# Parallel Programming Models – Part I

Lecture 04

# Outline

- Parallelism and Types of Parallelism
- Parallel Programming Models
  - Models of Coordination
  - Program Parallelization
  - Parallel Programming Patterns
- Summary

# PARALLELISM

# What is Parallelism?

- **Parallelism**:
  - Average number of units of work that can be performed in parallel per unit time
  - Example: MIPS, MFLOPS, average number of threads (processes) per second
- Limits in exploiting parallelism
  - Program dependencies – data dependencies, control dependencies
  - Runtime – memory contention, communication overheads, thread/process overhead, synchronization (coordination)
- Work = tasks + dependencies

# Types of Parallelism

## Data parallelism

- **Partition the data** used in solving the problem among the processing units; each processing unit carries out *similar operations* on its part of the data

## Task parallelism

- **Partition the tasks** in solving the problem among the processing units

# Data Parallelism

- **Same operation** is applied to **different elements** of a data set
  - If operations are independent, elements can be distributed among cores for parallel execution → **data parallelism**

- SIMD computers / instructions are designed to exploit data parallelism

- Example:

```
for (i = 0; i < N; i++)
    a[i] = b[i-1] + c[i]
```

# Loop Parallelism – aka Data Parallelism

- Many algorithms perform computations by iteratively traversing a large data structure
  - Commonly expressed as a loop

- **If the iterations are independent**:
  - Iterations can be executed in arbitrary order and in parallel on different cores

# Example: Parallel For in OpenMP

- Iterations of the for loop executed in parallel by a group threads
- Using OpenMP (Open Multi-Processing): application programming interface (API), multi-platform shared-memory multiprocessing programming

```
// Parallelize the matrix multiplication (result = a x b)
// Each thread will work on one iteration of the outer-most loop
// Variables are shared among threads (a, b, result)
// and each thread has its own private copy (i, j, k)


#pragma omp parallel for num_threads(8)
        shared(a, b, result) private (i, j, k)

for (i = 0; i < size; i++)
    for (j = 0; j < size; j++)
        for (k = 0; k < size; k++)
            result.element[i][j] += a.element[i][k] *
                                    b.element[k][j];
```

# Data Parallelism on MIMD

- Common model: **SPMD** (Single Program Multiple Data)
  - One parallel program is executed by all cores in parallel (both shared and distributed address space)
- Example: Scalar product of **x·y** on p processing units

```
local_size = size/p;
local_lower = me * local_size;
local_upper = (me+1) * local_size - 1;
local_sum = 0.0;

for (i=local_lower; i<=local_upper; i++)
  local_sum += x[i] * y[i];

Reduce(&local_sum, &global_sum, 0, SUM);
```

Same program executed by **p** processing units.

**"me"** is the processing units index (0 to p-1)

# Task (Functional) Parallelism

- Independent program parts (**tasks**) can be executed in parallel
  - task (functional) parallelism

- Tasks: single statement, series of statements, loops or function calls

- Further decomposition:
  - A single task can be executed sequentially by one processing units, or in parallel by multiple processing unitss

# Example: Task Parallelism

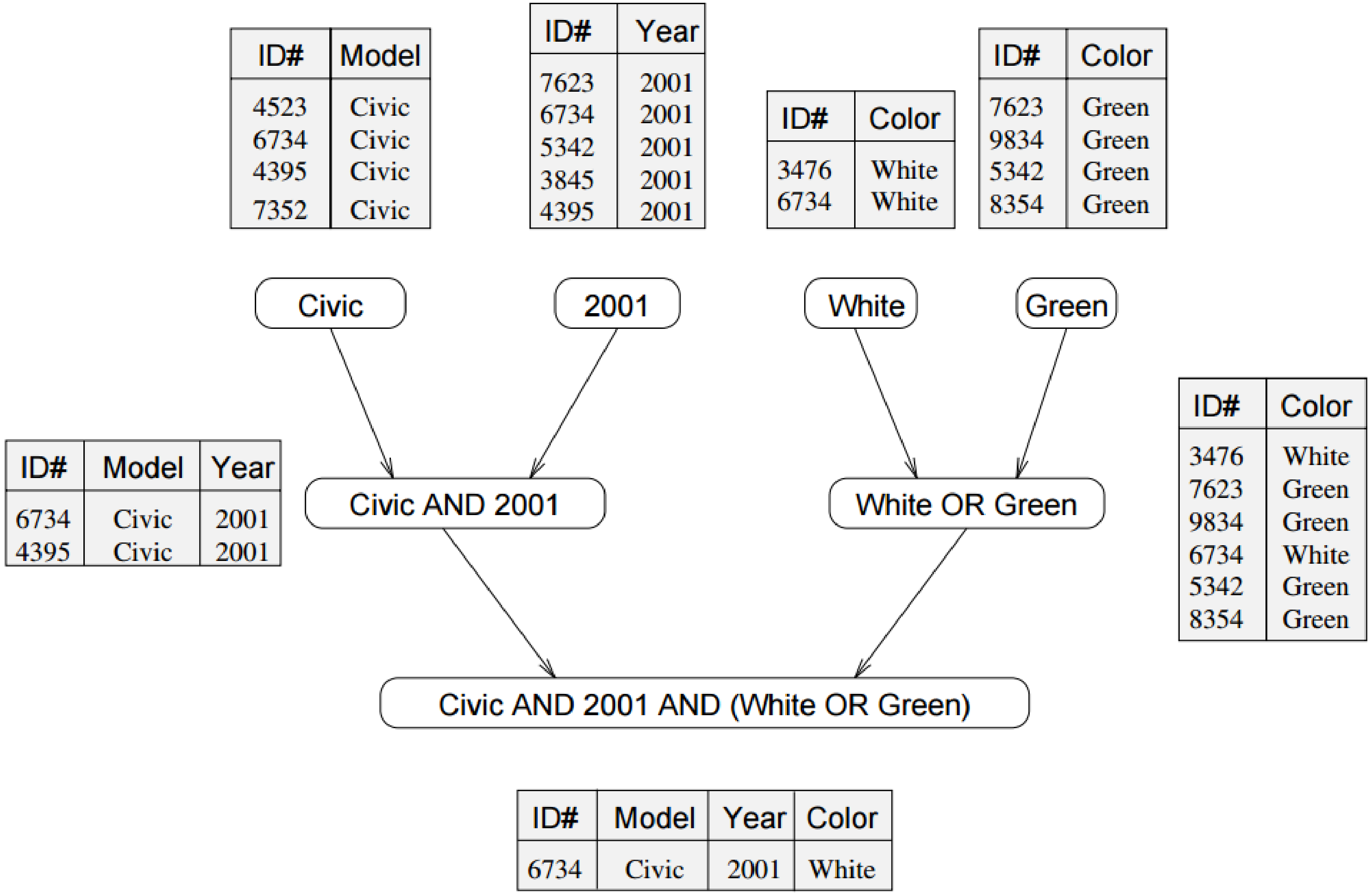
- Consider the database query:

Model ="civic" **AND** Year = "2001" **AND**
(Color = "green" **OR** Color = "white")

| ID# | Model | Year | Color | Dealer | Price |
|---|---|---|---|---|---|
| 4523 | Civic | 2002 | Blue | MN | $18,000 |
| 3476 | Corolla | 1999 | White | IL | $15,000 |
| 7623 | Camry | 2001 | Green | NY | $21,000 |
| 9834 | Prius | 2001 | Green | CA | $18,000 |
| 6734 | Civic | 2001 | White | OR | $17,000 |
| 5342 | Altima | 2001 | Green | FL | $19,000 |
| 3845 | Maxima | 2001 | Blue | NY | $22,000 |
| 8354 | Accord | 2000 | Green | VT | $18,000 |
| 4395 | Civic | 2001 | Red | CA | $17,000 |
| 7352 | Civic | 2002 | Red | WA | $18,000 |

Taken from "Introduction to Parallel Computing" [1]

# Example: **Decomposition A**




| ID# | Model |
|---|---|
| 4523 | Civic |
| 6734 | Civic |
| 4395 | Civic |
| 7352 | Civic |

| ID# | Year |
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| 5342 | 2001 |
| 3845 | 2001 |
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| ID# | Color |
|---|---|
| 3476 | White |
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| ID# | Color |
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| ID# | Model | Year |
|---|---|---|
| 6734 | Civic | 2001 |
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| ID# | Model | Year | Color |
|---|---|---|---|
| 6734 | Civic | 2001 | White |

