A Sophomoric Introduction to Shared-Memory Parallelism and Concurrency

Lecture 3
Parallel Prefix, Pack, and Sorting

Steve Wolfman, based on work by Dan Grossman

Learning Goals

- Judge appropriate contexts for and apply the parallel map, parallel reduce, and parallel prefix computation patterns.
- And also... lots of practice using map, reduce, work, span, general asymptotic analysis, tree structures, sorting algorithms, and more!

Outline

Done:

- Simple ways to use parallelism for counting, summing, finding
- (Even though in practice getting speed-up may not be simple)
- Analysis of running time and implications of Amdahl's Law

Now: Clever ways to parallelize more than is intuitively possible

- Parallel prefix
- Parallel pack (AKA filter)
- Parallel sorting
 - quicksort (not in place)
 - mergesort

The prefix-sum problem

Given a list of integers as input, produce a list of integers as output where output[i] = input[0]+input[1]+...+input[i]

Sequential version is straightforward:

```
Vector<int> prefix_sum(const vector<int>& input) {
  vector<int> output(input.size());
  output[0] = input[0];
  for(int i=1; i < input.size(); i++)
    output[i] = output[i-1]+input[i];
  return output;
}</pre>
```

Example:

input	42	3	4	7	1	10
output						

The prefix-sum problem

Given a list of integers as input, produce a list of integers as output where output[i] = input[0]+input[1]+...+input[i]

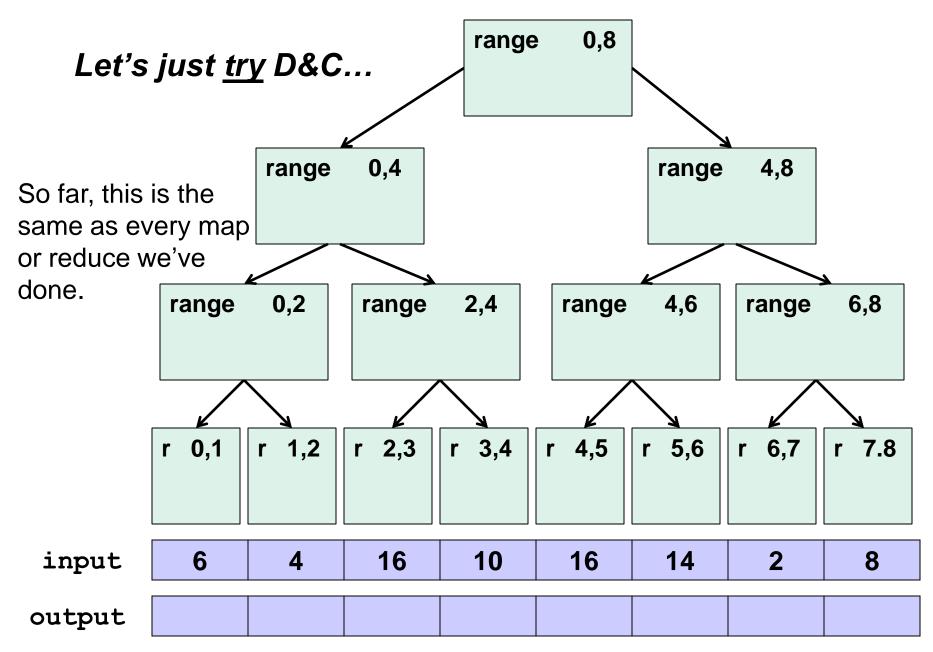
Sequential version is straightforward:

