
Clustering Algorithms for Non-Profiled Single-Execution Attacks on Exponentiations



Johann Heyszl¹ Andreas Ibing² Stefan Mangard^{3,4}
Fabrizio De Santis^{2,4} Georg Sigl²

¹Fraunhofer Research Institution AISEC, Munich, Germany

²Technische Universität München, Munich, Germany

³Graz University of Technology, Graz, Austria

⁴Infineon Technologies AG, Munich, Germany

Motivation

- Single execution side-channel attacks on exponentiations
- Previous ones **require profiling or manual tuning or use ad-hoc algorithms**
- We describe **how to use cluster classification algorithms instead**

Reminder: Exponentiation Algorithms

- Exponentiations in asymm. crypto
 - Modular exponentiations in RSA
 - Elliptic curve scalar multiplications in ECC
- Popular algorithms:
 - Square-and-multiply-always (RSA) / double-and-add-always (ECC)
 - Montgomery ladder (RSA, ECC)
- Key features of exponentiation algorithms
 - Secret exponent processed bit/digit-wise in loop
 - Mostly timing-safe, hence, operation sequence uniform (against SPA)

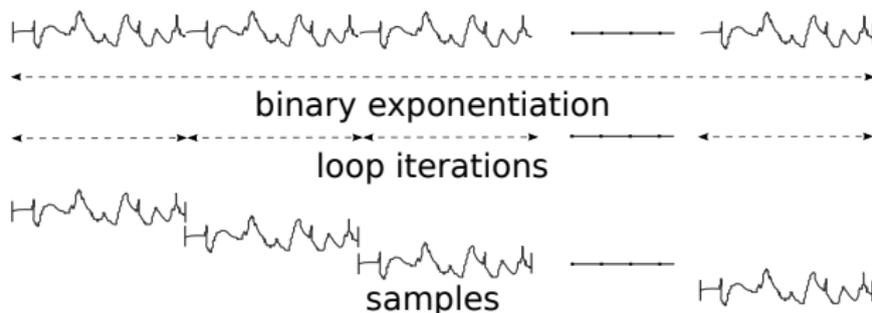
Single-Execution Leakage

- Side-Channel Attackers only have **single observations** to exploit
 - Due to ephemeral exponent or e.g. blinding countermeasure

Single-Execution Leakage

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 - Due to ephemeral exponent or e.g. blinding countermeasure
- **Certain amount of information about exponent bits** (binary alg.) is still leaking in most cases → **single-execution leakage** (address-bit-related, localized leakage, ...)

Exploiting Single-Execution Leakage



- Cut recorded exponentiation trace into samples
- Each corresponds to different secret bit (binary exp. alg.)
- **Attack basically means to find correct partition = Classification**

Exploiting Single-Execution Leakage

Previously and Strongly Related

- **Template attacks**
 - **Require profiling** (difficult, think of e.g. blinding)
- **Cross-correlation-based attacks**
 - Requires **manually tuned thresholds**
 - Correlation disregards information (absolute values)
 - Some are based on heuristic power models (corr. coeff. makes more sense then)
- **Walter's Big Mac attack** from 2001
 - Ad hoc engineered algorithm

Our Proposal

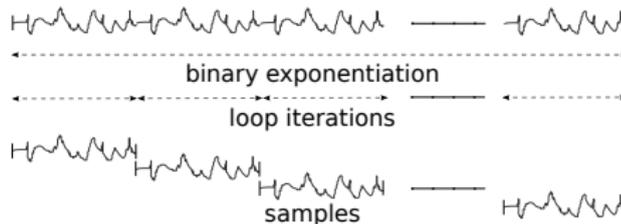
Using Unsupervised Clustering for an Attack

- Use algorithms from the established research-field of **'Pattern classification'**
 - Those are already heavily researched in other applications
- We propose to use **unsupervised cluster classification algorithms**
 - Exploit single execution leakage of exponentiation algorithms

Our Proposal

Using Unsupervised Clustering for an Attack

- Reminder: In *profiled template attack*, cut-out samples are *classified* by *matching to templates*



