

# 2024 - 257 LatticeFold

## I. Preparation

### 1 notations

$$R_q = \mathbb{Z}_q / (x^d + 1)$$

For  $a = \sum_{i=1}^d a_i X^{i-1} \in R_q$ ,  $\vec{a} = (a_1, \dots, a_m) \in R_q^m$   $A \in R_q^{k \times m}$

$\text{vec}(\cdot)$  vectors or matrices (over  $\mathbb{Z}_q$ )

$$\text{vec}(a) = \begin{bmatrix} a_1 \\ \vdots \\ a_d \end{bmatrix} = (a_1, \dots, a_d)^T \in \mathbb{Z}_q^d \quad \text{--- coefficient vector}$$

$$\text{vec}(\vec{a}) = [\text{vec}(a_1), \dots, \text{vec}(a_m)] \in \mathbb{Z}_q^{m \times d} \quad \text{a matrix}$$

$f\text{vec}(\vec{a})$  concatenation of  $\text{vec}(\vec{a})$ 's row vectors

$\text{Rot}(\cdot)$  rotation matrices (over  $\mathbb{Z}_q$ )

$$\text{Rot}(a)$$

$$\text{vec}(a \cdot b) = \text{Rot}(a) \cdot \text{vec}(b)$$

$$\text{Rot}(A) = [\text{Rot}(a_{i,j})]_{A \in \mathbb{Z}_q^{k \times m}}$$

$$f\text{vec}(A\vec{f}) = \text{Rot}(A) f\text{vec}(\vec{f})$$

$\text{RotSum}(\cdot)$   $R_q \times F_{q^d}^d \rightarrow F_{q^d}^d$

$$\text{for } \beta \in F_{q^d}$$

$$\text{RotSum}(a, \beta) = \text{Rot}(a) \cdot \beta \Rightarrow \text{RotSum}(a, \text{vec}(b)) = \text{vec}(a \cdot b)$$

## 2. Reduction of Knowledge (from $R_1$ to $R_2$ )



Def. Setup ( $1^{\lambda}$ )  $\rightarrow$  pp

$$\langle P(pp, x_1, w_1), V(pp, x_1) \rangle \longrightarrow (x_2, w_2)$$

Properties. Completeness :

If  $(x_1, w_1) \in R_1$  and  $V$  accepts, then  $(x_2, w_2) \in R_2$

Knowledge Soundness : Extract  $w_1$

$\exists$  an extractor  $\text{Ext}$ , given  $(x_2, w_2)$ ,

$$\text{Ext}(pp, x_1, st) \rightarrow w_1, \text{ st } (x_1, w_1) \in R_1$$

Public reducibility : Public F

有确定再该可以从前  $x_1$  中提取出  $x_2$

$\exists$  deterministic PT algorithm F, transcript tr

$$F(pp, x_1, tr) = x_2$$

$$\Pi_1: R_1 \rightarrow R_2 \quad \Pi_2: R_2 \rightarrow R_3 \quad \Pi_1 \circ \Pi_2: R_1 \rightarrow R_3$$

$$\Pi_1: R_1 \rightarrow R_3$$

$$\Pi_2: R_2 \rightarrow R_4$$

$$\Pi_1 \times \Pi_2: R_1 \times R_2 \rightarrow R_3 \times R_4$$

## 3 Ajtai Commitment

message  $|\vec{x}|_\infty < B$

$$\text{Setup}: A \leftarrow R_q^{k \times m}$$

provide binding only

$$\text{Com}(A, \vec{x}): cm = A\vec{x} \bmod q$$

## II Folding Scheme for Ajtai Com

### 1. Relations $R_{cm}$ & $R_{val}$

$$R_{cm} = \{ (pp, cm \in R_q^k ; \vec{f} \in R_q^m) : cm = A\vec{f} \wedge \|f\|_\infty < B \}$$

$$R_{val} = \left\{ (pp, cm, \vec{r}, v ; \hat{\vec{f}}) : (pp, cm, \hat{\vec{f}}) \in R_{cm} \wedge \begin{array}{l} \\ m \in [\hat{f}](\vec{r}) = v \end{array} \right\}$$

$$NTT(\hat{f}) = \text{vec}(\hat{f}) \quad \hat{f} = (\hat{f}_1, \dots, \hat{f}_m) \in R_q^m$$

then  $v = \hat{f}_r$  iff  $\text{eq}(r, X) = 1$  VERQ

像在  $F_q$  上做 mle - 样  $a = (a_1, \dots, a_m) \in F_q^m$

$$\begin{aligned} \text{把 } F_q \text{ 中的元素换成 } R_q \text{ 中的} \quad mle(a)(x) &= \sum_{i=1}^m a_i \cdot \text{eq}(i, X) \\ &= \langle a, \text{eq}(i, X) \rangle \end{aligned}$$

### 2. Framework

1. Expansion: reduction of knowledge  $\Pi_{cm}$ :  $R_{val}^B \times R_{cm}^B \rightarrow R_{val}^B \times R_{val}^B$
2. Decomposition:  $\Pi_{dec}$ :  $R_{val}^B \times R_{val}^B \rightarrow (R_{val}^B)^{2k}$
3. Folding:  $\Pi_{fold}$ :  $(R_{val}^B)^{2k} \rightarrow R_{val}^B$

Warm-up:

prove  $\|\vec{f}\|_\infty < B$  for  $\vec{f} \in R_q^m$

$$\vec{f} \cdot [\circ_{i=1}^{B-1} (\vec{f} - \vec{i}) \circ (\vec{f} + \vec{i})] = \vec{0}$$

$$\vec{f} \in \mathbb{Z}_q^{md}$$

$$\vec{i} = (i, i, \dots, i)$$

define  $NTT(\hat{f}) = \vec{f}$ ,  $NTT(\hat{i}) = \vec{i}$

$$NTT(\hat{f}) \cdot [\circ_{i=1}^{B-1} (NTT(\hat{f}) - NTT(\hat{i})) (NTT(\hat{f}) + NTT(\hat{i}))] = \vec{0}$$

go back to  $R_q$

$$\hat{f} \cdot \prod_{i=1}^{B-1} (\hat{f} - \hat{i})(\hat{f} + \hat{i}) = \vec{0} \quad \checkmark$$