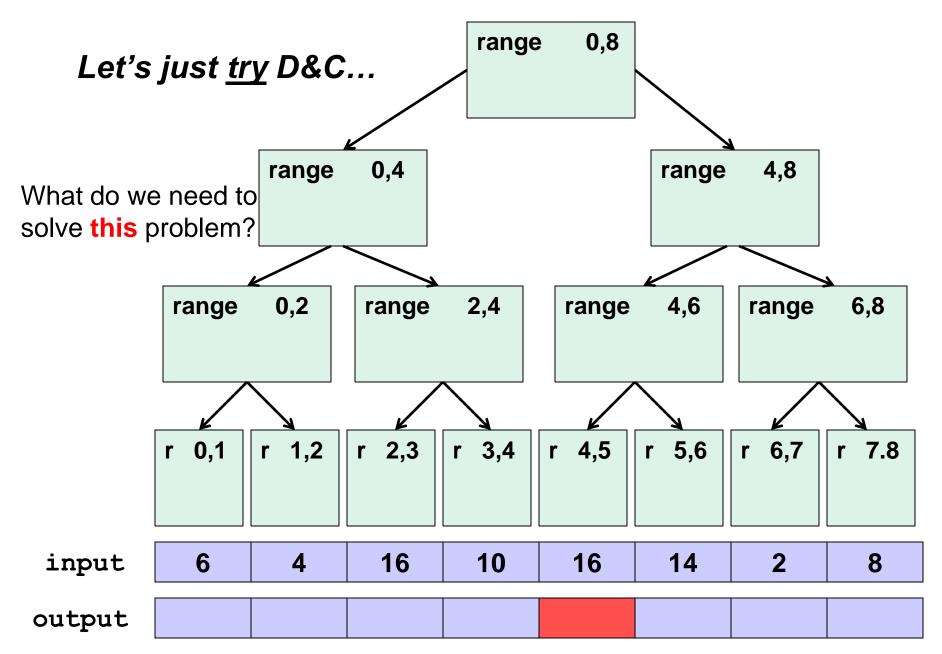
```
Vector<int> prefix_sum(const vector<int>& input) {
  vector<int> output(input.size());
  output[0] = input[0];
  for(int i=1; i < input.size(); i++)
    output[i] = output[i-1]+input[i];
  return output;
}</pre>
```

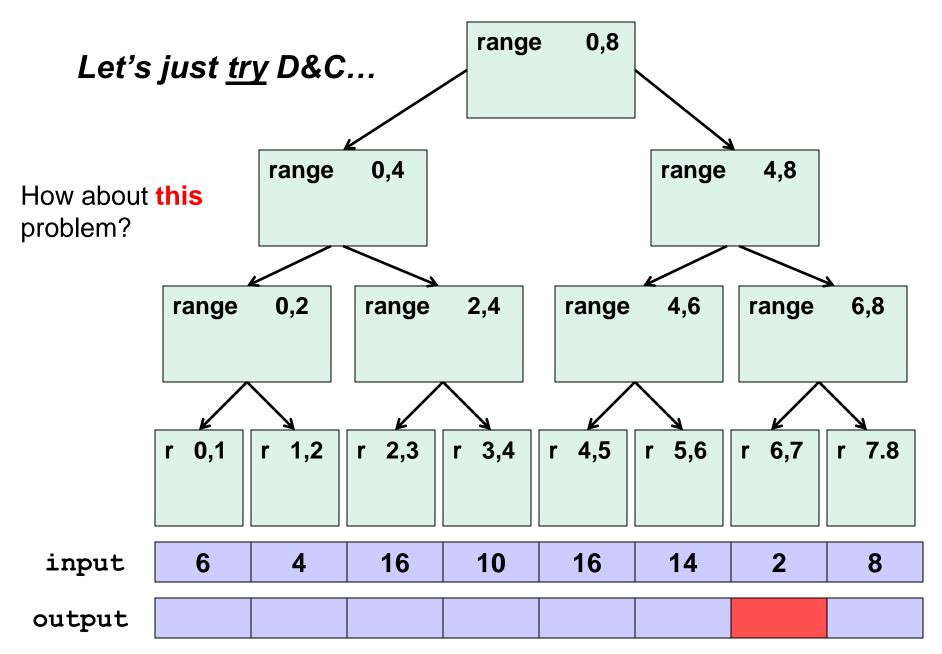
Why isn't this (obviously) parallelizable? Isn't it just map or reduce?

