

## Lecture 5

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In the last class, we studied methods for (approximately) solving the following two problems:

- The approximate shortest vector problem, denoted  $SVP_\gamma$ : We saw that for  $\gamma = 2^{n/2}$ ,  $SVP_\gamma$  can be solved in time polynomial in the length of its input (this is the LLL algorithm). For  $\gamma = 1$ , the best known algorithm runs in time  $2^{O(n)}$  (this follows from the work of Ajtai, Kumar and Sivakumar who exhibit a randomized  $2^{O(n)}$ -time algorithm, and Voulgaris and Micciancio who exhibit a deterministic algorithm with the same running time).
- The approximate closest vector problem, denoted  $CVP_\gamma$ : We saw that for  $\gamma = 2^{n/2}$ ,  $CVP_\gamma$  can be solved in polynomial time (this is Babai's Nearest Plane algorithm). For  $\gamma = 1$ , the best known is a randomized  $2^{O(n)}$ -time algorithm (due to Ajtai, Kumar and Sivakumar) and an  $n^{O(n)}$ -time deterministic algorithm (due to Kannan).

Obtaining a deterministic  $2^{O(n)}$ -time algorithm is a tantalizing open question.

**Today:**

- We will first show that  $CVP_\gamma$  is NP-complete for  $\gamma = 1$ . The NP-completeness is shown by a reduction from the Subset Sum problem, which is a well-known NP-complete problem.  
For  $\gamma > \sqrt{n}$ , it is generally believed that  $CVP_\gamma$  is unlikely to be NP-hard.
- We will then take a look at the NP-completeness in a different way, and use it to attack a cryptographic one-way function based on the Subset Sum problem.

In particular, the NP-completeness reduction gives us a way to solve the Subset Sum problem, given an oracle that solves CVP exactly. Of course, CVP is hard to solve exactly in polynomial time. However, upon closer look at the reduction, we observe that the reduction in fact gives us a way to solve Subset Sum problems *on the average, for certain parameters*, given only an *approximate* solution to CVP. Instantiating this with Babai's nearest plane algorithm that computes a  $2^{n/2}$ -approximation to CVP, we obtain an algorithm that solves random subset sum instances for certain classes of parameters which suffices to break a proposed one-way function based on Subset Sum.

## 1 The Hardness of gapCVP

Before we give the hardness result, let us define the decision version of  $CVP_\gamma$ .

**Definition 1** (gapCVP). Given a basis  $\mathbf{B} \in \mathbb{Z}^{m \times n}$ , a target vector  $\mathbf{t} \in \mathbb{Z}^m$ , and  $r \in \mathbb{Q}$ , output: 1 if  $\text{dist}(\mathbf{t}, \mathcal{L}(\mathbf{B})) \leq r$ , or 0 if  $\text{dist}(\mathbf{t}, \mathcal{L}(\mathbf{B})) > r$ .

**Definition 2** (gapCVP $_\gamma$ ). Given a basis  $\mathbf{B} \in \mathbb{Z}^{m \times n}$ , a target vector  $\mathbf{t} \in \mathbb{Z}^m$ , and  $r \in \mathbb{Q}$ , output: 1 if  $\text{dist}(\mathbf{t}, \mathcal{L}(\mathbf{B})) \leq r$ , or 0 if  $\text{dist}(\mathbf{t}, \mathcal{L}(\mathbf{B})) > \gamma \cdot r$ .

**Lemma 3** (without proof).  $CVP \leq_t \text{gapCVP}$

**Theorem 4.** gapCVP is NP-Complete.

*Proof.* Observe that gapCVP is in NP. This is because a witness to a gapCVP instance  $(\mathbf{B}, \mathbf{t}, r)$  is a vector  $\mathbf{x} \in \mathcal{L}(\mathbf{B})$  such that  $\|\mathbf{t} - \mathbf{x}\| \leq r$ . First, it is easy to see that the witness  $\mathbf{x}$  can be written down using a polynomial number of bits. Indeed, each coefficient of  $\mathbf{x}$  differs from the corresponding coefficient of  $\mathbf{t}$  by at

most  $r$ , meaning that representing  $\mathbf{x}$  requires at most  $n\lceil\log r\rceil$  bits. Furthermore, given such an  $\mathbf{x}$ , checking that it is a lattice vector and that  $\|\mathbf{x} - \mathbf{t}\| \leq r$  can both be done in time polynomial in the input length.