- Clustering algorithms **classify** the cut-out samples **automatically without profiling or manual tuning**
 - Unknown if **0** or **1** bits, but easy try-out
- Success depends on available leakage of course

Unsupervised Cluster Classification Algorithms

- Unsupervised means no training data, no profiling
- Input a set of multi-dimensional samples/vectors e.g. cut-out trace-parts
- Algorithm estimates distributions
- Define free parameters of distribution (e.g. *two* cluster centers)
- Optimal algorithm depends on the distribution model (shape of clusters)

Unsupervised Cluster Classification Algorithms

K-Means

- Example algorithm:
***k*-means algorithm for unsupervised clustering**
 - Finds ***k*** cluster centers and corresponding classification
 - Distribution assumption - shape of clusters:
 - ***k*** equal Gaussian distributions
 - Independent values in samples (dimensions are independent)
 - Variance equal within clusters

Unsupervised Cluster Classification Algorithms

K-Means

- **Input:** Samples (cut-out trace parts) and number of clusters k
- Starts by choosing k **random** samples as initial cluster means
- Then iteratively:
 - Compute *Euclidean distance* from all samples to current k means
 - Classification: *Assign all samples to closest mean* $\rightarrow k$ classes
 - **Compute new means** of k classes from current classification
 - Repeat *until no change in class assignment*
- **Output:** k cluster means and classification
- Repeat with different starting points to prevent local maxima (best outcome based on sum-of-squared-error criterion selected)

Practical Evaluation

- **Laboratory setup** (FPGA-based , trigger output, synchronized clock)
(Definitely not real world ;)
- Same setup as in our CT-RSA'12 paper:
Template attacks exploiting location-based leakage

Practical Evaluation

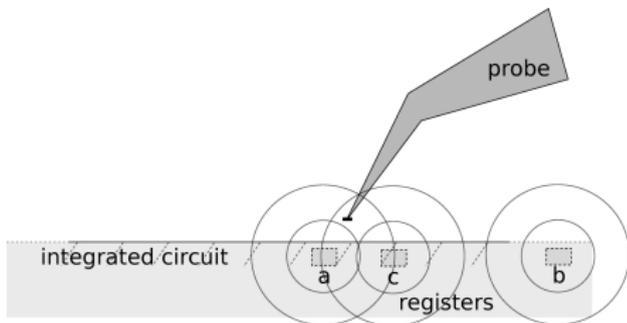
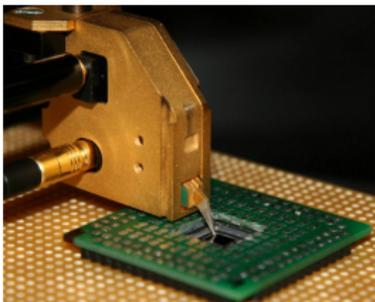
FPGA DUT

- Straight-forward FPGA-based digital HW implementation:
 - Elliptic curve scalar multiplication ($Q = d \cdot P$) with affine input/output
 - López and Dahab Montgomery ladder 'exponentiation' algorithm, binary field $GF(2^{163})$, NIST parameters

Practical Evaluation

Location-Based Leakage

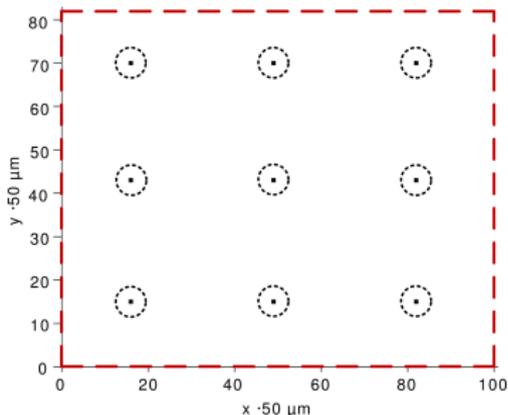
- High-resolution inductive near-field probe ($100\ \mu\text{m}$ resolution)
- Probe is closer to one of two registers
- Register access depends on current secret bit in loop



