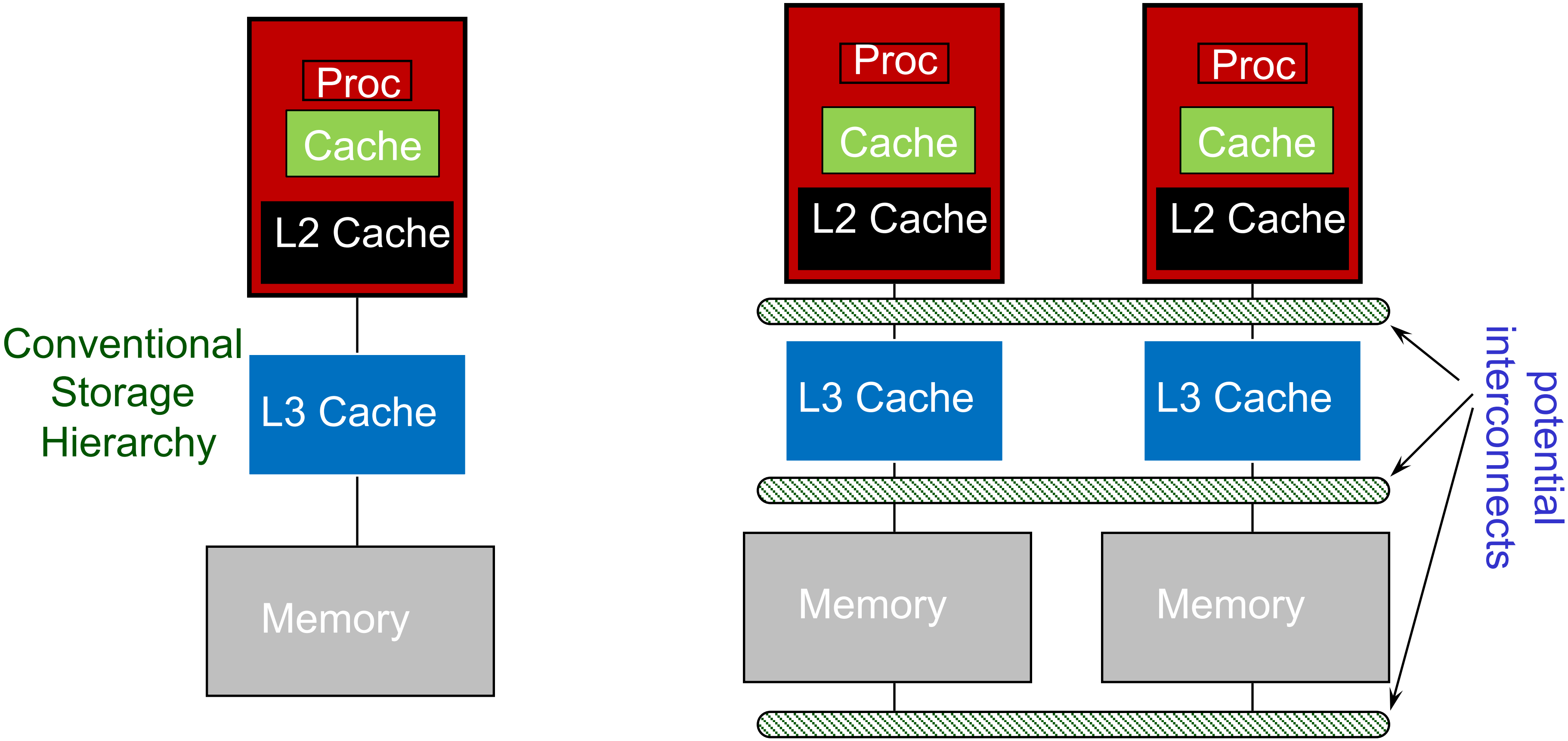
CSC367 Parallel computing

Lecture 6: Parallel Architectures and Parallel Algorithm Design

Thanks to Scinet, NSF XSEDE, James Demmel

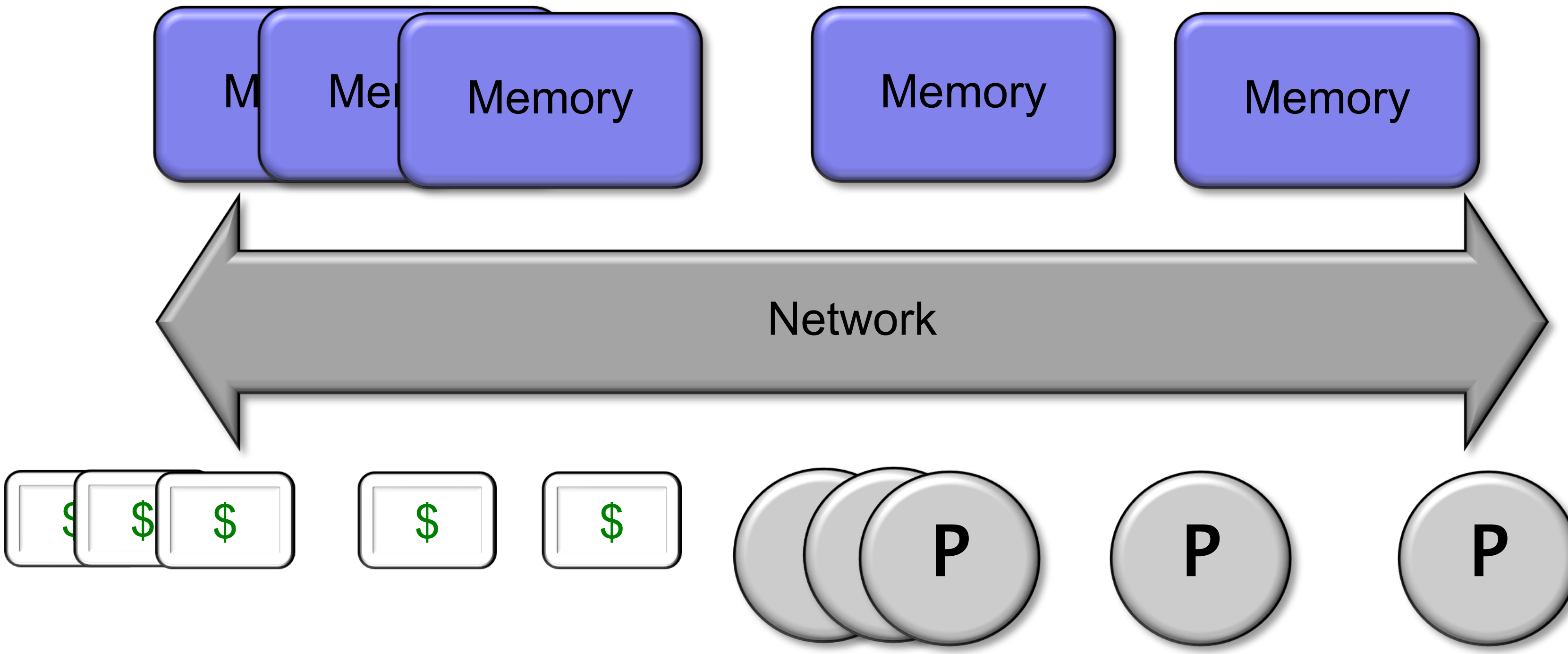
Serial and Parallel Architectures



Serial Architecture

Parallel Architecture

Essential Components of Parallel Architectures



Where is the memory physically located?

Is it connected directly to processors?

What is the connectivity of the network?

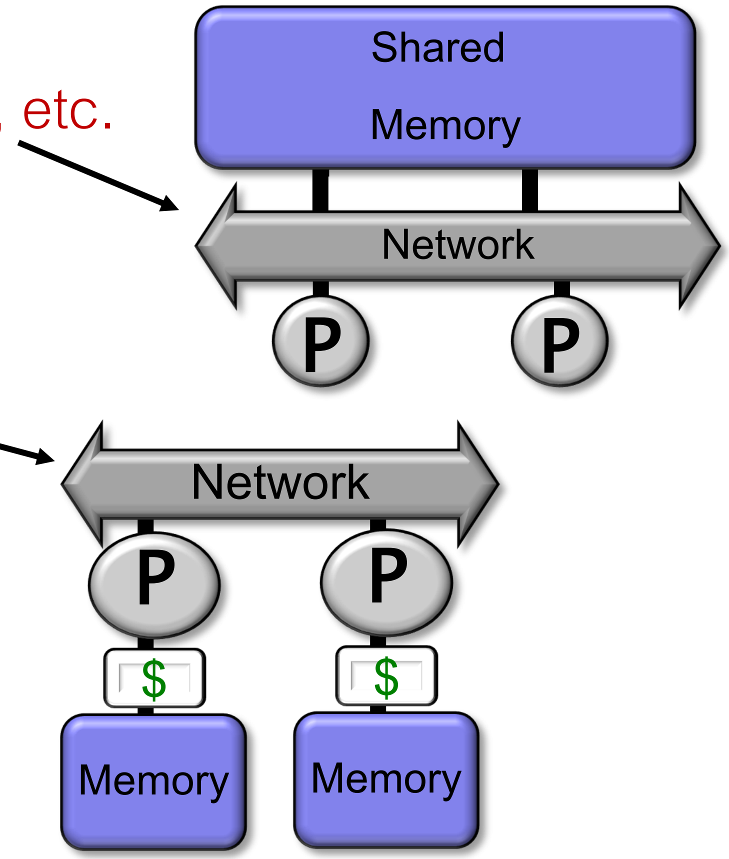
Parallel Machine Models and Their Programming Models Covered on this class!

Shared Memory: Pthreads, OpenMP, etc.

Distributed Memory: MPI

SIMD and Vector: CUDA

Hybrid: A mix of the above!



Up Next!

Parallel Algorithm Design: Tasks, decomposition, mapping, etc.

Recommended reading for this section (not mandatory but highly recommended, we do cover what is needed in class/slides!): Introduction to Parallel Computing - A. Grama, A. Gupta, G. Karypis, V. Kumar

Parallel Algorithm Design

General guidelines:

- Identify tasks in your program that can be performed concurrently
- Map concurrent tasks onto multiple threads or processes, to be run in parallel
- Partition the input, output, and/or intermediate data and assign to processes
- Handle concurrent accesses to shared data by multiple processes
- Add synchronization between stages of the parallel execution, where necessary
- Keep in mind the underlying parallel architecture, its advantages and limitations
- Profile performance and determine what the bottlenecks are
- Target optimizations based on profiling information and performance analysis
- Write small benchmarks to test your program in a variety of configurations

Parallel Algorithm Design: Outline

- Tasks: Decomposition, Task Dependency, Granularity, Interaction, Mapping, Balance
- Decomposition techniques
- Mapping techniques to reduce parallelism overhead
- Parallel algorithm models
- Parallel program performance model

