Lecture 4: Gentle Introduction to Parallel Programming

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Models ... Models

- Programming Model
- Computational Model
- Architecture Model
- Machine Model
- Interconnection
- Mem hierarchy
- Execution mode
- Hardware Description
- Cost model
- Programmer’s view
Let’s Start With A Simple Example

• Compute n values and add them together.
• Serial solution:

```c
sum = 0;
for (i = 0; i < n; i++) {
    x = Compute_next_value(. . .);
    sum += x;
}
```
Example (cont.)

- We have $p$ cores, $p$ much smaller than $n$.
- Each core performs a partial sum of approximately $n/p$ values.

```c
my_sum = 0;
my_first_i = ...;
my_last_i = ...;
for (my_i = my_first_i; my_i < my_last_i; my_i++) {
    my_x = Compute_next_value(...);
    my_sum += my_x;
}
```

Each core uses its own private variables and executes this block of code independently of the other cores.
Example (cont.)

• Once all the cores are done computing their private `my_sum`, they form a global sum by sending results to a designated “master” core which adds the final result.
Example (cont.)

```c
if (I'm the master core) {
    sum = my_x;
    for each core other than myself {
        receive value from core;
        sum += value;
    }
} else {
    send my_x to the master;
}
```
But wait!
There’s a much better way to compute the global sum.
Better parallel algorithm

• Don’t make the master core do all the work.
• Share it among the other cores.
• Pair the cores so that core 0 adds its result with core 1’s result.
• Core 2 adds its result with core 3’s result, etc.
• Work with odd and even numbered pairs of cores.
Better parallel algorithm (cont.)

• Repeat the process now with only the evenly ranked cores.
  • Core 0 adds result from core 2.
  • Core 4 adds the result from core 6, etc.

• Now cores divisible by 4 repeat the process, and so forth, until core 0 has the final result.
Multiple cores forming a global sum
Analysis

• In the first example, the master core performs 7 receives and 7 additions.

• In the second example, the master core performs 3 receives and 3 additions.

• The improvement is more than a factor of 2!
Analysis (cont.)

• The difference is more dramatic with a larger number of cores.

• If we have 1000 cores:
  – The first example would require the master to perform 999 receives and 999 additions.
  – The second example would only require 10 receives and 10 additions.

• That's an improvement of almost a factor of 100!
Another Quick Example

• **Problem:** Count the number of times each ASCII character occurs on a page of text.

• **Input:** ASCII text stored as an array of characters.

• **Output:** A histogram with 128 buckets – one for each ASCII character

[source: http://www.futurechips.org/tips-for-power-coders/writing-optimizing-parallel-programs-complete.html]
Let's See A Quick Example

```c
1: void compute_histogram_st(char *page, int page_size, int *histogram){
2:     for(int i = 0; i < page_size; i++){
3:         char read_character = page[i];
4:         histogram[read_character]++;
5:     }
6: }
```

Sequential Version

Speed on Quad Core: 10.36 seconds

source: http://www.futurechips.org/tips-for-power-coders/writing-optimizing-parallel-programs-complete.html
Let's See A Quick Example

We need to parallelize this.

source: http://www.futurechips.org/tips-for-power-coders/writing-optimizing-parallel-programs-complete.html
Let's See A Quick Example

```c
1: void compute_histogram_st(char *page, int page_size, int *histogram){
2: #pragma omp parallel for
3: for(int i = 0; i < page_size; i++){
4:     char read_character = page[i];
5:     histogram[read_character]++;
6: }
```

The above code does not work!! Why?

source: http://www.futurechips.org/tips-for-power-coders/writing-optimizing-parallel-programs-complete.html
Let's See A Quick Example

```c
1: void compute_histogram_mt2(char *page, int page_size, int *histogram){
2:     #pragma omp parallel for
3:     for(int i = 0; i < page_size; i++){
4:         char read_character = page[i];
5:         #pragma omp atomic
6:         histogram[read_character]++;
7:     }
8: }
```

**Speed on Quad Core:**
114.89 seconds

> 10x slower than the single thread version!!

