Evolutionary Computation and Machine Learning in Cryptology

Stjepan Picek* and Domagoj Jakobovic**

* TU Delft, The Netherlands
** University of Zagreb, Croatia
s.picek@tudelft.com, domagoj.jakobovic@fer.hr
www.aisylab.com

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Instructors

Stjepan Picek finished his PhD in 2015 as a double doctorate under the supervision of Lejla Batina, Elena Marchiori (Radboud University Nijmegen, The Netherlands), and Domagoj Jakobovic (Faculty of Electrical Engineering and Computing, Croatia). Currently, Stjepan is working as an assistant professor at TU Delft, The Netherlands. Before that, Stjepan worked at MIT, USA and KU Leuven, Belgium. Stjepan also has several years of experience working in industry and government. He regularly publishes papers in both evolutionary computation and cryptographic conferences and journals. Besides that, he is a member of several professional societies (ACM, IEEE, IACR).

Domagoj Jakobovic received his Ph.D. degree in 2005 at the University of Zagreb, Croatia, on the subject of generating scheduling heuristics with genetic programming. He is currently a full professor at the Department of Electronics, Microelectronics, Computer and Intelligent Systems at the University of Zagreb. His research interests include evolutionary algorithms, optimization methods, and parallel algorithms. Most notable contributions are in the area of a machine supported scheduling, optimization problems in cryptography, parallelization, and improvement of evolutionary algorithms. He has published more than 100 papers, lead several research projects, and serves as a reviewer for many international journals and conferences.

Outline

Evolutionary Computation

- Research area within computer science that draws inspiration from the process of natural evolution.
- Evolutionary computation (EC): population based metaheuristic optimization methods that use biology inspired mechanisms like selection, crossover or survival of the fittest.
- Genetic Algorithm (GA), Tree based Genetic Programming (GP), Cartesian Genetic Programming (CGP), Evolution Strategy (ES), NSGA-II, etc.
- [60, 77, 113, 11, 40]

Machine Learning

- Machine Learning (ML) is a subfield of computer science that evolved from the study of pattern recognition and computational learning theory in artificial intelligence.
- Deep learning (DL) is a special type of machine learning.
- Deep learning is designed to overcome problems that traditional machine learning cannot.
- Such problems are working with high-dimensional data, how to achieve generalization.
- In cryptology applications, mostly supervised learning is used.
- Supervised learning represents learning algorithms that learn to associate some input with some output, given a training set of examples of inputs and outputs.
- [13, 114, 50]

Cryptology

- Cryptology (from Greek words kryptos, which means hidden and logos, which means word) is the scientific study of cryptography and cryptanalysis.
- Cryptography is a science (and art) of secret writing to hide the meaning of a message.
- Cryptanalysis is a science of analyzing ciphers in order to find weaknesses in them.

What is Cryptography?

Historically: cryptography has been the art of hiding the meaning of messages to protect their confidentiality.

- Origins dating back to ancient Egypt (˜2000 BCE).
- Combination of the Greek words *kryptòs* (hidden) and *graphìa* (writing).
- Mainly relied on unsound methods till the 20th century, e.g.:
  - Monoalphabetic and polyalphabetic substitutions (*Caesar's cipher*, *Vigenère's cipher*, ...)
  - Transpositions (The *Scytale*, ...)
- Collectively, these methods are also known as *classical* cryptography.
- We will not be investigating AI for classical cryptography!

Modern Cryptography

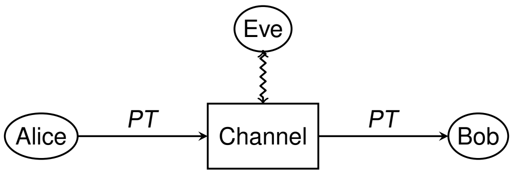
Modern cryptography is a science that studies the methods to allow *secure communication* in presence of *adversaries*.

- Started in the mid 20th century, with the seminal work by Shannon.
- Reliance on *precise* mathematical definitions and *rigorous* proofs to guarantee certain security levels.
- Used also for other goals other than message confidentiality:
  - Message integrity
  - Authentication
  - Non-repudiation
- Nowadays, modern cryptography is at the core of many protocols for secure digital communication (e.g., SSL/TLS, ...).

The Basic Scenario

- *Alice* wants to send a message to *Bob* over a communication *channel*, so that only Bob can read it (confidentiality).
- We call the message *plaintext* (PT), and assume that it is a string over an alphabet Σ, that is

$$PT \in \Sigma^* = \bigcup_{i=0}^{\infty} \Sigma^i, \quad \Sigma^i \text{ is the set of strings of length } i$$



- *Eve*, the adversary, can read *everything* transmitted over the channel.

The Basic Scenario – Introducing Cryptosystems

To prevent Eve from reading PT, Alice and Bob adopt the following protocol:

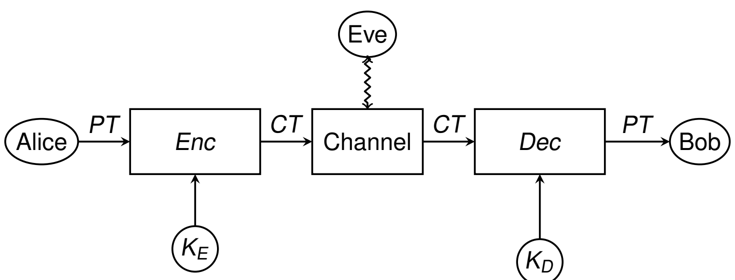
1. Alice uses an *Encryption function*, *Enc*, which depends on an *encryption key* K_E, and transforms PT into a *ciphertext* CT:

$$CT = Enc_{K_E}(PT)$$

2. Alice sends CT over the channel, and Eve observes CT.
3. Bob uses a *Decryption function*, *Dec*, that depends on a *decryption key* K_D, to transform CT back into PT:

$$PT = Dec_{K_D}(CT)$$

Cryptosystem – Block scheme



0.5

- PT: plaintext
- *Enc*: encryption function
- K_E: encryption key

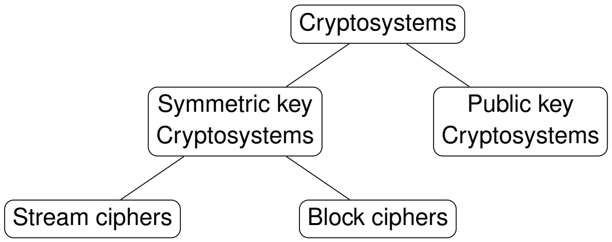
0.5

- CT: ciphertext
- *Dec*: decryption function
- K_D: decryption key

Cryptosystem – Basic properties

- *Unique decodability*: given K_E and K_D, for all plaintext PT it must be the case that $Dec_{K_D}(Enc_{K_E}(PT)) = PT$.
- For all PT, it must be *easy* for Alice to compute the ciphertext $CT = Enc_{K_E}(PT)$ by knowing K_E and *Enc*.
- For all CT, it must be *easy* for Bob to recover the plaintext $PT = Dec_{K_D}(CT)$ by knowing K_D and *Dec*.
- Given CT, it must be *extremely difficult* for Eve to recover PT *without* knowing the decryption key K_D.
- It is always assumed that the encryption and decryption functions are known to Eve (*Kerchoff's principle*).

Classification of Cryptosystems



Symmetric and Public Key Cryptosystems

Symmetric key cryptosystems:

- The key used for encryption and decryption is the same.
- Alice and Bob must agree on this key before the communication takes place.
- Can be further classified in:
  - *Stream ciphers*: Encryption and decryption process single symbols of the plaintext and the ciphertext.
  - *Block ciphers*: Encryption and decryption work over *blocks* of fixed length of symbols.

Public key (or *asymmetric key*) cryptosystems:

- The keys used for encryption and decryption differ.
- Alice uses Bob's *public key* K_E to encrypt, while Bob uses his own *private key* K_D to decrypt.
- [72, 75, 106, 181]

Cryptanalysis

- A study of methods for obtaining the meaning of encrypted information, without access to the secret information that is typically required to do so.
- Commonly, it involves knowing how the system works and finding a secret key.
- The major categories of cryptanalysis are *ciphertext only*, *known plaintext*, *chosen plaintext*, and *chosen ciphertext*.
- Common examples are linear and differential cryptanalysis.

Implementation Attacks

- Implementation attacks do not aim at the weaknesses of the algorithm itself but at the actual implementations on cryptographic devices.
- Power, sound, light, electromagnetic radiation.
- Implementation attacks are among the most powerful known attacks against cryptographic devices.
- Common types of implementation attacks are side-channel attacks and fault injection attacks.
- Side-channel attacks are passive and non-invasive attacks [96].
- Fault injection attacks are active attacks since they enforce the target to work outside the nominal operating range.

Evolutionary Computation and Machine Learning in Cryptology

- We will notice that such artificial intelligence (AI) techniques are used more often in **attacks** than in **constructions**.
- More precisely, they are used more often in attacks by the crypto community.
- There are two main reasons for this:
  1. It is easier to validate that the attack works. Indeed, we require only a successful attack as proof. For constructions, it is difficult to capture all the notions of security when using data or fitness functions.
  2. Attacks are made after the constructions are done. So, there is the effect of timeliness. For constructions, one needs to use AI while designing the system, which is often not possible. Later, even if AI produces improved constructions, it is hard to change the already made design.
- [137, 24, 135, 136].

Evolutionary Computation and Machine Learning in Cryptology

- For machine learning, a common tool is scikit-learn.
- For deep learning, Keras.
- For EC, different approaches use different tools.
- ECF is a C++ framework intended for application of any type of evolutionary computation: http://gp.zemris.fer.hr/
- Details about projects concerning evolutionary computation and cryptology: http://evocrypt.zemris.fer.hr/

Evolutionary Computation and Machine Learning in Cryptology

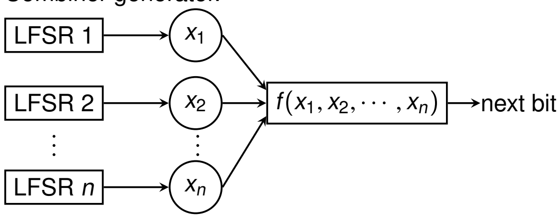
- How to solve hard problems in cryptology?
- Problems need to be hard (to be worthwhile), but not too difficult (to be impossible to solve).
- Plenitude of problems and possible methods to solve them.

Boolean Functions

- The easiest problem to start.
- A natural mapping between the truth table representation of Boolean functions and representation of solutions in EC.
- Boolean functions are important cryptographic primitive and often used in stream ciphers as the source of nonlinearity.
- Boolean functions are commonly used in combiner or filter generators.

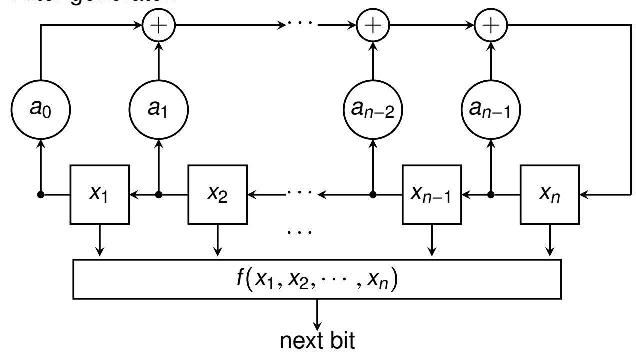
Boolean Functions

Combiner generator.



Boolean Functions

Filter generator.