# Example: **Decomposition B**

| ID# | Model |
|---|---|
| 4523 | Civic |
| 6734 | Civic |
| 4395 | Civic |
| 7352 | Civic |

| ID# | Year |
|---|---|
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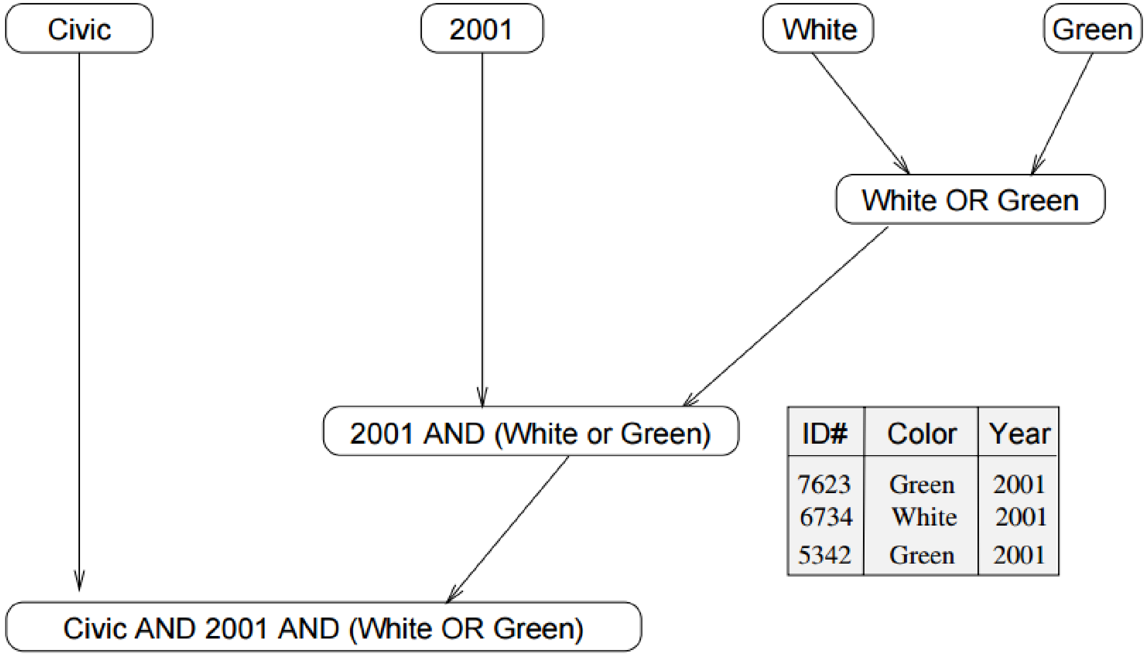


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| 7623 | Green | 2001 |
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| ID# | Model | Year | Color |
|---|---|---|---|
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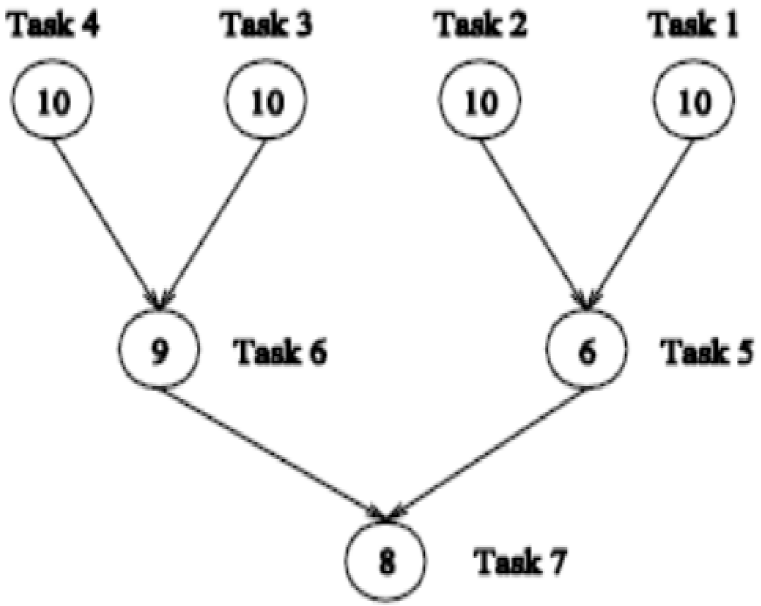
# Task Dependence Graph

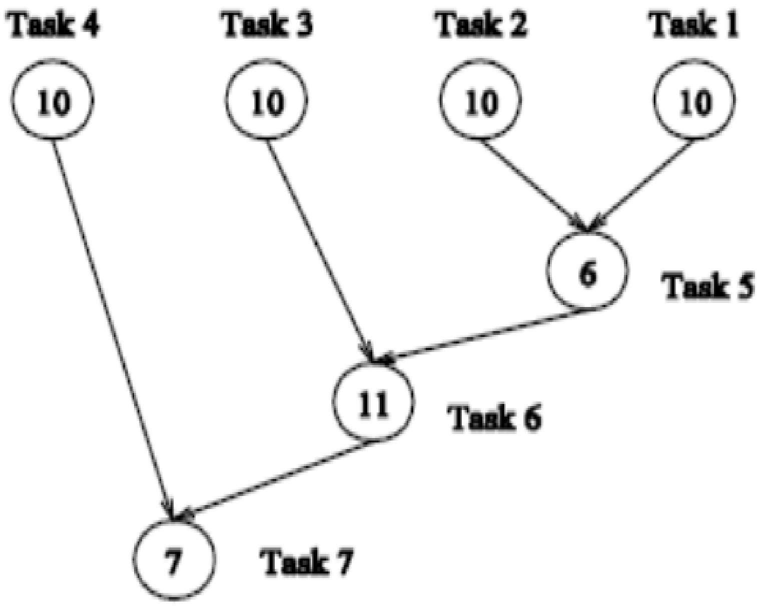
- Can be used to visualize and evaluate the task decomposition strategy
- A **directed acyclic graph**:
  - Node: Represent each task, node value is the expected execution time
  - Edge: Represent **control dependency** between task

- Properties:
  - Critical path length: Maximum (slowest) completion time
  - Degree of concurrency = Total Work / Critical Path Length
    - An indication of amount of work that can be done concurrently

# Task Dependence Graph - Example

- Decompositions A and B can be visualized as:

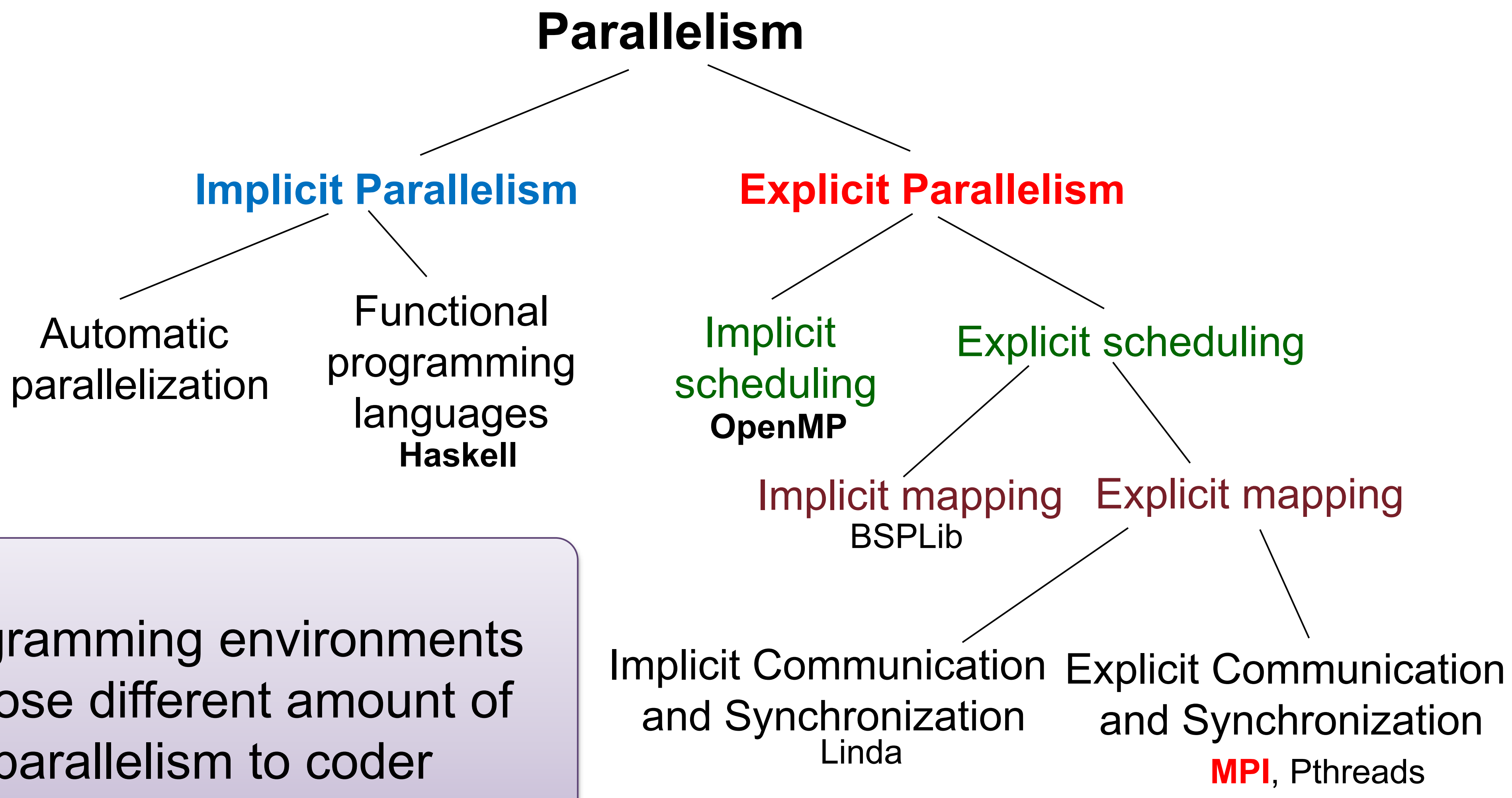



Critical Path = (Task 4 → 6 → 7)
Critical Path Length = **27**
Degree of concurrency = 63 / 27 = **2.33**

Critical Path = (Task 1 → 5 → 6 → 7)
Critical Path Length = **34**
Degree of concurrency = 64 / 34 = **1.88**

# Representation of Parallelism




Programming environments expose different amount of parallelism to coder

# MODELS OF COORDINATION

# Overheads of Parallelism

- Given enough parallel work, overheads are the biggest barrier to getting desired speedup (improvement in performance)
  - cost of starting a parallel task
  - manage and coordinate large number of inter-processor/task interactions
- Overheads can be in the range of milliseconds (= millions of flops) on some systems

# Models of Coordination (Communication)

- Shared address space
- Data parallel
- Message passing

# Shared Address Space

- Communication abstraction
  - Tasks communicate by reading/writing from/to shared variables
  - Ensure mutual exclusion via use of locks
  - Logical extension of uniprocessor programming
- Requires hardware support to implement efficiently
  - Any processor can load and store from any address – contention
  - Even with NUMA, costly to scale
- Matches shared memory systems – UMA, NUMA, etc.

