



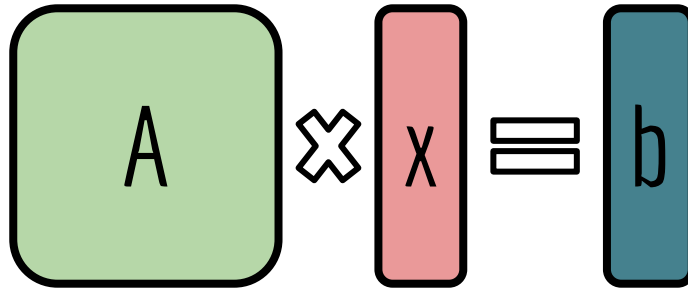
# High Performance Computing Project

Abdurahman Kanit Bensaidi, Louis Peyrondet,  
Kévin Shao & Alexandre Tabouret



# Context

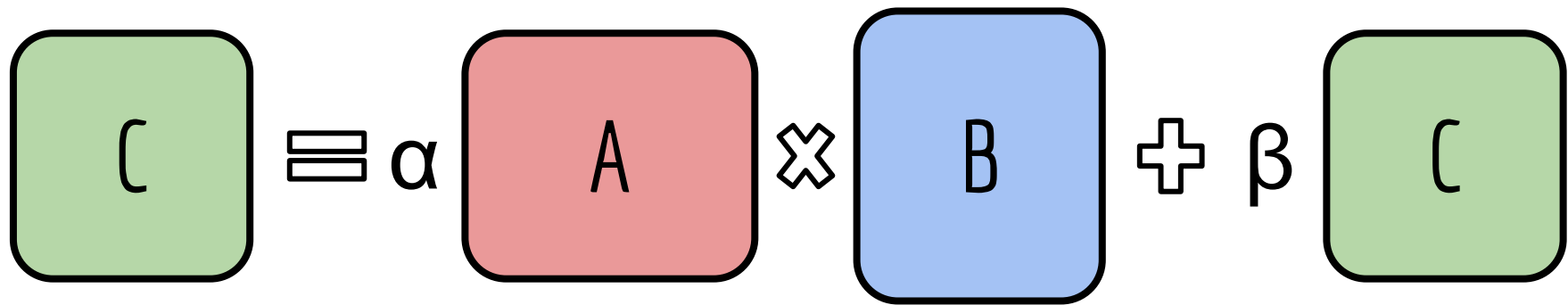
Goal: Solve



A diagram illustrating a linear equation. It consists of three main components: a green rounded square containing the letter 'A', a red rounded rectangle containing the letter 'x', and a blue rounded rectangle containing the letter 'b'. These are connected by a multiplication symbol '×' and an equals sign '≡'. The entire equation is rendered in a stylized, hand-drawn font.

$$A \times x = b$$

# GEMM (GEneral Matrix Multiplication)



C has size of  $M \times N$

A has size of  $M \times K$  B has size of  $K \times N$

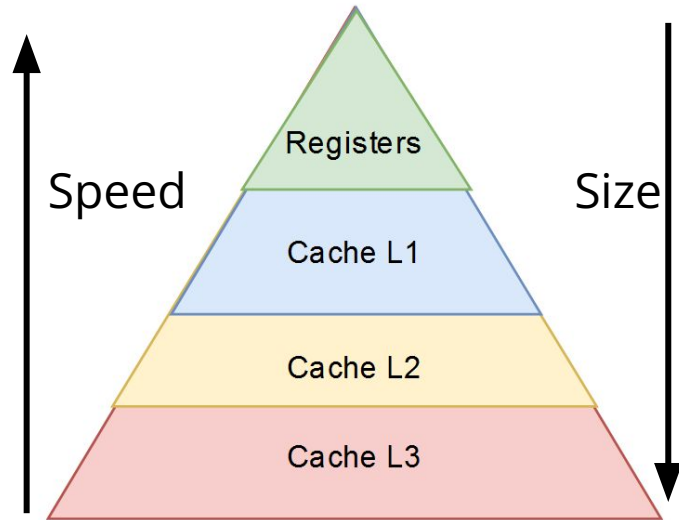
# GEMM : Kernels

The goal of a kernel is to be do an operation very efficiently on a small subset of the problem.

We just have to divide our big problem into multiple smaller ones and apply the kernel on them.

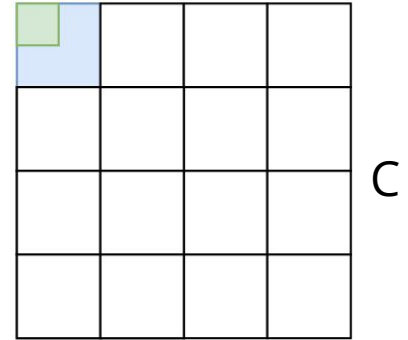
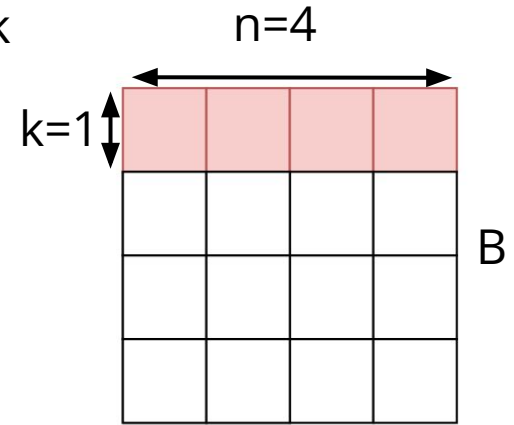
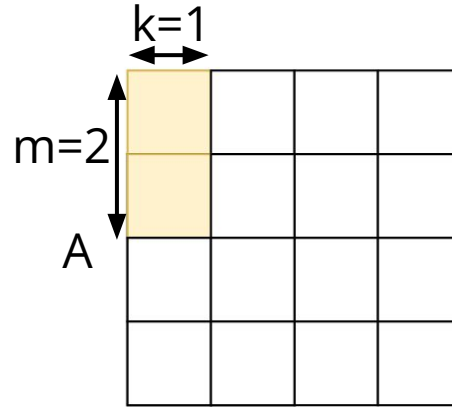
# GEMM : Blocks

Goal : Maximize cache utilization



Blocks of sizes  $m, n, k$

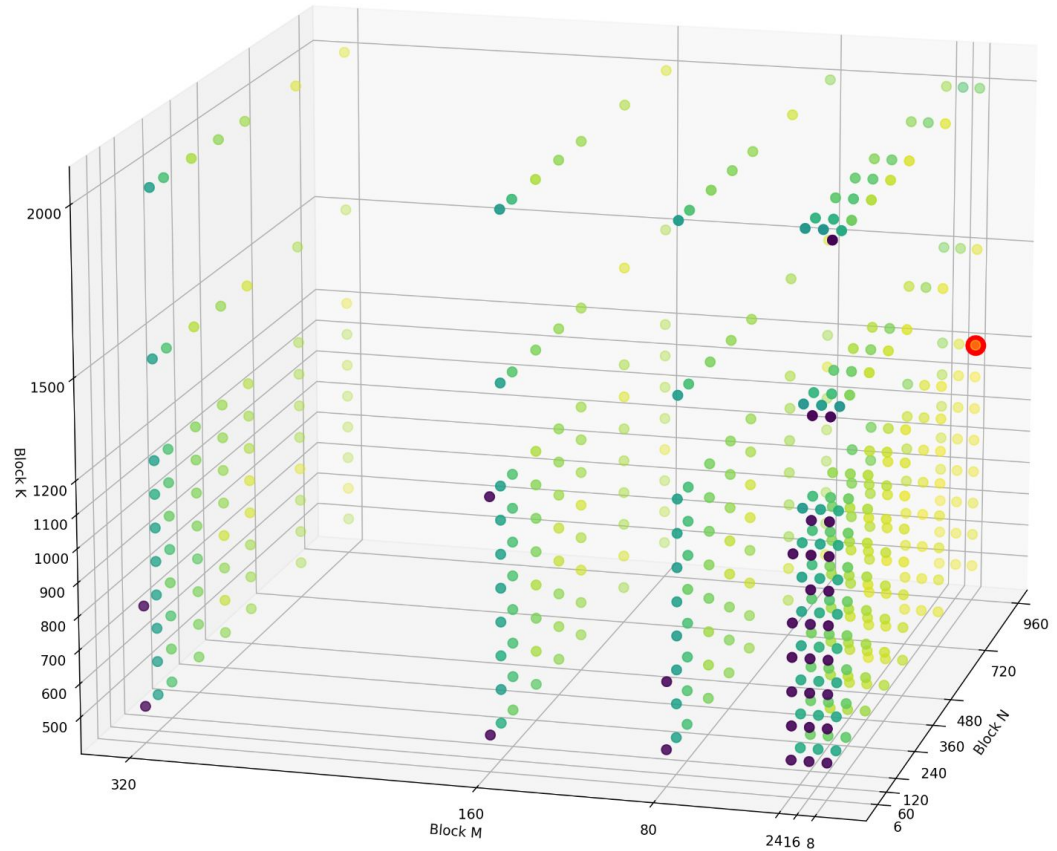
for blocks in B:  
for blocks in A:  
for kernels