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Decomposition and tasks

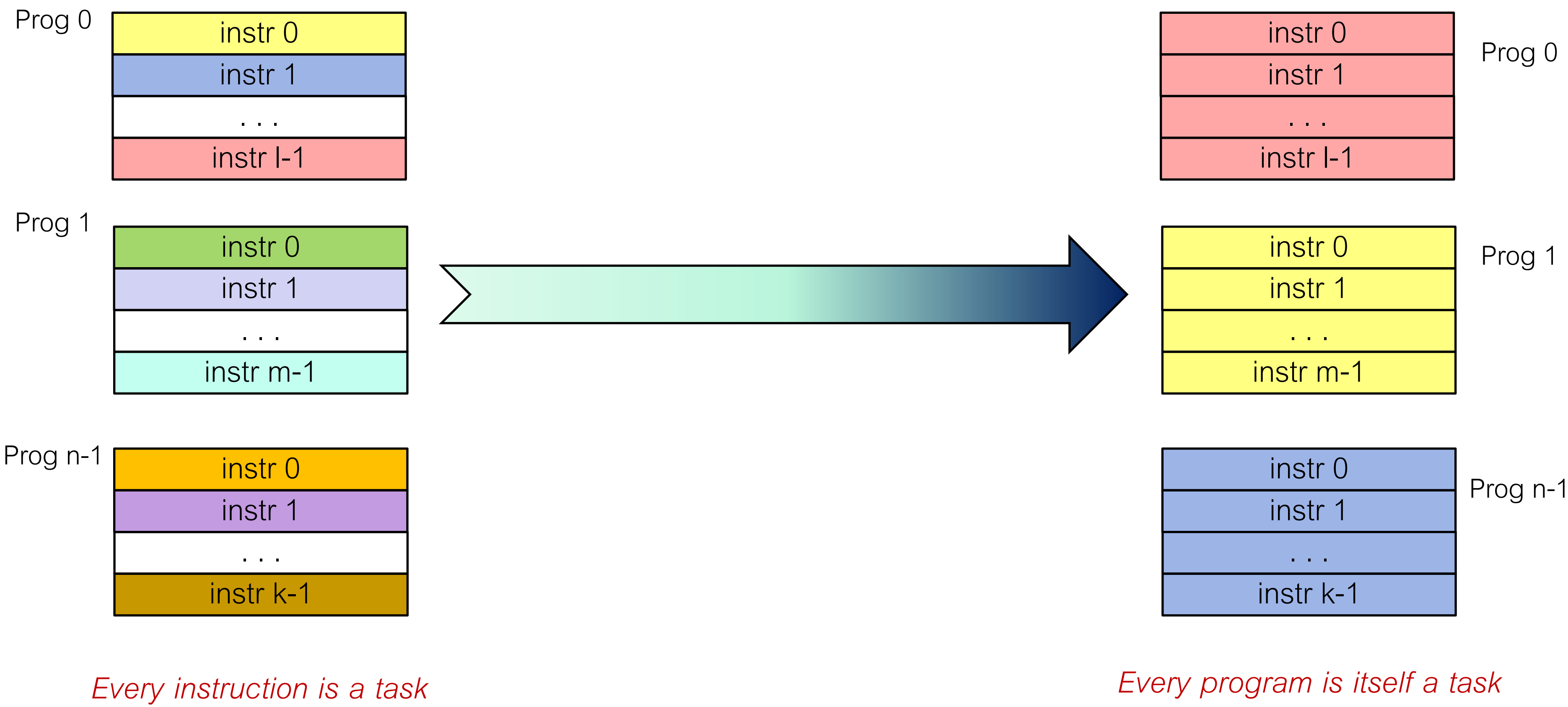
- Decomposition: dividing the computation in a program into **tasks** that could be executed in parallel

- Task: unit of computation that can be extracted from the main program and assigned to a process, and which can be run concurrently with other tasks

- The way to extract tasks and the mapping to processes affects performance!

Parallel task decomposition

- Tasks can range from individual instructions to entire programs



- Which one is best?

Parallel task decomposition

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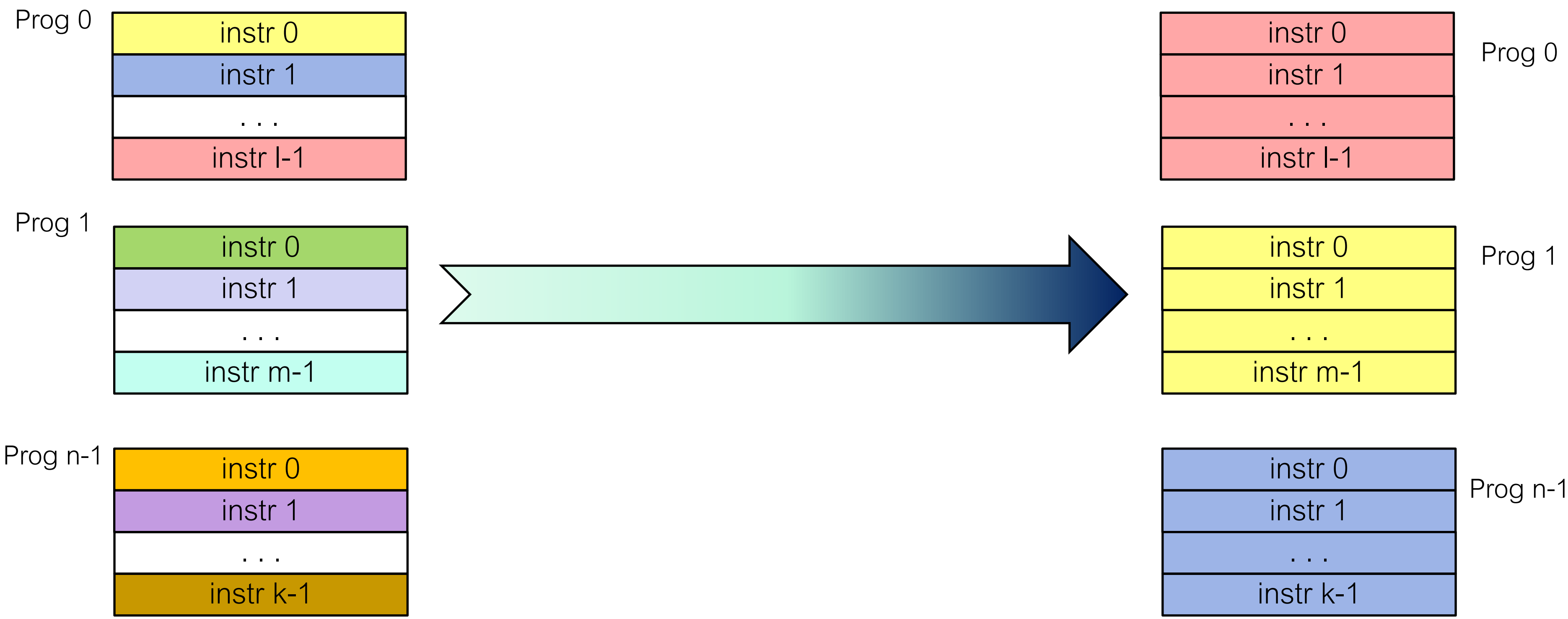


Every instruction is a task

Every program is itself a task

- Which one is best?
  - The answer is always "it depends" .. on the specific application and the parallel platform

Example: matrix-vector multiplication

- Multiply 4 x 4 dense matrix A with vector b of size 4 => calculate A x b = c

$$\begin{bmatrix} A00 & A01 & A02 & A03 \\ A10 & A11 & A12 & A13 \\ A20 & A21 & A22 & A23 \\ A30 & A31 & A32 & A33 \end{bmatrix} \times \begin{bmatrix} b0 \\ b1 \\ b2 \\ b3 \end{bmatrix} = \begin{bmatrix} c0 & c1 & c2 & c3 \end{bmatrix}$$

- Say that computing each output item is a task (T0-3)

$$\begin{bmatrix} A00 & A01 & A02 & A03 \\ A10 & A11 & A12 & A13 \\ A20 & A21 & A22 & A23 \\ A30 & A31 & A32 & A33 \end{bmatrix} \times \begin{bmatrix} b0 \\ b1 \\ b2 \\ b3 \end{bmatrix} = \begin{array}{cccc} T0 & T1 & T2 & T3 \\ \hline c0 & c1 & c2 & c3 \end{array}$$

- Consider what each task needs, and if there are data dependencies

Task dependencies

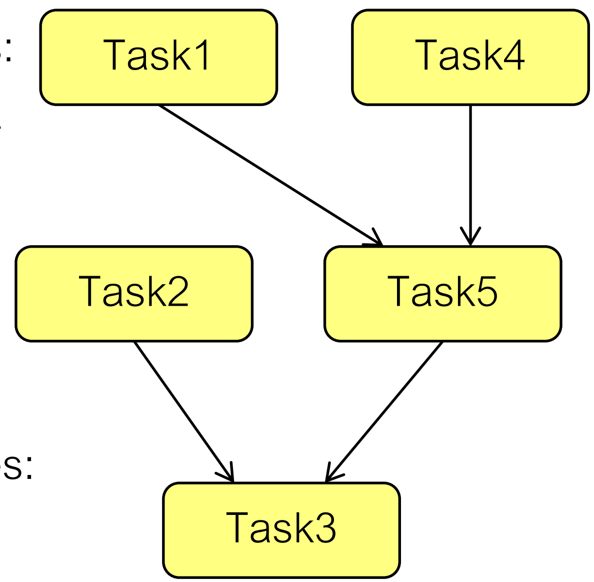
- Tasks are not independent if they have dependencies on other tasks
- A task might need data produced by other tasks => must wait until input is ready
- Dependencies create an ordering of task execution => task dependency graph
  - Directed acyclic graph (DAG): tasks as nodes, dependencies as edges
  - "Start nodes" = no incoming edges; "Finish nodes" = no outgoing edges
- Examples:

Start nodes:

Tasks 1,2,4

Finish nodes:

Task 3

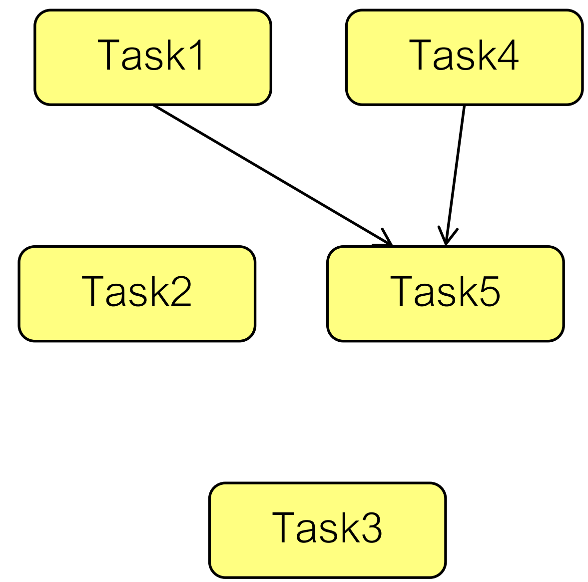


Start nodes:

Tasks 1,2,3,4

Finish nodes:

Tasks 2,3,5

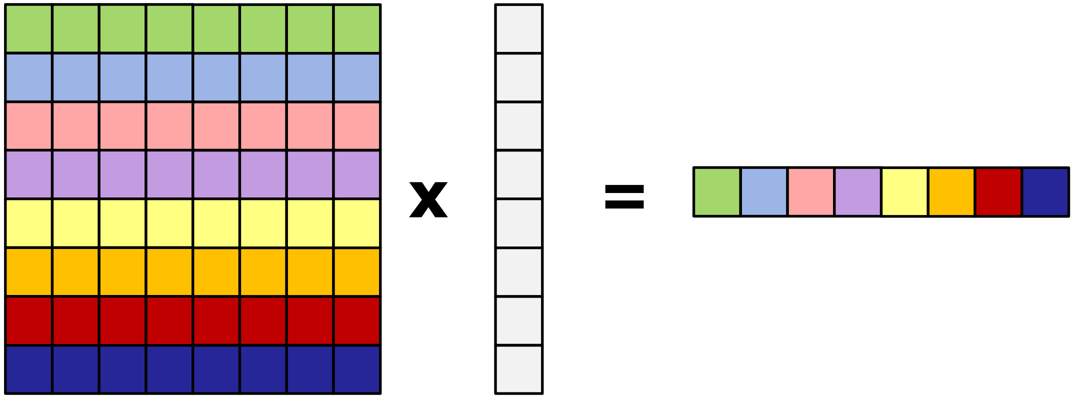


Granularity

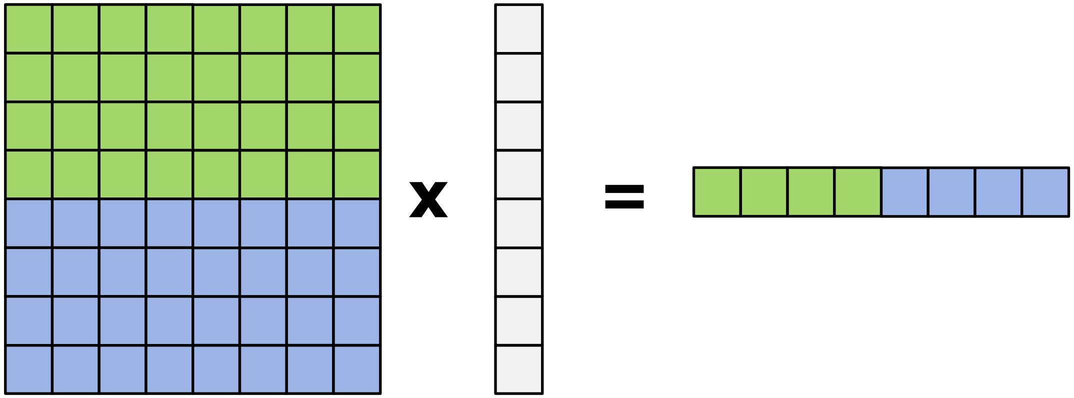
- Granularity: determined by how many tasks and what their sizes are
  - Coarse-grained: a small number of large tasks
  - Fine-grained: a large number of small tasks

Example: matrix-vector multiplication

- Fine-grained: each task = process a single element of c



- Coarse-grained: each task = process half the elements of c



- Note: we are decomposing into tasks, we will talk later about partitioning data!

