COMP 322: Fundamentals of Parallel Programming

Lecture 9: Ideal Parallelism, Data-Driven Tasks

Mack Joyner
mjoyner@rice.edu

http://comp322.rice.edu

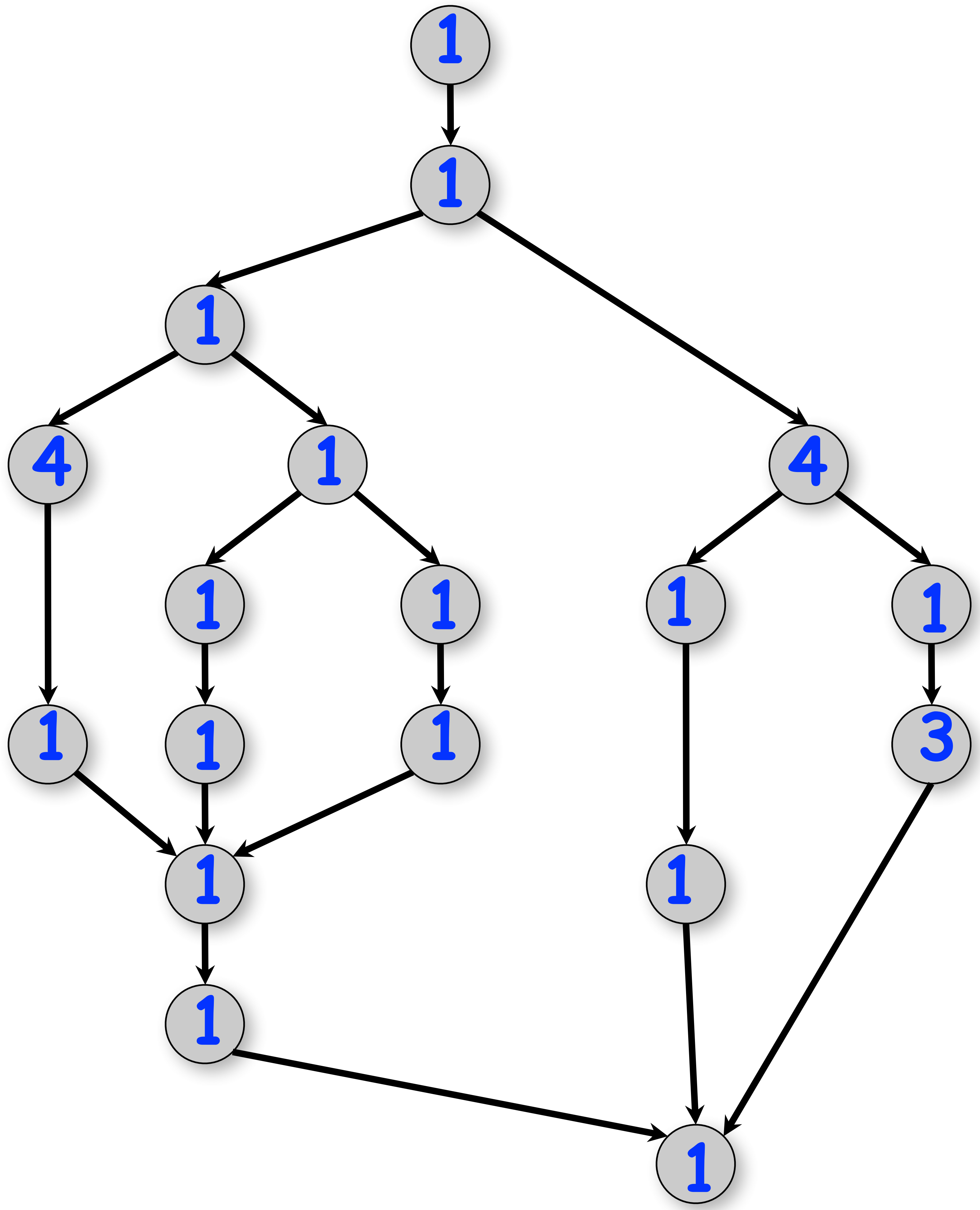
Complexity Measures for Computation Graphs