Rewrite  $R_{cm} = \left\{ (pp, cm \in R_q^k; \vec{f} \in R_q^m) : \begin{array}{l} cm = A\vec{f} \wedge \\ \hat{f} \cdot \prod_{i=1}^{B-1} (\hat{f} - \hat{i})(\hat{f} + \hat{i}) = \vec{0} \end{array} \right\}$

Step 1

$R_{val} = \left\{ (pp, cm, v; \vec{f} \in R_q^m) \right.$

$$\begin{array}{l} y = L(\vec{f}) \\ cm = A\vec{f} \wedge \|\vec{f}\|_\infty < B \\ mle[\vec{f}](o) = v \end{array} \right\}$$

Step 2

$R_{val} \times R_{val}$

split:  $y = \sum b^i y_i \quad y = cm \quad \rightarrow \underline{y_i = L(\vec{f}_i)}$        $L$ : homomorphic

$$\vec{f} = \sum b^i \vec{f}_i$$

$$v = \sum b^i v_i$$

$$\hat{f} = NTT(\vec{f}) \quad mle(\hat{f})[r] = v \xrightarrow{\text{NTT运算同构}} mle(\hat{f}_i)[r] = v_i$$

Lemma 3.1

**Input:**  $(\mathbf{x}; \mathbf{w}) := (\mathbf{cm}; \vec{\mathbf{f}})$ .

**Output:**  $(\mathbf{x}_o; \mathbf{w}_o) := ((0^{\log m}, \mathbf{v}, \mathbf{cm}); \vec{\mathbf{f}})$ .

**The protocol**  $\langle P(pp, \mathbf{x}; \mathbf{w}), V(pp, \mathbf{x}) \rangle$ :

1.  $P \rightarrow V$ :  $P$  sends  $V$  the evaluation  $\mathbf{v} := \text{mle} \left[ \hat{\mathbf{f}} \right] (0^{\log m})$ . P转化为关系，不做计算
2.  $V$  outputs  $\mathbf{x}_o := (0^{\log m}, \mathbf{v}, \mathbf{cm})$ .  $P$  outputs  $\mathbf{w}_o := \vec{\mathbf{f}}$ .

Figure 1: The protocol  $\Pi_{\text{cm}}$  that reduces  $\mathcal{R}_{\text{cm}}^B$  to  $\mathcal{R}_{\text{eval}}^B$ .

**Input:**  $\mathbf{x} := (\vec{\mathbf{r}}, \mathbf{v}, y)$  and  $\mathbf{w} := \vec{\mathbf{f}}$ .

**Output:**  $[\mathbf{x}_i = (\vec{\mathbf{r}}, \mathbf{v}_i, y_i), \mathbf{w}_i = \vec{\mathbf{f}}_i]_{i=0}^{k-1}$ .

**The protocol**  $\langle P(pp, \mathbf{x}; \mathbf{w}), V(pp, \mathbf{x}) \rangle$ :

1.  $P \rightarrow V$ : Let  $\vec{\mathbf{F}} := (\vec{\mathbf{f}}_0, \dots, \vec{\mathbf{f}}_{k-1}) := \text{split}_{b,k}(\vec{\mathbf{f}})$ .  $P$  sends  $V$  the values  $[y_i, \mathbf{v}_i]_{i=0}^{k-1}$  where

$$y_i := \mathcal{L}(\vec{\mathbf{f}}_i), \quad \mathbf{v}_i := \text{mle} \left[ \vec{\mathbf{f}}_i \right] (\vec{\mathbf{r}}) \quad \begin{array}{l} \text{直接拆开} \\ \text{A} \cdot \vec{\mathbf{f}}_i \end{array}$$

for every  $i \in [0, k)$ .

2.  $V$  checks that  $\sum_{i=0}^{k-1} b^i \cdot y_i \stackrel{?}{=} y$ , and  $\sum_{i=0}^{k-1} b^i \cdot \mathbf{v}_i \stackrel{?}{=} \mathbf{v}$ .
3.  $V$  outputs  $[\mathbf{x}_i = (\vec{\mathbf{r}}, \mathbf{v}_i, y_i)]_{i=0}^{k-1}$ .  $P$  outputs  $[\mathbf{w}_i = \vec{\mathbf{f}}_i]_{i=0}^{k-1}$ .

Figure 2: The protocol  $\Pi_{\text{dec}}^*$  that reduces  $\mathcal{R}_{\text{hom}}^B$  to  $(\mathcal{R}_{\text{hom}}^b)^k$ .

$\mathcal{L}$ : 同态映射, eg.  $\vec{\mathbf{y}} = A \vec{\mathbf{f}}$

$\Pi_{\text{dec}}$  不改变  $\vec{\mathbf{r}}$

Figure 2  $\Pi_{\text{dec}}^*$  is a reduction of knowledge

1. Public reducibility extract  $\mathbf{x}_2$

given  $\mathbf{x} = (\vec{\mathbf{r}}, \mathbf{v}, y)$  and trans  $[y_i, \mathbf{v}_i]_{i=0}^{k-1}$ , one can output  $[\vec{\mathbf{r}}, y_i, \mathbf{v}_i]_{i=0}^{k-1}$

2. Completeness  $(\mathbf{x}_2, \mathbf{w}_2) \in R_2$  if  $V$  accepts.

(1)  $V$  accepts (as discussed on last page,  $\mathcal{L}$  homomorphic, NTT isomorphic)

$$(2) (x_2, w_2) \in R_2 \quad \left\{ \begin{array}{l} \|f_i\|_\infty < b \text{ for all } i \in [0, k) \\ y_i = L(\vec{f}_i) \\ v_i = \text{mle}[\hat{f}_i](r) \end{array} \right.$$

3. Knowledge Soundness extract  $w_1 (\vec{f})$

given  $(x_2, w_2) = [(\vec{r}, v_i, y_i); \vec{f}_i]_{i=0}^{k-1}$  output  $\vec{f} = \sum b^i \vec{f}_i$   
 $\|\vec{f}\|_\infty < B$   
 $b = B^{1/k}$

