

# Distributed Matrix Multiplication

Umberto Martínez-Peñas  
University of Valladolid (UVA)

SecureCAT Workshop,  
Aguilar de Campoo 2023

# Distributed Matrix Multiplication

- Let  $A \in \mathbb{F}^{s \times r}$  and  $B \in \mathbb{F}^{s \times t}$ , for  $r, s, t \in \mathbb{Z}_+$  and a field  $\mathbb{F}$ .
- We want to compute  $C = A^T B$  in a **distributed** way.
- If we have  **$mn$  workers**, we divide

$$A = (A_0, A_1, \dots, A_{m-1}) \quad \text{and} \quad B = (B_0, B_1, \dots, B_{n-1}),$$

with appropriate sizes  $A_i \in \mathbb{F}^{s \times r'}$  and  $B_j \in \mathbb{F}^{s \times t'}$ ,  $r = mr'$  and  $t = nt'$ .

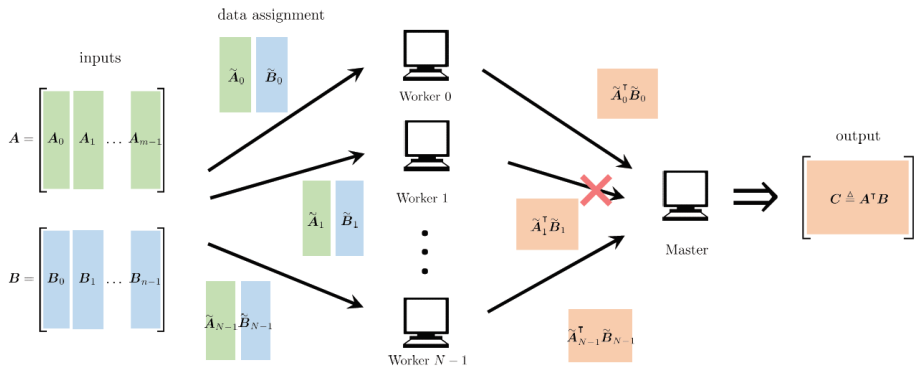
- Each worker computes a **smaller product**  $A_i^T B_j$ , and we recover  $C$  by **appending** these products, since

$$C = A^T B = \begin{pmatrix} A_0^T B_0 & A_0^T B_1 & \dots & A_0^T B_{n-1} \\ A_1^T B_0 & A_1^T B_1 & \dots & A_1^T B_{n-1} \\ \vdots & \vdots & \ddots & \vdots \\ A_{m-1}^T B_0 & A_{m-1}^T B_1 & \dots & A_{m-1}^T B_{n-1} \end{pmatrix}.$$

# Distributed Matrix Multiplication

- In this way, we **parallelize** the multiplication of two **large matrices**.
- A typical **problem** is that some workers may take too long to perform the computation (**stragglers**).
- In fact, the stragglers may take orders of magnitude longer, and thus they are considered **non-responsive**.
- However, in the previous parallelization method, the output of **every worker** is necessary to recover the whole product  $C = A^T B$ .
- **Solution**: Error-correcting codes.

# Distributed Matrix Multiplication



# Polynomial Codes

- Polynomial codes are essentially **Reed–Solomon codes**, but with the previous **matrix subdivision** and appropriate **degree choices**.
- We have  **$N$  workers** and divide

$$A = (A_0, A_1, \dots, A_{m-1}) \quad \text{and} \quad B = (B_0, B_1, \dots, B_{n-1}),$$

and as before, we only need to **compute  $A_i^T B_j$**  for all  $i, j$ .

- For  $\alpha, \beta \in \mathbb{Z}_+$ , we define the  **$(\alpha, \beta)$ -polynomial code** by

$$\tilde{A}_i = \sum_{j=0}^{m-1} A_j x_i^{\alpha j} \quad \text{and} \quad \tilde{B}_i = \sum_{k=0}^{n-1} B_k x_i^{\beta k},$$

for distinct points  $x_0, x_1, \dots, x_{N-1} \in \mathbb{F}$ .