Boolean Functions

- Filter and combiner generators, as depicted in previous slides are not commonly used in crypto anymore.
- Evolving Boolean functions is more interesting from the perspective of a difficult optimization problem, and not designing cryptographic primitive that will be used in ciphers.

Truth table input		Truth table output
x_1	x_0	y
0	0	0
0	1	1
1	0	1
1	1	0

Figure: Boolean function representation with truth table (two variables).

Boolean Functions

- Three main directions in the evolution of Boolean functions:
  1. Evolution of Boolean functions fulfilling a number of cryptographic properties (that can be used in combiner or filter generators). Additionally, with some special properties that are useful for masking countermeasures against side-channel attacks.
  2. Evolution of bent Boolean functions. Bent Boolean functions are maximally nonlinear but not balanced, and as such, not directly usable in crypto. Still, this represents an interesting benchmark problem.
  3. Evolution of algebraic constructions that are used to design Boolean functions.

Boolean Functions

- Depending on the setting, we are interested in a number of properties (balancedness, nonlinearity, algebraic degree, correlation immunity, algebraic immunity), where some of those properties are conflicting.
- Search space size is 2^{2^n}.
- Representing solutions in the truth table form requires a string of bits of length 2^n.
- For smaller sizes, bitstring, integer, and floating-point also give good results.
- Currently, the best results, in general, are achieved with GP/CGP.
- Such results are comparable with those from algebraic constructions.

Boolean Functions

- The problem is scaling as algebraic constructions work for many dimensions, while EC has problems when considering Boolean functions with more than, e.g., 16 variables.
- Interesting research directions: *i*) finding Boolean functions with specific properties that were not found with algebraic constructions, *ii*) extending EC to work with larger Boolean functions, and *iii*) evolving constructions of Boolean functions.
- General information about Boolean functions in cryptography [19, 31, 20].
- [112, 108, 154, 140, 109, 2, 110, 111, 27, 28, 25, 64, 159, 156, 143, 163, 98, 97, 101, 148, 100, 99, 134, 167, 142, 152, 155, 15, 102, 70].

Boolean Functions

Bitstring representation

```
<Individual size="1">
        <FitnessMax value="116.727"/>
        <BitString size="256">11110000001011100110101111010001110110000010110
        011100000001010001110101011010101001010001001110110000100001111001100
        1000010110000001010101111111111111101110110000111101011101111000101010
        001011110000001101001010010001111101001111011101000111010010010001001
        00</BitString>
</Individual>

correlation immunity: 0; nonlinearity: 116; algebraic degree: 6
```

- Boolean function of eight variables represented with a binary array of size 256 (ECF).
- Optimization of nonlinearity while maintaining balancedness.

Boolean Functions

Floating point representation

```
<Individual size="1">
        <FitnessMax value="114.938"/>
        <FloatingPoint size="32">       0.26875         0.669872        0.762153        0.246787
        0.443393        0.498733        0.664411        0.00021305        0.278248        0.622918
        0.889779        0.321942        0.982994        0.554419        0.0779042        0.663329
        0.125795        0.595173        0.540512        0.132081        0.112745        0.59266
        0.847716        0.888488        0.592867        0.655954        0.770198        0.198452
        0.348636        0.620424        0.767249        0.673829</FloatingPoint>
</Individual>

Truth table:
0100010010101011110000110011111101110001011111111010101000000000010001111
00111111110001101010010111110111000110100010011101010010010000001001100010
0010100010000100011100100101111101100111100011100101111010011111000101001
1001001011001100111101100010010101100
correlation immunity: 0; nonlinearity: 114; algebraic degree: 7
```

- Boolean function of eight variables represented with a floating point array (ECF).
- In this example, each floating point value maps to eight bits in the truth table (either binary or Gray encoding, concatenated or distributed bits).

Boolean Functions

GP representation

```
<Individual size="1">
        <FitnessMax value="120"/>
        <Tree size="29">XOR XOR OR XNOR v0 XOR v5 v3 AND NOT v0 NOT v3
        NOT XOR OR v1 v6 OR v7 v3 XOR AND2 v5 v6 IF v4 v2 v1 </Tree>
</Individual>

infix: ((((v0 XNOR (v5 XOR v3)) OR (˜(v0) AND ˜(v3))) XOR ˜(((v1 OR v6)
XOR (v7 OR v3)))) XOR ((v5 AND2 v6) XOR IF(v4, v2, v1)))

Truth table:
0101010111111111011010011100001111111111010101011100001101101001100110010
0110011101001010000011111100110001100110111100000101101010101010111111110
0101101100001100000000001010101001111000110100101100110001100110101011010000
0111100110011011001100000111101011010
correlation immunity: 0; nonlinearity: 120; algebraic degree: 2
```

- Boolean function of eight variables represented with a GP tree (ECF).
- Optimizing for maximally nonlinear functions (bent functions).

S-boxes

- Natural extension from the Boolean function case.
- S-boxes (Substitution Boxes) are also called vectorial Boolean functions.
- Often used in block ciphers as a source of nonlinearity.
- However, this problem is much more difficult!
- S-box of dimension $n \times m$ has m output Boolean functions, but for several cryptographic properties we need to check all linear combinations of those functions (there are $2^n - 1$ linear combinations to consider).

Truth table input		Linear combinations			Walsh-Hadamard spectrum		
x_1	x_0	y_1	y_0	$y_1 \oplus y_0$	y_1	y_0	$y_1 \oplus y_0$
0	0	0	1	1	0	0	0
0	1	1	0	1	0	-4	0
1	0	1	1	0	0	0	-4
1	1	0	0	0	4	0	0

Figure: S-box with two inputs x and outputs y.

S-boxes

- For an S-box of size $n \times m$, the search space size equals 2^{m2^n}.
- Commonly (with EC), we explore cases where $n = m$, which means that for $n = m = 8$, the search space size equals $2^{2\,048}$.
- Common sizes to evolve with EC are from 3×3 to 8×8.
- Common solution representations are the same as for Boolean functions, plus permutation (which enforces bijectivity).
- Note, if using the tree representation, one actually evolves n trees.
- For smaller sizes, (up to 4×4) all solution representations work well.