We will now reduce the **NP**-complete problem of Subset Sum to **gapCVP**.

**Definition 5** (Subset Sum). *Given  $A_1, \dots, A_n \in \mathbb{Z}$  and  $T \in \mathbb{Z}$  (a target value), decide if there are numbers  $x_1, \dots, x_n \in \{0, 1\}$  such that  $\sum_{i=1}^n A_i \cdot x_i = T$ .*

Subset-Sum is known to be **NP**-Complete. We will now reduce it to the **gapCVP** problem. Given an instance of Subset-Sum  $(A_1, \dots, A_n, T)$ , construct a lattice basis, target vector, and gap value as follows:

$$\mathbf{B} = [\mathbf{b}_1, \dots, \mathbf{b}_n] = \begin{pmatrix} A_1 & A_2 & \cdots & \cdots & A_n \\ 2 & 0 & 0 & \cdots & 0 \\ 0 & 2 & 0 & \cdots & 0 \\ 0 & 0 & 2 & \cdots & 0 \\ \vdots & & \vdots & & \vdots \\ 0 & \cdots & & 0 & 2 \end{pmatrix} \in \mathbb{Z}^{(n+1) \times n}, \quad \mathbf{t} = \begin{pmatrix} T \\ 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix} \in \mathbb{Z}^{n+1}, \quad r = \sqrt{n}$$

**Claim 6.** *If  $(A_1, \dots, A_n, T)$  is a Subset-Sum instance, then  $(\mathbf{B}, \mathbf{t}, r)$  is a **gapCVP** instance.*

*Proof.* Let  $\mathbf{x} = (x_1, \dots, x_n)$  be a solution to the Subset-Sum instance; i.e.,  $\sum_{i=1}^n A_i x_i = T$ . Then the corresponding lattice vector  $\mathbf{v} = \mathbf{B}\mathbf{x}^T = \left( \sum_{i=1}^n A_i x_i, 2x_1, 2x_2, \dots, 2x_n \right)$ . Thus,

$$\|\mathbf{v} - \mathbf{t}\| = \left\| \begin{pmatrix} \sum_{i=1}^n A_i x_i \\ 2x_1 \\ \vdots \\ 2x_n \end{pmatrix} - \begin{pmatrix} T \\ 1 \\ \vdots \\ 1 \end{pmatrix} \right\| = \sqrt{n}$$

where the last inequality follows from the fact that since  $x_i \in \{0, 1\}$ ,  $|2x_i - 1| = 1$  for all  $i = 1, \dots, n$ .  $\square$

**Claim 7.** *If there exists a  $\mathbf{v} \in \mathcal{L}(\mathbf{B})$  such that  $\|\mathbf{v} - \mathbf{t}\| \leq \sqrt{n}$  then  $(A_1, \dots, A_n, T)$  is a Subset-Sum instance.*

*Proof.* Let  $\mathbf{v} = (v_0, \dots, v_n) \in \mathcal{L}(\mathbf{B})$  such that  $\text{dist}(\mathbf{v}, \mathbf{t}) \leq \sqrt{n}$ . Now,  $v_1, \dots, v_n$  are all even. Thus, for all  $i$ ,  $|v_i - 1| \geq 1$ , which gives us that

$$\text{dist}(\mathbf{v}, \mathbf{t}) = \sqrt{(v_0 - T)^2 + (v_1 - 1)^2 + \cdots + (v_n - 1)^2} \leq \sqrt{n}$$

only if  $v_0 = T$  (meaning,  $(v_0 - T)^2 = 0$ ) and for all  $1 \leq i \leq n$ ,  $v_i \in \{0, 2\}$ .

