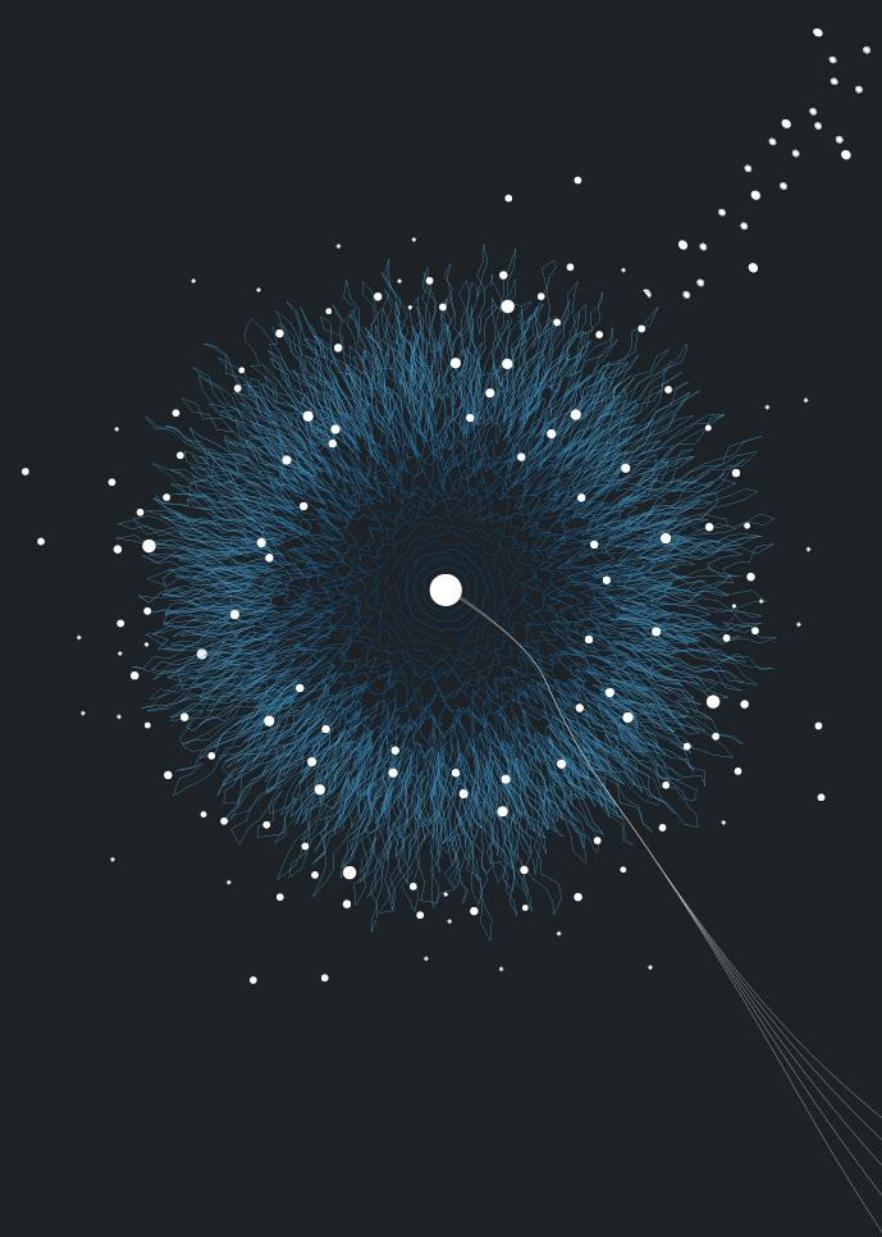


EEMCS - SCS

METAHEURISTIC ALGORITHMS IN CRYPTOGRAPHY

GUEST LECTURE – SEPTEMBER 21, 2026

LUCA MARIOT



ABOUT ME



Dr. Luca Mariot

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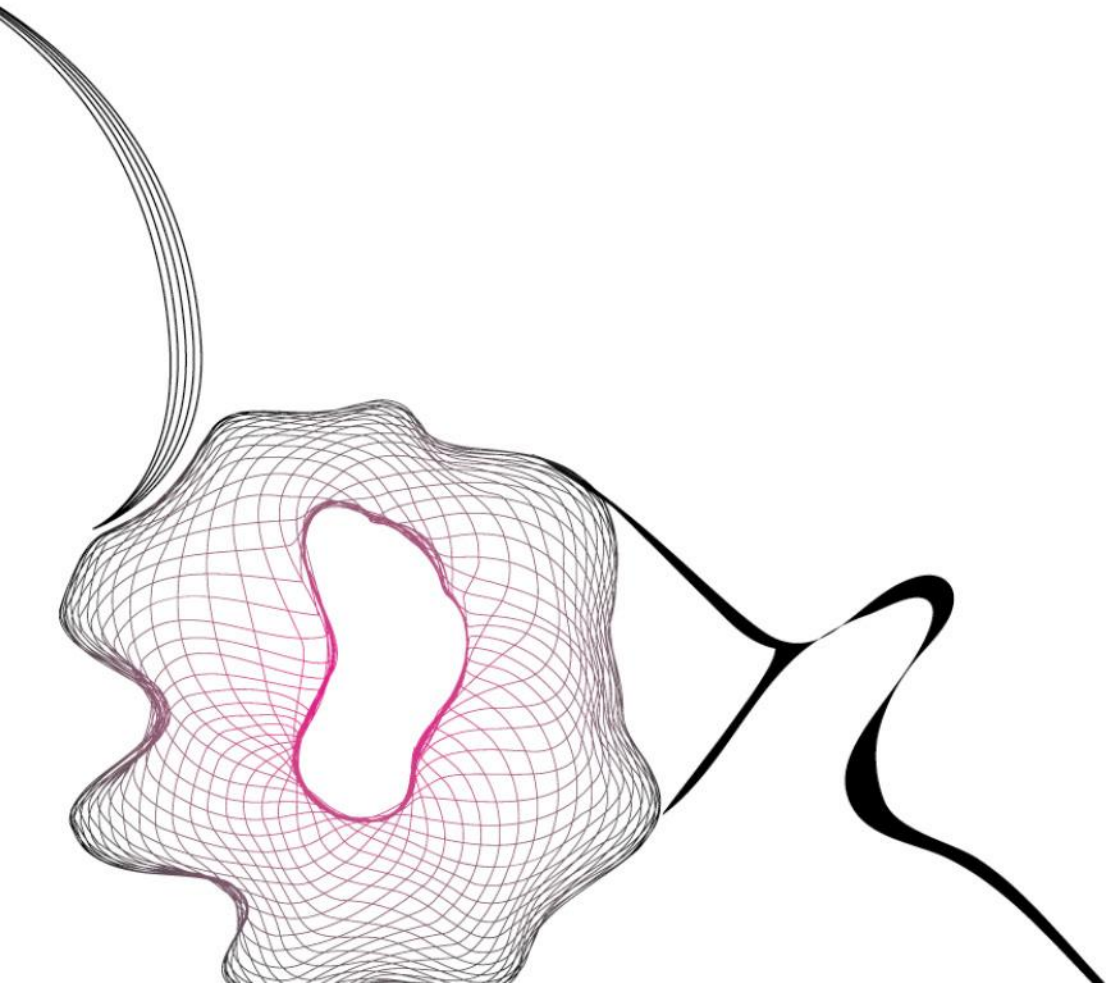
Research Interests:

- Cryptography
- Cellular Automata
- Evolutionary Computing
- Boolean functions
- Machine Learning

Website: <https://lucamariot.org>

SUMMARY

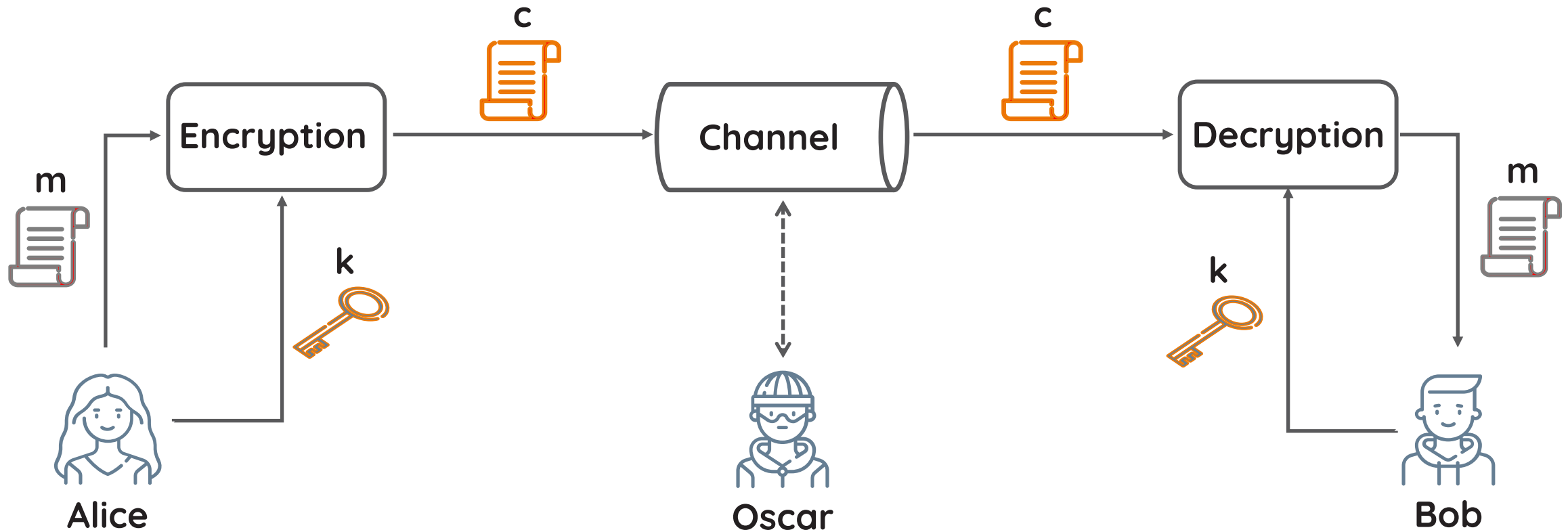
- AI-driven design in symmetric cryptography
- EA for Boolean Functions
- EA for S-boxes
- Neuroevolution for Side-Channel Analysis



AI-DRIVEN DESIGN IN SYMMETRIC CRYPTOGRAPHY



SYMMETRIC-KEY ENCRYPTION SCENARIO

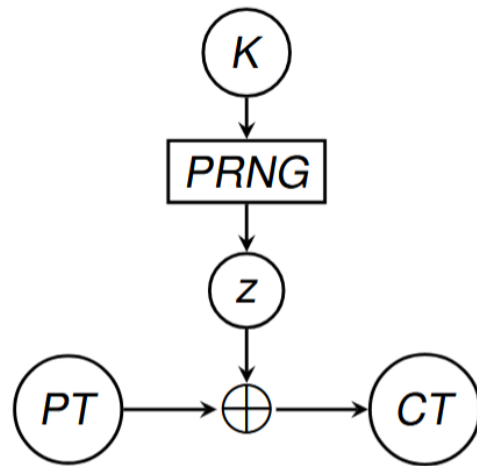


m: plaintext message

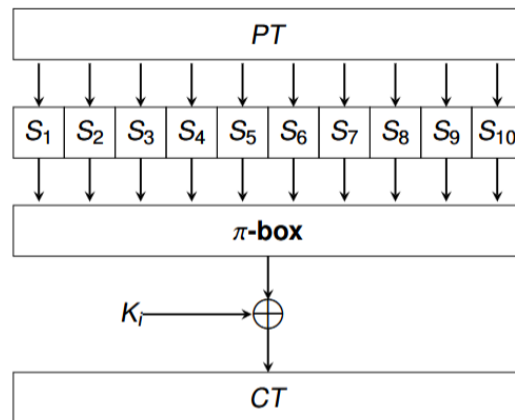
k: encryption/decryption key

c: ciphertext message

PRIMITIVES IN SYMMETRIC CRYPTOGRAPHY



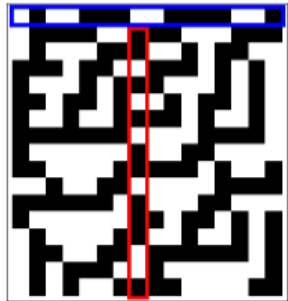
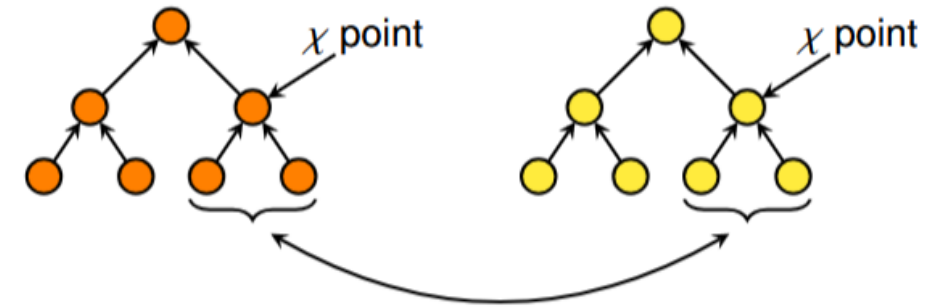
(a) Stream cipher



(b) Block cipher

- Symmetric ciphers require several low-level **primitives**:
 - Pseudorandom number generators (PRNG)
 - Boolean functions $f : \{0, 1\}^n \rightarrow \{0, 1\}$
 - S-boxes $F : \{0, 1\}^n \rightarrow \{0, 1\}^n$
 - Diffusion layers, ...
- Classic methods to build them: **algebraic constructions** [4]

