AI and Cryptography

Lecture 8 – Wrap up and discussion

Luca Mariot

Semantics, Cybersecurity and Services Group, University of Twente

l.mariot@utwente.nl

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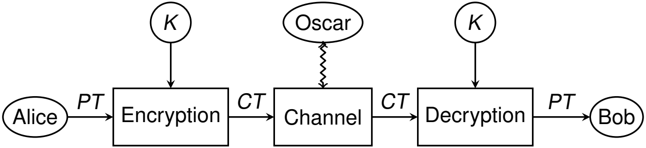
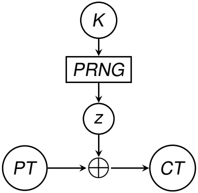
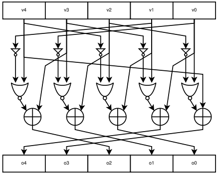
AI Methods for Symmetric Cryptography



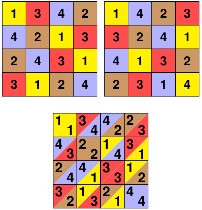
Symmetric ciphers require several low-level primitives, such as:



(a) Pseudorandom Generators



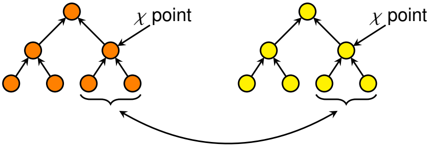
(b) Boolean functions and S-boxes



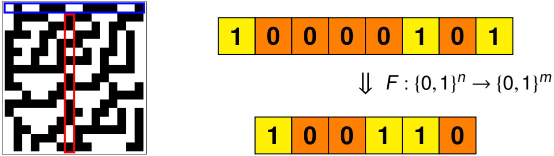
(c) Latin Squares and Orthogonal Arrays

AI approach for symmetric crypto

- "Traditional" approach: ad-hoc and algebraic constructions
- "AI" approach: support the designer using AI methods:
  - Optimization (Evolutionary algorithms, swarm intelligence...)

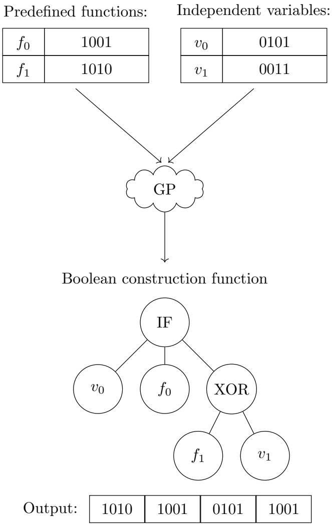


  - Computational models (cellular automata, neural networks...)



New Direction 1:
Evolve constructions of crypto primitives

Evolving Constructions of Boolean functions with GP

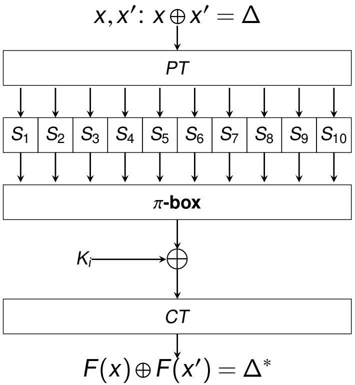


- **Idea:** Do not evolve primitives directly, but rather their mathematical constructions [C22]
- Use Boolean minimizers to interpret the constructions
- **Research Question**: Does GP obtain previously known constructions or new ones?

New Direction 2: Evolutionary-based distinguishers

Differential Cryptanalysis

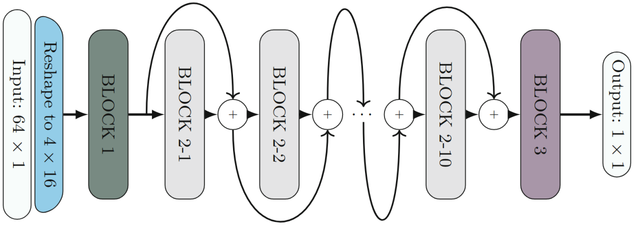
- **Idea**: chosen plaintext attack, see how differences propagate to the ciphertext



- **Goal**: Compute differential probability of $\Delta \rightarrow \Delta^*$
- **Distinguishing attack**: given (x, x'), classify if it is a *random* or *real* pair
- **Tool**: Difference Distribution Table (DDT)

Deep learning-based differential distinguishers

- A. Gohr (CRYPTO 2019): train a CNN as a differential distinguisher
- Better accuracy than pure distinguishers on SPECK32/64



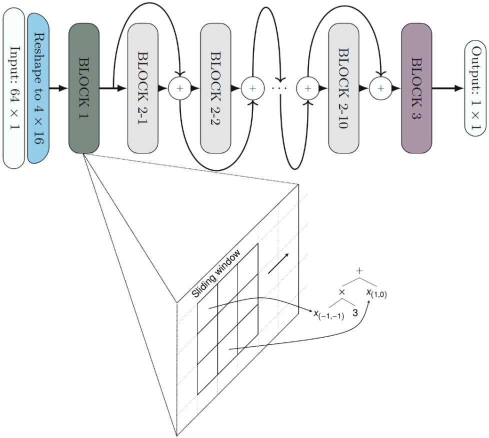
[1]

- **Problem**: learned models are hardly interpretable!

