Programming Models

Parallel Computing Patterns

Parallel Computing Patterns

- Design guidelines to implement a parallelized version from a sequential code
- Based on 4 design spaces concerning both algorithm expression and software construction:

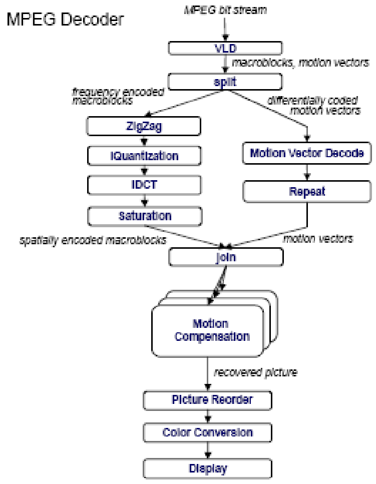
Algorithm Expression

1. Finding Concurrency
   - Expose concurrent tasks
2. Algorithm Structure
   - Map tasks to processes to
   - exploit parallel architecture

Software Construction

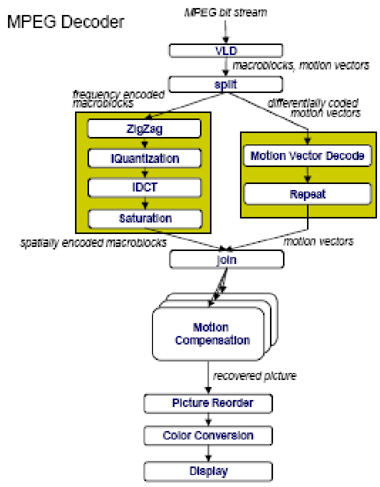
3. Supporting Structures
   - Code and data structuring patterns
4. Implementation Mechanisms
   - Low level mechanisms used to write parallel programs

Motivation



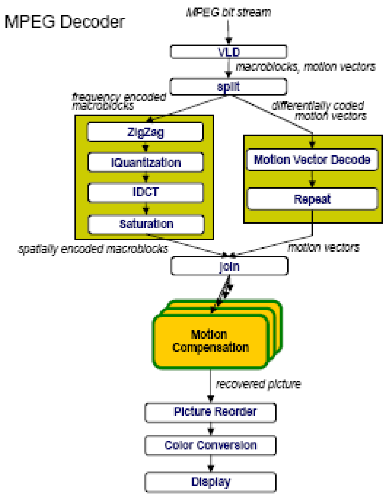
- Example: MPEG decoder
- Program complexity ask for design guidelines for parallelization

Example: MPEG Decoder



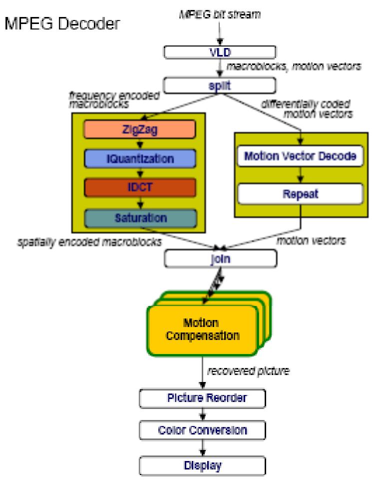
- Task decomposition
  - Independent coarse-grained computation
  - Inherent to algorithm
- Sequence of statements (instructions) that operate together as a group
  - Corresponds to some logical part of program
  - Usually follows from the way programmer thinks about a problem

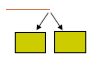
Example: MPEG Decoder



- Task decomposition
  - Parallelism in the application
- Data decomposition
  - Same computation is applied to small data chunks derived from large data set

Example: MPEG Decoder



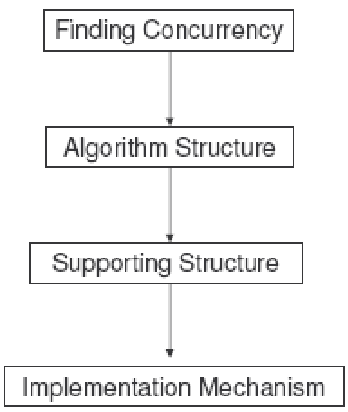
- Task decomposition 
  - Parallelism in the application
- Data decomposition 
  - Same computation many data
- Pipeline decomposition
  - Data assembly lines
  - Producer-consumer chains 

Patterns & Decompositions

- Patterns are more specific than decomposition strategies as we discussed earlier in the course

Pattern	Decomposition
Task-level parallelism	Task
Divide and Conquer	Task/Data
Geometric Decomposition	Data
Pipeline	Data Flow
Wavefront	Data Flow

Design Spaces in Constructing a Parallel Program



- Structure the problem to expose exploitable concurrency
- Structure the algorithm to take advantage of concurrency
- Intermediate stage between Algorithm Structure and Implementation
  - program structuring
  - definition of shared data structures
- Mapping of the higher level patterns onto a programming environment

Finding Concurrency Design Space

- Result
  - A task decomposition that identifies tasks that can execute concurrently
  - A data decomposition that identifies data local to each task and data shared among tasks
  - A way of grouping tasks and ordering them according to data dependencies and temporal constraints
- This will be used as an input for the Algorithm Structure design space

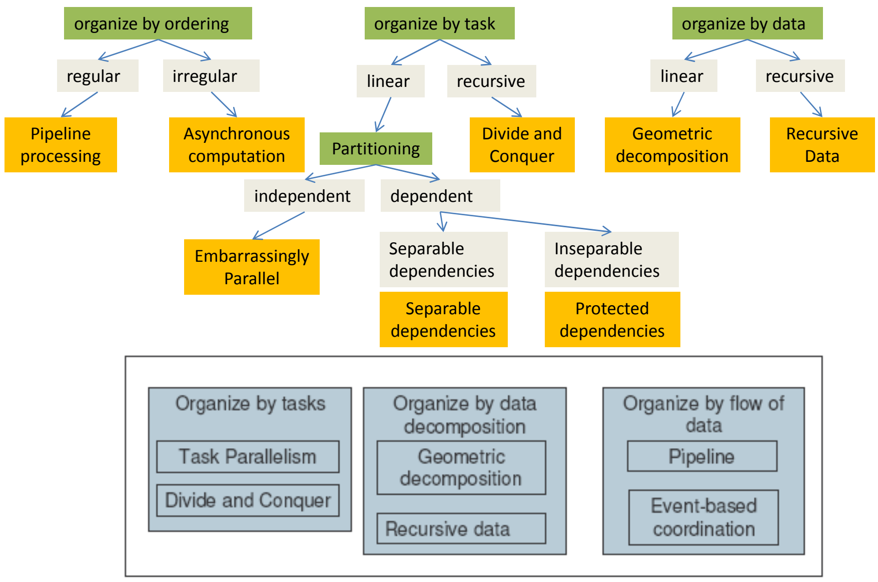
Algorithm Structure Design Space

- Given a collection of concurrent tasks, what’s the next step?
- Map tasks to units of execution (e.g., threads)
- Important considerations
  - Magnitude of number of execution units platform will support
  - Cost of sharing information among execution units
  - Avoid tendency to over constrain the implementation
    - Work well on the intended platform
    - Flexible enough to easily adapt to different architectures