AI-DRIVEN DESIGN OF CRYPTO PRIMITIVES



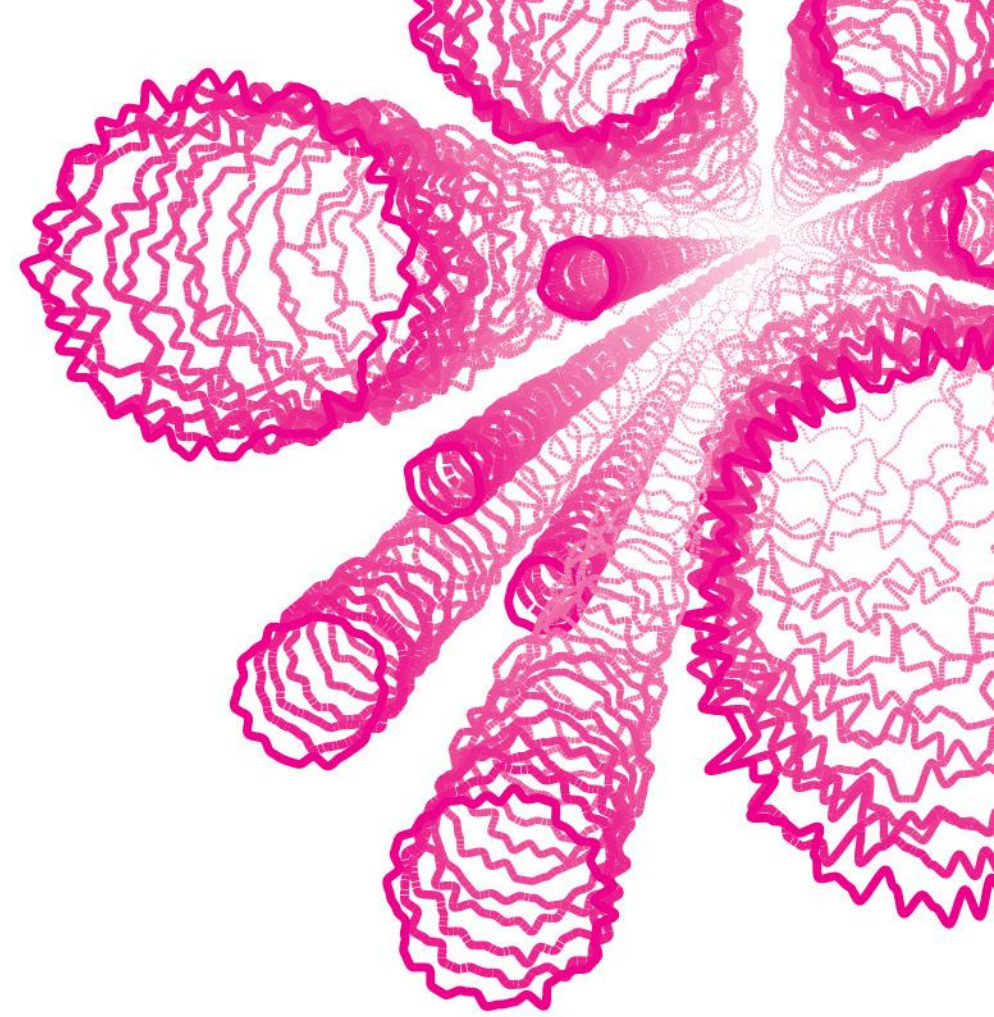
1 0 0 0 0 1 0 1

$\Downarrow F : \{0,1\}^n \rightarrow \{0,1\}^m$

1 0 0 1 1 0

- Algebraic constructions are not flexible
- **AI-driven approach:** support the cipher designer in designing the primitives with:
 - Metaheuristic optimization techniques (Evolutionary Algorithms, ...) [6]
 - Nature-inspired computational models (Cellular Automata, ...) [11]

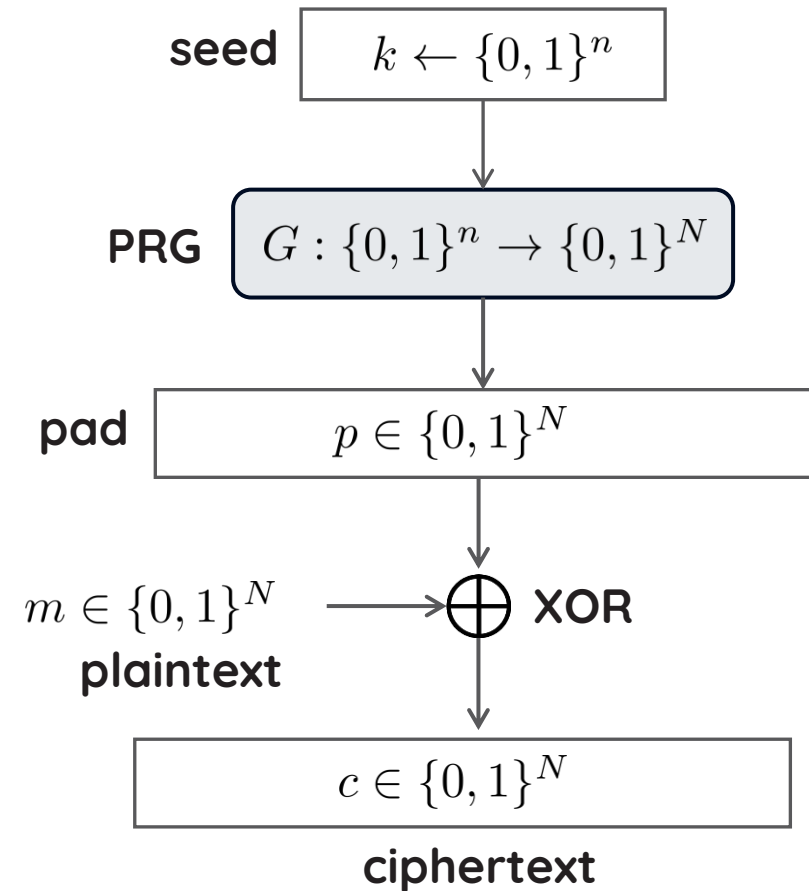
EVOLUTIONARY ALGORITHMS FOR BOOLEAN FUNCTIONS



STREAM CIPHERS - ENCRYPTION

- **Idea:** Alice encode all messages as stream of bits, $m \in \{0, 1\}^N$
- A **Pseudo Random Generator (PRG)** is used to generate a **pad** $p \in \{0, 1\}^N$ of the same length of the message [7]
- The seed of the PRG is the **key** $k \leftarrow \{0, 1\}^n$
- **Encryption:** Bitwise XOR between message and pad

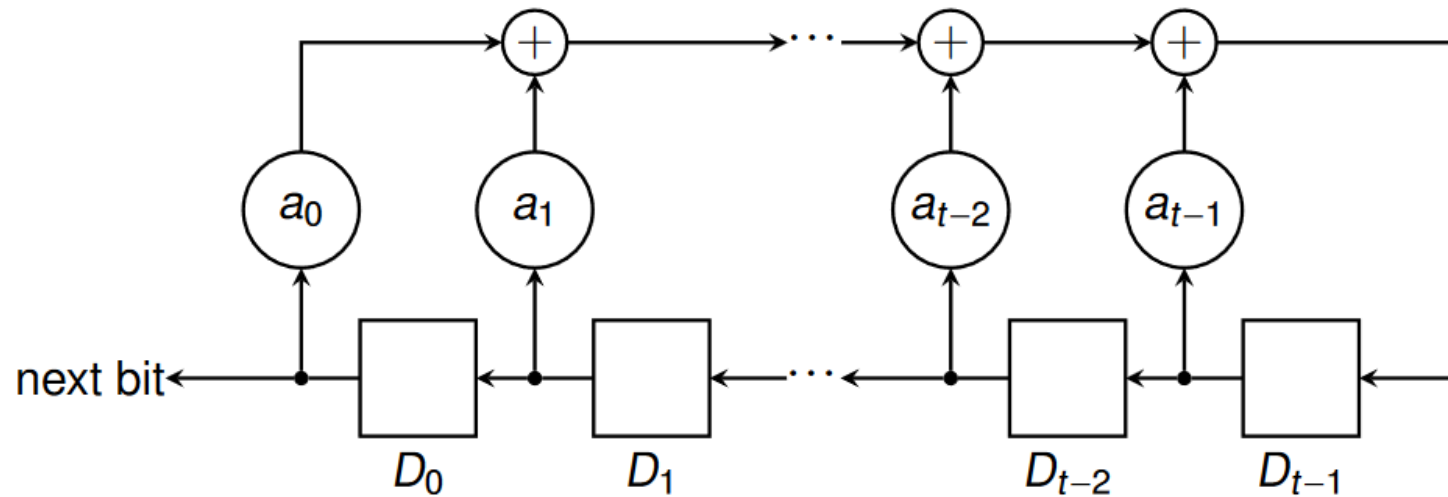
$$c_i := m_i \oplus p_i, \text{ for all } i \in \{1, \dots, N\}$$



LINEAR FEEDBACK SHIFT REGISTERS (LFSR)

- A device computing a *linear recurring sequence* (LRS)

$$z_i = a_0 \cdot z_{i-t} \oplus a_1 \cdot z_{i-t+1} \oplus \cdots \oplus a_{t-1} \cdot z_{i-1} \quad a_j, z_j \in \{0, 1\}$$



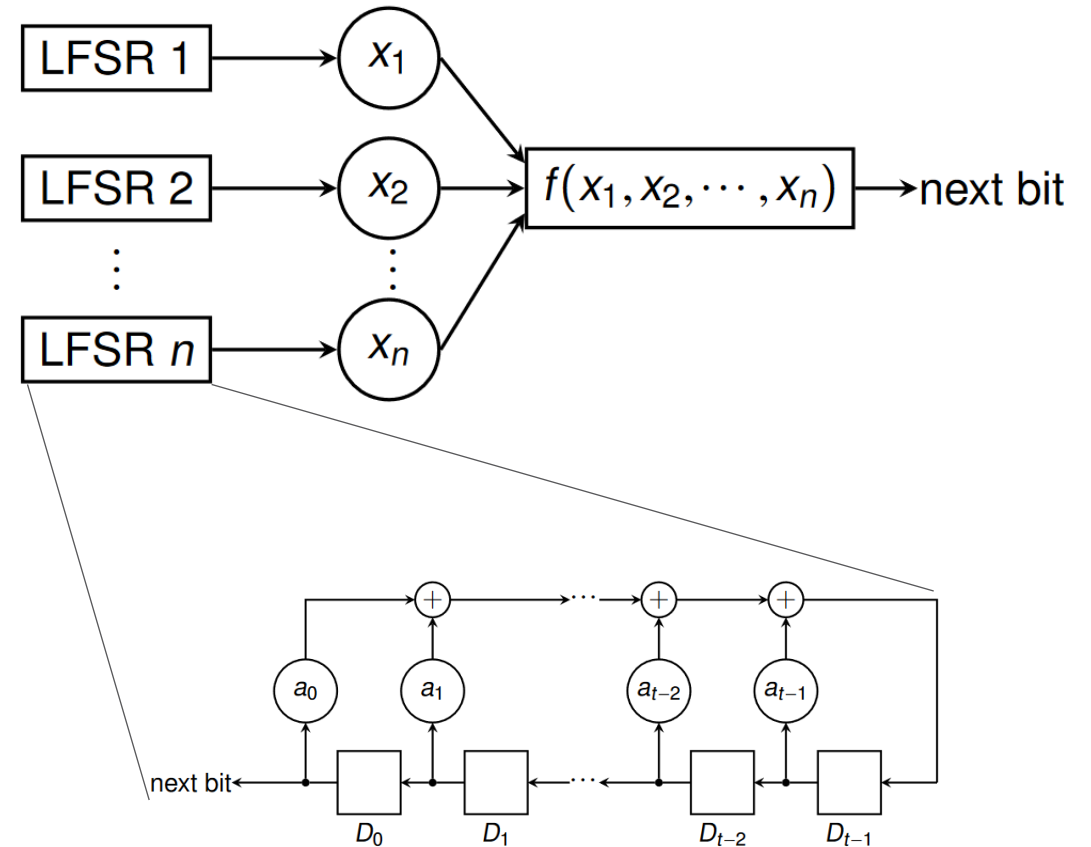
- Problem:** very weak as a cryptographic PRG [4, 7]

IMPROVING LFSR – COMBINER MODEL FOR PRG

- **Idea:** use n LFSRs instead of one [4]
- LFSRs outputs *combined* using a Boolean function:

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

- Security of the PRG: **cryptographic properties of** $f : \{0, 1\}^n \rightarrow \{0, 1\}$



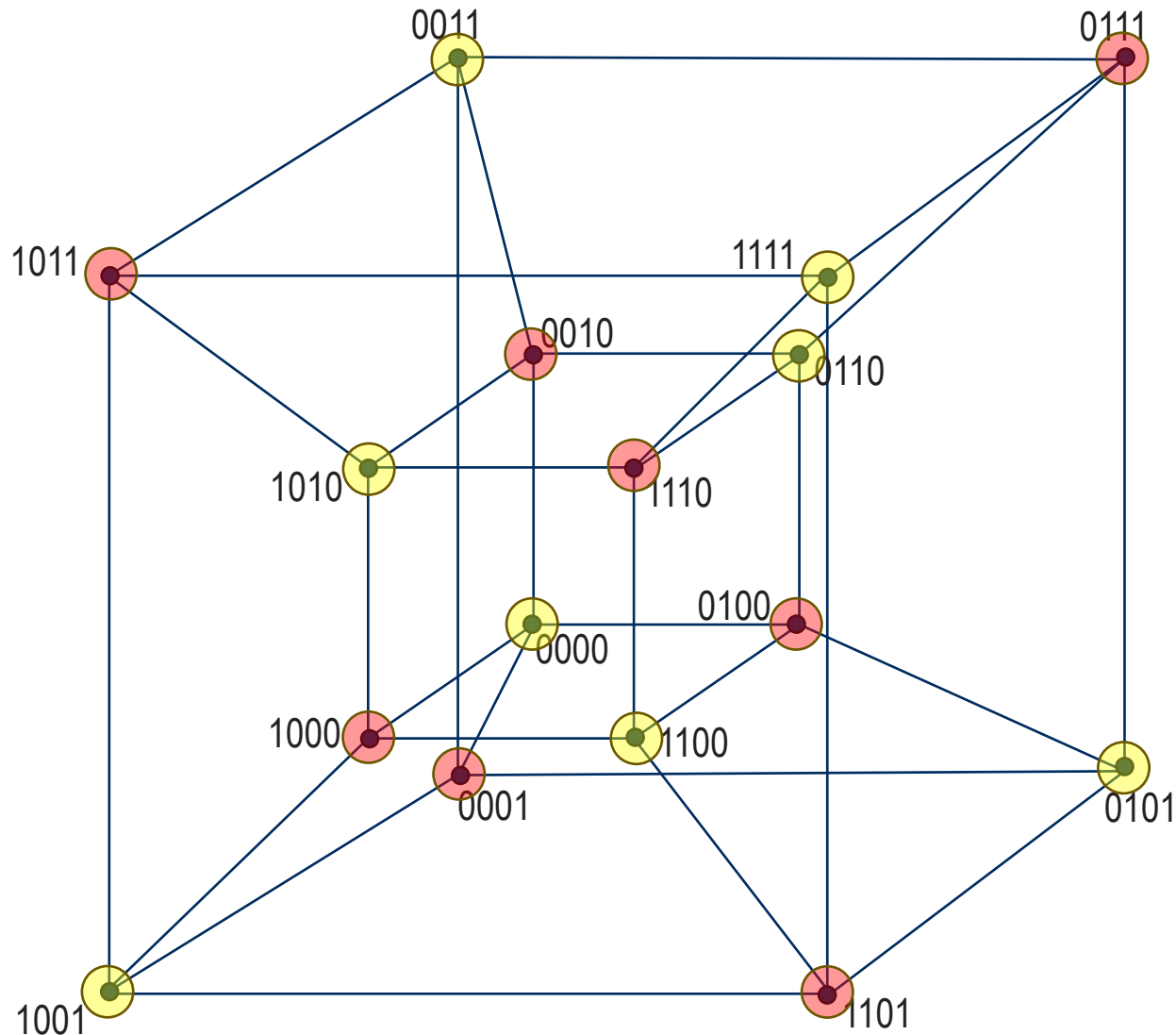
BOOLEAN FUNCTIONS

- A mapping $f : \{0, 1\}^n \rightarrow \{0, 1\}$ represented by a *truth table*

(x_1, x_2, x_3)	000	001	010	011	100	101	110	111
$f(x_1, x_2, x_3)$	0	1	1	0	1	0	1	0

