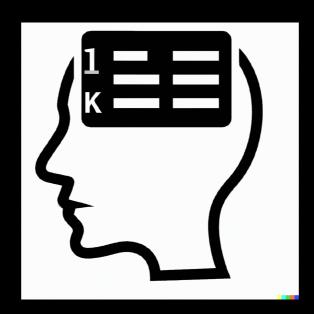
Dynamic Programming



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Today's Plan



Recap

Motivation

Dynamic Programming

Recap

Basic Recursion

May have one or more recursive calls

May reduce the problem by different amounts

Base case implicit or explicit

May or may not return a value

Recursive Backtracking

Recursive call within loop (try all options at this state)
Recursive call returns bool to determine whether current choice lead to solution

Motivation

Recursion

Elegant / Intuitive solution

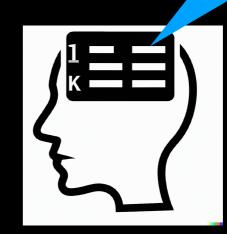
Overhead: repeated work - recursive calls on same subproblems

Solution: Dynamic Programming

Store solution to subproblems

Look-up instead of re-computing

Essentially,
STORE what
you compute
for quick
RETRIEVAL

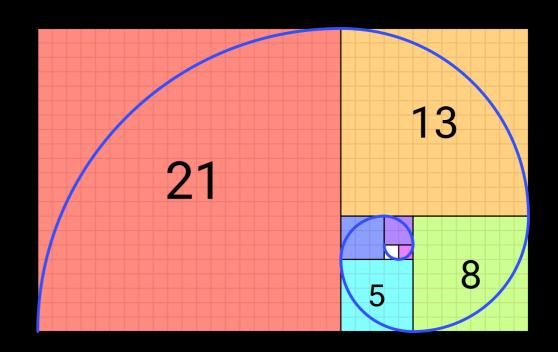


Fibonacci

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

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

With $F_0 = 1$ and $F_1 = 1$

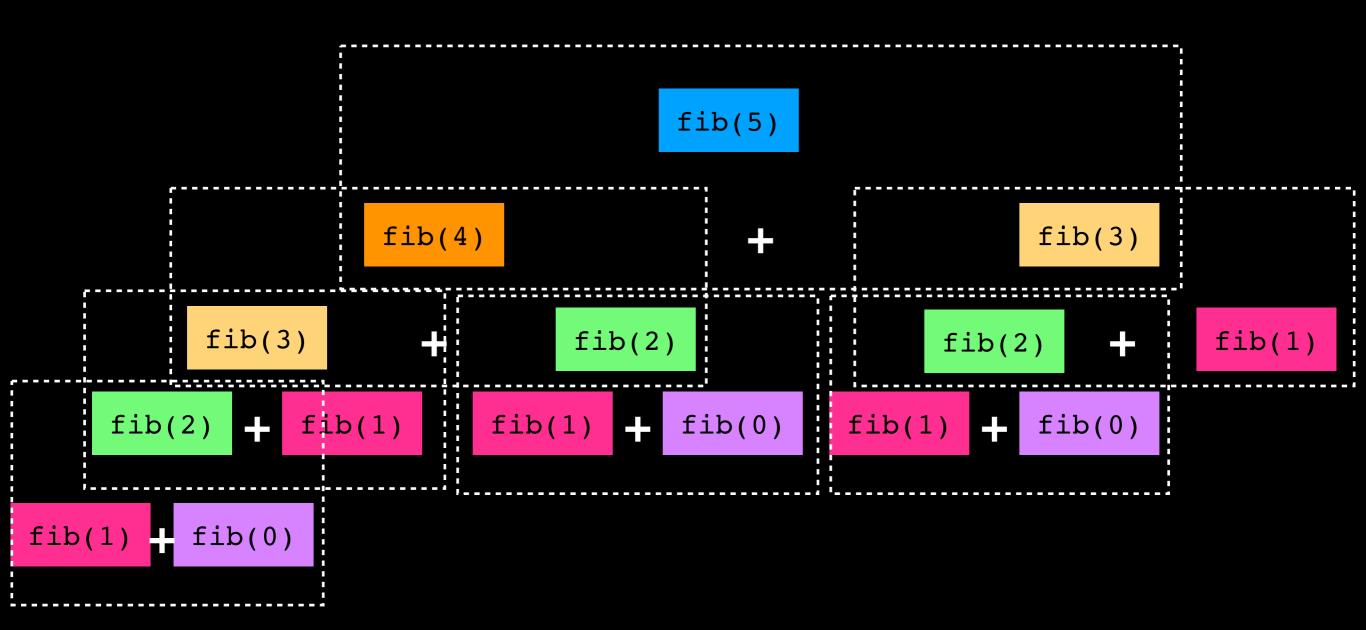


Fibonacci - Recursion

13

```
int fib(int n)
     // Base case
                                    Each fib() calls fib() twice
     if (n <= 1)
                                   T(n) = T(n-1) + T(n-2) + c
          return 1;
                                   T(n) = 2 * 2 * 2 * ... * 2 = 2^n
     // recursive calls
     return fib(n-1) + fib(n-2);
```

Fibonacci - Recursion



Dynamic Programming

Remember instead of Recomputing

Two approaches:

Memoization: recursive approach but compute subproblem only once and store result in table.