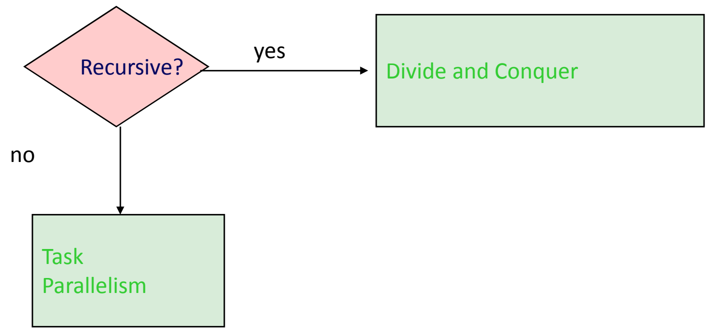
Major Organizing Principle

- How to determine the algorithm structure that represents the mapping of tasks to units of execution?
- Concurrency usually implies major organizing principle
  - Organize by tasks
  - Organize by data decomposition
  - Organize by flow of data

Organizing Principles



Organize by Tasks?



Task Parallelism

- Problem can be decomposed into a collection of tasks that can execute concurrently
- Tasks can be completely independent (embarrassingly parallel) or can have dependencies among them
- All tasks might be known at the beginning or might be generated dynamically

Task Parallelism

- Tasks:
  - There should be at least as many tasks as UEs (Units of Execution) - typically many, many more
  - Computation associated with each task should be large enough to offset the overhead associated with managing tasks and handling dependencies
- Types of dependencies:
  - Ordering constraints: sequential composition of task-parallel computations
  - Shared-data dependencies: several tasks have to access the same data structure

Shared Data Dependencies

- Shared data dependencies can be categorized as follows:
  - Removable dependencies: an apparent dependency that can be removed by code transformation

```
int i, ii=0, jj=0;
for (i=0; i<N; i++ ) {
  ii = ii + 1;
  d[ii] = big_time_consuming_work (ii);
  jj = jj + i;
  a[jj] = other_big_time_consuming_work (jj);
}
```

Apparent dependency (variable ii and jj

```
for (i=0; i<N; i++ ) {
  d[i] = big_time_consuming_work (i);
  a[(i*i+i)/2] = other_big_time_consuming_work((i*i+i)/2);
}
```

Removed dependency using closed form expression

Shared Data Dependencies

- Separable dependencies:
  - Write-once updates or accumulative sum on shared variables
  - Can be pulled outside the concurrent execution by replicating the shared data structure before and combine the copies into a single structure after the concurrent execution
- Other dependencies: non-resolvable, have to be followed
  - Protected dependencies: variables read and written during the concurrent execution

Embarrassingly Parallel Pattern

- Independent tasks
- Computation of solutions
  - Independent on distinct variables
  - Accumulated in a shared data structure (if no ordering is required)
  - …
- Examples:
  - Vector addition
  - Ray tracing codes
  - Database searches
  - Branch and bound

Application Examples

- Low level image processing
- Mandelbrot set
- Monte Carlo Calculations

Partitioning into Regions for Individual Processes

Shifting

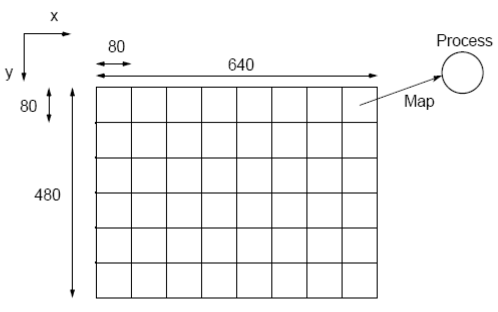
- Object shifted by Dx *in the x-dimension and Dy in the y-dimension:*
  $x' = x + \Delta x$
  $y' = y + \Delta y$
- where *x and y are the original and x¢ and y¢ are the new coordinates.*

Scaling

- Object scaled by a factor S_x *in x-direction and* S_y *in y-direction:*
  $x' = x S_x$
  $y' = y S_y$

Rotation

- Object rotated through an angle ϑ system:
  $x' = x \cos\vartheta + y \sin\vartheta$
  $y' = -x \sin\vartheta + y \cos\vartheta$



Square region for each process (can also use strips)

Complexity Analysis: Sequential

- Suppose each pixel requires one computational step and there are *n x n pixels.*

Sequential

- $t_s = n^2$ and a sequential time complexity of $O(n^2)$

Pseudocode to Perform Image Shift

Master

```
for (i = 0, row = 0; i < 48; i++, row = row + 10)/* for each process*/
   send(row, P_i);                              /* send row no.*/

for (i = 0; i < 480; i++)                       /* initialize temp */
   for (j = 0; j < 640; j++)
      temp_map[i][j] = 0;

for (i = 0; i < (640 * 480); i++) {             /* for each pixel */
   recv(oldrow,oldcol,newrow,newcol, P_ANY);    /* accept new coords */
   if !((newrow < 0)||(newrow >= 480)||(newcol < 0)||(newcol >= 640))
      temp_map[newrow][newcol]=map[oldrow][oldcol];
}
for (i = 0; i < 480; i++)                       /* update bitmap */
   for (j = 0; j < 640; j++)
      map[i][j] = temp_map[i][j];
```

Slave

```
recv(row, P_master);                            /* receive row no. */
for (oldrow = row; oldrow < (row + 10); oldrow++)
   for (oldcol = 0; oldcol < 640; oldcol++) { /* transform coords */
      newrow = oldrow + delta_x;                /* shift in x direction */
      newcol = oldcol + delta_y;                /* shift in y direction */
      send(oldrow,oldcol,newrow,newcol, P_master); /* coords to master */
   }
```

Complexity Analysis: Parallel

Parallel

- **Communication**
  - $t_{comm} = t_{startup} + mt_{data}$
  - $t_{comm} = p(t_{startup} + 2t_{data}) + 4n^2(t_{startup} + t_{data}) = O(p + n^2)$

oldcol, oldraw, newcol, newraw
for each pixel

send raw
For each process

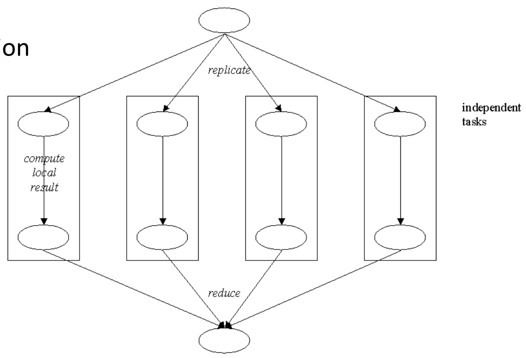
- **Computation**
  - $t_{comp} = 2(n^2/p) = O(n^2/p)$

newrow=, newcol=
for each pixel

- **Overall Execution Time**
  - $t_p = t_{comp} + t_{comm}$
  - For constant p, this is $O(n^2)$.
- However, the constant hidden in the communication part far exceeds those constants in the computation in most practical situations.