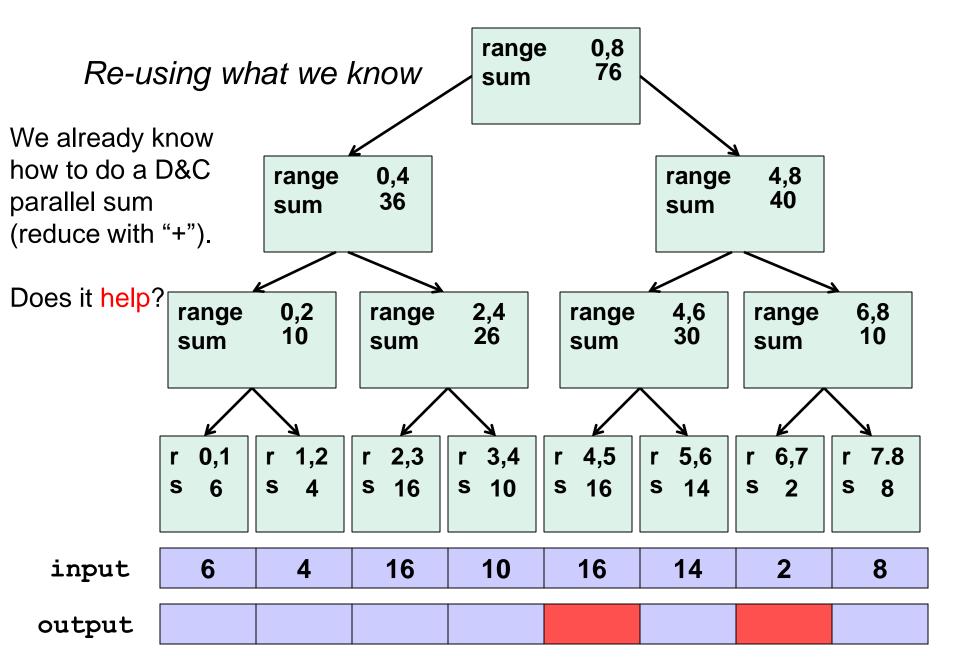
Work:

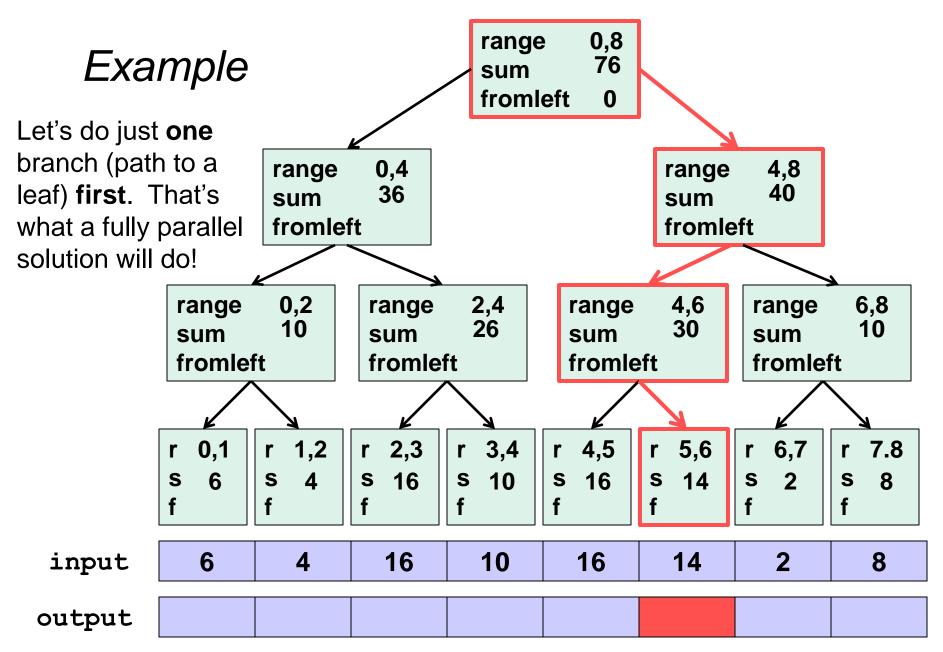
Span:











Parallel prefix-sum

The parallel-prefix algorithm does two passes:

- 1. build a "sum" tree bottom-up
- 2. traverse the tree top-down, accumulating the sum from the left

The algorithm, step 1

- 1. Step one does a parallel sum to build a binary tree:
 - Root has sum of the range [0, n)
 - An internal node with the sum of [lo,hi) has
 - Left child with sum of [lo,middle)
 - Right child with sum of [middle, hi)
 - A leaf has sum of [i,i+1), i.e., input[i]

How? Parallel sum but explicitly build a tree:

Step 1: Work? Span?