Tabulation: unravel problem and compute all subproblems bottom-up, iteratively, and store results in table

Fibonacci - Memoization

```
13
std::vector<int> res(n+1, 0);
//assume table accessible across calls
int fib(int n)
    // base case
    if (n <= 1)
        return 1;
                                       Each fib()computed only ONCE
                                      n fib() computations in total
    if (res[n] != 0) //look-up
                                       Table lookup is constant
        return res[n];
    else { //compute and store
        res[n] = fib(n - 1) + fib(n - 2);
        return res[n];
```

Fibonacci - Memoization

Same logic as recursion

Compute subproblem when encountered

Computes only necessary subproblems

Not all entry in lookup table may be filled in

Still, generally less efficient than iterative solution due to function-call overhead

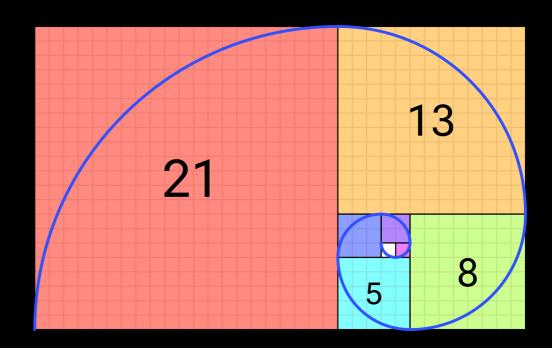
Fibonacci

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

Memoization

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

With $F_0 = 1$ and $F_1 = 1$



Fibonacci

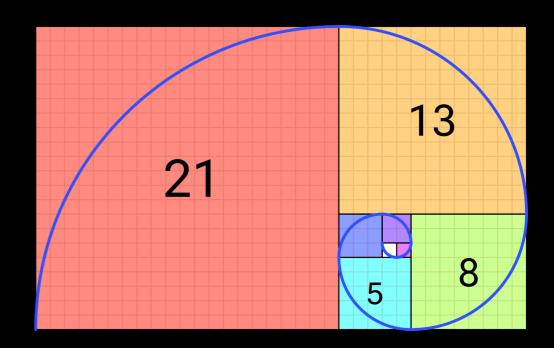


1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 144

Memoization

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

With $F_0 = 1$ and $F_1 = 1$



Fibonacci - Tabulation

```
13
int fib(int n)
    std::vector<int> res = {};
    res.push back(1); //fib(0)
    res.push back(1); //fib(1)
    for(int i = 2; i \le n; i++)
        res.push back(res[i-1] + res[i-2]);
    return res[n];
                                 Bottom-up single iteration
```

Fibonacci - Tabulation

Iterative (not recursive)

Start from smallest problem (base case) and work your way up

Computes ALL subproblems

Look-up table full from smallest (0 or 1) up to n, even if some subproblems are not needed

Dynamic Programming Requirements

When can we apply dynamic programming solutions?

Original problem can be broken down into subproblems

Optimal substructure: optimal solution to subproblems contributes to optimal solution of original problem

When multiple solutions are possible, may not be possible to compute optimal subproblems backwards (difficult to memoize)

Sometimes it may be hard to unravel the problem into a bottom-up iteration (difficult to tabulate)

Imagine traveling from S to E, but no direct path, must make stops in between

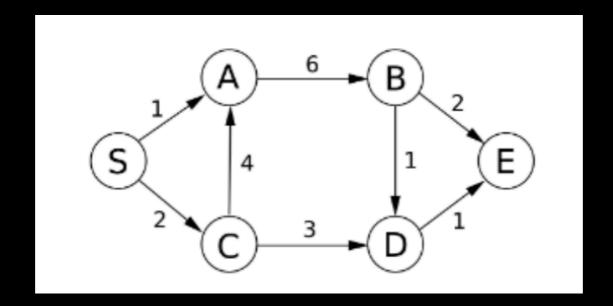
Cost or distance of each direct connection can be calculated

Which sequence (path) is cheapest/shortest?

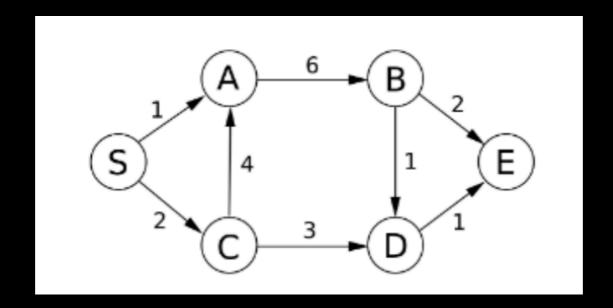
Problem can be represented as a Directed Acyclic Graph (DAG)

Approaches

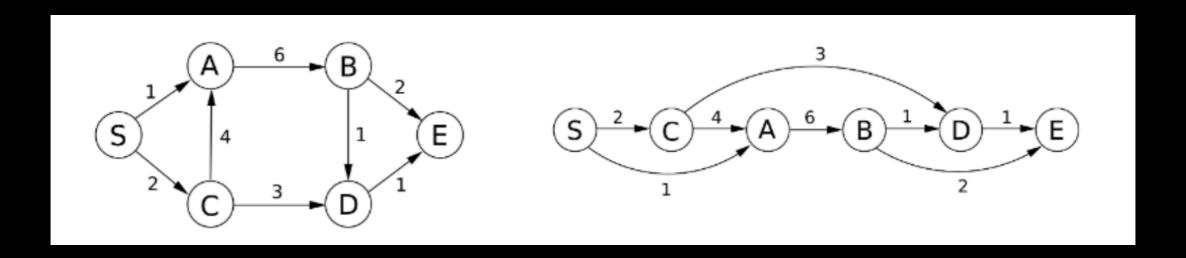
- Exhaustive search: try all paths and choose the best (shortest/cheapest) Exponential
- Greedy Search: start with cheapest route and make cheapest choice at each state. Not guaranteed to find optimal solution
- Can we break it down into subproblems?