Separable Dependencies Pattern

- Necessary global data are replicated and partial results are stored in local data structures
- Global results are obtained by reducing results from individual tasks
- Examples
  - Matrix-vector multiplication
  - Numerical integration

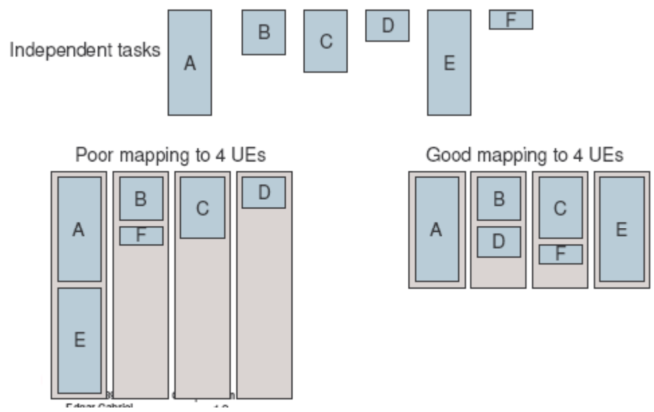


Task scheduling

- Schedule: the way in which tasks are assigned to UEs for execution
  - Minimize the overall execution of all tasks
  - Finish the work at the same time (load balance)
- Two classes of schedule:
  - Static schedule: distribution of tasks to UEs is determined at the start of the computation and not changed anymore
  - Dynamic schedule: the distribution of tasks to Ues changes as the computation proceeds

Task scheduling - example

- Embarrassingly parallel pattern



Static Schedule

- Tasks are associated into blocks
  - Blocks are assigned to Ues
  - Each UE should take approximately same amount of time to complete task
- Static schedule usually used when
  - Availability of computational resources is predictable (e.g. dedicated usage of nodes)
  - UEs are identical (e.g. homogeneous parallel computer)
  - Size of each task is nearly identical

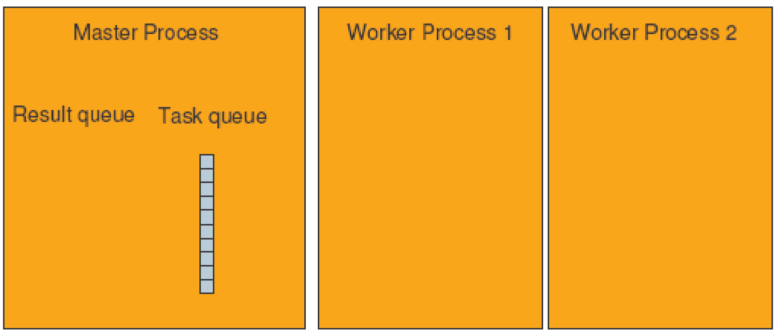
Dynamic scheduling

- Used when
  - Effort associated with each task varies widely/is unpredictable
  - Capabilities of UEs vary widely (heterogeneous parallel machine)
- Common implementations:
  - usage of task queues: if a UE finishes current task, it removes the next task from the task-queue
  - Work-stealing:
    - each UE has its own work queue
    - once its queue is empty, a UE steals work from the task queue of another UE

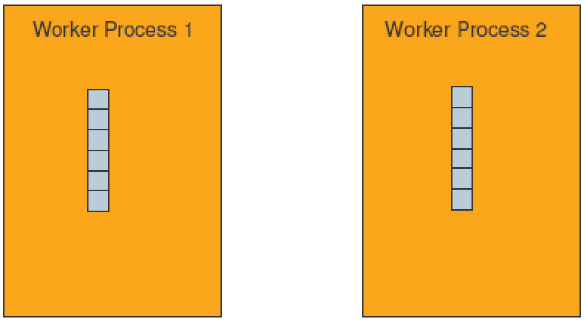
Dynamic scheduling

- Trade-offs:
  - Fine grained (=shorter, smaller) tasks allow for better load balance
  - Fine grained task have higher costs for task management and dependency management

Task Parallelism using Master-Worker framework



Task Parallelism using work stealing



Divide and Conquer

```
int solve ( Problem P )
{
  int solution;

  /* Check whether we can further partition the problem */
  if (baseCase(P) ) {
      solution = baseSolve(P);    /* No, we can't */
  }
  else {                        /* yes, we can */
    Problem subproblems[N];
    int subsolutions[N];

    subproblems = split (P);   /* Partition the problem */
    for ( i=0; i < N; i++ ) {
      subsolutions[i] = solve ( subproblems[i]);
    }
    solution = merge (subsolutions);
  }
  return ( solution );
}
```

Divide and Conquer

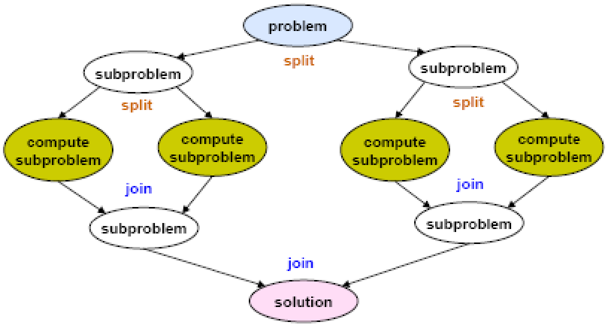
- A problem is split into a number of smaller sub-problems
- Each sub-problem is solved independently
- Sub-solutions of each sub-problem will be merged to the solution of the final problem
  - Useful if the base case is large compared to the work needed for splitting-merging
- Problems of Divide and Conquer for Parallel Computing:
  - Amount of exploitable concurrency decreases over the lifetime
  - Trivial parallel implementation: each function call to solve is a task on its own. For small problems, no new task should be generated, but the baseSolve should be applied

