

# Chapter 3

## Shared Memory Parallel Programming

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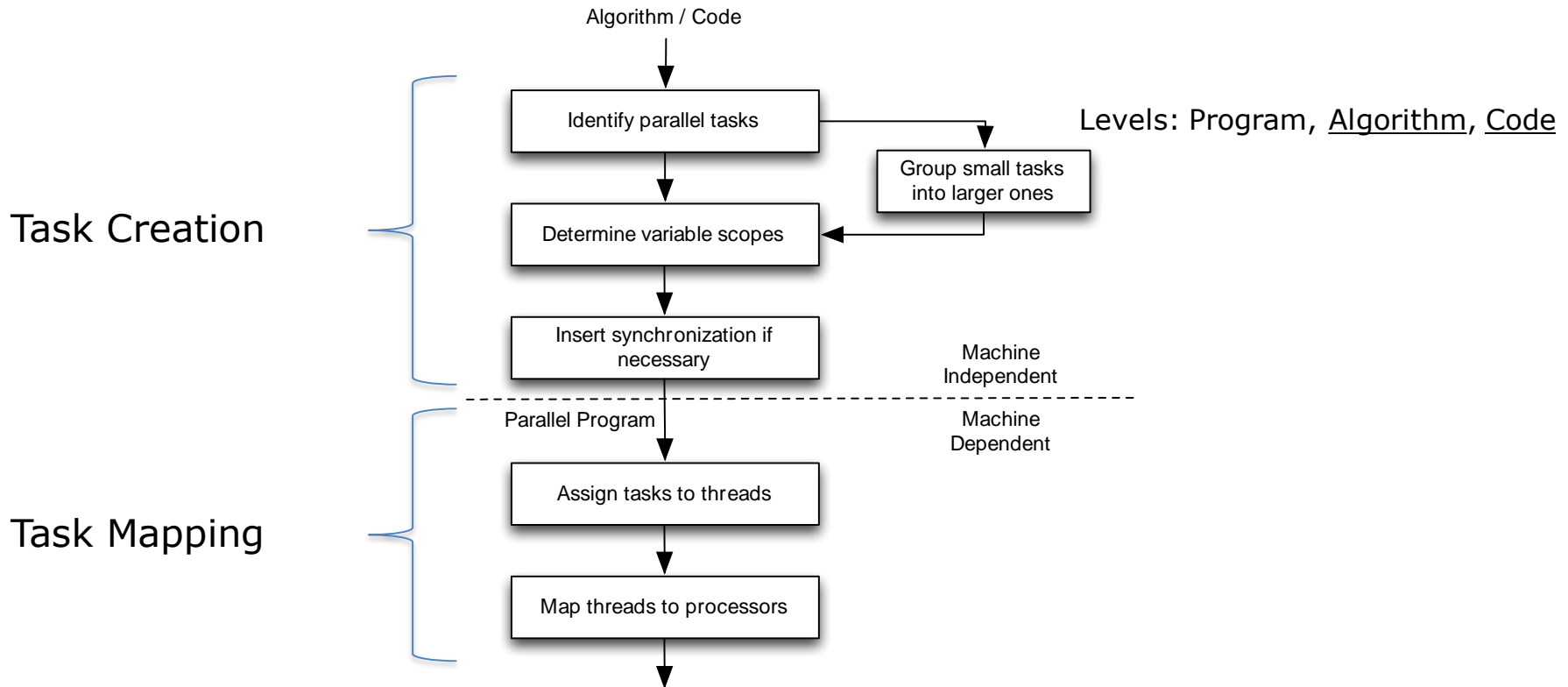
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# Steps in Parallel Programming