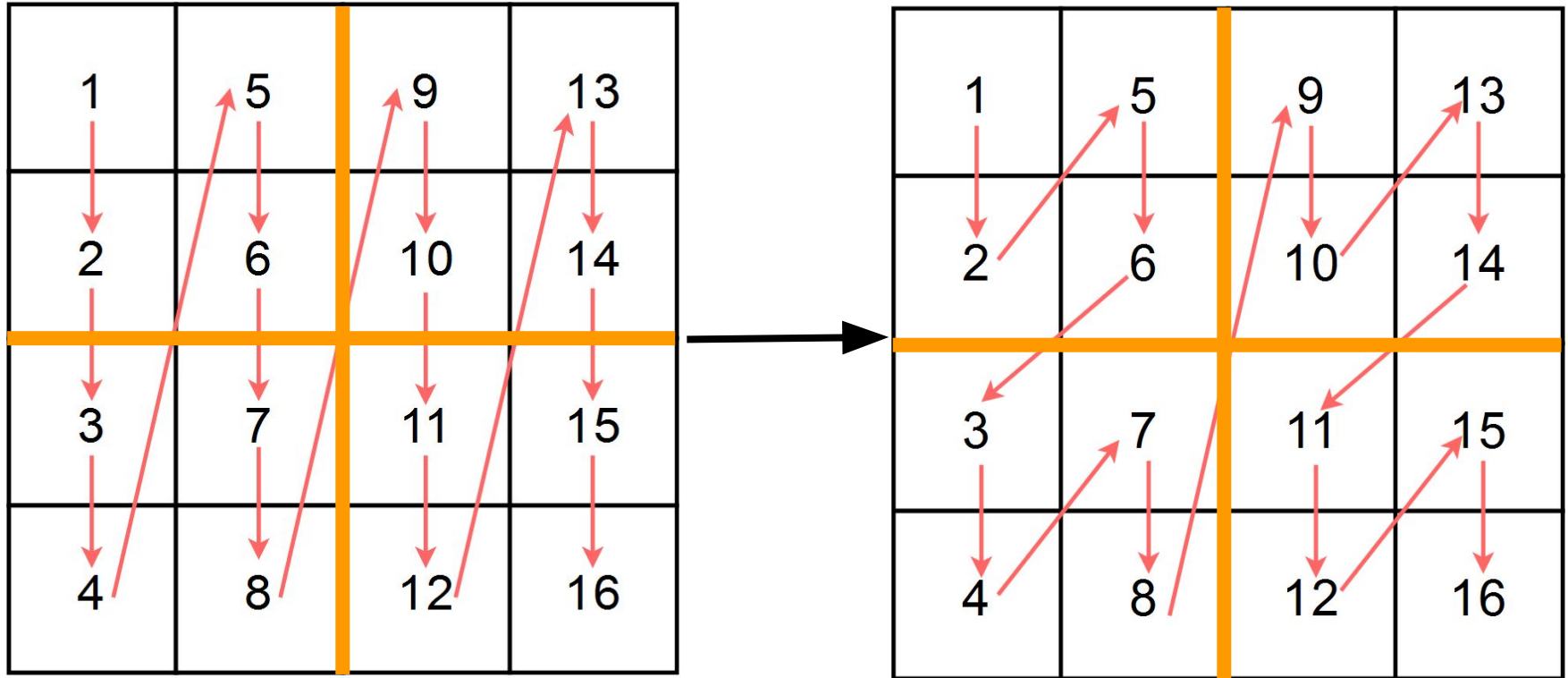
# GEMM : Blocks

In practice slightly  
tweaked block sizes gives  
better performances

$M=8$ ,  $K=1200$ ,  $N=960$

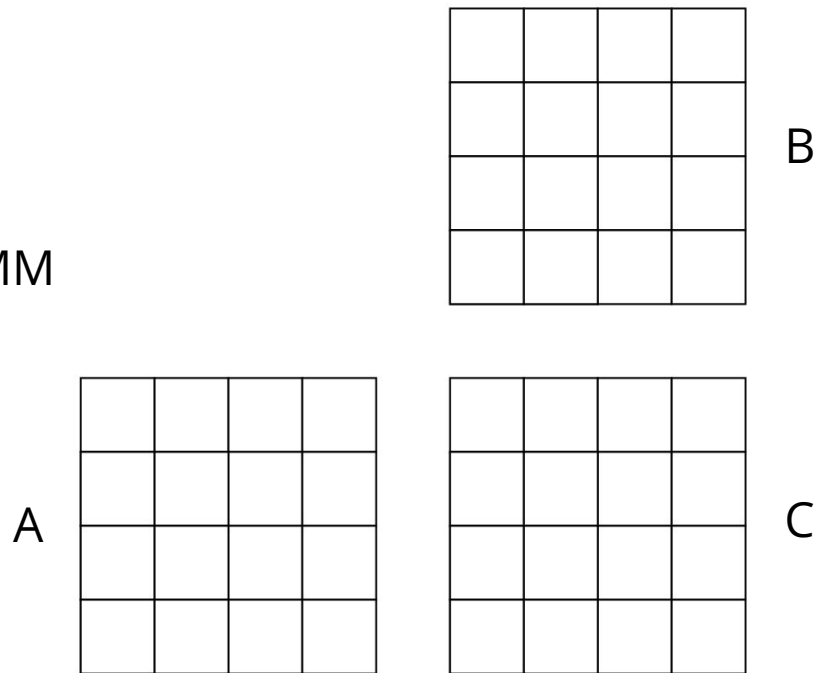


# GEMM : Packing to optimize the memory layout



# GEMM : Kernels

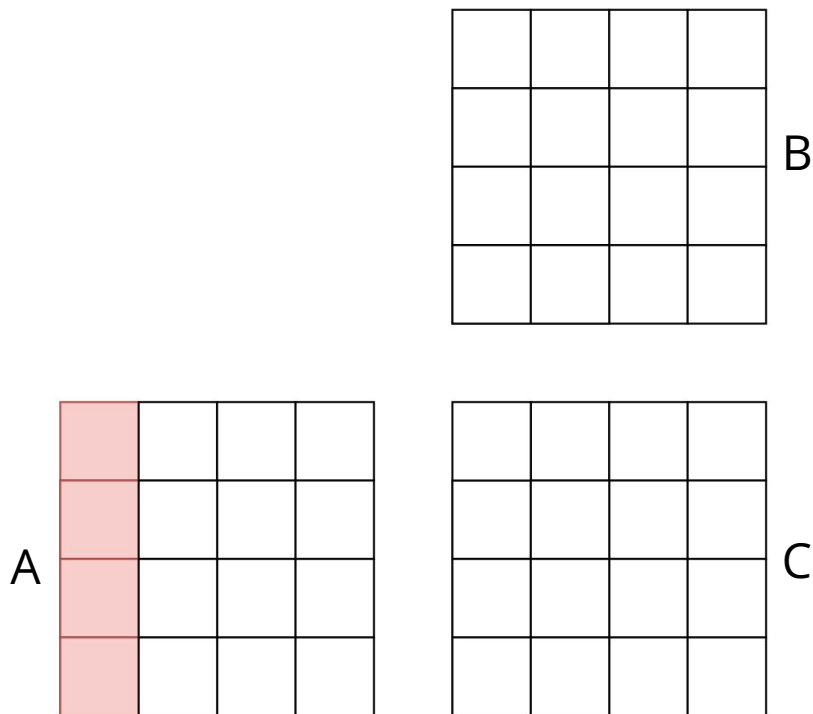
4\*4 kernel for GEMM



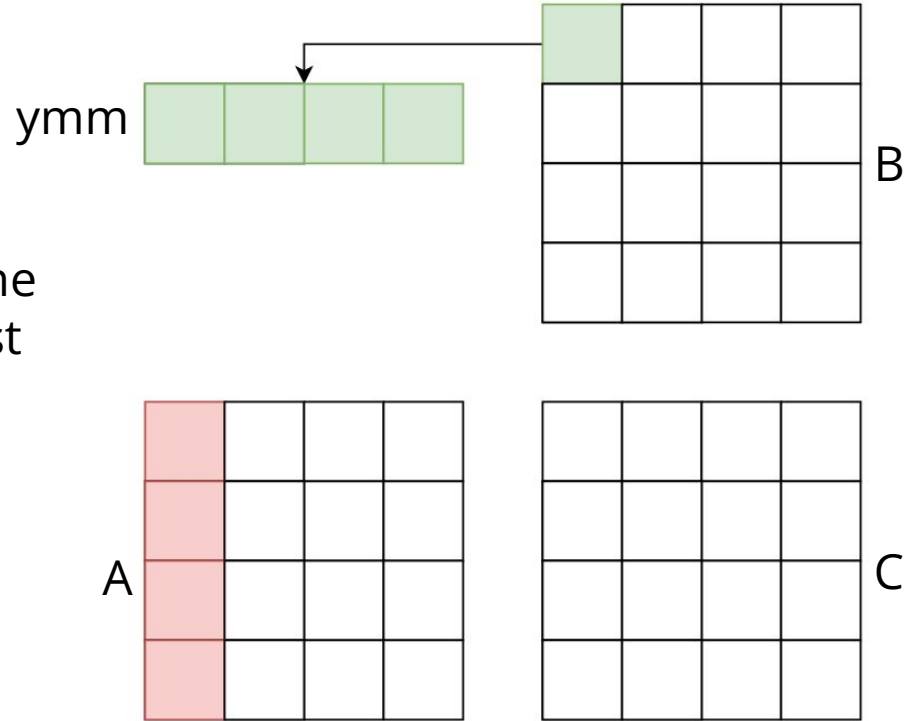


# GEMM : Kernels

Load first column of A



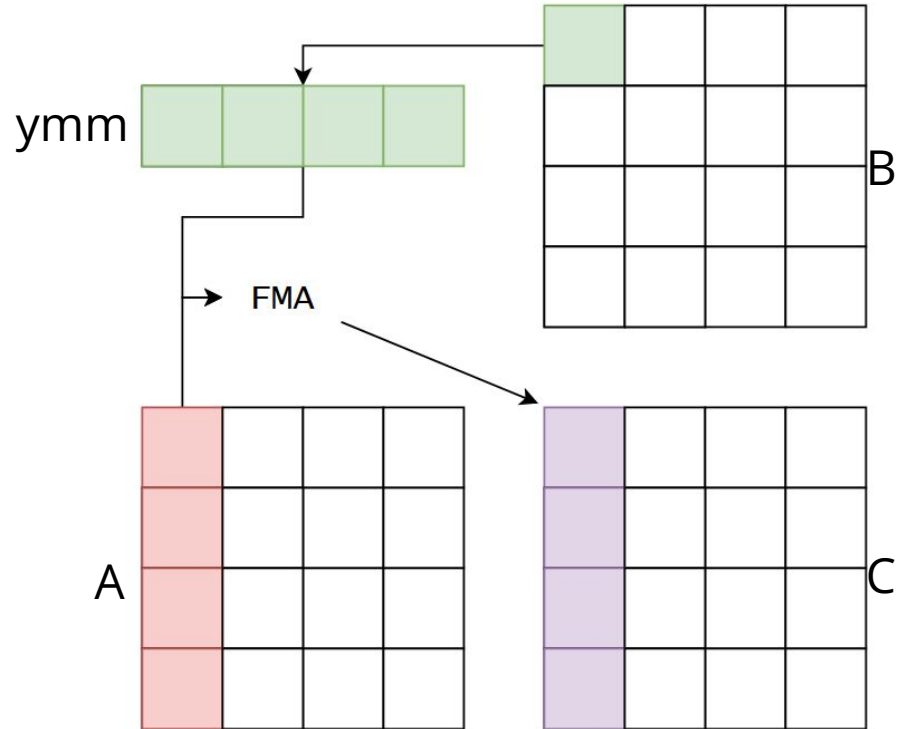
# GEMM : Kernels



Fill a register with the first value of the first row of B

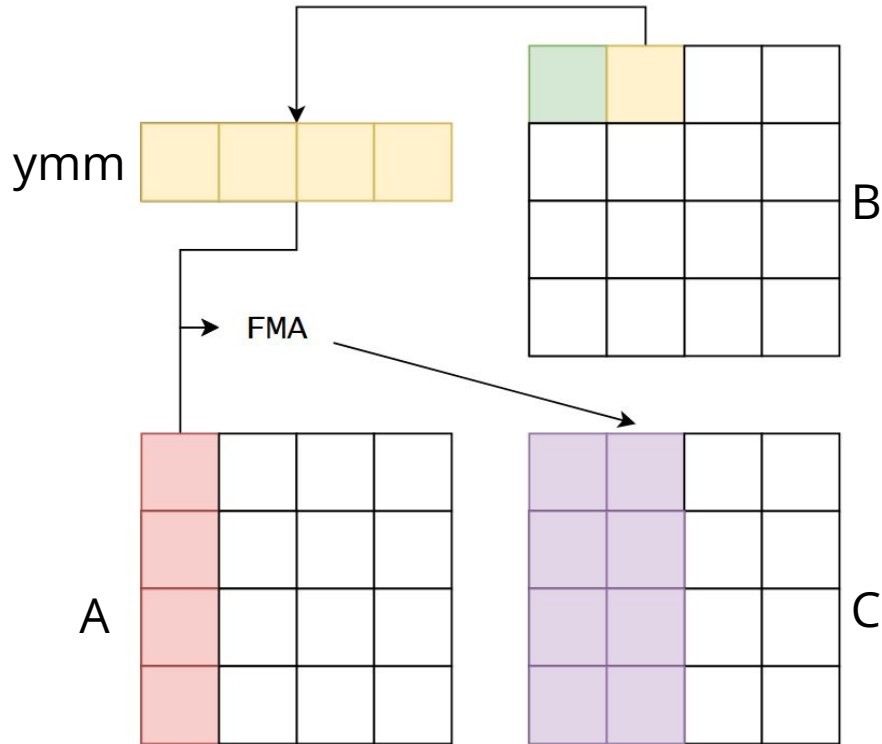
# GEMM : Kernels

FMA the 2 registers  
into C



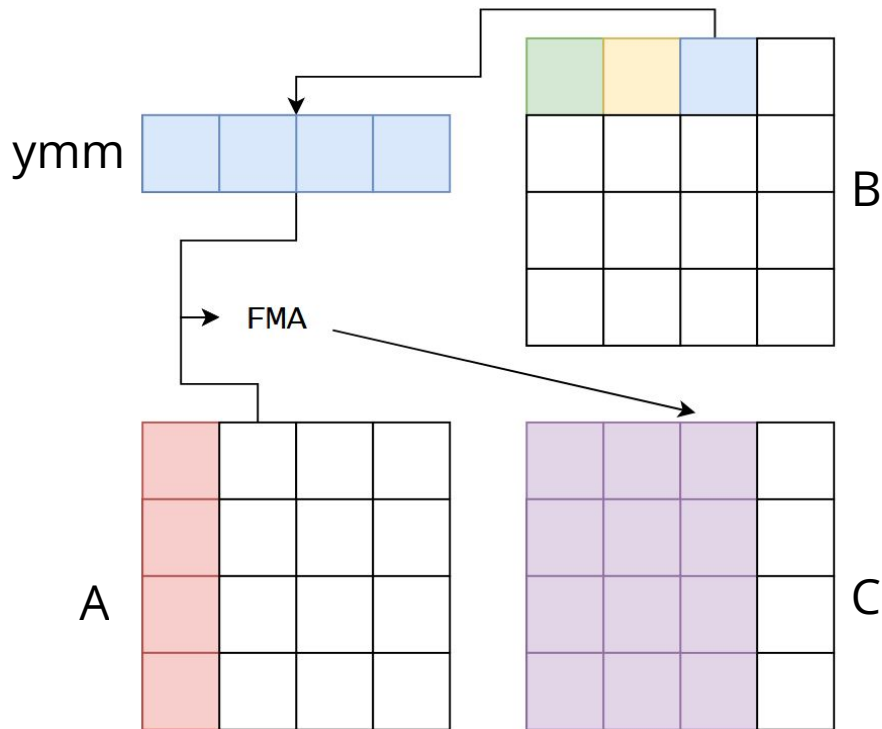
# GEMM : Kernels

Get the next value in the row of B



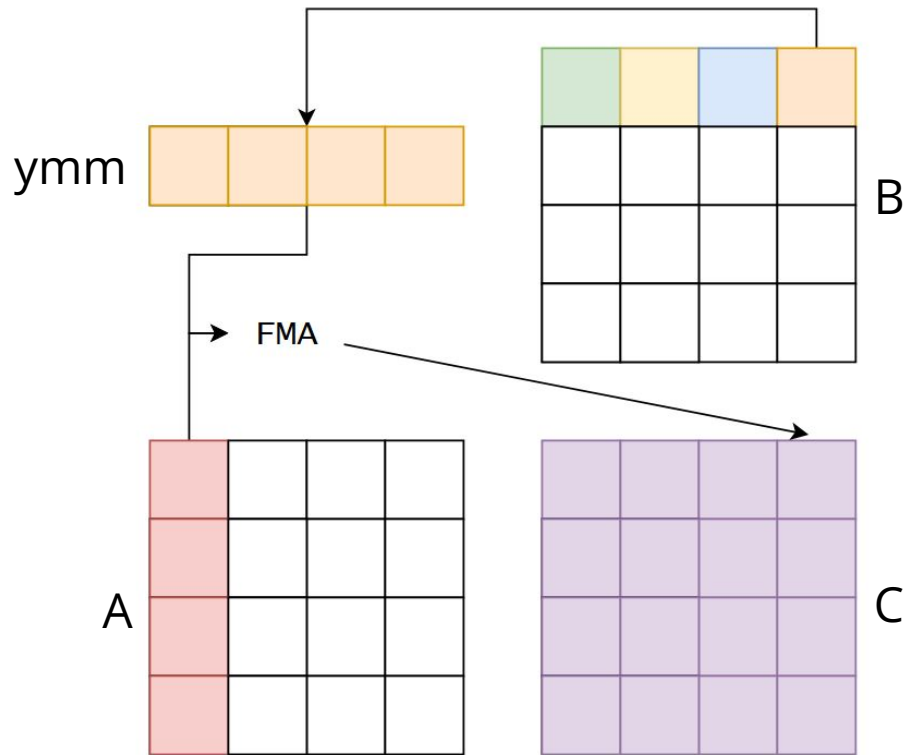
# GEMM : Kernels

Again



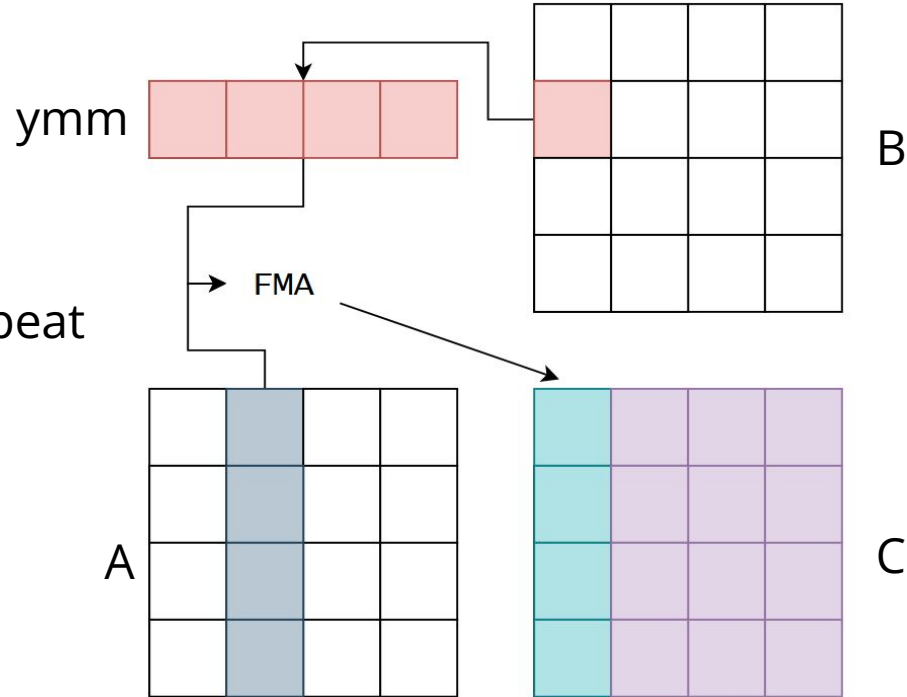
# GEMM : Kernels

And again



# GEMM : Kernels

Then load the next  
column of A and repeat



# GEMM : Kernels

The kernel should maximise the amount of registers used.  
Haswell processors have 16 ymm registers.

We chose a kernel  $m \times n$  of size  $8 \times 6$  :

- 1 register for the B value
- 2 registers for the column of A (8 elements)
- 12 registers to load C (48 elements)
  - 15 out of 16 register used



# GEMM : Kernels

*"We don't care about implementation details"*

In this case, we **DO** care : that's what makes the difference

Not shown :  
Unroll x4

kernel8x6\_asm:

.LOOP\_K:

# Load A matrix

vmovapd (%rdi), %ymm12 # Load A[0:3]