Divide and Conquer

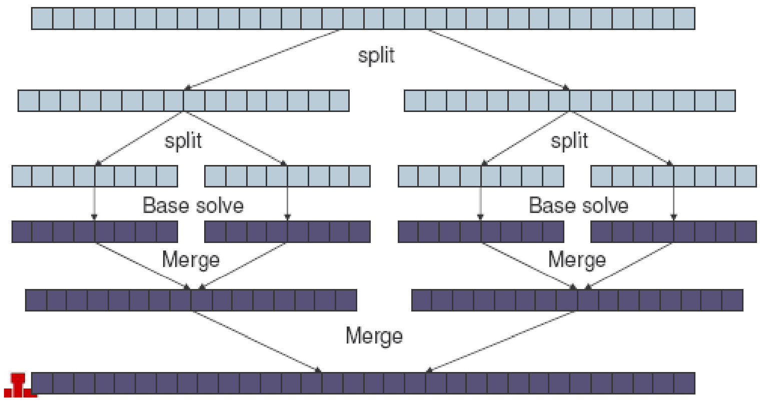
- Implementation:
  - On shared memory machines, a divide and conquer algorithm can easily be mapped to a fork/join model
    - A new task if forked(=created)
    - After this task is done, it joins the original task (=destroyed)
  - If the problem is not regular, better to use fine grained tasks and a task queue
    - Often implemented using the Master/Worker framework
  - OpenMP can be used to parallelize the loop only if it supports nesting of parallel regions which is not always true [Mat03]

Divide and Conquer

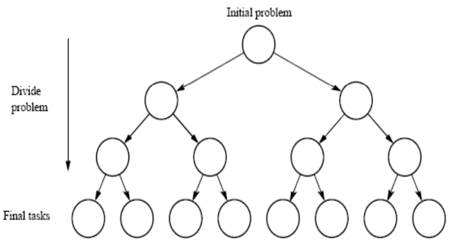
- Issues:
  - Sub-problems may not be uniform
  - May require dynamic load balancing

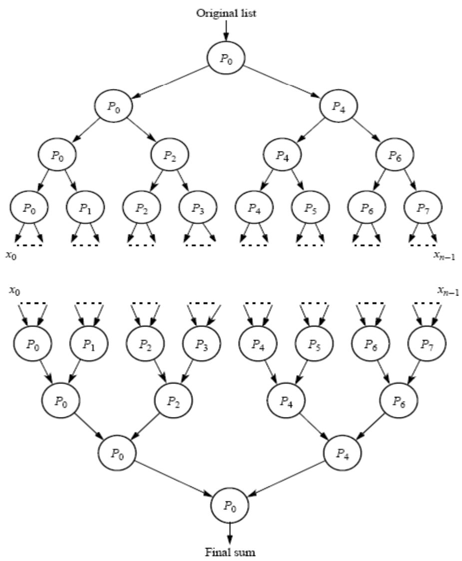


Divide and Conquer



Divide and Conquer: Task Assignment





Example: Mergesort

```
function mergesort(m)
    var list left, right
    if length(m) ≤ 1
        return m
    else
        middle = length(m) / 2
        for each x in m up to middle
            add x to left
        for each x in m after middle
            add x to right
        left = mergesort(left)
        right = mergesort(right)
        result = merge(left, right)
        return result
    end if
}
```

Example: Adding a List of Numbers

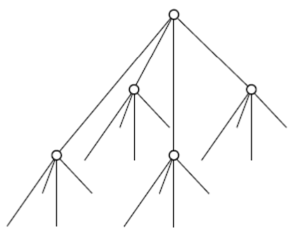
- A sequential recursive definition for adding a list of numbers is

```
int add(int *s)                          /* add list of numbers, s */
{
   if (number(s) =< 2) return (n1 + n2);   /* see explanation */
   else {
      Divide (s, s1, s2);       /* divide s into two parts, s1 and s2 */
      part_sum1 = add(s1);      /*recursive calls to add sub lists */
      part_sum2 = add(s2);
      return (part_sum1 + part_sum2);
   }
}
```

M-ary Divide and Conquer

- Divide and conquer can also be applied where a task is divided into more than two parts at each stage
- For example, if the task is broken into four parts, the sequential recursive definition would be

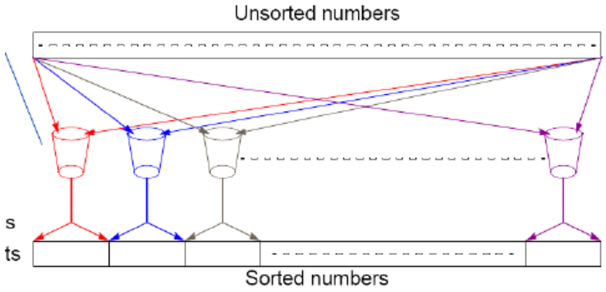
```
int add(int *s)                    /* add list of numbers, s */
{
   if (number(s) =< 4) return(n1 + n2 + n3 + n4);
   else {
      Divide (s,s1,s2,s3,s4);       /* divide s into s1,s2,s
      part_sum1 = add(s1);          /*recursive calls to add
      part_sum2 = add(s2);
      part_sum3 = add(s3);
      part_sum4 = add(s4);
      return (part_sum1 + part_sum2 + part_sum3 + part_sum4);
   }
}
```



quadtree

Bucket Sort

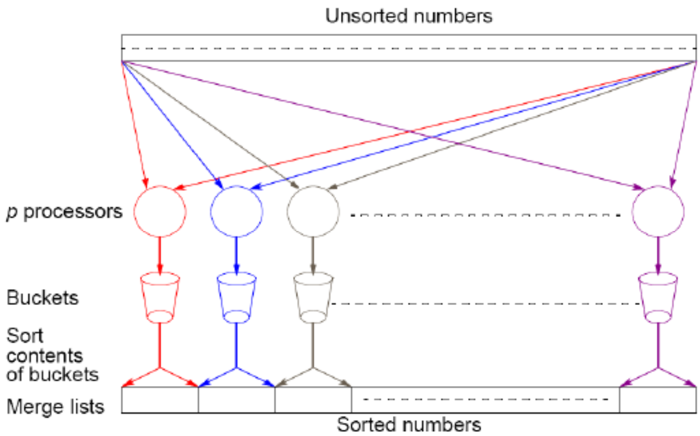
- One "bucket" assigned to hold numbers that fall within each region. Numbers in each bucket sorted using a sequential sorting algorithm



- Sequential sorting time complexity: O(nlog(n/m)).
- Works well if the original numbers uniformly distributed across a known interval, say 0 to *a -1.*

