

# Lattice Attacks against Elliptic-Curve Signatures with Blinded Scalar Multiplication

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# Outline

- EC signature schemes based on random nonces
  - ▶  $\sigma$  computed from  $[k]P, k \leftarrow \mathcal{R}$
  - ▶  $\sigma + k \Rightarrow$  secret key
  - ▶ lattice attack: few bits of several  $k_i \Rightarrow$  secret key
- Scenario:
  - ▶ implementation with countermeasures against SCA
  - ▶ blinding of the nonce
  - ▶ noisy side-channel leakage on the bits of the blinded nonce
- Issue: **noisy information** on **blinded** nonces  $\Rightarrow$  lattice attack

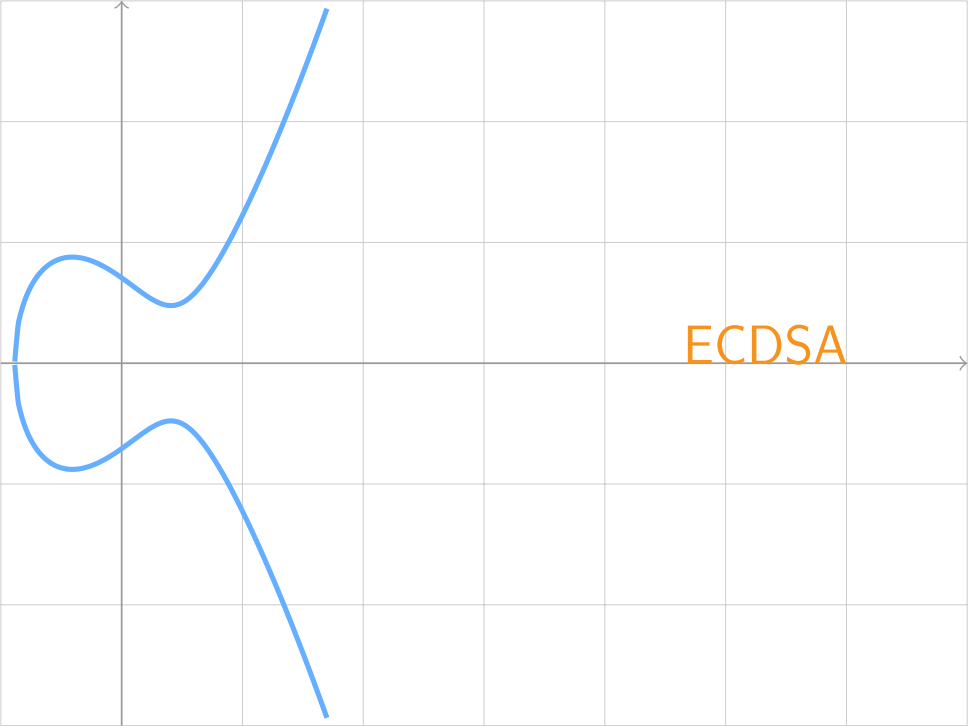
# Outline

- Approach:

- ▶ template attack  $\Rightarrow$  probability scores
- ▶ probability scores  $\Rightarrow$  bit-selection algorithm
- ▶ selected bits  $\Rightarrow$  lattice attack
- ▶ dealing with blinding

- Presentation:

- ▶ ECDSA
- ▶ target implementation & leakage model
- ▶ Howgrave-Graham and Smart lattice attack
- ▶ bit selection
- ▶ experimental results



ECDSA

- Key pair  $(x, Q)$  with  $Q = [x]P \in E(\mathbb{K})$

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- Signature of  $h = H(m)$

$$k \xleftarrow{\$} [1; q] \quad (q = |E(\mathbb{K})|)$$

$$t = \text{xcoord}([k]P)$$

$$s = \frac{h + t \cdot x}{k} \pmod{q}$$

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■ Verification of  $\sigma = (t, s)$

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$$s = \frac{h + t \cdot x}{k} \pmod{q} \quad \Rightarrow \text{signature } \sigma = (t, s)$$

■ Verification of  $\sigma = (t, s)$

$$k = \frac{h + t \cdot x}{s}$$
$$\underbrace{[k]P}_t \stackrel{?}{=} \underbrace{\begin{bmatrix} h \\ s \end{bmatrix} P}_{[t/s]Q} + \underbrace{\begin{bmatrix} t \cdot x \\ s \end{bmatrix} P}_{[t/s]Q}$$



Target implementation  
and leakage model

# Target implementation

- Regular binary algorithm (e.g. Montgomery ladder)
- Classical side-channel countermeasures:
  - ▶ randomization of point coordinates
  - ▶ scalar blinding