vmovapd 32(%rdi), %ymm13 # Load A[4:7]

prefetcht0 512(%rdi) # Prefetch 2 4-unroll iterations ahead for A

prefetcht0 576(%rdi)

prefetcht0 640(%rdi)

prefetcht0 704(%rdi)

prefetcht0 384(%rsi) # Prefetch 2 4-unroll iterations ahead for B

prefetcht0 432(%rsi)

prefetcht0 480(%rsi)

prefetcht0 528(%rsi)

# Broadcast B matrix elements and multiply

vbroadcastsd (%rsi), %ymm14 # Broadcast B[0]

vbroadcastsd 8(%rsi), %ymm15 # Broadcast B[1]

vfmadd231pd %ymm12, %ymm14, %ymm0 # C += A \* B[0]

vfmadd231pd %ymm13, %ymm14, %ymm1

vfmadd231pd %ymm12, %ymm15, %ymm2

vfmadd231pd %ymm13, %ymm15, %ymm3

vbroadcastsd 16(%rsi), %ymm14 # Broadcast B[2]

vbroadcastsd 24(%rsi), %ymm15 # Broadcast B[3]

vfmadd231pd %ymm12, %ymm14, %ymm4

vfmadd231pd %ymm13, %ymm14, %ymm5

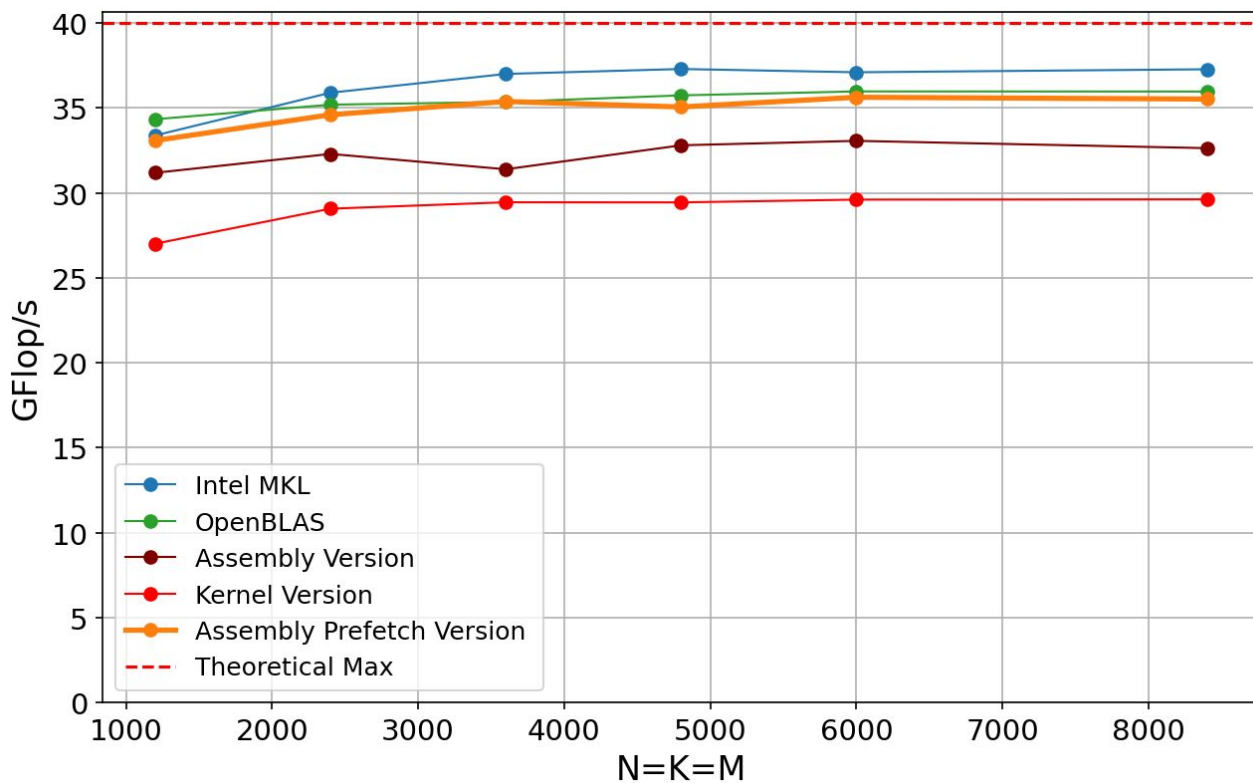
vfmadd231pd %ymm12, %ymm15, %ymm6

vfmadd231pd %ymm13, %ymm15, %ymm7

# Repeat for the other columns ...

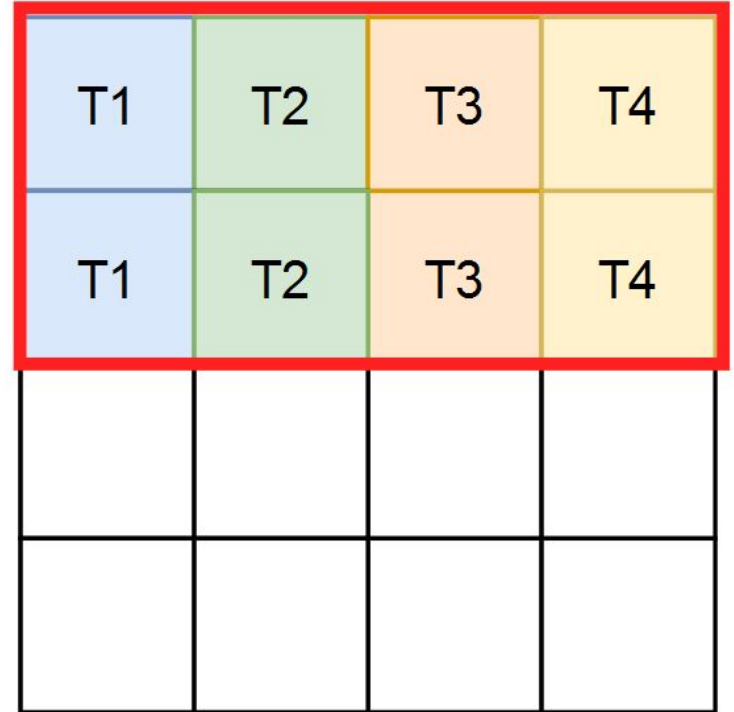
# GEMM : Performances

- Reaches **performance equivalent to OpenBLAS** and 95% of IntelMKL
- Using assembly allow explicit control over register spilling
- Works for every kind of matrices
- A and/or B transposed doesn't affect performances



# GEMM : Multithreading

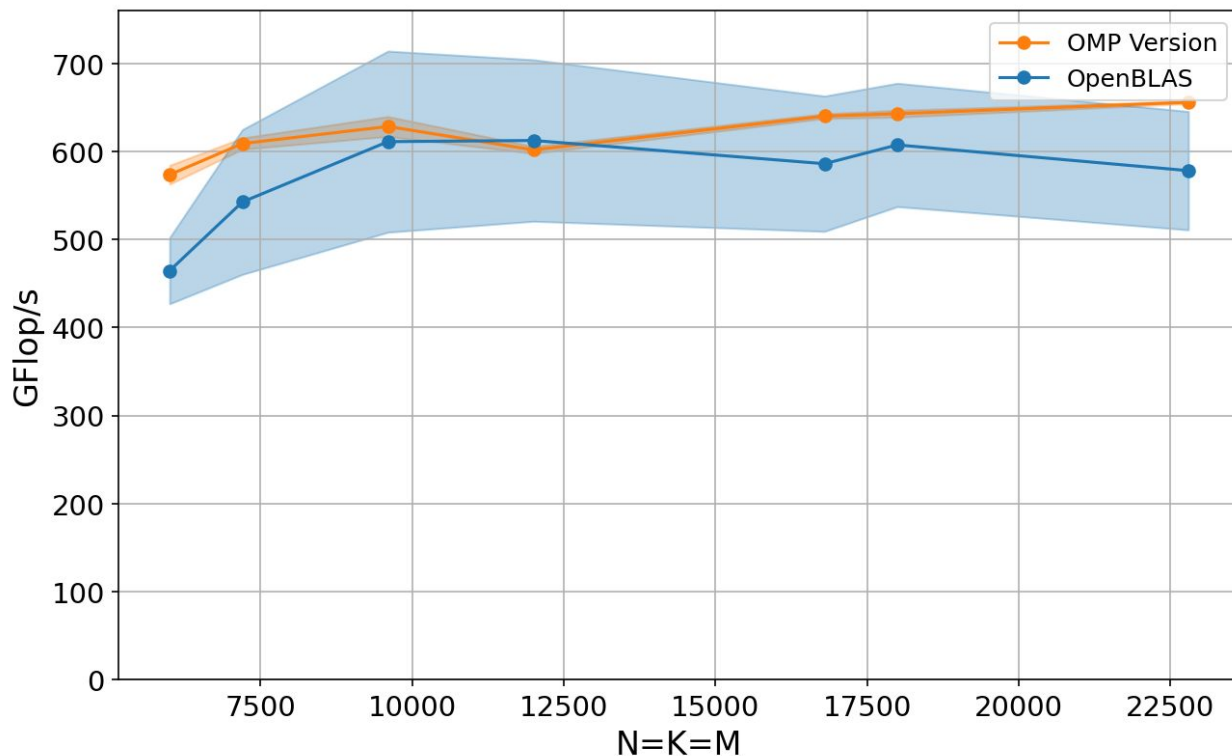
- Multithreading using OpenMP
- Dispatch threads to each compute a group of kernels inside a block
- Each thread have the same amount of work



# GEMM : Multithreading

Our implementation :