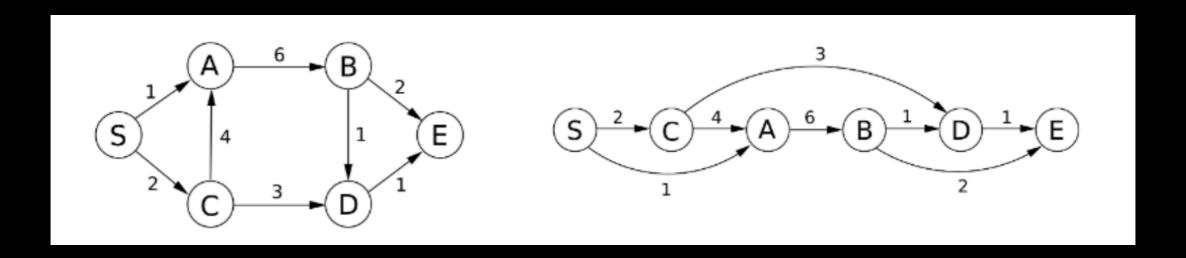
- Dynamic Programming:
 Let d(X,Y) be the distance/cost between nodes X and Y
 Subproblems: sol(S) = min{sol(A) + d(S,A),
 sol(C) + d(S,C)}
- Recursively this too is exponential, not guaranteed to have many repeated subproblems to exploit



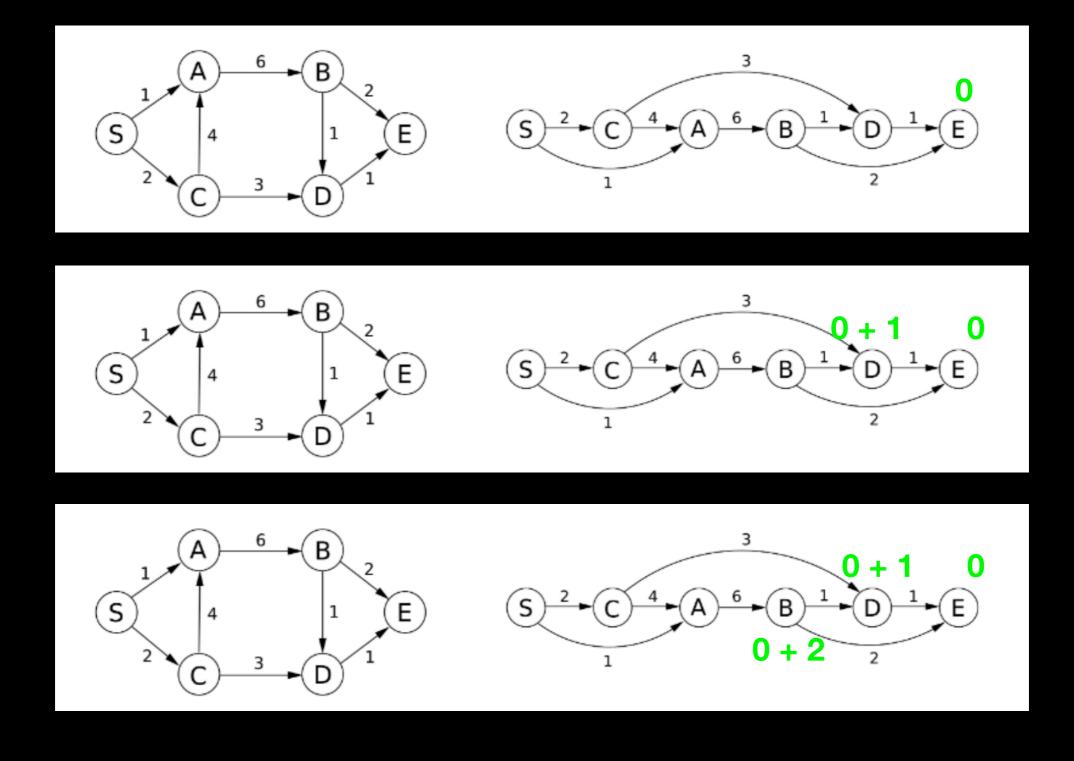
- Dynamic Programming:
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 Subproblems: sol(S) = min{sol(A) + d(S,A),
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- Recursively this too is exponential, Memoization not guaranteed to have many repeated subproblems to exploit