Parallel Version of Bucket Sort

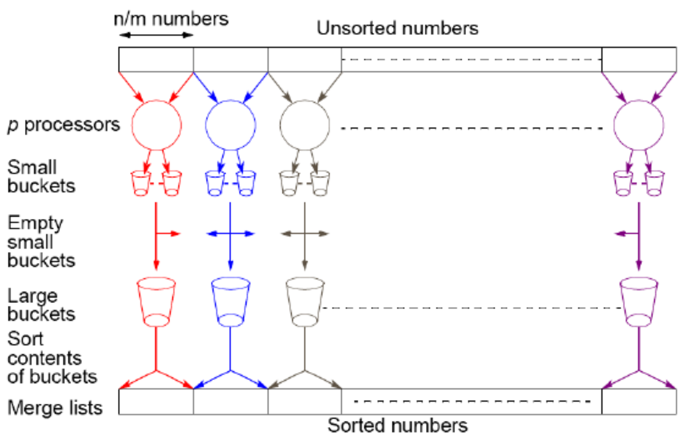
- Assign one processor for each bucket



Further Parallelization

- By partitioning the sequence into *m regions, one region for each processor*
- Each processor maintains *p "small"* buckets and separates the numbers in its region into its own small buckets
- These small buckets are then "emptied" into the *p final buckets for sorting, which requires* each processor to send one small bucket to each of the other processors (bucket *i to processor i)*

Another Parallel Version



Introduces new message-passing operation - all-to-all broadcast.

Analysis

- The following phases are needed:
  1. Partition numbers
  2. Sort into small buckets.
  3. Send to large buckets.
  4. Sort large buckets.

Phase 1 — Computation and Communication

- $t_{comp1} = n$
- $t_{comm1} = t_{startup} + t_{data}n$

Phase 2 — Computation

- $t_{comp2} = n/p$

Analysis

Phase 3 — Communication

- If all the communications could overlap:
- $t_{comm3} = (p - 1)(t_{startup} + (n/p^2)t_{data})$

total number of small buckets=p^2

Phase 4 — Computation

- $t_{comp4} = (n/p)\log(n/p)$

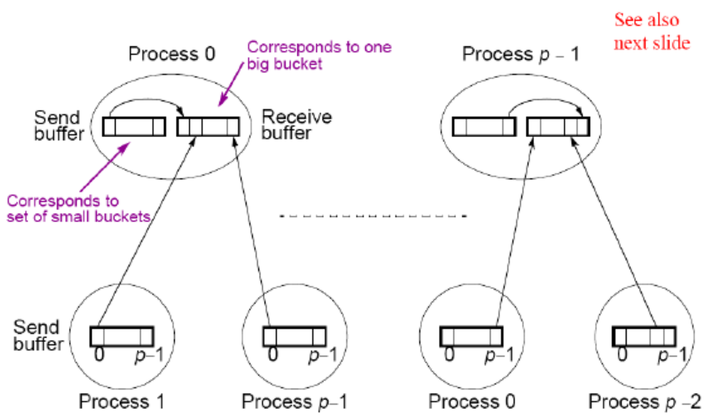
Overall

- $t_p = t_{startup} + t_{data}n + n/p + (p - 1)(t_{startup} + (n/p^2)t_{data}) + (n/p)\log(n/p)$

- It is assumed that the numbers are uniformly distributed to obtain these formulas. The worst-case scenario would occur when all the numbers fell into one bucket!

All-to-all Routine

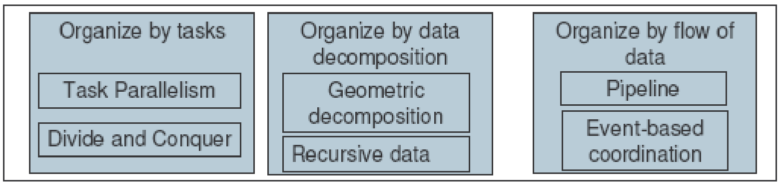
- Sends data from each process to every other process



Other Interesting Examples

- Gravitational N-Body problem
  - Barnes-Hut algorithm
  - Orthogonal recursive bisection

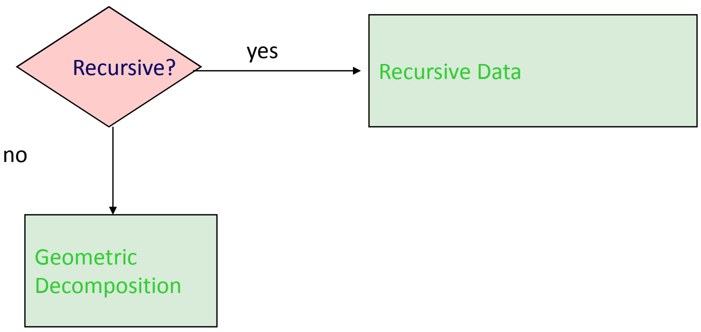
Algorithm Structure – Summary so far



- Task parallelism:
  - Implemented by Task queues
  - Task distribution vs. work stealing
- Divide and Conquer for recursive problems
  - Split problem into sub-problems until a lower limit in the problem size has been reached
  - Solve the sub-problem
  - Merge the results of the sub-problems into the final result

Organize by Data?

- Operations on a central data structure
  - Arrays and linear data structures
  - Recursive data structures



Geometric Decomposition

- For all applications relying on data decomposition
  - All processes should apply the same operations on different data items
- Key elements:
  - Data decomposition
  - Exchange and update operation
  - Data distribution and task scheduling

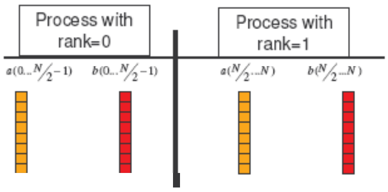
Geometric Decomposition: Example

- Scalar product and matrix vector multiplications are used to solve differential equations
- They can be performed in parallel using geometric decomposition

Scalar Product

- Scalar product:

$$s=\sum_{i=0}^{N-1} a[i]*b[i]$$



- Parallel algorithm:

$$s=\sum_{i=0}^{N/2-1}(a[i]*b[i])+\sum_{i=N/2}^{N-1}(a[i]*b[i])$$

$$=\underbrace{\sum_{i=0}^{N/2-1}(a_{local}[i]*b_{local}[i])}_{rank=0}+\underbrace{\sum_{i=0}^{N/2-1}(a_{local}[i]*b_{local}[i])}_{rank=1}$$

– requires communication between the processes

Matrix-Vector product in Parallel

$$\begin{bmatrix}-50 & 30 & & \\ 20 & -50 & 30 & \\ & 20 & -50 & 30 \\ & & 20 & -50\end{bmatrix}\begin{bmatrix}x_1\\x_2\\x_3\\x_4\end{bmatrix}\begin{bmatrix}rhs_1\\rhs_2\\rhs_3\\rhs_4\end{bmatrix}$$

