

# A Refined Hardness Estimation of LWE in Two-step Mode

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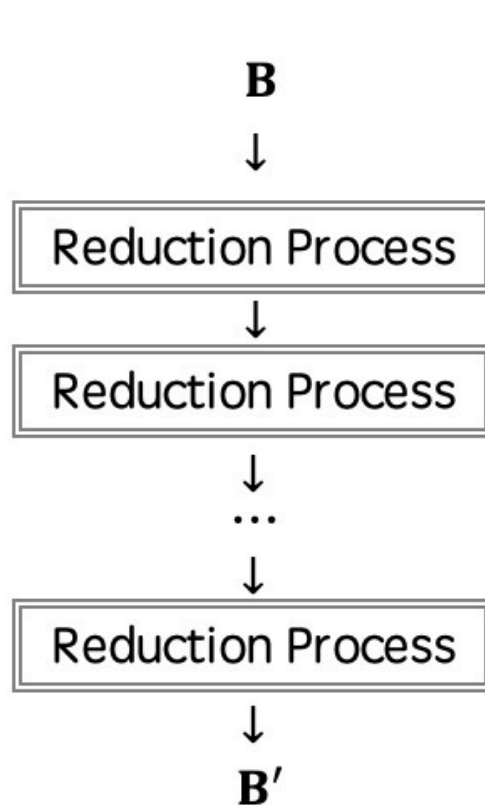
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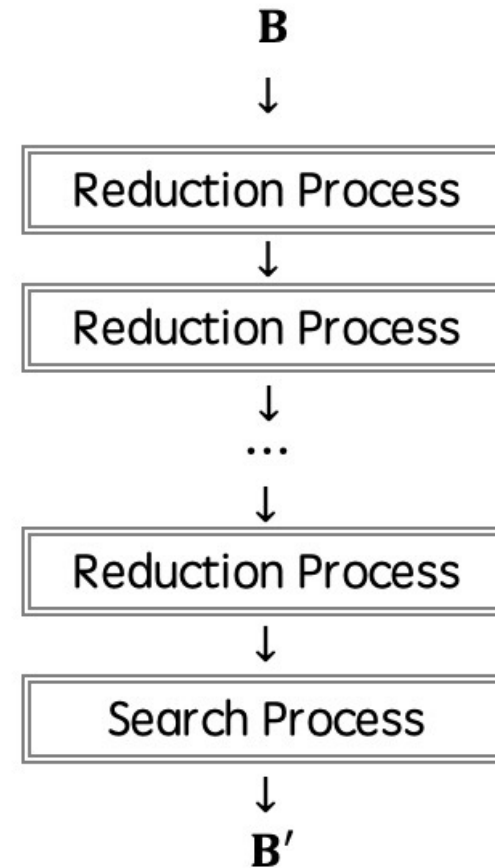
**01**