- The function must satisfy some properties to resist specific attacks [4]:
 - **Balancedness** (equal number of 0s and 1s)
 - High **Nonlinearity** (Hamming distance from linear functions)
 - High algebraic degree, etc. ...

NONLINEARITY – GEOMETRIC INTUITION



- **Example:** $n = 2$ variables (truth tables of $2^2 = 4$ bits, 16 functions in total)
- Linear functions and complements:

$a_1x_1 \oplus a_2x_2$	TT	TT $\oplus 1$
0	0000	1111
x_1	0011	1100
x_2	0101	1010
$x_1 \oplus x_2$	0110	1001

- Hamming distance from linear functions: **1**, e.g.: $f(x_1, x_2) = x_1x_2$

WALSH TRANSFORM

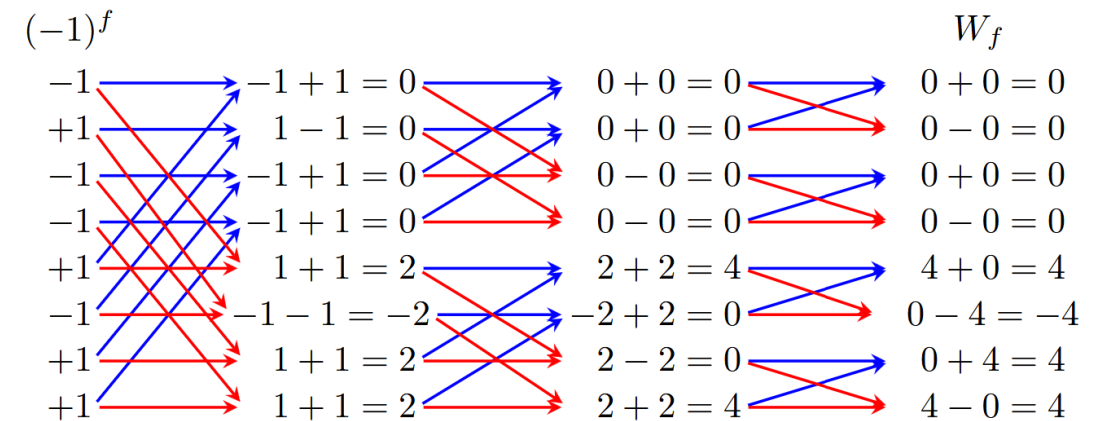
$$W_f(a) = \sum_{x \in \mathbb{F}_2^n} (-1)^{f(x) \oplus a \cdot x}$$

- Measures correlation with *linear* functions:

$$L_a(x) = a \cdot x = a_1 x_1 \oplus \dots \oplus a_n x_n,$$

- Can be computed in $\mathcal{O}(n2^n)$ steps (FFT-like algorithm)
- Nonlinearity is equal to:

$$nl_f = 2^{n-1} - \frac{1}{2} \max_{a \in \mathbb{F}_2^n} |W_f(a)|$$

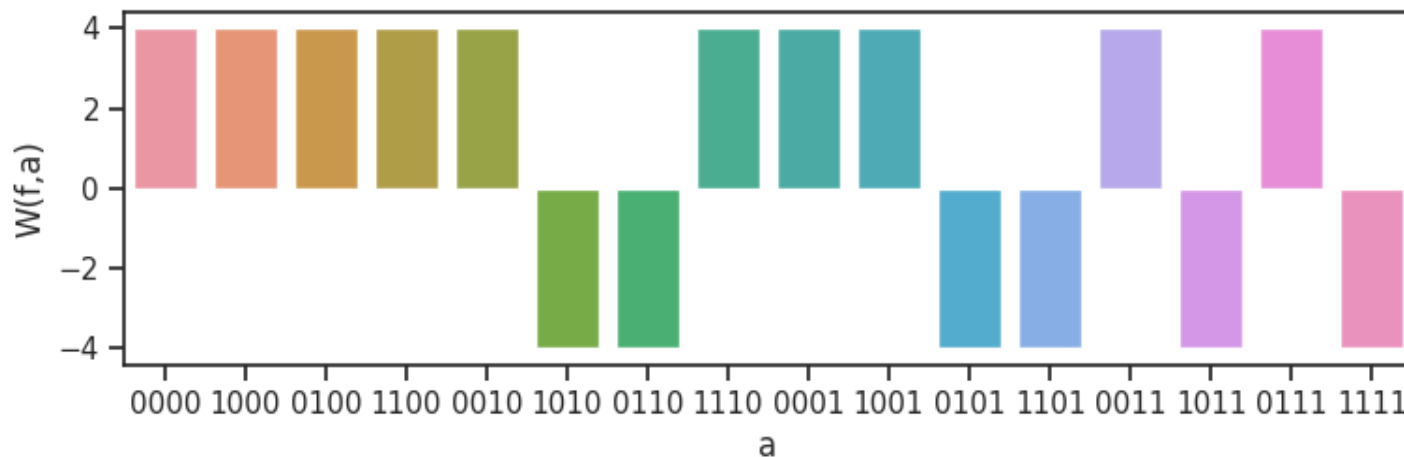


Example of Fast Walsh Transform calculation with 3-variable functions

BENT FUNCTIONS



- Only two spectral values: $W_f(a) \in \{-2^{\frac{n}{2}}, +2^{\frac{n}{2}}\}$
- **PRO:** highest possible nonlinearity $nl_f = 2^{n-1} - 2^{\frac{n}{2}-1}$
- **CONS:** unbalanced, exist only for n even [4]



Example of Walsh spectrum of a bent function in 4 variables

OPTIMIZATION PROBLEM

- Given $n \in \mathbb{N}$, how do we fill the table so that f is balanced and highly nonlinear?

(x_1, x_2, x_3)	000	001	010	011	100	101	110	111
$f(x_1, x_2, x_3)$	?	?	?	?	?	?	?	?

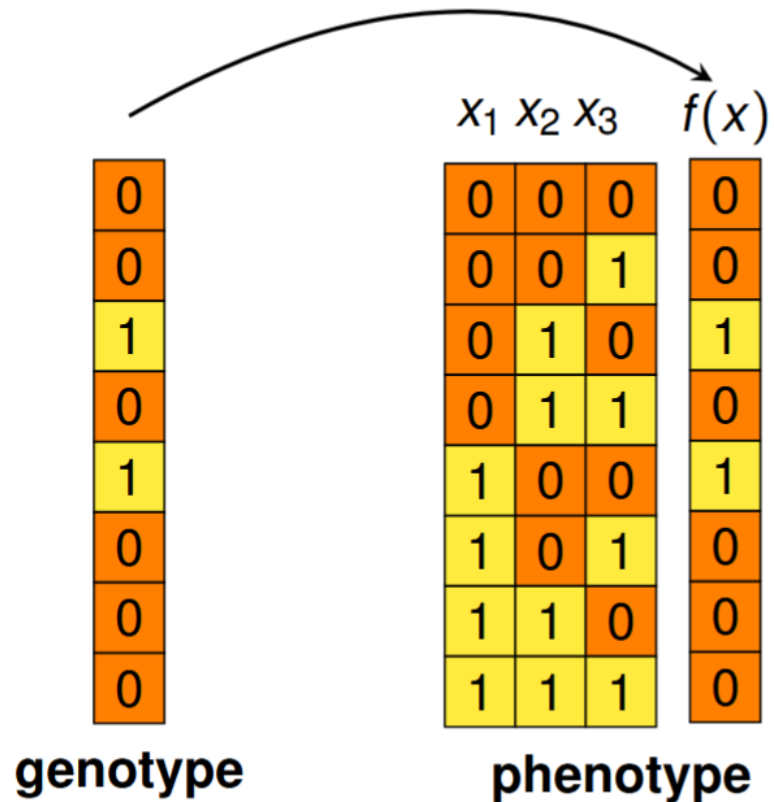
$$f^* = \operatorname{argmax}_{f: \{0,1\}^n \rightarrow \{0,1\}} (BAL(f) + NL(f))$$

- The truth table has size 2^n so there are 2^{2^n} combinations

n	3	4	5	6	7	8
2^{2^n}	256	65536	$4.3 \cdot 10^9$	$1.8 \cdot 10^{19}$	$3.4 \cdot 10^{38}$	$1.2 \cdot 10^{77}$

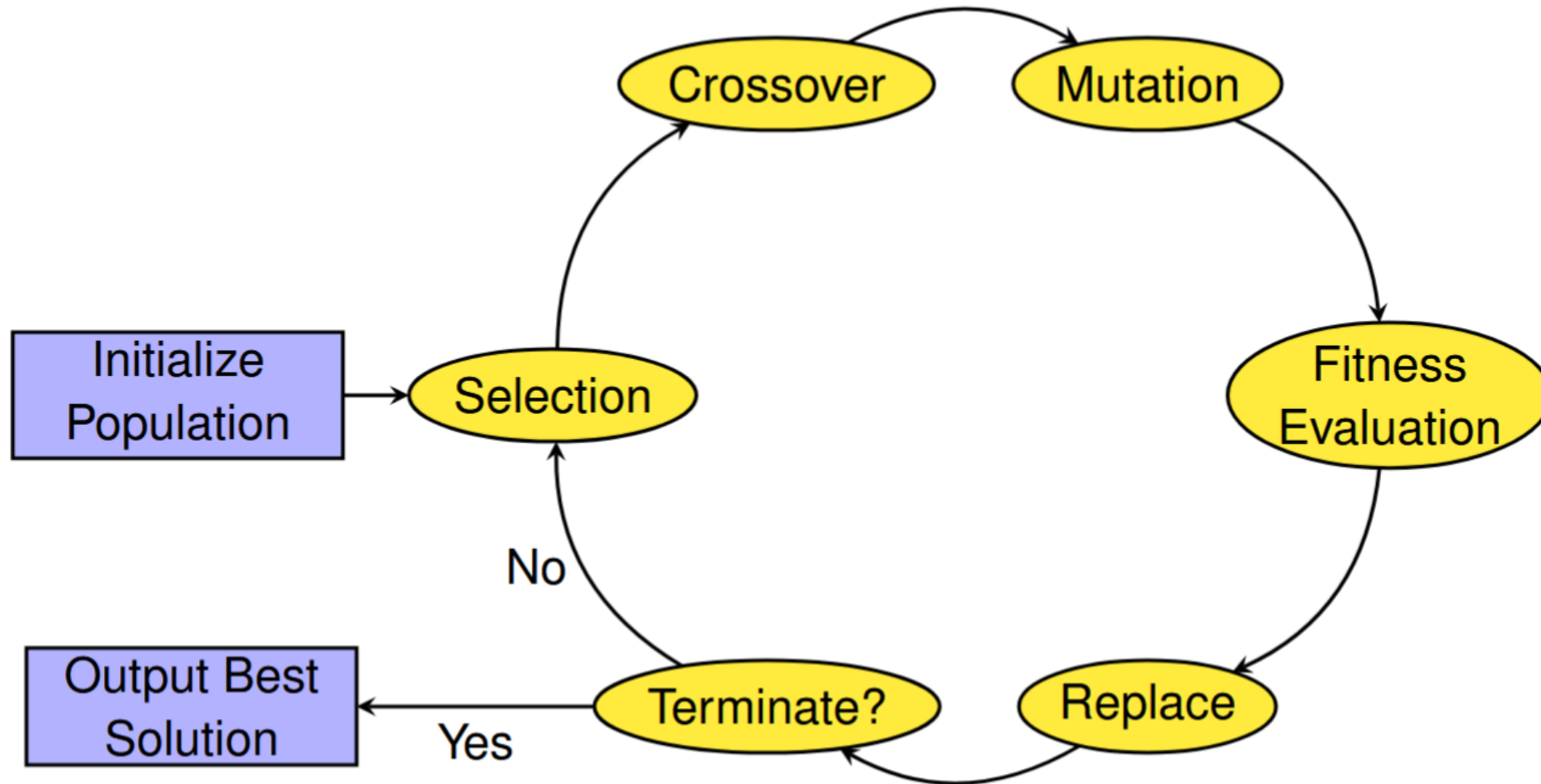
- Exhaustive search is already unfeasible for $n > 5$!