# Data Parallel

- Historically: same operation on each element of an array
  - SIMD, vector processors
- Basic structure: map a function onto a large collection of data
  - Functional: side-effect-free execution
  - No communication among distinct function invocations
    - Allows invocations to be scheduled in parallel
  - Stream programming model
- Modern performance-oriented data-parallel languages do not enforce this structure anymore
  - CUDA, OpenCL, ISPC

# Message passing

- Tasks operate within their own private address spaces
  - Tasks communicate by explicitly sending/receiving messages
- Popular software library: MPI (message passing interface)
- Hardware does not implement system-wide loads and stores
  - Can connect commodity systems together to form large parallel machine
- Matches distributed memory systems
  - Programming model for clusters, supercomputers, etc.

# Coordination and Hardware

- Shared memory space matches shared memory systems – UMA, NUMA, etc.
- Message passing matches distributed memory systems
  - Programming model for clusters, supercomputers, etc.
- But any type of coordination can be implemented in any hardware

# Correspondence with Hardware Implementations

- It is common to implement message-passing abstractions on shared memory machines (hardware)
  - "Sending message" means copying data into message library buffers "Receiving message" means copying data from message library buffers
- It is possible to  implement shared address space abstraction on machines that do not support it in hardware
  - Less efficient software solutions
  - Modify a shared variable: send messages to invalidate all (mem) pages containing the shared variable
  - Reading a shared variable: page-fault handler issues appropriate network requests (messages)

# Summary of Coordination Models

- Shared address space: very little structure
  - All threads can read and write to all shared variables
  - Drawback: not all reads and writes have the same cost (and that cost is not apparent in program text)
- Data-parallel: very rigid computation structure
  - Programs perform the same function on different data elements in a collection
- Message passing: highly structured communication
  - All communication occurs in the form of messages

# PROGRAM PARALLELIZATION

# Program Parallelization

- Parallelization: transform sequential into parallel computation
  - Define parallel tasks of the appropriate granularity

- Granularity of computation can be:

| | |
|---|---|
| Fine-Grain | A sequence of **instructions** |
| | A sequence of **statements** where each statement consists of several instructions |
| Coarse-Grain | A **function / method** which consists of several statements |

# Foster’s Design Methodology

### 1. Partitioning

- First partition a problem into many smaller pieces, or tasks

### 2. Communication

- Provides data required by the partitioned tasks (cost of parallelism)

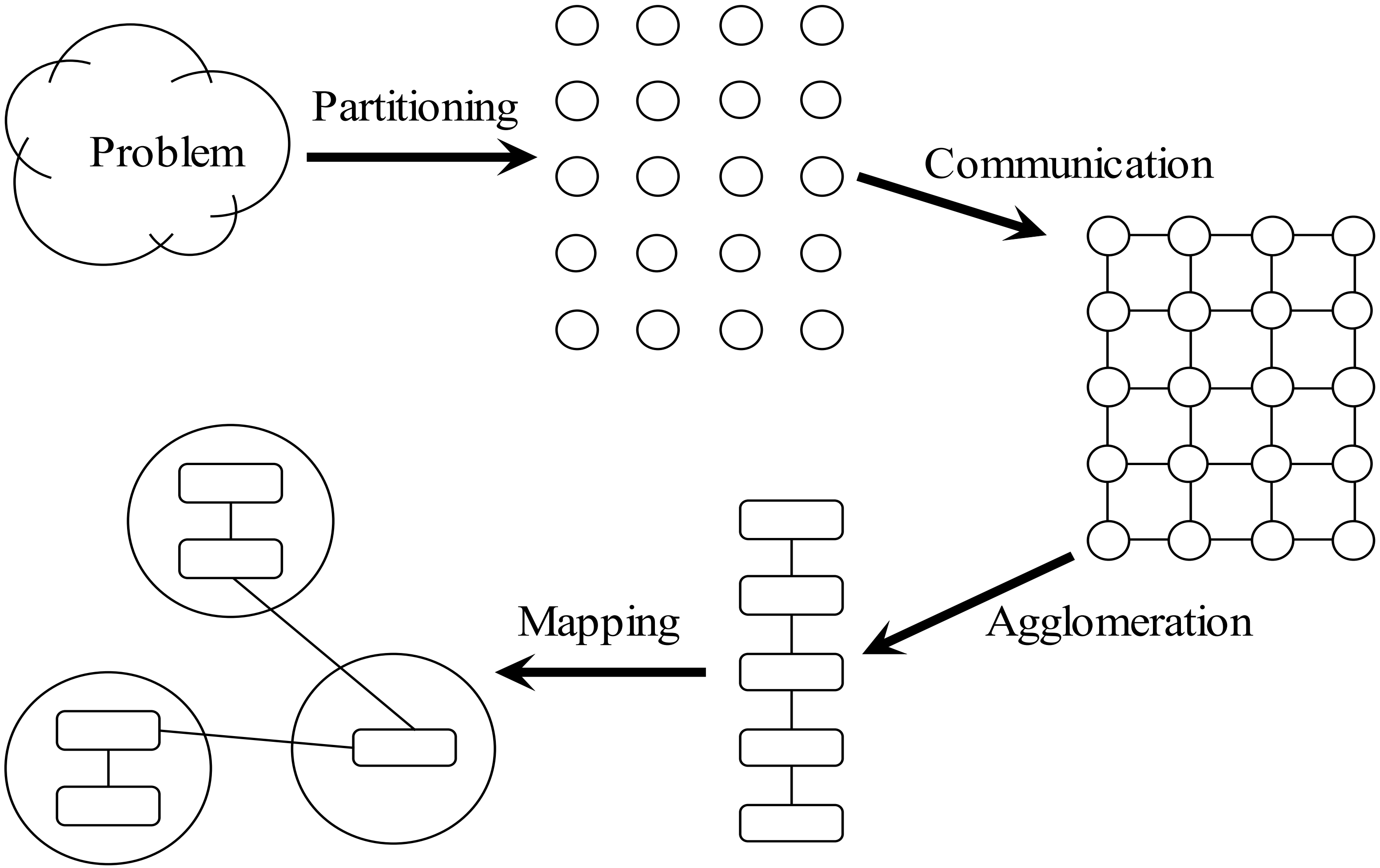
### 3. Agglomeration

- Decrease communication and development costs, while maintaining flexibility

### 4. Mapping

- Map tasks to processors (cores), with the goals of minimizing total execution time

# Foster's Methodology



# 1. Partitioning

- Divide **computation** and **data** into independent pieces to discover maximum parallelism
  - Different way of thinking about problems – reveals structure in a problem, and hence opportunities for optimization

**Data Centric - Domain decomposition**

- Divide data into pieces of approximately equal size
- Determine how to associate computations with the data

