From Concurrent to Parallel

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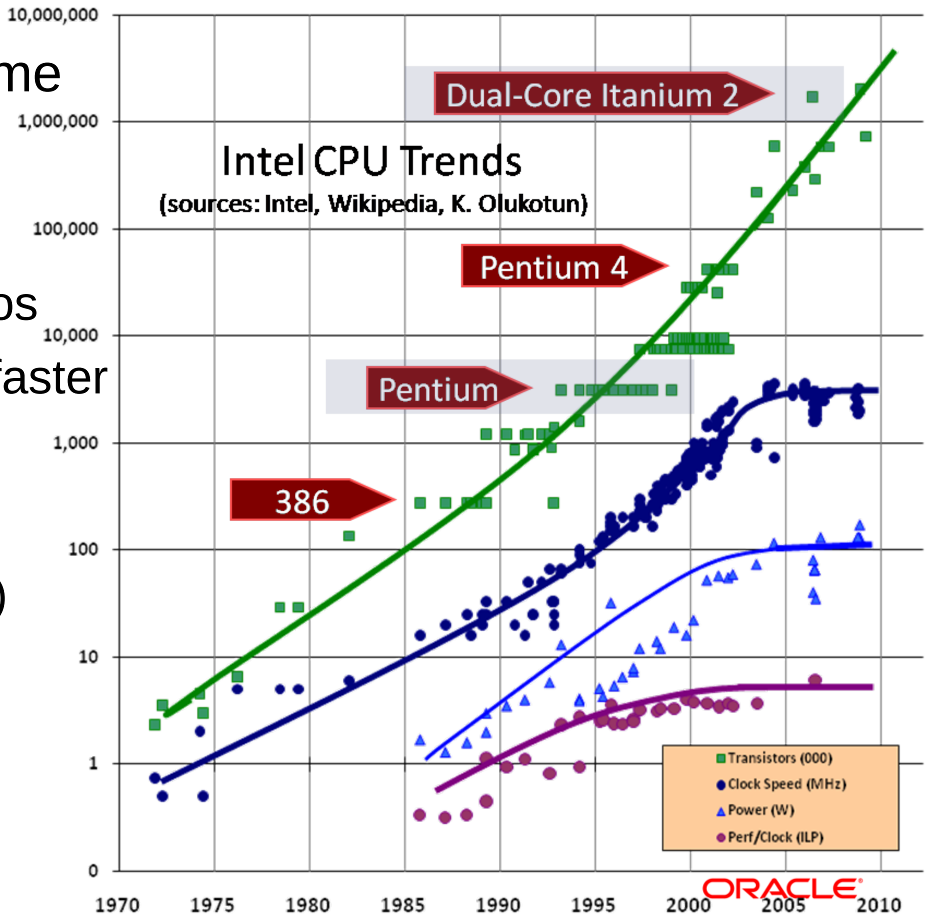
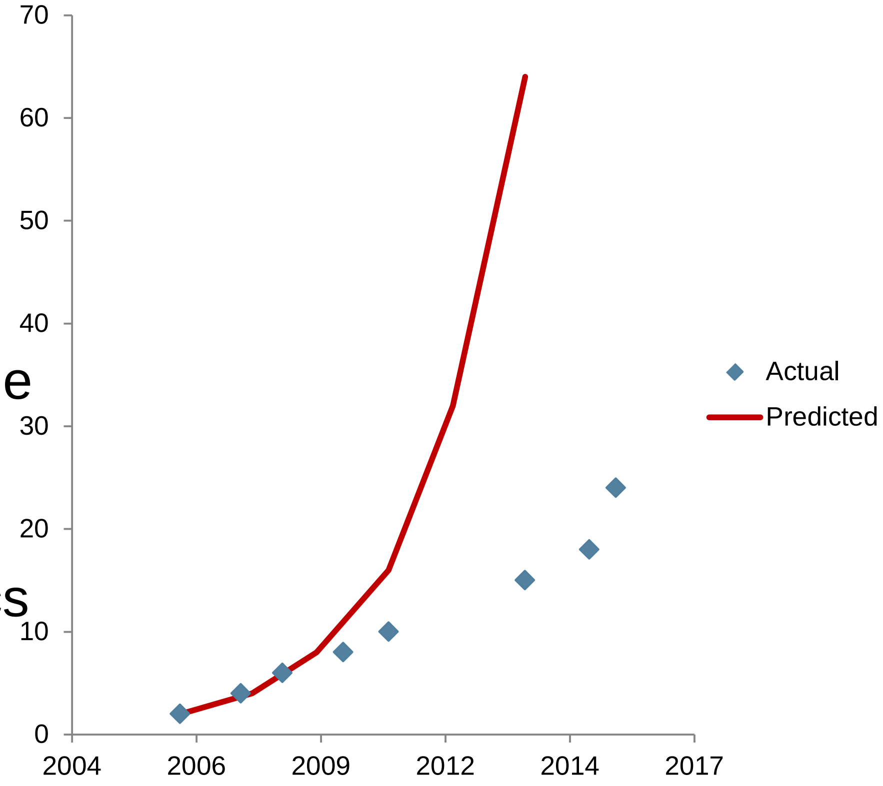
Hardware Trends

