

CSDS 451: Designing High Performant Systems for AI

Lecture 6

9/11/2025

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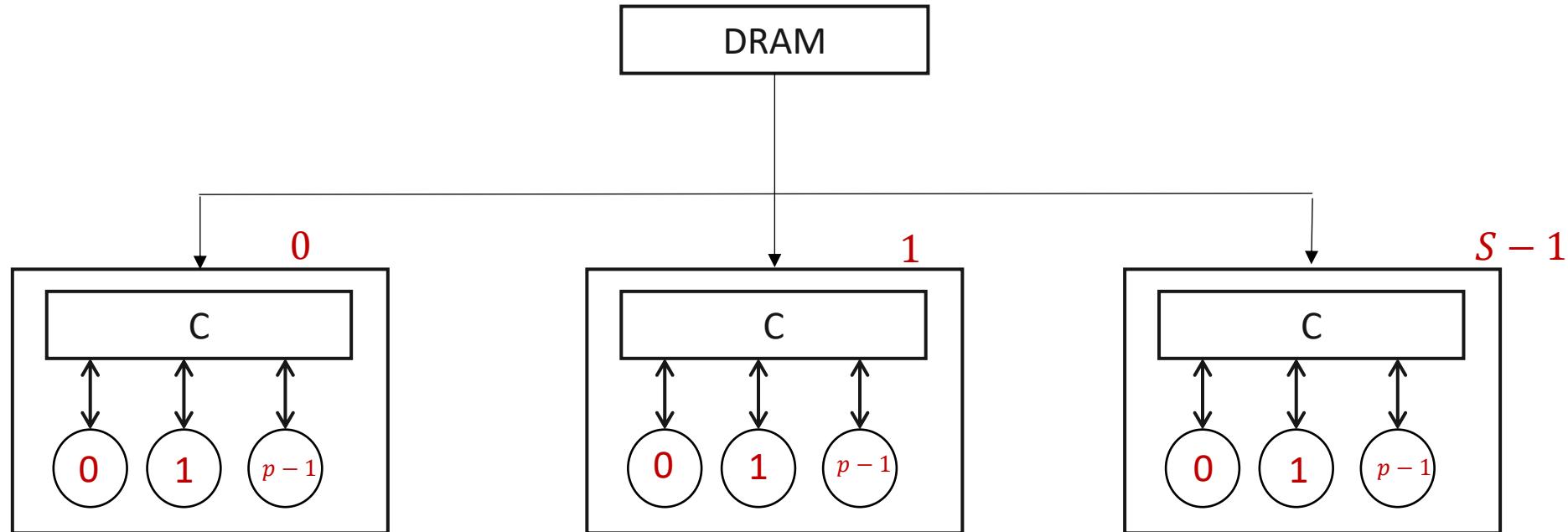
Outline

- Data Parallel Programming
 - Data Parallel Programming Approaches
 - Parallel Program Analysis

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- Data Parallel Programming
 - Data Parallel Programming Approaches
 - Parallel Program Analysis

Modeling GPU Architectures



- Number of Blocks can be (in fact should be) greater than the number of SMPs
- Number of threads per block need not be equal to the number of compute cores per SMP
 - It is good to have it as a multiple though
- We will discuss these considerations when we discuss GPU programming later
- For now, assume the simple model above.
 - S Blocks
 - p Threads per block

GPU Model

- Think in terms of what each block computes, and what each thread within a block computes
- Each thread on the GPU executes the *same instructions* on *different data*
- We need to rethink our algorithms in terms of the above
- Think Data Parallel

Data Parallelism

- Key Idea:
 - Partition data into chunks → Each chunk should require similar amount of work
 - Assign tasks to each partition so that they can proceed concurrently
- Note: data parallelism doesn't mean each task "need" to perform exact same computations
 - Usually it is true
- SPMD (Single Program Multiple Data) is a special case of data parallelism where same "program" is run on different data

Data Parallelism - Approaches

- #1 Partition Output data
 - Each task is responsible for computing an output partition

Output



Data Parallelism - Approaches

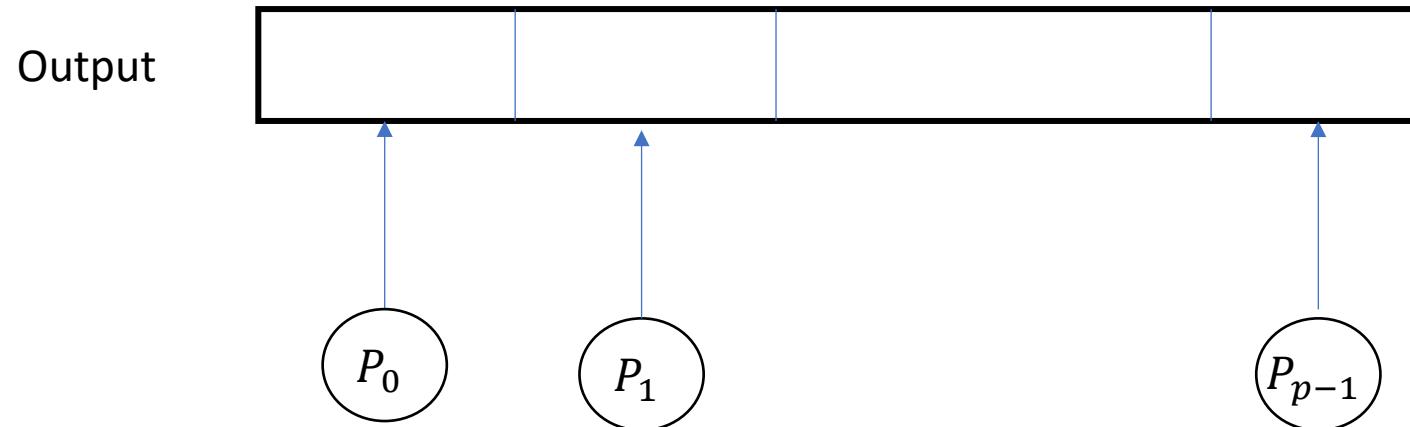
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Output



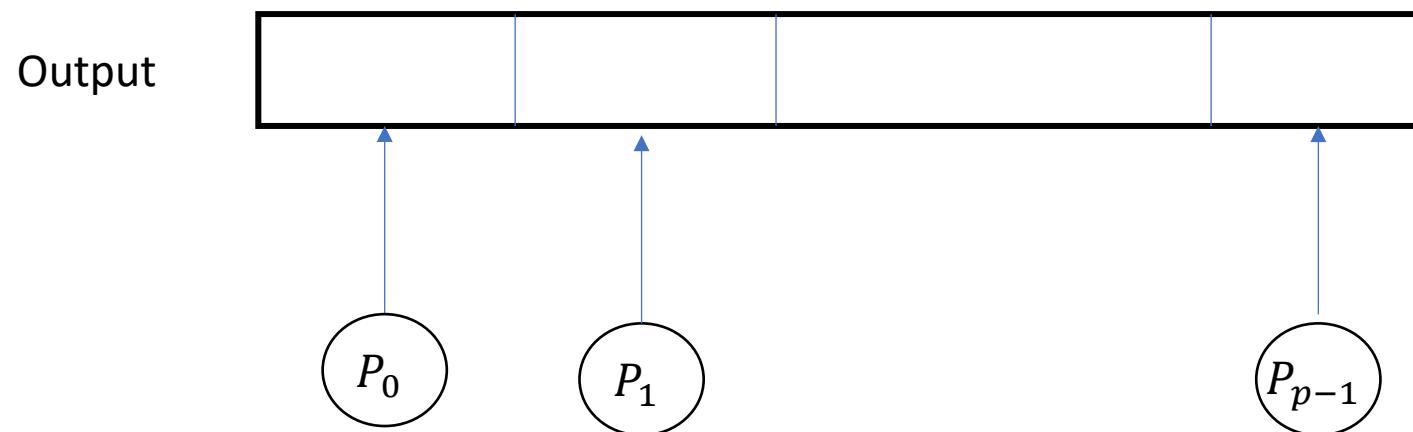
Data Parallelism - Approaches

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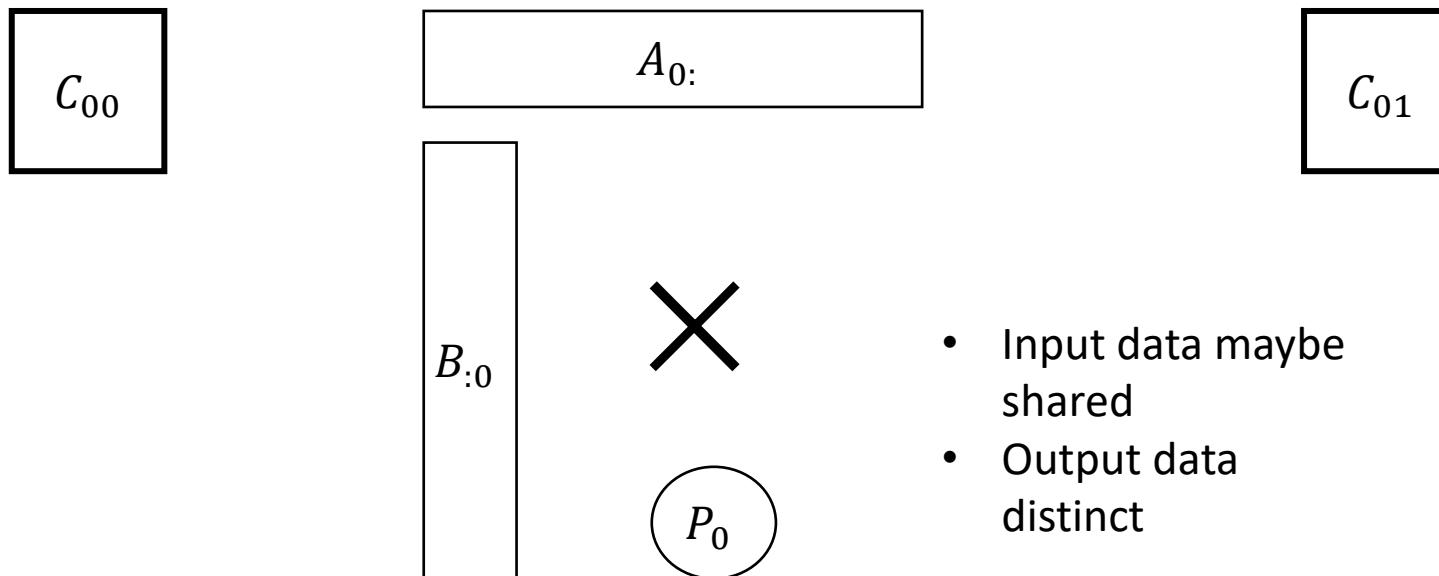
Data Parallelism - Approaches

- #1 Partition Output data
 - Useful when partitions of output can be computed independently of each other
 - Example: Blocked Matrix Multiplication

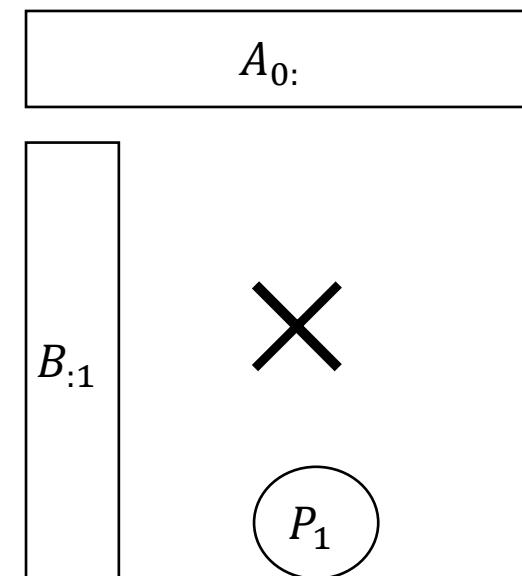


Data Parallelism – Approaches

- #1 Partition Output data
 - Matrix Multiplication

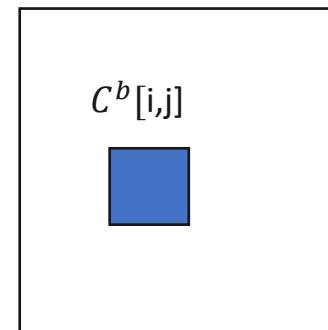
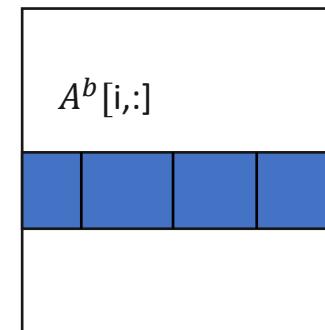
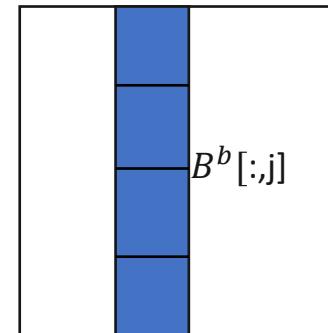


