

**ORACLE®**

# Thinking in Parallel

Stuart Marks  
Brian Goetz  
Java Platform Group, Oracle

Questions/comments: #DevoxxParallel

Java  
Your  
Next  
(Cloud)



# Thinking in Parallel

# Thinking

## The First Trivial Example

- Convert an array of strings to upper case
  - Conventional (iterative) approach
  - Streams (aggregate) approach

## Convert Array of Strings to Upper Case

```
String[] upcase(String[] input) {  
    String[] result = new String[input.length];  
  
    for (int i = 0; i < input.length; i++) {  
        result[i] = input[i].toUpperCase();  
    }  
  
    return result;  
}
```

## Convert Array of Strings to Upper Case

a            b            c            d            e

## Convert Array of Strings to Upper Case

a            b            c            d            e

↓

A



## Convert Array of Strings to Upper Case

a      b      c      d      e

↓

A      B

## Convert Array of Strings to Upper Case

a	b	c	d	e
		↓		
A	B	C		

## Convert Array of Strings to Upper Case

a	b	c	d	e
A	B	C	D	

A vertical arrow points from the letter 'd' in the top row to the letter 'D' in the bottom row, indicating the conversion of lowercase to uppercase.

## Convert Array of Strings to Upper Case

a	b	c	d	e
				↓
A	B	C	D	E

## What Parts Are Essential?

```
String[] uppercase(String[] input) {  
    String[] result = new String[input.length];  
  
    for (int i = 0; i < input.length; i++) {  
        result[i] = input[i].toUpperCase();  
    }  
  
    return result;  
}
```

*notion: same computation applied  
to every element, partially  
obscured by indexing and bounds*

*the actual computation*

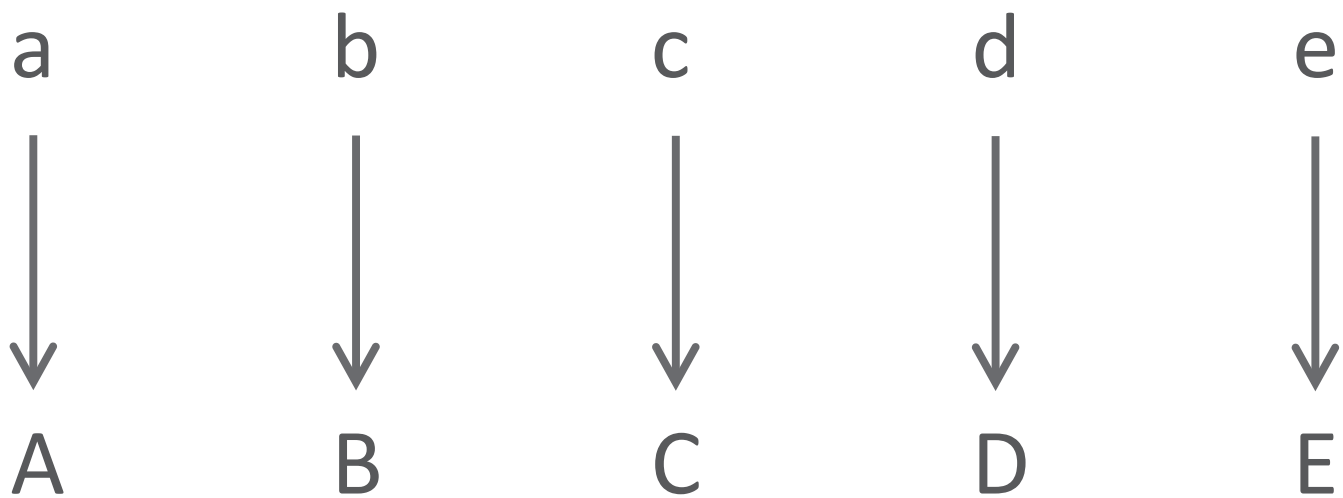
## Observations

- For-loop processing
  - Sequential
  - Left-to-right ordering
- Most of this is accidental, not essential
  - Key: each upper-case computation is independent of all others
    - (this is important, stay tuned)
  - But why are they done sequentially, in order?
  - With a for loop, that's all we've got!
    - you have to do extra work to do anything else
    - enhanced-for (“for-each”) loop helps, but only a little

## Convert Array of Strings to Upper Case – Streams

```
String[] upcase(String[] input) {  
    return Arrays.stream(input)  
        .map(String::toUpperCase)  
        .toArray(String[]::new);  
}
```

Can be done in any order, or all at once!