- Now, the  **$i$ th worker** computes

$$\tilde{C}_i = \tilde{A}_i^T \tilde{B}_i = \sum_{j=0}^{m-1} \sum_{k=0}^{n-1} A_j^T B_k x_i^{\alpha j + \beta k}.$$

# Polynomial Codes

- Now, the  $i$ th worker computes

$$\tilde{C}_i = \tilde{A}_i^T \tilde{B}_i = \sum_{j=0}^{m-1} \sum_{k=0}^{n-1} A_j^T B_k x_i^{\alpha j + \beta k}.$$

- To recover the  $mn$  products  $A_j^T B_k$ , we need to choose  $(\alpha, \beta)$  such that no two products share the same monomial  $x^{\alpha j + \beta k}$ .
- In this scenario, a simple choice is  $(\alpha, \beta) = (1, m)$ , that is,

$$\tilde{C}_i = \tilde{A}_i^T \tilde{B}_i = \sum_{j=0}^{m-1} \sum_{k=0}^{n-1} A_j^T B_k x_i^{j+mk}.$$

- We define now the **matrix polynomial**

$$h(x) = \sum_{j=0}^{m-1} \sum_{k=0}^{n-1} A_j^T B_k x^{j+mk} \in \mathbb{F}^{r' \times t'}[x].$$

# Polynomial Codes

- We define now the **matrix polynomial**

$$h(x) = \sum_{j=0}^{m-1} \sum_{k=0}^{n-1} A_j^T B_k x^{j+mk} \in \mathbb{F}^{r' \times t'}[x].$$

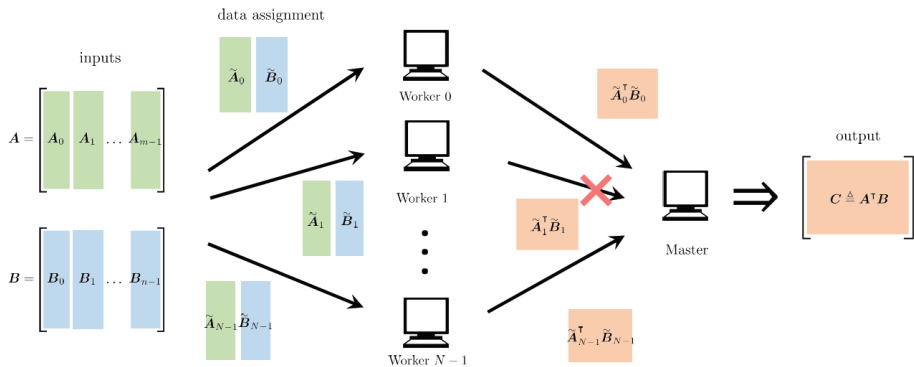
- Since  $\deg(h(x)) = mn - 1$ , and the products  $A_j^T B_k$  appear with different monomials, then we only need to collect **outputs** from  **$mn$  workers** and apply **Lagrange interpolation**.
- The **number of workers**  $N$  is arbitrary with  $N \geq mn$ .
- Hence the polynomial code can tolerate up to  **$N - mn$**  stragglers.

 Q. Yu, M. Maddah-Ali and S. Avestimehr.

Polynomial codes: an optimal design for high-dimensional coded matrix multiplication.

*Advances in Neural Information Processing Systems*, 30, 2017.

# Polynomial Codes





- Polynomial codes are **optimal** only for some metrics (more later).
- Consider now  $A, B \in \mathbb{F}^{N \times N}$  and let's compute  $C = AB$ .
- As a toy example, for **polynomial codes** we subdivide  $A$  and  $B$  as

$$A = \begin{pmatrix} A_0 \\ A_1 \end{pmatrix} \quad \text{and} \quad B = \begin{pmatrix} B_0 & B_1 \end{pmatrix}.$$

- The product  $C = AB$  can be **decomposed** as

$$C = AB = \begin{pmatrix} A_0 B_0 & A_0 B_1 \\ A_1 B_0 & A_1 B_1 \end{pmatrix}.$$

- As we have seen, for these codes we need to recover (by **interpolation**) the polynomial

$$h(x) = A_0 B_0 + A_1 B_0 x + A_0 B_1 x^2 + A_1 B_1 x^3 \in \mathbb{F}^{N/2 \times N/2}[x].$$

