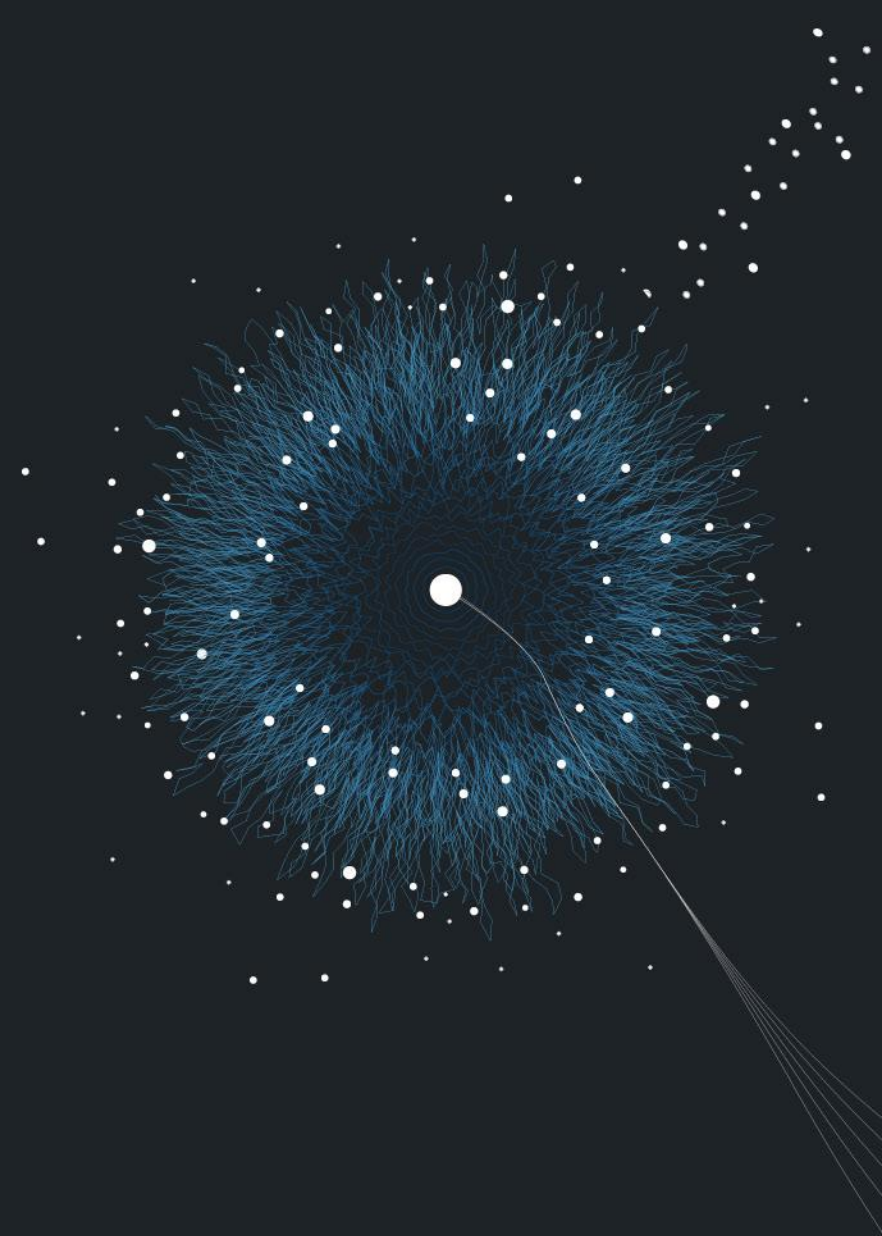


EEMCS - SCS

# EVOLUTIONARY ALGORITHMS FOR CYBERSECURITY

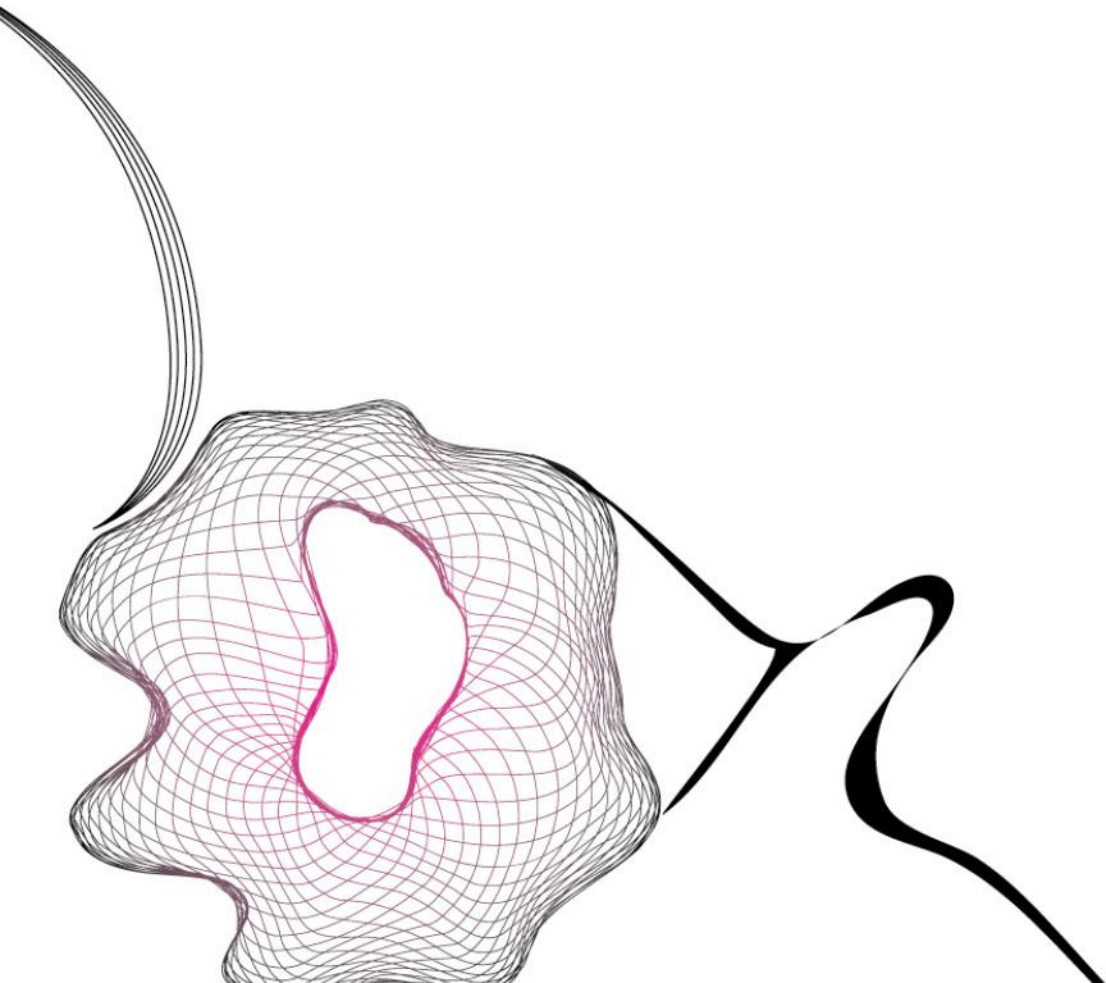
GUEST LECTURE – APRIL 3, 2025

LUCA MARIOT

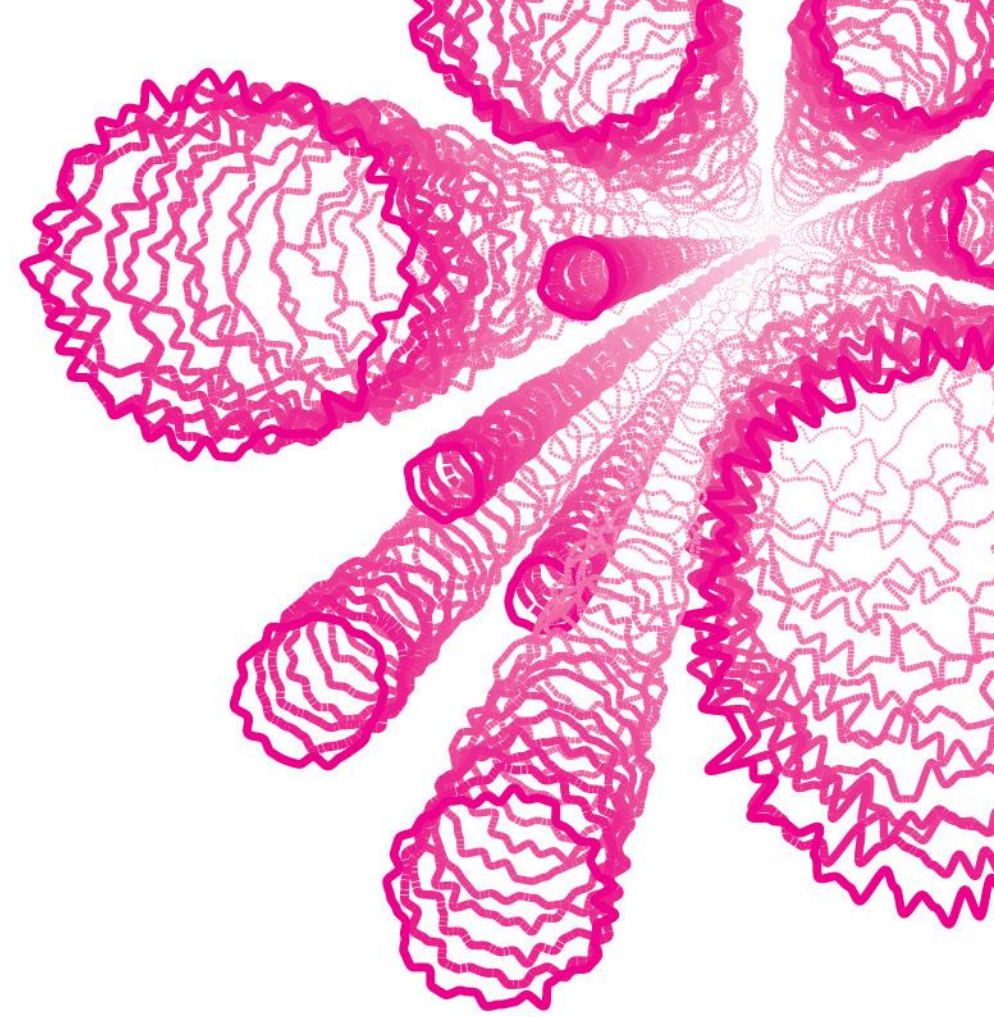


# SUMMARY

- Intro to Cybersecurity
- Cryptography & EA
- Network Intrusion Detection & EA



# INTRO TO CYBERSECURITY



# THE CIA TRIAD OF SECURITY

When building a secure system, we focus on three aspects [1]:

## Confidentiality

Data are protected from unauthorized access/use

## Integrity

Data have not been altered by unauthorized parties

## Availability

Data are available to authorized parties when needed

# THREAT MODELING

- Threat: potential violation of a security goal
- Attack: intentional violation of a security goal
- Security: protection from attacks vs. cost



Security is economics!