Consider as aggregate operation, not individual operations

a            b            c            d            e



A            B            C            D            E

## Which is Better?

- Streams version is better
  - more compact
  - new and cool
  - more functional
- For-loop is better
  - more efficient
  - more familiar
  - more straightforward

## Which is Better?

- Streams version is better
  - more compact
  - new and cool
  - more functional
- For-loop is better
  - more efficient
  - more familiar
  - more straightforward

***WRONG!***

## Verdict: Streams Version is Better

- Why? Higher level of abstraction
  - Expresses independence of each computation
  - Less accidental complexity, e.g., index computations
  - Implicitly operates on all elements, not individual elements
  - Focus on desired results than mechanics of computing it
- Why hasn't he said anything about parallelism yet?
  - Making it parallelizable isn't what makes it better
    - you might never want to run this code in parallel (see Brian's part)
    - but this code is still better
  - Making the code better makes it parallelizable, as a bonus

## A Less Trivial Example

- Splitting a list
  - Split at elements selected by a predicate
  - Result list should be sublists of original list (using List.subList method)

- Example

- Split the list:

```
[a, b, #, c, #, d, e]
```

- At elements that equal "#"

- Expected result:

```
[[a, b], [c], [d, e]]
```

## Shameless Plug

- *Splitting List into sublists along elements*
  - link to my answer:  
<http://stackoverflow.com/a/29111023/1441122>
  - please upvote!
- There are several other answers worth reading
  - some of them are ... interesting



