

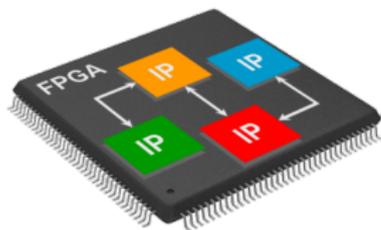
Support Vector Machines for Improved IP Detection with Soft Physical Hash Functions.

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UNIVERSITE CATHOLIQUE DE LOUVAIN

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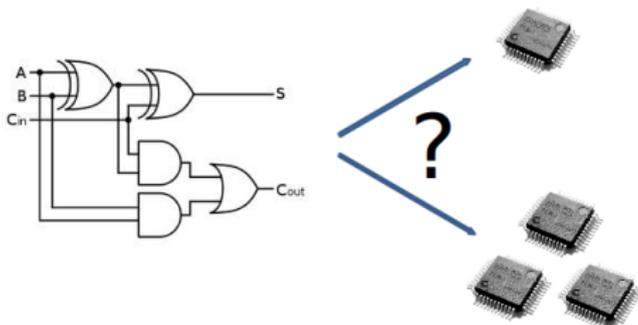


Integrated circuit design and fabrication:

- More and more complex hardware designs
- Designs sold as Intellectual Property (IP)
- IP market growing

Problem

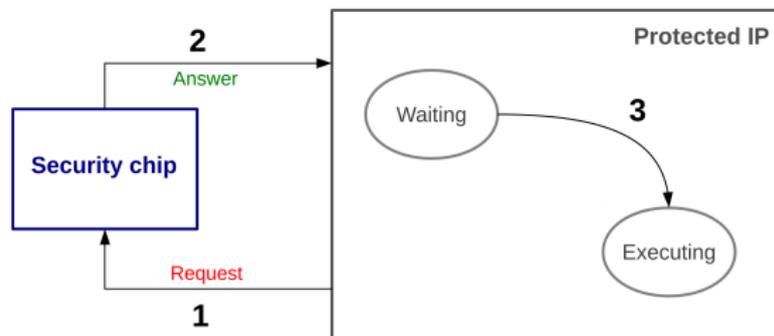
- Counterfeiting



Existing Solutions

Permission-based protections (e.g. security chip, PUFs):

- Key needed to use the IP
- A *priori* solution



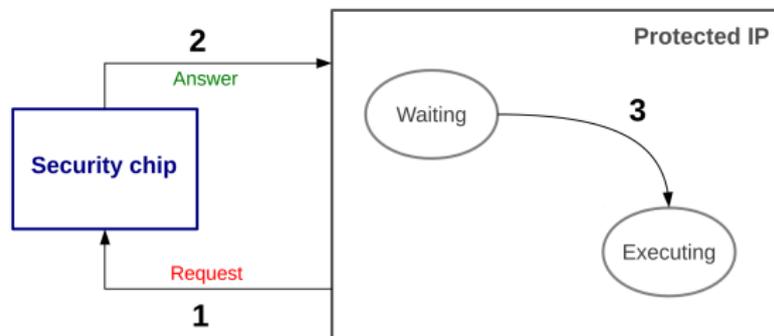
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Limitation:

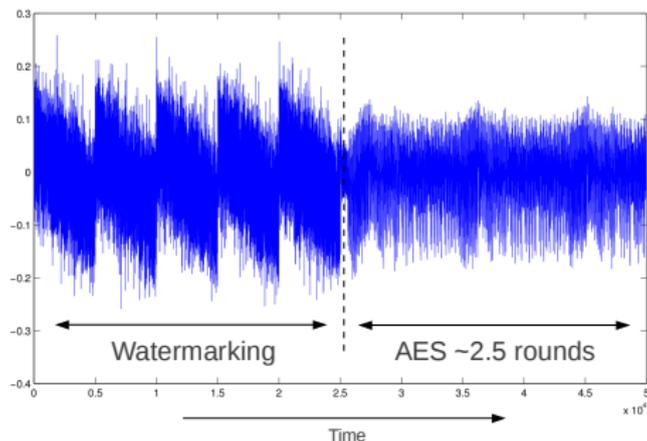
- **Difficulty to integrate in customers' products**