GENETIC ALGORITHMS (GA)

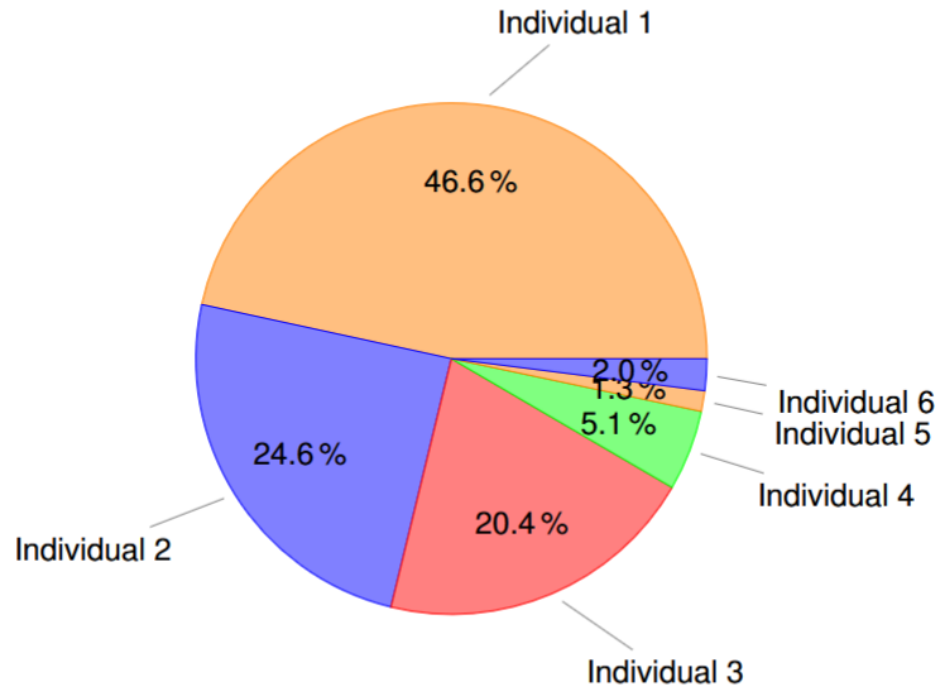


- Introduced by John Holland (1975)
- Optimization algorithms loosely based on evolutionary principles
- **GA genotype:** fixed-length bitstrings
- **phenotype:** truth table of f [14]

THE EA LOOP



SELECTION

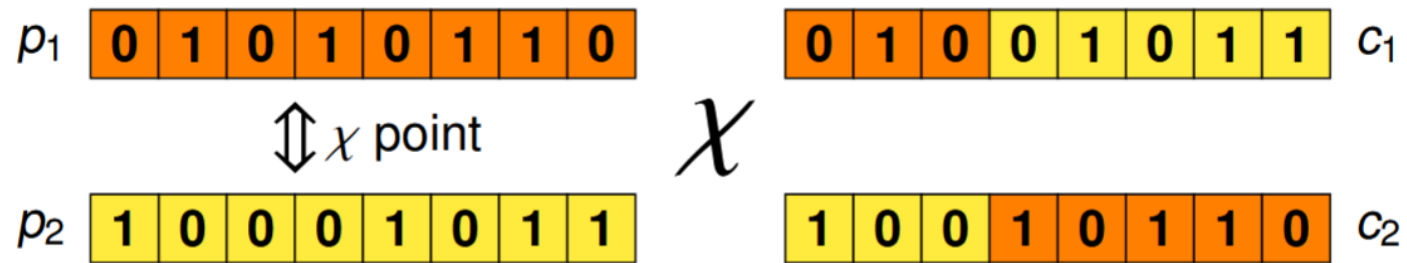


- **Roulette-Wheel:** selection probability proportional to individual's fitness
- **Tournament:** select the fittest individual from a random sample of t individuals
- In general: tournaments work better

CROSSOVER

- **Idea:** recombine the genes of two parents (**Exploitation**)

GA Example: One-Point Crossover

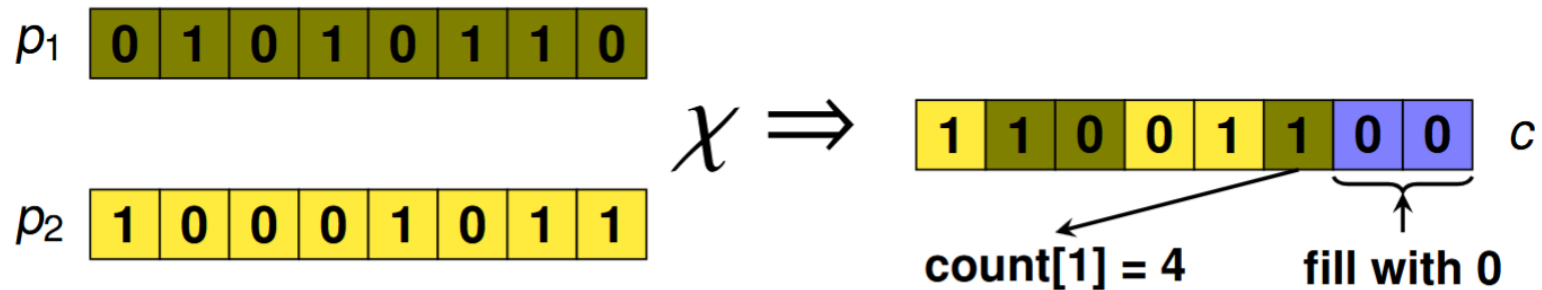


- **Problem:** how do we ensure balancedness for cryptography?
- We could optimize it in the fitness function...

BALANCED CROSSTOVERS

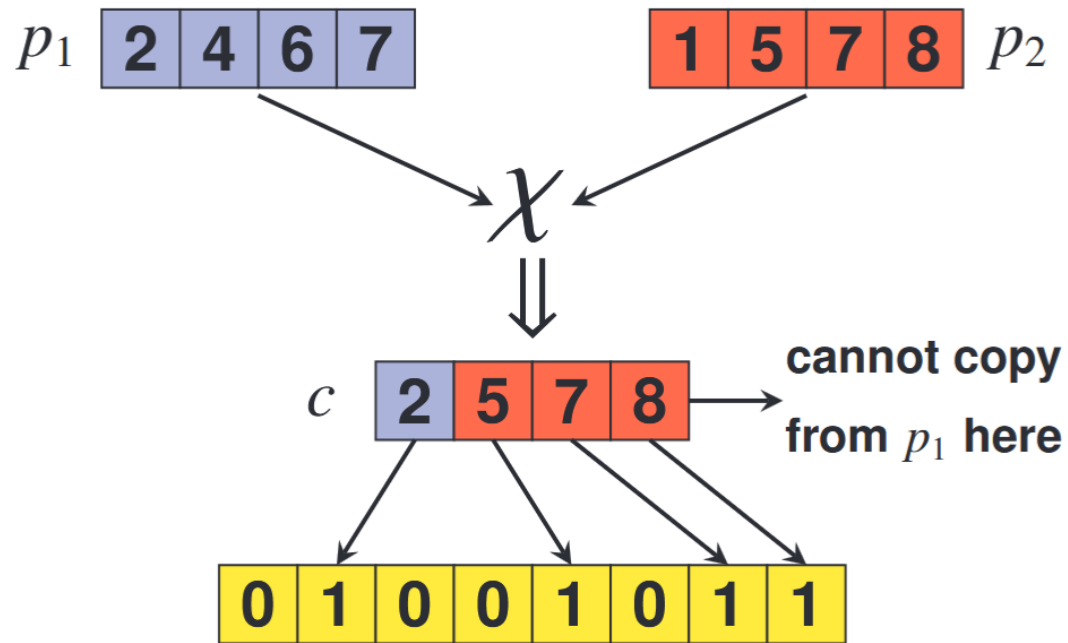
- **Idea:** use **counters** to keep track of the numbers of 1s in the child [9,]

GA Example: Counter-based Crossover



- If we start from balanced parents, we get balanced children

BALANCED CROSSTOVERS



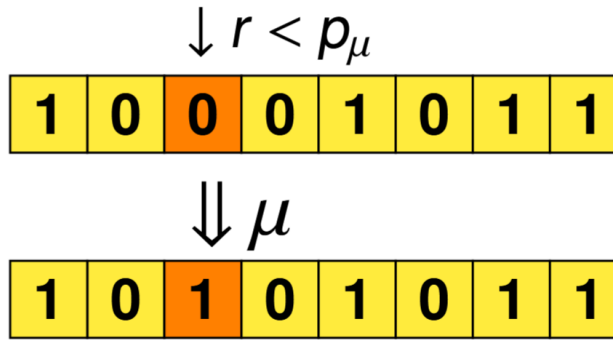
GA Example: Map-of-Ones Crossover

- **Other variant:** encode the positions of the 1s in the bitstring [9, 14]
- Randomly copy from the first or the second parent, going left to right
- Make sure there are no *repeated* values in the offspring

MUTATION

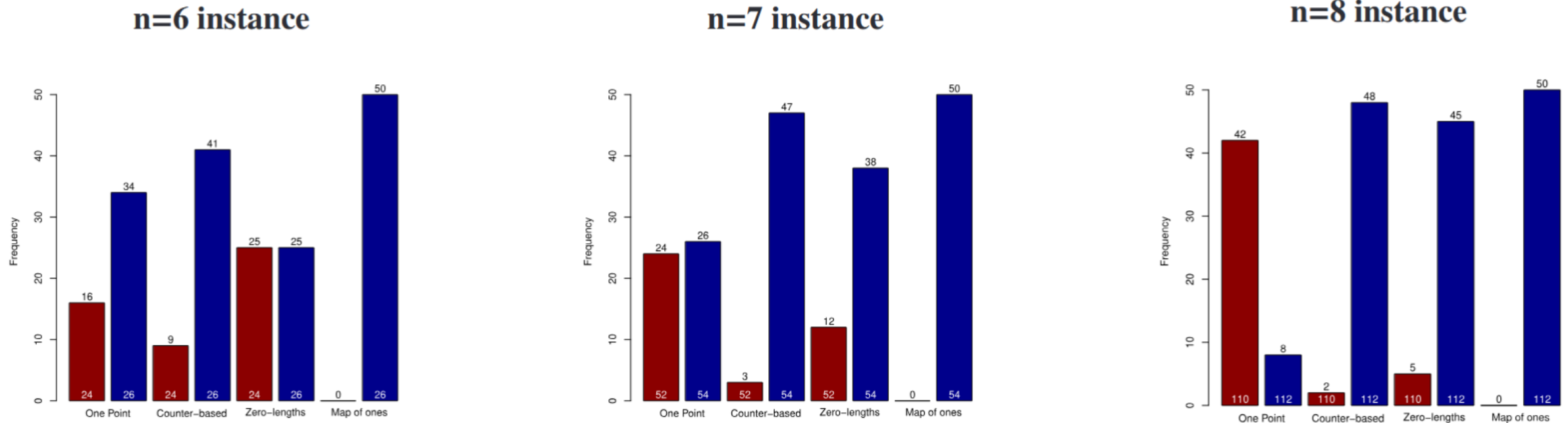
- **Idea:** introduce new “genetic material” in the offspring (**Exploration**)

GA Example: Bit-flip mutation



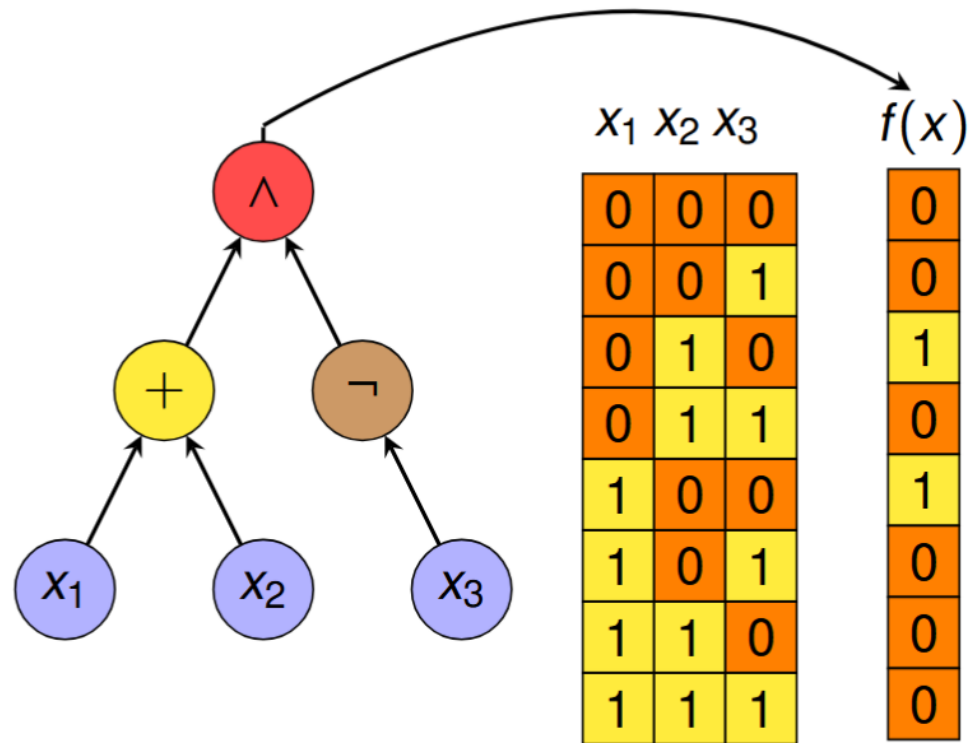
- For balancedness: randomly **swap** some bits instead of flipping them

EXPERIMENTAL COMPARISON



In general: balanced operators perform better than one-point crossover,
Map-of-Ones is the operator with the best success rate [9]

