

# Practical lattice reductions

for CTF challenges

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## Outline

1. Lattices?
2. Why lattices?
3. How lattices?
4. Lattice tips and tricks
5. Common lattice problems
6. Building with lattices
7. Get your hands dirty

# Lattices?

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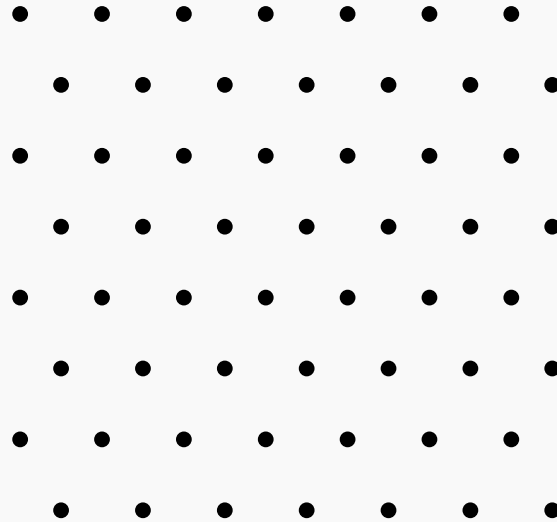
# Lattices

- “A lattice  $\mathcal{L}$  of dimension  $n$  is a discrete additive subgroup of  $\mathbb{R}^n$ .”
- It’s a group  $\Rightarrow$  addition, scalar mult
- Discrete  $\Rightarrow$  we can map it to  $\mathbb{Q}^n$  or  $\mathbb{Z}^n$
- A group is a  $\mathbb{Z}$ -module, so think vector spaces
- Pick a basis  $B = (\mathbf{b}_1, \dots, \mathbf{b}_n) \in \mathbb{R}^n$ 
  - We usually write  $\mathbf{b}_i$  as rows of  $B$
- $\mathcal{L} = \{ \sum a_i \cdot \mathbf{b}_i \mid \mathbf{a} \in \mathbb{Z}^n \}$
- Many choices of  $B$