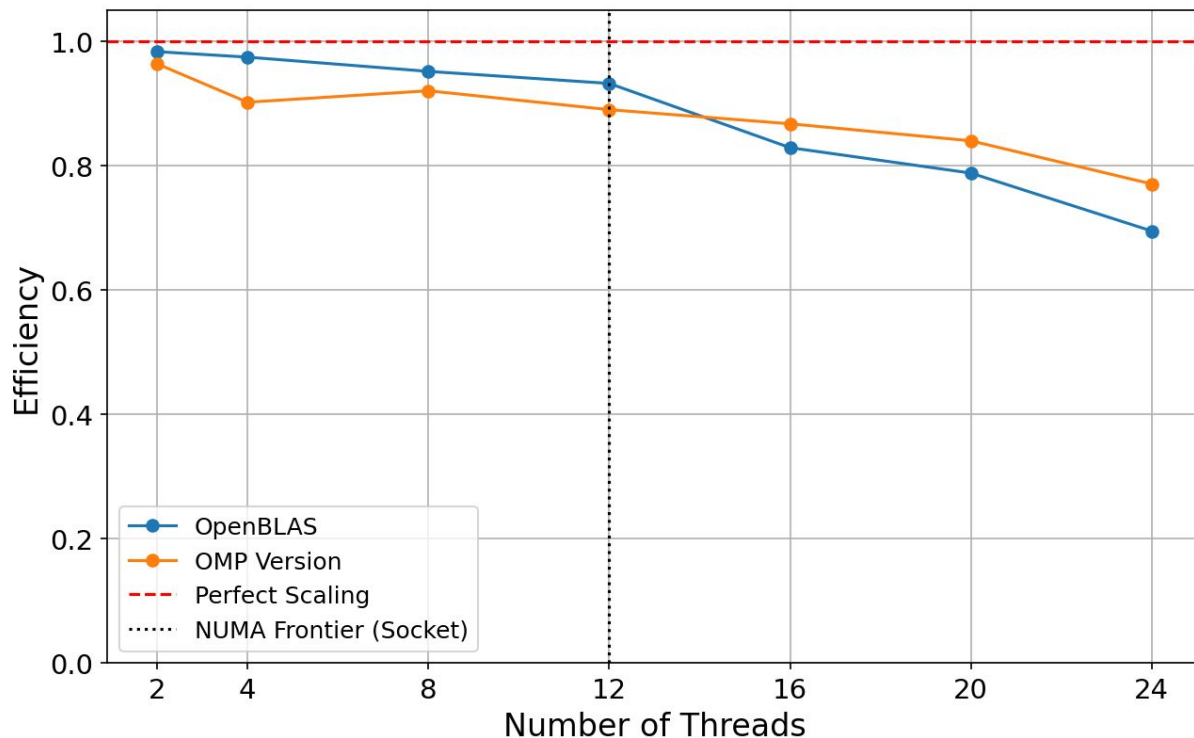
- Beats OpenBLAS with 650 GFlop/s
- Achieves a small standard deviation (8 GFlop/s vs 75 GFlop/s)



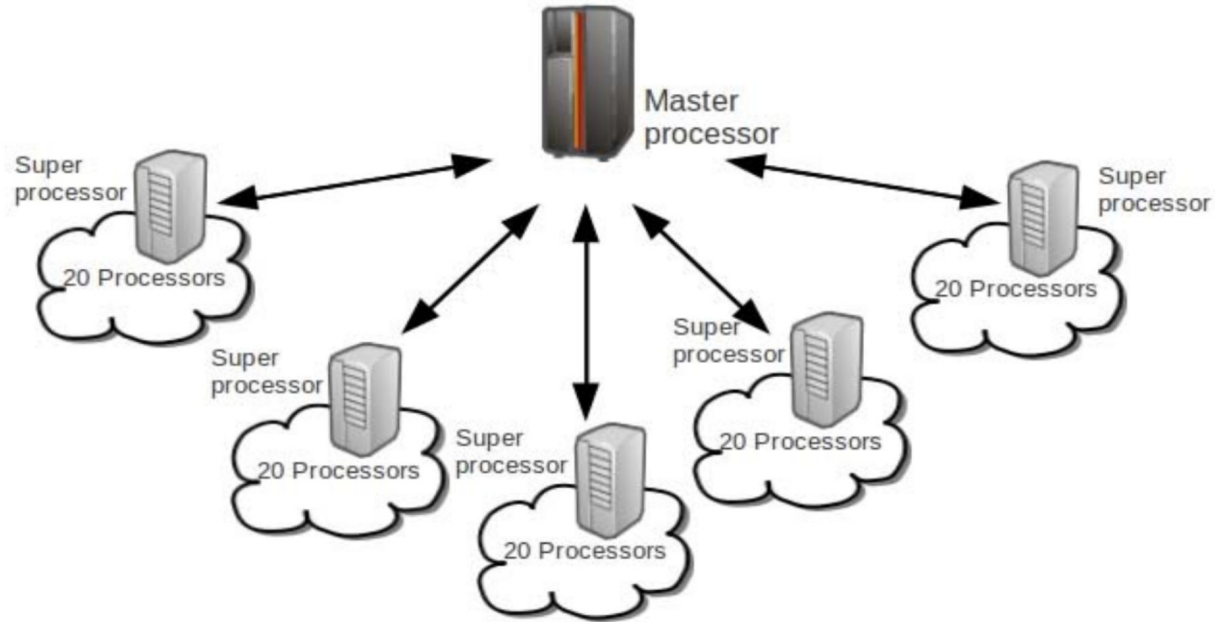
# GEMM : Multithreading efficiency

Matrix N=M=K=16800

- Better efficiency than OpenBLAS for threads  $\geq 16$
- OpenBLAS impacted by NUMA
- Could achieve better efficiency



