



# CSE332: Data Abstractions

## Lecture 20: Parallel Prefix, Pack, and Sorting

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### Outline

Done:

- Simple ways to use parallelism for counting, summing, finding
- Analysis of running time and implications of Amdahl's Law

Now: Clever ways to parallelize more than is intuitively possible

- **Parallel prefix:**
  - This "key trick" typically underlies surprising parallelization
  - Enables other things like **packs**
- **Parallel sorting:** quicksort (not in place) and mergesort
  - Easy to get a little parallelism
  - With cleverness can get a lot

### The prefix-sum problem

Given `int[] input`, produce `int[] output` where `output[i]` is the sum of `input[0]+input[1]+...+input[i]`

Sequential can be a CSE142 exam problem:

```
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;
}
```

Does not seem parallelizable

- Work:  $O(n)$ , Span:  $O(n)$
- This *algorithm* is sequential, but a *different algorithm* has Work:  $O(n)$ , Span:  $O(\log n)$

### Parallel prefix-sum

- The parallel-prefix algorithm does two passes
  - Each pass has  $O(n)$  work and  $O(\log n)$  span
  - So in total there is  $O(n)$  work and  $O(\log n)$  span
  - So like with array summing, parallelism is  $n/\log n$ 
    - An exponential speedup
- First pass builds a tree bottom-up: the "up" pass
- Second pass traverses the tree top-down: the "down" pass

### Local bragging

Historical note:

- Original algorithm due to R. Ladner and M. Fischer at UW in 1977
- Richard Ladner joined the UW faculty in 1971 and hasn't left

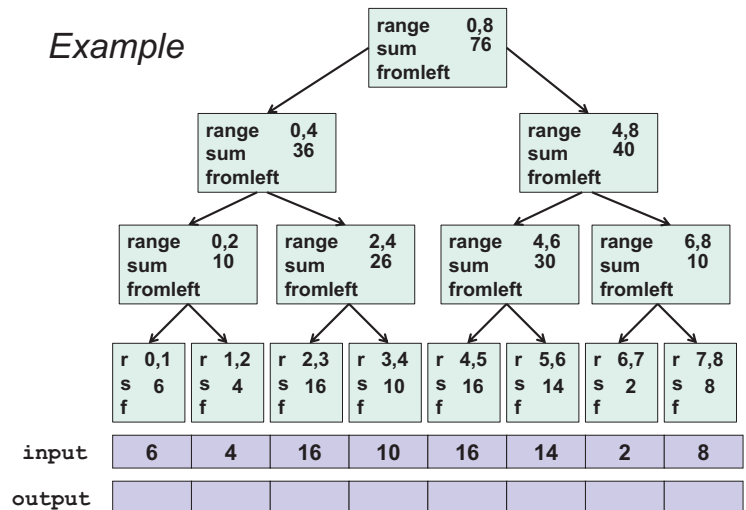


1968? 1973?

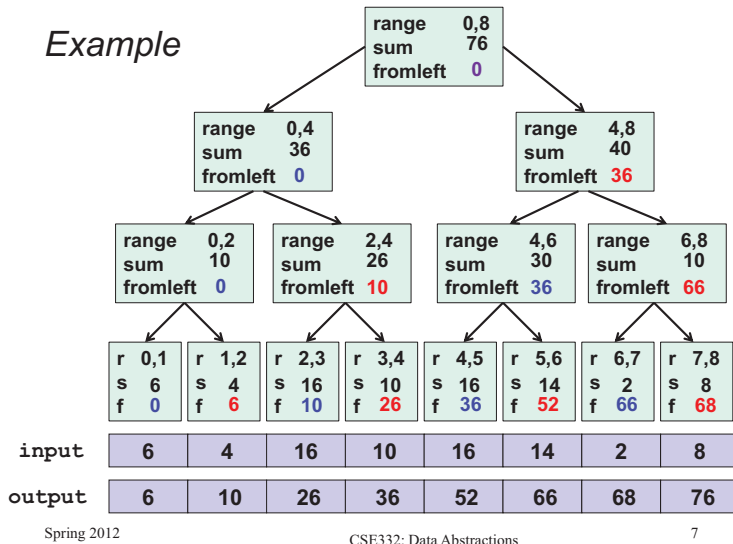


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### Example



## Example



## The algorithm, part 1

- Up: Build a binary tree where
  - Root has sum of the range  $[x, y]$
  - If a node has sum of  $[lo, hi]$  and  $hi > lo$ ,
    - Left child has sum of  $[lo, middle]$
    - Right child has sum of  $[middle, hi]$
    - A leaf has sum of  $[i, i+1)$ , i.e.,  $input[i]$

This is an easy fork-join computation: combine results by actually building a binary tree with all the range-sums

- Tree built bottom-up in parallel
- Could be more clever with an array like with heaps

Analysis:  $O(n)$  work,  $O(\log n)$  span

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## The algorithm, part 2

- Down: Pass down a value `fromLeft`
  - Root given a `fromLeft` of 0
  - Node takes its `fromLeft` value and
    - Passes its left child the same `fromLeft`
    - Passes its right child its `fromLeft` plus its left child's `sum` (as stored in part 1)
  - At the leaf for array position  $i$ ,  $output[i] = fromLeft + input[i]$

This is an easy fork-join computation: traverse the tree built in step 1 and produce no result

- Leaves assign to `output`
- Invariant: `fromLeft` is sum of elements left of the node's range

Analysis:  $O(n)$  work,  $O(\log n)$  span

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## Sequential cut-off

Adding a sequential cut-off is easy as always:

- Up:
  - just a sum, have leaf node hold the sum of a range
- Down:
 

```
output[lo] = fromLeft + input[lo];
for (i=lo+1; i < hi; i++)
    output[i] = output[i-1] + input[i]
```

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## Parallel prefix, generalized

Just as sum-array was the simplest example of a common pattern, prefix-sum illustrates a pattern that arises in many, many problems

- Minimum, maximum of all elements to the left of  $i$
- Is there an element to the left of  $i$  satisfying some property?
- Count of elements to the left of  $i$  satisfying some property
  - This last one is perfect for an efficient parallel pack...
  - Perfect for building on top of the "parallel prefix trick"
- We did an *inclusive* sum, but *exclusive* is just as easy

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## Pack

[Non-standard terminology]

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`  
`output` [17, 11, 13, 19, 24]

Parallelizable?

- Finding elements for the output is easy
- But getting them in the right place seems hard

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## 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.length; i++){
  if (bits[i]==1)
    output[bitsum[i]-1] = input[i];
}
```

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## Pack comments

- First two steps can be combined into one pass
  - Just using a different base case for the prefix sum
  - No effect on asymptotic complexity
- Can also combine third step into the down pass of the prefix sum
  - Again no effect on asymptotic complexity
- Analysis:  $O(n)$  work,  $O(\log n)$  span
  - 2 or 3 passes, but 3 is a constant
- Parallelized packs will help us parallelize quicksort...

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## Quicksort review

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

- |  | Best / expected case <i>work</i> |
|--|----------------------------------|
| 1. Pick a pivot element  | $O(1)$                           |
| 2. Partition all the data into:<br>A. The elements less than the pivot<br>B. The pivot<br>C. The elements greater than the pivot | $O(n)$                           |
| 3. Recursively sort A and C  | $2T(n/2)$                        |

How should we parallelize this?

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## Quicksort

- |  | Best / expected case <i>work</i> |
|--|----------------------------------|
| 1. Pick a pivot element  | $O(1)$                           |
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| 3. Recursively sort A and C  | $2T(n/2)$                        |

Easy: Do the two recursive calls in parallel

- Work: unchanged of course  $O(n \log n)$
- Span: now  $T(n) = O(n) + 1T(n/2) = O(n)$
- So parallelism (i.e., work / span) is  $O(\log n)$

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## Doing better

- $O(\log n)$  speed-up with an infinite number of processors is okay, but a bit underwhelming
  - Sort  $10^9$  elements 30 times faster
- Google searches strongly suggest quicksort cannot do better because the partition cannot be parallelized
  - The Internet has been known to be wrong ☺
  - But we need auxiliary storage (no longer in place)
  - In practice, constant factors may make it not worth it, but remember Amdahl's Law
- Already have everything we need to parallelize the partition...

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## Parallel partition (not in place)

- Partition all the data into:**
- A. The elements less than the pivot
  - B. The pivot
  - C. The elements greater than the pivot
- This is just two packs!
    - We know a pack is  $O(n)$  work,  $O(\log n)$  span
    - Pack elements less than pivot into left side of **aux** array
    - Pack elements greater than pivot into right side of **aux** array
    - Put pivot between them and recursively sort
    - With a little more cleverness, can do both packs at once but no effect on asymptotic complexity
  - With  $O(\log n)$  span for partition, the total span for quicksort is  $T(n) = O(\log n) + 1T(n/2) = O(\log^2 n)$

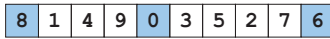
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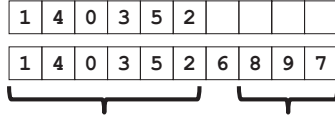
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## Example

- 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 sort back into original array (like in mergesort)

## Now mergesort

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

- Sort left half and right half  $2T(n/2)$
- Merge results  $O(n)$

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

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

## Parallelizing the merge

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

## Parallelizing the merge



## Parallelizing the merge



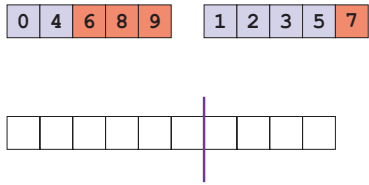
- Get median of bigger half:  $O(1)$  to compute middle index

## Parallelizing the merge



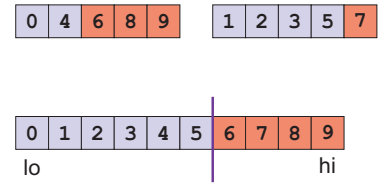
- Get median of bigger half:  $O(1)$  to compute middle index
- Find how to split the smaller half at the same value as the left-half split:  $O(\log n)$  to do binary search on the sorted small half

## Parallelizing the merge



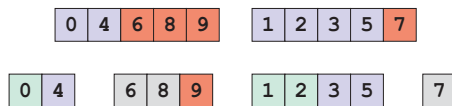
1. Get median of bigger half:  $O(1)$  to compute middle index
2. Find how to split the smaller half at the same value as the left-half split:  $O(\log n)$  to do binary search on the sorted small half
3. Size of two sub-merges conceptually splits output array:  $O(1)$

## Parallelizing the merge



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:  $O(\log n)$  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  $O(n \log n)$
- 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  $O(\log n)$  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:

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

So for mergesort with parallel merge overall:

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

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

- Not quite as good as quicksort’s  $O(n / \log n)$ 
  - But worst-case guarantee
- And as always this is just the asymptotic result