

# Set-swapping Attack on the Classic McEliece Cryptosystem

PQ-TLS project – Axis 3

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- Lilian Bossuet (SESAM team, LabHC, Saint-Étienne)


## ① Classic McEliece

 Encapsulation

## ② Syndrome decoding problem (which is NP-complete)

 How to make it “easier” to solve  
and actually solve it

## ③ Practical aspects

 How to make it happen by way of physical attacks

# Classic McEliece encapsulation

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## Classic McEliece is a **Key Encapsulation Mechanism**

- $\text{KeyGen}() \rightarrow (\mathbf{H}_{\text{pub}}, k_{\text{priv}})$
- $\text{Encap}(\mathbf{H}_{\text{pub}}) \rightarrow (\mathbf{s}, k_{\text{session}})$
- $\text{Decap}(\mathbf{s}, k_{\text{priv}}) \rightarrow (k_{\text{session}})$

The Encapsulation procedure (Niederreiter encryption [Nie86]) establishes a **shared secret**.

- $\text{Encap}(\mathbf{H}_{\text{pub}}) \rightarrow (\mathbf{s}, k_{\text{session}})$ 
  - Generate a random vector  $\mathbf{e} \in \mathbb{F}_2^n$  of Hamming weight  $\mathbf{t}$        $((\mathbf{n}; \mathbf{t})$ : security parameters)
  - Compute  $\mathbf{s} = \mathbf{H}_{\text{pub}}\mathbf{e}$
  - Compute the hash:  $k_{\text{session}} = H(1, \mathbf{e}, \mathbf{s})$

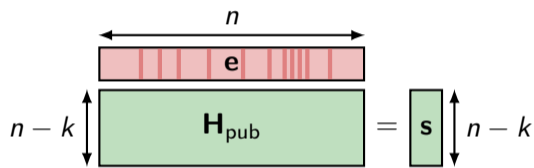
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# Classic McEliece parameters



$n$	$k$	$(n-k)$	$t$
3488	2720	768	64
4608	3360	1248	96
6688	5024	1664	128
6960	5413	1547	119
8192	6528	1664	128

The public key  $H_{\text{pub}}$  is **very large**.

# Hardware implementations

Embedded/hardware implementations are now feasible: [RKK20] [CC21] [Che+22] [NM24]

Several **strategies** exist to store the (very large) keys:

- Streaming the public key from somewhere else,
- Use a structured code,
- Use a very large microcontroller.

## New threats

That makes them vulnerable to **physical attacks** (fault injection & side-channel analysis)

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[RKK20] Johannes Roth, Evangelos G. Karatsiolis, and Juliane Krämer. “Classic McEliece Implementation with Low Memory Footprint”. In: **CARDIS**. 2020

[CC21] Ming-Shing Chen and Tung Chou. “Classic McEliece on the ARM Cortex-M4”. In: **IACR TCHES** (2021)

[Che+22] Po-Jen Chen et al. “Complete and Improved FPGA Implementation of Classic McEliece”. In: **IACR TCHES** (2022)

[NM24] Cyrius Nugier and Vincent Migliore. “Acceleration of a Classic McEliece Postquantum Cryptosystem With Cache Processing”. In: **IEEE Micro** (2024)



# Syndrome decoding problem

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# Syndrome decoding problem

## Syndrome decoding problem

**Input:** a binary parity-check matrix  $\mathbf{H} \in \mathbb{F}_2^{(n-k) \times n}$   
a binary vector  $\mathbf{s} \in \mathbb{F}_2^{n-k}$   
a scalar  $t \in \mathbb{N}^+$

**Output:** a binary vector  $\mathbf{x} \in \mathbb{F}_2^n$  with a Hamming weight  $\text{HW}(\mathbf{x}) \leq t$  such that:  $\mathbf{H}\mathbf{x} = \mathbf{s}$

Known to be an NP-complete problem [BMT78].

# Syndrome decoding problem

## Binary syndrome decoding problem (Binary SDP)

**Input:** a binary parity-check matrix  $\mathbf{H} \in \mathbb{F}_2^{(n-k) \times n}$   
a binary vector  $\mathbf{s} \in \mathbb{F}_2^{n-k}$   
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**Output:** a binary vector  $\mathbf{x} \in \mathbb{F}_2^n$  with a Hamming weight  $\text{HW}(\mathbf{x}) \leq t$  such that:  $\mathbf{H}\mathbf{x} = \mathbf{s}$

## Integer syndrome decoding problem ( $\mathbb{N}$ -SDP)

**Input:** a binary parity-check matrix  $\mathbf{H} \in \{0, 1\}^{(n-k) \times n}$   
a binary vector  $\mathbf{s} \in \mathbb{N}^{n-k}$   
a scalar  $t \in \mathbb{N}^+$

**Output:** a binary vector  $\mathbf{x} \in \{0, 1\}^n$  with a Hamming weight  $\text{HW}(\mathbf{x}) \leq t$  such that:  
 $\mathbf{H}\mathbf{x} = \mathbf{s}$

# $\mathbb{N}$ -SDP as an optimisation problem

**Option 1:** Consider  $\mathbf{H}_{\text{pub}}\mathbf{e} = \mathbf{s}$  as an **optimization problem** and solve it.

## Integer syndrome decoding problem ( $\mathbb{N}$ -SDP)

**Input:** a matrix  $\mathbf{H}_{\text{pub}} \in \mathcal{M}_{n-k,n}(\mathbb{N})$  with  $h_{i,j} \in \{0, 1\}$  for all  $i, j$   
a vector  $\mathbf{s} \in \mathbb{N}^{n-k}$   
a scalar  $t \in \mathbb{N}^+$