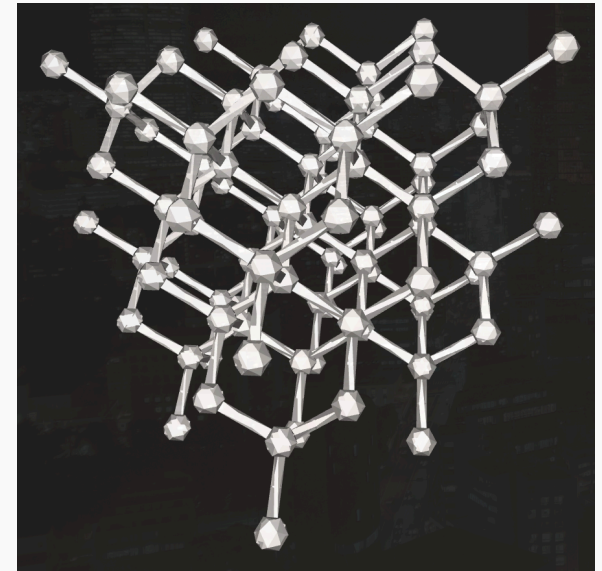
# Lattices



<https://www.redwoodstore.com/spectre-fan-lattice>

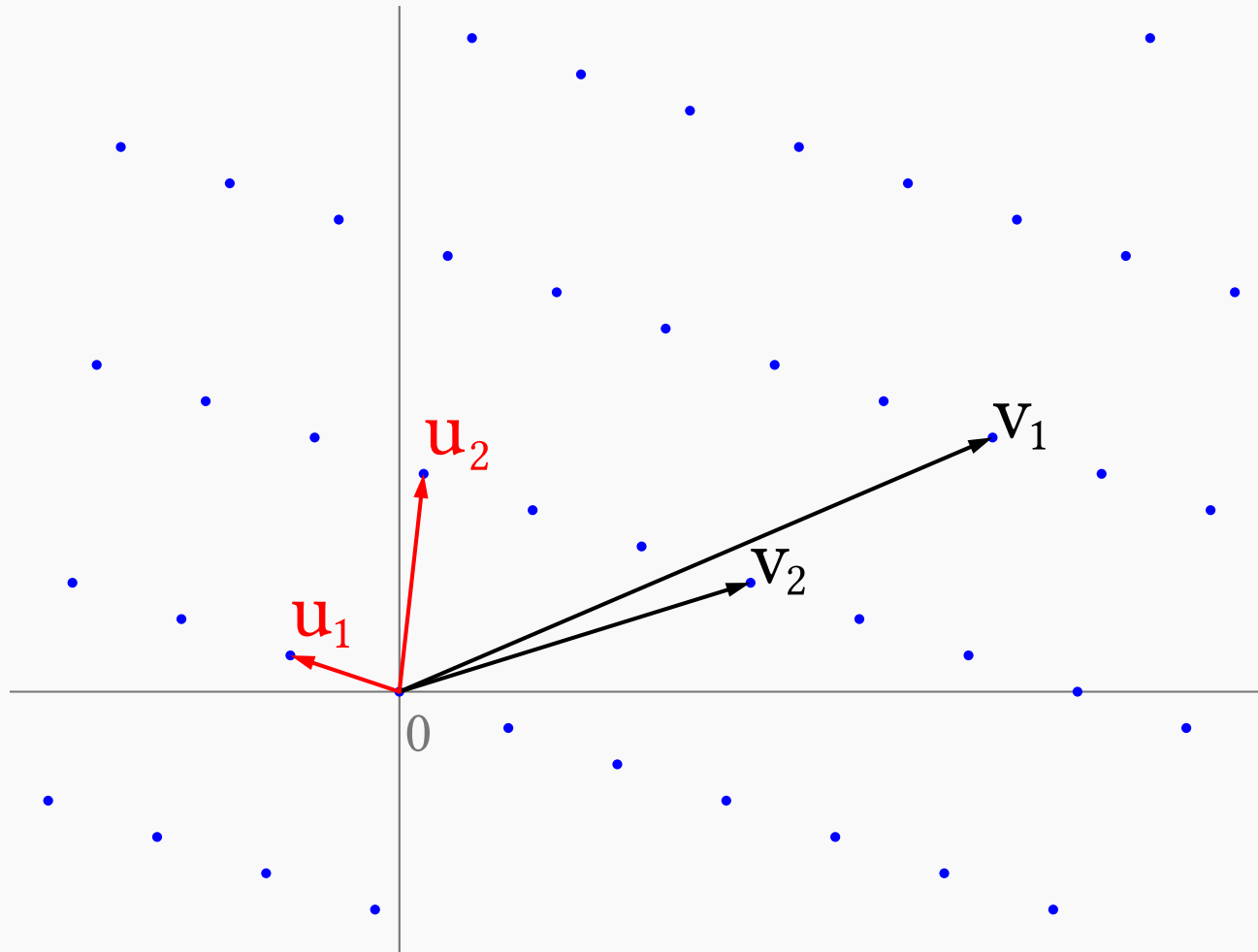


[https://en.wikipedia.org/wiki/Lattice\\_%28group%29](https://en.wikipedia.org/wiki/Lattice_%28group%29)



[https://en.wikipedia.org/wiki/File:Diamond\\_lattice.stl](https://en.wikipedia.org/wiki/File:Diamond_lattice.stl)