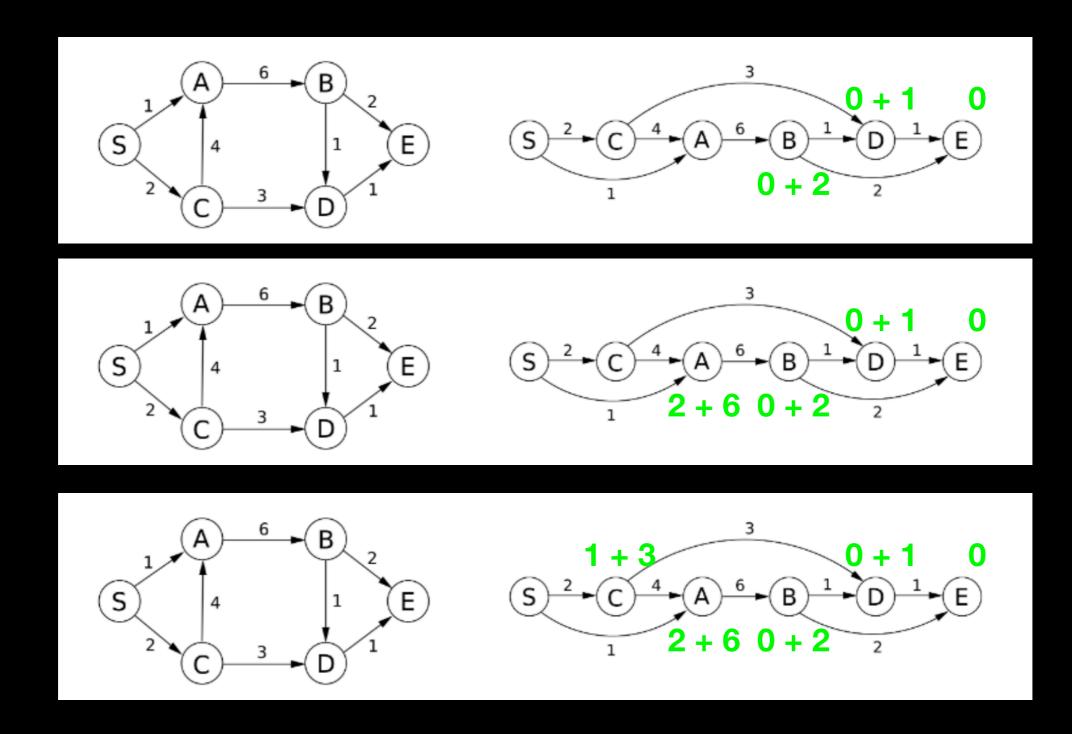
- Dynamic Programming:
 Let d(X,Y) be the distance/cost between nodes X and Y
 Subproblems: sol(S) = min{sol(A) + d(S,A),
 sol(C) + d(S,C)}
- Tabulation: fill out table starting from smaller subproblem



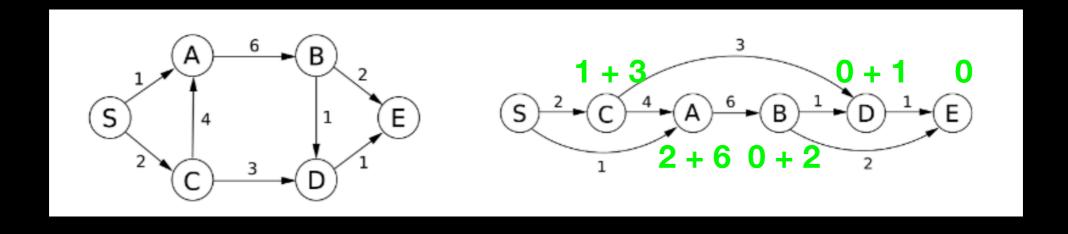
 $sol(S) = min{sol(A) + d(S,A), sol(C) + d(S,C)}$

