

# Balanced Solutions of Linear Diophantine Equations

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- If with  $|x_j| \leq X_j$  then the problem is NP-complete.

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- The decidability problem of the existence of a solution of Extended gcd under the bound  $|x_j| < X_j$  is proved to be NP-complete.
- We shall study this problem and we develop an algorithm which give us a solution for the Egcd problem (under some assumptions)

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- If we restrict the solutions  $x_j \in \{0, 1\}$ , then we have the 0 – 1 Knapsack or subset sum problem. That is, given a set  $I = \{a_1, a_2, \dots, a_n\}$  and  $s$  (all positive integers) find a subset of the set  $I$  which have sum  $s$ .

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- NP-complete means, if there is a polynomial algorithm which solves the problem, then there is also a polynomial algorithm for the problems in the NP-class.
- If we have an oracle that solves the decisional knapsack problem, then after  $n$  calls to the oracle we can solve the computational knapsack problem.

# Some Applications.

- The knapsack cryptography uses a public set of weights  $a_1, \dots, a_n$  and in order Bob to encode a message consisting from the bits  $(x_1, \dots, x_n)$  he calculate  $\sum_{j=1}^n a_j x_j = s$ . Then Bob transmits  $s$ . An enemy would see  $s$ , so he has to solve a knapsack instance in order to decode the message.

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- The first cryptographic system based on the Knapsack problem is given by Merkle and Hellman in 1978 and was broken by Shamir after three years. Shamir uses Lattice reduction methods in order to break the scheme.

# LLL reduction algorithm

- In 1982, A.Lenstra, H.Lenstra and Lovasz published in their landmark paper the LLL-algorithm, which is a basis reduction algorithm for lattices, based on Hermite's inequality. The aim of LLL algorithm is to find a short vector that approximates the shortest nonzero vector of the lattice. The LLL algorithm runs in polynomial time as a function of the rank of the lattice.



# LLL reduction algorithm.

- Let a basis  $\{\mathbf{b}_1, \dots, \mathbf{b}_n\}$  of a lattice  $L = \mathbf{Z}\mathbf{b}_1 + \dots + \mathbf{Z}\mathbf{b}_n \subset \mathbf{R}^k$ . We associate the Gramm-Schmidt orthogonalization vectors  $\{\mathbf{g}_1, \dots, \mathbf{g}_n\}$  defined by the relations

$$\mathbf{g}_1 = \mathbf{b}_1, \quad \mathbf{g}_i = \mathbf{b}_i - \sum_{j=1}^{i-1} \mu_{ij} \mathbf{b}_j,$$

where the GSO coefficients

$$\mu_{ij} = \frac{\mathbf{b}_i \cdot \mathbf{g}_j}{B_j^2}, \quad B_j = \|\mathbf{g}_j\|.$$

The GSO process produce vectors that form an orthogonal basis of  $\mathbf{R}^k$ .

# LLL reduction algorithm.

- An LLL-basis has two characteristics.
  - i. Is size reduced, that is  $|\mu_{ij}| < 1/2$ ,  $1 \leq j < i < n$  and
  - ii. The vectors of the basis are almost orthogonal to each other. This, is translated to the following (Lovasz) relation  $\delta \|\mathbf{g}_i\|^2 \leq \|\mathbf{g}_{i+1} + \mu_{i+1,i} \mathbf{g}_i\|^2$  for some  $\delta \in (1/4, 1)$ .

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- The LLL-algorithm achieve to give us a small length vector, more specific

$$\|\mathbf{b}_1\| \leq 2^{n-1} d(L)^{1/n},$$

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- Some applications are
  - to the factorization of polynomials over  $\mathbf{Z}[x]$
  - to find integer relations between some real numbers  $k_1, \dots, k_n$ .

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- $red(k, \ell)$  consists from the following steps.
  - for  $k = 1, 2, \dots, \ell - 1$  do
    - if  $|\mu_{k\ell}| = \left| \frac{\mathbf{b}_k \cdot \mathbf{b}_\ell^*}{B_k} \right| < 1/2$  where  $B_k = \|\mathbf{b}_k^*\|^2$  then set
 
$$r = \lceil \mu_{k\ell} \rceil, \quad \mathbf{b}_k \leftarrow \mathbf{b}_k - r\mathbf{b}_\ell$$
    - $\mu_{kj} \leftarrow \mu_{kj} - r\mu_{\ell j}$

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- this make a swap between two vectors  $\mathbf{b}_k, \mathbf{b}_{k+1}$  if the Lovasz condition (for  $\delta = 3/4$ ) does not hold, that is :

$$\frac{3}{4}|\mathbf{b}_{k-1}^*|^2 > |\mathbf{b}_k^* + \mu_{k,k-1}\mathbf{b}_{k-1}^*|^2$$

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- Now LLL algorithrm excute the following loop  
 set  $k = 2$   
 while  $k \leq n$  do  
    $red(k, \ell)$   $\ell = k - 2, \dots, 1$  and then call  $swap(k)$ .