Parallelism and granularity

- Communication between tasks may or may not be necessary
- Ideal parallelism: no communication needed
- Coarse-grained parallelism: Lots of computation performed before communication is necessary
  - Good match for message-passing environments (MPI, covered later in class)
- Fine-grained parallelism: Frequent communication may be necessary
  - More suitable for shared memory environments (Pthreads, OpenMP)
- Parallelism granularity = how much processing is performed before communication is necessary between processes

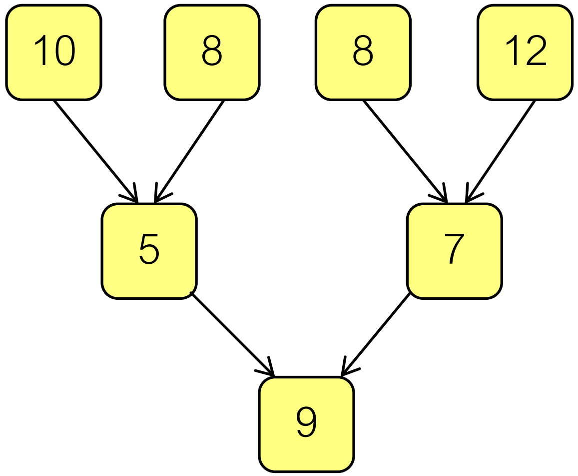
Degree of concurrency

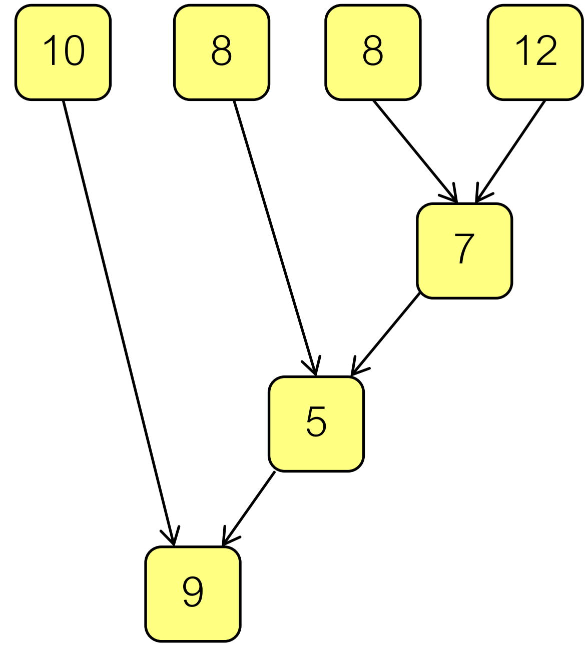
- **Maximum degree of concurrency** = max number of tasks that can be executed simultaneously at any given time
  - Typically less than total number of tasks, if tasks have dependencies

- **Average degree of concurrency** = average number of tasks that can be executed concurrently, during the program's execution

Degree of concurrency

- Nodes can have weights too – tasks may be doing different amounts of work



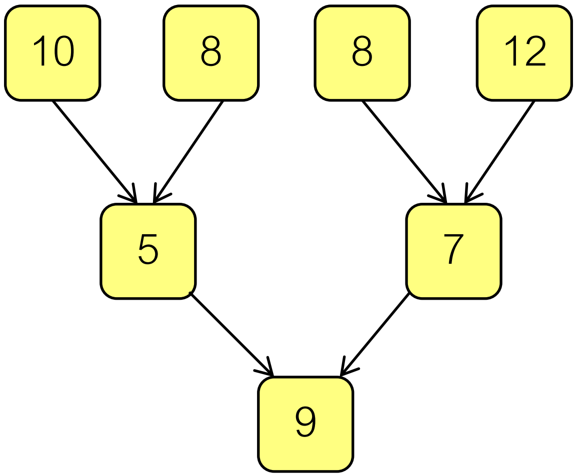


- Max degree of concurrency:
  - a) Max(38, 12, 9) = 38 b) Max(38, 7, 5, 9) = 38
- Average degree of concurrency:
  - a) (38+12+9)/(12+7+9) = 59/28 = 2.11 b) (38+7+5+9)/(12+7+5+9) = 59/33 = 1.79

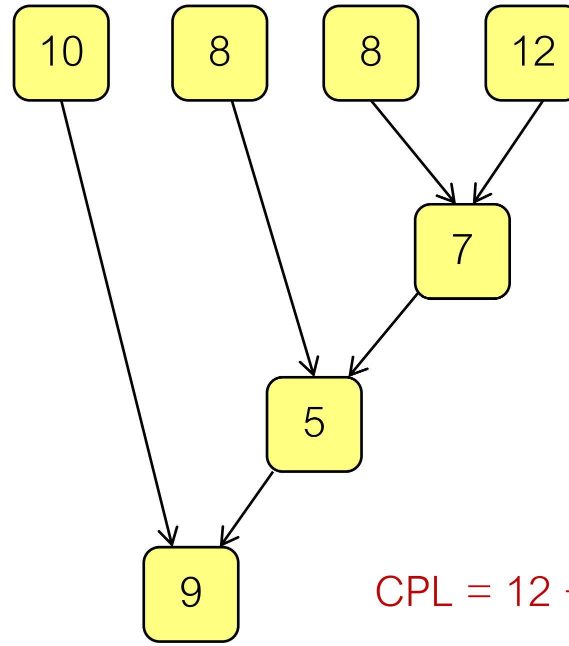
critical path (next slide)

Critical path

- Critical path = The longest path between any pair of start and finish nodes
- Critical path length = sum of node weights along the critical path



CPL = 12 + 7 + 9



CPL = 12 + 7 + 5 + 9

- Average degree of concurrency = total amount of work / critical path length
- Shorter critical path => higher degree of concurrency

Granularity and concurrency

- If granularity of decomposition is more fine-grain, more concurrency available
- More concurrency => more potential tasks to run in parallel
- If so, then reduce program execution time by just increasing granularity of tasks?

Granularity and concurrency

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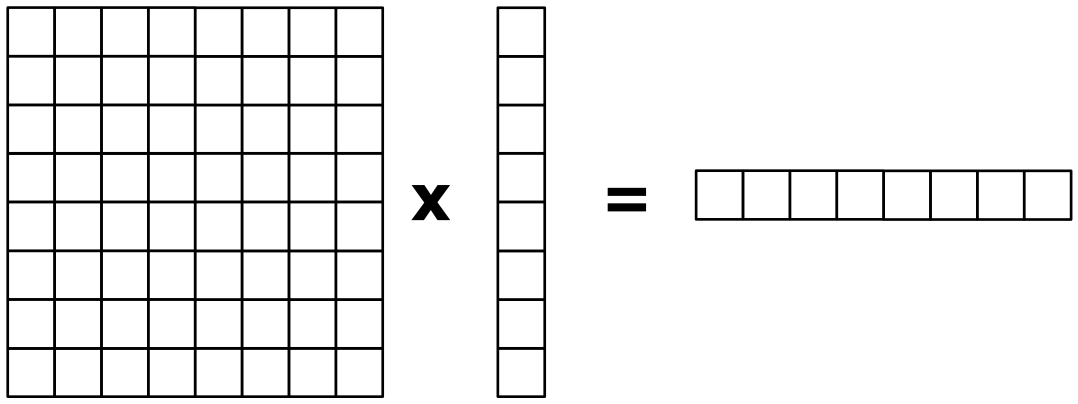
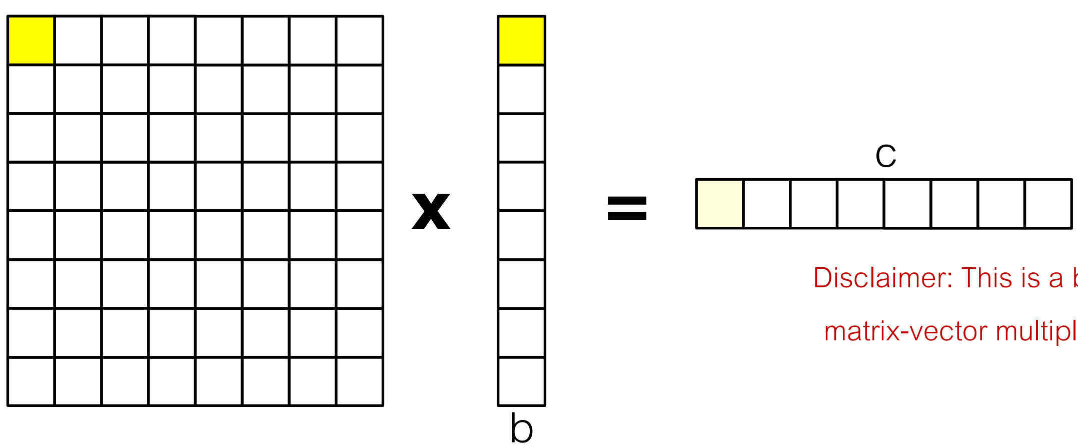
- If so, then reduce program execution time by just increasing granularity of tasks?
- Not quite true!
  - Inherent limits to fine-grained decomposition, e.g., hitting individible tasks, or tasks which cause slowdown if split up



Granularity and concurrency

- If granularity of decomposition increases (finer-grain), more concurrency available
- More concurrency => more potential tasks to run in parallel
- If so, then reduce program execution time by just increasing granularity of tasks?
- Not quite true!
  - Inherent limits to fine-grained decomposition, e.g., hitting individible tasks, or tasks which cause slowdown if split up
  - For example if a task multiplies one element of A with one element of b to store a partial value of one element of c then all tasks working on the first row of A have to interact!

