Distributed Computing Paradigms

- Bag of Tasks
- Heartbeat Algorithms
- Pipelining

Bag of Tasks (also called Administrator/Workers)

- Basic idea
  - Server maintains a list (bag) of tasks to be performed
  - Clients send requests to server, receive a task, then may send back additional tasks to server
- Main advantage
  - Automatic load balancing
    - When client needs work, gets some from server

Bag of Tasks Picture (on board)

Bag of Tasks Pseudocode

```
struct task {
   field1; field2; …; fieldN
}
process Manager {
   create initial task
   taskQ.enqueue(task)
   while (1) {
     in getTask(&task) such that taskQ.size > 0
       task = taskQ.dequeue( )
     [] putTask(task)
       taskQ.enqueue(task)
     [] result(val)
       incorporate val into final answer
     ni
   }
}
```

task is a reference parameter to getTask( )

Bag of Tasks Pseudocode

```
process Worker {
  while (1) {
    call getTask(&task)  // procedure call---blocks
    work on task
    if (this task does not need to be subdivided further)
      send result(val)   // val is whatever the "answer" is
    else {    // send task or tasks back into the bag
      send putTask(task1)  // send msg---doesn’t block
      send putTask(task2)  // send msg---doesn’t block
      ...
      send putTask(taskN) // send msg---doesn’t block
    }
  }
}
```

Bag of Tasks Details

- Worker should keep a task for itself
  - When it finishes its task, it needs another
  - Relatively simple to restructure code on last two slides
- Want to avoid too many tasks
  - Just as in recursive parallelism
- Termination is in deadlock
  - Some languages allow this (they detect deadlock)
  - Need a more complicated design to avoid this

Heartbeat Algorithms

- Useful for data parallel, iterative applications
- Basic outline:

```
initialize local variables
while not done
     send values to neighbors
     receive values from neighbors
     perform local computations
```

Region Labeling

- Assume that we are given an image with a given number of lit pixels
- Goal: find sets of connected lit pixels; give each set a unique label

Region Labeling Picture (on board)

Region Labeling

```
process worker [k = 0 to P-1] {
  double pixel[N/P][N], label[N/P][N]
  initialize pixel and label arrays in my strip (the label elements are
    zero if pixel off and unique if pixel on)
  send/receive top/bottom rows of *pixel array* to neighbor
  while not done
      send/receive top/bottom rows of *label array* to neighbor
      *update label array in my strip* (see next slide)
      if any label[i][j] changed
         send "yes" to coordinator
      else
         send " no" to the coordinator
      receive whether to continue from coordinator
}  // end of worker
```

Region Labeling

Updating label array is done as follows:

```
for each of my pixels
  if pixel[i][j] == 1
    for each (N/E/W/S) neighbor who has pixel[i][j] == 1
      if neighbor's label[i][j] > my label[i][j]
        replace my label[i][j] with neighbor's
```

North/East/West/South

Note: this algorithm takes time N^2 if there is a “snake”

Region Labeling

```
process coordinator {
  for each iteration
     collect change flag from each process ("yes" or "no")
     if at least one process sends "yes"
        send "go on" to each process
     else
        send "done" to each process and exit
}    // end of coordinator
```

Can also be done via a global reduction (e.g., Allreduce in MPI)
--do not actually need a separate coordinator process

Region Labeling—Overlapping Communication and Computation

```
process worker [k = 0 to P-1] {
  …same as previous version of worker process…
  while not done
      send top/bottom rows of label to neighbor
      update label array based only on local data
      receive top/bottom rows of label from neighbor
      update label array based on the top and bottom rows
      if any label[i][j] changed, send "yes" to coordinator
      receive whether to continue from coordinator
}  // end of worker
```

Nonblocking send

(New parts in blue; unchanged in gray)