Existing Solutions

Watermarking (e.g. temperature, power consumption):

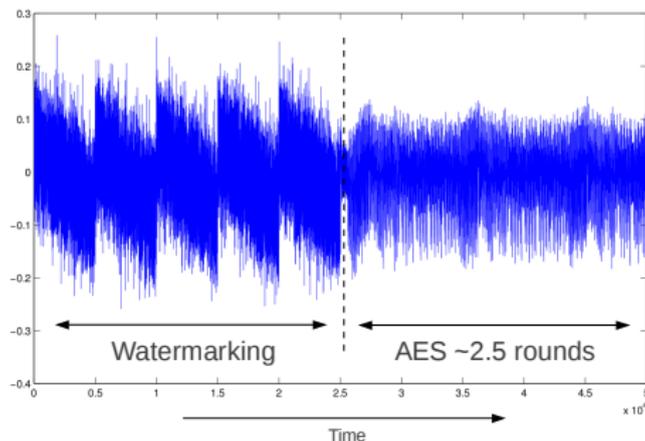
- Specific piece of information inserted
- A *posteriori* solution



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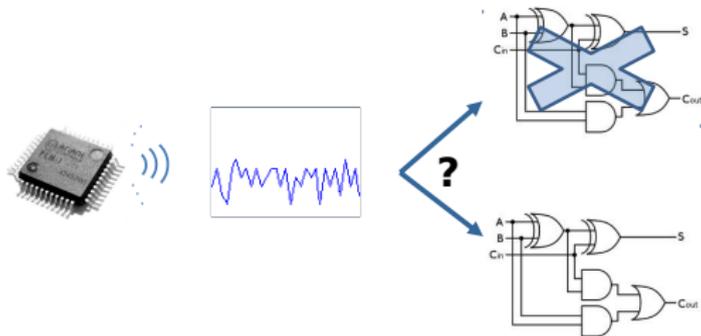


Limitations of both solutions :

- Early integration in design process
- May be removed

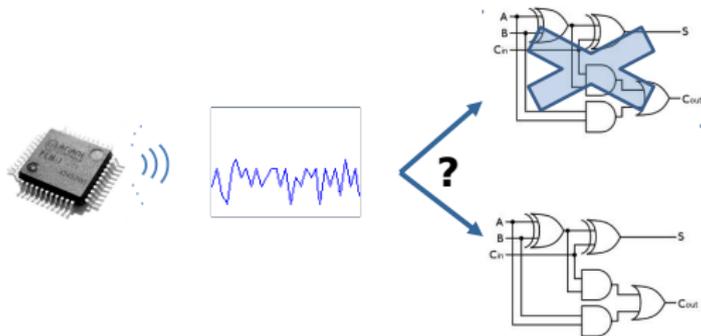
Use of side-channel leakage as an IP signature

- A *posteriori* solution
- Hash (IP "signature") extracted from power traces
- Cannot be removed since intrinsic to the IP execution
- No chip modification required