**Introduction of LWE Estimator**

# Introduction of LWE Estimator

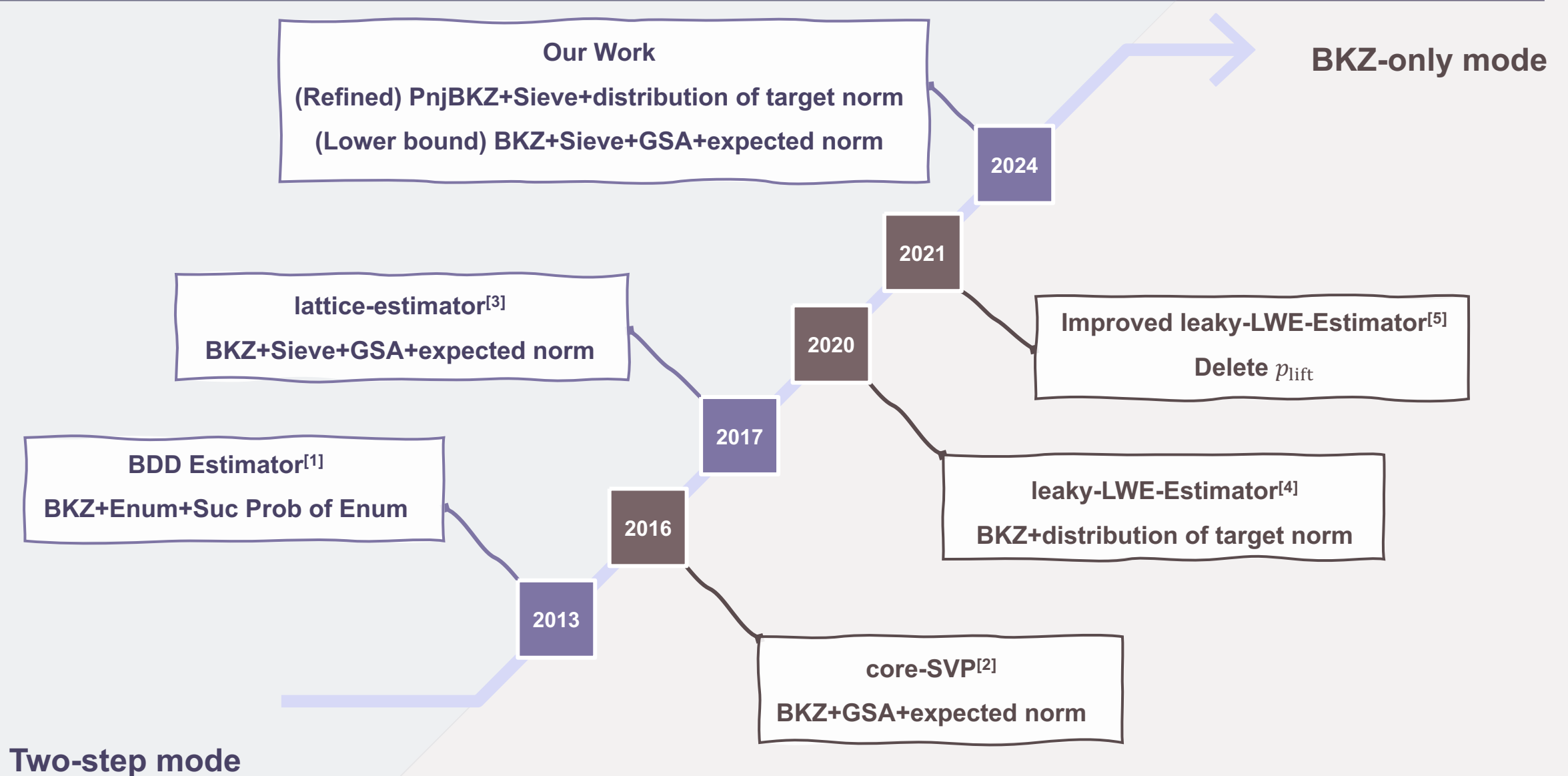


BKZ-only Mode



Two-step Mode

# Introduction of LWE Estimators



# Introduction of LWE Estimators

## Comparison among different LWE Estimators

Estimator	Mode	Reduction Process	Search Process	Terminal Condition	Cost
BDD Estimator	Two-step	BKZ	Enumeration	<b>Success Probability</b> of last Enumeration	$\frac{T_{redu} + T_{Enum}}{p_{succ}}$
core-SVP	BKZ-only	BKZ	/	Minimize $\beta$ by <b>GSA</b> and <b>expected target norm</b>	$T_{sieve}(\beta)$
lattice-estimator	Two-step	BKZ	Sieve	Minimize $\beta$ and $d_{svp}$ by <b>GSA</b> and <b>expected target norm</b>	$T_{BKZ}(\beta) + T_{sieve}(d_{svp})$
(Improved) leaky-LWE-Estimator	BKZ-only	BKZ	/	Estimate $\bar{\beta}$ by <b>distribution of target norm</b>	$T_{BKZ}(\bar{\beta})$
<b>Our work(Refined)</b>	Two-step	PnjBKZ with jump>1	Sieve	Minimize $d_{svp}$ by <b>distribution of target norm</b>	$\overline{T_{PnjBKZ}(\beta, J) + T_{sieve}(d_{svp})}$
<b>Our work(Lower Bound)</b>	Two-step	BKZ	Sieve	Estimate $d_{svp}$ by <b>GSA</b> and <b>expected target norm</b>	$T_{sieve}(d_{svp})$



**02**

**Our Contribution**

# Our Contribution

1. **Prove in theory** that the **Two-step mode** is **faster** in solving uSVP than the **BKZ-only mode** under Geometric Series Assumption.
2. Construct a **Refined LWE Hardness Estimator** in Two-step mode. Give Experiments:
  - (1) **Accuracy verification** of Success Probability used in Refined LWE Hardness Estimator;
  - (2) **Verification** Experiments for **Efficiency of Two-step Mode** by Refined LWE Hardness Estimator.
3. Give a **Lower Bound Estimation** for LWE in Two-step mode.
4. Re-evaluate the security bit of **NIST PQC schemes** both by the Refined LWE Hardness Estimator and Lower Bound Estimation .





**03**

**Efficiency of Two-step  
Mode**

# Efficiency of Two-step Mode

**Heuristic 1 (Gaussian Heuristic)** *The expected first minimum of a lattice  $\mathcal{L}$  (denoted as  $\lambda_1(\mathcal{L}(\mathbf{B}))$ ) according to*

*the Gaussian Heuristic denoted by  $GH(\mathcal{L})$  is given by  $\lambda_1(\mathcal{L}(\mathbf{B})) \approx GH(\mathcal{L}) = \frac{(\Gamma(\frac{d}{2}+1) \cdot \text{Vol}(\mathcal{L}))^{\frac{1}{d}}}{\sqrt{\pi}} \approx \sqrt{\frac{d}{2\pi e}} \cdot \text{Vol}(\mathcal{L})^{\frac{1}{d}}$ .*

*We also write  $GH(\mathbf{B}) = GH(\mathcal{L}(\mathbf{B}))$  and  $GH(\text{rr}_{[i:j]}) = GH(\mathbf{B}_{\pi[i:j]})$ .*

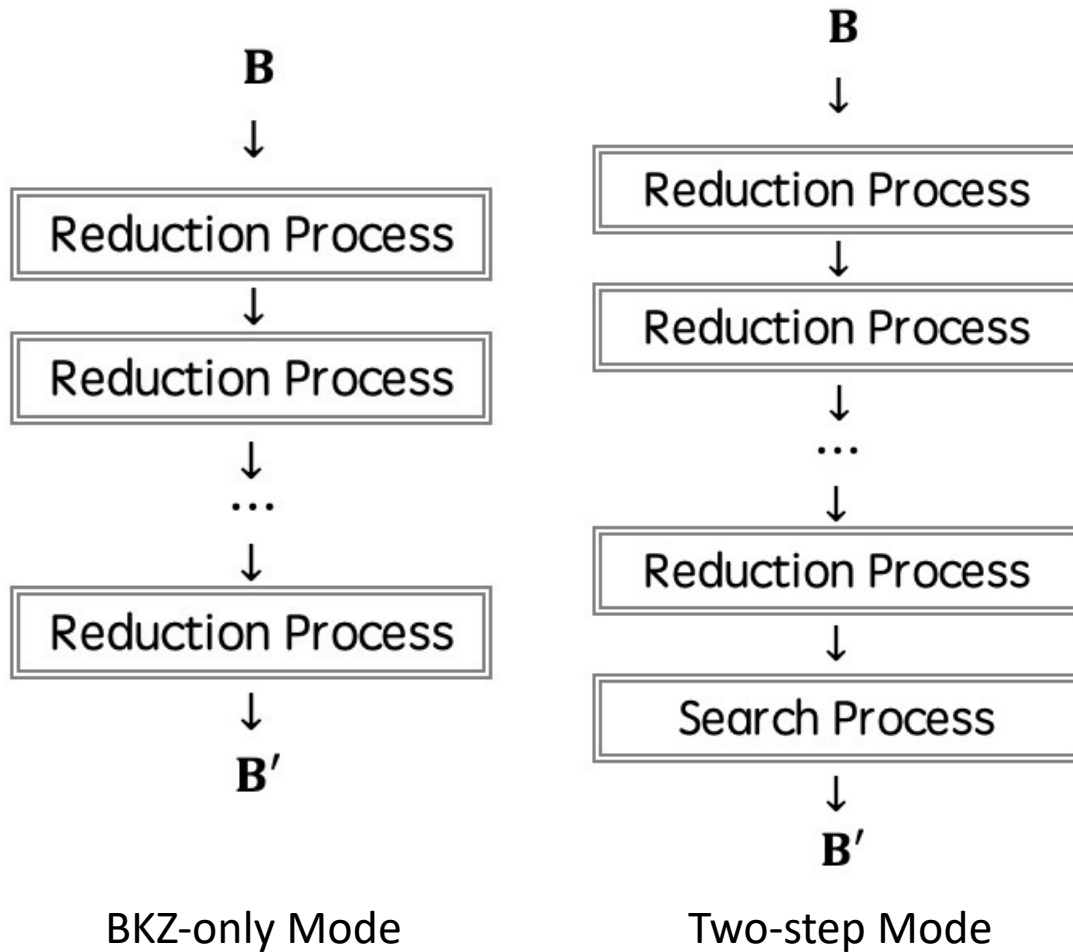
**Heuristic 2 (Geometric Series Assumption (GSA))** *Let  $\mathbf{B}$  be a lattice basis after lattice reduction, then Geometric Series Assumption states that  $\|\mathbf{b}_i^*\| \approx \alpha \cdot \|\mathbf{b}_{i-1}^*\|$ ,  $0 < \alpha < 1$ . Combine the GSA with root-Hermite factor and*

