Concurrency Wrap-up Deadlock Handling

Computer Operating Systems, Fall 2023 Instructor: Travis McGaha

Head TAs: Nate Hoaglund & Seungmin Han

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Administrivia

Full PennOS is due Wed Nov 29

- You will schedule a time to meet with your TA to demonstrate your working code
- Can submit via gradescope now
- Reach out to TA's to schedule PennOS Demo
- Check-in due before Lecture next week
- Recitation after class is open OH



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Any questions, comments or concerns from last lecture?

Lecture Outline

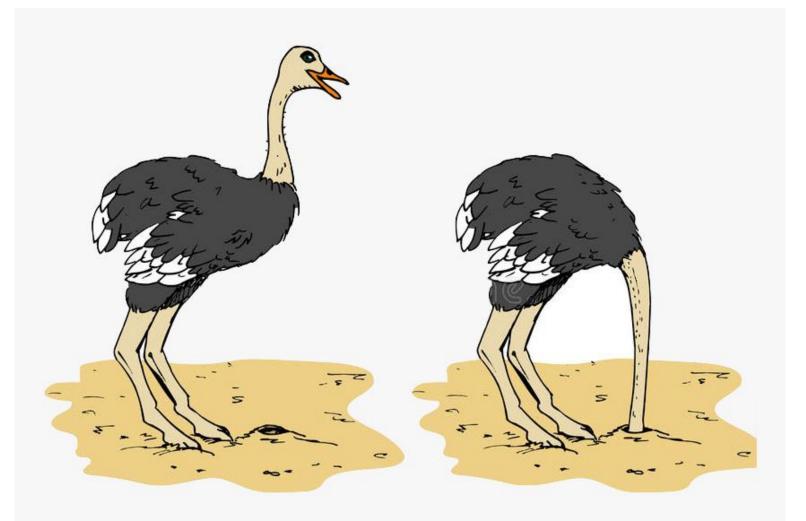
Deadlock Handling (start)

- Ostrich
- Prevention
- Detection
- Avoidance
- Parallel Analysis
 - Recurrences
 - Amdahl's Law

Deadlock Handling: Ostrich Algorithm



Deadlock Handling: Ostrich Algorithm



Ostriches don't actually do this, but it is an old myth

Deadlock Handling: Ostrich Algorithm

- Ignoring potential problems
 - Usually under the assumption that it is either rare, too expensive to handle, and/or not a fatal error
- Used in real world contexts, there is a real cost to tracking down every possible deadlock case and trying to fix it
 - Cost on the developer side: more time to develop
 - Cost on the software side: more computation for these things to do, slows things down

Deadlock Handling: Prevention

- Ad Hoc Approach
 - Key insights into application logic allow you to write code that avoids cycles/deadlock
 - Example: Dining Philosophers breaking symmetry with even/odd philosophers
- Exhaustive Search Approach
 - Static analysis on source code to detect deadlocks
 - Formal verification: model checking
 - Unable to scale beyond small programs in practice Impossible to prove for any arbitrary program (without restrictions)

Detection

- If we can't guarantee deadlocks won't happen, we can instead try to detect a deadlock just before it will happen and then intervene.
- Two big parts
 - Detection algorithm. This is usually done with tracking metadata and graph theory
 - The intervention/recovery. We typically want some sort of way to "recover" to a safe state when we detect a deadlock is going to happen

Detection Algorithms

- The common idea is to think of the threads and resources as a graph.
 - If there is a cycle: deadlock
 - If there is no cycle: no deadlock
- Finding cycles in a graph is a common algorithm problem with many solutions.

