
Efficient Recursion, and Dynamic Programming

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Efficient Recursion: Memoization and Dynamic programming

Fibonacci Recursive code

```
Counter = 0
```

```
def fib(n):  
    global counter  
    counter += 1  
    if n == 1:  
        return 1  
    elif n == 2:  
        return 1  
    else:  
        return fib(n-1) + fib(n-2)
```

Fibonacci sequence F_n :

$$F_1 = 1,$$

$$F_2 = 1,$$

for $n > 2$:

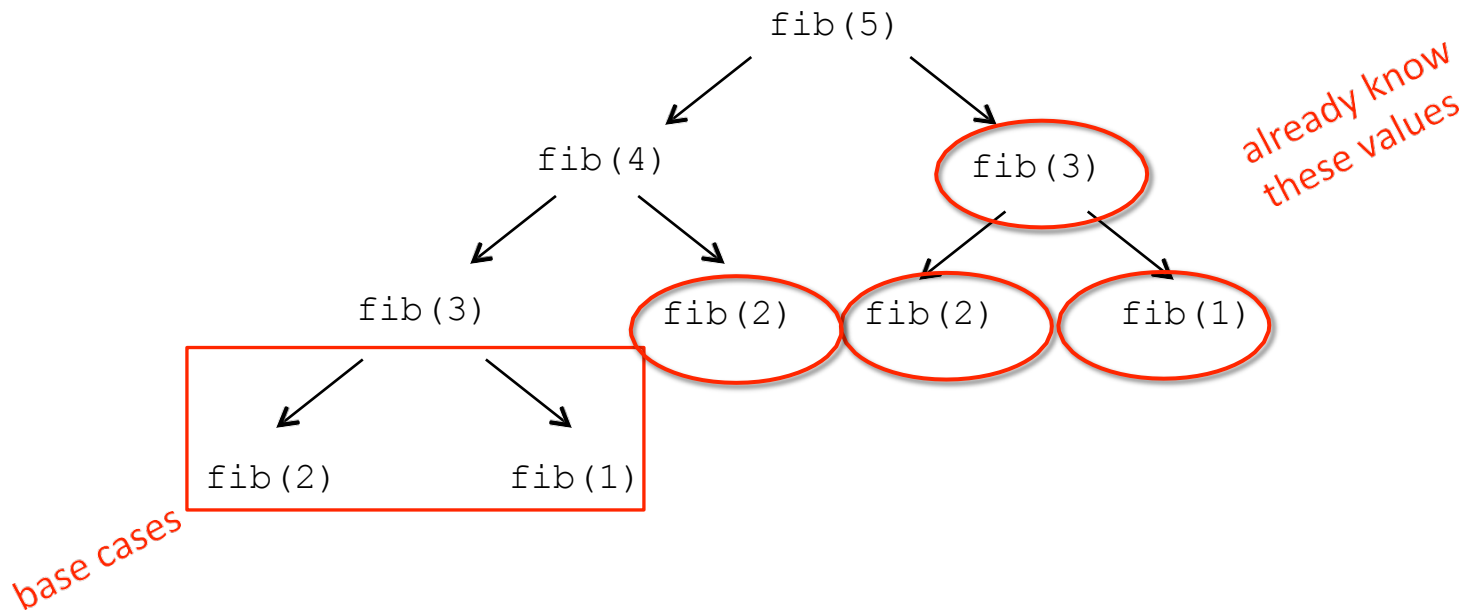
$$F_n = F_{n-1} + F_{n-2}$$

1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 144, ...

- two base cases
- calls itself "twice" -- **this code is very inefficient**

Inefficient Fibonacci code

$$\text{fib}(n) = \text{fib}(n-1) + \text{fib}(n-2)$$



- **recalculating** the same values many times! Try `fib(134)` !
- Instead, we could keep **track** of already calculated values!

Fibonacci with a dictionary

```
Counter = 0
```

```
def fib_efficient(n, d):  
    global counter  
    counter += 1  
    if n in d:  
        return d[n]  
    else:  
        ans = fib_efficient(n-1, d) + fib_efficient(n-2, d)  
        d[n] = ans  
        return ans
```

Method sometimes
called "memoization"

```
d = {1:1, 2:1}  
print(fib_efficient(134, d))
```

Initialize dictionary
with base cases

- do a **lookup first** in case already calculated the value
- **modify dictionary** as progress through function calls

The efficiency gain

- Calling **fib(n)** results in $2F_n - 1 \approx (1.6)^n$ recursive calls to the procedure (why?)
- The **first** calling of **fib_efficient(n)** results in $2n - 3$ recursive calls to the procedure (why?). How about if calling again any smaller n ?
- **Memoization** is **very efficient**
- This only works for procedures **without side effects** (i.e., the procedure will always produce the same result for a specific argument independent of any other computations between calls)

Dynamic programming (intro)

