

Module 8: Concrete Security

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July 16-17, 2024

Module 8: Concrete Security

July 16-17, Tuesday and Wednesday afternoons (7h)

Focus:

How to estimate concrete security of PQC schemes?

- Lecture + Tutorial
- 16th, Tuesday
 - Lattice Estimator (Lecture + short Tutorial)
 - Kyber (Lecture)
 - Smaug (Tutorial)

- 17th, Wednesday
 - Falcon (Lecture)
 - Dilithium (Tutorial)

The <u>Lattice Estimator</u> (formerly the <u>LWE Estimator</u>) is a tool used throughout industry and academia to estimate the security level of Learning with Errorsbased parameter sets.

- Ben Curtis

Bunch of existing attacks against Lattice problems

```
LWE primal
                                               Arora-GB
(uSVP, BDD, hybrid, ..)
                                           (Gröbner bases)
                          LWE dual
                (dual, hybrid, mitm-hybrid, ..)
                                                       SIS
                                                    (BKZ, ..)
     Coded-BKW
                           NTRU primal
              (uSVP, BDD, hybrid, dense sublattice, ..)
```

Bunch of existing attacks against Lattice problems, all of them must be considered when setting parameters.

Cost of lattice attacks: "estimated," not "measured." Accuracy of the estimation is important.



Lattice estimator: Publicly available tool for security estimation for schemes using Lattice problems!

Thanks to Martin R Albrecht, Rachel Player, Sam Scott, Benjamin Curtis, and may others..

Available at:

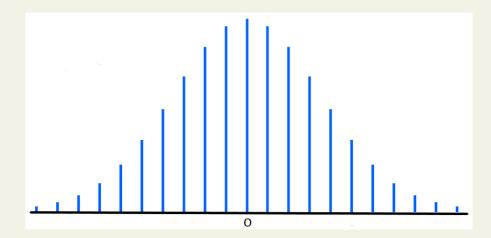
https://github.com/malb/lattice-estimator

- Keep updated following new State-of-the-Art attacks.
- Not perfectly correct, but reasonable estimation.
- Not targeting "very" insecure parameters
 - e.g., BKZ block-size $\beta \leq 40$.

- LWE instance includes two distributions:
 - secret $s \leftarrow \chi_s$
 - error $e \leftarrow \chi_e$
- Supported distributions "estimator/nd.py"
 - Discrete Gaussian
 - Centered Binomial (CBD)
 - Uniform
 - Sparse Binary/Ternary
 - and User-define distributions

Discrete Gaussian Distribution

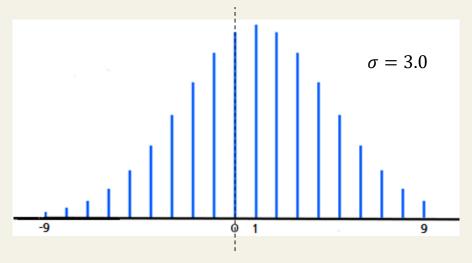
DiscreteGaussian(stddev, mean=0, n=None)



- discrete Gaussian with $\sigma = \text{stddev}$, centered at mean
 - tail bound: $\lceil \log_2 n \rceil \sigma$
- Variant: DiscreteGaussianAlpha, where $\alpha q = \sigma$

Discrete Gaussian Distribution (E.g.)

- >>> from estimator.nd import NoiseDistribution as ND
- >>> ND.DiscreteGaussian(3.0, 1.0, 8)
- discrete Gaussian with $\sigma=3.0$, centered at 1.0, tail bound $[\log_2 8]\sigma=3\sigma=9.0$
- distribution ranges from -9.0 to 9.0



Centered Binomial (CBD)

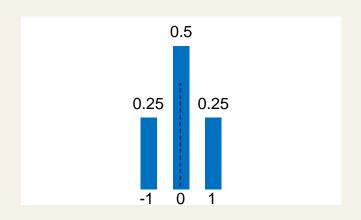
CenteredBinomial(eta, n=None)

- lacktriangleq CBD that samples $a_1,\ldots,a_\eta,b_1,\ldots,b_\eta$ and return $\Sigma(a_i-b_i)$
 - ranges from η to η
 - for $k \in [-\eta, \eta]$, probability $= \binom{2\eta}{k+\eta}/2^{2\eta}$