Pipelining

- Another parallel programming paradigm
- First must explain strip mining

Strip Mining

- Original code

```
for i = 1 to n {
    for j = 1 to n {                (j loop is parallel)
      A[i][j] = f(A[i-1][j])
    }
}
```

Problem is that j loop is in many cases too fine-grain to parallelize effectively

Strip Mining

- Could try loop interchange

```
for j = 1 to n {
    for i = 1 to n {
        A[i][j] = f(A[i-1][j])
    }
}
```

(Interchange loops; legal in this case)

Problem is that now there are cache problems with parallelizing j loop

Strip Mining

- First step

```
for i = 1 to n {
    for k = 1 to n by blocksize {
        for j = k to k + blocksize - 1 {
            A[i][j] = f(A[i-1][j])
        }
    }
}
```

(Add an extra loop)

Adding extra loops is generally not a good idea! What's going on?

Strip Mining

- Second step

```
for k = 1 to n by blocksize {
    for i = 1 to n  {                    (Interchange first two loops)
        for j = k to k + blocksize - 1 {
            A[i][j] = f(A[i-1][j])
        }
    }
}
```

Still, we transformed two loops into three. Again…why is this a good idea?

Pipelining

```
for i = 1 to n
    for j = 1 to n
      A[i][j] = f(A[i][j-1])
for i = 1 to n
    for j = 1 to n
      A[i][j] = f(A[i-1][j])
```

How do we parallelize this program?

Options to Parallelize

- Transpose array between first and second loop nests (and between second and first loop nests, if both loops are nested within another loop)
  - Advantage: full parallelization in both loops
  - Disadvantage: transpose is slow (requires all-to-all)
- Sequentialize second loop nest
  - Bad idea: requires data movement and is sequential
- Pipeline second phase
  - Avoids transpose, but suffers pipeline latency and requires a larger number of messages

Pipelining Step 1: parallelize first loop

```
for i = start to end
    for j = 1 to n
      A[i][j] = f(A[i][j-1])
for i = 1 to n
    for j = 1 to n
      A[i][j] = f(A[i-1][j])
```

Standard parallelization of first loop

Pipelining Step 2: rewrite second loop nest via strip mining

```
for i = start to end
    for j = 1 to n
      A[i][j] = f(A[i][j-1])
for k = 1 to n by blocksize
  for i = 1 to n
    for j = k to k + blocksize - 1
      A[i][j] = f(A[i-1][j])
```

We transformed two loops into three via strip mining. Again, why is this a good idea?

