## Mitaka

## A Simpler, Parallelizable, Maskable Variant of Falcon

Thomas Espitau, Akira Takahashi, Mehdi Tibouchi, Alexandre Wallet

NIST 3rd Workshop

## Lattice signatures

## Two finalists are based on structured lattices:

## FALCON

"Hash-and-sign" in lattices [GPV'08] + NTRU trapdoors [DLP'14]
$\checkmark$ compact, fast
restricted parameter set, quite hard to implement and protect against side-channels

## CRYSTALS-DILITHIUM

## Fiat-Shamir "with abort" [Lyu12]

 + module lattices$\times$ larger bandwdith
$\checkmark$ large range of parameter sets, easier to implement and protect against side-channels

## Two finalists are based on structured lattices:

## FALCON

"Hash-and-sign" in lattices [GPV'08] NTRU trapdoors [DLP'14]

## CRYSTALS-DILITHIUM

Fiat-Shamir "with abort" [Lyu12] module lattices

Introducing: [ Mitaka ]<br>trying to reach best of both worlds

$\checkmark$ compact, fast
$\checkmark$ large range of parameters sets
$\checkmark$ easier to implement and protect against side-channels


NTRU lattices: free rank 2 modules over cyclotomic rings

Quasi-linear thanks to the ring but

- Few parameter sets
- Complicated implementation
- Complicated masking


## Towards Mitaka



Security | Dimension 512


## Towards Mitaka



Security | Dimension 512


## Towards Mitaka



Security | Dimension 512






Hash-and-sign over lattices

## The GPV Framework [GPV’08]

Simplified Sign $_{\text {sk }, \sigma}(\mathrm{msg})$ :

1. $\mathbf{m}=\mathcal{H}(\mathrm{msg})$
2. $\mathbf{v} \leftarrow$ GaussianSampler $(\mathbf{s k}, \mathbf{m}, \sigma)$
3. Signature: $\mathbf{s}=\mathbf{m}-\mathbf{v}$.

Simplified $\operatorname{Verif}_{\mathcal{L}=\mathrm{pk}}(\mathrm{msg}, \mathbf{s})$ :

1. If $\|\mathbf{s}\|$ too big, reject.
2. If $\mathbf{m}-\mathbf{s} \notin \mathcal{L}$, reject.
3. Accept.
"Good basis" sk of $\mathcal{L}$, bad basis pk


## The GPV Framework [GPV'08]

Simplified Sign $_{\text {sk, } \sigma}(\mathrm{msg})$ :

1. $\mathbf{m}=\mathcal{H}(\mathrm{msg})$
2. $\mathbf{v} \leftarrow$ GaussianSampler $(\mathbf{s k}, \mathbf{m}, \sigma)$
3. Signature: $\mathbf{s}=\mathbf{m}-\mathbf{v}$.

Simplified $\operatorname{Verif}_{\mathcal{L}=\mathrm{pk}}(\mathrm{msg}, \mathbf{s})$ :

1. If $\|\mathbf{s}\|$ too big, reject.
2. If $\mathbf{m}-\mathbf{s} \notin \mathcal{L}$, reject.
3. Accept.

## Requirements

Hard Forgery $\Rightarrow \sigma$ small $\Rightarrow$ sk has short vectors

Hard to compute sk just from pk

Easy to generate pk just from sk

> sk is called "a trapdoor"

Generating trapdoors is an interesting challenge [HPSS'00, AP'09, MP'12, DLP'14, CGM'19, GL'20, CPSWX'20...]