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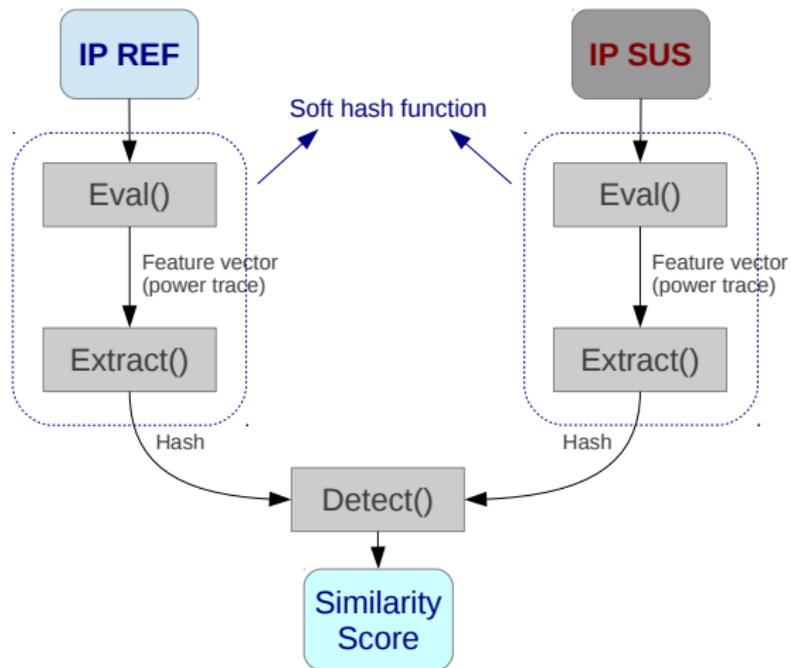


This work :

- Soft Physical Hash (**SPH**) based framework
- Support Vector Machines (**SVM**) detection tool

- 1 Background
 - Generic detection framework - SPH
 - Binary SVM
 - One-class SVM (OSVM)
- 2 Specification of the detection framework
- 3 Case studies
- 4 Conclusion

Generic detection framework - Soft Physical Hash Function (SPH)



Perceptual robustness

- Same IPs \Rightarrow high similarity scores
- Linked to the non-detection error probability

Content sensitivity

- Different IPs \Rightarrow low similarity scores
- Linked to false-alarm error probability

Previous experiment :

- **FPGA Designs** : Xilinx Virtex-II Pro FPGA, 6 block ciphers
- Promising experimental results
- Essentially, correlation-based statistics (Pearson's correlation coefficient)

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This study : Usage of machine learning's **Support Vector Machines (SVM)** to extract information from power traces (FPGA's block ciphers studied in [2])

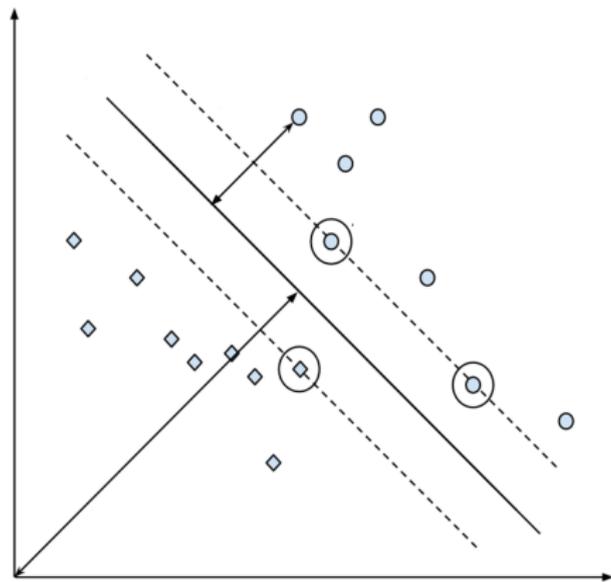
- Proven to effectively solves detection/classification tasks in various areas of application
- Learn automatically arbitrary complex functions
- Handle large dimensionality

Support Vector Machines - Binary classification

Estimation of classification function(s) of **hash vectors** $\hat{f}_c : \mathbf{x} \rightarrow \{-1, +1\}$:

Support Vector Machines - Binary classification

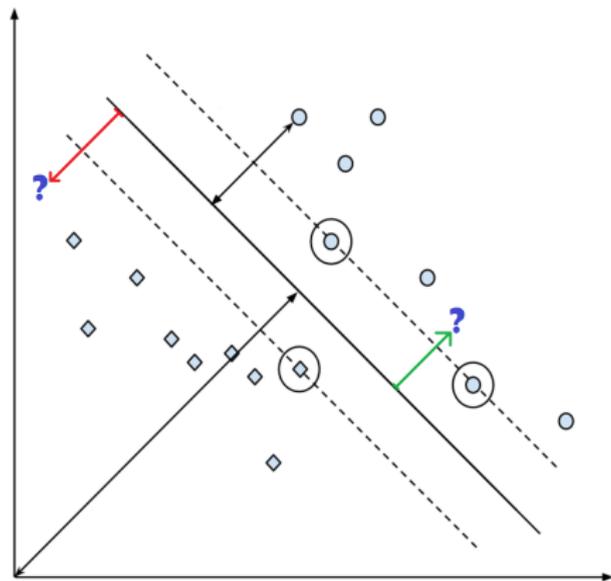
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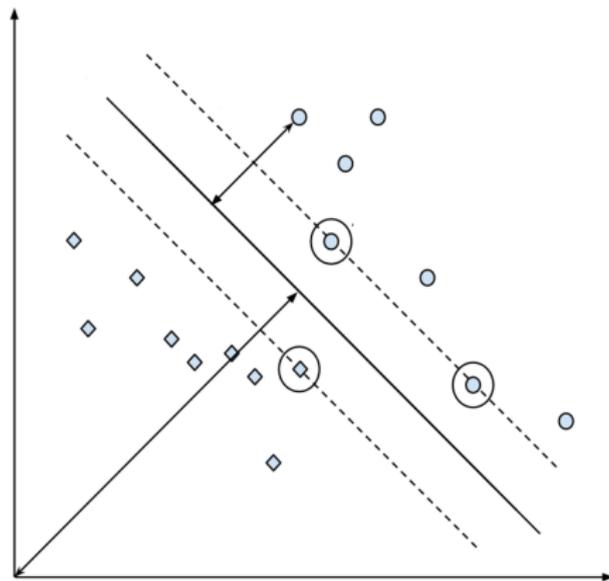
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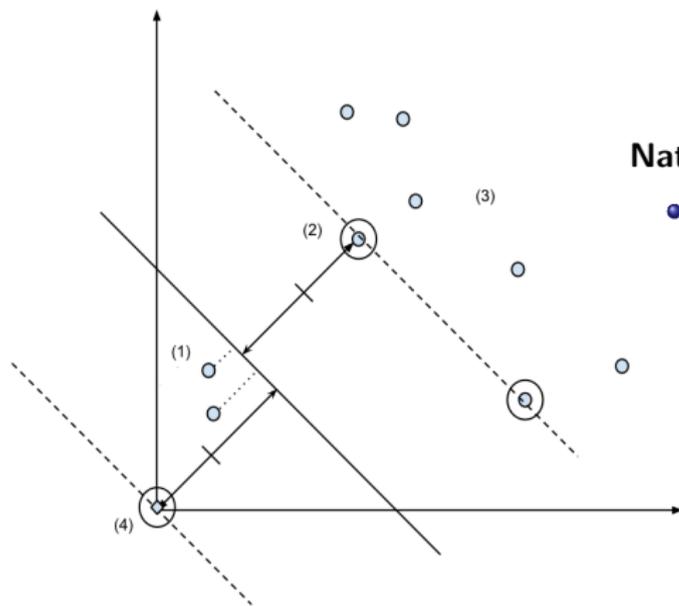
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- Predict y_i for **unseen observation**, with *separating hyperplane*
- Non-linear frontiers are possible

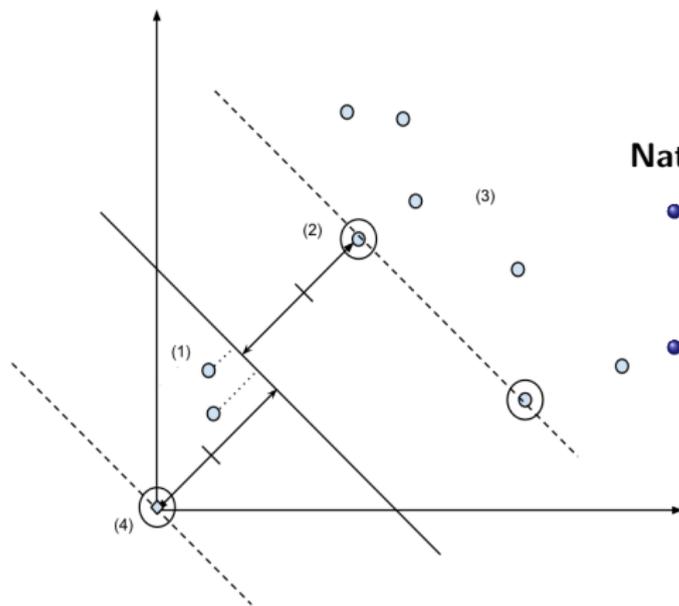
One-class SVM (OSVM)