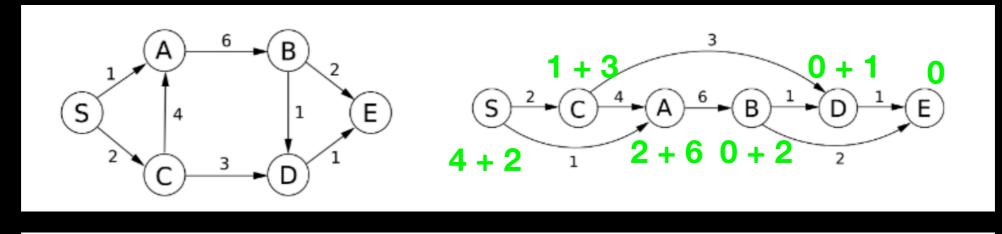


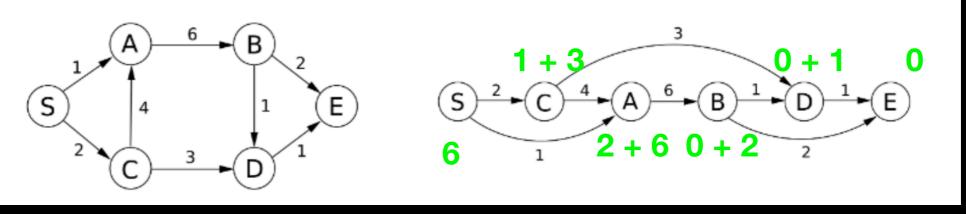
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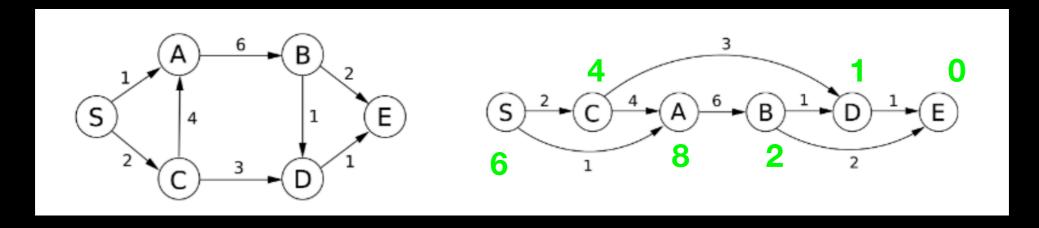
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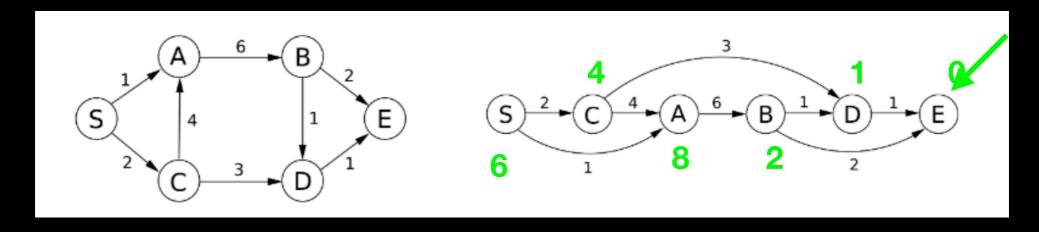


Adjacency Matrix

	S	С	Α	В	D	E
S	0	2	1	-1	-1	-1
С	-1	0	4	-1	3	-1
Α	-1	-1	0	6	-1	-1
В	-1	-1	-1	0	1	2
D	-1	-1	-1	-1	0	1
Е	-1	-1	-1	-1	-1	0

No negative edges. -1 means no edge.

 $sol(S) = min{sol(A) + d(S,A), sol(C) + d(S,C)}$

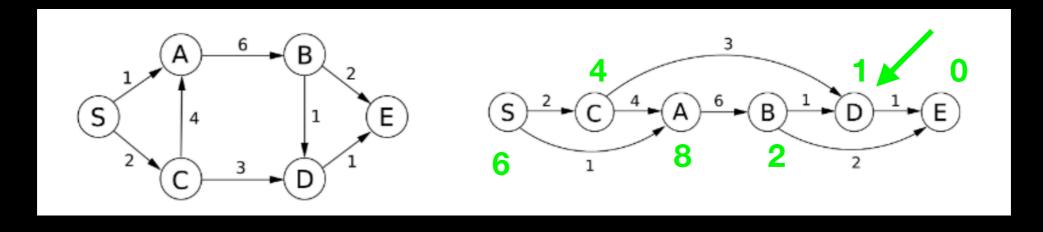


Adjacency Matrix

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S	0	2	1	-1	-1	-1
С	-1	0	4	-1	3	-1
Α	-1	-1	0	6	-1	-1
В	-1	-1	-1	0	1	2
D	-1	-1	-1	-1	0	1
E	-1	-1	-1	-1	-1	0

	S	С	Α	В	D	Е
Sp						0

 $sol(S) = min{sol(A) + d(S,A), sol(C) + d(S,C)}$

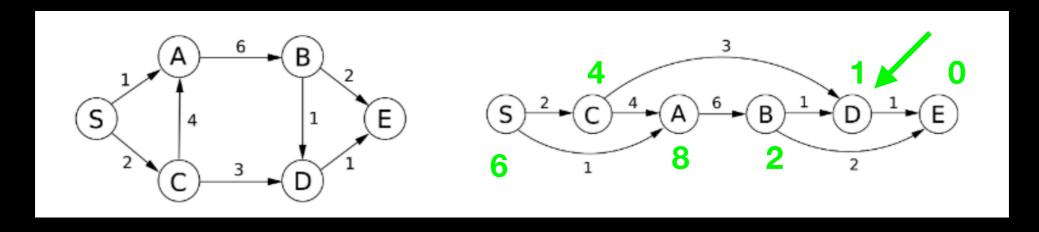


Adjacency Matrix

	S	С	Α	В	D	Ε
S	0	2	1	-1	-1	-1
С	-1	0	4	-1	3	-1
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В	-1	-1	-1	0	1	2
D	-1	-1	-1	-1	0	1
E	-1	-1	-1	-1	-1	0

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Sp						0

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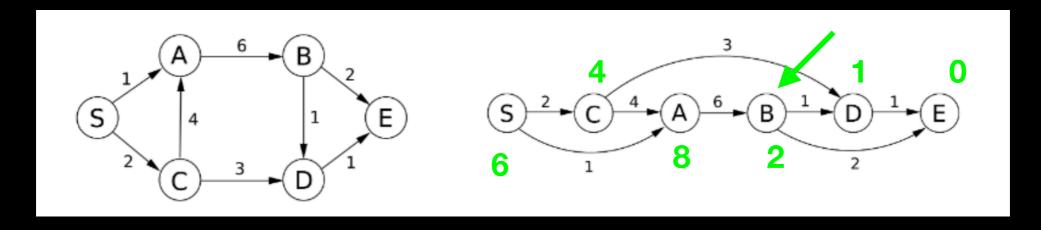


