Parallel Programming

- Overview
- Parallel programming models
- MPI/OpenMP examples

What is parallel computing?

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- Data parallelism – The program models a physical object, which gets partitioned and divided over the processors.
- Task parallelism – There is a list of tasks (for instance runs of a small program) and processors cycle through this list until it is exhausted.

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  - available memory
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  - solve problems that don't fit on a single CPU
  - solve problems that can't be solved in a reasonable time
- We can solve
  - larger problems
  - faster
  - more cases

Speedup and parallel efficiency

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- Parallel efficiency:

$$E_p = \frac{S_p}{p}$$

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- Practical Limits
  - Load balancing
  - Non-computational sections
- Other Considerations – time to re-write code

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- Suppose we have a sequential code and that a fraction f of its computation is parallelized and run on N processing units working in parallel, while the remaining fraction $(1-f)$ cannot be parallelized. Amdahl's law states that the speedup achieved by parallelization is

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- In reality, the situation is even worse than predicted by Amdahl's law due to:
  - Load balancing (waiting)
  - Scheduling (shared processors or memory)
  - Cost of Communications
  - I/O

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- A parallel platform does more than speeding up the execution of a code: it enables dealing with larger problems.
- Suppose to have an application taking a time t_s to be executed on N processing units. Of that computing time, a fraction $(1 - f)$ must be run sequentially. Accordingly, this application would run on a fully sequential machine in a time t equal to

$$t = t_s(1 - f) + Nt_s f$$

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- If we increase the problem size, we can increase the number of processing units to keep the fraction of time the code is executed in parallel equal to ft_s. In this case, the sequential execution time increases with N which now becomes a measure of the problem size. The speedup then becomes

$$S_N = (1 - f) + Nf$$

Scaling: Strong vs. Weak

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- We want to know how quickly we can complete analysis on a particular data set by increasing the processor count
  - Amdahl's law
  - Known as 'strong scaling'
- We want to know if we can analyze more data in approximately the same amount of time by increasing the processor count
  - Gustafson's law
  - Known as 'weak scaling'

Hardware in parallel computing

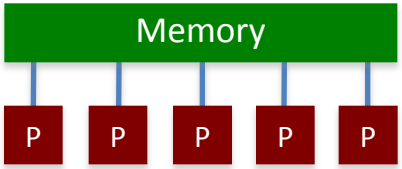
Memory access

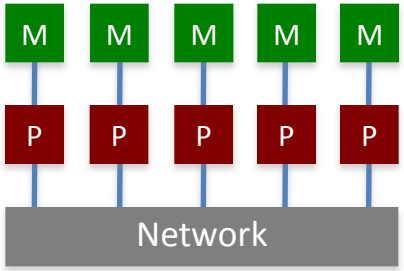
- Shared memory
  - SGI Altix
  - Cluster nodes
- Distributed memory
  - Uniprocessor clusters
- Hybrid
  - Multi-processor clusters

Processor type

- Single core CPU
  - Intel Xeon (Prestonia, Wallatin)
  - AMD Opteron (Sledgehammer, Venus)
  - IBM POWER (3, 4)
- Multi-core CPU (since 2005)
  - Intel Xeon (Paxville, Woodcrest, Harpertown…)
  - AMD Opteron (Barcelona, Shanghai, Istanbul,…)
  - IBM POWER (5, 6…)
- GPU based
  - Tesla systems