Practical Evaluation

Measurement Positions

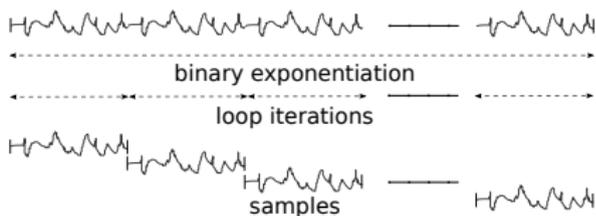
- FPGA die surface
- Multiple measurement positions in geometric regular array (no profiling to find locations)



Practical Evaluation

Trace Example

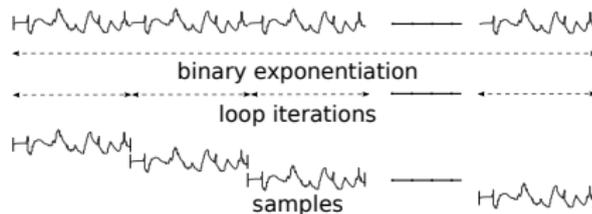
- Reminder: Cutting a trace into samples



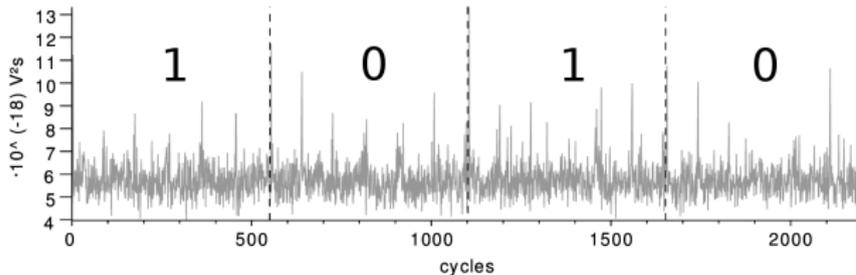
Practical Evaluation

Trace Example

- Reminder: Cutting a trace into samples



- Example from one measurement - 4 samples



Practical Evaluation

Result from One Position

- Single measurement **after** clustering
 - Returns 2 sample means and corresp. classification

Practical Evaluation

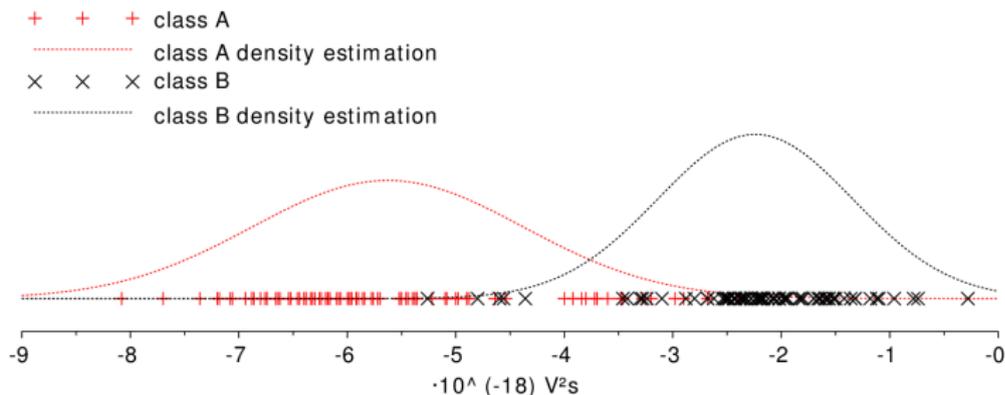
Result from One Position

- Single measurement **after** clustering
 - Returns 2 sample means and corresp. classification
 - **For visualization:**
 - Regard the samples/means as vectors in multi-dim. space
 - Draw line through to means
 - 1-D projection of samples on this line

Practical Evaluation

Result from One Position

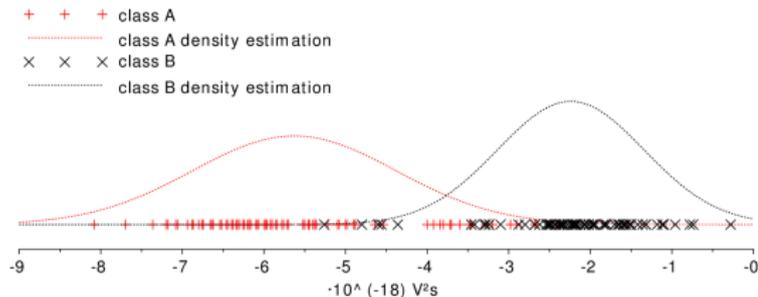
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Practical Evaluation

How to Cope with Errors?

