CSC367 Parallel computing

Lecture 7: Parallel Architectures and Parallel Algorithm Design Continued!

Thanks to Scinet, NSF XSEDE, James Demml

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

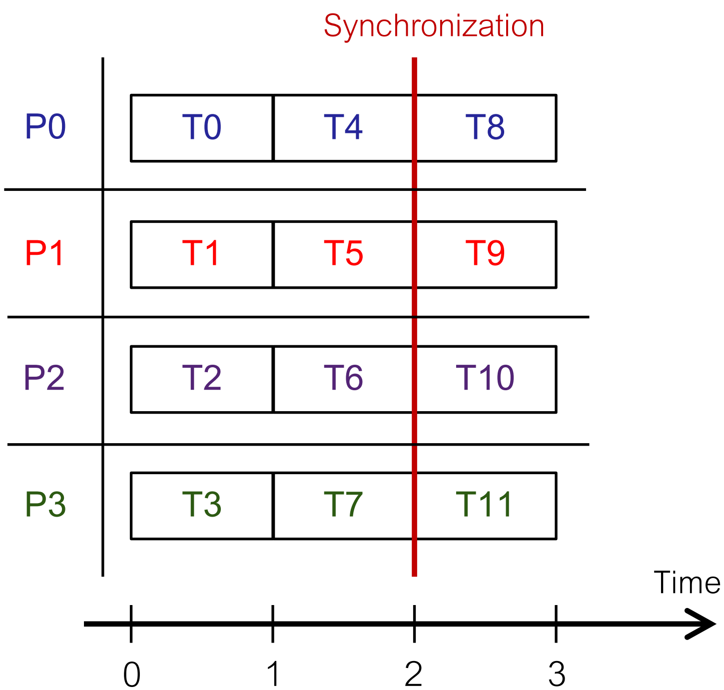
- Why care about mapping the task, what if we just randomly assign tasks to processors?
  - An efficient task mapping is critical to minimize parallel processing overheads: What overheads!
    - Load imbalance
    - Inter-process communication: culprits are synchronization and data sharing

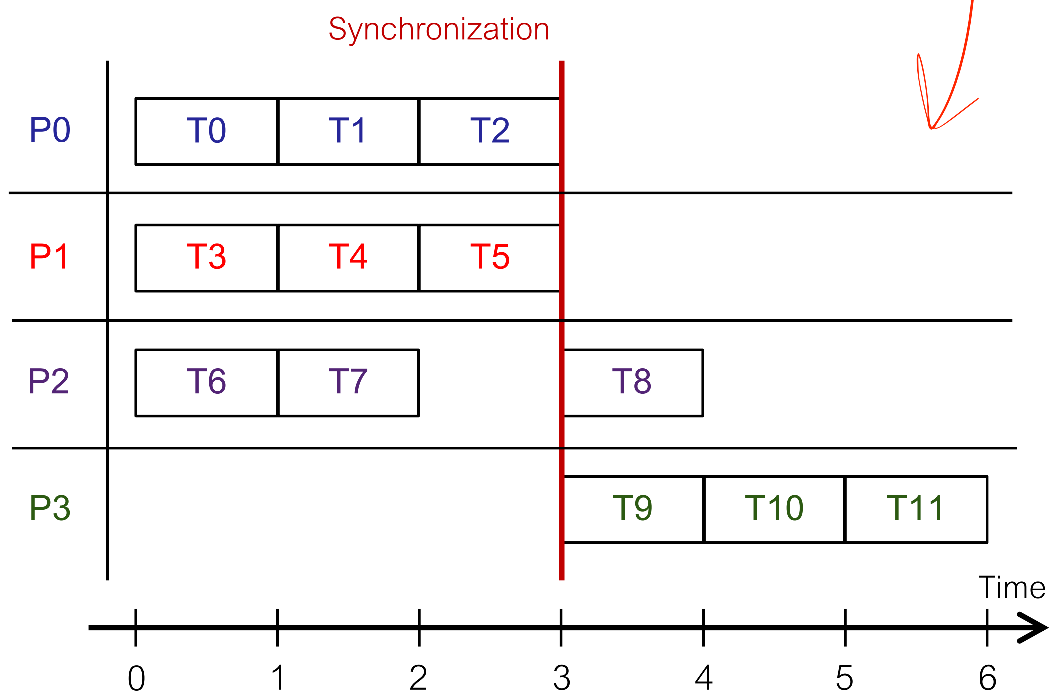
Mapping tasks to processes

- 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:





optimize for load balance

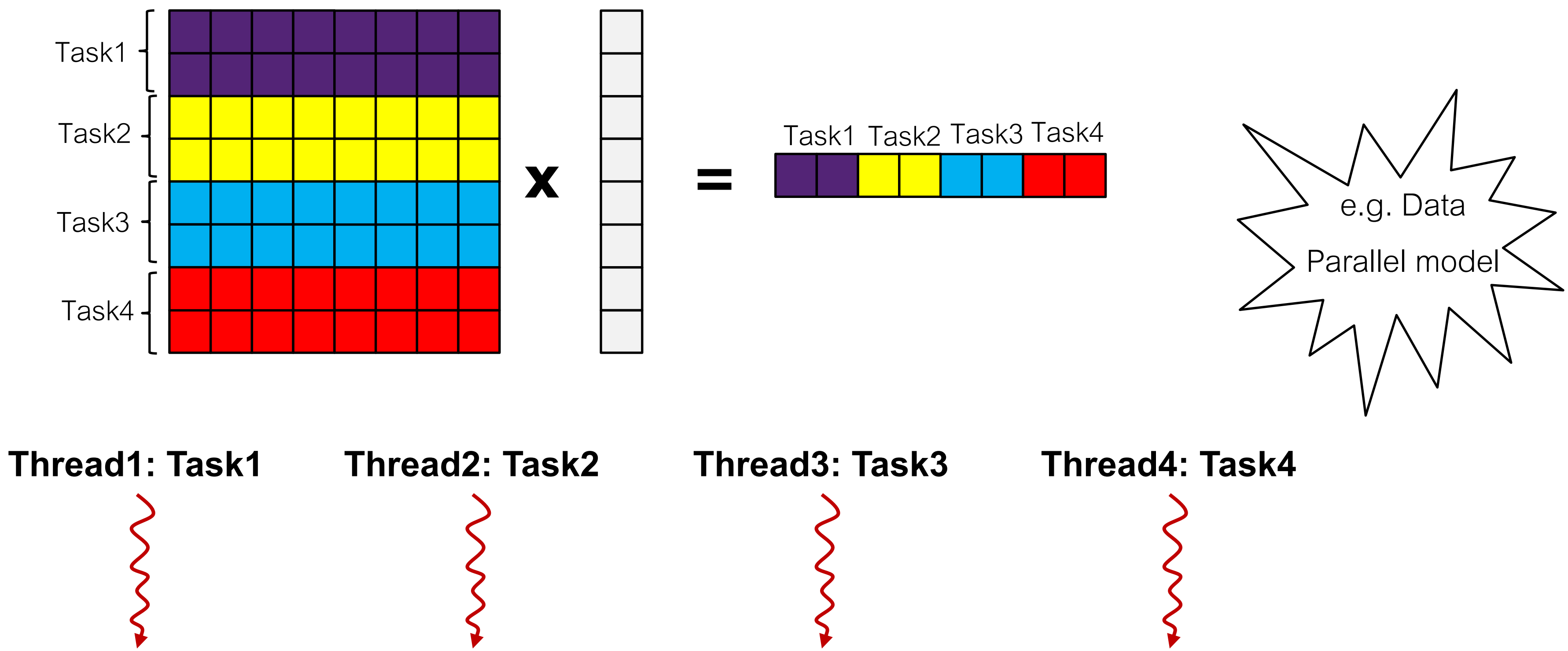
- Must ensure that computations and interactions are well-balanced at each stage

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!

