

# Manipuler les réseaux euclidiens

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ÉNS de Lyon – équipe ARIC

SIESTE, Lyon, Octobre 2012

# L'équipe ARIC (Arithmetic and Computing)

- 5 enseignants-chercheurs
- 7 chercheurs
- 2 post-doctorants
- 8 doctorants

Objectif : Améliorer les calculs, en se focalisant sur l'arithmétique

- Arithmétique flottante  
(opérateurs, fonctions élémentaires, FPGA, validation)
- Calcul formel (algèbre linéaire flottante et exacte)
- **Réseaux euclidiens** (algorithmes et cryptographie)
- Théorie des nombres

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# Goals and plan of the talk

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- An introduction to the computational aspects of lattices
- An example of how **floating-point arithmetic** can be used to accelerate an **algebraic computation**

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- 1 **Euclidean lattices**
- 2 Applications of euclidean lattices
- 3 The LLL algorithm and its accelerations

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# Euclidean lattices

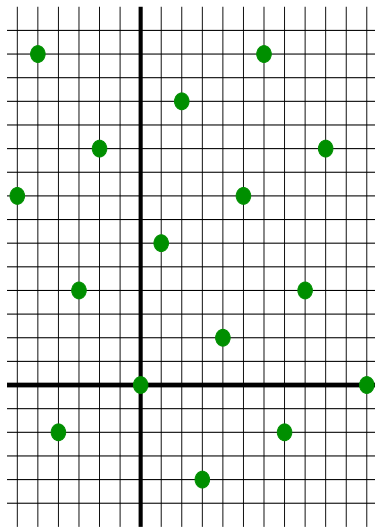
Lattice  $\equiv$  discrete subgroup of  $\mathbb{R}^n$

$$\equiv \left\{ \sum_{i \leq n} x_i \mathbf{b}_i : x_i \in \mathbb{Z} \right\}$$

If the  $\mathbf{b}_i$ 's are linearly independent, they are called a **basis**.

Bases are not unique, but they can be obtained from each other by integer transforms of determinant  $\pm 1$ :

$$\begin{bmatrix} -2 & 1 \\ 10 & 6 \end{bmatrix} = \begin{bmatrix} 4 & -3 \\ 2 & 4 \end{bmatrix} \cdot \begin{bmatrix} 1 & 1 \\ 2 & 1 \end{bmatrix}.$$



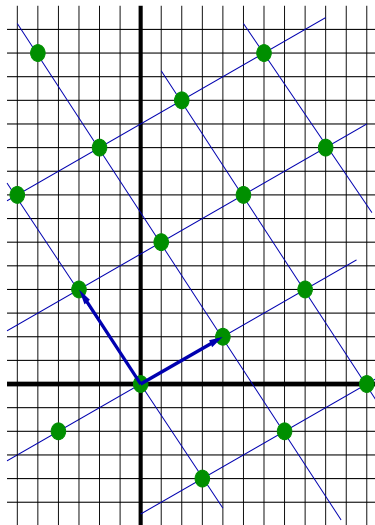
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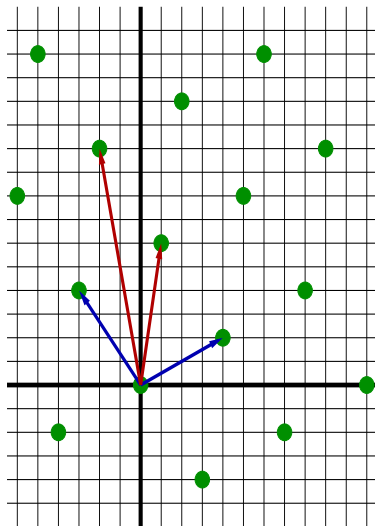
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# Lattice invariants

**First minimum:**

$$\lambda(L) = \min(\|\mathbf{b}\| : \mathbf{b} \in L \setminus \mathbf{0}).$$

**Determinant:**

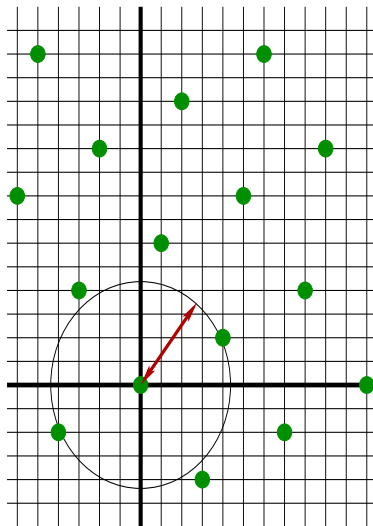
$$\det L = |\det(\mathbf{b}_i)_i|, \text{ for any basis}$$

**Minkowski theorem:**

$$\lambda(L) \leq \sqrt{n} \cdot (\det L)^{1/n}.$$

**Algorithmic approach: lattice reduction**

Start from a basis, and progressively improve its norm/orthogonality.