Process 0

Process 1

$$\begin{aligned}-50x_1+30x_2 &= rhs_1\\ 20x_1-50x_2+30x_3 &= rhs_2\\ 20x_2-50x_3+30x_4 &= rhs_3\\ 20x_3-50x_4 &= rhs_4\end{aligned}$$

Process 0 needs x_3

Process 1 needs x_4

Matrix-Vector product in Parallel

- Introduction of ghost cells

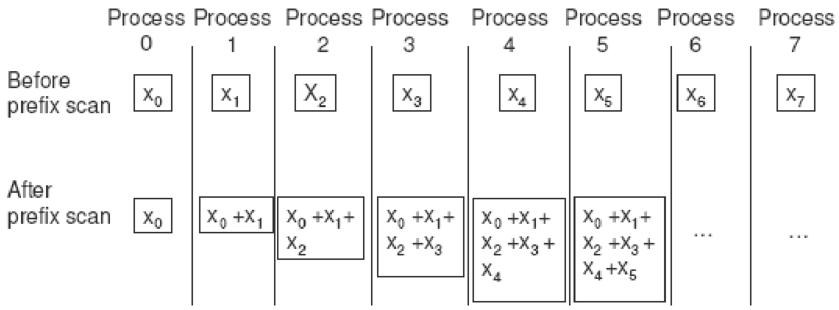
- Looking at the source code, e.g …
- …since the vector used in the matrix vector multiplication changes every iteration, you always have to update the ghost cells before doing the calculation

Recursive Data

- Typically applied in recursive data structures
  - Lists, trees, graphs
- Data decomposition: recursive data structure is completely decomposed into individual elements
- Example: prefix scan operation
  - Each process has an element of an overall structure (e.g. a linked list), e.g. an integer x
- Lets denote the value of the x on process i xi
  - At the end of the prefix scan operation process k holds the sum of all elements of xi for i=0…k

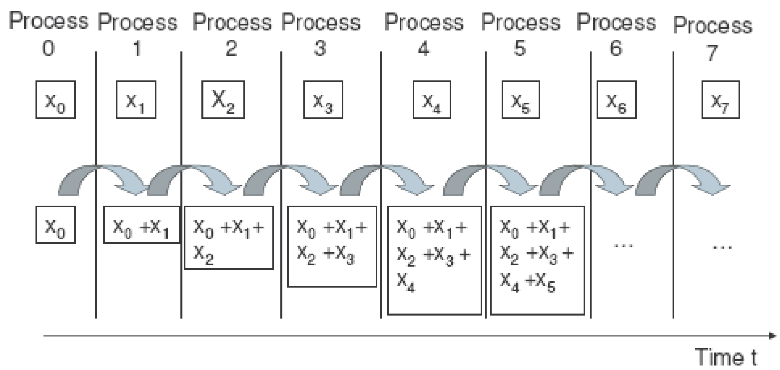
Recursive Data

- Example for eight processes

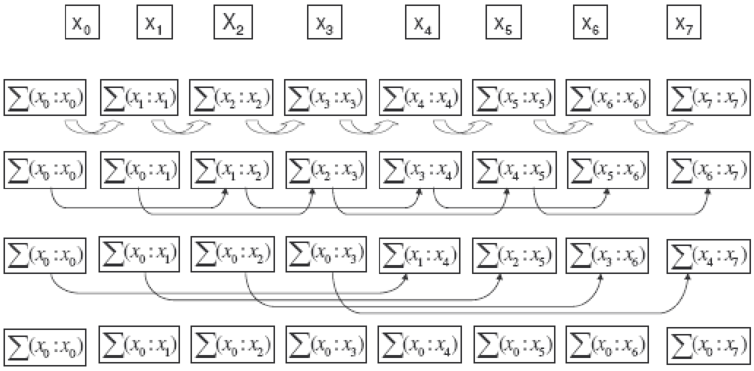


Sequential implementation

- Each process forwards its sum to the next process
  - n messages/ time steps required for n processes

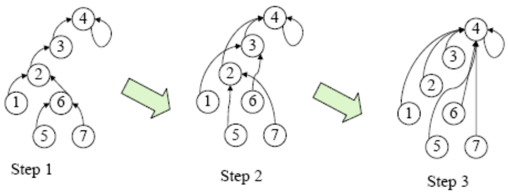


Recursive data approach



Another Example: Find the Root

- Given a forest of rooted directed trees, for each node, find the root of the tree containing the node
  - Parallel approach: for each node, find its successor's successor, repeat until no changes
    - O(log n) vs. O(n)

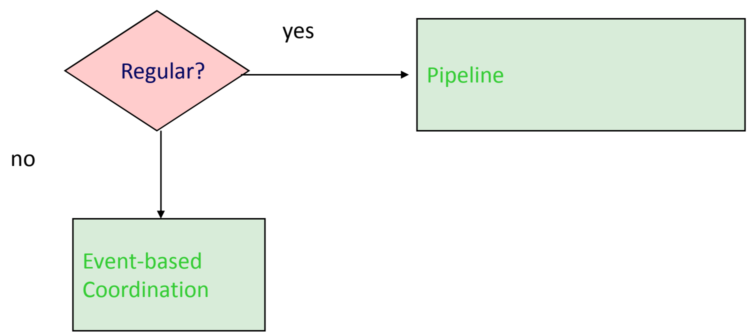


- In the example, three steps are needed to converge (all the nodes have no more iterations to do)

Recursive data approach

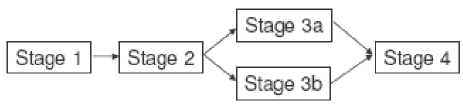
- Very fine grained concurrency
- Restructuring of the original algorithm often required
- Parallel algorithm requires substantially more work, which can however be executed in less time-steps

Organize by Ordering or Flow of Data?



