

**Regev's Main Average-Case to Worst-Case Lemma**

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We show the main part of Regev's [Reg09] proof that (under certain conditions) it is possible to relate the *average-case* hardness of the learning with errors problem (LWE) to the *worst-case* hardness of bounded distance decoding in a given lattice (BDD).

**Preliminaries.** We use the following parameters:

$n$  - security parameter.

$\alpha$  - noise parameter ( $= \frac{1}{\text{poly}(n)}$ ).

$q$  - modulus ( $\gg \frac{1}{\alpha}$ , sometimes even  $q = \exp(n)$ ).

Recall that for a continuous distribution  $D_r$  (with standard deviation  $r$ ),  $\tilde{D}_{L,r}$  denotes a discrete distribution over a lattice (or coset of a lattice)  $L$  such that every vector  $\vec{z} \in L$  has probability mass proportional to  $D_r(\vec{z})$ .

## 1 The Main Lemma

In addition to an oracle that solves LWE, the reduction from BDD to LWE also needs access to an oracle that samples short vectors in  $\Lambda^*$  (Regev [Reg09] and Peikert [Pei09] show how to construct such an oracle in specific settings). Additionally it relies on the following properties of the LWE error distribution:

- The LWE error distribution is a projection of a spherical distribution  $D_{\alpha q}$  onto its first coordinate.
- The distribution  $D_{\alpha q}$  is smooth in the following sense: If  $\Lambda$  is some lattice (or coset of a lattice) with  $\lambda_n(\Lambda) \ll \alpha q$  then if we choose  $\vec{x} \leftarrow \tilde{D}_{\Lambda,r}$  and  $\vec{y} \leftarrow D_s$  such that  $r^2 + s^2 = (\alpha q)^2$  then the induced distribution on  $\vec{x} + \vec{y}$  is close to  $D_{\alpha q}$ .

For example the  $n$ -dimensional discrete Gaussian has these properties (where  $\lambda_n \ll \alpha q$  means  $\lambda_n \cdot \omega(\sqrt{\log(n)}) < \alpha q$ ). In this case the LWE error distribution is just the one-dimensional Gaussian.

**Lemma 1** ([Reg09]). *There is an efficient algorithm that takes as input a basis  $B$  of an  $n$ -dimensional lattice  $\Lambda = \Lambda(B)$ , another parameter  $r \gg \frac{q}{\lambda_1(\Lambda)}$  and a point  $\vec{x} \in \mathbb{R}^n$  such that  $\text{dist}(\vec{x}, \Lambda) < \frac{\alpha q}{\sqrt{2}r}$  and has access to two oracles:*

- A “global” solver for  $\text{LWE}[n, \alpha, q]$  (“global” in the sense that it is unrelated to the input lattice).
- A “lattice specific” sampler from  $D_{\Lambda^*,r}$ .

The algorithm finds (with overwhelming probability) the (unique) point  $\vec{v} \in \Lambda$  closest to  $\vec{x}$ .

## 2 Proof Sketch of Lemma 1

Let  $\vec{v} \in \Lambda$  be the closest point to  $\vec{x}$  in  $\Lambda$  and let  $\vec{t} \in \mathbb{Z}^n$  be the coefficients of  $\vec{v}$  when expressed in basis  $B$  (i.e.,  $\vec{v} = B\vec{t}$ ) and denote  $\vec{s} \stackrel{\text{def}}{=} \vec{t} \bmod q$ . We show a procedure that uses the sampler for  $\tilde{D}_{\Lambda^*,r}$  to generate instances of the distribution  $\text{LWE}_{\vec{s}}$ . Then, we use the LWE solver to find  $\vec{s}$ . (Note

that  $\vec{s}$  was not chosen uniformly at random in this case, but we previously showed a random self reduction for LWE from a random  $\vec{s}$  to any specific  $\vec{s}$ .) Later we show how from  $\vec{s}$  one can find  $\vec{t}$  thereby solving BDD.

**LWE-Generate**( $B, \vec{x}$ ) (With access to  $\tilde{D}_{\Lambda^*, r}$ )

1. Draw a sample  $\vec{y} \leftarrow \tilde{D}_{\Lambda^*, r}$ . Let  $\vec{a}$  be the coefficients of  $\vec{y}$  in basis  $B^*$  (i.e.  $\vec{a} = B^T \vec{y}$ ).
2. Draw an error term  $e \leftarrow \Phi_{\frac{\alpha}{2\sqrt{\pi}}}$ .
3. Output  $(\vec{a}, b = \langle \vec{x}, \vec{y} \rangle + e \bmod q)$ .

**Claim 1.** *The output of LWE-Generate is statistically close to  $\text{LWE}_{\vec{s}}$  except that the error parameter is  $\beta \leq \alpha$ .*

*Proof.* Need to show:

- (A.)  $\vec{a}$  is close to uniform in  $\mathbb{Z}_q^n$ .
- (B.) Once  $\vec{a}$  is fixed,  $\vec{b} = \langle \vec{s}, \vec{a} \rangle + \Phi_{\beta q}$  ( $\beta \leq \alpha$ ).