# ACHIEVING SECURITY

## Prevention

- Cryptography
- Intrusion Protection

Prevention

Analysis

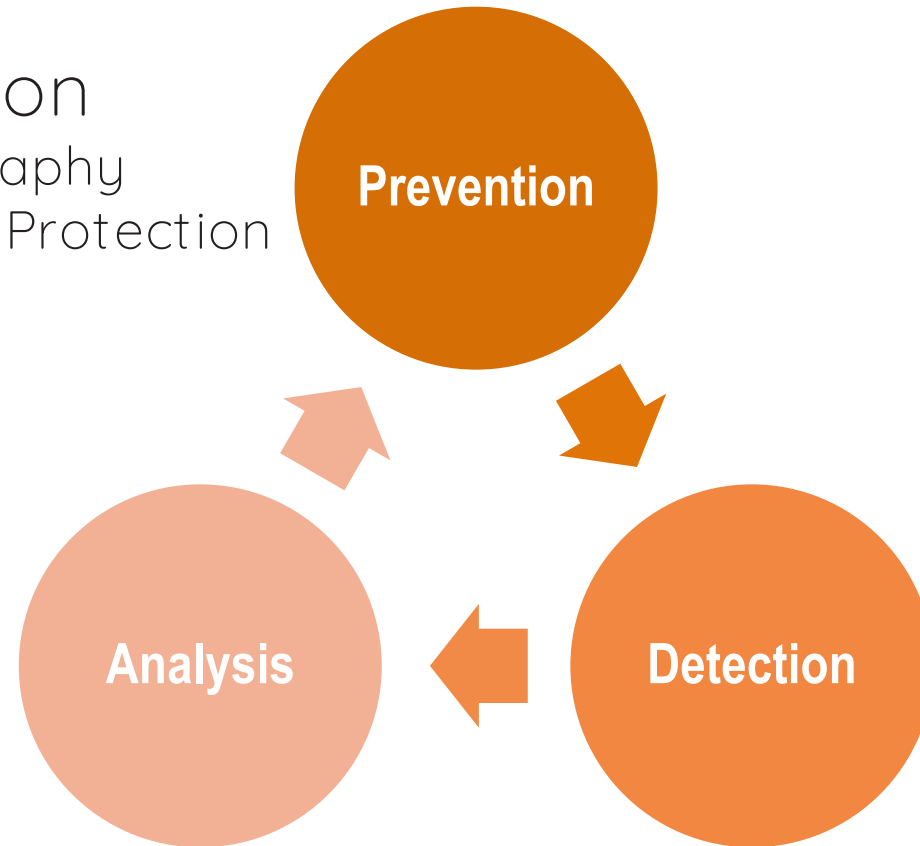
## Analysis

- Forensics
- Incident Response

Detection

## Detection

- Intrusion Detection
- Malware Detection



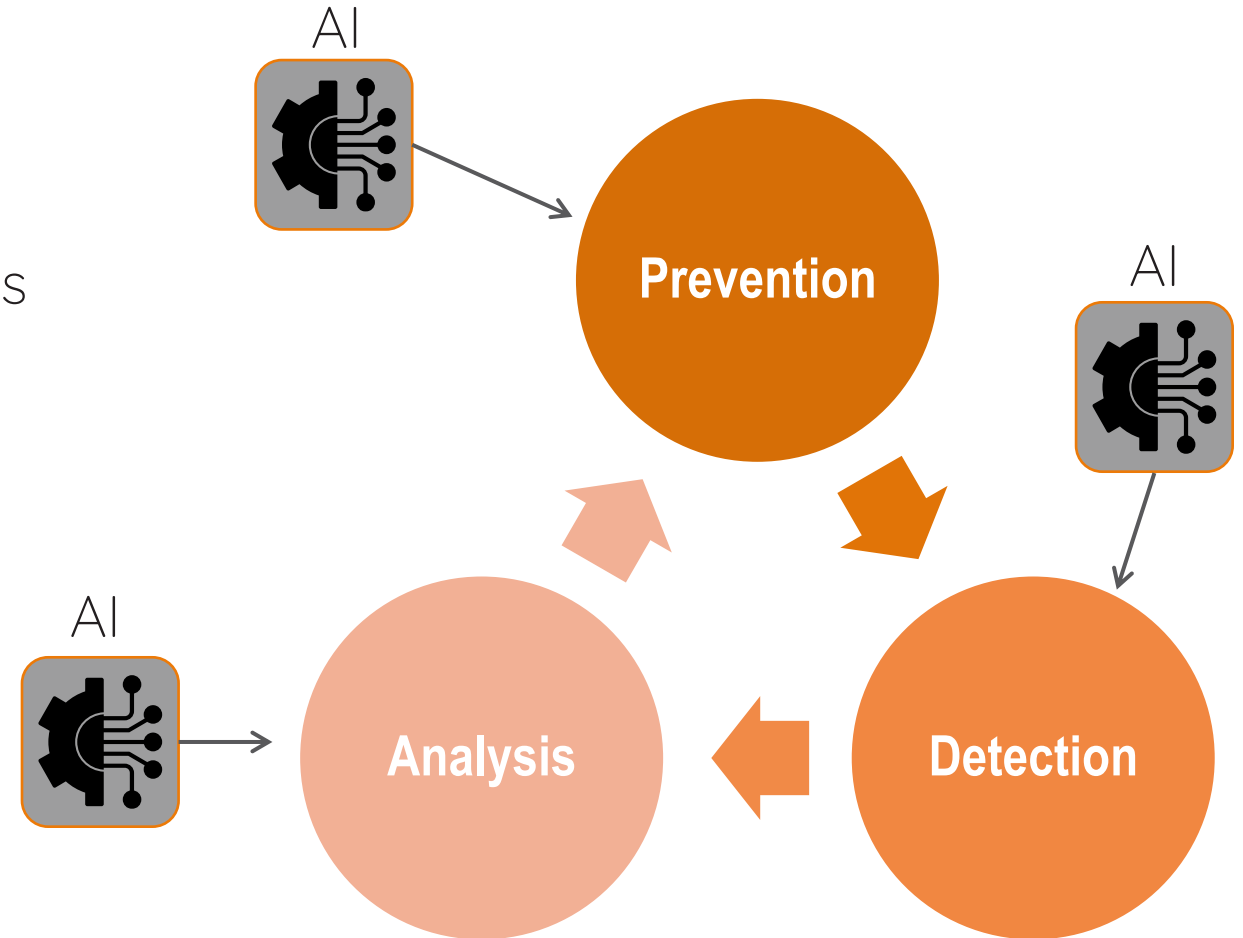
# AI FOR SECURITY

Challenges:

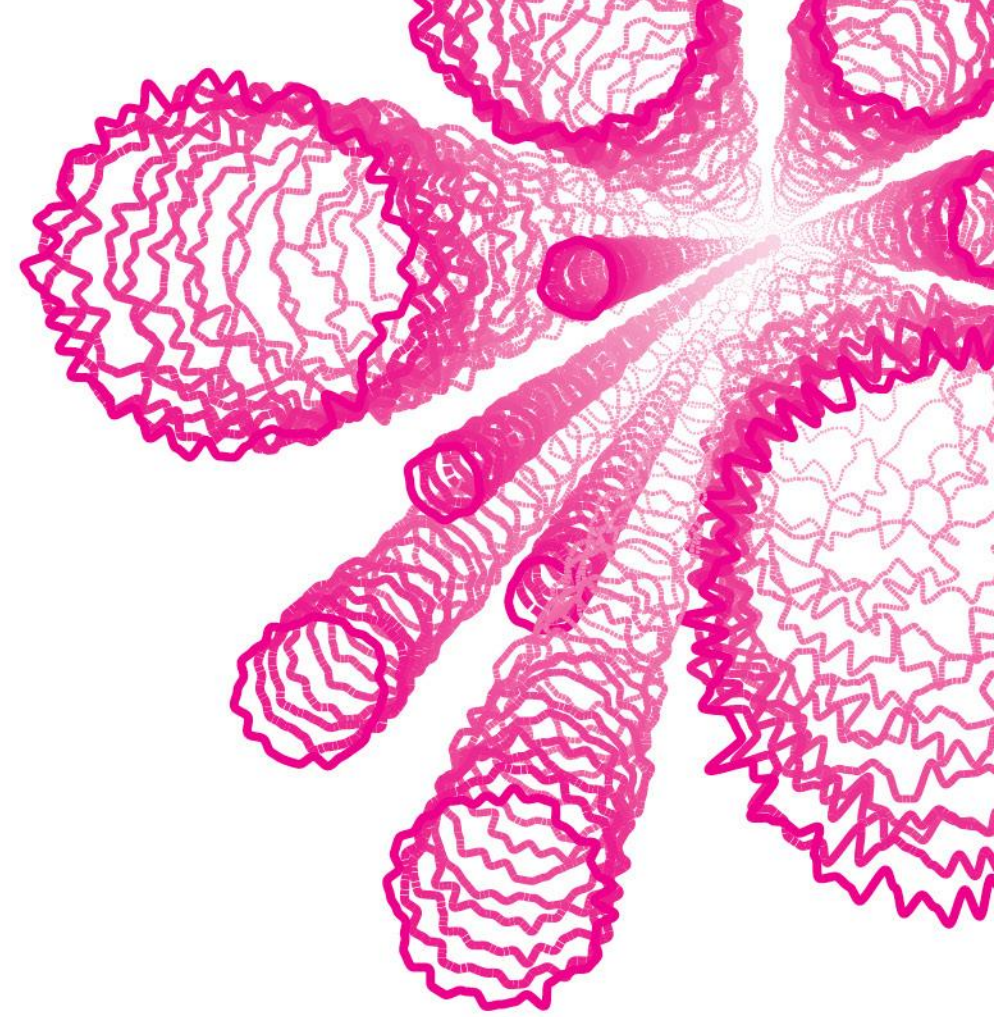
- New vulnerabilities, new attack vectors
- Reducing human intervention

Approach: “Smarter” Security

- Automate the design process
- Use AI techniques (e.g. Evolutionary Computing) for the automation