# MatDot Codes

- Polynomial codes are **optimal** only for some metrics (more later).
- Consider now  $A, B \in \mathbb{F}^{N \times N}$  and let's compute  $C = AB$ .
- As a toy example, for **MatDot codes** we subdivide  $A$  and  $B$  as

$$A = \begin{pmatrix} A_0 & A_1 \end{pmatrix} \quad \text{and} \quad B = \begin{pmatrix} B_0 \\ B_1 \end{pmatrix}.$$

- With this **decomposition**, we simply have

$$C = AB = A_0B_0 + A_1B_1.$$

- If we set  $p_A(x) = A_0 + A_1x$  and  $p_B(x) = B_0x + B_1$ , then

$$h(x) = p_A(x)p_B(x) = A_0B_1 + (A_0B_0 + A_1B_1)x + A_1B_0x^2.$$

- We can **recover**  $AB = A_0B_0 + A_1B_1$  from any **3 workers** by collecting 3 evaluations  $h(x_{i_1})$ ,  $h(x_{i_2})$  and  $h(x_{i_3})$ .

# MatDot Codes

- In general, for **MatDot codes** we subdivide

$$A = ( A_0 \quad A_1 \quad \dots \quad A_{m-1} ) \quad \text{and} \quad B = \begin{pmatrix} B_0 \\ \vdots \\ B_{m-1} \end{pmatrix},$$

where  $m \mid N$ ,  $A, B \in \mathbb{F}^{N \times N}$ ,  $A_i \in \mathbb{F}^{N \times N/m}$ ,  $B_j \in \mathbb{F}^{N/m \times N}$ .

- We choose **distinct**  $x_1, x_2, \dots, x_P \in \mathbb{F}$ , and set

$$p_A(x) = \sum_{i=0}^{m-1} A_i x^i \quad \text{and} \quad p_B(x) = \sum_{j=0}^{m-1} B_j x^{m-1-j}.$$

- The  $i$ th **worker** obtains  $p_A(x_i)$  and  $p_B(x_i)$  and **computes**  $h(x_i) = p_A(x_i)p_B(x_i)$ , for  $i = 1, 2, \dots, P$ .
- We have that  $AB = \sum_{j=0}^{m-1} A_j B_j$  is the **coefficient** of  $x^{m-1}$  in  $h(x)$ .
- Since  $\deg(h(x)) \leq 2m - 2$ , we only need to collect the **evaluations** of  $2m - 1$  (out of  $P$ ) workers.

# PolyDot Codes

- We can also obtain **hybrid solutions**: PolyDot codes.
- **Toy example**: We split  $A, B \in \mathbb{F}^{N \times N}$  as

$$A = \begin{pmatrix} A_{0,0} & A_{0,1} \\ A_{1,0} & A_{1,1} \end{pmatrix} \quad \text{and} \quad B = \begin{pmatrix} B_{0,0} & B_{0,1} \\ B_{1,0} & B_{1,1} \end{pmatrix}.$$

- We have that

$$AB = \begin{pmatrix} A_{0,0}B_{0,0} + A_{0,1}B_{1,0} & A_{0,0}B_{0,1} + A_{0,1}B_{1,1} \\ A_{1,0}B_{0,0} + A_{1,1}B_{1,0} & A_{1,0}B_{0,1} + A_{1,1}B_{1,1} \end{pmatrix}.$$

- Set  $p_A(x) = A_{0,0} + A_{1,0}x + A_{0,1}x^2 + A_{1,1}x^3$  and  $p_B(x) = B_{0,0}x^2 + B_{1,0} + B_{0,1}x^8 + B_{1,1}x^6$ .
- The **4 block components** of  $AB$  are the coefficients of

$$x^2, \quad x^8, \quad x^3 \quad \text{and} \quad x^9.$$

- We may recover  $AB$  from **4 evaluations** of  $h(x) = p_A(x)p_B(x)$ .

