# Ideal-SVP is Hard for Small-Norm Uniform Prime Ideals

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- New reduction:  $\mathcal{P}^{-1}$ -ideal-SVP to  $\mathcal{P}$ -ideal-SVP.
- Application: new distribution of NTRU instances with difficulty based on wc-ideal-SVP.

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# Definitions

### Lattices



A 2-dimensional lattice

#### Definition

For  $\mathbf{b}_1, \ldots, \mathbf{b}_n \in \mathbb{Z}^n$  linearly independent, the lattice spanned by the basis  $\mathbf{b}_1, \ldots, \mathbf{b}_n$  is  $\mathcal{L} = \sum_i \mathbb{Z} \cdot \mathbf{b}_i \subset \mathbb{R}^n$ . It is discrete and has a shortest non-zero vector.

Finding any short non-zero vector in  $\mathcal{L}$  given the  $(\mathbf{b}_i)_i$  is hard in general.

### Lattice-based cryptography



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**Note**:  $\mathcal{L}$  must be chosen at random.

We use the field  $K = \mathbb{Q}[X]/(X^n + 1)$ ,  $\mathcal{O}_K = \mathbb{Z}[X]/(X^n + 1)$  for  $n = 2^r$ . (K a number field,  $\mathcal{O}_K$  its ring of integers).

The size of an element  $a \in K$  is  $||a|| = \left(\sum_{i} |a_i|^2\right)^{1/2}$ .

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#### **Definition** (Ideal)

A set  $\mathfrak{a} \subseteq K$  is an ideal if it is discrete, stable by addition and by multiplication by any element of  $\mathcal{O}_{K}$ . It is then a lattice.

Norm of an ideal:  $\mathcal{N}(I) = \operatorname{Vol}(I)/\sqrt{\Delta_{\mathcal{K}}} \in \mathbb{Z}$ .

### Ideal inverse and factorization

Let  $\mathfrak{a}, \mathfrak{b}$  ideals of K, and  $a \in K$ .

**Principal ideal** 

 $(a) = \{x \cdot a, x \in \mathcal{O}_K\}.$ 

#### **Multiplication and inverse**

$$\mathfrak{a} \cdot \mathfrak{b} = \{\sum_{i} a_{i} \cdot b_{i}\}, \mathfrak{a}^{-1} = \{x \in \mathcal{K}, x \cdot \mathfrak{a} \subseteq \mathcal{O}_{\mathcal{K}}\}.$$
  
We have that  $\mathfrak{a} \cdot \mathfrak{a}^{-1} = \mathcal{O}_{\mathcal{K}}.$ 

#### Factorization

There exists a set of prime ideals  $\mathcal{P}$  such that any  $\mathfrak{a} \subset K$  can be written in a unique way

$$\mathfrak{a} = \prod_{\mathfrak{p} \in \mathcal{P}} \mathfrak{p}^{
u_\mathfrak{p}(\mathfrak{a})}$$

**Definition** (ideal-HSVP $_{\gamma}$ )

Given an ideal  $\mathfrak{a} \subseteq K$ , find  $x \in \mathfrak{a} \setminus \{0\}$  with  $||x|| \leq \gamma \cdot \operatorname{Vol}(\mathfrak{a})^{1/d}$ .

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- There are specifics attacks on ideal lattices<sup>1</sup>.
- Ideals are the simplest examples of module lattices (they are rank-1 modules), used in real world applications (KYBER, DILITHIUM).
- ideal-HSVP is related to other structured lattice problems (Module-SVP, NTRU, RingLWE).

<sup>&</sup>lt;sup>1</sup>[CDPR16, CDW17, PHS19]

## Why small ideal lattices?





**Typical lattice basis**:  $O(d^2)$  integers vs **Ideal lattice basis**: O(d) integers.<sup>2</sup>

<sup>&</sup>lt;sup>2</sup>Images from [Qua14]

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Also: faster algorithms.

<sup>2</sup>Images from [Qua14]

**Worst-case:** Solve  $\mathcal{P}$  for all instance of  $\mathcal{P}$  (for the worst instance). **Average-case for** D: Solve  $\mathcal{P}$  for  $I \leftarrow D$  with non-negligible probability.

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Two reductions here:

- Worst-case to average case.
- Average case for  $D_1$  to Average-case for  $D_2$ .

### Prior Works on ideal-HSVP



And also: ideal-HSVP reduces to RLWE

#### Random version of ideal-HSVP

W-ideal-HSVP: solving ideal-HSVP for a uniform element of W. **Idea:** W is the set of all public keys (a set of ideals).