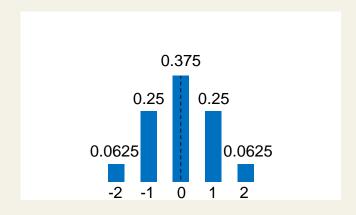
Centered Binomial (E.g.)

```
>>> ND.CenteredBinomial(1)
```

>>> ND.CenteredBinomial(2)



-1: 1/4, 0: 1/2, 1: 1/4



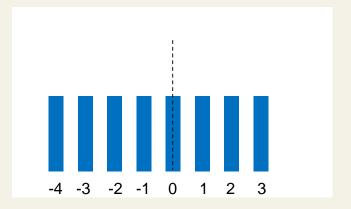
-2: 1/16, -1: 1/4, 0: 3/8, 1: 1/4, 2: 1/16

Uniform

- uniform distribution in a closed integer interval [a, b]
- each integer point has probability 1/(b-a+1)
- Variant: UniformMod, which is uniform modulo q
 - ranges [-q/2, q/2]
 - ModSwitch error (from q to p) is UniformMod(q/p)
 - will see in the tutorial!!

Uniform (E.g.)

- range: $\{-4, -3, -2, -1, 0, 1, 2, 3\}$
- each point has probability 1/8



Sparse Binary/Ternary (Fixed Hamming weight)

■ **Ternary**: length n vector $s \in \mathbb{Z}^n$ that has exactly p "+1"s and m "-1"s, and "0"s for the left:

$$\begin{cases} -1: & m \\ 0: n-m-p \\ 1: & p \end{cases} \approx \begin{cases} -1: \frac{m}{n} \\ 0: 1-\frac{m+p}{n} \\ 1: \frac{p}{n} \end{cases}$$

Binary: use m = 0 (or without an input m)

Sparse Binary/Ternary (Fixed Hamming weight) (E.g.)

```
>>> ND.SparseTernary(256, 64, 64)
>>> ND.SparseTernary(256, 128)
```

■ **Ternary**: length=256, Hamming weight = 128

$$\begin{cases}
-1: & 64 \\
0: & 128 \\
1: & 64
\end{cases}$$

■ **Binary:** length=256, Hamming weight = 128

```
\left\{ \begin{array}{ccc} 0: & 128 \\ 1: & 128 \end{array} \right.
```

User-define distributions "estimator/nd.py"

```
@staticmethod
def MyDistribution(n=None):
  # E.g. -1: 1/8, 0: 3/4, 1: 1/8
  # mean = 1/8*(-1) + 3/4*0 + 1/8*1 = 0
  # stddev = sqrt(1/8*(-1-0)**2 + 3/4*(0-0)**2 + 1/8*(1-0)**2) = 1/2
  # density (ratio of non-zero coefficients) = 1/8+1/8 = 1/4
  D = NoiseDistribution(
      n=n,
      stddev=RR(1/2),
      mean=RR(0),
      density=1/RR(4),
      bounds=(-1, 1),
      tag="MyDistribution")
  return D
```

Lattice Estimator: Cost Models

- Supported cost models "estimator/reduction.py"
 - ADPS16—New Hope
 - ABFKSW20
 - ABLR21
 - ChaLoy21
- We mainly focus on [ADPS16], with methodology a.k.a. *Core-SVP method*: for BKZ block-size β ,

```
Attack cost \approx \begin{cases} \text{Classical} : 2^{0.292\beta} \\ \text{Quantum} : 2^{0.265\beta} \text{ (or } 2^{0.257\beta} \text{ following [ChaLoy21])} \end{cases}
```

Install Sagemath (already there in 10-10 server: tenten.heaan.info:8000)

 Download lattice estimator from github.com/malb/latticeestimator
 Or

git clone https://github.com/malb/lattice-estimator.git

Make a Python file or a Jupyter notebook in "latticeestimator" directory using sagemath console.