## Sampling over (structured) lattices

## Lattice Gaussian samplers $=$ decoding + randomization

CVP solvers
Babai's Round-off:

$$
\mathbf{u}=\mathbf{B}\left\lceil\mathbf{B}^{-1} \mathbf{t}\right\rfloor
$$

Babai's Nearest Plane:
"adaptive" rounding on each $\mathbb{R} \tilde{\mathbf{b}}_{i}$

## Gaussian samplers

Randomize the whole integer rounding

Randomize each integer rounding

There are also "in-betweens", e.g. Ducas-Prest hybrid sampler (We'll cover that soon)

## Randomized Babai Rounding : Peikert's approach

Without randomization (not a Gaussian sampler)

$$
\text { Outputs } \mathbf{z}=\mathbf{B}\left\lceil\mathbf{B}^{-1} \mathbf{t}\right\rfloor
$$

## Randomized Babai Rounding : Peikert's approach

Without randomization (not a Gaussian sampler)

Randomize rounding w/ discrete Gaussians
(leaks the lattice basis)


$$
\mathbf{y} \leftarrow\left\lceil\mathrm{B}^{-1} \mathbf{t}\right\rfloor_{\mathrm{r}}
$$

$$
\text { means } \mathbf{y} \hookleftarrow \mathrm{D}_{\mathbb{Z}^{n}-\mathrm{B}-\mathrm{t}_{\mathbf{t}, \mathrm{r}}}
$$

$$
\text { Outputs } \mathbf{z}=\mathbf{B y}
$$

## Randomized Babai Rounding : Peikert's approach

Without randomization (not a Gaussian sampler)

Randomize rounding w/ discrete Gaussians (leaks the lattice basis)
[ $\left.\mathrm{P}^{\prime} 10\right]$ add Gaussian perturbation to "smooth out" the lattice
(works!)


$$
\begin{aligned}
& \text { Peikert }(\mathrm{B}, \mathbf{t}, \sigma, \mathrm{r}) \\
& \mathbf{x} \leftarrow \sigma \cdot \mathcal{N}(0,1) \\
& \mathbf{y} \leftarrow\left\lceil\mathrm{B}^{-1} \mathbf{t}-\mathbf{x}\right\rfloor_{\mathrm{r}}
\end{aligned}
$$

Outputs $z=B y$.

Without randomization
(not a Gaussian sampler)


Randomize rounding of each $t_{i} \in \mathbb{R}$
(leaks Gram-Schmidt basis)

On each $\mathbb{R} \widetilde{\mathbf{b}}_{i}$, rescale adaptively
$s_{i}:=\frac{s}{\left\|\widetilde{\mathbf{b}}_{i}\right\|}$

$$
\begin{aligned}
& \text { Klein }\left(B, \widetilde{B}, \mathbf{t}, s_{i}, r\right) \\
& \begin{array}{l}
\mathbf{v}=0, \mathbf{c}=\mathbf{t} \\
\text { for } i=\operatorname{dim}(B) \text { to } 1: \\
t_{i}=\left\lceil\frac{\left\langle\mathbf{c}, \widetilde{b}_{i}\right\rangle}{\left\|\mathfrak{b}_{i}\right\|^{2}}\right]_{s_{i}} \\
\mathbf{v}=\mathbf{v}+\mathrm{t}_{i} b_{i} \\
\mathbf{c}=\mathbf{c}-\mathrm{t}_{i} b_{i}
\end{array}
\end{aligned}
$$

Outputs v

## Hybrid sampling

Hybrid $=$ Klein decoding + Peikert randomization in $\operatorname{dim} \geqslant 1$.

Example: $\mathcal{R}$ power-of-2 cyclotomic

Well-suited for module lattices: rank $2 \mathcal{R}$-module $=$ rank 2d lattice.

Klein

decoding in $2 d$
randomization in $\mathbb{Z}$

Hybrid

decoding in rank 2 randomization in $\mathcal{R}$
$\operatorname{Hybrid}\left(B, \widetilde{B}_{\mathcal{R}}, \mathbf{t}, s_{1}, s_{2}\right)$

$$
\begin{aligned}
& \mathbf{v}=0, \mathbf{c}=\mathbf{t} \\
& \text { for } \mathfrak{i}=2 \text { to } 1: \\
& t_{i}=\text { Peikert }\left(\mathbf{l}, \frac{\left\langle\mathbf{c}, \tilde{b}_{i}\right\rangle_{\mathcal{R}}}{\left\langle\mathbf{b}_{i}, b_{i}\right\rangle_{\mathcal{R}}}, s_{i}, r\right) \\
& \mathbf{v}=\mathbf{v}+t_{i} b_{i} \\
& \mathbf{c}=\mathbf{c}-t_{i} b_{i}
\end{aligned}
$$