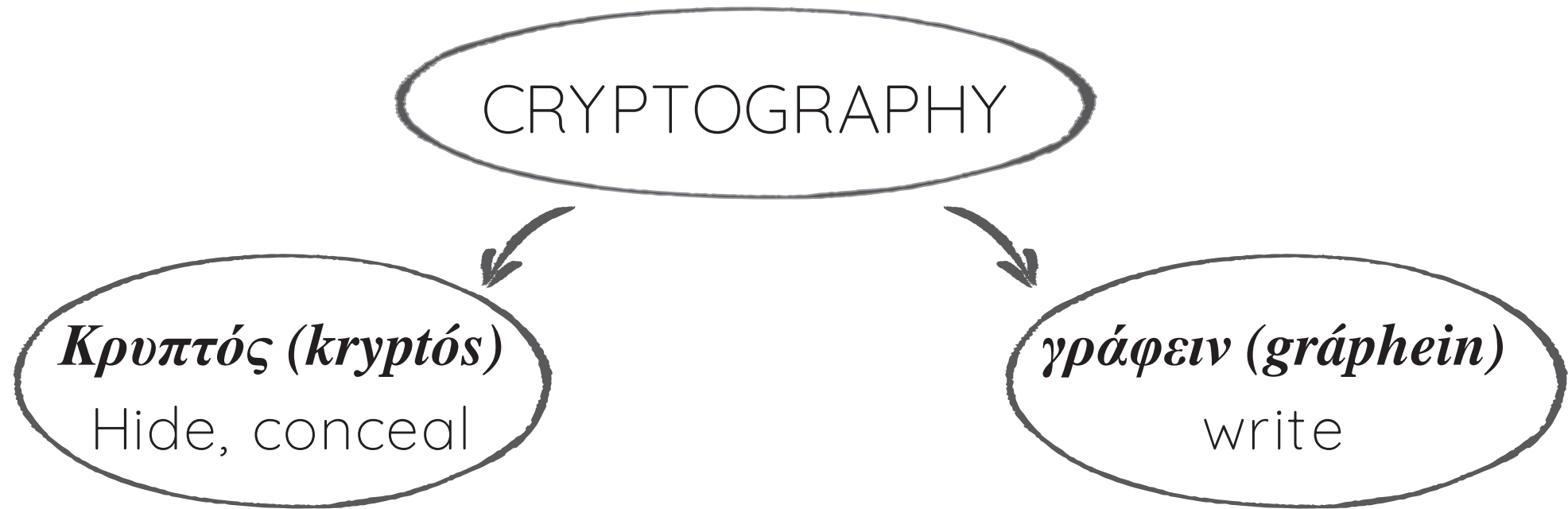


# CRYPTOGRAPHY





# WHAT IS CRYPTOGRAPHY?



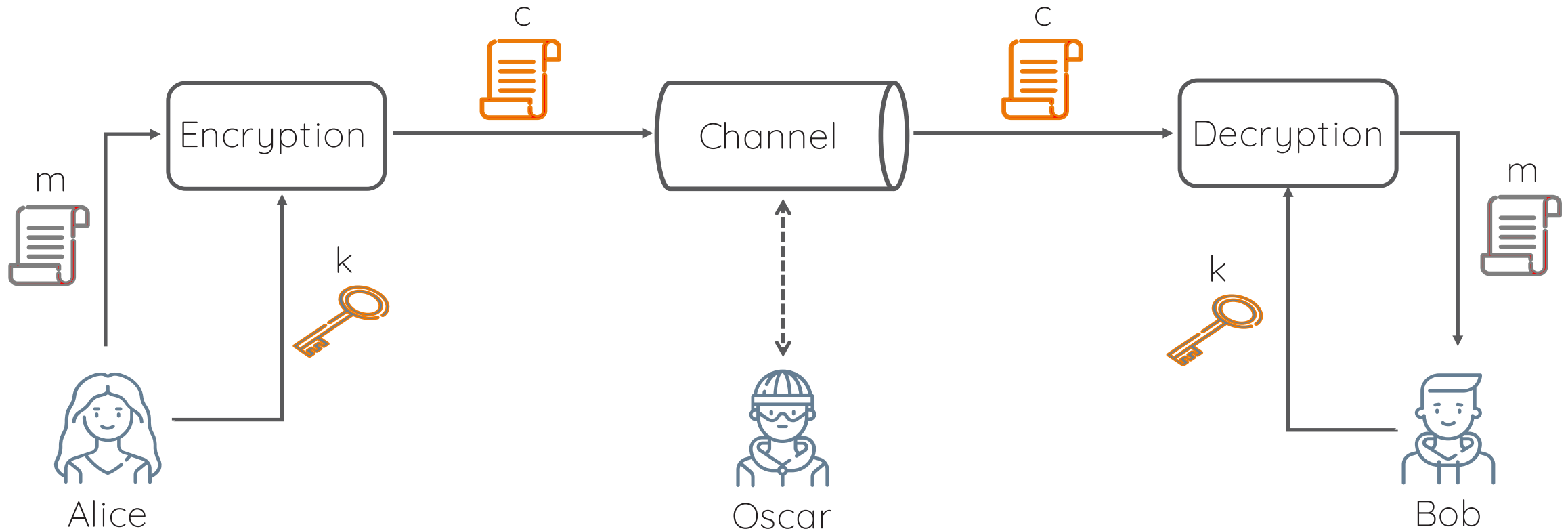
Historically: the art of hiding the meaning of messages, with the goal of protecting their confidentiality

# THE CIA TRIAD IN CRYPTOGRAPHY

In cryptography, the “A” is usually replaced by Authenticity:



# SYMMETRIC-KEY ENCRYPTION SCENARIO



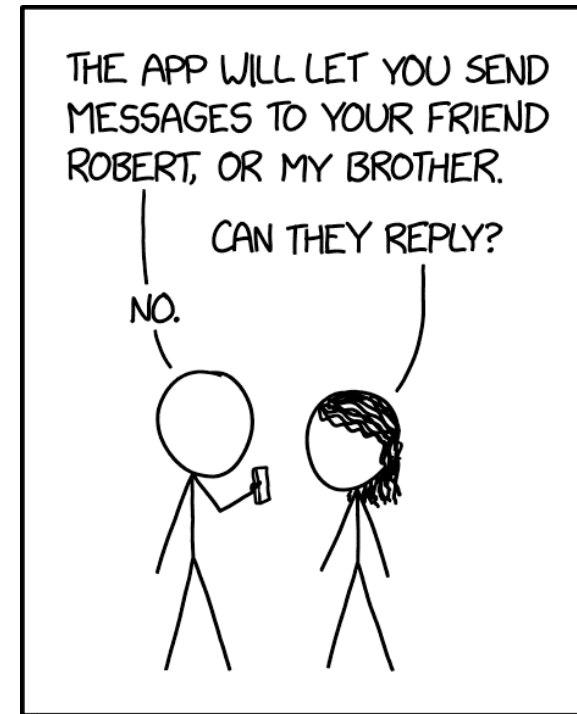
$m$ : plaintext message

$k$ : encryption/decryption key

$c$ : ciphertext message

# SYMMETRIC-KEY ENCRYPTION SCENARIO

- The same key  $k$  is used both for encryption *and* decryption [6]
- The scheme is “secure” as long as Oscar does not know  $k$
- Requires sharing  $k$  *before* communicating
- Here, we just assume Alice and Bob shared  $k$  somehow



MY NEW SECURE TEXTING APP ONLY ALLOWS PEOPLE NAMED ALICE TO SEND MESSAGES TO PEOPLE NAMED BOB.

# KERCHOFFS'S PRINCIPLE (1883)

- The encryption scheme is known to the attacker [7]
- Security relies *only* on the secrecy of the encryption key

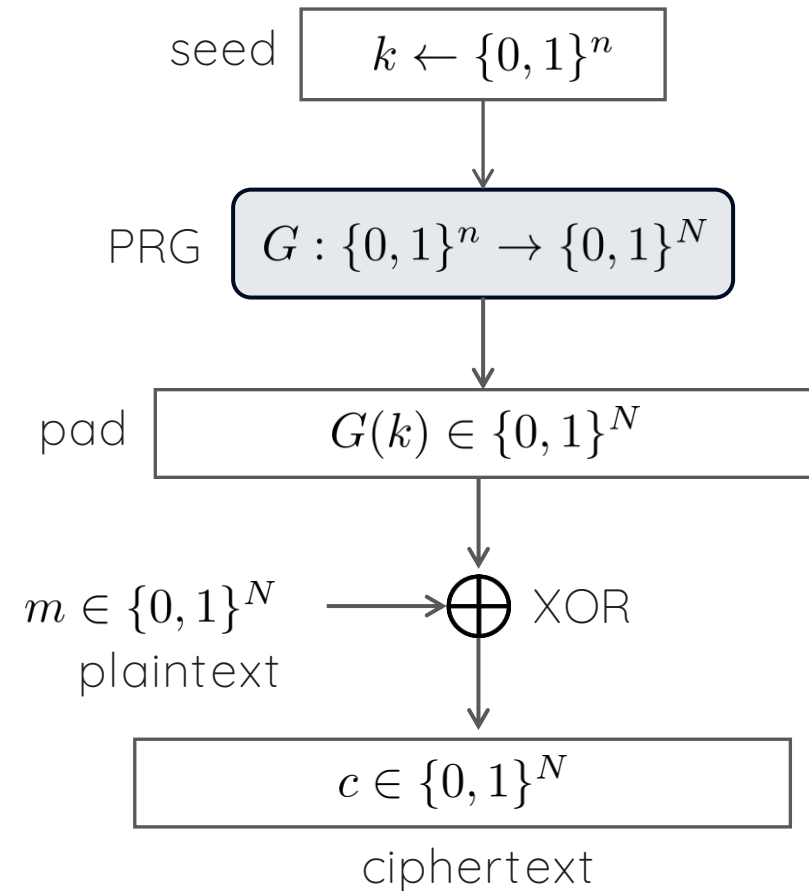
“The encryption/decryption system must not be kept secret, and can be stolen by the enemy without causing any problem.”



# 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 [6]
- The seed of the PRG is the key  $k \leftarrow \{0, 1\}^n$
- Encryption: Bitwise XOR between message and pad

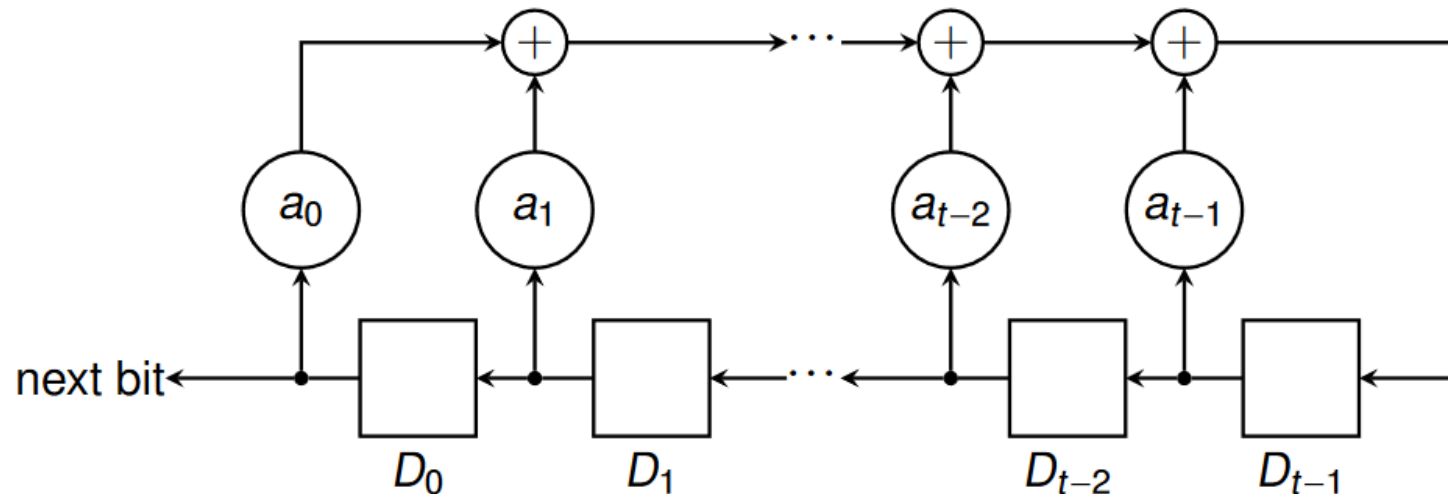
$$c_i := m_i \oplus p_i, \text{ for all } i \in \{1, \dots, N\}$$



# LINEAR FEEDBACK SHIFT REGISTERS (LFSR)

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

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



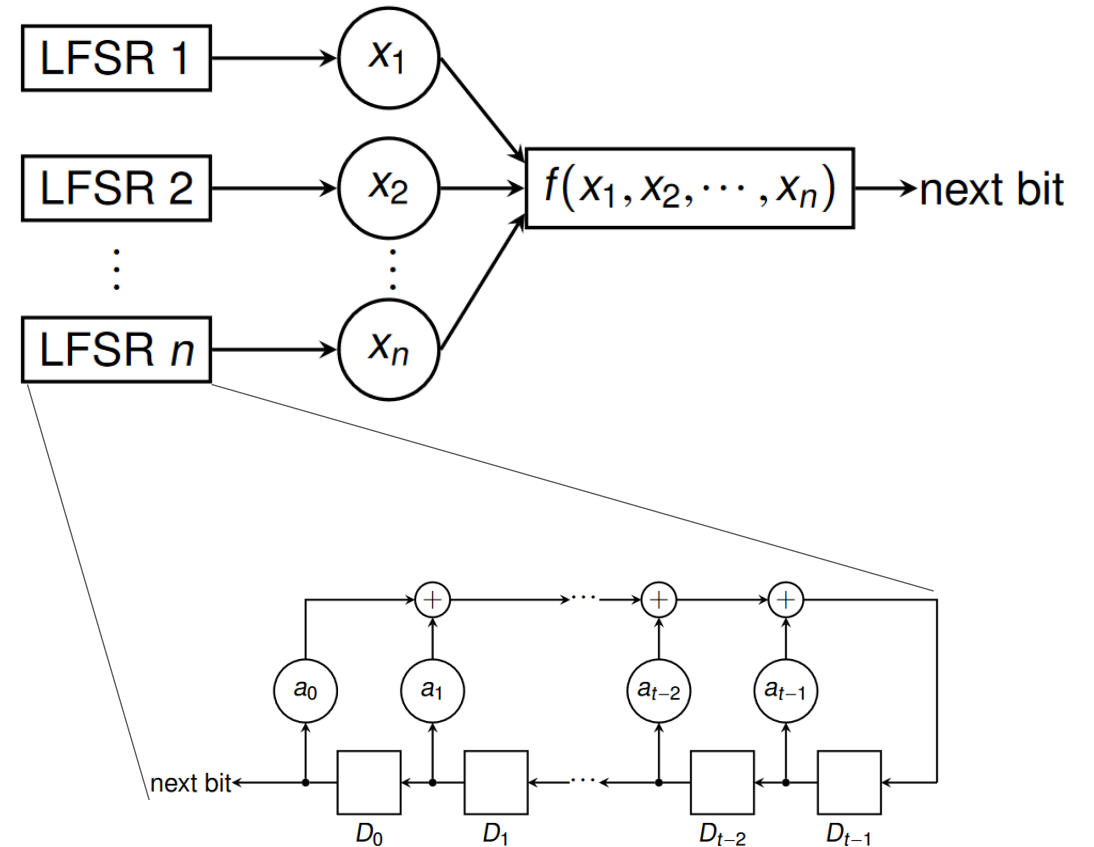
- Problem: very weak as a cryptographic PRG [6]