*$\text{Vol}(L(\mathbf{B})) = \prod_{i=0}^{d-1} \|\mathbf{b}_i^*\|$ , it infers that  $\alpha = \delta^{-\frac{2d}{d-1}} \approx \delta^{-2}$ .*

**Heuristic 4 in [7]**

*Let  $\mathbf{B}$  be a lattice basis after reduction of several PnjBKZ- $(\beta_i, J_i)$  tours,  $J_i \leq \frac{d4f(\beta_i)}{2}$ . If  $\mathbf{B}$  has same quality with a BKZ- $\beta$  reduced basis, then the basis cannot be further improved by a PnjBKZ- $(\beta, J)$  tour for any  $J \geq 1$ .*

# Efficiency of Two-step Mode



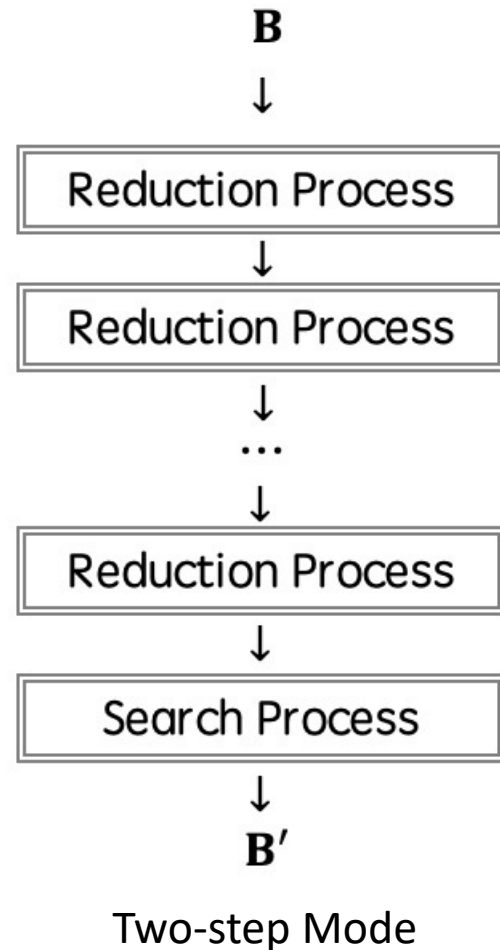
**Theorem 1.** Assume Gaussian Heuristic (Heuristic 1), GSA(Heuristic 2) and Heuristic 4 in [7] hold. Let  $d$  be the dimension of lattice,  $d \geq 100$ , we assume that  $uSVP_\gamma$  instance can be solved by BKZ-only mode through a BKZ- $\beta$  reduced basis with  $\frac{d+16}{9} \leq \beta \leq \frac{d}{2}$ , and let the time cost for sieving on  $d$ -dimensional lattice be  $2^{c \cdot d + c_0}$  where  $c \leq 0.35$ . Then, there exists a parameter choice for the two-step mode which solves the  $uSVP_\gamma$  instance in less time than BKZ-only mode.

The image shows the Sydney Opera House from a low angle across the water. The building's iconic white, shell-like roof is the central focus. A semi-transparent white rectangular box is centered over the building, containing the number '04' in a large, bold, dark blue font. Below the number, the text 'Our Refined LWE Estimator in Two-step Mode' is written in a bold, black, sans-serif font. The background is a clear blue sky and the blue water of the harbor.

**04**

**Our Refined LWE Estimator  
in Two-step Mode**

# Our Refined LWE Estimator in Two-step Mode



1. How to estimate the success probability of finding the target vector ?
  2. How to estimate the time cost and memory cost?
- 
1. Propose the success probability computation model combining BKZ and Sieve.
  2. Compute the expected time cost and memory cost through success probability.

# Our Refined LWE Estimator in Two-step Mode

- $W$ : The event of solving LWE successfully during running Progressive BKZ or the final high-dimension progressive sieve of Two-step mode.
- $W_{\beta}^{(1)}$ : The event of solving LWE by BKZ- $\beta$  successfully,  $F_{\beta}^{(1)} = \neg W_{\beta}^{(1)}$ .
- $E_{\beta_i}^{(1)}$ : The event of solving LWE successfully during the process of running Progressive BKZ: from BKZ- $\beta_1$  to BKZ- $\beta_i$ .
- $W_{d_{\text{svp}}}^{(2)}$ : The event of solving LWE by  $d_{\text{svp}}$ -dimensional progressive sieve successfully,  $F_{d_{\text{svp}}}^{(2)} = \neg W_{d_{\text{svp}}}^{(2)}$ .
- $E_{d_{\text{svp}}}^{(2)}$ : The event of finding the projection of the target vector exactly after a  $d_{\text{svp}}$ -dimensional sieve during progressive sieving.

