CSE332: Data Abstractions

Lecture 19: Introduction to Multithreading and Fork-Join Parallelism

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Summer 2010

Changing a major assumption

So far in 142, 143, 311, and 332, we have assumed

One thing happened at a time

Called sequential programming – everything part of one sequence

Removing this assumption creates major challenges & opportunities

- Programming: Divide work among threads of execution and coordinate (synchronize) among them
- Algorithms: How can parallel activity provide speed-up (more throughput: work done per unit time)
- Data structures: May need to support concurrent access (multiple threads operating on data at the same time)

Writing correct and efficient multithreaded code is often much more difficult than for single-threaded (i.e., sequential) code

A simplified view of history

From roughly 1980-2005, desktop computers got exponentially faster at running sequential programs

- About twice as fast every couple years

But nobody knows how to continue this

- Increasing clock rate generates too much heat
- Relative cost of memory access is too high
- But we can keep making "wires exponentially smaller" (Moore's "Law"), so put multiple processors on the same chip ("multicore")

What to do with multiple processors?

- Next computer you buy will likely have 4 processors
  - Wait a few years and it will be 8, 16, 32, …
  - The chip companies have decided to do this (not a "law")

- What can you do with them?
  - Run multiple totally different programs at the same time
    - Already do that? Yes, but with time-slicing
  - Do multiple things at once in one program
    - Our focus – more difficult
    - Requires rethinking everything from asymptotic complexity to how to implement data-structure operations

Parallelism vs. Concurrency

Note: These terms are not yet standard, but the difference in perspective is essential

- Many programmers confuse them
- Remember that Parallelism != Concurrency

Parallelism: Use more resources for a faster answer

Concurrency: Correctly and efficiently allow simultaneous access to something (memory, printer, etc.)

There is some connection:

- Many programmers use threads for both
- If parallel computations need access to shared resources, then something needs to manage the concurrency

CSE332: Next few lectures on parallelism, then a few on concurrency

Parallelism Example

Parallelism: Increasing throughput by using additional computational resources (code running simultaneously on different processors)

Ex: We have a huge array of numbers to add up; split between 4 people

Example in *pseudocode* (not Java, yet) below: sum elements of an array

- No such 'FORALL' construct, but we'll see something similar
- If you had 4 processors, might get roughly 4x speedup

```
int sum(int[] arr){
  res = new int[4];
  len = arr.length;
  FORALL(i=0; i < 4; i++) { //parallel iterations
    res[i] = help(arr,i*len/4,(i+1)*len/4);
  }
  return res[0]+res[1]+res[2]+res[3];
}
int help(int[] arr, int lo, int hi) {
   result = 0;
   for(j=lo; j < hi; j++)
      result += arr[j];
   return result;
}
```

Concurrency Example

Concurrency: Allowing simultaneous or interleaved access to shared resources from multiple clients

Ex: Multiple threads accessing a hash-table, but not getting in each others' ways

Example in *pseudo-code* (not Java, yet): chaining hash-table

- Essential correctness issue is preventing bad inter-leavings
- Essential performance issue not preventing good concurrency
  - One 'solution' to preventing bad inter-leavings is to do it all sequentially

```
class Hashtable<K,V> {
   …
   Hashtable(Comparator<K> c, Hasher<K> h) { … };
   void insert(K key, V value) {
      int bucket = …;
      prevent-other-inserts/lookups in table[bucket];
      do the insertion
      re-enable access to arr[bucket];
   }
   V lookup(K key) {
      (like insert, but can allow concurrent
       lookups to same bucket)
   }
}
```

An analogy

CSE142 idea: Writing a program is like writing a recipe for a cook

- One step at a time

Parallelism:

- Have lots of potatoes to slice?
- Hire helpers, hand out potatoes and knives
- But we can go too far: if we had 1 helper per potato, we'd spend too much time coordinating

Concurrency:

- Lots of cooks making different things, but only 2 stove burners
- Want to allow simultaneous access to both burners, but not cause spills or incorrect burner settings

Shared memory with Threads

The model we will assume is shared memory with explicit threads

Old story: A running program has

- One *call stack* (with each *stack frame* holding local variables)
- One *program counter* (current statement executing)
- Static fields
- Objects (created by **`new`**) in the *heap* (nothing to do with heap data structure)