# Lattices

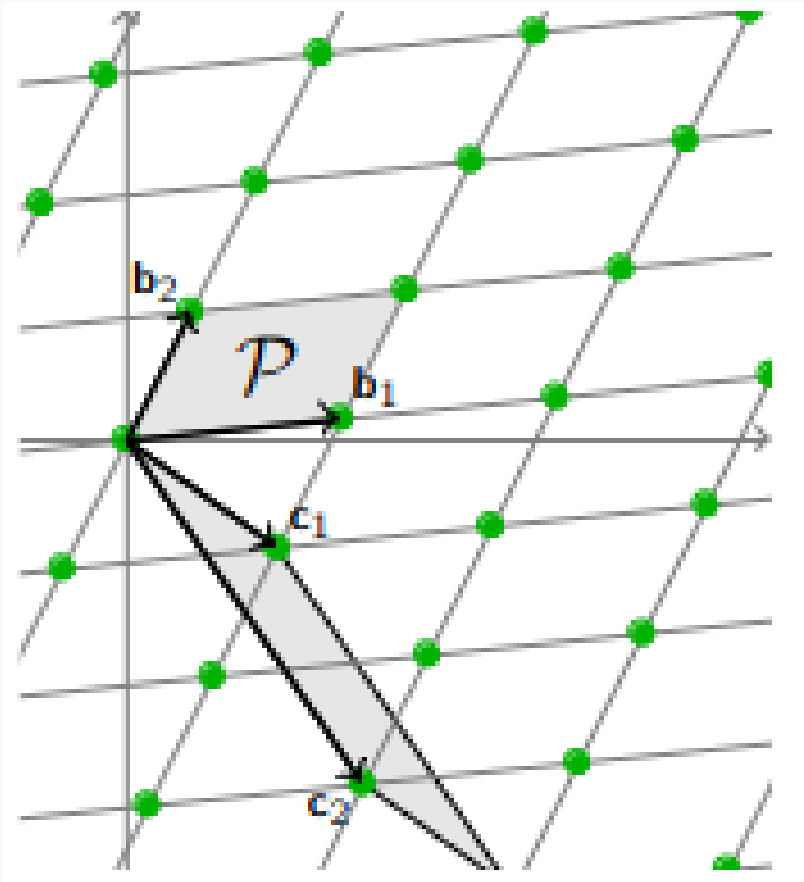


[https://en.wikipedia.org/wiki/Lattice\\_reduction](https://en.wikipedia.org/wiki/Lattice_reduction)

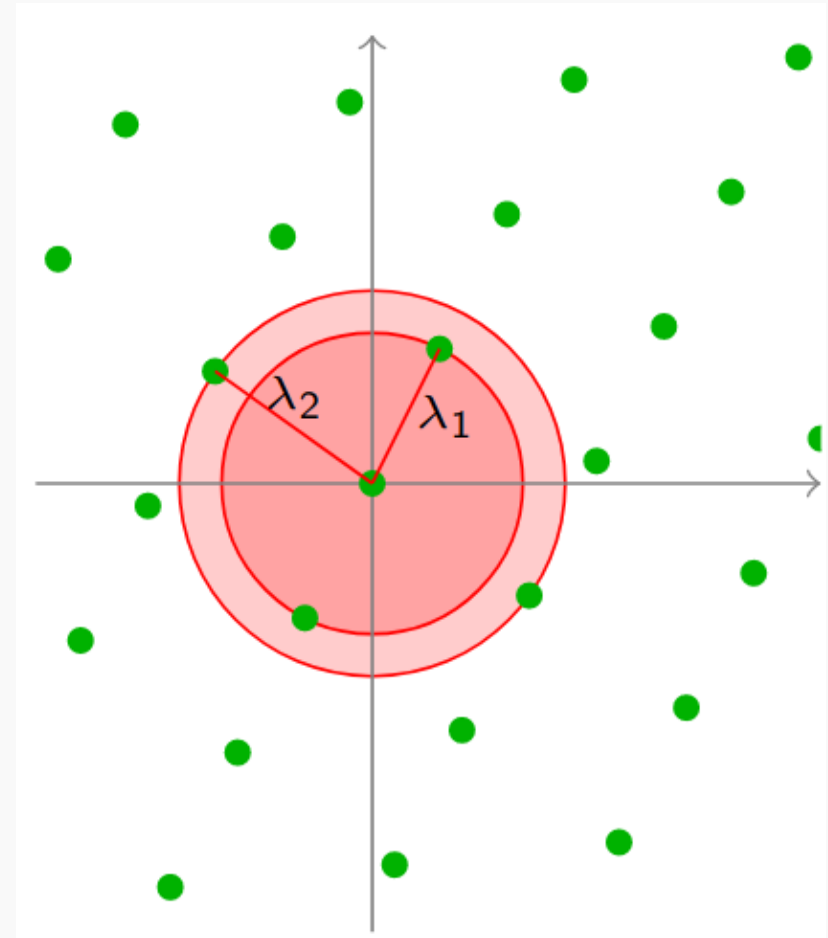
# Lattice properties

- “Fundamental parallelepiped”  $\mathcal{P}(\mathbf{B})$ : a single “enclosed region”
  - $\mathcal{P}(\mathbf{B}) = \{\sum a_i \cdot \mathbf{b}_i \mid \mathbf{a} \in [0, 1)\}$
  - $\mathbb{R}^n$  is tiled by  $\mathcal{P}(\mathbf{B})$
- $\det(\mathcal{L}) = \text{vol}(\mathcal{P}(\mathbf{B})) = |\det(\mathbf{B})|$ 
  - Invariant, independent of  $\mathbf{B}$
  - Base change: invertible and unimodular
- Successive minima:  $\lambda_i(\mathcal{L})$ 
  - $\lambda_1(\mathcal{L})$  length of **shortest vector**
  - $\lambda_1(\mathcal{L}) \leq \sqrt{n} |\det(\mathcal{L})|^{\frac{1}{n}}$
  - $\text{GM}(\lambda_1, \dots, \lambda_n) = (\prod \lambda_i)^{\frac{1}{n}} \leq \sqrt{n} |\det(\mathcal{L})|^{\frac{1}{n}}$
- Distance  $\mu(\mathbf{t}, \mathcal{L}) = \min_{\mathbf{v} \in \mathcal{L}} \|\mathbf{t} - \mathbf{v}\|$