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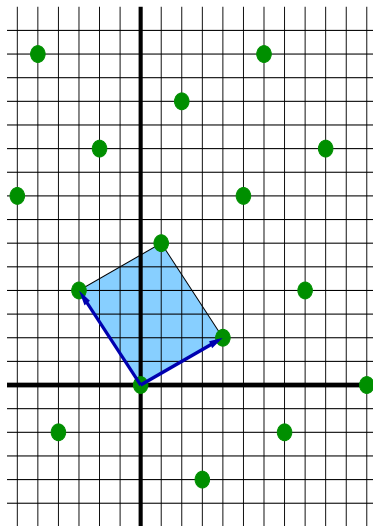
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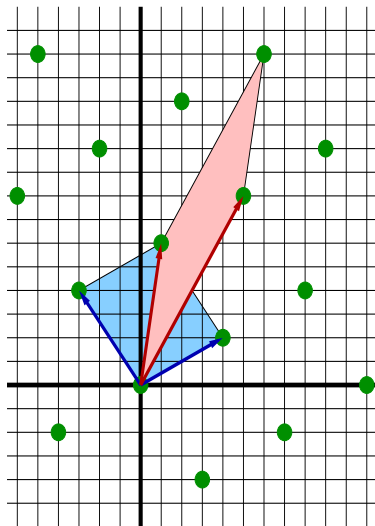
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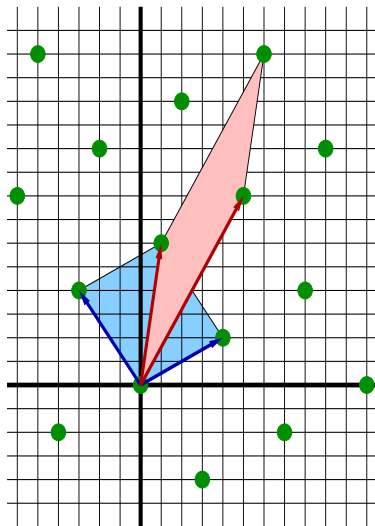
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# Why do we care about lattices?

- Computer algebra: factorisation of rational polynomials.
- Cryptanalysis of variants of RSA.
- Lattice-based cryptography.
- Communications theory: MIMO, GPS.
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# Main computational problem: SVP

- **SVP $_{\gamma}$** : Given a basis of  $L$ , find  $\mathbf{b} \in L$  with

$$0 < \|\mathbf{b}\| \leq \gamma \cdot \lambda(L).$$

- **Dec-SVP $_{\gamma}$** : Given a basis of  $L$ , and  $t > 0$ , reply:

YES if  $\lambda(L) \leq t$  and NO if  $\lambda(L) > \gamma \cdot t$ .