Pipeline pattern

- Amount of concurrency limited to the number of stages of the pipeline
- Patterns works best, if amount of work performed by various stages is roughly equal
- Filling the pipeline: some stages will be idle
- Draining the pipeline: some stages will be idle
- Non-linear pipeline: pattern allows for different execution for different data items

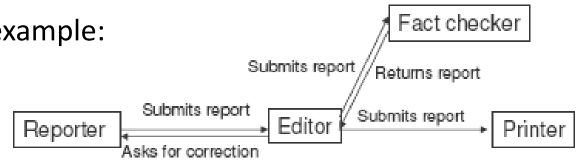


Pipeline pattern

- Implementation:
  – Each stage typically assigned to a process/thread
  – A stage might be a data-parallel task itself
  – Computation per task has to be large enough to compensate for communication costs between the tasks

Event-based coordination

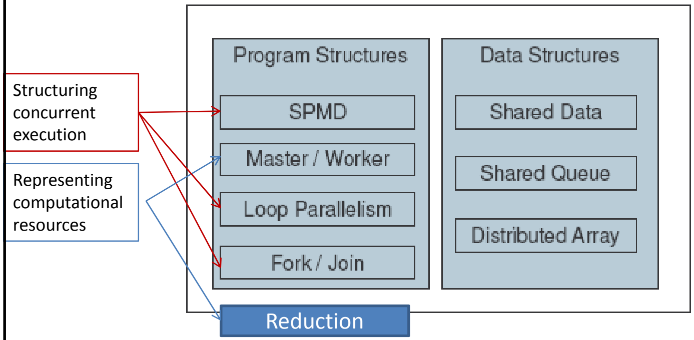
- Pipeline pattern assumes a regular, non-changing data flow
- Event-based coordination assumes irregular interaction between tasks
- Real world example:



- Data items might flow in both directions
  - Each data item might take a different path
- Major problem: deadlock avoidance

Supporting structures

- Supporting structures describe software constructions for parallel algorithms



SPMD

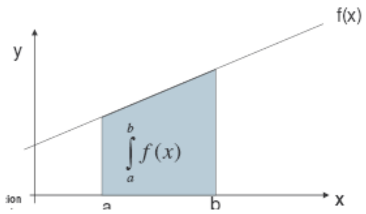
- SPMD – Single Program Multiple Data
- Each UE carries out similar/identical operations
- Interaction between UEs performance critical
  - Basically all applications scaling up to several thousand nodes/processors are written in the SPMD style

SPMD

- Basic elements:
  - Initialize: establish common context on each UE
  - Obtain unique identifier: e.g. using MPI_Comm_rank()
  - Run the same program on each UE using the unique identifier to differentiate behavior on different UEs
- Differentiation could also be done based on data items
  - Distribute data: e.g. geometric decomposition
  - Finalize

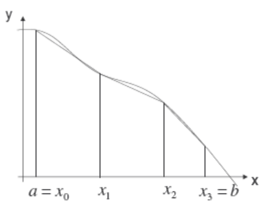
SPMD Example

- Anti-differentiation: Given a function *f(x),* find a function *F(x)* with the property that *F'(x) = f (x)*
- Example: $f(x) = ax^n \longrightarrow F(x) = \frac{1}{n+1}ax^{n+1} + c$
- Calculating the Integral of a function $\int_a^b f(x)dx = F(b) - F(a)$
- Graphical interpretation



Sequential Code using MPI

- Trapezoid rule $\int_a^b f(x)dx = \sum_{i=1}^{n} \int_{x_{i-1}}^{x_i} f(x)dx \approx \frac{1}{2}\sum_{i=1}^{n}(x_i - x_{i-1})[f(x_{i-1}) + f(x_i)]$

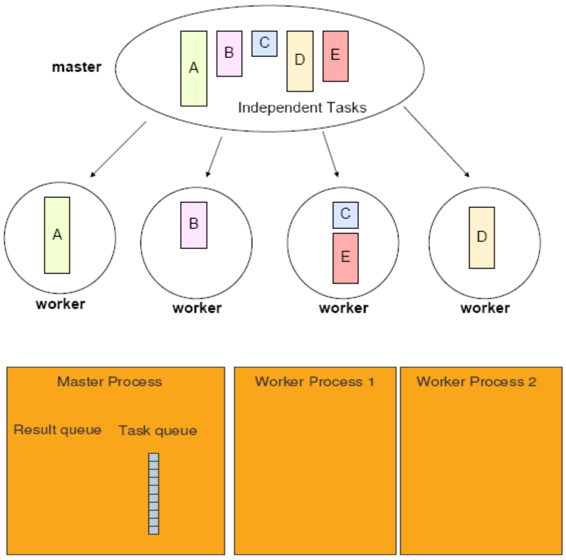



```
#include <stdio.h>

int main ( int argc, char **argv )
{
  int i, num_steps=100000;
  double x, xn, pi, step, sum=0.0;

  /* Required input:
     - a,b : boundaries of the integral
     - f(x): function
  */

  step = (b-a)/num_steps;
  for ( i=0; i<num_steps; i++) {
       x   = i * step;
       xn  = (i+1) * step;
       sum = sum + 0.5*(xn-x)*(f(x)+f(xn));
  }
  return (0);
}
```

Parallel Code using MPI

```
…
int rank, size, start, end, i, num_steps=100000;
double x, xn, end, step, sum, lsum=0.0;

MPI_Init ( &argc, &argv );
MPI_Comm_rank (MPI_COMM_WORLD, &rank );
MPI_Comm_size (MPI_COMM_WORLD, &size );

step  = (b-a)/num_steps;
start = rank * num_steps/size;
end   = start + num_steps/size;

for ( i=start; i<end; i++) {
   x   = i * step;
   xn  = (i+1) * step;
   lsum = lsum + 0.5*(xn-x)*(f(x)+f(xn);
}
MPI_Allreduce (lsum,sum,1,MPI_DOUBLE,MPI_SUM,MPI_COMM_WORLD);
MPI_Finalize ();
…
```

Master-Worker Pattern



Master-Worker Pattern

- Particularly relevant for problems using task parallelism pattern where task have no dependencies
  - Embarrassingly parallel problems
- In general, it is useful if
  - Workload associated with tasks are highly variable – MW has 'built-in' load balancing
  - Capabilities of PEs are strongly varying
  - Tasks are not tightly coupled – each worker process typically only has to communicate with the master process but not with other workers
- Not useful usually if the computationally intensive part of the program structure is organized in a big loop

Master-Worker Pattern

- Main challenge in determining when the entire problem is complete
- Approach:
  - Two logically different entities: master process managing a work-queue, worker processes executing a task assigned to them by the master
  - Completion: explicit notification of master to worker processes typically required
- Can become very complicated for adaptive and recursive problems, where a worker can also 'generate' new tasks

Example Code using MPI

- Main function

```
…
#define MASTERRANK 0
#define WORK_TAG         10
#define RES_TAG          11
#define NO_WORK_LEFT_TAG 12

int main ( int argc, char ** argv ) {
  int rank;

  MPI_Init ( &argc, &argv );
  MPI_Comm_rank (MPI_COMM_WORLD, &rank );

  if ( rank == MASTERRANK) {
       master();
  }else {
       worker();
  }
  MPI_Finalize ();
  return (0);
}
```

