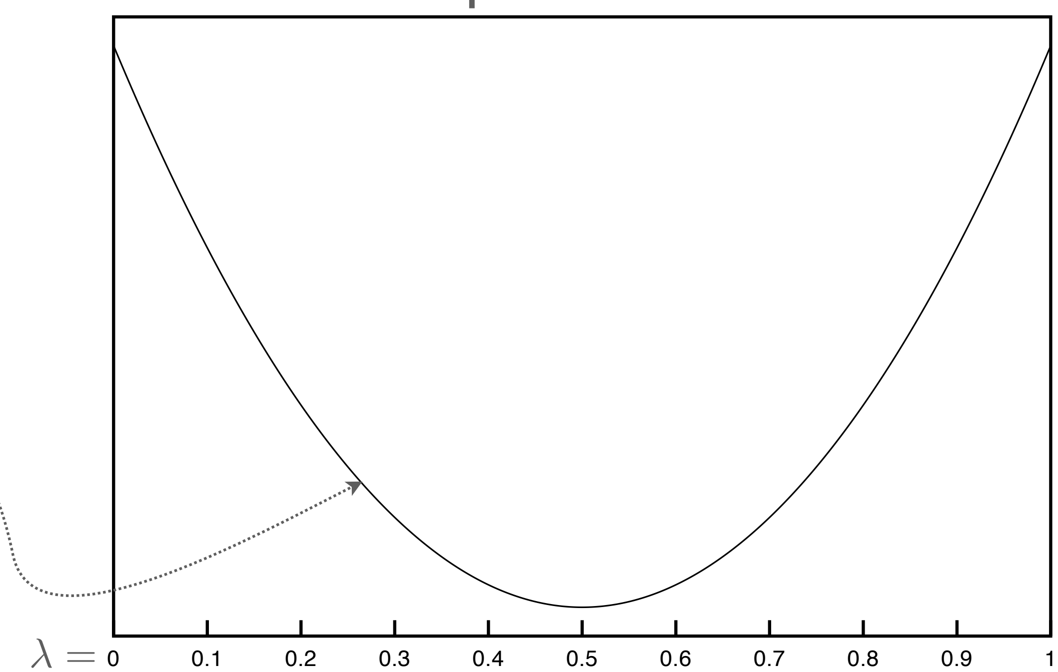

Possible Extensions

- Case where the distributions are "close" to each other
- Case where one of the hypotheses is composite
- Case where one of the two distributions is unknown
- etc.

Part I: On the (In)Security of Block Ciphers:

Tools for the Security Analysis

- Projection Based Distinguishers

On the Need for Projection-Based Distinguishers

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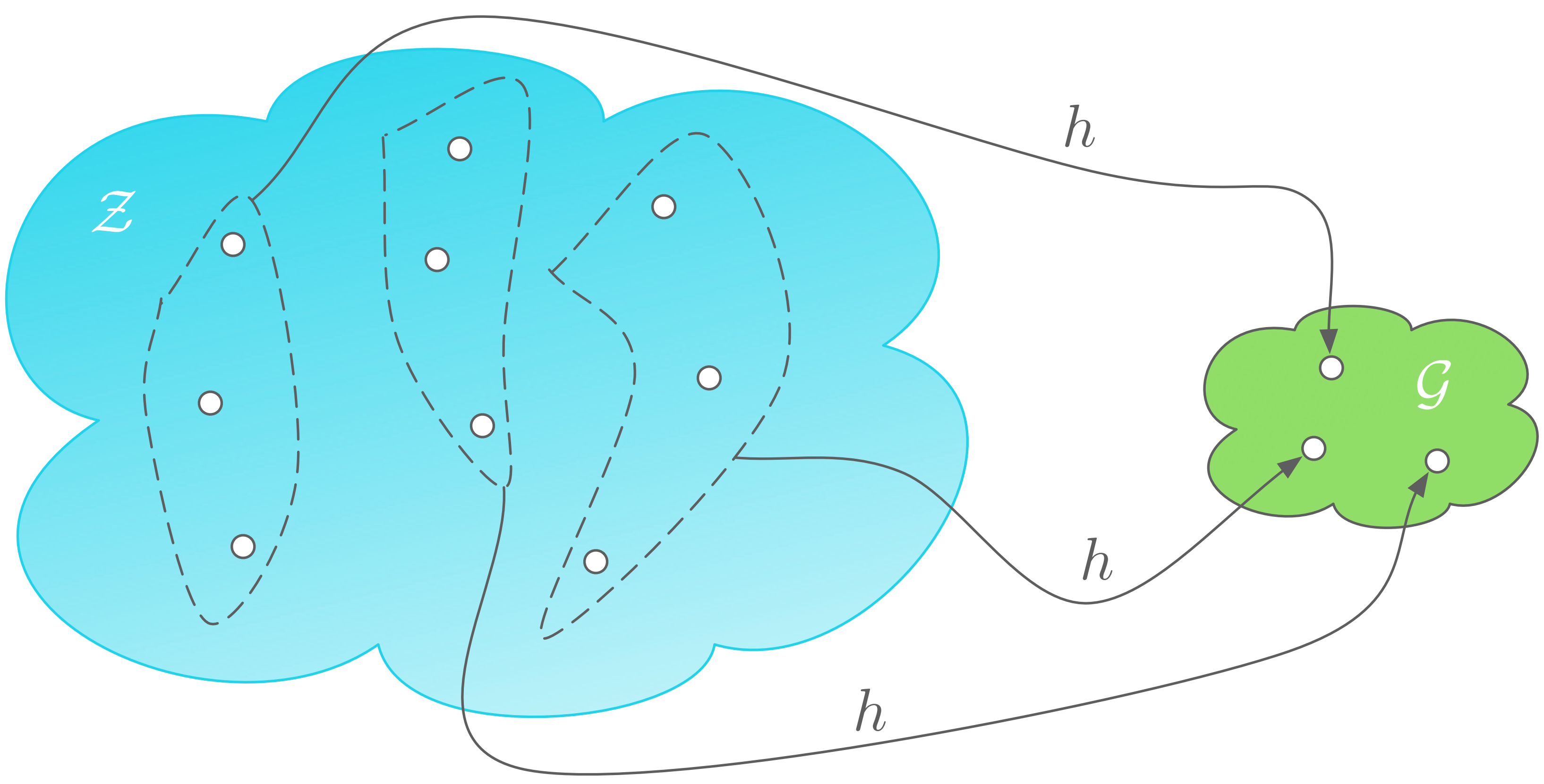
- Possible solution: reduce the sample size using a projection:



✔ Distinguish in $\mathcal{G}$ instead of $\mathcal{Z}$.

🚫 This reduces the power of the distinguisher.

Example: Linear Distinguishers

- $\mathcal{Z} = \{0,1\}^n \qquad \mathcal{G} = \{0,1\} \qquad \mathsf{P}_0 = \mathsf{U} \qquad \mathsf{P}_1 = \mathsf{P} \qquad h(Z) = a \cdot Z = a_1 Z_1 \oplus \cdots \oplus a_n Z_n$
- This is a linear distinguisher based on the mask a.

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- Roughly: $\mathrm{C}(\mathsf{U},\mathsf{P}) \approx \dfrac{\mathrm{LP}_a(\mathsf{P})}{8 \ln 2}$ $\Rightarrow$ $q \approx \dfrac{8 \ln 2}{\mathrm{LP}_a(\mathsf{P})}$ are enough (well known...)

Extending the Notion of Linear Probability

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- Consequence: when $\mathcal{Z} = \{0,1\}^n$ this new definition corresponds to the old one!

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Lemma 7.5 *Let* P_0 *be the uniform distribution on a finite subgroup* H *of* $\mathbf{C}^\times$ *of order* d. *Let* $\mathcal{D} = \{\mathsf{P}_u : u \in \mathsf{H}\}$ *be a set of* d *distributions on* H *defined by* (7.10). *The* q*-limited distinguisher between the null hypothesis* $\mathsf{H}_0 : \mathsf{P} = \mathsf{P}_0$ *and the alternate hypothesis* $\mathsf{H}_1 : \mathsf{P} \in \mathcal{D}$ *defined by the distribution acceptance region* $\Pi_q^\star = \Pi^\star \cap \mathcal{P}_q$, *where*

$$\Pi^\star = \left\{ \mathsf{P} \in \mathcal{P} \;:\; \|\mathsf{P}\|_\infty \geq \frac{\log(1-\epsilon)}{\log(1-\epsilon) - \log(1+(d-1)\epsilon)} \right\}, \tag{7.11}$$

is asymptotically optimal and its advantage $\mathrm{BestAdv}_q$ *is such that*

$$1 - \mathrm{BestAdv}_q(\mathsf{H}_0, \mathsf{H}_1) \doteq 2^{q \inf_{0<\lambda<1} \log \frac{1}{d}\left((1+(d-1)\epsilon)^\lambda + (d-1)(1-\epsilon)^\lambda\right)}.$$

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Which shows how to use the generalized LP to build a linear distinguisher over arbitrary sets...

and allows to conclude that a linear distinguisher needs $q \approx \dfrac{8 \ln 2}{(d-1)\mathrm{LP}^{\chi}(\mathsf{P})}$ to reach a good advantage.

Part I: On the (In)Security of Block Ciphers:

Tools for the Security Analysis

Practical Implications for Block Ciphers

Applications on SAFER K/SK

- We attack SAFER with a $\boxplus$-linear cryptanalysis.
- Use the toolbox to find characteristics within SAFER K/SK.
- To compute the complexities we consider several characteristics among the hull (i.e., all characteristics share the same input/output characters).
- To turn distinguishing attacks into key recovery attacks, we also take advantage of the linearity of the key schedule.

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Nbr Rounds	Complexity
2	$2^{23}/2^{31}$
3	2^{38}
4	2^{49}
5	2^{56}

Other Applications

- Two new Digital Encryption Algorithm for Numbers (based on the AES): DEAN18 and DEAN27 which respectively encrypts blocks made of 18 and 27 decimal digits.

- Resistance against our generalization of linear cryptanalysis.

- New attacks on TOY100 (toy cipher that encrypts blocks of 32 decimal digits).

- Break 9 (10 ?) rounds out of 12.