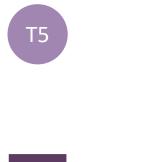
Poll Everywhere

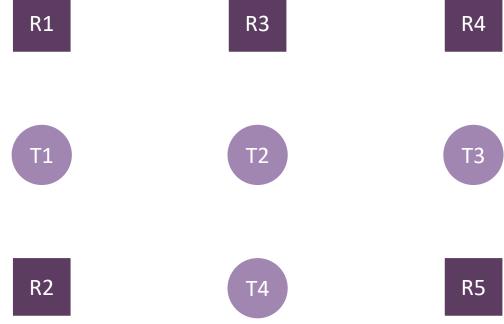
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- Consider the following example with 5 threads and 5 resources that require mutual exclusion is this a deadlock?
 - Thread 1 has R2 but wants R1
 - Thread 2 has R1 but wants R3, R4 and R5
 - Thread 3 has R4 but wants R5
 - Thread 4 has R5 but wants R2
 - Thread 5 has R3

- We can represent this deadlock with a graph:
 - Each resource and thread is a node
 - If a thread has a resource, draw an arrow pointing at the thread form that resource
 - If a thread wants to acquire a resource but can't, draw an arrow pointing at the resource from the thread trying to acquire it

- Thread 1 has R2 but wants R1
- Thread 2 has R1 but wants R3, R4 and R5
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R4

Resource Allocation Graph Example

R1

T1

R2

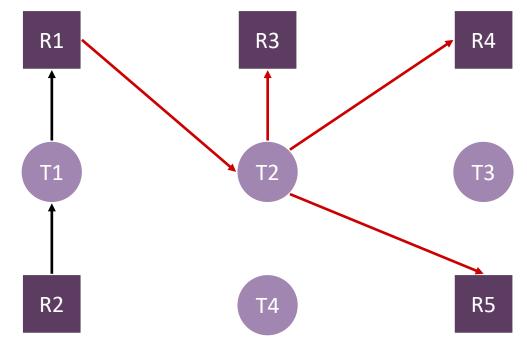
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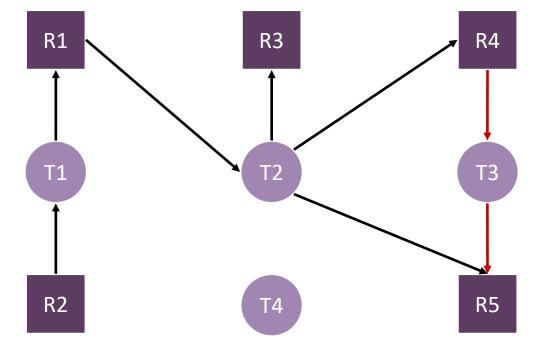
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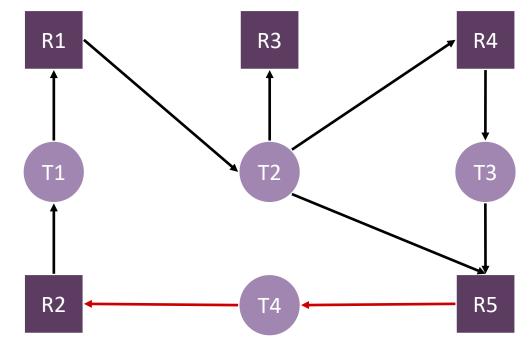
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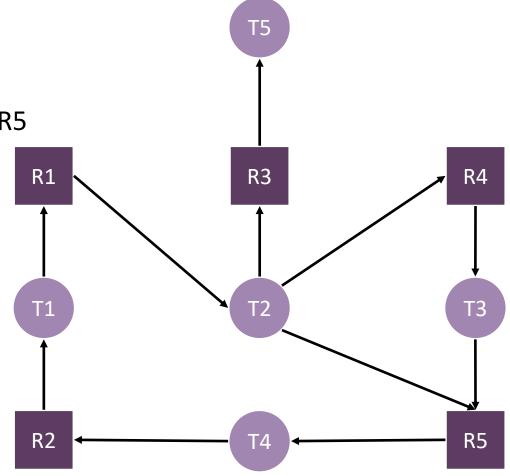