Try rough estimation..

```
from estimator import *
from estimator.nd import NoiseDistribution, stddevf
from estimator.lwe_parameters import LWEParameters
from estimator.lwe import estimate
MyParam = LWEParameters(n=256, q=1024,
        Xs=NoiseDistribution.CenteredBinomial(3),
        Xe=NoiseDistribution.SparseTernary(256, 40, 40),
        m = 256,
        tag="MyParam",
r = LWE.estimate.rough(MyParam)
                                         # usvp & dual_hybrid only
```

And full estimation..

```
r = LWE.estimate(MyParam) # more attacks
```

How to read?

```
usvp :: rop: ≈2^148.7, red: ≈2^148.7, δ: 1.003818, β: 425, d: 879, tag: usvp dual :: rop: ≈2^155.9, mem: ≈2^101.3, m: 414, β: 447, d: 926, ℧: 1, tag: dual
```

Default: MATZOV (classical)

- Attack costs
 - rop: number of required ring operations
 - i.e. $\geq 2^{148.7}$ and $\geq 2^{155.9}$ ring operations
 - red: rop for lattice reduction
 - β: BKZ block size
 - mem: memory requirement in integers mod q
 - i.e. $\geq 2^{101.3} \cdot \log q$ bits of memory
 - m: number of required samples
 - U: required number of expected repetitions

- Try different models:
 - ADPS16 (classical)

```
from estimator.reduction import *
r = LWE.estimate(MyParam, red_cost_model=ADPS16("classical"))
```

```
\beta: BKZ block size \begin{cases} \text{Core-SVP} \\ \text{Quantum} : 2^{0.292\beta} \end{cases}
```

ADPS16 (quantum)

```
r = LWE.estimate(MyParam, red_cost_model=ADPS16("quantum"))
```

ChaLoy21 (quantum only)

```
r = LWE.estimate(MyParam, red_cost_model=ChaLoy21)
```

Try SIS:

SIS with 2-norm bound

params = SIS.Parameters(n=113, q=2048, length_bound=512, norm=2) SIS.lattice(params)

SIS with ∞-norm bound

params = SIS.Parameters(n=113, q=2048, length_bound=50, norm=00) SIS.lattice(params)

Try NTRU:

NTRU usvp

```
params = NTRU.Parameters(n=200, q=7981, Xs=ND.UniformMod(3), Xe=ND.UniformMod(3))
NTRU.primal_usvp(params, red_shape_model="gsa")
NTRU.primal_usvp(params, red_shape_model=Simulator.CN11)
```

NTRU hybrid

NTRU.primal_hybrid(params, red_shape_model=Simulator.CN11)

NTRU overstretched parameters

```
params.possibly_overstretched
NTRU.primal_dsd(params, red_shape_model=Simulator.ZGSA)
# or with different model: NTRU.primal_dsd(params,
red_shape_model=Simulator.CN11)
```

IND-CCA security of Kyber.KEM reduces to MLWE instances.

- NIST's security levels 1, 3, and 5:
 - Target Core-SVP: 2¹²⁰, 2¹⁸⁰, 2²⁵⁰
 - Hash function entropy: 2^{192} , 2^{225} , 2^{257}

- IND-CCA security of Kyber.KEM reduces to MLWE instances, if there is no decryption failures.
 - NIST's security levels 1, 3, and 5:
 - Target Core-SVP: 2¹²⁰, 2¹⁸⁰, 2²⁵⁰
 - Hash function entropy: 2^{192} , 2^{225} , 2^{257}
- Decryption failure probability
 - Attacks exploiting failures exists [DKRV18][DGJ+19][DB22]
 - It should be low enough: (ideally) 2^{-120} , 2^{-180} , 2^{-250}

- Kyber Recap:
 - Matrices and vectors over $\mathcal{R}_q = \mathbb{Z}_q[x]/(x^N+1)$

pk:
$$\left(k \middle| A \middle| \right)$$

(compressed) CtXt:
$$\left(\left\lfloor \frac{2^{du}}{q} \cdot \left\lceil A^{t} \right\rceil + \left\lceil \frac{2^{dv}}{q} \cdot \left\lceil \frac{2^{dv}}{q} \cdot \left\lceil \frac{q}{q} \cdot M \right\rceil \right\rceil \right) \right] \right)$$

Kyber Security: MLWE

Public key

Cf. matrices and vectors over $\mathcal{R}_q = \mathbb{Z}_q[x]/(x^N+1)$

pk:
$$\left(\begin{array}{c} k \\ A \end{array}\right)$$
, $\left[\begin{array}{c} t \\ \end{array}\right] = \left[\begin{array}{c} A \\ \end{array}\right] + \left[\begin{array}{c} e \\ \end{array}\right]$