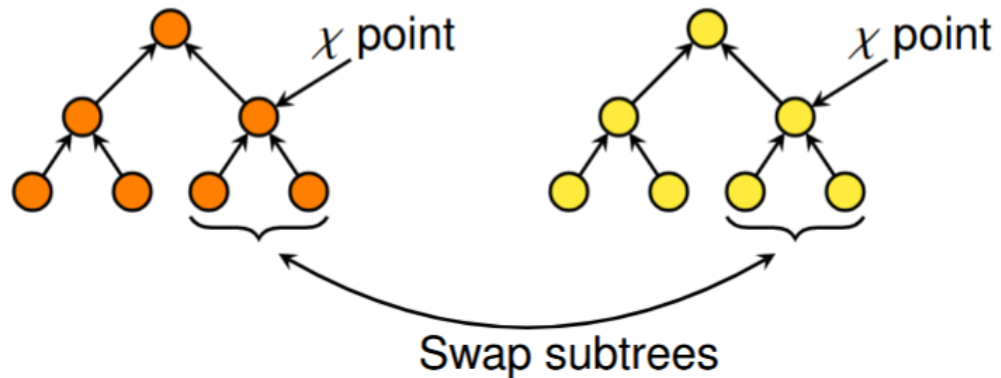
GENETIC PROGRAMMING (GP)



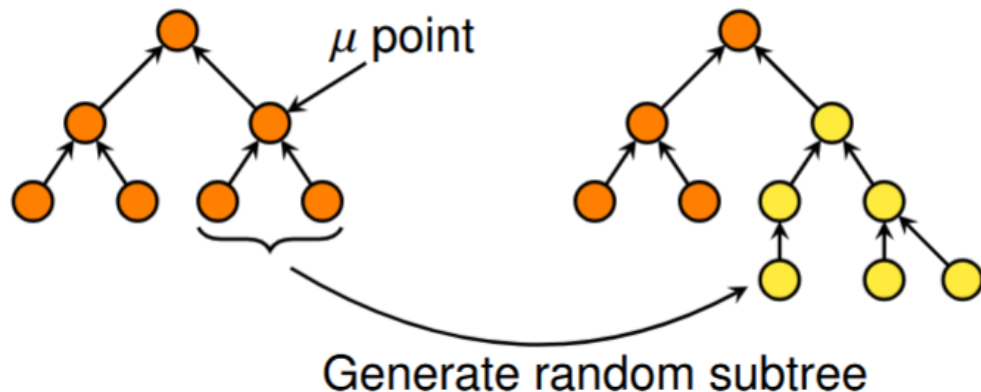
- **Idea:** evolve computer programs to solve specific tasks [8]
- **GP Genotype:** a syntactic tree
 - Leaf nodes: input variables
 - Internal nodes: operators (e.g. AND, OR, NOT, XOR, ...)
- **Phenotype:** evaluate the tree for all possible assignments of the leaf nodes

GP CROSSOVER & MUTATION

Subtree Crossover



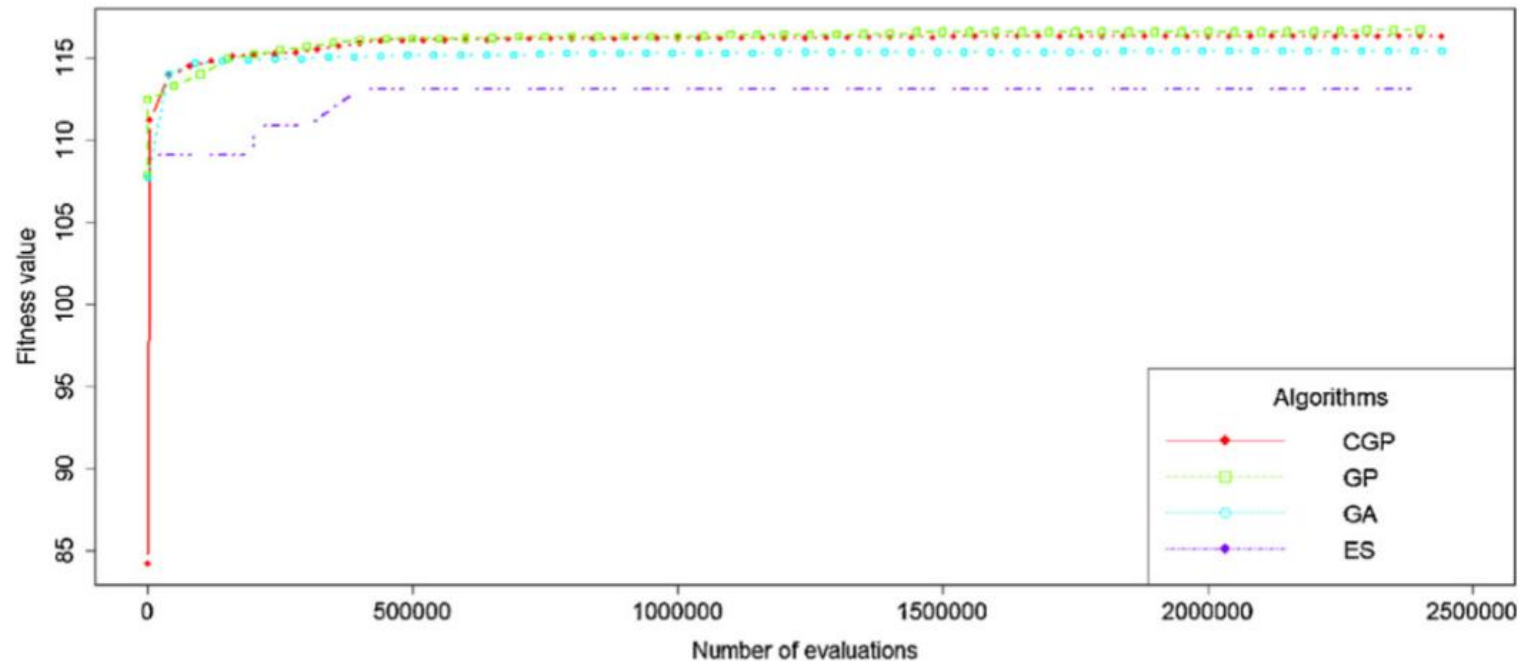
Subtree Mutation



- **Subtree crossover:** select random internal node and swap the two subtrees
- **Subtree mutation:** select random node and generate new random subtree
- **In general:** not possible to preserve the balancedness of the Boolean function
- Difference between the syntax of trees and the semantics of truth tables

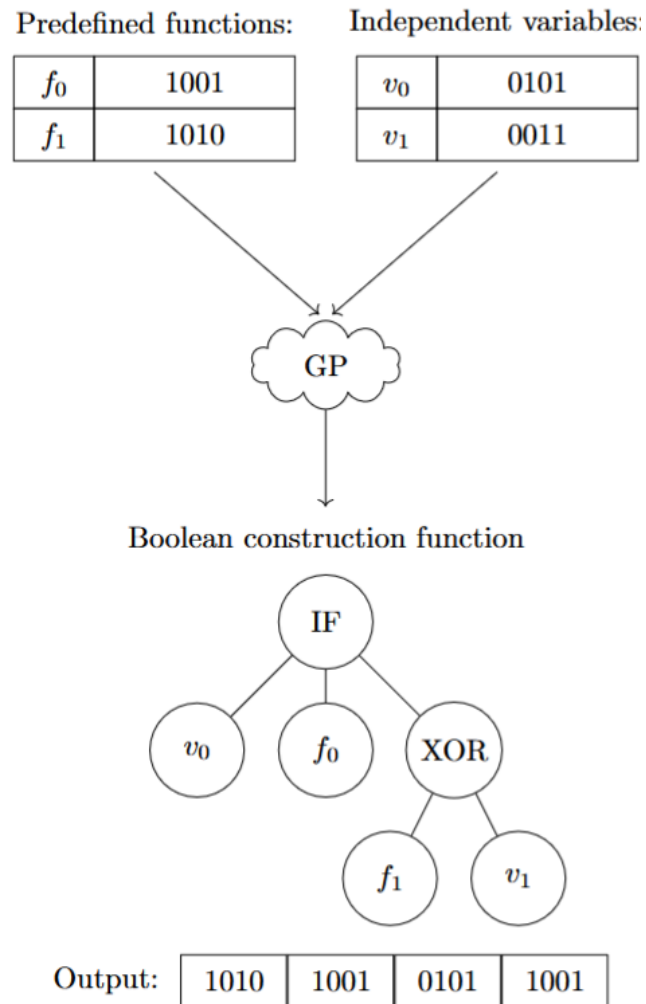
GP VS. GA PERFORMANCES

- GA with balanced operators explores a smaller search space than GP



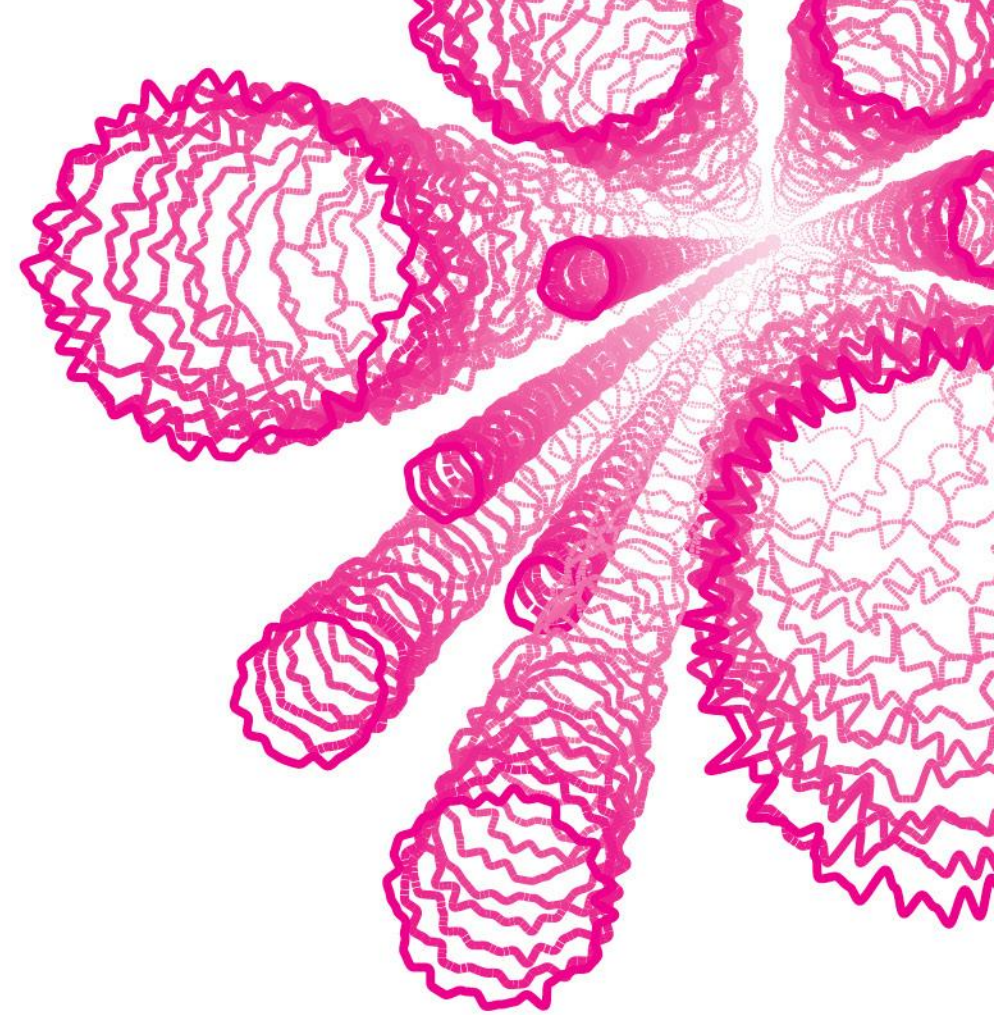
- Nevertheless:** GP usually fares better than (balanced) GA [6, 12, 17, 19]

EVOLVING ALGEBRAIC CONSTRUCTIONS WITH GP



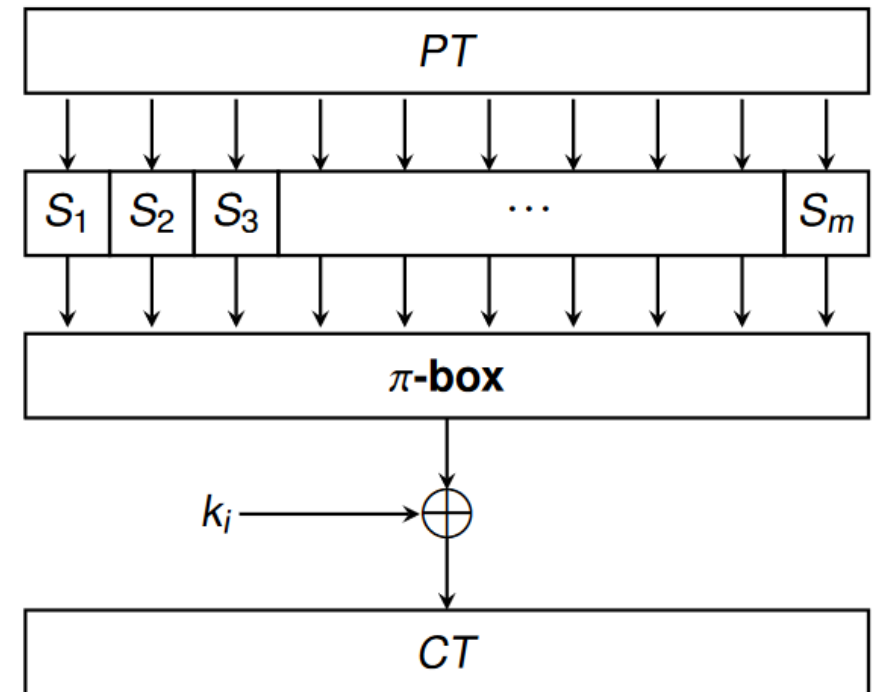
- **Idea:** Do not evolve functions directly, but rather their algebraic constructions [3, 10, 20]
- Use Boolean minimizers to interpret the constructions
- **Research Question:** Does GP obtain new constructions?
- **Finding:** GP always generates the same known construction, but in a very complicated way [20]

EVOLUTIONARY ALGORITHMS FOR S-BOXES



SPN BLOCK CIPHERS

- Round function: composed of **confusion layer** and **diffusion layer** [7]
- Confusion: Substitution boxes (**S-boxes**) of the form $S_i : \{0, 1\}^n \rightarrow \{0, 1\}^n$
- Diffusion: Permutation box (**P-box**) of the form $\pi : \{0, 1\}^b \rightarrow \{0, 1\}^b$
- Result is bitwise XORed with round key
- All S-boxes and P-boxes are invertible