The algorithm, step 2

- 2. Parallel map, passing down a fromLeft parameter
 - Root gets a fromLeft of 0
 - Internal node along:
 - to its left child the same fromLeft

(already calculated in step 1!)

- to its right child fromLeft plus its left child's sum
- At a leaf node for array position i, output[i]=fromLeft+input[i]

How? A map down the step 1 tree, leaving results in the output array. Notice the *invariant*: **fromLeft** is the sum of elements left of the node's range

Step 2: Work? Span?

Parallel prefix-sum

The parallel-prefix algorithm does two passes:

1. build a "sum" tree bottom-up

2. traverse the tree top-down, accumulating the sum from the left

Step 1: Work: *O*(*n*) Span: *O*(**lg** *n*)

Step 2: Work: O(n) Span: $O(\lg n)$

Overall: Work? Span?

Paralellism (work/span)?

Parallel prefix, generalized

Can we use parallel prefix to calculate the minimum of all elements to the left of i?

In general, what property do we need for the operation we use in a parallel prefix computation?

Outline

Done:

- Simple ways to use parallelism for counting, summing, finding
- (Even though in practice getting speed-up may not be simple)
- Analysis of running time and implications of Amdahl's Law

Now: Clever ways to parallelize more than is intuitively possible

- Parallel prefix
- Parallel pack (AKA filter)
- Parallel sorting
 - quicksort (not in place)
 - mergesort

Pack

AKA, filter ©

Given an array input, produce an array output containing only elements such that f(elt) is true

Parallelizable? Sure, using a list concatenation reduction.

Efficiently parallelizable on arrays?

Can we just put the output straight into the array at the right spots?

Pack as map, reduce, prefix combo??

Given an array input, produce an array output containing only elements such that f(elt) is true

```
Example: input [17, 4, 6, 8, 11, 5, 13, 19, 0, 24] f: is elt > 10
```

Which pieces can we do as maps, reduces, or prefixes?

Parallel prefix to the rescue

1. Parallel map to compute a bit-vector for true elements

```
input [17, 4, 6, 8, 11, 5, 13, 19, 0, 24] bits [1, 0, 0, 0, 1, 0, 1, 1, 0, 1]
```

2. Parallel-prefix sum on the bit-vector

```
bitsum [1, 1, 1, 1, 2, 2, 3, 4, 4, 5]
```

3. Parallel map to produce the output output [17, 11, 13, 19, 24]

```
output = new array of size bitsum[n-1]
FORALL(i=0; i < input.size(); i++) {
  if(bits[i])
   output[bitsum[i]-1] = input[i];
}</pre>
```

Pack Analysis

Step 1: Work? Span?

(compute bit-vector w/a parallel map)

Step 2: Work? Span?

(compute bit-sum w/a parallel prefix sum)

Step 3: Work? Span?

(emplace output w/a parallel map)

Algorithm: Work? Span?

Parallelism?

Outline

Done:

- Simple ways to use parallelism for counting, summing, finding
- (Even though in practice getting speed-up may not be simple)
- Analysis of running time and implications of Amdahl's Law

Now: Clever ways to parallelize more than is intuitively possible

- Parallel prefix
- Parallel pack (AKA filter)
- Parallel sorting
 - quicksort (not in place)
 - mergesort

Parallelizing Quicksort

Recall quicksort was sequential, in-place, expected time $O(n \lg n)$

Best / expected case work

- 1. Pick a pivot element O(1)
- 2. Partition all the data into: O(n)
 - A. The elements less than the pivot
 - B. The pivot
 - C. The elements greater than the pivot
- 3. Recursively sort A and C 2T(n/2)

How do we parallelize this?

