

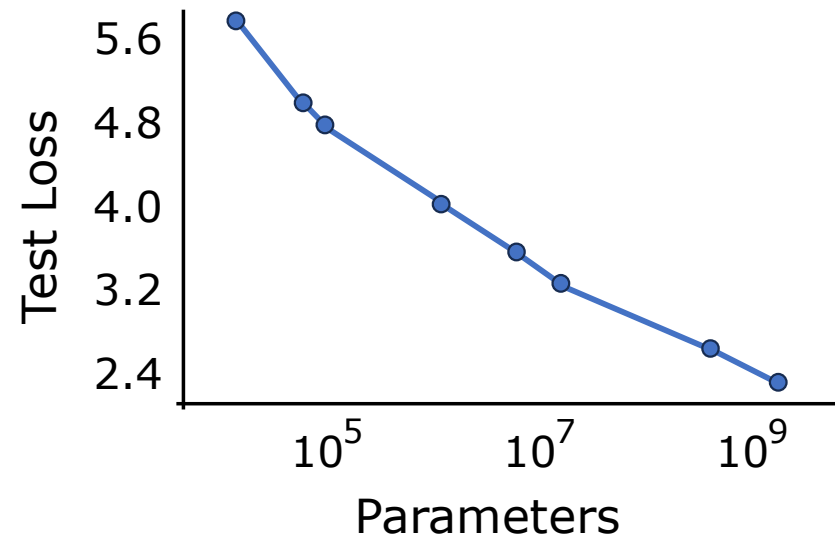
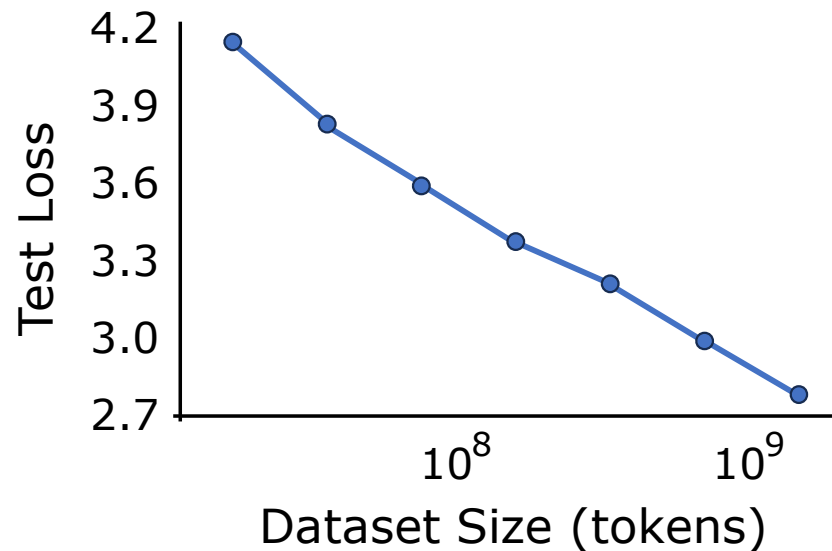
PrimePar: Efficient Spatial-temporal Tensor Partitioning for Large Transformer Model Training

**Haoran Wang, Lei Wang, Haobo Xu, Ying Wang,
Yuming Li, Yinhe Han**

Research Center for Intelligent Computing Systems
Institute of Computing Technology, Chinese Academy of Sciences

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Training Large Language Models (LLM) is Challenging



Kaplan J, McCandlish S, Henighan T, et al. Scaling laws for neural language models[J]. arXiv preprint arXiv:2001.08361, 2020.

Model	Corpus size	Model Parameters
GPT	800M tokens	117M
GPT-3	300B tokens	175B
Llama 2	2T tokens	70B
Llama 3	15T tokens	70B

LLM training:

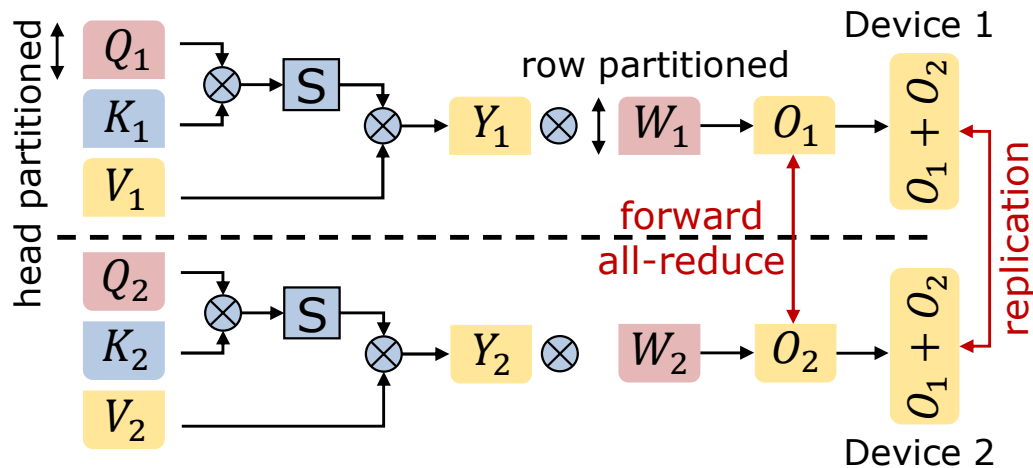
- Larger dataset size
- Larger model parameter size

Training LLM is Challenging

3D parallelism

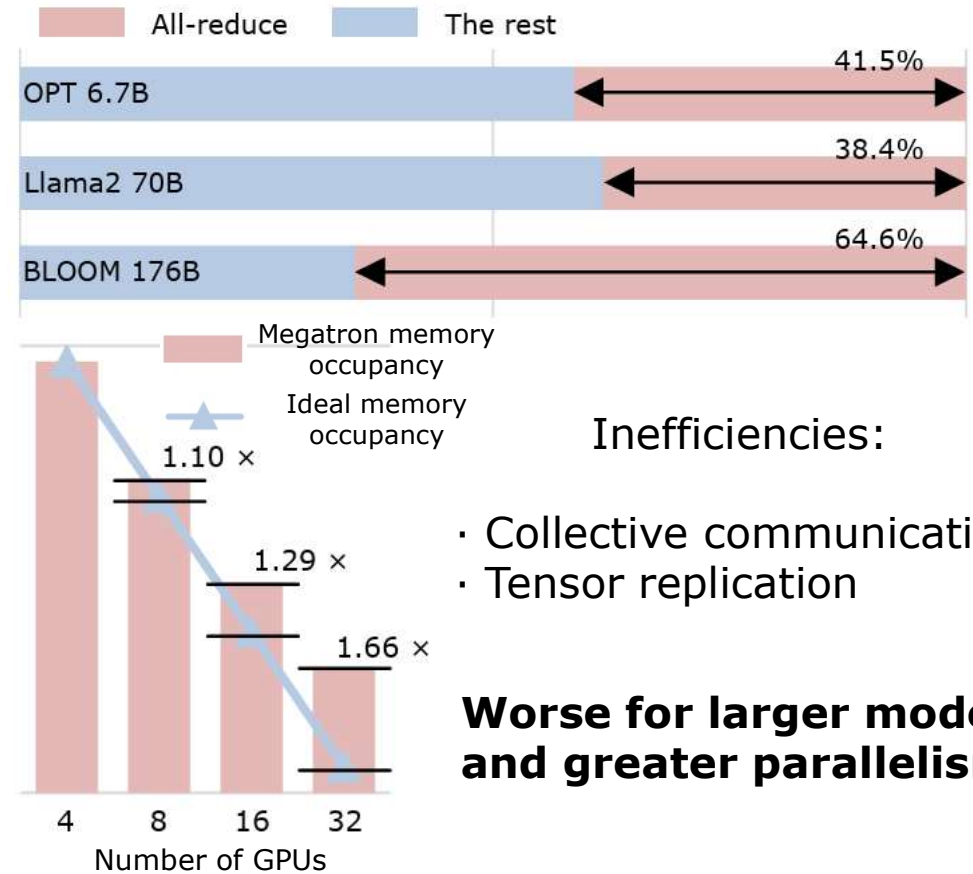
Pipeline parallelism

Tensor partition: data/model parallelism



SOTA tensor partition of attention layer

Shoeybi M, Patwary M, Puri R, et al. Megatron-Lm: Training multi-billion parameter language models using model parallelism[J]. arXiv preprint arXiv:1909.08053, 2019.



Inefficiencies:

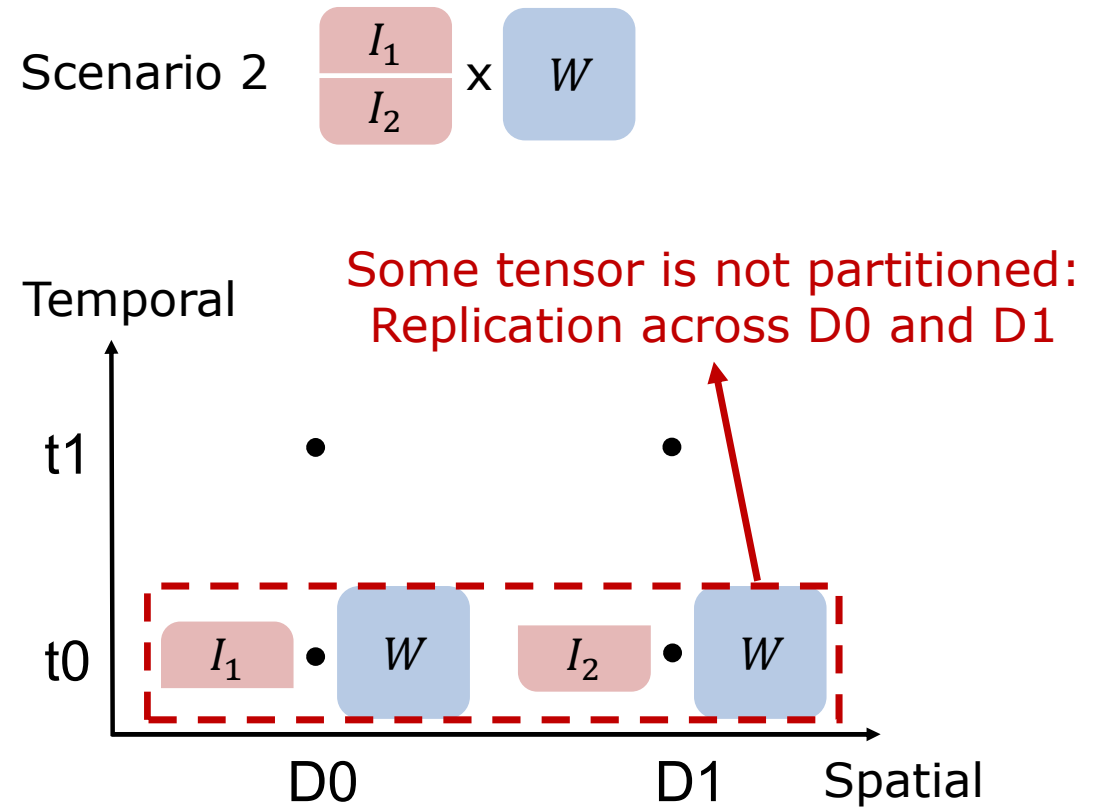
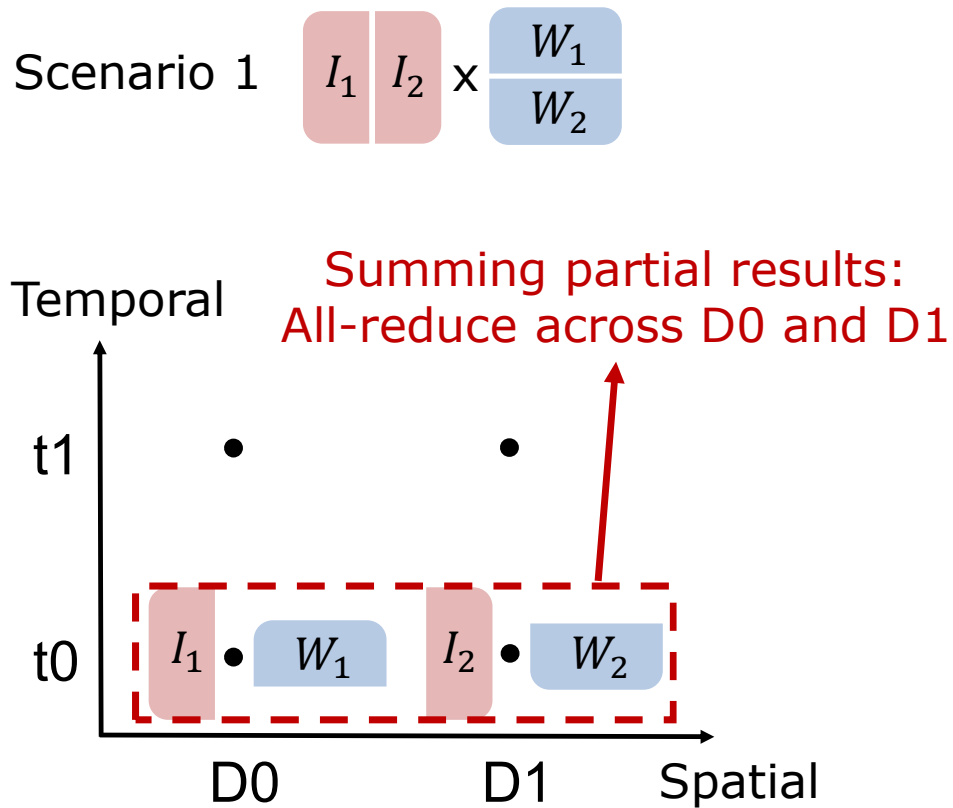
- Collective communication
- Tensor replication

Worse for larger model and greater parallelism

Focus of this work: better tensor partition with **less collective communication and tensor replication**