## Classic blinding:

1.  $r \xleftarrow{\$} \llbracket 0, 2^\lambda - 1 \rrbracket$
2.  $a \leftarrow k + r \cdot q$
3. return  $[a]\mathbf{P}$

## Euclidean blinding:

1.  $r \xleftarrow{\$} \llbracket 1, 2^\lambda - 1 \rrbracket$
2.  $a \leftarrow \lfloor k/r \rfloor; b \leftarrow k \bmod r$
3. return  $[r]([a]\mathbf{P}) + [b]\mathbf{P}$

# Leakage model

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**Algorithm 1** Montgomery ladder

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**Input:** blinded nonce  $a$

**Output:**  $[a]P$

1.  $P_0 \leftarrow \mathcal{O}; P_1 \leftarrow P$
  2. **for**  $i = \ell - 1$  **downto** 0 **do**
  3.    $P_{1-a_i} \leftarrow P_{1-a_i} + P_{a_i}$
  4.    $P_{a_i} \leftarrow 2P_{a_i}$
  5. **end for**
  6. **return**  $P_0$
- 

- Loop iteration:  $(P_0, P_1) \leftarrow f(a_i, P_0, P_1)$   
 $\Rightarrow$  leaks  $\Psi(a_i, P_0, P_1)$

- Gaussian leakage assumption:

$$\Psi(a_i, P_0, P_1) \sim \mathcal{N}(m_{a_i}, \Sigma)$$

# Template attacker

- Get a side-channel trace  $(\psi_{\ell-1}, \dots, \psi_1, \psi_0)$
- For every  $i$ , use leakage templates to decide

$$\psi_i \sim \Psi(0) \quad \text{or} \quad \psi_i \sim \Psi(1)$$

- Maximum likelihood

$$\Pr[a_i = 0 \mid \psi_i] = \text{cst} \cdot \exp\left(-\frac{1}{2}(\psi_i - m_0)^t \cdot \Sigma^{-1} \cdot (\psi_i - m_0)\right)$$

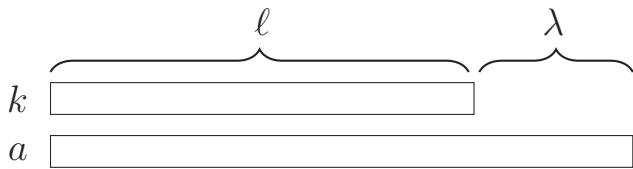
$$\Pr[a_i = 1 \mid \psi_i] = \text{cst} \cdot \exp\left(-\frac{1}{2}(\psi_i - m_1)^t \cdot \Sigma^{-1} \cdot (\psi_i - m_1)\right)$$

- We get  $\Pr[a_i = 0 \mid \psi_i] \sim \mathcal{D}_\theta(a_i)$  with

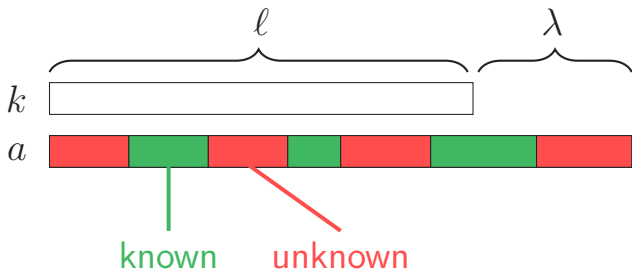
$$\underbrace{\theta = \Lambda \cdot (m_0 - m_1)}_{\text{multivariate SNR}} \quad \text{where} \quad \Lambda^t \Lambda = \Sigma$$

A blue curve is plotted on a grid. The curve starts on the left side of the grid, crosses the horizontal axis, and then rises steeply towards the top right. The text 'Howgrave-Graham and Smart attack with blinded nonces' is written in orange in the center of the grid.