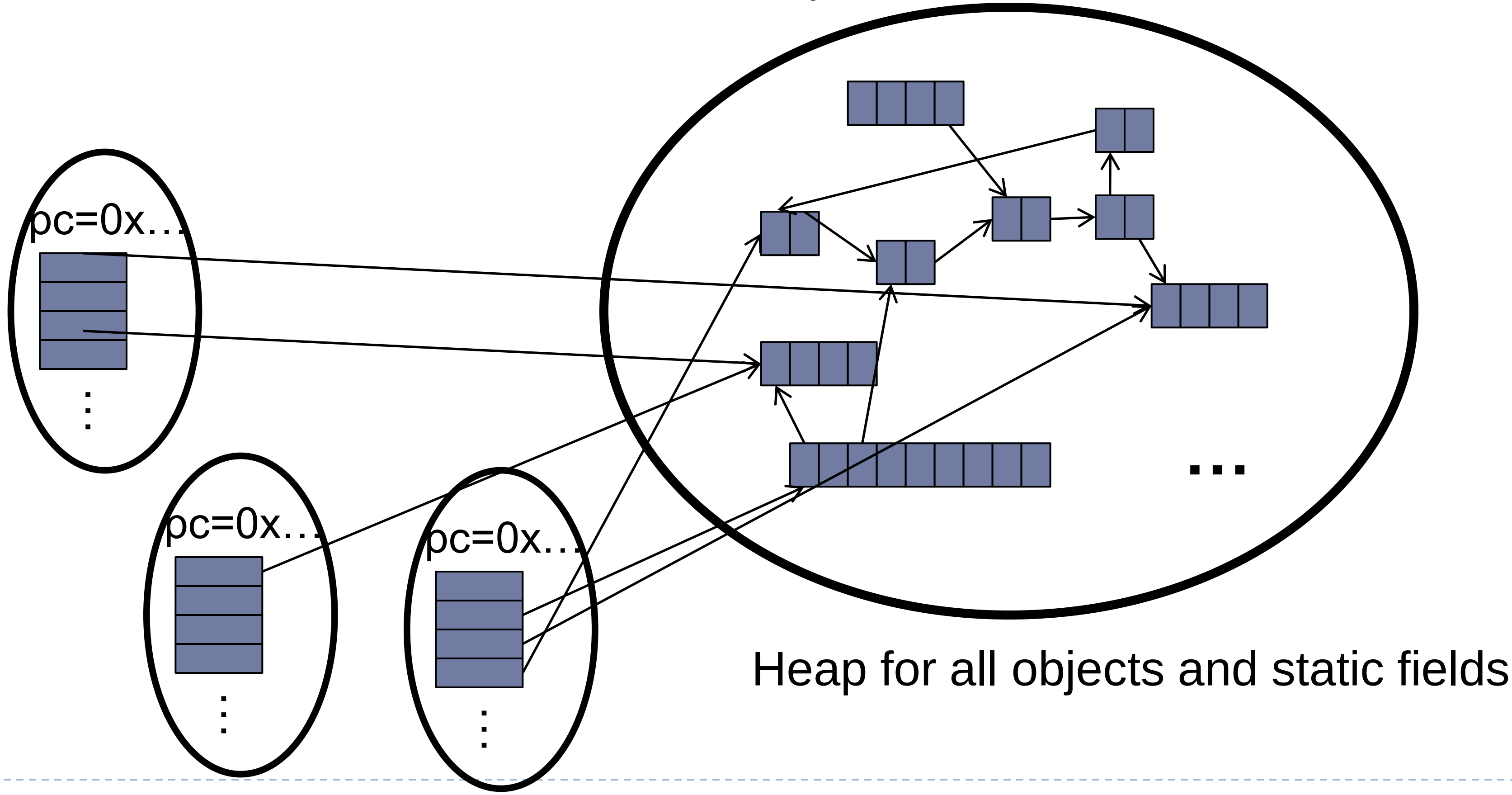
New story:

- A set of *threads*, each with its own call stack & program counter
  - No access to another thread's local variables
- Threads can (implicitly) share static fields / objects
  - To *communicate*, write somewhere another thread reads

Shared memory with Threads

Threads, each with own unshared call stack and current statement (pc for "program counter")