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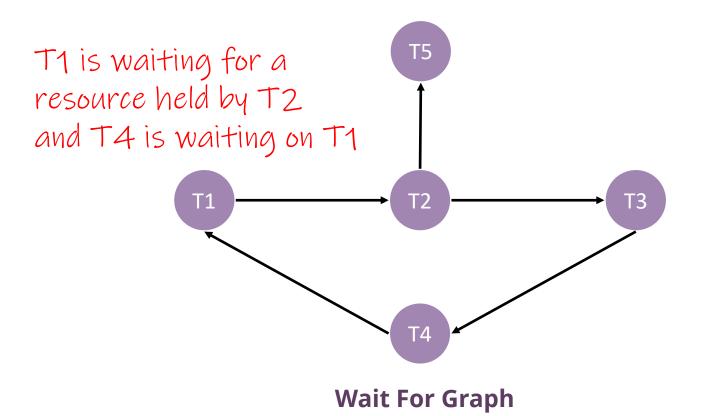


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Alternate graph

 Instead of also representing resources as nodes, we can have a "wait for" graph, showing how threads are waiting on each other



Recovery after Detection

- Preemption:
 - Force a thread to give up a resource
 - Often is not safe to do or impossible
- Rollback:
 - Occasionally checkpoint the state of the system, if a deadlock is detected then go back to the checkpointed "Saved state"
 - Used commonly in database systems
 - Maintaining enough information to rollback and doing the rollback can be expensive
- Manual Killing:
 - Kill a process/thread, check for deadlock, repeat till there is no deadlock
 - Not safe, but it is simple

Overall Costs

 Doing Deadlock Detection & Recovery solves deadlock issues, but there is a cost to memory and CPU to store the necessary information and check for deadlock

This is why sometimes the ostrich algorithm is preferred

Avoidance

- Instead of detecting a deadlock when it happens and having expensive rollbacks, we may want to instead avoid deadlock cases earlier
- Idea:
 - Before it does work, it submits a request for all the resources it will need.
 - A deadlock detection algorithm is run
 - If acquiring those resources would lead to a deadlock, deny the request. The calling thread can try again later
 - If there is no deadlock, then the thread can acquire the resources and complete its task
 - The calling thread later releases resources as they are done with them

Avoidance

- Pros:
 - Avoids expensive rollbacks or recovery algorithms
- Cons:
 - Can't always know ahead of time all resources that are required
 - Resources may spend more time being locked if all resources need to be acquired before an action is taken by a thread, could hurt parallelizability
 - Consider a thread that does a very expensive computation with many shared resources.
 - Has one resources that is only updated at the end of the computation.
 - That resources is locked for a long time and other threads that may need it cannot access it

Aside: Bankers Algorithm

- This gets more complicated when there are multiple copies of resources, or a finite number of people can access a resources.
- The Banker's Algorithm handles these cases
 - But I won't go into detail about this
 - There is a video linked on the website under this lecture you can watch if you want to know more

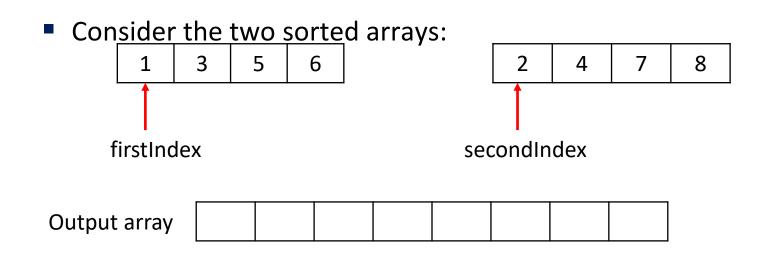
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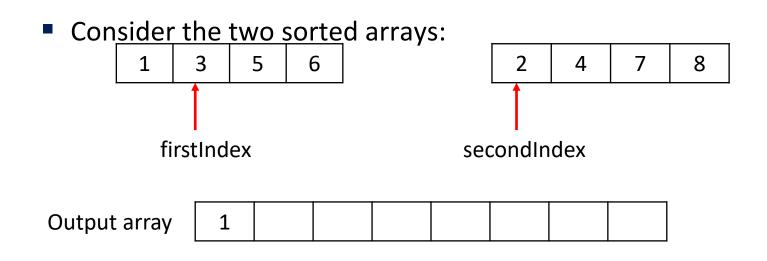
Parallel Algorithms