Part II: Designs and Security Proofs

Outline

Block Ciphers

Dial $\mathbf{C}$ for Cipher

KFC: the Krazy Feistel Cipher

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- Block Ciphers
- Dial $\mathbf{C}$ for Cipher
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- The Luby-Rackoff Model
- Vaudenay’s decorrelation theory

Outline

Block Ciphers

Dial C for Cipher

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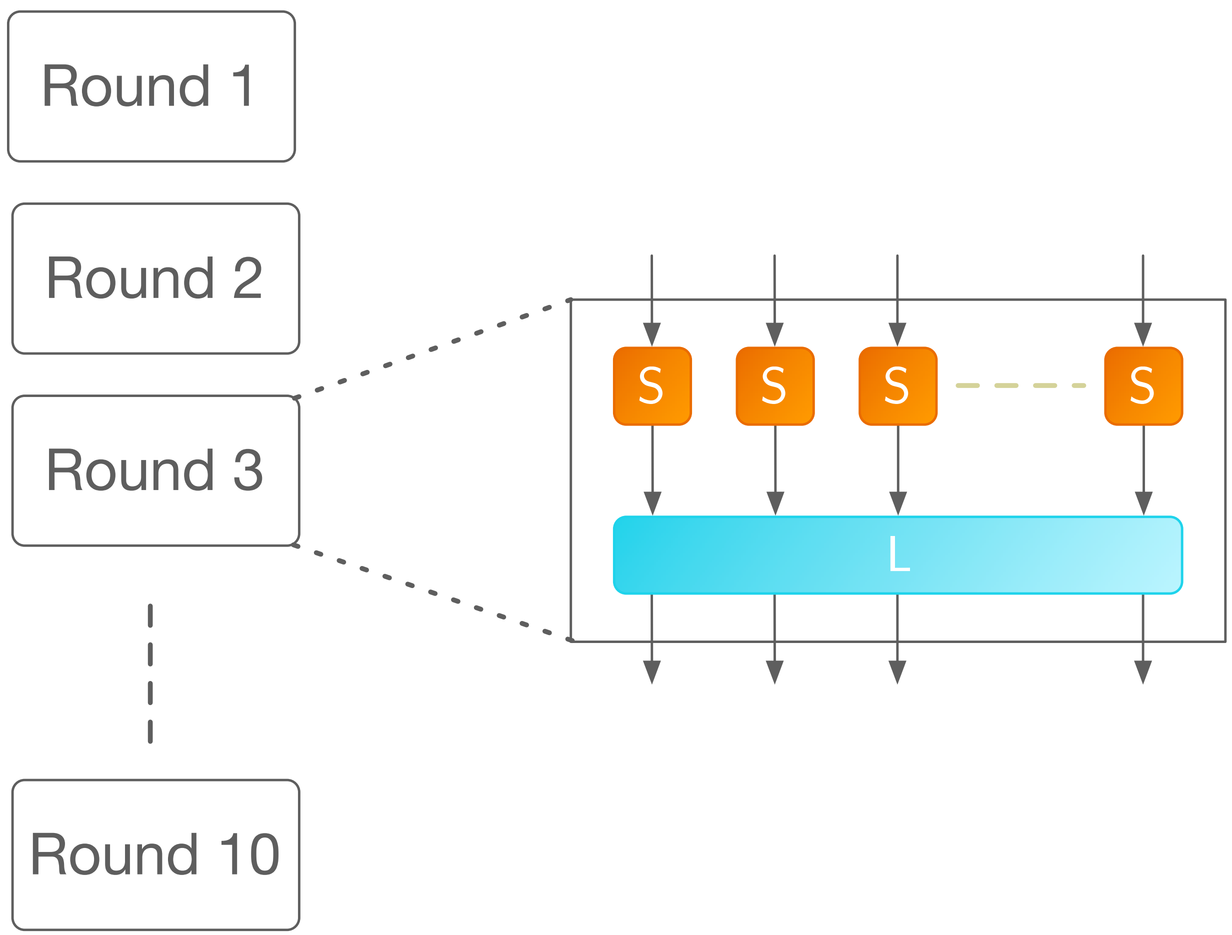

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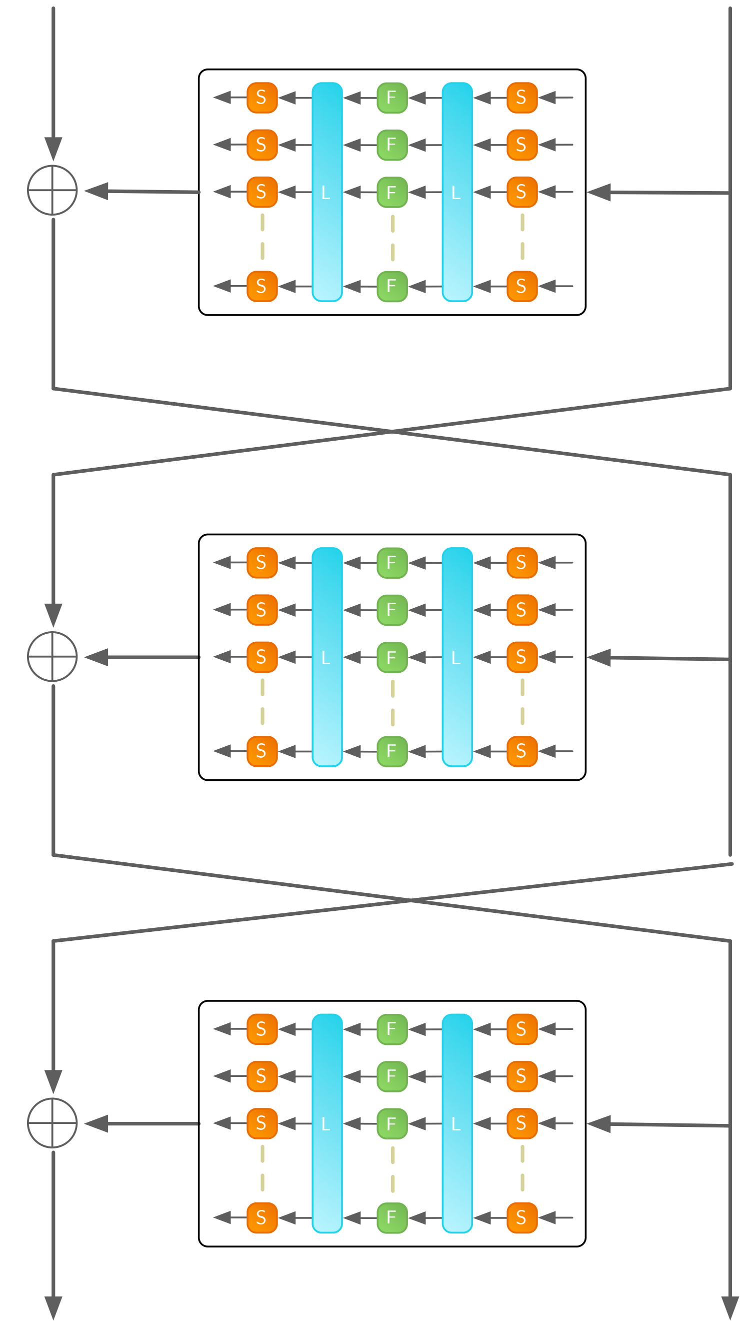

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[BVsac05] [BFsac06] [BFa06]

Part II: Designs and Security Proofs

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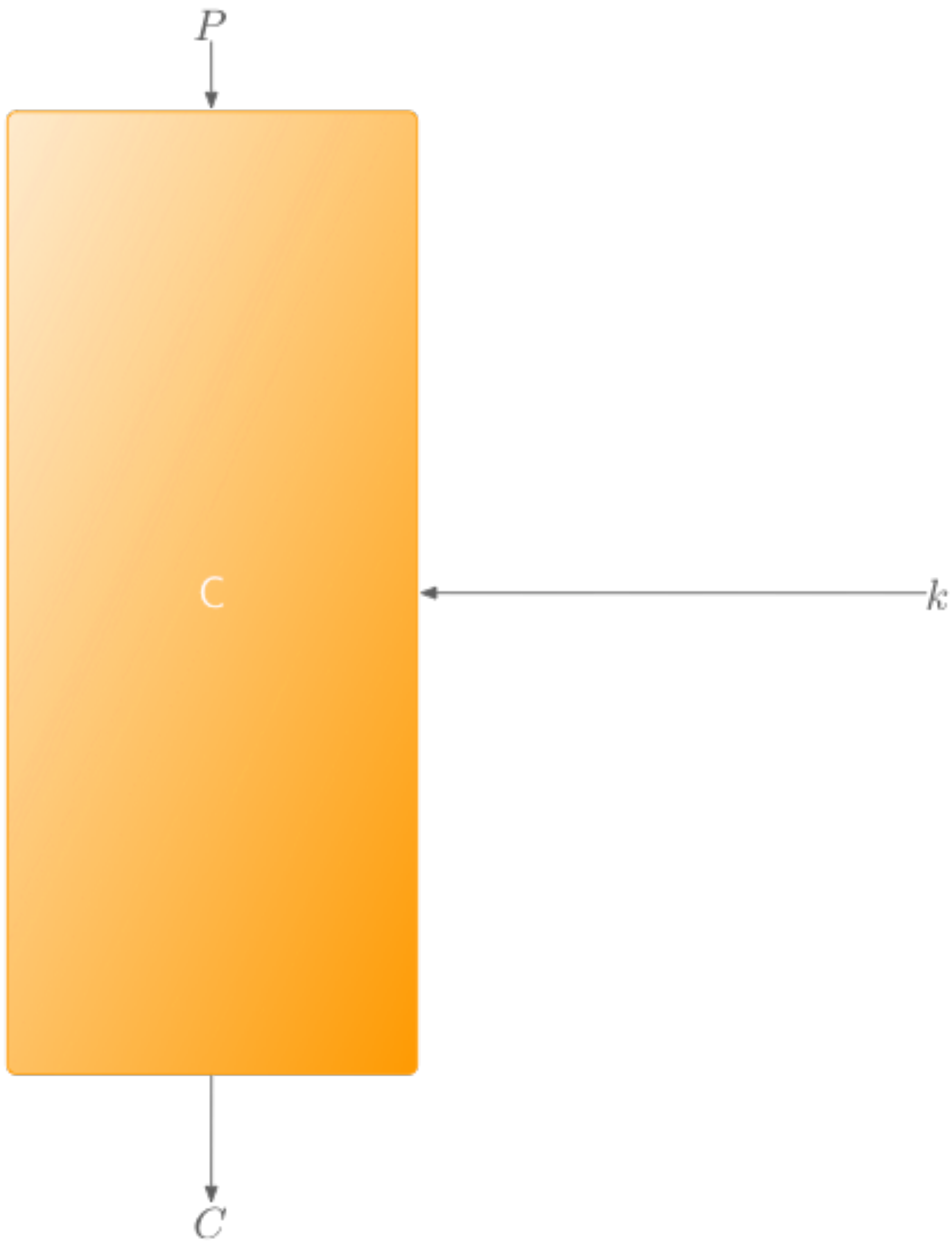
A Typical Iterated Block Cipher

- A block cipher on a finite set is a family of permutations on that set, indexed by a parameter call the key.