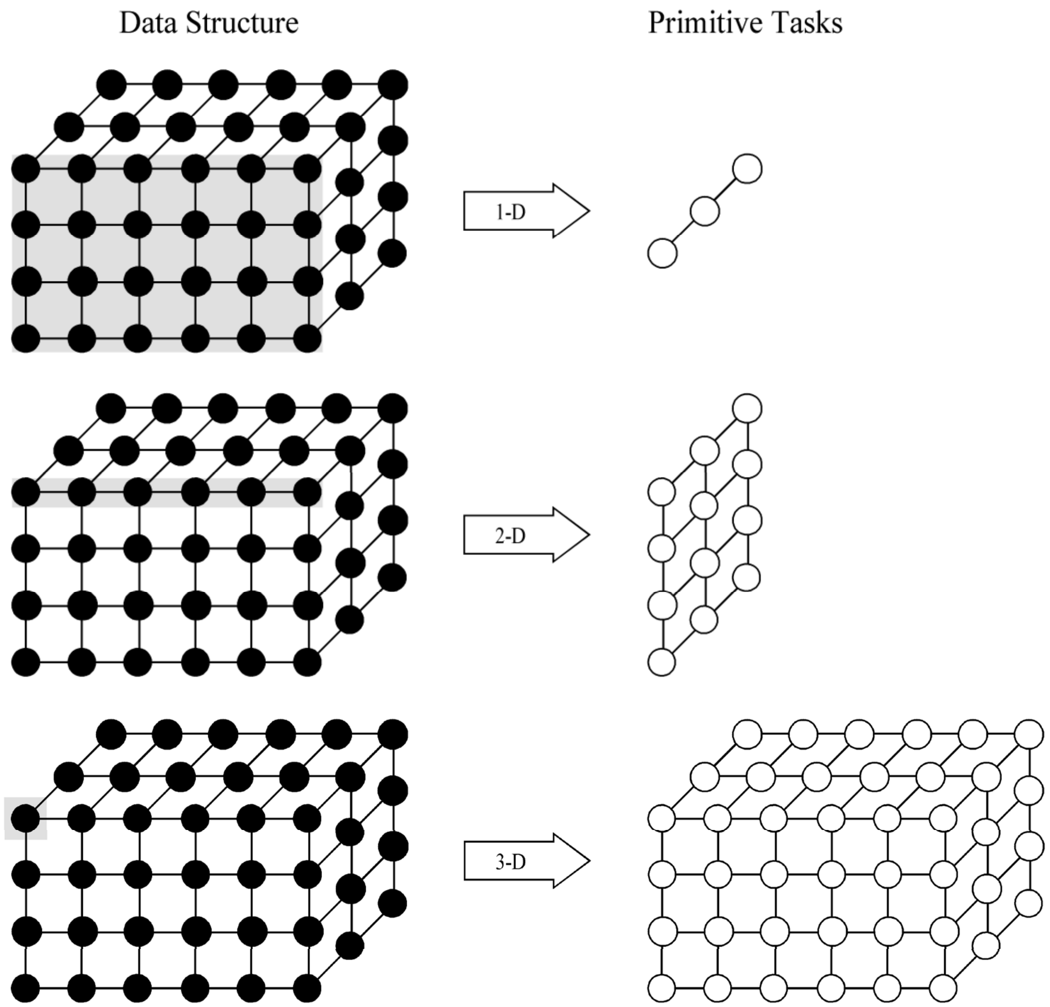
**Data parallelism**

**Computation Centric - Functional decomposition**

- Divide computation into pieces (tasks)
- Determine how to associate data with the computations

**Task parallelism**

# Example: Domain Decompositions



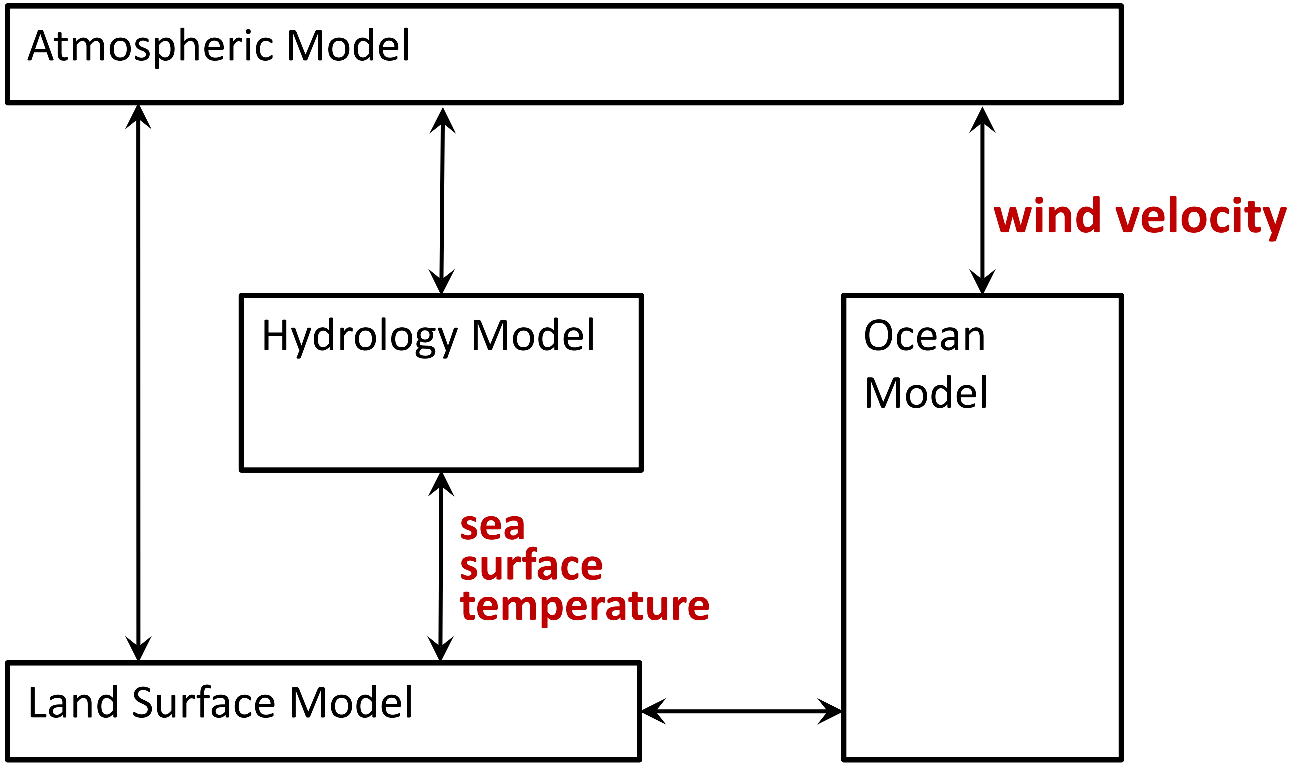

24 tasks, each task with 3 grid points

6 tasks, each task with 12 grid points

1 task with 72 grid points

**3-D Matrix (common data structure)**

# Example: Functional Decomposition




**Computer Model of Climate**

# Partitioning Rules of Thumb

- At least 10x more primitive tasks than cores in target computer
- Minimize redundant computations and redundant data storage
- Primitive tasks roughly of the same size
- Number of tasks an increasing function of problem size

# 2. Communication (Coordination)

- Tasks are intended to execute in parallel
  - but generally not executing independently
  - → Need to determine data passed among tasks

- **Local communication**
  - Task needs data from a small number of other tasks (“neighbors”)
  - Create channels illustrating data flow

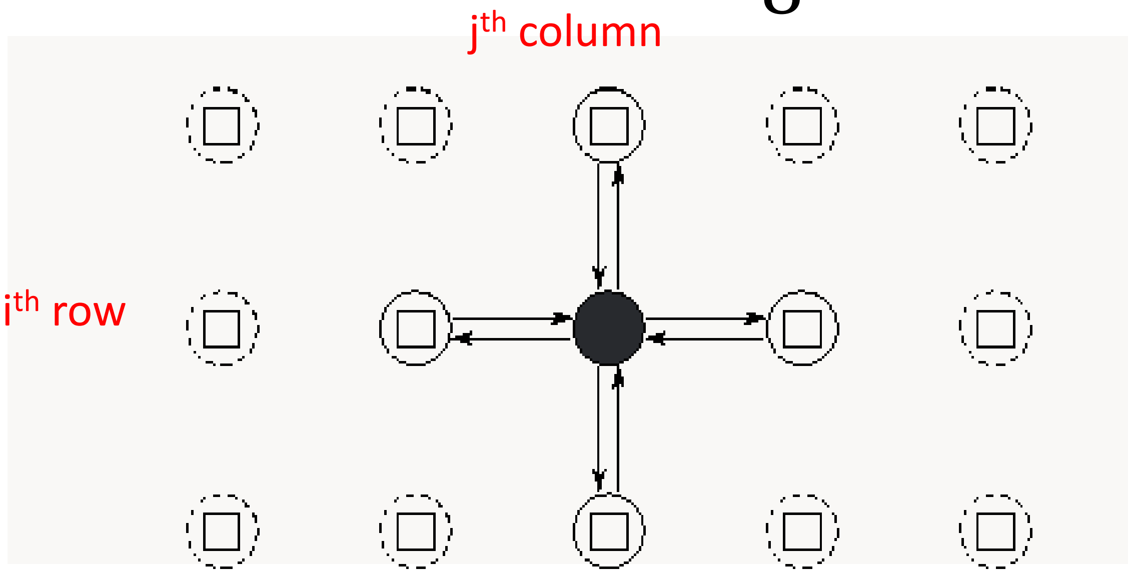
- **Global communication**
  - Significant number of tasks contribute data to perform a computation
  - Don’t create channels for them early in design

- Ideally, distribute and overlap computation and communication

# Local Communication

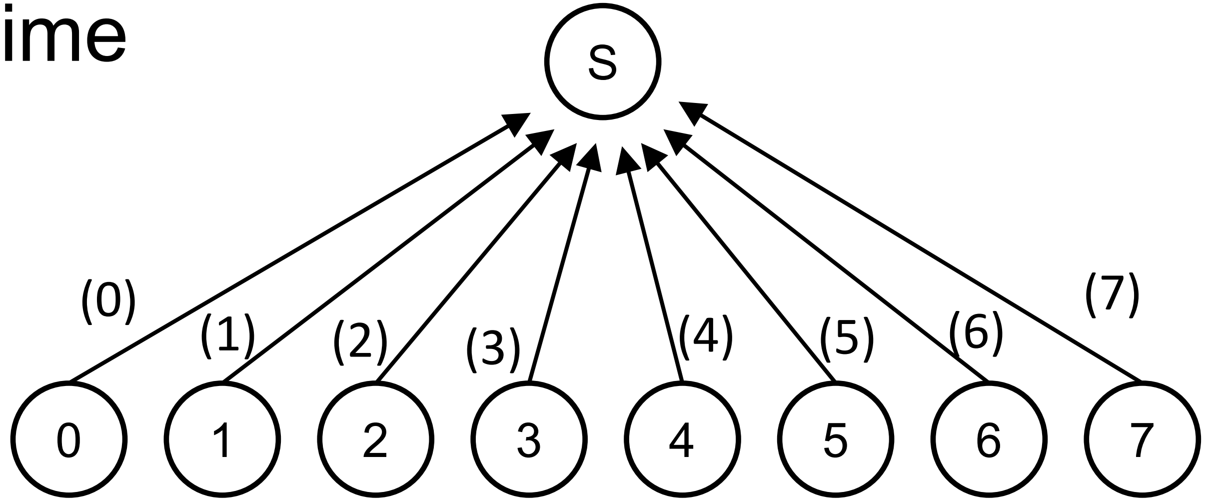
- 2-D Finite Difference Computation
- 2-D grid: at time t+1, requires five points (values at time t) to update each element

$$X_{i,j}^{(t+1)} = \frac{4X_{i,j}^{(t)} + X_{i-1,j}^{(t)} + X_{i+1,j}^{(t)} + X_{i,j-1}^{(t)} + X_{i,j+1}^{(t)}}{8}$$