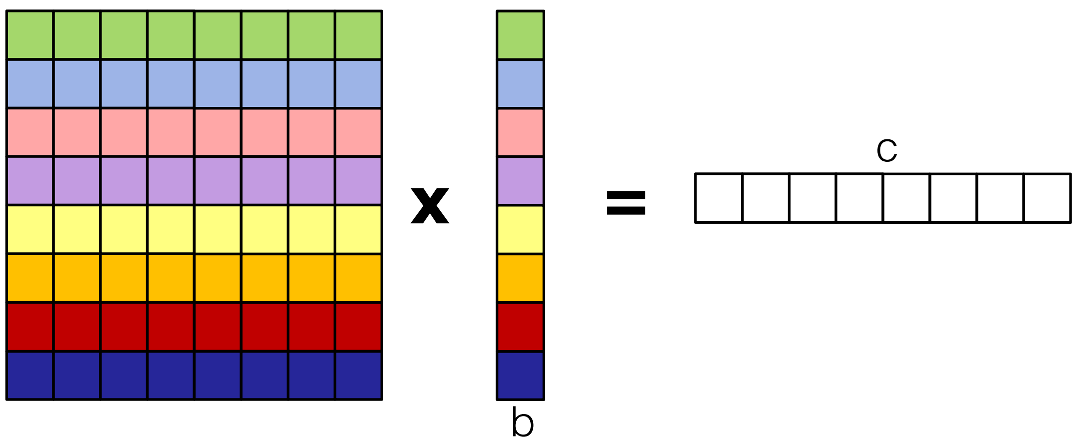


Disclaimer: This is a bad way of defining a task in matrix-vector multiply, used only as an example

  - More tasks => potentially more dependencies => more overhead

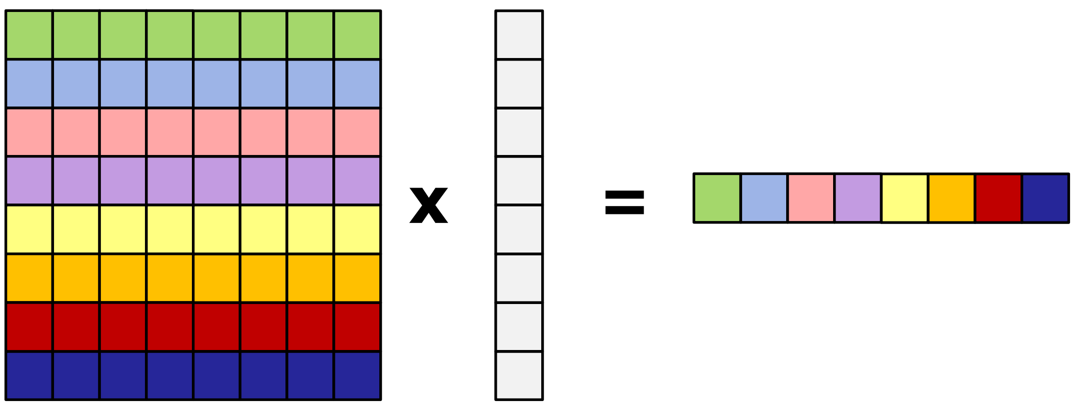
Task interactions

- A task dependency graph only captures producer-consumer interactions
  - A task's output is used as another task's input
- Interactions might occur among tasks that are independent in the task dependency graph
  - Tasks on different processors might need to **exchange data** or **synchronize**
  - e.g., in the below if each task stores one item from b, must exchange their data to get all of b



Task interactions

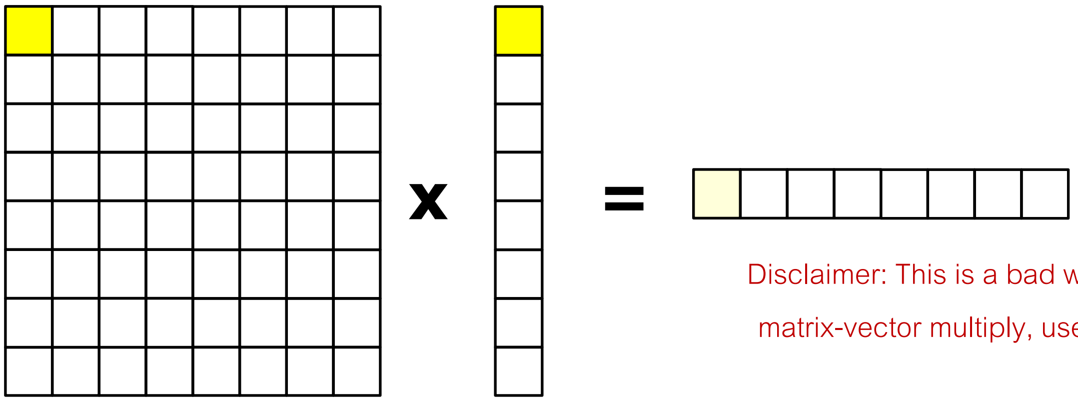
- Tasks may share data via task interactions
  - Read-only interactions: tasks only need to read data shared with other tasks



Read-only interactions: all tasks read c

Task interactions

- Tasks may share data via task interactions
  - Read-only interactions: tasks only need to read data shared with other tasks
  - Read-write interactions: tasks can read or write data shared with other tasks



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Read-write interactions: task write partial sums to b

Task interactions

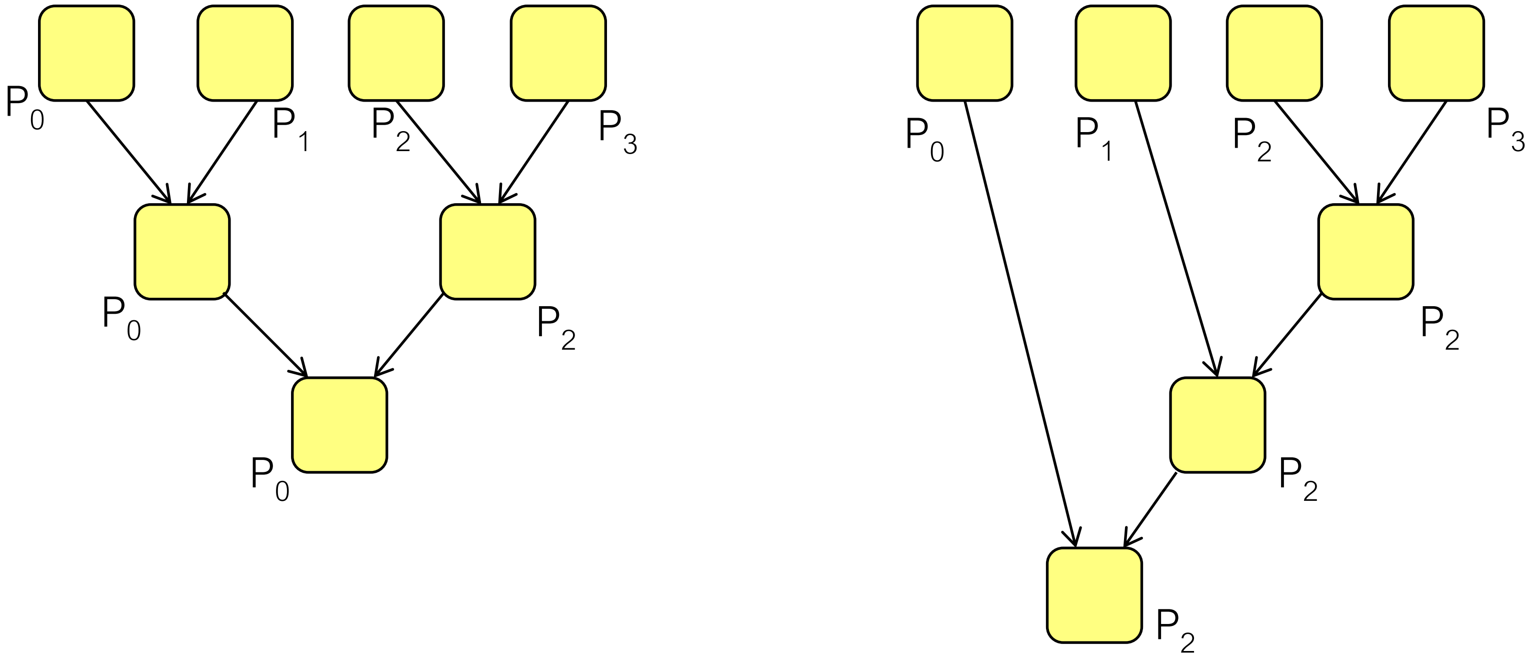
- Tasks may share data via task interactions
  - Read-only interactions: tasks only need to read data shared with other tasks
  - Read-write interactions: tasks can read or write data shared with other tasks
  - Think of the kind of interactions found in the following problem, when solved in parallel:
    - matrix-vector multiplication
- Type of sharing can affect which tasks should get mapped to which processes
  - Read-write interactions should be kept on the same process as much as possible

Mapping tasks to processes

- Mapping = Assigning tasks to processes (more on this later!)
- The choice of decomposition affects the ability to select a good mapping
- Goals of a good mapping:
  - Maximize the use of concurrency
  - Minimize the total completion time
  - Minimize interaction among processes
- Often, the task decomposition and mapping can result in conflicting goals
  - Must find a good balance to optimize for all goals
- Degree of concurrency is affected by decomposition choice, but the mapping affects how much of the concurrency can be efficiently utilized

Example: mapping tasks to processes

- Map the tasks to processes, in each of the two situations
- Key questions: How many processes can be used? How effectively are you using them and why?



- Max degree of concurrency is 4 => max 4 useful processes
- Map first 4 tasks, each on a separate process, then consider the other 3

Task Size and Balance

- Task size = proportional to time needed to complete the task
  - Uniform tasks: require roughly the same amount of time
  - Non-uniform tasks: execution times vary widely

- Size of data associated with tasks = how much data does each task process
  - Impacts whether the tasks are well-balanced
  - Affects performance if a task's data must be moved from a remote processor
  - Input data might be small, but output data is large, or vice-versa, etc.

Parallel Algorithm Design: Outline

- Tasks: Decomposition, Task Dependency, Granularity, Interaction, Mapping, Balance
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Two Commonly Used Decomposition techniques

- Recursive decomposition: Primarily decomposes tasks
- Data decomposition: Partitions the data to induce task decomposition

Recursive decomposition

- Recursive decomposition is primarily based on task decomposition
- Useful for problems that can be approached using a divide-and-conquer strategy
- Divide problem into subproblems, solve subproblems by subdividing recursively the same way and combining results
- Subproblems can be solved concurrently
- Example: Mergesort

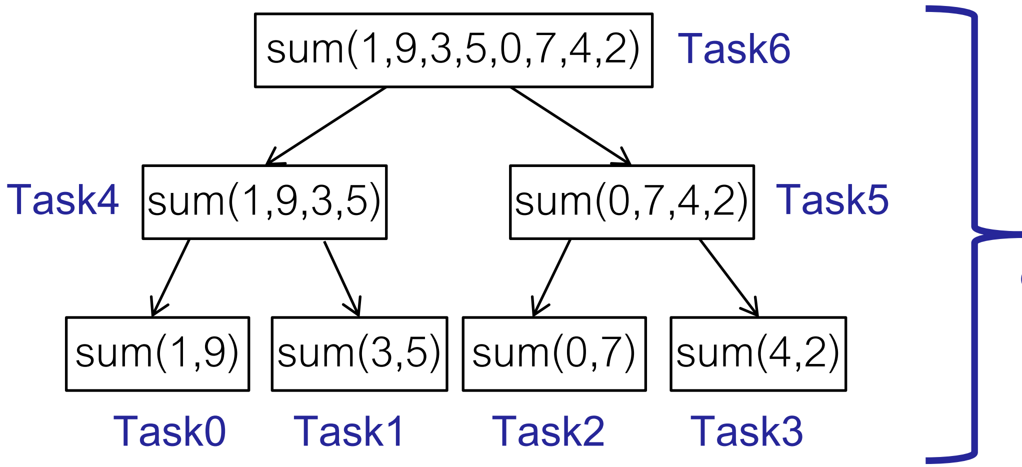
```
mergesort(A, lo, hi)
    if lo+1 < hi then // At least 2 elements
        mid = ⌊(lo + hi) / 2⌋
        mergesort(A, lo, mid)
        mergesort(A, mid, hi)
        merge(A, lo, mid, hi) // merge the 2 halves
```