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





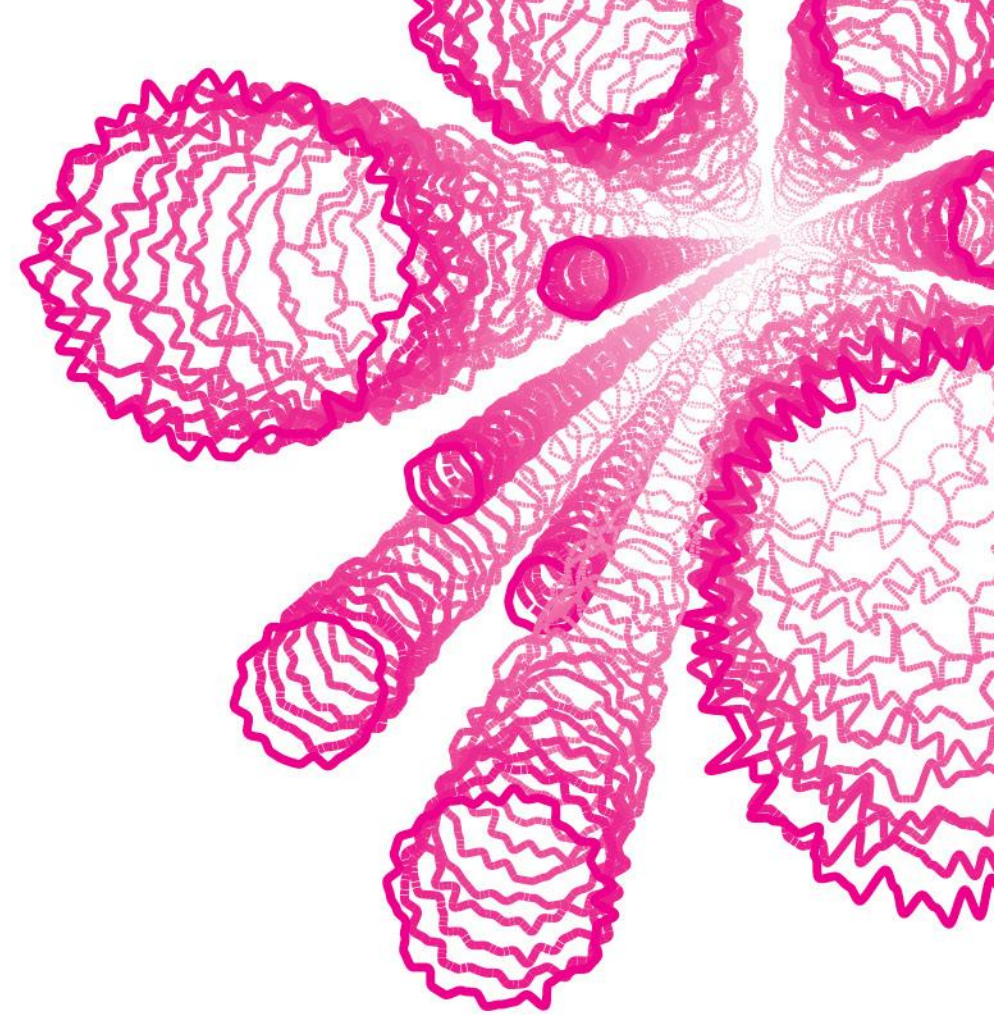
# BOOLEAN FUNCTIONS

- 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. ...

# EVOLUTIONARY ALGORITHMS FOR BOOLEAN FUNCTIONS



# OPTIMIZATION PROBLEM

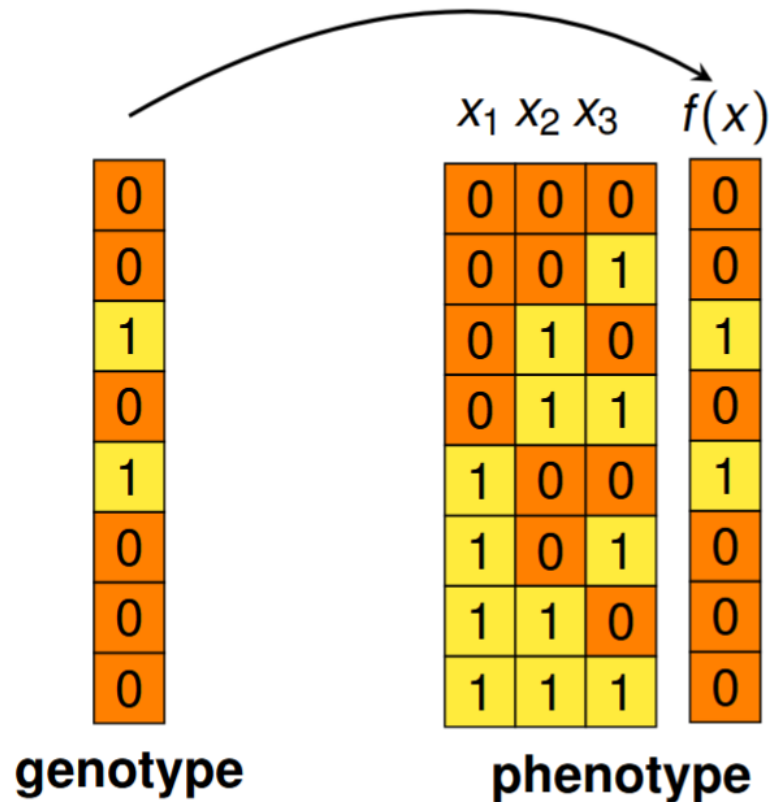
- Given  $n \in \mathbb{N}$ , how do we fill the table so that  $f$  is balanced and highly nonlinear?

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

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

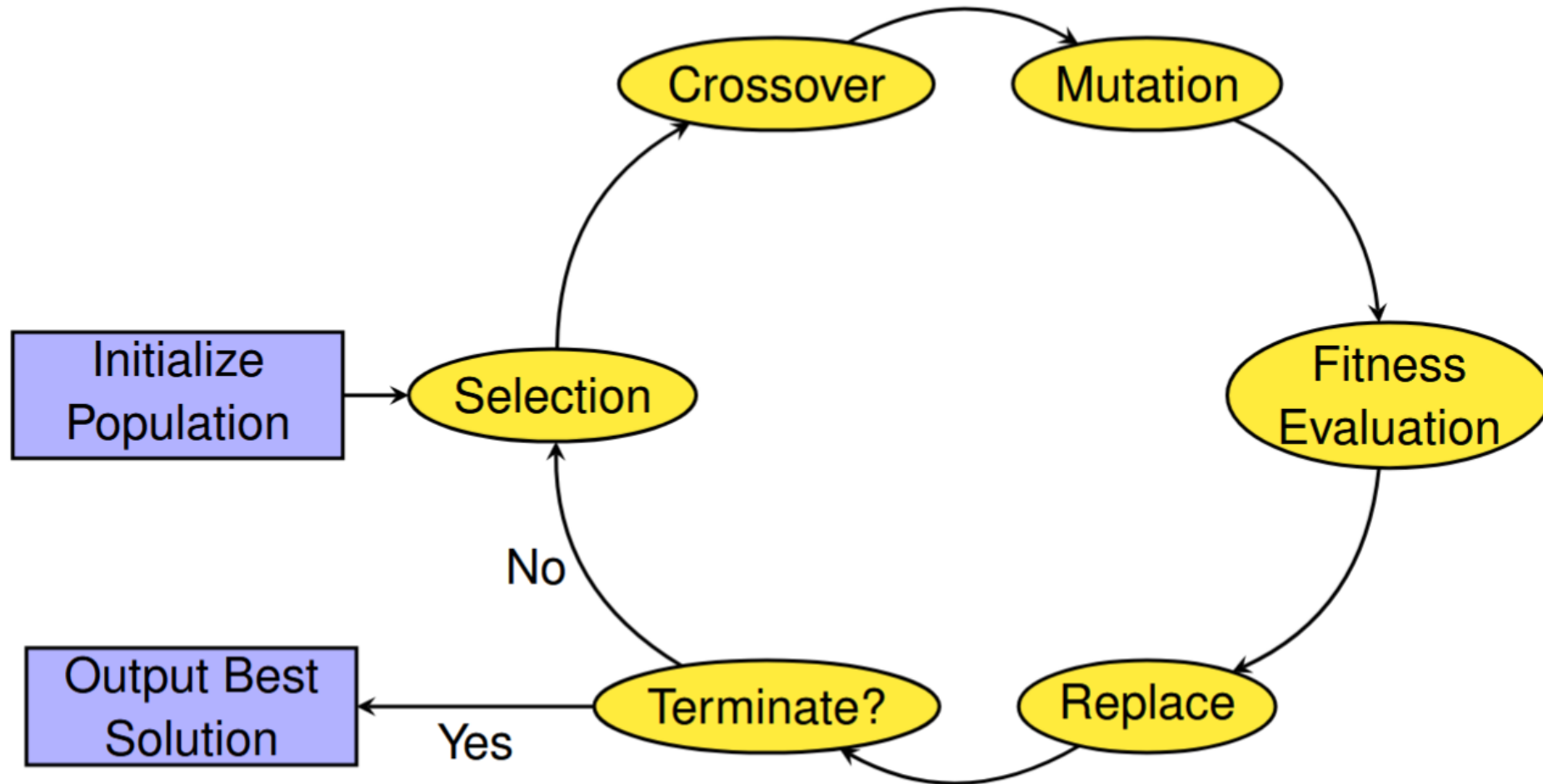
- The truth table has size  $2^n$  so there are  $2^{2^n}$  combinations
- For concrete security, we need  $n > 13$
- But exhaustive search is already unfeasible for  $n > 5$ !

# EVOLUTIONARY ALGORITHMS (EA)

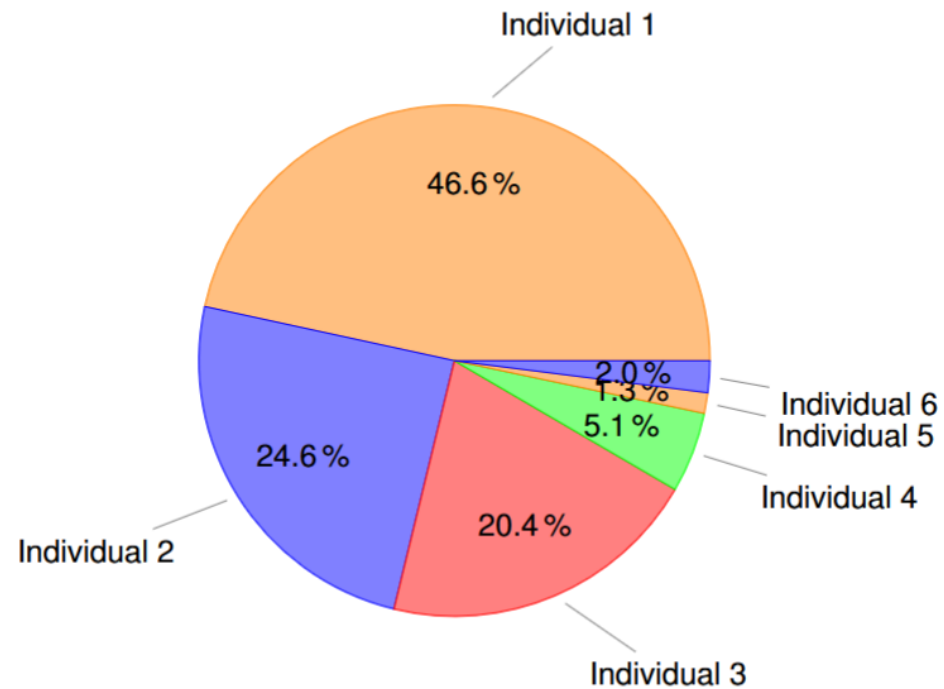


- Optimization algorithms loosely based on evolutionary principles
- Genetic Algorithms (GA): introduced by John Holland (1975)
- GA genotype: fixed-length bitstrings
- phenotype: truth table of  $f$  [5]

