Faster Dual Lattice Attacks by Using Coding Theory

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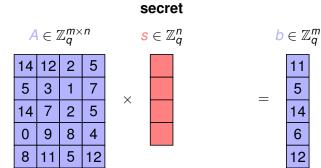
November 21, 2022







Let n = 4, m = 6 and q = 17.

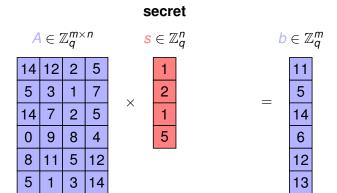


Given A and b, find s.

5

3 | 14

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→ Very easy (e.g. Gaussian elimination) and in polynomial time

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random				S	ecre	t ı	noise			
$A \in \mathbb{Z}_q^{m \times n}$				S	n q	$e \in \mathbb{Z}_q^n$	n I	$b \in \mathbb{Z}_q^m$		
14	12	2	5		1		-3		11	
5	3	1	7	×	2		-1	_	5	
14	7	2	5	^	1		2	_	14	
0	9	8	4		5		-3		6	
8	11	5	12				3		12	
5	1	3	14				-1		13	

Let n = 4, m = 6 and q = 17.

random				secret			noise				
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Given A and b, find s.

→ Suspected hard problem, even for quantum algorithms

Let $n, m, q \in \mathbb{Z}$ and χ_e, χ_s two distributions over \mathbb{Z}_q .

LWE $(n, m, q, \chi_e, \chi_s)$: probability distribution on $\mathbb{Z}_q^{m \times n} \times \mathbb{Z}_q^m$

- ▶ sample $A \leftarrow U(\mathbb{Z}_q^{m \times n})$
- ▶ sample $s \leftarrow \chi_s^n$
- ▶ sample $e \leftarrow \chi_e^m$
- ightharpoonup output (A, As + e).

Intuition: As + e is very close to a uniform distribution.

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Search LWE problem: given $(A, b) \leftarrow \text{LWE}(n, m, q, \chi_e, \chi_s)$, recover s.

Decision LWE problem:

distinguish LWE $(n, m, q, \chi_e, \chi_s)$ from $U(\mathbb{Z}_q^{m \times n} \times \mathbb{Z}_q^m)$.

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Lemma: Search LWE is easy if and only if decision LWE is easy.

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Secret distributions χ_s :

- ightharpoonup originally uniform in \mathbb{Z}_q
- ▶ now some distribution of small deviation σ_s (e.g. discrete Gaussian/centered Binormial, $\{-1,0,1\}$ whp)
- Fact: small secret is as hard as uniform secret
- small secret allows more efficient schemes

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Noise distributions χ_e :

- lacktriangle usually discrete Gaussian/centered Binormial of deviation σ_e
- ▶ most schemes (Kyber/Saber/...): σ_e small (≈ 1)

LWE: security and attacks

LWE is fundamental to lattice-based cryptography:

- several lattice-based NIST PQC candidates rely on LWE
- extensive literature
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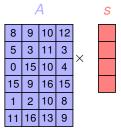
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Two types of attacks:

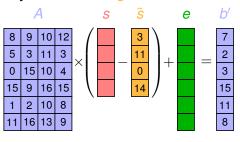
- Primal attacks:
 - more efficient in most cases
- Dual attacks:
 - originally less efficient, now catching up

Contribution: improvement on dual attacks using ideas from codes

Very naive attack:



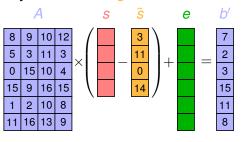
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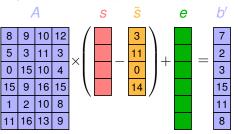
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Bad guess (
$$\mathbf{s} \neq \tilde{\mathbf{s}}$$
):

$$b' = e + A(s - \tilde{s})$$

follows a uniform¹ distribution (*A* uniform in $\mathbb{Z}_q^{m \times n}$)

¹Technically only true for fixed s, random A and s

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The entries are independent: given a sample from χ^m we obtain m independent samples from χ .

 \rightarrow if *m* large enough, we know how to distinguish.