– local variables are numbers/null or heap references



Other models

We will focus on shared memory, but you should know several other models exist

- Message-passing: Each thread has its own collection of objects. Communication is via explicit messages; language has primitives for sending and receiving them.
  - Cooks working in separate kitchens, with telephones
- Dataflow: Programmers write programs in terms of a DAG and a node executes after all of its predecessors in the graph
  - Cooks wait to be handed results of previous steps
- Data parallelism: Have primitives for things like "apply function to every element of an array in parallel"
- …

Java Threads (at a high level)

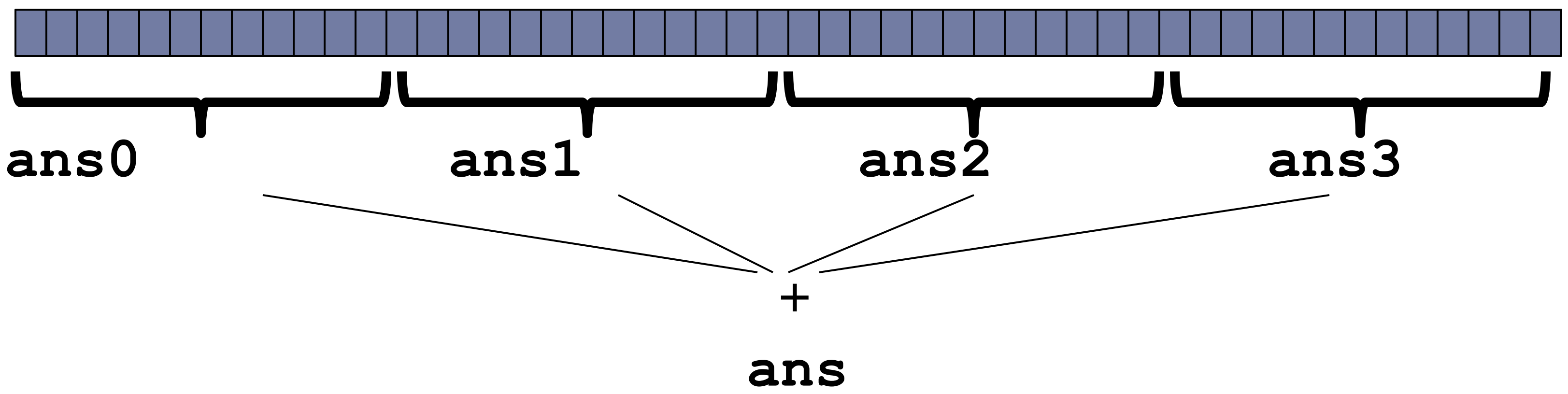
- Many languages/libraries (including Java) provide primitives for creating threads and synchronizing them

- Steps to creating another thread:
  1. Define a subclass **`C`** of **`java.lang.Thread`**, overriding **`run()`**
  2. Create an object of class **`C`**
  3. Call that object's **`start()`** method
     - The code that called start will continue to execute after start
     - A new thread will be created, with code executing in the object's **`run()`** method

- What happens if, for step 3, we called run instead of start?

Parallelism idea: First approach

- Example: Sum elements of an array (presumably large)
- Use 4 threads, which each sum 1/4 of the array



- Steps:
  - Create 4 thread objects, assigning their portion of the work
  - Call **`start()`** on each thread object to actually run it
  - Somehow 'wait' for threads to finish
  - Add together their 4 answers for the final result

Partial Code for first attempt (with Threads)

- Assume SumThread's run() simply loops through the given indices and adds the elements

```
int sum(int[] arr){
  int len = arr.length;
  int ans = 0;
  SumThread[] ts = new SumThread[4];
  for(int i=0; i < 4; i++){// do parallel computations
    ts[i] = new SumThread(arr,i*len/4,(i+1)*len/4);
    ts[i].start();
  }
  for(int i=0; i < 4; i++) { // combine results
    ts[i].join(); // wait for helper to finish!
    ans += ts[i].ans;
  }
  return ans;
}
```

- Overall, should work, but not ideal

Join: Our 'wait' method for Threads

- The `Thread` class defines various methods that provide the threading primitives you could not implement on your own
  - For example: `start`, which calls `run` in a new thread
- The `join` method is another such method, essential for coordination in this kind of computation
  - Caller blocks until/unless the receiver is done executing (meaning its `run` returns)
  - If we didn't use join, we would have a 'race condition' (more on these later) on `ts[i].ans`
    - Essentially, if it's a problem if any variable can be read/written simultaneously
- This style of parallel programming is called "fork/join"
  - If we write in this style, we avoid many concurrency issues