S-boxes

- Similar to the Boolean function case, there are three main approaches to construct S-boxes: *i*) algebraic constructions, *i*) random search, and *iii*) heuristics.
- EC is commonly used to:
  1. Find bijective S-boxes with high nonlinearity (and low differential uniformity). Note that for such S-boxes, we know several algebraic constructions.
  2. To find S-boxes with additional properties. These commonly go into the direction of resilience against side-channel attacks.
  3. To find more efficient implementations of S-boxes (efficient in terms of area, power).

S-boxes

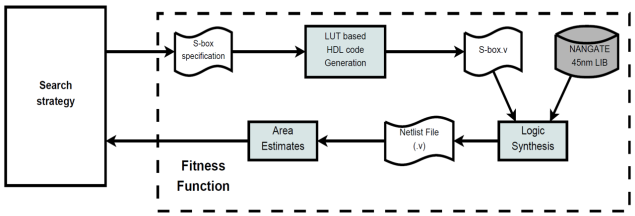


Figure: When considering S-box implementation properties, it is important to be able to communicate between the EC system and the system that checks the implementation perspective.

S-boxes

- The best results are obtained with tree representation and the cellular automata approach.
- CA representation was the first to obtain bijective S-boxes with optimal cryptographic properties for sizes up to 7×7 (not including 6×6 as there, no EC technique found the bijective S-box with the best possible differential uniformity).
- Already for size 8×8, EC results are far from those obtained with algebraic constructions (except if the initial population is seeded with good S-boxes).

S-boxes

Table: Best known values for bijective S-boxes. For 8×8, we give the best known results while for smaller sizes, we give the optimal values. For bijective S-boxes (and in $\mathbb{F}_2$), both nonlinearity and differential uniformity (δ) can be even values only. The worst possible values are 0 for nonlinearity (i.e., the S-box is linear), and 2^n for differential uniformity.

Property	3×3	4×4	5×5	6×6	7×7	8×8
nonlinearity	2	4	12	24	56	112
δ	2	4	2	2	2	4

S-boxes

- S-boxes are becoming less popular due to the rise of permutation-based cryptography, but they are still widely used.
- Naturally, most EC solutions are obtained much after the cipher design, so it is impractical to change the whole cipher simply to accommodate a new S-box.
- Interesting challenges for EC are *i*) obtain S-box of size 8×8 with the same properties as with algebraic constructions, and *ii*) evolve algebraic constructions of S-boxes (either primary or secondary).
- General information about S-boxes [19].

S-boxes

- Tool that evaluates cryptographic properties of Boolean functions and S-boxes [141].
- Discussion on benchmarking EC with cryptographic problems [157].
- [26, 39, 43, 66, 67, 107, 147, 130, 162, 164, 165, 104, 161, 160, 103, 16, 188, 6, 168, 170, 146, 132, 21, 133, 89, 46, 69, 153, 35].

S-boxes

```
<Individual size="1">
        <FitnessMax value="84.0938"/>
        <Tree size="13">XOR v1 IF v3 IF v0 v5 v3 XOR NOR v5 v0 v2 </Tree>
</Individual>
infix: (v1 XOR IF(v3, IF(v0, v5, v3), ((v5 NOR v0) XOR v2)))
Sbox:
1001011010011001100101101001100100111100110011000011110011001100
1000011101111000110100101101001010000111011110001101001011010010
1100000000111111001111111100000011110011000011001111001100001100
1111010100000101000010101111101001011111101011111010000001010000
1011101101110111010001000111011101000100100010001011101110001000
1001101010011010011010100110101001100101011001010110101001101010
Permutation:
63 12 24 57 48 11 51 26 33 18 22 55 39 28 52 29 3 50 36 7 44 21 47 4 15 62 56 27
41 16 58 17 6 6037 13 9 59 14 46 25 35 42 2 31 45 8 40 30 38 61 23 49 1 54 20 19
43 32 10 53 5 34 0
```

- S-box CA representation (cellular automata rule for a single column repeated six times).
- End result is a bijective S-box with six inputs and outputs (ECF).

Pseudorandom Number Generators

- In the same way one builds Boolean functions and S-boxes as cryptographic primitives, it is possible to extend the approach and build pseudorandom number generators (PRNGs).
- In cryptography, random number generators (RNGs) play an important role.
- Most of the time, we need true random number generators (TRNGs), but still, there are applications for pseudorandom number generators.
- TRNG is a device for which the output values depend on some unpredictable source that produces entropy.
- PRNGs represent mechanisms that produce random numbers by performing a deterministic algorithm on a randomly selected seed.

Pseudorandom Number Generators

- Commonly, we want to find extremely fast and small PRNGs that pass all NIST tests [5].
- We can use GP and CGP to evolve PRNGs.
- CGP has the advantage that it can have multiple outputs, which means it can output more bits.
- Fitness function needs to be simple yet powerful.
- We can use the approximate entropy test from the NIST statistical test suite as a fitness function.

Pseudorandom Number Generators

```
void CGP(uint x0,uint x1,uint x2,uint x3,
uint* z0,uint* z1,uint* z2,uint* z3) {
    uint y4 = x0 & x1;
    uint y5 = x2 ^ x3;
    uint y6 = (y5 >> 1) | (y5 << 31);
    uint y7 = p1(y6);
    uint y8 = x3 ^ y7;
    uint y9 = p1(y8);
    uint y10 = y6 ^ y9;
    uint y11 = (y9 << 1) | (y9 >> 31);
    uint y12 = const;
    uint y13 = p1(y10);
    uint y14 = y12 ^ y11;
    uint y15 = y12 ^ y13;
    uint y16 = (y15 >> 1) | (y15 << 31);
    uint y17 = y10 ^ y16;
    uint y18 = p1(y17);
    uint y19 = y18 >> 1;
    uint y20 = y18 ^ y4;
    uint y21 = p1(y20);
    uint y22 = y18 ^ y21;
    uint y23 = p1(y18);
    uint y24 = y19 ^ y18;
    uint y25 = y23 ^ y19;
    uint y26 = y22 ^ y14;
    *z0 = y18;
    *z1 = y25;
    *z2 = y26;
    *z3 = y24;
}
```

Figure: Example of a PRNG evolved with CGP.