If we have

- Overlapping Subproblems

and

- *Principle of Optimality* holds

and

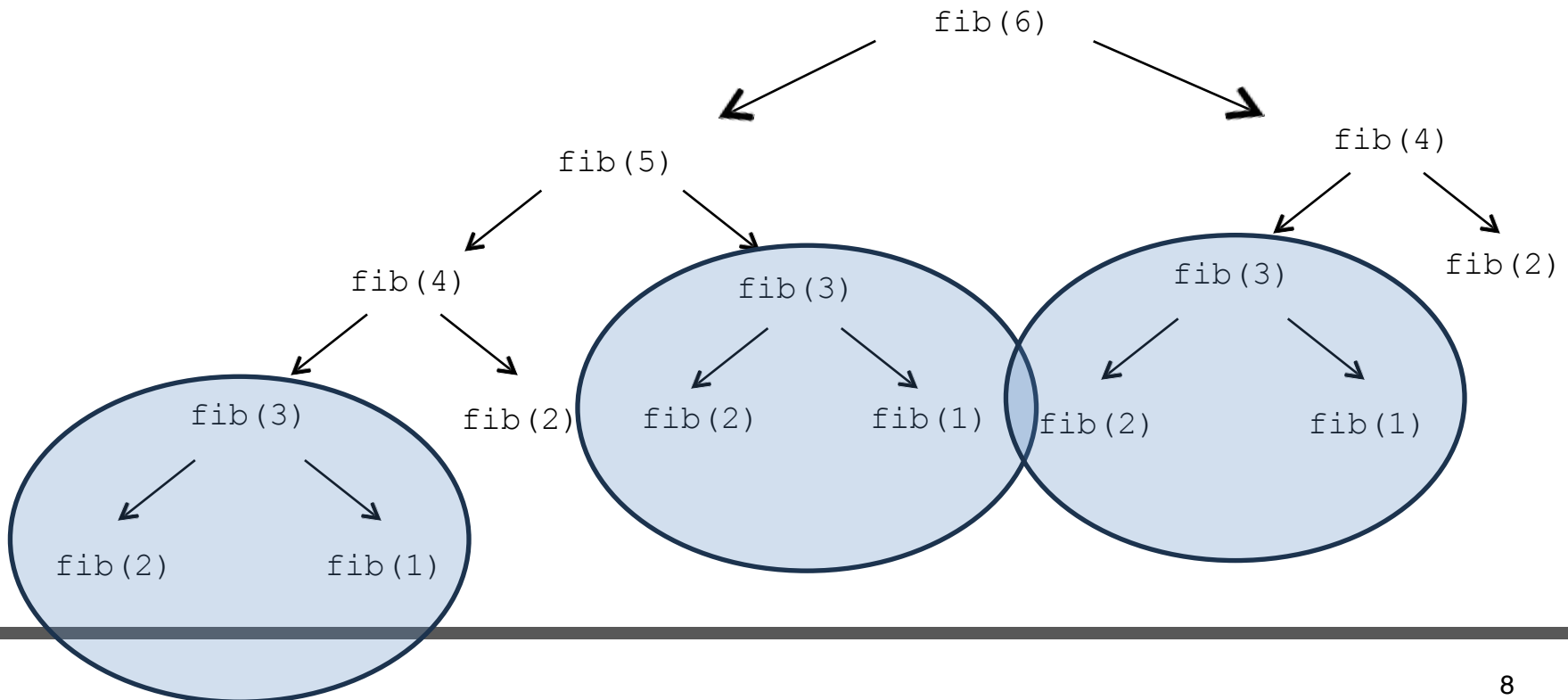
- Dependencies of subproblems are acyclic
(*Directed Acyclic Graph*)

Then the DP is the optimal efficient solution!

Dynamic programming (intro)

Overlapping Subproblems

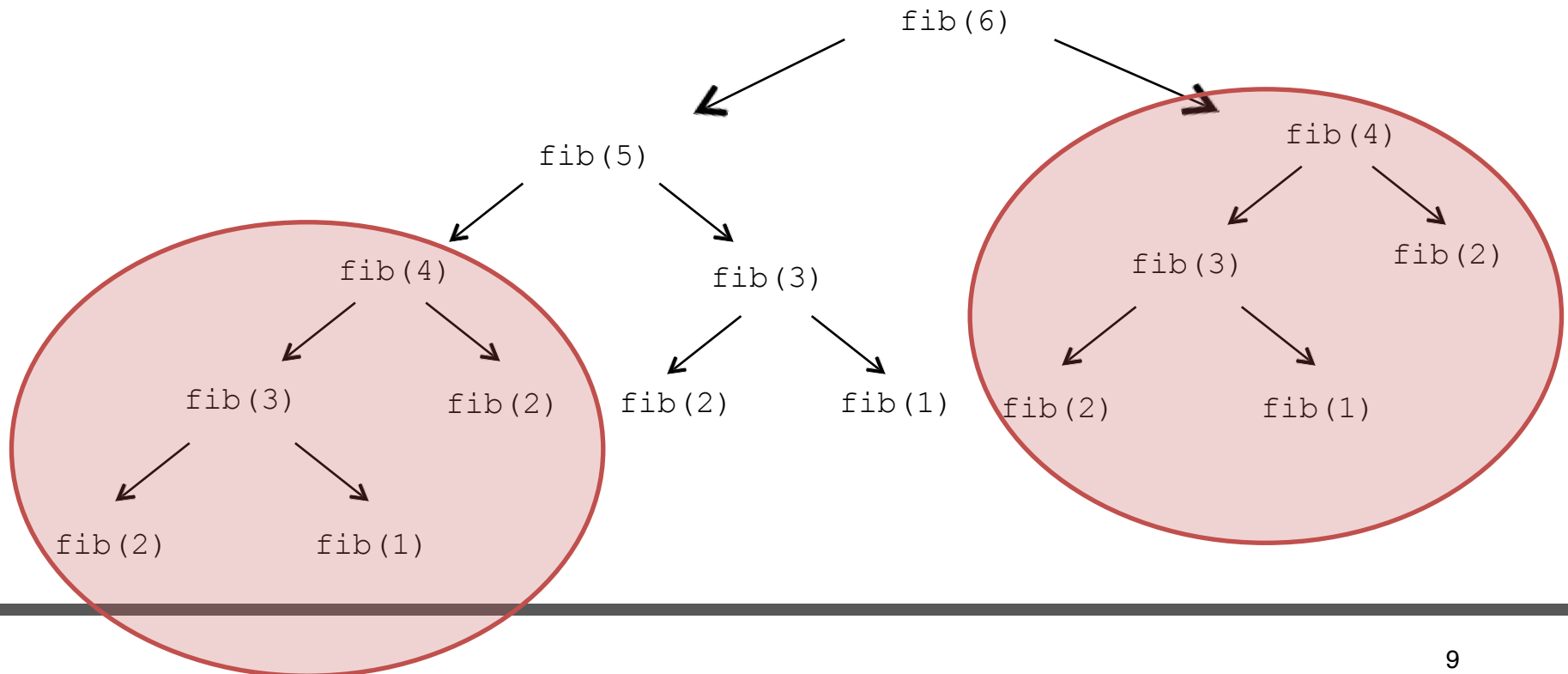
$$\text{fib}(n) = \text{fib}(n-1) + \text{fib}(n-2)$$



Dynamic programming (intro)

Overlapping Subproblems

$$\text{fib}(n) = \text{fib}(n-1) + \text{fib}(n-2)$$



Dynamic programming (intro)