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$$\mathbb{E}_{x \leftarrow \chi}[e^{2i\pi x/q}], \mathsf{Var}_{x \leftarrow \chi}[e^{2i\pi x/q}] \approx \begin{cases} 0, \mathbf{0} & \text{if } \chi = U(\mathbb{Z}_q) \\ e^{-2\left(\frac{\pi\sigma}{q}\right)^2}, e^{-8\left(\frac{\pi\sigma}{q}\right)^2} & \text{if } \chi = D_{\sigma,q} \end{cases}$$

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Attack:

- ▶ sample $N = \Omega(1/\varepsilon^2)$ values $x_1, ..., x_N$ from χ
- compute

$$S = \frac{1}{N} \sum_{j=1}^{N} e^{2i\pi x_j/q}$$

► Check if $S > e^{-2\left(\frac{\pi\sigma}{q}\right)^2}$

The quantity $\varepsilon = e^{-2\left(\frac{\pi\sigma}{q}\right)^2}$ is called the advantage.

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Can do better by guessing s in decreasing order of probability¹:

$$G(\chi_s^n) \cdot e^{4\left(\frac{\pi\sigma_e}{q}\right)^2} \leqslant (1.22\sqrt{2\pi}\sigma_s)^n \cdot e^{4\left(\frac{\pi\sigma_e}{q}\right)^2} = \text{too much}$$

where σ_s deviation of s, $G(\cdot) =$ guessing complexity

¹The complexity is now the expected running time

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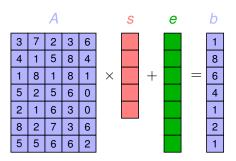
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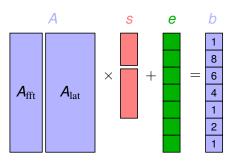
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Dual attacks: provide an efficient way to only guess a part of the secret

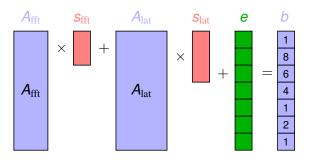
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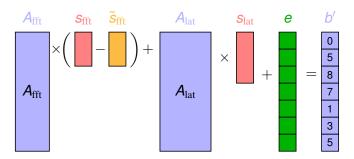
Split secret: $n = k_{\text{fft}} + k_{\text{lat}}$



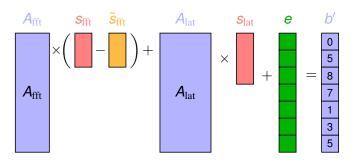
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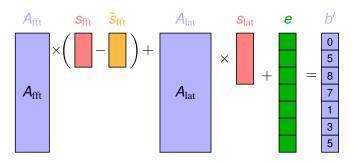


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$$b' = A_{lat} s_{lat} + e$$

so (A_{lat}, b') follows an LWE distribution

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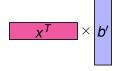
$$b' = A_{\text{fft}}(s_{\text{fft}} - \tilde{s}_{\text{fft}}) + \cdots$$

so (A_{lat}, b') follows a uniform distribution $(A_{fft}$ uniform)

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follows an approximate Gaussian distribution

Uniform/LWE distinguisher

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When
$$\chi = \text{Uniform}$$
:

$$x^Tb'$$

follows a uniform distribution (b' uniform, independent from A_{lat})

Naive dual attack:

- ▶ split secret $n = k_{\text{fft}} + k_{\text{lat}}$
- \triangleright compute dual vectors x and dot products x^Tb
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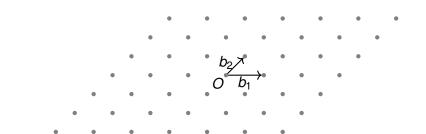
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 \rightarrow we want x to be short \rightarrow lattice reduction

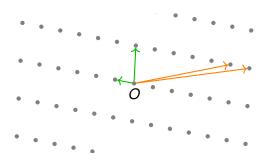
What is a (Euclidean) lattice?

Definition

$$\mathcal{L}(\boldsymbol{b}_1,\ldots,\boldsymbol{b}_n) = \left\{\sum_{i=1}^n x_i \boldsymbol{b}_i : x_i \in \mathbb{Z}\right\}$$
 where $\boldsymbol{b}_1,\ldots,\boldsymbol{b}_n$ is a basis of \mathbb{R}^n .

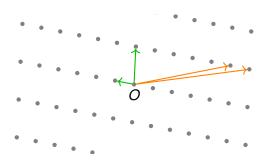


Lattice-based cryptography: fundamental idea



- good basis: private information, makes problem easy
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Basis reduction: transform a bad basis into a good one Main tool: BKZ algorithm and its variants

Requires to solve the (approx-)SVP problem in smaller dimensions.