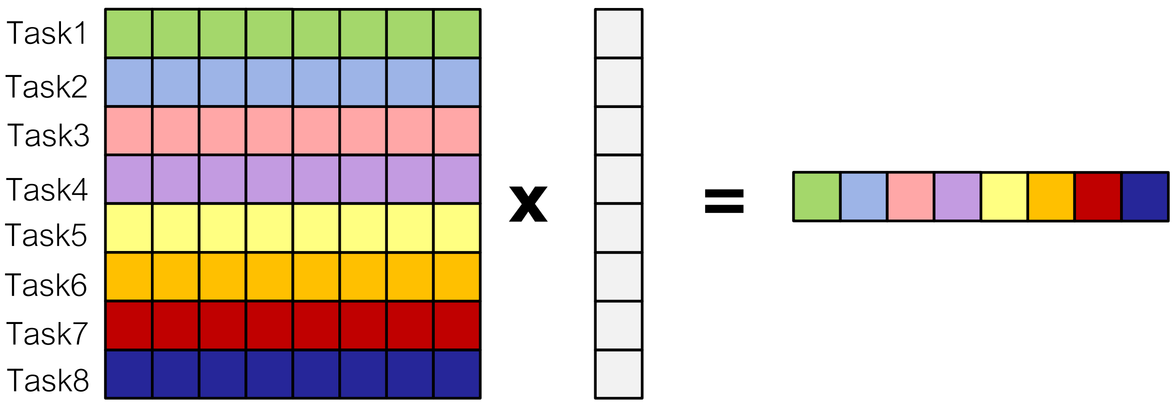


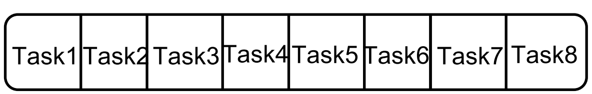
Dynamic mapping

- **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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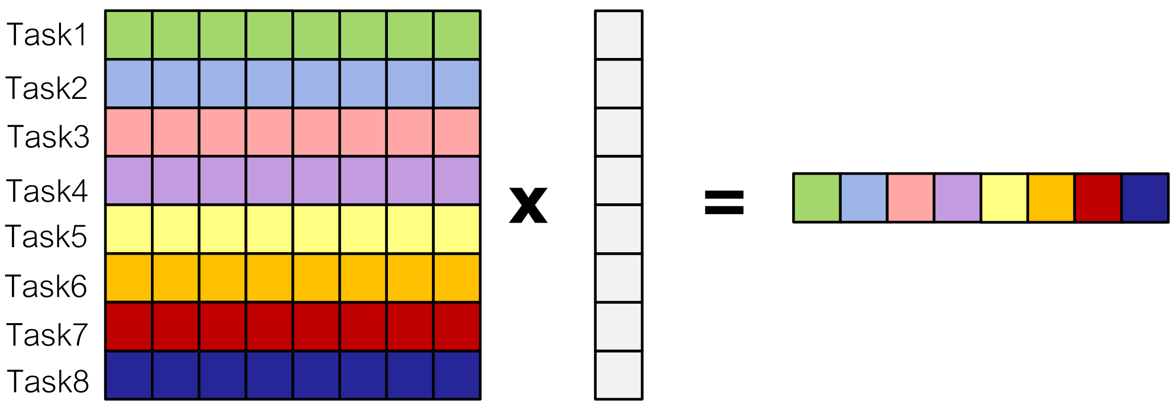

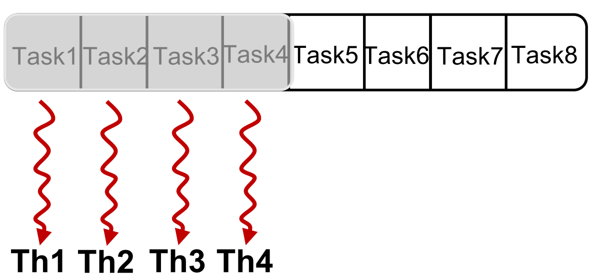

Each thread grabs a task from the work pool.