Recursive decomposition

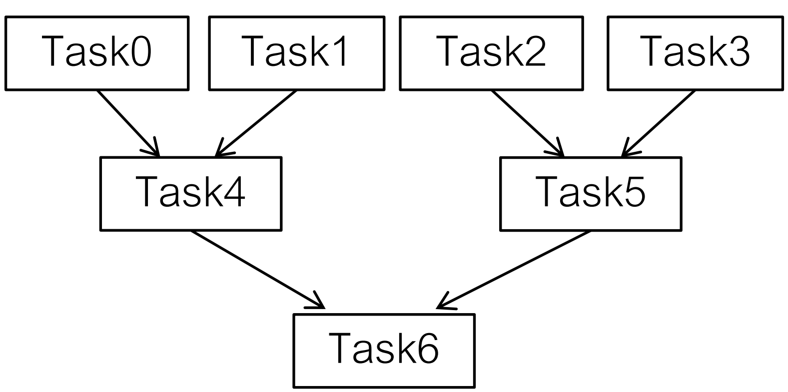
- Not just for naturally recursive problems like mergesort, quicksort, etc.
- Consider the problem of calculating the sum of an array – decompose it into tasks.

array:

1	9	3	5	0	7	4	2



Recursive decomposition



Task dependency graph

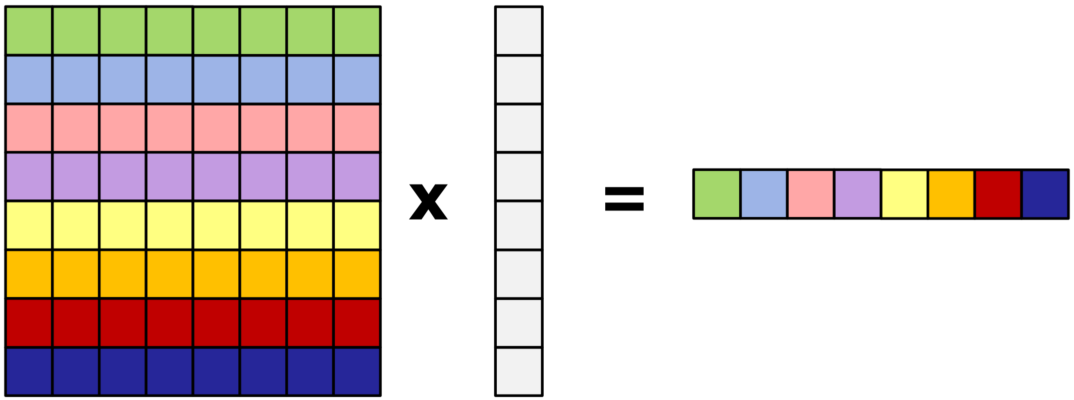
edge(Ti --> Tj) == output of Ti is input for Tj

Data decomposition

- Partition the data on which computations are performed
- Use the data partitioning to perform the decomposition of computation into tasks
- Used to exploit concurrency on problems that operate on large data
- Data decomposition is typically performed in two stages:
  - Step 1: Partition the data
  - Step 2: Induce task decomposition from the partitioned data (might have to re-iterate between steps 1 and 2)
- Data partitioning comes in different flavors:
  - Partition output data
  - Partition input data
  - Partition both input and output data

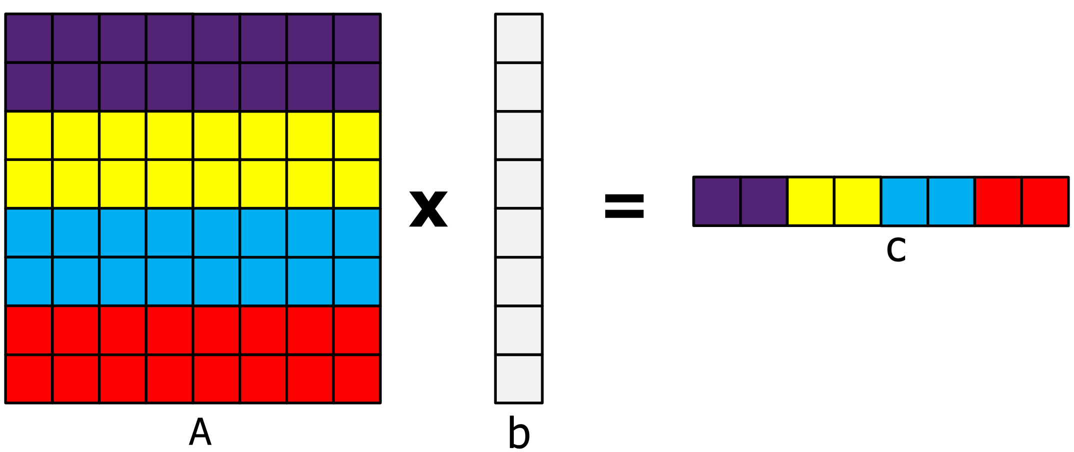
Partition output data

- Matrix-vector example: (1) each element of the output can be computed independently: In this case, this induces a partitioning of the input matrix as well



(2) Decompose the computation into tasks

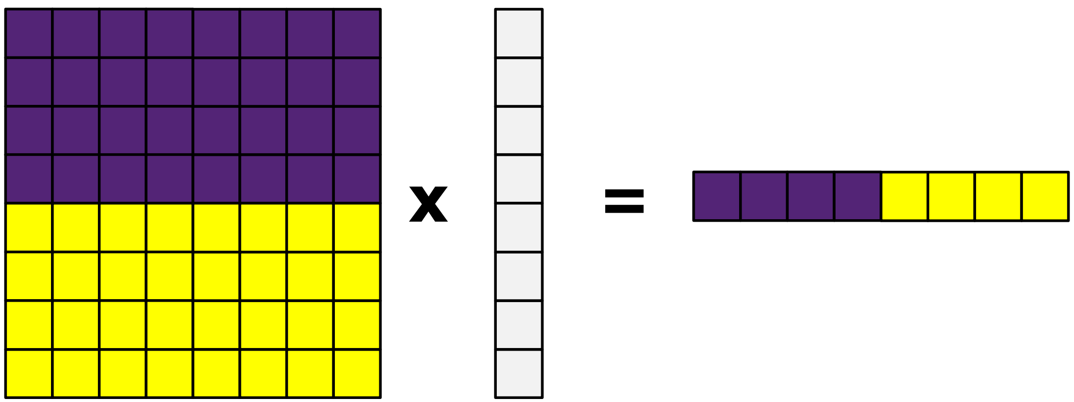
- Option 1: 4 tasks, each computes 2 consecutive elements of the result



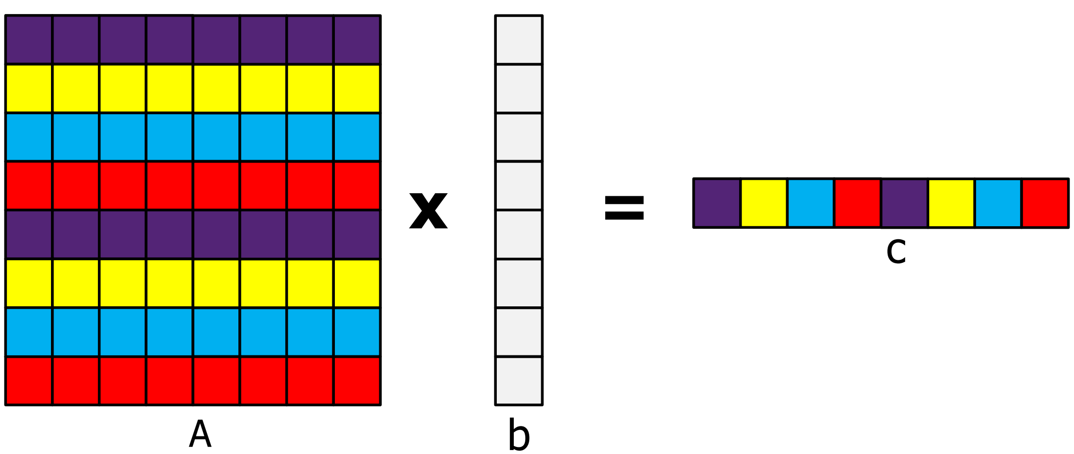
Partitioning data != Decomposing computation into tasks

Other task decompositions

- Option 2: 2 tasks, each computes 4 consecutive elements of c=> coarser-grained!
    - Is this better than the previous decomposition?



- Option 3: 4 tasks, each computes 2 non-consecutive (strided) elements c
    - How does this compare to previous decompositions?



Other task decompositions

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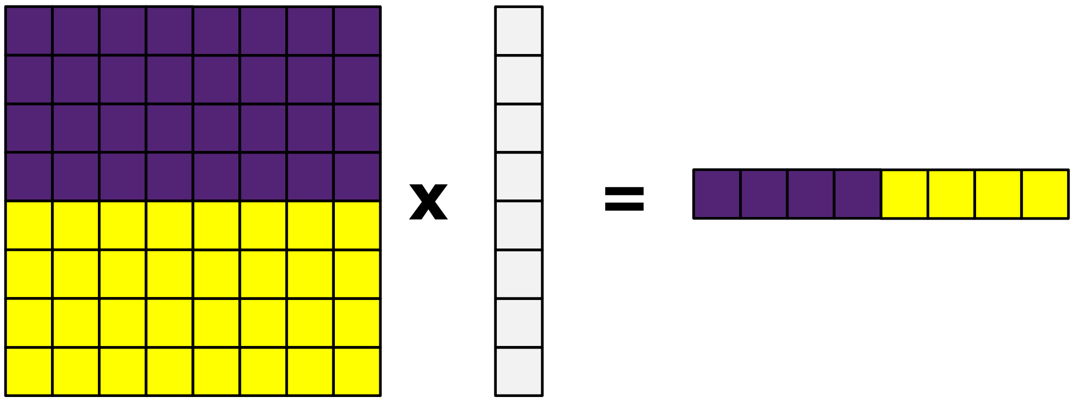
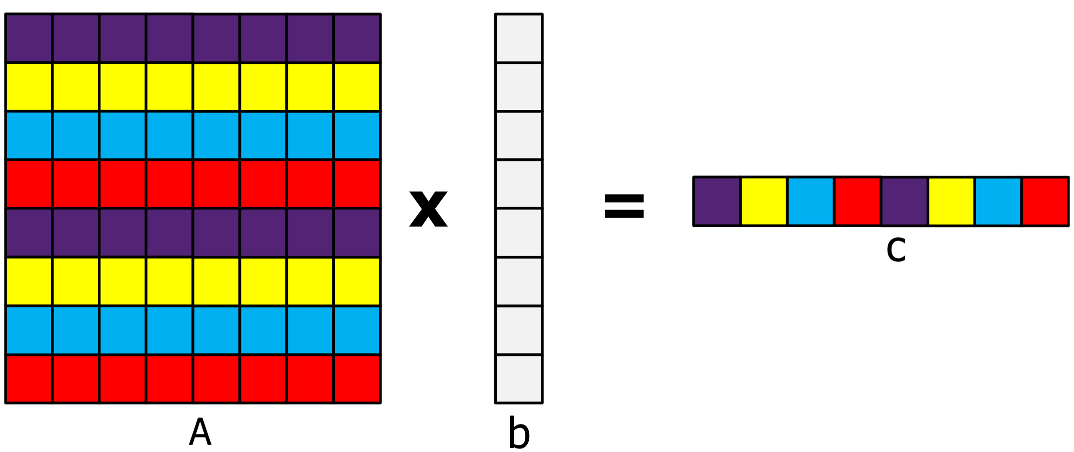


Cant say which one is better without knowing the mapping strategy and the parallel architecture/programming model!