An important optimization

- $b' = b A_{\text{fit}} \tilde{s}_{\text{fit}}$ comes from search to distinguish reduction
- \triangleright x_1, \dots, x_N is a list of dual vectors
- $\sim \alpha_i = x_i^T b'$ comes from uniform/LWE to uniform/Gaussian red.

To distinguish between unidimensional uniform/Gaussian, we compute

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Observation:
$$F(\tilde{s}_{fft}) = \hat{T}(\tilde{s}_{fft})$$
 Fourier transform of $T(x_j^T A_{fft}) = e^{\frac{2i\pi}{q}x_j^T b}$

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Algorithm:

- T ← k-dimensional array set to zero
- ► $T[x_j^T A_{\text{fft}}] \leftarrow e^{2i\pi x_j^T b/q}$ for all j
- ightharpoonup compute FFT \widehat{T} of T
- ightharpoonup check all $\widehat{T}[\tilde{s}_{\mathrm{fff}}]$ against threshold

Complexity: array filling time + FFT time + search time =
$$O(N + q^{k_{\rm fit}})$$

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$$L = \left\{ \mathbf{x} \in \mathbb{Z}^m : \mathbf{x}^T A_{\mathrm{lat}} = 0 \bmod q \right\}$$

Complexity estimate:

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- ▶ BKZ trade-off: short x ~> more expensive algorithm
- **best dual attack parameters** ($k_{\text{fit}},...$) found by optimization

Advanced dual attacks

Modulo switching: only guess part of secret modulo p ($p \ll q$)

- reduce guessing complexity
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BKZ with sieving

- obtain many dual vectors at once
- reducing the number of BKZ reductions

Hybrid dual attack

Combine enumeration with dual attack:

- lacktriangle enumerate $s_{ ext{enum}} \in \mathbb{Z}_q^{k_{ ext{enum}}}$
 - ightharpoonup enumerate all $s_{ ext{fft}} \in \mathbb{Z}_q^{k_{ ext{fft}}}$
 - compute a DFT-like sum
 - check if it is above the threshold

sampled from $\chi_{\mathcal{S}}^{k_{\mathrm{enum}}}$ uniform in $\mathbb{Z}_q^{k_{\mathrm{fit}}}$

Hybrid dual attack

Combine enumeration with dual attack:

- lacktriangle enumerate $s_{ ext{enum}} \in \mathbb{Z}_q^{k_{ ext{enum}}}$
 - lacktriangle enumerate all $oldsymbol{s}_{ ext{fft}} \in \mathbb{Z}_q^{k_{ ext{fft}}}$
 - compute a DFT-like sum
 - check if it is above the threshold

sampled from $\chi_s^{k_{\rm enum}}$ uniform in $\mathbb{Z}_a^{k_{\rm fit}}$

- ightharpoonup guessing complexity: try s_{enum} in decreasing order of probability
- FFT: compute all DFT-sums in one go with a FFT
- dual vectors: compute them once, reuse for all senum

$$G(\chi_s^{k_{ ext{enum}}}) \cdot \left(q^{k_{ ext{fit}}} + e^{4\left(rac{\pi \|x\|\sigma_e}{q}
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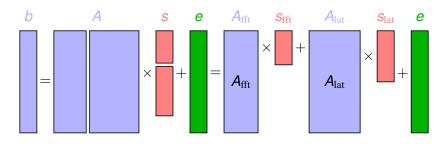
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$$G(\chi_s^{k_{\text{enum}}}) \cdot \left(q^{k_{\text{fift}}} + e^{4\left(\frac{\pi \|x\|\sigma_e}{q}\right)^2}\right) + T_{\text{BKZ}}$$

Gain: reduce $k_{lat} \sim$ decrease BKZ cost

Recall: split secret + dual vector

Combine: split secret



Recall: split secret + dual vector

Combine: split secret

With: dual vector x such that $x^T A_{lat} = 0$

▶ split secret, find (x, y) such that $x^T A_{lat} = 0$ and $y^T = x^T A_{fft}$

- ▶ split secret, find (x, y) such that $x^T A_{lat} = 0$ and $y^T = x^T A_{fft}$
- guess secret s and subtract

$$\boxed{ \mathbf{x}^T \times \mathbf{b} - \boxed{\mathbf{y}^T \times \mathbf{\tilde{s}_{fit}}} = \boxed{\mathbf{y}^T \times \left(\boxed{\mathbf{s}_{fit}} - \boxed{\mathbf{\tilde{s}}_{fit}} \right) + \boxed{\mathbf{x}^T \times \mathbf{e}} }$$