**source:** http://www.futurechips.org/tips-for-power-coders/writing-optimizing-parallel-programsm-complete.html
Let's See A Quick Example

```c
1: void compute_histogram_mt3(char *page,
        int page_size,
        int *histogram, int num_buckets){
 2: #pragma omp parallel
 3: {
 4:    int local_histogram[111][num_buckets];
 5:    int tid = omp_get_thread_num();
 6:    #pragma omp for nowait
 7:      for(int i = 0; i < page_size; i++){
 8:          char read_character = page[i];
 9:          local_histogram[tid][read_character]++;
 10:      }
 11:      for(int i = 0; i < num_buckets; i++){
 12:          #pragma omp atomic
 13:          histogram[i] += local_histogram[tid][i];
 14:      }
 15:  }
 16: }
```

source: http://www.futurechips.org/tips-for-power-coders/writing-optimizing-parallel-programs-complete.html
Let's See A Quick Example

```c
void compute_histogram_mt4(char *page, int page_size,
                            int *histogram, int num_buckets){
    int num_threads = omp_get_max_threads();
    #pragma omp parallel
    {
        __declspec(align(64)) int local_histogram[num_threads+1][num_buckets];
        int tid = omp_get_thread_num();
        #pragma omp for
        for(int i = 0; i < page_size; i++){
            char read_character = page[i];
            local_histogram[tid][read_character]++;
        }
        #pragma omp barrier
        #pragma omp single
        for(int t = 0; t < num_threads; t++){
            for(int i = 0; i < num_buckets; i++)
                histogram[i] += local_histogram[t][i];
        }
    }
}
```

Speed is 4.42 seconds. Slower than the previous version.
void compute_histogram_mt4(char *page, int page_size, int *histogram, int num_buckets) {
    int num_threads = omp_get_max_threads();
    #pragma omp parallel
    {
        __declspec (align(64)) int local_histogram[num_threads+1][num_buckets];
        int tid = omp_get_thread_num();
        #pragma omp for
        for(int i = 0; i < page_size; i++) {
            char read_character = page[i];
            local_histogram[tid][read_character]++;
        }
        #pragma omp for
        for(int i = 0; i < num_buckets; i++) {
            for(int t = 0; t < num_threads; t++)
                histogram[i] += local_histogram[t][i];
        }
    }
    Speed is 3.60 seconds.
}

source: http://www.futurechips.org/tips-for-power-coders/writing-optimizing-parallel-programs-complete.html
What Can We Learn from the Previous Examples?

• Parallel programming is not only about finding a lot of parallelism.

• Critical section and atomic operations
  – Race condition
  – Again: correctness vs performance loss

• Know your tools: language, compiler and hardware
What Can We Learn from the Previous Examples?

• Atomic operations
  – They are expensive
  – Yet, they are fundamental building blocks.

• Synchronization:
  – correctness vs performance loss
  – Rich interaction of hardware-software tradeoffs
  – Must evaluate hardware primitives and software algorithms together
Sources of Performance Loss in Parallel Programs

• Extra overhead
  – load
  – synchronization
  – communication

• Bigger code than sequential version
• Contention due to hardware resources
• Coherence
• Load imbalance
• Artificial dependence
Artificial Dependencies

int result;
//Global variable

for (...) // The OUTER loop
    modify_result(...);
    if(result > threshold)
        break;

void modify_result(...)
    ...
    ...
    result = ...

What is wrong with that program when we try to parallelize it?
Coherence

• Extra bandwidth (scarce resource)
• Latency due to the protocol
• False sharing
Load Balancing
Load Balancing

- Assignment of work not data is the key
- If you cannot eliminate it, at least reduce it.
- Static assignment
- Dynamic assignment
  - Has its overhead
So ...

- We have a serial program.
- How to parallelize it?
- We know that we need to divide work, ensure load balancing, manage synchronization, and reduce communication! → Nice! How to do that?
- Unfortunately: there is no mechanical process.
- Ian Foster has some nice framework.
Foster’s methodology

1. **Partitioning**: divide the computation to be performed and the data operated on by the computation into small tasks.

   The focus here should be on identifying **tasks that can be executed in parallel**.
2. **Communication**: determine what communication needs to be carried out among the tasks identified in the previous step.
Foster’s methodology

3. **Agglomeration or aggregation**: combine tasks and communications identified in the first step into larger tasks.

For example, if task A must be executed before task B can be executed, it may make sense to aggregate them into a single composite task.
4. **Mapping**: assign the composite tasks identified in the previous step to processes/threads.

This should be done so that communication is minimized, and each process/thread gets roughly the same amount of work.
Example - histogram

- 1.3, 2.9, 0.4, 0.3, 1.3, 4.4, 1.7, 0.4, 3.2, 0.3, 4.9, 2.4, 3.1, 4.4, 3.9, 0.4, 4.2, 4.5, 4.9, 0.9
Serial program - input