Pipelining Step 3: partition middle loop in second loop nest

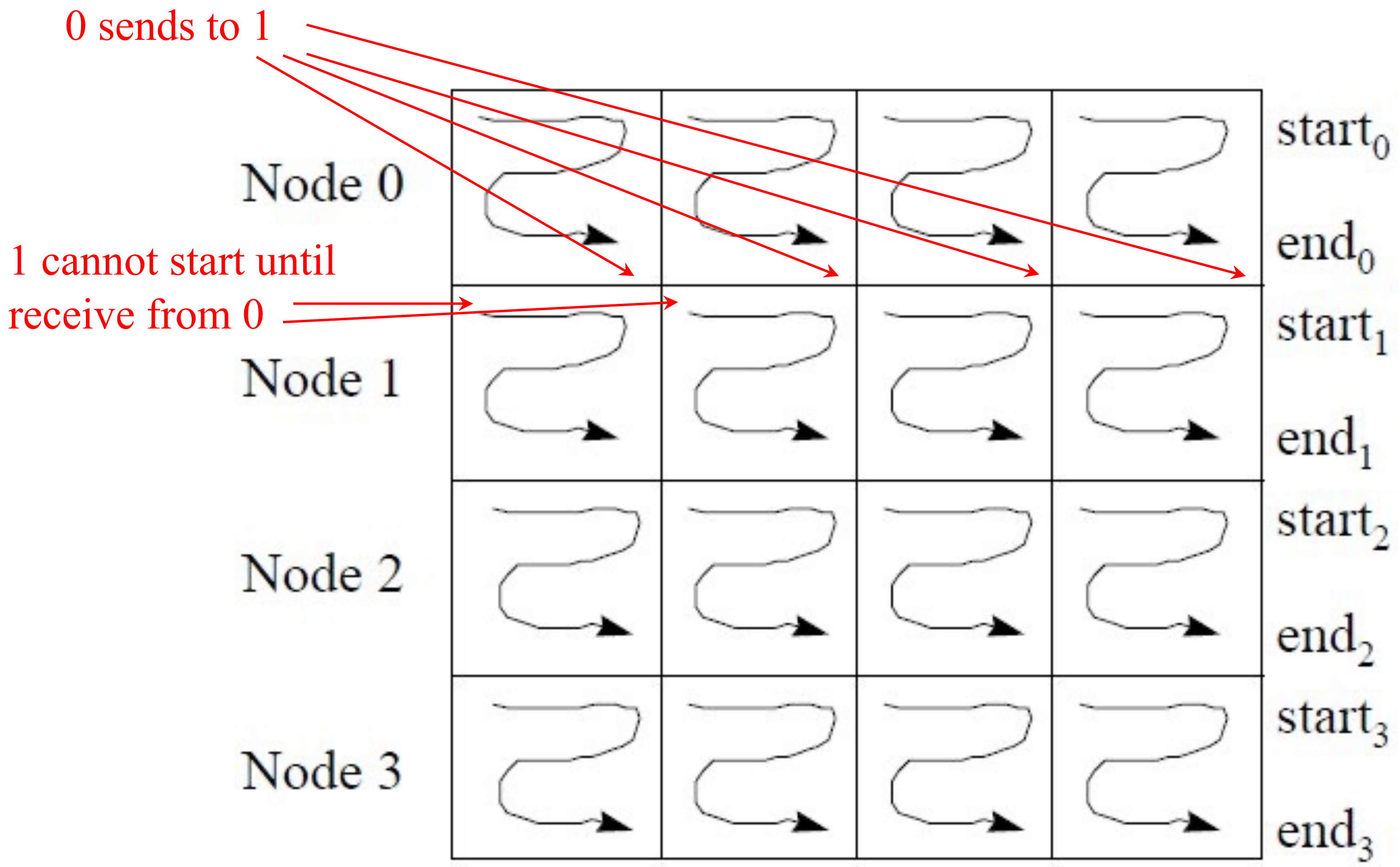
```
for i = start to end
      for j = 1 to n
         A[i][j] = f(A[i][j-1])
for k = 1 to n by blocksize
   for i = start to end
      for j = k to k + blocksize - 1
         A[i][j] = f(A[i-1][j])
```

Note the parallelization is not in the outermost loop

Pipelining Step 4: Insert Synchronization/Communication (code is for each process X, distributed memory, not a "boundary process" [not the first or the last])

```
for i = start to end
    for j = 1 to n
        A[i][j] = f(A[i][j-1])
for k = 1 to n by blocksize
    receive predecessor subrow from process X-1
    for i = start to end
        for j = k to k + blocksize - 1
            A[i][j] = f(A[i-1][j])
    send bottom subrow just computed to process X+1
```

Picture of pipelining



Node 0 computes its second block in parallel with Node 1 computing its first block
Node 1 computes its second block in parallel with Node 2 computing its first block

Pipelining Step 4: Insert Synchronization/Communication (code is for each thread X, shared memory, not a “boundary thread” [not the first or the last])

```
(Global) sem s[0:numThreads-1] = {1,0,0…,0}
for i = start to end
        for j = 1 to n
           A[i][j] = f(A[i][j-1])
  for k = 1 to n by blocksize
        P(s[X-1])
        for i = start to end
            for j = k to k + blocksize - 1
                A[i][j] = f(A[i-1][j])
        V(s[X])
```