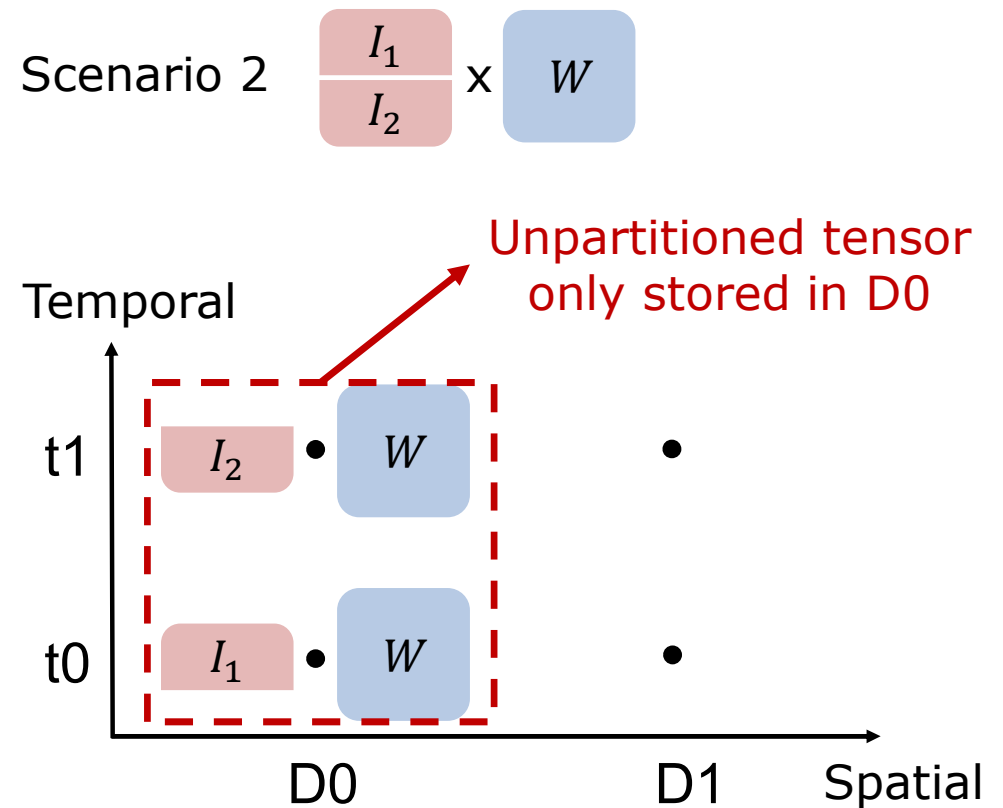
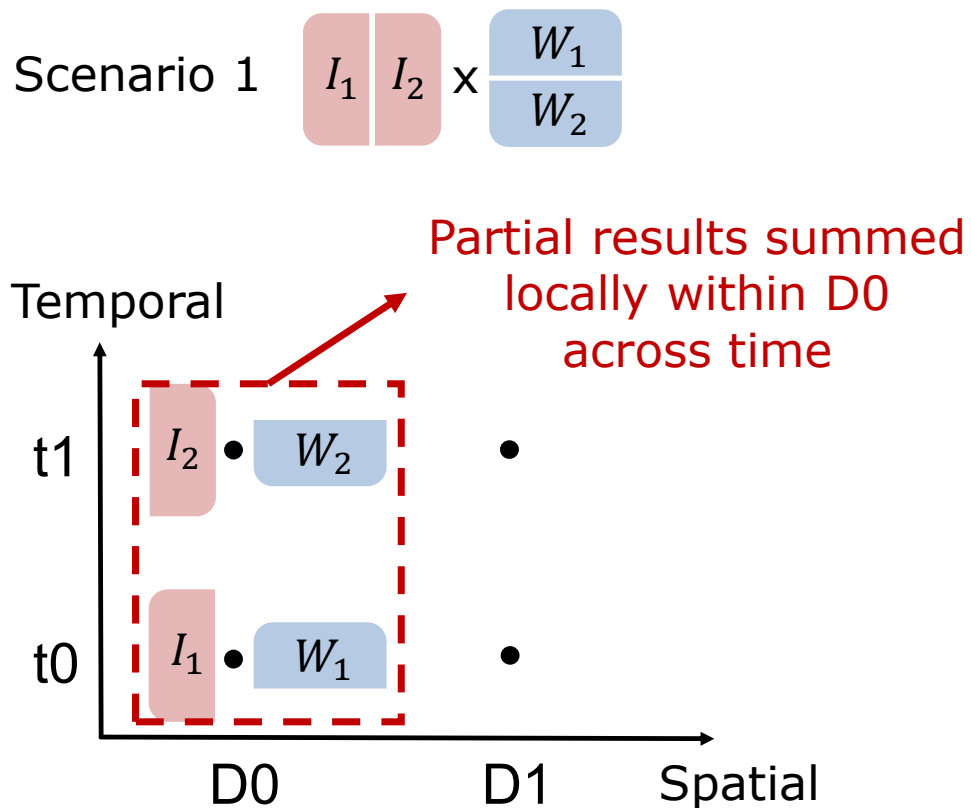
Motivational ideas

Distributing sub-operators along spatial dimension



Motivational ideas

Distributing sub-operators along temporal dimension provides extra opportunities



Optimizing both throughput and memory footprint

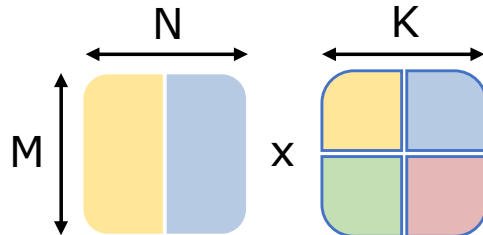
Tensor Partition Notations

Spatial index: device ID $\mathbf{D} = (d_1, d_2, \dots, d_n)$, $d_i = 0, 1$

Temporal index: $t = 0, 1, 2, \dots$

Dimension slice index (DSI): $I_X(\mathbf{D}, t)$

Example:



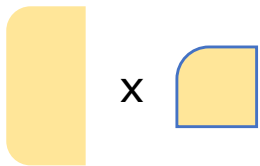
Given DSIs:

$$I_M(\mathbf{D}, t) = 0$$

$$I_N(\mathbf{D}, t) = d_1$$

$$I_K(\mathbf{D}, t) = d_2$$

Device ($d_1 = 0, d_2 = 0$)

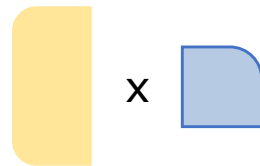


$$I_M = 0$$

$$I_N = d_1 = 0$$

$$I_K = d_2 = 0$$

Device ($d_1 = 0, d_2 = 1$)

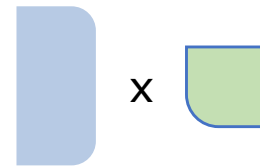


$$I_M = 0$$

$$I_N = d_1 = 0$$

$$I_K = d_2 = 1$$

Device ($d_1 = 1, d_2 = 0$)

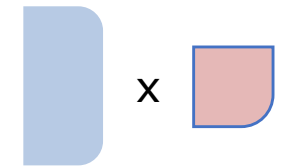


$$I_M = 0$$

$$I_N = d_1 = 1$$

$$I_K = d_2 = 0$$

Device ($d_1 = 1, d_2 = 1$)



$$I_M = 0$$

$$I_N = d_1 = 1$$

$$I_K = d_2 = 1$$

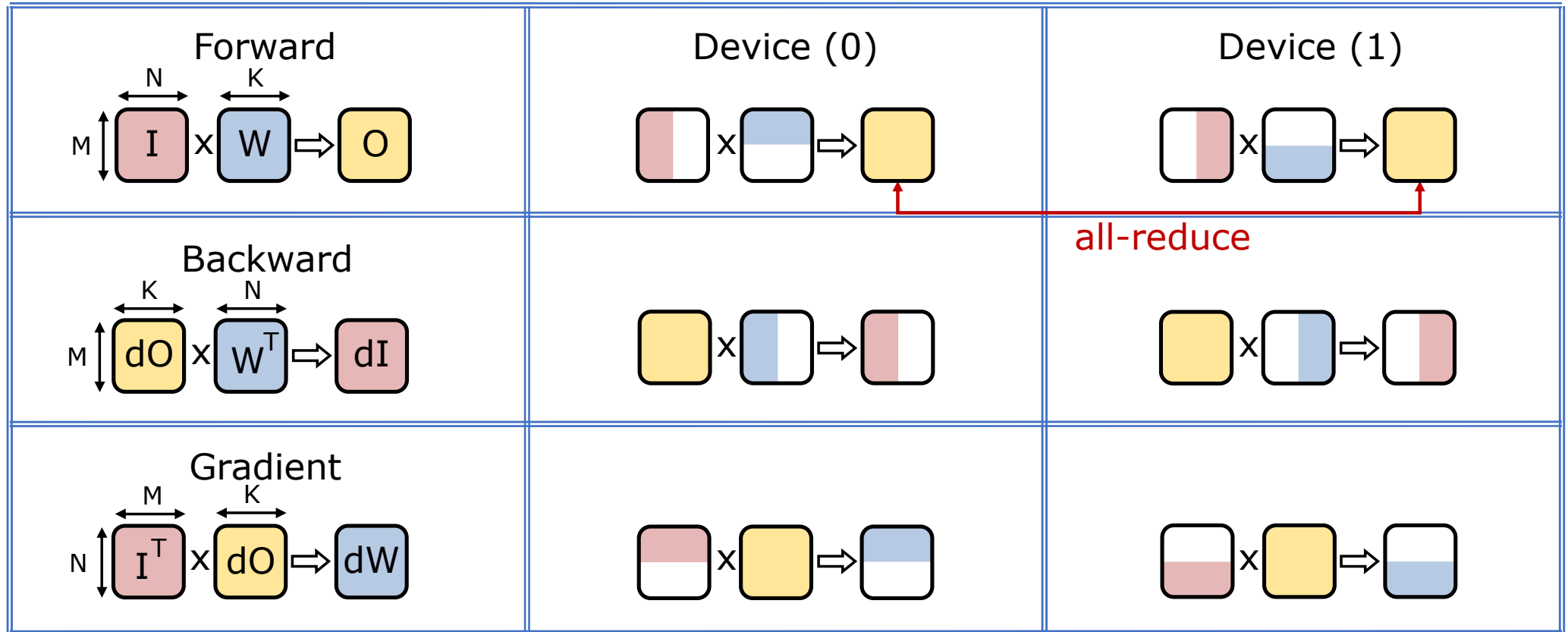
Existing Spatial Tensor Partition

Partition dimension N

$$I_M^F = I_M^B = I_M^G = 0$$

$$I_N^F = I_N^B = I_N^G = d_1$$

$$I_K^F = I_K^B = I_K^G = 0$$



Each time choose one dimension to partition and partition recursively

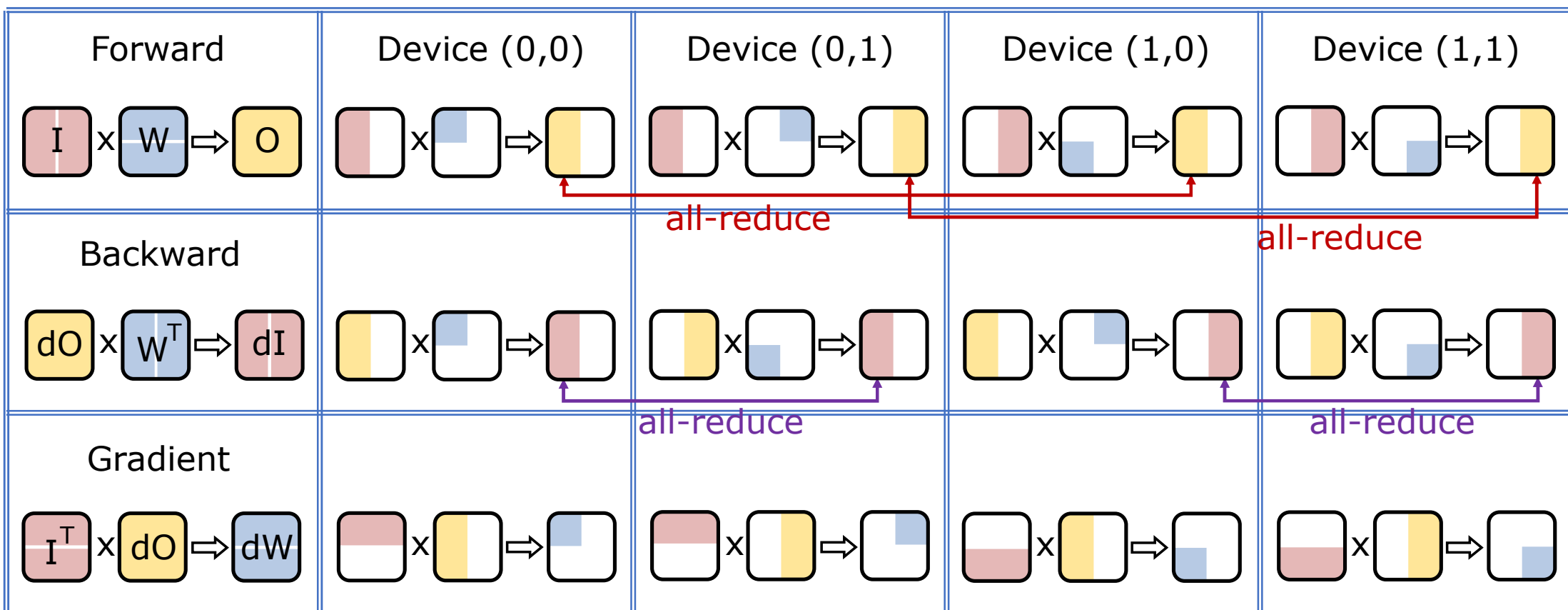
Existing Spatial Tensor Partition

Partition dimension K

$$I_M^F = I_M^B = I_M^G = 0$$

$$I_N^F = I_N^B = I_N^G = d_1$$

$$I_K^F = I_K^B = I_K^G = d_2$$



Each time choose one dimension to partition and partition recursively

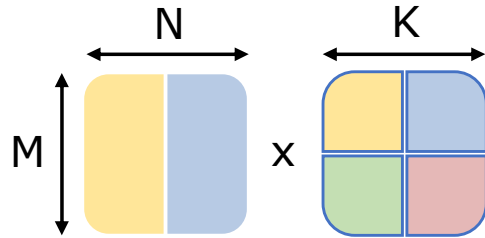
Essence of Inefficiencies: the DSI perspective