# Steps in Creating a Parallel Program



Task Creation: identifying parallel tasks, variable scopes, synchronization

=> Create tasks that can cooperate to perform a single computation

Task Mapping: grouping tasks, mapping to processors/memory

=> May be hidden from programmers

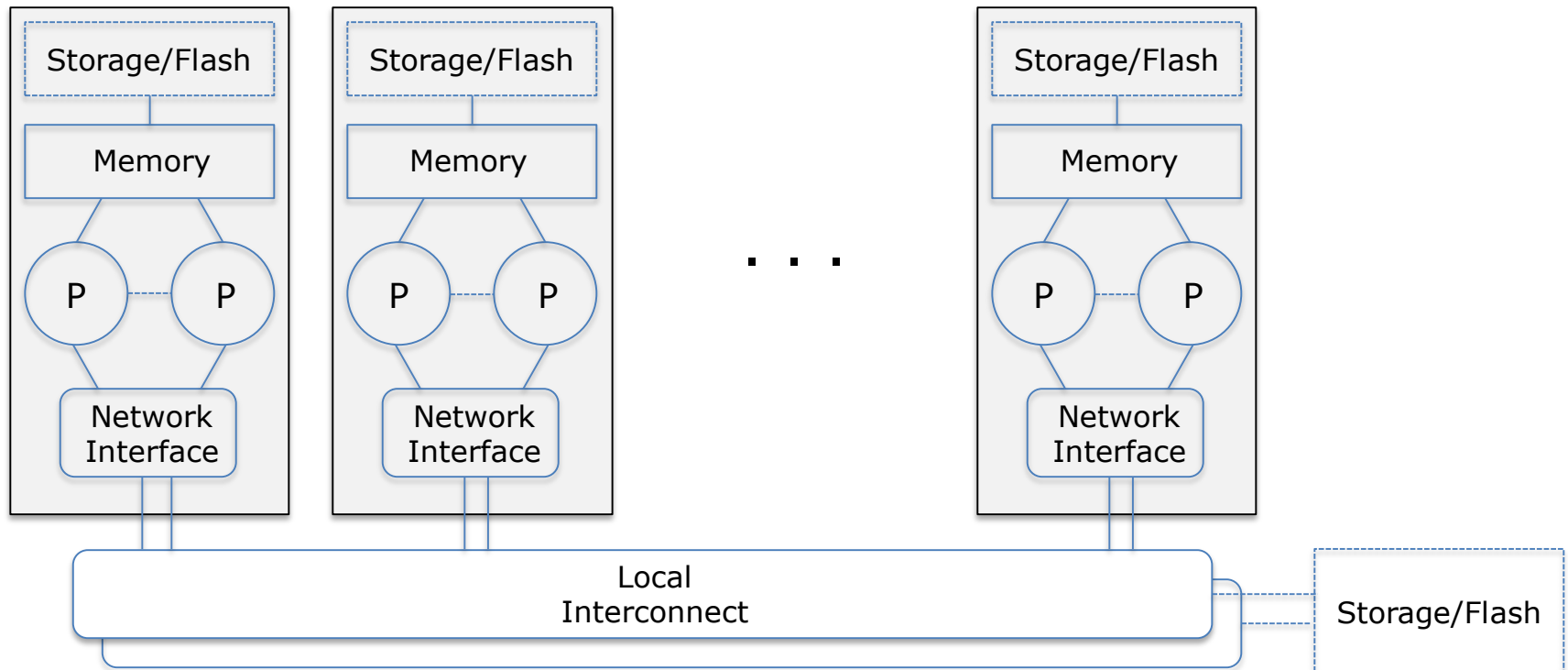
# Multiprocessor Systems

Initial focus: Shared memory programming model

=> Concepts important to understand multicore architectures

=> It's a dominant programming model for multicore

=> Multicore processors (P) are the building block for base systems



A balanced system design necessary

# Storage Rich Server Example

	Capacity Optimized	Performance Optimized	All Flash
CPU	1x Intel Xeon E5-2620v4 8cores	2x Intel Xeon E5-2620v4 8cores	2x Intel Xeon E5-2620v4 8cores
RAM	64GB RAM DDR4;	128GB RAM DDR4;	128GB RAM DDR4;
Storage	12x3.5" (6TB or 10TB)	24x2.5" 28TB+	24 x Intel 1200GB SATA SSD
Cache(R/W)	1xIntel® P3700/P4800 400GB NVMe	2x Intel P3700/P4800 400GB NVMe	3 x Intel® P4800X 375GB NVMe
HBA	Broadcom SAS 3008 IT-mode (HBA)		
NIC	Intel® X520 2x10GbE NIC SFP+	Intel® X520 2x10GbE NIC SFP+	2 x Mellanox ConnectX-4 25/100GbE
All Configurations require 2 switches: 1 for client connections, 1 for intra-cluster communication			

Spectrum NAS can run on any x86 storage rich server but the items in purple must be the same family model/vendor as listed above  
(See following page)

# Parallelism and Amdahl's Law

The text states there are three levels of parallelism:

- program level => e.g., parallel compilation of file (not a focus)
- algorithm level
- code level

## **The limits of parallelism: Amdahl's law**

*Speedup* is defined as

$$\frac{\text{time for serial execution}}{\text{time for parallel execution}}$$

or, more precisely, as

$$\frac{\text{time for serial execution of best serial algorithm}}{\text{time for parallel execution of our algorithm}}$$

# Parallelism and Amdahl's Law

## Taken Deeper

Consider the execution of a given program on a uniprocessor system with a total execution time of  $T$  minutes

Let's say the program has been parallelized or partitioned for parallel execution on a cluster of many processing nodes

Assume that a fraction  $\alpha$  of the code must be executed sequentially, called the *sequential bottleneck*

Therefore,  $(1 - \alpha)$  of the code can be compiled for parallel execution by  $n$  processors

The total execution time of the program is calculated by  $\alpha T + (1 - \alpha)T/n$ , where the first term is the sequential execution time on a single processor and the second term is the parallel execution on  $n$  processing nodes

Amdahl's Law states that the *speedup factor* of using the  $n$ -processor system over the use of a single processor is expressed by:

$$\text{Speedup} = S = T / [\alpha T + (1 - \alpha)T/n] = 1 / [\alpha + (1 - \alpha)/n]$$

Note: All system or communication overhead is ignored. The I/O time or exception handling time is also not included.

# Parallelism and Amdahl's Law

## What do we learn?

$$\text{Speedup} = S = T / [\alpha T + (1 - \alpha)T/n] = 1 / [\alpha + (1 - \alpha)/n]$$

The maximum speedup of  $n$  is achieved only if:

- The sequential bottleneck  $\alpha$  is reduced to zero
- Or the code is fully parallelizable with  $\alpha = 0$

As the cluster becomes sufficiently large, that is,  $n \rightarrow \infty$

$S$  approaches  $1/\alpha$ , an upper bound

Hence, the benefit of optimizing for parallelization



# Parallel Programming

- Task Creation
  - Identifying parallel tasks
    - **Code analysis**
    - Algorithm analysis
  - Variable partitioning
    - Shared vs. private vs. reduction
  - Synchronization
- Task mapping (performance)
  - Tasks to threads
    - Typically more tasks than processors, so multiple tasks assigned to threads
    - A goal may be to balance workload of the threads
  - Mapping threads to processors, including data layout in memory
    - Goal is to achieve communication locality between processors and data locality based on access

# Code Analysis

- Goal: Given a code, without the knowledge of the algorithms, find parallel tasks
- Focus on loop dependence analysis
- Notations:
  - $S$  is a statement or group of statements in the source code
  - If there are two statements  $S_1$  and  $S_2$
  - $S_1 \rightarrow S_2$  means that  $S_1$  *happens before*  $S_2$
  - If  $S_1 \rightarrow S_2$ :
    - $S_1 \rightarrow^T S_2$  denotes true dependence, i.e.  $S_1$  writes to a location that is read by  $S_2$
    - $S_1 \rightarrow^A S_2$  denotes anti dependence, i.e.  $S_1$  reads a location written by  $S_2$
    - $S_1 \rightarrow^O S_2$  denotes output dependence, i.e.  $S_1$  writes to the same location written by  $S_2$
  - $S[i,j]$  denotes a statement in the loop iteration  $[i,j]$

# Example

$S_1: x = 2;$
$S_2: y = x;$
$S_3: y = x + z;$
$S_4: z = 6;$

- Dependences:

- $S_1 \rightarrow^T S_2$

- x is written in statement  $S_1$  and read in statement  $S_2$

- $S_1 \rightarrow^T S_3$

- x is written in statement  $S_1$  and read in statement  $S_3$

- $S_3 \rightarrow^A S_4$

- z is read in statement  $S_3$  and written in statement  $S_4$

- $S_2 \rightarrow^O S_3$

- y is written in statement  $S_2$  and also written in statement  $S_3$

# Statements can be Grouped

$S_{12}:$	$x = 2;$
	$y = x;$
$S_{34}:$	$y = x + z;$
	$z = 6;$

- Dependences:

- $S_{12} \rightarrow^T S_{34}$

Statement group  $S_{12}$  produces a value  $x$  that is read by statement group  $S_{34}$

- $S_{12} \rightarrow^O S_{34}$

Statement group  $S_{12}$  writes onto  $y$  that is later written in statement group  $S_{34}$

# Loop-independent vs. loop-carried dependence

- Loop-carried dependence: dependence exists across iterations
  - i.e., if the loop is removed, the dependence no longer exists
- Loop-independent dependence: dependence exists within an iteration
  - i.e., if the loop is removed, the dependence exists

```
for (i=1; i<n; i++) {  
    S1: a[i] = a[i-1] + 1;  
    S2: b[i] = a[i];  
}  
  
for (i=1; i<n; i++)  
    for (j=1; j< n; j++)  
        S3: a[i][j] = a[i][j-1] + 1;  
  
for (i=1; i<n; i++)  
    for (j=1; j< n; j++)  
        S4: a[i][j] = a[i-1][j] + 1;
```

$S_1[i] \rightarrow^T S_1[i+1]$ : loop-carried  
 $S_1[i] \rightarrow^T S_2[i]$ : loop-independent

$S_3[i,j] \rightarrow^T S_3[i,j+1]$ :  
-loop-carried on for j loop  
-No loop-carried dependence for i loop

