# Ajtai commitment and its proof of opening

## **Recall SIS**

**Definition 4.1.1 (Short Integer Solution (SIS**<sub> $n,q,\beta,m$ </sub>)). Given m uniformly random vectors  $\mathbf{a}_i \in \mathbb{Z}_q^n$ , forming the columns of a matrix  $\mathbf{A} \in \mathbb{Z}_q^{n \times m}$ , find a nonzero integer vector  $\mathbf{z} \in \mathbb{Z}^m$  of norm  $\|\mathbf{z}\| \leq \beta$  such that

$$f_{\mathbf{A}}(\mathbf{z}) := \mathbf{A}\mathbf{z} = \sum_{i} \mathbf{a}_{i} \cdot z_{i} = \mathbf{0} \in \mathbb{Z}_{q}^{n}.$$
 (4.1.1)

### **CRHF**

DEFINITION 2 A family of collision resistant hash functions (CRHF) is a sequence  $\{\mathcal{F}_n\}_{n=1}^{\infty}$ , where each  $\mathcal{F}_n$  is a family of functions  $f: \{0,1\}^{m(n)} \to \{0,1\}^{k(n)}$ , with the following properties.

- 1. There exists an algorithm that given any  $n \geq 1$  outputs a random element of  $\mathcal{F}_n$  in time polynomial in n.
- 2. Every function  $f \in \mathcal{F}_n$  is efficiently computable.
- 3. For any c > 0, there is no polynomial-time algorithm that with probability at least  $\frac{1}{n^c}$ , given a random  $f \in \mathcal{F}_n$  outputs x, y such that  $x \neq y$  and f(x) = f(y) (i.e., there is no polynomial-time algorithm that with non-negligible probability finds a collision).

Collision resistant functions from the SIS problem The key space  $\mathcal{K} = \mathbb{Z}_q^{n \times m}$ , is the set of all  $n \times m$  matrices with coefficients in  $\mathbb{Z}_q$ . Set  $\mathcal{M} = \{0,1\}^m$  and  $\mathcal{H} = \mathbb{Z}_q^n \approx \{0,1\}^{n \log_2 q}$ . For key **A** and input message  $x \in \mathcal{M}$ , set

$$f_{\mathbf{A}}(\mathbf{x}) := \mathbf{A}\mathbf{x} \bmod q$$
.

**Lemma 10** Is  $SIS_{m,n,q,1}$  is hard, then  $f: \mathcal{K} \times \mathcal{M} \to \mathcal{H}$  is hard.

PROOF: Let  $\mathbf{A} \in \mathcal{K}$ . Suppose we are able to find two  $\mathbf{m}_1 \neq \mathbf{m}_2 \in \mathcal{M}$  such that  $f_{\mathbf{A}}(\mathbf{m}_1) = f_{\mathbf{A}}(\mathbf{m}_2)$ . Let  $\mathbf{x} = \mathbf{m}_1 - \mathbf{m}_2$ . Then  $\mathbf{A}\mathbf{x} = 0$ , with  $\|\mathbf{x}\|_{\infty} \leq 1$ . So any algorithm that finds a collision of f., solves SIS.  $\square$ 

#### 4.3 Construction of a commitment scheme from SIS

An example of a lattice-based commitment scheme can be obtained by considering SIS-related function  $f_{\mathbf{A}} = \mathbf{A}\mathbf{x} \mod q$ . One obtains such a scheme by putting the triple of functions Keygen, Commit and Verif as follows.

The key generating function KeyGen takes as input  $1^n$  and outputs a matrix (that serves as public key)  $\mathbf{A} =: pk$  uniformly random from  $\mathbb{Z}_q^{n \times m}$ , where m is a parameter whose value will be decided later. For the random set R and its distribution D, put  $R = \mathbb{Z}^{m-1}$  and  $D = D_{\mathbb{Z}^{m-1},\sigma}$  the discrete Gaussian distribution on  $\mathbb{Z}^{m-1}$ , where  $\sigma \in \operatorname{poly}(n)$ .

The commitment function is defined as follows:  $\mathtt{Commit}(pk = \mathbf{A}, \mu, r) := \mathbf{A} \cdot \begin{pmatrix} \mu \\ \mathbf{r} \end{pmatrix} \bmod q$ , where  $\mu \in \{0,1\}$ . Here,  $\begin{pmatrix} \mu \\ \mathbf{r} \end{pmatrix}$  is the vector that is obtained by concatenating;  $(\mu | \mathbf{r})$ .

To verify the commitment on input  $(pk, \mu, r, c)$ , check whether  $\mathbf{A} \cdot \begin{pmatrix} \mu \\ \mathbf{r} \end{pmatrix} = c \mod q$  and  $\| \begin{pmatrix} \mu \\ \mathbf{r} \end{pmatrix} \| \leq \beta$ . If this is both true, set  $\mathrm{Verif}(pk, \mu, r, c) = 1$ , otherwise 0.