- NP-hard for any  $\gamma \leq \mathcal{O}(1)$ , under randomized reductions.
- Most likely not NP-hard for  $\gamma \geq \sqrt{n}$ .
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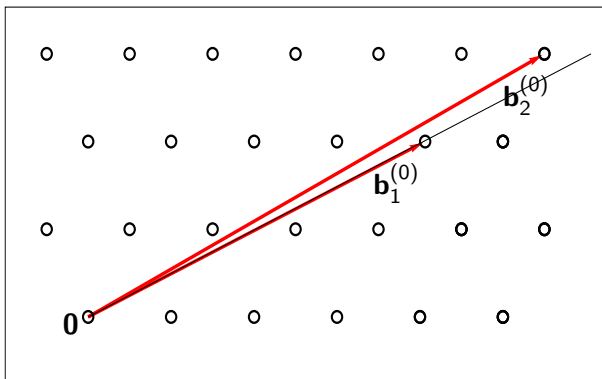
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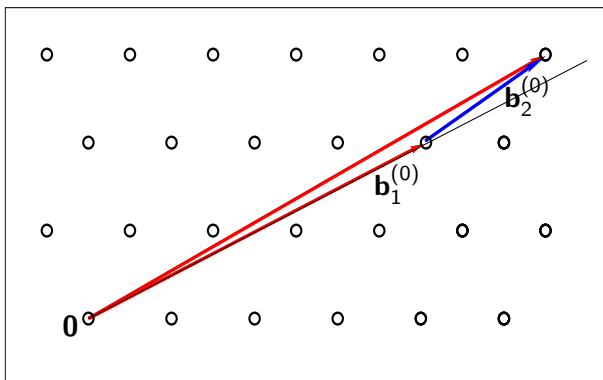
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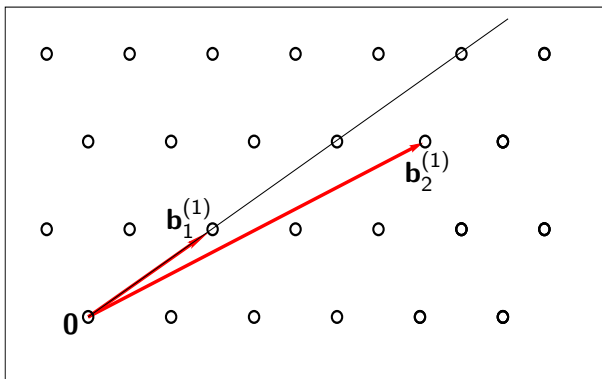
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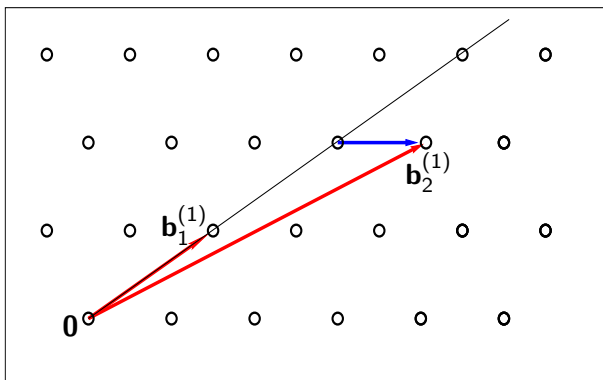
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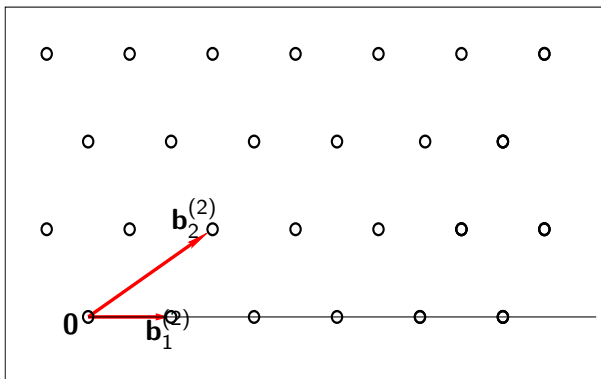
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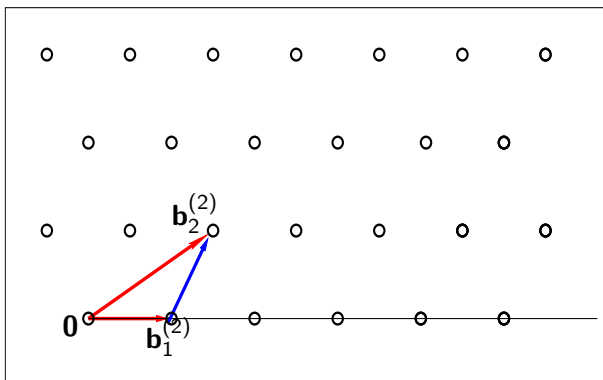
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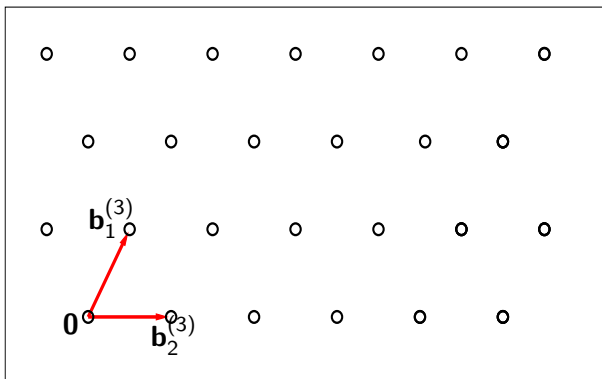
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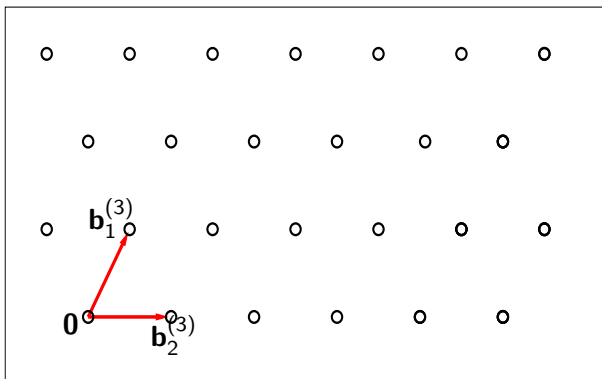
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- 2 **Applications of euclidean lattices**
- 3 The LLL algorithm and its accelerations