(A.) Consider the lattice  $q \cdot \Lambda^*$  and all its  $q^n$  cosets

$$\vec{a}\text{-coset} = \{B^* \vec{a} + q\Lambda^*\} = \{B^* \vec{z} : \vec{z} = \vec{a} \bmod q\}$$

The vector  $\vec{a}$  output by the procedure is exactly the coset of  $\vec{y}$ . Due to our choice of parameters, all cosets are (almost) equally likely. Indeed, since  $r \gg \frac{q}{\lambda_1(\Lambda)} = \frac{q\lambda_n(\Lambda^*)}{n}$  then  $\tilde{D}_{\Lambda^*, r}$  is nearly uniform among the cosets.

(B.) Conditioned on any fixed  $\vec{a} \in \mathbb{Z}_q^n$ , the vector  $\vec{y}$  is chosen from the discrete distribution  $D_{q\Lambda^* + \vec{a}, r}$  on the  $\vec{a}$ -coset. Denoting  $\vec{w} \stackrel{\text{def}}{=} \vec{x} - \vec{v}$  we have

$$\begin{aligned} \langle \vec{x}, \vec{y} \rangle &= \langle \vec{v} + \vec{w}, \vec{y} \rangle \\ &= \langle \vec{v}, \vec{y} \rangle + \langle \vec{w}, \vec{y} \rangle \\ &= \langle B\vec{t}, \vec{y} \rangle + \langle \vec{w}, \vec{y} \rangle \\ &= \langle \vec{t}, B^T \vec{y} \rangle + \langle \vec{w}, \vec{y} \rangle \\ &= \langle \vec{s}, \vec{a} \rangle + \langle \vec{w}, \vec{y} \rangle \bmod q \end{aligned}$$

hence  $b = \langle \vec{s}, \vec{a} \rangle + \langle \vec{w}, \vec{y} \rangle + e \bmod q$ . Notice that  $\vec{s}$ ,  $\vec{a}$  and  $\vec{w}$  are fixed and the random part is just  $\vec{y}$  and  $e$ .

Recall that  $\Phi_{\frac{\alpha}{2\sqrt{\pi}}}$  is the projection of  $D_{\frac{\alpha}{2\sqrt{\pi}}}$  onto the first coordinate, namely  $\langle e_1, D_{\frac{\alpha}{2\sqrt{\pi}}} \rangle$  and since  $D$  is spherical then this is also the same as  $\langle \vec{u}, D_{\frac{\alpha}{2\sqrt{\pi}}} \rangle$  for any other unit vector  $\vec{u}$ . In particular,  $\Phi_{\frac{\alpha}{2\sqrt{\pi}}} \equiv \langle \vec{w}, D_{\frac{\alpha}{2\sqrt{\pi}}} \rangle \frac{1}{\|\vec{w}\|} \equiv \langle \vec{w}, D_{\frac{\alpha}{2\sqrt{\pi}\|\vec{w}\|}} \rangle$ .

Hence  $\langle \vec{w}, \vec{y} \rangle + e \equiv \langle \vec{w}, \vec{y} \rangle + \langle \vec{w}, \vec{z} \rangle = \langle \vec{w}, \vec{y} + \vec{z} \rangle$  where  $y \in_R \tilde{D}_{q\Lambda^* + \vec{a}, r}$  and  $z \in_R D_s$  where  $s = \frac{\alpha}{2\sqrt{\pi}\|\vec{w}\|}$ . Now  $\|\vec{w}\|$  is “short” so  $s$  is “large”. The parameters  $r, s$  are chosen large enough so that  $\tilde{D}_{q\Lambda^* + \vec{a}, r}$  is close to the continuous  $D_t$  where  $t = \sqrt{r^2 + s^2}$ . Therefore  $\langle \vec{w}, \vec{y} \rangle + e \approx \langle \vec{w}, D_t \rangle = \Phi_{\|\vec{w}\| \cdot t}$  and the parameters are such that  $\|\vec{w}\| \cdot t \leq \alpha q$ .  $\square$

To solve BDD for  $\vec{x}$  we can apply the LWE-solver with samples from LWE-Generate to find the vector  $\vec{s}$ . However, to solve BDD we need to find  $\vec{t}$  (recall  $\vec{s} = \vec{t} \bmod q$ ). To do this, first observe that  $\vec{v} = B\vec{t} = B\vec{s} + B(q\vec{z})$  for some  $\vec{z} \in \mathbb{Z}^n$  and consider  $\vec{x}' = \frac{\vec{x} - B\vec{s}}{q} = \frac{\vec{x} - \vec{v}}{q} + B\vec{z}$ . Notice that by this calculation, the vector  $\vec{x}'$  is at distance  $\frac{\|\vec{w}\|}{q}$  (where  $\vec{w} = \vec{x} - \vec{v}$ ) from the lattice (specifically the point  $B\vec{z}$ ). If we could find the closest lattice point to  $\vec{x}'$  we would have  $\vec{z}$  and therefore also  $\vec{v}$ . To do this just repeat the above argument again and again and at each iteration the distance from the lattice is reduced by a factor of  $q$ . After  $n$  such iterations we can solve the problem by using, e.g., Babai's nearest plane algorithm.

## References

- [Pei09] Chris Peikert. Public-key cryptosystems from the worst-case shortest vector problem: extended abstract. In *41st Annual ACM Symposium on Theory of Computing, STOC 2009*, pages 333–342. ACM, 2009.
- [Reg09] Oded Regev. On lattices, learning with errors, random linear codes, and cryptography. *JACM*, 56(6), 2009.