Shared and distributed memory

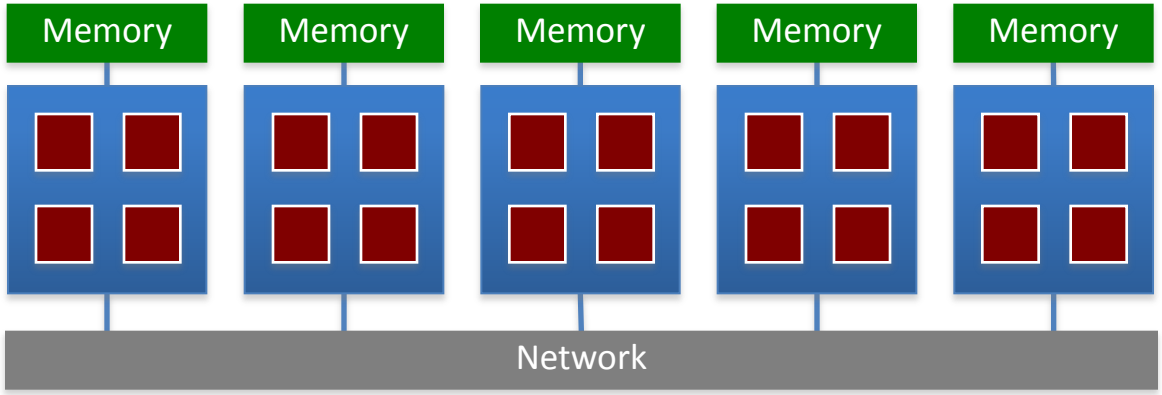




- All processors have access to a pool of shared memory
- Access times vary from CPU to CPU in NUMA systems
- Example: SGI Altix, IBM P5 nodes

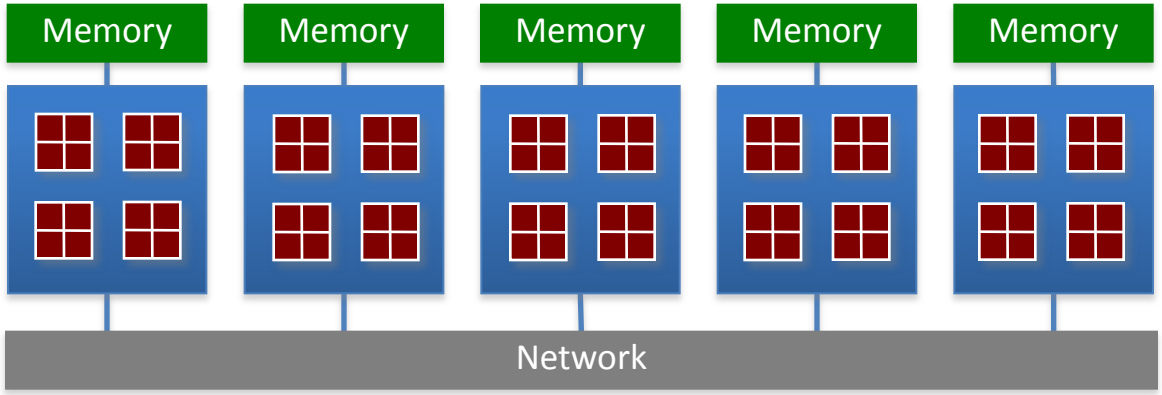
- Memory is local to each processor
- Data exchange by message passing over a network
- Example: Clusters with single-socket blades