Howgrave-Graham and Smart  
attack with blinded nonces

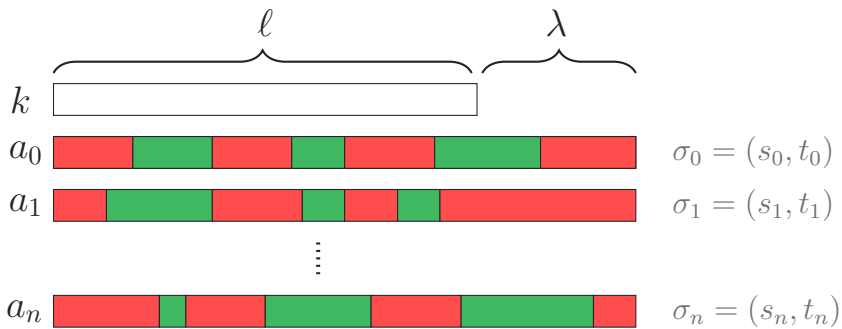


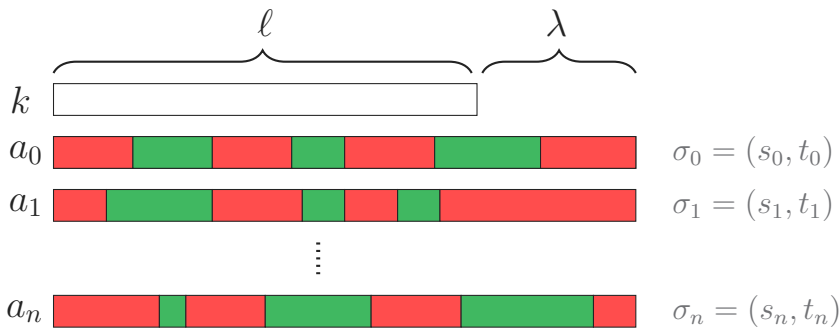
$$a = k + r \cdot q$$



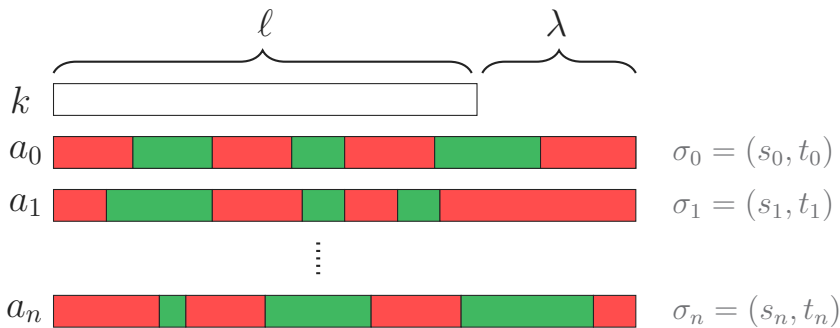
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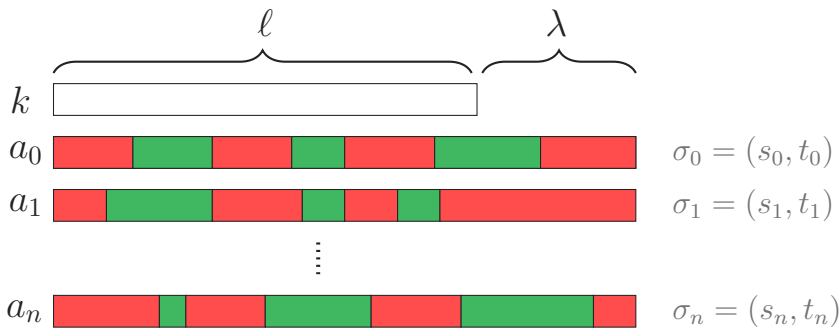




$$x \equiv \frac{a_i \cdot s_i - h_i}{t_i} \pmod{q}$$



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$$\Leftrightarrow a_i + A a_0 + B \equiv 0 \pmod{q}$$

$$\begin{array}{c}
 \overbrace{\text{[Red][Green][Red][Green][Red][Green][Red]}}^{a_i} \\
 + A \times \overbrace{\text{[Red][Green][Red][Green][Red][Green][Red]}}^{a_0} \\
 + B \equiv 0 \pmod{q}
 \end{array}$$

$$\begin{array}{c}
 \overbrace{\text{[red][green][red][green][red][green][red]}}^{a_i} \\
 + A \times \overbrace{\text{[red][green][red][green][red][green][red]}}^{a_0} \\
 + B \equiv 0 \pmod{q} \\
 \Leftrightarrow
 \end{array}$$

$$\begin{array}{l}
 \text{[red]} x_{i,1} + \alpha_{i,2} \cdot \text{[red]} x_{i,2} + \alpha_{i,3} \cdot \text{[red]} x_{i,3} + \cdots \\
 + \beta_{i,1} \cdot \text{[red]} x_{0,1} + \beta_{i,2} \cdot \text{[red]} x_{0,2} + \beta_{i,3} \cdot \text{[red]} x_{0,3} + \cdots \\
 + \gamma_i \equiv 0 \pmod{q}
 \end{array}$$