## Thinking Through the Problem

a b # c # d e

## Thinking Through the Problem

0	1	2	3	4	5	6
a	b	#	c	#	d	e

*List.subList() wants indexes,  
so conceptually, number all  
the elements*

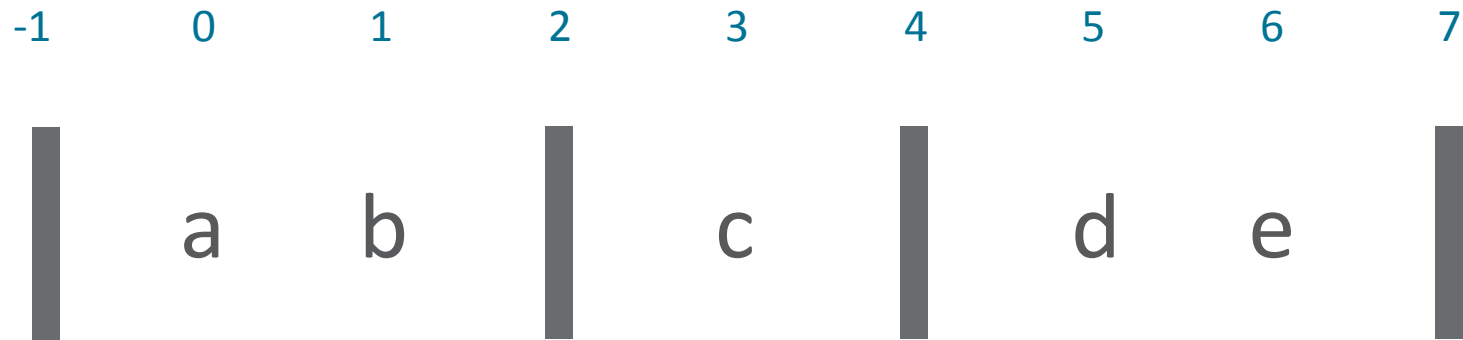


## Thinking Through the Problem

0	1	2	3	4	5	6
a	b		c		d	e

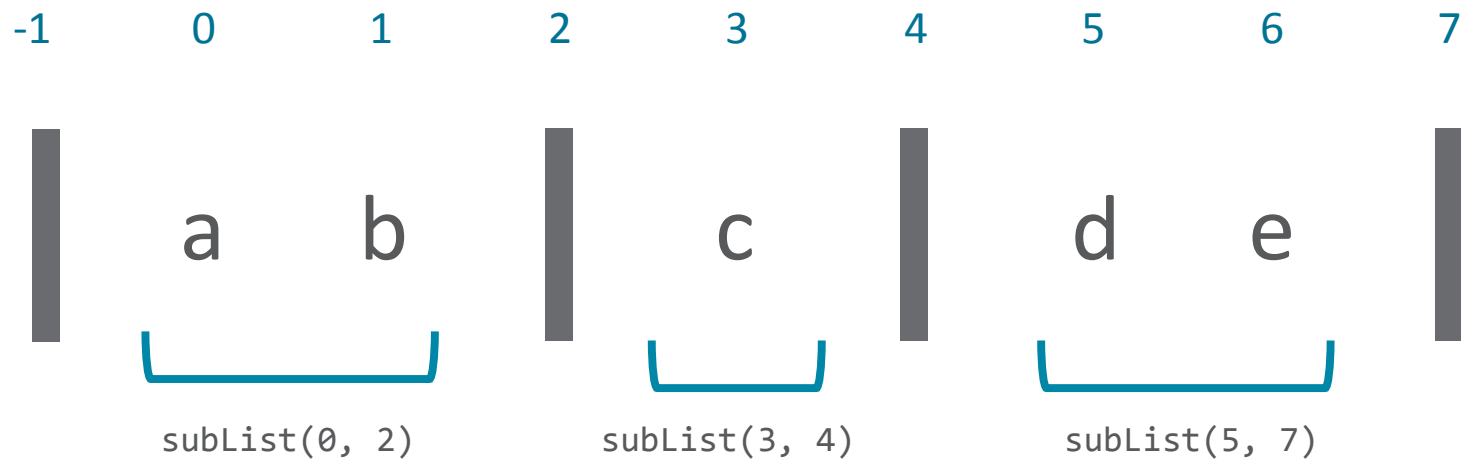
*split points are the  
edges of the sublists*

## Thinking Through the Problem



*we also need to “synthesize” split points at each end to create bounds for exterior sublists*

## Thinking Through the Problem



*each subList starts at **this** split point +1 and runs until the **next** split point (since subList is half-open on the right) implicitly handles corner cases correctly*

## Start with this method signature

```
<T> List<List<T>> split(List<T> input, Predicate<T> pred) {  
  
}
```

## Conventional Approach

```
<T> List<List<T>> split(List<T> input, Predicate<T> pred) {
    List<List<T>> result = new ArrayList<>();
    int start = 0;

    for (int cur = 0; cur < input.size(); cur++) {
        if (pred.test(input.get(cur))) {
            result.add(input.subList(start, cur));
            start = cur + 1;
        }
    }
    result.add(input.subList(start, input.size()));

    return result;
}
```

## Conventional Approach

```
<T> List<List<T>> split(List<T> input, Predicate<T> pred) {  
    List<List<T>> result = new ArrayList<>();  
    int start = 0;  
  
    for (int cur = 0; cur < input.size(); cur++) {  
        if (pred.test(input.get(cur))) {  
            result.add(input.subList(start, cur));  
            start = cur + 1;  
        }  
    }  
    result.add(input.subList(start, input.size()));  
  
    return result;  
}
```

*apply predicate to  
each element*

*sublist creation*

## Conventional Approach

```
<T> List<List<T>> split(List<T> input, Predicate<T> pred) {  
    List<List<T>> result = new ArrayList<>();  
    int start = 0;  
  
    for (int cur = 0; cur < input.size(); cur++) {  
        if (pred.test(input.get(cur))) {  
            result.add(input.subList(start, cur));  
            start = cur + 1;  
        }  
    }  
    result.add(input.subList(start, input.size()));  
  
    return result;  
}
```