1. The number of measurements: \texttt{data\_count}
2. An array of \texttt{data\_count} floats: \texttt{data}
3. The minimum value for the bin containing the smallest values: \texttt{min\_meas}
4. The maximum value for the bin containing the largest values: \texttt{max\_meas}
5. The number of bins: \texttt{bin\_count}
• Data[0] = 1.3
• Data[1] = 2.9
• Data[2] = 0.4
• Data[3] = 0.3
• Data[4] = 1.3
• Data[5] = 4.4
• Data[6] = 1.7
• Data[7] = 0.4
• Data[8] = 3.2
• Data[9] = 0.3
• Data[10] = 4.9
• Data[11] = 2.4
• Data[12] = 3.1
• Data[13] = 4.4
• Data[14] = 3.9,
• Data[15] = 0.4
• Data[16] = 4.2
• Data[17] = 4.5
• Data[18] = 4.9
• Data[19] = 0.9

data_count = 20
• Data[0] = 1.3
• Data[1] = 2.9
• Data[2] = 0.4
• Data[3] = 0.3
• Data[4] = 1.3
• Data[5] = 4.4
• Data[6] = 1.7
• Data[7] = 0.4
• Data[8] = 3.2
• Data[9] = 0.3
• Data[10] = 4.9
• Data[11] = 2.4
• Data[12] = 3.1
• Data[13] = 4.4
• Data[14] = 3.9
• Data[15] = 0.4
• Data[16] = 4.2
• Data[17] = 4.5
• Data[18] = 4.9
• Data[19] = 0.9

\textbf{data\_count} = 20
\textbf{min\_meas} = 0.3
\textbf{max\_meas} = 4.9
\textbf{bin\_count} = 5
Serial program - output

1. `bin_maxes`: an array of `bin_count` floats → store the upper bound of each bin

2. `bin_counts`: an array of `bin_count` ints → stores the number of elements in each bin
• $\text{Data}[0] = 1.3$
• $\text{Data}[1] = 2.9$
• $\text{Data}[2] = 0.4$
• $\text{Data}[3] = 0.3$
• $\text{Data}[4] = 1.3$
• $\text{Data}[5] = 4.4$
• $\text{Data}[6] = 1.7$
• $\text{Data}[7] = 0.4$
• $\text{Data}[8] = 3.2$
• $\text{Data}[9] = 0.3$
• $\text{Data}[10] = 4.9$
• $\text{Data}[11] = 2.4$
• $\text{Data}[12] = 3.1$
• $\text{Data}[13] = 4.4$
• $\text{Data}[14] = 3.9$
• $\text{Data}[15] = 0.4$
• $\text{Data}[16] = 4.2$
• $\text{Data}[17] = 4.5$
• $\text{Data}[18] = 4.9$
• $\text{Data}[19] = 0.9$

$\text{bin\_maxes}[0] = 0.9$
$\text{bin\_maxes}[1] = 1.7$
$\text{bin\_maxes}[2] = 2.9$
$\text{bin\_maxes}[3] = 3.9$
$\text{bin\_maxes}[4] = 4.9$

$\text{bin\_counts}[0] = 6$
$\text{bin\_counts}[1] = 3$
$\text{bin\_counts}[2] = 2$
$\text{bin\_counts}[3] = 3$
$\text{bin\_counts}[4] = 6$
int bin = 0;
for( i = 0; i < data_count; i++){
    bin = find_bin(data[i], ...);
    bin_counts[bin]++;
}

First two stages of Foster’s Methodology

Find_bin ... data[i-1]  data[i]  data[i+1] ...

Increment bin_counts ... bin_counts[b-1]++  bin_counts[b]++ ...

Find_bin returns the bin that data[i] belongs to.
Alternative definition of tasks and communication

Find_bin

\[ \text{data}[i-1] \]
\[ \text{data}[i] \]
\[ \text{data}[i+1] \]
\[ \text{data}[i+2] \]

\[ \text{loc_bin_cts}[b-1]++ \]
\[ \text{loc_bin_cts}[b]++ \]
\[ \text{loc_bin_cts}[b-1]++ \]
\[ \text{loc_bin_cts}[b]++ \]

\[ \text{bin_counts}[b-1]+= \]
\[ \text{bin_counts}[b]+= \]
Adding the local arrays
There are several ways for parallelizing an algorithm ... depending on the problem at hand.

What are these ways (or patterns)?
Patterns in Parallelism

• Task-level (e.g. Embarrassingly parallel)
• Divide and conquer
• Pipeline
• Iterations (loops)
• Client-server
• Geometric (usually domain dependent)
• Hybrid (different program phases)
Task Level

Independent Tasks

A
B
C
D
E

A
B
C
E
D
Task Level

- Break application into tasks, decided offline (a priori).
- Generally this scheme does not have strong scalability.
Example 1

```c
while (true) {
    readUserInput();
    drawScreen();
    playSounds();
    strategize();
}
```

