

We need to check how many iterations we need  
to get the index of all cones below 2:

17.1

After  $n$  iterations a cone  $D$  in our list has index

$$\text{ind } D \leq (\text{ind } C)^{\left(\frac{d-1}{\alpha}\right)^n}$$

→ need to find smallest  $n$  s.t. RHS is less than 2

(and thus  $\text{ind } D = 1$ )

Consider:

$$\begin{aligned} \lg_2 \lg_2 (\text{ind } C)^{\left(\frac{d-1}{\alpha}\right)^n} &= \lg_2 \left(\frac{d-1}{\alpha}\right)^n \lg_2 \text{ind } C \\ &= n \lg_2 \left(\frac{d-1}{\alpha}\right) + \lg_2 \lg_2 \text{ind } C \\ &= -n \lg_2 \left(\frac{\alpha}{d-1}\right) + \dots \quad (*) \end{aligned}$$

$$\Rightarrow \text{if } n > \frac{\lg_2 \lg_2 \text{ind } C}{\lg_2 \left(\frac{\alpha}{d-1}\right)} = \Theta(d \lg_2 \lg_2 \text{ind } C)$$

then the RHS of  $(*)$  is negative, so that

$$\lg_2 (\text{ind } C)^{\left(\frac{d-1}{\alpha}\right)^n} < 1$$

$$\Rightarrow (\text{ind } C)^{\left(\frac{d-1}{\alpha}\right)^n} < 2$$

$$\Rightarrow \text{ind } D < 2 \Rightarrow \text{ind } D = 1$$

Hence, we need only a polynomial number of steps for fixed dimension in the size of the input.

7.2

For a polynomial time algorithm we also need to control the number of cones in our subdivision.

We produce at most

$$\begin{aligned}
 (d \cdot 2^d)^n &= 2^{nd \lg_2 d} \leq 2^{\left( \frac{\lg_2 \lg_2 \text{ind } C}{\lg_2(\frac{d}{d-1})} + 1 \right) d \lg_2 d} \\
 &= 2^{d \lg_2 d} \cdot 2^{\frac{1}{\lg_2(\frac{d}{d-1})} d \lg_2 d \cdot \lg_2 \lg_2 \text{ind } C} \\
 &= 2^{d \lg_2 d} (\lg_2 \text{ind } C)^{\frac{1}{\lg_2(\frac{d-1}{d})} d \lg_2 d} \\
 &= O(d \lg_2 \text{ind } C)
 \end{aligned}$$

→ need only a polynomial number of cones in decomposition

The  $d \in \mathbb{N}_{\geq 1}$  fixed

There is a polynomial time algorithm that computes

$$g_C(x) = \sum_{i \in I} \varepsilon_i \frac{1}{\prod_{j=1}^d (1 - x_j^{v_{ij}})} + \begin{pmatrix} \text{lower dim} \\ \text{contributions} \end{pmatrix}$$

for cones  $C_i = \text{conv}(v_{i,1}, \dots, v_{i,d})$  and  $\varepsilon_i \in \{-1\}$

→ we can use this result to compute

(1)  $h^+$  for a decomposition of  $C(\gamma)$

(2)  $|\mathcal{P}_n \cap \mathbb{Z}^d|$  and  $e_p(\gamma)$  via the Theorem of Brion

17.3

This usually requires us to evaluate sums of the form

$$\sum_{i \in I} \varepsilon_i \frac{x^{v_i}}{\prod_{j} (1 - x^{a_{ij}})}$$

at  $x = M$  or  
 $x = (t, M)$

however, in most cases this is a pole of the sum.

We know that it must be removable as the Taylor series expansion produces the generating series, which we can evaluate.

Yet, this is not a polynomial time method to achieve this.

Here is one option:

choose a sufficiently generic vector  $m = (m_1, \dots, m_d) \in \mathbb{N}^d$  s.t.

$$\langle m, v_i \rangle \neq 0, \quad \langle m, a_{ij} \rangle \neq 0$$

c.g. use the moment curve  $m(\lambda) := (1, \lambda, \dots, \lambda^{d-1}) \in (\mathbb{R}^d)^*$

$$\text{Then } \lambda \mapsto m(\lambda)(v_i), \alpha_\lambda(a_{ij})$$

is a polynomial of degree  $d-1$  but not  $\equiv 0$

$\Rightarrow$  it has at most  $(d-1)d+1$  zeros, so we can just try sufficiently many different values for  $\lambda$ .  
This is polynomial in the input size.

For  $r \in \mathbb{C}$  consider

$$x(r) := (e^{ru_1}, \dots, e^{ru_d})$$

We get our evaluation at  $x = 1$  via

$$\lim_{r \rightarrow 0} g_C(x(r))$$

$$\text{Let } v_i := \langle u, v_i \rangle, \alpha_{ij} := \langle u, q_{ij} \rangle$$

Then

$$g_C(x(r)) = \sum_{i \in I} \varepsilon_i \underbrace{\frac{e^{v_i r}}{\prod_{j=1}^k (1 - e^{\alpha_{ij} r})}}$$

This is a meromorphic function

→ want constant term of Laurent expansion at  $r = 0$ .