- ▶ split secret, find (x, y) such that $x^T A_{lat} = 0$ and $y^T = x^T A_{fft}$
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Good guess (
$$s_{fft} = \tilde{s_{fft}}$$
):

follows a discrete Gaussian of small deviation (depends on ||x||)

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Bad guess
$$(s_{\text{fft}} \neq \tilde{s_{\text{fft}}})$$
:
 $y^T(s_{\text{fft}} - \tilde{s_{\text{fft}}}) + x^T e$

follows a uniform distribution $(y \approx \text{uniform in } \mathbb{Z}_{q}^{k_{\text{fift}}})$

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 $y^T(s_{\text{fft}} - \tilde{s_{\text{fft}}}) + x^T e$

follows a uniform distribution (${\it y} pprox {\it uniform in } \mathbb{Z}_q^{\it k_{\rm fit}}$)

Problem: cost of distinguishing grows as $q^{k_{\rm fit}}$ \sim can we change to a modulo $p \ll q$ to reduce the cost?

▶ split secret, find (x, y) s.t. $x^T A_{lat} = 0$ and $y^T = x^T A_{fft}$, guess \tilde{s}

$$\boxed{x^T \cdot b} - \boxed{y^T \cdot \tilde{s}_{fft}} = \boxed{y^T \cdot \left(\boxed{s_{fft}} - \tilde{s}_{fft} \right)} + \boxed{x^T \cdot e} \mod q$$

- ▶ split secret, find (x, y) s.t. $x^T A_{lat} = 0$ and $y^T = x^T A_{fft}$, guess \tilde{s}
- ► change modulo to p

$$\frac{p}{q} \underbrace{x^T} \cdot b - \frac{p}{q} \underbrace{y^T} \cdot \underbrace{\tilde{\mathbf{s}}_{\text{fit}}} = \frac{p}{q} \underbrace{y^T} \cdot \left(\underbrace{\mathbf{s}_{\text{fit}}} - \underbrace{\tilde{\mathbf{s}}_{\text{fit}}} \right) + \frac{p}{q} \underbrace{x^T} \cdot e \mod p$$

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Good guess (
$$s_{\text{fft}} = \tilde{s_{\text{fft}}}$$
): $\frac{p}{g} x^T e$

follows a discrete Gaussian of small deviation (depends on ||x||)

Bad guess (
$$s_{\text{fft}} \neq \tilde{s_{\text{fft}}}$$
):
$$\frac{p}{q} y^T (s_{\text{fft}} - \tilde{s_{\text{fft}}}) + \frac{p}{q} x^T e$$

follows a uniform distribution $(y \approx \text{uniform in } \mathbb{Z}_q^{k_{\text{fit}}})$

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Good guess (
$$\frac{s_{fft}}{e} = \frac{\tilde{s_{fft}}}{\tilde{s_{fft}}}$$
):

follows a discrete Gaussian of small deviation (depends on ||x||)

Bad guess (
$$s_{\text{fft}} \neq \tilde{s}_{\text{fft}}$$
):
$$\frac{p}{q} y^{T} (s_{\text{fft}} - \tilde{s}_{\text{fft}}) + \frac{p}{q} x^{T} e$$
follows a uniform distribution

 $(y \approx \text{uniform in } \mathbb{Z}_q^{k_{\text{fit}}})$

Problem: $\frac{\rho}{q}y^T$ is not integral \sim FFT distinguisher not applicable

Notation:
$$[x] = \text{integer part}, \{x\} = \text{fractional part}, x = [x] + \{x\}$$

$$\frac{p}{q} X^{T} \cdot b - \frac{p}{q} Y^{T} \cdot \tilde{\mathbf{s}}_{fff} = \frac{p}{q} Y^{T} \cdot \left(\mathbf{s}_{fff} - \tilde{\mathbf{s}}_{fff} \right) + \varepsilon \mod p$$

where
$$\varepsilon = \frac{p}{q} X^T \cdot e$$

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where
$$\varepsilon = \left\{\frac{\rho}{q} \mid y^T\right\} \cdot s_{\text{fit}} + \frac{\rho}{q} \mid x^T \cdot e$$