# Lattice properties



<https://simons.berkeley.edu/sites/default/files/docs/14953/intro.pdf>



<https://simons.berkeley.edu/sites/default/files/docs/14953/intro.pdf>



```
from sage.modules.free_module_integer import IntegerLattice
B = Matrix(QQ, [[1, 0], [0, 2]])/2
L = IntegerLattice(B.denominator() * B, lll_reduce=False)
# Warning, may be slow :)
L.shortest_vector() # (1, 0)
L.closest_vector((123/42, 345/12)) # (3, 28)

L.volume() # 2
```

# Why lattices?

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# Why lattices? Part 1: construction

- Many things in lattices are hard
- SVP: “shortest vector problem”
- CVP: “closest vector problem”
- SIS: “short integer solutions”
- $\Rightarrow$  build trapdoors, e.g. LWE
- Hopefully post-quantum too
- See later

# Why lattices? Part 2: destruction

- Many things are “small”
- Many things are discrete
- e.g. some instances of integer programming
- RSA:  $pq - \varphi(pq) = p + q - 1$  is “small” wrt.  $pq$
- Breaking lattice schemes
- Generally: linear structure
- **Think about linear systems with small solutions**

# Why lattices? Part 2: destruction

- Known to break many crypto “weaknesses”
- Some bias in your RNG? Lattices will break it.
- Chose your RSA private key wrong? Lattices will break it.
- Lost some precision in your floating points calculations? Lattices might help.
- Some think they even might break factoring :)

How lattices?

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# Improving a basis

- Starting point: *some* basis  $B$
- Goal: *good* basis  $B'$
- But what is good?
- And how do we find it?

# Good lattices

- Goal: find a better basis
- Good basis?
  - Shorter basis vectors
  - Close to orthogonal
  - Find some short vectors
- Great basis?
  - Read off  $\lambda_1(\mathcal{L})$
  - Read off all  $\lambda_i(\mathcal{L})$ ?



# Intuition from linear algebra

- We know  $\det(\mathcal{L})$  is constant
- Want: shorter  $\mathbf{b}_i$
- So we need wider angles between all  $\mathbf{b}_i$  to have more area
- Hence, more orthogonal
  
- Gram-Schmidt orthogonalization
- But breaks the lattice
- Use it as a guideline

# Lattice reduction algorithms

- LLL (Lenstra–Lenstra–Lovász)
  - Polynomial time  $\mathcal{O}\left(n^6 \log^3 \|B\|_\infty\right)$
  - $\|b'_1\| \leq 2^{\frac{n-1}{2}} \lambda_1(\mathcal{L})$
- HKZ (Hermite–Korkine–Zolotarev)
  - Exponential time
  - $\|b'_1\| = \lambda_1(\mathcal{L})$
- BKZ (Block (H)KZ)
  - Parametrized by block size  $\beta$
  - Larger  $\beta$ : slower
  - Smaller  $\beta$ : worse basis
- Sieving and other costly approaches

# Basis reduction in 2D

- In two dimensions, exact is easy
- Provides some basic intuition for LLL
- Looks like GCD

```
def gauss_reduction(v1, v2):  
    while True:  
        if v2.norm() < v1.norm():  
            v1, v2 = v2, v1 # swap step  
        m = round( (v1 * v2) / (v1 * v1) )  
        if m == 0:  
            return (v1, v2)  
        v2 = v2 - m*v1 # reduction step
```

# A brief look at LLL

```
def LLL(B, delta):
    Q = gram_schmidt(B)

    def mu(i,j):
        v = B[i]
        u = Q[j]
        return (v*u) / (u*u)

    n, k = B.nrows(), 1
    while k < n:

        # length reduction step
        for j in reversed(range(k)):
            if abs(mu(k,j)) > .5:
                B[k] = B[k] - round(mu(k,j))*B[j]
                Q = gram_schmidt(B)

        # swap step
        if Q[k]*Q[k] >= (delta - mu(k,k-1)**2)*(Q[k-1]*Q[k-1]):
            k = k + 1
        else:
            B[k], B[k-1] = B[k-1], B[k]
            Q = gram_schmidt(B)
            k = max(k-1, 1)

    return B
```