Outputs v
Operations in $\mathcal{R}$ instead of $\mathbb{Z} \Rightarrow$ need "good FFT domain"

|  | Quality | Pros | Cons |
| :--- | :---: | :---: | :---: |
| Peikert | $s_{1}(\mathbf{B})$ <br> (largest sing. value) | fast <br> simple | worst quality <br> (lower security) |
| Klein | max $_{i}\left\\|\widetilde{\mathbf{b}_{i}}\right\\|$ <br> $($ Gram-Schmidt) | best quality <br> (higher security) | slower <br> more involved |
|  | $s_{1}(\widetilde{\mathbf{B}})$ | Good tradeoffs when $\mathcal{R}$ <br> has a good basis |  |

When $\mathcal{R}=\mathbb{Z}[x] /\left(x^{d}+1\right), d=2^{n}$, and for NTRU q-ary lattices, qualities are $\alpha \sqrt{q}$

Asymptotic quality

| Sampler | $\alpha \sqrt{q}$ | Best achievable $\alpha$ |
| :--- | :---: | :--- |
| Peikert | $s_{1}(\mathbf{B})$ | $O\left(d^{1 / 4} \sqrt{\log \mathrm{~d}}\right)$ |
| Hybrid | $s_{1}(\widetilde{\mathbf{B}})$ | $\mathrm{O}\left(\mathrm{d}^{1 / 8} \log ^{1 / 4} \mathrm{~d}\right)$ |
| Klein | $\max _{i}\left\\|\widetilde{\mathbf{b}_{i}}\right\\|$ | $\mathrm{O}(1)$ |

Concrete bitsecurity as a function of $\alpha, d=512$


## Improving the Keygen

NTRU lattice $\mathcal{L}_{\text {NTRU }}(a)$

$$
\begin{aligned}
& \mathrm{f}, \mathrm{~g} \in \mathcal{R} \rightarrow \mathrm{a}:=\mathrm{f}^{-1} \mathrm{~g}[\mathrm{q}] \\
& {\left[\begin{array}{ll}
u & v
\end{array}\right]\left[\begin{array}{c}
\mathrm{a} \\
-1
\end{array}\right]=0[\mathrm{q}]}
\end{aligned}
$$

## Trapdoor

Short basis B of $\mathcal{L}_{\text {NTRU }}(a)$ with good quality wrt. a sampler.

## NTRU lattice $\mathcal{L}_{\mathrm{NTRU}}(\mathrm{a})$

$$
\mathrm{f}, \mathrm{~g} \in \mathcal{R} \rightarrow \mathrm{a}:=\mathrm{f}^{-1} \mathrm{~g}[\mathrm{q}]
$$

$$
\left[\begin{array}{ll}
u & v
\end{array}\right]\left[\begin{array}{c}
a \\
-1
\end{array}\right]=0[q]
$$

## Trapdoor

Short basis B of $\mathcal{L}_{\text {NTRU }}(a)$ with good quality wrt. a sampler.

## Computing B

- Sample f, g Gaussians so that

$$
\|(f, g)\| \approx \sqrt{q}
$$

- Complete the basis: unimodularity problem: Euclid+geometry


## Achieve good quality

Sample ( $f, g$ )'s until:

- Falcon: $\max \left(\left\|\widetilde{\mathbf{b}}_{1}\right\|,\left\|\widetilde{\mathbf{b}}_{\mathrm{d}+1}\right\|\right) \approx 1.17 \sqrt{\mathrm{q}}$
- Hybrid: $s_{1}(\widetilde{\mathbf{B}})$ as close as possible to $\sqrt{q}$