# Global Communication

- Unoptimized sum N numbers distributed among N (= 8) tasks need O(N) time




**Centralised Summation Algorithm**

- Algorithm is:
  - Centralised – does not distribute computation and communication
  - Sequential – does not allow overlap of computation and communication operations

# Communication Rules of Thumb

- Communication operations balanced among tasks
- Each task communicates with only a small group of neighbors
- Tasks can perform communication in parallel
- Overlap computation with communication

# 3. Agglomeration

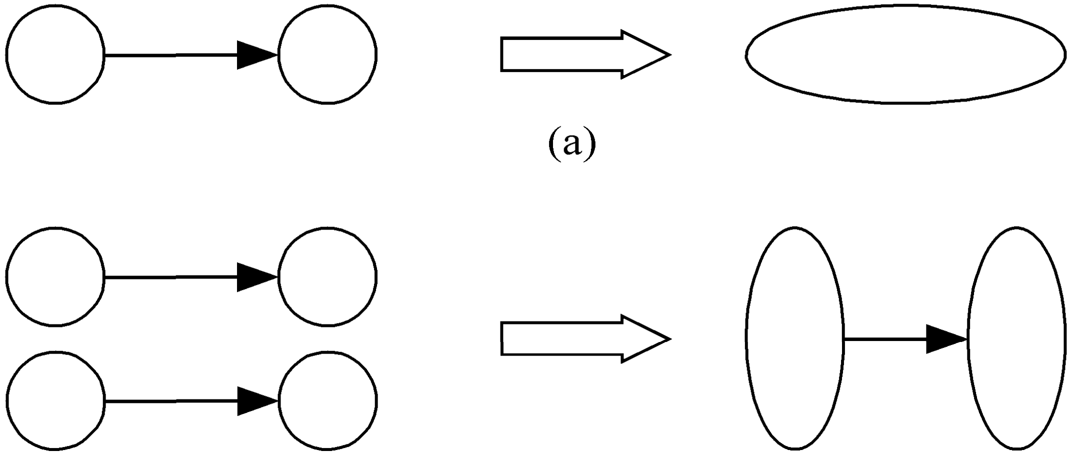
- Combine tasks into larger tasks
  - Number of tasks >= number of cores

- Goals:
  - Improve performance (cost of task creation + communication)
  - Maintain scalability of program
  - Simplify programming

# Motivation of Agglomeration

- Eliminate communication between primitive tasks agglomerated into consolidated task

- Eg. Combine groups of sending and receiving tasks



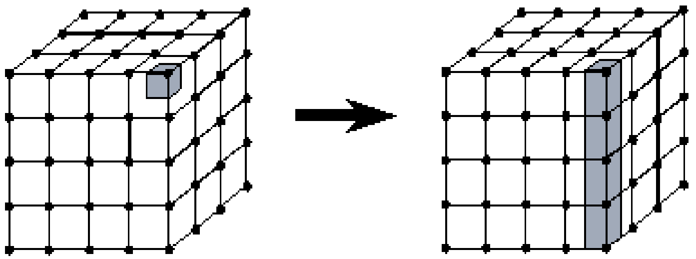
(a)

(b)

Reduce number of sends and receives

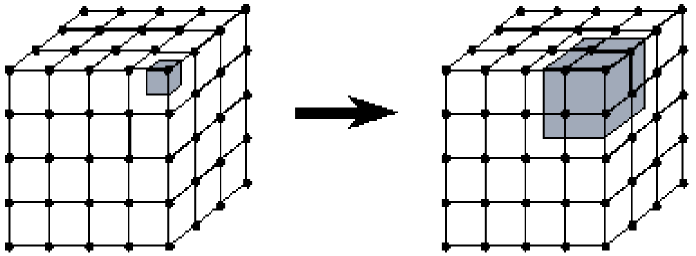
# Examples of Agglomeration

(a)



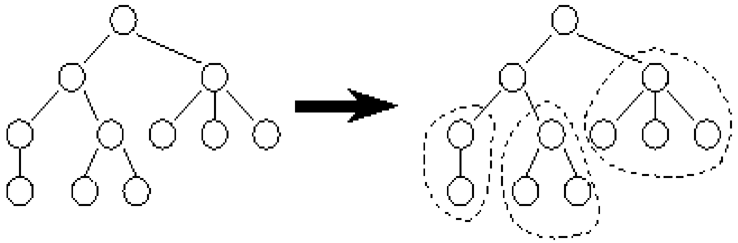
- Reduce dimension of decomposition from 3 to 2

(b)



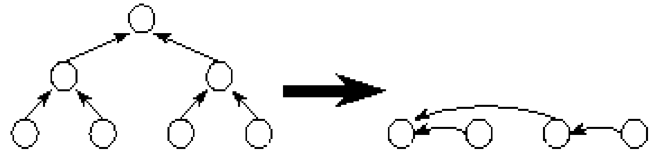
- 3-D decomposition (adjacent tasks are combined)

(c)



- Divide-and-conquer – sub-tree are coalesced

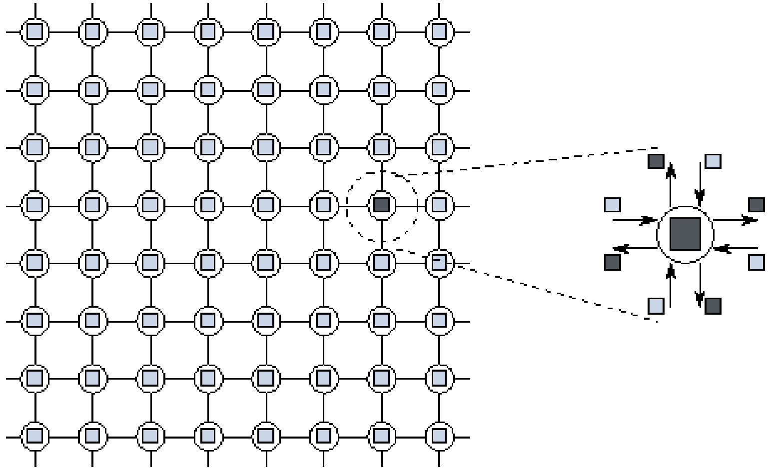
(d)



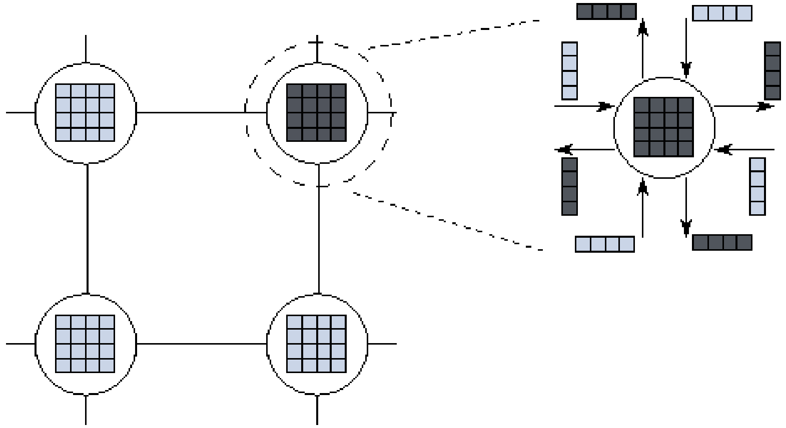
- Tree algorithm – nodes are combined

# Task Granularity: Impact on Communication

(a)



(b)



## 2-D 8 x 8 Grid Problem

a. **Fine-grain Task Partition**

- One grid point per task:
- **? tasks** 8*8 = 64 tasks
- **? data transfers (messages)** 64*4*2 = 512 data transfers

b. **Coarse-grain Task Partition**

- Each task is a 4 x 4 grid with a total of 16 grid points:
- **? tasks** 2*2 = 4 tasks
- **? data transfers (messages)** 4*4*2 = 32 data transfers

# Agglomeration Rules of Thumb

- Locality of parallel algorithm has increased
- Number of tasks increases with problem size
- Number of tasks suitable for likely target systems
- Tradeoff between agglomeration and code modifications costs is reasonable