# THE EA LOOP



# SELECTION

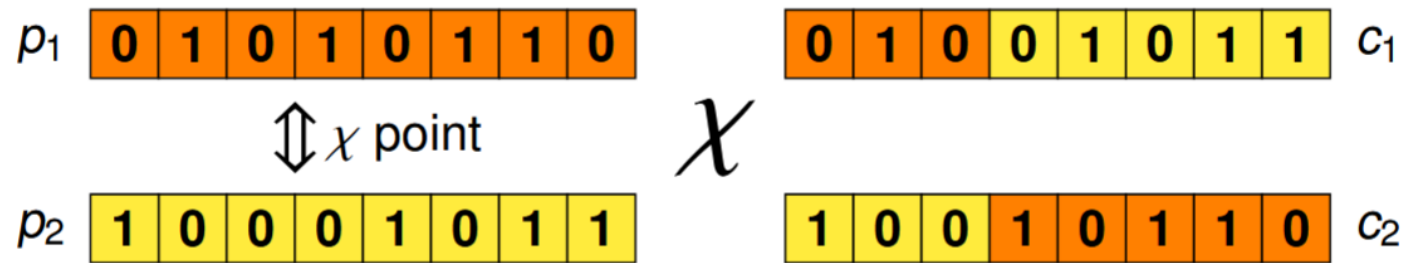


- Roulette-Wheel: selection probability proportional to individual's fitness
- Tournament: select the fittest individual from a random sample of  $t$  individuals

# CROSSOVER

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

GA Example: One-Point Crossover

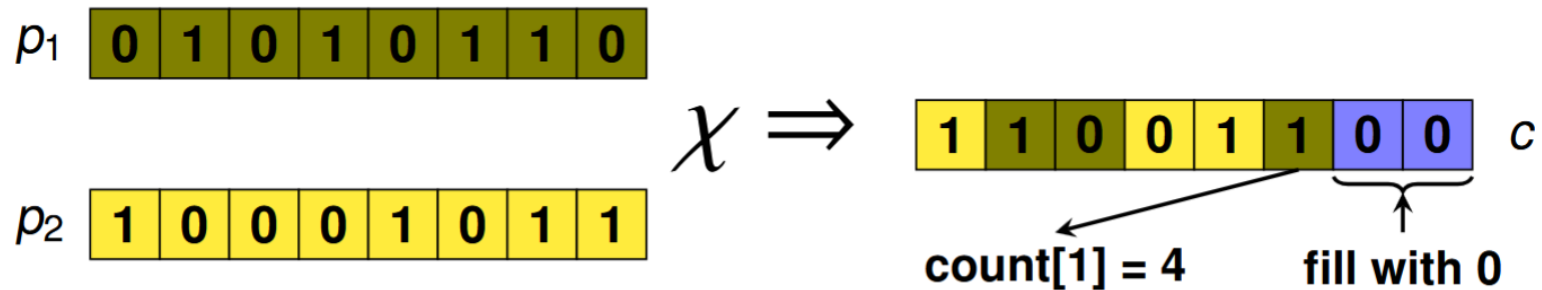


- Problem: how do we ensure balancedness for cryptography?
- We could optimize it in the fitness function...

# BALANCED CROSSOVER

- Idea: use counters to keep track of the numbers of 1s in the child [9, 13]

GA Example: Counter-based Crossover



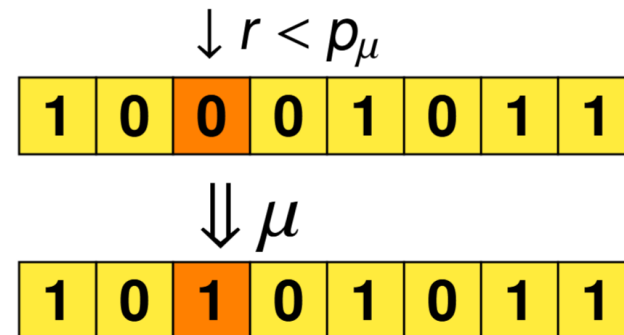
- If we start from balanced parents, we get balanced children



# MUTATION

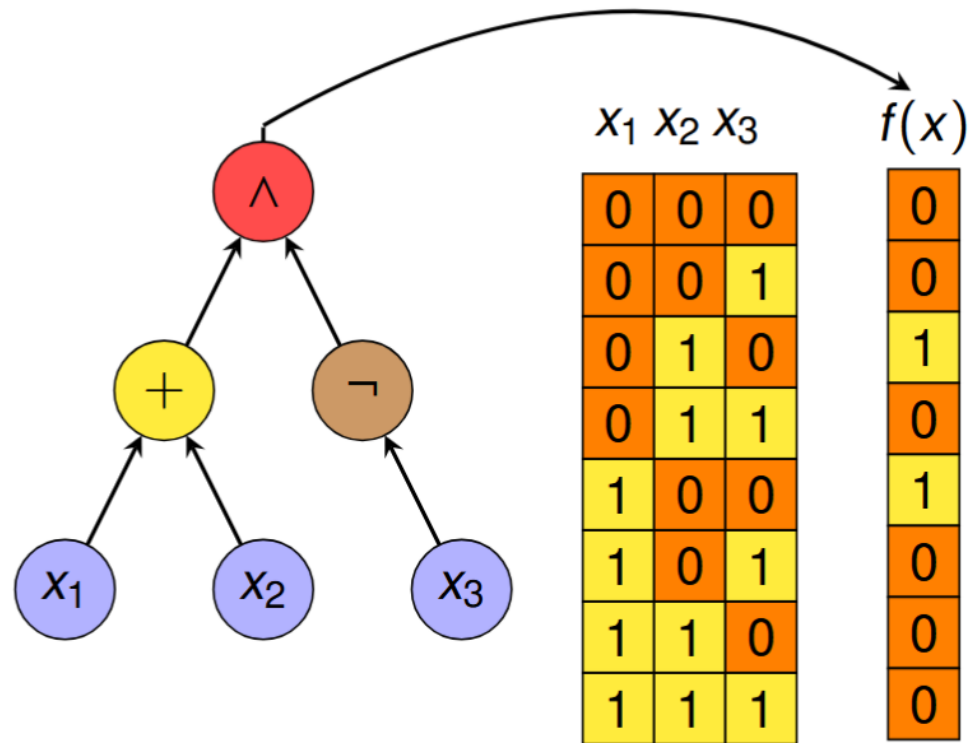
- Idea: introduce new “genetic material” in the offspring (Exploration)

GA Example: Bit-flip mutation



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

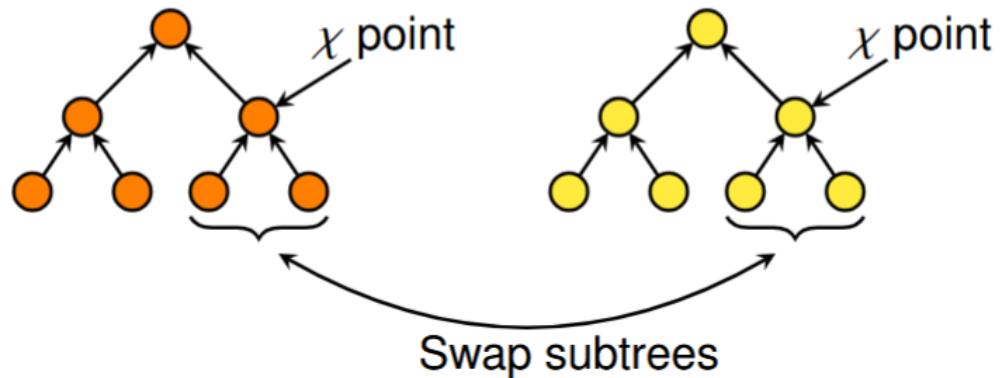
# GENETIC PROGRAMMING (GP)



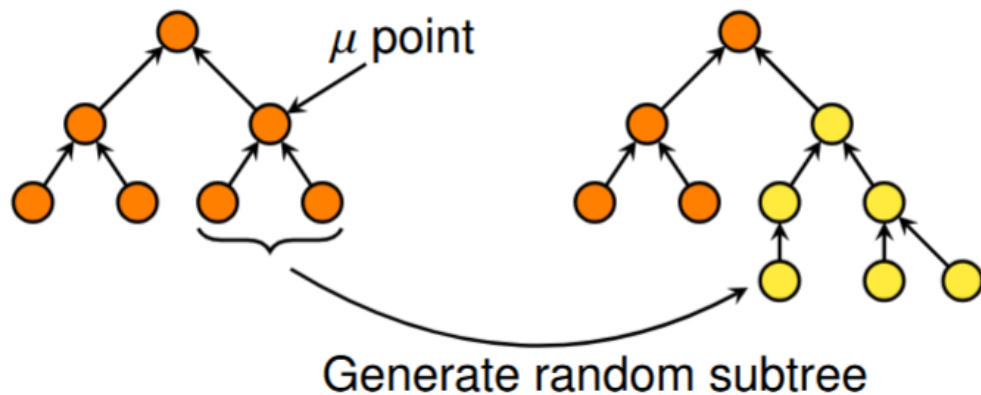
- Idea: evolve computer programs to solve specific tasks
- GP Genotype: a syntactic tree
  - Leaf nodes: input variables
  - Internal nodes: operators (e.g. AND, OR, NOT, XOR, ...)
- Phenotype: evaluate the tree for all possible assignments of the leaf nodes

# GP CROSSOVER & MUTATION

## Subtree Crossover

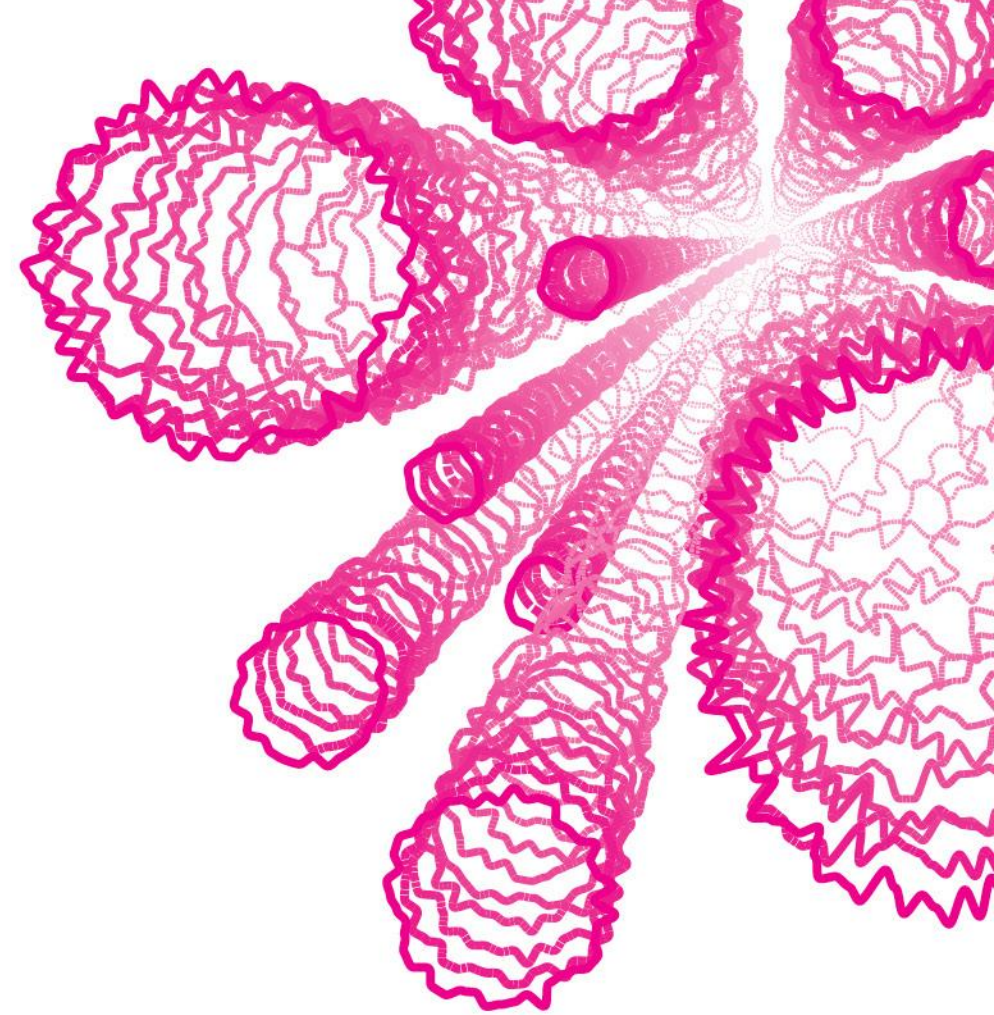


## Subtree Mutation



- In general: not possible to preserve the balancedness of the Boolean function
- Nevertheless: GP usually fares better than (balanced) GA [10, 12, 14, 15]
- Other approaches: use GP to combine existing functions with high nonlinearity [3, 10]