# Hybrid Solution: PolyDot Codes

- **In general:** We split  $A, B \in \mathbb{F}^{N \times N}$  as

$$A = \begin{pmatrix} A_{0,0} & \cdots & A_{0,s-1} \\ \vdots & \ddots & \vdots \\ A_{t-1,0} & \cdots & A_{t-1,s-1} \end{pmatrix}, \quad B = \begin{pmatrix} B_{0,0} & \cdots & B_{0,s-1} \\ \vdots & \ddots & \vdots \\ B_{t-1,0} & \cdots & B_{t-1,s-1} \end{pmatrix}.$$

- We define

$$p_A(x) = \sum_{i=0}^{t-1} \sum_{j=0}^{s-1} A_{i,j} x^{i+tj},$$

$$p_B(x) = \sum_{k=0}^{s-1} \sum_{l=0}^{t-1} B_{k,l} x^{t(s-1-k)+t(2s-1)l}.$$

- If  $h(x) = p_A(x)p_B(x)$ , then

$$h(x) = \sum_{i,j,k,l} A_{i,j} B_{k,l} x^{i+t(s-1+j-k)+t(2s-1)l}.$$

# Hybrid Solution: PolyDot Codes

- If  $h(x) = p_A(x)p_B(x)$ , then

$$h(x) = \sum_{i,j,k,l} A_{i,j} B_{k,l} x^{i+t(s-1+j-k)+t(2s-1)l}.$$

- It can be shown that for **different pairs** of  $(i, j, k, l)$  we get **different powers** of  $x$ .
- For the powers such that  $j - k = 0$ , we have the **term**

$$\left( \sum_{k=0}^{s-1} A_{i,k} B_{k,l} \right) x^{i+t(s-1)+t(2s-1)l} = C_{i,l} x^{i+t(s-1)+t(2s-1)l}.$$

- Notice that

$$\deg(h(x)) \leq t - 1 + 2t(s - 1) + t(2s - 1)(t - 1) = t^2(2s - 1).$$

- Thus we need  **$t^2(2s - 1)$  responses** from the workers.

# Communication - Recovery Trade-Off

- We have divided  $A, B \in \mathbb{F}^{N \times N}$  into  $m := st$  submatrices. Each worker stores  $2N^2/m$  symbols in  $\mathbb{F}$ .
- Keeping storage cost constant, i.e.  $m = st$  constant, the recovery threshold

$$t^2(2s - 1) = m^2 \cdot \frac{2s - 1}{s^2}$$

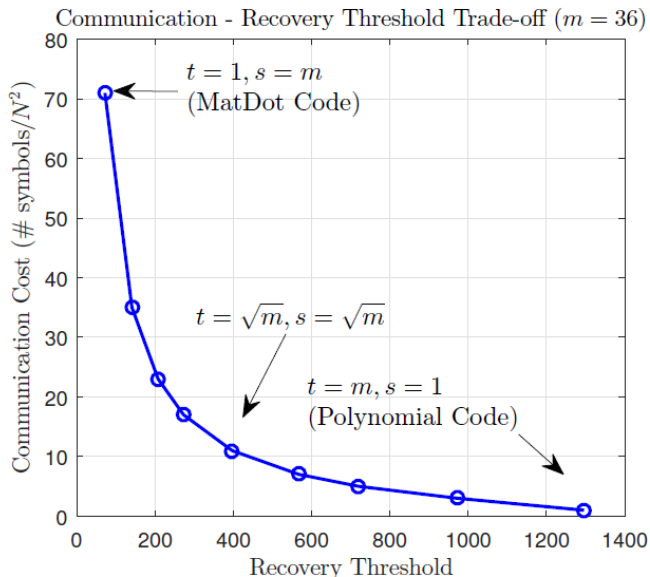
decreases as  $s$  increases, i.e., increases as  $t$  increases.

- In terms of communication cost, the master node sends  $\mathcal{O}(N^2/m)$  symbols to each worker, and each worker sends  $\mathcal{O}(N^2/t^2)$  symbols to the fusion node.
- Since we collect outputs from  $t^2(2s - 1)$  workers, the total communication cost from the workers to the fusion node is

$$\mathcal{O}\left(t^2(2s - 1) \cdot \frac{N^2}{t^2}\right) = \mathcal{O}(N^2(2s - 1)),$$

- which increases as  $s$  increases, i.e., decreases as  $t$  increases.