# GEMM : Distributed version



# GEMM : Giving data to each node

1	2	1	2
3	4	3	4
1	2	1	2
3	4	3	4

1	2	1	2
3	4	3	4
1	2	1	2
3	4	3	4

1	2	1	2
3	4	3	4
1	2	1	2
3	4	3	4

# GEMM : Giving data to each node

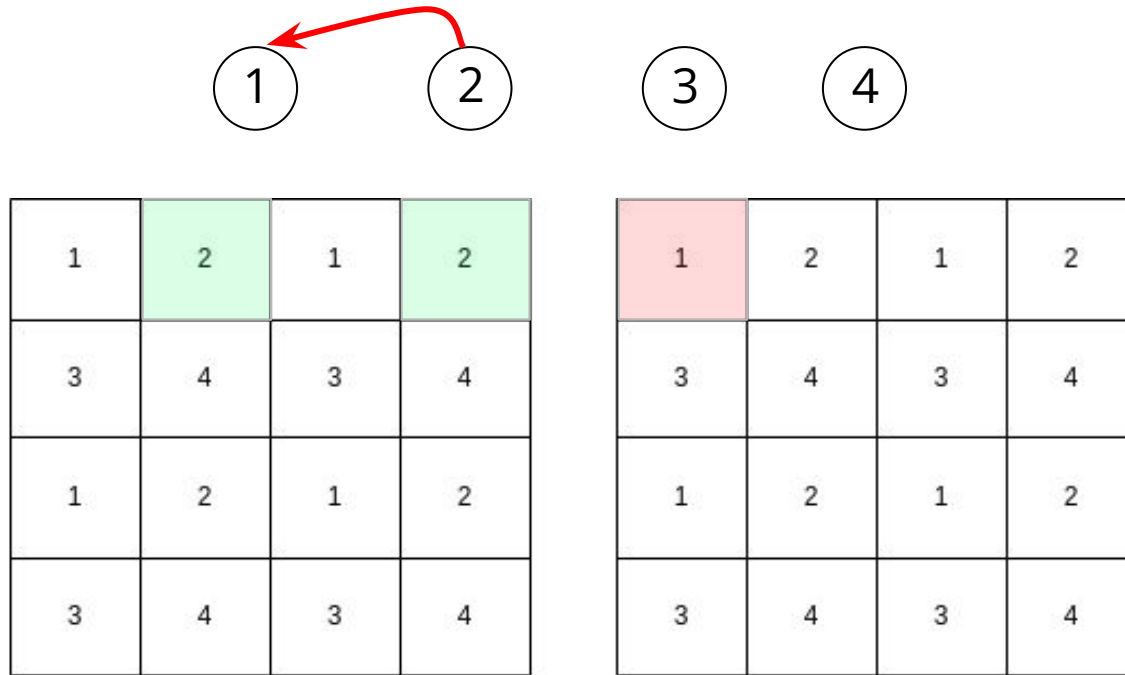
1	2	1	2
3	4	3	4
1	2	1	2
3	4	3	4

1	2	1	2
3	4	3	4
1	2	1	2
3	4	3	4

1	2	1	2
3	4	3	4
1	2	1	2
3	4	3	4



# GEMM : Giving data to each node



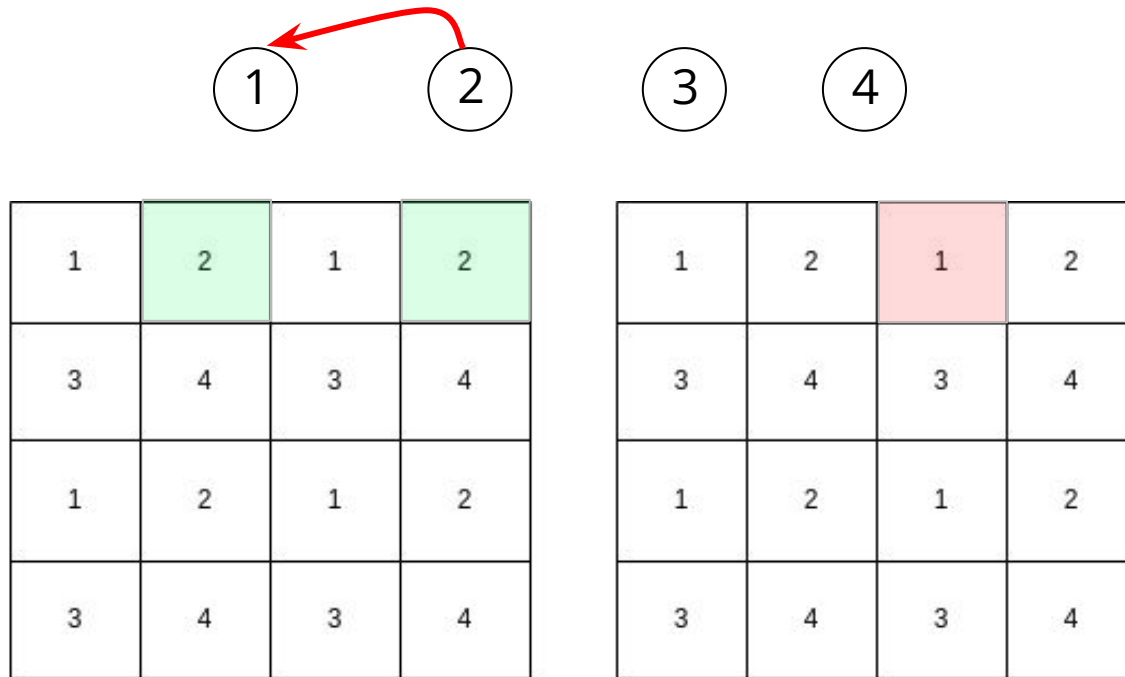
# GEMM : Giving data to each node

1	2	1	2
3	4	3	4
1	2	1	2
3	4	3	4

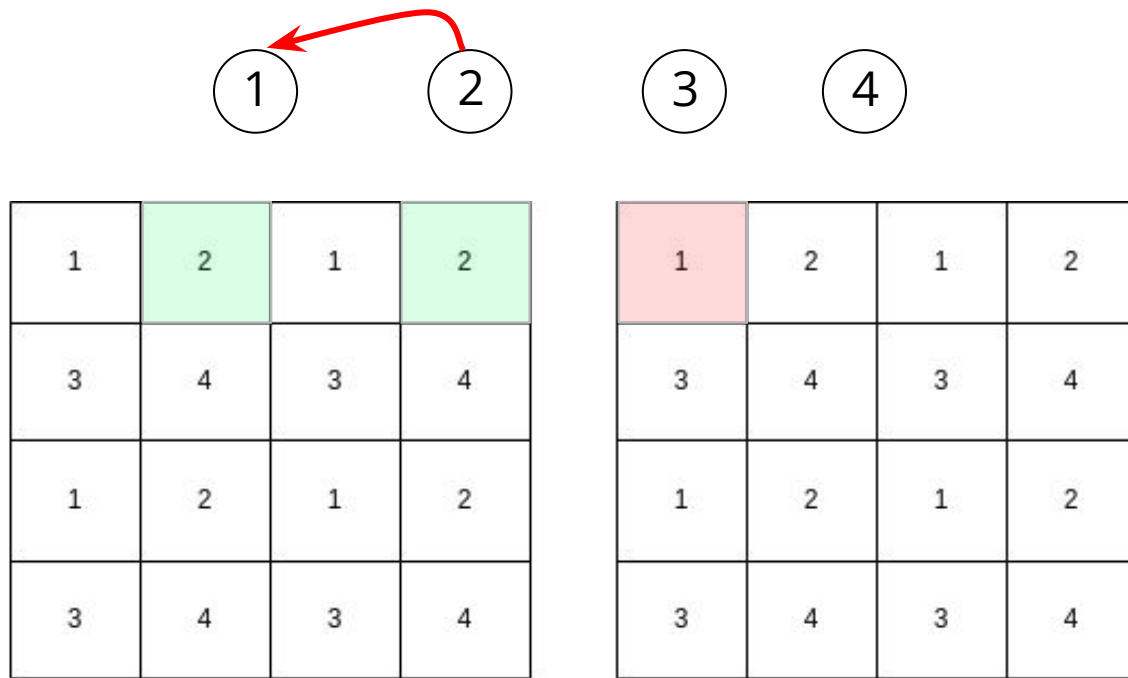
1	2	1	2
3	4	3	4
1	2	1	2
3	4	3	4

1	2	1	2
3	4	3	4
1	2	1	2
3	4	3	4

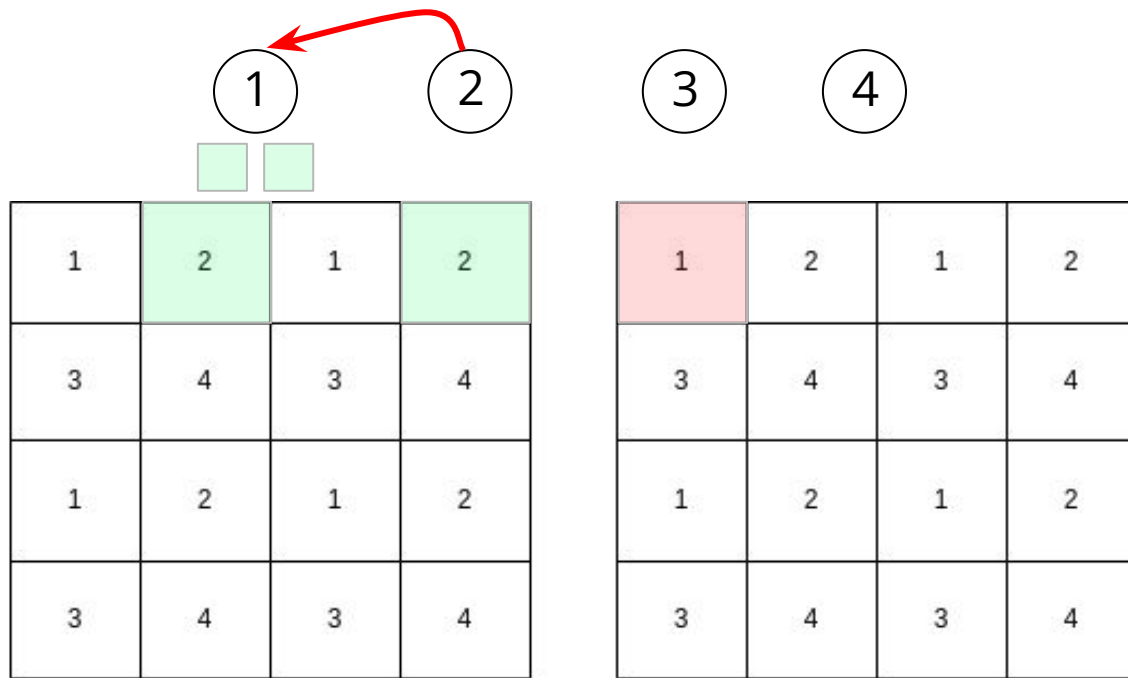
# GEMM : Giving data to each node



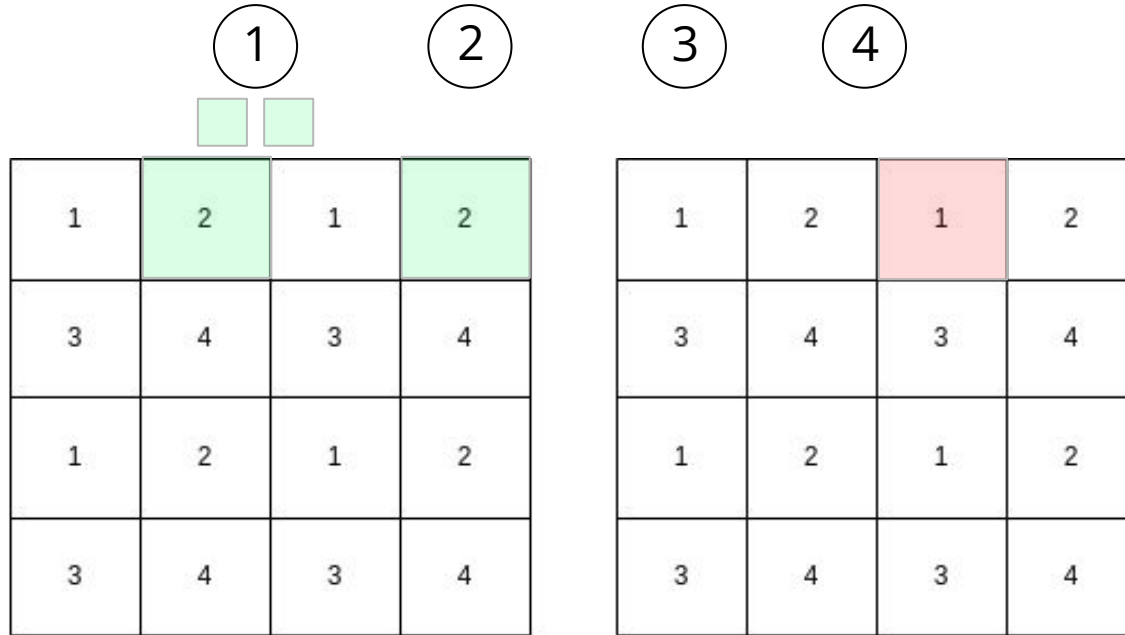
# GEMM : Giving data to each node



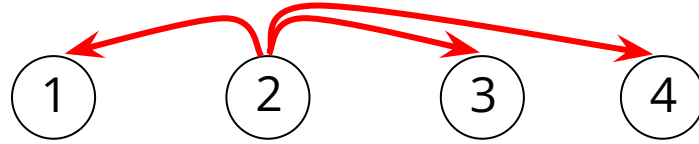
# GEMM : Giving data to each node



# GEMM : Giving data to each node



# GEMM : Giving data to each node



1	2	1	2
3	4	3	4
1	2	1	2
3	4	3	4

1	2	1	2
3	4	3	4
1	2	1	2
3	4	3	4

# GEMM : Giving data to each node

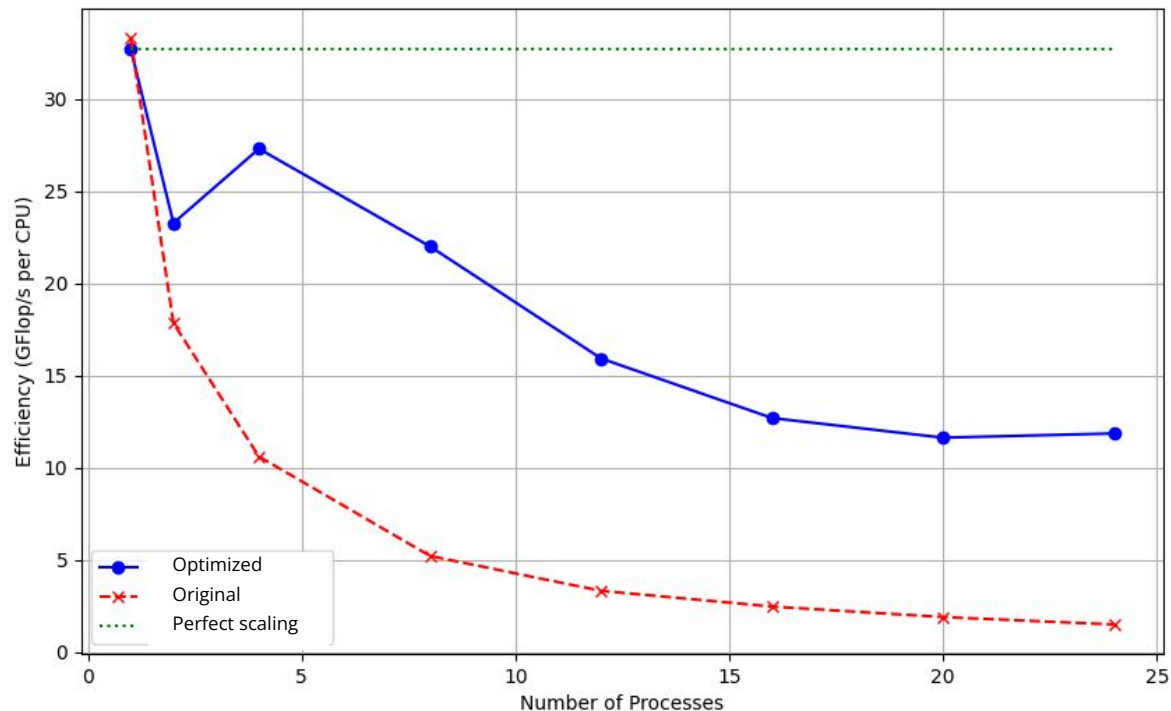
1	2	1	2
3	4	3	4
1	2	1	2
3	4	3	4

1	2	1	2	(1,2)
3	4	3	4	(3,4)
1	2	1	2	(1,2)
3	4	3	4	(3,4)