- Input data maybe shared
- Output data distinct

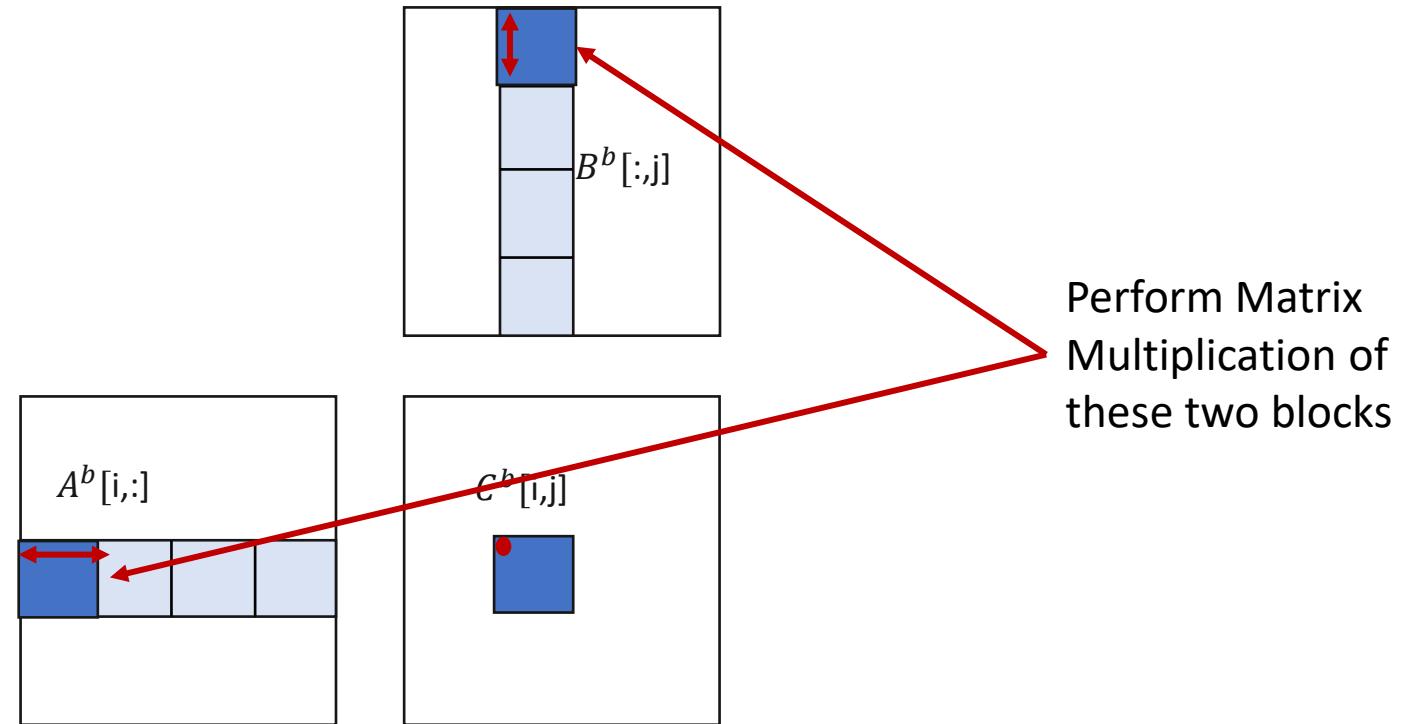


Block Matrix Multiplication

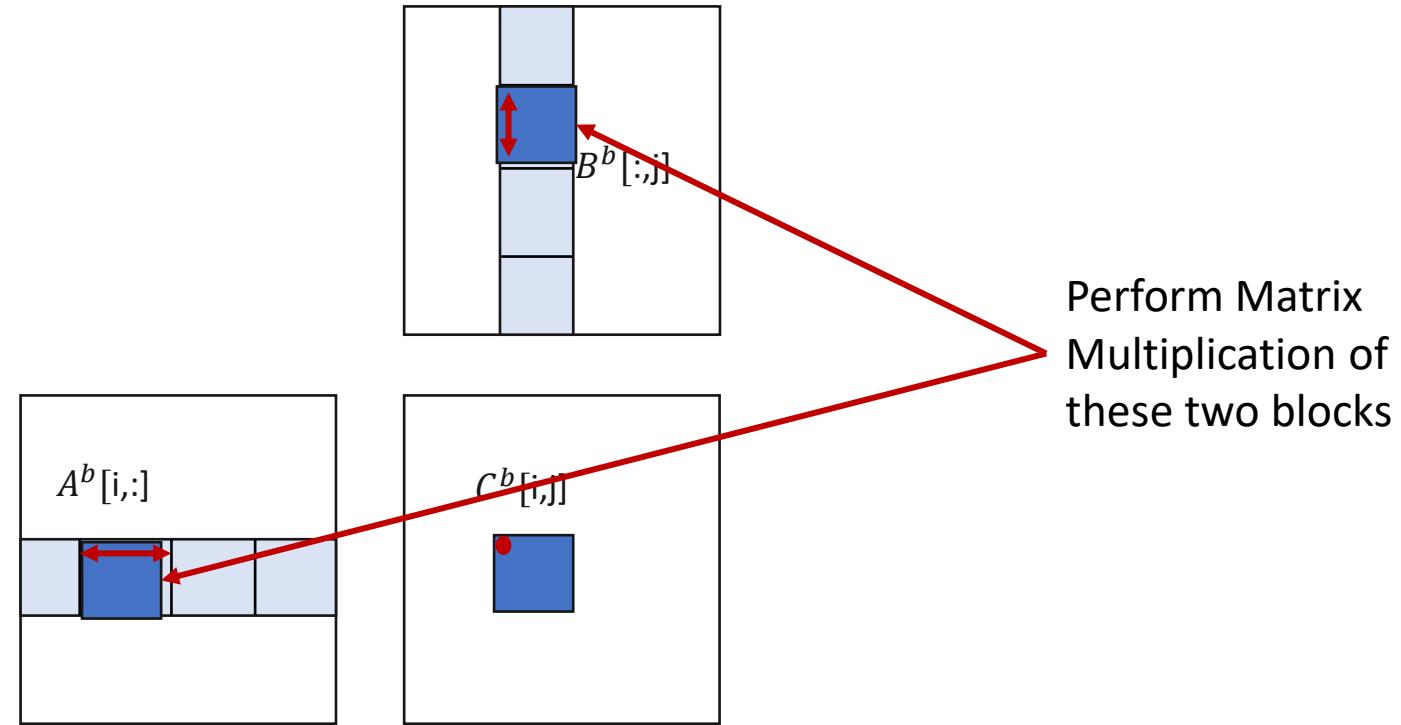
- Key Idea: Partition matrices A/B/C into $b \times b$ size blocks
- Blocks denoted as $A^b[1:\frac{N}{b}][1:\frac{N}{b}]$ / $B^b[1:\frac{N}{b}][1:\frac{N}{b}]$ / $C^b[1:\frac{N}{b}][1:\frac{N}{b}]$
- $C^b[i][j] = \text{BlockedMM}(A^b[i][:], B^b[:,j])$
- For $k = 0$ to N/b
 - Fetch $A^b[i][k]$, $B^b[k][j]$
 - Matrix Multiply $A^b[i][k]$, $B^b[k][j]$ and Accumulate $C^b[i][j]$



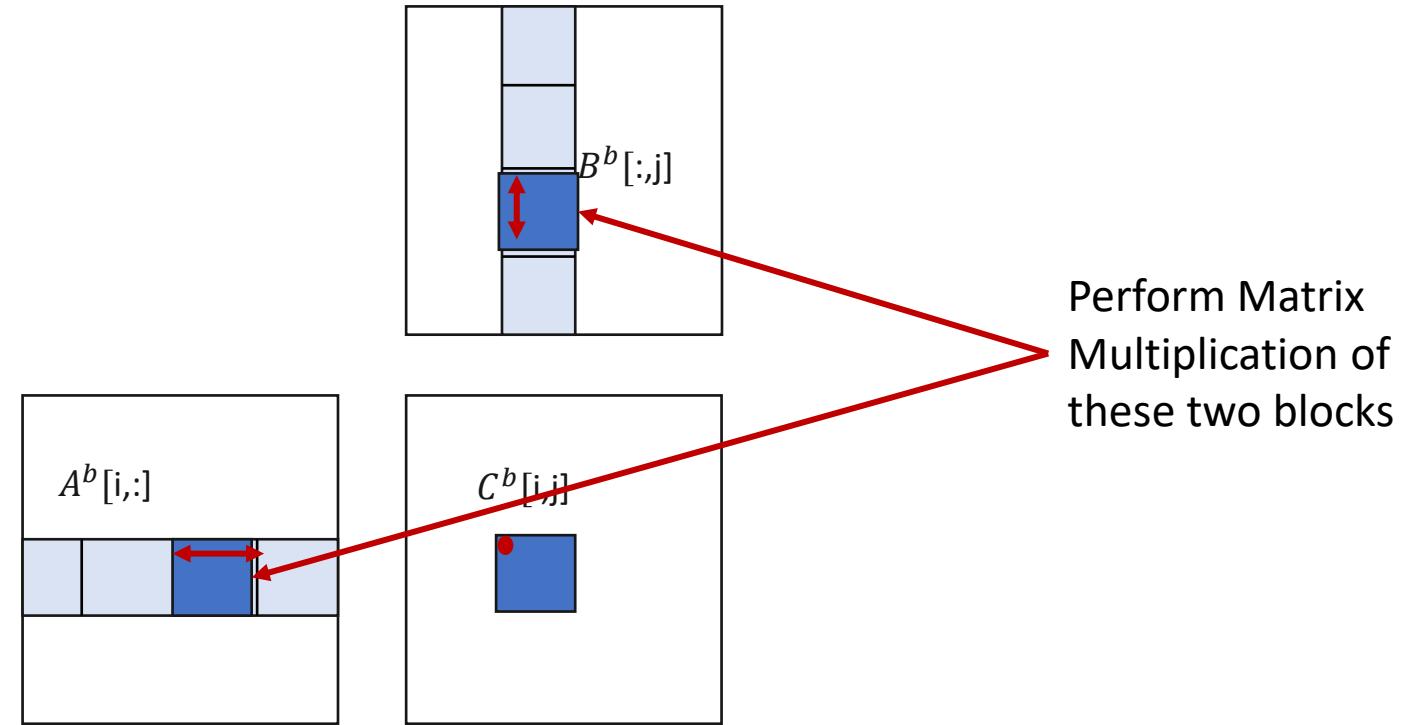
Block Matrix Multiplication



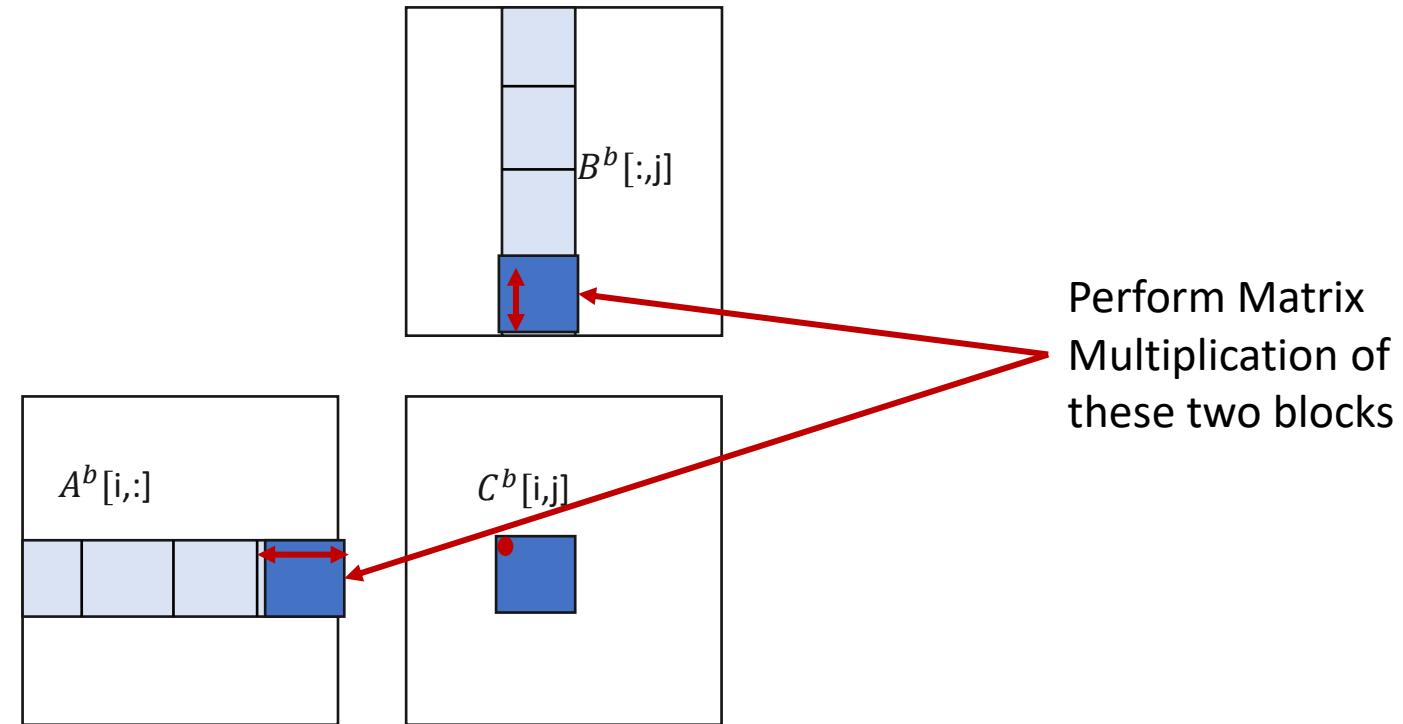
Block Matrix Multiplication



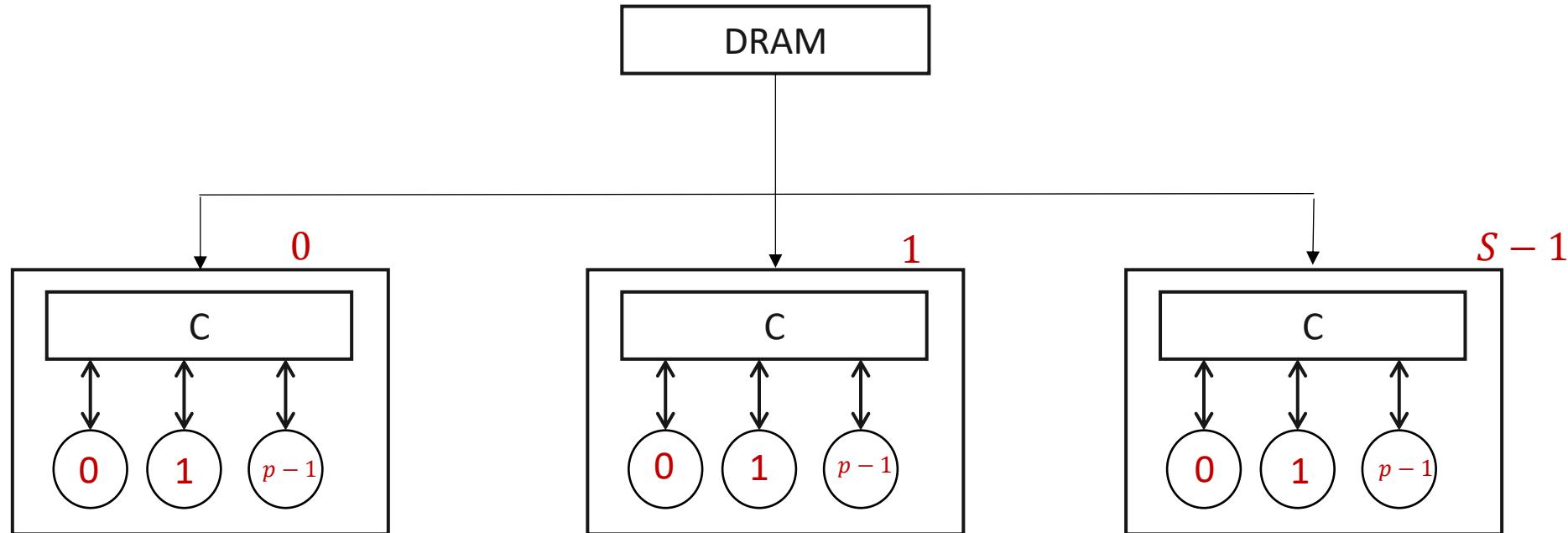
Block Matrix Multiplication



Block Matrix Multiplication



Modeling GPU Architectures



- S Blocks (I will call them SMPs in the next few slides to avoid confusion with Blocks of matrices)
- p Threads per block

Block Matrix Multiplication

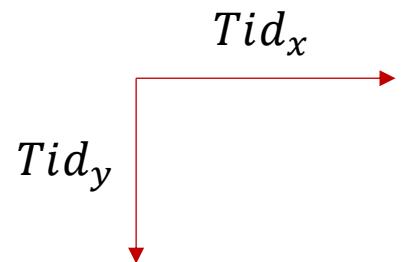
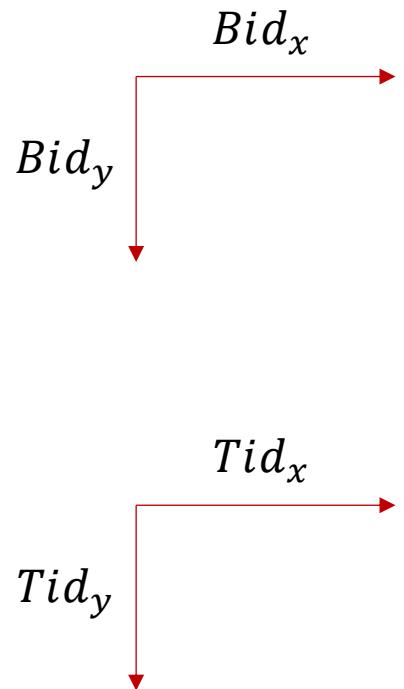
- What is a natural way to split the computations of Matrix Multiplication to the SMPs of GPUs?

Block Matrix Multiplication

- What is a natural way to split the computations of Matrix Multiplication to the SMPs of GPUs?
- Assign each output block $C^b[i][j]$ to an SMP
- Use the p threads to compute N/b block matrix multiplication

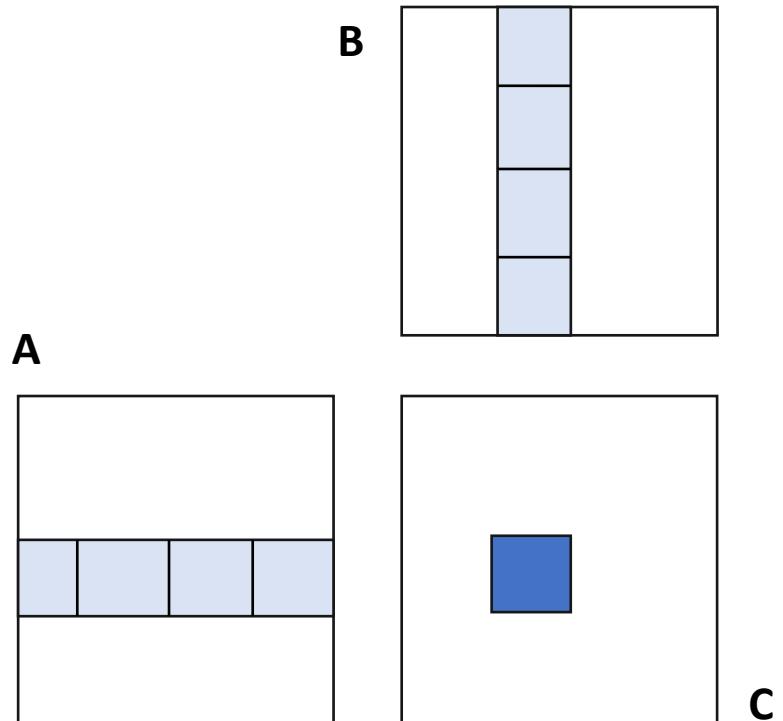
Block Matrix Multiplication

- Assume $S = \frac{N}{b} \times \frac{N}{b}$ SMPs
 - With block IDs: Bid_y, Bid_x
- Assume $p = b \times b$ threads
 - With thread IDs: Tid_y, Tid_x
- Need to convert the following into GPU model:
 - For $k = 0$ to N/b
 - Fetch $A^b[i][k], B^b[k][j]$
 - Matrix Multiply $A^b[i][k], B^b[k][j]$ and Accumulate $C^b[i][j]$



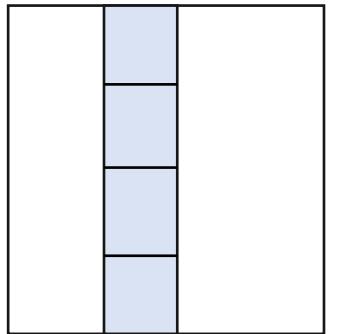
Block Matrix Multiplication

- In $Bid_y, Bid_x, Tid_y, Tid_x \{$
- For $k = 0$ to $\frac{N}{b} - 1$
 - Read $A[Bid_y * \frac{N}{b} + Tid_y][k*N/b+Tid_x]$
 - Read $B[k * \frac{N}{b} + Tid_y][Bid_x * \frac{N}{b} + Tid_x]$
 - `Syncthreads()`
 - For $l = 0$ to $b - 1$:
 - $C[Bid_y * \frac{N}{b} + Tid_y][Bid_x * \frac{N}{b} + Tid_x] +=$
 - $A[Bid_y * \frac{N}{b} + Tid_y][k*N/b+l]* B[k * \frac{N}{b} + l][Bid_x * \frac{N}{b} + Tid_x]$
 - `Syncthreads()`
- Store $C[Bid_y * \frac{N}{b} + Tid_y][Bid_x * \frac{N}{b} + Tid_x] \}$



SMP Bid_y, Bid_x produces the output block Bid_y, Bid_x

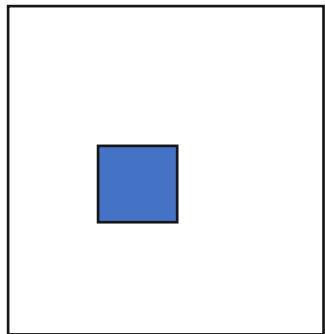
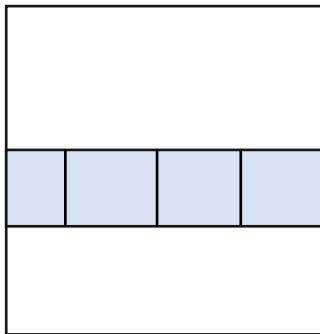
Block Matrix Multiplication



B

What are the elements of C that will
be output by SMP Bid_y, Bid_x ?

