

# Summary: Task Level Parallelism

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## Task Creation & Termination

the **async** notation for task creation: “*async <stmt1>*”, causes the parent task (*i.e.*, the task executing the statement) to create a new child task to execute the body of the *async*, *<stmt1>*, *asynchronously* (i.e., in parallel) with the remainder of the parent task.

the **finish** notation for task termination: “*finish <stmt2>*” causes the parent task to execute *<stmt2>* and all *async* tasks created within *<stmt2>* have completed. Async and finish constructs may be nested.

```
finish {
```

```
    async Sum1; // asynchronously compute sum of the left half of the array
```

```
    async Sum2; // compute sum of the right half of the array in parallel with S1
```

```
}
```

```
Sum3 = Sum1 + Sum2; // combine the two partial sums after both Sum1 and Sum2 have finished
```

## Tasks in Java's Fork / Join Framework

A task can be specified in the **`compute()`** method of a user-defined class that extends the standard `RecursiveAction` class in the FJ framework. In our Array Sum example, we created class **SumNumber** with fields **A** and **HI** for the subrange for which the sum is to be computed, and **SUM** for the result for that subrange. In this user-defined class (e.g., **L** in the lecture), we learned that the method call, **L.fork()**, creates a new task that executes **L**'s `compute()` method. This implements the functionality of the `async` construct that we saw in the previous section. A call to **L.join()** then waits until the computation created by **L.fork()** has completed. Note that **join()** is a more primitive than `finish` because `join()` waits for a specific task, whereas `finish` implicitly waits for all tasks in the scope. To implement the `finish` construct using `join()` operations, you have to be sure to call `join()` in the `finish` scope.

A sketch of the Java code for the **SumNumber** class is as follows:

```
class SumNumber extends RecursiveAction {  
    int[] A; // input array
```

ting the async  
(*i.e.*, before, after, or in

2), and then wait until  
may be arbitrarily

rd **RecursiveAction**  
for the input array, **LO**  
brange. For an instance  
s a new task that  
e learned earlier. The  
**n()** is a lower-level  
tasks created in its  
( ) on every task created

```

int LO, HI; // subrange
int SUM; // return value
@Override
protected void compute() {
    SUM = 0;
    for (int i = LO; i <= HI; i++)
        SUM += A[i];
} // compute()
}

```

FJ tasks are executed in a ForkJoinPool, which is a pool of Java threads. This pool supports the `invokeAll` method, which combines both the fork and join operations by executing a set of tasks in parallel, and waiting for all to complete. For example, `ForkJoinTask.invokeAll(left, right)` implicitly performs `fork()` operations on `left` and `right`, and then performs join operations on both objects.

## Computation Graphs, Work, Span

Computation Graphs (CGs) models the execution of a parallel program as a partially ordered set. A CG consists of:

- A set of vertices or nodes, in which each node represents a step consisting of an arbitrary computation.
- A set of directed edges that represent ordering constraints among steps.

For fork–join programs, it is useful to partition the edges into three cases:

1. Continue edges that capture sequencing of steps within a task.
2. Fork edges that connect a fork operation to the first step of child tasks.
3. Join edges that connect the last step of a task to all join operations on that task.

CGs can be used to define data races, an important class of bugs in parallel programs. We say there is a data race on location `L` in a computation graph, `G`, if there exist steps `S1` and `S2` in `G` such that there is no path from `S1` to `S2` or from `S2` to `S1` in `G`, and both `S1` and `S2` read or write `L` (with at least one of the accesses being a write; two parallel reads do not pose a problem).

CGs can also be used to reason about the ideal parallelism of a parallel program as follows:

Define **WORK(*G*)** to be the sum of the execution times of all nodes in CG `G`,

Define **SPAN(*G*)** to be the length of a longest path in `G`, when adding up the execution times of all nodes on the path. The longest paths are known as critical paths, so SPAN also represents the critical path length (CPL).

Given the above definitions of WORK and SPAN, we define the ideal parallelism of Computation Graph `G` as:

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all nodes in the path.  
PL) of G.

Graph G as the ratio,

$WORK(G)/SPAN(G)$ . The ideal parallelism is an upper limit on the speedup factor that can be obtained from the execution of nodes in computation graph  $G$ . Note that ideal parallelism is only a function of the structure of  $G$  and does not depend on the actual parallelism available in a physical computer.

## Multiprocessor Scheduling, Parallel Speedup

In this section, we will study the possible executions of a Computation Graph (CG) on an idealized parallel machine. It is idealized because all processors are assumed to be identical, and the execution time of a node is fixed, regardless of which processor it executes on. A *legal schedule* is one that obeys the dependencies of the CG, such that for every directed edge  $(A, B)$ , the schedule guarantees that step  $B$  is only scheduled after step  $A$  completes. Unless otherwise specified, we will restrict our attention in this course to schedules with no *unforced idleness*, i.e., schedules in which a processor is not permitted to be idle if a CG node is scheduled on it. Such schedules are also referred to as "greedy" schedules.

We defined  $T(P)$  as the execution time of a CG on  $P$  processors, and observed that

$$T(\infty) \leq T(P) \leq T(1)$$

We also saw examples for which there could be different values of  $T(P)$  for different schedules on  $P$  processors.

We then defined the parallel speedup for a given schedule of a CG on  $P$  processors as  $Speedup(P) = T(1)/T(P)$ . We observed that  $Speedup(P)$  must be  $\leq$  the number of processors  $P$ , and also  $\leq$  the ideal parallelism.

## Amdahl's Law

If  $q \leq 1$  is the fraction of  $WORK$  in a parallel program that must be executed *sequentially*, then the maximum speedup that can be obtained for that program for any number of processors,  $P$ , is  $Speedup(P) \leq 1/q$ .

This observation follows directly from a lower bound on parallel execution time that you are familiar with, namely  $T(P) \geq SPAN(G)$ . If fraction  $q$  of  $WORK(G)$  is sequential, it must be the case that  $SPAN(G) \geq q \times WORK(G)$ . Therefore,  $Speedup(P) = T(1)/T(P)$  must be  $\leq WORK(G)/(q \times WORK(G)) = 1/q$  since  $T(1) = WORK(G)$ .

Amdahl's Law reminds us to watch out for sequential bottlenecks both when designing parallel algorithms and when implementing programs on real machines. As an example, if  $q = 10\%$ , then Amdahl's Law reminds us that the possible speedup must be  $\leq 10$  (which equals  $1/q$ ), regardless of the number of processors available.

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