Hybrid systems



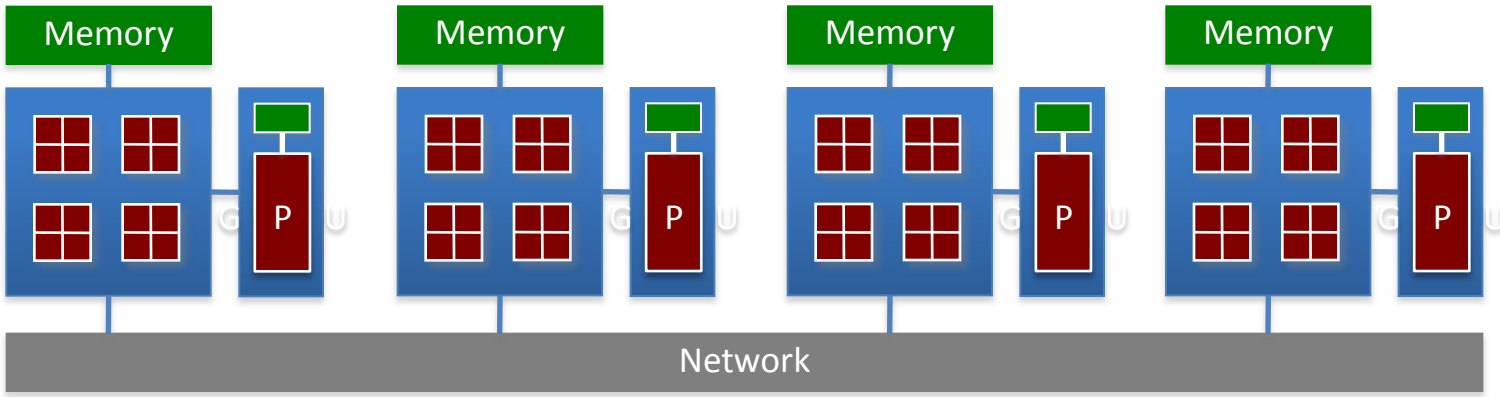
- A limited number, N, of processors have access to a common pool of shared memory
- To use more than N processors requires data exchange over a network
- Example: Cluster with multi-socket blades

Multi-core systems



- Extension of hybrid model
- Communication details increasingly complex
  - Cache access
  - Main memory access
  - Quick Path / Hyper Transport socket connections
  - Node to node connection via network

GPGPU Systems



- Calculations made in both CPUs and Graphical Processing Unit
- No longer limited to single precision calculations
- Load balancing critical for performance
- Requires specific libraries and compilers (CUDA, OpenCL)

Parallel programming models

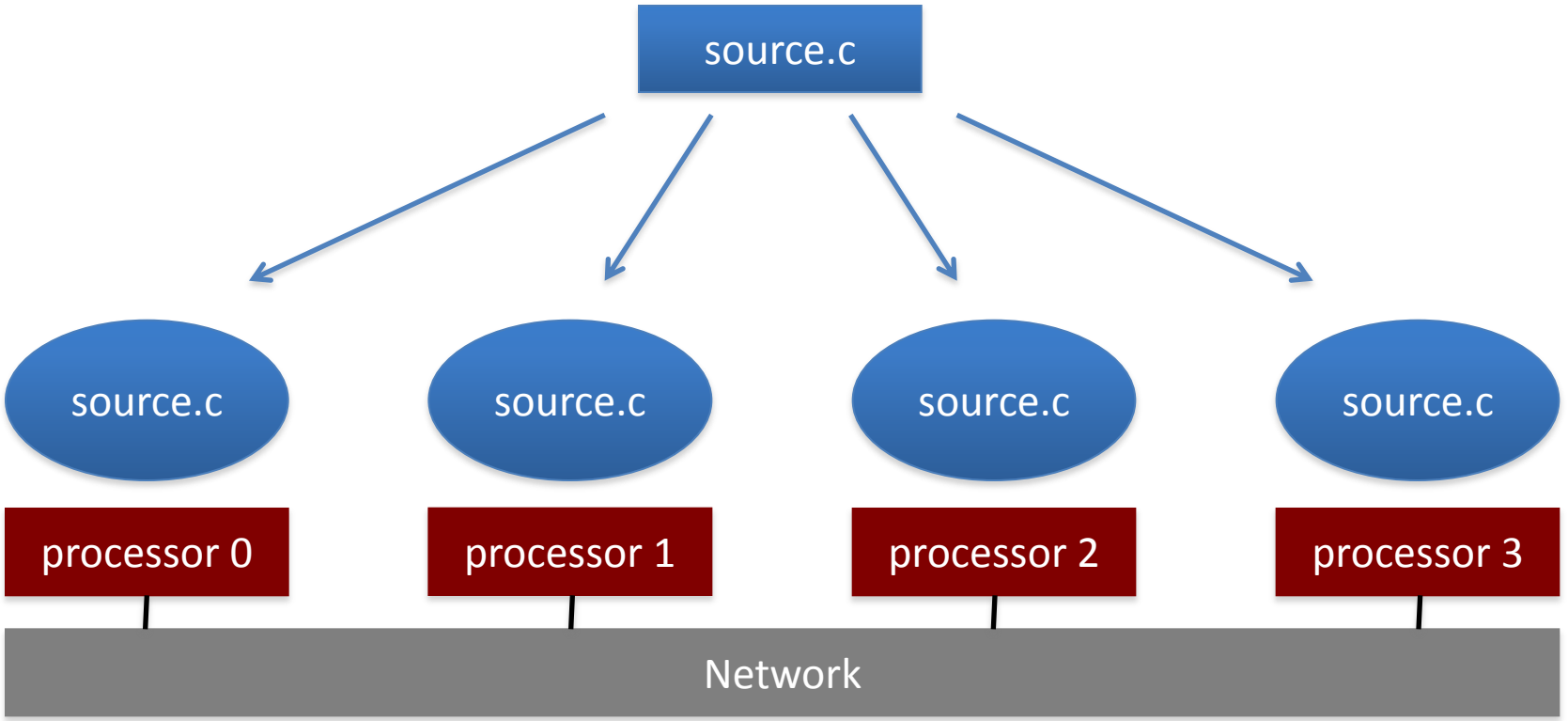
- Data Parallelism
  - Each processor performs the same task on different data
- Task Parallelism
  - Each processor performs a different task on the same data
- Most applications fall between these two