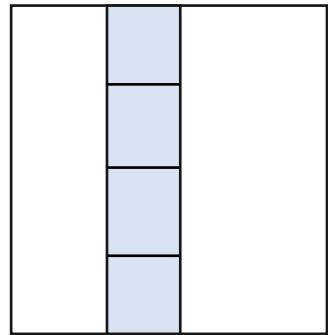
A



C

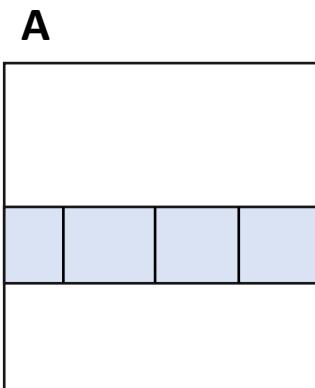
SMP Bid_y, Bid_x produces the output block Bid_y, Bid_x

Block Matrix Multiplication

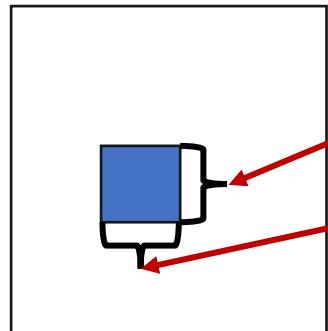


B

What are the elements of C that will be output by SMP Bid_y, Bid_x ?



A



C

$C[Bid_y * \frac{N}{b}: Bid_y * \frac{N}{b} + b - 1][Bid_x * \frac{N}{b}: Bid_x * \frac{N}{b} + b - 1]$

SMP Bid_y, Bid_x produces the output block Bid_y, Bid_x

Block Matrix Multiplication

- In $Bid_y, Bid_x, Tid_y, Tid_x \{$
- For $k = 0$ to $\frac{N}{b} - 1$
 - Read $A[Bid_y * \frac{N}{b} + Tid_y][k*N/b+Tid_x]$
 - Read $B[k * \frac{N}{b} + Tid_y][Bid_x * \frac{N}{b} + Tid_x]$
 - `Syncthreads()`
 - For $l = 0$ to $b - 1$:
 - $C[Bid_y * \frac{N}{b} + Tid_y][Bid_x * \frac{N}{b} + Tid_x] +=$
 - $A[Bid_y * \frac{N}{b} + Tid_y][k*N/b+l]* B[k * \frac{N}{b} + l][Bid_x * \frac{N}{b} + Tid_x]$
 - `Syncthreads()`
- **Store $C[Bid_y * \frac{N}{b} + Tid_y][Bid_x * \frac{N}{b} + Tid_x] \}$**

Looking at the store instruction of this code, can you explain how this is happening?

Block Matrix Multiplication

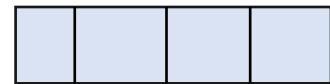
- In $Bid_y, Bid_x, Tid_y, Tid_x$ {
- For $k = 0$ to $\frac{N}{b} - 1$
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Looking at the store instruction of this code, can you explain how this is happening?

Tid_y, Tid_x vary from 0 to $b - 1$

Block Matrix Multiplication

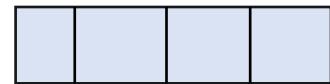
- In $Bid_y, Bid_x, Tid_y, Tid_x \{$
- We go block by block as before.
- For $k = 0$ to $\frac{N}{b} - 1$
 - Read $A[Bid_y * \frac{N}{b} + Tid_y][k*N/b+Tid_x]$
 - Read $B[k * \frac{N}{b} + Tid_y][Bid_x * \frac{N}{b} + Tid_x]$
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 - Store $C[Bid_y * \frac{N}{b} + Tid_y][Bid_x * \frac{N}{b} + Tid_x] \}$



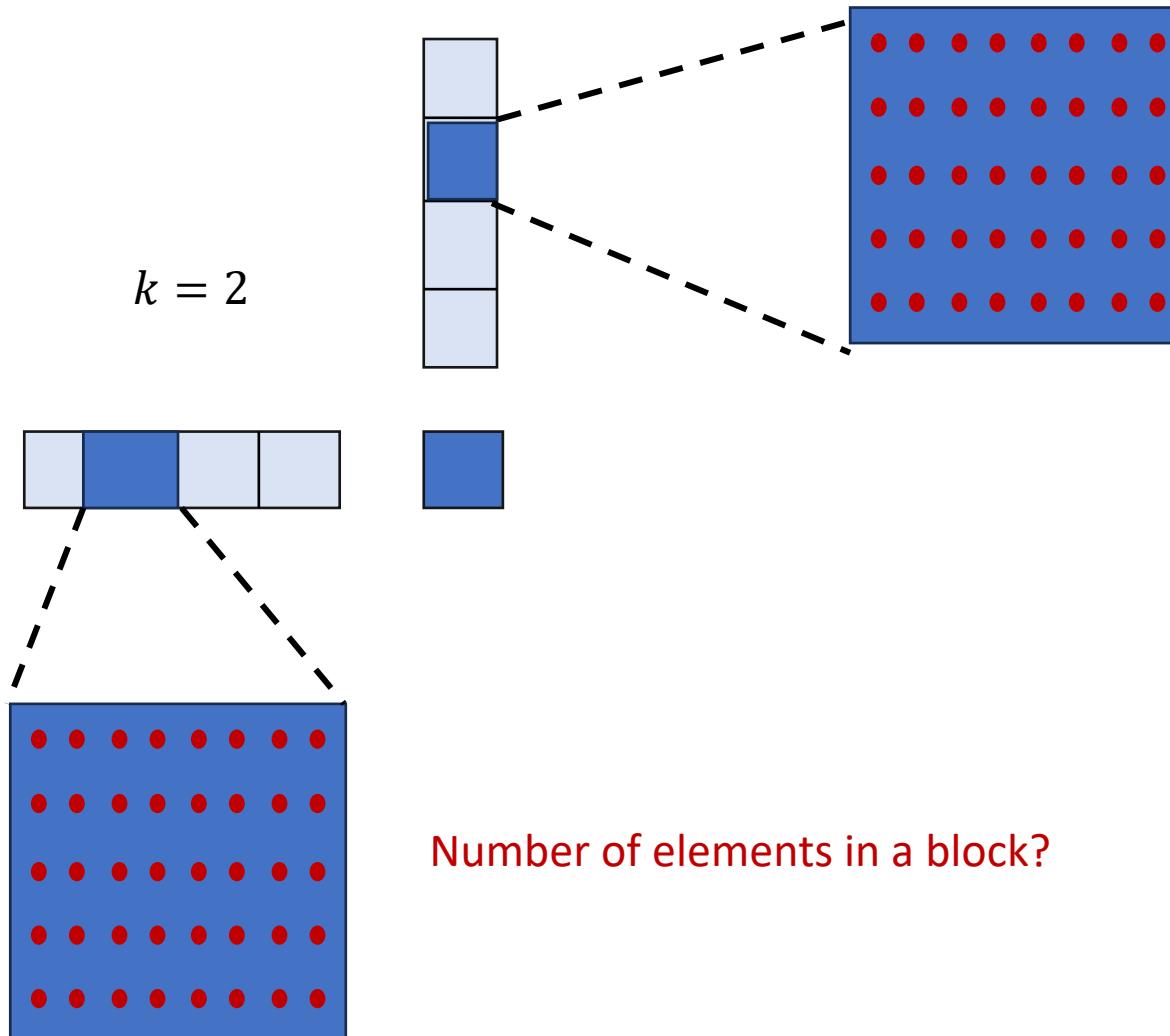
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 - Syncthreads()
 - Store $C[Bid_y * \frac{N}{b} + Tid_y][Bid_x * \frac{N}{b} + Tid_x] \}$

For each k , we fetch the blocks of A and B first before performing computations



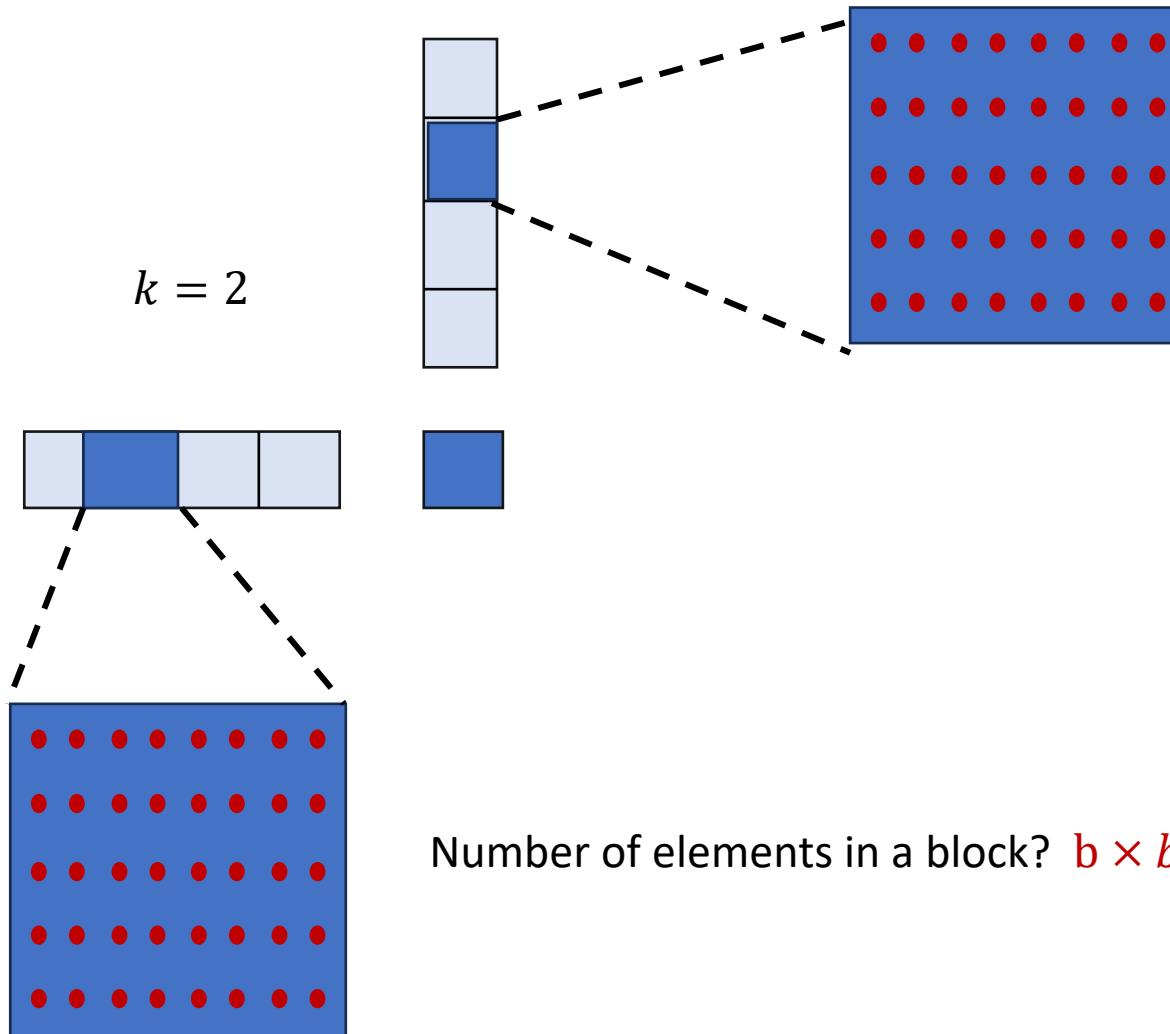
Block Matrix Multiplication



For a given K, each thread fetches exactly 1 element from A and B blocks

Read A[$Bid_y * \frac{N}{b} + Tid_y$][$k*N/b+Tid_x$]
 Read B[$k * \frac{N}{b} + Tid_y$][$Bid_x * \frac{N}{b} + Tid_x$]