S-BOXES

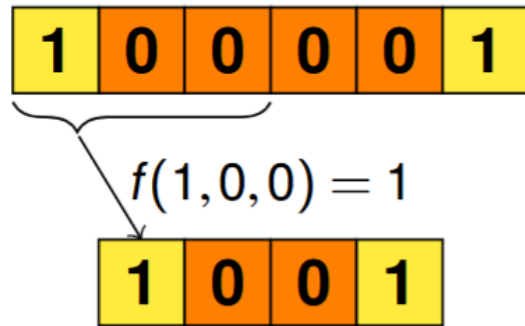
- Vectorial mapping $F : \{0, 1\}^n \rightarrow \{0, 1\}^m$
- Defined by m *coordinate Boolean functions* $f_i : \{0, 1\}^n \rightarrow \{0, 1\}$

(x_1, x_2, x_3)	000	001	010	011	100	101	110	111
$dec(x_1, x_2, x_3)$	0	1	2	3	4	5	6	7
$F(x_1, x_2, x_3)$	0	5	6	1	3	2	4	7
$f_1(x_1, x_2, x_3)$	0	1	1	0	0	0	1	1
$f_2(x_1, x_2, x_3)$	0	0	1	0	1	1	0	1
$f_3(x_1, x_2, x_3)$	0	1	0	1	1	0	0	1

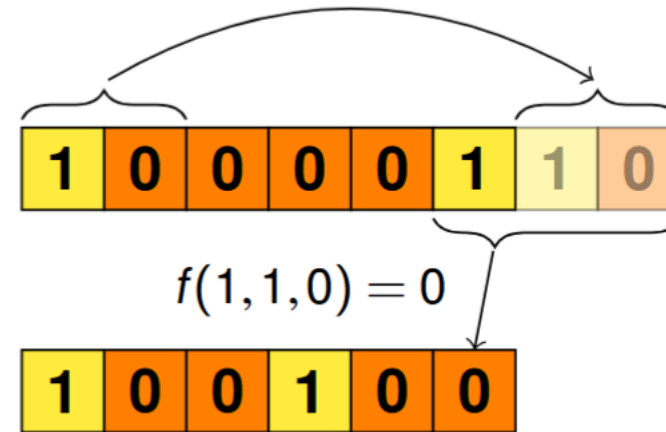
- Again, an S-box needs to satisfy some properties to resist specific attacks (balancedness, nonlinearity, differential uniformity, ...) [4]

CELLULAR AUTOMATA (CA)

- Discrete parallel computation model composed of a finite array of *cells*



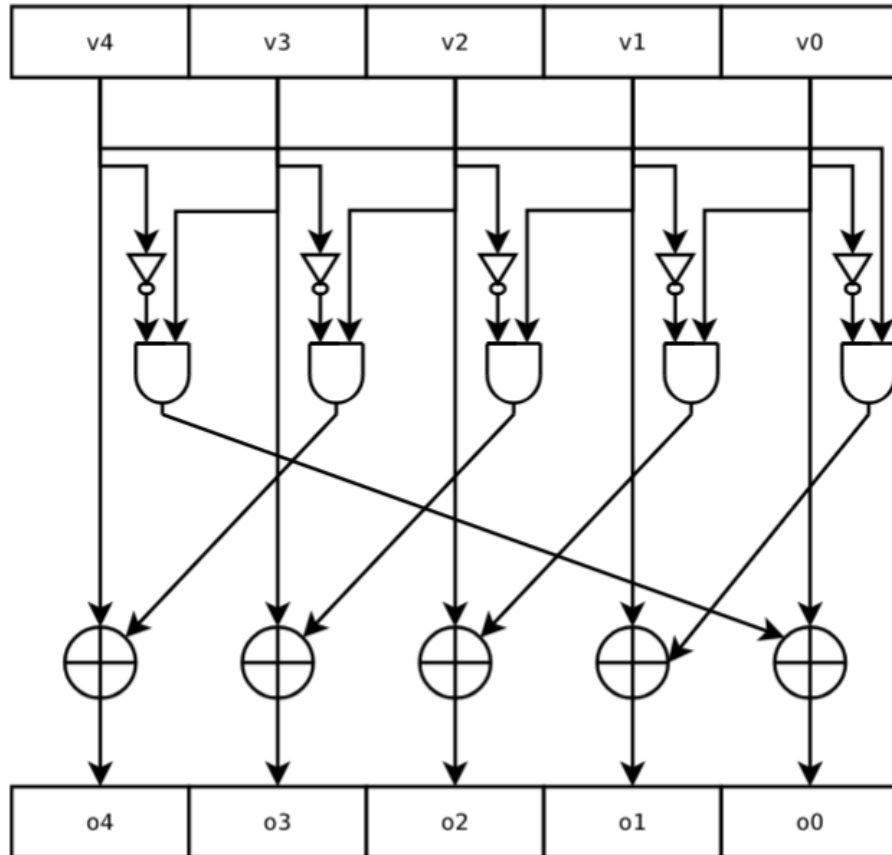
No Boundary CA – NBCA



Periodic Boundary CA – PBCA

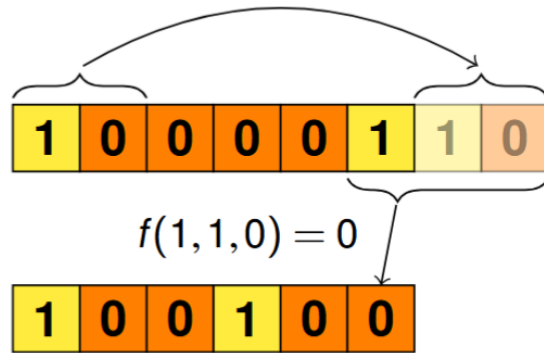
- Each cell updates its state by applying a **local rule** $f : \{0, 1\}^d \rightarrow \{0, 1\}$ on itself and the $d-1$ right neighboring cells [13]

CA-BASED CRYPTO: KECCAK χ MAPPING

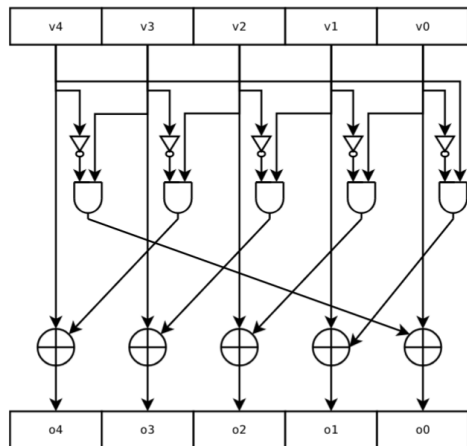


- Local rule of diameter d=3:
$$\chi(x_1, x_2, x_3) = x_1 \oplus (1 \oplus (x_2 \cdot x_3))$$
- Invertible PBCA for every odd size of the CA array [5]
- Used as a 5x5 S-box in the *Keccak* specification of the SHA-3 standard [2]
- What about larger diameters?

OPTIMIZATION OF CA-BASED S-BOXES PROPERTIES



Periodic Boundary CA – PBCA



- **Advantage:** optimize only the CA local rule, which is single-output Boolean function of d variables
- **Goal:** find PBCA of length n and diameter $d = n$ with:
 - good cryptographic properties [13]
 - low implementation cost [18]
- GP optimizing both crypto (nonlinearity, differential uniformity) and implementation properties (GE measure)

RESULTS – CRYPTO PROPERTIES

- Except for $n=8$, GP obtains CA-based S-boxes with optimal cryptographic properties [18]

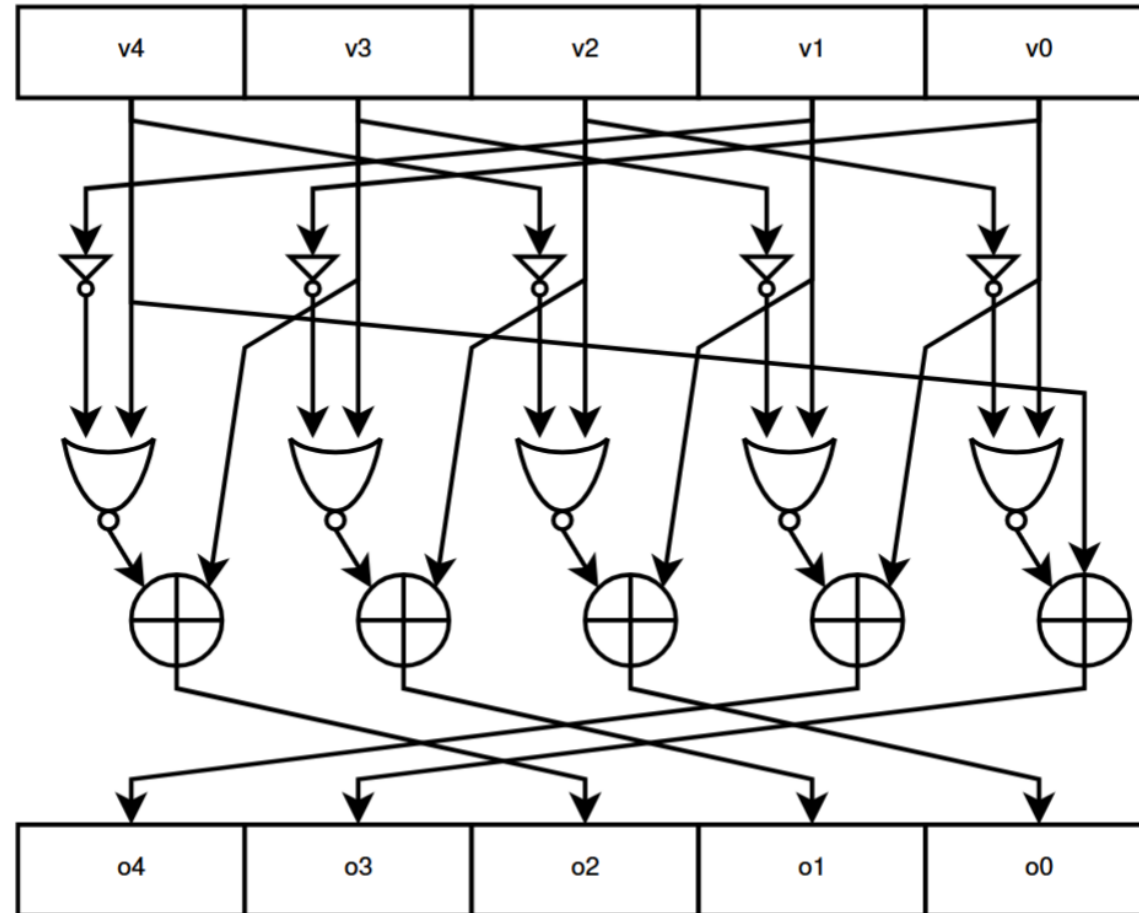
S-box size	T_{max}	GP			N_F	δ_F
		Max	Avg	Std dev		
4×4	16	16	16	0	4	4
5×5	42	42	41.73	1.01	12	2
6×6	86	84	80.47	4.72	24	4
7×7	182	182	155.07	8.86	56	2
8×8	364	318	281.87	13.86	82	20

RESULTS – IMPLEMENTATION PROPERTIES

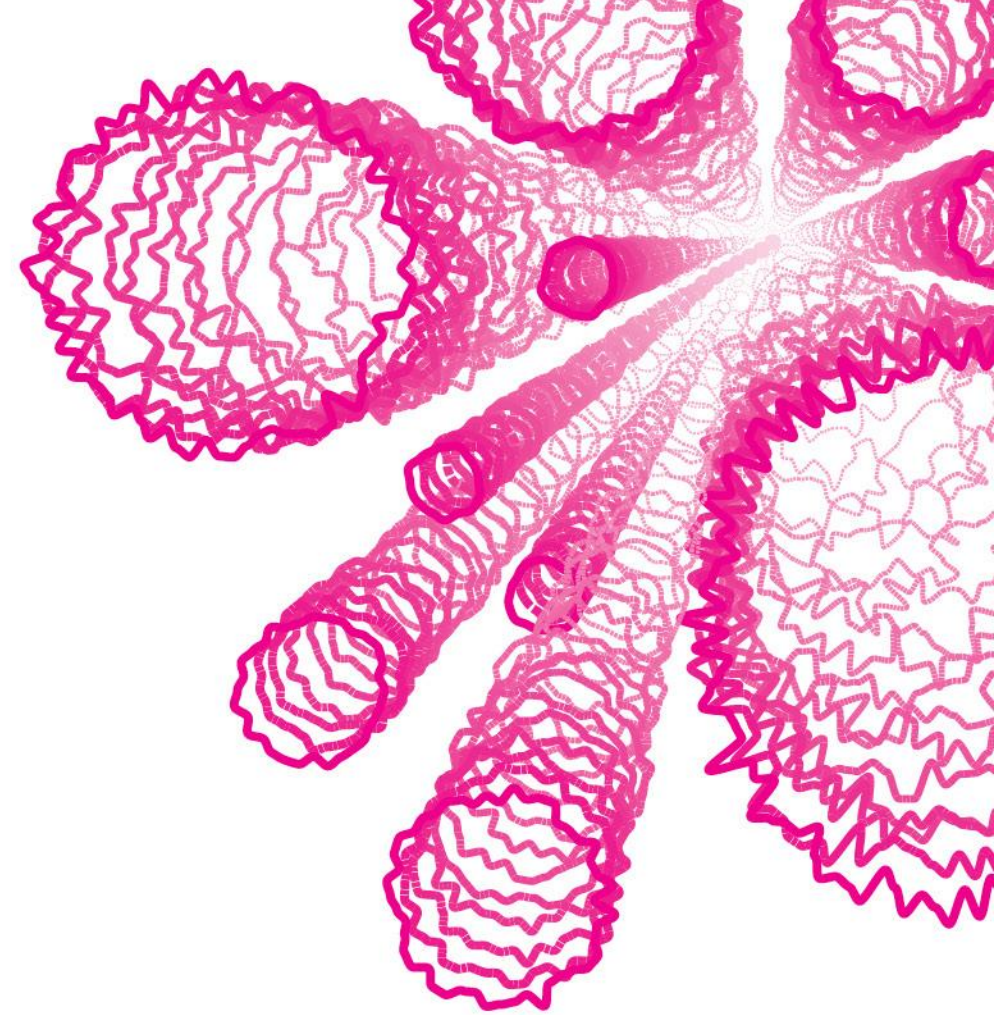
- GE measure of CA-based S-boxes on par with Keccak S-box [18]