Problems with our current approach

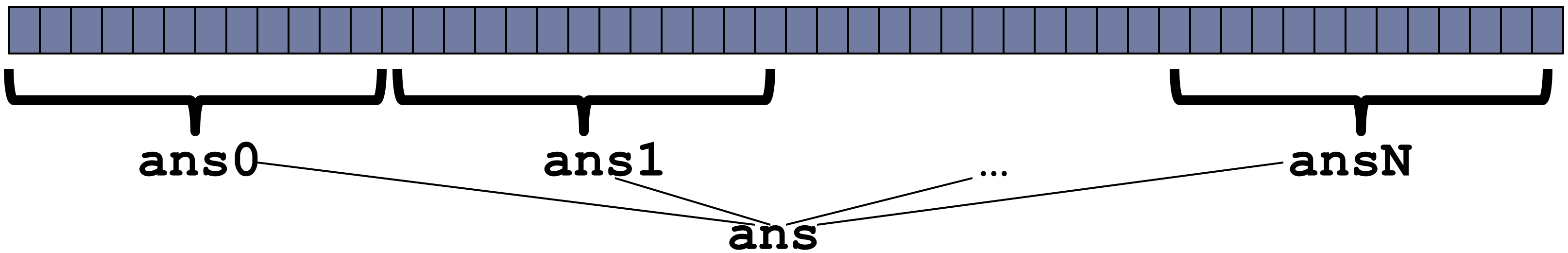
The above method would work, but we can do better for several reasons:

1. Want code to be reusable and efficient across platforms
   - Be able to work for a variable number of processors (not just hardcoded to 4); ‘forward portable’
2. Even with knowledge of # of processors on the machine, we should be able to use them more dynamically
   - This program is unlikely to be the only one running; shouldn’t assume it gets all the resources
   - # of ‘free’ processors is likely to change over the course of time; be able to adapt
3. Different threads may take significantly different amounts of time (unlikely for sum, but common in many cases)
   - Example: Apply method `f` to every array element, but maybe `f` is much slower for some data items than others; say, verifying primes
   - If we create 4 threads and all the slow data is processed by 1 of them, we won’t get nearly a 4x speedup (‘load imbalance’)

Improvements

The perhaps counter-intuitive solution to all these problems is to cut up our problem into many pieces, far more than the number of processors

- Idea: When processor finishes one piece, it can start another
- This will require changing our algorithm somewhat



1. Forward-portable: Lots of threads each doing a small piece
2. Processors available used well: Hand out threads as you go
   - Processors pick up new piece when done with old
3. Load imbalance: No problem if slow thread scheduled early enough
   - Variation probably small anyway if pieces of work are small

Naïve algorithm that doesn't work

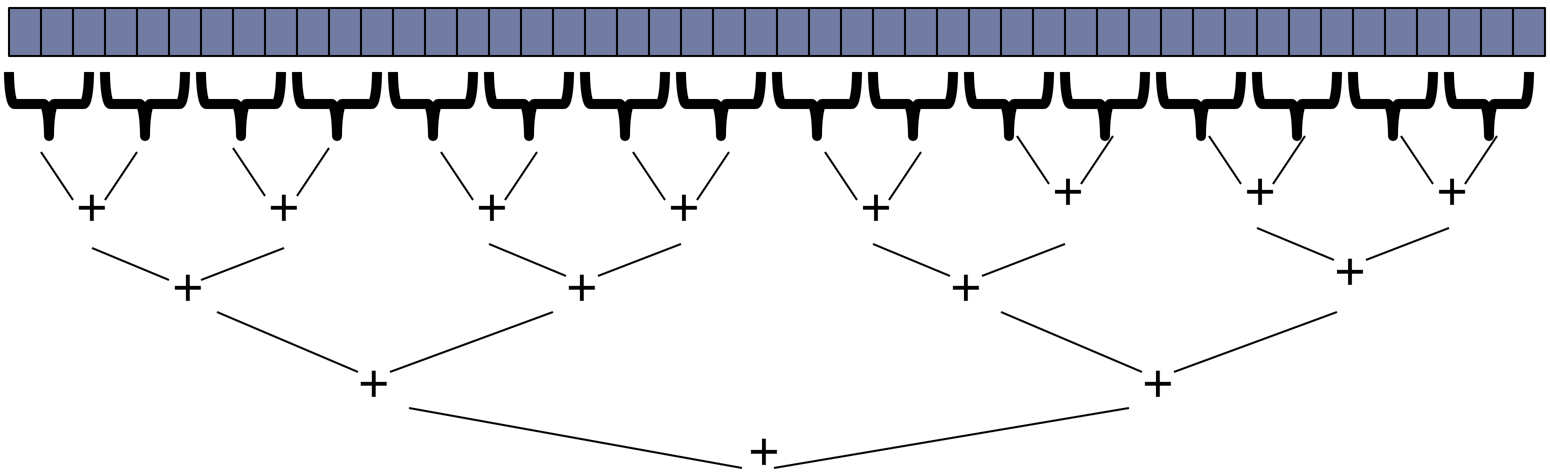
- Suppose we create 1 thread to process every 100 elements

```
int sum(int[] arr){
   …
   int numThreads = arr.length / 100;
   SumThread[] ts = new SumThread[numThreads];
   …
}
```