- Graph shows Intel CPUs over time
  – (graph courtesy Herb Sutter)
- Moore's Law still in full force
  – Transistor count doubles ~18mos
  – Now giving us *more* cores, not faster
- CPU clock rates stopped going up in 2003
  – (some period of denial followed)



Dude, Where's My Cores?

- If Moore's law is plowed into core count, we'd see red line
- Reality is blue marks
  - For enterprise chips (-EX)
  - Lower for consumer chips
- Chipmakers not delivering all the cores they can
  - Because software isn't ready!
- Except for data-parallel analytics
  - And GPUs



Concurrency, Through The Ages

- Primary goal of using concurrency is maximizing use of CPU(s)
  - Though sometimes used to manage program structure (e.g., CSP, Actors)
- Dominant maximization strategy changes over time
  - Single-core era
    - Alternative to blocking – nonblocking IO, prioritized background tasks
  - Multi-core era
    - Coarse-grained, task-based concurrency
    - Largely about *throughput* – pushing more requests through a server
  - Many-core era
    - Fine-grained data parallelism
    - Largely about *latency* – use more cores to get the answer faster

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Hardware Trends Drive Software Trends

- Languages, libraries, and frameworks shape the programs we write
  - We follow the path of least resistance…
- Hardware shapes the languages, library, and frameworks we write
  - Java 1 supported threads, locks, condition queues
  - Java 5 added thread pools, blocking queues, concurrent collections
  - Java 7 added the fork-join library
  - Java 8 added parallel streams

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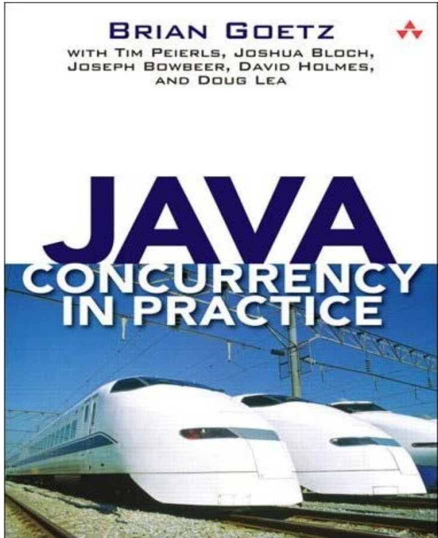
Terminology

- Sadly, definitions for *concurrency* and *parallelism* are not standard
  - Often (mistakenly) used interchangeably
- Historically…
  - *Concurrency* is a property of a program's *structure*
    - Organized as the interaction between multiple cooperating activities
  - Parallelism is a property of a program's *execution*
    - Do things *really* happen simultaneously, or is this just an illusion?
  - Concurrency is the *potential for* parallelism
  - Useful distinction when true concurrent execution was mostly a theoretical concern
  - Less useful distinction today

Terminology

- More commonly today…
  - *Concurrency* is about *correctly* and *efficiently* controlling access to shared resources
    - Example: constructing thread-safe data structures
    - Primitives: Locks, events, semaphores, coroutines, STM
  - *Parallelism* is about using additional resources to produce an answer faster
    - Example: searching a large data set by partitioning
- Why should we care?
  - Concurrency is hard!
    - Reasoning about shared state and locks requires wizardry
    - Not easy even with secret wizard spell book!
  - Parallelism is much easier!
    - Standard trick is *partitioning*
    - And a little bit of discipline



Parallelism

- Parallelism is about using more resources to get the answer faster
  - ***Strictly an optimization!***
  - If additional resources are not available, can still compute sequentially
- Corollary: Only useful if it really does get the answer faster!
- Just because we use more resources …
  - Doesn't mean the computation is always faster than a sequential one
  - Or even as fast…
- Analyze → implement → measure → repeat...
  - Prefer sequential implementation until parallel is proven effective
- Measure of parallel effectiveness is *speedup*
  - How much faster (or slower) compared to sequential?