Spatial

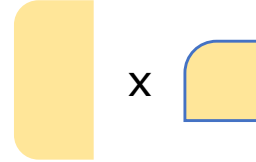
$$I_M = 0$$

$$I_N = d_1$$

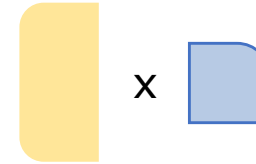
$$I_K = d_2$$



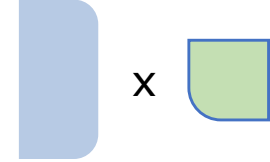
Device ($d_1 = 0, d_2 = 0$)



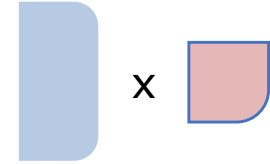
Device ($d_1 = 0, d_2 = 1$)



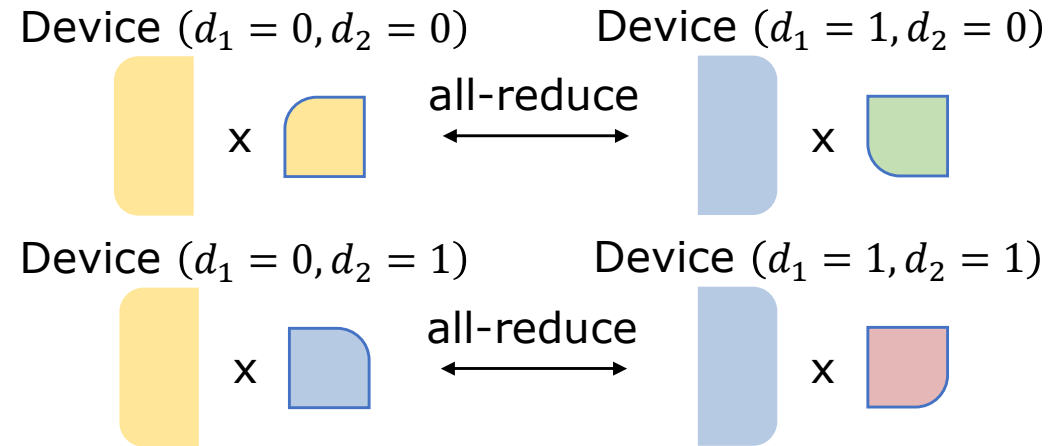
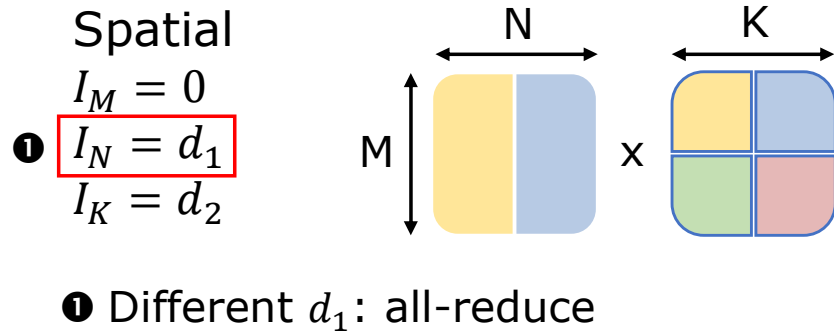
Device ($d_1 = 1, d_2 = 0$)



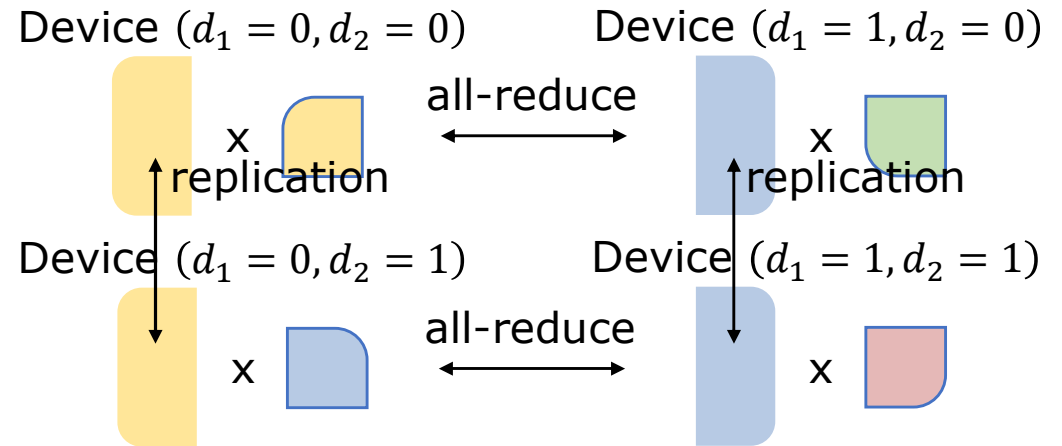
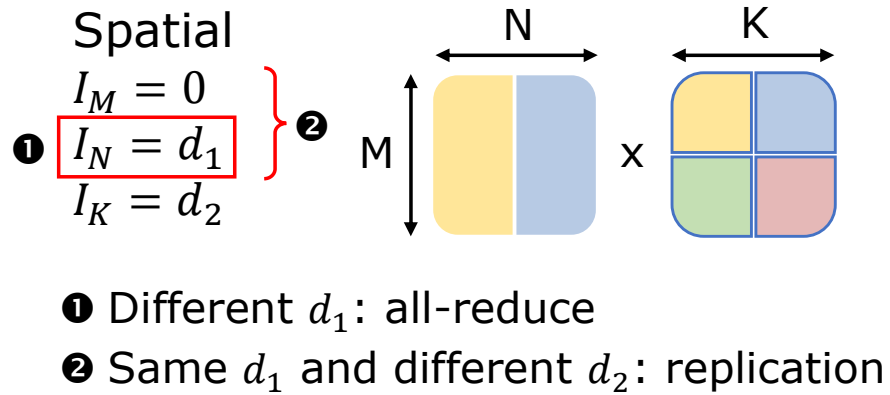
Device ($d_1 = 1, d_2 = 1$)



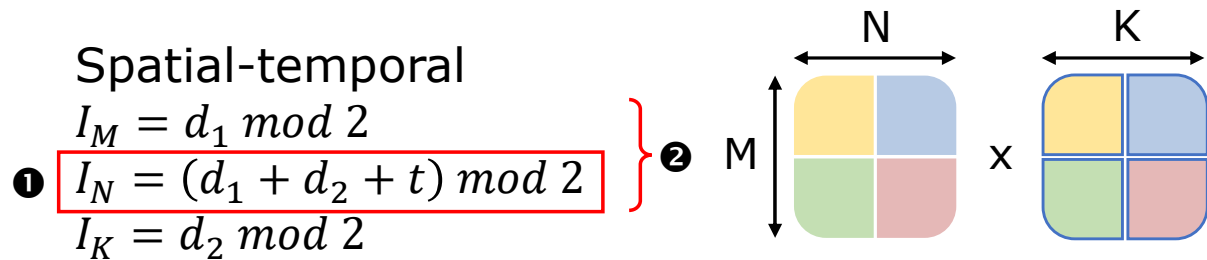
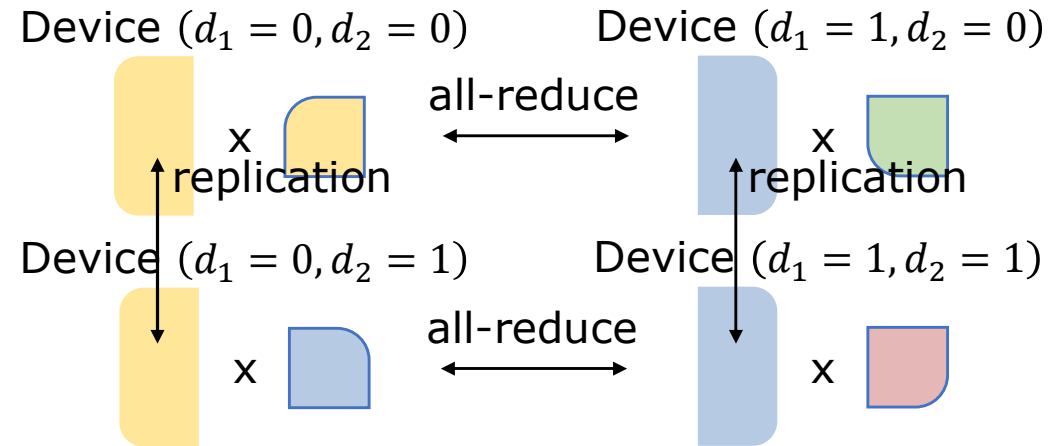
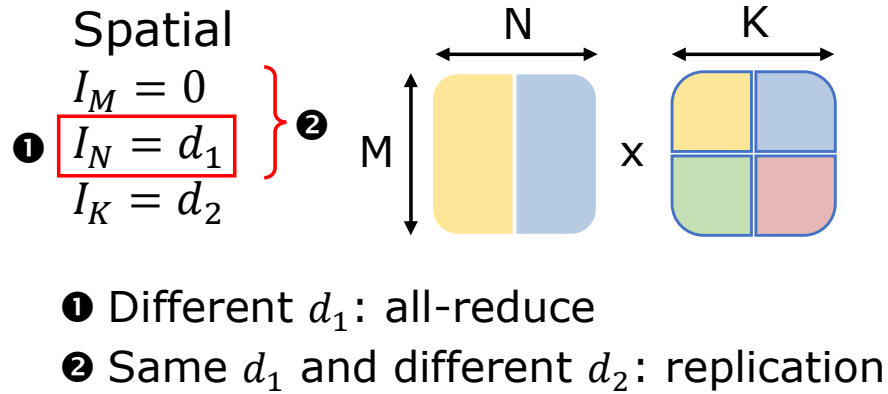
Essence of Inefficiencies: the DSI perspective



Essence of Inefficiencies: the DSI perspective

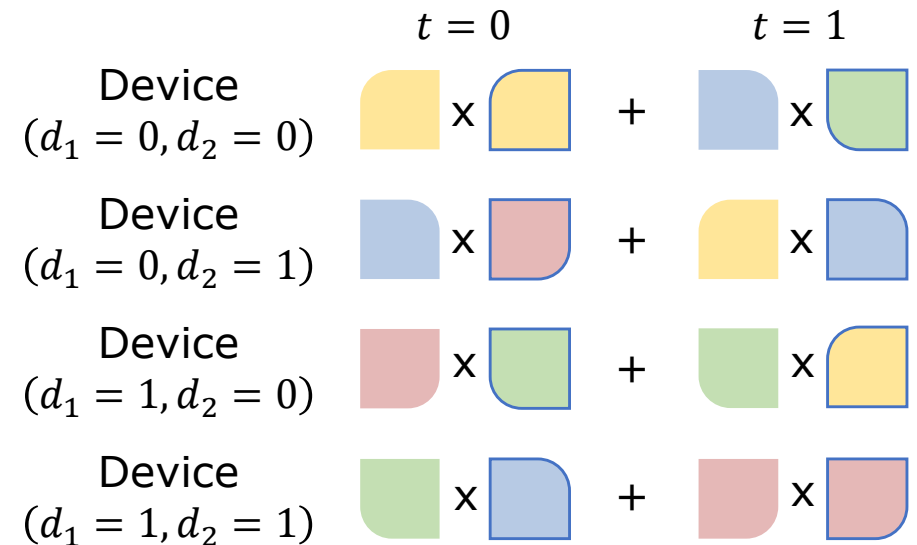


Essence of Inefficiencies: the DSI perspective



① I_N takes all possible values as t variates: **no all-reduce**

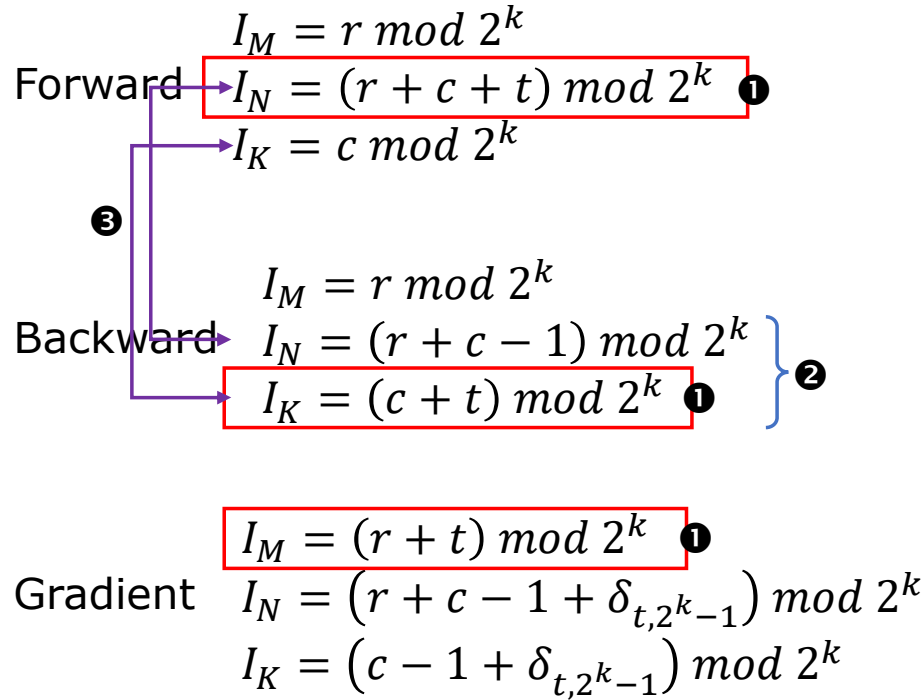
② Fixing t , (I_M, I_N) can't be the same for different devices: **no replication**