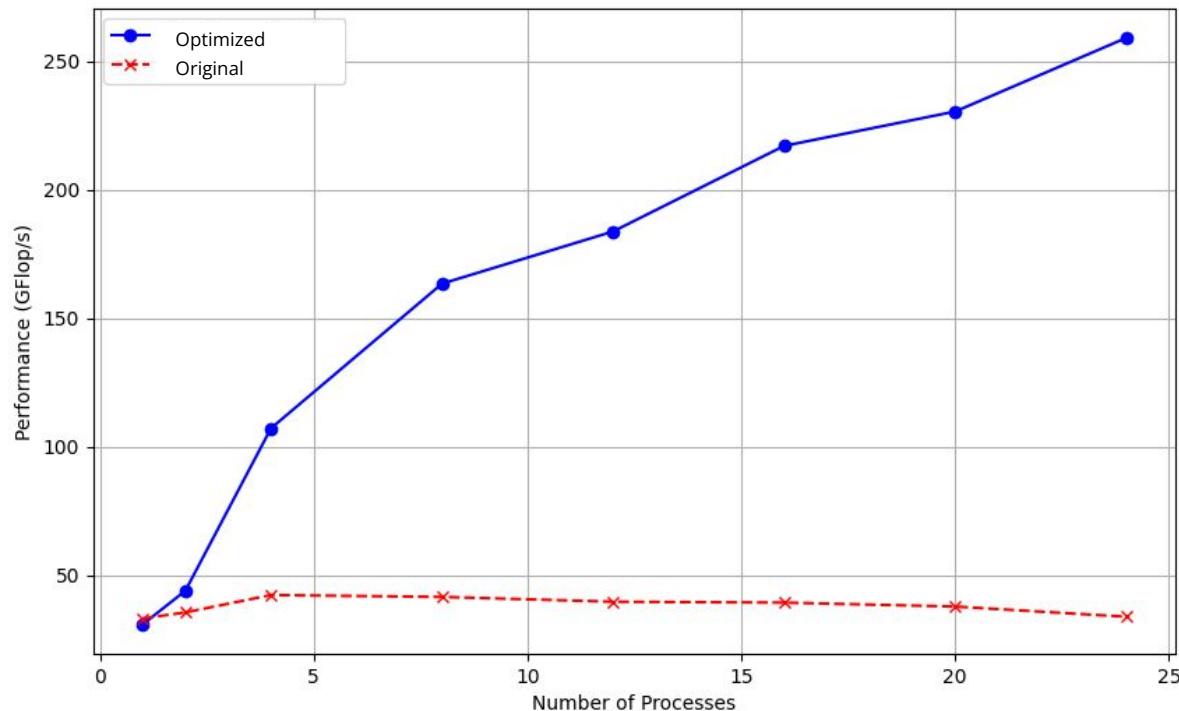
# GEMM : MPI Results

Weak scalability,  
with each process  
computing  $5000^3$   
flops



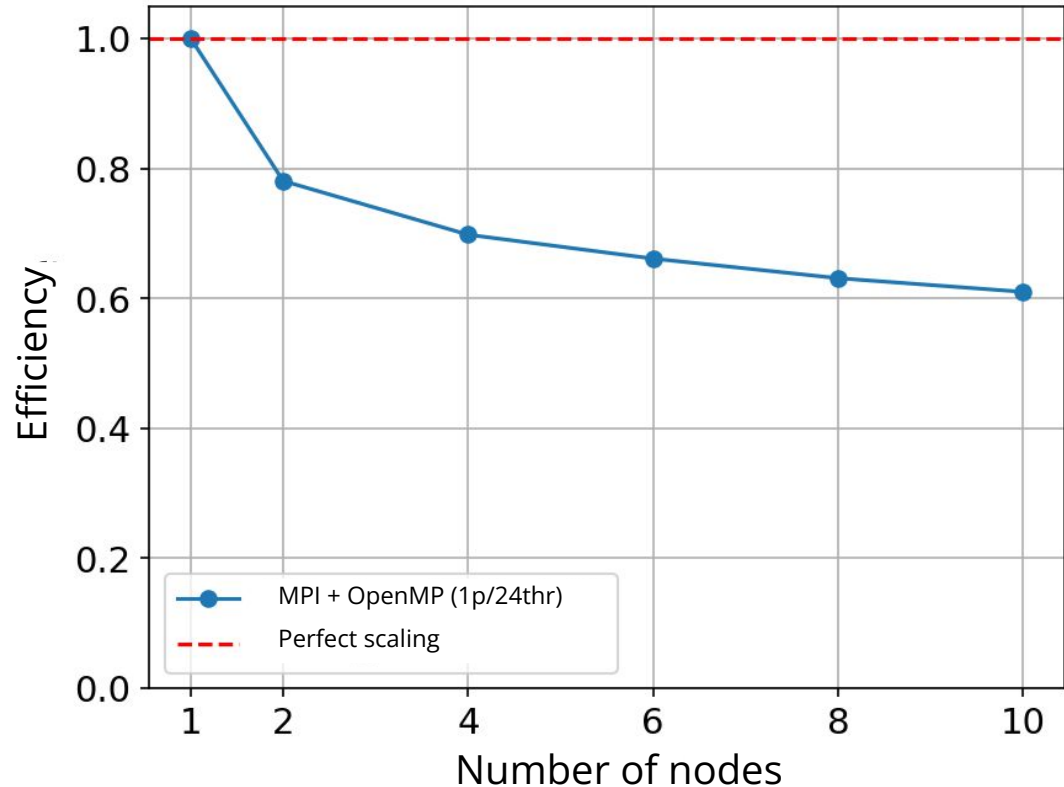
# GEMM : MPI Results

Strong scalability  
for  $N = M = K =$   
13440 and  $b =$   
 $13440/n$



# GEMM : MPI + X weak scaling

MPI + OpenMP with 1  
process per node with  
24 threads each



# GEMM : MPI + X

Peak performance on 10 nodes :  
**4 TFlop/s !!!**

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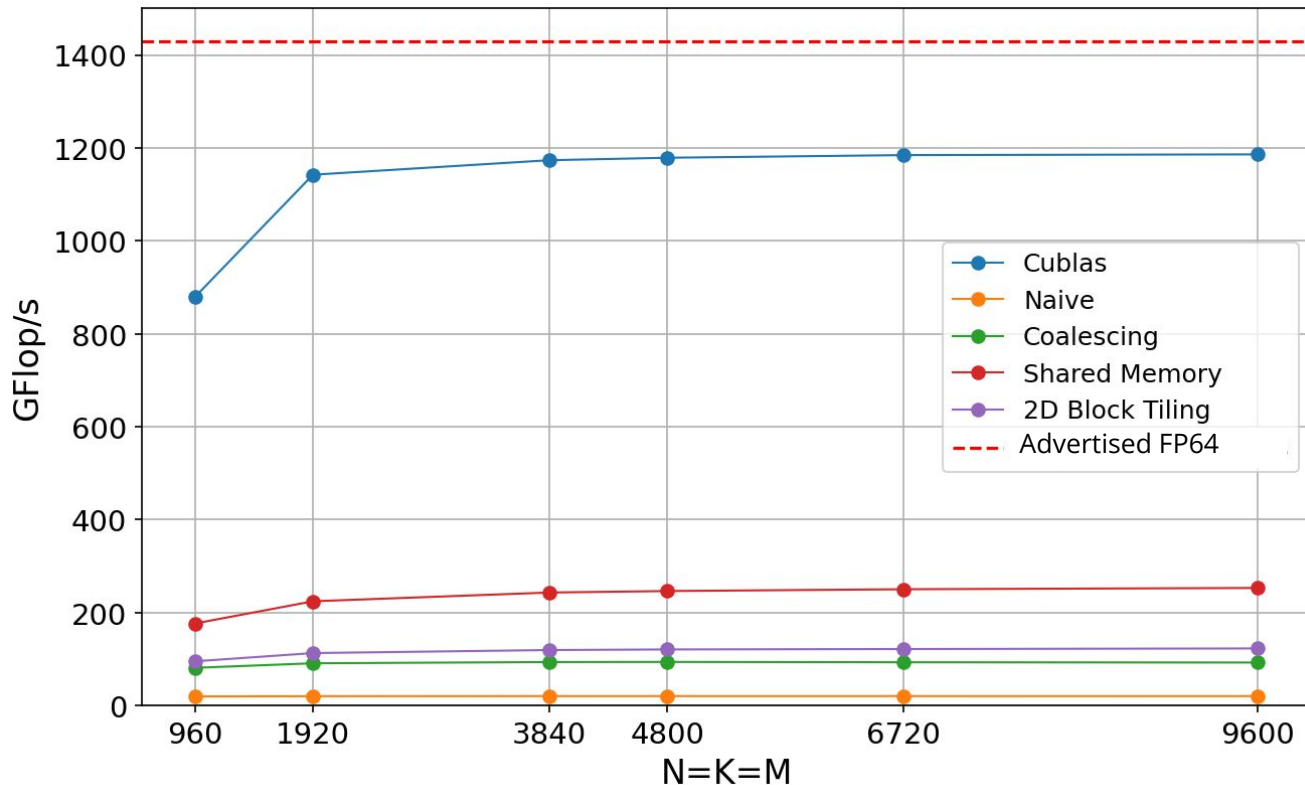
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Rank	System	Cores	Rmax (GFlop/s)	Rpeak (GFlop/s)	Power (kW)
1	Plafrim, LAKA ENSEIRB-MATMECA France	240	4000.00	4000.00	
2	ASCI Blue-Pacific SST, IBM SP 604e, IBM Lawrence Livermore National Laboratory United States	5,808	2,144.00	3,856.50	
3	ASCI Blue Mountain, HPE Los Alamos National Laboratory United States	6,144	1,608.00	3,072.00	
4	EP-Server 2375-M15-IBM	1,224	1,112.00	2,000.00	

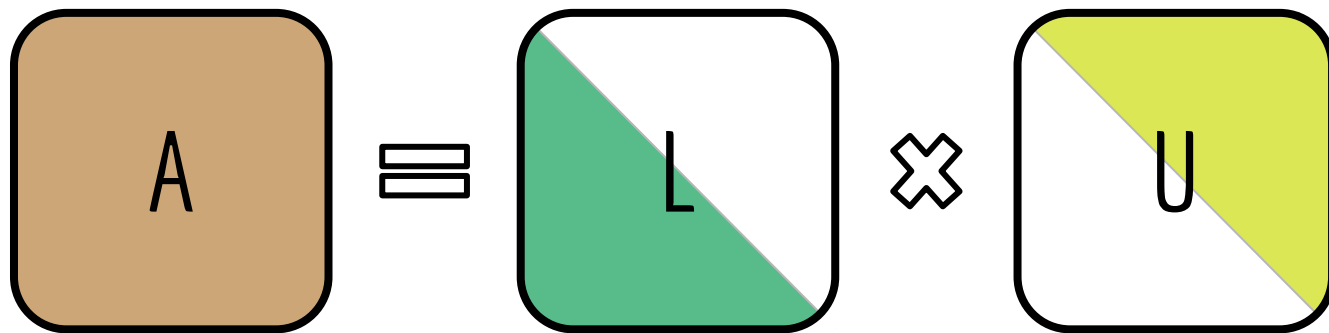
*(Do not take this seriously, this is a joke)*

# GEMM : CUDA

- Best version is shared memory with 250 GFlop/s
- 2D Block Tiling needs more work (each thread computes a sub-block of C)



# GETRF (GEneral TRiangular Factorization)



$A$  has size of  $M \times N$

Lower triangular

Upper triangular

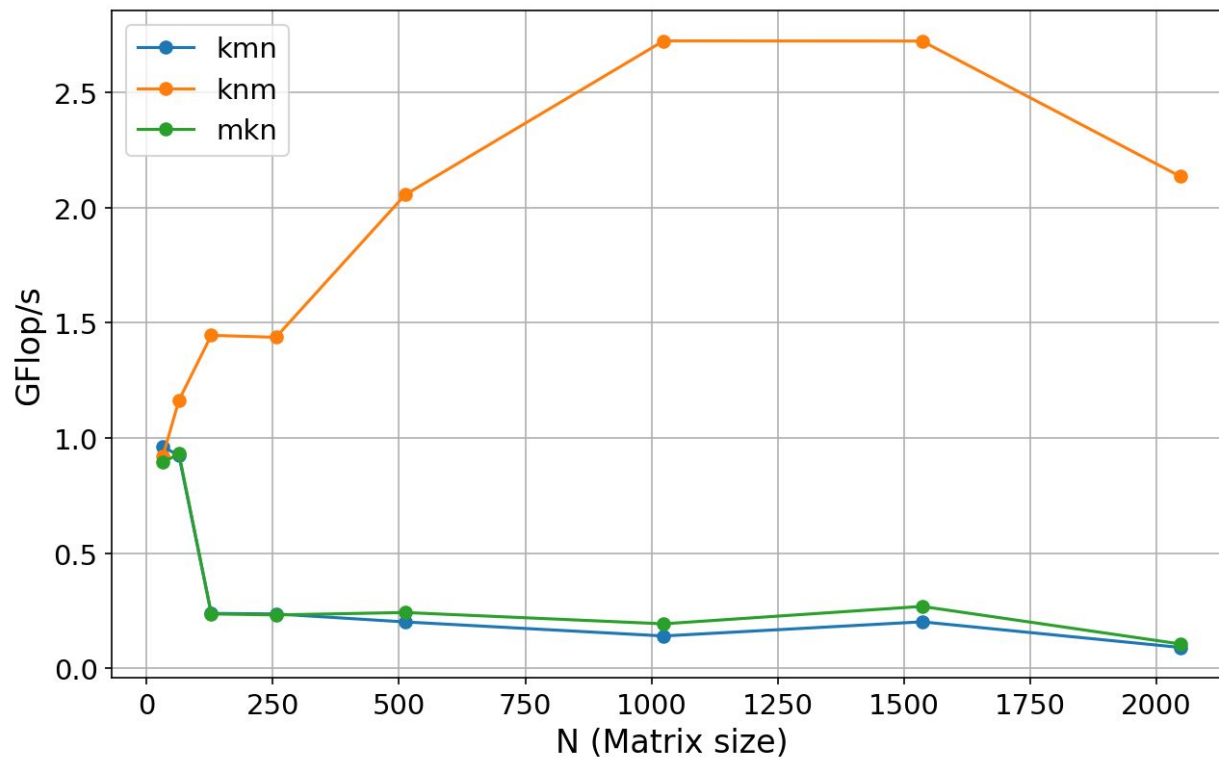
# GETRF : Sequential Version

```
int dgetrf_seq(int M, int N, double *A)
{
    int m, n, k;

    for( k=0; k<K; k++ ) {
        for( m=k+1; m<M; m++ ) {
            A[m, k] = A[m, k]/A[k, k];
            for( n=k+1; n<N; n++ ) {
                A[m, n] = A[m, n] - A[m, k]*A[k, n];
            }
        }
    }
    return ALGONUM_SUCCESS; /* Success */
}
```

$$\begin{pmatrix} 1 & 7 & 3 & 4 & 9 \\ 2 & 3 & 5 & 2 & 2 \\ 4 & 6 & 8 & 6 & 6 \\ 9 & 3 & 4 & 7 & 1 \\ 1 & 8 & 0 & 6 & 3 \end{pmatrix}$$

# GETRF : Sequential Version (Loop Orders)



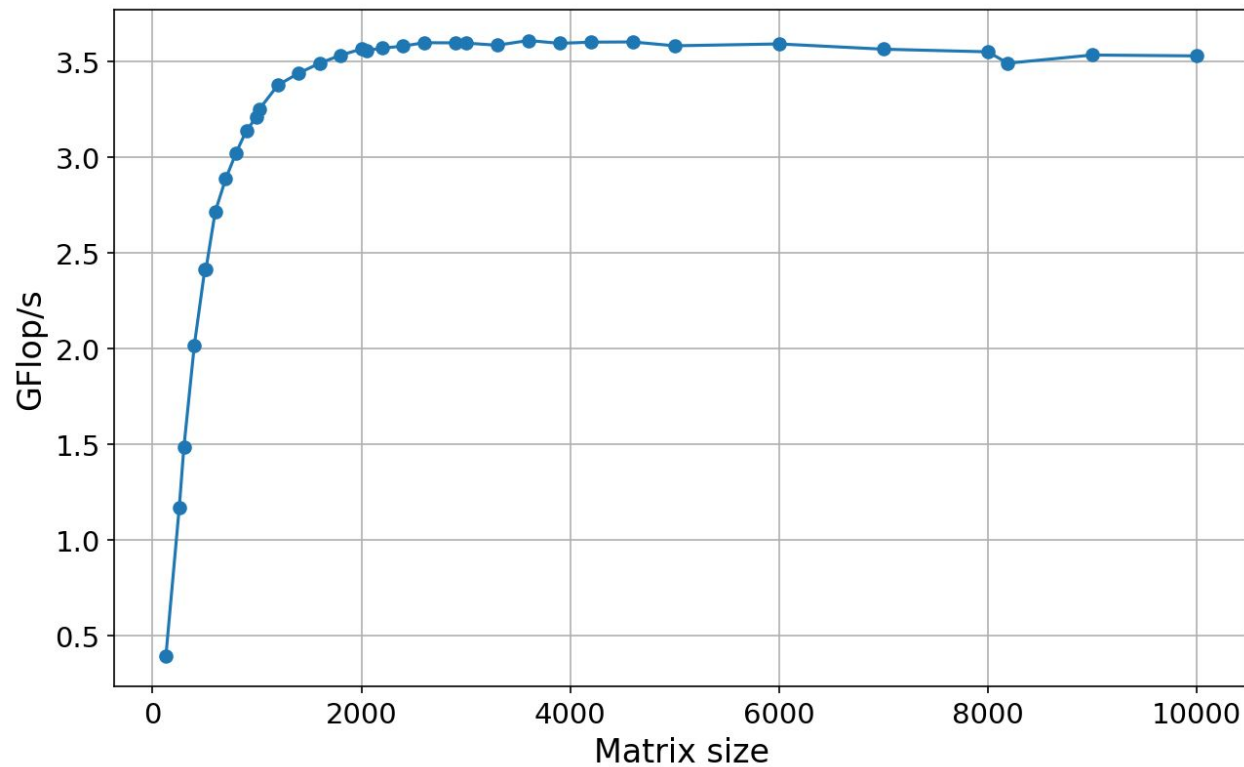


# GETRF : Vectorization

$$\begin{pmatrix} 1 & 7 & 3 & 4 & 9 \\ 2 & 3 & 5 & 2 & 2 \\ 4 & 6 & 8 & 6 & 6 \\ 9 & 3 & 4 & 7 & 1 \\ 1 & 8 & 0 & 6 & 3 \end{pmatrix}$$