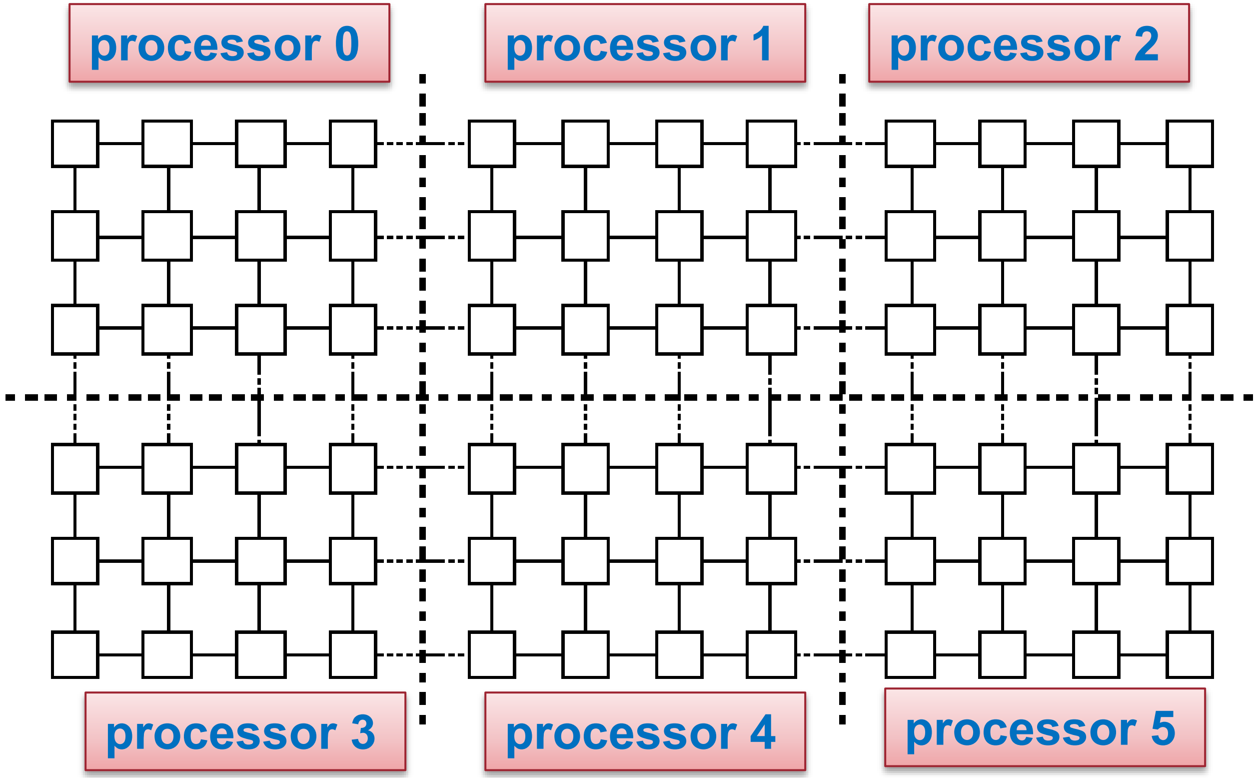
# 4. Mapping

- **Assignment of tasks** to execution units

- Conflicting goals:
  - **Maximize processor utilization** – place tasks on different processing units to increase parallelism
  - **Minimize inter-processor communication** – place tasks that communicate frequently on the same processing units to increase locality

- Mapping may be performed by:
  - OS for centralized multiprocessor
  - User for distributed memory systems

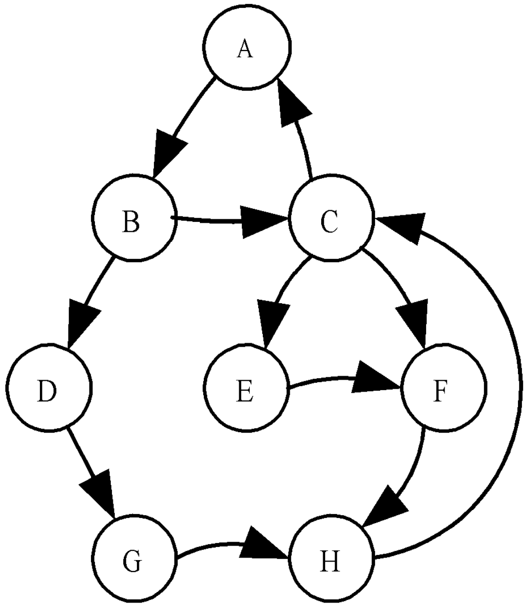
# Mapping Example



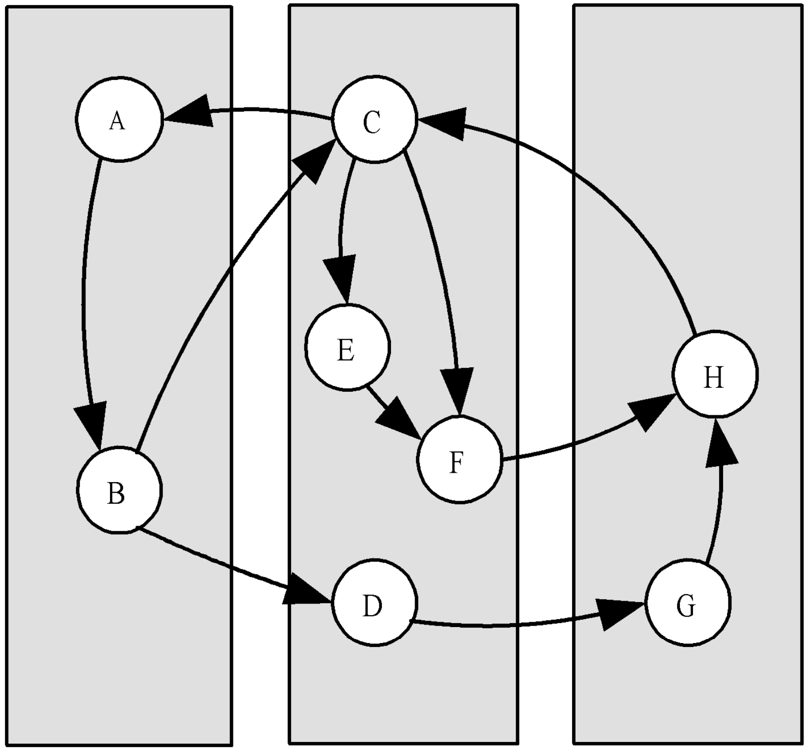

**12 x 6 Grid Problem**

- Same amount of work on each processing units and to minimize off-processor communications

# Mapping Example




a. Task/Channel Graph




b. Mapping on Three Processors

# Mapping Rules of Thumb

- Finding optimal mapping is NP hard in general
  - Must rely on heuristic

- Consider designs based on one task per core and multiple tasks per core

- Evaluate static and dynamic task allocation
  - If dynamic task allocation is chosen, the task allocator should not be a bottleneck to performance
  - If static task allocation is chosen, the ratio of tasks to cores is at least 10:1

# Foster's Design Methodology

**1. Partitioning**

- First partition a problem into many smaller pieces, or tasks

**2. Communication**

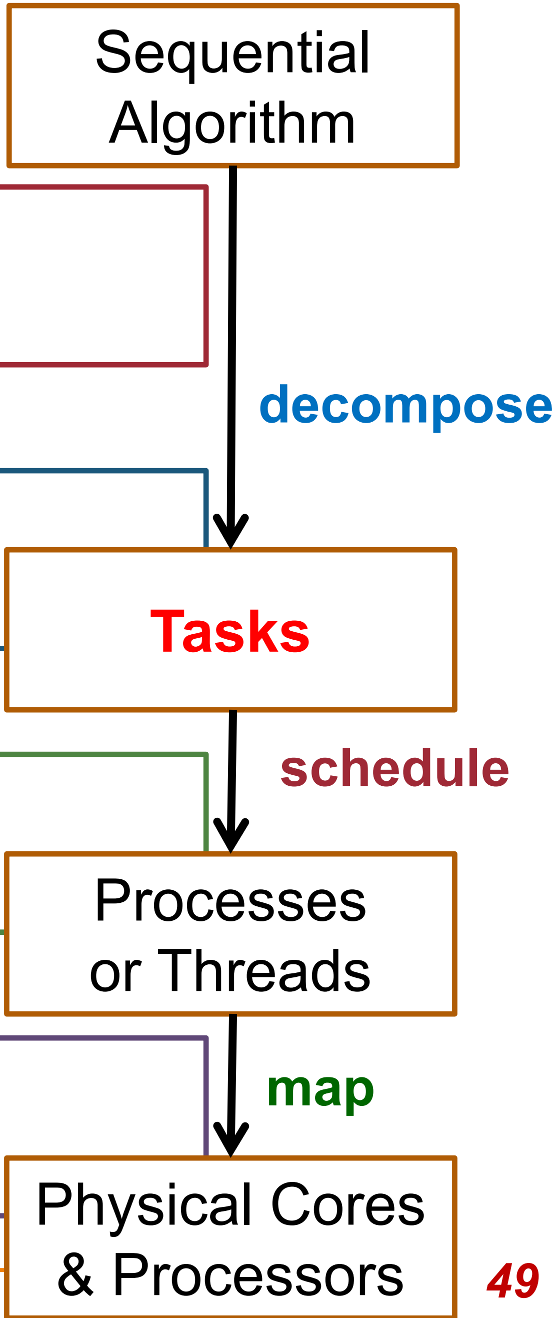
- Provides data required by the partitioned tasks (cost of parallelism)

**3. Agglomeration**

- Decrease communication and development costs, while maintaining flexibility

**4. Mapping**

- Map tasks to processors (cores), with the goals of minimizing total execution time