# Our Refined LWE Estimator in Two-step Mode

**Heuristic 3.** The lattice basis is randomized each time by a reduction of BKZ- $\beta$  with larger  $\beta$ . Then, events  $W_{\beta_i}^{(1)}$  and  $F_{\beta_j}^{(1)}$  are independent for  $i \neq j$ .

Success event of each BKZ is independently.

Based on **Heuristic 3**, 
$$\Pr \left[ E_{\beta_k}^{(1)} \right] = \sum_{i=1}^k \Pr \left[ W_{\beta_i}^{(1)} \wedge \bigwedge_{i>1, j=1}^{i-1} F_{\beta_j}^{(1)} \right] = \Pr \left[ E_{\beta_{k-1}}^{(1)} \right] + \Pr \left[ W_{\beta_k}^{(1)} \right] \cdot \left( 1 - \Pr \left[ E_{\beta_{k-1}}^{(1)} \right] \right). \quad (2)$$

**Heuristic 4.** For  $i \in \{2, \dots, d_{\text{svp}}\}$ ,  $W_i^{(2)} \supseteq W_{i-1}^{(2)} \supseteq W_{i-2}^{(2)} \supseteq \dots \supseteq W_2^{(2)}$ . Then  $E_i^{(2)} = W_i^{(2)} - W_{i-1}^{(2)}$ .

Success event of each sieve in a Progressive sieve is dependently.

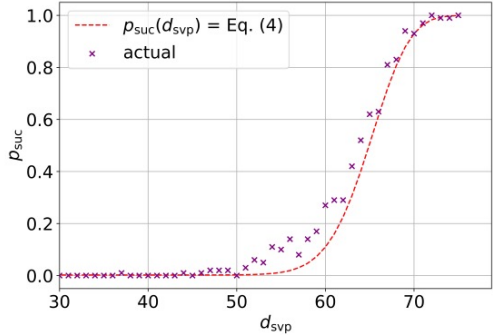
Let  $\Pr[W_{d_{\text{start}}-1}^{(2)}] = 0$ . Based on **Heuristic 4**, 
$$\Pr \left[ E_{d_{\text{svp}}}^{(2)} \right] = \Pr \left[ W_{d_{\text{svp}}}^{(2)} \right] - \Pr \left[ W_{d_{\text{svp}}-1}^{(2)} \right]. \quad (3)$$

The cumulative probability of solving LWE in our refined LWE estimator in Two-step mode:

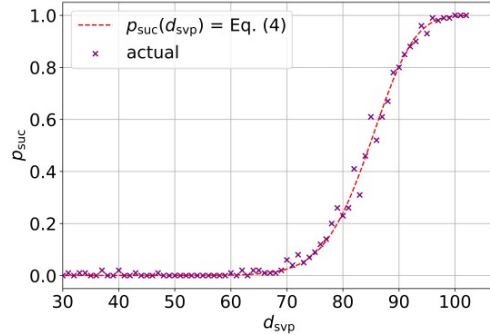
$$\begin{aligned} \Pr[W] &= \Pr \left[ W_{\beta_1}^{(1)} \right] + \Pr \left[ W_{\beta_2}^{(1)} \wedge F_{\beta_1}^{(1)} \right] + \Pr \left[ W_{\beta_2}^{(1)} \wedge F_{\beta_2}^{(1)} \wedge F_{\beta_1}^{(1)} \right] + \dots + \Pr \left[ W_{\beta_2}^{(1)} \wedge \bigwedge_{j=1}^{\text{end}-1} F_{\beta_j}^{(1)} \right] + \Pr \left[ W_{d_{\text{svp}}}^{(2)} \wedge \bigwedge_{j=1}^{\text{end}} F_{\beta_j}^{(1)} \right] \\ &= \left( \sum_{i=1}^{\text{end}} \Pr \left[ W_{\beta_i}^{(1)} \wedge \bigwedge_{i>1, j=1}^{i-1} F_{\beta_j}^{(1)} \right] \right) + \Pr \left[ W_{d_{\text{svp}}}^{(2)} \wedge \bigwedge_{j=1}^{\text{end}} F_{\beta_j}^{(1)} \right] \quad (1) \\ &= \Pr \left[ E_{\beta_{\text{end}}}^{(1)} \right] + \left( 1 - \Pr \left[ E_{\beta_{\text{end}}}^{(1)} \right] \right) \cdot \sum_{i=d_{\text{start}}}^{d_{\text{svp}}} \Pr \left[ E_i^{(2)} \right] \\ &= \Pr \left[ E_{\beta_{\text{end}}}^{(1)} \right] + \left( 1 - \Pr \left[ E_{\beta_{\text{end}}}^{(1)} \right] \right) \cdot \Pr \left[ W_{d_{\text{svp}}}^{(2)} \right]. \quad (4) \end{aligned}$$

If  $\Pr[W] = 1$ , then it implies all the LWE instance with specific average value and variance could be solved, time to terminate estimator.