Note: there are sets W such that W-ideal-HSVP is easy [BGP22].

#### **Random version of** ideal-HSVP

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We show that  $\mathcal{P}^{-1}$ -ideal-HSVP reduces to  $\mathcal{P}$ -ideal-HSVP.

#### **Two reasons**

- 1. [Gen09]: ideal-HSVP (for all ideals) reduces to  $\mathcal{P}^{-1}$ -ideal-HSVP, we complete this reduction.
- 2. The  ${\rm NTRU}$  reduction from [PS21] works only for integral ideals.

In fact we prove a more general reduction: ideal-HSVP( $\mathcal{W}^{-1}$ ) reduces to ideal-HSVP( $\mathcal{W}$ ) + ideal-HSVP( $\mathcal{I}_{A,B}$ )

# Prior work: Gentry's reduction

## **Rounding ideals**

Two types of ideals: *integral*  $\mathfrak{a} \subseteq \mathcal{O}_{K}$  and *fractional*:  $I \subseteq K$ . (And replete:  $I = x \cdot \mathfrak{a} \subset K_{\mathbb{R}}$  with  $x \in K_{\mathbb{R}}^{\times}$ )

#### Note

If a is integral,  $a^{-1}$  is fractional.

#### How to round an ideal

Take  $x \leftarrow I^{-1}$  with  $x \sim \lambda \cdot (1, \dots, 1)^T$  with  $\lambda$  large, then  $x \cdot I \subseteq \mathcal{O}_K$  and:  $s = \text{ideal-HSVP}(I) \stackrel{\sim}{\longleftrightarrow} x \cdot s = \text{ideal-HSVP}(x \cdot I).$ 

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 $s = \text{ideal-HSVP}(I) \iff x \cdot s = \text{ideal-HSVP}(x \cdot I).$ 

Rounding allows to **randomize** our ideals (sample random *x*).

 $x \in I^{-1}$  is small  $\Rightarrow x \cdot I$  has small volume.

In [BDPW20], rounding is done with large elements (due to LLL).

The oracle  $\mathcal{O}$  solves ideal-HSVP for  $\mathfrak{p}^{-1}$  with  $\mathfrak{p}$  uniform small prime.

Algorithm 2.1 Outline of the reduction of [Gen09]

**Input:** An ideal  $I = \mathfrak{b}^{-1}$ .

**Output:**  $x \in I \setminus \{0\}$  small.

1: Let 
$$x = 1$$
.

- 2: while b is large do
- 3: **Round**  $\mathfrak{b}$ : sample v in  $\mathfrak{b}^{-1}$ , let  $\mathfrak{a} = v \cdot \mathfrak{b} \subseteq \mathcal{O}_{\mathcal{K}}$ .
- 4: **Factor** a: write  $a = p_1^{e_1} \cdot \ldots \cdot p_k^{e_k}$  with  $p_i$  primes. (Quantum)
- 5: **Sample:**  $\mathfrak{p}_i$  uniformly, and let  $w = \mathcal{O}(\mathfrak{p}_i^{-1})$ .
- 6: **Update:**  $x \leftarrow w \cdot x$ ,  $\mathfrak{b} \leftarrow (w) \cdot \mathfrak{b}$ .

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7: Return *x* 

# Sampling ideals

You are not allowed to pre-compute the set of primes numbers in [A, B]!

#### Idea 1: rejection sampling

Sample N uniform in [A, B] until it is prime, then output it.

 $\rightarrow$  Not fitted our case, more on that later.

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Sample N uniform in [A, B]. Factor  $N = \prod p_i^{e_i}$  and output a random  $p_i \in [A, B]$ .

 $\rightarrow$  Need rejection sampling: 2 more frequent than 7919.

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We are going to use Idea 2 in order to sample prime ideals with a trapdoor.