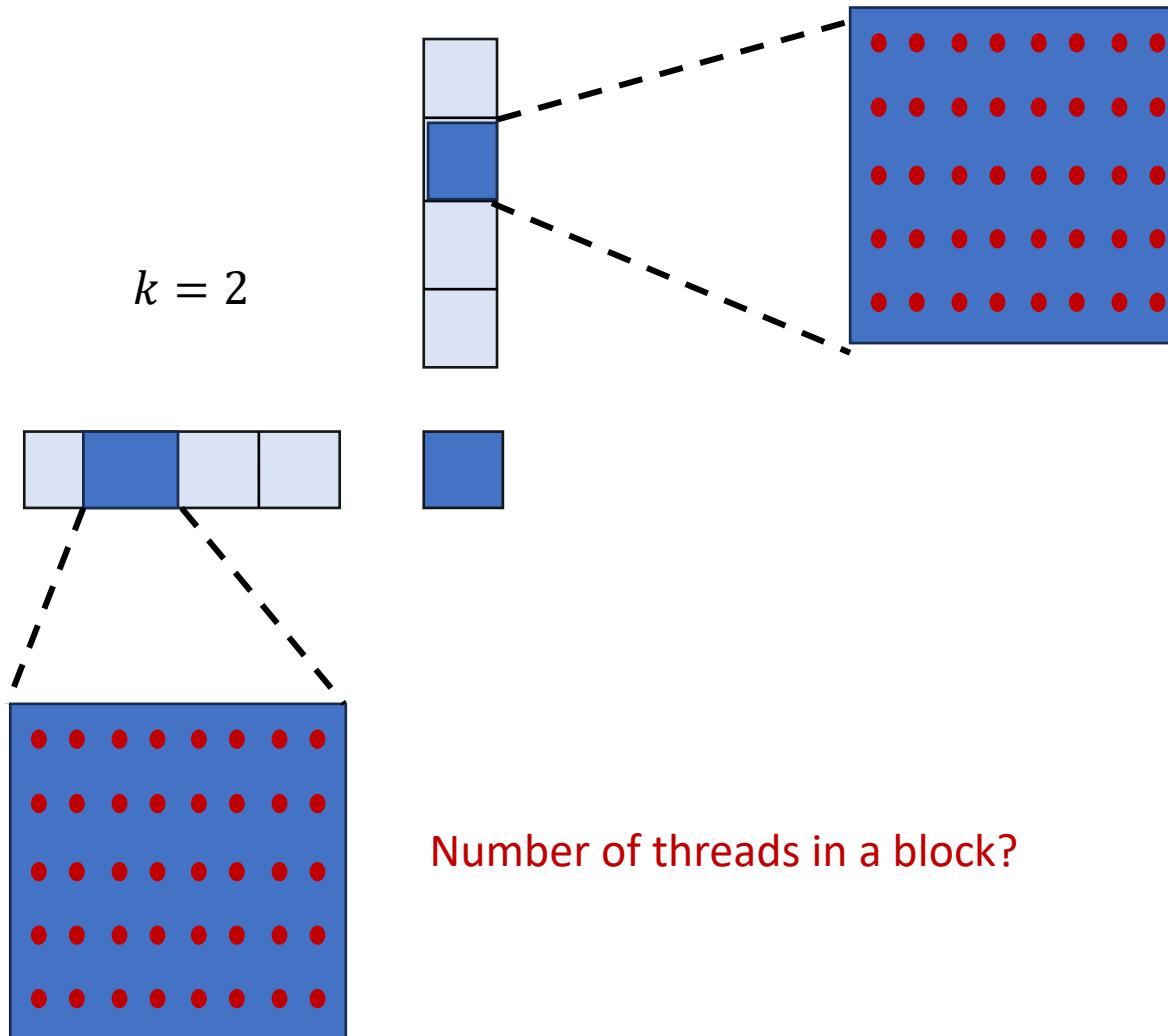
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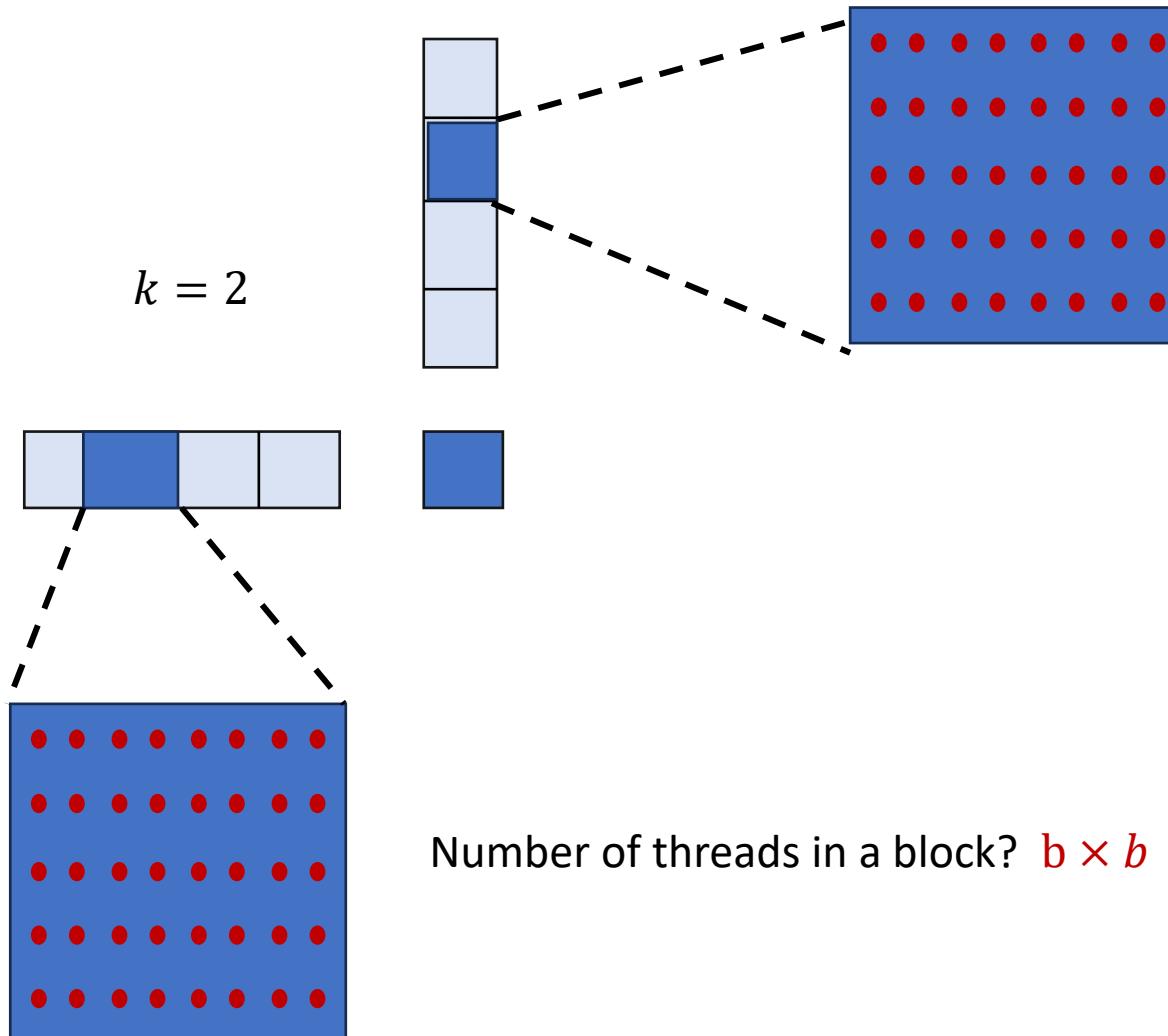
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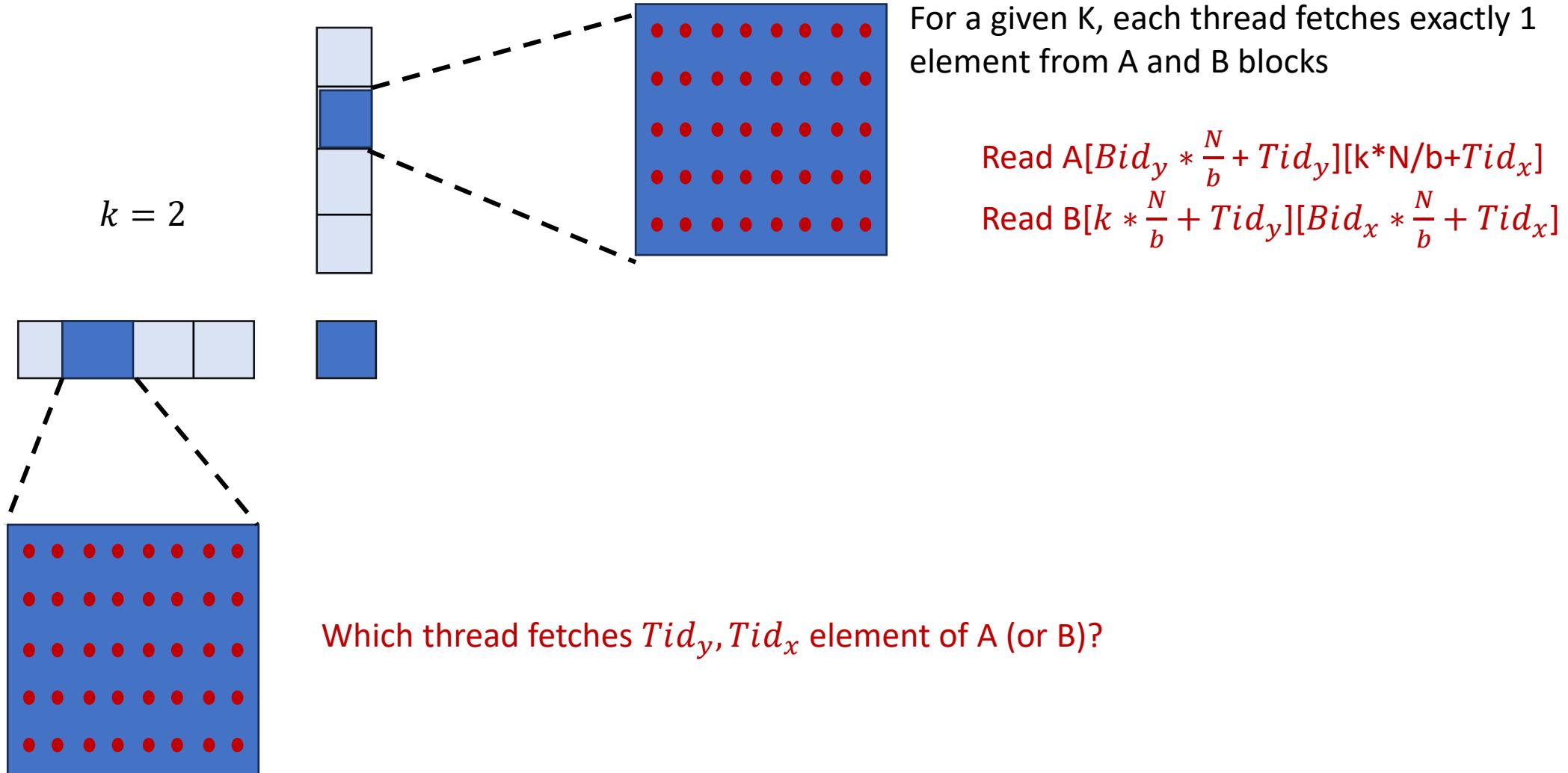
Block Matrix Multiplication



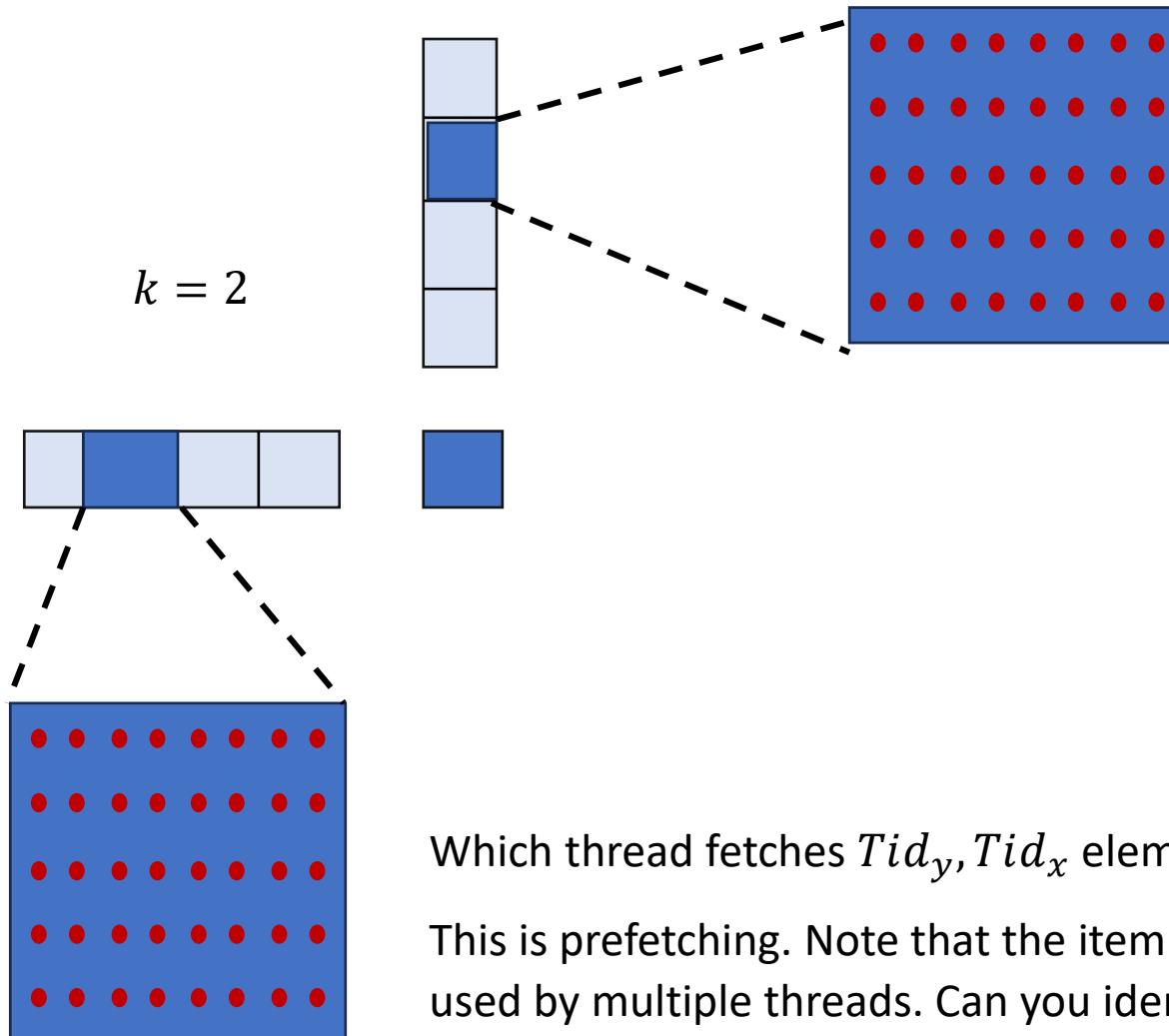
For a given K, each thread fetches exactly 1 element from A and B blocks

Read A[$Bid_y * \frac{N}{b} + Tid_y$][$k*N/b+Tid_x$]
 Read B[$k * \frac{N}{b} + Tid_y$][$Bid_x * \frac{N}{b} + Tid_x$]

Block Matrix Multiplication



Block Matrix Multiplication



For a given K , each thread fetches exactly 1 element from A and B blocks

$$\text{Read } A[Bid_y * \frac{N}{b} + Tid_y][k*N/b+Tid_x]$$

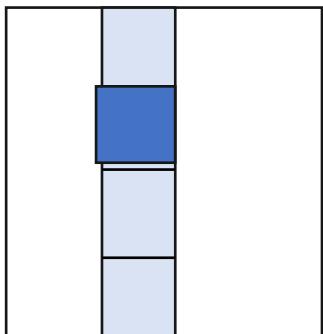
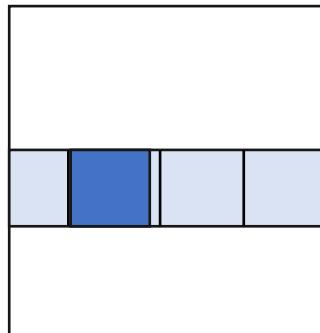
$$\text{Read } B[k * \frac{N}{b} + Tid_y][Bid_x * \frac{N}{b} + Tid_x]$$

Which thread fetches Tid_y, Tid_x element of A (or B)? Tid_y, Tid_x

This is prefetching. Note that the item fetched by Tid_y, Tid_x will be used by multiple threads. Can you identify the range of threads that will use it? (I may ask such questions in the exam)

Block Matrix Multiplication

A

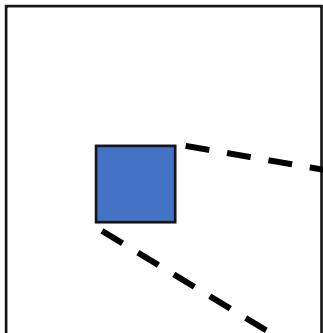


B

For a given K, each thread computes exactly 1 element of C block

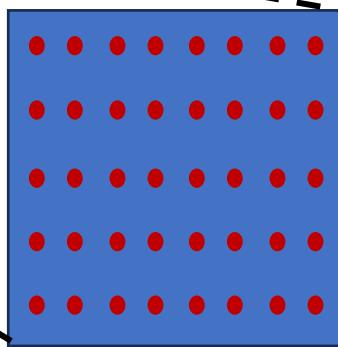
$$\begin{aligned}
 & C[Bid_y * \frac{N}{b} + Tid_y][Bid_x * \frac{N}{b} + Tid_x] += \\
 & A[Bid_y * \frac{N}{b} + Tid_y][k * N/b + l] * \\
 & B[k * \frac{N}{b} + l][Bid_x * \frac{N}{b} + Tid_x]
 \end{aligned}$$

HW: check the equation above to see if it correct or not.



C

SMP Bid_y, Bid_x produces the output block Bid_y, Bid_x



Data Parallelism – Approaches

- #1 Partition Output data
- Notice how we thought about how to divide the output that is being produced among the parallel blocks and threads?
- Notice how there are no write conflicts and each block can execute independently?
 - Threads can too for the most part, but need synchronization steps in between.
- This approach, if applicable, leads to the best parallelism on GPUs

Data Parallelism - Approaches

- #2 Partition Input data
 - Each task is responsible for performing “all” operations on the partition

Input



Data Parallelism - Approaches

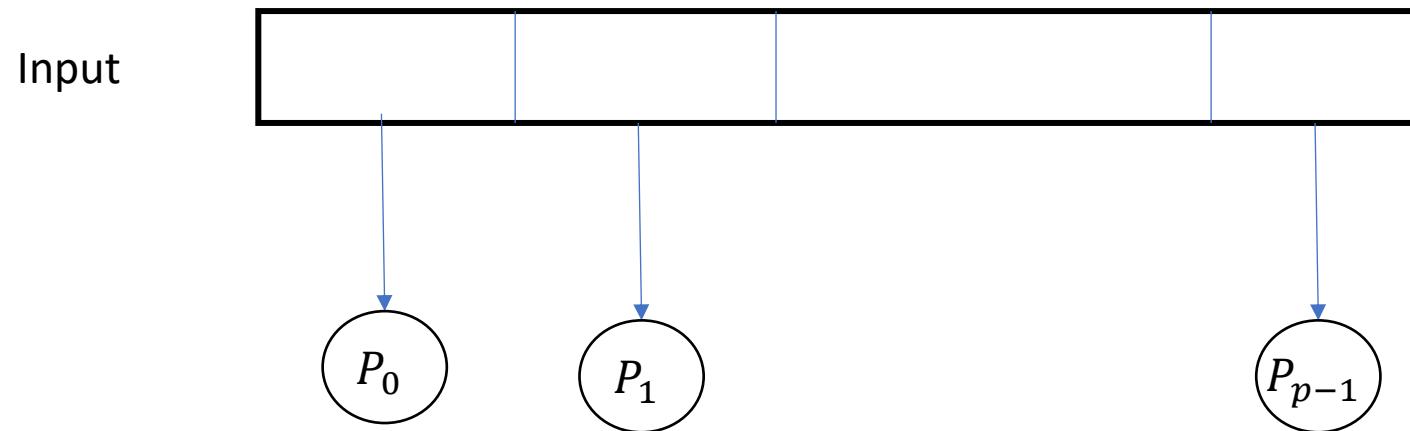
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Input