Step 3

$$\begin{aligned} & [x_i = (\vec{r}_i, v_i, y_i)]_{i=1}^{2k} \quad [w_i = \vec{f}_i]_{i=1}^{2k} \quad \|f_i\|_\infty < b \\ \hookrightarrow & x_0 = (\vec{r}_0, v_0, y_0) \quad w_0 = \vec{f}_0 \quad \|f_0\|_\infty < B \end{aligned}$$

$$\vec{r}_0 \leftarrow C, \quad NTT(v_0) = \sum_{i=1}^{2k} \text{RotSum}(p_i, NTT(r_i)) \quad y_0 = \sum_{i=1}^{2k} p_i y_i \quad w_0 = f_0 = \sum_{i=1}^{2k} p_i f_i$$

用 Sumcheck 证明 1.  $v_i = \text{mle}[\hat{f}_i](\vec{r}_i)$

$$2. \|f_i\|_\infty < b$$

$$\text{define } g_{1,i}(x) = \text{eq}(\vec{r}_i, \vec{x}) \text{ mle}[\hat{f}_i](\vec{x})$$

$$\text{define } g_{2,i}(x) = \sum_{j=(b-1)}^{b-1} (\text{mle}[\hat{f}_i](\vec{x}) - j)$$

combine  $g_{1,i}, g_{2,i}$  into one:

$$\text{Thus } \sum_b g(b) = \sum_{i=1}^{2k} \alpha_i v_i \quad \text{our claim}$$

$$\text{we have } 1. g_{1,i}(\vec{r}_i) = v_i$$

$$2. g_{2,i}(x) = 0 \text{ for all } x$$

$$g(x) = \sum_{i=1}^{2k} [\alpha_i g_{1,i}(x) + \mu_i g_{2,i}(x)]$$

**Parameters:**  $c \in \mathbb{N}$ ,  $\mathcal{C} := \mathbb{Z}_q \subseteq \mathcal{R}_q$ , and a strong sampling set  $\mathcal{C}_{\text{small}} \subseteq \mathcal{R}_q$  with expansion factor  $\|\mathcal{C}_{\text{small}}\|_{\text{op}} \leq c$  (Defn. 5).

**Input:**  $[\mathbf{x}_i := (\vec{\mathbf{r}}_i, \mathbf{v}_i, y_i)]_{i=1}^{2k}$  and  $[\mathbf{w}_i := \vec{\mathbf{f}}_i]_{i=1}^{2k}$ .

fold 时, 2个 r 来自不同的 statements

**Output:**  $\mathbf{x}_o := (\vec{\mathbf{r}}_o, \mathbf{v}_o, y_o)$ ,  $\mathbf{w}_o := \vec{\mathbf{f}}_o$ .

**The protocol**  $\langle \mathsf{P}(\mathsf{pp}, \mathbf{x}; \mathbf{w}), \mathsf{V}(\mathsf{pp}, \mathbf{x}) \rangle$ :

1.  $\mathsf{V} \rightarrow \mathsf{P}$ :  $\mathsf{V}$  sends  $\mathsf{P}$  challenges  $[\alpha_i]_{i=1}^{2k} \stackrel{\$}{\leftarrow} \mathcal{C}^{2k}$ ,  $[\mu_i]_{i=1}^{2k-1} \stackrel{\$}{\leftarrow} \mathcal{C}^{2k-1}$  and  $\vec{\beta} \stackrel{\$}{\leftarrow} \mathcal{C}^{\log m}$ .
2.  $\mathsf{V} \leftrightarrow \mathsf{P}$ :  $\mathsf{P}$  and  $\mathsf{V}$  run a sum-check protocol for the claim

$$\sum_{\vec{\mathbf{b}} \in \{0,1\}^{\log m}} g(\vec{\mathbf{b}}) = \sum_{i=1}^{2k} \alpha_i \mathbf{v}_i.$$

Set  $\mu_{2k} := 1$ , here the polynomial  $g(\vec{\mathbf{x}}) \in \mathcal{R}_q^{\leq 2b}[X_1, \dots, X_{\log m}]$  is defined as

$$g(\vec{\mathbf{x}}) := \sum_{i=1}^{2k} [\alpha_i g_{1,i}(\vec{\mathbf{x}}) + \mu_i g_{2,i}(\vec{\mathbf{x}})], \quad (14)$$

$$\forall i \in [2k] : g_{1,i}(\vec{\mathbf{x}}) := eq(\vec{\mathbf{r}}_i, \vec{\mathbf{x}}) \cdot \text{mle} \left[ \hat{\mathbf{f}}_i \right] (\vec{\mathbf{x}}), \quad \text{red}$$

$$\forall i \in [2k] : g_{2,i}(\vec{\mathbf{x}}) := eq(\vec{\beta}, \vec{\mathbf{x}}) \cdot \prod_{j=-b+1}^{b-1} \left( \text{mle} \left[ \hat{\mathbf{f}}_i \right] (\vec{\mathbf{x}}) - j \right). \quad (16)$$

The protocol reduces to check the evaluation claim  $g(\vec{\mathbf{r}}_o) \stackrel{?}{=} s$  where  $\vec{\mathbf{r}}_o \stackrel{\$}{\leftarrow} \mathcal{C}^{\log m}$  is the sum-check challenge vector sampled by  $\mathsf{V}$ .