Define

- TIME(N) = execution time of node N
- WORK(G) = sum of TIME(N), for all nodes N in CG G
  - WORK(G) is the total work to be performed in G
- CPL(G) = length of a longest path in CG G, when adding up execution times of all nodes in the path
  - Such paths are called *critical paths*
  - CPL(G) is the length of these paths (critical path length, also referred to as the *span* of the graph)
  - CPL(G) is also the shortest possible execution time for the computation graph

Ideal Parallelism

- Define ideal parallelism of Computation G Graph as the ratio, WORK(G)/CPL(G)
- Ideal Parallelism only depends on the computation graph, and is the speedup that you can obtain with an unbounded number of processors



Does ideal parallelism tell us we'll need at least x processors and/or at most y processors to get max speedup?

Example:

WORK(G) = 26

CPL(G) = 11

Ideal Parallelism = WORK(G)/CPL(G) = 26/11 ~ 2.36

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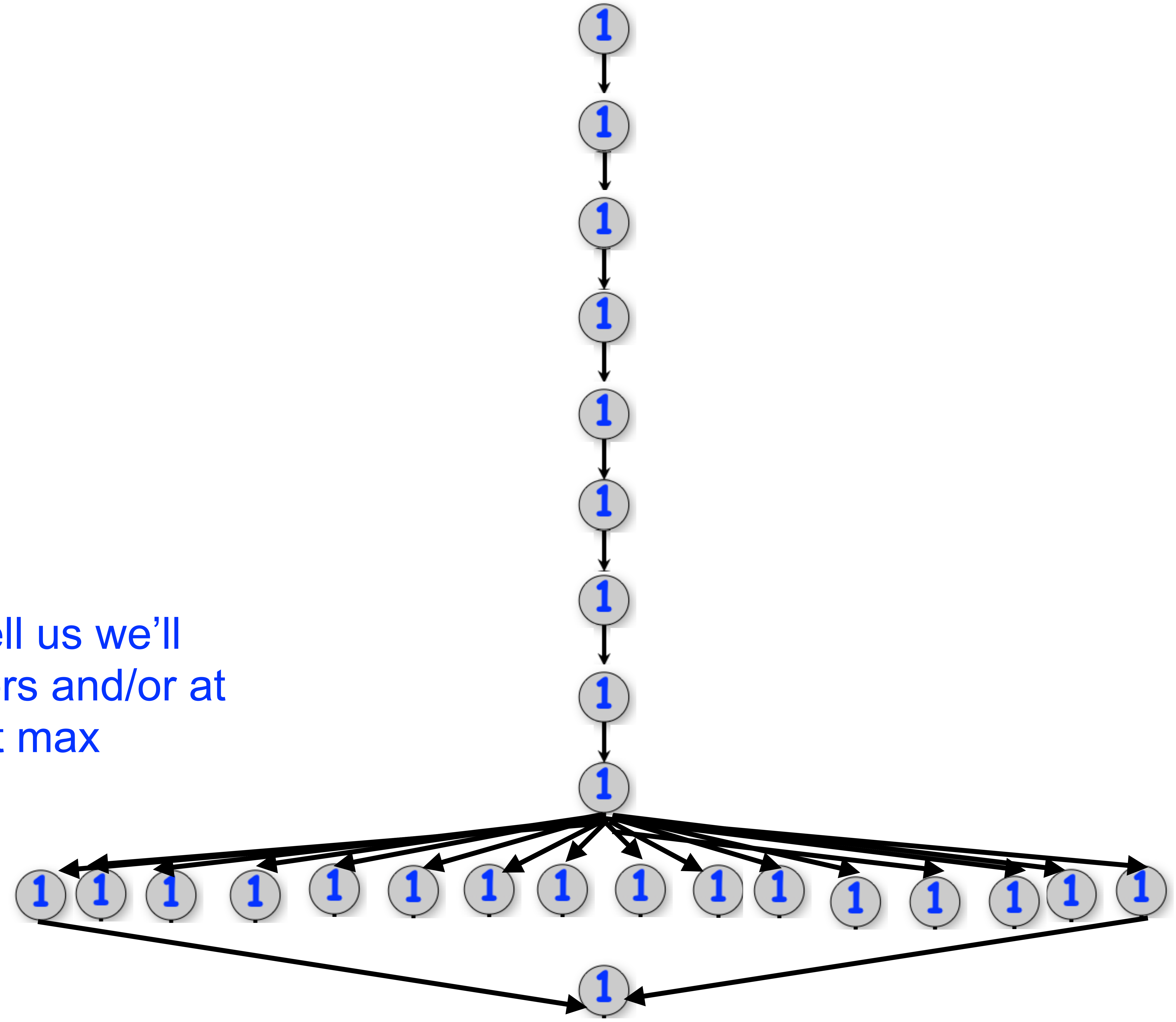