#### Algorithm 3.1 SampleWithTrap algorithm

**Input:**  $2 \le A < B$  integers

**Output:**  $(\mathfrak{p}, x)$  such that  $x \in \mathfrak{p}$  and  $\mathcal{N}(\mathfrak{p}) \in [A, B]$ .

- 1: repeat
- 2: Sample a small Gaussian x in  $\mathcal{O}_K$ . (Need a good basis of  $\mathcal{O}_K$ )
- 3: Factor (x): write  $(x) = \mathfrak{p}_1^{e_1} \cdot \ldots \cdot \mathfrak{p}_k^{e_k}$  with  $\mathfrak{p}_i$  primes. (Quantum)
- 4: **until**  $\{\mathfrak{p}_i, \mathcal{N}(\mathfrak{p}_i) \in [A, B]\} \neq \emptyset$ .
- 5: Pick:  $\mathfrak{p} \leftarrow {\mathfrak{p}_i, \mathcal{N}(\mathfrak{p}_i) \in [A, B]}$  uniformly. (Rejection sampling here)
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#### Theorem

This algorithms runs in quantum poly-time and outputs  $\mathfrak{p}$  almost uniform in  $\mathcal{P}_{A,B}$  along with small  $x \in \mathfrak{p} \setminus \{0\}$ .

Algorithm 3.2 ArakelovSampling algorithm

 $\textbf{Output:} \ \, \text{An ideal} \ \, \mathfrak{b}$ 

- 1: Let q an uniform small prime ideal.
- 2: Sample a small continuous Gaussian  $\zeta$  and a uniform rotation u.
- 3: Let  $I = \exp(\zeta) \cdot u \cdot \mathfrak{q} / \mathcal{N}(\mathfrak{q})^{1/d}$ .
- 4: Sample  $x \leftarrow \mathcal{U}(\mathcal{B}_{\infty}(r) \cap I)$
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- 1: Let  $(q, v_q) \leftarrow \texttt{SampleWithTrap}(\cdot)$ . (Quantum)
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The element  $y = x^{-1} \cdot s_l$  can be very large compared to  $\mathcal{N}(\mathfrak{b}^{-1})^{1/d}$ .

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#### Drawback

The element  $y = x^{-1} \cdot s_l$  can be very large compared to  $\mathcal{N}(\mathfrak{b}^{-1})^{1/d}$ .  $\rightarrow$  This happens if x is **unbalanced** 

#### Some details on ArakelovSampling



Figure 2:  $\mathcal{B}_{\infty}(r)$ 

- 1. We pick  $I \approx \mathfrak{q}/\mathcal{N}(\mathfrak{q})^{1/d}$ .
- 2. We sample  $x \leftarrow \mathcal{U}(\mathcal{B}_{\infty}(r) \cap I)$ .
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#### Necessary for uniform b

- 1.  $|\mathcal{B}_{\infty}(r) \cap I|$  do not depend on I (too much).
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#### Drawback

There are (a non-negligible proportion of)  $x \in \mathcal{B}_{\infty}(r)$  with  $||x^{-1}||$  very large.

# Main contribution: $\mathcal{P}^{-1}$ -ideal-SVP to $\mathcal{P}$ -ideal-SVP

We generalize the approach of [BDPW20, Boe22]:

Algorithm 4.1 SampleIdeal  $B_{A,B}$  algorithm

**Input:** a an ideal,  $s_a \in a$  small,  $\mathcal{B}_{A,B} \subset \mathcal{K}_{\mathbb{R}}$  a well chosen set. **Output:**  $(\mathfrak{b}, y)$  such that  $y \in (\mathfrak{b} \cdot \mathfrak{a})^{-1}$ .

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(Normalization factors omitted)

#### Theorem

Let  $(\mathfrak{b}, y) = \text{SampleIdeal}_{\mathcal{B}_{A,B}}(\mathfrak{a}, s_{\mathfrak{a}}, A, B)$ . If  $\mathcal{B}_{A,B}$  is well chosen then  $\mathfrak{b}$  is almost uniform in  $\mathcal{I}_{A,B}$  and y is small.



- $|\mathcal{B}_{A,B} \bigcap \mathfrak{a}|$  do not depend on  $\mathfrak{a}$  (too much).
- Vol(Log( $\mathcal{B}_{A,B}$ )  $\cap$  { $\sum x_i = t$ }) is constant for  $t \in [A, B]$ .
- Its elements must be balanced.

Balanced elements (for Minkowski embedding)

 $x \in K$  is balanced if for all *i*,

$$1/\eta \le x_i / \prod_j x_j^{1/d} \le \eta.$$

This is the same as saying  $x \approx \mathcal{N}(x)^{1/d} \cdot (1, \dots, 1)$ .



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In [BDPW20]:  $\mathcal{B}_{\infty}(r)$ : verify points 1 and 2 but not 3!