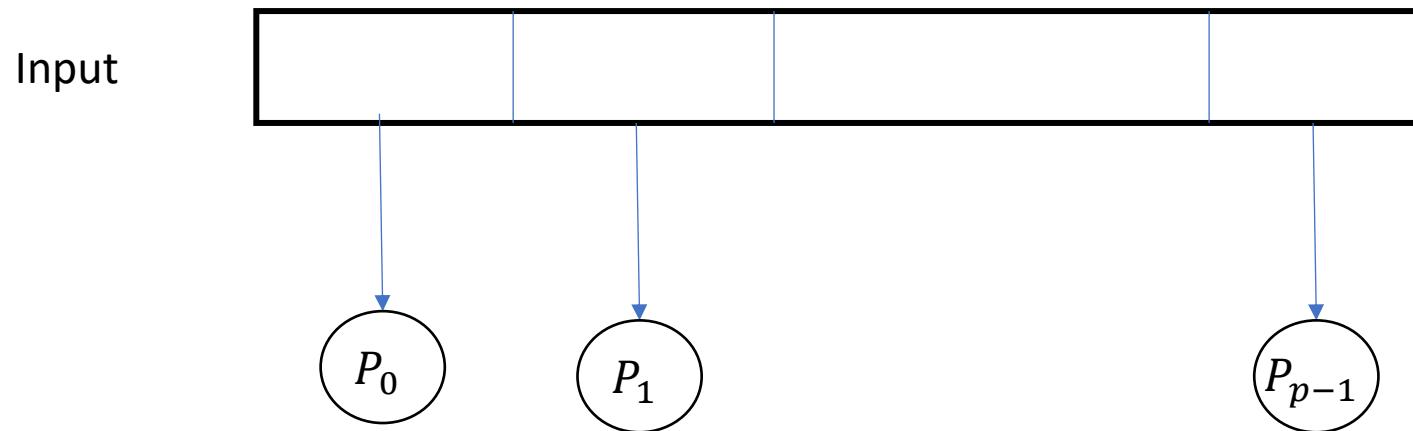
Data Parallelism - Approaches

- #2 Partition Input data
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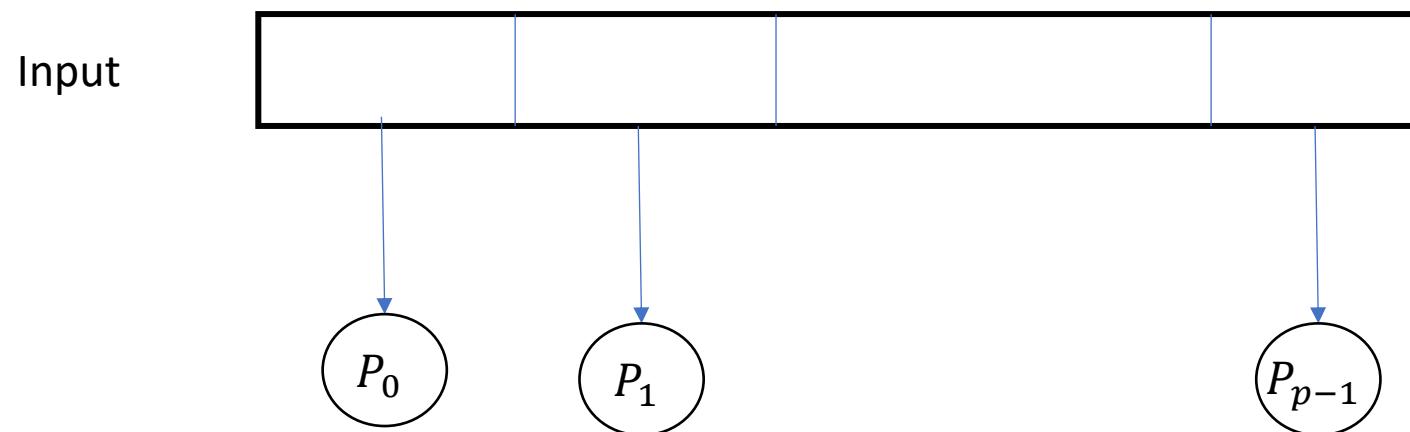
Data Parallelism - Approaches

- #2 Partition Input data
 - Tasks can either directly produce the final output
 - Or produce intermediate output which require another set of tasks to produce the final output



Data Parallelism - Approaches

- #2 Partition Input data
 - Suitable when outputs cannot be independently computed
 - Example: Aggregation functions, Hashing, ...



Sum of Elements in an Array

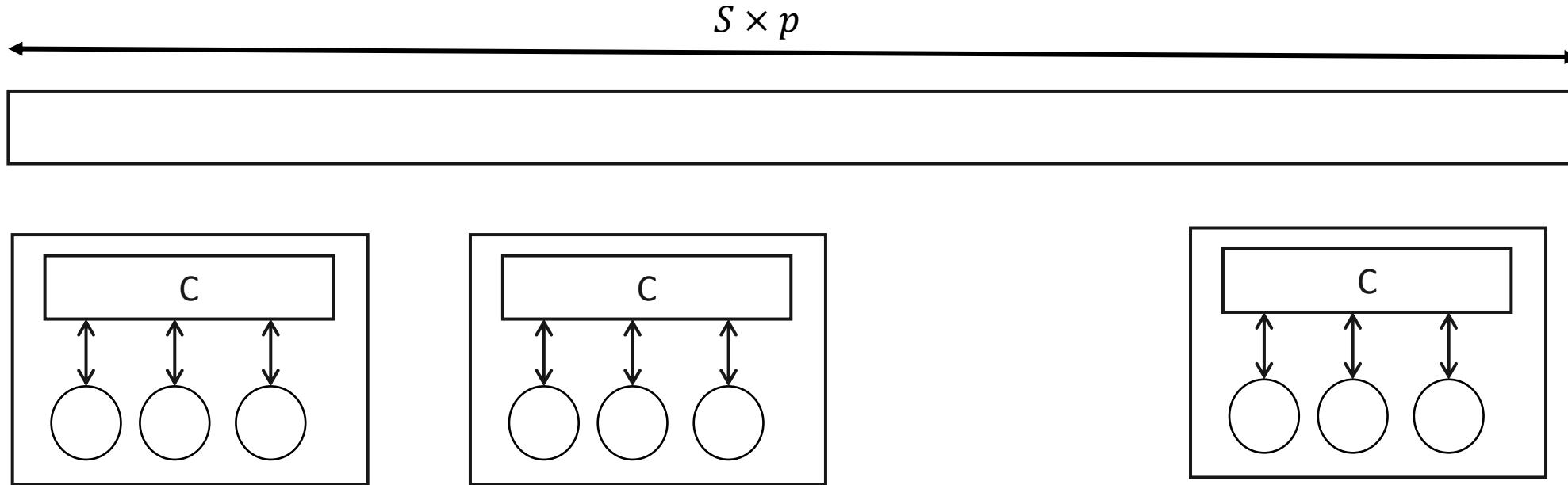
- Input: An array A of N elements
- Output: An array with element $N - 1$ storing $\sum_i A[i]$
- Assume $N = S \times p$
- Resources:
 - <https://developer.nvidia.com/gpugems/gpugems3/part-vi-gpu-computing/chapter-39-parallel-prefix-sum-scan-cuda>
 - <https://courses.cs.washington.edu/courses/cse332/21sp/lectures/19-ParallelPrefix.pdf>
 - They discuss the more general (and complicated) version called prefix sum
 - But consider only single SMP
 - Ungraded HW assignment: Review the algorithm presented on this link, may ask in exam

Sum of Array

- Input: [1, 3, 5, 7, 9]
- Output: [x, x, x, x, 25]

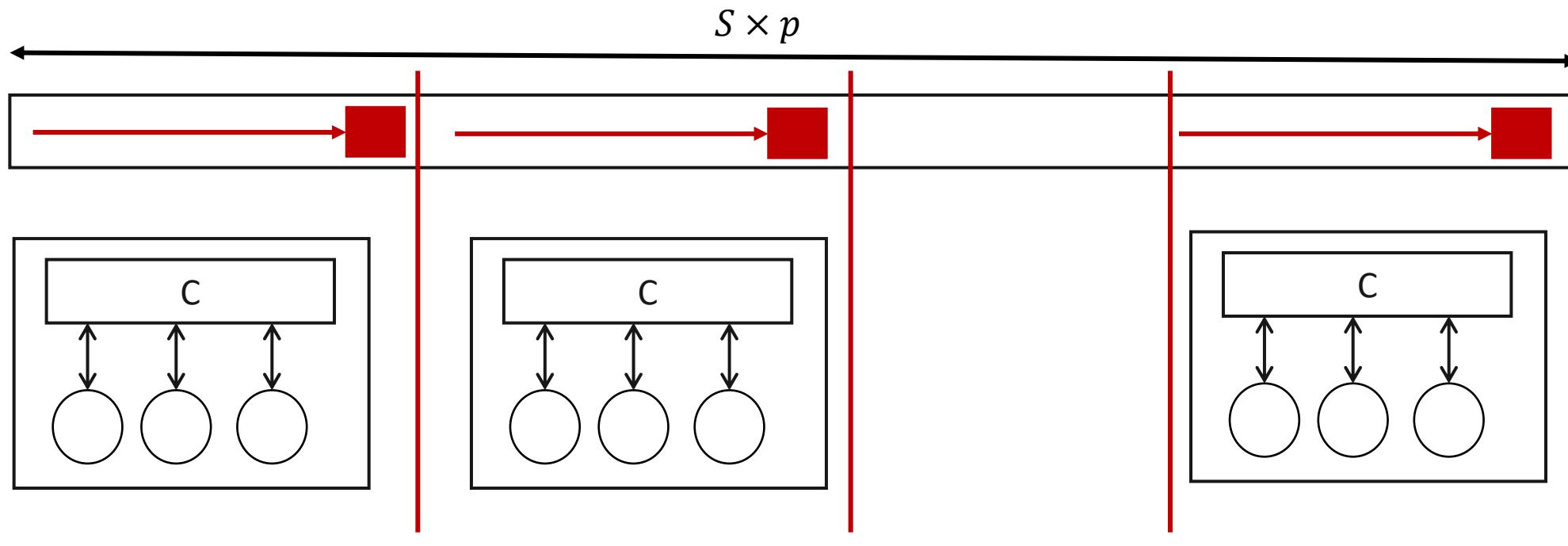
Sum of Array

- Key Idea:
 - Tree like computation to achieve independent computations
 - Two phase algorithm, 1 within a SMP and 1 across SMPs



Sum of Array

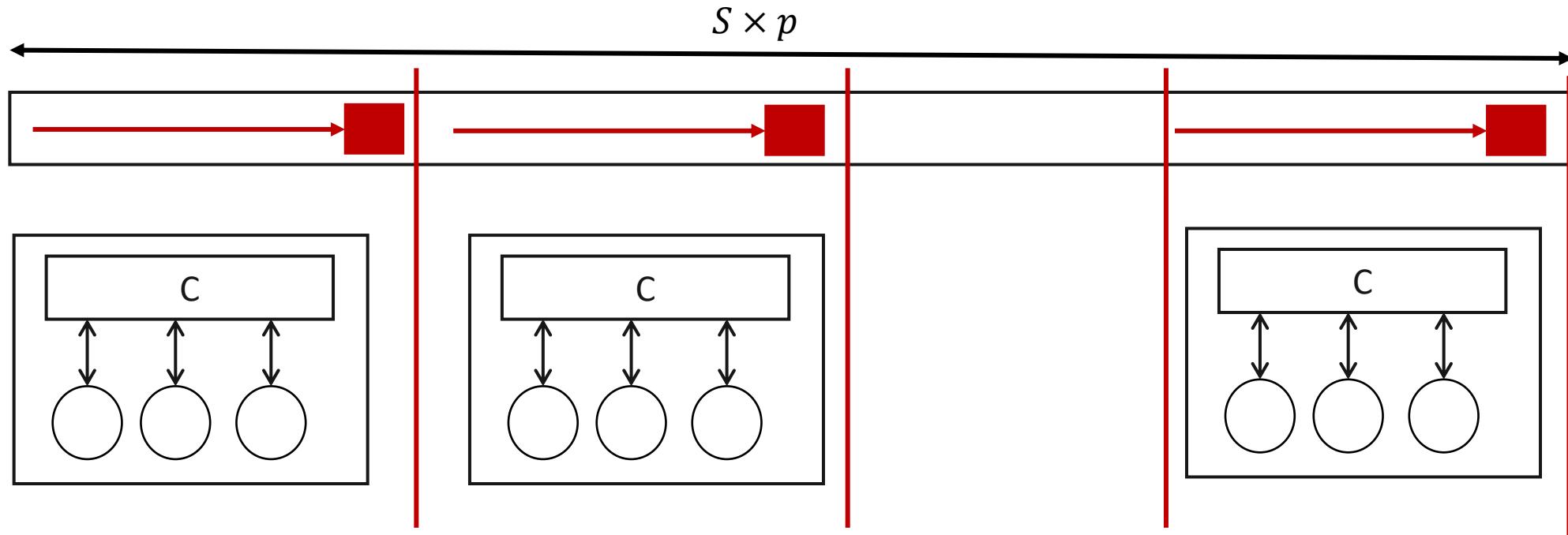
- Key Idea:
 - Tree like computation to achieve independent computations
 - Two phase algorithm, 1 within a SMP and 1 across SMPs



Phase I – Compute the sum of p elements per
Block

Sum of Array

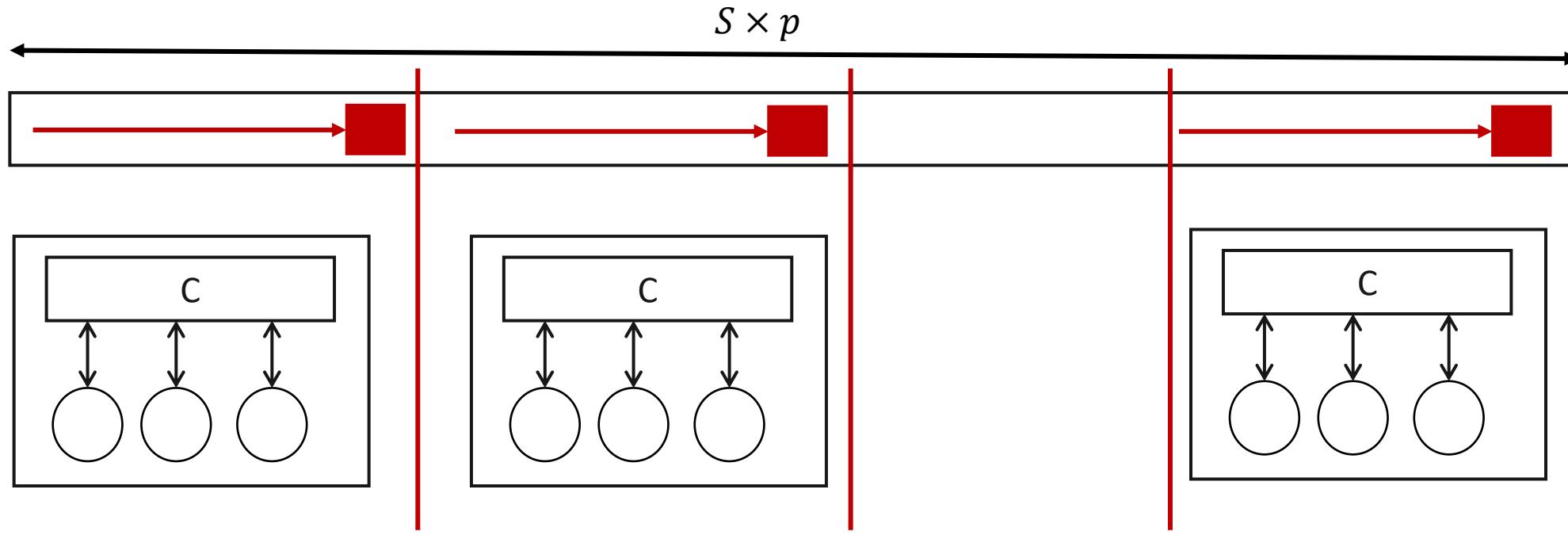
- Key Idea:
 - Tree like computation to achieve independent computations
 - Two phase algorithm, 1 within a SMP and 1 across SMPs



How many sums will remain after Phase I?