Both metrics can be computed just with $\mathrm{f}, \mathrm{g}$

## (naive) KeyGen:

1) Do

$$
\begin{aligned}
& \mathrm{f}, \mathrm{~g} \leftarrow \mathrm{D}_{\mathbb{Z}^{\mathrm{d}}, \sqrt{\frac{\mathrm{q}}{2 \mathrm{~d}}}} \\
& \text { Until finv. mod } \mathrm{q} \text { And }\|\mathrm{f}, \mathrm{~g}\| \leqslant 1.17 \sqrt{\mathrm{q}} ;
\end{aligned}
$$

2) (F) quality check: $\left\|\widetilde{\mathbf{b}}_{\mathrm{d}+1}\right\| \leqslant 1.17 \sqrt{\mathrm{q}}$ ? else restart;
3) $\mathbf{b}_{\mathrm{d}+1} \leftarrow \operatorname{NTRUSolve(f,g,q)\text {;}}$

Compute all needed data;
Output (pk, sk).

## (naive) KeyGen:

1) Do

$$
\mathrm{f}, \mathrm{~g} \leftarrow \mathrm{D}_{\mathbb{Z}^{\mathrm{d}}, \sqrt{\frac{q}{2 d}}}
$$

Until finv. mod q And $\|\mathrm{f}, \mathrm{g}\| \leqslant 1.17 \sqrt{\mathrm{q}}$;
2) (F) quality check: $\left\|\widetilde{\mathbf{b}}_{\mathrm{d}+1}\right\| \leqslant 1.17 \sqrt{\mathrm{q}}$ ?
else restart;
4) $\mathbf{b}_{\mathrm{d}+1} \leftarrow$ NTRUSolve(f, g, q);

Compute all needed data;
Output (pk, sk).
(naive) KeyGen:

1) Do

$$
\mathrm{f}, \mathrm{~g} \leftarrow \mathrm{D}_{\mathbb{Z}^{\mathrm{d}}, \sqrt{\frac{\mathrm{q}}{2 \mathrm{~d}}}}
$$

Until finv. mod $q$ And $\|f, g\| \leqslant 1.17 \sqrt{\mathrm{q}}$;
2) (F) quality check: $\left\|\widetilde{\mathbf{b}}_{\mathrm{d}+1}\right\| \leqslant 1.17 \sqrt{\mathrm{q}}$ ? else restart;

2-bis) (M) quality check: $s_{1}(\widetilde{\mathbf{B}}) \leqslant 2.05 \sqrt{q}$ ?
else restart;
4) $\mathbf{b}_{\mathrm{d}+1} \leftarrow \operatorname{NTRUSolve(f,g,q)\text {;}}$

Compute all needed data; Output (pk, sk).
(naive) KeyGen:

1) Do

$$
\mathrm{f}, \mathrm{~g} \leftarrow \mathrm{D}_{\mathbb{Z}^{\mathrm{d}}, \sqrt{\frac{q}{2 \mathrm{~d}}}}
$$

Until finv. mod q And $\|\mathrm{f}, \mathrm{g}\| \leqslant 1.17 \sqrt{\mathrm{q}}$;
2) (F) quality check: $\left\|\widetilde{\mathbf{b}}_{\mathrm{d}+1}\right\| \leqslant 1.17 \sqrt{\mathrm{q}}$ ? else restart;

2-bis) (M) quality check: $s_{1}(\widetilde{\mathbf{B}}) \leqslant 2.05 \sqrt{\text { q }}$ ? else restart;
4) $\mathbf{b}_{\mathrm{d}+1} \leftarrow \operatorname{NTRUSolve(f,g,q)\text {;}}$

Compute all needed data;
Output (pk, sk).