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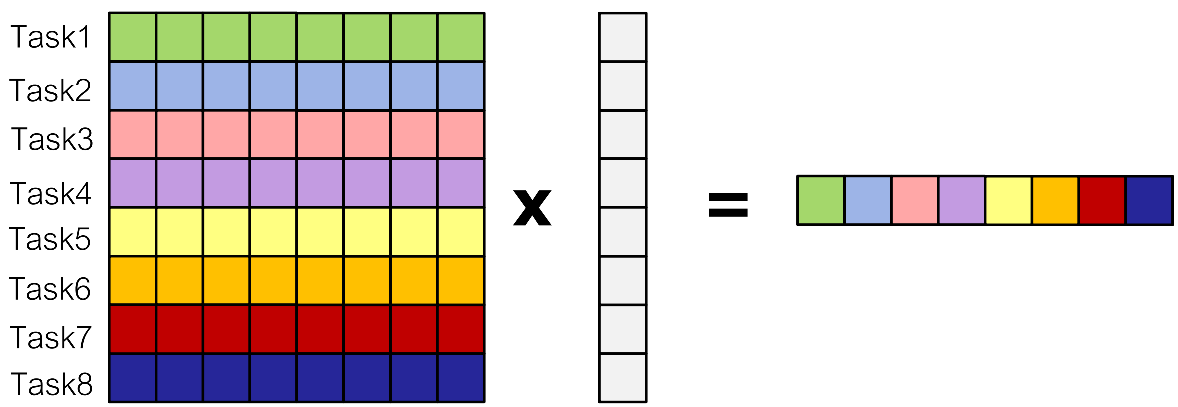

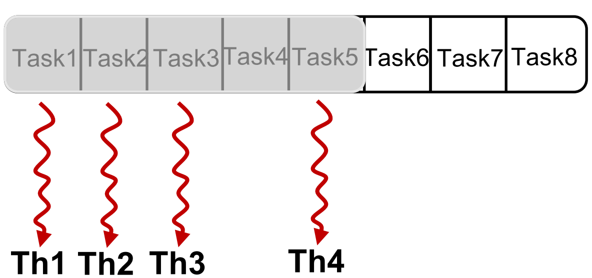

Thread 4 finished its work on task 4 and is now ready to start working on the next available task (task 5), the other threads are still working on their initially assigned tasks!

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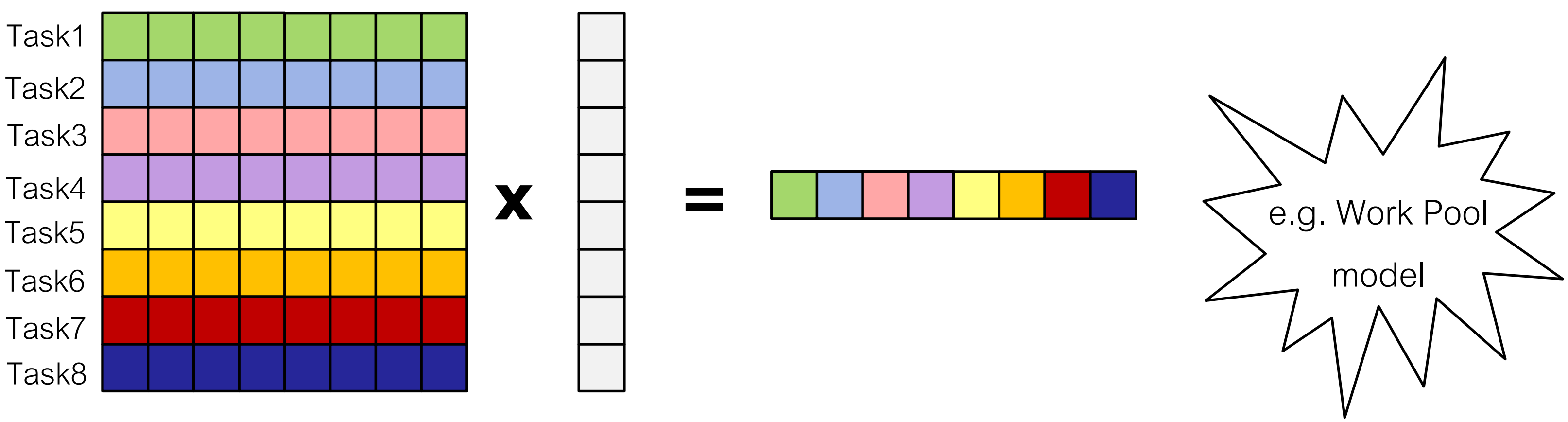

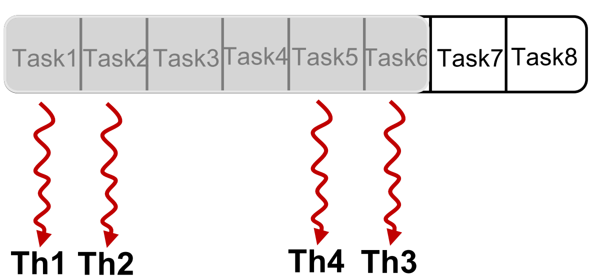

Thread 3 finished its work on task 3 and is now ready to start working on the next available task (task 6). This will go on until the work pool is empty!