# Our shape

Reminder: conditions for being well chosen:

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The algorithm SampleIdeal<sub> $\mathcal{B}_{A,B}$ </sub>:

- 1. Takes as input  $\mathfrak{a} \subseteq \mathcal{O}_K$  and  $s_\mathfrak{a} \in \mathfrak{a}$  small.
- 2. Output  $\mathfrak{b} \subseteq \mathcal{O}_{\mathcal{K}}$  uniform and  $y \in \mathfrak{b}^{-1} \cdot \mathfrak{a}^{-1}$  small.

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$$\mathrm{ideal}\text{-}\mathrm{HSVP}(\mathfrak{a}) + \mathrm{ideal}\text{-}\mathrm{HSVP}(\mathfrak{b}) \xrightarrow[]{\mathrm{SampleIdeal}_{\mathcal{B}_{A,B}}} \mathrm{ideal}\text{-}\mathrm{HSVP}(\mathfrak{a}^{-1})$$

Algorithm 4.2 Outline of the  $\mathcal{P}^{-1}$ -ideal-SVP to  $\mathcal{P}$ -ideal-SVP reduction **Input:** An ideal  $I = \mathfrak{p}^{-1}$  with  $\mathfrak{p}$  uniform prime of norm in [A, B]. **Output:**  $x \in I \setminus \{0\}$  small. 1: Let  $s_{\mathfrak{p}} = \mathcal{O}(\mathfrak{p})$ . ( $\mathfrak{p}$  is uniform) 2: Let  $(\mathfrak{b}, y) = \text{SampleIdeal}_{AB}(\mathfrak{p}, s_{\mathfrak{p}})$ 3: if b is not prime. (with probability (poly  $\rho_{K}$ )<sup>-1</sup>) then Fail. 4. 5: Let  $s_{\mathfrak{b}} = \mathcal{O}(\mathfrak{b})$ . 6: **Return**  $s_b \cdot y$ .

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We fail if  $\mathfrak{b}$  is not prime: we have to do rejection sampling. The expected number of rejection is

$$\frac{|\mathcal{I}_{A,B}|}{|\mathcal{P}_{A,B}|} \approx \rho_{K} = \operatorname{Res}_{s=1} \zeta_{K}(s).$$

This quantity can be exponential for some fields (E.g., multiquadratics).

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Also, we lack good approximations for small A, B.

# **Application to NTRU**

Proposed first in [HPS96]. In NIST's post-quantum standardization process: **NTRU** and **NTRUPrime**.

```
Let q be an integer.
```

```
Definition (NTRU<sub>q</sub>)
```

Let  $f, g \in \mathcal{O}_K$  with coefficients  $\ll \sqrt{q}$  and f invertible mod q. Given  $h \in \mathcal{O}_K$  such that  $f \cdot h = g \mod q$ , find a small multiple of (f, g).

#### Advantages:

- Small keys.
- Fast encryption/decryption (much faster than RSA).
- Old.

[HPS96]: J. Hoffstein, J. Pipher, J. Silverman. ANTS 1998.

Karp reduction from [PS21].

Ideal SVP  $a = (z) \bigcap \mathcal{O}_{K}.$  Vol(a) = V.SVP(a) = s  $\begin{aligned} \textbf{NTRU} \\ q &\approx V^{2/d}. \\ h &= \lfloor q/z \rceil. \\ (g, f) &= (s, s \cdot \{q/z\}) \end{aligned}$ 

Karp reduction from [PS21].

Ideal SVP	NTRU
$\mathfrak{a} = (z) \bigcap \mathcal{O}_{K}.$	$qpprox V^{2/d}.$
$Vol(\mathfrak{a}) = V.$	$h = \lfloor q/z  ceil.$
$\mathrm{SVP}(\mathfrak{a}) = s$	$(g, f) = (s, s \cdot \{q/z\})$

**Distribution of** NTRU **instances** ( $D^{NTRU}$ ): sample p uniform small prime and apply the reduction.

Consequence: worst-case based distribution for NTRU NTRU for  $D^{NTRU} \ge \mathcal{P}$ -ideal-SVP  $\ge$  wc-ideal-SVP. Wrapping up

#### **Contributions:**

- We show that solving ideal-HSVP on average over inverse of primes is as hard as solving ideal-HSVP on average over primes.
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- We show that solving ideal-HSVP on average over inverse of primes is as hard as solving ideal-HSVP on average over primes.
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#### **Open problems:**

- Can we have such reduction without factoring?
- Can we get rid of the cost in  $\rho_K$ ?
- Can we have more precise approximates for  $|\mathcal{I}_{A,B}|/|\mathcal{P}_{A,B}|$ ?

#### Any question?





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