Example Code using MPI

- Worker

```
int worker ( void )
{
  int done=0;  /* condition set to false */
  MPI_Status status;

  while ( !done ) {
    MPI_Recv ( &work, maxcnt, MPI_DOUBLE, MASTERRANK,
               MPI_ANY_TAG, MPI_COMM_WORLD, &status);
    if ( status.MPI_TAG == NO_WORK_LEFT_TAG ) {
       done = 1; /* condition set to true */
    }
    else {
     result = do_calculations ( work );
     MPI_Send (&result, rescnt, MPI_DOUBLE, MASTERRANK,
               RES_TAG, MPI_COMM_WORLD );
    }
  return (0);
}
```

Example Code using MPI

- Master part I

```
int master ( void )
{
  int done = 0;

  /* distribute initial work */
  for ( proc=1; proc<maxworkers; proc++ ) {
       next = get_next_work ();
       MPI_Send ( &next, xx, MPI_DOUBLE, proc, WORK_TAG,
                  MPI_COMM_WORLD);
       marc_work_as_assigned ( proc, next );
  }

  while ( done < maxworkers ) {
     MPI_Recv ( &deltares, xy, MPI_DOUBLE, MPI_ANY_SOURCE,
                RES_TAG, comm, &status);
     proc = status.MPI_SOURCE;
     store_work_result ( proc, deltares );
     next = get_next_work ();
```

Example Code using MPI

- Master part II

```
     if ( next != NO_WORK_LEFT ) {
        MPI_Send ( &next, xx, MPI_DOUBLE, proc, WORK_TAG,
                   MPI_COMM_WORLD );
     }
     else {
       MPI_Send ( &next, 0, MPI_DOUBLE, j, NO_WORK_LEFT_TAG,
                  MPI_COMM_WORLD);
       done ++;
     }
  } /* end while loop */

  return  (0);
}
```

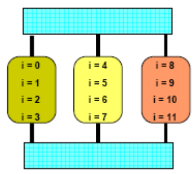
Master-Worker Pattern

- Master/worker pattern works well, if a master has sufficient worker processes
- Master process can become a bottleneck if tasks are too small and number of worker processes is very large

Loop Parallelism Pattern

- In many scientific applications, the most compute intensive part is organized in a large loop
- Splitting the loop execution onto different processes is a straight forward parallelization, if the internal structure (=dependencies) allow that
- Most applications of the loop parallelism pattern rely on OpenMP
- Especially good when code cannot be massively restructured

```
#pragma omp parallel for
for(i = 0; i < 12; i++)
        C[i] = A[i] + B[i];
```



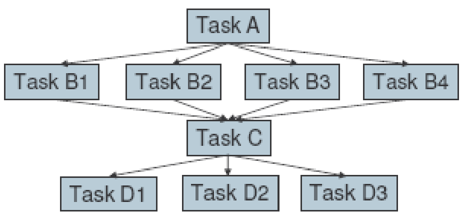
Loop Parallelism: OpenMP Example

- Numerical integration

```
#include <stdio.h>
#include "omp.h>

int main ( int argc, char **argv )
{
  int i, num_steps=100000;
  double x, xn, pi, step, sum=0.0;

  step = (b-a)/num_steps;

#pragma omp parallel for private(x,xn) reduction(+:sum)
  for ( i=0; i<num_steps; i++) {
       x   = i * step;
       xn  = (i+1) * step;
       sum = sum + 0.5*(xn-x)*(f(x)+f(xn));
  }
  return (0);
}
```

Fork/Join Pattern

- Useful if the number of concurrent tasks varies during execution
  - Tasks are created dynamically (= forked)
  - Tasks are terminated when done (= join with parents)

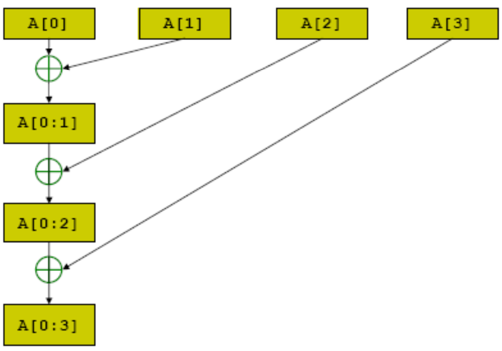


Fork/Join Pattern

- Can be useful for divide and conquer algorithms
- Often used with OpenMP
  - Can be used with MPI – 2 dynamic process management as well
- Creating and terminating processes/threads has a significant overhead

Reduction Pattern

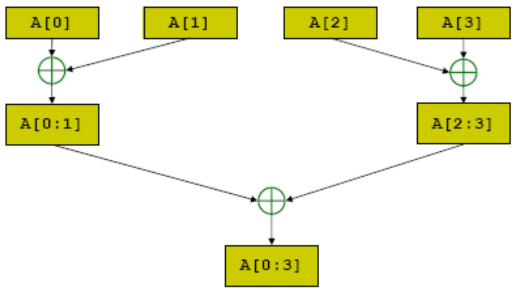
- Concurrently executing processes or threads cooperate
- A collection of data items is reduced to a single item by repeatedly combining them pairwise with a binary operator
- Exploit concurrency in reduction operation



Serial reduction
(computing sum of a[0] through a[3])

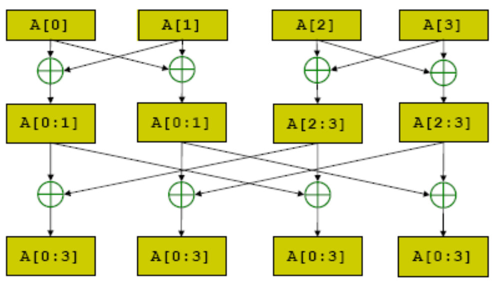
Three-Based Reduction

- n steps for 2^n units of execution
- When reduction operator is associative
- Especially attractive when only one task needs result



Recursive-Doubling Reduction

- n steps for 2^n units of execution
- If all units of execution need the result of the reduction



Advantages

- Better than tree-based approach with broadcast
  - Each units of execution has a copy of the reduced value at the end of n steps
  - In tree-based approach with broadcast to send the result to all the processors:
    - In recursive approach reduction takes n steps
    - Broadcast cannot begin until reduction is complete
    - Broadcast takes n steps (architecture dependent)
    - O(n) vs. O(2n)

Summary: Algorithm vs Supporting Space

- Patterns can be hierarchically composed so that a program uses more than one pattern

	Task parallelism	Divide and conquer	Geometric decomposition	Recursive data	Pipeline	Event-based coordination
SPMD	****	***	****	**	***	**
Loop Parallelism	****	**	***			
Master/ Worker	****	**	*	*	****	*
Fork/ Join	**	****	**		****	****