Parallelism

- A parallel computation *always involves more work* than the best sequential alternative
  - How could it not? It still has to solve the problem!
  - And also:
    - Decompose the problem
    - Launch tasks, manage tasks, wait for tasks to complete
    - Combine results
- Parallel version always starts out “behind”
  - We hope to make up for this initial deficit by burning more resources
  - To succeed, we need
    - A parallelizable problem
    - A good implementation
    - Good runtime support for execution
    - Enough data

Exploitable Parallelism

- Not all problems parallelize equally!
- Given a function *f*, define

$g(0) = f(0)$

$g(n) = f(\, g(n-1)\,),\ for\ n > 0$

$h(0) = f(0)$

$h(n) = f(n) + h(n-1),\ for\ n > 0$

- How well can we parallelize computing *g* and *h*?
  - Their definitions look very similar
  - Are they equally parallelizable?

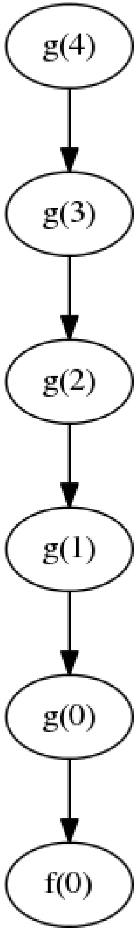
Exploitable Parallelism

$g(0) = f(0)$

$g(n) = f(\ g(n\text{-}1)\ ),\ \text{for}\ n > 0$

- Parallelizing g turns out to be a lost cause
- Can rewrite as

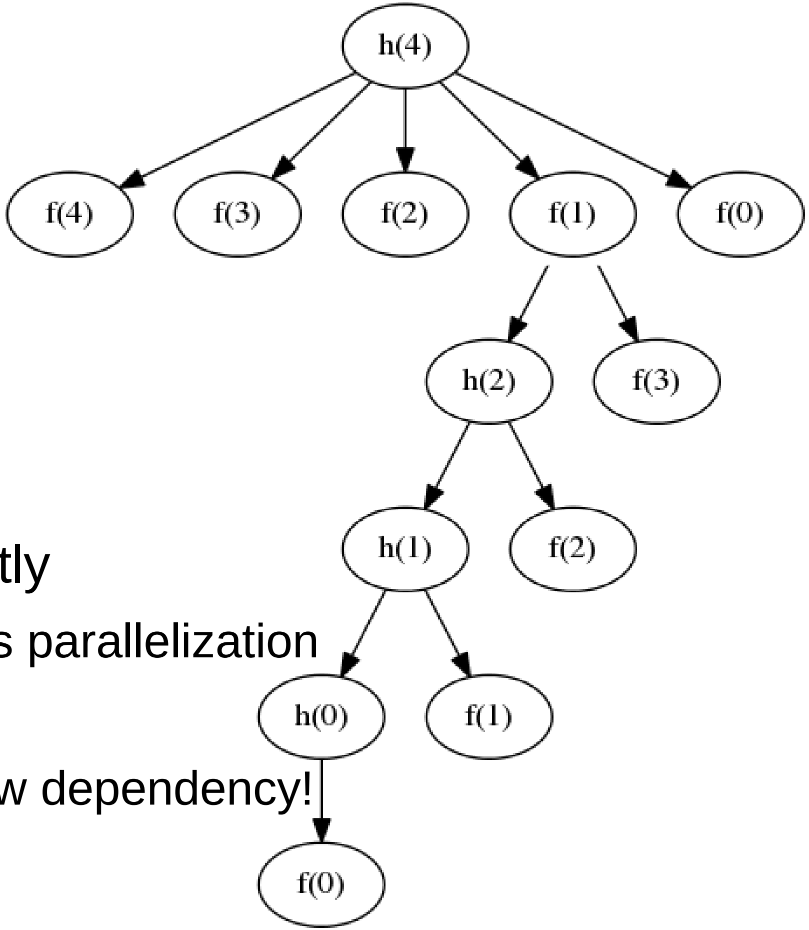
  $g(n) = f(\ f(\ \ldots\ {\scriptstyle n\ \text{times}}\ \ldots\ f(\ 0\ )\ \ldots\ )$
- Can't compute f(f(0)) until we know f(0)
  - Problem is *fundamentally sequential*
  - Parallelism limited by dataflow dependency



Exploitable Parallelism

h(0) = f(0)

h(n) = f(n) + h(n-1), for n > 0



- Parallelizing h turns out to be easy!
- Can rewrite as
  h(n) = f(1) + f(2) + … f(n)
- Can compute each term independently
  - Then add them up, which also admits parallelization
  - Problem is *embarassingly parallel*
  - Though beware of *accidental* dataflow dependency!