# Lattice tips and tricks

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# Weights

$$z = a_1 v_1 + \dots + a_m v_m$$

- $m > n$
- All  $a_i$  small
- Linear system with a small solution
  - But underdetermined
  - So not just linear algebra
- (approximate) SVP would find a short solution

$$\begin{pmatrix} z & 0 & 0 & \dots & 0 \\ -v_1 & 1 & 0 & \dots & 0 \\ -v_2 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -v_m & 0 & 0 & \dots & 1 \end{pmatrix}$$

- **But**, what if we have some remaining *short*  $r = z - \sum a_i v_i$ ?
- To LLL, short is short
- Assign higher weights  $W$  to first columns
  - $\Rightarrow W r$  not so short anymore
  - Could even vary  $W_i$  for element of  $z$
- **Note:** short vectors can also be the negation of what you search

# Weights

$$\begin{pmatrix} Wz & 0 & 0 & \dots & 0 \\ -Wv_1 & 1 & 0 & \dots & 0 \\ -Wv_2 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -Wv_m & 0 & 0 & \dots & 1 \end{pmatrix}$$

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```
z = vector(ZZ, [...])
v = Matrix(ZZ, m, n, [[...], ...])
L = Matrix.block([[Matrix(z), 0], [v, 1]])
W = Matrix.diagonal([w1, w2, ..., wn, 1, 1, ..., 1])
L = (L * W).LLL() / W
```



# How to determine weights

1. Wing it and hope for the best :)
  - Works fairly often
  - Can finetune with synthetic data
  - Wiggling weights can even help finding different solutions
2. Investigate expected weights
  - Mostly when different columns have different expected weights in the target vector
  - Observe: outliers in  $\|\mathbf{v}\| = \sqrt{v_1^2 + \dots + v_n^2}$  weigh more
  - So the goal is: make all  $v_i$  roughly equal
    - Investigate expected result in target vector
    - Modify weights per column so target vector is all 1 (or arbitrary constant like  $2^{128}$ )

- Sometimes, switch view to CVP
- Rather than solving a linear system, you're close to some lattice point
- e.g. integer multiple + random noise (see LWE later)
- So looking for a lattice vector close to our target
  - Either close vector is final goal
  - Or just solve with linear algebra after
- If you have a range of values, put the target in the center

## Kannan embedding

$$\begin{pmatrix} B & 0 \\ t & q \end{pmatrix}$$

- Embed CVP into an SVP instance
- Likely close to what you started with
- Short vector:  $(t - Bc, q)$
- $q \sim$  a weight, matters for results

## Babai's closest plane

- Uses a reduced basis for the original lattice
- Greedy algorithm
- Iteratively project each coordinate onto the closest hyperplane
- In sage, over  $\mathbb{Q}$ : GS step is generally slow
  - Exact numbers that grow fast-ish

```
def Babai_CVP(mat, target):  
    M = IntegerLattice(mat, lll_reduce=True).reduced_basis  
    G = M.gram_schmidt()[0]  
    diff = target  
    for i in reversed(range(G.nrows())):  
        diff -= M[i] * ((diff * G[i]) / (G[i] * G[i])).round()  
    return target - diff
```

# Try different reductions

- When LLL is fast enough, but gives no results
- Consider trying BKZ instead
- Experiment with block size  $\beta$ , synthetic data is good
- $(\beta = n) \equiv \text{HKZ}$
- For more speed (especially coppersmith): consider flatter

# Magic tricks for fast exploration

- Got a linear system and some bounds?
- Why not try asking nicely
- rkm0959 made a tool/library: `rkm0959/Inequality_Solving_with_CVP`
- Could even make a wrapper for convenience
- Good for first exploration, not always foolproof

# Enumeration

- Your target is not always the shortest
- Or even in the basis for that matter
- It's still short though
  - It's a small linear combination of basis vectors
  - Try bruteforce
  - Or random combinations
- `fp(y)lll` also has structured enumeration
- Optionally with extra pruning
- badly documented
  - <https://fpylll.readthedocs.io/en/latest/modules.html>

# fpyll enumeration

```
from fpylll import IntegerMatrix
from fpylll.fplll.gso import MatGSO
from fpylll.fplll.enumeration import (Enumeration,
                                       EvaluatorStrategy)