# Communication - Recovery Trade-Off





# Computation - Recovery Trade-Off

- We have divided  $A, B \in \mathbb{F}^{N \times N}$  into  $m := st$  submatrices. Each worker stores  $2N^2/m$  symbols in  $\mathbb{F}$ .
- Keeping storage cost constant, i.e.  $m = st$  constant, the recovery threshold

$$t^2(2s - 1) = m^2 \cdot \frac{2s - 1}{s^2}$$

decreases as  $s$  increases, i.e., increases as  $t$  increases.

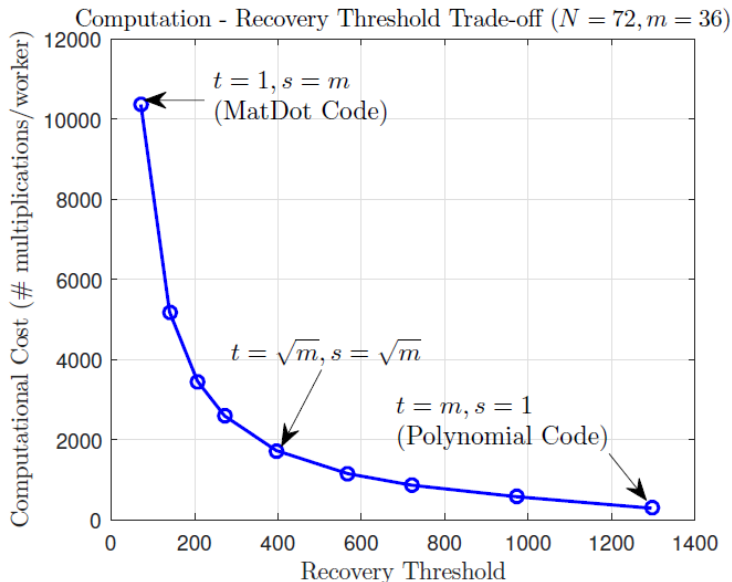
- In terms of computation cost, each worker computes the product of  $N/t \times N/s$  and  $N/s \times N/t$  matrices, which has a computational cost (over  $\mathbb{F}$ ) of

$$\mathcal{O}\left(\frac{N^3}{st^2}\right) = \mathcal{O}\left(\frac{N^3}{m^2} \cdot s\right),$$

- which increases as  $s$  increases, i.e., decreases as  $t$  increases.
- For the decoding to be negligible in comparison, we need

$$m^2 t^2 = \frac{m^4}{s^2} = o(N).$$

# Computation - Recovery Trade-Off



# PolyDot Codes

- **MatDot codes** and **PolyDot codes**, together with the previous **trade-offs**, were introduced in
  - 📄 S. Dutta, M. Fahim, F. Haddadpour, H. Jeong, V. Cadambe and P. Grover.  
On the optimal recovery threshold of coded matrix multiplication.  
*IEEE Trans. Info. Theory*, 66(1):278–301, 2019.
- They also give **upper bounds** and show that **PolyDot codes** always attain the bounds.
- For  $\mathbb{F} = \mathbb{R}$  or  $\mathbb{C}$ , the **number of workers** is unrestricted, the main issues have to do with **numerical stability**:
  - 📄 M. Fahim and V. Cadambe.  
Numerically stable polynomially coded computing.  
*IEEE Trans. Info. Theory*, 67(5):2758–2785, 2021.

# PolyDot Codes

- For  $\mathbb{F} = \mathbb{F}_q$ , numerical stability is not a problem, but the  $q$  may be.
- We need the **number of workers** to satisfy  $P \leq q$ .
- But the **recovery threshold** also needs to satisfy

$$t^2(2s - 1) \leq P$$

- Hence **PolyDot codes** require

$$q \geq t^2(2s - 1) = m^2 \cdot \frac{2s - 1}{s^2}.$$

- **Alternatives:** 1) Using ideas from Algebraic-Geometry codes?  
**Problem:** Degrees. Maybe we need to choose **algebraic functions** appropriately.
- **Alternatives:** 2) Using polynomials in **several variables** and/or **certain evaluation points**.
- **Alternatives:** 3) Using ideas from **subfield subcodes**.