3.  $\mathsf{P} \rightarrow \mathsf{V}$ :  $\mathsf{P}$  sends  $\mathsf{V}$  values  $[\theta_i := \text{mle} \left[ \hat{\mathbf{f}}_i \right] (\vec{\mathbf{r}}_o)]_{i=1}^{2k}$ .  
 4.  $\mathsf{V}$  computes  $[\mathbf{e}_i := eq(\vec{\mathbf{r}}_i, \vec{\mathbf{r}}_o)]_{i=1}^{2k}$  and  $\mathbf{e}^* := eq(\vec{\beta}, \vec{\mathbf{r}}_o)$  and checks that

*g is well-formed*

$$s \stackrel{?}{=} \sum_{i=1}^{2k} \left[ \alpha_i \mathbf{e}_i \theta_i + \mu_i \mathbf{e}^* \cdot \prod_{j=1-b}^{b-1} (\theta_i - j) \right].$$

5.  $\mathsf{V} \rightarrow \mathsf{P}$ :  $\mathsf{V}$  sends  $\mathsf{P}$  random challenge  $[\rho_i]_{i=2}^{2k} \stackrel{\$}{\leftarrow} \mathcal{C}_{\text{small}}^{2k-1}$ . Set  $\rho_1 := 1$ . 生成挑战值  
 6.  $\mathsf{V}$  outputs  $\mathbf{x}_o := (\vec{\mathbf{r}}_o, \mathbf{v}_o, y_o)$  where 将 f\_i 合并成 f\_o。

由于验证时已经将 f\_i 代入为 0

合并时直接用

$$\text{NTT}(\mathbf{v}_o) = \sum_{i=1}^{2k} \text{RotSum}(\rho_i, \text{NTT}(\theta_i)), \quad y_o := \sum_{i=1}^{2k} \rho_i y_i.$$

7.  $\mathsf{P}$  further outputs  $\mathbf{w}_o := \vec{\mathbf{f}}_o = \sum_{i=1}^{2k} \rho_i \cdot \vec{\mathbf{f}}_i$ .

*f 和 y 直接合并*

Figure 3: The protocol  $\Pi_{\text{fold}}$  that reduces  $(\mathcal{R}_{\text{bind}}^b)^{2k}$  to  $\mathcal{R}_{\text{bind}}^B$ .

Figure 3 is a reduction of knowledge

## 1. Public Reducibility

from  $[x_i = (\vec{r}_i, v_i, y_i)]_{i=1}^{2k}$   $[w_i = \vec{f}_i]_{i=1}^{2k}$  to  $[x_o = (\vec{r}_o, v_o, y_o)]$   $[w_o = \vec{f}_o]$

sample challenges  $\vec{r}_o$  (sumcheck) set  $\vec{r}_o$   $NTT(r_o) = \dots$

$[\rho_i]_{i=1}^{2k}$  (fold)  $y_o = \sum \rho_i y_i$

## 2. Completeness

(1)  $V$  accepts  $s = \sum_{i=1}^{2k} [\alpha e_i \theta_i + \mu_i e^* \cdot \prod_{j=i+1}^{2k} (\theta_{i+j})]$   $g$  is well-formed

(2)  $R_2$  is satisfied

$(x_o, w_o) = ((\vec{r}_o, v_o, y_o), f_o)$  satisfy :  $\begin{cases} L(f_o) = y_o \quad (Af_o = y_o) \\ mle(f_o)[r_o] = v_o \\ \|f_o\|_\infty \leq B \end{cases}$

**Lemma 3.3.** Given any  $\ell \in \mathbb{N}$  and a power-of-two  $m \in \mathbb{N}$ , let  $\vec{r} \in \mathbb{Z}_q^{\log m}$  be a vector and let  $\mathcal{L} : \mathcal{R}_q^m \rightarrow \mathcal{Y}$  be any  $\mathcal{R}_q$ -module homomorphism. Given any  $[\rho_i]_{i=1}^\ell \in \mathcal{R}_q^\ell$  and any  $[\mathbf{v}_i, y_i; \vec{f}_i]_{i=1}^\ell$  such that  $y_i = \mathcal{L}(\vec{f}_i)$  and  $mle[\hat{f}_i](\vec{r}) = \mathbf{v}_i$  for all  $i \in [\ell]$ . Set  $\mathbf{v}_o, y_o, \vec{f}_o$  such that

$$NTT(v_o) = \sum_{i=1}^\ell \text{RotSum}(\rho_i, NTT(v_i)), \quad y_o := \sum_{i=1}^\ell \rho_i \cdot y_i, \quad \vec{f}_o := \sum_{i=1}^\ell \rho_i \cdot \vec{f}_i,$$

$v_o = \sum \text{RotSum}(\rho_i, v_i)$

where  $\text{RotSum}$  is defined in Lemma 2.1. Then we have that  $y_o = \mathcal{L}(\vec{f}_o)$  and  $mle[\hat{f}_o](\vec{r}) = \mathbf{v}_o$ .

线性运算 (同态)

proof (1).  $L(f_o) = y_o$

(2)  $NTT(v_o) = \sum \text{RotSum}(\rho_i, NTT(v_i))$

according to Lemma 3.1

$$\text{since } \text{mle}[\hat{f}_i](\vec{r}) = v_i, \text{ then } \text{mle}[NTT(\hat{f}_i)](\vec{r}) = NTT(v_i)$$

单个  $\mathcal{R}_q$  中的元素在 NTT 前后有一一对应关系 (同构),  $\mathcal{R}_q$  中的向量在 NTT 前后也是

**Lemma 3.1.** Let  $m \in \mathbb{N}$  be a power-of-two and  $\mathcal{R}_q \cong \mathbb{F}_{q^\tau}^{d/\tau}$  for some  $\tau \in \mathbb{N}$  where  $\tau \mid d$ . For any  $\vec{f} \in \mathcal{R}_q^m$  and any vector  $\vec{r} \in \mathcal{R}_q^{\log m}$  such that  $NTT(\vec{r}) = (\underbrace{\vec{r}^*, \dots, \vec{r}^*}_{d/\tau})$  (where  $\vec{r}^* \in \mathbb{F}_{q^\tau}^{\log m}$ ),  
 $\vec{r} \in \{0, 1\}^{\log m}$  常数的 NTT 是重复的常数

let  $\hat{f} := (\hat{f}_1, \dots, \hat{f}_\tau) \in \mathcal{R}_q^{m \times \tau}$  denote the vector such that  $NTT(\hat{f}) = \text{vec}(\vec{f})$ . We have that

$$\text{mle}[\hat{f}](\vec{r}) \cong \text{mle}[\text{vec}(\vec{f})](\vec{r}^*) \text{ where}$$

$$\text{mle}[\hat{f}](\vec{r}) := (\text{mle}[\hat{f}_1](\vec{r}), \dots, \text{mle}[\hat{f}_\tau](\vec{r})) \in \mathcal{R}_q^\tau, \quad \text{NTT 前的 Eval}$$

$$\text{mle}[\text{vec}(\vec{f})](\vec{r}^*) := (\text{mle}[\text{vec}_1(\vec{f})](\vec{r}^*), \dots, \text{mle}[\text{vec}_d(\vec{f})](\vec{r}^*)) \in \mathbb{F}_{q^\tau}^d. \quad \text{NTT 后的 Eval}$$

Recall that  $\text{mle}[\cdot]$  denotes multilinear extensions (Defn. 2.4) and  $\text{vec}_i(\vec{f}) \in \mathbb{Z}_q^m$  is the  $i$ -th ( $1 \leq i \leq d$ ) column of the coefficient embedding matrix  $\text{vec}(\vec{f})$ .