Single Program Multiple Data

- SPMD: dominant programming model for shared and distributed memory machines.
  - One source code is written
  - Code can have conditional execution based on which processor is executing the copy
  - All copies of code start simultaneously and communicate and sync with each other periodically

- MPMD: more general, and possible in hardware, but no system/programming software enables it

SPMD Model


source.c
source.c
source.c
source.c
source.c
processor 0
processor 1
processor 2
processor 3
Network

Data Parallel Programming Example

- One code will run on 2 CPUs
- Program has array of data to be operated on by 2 CPUs so array is split into two parts.

```
program:
…
if CPU=a then
   low_limit=1
   upper_limit=50
elseif CPU=b then
   low_limit=51
   upper_limit=100
end if
do I = low_limit,
upper_limit
   work on A(I)
end do
...
end program
```

CPU A

```
program:
…
low_limit=1
upper_limit=50
do I= low_limit,
upper_limit
   work on A(I)
end do
…
end program
```

CPU B

```
program:
…
low_limit=51
upper_limit=100
do I= low_limit,
upper_limit
   work on A(I)
end do
…
end program
```

Task Parallel Programming Example

- One code will run on 2 CPUs
- Program has 2 tasks (a and b) to be done by 2 CPUs

```
program.f:
…
initialize
...
if CPU=a then
   do task a
elseif CPU=b then
   do task b
end if
….
end program
```

CPU A

```
program.f:
…
initialize
…
do task a
…
end program
```

CPU B

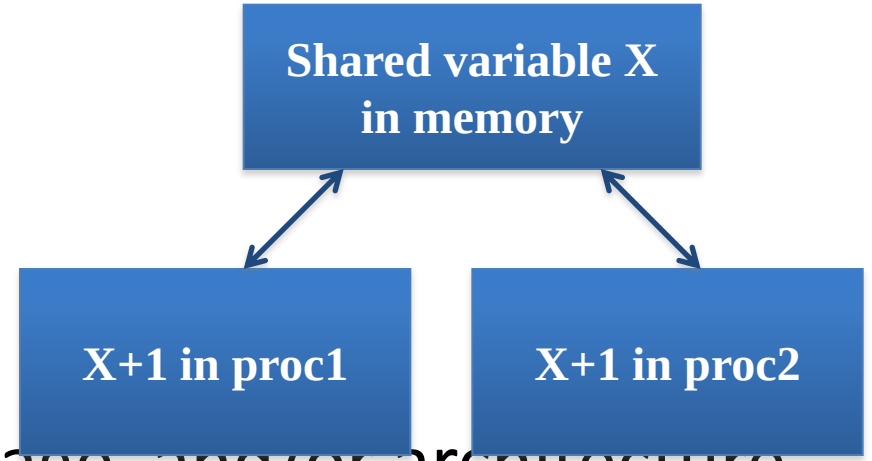
```
program.f:
…
initialize
…
do task b
…
end program
```

