Programming Models

Implementations and Examples

Identification of Parallelism

- We can run computations in parallel if they not share data
- Refinement:
  - Both read: OK
  - Write and (read or write): NOK
- The order becomes important: data races
- Formalization [Bernstein-1960]: Two computations C1 and C2 can be done in parallel if none of the following conditions hold:
  1. *C1 writes into a location that is later read by C2: a read-after-write (RAW) race.*
  2. *C1 reads from a location that is later written into by C2: a write-after-read (WAR) race.*
  3. *C1 writes into a location that is later overwritten by C2: a write-after-write (WAW) race.*

Parallel Loop Programming

- Different iterations to different processors
- On shared memory systems we can do a PARALLEL DO loop
  - The loop must be examined to find dependencies

Example

- Loop with NO data sharing:
  ```
  DO I = 1, N
  A(I) = A(I) + C
  END DO
  ```
- Loop with possible WAR race
  ```
  DO I = 1, N
  A(I) = A(I+1) + C
  END DO
  ```
- In some cases it is possible to achieve significant parallelism in the presence of races:
  ```
  SUM = 0.0
  DO I = 1, N
  R = F(B(I),C(I))          ! an expensive computation
  SUM = SUM + R
  END DO
  ```
- There is a race involving SUM, but if that floating-point addition is commutative and associative the order in which the results are added to SUM does not matter
- If F is expensive, we can gain by computing the values of F in parallel and then update the SUM in the order in which computations finish

Example

- However, to make this work, SUM updates must be in a critical region

```
SUM = 0.0
PARALLEL DO I = 1, N
    R = F(B(I),C(I)) ! an expensive computation
    BEGIN CRITICAL REGION
        SUM = SUM + R
    END CRITICAL REGION
END DO
```

SPMD Programming

- To implement the SUM reduction on a message passing system the SPMD can be used
  - Scalar variables replicated
  - Explicit communication

```
! This code is executed by all processors
! MYSUM, MYFIRST, MYLAST, R, and I are private local variables
! MYFIRST and MYLAST are computed separately on each processor
! to point to nonintersecting sections of B and C
! GLOBALSUM is a global collective communication primitive
MYSUM = 0.0
DO I = MYFIRST, MYLAST
    R = F(B(I),C(I)) ! an expensive computation
    MYSUM = MYSUM + R
ENDDO
SUM = GLOBALSUM(MYSUM)
```

- Here the communication is built into the function GLOBALSUM, which takes one value of its input parameter from each processor and computes the sum of all those inputs, storing the result into a variable that is replicated on each processor

Finite Difference Calculation Example

- Take a simple Fortran code that computes a new average value for each data point in array A using a two-point stencil and stores the average into array ANEW
- Parallel version on a shared memory machine with four processors, using a parallel-loop dialect of Fortran
- This code may not have sufficient granularity to compensate for the overhead of dispatching parallel threads

```
REAL A(100), ANEW(100)
:
:
DO I = 2, 99
   ANEW(I) = (A(I-1) + A(I+1)) * 0.5
ENDDO
```

```
REAL A(100), ANEW(100)
:
:
PARALLEL DO I = 2, 99
   ANEW(I) = (A(I-1) + A(I+1)) * 0.5
ENDDO
```

Version with Higher Granularity

- Each processor gets ¼ of the work
- The PRIVATE statement specifies that each iteration of the IB-loop has its own private value of each variable in the list
- This permits each instance of the inner loop to execute independently without simultaneous updates of the variables that control the inner loop iteration

```
REAL A(100), ANEW(100)
:
:
PARALLEL DO IB = 1, 100, 25
   PRIVATE I, myFirst, myLast
   myFirst = MAX(IB, 2)
   myLast =  MIN(IB + 24, 99)
   DO I = myFirst, myLast
      ANEW(I) = (A(I-1) + A(I+1)) * 0.5
   ENDDO
ENDDO
```

