

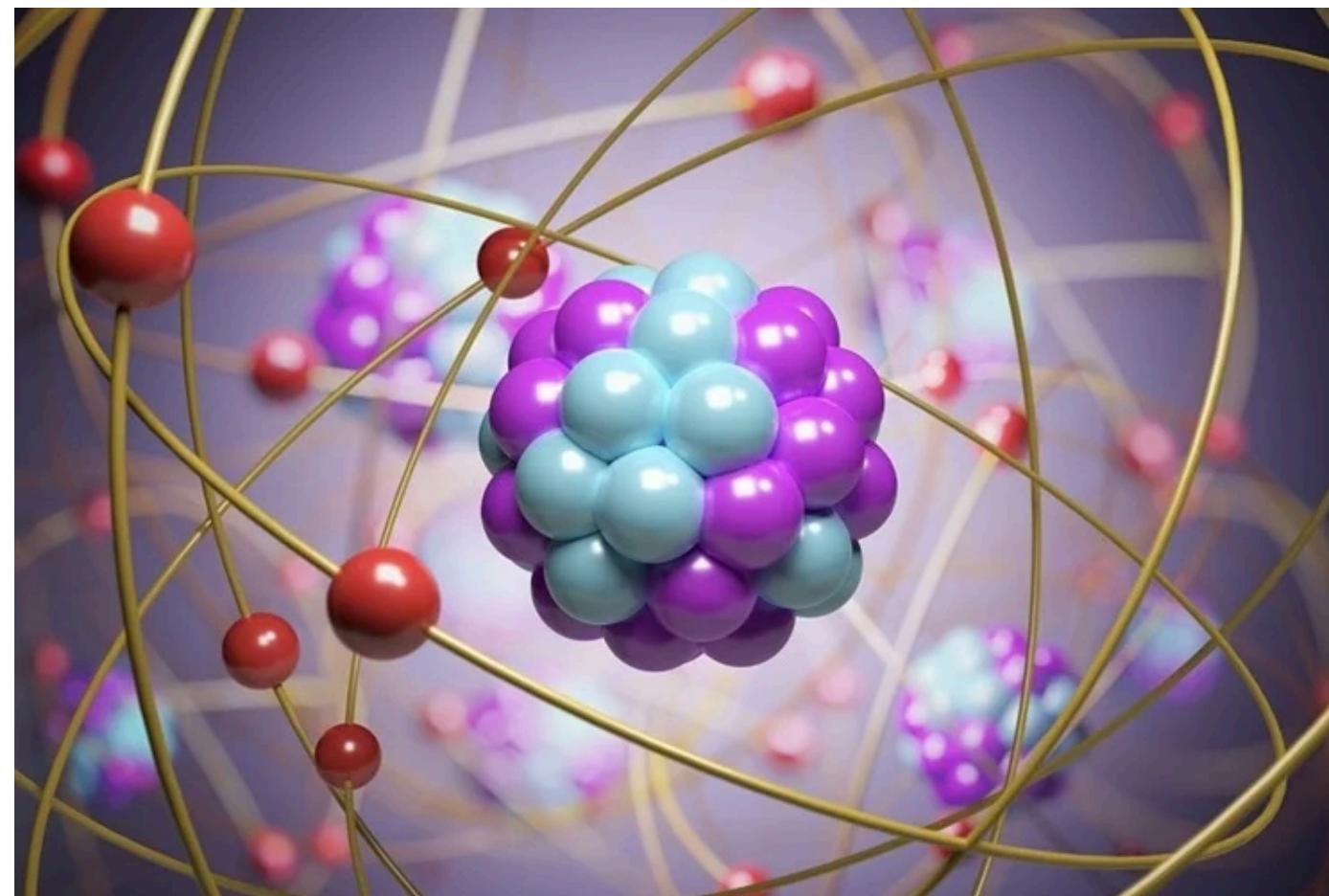
DISTAL: Compiling Tensor Algebra to Distributed Machines

Rohan Yadav, Fred Kjolstad, Alex Aiken

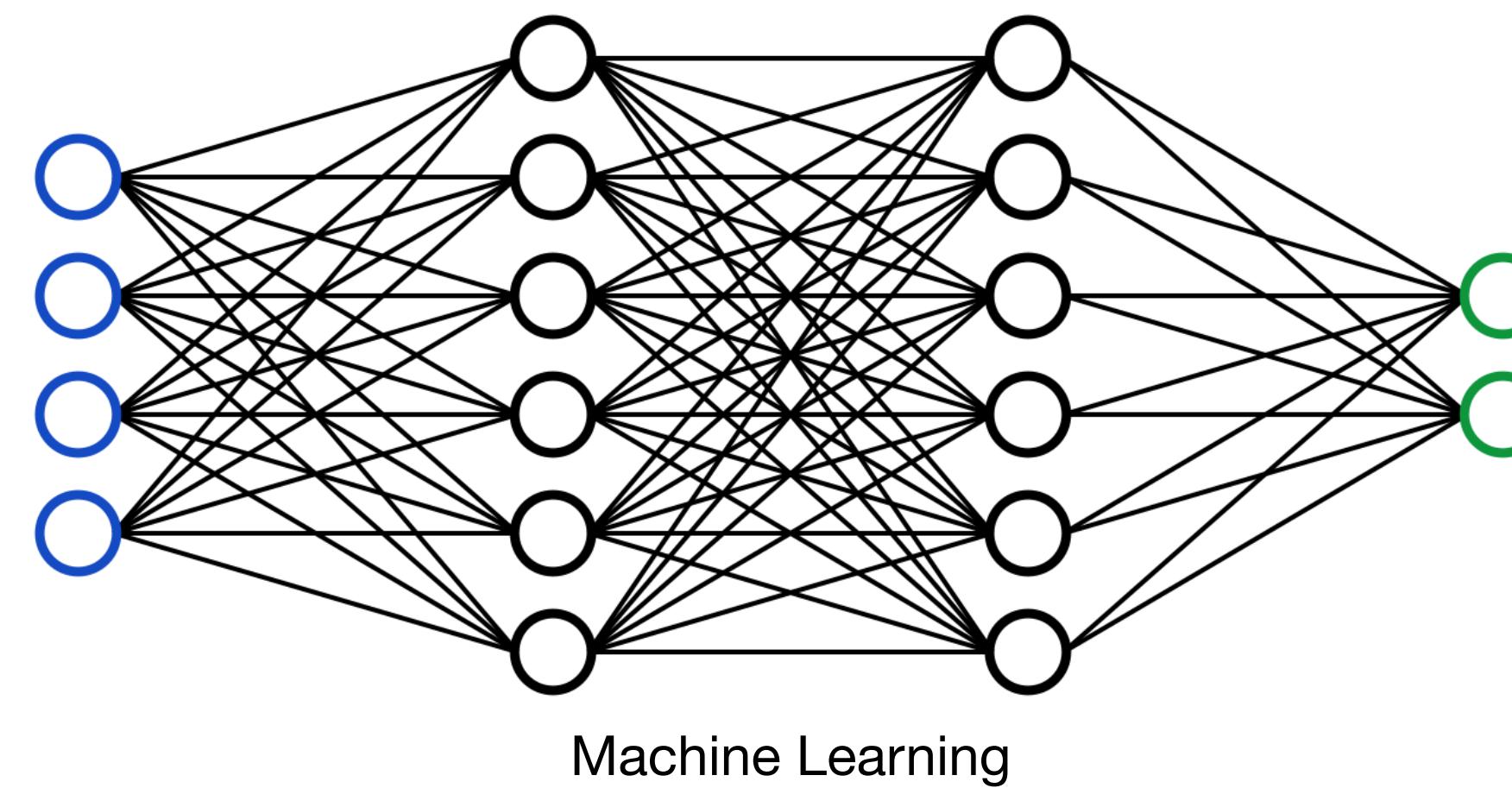
$$A(i, j) = B(i, j, k) \cdot c(k) \longrightarrow$$



Tensor computations are ubiquitous



Scientific Computing



Data Analytics

Key Challenge:

Correctness

Productivity

Performance

Why is achieving good performance hard?

Optimizations are intertwined with correctness

```
int n5;
__m512d x05, x15, x25, x35;
__m512d __alpha5;
n5 = n & ~7;

x05 = _mm512_broadcastsd_pd(_mm_load_sd(&x[0]));
x15 = _mm512_broadcastsd_pd(_mm_load_sd(&x[1]));
x25 = _mm512_broadcastsd_pd(_mm_load_sd(&x[2]));
x35 = _mm512_broadcastsd_pd(_mm_load_sd(&x[3]));

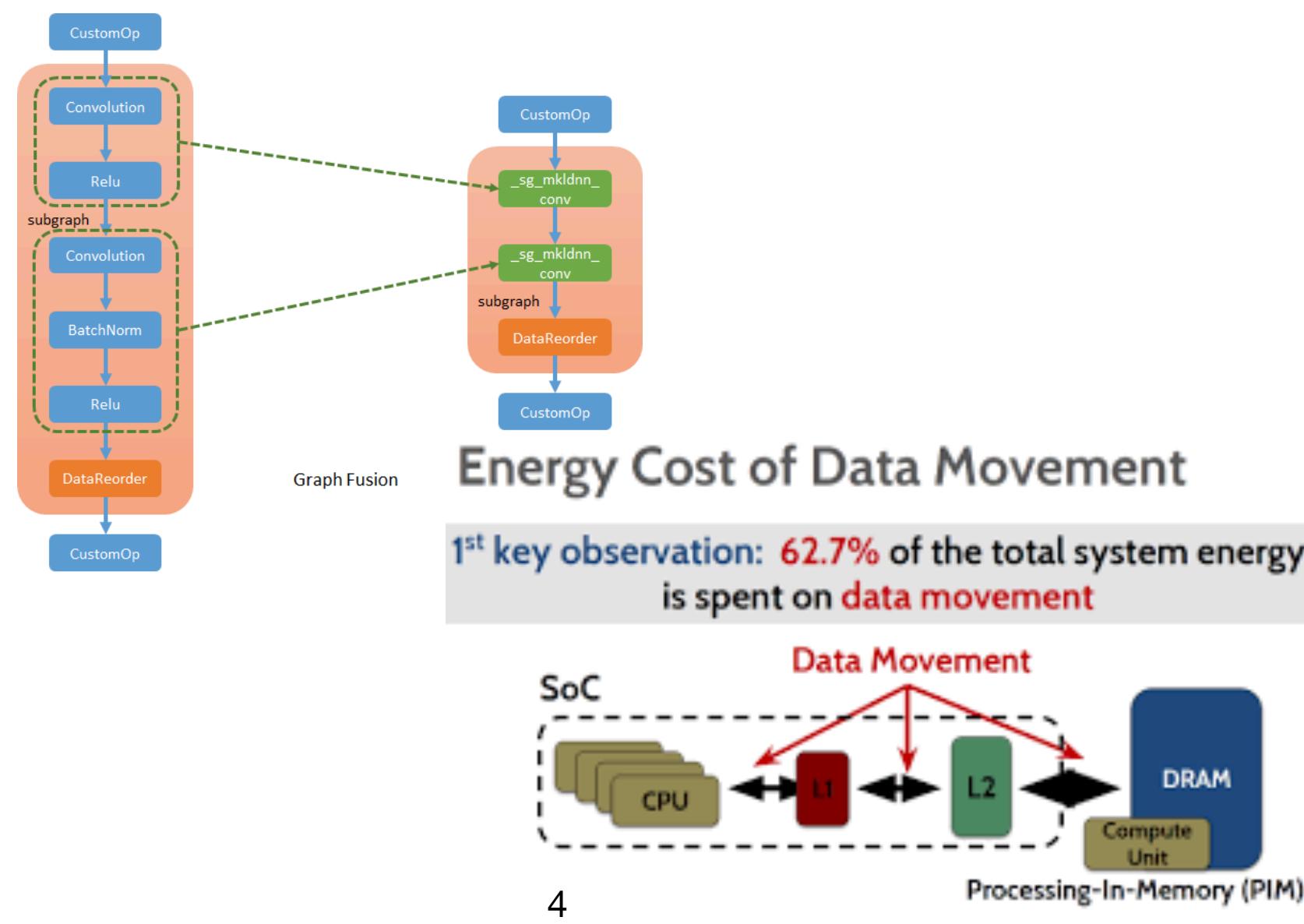
__alpha5 = _mm512_broadcastsd_pd(_mm_load_sd(alpha));

for (; i < n5; i+= 8) {
    __m512d tempY;
    __m512d sum;

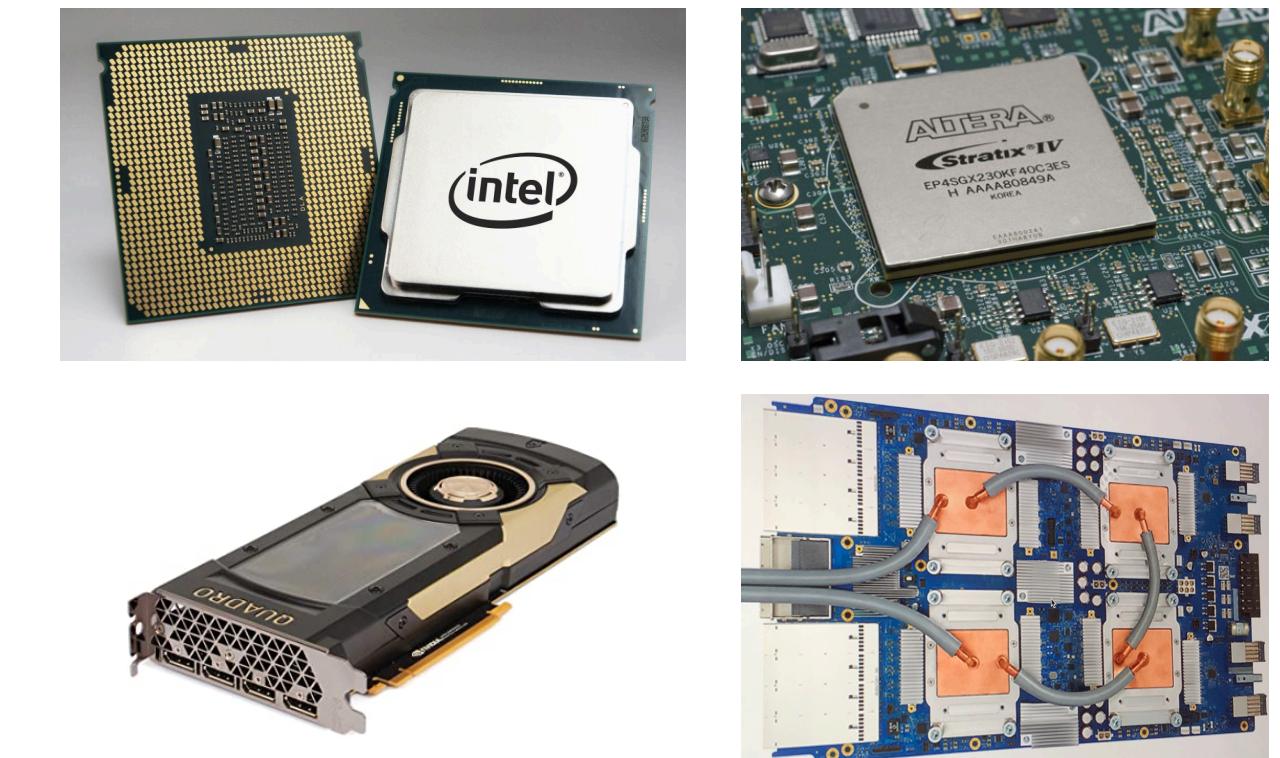
    sum = _mm512_loadu_pd(&ap[0][i]) * x05 +
        _mm512_loadu_pd(&ap[1][i]) * x15 +
        _mm512_loadu_pd(&ap[2][i]) * x25 +
        _mm512_loadu_pd(&ap[3][i]) * x35;

    tempY = _mm512_loadu_pd(&y[i]);
    tempY += sum * __alpha5;
    _mm512_storeu_pd(&y[i], tempY);
}
```

Performance doesn't compose



Variability of target architectures



**DSLs and compilation-based approaches have
been successful**

Halide, TVM, TACO (and many more!)

How can compilers help?

Optimizations are intertwined with correctness

```
int n5;
__m512d x05, x15, x25, x35;
__m512d __alpha5;
n5 = n & ~7;

x05 = _mm512_broadcastsd_pd(_mm_load_sd(&x[0]));
x15 = _mm512_broadcastsd_pd(_mm_load_sd(&x[1]));
x25 = _mm512_broadcastsd_pd(_mm_load_sd(&x[2]));
x35 = _mm512_broadcastsd_pd(_mm_load_sd(&x[3]));

__alpha5 = _mm512_broadcastsd_pd(_mm_load_sd(alpha));

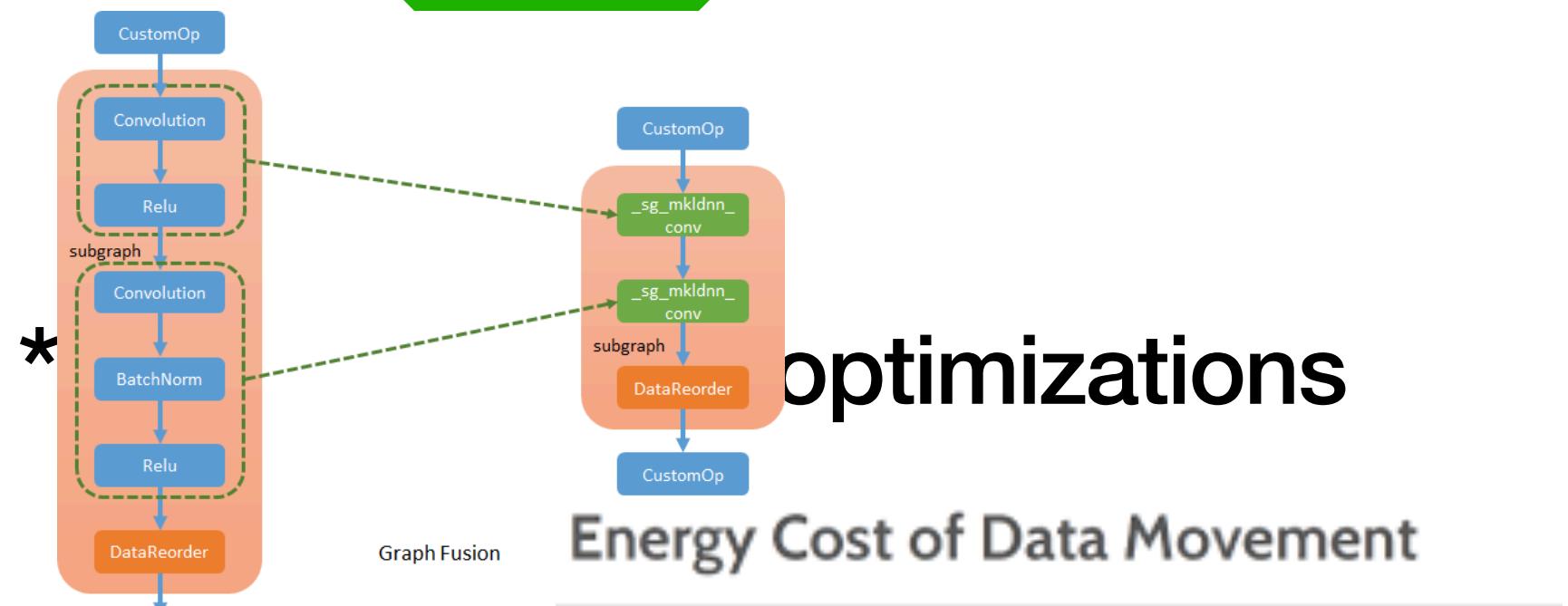
for (; i < n5; i+= 8) {
    __m512d tempY;
    __m512d sum;

    sum = _mm512_loadu_pd(&ap[0][i]) * x05 +
        _mm512_loadu_pd(&ap[1][i]) * x15 +
        _mm512_loadu_pd(&ap[2][i]) * x25 +
        _mm512_loadu_pd(&ap[3][i]) * x35;

    tempY = _mm512_loadu_pd(&y[i]);
    tempY += sum * __alpha5;
    _mm512_storeu_pd(&y[i], tempY);
}
```

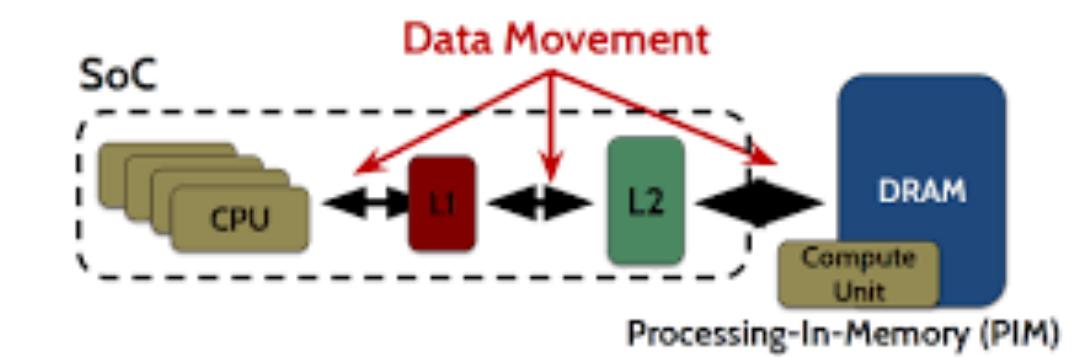
- * Compiler abstraction
- * Algorithm scheduling through
- * Optimizing correctness

Performance doesn't compose



optimizations

Energy Cost of Data Movement
1st key observation: 62.7% of the total system energy is spent on data movement

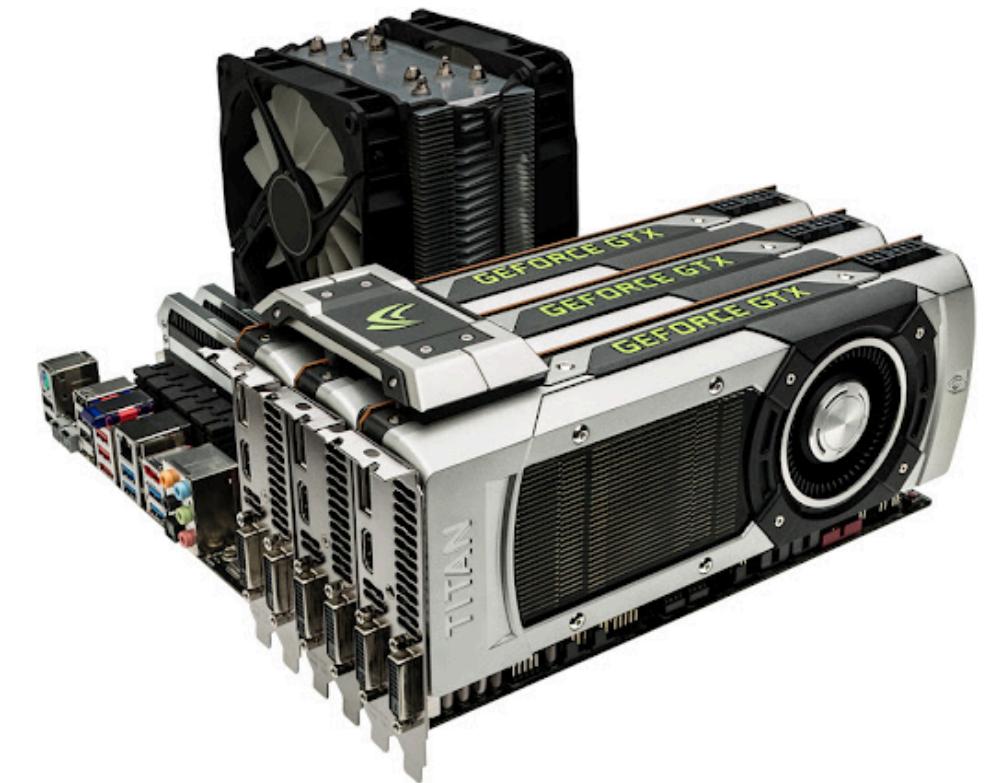


Variability of target architectures



leads to each other

What about distributed systems?



Distributed systems exacerbate prior problems. We need compilers for this case too!

Optimizations are
intertwined with
correctness

- * Inter-address space communication

Performance
doesn't compose

- * Expensive data movement
- * Reorganize data to fit library interfaces

Variability of target
architectures

- * Machines are heterogenous

What are the right abstractions for distributed tensor compilation?

Simpler for end users

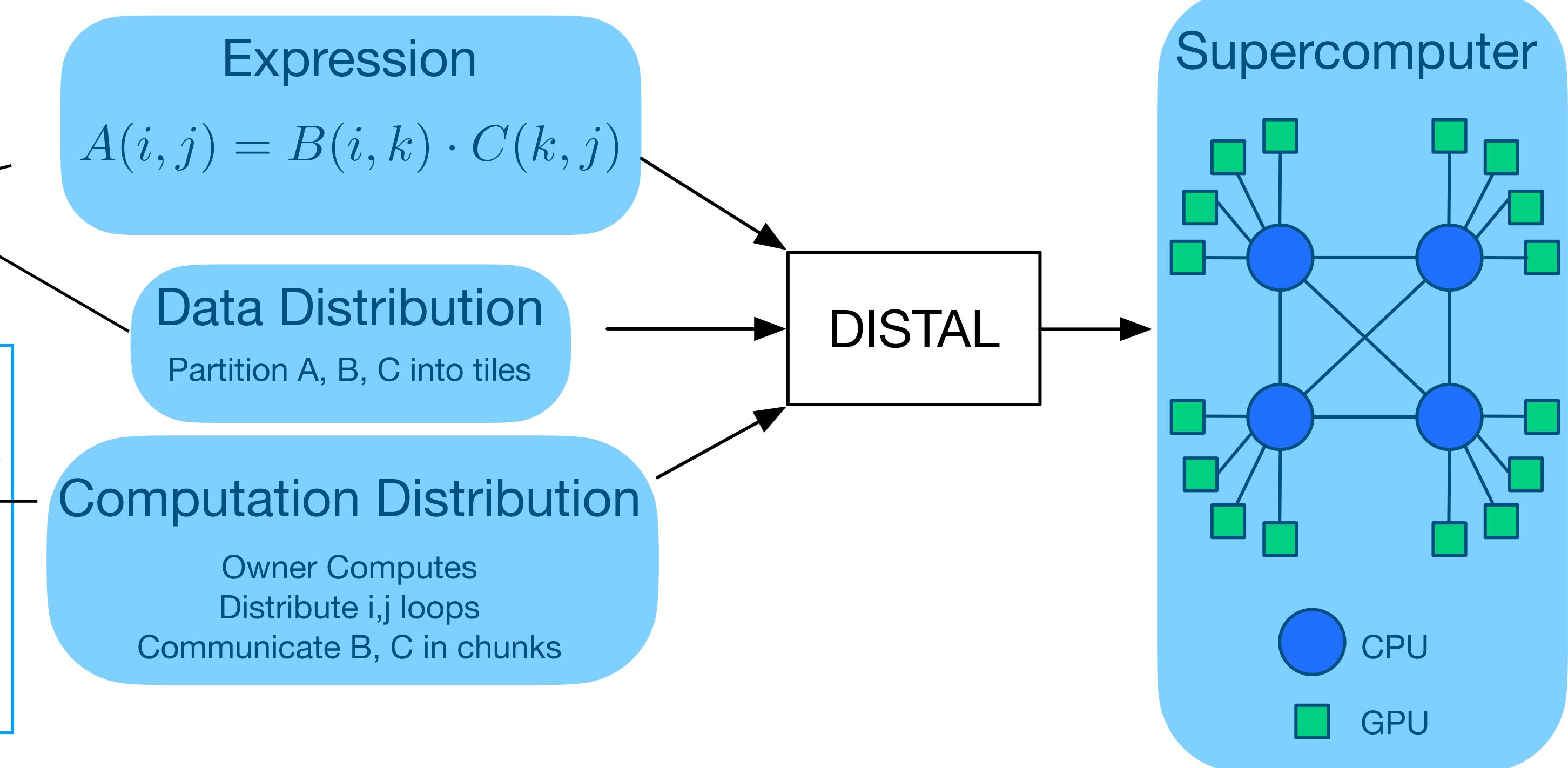
Capture existing algorithms

Generalize to all tensor programs

DISTAL: The Distributed Tensor Algebra Compiler

Decouple computation, performance optimizations, and data distribution

```
1 Param gx, gy, n;
2 Machine m(Grid(gx, gy));
3
4 Distribution tiles(m, {0, 1});
5 Format f({dense, dense}, tiles);
6 Tensor<double> a({n, n}, f), b({n, n}, f), c({n, n}, f);
7
8 IndexVar i, j, k;
9 a(i, j) = b(i, k) * c(k, j);
10
11 IndexVar in, jn, il, jl, ko, ki;
12 a.schedule()
13     .divide(i, in, il, m.x).divide(j, jn, jl, m.y).divide(k, ko, ki, m.x)
14     .reorder({in, jn, il, jl})
15     .distribute({in, jn}, DistributedGPU)
16     .reorder({ko, il, il, ki})
17     .communicate(a, jn).communicate({b, c}, ko)
18     .substitute({il, jl, ki}, CuBLAS::GeMM)
19 ;
20
21 a.compile();
```