*Proof.* By definition of  $\hat{f}$ , we have that

$$NTT(\hat{f}) = (NTT(\hat{f}_1), \dots, NTT(\hat{f}_\tau)) = (\text{vec}_1(\vec{f}), \dots, \text{vec}_d(\vec{f})). \quad (9)$$

Also observe that

$$(\text{mle}[\hat{f}_1](\vec{r}), \dots, \text{mle}[\hat{f}_\tau](\vec{r})) = \left( \left\langle \hat{f}_j, \bigotimes_{i=1}^{\log m} (\vec{r}_i, 1 - \vec{r}_i) \right\rangle \right)_{j=1}^\tau \quad \begin{matrix} \text{tensor}(\vec{r}) \\ \text{mle operation} \end{matrix} \quad (10)$$

where  $\bigotimes$  denotes tensor product over  $\mathcal{R}_q$ . Thus the lemma holds by the Chinese Remainder Theorem.  $\square$

$$\begin{aligned} \text{Thus } NTT(v_0) &= \sum \text{RotSum}(p_i, NTT(v_i)) = \sum \text{RotSum}(p_i, \text{mle}[NTT(\hat{f}_i)](\vec{r})) \\ &= \sum \text{RotSum}(p_i, \langle NTT(f_i), \otimes r_i (1 - r_i) \rangle) \\ &= \sum \langle \text{RotSum}(p_i, NTT(f_i)), \otimes r_i (1 - r_i) \rangle = \sum \langle \text{vec}(p_i \cdot NTT(f_i)), \otimes r_i (1 - r_i) \rangle \\ &= \langle \text{vec}(\sum p_i \cdot NTT(f_i)), \text{tensor}(\vec{r}) \rangle = \langle NTT(f_0), \text{tensor}(\vec{r}) \rangle \\ v_0 &= NTT^{-1} \langle NTT(f_0), \text{tensor}(\vec{r}) \rangle \end{aligned}$$

直接用  $v_0 \oplus \sum_{i=1}^l \text{RotSum}(p_i, v_i)$  也可以得到类似的结果, 但需要转化 vectors 与 polynomials

$$(3) \|f\|_\infty \leq B = b^k$$

$$\|f\|_\infty = \left\| \sum_{i=1}^{2k} p_i \vec{f}_i \right\|_\infty \leq \sum_i \|p_i \vec{f}_i\|_\infty \leq \sum_i c \|\vec{f}_i\|_\infty \leq \sum_{i=1}^{2k} c \cdot (b-1) = 2kc(b-1)$$

by choosing  $c$  properly, it holds.

### 3. Knowledge Soundness

Ext 作为 V 与 A、P 交互时提取  $\vec{f}$ :

A 产生初始 input, P 执行协议产生 proof

用 P, 当 P 产生一组满足条件的  $f_0$  时, 使用 randomness  $P_2$  rewind P

因此, 可以得到 2 组  $f_0^{(1)}$ ,  $f_0^{(2)}$  满足  $\begin{cases} f_1 + p_1 f_2 = f_0^{(1)} \\ f_1 + p_2 f_2 = f_0^{(2)} \end{cases}$  则可求解  $f_1, f_2$

requirement:  $p_1, p_2$  are small and invertible (lattice 常用的 challenge space)

## III Latticefold for CCS

### 1. CCS over Rings

#### 1. CCS construction

RCCS  $Az \circ Bz = Cz$

- size bounds  $m, n, l, t, q, d \in \mathbb{N}, n > l$   $-1Cz + (Az \circ Bz) = \vec{0}$
- matrices  $\{M_j \in F^{m \times n}\}_{j \in [t]}$
- $q$  个 multisets  $\{S_i\}_{i \in [q]}$   
 $S_i$  中每个元素都是  $1, \dots, t$  组成, 至多  $d$  个, 例如  $(1, 2, 3, \dots, d)$ , 若  $d < t$
- $q$  个 constants  $\{c_i\}_{i \in [q]}, c_i \in F$

一个 CCS instance  $(S, x)$  满足  $\sum_{i \in [q]} c_i \circ_{j \in [S_i]} (M_j \cdot \vec{z}) = \vec{0}$ , 其中  $z = (w, 1, x) \in F^n$   
 $w \in F^{n-l-1}, x \in F^t$

## 2. CCS over Rings

$$\sum_{i=1}^{n_s} c_i \circ_{j \in [S_i]} (M_j \cdot \vec{z}) = \vec{0} \quad pp = (nr, nc, t, n_s, \deg, lin)$$

其中  $c_i \in R$ ,  $M_j \in R^{n_r \times n_c}$ ,  $\vec{z} = (x, h, w) \in R^{nc}$

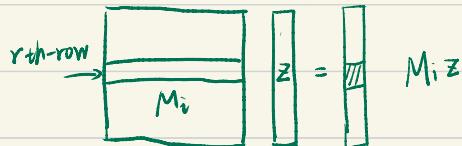
Linear CCS (mle)  $x_{1ccs} = (\vec{r}, [u_i]_{i=1}^t, x_{ccs}, h)$ ,  $w = w_{ccs}$

$$u_i = \sum_{b \in \{0, 1\}^{\log n}} mle[M_i](\vec{r}, \vec{b}) \cdot mle[\vec{z}](\vec{b})$$