Sum of Array

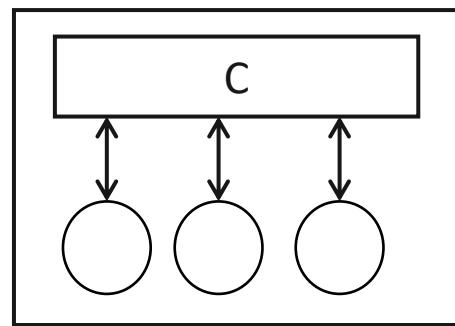
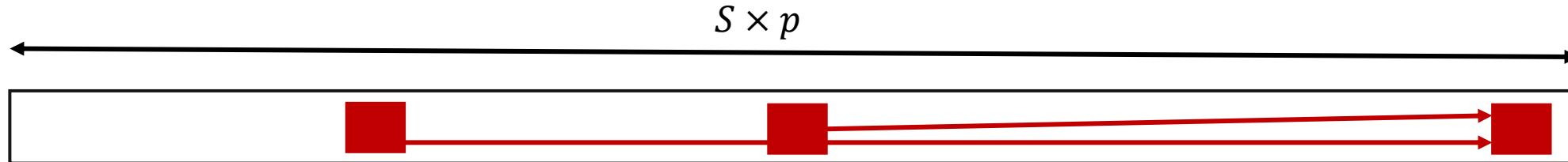
- Key Idea:
 - Tree like computation to achieve independent computations
 - Two phase algorithm, 1 within a SMP and 1 across SMPs



How many sums will remain after Phase I? ***S***

Sum of Array

- Key Idea:
 - Tree like computation to achieve independent computations
 - Two phase algorithm, 1 within a SMP and 1 across SMPs



Phase II – Using one SMP compute the sum of the S partial sums
(Assume, $S < p$)

Sum of Array

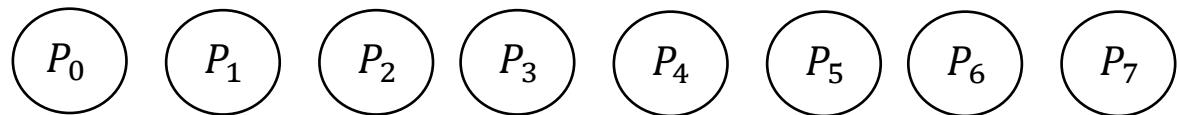
- Phase I: Calculate the sum of p elements and store into the last location of the array
 - Use p processors
- Recursive Doubling Algorithm

Sum of Array

Data Array

1	2	3	4	5	6	7	8
---	---	---	---	---	---	---	---

Processors



Recursive Doubling

Algorithm runs in $\log_2 p$ steps,
• $k = 1$ to $\log_2 p$

In step k

We say, Processor i is active if $i = m2^k - 1$, where m is an integer

Processor i

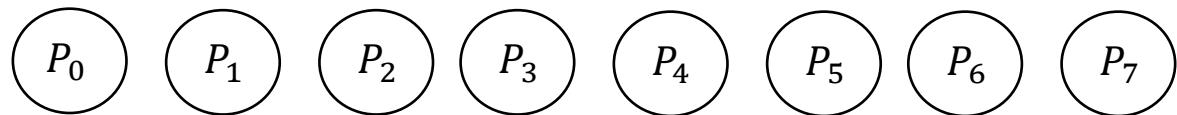
$$A[i] \leftarrow A[i] + A[i - 2^{k-1}]$$

Sum of Array

Data Array

1	2	3	4	5	6	7	8
---	---	---	---	---	---	---	---

Processors



Step 1: $k = 1$ Active Processors??

Recursive Doubling

Algorithm runs in $\log_2 p$ steps,

- $k = 1$ to $\log_2 p$

In step k

We say, Processor i is active if $i = m2^k - 1$, where m is an integer

Processor i

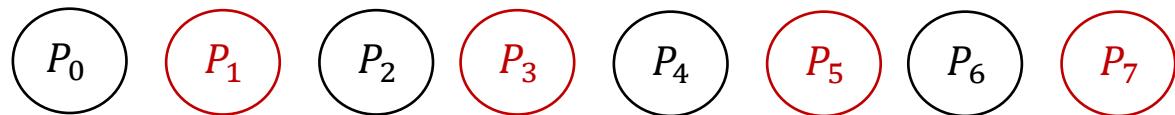
$$A[i] \leftarrow A[i] + A[i - 2^{k-1}]$$

Sum of Array

Data Array

1	2	3	4	5	6	7	8
---	---	---	---	---	---	---	---

Processors



Step 1: $k = 1$ Active Processors?? 1, 3, 5, 7

Recursive Doubling

Algorithm runs in $\log_2 p$ steps,

- $k = 1$ to $\log_2 p$

In step k

We say, Processor i is active if $i = m2^k - 1$, where m is an integer

Processor i

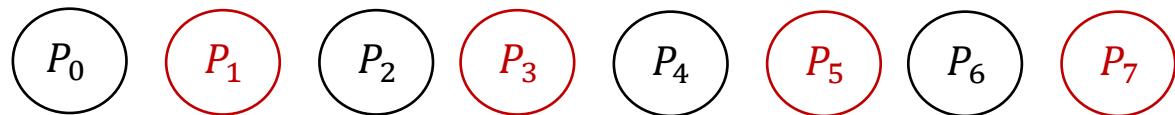
$$A[i] \leftarrow A[i] + A[i - 2^{k-1}]$$

Sum of Array

Data Array

1	2	3	4	5	6	7	8
---	---	---	---	---	---	---	---

Processors



Step 1: $k = 1$ Result of Computation?

Recursive Doubling

Algorithm runs in $\log_2 p$ steps,

- $k = 1$ to $\log_2 p$

In step k

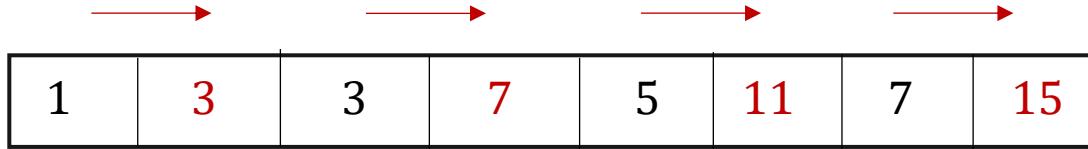
We say, Processor i is active if $i = m2^k - 1$, where m is an integer

Processor i

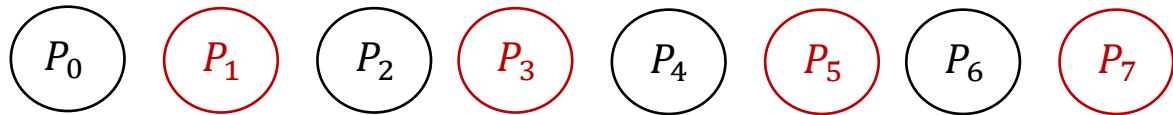
$$A[i] \leftarrow A[i] + A[i - 2^{k-1}]$$

Sum of Array

Data Array



Processors



Step 1: $k = 1$ Result of Computation?

Recursive Doubling

Algorithm runs in $\log_2 p$ steps,

- $k = 1$ to $\log_2 p$

In step k

We say, Processor i is active if $i = m2^k - 1$, where m is an integer

Processor i

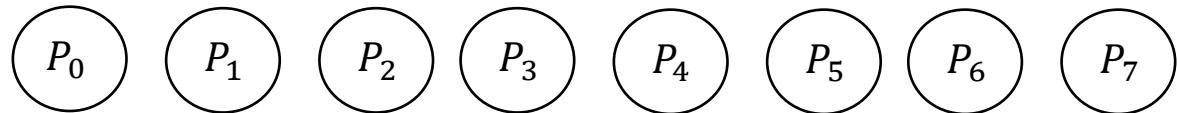
$$A[i] \leftarrow A[i] + A[i - 2^{k-1}]$$

Sum of Array

Data Array

1	3	3	7	5	11	7	15
---	---	---	---	---	----	---	----

Processors



Step 1: $k = 2$ Active Processors??

Recursive Doubling

Algorithm runs in $\log_2 p$ steps,

- $k = 1$ to $\log_2 p$

In step k

We say, Processor i is active if $i = m2^k - 1$, where m is an integer

Processor i

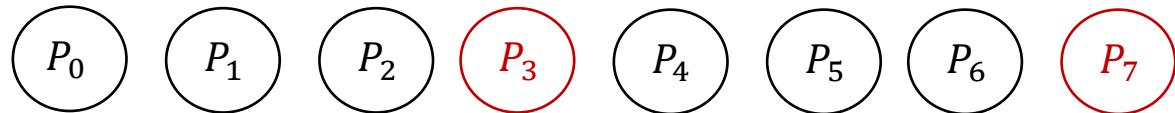
$$A[i] \leftarrow A[i] + A[i - 2^{k-1}]$$

Sum of Array

Data Array

1	3	3	7	5	11	7	15
---	---	---	---	---	----	---	----

Processors



Step 1: $k = 2$ Active Processors?? 3,7

Recursive Doubling

Algorithm runs in $\log_2 p$ steps,

- $k = 1$ to $\log_2 p$

In step k

We say, Processor i is active if $i = m2^k - 1$, where m is an integer

Processor i

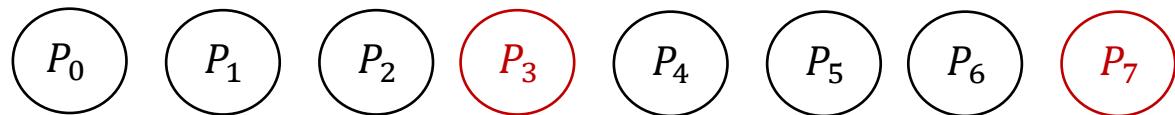
$$A[i] \leftarrow A[i] + A[i - 2^{k-1}]$$

Sum of Array

Data Array

1	3	3	7	5	11	7	15
---	---	---	---	---	----	---	----

Processors



Step 1: $k = 2$ Computations?

Recursive Doubling

Algorithm runs in $\log_2 p$ steps,

- $k = 1$ to $\log_2 p$

In step k

We say, Processor i is active if $i = m2^k - 1$, where m is an integer

Processor i

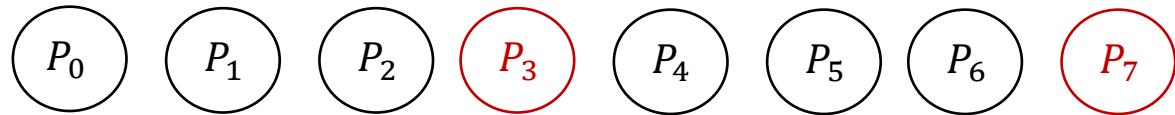
$$A[i] \leftarrow A[i] + A[i - 2^{k-1}]$$

Sum of Array

Data Array

1	3	3	10	5	11	7	26
---	---	---	-----------	---	----	---	-----------

Processors



Step 1: $k = 2$ Computations?

Recursive Doubling

Algorithm runs in $\log_2 p$ steps,

- $k = 1$ to $\log_2 p$

In step k

We say, Processor i is active if $i = m2^k - 1$, where m is an integer

Processor i

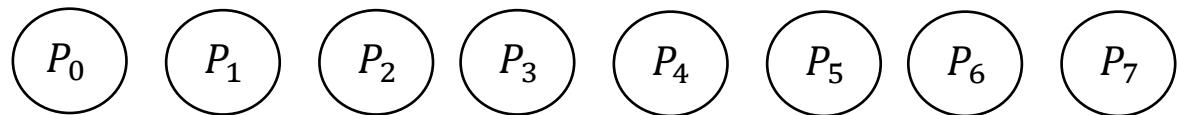
$$A[i] \leftarrow A[i] + A[i - 2^{k-1}]$$

Sum of Array

Data Array

1	3	3	10	5	11	7	26
---	---	---	----	---	----	---	----

Processors



Step 1: $k = 3$ Active Processors?

Recursive Doubling

Algorithm runs in $\log_2 p$ steps,

- $k = 1$ to $\log_2 p$

In step k

We say, Processor i is active if $i = m2^k - 1$, where m is an integer

Processor i

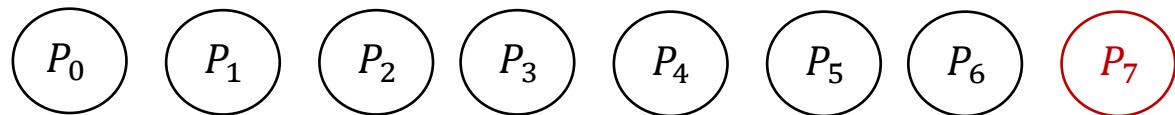
$$A[i] \leftarrow A[i] + A[i - 2^{k-1}]$$

Sum of Array

Data Array

1	3	3	10	5	11	7	26
---	---	---	----	---	----	---	----

Processors



Step 1: $k = 3$ Active Processors? 7

Recursive Doubling

Algorithm runs in $\log_2 p$ steps,

- $k = 1$ to $\log_2 p$

In step k

We say, Processor i is active if $i = m2^k - 1$, where m is an integer

Processor i

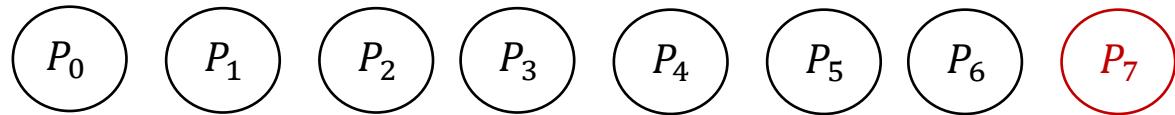
$$A[i] \leftarrow A[i] + A[i - 2^{k-1}]$$

Sum of Array

Data Array

1	3	3	10	5	11	7	26
---	---	---	----	---	----	---	----

Processors



Step 1: $k = 3$ Computations?

Recursive Doubling

Algorithm runs in $\log_2 p$ steps,

- $k = 1$ to $\log_2 p$

In step k

We say, Processor i is active if $i = m2^k - 1$, where m is an integer

Processor i

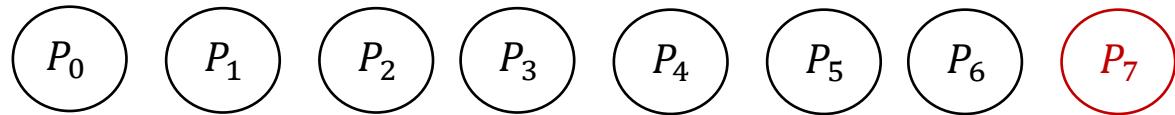
$$A[i] \leftarrow A[i] + A[i - 2^{k-1}]$$

Sum of Array

Data Array

1	3	3	10	5	11	7	36
---	---	---	----	---	----	---	----

Processors



Step 1: $k = 3$ Computations?

Recursive Doubling

Algorithm runs in $\log_2 p$ steps,

- $k = 1$ to $\log_2 p$

In step k

We say, Processor i is active if $i = m2^k - 1$, where m is an integer

Processor i

$$A[i] \leftarrow A[i] + A[i - 2^{k-1}]$$

Sum of Array – Phase II

- Use S processors to calculate the sum of S elements produced in Phase I
- Ungraded HW Assignment: Write a GPU code for this algorithm using BlockID and ThreadID notation that we have been using
- Ungraded HW Assignment: Can you now improve Matrix Vector Multiplication using this approach?

Data Parallelism – Hybrid Approaches

- #3 Partition both Input and Output data
- For each output partition, further partition the inputs
- Blocked MM
 - Input blocks can be further assigned to different SMPs, achieving input parallelism in addition to output parallelism

Data Parallelism

- We will discuss a couple more algorithms in the next class

Outline

- Data Parallel Programming
 - Data Parallel Programming Approaches
- Parallel Program Analysis

Techniques to Improve Application Performance

- Compute Parallelization
 - Decompose tasks to enable concurrent processing
- Memory Optimizations
 - Optimizations addressing latency
 - Optimizations targeted toward maximizing bandwidth utilization
 - Optimizations that reduce the amount of data transfer

But...