A = IntegerMatrix.from_matrix(M.LLL())
count = 2000
G = MatGSO(A)
G.update_gso()
enum = Enumeration(G, nr_solutions=count,
                  strategy=EvaluatorStrategy.BEST_N_SOLUTIONS)
n = M.nrows()
for vec, length in enum.enumerate(0, n, max_dist, 0, t):
    ...
```



# Polynomials

- Polynomials form a vector space
  - If degree is bounded/fixed
  - Over  $\mathbb{R}$  or otherwise
- So we can take a discrete additive subgroup of them
- Look, ma, it's a lattice!
- Basis for coppersmith's method and ring-LWE (see later)

- Hmm, I have a lattice over  $\mathbb{F}_2$
- While that may be true, “small” mostly breaks down
- Have a look at coding theory instead
- Techniques like *ISD* can be very powerful here
- Can also apply over
  - $\mathbb{F}_3$  or other small fields
  - Fields of small characteristic ( $\mathbb{F}_{2^k}$  etc)

# Common lattice problems

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# Making things modular

- Instead of working over  $\mathbb{Z}$ , we now want  $\mathbb{Z}/q\mathbb{Z}$
- Keep thinking about linear systems
- $\sum a_i x_i \equiv y \pmod{q}$
- $\sum a_i x_i = y + kq$
- Repeat a few times
- Stack  $q \cdot I_m$  under your matrix

# Knapsack and Subset Sum

- Given:
  - A set  $S = \{s_1, \dots, s_n\}$
  - A value  $v = \sum b_i s_i$ , with  $b_i \in \{0, 1\}$
- Find appropriate  $b_i$
- Often called a knapsack problem
- More accurately it's a subset sum problem
  - there are no values attached
- Known public key cryptosystem
  - Merkle-Damgård
  - Broken by lattices (low density)

# Knapsack and Subset Sum

$$\begin{pmatrix} v & 0 & 0 & \dots & 0 \\ -s_1 & 1 & 0 & \dots & 0 \\ -s_2 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -s_n & 0 & 0 & \dots & 1 \end{pmatrix}$$

- Short vector  $(0, b_1, b_2, \dots, b_n)$
- Rephrase as CVP
  - Leave out first row
  - Target:  $(v, 0, 0, \dots, 0)$
- Optimize CVP:
  - Want  $b_i \in \{0, 1\}$ , so centered around  $\frac{1}{2}$
  - Can do the same trick in the original lattice

# Knapsack and Subset Sum

## Think about it:

- What about a more general version
  - $b_i \in \mathcal{X}$
  - Knapsack: optimize for some value  $t_i$
  - Dealing with negative numbers
  - Parallel instances
  - Modular
  - ...
- *Hidden* Subset Sum problem
- Don't forget to look at the negatives in your reduced basis!

# Approximate GCD

- Given: samples  $x_i = q_i p + r_i$ , with small  $r_i$
- Target: Find  $p$ , the gcd of the samples, up to errors  $r_i$
- *Partial* AGCD:  $r_0 = 0$ 
  - i.e.  $x_0 = q_0 p$
  - e.g. RSA with extra information



- $\frac{x_i}{x_0} \approx \frac{q_i}{q_0}$
- Find candidate  $q_0$
- Recover  $p$  from  $x_0, q + 0$
- Short vector:  $(Wq_0, q_0r_1 - q_1r_0, \dots)$

$$\begin{pmatrix} W & x_1 & x_2 & \dots & x_n \\ 0 & x_0 & 0 & \dots & 0 \\ 0 & 0 & x_0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & x_0 \end{pmatrix}$$

# AGCD: Orthogonal lattice

- Orthogonal lattice
  - $\mathcal{L}^\perp = \{v \mid \forall b \in \mathcal{L}, \langle v, b \rangle = 0\}$
  - Observe:  $\mathcal{L} \subseteq (\mathcal{L}^\perp)^\perp$
  - Useful for some problems, including hidden subset sum
- General idea: find short vector *orthogonal* to some target
  - Often just to one vector or a lattice with 2 basis vectors
  - Then derive some useful quantity
- $\mathcal{L}(q, r)^\perp \subseteq \mathcal{L}(x)^\perp$ , and short
- reduce  $\mathcal{L}(x)^\perp$  to find a sub-basis spanning  $\mathcal{L}(q, r)$
- recover  $q, r$

# Hidden Number Problem

$$\alpha_i x + \rho_i k_i \equiv \beta_i \pmod{N}$$

- $k_i$  bounded
- See (EC)DSA biased nonce attacks
