# Project 1: Robust Deep-learning-based Side-Channel Attacks

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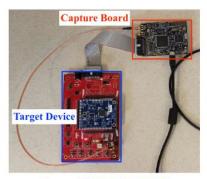
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# Side-Channel Attacks (SCA)

- An attacker analyzes power or electromagnetic (EM) signals of a target (microcontroller or FGPA) when it runs encryption algorithm (e.g., AES) and recover encryption keys
- Why? power consumption is correlated with the value processed by target
  - 0x00 requires less power than 0xFF



Arm STM32F3



Attack Window [1800, 2800]

0.2

0.1

0.0

-0.1

-0.2

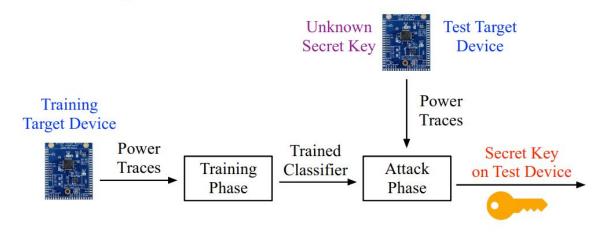
-0.3

-0.4

Dower Pattern of AES

## Deep-Learning SCA

- Advantages compared to traditional SCA attacks
  - No need to pre-process traces
  - Can defeat existing countermeasures (masking & random delays)
- High accuracy (>90%) in the same-device setting
  - Train with device A, test with device A

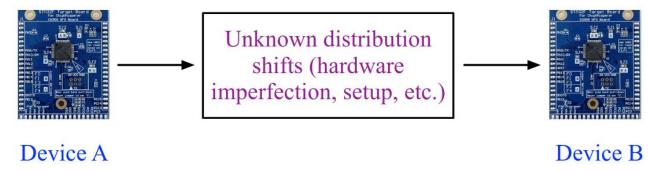


RHEST

Large number of traces

Challenge:
Limited number of traces

RHEST



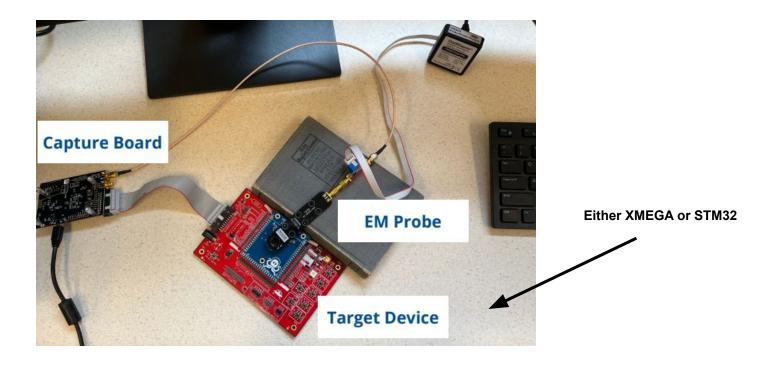
- Poor performance (<10% accuracy or fail to recover keys) in cross-device setting (a real-world attacker)
  - Train with device A, test with device B
- Challenges: (1) Limited traces from Device B; (2) unknown key from Device B;
   (3) complex discrepancies caused by hardware and software

## Objectives

- Task 1: Collect EM traces on microcontrollers and test results with our existing ML code
- Task 2: Study instruction rewriting in assembly on AVR XMEGA and ARM STM32 as well as examine the impact of instructions rewriting in deep learning side channel attacks
- Task 3: Collect EM traces of AES encryption compiled with different optimizations and study the optimizations' effects



## **EM Data Collection Setup**



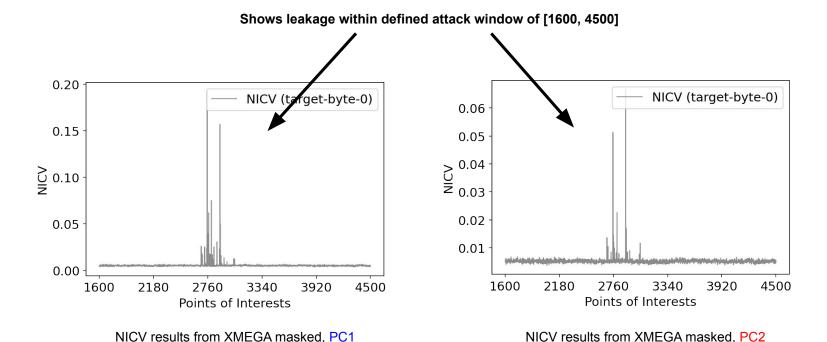
## **EM Data Collection**

XMEGA	STM32
<ul> <li>50k unmasked AES, PC1</li> <li>50k unmasked AES, PC2</li> <li>50k masked AES, PC1</li> <li>50k masked AES, PC2</li> </ul>	<ul><li>50k unmasked AES, PC1</li><li>50k unmasked AES, PC2</li></ul>