- 1 Integer relation detection
- 2 Polynomial factorisation
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## Finding small integer relations between real numbers

Lattices may be used to find the Bailey-Borwein-Plouffe formula:

$$\pi = \sum_{i \geq 0} \frac{1}{16^i} \left( \frac{4}{8i+1} - \frac{2}{8i+4} - \frac{1}{8i+5} - \frac{1}{8i+6} \right).$$

Interesting to compute a given hexadecimal digit of  $\pi$

Assume we search a small integer relation between  $y_1, \dots, y_d \in \mathbb{R}$ .

Consider  $L := L[(\mathbf{b}_i)_i]$ , with  $B = \begin{bmatrix} y_1 & y_2 & \dots & y_d \\ 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix}$

A relation  $\mathbf{x} \in \mathbb{Z}^{d+1}$  leads to a small vector  $(0, x_1, \dots, x_d)^T$ .

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# Factoring integer polynomials

This idea may be used to factor polynomials over  $\mathbb{Z}[x]$ .

*Factoring polynomials with rational coefficients,*

A. K. Lenstra, H. W. Lenstra Jr. and L. Lovász. Math. Ann., 1982

⇒ Cited 2544 times!

- Step 0: If  $\deg P \leq 1$ , then stop
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# Cryptanalysis of RSA with small decryption exponent

## RSA:

- $N = p \cdot q$  with  $p, q \approx \sqrt{N}$  prime
- $e, d$  with  $e \cdot d = 1 \pmod{(p-1) \cdot (q-1)}$
- $PK = (N, e)$ ,  $sk = d$

RSA with **small decryption exponent**:  $d \ll N^{1/4}$ ,  $e \approx N$ .

Some orders of magnitude:

$$\begin{aligned} e \approx N &\quad \Rightarrow \quad k \approx d \ll N^{1/4} \\ ed = 1 + k\phi(N) &\quad \Rightarrow \quad |ed - kN| \ll N^{3/4} \end{aligned}$$

**Cryptanalysis:** Consider  $L(\mathbf{b}_1, \mathbf{b}_2)$  with  $[\mathbf{b}_1 | \mathbf{b}_2] = \begin{bmatrix} e & N \\ \sqrt{N} & 0 \end{bmatrix}$ .

$\lambda(L)$  expected to be  $\approx \sqrt{\det(L)} = N^{3/4}$ .

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# Cryptographic design

Lattice-based cryptography:

- Secret key: very short basis of a lattice
- Public key: long basis of the same lattice
- Relies on the assumed hardness of SVP

Very popular research topic, because LBC is:

- More secure: post-quantum
- More efficient: no modular exponentiation
- More flexible: fully homomorphic encryption

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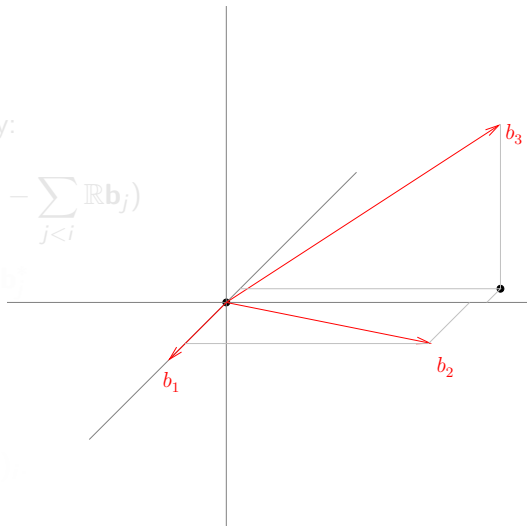
$(\mathbf{b}_i)_i$  linearly independent.