Principle of Optimality

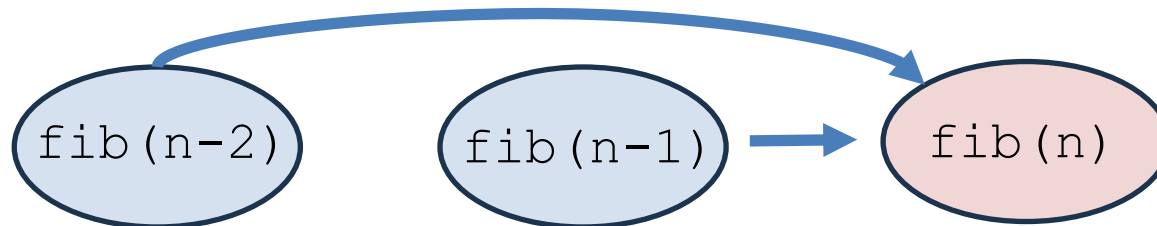
The problem has **optimal substructures**:

- A problem has optimal substructure if the optimal solution can be built from optimal solutions to its subproblems

In other words:

- We can solve main problem using **smaller instance solutions of the same problem!**

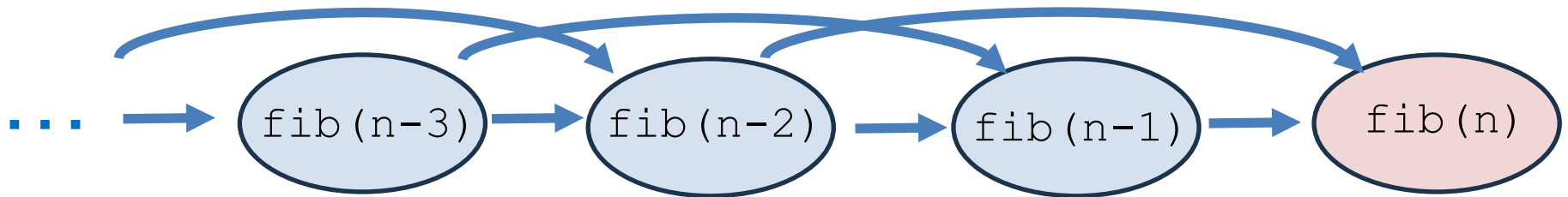
Example: Fibonacci



Dynamic programming (intro)

Acyclic Dependencies

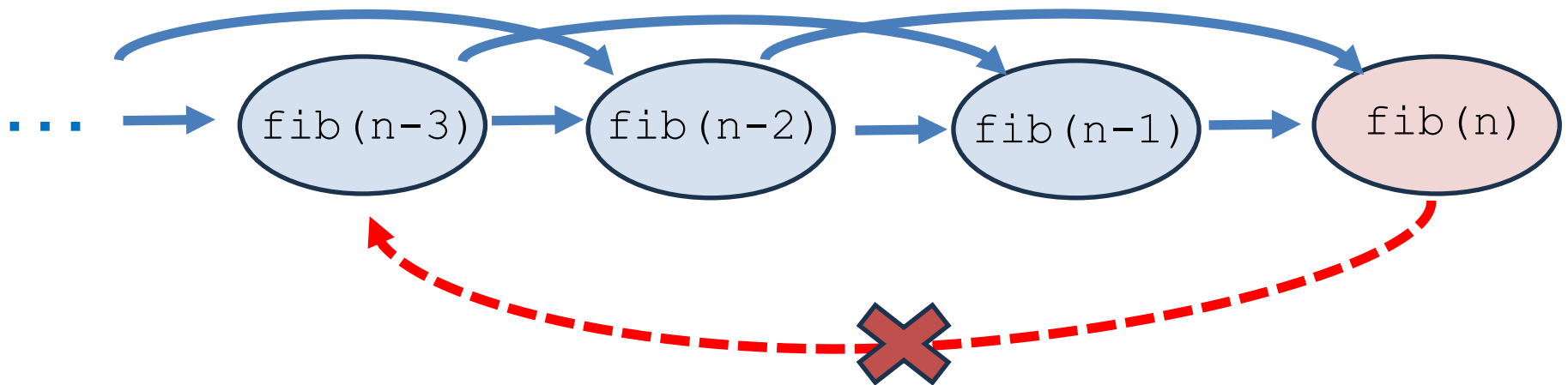
The dependencies of the subproblems must be **acyclic**
→ **Directed Acyclic Graph**



Dynamic programming (intro)

Acyclic Dependencies

The dependencies of the subproblems must be **acyclic** → **Directed Acyclic Graph**