**Output:** a vector  $\mathbf{e}$  in  $\mathbb{N}^n$  with  $x_i \in \{0, 1\}$  for all  $i$   
and with a Hamming weight  $\text{HW}(\mathbf{x}) \leq t$  such that:  $\mathbf{H}_{\text{pub}}\mathbf{e} = \mathbf{s}$

## ILP problem

Let  $\mathbf{b} \in \mathbb{N}^n$ ,  $\mathbf{c} \in \mathbb{N}^m$  and  $\mathbf{A} \in \mathcal{M}_{m,n}(\mathbb{N})$  then:

$$\min\{\mathbf{b}^T \mathbf{x} \mid \mathbf{A}\mathbf{x} = \mathbf{c}, \mathbf{x} \in \mathbb{N}^n, \mathbf{x} \geq 0\}$$

with  $\mathbf{b} = (1, 1, \dots, 1)$  and  $\mathbf{x} \in \{0, 1\}^n$

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## ILP problem

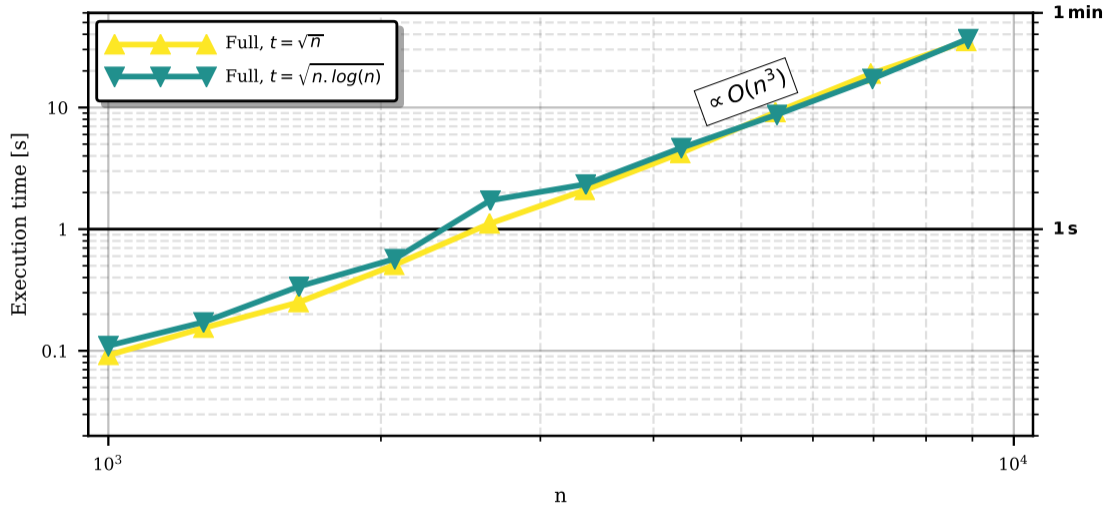
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$$\min\{\mathbf{b}^T \mathbf{x} \mid \mathbf{A}\mathbf{x} = \mathbf{c}, \mathbf{x} \in \mathbb{N}^n, \mathbf{x} \geq 0\}$$

with  $\mathbf{b} = (1, 1, \dots, 1)$  and  $\mathbf{x} \in \{0, 1\}^n$

Solved by **integer linear programming**  
(using `Scipy.optimize.linprog` for example)

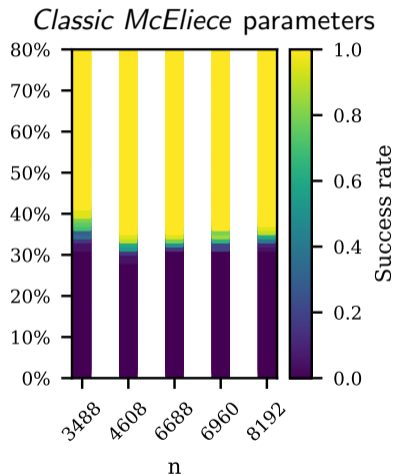
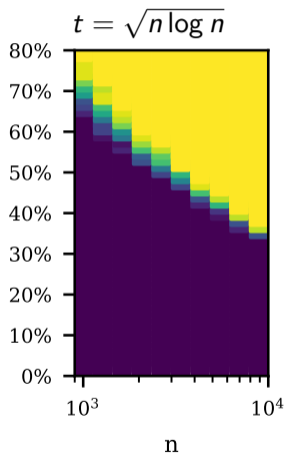
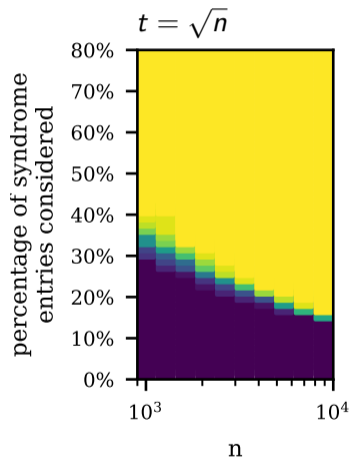
# Integer Linear Programming