What span do we get?

$$T_{\infty}(n) =$$

How good is O(1g n) Parallelism?

Given an infinite number of processors, O(1g n) faster.

So... sort 109 elements 30 times faster?! That's not much 🕾

Can't we do better? What's causing the trouble?

(Would using **O**(n) space help?)

Parallelizing Quicksort

Recall quicksort was sequential, in-place, expected time $O(n \lg n)$

Best / expected case work

- 1. Pick a pivot element O(1)
- 2. Partition all the data into: O(n)
 - A. The elements less than the pivot
 - B. The pivot
 - C. The elements greater than the pivot
- 3. Recursively sort A and C 2T(n/2)

How do we parallelize this?

What span do we get?

$$T_{\infty}(n) =$$

Analyzing
$$T_{\infty}(n) = 1g n + T_{\infty}(n/2)$$

Turns out our techniques from way back at the start of the term will work just fine for this:

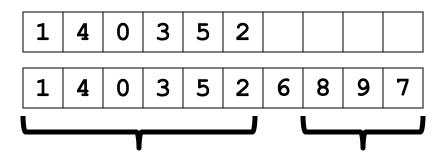
$$T_{\infty}(n) = 1g n + T_{\infty}(n/2)$$
 if $n > 1$
= 1 otherwise

Parallel Quicksort Example

Step 1: pick pivot as median of three



- Steps 2a and 2c (combinable): pack less than, then pack greater than into a second array
 - Fancy parallel prefix to pull this off not shown



 Step 3: Two recursive sorts in parallel (can limit extra space to one array of size n, as in mergesort)

Outline

Done:

- Simple ways to use parallelism for counting, summing, finding
- (Even though in practice getting speed-up may not be simple)
- Analysis of running time and implications of Amdahl's Law

Now: Clever ways to parallelize more than is intuitively possible

- Parallel prefix
- Parallel pack (AKA filter)
- Parallel sorting
 - quicksort (not in place)
 - mergesort

mergesort

Recall mergesort: sequential, not-in-place, worst-case $O(n \lg n)$

- 1. Sort left half and right half
- 2. Merge results

2T(n/2)

O(n)

Just like quicksort, doing the two recursive sorts in parallel changes the recurrence for the span to $T(n) = O(n) + 1T(n/2) \in O(n)$

- Again, parallelism is O(1g n)
- To do better, need to parallelize the merge
 - The trick won't use parallel prefix this time

Need to merge two *sorted* subarrays (may not have the same size)



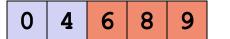


Idea: Suppose the larger subarray has *n* elements. In parallel:

- merge the first *n*/2 elements of the larger half with the "appropriate" elements of the smaller half
- merge the second n/2 elements of the larger half with the rest of the smaller half

0 4 6 8 9

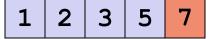
1 2 3 5 7



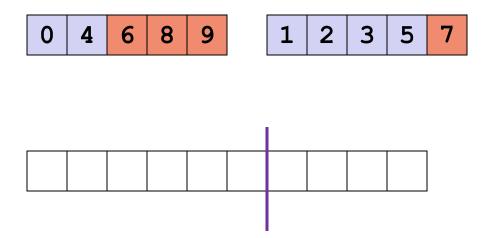


1. Get median of bigger half: O(1) to compute middle index

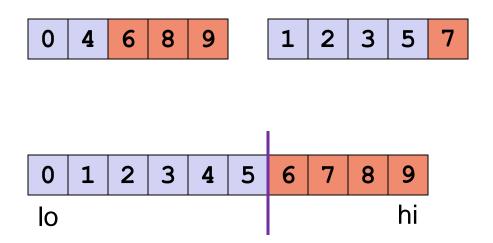




- 1. Get median of bigger half: O(1) to compute middle index
- Find how to split the smaller half at the same value as the lefthalf split: O(1g n) to do binary search on the sorted small half