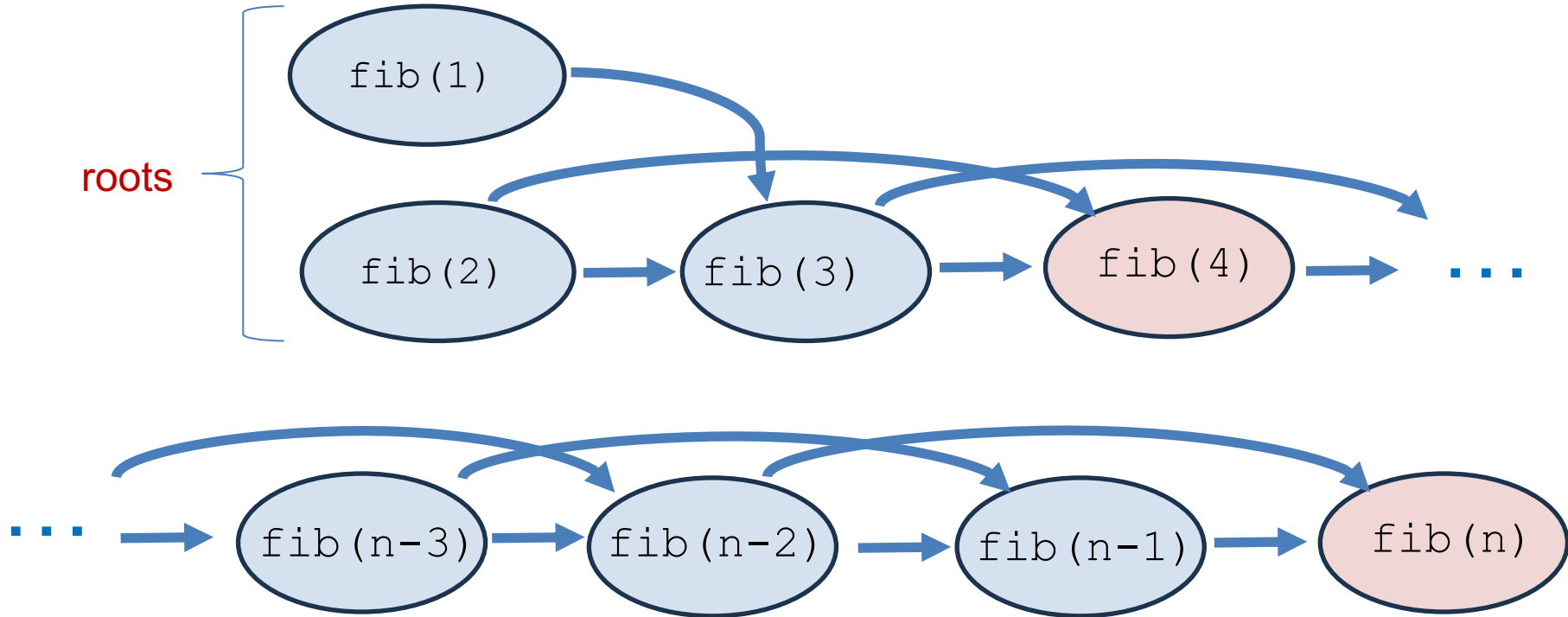


If dependencies has **cycles**, then DP might never converge

Dynamic programming (intro)

Solution

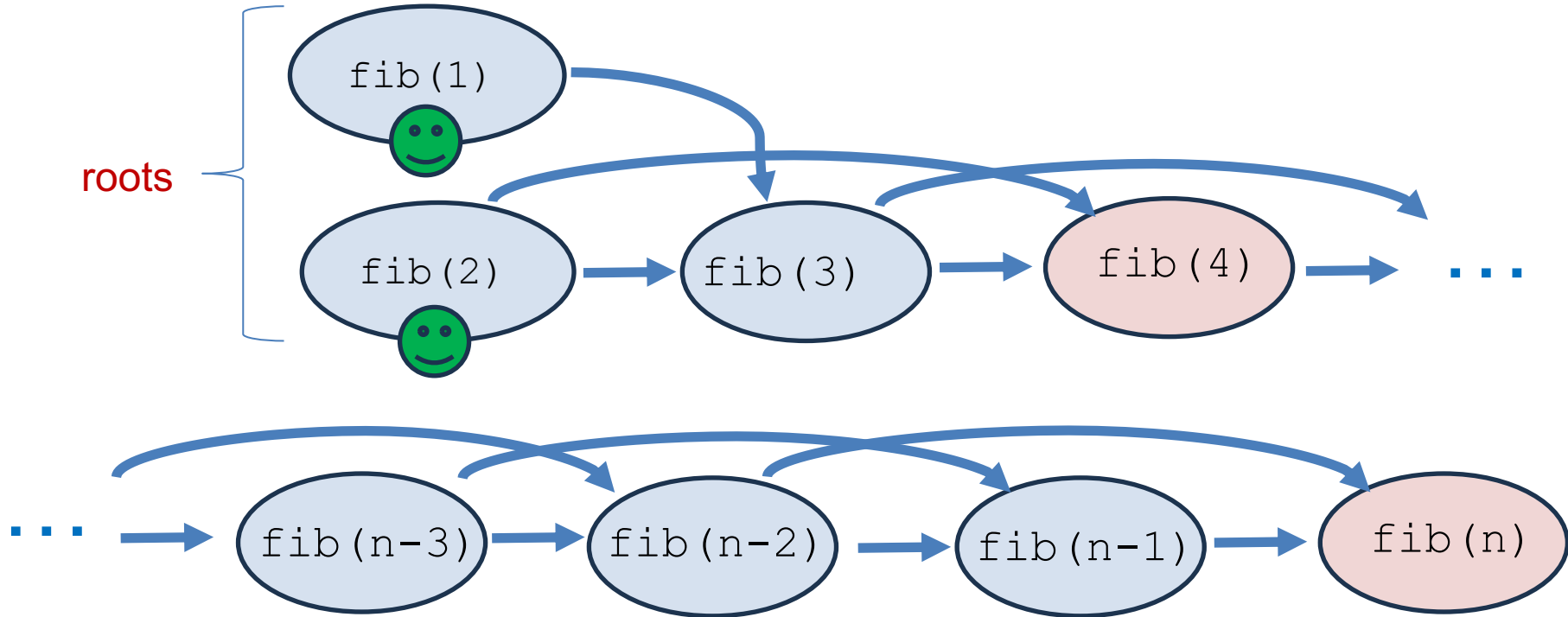
Find the **root(s)** and start **solving recursively** from there:



Dynamic programming (intro)