*initialization of result and state*

*exposed loop mechanics*

*why do we have to add one here?*

*extra addition to result list??*

## Conventional Approach – Observations

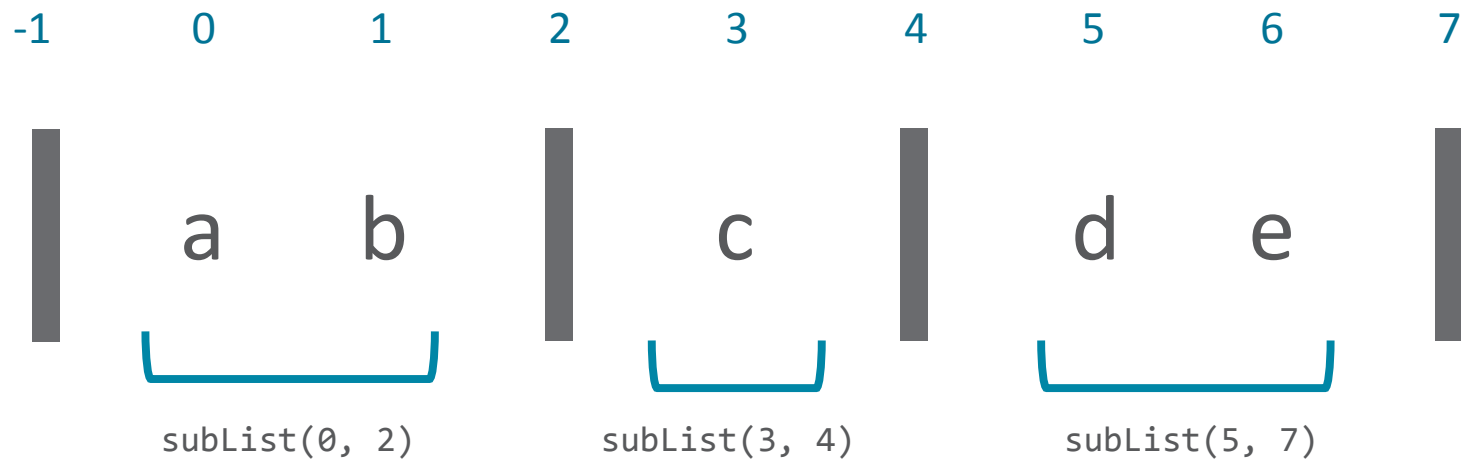
- How do we know this is correct?
  - Does this handle all the corner cases?
  - Handling of trailing sublist is treated non-uniformly (edge cases)
  - Reasoning about loop invariants is subtle
- Hard to see relationship between this code and the model we developed
  - Can you reverse-engineer the diagram from the code?
- Accidental data dependency
  - Each loop iteration depends on state from the previous iteration
  - ***Even though computations of split points are all independent!***



## Streams Approach

- Rethink the problem, avoiding iteration
- We are interested in indexes (because of `List.subList`)
  - Stream over indexes instead, e.g., `IntStream.range(0, last)`
  - Instead of typical stream over values, e.g., `input.stream()`
- Computation of an edge is independent of all other computations
  - Apply the predicate to each element
  - No dependencies on result of predicate on any other result
  - Contrast with the preceding looping approach

## Streams Approach



*each subList starts at **this** split point +1 and runs until the **next** split point (since subList is half-open on the right) implicitly handles corner cases correctly*

## Streams Approach – Outline

1. Filter indexes to find interior sublist edges
2. Synthesize exterior edges at each end
3. Compute sublist from *this* edge and the *next* one

## Streams Approach

```
<T> List<List<T>> split(List<T> input, Predicate<T> pred) {  
    int[] temp = IntStream.range(0, input.size())  
        .filter(i -> pred.test(input.get(i)))  
        .toArray();
```

*compute interior edges  
by applying the predicate  
to every element*

## Streams Approach

```
<T> List<List<T>> split(List<T> input, Predicate<T> pred) {  
    int[] temp = IntStream.range(0, input.size())  
        .filter(i -> pred.test(input.get(i)))  
        .toArray();
```

```
    int[] edges = new int[temp.length+2];  
    System.arraycopy(temp, 0, edges, 1, temp.length);  
    edges[0] = -1;  
    edges[edges.length-1] = input.size();
```

*Synthesize exterior edges.  
OK, we admit it, these array  
operations are ugly.*

## Streams Approach

```
<T> List<List<T>> split(List<T> input, Predicate<T> pred) {
    int[] temp = IntStream.range(0, input.size())
                        .filter(i -> pred.test(input.get(i)))
                        .toArray();

    int[] edges = new int[temp.length+2];
    System.arraycopy(temp, 0, edges, 1, temp.length);
    edges[0] = -1;
    edges[edges.length-1] = input.size();

    return IntStream.range(0, edges.length-1)
                    .mapToObj(k -> input.subList(edges[k]+1, edges[k+1]))
                    .collect(toList());
}
```