- Option 3: 4 tasks, each computes 2 non-consecutive (strided) elements c
  - How does this compare to previous decompositions?



Other task decompositions

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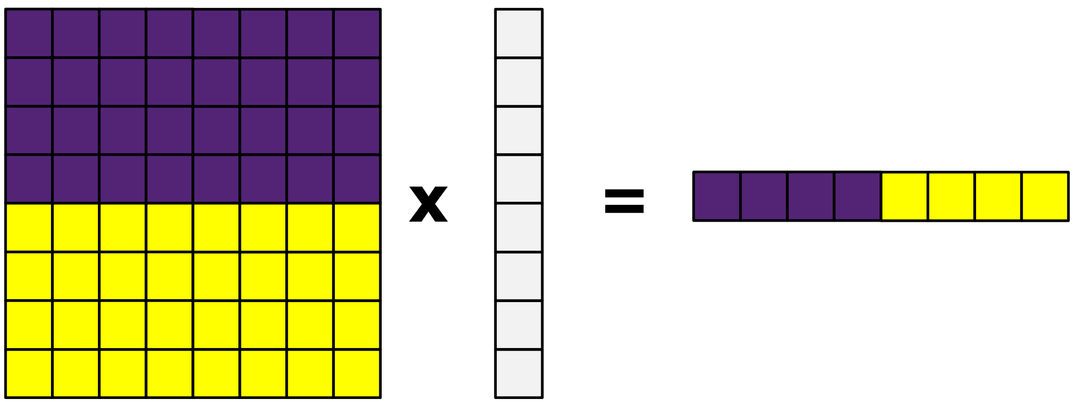

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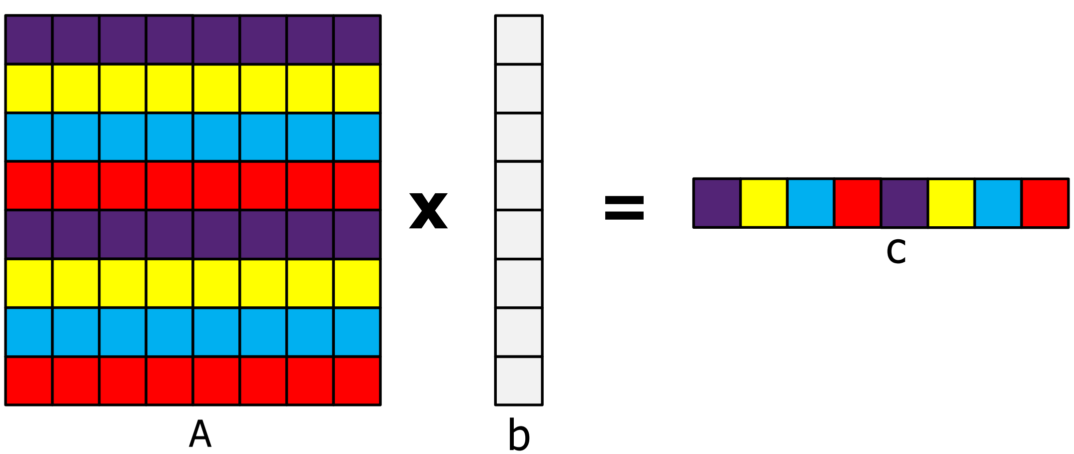


Output data partitioning: typically good if parts of the output can be naturally computed as a function of the input data!

Another example – partition output data

- Analysis of items bought together frequently – how frequently is each item set found in the store's recent transactions record:

Transactions
Milk, eggs, bread, cheese, tomatoes
Bread, ham, cheese, lettuce, oranges
Milk, lettuce, bananas, apples, yogurt
Eggs, bread, cheese, apples, jam
Ham, cheese, bananas, oranges, yogurt
Milk, cheese, tomatoes, lettuce, jam
Eggs, lettuce, oranges, yogurt, jam
Bread, bananas, yogurt, chocolate
Eggs, ham, apples, bananas, chocolate
Milk, cheese, tomatoes, yogurt

Itemsets	
Milk, bread, eggs	Task0
Bread, ham, cheese	
Eggs, cheese	Task1
Tomatoes, lettuce	
Yogurt, jam	Task2
Bananas, oranges	
Apples, oranges	Task3
Bananas, yogurt	

- Partition based on the output data and decompose into tasks - one example:
  - Partition output data into 4 chunks, decompose into 1 task per chunk
  - Each task computes frequencies of its itemsets against all the store transactions

Partition input data

- Analysis of items bought together frequently – how frequently is each item set found in the store's recent transactions record:

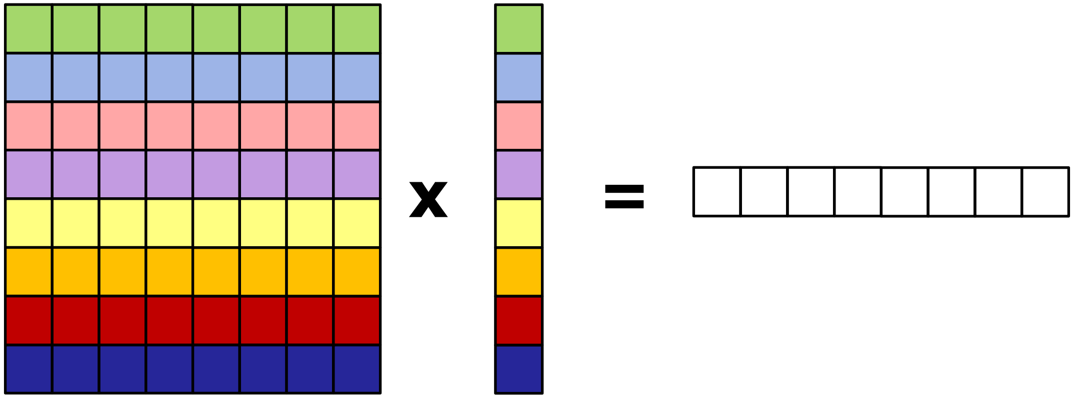
	Transactions	
Task0	Milk, eggs, bread, cheese, tomatoes	Task0
	Bread, ham, cheese, lettuce, oranges	
	Milk, lettuce, bananas, apples, yogurt	
	Eggs, bread, cheese, apples, jam	Task1
	Ham, cheese, bananas, oranges, yogurt	
Task1	Milk, cheese, tomatoes, lettuce, jam	Task2
	Eggs, lettuce, oranges, yogurt, jam	
	Bread, bananas, yogurt, chocolate	
	Eggs, ham, apples, bananas, chocolate	Task3
	Milk, cheese, tomatoes, yogurt	

Itemsets
Milk, bread, eggs
Bread, ham, cheese
Eggs, cheese
Tomatoes, lettuce
Yogurt, jam
Bananas, oranges
Apples, oranges
Bananas, yogurt

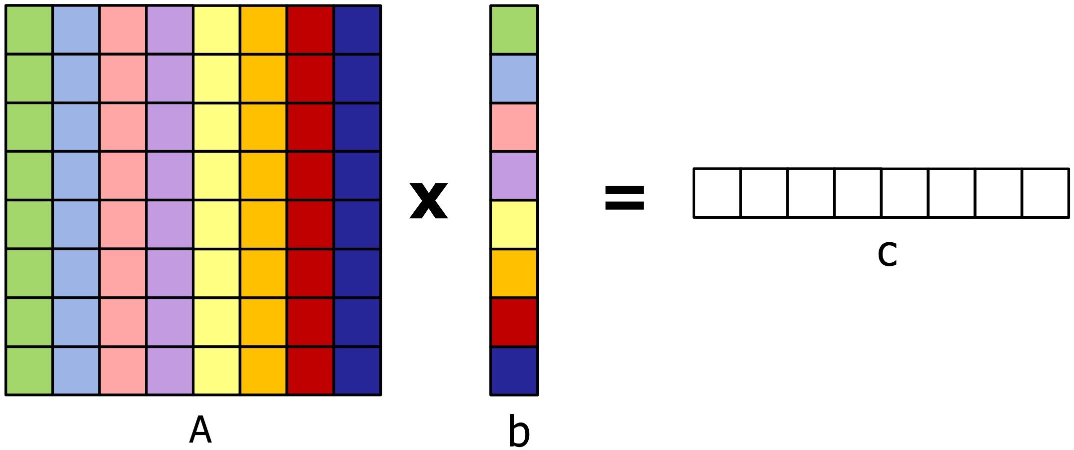
- Partition based on the input data and decompose into tasks - one example:
  - Partition input data into 4 roughly-equal chunks, decompose into 2 chunks per task
  - Each task computes frequencies of all itemsets against its chunk of store transactions

Partition input data – other examples

- Matrix-vector example: row-wise partitioning, partition b similarly
  - If each task takes one row of A and one item of b, any task dependencies?
  - Task interactions?



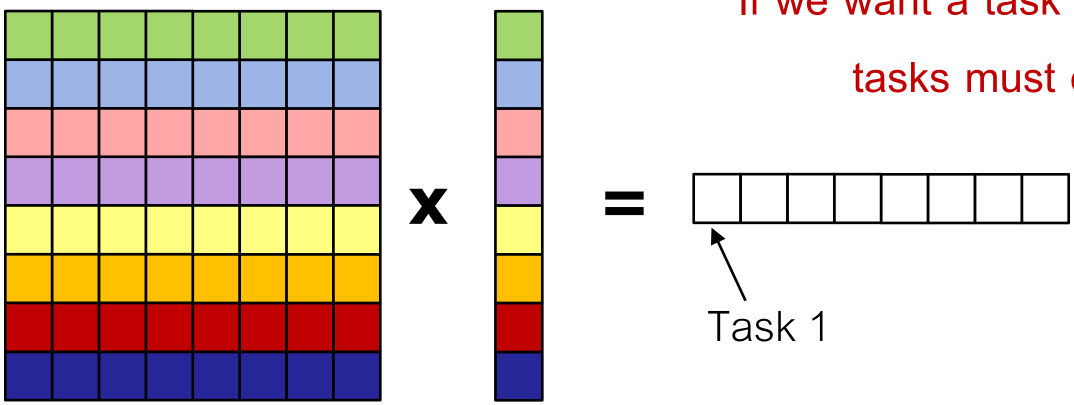
- Now let's choose the partitioning below:



Partition input data – other examples

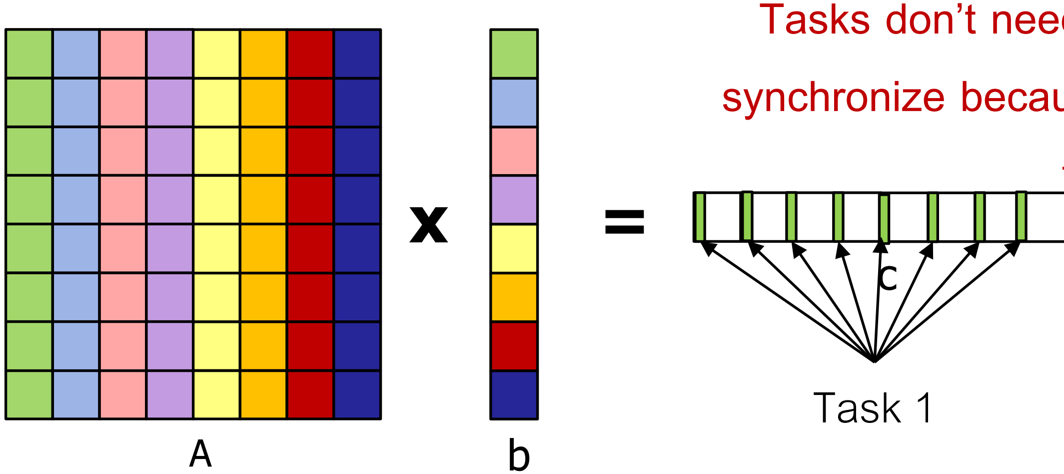
- Matrix-vector example: row-wise partitioning, partition b similarly
  - If each task takes one row of A and one item of b, any task dependencies?
  - Task interactions?