For *Classic McEliece*:  $3488 < n < 8192$

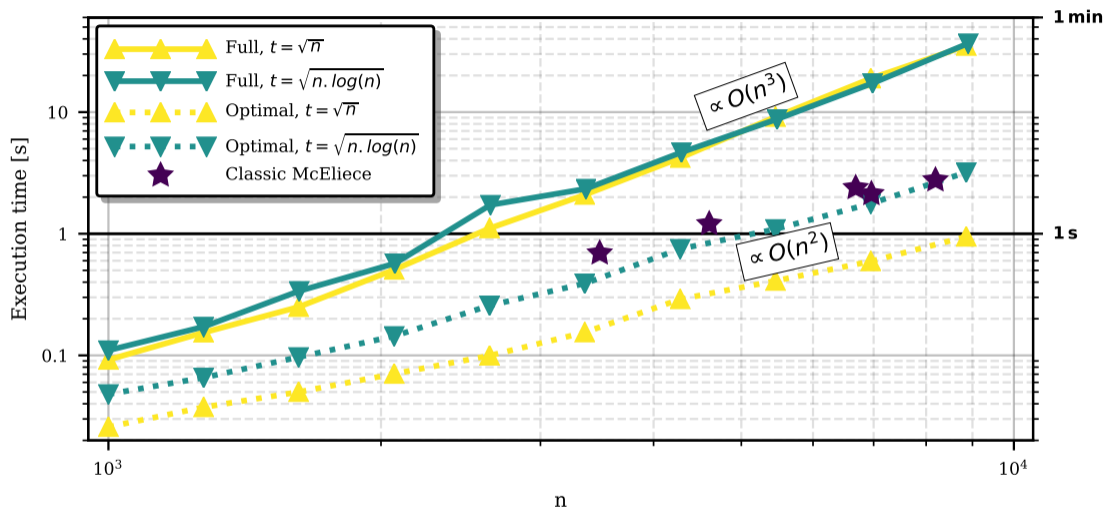
# Required fraction of faulty syndrome entries

We observed that only a **fraction** of the faulty syndrome entries is enough to solve the problem.



For *Classic McEliece*, **less than 40%** faulty syndrome entries is enough.

# Experimental results



When considering the **optimal fraction**, time complexity drops from  $\mathcal{O}(n^3)$  to  $\mathcal{O}(n^2)$ . The largest parameters can be attacked in **a few seconds** on a desktop computer.



Considering the  $\mathbb{N}$ -SDP as an optimization problem [Cay+21]

- 👍 easy to **express**,
- 👍 allows to use a **generic ILP solver**,
- 👍 is reasonably **efficient**,
- 👎 does not tolerate **errors** in the integer syndrome.

**Option 2:** Reframe  $\mathbf{H}_{\text{pub}}\mathbf{e} = \mathbf{s}$  as the Quantitative Group Testing problem [FL20]

## Abstract

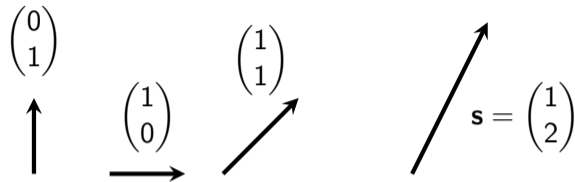
Given a random Bernoulli matrix  $A \in \{0, 1\}^{m \times n}$ , an integer  $0 < k < n$  and the vector  $y := Ax$ , where  $x \in \{0, 1\}^n$  is of Hamming weight  $k$ , the objective in the *Quantitative Group Testing* (QGT) problem is to recover  $x$ .

We want to find **which columns** of  $\mathbf{H}_{\text{pub}}$  **contributed the most** to  $\mathbf{s}$ .

# The score function

**Example:**  $t = 2 = \text{HW}(\mathbf{e})$

$$\mathbf{H}_{\text{pub}} \mathbf{e} = \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \end{pmatrix} \cdot \mathbf{e} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$



The dot product [FL20] can be used to compute a **score** for a column:

## Score function

$$\psi_i(\mathbf{s}) = \mathbf{H}_{\text{pub}[,i]} \cdot \mathbf{s} + \bar{\mathbf{H}}_{\text{pub}[,i]} \cdot \bar{\mathbf{s}}$$

$$\text{with } \bar{\mathbf{H}} = \mathbf{1} - \mathbf{H}$$

$$\text{and } \bar{\mathbf{s}} = t - \mathbf{s}$$

$$\psi_0(\mathbf{s}) = 3$$

$$\psi_1(\mathbf{s}) = 1$$

$$\psi_2(\mathbf{s}) = 3$$

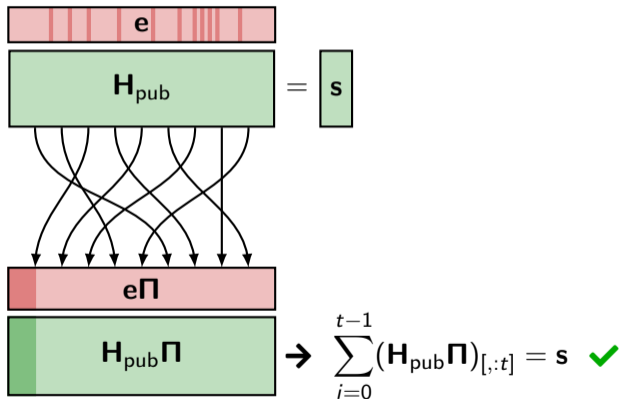
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**Algorithm 1** Permutation from score

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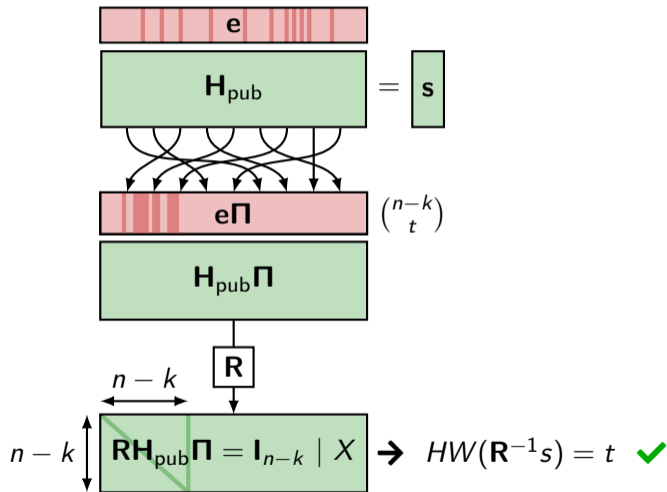
- 1: **for**  $i \leftarrow 0$  to  $n - 1$  **do**
  - 2:   Compute  $\psi_i(\mathbf{s})$
  - 3:  $\Pi \leftarrow$  sort  $\psi(\mathbf{s})$  in descending order
  - 4: **Return**  $\Pi$
- 