# Secure Distributed Matrix Multiplication

- We now consider the problem of **multiplying** two matrices in a **secure** way.
- We want to multiply  $A$  and  $B$  using  $N$  workers in a way that **no**  $T$  of them can obtain **any information** about  $A$  or  $B$  (in an **IT sense**).
- In this scenario, we assume **all**  $N$  workers are responsive (on time and correct) (honest but curious).
- For this problem, it is usual to consider as **performance metric** the **download rate**, which is inverse to the **communication cost**.
- Recall that for **PolyDot codes** the communication cost was

$$\mathcal{O}(N^2(2s - 1)),$$

which is minimum for **polynomial codes**,  $s = 1$ .

- For this reason, most works on SDMM follow the same **matrix subdivision** as polynomial codes.

# Secure Distributed Matrix Multiplication

We start with the **matrix subdivision** of polynomial codes

$$A = \begin{pmatrix} A_1 \\ A_2 \\ \vdots \\ A_K \end{pmatrix} \quad \text{and} \quad B = ( B_1 \ B_2 \ \dots \ B_L ),$$

so that

$$C = AB = \begin{pmatrix} A_1 B_1 & A_1 B_2 & \dots & A_1 B_L \\ A_2 B_1 & A_2 B_2 & \dots & A_2 B_L \\ \vdots & \vdots & \ddots & \vdots \\ A_K B_1 & A_K B_2 & \dots & A_K B_L \end{pmatrix}.$$

# Secure Distributed Matrix Multiplication

- We fix  $T$  such that **no  $T$  workers** will be able to obtain any **information** about  $A$  or  $B$ .
- Fix **degree** sequences

$$\alpha = (\alpha_1, \alpha_2, \dots, \alpha_{K+T}) \quad \text{and} \quad \beta = (\beta_1, \beta_2, \dots, \beta_{L+T}).$$

- Generate **random matrices**  $R_1, R_2, \dots, R_T$  and  $S_1, S_2, \dots, S_T$ , of appropriate sizes, and define

$$f(x) = \sum_{k=1}^K A_k x^{\alpha_k} + \sum_{t=1}^T R_t x^{\alpha_{K+t}},$$
$$g(x) = \sum_{\ell=1}^L B_\ell x^{\beta_\ell} + \sum_{t=1}^T S_t x^{\beta_{L+t}}.$$

# Secure Distributed Matrix Multiplication

- Fix also distinct  $a_1, a_2, \dots, a_N \in \mathbb{F}$ . We send  $f(a_i)$  and  $g(a_i)$  to the  $i$ th worker, who computes

$$h(a_i) = f(a_i)g(a_i).$$

- As in Shamir's scheme, we want to recover all products  $A_k B_\ell$  from  $h(a_1), h(a_2), \dots, h(a_N)$ ,
- while no information about  $A$  and  $B$  (i.e., the matrices  $A_k$  and  $B_\ell$ ) is leaked from any  $T$  evaluations of  $h(x)$ :

$$I(f(a_{i_1}), g(a_{i_1}), \dots, f(a_{i_T}), g(a_{i_T}); A, B) = 0.$$

- The download rate of the scheme is defined as

$$\mathcal{R} = \frac{KL}{N}.$$



# Secure Distributed Matrix Multiplication

- We define the **degree table** as

$$\alpha \oplus \beta = \begin{pmatrix} \alpha_1 + \beta_1 & \dots & \alpha_1 + \beta_{L+T} \\ \vdots & \ddots & \vdots \\ \alpha_{K+T} + \beta_1 & \dots & \alpha_{K+T} + \beta_{L+T} \end{pmatrix}.$$

- The scheme satisfies the **recovery** and **secrecy** conditions iff
  - $\alpha_k + \beta_\ell \neq \alpha_{k'} + \beta_{\ell'}$ , for all  $(k, \ell) \in [K] \times [L]$  and all  $(k', \ell') \in [K+T] \times [L+T]$ .
  - $\alpha_{K+t} \neq \alpha_{K+t'}$  and  $\beta_{L+t} \neq \beta_{L+t'}$ , for all  $t \neq t' \in [T]$ .