The GSO  $(\mathbf{b}_i^*)_i$  is defined by:

$$\forall i, \mathbf{b}_i^* = \operatorname{argmin}_{\mathbb{R}\mathbf{b}_j} \|\mathbf{b}_i - \sum_{j < i} \mathbb{R}\mathbf{b}_j\|$$

$$= \mathbf{b}_i - \sum_{j < i} \mu_{ij} \mathbf{b}_j$$

$$\forall i > j, \mu_{ij} = \frac{(\mathbf{b}_i, \mathbf{b}_j)}{\|\mathbf{b}_j\|^2}$$



Exercise: For any basis  $(\mathbf{b}_i)_i$  of  $L$ , we have  $\lambda(L) \geq \min_i \|\mathbf{b}_i^*\|$ .

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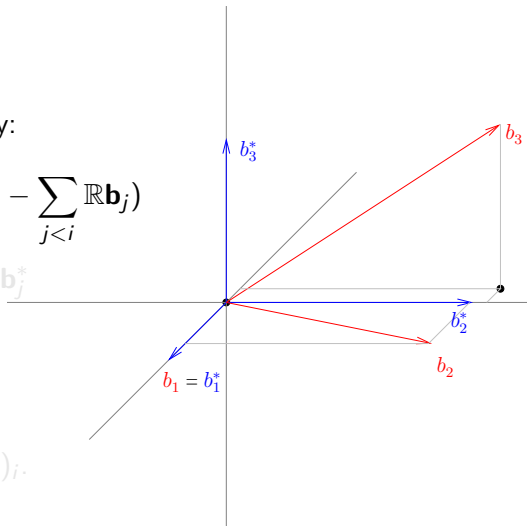
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Triangularisation of  $B = (\mathbf{b}_i)_i$ .

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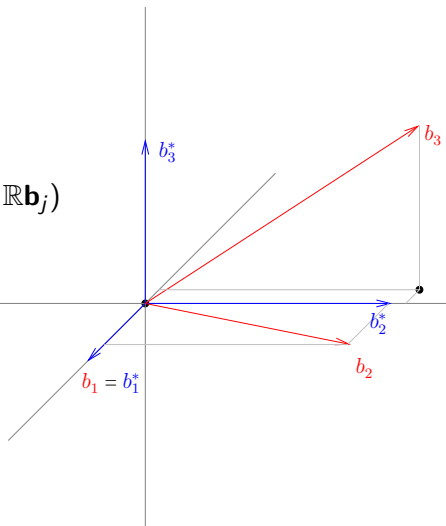
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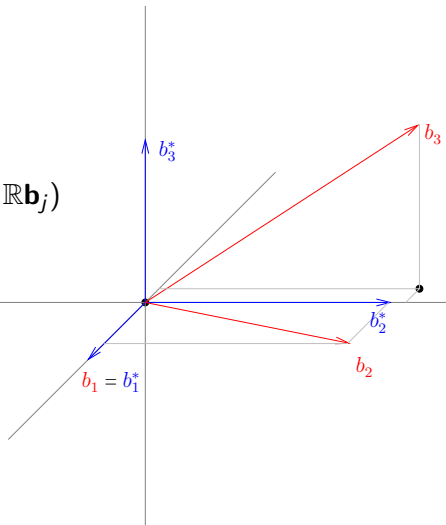
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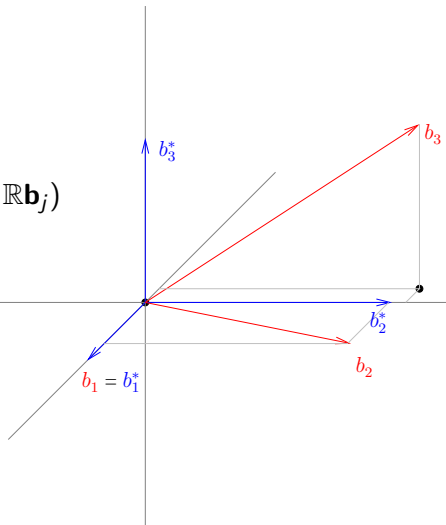
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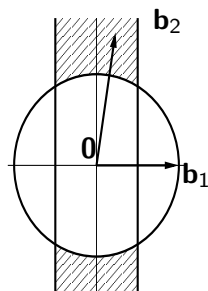
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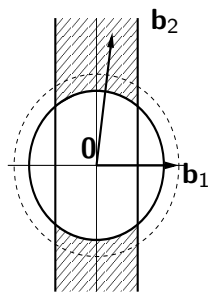
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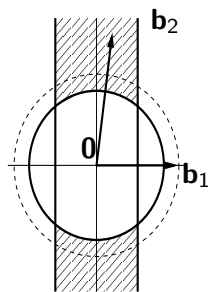
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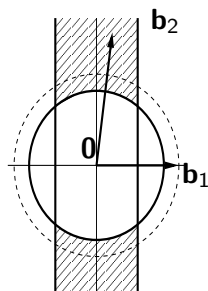
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# Complexity of LLL and practical run-time