Modeling Machines

Expression

$$A(i, j) = B(i, k) \cdot C(k, j)$$

$$A(i, l) = B(i, j, k) \cdot C(j, l) \cdot D(k, l)$$

$$a = B(i, j, k) \cdot C(i, j, k)$$

$$A(i, j, l) = B(i, j, k) \cdot C(k, l)$$

$$A(i, j) = B(i, j, k) \cdot c(k)$$

Data Distribution

Partition A into tiles

Replicate B onto all nodes

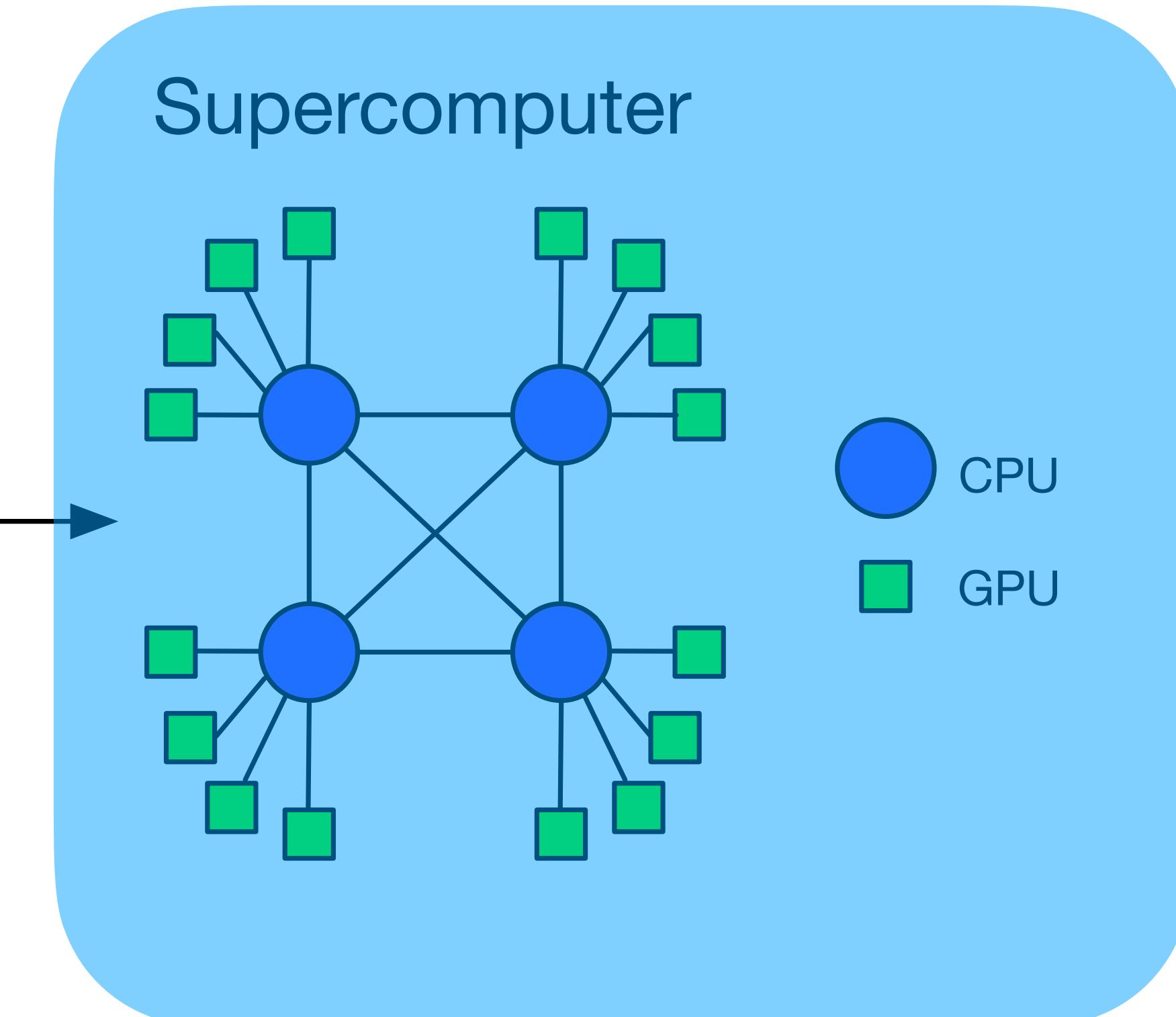
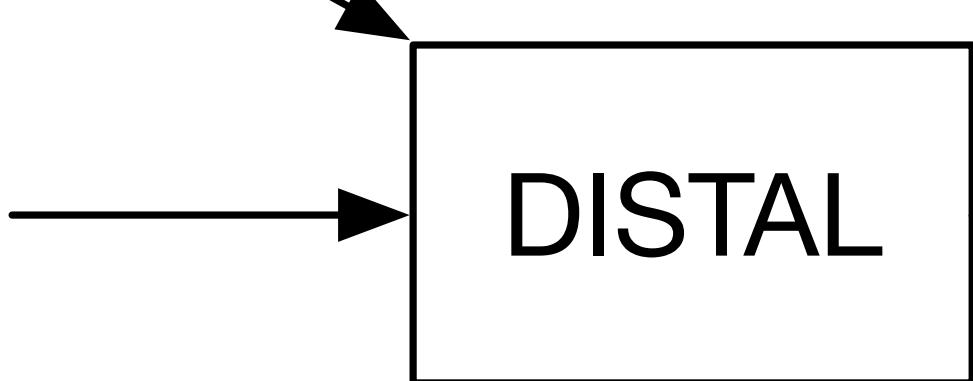
Place C onto only some nodes

Computation Distribution

Owner Computes

Distribute i,j loops

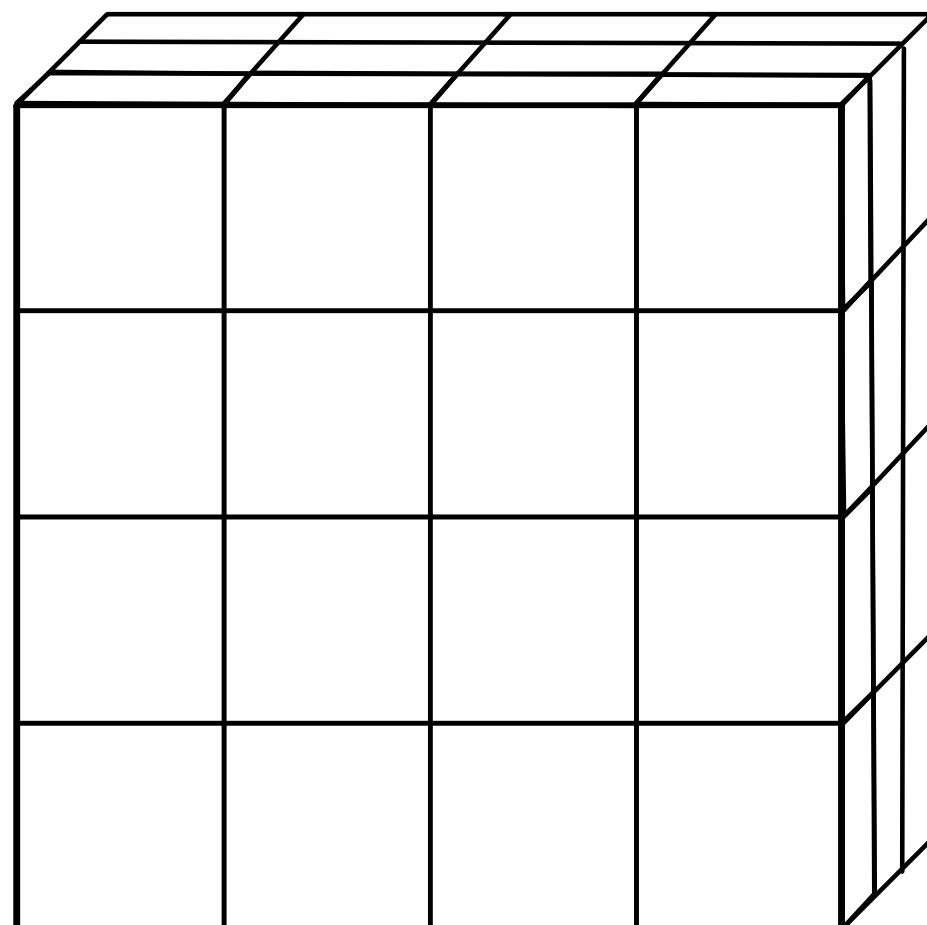
Communicate in chunks



View machines as hyper-rectangular grids of processors, where each processor has a local memory

Expose locality in the physical machine

Structure machine like target computations



Distributing Data

Expression

$$A(i, j) = B(i, k) \cdot C(k, j)$$

$$A(i, l) = B(i, j, k) \cdot C(j, l) \cdot D(k, l)$$

$$a = B(i, j, k) \cdot C(i, j, k)$$

$$A(i, j, l) = B(i, j, k) \cdot C(k, l)$$

$$A(i, j) = B(i, j, k) \cdot c(k)$$

Data Distribution

Partition A into tiles

Replicate B onto all nodes

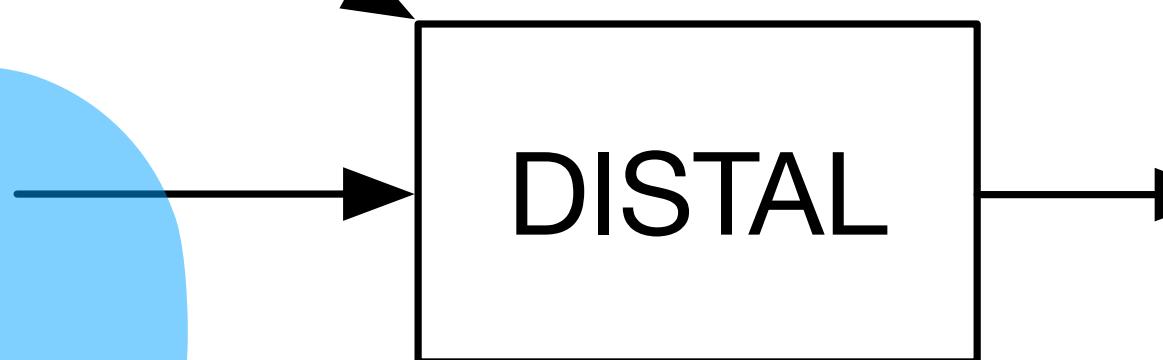
Place C onto only some nodes

Computation Distribution

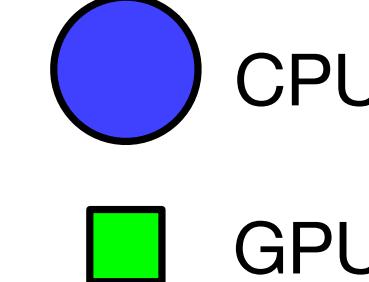
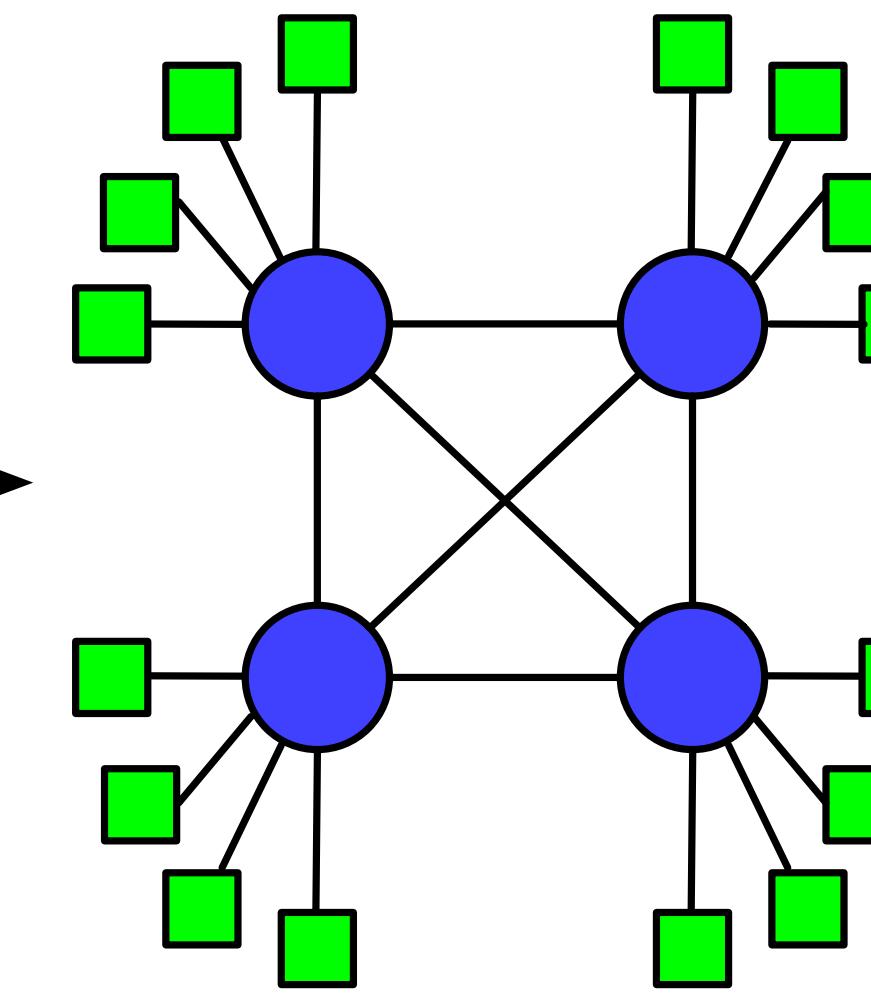
Owner Computes

Distribute i,j loops

Communicate in chunks



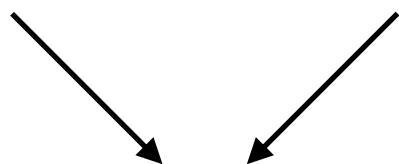
Supercomputer



Tensor Distribution Notation

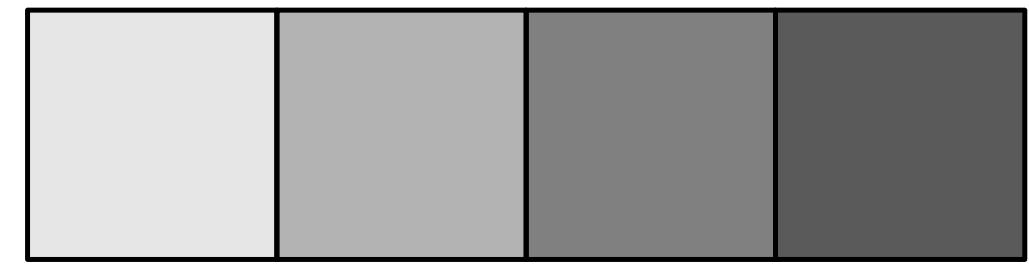
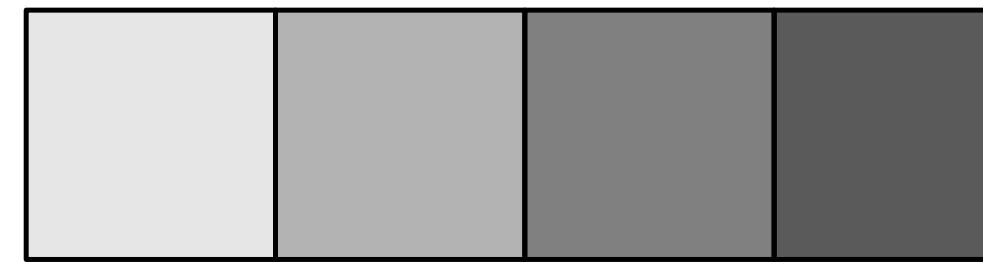
Describe how dimensions of a tensor \mathcal{T} map onto a machine \mathcal{M}

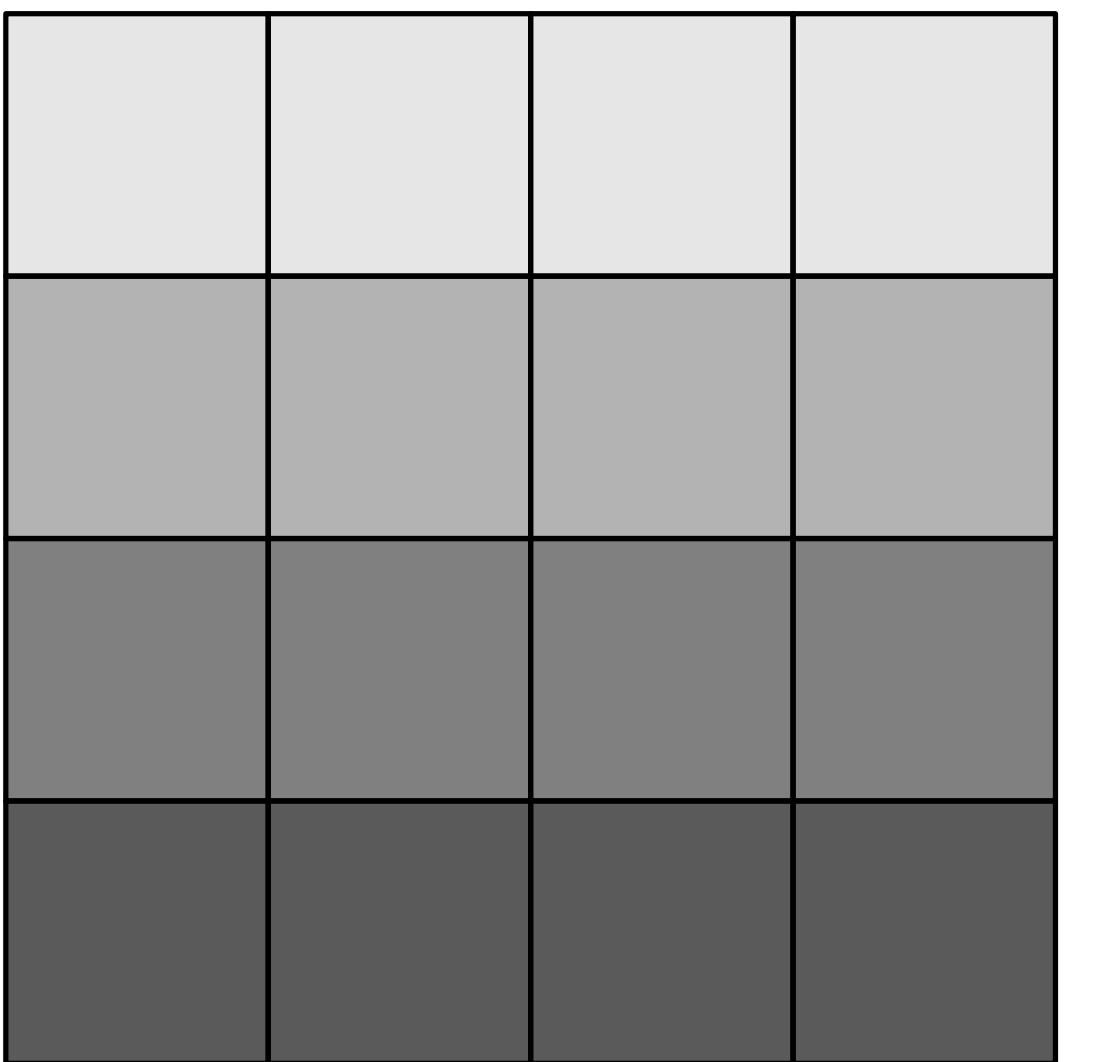
$$\mathcal{T}_{xy} \mapsto_x \mathcal{M}$$

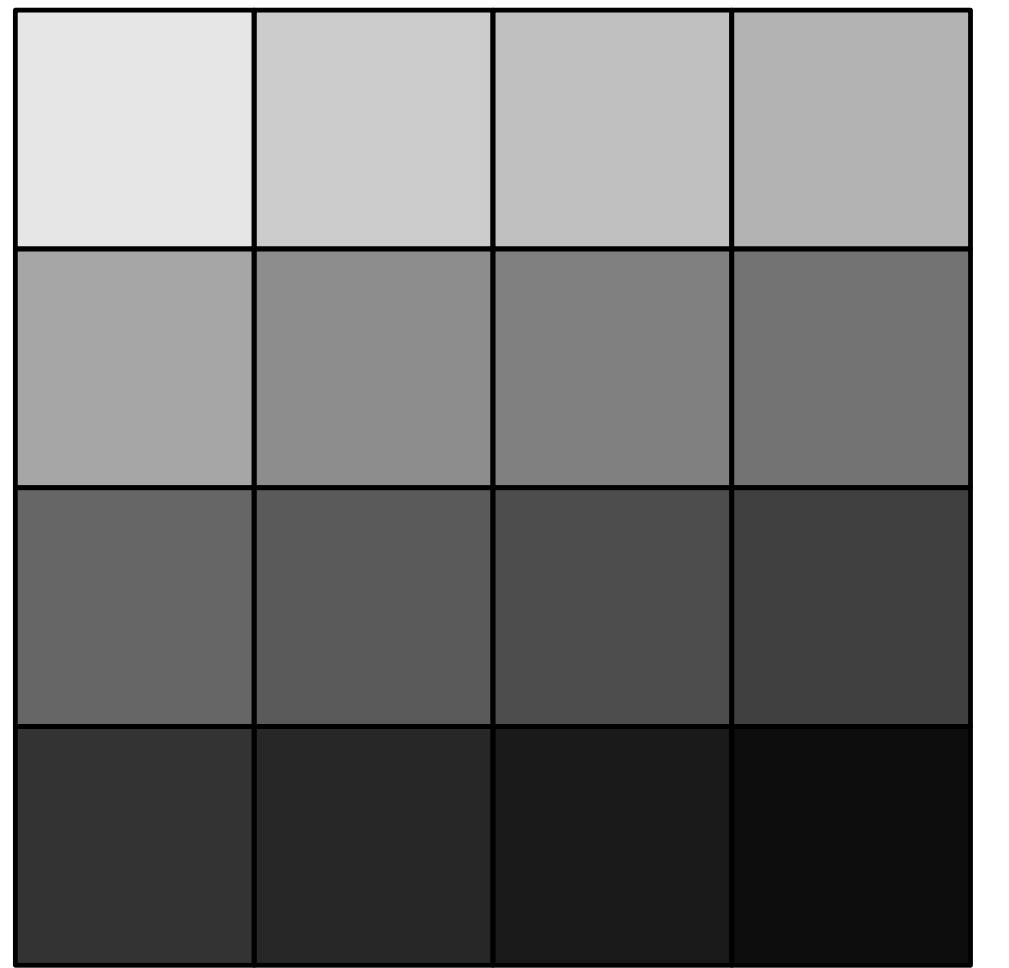
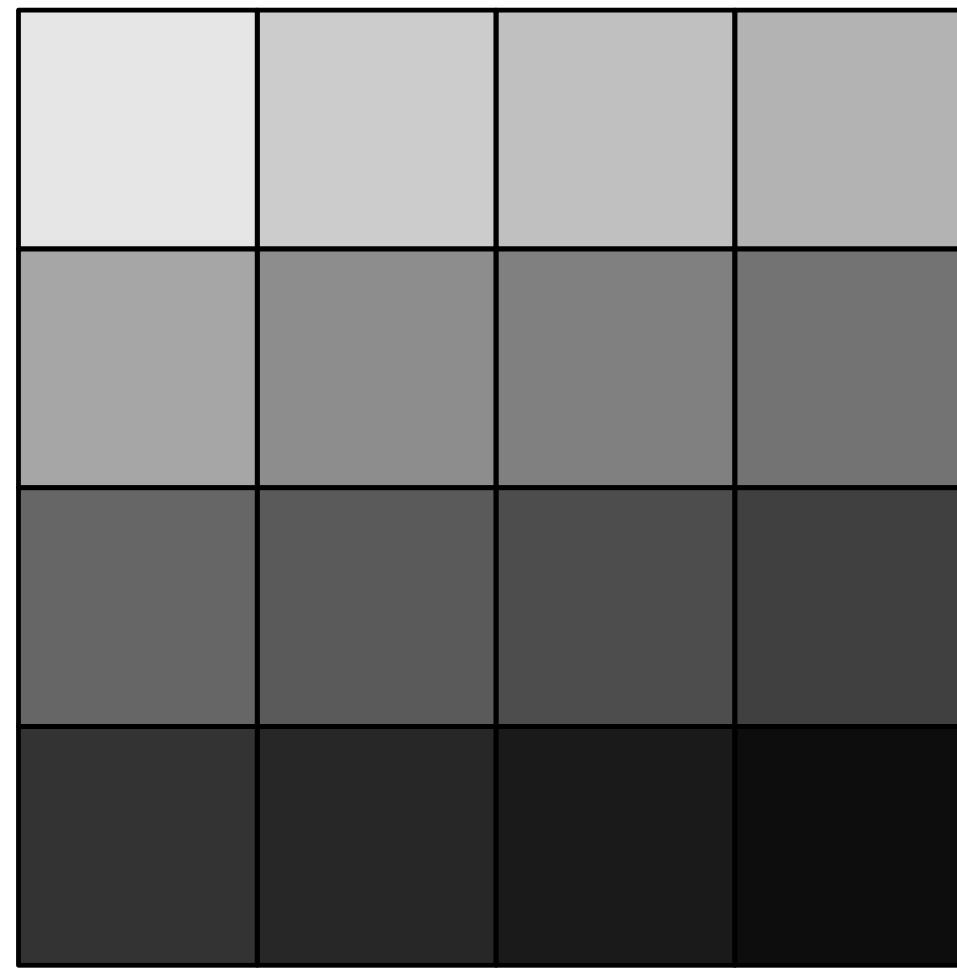


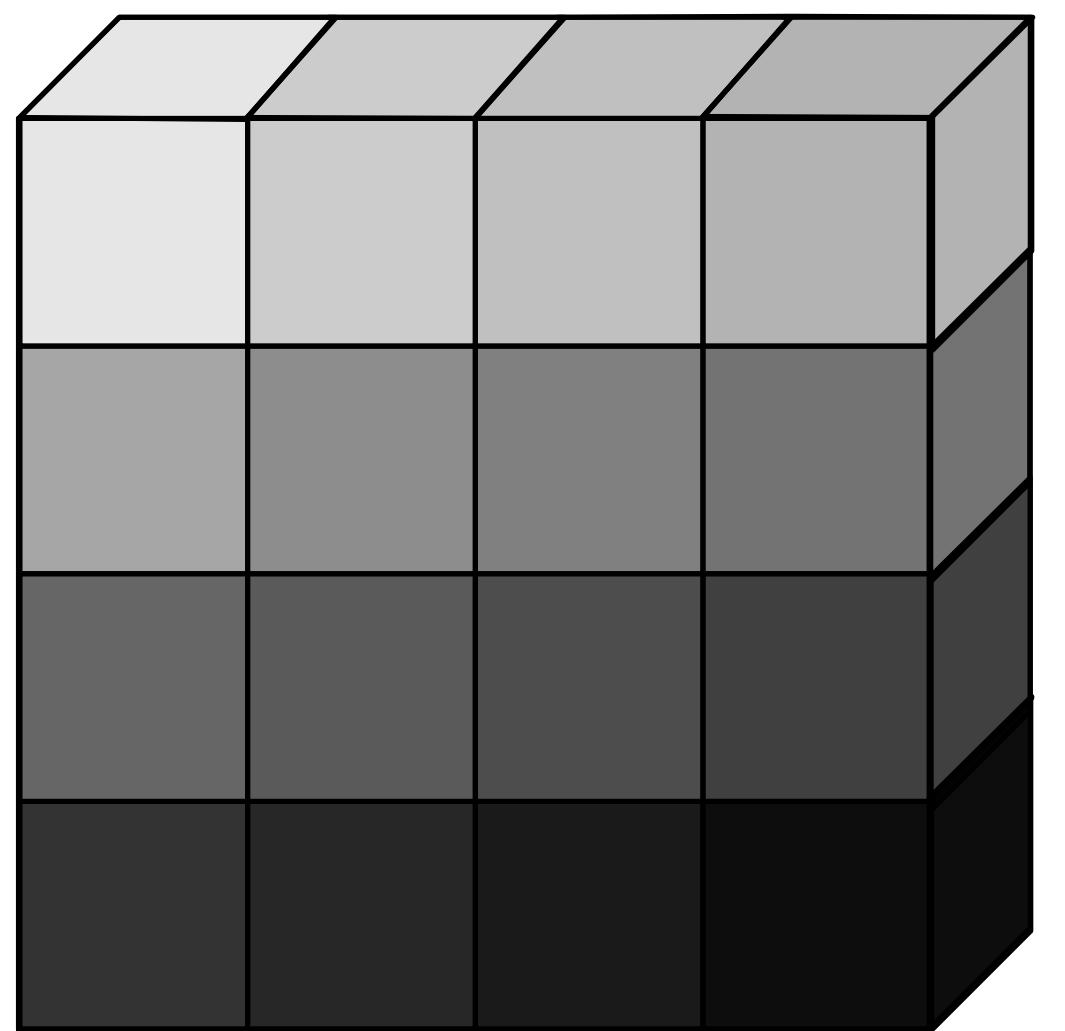
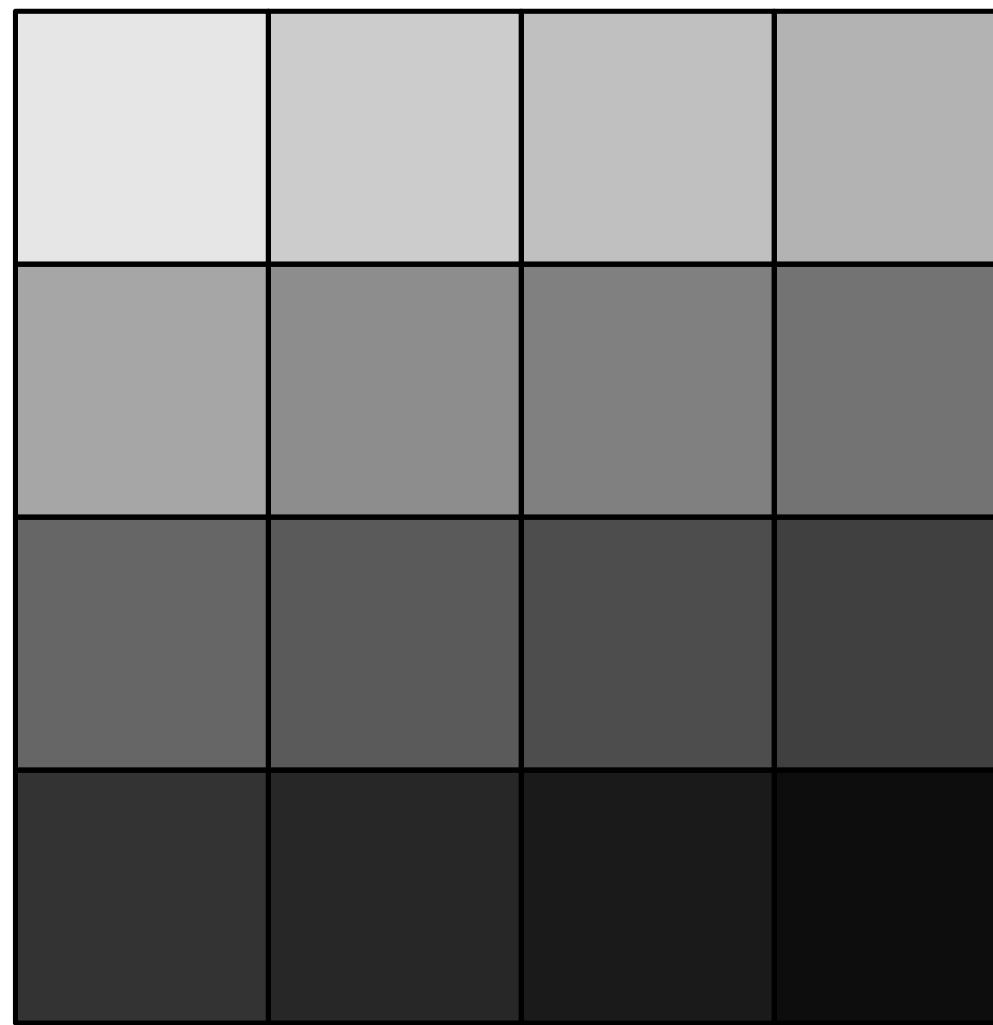
Name each dimension of \mathcal{T} and \mathcal{M}