Speedup of 1.5 by vectorizing

# GETRF : Cuda



# GETRF : Block-ing



1 - Compute  $L/U_{00}$  using GETRF



2 - Compute  $L_{10}$  and  $U_{01}$  using TRSM

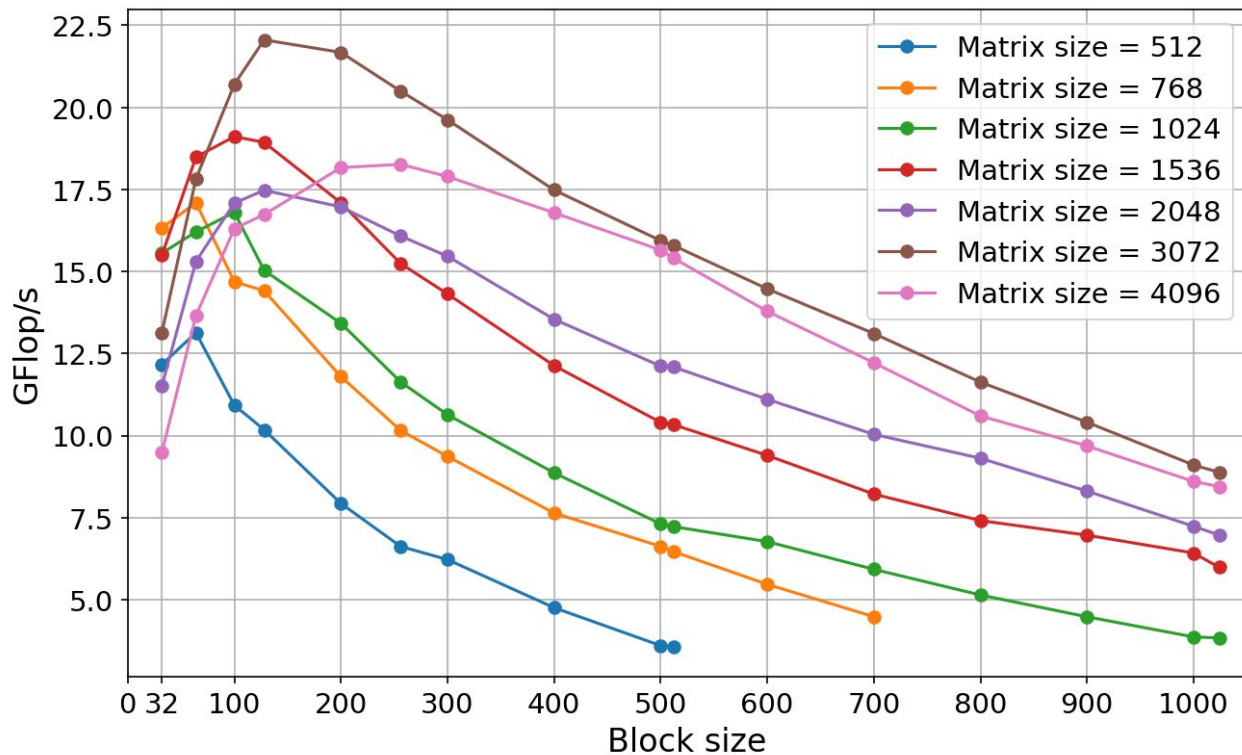


3 - Compute  $A'_{11}$  using GEMM

4 - Apply the process on  $A'_{11}$

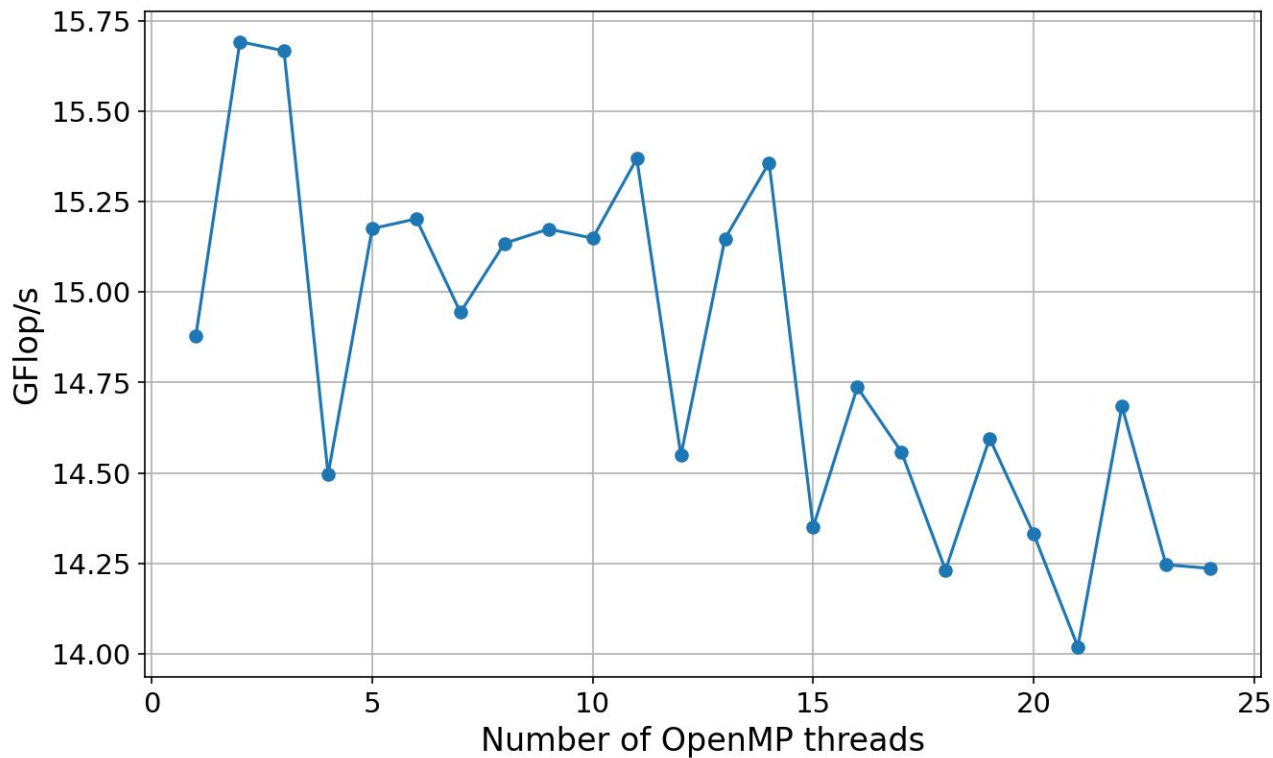
GETRF	TRSM	TRSM	TRSM	TRSM
TRSM	GEMM	GEMM	GEMM	GEMM
TRSM	GEMM	GEMM	GEMM	GEMM
TRSM	GEMM	GEMM	GEMM	GEMM
TRSM	GEMM	GEMM	GEMM	GEMM

# GETRF : Sequential Version (Block-ed)



# GETRF : OpenMP

Matrix size: 2048  
Block size: 64



# GETRF : MPI (1)



1 - GETRF → broadcast result



2 - Broadcast TRSM results of the first line  
Send TRSM results of the second line to  
processes computing GEMM



3 - Receive TRSM results if needed and  
compute GEMM

4 - Apply the process on  $A'_{11}$

Block-cyclic distribution

0	2	0	2	0	2
1	3	1	3	1	3
0	2	0	2	0	2
1	3	1	3	1	3
0	2	0	2	0	2
1	3	1	3	1	3

# GETRF : MPI (2)



1 - GETRF  $\rightarrow$  broadcast result



2 - Each process compute its TRSM in the first line / Process 0 computes the TRSM in the second line and broadcast the result.



3 - Compute GEMM of the second line

4 - Repeat 2 and 3 on remaining lines

5 - Apply the process on  $A'_{11}$

Column distribution

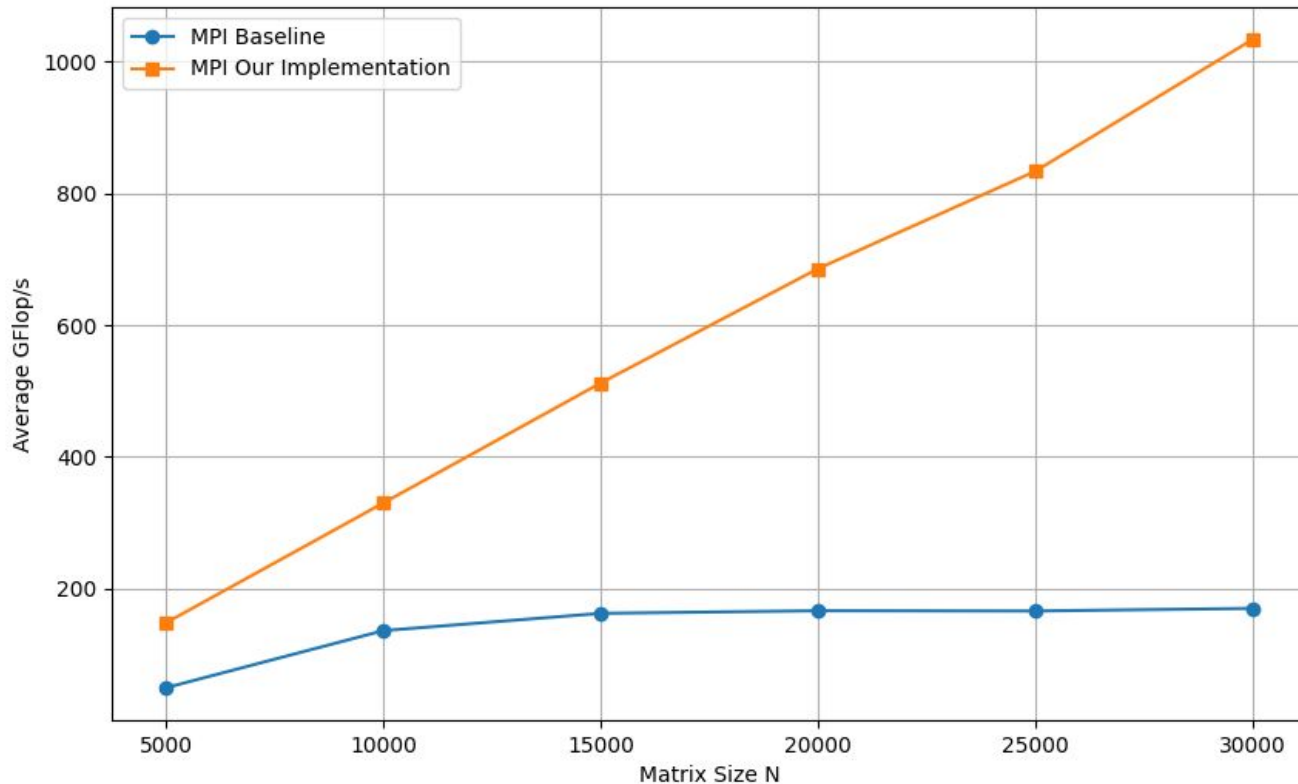
0	1	2	3	0	1
0	1	2	3	0	1
0	1	2	3	0	1
0	1	2	3	0	1
0	1	2	3	0	1
0	1	2	3	0	1