Message Passing Version

- This code is written in SPMD style so that the scalar variables myP, myFirst, and myLast are all automatically replicated on each processor—the equivalent of PRIVATE variables in shared memory
- Each global array is replaced by a collection of local arrays in each memory
- Two extra storage locations on each processor—A(0) and A(26)—are used to hold values communicated from neighboring processors. These cells are often referred to as *ghost cells, halo cells, or overlap areas.*

```
! This code is executed by all processors
! myP is a private local variable containing the processor number
!     myP runs from 0 to 3
! Alocal and ANEWlocal are local versions of arrays A and ANEW

IF (myP .NE. 0) send Alocal(1) to myP-1
IF (myP .NE. 3) send Alocal(25) to myP+1
IF (myP .NE. 0) receive Alocal(0) from myP-1
IF (myP .NE. 3) receive Alocal(26) from myP+1
myFirst = 1
myLast = 25
IF (myP == 0) myFirst = 2
IF (myP == 3) myLast = 24
DO I = myFirst, myLast
   ANEWlocal(I) = (Alocal(I-1) + Alocal(I+1)) * 0.5
ENDDO
```

Improved Version

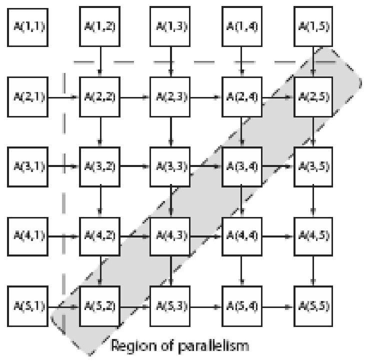
- Insertion of local computation between the sends and receives
- Communication is overlapped with the local computation to achieve better overall parallelism

```
! This code is executed by all processors
! myP is a private local variable containing the processor number
!     myP runs from 0 to 3
! Alocal and ANEWlocal are local versions of arrays A and ANEW

IF (myP .NE. 0) send Alocal(1) to myP-1
IF (myP .NE. 3) send Alocal(25) to myP+1
DO I = 2, 24
   ANEWlocal(I) = (Alocal(I-1) + Alocal(I+1)) * 0.5
ENDDO
IF (myP .NE. 0) THEN
   receive Alocal(0) from myP-1
   ANEWlocal(1) = (Alocal(0) + Alocal(2)) * 0.5
ENDIF
IF (myP .NE. 3) THEN
   receive Alocal(26) from myP+1
   ANEWlocal(25) = (Alocal(24) + Alocal(26)) * 0.5
ENDIF
```

Pipeline Parallelism

- Some parallelism may be achievable by staggering initiation of tasks and synchronizing them so that subsections with no interdependencies are run at the same time
- Although neither of the loops can be run in parallel, there is some parallelism
- All of the values on the shaded diagonal can be computed in parallel because there are no dependences between any of these elements

```
DO J = 2, N-1
   DO I = 2, N-1
      A(I,J) = (A(I-1,J) + A(I+1,J) + A(I,J-1) + A(I,J+1)) * 0.25
   ENDDO
ENDDO
```



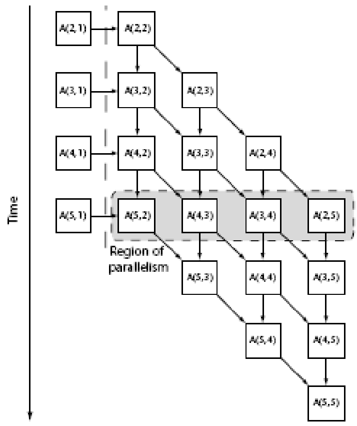
Pipeline Parallelism

- If we compute all the elements in any column on the same processor, so that A(*,J) would be computed on the same processor for all values of J
- If we compute the elements in any column in sequence, all of the dependences along that column are satisfied. However, we must still be concerned about the rows.
- To get the correct result, we must delay the computation on each row by enough to ensure that the corresponding array element on the previous row is completed before the element on the current row is computed.
- This strategy can be implemented via the use of *events*

```
EVENT READY(N,N) ! Initialized to false
PARALLEL DO I = 1, N
   POST(READY(I,1))
ENDDO
PARALLEL DO J = 2, N-1
   DO I = 2, N-1
      WAIT(READY(I,J-1))
      A(I,J) = (A(I-1,J) + A(I+1,J) + A(I,J-1) + A(I,J+1)) * 0.25
      POST(READY(I,J))
   ENDDO
ENDDO
```