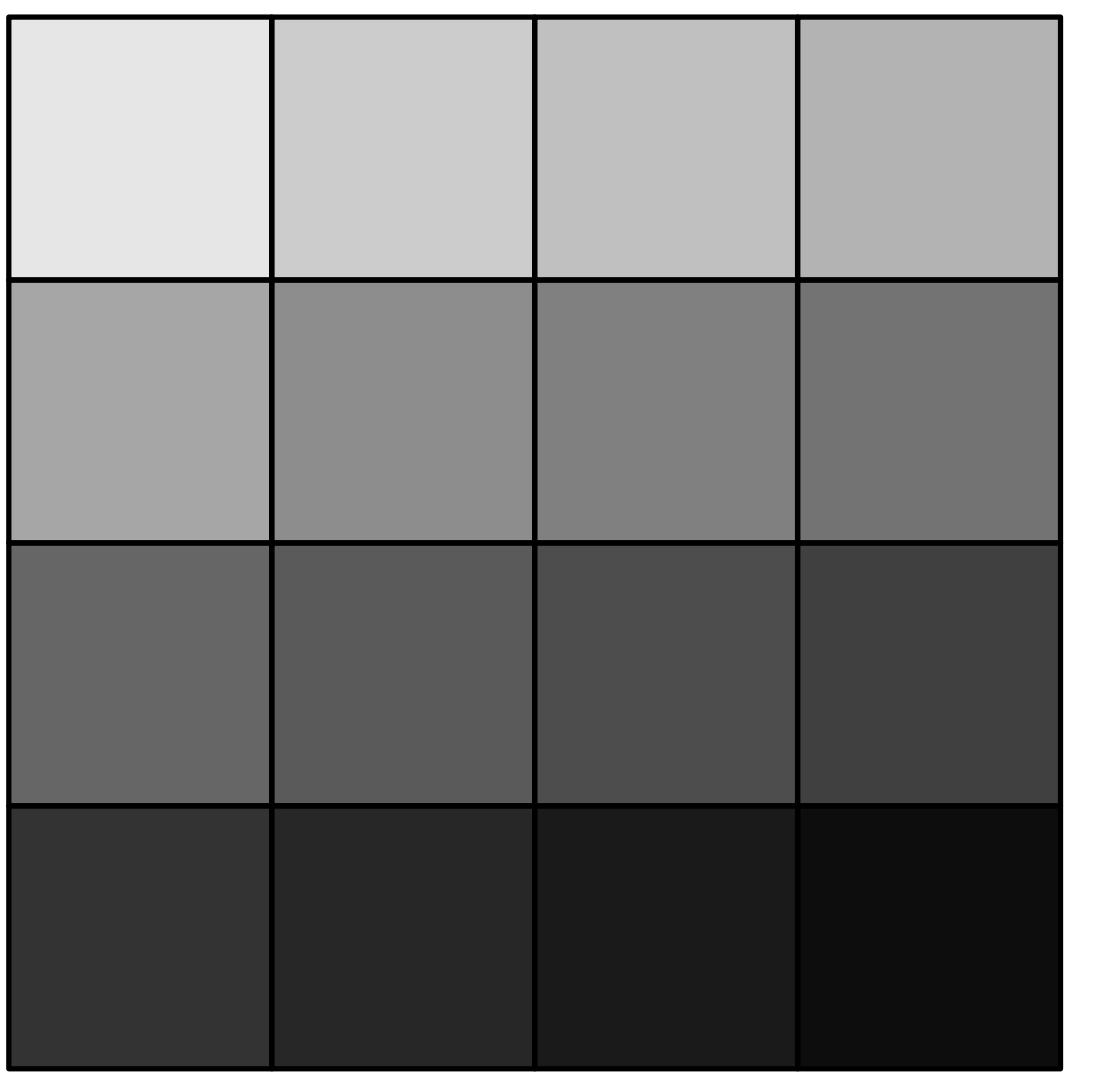
Dimensions of \mathcal{T} are partitioned by dimensions of \mathcal{M} with the same name

 \mathcal{T} $\mathcal{T}_x \mapsto_x \mathcal{M}$  \mathcal{M}

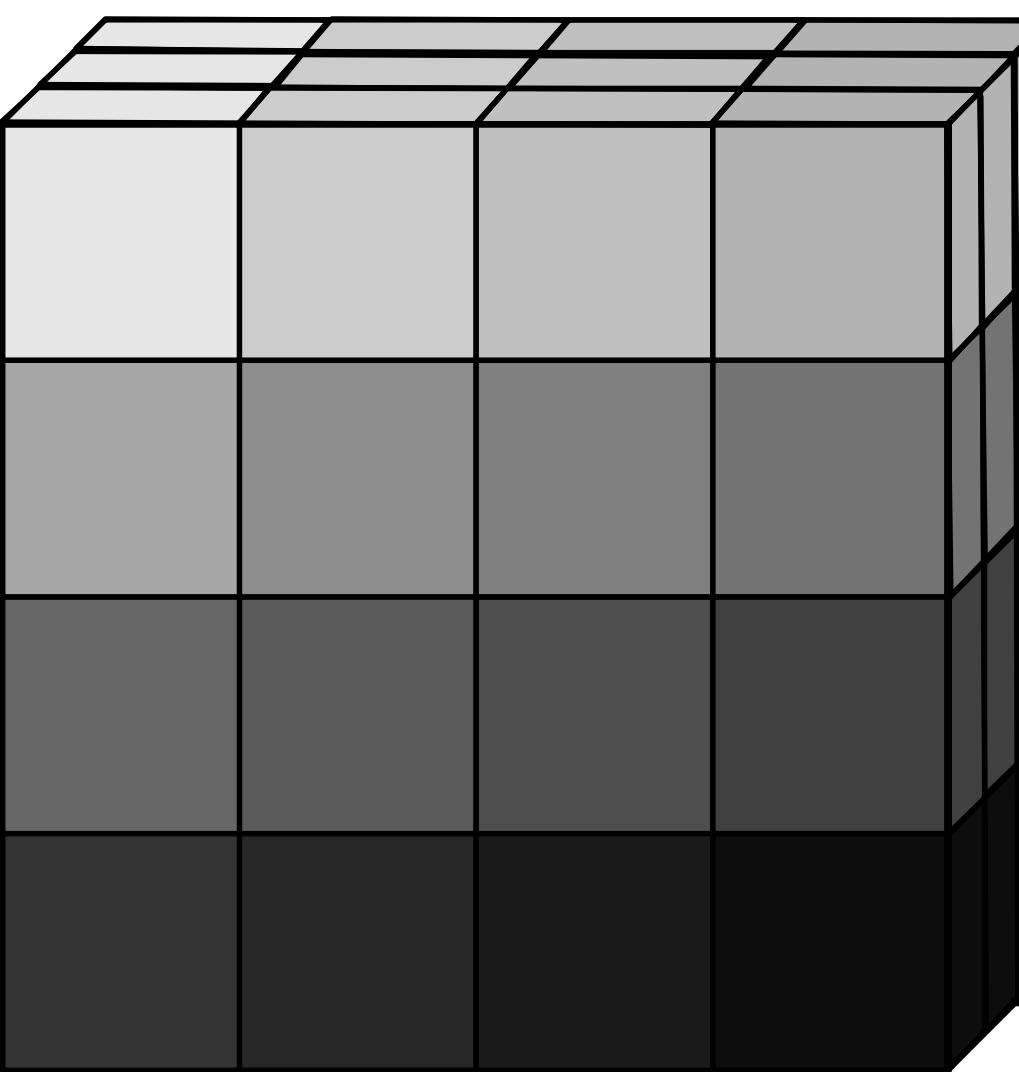
 \mathcal{T} $\mathcal{T}_{xy \mapsto_x} \mathcal{M}$  \mathcal{M}

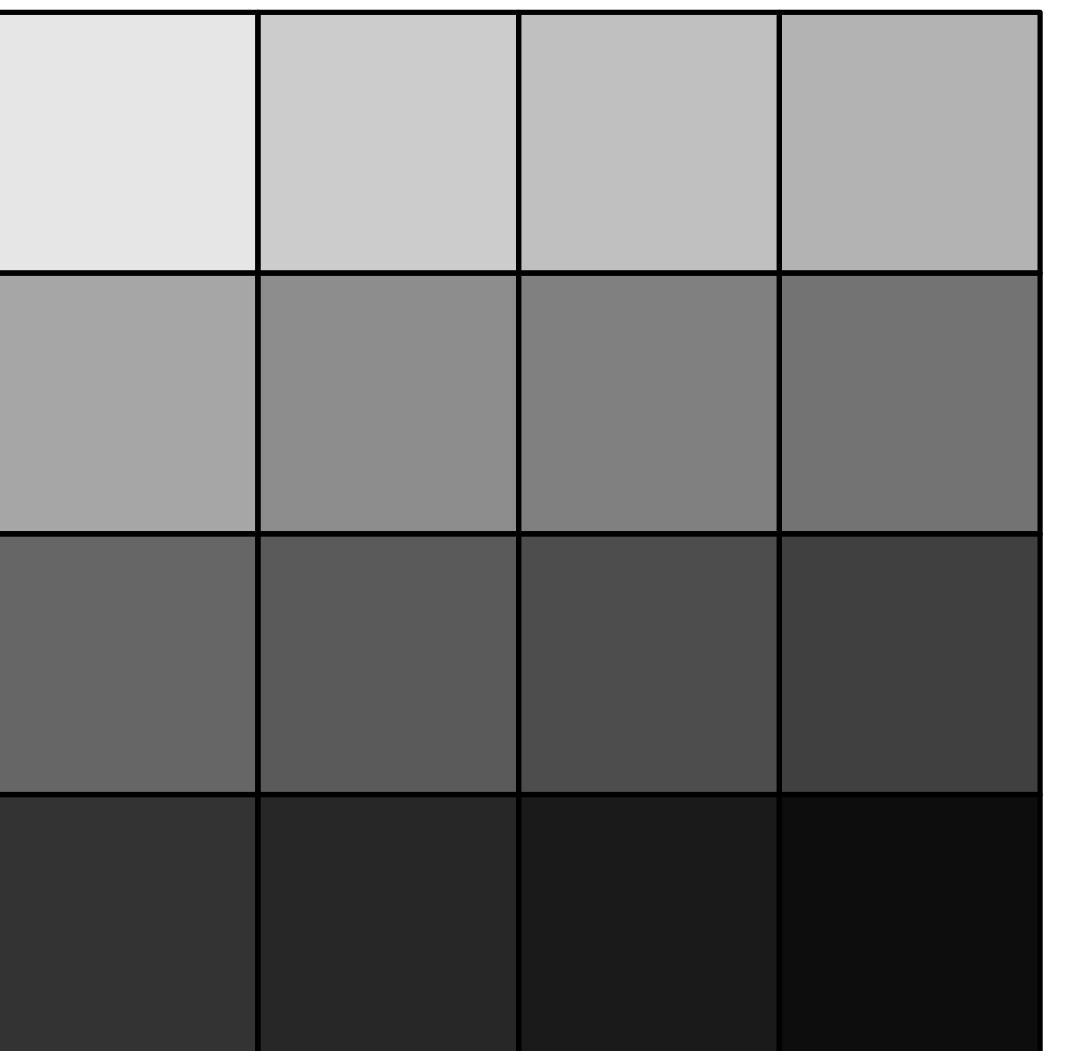
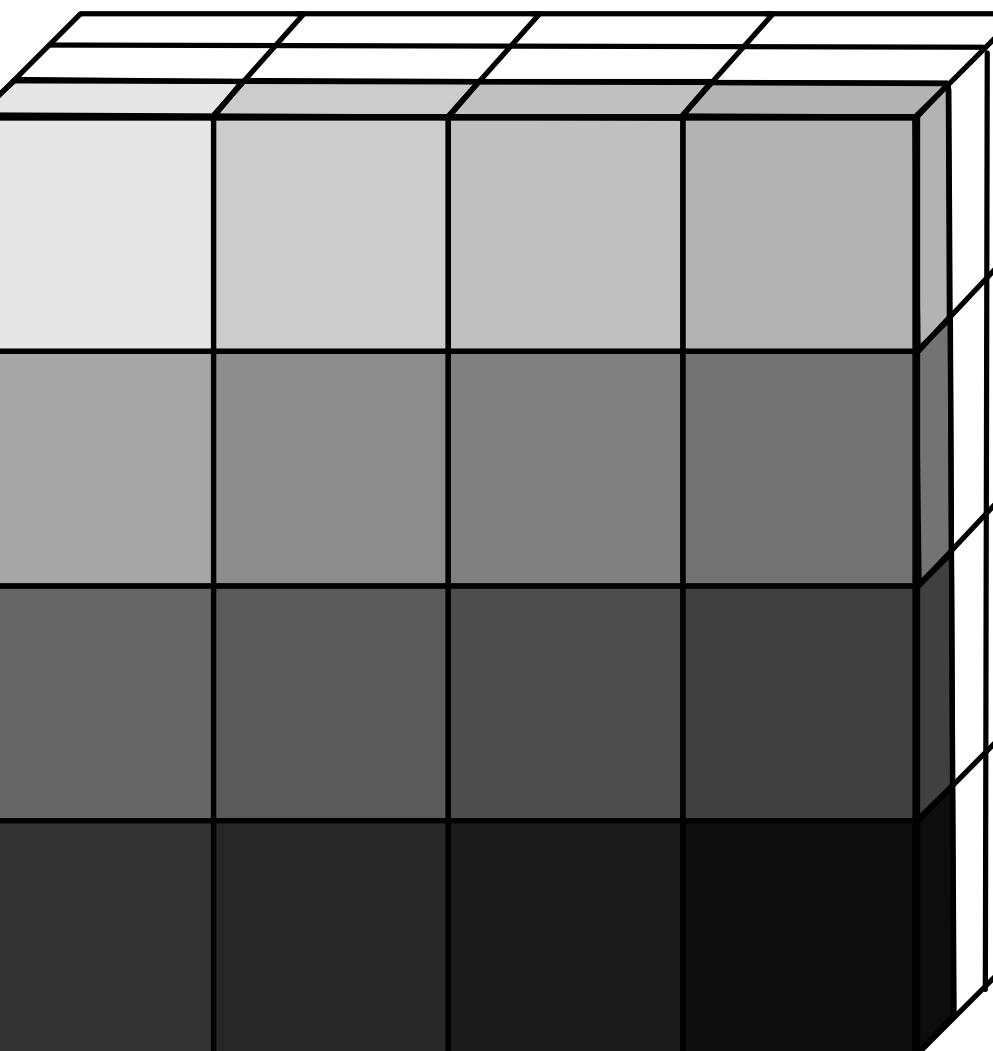
 \mathcal{T} $\mathcal{T}_{xy \mapsto_{xy} \mathcal{M}}$  \mathcal{M}

 \mathcal{T} $\mathcal{T}_{xyz \mapsto xy} \mathcal{M}$  \mathcal{M}

 \mathcal{T}

$$\mathcal{T}_{xy} \mapsto_{xy^*} \mathcal{M}$$

 \mathcal{M}

 \mathcal{T} $\mathcal{T}_{xy} \mapsto_{xy0} \mathcal{M}$  \mathcal{M}

Distributing Computation

Expression

$$A(i, j) = B(i, k) \cdot C(k, j)$$

$$A(i, l) = B(i, j, k) \cdot C(j, l) \cdot D(k, l)$$

$$a = B(i, j, k) \cdot C(i, j, k)$$

$$A(i, j, l) = B(i, j, k) \cdot C(k, l)$$

$$A(i, j) = B(i, j, k) \cdot c(k)$$

Data Distribution

Partition A into tiles

Replicate B onto all nodes

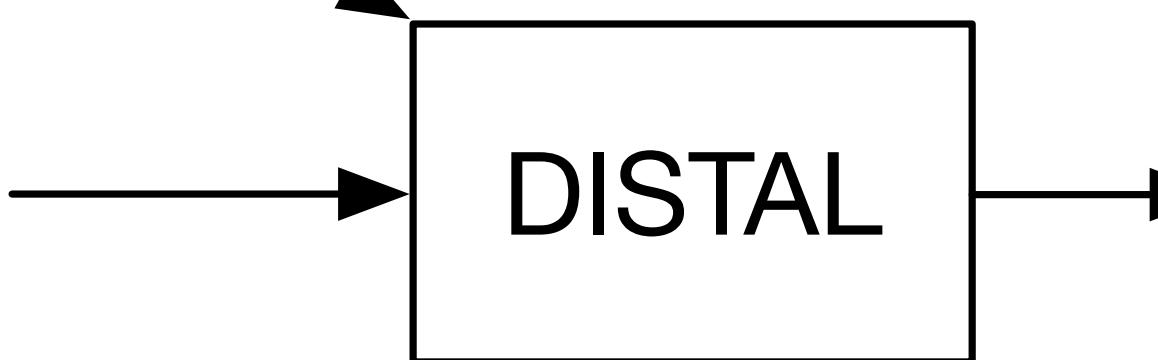
Place C onto only some nodes

Computation Distribution

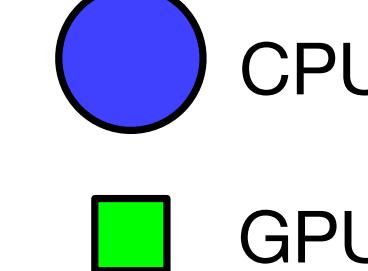
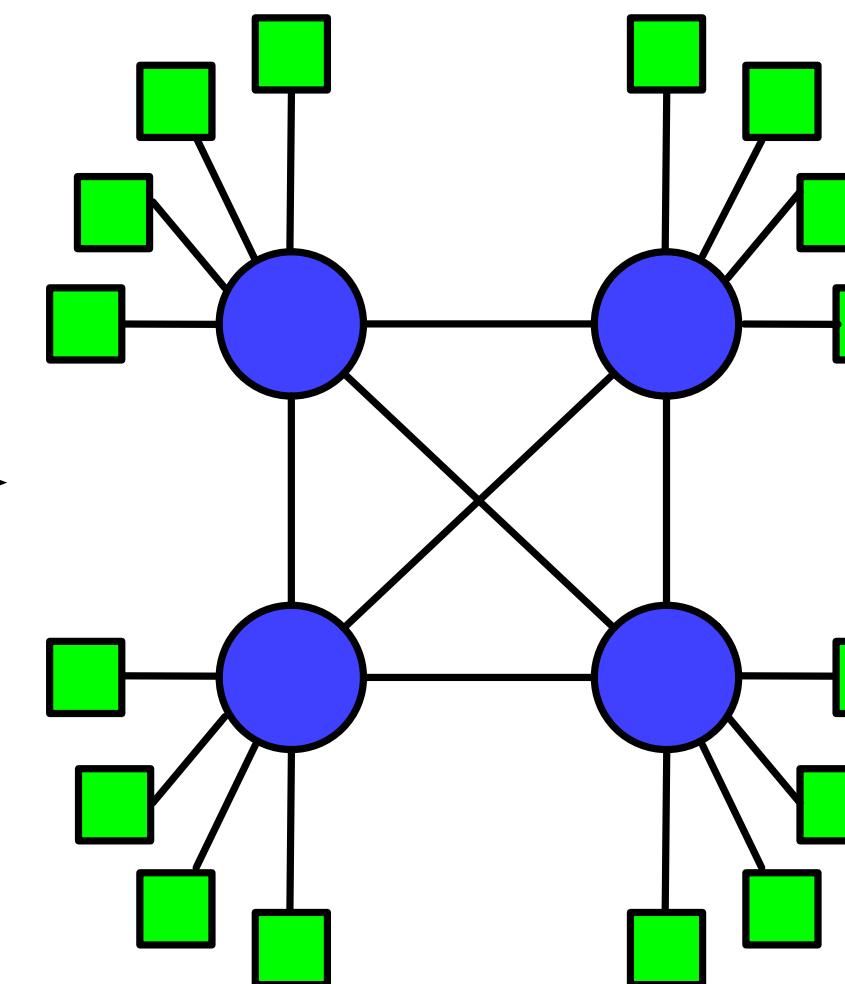
Owner Computes

Distribute i,j loops

Communicate in chunks



Supercomputer



Iteration Spaces

Hyper-rectangular grid of points representing each point in a set of nested loops

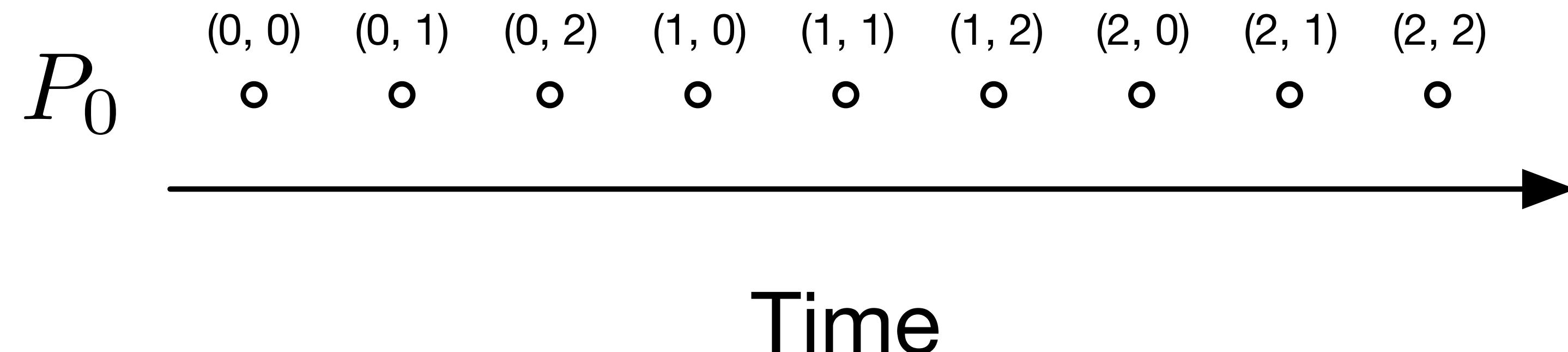
$$\forall_i \ a(i) = \sum_j b(j) \quad (i, j) \in \{0, 1, 2\} \times \{0, 1, 2\}$$

```
for i in (0, len(a)):
    for j in (0, len(b)):
        a[i] += b[j]
```

Execution Spaces

Space of all processors in \mathcal{M} cross a time dimension

$$\forall_i \ a(i) = \sum_j b(j) \quad (i, j) \in \{0, 1, 2\} \times \{0, 1, 2\}$$

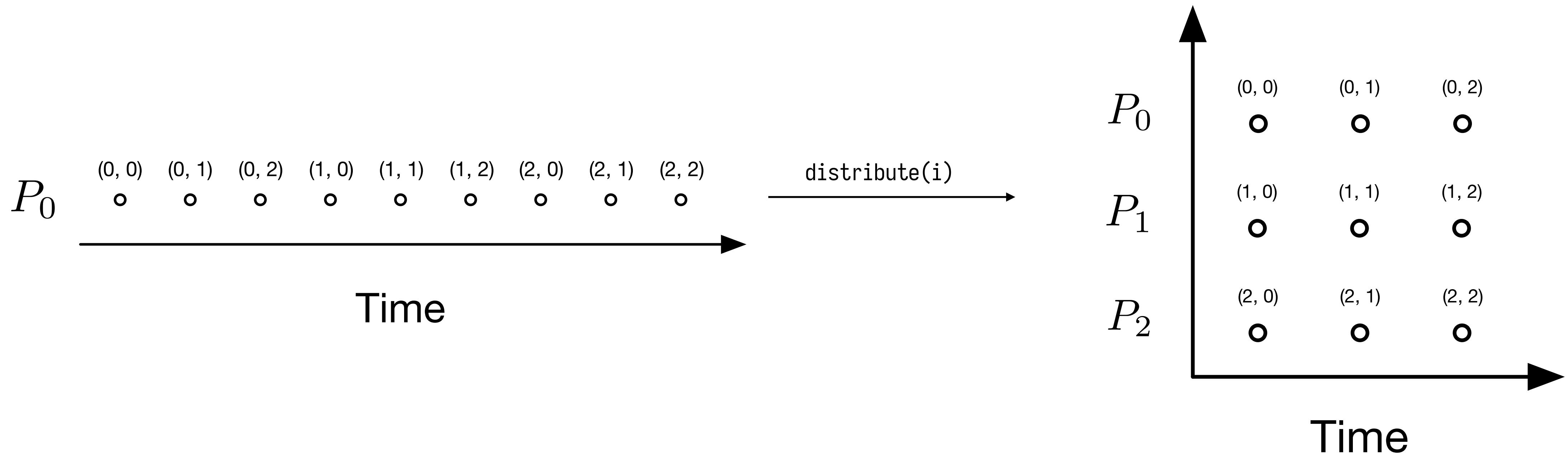


Scheduling

Change execution of iteration space through scheduling transformations

distribute

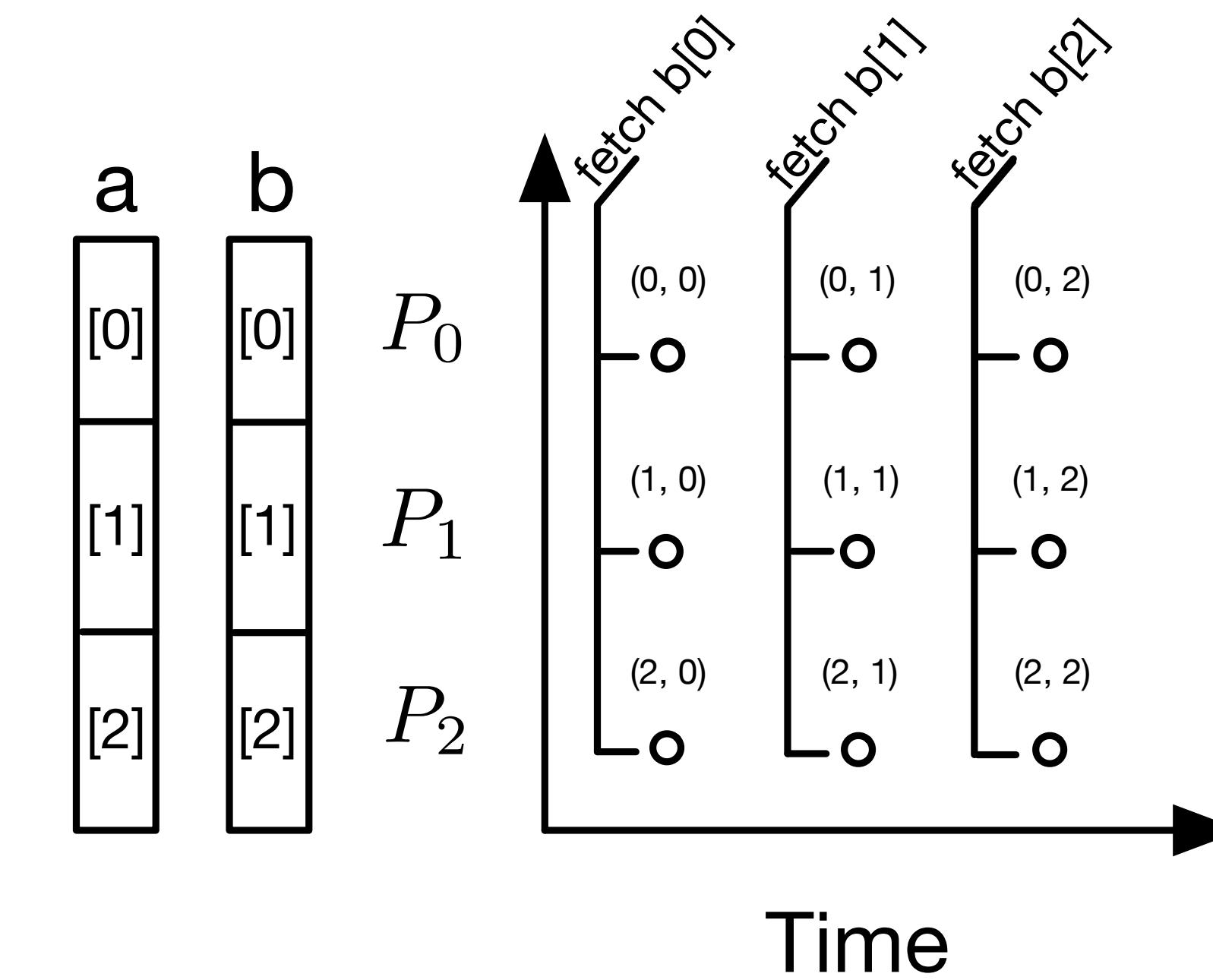
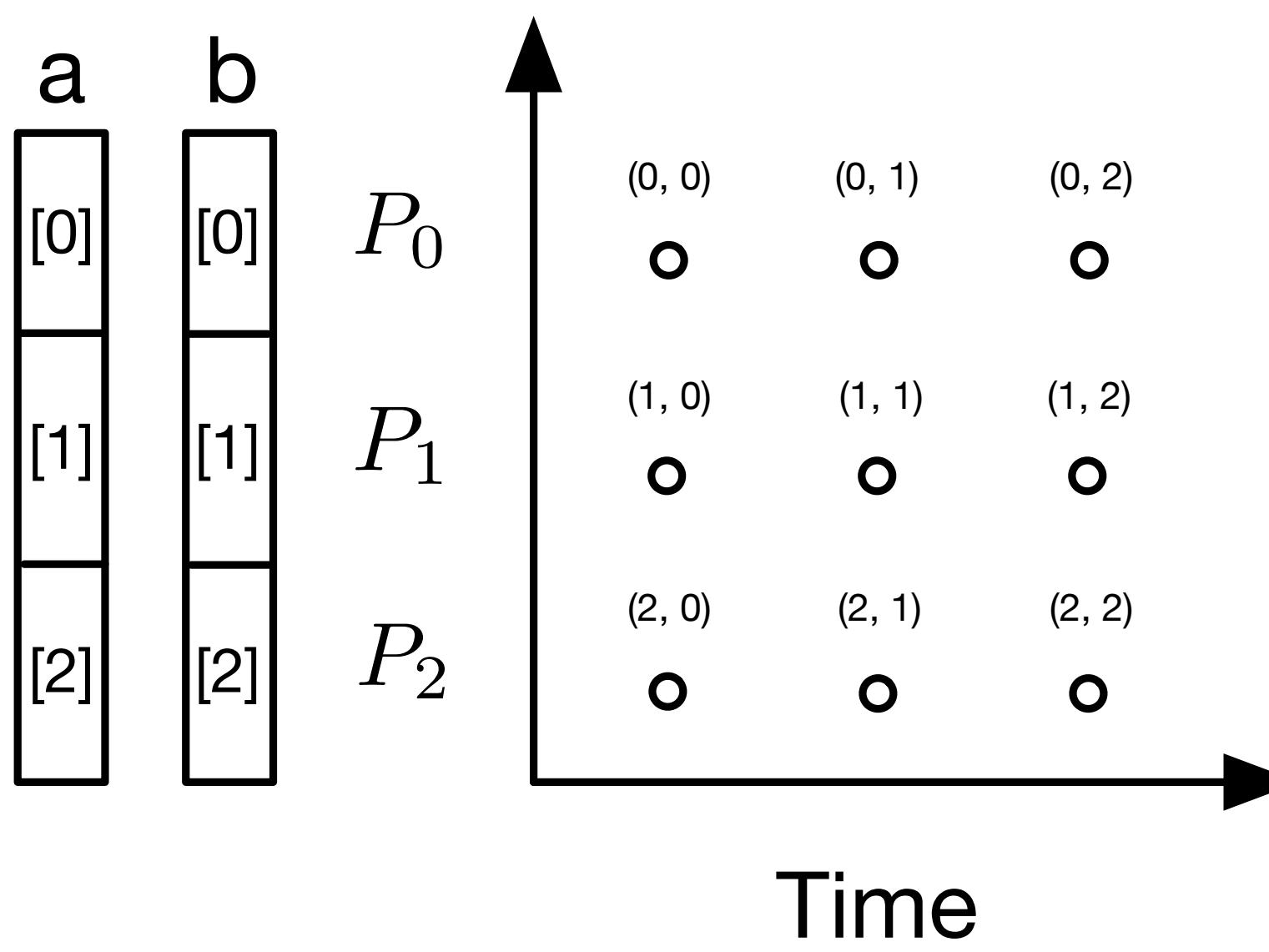
$$\forall_i \ a(i) = \sum_j b(j) \quad (i, j) \in \{0, 1, 2\} \times \{0, 1, 2\}$$



