CSE373: Data Structures & Algorithms
Lecture 27: Parallel Reductions, Maps, and Algorithm Analysis

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This week….

• Homework 6 due today!
  – Done with all homeworks 😊

• Course Evaluations – Time at the end of lecture

• Lecture Friday
  – Final exam review

• Final exam next Tuesday in this room at 2.30pm
  – Details are on the website
  – Practice past midterms
Outline

Done:
• How to write a parallel algorithm with fork and join
• Why using divide-and-conquer with lots of small tasks is best
  – Combines results in parallel
  – (Assuming library can handle “lots of small threads”)

Now:
• More examples of simple parallel programs that fit the “map” or
  “reduce” patterns
• Teaser: Beyond maps and reductions
• Asymptotic analysis for fork-join parallelism
• Amdahl’s Law
What else looks like this?

• Saw summing an array went from $O(n)$ sequential to $O(\log n)$ parallel (assuming a lot of processors and very large $n$)
  – Exponential speed-up in theory ($n / \log n$ grows exponentially)

• Anything that can use results from two halves and merge them in $O(1)$ time has the same property…
Examples

• Maximum or minimum element
• Is there an element satisfying some property (e.g., is there a 17)?
• Left-most element satisfying some property (e.g., first 17)
• Corners of a rectangle containing all points (a “bounding box”)
• Counts, for example, number of strings that start with a vowel
  – This is just summing with a different base case
  – Many problems are!
Reductions

• Computations of this form are called reductions

• Produce single answer from collection via an associative operator
  – Associative: \( a + (b+c) = (a+b) + c \)
  – Examples: max, count, leftmost, rightmost, sum, product, …
  – Non-examples: median, subtraction, exponentiation
Even easier: Maps (Data Parallelism)

- A map operates on each element of a collection independently to create a new collection of the same size
  - No combining results
  - For arrays, this is so trivial some hardware has direct support
- Canonical example: Vector addition

```java
int[] vector_add(int[] arr1, int[] arr2) {
    assert (arr1.length == arr2.length);
    result = new int[arr1.length];
    FORALL (i=0; i < arr1.length; i++) {
        result[i] = arr1[i] + arr2[i];
    }
    return result;
}
```
Maps and reductions

Maps and reductions: the “workhorses” of parallel programming

– By far the two most important and common patterns

– Learn to recognize when an algorithm can be written in terms of maps and reductions

– Use maps and reductions to describe (parallel) algorithms

– Programming them becomes “trivial” with a little practice
  • Exactly like sequential for-loops seem second-nature
Beyond maps and reductions

• Some problems are “inherently sequential”
  “Six ovens can’t bake a pie in 10 minutes instead of an hour”

• But not all parallelizable problems are maps and reductions

• If had one more lecture, would show “parallel prefix”, a clever algorithm to parallelize the problem that this sequential code solves

```java
int[] prefix_sum(int[] input){
    int[] output = new int[input.length];
    output[0] = input[0];
    for(int i=1; i < input.length; i++)
        output[i] = output[i-1]+input[i];
    return output;
}
```

<table>
<thead>
<tr>
<th>input</th>
<th>6</th>
<th>4</th>
<th>16</th>
<th>10</th>
<th>16</th>
<th>14</th>
<th>2</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>output</td>
<td>6</td>
<td>10</td>
<td>26</td>
<td>36</td>
<td>52</td>
<td>66</td>
<td>68</td>
<td>76</td>
</tr>
</tbody>
</table>
**Digression: MapReduce on clusters**

- You may have heard of Google’s “map/reduce”
  - Or the open-source version Hadoop
- Idea: Perform maps/reduces on data using many machines
  - The system takes care of distributing the data and managing fault tolerance
  - You just write code to map one element and reduce elements to a combined result
- Separates how to do recursive divide-and-conquer from what computation to perform
  - Separating concerns is good software engineering
Analyzing algorithms

• Like all algorithms, parallel algorithms should be:
  – Correct
  – Efficient

• For our algorithms so far, correctness is “obvious” so we’ll focus on efficiency
  – Want asymptotic bounds
  – Want to analyze the algorithm without regard to a specific number of processors
  – Here: Identify the “best we can do” if the underlying thread-scheduler does its part
Work and Span

Let $T_P$ be the running time if there are $P$ processors available

Two key measures of run-time:

- **Work**: How long it would take 1 processor = $T_1$
  - Just “sequentialize” the recursive forking