*compute sublists from each edge and the one to its right*

## Quick Aside: Adjust Bounds to Synthesize Exterior Edges

```
<T> List<List<T>> split(List<T> input, Predicate<T> pred) {  
    int[] edges = IntStream.range(-1, input.size()+1)  
        .filter(i -> i == -1 || i == input.size() ||  
            pred.test(input.get(i)))  
        .toArray();  
  
    return IntStream.range(0, edges.length-1)  
        .mapToObj(k -> input.subList(edges[k]+1, edges[k+1]))  
        .collect(toList());  
}
```

## Streams Approach – Observations

- Which is better?
- Streams code is better
  - Not because it's new, cool, shorter, more functional
  - But because it's at a higher level of abstraction
- Characteristics
  - Independent computations are independent
    - No accidental dependencies are introduced
  - Problem setup treats all cases uniformly
  - Operations on aggregates, not element-at-a-time
  - No loop mechanics to worry about



## Streams Approach – Observations

- Useful technique: stream over indexes, not over elements
  - Many, but not all, problems can be solved by streaming over elements
  - If you're fighting the Streams API, try this, it might work
  - Broadly, but not universally applicable
- By the way, you can also run this in parallel!
- But, *should* you run it in parallel?

Now, over to Brian...

## 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?

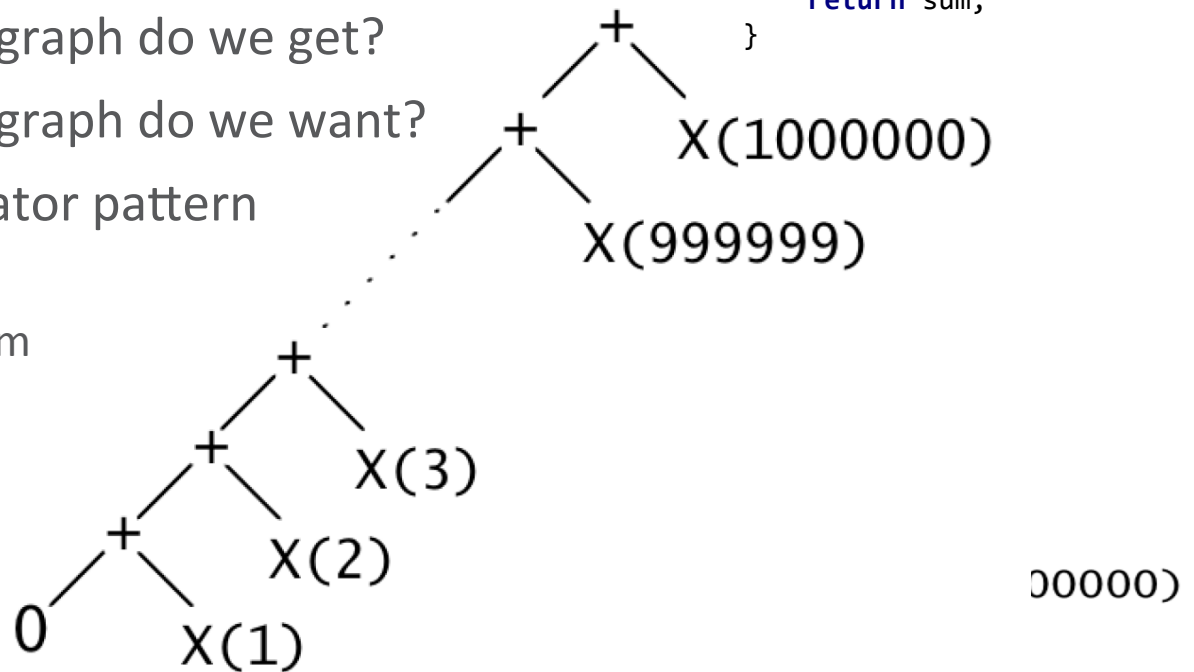
## Parallelism

- 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

## Towards Parallel Computation

- 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

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



## Divide And Conquer

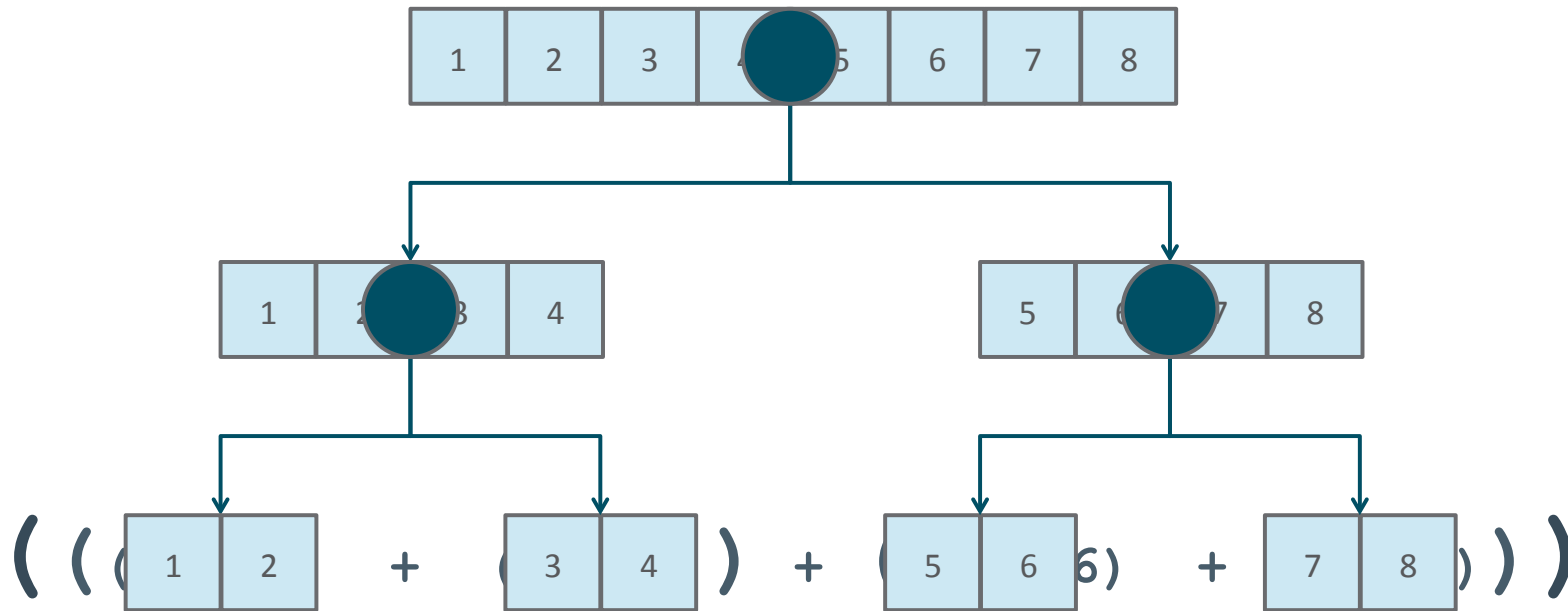
- Standard tool for parallel execution is *divide-and-conquer*
  - Partition the input into chunks that can be independently operated on
  - Recursively decompose problem until it is small enough for sequential

```
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

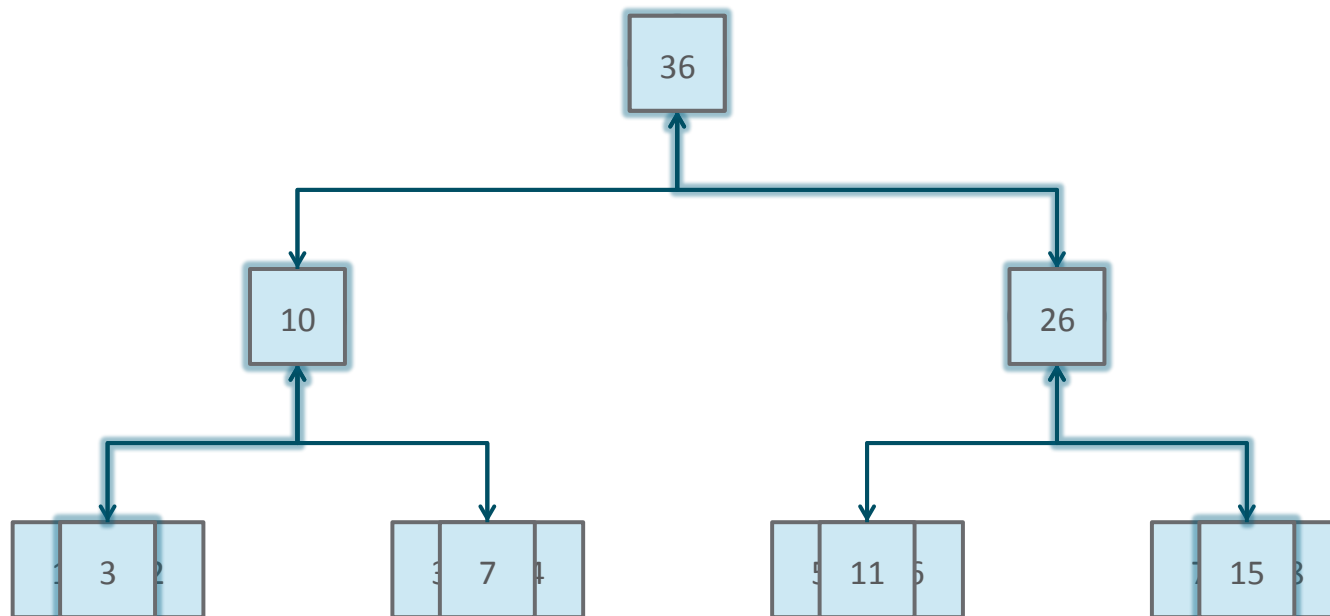
- Recursive decomposition is *simple*