**Best-case** scenario:  $t$ -threshold decoder



# Information-set decoding-based strategies

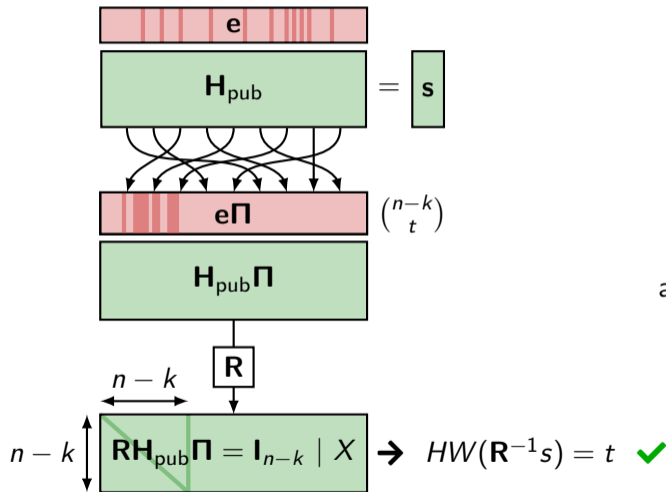
Rank-threshold score decoder: Information Set Decoding *à la* Prange [Pra62]



[Pra62] Eugene Prange. "The Use of Information Sets in Decoding Cyclic Codes". In: *IRE Transactions on Information Theory* (1962)

# Information-set decoding-based strategies

Rank-threshold score decoder: Information Set Decoding à la Prange [Pra62]



Can be improved by allowing  $\delta$  ones in the last  $k$  positions of  $e\Pi$  and use more advanced ISD variants.

Solving  $\mathbb{N}$ -SDP with the score function [Col+22]

- 👍 is computationally efficient
- 👍 tolerates some errors in the integer syndrome
- 👍 gets more efficient with larger cryptographic parameters
- 👎 does not cope so well with high noise levels

# Practical aspects: physical attacks

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$\mathbb{N}$ -SDP framework: compute  $\mathbf{s} = \mathbf{H}_{\text{pub}} \mathbf{e}$  over  $\mathbb{N}$  instead of  $\mathbb{F}_2$

---

**Algorithm 2** Schoolbook matrix-vector multiplication over  $\mathbb{F}_2$ 

---

```
1: function MAT_VEC_MULT_SCHOOLBOOK(mat, vec)
2:   for row  $\leftarrow$  0 to  $n - k - 1$  do
3:     syn[row] = 0 ▷ Initialization
4:   for row  $\leftarrow$  0 to  $n - k - 1$  do
5:     for col  $\leftarrow$  0 to  $n - 1$  do
6:       syn[row] ^= mat[row][col] & vec[col] ▷ multiply-accumulate
7:   return syn
```

---

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6:       syn[row]  $\hat{=}$  mat[row][col] & vec[col] ▷ multiply-accumulate
7:   return syn
```

---

# Option 1: laser fault injection attack

Targeting the XOR operation, considering the Thumb instruction set.

bits	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
EORS: $Rd = Rm \oplus Rn$	0	1	0	0	0	0	0	0	0	1	Rm		Rdn			
EORS: $R1 = R0 \oplus R1$	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1

Laser fault injection in flash memory : **mono-bit, bit-set fault model** [Col+19][Men+20].

ADCS: $R1 = R0 + R1$	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	1
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[Col+19] Brice Colombier et al. "Laser-induced Single-bit Faults in Flash Memory: Instructions Corruption on a 32-bit Microcontroller". In: **IEEE HOST**. 2019

[Men+20] Alexandre Menu et al. "Single-bit Laser Fault Model in NOR Flash Memories: Analysis and Exploitation". In: **FDTC**. 2020

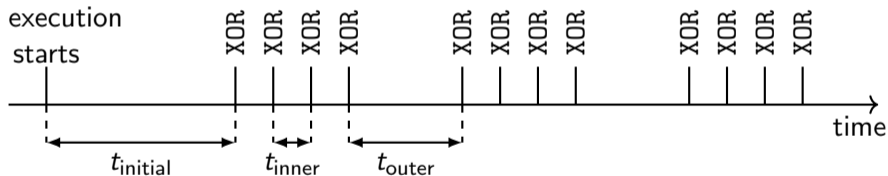
# Multiple faults

**Three independent** delays must be tuned to fault the full matrix-vector multiplication:

$t_{\text{initial}}$  **initial** delay before the multiplication starts

$t_{\text{inner}}$  delay in the **inner** for loop

$t_{\text{outer}}$  delay in the **outer** for loop



## Outcome

After  $n \cdot (n - k)$  faults, we get an **integer syndrome**  $\mathbf{s} \in \mathbb{N}^{n-k}$

# Packed matrix-vector multiplication

**Objection:** the schoolbook matrix-vector multiplication algorithm is **highly inefficient!**  
Each **machine word** stores only **one bit**: a **lot** of memory is wasted.

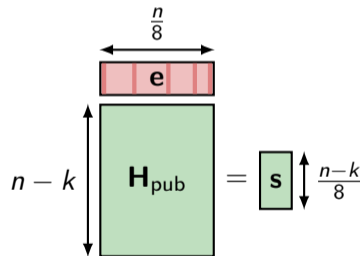
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## Algorithm 3 Packed matrix-vector multiplication

---