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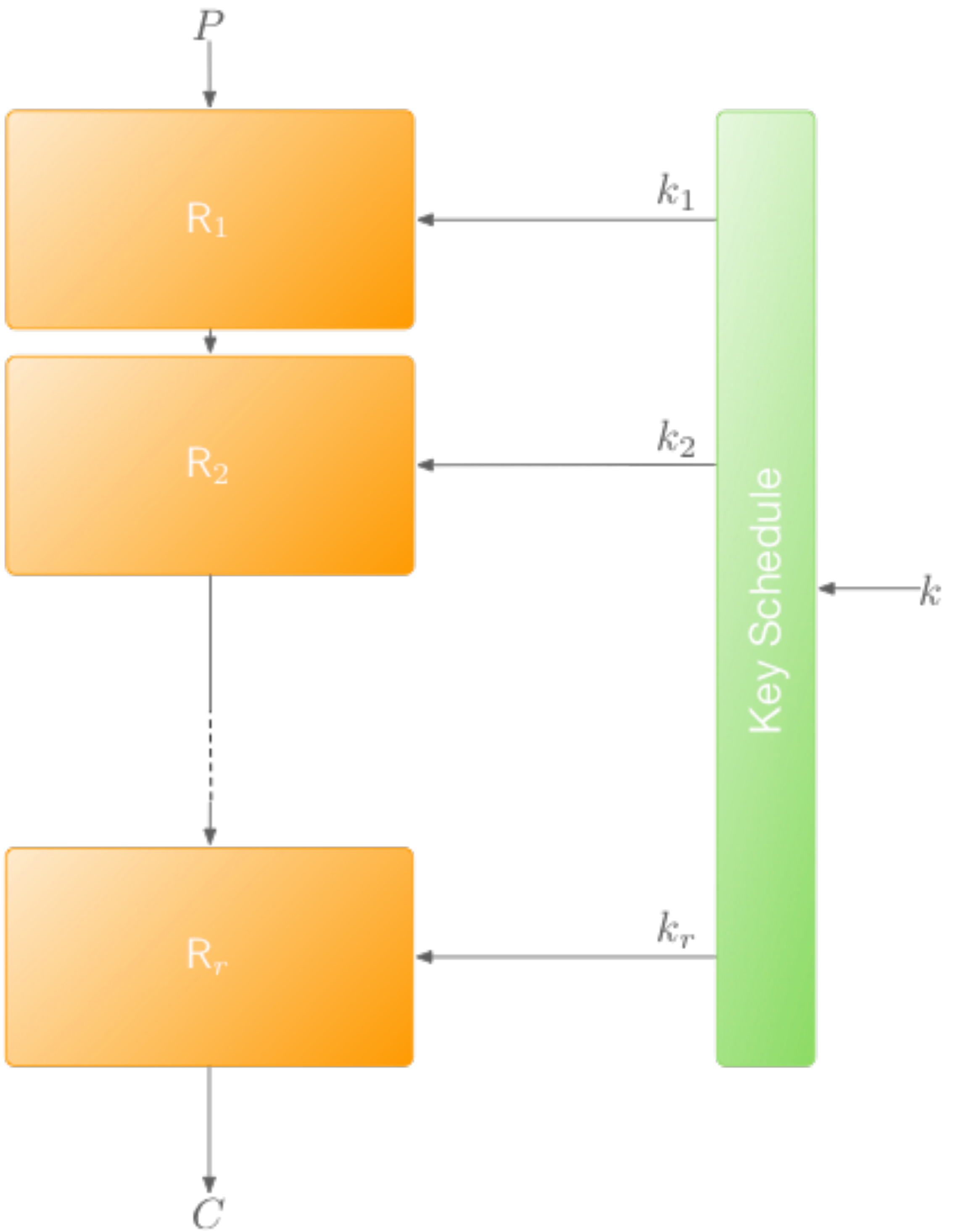

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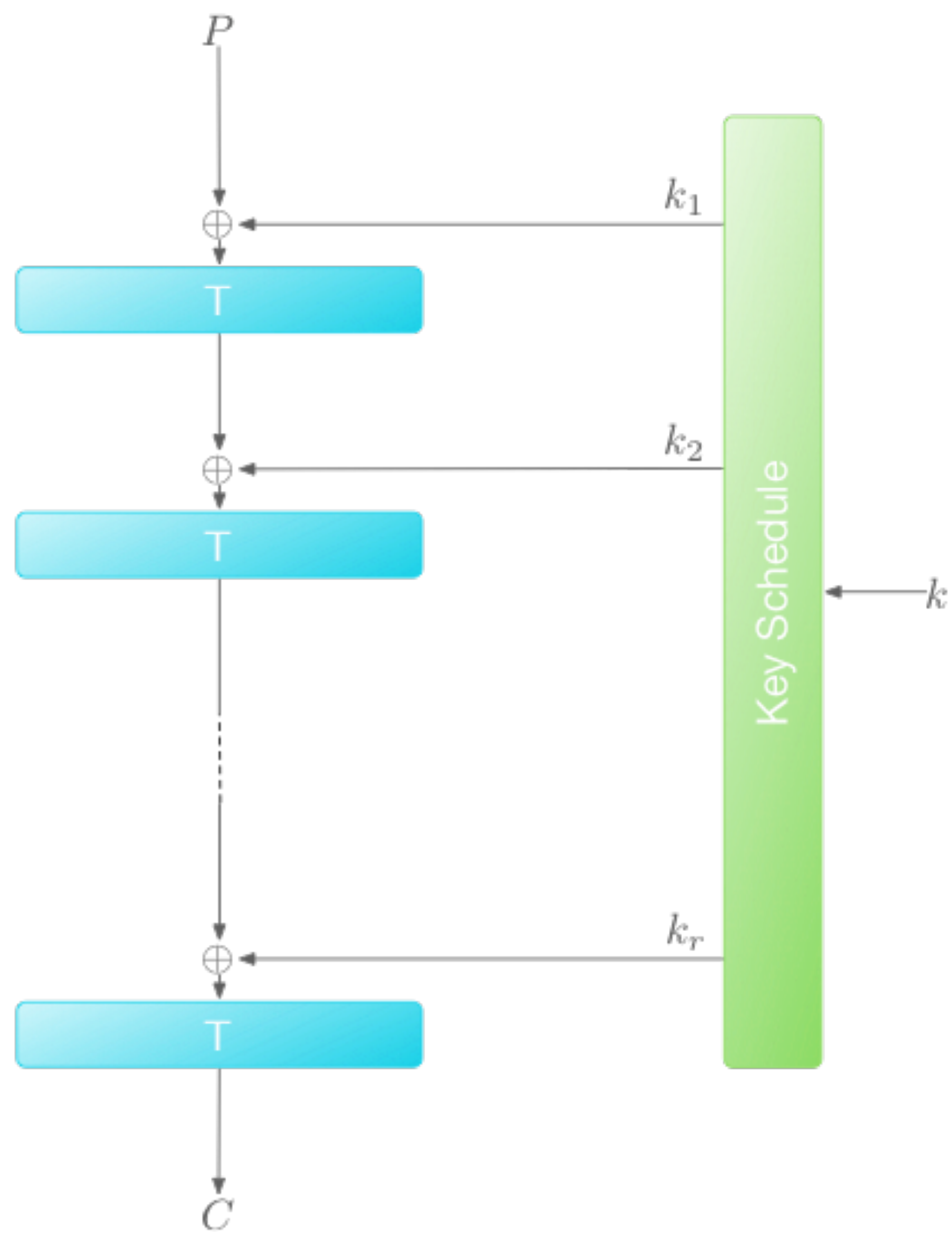
- Usually, the rounds all share the same design, e.g., a round key addition followed by a fixed (nonlinear) transformation.



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It should be fast and secure!

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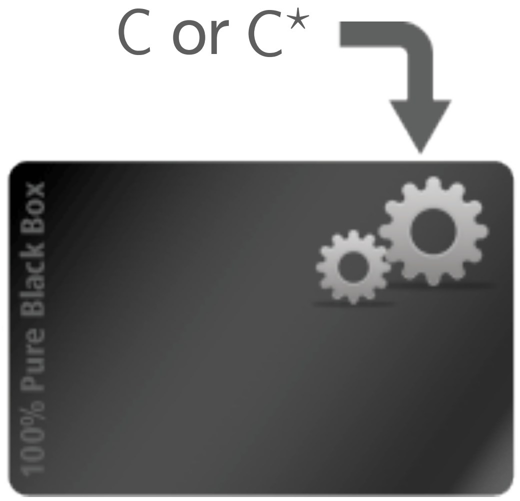

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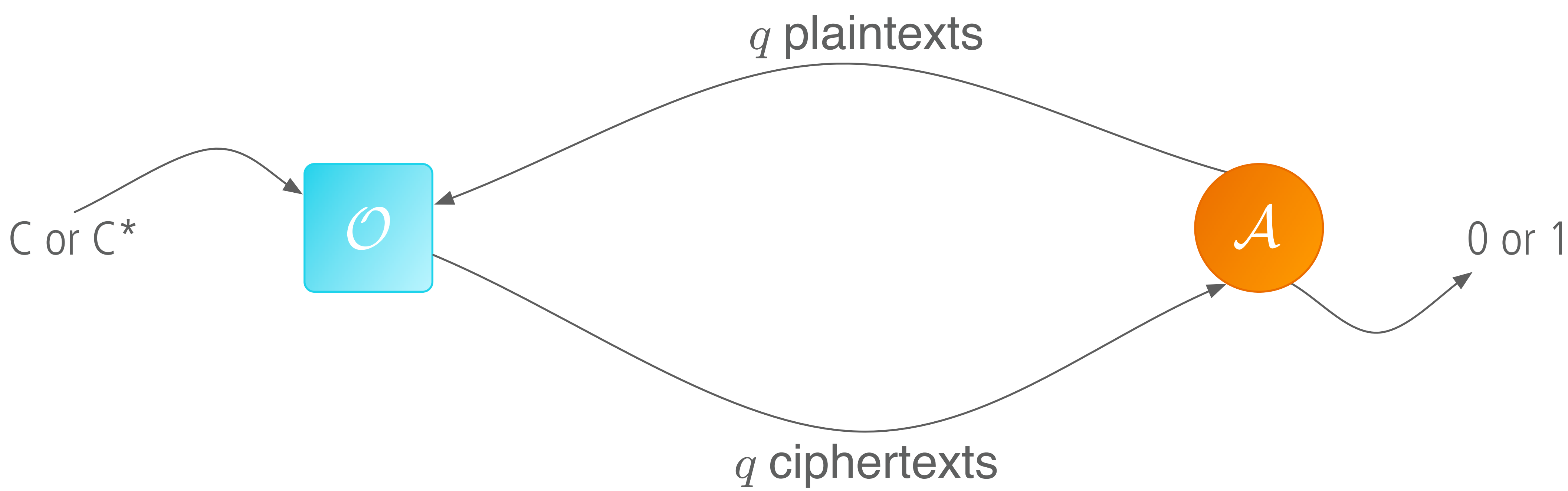
$P_1, P_2, \ldots, P_q$ →  → $C_1, C_2, \ldots, C_q$

The Luby-Rackoff Model

We consider a q-limited adversary $\mathcal{A}$ in the Luby-Rackoff Model:



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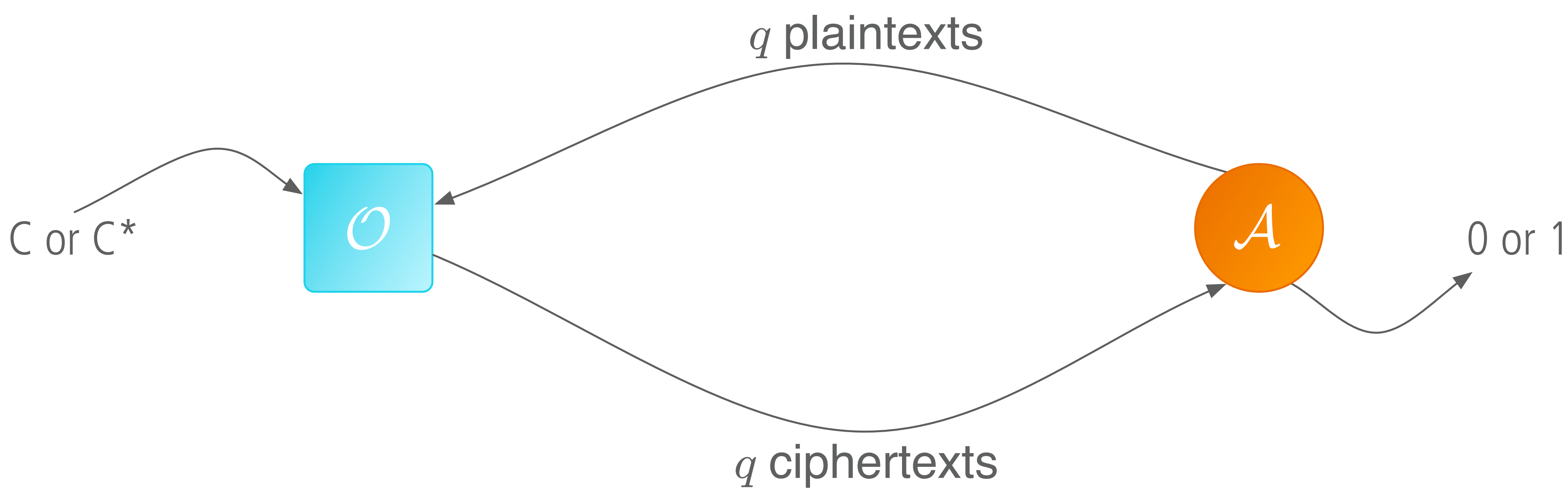

$$\mathrm{Adv}_{\mathcal{A}}(\mathsf{C}, \mathsf{C}^\star) = |\Pr[\mathcal{A}(\mathsf{C}) = 1] - \Pr[\mathcal{A}(\mathsf{C}^\star) = 1]|$$

Advantage of the q-limited adversary $\mathcal{A}$ between C and $\mathsf{C}^\star$

✔ The block cipher C is secure if the advantage of $\mathcal{A}$ is negligible for all $\mathcal{A}$'s.

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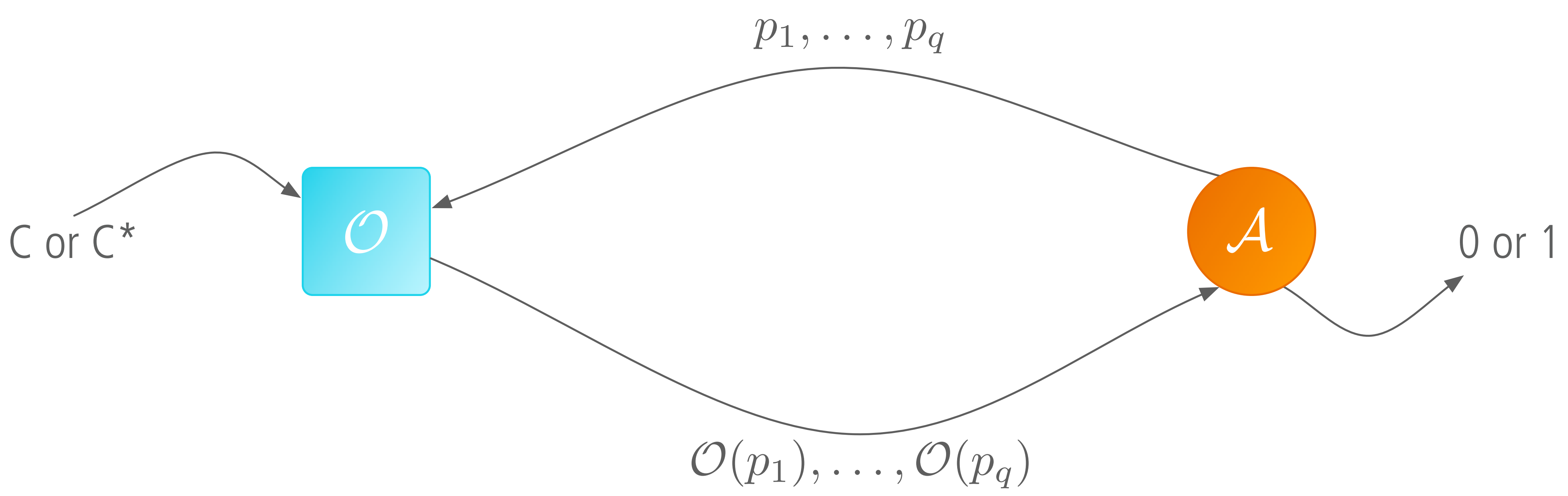

$\mathcal{A}$ is non-adaptive if the q plaintexts are chosen "at once".

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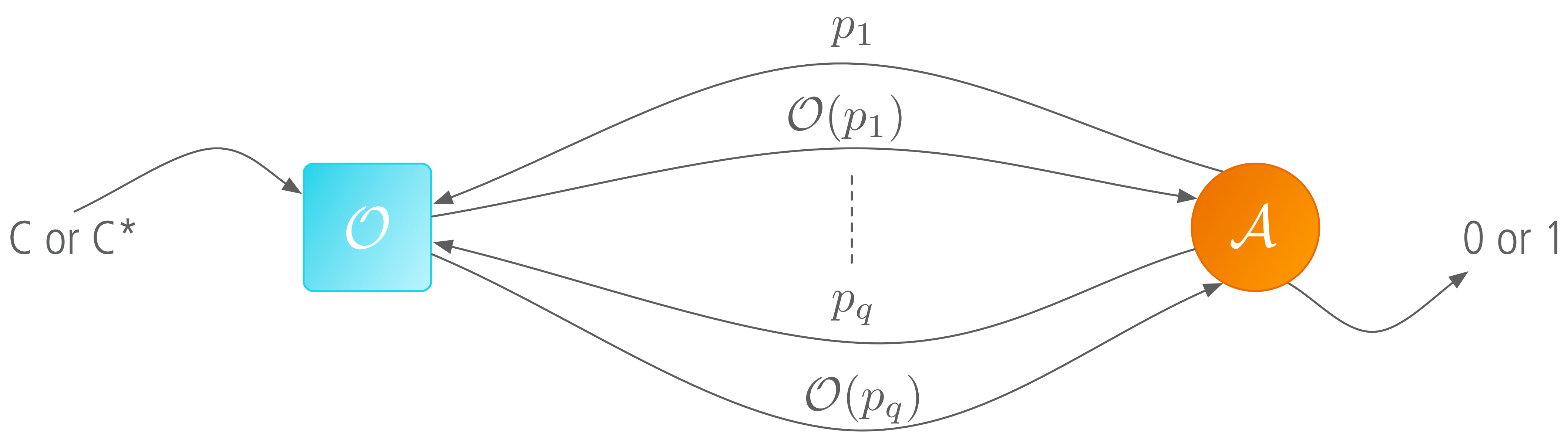
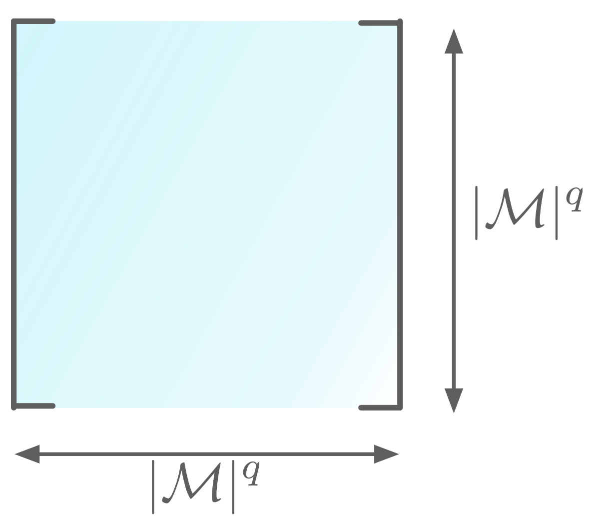


$\mathcal{A}$ is adaptive if plaintext i depends on ciphertexts $1, \ldots, i-1$.

Computing $\mathrm{Adv}_{\mathcal{A}}(\mathsf{C}, \mathsf{C}^\star)$

- Computing the advantage is not a trivial task in general.
- Possible solution: use Vaudenay's Decorrelation Theory.

$$\max_{\mathcal{A}} \mathrm{Adv}_{\mathcal{A}}(\mathsf{C}, \mathsf{C}^\star) = \frac{1}{2} \| [\mathsf{C}]^q - [\mathsf{C}^\star]^q \|$$

$[\mathsf{C}]^q =$ 

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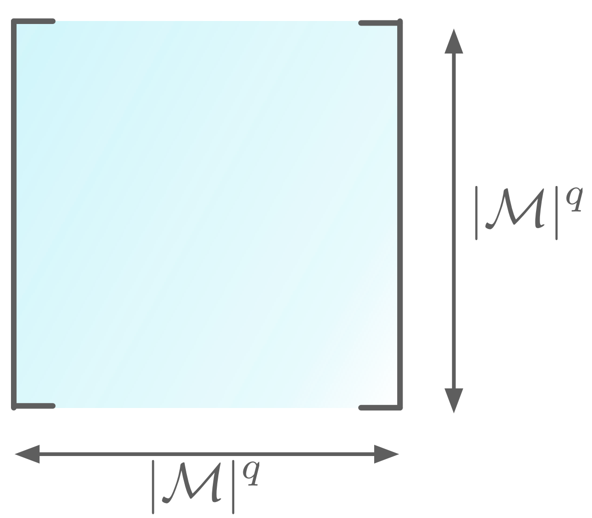

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Tricks for Computing $\mathrm{Adv}_{\mathcal{A}}(\mathsf{C}, \mathsf{C}^\star)$

To deal with the size of the distribution matrices:

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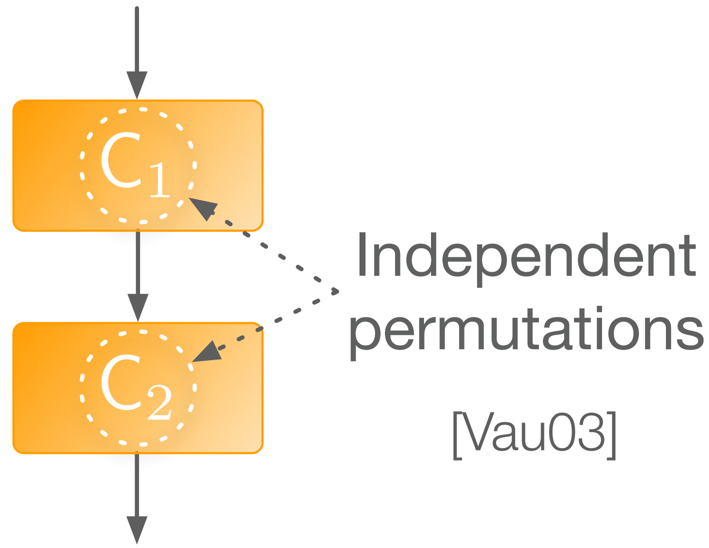

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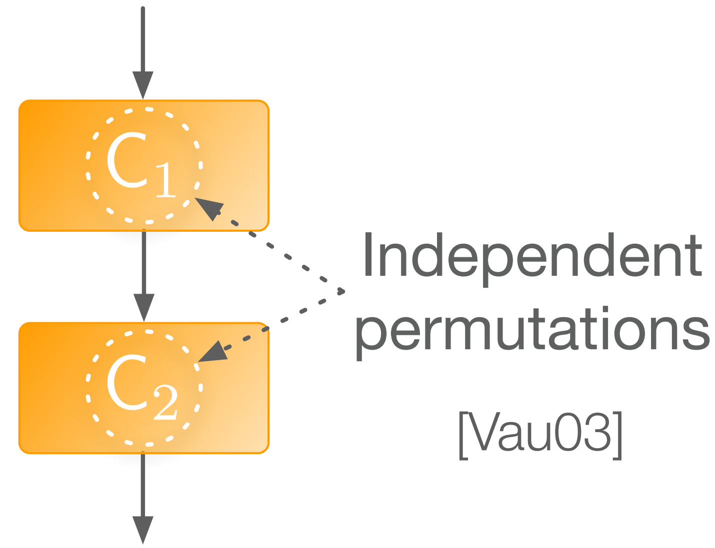


- Take advantage of the symmetries of the block cipher in order to compute the distribution matrix of each round

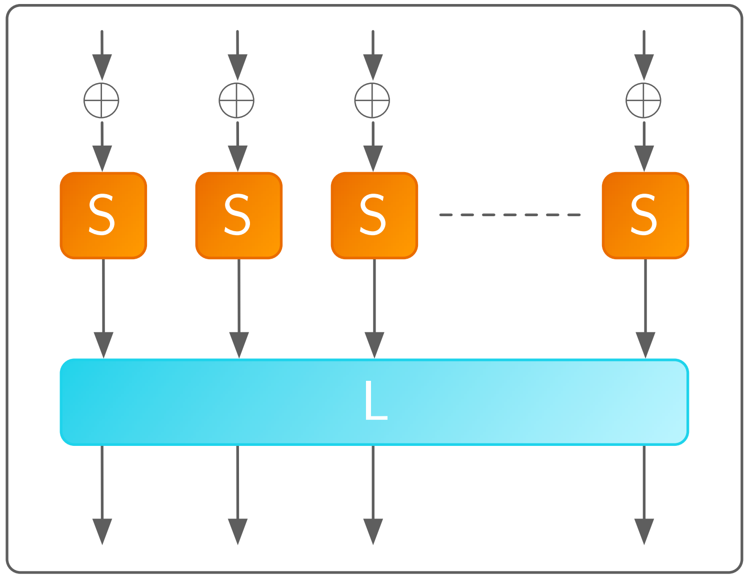
Part II: Designs and Security Proofs

- Dial C for Cipher

Description of $\mathbf{C}$

$\mathbf{C}$ corresponds to the AES where "`addRoundKeys` → `SubBytes`" is replaced by mutually independent random permutations.

AES



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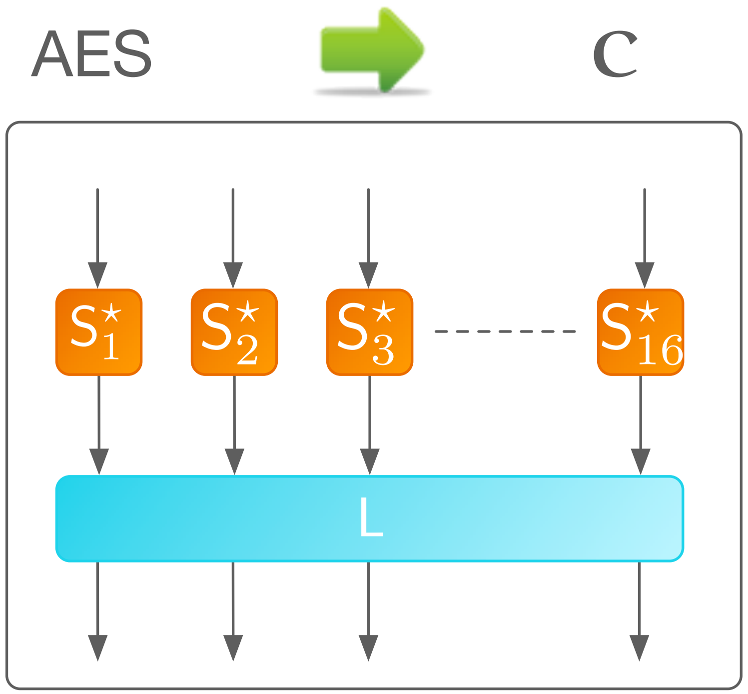
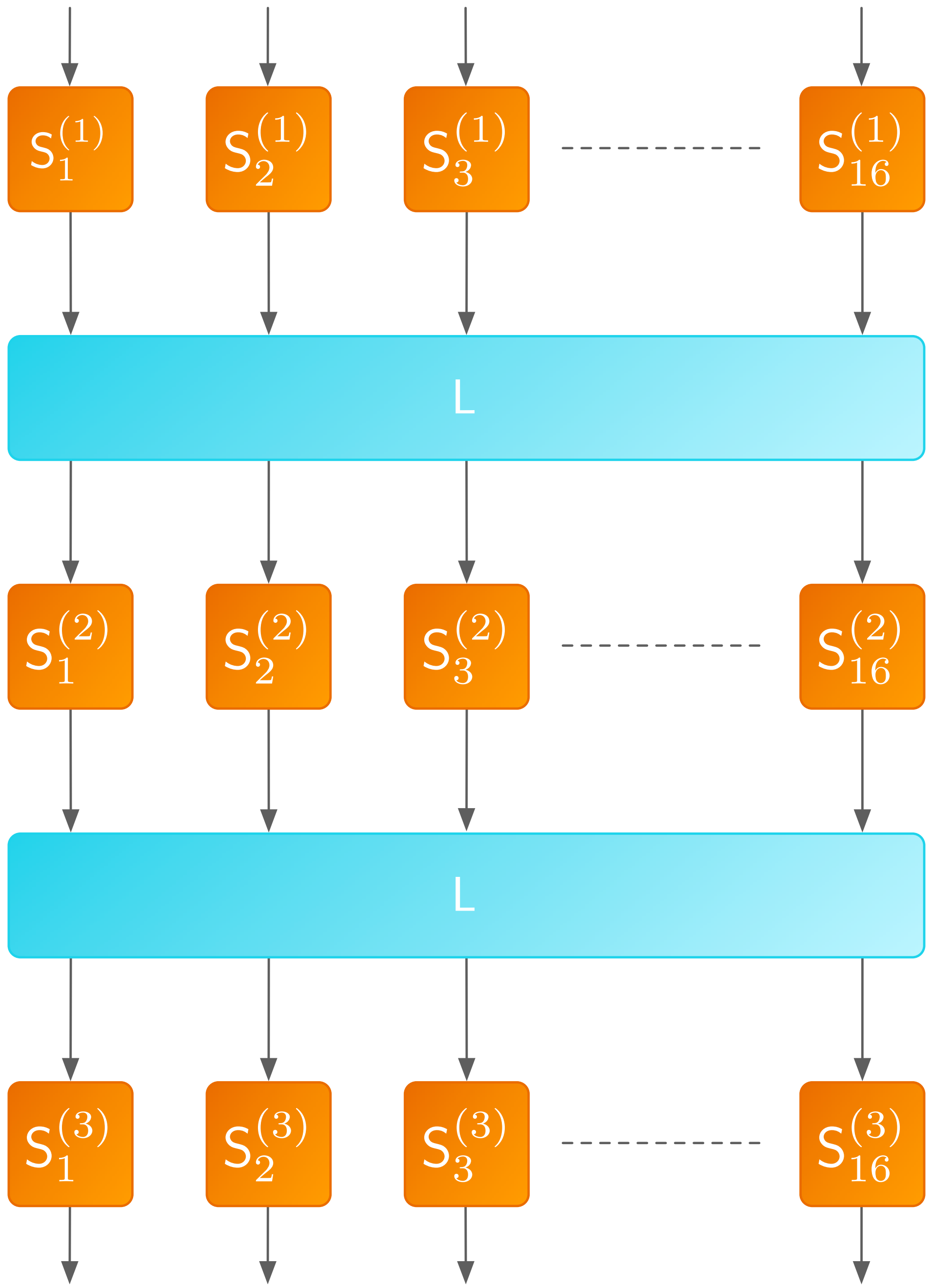


- $\mathbf{C}$ is made of 9 identical rounds, followed by a layer of substitution boxes.
- $\mathbf{C}$ uses $16 \cdot 10 = 160$ mutually independent random 8-bits substitution boxes

Computing $[\mathbf{C}]^2$

We consider a version of $\mathbf{C}$ reduced to 3 rounds:



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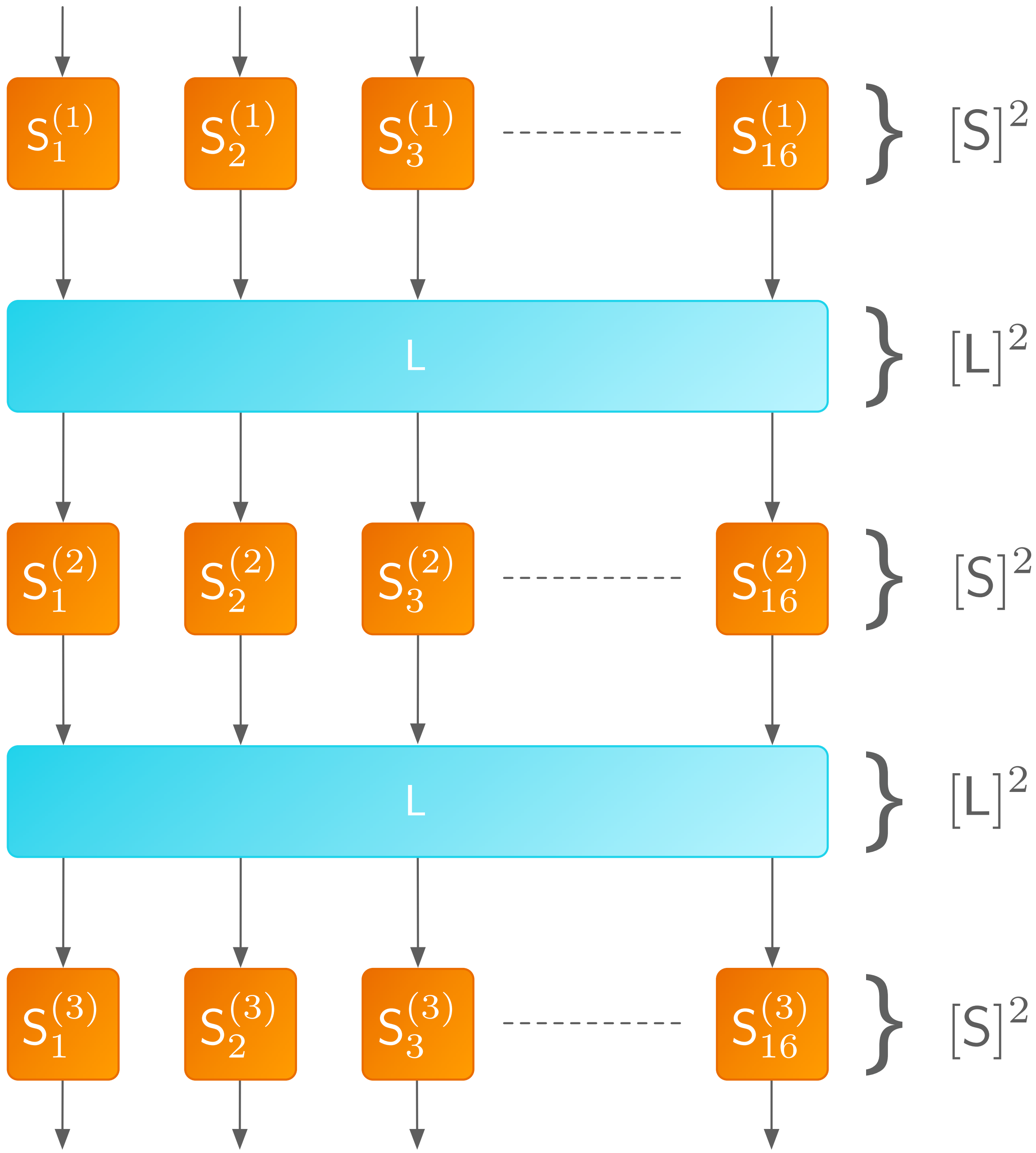

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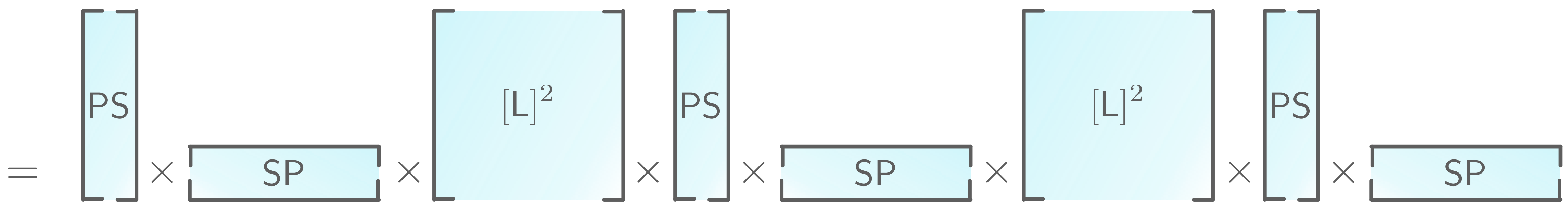

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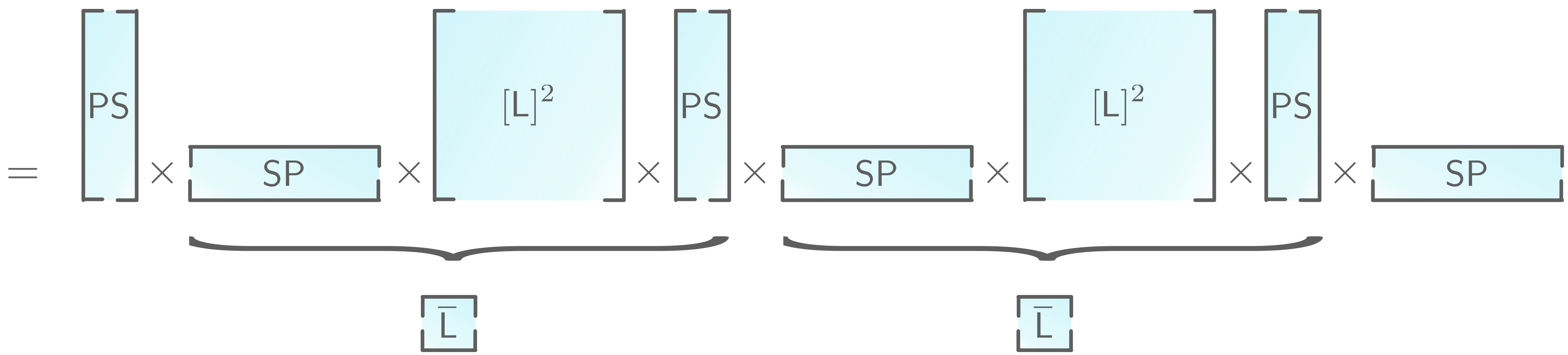

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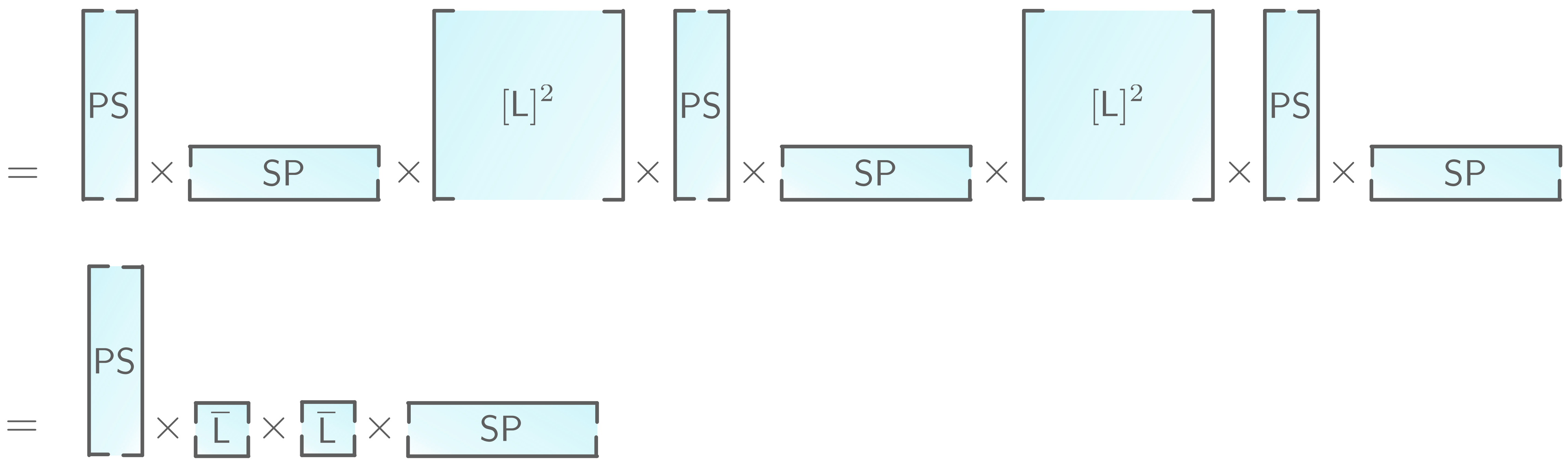

Computing $\mathrm{Adv}_{\mathcal{A}}(\mathbf{C}, \mathsf{C}^\star)$

For a r-round version of $\mathbf{C}$ we have:

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Computing the advantage of the best distinguisher (either adaptive or not) only requires operations on 625×625 matrices (instead of $2^{256} \times 2^{256}$ initially).

Values of $\mathrm{Adv}_{\mathcal{A}}(\mathbf{C}, \mathsf{C}^\star)$

r	1	2	3	4	5	6
$\mathrm{Adv}(\mathsf{C}, \mathsf{C}^\star)$	1	1	$2^{-4.0}$	$2^{-23.4}$	$2^{-45.8}$	$2^{-71.0}$

r	7	8	9	10	11	12
$\mathrm{Adv}(\mathsf{C}, \mathsf{C}^\star)$	$2^{-126.3}$	$2^{-141.3}$	$2^{-163.1}$	$2^{-185.5}$	$2^{-210.8}$	$2^{-238.9}$

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$\mathrm{Adv}(\mathsf{C}, \mathsf{C}^\star)$	1	1	$2^{-4.0}$	$2^{-23.4}$	$2^{-45.8}$	$2^{-71.0}$

r	7	8	9	10	11	12
$\mathrm{Adv}(\mathsf{C}, \mathsf{C}^\star)$	$2^{-126.3}$	$2^{-141.3}$	$2^{-163.1}$	$2^{-185.5}$	$2^{-210.8}$	$2^{-238.9}$

7 rounds of $\mathbf{C}$ are enough to obtain provable security against 2-limited adversaries

Part II: Designs and Security Proofs

- KFC: the Krazy Feistel Cipher

What about Higher Orders?

We did not manage to prove the security of $\mathbf{C}$ against higher q-limited adversaries for $q > 2$.