Methods for containing interaction overheads

- Maximizing data locality
- Minimizing contention and hot spots
- Overlapping computations with interactions
- Replicating data or computations

Maximize data locality

- Processes share data and/or may require data generated by other processes
- Goals:
  - 1. Minimize the volume of interaction overheads (minimize non-local data accesses and maximize local data utilization)
    - Minimize the volume of shared data and maximize cache reuse
    - Use a suitable decomposition and mapping
    - Use local data to store intermediate results (decreases the amount of data exchange)
  - 2. Minimize the frequency of interactions
    - Restructure the algorithm to access and use large chunks of shared data (amortize interaction cost by reducing frequency of interactions)
    - Shared address space: spatial locality in a cache line, etc.

Minimizing contention and hotspots

- Accessing shared data concurrently can generate contention
  - e.g., concurrent accesses to the same memory block, flooding a specific process with messages, etc.
- Solutions:
  - Restructure the program to reorder accesses in a way that does not lead to contention
  - Decentralize the shared data, to eliminate the single point of contention

Overlap computations with interactions

- Process may idle waiting for shared data => do useful computations while waiting
- Strategies:
  - Initiate an interaction earlier than necessary, so it's ready when needed
    - Identify computations that precede the interaction and which are independent of it
    - Interactions must be relatively static / predictable
    - Typically must use fine granularity, but careful with inherent overheads of doing so
  - Grab more tasks in advance, before current task is completed
    - Eliminates the overhead for a request being granted and new task being assigned
    - Estimating the amount of remaining work in the current task may be hard though
- May be supported in software (compiler, OS), or hardware (e.g., prefetching hardware, etc.). Harder to implement with shared memory models (Pthreads, OpenMP), applies more to distributed and GPU architectures (more on it later in class!)

Replicate data or computations

- To reduce contention for shared data, may be useful to replicate it on each process => no interaction overheads
- Beneficial if the shared data is accessed in read-only fashion
    - Shared-address space paradigm: cache local copies of the data
    - Message-passing paradigm (MPI), more on this later: replicate data to eliminate data transfer overheads
- Disadvantages:
    - Increases overall memory usage by keeping replicas => use sparingly
    - If shared data is read-write, must keep the copies coherent => overheads might dwarf the benefits of local accesses via replication

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Parallel algorithm models

Model = 1 decomposition type + 1 mapping type + strategies to minimize interactions

Commonly used parallel algorithm models:

- Data parallel model
- Work pool model
- Master slave model

Data parallel model

- Decomposition: typically static and uniform data partitioning
- Mapping: static (mostly)
- Same operations on different data items, aka data parallelism
- Possible optimization strategies (depending on the problem and paradigm):
  - Choose a locality-preserving decomposition
  - Overlap computation with interaction
- This model scales really well with problem size (by adding more processes)

Work pool model

- Tasks are taken by processes from a common pool of work
- Decomposition: highly depends on the problem (data, recursive, etc.)
  - Can be statically available at start, or dynamically create more tasks during execution
- Mapping: dynamic
  - Any task can be performed by any process
- Possible strategies for reducing interactions:
  - Adjust granularity: tradeoff between load imbalance and overhead of accessing work pool

Master slave model

- Commonly used in distributed parallel architectures (more on this later)
- A master process generates work and allocates to worker (slave) processes
  - Could involve several masters, or a hierarchy of master processes
- Decomposition: highly depends on the problem (data, recursive)
  - Might be static if tasks are easy to break down a priori, or dynamic
- Mapping: Often dynamic
  - Any worker can be assigned any of the tasks
- Possible strategies for reducing interactions:
  - Choose granularity carefully so that master does not become a bottleneck
  - Overlap computation on workers with master generating further tasks