- One interesting applications of threads is for faster algorithms
- Common Example: Merge sort

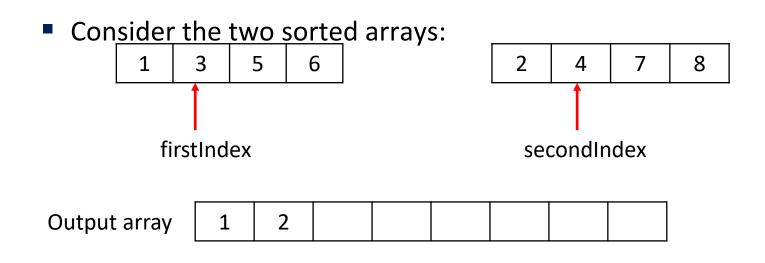
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- It is quicker to merge two sorted arrays than sort an unsorted array



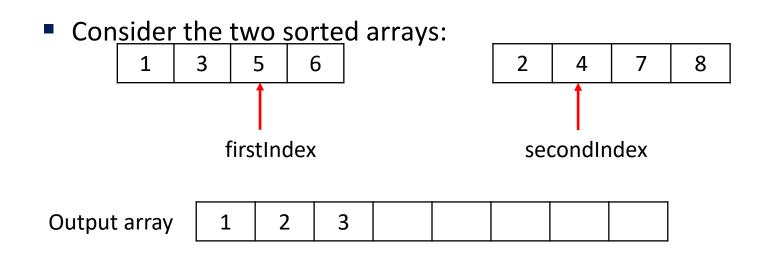
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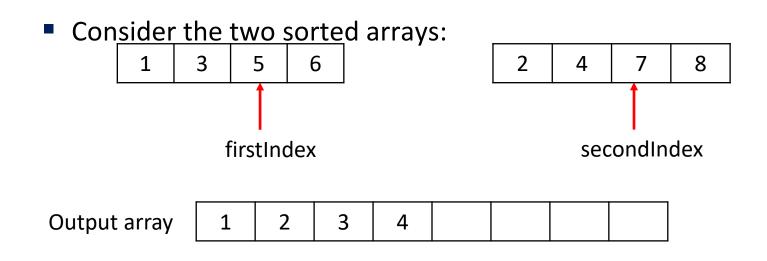
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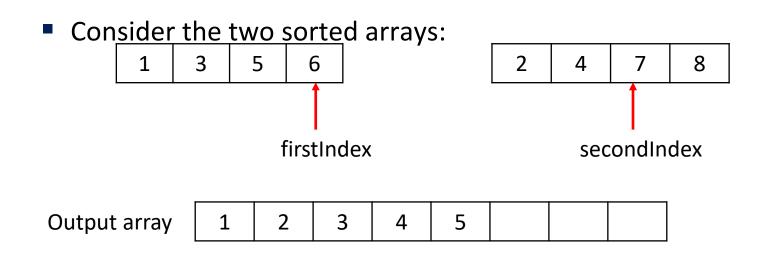
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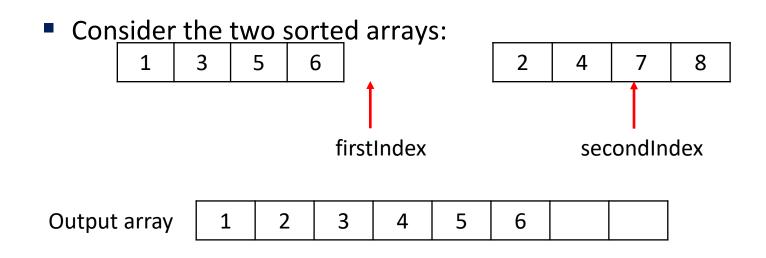
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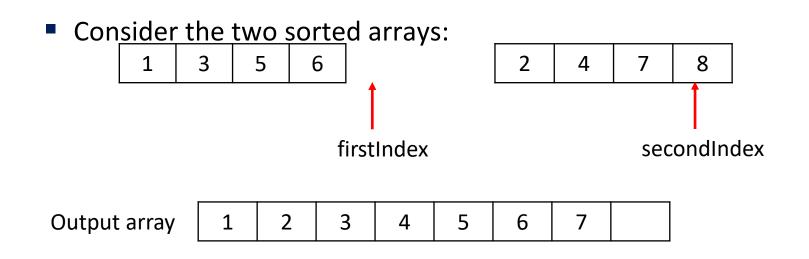
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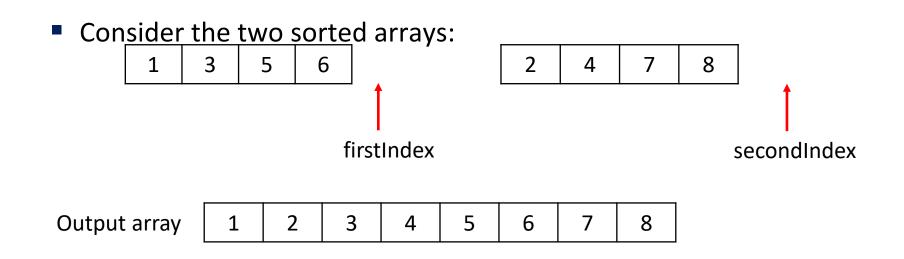
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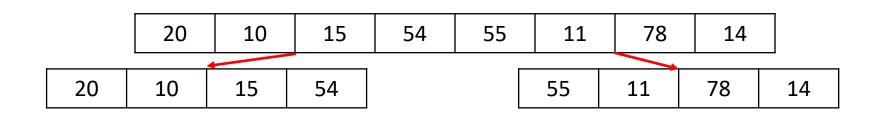