其中  $\vec{z} = (x, h, w)$

$mle[z]$  取遍

$mle[M_i]$  取  $r$  总



## 2 committed CCS

把 CCS 中的  $\vec{z}$  用 gadget matrix 作 B 进制分解，使得每个分量都小于 B

用 Ajtai 子诺对分解后的  $\vec{z}$  (即  $\vec{f}$ ) 来讲

分别说明  $\vec{z}$  满足 CCS 约束、 $\vec{f}$  满足子诺等式

{  $\vec{z}$  是正确分解的 }

$$R_{ccmcs} = \left\{ \begin{array}{l} pp, x = (cm \in R_q^k, x_{ccs} \in R_q^{lin}); \\ w = (\vec{f} \in R_q^m, w_{ccs} \in R_q^{n_r - lin - 1}) \end{array} \right| \begin{array}{l} (pp_{cm}, cm, f) \in R_{cm}^B \\ \wedge (pp_{ccs}, x_{ccs}; w_{ccs}) \in R_{ccs} \\ \wedge x_{ccs} = G\vec{f} \end{array} \right\}$$

## Evaluation CCS

分别表示  $\vec{f}$  的 mle 计算和 CCS 约束中  $\vec{z}$  的 mle 计算，用 gadget matrix 连接起来

$$R_{evalcs}^B = \left\{ \begin{array}{l} pp, x = (\vec{r}, cm, v, [u_i]_{i=1}^t, x_{cls}, h); z_{cls} = G_f \wedge (pp_{cm}, (cm, v, \vec{r})_f) \in R_{real}^B \\ w = (\vec{f}, w_{cls}) \\ \wedge (pp_{cls}, (\vec{r}_{cls}, [u_i]_{i=1}^t, x_{cls}, h), w_{cls}) \in R_{cls} \end{array} \right\}$$

### 3. Folding

Step 1: from committed CCS to eval CCS

Step 2: Decomposition

Step 3: Folding

Step 1  $R_{evalcs} \times R_{cmcs} \rightarrow R_{evalcs} \times R_{evalcs}$

Apply sumcheck

1. 定义  $g(x)$  为 CCS 约束的多项式，若  $g(x)=0$ ，不论  $x$  是任何取值

$$g(\vec{x}) := eq(\vec{\beta}, \vec{x}) \cdot \left( \sum_{i=1}^{n_s} c_i \cdot \left[ \prod_{j \in S_i} \left( \sum_{\vec{b} \in \{0,1\}^{\log n_c}} \text{mle}[M_j](\vec{x}, \vec{b}) \cdot \text{mle}[z_{cls}](\vec{b}) \right) \right] \right).$$

求  $c_i$  和 (表示  $M_j$  在  $x$  点取值)

理解  $g(x)$  取一个 CCS instance  $c_1 M_1 z + c_2 (M_2 z \odot M_3 z) = \vec{0}$

表示 CCS 约束计算的向量在  $x$  处的 entry

$$\Rightarrow g(x) = 0$$

$$c_1 \boxed{\phantom{00}} + c_2 \boxed{\phantom{00}} \odot \boxed{\phantom{00}} = \boxed{\phantom{00}}$$

2. 做 evaluation 的转化

3. 证明 2 的转化是正确的 (通过 sumcheck 的等式说明)

**Parameters:** A strong sampling set  $\mathcal{C} := \mathbb{Z}_q \subseteq \mathcal{R}_q$  (Defn. 2.3).

**Input:**  $\mathbf{x} := (\mathbf{cm}, \mathbf{x}_{\text{ccs}}) \in \mathcal{R}_q^\kappa \times \mathcal{R}_q^{\ell_{\text{in}}}$  and  $\mathbf{w} := (\vec{\mathbf{f}}, \mathbf{w}_{\text{ccs}}) \in \mathcal{R}_q^m \times \mathcal{R}_q^{n_c - \ell_{\text{in}} - 1}$ .

**Output:**  $\mathbf{x}_o := (\vec{\mathbf{r}}_o \in \mathcal{R}_q^{\log m}, \mathbf{v} \in \mathcal{R}_q, \mathbf{cm}, [\mathbf{u}_i \in \mathcal{R}_q]_{i=1}^t, \mathbf{x}_{\text{ccs}}, 1)$  and  $\mathbf{w}_o := (\vec{\mathbf{f}}, \mathbf{w}_{\text{ccs}})$ .

The protocol  $\langle P(\mathbf{pp}, \mathbf{x}; \mathbf{w}), V(\mathbf{pp}, \mathbf{x}) \rangle$ :

1.  $V \rightarrow P$ :  $V$  sends  $P$  a random vector  $\vec{\beta} \xleftarrow{\$} \mathcal{C}^{\log m}$ .

2.  $P \leftrightarrow V$ :  $P$  and  $V$  run a sum-check protocol for the claim  $\sum_{\vec{\mathbf{b}} \in \{0,1\}^{\log m}} g(\vec{\mathbf{b}}) = 0$ . Let  $\mathbf{z}_{\text{ccs}} := (\mathbf{x}_{\text{ccs}}, 1, \mathbf{w}_{\text{ccs}})$ .  $g \in \mathcal{R}_q^{\leq \deg + 1}[X_1, \dots, X_{\log m}]$  is defined as<sup>a</sup>

$$g(\vec{\mathbf{x}}) := eq(\vec{\beta}, \vec{\mathbf{x}}) \cdot \left( \sum_{i=1}^{n_s} c_i \cdot \left[ \prod_{j \in S_i} \left( \sum_{\vec{\mathbf{b}} \in \{0,1\}^{\log n_c}} \text{mle}[M_j](\vec{\mathbf{x}}, \vec{\mathbf{b}}) \cdot \text{mle}[\mathbf{z}_{\text{ccs}}](\vec{\mathbf{b}}) \right) \right] \right).$$

The protocol reduces to a random evaluation check  $g(\vec{\mathbf{r}}_o) \stackrel{?}{=} s$  for some  $s \in \mathcal{R}_q$ , and  $\vec{\mathbf{r}}_o \xleftarrow{\$} \mathcal{C}^{\log m}$  is the sum-check challenge vector sampled by  $V$ .