This shows us that  $\sum_{i=1}^n A_i (v_i/2) = T$ , concluding the proof.  $\square$

Clearly, since the reduction above runs in polynomial time, it shows that **CVP** is **NP**-complete.  $\square$

A natural thought to show the hardness of **SVP** is to come up with a reduction from **CVP** to **SVP** that works as follows: Given an instance  $(\mathbf{B}, \mathbf{t})$  of **CVP**, consider the matrix  $\mathbf{B}' = [\mathbf{B}|\mathbf{t}]$ . The shortest vector would then be:  $\arg \min \left\| \sum_{i=1}^n x_i b_i + x_{n+1} \mathbf{t} \right\|$ . However, this reduction does not help us in general.

## 2 Solving Subset Sum on the Average using Approximate CVP

**Context:** A proposal for a one-way function based on the Subset-Sum problem.

**Definition 8** (one-way function). Let  $F = \{f_n : D_n \rightarrow \mathbb{R}_n\}_{n>0}$  be a family of functions domain  $D_n$ .  $f_n \in F$  is one-way if for all (probabilistic) polynomial time algorithm  $A$ , and for a sufficiently large  $n$

$$\Pr[f_n(A(f_n(x))) = f_n(x)] < \frac{2}{3}$$

assuming that  $x$  is chosen from  $D_n$  according to the uniform distribution.

**Proposal:** Let  $p$  be an  $n$ -bit prime ( $2^{n-1} < p \leq 2^n$ ). Define a function  $f(A_1, \dots, A_m, x_1, \dots, x_m) = (A_1, \dots, A_m, \sum_{i=1}^n A_i x_i)$ , where  $x_1, \dots, x_n \in \{0, 1\}$ , and  $0 \leq A_i \leq p - 1 < 2^n$ .

**Theorem 9** (Lagarias-Odlyzko). If  $n > 2m^2$  then  $f$  is not one-way.

*Proof.* 1. Pick a large enough number  $c > m \cdot 2^m$

2. Construct an instance of CVP:

$$\mathbf{B} = \begin{pmatrix} cA_1 & cA_2 & \cdots & cA_m \\ 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & & \ddots & \vdots \\ 0 & & & 1 \end{pmatrix}_{(m+1) \times n} \quad \mathbf{t} = \begin{pmatrix} cT \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

3. Run  $\mathbf{x}^* \leftarrow \text{NearestPlane}(\mathbf{B}, \mathbf{t})$ . Output  $\mathbf{x}^*$ .

Does this work?

**Claim 10.**  $\text{dist}(\mathbf{t}, \text{lat}(\mathbf{B})) \leq \sqrt{m}$ .

**Proof Idea** This is true since by definition  $T = \sum_{i=1}^n x_i A_i$  for some  $\mathbf{x} \in \{0, 1\}^m$ . □

Reminder: The *NearestPlane* algorithm returns a vector  $\mathbf{x}^* \in \mathbb{Z}^m$  such that  $\|\mathbf{B}\mathbf{x}^* - \mathbf{t}\| \leq \sqrt{m} \cdot 2^{m/2}$ . In order to conclude the proof, two things need to be proved:

1.  $\mathbf{x} \in \{0, 1\}^m$

2.  $\sum_{i=1}^n A_i x_i^* = T$  (i.e. the returned vector is an exact solution).

We will begin with the second item first.

**Claim 11.**  $\sum_{i=1}^n A_i x_i^* = T$

*Proof.* Say  $\sum_{i=1}^n A_i x_i^* \neq T$ . Then  $\|\mathbf{B}\mathbf{x}^* - \mathbf{t}\| \geq c > m \cdot 2^m$  (contradicting the approximation of *NearestPlane*). □

**Claim 12.**  $|x_i^*| \leq 2^{m/2} \cdot \sqrt{m} < 2^m$

*Proof.* Suppose for contradiction that the claim is false. Then  $\|\mathbf{B}\mathbf{x}^* - \mathbf{t}\| \geq |x_i^*| > 2^{m/2} \cdot \sqrt{m}$ , which is a contradiction to the approximation of the *NearestPlane* algorithm.  $\square$

We now claim that the probability of having a different solution vector  $\mathbf{x} \in \{0, 1\}^m$  than  $\mathbf{x}^*$ , returned by the *NearestPlane* algorithm is small. We let  $\mathbf{z} = \mathbf{x} - \mathbf{x}^*$ . Note that due to the previous claim,  $|z_i| \leq 2^m + 1$ .