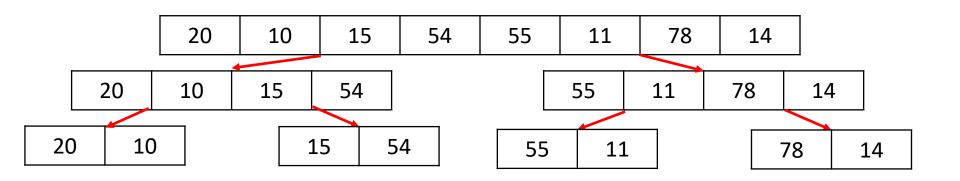
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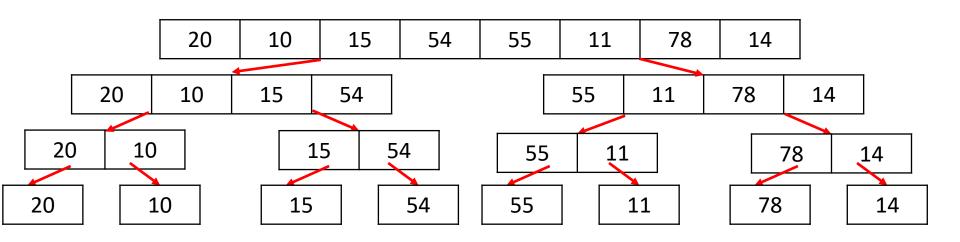