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$$[x]$$
 = integer part, $\{x\}$ = fractional part, $x = [x] + \{x\}$

$$\frac{p}{q} \mathbf{x}^{T} \cdot \mathbf{b} - \left[\frac{p}{q} \mathbf{y}^{T}\right] \cdot \tilde{\mathbf{s}}_{\mathsf{m}} = \left[\frac{p}{q} \mathbf{y}^{T}\right] \cdot \left(\mathbf{s}_{\mathsf{m}} - \tilde{\mathbf{s}}_{\mathsf{m}}\right) + \mathbf{\varepsilon} \mod p$$

where
$$\varepsilon = \left\{\frac{p}{q} \ y^T\right\} \cdot s_{\text{fit}} + \frac{p}{q} \ x^T \cdot e$$

Good guess (
$$\mathbf{s}_{\text{fft}} = \tilde{\mathbf{s}}_{\text{fft}}$$
):

$$\varepsilon = \{\frac{p}{q}\mathbf{x}^T\}\mathbf{s}_{\text{fft}} + \frac{p}{q}\mathbf{x}^T\mathbf{e}$$

follows an almost discrete Gaussian of small deviation (now depends on $\|\mathbf{x}\|$ and $\|\mathbf{s}_{\text{fit}}\|$)

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Bad guess
$$(s_{\text{fft}} \neq \tilde{s_{\text{fft}}})$$
:
$$[\frac{p}{q}y^{T}](s_{\text{fft}} - \tilde{s}_{\text{fft}})$$

not obviously uniform, but saved by the hybrid search hinted at in this presentation

Modulo switching (cont)

Notation: [x] = integer part, $\{x\}$ = fractional part, $x = [x] + \{x\}$

$$\frac{p}{q} \underbrace{x^T} \cdot \underbrace{b} - \left[\frac{p}{q} \underbrace{y^T}\right] \cdot \underbrace{\tilde{s}_{\text{fit}}} = \left[\frac{p}{q} \underbrace{y^T}\right] \cdot \left(\underbrace{s_{\text{fit}}} - \underbrace{\tilde{s}_{\text{fit}}}\right) + \underbrace{\varepsilon} \mod p$$

$$\text{where } \underbrace{\varepsilon} = \left\{\frac{p}{q} \underbrace{y^T}\right\} \cdot \underbrace{s_{\text{fit}}} + \frac{p}{q} \underbrace{x^T} \cdot e$$

Good guess (
$$\underline{s}_{\text{fft}} = \underline{s}_{\text{fft}}^{\circ}$$
):

$$\varepsilon = \{\frac{p}{q}x^{\mathsf{T}}\}\underline{s}_{\text{fft}} + \frac{p}{q}x^{\mathsf{T}}e$$

follows an almost discrete Gaussian of small deviation (now depends on $\|x\|$ and $\|s_{fit}\|$)

Bad guess
$$(s_{\text{fft}} \neq \tilde{s_{\text{fft}}})$$
: $[\frac{p}{q}y^T](s_{\text{fft}} - \tilde{s}_{\text{fft}})$

not obviously uniform, but saved by the hybrid search hinted at in this presentation

Conclusion: it works but increases the number of samples:

from
$$4\left(\frac{\pi \|\mathbf{x}\|\sigma_e}{q}\right)^2$$
 to $4\left(\frac{\pi \|\mathbf{x}\|\sigma_e}{q}\right)^2 + \frac{1}{3}\left(\frac{\pi \|\mathbf{s}_{\mathrm{fit}}\|q}{p}\right)^2$

Going further: using ideas from coding theory

Everyting until this point is in the LWE report by the MATZOV group.