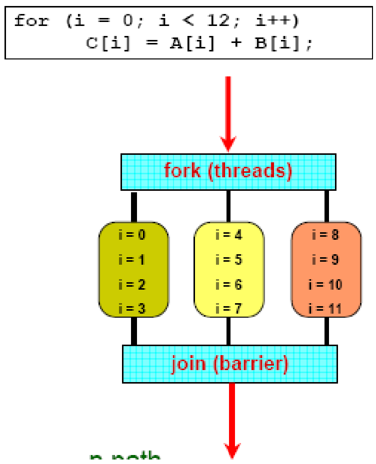
Pipeline Parallelism

- Initially all the events are false—a wait on a false event will suspend the executing thread until a post for the event is executed
- All of the READY events for the first column are then posted, so the computation can begin
-
- The computation for the first computed column, A(*,2), begins immediately.
- As each of the elements is computed, its READY event is posted so that the next column can begin computation of the corresponding element



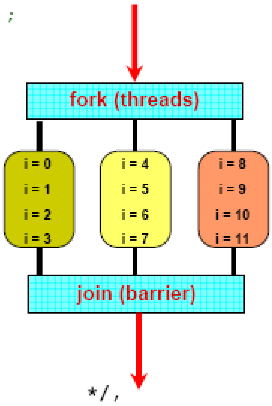
Example Parallelization with Threads

- A single process can fork multiple concurrent threads
  - Each thread encapsulate its own execution path
  - Each thread has local state and shared resources
  - Threads communicate through shared resources such as global memory



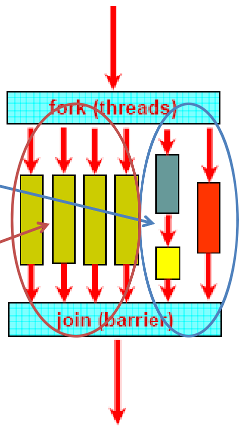
Example Code with Threads

```
int A[12] = {...}; int B[12] = {...}; int C[12];

void add_arrays(int start)
{
  int i;
  for (i = start; i < start + 4; i++)
    C[i] = A[i] + B[i];
}

int main (int argc, char *argv[])
{
  pthread_t threads_ids[3];
  int rc, t;
  for(t = 0; t < 4; t++) {
    rc = pthread_create(&thread_ids[t],
                        NULL       /* attributes      */,
                        add_arrays /* function        */,
                        t * 4      /* args to function */);
  }
  pthread_exit(NULL);
}
```



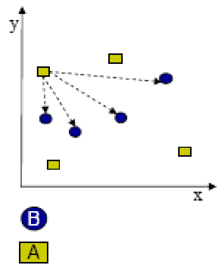
Functional and Domain Decomposition with Threads

- Functional decomposition or control parallelism
  - Each thread performs a different function
- Domain decomposition
  - Several threads perform same computation but operate on different data

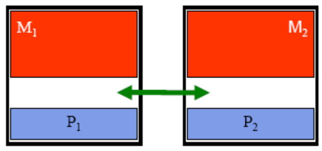


Performance Evaluation

- Example
  - Calculate the distance from each point in **A[1..4]** to every other point in **B[1..4] and store results to C[1..4][1..4]**

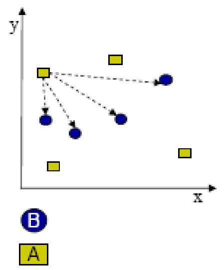



```
for (i = 1 to 4)
  for (j = 1 to 4)
    C[i][j] = distance(A[i], B[j])
```

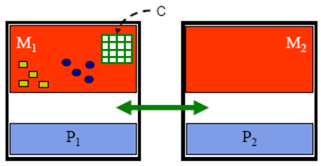


Performance Evaluation

- Example
  - Calculate the distance from each point in **A[1..4]** to every other point in **B[1..4] and store results to C[1..4][1..4]**




```
for (i = 1 to 4)
  for (j = 1 to 4)
    C[i][j] = distance(A[i], B[j])
```