What about communication?

$$\forall_i \quad a(i) = \sum_j b(j) \quad \text{s.t.} \quad a \xrightarrow{x} \mathcal{M} \quad b \xrightarrow{x} \mathcal{M}$$

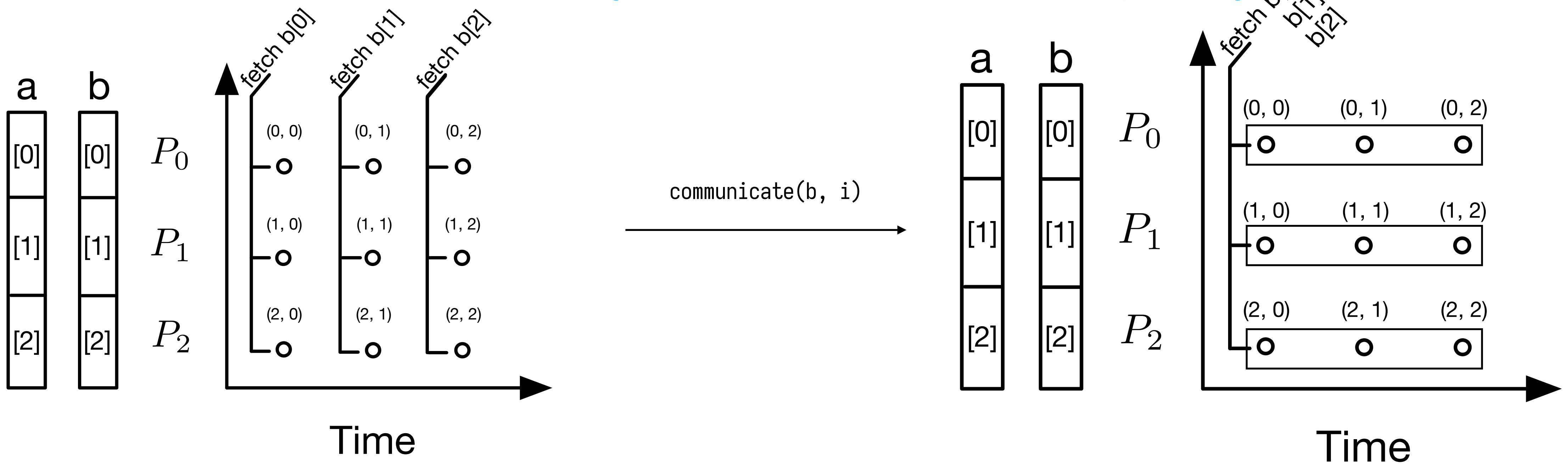
Insert communication at each iteration space point, as needed



communicate

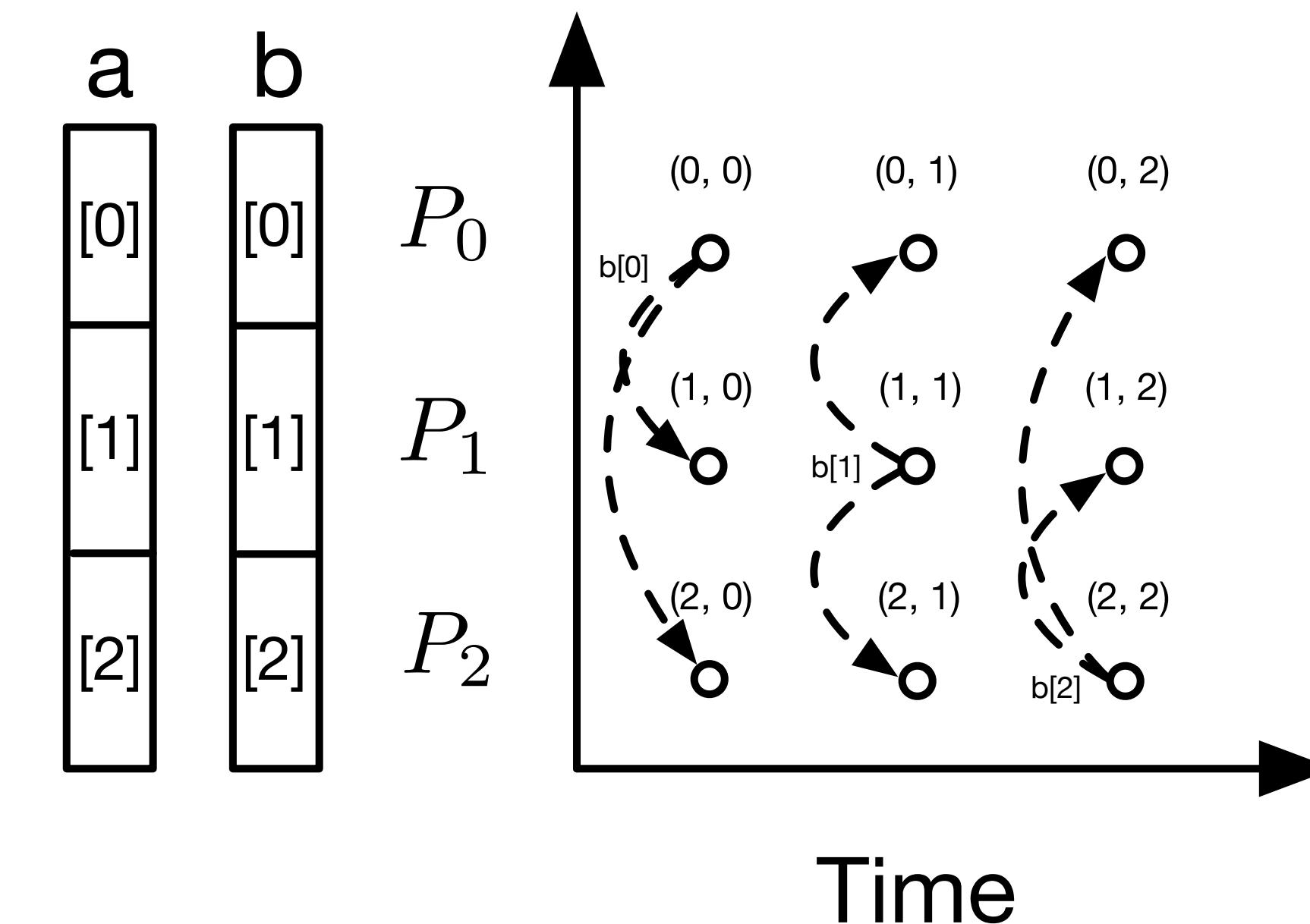
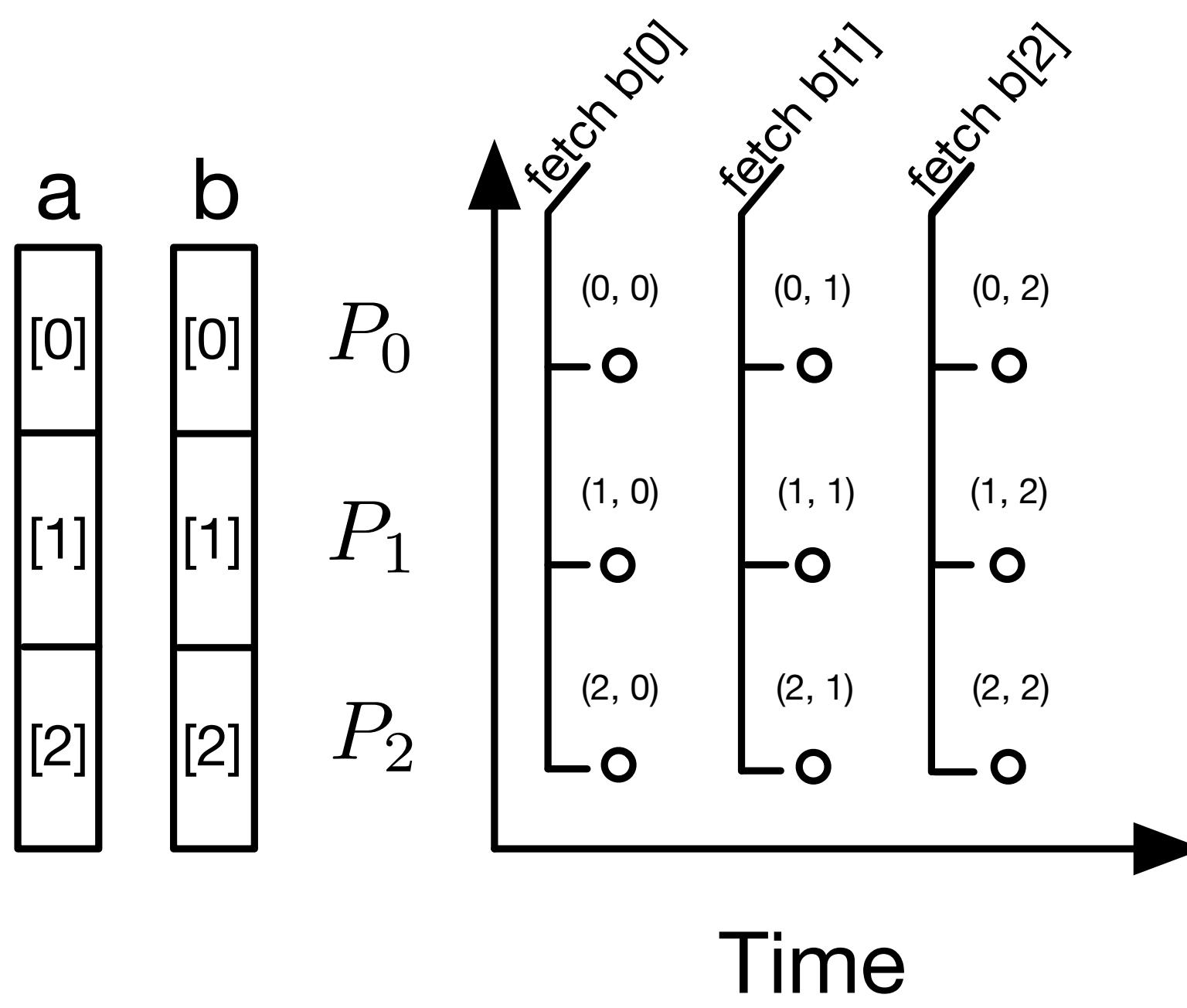
$$\forall_i \quad a(i) = \sum_j b(j) \quad \text{s.t.} \quad a \xrightarrow{x} \mathcal{M} \quad b \xrightarrow{x} \mathcal{M}$$

Tradeoff: memory vs communication frequency!



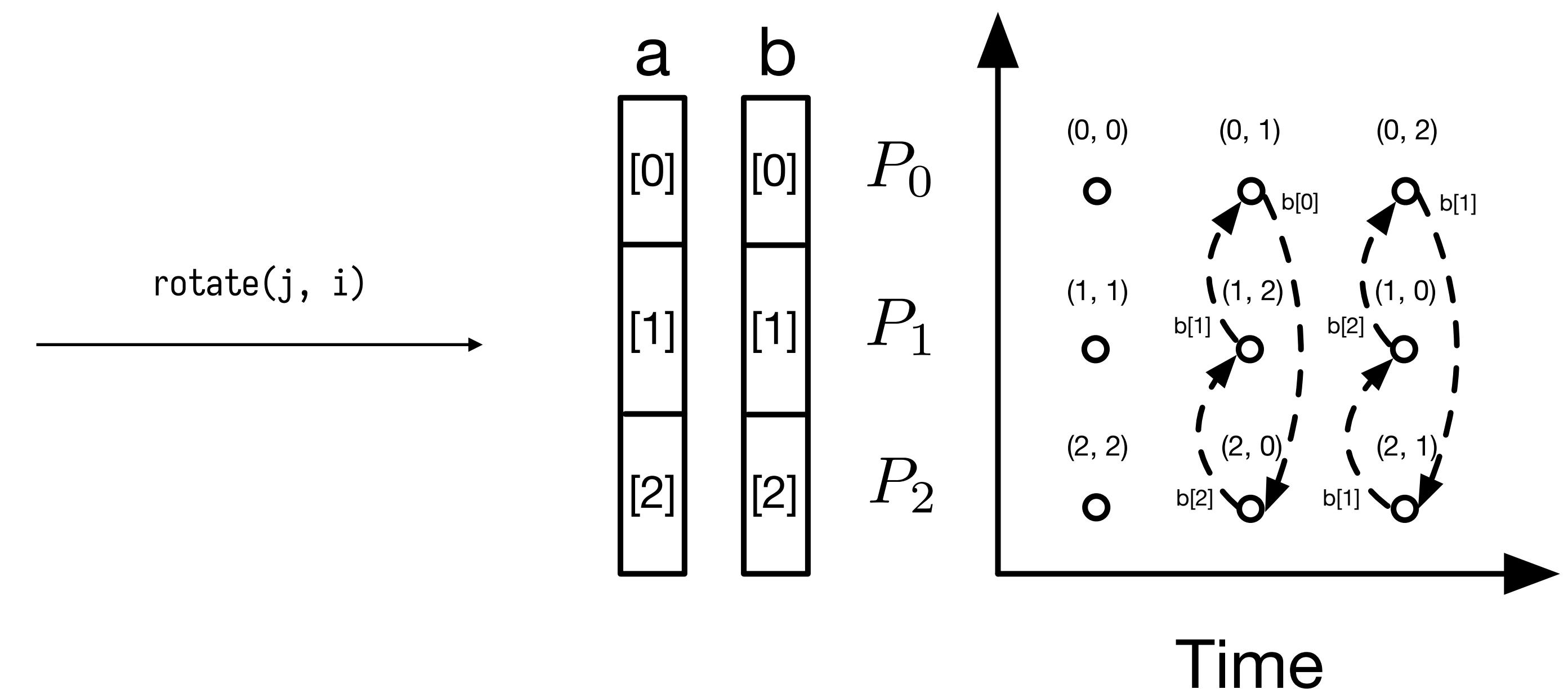
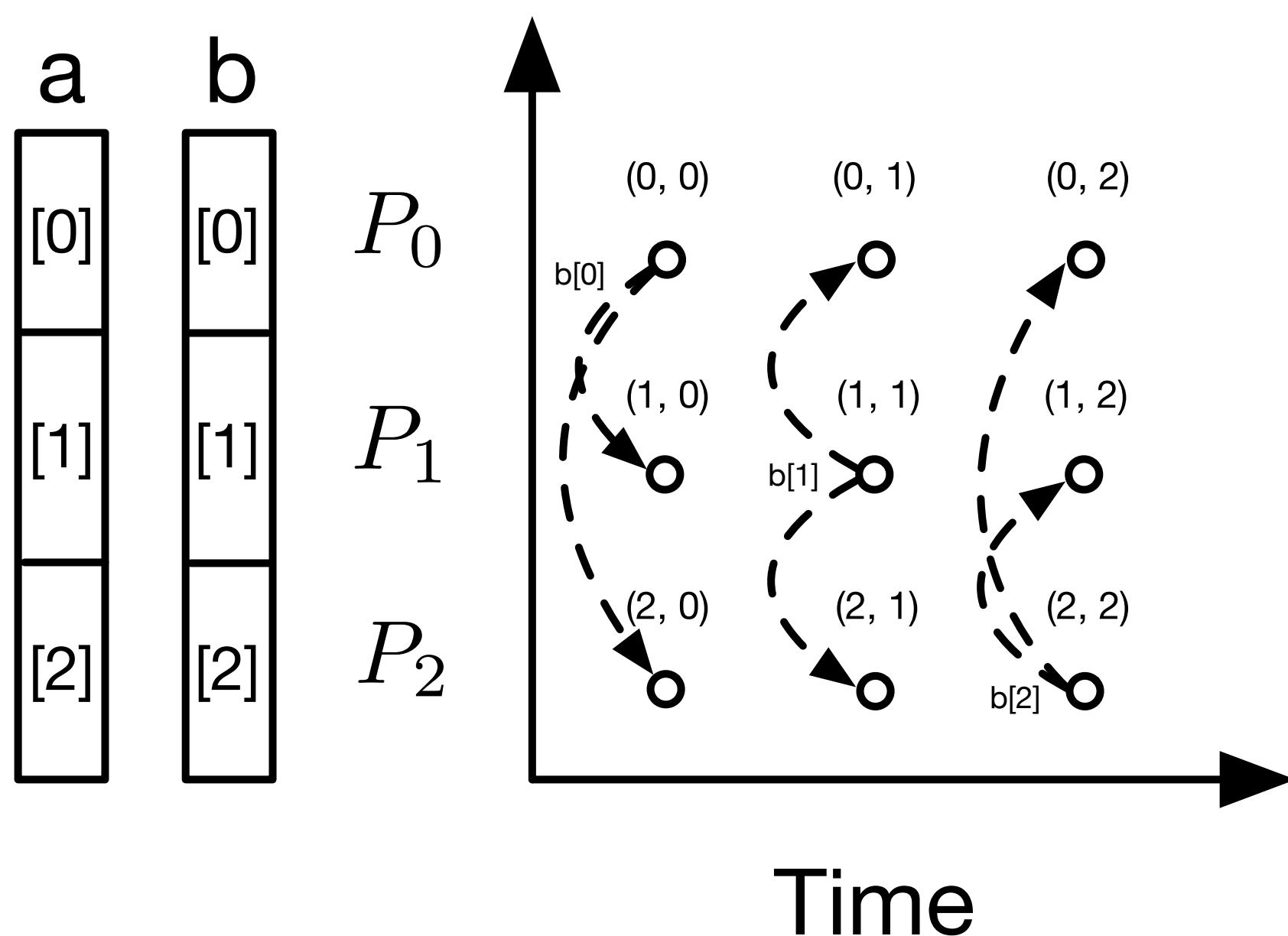
Breaking symmetry with rotate

$$\forall_i \ a(i) = \sum_j b(j) \quad \text{s.t.} \quad a \xrightarrow{x} \mathcal{M} \quad b \xrightarrow{x} \mathcal{M}$$

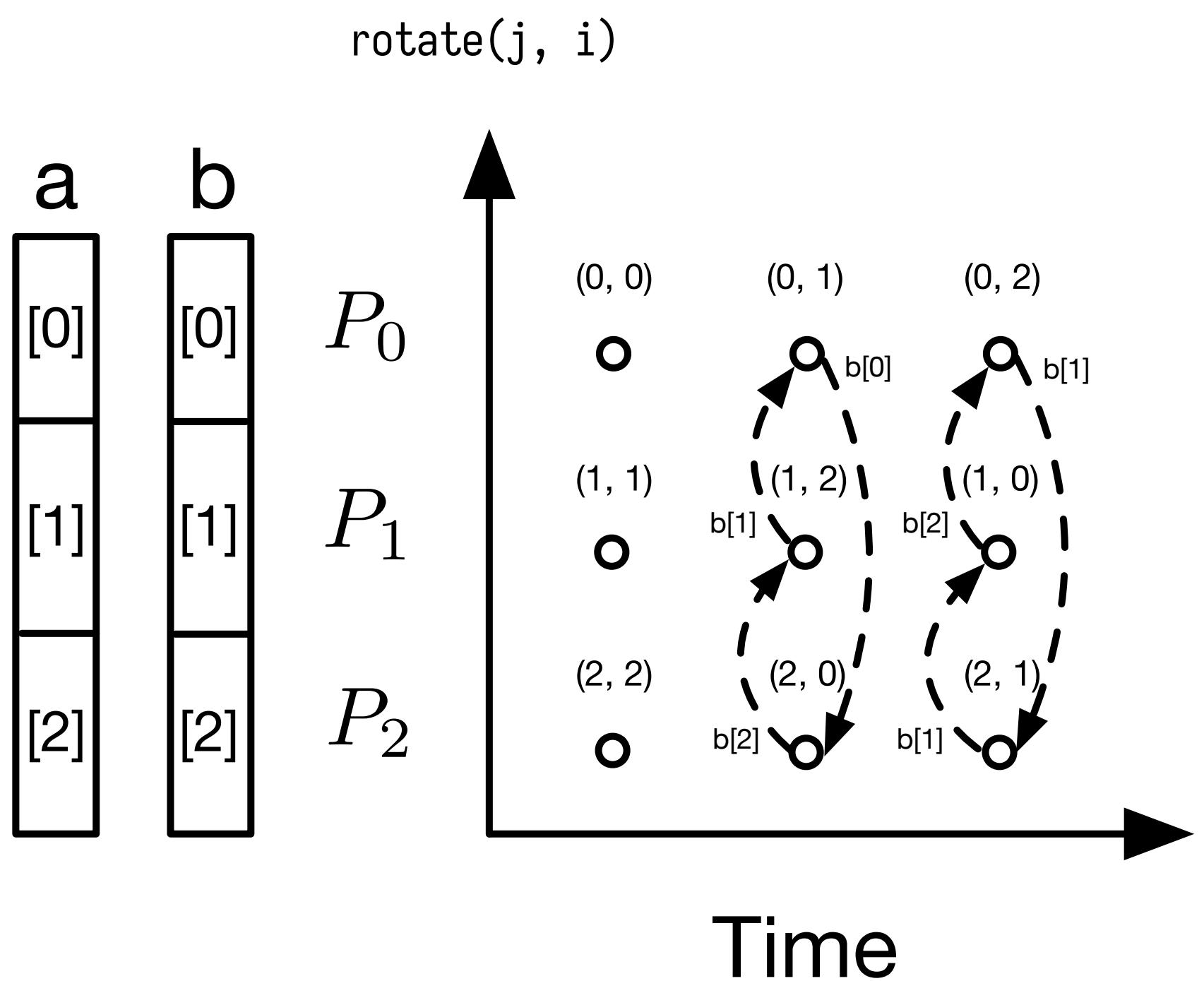


rotate

$$\forall_i \ a(i) = \sum_j b(j) \quad \text{s.t.} \quad a \xrightarrow{x} \mathcal{M} \quad b \xrightarrow{x} \mathcal{M}$$



rotate



Use the modulus operator!

```
for j in (0, extent(j)):    →    for j' in (0, extent(j)):  
...                                j = j' + i mod extent(j)  
...
```

How expressive are these abstractions?

Cannon's Algorithm

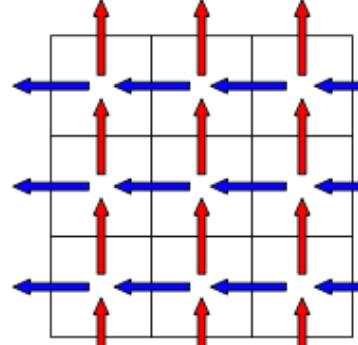
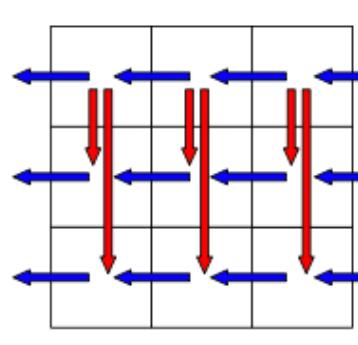
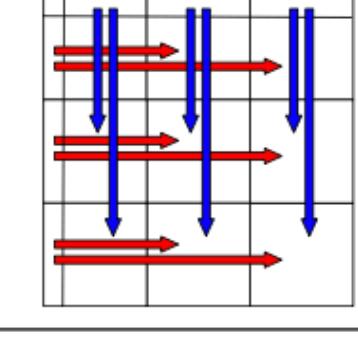
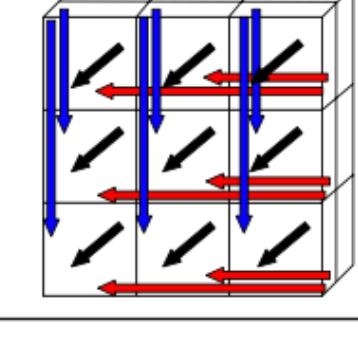
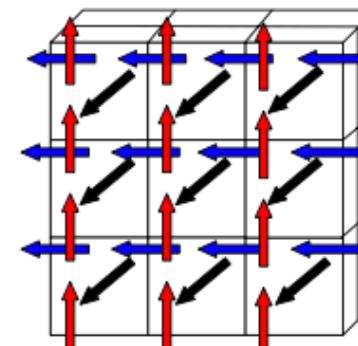
PUMMA

SUMMA

Johnson's Algorithm

Solomonik's Algorithm

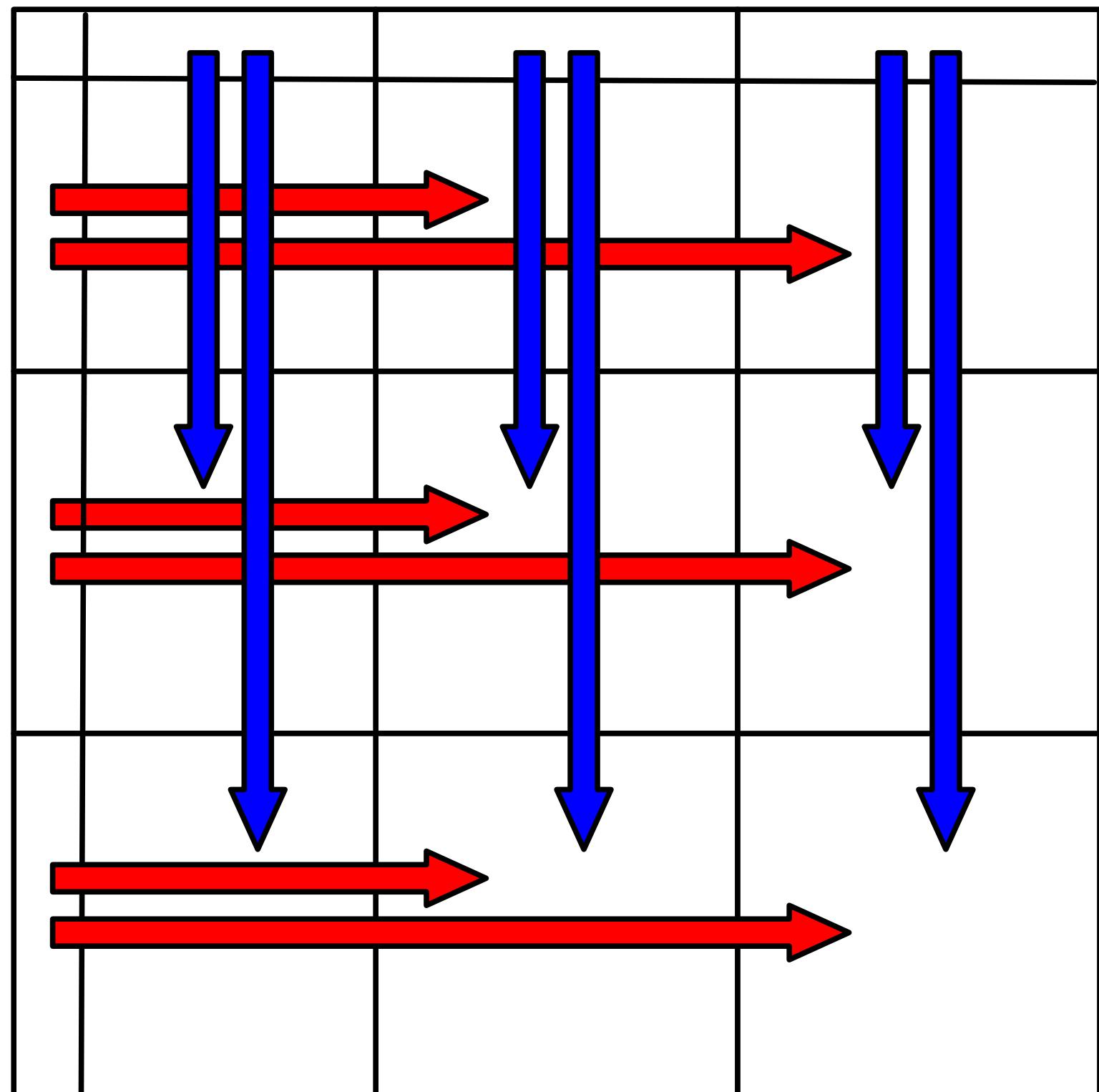
COSMA

Comm. Pattern	Target Machine	Data Distribution	Schedule
	$\mathcal{M}(gx, gy)$	$A_{ij} \mapsto_{ij} \mathcal{M}$ $B_{ij} \mapsto_{ij} \mathcal{M}$ $C_{ij} \mapsto_{ij} \mathcal{M}$.distribute({i, j}, {in, jn}, {il, jl}, Grid(gx, gy)) .divide(k, ko, ki, gx) .reorder({ko, il, jl, ki}) .rotate(ko, {in, jn}, kos) .communicate(A, jn) .communicate({B, C}, kos)
	$\mathcal{M}(gx, gy)$	$A_{ij} \mapsto_{ij} \mathcal{M}$ $B_{ij} \mapsto_{ij} \mathcal{M}$ $C_{ij} \mapsto_{ij} \mathcal{M}$.distribute({i, j}, {in, jn}, {il, jl}, Grid(gx, gy)) .divide(k, ko, ki, gx) .reorder({ko, il, jl, ki}) .rotate(ko, {in}, kos) .communicate(A, jn) .communicate({B, C}, kos)
	$\mathcal{M}(gx, gy)$	$A_{ij} \mapsto_{ij} \mathcal{M}$ $B_{ij} \mapsto_{ij} \mathcal{M}$ $C_{ij} \mapsto_{ij} \mathcal{M}$.distribute({i, j}, {in, jn}, {il, jl}, Grid(gx, gy)) .split(k, ko, ki, chunkSize) .reorder({ko, il, jl, ki}) .communicate(A, jn) .communicate({B, C}, ko)
	$\mathcal{M}(\sqrt[3]{p}, \sqrt[3]{p}, \sqrt[3]{p})$	$A_{ij} \mapsto_{ij0} \mathcal{M}$ $B_{ik} \mapsto_{i0k} \mathcal{M}$ $C_{kj} \mapsto_{0jk} \mathcal{M}$.distribute({i, j, k}, {in, jn, kn}, {il, jl, kl}, Grid($\sqrt[3]{p}$, $\sqrt[3]{p}$, $\sqrt[3]{p}$)) .communicate({A, B, C}, kn)
	$\mathcal{M}(\sqrt{\frac{p}{c}}, \sqrt{\frac{p}{c}}, c)$	$A_{ij} \mapsto_{ij0} \mathcal{M}$ $B_{ij} \mapsto_{ij0} \mathcal{M}$ $C_{ij} \mapsto_{ij0} \mathcal{M}$.distribute({i, j, k}, {in, jn, kn}, {il, jl, kl}, Grid($\sqrt{\frac{p}{c}}$, $\sqrt{\frac{p}{c}}$, c)) .divide(kl, k1, k2, $\sqrt{\frac{p}{c^3}}$) .reorder({k1, il, jl, k2}) .rotate(k1, {in, jn}, k1s) .communicate(A, jn) .communicate({B, C}, k1s)
	induced by schedule	induced by schedule	// gx, gy, gz, numSteps computed by COSMA scheduler. .distribute({i, j, k}, {in, jn, kn} {il, jl, kl}, Grid(gx, gy, gz)) .divide(kl, klo, kli, numSteps) .reorder({klo, il, jl, kli}) .communicate(A, kn) .communicate({B, C}, klo)