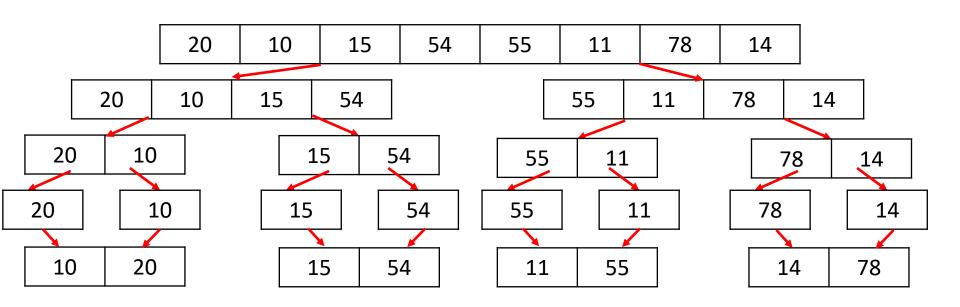
Merge Sort: High Level Example

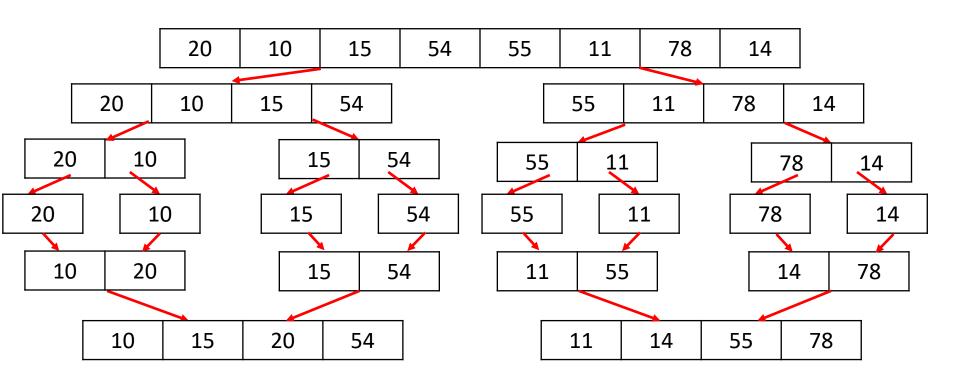
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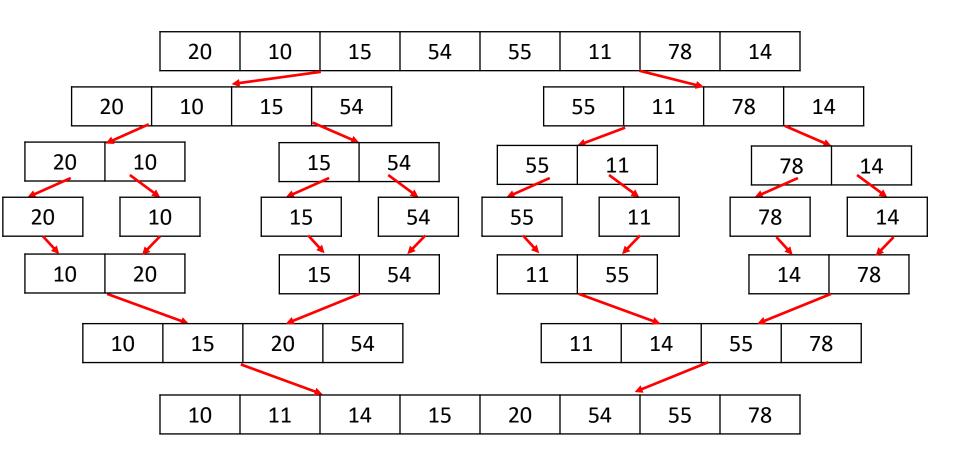












Merge Sort Algorithmic Analysis

 Algorithmic analysis of merge sort gets us to O(n * log(n)) runtime.

```
void merge_sort(int[] arr, int lo, int hi) {
    // lo high start at 0 and arr.length respectively
    int mid = (lo + hi) / 2;
    merge_sort(arr, lo, mid); // sort the bottom half
    merge_sort(arr, mid, hi); // sort the upper half
    // combine the upper and lower half into one sorted
    // array containing all eles
    merge(arr[lo : mid], arr[mid : hi]);
}
```