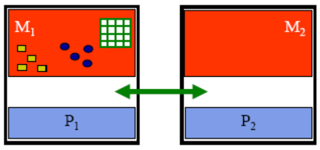


Performance Evaluation

- Example
  - Calculate the distance from each point in **A[1..4]** to every other point in **B[1..4] and store results to C[1..4][1..4]**

```
for (i = 1 to 4)
  for (j = 1 to 4)
    C[i][j] = distance(A[i], B[j])
```

- Can break up work between the two processors
  - P1 sends data to P2

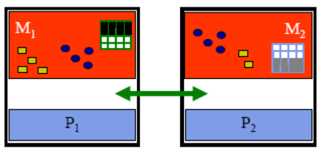


Performance Evaluation

- Example
  - Calculate the distance from each point in **A[1..4]** to every other point in **B[1..4] and store results to C[1..4][1..4]**

```
for (i = 1 to 4)
  for (j = 1 to 4)
    C[i][j] = distance(A[i], B[j])
```

- Can break up work between the two processors
  - P_1 sends data to P_2
  - P_1 and P_2 compute
  - P_2 sends output to P_1



Example Message Passing Program

processor 1

```
for (i = 1 to 4)
  for (j = 1 to 4)
    C[i][j] = distance(A[i], B[j])
```

sequential

parallel with messages

processor 1

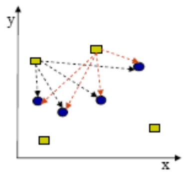
```
A[n] = {…}
B[n] = {…}

Send (A[n/2+1..n], D[1..n])

for (i = 1 to n/2)
  for (j = 1 to n)
    C[i][j] = distance(A[i], B[j])

Receive(C[n/2+1..n][1..n])
```

processor 2

```
A[n] = {…}
B[n] = {…}

Receive(A[n/2+1..n], D[1..n])

for (i = n/2+1 to n)
  for (j = 1 to n)
    C[i][j] = distance(A[i], B[j])

Send (C[n/2+1..n][1..n])
```

Performance Analysis

- Distance calculations between points are independent of each other
  - Dividing the work between two processors: 2x speedup
  - Dividing the work between four processors: 4x speedup
- Communication
  - 1 copy of **B[] sent to each processor**
  - 1 copy of **subset of A[] to each processor**
- Granularity of **A[] subsets directly impact communication costs**
  - Communication is not free



Understanding Performance

- What factors affect performance of parallel programs?
- **Coverage or extent of parallelism in algorithm**
- **Granularity of partitioning among processors**
- **Locality of computation and communication**

Limits to Performance Scalability

- Not all programs are “embarrassingly” parallel
- Programs have sequential parts and parallel parts

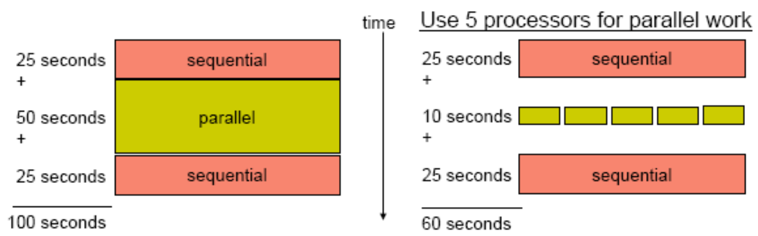
Sequential part
(data dependence)

Parallel part
(no data dependence)

```
a = b + c;
d = a + 1;
e = d + a;
for (i=0; i < e; i++)
    M[i] = 1;
```

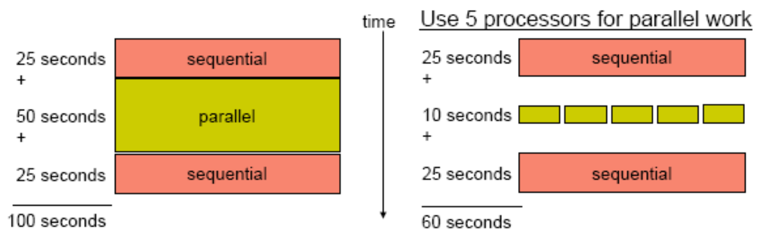
Amdhal's Law

- **Amdahl's Law:** ***The performance improvement to*** *be gained from using some faster mode of execution is limited by the fraction of the time the faster mode can be used*
- Potential program speedup is defined by the fraction of code that can be parallelized