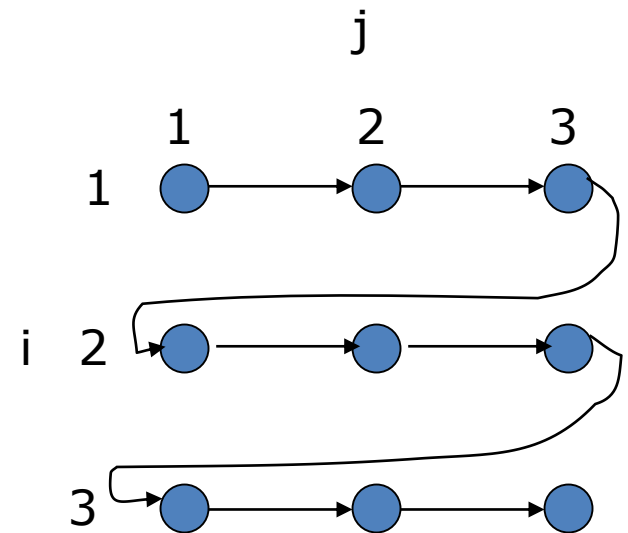
$S_4[i,j] \rightarrow^T S_4[i+1,j]$ :  
No loop-carried dependence for j loop  
Loop-carried on for i loop

# Iteration-space Traversal Graph (ITG)

- ITG shows graphically the order of traversal in the iteration space (happens-before relationship)
- Node = a point in the iteration space
- Directed Edge = the next point that will be encountered after the current point is traversed

Example:

```
for (i=1; i<4; i++)  
  for (j=1; j<4; j++)  
    S3: a[i][j] = a[i][j-1] + 1;
```



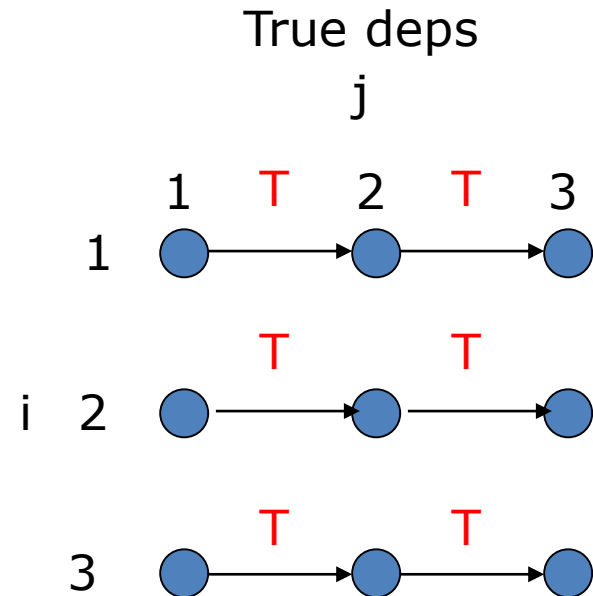
# Loop-carried Dependence Graph (LDG)

- LDG shows the true/anti/output dependence relationship graphically
- Node = a point in the iteration space
- Directed Edge = the dependence

Example:

```
for (i=1; i<4; i++)  
  for (j=1; j<4; j++)  
    S3: a[i][j] = a[i][j-1] + 1;
```

$$S_3[i,j] \rightarrow^T S_3[i,j+1]$$



# Further example

```
for (i=1; i<=n; i++)
  for (j=1; j<=n; j++)
    S1: a[i][j] = a[i][j-1] + a[i][j+1] + a[i-1][j] + a[i+1][j];

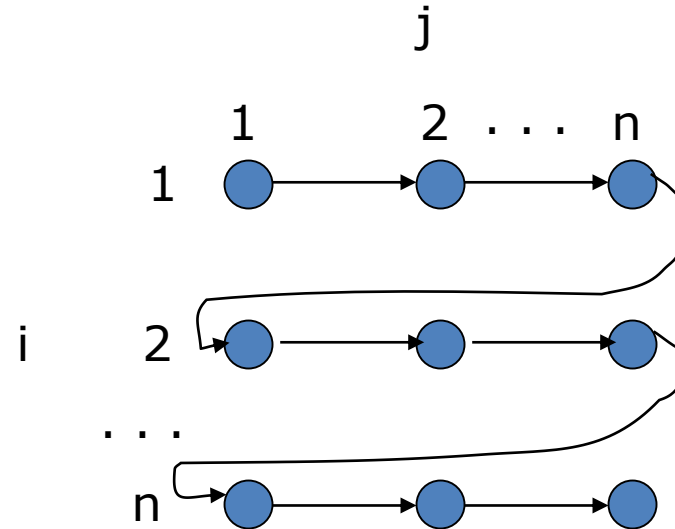
for (i=1; i<=n; i++)
  for (j=1; j<=n; j++) {
    S2: a[i][j] = b[i][j] + c[i][j];
    S3: b[i][j] = a[i][j-1] * d[i][j];
  }
```

- Draw the ITG
- List all the dependence relationships
- Draw the LDG



# Answer for Loop Nest 1

- ITG



```

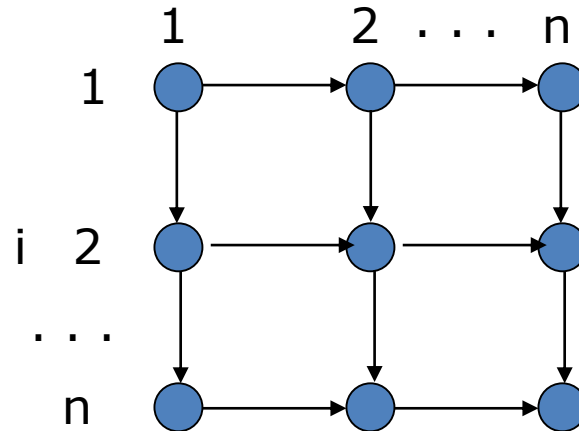
for (i=1; i<=n; i++)
  for (j=1; j<=n; j++)
    S1: a[i][j] = a[i][j-1] + a[i][j+1] + a[i-1][j] + a[i+1][j];

for (i=1; i<=n; i++)
  for (j=1; j<=n; j++) {
    S2: a[i][j] = b[i][j] + c[i][j];
    S3: b[i][j] = a[i][j-1] * d[i][j];
  }

```

# Answer for Loop Nest 1

- True dependences:
  - $S_1[i,j] \rightarrow^T S_1[i,j+1]$
  - $S_1[i,j] \rightarrow^T S_1[i+1,j]$
- Output dependences:
  - None
- Anti dependences:
  - $S_1[i,j] \rightarrow^A S_1[i+1,j]$
  - $S_1[i,j] \rightarrow^A S_1[i,j+1]$
- LDG:



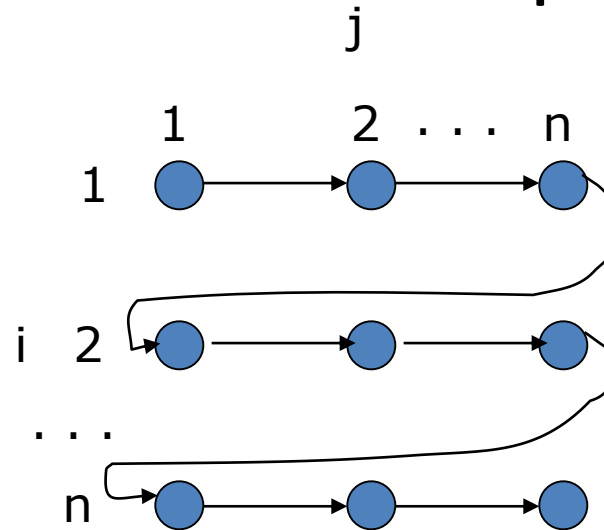
Note: each Edge represents both true, and anti dependences

```
for (i=1; i<=n; i++)
  for (j=1; j<=n; j++)
    S1: a[i][j] = a[i][j-1] + a[i][j+1] + a[i-1][j] + a[i+1][j];

for (i=1; i<=n; i++)
  for (j=1; j<=n; j++) {
    S2: a[i][j] = b[i][j] + c[i][j];
    S3: b[i][j] = a[i][j-1] * d[i][j];
  }
```

# Answer for Loop Nest 2

- ITG



```

for (i=1; i<=n; i++)
  for (j=1; j<=n; j++)
    S1: a[i][j] = a[i][j-1] + a[i][j+1] + a[i-1][j] + a[i+1][j];

for (i=1; i<=n; i++)
  for (j=1; j<=n; j++) {
    S2: a[i][j] = b[i][j] + c[i][j];
    S3: b[i][j] = a[i][j-1] * d[i][j];
  }
    
```

# Answer for Loop Nest 2

- True dependences:

- $S2[i,j] \rightarrow_T S3[i,j+1]$

- Output dependences:

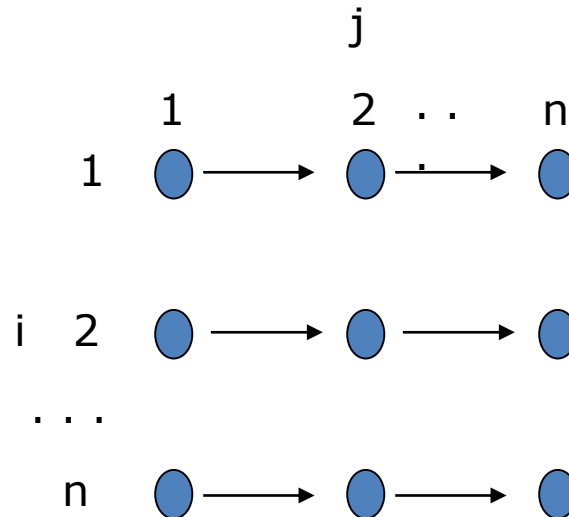
- None

- Anti dependences:

- $S2[i,j] \rightarrow_A S3[i,j]$

(loop-independent  
dependence)

- LDG:



Note: each edge represents only true dependences

```
for (i=1; i<=n; i++)
  for (j=1; j<=n; j++)
    S1: a[i][j] = a[i][j-1] + a[i][j+1] + a[i-1][j] + a[i+1][j];

for (i=1; i<=n; i++)
  for (j=1; j<=n; j++) {
    S2: a[i][j] = b[i][j] + c[i][j];
    S3: b[i][j] = a[i][j-1] * d[i][j];
  }
```

# Review Questions

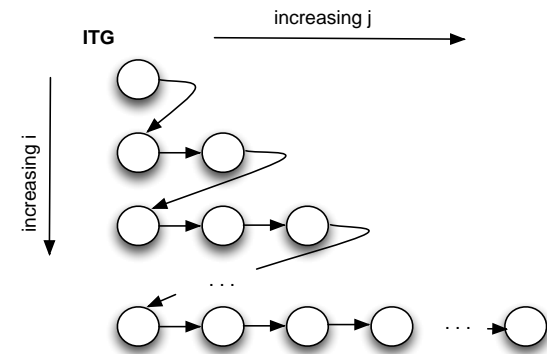
- What are three types of dependences?
- What are types of dependences related to loop structure?
- For the following code, show the ITG

```
...  
for (i=1; i<=N; i++) {  
    for (j=1; j<=i; j++) { // note the index range!  
        S1: a[i][j] = b[i][j] + c[i][j];  
        S2: b[i][j] = a[i][j-1];  
        S3: c[i][j] = a[i][j];  
    }  
}
```

# Review Questions

- What are three types of dependences?
  - True (producer consumer), anti, and output
- What are types of dependences related to loop structure?
  - Loop carried (across loop iterations) and loop independent
- For the following code, show the ITG

```
...  
for (i=1; i<=N; i++) {  
    for (j=1; j<=i; j++) { // note the index range!  
        S1: a[i][j] = b[i][j] + c[i][j];  
        S2: b[i][j] = a[i][j-1];  
        S3: c[i][j] = a[i][j];  
    }  
}
```



# Review Questions

- For the following code, show the LDG

```
...  
for (i=1; i <=N; i++) {  
    for (j=2; j <=N; j++) {  
        S1: a[i][j] = a[i][j-1] + a[i][j-2];  
        S2: a[i+1][j] = a[i][j] * b[i-1][j];  
        S3: b[i][j] = a[i][j];  
    }  
}
```

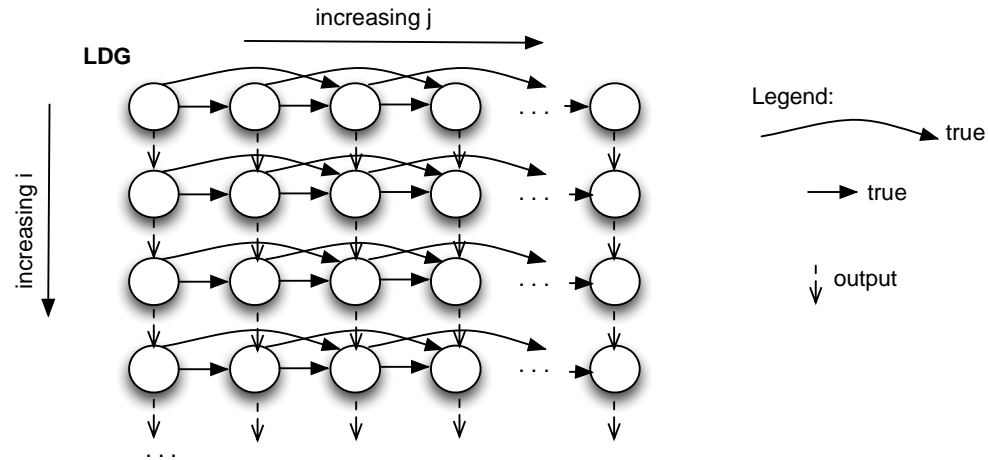
# Review Questions

- For the following code, show the LDG

```

...
for (i=1; i <=N; i++) {
  for (j=2; j <=N; j++) {
    S1: a[i][j] = a[i][j-1] + a[i][j-2];
    S2: a[i+1][j] = a[i][j] * b[i-1][j];
    S3: b[i][j] = a[i][j];
  }
}