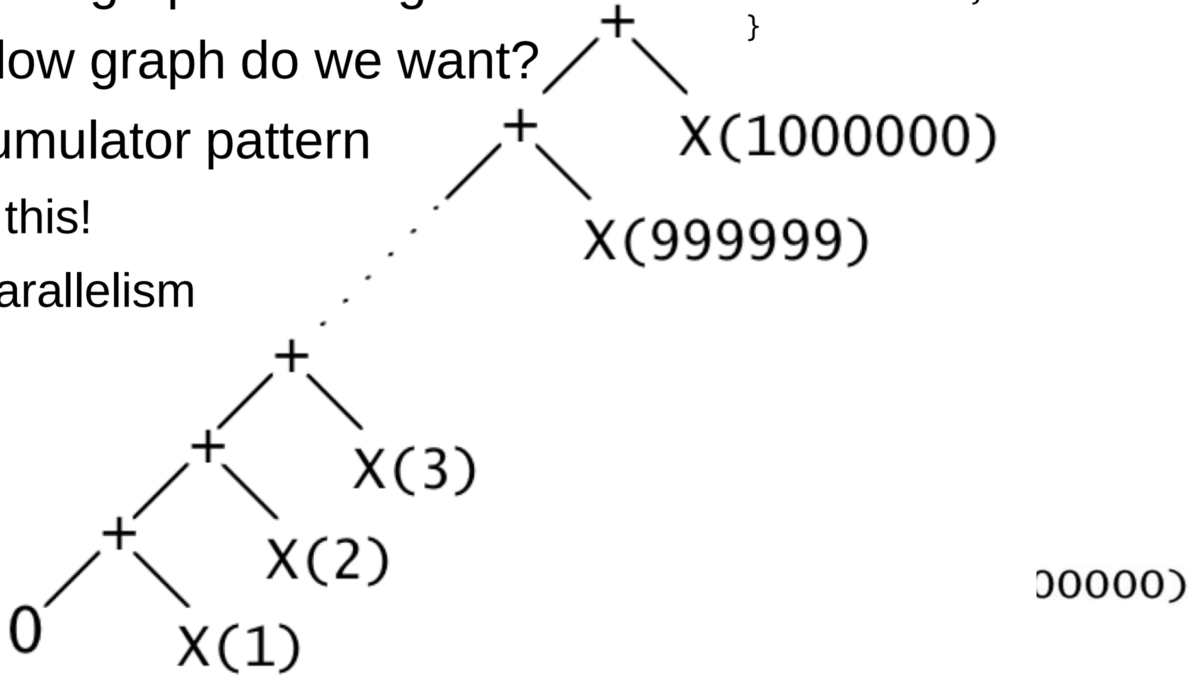
Exploiting Parallelism

- Despite similar-looking definition, *h* was parallelizable but *g* was not
  - But, a naïve implementation of h would have a dataflow graph just like g!
- Its not enough to have exploitable parallelism
  - You have to structure the computation to actually exploit it!
  - Many of the techniques we naturally use in sequential algorithms are impediments in parallel ones
    - Need to unlearn some bad habits

Towards Parallel Computation

```java
int sumSeq(int[] array) {
    int sum = 0;
    for (int i : array)
        sum = sum + i;
    return sum;
}
```

- Simple problem: add numbers from 1..n
- What kind of dataflow graph do we get?
- What kind of dataflow graph do we want?
- Problem #1 – Accumulator pattern
  - Need to unlearn this!
  - Impediment to parallelism



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Towards Parallel Computation

- Might try solving the problem with concurrency
- But, the obvious approach is broken!
  - Data race on every access to sum
  - Will get the wrong answer

```
int sumBroken(int[] array) {
    int mid = array.length / 2;
    int sum = 0;
    CONCURRENT {
        {
            for (int i = 0; i < mid; i++)
                sum = sum + array[i];
        }
        {
            for (int i = mid; i < array.length; i++)
                sum = sum + array[i];
        }
    }
    return sum;
}
```

Towards Parallel Computation

- We can fix this, of course…
  - But now it is *much* slower than sequential!
  - Cores are stalled waiting for lock, not doing work
- Problem has exploitable parallelism
  - Failed attempt to exploit it

```
int sumConcurrent(int[] array) {
    int mid = array.length / 2;
    int sum = 0;
    CONCURRENT {
        {
            for (int i = 0; i < mid; i++)
                ATOMIC { sum = sum + array[i]; }
        }
        {
            for (int i = mid; i < array.length; i++)
                ATOMIC { sum = sum + array[i]; }
        }
    }
    return sum;
}
```


Shared State

- There are three ways to safely handle state…
  – Don't share
  – Don't mutate
  – Coordinate access
- The first two are far easier to get right than the third…
  – Let's try "don't share"
  – Partition the array in two chunks, and operate on them separately

Towards Parallel Computation

- First cut at a parallel solution
- Decompose the problem into subproblems
- Solve the subproblems
- Combine the result
- How will this perform?
  - Given enough data ….
    - OK on 1 or 2 cores
    - No further speedup for N > 2 cores
- No shared access to mutable state

```
int sumPartitioned(int[] array) {
    int mid = array.length / 2;
    int leftSum = 0, rightSum = 0;
    CONCURRENT {
        {
            for (int i = 0; i < mid; i++)
                leftSum = leftSum + array[i];
        }
        {
            for (int i = mid; i < array.length; i++)
                rightSum = rightSum + array[i];
        }
    }
    return leftSum + rightSum;
}
```