# NETWORK INTRUSION DETECTION

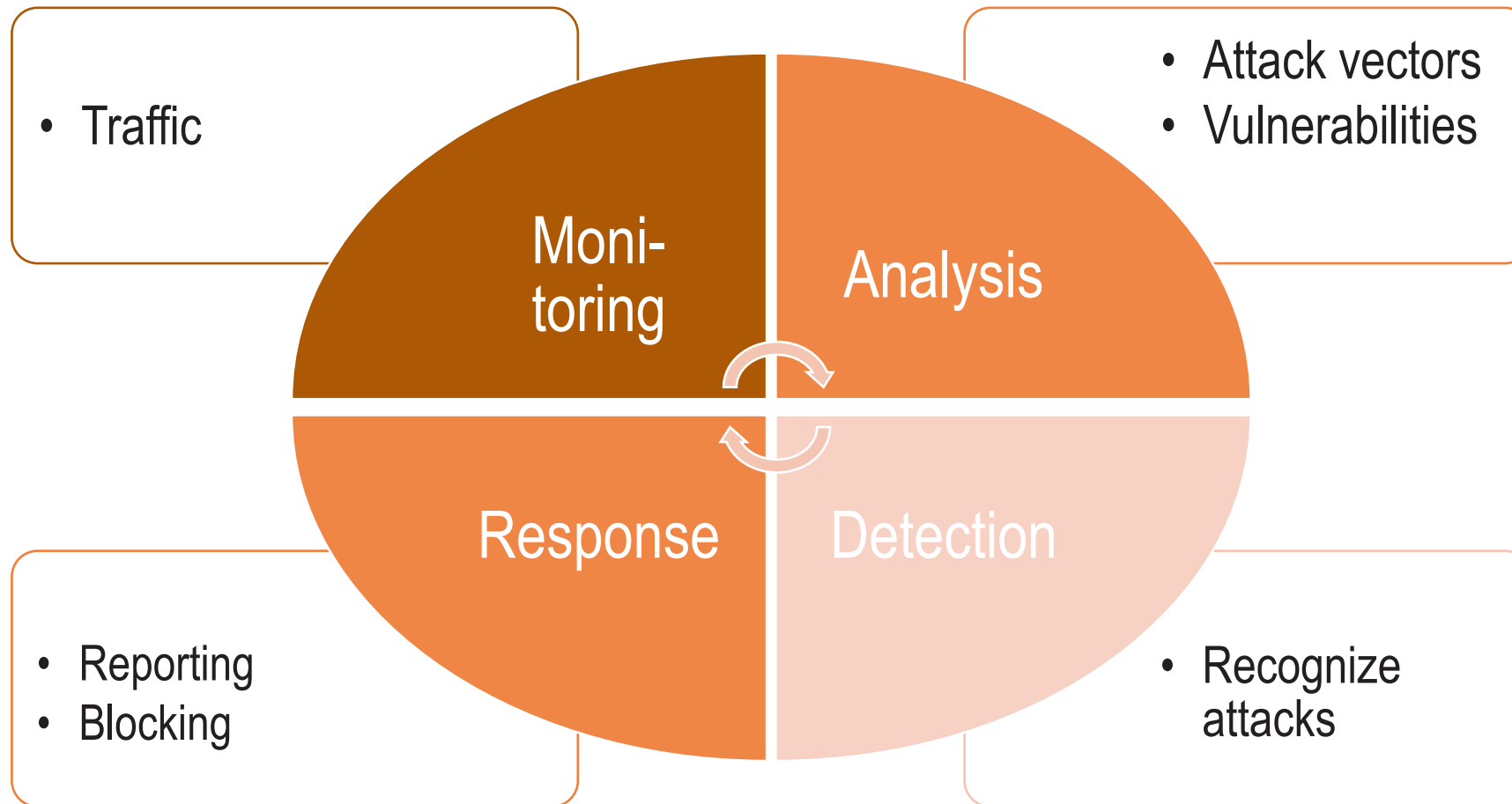


# INTRUSION DETECTION

- Intrusion Detection System: Monitoring for attacks
- Attack: attempt to compromise confidentiality, integrity, or availability
- Several types of IDS:
  - Monitor source: network, application, server, ...
  - Analysis type: signatures, rules, machine learning, ...

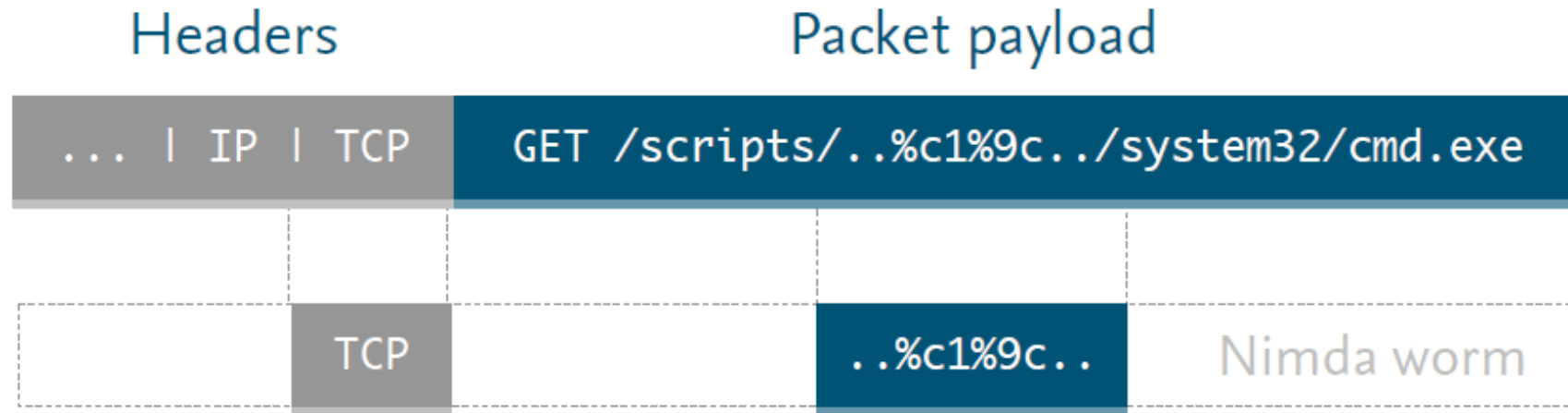


# NETWORK INTRUSION DETECTION (NIDS)



# SIGNATURE-BASED NIDS

- Traditional type of NIDS: signature-based [16]

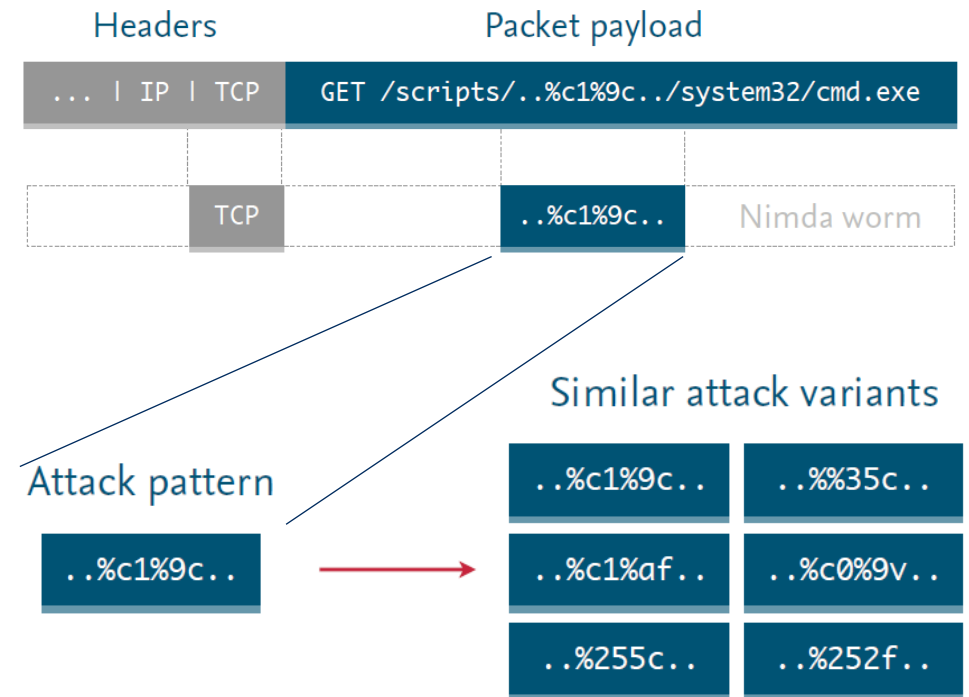


- Leverages pattern detection of known attacks (e.g., with Regular Expressions)

# SIGNATURE-BASED NIDS

Common problems:

- Signatures from known attacks required
- Signature updates required
- Scalability issues, complexity and attack frequency
- Unable to detect unknown attacks

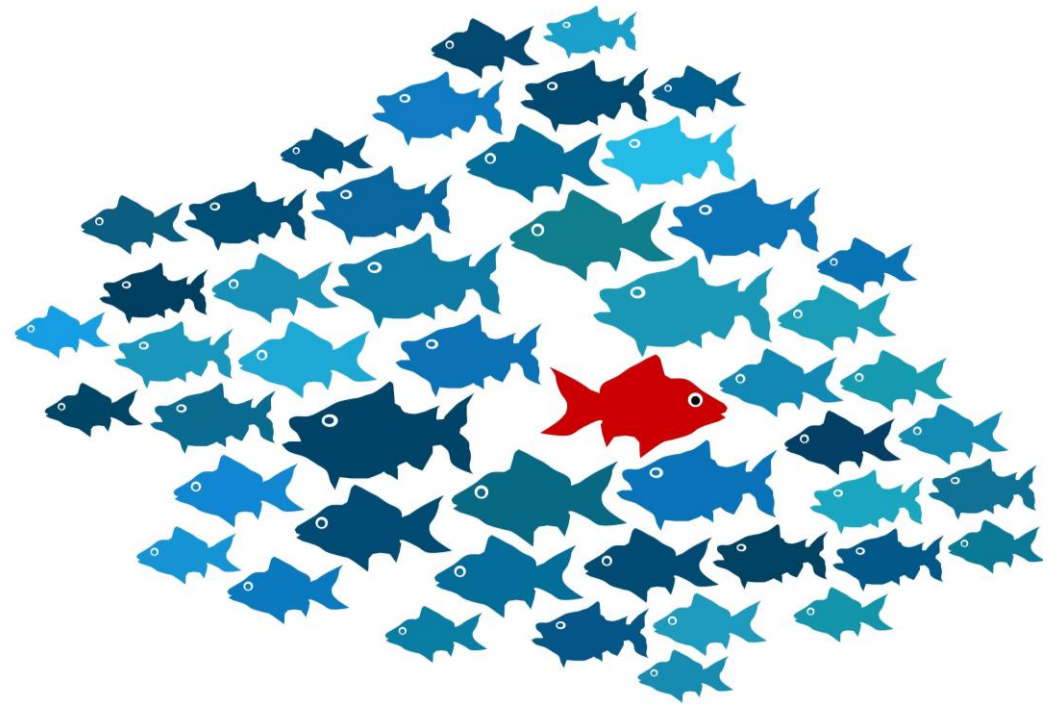




# ANOMALY-BASED NIDS

- Idea: focus on benign traffic only [16]
- Learn a model of “normal” network traffic
- Assumptions:
  - Mainly benign training data
  - Unknown attacks differ from benign data
- Requires careful feature engineering

Easy example: spot the anomalous fish



# ANOMALY-BASED NIDS

Another example: who is not Homer?