Size	5×5	Rule	Keccak			
DPow.	321.684	LPow:	299.725	Area:	17	Latency: 0.14
Size	5×5	Rule	$((v2 \text{ NOR } \text{NOT}(v4)) \text{ XOR } v1)$			
DPow.	324.849	LPow:	308.418	Area:	17	Latency: 0.14
Size	5×5	Rule	$((v4 \text{ NAND } (v2 \text{ XOR } v0)) \text{ XOR } v1)$			
DPow.	446.782	LPow:	479.33	Area:	24.06	Latency: 0.2
Size	5×5	Rule	$(\text{IF}(v1, v2, v4) \text{ XOR } (v0 \text{ NAND } \text{NOT}(v3)))$			
DPow.	534.015	LPow:	493.528	Area:	26.67	Latency: 0.17

EXAMPLE OF CA-BASED S-BOX EVOLVED BY GP

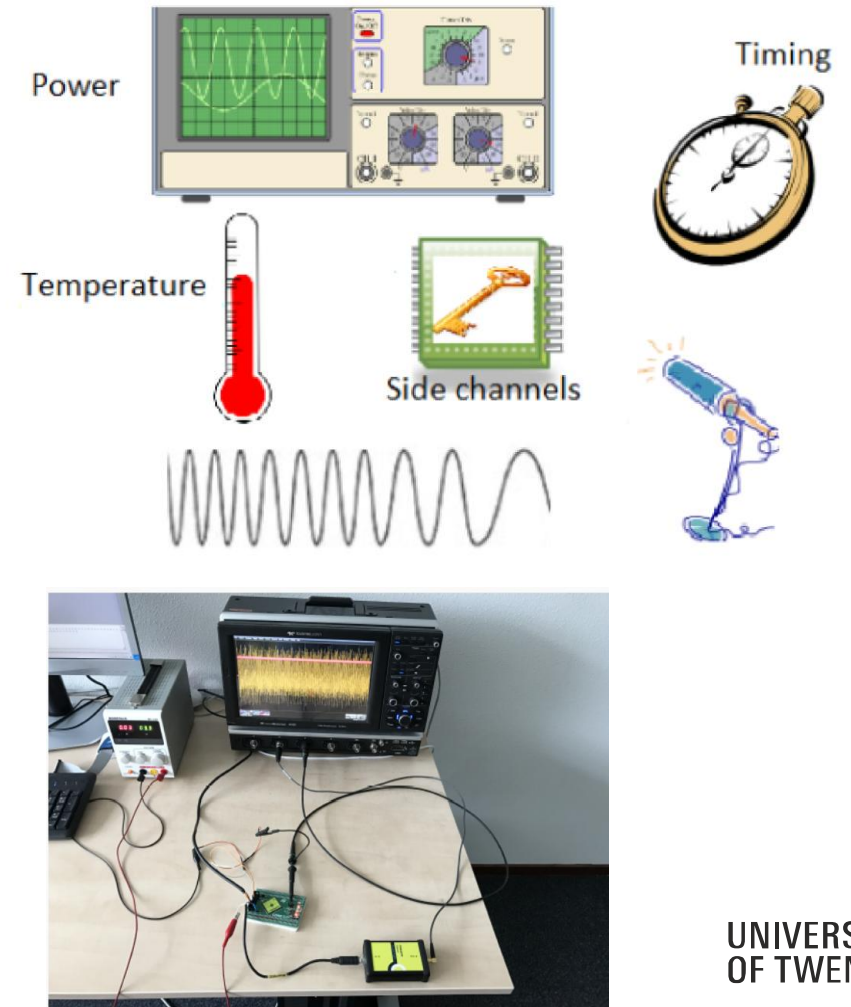


NEUROEVOLUTION FOR SIDE-CHANNEL ANALYSIS

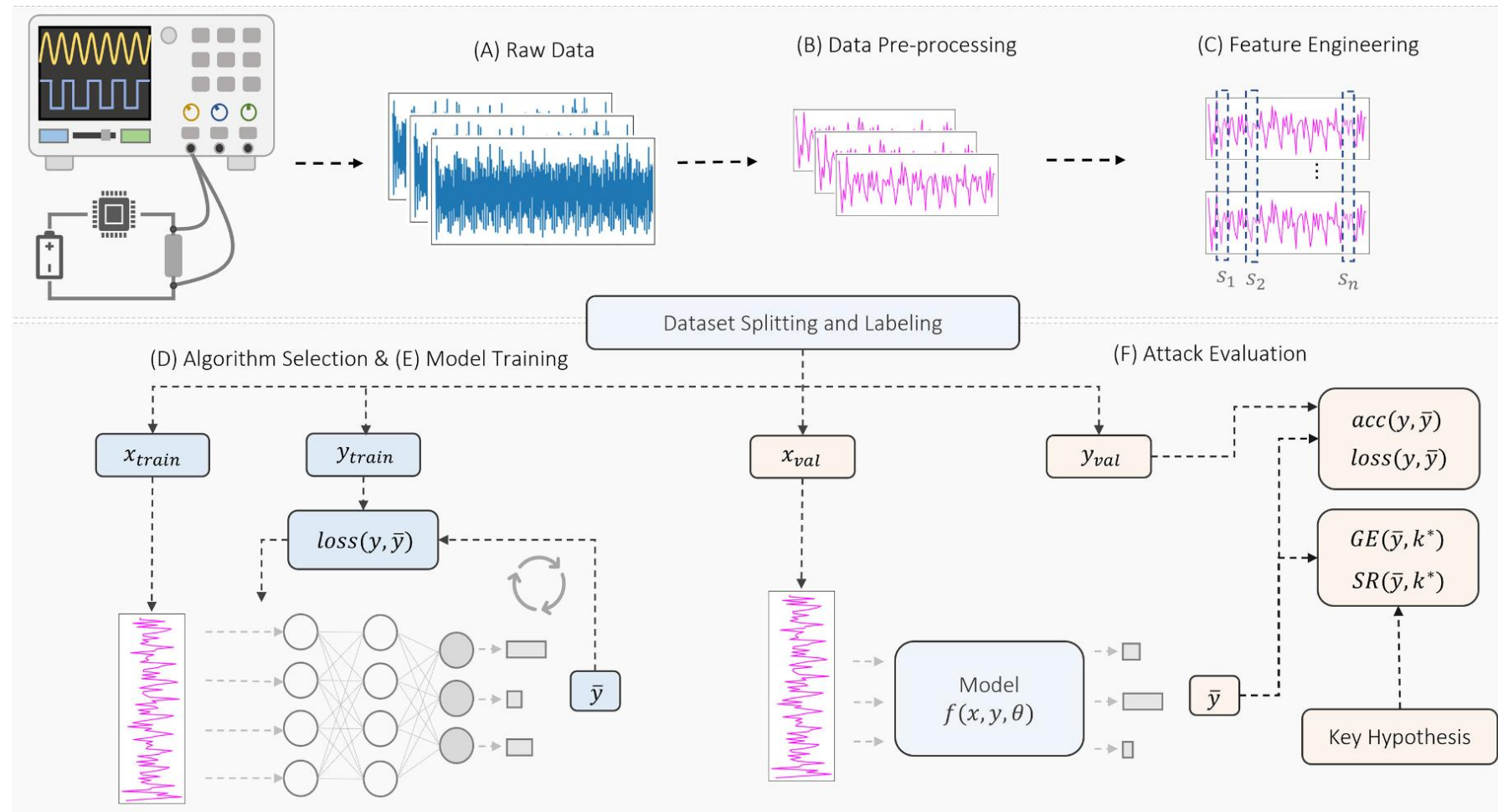


SIDE-CHANNEL ANALYSIS (SCA)

- **Idea:** Attack the *physical implementation* of a cipher, instead of its *mathematical structure*
- Exploits various physical leakages (timing delays, EM emanations, power consumption, ...)
- **Profiling SCA:** the adversary estimates the leakage on a clone device, then exploited to extract secret information in the attack phase
- **Deep Learning-based SCA (DL-SCA):** use a DL model to estimate the leakage [16]



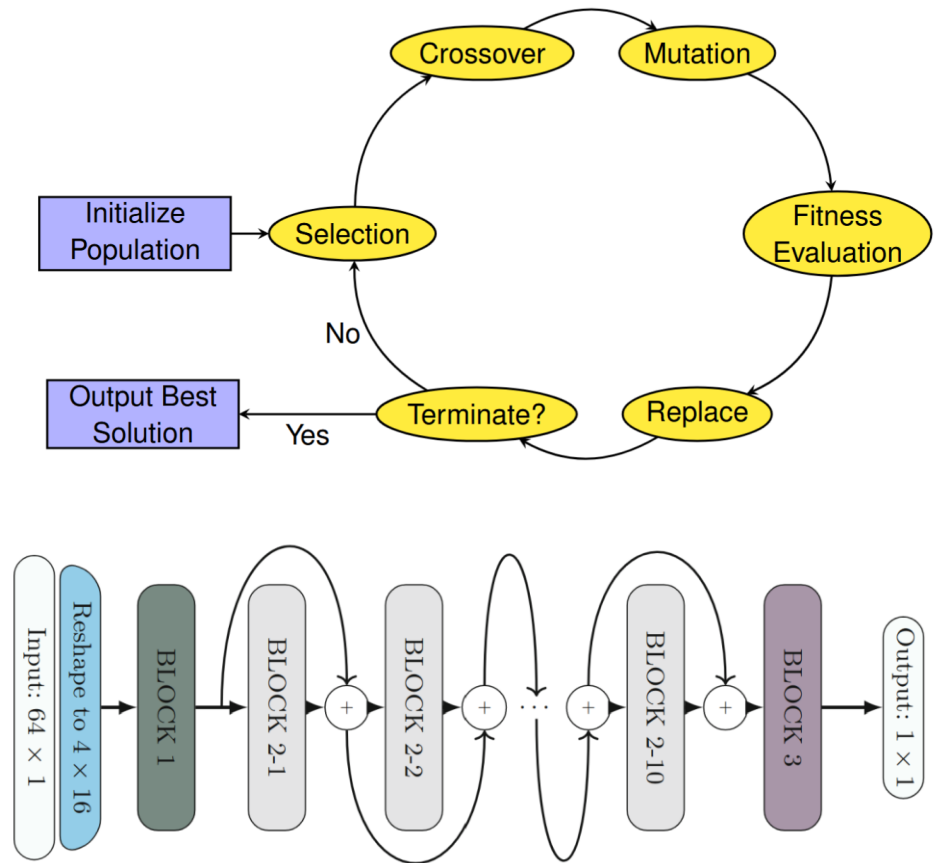
SIDE-CHANNEL ATTACKS



DL-SCA pipeline [16]

NEUROEVOLUTION

- Most of the models used in DL-SCA (CNN, ResNets, etc.) have been manually designed
- **Question:** is it possible to *automate* the design of neural networks for DL-SCA?
- **Neuroevolution:** employ EA to optimize the *architecture* of a neural network [NE]
- Many different approaches (NEAT [1], Grammatical Evolution [15], GA [19], ...)



GRAMMATICAL EVOLUTION

- **Genotype:** string of integer numbers indexing the production rules
- **Evaluation:** apply production rules from left to right (with recursion if needed)
- Evolution works by evolving the genotype as a string of integers

Grammar:

```
<expr> ::= <expr> <op> <expr> | (<expr> <op> <expr>)  
        | <pre-op> <expr> | <var>  
<op>    ::= + | - | * | \  
<pre-op> ::= Sin | Cos | Tan | Log  
<var>   ::= X | 0.5
```

Genotype:

2	2	0	3	0	0	1	3	1	2	3	0
---	---	---	---	---	---	---	---	---	---	---	---

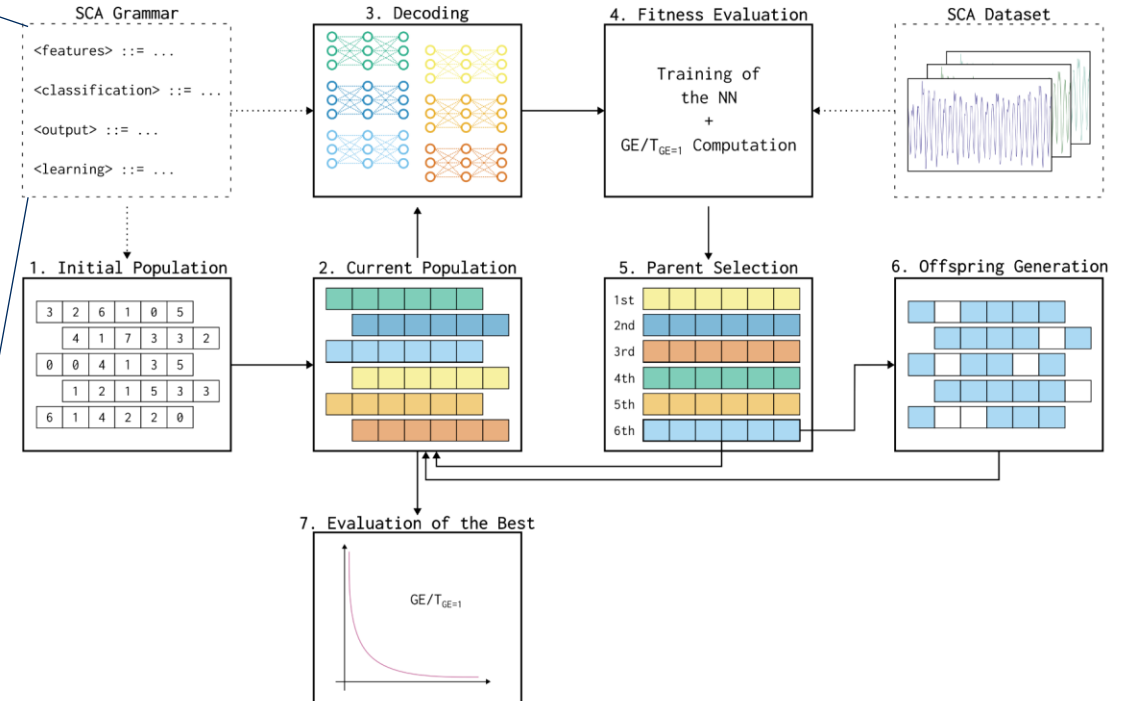
Decoding:

```
<expr> (2)  
=> <pre-op> (<expr>) (2)  
=> Tan (<expr>) (0)  
=> Tan (<expr> <op> <expr>) (3)  
=> Tan (<var> <op> <expr>) (0)  
=> Tan (X <op> <expr>) (0)  
  
=> Tan (X + (0.5 * X))
```