If we want a task to compute one element of b, then tasks must exchange data to get all of b



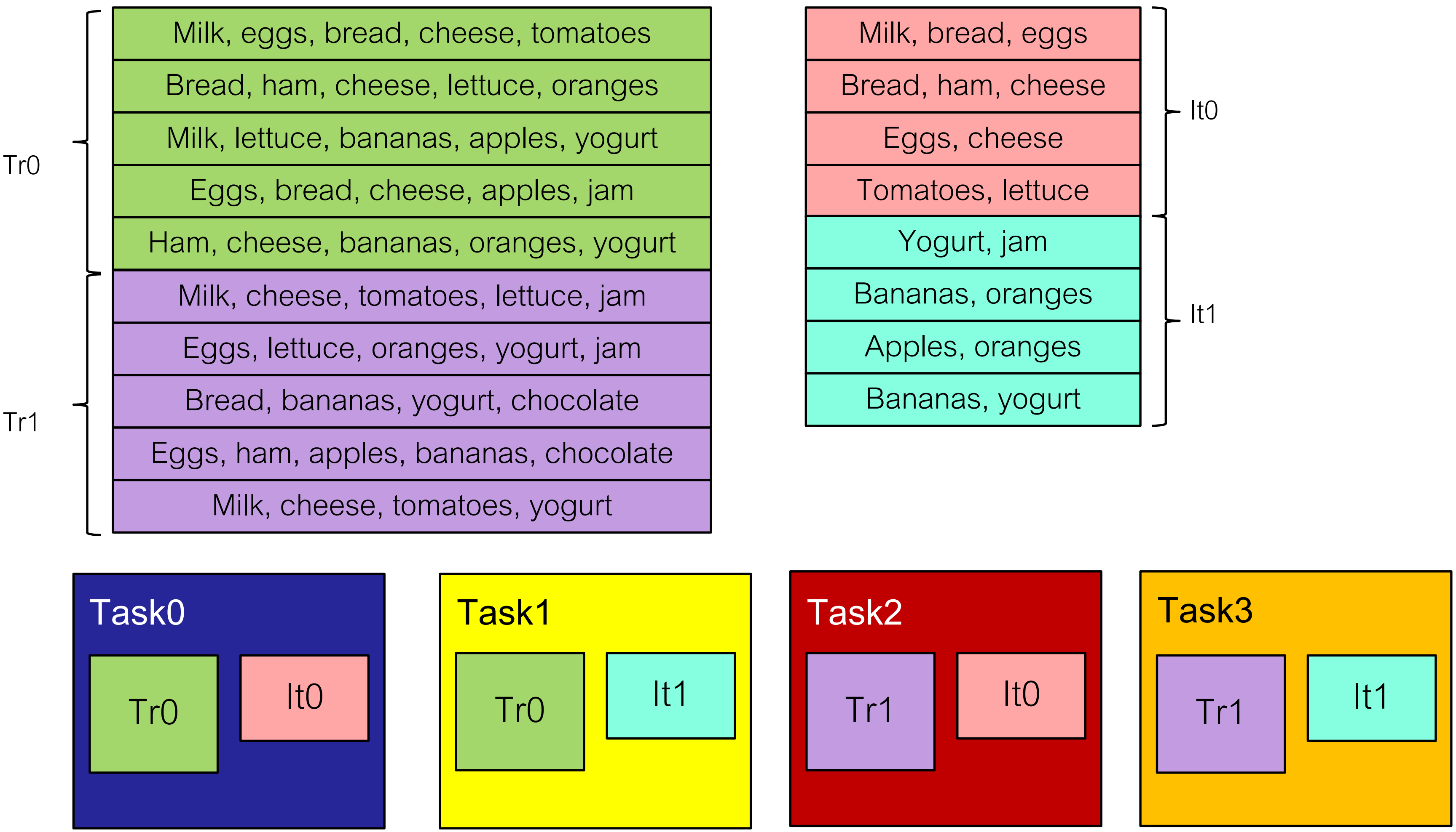
- Now let's choose the partitioning below:

Tasks don't need to exchange data but they have to synchronize because one element of c is computed with the help of all tasks!



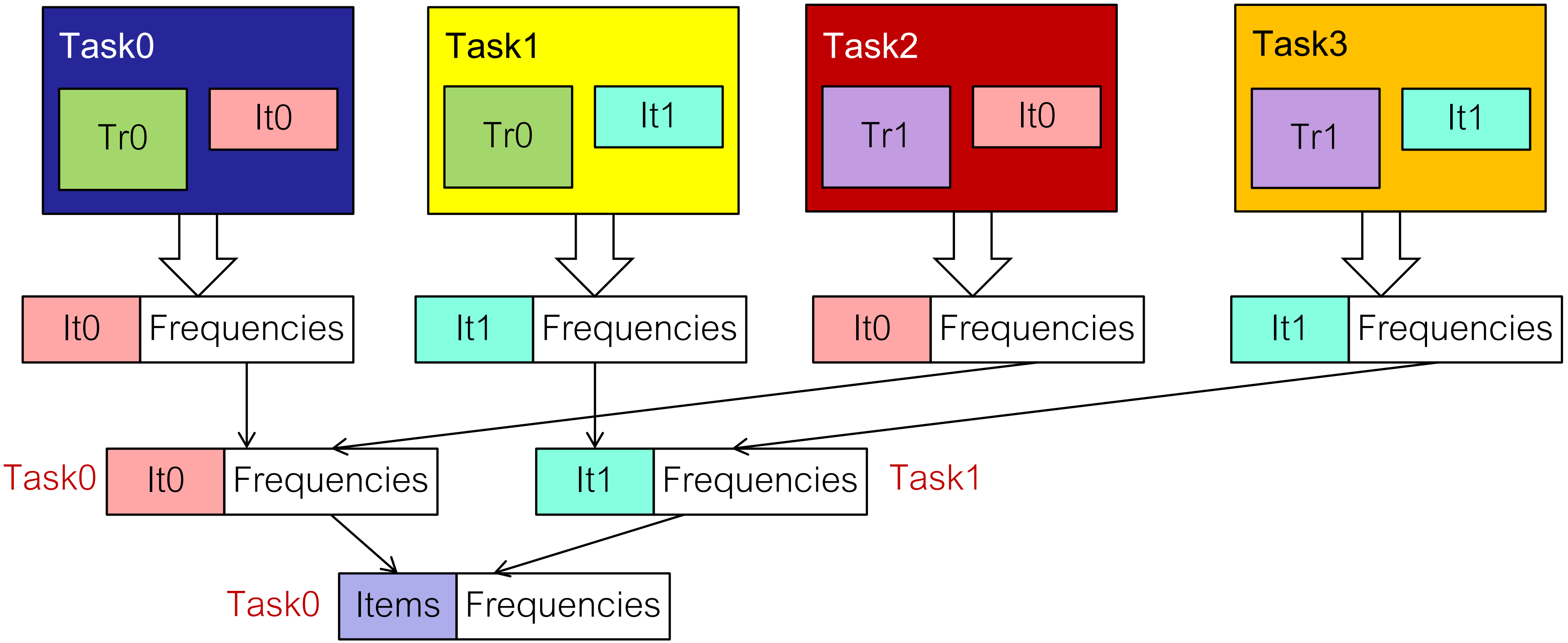
Partition both input and output data

- Partition based on both the input data and output data and create tasks
  - Each task handles the frequency of 1 chunk of itemsets into 1 chunk of transactions



Partition both input and output data

- Each Task produces a number of matches for each itemset in its chunk of itemsets => must combine the intermediate data



- One possibility: One of the tasks for It0 and It1 will fetch the results to combine them, then one of them combines the final result

Important Scinet and Lab Policies

- If you use vscode remote run "pkill code" before logging off.
- Do not run watch squeue!
- Do not run your long jobs on the login node!
- No lab this week (Friday Oct 8^{th}), instead we have a (research topic) tutorial! Join the Lab Zoom Link to hear your TA talk about cutting edge research on building domain-specific compilers for sparse computations.

Parallel Algorithm Design: Outline

- Tasks: Decomposition, Task Dependency, Granularity, Interaction, Mapping, Balance
- Decomposition techniques
- Mapping techniques to reduce parallelism overhead
- Parallel algorithm models
- Parallel program performance model

Mapping the Tasks

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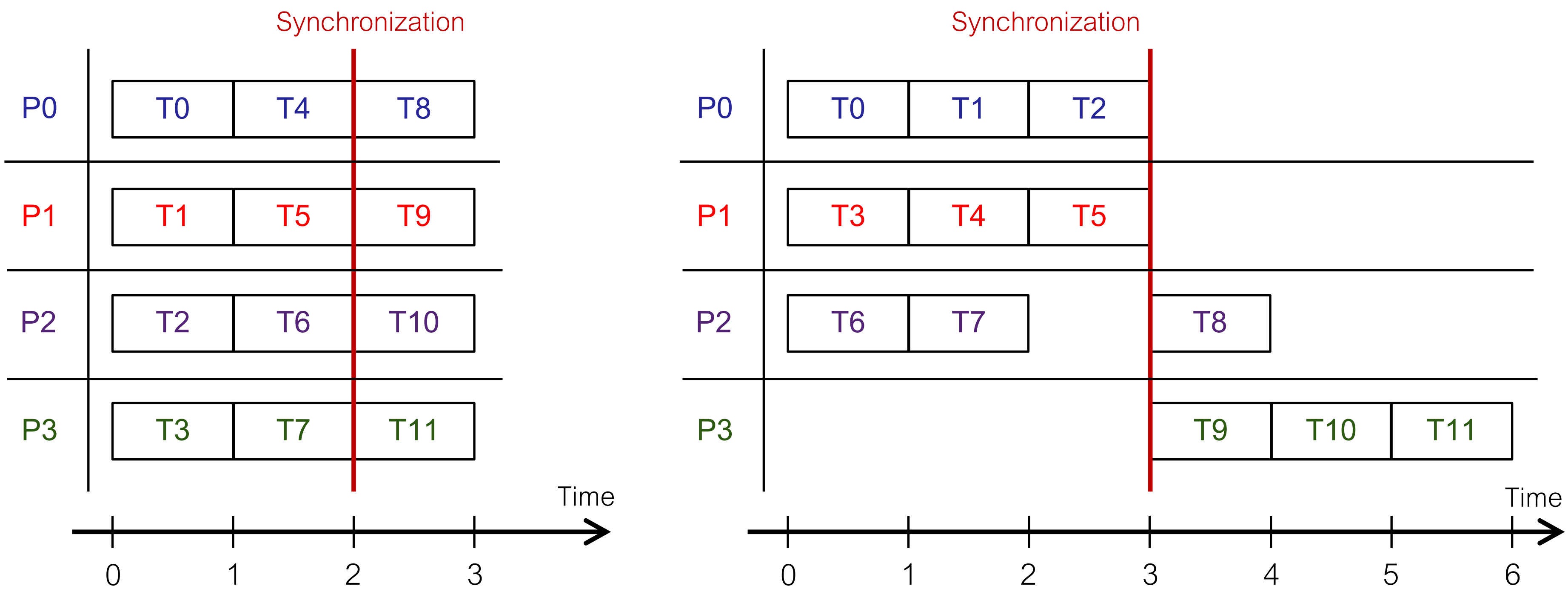
    - Load imbalance
    - Inter-process communication: culprits are synchronization and data sharing

Mapping tasks to processes

- Mapping goal: all tasks must complete in shortest possible time
- To do so, minimize overheads of task execution
  - 1. Load Balancing: Minimize the time spent idle by some processes
  - 2. Minimize the time spent in interactions among processes
- The two goals can be conflicting
  - To optimize 2, put interacting tasks on the same processor => can lead to load imbalance and idling (extreme case: assign all tasks to the same processor)
  - To optimize 1, break down tasks into fine-grained pieces, to ensure good load balance => can lead to a lot more interaction overheads
- Must carefully balance the two goals in the context of the problem!