- MLWE instances $MLWE_{n, k, l, q, \chi_s, \chi_e}$ with
 - n = 256 (ring dimension)
 - k = l = 2, 3, 4 (depending on security level)
 - q = 3329
 - $\chi_s = \text{CBD}(\eta_1)$, $\eta_1 = 2 \text{ or } 3$ (depending on security level)

 \Rightarrow LWE instances $LWE_{nk, nk, q, CBD(\eta_1), CBD(\eta_1)}$

Kyber Security: MLWE

Ciphertext

Cf. matrices and vectors over $\mathcal{R}_q = \mathbb{Z}_q[x]/(x^N + 1)$

(raw) ctxt:
$$\left(\begin{array}{c|c} A^{t} & r + e \\ \hline \end{array} \right)$$

$$\approx \left(\begin{array}{c|c} k \\ \hline A \\ \hline \end{array} \right)$$

$$\approx \left(\begin{array}{c|c} k \\ \hline A \\ \hline \end{array} \right)$$

$$A^{t} & r + e \\ \hline \end{array} \right)$$

- MLWE instances $MLWE_{n, k, l, q, \chi_s, \chi_e}$ with
 - l = k + 1
 - for all other parameters, the same as before

 \Rightarrow LWE instances $LWE_{nk, n(k+1), q, CBD(\eta_1), CBD(\eta_1)}$

Kyber Security: MLWE

```
Kyber512 = LWEParameters(n=256*2, q=3329,
         Xs=NoiseDistribution.CenteredBinomial(3),
         Xe=NoiseDistribution.CenteredBinomial(2),
         m=256*3, tag="Kyber512")
Kyber768 = LWEParameters(n=256*3, q=3329,
         Xs=NoiseDistribution.CenteredBinomial(2),
         Xe=NoiseDistribution.CenteredBinomial(2),
         m=256*4, tag="Kyber512")
Kyber1024 = LWEParameters(n=256*4, q=3329,
         Xs=NoiseDistribution.CenteredBinomial(2),
         Xe=NoiseDistribution.CenteredBinomial(2),
         m=256*5, tag="Kyber1024")
r512 =
         LWE.estimate(Kyber512,
                                    red cost model=ADPS16("classical"))
r768 =
         LWE.estimate(Kyber768,
                                    red cost model=ADPS16("classical"))
r1024 =
         LWE.estimate(Kyber1024,
                                    red cost model=ADPS16("classical"))
```

- Decryption Failure Probability
 - Many sources of error:
 - inherent MLWE errors: e, e_1 , e_2
 - compression errors: c_1 , c_2
 - occurs during modulus switching from q to 2^{d_1} or 2^{d_2}
 - combination of the errors
 - multiplied and added
 - \blacksquare Decryption fails (i.e. not output m) with probability

$$\delta = \Pr\left[\|\boldsymbol{e}^t \cdot \boldsymbol{r} + \boldsymbol{e}_2 + \boldsymbol{c}_2 - \boldsymbol{s}^t \cdot \boldsymbol{e}_1 - \boldsymbol{s}^t \cdot \boldsymbol{c}_1\|_{\infty} \ge \left\lfloor \frac{q}{4} \right\rfloor\right]$$

- DFP estimator:
 - available at https://github.com/pq-crystals/security-estimates
 - use their "proba_util.py"

```
import operator as op-
from math import factorial as fac
from math import sqrt, log
import sys
from proba_util import *
q = 3329
eta1=3
eta2=3
                   # ctxt error distribution (CBD(2)) for level 1,
eta3=2
n = 256
                                                        # otherwise eta2=eta3
k=2
d1=10
d2 = 4
```

DFP estimator (Cont'd)

```
\delta = \Pr\left[\|\boldsymbol{e}^t \cdot \boldsymbol{r} + \boldsymbol{e}_2 + \boldsymbol{c}_2 - \boldsymbol{s}^t \cdot \boldsymbol{e}_1 - \boldsymbol{s}^t \cdot \boldsymbol{c}_1\|_{\infty} \ge \left\lfloor \frac{q}{4} \right\rfloor\right]
```