```
1: function MAT_VEC_MULT_PACKED(mat, vec)
2:   for row  $\leftarrow$  0 to  $((n - k)/8 - 1)$  do
3:     syn[row] = 0 ▷ Initialisation
4:   for row  $\leftarrow$  0 to  $(n - k - 1)$  do
5:     b = 0
6:     for col  $\leftarrow$  0 to  $(n/8 - 1)$  do
7:       b ^= mat[row][col] & vec[col]
8:       b ^= b >> 4
9:       b ^= b >> 2 ▷ Exclusive-OR folding
10:      b ^= b >> 1
11:      b &= 1 ▷ LSB extraction
12:      syn[row/8] |= b << (row % 8) ▷ Packing
13:   return syn
```

---



## Option 2: side-channel analysis

---

### Algorithm 4 Packed matrix-vector multiplication

---

```
1: ...  
2: for col  $\leftarrow$  0 to  $(n/8 - 1)$  do  
3:   b  $\hat{=}$  mat[row][col] & vec[col]  
4: ...
```

---

b = 00000000

b = 00000000

b = 00001000

b = 00001000

b = 00001010

## Option 2: side-channel analysis

---

### Algorithm 4 Packed matrix-vector multiplication

---

```
1: ...  
2: for col  $\leftarrow$  0 to  $(n/8 - 1)$  do  
3:   b  $\hat{=}$  mat[row][col] & vec[col]  
4: ...
```

---

HD = 0  $\left\{ \begin{array}{l} b = 00000000 \text{ HW}=0 \\ b = 00000000 \text{ HW}=0 \end{array} \right.$

HD = 1  $\left\{ \begin{array}{l} b = 00001000 \text{ HW}=1 \\ b = 00001000 \text{ HW}=1 \end{array} \right.$

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HD = 1  $\left\{ \begin{array}{l} b = 00001010 \text{ HW}=2 \\ b = 00001010 \text{ HW}=2 \end{array} \right.$

## Option 2: side-channel analysis

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### Algorithm 4 Packed matrix-vector multiplication

---