<u>Example</u>:

WORK(G) = 26

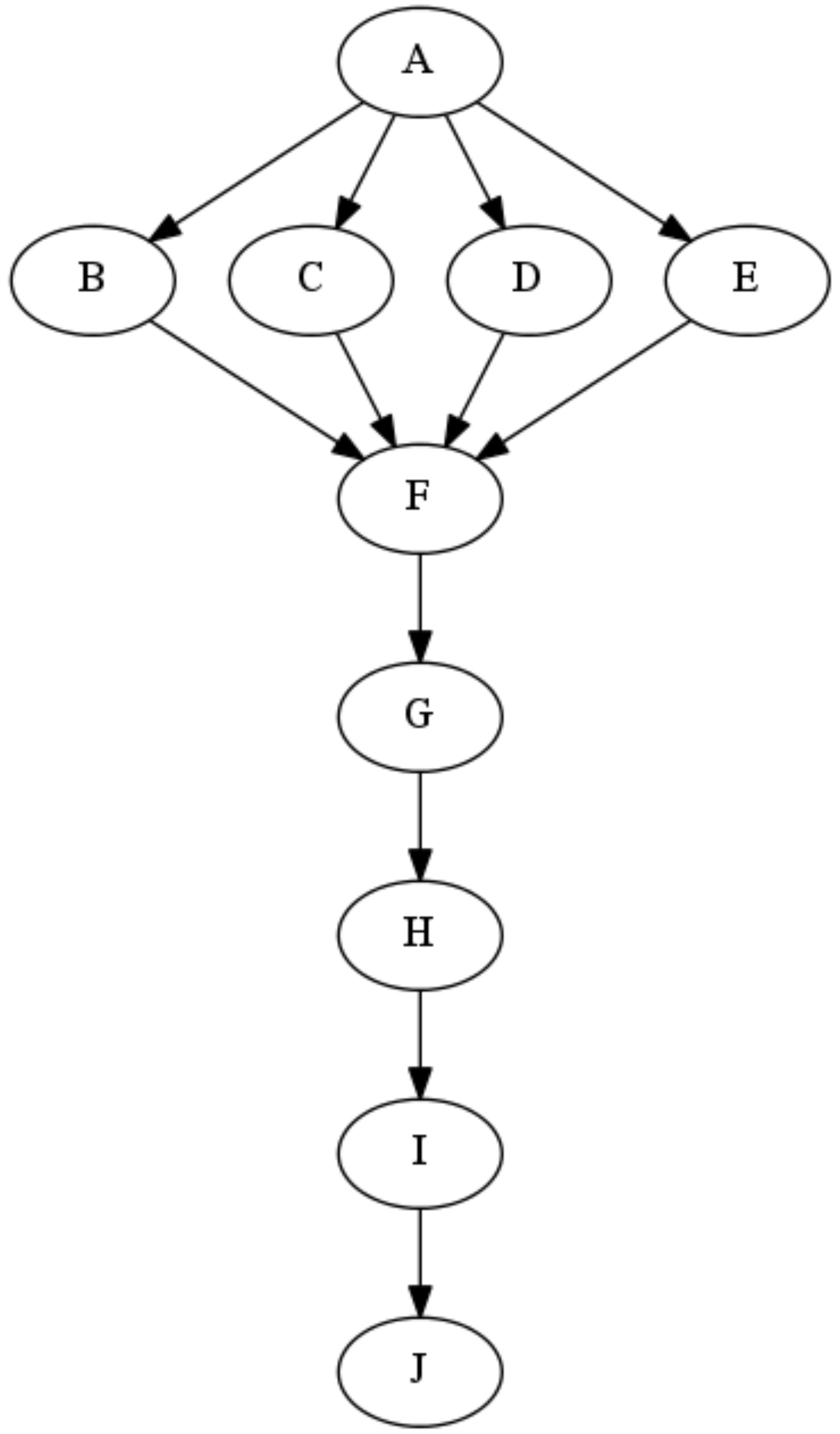
CPL(G) = 11

Ideal Parallelism = WORK(G)/CPL(G) = 