Speedup

- Speedup = old running time / new running time
  = 100 seconds / 60 seconds
  = 1.67
  (parallel version is 1.67 times faster)



Implications of Amdhal's Law

- *p = fraction of work that can be parallelized*
- *n = the number of processor*

$$speedup = \frac{\text{old running time}}{\text{new running time}}$$

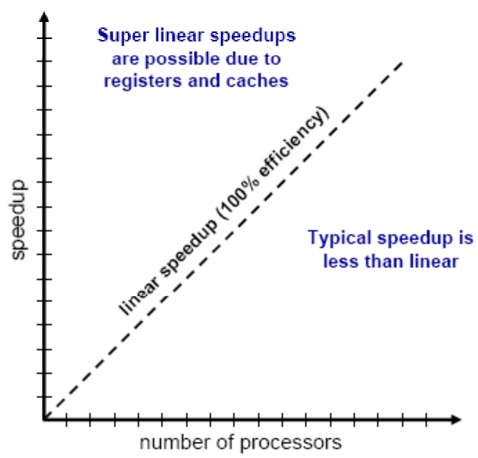
$$= \frac{1}{(1-p) + \frac{p}{n}}$$

fraction of time to complete sequential work

fraction of time to complete parallel work

- Speedup tends to as number of processors tends to infinity
- Parallel programming is worthwhile when programs have a lot of work that is parallel in nature

Performance Scalability

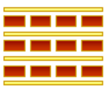


Granularity

- Granularity is a qualitative measure of the ratio of computation to communication
- Computation stages are typically separated from periods of communication by synchronization events

Fine vs Coarse Grain Parallelism

- Fine-grain Parallelism
  - Low computation to communication ratio
  - Small amounts of computational work between communication stages
  - Less opportunity for performance enhancement
  - High communication overhead



- Coarse-grain Parallelism
  - High computation to communication ratio
  - Large amounts of computational work between communication stages
  - More opportunity for performance enhancement
  - Harder to balance efficiently

Communication Cost Model

total data sent

number of messages

$$C = f * (o + l + \frac{n/m}{B} + t - overlap)$$

frequency of messages

overhead per message (at both ends)

network delay per message

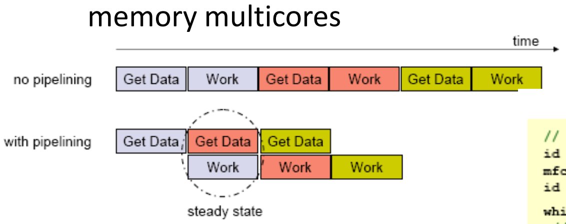
bandwidth along path (determined by network)

cost induced by contention per message

amount of latency hidden by concurrency with computation

Overlapping Messages and Computation

- Computation and communication concurrency can be achieved with pipelining
- Essential for performance on Cell and similar distributed memory multicores

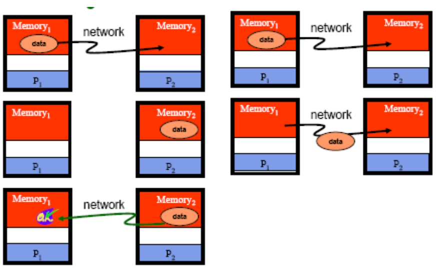


Cell buffer pipelining example

```
// Start transfer for first buffer
id = 0;
mfc_get(buf[id], addr, BUFFER_SIZE, id, 0, 0);
id ^= 1;

while (!done) {
 // Start transfer for next buffer
 addr += BUFFER_SIZE;
 mfc_get(buf[id], addr, BUFFER_SIZE, id, 0, 0);
 // Wait until previous DMA request finishes
 id ^= 1;
 mfc_write_tag_mask(1 << id);
 mfc_read_tag_status_all();
 // Process buffer from previous iteration
 process_data(buf[id]);
}
```

Types of Messages

- Synchronous vs Asynchronous
- Blocking vs Non-blocking



SYNC
- Sender notified when message is received

BLOCKING
- Sender waits until message is transmitted: **buffer is empty**
- Receiver waits until message is received: **buffer is full**
- Potential for deadlock