Solution

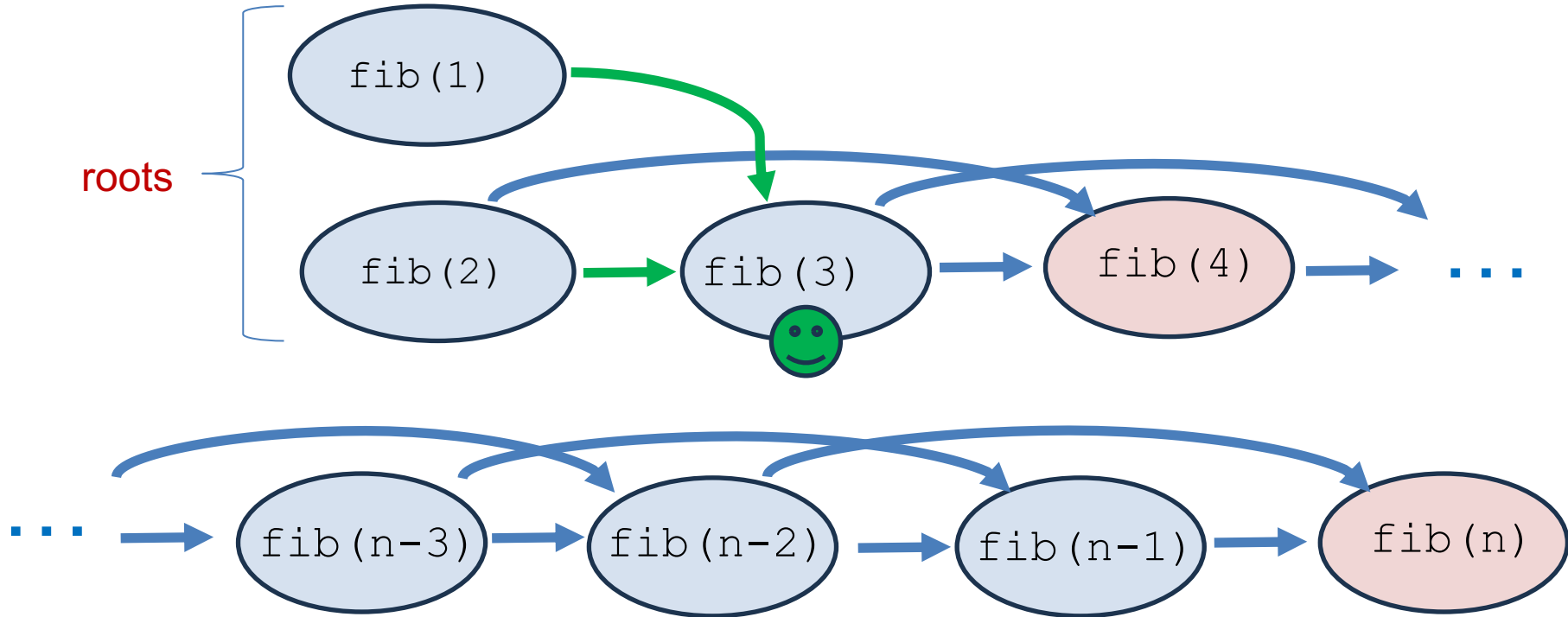
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Dynamic programming (intro)

Solution

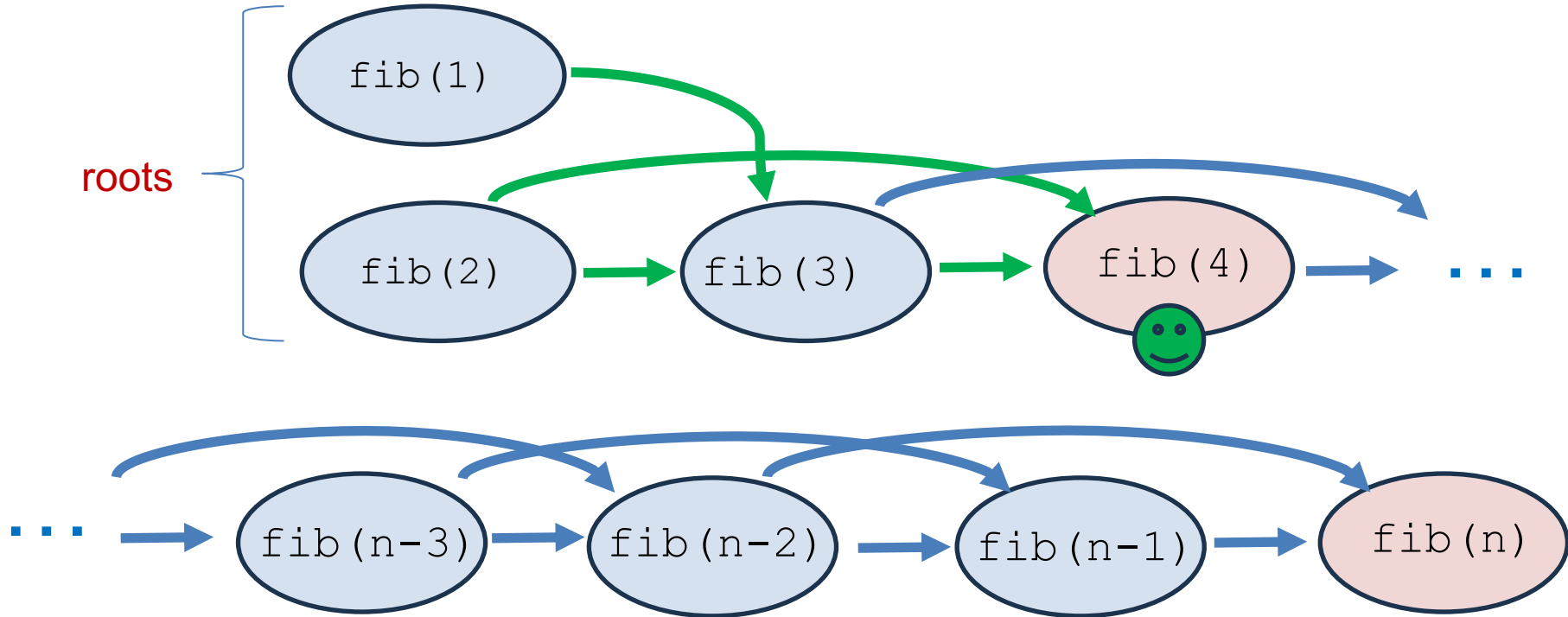
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Dynamic programming (intro)