# Solutions of linear diophantine equations.

- The method which we usually apply in order to find small solutions of the linear equation

$$f(x_1, \dots, x_n) = \sum_{j=1}^n a_j x_j = a_0 \quad (2)$$

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$$f(x_1, \dots, x_n) = \sum_{j=1}^n a_j x_j = 0.$$

- This is a lattice of dimension  $n - 1$  since  $L = \mathbf{Z}\mathbf{b}_1 + \dots + \mathbf{Z}\mathbf{b}_{n-1}$  where  $\mathbf{b}_j$  are the solutions.

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- Implementations of CVP can be found in fplll and in Magma.

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- Let  $X_j$ ,  $j = 1, 2, \dots, n$  be positive integers and  $B$  be the lattice generated by the following vectors.

$$\{\mathbf{b}_j : \mathbf{b}_j = (0, \dots, \frac{1}{X_j}, 0, \dots, 0, a_j) \in \mathbf{R}^{n+2}, j = 1, 2, \dots, n\}$$

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- Finally, using the Gramm-Schmidt orthogonalization process to the LLL reduced basis  $B'$ , we get the set  $G = \{\mathbf{g}_1, \mathbf{g}_2, \dots, \mathbf{g}_n\}$ . We define  $B_j = \|\mathbf{g}_j\|$ .

# Solutions of linear diophantine equations.

- We shall prove the following Theorem.

Let  $\gcd(a_1, \dots, a_n) = 1$ . If the following two assumptions hold

$$A_1. (a_n X_n)^2 + (a_j X_j)^2 < \frac{1}{2^{n+1}} (X_n X_j)^2, \quad j = 1, 2, \dots, n-1,$$

$$A_2. \left\lceil \frac{a_0}{B_n^2} \right\rceil = a_0,$$

then we can find in polynomial time, an integer solution

$(x_1, \dots, x_n)$  of the equation  $\sum_{j=1}^n a_j x_j = a_0$ , such that

$$|x_j| < c(n) X_j \prod_{i=1}^n X_i, \quad j = 1, 2, \dots, n, \quad c(n) = \sqrt{3}(1.25)^{(n-1)/2}$$

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- Also, the proof of the Theorem provide us with an algorithm.

# The Algorithm

- There are two basic steps, first LLL to the lattice  $B$ , and second size reduction to a new lattice of the form  $M = B + \mathbf{Zb}$ .



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- Say that we have the linear diophantine equation

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- We apply LLL to the rows of the Lattice given by the matrix

$$M = \begin{bmatrix} \frac{1}{X_1} & 0 & 0 & 0 & 0 & 0 & a_1 \\ 0 & \frac{1}{X_2} & 0 & 0 & 0 & 0 & a_2 \\ 0 & 0 & \frac{1}{X_3} & 0 & 0 & 0 & a_3 \\ 0 & 0 & 0 & \frac{1}{X_4} & 0 & 0 & a_4 \\ 0 & 0 & 0 & 0 & \frac{1}{X_5} & 0 & a_5 \end{bmatrix}$$

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- Then to the new reduced basis we add the row  $(0, 0, 0, 0, 0, 1, -a_0)$ .

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- Then to the new reduced basis we add the row  $(0, 0, 0, 0, 0, 1, -a_0)$ .
- Then apply size reduction to the rows, that is (here  $n = 5$ )

$$\text{row}(n+1) \leftarrow \text{row}(n+1) - \lceil \mu_{n+1,j} \rceil \text{row}(j)$$

$$\mu_{ij} = \frac{\mathbf{b}'_i \cdot \mathbf{g}_j}{B_j^2}, \quad B_j = \|\mathbf{g}_j\|.$$

first for  $j = n$  and then  $j = 1, 2, \dots, n-1$ .

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- The resulting vector gives a solution of the diophantine equation which satisfies the bound of our theorem.
- But, at least experimentally satisfies the better bound  $|x_j| < X_j$ .

# Examples

- Let

$$84 \cdot 10^5 x_1 + 4 \cdot 10^6 x_2 + 15688 x_3 + 6720 x_4 + 15 x_5 = 371065262.$$

This is example 1 of Aardal, Hurkens, Lenstra

Ref : Aardal, K.; Hurkens, C.; Lenstra, A.; Solving a linear Diophantine equation with lower and upper bounds on the variables. *Integer programming and combinatorial optimization*, LNCS, **1412**.

and they get the solution  $\mathbf{x} = (36, 17, 39, 8, -22)$ , with  $\|\mathbf{x}\| \simeq 60.44$ . Assumption  $A_1$  is fulfilled if

$$\max_{1 \leq j \leq 4} |a_j| < \frac{1}{8} X_5, \quad |a_5| < \frac{1}{8} \max_{1 \leq j \leq 5} X_j.$$

So it is enough to choose

$$X = X_1 = \dots = X_5 = 8 \cdot 84 \cdot 10^5 + 1.$$



# Examples

- We consider the matrix

$$M = \begin{bmatrix} \frac{1}{67200001} & 0 & 0 & 0 & 0 & 0 & 8400000 \\ 0 & \frac{1}{67200001} & 0 & 0 & 0 & 0 & 4000000 \\ 0 & 0 & \frac{1}{67200001} & 0 & 0 & 0 & 15688 \\ 0 & 0 & 0 & \frac{1}{67200001} & 0 & 0 & 6720 \\ 0 & 0 & 0 & 0 & \frac{1}{67200001} & 0 & 15 \end{bmatrix}$$