Pseudorandom Number Generators

- The same technique can be used to produce PRNGs on-the-fly.
- Then, we can use evolvable hardware [182] that constantly updates the PRNG part.

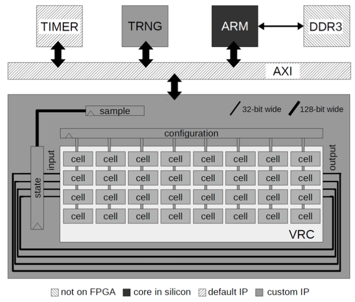


Figure: Example of a system that uses CGP and evolves PRNGs on-the-fly.

Pseudorandom Number Generators

- Common challenges are to find fast, reliable, and small PRNGs with EC.
- Usually, the problem is to have an efficient fitness function.
- [84, 128, 76, 54, 172, 200, 171, 169]

Ciphers

- Instead of evolving only parts of ciphers as we discussed up to now, we can consider whether AI could build the whole cipher.
- There are commonalities with the previous topic as one can consider PRNG as the whole system and not only a part of it.
- The first effort in this direction uses adversarial neural networks.
- There are three networks representing Alice, Bob, and Eve and they compete to find a cipher that is usable and secure [1].

Ciphers

- It is also possible to evolve ciphers with evolutionary algorithms [158].
- One can use competitive coevolutionary algorithms to train a cipher (Alice) and attacker (Eve).
- Still, these works can be regarded as proofs of concept only.
- There are multiple possible research directions: *i*) making the ciphers more efficient and secure as now, they work with very small inputs and are trivial to break, *ii*) making the attacker strategies smarter, *iii*) explore different levels of information provided to Alice and Eve – do they design all from scratch, or do they have background info? *iv*) extending to other concepts and not only block ciphers (and in block ciphers, consider whether evolving the round function or the whole cipher), and *v*) AI “reinventing” of crypto techniques that are well-known and commonly used.

Ciphers

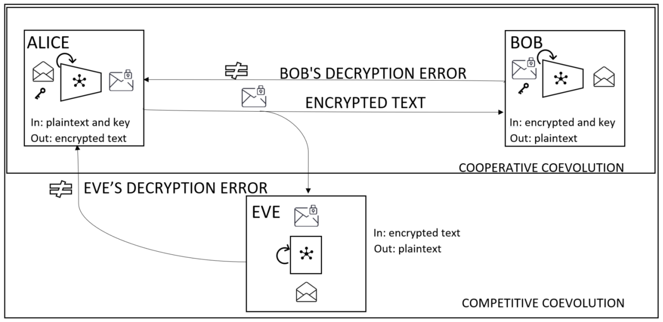


Figure: Coevolutionary system for the evolution of ciphers.

Attacks on Ciphers

- Up to now, EC has been successfully applied to break classical cryptography, see, e.g., [120] or simplified ciphers [38].
- Additionally, EC was also used as a helper tool in SAT-based attacks [123].
- To the best of our knowledge, these results are still far from being able to say that EC was used to conduct cryptanalysis of a modern cipher.
- On the other hand, neural networks proved to be a more suitable option here.
- A common direction is to use neural networks to exploit the properties of ciphers.

Attacks on Ciphers

- For example, train neural networks to distinguish the output of a cipher with a given input difference from random data.
- These approaches represent very interesting research direction as with neural networks, one can reach/surpass state-of-the-art cryptanalysis results.
- [49, 85, 83, 33, 32, 23, 3, 10, 187, 74, 63, 65, 9].

Quantum Protocols

- Instead of operating on primitive or cipher level, EC can be used to evolve protocols also.
- As an example, it is possible to use EC to evolve novel quantum key distribution (QKD) protocols designed to counter attacks against the system in order to optimize the speed of secure communication.
- In essence, the goal is to evolve protocols as quantum circuits [185].
- Then, it is possible to define whether EC must work on the specific, user-defined template of a protocol or without explicit rules on how to access quantum communication channel.

Quantum Protocols

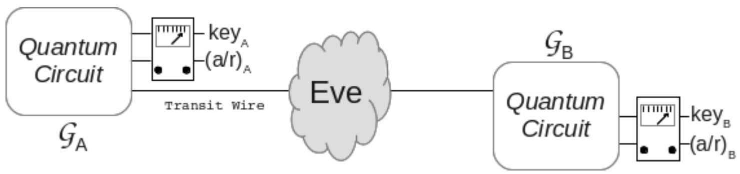


Figure: QKD protocol depicted as two circuits G_A and G_B. First, run circuit G_A, and then, the wire is measured, yielding a classical bit. Then, Eve is allowed to attack the transit line. Finally, G_B circuit is run, acting on the transit wire, and additional wires private to party B. Then, B's wire is measured.

Quantum Protocols

- This research direction looks very interesting as the current results are very good and there are not many other approaches to solve this.
- [78, 79, 80].