3.  $P \rightarrow V$ :  $P$  sends  $V$  the values  $(\mathbf{v}, [\mathbf{u}_i]_{i=1}^t)$  where  $\mathbf{v} := \text{mle}[\hat{\mathbf{f}}](\vec{\mathbf{r}}_o)$  and for every  $i \in [t]$ ,  $\mathbf{u}_i$  is computed as

$$\mathbf{u}_i := \sum_{\vec{\mathbf{b}} \in \{0,1\}^{\log n_c}} \text{mle}[M_i](\vec{\mathbf{r}}_o, \vec{\mathbf{b}}) \cdot \text{mle}[\mathbf{z}_{\text{ccs}}](\vec{\mathbf{b}}).$$

4.  $V$  computes  $\mathbf{e} := eq(\vec{\beta}, \vec{\mathbf{r}}_o)$  and checks that

$$\mathbf{e} \cdot \left( \sum_{i=1}^{n_s} c_i \cdot \prod_{j \in S_i} \mathbf{u}_j \right) \stackrel{?}{=} s.$$

5.  $V$  outputs  $\mathbf{x}_o := (\vec{\mathbf{r}}_o, \mathbf{v}, \mathbf{cm}, [\mathbf{u}_i]_{i=1}^t, \mathbf{x}_{\text{ccs}}, 1)$ .  $P$  outputs  $\mathbf{w}_o := (\vec{\mathbf{f}}, \mathbf{w}_{\text{ccs}})$ .

---

<sup>a</sup> $\deg$  is the CCS gate degree.

Figure 4: The protocol  $\Pi_{\text{ccs}}$  that reduces  $\mathcal{R}_{\text{cmccs}}^B$  to  $\mathcal{R}_{\text{evalccs}}^B$ .

Step 2 在  $\text{mle}[\mathbf{f}](\mathbf{r})$  拼分后，加上了 CCS 的计算

用拼分的  $\vec{\mathbf{f}}$  做后续 CCS 计算（由于  $\mathbf{f}$  与  $\vec{\mathbf{f}}$  是一致的）

**Input:**  $\mathbf{z} := (\vec{\mathbf{r}}, \mathbf{v}, y, \mathbf{u}, \mathbf{z}_w)$  and  $\mathbf{w} := (\vec{\mathbf{f}}, \vec{\mathbf{w}})$ .

**Output:**  $[\mathbf{z}_i = (\vec{\mathbf{r}}, \mathbf{v}_i, y_i, \mathbf{u}_i, \mathbf{z}_{w,i}), \mathbf{w}_i = (\vec{\mathbf{f}}_i, \vec{\mathbf{w}}_i)]_{i=0}^{k-1}$ .

**The protocol**  $\langle \mathsf{P}(\mathbf{pp}, \mathbf{z}; \mathbf{w}), \mathsf{V}(\mathbf{pp}, \mathbf{z}) \rangle$ :

1.  $\mathsf{P}$  computes  $(\vec{\mathbf{f}}_0, \dots, \vec{\mathbf{f}}_{k-1}) \leftarrow \mathsf{split}_{b,k}(\vec{\mathbf{f}})$  (Eqn. 12).
2.  $\mathsf{P} \rightarrow \mathsf{V} : \mathsf{P}$  sends  $\mathsf{V}$  the values  $[y_i, \mathbf{v}_i, \mathbf{u}_i, \mathbf{z}_{w,i}]_{i=0}^{k-1}$ :

$$y_i := \mathcal{L}(\vec{\mathbf{f}}_i), \quad \mathbf{v}_i := \mathsf{mle} \left[ \hat{\mathbf{f}}_i \right] (\vec{\mathbf{r}}),$$

$$\mathbf{u}_i := \left\langle M \cdot \mathsf{tensor}(\vec{\mathbf{r}}), \mathcal{L}_w(\vec{\mathbf{f}}_i) \right\rangle, \quad \mathbf{z}_{w,i} := \mathcal{L}_w(\vec{\mathbf{f}}_i)[1, n_{\text{in}}]$$

for every  $i \in [0, k)$ .

3.  $\mathsf{V}$  checks that  $\sum_{i=0}^{k-1} b^i \cdot [y_i, \mathbf{v}_i, \mathbf{u}_i, \mathbf{z}_{w,i}] \stackrel{?}{=} [y, \mathbf{v}, \mathbf{u}, \mathbf{z}_w]$ .
4.  $\mathsf{V}$  outputs  $[\mathbf{z}_i = (\vec{\mathbf{r}}, \mathbf{v}_i, y_i, \mathbf{u}_i, \mathbf{z}_{w,i})]_{i=0}^{k-1}$ .  $\mathsf{P}$  outputs  $[\mathbf{w}_i = (\vec{\mathbf{f}}_i, \mathcal{L}_w(\vec{\mathbf{f}}_i))]_{i=0}^{k-1}$ .

Figure 5: The protocol  $\Pi_{\text{ccsdec}}^*$  that reduces  $\mathcal{R}_{\text{ccshom}}^B$  to  $(\mathcal{R}_{\text{ccshom}}^b)^k$ .

**Parameters:**  $c \in \mathbb{N}$ ,  $\mathcal{C} := \mathbb{Z}_q \subseteq \mathcal{R}_q$  and a strong sampling set  $\mathcal{C}_{\text{small}}$  with expansion factor  $\|\mathcal{C}_{\text{small}}\|_{\text{op}} \leq c$ .

**Input:**  $\mathbf{x} := [\mathbf{x}_i := (\vec{\mathbf{r}}_i, \mathbf{v}_i, y_i, \mathbf{u}_i, \mathbf{z}_{w,i})]_{i=1}^{2k}$  and  $\mathbf{w} := [\mathbf{w}_i := (\vec{\mathbf{f}}_i, \vec{\mathbf{w}}_i)]_{i=1}^{2k}$ .

**Output:**  $\mathbf{x}_o := (\vec{\mathbf{r}}_o, \mathbf{v}_o, y_o, \mathbf{u}_o, \mathbf{z}_{w,o})$ ,  $\mathbf{w}_o := (\vec{\mathbf{f}}_o, \vec{\mathbf{w}}_o)$ .