- This already happens often in Falcon
- Need *a lot* of tries to reach 2.05

And randomness is expensive.
(naive) KeyGen:

1) Do
$\mathrm{f}, \mathrm{g} \leftarrow \mathrm{D}_{\mathbb{Z}^{\mathrm{d}}, \sqrt{\frac{\mathrm{q}}{2 \mathrm{~d}}}}$
Until finv. mod q And $\|\mathrm{f}, \mathrm{g}\| \leqslant 1.17 \sqrt{\mathrm{q}}$;
2) (F) quality check: $\left\|\widetilde{\mathbf{b}}_{\mathrm{d}+1}\right\| \leqslant 1.17 \sqrt{\mathrm{q}}$ ? else restart;

2-bis) (M) quality check: $s_{1}(\widetilde{\mathbf{B}}) \leqslant 2.05 \sqrt{\text { q }}$ ? else restart;
4) $\mathbf{b}_{\mathrm{d}+1} \leftarrow \operatorname{NTRUSolve(f,g,q)\text {;}}$

Compute all needed data; Output (pk, sk).

Solution: amortize the rnd generation

+ Reuse randomness
+ Galois automorphisms
= "Free" blow-up of search-space
() better trapdoors in reasonable time

KeyGen (Std. dev. $\sigma$ of $f$ and $g$, number of samples $m, n$, set $\mathfrak{G}$ of Galois automorphisms)

1) [Sampling]

- Generate 2 m Gaussians vectors of std. dev. $\sigma / \sqrt{2}$ and store them in two lists $F^{\prime}, F^{\prime \prime}$.
- Generate 2 m Gaussians vectors of std. dev. $\sigma / \sqrt{2}$ and store them in two lists $\mathrm{G}^{\prime}, \mathrm{G}^{\prime \prime}$.

2) [Blowing up]

- Pair two lists $F \leftarrow F^{\prime}+F^{\prime \prime}, G \leftarrow G^{\prime}+G^{\prime \prime}$
- Let $\mathfrak{G}$ acts on $\mathrm{G}: \mathrm{G} \leftarrow \bigcup_{\sigma \in \mathfrak{G}} \sigma(\mathrm{G})$

KeyGen (Std. dev. $\sigma$ of $f$ and $g$, number of samples $m, n$, set $\mathfrak{G}$ of Galois automorphisms)

1) [Sampling]

- Generate 2 m Gaussians vectors of std. dev. $\sigma / \sqrt{2}$ and store them in two lists $F^{\prime}, F^{\prime \prime}$.
- Generate 2 m Gaussians vectors of std. dev. $\sigma / \sqrt{2}$ and store them in two lists $\mathrm{G}^{\prime}, \mathrm{G}^{\prime \prime}$.

2) [Blowing up]

- Pair two lists $F \leftarrow F^{\prime}+F^{\prime \prime}, G \leftarrow G^{\prime}+G^{\prime \prime}$
- Let $\mathfrak{G}$ acts on $\mathrm{G}: \mathrm{G} \leftarrow \bigcup_{\sigma \in \mathfrak{G}} \sigma(\mathrm{G})$

3) [Testing] For $f \in F, g \in G$ do

If quality-testing $(f, g)$
Output (pk(f,g), sk(f,g)).

KeyGen (Std. dev. $\sigma$ of $f$ and $g$, number of samples $m, n$, set $\mathfrak{G}$ of Galois automorphisms)

1) [Sampling]

- Generate 2 m Gaussians vectors of std. dev. $\sigma / \sqrt{2}$ and store them in two lists $F^{\prime}, F^{\prime \prime}$.
- Generate 2 m Gaussians vectors of std. dev. $\sigma / \sqrt{2}$ and store them in two lists $\mathrm{G}^{\prime}, \mathrm{G}^{\prime \prime}$.

2) [Blowing up]

- Pair two lists $F \leftarrow F^{\prime}+F^{\prime \prime}, G \leftarrow G^{\prime}+G^{\prime \prime}$
- Let $\mathfrak{G}$ acts on $\mathrm{G}: \mathrm{G} \leftarrow \bigcup_{\sigma \in \mathfrak{G}} \sigma(\mathrm{G})$

3) [Testing] For $f \in F, g \in G$ do

If quality-testing $(f, g)$
Output (pk(f,g), sk(f,g)).