SUMMA Algorithm

$$A(i, j) = B(i, k) * C(k, j)$$

```
# Arrange  $p$  processors into a 2D grid.  
# Assign a tile of  $A$ ,  $B$ ,  $C$  to each processor.  
for all  $P_{ij}$  in parallel:  
    for kc in (0, k, chunkSize):  
         $B_l$  = row broadcast the kc to kc+chunkSize columns of  $B$   
         $C_l$  = col broadcast the kc to kc+chunkSize rows of  $C$   
         $A += B_l * C_l$ 
```

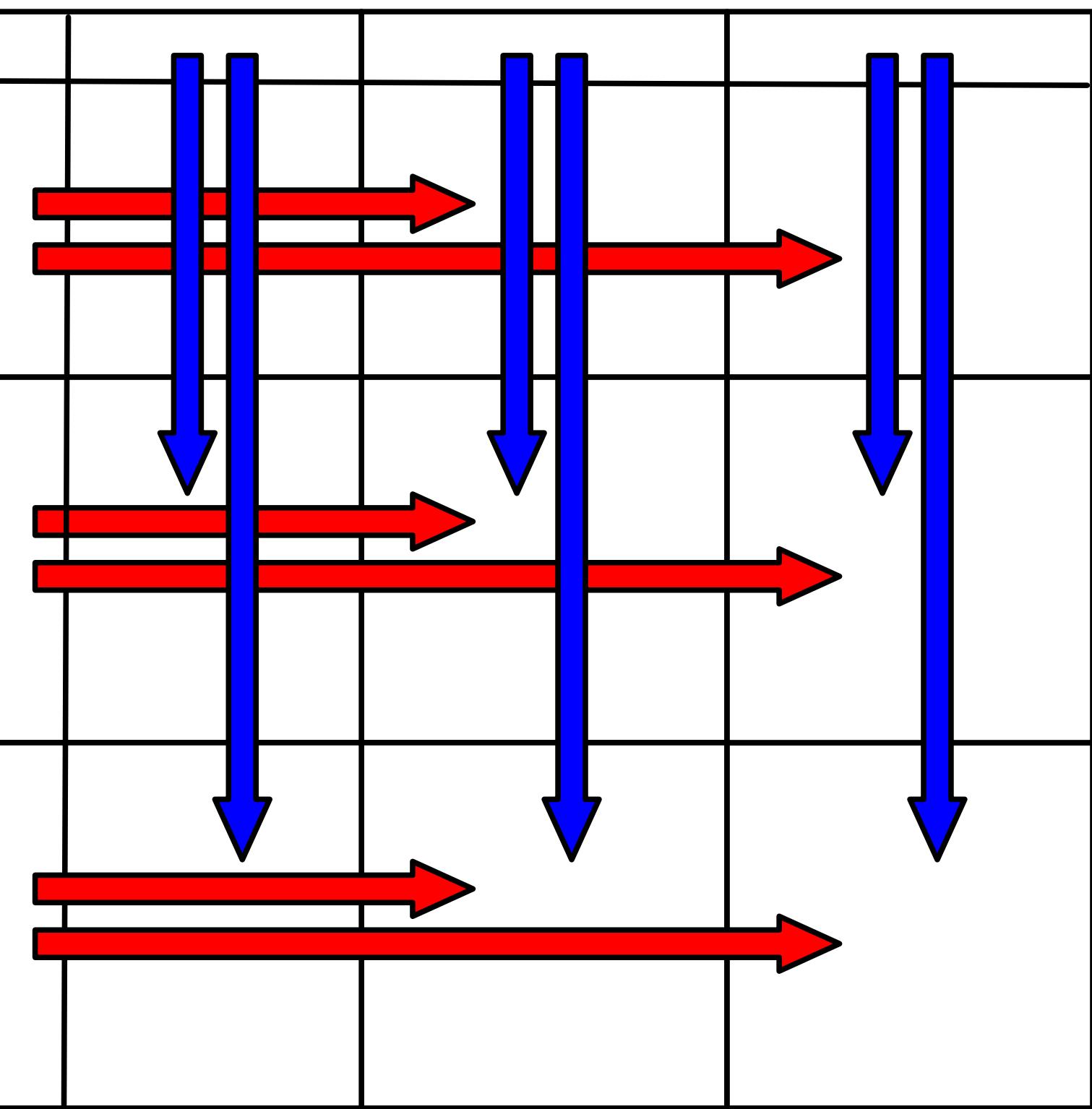


$$\mathcal{M} = \text{Grid}(gx, gy)$$

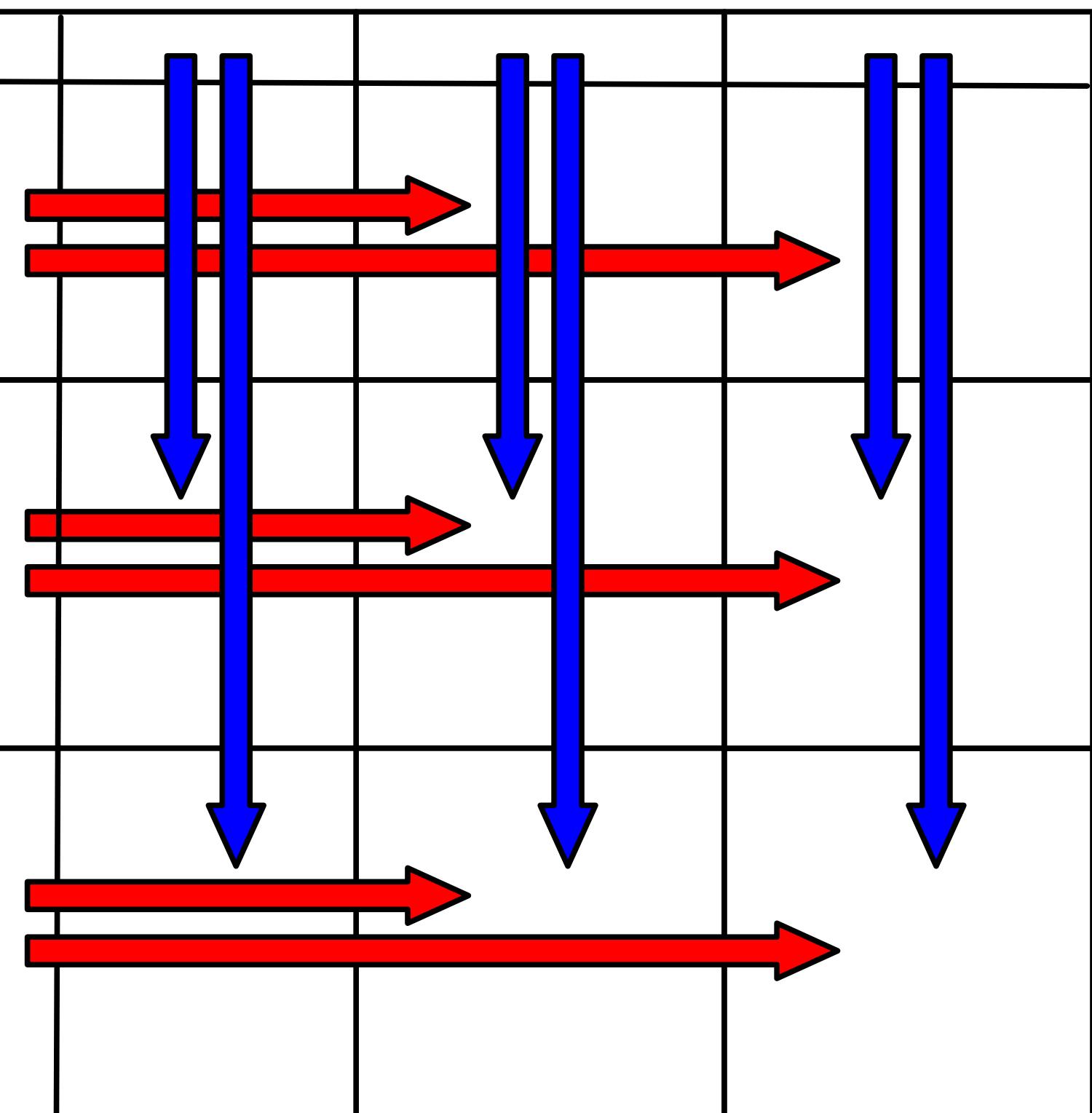
$$A_{xy} \mapsto_{xy} \mathcal{M}$$

$$B_{xy} \mapsto_{xy} \mathcal{M}$$

$$C_{xy} \mapsto_{xy} \mathcal{M}$$



```
for i:  
  for j:  
    for k:  
      A(i, j) += B(i, k) * C(k, j)
```

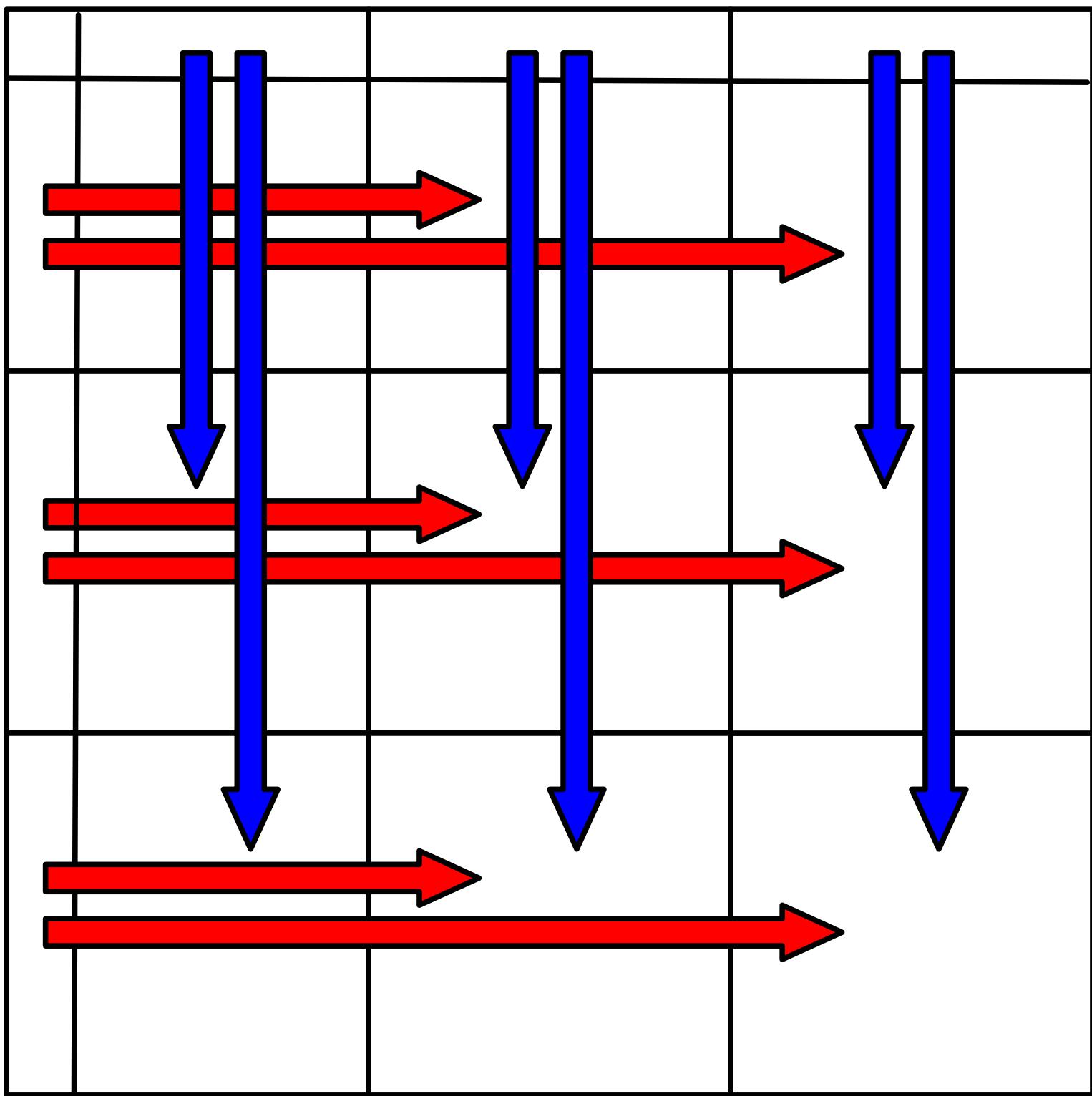


```

divide(i, il, in, gx)
divide(j, jl, jn, gy)
reorder({in, jn, il, jl})

for in:
    for jn:
        for il:
            for jl:
                for k:
                    A(i, j) += B(i, k) * C(k, j)

```

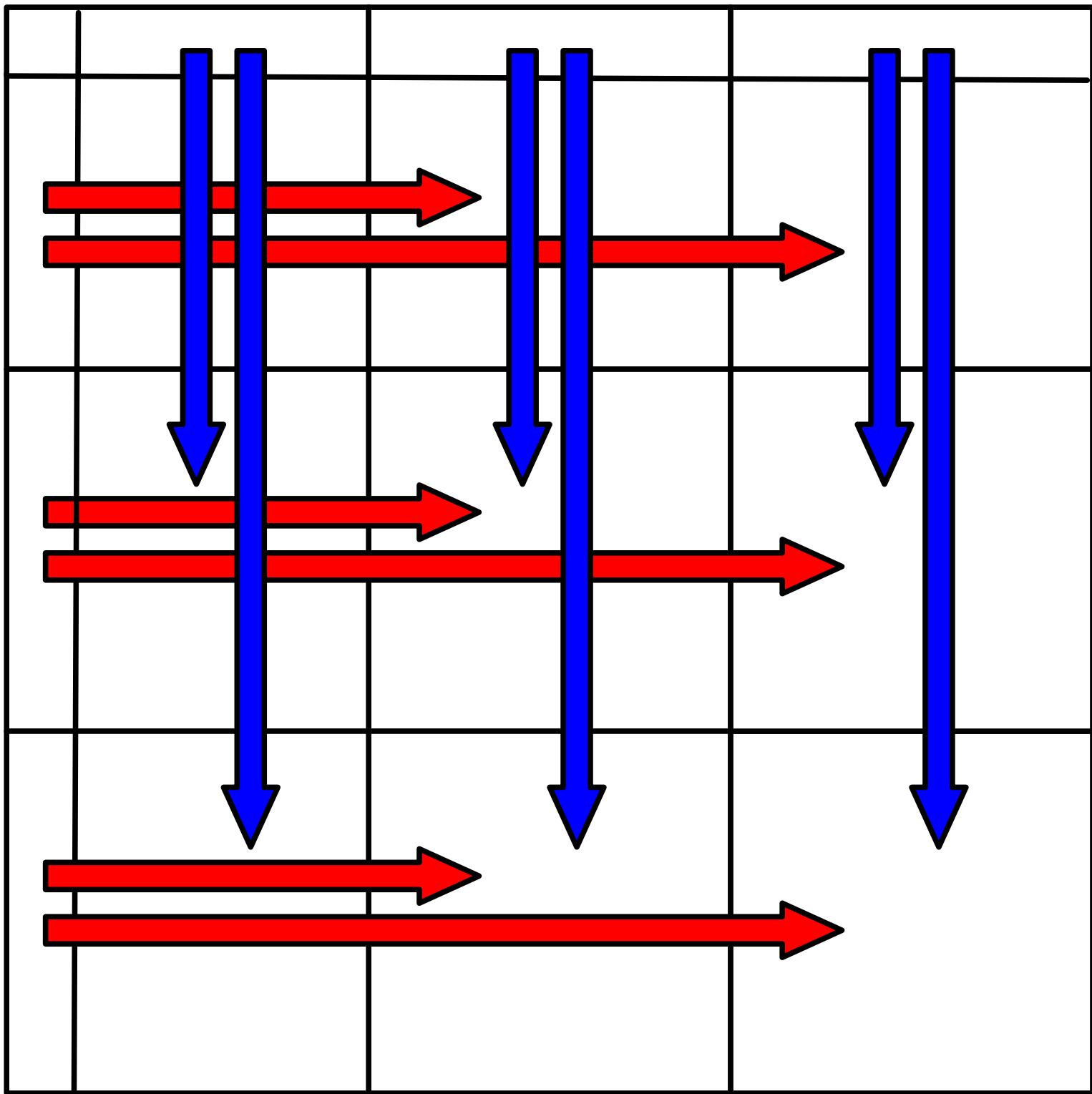


```

for in:
    for jn:
        for ko:
            for il:
                for jl:
                    for ki:
                        A(i, j) += B(i, k) * C(k, j)

```

divide(i, il, in, gx)
 divide(j, jl, jn, gx)
 reorder({in, jn, il, jl})
 split(k, ko, ki, chunkSize)
 reorder(ko, il, jl, ki)

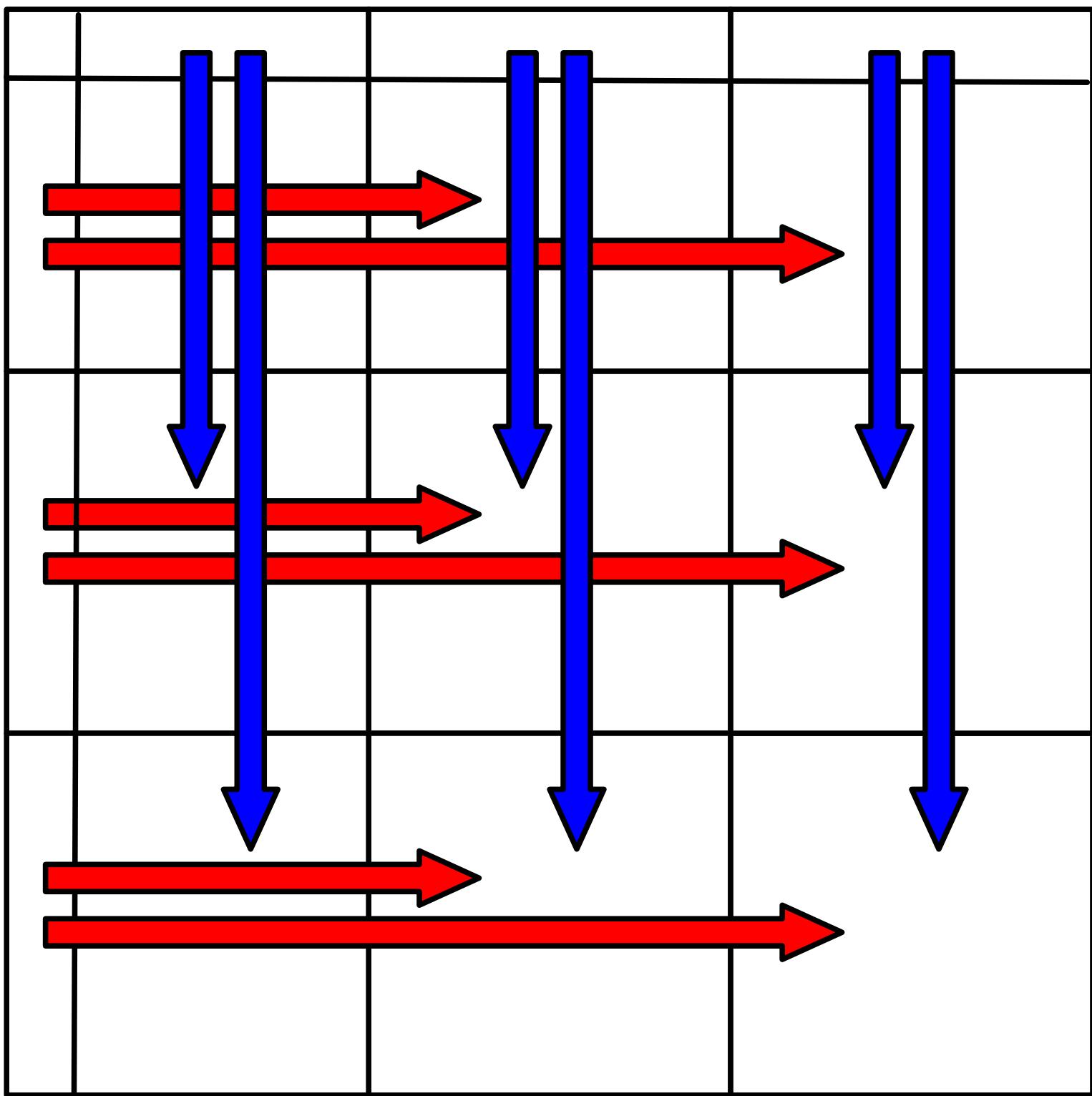


```

distributed for in, jn:
for ko:
  for il:
    for jl:
      for ki:
        A(i, j) += B(i, k) * C(k, j)

```

divide(i, il, in, gx)
 divide(j, jl, jn, gx)
 reorder({in, jn, il, jl})
 split(k, ko, ki, chunkSize)
 reorder(ko, il, jl, ki)
distribute(in, jn)

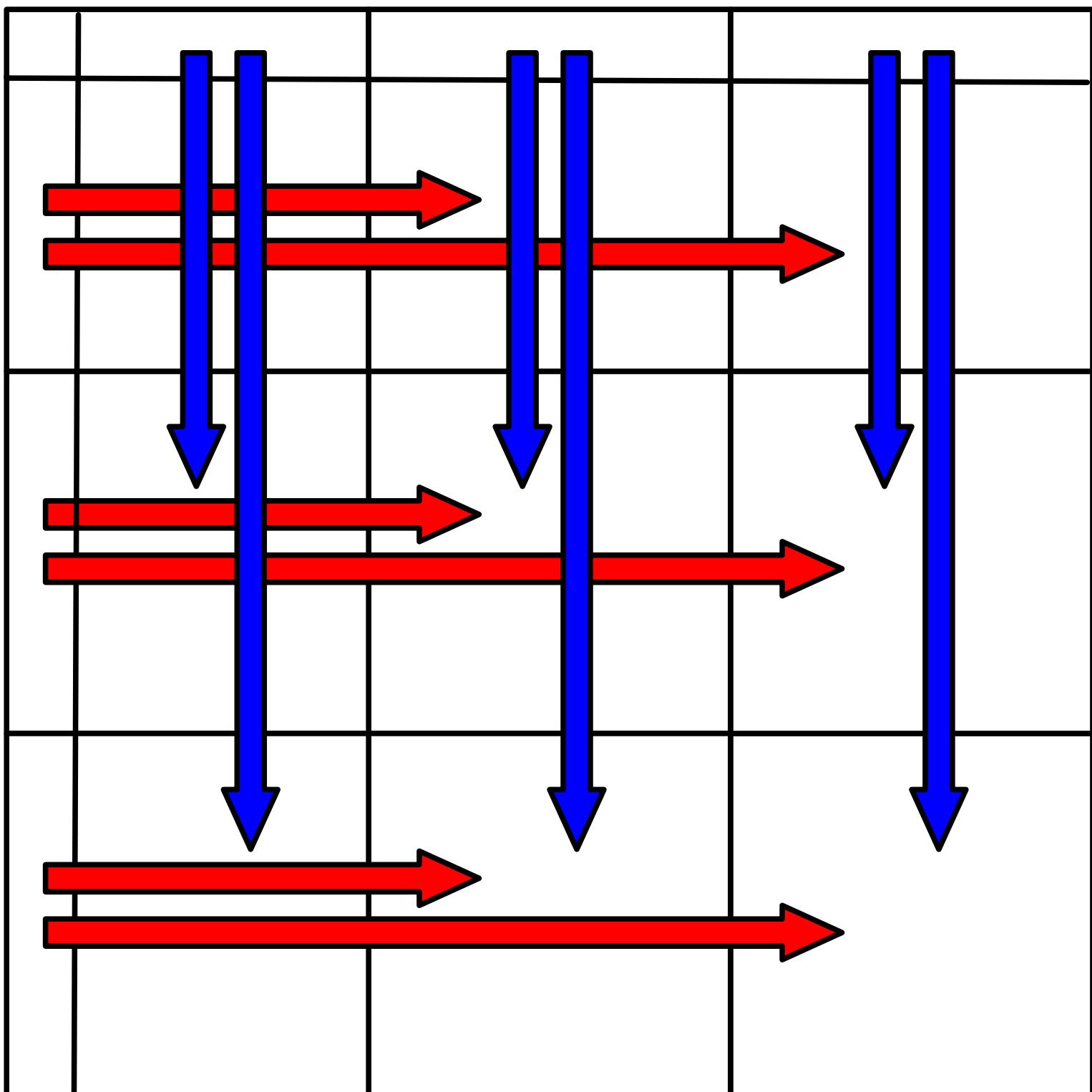


```

distributed for in, jn:
communicate A
for ko:
    communicate B, C
    for il:
        for jl:
            for ki:
                A(i, j) += B(i, k) * C(k, j)

```

divide(i, il, in, gx)
divide(j, jl, jn, gx)
reorder({in, jn, il, jl})
split(k, ko, ki, chunkSize)
reorder(ko, il, jl, ki)
distribute(in, jn)
communicate(A, jn)
communicate({B, C}, ko)



Compilation Process

Expression

$$A(i, j) = B(i, k) \cdot C(k, j)$$

$$A(i, l) = B(i, j, k) \cdot C(j, l) \cdot D(k, l)$$

$$a = B(i, j, k) \cdot C(i, j, k)$$

$$A(i, j, l) = B(i, j, k) \cdot C(k, l)$$

$$A(i, j) = B(i, j, k) \cdot c(k)$$

Data Distribution

Partition A into tiles

Replicate B onto all nodes

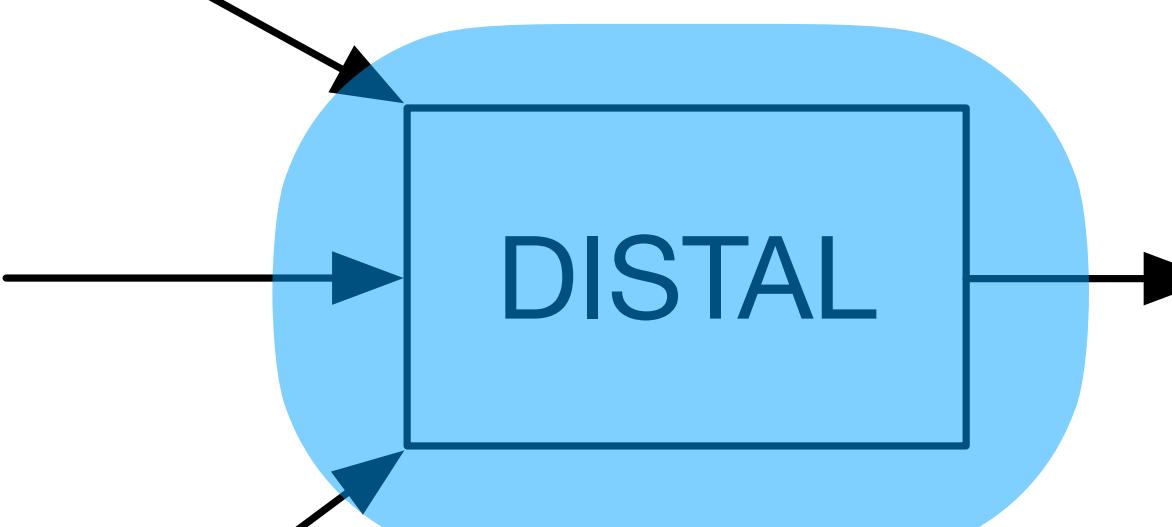
Place C onto only some nodes

Computation Distribution

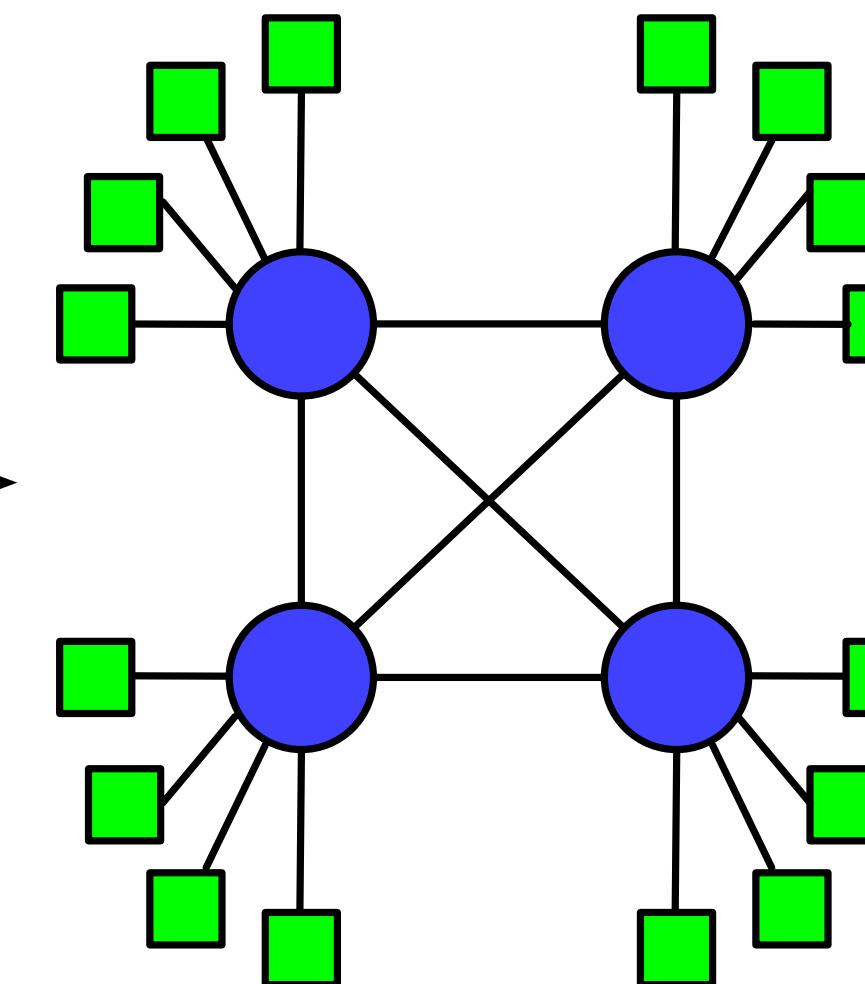
Owner Computes

Distribute i,j loops

Communicate in chunks



Supercomputer



CPU
GPU

Translate to Concrete Index Notation

$$A(i, j) = B(i, j, k) \cdot c(k) \longrightarrow \forall_i \forall_j \forall_k A(i, j) += B(i, j, k) \cdot c(k)$$

Iteration order unspecified

Specified Iteration Order

Scheduling operations rewrite Concrete Index Notation

$$\dots \forall_i S \xrightarrow{\text{divide}(i, i_o, i_i, c)} \dots \forall_{i_o} \forall_{i_i} S \text{ s.t. } \text{divide}(i, i_o, i_i, c)$$

$$\dots \forall_i S \xrightarrow{\text{distribute}(i)} \dots \forall_i S \text{ s.t. } \text{distribute}(i)$$

$$\dots \forall_I \forall_t S \xrightarrow{\text{rotate}(t, I, r)} \dots \forall_I \forall_r S \text{ s.t. } \text{rotate}(t, I, r)$$

$$\dots \forall_i S \xrightarrow{\text{communicate}(\mathcal{T}, i)} \dots \forall_i S \text{ s.t. } \text{communicate}(\mathcal{T}, i)$$

Target specific backend handles these constructs now!