# Automatic Parallelization

- Parallelizing compilers perform decomposition and scheduling

- **Drawbacks:**
  - Dependence analysis is difficult for pointer-based computations or indirect addressing
  - Execution time of function calls or loops with unknown bounds is difficult to predict at compile time

# Functional Programming Languages

- Describe the computations of a program as the evaluation of mathematical functions without side effects

- Advantages:
  - New language constructs are not necessary to enable a parallel execution

- Challenge:
  - Extract the parallelism at the right level of recursion

# PARALLEL PROGRAMMING PATTERNS

# Overview

- A **parallel programming pattern** provides a coordination structure for tasks:
  - Similar to design pattern from Software Engineering
  - Not mutually exclusive, use the best match to describe your solution design
- Examples
  - Fork–Join
  - Parbegin-Parend
  - SPMD and SIMD
  - Master-Worker (Master-Slave)
  - Task pool
  - Producer-consumer
  - Pipelining

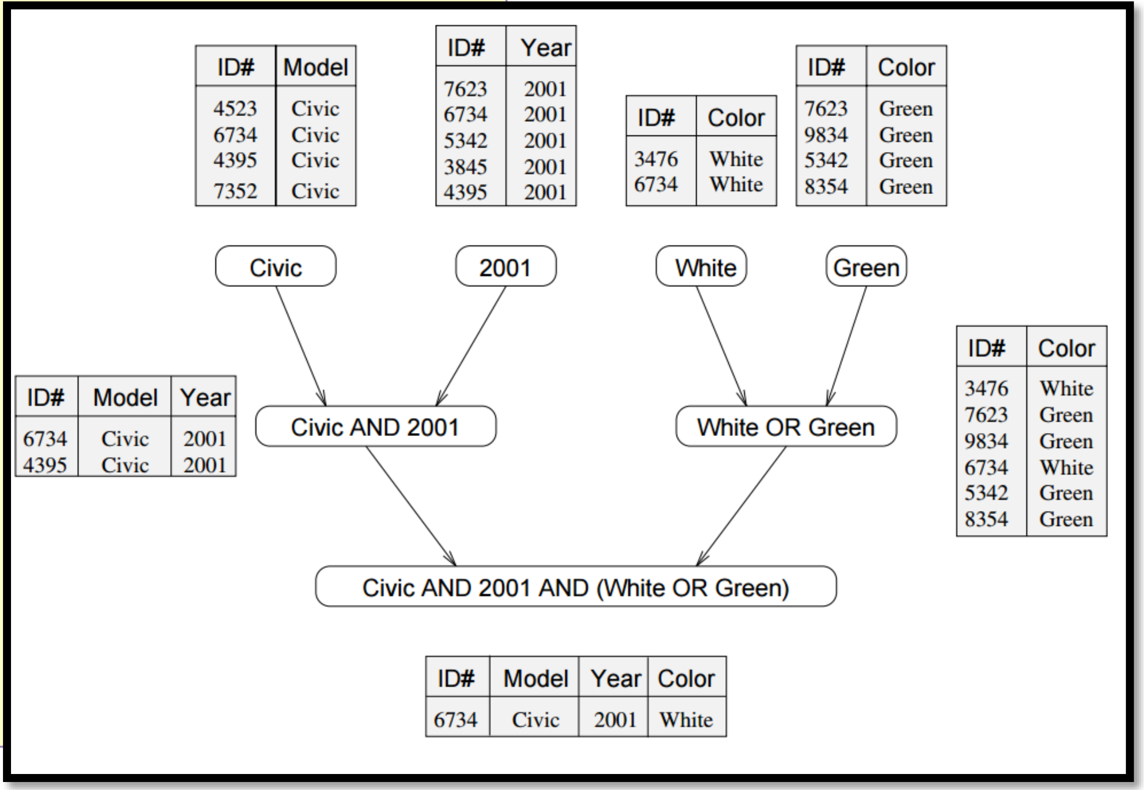
# Fork-Join

- Task T creates child tasks
  - Children run in parallel, but they are independent of each other
  - The children can execute the same or a different program part, or function
  - Children might join the parent at different times

- **Implementation**:
  - Processes, threads, and any paradigm that makes use of these concepts

# Example: Database Query (A)

```
P1 = Fork {
     P3 = Fork { return Model = "civic" }
     P4 = Fork { return Year = "2001" }
     Join P3, P4
     Return P3 AND P4
}
P2 = Fork {
     P5 = Fork { return Color = "green" }
     P6 = Fork { return Color = "white" }
     Join P5, P6
     Return P5 OR P6
}
Join P1, P2
Return P1 AND P2
```

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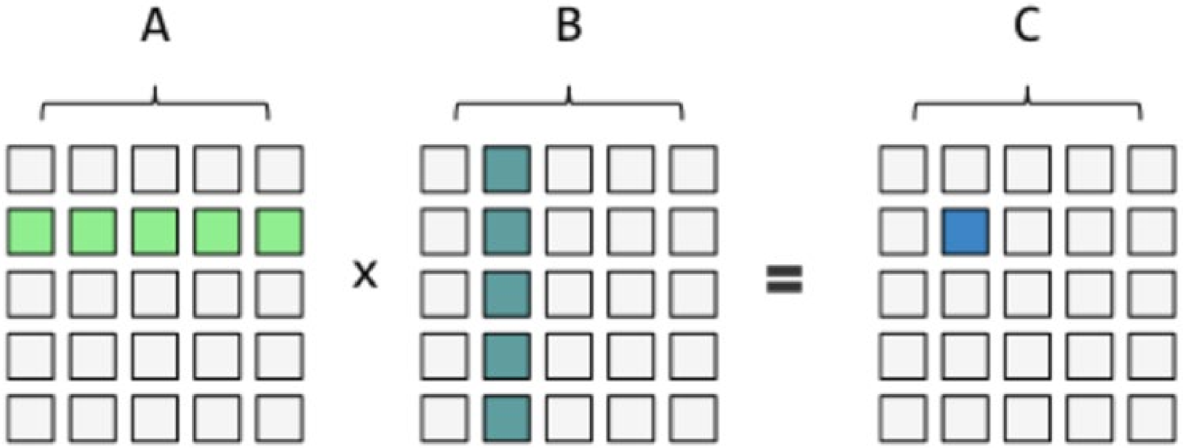
# Parbegin–Parend

- Programmer specifies a sequence of statements (function calls) to be executed by a set of cores in parallel
  - When an executing thread reaches a **parbegin–parend construct**, a set of threads is created and the statements of the construct are assigned to these threads for execution
  - Usually, the threads execute the same code (function)
- The statements following the **parbegin–parend construct** are only executed after all these threads have finished their work
- Like a fork-join pattern, where all forks are done at the same time, and all joins are done at the same time
- Implementation:
  - A language construct such as OpenMP or compiler directives

# Matrix Multiplication




```
for i ← 0 to n-1
   for j ← 0 to n-1
      c[i, j] ← 0
      for k ← 0 to n-1
         c[i, j] ← c[i, j] + a[i, k] x b[k, j]
```

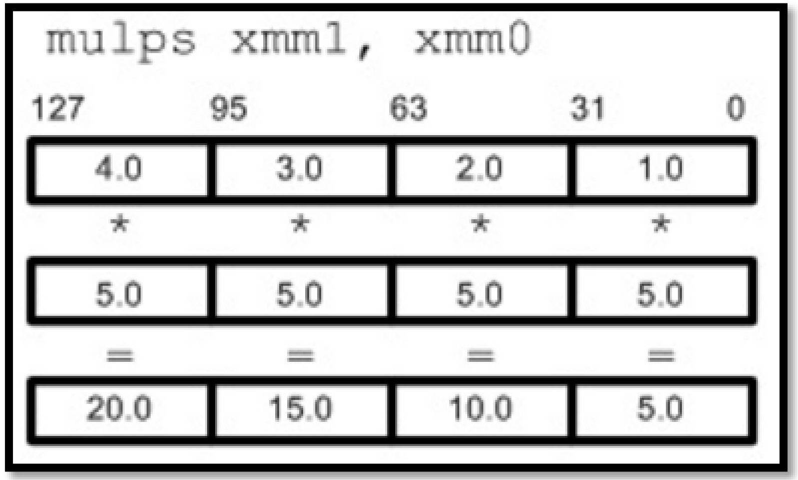
# Example: Parallel For in **OpenMP**

- Iterations of the for loop executed in parallel by a group threads

```
// Parallelize the matrix multiplication (result = a x b)
// Each thread will work on one iteration of the outer-most loop
// Variables are shared among threads (a, b, result)
// and each thread has its own private copy (i, j, k)

#pragma omp parallel for shared(a, b, result)
                         private (i, j, k)

for (i = 0; i < size; i++)
    for (j = 0; j < size; j++)
        for (k = 0; k < size; k++)
            result.element[i][j] += a.element[i][k] *
                                    b.element[k][j];
```

# SIMD

- **Single instructions** are executed synchronously by the different threads on different data
  - Similar to parbegin-parend, but the threads execute synchronously (all threads execute the same instruction at the same time)
- Implementation:
  - AVX/SSE Instruction on Intel processor