  - Especially with recursively-defined data structures, like trees
  - No shared mutable state – just partitioned reading
  - Intermediate results live on the stack
- Starts forking work early!
  - Beware Amdahl's Law
- Decomposition is dynamic
  - Can incorporate 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

## Parallel Stream Performance

- Streams is about *possibly-parallel, aggregate operations* on datasets
  - Streams are efficient, and (usually) merge computation into a single pass
  - But they are NOT magic parallelism dust!
- Still have to ensure that our problem is amenable to parallel solution
  - How easily splittable is the source?
  - How expensive is result combination?
    - Adding numbers is cheap; merging sets is expensive
  - What kind of locality does our computation get?
    - 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
- Most simple stream examples have very low Q
  - Meaning everything else has to go well to get a speedup

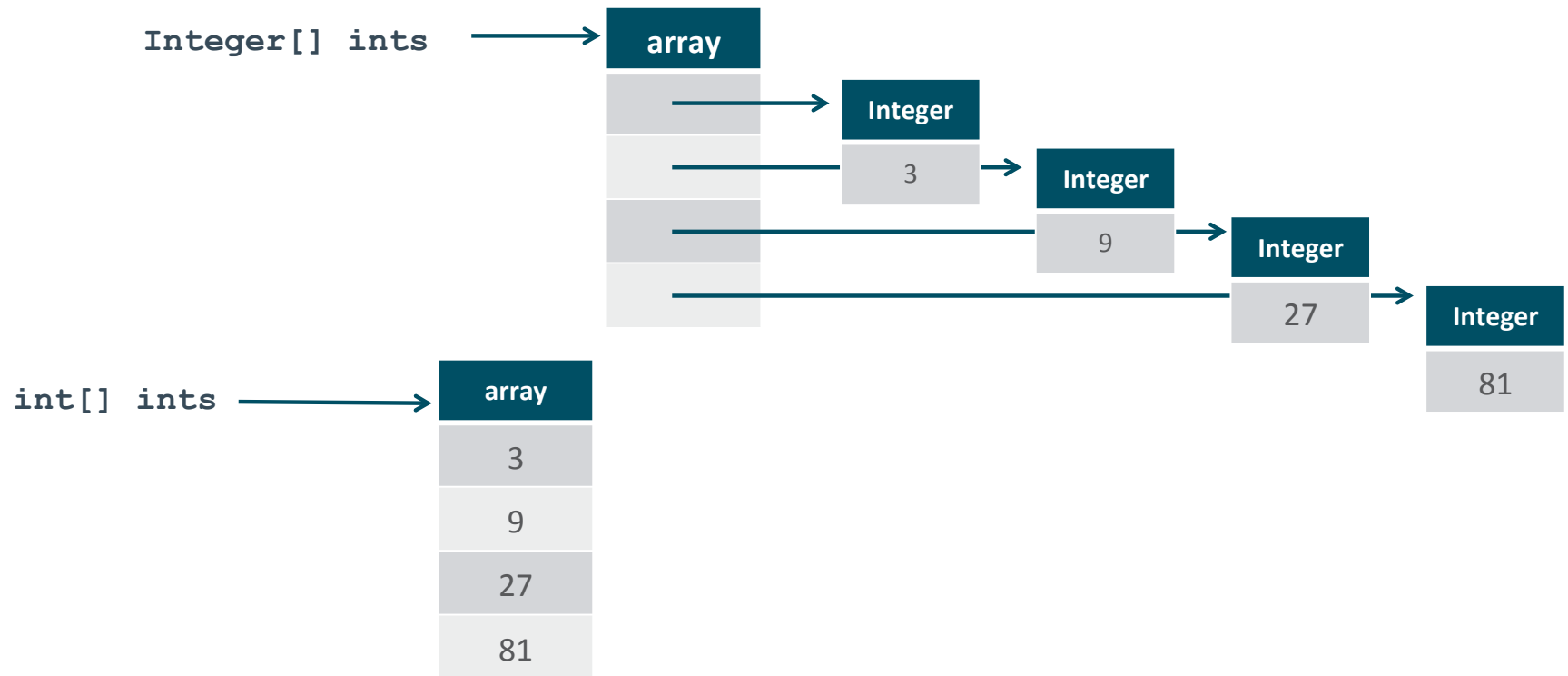