```





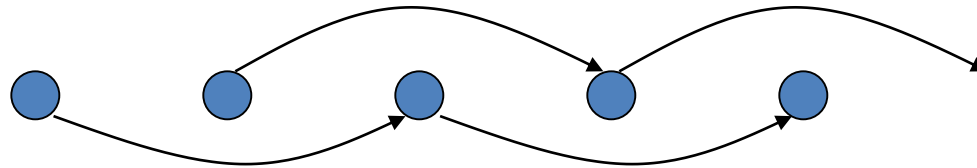
# Finding parallel tasks across iterations

- Analyze loop-carried dependences:
  - Dependence must be obeyed (esp. true dependences)
  - There are opportunities when some dependences are missing

- Example 1:

```
for (i=2; i<=n; i++)  
  S: a[i] = a[i-2];
```

- LDG:



- Can divide the loop into two parallel tasks (one with odd iterations and another with even iterations):

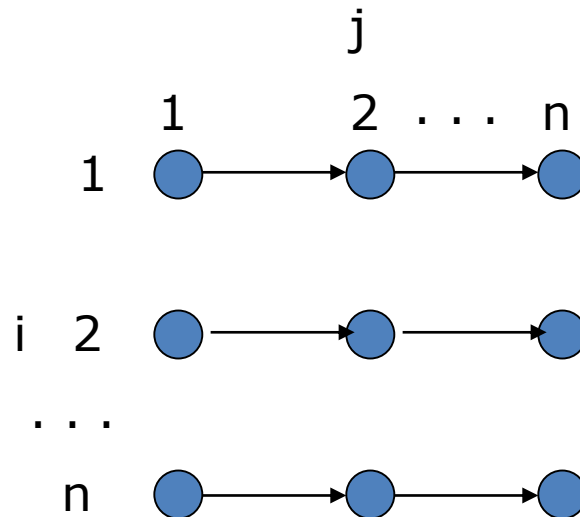
```
for (i=2; i<=n; i+=2)  
  S: a[i] = a[i-2];  
for (i=3; i<=n; i+=2)  
  S: a[i] = a[i-2];
```

# Example 2

- Example 2:

```
for (i=0; i<n; i++)  
  for (j=0; j< n; j++)  
    S3: a[i][j] = a[i][j-1] + 1;
```

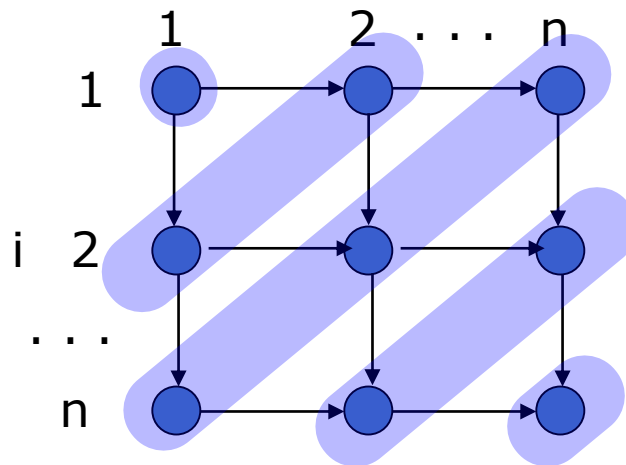
- LDG:



- There are n parallel tasks (one task per i iteration)

## Example 3

- Identify which nodes are not dependent on each other
- In each anti-diagonal, the nodes are independent of each other



Note: each  
Edge represents  
both true, and  
anti dependencies

- Need to rewrite the code to iterate over anti-diagonals

# Structure of Rewritten Code

- Iterate over anti-diagonals, and over elements within an anti-diagonal:

```
Calculate number of anti-diagonals
Foreach anti-diagonal do:
    calculate number of points in the current anti-diagonal
    For each point in the current anti-diagonal do:
        compute the current point in the matrix
```

- Parallelize the highlighted loop
- Write the code...

# DOACROSS Parallelism

```
for (i=1; i<=N; i++) {  
    S: a[i] = a[i-1] + b[i] * c[i];  
}
```

Opportunity for parallelism?

$S[i] \rightarrow^T S[i+1]$

So it has loop-carried dependence

But, notice that the  $b[i] * c[i]$  part has no  
Loop-carried dependence

Can change to:

```
for (i=1; i<=N; i++) {  
    S1: temp[i] = b[i] * c[i];  
}  
for (i=1; i<=N; i++) {  
    S2: a[i] = a[i-1] + temp[i];  
}
```

- Now the first loop is parallel, but the second one is not
- Execution time  $N \times (TS_1 + TS_2) \Rightarrow TS_1 + N \times TS_2$
- array temp[] introduces storage overhead
- Better solution?

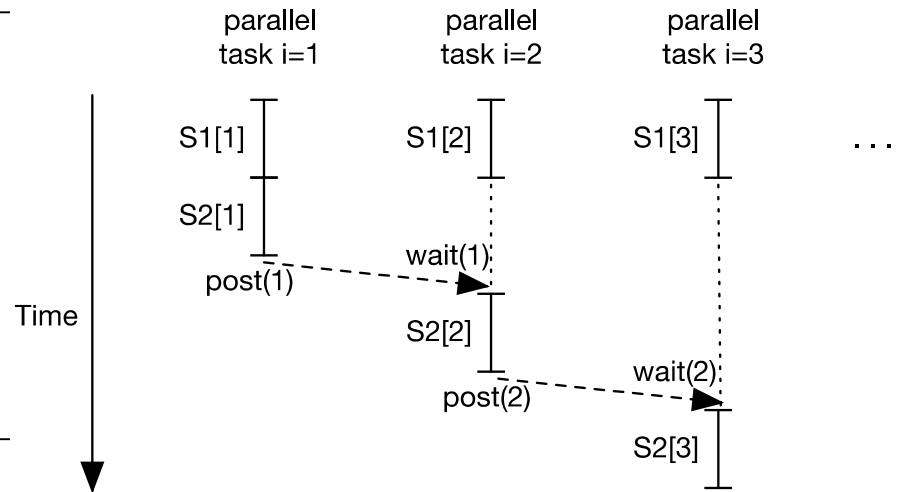
# Post-Wait Synchronization Pair

- `Post(unique name x)`
  - Increments memory address  $m(x)$  that corresponds to name  $x$
- `Wait(x)`
  - Blocks if  $m(x) \leq 0$ , unblocks if  $m(x) > 0$
  - Decrements  $m(x)$
- Example
  - `Post(flag), wait(flag)`
  - `Post(i+1), wait(i)`
  - `Post(i,j,k), wait(i,j,k)`

# DOACROSS Parallelism

## DOACROSS Parallelism

```
Post(0);           //inserted to
                   //not block
                   //first iteration
for (i=1; i<=N; i++) {
    S1: temp = b[i] * c[i];
    wait(i-1);
    S2: a[i] = a[i-1] + temp;
    post(i);
}
```