	$\beta_1$	$\dots$	$\beta_L$	$\beta_{L+1}$	$\dots$	$\beta_{L+T}$
$\alpha_1$	$\alpha_1 + \beta_1$	$\dots$	$\alpha_1 + \beta_L$	$\alpha_1 + \beta_{L+1}$	$\dots$	$\alpha_1 + \beta_{L+T}$
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
$\alpha_K$	$\alpha_K + \beta_1$	$\dots$	$\alpha_K + \beta_L$	$\alpha_K + \beta_{L+1}$	$\dots$	$\alpha_K + \beta_{L+T}$
$\alpha_{K+1}$	$\alpha_{K+1} + \beta_1$	$\dots$	$\alpha_{K+1} + \beta_L$	$\alpha_{K+1} + \beta_{L+1}$	$\dots$	$\alpha_{K+1} + \beta_{L+T}$
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
$\alpha_{K+T}$	$\alpha_{K+T} + \beta_1$	$\dots$	$\alpha_{K+T} + \beta_L$	$\alpha_{K+T} + \beta_{L+1}$	$\dots$	$\alpha_{K+T} + \beta_{L+T}$

# Secure Distributed Matrix Multiplication

A first valid choice of  $\alpha$  and  $\beta$  is

$$\alpha_k = \begin{cases} k - 1 & \text{if } 1 \leq k \leq K, \\ KL + t - 1 & \text{if } k = K + t \text{ and } 1 \leq t \leq T, \end{cases}$$

$$\beta_\ell = \begin{cases} K(\ell - 1) & \text{if } 1 \leq \ell \leq L, \\ KL + t - 1 & \text{if } \ell = L + t \text{ and } 1 \leq t \leq T, \end{cases}$$

if  $L \leq K$ , and

$$\alpha_\ell = \begin{cases} K(\ell - 1) & \text{if } 1 \leq \ell \leq L, \\ KL + t - 1 & \text{if } \ell = L + t \text{ and } 1 \leq t \leq T, \end{cases}$$

$$\beta_k = \begin{cases} k - 1 & \text{if } 1 \leq k \leq K, \\ KL + t - 1 & \text{if } k = K + t \text{ and } 1 \leq t \leq T, \end{cases}$$

if  $K < L$ .

# Secure Distributed Matrix Multiplication

$$\alpha_k = \begin{cases} k - 1 & \text{if } 1 \leq k \leq K, \\ KL + t - 1 & \text{if } k = K + t \text{ and } 1 \leq t \leq T, \end{cases}$$

$$\beta_\ell = \begin{cases} K(\ell - 1) & \text{if } 1 \leq \ell \leq L, \\ KL + t - 1 & \text{if } \ell = L + t \text{ and } 1 \leq t \leq T, \end{cases}$$

if  $L \leq K$ .

	$\beta_1 = 0$	...	$\beta_L = K(L - 1)$	$\beta_{L+1} = KL$	$\beta_{L+2} = KL + 1$	...	$\beta_{L+T} = KL + T - 1$
$\alpha_1 = 0$	0	...	$K(L - 1)$	$KL$	$KL + 1$	...	$KL + T - 1$
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
$\alpha_K = K - 1$	$K - 1$	...	$KL - 1$	$KL + K - 1$	$KL + K$	...	$KL + K + T - 2$
$\alpha_{K+1} = KL$	$KL$	...	$2KL - K$	$2KL$	$2KL + 1$	...	$2KL + T - 1$
$\alpha_{K+2} = KL + 1$	$KL + 1$	...	$2KL - K + 1$	$2KL + 1$	$2KL + 2$	...	$2KL + T$
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
$\alpha_{K+T} = KL + T - 1$	$KL + T - 1$	...	$2KL - K + T - 1$	$2KL + T - 1$	$2KL + T$	...	$2KL + 2T - 2$

# Secure Distributed Matrix Multiplication

- The **number of workers** is given by

$$N = \begin{cases} (K + T)(L + 1) - 1 & \text{if } T < K, \\ 2KL + 2T - 1 & \text{if } T \geq K, \end{cases}$$

if  $L \leq K$ , and

- 

$$N = \begin{cases} (L + T)(K + 1) - 1 & \text{if } T < L, \\ 2KL + 2T - 1 & \text{if } T \geq L, \end{cases}$$

if  $L < K$ .