## Source Splitting

- 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()`

## 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

# Locality



## Encounter Order

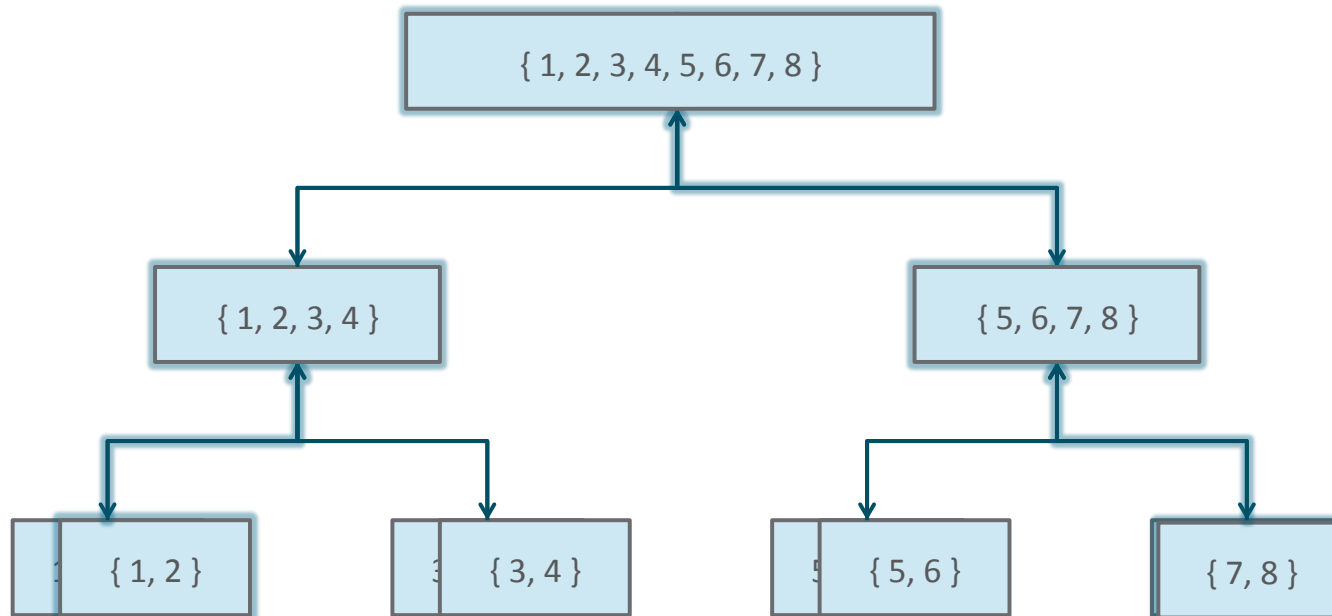
- Some operations have semantics tied to *encounter order*
  - Encounter order is the order implied by the source
  - Some sources have no defined encounter order (e.g., HashSet)
  - Operations like `limit()`, `skip()`, and `findFirst()` are tied to encounter order
  - Less exploitable parallelism
- 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

## Safe Harbor Statement

The preceding is intended to outline our general product direction. It is intended for information purposes only, and may not be incorporated into any contract. It is not a commitment to deliver any material, code, or functionality, and should not be relied upon in making purchasing decisions. The development, release, and timing of any features or functionality described for Oracle's products remains at the sole discretion of Oracle.

**ORACLE®**