26/11 ~ 2.36

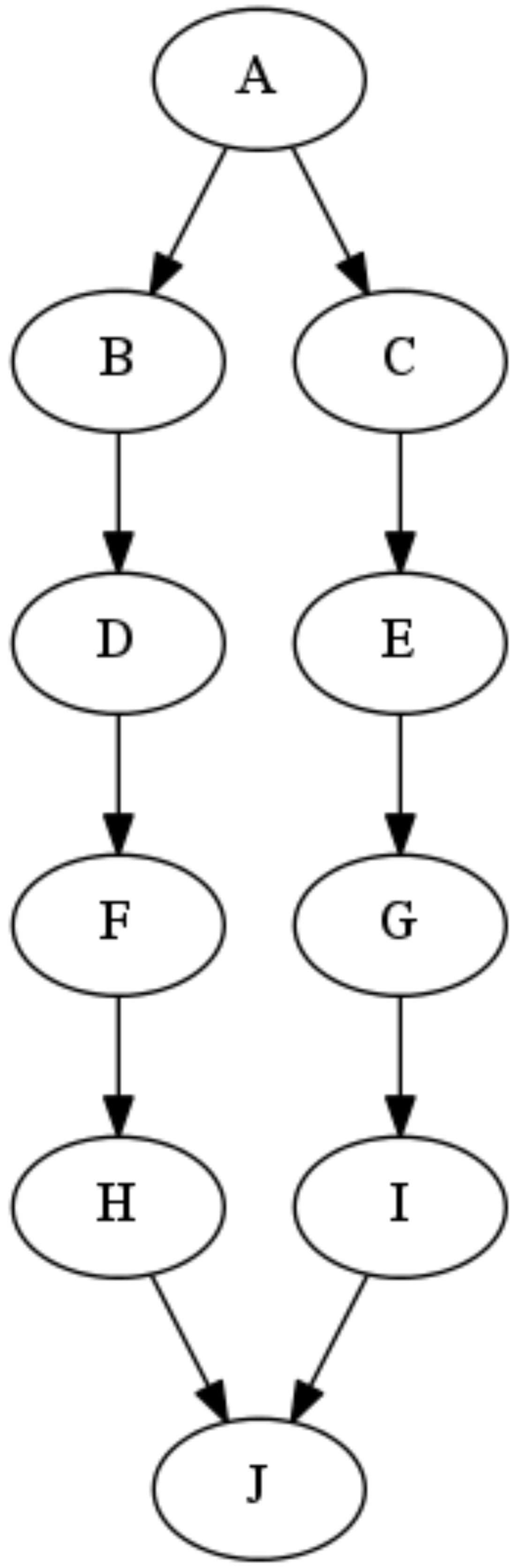
Which Computation Graph has more ideal parallelism?