Compiling Tensor Distribution Notation

$$\mathcal{T}_{xy \mapsto_x \mathcal{M}}$$

$$\forall_x \forall_y \mathcal{T}(x, y)$$

$$\forall_{xo} \forall_{xi} \forall_y \mathcal{T}(x, y) \text{ s.t. } \text{divide}(x, xo, xi, gx)$$

$$\forall_{xo} \forall_{xi} \forall_y \mathcal{T}(x, y) \text{ s.t. } \text{divide}(x, xo, xi, gx), \text{distribute}(xo), \text{comm.}(\mathcal{T}, xo)$$

What's the backend?

Legion

Distributed task-based runtime system

Tasks operate on bulk data

System moves memory between processors for tasks to use

distribute → launch a set of tasks

communicate → tell Legion the data to transfer

rotate → perform a loop transformation with modulus

Evaluation

Comparisons

Distributed GEMM – evaluate performance on a highly optimized kernel

Compare against COSMA, Cyclops Tensor Framework, ScaLAPACK

Higher order tensor kernels – evaluate performance on the long tail

Compare against Cyclops Tensor Framework

Results (Methodology)

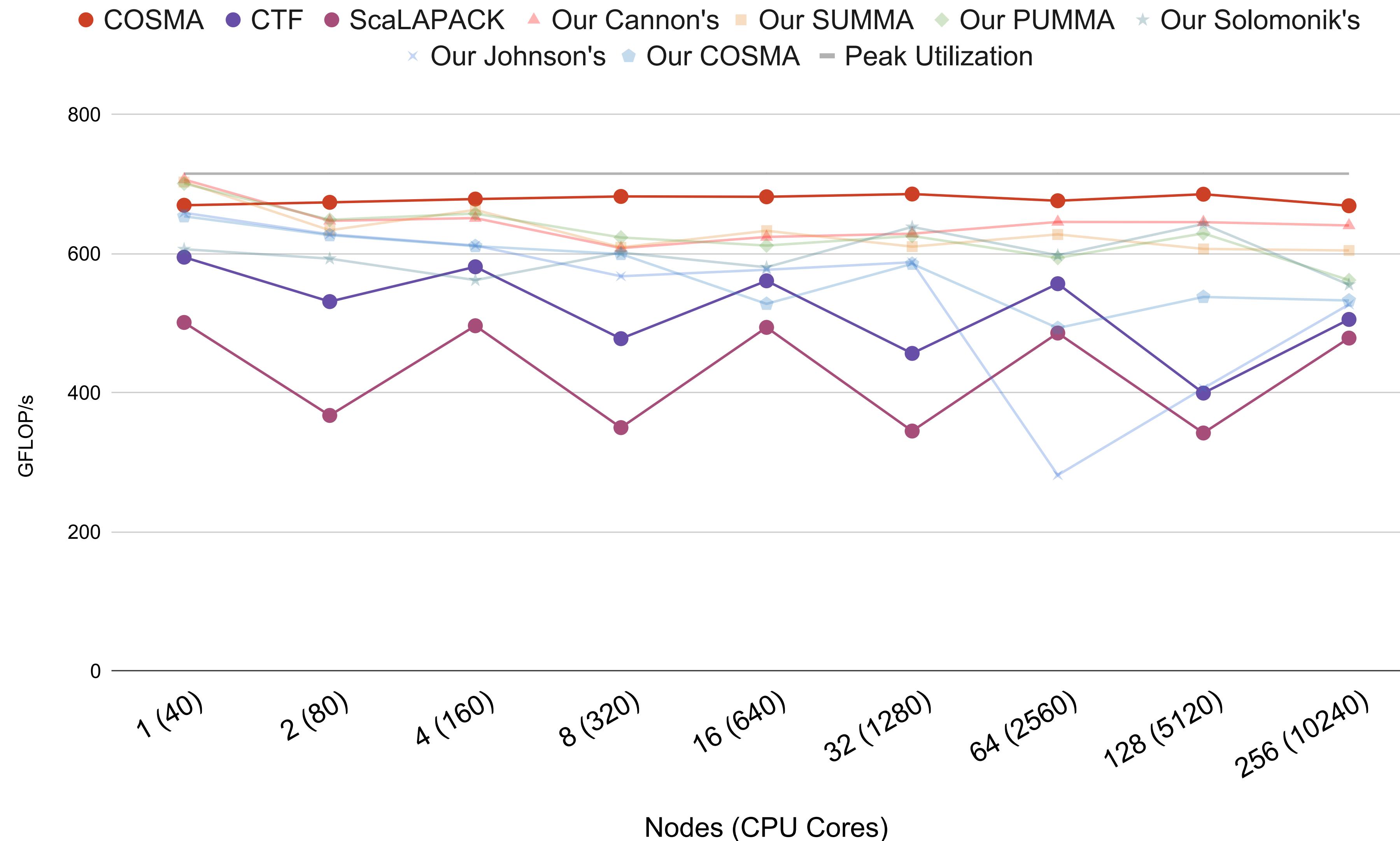
Experiments run on up to 256 nodes of Lassen (4 V100 GPUs/node, 40 Power9 CPUs/node, IB interconnect)

All systems configured to use the same BLAS / CuBLAS for GEMM

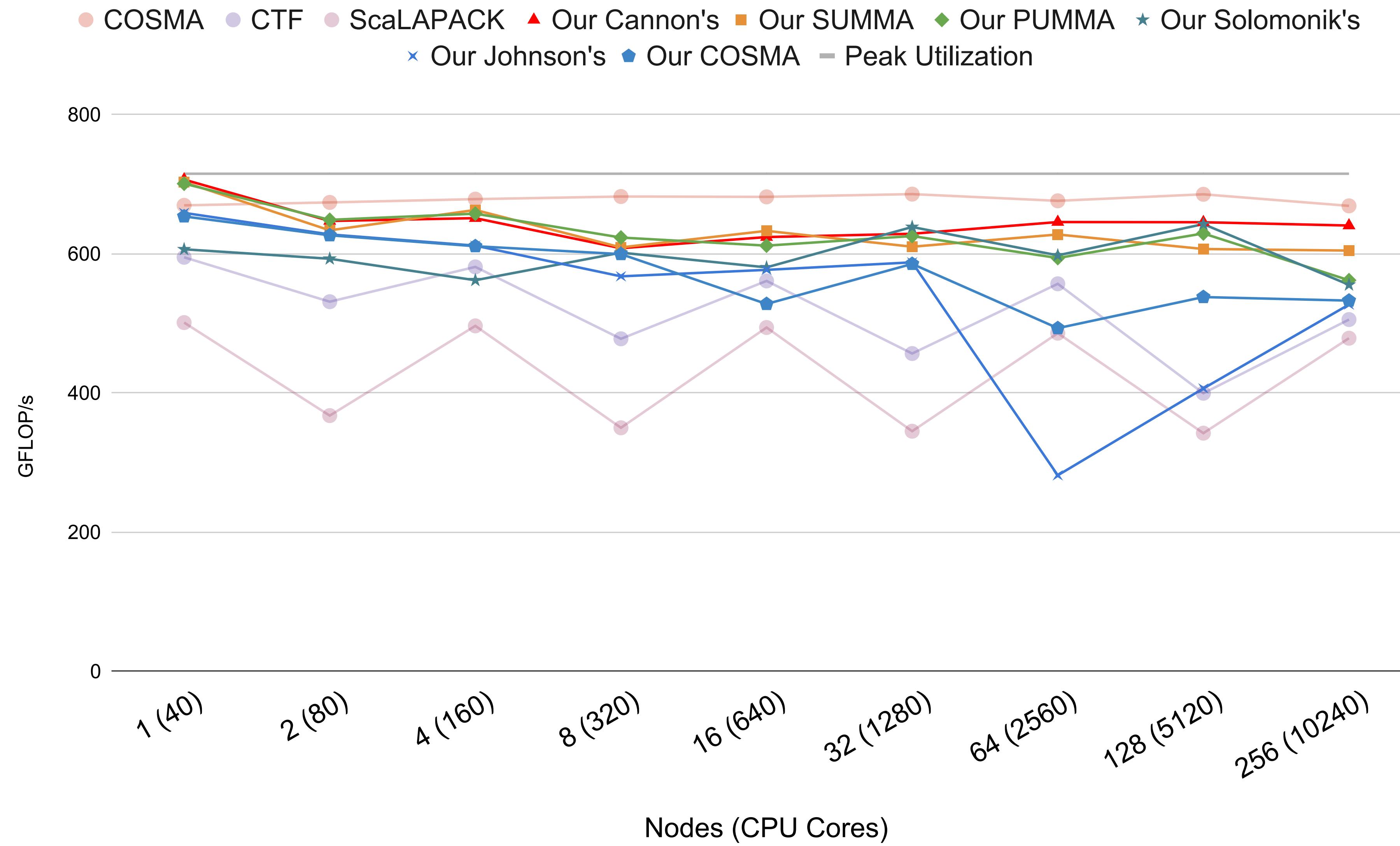
All experiments are weak-scaling (memory / node stays constant)

Results reported in GFLOP/s (compute bound) and GB/s (bandwidth bound) per node

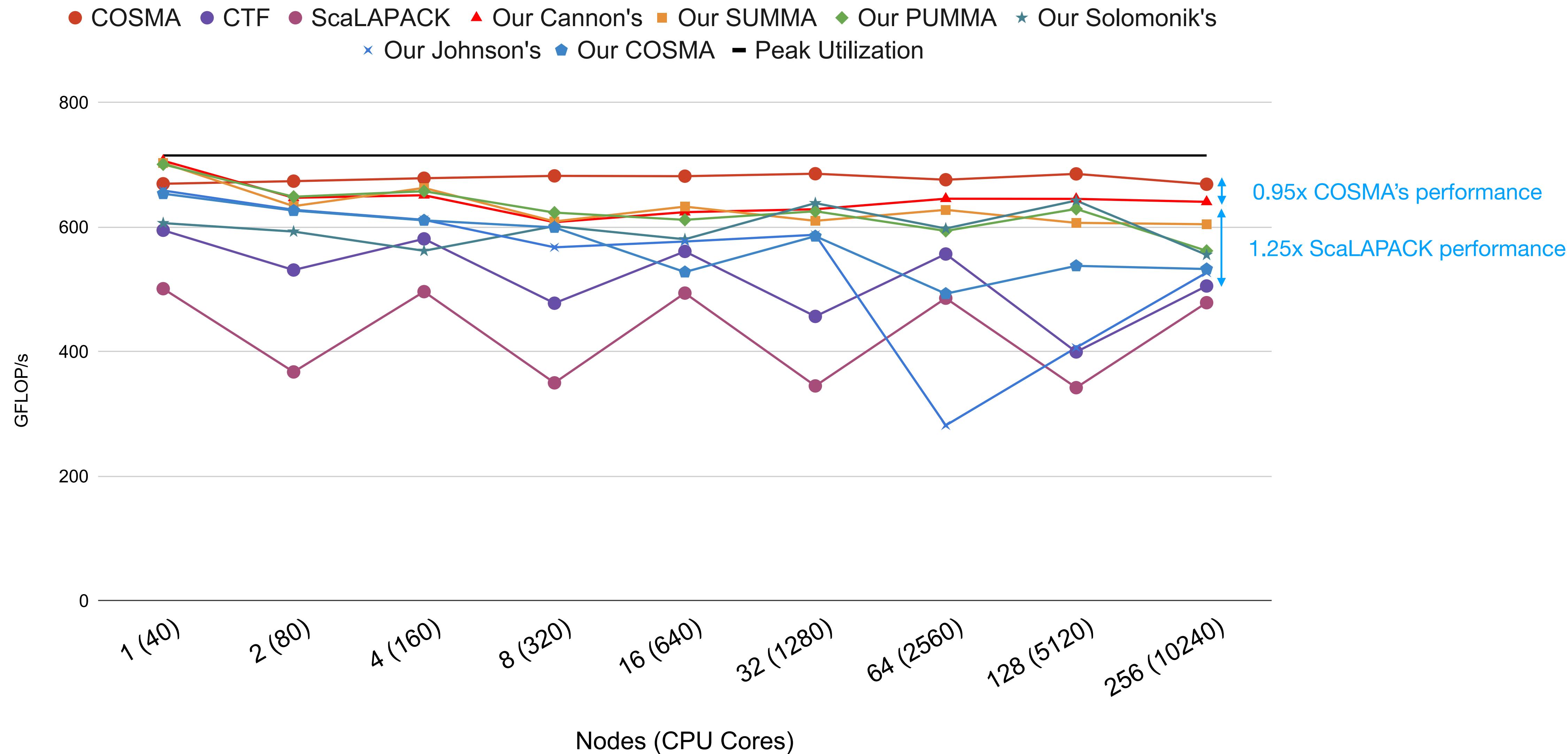
GEMM (CPU)



GEMM (CPU)

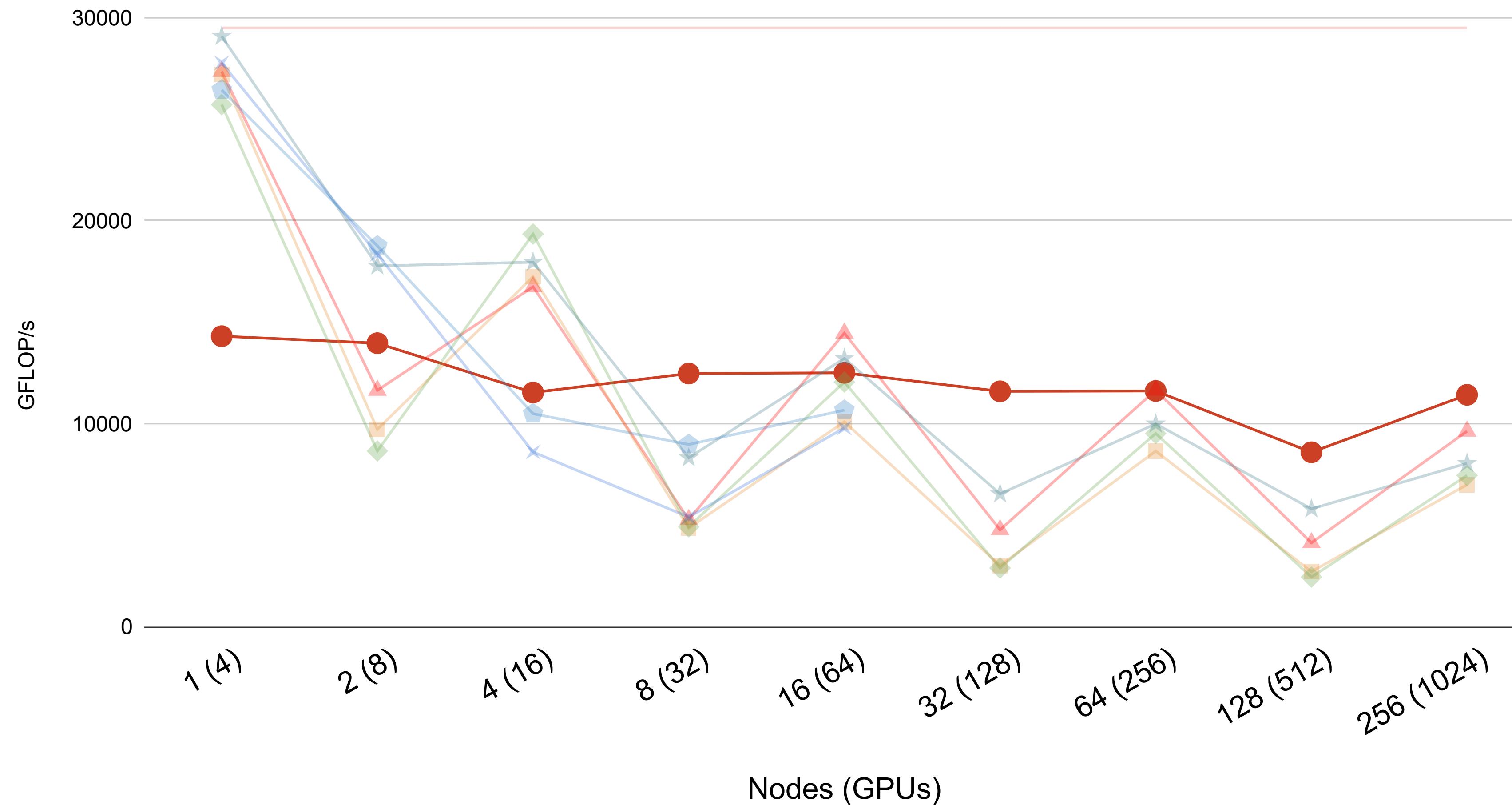


GEMM (CPU)



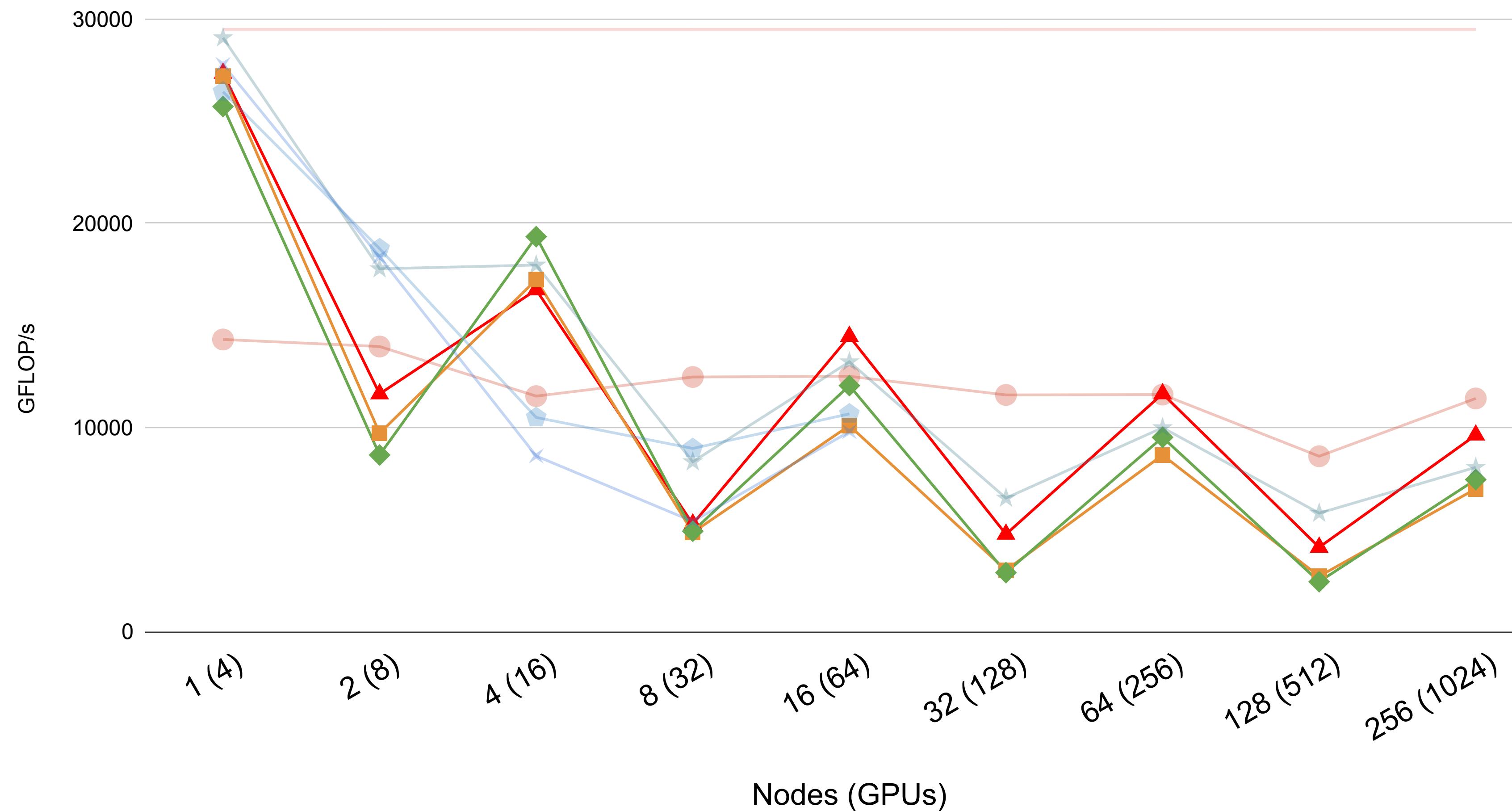
GEMM (GPU)

● COSMA ▲ Our Cannon's □ Our SUMMA ▲ Our PUMMA ★ Our Solomonik's ✕ Our Johnson's ⬤ Our Cosma
— Peak Utilization



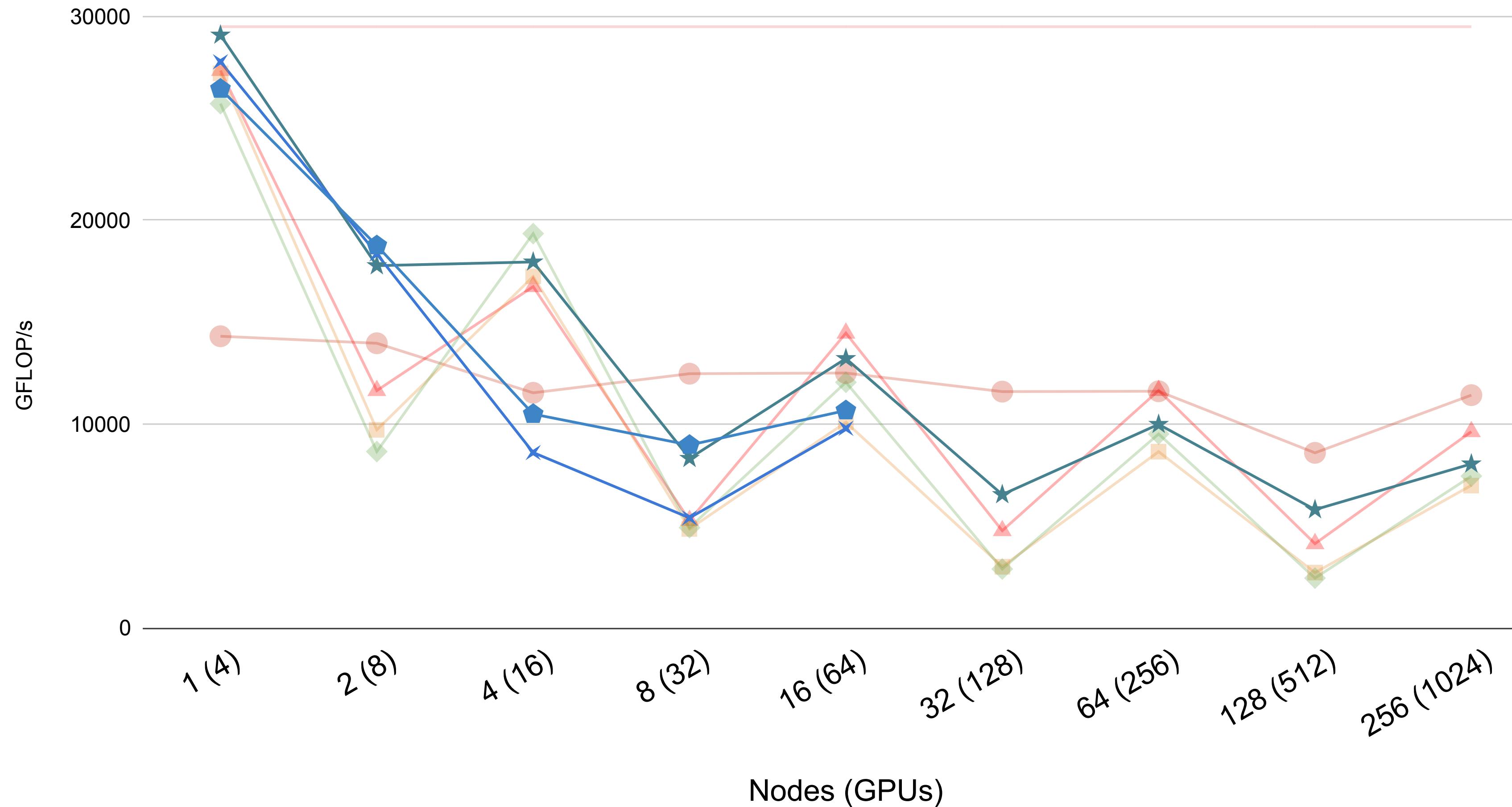
GEMM (GPU)

● COSMA ▲ Our Cannon's □ Our SUMMA ▲ Our PUMMA ★ Our Solomonik's ✕ Our Johnson's ⬤ Our Cosma
— Peak Utilization

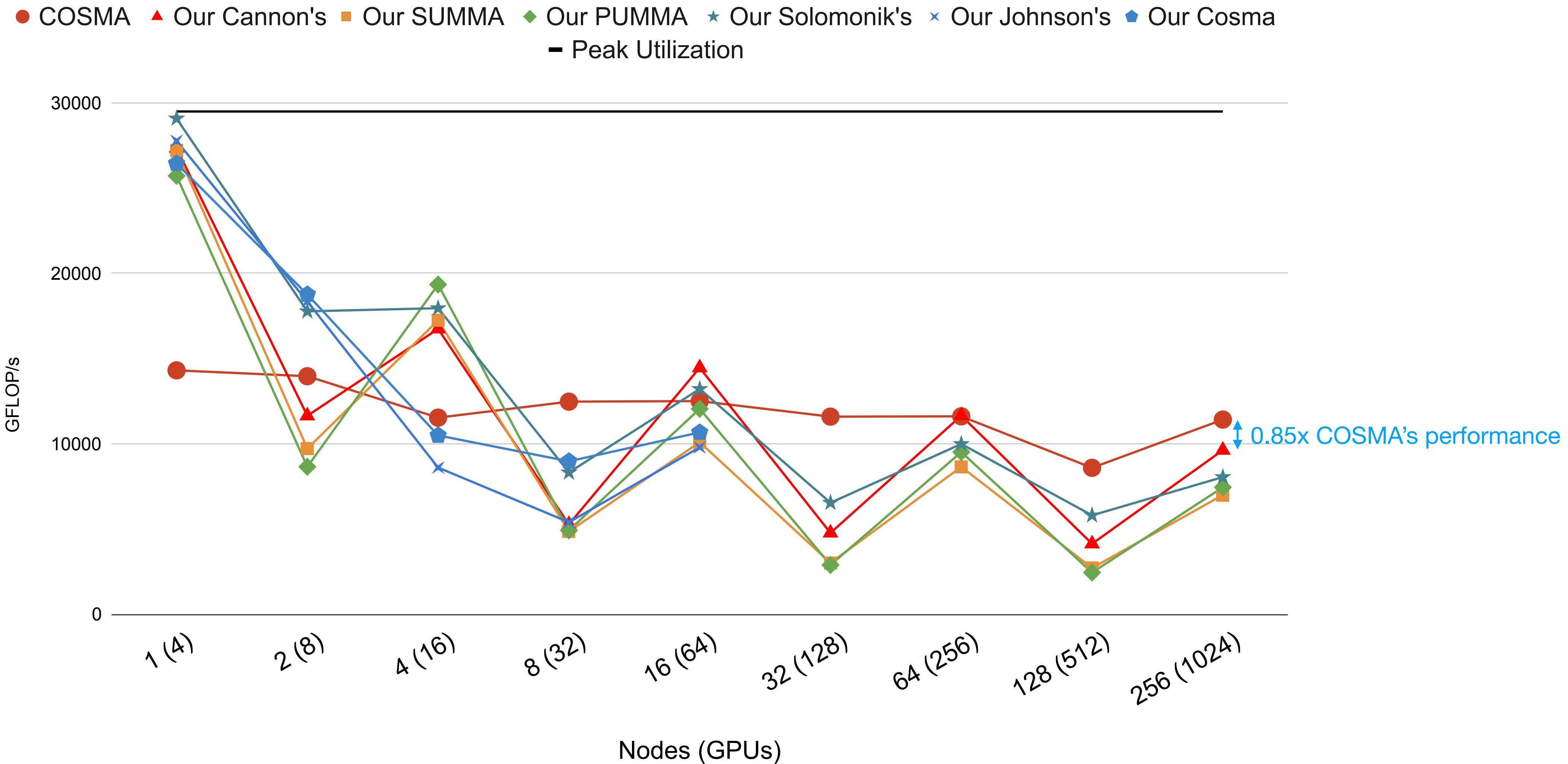


GEMM (GPU)

● COSMA ▲ Our Cannon's □ Our SUMMA ▲ Our PUMMA ★ Our Solomonik's ✕ Our Johnson's ⬤ Our Cosma
— Peak Utilization