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В	-1	-1	-1	0	1	2
D	-1	-1	-1	-1	0	1
Ε	-1	-1	-1	-1	-1	0

	S	С	A	В	D	Е
Sp					1	0

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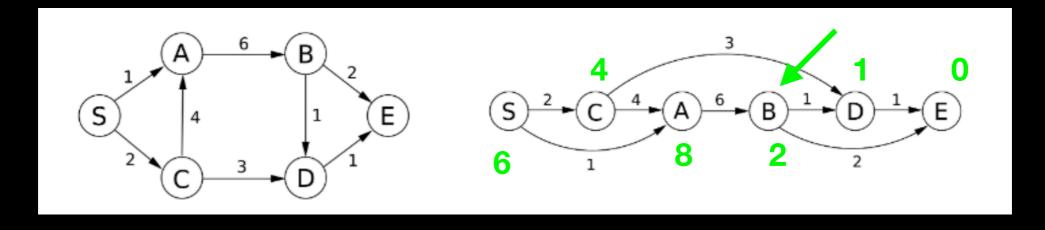


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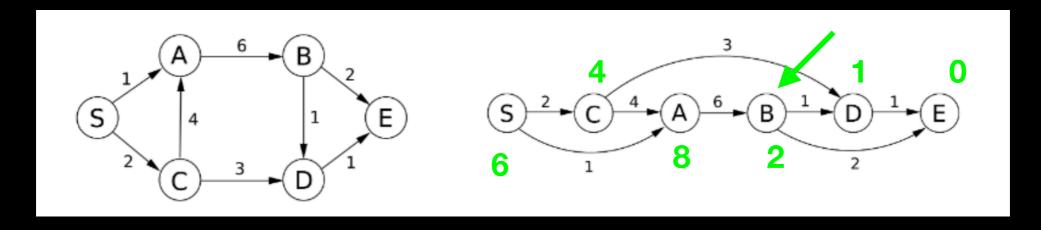


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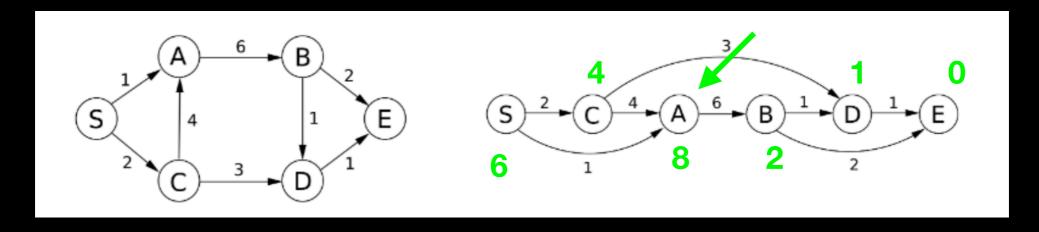


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В	-1	-1	-1	0	1	2
D	-1	-1	-1	-1	0	1
E	-1	-1	-1	-1	-1	0

	S	С	Α	В	D	Е
Sp				2	1	0

 $sol(S) = min{sol(A) + d(S,A), sol(C) + d(S,C)}$

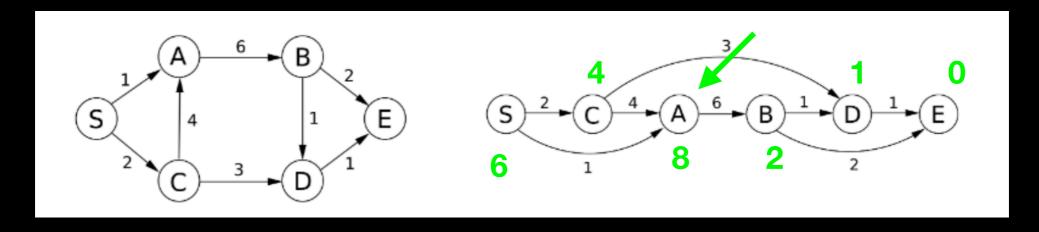


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Sp				2	1	0

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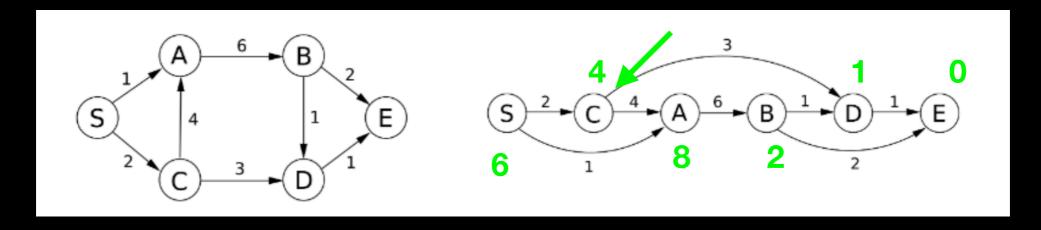


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В	-1	-1	-1	0	1	2
D	-1	-1	-1	-1	0	1
Е	-1	-1	-1	-1	-1	0