Novel Spatial-temporal Tensor Partition Primitive

Regard 2^{2k} devices as a square with row and column indices $0 \leq r, c < 2^k$

Temporal index $0 \leq t < 2^k$



❶ Collective communication free:
Summed-over dimensions take all possible values
when t variates

❷ No tensor replication:

$$\begin{cases} (r + c - 1) \equiv (r' + c' - 1) \bmod 2^k \\ (c' + t) \equiv (c + t) \bmod 2^k \end{cases} \longrightarrow r = r', c = c'$$

❸ Continuity between training phases:
Forward last step

$I_N = (r + c + 2^k - 1) \bmod 2^k$ $I_K = c \bmod 2^k$
 Backward first step
 $I_N = (r + c - 1) \bmod 2^k$ $I_K = (c + 0) \bmod 2^k$

match

Example: $k = 2$ Forward step $t = 0$

Communicate tensor I

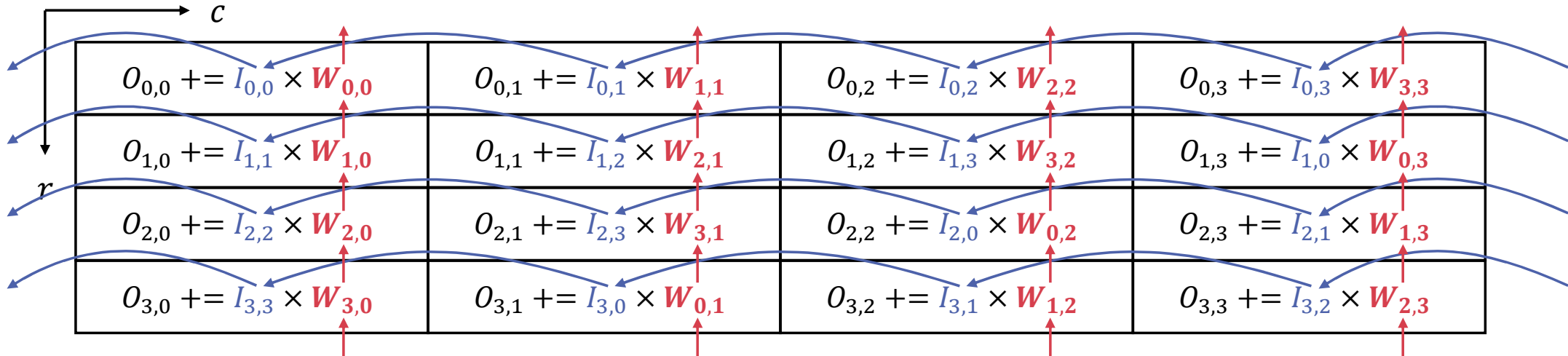
$$\begin{array}{ccc}
 (r, c+1, t): & \xrightarrow{\text{from right}} & (r, c, t+1): \\
 I_M = r \bmod 4 & & I_M = r \bmod 4 \\
 I_N = (r + c + 1 + t) \bmod 4 & \xleftarrow{\text{match}} & I_N = (r + c + t + 1) \bmod 4
 \end{array}$$

Communicate tensor W

$$\begin{array}{ccc}
 (r+1, c, t): & \xrightarrow{\text{from bottom}} & (r, c, t+1): \\
 I_N = (r + 1 + c + t) \bmod 4 & & I_N = (r + c + t + 1) \bmod 4 \\
 I_K = c \bmod 4 & \xleftarrow{\text{match}} & I_K = c \bmod 4
 \end{array}$$

Forward DSIs

$$\begin{aligned}
 I_M &= r \bmod 4 \\
 I_N &= (r + c + t) \bmod 4 \\
 I_K &= c \bmod 4
 \end{aligned}$$



Example: $k = 2$ Forward step $t = 1$

Communicate tensor I

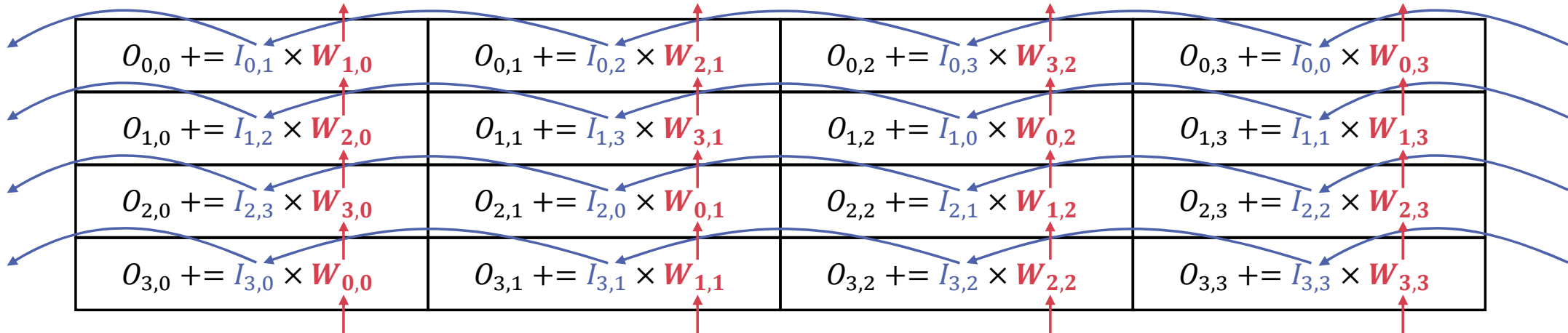
$$\begin{array}{ccc}
 (r, c+1, t): & \xrightarrow{\text{from right}} & (r, c, t+1): \\
 I_M = r \bmod 4 & & I_M = r \bmod 4 \\
 I_N = (r + c + 1 + t) \bmod 4 & \xleftarrow{\text{match}} & I_N = (r + c + t + 1) \bmod 4
 \end{array}$$

Communicate tensor W

$$\begin{array}{ccc}
 (r+1, c, t): & \xrightarrow{\text{from bottom}} & (r, c, t+1): \\
 I_N = (r + 1 + c + t) \bmod 4 & & I_N = (r + c + t + 1) \bmod 4 \\
 I_K = c \bmod 4 & \xleftarrow{\text{match}} & I_K = c \bmod 4
 \end{array}$$

Forward DSIs

$$\begin{aligned}
 I_M &= r \bmod 4 \\
 I_N &= (r + c + t) \bmod 4 \\
 I_K &= c \bmod 4
 \end{aligned}$$



Example: $k = 2$ Forward step $t = 2$

Communicate tensor I

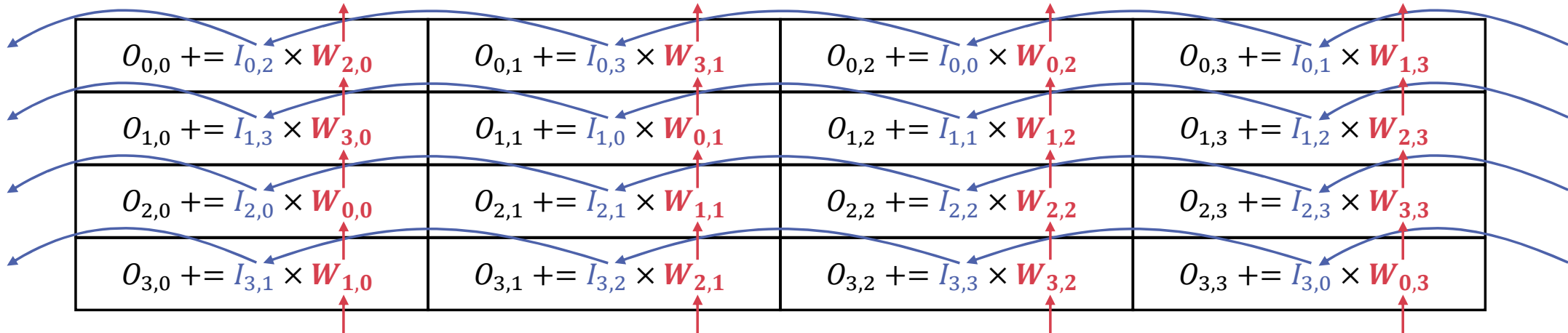
$$\begin{array}{ccc}
 (r, c+1, t): & \xrightarrow{\text{from right}} & (r, c, t+1): \\
 I_M = r \bmod 4 & & I_M = r \bmod 4 \\
 I_N = (r + c + 1 + t) \bmod 4 & \xleftarrow{\text{match}} & I_N = (r + c + t + 1) \bmod 4
 \end{array}$$

Communicate tensor W

$$\begin{array}{ccc}
 (r+1, c, t): & \xrightarrow{\text{from bottom}} & (r, c, t+1): \\
 I_N = (r + 1 + c + t) \bmod 4 & & I_N = (r + c + t + 1) \bmod 4 \\
 I_K = c \bmod 4 & \xleftarrow{\text{match}} & I_K = c \bmod 4
 \end{array}$$

Forward DSIs

$$\begin{aligned}
 I_M &= r \bmod 4 \\
 I_N &= (r + c + t) \bmod 4 \\
 I_K &= c \bmod 4
 \end{aligned}$$



Example: $k = 2$ Forward step $t = 3$

Last step of Forward, no communication:

- W alignment

$$\begin{array}{ll} \text{Forward} & O = I \times W \\ \text{Backward} & dI = dO \times W^T \end{array}$$

Forward ($r, c, t = 3$):

$$I_N = (r + c + 3) \bmod 4$$

$$I_K = c \bmod 4$$

← match →

Backward ($r, c, t = 0$):

$$I_N = (r + c - 1) \bmod 4$$

$$I_K = (c + 0) \bmod 4$$

$O_{0,0} += I_{0,3} \times W_{3,0}$	$O_{0,1} += I_{0,0} \times W_{0,1}$	$O_{0,2} += I_{0,1} \times W_{1,2}$	$O_{0,3} += I_{0,2} \times W_{2,3}$
$O_{1,0} += I_{1,0} \times W_{0,0}$	$O_{1,1} += I_{1,1} \times W_{1,1}$	$O_{1,2} += I_{1,2} \times W_{2,2}$	$O_{1,3} += I_{1,3} \times W_{3,3}$
$O_{2,0} += I_{2,1} \times W_{1,0}$	$O_{2,1} += I_{2,2} \times W_{2,1}$	$O_{2,2} += I_{2,3} \times W_{3,2}$	$O_{2,3} += I_{2,0} \times W_{0,3}$
$O_{3,0} += I_{3,2} \times W_{2,0}$	$O_{3,1} += I_{3,3} \times W_{3,1}$	$O_{3,2} += I_{3,0} \times W_{0,2}$	$O_{3,3} += I_{3,1} \times W_{1,3}$

Example: $k = 2$ Backward step $t = 0$

Communicate tensor dO

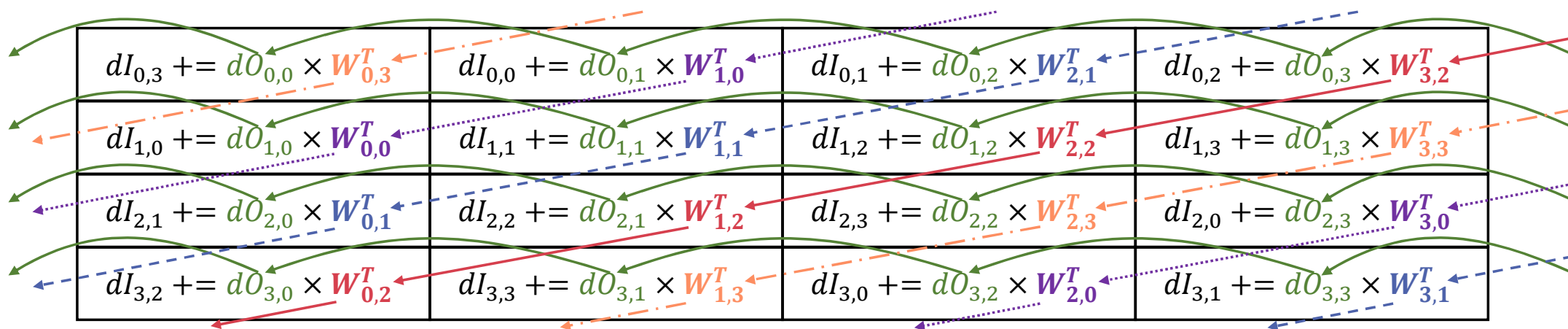
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 (r, c+1, t): & \xrightarrow{\text{from right}} & (r, c, t+1): \\
 I_M = r \bmod 4 & & I_M = r \bmod 4 \\
 I_K = (c+1+t) \bmod 4 & \xleftarrow{\text{match}} & I_K = (c+t+1) \bmod 4
 \end{array}$$

Communicate tensor W

$$\begin{array}{ccc}
 (r-1, c+1, t): & \xrightarrow{\text{from right-top}} & (r, c, t+1): \\
 I_N = (r-1+c+1-1) \bmod 4 & & I_N = (r+c-1) \bmod 4 \\
 I_K = (c+1+t) \bmod 4 & \xleftarrow{\text{match}} & I_K = (c+t+1) \bmod 4
 \end{array}$$

Backward DSIs

$$\begin{aligned}
 I_M &= r \bmod 4 \\
 I_N &= (r+c-1) \bmod 4 \\
 I_K &= (c+t) \bmod 4
 \end{aligned}$$