Natural extension of the binary case

- No assumption on the negative population : hyperplane H separates most of the data from the origin

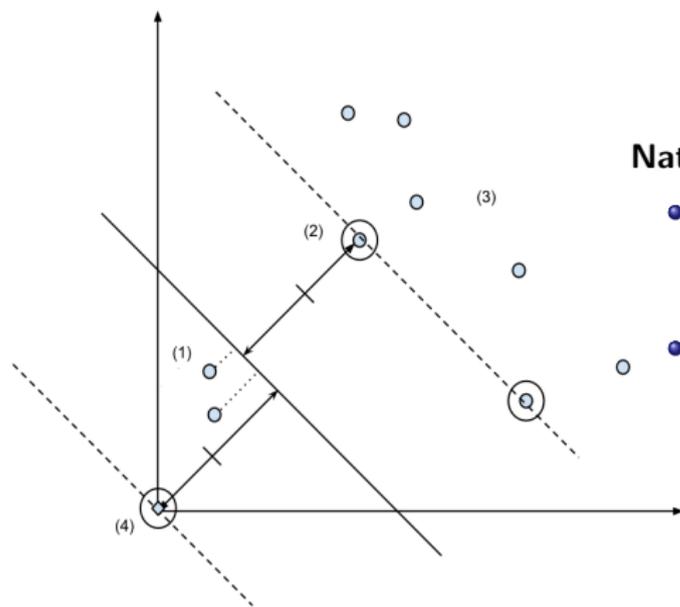
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Similarity score \sim distance of a classified vector to the hyperplane

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- 2 Specification of the detection framework**
- 3 Case studies
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Object to protect

5 lightweight block ciphers : HIGHT, ICEBERG, KATAN, NOEKEON, PRESENT running on a Xilinx Virtex-II Pro FPGA .

Specification of the detection framework

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Detection

Distance metrics to the hyperplane.

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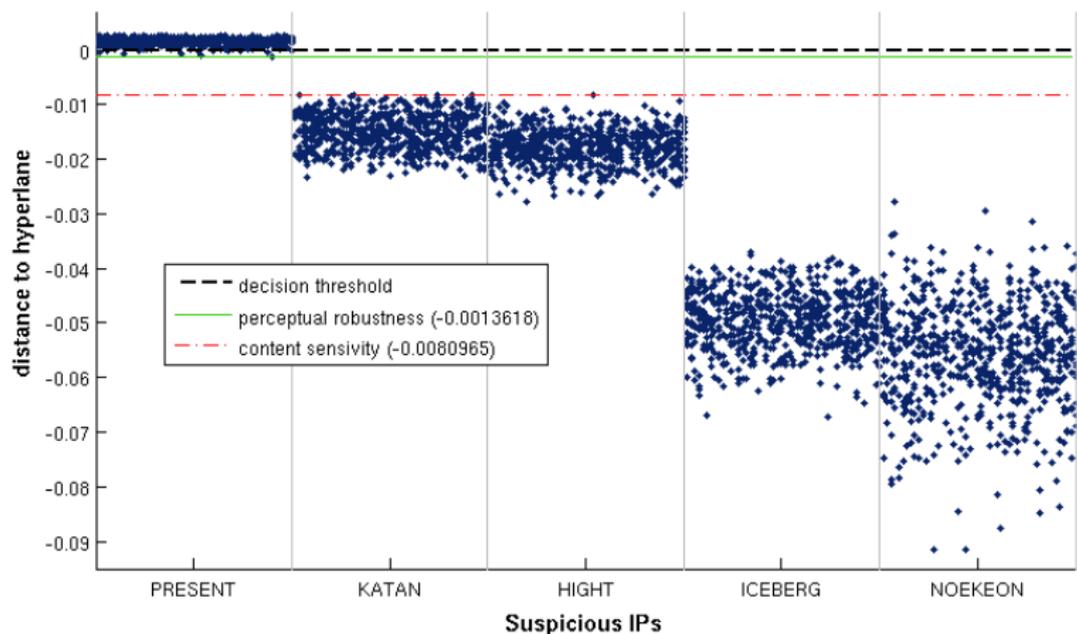
2 Specification of the detection framework