Masking Mitaka

## t-probing attacker model [ISW03]

- Adversary obtains $t$ intermediate values of the computation
- Successfully models practical noisy side-channel leakage [DDF14]


## Provable security: t-probing security

- Any set of at most $t$ intermediate variables is independent of the secret.


## Protecting Mitaka from t-probing adversary: an overview

## Arithmetic masking of $x \in \mathcal{R}$

- $\left(x_{0}, \ldots, x_{t-1}\right) \leftarrow \operatorname{rand}(\mathcal{R})$.
- $x_{t}=x-\left(x_{0}+\cdots+x_{t-1}\right)$.
- Secret-share $x:[x]:=\left(x_{0}, \ldots, x_{t}\right)$.
- Masked $a \in \mathbb{R}$ can be approximated by $\frac{\left[a^{\prime}\right]}{C}$ with some $a^{\prime}, C \in \mathbb{Z}$


## Computation on secret-shares

- Linear operation is easy! $z_{i}=x_{i}+y_{i}$
- Non-linear operation with masked polynomial multiplication gadget PolyMult


## Protecting Mitaka from t-probing adversary: an overview

## Arithmetic masking of $x \in \mathcal{R}$

- $\left(x_{0}, \ldots, x_{t-1}\right) \leftarrow \operatorname{rand}(\mathcal{R})$.
- $x_{t}=x-\left(x_{0}+\cdots+x_{t-1}\right)$.
- Secret-share $x:[x]:=\left(x_{0}, \ldots, x_{t}\right)$.
- Masked $a \in \mathbb{R}$ can be approximated by $\frac{\left[a^{\prime}\right]}{C}$ with some $a^{\prime}, C \in \mathbb{Z}$


## Computation on secret-shares

- Linear operation is easy! $z_{i}=x_{i}+y_{i}$
- Non-linear operation with masked polynomial multiplication gadget PolyMult


## Precompute

$$
\left[\boldsymbol{\beta}_{i}\right]:=\left[\frac{\tilde{\mathbf{b}}_{i}^{*}}{\left\langle\mathbf{b}_{i}, \hat{\mathbf{b}}_{i}\right\rangle_{\mathcal{R}}}\right]
$$

MaskHybrid([B], $\left.\left[\boldsymbol{\beta}_{1}\right],\left[\boldsymbol{\beta}_{2}\right],\left[s_{1}\right],\left[s_{2}\right],[c]\right)$

$$
\begin{aligned}
& {\left[\mathbf{v}_{2}\right]:=[\mathbf{0}],\left[\mathbf{c}_{2}\right]:=[\mathbf{c}]} \\
& \text { for } \mathfrak{i}=2 \text { to } 1 \text { : } \\
& {\left[d_{i}\right]=\sum_{j=1}^{2} \operatorname{PolyMult}\left(\left[{\left.\left.c_{i, j}\right],\left[\beta_{i, j}\right]\right)}_{\left[t_{i}\right]=\operatorname{MaskPeikert}\left(\mathbf{I},\left[d_{i}\right],\left[s_{i}\right], r\right)} \begin{array}{l}
{\left[\mathbf{v}_{i-1}\right]=\left[\mathbf{v}_{i}\right]+\operatorname{PolyMult}\left(\left[\mathrm{t}_{\mathrm{i}}\right],\left[\mathbf{b}_{\mathbf{i}}\right]\right)} \\
{\left[\mathbf{c}_{\mathbf{i}-1}\right]=\left[\mathbf{c}_{\mathrm{i}}\right]-\operatorname{PolyMult}\left(\left[\mathrm{t}_{\mathrm{i}}\right],\left[\mathbf{b}_{\mathrm{i}}\right]\right)}
\end{array}\right.\right.}
\end{aligned}
$$

Outputs Unmask([vol)