ASYNC
- Sender only knows that message is sent

NON-BLOCKING
- Processing continues even if message hasn't been transmitted
- Avoid idle time and deadlocks

Example

- Cell processor
  – SPE and PPU message passing

Cell blocking mailbox “send”

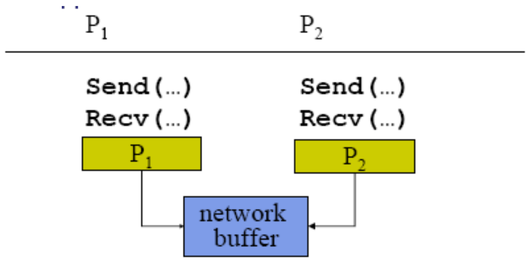
```
// SPE does some work
...
// SPE notifies PPU that task has completed
spu_write_out_mbox(<message>);

// SPE does some more work
...
// SPE notifies PPU that task has completed
spu_write_out_mbox(<message>);
```

Cell non-blocking data “send” and “wait”

```
// DMA back results
mfc_put(data, cb.data_addr, data_size, ...);

// Wait for DMA completion
mfc_read_tag_status_all();
```

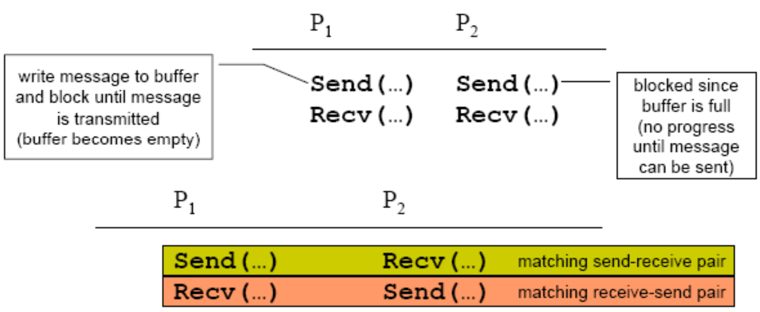
Source of Deadlocks

- If there is insufficient buffer capacity, sender waits until additional storage is available
- What happens with the following code depends on length of message and available buffer



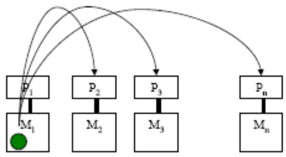
Solutions

- Increasing local or network buffering
- Order the sends and receives more carefully



Broadcast

- One processor sends the same information to many other processors
  - **MPI_BCAST (in MPI language)**



```
for (i = 1 to n)
  for (j = 1 to n)
    C[i][j] = distance(A[i], B[j])
```

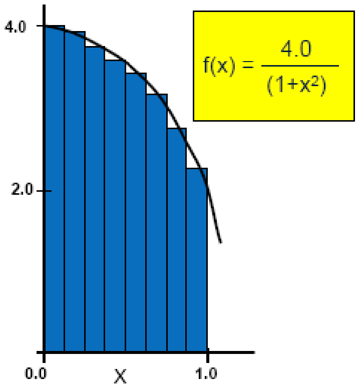
```
A[n] = {…}
B[n] = {…}
Broadcast(B[1..n])
for (i = 1 to n)
  // round robin distribute B
  // to m processors
  Send(A[i % m])
…
```

Reduction

- Example: every processor starts with a value and needs to know the sum of values stored on all processors
- A reduction combines data from all processors and returns it to a single process
  - **MPI_REDUCE**
  - Can apply any associative operation on gathered data
    - ADD, OR, AND, MAX, MIN, etc.
  - No processor can finish reduction before each processor has contributed a value
- **BCAST/REDUCE can reduce programming complexity and may** be more efficient in some programs

Example

- Parallel numerical integration




```
static long num_steps = 100000;

void main()
{
   int i;
   double pi, x, step, sum = 0.0;

   step = 1.0 / (double) num_steps;
   for (i = 0; i < num_steps; i++){
      x = (i + 0.5) * step;
      sum = sum + 4.0 / (1.0 + x*x);
   }

   pi = step * sum;
   printf("Pi = %f\n", pi);
}
```

Computing Pi with Integration (OpenMP)