  - $\alpha_i = -r_i$ ,  $\rho_i = s_i$ ,  $\beta_i = H - 2^t \text{MSB}_{\text{nonce}}$ ,  $k_i = \text{LSB}_{\text{nonce}}$
- Key realization:  $k_i \equiv \frac{\beta_i - \alpha_i x}{\rho_i}$  is bounded/small
  - Try to build the lattice ;)
  - Or read biased nonce papers
- Generalization: EHNP
  - Support multiple “holes”
  - Formulation gets complex
  - “Just” implementing the paper is feasible

# Coppersmith's Method

- Shift in focus
  - No longer linear systems... one polynomial
- $f(x) \equiv 0 \pmod{N}$ , monic,  $x < X$  bounded
  - Or even  $\text{mod } d \approx N^\beta$  with  $d \mid N$
- Sage has `f.small_roots()`, with some parameters
  - or use implementation from `kiona/defund/...`
  - `flatter` usually works very well for these
- $X < N^{\frac{\beta^2}{\deg(f)} - \varepsilon}$ 
  - $\varepsilon$  is a useful parameter for sage
  - Smaller  $\varepsilon$  is slower, maybe brute some bits
- Multivariate (heuristic) generalizations

# Coppersmith intuition

- Generate polynomials sharing roots (mod  $N$ )
  - $x^k f(x)$
  - $N^k f(x)$
  - $f^k(x)$
  - $\Rightarrow x^i N^j f^k(x)$
- Find small  $f'$  over  $\mathbb{Z}$ 
  - Lattice reduction
  - Factor over  $\mathbb{Z}$
  - Check results (mod  $N$ )
- Multivariate
  - Extract roots from multiple polynomials
  - Gröbner basis, resultants, ...

# Coppersmith attacks

- RSA: stereotyped message
  - $f(x) = (K + x)^e - c \equiv 0 \pmod{N}$ ,  $x$  small
- RSA: partially known factor
  - $f(x) = (p_{\text{high}} + x) \equiv 0 \pmod{p}$ ,  $x < N^{\frac{1}{4}}$ ,  $p \mid N$
- Boneh-Durfee
  - $f(x, y) = x((N + 1) - y) \equiv 0 \pmod{e}$
  - $y = -(p + q)$ ,  $x$  modular “wraps”
- AGCD
  - Multivariate

# Building with lattices

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# Learning With Errors

$$\begin{aligned} \mathbf{s} &\leftarrow \chi_{\mathbf{k}}^n \\ \mathbf{a}_i &\leftarrow \mathbb{Z}_q^n \\ e_i &\leftarrow \chi_e \\ b_i &= \langle \mathbf{s}, \mathbf{a}_i \rangle + e_i \end{aligned}$$

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$$\mathbf{b} = \mathbf{A}\mathbf{s} + \mathbf{e}$$



- Distinguishing
- Key recovery
- Embedding messages
  - $b = \langle \mathbf{s}, \mathbf{a} \rangle + e + \frac{q}{p} \cdot m$
  - $b = \langle \mathbf{s}, \mathbf{a} \rangle + p \cdot e + m$

$$R = \mathbb{Z}[X]/f(X), f \text{ monic irreducible, } \deg(f) = N$$

$$R_q = R/qR$$

$$s(X) \leftarrow \chi_{\mathbf{k}}^N \in R_q$$

$$e(X) \leftarrow \chi_{\mathbf{e}}^N \in R_q$$

$$b_i(X) = a_i(X) \cdot s(X) + e_i(X)$$

$$b_i(X) = a_i(X) \cdot s(X) + e_i(X)$$

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$$b_i = \begin{pmatrix} a_{i,1} & (X^{-1}a)_1 & \dots & (X^{-N+1}a)_1 \\ a_{i,2} & (X^{-1}a)_2 & \dots & (X^{-N+1}a)_2 \\ \vdots & \vdots & \ddots & \vdots \\ a_{i,N} & (X^{-1}a)_N & \dots & (X^{-N+1}a)_N \end{pmatrix} \cdot s + e_i$$

$$R = \mathbb{Z}[X]/(X^N \pm 1)$$

$$R_q = R/qR$$

$$f \leftarrow \chi^N \in R_q, \exists f^{-1}$$

$$g \leftarrow \chi^N \in R_q$$

$$h = \frac{g}{f}$$

- Distinguishing
- Recover  $f$
- Embedding messages
  - $f = p \cdot f' + 1$
  - $c = \frac{g}{f} + \frac{q}{p} \cdot m$
  - $c \cdot f \equiv g + \frac{q}{p} \cdot m \cdot p \cdot f' + \frac{q}{p} \cdot m$
- Alternative:
  - $h = p \cdot \frac{g}{f}, c = r \cdot h + m$
- Parameters matter: NTRU fatigue/overstretched NTRU

$$\begin{pmatrix} 1 & h \\ 0 & q \end{pmatrix}$$

- Matrix form for  $h$  (and  $0, 1, q$ )
  - (anti-)circulant matrix
- short vector:  $(f, g) = f \cdot (1, h) + k \cdot (0, q)$

# Estimating difficulty

- <https://github.com/malb/lattice-estimator>
  - Viability