3 Case studies

- Standalone FPGA designs
- Re-synthesized standalone FPGA designs
- Parasitic IP running in parallel
- Advanced detection scenario

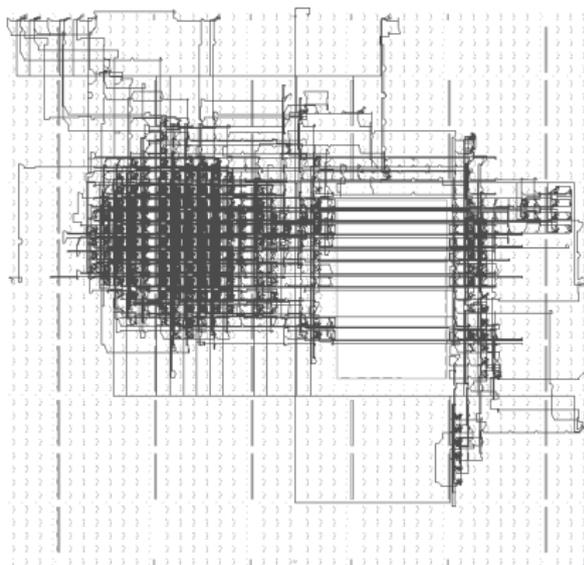
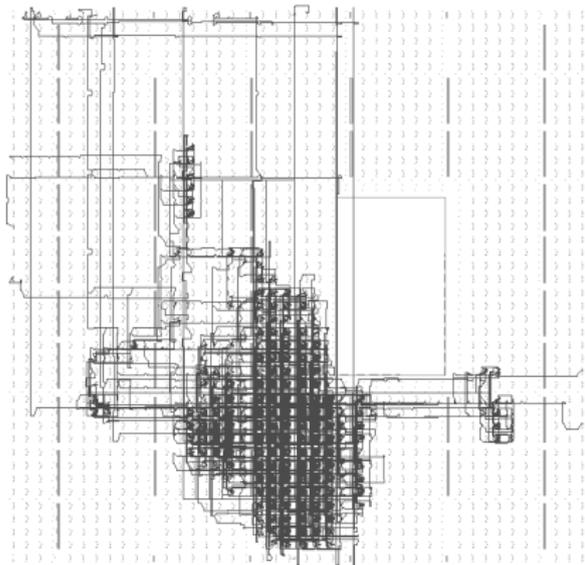
4 Conclusion