```
1: ...
2: for col  $\leftarrow$  0 to  $(n/8 - 1)$  do
3:   b  $\hat{=}$  mat[row][col] & vec[col]
4: ...
```

---

HD = 0  $\left\{ \begin{array}{l} b = 00000000 \text{ HW}=0 \\ b = 00000000 \text{ HW}=0 \end{array} \right.$

HD = 1  $\left\{ \begin{array}{l} b = 00000000 \text{ HW}=0 \\ b = 00001000 \text{ HW}=1 \end{array} \right.$

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HD = 1  $\left\{ \begin{array}{l} b = 00001000 \text{ HW}=1 \\ b = 00001010 \text{ HW}=2 \end{array} \right.$

### Integer syndrome from Hamming distances or Hamming weights

$$s_j = \sum_{i=1}^{\frac{n}{8}-1} \text{HD}(\mathbf{b}_{j,i}, \mathbf{b}_{j,i-1})$$

$$= \sum_{i=1}^{\frac{n}{8}-1} | \text{HW}(\mathbf{b}_{j,i}) - \text{HW}(\mathbf{b}_{j,i-1}) | \quad \text{if } \text{HD}(\mathbf{b}_{j,i}, \mathbf{b}_{j,i-1}) \leq 1$$

HD = 2  $\left\{ \begin{array}{l} b = 00001000 \text{ HW}=1 \\ b = 00000100 \text{ HW}=1 \end{array} \right.$

Happens if:

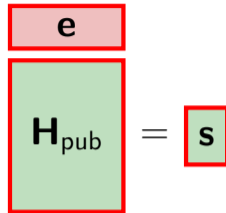
$\text{HW}(\text{mat}[r][c] \& \text{vec}[c]) > 1$

**Unlikely** since  $\text{HW}(\mathbf{e}) = t$  is low.



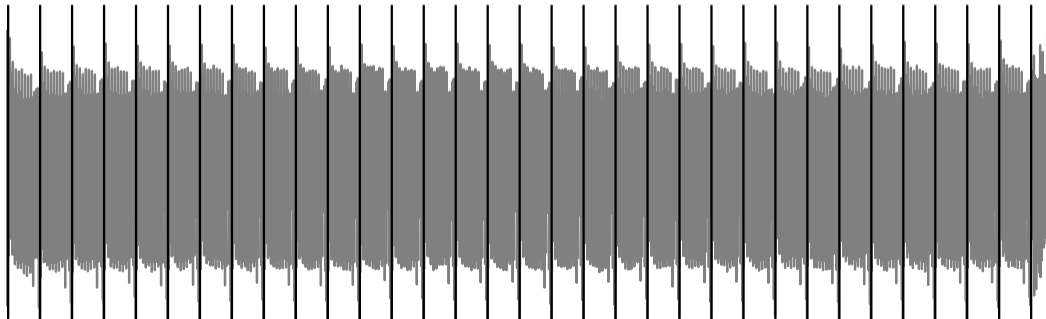
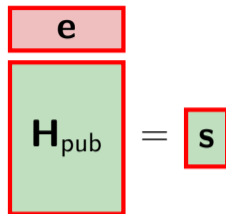
# Side-channel analysis for Hamming weight recovery

$$\mathbf{s} = \mathbf{H}_{\text{pub}} \mathbf{e}$$



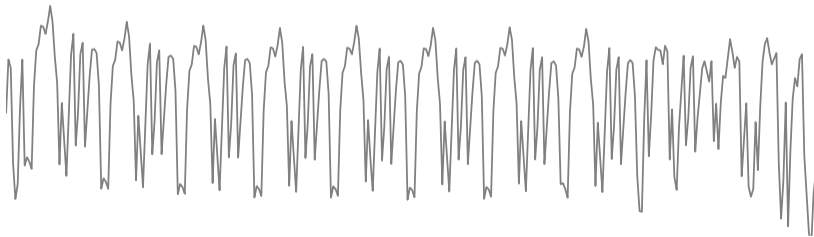
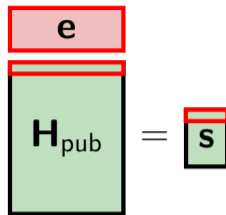
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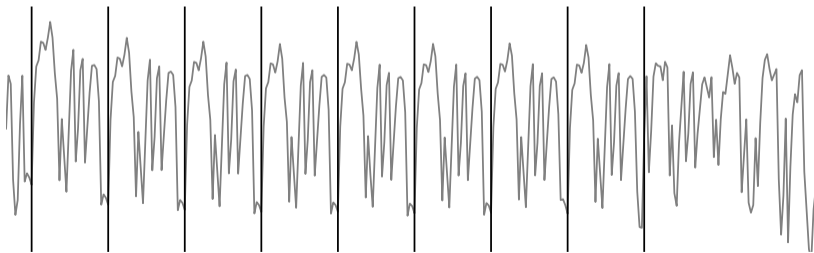
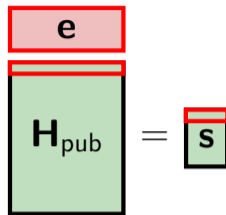
# Side-channel analysis for Hamming weight recovery

$$\mathbf{s}_j = \mathbf{H}_{pub[j,:]} \mathbf{e}$$



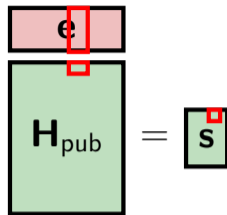
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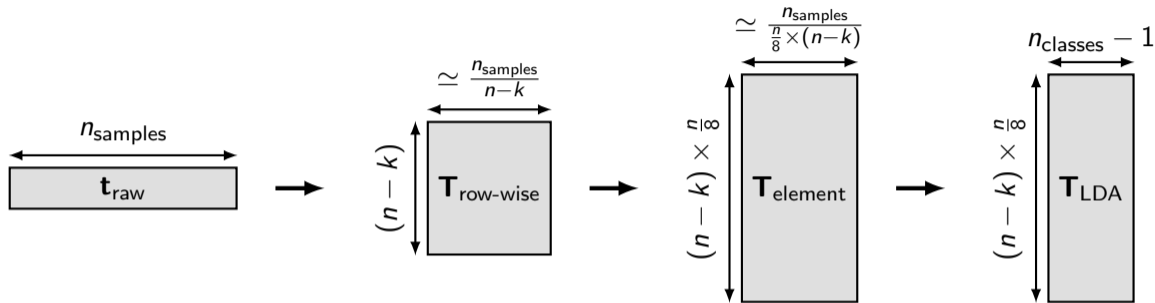


# Side-channel analysis for Hamming weight recovery

$$\hat{b} = \mathbf{H}_{pub[j,i]} \mathbf{e}_i$$



# Trace reshaping process



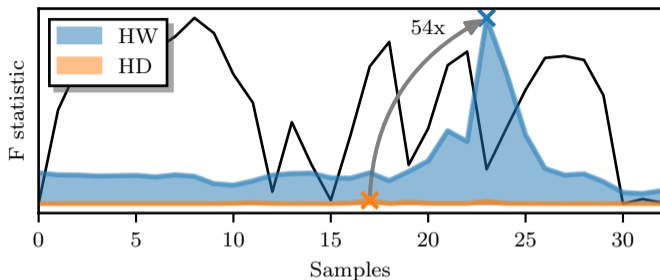
## Training phase

- Linear Discriminant Analysis (LDA) for **dimensionality reduction**,
- **One** trace gives  $(n-k) \times \frac{n}{8}$  **training samples**       $n = 8192 \rightarrow$  more than  $1.7 \times 10^6$
- Fed to a **single** RF classifier (`sklearn.ensemble.RandomForestClassifier`)