	S	С	Α	В	D	Е
Sp			8	2	1	0

 $sol(S) = min{sol(A) + d(S,A), sol(C) + d(S,C)}$

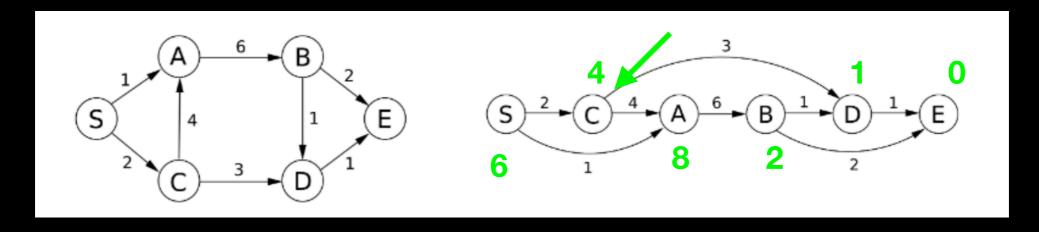


Adjacency Matrix

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В	-1	-1	-1	0	1	2
D	-1	-1	-1	-1	0	1
Е	-1	-1	-1	-1	-1	0

	S	С	Α	В	D	Ε
Sp			8	2	1	0

 $sol(S) = min{sol(A) + d(S,A), sol(C) + d(S,C)}$

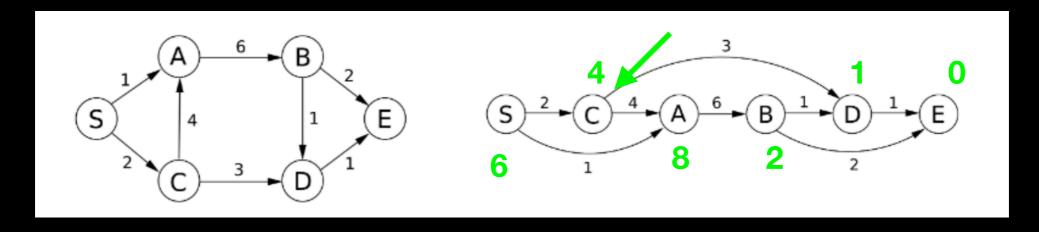


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D	-1	-1	-1	-1	0	1
E	-1	-1	-1	-1	-1	0

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Sp			8	2	1	0

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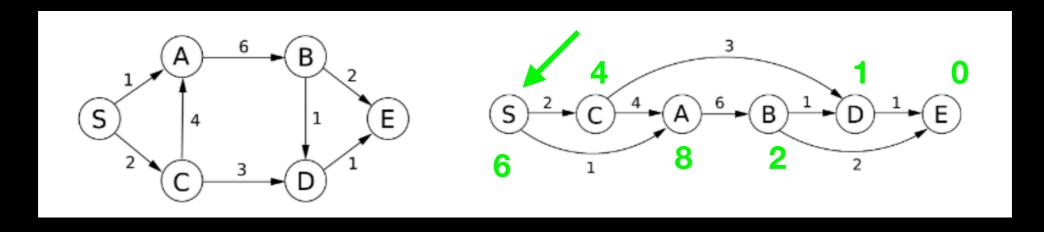


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В	-1	-1	-1	0	1	2
D	-1	-1	-1	-1	0	1
Е	-1	-1	-1	-1	-1	0

	S	С	Α	В	D	E
Sp		4	8	2	1	0

 $sol(S) = min{sol(A) + d(S,A), sol(C) + d(S,C)}$

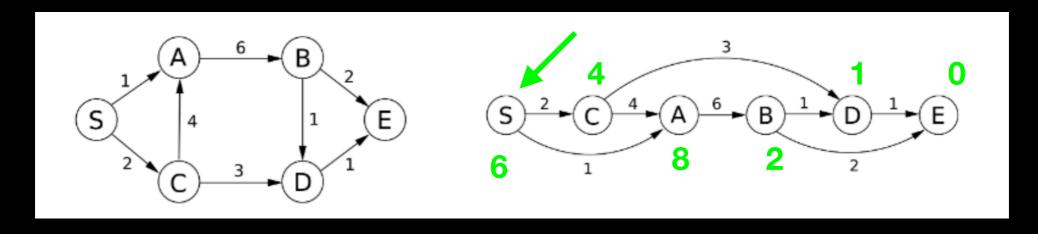


Adjacency Matrix

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Α	-1	-1	0	6	-1	-1
В	-1	-1	-1	0	1	2
D	-1	-1	-1	-1	0	1
E	-1	-1	-1	-1	-1	0