## Protecting Mitaka from t-probing adversary: an overview

## Arithmetic masking of $x \in \mathcal{R}$

- $\left(x_{0}, \ldots, x_{t-1}\right) \leftarrow \operatorname{rand}(\mathcal{R})$.
- $x_{t}=x-\left(x_{0}+\cdots+x_{t-1}\right)$.
- Secret-share $x:[x]:=\left(x_{0}, \ldots, x_{t}\right)$.
- Masked $a \in \mathbb{R}$ can be approximated by $\frac{\left[a^{\prime}\right]}{C}$ with some $a^{\prime}, C \in \mathbb{Z}$


## Computation on secret-shares

- Linear operation is easy! $z_{i}=x_{i}+y_{i}$
- Non-linear operation with masked polynomial multiplication gadget PolyMult


## Precompute

$$
\left[\boldsymbol{\beta}_{i}\right]:=\left[\frac{\tilde{\mathbf{b}}_{i}^{*}}{\left\langle\mathbf{b}_{i}, \hat{\mathbf{b}}_{i}\right\rangle_{R}}\right]
$$

MaskHybrid( $\left.[B],\left[\beta_{1}\right],\left[\beta_{2}\right],\left[s_{1}\right],\left[s_{2}\right],[c]\right)$

$$
\begin{aligned}
& {\left[\mathbf{v}_{2}\right]:=[\mathbf{0}],\left[\mathbf{c}_{2}\right]:=[\mathbf{c}]} \\
& \text { for } i=2 \text { to } 1 \text { : } \\
& \quad\left[d_{i}\right]=\sum_{j=1}^{2} \operatorname{PolyMult}\left(\left[c_{i, j}\right],\left[\beta_{i, j}\right]\right) \\
& {\left[t_{i}\right]=\operatorname{MaskPeikert}\left(\mathbf{I},\left[d_{i}\right],\left[s_{i}\right], r\right)} \\
& {\left[\mathbf{v}_{i-1}\right]=\left[\mathbf{v}_{i}\right]+\operatorname{PolyMult}\left(\left[t_{i}\right],\left[\mathbf{b}_{i}\right]\right)} \\
& {\left[\mathbf{c}_{i-1}\right]=\left[\mathbf{c}_{i}\right]-\operatorname{PolyMult}\left(\left[\mathrm{t}_{\mathrm{i}}\right],\left[\mathbf{b}_{i}\right]\right)}
\end{aligned}
$$

Outputs Unmask ([ $\left.\mathbf{v}_{0}\right]$ )
Signing operations outside the sampler are not sensitive!

1) [Offline]

- Outputs continuous Gaussian samples in arithmetically masked form


## Masking Peikert sampler

1) [Offline]

- Outputs continuous Gaussian samples in arithmetically masked form

2) $[$ Online]

- Generate discrete Gaussian samples share-by-share on each random share $c_{i}$ of $[c]=\left(c_{0}, \ldots, c_{t}\right)$.


## ShareByShareGauss $_{\mathrm{r}}([\mathrm{c}])$ <br> for $\mathfrak{i}=0$ to t : <br> $z_{\mathrm{i}} \leftarrow \mathrm{D}_{\mathbb{Z}, \mathfrak{c}_{\mathrm{i}}, \mathrm{r} / \sqrt{t+1}}$ <br> Outputs $\left(z_{0}, \ldots, z_{\mathrm{t}}\right)$

## Masking Peikert sampler

1) [Offline]

- Outputs continuous Gaussian samples in arithmetically masked form

2) [Online]

- Generate discrete Gaussian samples share-by-share on each random share $c_{i}$ of $[c]=\left(c_{0}, \ldots, c_{t}\right)$.