# Random Forest classifier

Random Forest classifier training:

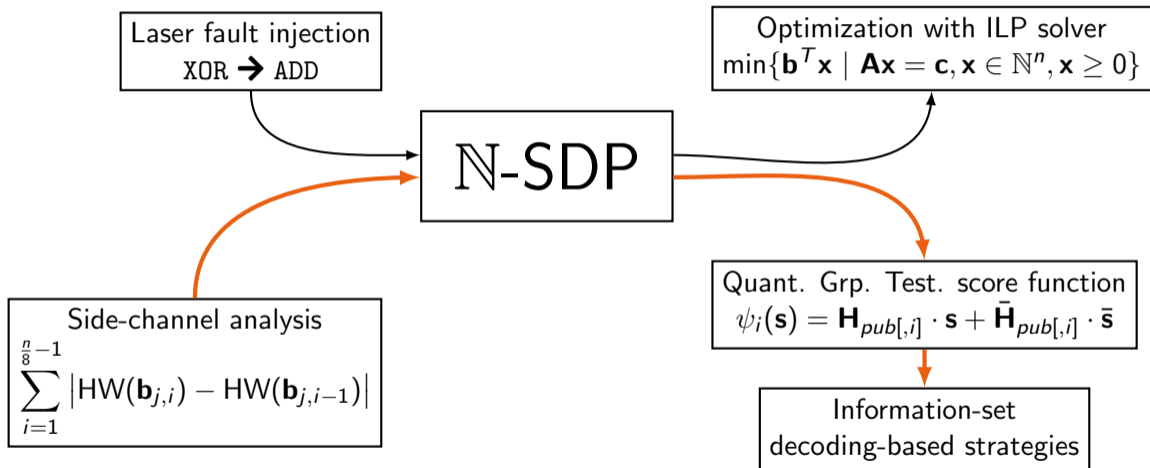
- Hamming weight:
  - $> 99.5\%$  test accuracy,
- Hamming distance:
  - $\approx 80\%$  test accuracy.



## Outcome

- We can recover the **Hamming weight** very accurately,
- but **not the Hamming distance**...
- We can compute a *slightly inaccurate* integer syndrome.<sup>7</sup>

<sup>7</sup>Brice Colombier et al. "Profiled Side-Channel Attack on Cryptosystems Based on the Binary Syndrome Decoding Problem". In: **IEEE TIFS** (2022)





# Dealing with errors in the integer syndrome

The integer syndrome, derived from HW side-channel leakage, is often incorrect [Gro+23]:

🗨️ **double-cancellation** errors : **same** Hamming weight but **different** value

$$\text{HD} = 2 \begin{cases} b = 0000\mathbf{1}000 & \text{HW}=1 \\ b = 00000\mathbf{1}00 & \text{HW}=1 \end{cases}$$

only gets **worse** when the register size grows (32, 64)...

🗨️ classifier inaccuracy for **high noise-levels** [Dra+22].

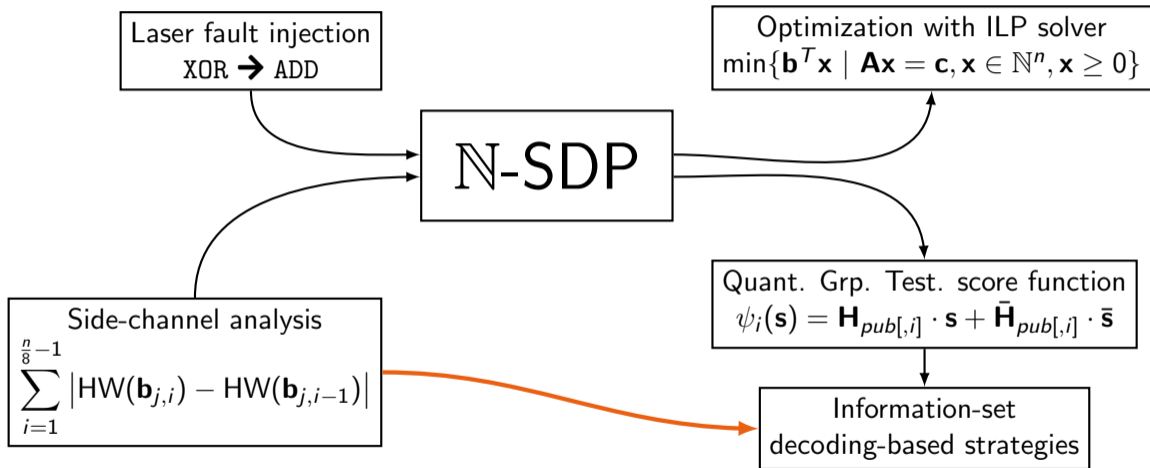
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[Gro+23] Vincent Grosso et al. "Punctured Syndrome Decoding Problem - Efficient Side-Channel Attacks Against Classic McEliece". In: **COSADE**. 2023

[Dra+22] Vlad-Florin Dragoi et al. "Integer Syndrome Decoding in the Presence of Noise". In: **IEEE ITW**. 2022

Back to SDP

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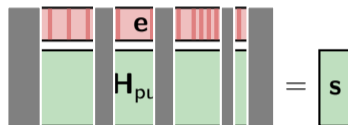


# Back to SDP: punctured syndrome decoding problem

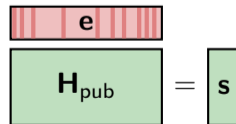
SDP



Punctured SDP [Gro+23]



Removing columns associated with an all-zero word in  $e$ .  
(can be detected by side-channel analysis)

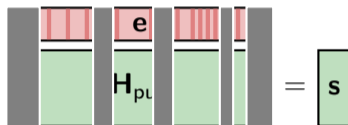


# Back to SDP: punctured syndrome decoding problem

SDP



Punctured SDP [Gro+23]



Removing columns associated with an all-zero word in  $e$ .  
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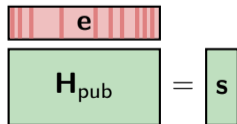
reduces the code **size**

- ISD strategies more applicable



not for large **registers** (32, 64)

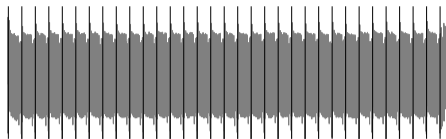
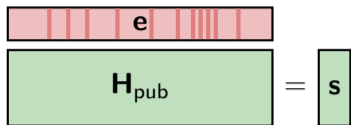
- not enough all-zero words in  $e$



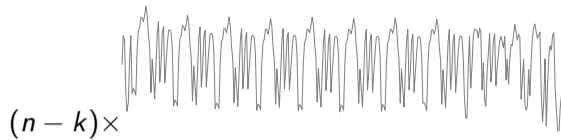
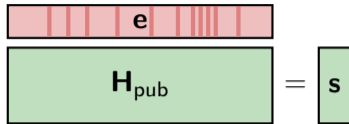