## Examples

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- Applying *LLL* to the rows of  $M$  we get  
 $M_{LLL} =$

$$\begin{bmatrix} -\frac{10}{67200001} & \frac{21}{67200001} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{15}{67200001} & -\frac{35}{67200001} & -\frac{8}{67200001} & 0 & 0 \\ \frac{1}{67200001} & -\frac{2}{67200001} & -\frac{25}{67200001} & -\frac{1}{67200001} & -\frac{72}{67200001} & 0 & 0 \\ \frac{5}{67200001} & -\frac{10}{67200001} & -\frac{95}{67200001} & -\frac{76}{67200001} & \frac{72}{67200001} & 0 & 0 \\ \frac{2}{67200001} & -\frac{4}{67200001} & -\frac{42}{67200001} & -\frac{21}{67200001} & \frac{1}{67200001} & 0 & -1 \end{bmatrix}$$

## Examples

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- We add a new row  $\mathbf{b}_6 = (0, 0, 0, 0, 0, 1, -a_0)$ .

$$\begin{bmatrix} -\frac{10}{67200001} & \frac{21}{67200001} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{15}{67200001} & -\frac{35}{67200001} & -\frac{8}{67200001} & 0 & 0 \\ \frac{1}{67200001} & -\frac{2}{67200001} & -\frac{25}{67200001} & -\frac{1}{67200001} & -\frac{72}{67200001} & 0 & 0 \\ \frac{5}{67200001} & -\frac{10}{67200001} & -\frac{95}{67200001} & -\frac{76}{67200001} & \frac{72}{67200001} & 0 & 0 \\ \frac{2}{67200001} & -\frac{4}{67200001} & -\frac{42}{67200001} & -\frac{21}{67200001} & \frac{1}{67200001} & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & 1 & -a_0 \end{bmatrix}$$

# Examples

- Then applying size reduction to the previous lattice i.e.

$$\text{row}(6) \leftarrow \text{row}(6) - \lceil \mu_{6,j} \rceil \text{row}(j),$$

first for  $j = 6$  and then for  $j = 1, 2, 3, 4, 5$ , we shall get

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- We take the 6th row and multiply each entry with  $X$ , then we shall get the vector  $\mathbf{x} = (36, 17, 39, 8, -22)$ . Which is the same as was found in Lenstra's paper.

# Examples

- Now if we choose  $X_1 = 30, X_2 = X_3 = X_4 = X_5 = 50$  and we repeat the previous procedure we shall get the solution  $\mathbf{y} = (26, 38, 39, 8, -22)$ . This solution has euclidean length  $\simeq 64.72$ . Note that is larger than the previous solution  $\mathbf{x} = (36, 17, 39, 8, -22)$ , with  $\|\mathbf{x}\| \simeq 60.44$ . It has the advantage that satisfy our constraints (the solution  $\mathbf{x}$  does not).

# Examples

- We consider now  $n = 50$

$\{a_j\}_j = [872934629013064, 362643350651979, 231593889792433, 1084529488472651, 152647947850799,$   
 $739407904067188, 1078361055147110, 522287723336618, 1048278073142822, 71464720981315,$   
 $1026144865997912, 401128969656441, 1104125375426692, 223040948030783, 259134135114376,$   
 $477165086702863, 693696459173357, 956101007737750, 1076391779531258, 887808907972169,$   
 $154289043341408, 1123813906929138, 100640784930380, 1028038257417354, 126747913149526,$   
 $345001039716371, 173180910604612, 376756743710801, 462057825850822, 105084485099476,$   
 $193285152829384, 663950233902816, 1005024177016821, 350981819196027, 1049577315489835,$   
 $455051495653072, 1014366278972062, 905067265314795, 972603957926899, 1110054606397627,$   
 $768533772552959, 798515502008744, 705587377794293, 64248048456242, 771519628719865,$   
 $190006526706907, 481482852515889, 916067763534188, 768875611228651, 666640039086558]$   
 $a_0 = 17297404087862459$



# Examples

- We consider now  $n = 50$

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 $190006526706907, 481482852515889, 916067763534188, 768875611228651, 666640039086558]$   
 $a_0 = 17297404087862459$

- Using our algorithm with  $X_j = 3$  ( $1 \leq j \leq n$ ) we get

$$\begin{aligned}
 x_1 = [1, 0, 1, 2, 0, 0, 1, -1, 0, 0, 1, 2, -1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 2, 2, 0, 0, -1, \\
 1, 1, -1, -1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0]
 \end{aligned}$$

with norm 6.3.

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with norm 6.3.

- Now using CVP method (as implemented in fplll) we manage to get the vector

$$x_4 = [0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 2, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, -1, 1, 0, 0, 1, 0, 0, 0, 2, 1, 0, 0, 0, 1, 0, 0, 1]$$

which has norm 5.

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- Thank you!