- Then combining results will have **`arr.length / 100`** additions to do – still linear in size of array

- In the extreme, suppose we create a thread to process every 1 element – then we're back to where we started even though we said more threads was better

A better idea… look familiar?

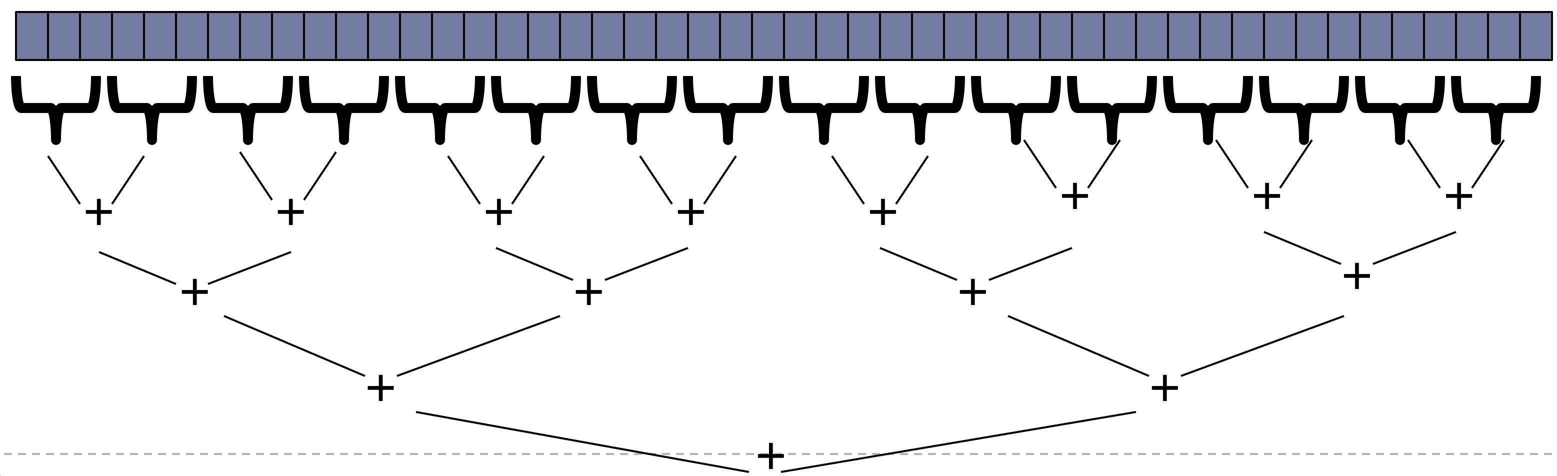


- Start with full problem at root
- Halve and make new thread until size is at some cutoff
- Combine answers in pairs as we return
- This will start small, and ‘grow’ threads to fit the problem
- This is straightforward to implement using divide-and-conquer

Divide-and-conquer really works

- The key is divide-and-conquer parallelizes the result-combining
  - *If* you have enough processors, total time is depth of the tree: $O(\texttt{log}\ n)$
    - Exponentially faster than sequential $O(n)$
  - Compare to, say, dividing into 100 chunks then linearly summing them
  - Next lecture: study reality of **P** < $O(n)$ processors

- We'll write all our parallel algorithms in this style
  - But using a special library designed for exactly this
    - Takes care of scheduling the computation well
    - Java Threads have high overhead; not ideal for this
  - Often relies on operations being associative like +