We recurse log₂(N) times, each recursive "layer" does
 O(N) work

Merge Sort Algorithmic Analysis

```
We can use threads to speed this up:
```

```
void merge_sort(int[] arr, int lo, int hi) {
    // lo high start at 0 and arr.length respectively
    int mid = (lo + hi) / 2;
```

```
// sort bottom half in parallel
pthread_create(merge_sort(arr, lo, mid));
merge sort(arr, mid, hi); // sort the upper half
```

pthread_join(); // join the thread that did bottom half

// combine the upper and lower half into one sorted
// array containing all eles
merge(arr[lo : mid], arr[mid : hi]);

Now we are sorting both halves of the array in parallel!



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// combine the upper and lower half into one sorted
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merge(arr[lo : mid], arr[mid : hi]);

- Now we are sorting both halves of the array in parallel!
- How long does this take to run?
- How much work is being done?

Parallel Algos:

- Will not test you on this
- We can define T(n) to be the running time of our algorithm
- We can split up our work between two parts, the part done sequentially, and the part done in parallel
 - T(n) = sequential_part + parallel_part
 - T(n) = O(n) merging + T(n/2) sort half the array
 - This is a recursive definition
- ✤ If we start recurring...
 - T(n) = O(n) + O(n/2) + T(n/4)
 - T(n) = O(n) + O(n/2) + O(n/4) + T(n/8)

Will not test you on this

Parallel Algos:

- ✤ If we start recurring...
 - T(n) = O(n) + O(n/2) + T(n/4)
 - T(n) = O(n) + O(n/2) + O(n/4) + T(n/8)
 - Eventually we stop, there is a limit to the length of the array.
 And we can say an array of size 1 is already sorted, so T(1) = O(1)
- This approximates to T(n) = 2 * O(n) = O(n)
 - This parallel merge sort is O(n), but there are further optimizations that can be done to reach ~O(log(n))
- There is a lot more to parallel algo analysis than just this, I am just giving you a sneak peek

Amdahl's Law

- For most algorithms, there are parts that parallelize well and parts that don't. This causes adding threads to have diminishing returns
 - (even ignoring the overhead costs of creating & scheduling threads)
- Consider we have some parallel algorithm $T_1 = 1$
 - The 1 subscript indicates this is run on 1 thread
 - we define the work for the entire algorithm as 1
- We define S as being the part that can be parallelized
 - $T_1 = S + (1 S) // (1-S)$ is the sequential part

Amdahl's Law

- For running on one thread:
 - T₁ = (1 − S) + S
- If we have P threads and perfect linear speedup on the parallelizable part, we get

•
$$T_P = (1-S) + \frac{S}{P}$$

Speed up multiplier for P threads from sequential is:

$$T_1 = \frac{1}{1 - S + \frac{S}{P}}$$

Amdahl's Law

Let's say that we have 100000 threads (P = 100000) and our algorithm is only 2/3 parallel? (s = 0.6666..)

• $\frac{T_1}{T_p} = \frac{1}{1 - 0.6666 + \frac{0.6666}{100000}} = 2.9999 \ times \ faster \ than \ sequential$

What if it is 90% parallel? (S = 0.9):

•
$$\frac{T_1}{T_p} = \frac{1}{1 - 0.9 + \frac{0.9}{100000}} = 9.99 \text{ times faster than sequential}$$

✤ What if it is 99% parallel? (S = 0.99):

$$\frac{T_1}{T_p} = \frac{1}{1 - 0.99 + \frac{0.99}{100000}} = 99.99 \text{ times faster than sequential}$$

Limitation: Hardware Threads

- These algorithms are limited by hardware.
- Number of Hardware Threads: The number of threads can genuinely run in parallel on hardware
- We may be able to create a huge number of threads, but only run a few (e.g. 4) in parallel at a time.
- Can see this information in with lscpu in bash
 - A computer can have some number of CPU sockets
 - Each CPU can have one or more cores
 - Each Core can run 1 or more threads