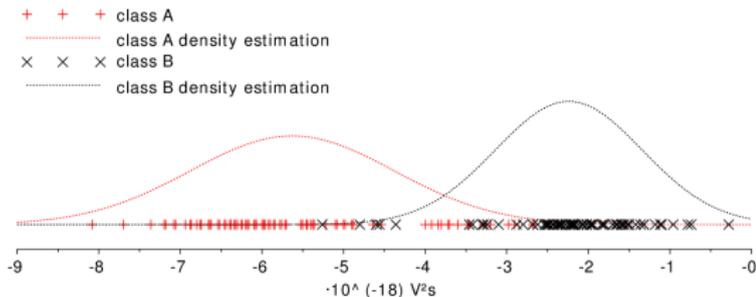
- Clustering algorithms allow to derive **posterior probabilities** for each sample describing likelihood of correct classification (basically low if close to separation plane)



Practical Evaluation

How to Cope with Errors?

- Clustering algorithms allow to derive **posterior probabilities** for each sample describing likelihood of correct classification (basically low if close to separation plane)



- Attacker may use this in a brute-force strategy:
 - Trial bits with low post. probabilities first
 - Repeat and increase number of trialed bits until correct exponent found

Practical Evaluation

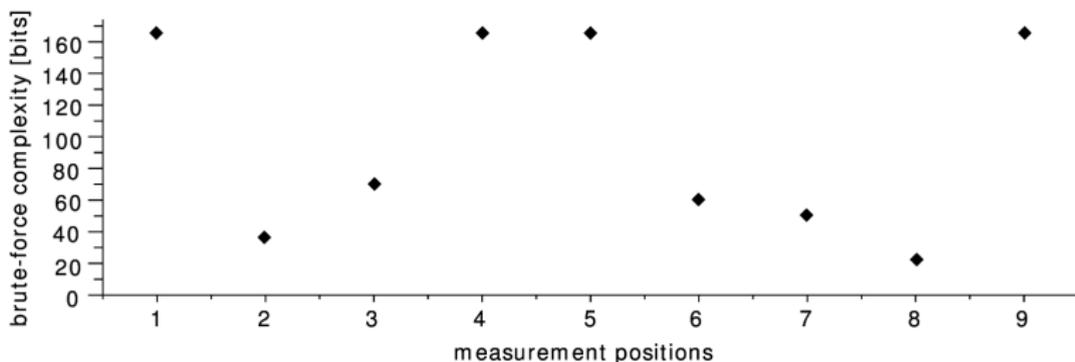
Results for All Positions

- Estimate remaining brute-force complexity **after** clustering attack

Practical Evaluation

Results for All Positions

- Estimate remaining brute-force complexity **after** clustering attack
- All individual measurement positions:



- In **2 out of 9** cases, brute-force complexity is clearly feasible for attackers (only 2^{22} and 2^{37} trials)

Practical Evaluation

Combining Simultaneous Measurements

- What if exploited leakage is insufficient?
- Repeating measurements is impossible because exponent changes
- Cluster analysis provides straight-forward possibility to combine (simultaneous) measurements:
 - Simply concatenate cut-out samples