Assume that all nodes have TIME = 1, so WORK = 10 for both graphs.

Computation Graph 1

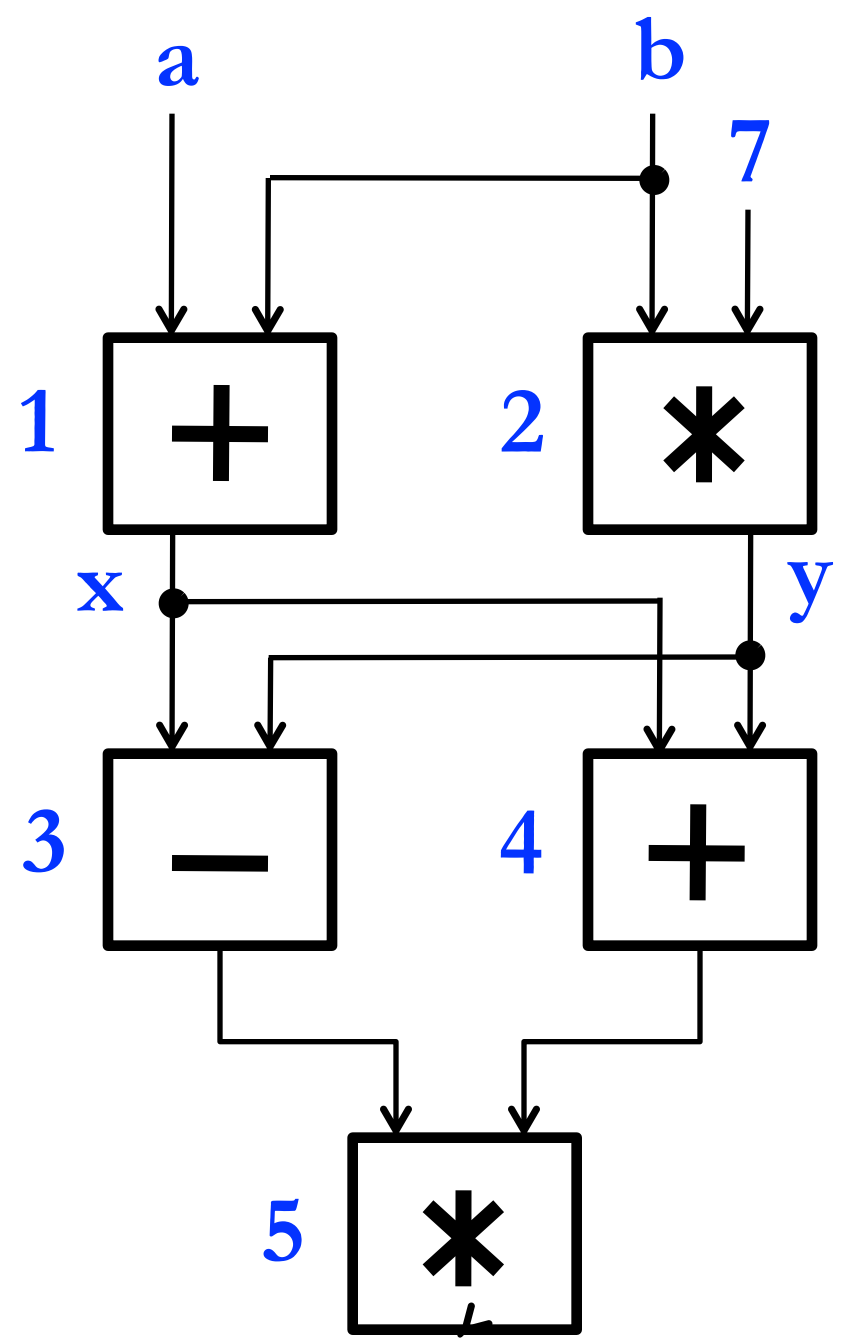


Computation Graph 2



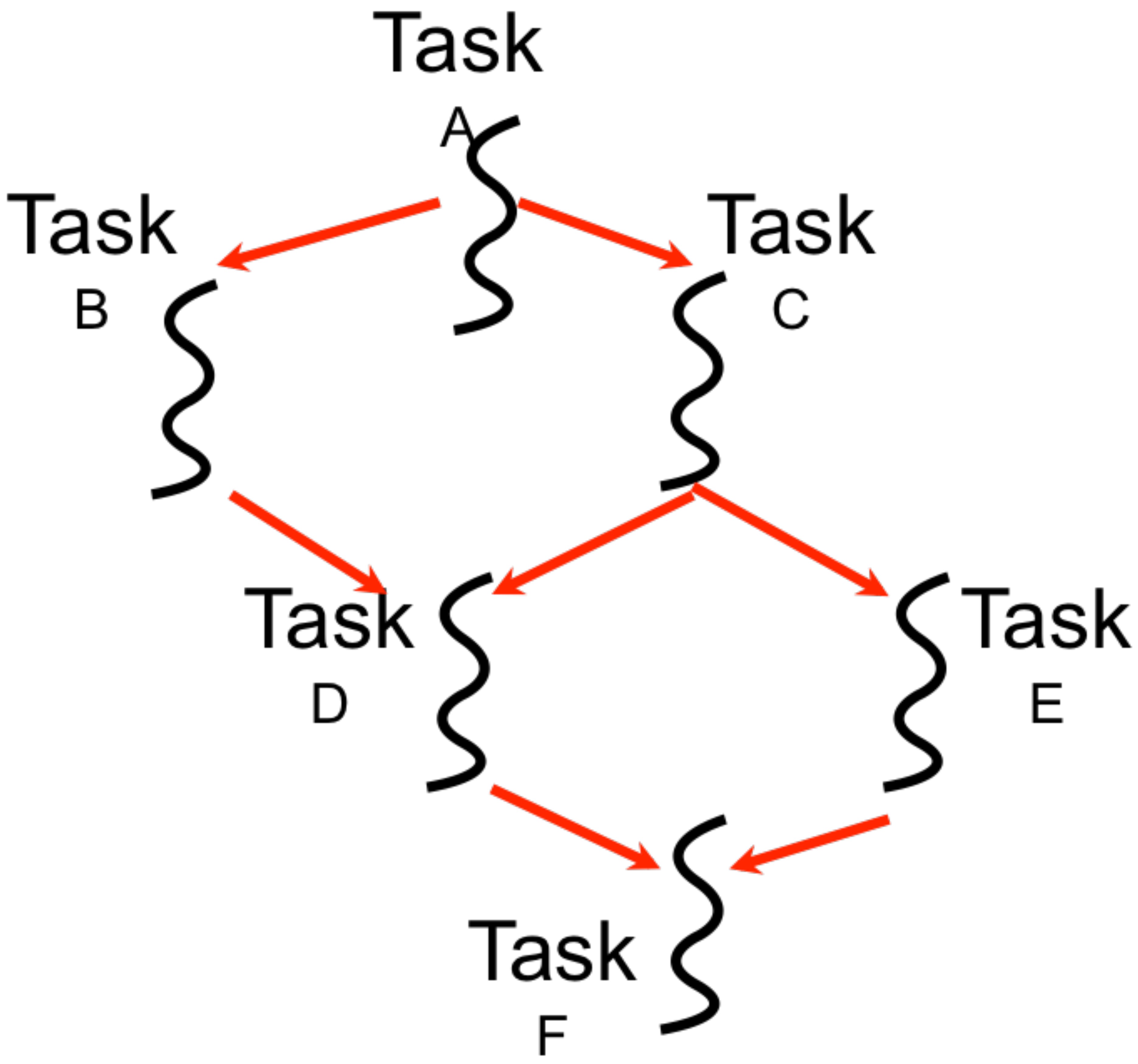
Example instruction sequence and its dataflow graph

```
x = a + b;
y = b * 7;
z = (x-y) * (x+y);
```



An operator executes <u>when all its input values are present</u>; copies of the result value are distributed to the destination operators.