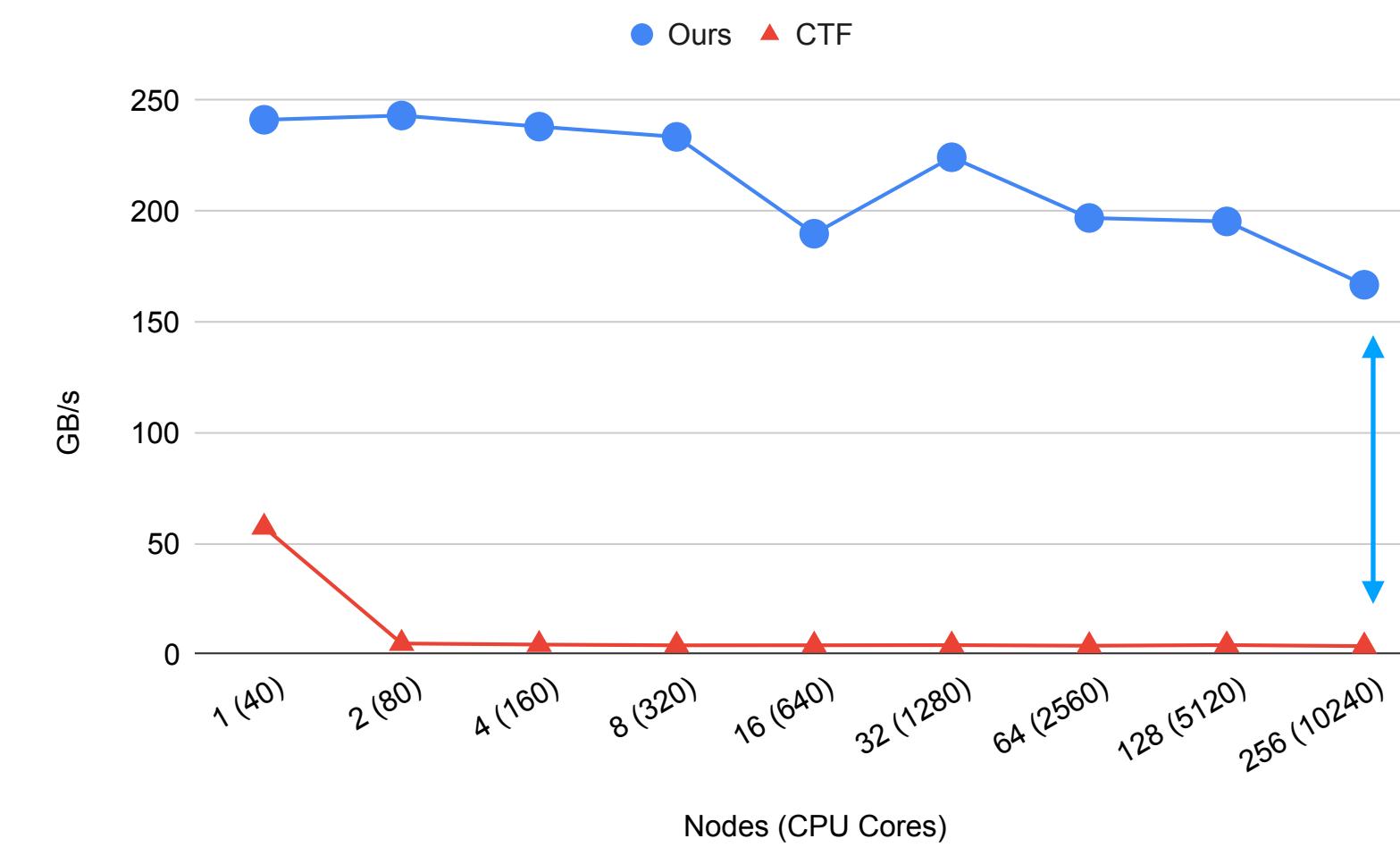
GEMM (GPU)



Higher Order Tensor Operations (CPU)

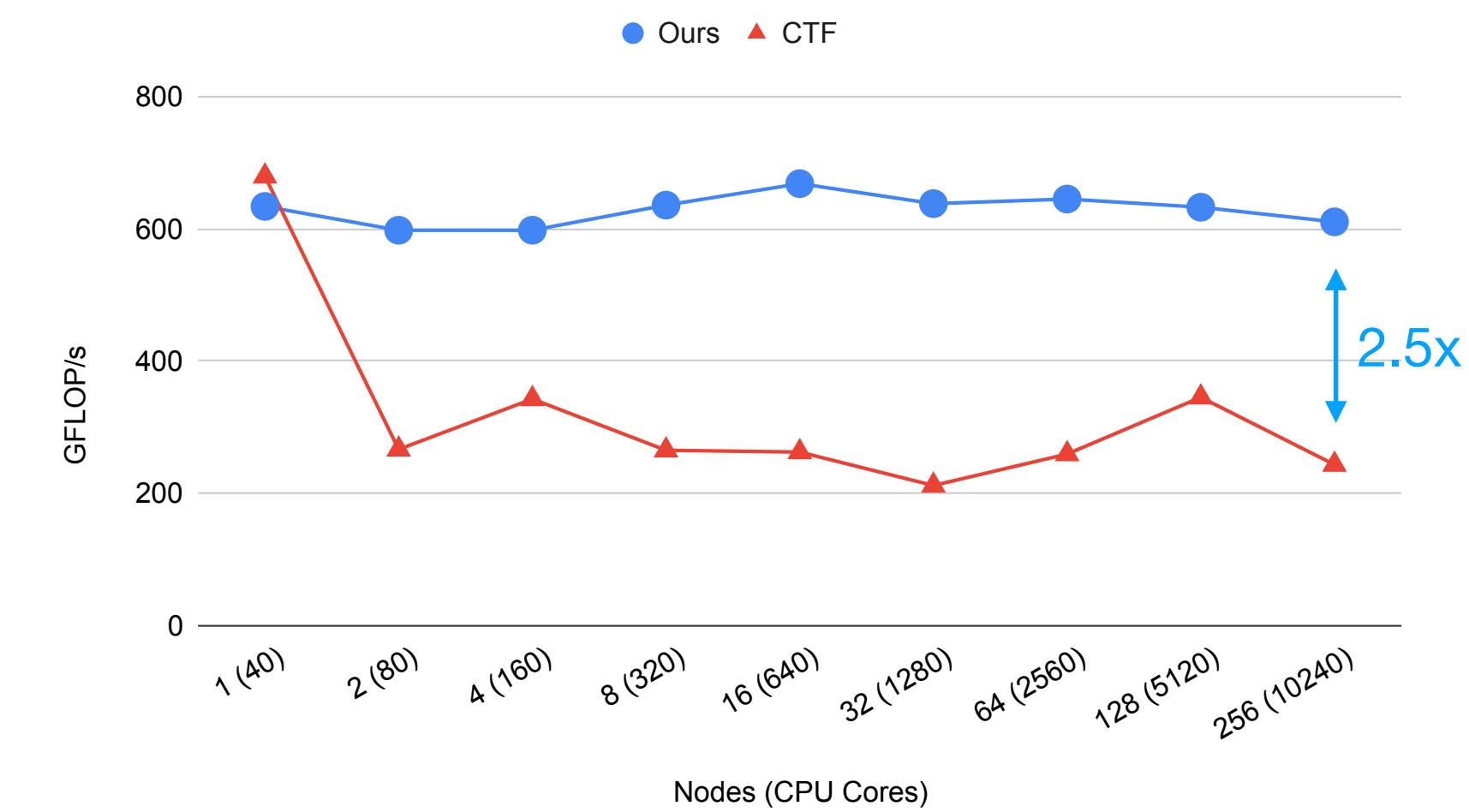
TTV

$$A_{ij} = B_{ijk} \cdot C_k$$



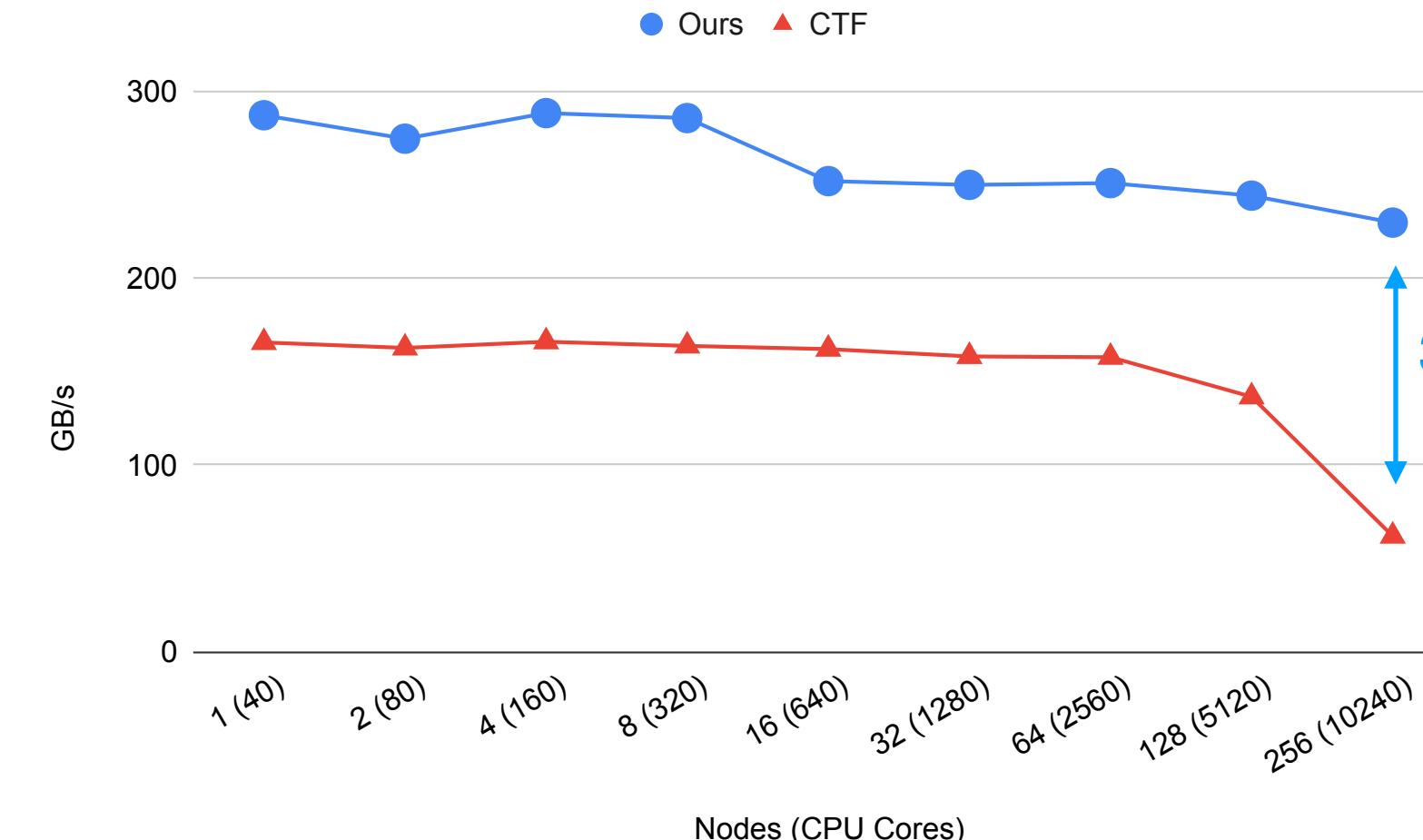
TTM

$$A_{ijl} = B_{ijk} \cdot C_{kl}$$



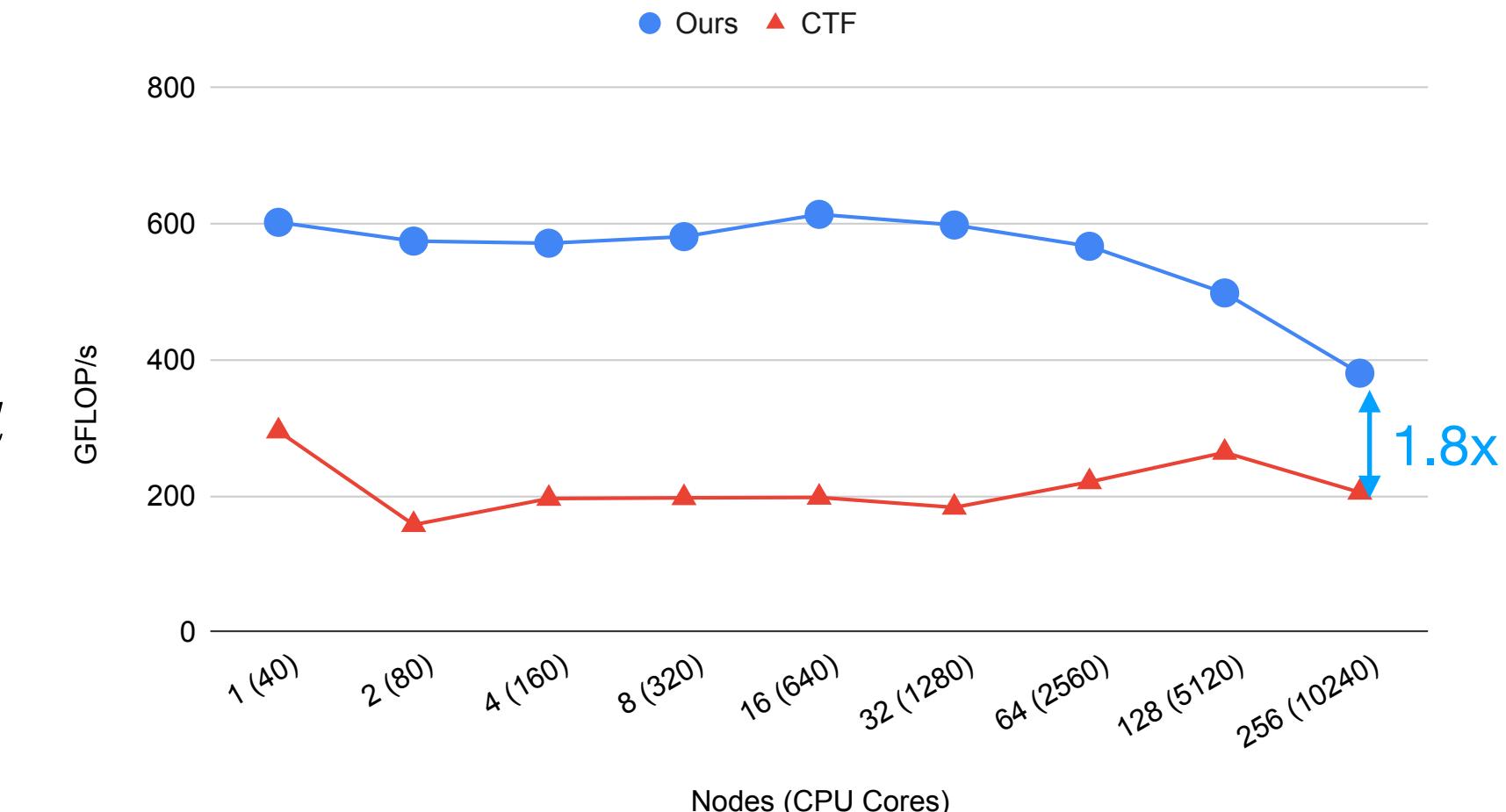
InnerProd

$$a = B_{ijk} \cdot C_{ijk}$$



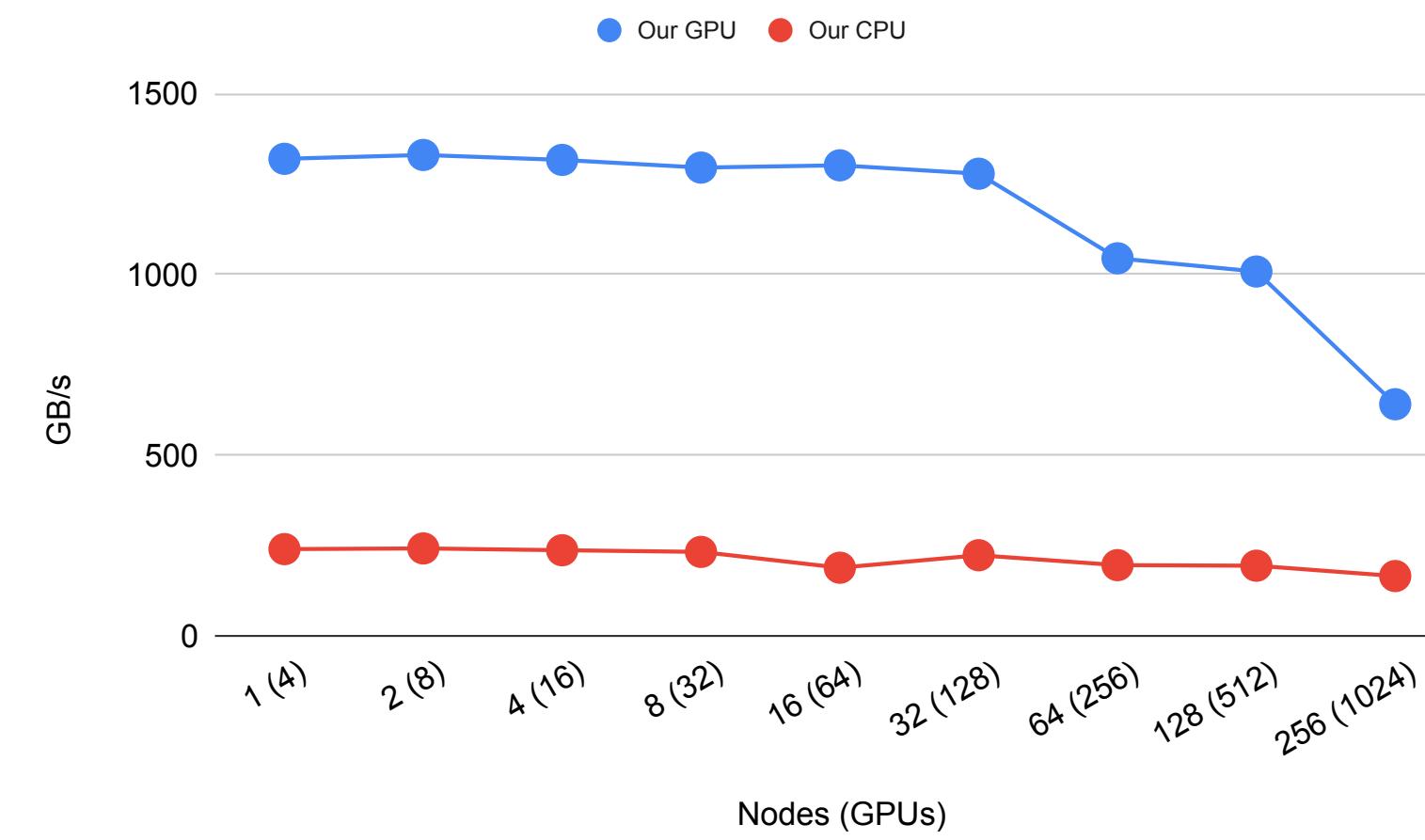
MTTKRP

$$A_{il} = B_{ijk} \cdot C_{jl} \cdot D_{kl}$$

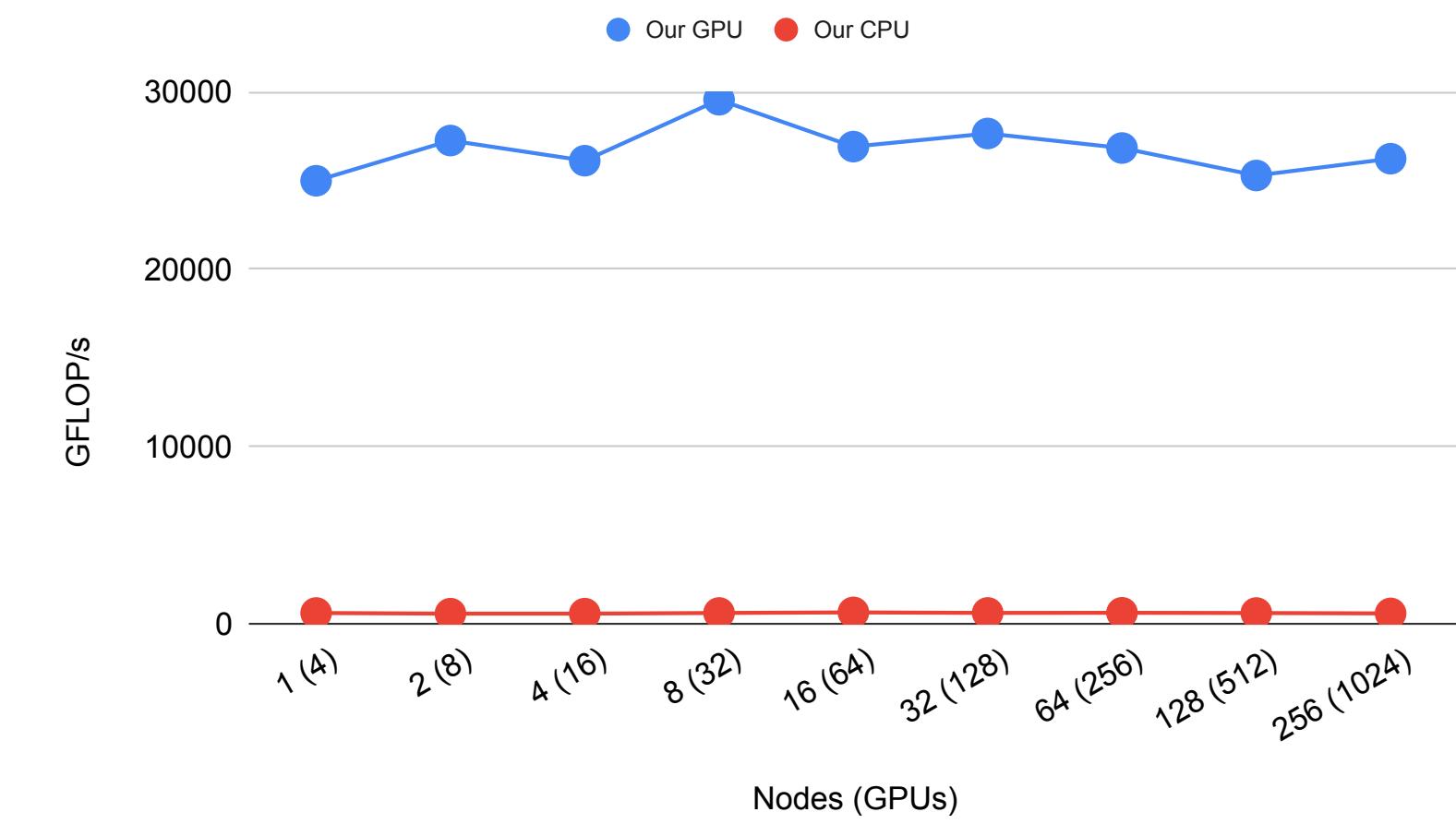


Higher Order Tensor Operations (GPU)

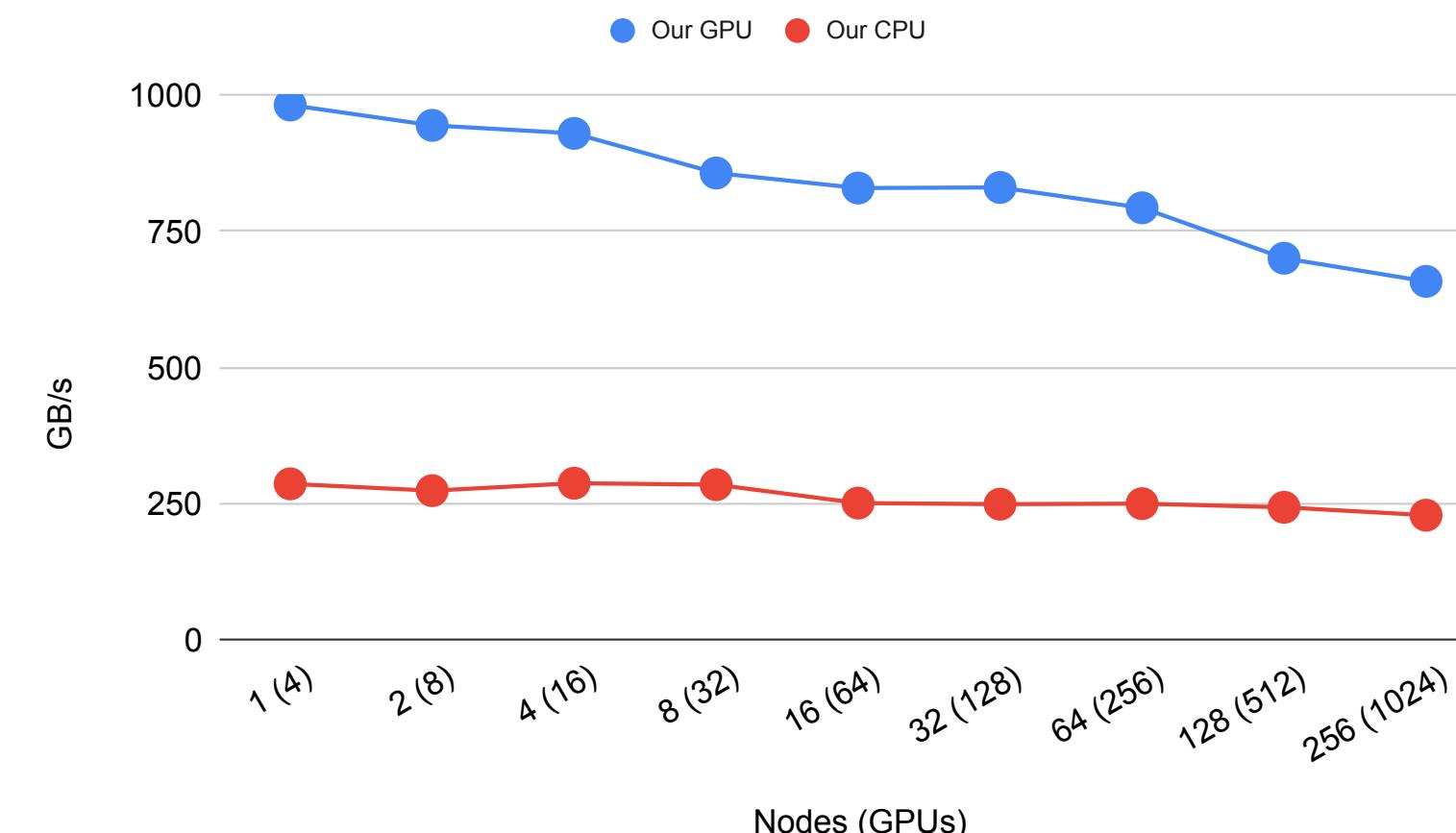
TTV
 $A_{ij} = B_{ijk} \cdot C_k$



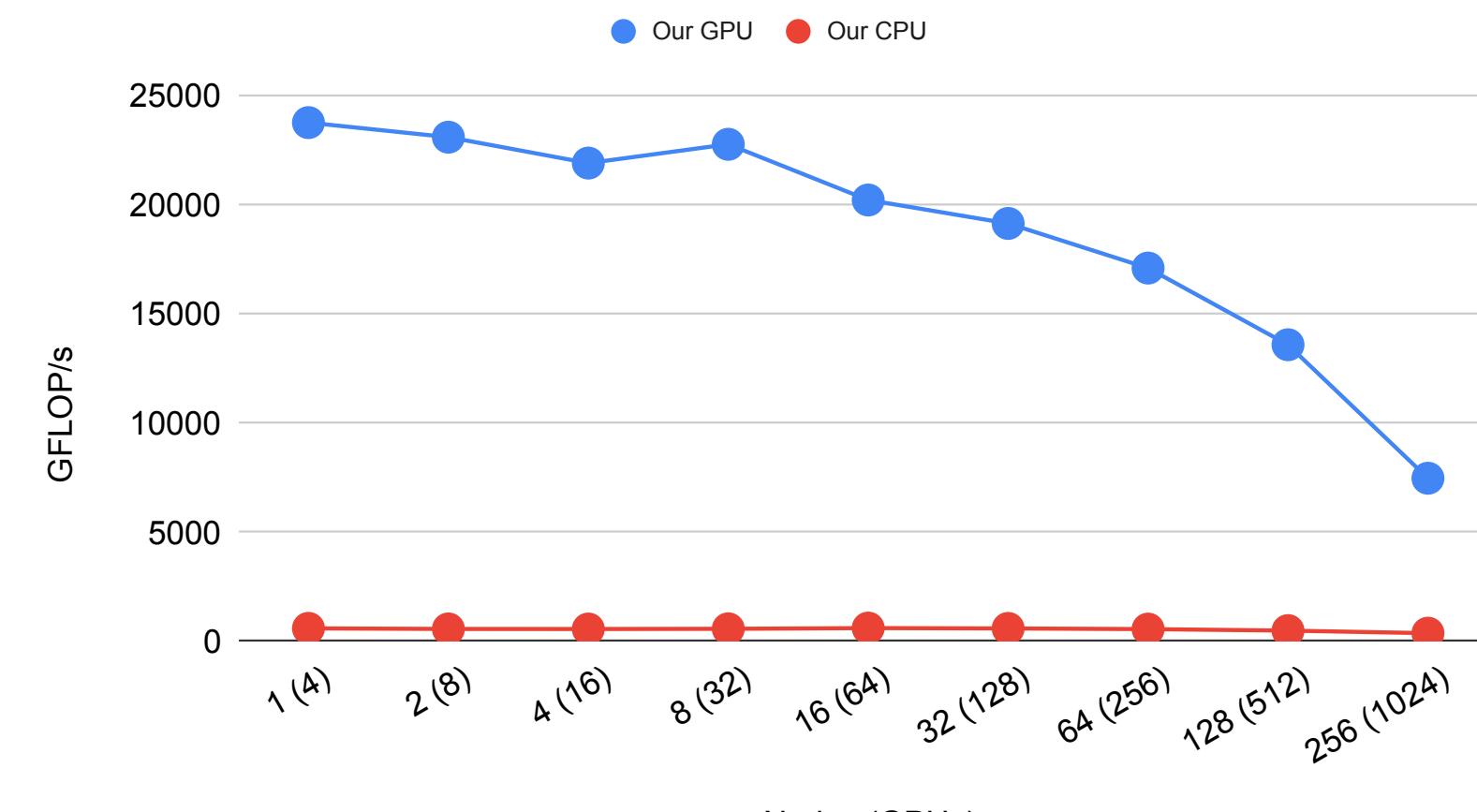
TTM
 $A_{ijl} = B_{ijk} \cdot C_{kl}$



InnerProd
 $a = B_{ijk} \cdot C_{ijk}$



MTTKRP
 $A_{il} = B_{ijk} \cdot C_{jl} \cdot D_{kl}$



Conclusion

DISTAL combines separate specifications of data and computation distribution

DISTAL can represent many existing algorithms

DISTAL can achieve high performance

Future work — extending to sparse tensors.

Vision: distributed implementations of ANY tensor program with ANY tensor formats!

Contact: rohany@cs.stanford.edu

Extra slides

DISTAL

- Decouple computation, performance optimizations, and data distribution
- Extension to TACO

Einsum notation programs



Format-based data distribution



Schedule for compute distribution



Expression

$$A(i,j) = B(i,k) \cdot C(k,j)$$
$$A(i,l) = B(i,j,k) \cdot C(j,l) \cdot D(k,l)$$
$$a = B(i,j,k) \cdot C(i,j,k)$$
$$A(i,j,l) = B(i,j,k) \cdot C(k,l)$$
$$A(i,j) = B(i,j,k) \cdot c(k)$$

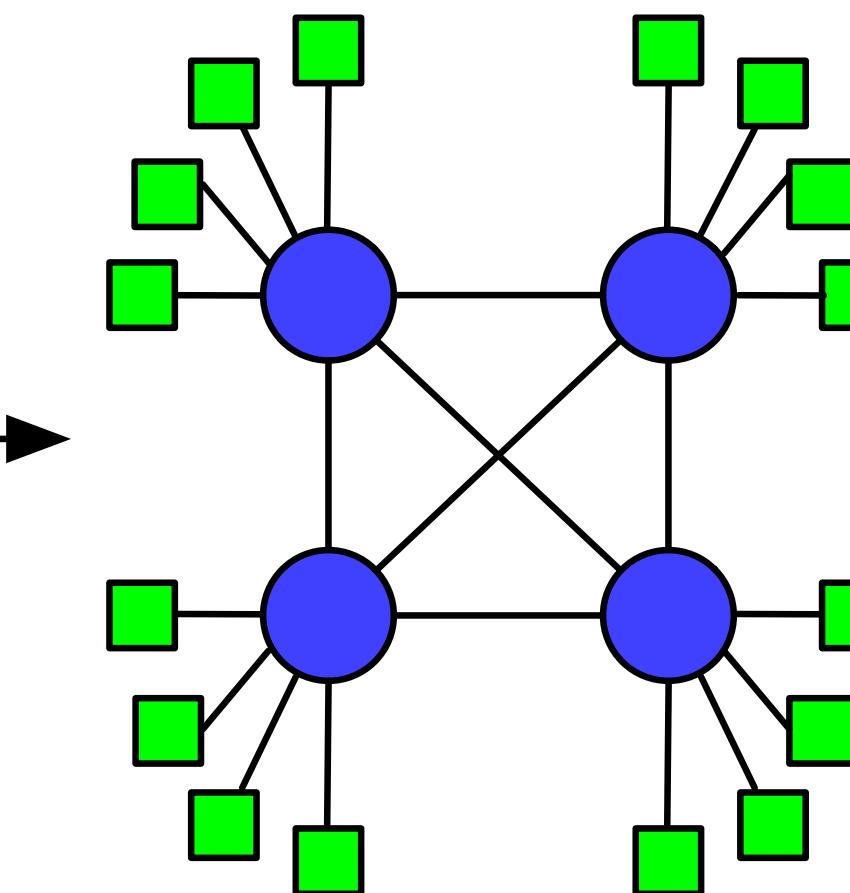
Data Distribution

Partition A into tiles
Replicate B onto all nodes
Place C onto only some nodes

Computation Distribution

Owner Computes
Distribute i,j loops
Communicate in chunks

Supercomputer



CPU
GPU

Too many to code by hand!