**Claim 13.**

$$Pr[\exists \mathbf{z} \neq 0 : \sum_{i=1}^m z_i A_i] \leq \frac{1}{2}$$

*Proof.* Fix  $z_1, \dots, z_m$ , then since  $A_1, \dots, A_m$  are chosen uniformly at random,  $Pr[\sum_{i=1}^m z_i \cdot A_i = 0 \pmod{p}] = \frac{1}{p}$ .

Note: we choose  $1 < 2^{n-1} \leq 2^n$  in such a way that we get uniform randomness over  $\mathbb{Z}_p$ . Using the union bound we get:

$$Pr[\exists \mathbf{z} : \sum_{i=1}^m m z_i \cdot A_i = 0] \leq (2 \cdot 2^m + 1)^m \cdot \frac{1}{p} \leq \frac{1}{p} \cdot 2^{m^2} \leq \frac{1}{2}$$

where in the first inequality we use the fact the bound on the sum in  $\mathbb{Z}_p$  provides an upper bound on the sum in  $\mathbb{Z}$ .  $\square$

$\square$

### 3 Small Solutions to Polynomial Equations Modulo Composites

**Theorem 14** (Håstad, Coppersmith). *Let  $f(x) \in \mathbb{Z}_N[x]$  be of degree  $d$  and monic (the leading coefficient is 1). There is a polytime (in  $(\log N, d)$ ) algorithm that finds all  $x$  such that (1)  $f(x) = 0 \pmod{N}$  (2)  $|x| \leq N^{1/d} = \beta$ . (today we will discuss cases where  $|x| \leq N^{\frac{2}{d+1}}$ )*

Note:

1.  $f$  has to be monic: consider  $p \cdot x = 0 \pmod{2p}$ . In that case, all the even numbers are solutions to this equation (in which case, the given running time is insufficient).
2.  $|x| \leq N^{1/d}$ : consider  $x^r = 0 \pmod{p^r}$ .

**Proof Idea** Let  $f(x) = \sum_{i=0}^d a_i x^i$ . If we assume that  $|a_i \beta^i| \leq \frac{N}{d+1}, \forall i$ , then  $|f(x)| \leq |f(\beta)| < N \Rightarrow f(x) = 0$

(over  $\mathbb{Z}$ ). Hence, we would want to find an equivalent polynomial with the same solutions that satisfies the inequality (but with small coefficients). Let  $Z = \{N, N\beta, \dots, N\beta^{d-1}, f(x)\}$ .

**Fact 15.** *Let  $a_1, \dots, a_{d+1} \in \mathbb{Z}_N$ . Then  $\sum_{i=0}^d a_i N x^i + a_{d+1} f(x) = 0 \pmod{N}$  iff  $f(x) = 0 \pmod{N}$ .*

1. Consider the lattice defined by the following basis:

$$\mathbf{B} = \begin{pmatrix} N & 0 & \dots & & a_0 \\ 0 & N\beta & 0 & \dots & a_1\beta \\ \vdots & & N\beta^2 & \dots & a_2\beta^2 \\ & & & \ddots & \vdots \\ 0 & & \dots & N\beta^{d-1} & a_d\beta^d = \beta^d \end{pmatrix}_{(d+1) \times (d+1)}$$

2. Run  $LLL(\mathbf{B})$  to get  $\mathbf{z} = (z_0, \dots, z_{d+1}) \in \mathbb{Z}^{d+1}$  such that  $\|\mathbf{Bz}\|$  is approximately small (i.e. an approximation to the SVP).

3. Output  $\sum_{i=1}^d z_i(Nx_i) + z_{d+1} \cdot F(x) \triangleq g(x)$ .

By LLL and Minkowski's first theorem:

$$\begin{aligned} \|\mathbf{Bz}\| &\leq 2^{d+1}(\det(\mathcal{L}))^{1/(d+1)} = c_d \cdot (N^d \left(\prod_{i=1}^d \beta^i\right))^{\frac{1}{d+1}} = c_d \cdot N^{d/(d+1)} \cdot \beta^{d/2} < \frac{N}{d+1} \\ &\Rightarrow \beta \leq c_d N^{\frac{2}{d(d+1)}} \end{aligned}$$

□