SCA DRIVEN BY GRAMMATICAL EVOLUTION (SCAGE)

```

<features> ::= <convolution>
              | <pooling>
              | <batch-norm>
<convolution> ::= layer:conv1d [num-filters ,int ,1,4,512]
                ↳ [filter-shape ,int ,1,2,80] [stride ,int ,1,30,50]
                ↳ <activation-function>
<pooling> ::= <pool-type> [kernel-size ,int ,1,2,20] [stride ,int ,1,2,20]
<pool-type> ::= layer:pool-avg1d | layer:pool-max1d
<batch-norm> ::= layer:batch-norm
<classification> ::= <fully-connected> | <dropout>
<fully-connected> ::= layer:fc <activation-function> <regularizer>
                    ↳ [num-units ,int ,1,10,1000]
<regularizer> ::= <regularizer-type> [regrate ,float ,1,0.00001,0.05]
<regularizer-type> ::= reg:l1 | reg:l2 | reg:none
<dropout> ::= layer:dropout [rate ,float ,1,0.05,0.5]
<activation-function> ::= act:relu | act:selu
<output> ::= layer:fc act:softmax num-units:256 reg:none
<learning> ::= <optimizer> [lr ,float ,1,0.0001,0.001] <early-stop>
               ↳ [batch_size ,int ,1,100,1000] epochs:100
<optimizer> ::= learning:adam | learning:rmsprop
<early-stop> ::= [early_stop ,int ,1,5,20]
    
```



SCAGE iteration diagram and grammar [15]

SCAGE RESULTS ON ASCAD DATASET

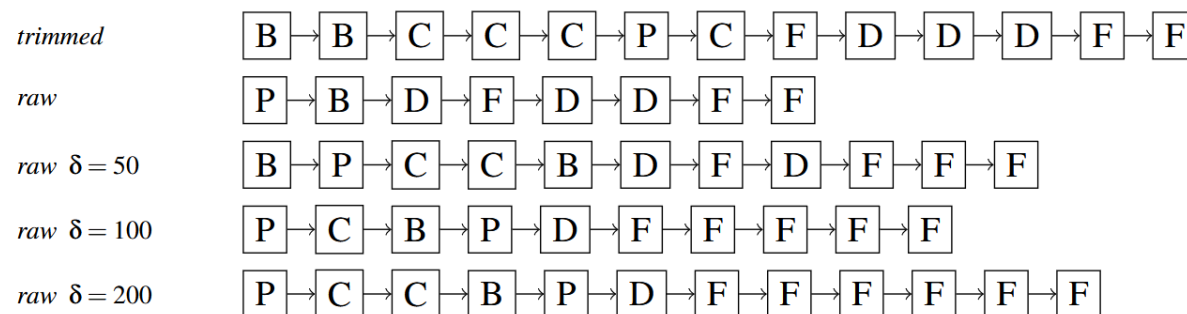
Dataset	Average $T_{GE=1}$		Search Success Rate	
	SCAGE	RS	SCAGE	RS
<i>trimmed</i>	115	792	100%	20%
<i>raw</i> $\delta_{max} = 0$	25	648.33	70%	1.2%
<i>raw</i> $\delta_{max} = 50$	168	x	16.6%	0.0%
<i>raw</i> $\delta_{max} = 100$	4	x	3.3%	0.0%
<i>raw</i> $\delta_{max} = 200$	58	x	6.6%	0.0%

SCAGE vs. Random Search

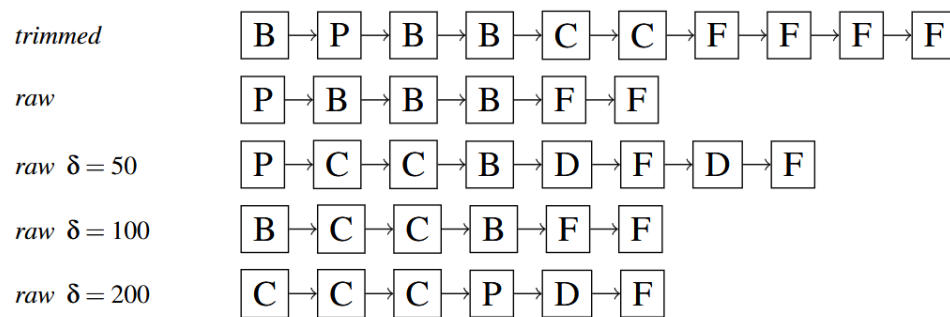
Dataset	$T_{GE=1}$					
	SCAGE	RS	[26]	[12]	[2]	[20]
<i>trimmed</i>	23	85	78	–	120	–
<i>raw</i> $\delta_{max} = 0$	1	1	1	5	–	–
<i>raw</i> $\delta_{max} = 50$	1	2	–	–	–	33
<i>raw</i> $\delta_{max} = 100$	1	x	73	5	–	251
<i>raw</i> $\delta_{max} = 200$	1	x	–	4	–	44

SCAGE vs. SoTA in DL-SCA

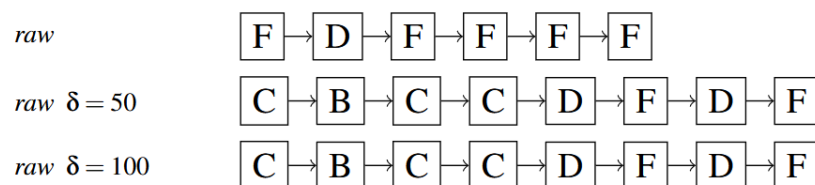
SCAGE – EVOLVED NEURAL NETWORKS



(a) ASCADf NN architectures



(b) ASCADr NN architectures

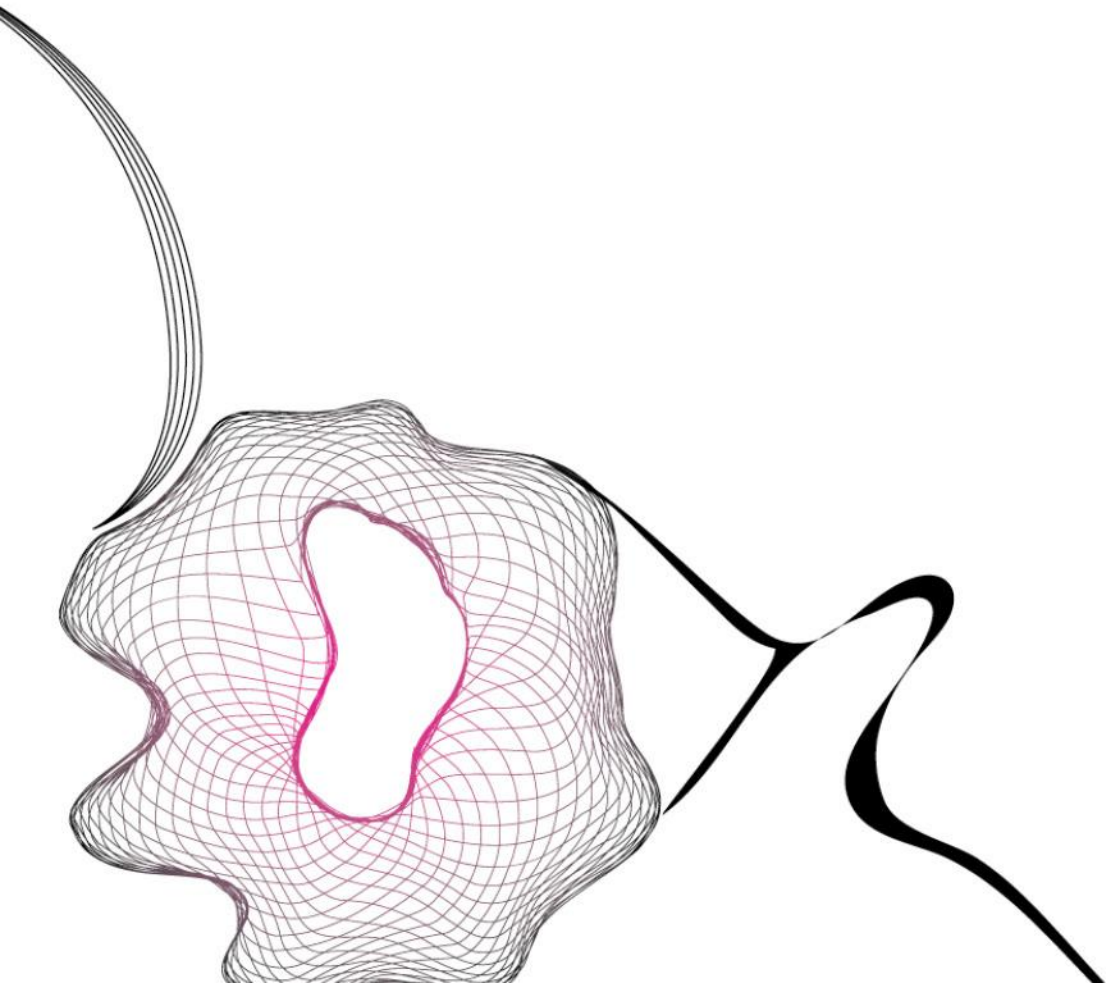


(c) CHES CTF 2018 NN architectures

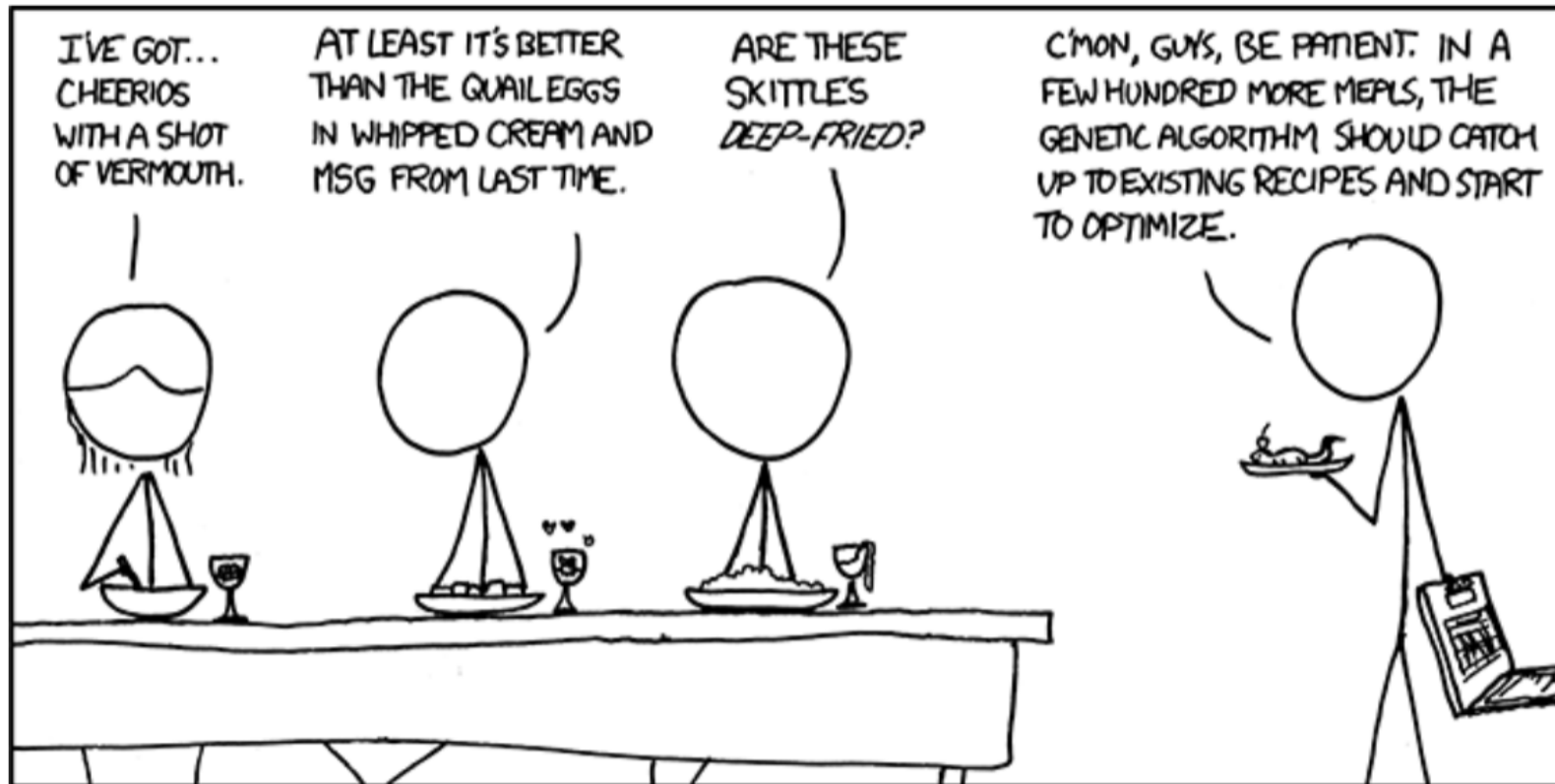
- Architectures of some of the best neural networks discovered by SCAGE in various scenarios [15]
- C stands for convolutional layer, P for pooling, B for batch normalization, F for fully connected, and D for dropout.

SUMMARY

- AI-driven design in symmetric cryptography
- EA for Boolean Functions
- EA for S-boxes
- Neuroevolution for Side-Channel Analysis



THANKS! QUESTIONS?



WE'VE DECIDED TO DROP THE CS DEPARTMENT FROM OUR WEEKLY DINNER PARTY HOSTING ROTATION.

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