3) [Polynomial multiplication]

- NTT/FFT on arithmetic shares (linear op.)
- Coordinate-wise multiplication with the standard ISW multiplier


## ShareByShareGauss $_{\mathrm{r}}([\mathrm{c}])$

for $i=0$ to $t:$
$z_{\mathrm{i}} \leftarrow \mathrm{D}_{\mathbb{Z}, \mathrm{c}_{\mathrm{i}}, r / \sqrt{t+1}}$
Outputs $\left(z_{0}, \ldots, z_{\mathrm{t}}\right)$

```
PolyMult([a], [b])
    \([\widehat{a}]=\operatorname{NTT}([a])\)
    \([\widehat{b}]=\operatorname{NTT}([\mathrm{b}])\)
    for \(j=0\) to \(d-1\) :
        \(\left[\widehat{c}_{j}\right]=\operatorname{Mult}\left(\left[\widehat{a}_{j}\right],\left[\widehat{b}_{j}\right]\right)\)
    \([\mathrm{c}]:=\mathrm{iNTT}\left(\left[\hat{\mathfrak{c}}_{0}\right], \ldots,\left[\hat{\mathfrak{c}}_{\mathrm{d}-1}\right]\right)\)
    Outputs [c]
```


## Masking Peikert sampler

1) [Offline]

- Outputs continuous Gaussian samples in arithmetically masked form

2) [Online]

- Generate discrete Gaussian samples share-by-share on each random share $c_{i}$ of $[c]=\left(c_{0}, \ldots, c_{t}\right)$.

3) [Polynomial multiplication]

- NTT/FFT on arithmetic shares (linear op.)
- Coordinate-wise multiplication with the standard ISW multiplier


## ShareByShareGauss $_{\mathrm{r}}([\mathrm{c}])$

for $i=0$ to $t:$
$z_{\mathrm{i}} \leftarrow \mathrm{D}_{\mathbb{Z}, \mathrm{c}_{\mathrm{i}}, r / \sqrt{t+1}}$
Outputs $\left(z_{0}, \ldots, z_{\mathrm{t}}\right)$

```
PolyMult([a], [b])
    \([\widehat{a}]=\operatorname{NTT}([a])\)
    \([\widehat{b}]=\operatorname{NTT}([\mathrm{b}])\)
    for \(j=0\) to \(d-1\) :
        \(\left[\widehat{c}_{j}\right]=\operatorname{Mult}\left(\left[\widehat{a}_{j}\right],\left[\widehat{b}_{j}\right]\right)\)
    \([\mathrm{c}]:=\mathrm{iNTT}\left(\left[\hat{\mathfrak{c}}_{0}\right], \ldots,\left[\hat{\mathfrak{c}}_{\mathrm{d}-1}\right]\right)\)
    Outputs [c]
```


## Masking Peikert sampler

1) [Offline]

- Outputs continuous Gaussian samples in arithmetically masked form

2) $[$ Online]

- Generate discrete Gaussian samples share-by-share on each random share $c_{i}$ of $[c]=\left(c_{0}, \ldots, c_{t}\right)$.

3) [Polynomial multiplication]

- NTT/FFT on arithmetic shares (linear op.)
- Coordinate-wise multiplication with the standard ISW multiplier


## ShareByShareGauss $_{\mathrm{r}}([\mathrm{c}])$

for $i=0$ to $t:$
$z_{i} \leftarrow \mathrm{D}_{\mathbb{Z}, \mathrm{c}_{\mathrm{i}}, r / \sqrt{t+1}}$
Outputs $\left(z_{0}, \ldots, z_{\mathrm{t}}\right)$
PolyMult([a], [b])
$[\widehat{a}]=\operatorname{NTT}([a])$
$[\widehat{b}]=\operatorname{NTT}([\mathrm{b}])$
for $j=0$ to $d-1$ :
$\left[\widehat{c}_{j}\right]=\operatorname{Mult}\left(\left[\hat{a}_{j}\right],\left[\hat{b}_{j}\right]\right)$
$[c]:=\operatorname{iNTT}\left(\left[\hat{c}_{0}\right], \ldots,\left[\widehat{c}_{d-1}\right]\right)$
Outputs [c]
© No boolean-arithmetic share conversion in the online phase

Wrapping-up

## Wrapping up



## Simple | Efficient | Compact | Versatile | Maskable