- **Span**: How long it would take infinite processors = $T_\infty$
  - The longest dependence-chain
  - Example: $O(\log n)$ for summing an array
    - Notice having $> n/2$ processors is no additional help
Our simple examples

- Picture showing all the “stuff that happens” during a reduction or a map: it’s a (conceptual!) DAG
Connecting to performance

• Recall: $T_P = \text{running time if there are } P \text{ processors available}$

• Work = $T_1 = \text{sum of run-time of all nodes in the DAG}$
  – That lonely processor does everything
  – Any topological sort is a legal execution
  – $O(n)$ for maps and reductions

• Span = $T_\infty = \text{sum of run-time of all nodes on the most-expensive path in the DAG}$
  – Note: costs are on the nodes not the edges
  – Our infinite army can do everything that is ready to be done, but still has to wait for earlier results
  – $O(\log n)$ for simple maps and reductions
Speed-up

Parallel algorithms is about decreasing span without increasing work too much

• Speed-up on $P$ processors: $T_1 / T_P$

• Parallelism is the maximum possible speed-up: $T_1 / T_\infty$
  – At some point, adding processors won’t help
  – What that point is depends on the span

• In practice we have $P$ processors. How well can we do?
  – We cannot do better than $O(T_\infty)$ (“must obey the span”)
  – We cannot do better than $O(T_1 / P)$ (“must do all the work”)
Examples

\[ T_P = O(\max((T_1 / P), T_\infty)) \]

• In the algorithms seen so far (e.g., sum an array):
  – \( T_1 = O(n) \)
  – \( T_\infty = O(\log n) \)
  – So expect (ignoring overheads): \( T_P = O(\max(n/P, \log n)) \)

• Suppose instead:
  – \( T_1 = O(n^2) \)
  – \( T_\infty = O(n) \)
  – So expect (ignoring overheads): \( T_P = O(\max(n^2/P, n)) \)
Amdahl’s Law (mostly bad news)

- So far: analyze parallel programs in terms of work and span

- In practice, typically have parts of programs that parallelize well…
  - Such as maps/reductions over arrays

  …and parts that don’t parallelize at all

  - Such as reading a linked list, getting input, doing computations where each needs the previous step, etc.
Amdahl’s Law (mostly bad news)

Let the work (time to run on 1 processor) be 1 unit time.

Let $S$ be the portion of the execution that can’t be parallelized.

Then:

$$T_1 = S + (1-S) = 1$$

Suppose parallel portion parallelizes perfectly (generous assumption).

Then:

$$T_P = S + (1-S)/P$$

So the overall speedup with $P$ processors is (Amdahl’s Law):

$$T_1 / T_P = 1 / (S + (1-S)/P)$$

And the parallelism (infinite processors) is:

$$T_1 / T_\infty = 1 / S$$
Why such bad news

\[ \frac{T_1}{T_P} = \frac{1}{S + \frac{1-S}{P}} \quad \text{and} \quad \frac{T_1}{T_\infty} = \frac{1}{S} \]

- Suppose 33% of a program’s execution is sequential
  - Then a billion processors won’t give a speedup over 3

- Suppose you miss the good old days (1980-2005) where 12ish years was long enough to get 100x speedup
  - Now suppose in 12 years, clock speed is the same but you get 256 processors instead of 1
  - For 256 processors to get at least 100x speedup, we need
    \[ 100 \leq \frac{1}{S + \frac{1-S}{256}} \]
    Which means \( S \leq 0.0061 \) (i.e., 99.4% perfectly parallelizable)
All is not lost

Amdahl’s Law is a bummer!
   – Unparallelized parts become a bottleneck very quickly
   – But it doesn’t mean additional processors are worthless

• We can find new parallel algorithms
   – Some things that seem sequential are actually parallelizable

• We can change the problem or do new things
   – Example: computer graphics use tons of parallel processors
     • Graphics Processing Units (GPUs) are massively parallel
     • They are not rendering 10-year-old graphics faster
     • They are rendering more detailed/sophisticated images
Moore and Amdahl

- Moore’s “Law” is an observation about the progress of the semiconductor industry
  - Transistor density doubles roughly every 18 months
- Amdahl’s Law is a mathematical theorem
  - Diminishing returns of adding more processors
- Both are incredibly important in designing computer systems
Course evals....

• PLEASE do them
  – I’m giving you time now 😊

• What you liked, what you didn’t like

• https://uw.iasystem.org/survey/146029