Solution

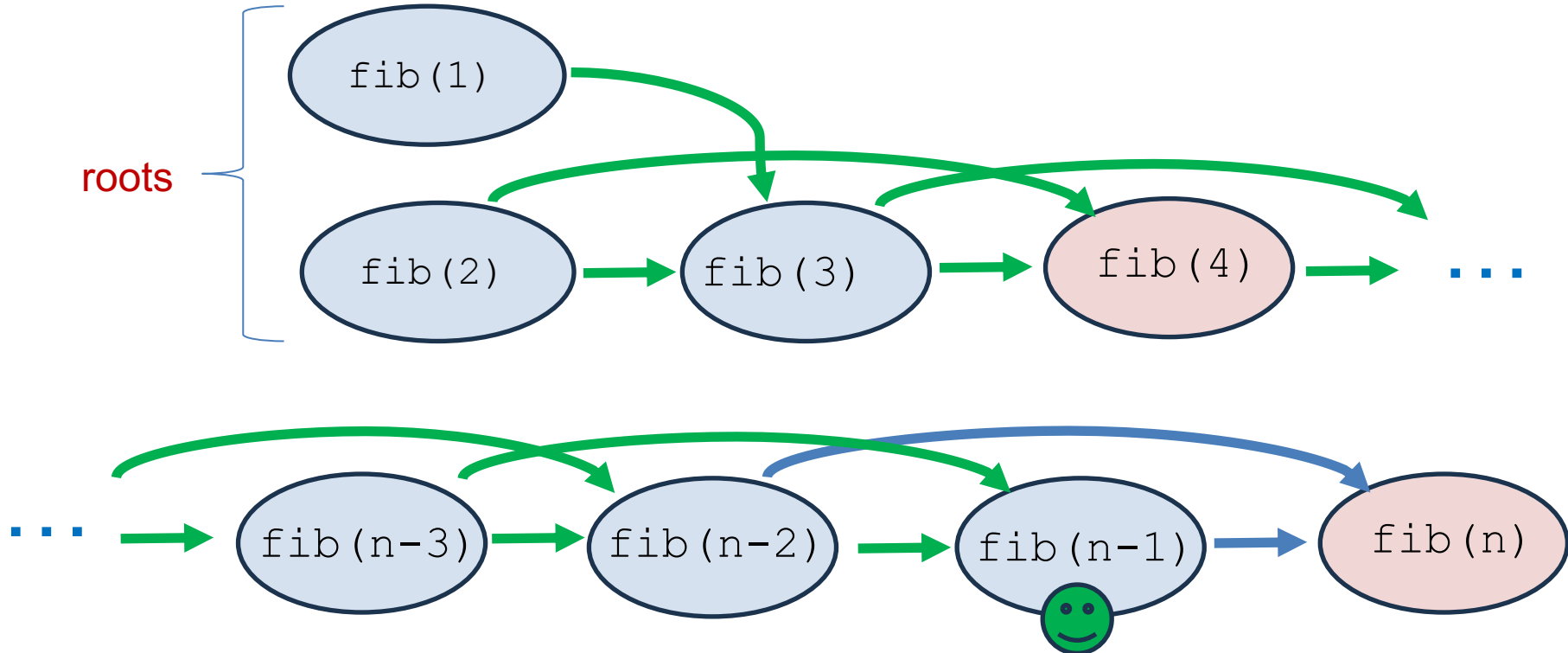
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Dynamic programming (intro)

Solution

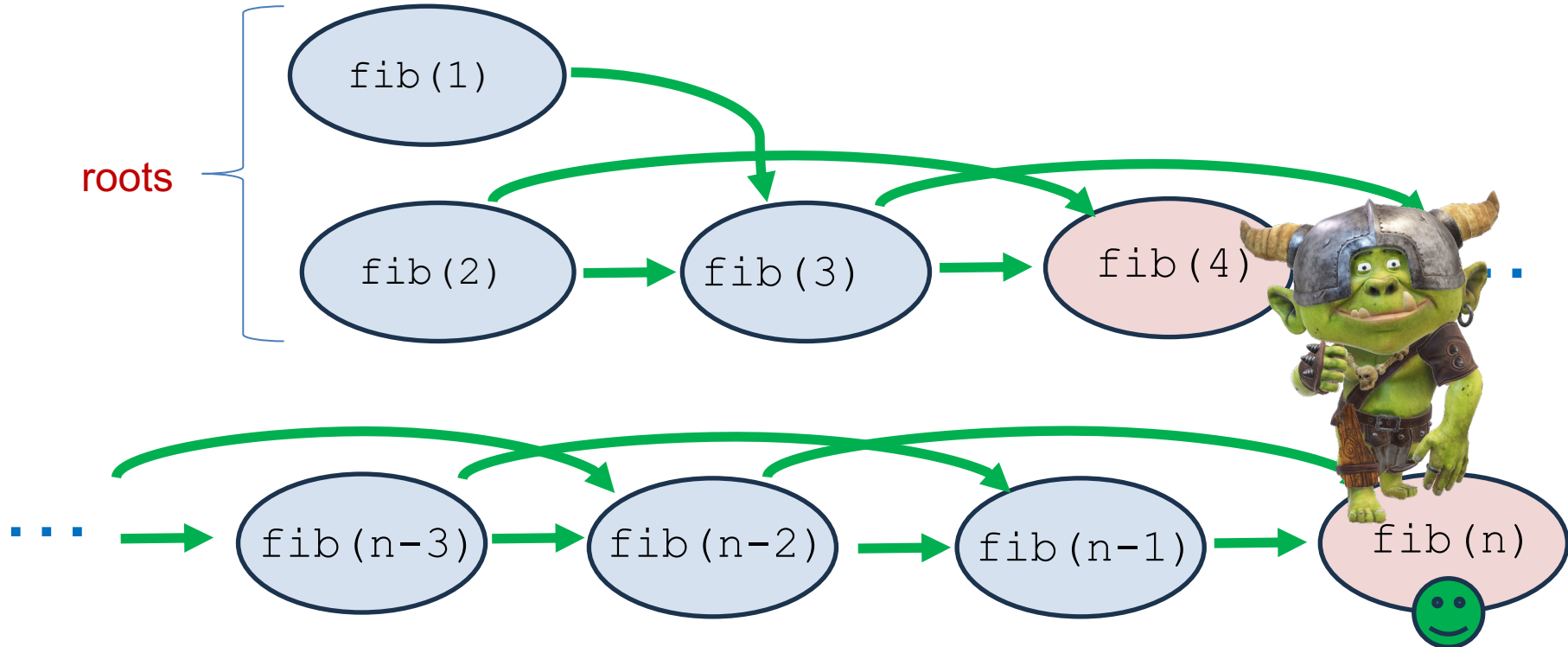
Find the **root(s)** and start **solving recursively** from there:



Dynamic programming (intro)

Solution

Find the **root(s)** and start **solving recursively** from there:



Dynamic programming

Reflecting back

If we have

- Overlapping Subproblems ✓

and

- *Principle of Optimality* holds ✓

and

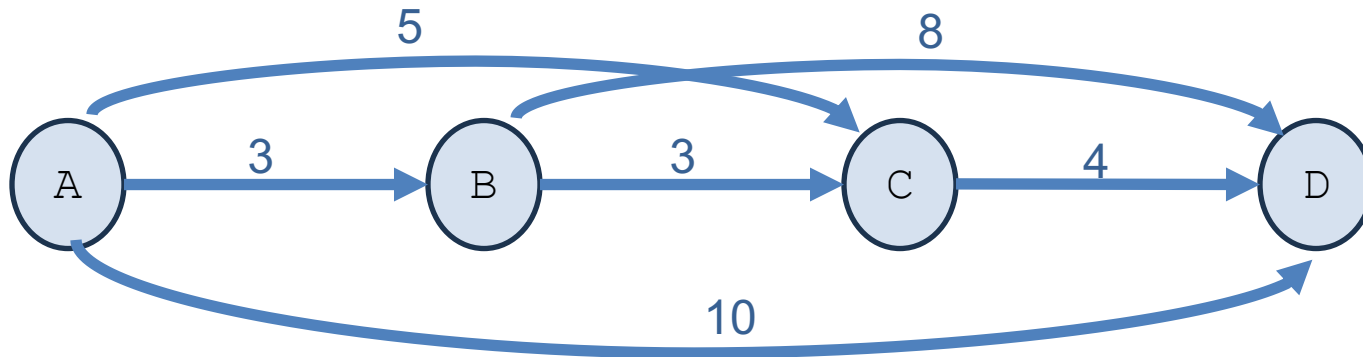
- Dependencies of subproblems are acyclic
(*Directed Acyclic Graph*) ✓

Then the **DP** is the optimal efficient solution!

Application of DP:

Shortest path on Acyclic Directed Graph

Find the shortest path from A to D:

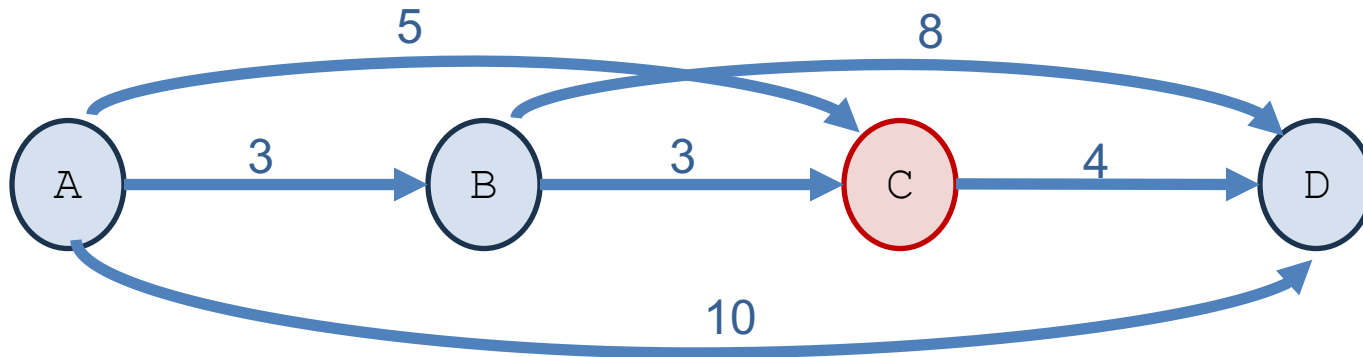


- What are the overlapping subproblems?

Application of DP:

Shortest path on Acyclic Directed Graph

Find the shortest path from A to D:

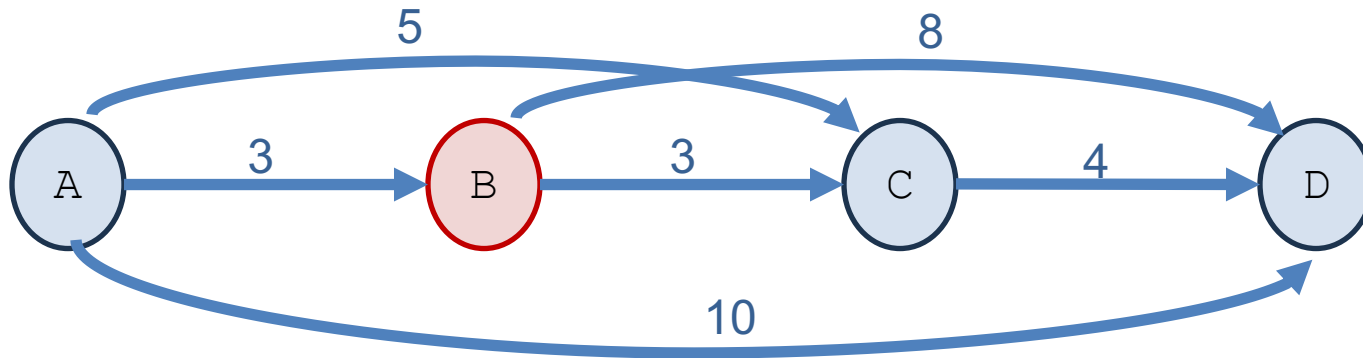


- What are the overlapping subproblems?
 - Optimal path from **first-hop** neighbors of D to D?