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Modulo switching: approximate a vector $x \in \mathbb{Z}_q^n$ by

$$X = \frac{q}{p} \cdot \left[\frac{p}{q}X\right] + \frac{q}{p}\left\{\frac{p}{q}X\right\} = \frac{q}{p} \cdot u + e$$

- $u \in \mathbb{Z}_p^n$: smaller domain (field is smaller)
- ▶ $||e|| \leq \frac{q}{p}$: "small error"

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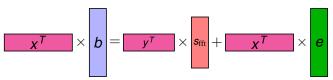
Our observation: this looks like a special case of lattice codes

$$x = Gu + t$$

- ► $G \in \mathbb{Z}_q^{n \times m}$: defines a code
- ▶ $u \in \mathbb{Z}_q^m$: smaller domain (dimension is smaller)
- ightharpoonup ||t|| is small (depends on G)

Applying lattice codes

Recall: find (x, y) such that $x^T A_{lat} = 0$ and $y^T = x^T A_{fit}$



Applying lattice codes

Recall: find (x, y) such that $x^T A_{lat} = 0$ and $y^T = x^T A_{fft}$

Choose a code $G \in \mathbb{Z}_q^{k_{\mathrm{fift}} \times k_{\mathrm{cod}}}$, decode y as

$$y = G \times u + t$$

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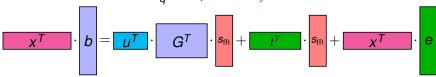
Choose a code $G \in \mathbb{Z}_q^{k_{\mathrm{fit}} \times k_{\mathrm{cod}}}$, decode y as

$$y = G \times u + t$$

New fundamental equation:

$$\begin{array}{c|c}
 & X^T \\
\hline
 & b
\end{array} =
\begin{array}{c|c}
 & u^T \\
\hline
 & G^T
\end{array} \cdot
\begin{array}{c|c}
 & s_{\text{fit}} \\
\hline
 & t^T
\end{array} \cdot
\begin{array}{c|c}
 & s_{\text{fit}} \\
\hline
 & t^T
\end{array} \cdot
\begin{array}{c|c}
 & e
\end{array}$$

- ▶ find (x, y) such that $x^T A_{lat} = 0$ and $y^T = x^T A_{fft}$ ▶ choose a code $G \in \mathbb{Z}_q^{k_{fft} \times k_{cod}}$, decode y = Gu + t



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where

$$egin{aligned} egin{aligned} egin{aligned\\ egin{aligned} egi$$

- ▶ find (x, y) such that $x^T A_{\text{lat}} = 0$ and $y^T = x^T A_{\text{fft}}$ ▶ choose a code $G \in \mathbb{Z}_q^{k_{\text{fft}} \times k_{\text{cod}}}$, decode y = Gu + t

where

$$s_{
m cod} = G^T \cdot s_{
m fit}$$
 $\varepsilon' = t^T \cdot s_{
m fit} + x^T \cdot e$

Observations:

- we directly guess s_{cod} instead of s_{fff}
- $ightharpoonup S_{\text{cod}} = G^{T} S_{\text{fit}} \in \mathbb{Z}_{q}^{k_{\text{cod}}}$ has smaller dimension $k_{\text{cod}} \ll k_{\text{fft}}$

- ▶ find (x, y) such that $x^T A_{lat} = 0$ and $y^T = x^T A_{fft}$ ▶ choose a code $G \in \mathbb{Z}_q^{k_{fft} \times k_{cod}}$, decode y = Gu + t

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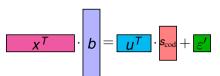
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- $\epsilon = t^T s_m + x^T e$ follows a discrete Gaussian whose **deviation** depends on ||x||, $||s_{fft}||$ and ||t||
- ightharpoonup ||t|| is **small** for a good code G

Lattice codes vs modulo switching

Lattice codes

Modulo switching



Lattice codes vs modulo switching

Lattice codes

$$b = u^T \cdot s_{cod} + \varepsilon'$$

- ightharpoonup FFT cost: $q^{k_{\rm cod}}$
- error ε' : Gaussian of stddev

$$au_{ ext{MS}}^2 = \|\mathbf{x}\|^2 \cdot \sigma_{ ext{e}}^2 + \|\mathbf{s}_{ ext{fit}}\|^2 \cdot \frac{q^{2-2} \frac{K_{ ext{cod}}}{K_{ ext{fit}}}}{2\pi e}$$

for an asymptotically optimal code

Modulo switching

- ► FFT cost: p^kfft
- error ε : Gaussian of stddev

$$\tau_{\mathrm{LC}}^2 = \|\mathbf{x}\|^2 \cdot \sigma_{\mathrm{e}}^2 + \|\mathbf{s}_{\mathrm{fit}}\|^2 \cdot \frac{q^2}{12\rho^2}$$