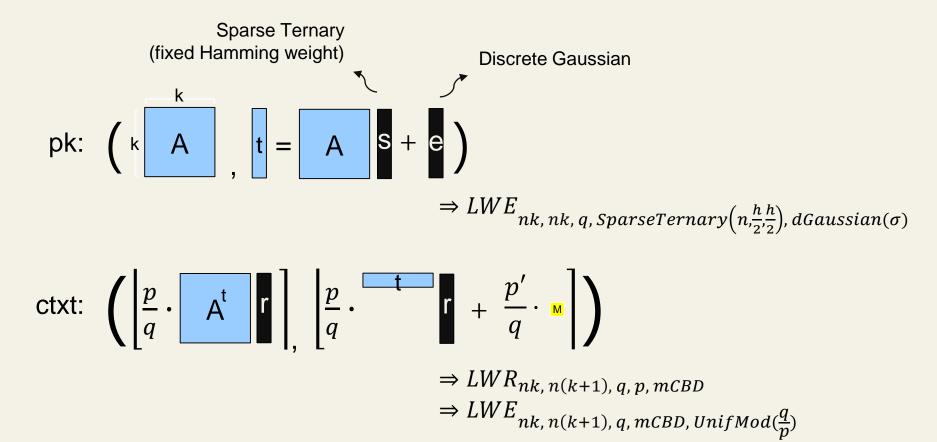
```
# Initialize secrets and errors
Ds = build_centered_binomial_law(eta1)
                                                 # identical to Dr
De = build_centered_binomial_law(eta2)
                                                 # identical to De1, De2
De1 = build_centered_binomial_law(eta3)
                                                 # identical to De2
# Compression errors
Dc1 = build_mod_switching_error_law(q, 2**d1)
Dc2 = build_mod_switching_error_law(q, 2**d2)
# Combinations
Dc1_e1 = law_convolution(Dc1, De1)
                                                                     # c1+e1
Der = iter_law_convolution(law_product(De, Ds), n*k)
                                                                     # er
Dse1_sc1 = iter_law_convolution(law_product(Ds, Dc1_e1), n*k)
                                                                     # se1+sc1
D = law_convolution(Der, Dse1_sc1)
                                                           # er-se1-sc1
D = law_convolution(D, De1)
                                                           # er+e2-se1-sc1
D = law\_convolution(D, Dc2)
                                                           # final
prob = tail_probability(D, q/4)
print("DFP:", log(n*prob)/log(2))
```

```
import operator as op
from math import factorial as fac
from math import sqrt, log
import sys
from proba util import *
q=3329
eta1=3
eta2=3
eta3=2
                                                   # ctxt error distribution (CBD(2)) for level 1, otherwise eta2=eta3
n=256
k=2
d1 = 10
d2 = 4
# Initialize secrets and errors
Ds = build centered binomial law(eta1)
                                                   # equal to Dr
De = build_centered_binomial_law(eta2)
                                                   # equal to De1, De2
De1 = build centered binomial law(eta3)
                                                   # equal to De2
# Compression errors
Dc1 = build mod switching error law(q, 2**d1)
Dc2 = build mod switching error law(q, 2**d2)
# Combinations
Dc1 e1 = law convolution(Dc1, De1)
                                                                    # c1+e1
Der = iter_law_convolution(law_product(De, Ds), n*k)
                                                                    # er
Dse1 sc1 = iter law convolution(law product(Ds, Dc1 e1), n*k)
                                                                    # se1+sc1
D = law_convolution(Der, Dse1_sc1)
                                                   # er-se1-sc1
D = law convolution(D, De1)
                                                   # er+e2-se1-sc1
D = law convolution(D, Dc2)
                                                   # final
prob = tail probability(D, q/4)
print("DFP:", log(n*prob)/log(2))
```

```
ps_light = KyberParameterSet(256, 2, 3, 3, 3329, 2**12, 2**10, 2**4, ke_ct=2) ps_recommended = KyberParameterSet(256, 3, 2, 2, 3329, 2**12, 2**10, 2**4) ps_paranoid = KyberParameterSet(256, 4, 2, 2, 3329, 2**12, 2**11, 2**5)
```

Note, we will take a look on Smaug v4.0, which is not yet public ©

 IND-CCA security of Smaug.KEM reduces to MLWE and MLWR instances with low enough DFPs.