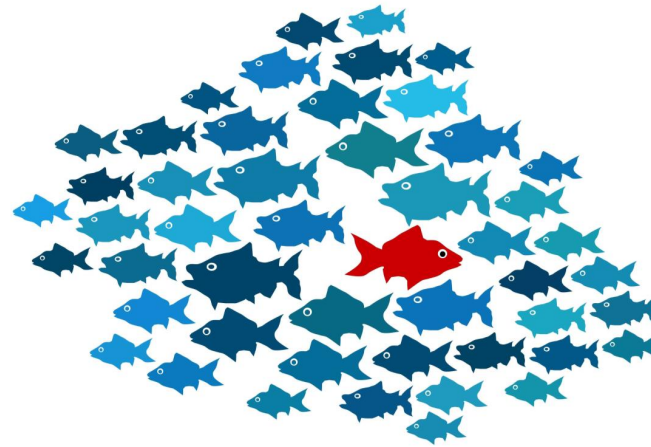


Features:

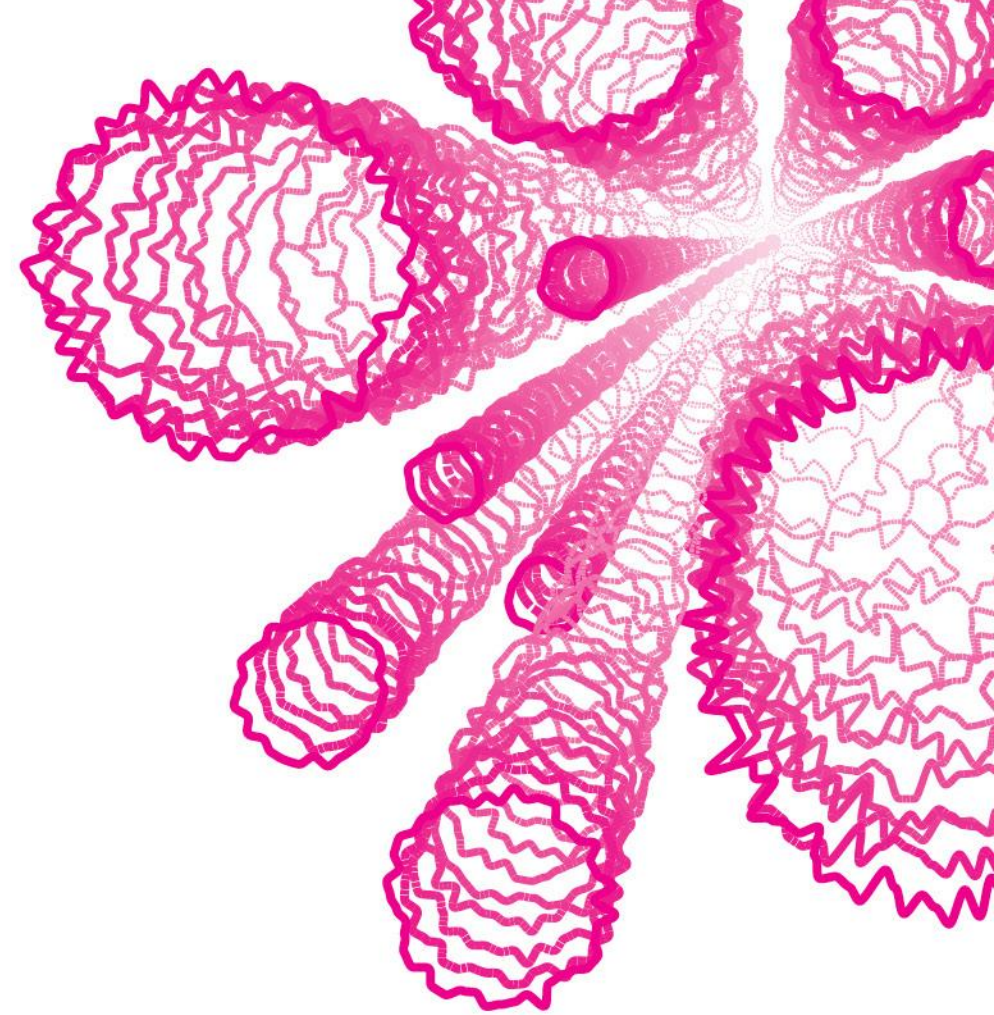
1. Size
2. Accessories
3. ...

# ANOMALY-BASED NIDS

- Risk: detection of irrelevant anomalies as attacks (false positives)
- Choice of features is crucial
- Attacks are deviations from normality
- Various techniques: SVM, KDE, evolutionary algorithms...

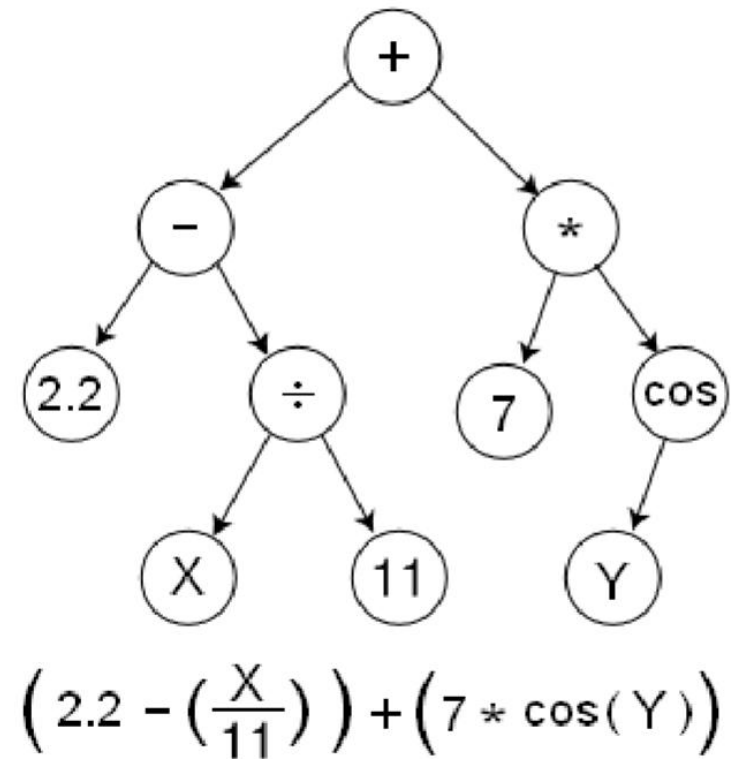
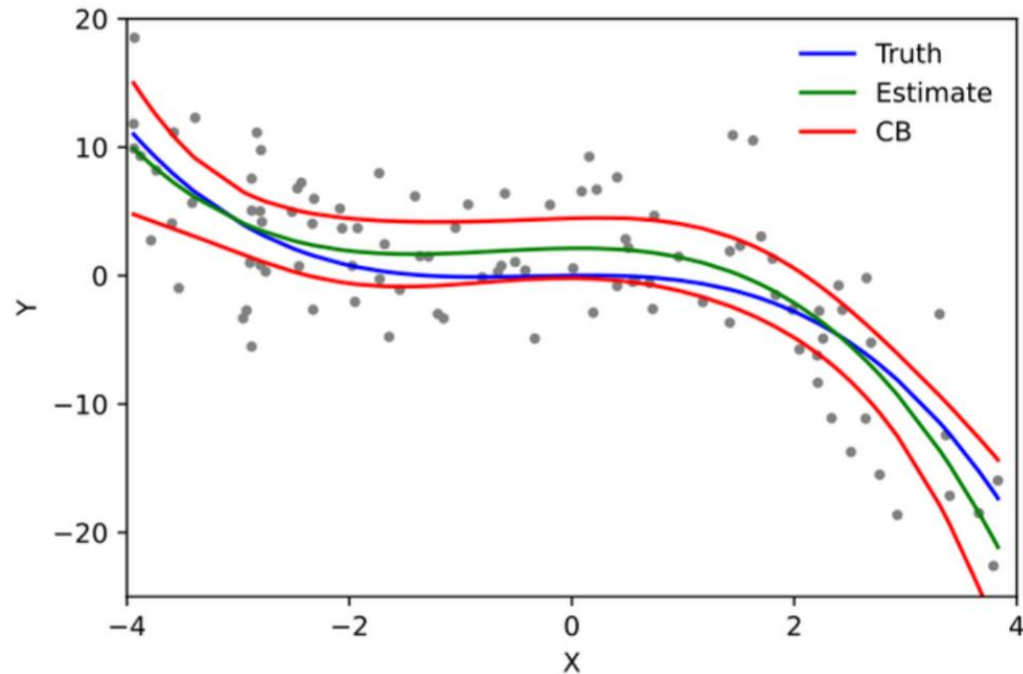


# ANOMALY-BASED NIDS WITH GENETIC PROGRAMMING



# SYMBOLIC REGRESSION WITH GP

- Problem: use GP to find a symbolic expression that minimizes the errors in approximating a given set of data points

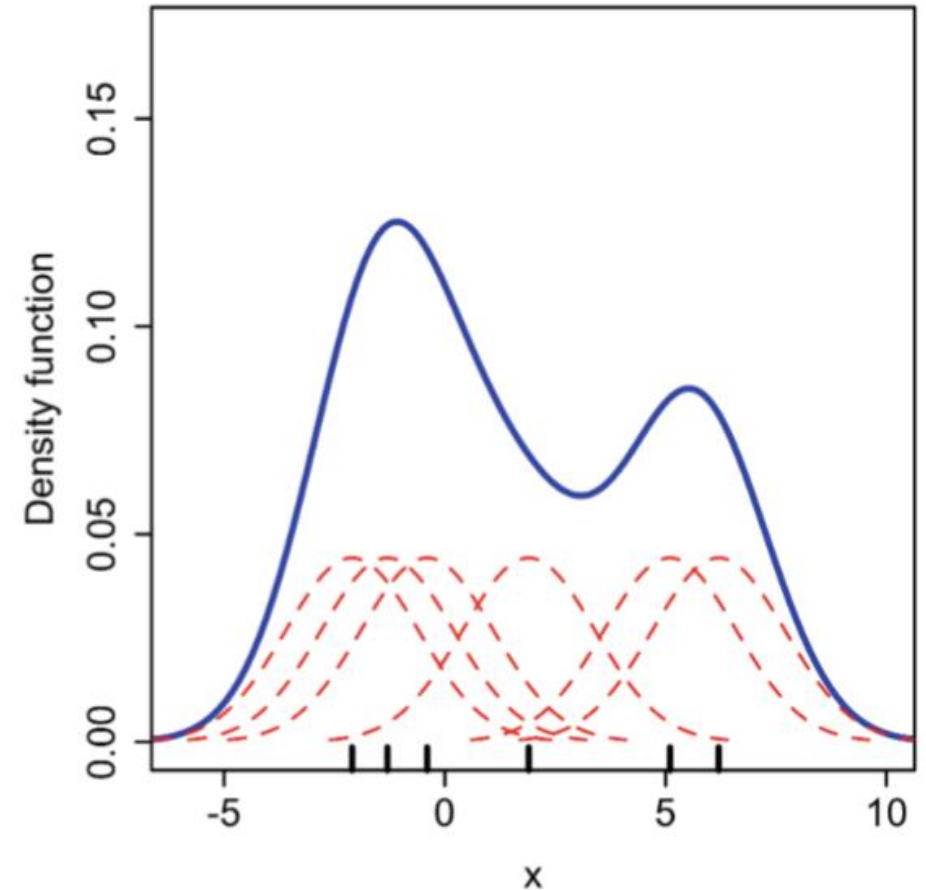


# KERNEL DENSITY ESTIMATION FOR NIDS

- Problem: given a dataset of “normal” network packets, identify anomalies
- Possible approach: use kernel density estimation (KDE) [2]
- Given training points  $x_1, \dots, x_n \in \mathbb{R}^d$ , estimate the density at  $x$  as:

$$\hat{p}(x) = \frac{1}{n} \sum_{i=1}^n K_h(x - x_i)$$

where  $K_h$  is a kernel function (e.g., a Gaussian distribution)