(1) Ref. PRESENT - Susp. *standalone*



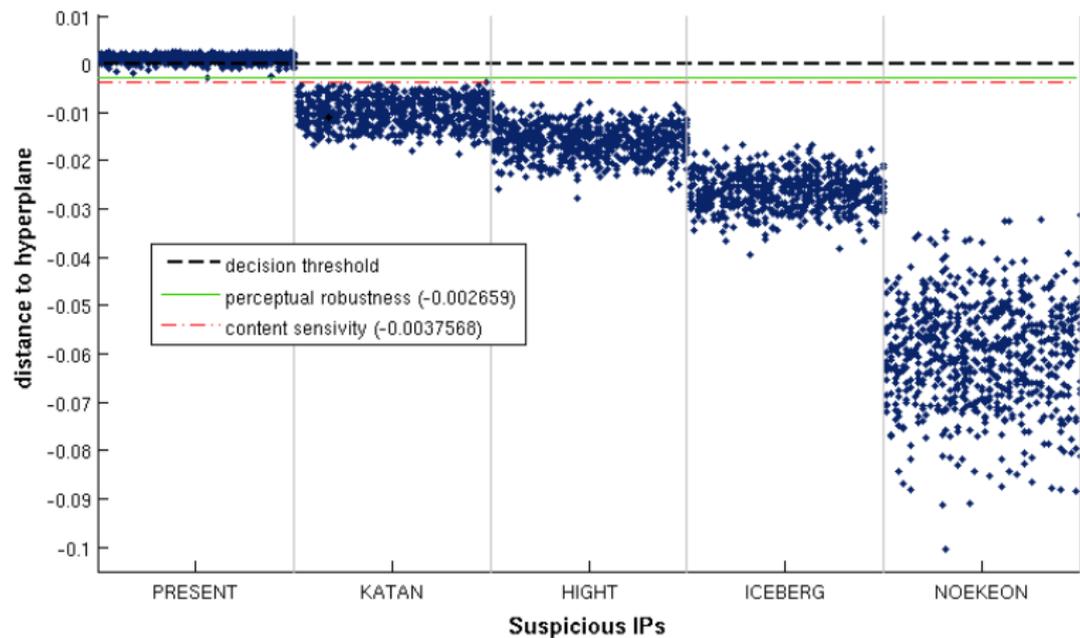
- Classification outcome (binary output) vs distance metrics
- Green threshold : **min** score for PRESENT traces (protected IP).
- Red threshold : **max** score for traces from other IPs.

(2) Ref. PRESENT - Susp. *resynthesized*



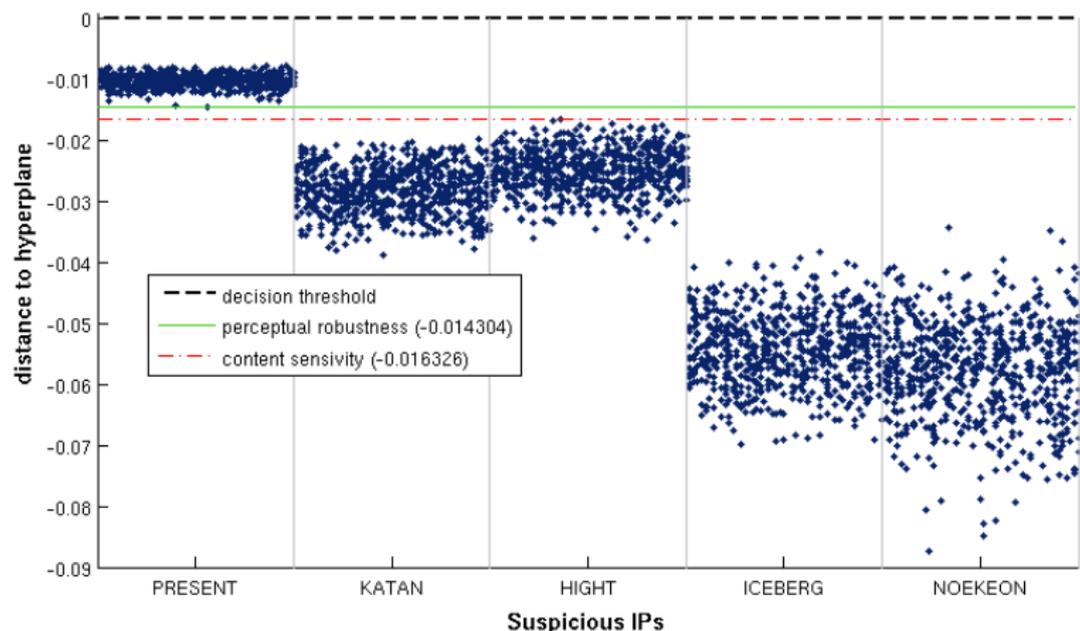
Resynthesized : New placement and routing, under area optimisation constraints.