- Modified CBD, base 16:
 - CBD(1)=mCBD(4): -1: 4/16, 0: 8/16, 1: 4/16
 - mCBD(3):
 -1: 3/16, 0: 10/16, 1: 3/16
 - mCBD(2): -1: 2/16, 0: 12/16, 1: 2/16
 - mCBD(1): -1: 1/16, 0: 14/16, 1: 1/16
- ModSwitch error (when p|q)
 - $a \mapsto a' \coloneqq \left(\left\lfloor \frac{p}{q} \cdot (a \bmod q) \right\rfloor \bmod p \right)$

- Level 1:
 - n=256, k=2, q=1024, p=256, p'=32
 - Public key:
 - Secret (s): fixed Hamming weight of h=140
 - Ds=SparseTernary(n, 70, 70)
 - - D $LWE_{nk, nk, q, SparseTernary(n, \frac{h}{2}, \frac{h}{2}), dGaussian(\sigma)}$
 - Cipl & $LWE_{nk, n(k+1), q, mCBD, UnifMod(\frac{q}{p})}$
 - Secret (r): mCBD(2)
 - Need to define this distribution!
 - Error: ModSwitch error from q to p (and p')
 - UniformMod(q/p) and UniformMod(q/p')

Smaug Security: DFP

- Decryption Failure Probability
 - Sources of error:
 - MLWE error:
 - $e \sim dGaussian(sigma)$
 - MLWR ModSwitch errors:
 - $e_1 \sim \text{UniformMod(q/p)}$
 - $e_2 \sim \text{UniformMod(q/p')}$
 - Decryption fails (i.e. not output m) with probability

$$\delta = \Pr\left[\|\boldsymbol{e}^t \cdot \boldsymbol{r} + e_2 - \boldsymbol{s}^t \cdot \boldsymbol{e}_1\|_{\infty} \ge \frac{q}{4}\right],$$

where

- $s \sim \text{SparseTernary}(\text{nk}, \text{h/2}, \text{h/2}),$
- $r \sim \text{mCBD}(2)$

Smaug Security: Tutorial Guideline 1

User-define modules for mCBD

```
CBD(1)=mCBD(4): -1: 4/16, 0: 8/16, 1: 4/16
mCBD(3): -1: 3/16, 0: 10/16, 1: 3/16
mCBD(2): -1: 2/16, 0: 12/16, 1: 2/16
mCBD(1): -1: 1/16, 0: 14/16, 1: 1/16
```

- 'ModifiedCBD(numCBD, n=None)' in "estimator/nd.py"
 - for security estimation
- 'build_mCBD_law(numCBD)' in "security-estimates/proba_util.py"
 - for DFP calculation

Smaug Security: Tutorial Guideline 2

- Security Estimation
 - Lvl 1.
 - n=256, k=2, q=1024, p=256, p'=32, sig=1.0625, h=140, numCBD=2
 - Lvl 3.
 - n=256, k=3, q=2048, p=512, p'=16, sig=1.0625, h=264, numCBD=4
 - Lvl 5.
 - n=256, k=4, q=2048, p=512, p'=128, sig=1.0625, h=348, numCBD=3

 $LWE_{nk, nk, q, SparseTernary(nk, h/2, h/2), dGaussian(\sigma)}$ & $LWE_{nk, n(k+1), q, mCBD, UnifMod(q/p)}$

Smaug Security: Tutorial Guideline 3

- Decryption Failures
 - MLWE error $e \sim dGaussian(sigma)$
 - MLWR ModSwitch errors:
 - $e_1 \sim \text{UniformMod(q/p)}$
 - $e_2 \sim \text{UniformMod}(q/p')$
 - Secret vectors:
 - $s \sim \text{SparseTernary}(\text{nk}, \text{h/2}, \text{h/2}),$
 - $r \sim \mathsf{mCBD}(*)$

$$\delta = \Pr\left[\|\boldsymbol{e}^t \cdot \boldsymbol{r} + \boldsymbol{e}_2 - \boldsymbol{s}^t \cdot \boldsymbol{e}_1\|_{\infty} \ge \frac{q}{4} \right]$$

Thank You!