Task 1
```c
while (true) {
    readUserInput();
    barrier();
}
```

Task 2
```c
while (true) {
    drawScreen();
    barrier();
}
```

Task 3
```c
while (true) {
    playSounds();
    barrier();
}
```

Task 4
```c
while (true) {
    strategize();
    barrier();
}
```
Example 2

Assume we have a large array and we want to compute its minimum (T1), average (T2), and maximum (T3).

```c
#define maxN 1000000000
int m[maxN];
int i;
int min = m[0];
int max = m[0];
double avrg = m[0];

for(i=1; i < maxN; i++) {
    if(m[i] < min)
        min = m[i];
    avrg = avrg + m[i];
    if(m[i] > max)
        max = m[i];
}
avrg = avrg / maxN;

int i; int min = m[0];
for(i=1; i < maxN; i++) {
    if(m[i] < min)
        min = m[i];
}

int j;
double avrg = m[0];
for(j=1; j < maxN; j++) {
    avrg = avrg + m[j];
}
avrg = avrg / maxN;

int k; int max = m[0];
for(k=1; k < maxN; k++) {
    if(m[k] > max)
        max = m[k];
}
```
Divide-And-Conquer

solution

subproblem

Compute subproblem

merge

subproblem

Compute subproblem

merge

subproblem

Compute subproblem

split

subproblem

Compute subproblem

split

subproblem

Compute subproblem

split

subproblem

Compute subproblem

split

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Compute subproblem

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Compute subproblem

split

subproblem

Compute subproblem

split

subproblem
Divide-And-Conquer

Sequentially, it looks like this:

```// Input: A
DnD(A) {
    if(A is a base case)
        return solution(A);
    else {
        split A into N subproblems B[N];
        for(int i=0;i<N;i++)
            sol[i] = DnD(B[i]);  //
        return mergeSolution(sol);
    }
}
Divide-And-Conquer

Parallel Version:

```java
// Input: A
DnD(A) {
    if(isBaseCase(A))
        return solution(A);
    else {
        if(bigEnoughForSplit(A)) { // if problem is big enough
            split A into N subproblems B[N];
            for(int i=0;i<N;i++)
                task[i] = newTask(DnD(B[i])); // non-blocking

            for(int i=0;i<N;i++)
                sol[i] = getTaskResult(task[i]); // blocking results

            return mergeSolution(sol);
        }
        else { // else solve sequentially
            return solution(A);
        }
    }
}
```
A series of ordered but independent computation stages need to be applied on data.
Pipeline

• Useful for
  – streaming workloads
  – Loops that are hard to parallelize
    • due inter-loop dependence

• How to do it?
  1. Split each loop iteration into independent stages (e.g. S1, S2, S3, ...)
  2. Assign each stage to a thread (e.g. T1 does S1, T2 does S2, ...).
  3. When a thread is done with each stage, it can start the same stage for the following loop iteration (e.g. T1 finishes S1 of iteration 0, then start S1 of iteration 1, etc.).

• Advantages
  – Expose intra-loop parallelism
  – Locality increases for variables used across stages

• How shall we divide an iteration into stages?
  – number of stages
  – inter-loop vs intra-loop dependence
Example of pipeline parallelism

while(!done) {
    Read block;
    Compress the block;
    Write block;
}

Source of example:
Example of pipeline parallelism

Assume 8 iterations

Source of example:
Whenever a thread is done with its task it can take another one from a repository.
The Big Picture of Parallel Programming

Decomposition

- Task Decomposition
- Data Decomposition

Dependence Analysis

- Group Tasks
- Order Tasks
- Data Sharing

Design Evaluation

Source: David Kirk/NVIDIA and Wen-mei W. Hwu /UIUC
BUGS

• Sequential programming bugs + more
• Hard to find
• Even harder to resolve 😞
• Major reason for bugs: race condition
How to Avoid Race Condition?

- Prohibit more than one process from reading and writing the shared data at the same time -> **mutual exclusion**
- The part of the program where the shared memory is accessed is called the **critical region**

**source:** http://www.futurechips.org/wp-content/uploads/2011/06/Screenshot20110618at12.11.05AM.png
Conditions of Good Solutions to Race Condition

1. No two threads may be simultaneously inside their critical region
2. No assumptions may be made about speeds or the number of CPUs/Cores
3. No thread running outside its critical region may block other processes
4. No thread has to wait forever to enter its critical region
About Threads

• Thread vs Process
  – Process consists of one or more threads
  – Each thread has its own stack

• Once created a thread can be in one of 4 states: ready, running, waiting (blocked), or terminated.
Multithreaded Programs

• Using established APIs at the application program
  – Example: Pthreads and OpenMP

• OpenMP:
  – developer-friendly
  – Requires compiler supporting OpenMP API

• Pthreads
  – More lower-level
  – More control and richer constructs

• Higher-level languages exist, but they tend to
  sacrifice performance to make program-
  development easier.
  – Example: Haskell
Conclusions

• Pick your programming model
• Task decomposition vs Data decomposition
• Refine based on:
  – What compiler can do
  – What runtime can do
  – What the hardware provides