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 + \gamma_i = \text{[red]} \eta_i \cdot q
 \end{array}$$

$$\begin{aligned} & x_{i,1} + \alpha_{i,2} \cdot x_{i,2} + \alpha_{i,3} \cdot x_{i,3} + \dots \\ & + \beta_{i,1} \cdot x_{0,1} + \beta_{i,2} \cdot x_{0,2} + \beta_{i,3} \cdot x_{0,3} + \dots \\ & + \gamma_i = \eta_i \cdot q \end{aligned}$$

$\Rightarrow n$  equations (for  $i = 1, 2, \dots, n$ )



$$\begin{aligned} & \alpha_{i,2} \cdot x_{i,2} + \alpha_{i,3} \cdot x_{i,3} + \cdots \\ + \beta_{i,1} \cdot x_{0,1} & + \beta_{i,2} \cdot x_{0,2} + \beta_{i,3} \cdot x_{0,3} + \cdots \\ \eta_i \cdot q & = x_{i,1} + \gamma_i \end{aligned}$$

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 & \eta_i \cdot q = x_{i,1} + \gamma_i \\
 \Rightarrow & n \text{ equations (for } i = 1, 2, \dots, n)
 \end{aligned}$$

$$\begin{pmatrix}
 \text{red} \\
 \text{red} \\
 \text{red} \\
 \text{red} \\
 \vdots \\
 \text{red} \\
 \text{orange} \\
 \text{orange} \\
 \vdots \\
 \text{orange} \\
 \text{blue} \\
 \text{blue} \\
 \vdots \\
 \text{blue}
 \end{pmatrix}$$

$$\left( \begin{array}{cccc|c}
 (\alpha_{1,j})_j & & & (\beta_{1,j})_j & q \\
 & (\alpha_{2,j})_j & & (\beta_{2,j})_j & q \\
 & & \dots & & \dots \\
 & & & (\alpha_{n,j})_j & (\beta_{n,j})_j & q
 \end{array} \right) \times = \begin{pmatrix}
 \gamma_1 + \text{red} \\
 \gamma_2 + \text{red} \\
 \vdots \\
 \gamma_n + \text{red}
 \end{pmatrix}$$

$$\begin{aligned}
 & \alpha_{i,2} \cdot x_{i,2} + \alpha_{i,3} \cdot x_{i,3} + \dots \\
 & + \beta_{i,1} \cdot x_{0,1} + \beta_{i,2} \cdot x_{0,2} + \beta_{i,3} \cdot x_{0,3} + \dots \\
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 \end{aligned}$$

$$\begin{pmatrix}
 \text{red} \\
 \text{red} \\
 \text{red} \\
 \text{red} \\
 \vdots \\
 \text{red} \\
 \text{orange} \\
 \text{orange} \\
 \vdots \\
 \text{orange} \\
 \text{blue} \\
 \text{blue} \\
 \vdots \\
 \text{blue}
 \end{pmatrix}$$

$$\left( \begin{array}{cccc|cc}
 (\alpha_{1,j})_j & & & & & q \\
 & (\alpha_{2,j})_j & & & (\beta_{1,j})_j & q \\
 & & \dots & & (\beta_{2,j})_j & q \\
 & & & (\alpha_{n,j})_j & (\beta_{n,j})_j & q \\
 \hline
 1 & & & & & \\
 & 1 & & & & \\
 & & \dots & & & \\
 & & & & & 1
 \end{array} \right)$$

× =

$$\begin{pmatrix}
 \gamma_1 + \text{red} \\
 \gamma_2 + \text{red} \\
 \vdots \\
 \gamma_n + \text{red} \\
 \text{red} \\
 \text{red} \\
 \text{red} \\
 \vdots \\
 \text{red} \\
 \text{orange} \\
 \text{orange} \\
 \vdots \\
 \text{orange}
 \end{pmatrix}$$

# Lattice problem

- There exists  $\mathbf{y}$  st:

$$M \cdot \mathbf{y} = \mathbf{v} + \mathbf{x}$$

where

$$\mathbf{v} = (\gamma_1, \gamma_2, \dots, \gamma_n, 0, 0, \dots, 0)$$

$\mathbf{x}$  is the vector of unknown blocks

- CVP (Closest Vector Problem):  $\mathbf{v} \Rightarrow (\mathbf{v} + \mathbf{x})$

$$\underbrace{\|(\mathbf{v} + \mathbf{x}) - \mathbf{v}\|}_{\|\mathbf{x}\|} \leq c_0 \sqrt{\dim(M)} \det(M)^{\frac{1}{\dim(M)}}$$