Quantum Protocols


```
<Individual size="5">
        <FitnessMax value="0.152422"/>
        <IntGenotype size="5">        2        0        3        0        0</IntGenotype>
        <IntGenotype size="5">        2        0        2        1        3</IntGenotype>
        <BitString size="5">01011</BitString>
        <IntGenotype size="5">        2        2        2        0        1</IntGenotype>
        <FloatingPoint size="15">        0.471412        0.248858        0.560975        0.554435
        0.397848        0.448713        0.328381        0.582966        0.310332        0.273257
        0.623984        0.782299        0.0205793        0.799614        0.0182854</FloatingPoint>
</Individual>
Gates A:
type 2 target 2 mode 0 control: 2
type 0 target 0 mode 1 control: 2
type 3 target 2 mode 0 control: 2
Gates B:
type 0 target 3 mode 1 control: 2
type 0 target 2 mode 1 control: 3
```


- QKD circuit representation (ECF).
- Optimization of a one-way QKD protocol, five gates total.
- The fitness function reflects the maximum obtainable key-rate.

Physically Unclonable Functions

- Physically Unclonable Functions (PUFs) are embedded or standalone devices used as a means to generate either a source of randomness or to obtain an instance-specific uniqueness for secure identification.
- This is achieved by relying on inherent uncontrollable manufacturing process variations, which results in each chip having a unique response.
- No two PUFs will give the same response when supplied with the same challenge.
- There exists no ideal PUF.
- Ideal PUF is unpredictable and without noise.
- Practical realizations depend on noise, aging, environmental variables, and process variations.

Physically Unclonable Functions

- Two types of PUFs: strong and weak.
- The difference with respect to the number of challenge-response pairs (CRPs) an attacker is allowed to obtain.
- The number of unique challenges *c* scales polynomially with the circuit area of a weak PUF.
- The number of unique challenges *c* scales exponentially with the circuit area of a strong PUF.

Physically Unclonable Functions

- Weak PUF has a limited number (typically, one or few) of responses to challenges.
- Strong PUFs have a large number of responses (with respect to different challenges).
- Strong PUFs have a virtually unlimited number of challenges *c*, but their CRPs are highly correlated.
- Given enough (often small amount) of CRPs, it is possible to build a predictive model of a strong PUF (in a way, we build a mathematical clone since it is not feasible to make analog physical clone).
- There exists no validated design of a strong PUF that is fully resilient against modeling attacks.

Physically Unclonable Functions

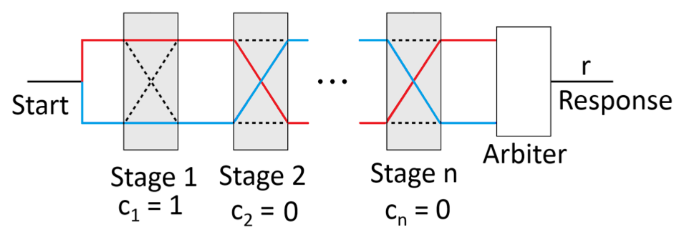


Figure: An example of a strong PUF - Arbiter PUF with *n* stages.

Physically Unclonable Functions

- Several techniques are commonly used to break strong PUFs.
- From ML domain, logistic regression, and from EC, evolution strategy.
- This domain is very interesting as AI provided results that were not possible to obtain with any other technique.
- What is more, even simple AI techniques can easily break strong PUFs.
- This also means there is not much development in the domain as attacks are easy to do, so no clear benefit of using more complex techniques, e.g., deep learning.
- [8, 198, 178, 177, 176, 7, 191, 34, 190, 186, 199, 44, 207].

Hardware Trojans

- Hardware Trojans (HTHs) are malicious hardware components that intend to leak secret information or cause malfunctioning at run-time in the chip in which they are integrated.
- Over the last decade, HTHs have gained increasing attention.
- There are no HTHs in ICs reported in real-world applications yet, there are many examples of academic research results, both on injecting and detecting/preventing HTHs.
- HTHs can be inserted by untrusted foundries and actors at different stages in the design and development of FPGAs and ASICs (Application-Specific Integrated Circuits).

Hardware Trojans

- Conventional HTHs typically modify the functionality of target circuits at the register transfer level, net-list level, layout level, or dopant level to obtain secret information directly, to induce a fault for differential fault analysis, or to disable/degrade an embedded (pseudo) random number generator.
- HTH consists of two parts: a trigger and a payload.
- The trigger usually corresponds to a rare data input (sequence), while the payload is the activity that causes the data leakage or the malfunctioning when the HTH is triggered.
- HTHs are usually inserted in special places in the design that have low testability or high slack time.
- Testability is measured through two parameters: controllability and observability.

Hardware Trojans

- Compared to research concerned with the design of Hardware Trojans, considerably more results exist related to different Hardware Trojan detection mechanisms and countermeasures.
- Most research focuses on detecting Hardware Trojans inserted during manufacturing.
- In many cases, a golden model is used that is supposed to be Trojan free to serve as a reference.
- One important question is how to get to a Trojan-free golden model.

Hardware Trojans

- Common research directions include EC for detection and prevention of HTH, ML for detection, but also EC to insert HTH.
- [53, 68, 81, 71, 179, 45, 82, 91].

Side-channel Analysis

- SCAs represent one of the most powerful categories of attacks on crypto devices.
- Profiled attacks have a prominent place as the most powerful among side-channel attacks.
- Some machine learning techniques can also serve as profiled attacks.
- There is a natural mapping between the profiled attacks and supervised learning.
- Recently, deep learning started to gain attention in the SCA community.

Side-channel Analysis

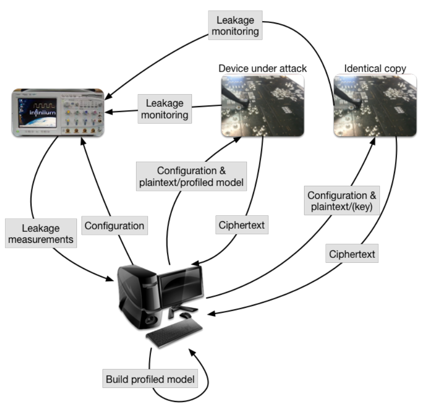


Figure: A depiction of profiled SCA.