- The **rate** is given by  $\mathcal{R} = KL/N$  with  $N$  as above.
- They **all satisfy**  $N \leq (K + T)(L + 1) - 1$ , so

$$\mathcal{R} \geq \frac{KL}{(K + T)(L + 1) - 1}.$$

# Secure Distributed Matrix Multiplication

- This scheme was introduced in



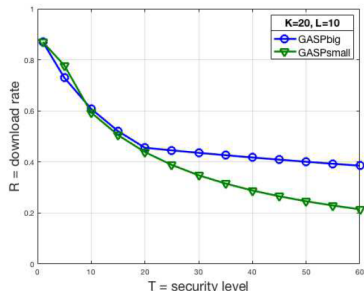
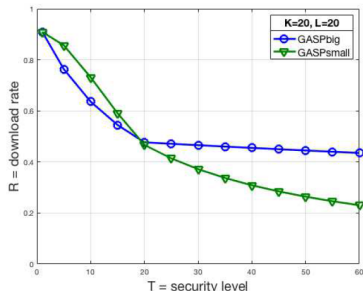
R. D'Oliveira, S. El Rouayheb and D. Karpuk.

GASP codes for secure distributed matrix multiplication.

*IEEE Trans. Info. Theory*, 66(7):4038–4050, 2020.

- They also provide another scheme that is slightly better for

$$T < \max\{K, L\}.$$



# Secure Distributed Matrix Multiplication

- As in the case of [recovery](#), for  $\mathbb{F} = \mathbb{R}$  or  $\mathbb{C}$ , the main problem seems to be [numerical stability](#).
- For  $\mathbb{F} = \mathbb{F}_q$ , since the [number of workers](#) is about  $N \cong (K + T)(L + 1) - 1$ , therefore we need

$$q \geq (K + T)(L + 1) - 1.$$

- Alternative solutions may require [algebraic-geometry codes](#), [multivariate polynomials](#), etc.
- The previous work only considered [communication cost](#) (i.e. download rate) as performance [metric](#).
- Finding good codes for [other metrics](#), such as recovery threshold (i.e. [PolyDot codes](#)) seems to be an open problem.

# Related Problems

- **Private computation** consists in distributing a computation among workers while maintaining **private** the **computation** itself.



N. Raviv and D. Karpuk.

Private polynomial computation from Lagrange encoding.

*IEEE Trans. Info. Forensics and Security*, 15:553–563, 2019.

- Another approach to distributed matrix multiplication is **using partial results** from all workers:



N. Ferdinand and S. Draper.

Anytime stochastic gradient descent: A time to hear from all the workers.

*56th Allerton Conf. Comm. Control Comp.*, 552–559, 2018.



S. Kianidehkordi, N. Ferdinand and S. Draper.

Hierarchical coded matrix multiplication.

*IEEE Trans. Info. Theory*, 67(2):726–754, 2020.

# Related Problems

- There are works considering simultaneously **recovery**, **security** and **privacy**.



Q. Yu, S. Li, N. Raviv, S. Kalan, M. Soltanolkotabi,  
S. Avestimehr.

Lagrange coded computing: Optimal design for resiliency,  
security, and privacy.

*22nd Int. Conf. Artif. Intel. Stat.*, 1215–1225, 2019.

- There are **coding solutions** to straggler mitigation for specific Machine Learning **algorithms**, such as gradient descent:



N. Raviv, I. Tamo, R. Tandon and A. Dimakis.

Gradient coding from cyclic MDS codes and expander graphs.

*IEEE Trans. Info. Theory*, 66(12):7475–7489, 2020.



Thank you for your attention.