[1] Image credits: A. Benamira et al., *A Deeper Look at Machine Learning-Based Cryptanalysis*, EUROCRYPT 2021

New Direction 2: GP-based distinguishers

- **Idea**: Replace convolutional layers with convolutional GP [J21]



- **Research Question**: Is "convolutional" GP able to reach CNN performances, and yield models easier to interpret?

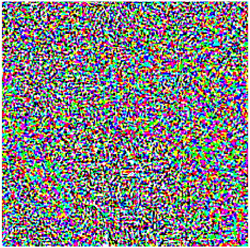
New Direction 3: Evolutionary approach to adversarial examples

Adversarial Examples in DNN

- DNN known to be vulnerable to **adversarial examples** (AE)
- **Idea**: perturb a valid example to mess the DNN's classification

Classification: Panda

+



Noise perturbation

$\Rightarrow$

[2]

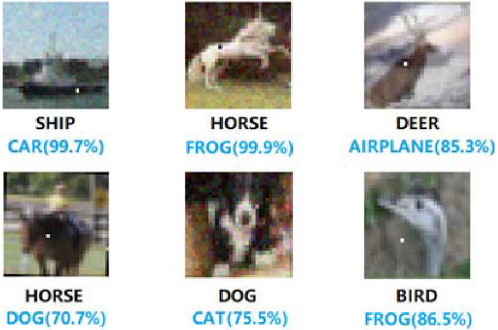
Classification: Gibbon

- Perturbation moves the example beyond the *decision boundary* of a DNN

[2] Example credits: I.J. Goodfellow, J. Shlens, C. Szegedy, *Explaining and Harnessing Adversarial Examples*, ICLR 2015

Evolutionary Construction of AE

- Perturbations for AE can be **minimal**
- **One-pixel attack**: Modify just one pixel in a valid example



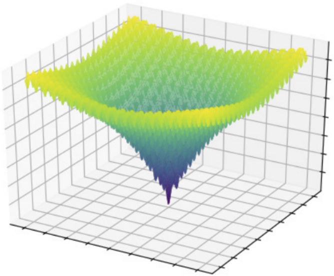
[3]

- Pixel selection done with **Evolutionary Algorithms**

[3] Image credit: J. Su et al., *One Pixel Attack for Fooling Deep Neural Networks*. IEEE Trans. Evol. Comput 23(5):828-840 (2019)

New Direction 3: LON Analysis of Loss Landscapes

- **Idea**: use fitness landscape analysis on the space of AE
- **Approach**: continuous variant of Local Optima Networks



$\Rightarrow$

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Research Questions:

- Is it possible to improve EA-based one-pixel attacks?
- Gain insights to build more robust DNN?

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[4] Image credit: J. Adair et al., *Local Optima Networks for Continuous Fitness Landscapes*. In: GECCO'21 (Companion), pp.1407-1414. ACM (2019)

Wrapping Up

Wrap-Up

Other ideas for future work:

- **Side-channel analysis**: use *neuroevolution* techniques to design DNN for SCA
- **Private ML (1)**: use evolutionary algorithms (EA) to design MPC-friendly activation functions
- **Private ML (2)**: generate "adversarial examples" in MPC-hardened ML models with

In summary: Plenty of open problems, in both directions:

- AI for cryptography
- Cryptography for AI

Thank you!

References

[B11] G. Bertoni, J. Daemen, M. Peeters, G. Van Assche: The Keccak reference. (January 2011)

[C21] C. Carlet: Boolean functions for cryptography and coding theory. Cambridge University Press (2021)

[C22] C. Carlet, M. Djurasevic, D. Jakobovic, L. Mariot, S. Picek: Evolving constructions for balanced, highly nonlinear boolean functions. Proceedings of GECCO 2022, pp. 1147-1155 (2022)

[J21] D. Jakobovic, L. Manzoni, L. Mariot, S. Picek, M. Castelli: CoInGP: convolutional inpainting with genetic programming. Proceedings of GECCO 2021, pp. 795-803 (2021)

[L13] A. Leporati and L. Mariot: 1-Resiliency of Bipermutive Cellular Automata Rules. Proceedings of Automata 2013, pp. 110-123 (2013)

[L15] S. Luke. Essentials of Metaheuristics. Lulu, 2015. 2nd ed.

[M22] L. Mariot, D. Jakobovic, T. Bäck, J. Hernandez-Castro: Artificial Intelligence for the Design of Symmetric Cryptographic Primitives. Security and Artificial Intelligence 2022, pp. 3-24 (2022)

[M19a] L. Mariot, S. Picek, A. Leporati, and D. Jakobovic. Cellular automata based S-boxes. Cryptography and Communications 11(1):41–62 (2019)

[M19b] L. Mariot, D. Jakobovic, A. Leporati, S. Picek: Hyper-bent Boolean Functions and Evolutionary Algorithms. Proceedings of EuroGP 2019, pp. 262-277 (2019)

[P16] S. Picek, D. Jakobovic, J.F. Miller, L. Batina, M. Cupic: Cryptographic Boolean functions: One output, many design criteria. Appl. Soft Comput. 40: 635-653 (2016)

[P17] S. Picek, L. Mariot, B. Yang, D. Jakobovic, N. Mentens: Design of S-boxes defined with cellular automata rules. Conf. Computing Frontiers 2017: 409-414 (2017)

[W86] S. Wolfram. Cryptography with cellular automata. In CRYPTO '85, pp. 429–432 (1986)