# Back to SDP: $t$ -test attack



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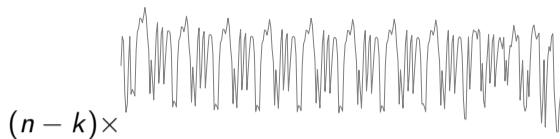
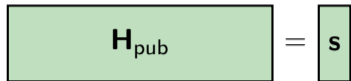
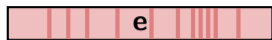


# Back to SDP: $t$ -test attack





# Back to SDP: $t$ -test attack



Identify the top  $t$  columns of  $\mathbf{H}_{\text{pub}}$  that **best explain** the observed power consumption.

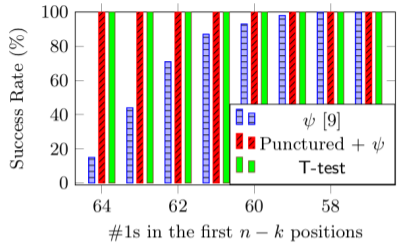
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## Algorithm 5 $t$ -test attack

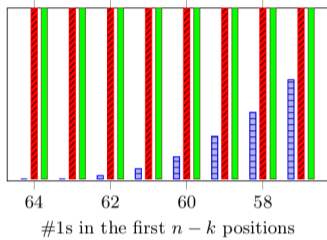
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- 1: **for**  $i \leftarrow 0$  to  $n - 1$  **do**
  - 2:   **for** every sample **do**
  - 3:      $G_0 := \text{subtraces}[\text{sample}]$  where  $H[:, i] = 0$
  - 4:      $G_1 := \text{subtraces}[\text{sample}]$  where  $H[:, i] = 1$
  - 5:      $t\text{-test}(G_0, G_1)$
  - 6:    $t\_vals[i] = \max(t\text{-tests})$
  - 7: **Return** indexes of top  $t$  values in  $t\_vals$
-

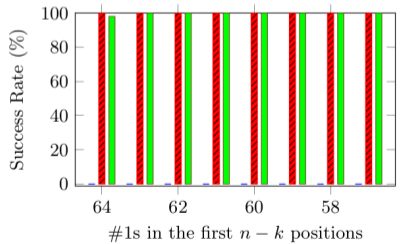
# Experimental results



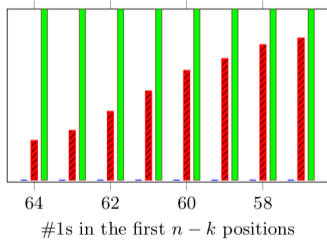
(a)  $\sigma = 0.1, \text{Accuracy} = 0.9999$ .



(b)  $\sigma = 0.18, \text{Accuracy} = 0.99453$ .



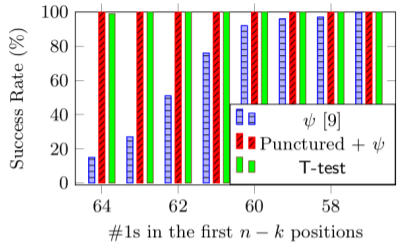
(c)  $\sigma = 0.26, \text{Accuracy} = 0.94553$ .



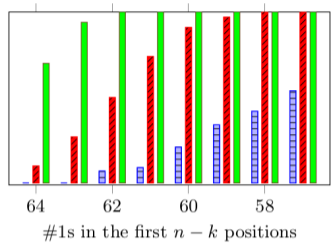
(d)  $\sigma = 0.30, \text{Accuracy} = 0.90442$ .

Fig. 3: Success rate of the three methods for 8-bit words and different noise levels.

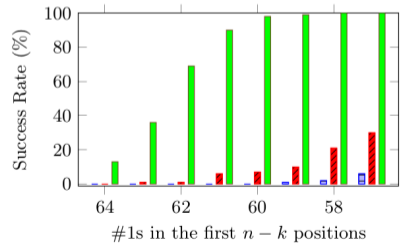
# Experimental results



(a)  $w = 8$ .



(b)  $w = 32$ .

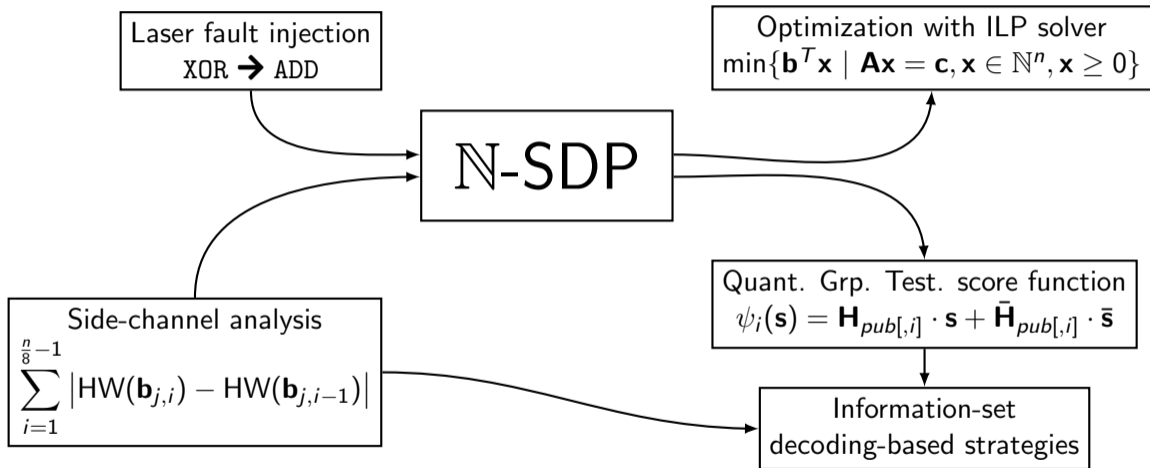


(c)  $w = 64$ .

Fig. 5: Comparison of the three methods for different register sizes at noise level  $\sigma = 0.16$ .

# Conclusion

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## Future works:

- Study the ISD **enumeration** step starting with the **initial permutation**
- Better understand the “**noise**” on the integer syndrome, and remove it?
- Target **hardware** implementations and exploit **Hamming distance** leakage

## Perspectives:

- Recover **long-term secrets** too
- Swap the sets on **other cryptosystems!**

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— Questions ? —