Consider a single fraction:

$$\frac{e^{v_i r}}{\prod_{j=1}^k (1 - e^{\alpha_{ij} r})} = \frac{1}{r^k} e^{v_i r} \sqrt[k]{\frac{r}{1 - e^{\alpha_{ij} r}}}$$

Each  $\frac{r}{1 - e^{\alpha_{ij} r}}$  is an analytic function, and we

can compute the Taylor expansion up to degree  $k+1$ :

$$\frac{r}{1 - e^{\alpha_{ij} r}} = T_{ij}(r) + R_{ij}(r^{k+1})$$

Also:

$$e^{V_i(r)} = S_{ij}(r) + R_j^l(r^{k+1})$$

17.5

We compute the product up to degree  $k+1$ :

$$P_i(r) = \overline{T}_{i1}(r) \cdots \overline{T}_{iL}(r) S_i(r) + R_i^l(r^{k+1})$$

and

$$P(r) = \sum P_i(r) + R(r^{k+1})$$

Then the coefficient of  $r^k$  is the limit  $\lim_{r \rightarrow 0} g_c(x(r))$

and thus the evaluation at  $x = M$

Remark: Using the Todd-polynomials

$$\prod_{i=1}^k \frac{x \xi_i}{1 - e^{-x \xi_i}} = \sum_{m=0}^{\infty} \underbrace{\text{td}_m(\xi_1, \dots, \xi_k)}_{\text{m.th Todd polynomial}} x^m$$

we can get a closed expression

$$g_c(M) = \sum_{i \in I} \prod_{j=1}^d \frac{1}{v_{ij}} \sum_{k=0}^d \frac{v_{ij}^k}{k!} \text{td}_{d-k}(-\alpha_{i1}, \dots, -\alpha_{id})$$

## 16. The Shortest Vector Problem

Ft. 6

(SVP)  $\Lambda$  with basis  $a_1, \dots, a_d$  find, in polynomial time  
a vector  $u \in \Lambda \setminus \{0\}$  of shortest possible length

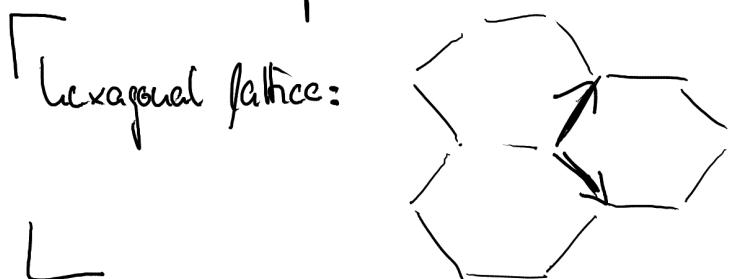
$$\|u\| = \lambda_1(\Lambda)$$

$u$  need not be part of the given basis  $a_1, \dots, a_d$

→ it will be if the lattice basis is orthogonal:

$$\|u\|^2 = \sum |\lambda_i|^2 \|a_i\|^2 \geq \min_i \|a_i\|^2$$

However (1) not all lattices have orthogonal bases  
(2) we don't know how to find them.



If we forget the lattice structure we can efficiently compute an orthogonal basis with the Gram-Schmidt algorithm.

→ how close can we get?

→ leads to reduced bases.

But such can be computed with the LLL-algorithm  
(next section)

Assume bases are ordered.

R.7

Consider

$$V_0 := \{0\}, \quad V_k := \text{span}(v_1, \dots, v_k), \quad \Lambda_k := \Lambda \cap V_k$$

$\pi_k : \text{orthogonal projection } \mathbb{R}^d \rightarrow V_k$

The Gram-Schmidt orthogonalization  $w_1, \dots, w_d$  is given by

$$w_k := v_k - \pi_{k-1}(v_k) = v_k - \sum_{j=1}^{k-1} \lambda_{j,k} w_j \quad \text{for } \lambda_{j,k} := \frac{\langle v_k, w_j \rangle}{\|w_j\|^2}$$

with

$$\langle w_i, w_j \rangle = \begin{cases} 1 & i=j \\ 0 & \text{else} \end{cases} \quad \text{and } \det(v_k, v_{k-1}) = \|w_k\|$$

$$\left[ \text{Ex: } v_1 = \begin{pmatrix} 2 \\ 1 \end{pmatrix} \quad v_2 = \begin{pmatrix} 1 \\ 2 \end{pmatrix} \right]$$

$$\Rightarrow w_1 = v_1, \quad w_2 = -\frac{4}{5}v_1 + v_2 = \begin{pmatrix} -3/5 \\ 6/5 \end{pmatrix}$$

$$\text{Conversely } v_k = w_k + \sum_{j=1}^{k-1} \lambda_{j,k} w_j$$

$$\Rightarrow \det \Lambda = \prod_{j=1}^d \|w_j\| \quad \det \Lambda_k = \prod_{j=1}^k \|w_j\|$$

Def: The orthogonality defect of  $\Lambda$  is

$$\eta := \frac{1}{\det \Lambda} \sqrt{\sum_{i=1}^d \|v_i\|^2}$$

Note  $v_1, \dots, v_d$  orthogonal  $\Leftrightarrow \eta = 1$

Def:  $v_1, \dots, v_d$  is a reduced basis if the orthogonality defect is bounded by a constant  $\eta_d$  depending only on the dimension  $d$ .