Example: $k = 2$ Backward step $t = 1$

Communicate tensor dO

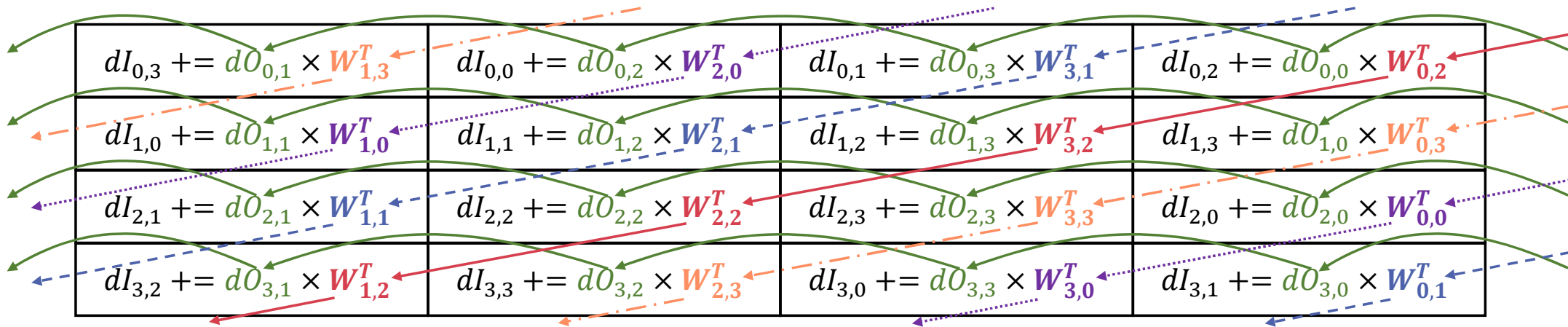
$$\begin{array}{ccc}
 (r, c+1, t): & \xrightarrow{\text{from right}} & (r, c, t+1): \\
 I_M = r \bmod 4 & & I_M = r \bmod 4 \\
 I_K = (c+1+t) \bmod 4 & \xleftarrow{\text{match}} & I_K = (c+t+1) \bmod 4
 \end{array}$$

Communicate tensor W

$$\begin{array}{ccc}
 (r-1, c+1, t): & \xrightarrow{\text{from right-top}} & (r, c, t+1): \\
 I_N = (r-1+c+1-1) \bmod 4 & & I_N = (r+c-1) \bmod 4 \\
 I_K = (c+1+t) \bmod 4 & \xleftarrow{\text{match}} & I_K = (c+t+1) \bmod 4
 \end{array}$$

Backward DSIs

$$\begin{aligned}
 I_M &= r \bmod 4 \\
 I_N &= (r+c-1) \bmod 4 \\
 I_K &= (c+t) \bmod 4
 \end{aligned}$$



Example: $k = 2$ Backward step $t = 2$

Communicate tensor dO

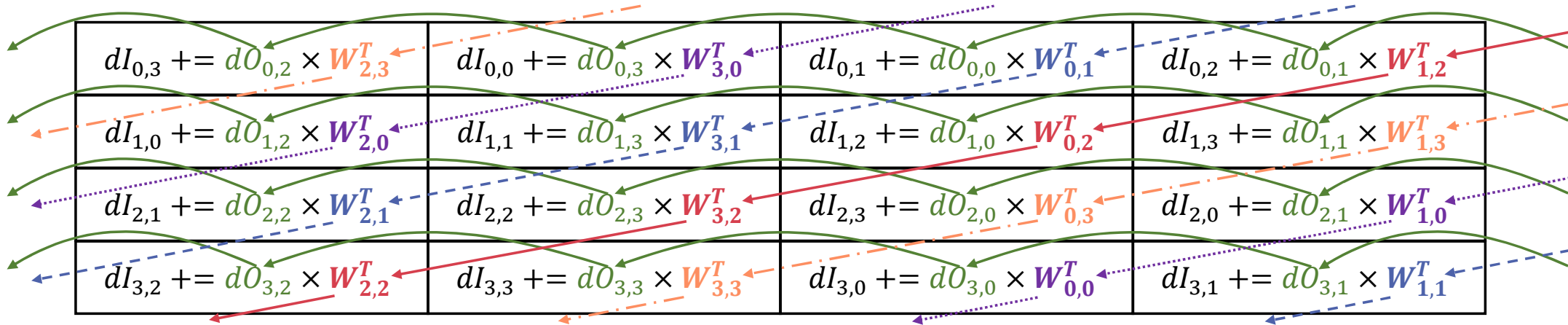
$$\begin{array}{ccc}
 (r, c+1, t): & \xrightarrow{\text{from right}} & (r, c, t+1): \\
 I_M = r \bmod 4 & & I_M = r \bmod 4 \\
 I_K = (c+1+t) \bmod 4 & \xleftarrow{\text{match}} & I_K = (c+t+1) \bmod 4
 \end{array}$$

Communicate tensor W

$$\begin{array}{ccc}
 (r-1, c+1, t): & \xrightarrow{\text{from right-top}} & (r, c, t+1): \\
 I_N = (r-1+c+1-1) \bmod 4 & & I_N = (r+c-1) \bmod 4 \\
 I_K = (c+1+t) \bmod 4 & \xleftarrow{\text{match}} & I_K = (c+t+1) \bmod 4
 \end{array}$$

Backward DSIs

$$\begin{aligned}
 I_M &= r \bmod 4 \\
 I_N &= (r+c-1) \bmod 4 \\
 I_K &= (c+t) \bmod 4
 \end{aligned}$$



Example: $k = 2$ Backward step $t = 3$

- W alignment

Backward ($r, c + 1, t = 3$): $\xrightarrow{\text{from right}}$ Forward ($r, c, t = 0$):
 $I_N = (r + c + 1 - 1) \bmod 4$ $I_N = (r + c) \bmod 4$
 $I_K = (c + 1 + 3) \bmod 4$ $I_K = (c) \bmod 4$
 $\xleftarrow{\text{match}}$

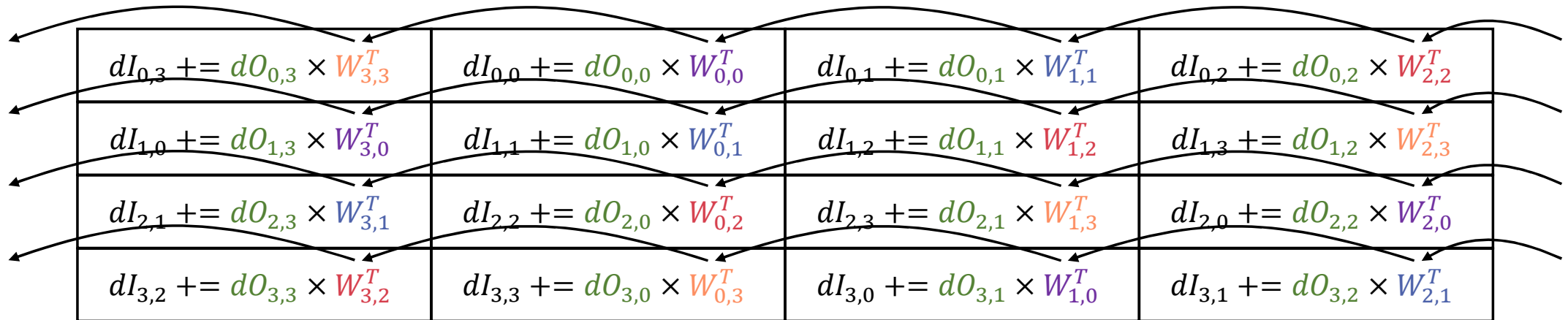
Forward $O = I \times W$
 Backward $dI = dO \times W^T$
 Gradient $dW = I^T \times dO$

- dO alignment

Backward ($r, c, t = 3$): $\xleftarrow{\text{match}}$ Gradient ($r, c, t = 0$):
 $I_M = r \bmod 4$ $I_M = (r + 0) \bmod 4$
 $I_K = (c + 3) \bmod 4$ $I_K = (c - 1) \bmod 4$

- I alignment

Forward ($r, c, t = 3$): $\xleftarrow{\text{match}}$ Gradient ($r, c, t = 0$):
 $I_M = r \bmod 4$ $I_M = (r + 0) \bmod 4$
 $I_N = (r + c + 3) \bmod 4$ $I_K = (r + c - 1) \bmod 4$



Example: $k = 2$ Gradient step $t = 0$

Communicate tensor I

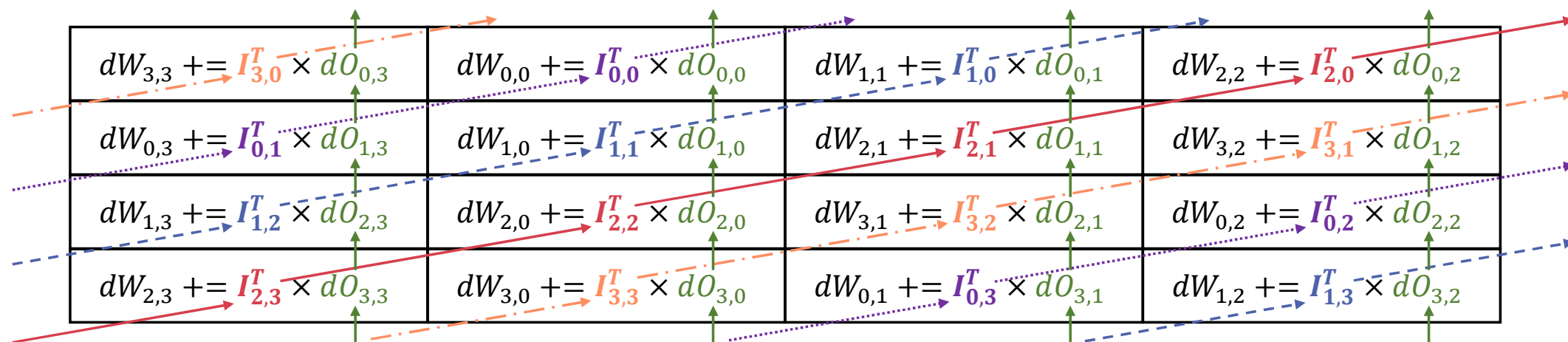
$$\begin{array}{lcl}
 (r+1, c-1, t): & \xrightarrow{\text{from bottom left}} & (r, c, t+1): \\
 I_M = (r+1+t) \bmod 4 & & I_M = (r+t+1) \bmod 4 \\
 I_N = (r+1+c-1-1+\delta_{0,3}) \bmod 4 & \xleftarrow{\text{match}} & I_N = (r+c-1+\delta_{1,3}) \bmod 4
 \end{array}$$

Communicate tensor dO

$$\begin{array}{lcl}
 (r+1, c, t): & \xrightarrow{\text{from bottom}} & (r, c, t+1): \\
 I_M = (r+1+t) \bmod 4 & & I_M = (r+t+1) \bmod 4 \\
 I_K = (c-1+\delta_{0,3}) \bmod 4 & \xleftarrow{\text{match}} & I_K = (c-1+\delta_{1,3}) \bmod 4
 \end{array}$$

Gradient DSIs

$$\begin{array}{l}
 I_M = (r+t) \bmod 4 \\
 I_N = (r+c-1+\delta_{0,3}) \bmod 4 \\
 I_K = (c-1+\delta_{0,3}) \bmod 4
 \end{array}$$



Example: $k = 2$ Gradient step $t = 1$

Communicate tensor I

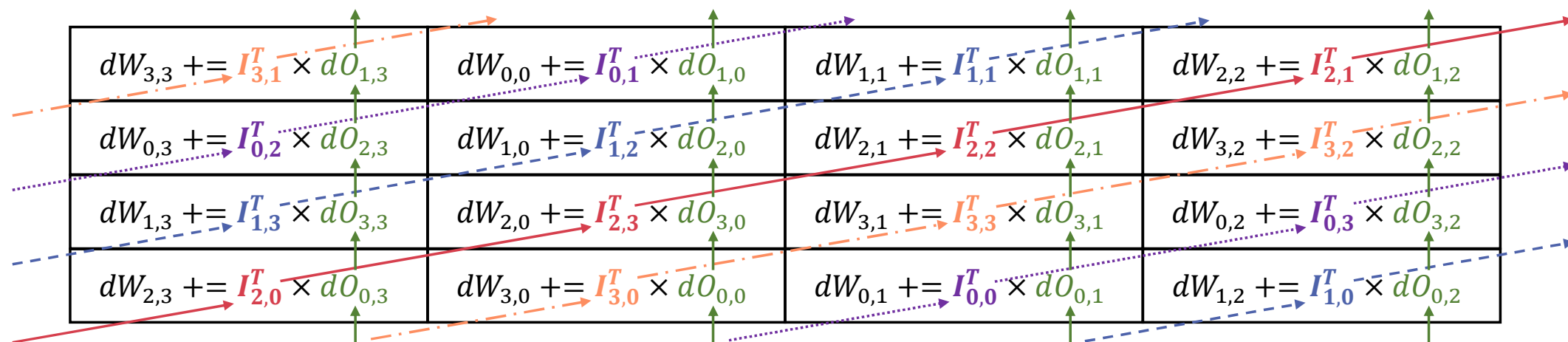
$$\begin{array}{lcl}
 (r+1, c-1, t): & \xrightarrow{\text{from bottom left}} & (r, c, t+1): \\
 I_M = (r+1+t) \bmod 4 & & I_M = (r+t+1) \bmod 4 \\
 I_N = (r+1+c-1-1+\delta_{1,3}) \bmod 4 & \xleftarrow{\text{match}} & I_N = (r+c-1+\delta_{2,3}) \bmod 4
 \end{array}$$