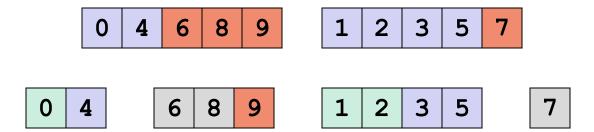


- 1. Get median of bigger half: O(1) to compute middle index
- Find how to split the smaller half at the same value as the lefthalf split: O(1g n) to do binary search on the sorted small half
- 3. Size of two sub-merges conceptually splits output array: O(1)



- 1. Get median of bigger half: O(1) to compute middle index
- 2. Find how to split the smaller half at the same value as the left-half split: $O(\lg n)$ to do binary search on the sorted small half
- 3. Size of two sub-merges conceptually splits output array: O(1)
- 4. Do two submerges in parallel

The Recursion



When we do each merge in parallel, we split the bigger one in half and use binary search to split the smaller one

Analysis

Sequential recurrence for mergesort:

$$T(n) = 2T(n/2) + O(n)$$
 which is $O(n \lg n)$

- Doing the two recursive calls in parallel but a sequential merge: work: same as sequential span: T(n)=1T(n/2)+O(n) which is O(n)
- Parallel merge makes work and span harder to compute
 - Each merge step does an extra O(1g n) binary search to find how to split the smaller subarray
 - To merge n elements total, do two smaller merges of possibly different sizes
 - But worst-case split is (1/4)n and (3/4)n
 - When subarrays same size and "smaller" splits "all" / "none"

Analysis continued

For just a parallel merge of *n* elements:

- Span is $T(n) = T(3n/4) + O(\lg n)$, which is $O(\lg^2 n)$
- Work is $T(n) = T(3n/4) + T(n/4) + O(\lg n)$ which is O(n)
- (neither bound is immediately obvious, but "trust me")

So for mergesort with parallel merge overall:

- Span is $T(n) = 1T(n/2) + O(1g^2 n)$, which is $O(1g^3 n)$
- Work is T(n) = 2T(n/2) + O(n), which is $O(n \lg n)$

So parallelism (work / span) is $O(n / \lg^2 n)$

- Not quite as good as quicksort, but worst-case guarantee
- And as always this is just the asymptotic result

Looking for Answers?

The prefix-sum problem

Given a list of integers as input, produce a list of integers as output where output[i] = input[0]+input[1]+...+input[i]

Sequential version is straightforward:

```
Vector<int> prefix_sum(const vector<int>& input) {
  vector<int> output(input.size());
  output[0] = input[0];
  for(int i=1; i < input.size(); i++)
    output[i] = output[i-1]+input[i];
  return output;
}</pre>
```

Example:

input	42	3	4	7	1	10
output	42	45	49	56	57	67

The prefix-sum problem

Given a list of integers as input, produce a list of integers as output where output[i] = input[0]+input[1]+...+input[i]

Sequential version is straightforward:

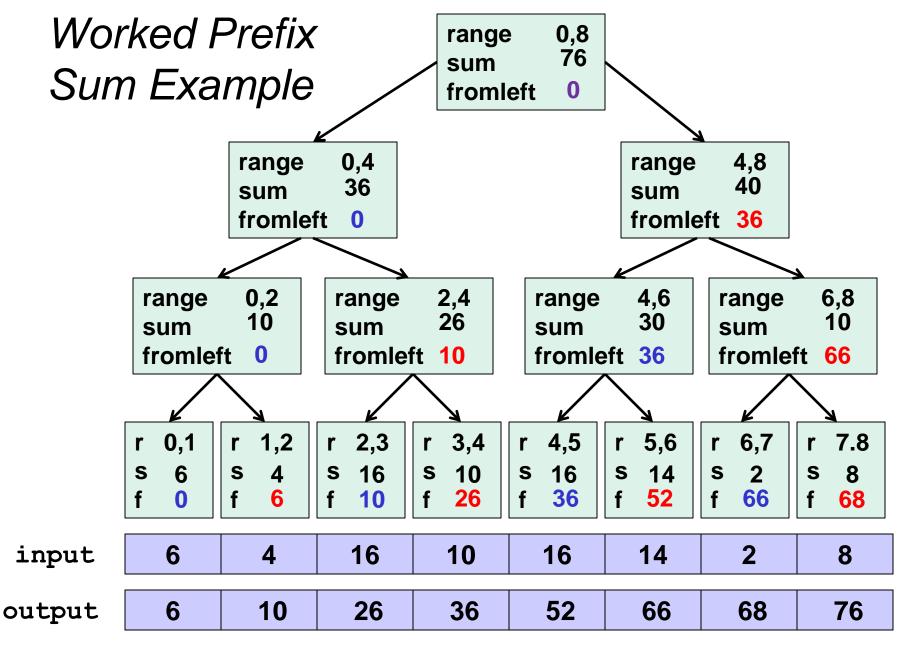
```
Vector<int> prefix_sum(const vector<int>& input) {
   vector<int> output(input.size());
   output[0] = input[0];
   for(int i=1; i < input.size(); i++)
      output[i] = output[i-1]+input[i];
   return output;
}</pre>
```