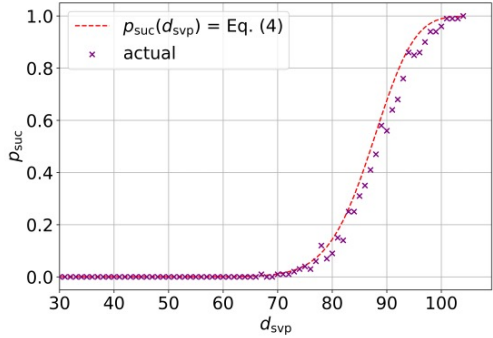
# Our Refined LWE Estimator in Two-step Mode



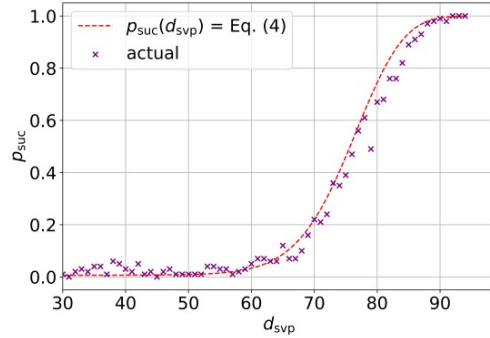
(a)  $n = 40, \alpha = 0.005, q = 1601$



(b)  $n = 40, \alpha = 0.015, q = 1601$



(c)  $n = 60, \alpha = 0.005, q = 3607$



(d)  $n = 45, \alpha = 0.010, q = 2027$

## Success Probability Verification Experiments

The cumulative probability of solving LWE in our refined LWE estimator in Two-step mode:

$$\begin{aligned}
 \Pr[W] &= \Pr[W_{\beta_1}^{(1)}] + \Pr[W_{\beta_2}^{(1)} \wedge F_{\beta_1}^{(1)}] + \Pr[W_{\beta_2}^{(1)} \wedge F_{\beta_2}^{(1)} \wedge F_{\beta_1}^{(1)}] + \dots \\
 &\quad + \Pr[W_{\beta_2}^{(1)} \wedge \wedge_{j=1}^{\text{end}-1} F_{\beta_j}^{(1)}] + \Pr[W_{d_{\text{svp}}}^{(2)} \wedge \wedge_{j=1}^{\text{end}} F_{\beta_j}^{(1)}] \\
 &= \left( \sum_{i=1}^{\text{end}} \Pr[W_{\beta_i}^{(1)} \wedge \wedge_{i>1, j=1}^{i-1} F_{\beta_j}^{(1)}] \right) + \Pr[W_{d_{\text{svp}}}^{(2)} \wedge \wedge_{j=1}^{\text{end}} F_{\beta_j}^{(1)}] \\
 (1) \quad &= \Pr[E_{\beta_{\text{end}}}^{(1)}] + \left(1 - \Pr[E_{\beta_{\text{end}}}^{(1)}]\right) \cdot \sum_{i=d_{\text{start}}}^{d_{\text{svp}}} \Pr[E_i^{(2)}] \\
 &= \underbrace{\Pr[E_{\beta_{\text{end}}}^{(1)}]}_0 + \left(1 - \underbrace{\Pr[E_{\beta_{\text{end}}}^{(1)}]}_1\right) \cdot \Pr[W_{d_{\text{svp}}}^{(2)}]. \quad (4)
 \end{aligned}$$

- The predication of the success rate of solving LWE given by Eq. (4) is consistent with the experimental results.



# Our Refined LWE Estimator in Two-step Mode

$\text{gate}(\beta)$ : The gate count of a sieve algorithm with dimension  $\beta$ .

$\text{pgate}(\beta) = C \cdot \text{gate}(\beta)$ : The gate count of a progressive sieve algorithm with dimension  $\beta$ .

$\text{pbgate}(\beta) = (d - \beta + 1) \cdot \text{pgate}(\beta)$ : The gate count of BKZ- $\beta$ .

$\text{pbgate}(\beta, J) = \frac{d - \beta + 1}{J} \cdot \text{pgate}(\beta)$ : The gate count of PnjBKZ- $(\beta, J)$ .

Gate Count of reduction step:  $G_1 = \sum_{i=1}^{\text{end}} \Pr \left[ W_{\beta_i}^{(1)} \right] \cdot \left( 1 - \Pr \left[ E_{\beta_{i-1}}^{(1)} \right] \right) \cdot \left[ \sum_{j=0}^i \text{pbgate} \left( \beta_j - d4f(\beta_j) \right) \right]$

Gate Count of search step:  $G_2 = \sum_{i=d_{\text{start}}}^{d_{\text{svp}}} \Pr \left[ E_i^{(2)} \right] \cdot \left( 1 - \Pr \left[ E_{\beta_{\text{end}}}^{(1)} \right] \right) \cdot \left[ \left( \sum_{j=0}^{\text{end}} \text{pbgate} \left( \beta_j - d4f(\beta_j) \right) \right) + \text{pgate}(i - d4f(i)) \right]$

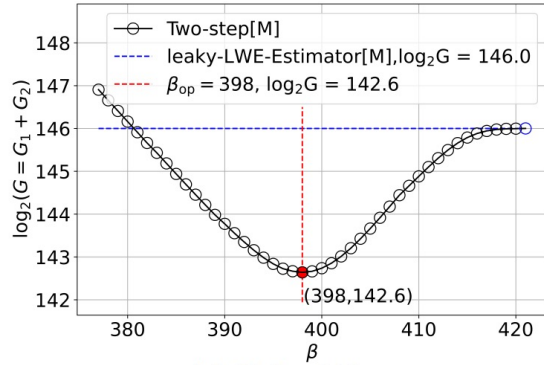
**Total Gate Count:**  $G = G_1 + G_2$

Memory Count of reduction step:  $B_1 = \sum_{i=1}^{\text{end}} \Pr \left[ W_{\beta_i}^{(1)} \right] \cdot \left( 1 - \Pr \left[ E_{\beta_{i-1}}^{(1)} \right] \right) \cdot \text{bit} \left( \beta_j - d4f(\beta_j) \right)$

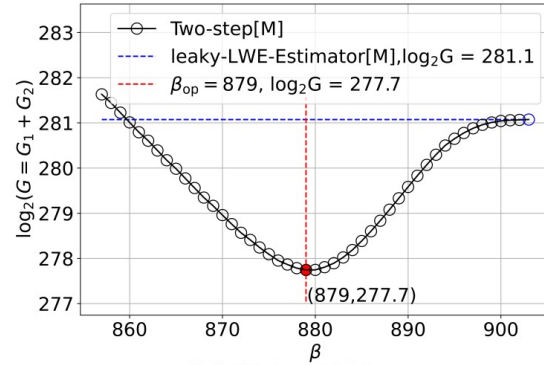
Memory Count of search step:  $B_2 = \sum_{i=d_{\text{start}}}^{d_{\text{svp}}} \Pr \left[ E_i^{(2)} \right] \cdot \left( 1 - \Pr \left[ E_{\beta_{\text{end}}}^{(1)} \right] \right) \cdot \max \left\{ \text{bit} \left( \beta_j - d4f(\beta_j) \right), \text{bit}(i - d4f(i)) \right\}$