Communicate tensor dO

$$\begin{array}{lcl}
 (r+1, c, t): & \xrightarrow{\text{from bottom}} & (r, c, t+1): \\
 I_M = (r+1+t) \bmod 4 & & I_M = (r+t+1) \bmod 4 \\
 I_K = (c-1+\delta_{1,3}) \bmod 4 & \xleftarrow{\text{match}} & I_K = (c-1+\delta_{2,3}) \bmod 4
 \end{array}$$

Gradient DSIs

$$\begin{array}{l}
 I_M = (r+t) \bmod 4 \\
 I_N = (r+c-1+\delta_{1,3}) \bmod 4 \\
 I_K = (c-1+\delta_{1,3}) \bmod 4
 \end{array}$$



Example: $k = 2$ Gradient step $t = 2$

Communicate tensor I

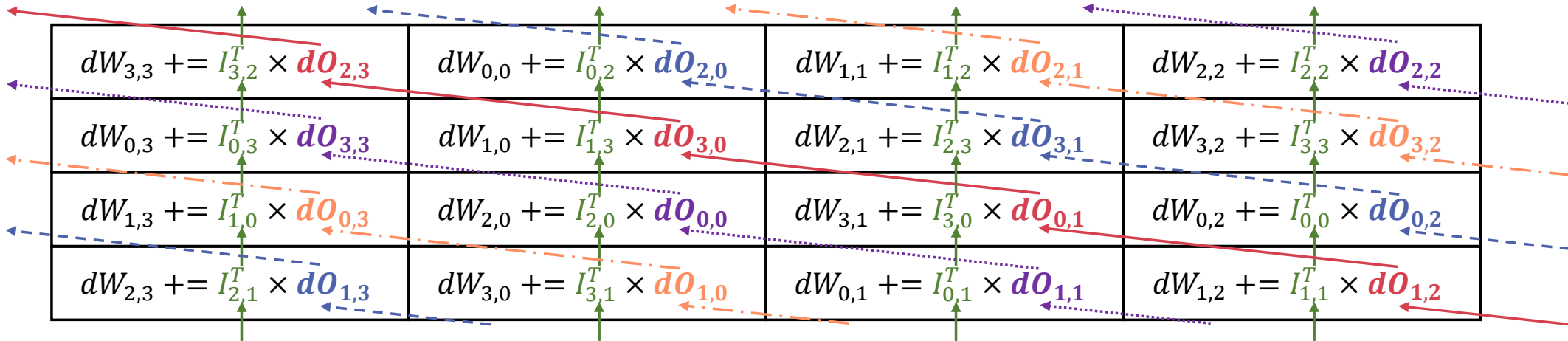
$$\begin{array}{lcl}
 (r+1, c, t): & \xrightarrow{\text{from bottom}} & (r, c, t+1): \\
 I_M = (r+1+2) \bmod 4 & & I_M = (r+3) \bmod 4 \\
 I_N = (r+1+c-1+\delta_{2,3}) \bmod 4 & \xleftarrow{\text{match}} & I_N = (r+c-1+\delta_{3,3}) \bmod 4
 \end{array}$$

Communicate tensor dO

$$\begin{array}{lcl}
 (r+1, c+1, t): & \xrightarrow{\text{from bottom right}} & (r, c, t+1): \\
 I_M = (r+1+2) \bmod 4 & & I_M = (r+3) \bmod 4 \\
 I_K = (c+1-1+\delta_{2,3}) \bmod 4 & \xleftarrow{\text{match}} & I_K = (c-1+\delta_{3,3}) \bmod 4
 \end{array}$$

Gradient DSIs

$$\begin{array}{l}
 I_M = (r+t) \bmod 4 \\
 I_N = (r+c-1+\delta_{2,3}) \bmod 4 \\
 I_K = (c-1+\delta_{2,3}) \bmod 4
 \end{array}$$



Example: k = 2 Gradient step t = 3

- dW alignment

Gradient ($r, c + 1, t < 3$): $\xrightarrow{\text{from right}}$ Gradient ($r, c, t = 3$):

$$I_N = (r + c + 1 - 1 + \delta_{t,3}) \bmod 4 \quad I_N = (r + c - 1 + \delta_{3,3}) \bmod 4$$

$$I_K = (c + 1 - 1 + \delta_{t,3}) \bmod 4 \quad \xleftarrow{\text{match}} \quad I_K = (c - 1 + \delta_{3,3}) \bmod 4$$

Forward ($r, c, t = 0$):

$$I_N = (r + c + 0) \bmod 4$$

$$I_K = c \bmod 4$$

match

Accumulated dW when $t < 3$

$dW_{3,3}$	$dW_{0,0}$	$dW_{1,1}$	$dW_{2,2}$
$dW_{0,3}$	$dW_{1,0}$	$dW_{2,1}$	$dW_{3,2}$
$dW_{1,3}$	$dW_{2,0}$	$dW_{3,1}$	$dW_{0,2}$
$dW_{2,3}$	$dW_{3,0}$	$dW_{0,1}$	$dW_{1,2}$

Add dW computed during step $t = 3$ with shifted accumulated dW

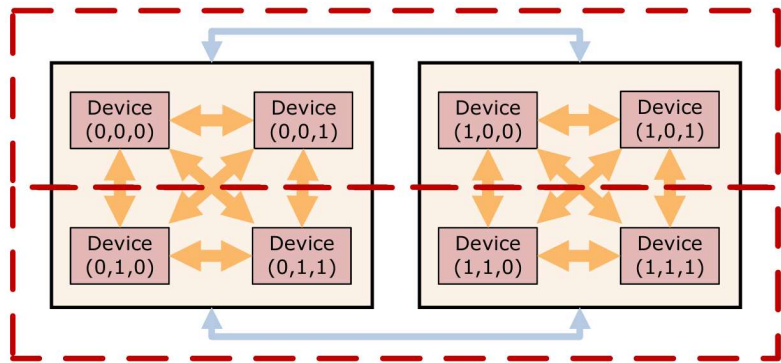
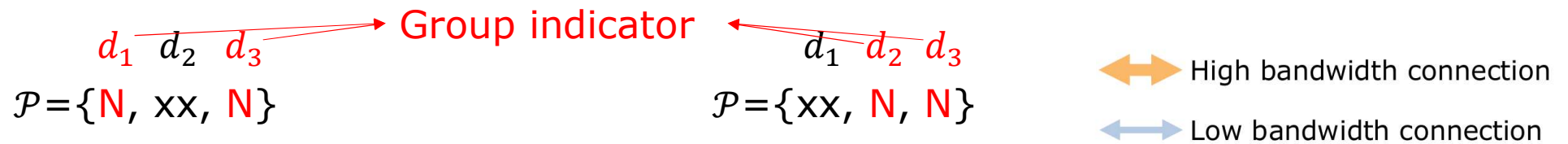
$dW_{0,0} += I_{0,3}^T \times dO_{3,0}$	$dW_{1,1} += I_{1,3}^T \times dO_{3,1}$	$dW_{2,2} += I_{2,3}^T \times dO_{3,2}$	$dW_{3,3} += I_{3,3}^T \times dO_{3,3}$
$dW_{1,0} += I_{1,0}^T \times dO_{0,0}$	$dW_{2,1} += I_{2,0}^T \times dO_{0,1}$	$dW_{3,2} += I_{3,0}^T \times dO_{0,2}$	$dW_{0,3} += I_{0,0}^T \times dO_{0,3}$
$dW_{2,0} += I_{2,1}^T \times dO_{1,0}$	$dW_{3,1} += I_{3,1}^T \times dO_{1,1}$	$dW_{0,2} += I_{0,1}^T \times dO_{1,2}$	$dW_{1,3} += I_{1,1}^T \times dO_{1,3}$
$dW_{3,0} += I_{3,2}^T \times dO_{2,0}$	$dW_{0,1} += I_{0,2}^T \times dO_{2,1}$	$dW_{1,2} += I_{1,2}^T \times dO_{2,2}$	$dW_{2,3} += I_{2,2}^T \times dO_{2,3}$

Cost Model

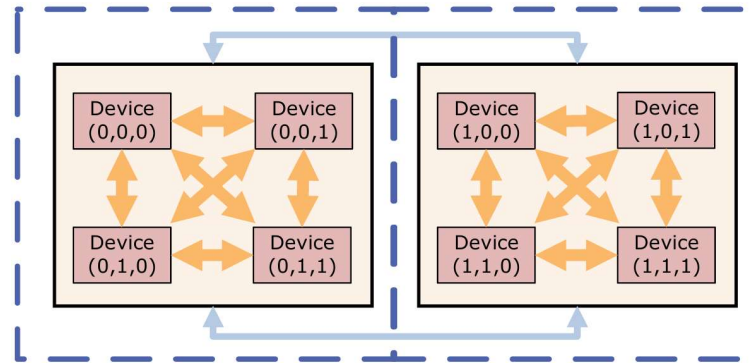
Intra-operator communication: all-reduce, ring

Example:

all-reduce of forward linear operator output tensor O – induced by partition N



$$latency = \alpha_1 \cdot sizeof(O) + \beta_1$$



$$latency = \alpha_2 \cdot sizeof(O) + \beta_2$$

Profile a set of α, β
for each grouping
pattern

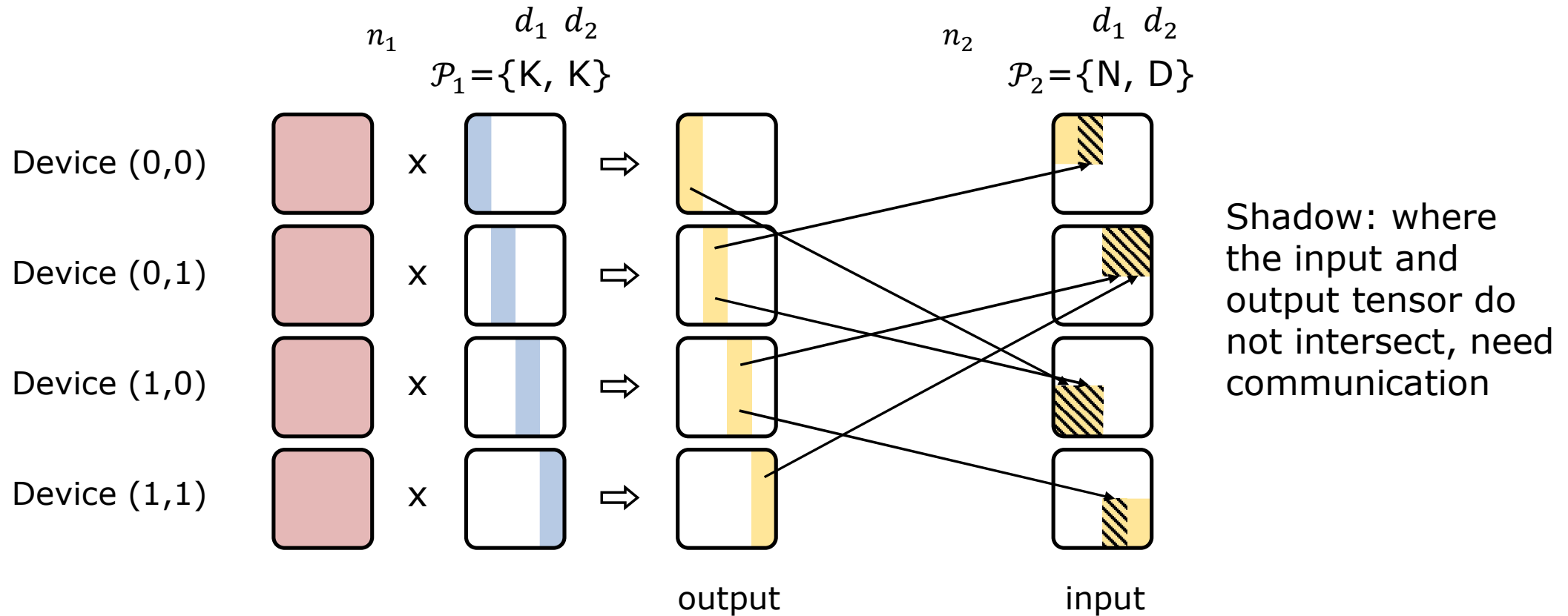
$$\alpha_1 > \alpha_2$$

Cost Model

Inter-operator communication: redistribution between operators

Example:

redistribution during forward between linear (n_1) and relu (n_2)



Cost Model

Overall cost

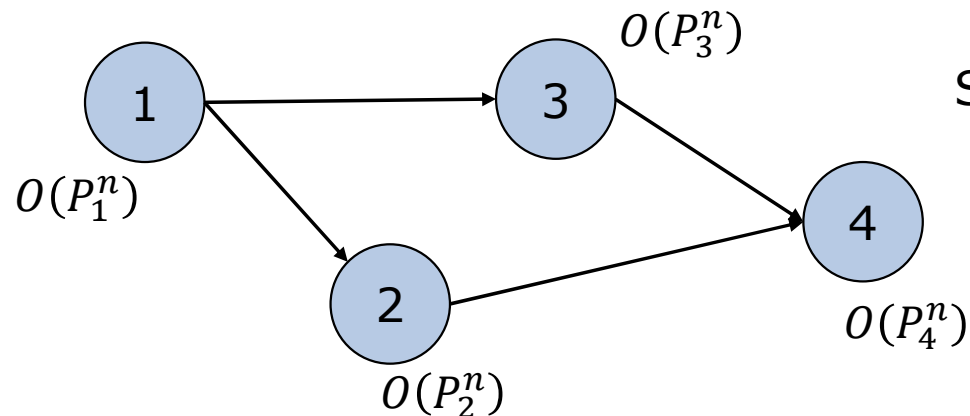
Counting all intra- and inter- operator cost

Computation graph $G = \langle N, E \rangle$, suppose operator n_i is partitioned with strategy \mathcal{P}_i

$$Cost = \sum_{n_i \in N} intraCost(n_i, \mathcal{P}_i) + \sum_{(n_i, n_j) \in E} interCost(n_i, n_j, \mathcal{P}_i, \mathcal{P}_j)$$