  - Ideas for attacks to look at
  - Making sure your own lattices are safe?
- <https://github.com/WvanWoerden/NTRUFatigue>
  - Specifically for NTRU
  - Fatigue/overstretched regime

# Breaking things

## Linear algebra

- Basis is linear algebra + noise
- Sometimes the noise is not there
- Or not enough
- So just throw matrices at it

## Lattice reduction

- AKA primal attack
- The straightforward thing



## Weak structure

- RLWE/NTRU/... in a weird ring
  - Composite modulus
  - Reducible polynomial
  - ...
- Chinese remainder theorem
  - AKA working mod a factor
- Depends on end goal

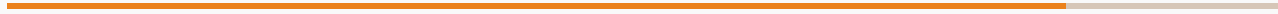
## Linearization

- Arora-Ge attack
- Consider  $e \in \{-1, 0, 1\}$
- Write  $v = \langle \mathbf{s}, \mathbf{a} \rangle - b$
- $v \cdot (v - 1) \cdot (v + 1) \equiv 0$
- Max degree: 3
- Enough samples  $\rightarrow$  each monomial becomes 1 **linear** variable
- Linear algebra

# Some resources

- <https://eprint.iacr.org/2023/032.pdf>
- <https://eprint.iacr.org/2020/1506.pdf>
- <https://kel.bz/post/lll/>
- [https://github.com/rkm0959/Inequality\\_Solving\\_with\\_CVP](https://github.com/rkm0959/Inequality_Solving_with_CVP)
- <https://github.com/jvdsn/crypto-attacks>
- <https://github.com/kionactf/coppersmith>
- <https://gist.github.com/RobinJadoul/796857fa33b118c17a4e54ff1b7ccfbe>
- [https://doi.org/10.1007/3-540-44670-2\\_12](https://doi.org/10.1007/3-540-44670-2_12)

Get your hands dirty



## **ImaginaryCTF (round 25)**

*A multiplicative knapsack, kinda.*

**Author** Robin\_Jadoul

**Flag format** `ictf{...}`

## ImaginaryCTF 2023

*tan(x) is a broken hash function in terms of collision resistance and second preimage resistance. But you surely can't find the preimage of tan(flag), right?*

**Author** maple3142

**Flag format** ictf{...}

## ImaginaryCTF 2023

*I threw in a bit of source-given rev, because why not.*

*> I hate crypto and rev because both are math*

*Sorry to people who feel like this and even say so in the ictf discord ;)*

**Author** Robin\_Jadoul

**Flag format** `ictf{...}`

## **ECSC 2023**

*Champagne for my real friends, real pain for my sham friends.*

**Author** Robin\_Jadoul

**Flag format** ECSC{...}



## ICC 2022

*I want to keep my private key small, but I've heard this is dangerous. I think I've found a way around this though!*

**Author** jack

**Flag format** ICC{...}

## **pbctf 2020**

*I know there's a famous attack on biased nonces. Then, how about this?*

**Author** rbtree

**Flag format** pbctf{...}

**Extra note** (try the harder approach, just for fun)

## **pbctf 2021**

*I came up with this fun game that only lucky people can win. Do you feel lucky?*

**Author** UnblvR

**Flag format** `pbctf{...}`

## SECCON finals 2022

*Recently, I learned that this random number generator is called “MRG”.*

**Author** Xornet

**Flag format** SECCON{...}

## SEETF 2023

*How to bypass this line?*

```
assert __import__('re').fullmatch(r'SEE{\w{23}}', flag:=input()) and not int.from_bytes(flag.encode(), 'big') % 13**37
```

**Author** Neobeo

**Flag format** SEE{...}

## TSJ CTF 2022

*I encrypted the flag and messages by xoring them with a random number generator again. But it should be harder to break this time.*

**Author** maple3142

**Flag format** TSJ{...}

# Random Shuffling Algorithm

## HITCON CTF 2023

*I think you already know what is this challenge about after seeing the challenge name :)*

**Author** maple3142

**Flag format** hitcon{...}

# Reality (remake)

**<Mostly new>**

*Based upon the challenge reality from google ctf 2019*

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