Divide And Conquer

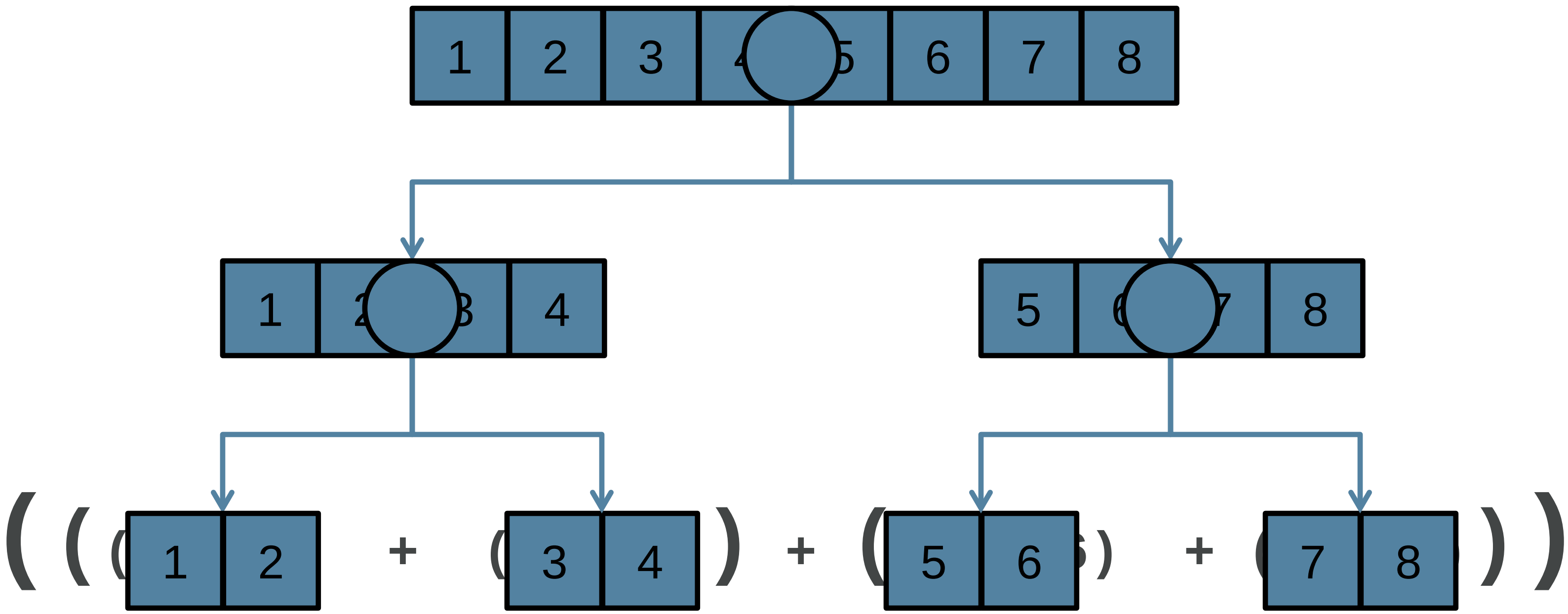
- Standard tool for parallel execution is *divide-and-conquer*
  – Recursively decompose problem until it is small enough for sequential

```
R solve(Problem<R> problem) {
    if (problem.isSmall())
        return problem.solveSequentially();
    R leftResult, rightResult;
    CONCURRENT {
        leftResult = solve(problem.left());
        rightResult = solve(problem.right());
    }
    return problem.combine(leftResult, rightResult);
}
```