Application of DP:

Shortest path on Acyclic Directed Graph

Find the shortest path from A to D:

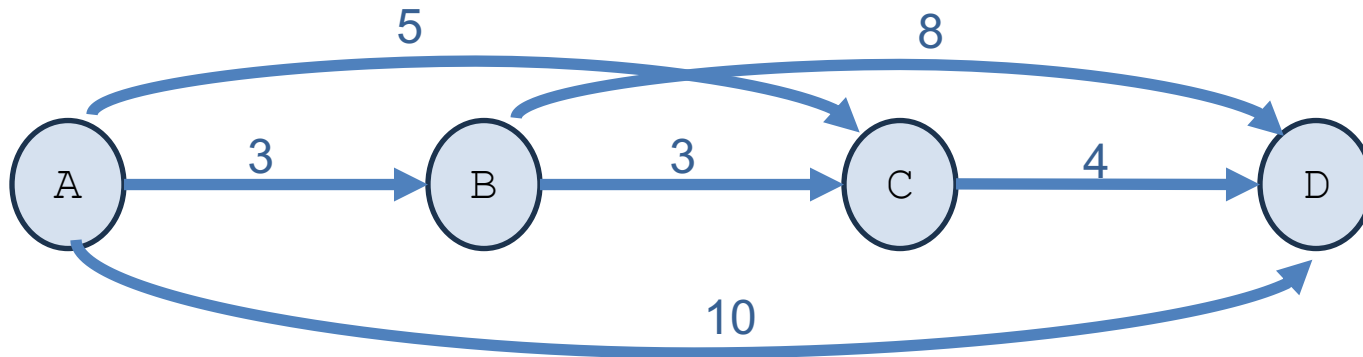


- What are the overlapping subproblems?
 - Optimal path from **first-hop** neighbors of D to D?
 - Optimal path from **second-hop** neighbors of D to D?
 - ...

Application of DP:

Shortest path on Acyclic Directed Graph

Find the shortest path from A to D:

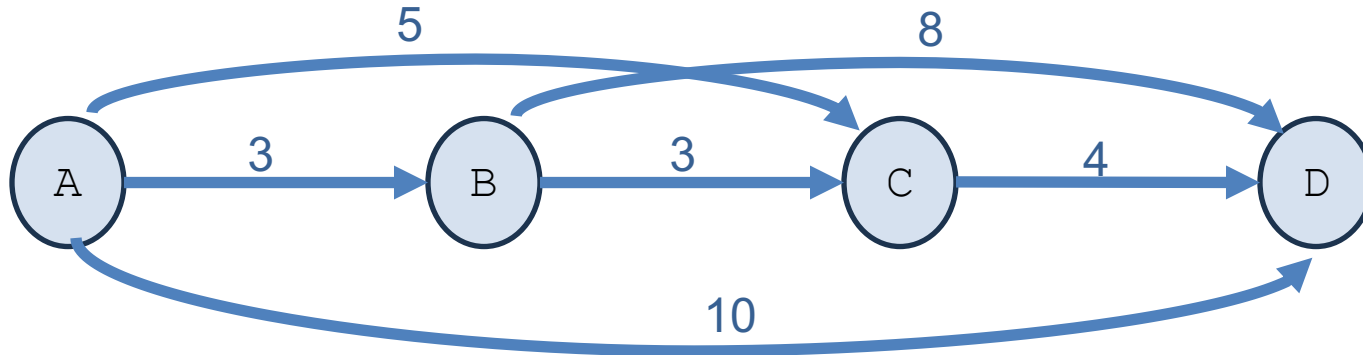


- Does Principle of Optimality hold?

if x is a node on the shortest path $A \dots x \dots D$ from A to D
then $x \dots D$ is also shortest path from x to D

Application of DP:

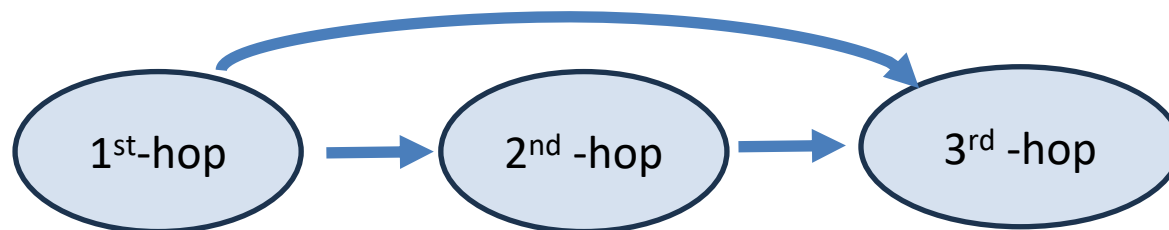
Shortest path on Acyclic Directed Graph



- Are the dependencies acyclic?

Because the graph is acyclic,

the n^{th} -hop neighbor subproblems form an acyclic directed graph

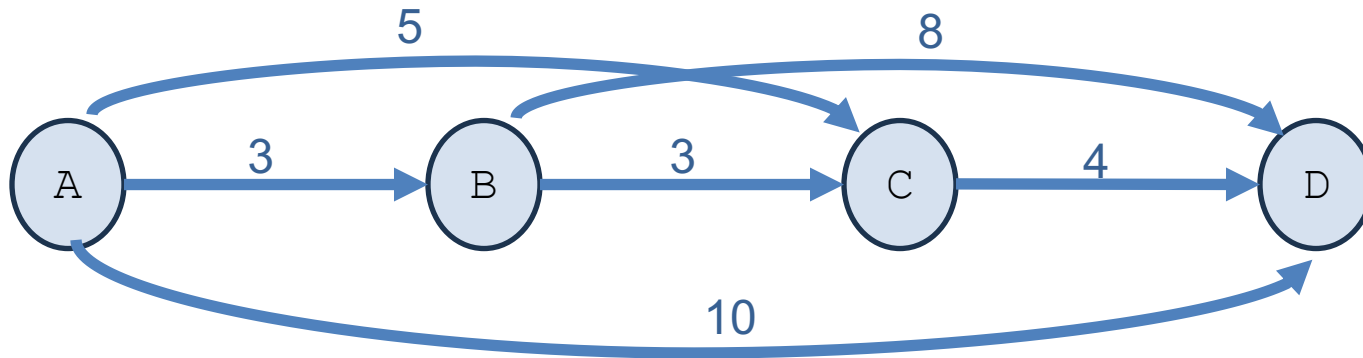


$A \rightarrow D$: 10	$A \rightarrow B \rightarrow D$: 3 + (8)	$A \rightarrow B \rightarrow C \rightarrow D$: 3 + (3 + (4))
$B \rightarrow D$: 8	$A \rightarrow C \rightarrow D$: 5 + (4)	
$C \rightarrow D$: 4	$B \rightarrow C \rightarrow D$: 3 + (4)	

Application of DP:

Shortest path on Acyclic Directed Graph

Find the shortest path from A to D:



- What are the overlapping subproblems?
- Does Principle of Optimality hold?
- Are the dependencies Acyclic?

What if there are also Cycles? **Dijkstra's algorithm**