$$c_0 \approx 1/\sqrt{2\pi e} \text{ (heuristic)}$$

# Lattice attack parameters

- Sum of contributions:

$$\sum_{i=0}^n (\delta_i - \lambda - c_1 \cdot N_i) \geq \ell$$

where  $\delta_i =$  number of known bits in  $a_i$

$N_i =$  number of unknown blocks in  $a_i$

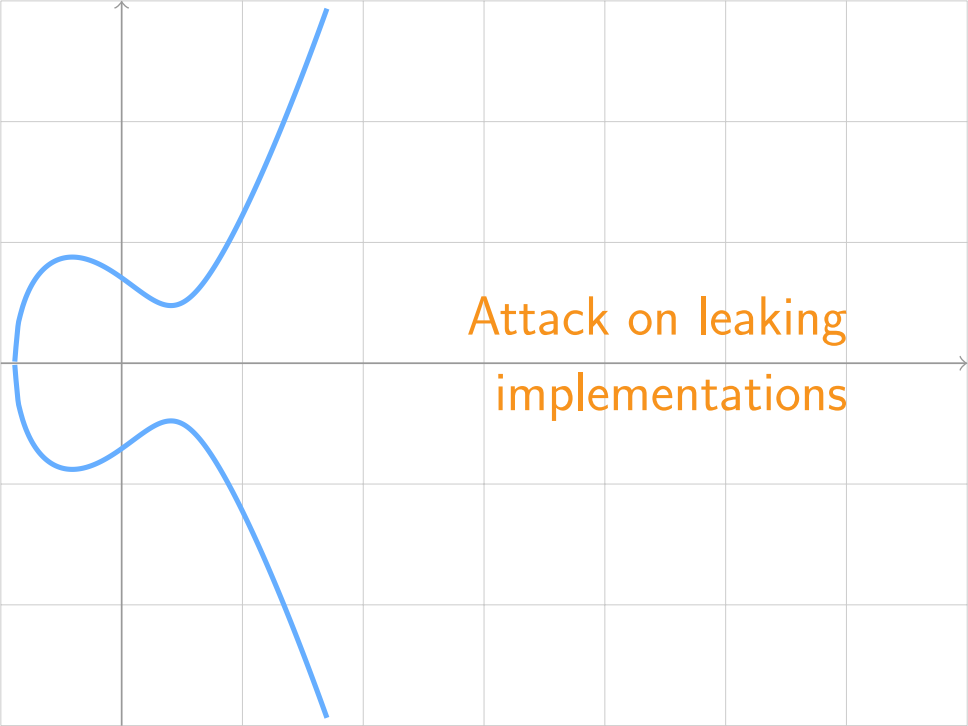
- Loss  $\lambda$  bits per blinded nonce
- Linear term  $c_1 \cdot N_i$ 
  - ▶ overlooked in the original paper
  - ▶ significant in our context
  - ▶ heuristically  $c_1 \approx -\log_2(c_0) \approx 2.05$
  - ▶ higher in practice

# Experiments

Practical  $c_1$  values for a 95% success rate:

$N_b =$	$(n + 1) = 5$				$(n + 1) = 10$				$(n + 1) = 20$		
	5	10	25	50	10	20	50	100	20	40	100
$\lambda = 0$	3.60	2.60	2.56	2.90	4.10	3.30	3.52	3.57	4.85	4.42	4.51
$\lambda = 16$	3.40	2.60	2.40	3.02	4.20	3.15	3.40	4.20	5.25	4.77	4.96
$\lambda = 32$	3.40	2.60	2.60	2.68	3.90	3.10	3.60	n/a	4.95	4.50	n/a
$\lambda = 64$	3.20	2.80	2.36	n/a	3.70	3.55	3.68	n/a	4.80	4.60	n/a

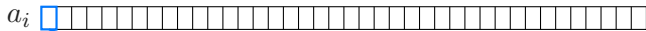
- CVP algorithm: the embedding method
- For tested parameters:  $2.3 < c_1 < 5.3$