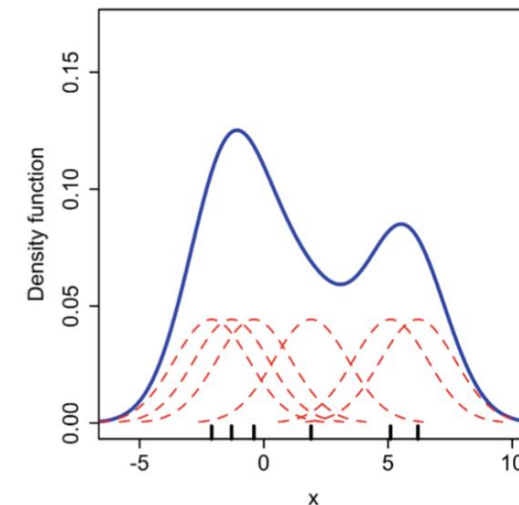
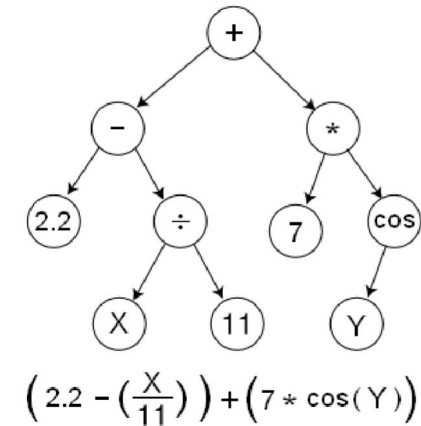
# GENETIC PROGRAMMING FOR NIDS

- KDE is expensive to compute at query time
- Need to compute  $\hat{p}(x) = \frac{1}{n} \sum_{i=1}^n K_h(x - x_i)$  for every new network packet
- Idea: use GP to learn a surrogate  $f$  that approximates well the density [2]:

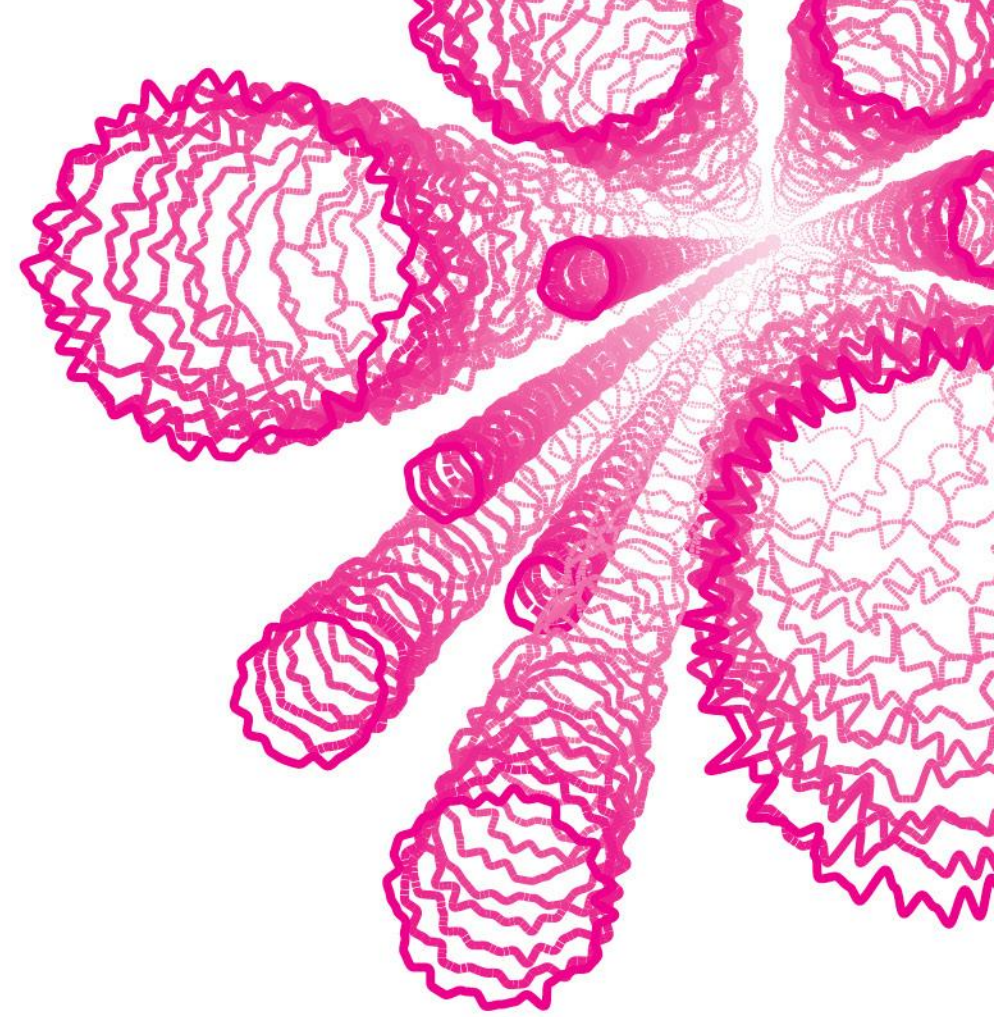
$$f(x_i) \approx d(x_i)$$

- Symbolic regression problem:

$$fit(f) = \sqrt{\frac{\sum_{i=1}^n (f(x_i) - d(x_i))^2}{n}}$$



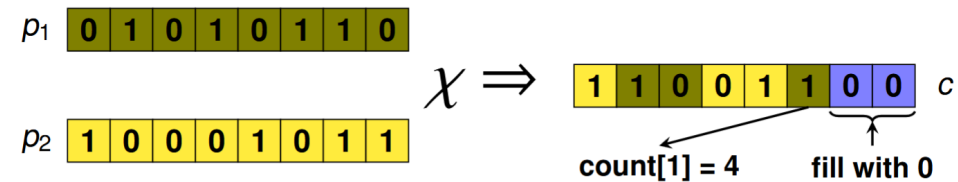
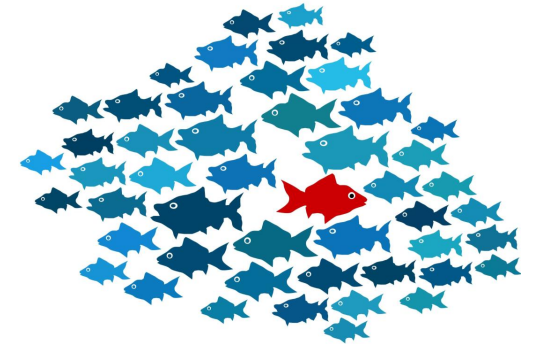
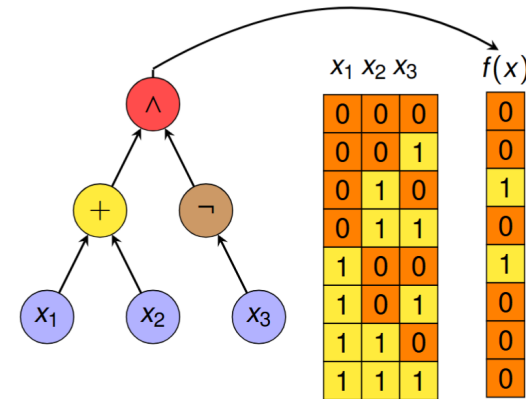
# SUMMARY



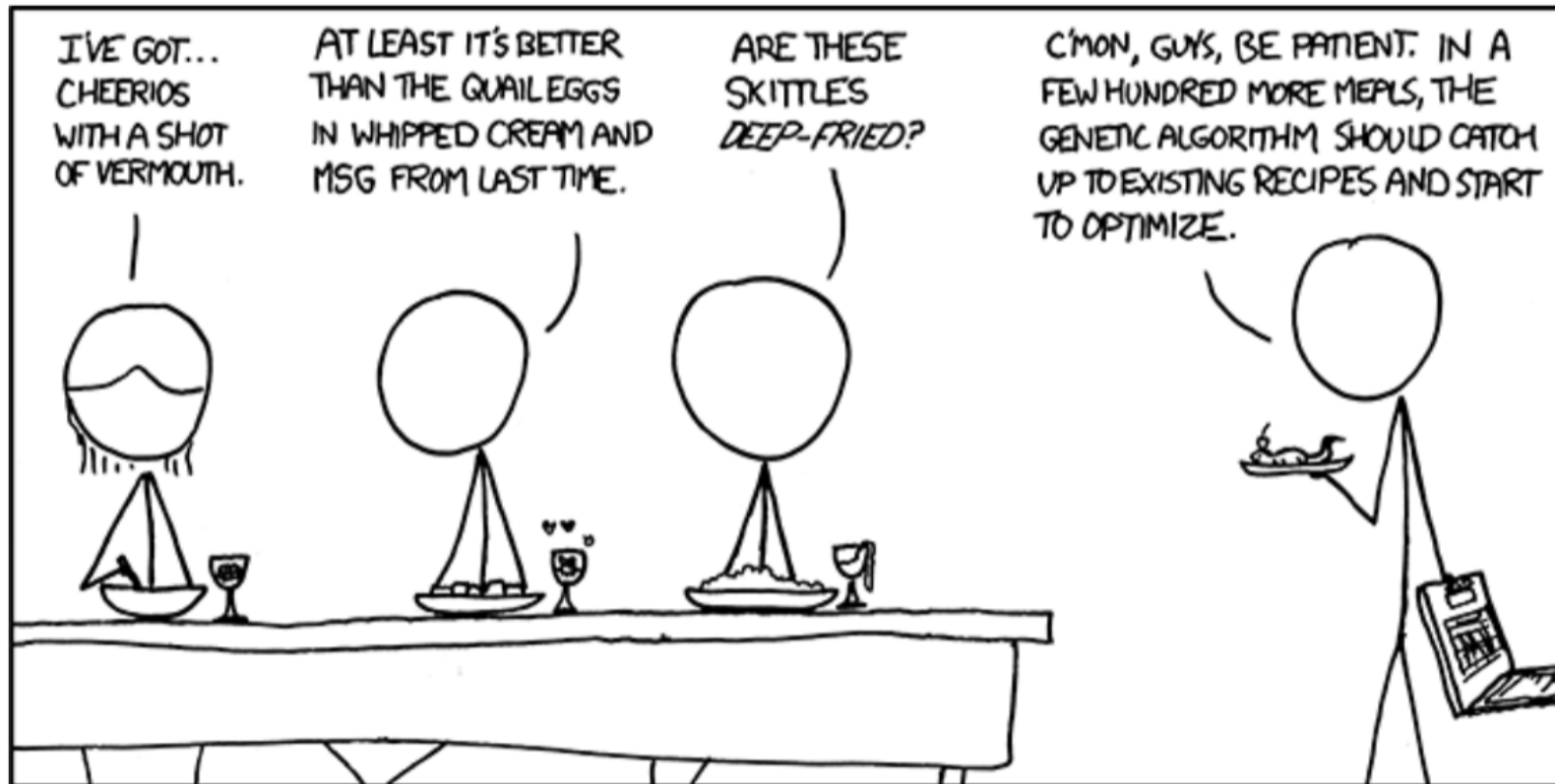


# CONCLUDING THOUGHTS

- EA are quite versatile to solve different problems in cybersecurity
- Examples seen here:
  - Cryptography
  - Network Intrusion Detection
- Many other applications!
  - Side-channel analysis [17]
  - Adversarial learning [18]
  - ...



# THANKS! QUESTIONS?



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

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