**Lemma 7** For appropriate parameters, above scheme is correct, statistically hiding and computationally binding, assuming that the  $SIS_{n,m,q,2\beta}$  is hard.

- (Computationally binding) Suppose a probabilistic polynomial time algorithm is able to find (on input  $\bf A$ ) a triple  $({\bf r}_0,{\bf r}_1,c)$  such that  $\bf A \begin{pmatrix} 0 \\ {\bf r}_0 \end{pmatrix} = c = {\bf A} \begin{pmatrix} 1 \\ {\bf r}_1 \end{pmatrix}$  mod q with nonnegligible probability. Then the vector  ${\bf v} = \begin{pmatrix} 1 \\ {\bf r}_0 {\bf r}_1 \end{pmatrix}$  is a SIS<sub> $n,m,q,2\beta$ </sub> solution. Therefore, this adversary solves SIS with these parameters, which is a contradiction, as we assumed that this was hard.
- (Statistically hiding) The goal is to prove that  $\tilde{\forall} \mathbf{A} = pk \leftarrow \texttt{KeyGen}(1^n)$  holds  $\texttt{Commit}(pk, 0, r) \approx_s \texttt{Commit}(pk, 1, r)$ , i.e., that the statistical distance is negligible. Decompose A into a first column  $\mathbf{a}_0$  and the rest of the matrix  $\mathbf{A}'$ :  $\mathbf{A} = (\mathbf{a}_0 | \mathbf{A}')$ . Our aim is to prove that

$$\Delta = \frac{1}{2} \sum_{c \in \mathcal{C}} |\mathbb{P}[\mathbf{A}'r = c] - \mathbb{P}[\mathbf{A}'r + a_0 = c]| \le \text{negl}(n).$$

Define  $\Lambda_q^{\perp c} = \{ \mathbf{x} \in \mathbb{Z}^m \mid \mathbf{A}\mathbf{x} \equiv c \mod q \}$ . Then, by construction

$$\mathbb{P}_{r \leftarrow D_{\mathbb{Z}^{m-1}, \sigma}}[\mathbf{A}r = c] = \frac{\rho_{\sigma}(\Lambda_q^{\perp c}(\mathbf{A}'))}{\rho_{\sigma}(\mathbb{Z}^{m-1})}$$

If  $\sigma \geq \eta_{\varepsilon}(\Lambda_{q}^{\perp c}(\mathbf{A}))$ , the smoothing parameter of  $\Lambda_{q}^{\perp c}(\mathbf{A}')$ , then we know that (informally) the cumulative weight of the Gaussians of any coset of  $\Lambda_{q}^{\perp c}(\mathbf{A}')$  is the same, up to a factor  $(1 \pm \varepsilon)$  [Lecture 8, Lemma 5]. In particular,  $\rho_{\sigma}(\Lambda_{q}^{\perp (c-a_{0})}(\mathbf{A}')) \in [1 - \varepsilon, 1 + \varepsilon] \cdot \rho_{\sigma}(\Lambda_{q}^{\perp c}(\mathbf{A}'))$ . Therefore

$$\Delta = \frac{1}{2} \sum_{c \in \mathcal{C}} |\mathbb{P}[\mathbf{A}'r = c] - \mathbb{P}[\mathbf{A}'r + a_0 = c]| = \frac{1}{2\rho_{\sigma}(\mathbb{Z}^{m-1})} \sum_{c \in \mathcal{C}} |\rho_{\sigma}(\Lambda_q^{\perp (c - a_0)}(\mathbf{A}')) - \rho_{\sigma}(\Lambda_q^{\perp c}(\mathbf{A}'))|$$

$$\leq \frac{1}{2\rho_{\sigma}(\mathbb{Z}^{m-1})} \sum_{c \in \mathcal{C}} \varepsilon \cdot \rho_{\sigma}(\Lambda_q^{\perp c}(\mathbf{A}')) \leq \varepsilon/2$$

In order to know the parameter choice for  $\sigma$ , we need to estimate  $\eta_{\varepsilon}(\Lambda_q^{\perp c}(\mathbf{A}))$  with  $\varepsilon \in \text{negl}(n)$ . This is because  $\sigma$  needs to be larger than the smoothing parameter.