To 2^n devices

- Number of partition primitives of operator n_i : P_i
- Tensor partition space size of n_i : $O(P_i^n)$

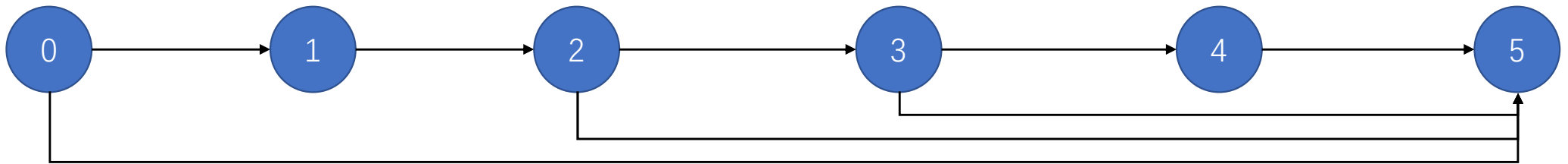


Search space size

$$\prod_i P_i^n$$

Optimization Algorithm: naïve dynamic programming

Complicated optimal substructure



$$C_0(\mathcal{P}_0) \longrightarrow C_{0,1}(\mathcal{P}_0, \mathcal{P}_1) \longrightarrow C_{0,2}(\mathcal{P}_0, \mathcal{P}_2) \longrightarrow C_{0,3}(\mathcal{P}_0, \mathcal{P}_2, \mathcal{P}_3) \longrightarrow C_{0,4}(\mathcal{P}_0, \mathcal{P}_2, \mathcal{P}_3, \mathcal{P}_4) \longrightarrow C_{0,5}(\mathcal{P}_0, \mathcal{P}_5)$$

$$O(P_0^n P_1^n)$$

$$O(P_0^n P_1^n P_2^n)$$

$$O(P_0^n P_2^n P_3^n)$$

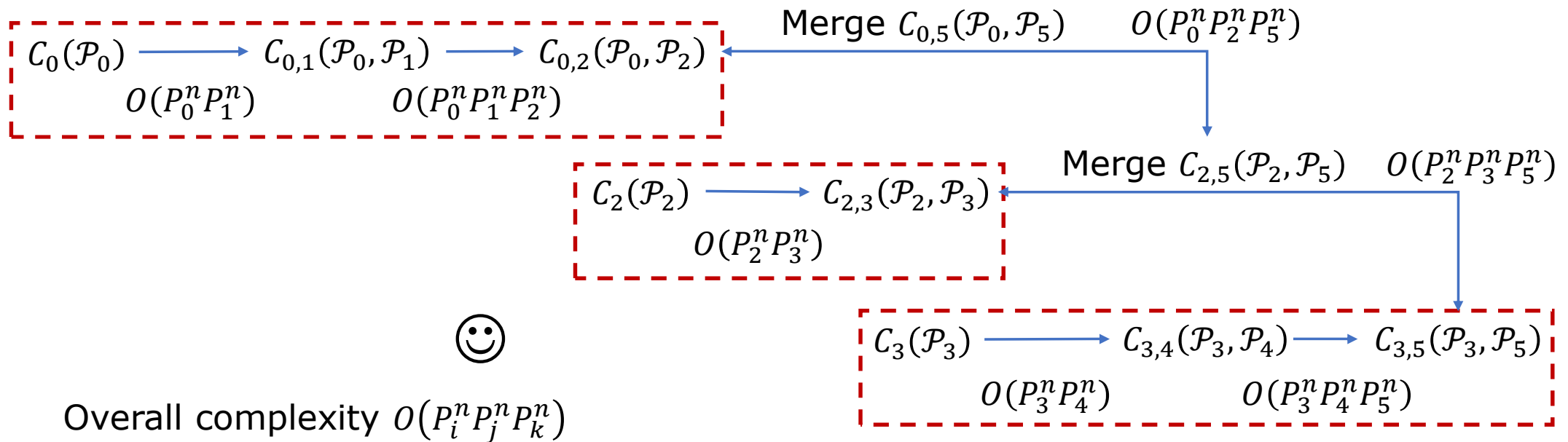
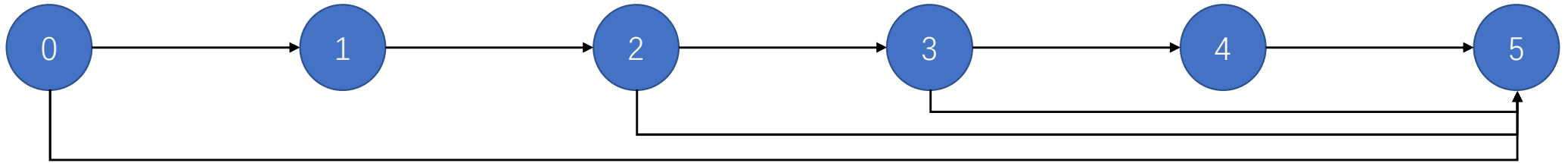
$$O(P_0^n P_2^n P_3^n P_4^n)$$

$$O(P_0^n P_2^n P_3^n P_4^n P_5^n)$$

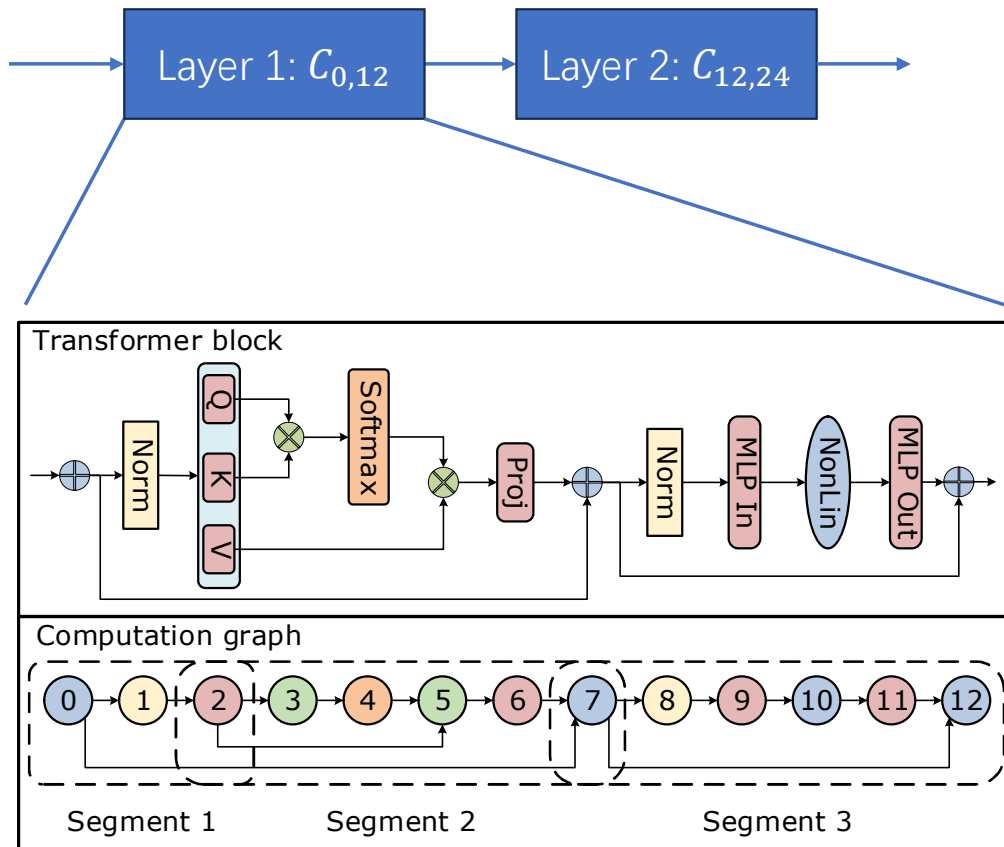


Overall complexity $O(P_0^n P_2^n P_3^n P_4^n P_5^n)$

Optimization Algorithm: segmented dynamic programming



Segmentation of Transformer Models



- Dynamic programming within each segment:
Optimal substructures $C_{0,2}, C_{2,7}, C_{7,12}$

- Merge segments:

$$C_{0,7}(\mathcal{P}_0, \mathcal{P}_7) = \min_{\mathcal{P}_2} \{C_{0,2}(\mathcal{P}_0, \mathcal{P}_2) + C_{2,7}(\mathcal{P}_2, \mathcal{P}_7) - n_2(\mathcal{P}_2) + e_{0,7}(\mathcal{P}_0, \mathcal{P}_7)\}$$

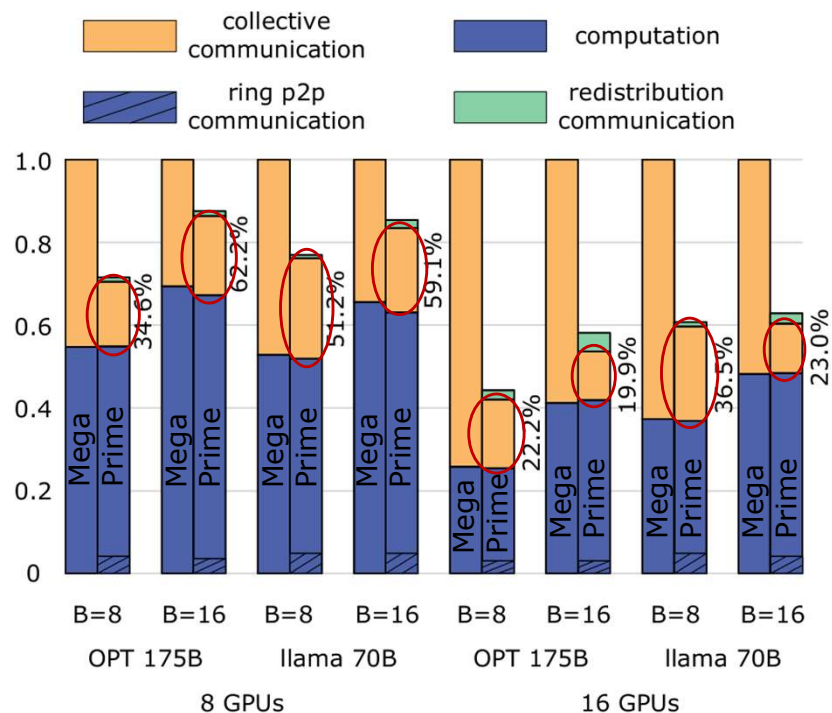
$$C_{0,12}(\mathcal{P}_0, \mathcal{P}_{12}) = \min_{\mathcal{P}_7} \{C_{0,7}(\mathcal{P}_0, \mathcal{P}_7) + C_{7,12}(\mathcal{P}_7, \mathcal{P}_{12}) - n_7(\mathcal{P}_7)\}$$

- Merge layers:

$$C_{0,24}(\mathcal{P}_0, \mathcal{P}_{24}) = \min_{\mathcal{P}_{12}} \{C_{0,12}(\mathcal{P}_0, \mathcal{P}_{12}) + C_{12,24}(\mathcal{P}_{12}, \mathcal{P}_{24}) - n_{12}(\mathcal{P}_{12})\}$$

Evaluation: Breakdown and Ablation

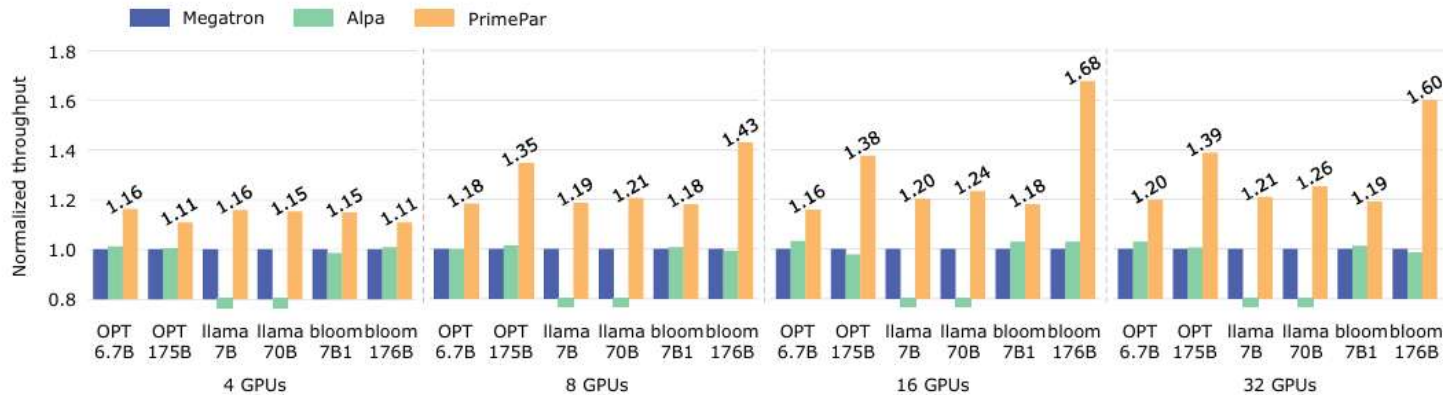
MLP blocks latency breakdown comparison



- The latency of collective communications are reduced to 19.9–62.2%

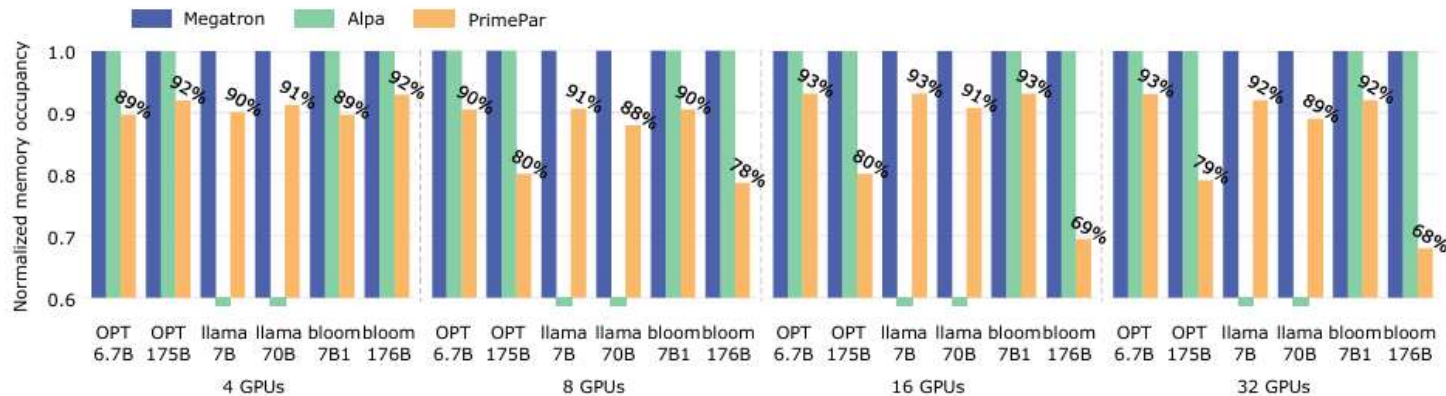
Evaluation: Performance and Memory Occupation