Execution time

$$TS_1 + N \times TS_2$$

**And** smaller storage overhead

- Temp is duplicated per thread, rather than per iteration

# DOACROSS Parallelism

If assume  $TS_1 = TS_2 = T$  and  $N \gg T$

The **speedup ratio** becomes

$$[N \times (TS_1 + TS_2)] / [TS_1 + (N \times TS_2)]$$

$$= 2NT / (N+1)T \approx 2 \text{ times}$$



# DOPIPE Parallelism

```
for (i=1; i<=N; i++) {  
  S1: a[i] = a[i-1] + b[i];  
  S2: c[i] = c[i] + a[i];  
}
```

Loop-carried dependences:

$S1[i] \rightarrow^T S1[i+1]$

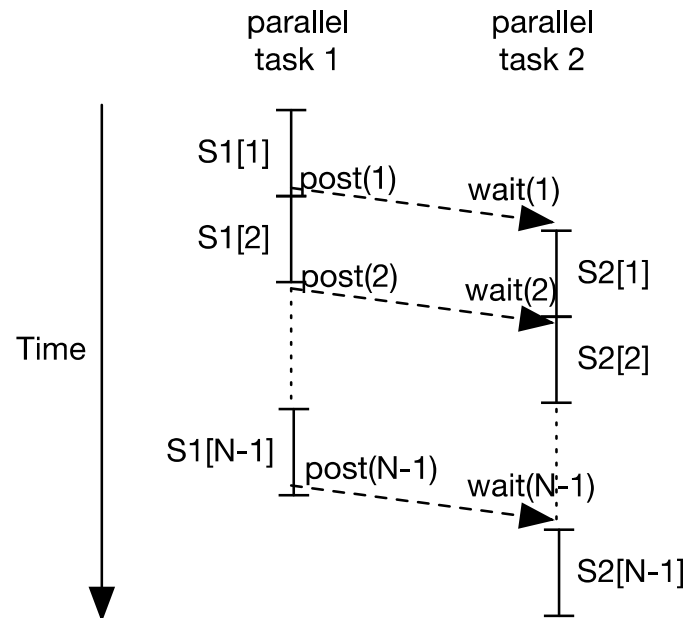
Loop independent dependence:

$S1[i] \rightarrow^T S2[i]$

So, where is the parallelism opportunity?

## DOPIPE Parallelism

```
for (i=1; i<=N; i++) {  
  a[i] = a[i-1] + b[i];  
  post(i);  
}  
  
for (i=1; i<=N; i++) {  
  wait(i);  
  c[i] = c[i] + a[i];  
}
```



i.e., Distribute the loop and introduce pipelined parallelism

# Summary

- The main purpose of employing loop-level parallelism is to search and split sequential tasks of a program and convert them into parallel tasks without any prior information about the algorithm.
- Parts of data that are recurring and consume significant amount of execution time are good candidates for loop-level parallelism.
- Some common applications of loop-level parallelism are found in mathematical analysis that uses multiple-dimension matrices which are iterated in nested loops.
- There are different kind of parallelization techniques which are used on the basis of data storage overhead, degree of parallelization and data dependencies.

# Summary

- **DOALL**

- Technique used where we can parallelize each iteration of the loop without any interaction between the iterations.
- Hence, the overall run-time gets reduced from  $N * T$  (for a serial processor, where  $T$  is the execution time for each iteration) to only  $T$  (since all the  $N$  iterations are executed in parallel).

- **DOACROSS**

- Technique used wherever there is a possibility for data dependencies.
- Hence, we parallelize tasks in such a manner that all the data independent tasks are executed in parallel, but the dependent ones are executed sequentially.
- There is a degree of synchronization used to sync the dependent tasks across parallel processors.

- **DOPIPE**

- Method to perform loop-level parallelism by pipelining the statements in a loop.
- Pipelined parallelism may exist at different levels of abstraction like loops, functions and algorithmic stages.
- The extent of parallelism depends upon the programmers' ability to make best use of this concept.
- It also depends upon factors like identifying and separating the independent tasks and executing them in parallel

# Parallel Programming

- Task Creation
  - Identifying parallel tasks
    - Code analysis
    - **Algorithm analysis**
  - Variable partitioning
    - Shared vs. private vs. reduction
  - Synchronization
- Task mapping (performance)
  - Tasks to threads
    - Typically more tasks than processors, so multiple tasks assigned to threads
    - A goal may be to balance workload of the threads
  - Mapping threads to processors, including data layout in memory
    - Goal is to achieve communication locality between processors and data locality based on access

# Task Creation: Algorithm Analysis

- Goal: code analysis misses parallelization opportunities available at the algorithm level
- Sometimes, the ITG introduces unnecessary serialization
- Consider the “ocean” algorithm
  - Numerical goal: at each sweep, compute how each point is affected by its neighbors
  - Hence, any order of update (within a sweep) is an approximation
  - Different ordering of updates: may converge quicker or slower
  - Change ordering to improve parallelism
  - Partition iteration space into red and black points
  - Red sweep and black sweep are each fully parallel

# Example 3: Simulating Ocean Currents

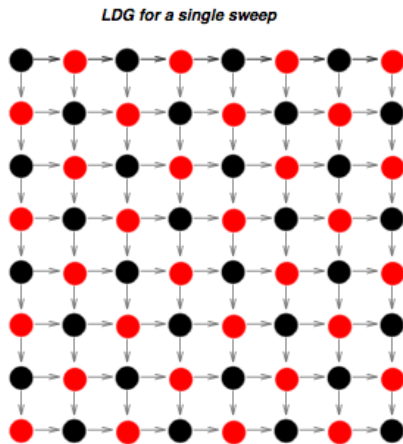
## Algorithm:

```
While not converging to a solution do:
  foreach timestep do:
    foreach cross section do a sweep:
      foreach point in a cross section do:
        compute the force interaction with its neighbors
```

## compare with the code that implements the algorithm:

```
for (i=1; i<=N; i++) {
  for (j=1; j<=N; j++) {
    S1: temp = A[i][j];
    S2: A[i][j] = 0.2 * (A[i][j]+A[i][j-1]+A[i-1][j]+
                        +A[i][j+1]+A[i+1][j]);
    S3: diff += abs(A[i][j] - temp);
  }
}
```