Attack on leaking  
implementations







$$\text{leak} \sim \Psi(a_{i,0})$$



$$\Pr[a_{i,0} = 0]$$



$$\text{leak} \sim \Psi(a_{i,1})$$



$$\Pr[a_{i,1} = 0]$$



$$\text{leak} \sim \Psi(a_{i,2})$$



$$\Pr[a_{i,2} = 0]$$



$$\text{leak} \sim \Psi(a_{i,j})$$



$$\Pr[a_{i,j} = 0]$$



$$\text{leak} \sim \Psi(a_{i,j})$$



$$\Pr[a_{i,j} = 0]$$



$$\text{leak} \sim \Psi(a_{i,j})$$



$$\Pr[a_{i,j} = 0]$$

- Guess

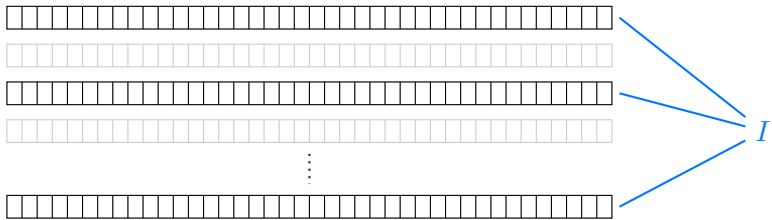
$$\hat{a}_{i,j} = \operatorname{argmax}_{b \in \{0,1\}} \Pr[a_{i,j} = b]$$

- Good-guess probability

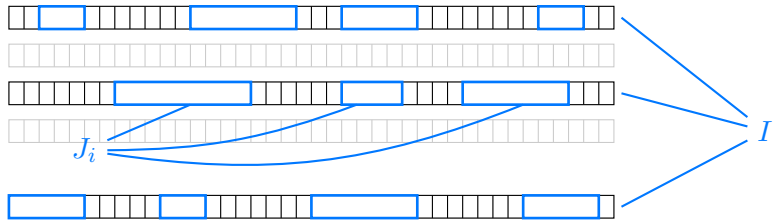
$$p_{i,j} := \Pr[a_{i,j} = \hat{a}_{i,j}] = \max_{b \in \{0,1\}} \Pr[a_{i,j} = b]$$

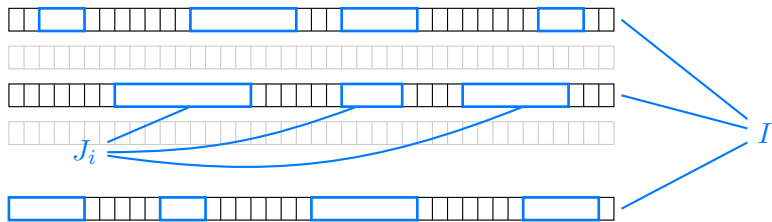
- Select some guess bits to construct the lattice











- Goal: select  $I$  and  $(J_i)_{i \in I}$  to maximize

$$\text{success proba} = \prod_{i \in I} \prod_{j \in J_i} p_{i,j}$$

such that

$$\underbrace{\sum_{i \in I} (|J_i| - \lambda - c_1 \cdot N_i) \geq \ell}_{\text{CVP constraint}} \quad \text{and} \quad \underbrace{\sum_{i \in I} N_i \leq \Delta_{max}}_{\text{lattice dimension}}$$

- For each selected set  $J_i$

CVP constraint  $\doteq |J_i| - \lambda - c_1 \cdot N_i$  (must reach  $\ell$ )

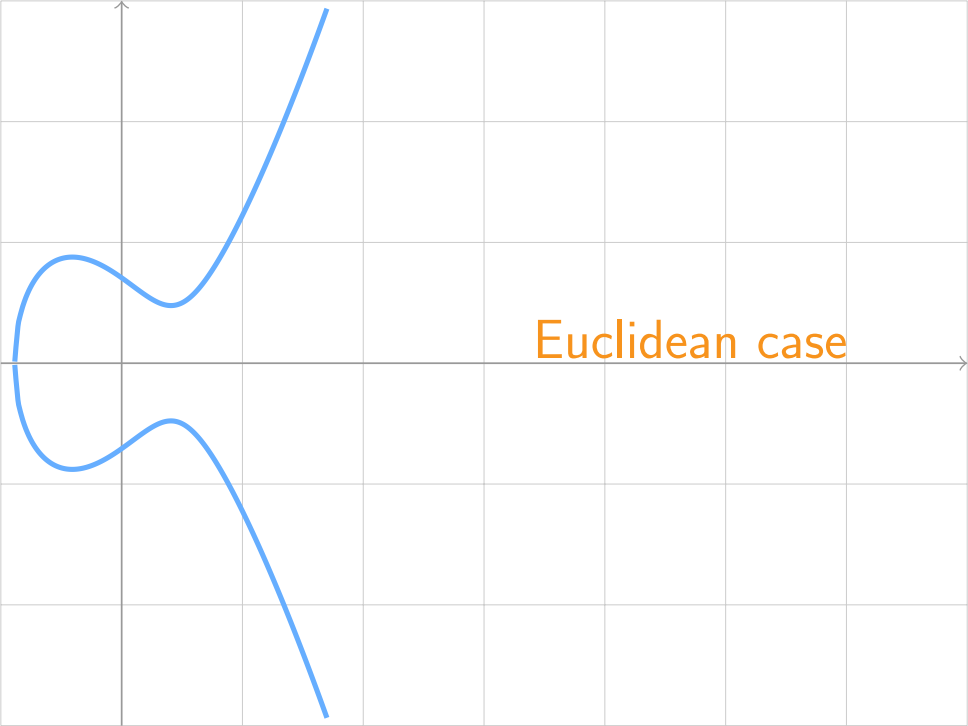
$\dim(\mathcal{L}) \doteq N_i$  (must not exceed  $\Delta_{max}$ )