Mapping tasks to processes to balance load

- Warning: a balanced load may not necessarily mean no idling!
    - If the work is carried out in stages, but assigned workload is not balanced for every stage
- Example: Tasks T0-11, data dependency: T8-11 must all wait for T0-7 to finish
    - Possible decompositions:



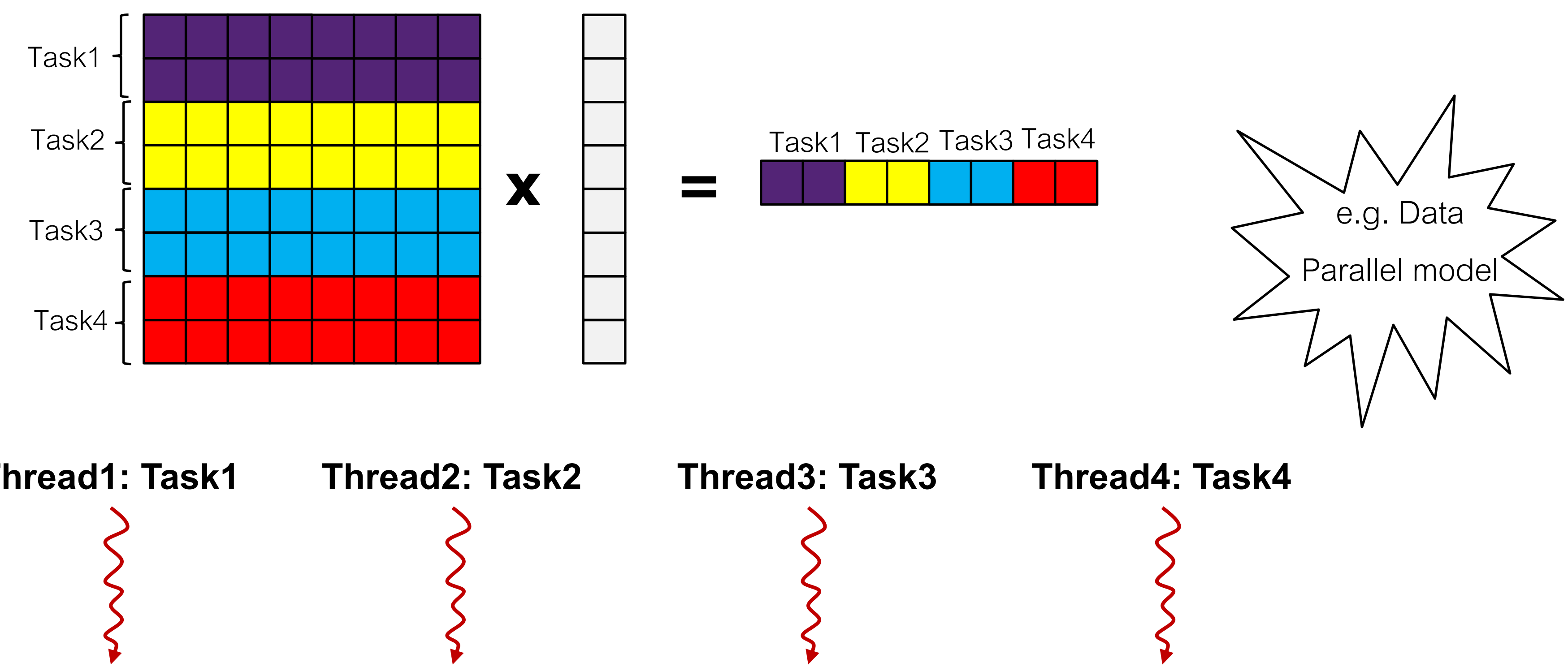
- Must ensure that computations and interactions are well-balanced at each stage

Static mapping

- Static mapping: assign tasks to processes before execution starts
- Static mapping allows for static load balancing
- Mapping quality depends on knowledge of task sizes, size of data associated with tasks, characteristics of task interactions, and parallel programming paradigm
- If task sizes not known => can potentially lead to severe load imbalances
- Usually done with static and uniform partitioning of data: data parallel problems!
- Tasks are tied to chunks of data generated by the partitioning approach
- Mapping tasks to processes essentially closely tied to mapping data to processes

Static mapping

- We create 4 tasks, each computing on 2 elements of c, and statically assign a process/thread to a task before execution. As you see our task assignment is tied to uniform partitioning of data!

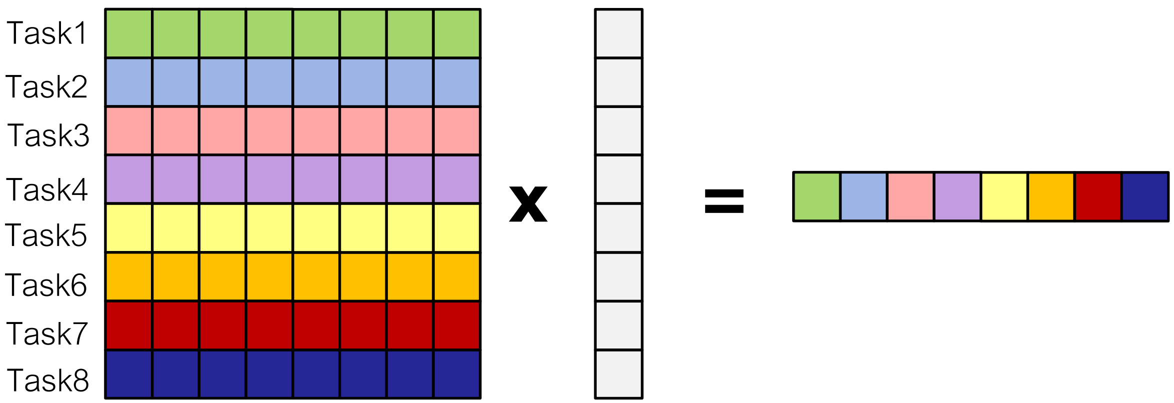


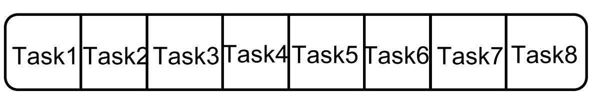
Dynamic mapping

- Dynamic mapping: assign tasks to processes during execution
- Dynamic mapping allows for dynamic load balancing
  - If task sizes are unknown => dynamic mappings are more effective than static ones
  - If much more data than computation => large overheads for data movement => static may be preferable
  - Depends on the parallel paradigm and interaction type though (shared address space vs distributed memory, read-only vs read-write interaction, etc.)

Common scheme for dynamic mapping

- Keep tasks in a centralized pool of tasks, assign them as processes become idle
    - The process managing the pool of ready tasks = master process
    - Other processes performing the tasks = worker processes, or slaves
- Tasks may get added to the pool, concurrently with the workers taking tasks out
- e.g., matrix-vector multiplication: task pool has tasks that each computes an item in c:





You can create a work pool where the tasks are put inside a queue and the next free thread will grab the next available task.

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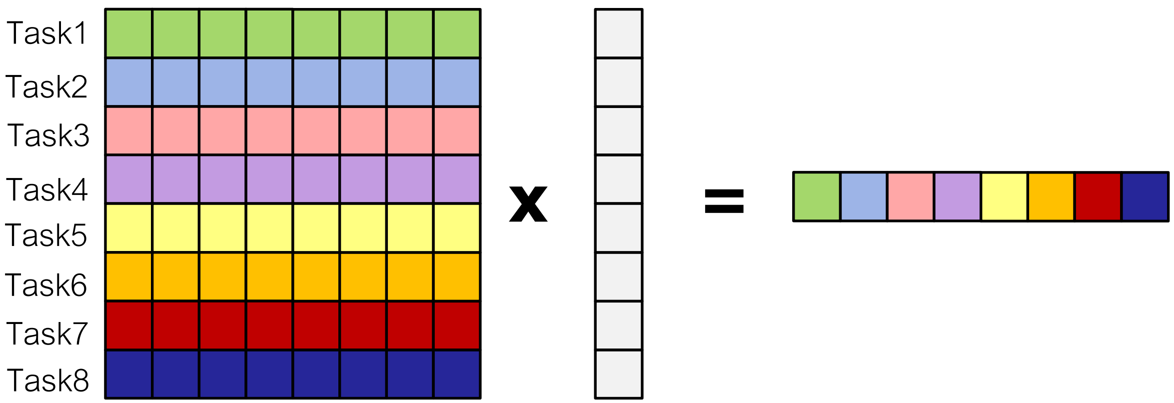

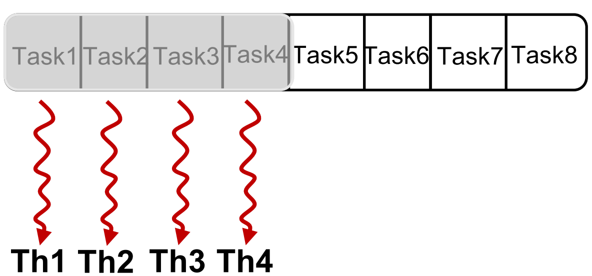

Each thread grabs a task from the work pool.

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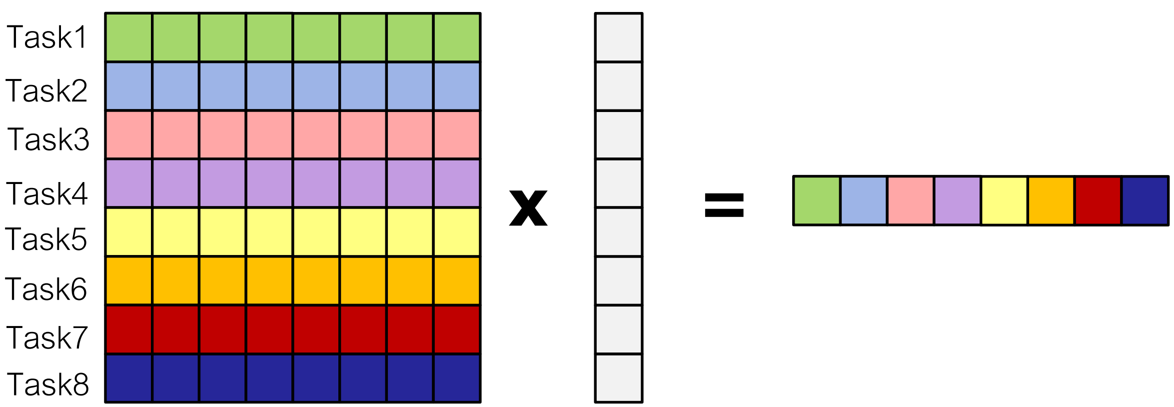

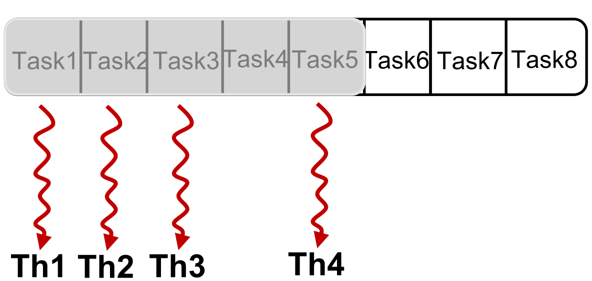

Thread 4 finished its work on task 4 and is now ready to start working on the next available task (task 5), the other threads are still working on their initially assigned tasks!