Side-channel Analysis

- ML in SCA is an active domain for almost 20 years.
- Even the first profiled attacks - template attack and stochastic attacks are well-known techniques, quadratic discriminant analysis, and linear regression, respectively.
- Machine learning techniques were successfully applied in the attack phase, but also for pre-processing and feature engineering.
- Deep learning thrives from advantages that it does not require feature selection and that it can break implementations protected with countermeasures.
- Interesting additional ML applications are noise removal and data augmentation.

Side-channel Analysis

- This is a very active research domain with new papers appearing all the time.
- This makes this domain attractive for new researchers but also difficult due to large competition.
- There are some extra problems like lack of publicly available datasets, inconsistency between ML metrics and SCA metrics.
- Common techniques are random forest, support vector machines, multilayer perceptron, convolutional neural networks.
- While the common attack target is AES (block cipher), recently, more people are interested in attacking public-key cryptosystems also.
- While ML is mostly used in this domain, there are attempts to use evolutionary algorithms to find better leakage models (e.g., to use information from multiple S-boxes).

Side-channel Analysis

- A framework for deep learning-based SCA [126].
- [149, 57, 151, 56, 17, 93, 47, 173, 166, 73, 4, 61, 55, 150, 88, 58, 62, 138, 197, 131, 208, 124, 59, 125, 204, 210, 209, 202, 105, 127, 175, 196, 192, 203, 90, 12, 189].
- EC applications [211, 194].

Fault Injection

- A fault injection (FI) attack is successful if, after exposing the device to a specially crafted external interference, it shows an unexpected behavior exploitable by the attacker.
- Insertion of signals has to be precisely tuned for the fault injection to succeed.
- Finding the correct parameters for a successful FI can be considered as a search problem where one aims to find, within a minimum time, the parameter configurations which result in a successful fault injection.
- The source of fault can be, e.g., voltage glitching, laser, electromagnetic radiation.
- Depending on the source of the fault, the search space of possible parameters changes significantly.
- In general, the search space is too big to conduct an exhaustive search.

Fault Injection

- Commonly, one defines several possible classes for classifying a single measurement:
  1. NORMAL: smart card behaves as expected, and the glitch is ignored
  2. RESET: smart card resets as a result of the glitch
  3. MUTE: smart card stops all communication as a result of the glitch
  4. CHANGING: the response is changing when repeating measurements.
  5. SUCCESS: smart card response is a specific, predetermined value that does not happen under normal operation

Fault Injection

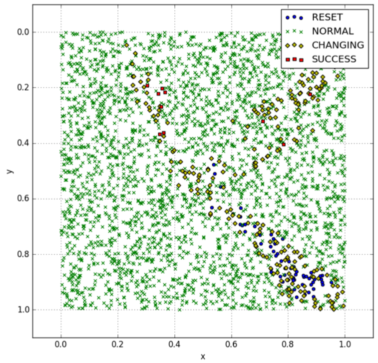


Figure: A depiction of search space for voltage glitching and two parameters.

Fault Injection

- Research domain with not many results from AI.
- Commonly used techniques are random search and grid search, so EC makes a strong alternative.
- The main issue is very expensive equipment to run fault injection campaigns.
- Mostly, EC is used, but recently, also deep learning found its place.
- Deep learning can be used to predict what a target would respond to a specific parameter combination.

Fault Injection

- Interesting research directions include *i*) working with more relevant parameters, *ii*) attacking targets with countermeasures, and *iii*) making the search algorithm more powerful, especially by considering the differences between faults and exploitable faults (those that would result in target break).
- [22, 129, 139, 205, 95, 94, 180].

Addition Chains

- Up to now, we considered EC and ML applications that directly contributed to the security of ciphers or, on the other hand, were used to break ciphers.
- Still, it is possible to use AI techniques as a helper tool to improve the systems, either from an attack or defense perspective.
- In a way, one could consider the evolution of S-boxes with good implementation properties to also belong to the setting that helps improve the system, but not necessarily its security.
- Another example of a problem like that is the finding of short *addition chains*.
- Addition chain: a sequence of positive integers where each value is a sum of two values appearing previously in the chain.
- Addition chains are used in public-key cryptosystems (e.g., for modular exponentiation).

Addition Chains

- Example: form an addition chain to target value of 60.
- Binary method: write 60 in binary: 111100; replace “1” with “DA” and “0” with “D”; cross out the first “DA” on the left; “DADADADD”, calculate:

$$1 \to 2 \to 3 \to 6 \to 7 \to 14 \to 15 \to 30 \to 60$$

- Addition chain (7 operations):

$$A^1; A^2 = A^1 * A^1; A^4 = A^2 * A^2; A^6 = A^4 * A^2; A^{12} = A^6 * A^6;$$

$$A^{24} = A^{12} * A^{12}; A^{30} = A^{24} * A^6; A^{60} = A^{30} * A^{30}$$

Addition Chains

- The problem of finding the shortest addition chain for a given exponent is relevant in cryptography.
- The problem is believed to be NP-hard.
- There is no single algorithm that can be used for any exponent.
- The best solutions so far are obtained by pen and paper method (!).
- Huge numbers, so exhaustive search is impossible.
- Heuristics should be able to help.
- The values in the ascending addition chain have the property that they are the sum of two values appearing previously in the chain.

Addition Chains

- Common solution representations are binary encoding where value 1 means that the entry number is in the chain, and 0 means the opposite, and integer encoding where every value represents an element of the chain.
- Extra care needs to be taken with crossover and mutation operators: as one changes elements, it is required to ensure that the chain remains valid!

Addition Chains

- Interesting research directions are *i*) improve the speed of the algorithm, *ii*) look for optimal chains for even larger numbers, *iii*) support special structures of numbers, and *iv*) explore different types of addition chains.
- [115, 116, 118, 30, 29, 122, 87, 145, 144, 117, 119, 36, 37].