[LLL82,Kaltofen83]

The LLL algorithm terminates within  $\mathcal{O}(n^4\beta^2(n + \beta))$  bit operations, with  $\beta = \log \max_i \|\mathbf{b}_i^{init}\|$ .

With MAGMA V2.16:

```
> n := 25; B := RMatrixSpace(Integers(),n,n)!0;  
> for i:=1 to 25 do  
>   B[i][i]:=1; B[i][1]:=RandomBits(2000);  
> end for;  
> time C := LLL(B:Method:='Integral');
```

**Time: 11.700**

```
> time C := LLL(B);
```

**Time: 0.240**

## LLL in practice: the numeric-symbolic approach

The Gram-Schmidt computations dominate the cost

### Odlyzko's hybrid approach

Replace the rational computations on the GSO by floating-point approximations, but keep the basis operations exact

Floating-point numbers:  $x_1.x_2x_3 \dots x_p \cdot B^e$ , where:

- $p$  is the precision
- $B$  is the base, and  $x_i \in \{0, \dots, B - 1\}$  for all  $i$
- $e \in \mathbb{Z}$  is the exponent
- $x_1.x_2 \dots x_p$  is called the mantissa

Arithmetic:  $fl(a \text{ op } b)$  is a nearest floating-point number to  $a \text{ op } b$ .  
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But Odlyzko's approach is heuristic:

- Fp arithmetic is inexact:  $fl(a \text{ op } b)$  differs from  $a \text{ op } b$  by little, but errors can be amplified in case of a sequence of operations.
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# Making the numeric-symbolic approach rigorous

## Underlying mathematical phenomenon

Any LLL-reduced basis is well-conditioned with respect to GSO computations

- Well-conditioned? The GSO computed in small precision fp arithmetic is close to the true GSO

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LLL can be accelerated further by using approximations for the bases too, in a recursive manner!  $\Rightarrow \tilde{\mathcal{O}}(n^5\beta)$  bit operations.

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# Plan of the talk

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- ① Euclidean lattices
- ② Applications of euclidean lattices
- ③ The LLL algorithm and its accelerations
- ④ **Conclusion**

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- Lowering the cost of LLL-reduction
- Algorithms computing shorter vectors than LLL
  - If paying  $\mathcal{P}oly(n, 2^k)$ , we can replace LLL's  $2^{O(n)}$  by  $k^{O(n/k)}$ .
  - Can we achieve a better time/quality trade-off?
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- Hardness proofs
  - NP hardness of SVP under deterministic reductions?
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## Further readings

L. Lovász: *An Algorithmic Theory of Numbers, Graphs, and Convexity*

D. Micciancio & S. Goldwasser: *Complexity of Lattice Problems, A Cryptographic Perspective*

I. Morel, D. Stehlé & G. Villard: *Analyse numérique et réduction de réseaux*

D. Micciancio: *The Geometry of Lattice Cryptography*

F. Eisenbrand: *Integer Programming and Algorithmic Geometry of Numbers*