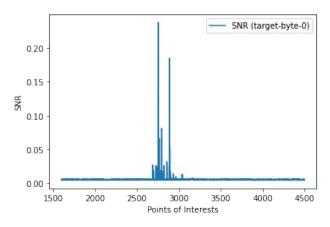
## **EM Data Analysis**

Performed Normal Inter-Class Variance (NICV)

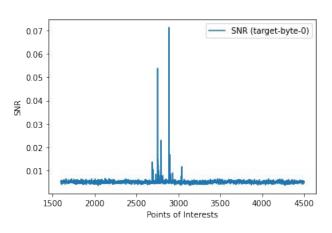


## **EM Data Analysis**

Performed Signal to Noise Ratio (SNR)



SNR results from XMEGA masked, PC1



SNR results from XMEGA masked, PC2

Ran CPA attack

Key guess: 0xc6

Correlation: 0.25582897783658465

Correct Key: 0xc6

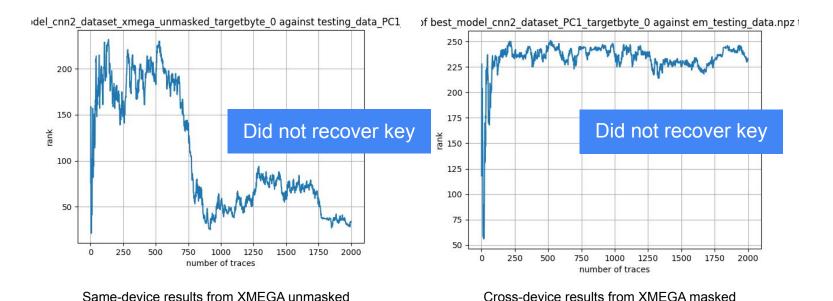
Key guess: 0x70

Correlation: 0.11420753433103399

Correct Key: 0x70

## EM Data Convolutional Neural Network (CNN) Results

- Train and test data using Convolutional Neural Network (CNN)
  - For cross-device scenario, use 40k for training (PC1) and 10k for testing (PC2)



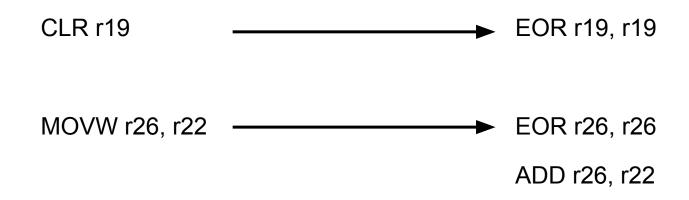
### Working with EM Data

- Collecting EM data is much more difficult than power traces. (And results produced by CNN are not always promising even with same-device)
- Improved data collection process would benefit the data, as it is easy for the EM probe to move positions during the collection.
- Although CNN did not always show us the results we were hoping for, we did
  get a lot of promising pics from NICV and from the CPA attack which was able
  to recover most keys.



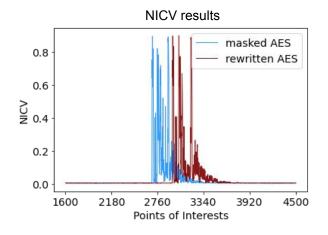
## Instruction Rewriting

- Causes software discrepancy
- Train with masked AES, test with rewritten AES
- Rewrote lines of assembly code with 1-3 comparable lines
- Focused on SubBytes and addRoundKey routines
- 24 lines rewritten



#### **Power Trace Data Collection**

- Collect 50k masked AES power traces
- Collect 50k rewritten masked AES power traces
  - 40k traces for training
  - 10k traces for testing
- Run NICV and CPA