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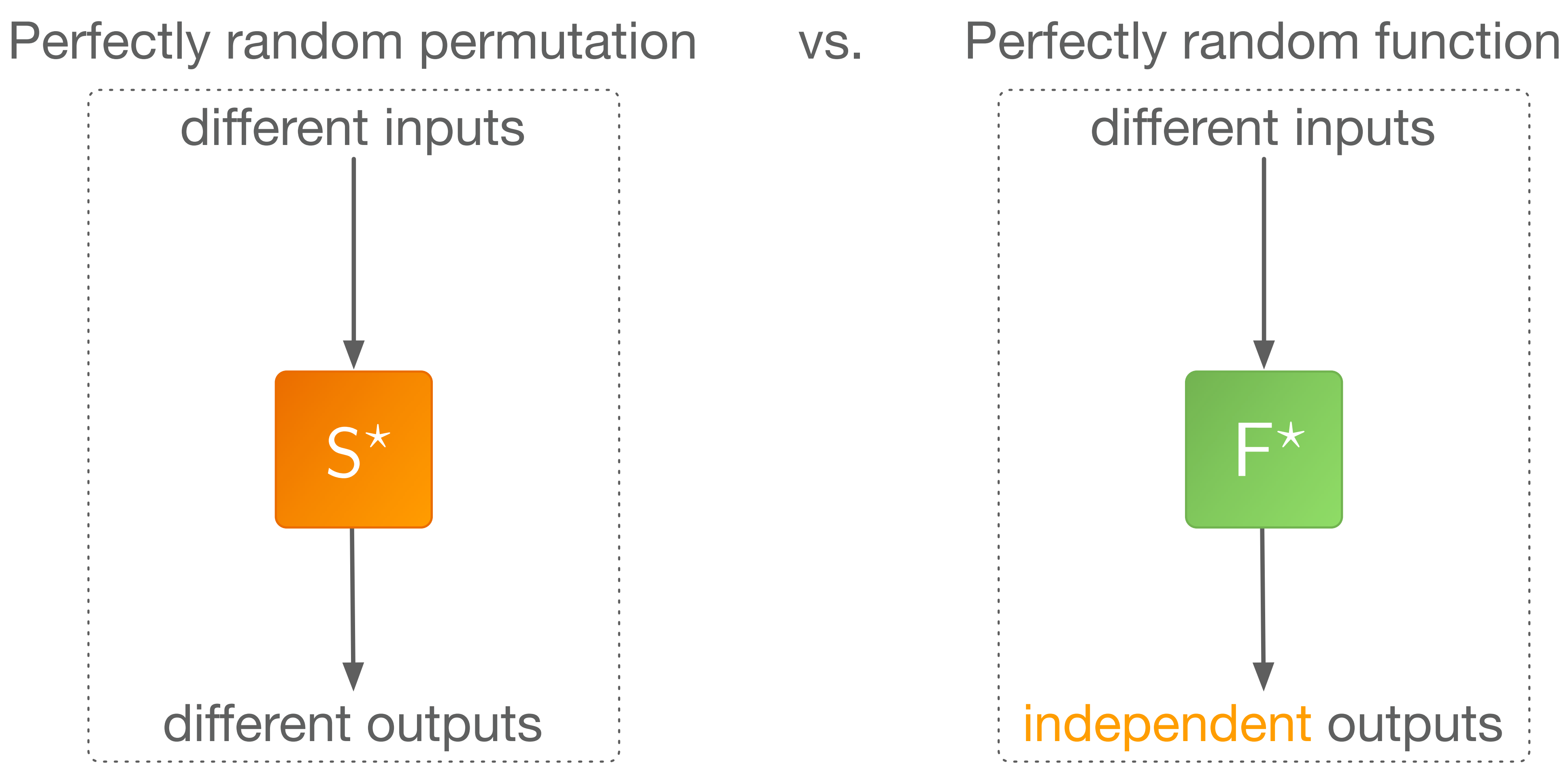
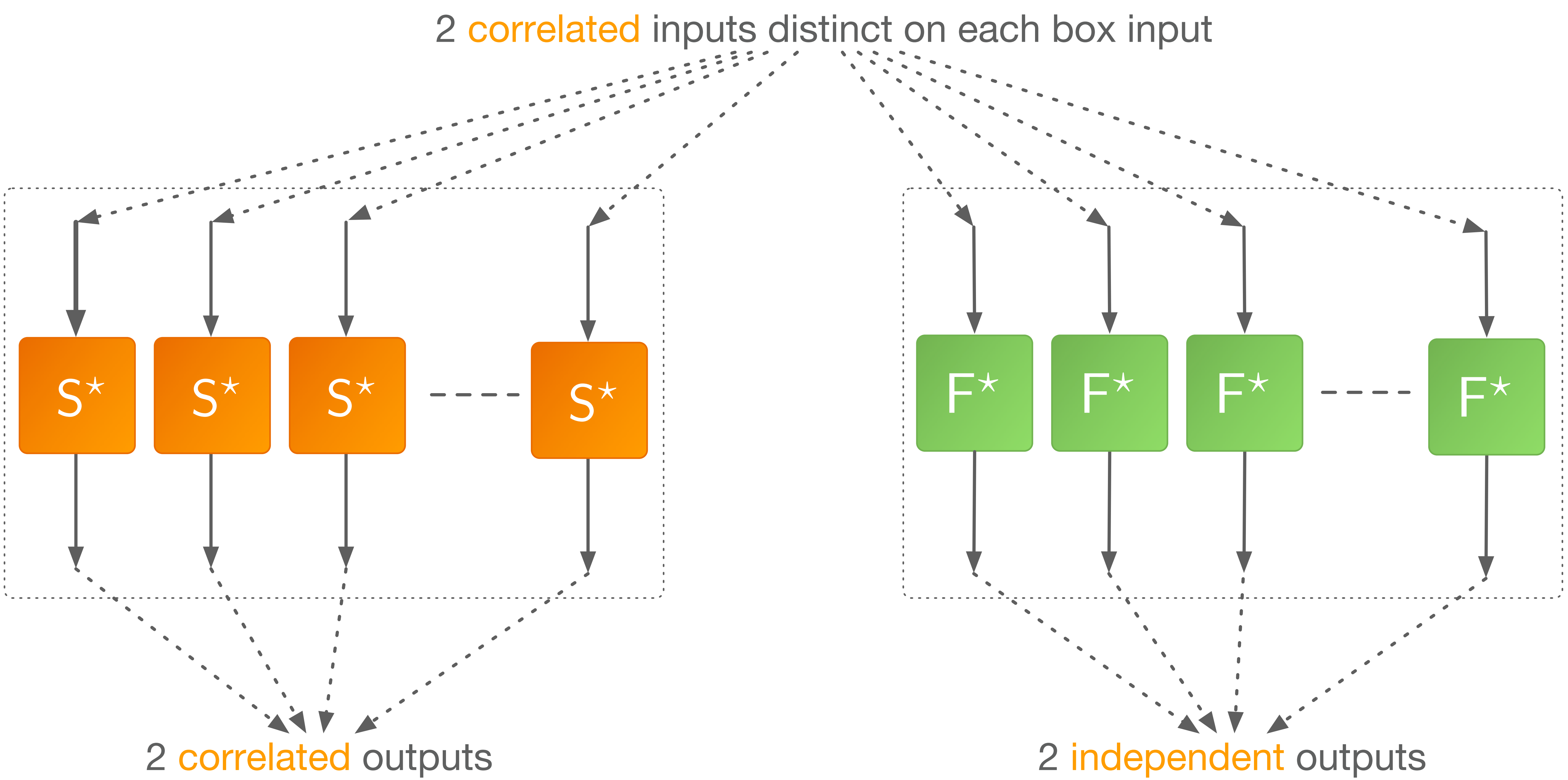
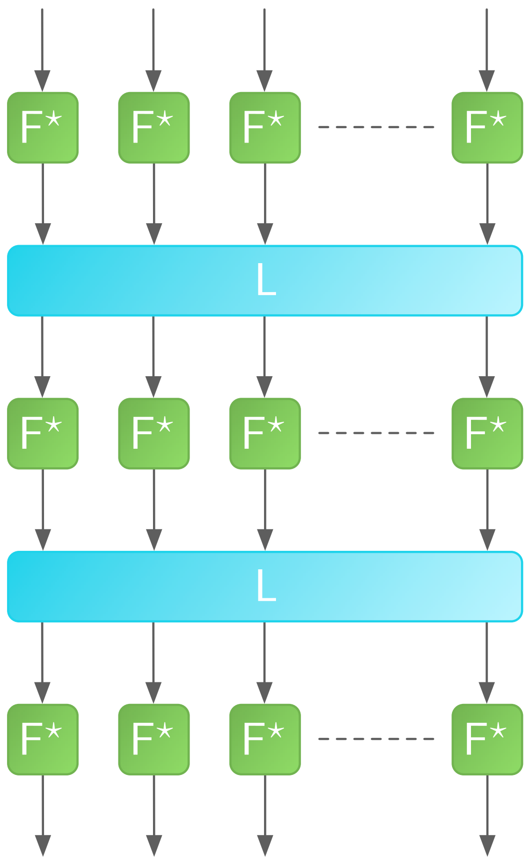
Idea: try to bound the advantage of the best q-limited adversary by that of the best (q-1)-limited adversary.