- Which variables are shared?
  - **step**
- Which variables are private?
  - **x**
- Which variables does reduction apply to?
  - **sum**

```
static long num_steps = 100000;

void main()
{
   int i;
   double pi, x, step, sum = 0.0;

   step = 1.0 / (double) num_steps;

   #pragma omp parallel for \
       private(x) reduction(+:sum)

   for (i = 0; i < num_steps; i++){
      x = (i + 0.5) * step;
      sum = sum + 4.0 / (1.0 + x*x);
   }

   pi = step * sum;
   printf("Pi = %f\n", pi);
}
```

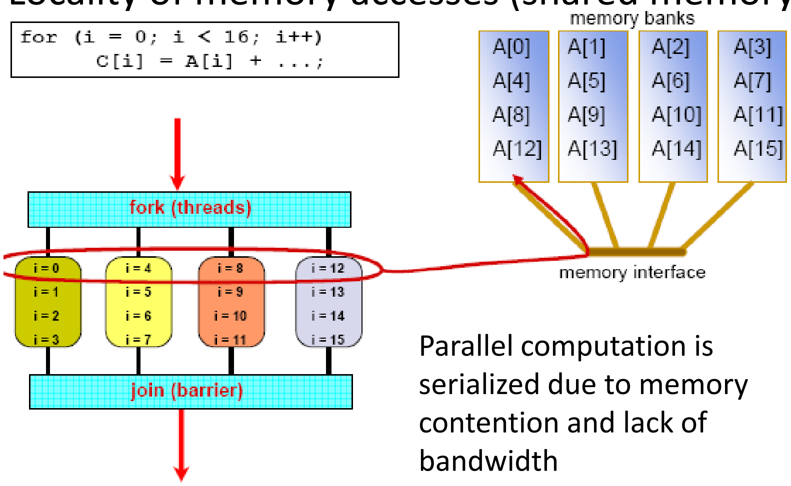
Computing Pi with Integration (MPI)

```
static long num_steps = 100000;
void main(int argc, char* argv[])
{
   int i_start, i_end, i, myid, numprocs;
   double pi, mypi, x, step, sum = 0.0;

   MPI_Init(&argc, &argv);
   MPI_Comm_size(MPI_COMM_WORLD, &numprocs);
   MPI_Comm_rank(MPI_COMM_WORLD, &myid);

   MPI_BCAST(&num_steps, 1, MPI_INT, 0, MPI_COMM_WORLD);

   i_start = my_id * (num_steps/numprocs)
   i_end = i_start + (num_steps/numprocs)

   step = 1.0 / (double) num_steps;

   for (i = i_start; i < i_end; i++) {
        x = (i + 0.5) * step
        sum = sum + 4.0 / (1.0 + x*x);
   }
   mypi = step * sum;

   MPI_REDUCE(&mypi, &pi, 1, MPI_DOUBLE, MPI_SUM, 0, MPI_COMM_WORLD);

   if (myid == 0)
        printf("Pi = %f\n", pi);

   MPI_Finalize();
}
```

Importance of Locality

- Locality of memory accesses (shared memory)

```
for (i = 0; i < 16; i++)
     C[i] = A[i] + ...;
```

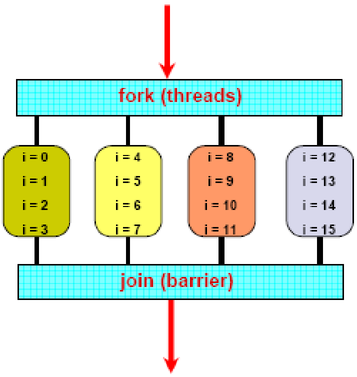


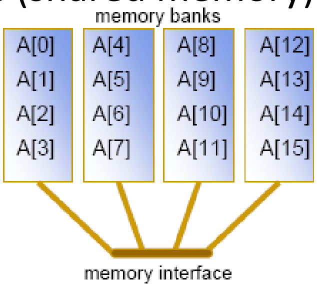
Parallel computation is serialized due to memory contention and lack of bandwidth

Importance of Locality

- Locality of memory accesses (shared memory)

```
for (i = 0; i < 16; i++)
    C[i] = A[i] + ...;
```





Distribute data to relieve contention and increase effective bandwidth