Lattice codes vs modulo switching

Lattice codes

$$\begin{array}{c|c}
x^T \\
\hline
b
\end{array} =
\begin{array}{c|c}
u^T \\
\hline
s_{cod}
\end{array} +
\begin{array}{c|c}
\varepsilon'
\end{array} \qquad
\begin{array}{c|c}
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Modulo switching

$$X^T$$
 $b = \begin{bmatrix} \frac{p}{q} & y^T \end{bmatrix}$

- ► FFT cost: p^kfft
- error ε: Gaussian of stddev

$$\tau_{\mathrm{LC}}^2 = \|\mathbf{x}\|^2 \cdot \sigma_{\mathrm{e}}^2 + \|\mathbf{s}_{\mathrm{fft}}\|^2 \cdot \frac{q^2}{12p^2}$$

Comparison for same FFT cost: $q^{k_{\text{cod}}} = p^{k_{\text{fft}}}$

$$\frac{q^{2-2}\frac{k_{\rm cod}}{k_{\rm fit}}}{2\pi e} = \frac{q}{2\pi e p} \approx \frac{q}{17p} \ll \frac{q}{12p}$$

→ lattice codes are always better than modulo switching!

Other important details

- FFT is more efficient for powers of two
- $ightharpoonup q^{k_{\text{cod}}}$ has coarse granularity for big q

 \rightarrow use modulo switching to change q to $p = 2^m$ then use lattice codes: best of both, allow more "continuous" parameter choice

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- we only need to decode to a close codeword, not the closest
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- \sim use modulo switching to change q to $p = 2^m$ then use lattice codes: best of both, allow more "continuous" parameter choice
 - optimal codes are expensive but we need a fast decoder
 - we only need to decode to a close codeword, not the closest
- → we suggest to use polar codes which are asymptotically optimal
 - \blacktriangleright many parameters to choose (p, $k_{\rm fft}$, $k_{\rm cod}$, BKZ block size, ...)
 - no obvious way to choose them
- → search for optimal parameters with an optimisation program

Overall attack so far:

- lacktriangleright enumerate $m{s}_{ ext{enum}} \in \mathbb{Z}_q^{k_{ ext{enum}}}$ sampled from $\chi_s^{k_{ ext{enum}}}$
 - perform dual attack with codes and modulo switching and check if s_{enum} was correct

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- ▶ G = expected number of guesses to find s_{enum}
- ➤ T = complexity of attack

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Prange bet:

- ightharpoonup some values of s_{enum} are much more likely than others (e.g. 0)
- only enumerate a few most likely values
- ▶ if it fails, retry with a permutation of the secret

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- only enumerate a few most likely values
- if it fails, retry with a permutation of the secret
- ▶ if we do not permute the lattice part (s_{lat}) , we can even reuse the BKZ computation just like in the "normal attack"

Prange bet: implementation

New attack: fix betting set Bet

- for each permutation τ that leaves the "lat part" fixed
 - ▶ enumerate $s_{\text{enum}} \in \text{Bet}$
 - perform¹ dual attack on τ -permuted instance with codes and modulo switching and check if $s_{\rm enum}$ was correct

¹Not shown here: dual vectors reused accross iterations since lat part untouched

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Which bet? Bet = $\{0\}$ optimal in our case

¹Not shown here: dual vectors reused accross iterations since lat part untouched

Results

- CC: classical circuit model (most detailed cost)
- CN: intermediate model
- ▶ C0: "Core-SVP" cost model

	MATZOV			Codes w/o Prange			Codes w/ Prange		
Scheme	CC	CN	C0	CC	CN	C0	CC	CN	C0
Kyber 512	138.5	133.7	114.8	137.8	133.0	114.0	137.5	132.6	113.9
Kyber 768	195.7	190.4	173.1	192.5	187.2	170.2	191.9	186.7	169.8
Kyber 1024	261.4	255.4	240.7	256.2	250.5	235.7	255.5	249.5	235.5
LightSaber	137.1	132.3	113.1	136.8	131.5	112.3	136.7	131.8	112.2
Saber	201.1	195.1	178.3	199.7	194.9	177.0	199.0	193.8	176.9
FireSaber	263.6	257.7	242.8	259.9	254.4	239.4	259.3	253.9	239.0

- 1 to 5 bit gain without Prange over MATZOV
- further 1 bit gain with Prange bet