Macro-Dataflow Programming



Communication via "single-assignment" variables

- "Macro-dataflow" = extension of dataflow model from instruction-level to task-level operations
- General idea: build an arbitrary task graph, but restrict all inter-task communications to single-assignment variables (like futures)
  - Static dataflow ==> graph fixed when program execution starts
  - Dynamic dataflow ==> graph can grow dynamically
- Semantic guarantees: race-freedom, determinism
  - "Deadlocks" are possible due to unavailable inputs (but they are deterministic)

Extending HJ Futures for Macro-Dataflow: Data-Driven Futures (DDFs)

final HjDataDrivenFuture<T1> ddfA = newDataDrivenFuture();

- Allocate an instance of a data-driven-future object (container)
- Object in container must be of type T1, and can only be assigned once via put() operations
- HjDataDrivenFuture extends the HjFuture interface

ddfA.put(V) ;

- Store object V (of type T1) in ddfA, thereby making ddfA available
- Single-assignment rule: at most one put is permitted on a given DDF

Extending HJ Futures for Macro-Dataflow: Data-Driven Tasks (DDTs)

asyncAwait(ddfA, ddfB, …, () -> Stmt);

- Create a new <u>data-driven-task</u> to start executing Stmt after all of ddfA, ddfB, … become available (i.e., after task becomes "enabled")
- Alternatively, you can pass a list to asyncAwait
- Await clause can be used to implement "nodes" and "edges" in a computation graph

ddfA.get()

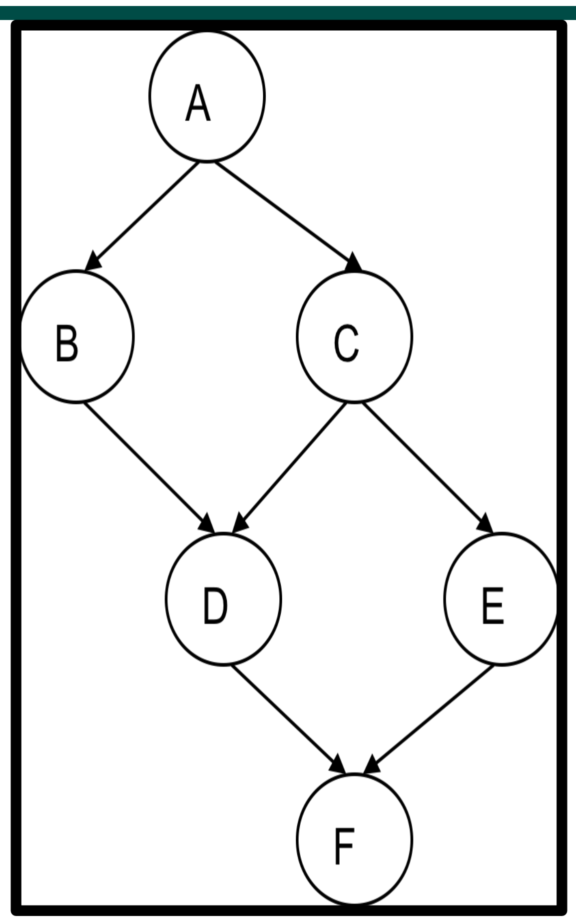
- Return value (of type T1) stored in ddfA
- Throws an exception if put() has not been performed

ddfA.safeGet()