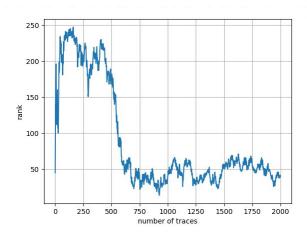
Key guess: 0x2b

Correlation: 0.9446525225032248

Correct Key: 0x2b

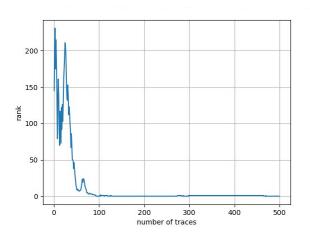
CPA results for masked AES dataset

#### Did not recover key



attack window: [1600,4500]

#### Recovered key



attack window: [1900,4800]



## **EM Data Collection with Optimization**

- Optimization → software discrepancy
- Compiled with either o1, o2, or o3 optimization in gcc

Gcc command before optimization:

make PLATFORM=CWLITEXMEGA CRYPTO\_TARGET= TINYAES128C

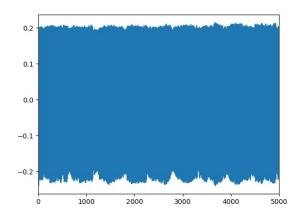
Gcc command after optimization (o1):

make PLATFORM=CWLITEXMEGA CRYPTO\_TARGET= TINYAES128C OPT=1



## EM Data Collection with Optimization

- Collected 4 50k EM datasets:
  - XMEGA masked, (modified with instruction rewriting), PC2
  - XMEGA unmasked, (compiled with o1 optimization in gcc), PC2
  - XMEGA unmasked, (compiled with o2 optimization in gcc), PC2
  - XMEGA unmasked, (compiled with o3 optimization in gcc), PC2

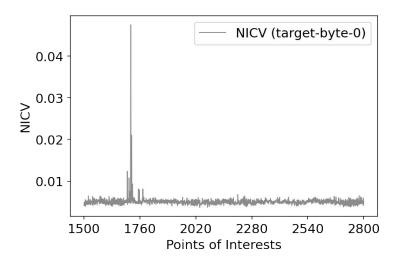


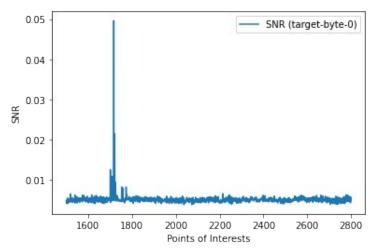
First 5,000 traces from dataset compiled with o1 optimization



## **EM Data with Optimization Analysis**

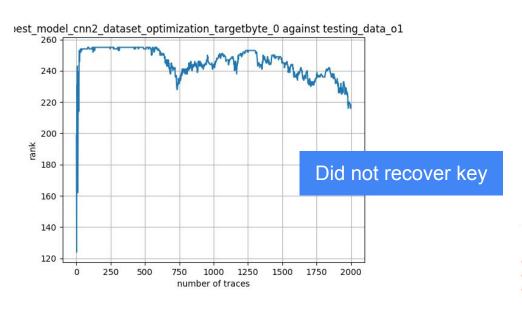
 Performed Normal Inter-Class Variance (NICV), Signal to Noise Ratio (SNR), and CPA attack on XMEGA unmasked EM dataset compiled with o1, o2, and o3 optimization in gcc.





## EM Data with Optimization Results (CNN)

- Trained (40k) and tested (10k) EM dataset compiled with o1 optimization in gcc on Convolutional Neural Network (CNN) on same-device scenario.





## Limitations & Challenges

- Pre-Data Collection (being able to run required scripts).
- ChipWhisperer has a limited number of integrated AES implementations.
- EM datasets are noisy, which oftentimes doesn't show promising results.



#### **Future Direction**

- Instruction rewriting STM32
- Analyzing Trojans on FPGA's
- Transfer learning with datasets
- Improving data collection process of EM data
- EM data collection and analysis of STM32 masked



## Thank you!

- Collected 10 EM datasets and 2 power datasets used for instruction rewriting
  - 700k power and EM traces
  - 52 gb of data
- GitHub link: <a href="https://github.com/UCdasec/CrossSide">https://github.com/UCdasec/CrossSide</a>



This work is supported by National Science Foundation (NSF), CNS-2150086, RHEST: NSF REU Site In Hardware and Embedded Systems Security and Trust