(2) Ref. PRESENT - Susp. *resynthesized*



Resynthesized : New placement and routing, under area optimisation constraints.

(3) Ref. PRESENT - Susp. with parasitic IP



Parasitic IP : Linear feedback shift register (LFSR) of 2048 bits.

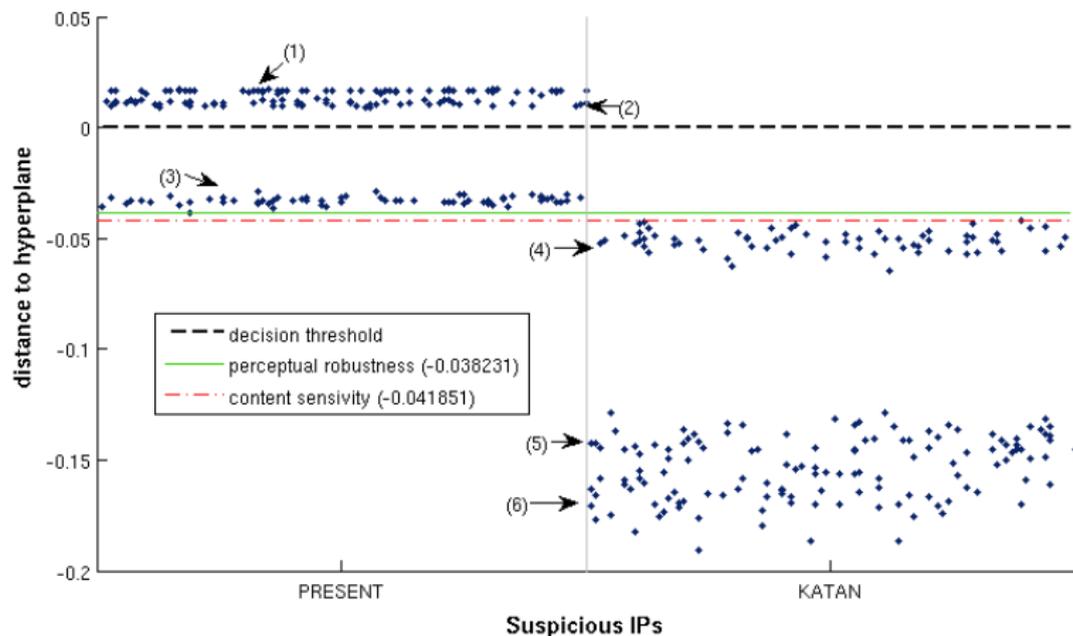
Below the 0 threshold : Failure of the classifier, but still a detection area.

Identified problem

We can't find a correct decision threshold when combining cases :

- lowest PRESENT (parasited) < highest KATAN (re-synthetized)
 - ▶ \Rightarrow no detection gap
 - ▶ misclassification(s) can occur
- Two tweaks are needed to enhance detection : exploiting **data dependencies** and **noise reduction**

(4) Ref. PRESENT - Susp. *all combined*, 5x avg. traces & known inputs



Known inputs : Takes advantage of data dependencies

Averaging : Reduce algorithmic noise

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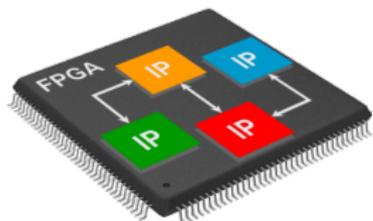
OSVM

Pros

- Can handle large dimensionality
- Realistic model : no assumption made on negative examples
- Better results than previously reached :
 - ▶ Only the more complex case required to exploit data dependencies and noise reduction
 - ▶ But more measurement traces needed (1300)

Cons

- Unsupervised : difficulty to build good heuristics to select model's parameters
- Failure of the classifier on datasets with parasitic algorithm noise.
 - ▶ new threshold choice
- Necessary rejection of outliers (intrinsic bias).
 - ▶ new threshold choice



More complex and richer set of IPs and transformations of IPs.

Improving detection quality :

- *Evaluation*, other feature vectors potentially interesting



Thank you for your attention !