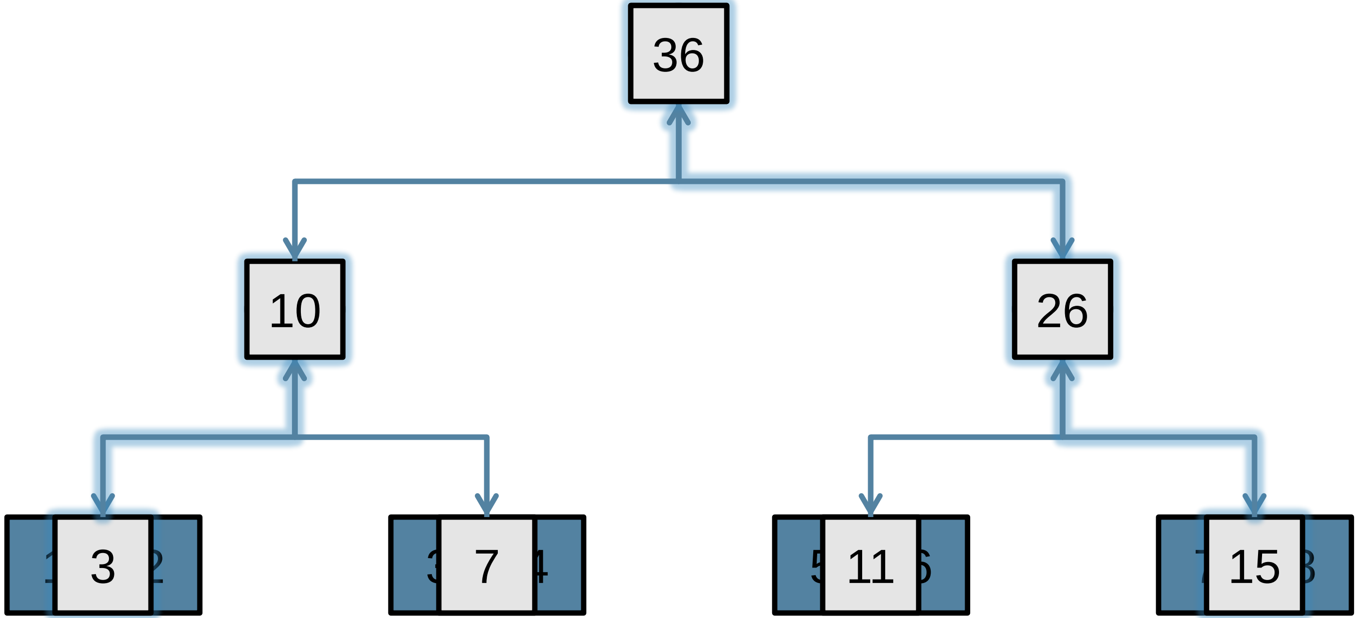

Divide And Conquer

- Recursive decomposition is *simple*
  - Especially with recursively-defined data structures, like trees
  - No shared mutable state – just partitioned reading
  - Intermediate results live on the stack
- Starts forking work early!
  - Beware Amdahl's Law
- Decomposition is dynamic
  - Can incorporate runtime knowledge of core count and load
  - Portable expression of parallel computation

Summing an array in parallel



Summing an array in parallel



Performance Considerations

- Splitting / decomposition costs
  - Sometimes splitting is more expensive than just doing the work!
- Task dispatch / management costs
  - Can do a lot of work in the time it takes to hand work to another thread
- Result combination costs
  - Sometimes combination involves copying lots of data
- Locality
  - The elephant in the room
- Each can steal away potential speedup!
  - In general, need a lot of data to make up for decomposition startup

Fork-Join

- Java SE 7 added the *fork-join* framework to java.util.concurrent
  - Task management framework for *fine-grained*, *CPU-intensive* tasks
    - Scales well from 1 thread to hundreds
  - Specialized and optimized for divide-and-conquer
  - Based on concept of *work stealing*
    - Minimizes contention costs
- Two basic operations
  - Fork a task
  - Wait for (or get callback on) task completion
- Efficient substrate for our CONCURRENT { t1, t2 } construct
  - Relatively low task-management overhead

Streams

- Streams is about *possibly-parallel*, *aggregate operations* on datasets
- Sources can be collections, arrays, generator functions, IO…
  - Support (including parallel) deeply woven into Collections
- Encourages a declarative style – what, not how
  - If done well, more readable and less error-prone
- Pipelines built from basic primitives – filter, map, reduce, sort
  - Exploits laziness – all operations fused into a single pass on the data
- All operations can be executed in parallel
  - But not magic parallelism dust!
- Couldn't get to a library like this without lambdas

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Streams

```java
Set<Seller> sellers = new HashSet<>();
for (Txn t : txns) {
    if (t.getBuyer().getAge() >= 65)
        sellers.add(t.getSeller());
}
List<Seller> sorted = new ArrayList<>(sellers);
Collections.sort(sorted, new Comparator<Seller>() {
    public int compare(Seller a, Seller b) {
        return a.getName().compareTo(b.getName());
    }
});
for (Seller s : sorted)
    System.out.println(s.getName());
```

```java
txns.stream()
    .filter(t -> t.getBuyer().getAge() >= 65)
    .map(Txn::getSeller)
    .distinct()
    .sorted(comparing(Seller::getName))
    .forEach(s -> System.out.println(s.getName()));
```

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Parallel Stream Performance

- Splitting / decomposition costs
  - How easily splittable is the source?
- Task dispatch / management costs
  - Handled by FJ framework
- Result combination costs
  - Adding numbers is cheap; merging sets is expensive
- Locality
  - Array-based sources are best