Practical Evaluation

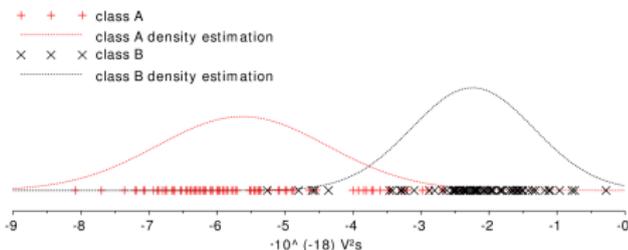
Improvement Through Combination

- Due to lack of mult. probes, meas. are repeated with const. inputs

Practical Evaluation

Improvement Through Combination

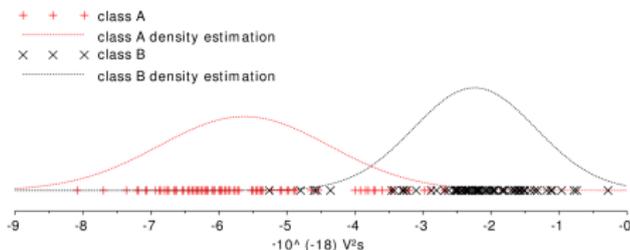
- Due to lack of mult. probes, meas. are repeated with const. inputs
- **One** measurement (**after** clustering, 1-D projection): **Many Errors**



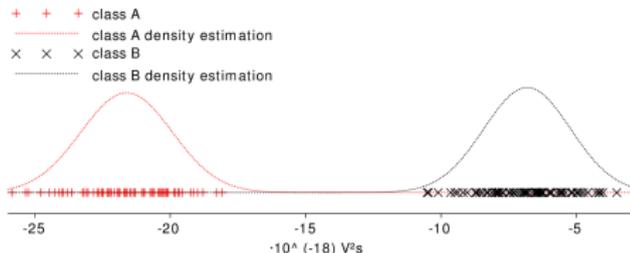
Practical Evaluation

Improvement Through Combination

- Due to lack of mult. probes, meas. are repeated with const. inputs
- **One** measurement (after clustering, 1-D projection): **Many Errors**



- **All** measurements (after clustering, 1-D projection): **No Errors**



Countermeasures

- Exponent blinding or coordinate randomization do not help
- Reduce SNR of single-execution leakage as far as possible
- Address sources of specific single-execution leakage.
E.g. Reduce location-based leakage using interleaved placement

Conclusion

- **Non-profiled attack** against exponentiations
 - Well established clustering algorithms
 - No manual tuning
 - Can be generalized to any single-/multi-variate single execution leakage of exponentiation algorithms
 - Combination of measurements can improve attack
 - no need to find best positions
- In our opinion, this should make cross correlation-based single-execution attacks obsolete
- Clustering may also be interesting e.g. for SCA collision attacks

Thank You

Back-Up

K-Means

- Example: Graphical representation of 2-dimensional samples (not my data)
 - In this example: samples cluster around two means/centroids
 - This corresponds to binary exponentiation case
 - The segmentation can be found through unsupervised algorithms

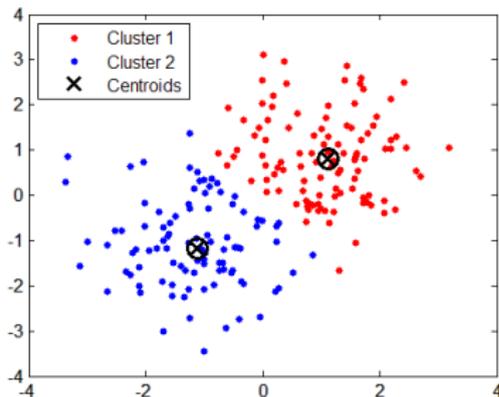


Figure: Source: <http://www.mathworks.de/de/help/stats/kmeans.html>

Back-Up

ECC Implementation

- Elliptic curve scalar multiplication ($Q = d \cdot P$)
- Binary field $GF(2^{163})$, NIST Curve B-163 parameters
- López and Dahab Montgomery ladder 'exponentiation' algorithm
- Affine x - and y -coordinates as input and output

- Fulfills requirements for successful attack
 - Bitwise processing of **163** bit scalar
 - Uniform operation sequence for each bit
 - Register usage **depends** on bits

Back-Up

Locations with High Leakage vs. High Amplitudes