**The protocol**  $\langle P(\mathbf{pp}, \mathbf{x}; \mathbf{w}), V(\mathbf{pp}, \mathbf{x}) \rangle$ :

1.  $V \rightarrow P : V$  sends  $P[\alpha_i, \zeta_i]_{i=1}^{2k} \xleftarrow{\$} (\mathcal{C} \times \mathcal{C})^{2k}$ ,  $[\mu_i]_{i=1}^{2k-1} \xleftarrow{\$} \mathcal{C}^{2k-1}$ , and  $\vec{\beta} \xleftarrow{\$} \mathcal{C}^{\log m}$ .
2.  $V \leftrightarrow P : P$  and  $V$  run a sum-check protocol for the claim

$$\sum_{\vec{\mathbf{b}} \in \{0,1\}^{\log m}} g(\vec{\mathbf{b}}) = \sum_{i=1}^{2k} (\alpha_i \mathbf{v}_i + \zeta_i \mathbf{u}_i).$$

Set  $\mu_{2k} := 1$ , here the polynomial  $g(\vec{\mathbf{x}}) \in \mathcal{R}_q^{\leq 2b}[X_1, \dots, X_{\log m}]$  is defined as

$$g(\vec{\mathbf{x}}) := \sum_{i=1}^{2k} [\alpha_i g_{1,i}(\vec{\mathbf{x}}) + \mu_i g_{2,i}(\vec{\mathbf{x}}) + \zeta_i g_{3,i}(\vec{\mathbf{x}})], \quad (30)$$

where for all  $i \in [2k]$ ,

$$\begin{aligned} g_{1,i}(\vec{\mathbf{x}}) &:= eq(\vec{\mathbf{r}}_i, \vec{\mathbf{x}}) \cdot \text{mle}[\hat{\mathbf{f}}_i](\vec{\mathbf{x}}), \quad g_{2,i}(\vec{\mathbf{x}}) := eq(\vec{\beta}, \vec{\mathbf{x}}) \cdot \prod_{j=-b+1}^{b-1} \left( \text{mle}[\hat{\mathbf{f}}_i](\vec{\mathbf{x}}) - j \right), \\ g_{3,i}(\vec{\mathbf{x}}) &:= eq(\vec{\mathbf{r}}_i, \vec{\mathbf{x}}) \cdot \left( \sum_{\vec{\mathbf{b}} \in \{0,1\}^{\log(n+n_{\text{in}})}} \text{mle}[M_i](\vec{\mathbf{x}}, \vec{\mathbf{b}}) \cdot \text{mle}[\mathbf{z}_i](\vec{\mathbf{b}}) \right). \end{aligned}$$

Here  $\mathbf{z}_i := (\mathbf{z}_{w,i} || \vec{\mathbf{w}}_i)$  for all  $i \in [2k]$ . The protocol reduces to check the evaluation claim  $g(\vec{\mathbf{r}}_o) \stackrel{?}{=} s$  where  $\vec{\mathbf{r}}_o \xleftarrow{\$} \mathcal{C}^{\log m}$  is the sum-check challenge sampled by  $V$ .

3.  $P \rightarrow V : P$  sends  $V$  values  $[\theta_i := \text{mle}[\hat{\mathbf{f}}_i](\vec{\mathbf{r}}_o), \eta_i]_{i=1}^{2k}$ , where for all  $i \in [2k]$ ,

$$\eta_i := \sum_{\vec{\mathbf{b}} \in \{0,1\}^{\log(n+n_{\text{in}})}} \text{mle}[M_i](\vec{\mathbf{r}}_o, \vec{\mathbf{b}}) \cdot \text{mle}[\mathbf{z}_i](\vec{\mathbf{b}}).$$

4.  $V$  computes  $[\mathbf{e}_i := eq(\vec{\mathbf{r}}_i, \vec{\mathbf{r}}_o)]_{i=1}^{2k}$  and  $\mathbf{e}^* := eq(\vec{\beta}, \vec{\mathbf{r}}_o)$  and checks that

$$s \stackrel{?}{=} \sum_{i=1}^{2k} \left[ \alpha_i \mathbf{e}_i \theta_i + \mu_i \mathbf{e}^* \cdot \prod_{j=1-b}^{b-1} (\theta_i - j) + \zeta_i \mathbf{e}_i \eta_i \right].$$

5.  $V \rightarrow P : V$  sends  $P$  random challenges  $[\rho_i]_{i=2}^{2k} \xleftarrow{\$} \mathcal{C}_{\text{small}}^{2k-1}$ . Set  $\rho_1 := 1$ .
6.  $V$  output  $\mathbf{x}_o := (\vec{\mathbf{r}}_o, \mathbf{v}_o, y_o, \mathbf{u}_o, \mathbf{z}_{w,o})$  where  $\text{NTT}(\mathbf{v}_o) = \sum_{i=1}^{2k} \text{RotSum}(\rho_i, \text{NTT}(\theta_i))$  and  $[y_o, \mathbf{u}_o, \mathbf{z}_{w,o}] := \sum_{i=1}^{2k} \rho_i \cdot [y_i, \eta_i, \mathbf{z}_{w,i}]$ .
7.  $P$  outputs  $\vec{\mathbf{f}}_o = \sum_{i=1}^{2k} \rho_i \cdot \vec{\mathbf{f}}_i$  and  $\vec{\mathbf{w}}_o := \mathcal{L}_w(\vec{\mathbf{f}}_o)[n_{\text{in}} + 1, n_{\text{in}} + n]$ .

Figure 6: The protocol  $\Pi_{\text{ccsfold}}$  that reduces  $(\mathcal{R}_{\text{ccsbind}}^b)^{2k}$  to  $\mathcal{R}_{\text{ccsbind}}^B$ . We set the  $\mathcal{R}_q$ -module  $\mathcal{U}$  to be  $\mathcal{U} := \mathcal{R}_q$ . The protocol naturally extends to any  $\mathcal{U} := \mathcal{R}_q^t$  where  $t > 1$ .