The NQ Model

- Simple model for parallel performance
  - N = number of data items
  - Q = amount of work per item
- Rule of thumb
  - Need NQ > 10,000 to have a chance for parallel speedup

Source Splitting

- Some sources split better than others
  - Cost of computing split
  - Evenness of split
  - Predictability of split
- Arrays split cheaply, evenly, and with perfect knowledge of split sizes
  - Linked lists have none of these properties
  - Iterative generators behave like linked lists, stateless generators behave like arrays
- Compare
  - `IntStream.iterate(0, i -> i+1).limit(n).sum()`
  - vs `IntStream.range(0, n).sum()`

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Locality

- Locality is the elephant in the room
- Parallelism wins when we can keep the CPUs busy doing useful work
  - Waiting for cache misses is not useful work
- Memory bandwidth often the limiting factor on many systems
- Array-based, numeric problems parallelize best
- Benchmark: Stream.of(int[]).sum() vs Stream.of(Integer[]).sum()
  - 8-core i7, Java SE 8, Linux

Speedup over Sequential	N=1k	N=10k	N=1M
int	1x	6.2x	7.9x
Integer	(4.9x)	1.5x	3.5x

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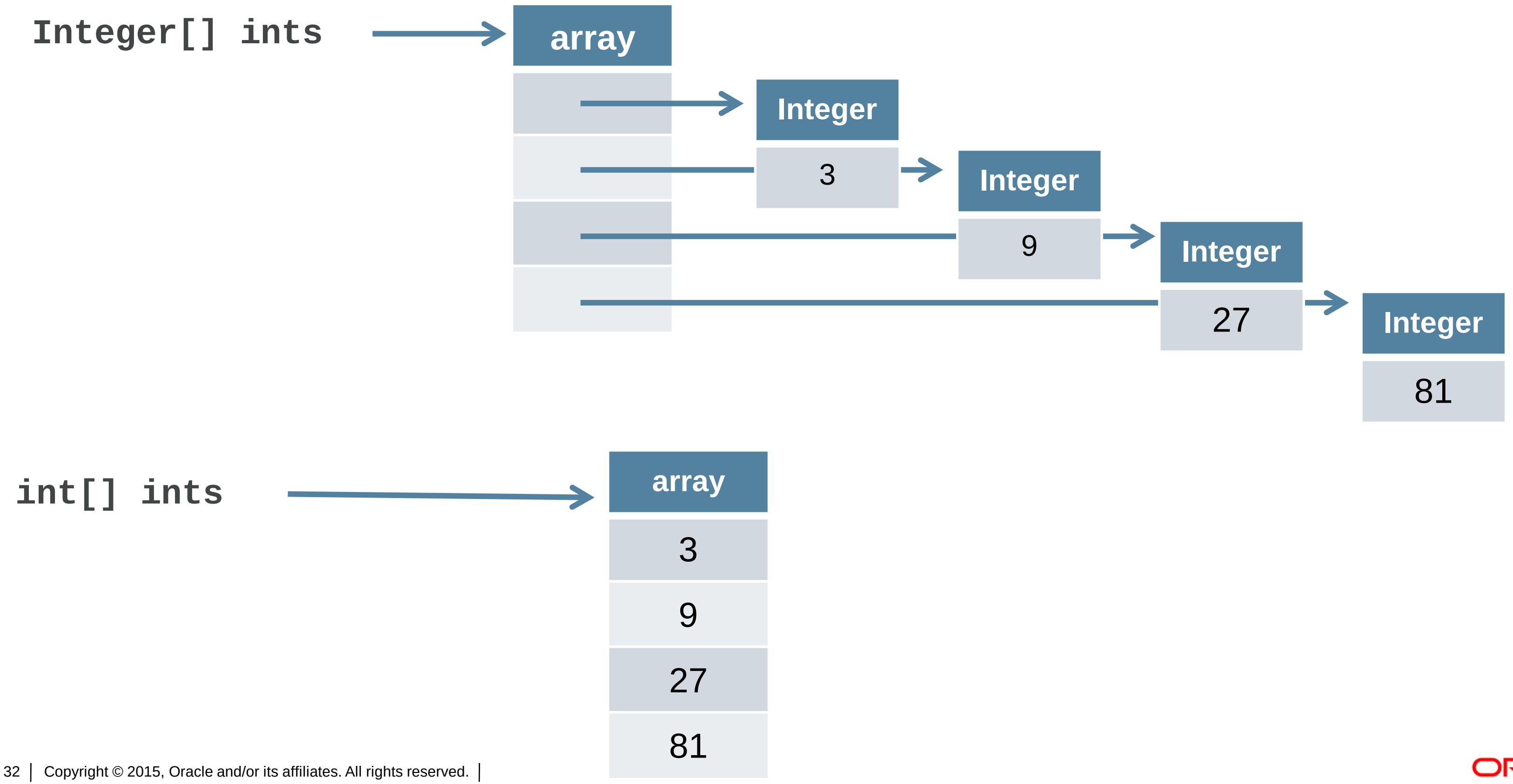
Locality