# GETRF : MPI (4)

blocks size = 320

8 nodes

12 processes per  
node

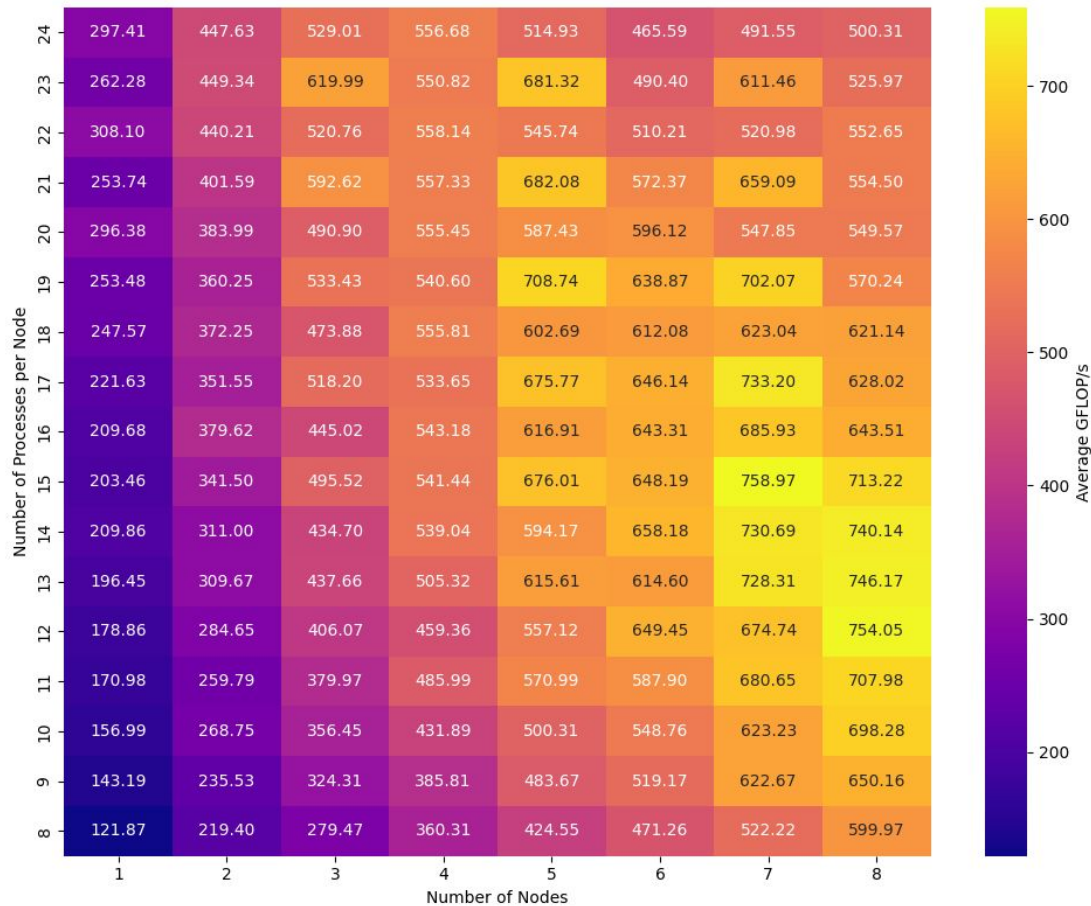




# GETRF : MPI (5)

$M = N = 30000$

blocks = 150

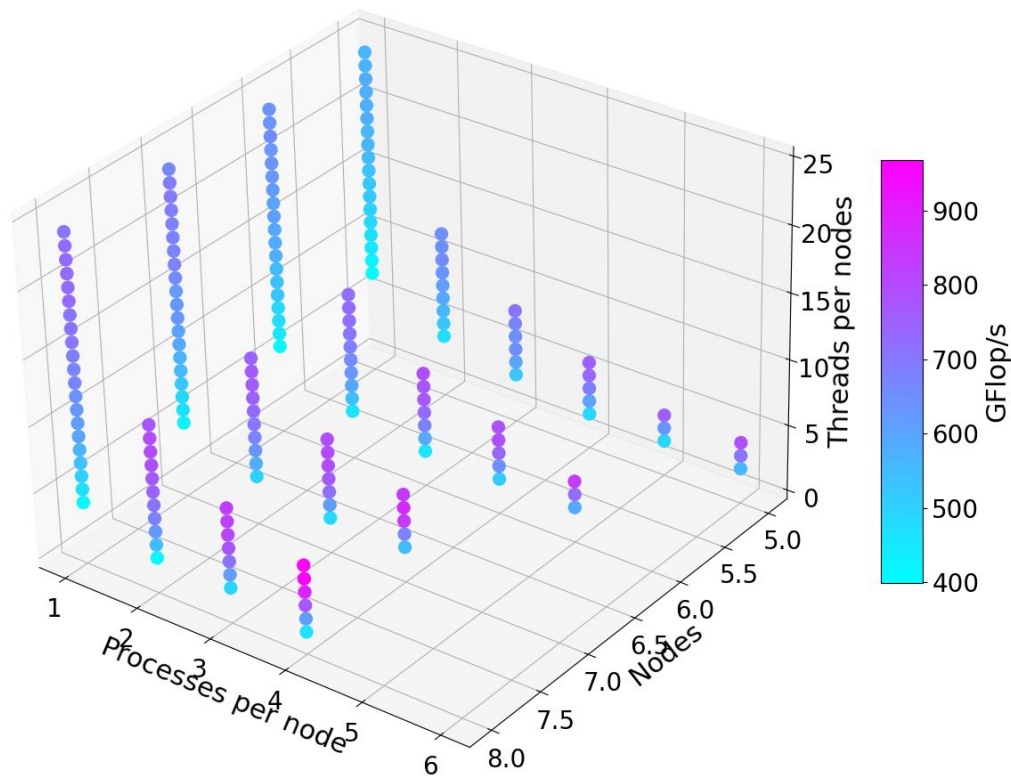


# GETRF : MPI + OpenMP

$M = N = 35000$

MPI blocks size = 1024

OMP blocks size = 100



# Experimentation

- Turbo boost enabled on miriel039 and miriel040;
- Cluster-On-Die BIOS option is disabled on miriel023;
  - We noticed those misconfigurations during the analysis of our results and benchmarks.

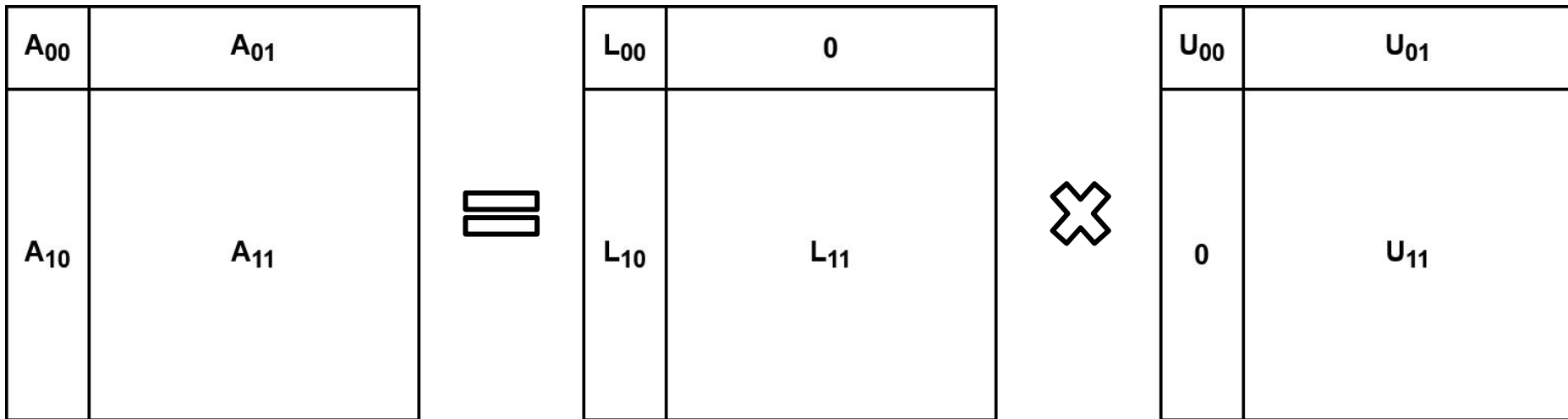
# Conclusion

- **Great performance** for **GEMM**, and works on any matrix size and transposition;
- **Relatively good results** for **GETRF**, and works on any matrix size;
- Many **parameters left to be tested** such as:
  - Optimize MPI + OpenMP block sizes
  - Process binding for MPI
- **Improvements** to be done:
  - GEMM MPI algorithm (Cannon's algorithm, 2.5D algorithms)
  - Cuda (GETRF especially)
- **Other solutions/implementations** to test:
  - GETRF OpenMP with for (instead of tasks)

Questions ?



# GETRF : Blocking (1)



$$(1) \quad L_{00}U_{00} = A_{00}$$

$$(3) \quad L_{00}U_{01} = A_{01}$$

$$(2) \quad L_{10}U_{00} = A_{10}$$

$$(4) \quad L_{10}U_{01} + L_{11}U_{11} = A_{11}$$

# GETRF : Blocking (2)

$$(1) \quad L_{00}U_{00} = A_{00}$$

$$GETRF(A_{00}) = (L_{00}, U_{00})$$

<b>L/U<sub>00</sub></b>	<b>A<sub>01</sub></b>
<b>A<sub>10</sub></b>	<b>A<sub>11</sub></b>

# GETRF : Blocking (3)

$$(2) \quad L_{10}U_{00} = A_{10}$$

$$TRSM(A_{10}, U_{00}) = L_{10}$$

<b>L/U<sub>00</sub></b>	<b>A<sub>01</sub></b>
<b>L<sub>10</sub></b>	<b>A<sub>11</sub></b>



# GETRF : Blocking (4)

$$(3) \quad L_{00}U_{01} = A_{01}$$

$$TRSM(A_{01}, L_{00}) = U_{01}$$

<b>L/U<sub>00</sub></b>	<b>U<sub>01</sub></b>
<b>L<sub>10</sub></b>	<b>A<sub>11</sub></b>

# GETRF : Blocking (5)

$$(4) \quad L_{10}U_{01} + L_{11}U_{11} = A_{11}$$

$$(4) \quad A'_{11} = \underbrace{A_{11} - L_{10}U_{01}}_{\text{GEMM}} = L_{11}U_{11}$$

GEMM

Apply the process on  $A'_{11}$  to  
compute  $L_{11}$  and  $U_{11}$

$L/U_{00}$	$U_{01}$
$L_{10}$	$A'_{11}$

# GETRF : Blocking (6)



1 - Compute  $L/U_{00}$  using GETRF



2 - Compute  $L_{10}$  and  $U_{01}$  using TRSM



3 - Compute  $A'_{11}$  using GEMM

4 - Apply the process on  $A'_{11}$

GETRF	TRSM	TRSM	TRSM	TRSM
TRSM	GEMM	GEMM	GEMM	GEMM
TRSM	GEMM	GEMM	GEMM	GEMM
TRSM	GEMM	GEMM	GEMM	GEMM
TRSM	GEMM	GEMM	GEMM	GEMM

# GEMM : Theoretical performances

$$\text{GFlop/s} = \text{CPU Freq} \times \frac{\text{SIMD Width}}{\text{Type size}} \times \text{FMA} \times \text{FMA Throughput}$$

# GEMM : Theoretical performances

model name : Intel(R) Xeon(R)  
CPU E5-2680 v3 @ 2.50GHz

$$\text{GFlop/s} = 2.5 \text{ GHz} \times \frac{256}{64} \times 2 \times 2 = 40 \text{ GFlop/s}$$

AVX2

FMA (a += b\*c)

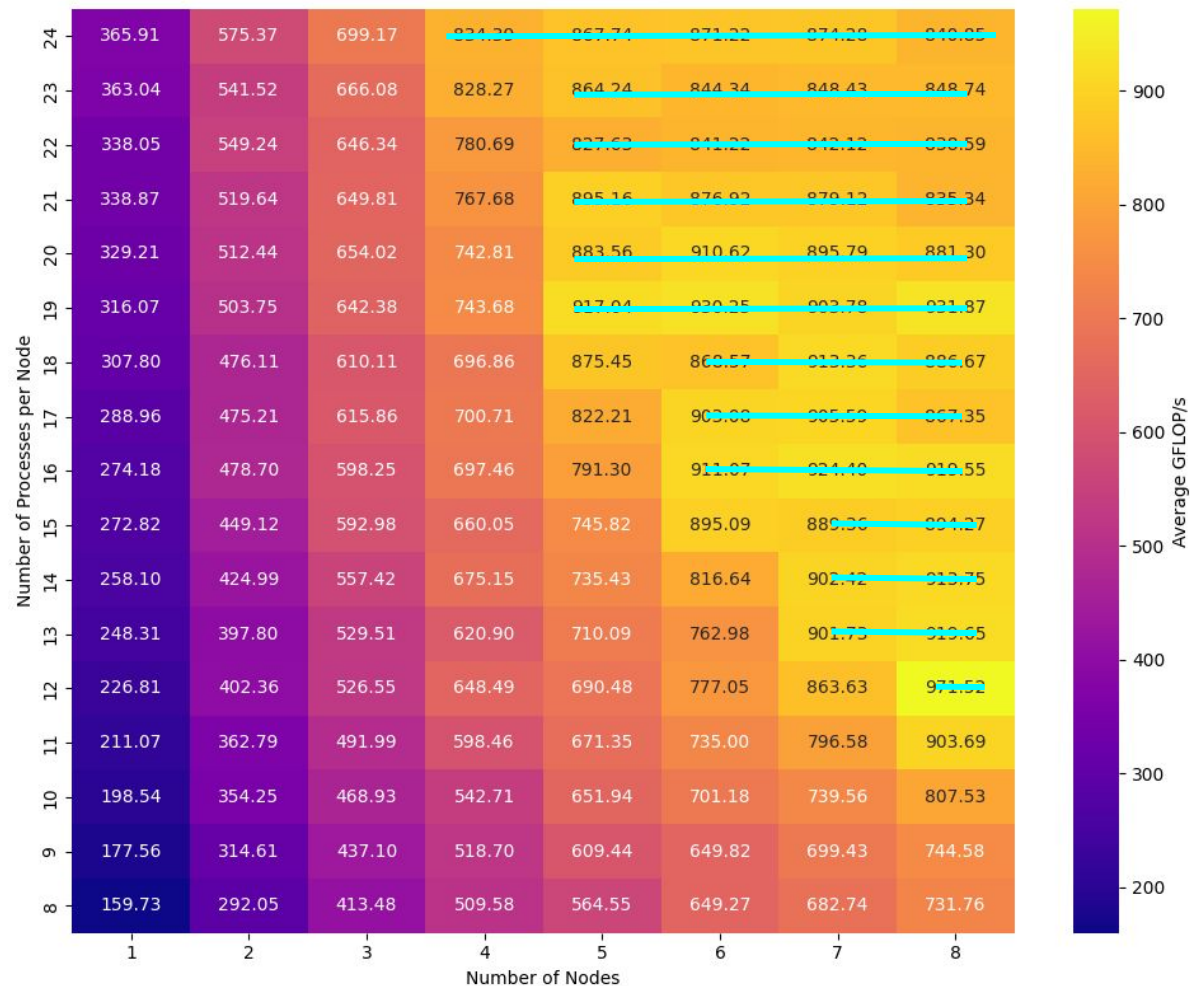
sizeof(double)

Latency and Throughput

Architecture	Latency	Throughput (CPI)
Alderlake	4	0.5
Icelake Intel Core	4	0.5
Icelake Xeon	4	0.5
Sapphire Rapids	4	0.5
Skylake	4	0.5

$$\text{GFlop/s} = \text{CPU Freq} \times \frac{\text{SIMD Width}}{\text{Type size}} \times \text{FMA} \times \text{FMA Throughput}$$

$M = N = 30000$   
blocks = 320



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