- Before we dig into parallelizing an application, how do we know if it is worth parallelizing?
- Performance Metrics discussed till now can reason about an algorithm as a whole
 - Cannot reason about what kinds of benefits we may get from parallelization
 - Cannot reason about the maximum benefit that can be obtained and if it is worth spending the effort on parallelization or not

Speedup

- Improvement in time due to parallelization

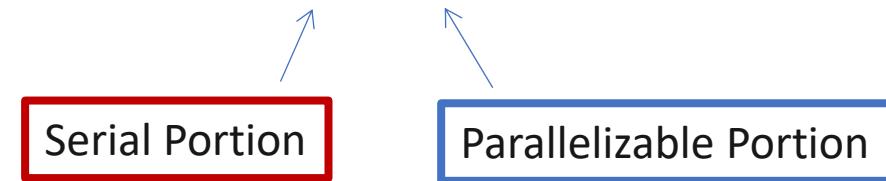
$$\text{Speedup} = \frac{\text{Serial time (on a uniprocessor system)}}{\text{Time after parallelization}}$$

- Serial Time = 1
- Parallel Time = 0.8
- Speedup = $\frac{1}{0.8} = 1.25$

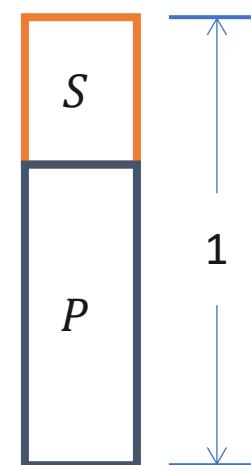
Amdahl's Law

- Amdahl's Law — Limit on speedup achievable when a program is run on a parallel machine
- Given an input program

- Total execution time: $S + P$



- Time on a uni-processor machine: $1 = S + P$
 - Time on a parallel machine: $S + P/f$
 f = speedup factor

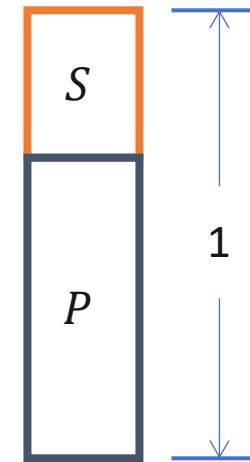


Amdahl's Law

$$\begin{aligned}
 &= \frac{\text{Serial Time}}{\text{Parallel Time}} \\
 &= \frac{S + P}{S + P/f} \quad f = \text{speedup factor} \\
 &= \frac{1}{S + P/f} \\
 &\leq \frac{1}{S}
 \end{aligned}$$

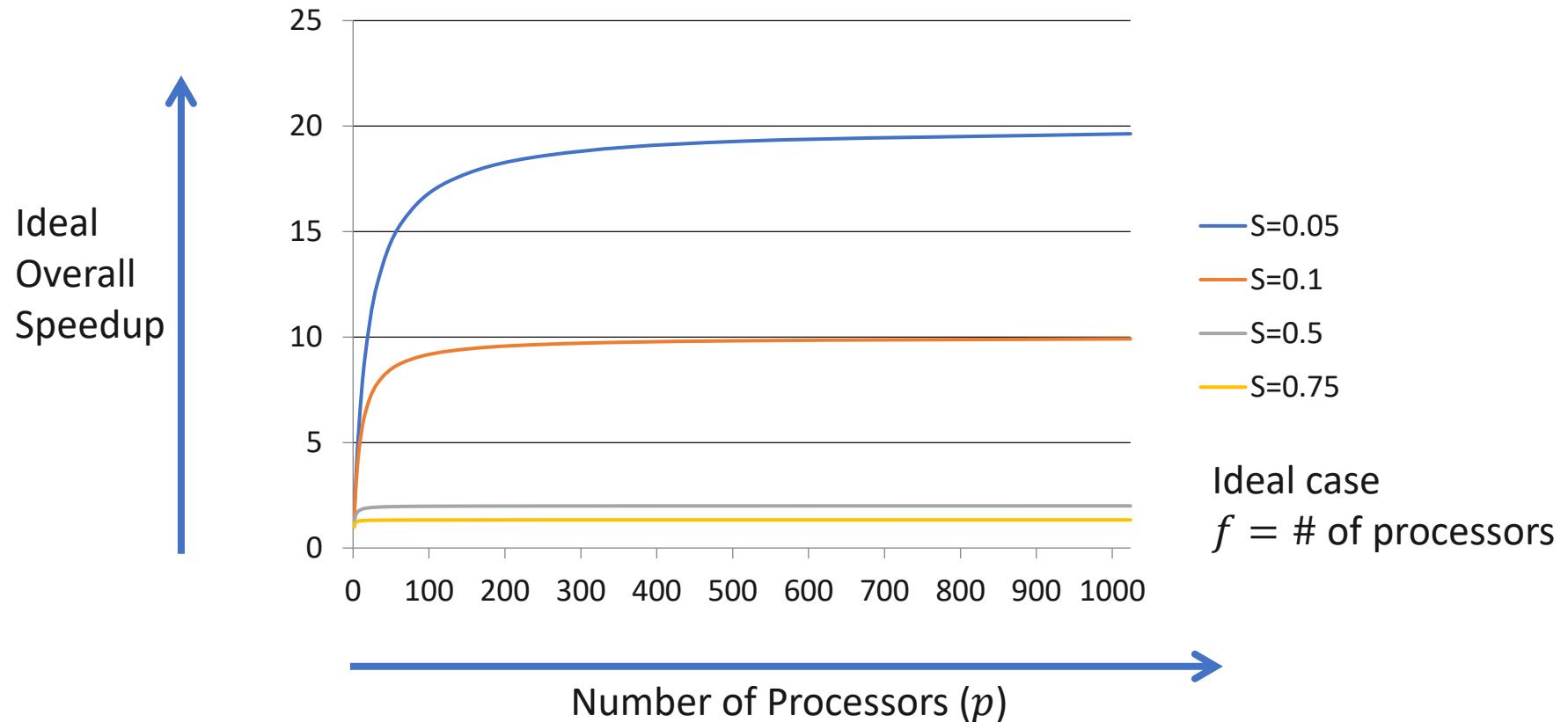
If serial portion is 50 %, then the **overall speedup ≤ 2**

Note: Speedup factor (f) \leq # of processors



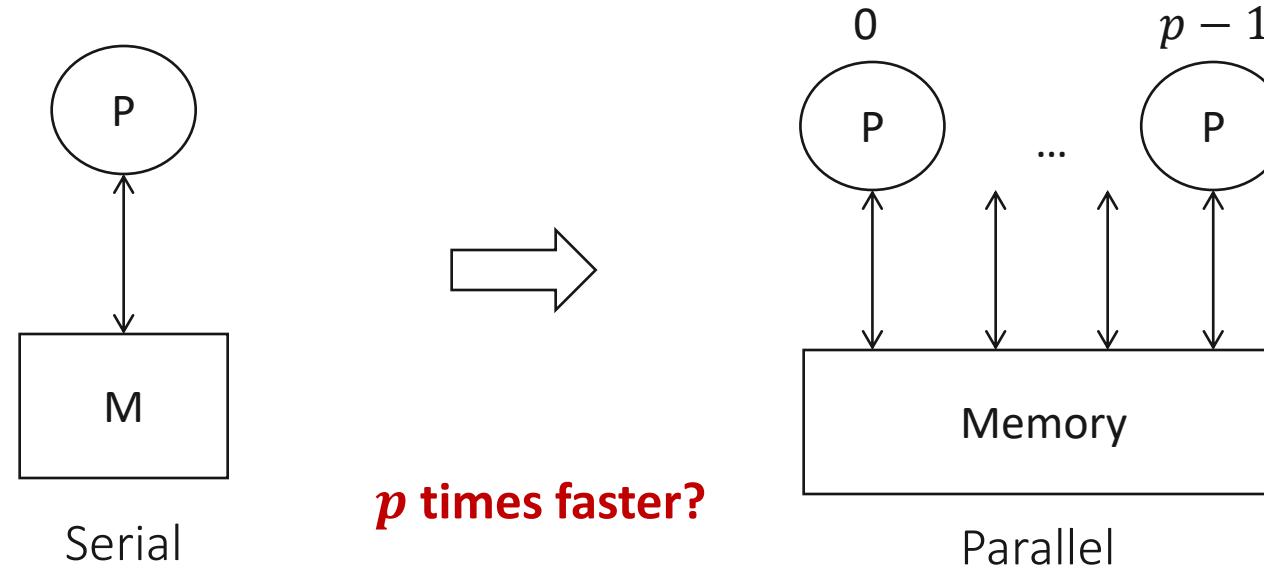
Amdahl's Law

$$\text{Overall Speedup} = \frac{1}{S + P/f} = \frac{1}{S + (1 - S)/f} \rightarrow \frac{1}{S}$$



Scalability (1)

Does performance (execution time) improve as we use more resources (processors)



Scalability (2)

$$\text{Speedup} = \frac{\text{Serial time (on a uniprocessor system)}}{\text{Parallel time using } p \text{ processors}}$$

If speedup = $O(p)$, then it is a **scalable** solution

Overheads in Parallel Computation

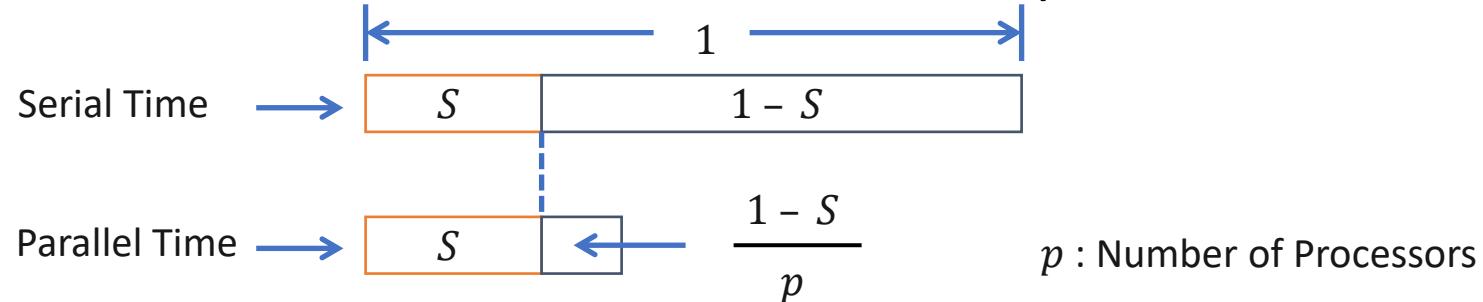
- Communication
- Synchronization
- Load balance (processors may idle)
- Resource contention

Scaled Speedup (Gustafson's Law) (1)

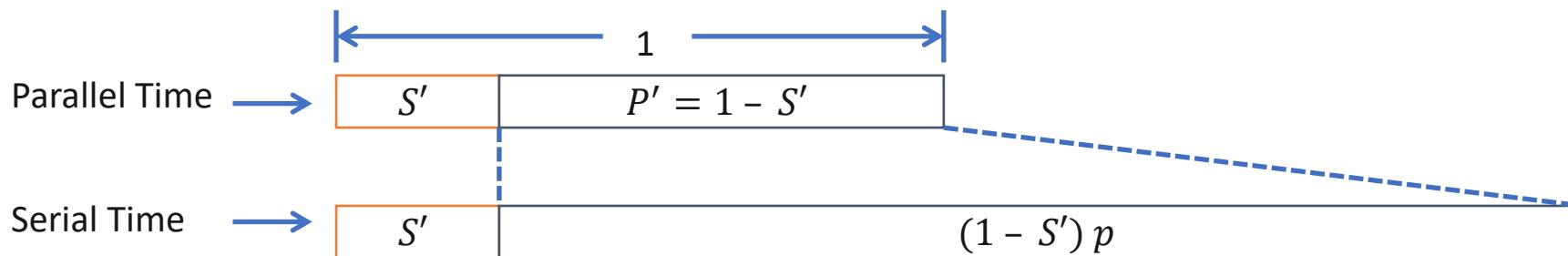
- Amdahl's Law — Serial portion of code limits performance
(As we use more processors)
- As we use more processors
 - we use more data
 - e.g., more fine grained model
- E.g. Processing $N \times N$ image
 - Using p processors
 - As we increase p we usually increase image size

Scaled Speedup (Gustafson's Law) (2)

Amdahl's Law: Fixed amount of computations



Gustafson's Law: Increase p and amount of computations



If parallelism scales linearly with p , number of processors

$$\text{Scaled Speedup} = \frac{\text{Serial time}}{\text{Parallel time}} = \frac{S' + (1 - S')p}{S' + P'} = \frac{S' + (1 - S')p}{1}$$

Scaled Speedup (Gustafson's Law) (3)

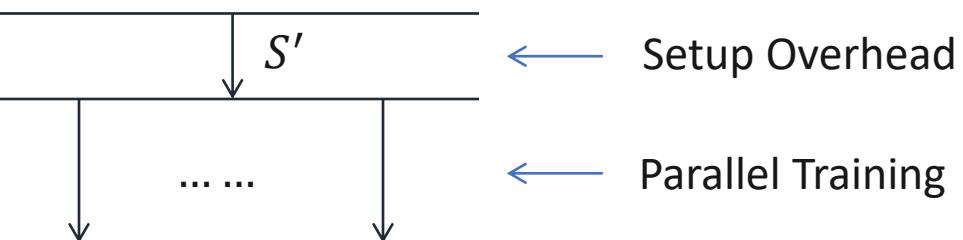
Gustafson's Law

$$\begin{aligned}\text{Scaled Speedup} &= S' + (1 - S')p \\ &\approx (1 - S')p\end{aligned}$$

$S' = 0 \rightarrow \text{Scaled Speedup} = \text{Ideal speedup } (p)$

$S' = 0.5 \rightarrow \text{Scaled Speedup} = 0.5 p, 50\% \text{ of Ideal speedup}$

Example: ML Training



$$\text{Scaled Speedup} \propto (1 - S') \times \# \text{ of threads}$$

Scaled Speedup (Gustafson's Law) (4)

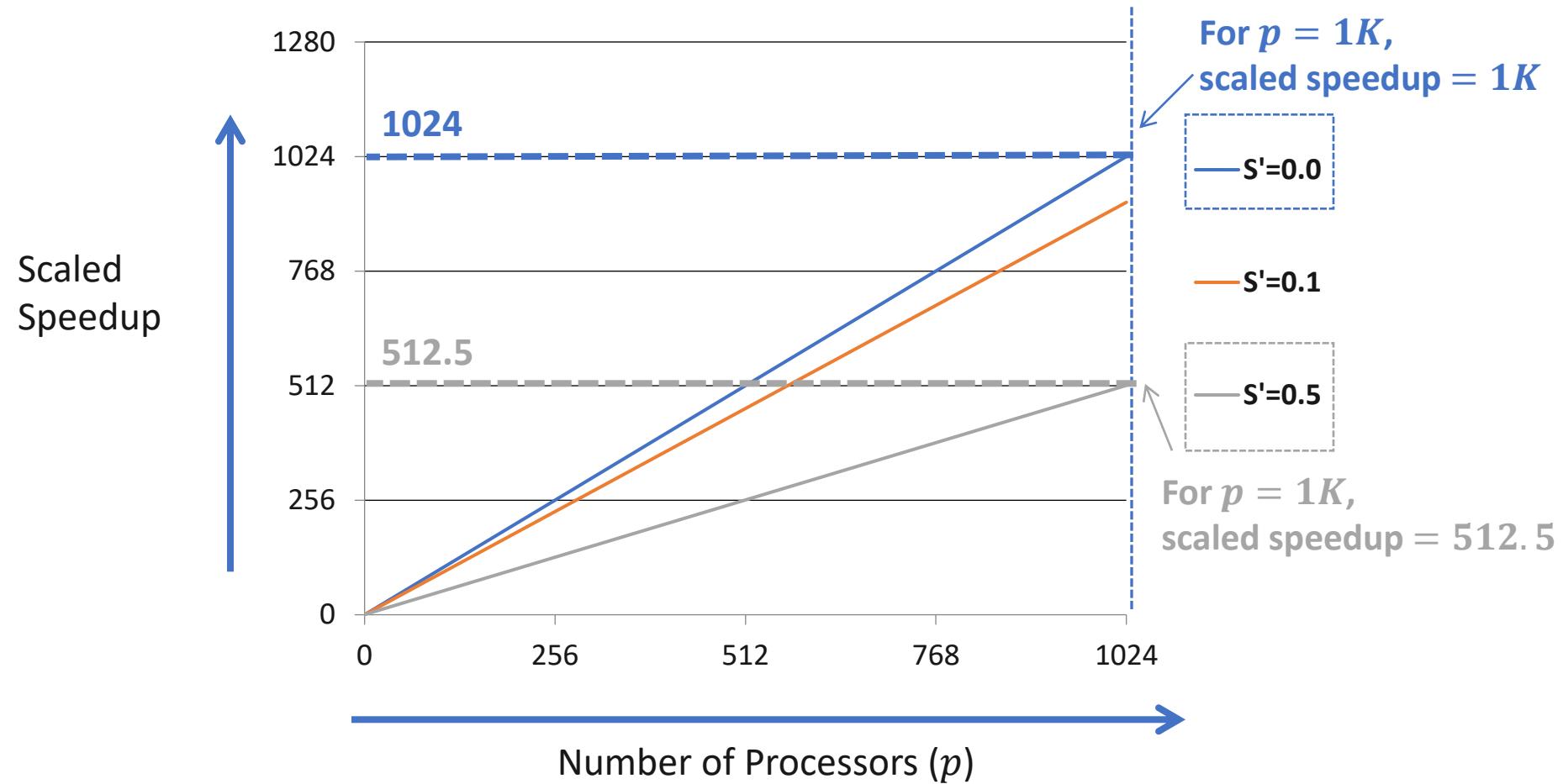
Gustafson's Law

- If we increase
 - the number of processors (p)
 - the amount of parallelizable portion of computations
- Scaled speedup is limited by the fraction of program that can be parallelized (higher the fraction, higher the speedup).