	S	С	A	В	D	Е
Sp		4	8	2	1	0

 $sol(S) = min{sol(A) + d(S,A), sol(C) + d(S,C)}$

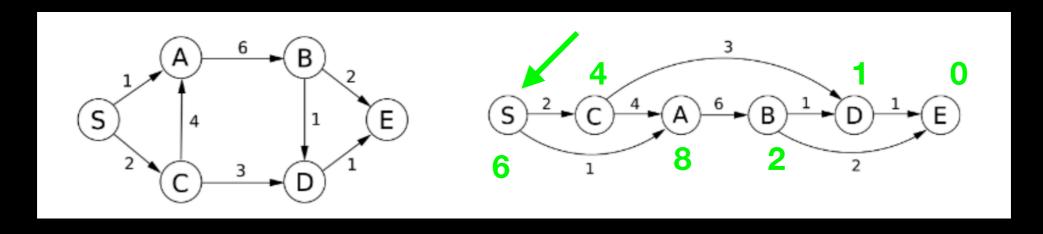


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E	-1	-1	-1	-1	-1	0

	S	С	Α	В	D	Е
Sp		4	8	2	1	0

 $sol(S) = min{sol(A) + d(S,A), sol(C) + d(S,C)}$

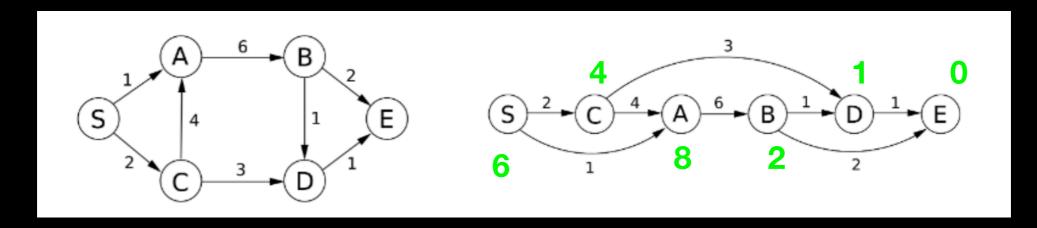


Adjacency Matrix

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D	-1	-1	-1	-1	0	1
E	-1	-1	-1	-1	-1	0

	S	С	Α	В	D	Е
Sp	6	4	8	2	1	0

 $sol(S) = min{sol(A) + d(S,A), sol(C) + d(S,C)}$



Adjacency Matrix

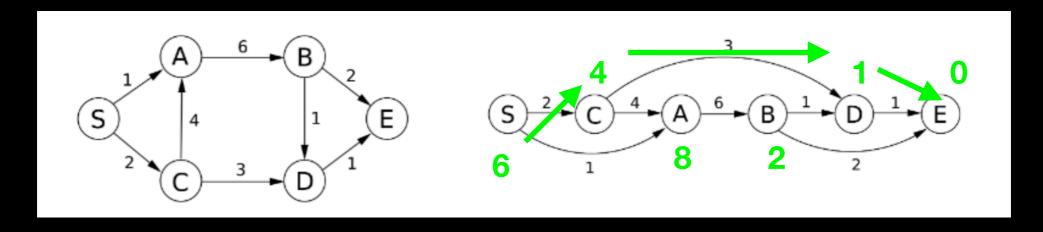
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В	-1	-1	-1	0	1	2
D	-1	-1	-1	-1	0	1
ш	-1	-1	-1	-1	-1	0

Shortest Path

	S	С	Α	В	D	Е
Sp	6 _	_4_	8	2		0

Cost of shortest path

 $sol(S) = min{sol(A) + d(S,A), sol(C) + d(S,C)}$



Adjacency Matrix

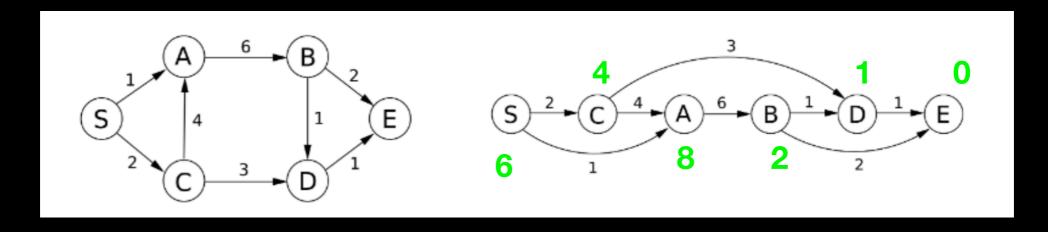
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Е	-1	-1	-1	-1	-1	0

Shortest Path

	S	С	Α	В	D	Е
Sp	6	4	8	2	1	0

Using adjacency matrix AND shortest path table, follow cheapest neighbor+edge (not cheapest edge)

 $sol(S) = min{sol(A) + d(S,A), sol(C) + d(S,C)}$



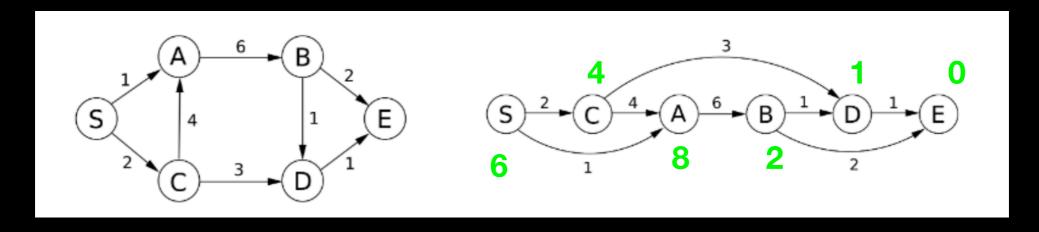
Adjacency Matrix

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В	-1	-1	-1	0	1	2
D	-1	-1	-1	-1	0	1
E	-1	-1	-1	-1	-1	0

	S	С	Α	В	D	Е
Sp	6	4	8	2	1	0



 $sol(S) = min{sol(A) + d(S,A), sol(C) + d(S,C)}$



Adjacency Matrix

	S	С	Α	В	D	E
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D	-1	-1	-1	-1	0	1
Ε	-1	-1	-1	-1	-1	0

	S	С	Α	В	D	Е
Sp	6	4	8	2	1	0