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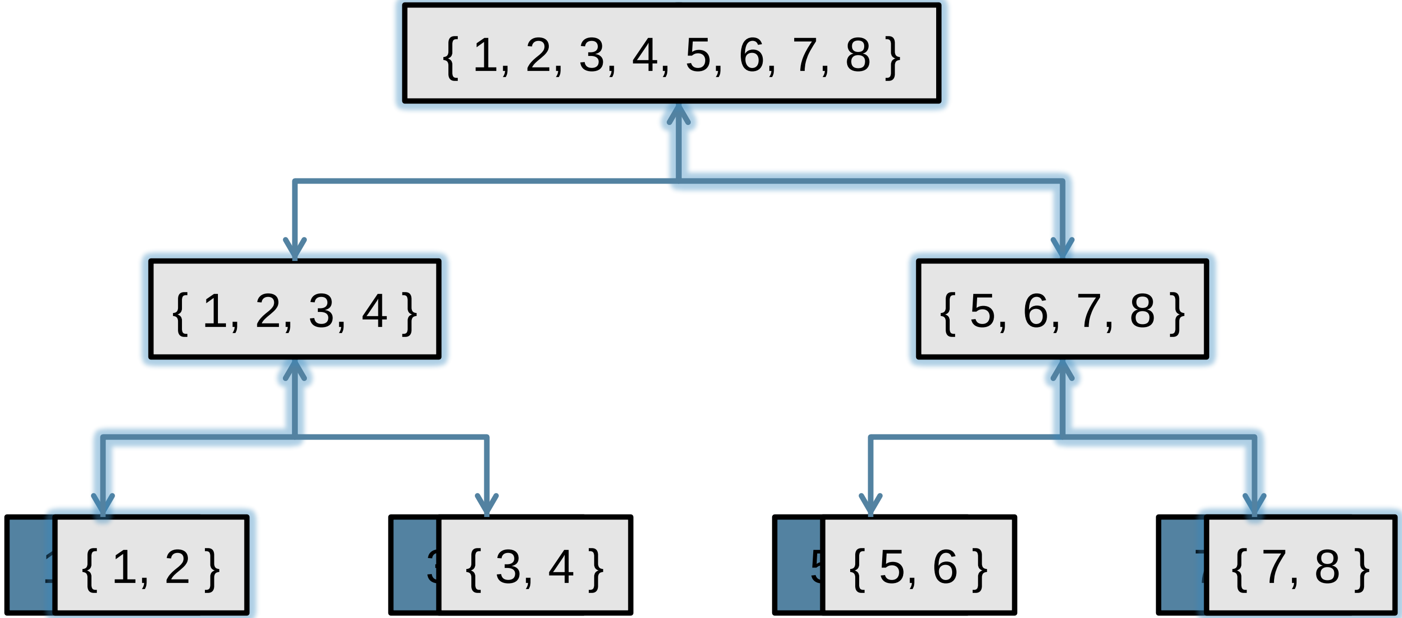
Encounter Order

- Some operations have semantics tied to *encounter order*
  - Encounter order is the order implied by the source
  - Some sources have no defined encounter order (e.g., HashSet)
  - Operations like limit(), skip(), and findFirst() are tied to encounter order
  - Less exploitable parallelism
- Sometimes the encounter order is meaningful, sometimes not
  - Call .unordered() to indicate encounter order is not meaningful to you
  - Ops like limit(), skip(), and findFirst() will optimize in the presence of unordered sources

Merging

- For some operations (sum, max) the merge operation is really cheap
- For others (groupingBy to a HashMap) it is insanely expensive!
  - Involves a lot of copying
  - And repeatedly, up the tree
  - Cost of merging overwhelms the parallelism advantage
- Measuring IntStream.range(0, n).collect(toSet())…
  - For n=10K, approximately 4x *slowdown* going parallel

Merging a set in parallel



Parallel Streams

- Any of the following factors can conspire to undermine speedup
  - NQ is insufficiently high
  - Cache-miss ratio is too high (too many indirections)
  - Source is expensive to split
  - Result combination cost is too high
  - Pipeline uses encounter-order-sensitive operations

Summary

- Streams are cool!
- Parallelism is cool!
- But… parallelism is an optimization
  – And parallel streams are not magic performance dust
- Before optimizing, always …
  – Have actual performance requirements
  – Have reliable performance measurements (not easy!)
  – Ensure that your performance doesn’t meet requirements