**Total Memory Count:**  $B = B_1 + B_2$

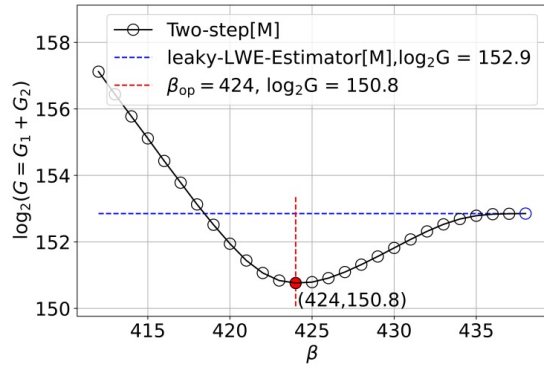
# Our Refined LWE Estimator in Two-step Mode



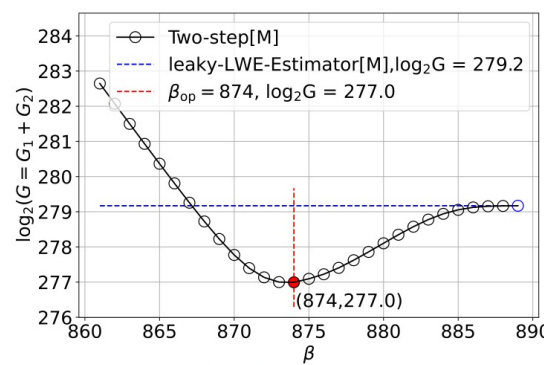
(a) Kyber512



(b) Kyber1024



(c) Dilithium-II



(d) Dilithium-V

## Estimation Comparison with leaky-LWE-Estimator

- The Two-step mode is faster than that of using BKZ reduction only.

```

input :  $n, m, q, \chi, S$ ;
output:  $GB_{\min}$ ;
1 Function TwoStepLWEEsimator( $n, m, q, \chi, S$ ):
2    $GB_{\min} \leftarrow (+\infty, +\infty)$ ;  $GB \leftarrow (0, 0)$ ;  $GB_{\text{pre}} \leftarrow (0, 0)$ ;  $p_{\text{tot}} \leftarrow 0$ ;
3    $rr \leftarrow$  expected length of GS-basis of an LLL reduced  $LWE_{n,m,q,\chi}$  instance
4   for  $\beta \in S$  or  $(\beta, J) \in S$  do
5      $rr \leftarrow \text{BKZSim}(rr, \beta)$ ; // PnjBKZSim( $rr, \beta, J$ ) if  $J > 1$ ;
6      $P(\beta) \leftarrow \Pr \left[ x \leftarrow \chi_{\beta}^2 \mid x \leq (rr[d - \beta])^2 \right]$ ;
7      $GB_{\text{cum}} \leftarrow (\sum_{b=\beta_0}^{\beta} \text{pgate}(b - d4f(b)), \text{bit}(\beta - d4f(\beta)))$ ;
8      $GB_{\text{pre}} \leftarrow GB_{\text{pre}} + GB_{\text{cum}} \cdot (1 - p_{\text{tot}}) \cdot P(\beta)$ ;
9      $p_{\text{tot}} \leftarrow p_{\text{tot}} + (1 - p_{\text{tot}}) \cdot P(\beta)$ ;  $GB_{\text{csieve}} \leftarrow (0, 0)$ ;  $P(d_{\text{start}} - 1) \leftarrow 0$ ;
10    for  $d_{\text{svp}} \leftarrow d_{\text{start}}$  to  $d$  do
11       $P(d_{\text{svp}}) \leftarrow \Pr \left[ x \leftarrow \chi_{d_{\text{svp}}}^2 \mid x \leq (\text{GH}(rr_{[d-d_{\text{svp}}:d]})^2 \right]$ ;
12       $GB_{\text{cum}}[0] \leftarrow GB_{\text{cum}}[0] + \text{pgate}(d_{\text{svp}} - d4f(d_{\text{svp}}))$ ;
13       $GB_{\text{cum}}[1] \leftarrow \max\{GB_{\text{cum}}[1], \text{bit}(d_{\text{svp}} - d4f(d_{\text{svp}}))\}$ ;
14       $GB_{\text{csieve}} \leftarrow GB_{\text{csieve}} + GB_{\text{cum}} \cdot (1 - p_{\text{tot}}) \cdot (P(d_{\text{svp}}) - P(d_{\text{svp}} - 1))$ ;
15      if  $p_{\text{tot}} + (1 - p_{\text{tot}}) \cdot P(d_{\text{svp}}) \geq 0.999$  then
16        break;
17     $GB \leftarrow GB_{\text{pre}} + GB_{\text{csieve}}$ ;
18    if  $GB[0] < GB_{\min}[0]$  then
19       $GB_{\min} \leftarrow GB$ ;
20  return  $GB_{\min}$ ;

```

Algorithm 2: Two-step LWE Estimator

A photograph of the Sydney Opera House, a world-famous architectural landmark, viewed from the water. The building's iconic white, shell-like roof is the central focus. The sky is a clear, bright blue. In the foreground, the blue water of the harbor is visible, with some people and structures on the pier. A semi-transparent white rectangular box is overlaid on the center of the image, containing the number '05' and the title 'Improved Conservative Estimation for LWE' in a bold, black, sans-serif font.

**05**

**Improved Conservative  
Estimation for LWE**

# Improved Conservative Estimation for LWE

## Notation

$V$ : Lattice Volume.

$\delta(\beta)$ : The root Hermite factor of a BKZ- $\beta$  reduced lattice basis.

$\text{rhf}(\delta, \beta)$ : A new root Hermite factor of lattice basis after **one** BKZ- $\beta$  tour under GSA.