success proba  $\times = \prod_{j \in J_i} p_{i,j}$

- Select  $J_i$  to maximize

$$\gamma_i = \left( \prod_{j \in J_i} p_{i,j} \right)^{\frac{1}{|J_i| - \lambda - c_1 N_i}}$$

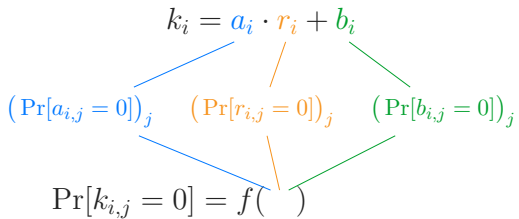
- Efficient algorithm based on dynamic programming



Euclidean case

$$k_i = a_i \cdot r_i + b_i$$

$(\Pr[a_{i,j} = 0])_j$      $(\Pr[r_{i,j} = 0])_j$      $(\Pr[b_{i,j} = 0])_j$

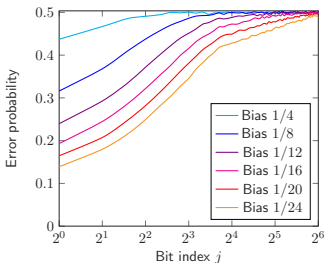


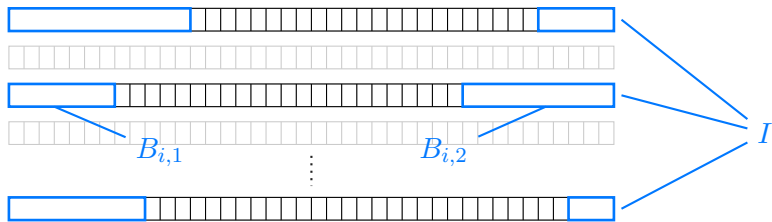
$$k_i = a_i \cdot r_i + b_i$$

$$\left( \Pr[a_{i,j} = 0] \right)_j \quad \left( \Pr[r_{i,j} = 0] \right)_j \quad \left( \Pr[b_{i,j} = 0] \right)_j$$