Shared Memory Programming: OpenMP

- Shared memory systems (SMPs, cc-NUMAs) have a single address space:
  - applications can be developed in which loop iterations (with no dependencies) are executed by different processors
  - shared memory codes are mostly data parallel, 'SPMD' kinds of codes
  - OpenMP is the standard for shared memory programming (compiler directives)
  - Vendors offer native compiler directives

Accessing Shared Variables

- If multiple processors want to write to a shared variable at the same time, there could be conflicts :
  - Process 1 and 2
  - read X
  - compute X+1
  - write X



- Programmer, language, and/or architecture must provide ways of resolving conflicts

OpenMP Example #1: Parallel Loop

```
!$OMP PARALLEL DO
    do i=1,128
      b(i) = a(i) + c(i)
    end do
!$OMP END PARALLEL DO
```

- The first directive specifies that the loop immediately following should be executed in parallel.
- The second directive specifies the end of the parallel section (optional).
- For codes that spend the majority of their time executing the content of simple loops, the PARALLEL DO directive can result in significant parallel performance.

OpenMP Example #2: Private Variables

```
!$OMP PARALLEL DO SHARED(A,B,C,N) PRIVATE(I,TEMP)
do I=1,N
  TEMP = A(I)/B(I)
  C(I) = TEMP + SQRT(TEMP)
end do
!$OMP END PARALLEL DO
```

- In this loop, each processor needs its own private copy of the variable TEMP.

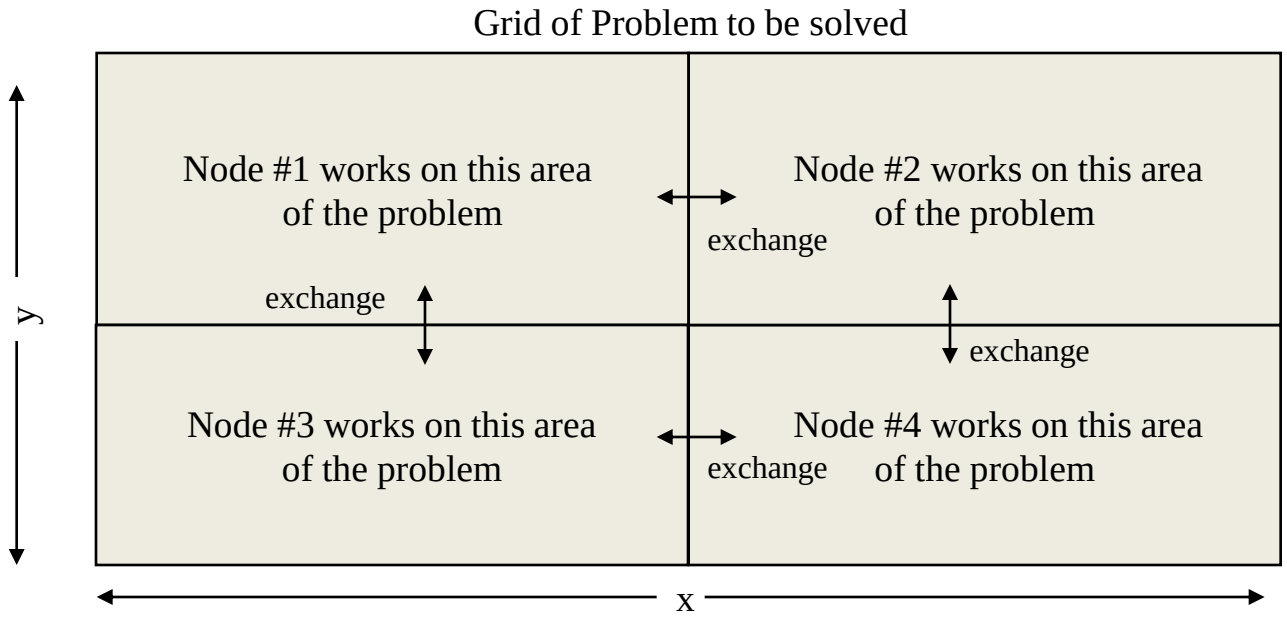
- If TEMP were shared, the result would be unpredictable since multiple processors would be writing to the same memory location.