# Red-Black Coloring

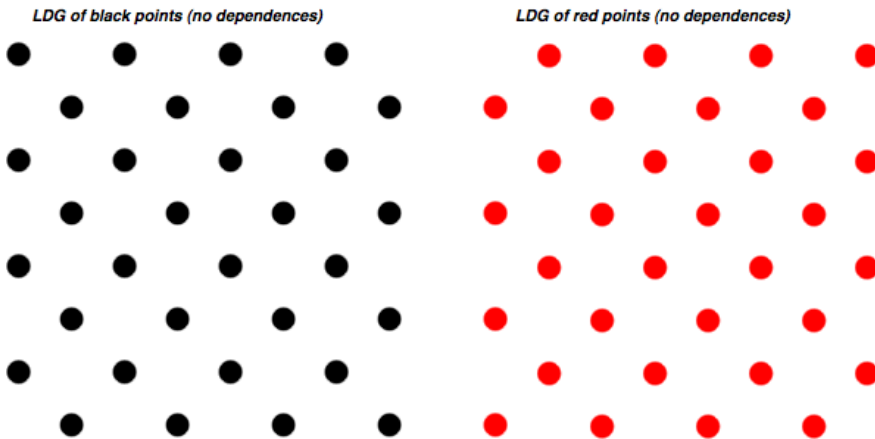


in one sweep:  
- no dependence between  
black and red points

**restructured algorithm:**

```
While not converging to a solution do:  
  foreach timestep do:  
    foreach cross section do:  
      foreach red point do: //red sweep  
        compute the force interaction  
      wait until red sweep  
      foreach black point do: //blk sweep  
        compute the force interaction
```

**see textbook for code**



# Module Review Questions

- Describe the differences between DOALL, DACROSS, function, and DOPIPE parallelism



# Module Review Questions

- Describe the differences between DOALL, DACROSS, function, and DOPIPE parallelism
  - DOALL: parallelism between independent loop iterations
  - DOACROSS: parallelism between dependent loop iterations guarded by synchronization
  - Function: parallelism between independent code sections. In the context of loops, the code sections come from different statements in a loop
  - DOPIPE: parallelism between dependent statements in a loop, guarded by synchronization

# Parallel Programming

- Task Creation
  - Identifying parallel tasks
    - Code analysis
    - Algorithm analysis
  - Variable partitioning
    - **Shared vs. private vs. reduction**
  - Synchronization
- Task mapping (performance)
  - Tasks to threads
    - Typically more tasks than processors, so multiple tasks assigned to threads
    - A goal may be to balance workload of the threads
  - Mapping threads to processors, including data layout in memory
    - Goal is to achieve communication locality between processors and data locality based on access

# Determining Variable Scope

- This step is specific to shared memory programming model
- Analyze how each variable may be used across parallel tasks:
  - Read-only:
    - variable is only read by all tasks
  - R/W non-conflicting:
    - variable is read, written, or both by only one task
  - R/W Conflicting:
    - variable written by one task may be read by another

# Example 1

```
for (i=1; i<=n; i++)  
  for (j=1; j<=n; j++) {  
    S2: a[i][j] = b[i][j] + c[i][j];  
    S3: b[i][j] = a[i][j-1] * d[i][j];  
  }
```

- Define a parallel task as each “for i” loop iteration
- Read-only:
  - n, c, d
- R/W non-conflicting:
  - a, b
- R/W conflicting:
  - i, j

## Example 2

```
for (i=1; i<=n; i++)  
  for (j=1; j<=n; j++) {  
    S1: a[i][j] = b[i][j] + c[i][j];  
    S2: b[i][j] = a[i-1][j] * d[i][j];  
    S3: e[i][j] = a[i][j];  
  }
```

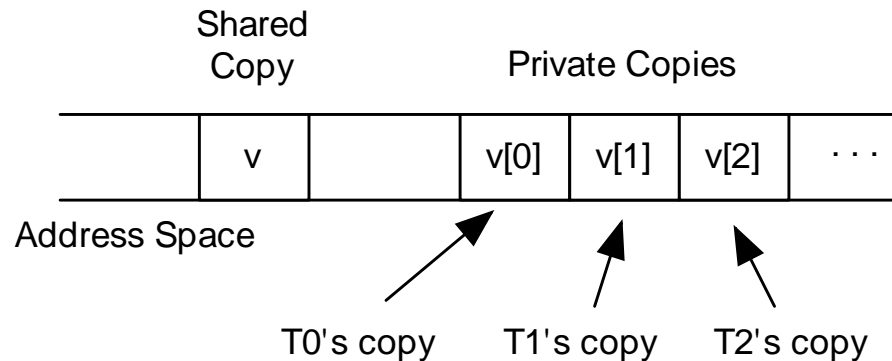
- Parallel task = each “for j” loop iteration
- Read-only:
  - n, i, c, d
- R/W Non-conflicting:
  - a, b, e
- R/W Conflicting:
  - j

# Privatization

- Privatization = converting a shared variable into a private variable in order to remove conflicts
  - Goal: R/W Conflicting → R/W Non-conflicting
- A conflicting variable is privatizable if
  - In program order, the variable is always defined (=written) by a task before use (=read) by the same task
  - The values for different parallel tasks are known ahead of time (hence, private copies can be initialized to the known values)
- Consequence
  - Conflicts disappear when the variable is “privatized”
- Privatization
  - involves making private copies of a shared variable
  - One private copy per *thread* (not per task)

# Illustration

- Privatization of “v”



One way to think of private copies as arrays of variables with the Task IDs used as the index for private copies

# Example 1

```
for (i=1; i<=n; i++)  
  for (j=1; j<=n; j++) {  
    S2: a[i][j] = b[i][j] + c[i][j];  
    S3: b[i][j] = a[i][j-1] * d[i][j];  
  }
```

- Define a parallel task as each “for i” loop iteration
- Read-only:
  - n, c, d
- R/W non-conflicting:
  - a, b
- R/W conflicting **but privatizable**:
  - i, j
  - After privatization: i[ID], j[ID]



# Example 2

```
for (i=1; i<=n; i++)  
  for (j=1; j<=n; j++) {  
    S1: a[i][j] = b[i][j] + c[i][j];  
    S2: b[i][j] = a[i-1][j] * d[i][j];  
    S3: e[i][j] = a[i][j];  
  }
```

- Parallel task = each “for j” loop iteration
- Read-only:
  - n, i, c, d
- R/W Non-conflicting:
  - a, b, e
- R/W Conflicting **but privatizable**:
  - j
  - After privatization: j[ID]

# Reduction

- Reduction
  - A special case of privatization, where:
  - Results are accumulated by each thread to a private copy
  - Private copies are merged into the shared copy at the end of computation
- Example: summing up array elements
  - Each thread works on its part of the array and accumulates its sum to a private sum
  - Private sums are accumulated into the shared sum at the end of computation

# Reduction Variables and Operations

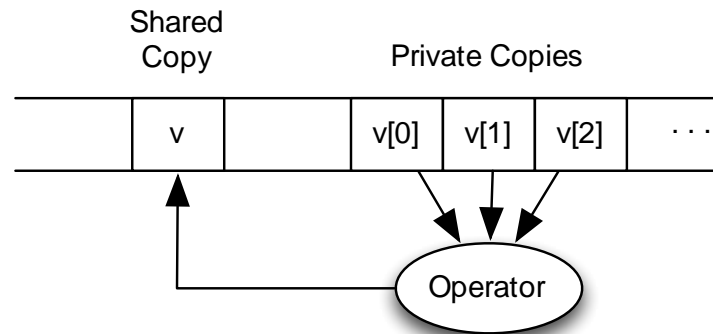
- Reduction Operation examples:
  - SUM (+), multiplication (\*)
  - Logical (AND, OR, ...)
- Reduction variable =
  - The scalar variable that is the result of a reduction operation
- Criteria for reducibility:
  - Reduction variable is updated by each task, and the order of update is not important
  - Hence, the reduction operation must be **commutative** and **associative**