$$\Pr[k_{i,j} = 0] = f(\quad)$$

- Bias decreases exponentially as  $j \rightarrow \frac{\ell}{2}$





$$\Rightarrow |J_i| = |B_{i,1}| + |B_{i,2}| \quad N_i = 1 \quad \lambda = 0$$

$$\sum_{i \in I} (|J_i| - \lambda - c_1 \cdot N_i) \geq \ell$$

$$\Rightarrow \sum_{i \in I} (|B_{1,i}| + |B_{2,i}| - c_1) \geq \ell$$

$$\sum_{i \in I} N_i \leq \Delta_{max}$$

$$\Rightarrow |I| \leq \Delta_{max}$$



- Block probabilities

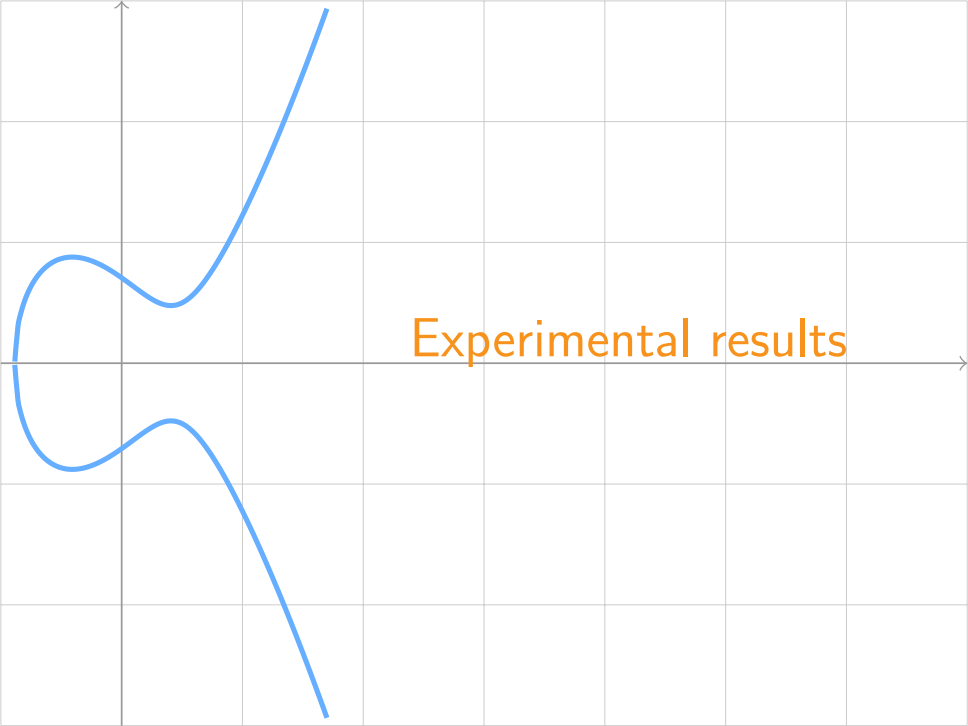
$$\Pr[B_{i,j} = x] \\ = f\left(\left(\Pr[a_{i,j} = 0]\right)_j; \left(\Pr[r_{i,j} = 0]\right)_j; \left(\Pr[b_{i,j} = 0]\right)_j; x\right)$$

- Block guesses

$$\hat{B}_{i,j} = \underset{x}{\operatorname{argmax}} \Pr[B_{i,j} = x] \\ \Pr[B_{i,j} = \hat{B}_{i,j}] = \max_x \Pr[B_{i,j} = x]$$

- Select blocks maximizing

$$\gamma_i = \left( \Pr[\hat{B}_{i,1} = B_{i,1}] \cdot \Pr[\hat{B}_{i,2} = B_{i,2}] \right)^{\frac{1}{|B_{1,i}| + |B_{2,i}| - c_1}}$$



Experimental results

# Experimental setting

- ANSSI 256-bit elliptic curve (*i.e.*  $\ell = 256$ )
- Three different random sizes  $\lambda \in \{16, 32, 64\}$
- Probability scores simulated using  $\mathcal{D}_\theta(\cdot)$  with

$$\theta = \alpha \cdot (0.5, 1, 2)$$

with  $\alpha \in \{1.5, 2\}$

- Attack parameters
  - ▶  $n_{sig}$  signatures (with leaking blinded nonces)
  - ▶  $n_{tr}$  trials for the subset  $I$   
 $(n_{sig}, n_{tr}) \in \{(10, 1), (20, 5), (20, 10), (100, 10), (100, 50), (100, 100)\}$
  - ▶ Linear factor  $c_1$  set to 4

# Experimental results

$(n_{sig}, n_{tr})$		(10,1)	(20, 5)	(20, 10)	(100, 10)	(100, 50)	(100, 100)
Classic blinding							
$\alpha = 1.5$	$\lambda = 16$	13.5 %	38.3 %	54.0 %	70.1 %	99.0 %	99.9 %
	$\lambda = 32$	3.5 %	13.6 %	22.7 %	27.8 %	73.9 %	91.9 %
	$\lambda = 64$	0.2 %	0.6 %	1.2 %	1.5 %	6.2 %	11.7 %
$\alpha = 2$	$\lambda = 16$	91.2 %	99.9 %				
	$\lambda = 32$	90.5 %	99.5 %	100 %	100 %	100 %	100 %
	$\lambda = 64$	85.7 %	99.3 %				
Euclidean blinding							
$\alpha = 1.5$	$\lambda = 16$						
	$\lambda = 32$	0 %	0 %	0 %	0 %	0 %	0 %
	$\lambda = 64$						
$\alpha = 2$	$\lambda = 16$	0.7 %	3.1 %	5.8 %	42.8 %	76.8 %	83.3 %
	$\lambda = 32$	0.1 %	0.4 %	0.8 %	41.1 %	74.9 %	82.6 %
	$\lambda = 64$	0.1 %	0.4 %	1.0 %	40.2 %	75.0 %	82.8 %

- Lattice reduction (almost) always works (for correct guesses)
  - ⇒ sound choice for  $c_1$
- $\lambda$  has small impact for Euclidean blinding
- Classic blinding more sensitive to our attack than Euclidean blinding