Scaled Speedup (Gustafson's Law) (5)

- $S = 0.5$
- $p = 32$
- Amdahl's Law – Cannot achieve more than 2x speedup
- Gustafson's Law – Can achieve 16x speedup

Scaled Speedup (Gustafson's Law) (6)



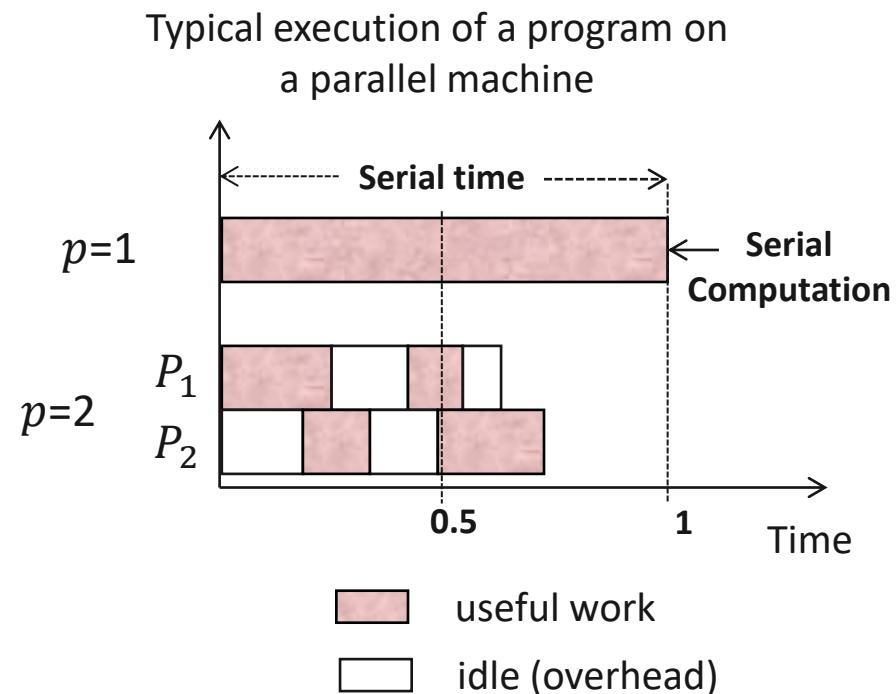
Strong or Weak Scaling

- Strong Scaling
 - Governed by Amdahl's Law
 - The number of processors is **increased** while the problem size **remains constant**
 - Results in a **reduced** workload per processor
- Weak Scaling
 - Governed by Gustafson's Law
 - **Both** the number of processors and the problem size are **increased**
 - Results in a **constant** workload per processor

Performance (1)

Efficiency

- Question: If we use p processors, is speedup = p ?
- Efficiency \triangleq Fraction of time a processor is usefully employed during the computation
- $E = \text{Speedup} / \# \text{ of processors used}$
 - E is the average efficiency over all the processors
 - Efficiency of each processor can be different from the average value

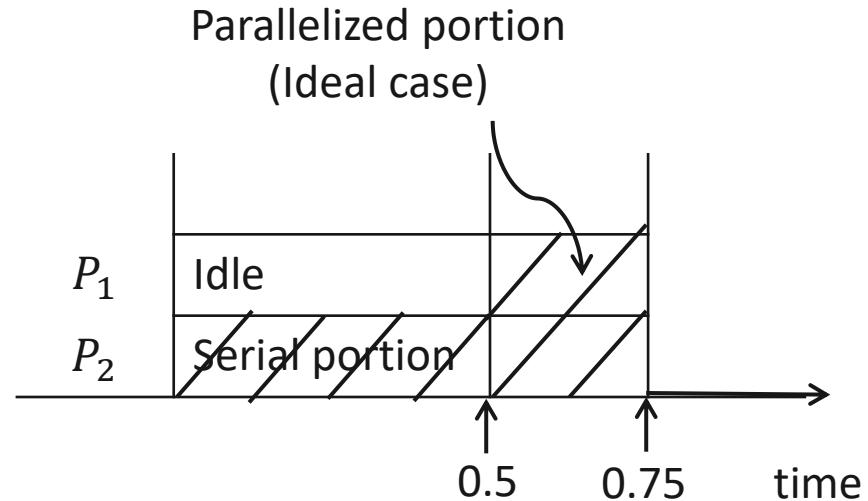


Performance (2)

Ex.

$$\begin{aligned} S &= 0.5 \\ P &= 0.5 \end{aligned}$$

2 processor system



$$\text{Speedup} = \frac{1}{0.75} = 4/3$$

$$(\text{Average}) \text{ Efficiency} = \frac{4/3}{2} = 2/3$$

$$\text{Efficiency of } P_1 = \frac{0.25}{0.75} = 1/3$$

$$\text{Efficiency of } P_2 = \frac{0.75}{0.75} = 1$$

$$(\text{Average}) \text{ Efficiency} = \frac{1/3+1}{2} = 2/3$$

Performance (3)

- Cost = Total amount of work done by a parallel system
 - = Parallel Execution Time \times Number of Processors
 - = $T_p \times p$
- Cost is also called **Processor Time Product**
- COST OPTIMAL (or WORK OPTIMAL) Parallel Algorithm
 - Total work done = Serial Complexity of the problem

Blocked Matrix Multiplication

- Serial Algorithm - $O(n^3)$

- Parallel Algorithm:
- Number of steps n/b
- Work done by each processor in each step: $O(b)$

Cost of the algorithm: $O\left(n^2 \times \left[\frac{n}{b} \times b\right]\right) = O(n^2 \times n) = O(n^3)$

Total Number
of Processors

Work done in
each processor

- Cost of the algorithm \sim serial complexity. So work optimal.

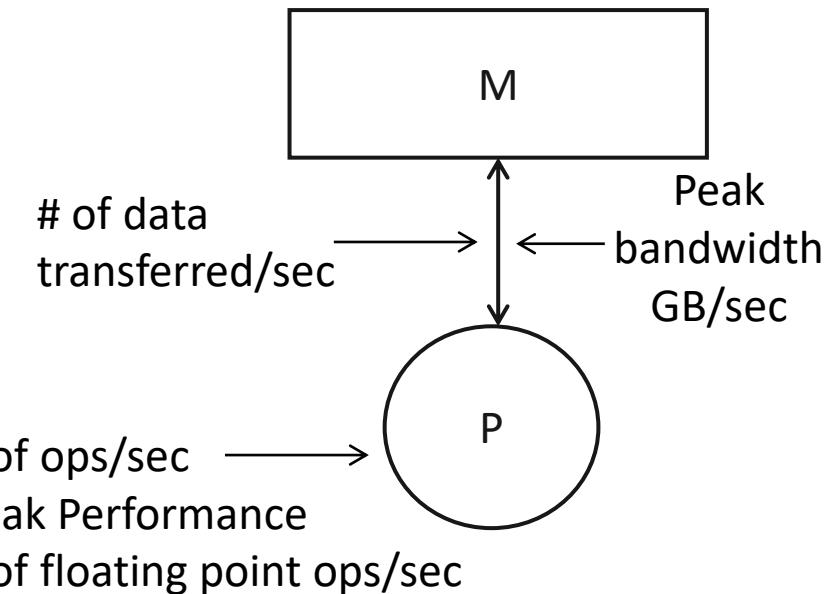
Sum of Elements in an Array

- Serial Algorithm: $O(p)$
- Parallel Algorithm:
- Number of steps - $O(\log_2 p)$
- Number of processors in each step - $O(p)$
 - Note: We can also consider only active processors to come up with a different analysis.
- Cost of the Algorithm - $O(p \log_2 p)$
- Cost of the algorithm !~ serial complexity. So not work optimal (assuming GPU model). It is work optimal if we only consider active processor in the analysis.

Roofline Model

- **In Practice:** Processor Performance \gg Memory Performance
- Processor may idle waiting for data

$$\text{Machine Balance} = \frac{\text{Peak Performance (Flops/sec)}}{\text{Peak Bandwidth (GB/sec)}}$$



The Roofline Model
 Samuel Williams, Lawrence Berkeley National Lab
<https://escholarship.org/content/qt0qs3s709/qt0qs3s709.pdf>

Roofline Model

- Arithmetic Intensity (AI) = For every fetched data (from memory) how many ops make use of them

$$= \frac{\# \text{ of } \text{ops} \text{ performed}}{\text{Amount of data moved from external memory}}$$

- Algorithm Dependent

- Example

$$\text{AI of vector inner product} = \frac{2n}{2n} = O(1)$$

$$\text{AI of Dense matrix multiplication} = \frac{2n^3}{2n^2} = O(n)$$

Roofline Model

- Understand system bottlenecks – Computation vs Memory
- High level model using few parameters (ignores ISA etc.)
- Can be used to understand and evaluate an application performance on a target
- Can be used to make architectural decisions for custom accelerators

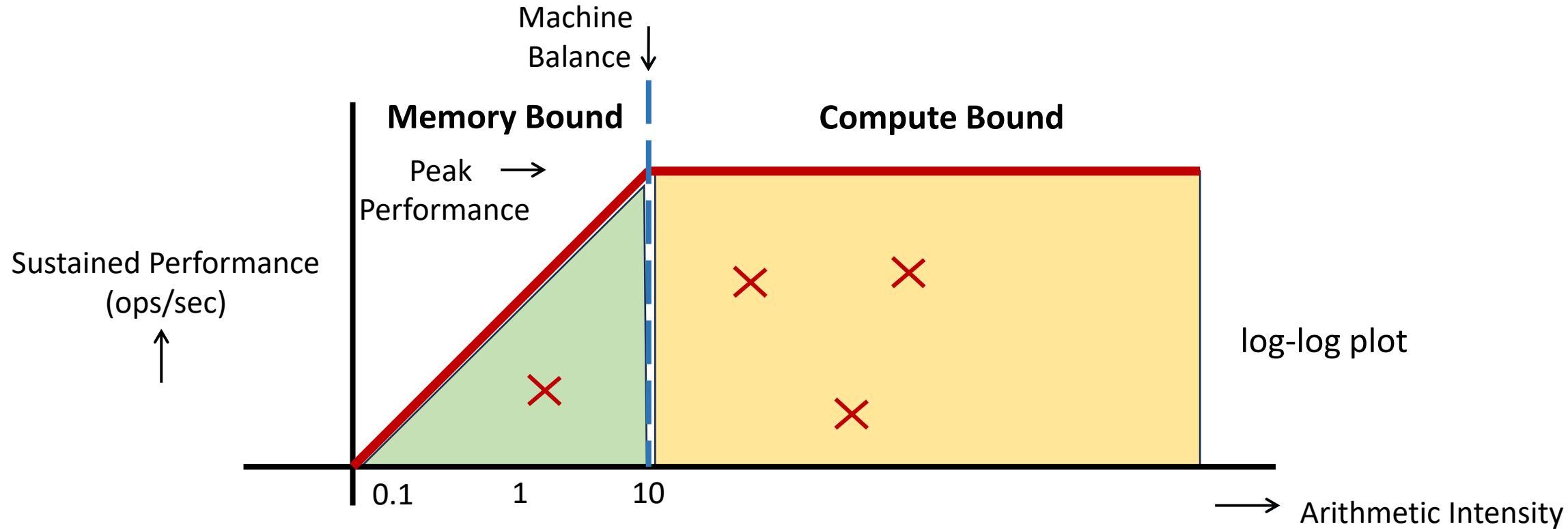
The Roofline Model

Samuel Williams, Lawrence Berkeley National Lab

<https://escholarship.org/content/qt0qs3s709/qt0qs3s709.pdf>

Compute Bound vs Memory Bound

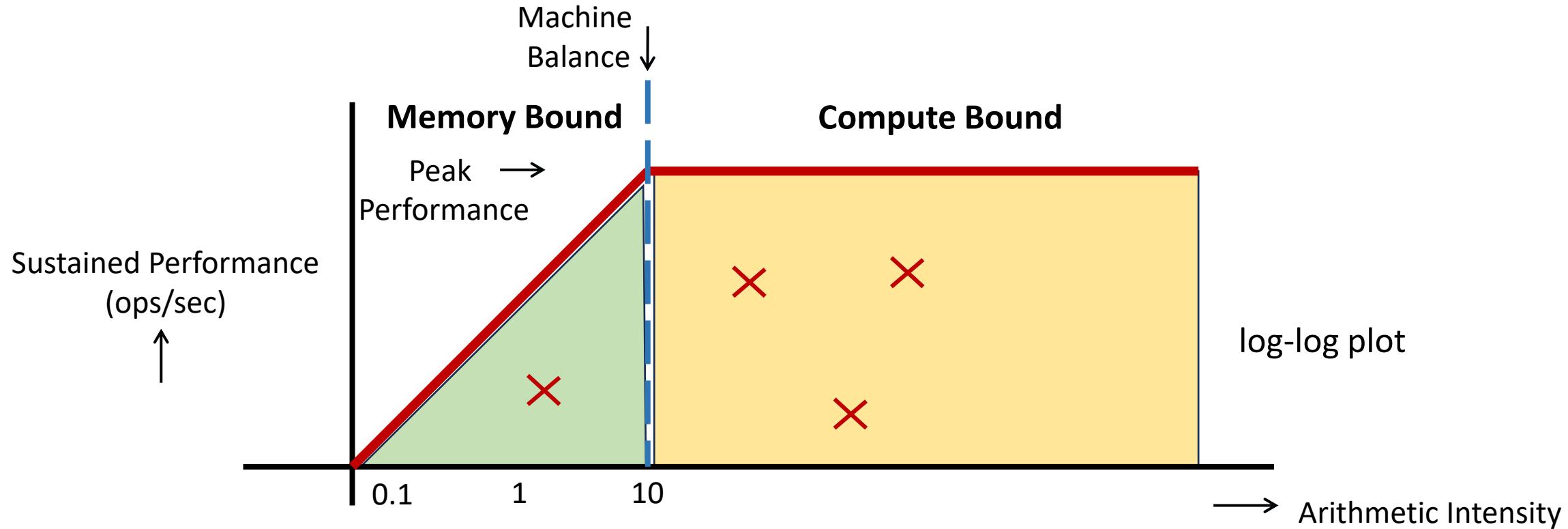
Roofline Model (for a given platform)





Compute Bound vs Memory Bound

Roofline Model (for a given platform)

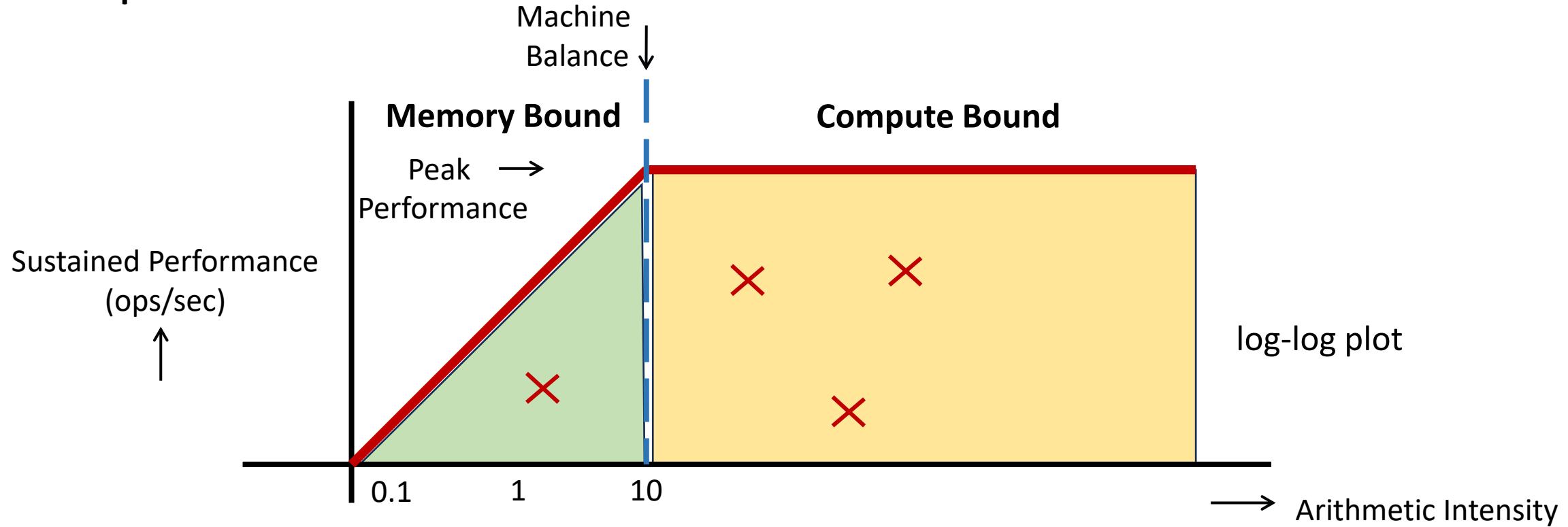


- Bold Red line denotes the maximum achievable performance for a given arithmetic intensity
- Memory bound region: maximum achievable performance bounded by memory bandwidth
- Compute bound region: maximum achievable performance bounded by compute capability

Compute Bound vs Memory Bound Roofline Model (for a given platform)

- Compute Bound: Maximum Performance is limited by available compute resources
 - if we add more compute resources, the performance may improve (for a given bandwidth)
 - Useful in designing accelerators. Not a focus of this class
- Memory Bound: Maximum Performance is limited by memory bandwidth
 - Reorder computations to more efficiently utilize bandwidth
 - In other words, improve arithmetic intensity to move right on x axis, which also improves y axis

Roofline Model – What about actual performance?



- For a fixed AI: improving performance (going up) requires better parallelism – Data and Task Parallel Techniques
- Once the Red bold line is reached
 - Green Region: Write better algorithm to improve arithmetic intensity
 - Yellow Region: No algorithmic solution, need to add more computation power

WA 1

- You should be able to answer all questions except the sorting one. We will discuss parallel sort in the next class

Next Class

- 9/16 Lecture 7 – Parallel Sorting; Task Parallelism

Thank You

- Questions?
- Email: sanmukh.kuppannagari@case.edu