Addition chains

Custom addition chain genotype

```
<Individual size="1">
        <FitnessMin value="37"/>
        <Chain size="38">1 2 4 8 16 32 64 128 256 512 1024 2048 4096 8192 16384
        32768 65536 131072 262144 524288 1048576 2097152 4194304 8388608 16777216
        17039360 17040384 17040385 34080769 68161538 68177922 136355844 204533766
        340889610 374970379 375494667 375494699 375494703 </Chain>
</Individual>
construction:
0/0 1/1 2/2 3/3 4/4 5/5 6/6 7/7 8/8 9/9 10/10 11/11 12/12 13/13 14/14 15/15 16/16
17/17 18/18 19/19 20/20 21/21 22/22 23/23 18/24 10/25 0/26 26/27 28/28 14/29 30/30
30/31 31/32 28/33 19/34 5/35 2/36
```

- Chain optimization with target exponent value 375 494 703 (ECF).
- The construction steps are reproduced below the chain.

Cybersecurity

- Cybersecurity is the security of computer systems and networks from information disclosure.
- While often it is considered to include only the defensive side (i.e., protection), we also consider the attack perspective.
- Cryptography is just one aspect of cybersecurity.
- In general, going from cryptography to cybersecurity increases the number of AI applications.
- We can also talk about AI for cybersecurity and the security of AI.

Intrusion Detection

- Intrusion detection: the process of monitoring the events occurring in a computer system or network and analyzing them for intrusions.
  - Intrusions: attempts to bypass the security mechanisms of a computer or network
- Detection can be *signature based* and *anomaly detection based*.
- Anomaly detection: recognizes normal network traffic and categorizes different traffic as an anomaly
- Common approaches: supervised/unsupervised classification (machine learning).
- Problems with anomaly detection: 1) the data is usually too expensive to be labeled manually, 2) data is imbalanced (much more normal than anomaly traffic), and 3) the existence of unknown attacks.
- Assumption: only one class of data (normal network traffic) is available for training!

Intrusion Detection

- GP can be used in classification (e.g., decision tree, regression tree).
- Use regression GP as *one-class classifier*.
- Procedure: learn the model on normal traffic data, test on unseen data containing anomalies (intrusions).
- Learn a model (GP function) that forces the tree output (function value) to a certain output range.
  - e.g., [1, 2], [4, 5] or [8, 9]; *same* range for all normal traffic instances
- Penalize 'trivial' models - reward/force the use of most features.
- Test the model on unseen data containing intrusions (heavily imbalanced!).
- Interpretation: outputs falling outside the defined range are classified as anomalies.
- GP results: comparable to one-class SVM.
- References: [18, 52, 14, 183, 206, 121, 41, 184, 42]

Fuzzing

- Fuzzing (fuzz testing): automated software testing technique.
- Generating inputs and feeding them to the program being tested in the hope of evoking erroneous behavior or increasing code coverage.
- *Mutation-based fuzzing*: uses a dataset of test cases (a corpus):
  - selects a test case,
  - modifies it by applying *mutation operators*,
  - feeds it to the tested program.
- Example mutation operators: bit flip, random byte value, set byte to *interesting* value, insert byte, delete byte, ...
- Optimization of fuzzing: finding an appropriate sequence of mutation operators (*mutation scheduling*).

Fuzzing

- The fuzzing loop contains a deterministic stage (uses a predefined order of mutations) and randomized stage (random choice of mutations).
- The optimization is applied to the randomized stage, with the goal of finding the effective. *probability distribution* of mutation operators
- An example of *online* learning: optimization is performed concurrently with the process being optimized:
  - the mutation scheduler uses the current, solution (probability distribution) to select mutation operators,
  - the reported feedback is used to optimize the distribution,
  - the updated probability distribution is applied in the next iteration.
- Optimization is made under uncertainty: the fitness of a solution may only be estimated.

Fuzzing

- Examples including evolutionary optimization in mutation-based fuzzing:
- MOPT fuzzer: uses a variant of PSO to learn globally optimal mutation probability distribution
  - heavily dependent on choice of parameters and the tested program
  - may exhibit slow convergence due to multiple solutions in the population
- An approach with single-solution metaheuristic (e.g. $(\mu + \lambda)$ ES) could increase effectiveness:
  - focuses on increasing the speed of convergence,
  - more robust over different target programs.
- EC-based mutation schedulers outperform standardized fuzzing platforms.
- References: [193, 51, 201, 174, 48, 92, 86, 195]

Conclusions - EC

- Up to now, EC proved to be successful in cryptography and cybersecurity.
- EC is used:
  1. When there exist no other, specialized approaches.
  2. To rapidly check whether some concept (e.g., formula) is correct.
  3. To assess the quality of some other method.
  4. To produce “good-enough” solutions.
  5. To produce novel and human-competitive solutions (solutions produced by EC that can rival the best solutions created by humans).

Conclusions - ML

- Machine learning is a data-driven approach, and as such limited to scenarios where we can obtain data.
- In cryptography, in domains like attacks on strong PUFs and profiled SCA, machine learning achieved excellent results.
- In cybersecurity, the applications are more diverse: intrusion detection and fuzzing are examples of well-explored and active research domains.
- While this tutorial covers topics that could be considered as AI for security, security of AI is also very active domain!

Conclusions

- We presented here only a handful of applications, there are more options.
- Even for each of the applications, there is a plethora of options still to try:
  1. New algorithms.
  2. Combinations of parameters.
  3. Representations.
  4. Fitness functions.
- The results obtained up to now are good, but there is still much room for improvement.

Conclusions

- As already said, there is a difference between attack and constructive perspectives, which makes it often easier for AI techniques to be used as attack mechanisms (at least for now).
- As a general research direction, it would be interesting to consider new applications (while some of the current ones are still very active, it would not be necessarily easy for new researchers to join the research effort).

Thank you for your attention!

Questions?

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