Normalized training throughput



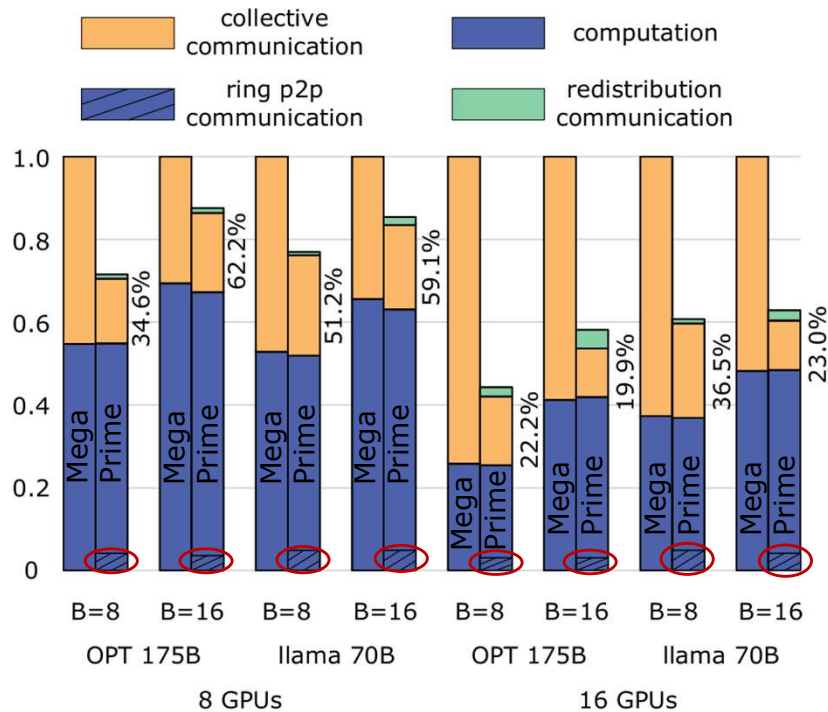
- 1.11–1.68x training speedup and 68–93% peak memory
- Optimized tensor partitions improve training speed and save memory simultaneously
- Benefits are more significant when scaling larger models to more GPUs

Peak memory occupation



Evaluation: Breakdown and Ablation

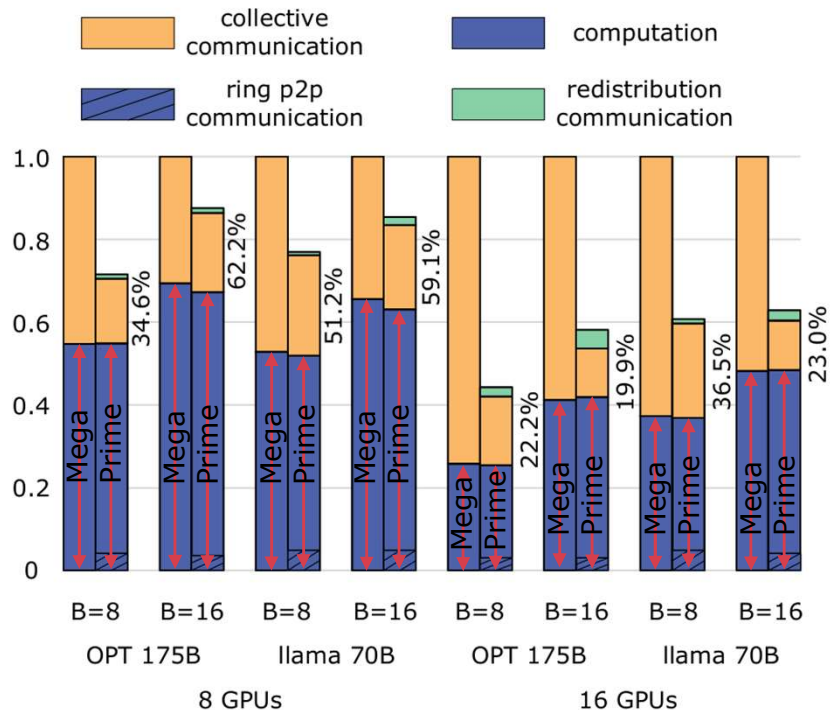
MLP blocks latency breakdown comparison



- The latency of collective communications are reduced to 19.9–62.2%
- Induced ring point-to-point communications are cheaper and fully overlapped with computation latency

Evaluation: Breakdown and Ablation

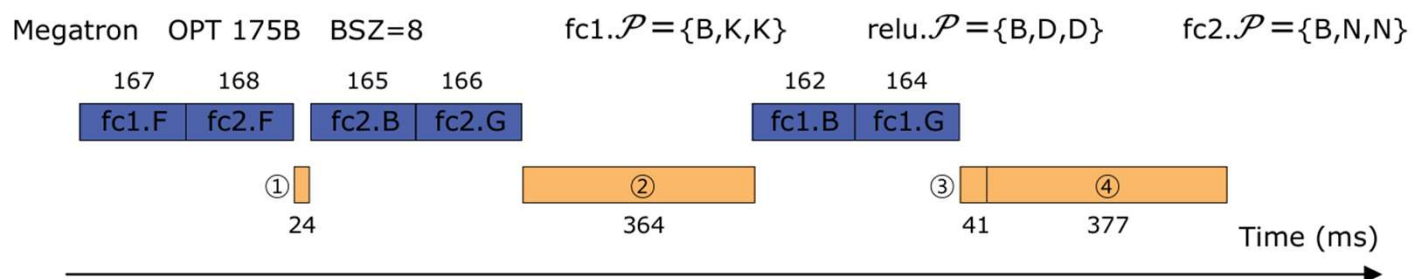
MLP blocks latency breakdown comparison



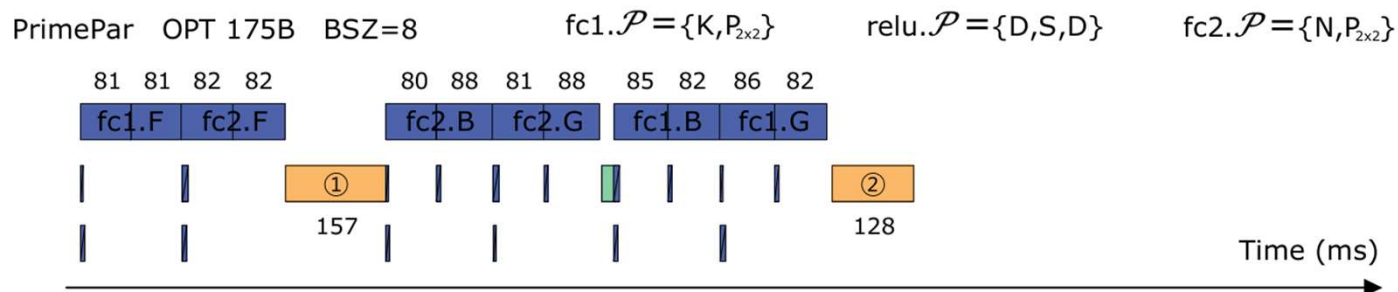
- The latency of collective communications are reduced to 19.9–62.2%
- Induced ring point-to-point communications are cheaper and fully overlapped with computation latency
- Computation latency remains the same: does not compromise computation efficiency

Evaluation: Breakdown and Ablation

Kernel execution timelines of the MLP block



- ① $fc2.\mathcal{P} = \{B, \textcolor{brown}{N}, N\}$, Intra-node reduce($\text{size}(O)/2$) ② $fc2.\mathcal{P} = \{\textcolor{brown}{B}, N, N\}$, Inter-node reduce($\text{size}(W)/4$)
 ③ $fc1.\mathcal{P} = \{B, \textcolor{brown}{K}, K\}$, Intra-node reduce($\text{size}(I)/2$) ④ $fc1.\mathcal{P} = \{\textcolor{brown}{B}, K, K\}$, Inter-node reduce($\text{size}(W)/4$)



- ① $fc2.\mathcal{P} = \{\textcolor{brown}{N}, P_{2 \times 2}\}$, Inter-node reduce($\text{size}(O)/4$) ② $fc2.\mathcal{P} = \{\textcolor{brown}{K}, P_{2 \times 2}\}$, Inter-node reduce($\text{size}(I)/4$)

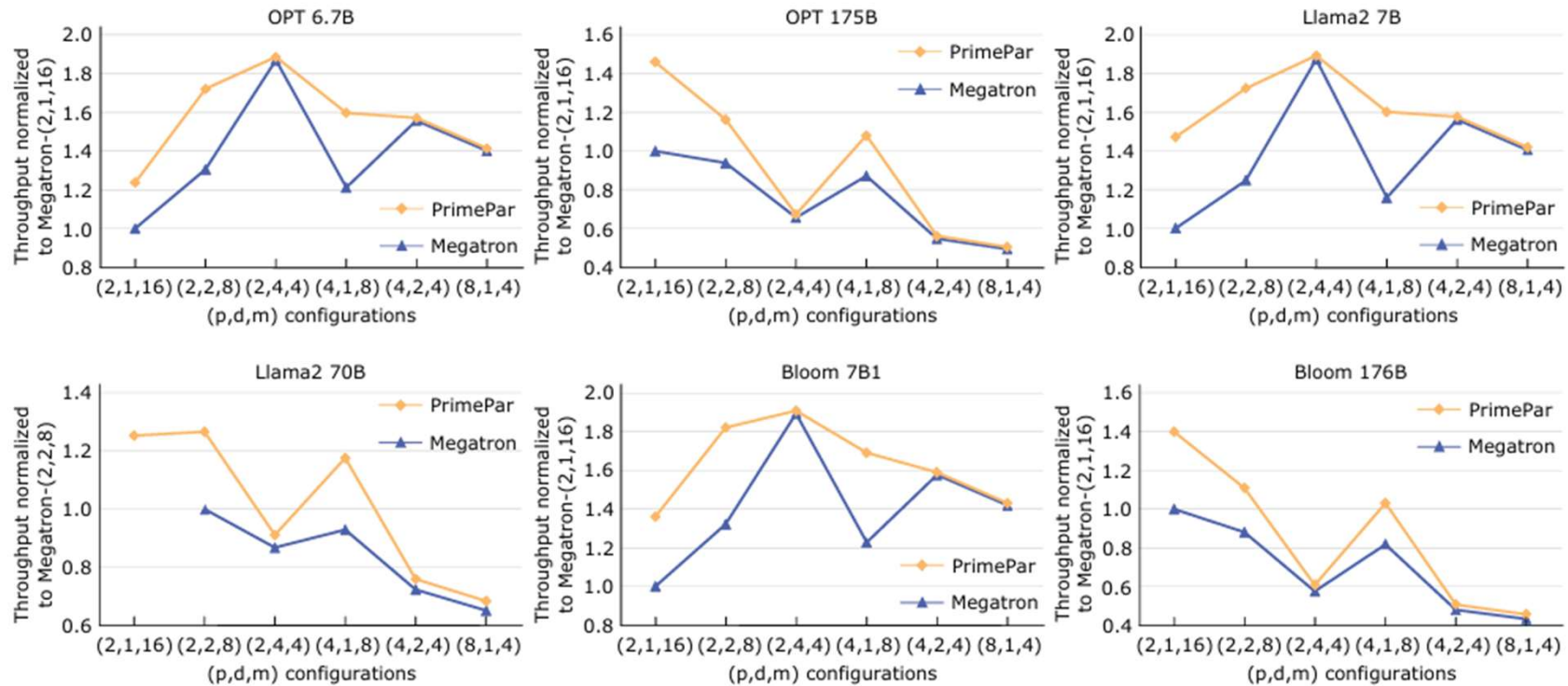
- Baseline:
Intra-node collective:
 $\text{size}(O)/2 + \text{size}(I)/2$

Inter-node collective:
 $\text{size}(W)/2$

- PrimePar:
Intra-node collective:
0

Inter-node collective:
 $\text{size}(O)/4 + \text{size}(I)/4$
 $< \text{size}(W)/2$

Evaluation: Impact on 3D Parallelism



- 1.46, 1.27, 1.40x speedups for OPT 175B, Llama2 70B, Bloom 176B
- Larger models prefer higher degree of model parallelism, where PrimePar yields greater performance improvements

Conclusion

- Spatial-temporal tensor partition: more efficient communication and better utilization of hardware resources
- Formulate spatial-temporal sub-operator distribution: help design efficient tensor partition primitive and analyze communication patterns
- Further exploration into spatial-temporal tensor partition space is worthwhile

Thank you!

Please contact us at the email address
below if you have any questions:
wanghaoran20g@ict.ac.cn