Distributed Memory Programming: MPI

- Distributed memory systems have separate address spaces for each processor
  - Local memory accessed faster than remote memory
  - Data must be manually decomposed
  - MPI is the standard for distributed memory programming (library of subprogram calls)
  - Older message passing libraries include PVM and P4; all vendors have native libraries such as SHMEM (T3E) and LAPI (IBM)

Data Decomposition

- For distributed memory systems, the 'whole' grid or sum of particles is decomposed to the individual nodes
  - Each node works on its section of the problem
  - Nodes can exchange information



MPI Example #1

- Every MPI program needs these:

```
#include "mpi.h"
int main(int argc, char *argv[])
{
  int nPEs, iam;
  /* Initialize MPI */
  ierr = MPI_Init(&argc, &argv);
  /* How many total PEs are there */
  ierr = MPI_Comm_size(MPI_COMM_WORLD, &nPEs);
  /* What node am I (what is my rank?) */
  ierr = MPI_Comm_rank(MPI_COMM_WORLD, &iam);
  ...
  ierr = MPI_Finalize();
}
```

MPI Example #2

```
#include "mpi.h"
int main(int argc, char *argv[])
{
  int numprocs, myid;
  MPI_Init(&argc,&argv);
  MPI_Comm_size(MPI_COMM_WORLD,&numprocs);
  MPI_Comm_rank(MPI_COMM_WORLD,&myid);
  /* print out my rank and this run's PE size */
  printf("Hello from %d of %d\n", myid, numprocs);
  MPI_Finalize();
}
```

MPI: Sends and Receives

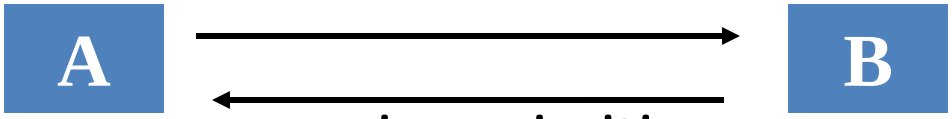
- MPI programs must send and receive data between the processors (communication)

- The most basic calls in MPI (besides the three initialization and one finalization calls) are:
  - MPI_Send
  - MPI_Recv

- These calls are blocking: the source processor issuing the send/receive cannot move to the next statement until the target processor issues the matching receive/send.

Message Passing Communication

- Processes in message passing programs communicate by passing messages



- Basic message passing primitives
- Send (parameters list)
- Receive (parameter list)
- Parameters depend on the library used

MPI Example #3: Send/Receive

```
#include "mpi.h"

int main(int argc,char *argv[])
{
    int numprocs,myid,tag,source,destination,count,buffer;
    MPI_Status status;

    MPI_Init(&argc,&argv);
    MPI_Comm_size(MPI_COMM_WORLD,&numprocs);
    MPI_Comm_rank(MPI_COMM_WORLD,&myid);
    tag=1234;
    source=0;
    destination=1;
    count=1;

    if(myid == source){
        buffer=5678;
        MPI_Send(&buffer,count,MPI_INT,destination,tag,MPI_COMM_WORLD);
        printf("processor %d sent %d\n",myid,buffer);
    }
    if(myid == destination){
        MPI_Recv(&buffer,count,MPI_INT,source,tag,MPI_COMM_WORLD,&status);
        printf("processor %d got %d\n",myid,buffer);
    }
    MPI_Finalize();
}
```