$\text{md}(\delta, M)$ : Minimum dimension for sieving to find the target vector with norm  $M$ .

## Heuristic 5

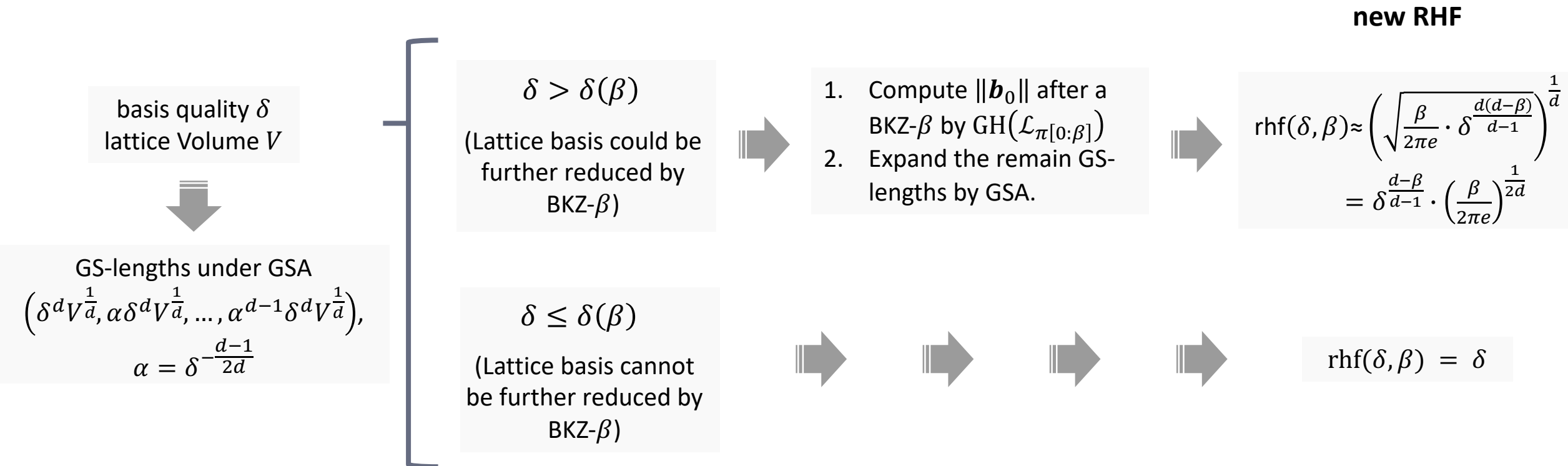
*BKZ is the optimal algorithm for lattice reduction, i.e. generating a lattice basis satisfying GSA.*

## Heuristic 6

*The best way of solving  $u\text{SVP}_\gamma$  or LWE is by performing lattice sieving on a projected sublattice of a reduced lattice basis satisfying GSA.*

# Improved Conservative Estimation for LWE

How to compute  $\text{rhf}(\delta, \beta)$ ?



# Improved Conservative Estimation for LWE

```
input :  $M, V \leftarrow \text{Vol}(\mathcal{L})$ ;  
output:  $T$ ;  
1 Function LowerBoundEst( $M, V \leftarrow \text{Vol}(\mathcal{L})$ ):  
2   for  $\beta \leftarrow \beta_0$  to  $d$  do  
3      $\text{con} \leftarrow \text{true}$ ;  
4      $d_{\text{svp}} \leftarrow \text{md}(\delta(\beta), M)$ ;  
5     for  $\beta' \leftarrow \beta + 1$  to  $d$  do  
6        $\delta' \leftarrow \text{rhf}(\delta(\beta), \beta')$ ;  
7       if  $T_{\text{sieve}}(d_{\text{svp}}) > T_{\text{BKZ}}(\beta') + T_{\text{sieve}}(\text{md}(\delta', M))$  then  
8          $\text{con} \leftarrow \text{false}$ ; break;  
9     if  $\text{con}$  then  
10       $\beta_{\text{optimal}} \leftarrow \beta$ ;  
11      return  $\beta_{\text{optimal}}, d_{\text{svp}}, T_{\text{sieve}}(d_{\text{svp}})$ ;
```

**Algorithm 4:** Lower Bound Estimation

Find a  $\beta$  and  $d_{\text{svp}} = \text{md}(\delta(\beta), M)$  such that

$T_{\text{sieve}}(d_{\text{svp}}) \leq T_{\text{BKZ}}(\beta') + T_{\text{sieve}}(\text{md}(\delta', M))$   
holds for all  $\beta' \geq \beta + 1$ , where  $\delta' = \text{rhf}(\delta(\beta), \beta')$ .  
Then, output  $T_{\text{sieve}}(d_{\text{svp}})$  as the Lower Bound  
Estimation of LWE(or uSVP).

Find a  $\beta$  and  $d_{\text{svp}}$  such that one more BKZ- $\beta'$  before  
last sieve cannot shorten the total cost for solving  
LWE( or uSVP).

**Theorem 2.** Assume that Gaussian Heuristic (Heuristic 1),  
GSA(Heuristic 2), Heuristic 5, 6, and Heuristic 4 in [7]  
hold, then the estimated cost of our lower bound  
estimation is **strictly lower than** the actual cost for  
solving  $\text{uSVP}_\gamma$  in almost all lattices.