# Reduction Operation

- Compute:
  - $y = y\_init \ \underline{op} \ x1 \ \underline{op} \ x2 \ \underline{op} \ x3 \ \dots \ \underline{op} \ x_n$
- $op$  is a reduction operator if it is *commutative*
  - $u \ \underline{op} \ v = v \ \underline{op} \ u$
- and *associative*
  - $(u \ \underline{op} \ v) \ \underline{op} \ w = u \ \underline{op} \ (v \ \underline{op} \ w)$
- Certain operations can be transformed into reduction operations (see Homeworks)

# Illustration

- Reduction of “v”



# Variable Scope Determination

- Should be declared private:
  - Privatizable variables
- Should be declared shared:
  - Read-only variables
  - R/W Non-conflicting variables
- Should be declared reduction:
  - Reduction variables
- Other R/W Conflicting variables:
  - Privatization possible? If so, privatize them
  - Otherwise, declare as shared, but protect with synchronization

# Example 1

```
for (i=1; i<=n; i++)  
  for (j=1; j<=n; j++) {  
    S2: a[i][j] = b[i][j] + c[i][j];  
    S3: b[i][j] = a[i][j-1] * d[i][j];  
  }
```

- Declare as shared:
  - n, c, d, a, b
- Declare as private:
  - i, j

## Example 2

```
for (i=1; i<=n; i++)  
  for (j=1; j<=n; j++) {  
    S1: a[i][j] = b[i][j] + c[i][j];  
    S2: b[i][j] = a[i-1][j] * d[i][j];  
    S3: e[i][j] = a[i][j];  
  }
```

- Parallel task = each “for j” loop iteration
- Declare as shared:
  - n, i, c, d, a, b, e
- Declare as private:
  - j



# Module Review Questions

- Describe various variable scope definitions
- Determine appropriate variable scope when we parallelize the for j loop:

```
for (i=0; i<n; i++) {  
    for (j=0; j<p; j++) {  
        x = 0;  
        for (k=0; k<m; k++)  
            x = x + A[i][k] * B[k][j];  
        Y[i][j] = x + C[i][j];  
    }  
}
```

# Module Review Questions

- Describe various variable scope definitions
  - Shared: all threads share one copy
  - Private: each thread has a copy, further divided into firstprivate and lastprivate in OpenMP
- Determine appropriate variable scope when we parallelize the for j loop:
  - Shared: i, n, m, A, B, C, Y
  - Private: j, k, x

```
for (i=0; i<n; i++) {  
    for (j=0; j<p; j++) {  
        x = 0;  
        for (k=0; k<m; k++)  
            x = x + A[i][k] * B[k][j];  
        Y[i][j] = x + C[i][j];  
    }  
}
```

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  - **Synchronization**
- Task mapping (performance)
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# Synchronization Primitives

- Point-to-point
  - a pair of `post()` and `wait()`
  - a pair of `send()` and `recv()` in message passing
- Lock
  - ensures mutual exclusion, only one thread can be in a locked region at a given time
- Barrier
  - a point where a thread is allowed to go past it only when all threads have reached the point.

# Lock

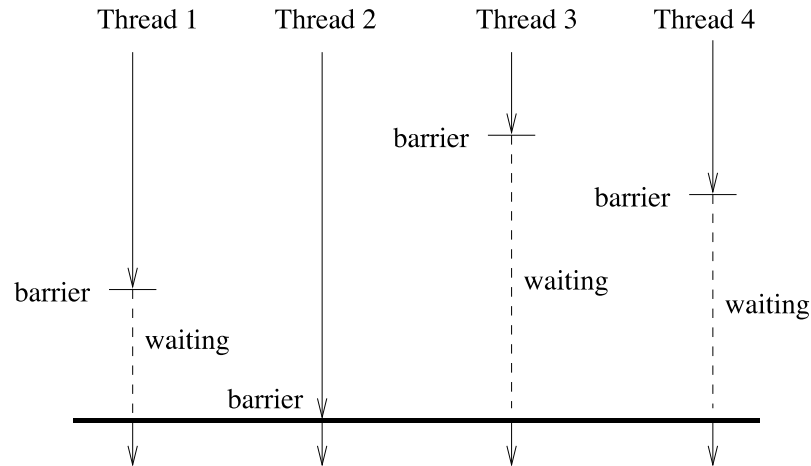
- What problem may arise here?

```
// inside a parallel region
for (i=start_iter; i<end_iter; i++)
    sum = sum + a[i];
```

- Lock ensures only one thread inside the locked region

```
// inside a parallel region
for (i=start_iter; i<end_iter; i++) {
    lock(x);
    sum = sum + a[i];
    unlock(x);
}
```

# Barrier: Global Event Synchronization



- Load balance important: execution time dependent on the slowest thread
- Artificial load imbalance occurs with context switching  
=> avoid by gang scheduling

# Module Review Questions

- What common synchronization primitives are supported in shared memory system?
- Why is load balancing important when barriers are used?
- What problems are solved (and unsolved) with gang scheduling?

# Module Review Questions

- What common synchronization primitives are supported in shared memory system?
  - Lock, barrier, and point-to-point (e.g. post-wait)
- Why is load balancing important when barriers are used?
  - Parallel region execution time is determined by the slowest thread
- What problems are solved (and unsolved) with gang scheduling?
  - GS prevents no-forward progress when a thread is switched out
  - GS frees up CPUs for other uses when a thread is switched out
  - GS does not remove load imbalance and its effects



# Parallel Programming

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# Tasks to Threads

- Typically, more tasks than threads, which leads to questions...
  - What tasks should be assigned to a thread?
  - How they should be assigned?
- Important Issues
  - Task management overheads (larger tasks incur lower overheads)
  - Load balance (larger tasks may reduce load balance)
  - Data locality (increasingly important with data growth trends)
- Static or Dynamic?
  - Static task mapping means tasks are preassigned to threads before execution
  - Dynamic task mapping means they're not preassigned prior to execution, but instead a task queue is created and maintained. i.e., whenever a thread becomes idle, it takes a task from the queue and executes it.

# Parallel Programming

- Task Creation
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# Threads to Processors

- Aspects to consider...
  - Leave it to the OS thread scheduler to decide. i.e., do nothing
    - The OS thread scheduler decides when ready threads should run and which processors they should run on
    - It takes into account response time, fairness, thread priority, utilization of processors, and overheads of context switching
    - A challenge is that parallel threads need to synchronize (locks, barriers, etc.) and some OS schedulers offer gang scheduling (all or none)
  - Data Locality
    - Threads run on same node where data (especially large amounts) resides
      - e.g., a NUMA system has memory with varying access times
    - Another approach is to allocate or migrate data to the thread that accesses it
      - e.g., Page allocation and migration policy (LRU, First touch, round robin, etc.)