- Doesn't throw an exception
  - Should be performed by async's that contain ddfA in their await clause, or if there's some other synchronization to guarantee that the put() was performed

Converting previous Future example to Data-Driven Futures and AsyncAwait Tasks

```
finish(() -> {
  final HjDataDrivenFuture<Void> ddfA = newDataDrivenFuture();
  final HjDataDrivenFuture<Void> ddfB = newDataDrivenFuture();
  final HjDataDrivenFuture<Void> ddfC = newDataDrivenFuture();
  final HjDataDrivenFuture<Void> ddfD = newDataDrivenFuture();
  final HjDataDrivenFuture<Void> ddfE = newDataDrivenFuture();
  asyncAwait(ddfA, () -> { ... ;  ddfB.put(…); }); // Task B
  asyncAwait(ddfA, () -> { ... ;  ddfC.put(…); }); // Task C
  asyncAwait(ddfB, ddfC, ()->{ ... ; ddfD.put(…); }); // Task D
  asyncAwait(ddfC, () -> { ... ;  ddfE.put(…); }); // Task E
  asyncAwait(ddfD, ddfE, () -> { ... }); // Task F
  // Note that creating a "producer" task after its "consumer"
  // task is permitted with DDFs & DDTs, but not with futures
  async(() -> { ... ; ddfA.put(…); }); // Task A
}); // finish
```



What is Deadlock?

- A parallel program execution contains a deadlock if some task's execution remains incomplete due to it being *blocked indefinitely* awaiting some condition
- Example of a program with a deadlocking execution

```
final HJDataDrivenFuture<Object> left = newDataDrivenFuture();
final HJDataDrivenFuture<Object> right = newDataDrivenFuture();
finish {
   asyncAwait ( left ) right.put(rightBuilder()); // Task1
   asyncAwait ( right ) left.put(leftBuilder()); // Task2
}
```

- In this case, Task1 and Task2 are in a deadlock cycle.

Implementing Future Tasks using DDTs

- Future version

```
var f = future(() -> { return g(); });
S1
async(() -> {
  ... = f.get(); // blocks if needed
  S2;
  S3;
});
```

- DDT version

```
var f = newDataDrivenFuture();
async(() -> { f.put(g()) });
S1
asyncAwait(f, () -> {
  ... = f.safeGet(); // does not need to block -- why?
  S2;
  S3;
});
```

Differences between Futures and DDTs

- Consumer task blocks on get() for each future that it reads, whereas async-await does not start execution till all futures are available
- Future tasks cannot deadlock, but it is possible for a DDT to block indefinitely ("deadlock") if one of its input futures never becomes available
- DDTs and DDFs are more general than futures
  - Producer task can only write to a single future object, whereas a DDT can write to multiple DDF objects
  - The choice of which future object to write to is tied to a future task at creation time, where as the choice of output DDF can be deferred to any point with a DDT
  - Consumer DDTs can be created before the producer tasks
- DDTs and DDFs can be implemented more efficiently than futures
  - An "asyncAwait" statement does not block the worker, unlike a future.get()

Two Exception (error) cases for DDFs that cannot occur with futures

- Case 1: If two put's are attempted on the same DDF, an exception is thrown because of the violation of the single-assignment rule
  - There can be at most one value provided for a future object (since it comes from the producer task's return statement)

- Case 2: If a get is attempted by a task on a DDF that was not in the task's await list, then an exception is thrown because DDF's do not support blocking gets
  - Futures support blocking gets

Deadlock example with DDTs (cannot be reproduced with futures)

- A parallel program execution contains a deadlock if some task's execution remains incomplete due to it being *blocked indefinitely* awaiting some condition

```
var left = newDataDrivenFuture();
var right = newDataDrivenFuture();
finish(() -> {
  asyncAwait(left, () -> {
     right.put(rightWriter()); });
  asyncAwait(right, () -> {
     left.put(leftWriter()); });
});
```

Can you think of a deadlock example or explain why it can't happen?