# Improved Conservative Estimation for LWE

```
input  :  $m_{\max}, n, \sigma, q$ ;  
output:  $\beta_{\text{optimal}}, d_{\text{svp}}, T_{\text{sieve}}(d_{\text{svp}})$ ;  
1 Function LowerBoundEstWithOptimalM( $m_{\max}, n, \sigma, q$ ):  
2    $d_{\text{svp}}^* \leftarrow m_{\max} + n + 1$ ;  $m_{\text{optimal}} \leftarrow m_{\max}$ ;  $\beta_{\text{optimal}} \leftarrow m_{\max} + n + 1$ ;  
3   for  $m \leftarrow m_{\max}$  to 1 do  
4      $d \leftarrow n + m + 1$ ;  $M \leftarrow \sigma \cdot \sqrt{d}$ ;  $V \leftarrow q^m$ ;  
5      $\beta_{\text{current}}, d_{\text{svp}}, T_{\text{sieve}}(d_{\text{svp}}) \leftarrow \text{LowerBoundEst}(M, V)$ ;  
6     if  $d_{\text{svp}}^* > d_{\text{svp}}$  then  
7        $d_{\text{svp}}^* \leftarrow d_{\text{svp}}$ ;  $m_{\text{optimal}} \leftarrow m$ ;  $\beta_{\text{optimal}} \leftarrow \beta_{\text{current}}$ ;  
8    $d_{\text{optimal}} \leftarrow m_{\text{optimal}} + n + 1$ ;  
9   return  $d_{\text{optimal}}, \beta_{\text{optimal}}, d_{\text{svp}}^*, T_{\text{sieve}}(d_{\text{svp}}^*)$ ;
```

**Algorithm 5:** Lower Bound Estimation with Optimal  $m$

- Numerically optimize the number of LWE samples  $m$  to minimize the lower-bound security estimation by Alg. 5.

**06**

**Estimated Results**





# Estimated Results

NIST standards	$\log_2 G / \log_2(\text{gates})^*$			$\log_2 B / \log_2(\text{bits})$			$\Delta \log_2 G$	
	Previous	Our Refined LWE Estimator		Previous	Our Refined LWE Estimator			
		$S_0$	$S_{op}$		$S_0$	$S_{op}$	$S_0$	$S_{op}$
<b>Kyber512</b>	146.0	142.6	141.4	94.0	99.1	98.1	3.4	4.6
<b>Kyber768</b>	208.9	205.5	204.4	138.7	144	143.2	3.4	4.5
<b>Kyber1024</b>	281.1	277.7	276.9	189.78	195.4	194.6	3.3	4.2
<b>Dilithium-II</b>	152.9	150.8	150.6	98.0	104.3	104.4	2.1	2.3
<b>Dilithium-III</b>	210.2	207.9	207.9	138.8	145.3	145.3	2.3	2.3
<b>Dilithium-V</b>	279.2	277.0	277.0	187.5	194.1	194.1	2.2	2.2

- $S_0$ : Trivial Progressive BKZ in Two-step mode
- $S_{op}$ : Progressive BKZ in Two-step mode with strategy generated by EnumBS<sup>[7]</sup>
- \* : Gate Count of all estimations in this Table uses the improved list-decoding technique proposed by MATZOV<sup>[6]</sup>
- The security bit drops by 2.2~4.6 bits.

Estimation of NIST standards by Our Refined LWE Estimator

# Estimated Results

NIST standards	Kyber512	Kyber768	Kyber1024	DilithiumII	DilithiumIII	DilithiumV
Lattice Dim $d$	1003	1424	1885	2049	2561	3582
BKZ $\beta$	406	625	877	423	624	863
CoreSVP	118	182	256	123	182	252
Lattice Dim $d$	1025	1477	1954	2039	2672	3461
$\beta_{\text{optimal}}$	392	608	857	415	614	853
$d_{\text{svp}}$	423	641	891	449	649	889
LBE	123.52	187.17	260.17	131.11	189.51	259.59
LBE(d4f)	112.44	172.32	241.24	119.57	174.52	240.69
$\Delta\text{Hardness}$	5.52	5.17	4.17	8.11	7.51	7.59
$\Delta\text{Hardness(d4f)}$	-5.56	-9.68	-14.76	-3.43	-7.48	-11.31

- Our lower bound estimation is 4.17~8.11 bits higher than the Core-SVP estimation.
- If considering d4f technique, lower bound estimation will decrease by 3.42 ~ 14.76 bits, which declares that Core-SVP model is not conservative enough to offset the influence of the d4f technique.

Estimation of NIST standards by Our Lower Bound LWE Estimator



# Thanks

Article Access: <https://eprint.iacr.org/2024/067.pdf>

Open Source Code for Estimator: <https://github.com/Summwer/lwe-estimator-with-pnjbkz/tree/refined-lwe-estimator>

Open Source Code for Verification Experiments: <https://github.com/Summwer/test-for-refined-lwe-estimator>

# Reference

- [1] Mingjie Liu, and Phong Q. Nguyen. “Solving BDD by Enumeration: An Update.” In *Topics in Cryptology – CT-RSA 2013*, edited by Ed Dawson, 293 – 309. Lecture Notes in Computer Science. Berlin, Heidelberg: Springer, 2013.
- [2] Alkim, Erdem, Léo Ducas, Thomas Pöppelmann, and Peter Schwabe. “Post-Quantum Key Exchange—A New Hope,” 327 – 43, 2016.
- [3] <https://github.com/malb/lattice-estimator>
- [4] Dachman-Soled, Dana, Léo Ducas, Huijing Gong, and Mélissa Rossi. “LWE with Side Information: Attacks and Concrete Security Estimation.” In *Advances in Cryptology – CRYPTO 2020: 40th Annual International Cryptology Conference, CRYPTO 2020*, Santa Barbara, CA, USA, August 17 – 21, 2020, Proceedings, Part II, 329 – 58. Berlin, Heidelberg: Springer-Verlag, 2020. [https://doi.org/10.1007/978-3-030-56880-1\\_12](https://doi.org/10.1007/978-3-030-56880-1_12).
- [5] Postlethwaite, Eamonn W., and Fernando Virdia. “On the Success Probability of Solving Unique SVP via BKZ.” In *Public-Key Cryptography – PKC 2021*, edited by Juan A. Garay, 12710:68 – 98. Lecture Notes in Computer Science. Cham: Springer International Publishing, 2021.
- [6] MATZOV, “Report on the Security of LWE: Improved Dual Lattice Attack.” Accessed April 12, 2022.
- [7] W. Xia, L. Wang, GengWang, D. Gu, and B. Wang, “Improved progressive bkz with lattice sieving.” Cryptology ePrint Archive, Paper 2022/1343, 2022. <https://eprint.iacr.org/archive/2022/1343/1697360937.pdf>.