`xmm` registers are 128 bits long

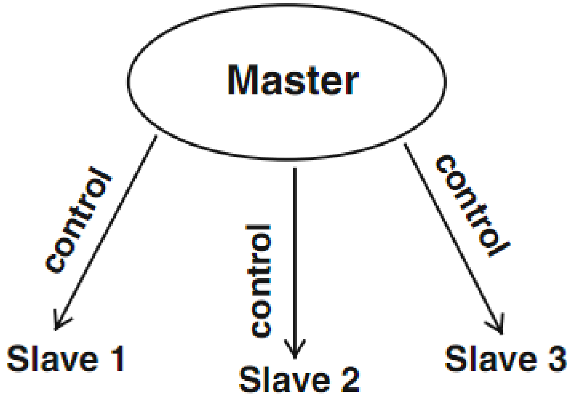
**SSE instruction treats the xmm registers as 4 individual 32-bit floating point value**

# SPMD

- **Same program** executed on different cores but operate on different data
  - Different threads may execute different parts of the parallel program because of
    - Different speeds of the executing cores
    - Control statement in the program, e.g., If statement
  - Similar to parbegin-parend, but SPMD is the preferred name when we do not follow the pattern
- No implicit synchronization
  - Synchronization can be achieved by explicit synchronization operations
- Implementation:
  - Programs running on GPGPU

# Master–Worker (previously, Master–Slave)

- A single program (master) controls the execution of the program
  - Master executes the main function
  - Assigns work to worker threads




- **Master task**:
  - Generally responsible for coordination and perform initializations, timings, and output operations
- **Worker task**:
  - Wait for instruction from master task

# Matrix Multiplication – Master-Worker

```
int main(int argc, char ** argv)
{
        int nprocs;
        MPI_Init(&argc,&argv);
        MPI_Comm_size(MPI_COMM_WORLD, &nprocs);
        MPI_Comm_rank(MPI_COMM_WORLD, &myid);
        size = 2048;
        // One master (rank = 0) and nprocs-1 workers
        if (myid == 0)   {
            master();
        } else {
            worker();
        }
        MPI_Finalize();
        return 0;
}
```

# Matrix Multiplication – Master-Worker

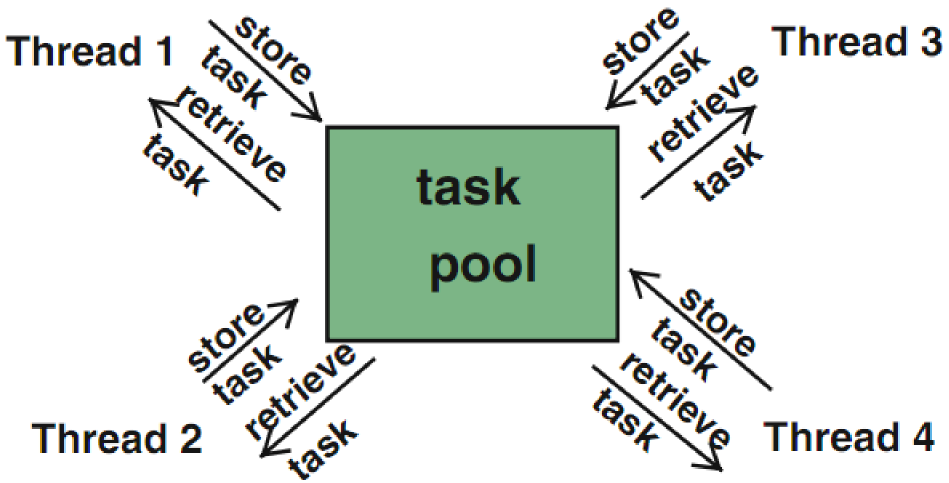
```
void master()
{
        matrix a, b, result;

        // Allocate memory for matrices
        allocate_matrix(&a);
        allocate_matrix(&b);
        allocate_matrix(&result);

        // Initialize matrix elements
        init_matrix(a);
        init_matrix(b);

        // Distribute data to workers
        master_distribute(a, b);

        // Gather results from workers
        master_receive_result(result);

        // Print the result matrix
        print_matrix(result);
}
```

# Matrix Multiplication – Master-Worker

```
void worker()
{
        int rows_per_worker = size / workers ;
        float row_a_buffer[rows_per_worker][size];
        matrix b;
        float result[rows_per_worker][size];

         // Receives data
        worker_receive_data(&b, row_a_buffer);

         // Performs computations
         worker_compute(b, row_a_buffer, result);

         // Sends the results to master
         worker_send_result(result);

}
```

# Task (Work) Pools

- A common data structure from which threads can access to retrieve tasks for execution




- Number of threads is fixed
  - Threads are created statically by the main thread
  - Once a task is finished, the worker thread retrieves another task from the pool
  - Work is not pre-allocated to the worker threads; instead, a new task is retrieved from the pool by the worker thread
- During the processing of a task, a thread can generate new tasks and insert them into the task pool

# Task (Work) Pools

- Access to the task pool must be synchronized to avoid race conditions

- Execution of a parallel program is completed when
  - Task pool is empty
  - Each thread has terminated the processing of its last task

- Advantages:
  - Useful for adaptive and irregular applications
    - Tasks can be generated dynamically
  - Overhead for thread creation is independent of the problem size and the number of tasks

- Disadvantages:
  - For fine-grained tasks, the overhead of retrieval and insertion of tasks becomes important

# Example: Java Thread Pool Executor

```
class ThreadPoolExample {

    public static void main(String[] args) {
        ExecutorService executor =
                    Executors.newFixedThreadPool(5);

        for (int i = 0; i < 10; i++) {
            Runnable Task = new Task( ..... );
            executor.execute( Task );
        }
        ......
    }
}
```

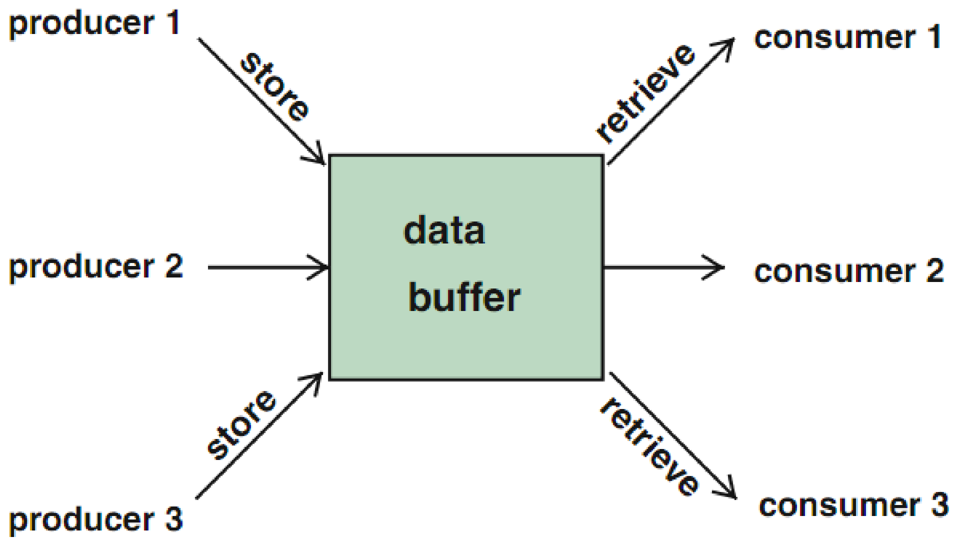
5 threads

10 tasks added to the pool.

- The executor will assign task to the 5 threads:
    - After a thread finishes its task, another task from the pool will be assigned

# Producer–Consumer

- Producer threads produce data which are used as input by consumer threads




- Synchronization has to be used to ensure correct coordination between producer and consumer threads

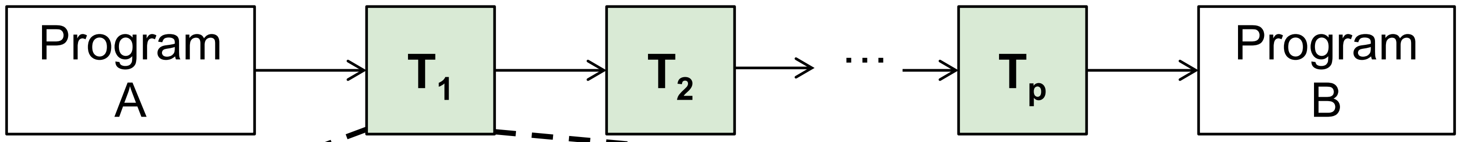
# Producer–Consumer: Shared Buffers

```
void produce() {
    synchronized (buffer) {
        while (buffer is full)
            buffer.wait();
        Store an item to buffer;
        if (buffer was empty)
            buffer.notify();
    }
}
```

```
void consume() {
    synchronized (buffer) {
        while (buffer is empty)
            buffer.wait();
        Retrieve an item from buffer;
        if (buffer was full)
            buffer.notify();
    }
}
```

# Pipelining

- Data in the application is partitioned into a stream of data elements that flows through the pipeline stages one after the other to perform different processing steps
  - A form of functional parallelism: **Stream parallelism**




```
initialize
while (more data) {
  receive data element from previous stage
  perform operation on data element
  send data element to next stage
}
finalize
```

# Summary

- Models of Communication
- Types and representation of parallelism
- Foster's methodology for program parallelization
- Main parallel programming patterns

# References

- **Main Reference Book**
  - Chapter 3

- **Introduction to Parallel Computing**
  - by Grama, Gupta, Karypis, Kumar
  - http://www-users.cs.umn.edu/~karypis/parbook/