### LYU SIGNATURE

Prove the knowledge of a SIS secret

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Signing Key: \mathbf{S} \stackrel{\$}{\leftarrow} \{-d, \dots, 0, \dots, d\}^{m \times k}

Verification Key: \mathbf{A} \stackrel{\$}{\leftarrow} \mathbb{Z}_q^{n \times m}, \mathbf{T} \leftarrow \mathbf{AS}

Random Oracle: \mathbf{H} : \{0,1\}^* \to \{\mathbf{v} : \mathbf{v} \in \{-1,0,1\}^k, \|\mathbf{v}\|_1 \le \kappa\}

Sign(\mu, \mathbf{A}, \mathbf{S})

1: \mathbf{y} \stackrel{\$}{\leftarrow} D_\sigma^m

2: \mathbf{c} \leftarrow \mathbf{H}(\mathbf{A}\mathbf{y}, \mu)

3: \mathbf{z} \leftarrow \mathbf{Sc} + \mathbf{y}

4: output (\mathbf{z}, \mathbf{c}) with probability min \left(\frac{D_\sigma^m(\mathbf{z})}{MD_{\mathbf{Sc},\sigma}^m(\mathbf{z})}, 1\right)
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Fig. 1. Signature Scheme.

# Zero-Knowledge

**Theorem 4.6.** Let V be a subset of  $\mathbb{Z}^m$  in which all elements have norms less than T,  $\sigma$  be some element in  $\mathbb{R}$  such that  $\sigma = \omega(T\sqrt{\log m})$ , and  $h: V \to \mathbb{R}$  be a probability distribution. Then there exists a constant M = O(1) such that the distribution of the following algorithm A:

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1: \mathbf{v} \overset{\$}{\leftarrow} h

2: \mathbf{z} \overset{\$}{\leftarrow} D^{m}_{\mathbf{v},\sigma}

3: output (\mathbf{z}, \mathbf{v}) with probability min \left(\frac{D^{m}_{\sigma}(\mathbf{z})}{MD^{m}_{\mathbf{v},\sigma}(\mathbf{z})}, 1\right)
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is within statistical distance  $\frac{2^{-\omega(\log m)}}{M}$  of the distribution of the following algorithm  $\mathcal{F}$ :

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1: \mathbf{v} \overset{\$}{\leftarrow} h

2: \mathbf{z} \overset{\$}{\leftarrow} D_{\sigma}^{m}

3: output (\mathbf{z}, \mathbf{v}) with probability 1/M
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Moreover, the probability that A outputs something is at least  $\frac{1-2^{-\omega(\log m)}}{M}$ .

More concretely, if  $\sigma = \alpha T$  for any positive  $\alpha$ , then  $M = e^{12/\alpha + 1/(2\alpha^2)}$ , the output of algorithm  $\mathcal{A}$  is within statistical distance  $\frac{2^{-100}}{M}$  of the output of  $\mathcal{F}$ , and the probability that  $\mathcal{A}$  outputs something is at least  $\frac{1-2^{-100}}{M}$ .

# Soundness

**Definition 2.3** (Relaxed Binding Commitment [ALS20; ACK21; Ajt96; PR06; LM06]). Fix  $q = q(\lambda), \kappa = \kappa(\lambda)$ ,  $m = m(\lambda)$ , bound  $b \in \mathbb{N}$  and a set  $S \subseteq R_q^*$  with invertible elements. We say that a randomly sampled linear function  $\mathbf{A} \stackrel{\mathbb{R}}{\leftarrow} R_q^{\kappa \times m}$  is  $(b, \mathcal{S})$ -relaxed binding if for all expected polynomial-time adversary  $\mathcal{A}$ ,

$$\Pr\left[\begin{array}{c|c} 0<\|\mathbf{z}_1\|_{\infty},\|\mathbf{z}_2\|_{\infty}< b \wedge s_1, s_2 \in \mathcal{S} \wedge \\ \mathbf{A}\mathbf{z}_1s_1^{-1}=\mathbf{A}\mathbf{z}_2s_2^{-1} \wedge \\ \mathbf{z}_1s_1^{-1}\neq \mathbf{z}_2s_2^{-1} \end{array} \right| \begin{array}{c} \mathbf{A} \xleftarrow{\mathbb{R}} R_q^{\kappa \times m} \\ (\mathbf{z}_1,\mathbf{z}_2 \in R_q^m, s_1, s_2) \leftarrow \mathcal{A}(\mathbf{A}) \end{array}\right] = \mathsf{negl}(\lambda) \,.$$

It is clear that if the  $(b, \mathcal{S})$ -relaxed binding property doesn't hold, then we can find  $\mathbf{x} := s_2\mathbf{z}_1 - s_1\mathbf{z}_2 \neq \mathbf{0} \in \mathbb{R}^m$  such that  $\mathbf{A}\mathbf{x} = 0 \mod q$ . Here  $s_2\mathbf{z}_1 - s_1\mathbf{z}_2$  is computed over R by first lifting  $s_1, s_2, \mathbf{z}_1, \mathbf{z}_2$  to R. Moreover,  $\|\mathbf{x}\|_{\infty} < B := 2b\|\mathcal{S}\|_{\text{op}}$ , thus we can reduce the  $(b, \mathcal{S})$ -relaxed binding property to the MSIS assumption  $\text{MSIS}_{a,\kappa,m,B}^{\infty}$ .

If we don't care ZK...