Legion

Handles many features necessary for performance on modern machines

- Overlap of communication and computation

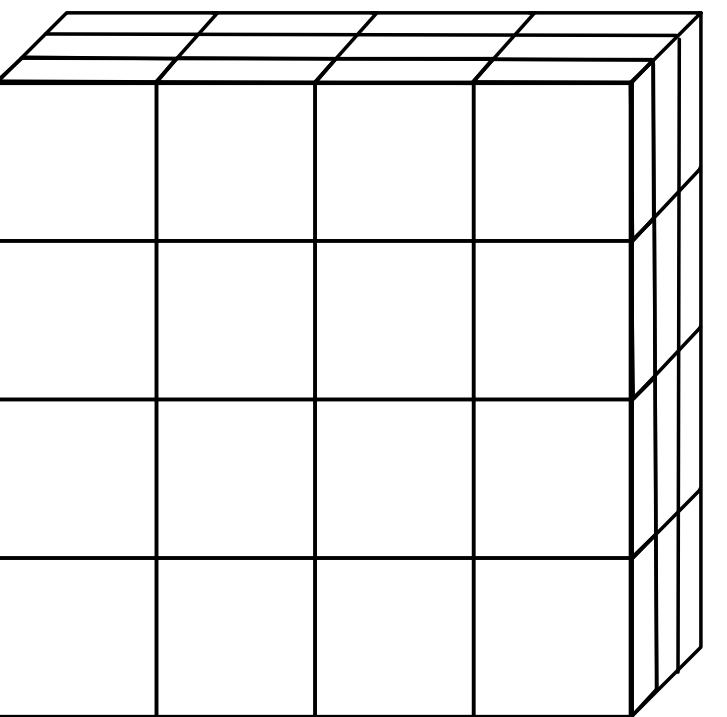
- Data movement through deep memory hierarchies

- Native support for accelerators

- Control over placement of computation and data

Legion API

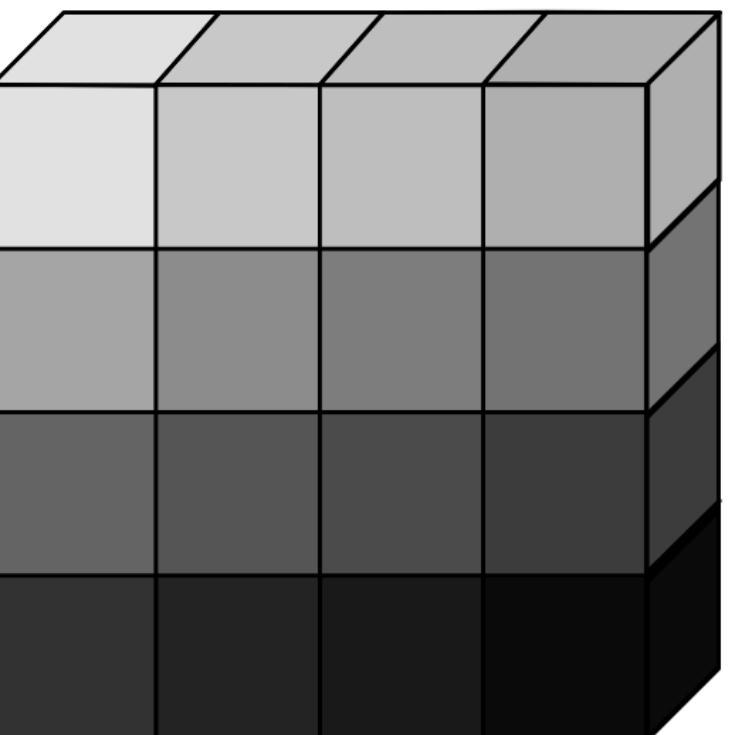
Regions



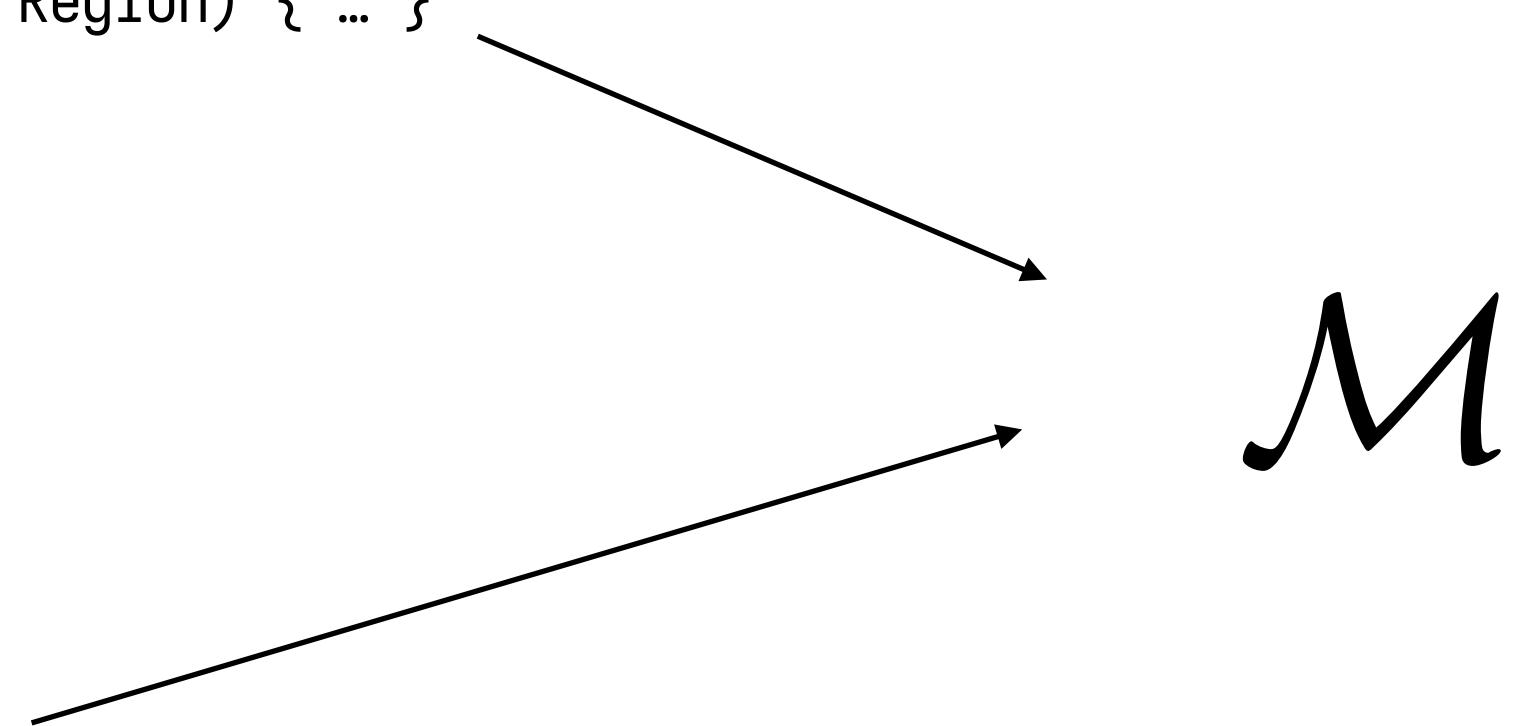
Tasks

```
void task(r1 : Region, r2 : Region, r3 : Region) { ... }
```

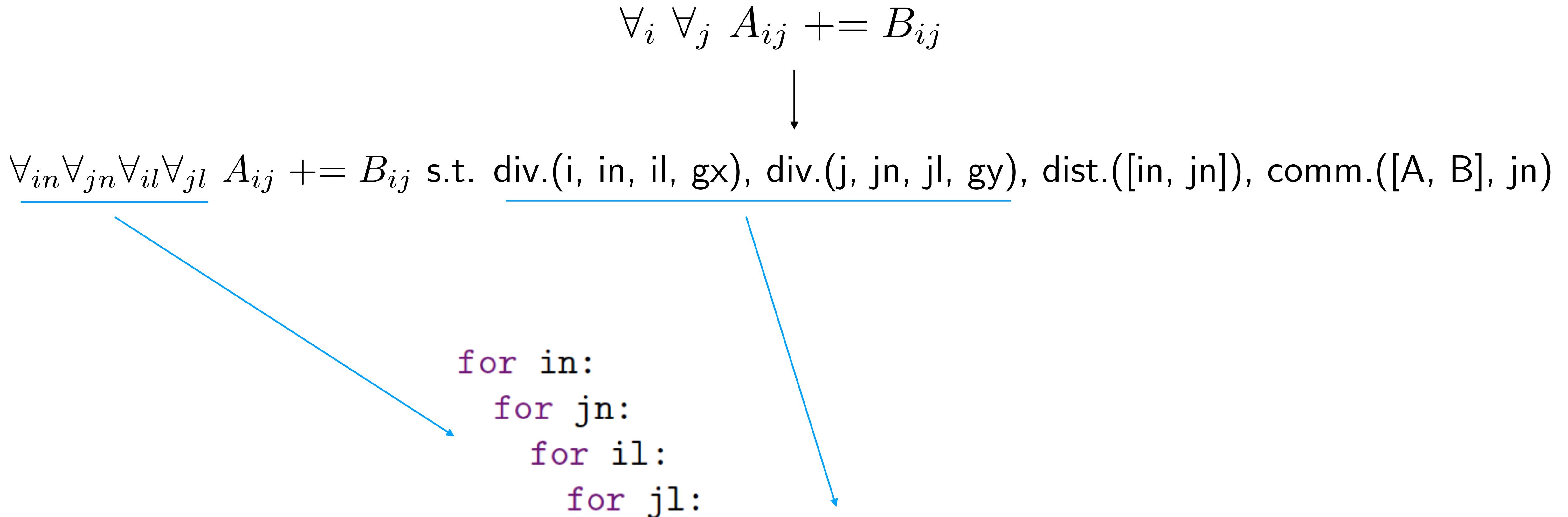
Partitions



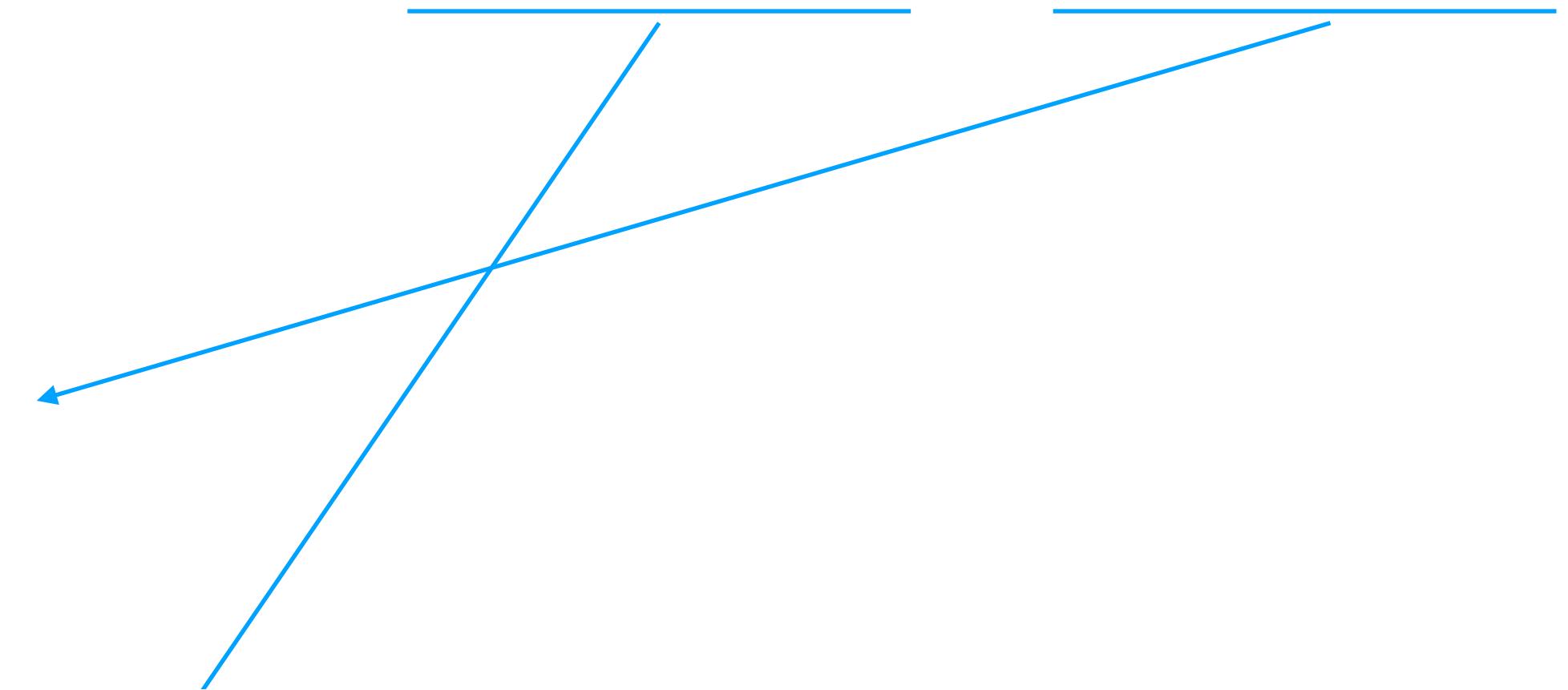
Mapping



Lowering Concrete Index Notation to Legion

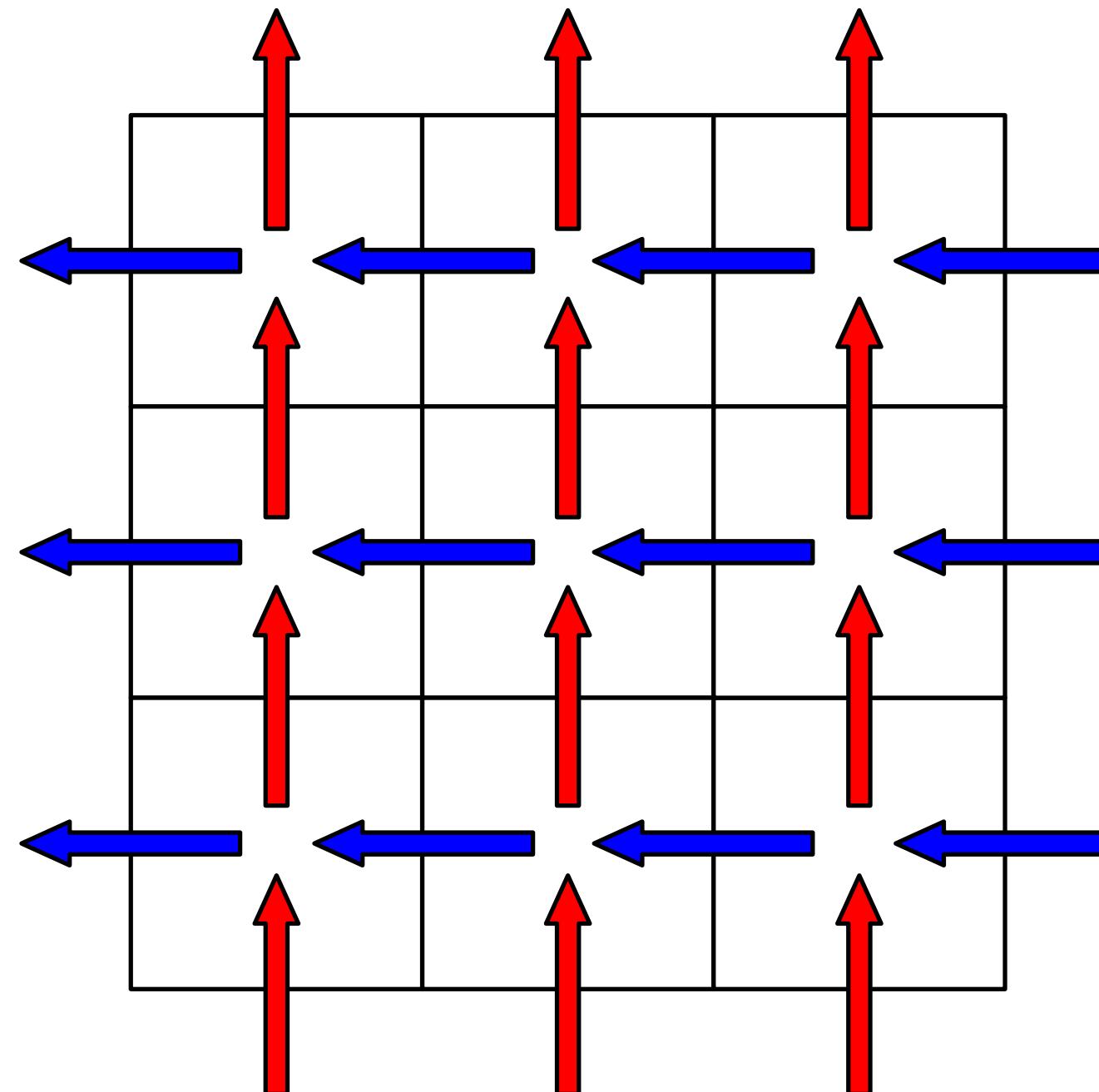


Lowering Concrete Index Notation to Legion

$$\forall_{in} \forall_{jn} \forall_{il} \forall_{jl} \ A_{ij} += B_{ij} \text{ s.t. } \text{div.}(i, in, il, gx), \text{div.}(j, jn, jl, gy), \text{dist.}([in, jn]), \text{comm.}([A, B], jn)$$


```
index for in:  
    A      for jn:  
    B      for il:  
    for jl:  
        i = in * (il.hi - il.lo) + il  
        j = jn * (jl.hi - jl.lo) + jl  
        A(i, j) += B(i, j)
```

Cannon's Algorithm



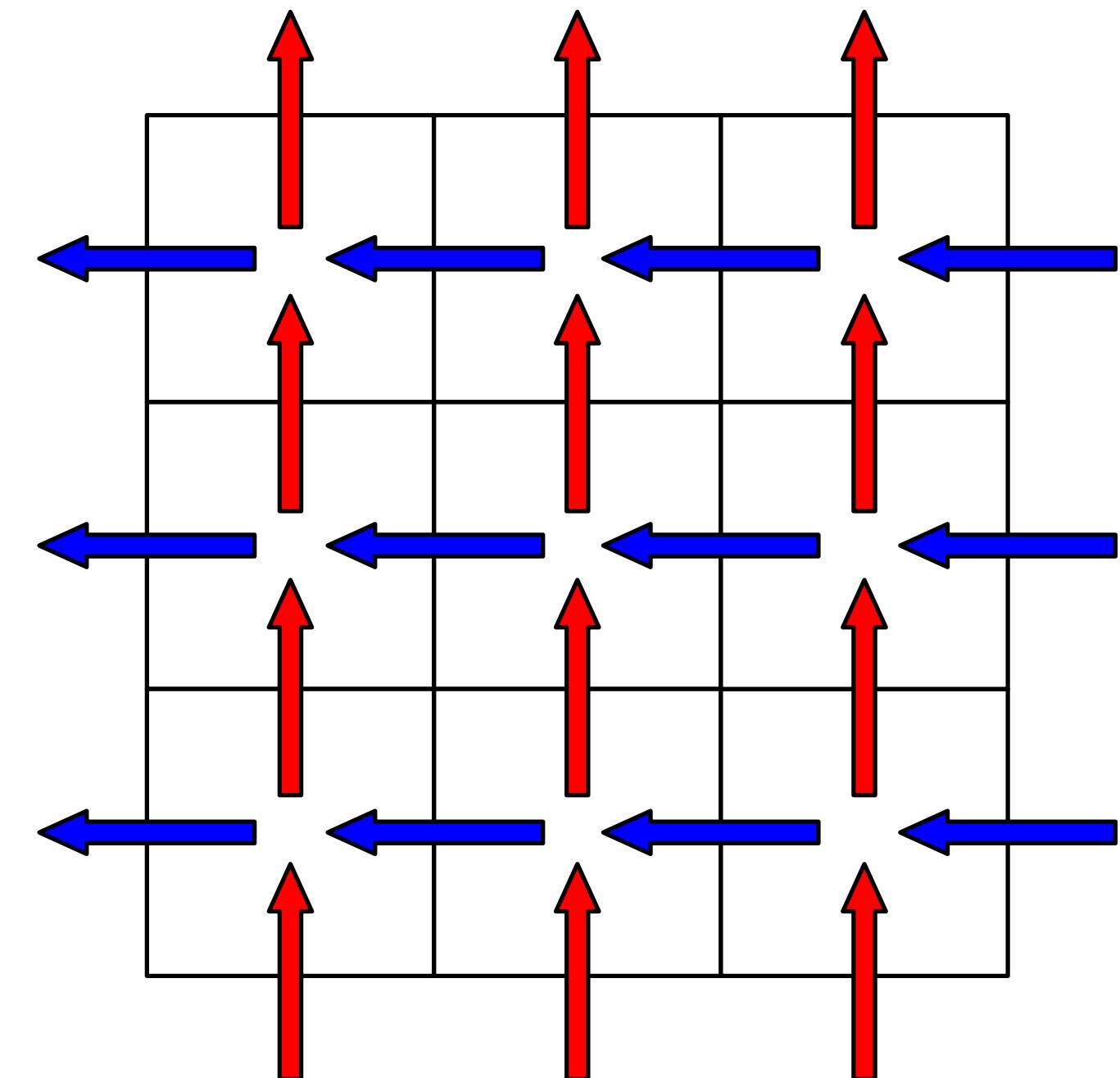
```
# Arrange  $p$  processors into a 2D grid,  $\sqrt{p} \times \sqrt{p}$ .  
# Assign a tile of  $A$ ,  $B$ ,  $C$  to each processor.  
# Perform an initial data shift.  
for all  $P_{ij}$  in parallel:  
    shift  $B_{ij}$   $i$  spaces to the left  
    shift  $C_{ij}$   $j$  spaces upwards  
for all  $P_{ij}$  in parallel:  
    for  $k$  in  $(0, \sqrt{p})$ :  
         $A_{ij} += B_{ij} * C_{ij}$   
        shift  $B_{ij}$  to the left  
        shift  $C_{ij}$  upwards
```

```

distributed for in, jn:
communicate A
for ko:
    communicate B, C
    for il:
        for jl:
            for ki:
                A(i, j) += B(i, k) * C(k, j)

```

divide(i, il, in, gx)
divide(j, jl, jn, gx)
reorder({in, jn, il, jl})
split(k, ko, ki, chunkSize)
reorder(ko, il, jl, ki)
distribute(in, jn)
communicate(A, jn)
communicate({B, C}, ko)



```

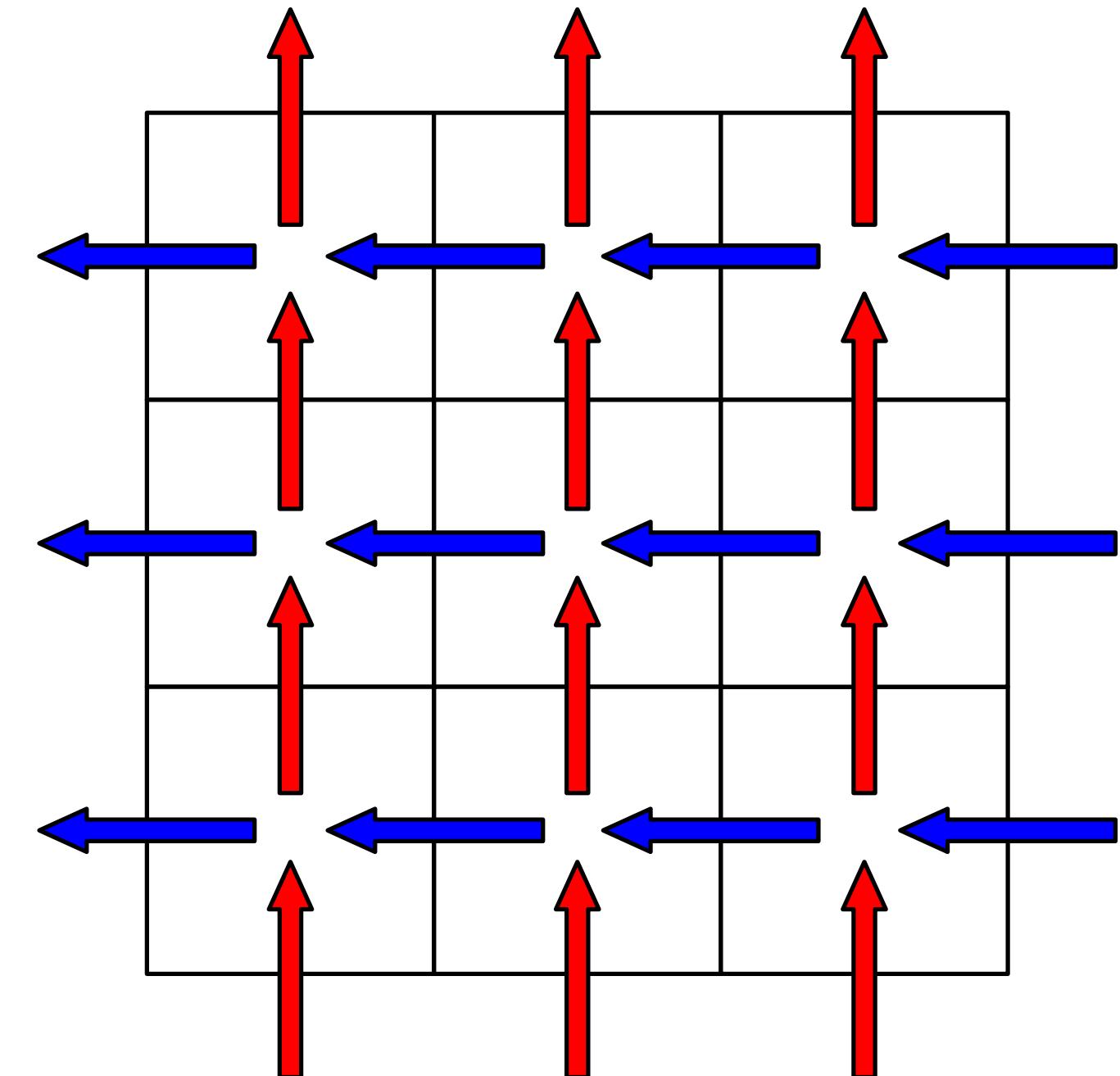
distributed for in, jn:
communicate A
for kr:
    communicate B, C
    for il:
        for jl:
            for ki:
                A(i, j) += B(i, k) * C(k, j)

```

```

divide(i, in, il, gx)
divide(j, jn, jl, gy)
divide(k, ko, ki, gx)
rotate(ko, {in, jn}, kr)
reorder({in, jn, kr, il, jl, ki})
distribute(in, jn)
communicate(A, jn)
communicate({B, C}, kr)

```

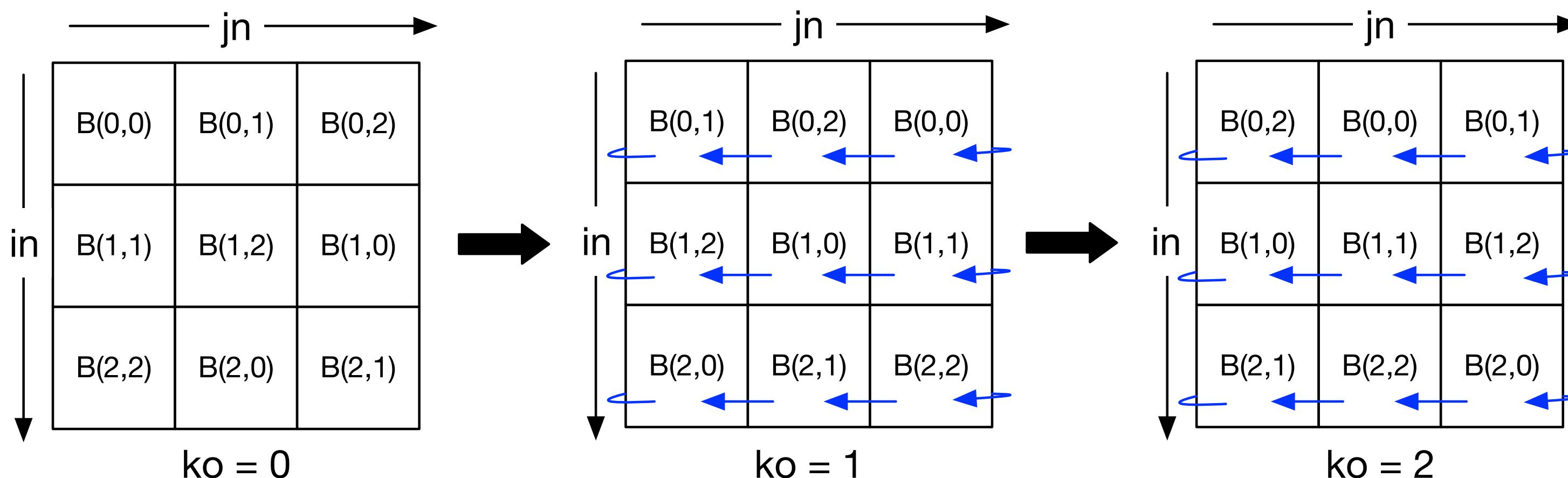


Emergence of systolic communication

$$A(i, j) = B(i, k) * C(k, j)$$

$$kr = ko + in + jn \bmod 3$$

distributed for in, jn:
communicate A
for kr:
communicate B, C
for il:
for jl:
for ki:
 $A(i, j) += B(i, k) * C(k, j)$



GEMM (CPU)