Rand. Permutations vs. Rand. Functions

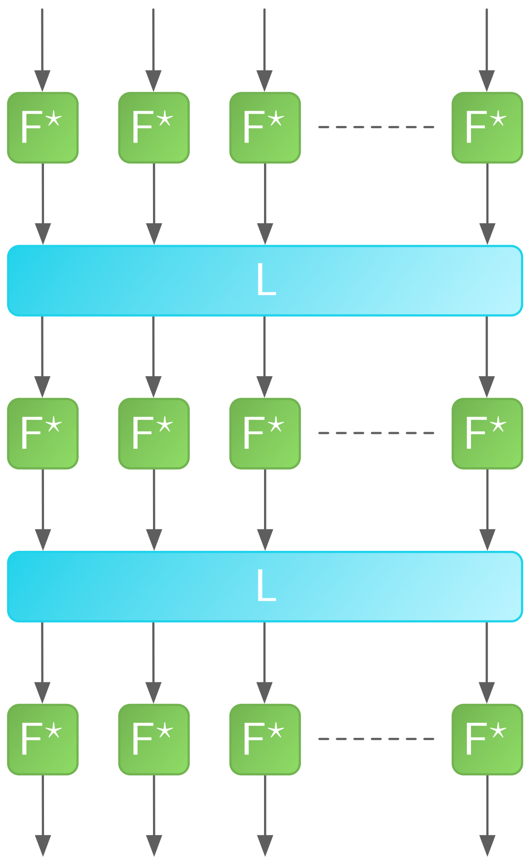


Towards a New Construction



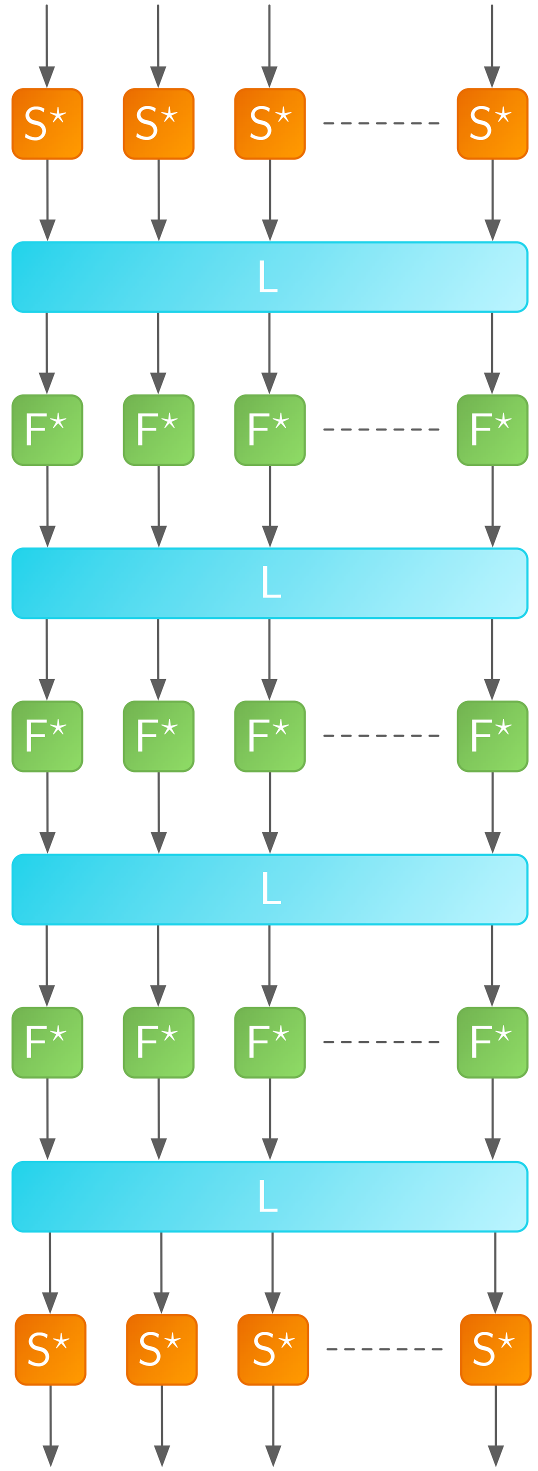
Towards a New Construction

- Non negligible risk of collision after a F-box



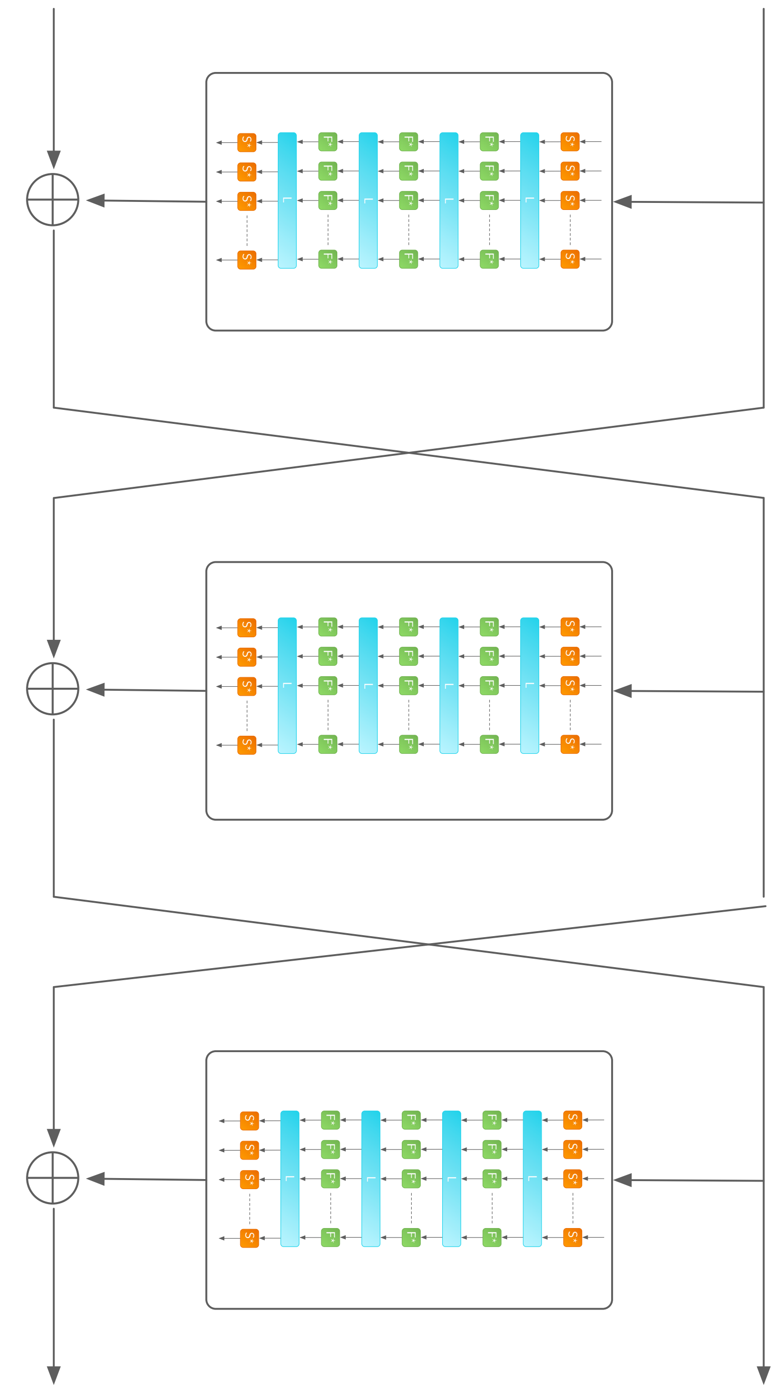
Towards a New Construction

- Non negligible risk of collision after a F-box
- Use the “sandwich technique” to obtain (almost) pairwise independent inputs before the layer of random functions.



Towards a New Construction

- Non negligible risk of collision after a F-box
- Use the “sandwich technique” to obtain (almost) pairwise independent inputs before the layer of random functions.
- The construction is not invertible. We plug it in a Feistel scheme.



Results obtained on KFC

- With this approach, we manage to prove the security against adversaries up to the order 70 (for an unreasonable set of parameters).
- The bounds are not tight at all   it is certainly possible to improve our results.

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Conclusion

"[...] the methodology of provable security has become unavoidable in designing and evaluating new schemes"

[JSe03]

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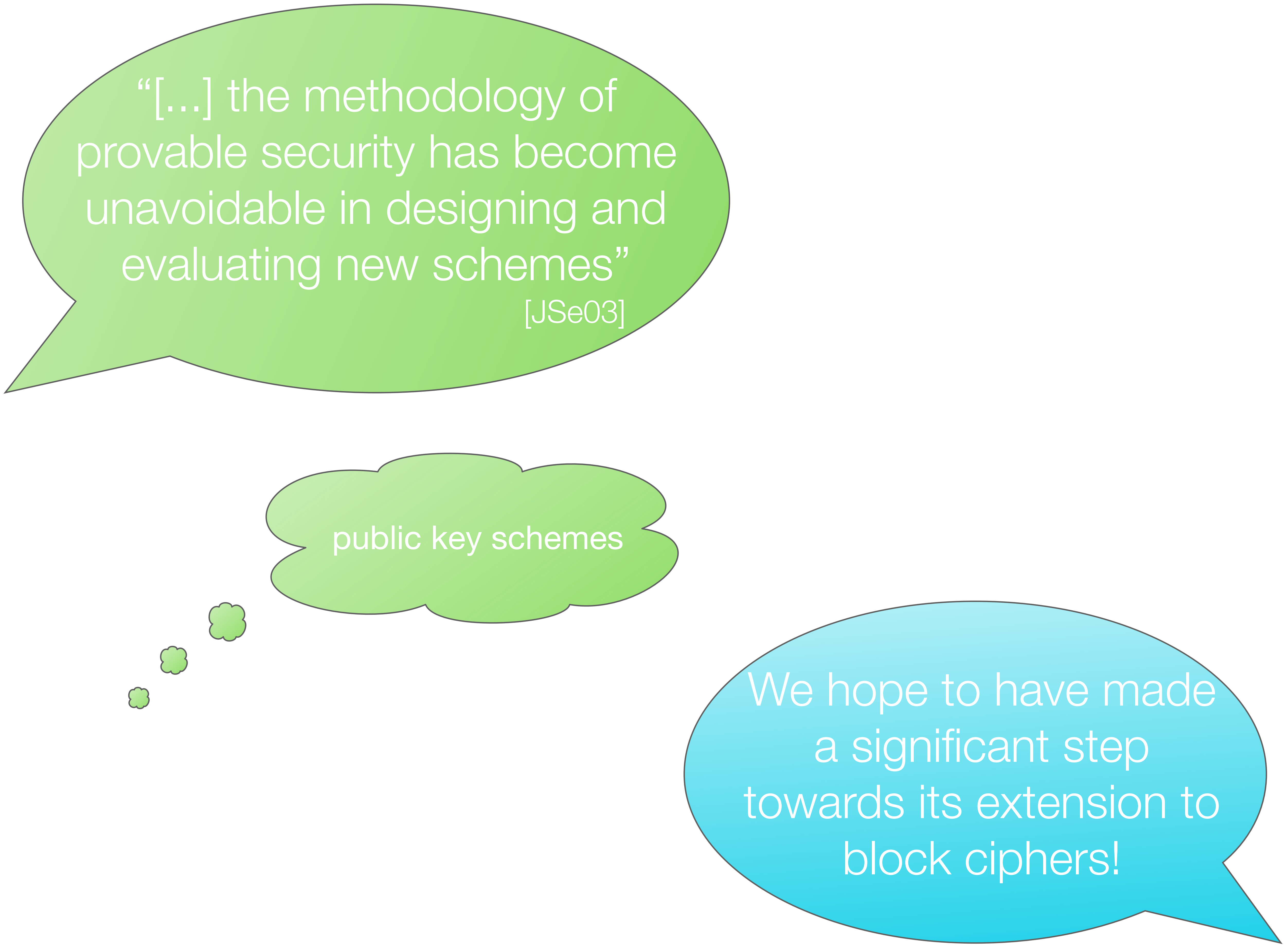
public key schemes


"[...] the methodology of provable security has become unavoidable in designing and evaluating new schemes"
[JSe03]
public key schemes
We hope to have made a significant step towards its extension to block ciphers!

Thank you for your attention!

☺

Publications

[BVicits08] *The Complexity of Distinguishing Distributions*
Joint work with Serge Vaudenay
Published in the proceedings of ICITS 08 (Calgary, Canada)

[BSVsac07] *Linear Cryptanalysis of Non Binary Ciphers (with an application to* SAFER*)*
Joint work with Jacques Stern & Serge Vaudenay
Published in the proceedings of SAC 07 (Ottawa, Canada)

[BFa06] KFC - *The Krazy Feistel Cipher*
Joint work with Matthieu Finiasz
Published in the proceedings of Asiacrypt 06 (Shangai, China)

[BFsac06] *Dial* C *for Cipher*
Joint work with Matthieu Finiasz
Published in the proceedings of SAC 06 (Montreal, Canada)

[BVsac05] *Proving the Security of the* AES *Substitution-Permutation Network*
Joint work with Serge Vaudenay
Published in the proceedings of SAC 05 (Kingston, Canada)

[BJVa04] *How Far Can We Go Beyond Linear Cryptanalysis?*
Joint work with Pascal Junod & Serge Vaudenay
Published in the proceedings of Asiacrypt 04 (Jeju Island, Korea)