Code would look something like this (still using Java Threads)

```
class SumThread extends java.lang.Thread {
  int lo; int hi; int[] arr;//fields to know what to do
  int ans = 0; // for communicating result
  SumThread(int[] a, int l, int h) { … }
  public void run(){
    if(hi – lo < SEQUENTIAL_CUTOFF)
      for(int i=lo; i < hi; i++)
        ans += arr[i];
    else {
      SumThread left = new SumThread(arr,lo,(hi+lo)/2);
      SumThread right= new SumThread(arr,(hi+lo)/2,hi);
      left.start();
      right.start();
      left.join(); // don't move this up a line – why?
      right.join();
      ans = left.ans + right.ans;
    }
  }
}
int sum(int[] arr){
   SumThread t = new SumThread(arr,0,arr.length);
   t.run();
   return t.ans;
}
```

Being realistic

- In theory, you can divide down to single elements, do all your result-combining in parallel and get optimal speedup
  - Total time $O(n/numProcessors + \log n)$

- In practice, creating all that inter-thread communication swamps the savings, so:
  - Use a sequential cutoff, typically around 500-1000
    - As in quicksort, eliminates almost all recursion, but here it is even more important
  - Don't create two recursive threads; create one and do the other "yourself"
    - Cuts the number of threads created by another 2x

Half the threads created

```
// wasteful: don't
SumThread left  = …
SumThread right = …
left.start();
right.start();
left.join();
right.join();
ans=left.ans+right.ans;
```

```
// better: do
SumThread left  = …
SumThread right = …
// order of next 4 lines
// essential – why?
left.start();
right.run();
left.join();
ans=left.ans+right.ans;
```

- If a *language* had built-in support for fork-join parallelism, I would expect this hand-optimization to be unnecessary
- But the *library* we are using expects you to do it yourself
  - And the difference is surprisingly substantial
- No difference in theory

That library, finally

- Even with all this care, Java's threads are too "heavy-weight"
  - Constant factors, especially space overhead
  - Creating 20,000 Java threads just a bad idea ☹
- The ForkJoin Framework is designed to meet the needs of divide-and-conquer fork-join parallelism
  - Will be in Java 7 standard libraries, but available in Java 6 as a downloaded `.jar` file
  - Section will focus on pragmatics/logistics
  - Similar libraries available for other languages
    - C/C++: Cilk (inventors), Intel's Thread Building Blocks
    - C#: Task Parallel Library

Different terms, same basic idea

Thread vs.	ForkJoin Framework:
Don't subclass **`Thread`**	Do subclass **`RecursiveTask<V>`**
Don't override **`run`**	Do override **`compute`**
Do not use an **`ans`** field	Do return a **`V`** from **`compute`**
Don't call **`start`**	Do call **`fork`**
Don't just call **`join`**	Do call **`join`** which returns answer
Don't call **`run`** to hand-optimize	Do call **`compute`** to hand-optimize

Also, ForkJoin kicks the whole thing off with an 'invoke()' (example on the next slide)

Example: final version (minus imports)

```
class SumArray extends RecursiveTask<Integer> {
  int lo; int hi; int[] arr;//fields to know what to do
  SumArray(int[] a, int l, int h) { … }
  protected Integer compute(){// return answer
    if(hi - lo < SEQUENTIAL_CUTOFF) {
      int ans = 0;
      for(int i=lo; i < hi; i++)
        ans += arr[i];
      return ans;
    } else {
      SumArray left = new SumArray(arr,lo,(hi+lo)/2);
      SumArray right= new SumArray(arr,(hi+lo)/2,hi);
      left.fork();
      int rightAns = right.compute();
      int leftAns  = left.join();
      return leftAns + rightAns;
    }
  }
}
static final ForkJoinPool fjPool = new ForkJoinPool();
int sum(int[] arr){
  return fjPool.invoke(new SumArray(arr,0,arr.length));
}
```

Getting good results in practice

- Sequential threshold
  - Library documentation recommends doing approximately 100-5000 basic operations in each “piece” of your algorithm
- Library needs to “warm up”
  - May see slow results before the Java virtual machine re-optimizes the library internals
  - When evaluating speed, put your computations in a loop to see the “long-term benefit”
- Wait until your computer has more processors ☺
  - Seriously, overhead may dominate at 4 processors, but parallel programming is likely to become much more important
- Beware memory-hierarchy issues
  - Won’t focus on this, but often crucial for parallel performance