Why isn't this (obviously) parallelizable? Isn't it just map or reduce?

Work: O(n)

Span: O(n) b/c each step depends on the previous.

Joins everywhere!



Parallel prefix-sum

The parallel-prefix algorithm does two passes:

- 1. build a "sum" tree bottom-up
- 2. traverse the tree top-down, accumulating the sum from the left

Step 1: Work: O(n) Span: $O(\lg n)$

Step 2: Work: O(n) Span: $O(\lg n)$

Overall: Work: O(n) Span? $O(\lg n)$

Paralellism (work/span)? O(n/lg n)

Parallel prefix, generalized

Can we use parallel prefix to calculate the minimum of all elements to the left of i?

Certainly! Just replace "sum" with "min" in step 1 of prefix and replace fromLeft with a fromLeft that tracks the smallest element left of this node's range.

In general, what property do we need for the operation we use in a parallel prefix computation?

ASSOCIATIVITY! (And not commutativity, as it happens.)

Pack Analysis

Step 1: Work: O(n) Span: $O(\lg n)$

Step 2: Work: O(n) Span: $O(\lg n)$

Step 3: Work: O(n) Span: $O(\lg n)$

Algorithm: Work: O(n) Span: $O(\lg n)$

Parallelism: O(n/lg n)

Parallelizing Quicksort

Recall quicksort was sequential, in-place, expected time $O(n \lg n)$

Best / expected case work

1. Pick a pivot element O(1)

2. Partition all the data into: O(n)

A. The elements less than the pivot

B. The pivot

C. The elements greater than the pivot

3. Recursively sort A and C 2T(n/2)

How should we parallelize this?

Parallelize the recursive calls as we usually do in fork/join D&C. Parallelize the partition by doing two packs (filters) instead.

Parallelizing Quicksort

Recall quicksort was sequential, in-place, expected time $O(n \lg n)$

Best / expected case work

- 1. Pick a pivot element O(1)
- 2. Partition all the data into: O(n)
 - A. The elements less than the pivot
 - B. The pivot
 - C. The elements greater than the pivot
- 3. Recursively sort A and C 2T(n/2)

How do we parallelize this? First pass: parallel recursive calls in step 3. What span do we get?

$$T_{\infty}(n) = n + T_{\infty}(n/2) = n + n/2 + T_{\infty}(n/4) = n/1 + n/2 + n/4 + n/8 + ... + 1 \in \Theta(n)$$

(We replace the O(n) term in O(n) + T_{∞} (n/2) with just n for simplicity of analysis.)

Analyzing
$$T_{\infty}(n) = 1g n + T_{\infty}(n/2)$$

Turns out our techniques from way back at the start of the term will work just fine for this:

$$T_{\infty}(n) = 1g n + T_{\infty}(n/2)$$
 if $n > 1$
= 1 otherwise

We get a sum like:

$$lg n + (lg n) - 1 + (lg n) - 2 + (lg n) - 3 + ... 3 + 2 + 1$$

Let's replace lg n by x:

$$x + x-1 + x-2 + x-3 + ... + 3 + 2 + 1$$

That's our "triangle" pattern: $O(k^2) = O((\lg n)^2)$